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Predicting Cover Crop Nitrogen Content with a Handheld Normalized Difference Vegetation Index Meter

Charles M. White,* Brosi Bradley, Denise M. Finney, and Jason P. Kaye

Core Ideas

- Cover crop biomass N content (CC-N) can be estimated in the field with a handheld NDVI meter.
- Separate calibration equations exist for different cover crop types in fall and spring.
- Rapidly estimating CC-N could facilitate management of N-related services provided by cover crops.

Abstract: Cover crop (CC) biomass nitrogen content (CC-N; kg ha^{-1}) is related to a number of ecosystem services but is rarely measured by farmers and agronomists because of the expense of sampling and analysis. We hypothesized that normalized difference vegetation index (NDVI) measured by a handheld meter could predict CC-N. Using a dataset of 598 observations, we predicted fall biomass N with two separate calibrations for (i) clover-type legumes and (ii) CCs consisting of brassicas (*Brassica* spp.), cereal grasses, vining legumes, and grass–legume–brassica mixtures. Spring biomass N was predicted with three separate calibrations for (i) cereal grain CCs, (ii) brassicas, and (iii) CCs consisting of pure legumes and grass–legume–brassica mixtures. Quality of the calibrations ranged from r^2 = 0.72 to r^2 = 0.87. Rapidly and inexpensively estimating CC-N with an NDVI meter could enhance the ability of farmers and agronomists to routinely monitor and manage the N-related ecosystem services provided by CCs.

The quantity of nitrogen (N) contained in cover crop (CC) biomass is an important property related to nitrate leaching prevention and N supply to subsequent crops in the rotation (Tonitto et al., 2006; Dabney et al., 2010). Despite the importance of CC biomass N content (CC-N), it is rarely measured by farmers or agronomists because of the time and costs associated with sampling and analysis. A simple and inexpensive method to measure CC-N could facilitate decision support tools that quantify CC ecosystem services (e.g., residual soil N scavenging) or to estimate a fertilizer N credit for the CC (White et al., 2016, 2017).

The N content of plant biomass has been estimated in natural and agricultural plant communities using the normalized difference vegetation index (NDVI), a metric derived from remote sensing of plant canopy spectral reflectance (Gamon et al., 1995; Lukina et al., 2001; Li et al., 2008). In agricultural systems, use of NDVI sensors has primarily focused on in-season fertilizer management in cereal crops (Lukina et al., 2001; Tremblay et al., 2009) and quantification of ecophysiological plant traits in breeding programs (Cabrera-Bosquet et al., 2011; Liebisch et al., 2015). In recent years, sensors to measure agricultural crop canopy NDVI have become commercially available, including a low-cost handheld meter (e.g., GreenSeeker HCS-100, Trimble Navigation).

In this study, we tested whether a handheld NDVI meter could be used to predict CC-N in a wide range of CCs in fall and spring, including monocultures and mixtures of grasses, legumes, and brassicas (*Brassica* spp.). We hypothesized that unique calibration curves would be necessary for different CCs within fall and spring sampling times.

C.M. White, Dep. of Plant Science, Pennsylvania State Univ., University Park, PA 16802; B. Bradley and J.P. Kaye, Dep. of Ecosystem Science and Management, Pennsylvania State Univ., University Park, PA 16802; D.M. Finney, Dep. of Biology, Ursinus College, Collegeville, PA 19426.

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*Corresponding author (cmw29@psu.edu).

Abbreviations: CC, cover crop; CC-N, cover crop biomass nitrogen content; NDVI, normalized difference vegetation index.

Methods

The dataset used to calibrate the handheld NDVI meter against aboveground biomass N content (kg ha^{-1}) was assembled from observations across multiple site-years of CC experiments in Pennsylvania from 2012 to 2018 (White et al., 2016, 2017; Murrell et al., 2017; and several additional unpublished experiments). The experiments included monocultures and mixtures of 11 CC species, including Austrian winter pea (*Pisum sativum* L. ssp. *sativum* var. *arvense*), canola (*Brassica napus* L.), crimson clover (*Trifolium incarnatum* L.), forage radish (*Raphanus sativus* L.), hairy vetch (*Vicia villosa* Roth), oat (*Avena sativa* L.), red clover (*T. pratense* L.), annual ryegrass (*Lolium multiflorum* Lam.), cereal rye (*Secale cereale* L.), sweet clover [*Melilotus officinalis* (L.) Pall.], and triticale (×*Triticosecale* Wittm. ex A. Camus.). Cover crop treatments were classified into functional groupings to test whether different calibrations were needed for brassica monocultures, cereal rye monocultures, triticale monocultures, clover legumes, vining legumes including Austrian winter pea and hairy vetch, mixtures of grasses and legumes, and mixtures of grasses and/or legumes with brassicas.

Cover crops were planted in the fall following either small grains or corn (*Zea mays* L.) silage, with planting dates ranging from early August to early October. Cover crop biomass N content in each plot was quantified in fall and/or spring by measuring the total aboveground dry biomass (kg ha^{-1}) of all living plant species present and multiplying by the biomass N concentration according to procedures detailed in White et al. (2016).

The NDVI of CC plots was measured using a handheld NDVI meter (GreenSeeker HCS-100, Trimble Navigation). The meter uses an active light source optical sensor (660 nm red, 780 nm near infrared, ~25 nm full-width half-maximum), and displays the NDVI of the scanned area every ~0.5 s while the trigger is depressed. Upon release of the trigger, the average of measurements over the last 60 s is displayed. To measure NDVI of the CC plots, the meter was either walked across a transect of the entire plot (transect lengths ranged from 10 to 40 m depending on plot sizes) or spot measurements were taken from the same locations where quadrats of CC biomass were subsequently sampled. The meter was held at arm's length between 0.5 and 1 m above the top of the CC canopy. Cover crop plots where species were flowering (including grasses) were not included in the analysis due to interference between the inflorescences and NDVI measurement of foliage.

To analyze the relationship between CC-N and NDVI, we fit the data to an exponential model (Eq. [1]):

$$N_{cc} = ae^{b\mathrm{NDVI}} \qquad [1]$$

where N_{cc} is the CC-N (kg ha^{-1}), NDVI is the measurement from the handheld meter, and *a* and *b* are parameters fit to the data. Exponential models are widely used to predict dry biomass or biomass N content from NDVI because of the negative exponential relationship between leaf area index and radiation interception (Gamon et al., 1995).

To use general linear modeling to test the effect of CC type on parameter estimates, we converted Eq. [1] into a linear equation by natural log transforming both sides of the equation. This creates a straight-line relationship, where $\ln(N_{cc})$ is predicted by NDVI, with a slope of *b* and intercept of ln(*a*). Using the GLMSELECT procedure of SAS v. 9.4 (SAS Institute, 2017), we tested the relationship between NDVI and CC-N for all CC functional groups together and whether any functional groups had different parameter estimates for the slope or intercept. The GLMSELECT procedure used a stepwise selection process to add or remove unique slope and intercept terms for different CCs, using a significance level threshold of $\alpha = 0.01$. To prevent overfitting during stepwise selection, the model in the stepwise selection process that minimized the cross-validation predicted residual sum of squares was selected as the best model. This process was repeated separately for fall and spring CC samples. In each season, the best general linear model emerging from GLMSELECT was used to identify CCs that could be modeled together and those that needed to be modeled separately. The REG procedure in SAS v. 9.4 was then used to model the identified CC groupings for the purpose of determining parameter estimates and calculating a 95% confidence band of the mean and a 75% confidence band for individual predictions. These two bands differ in their interpretations: the individual prediction band shows the range within which the CC-N value will occur 75% of the time for any individual NDVI measurement in the future, whereas the confidence band of the mean brackets uncertainty in estimating the population mean. We substantially relaxed the α level of the confidence band for individual predictions because we felt that farmers and agronomists interested in using this relationship to make future predictions about CC-N content for individual fields would be willing to accept a lower confidence level than scientists, whose interests usually focus on estimating the population mean.

Results and Discussion

We found that NDVI of cover crop canopies measured by the handheld meter had a strong relationship with CC-N. Two calibration equations for fall measurements and three calibration equations for spring measurements were sufficient to predict CC-N for all cover crop types included in the study (Fig. 1). These results can encourage the development of handheld NDVI meters as a tool to assess and manage the N-related services provided by CCs.

When predicting CC-N from NDVI measurements taken in the fall, general linear modeling indicated that clover-type legumes required a separate calibration from the other CC types ($P < 0.001$ for different slope and intercept of clover-type legumes compared with the combined model, general linear model $r^2 = 0.84$). Regression models for the clover-type legumes and the other CCs combined in the fall were both high quality (Fig. 1A–B, $r^2 = 0.72$ and 0.86, respectively). In the spring, cereal rye, triticale, and brassica CCs required calibration separately from the combined CC model ($P < 0.001$ for different slope and intercept of brassicas and $P < 0.001$ for different intercepts of cereal rye and triticale

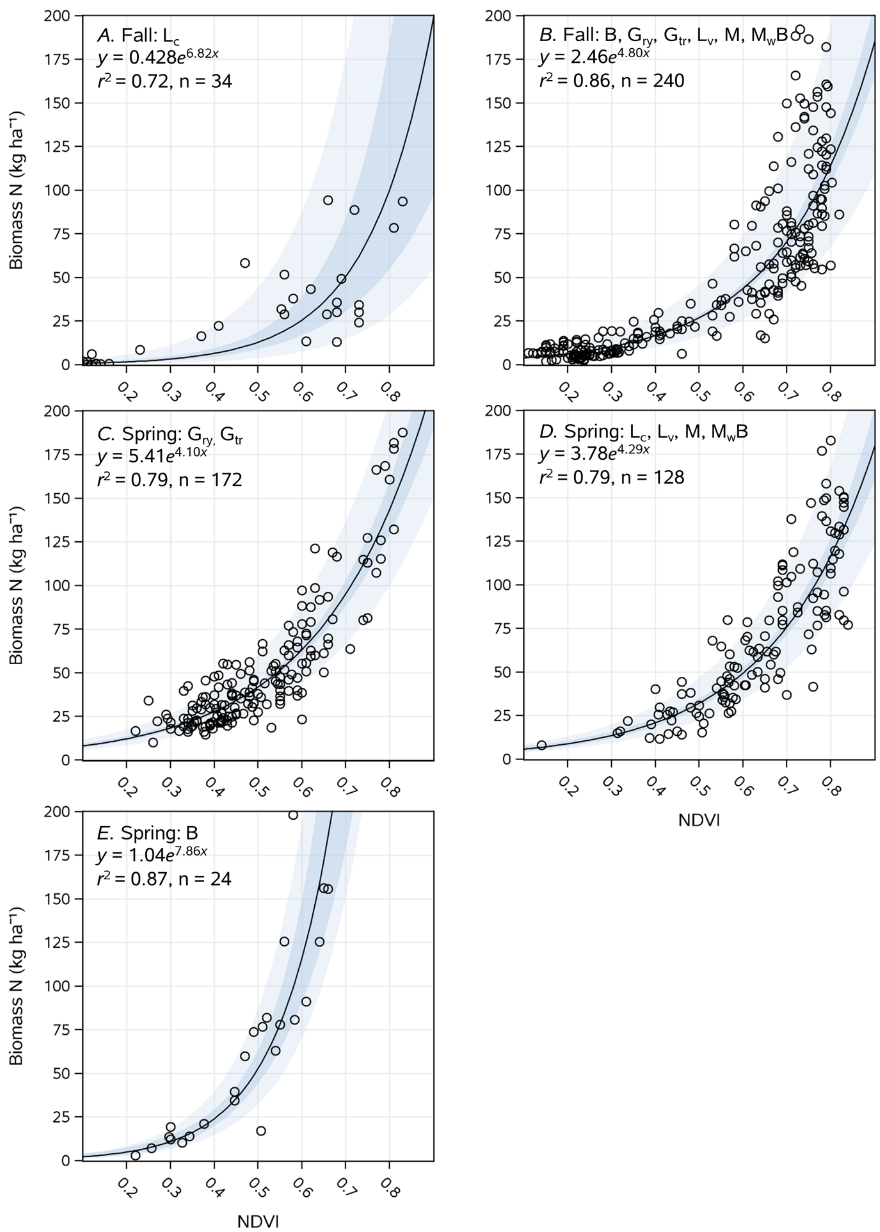

Fig. 1. The exponential models to predict CC-N from NDVI for different CCs by season (brassica monocultures [B], cereal rye monocultures [G_{ry}], triticale monocultures [G_{tr}] clover legumes [L_c], vining legumes [L_v], mixtures of grasses and legumes [M], and mixtures of grasses and/or legumes with brassicas [M_wB]). The solid line is the prediction, the outer band is the 75% confidence band of individual observations (the actual CC-N of a future observation will fall within this range 75% of the time), and the inner band is the 95% confidence band in estimating the population mean.

compared with combined model, general linear model r^2 = 0.81). Further analysis of parameter estimates for individual models of brassicas, rye, and triticale indicated that parameters for the rye and triticale models were not statistically different ($P < 0.05$); therefore, rye and triticale samples were combined into a single calibration. Regression models for each calibration in spring were high quality (Fig. 1C–E, r^2 ranged from 0.79 to 0.87).

For all models, the error in predicting CC-N increased as NDVI increased because of the exponential relationship between NDVI and CC-N. In our analysis, we report confidence bands for both estimating the population mean value and for future predictions of individual observations (Fig. 1). The 95% confidence band for estimating the mean CC-N (i.e., estimating the mean of a population from multiple measurements in or across fields) was quite narrow for calibrations with large numbers of observations, such as the brassica monoculture, cereal rye monoculture, triticale monoculture, vining legume, mixtures of grasses and legumes, and mixtures of grasses and/or legumes with brassicas calibration in fall (n = 240), the cereal rye monoculture and triticale monoculture calibration in spring (n = 172), and the clover legume, vining legume, mixtures of grasses and legumes, and mixtures of grasses and/or legumes with brassicas calibration in spring (n = 128). However, the 75% confidence band for predictions of individual observations was in some cases quite wide, such as for high NDVI values of clover-type legumes in fall. The confidence band for individual observations could be used to bracket a range of possible CC-N values when evaluating the uncertainty of ecosystem services related to CC-N content.

Our results provide the first systematic analysis of using NDVI to predict CC-N across a wide range of species and in different seasons. It is notable that the N content of such a large diversity in CCs, including monocultures and mixtures of different species across different seasons, can be predicted by NDVI with relatively few calibrations. While the use of NDVI as a tool to facilitate precision management in row crops has been relatively well studied, research on the use of remote sensing to monitor and manage ecosystem service provisioning by CCs is nascent. Large-scale satellite remote sensing of NDVI in agricultural fields has previously been used to predict the biomass of cereal CCs to evaluate the efficiency of conservation payment programs and to measure farmer adoption of cover cropping (Hively et al., 2009, 2015). Vehicle-mounted NDVI sensors were used to find correlations between CC biomass, corn yield, and soil and topographic characteristics (Muñoz and Kravchenko, 2012; Muñoz et al., 2014). Our calibrations of the handheld NDVI meter could facilitate further use of this tool to assess and manage CC services.

Others have also experimented with predicting winter wheat (*Triticum aestivum* L.) N content from vegetation indices other than NDVI, which may require multispectral radiometers that are significantly more expensive than the NDVI meter tested here. Li et al. (2008) and Moges et al. (2005) both found that NDVI generally had prediction accuracies comparable to other indices. In estimating CC dry biomass, Prabhakara et al. (2015) found that NDVI had similar predictive accuracy as the triangular vegetation index over the whole range of data but that the triangular vegetation index did not saturate at high biomass levels. Given that NDVI performs similarly to other vegetation indices, and that multispectral radiometers may be too expensive for routine use by farmers and agronomists, our results support the further use of an inexpensive handheld NDVI meter.

Conclusion

We demonstrated that a handheld NDVI meter can accurately predict CC-N across a wide range of CCs in fall and spring. These results give farmers and agronomists a new method to rapidly and inexpensively estimate CC-N, which could allow for more routine monitoring and management of the N-related ecosystem services provided by CCs. We are already coupling these measurements with models to predict N provisioning to cash crops (White et al., 2016, 2017), which may lead to advances in N decisions support.

Conflict of Interest

The authors declare no conflict of interest.

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