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Abstract.

In the 21st century agriculture has the unique responsibility to provide food, fuel, fiber and feed for the growing population under the stress of climate change and diminishing natural resources. This is a feat that will take considerable change to the sustainability of such practices. One such feat is the idea of assessing phenotypic expression of complex traits in response to environmental factors. This idea elevates the use of phenotyping and proximal remote sensing to quantitatively monitor nitrogen (N) stress throughout the growing season in irrigated and rainfed production systems. Therefore, the purpose of this study is to conduct a preliminary analysis that leverages the NU-Spidercam, field phenotyping facility, to explore the performance of N management techniques. The study was located at the Eastern Nebraska Research, Extension, and Education Center, near Mead, NE and consisted of two experiments in the years 2022 and 2023. The experiments consisted of irrigated and rainfed plots that received varying rates of N fertilizer to simulate a control, split, and full rate (2022: 0N, 80/80N, 200N; 2023: 0N, 50/100N, 150N). Data collected at the NU-Spidercam facility came from three major components: an automated cable-suspended sensing platform, Subsurface Drip Irrigation (SDI) system, and an onsite weather station. The sensors relevant to this study included a multispectral (Visible Near-Infrared, VNIR) camera, a VNIR spectrometer coupled with a bifurcating fiber optical cable, and a LIDAR (Light Detection and Ranging) sensor. These sensors captured plot scale crop canopy data used in this study. Canopy height was calculated from LiDAR point clouds by subtracting the distance from the sensor to canopy from the distance from the sensor to the ground. The vegetation index, NDVI-Red Edge (790/730 nm) was calculated from the incoming and canopy-reflected solar irradiance. In this study, it serves as a standard spectral trait for canopy conditions throughout the growing season. The focus of this preliminary analysis on the effect of N rate in irrigated and rainfed maize production on plant health and physical trait assessment. The weather-related patterns in 2022 and 2023 including air temperature, total rainfall, and shortwave solar radiation were summarized. The mean grain yield for each treatment from the two experiments assess the difference in yield for each nitrogen rate x water combination.

Keywords.

Field phenotyping, Stress, Nitrogen, technology, precision management, sustainability

Main Body

In the 21st century agriculture has the unique responsibility to provide food, fuel, fiber and feed for the growing population under the stress of climate change and diminishing natural resources. Therefore, the development of management practices balancing both practicality and sustainability are instrumental to the present and future challenges in agriculture. The rise of enhancing technology for sustainable purposes is one of the fore fronting drivers of the digital agriculture movement.

Digital agriculture, otherwise known as “Smart Farming,” is defined as the use of data-driven technologies to aid in precise, site-specific decision making for agricultural producers (Wolfert, S., et al., 2017). These technologies include but are not limited to sensors, GPS, drones, robotics, Internet of Things (IOT), artificial intelligence (AI), and decision support systems. The emphasis on leveraging such technology with agricultural production is to boost global food production, improve productivity, and potentially ease the pressures of resource demand (Wolfert et al., 2017; Walter et al., 2017; MacPherson et al., 2022). Regarding improving resource management techniques, advancements in technology could provide more precise methods for deciphering timing and stress detection across varying environments.

Therefore, with nutrients playing a critical role in agricultural production, the management of such practices has become more influential now than ever before. The concept of sustainable nutrient management, especially nitrogen (N) as a crop input, has been studied for over half a century (Holland, K. H., & Schepers, J. S., 2010). In the corn belt, N is categorized as an essential crop nutrient for corn production. In the last 40 years, data has shown a positive correlation between rising crop yields and increased use of fertilizers including N inputs (Kirk Hall, P., 2016). However, many areas within the corn belt are facing issues with the over application of N inputs in annual row crop production. The issue of over-application is important, environmentally and economically. Both of which are the current main driving forces for sustainable practices at the field level regarding N management.

From an environmental perspective, the role of nutrient management is more complex than simply applying less; it must consider its effect on an entire ecosystem of interactions. The introduction of nutrients, such as N, will impact and will continue to impact the overall health and ecosystem of soil as an interactive environment. Factors that can be impacted but are not limited to soil health, spatial properties, the microbial environment, the hydrological cycle, water quality, and temporal weather patterns. Therefore, when these factors are not considered in management plans for cropping systems, environmental issues will present themselves. Classic examples of such are natural bodies of water, the Gulf of Mexico, where the over application of N fertilizers has led to hypoxic zones (Franzen, D., et al., 2016).

In Nebraska, a major environmental concern in the last several decades is the contribution of increased ground water nitrate (NO_3^-)) levels due to the over application of N (Schepers, J. S., et al., 1997). It has become a public health issue as contaminated groundwater has reached unsafe levels (> 10 mg—N per liter) for drinking water. The consumption of high nitrate levels from groundwater has since been linked to methemoglobinemia and increased risk of cancer development (Ward, M. H., et al., 2018).

Economically, the cost of crop inputs for producers continues to rise across the corn belt now more than ever. Therefore, these conditions have encouraged the adoption of the most efficient practices to reduce a producers input costs (Lory, J. A., & Scharf, P. C., 2003; Zhang et al., 2015). In consideration, the priorities of N management in recent years are to reduce environmental impact and increase profitability. Therefore, it has been suggested that producers try to identify and incorporate an Economic Optimum N Rate (EONR). EONR is defined as the rate at which crop yield rises, yet not large enough to cover the cost of additional N (Miguez, F. E., & Poffenbarger, H., 2022). Thismethodology would allow producers to minimize N losses, optimize yield, and profit for their operation. Therefore, to assess the success of N optimization, the concept of quantifying a producers N Use Efficiency (NUE), a comparison of applied synthetic N fertilizer, and grain yield (Teten, S. L., 2021), has since been incorporated to understand the efficiency of such practices around N rates, application timing, and technology-based methods.

However, agriculture production does come with certain challenges in determining the economic optimum N rate. A substantial one being in rainfed sites, where the variable rainfall creates a dynamic of both temporal and spatial variability (Teten, S. L., 2021). The quantification of N within an agricultural system is also problematic since it is needed in such high demand and is influenced by environmental interactions leading to loss within the system. Therefore, with the digitalization of agriculture and the integration of a multitude of high-resolution data layers, site specific management can be improved upon for both irrigated and rainfed environments.

In consideration to these production systems, the assessment of plant health via stress manifestation by current technology within production systems is of much concern. As for nutrient management the quantification of abiotic stress is often broken down into questions of when and how. When is the critical timing of nutrient application and how does the rate of nutrient used affect stress manifestation over time. The next question is how does the management practices of choice impact stress over time. Currently, these questions have been approached by incorporating a variety of sensors to quantify plant health over time.

The use of sensor-based N management techniques is one way to incorporate the assessment of N demand at the plant level across a field site. This involves the agronomic application of canopy reflectance to correlate with leaf pigmentation as an indicator of plant properties from an optical perspective (Gausman, H. W., et al., 1975). These types of methodologies often incorporate vegetation indices (VIs) as indicators of plant health metrics. There have been many advancements of these methods to quantify N stress at the field scale. A prominent example of such is the development of multispectral remote sensing via unmanned aerial vehicles (UAVs) to provide real-time N status and detection of N stress in crop systems (Cai, Y., et al., 2019).

It is important in the deployment of these techniques to best understand the interactions between N and water in both irrigated and rainfed production systems.

However, challenges to these systems are,

- A system that involves the coupling of physiological aspects with the remote sensing techniques.
- Reliance of vegetative issues that do not precisely assess the N and water stress relationship.
- How does the physiological perspectives impact stress
- More precisely account for the stress in irrigated and non-irrigated production.

In Nebraska alone, there are 5.278 million irrigated acres and 4.022 million rainfed acres dedicated to corn production recorded in 2017 (N.A., Accessed 2024). Given the influence of both cropping systems on state and global corn production, it is essential to provide managed plans that are designed to uphold precision and account for the environmental factors that play a vital role in nutrient interactions. This concept has long been researched within the past decade and is making vast strides with the continued development of technology-based applications. These applications have been incorporating plant phenomics with the goal of precise cultivation. Plant phenomics was designed to incorporate finer methods of inspection of high-dimensional phenotypic data relating genes and desirable traits for plant growth, performance, and composition (Tao, H., et al., 2022). Therefore, phenotyping capabilities and methods have since appealed to the development of precise cultivation methods. The idea is to leverage plant phenotyping's ability to generate data that is of high-throughput, accurate, repeatable, and novel acquisition technologies (Tao, H., et al., 2022).

Phenotyping and remote sensing in a combined effort will modernize the relationship between phenotypic characteristics and the given environment. Remote sensing technology is defined as the acquisition of information without contact (Navalgund, R. R., et al., 2027). This type of data collected via sensors can be both quantitative and qualitative regarding plant characteristics. In the field of plant phenotyping, the collection of proximal and remote sensing data has become a fitting implement for nondestructive and repeatable measures. This allows for data to be collected across spatial, temporal, and spectral scales further increasing the dimensionality of phenotyping data (Tao, H., et al., 2022).

The evaluation of management practices under a system that utilizes phenotypic data collection and proximal remote sensing will quantify the effect of said practices on plant traits. Likely, the plant traits contribute to production and resource use efficiency at the interaction of plant growth given the environment (Machwitz, M., et al., 2021). In context to resource management, the phenotypic data collected gives insight into the target traits that remote sensing tools have been developed for. Therefore, this insight will likely allow the tools to be improved upon creating more sensitive and precise tools. The intersection of these two fields of science is demonstrated by RTMS models, developed by the remote sensing community, that have the capabilities to account for non-parametric models designed for uncertainty estimation in N concentration estimates (Berger, K., et al., 2022) developed from information on plant physiology and phenotyping.

The use of phenotyping techniques coupled with proximal remote sensing for resource managed would likely advance the assessment of nutrient induced abiotic stress within the field site. A study of such has been conducted regarding field-based scoring of soybean iron deficiency chlorosis. The study leveraged RGB imaging collected via a high-throughput field phenotyping platform to process images, in real time, and computer scoring for IDC symptomatology identification. The focus of iron induced chlorotic pronunciation in soybeans occurs with distinct color changes in the leaves at a specific growth stage. Therefore, the capturing of Red Green Blue (RGB) images allows for the capabilities to extract color-based information to automate the IDC scoring for severity of stress manifestation within a field site (Bai, G., et al., 2018). An approach that assesses abiotic stress utilizing both remote sensing and plant phenotyping improves productivity and accuracy for IDC screening.

A study of such elevates plant phenotyping as a diagnostic tool for identifying plant stress. In assessing plant health issues with plant phenotyping in conjunction with remote sensing has the potential to assess the adaptability of plant species to various abiotic stresses. How this adaptability is assessed over time in varying environments is an advantage of this system. These concepts are explored in the following context to the precise management of N inputs in irrigated and rainfed maize production systems in Nebraska. Therefore, the objective of this study include the use of high volume, multifaceted data to explore the impact of N rate and irrigation presence on biophysical plant traits and plant health metrics overtime. This study will also examine the strengths and limitations of field phenotyping and remote sensing techniques for N management strategies in maize production. The conjunction of field phenotyping and remote sensing may uncover finer details on the overall performance and timing of N rates in irrigated and rainfed production systems.

Methods

Experimental Design

The study was conducted at the NU-Spidercam Field Phenotyping facility (NU-Spidercam, Bai et al., 2019), located at the Eastern Nebraska Research, Extension, and Education Center, Mead, NE (41 08’ 44.4” N, 96 26’20.6” W, altitude 369 meters above sea level) in 2022 and 2023. The cumulative precipitation from May to September in 2022 and 2023 were 306 mm and 349 mm.

Field experiments were conducted on maize (*Zea mays* L.) details of which are outlined in Table 1. Each experiment followed a Complete Randomized Block Design with 24 plots. Each plot was 6.1 m long and 4.6 m wide accommodating 6 rows of crops spaced 0.76 m apart. Grain yield data was collected from the central two rows of each plot spanning a length of 3.1 m.

Table 1. Design and key information of the two field experiments for maize production.

EXP #	*EXP. Name*	*Planting Density (plant/ha)*	*Treatments*	*Plot Count*	*Planting/ Harvesting*	*Nitrogen Fertilizer (bu/ac)*	*Rates*	*Total irrigation depth (mm)*

					date		
I	Maize Nitrogen/ Water 2022	Maize 80k	1 genotype	24	May 13	Full: 200	Full:173
			2 water levels		Oct. 12	Split: 80/80	Rainfed:0
			3 nitrogen levels			None:0	
II	Maize Nitrogen / Water 2023	Maize 80k	1 genotype	24	May 19	Full: 150	Full:173
			2 water levels		Sept. 28-29	Split: 50/100	Rainfed:0
			3 nitrogen levels			None:0	

Data collection and preprocessing

The NU-Spidercam facility is a Field High Throughput Plant Phenotyping (FHTPP) system made of three major components. The first being an automated cable-suspended sensing platform equipped with 0.4-hectare scan coverage. Secondly, there is a Subsurface Drip Irrigation (SDI) system for precise irrigation at a depth of 0.3 m. Lastly, approximately 50 m from the site is weather station (Bai, G., et al., 2019). The sensors relevant to this study include a multispectral (Visible Near-Infrared, VNIR) camera, a VNIR spectrometer coupled with a bifurcating fiber optical cable, and a LiDAR (Light Detection and Ranging) sensor. These sensors captured plot scale crop canopy data used in this study.

Canopy height was calculated from LiDAR point clouds by subtracting the distance from the sensor to canopy from the distance from the sensor to the ground. The VI used in this study is calculated from the measured incoming and reflected solar energy measured by the VNIR spectrometer. In this study, it serves as a standard spectral trait for canopy conditions throughout the growing season.

$$NDVI - RED\ EDGE = \frac{(NIR - RE)}{(NIR + RE)} \qquad (1)$$

where

$$NIR = Near - Infrared\ (770\ nm)\ wavelengths$$

$$RE = Red\ Edge\ (730\ nm)\ wavelengths$$

The accuracy of the sensor readings was verified with ground truth measurements further specified in (Bai, G., et al., 2019). Weather data was collected by the onsite station at 1-minute intervals, including Air Temperature, total rain, and Shortwave solar radiation.

Statistical analysis

The focus of this preliminary analysis on the effect of nutrient rate, N, in irrigated and rainfed maize production is plant health and physical trait assessment. Therefore, the comparison of crop health at each rate and water presence was visualized in time series plots (fig.1). This represents the temporal relationship of crop health, quantified as a VI, over time for the nutrient and water management combinations. This was visualized for each growing season. Correlation plots further explored the VI in context of the canopy height for management combination in the years 2022 and 2023 (Fig.2). Linear regression and coefficients of determination (R^2) were used to describe the relationship between the select VI and canopy height. Lastly a heat map was used to compare weather related patterns in 2022 and 2023 including air temperature, total rainfall, and shortwave solar radiation (Fig.3). Mean grain yield for each treatment from the two experiments is summarized (Table 2) and Tukey's Honest Significant Difference post hoc test was performed to assess the difference in yield for each treatment combination.

Figures

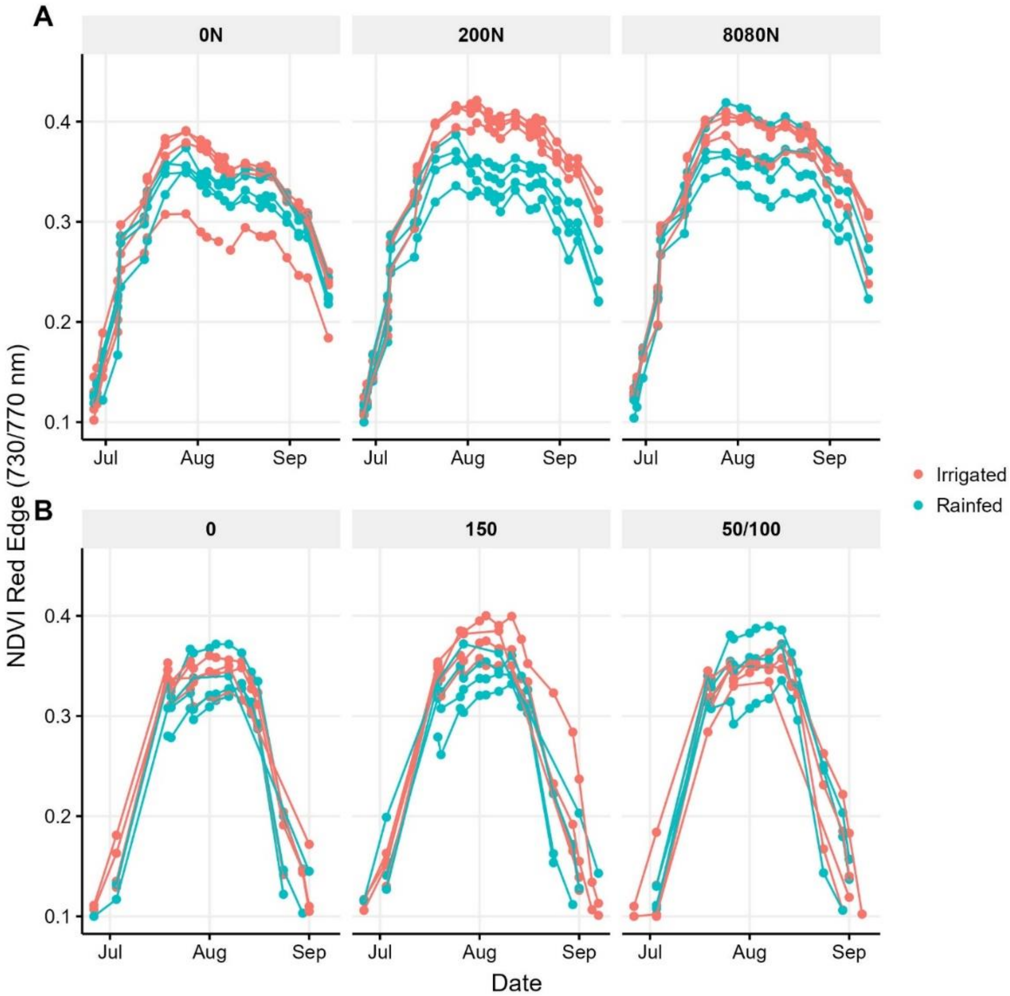

Fig 1. Time series of calculated Red-Edge NDVI (730/770 nm) throughout the growing season for each N rate between the irrigated and rainfed plots (Growing seasons: A = 2022, B = 2023). The lines are for each plot while the colors differentiate the irrigated and rainfed plots. For the split application, 1A (80/80), the second application occurred on July 1, 2022, at V8 phenological staging. While 1B (50/100), the split application occurred on July 3, 2023, at V6 – V9 phenological staging.

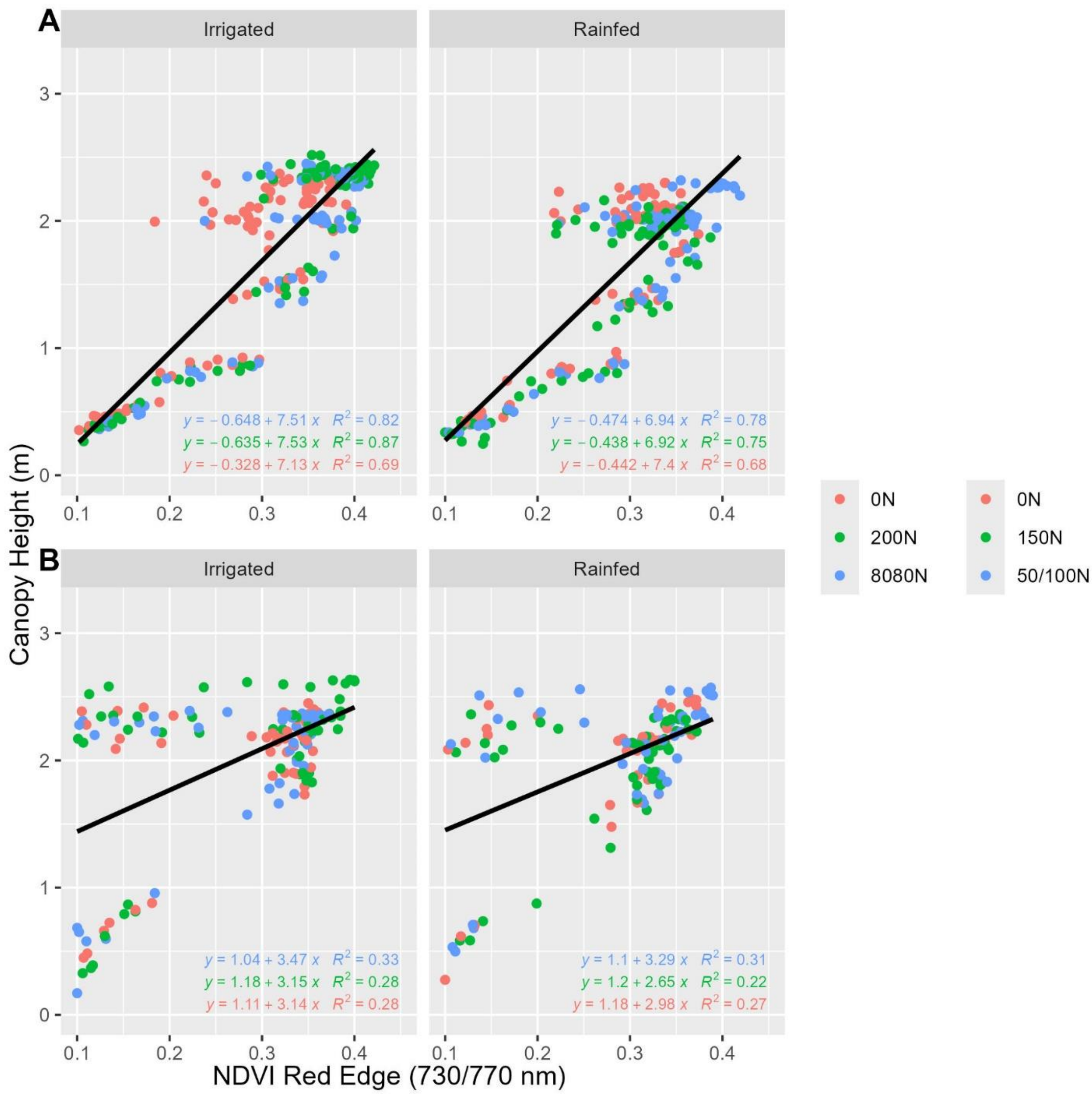

Fig 2. Correlation between the calculated Red-Edge NDVI (730/770 nm) and canopy height (m) (Growing seasons: A = 2022, B = 2023). Each data point represents data from each plot for everyday Red-Edge NDVI (730/770 nm) was calculated through the growing seasons. Different colors of the data points indicate the N rates. Linear regression lines between Red-Edge NDVI and canopy height are also shown with coefficients of determination (R2).

Year	Weather Metric	May	June	July	August	September
2022	Air temp. (Â°C)	16.77	22.98	24.74	23.85	19.75
	Shortwave solar radiation (W/m^2)	207.84	266.04	268.90	240.09	194.12
	Total Rainfall (mm)	3.39	2.68	0.63	2.25	0.96
2023	Air temp. (Â°C)	18.54	23.24	22.88	23.26	20.39
	Shortwave solar radiation (W/m^2)	242.86	269.48	239.00	221.42	185.70
	Total Rainfall (mm)	0.11	2.73	6.32	1.86	0.33

Fig 3. A heat map of mean weather metrics for each month of the growing season (May – September) in years 2022 and 2023. The red – green color scale was applied to show the temporal relationship of each metric, green is equivalent to the high value while red is equivalent to the low value.

Table 2. Mean of maize grain yield of each treatment from the two-field experiment. Different letters indicate the mean grain yields were significantly different at ($p < 0.05$) using ANOVA test with Tukey's Honest Significant Difference.

EXP #	Year	Treatment	Mean Grain yield (Bu/ac)
I	2022	200N, Irrigated	298.84a
		80-80N Irrigated	297.02a
		0N Irrigated	253.95b
		0N, Rainfed	219.43c
		80-80N, Rainfed	209.05c
		200N, Rainfed	208.23c
II	2023	150N, Irrigated	170.62a
		50-100N, Irrigated	143.72ab
		0N, Irrigated	141.48ab
		150N, Rainfed	125.91ab
		50-100N, Rainfed	125.27b
		0N, Rainfed	120.55b

Conclusion

This study introduced a preliminary analysis of utilizing field phenotyping in conjunction with remote sensing to explore the performance of N management techniques in irrigated and rainfed maize production. Two maize field experiments involving irrigation presence and N treatments were conducted at the NU-Spidercam facility in the years 2022 and 2023. In 2022, the irrigated plots had significantly higher grain yields than the rainfed plots. Strong linear correlations between NDVI-Red Edge and canopy height in irrigated plots (0N: 0.69, 80-80N: 0.87, 200N: 0.88) while in rainfed plots (0N: 0.68, 80-80N: 0.75, 200N: 0.76). In 2023, the plots with full and split N applications showed significantly higher yield than the rainfed plots with no N. The linear correlations between NDVI-Red Edge and canopy height in the irrigated and rainfed plots appeared to be much week ranging from 0.22 – 0.33. The preliminary comparison between the 2022 and 2023 growing seasons shows inconsistencies which may be further explained by the weather patterns during each season. In 2022, there was higher amount of rainfall during the beginning of the season. While in 2023, there was minimal rainfall in the beginning of the season which led to emergence issues within the plots. In July 2023, rainfall increased rapidly while in 2022 the season remained dry with a total of 2.88 mm of rain between July and August.

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