Evaluating Different Strategies for In-Season Potato Nitrogen Status Diagnosis using Two Leaf Sensors

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Abstract.

Accurate and efficient in-season diagnosis of potato nitrogen (N) status is key to the success of in-season N management for improved profitability and environmental protection. Sensor-based approaches will support more timely decision making compared to plant tissue-based approaches. SPAD-502 is a commonly used sensor for potato N status diagnosis. Dualex Scientific+ is a newer leaf chlorophyll meter and measures leaf chlorophyll using the transmittance characteristics of chlorophyll in wavelengths resistant to measurement saturation and the screening effect of polyphenols (i.e. flavanols and anthocyanins) on chlorophyll fluorescence. Dualex is expected to outperform SPAD when used independently, but the extent and context of such improvements has not been systematically evaluated, especially for potato. The objectives of this study were to 1) compare the Dualex fluorescence sensor and SPAD meter for potato N status diagnosis by predicting petiole nitrate-N concentration and N nutrition index (NNI), and 2) evaluate the effect of fusing ancillary information with sensor data on improving N status diagnosis. Plot-scale field experiments were conducted at the Sand Plain Research Farm in Becker, MN USA in 2018, 2019, 2021, and 2023 involving several varieties and N fertilizer treatments. Plant samples (i.e. petioles and whole plants) and leaf sensor data were collected multiple times at key growth stages each year. The on-site weather station provided daily weather information. The benefit of additional readings in the Dualex sensor was marginal. The N status indicators were predicted much better using the data fusion approach, where the sensor difference was greatly diminished. Random forest regressor predicted the petiole nitrate-N concentration and NNI with R^2 of 0.88 and 0.63, respectively. Upgrading sensors might be a valid strategy in situations without access to other ancillary data, but developing models using an available sensor and ancillary data is generally more effective in estimating in-season potato N status.

Keywords.

In-season nitrogen status diagnosis, Leaf sensor, SPAD, Dualex, Data fusion, Machine learning, Potato

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Introduction

There has been an increasing social pressure to better manage nitrogen (N) fertilizer application in production agriculture to conserve resources and protect the environment. Split N fertilizer application is an effective way to improve N use efficiency (NUE), especially in wet years, and this is particularly important for potatoes (Solanum tuberosum L.) with potentially low NUE due to their shallow roots and cultivation on coarse-textured soils (Bailey, 1999; Errebhi, Rosen, Gupta, et al., 1998; Phene & Sanders, 1976; Rosen & Bierman, 2008). Petiole analysis has been the most popular plant tissue analysis to guide in-season split N fertilizer applications (Errebhi, Rosen, & Birong, 1998; Rosen & Bierman, 2008; Zhang et al., 1996). Some studies are critical about the usefulness of petiole analysis due to its high variability (MacKerron et al., 1995). Nitrogen nutrition index (NNI) is another, more holistic N status indicator and is useful for diagnosing N status on crops including potatoes (Greenwood et al., 1990; Lemaire et al., 1984). However, NNI is not a practical approach as sampling and analyzing the whole plant biomass and N concentration is generally required. Whether petiole analysis or NNI, destructive sampling and tissue analysis is expensive and, thus, better to be avoided.

Radiometric sensors are useful for predicting plant N status using transmissive and reflective properties of plants. One of the most common handheld sensors for plant chlorophyll (Chl) estimation is SPAD-502 (SPAD; Konica Minolta, Tokyo, Japan) (Gianquinto et al., 2004). SPAD operates at wavelengths around 650 nm and 940 nm and outputs a relative Chl reading. Dualex Scientific+ (Dualex; METOS® by Pessl Instruments, Weiz, Austria) is a newer leaf chlorophyll meter and uses both leaf transmittance and chlorophyll fluorescence to measure Chl and Flavanol (Flav), which is a N stress induced substance. Cerovic et al. (2012) discussed the potential improvement of Dualex in N status diagnosis by mitigating measurement saturation through using 710 nm and 850 nm and the addition of Flav. However, the potential benefit of upgrading the leaf sensor has not been fully investigated. It is also important to compare the effectiveness of these leaf sensors in the presence of available ancillary information, as the data fusion approach using machine learning can diminish sensor differences (Wang et al., 2023). Therefore, the objectives of this research were to 1) compare the Dualex fluorescence sensor and SPAD meter for potato N status diagnosis by predicting petiole nitrate-N concentration and NNI, and 2) evaluate the effect of fusing ancillary information with sensor data on improving N status diagnosis and reducing sensor differences.

Materials and Methods

1. Study Sites

The studies were conducted at the Sand Plain Research Farm, Becker MN, USA. This research farm was located at 45° 23' N, 93° 53' W and characterized as a Hubbard loamy sand (sandy, mixed, frigid Entic Hapludolls) until 2018 and was relocated to 45° 20' N, 93° 49' W in 2019 and characterized as a Hubbard (Sandy, mixed, frigid Entic Hapludolls)-Mosford (Sady, mixed, frigid Typic Hapludolls) complex sand soil. The average air temperature ranged from 18.1 to 20.4°C with 291.8 to 517.0 mm total precipitation during the growing seasons according to the on-site and nearest regional airport weather station data. Soil samples were collected at the start of the season at 0-0.15 m and 0-0.6 m for standard macro- and micro-nutrients and sent to the Soil Testing and Research Analytical Laboratory at the University of Minnesota. The initial soil pH ranged from 6 to 7.4. The initial soil organic matter content and total N concentration were low at 1.2 to 2.2% and 1.7 to 11.7 ppm, respectively. All of the cultural practices followed the regional recommendations. The precipitation was supplemented using irrigation based on the checkbook method on a fixed schedule (Steele et al., 2010).

2. Study desgins and treatments

A total of four studies were conducted in 2018, 2019, 2021, and 2023.

Study 1 involved four cultivars (i.e. Clearwater Russet, Ivory Russet, Russet Burbank, and

Umatilla Russet) and three N treatments (i.e. 134.5, 269.0, and 403.5 kg N/ha). Study 2 involved the same five cultivars (i.e. Clearwater Russet, Lamoka, MN13142, Russet Burbank, and Umatilla Russet) and the same N treatments. The between-row spacing was 0.9 m and the within-row spacing was 0.23 m for Ivory Russet and 0.3 m for all of the other cultivars. Diammonium Phosphate (DAP; 18-46-0) was banded at planting at the 44.8 kg N/ha rate. Controlled-release fertilizer, Environmentally Smart Nitrogen (ESN; Nutrien, Canada; 44-0-0), was side-dressed and hilled in at emergence at varying N rates of 89.7, 179.3, and 269.0 kg/ha. The two higher-rate N treatments also received four fixed splits of 11.2 or 22.4 kg N/ha as urea ammonium nitrate (UAN; 28-0-0) after emergence. The UAN applications were immediately followed by irrigation simulating fertigation. Both Studies 1 and 2 used the split-plot design with three replications. More details of these two studies were reported (Gupta, 2018; Gupta & Rosen, 2019).

Study 3 involved two cultivars (i.e. Hamlin Russet and Russet Burbank) and five N treatments (i.e. 44.8, 89.7, 179.3, 269.0, and 358.7 kg N/ha). The between-row spacing was 0.9 m and the within-row spacing was 0.3 m for both cultivars. At planting, 44.8 kg N/ha was band-applied using DAP and the reminder of N was side-dressed and hilled in using ESN. Study 4 used the same two cultivars and five N treatments. The within-row spacing for Hamlin Russet was adjusted to 0.23 m. In addition to the five N treatments, four precision N management (PNM) treatments and three irrigation treatments were included. One of the PNM treatments was a fixed split treatment, where 89.7 or 179.3 kg N/ha was applied for Hamlin Russet or Russet Burbank using the above-mentioned design and four fixed splits of 16.8 kg N/ha were applied simulating fertigation after emergence. The total N rates for the fixed split treatments were 179.3 and 246.6 kg N/ha for Hamlin Russet and Russet Burbank, respectively. Other three PNM treatments were designed similarly except the decision on the post-emergence split N applications were based on leaf sensor-based plant N status diagnosis. The total N rates for Hamlin and Russet Burbank in these treatments ranged from 106.5 to 151.3 kg N/ha and from 196.1 to 224.2 kg N/ha. Three irrigation treatments included 60, 80, 100% of the irrigation rate determined by the checkbook method. The total accumulated moisture contents (i.e. precipitation + irrigation) were 169.9, 189.0, and 208.0 mm for 60, 80, and 100% irrigation treatments. For Studies 3 and 4, a split-plot design was used with three replications. The irrigation treatments in Study 4 were included as blocks without replications. More details of these two studies can be found in Miao et al. (2022, 2024).

3. Plant samples and sensor data collection

From the beginning of tuber initiation stage to the beginning of senescence, plant samples and leaf sensor data were collected two to four times. Studies 1 and 2 had four plant sampling and sensor data collection events on 6/26, 7/10, 7/18, and 7/31 or 6/26, 7/11, 7/24, and 8/7. There were two and three events for Studies 3 and 4 on 6/29 and 7/27 or 6/22, 7/20, and 7/27. As plant samples, twenty petioles on the fourth leaves from the shoot apex and three whole plants (i.e. shoot and tubers) were collected. Petioles were dried, ground, and water-extracted for NO_3-N concentration. The fresh weight of three whole plants were measured on site and a sub-sample was weighted fresh, dried, and weighted again for percent dry matter determination. The dried sub-samples were also ground and analyzed for N concentration. Plot-wise dry biomass was determined by extrapolating the product of the three-plant fresh weight and the percent dry matter using the spacings. Twenty or thirty SPAD meter readings were collected from the fourth leaves of the shoot apex and averaged on a plot basis. Similarly, fifteen Dualex meter readings were collected on the top fully expanded leaves and averaged on a plot basis.

4. Statistical analysis

4.1 Data imputataion and feature

Initial soil test results were sometimes absent for some replications. These replications received the study-wise average values of the initial soil test results. N fertilizer was applied at various rates and timings, so the amount of N fertilizer that had been applied until the day before sampling and sensing events were summed up and called as-applied N rates. The weather data was used to calculate growing degree days (GDDs) and total moisture as follows:

$$GDDs = (T_{max} + T_{min}) / 2 – 7°C \text{ where } GDDs > 0 \quad (1)$$

$$\text{Total moisture} = \text{Precipitation} + \text{Irrigation} \quad (2)$$

where T_{max} and T_{min} are daily maximum and minimum temperatures, and 7°C is the base temperature for potatoes (Worthington & Hutchinson, 2006). The GDDs and total moisture were summed up to the day of sampling and sensing events and called accumulated GDDs and total moisture. Lastly, NNI was calculated on a whole plant basis as the ratio of plant N concentration to critical N concentration (N_{cr}) (Lemaire et al., 1984). N_{cr} is defined as the plant N concentration required to achieve the maximum plant biomass. N_{cr} is characterized by an allometric negative power function:

$$N_{cr} = a(W)^{-b} \quad (3)$$

where N_c is critical N concentration in g/100g dry matter or %, W is dry weight biomass in Mg/ha, and a and b are estimated parameters. The parameter a represents the N concentration when W is 1 Mg/ha, while the parameter b describes the dilution of N concentration with increase in plant dry mass. According to Bohman et al. (2023), the parameters a and b were set to 4.75, 0.585; 4.74, 0.566; and 4.75, 0.588 for Clearwater Russet, Russet Burbank, and Umatilla Russet. All of the other cultivars used 4.75 and 0.582 for parameters a and b as specified for Minnesota. The total number of observations resulted in 458.

4.2 Feature and model selection

Simple relationships between the N status indicators of interest (i.e. PNN; petiole nitrate-N concentration and NNI) and leaf sensor readings were explored using the whole dataset first. Among linear, log, power, exponential, and polynomial regressions, the best fitted regression was selected for further analysis using partitioned datasets. The data were partitioned into training and testing datasets with an 8:2 ratio. All models were validated in the testing dataset after calibrated in the training dataset. Apart from the simple regression, multiple linear regression (MLR), Random Forest (RF) regression, and Extreme Gradient Boosting (XGBoost) regression were used to predict the N status indicators. In MLR, two approaches were used; 1) using only leaf sensor readings, and 2) using all of the available variables. For feature selection, the forward selection algorithm by the regsubsets function in the leap package in R was used. Cultivar names were converted to dummy variables. RF and XGBoost regressions were selected due to their compatibility with categorical variables and their ability to balance the variance bias tradeoff, especially in a small dataset. Important features were selected using the permutation-based importance metric called Boruta in R. The tuned hyperparameters included the number of variables used at each node, the number of trees, and the minimum number of observations in a leaf for RF regression. In addition to these hyperparameters, the sample size used for building each tree, learning rate, and lambda (i.e. L2 regularization term) were tuned in XGBoost regression. These hyperparameters were tuned using Bayesian optimization in a 5-fold cross validation. Mean absolute error was used as the metric for selecting the best set of hyperparameters considering the high variability of PNN concentration. Expected improvement with a tradeoff of 0 was the choice of acquisition function. To evaluate model performance, the coefficient of determination (R^2), mean absolute error (MAE), and root mean square error (RMSE) were used;

$$R^2 = 1 – \Sigma (y_i – \hat{y}_i)^2 / \Sigma (y_i – \overline{y})^2 \quad (4)$$

$$MAE = 1/n\ \Sigma |y_i – \hat{y}_i| \quad (5)$$

$$RMSE = \sqrt{\ } 1/n\ \Sigma (y_i – \hat{y}_i)^2 \quad (6)$$

where n is the number of observations, y_i is the actual value of the ith observation, $\hat{y}_i$ is the predicted value of the ith observation, and $\overline{y}$ is the mean of all the observations. For all model training and testing, the tidymodels package in R was used. All of the other data handling and statistical tasks were also performed in R (R Core Team, 2023).

Results

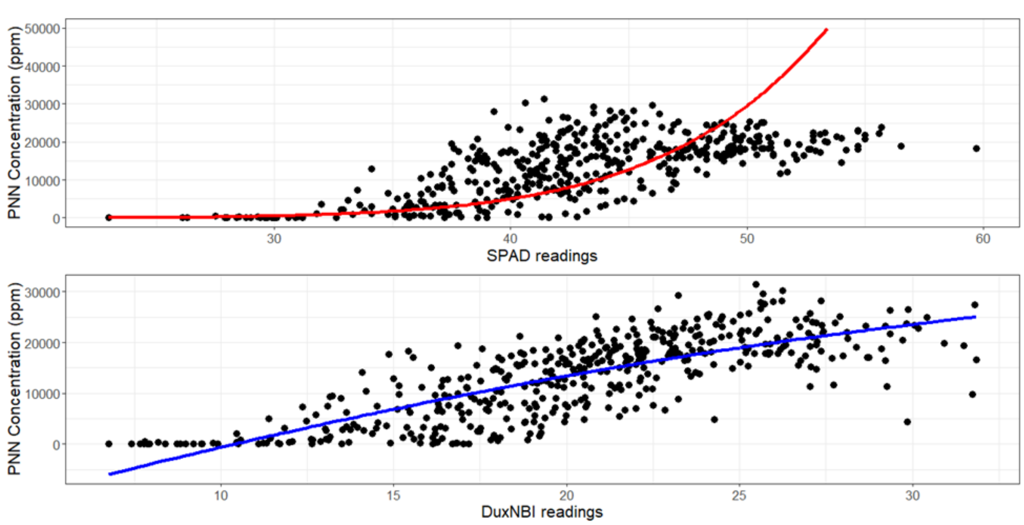
1. Leaf sensors vs. N status indicators

Table 1 shows the simple relationships between leaf sensor readings and N status indicators. The R^2 values were much higher for the relationship with PNN concentration than NNI. Both of the N status indicators were best represented by power or quadratic regressions. Dualex N balance index (NBI) reading had slightly higher R^2 values in relationships with both PPN concentration and NNI than SPAD reading. Figure 1 shows the relationships between the leaf sensor readings and the N status indicators for those with the highest R^2 values as bolded in Table 1. All three readings were selected for the Dualex only MLR models using forward selection in a whole dataset. Note that Dualex NBI reading was not part of forward selection here as the derivation of NBI, Chl/Flav, will cause multicollinearity quantified by a very high variance inflation factor value. The R^2 value was slightly higher at 0.63 for the relationship with PNN concentration, while slightly lower at 0.23 for the relationship with NNI. When calibrated and validated in the partitioned datasets, the validation R^2 values for the best simple regressions were 0.60, 0.56, 0.27, and 0.2, in the top to bottom order of those bolded in Table 1. Similarly, the validated R^2 values for PNN concentration and NNI predictions using the Dualex only MLR models were 0.62 and 0.21, respectively.

Table 1. Simple relationships between leaf sensors and N status indicators.

(Petiole NO_3-N)	Regression	Equation	R^2
SPAD	**power**	**$\log(y) = 7.98 \log(x) - 20.98$**	**0.56**
Dualex Chl	power	$\log(y) = 6.35 \log(x) - 12.03$	0.53
Dualex Flav	quadratic	$y = -21644 x^2 - 98686 x + 13241$	0.35
Dualex Anth	quadratic	$y = 81162 x^2 + 14765 x + 13241$	0.24
Dualex NBI	**quadratic**	**$y = -13902 x^2 + 132078 x + 13241$**	**0.61**

(NNI)	Regression	Equation	R^2
SPAD	**quadratic**	**$y = -3.03 x^2 + 2.38 x + 1.61$**	**0.21**
Dualex Chl	quadratic	$y = -2.15 x^2 + 2.69 x + 1.61$	0.17
Dualex Flav	exponential	$\log(y) = -0.475 x + 1.13$	0.19
Dualex Anth	quadratic	$y = 1.01 x^2 - 1.88 x + 1.61$	0.07
Dualex NBI	**power**	**$\log(y) = 0.449 \log(x) - 0.888$**	**0.25**



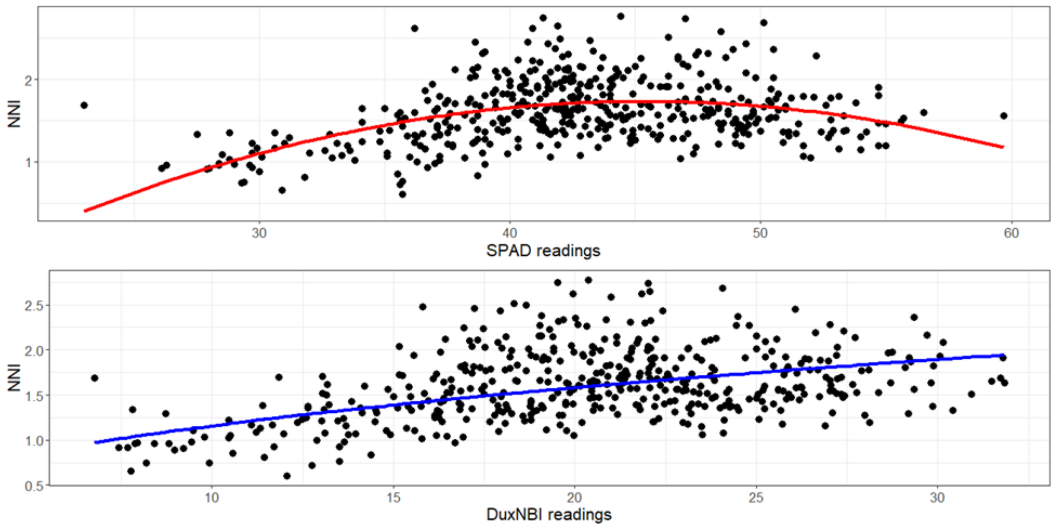


Figure 1. the relationships between the leaf sensor readings and the N status indicators.

2. Relationships using leaf sensor and ancillary data

Forward selection was used in the training dataset to identify the important features in the MLR models for PNN concentration and NNI predictions. Table 2 shows all of the MLR models with their R^2 values. Leaf sensor readings were mostly selected first for PNN concentration, followed by genetic x weather x management (GxExM) variables. On the other hand, the GxExM variables took precedence over leaf sensor readings when predicting NNI. Note that SPAD reading was not even selected for NNI prediction. Boruta found most of the variables in the dataset to be important, while similar variables ranked high in both forward selection and Boruta (Figure 2). Unlike forward selection, Boruta ranked leaf sensor readings high in NNI prediction. The top 10 most important features were included in RF and XGBoost regressions. Table 3 shows the validation results of these two tree-based models. RF demonstrated improved prediction accuracy for PNN concentration, especially considering the sufficiency thresholds proposed by Rosen & Bierman (2008). The NNI prediction accuracy did not improved much, whether RF or XGBoost was used.

Table 2. The summary of multiple liner regressions using leaf sensor readings and ancillary data

y	Sensor	Equation	R2
Petiole	SPAD	y = 92.90 SPAD - 13.85 acGDDs + 48.54 as_N - 38.44 acMoist + 11245.45 Ini_B - 18.78 HL - 3885.56 IR - 5249.36 LK - 2189.37 MN - 2291.40 RB - 1822.29 UL + 21430.79	0.78
Petiole	Dualex	y = 19.09 Chl - 11642.02 Flav -57.12 acMoist + 39.59 as_N + 21882.62 Ini_B - 1020.59 HL - 3026.65 IR - 5809.92 LK - 1946.91 MN - 3528.96 RB - 1466.00 UL + 37026.91	0.81
NNI	SPAD	y = 0.0031 as_N + 0.0005 acMoist - 2.3653 Ini_B - 0.0008 acGDDs + 0.0007 Ini_Ca + 0.4156 HL + 0.4788 IR + 0.2462 LK - 0.0603 MN + 0.3399 RB + 0.1738 UL + 1.1156	0.54
NNI	Dualex	y = 0.0028 as_N - 0.0006 acMoist - 0.3906 Flav - 0.9546 Ini_B + 0.2855 HL + 0.4934 IR + 0.2462 LK - 0.0413 MN + 0.2473 RB + 0.1760 UL + 1.8010	0.59

acGDD; accumulated GDDs, acMoist; accumulated total moisture, as_N; as-applied N rates, Chl; Dualex Chl, Flav; Dualex Flav, Ini_Ca; Initial soil test results for Ca, Ini_B; Initial soil test results for Boron, HL; Hamlin Russet, IR; Ivory Russet, LK; Lamoka, MN; MN13142, RB; Russet Burbank, UL; Umatilla Russet

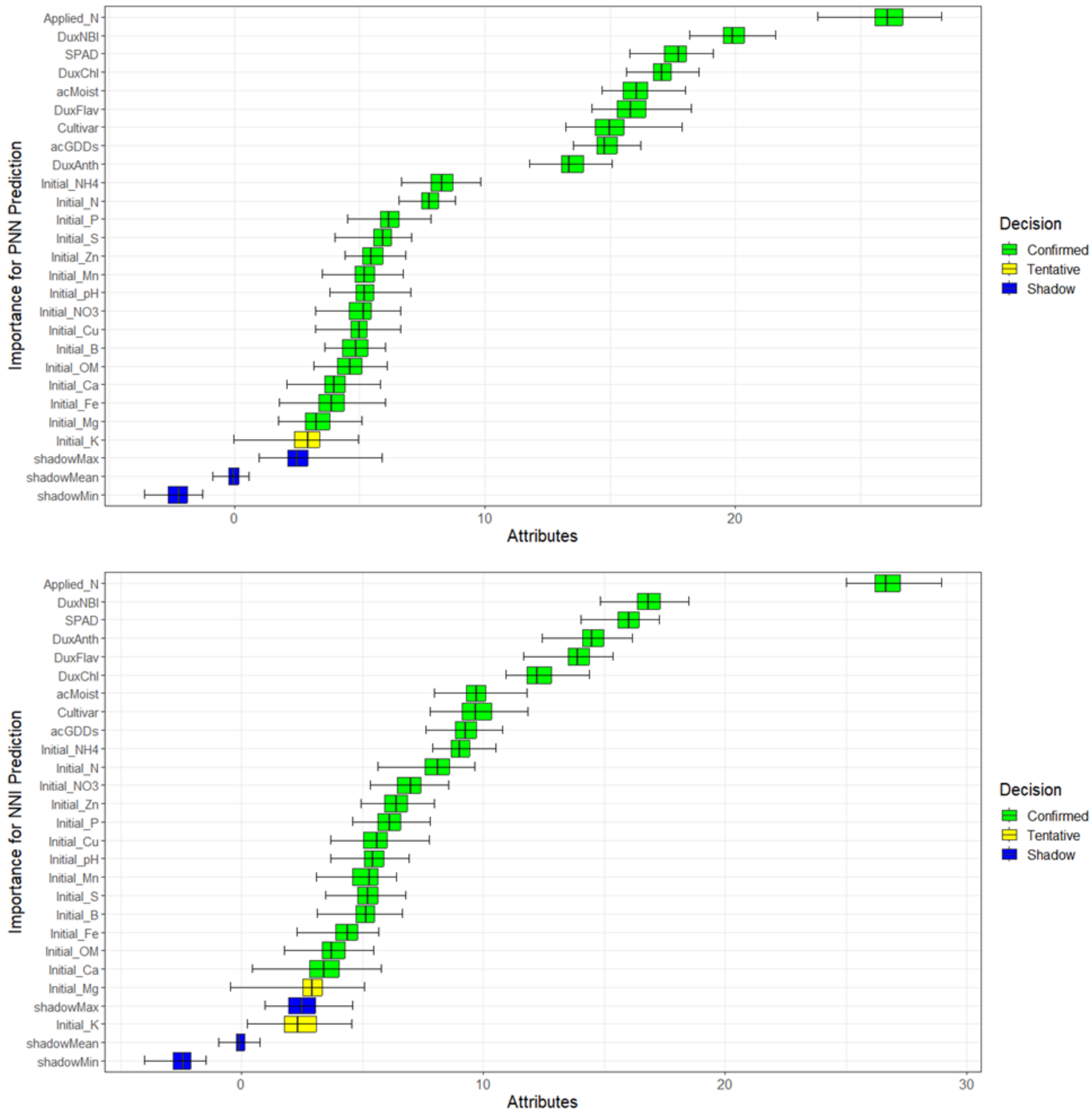


Figure 2. Permutation-based feature importance for PNN concentration and NNI prediction using Boruta

Table 3. The summary of tree-based ML model performance

ML	Response	Sensor	R^2	MAE	RMSE
RF	Petiole	SPAD	0.88	1898	2650
	Petiole	Dualex	0.86	2016	2818
	NNI	SPAD	0.61	0.19	0.26
	NNI	Dualex	0.63	0.19	0.25
XGBoost	NNI	SPAD	0.58	0.19	0.27
	NNI	Dualex	0.67	0.16	0.24

ML; Machine Learning

Discussion

1. Upgrading leaf sensor

Based on the results of the simple regression and sensor only MLR analyses, Dualex was slightly superior in PNN concentration prediction to SPAD. The sensor difference becomes a little more evident when the log-transformation of the SPAD-based best regression led to poor prediction performance on the original scale and the SPAD-based second best regression, quadratic, had an R^2 value of 0.48. Dualex particularly benefitted from the addition of Flav reading and its usefulness was better harnessed by allowing more flexibility with their coefficients in MLR than in the form of NBI. However, the degree of improvement would not be large enough to incentivize the sensor upgrade. There was no sensor difference in NNI prediction. As the performance of other more complicated models demonstrated, the data fusion approach using the GxExM information reduced the sensor difference and improved the model performance greatly. This is rather a preferred and effective approach for making valid predictions as previous studies also reported (Li et al., 2021, 2022; Wang et al., 2023).

2. Important variables for making N status predictions

As Pearson correlation in Figure 3 visualizes, many of the initial soil test results were not much correlated with the N status indicators of interest. Some of those that were moderately correlated with the N status indicators of interest were also correlated with other variables such as sensor readings. In other words, the initial soil test results were not as helpful for model performance. Weather forward selection or permutation-based importance metric was used, most important features for PNN concentration and NNI prediction were generally sensor readings and genetic, weather, and management information. However, the forward selection and Boruta for NNI prediction implies relatively diminished impacts of sensor readings, especially for SPAD and Dualex Chl. Relaxing the linear conformity by using RF and XGBoost further improved the model performance for both PNN concentration and NNI predictions. The XGBoost model was applied to NNI prediction to see if higher model complexity could make up for a lack of predictive powers in explanatory variables. The low prediction accuracy for NNI would have to be addressed by incorporating more useful features such as those that account for plant biomass (e.g. NDVI and NDRE) (Li et al., 2022; Wang et al., 2023).

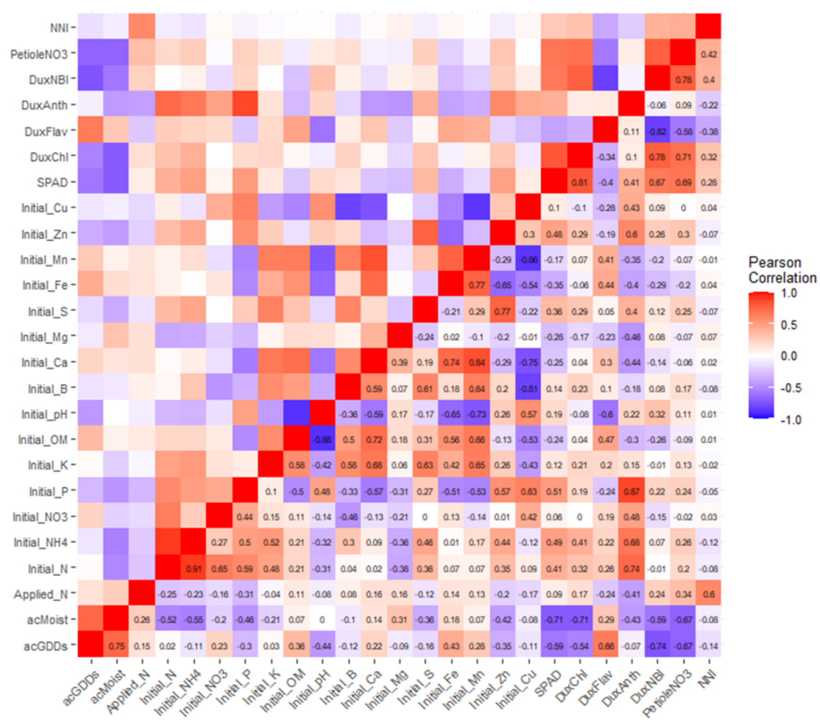


Figure 3. Pearson correlation coefficients among all variables

3. Poor NNI prediction using leaf sensors

Leaf sensors were effective in predicting PNN concentration but not NNI. Both SPAD and Dualex meters were designed to measure leaf Chl using leaf transmittance (Cerovic et al., 2012). Petiole is a plant organ that transports N to leaf, which is a plant organ for N storage. While different roles of these two plant organs result in reflecting different plant N status to be precise, their anatomical proximity should justify the correlation between the SPAD/Dualex Chl readings and PNN concentration. It is also important to note that the SPAD/Dualex Chl readings are surface-based and are compatible with N concentration prediction. Meanwhile, NNI is a whole plant-based approach and is, thus, greatly affected by the dynamics of N partitioning within the plant across the growth stages. Giletto et al. (2020) discussed the unique complexity of potato whole plant N dynamics involving not only the metabolic and structural compartments but reserve storage. Because the whole plant N dynamics of potato changes when the tubers come into play, the attempt to predict NNI across the season was not very successful. The difficulty of predicting NNI using SPAD/Dualex Chl readings was even higher as they do not account for leaf mass per area. Dualex Flav readings or Dualex NBI were more conducive to NNI prediction because Flav and leaf mass per area have a high correlation (Cerovic et al., 2012).

4. Limitations and future progress

The size of the data used here was somewhat small and constrained the data partitioning manner resulting in a random 8:2 split for the training and testing datasets. This is a case of moderate information leak. The overfitting in the training dataset was not necessarily penalized enough when validated in the testing dataset making the model performance optimistic, especially for complex models. When the models are applied in a new season, some of them will tend to underperform. As the feature importance metrics indicated and it makes sense agronomically, the as-applied N rate was one of the most important features for predicting N status indicators. A large quantity of total N fertilizer was applied in the form of controlled release fertilizer in the studies. However, the release rate of this fertilizer over time was not considered. Better characterizing the release rate could improve the prediction accuracy. The high variability of PNN concentration and the complex dynamics of NNI made their predictions challenging (Giletto et al., 2020; Goffart et al., 2008). NNI prediction will be further improved by characterizing the dynamics of N allocation within the plants. The sufficiency threshold must also be established for each cultivars to make decisions on in-season N fertilizer applications (Bélanger et al., 2003; Bohman et al., 2023; MacKerron et al., 1995; Zhang et al., 1996). NNI has the potential to make variable in-season N fertilizer applications (Giletto & Echeverría, 2013).

The raw sensor readings might provide an insight into potato N status through calibrated thresholds. For PNN concentration and NNI prediction, a few additional machine learning models will be explored, and their classification algorithms will be compared too. As demonstrated by Giletto et al. (2020), vine-based NNI can be an alternative to whole plant-based NNI. Using vine-based NNI instead might help isolate the effects of critical N dilution from the reserve storage to some degree and make better predictions using leaf sensors. However, it is also important to note that the usefulness of vine-based NNI is limited to a particular period of the season (i.e. 60-90 days after planting). Nitrogen Sufficiency Index (NSI) can be another approach, where one of the higher N treatments can be designated as N rich based on agronomic analysis. This is a cultivar, site, and year specific normalization approach, while the establishment of N rich plots is often considered a limitation to practical implementation.

Conclusion

Dualex demonstrated slight improvement in predicting PNN concentration and NNI owing to the addition of Flav reading. Meanwhile, the data fusion approach using GxExM information greatly improved the prediction accuracy of the N status indicators and diminished the sensor differences. Compared to PNN concertation, the models struggled to make good NNI predictions using leaf sensor readings due to the complex dynamics of N allocation within potato plants. The variables that account for plant biomass such as NDVI or NDRE will help improve the accuracy of NNI prediction. Overall, upgrading the leaf sensor is only justifiable in situations with no accessible ancillary data. The preferred and effective approach is to fuse leaf sensor readings with GxExM information using machine learning models. More analyses will be done for potato N status diagnosis using raw sensor data with calibrate thresholds, using other machine learning models and their classification algorithms, and predicting vine-based NNI instead of whole plant-based NNI.

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