Groundwater Research Report
WR17R001

LINKING GROUNDWATER AND NUTRIENTS TO MONITOR FEN ECOSYSTEMS USING AIRBORNE IMAGING SPECTROSCOPY

Eric G. Booth
Steven P. Loheide II
David Bart
Philip A. Townsend
Arthur C. Ryzak

2019

Project Number WR17R001

LINKING GROUNDWATER AND NUTRIENTS TO MONITOR FEN ECOSYSTEMS USING AIRBORNE IMAGING SPECTROSCOPY

Eric G. Booth
Department of Agronomy, Civil and Environmental Engineering
University of Wisconsin-Madison

Steven P. Loheide II
Department of Civil and Environmental Engineering
University of Wisconsin-XXX

David Bart
Department of Planning and Landscape Architecture
University of Wisconsin-Madison

Philip A. Townsend
Department of Forest and Wildlife Ecology
University of Wisconsin-Madison

Administered by:
University of Wisconsin Water Resources Institute

Funded by:
The National Institutes for Water Resources, U.S. Geological Survey 104b program
State of Wisconsin Groundwater Research and Monitoring Program

2019

This project was supported by the United States Geological Survey National Institutes for Water Resources 104b program. Under the provisions of section 104 of the Water Resources Research Act of 1984, annual base grants (104b) are awarded to the Institutes or Centers that have been established in each of the 50 states, the District of Columbia, Puerto Rico, the U.S. Virgin Islands, and Guam. The annual base grants help each Institute or Center to plan and conduct applied and peer reviewed research on water resource issues. Institutes also use their base grants to help train new scientists, disseminate research results to water managers and the public, and to cooperate with other colleges and universities in their respective states and with other institutes and other organizations in their regions to promote regional coordination.

This project was also supported, in part, by General Purpose Revenue funds of the State of Wisconsin to the University of Wisconsin System for the performance of research on groundwater quality and quantity. Selection of projects was conducted on a competitive basis through a joint solicitation from the University and the Wisconsin Departments of Natural Resources; Agriculture, Trade and Consumer Protection; Commerce; and advice of the Wisconsin Groundwater Research Advisory Council and with the concurrence of the Wisconsin Groundwater Coordinating Council.

FINAL REPORT

Project: WR17R001

Linking groundwater and nutrients to monitor fen ecosystems using airborne imaging spectroscopy

Prepared by:

Eric G. Booth, Steven P. Loheide II, David Bart, Philip A. Townsend, Arthur C. Ryzak

December 19, 2019

TABLE OF CONTENTS

LIST OF FIGURES AND TABLES

PROJECT SUMMARY

Title: Linking groundwater and nutrients to monitor fen ecosystems using airborne imaging spectroscopy

Project I.D.: WR17R001

Investigator(s):

Project Investigators – Eric G. Booth, Assistant Scientist, Department of Agronomy, Department of Civil & Environmental Engineering
Steven P. Loheide II, Professor, Department of Civil & Environmental Engineering
David Bart, Associate Professor, Department of Planning & Landscape Architecture
Philip A. Townsend, Professor, Department of Forest & Wildlife Ecology

Research Assistant - Arthur Ryzak, PhD student, Department of Civil & Environmental Engineering

Period of Contract: July 1, 2017 to June 30, 2019

Background/Need: Calcareous fens (referred hereafter as 'fens') are unique and often isolated ecosystems of high conservation value in Wisconsin because they provide habitat for many rare plant and animal species. Their identity is strongly linked to a dependence on a consistent discharge of groundwater that saturates the surface for most of the growing season. Thus, they are particularly susceptible to decreases in groundwater inputs from activities such as nearby pumping. Fen identification and monitoring has traditionally relied upon expert plant taxonomic knowledge and ground-based field work, which can be costly, time-consuming, and limited in temporal and spatial extent. In contrast, remote sensing can be used to identify, monitor, and map plant characteristics across a large spatial extent in a repeatable and consistent manner. In particular, the field of imaging spectroscopy using hyperspectral sensors has matured to the point where biophysical traits relevant to identifying specific plant community types and monitoring ecosystem quality can be readily quantified.

Objectives: The overall goal of this research was to develop a framework for identifying and monitoring groundwater-dependent fen ecosystems using biophysically-relevant spectral characteristics obtained using airborne imaging spectroscopy so that ecosystem impacts of reduced groundwater inputs can be quantified and mapped. The main objective was to link floristic quality and other site variables of groundwater-dependent calcareous fens to spectrometry of fen foliage, so that these traits can be determined remotely and mapped across large areas.

Methods: We collected site variables and floristic quality data needed to serve as ground truth, such as water table elevations, soil nutrients, foliar chemistry, and weighted floristic quality index (WFQI) at 20 test plots at each of six calcareous fens. We determined how all the site variables and floristic quality were correlated, and then used Partial Least Squares Regression (PLSR) to link site variables and floristic quality to spectrometry of dried/ground foliage samples collected from the test plots as well as spectrometry of the six fen sites remotely using an airborne hyperspectral imager (HySpex). We developed a processing technique that uses stability of PLSR predictor variables to optimize model predictive ability, as well as identify site variables and spectral wavelengths of special significance in predicting floristic quality.

Results and Discussion: We determined that foliar nutrients, hydrology, and soil chemistry are well correlated with floristic quality metrics, which is consistent with our mechanistic understanding of how fens are defined. Incorporation of these floristic, hydrologic, and soil factors into models of floristic quality of fens yielded our highest model performance when predicting floristic quality of fens. The correlation between foliar nutrients (such as phosphorus) and floristic quality is especially revealing because this represents our mechanistic link from groundwater-dependent ecosystems to the predictive power of spectral data; consistent with previous research we developed robust models to predict foliar nutrients using lab-based spectra. We then were able to extend this mechanistic link by developing robust models to predict floristic quality from lab-based spectra. Finally, this cascade of tight relationships (hydrology-->floristic quality-->foliar nutrients-->spectra) allowed us to create predictive models from airborne spectroscopic images and map floristic quality across large, spatially continuous areas.

Conclusions/Implications/Recommendations: These findings have several important implications. First, our research adds to the body of literature regarding which factors affect fen floristic quality, which has important implications regarding how to monitor and protect these rare ecosystems. Second, the spectroscopic methods developed here for assessing floristic quality are relatively efficient when compared to the traditional approaches of assessing floristic quality of fens over large areas, such as the time-meander approach with a team of fen expert botanists. With an appropriately calibrated model, several large regions can be imaged in a single flight with better than 1m spatial resolution, with perhaps hundreds of miles separating fen sites. Thus, fens can be consistently and efficiently monitored. Third, the ability to map fen floristic quality across extensive areas provides managers a unique and valuable way to monitor hydrologic change as fens can be viewed as sentinel ecosystems that are quick to respond to subtle changes in groundwater. We have shown that a high and consistent water table is critical to the floristic quality of fens, and that when groundwater conditions of a fen change, the floristic quality deteriorates rapidly. Thus, since we can detect the changes in floristic quality readily, we can also detect that it is highly likely that the groundwater regime has been altered.

These findings lead us to recommend further exploration of the feasibility of incorporating these fen floristic quality mapping techniques into ongoing groundwater and ecosystem monitoring programs at the WDNR. We see these maps being useful in at least two ways: 1) identifying unknown locations of fen ecosystems, where such knowledge can play a key role in conservation of these rare ecosystems, and 2) continuous (every 1-2 years) monitoring to assess changes in hydrology and the associated impacts on fen floristic quality. This further exploration would also need to include continued research and refinement of the methods developed by this project. For instance, the effects of seasonality and the presence of particular species of fen vegetation on model performance should be investigated. However, results from this project clearly show that airborne-based imaging spectroscopy is a viable tool for monitoring subtle changes in groundwater and fen ecosystem health.

Related Publications: none at time of submission

Key Words: wetland, fen, drawdown, vegetation, spectroscopy, remote sensing, ecosystem

Funding: University of Wisconsin – System, U.S. Geological Survey

INTRODUCTION

Calcareous fens (referred hereafter as ‘fens’) are unique and often isolated ecosystems of high conservation value in Wisconsin because they provide habitat for many rare plant and animal species. Their identity is inextricably linked to a dependence on a consistent discharge of groundwater that saturates the surface for most of the growing season, leading to the accumulation of carbon as peat or tufa. As a result of calcium-rich groundwater being the main water source to these wetlands and ensuing chemical reactions (precipitation), the availability of nutrients (e.g. nitrogen and phosphorus) is quite low (Fig. 1). The consistent saturation and low-nutrient stresses result in high native plant diversity including very high rare species richness compared to other ecosystems [1–3]. Decreases in the saturation stress by reduced groundwater inputs (e.g. from nearby pumping) can result in substantial and potentially irreversible ecosystem change [4]. Thus, fens can be viewed as ‘sentinel ecosystems’ that may indicate subtle changes to groundwater conditions.

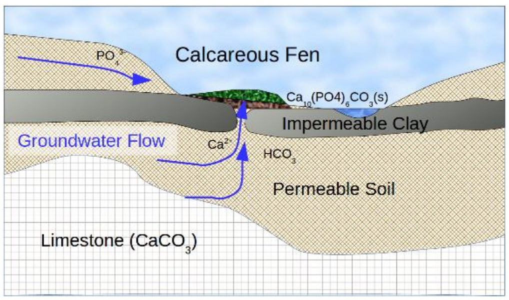


Figure 1: “A calcareous fen is an ecosystem whose hydrology is strongly and steadily controlled by high-mineral groundwater input, whose soils sequester carbon as both organic matter and carbonates, and whose vegetation is adapted to these edaphic conditions." (Carpenter, 1995) [7]

Fen identification and monitoring has traditionally relied upon expert plant taxonomic knowledge and ground-based field work, which can be costly, time-consuming, and limited in temporal and spatial extent. In contrast, remote sensing can be used to identify, monitor, and map plant characteristics across a large spatial extent in a repeatable and consistent manner. In particular, the field of imaging spectroscopy using hyperspectral sensors has matured to the point where biophysical traits relevant to identifying plant community types and monitoring ecosystem quality can be readily quantified [5-6].

In this project our overall goal was to develop a framework for identifying and monitoring groundwater-dependent fen ecosystems using biophysically-relevant spectral characteristics obtained with airborne imaging spectroscopy so that ecosystem impacts of reduced groundwater inputs can be quantified and mapped. The basic scheme of our approach involved collection and analysis of ground-based field data, collection and analysis of spectroscopic data, and linking of the two through statistical models. We focused our data collection on six fen sites that were intensively monitored for vegetation, hydrology, and soil properties as part of a project funded by the Environmental Protection Agency from 2016-2017. Paired sites are located in southeastern Wisconsin, the Madison area, and the Central Sands (Fig. 2). One of each pair is relatively pristine and the other is likely impacted by a decrease in groundwater inputs. Here we continued and expanded that ground monitoring through 2018 and collected new lab-based spectroscopic data and airborne hyperspectral imagery.

PROCEDURES AND METHODS

Overview

Our procedure involved *first*, maintaining and expanding a network of hydrologic and soil monitoring equipment to characterize the groundwater and edaphic regimes at 20-25 plots at and around each of six fens (Fig. 2). *Second*, we captured imagery at each site and surrounding area using an airborne hyperspectral sensor owned by the University of Wisconsin – Madison. *Third*, at each plot, we assessed floristic quality and took foliage/soil samples. *Fourth*, we dried and ground a portion of each foliage sample for lab-based spectroscopic analysis and had the rest of the samples analyzed for nutrients and various chemical properties at the UW Soil and Forage Lab. *Fifth*, we developed statistical relationships between all types of ground-based field data and floristic quality. ***Sixth***, we used the lab-based spectroscopy and airborne-collected reflectance imagery to determine statistical relationships between various spectral metrics and site variables including metrics of floristic quality. *Seventh*, we mapped out leaf biophysical traits and overall floristic quality. *Finally*, we determined pertinent spectral metrics that can be used to assess the quality and hydrology of existing fens.

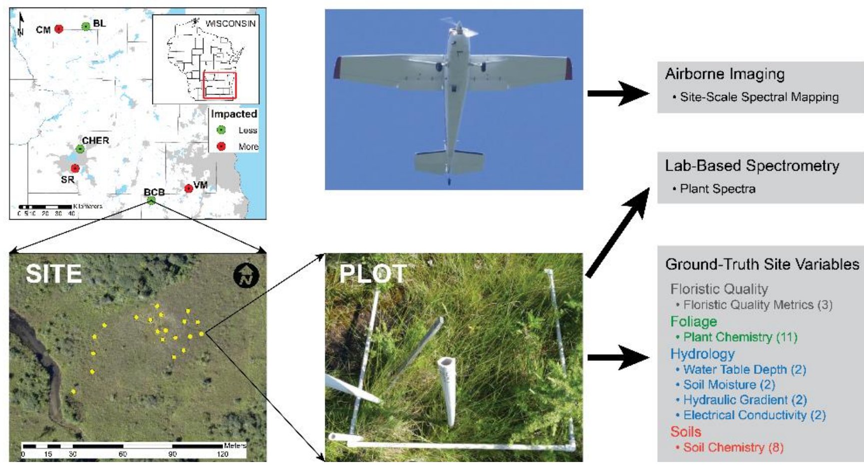


Figure 2: Data collection diagram showing locations of fen sites (see Appendix B for site names), example site and plot, and collected data.

Field Data Collection / Processing

We built upon field data collected by Bart et al [8] as part of an EPA study from 2016-2017 by continuing collection of site foliar (f_), hydrologic (h_), and soils (s_) data (parenthetical information indicates nomenclature of site variables of these types). That data included detailed Floristic Quality Assessment (FQA) of 20 test plots at each of our six fens in 2016. Continuous loggers at the core area of each fen also recorded weather, soil moisture, water table elevation, and soil electrical conductivity. Monthly hydrologic sampling at the twenty test plots at each fen included water table elevation (h_WTmed), piezometric head at 0.5m and 1.0m depth, from which we obtained hydraulic gradient (h_HGmed), and hand probe data of soil moisture (h_WCmed) and conductivity (h_ECmed). From the monthly samples we obtained the median, and standard deviation at each plot (e.g. h_WTmed and h_WTstd). For the present study, we continued all of these measurements through 2018. We also installed 2-5 new plots per fen around the periphery of the fens and collected the same data at these plots for 2017 and 2018. Soils were sampled in 2016 for nutrients (N and P), and we also collected additional soil samples at each plot in 2018, which we analyzed for pH, organic matter, calcium, ammonia, nitrate and phosphorus. We also collected a species abundance proportional clip sample of vegetation growing within each test plot, and dried and ground those samples to 2.0 mm using a "Wiley Mill".

Floristic Quality Assessment

We determined three separate floristic quality metrics. Firstly, a 1m x 1m test plot was established next to each monitoring well using a quadrat. Each test plot was visited monthly throughout the 2016 growing season and detailed observations of all herbaceous plant species present were recorded. Woody plant species growing in a larger, 5m x 5m area were also recorded. In FQA each species of plant has an associated coefficient of conservatism (C), which is determined by WDNR and botanical experts [9]. This C is a measure of the degree (0-10) to which a particular species is constrained to a particular niche environment, such as a calcareous fen. Species with C=10 include rare fen specialists, such as *Eleocharis rostellata* (Beak-spike rush) and *Cypripedium candidum* (White Lady's slipper orchid). Invasive species are assigned C=0. Vegetation at fens typically have a relatively high abundance weighted C, which is known as the Weighted Coefficient of Conservatism (wC). Multiplying the wC by the square root of the number of herbaceous species present (n) in the 1m x 1m plot, and woody species present in the 5m x 5m plot provides the Weighted Floristic Quality Index (WFQI):

$$WFQI = \sqrt{n} * wC = \sqrt{n} * \sum p_i * C_i$$

which is the first of our three floristic quality metrics (fq_WFQI). The number of fen-specialist species observed at the test plot (fq_specialists) during this identification process, is our second metric. Finally, in September 2018, at the time of airborne imagery collection, which coincided with collection of our vegetation clip samples and soil samples, we determined the dominant species present within the 1m x 1m test plot and the percent covers, which allowed us to calculate a wC (fq_wC) using the WDNR Floristic Quality Calculator [10]. Minor species present have little effect on wC and thus it represents a snapshot of floristic quality at the time of site data collection, which should be readily associated with proportional clip sampling of vegetation and collection of airborne imaging spectroscopy of the test plot.

Laboratory Analysis / Spectroscopy

Laboratory analysis involved spectroscopy of the dried and ground clip samples, chemical analysis of those same clip samples, and chemical analysis of the soils at each plot. For each clip sample (n=144) we prepared three subsamples and ran two replicates of spectroscopy on each of those subsamples. We used an ASD Fieldspec III laboratory spectrometer and generated spectra for each sample using reflectance values at 2151 wavelengths from the visible through short wave-infrared regions of the spectrum (350nm - 2500nm). A Spectralon white reference was used between samples for normalization of raw radiance values to determine reflectance. After inspecting each spectrum for integrity/correctness we averaged the six spectra to obtain one spectrum for each sample, representing the average reflectance at each wavelength of the six replicates. We vector-normalized each of these spectra by dividing by the total sum of all reflectances to minimize effects due to variation in overall brightness [11]. We calculated 1st derivative / 1st difference reflectance at each wavelength with respect to wavelength. We then standardized these reflectances and derivative reflectances by subtracting the mean and dividing by the standard deviation (of all samples) for each wavelength. The UW Soil and Forage Lab then analyzed these same leaf clip samples for total nitrogen (f_TN), phosphorus (f_P), potassium (f_K), calcium (f_Ca), magnesium (f_Mg), sulfur (f_S), zinc (f_Zn), manganese (f_Mn), boron (f_B), iron (f_Fe), and copper (f_Cu). The same laboratory analyzed soils for pH (s_pH), potassium (s_K), percent organic matter (s_OM), calcium (s_Ca), and magnesium (s_Mg). Soil nitrogen and phosphorus were analyzed in the 2016 project at the same laboratory using the Olsen method for phosphorus (sn_P), 2M KCl for nitrate (sn_NO3), and 2M KCl for ammonium (sn_NH4).

Airborne Remote Sensing Imaging Spectroscopy

We obtained hyperspectral imagery using the HySpex (Norsk Elektro Optikk, Norway) full-range (400-2500 nm) imaging system in operation at UW-Madison. Imagery was calibrated, orthorectified, atmospherically corrected following the established workflow described in Appendix C. We staked approximately 10 white plastic 5-gallon buckets at each fen to use as ground control points, and obtained their locations using a RTK GPS accurate to within two cm. We used these control points to further georectify the imagery, so that we could precisely locate the fen test plots on the imagery. At each test plot, we extracted the nine pixels of 0.5 m x 0.5m in and immediately adjacent to the 1m x 1m test plot, and then processed them similarly to the methodology described above for lab-based spectroscopy (vector normalization, derivatives, then standardization).

Correlative Investigations

We determined Pearson r correlations between all site variables and floristic quality. For variables with more than one sample, we used the median and standard deviation of all values (e.g. water table elevation = WTmed and WTstd). Prior to this analysis, we employed data quality control methods and removed outliers and data from malfunctioning equipment. We also correlated reflectance differences across the spectrum with floristic quality and site traits (Appendix D). This enabled us to identify important regions of the spectrum for predicting site variables from spectra and partially explained linkages in variables such as floristic quality and foliar nutrients / hydrology.

Partial Least Squares Regression (PLSR) Model Building

We utilized PLSR [12, 13] as our primary regressive model building tool for establishing relations between floristic quality and both site variable data (e.g., h_WTmed, f_P, sn_NO3) and spectrometry data (reflectance and derivatives at each of the 2100 different wavelengths). PLSR is especially appropriate as a regressive technique when predictor variable data is high in dimensionality and correlated. In order to avoid overfitting our models [14], we further reduced the predictor variable block by identifying important variables and regions of the spectrum using the correlative methods described above. We also limited our total number of PLSR components, selecting the optimal number less than or equal to 3. For the site variable and lab-based spectroscopy models, we removed 4 plots per site from the model development process and reserved them for external validation. PLSR models were then developed by successively leaving one fen out and using the remaining five fens to predict results for the external validation plots from the fen left out; this technique has been shown to increase model robustness [15]. For the airborne spectroscopy models, we used a leave-one-plot-out cross-validation technique.

We further reduced the dimensionality of our predictor variable data sets by eliminating unstable predictors. Beta values are the PLSR regression coefficients used to convert predictor variable values (site variable and spectrometry data) to response variable values (modelled floristic quality). Since we standardized all predictor and response variables, these beta values indicate the direction and magnitude of predicting behavior for the PLSR site variable of interest. Since it is possible for a variable, such as reflectance at a particular wavelength, to be a strong predictor but not a stable one, we calculated the p-value associated with the null hypothesis that there is a difference in means of beta values obtained from PLSR when each of the six fens (16 plots) are successively removed from the PLSR model generation [15]. High variations in beta values when moving between fens or plots would result in a high p-value, indicating that the variable is not a stable predictor in the model. To remove unstable predictor variables we ran PLSR leaving one fen out at a time (six trials). We then computed p values for all predictor variables based on how the beta values changed and eliminated the predictor variable that had the highest p-value. We continued this process until only one variable remained, and then selected as the final model the set of variables that had the best predictive performance.

In addition, we explored the utility of several different pruning methods to reduce the dimensionality of the predictor variable block and examined the effectiveness of various combinations of variables at modelling floristic quality (Table 1). For example, we used an automated process that began with all 28 of our site variables (Full Selection), selecting and eliminating the least stable and least important variables, one at a time until the best model performance was obtained. We also used an alternative initial selection of variables (Informed Selection) based on expert understanding of which variables are important to fens (f_P, f_Ca, h_WTmed, h_ECmed, sn_NO3, and s_pH). For the site variable models, we used site variables that could be readily obtained from the field with, for example, using only a handheld soil probe and soil test strips (Easy Collection Selection). Finally, for the spectrometry models, Full Selection involved selecting all wavelengths correlated with the variable of interest (Appendix D).

Mapping

We utilized the airborne imagery collected at each fen to generate maps of floristic quality. First, we obtained the spectra at each of the test plots as described above and used these spectra and known floristic quality metrics to develop new PLSR models in a manner similar to the procedure involving the laboratory spectrometry. We trained the model using data from a single fen instead of using data from all six fens. Consequently, we left one plot out at a time instead of leaving one fen out at a time, when determining the stability of beta regression coefficients. After obtaining suitable beta coefficients, we vector normalized and standardized the reflectances at each pixel of the imagery, and then multiplied the appropriate reflectances by our beta coefficients. This provided an estimate of floristic quality for each pixel of the imagery.

RESULTS AND DISCUSSION

The results presented here are organized as follows: Firstly, we present the relationships between site characteristics and floristic quality as correlations and as a predictive model. Secondly, we present the results of using lab-based spectrometry of the dried / ground tissue samples to predict floristic quality and other site characteristics. Finally, we present the results of using the airborne HYSPEX imaging spectrometry to predict floristic quality within a fen. These results are presented as a map of floristic quality and plots of PLSR model performance.

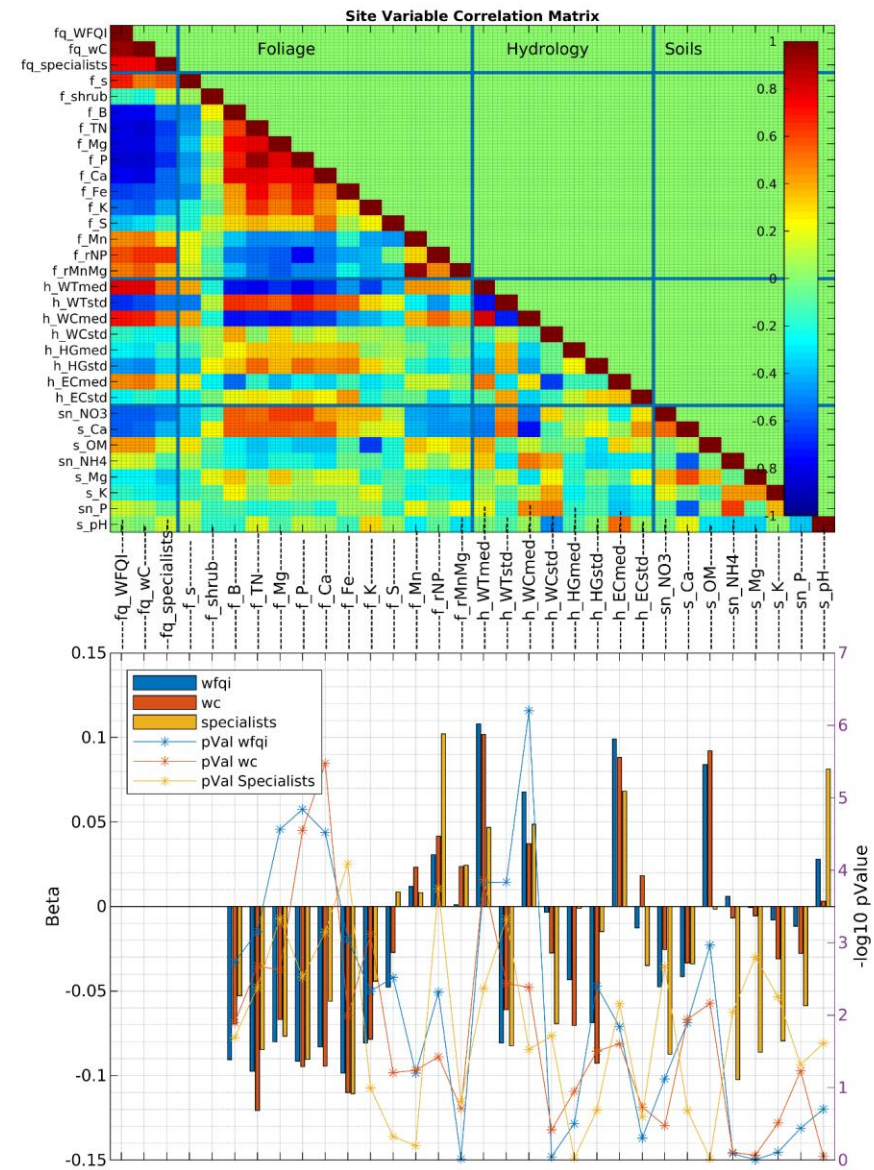


Figure 3: Top panel indicates in first three columns correlations between floristic quality metrics (WFQI, wC, Specialists) and site variable data collected. PLSR regression coefficients (betas) are shown in the bottom panel, when site variable data is used to predict floristic quality. Stability of those betas is reflected in the negative log of p-values of the mean. Site variables with a high magnitude beta and a high -log10 p-value should be the most important and stable predictors of floristic quality at the six fens studied.

Pearson correlation coefficients between three floristic quality variables [Weighted Floristic Quality Index (fq_WFQI), Weighted Coefficient of Conservatism (fq_wC), and Number of Rare and Specialist Species Present (fq_Specialists)] and the other site variable data collected are shown in the first three columns of Panel A of Fig. 3, respectively. These are the correlative relationships for all 120 fen plots of the six sites studied. Generally, floristic quality is strongly negatively correlated with foliar nutrients and strongly positively correlated with soil moisture and water table elevation. As previous research suggests low plant available nutrients in soils are expressed as lowered nutrient levels in leaves [7, 16]. Calcareous fens generally have low plant available nutrients [17] and plants adapted to survive under low nutrient conditions typically have high floristic quality [18]. Our results support these previous findings. Similarly, oxygen stress associated with a consistently high water table results in the presence of niche species adapted to survive under these conditions, resulting in higher FQA metrics.

In the bottom panel of Fig. 3, the negative log of these p-values is shown on the second axis for each of our floristic quality variables. A p-value below 0.01 (-log10 > 2) is indicative of a stable predictor, but these p-values should not be associated with formal confidence intervals as systematic error is likely present. We find that foliar nutrients are strong and stable predictors of floristic quality as are water table and soil moisture. These results are consistent with the definition of a calcareous fen, in that vegetation, hydrology, and soils are all important components of a fen ecosystem [7] and support our hypothesis that foliar nutrients and hydrology are robust predictors of floristic quality.

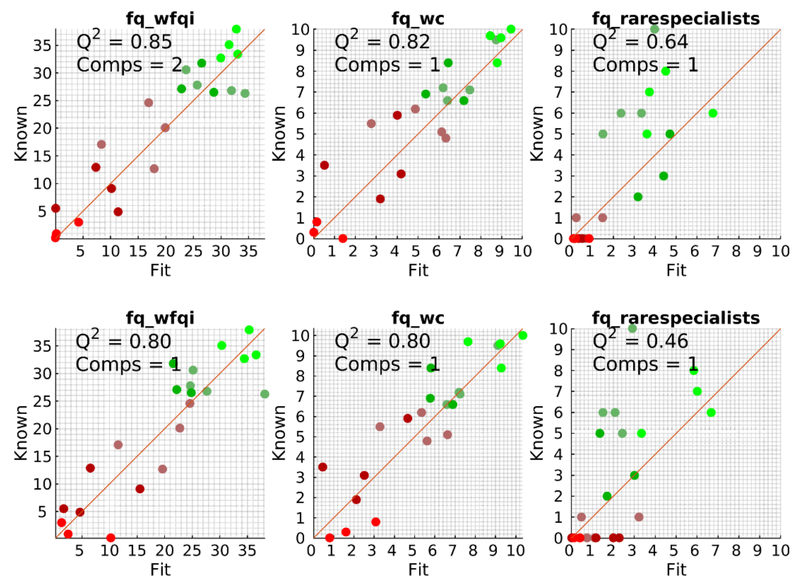


Figure 4: Floristic quality model results using site variable data as

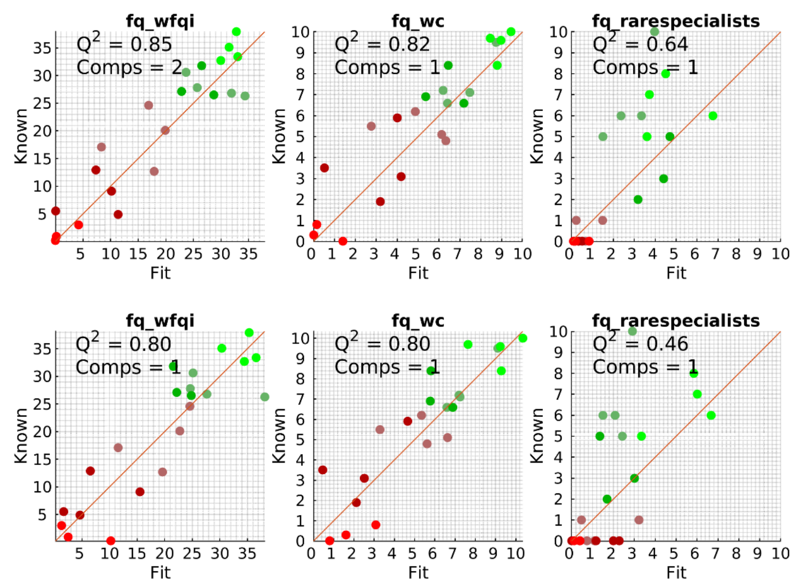


Figure 4: Floristic quality model results using site variable data as predictors (top subplots) and floristic quality model results using lab-based spectrometry as predictors (bottom subplots). Results are color-coded by fen site. PLSR models were developed by successively leaving one fen out at a time using the remaining five fens to predict results for the one left out. The percent of variation of the floristic quality metric explained by each model is shown (Q^2) along with the number of components used (comps).

We used lab-based spectrometry of the dried / ground plant tissue samples at each plot to predict floristic quality through a PLSR analysis similar to the method that was used for site variable data (described above). The predictive abilities of site variable data for floristic quality were slightly better than - but comparable with - the predictive abilities of lab spectrometry data for floristic quality (Fig. 4). Since the lab-based spectrometry data came from clip samples of the vegetation growing at each test plot, these results indicate that the reflectance properties of fen vegetation can be effective predictors of fen floristic quality. This strong predictive ability likely reflects a mechanistic connection between biophysical / chemical components in the leaves - which we previously determined to be highly correlated with floristic quality (Fig. 3) - and the spectral properties of the leaves. This finding is consistent with previous research showing that foliar nutrients such as nitrogen and phosphorus are readily detectable through spectroscopic analysis [19-22] and provides additional confidence in a mechanistic relationship between spectral properties and groundwater-dependent floristic quality.

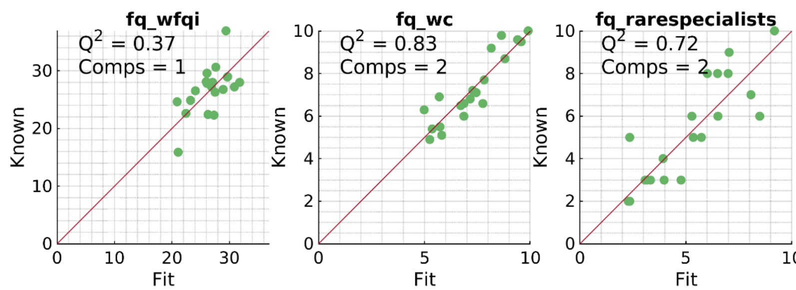


Figure 5: Regression model predictions of floristic quality metrics shown using airborne hyperspectral imagery. Results are determined using leave-one-sample-out validation, as opposed to the leave-one-fen-out validation used for the previously described models.

also used the airborne HySpex imagery to generate predictive models of floristic quality using identical PLSR methods as with lab-based spectroscopy. We present the predictive results for one of the six fens (Bluff Creek Fen, "BCB"). The predictive abilities of HySpex imagery data for floristic quality compare favorably to that of the lab-based spectrometry data for fq_wc and fq_rarespecialists but less favorably for fq_WFQI (Fig. 5). This model was trained on floristic quality data from only one fen, whereas the results from the models for field and lab spectroscopy data were trained on all six fens, the results should not be used to determine relative model efficacy. Because the training and validation plots in the present case came from a single fen a less robust model is expected, especially since there is a limited range of floristic qualities at that one fen.

When this regression model is applied to the airborne imagery obtained at Bluff Creek Fen on a pixel by pixel basis, a map of floristic quality can be generated (Fig. 6). Bluff Creek fen includes a core fen dome of very high floristic quality, which we know to be composed mostly of *Carex sterilis*, *Eleocharis rostellata*, and other fen specialists. In the map, this area appears as a circular region of high floristic quality (blue) surrounded by an area of lower floristic quality (red). To the north of the core area, invasive buckthorn and dogwood separate the pristine fen core from a drainage ditch that was cut into the fen in the 1960s. The modelled floristic quality shows many other “hotspots” at the site where it may be expected that fen conditions exist with high floristic quality. Preliminary investigation of the site following mapping indicates high floristic quality fen vegetation at locations expected from the map.

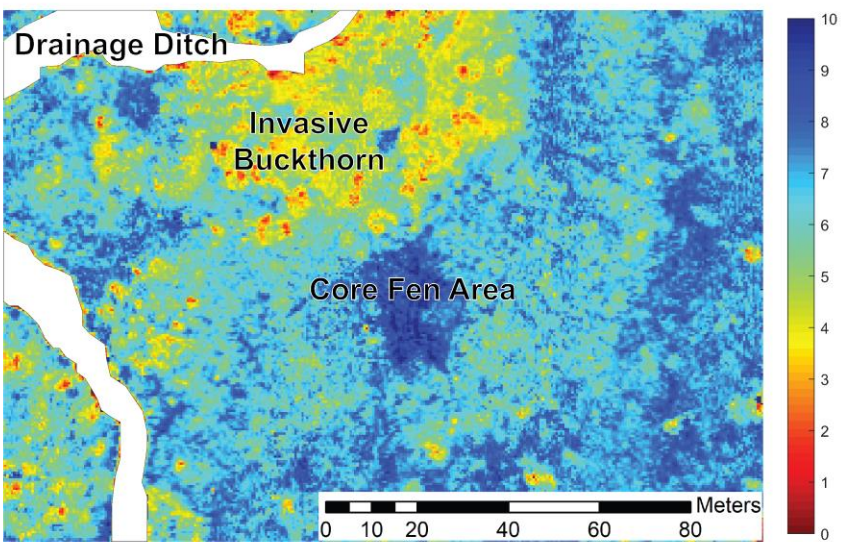


Figure 6: Weighted Coefficient of Conservatism of the Bluff Creek Fen mapped using PLSR model developed from Imaging Spectroscopy obtained from airborne hyperspectral imager. An area of invasive buckthorn divides the pristine core fen area from the drainage ditch that was cut into the area in the 1950s. Open water is masked.

Summary of Results

Summarized in Table 1 are the results for the PLSR FQA models that we created, of which there are three general types. First, we predicted floristic quality from site variables (Site Variable Models); second, we predicted floristic quality from lab-based spectrometry of dried ground foliage samples (Lab Spectrometry Models); and third, we predicted floristic quality from airborne HySpex imagery (Airborne Spectrometry Model). For each of these general model types, we used different sets of initial variables (e.g. Full dataset, Informed selection), and then used a pruning method which utilized stability of regression coefficients to select the most stable and important model variables. We call these the "Optimized Model Variables". The exception here is that for the lab-based spectrometry models, we only show the three most important and stable variables out of the many (up to twenty) variables that were part of the optimized set of variables.

PLSR FQA Model (Initial Variables)	**% WFQI**	**% wC**	**% Special.**	**Optimized Model Variables**	***FQ Variable**
Site Variable Complete Selection (Full Dataset)	85	82	64	*f_Mg , f_P, f_Ca, f_Fe, f_rNP, h_WTmed **f_TN, f_P, f_Ca, h_WTmed ***f_Mg, f_P, f_Ca, f_Fe, f_rNP, h_WTstd, h_ECmed, sn_NO3, s_Mg, s_K	*WFQI **wC ***Spec.
Site Variable Informed Selection (2Veg = f_P, f_Ca)	79	84	70	*f_P, f_Ca, h_WTmed **f_P, f_Ca, h_WTmed ***f_P, sn_NO3	*WFQI **wC ***Spec.

(2 Hydro = h_WTmed, h_ECmed) (2Soil = sn_NO3, s_pH)					
Site Variable Easy Collection Selection (h_SM, h_EC, s_pH, sn_NO3)	58	48	26	*h_WTmed **h_WTmed ***h_WTmed, h_WCmed, sn_NO3	*WFQI **wC ***Spec.
Lab Spectrometry Complete Selection (Full Initial Spectrum)	80	80	46	*D1_1699nm, D1_2461nm, D1_2465nm **D1_2146nm, D1_2360nm, D1,2461nm ***D1_1947nm, D1_2152nm, D1_2177nm	*WFQI **wC ***Spec.
Airborne Spectrometry Complete Selection (Full Spectrum)	37	83	72	*2380nm (Others unstable predictors) **412nm, 450nm, 550, nm, 689nm, 980nm, 1993nm, 2260nm, 2402nm ***412nm, 977nm, 1322nm, 2375nm	*WFQI **wC ***Spec.

Table 1: Percent of variation explained by various models of floristic quality.

We find that floristic quality of fens is strongly linked to nutrient content of fen vegetation and that variations in this nutrient content are readily apparent using spectrometry of dried ground samples as well as airborne hyperspectral imagery. A strong relationship between modeled floristic quality using site variables versus spectrometry also shows that spectrometry is tightly connected to biophysical site characteristics (Appendix E). PLSR models of the remote sensing imaging spectroscopy of a calcareous fen can be used to map out variations in floristic quality within that fen and potentially track these variations over time. We found these spectrometry models to be comparable in effectiveness to models built from a sophisticated suite of hydrologic, soil, and foliar observations. When the sophisticated site model was pruned to only include easy-to-collect field data, results deteriorated.

We found that selecting predictor variables consistent with previous definitions of calcareous fens [7] allowed us to build better predictive models than a fully automated procedure of variable selection. We furthermore found that reducing our number of initial predictor variables in this manner (both for site variable models and for spectrometry models) allowed us to build more robust models that performed better when transferring the application of the model to new fens (leave one fen out cross validation; Fig. 4). These models should yield similar results when applied to a new fen that was not part of the training process, as we used a leave-one-fen-out model development process whereby models were developed using five fens and then applied to a sixth fen. Furthermore, the validation plots were completely removed from the model development process and only used at the end to estimate predictive statistics.

CONCLUSIONS AND RECOMMENDATIONS

This project developed a novel methodology for identifying and monitoring groundwater-dependent fen ecosystems using biophysically-relevant spectral characteristics obtained using airborne imaging spectroscopy and demonstrated the feasibility of quantifying and mapping the impacts of reduced groundwater inputs on fen ecosystems. We determined that foliar nutrients, hydrology, and soil chemistry are well correlated with floristic quality metrics, which is consistent with our mechanistic understanding of fens being defined by their vegetation, hydrology, and soil conditions. Incorporation of these floristic, hydrologic, and soil factors into models of floristic quality of fens yielded our highest model performance when predicting floristic quality of fens. The correlation between foliar nutrients (such as phosphorus) and floristic quality is especially revealing because this represents our mechanistic link from groundwater-dependent ecosystems to the predictive power of spectral data. We were able to exploit this link and develop robust models to predict floristic quality from lab-based spectra. Finally, this cascade of tight relationships (hydrology→floristic quality→foliar nutrients→spectra) allowed us to create predictive models from airborne spectroscopic images and map floristic quality across large, spatially continuous areas.

These findings have several important implications. <u>First</u>, our research adds to the body of literature regarding which ***vegetative, hydrologic, and soil factors influence fen floristic quality***, which we demonstrate has important implications regarding monitoring and protecting these rare ecosystems. <u>Second</u>, the ***spectroscopic methods*** developed here for assessing floristic quality are shown to be a relatively ***efficient alternative to the traditional approaches of assessing floristic quality of fens*** over large areas, such as the time-meander approach with a team of fen expert botanists. With an appropriately calibrated model, several large regions can be imaged in a single flight with better than 1-m spatial resolution and perhaps hundreds of miles separating potential or known fen sites. Thus, fens can be consistently and efficiently monitored. <u>Third</u>, the ability to map fen floristic quality across extensive areas provides managers a unique and valuable way to ***monitor hydrologic change*** as fens can be viewed as ***sentinel ecosystems*** that are quick to respond to subtle changes in groundwater. We have shown that a high and consistent water table is critical to the floristic quality of fens, and that when groundwater conditions of a fen change (as seen in the effect of the drainage ditch in the map of Bluff Creek Fen – Fig. 6), the floristic quality deteriorates substantially, with invasive species such as buckthorn replacing fen specialists. Thus, since we can detect responses in floristic quality readily, we could use this methodology to determine where and when environmentally meaningful alterations to the groundwater regime are likely to have occurred.

These findings lead us to recommend further exploration of the feasibility of incorporating these fen floristic quality mapping techniques into ongoing groundwater and ecosystem monitoring programs. Specifically, continued research should include refinement of the methods to incorporate the effects of seasonality and the presence of particular species on model performance. Because previous research has shown that plant communities of calcareous fens can vary widely [23] and that plant species can in some cases be a more important predictor of foliar nutrient levels than the site variables [24], it would be useful to investigate how these factors affect model performance across a wider range of fens. Notwithstanding needs for methodological refinement, results from this first-of-its-kind project clearly show that airborne-based imaging spectroscopy is a viable tool for monitoring and mapping subtle changes in groundwater and fen ecosystem health. We see these maps being useful in at least two ways: 1) identifying unknown locations of fen ecosystems, where such knowledge can play a key role in conservation of these rare ecosystems, and 2) continuous (every 1-2 years) monitoring to assess changes in hydrology and the associated impacts on fen floristic quality.

<u>REFERENCES</u>

[1] J. T. Curtis, *The vegetation of Wisconsin : an ordination of plant communities*. Madison : University of Wisconsin Press, 1971..

[2] D. Bart, T. Davenport, and Q. Carpenter, “Stress and land-use legacies alter the relationship between invasive- and native- plant richness,” *J. Veg. Sci.*, vol. 26, no. 1, pp. 80–88, Jan. 2015.

[3] J. P. (John P. Grime, *Plant strategies, vegetation processes, and ecosystem properties*. Second edition. Chichester, West sussex ; New York, NY: Wiley, 2001.

[4] J. P. Amon, C. A. Thompson, Q. J. Carpenter, and J. Miner, “Temperate zone fens of the glaciated Midwestern USA,” *Wetlands*, vol. 22, no. 2, pp. 301–317, Jun. 2002.

[5] G. P. Asner, R. E. Martin, “Spectranomics: Emerging science and conservation opportunities at the interface of biodiversity and remote sensing,” *Glob. Ecol. Conserv.*, 8 (212–219), 2016.

[6] S. P. Serbin, A. Singh, B. E. McNeil, C. C. Kingdon, and P. A. Townsend, “Spectroscopic determination of leaf morphological and biochemical traits for northern temperate and boreal tree species,” *Ecological Applications*, vol. 24, no. 7, pp. 1651–1669, 2014.

[7] Q. J. Carpenter, *Toward a new definition of calcareous fen for Wisconsin (USA)*. University of Wisconsin, Madison, 1995.
[8] D. Bart, E. G. Booth, S. P. Loheide II, T. Bernthal, "Impacts of Groundwater Extraction on Calcareous Fen Floristic Quality," *Journal of Environmental Quality, in review*
[9] T. Bernthal, *Development of a floristic quality assessment methodology for Wisconsin, Final Report to the U.S. Environmental Protection Agency Region V*. Wisconsin DNR, Jun. 2003.
[10] WDNR, "Wetland assessment methods and tools - Wisconsin DNR." [Online]. Available: https://dnr.wi.gov/topic/wetlands/methods.html. [Accessed: 04-Nov-2019].
[11] H. Feilhauer, G. P. Asner, R. E. Martin, and S. Schmidtlein, "Brightness-normalized Partial Least Squares Regression for hyperspectral data," *Journal of Quantitative Spectroscopy and Radiative Transfer*, vol. 111, no. 12–13, pp. 1947–1957, Aug. 2010.
[12] S. Wold, A. Ruhe, H. Wold, and W. J. Dunn, III, "The Collinearity Problem in Linear Regression. The Partial Least Squares (PLS) Approach to Generalized Inverses," *SIAM J. Sci. and Stat. Comput.*, vol. 5, no. 3, pp. 735–743, Sep. 1984.
[13] P. Geladi and B. R. Kowalski, "Partial least-squares regression: a tutorial," *Analytica Chimica Acta*, vol. 185, pp. 1–17, Jan. 1986.
[14] P. Thenkabail, Lyon John G, and Huete Alfredo, *Hyperspectral Remote Sensing of Vegetation*, 2nd ed., 4 vols. CRC Press, 2018.
[15] H. Martens and M. Martens, "Modified Jack-knife estimation of parameter uncertainty in bilinear modelling by partial least squares regression (PLSR)," *Food Quality and Preference*, vol. 11, no. 1–2, pp. 5–16, Jan. 2000.
[16] L. Bombonato, C. Siffi, and R. Gerdol, "Variations in the foliar nutrient content of mire plants: effects of growth-form based grouping and habitat," *Plant Ecology*, vol. 211, no. 2, pp. 235–251, Dec. 2010.
[17] K. Boomer and B. Bedford, "Groundwater-induced redox-gradients control soil properties and phosphorus availability across four headwater wetlands, New York, USA," *Biogeochemistry*, vol. 90, no. 3, pp. 259–274, Sep. 2008.
[18] S. D. Eggers, *Wetland plants and plant communities of Minnesota & Wisconsin*. Second edition. [St. Paul, Minn.]: US Army Corps of Engineers, St. Paul District, 1997.
[19] G. P. Asner and R. E. Martin, "Convergent elevation trends in canopy chemical traits of tropical forests," *Glob. Change Biol.*, vol. 22, no. 6, pp. 2216–2227, Jun. 2016.
[20] P. J. Curran, "Remote-sensing of foliar chemistry," *Remote Sensing of Environment*, vol. 30, no. 3, pp. 271–278, Dec. 1989.
[21] G. R. Mahajan, R. N. Pandey, R. N. Sahoo, V. K. Gupta, S. C. Datta, and D. Kumar, "Monitoring nitrogen, phosphorus and sulphur in hybrid rice (Oryza sativa L.) using hyperspectral remote sensing," *Precision Agriculture*, vol. 18, no. 5, pp. 736–761, Oct. 2017.
[22] B. J. Yoder and R. E. Pettigrew-Crosby, "Predicting nitrogen and chlorophyll content and concentrations from reflectance spectra (400–2500 nm) at leaf and canopy scales," *Remote Sensing of Environment*, vol. 53, no. 3, pp. 199–211, Sep. 1995.
[23] D. M. Reed, "Environmental correlates of vegetation types in southeastern Wisconsin fens - Catalog - UW-Madison Libraries," 2002. PhD thesis. University of Wisconsin – Milwaukee.
[24] S. Gusewell and M. Koerselman, "Variation in nitrogen and phosphorus concentrations of wetland plants," *Perspectives in Plant Ecology Evolution and Systematics*, vol. 5, no. 1, pp. 37–61, 2002.

endix A – Awards, Publications, Reports, Patents, Presentations, Students, Impact
10

Presentations

E.G. Booth, A.C. Ryzak, S.P. Loheide, D. Bart, C. Klingdon, P. Townsend. 2017. Developing tools to better model and monitor the impacts of groundwater drawdown in Wisconsin fen wetlands. Water@UW Fall Poster Symposium. Madison, WI. October 24, 2017.

A.C. Ryzak, E.G. Booth, D. Bart, P.A. Townsend, C.C. Kingdon, S.P. Loheide. 2018. Linking Hydrology, Spectroscopy, and Floristic Quality of Fens. 42nd Annual Meeting of the American Water Resources Association – Wisconsin Section. Appleton, WI. March 8-9, 2018.

A.C. Ryzak, D. Bart, E.G. Booth, P.A. Townsend, S.P. Loheide. 2019. Hyperspectral Remote Sensing of Calcareous Fens. 43rd Annual Meeting of the American Water Resources Association – Wisconsin Section. Delavan, WI. March 1-2, 2019.

Other Outputs

StoryMap: https://water.wisc.edu/story-map-project/
Page on Loheide HydroEcology Lab Website: https://hydroecology.cee.wisc.edu/research/fens/

Students

Arthur C. Ryzak, PhD student, University of Wisconsin – Madison, Water Resources Engineering, Thesis title: Hyperspectral Characterization of Calcareous Fens in Southern Wisconsin. ryzak@wisc.edu

Impact

Calcareous fens are ecosystems with high conservation value in the state of Wisconsin. They are also highly dependent on consistent groundwater inputs, which both makes their health an excellent indicator of groundwater conditions and makes them susceptible to changes in groundwater conditions (e.g., decreased groundwater levels from pumping for irrigation or municipal uses). We used cutting-edge remote sensing technologies to develop an innovative and efficient method that assesses the health of calcareous fens and changes in groundwater conditions. We showed that hyperspectral remote sensing – which uses the part of the electromagnetic spectrum beyond what humans can see with their eyes – can accurately predict groundwater, vegetation, and soil characteristics. This new method of monitoring and assessing these important ecosystems offers an alternative to traditional methods of assessing fen health, which require expensive staffing and expertise resources. As ecosystems and the drivers that impact them continue to change in the near future, monitoring and assessment methods such as the one we developed will become increasingly important for adaptively and sustainably managing ecosystems and water resources.

Appendix B - Site Variable Descriptive Statistics

	Floristic Quality			Vegetation Variables												
	√ wfqi	√ wc	√ special	s	shrub	B	TN	Mg	P	Ca	Fe	K	S	Mn	rNP	rMnMg
	-	-	-	-	-	ppm	%	%	%	%	ppm	%	%	ppm	-	-
MEDIAN																
BCB	5.22	2.62	2.24	15.50	0.404	28.18	1.555	0.185	0.09	0.63	29.5	1.15	0.3	68.220	16.8	350.5
BL	5.93	3.01	2.45	19.00	0.123	21.41	1.330	0.130	0.06	0.43	36.5	0.75	0.2	115.340	21.3	817.1
CHER	5.38	2.81	1.73	17.00	0.000	16.72	1.960	0.180	0.11	0.63	46.7	1.09	0.2	91.785	18.3	479.8
CM	4.67	2.19	1.00	15.50	0.000	29.83	1.905	0.275	0.13	0.78	48.5	1.69	0.2	48.630	15.0	171.4
SR	2.86	1.70	0.00	10.00	0.123	66.40	2.090	0.340	0.16	0.97	59.6	0.98	0.2	40.655	14.6	105.5
VM	0.84	0.59	0.00	11.00	0.168	55.38	3.120	0.415	0.23	1.45	75.3	1.81	0.3	33.835	13.5	76.5
OVERALL	**4.99**	**2.49**	**1.41**	**16.00**	**0.123**	**26.07**	**1.890**	**0.230**	**0.11**	**0.69**	**45.4**	**1.15**	**0.2**	**64.550**	**16.9**	**312.3**
MEAN																
BCB	5.15	2.68	2.24	15.35	0.351	26.80	1.554	0.192	0.09	0.66	31.0	1.17	0.3	75.884	18.2	402.0
BL	5.83	3.00	2.34	18.60	0.215	20.82	1.331	0.137	0.06	0.45	39.1	0.79	0.2	145.562	22.4	1201.6
CHER	5.38	2.78	1.72	17.60	0.012	17.86	1.964	0.199	0.11	0.62	48.3	1.07	0.2	88.834	18.4	465.5
CM	4.41	2.11	0.73	14.75	0.018	31.23	2.059	0.298	0.14	0.93	50.1	1.83	0.2	54.205	15.5	201.3
SR	2.89	1.71	0.00	9.84	0.137	59.78	2.214	0.353	0.17	1.10	72.8	1.13	0.3	60.447	13.9	232.7
VM	1.12	0.65	0.22	11.26	0.245	53.87	3.097	0.424	0.23	1.42	85.0	2.04	0.3	40.038	13.9	100.6
OVERALL	**4.22**	**2.22**	**1.24**	**15.18**	**0.180**	**33.75**	**2.005**	**0.266**	**0.13**	**0.84**	**50.0**	**1.35**	**0.2**	**72.142**	**16.9**	**361.5**
STD DEV																
BCB	0.41	0.30	0.54	3.69	0.171	6.81	0.128	0.034	0.02	0.14	5.8	0.27	0.1	32.025	3.6	184.9
BL	0.41	0.13	0.39	6.26	0.164	6.52	0.110	0.038	0.02	0.10	7.8	0.11	0.1	90.150	5.1	972.3
CHER	0.48	0.12	0.68	3.19	0.038	3.88	0.152	0.041	0.01	0.08	6.7	0.12	0.0	22.309	1.2	139.4
CM	0.93	0.40	0.57	3.49	0.043	13.24	0.319	0.082	0.04	0.60	8.6	0.51	0.0	25.430	2.6	118.9
SR	0.82	0.54	0.00	3.69	0.139	21.51	0.343	0.127	0.06	0.55	40.3	0.44	0.1	45.278	3.2	247.5
VM	0.96	0.54	0.58	3.80	0.195	10.03	0.476	0.101	0.05	0.33	38.5	0.67	0.1	21.114	2.2	67.4
OVERALL	**1.77**	**0.83**	**1.06**	**5.12**	**0.192**	**19.90**	**0.605**	**0.123**	**0.06**	**0.43**	**20.1**	**0.64**	**0.1**	**42.671**	**3.5**	**299.9**

	Hydrology Variables								Soil Variables							
	WTmed	WTstd	WCmed	WCstd	HGmed	HGstd	ECmed	ECstd	NO3	Ca	OM	NH4	Mg	K	P	pH
	cm	cm	-	-	cm/cm	cm/cm	dS/cm	dS/cm	ppm	ppm	%	ppm	ppm	ppm	ppm	-
MEDIAN																
BCB	-1.350	1.5	0.685	0.044	-0.040	0.099	0.42	0.061	11.6	4485	44	27.8	677.00	58.0	23.3	7.4
BL	-0.075	3.5	0.728	0.081	0.042	0.127	0.28	0.046	6.8	2482	62	45.8	510.00	30.0	50.6	6.6
CHER	2.075	5.4	0.650	0.018	0.023	0.114	0.69	0.111	39.1	5000	59	15.2	654.50	27.5	21.8	7.5
CM	-0.100	1.8	0.720	0.096	-0.106	0.072	0.28	0.033	38.0	2725	24	60.4	636.00	104.0	63.8	7.2
SR	-16.625	18.5	0.550	0.111	0.034	0.243	0.24	0.114	78.0	6145	56	26.8	1115.50	67.5	31.7	6.6
VM	-34.750	16.7	0.540	0.043	0.107	0.380	0.30	0.093	58.2	6217	27	12.0	524.00	34.5	22.3	7.3
OVERALL	**-0.850**	**5.4**	**0.660**	**0.066**	**-0.005**	**0.129**	**0.34**	**0.071**	**36.8**	**4587**	**52**	**27.4**	**659.00**	**48.0**	**25.7**	**7.3**
MEAN																
BCB	-0.720	3.1	0.678	0.044	0.022	0.191	0.41	0.071	15.7	4477	39	27.6	683.32	54.8	23.1	7.4
BL	-0.092	3.6	0.736	0.087	-0.016	0.258	0.29	0.051	12.5	2604	60	46.2	505.70	35.7	48.7	6.7
CHER	1.952	5.4	0.653	0.023	0.021	0.131	0.70	0.108	38.9	4928	58	17.3	664.00	28.6	22.0	7.4
CM	-1.497	2.7	0.721	0.103	-0.119	0.103	0.27	0.042	40.4	2649	26	62.8	620.90	120.6	63.8	7.2
SR	-19.827	19.3	0.537	0.116	0.065	0.265	0.24	0.127	84.8	5966	52	30.1	1077.55	70.6	35.7	6.7
VM	-35.777	16.6	0.525	0.050	0.103	0.456	0.29	0.096	63.0	6084	28	14.4	662.15	44.1	25.8	7.3
OVERALL	**-8.751**	**8.2**	**0.639**	**0.067**	**0.044**	**0.215**	**0.40**	**0.084**	**43.5**	**4617**	**44**	**32.9**	**719.21**	**56.6**	**34.6**	**7.2**
STD DEV																
BCB	3.043	3.3	0.049	0.022	0.441	0.266	0.05	0.031	9.4	687	16	9.9	238.54	18.2	7.6	0.2
BL	1.977	2.0	0.043	0.031	0.480	0.453	0.04	0.025	17.2	631	10	7.7	158.68	19.7	8.9	0.3
CHER	2.133	0.7	0.007	0.013	0.103	0.091	0.07	0.021	15.5	531	5	8.4	73.06	10.1	2.9	0.2
CM	3.468	3.8	0.056	0.021	0.195	0.098	0.04	0.023	18.9	713	19	23.9	201.03	89.9	17.9	0.3
SR	16.187	8.3	0.103	0.044	0.107	0.176	0.11	0.053	43.5	1543	11	19.7	333.31	17.8	12.1	0.4
VM	18.418	8.2	0.077	0.034	0.530	0.293	0.14	0.061	38.4	1191	12	6.5	407.01	21.7	13.4	0.2
OVERALL	**17.962**	**8.8**	**0.103**	**0.043**	**0.321**	**0.238**	**0.20**	**0.049**	**33.9**	**1581**	**19**	**23.9**	**299.78**	**34.8**	**19.5**	**0.4**

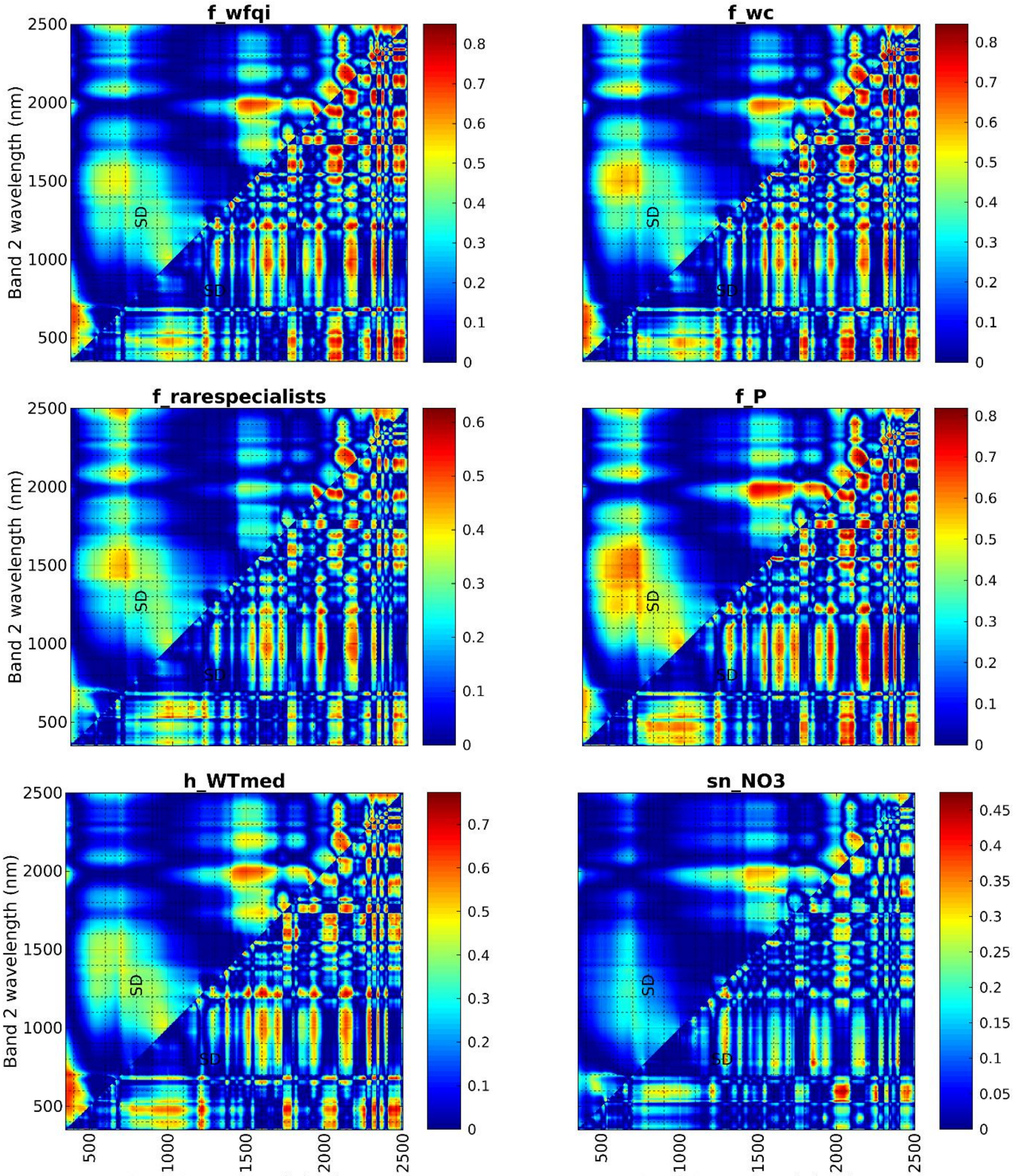
Appendix B: Site variable descriptive statistics for data collected at the six fen sites examined in this study. Site variable data collected are presented below. Fen codes are as follows: BCB = Bluff Creek Fen; BL = Bass Lake Fen; CHER = Cherokee Marsh Fen; CM = Chaffee Creek Fen; SR = Syene Road Fen; and VM = Vernon Fen. Descriptions of these fens can be found in Bart et al, 2019 (in press).

Appendix C - Hyperspectral Imagery Collection and Processing

Hyperspectral imagery data were collected using the HySpex (Norsk Elektro Optikk, Norway) full-range (400-2500 nm) imaging system in operation at UW-Madison by Phil Townsend Lab. The VNIR-1800 camera has 186 spectral bands between 400 and 1000 nm with a spectral resolution of 3.26 nm. The SWIR-384 camera has 288 spectral bands between 953 and 2518 nm with a resolution of 5.45 nm. The HySpex was flown on a Department of Natural Resources Cessna-180.

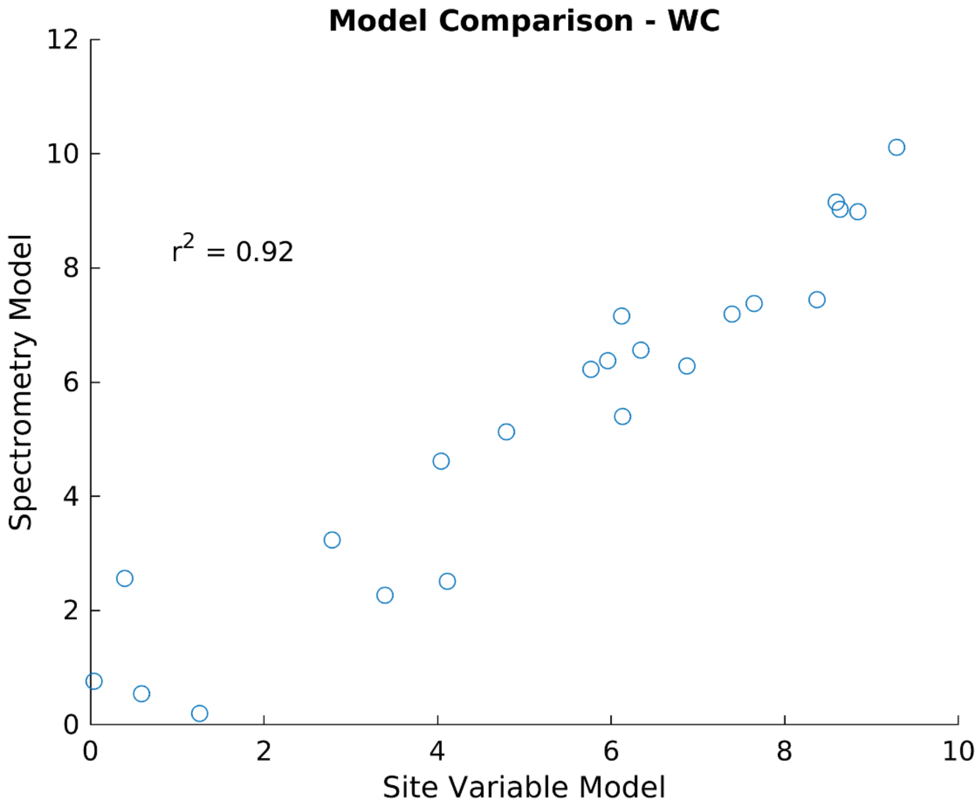
Imagery was calibrated, orthorectified, atmospherically corrected following an established workflow. The processing of Hyspex images includes: (1) radiometric calibration which converts DN (Digital Number) values to at-sensor radiance (in $mW \cdot nm^{-1} \cdot sr^{-1} \cdot cm^{-2}$) values; (2) atmospheric correction in ATCOR4 (Atmospheric and Topographic Correction for Airborne Scanner Data) which reduces atmospheric effects and converts at-sensor radiance to surface reflectance (range: 0-100, in %); (3) geometric correction in PARGE (Parametric Geocoding & Orthorectification for Airborne Optical Scanner Data) which ortho-rectifies images using GPS positions, attitude angles and DEM (Digital Elevation Model); (4) spectral extraction which retrieves the average spectra of each field plot; and (5) spectral vector normalization which reduces the bidirectional reflectance distribution function (BRDF) effects.

Appendix D - Spectrometry Correlations



Appendix D: Spectrometry correlations of reflectance and 1st derivative reflectance differences at indicated wavelength combinations with foristic quality metrics wC, WFQI, and Rare/Specialist Species, and site variables foliar phosphorus (f_P), and water table elevation (h_WTmed), and soil plant available Nitrate (sn_NO3). Spectrometry collected from dried / ground clip samples at fen test plots of varying floristic quality (n=120). Similarities in correlation "hotspots" between floristic quality metrics and site variables enable development of a mechanistic spectrometry model, selecting as input into PLSR specific wavelengths that are linked to fen variables of known importance, such as foliar nutrients, water table elevation, and soil available nutrients.

Appendix E - Comparison of Floristic Quality Model Predictions



Appendix E: Comparison of modelled Floristic Quality Metric Weighted Coefficient of Conservatism (wC) using PLSR model generated from all available site variable data (floristic chemistry, hydrology, soil chemistry), vs. model generated from spectrometry of dried ground vegetation samples. The high degree of correlation suggests that Spectrometry of dried ground leaf samples is comparable in effectiveness with collection of site variable data as a means of predicting floristic quality.