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REMOTE SENSING OF FOLIAR NITROGEN IN CULTIVATED GRASSLANDS OF HUMAN DOMINATED LANDSCAPES

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BY

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ABSTRACT

REMOTE SENSING OF FOLIAR NITROGEN IN CULTIVATED GRASSLANDS OF HUMAN DOMINATED LANDSCAPES

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Foliar nitrogen (N) in plant canopies plays a central role in a number of important ecosystem processes and continues to be an active subject in the field of remote sensing. Previous efforts to estimate foliar N at the landscape scale have primarily focused on intact forests and grasslands using aircraft imaging spectrometry and various techniques of statistical calibration and modeling. The present study was designed to extend this work by examining the potential to estimate the foliar N concentration of residential, agricultural and other cultivated grassland areas within a suburbanizing watershed. In conjunction with ground-based vegetation sampling, we developed Partial Least Squares Regression (PLSR) models for predicting mass-based foliar %N across management types using input from airborne and field based imaging spectrometers. Results yielded strong predictive relationships for both ground- and aircraft-based sensors across sites that included turf grass, grazed pasture, hayfields and fallow fields. We also report on relationships between imaging

spectrometer data and other important variables such as canopy height, biomass, and water content, results from which show promise for detection with imaging spectroscopy and suggest that cultivated grasslands offer opportunity for empirical study of canopy light dynamics. Finally, we discuss the potential for application of our results, and the challenges posed, to data from the planned HyspIRI satellite, which will provide global coverage of data useful for vegetation N estimation.

1. INTRODUCTION

Through its association with proteins and plant pigments, foliar nitrogen (N) plays an important regulatory role in photosynthesis, leaf respiration and net primary production in terrestrial ecosystems (Field & Mooney 1986, Ollinger & Smith 2005, Reich et al. 2006). Because N is a common and widespread limiting resource to plants, spatial patterns of foliar N are also related to fluxes of carbon, water and energy, and are therefore central to understanding the role that terrestrial ecosystems play within the larger Earth system (Ollinger et al. 2008, Ustin 2013). At the landscape scale these patterns are driven by environmental attributes including climate, species composition, soil condition, disturbance history and management practices. Given its importance, foliar N has been the focus of considerable attention in the field of remote sensing spanning several decades (e.g. Wessman et al. 1988, Martin et al. 2008, Ramoelo et al. 2012). While the foundational methods are rooted in laboratory and agricultural settings (Marten et al. 1984, Park et al. 1998), more recent efforts at estimating foliar N have primarily concentrated on intact forests and grasslands due to their spatial extent and documented importance to the Earth system (Smith et al. 2002, Townsend et al. 2003, He et al. 2006, McNeil et al. 2008, Ramoelo et al. 2012). Although these and other investigations have successfully classified N status in forests and grasslands, difficulties associated with the diversity of land ownership and land management objectives have been an impediment to applications in developed landscapes (Milesi et al. 2005). Several studies have successfully delineated lawns and other urban plant canopies using high spatial resolution imagery (Walton et al. 2008, Wu & Bauer 2012), but the use of remote sensing for estimating biochemistry and nutrient status in developed landscapes remains in its infancy (Davies et al. 2011).

The cultivation of grasses for animal forage or aesthetic purposes is a near ubiquitous practice in human-dominated landscapes and often represents important shifts in terms of ecosystem function and services from surrounding ecosystems (Foley et al. 2005). Turf grass surface area in the United States has been estimated at 163,812 km^2, an area larger than that of the nation's largest irrigated crop (Milesi et al. 2005). When pastures and hay fields are included, cultivated grasses comprise 707,627 km^2, or 8.76%, of total land area in the conterminous United States (NLCD 2006). As with many intensively managed systems, these grasslands embody tradeoffs among various ecosystem services, with consequences affecting both human and environmental welfare (Kaye et al. 2006). They comprise an important base of our food system and help define the locations we inhabit, while often requiring inputs of chemical fertilizers, irrigated water, and energy to meet desired management goals (Falk 1976, Cassman et al. 2002). Through these pathways, and by altering soil structure, ground water penetration, and surface water flow, the cultivation of grass has substantial influence on terrestrial and aquatic biogeochemical cycles (Pataki et al. 2011, Trowbridge et al. 2013, Kaushal et al. 2014).

From a remote sensing standpoint, the diversity of management objectives in developed systems poses challenges that are less prevalent in more natural ecosystems (Boegh et al. 2002, Booth & Tueller 2003). While remote sensing imagery has been used to detect water stress (Gao 1996, Tilling et al. 2007), N status (Gamon et al. 1993, Boegh et al. 2002, Ramoelo et al. 2012) and plant biomass (Paruelo et al. 1997, Running et al. 2004) in grasslands, our understanding of the combined effect of these factors on whole canopy reflectance is incomplete (Ollinger 2011). It remains unclear whether a generalizable approach for estimating foliar N via remote sensing can accommodate the range of management strategies encountered within a developed landscape. Resolving this is particularly pertinent in light of the planned HyspIRI mission, which will provide global coverage of high-fidelity imaging spectrometer data from an orbital platform. To address this question, we sought to examine the use of high spectral resolution remote sensing from both airborne and ground-based platforms for detecting foliar N within cultivated grasslands. Our study focused on a mixed-use landscape in southeastern New Hampshire that included a wide range of grass management strategies. Results are presented with respect to the utility of methods we tested and their potential application to environmental modeling, resource management and for future applications with HyspIRI.

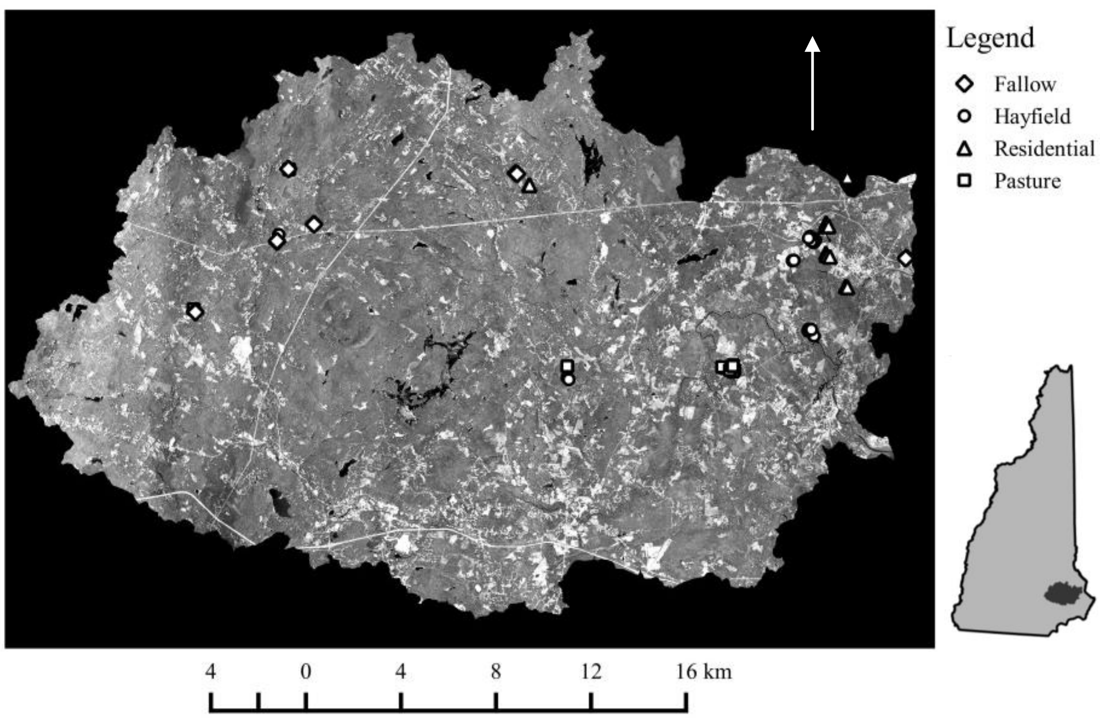
2. METHODS

2.1. Study Sites

The study was conducted within the Lamprey River Watershed (LRW) in southeastern New Hampshire (43.1032°N, 71.1104°W), a coastal area encompassing 479 km^2 and nine towns that drains into the Great Bay National Estuarine Research Reserve. The watershed has a diverse history with more than 300 hundred years of land use change following European settlement (Hamilton 1882). Today, rural to urban development gradients are present throughout the watershed and population densities range from zero to greater than 620 people per km^{-2}. Although the watershed is predominately forest, non-forested land accounts for 17.5% of the total area. Residential turf and agricultural grasslands are mixed throughout this fraction and represent important loci for human-environment interactions. The cultivation and maintenance of grasses has a strong influence on biogeochemistry within the watershed (Fissore et al. 2012) and the U.S. Environmental Protection Agency has established that water quality in both the Lamprey River, and the Great Bay estuary into which it drains, is impaired by excess N. Twenty-seven percent of the total non-point source N pollution coming into Great Bay is attributed to residential and agricultural fertilizer use (Trowbridge et al. 2013), highlighting the need for methods to better understand the N status of managed grasses.

In 2012, twenty field sites representing four management types (7 residential & commercial turf, 4 pasture, 3 hayfield, and 6 fallow) were selected for the purpose of vegetation sampling and image calibration (Figure 1). The sites were selected using a stratified random sampling design with access to private property influencing the final number included in each management type.

Figure 1. The Lamprey River Watershed, its location in New Hampshire, and distribution of field sites surveyed in this study. Dark gray areas of the Lamprey River Watershed are forest, while light gray areas are dominated by residential and agricultural grasslands.



2.2. Vegetation Sampling

At each of the 20 field sites, two to five plots were established for vegetation sampling such that a minimum of ten plots represented each management type (53 in total). Plots were 5m by 5m in size and were located to best characterize each site's management practices while avoiding potential edge effects of adjacent parcels. The mixed nature of management on a given parcel allowed some sites to include plots of more than one management type.

Plots were sampled for aboveground biomass, canopy nitrogen concentration (%N), leaf water content and canopy height. Plot-level values for each measured attribute represent the mean of data collected at the two to five locations within the plot boundaries. Biomass sampling consisted of shearing all standing foliage to ground level within a randomly placed 10x50 cm sampling frame. Once collected, samples were immediately enclosed in sealable plastic bags and stored on ice to prevent water loss. Samples were then weighed "wet" prior to being dried at 70°C for 48 hours and reweighed to determine water content. Dried samples were ground using a Wiley mill with a 1mm mesh screen. Canopy %N (g N · 100g biomass^{-1}) for all dried and ground samples was determined using a FOSS NIR 6500 bench-top spectrometer as described by Bolster et al. (1996). Because dried, ground samples included total biomass from grass species present within the sampling area, %N values represent multi-species means and were inherently weighted by the fractional abundance of each species present. Although existing calibration equations have proven accurate for grassland systems generally (Park et al. 1998, Park et al. 1997), we derived a calibration equation specific to this study in order to ensure that the full range of conditions would be captured. The calibration was based on a random subset of 103 samples collected during 2012, for which canopy %N values were measured with a mass spectrometer and independently validated using one-out repeat calibration (Shetty et al. 2011). To aid in the interpretation of grass canopy spectra, canopy height was measured at locations where biomass samples were taken and represents the mean height above ground as grasses were naturally displayed and is not necessarily a measure of total tiller/blade length.

In 2012, field sampling was conducted between late July and mid-August to ensure that samples were collected within fourteen days of the aircraft imaging spectrometer data collection (Section 2.4). Additional sampling in 2013 was conducted to expand the number of observations available for comparison with coincident ground-based spectra, but were not used in the calibration against 2012 aircraft image data. Sampling dates in 2013 were chosen to match 2012 in terms of position within the growing season and to capture similar conditions relative to time since mowing and other management practices. In total, 830 biomass samples were collected for foliar %N analysis (see Section 3.2 below).

2.3. Ground-based Spectroscopy

Ground-based reflectance was measured with an ASD FieldSpec 4 handheld spectroradiometer (www.asdi.com) under clear sky conditions at all sites, coincident with vegetation sampling. Data were collected within two hours of solar zenith in order to minimize the effect of shadows. The ASD has a spectral range of 350-2500 nm with an effective spectral resolution ranging from 1.4 to 2 nm and a target ground sampling resolution of 0.08 m^2 when equipped with an 18°fore optic at one meter above the canopy. Canopy reflectance was calculated using the average of 50 spectral reflectance signatures logged during a random walking survey of each 25 m^{-2} plot. Care was taken to avoid sampling areas where vegetation had been trampled by fieldworkers. Spectral surveys conducted during the 2012 field season occurred within two weeks of the airborne remote sensing mission to minimize temporal variation between the two datasets. During the 2013 field season, spectral surveys were conducted during the same time of year in conjunction with field sampling.

2.4. Airborne Remote Sensing Data Collection

Airborne visible and infrared reflectance for the entire LRW was collected in 33 flight lines on August 4th and 7th in 2012 to coincide with peak growing season conditions. Data were obtained by the ProSpecTIR-VS instrument, which is a dual sensor design with a visible/near-infrared (400-1000 nm) and a short-wave infrared (1000-2500 nm) sensor. Together, these sensors capture upwelling radiance in 360 continuous spectral bands with a nominal spectral resolution of 5 nm. The instrument was flown on a Cessna fixed wing aircraft at an altitude of ~3900 m, yielding a spatial resolution of 5 m. Flight lines were oriented in the principal plane of the sun to minimize cross-track brightness gradients.

2.5. Data Processing and Analysis

2.5.1. Spectral Preprocessing

Reflectance spectra from ground and aircraft instruments were processed using a combination of R version 2.15.1 (www.r-project.org) and ENVI 4.7 (www.exelisvis.com). Airborne data were converted from calibrated radiance to apparent surface reflectance using MODTRAN 4 atmospheric lookup tables with the ATCOR4 software. Field plots were located within the aerial imagery using GPS coordinates collected during field surveys and were represented as single 5x5m pixels centered at these locations. To facilitate comparison between datasets, ground-based spectra containing 2,150 one-nanometer bands were convolved (using full-width half-maximum) to match the coarser 360 band airborne data. This was done prior to the development of spectral calibrations (Section 2.5.2.). Spectral bands that fell within visibly noisy regions or where atmospheric absorbance resulted in no usable data (i.e. <400 nm, 1350-1450 nm, and 1800-2000 nm) were removed from both datasets.

Ground-based spectral data were further processed to remove spectra that were dominated by non-vegetation surfaces or shadows. This typically resulted in the removal of 0-5 spectra per plot. At the plot level, and across management types, simple linear regression was used to compare the overall shape and agreement of canopy reflectance from ground- and aircraft-based spectra.

2.5.2. Regression Model Development

Relationships between canopy reflectance and vegetation variables (canopy %N, water content, height, and biomass) were assessed using Partial Least Squares Regression (PLSR) in JMP Pro 10. PLSR is an eigen-based analysis designed to maximize the covariance between two datasets. In practice, PLSR reduces the full spectrum into a smaller set of ordinated factors to optimize the covariance within prediction factors (i.e. spectra) and observed data simultaneously (Martin et al. 2008). PLSR excels over traditional regression techniques with data containing many more prediction variables relative to the number of observations, making it particularly well suited for high spectral resolution data. The final number of latent factors incorporated in each PLSR prediction model was determined by minimizing the root mean predicted residual sum of squares (PRESS), generated by one-out cross validation (Tobias 1995, Denham 2000). In instances where this method resulted in a model with a large number of factors relative to observed sample size, the number of factors was decreased according to the method described by van der Voet (1994). The van der Voet T^2 is a permutation-based statistic that allows the comparison of predictive ability of multiple models by analyzing the distribution of prediction residuals. Models incorporating data from all plots were generated using the ground-based and airborne spectral datasets discretely. Predictive models that used ground-based spectra incorporated data collected during both study years and therefore tended to have larger sample sizes when compared with models based on airborne spectra, where data were only available for the 2012 season (see Table 2). The prediction accuracy and precision of the PLSR models was assessed by the coefficient of determination (R^2) and root mean square error (RMSE), respectively.

2.5.3. Image Application for %N Estimation

Developed, cultivated, and grassland pixels were extracted from the aerial imagery using the 2010 NOAA C-CAP land cover classification (DOC-NOAA 2013). Pixels classified as developed were included in the initial extraction due to the finely mosaicked nature of commercial and residential grasslands in our region of study. Buildings and roads within these pixels were then masked using the 2010 Impervious Surfaces in Coastal New Hampshire and Southern York County, Maine dataset (CSRC 2011). Both classification datasets are based on Landsat 5 imagery with a spatial resolution of 30m. Pixels classified as having less than 30% impervious surfaces were included in the final classification scheme in an effort to include grassland parcels smaller than 30 x 30 m. Canopy %N was then estimated for the remaining image data by applying the airborne PLSR model (described in the previous section).

3. RESULTS

3.1. Summary of Field Measurements

Canopy %N, height, and aboveground biomass differed significantly ($p<0.05$) by management type, with the exception of agricultural grasses (i.e. pasture and hay; Table 1). Pasture and hayfield canopy %N, height and biomass were not statistically significantly different from each other, but were significantly different from turf and fallow grasslands. No significant differences in canopy water content were observed across grass cover types. Average nitrogen concentration was highest in turf grasses followed by agricultural grasses and lowest in fallow fields.

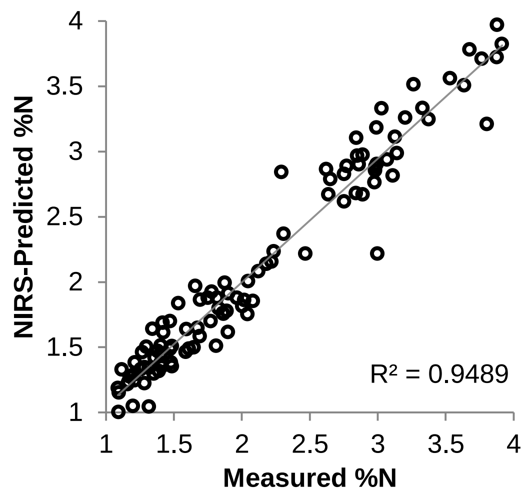
Table 1. Summary statistics of measured canopy attributes by management type. Canopy %N, height, and aboveground biomass differed significantly ($p<0.05$) across all management types with the exception of pastures and hayfields, which were statistically similar.

Cover Type	*%N ($gN\times100g^{-1}$)*			*Biomass ($g\times m^{-2}$)*			*Canopy Height (mm)*			*Water Content*		
	Min	*Max*	*Mean*	*Min*	*Max*	*Mean*	*Min*	*Max*	*Mean*	*Min*	*Max*	*Mean*
Turf	1.31	3.51	2.82	15.2	381	108	50	150	86	0.35	2.88	1.46
Pasture	1.03	3.09	1.96	105	387	262	104	620	338	1.03	3.09	1.96
Hay	1.06	5.55	2.76	101	596	264	157	602	356	1.06	5.55	2.76
Fallow	0.71	4.91	1.73	131	1060	500	175	1290	595	0.71	4.91	1.73

3.2. Lab-based Canopy N Calibration

Figure 2 shows foliar %N values measured by mass spectroscopy in relation to those predicted by the study-specific NIRS calibration. This calibration was based on a random subset of 103 samples (collected in 2012) and was used to determine the N concentration of the remaining samples (n=727). Of the total 830 biomass samples collected and analyzed for %N using laboratory NIRS (see section 2.2), six samples fell well below the range of N values included in the calibration dataset and were not included in the development of regression models used to estimate %N using airborne and ground-based spectra. These samples are believed to have included a large portion of dead biomass resulting resulted in low N values relative to the rest of the sample set.

Figure 2. NIRS predicted %N values of 103 dried and ground grass foliage samples. Prediction and fit based on partial least squares regression with 7 extracted factors. RMSE=0.1810, p<0.0001



3.3. Calibration of Ground- and Aircraft-based Spectra

PLSR models incorporating data from all plots and management types produced strong predictive calibrations for canopy %N using both aircraft and ground-based datasets (Figure 3, Table 2). The calibration using ground-based spectra yielded a better fit (r^2=0.76, RMSE= 0.29) than that based on aircraft data (r^2=0.67, RMSE=0.36) although both were highly significant ($p<0.0001$). Additionally, significant calibrations for water content, canopy height, and biomass were obtained using ground-based spectra (Figure 4, Table 2).

Table 2. Prediction statistics for measured canopy attributes resulting from PLSR. Significant (p<0.0001) relationships are indicated in bold.

Data Source	*Prediction*	*n*	*R^2*	*Mean Response*	*RMSEP*	*Min RM PRESS*	*Factor*
Ground Based	%N *($gN \cdot 100g^{-1}$)*	54	**0.7609**	2.1067	0.2911	0.4842	9
Airborne	%N *($gN \cdot 100g^{-1}$)*	39	**0.6723**	2.1478	0.3626	0.6683	6
Ground Based	Water Content	50	**0.6117**	2.0864	0.7661	0.8195	3
Airborne	Water Content	22	0.0465	57.44182	10.7958	12.5589	3
Ground Based	Canopy Height *(mm)*	55	**0.6122**	361.935	133.6353	204.9702	7
Airborne	Canopy Height *(mm)*	28	0.0022	412.7143	284.5958	293.9386	1
Ground Based	Biomass *($g \cdot m^{-2}$)*	56	**0.5494**	302.0243	137.5195	177.692	8
Airborne	Biomass *($g \cdot m^{-2}$)*	39	0.00787	224.3362	220.5728	228.3671	1

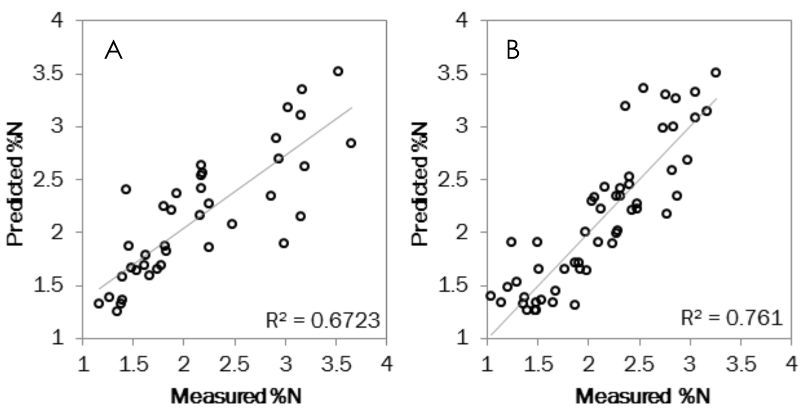


Figure 3. Relationships between %N measured using NIRS vs. %N predicted with PLS models incorporating (A) airborne and (B) ground-based canopy reflectance (p<0.0001)

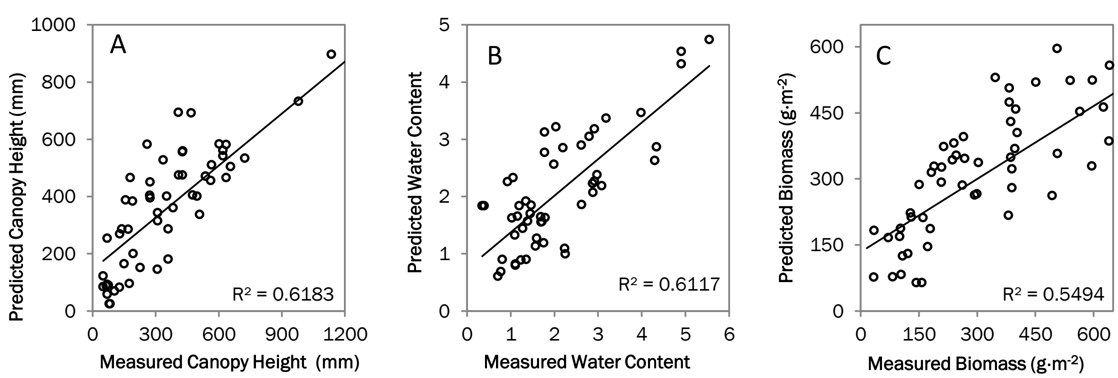
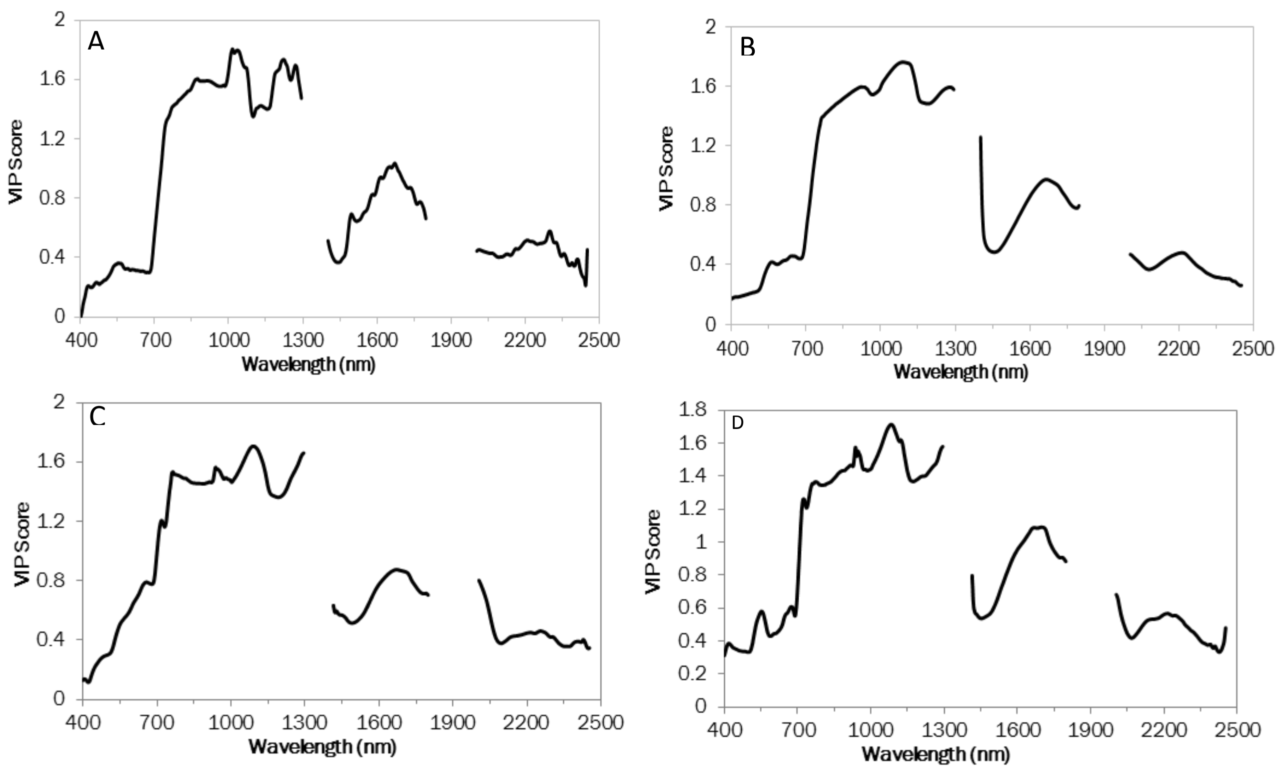


Figure 4. Relationships between PLSR prediction models incorporating ground-based canopy reflectance and measured (A) canopy height, (B) Water Content, and (C) Aboveground Biomass (P<0.0001)

3.4. Relative Importance of Spectral Bands in Calibrations

The contribution of spectral bands in each of the significant PLSR calibration models described above was assessed using the Variable Importance of Projection (VIP) statistic of Wold (1994; Figure 5). The VIP score describes the importance of a given predictor in the projection of the latent variables that underlie a PLSR model (Chong & Jun 2005). According to Wold (1996), predictors with a VIP score of one or higher are typically important in the



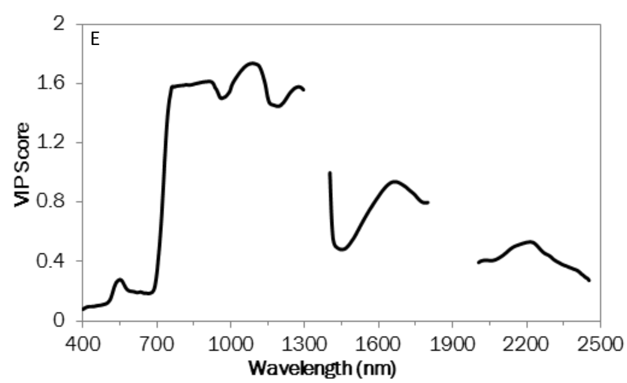


Figure 5. Important wavelengths as indicated by the variable importance of projection (VIP) in PLSR prediction models of (A) canopy %N predicted by airborne reflectance data, and (B) canopy %N, (C) canopy height, (D) Biomass, and (E) water content predicted by ground-based reflectance data.

resulting projection and those less than 0.8 tend to add little. VIP scores for both airborne and ground-based canopy %N calibrations indicate the importance of NIR bands located between 750-1300nm and, to a lesser extent, 1550-1750nm. These peaks are also important in the prediction of canopy height, biomass and water content.

3.5. Sensor Comparison

At the plot level and across management types, canopy reflectance derived from airborne and ground-based sensors showed agreement in the overall shape of spectral reflectance curves (e.g. Figure 5), although differences in brightness across some regions of the spectrum made direct comparison of these two data sources difficult. This can be seen in the differences in slope in Table 3. Generally, airborne spectra tended to be brighter in the visible region and dimmer throughout the NIR (750-1800nm) as compared to ground-based spectra.

Management Type	r^2	*Slope*
Turf	0.9253	0.9109
Pasture	0.8977	0.7476
Hay	0.9249	0.6036
Fallow	0.9064	0.8340

Table 3. Linear regression of ground-based and airborne spectra by management type. Correlation coefficients represent agreement across spectral shape and differences slope indicate change in overall brightness.

3.6. Predicted Canopy %N for Grassed within the Study Region

The distribution of cultivated grasslands in the LRW follows regional development trends concentrated in southern and eastern portions of the watershed (Figure 6). Predicted foliar %N values across the watershed exhibited a normal distribution with a mean of 2.24% and a range of 0.25% to 5.0%. These values fall within the range of foliar %N values of grasses compiled by Reich and Oleksyn in 2004 for their global study of plant N and phosphorous. While visual inspection of the watershed N prediction revealed a wide range of canopy %N values in all management groups, direct comparison of canopy %N across the four management types at the landscape level proved difficult due to the lack of an existing detailed classification that discriminates cultivated grasslands by management type.

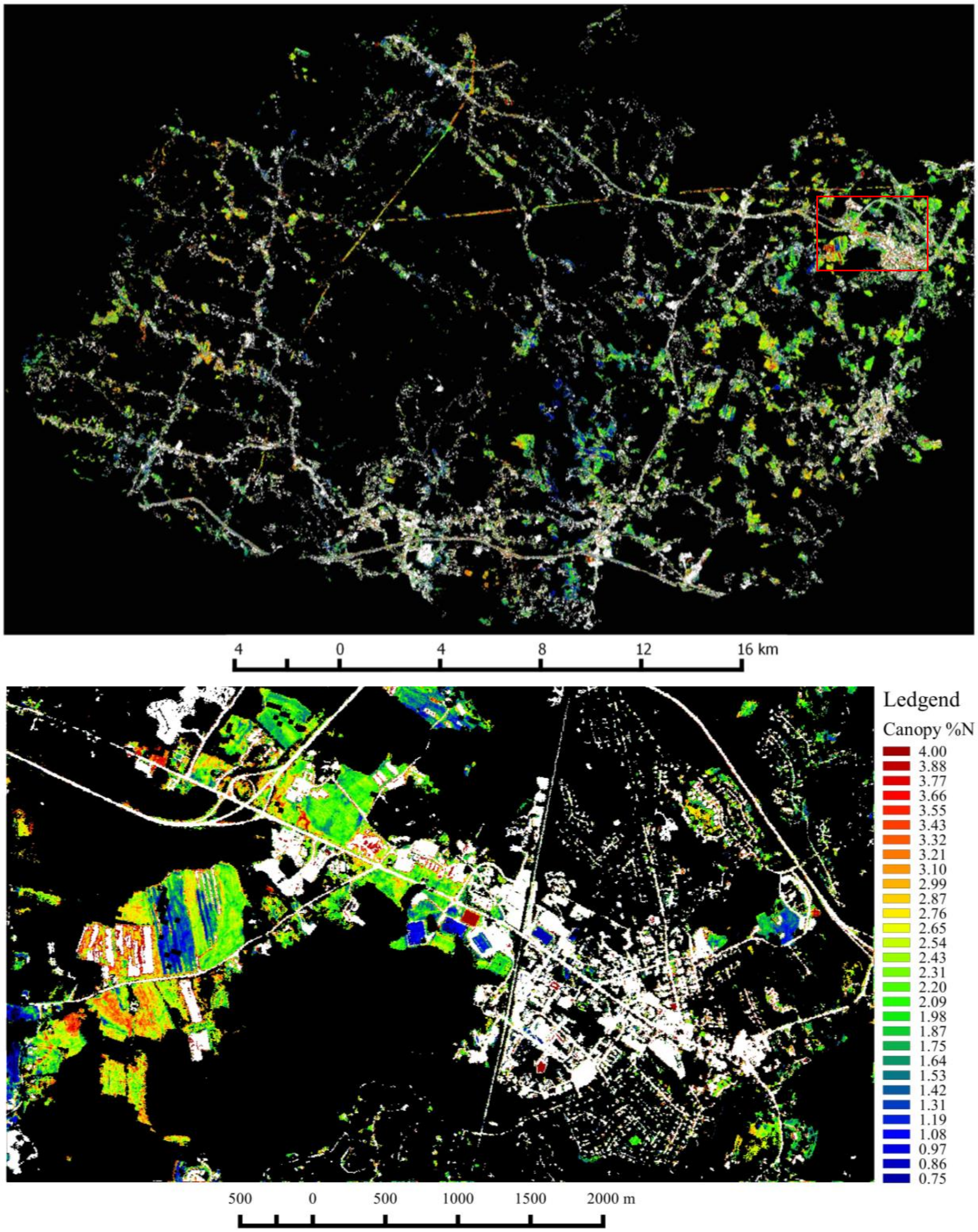


Figure 6. Canopy %N of cultivated grasslands in the Lamprey River Watershed**.** Areas in black represent non-grass vegetation. White areas are characterized as impervious and are included to provide context in residential and built areas. The inset image (outlined in red, top panel) is of the Durham New Hampshire area and illustrates the ability of the airborne imagery to delineate small grassland parcels and discriminate within-field differences in canopy %N.

4. DISCUSSION

4.1. N Detection in Cultivated Grasslands: Challenges and Opportunities

Cultivated grasslands are dynamic ecosystems that are heavily influenced by human management (Falk 1976). Management actions and the plant responses they induce affect canopy light interactions in complex ways posing challenges in the interpretation of remotely sensed data (e.g. Booth & Tueller 2003). Mowing and grazing—the primary mechanisms used to maintain cultivated grasslands—affect canopy reflectance in a number of ways, including altering aboveground biomass, leaf area index, leaf water content, soil background and leaf angle (Wu et al. 2012, Lee & Lathrop 2006). Imaging spectroscopy data from platforms such as those used in this study and the proposed HyspIRI mission allow for the inclusion of subtle yet influential reflectance features in the development of calibration equations that would otherwise be attenuated by traditional multispectral sensors (Chambers et al. 2007). In this regard, results of our study offer promise for the use of both ground- and aircraft-based high spectral resolution reflectance data and PLSR models to accommodate a range of grass conditions in predicting canopy %N. As with all PLSR-based approaches, these relationships are based on empirical observations and their application should be restricted to the range of conditions under which they were derived. Determining functional linkages between individual plant properties and spectral reflectance features at the canopy scale is often challenging given the complexity of plant canopies and the interrelated nature of many plant traits (Ollinger 2011). Determining these causal mechanisms has been an active field of research and often relies on the use of canopy light models (e.g. Zhang et al. 2006). Although such models have advanced our understanding of canopy light dynamics, they rarely include N because N itself has no distinct optical properties and because our understanding of relations between N and other optically important plant traits is incomplete. Grasses are potentially well suited to studying these relationships because they quickly respond to nutrient and water treatments and are easy to manipulate, isolating physical traits such as leaf area index and leaf angle distribution. Additionally, their short stature allows abundant collection of canopy reflectance data using handheld or laboratory instruments.

Through its association with plant proteins, foliar N represents an important measure not only of plant productivity but also of pasture and forage quality (e.g. Waramit et al. 2012). Detailed maps of canopy N in cultivated grasslands have several potential applications with respect to watershed management. In watersheds where agricultural grasslands are prevalent, the ability to detect canopy %N could aid managers in the application of fertilizers and management of livestock. The use of remote sensing to tailor management practices is not a novel idea (Knox et al. 2011, Thulin et al. 2012); however its adoption at the watershed to regional scale could provide interesting insights into agricultural systems and efficiencies. The spatial and temporal coverage of the upcoming HyspIRI mission has potential for estimating canopy % N and forage quality for large swaths of agricultural grasses that could lead to improved and adaptive grazing management practices (Thulin et al. 2012). When paired with ecosystem production (e.g. Ollinger & Smith 2005) and hydrologic flow models (Tague 2009), data such as those presented here may prove useful in modeling productivity, helping to close watershed N budgets, and potentially identify non-point sources of N pollution. Remotely sensed imagery offers the only effective means to produce the spatially explicit coverage necessary to study landscapes in this way. Although it lacks the spatial coverage necessary for broad-scale studies, ground-based spectroscopy enables rapid estimation of canopy %N at relatively low costs and allows for repeated sampling throughout the growing season, making it useful as a monitoring tool in cases where the temporal coverage of aircraft or satellite platforms is insufficient.

4.2. Relevance to HyspIRI

Remote sensing applications involving aircraft sensors come with the inherent limitation of the relatively small spatial coverage that can be achieved with aircraft. Because the spectral data used in our analysis are spectrally similar to those that will be provided globally by HyspIRI, our results hold promise for N estimation in cultivated grasslands over much larger areas. However, several hurdles will need to be overcome before this can be achieved. As an example, the spatial resolution of data used in our study was 5 x 5 m, which is typically adequate for capturing residential lawns (Zhou et al. 2008) as well as larger areas of agricultural grassland. The suggested spatial resolution for HyspIRI is 60 m, which is likely to be adequate for pasture, hay and other agricultural grasslands, but could present a challenge in residential areas given the smaller size of many private lawns. This challenge could potentially be addressed using spectral unmixing (Lee & Lathrop 2006), or through a multi-sensor scaling approach whereby small training areas within a HyspIRI scene are captured with aircraft data in order to aid in resolving sources of subpixel variation (e.g. Hope et al. 2004). Additionally, understanding the specific plant traits and management activities responsible for observed reflectance patterns will become more important as the areal extent of N estimation activities expands. A more mechanistic understanding would complement the empirical approaches used to date and aid in the effort to build leaf N concentrations and grassland management conditions into models that can be used to better interpret remote sensing signals where intensive field data are not available. Despite these challenges, results from this study suggest promise for applications of HyspIRI aimed at detecting patterns of vegetation condition in human-dominated landscapes as well as those containing native vegetation.

5. CONCLUSIONS

This study demonstrated that high spectral resolution canopy reflectance data from ground- and aircraft-based sensors offer a viable tool for estimating canopy %N of cultivated grasslands across the wide range of management types encountered in human-dominated landscapes. While the airborne %N calibration described here produced a good predictive relationship (r^2=0.67) the inclusion of additional samples in future calibration datasets will likely result in improved predictive ability. PLS regression techniques are well established in the remote sensing literature, but would be complemented by better understanding the underlying mechanisms governing canopy reflectance. Because they are fast growing, easily manipulated, and can be sampled from the ground, cultivated grasslands provide a useful environment in which to empirically test these mechanisms at multiple scales. Future remote sensing studies in human-dominated landscapes will benefit from a better understanding of these mechanisms, as well as improved landscape classification, and should strive to incorporate additional plant functional types such as crop and forests.

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