Value of Composite NDVI and GDD Data in Oklahoma, 1999 to 2018

Core Ideas

1. Grain yield prediction was improved using mathematically reproducible ranges in GDD>0 compared to a historical, and subjective, morphological scale
2. A climatologically identifiable metric that precisely determined when to collect sensor readings in future years
3. New yield prediction using exponential function justifies the adoption of a new YP0 equation for OSU's on-line Sensor Based Nitrogen Rate Calculator

Value of Composite NDVI and GDD Data in Oklahoma, 1999 to 2018

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ABSTRACT

For over twenty-five years, sensor-based NDVI data has been collected from both satellite imagery and near-plant (3 m) readings. Because calibrated NDVI data coming from active sensors is still relatively new, limited research has returned to evaluate databases that included multiple years and environments. Composite Normalized Difference Vegetative Index (NDVI) sensor readings and final grain yield were collected from 1999 to 2018. This included growing degree day (GDD) records for each mid-season sensor measurement. This was attempted to potentially improve the use of a historical and subjective morphological scale (Feekes, Large, 1954). Using location-specific-archived-data from the Oklahoma

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Mesonet, the exact number of days from planting to sensing where growing degree days were more than zero (GDD>0) for each date and location were compiled. The ensuing relationship between NDVI (for a predetermined GDD>0 range) and yield was determined. Grain yield prediction was improved between 80 and 115 GDD's. These ranges further targeted a climatologically identifiable metric that precisely determined when to collect sensor readings in future years. Compared to the current composite yield prediction equation for Oklahoma, the new exponential function created from this study was higher in the lower-yielding environments. Underestimation of fertilizer N rates has been voiced by producers in recent years. This has likely been the product of more current varieties, more efficient farming practices, and increased optimum N rates needed for higher yields. This validates the adoption of a new YP0 equation for OSU's on-line Sensor Based Nitrogen Rate Calculator, allowing accurate yield prediction between 80 to 115 GDD's.

INTRODUCTION

Absolute knowledge of how solar radiation interacts with plant matter and vegetation is required to interpret and use remote sensing data in agriculture (Knipling 1970). Some of the first sensor data that computed the normalized difference vegetative index (NDVI) was obtained from passive sensors that were reported by Rouse et al. (1974). Values for NDVI were calculated using near-infrared (NIR, 770 nm) and red (660 nm) wavelengths, and equal to (NIR-red)/NIR+red) (Stone et al., 1996). Sellers (1985) demonstrated that NDVI was directly related to photosynthetic capacity and in turn, serve as an indication of light absorption from plants.

This work that encompasses NDVI continues today using active sensors, instead of the passive sensors that required white-plate calibration (Ruiz-Garcia et al., 2009). The resultant NDVI formula is the same, but where constant adjustments for actual reflectance, required white plate readings that served as a reference for ambient light that changes throughout the day.

Early work by Benedetti and Rossini (1993) showed that National Oceanic and Atmospheric Administration (NOAA) satellite NDVI data could be used to predict plant photosynthetic capacity and efficiency. They further reported on the usefulness and affordability of real-time crop monitoring that was made possible using this index. Furthermore, they developed a linear model for estimating wheat yield forecast using NDVI integration during the wheat grain filling period. Quarmby et al. (1993) recommended added input from an agrometeorological model in addition to NDVI to better predict yield. Work by Meek and Hatfield (1994) noted the importance of automated meteorological stations that have become commonplace in many sectors of the agricultural landscape. Nonetheless, they highlighted problems associated with quality control and data archival. Raun et al. (2001) showed that the use of growing degree days (GDD) combined with NDVI readings over many locations, assisted in refining estimates of grain yield. Estimated grain yield levels were then used to refine in-season fertilizer N rates, based on that yield prediction level.

One of the more robust weather station networks in the world is The Oklahoma Mesonet with 121 automated environmental monitoring stations across 77 counties in Oklahoma (Fiebrich et al., 2006). For this network, environmental indices are measured using several instruments near a 10-meter-tall tower. Measurements are archived every 5 minutes, and observations transmitted to a central facility every 5 minutes, 24 hours per day, year-round (www.mesonet.org). Within this system, the Oklahoma Climatological Survey (OCS) receives observations, verifies data quality and offers data to the public free of charge. This includes air temperature, relative humidity, wind speed/direction, barometric pressure, rainfall, incoming solar radiation, soil moisture at 5, 25, and 60 cm, and soil temperature 10 cm below the surface (natural cover and bare surface).

The objective of this work was to compile multi-year, winter wheat grain yield data from several continuing experiments at Oklahoma State University, and to merge this information with archived climatological data. An additional objective was to further refine winter wheat grain yield prediction equations first established using NDVI by Aase and Siddoway (1981) and that have since been advanced by various researchers in winter wheat (Raun et al., 2001; Raun et al., 2002; Girma et al., 2006; Bushong et al., 2016) and maize (Sharma and Franzen, 2014; Bushong et al., 2018; Sharma et al., 2018).

MATERIALS AND METHODS

Winter wheat grain yield experiments were selected from a wide range of studies in Oklahoma that have been conducted since 1892. Both trials included a combination of N, P, and K rates, in randomized complete block experimental designs. All trials included in this work are reported in Table 1, as are the years included in this analysis where NDVI and wheat grain yield data were available. Many years had multiple NDVI sensor readings taken from each plot but on different dates. Soil classification for the sites included in this study is reported in Table 2.

Sensor NDVI readings were collected using an active Greenseeker 505 handheld sensor (Trimble.com Sunnyvale, CA). The Greenseeker sensor measures normalized difference vegetative index (NDVI) by using a self-illuminated (active sensor) light source in the red and near-infrared (NIR) wavelengths (660 +/- 10nm) and (780 +/-10 nm), respectively. The Greenseeker sensor calculates NDVI using the following formula (NDVI = (ρ NIR- ρ red)/(ρ NIR+ ρ red), where ρ NIR represents the fraction of emitted NIR radiation returned from the sensed area (reflectance), and ρ red represents the fraction of emitted red radiation from the sensed area (reflectance).

This sensor has an area of measurement of 1 cm x 60 cm when used in a normal operating range of 60 cm to 100 cm over the surface of the crop canopy. More than ten readings are collected per second, and where information is stored in an onboard Personal Digital Assistant (PDA) control unit.

For all sensor readings and final harvest dates, the cumulative number of days from planting to sensing where Growing Degree Days (GDD) were more than zero were recorded from the Oklahoma Mesonet. In order to count as one day where growth was possible, or where GDD>0, the following condition had to be met $(((T_{min} + T_{max})/2 - 4.4C) > 0)$.

Data analysis focused on finding the highest coefficient of determination (r2) for NDVI readings and wheat grain yield, but where this was cataloged or partitioned by ranges in GDD>0. Early sensor readings were not expected to provide improved correlation or improved prediction of wheat grain yield. Nonetheless, these readings were needed to delineate the minimum GDD>0, when robust yield prediction was possible. Similarly, later sensor readings, while usually better at predicting wheat grain yield, were used to identify dates when yield prediction no longer improved. These later dates were understandably beyond those times when fertilizer would be expected to be applied, but necessary to establish limits.

RESULTS AND DISCUSSION

Consistent with the initial concept that is embedding climatic data within the parameters and limits for predicting yield, surface scatter plots at both locations were evaluated (Figures 1, Experiments 222 and 502, respectively). Greenseeker NDVI data collected at specific points in the season, aligned to the actual number of days from planting to sensing where GDD>0, showed that moving from right to left (lower X-axis, or NDVI), increasing NDVI increased yield. This range or spread was widened as the number of days where GDD>0 increased from 80 to 115 (right Y-axis, bottom left to top right). Nonetheless, a consistent increase in yield was seen for each incremental change in GDD>0, when the range was between 80 and 115, at both locations. Moving from 80 to 115 GDD>0, the slope of NDVI versus yield increased, and that could, in turn, be embedded within the refined yield prediction equation, tied to the actual GDD>0 value. In general, the steeper the increase in NDVI (by GDD), the higher the correlation was with the final grain yield (Figures 1). Actual surface response models for Experiment 222 and Experiment 502 are reported in Figure 2. The same trends noted in the scatter plots were again repeated in the surface response models. As the GDD>0 increased, the separation in NDVI readings (range) increased, and the ability to detect differences in yield were enhanced.

When Greenseeker NDVI data excluded values where GDD>0 was less than 80 and more than 115, yield prediction was improved. Within this range, as the GDD>0 increased, the slope of NDVI versus yield also increased. This was not entirely clear when plotting slope by GDD>0, for NDVI versus yield (Table 3). Dhillon et al. (2019), noted a precise yield potential prediction was between 97 and 112 GDD's (GDD > 0).

Evaluation of the slope for the N rate versus the environment means is illustrated in Figure 3. As the environment means increased, the slope of N rate versus yield did as well, and that was computed by year from 1999 to 2018. What this indicates is that as yield increased, the demand for N also increased. Or in other words, yield level and N removal were related. Raun et al. (2011) and Dhital and Raun (2016) delineated the difference between N removal and N response, where they found that yield potential was independent of actual N response over the years (environment).

Finally, this work aimed to further refine wheat grain yield potential estimates using NDVI and the INSEY index that this group developed in the 1990s (Lukina et al., 2001). Estimates of YP0 employed an exponential function that had historically underestimated YP0 at low levels of INSEY and overestimated YP0 when INSEY values were higher. Consistent with observations of how yield goals have been determined by producers (average of the last five years + 20%) (Raun et al., 2017), our estimate of YP0 adds one standard deviation to the equation. This takes into consideration the assumed avoidance of risk that producers choose to not be short on N. For the past ten years, the following OK exponential function has been used (YP0=0.590*EXP(258.2*INSEY)

Modifications with time have included data coming from Kansas. For this paper, the added focus on Experiment 502 (Lahoma, OK) revealed a function that is expected to improve current understanding and adoption.

The underestimation of YP0 has been suspected/common when yields were low. Use of the Lahoma experiment station data for Oklahoma has been iconic over the years, and that better represented the potential for both higher yields and that reflected conditions in our state when yield potentials were expected to be lower. The latter includes years when yields were lower due to late planting or limited moisture at planting. In summary, trials at Lahoma have better reflected the ranges in yields that are encountered in this state. As such this specific sensor data has been more elucidating concerning the whole concept of yield and yield potential.

Conclusions

This work aimed to refine wheat grain yield potential estimates using NDVI and GDD from 1999 to 2018. Grain yield prediction was improved using mathematically reproducible ranges in GDD>0 compared to a historical, and subjective, morphological scale. The ensuing relationship between NDVI (for a predetermined GDD>0 range) targeted a climatologically identifiable metric that precisely determined when to collect sensor readings in future years. Compared to the current composite yield prediction equation for Oklahoma, the new exponential function created from this study was higher in the lower-yielding environments and further justifies the adoption of a new YP0 equation for OSU's on-line Sensor Based Nitrogen Rate Calculator.

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Table 1. The experiment included in the analysis, year established annual average rainfall and range in annual rainfall.

Experiment	Longitude Latitude	Year Started	Annual Avg. rainfall	Range	Mean Annual Temperature
			mm		ºC
222	36° 7’ 7” N 97° 5’ 30” W	1969	922	606-1493	15.0
502	36° 23’ 13” N 98° 6’ 29” W	1970	771	503-1314	15.6

Table 2. Location, experiment, and soil classification for all sites included in this study, Oklahoma.

Site	Series	Soil Classification
Experiment 222	Kirkland silt loam	Fine, mixed, thermic, Udertic, Paleustoll
Experiment 502	Grant silt loam	Fine, silty, mixed, superactive, thermic, Udic

Table 3. Linear regression of INSEY on wheat grain yield, partitioned by ranges when sensor readings were collected (GDD>0).

Location	GDD Range	Linear Model	R^2	PR>F, b1 $\neq$ 0	n
Lahoma	<70	y=1.73+27.19x	0.01	0.33	83
Stillwater	<70	y=0.31+128.3x	0.69	0.001	100
Lahoma	70 to 90	y=1.84+202.5x	0.1	0.001	637
Stillwater	70 to 90	y=1.38+109.1x	0.03	0.002	477
Lahoma	90 to 110	y=-0.22+611x	0.38	0.001	615
Stillwater	90 to 110	y=1.43+118.4x	0.04	0.001	781
Lahoma	>110	y=0.13+700.6x	0.47	0.001	448
Stillwater	>110	y=1.71+136.1x	0.04	0.001	488

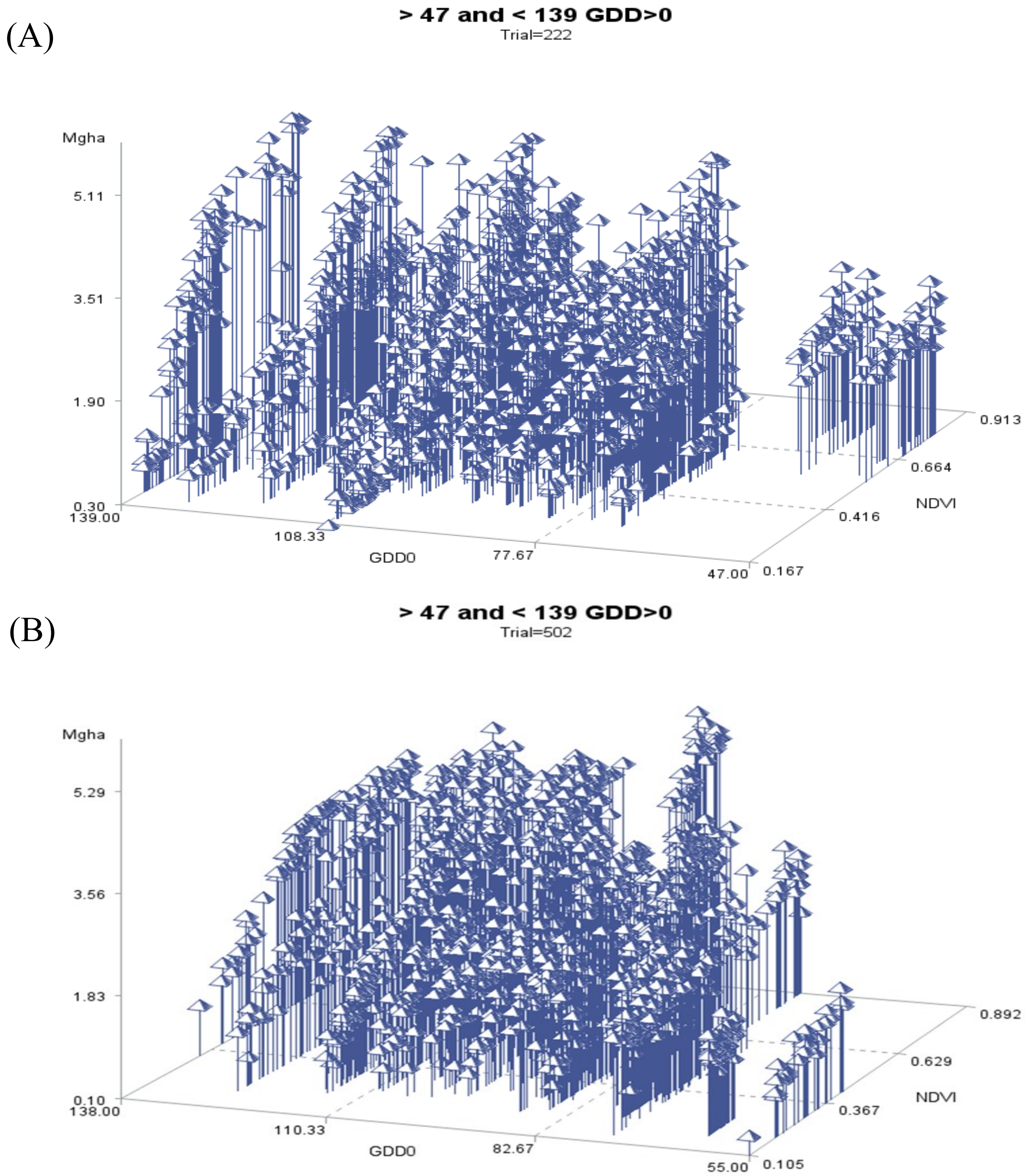

Figure 1. Surface scatter plot of wheat grain yield in Mg ha^{-1} versus normalized difference vegetative index (NDVI) readings and categorized by the number of days from planting to sensing where growing degree days (GDD, 47 to 139) were more than zero (1999 to 2018), Experiment 222, Stillwater, OK (A), and Experiment 502, Lahoma, OK (B).

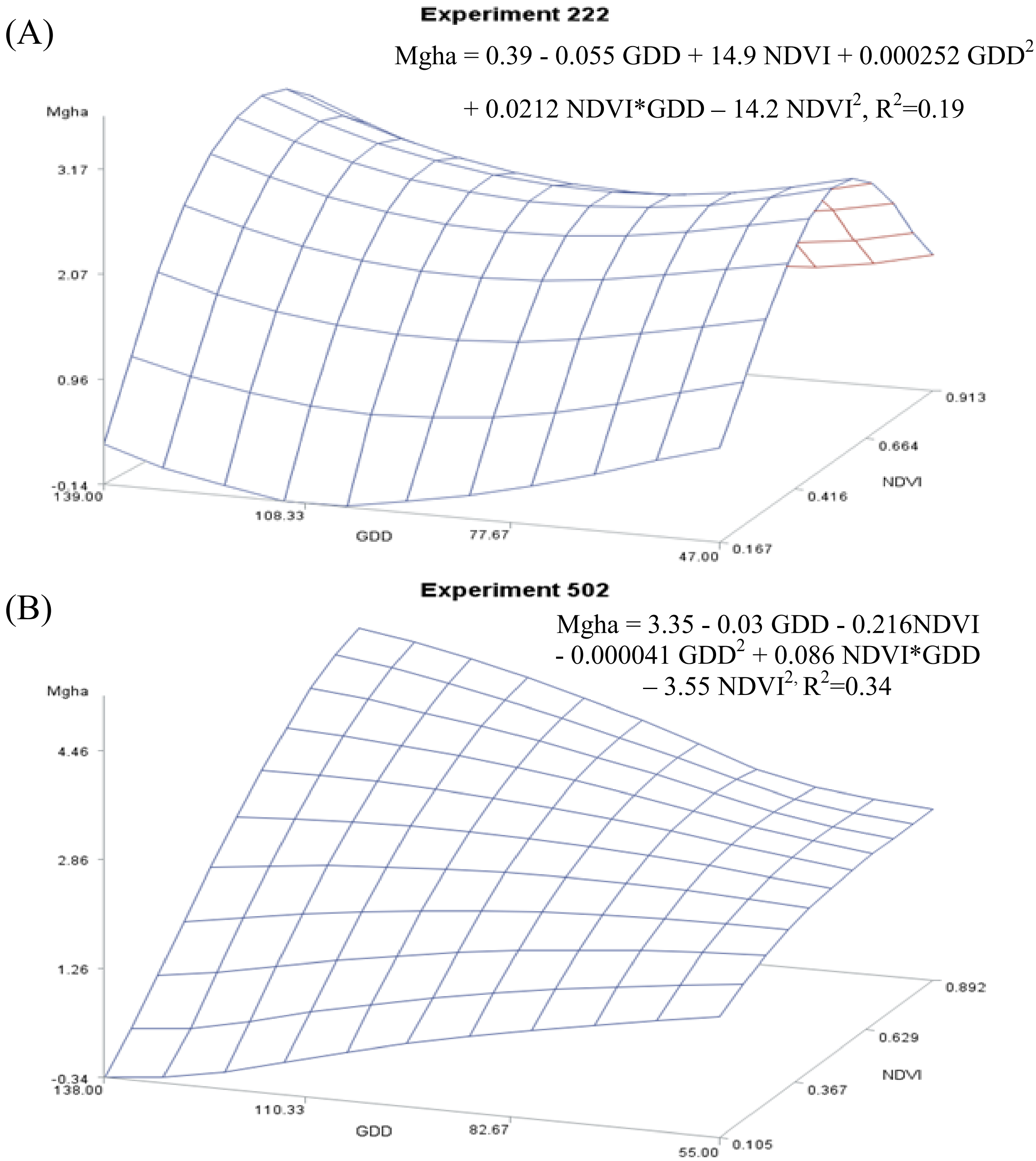

Figure 2. Surface response model delineating the relationship between NDVI and GDD>0 (47 to 139) with wheat grain yield (Mg ha^{-1}), Experiment 222, Stillwater (A), and Experiment 502, Lahoma (B), OK, 1999-2018.

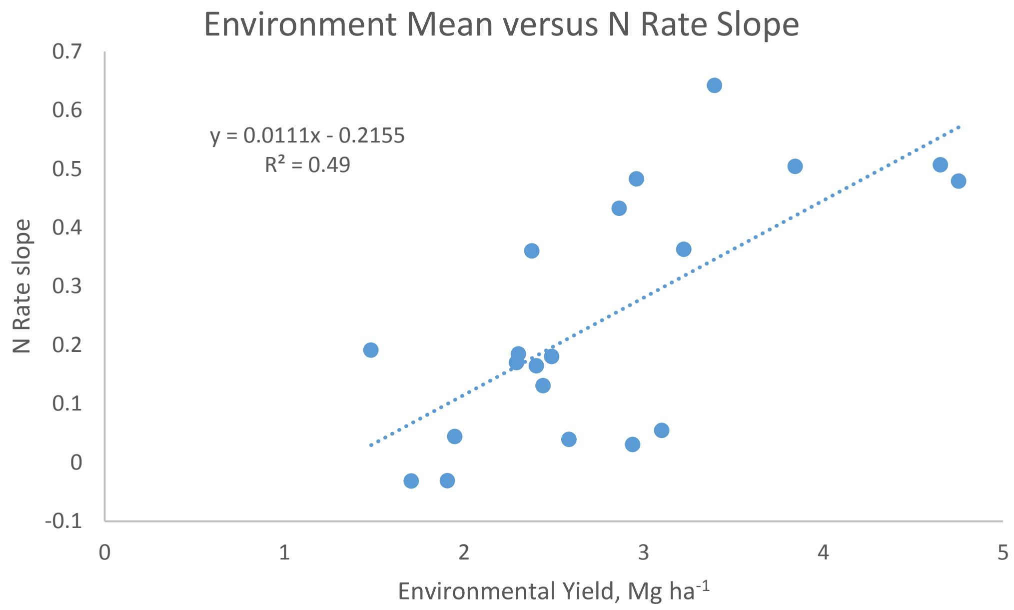

Figure 3. The relationship between the slope component from by-year linear regression of N rate versus environment yield, Experiment 502, Lahoma, OK, 1999-2018.