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### Study Information

1. **Title (required)**

**Can Remotely-Sensed Spectral Data Capture Arctic Plant Biodiversity?**

1. **Authors (required)**

Shawn Schneidereit

1. **Description**

Changes in plant communities are one of the most distinct responses to global climate change, yet we lack quantification of plant diversity and composition in the biome experiencing the highest rate of warming – the Arctic. Traditional methods of measuring biodiversity involve field studies and visual surveys, which are both resource intensive and limited in their spatial and temporal resolution. The synthesis of remotely sensed earth observation data with local climatic and topographical conditions, presents itself as a potential cost-effective and standardized technique to monitor biodiversity on an ecosystem wide scale. While high-resolution spectral data are becoming increasingly available at multiple scales, there is little known about the drivers of spectral diversity when transitioning from species to community-specific spectral data, particularly in tundra biomes.

My goal is to evaluate the capabilities of using plot scale and remotely sensed spectral data to assess ecological traits. Understanding how environmental factors correspond with spectral diversity have implications for the feasibility of using hyperspectral data for remote biodiversity estimation.

**Purpose of study:**

This will encompass using spectral signatures for the identification of Arctic vegetation type, as well as quantifying influencers of spectral diversity. Specifically, species richness, species evenness, and exposed soil will be investigated, as these factors contribute to spectral diversity in complex ways.

**Research questions**

1: Can Arctic Vegetation types be identified based on the mean and variance of hyperspectral signatures?

2: How does spectral diversity relate to species richness, evenness, canopy cover, and soil-background?

3: What parts of the full spectrum best discriminate vegetation types?

4: Are closer measurements more similar than more distant measurements?

5: Do plot and airborne spectra differ? Do plot or airborne spectra show more variation among vegetation types?

6: Can airborne remotely-sensed spectral diversity be used to identify vegetation types at the island scale?

1. **Hypotheses**

**1: How do Arctic Vegetation types be discriminate based on the mean and variance of hyperspectral signatures?**

**H1**: Arctic vegetation types can be identified based on the mean of their spectral signature (H1a) and spectral variance of their spectral signature (H1b). Spectral variance will have a larger correspondence with vegetation type, than the mean of spectral signatures (H1c). When ordinated, spectral signatures will discriminate among vegetation types (H1d) and year of measurement (corresponds with change in sensor type) (H1e).

**H1o:** Arctic vegetation types do not differ based on the mean or variance of their spectral signatures, and do not discriminate when ordinated.

Predicted results

I predict that both the mean and variance of spectral signatures can be used to identify Arctic vegetation types. The diversity of a spectral signature correlates with the chemical, anatomical, and morphological traits of communities (Schweiger et al., 2017). Given the compositional difference between communities, this should translate into observable differences in spectral signatures.

I predict that spectral variance will have higher correspondence with vegetation types, as it captures the spectral complexity within each vegetation type (Wang et al., 2018). If spectral variance has a higher correspondence with vegetation types, then the within group variation is more import in predicting vegetation type than between type optical differences. This would mean that the vegetation types would discriminate based on overall spectral diversity, which is variable at all spectral regions and is influenced by compositional differences, such as biological, functional, and phylogenetic diversity.

If the mean of spectral signatures has greater correspondence with vegetation type, this indicates that in within vegetation type spectral complexity is less important than between-type differences in spectral signatures. These differences would relate to course optical differences at specific spectral regions, resultant form a limited number of structural or chemical differences. The correspondence between spectral mean and vegetation type is likely to be limited by spectral differences not being concentrated a one region of the spectrum. Spectral differences occurring at both low and high wavelengths, overall result in a in between spectral mean that similar and does not account for internal spectral complexity.

When ordinated, spectral signatures will discriminate by year, due to the potential difference of reflectance measurements made by the different sensor types used in between 2018 & 2019, as well variation in flowering phenologyand community compositions between the two years.

**2: How does spectral diversity relate to species richness, evenness, and soil-background?**

**H2:** Vegetation type will significantly affect spectral diversity (H2a). Higher spectral diversity will correspond with both increases in species richness (H2b) and species evenness (H2c), with evenness having the stronger relationship (H2d). Soil-background cover will have the strongest positive influence on spectral diversity (H2e).

**H2o:** Species richness, evenness, and soil-background have no effect on spectral diversity, with no visible relationship observed.

Predicted results

Both increases in richness and evenness correlate with higher observed spectral diversity, across an array of different grassland/prairie habitats (Cavender‐Bares et al., 2017; Schweiger et al., 2017, 2018; Wang, Gamon, Cavender-Bares, et al., 2018a; Wang and Gamon, 2019). I predict evenness will have larger correspondence with spectral diversity, as more even representations of species are likely to increase the detection of the variable chemical and physical structures that ultimately influence spectral diversity. If richness has larger correspondence to spectral diversity, this indicates that 1) sensor resolution is adequate to detect additional species, (potentially even when at low relative abundances) and 2) this presence of additional species sufficient to significantly increase spectral diversity.

I predict that soil-background is the strongest predictor of spectral diversity, as soil has distinctly different reflectance than vegetation (Gholizadeh et al., 2018). Furthermore, soils reflectance is variable depending on local microclimatic conditions such as moisture and roughness. This potential for plot level variability therefor can alter spectral signatures in more complex ways, resulting having soil having the largest correspondence with spectral diversity.

**3: Does band selection influence correspondence between spectral diversity and vegetation types**

**H3.** Both band selection via a using a subset spectral region, as well as spectral zone unmixing will result in greater correspondence between spectral diversity and vegetation type (H3a). spectral zone unmixing will result in the selection of a small but spectrally diversity subset of bands (H3a), with overall regions in the visible part of the spectrum (400-700nm) having higher correspondence with vegetation type than bands in the near infrared range (700-100nm) (H3b).

**H3o:** Band selection does not visible influence the correspondence between spectral diversity and vegetation type. There are no specific spectral regions that are best suited to discriminate vegetation types.

Predicted results

Selecting a subset of bands will result in better discrimination of vegetation types, as reducing spectral dimensionality excludes variable and noisy regions of the spectrum. Spectral mixture analysis using spectral zone unmixing will result in finding what zones of the spectrum are best suited in differentiation vegetation types, by finding bands explain maximum between community variability while exhibiting the minimum within community variability.

If spectral zone unmixing (SZU) results in the selection of a small subsets of bands, this indicates that specific structural or chemical difference explain most of the spectral variation between the two vegetation types. Due to shared life histories, the two vegetation types would have traits are similar, aside from key divergent adaptations. These specific divergent traits would be most relevant for spectral discrimination. Furthermore, when collecting and disseminating spectral data, as well as running spectral analysis, high resolution measurement spectral bands/regions are more important for vegetation identification than coarsely capturing reflectance across the full spectrum.

If SZU results in the selection of a large sub-set of bands, this indicates that the differences between the two vegetation types are complex, with many regions of the spectrum (aka structural and chemical traits) being relevant and important for vegetation type discrimination. Furthermore, if SZU results in the selection of bands that correspond with and/or are not visually better than an informal literature derived selection of spectral bands, this indicates that structural and chemical differences may be relatively convergent between different Arctic vegetation types. This implies that trends between biological traits and spectral diversity may be generalizable, and that future research can aim to work at greater scales of observation, rather than synthesizing the findings at small sites. Furthermore, this is promising for the development of future satellites, as potentially selection of spectral regions may be sufficient to discriminate vegetation types.

If spectral regions in the visible spectrum (~400-700 nm) are found to best discriminate vegetation types, then chemical traits are primarily responsible for the key spectral differences between vegetation types. This spectral region corresponds with wavelengths carotenoid absorption (502-511 & 533 nm) green light reflectance (~550 nm), and chlorophyll absorption (644, 653, 672 nm). If spectral regions in the red-edge transition and near infra-red plateau (700-1000 nm) are found to best discriminate vegetation types, then physical structures are primarily responsible for the key spectral differences between vegetation types.

**4: Are closer measurements more similar than more distant measurements?**

**H4:** When tested for spatial autocorrelation closer measurements will be more similar than more distant measurements (H4a), with no visible autocorrelation occurring on a regional scale (H4a).

**H4o:** The is no visible level of autocorrelation between measurements at any distance.

Predicted results

Spatial autocorrelation of measurements will be present but weak between proximal plots and negligible at a regional scale, due to the between plot variability of both species composition and environmental factors such wetness and roughness.

**5: Do plot and airborne spectra differ from each other? Does plot or airborne spectra show more variation among vegetation types?**

**H5:** Plot and airborne spectra do visually differ from each other (H5a), with plot spectra showing more variation both within vegetation types (H5b), and between vegetation types (H5c).

**H5o:** There is no visible difference between plot and airborne spectra, with neither accounting more variation among vegetation types.

Predicted results

If plot spectra show more variance within vegetation types than small scale compositional differences are captured. If plot spectra show more variance between vegetation types, then

If airborne spectra show more variance within than external factors such as exposed soil are likely to play a larger effect. If plan spectra show more variance between vegetation types, then

Plot spectra will capture variation within and between vegetation types, due to plot spectra’s higher resolution. Higher resolution results in both the measurements within a plot to show Plot spectra are also likely to correspond to more variable continuous variables such as species, richness, evenness, and environmental conditions, while airborne spectra are likely to correspond with courser categorical factors such as vegetation type and visibility of soil-background.

Larger variance between plot and airborne spectra will be seen in the blue spectral region (500-540 nm) that correspond with carotenoid absorption and near infrared region (750-800 nm), the typical reflectance regions vascular structures. as at larger scales soil-background is more likely to be included in plots.

**6: Can airborne remotely-sensed spectral diversity be used to identify vegetation types at the island scale?**

**H6:** Airborne remotely-sensed spectral diversity can be used to identify vegetation types at an island scale (H6a), and when visually compared, will correspond with an existent mapping vegetation type (H6b).

**H6o:** Airborne remotely-sensed spectral diversity cannot be used to identify vegetation types at an island scale, and when visually compared does not correspond with an existent mapping of vegetation types.

Predictions

This should correspond to an existent mapping of vegetation types (Obu et al., 2017).

### Design Plan

In this section, you will be asked to describe the overall design of your study. Remember that this research plan is designed to register a single study, so if you have multiple experimental designs, please complete a separate preregistration.

1. Study type
   1. Observational Study - Data is collected from study subjects that are not randomly assigned to a treatment. This includes surveys, natural experiments, and regression discontinuity designs.
2. Blinding (required)

6.1. No blinding is involved in this study.

1. Study design (required)

My study aims to discriminate, and map vegetation types based on their hyperspectral signatures, as well as test the relationship between spectral diversity 1) species richness 2) species evenness 3) soil background and 4) scale of observation.

The analysis conducted will rely on plot level, as well as remotely sensed data collected team shrub in previous years of field work on Qikiqtaruk-Herschel Island. The hyperspectral signature of an individual or community is the unique expression of electromagnetic radiation interacting with physical plant structures (Schweiger et al., 2018). Different vegetation types have dissimilar chemical, anatomical, and morphological traits, which alter the absorbance and scattering of light, resulting in the distinct patterns reflectance that compose a spectral signature (Cavender‐Bares et al., 2017). It will be aimed to identify Herschel and Komakuk vegetation types based on the mean and variance in spectral signatures. This will use spectral data gathered from a regional field survey on the two vegetation types. Detailed data obtained from long-term plot monitoring, will be used to build a linear model that predicts how species richness, evenness, and soil-background influence spectral diversity. What spectral regions are most relevant at discriminating vegetation types will be investigated, by sub-setting the full spectrum into regions of bands. Band selection will occur through 1) informal literature derived selection of spectral bands and 2) performing spectral band unmixing for optimal band selection. Spectral measures will be tested for spatial autocorrelation using a variogram. Plot spectral data will be compared to airborne hyperspectral data measured at a plane scale. These airborne spectra will also be used to identify vegetation types. Categorical spectral classifications will be created and applied to remotely sensed spectral data to create a predictive map of the spatial distributions of vegetation types across Qikiqtaruk- Herschel Island.

### Sampling Plan

In this section we’ll ask you to describe how you plan to collect samples, as well as the number of samples you plan to collect and your rationale for this decision. Please keep in mind that the data described in this section should be the actual data used for analysis, so if you are using a subset of a larger dataset, please describe the subset that will actually be used in your study.

1. Existing data (required)
   1. Registration prior to accessing the data: As of the date of submission, the data exist, but have not been accessed by you or your collaborators. Commonly, this includes data that has been collected by another researcher or institution.

My study relies on pre-existing data, that was compiled by other researches in previous years of field work and open access data (“JPL | AVIRIS”, 2019; Obu et al., 2016). I have not been granted access to any of the data thus far and therefor have not conducted any summary statistics or exploratory analysis. Analysis will commence upon completion of the preregistration process. In supplementary information given by one of my supervisors, I have been made aware that the variability within spectral signatures tend to be better at discriminating vegetation types than difference in means.

1. Explanation of existing data (optional)
   1. If you indicate that you will be using some data that already exist in this study, please describe the steps you have taken to assure that you are unaware of any patterns or summary statistics in the data. This may include an explanation of how access to the data has been limited, who has observed the data, or how you have avoided observing any analysis of the specific data you will use in your study.
2. Data collection procedures (required)

The analysis conducted will rely on plot level, as well as remotely sensed data collected team shrub in previous years of field work (2018-19) on Qikiqtaruk-Herschel Island. 6 (1x1 m) long-term monitory plots have been established - each of the two vegetation communities (Komakuk and Herschel type). No blinding or randomization took place during the data collation process, as my analysis exclusively relied of previously collected data. From this existing data, point-framing data, and percent soil-background can be obtained. During point-framing sampling, present species are also recorded, which can be used to calculate the species biodiversity metrics of species richness and evenness. Regional plot scale hyperspectral data exists for both vegetation types. Vegetation type A is partitioned into plots and has data from both 2018 & 2019, while vegetation type B only has data available for 2019, obtained from a greater region without plot subdivision. Percent soil-background data across Qikiqtaruk exists at a drone scale of observation. Plane scale hyperspectral imagery is available from a mission conducted last summer by NASA, which passed over Qikiqtaruk on two occasions (early and late July)

1. Sample size (required)

For each of the two vegetation types, 6 long term monitoring plots exist, which will all be utilized in this analysis. Each plot was partitioned into 9 measurement points, with 2 replicate spectral measurements occurring at each point. Regional plot scale hyperspectral data exists for both vegetation types. Vegetation type A is partitioned into 30 plots and has data from both 2018 & 2019, while vegetation type B only has data available for 2019, obtained from 30 non-georeferenced plots across greater region. 3 measurement were taken at different areas within the plot. Remotely sensed hyperspectral data span across Qikiqtaruk-Herschel Island at two different dates (2.7.2019 & 27.7.2019) a spatial resolution of 5m per pixel.

1. Sample size rationale (optional)

Sample size for this study was predetermined by the existing data and the amount of long-term sampling plots, which will all be utilized in analysis. The sample size of the landscape-wide spectral measurements was determined by data availability, which was constrained by the time available to conduct field measurements. The rational for including both 2018 and 2019 plot scale spectral data is evaluating the variance of repeat measurements as different sensor types were used between the years.

### Variables

In this section you can describe all variables (both manipulated and measured variables) that will later be used in your confirmatory analysis plan. In your analysis plan, you will have the opportunity to describe how each variable will be used. If you have variables which you are measuring for exploratory analyses, you are not required to list them, though you are permitted to do so.

1. Measured variables (required)

**Response variables:**

Spectral mean: Mean value of spectral band at given wavelength (*continuous variable)*

Spectral reflectance (CV): The average between image variance for each spectral band (*continuous variable)*

**Explanatory variables:**

Vegetation type: If the vegetation corresponds with Herschel or Komakuk type *(categorical variable)*

Species richness: Number of species present in plot *(continuous variable)*

Species evenness: Relative abundance of species in a plot *(continuous variable)*

Soil-background: Percent of bare soil hits obtained during point-framing (*continuous variable)*

Confidence: The self-defined confidence that a field spectral measurment corresponds to its assigned categorical type *(categorical variable: confidence levels = “definitely plant, probably plant, probably panel, definitely panel”)*

**Meta data:**

Year: Year of measurement

Plot: measurement plot

1. Indices (optional)
2. Mean of spectral signature: Mean value of spectral band at given wavelength

**(1)**

*λ is reflectance at wavelength=n*

1. Spectral variance (band coefficient of variance): CVb of spectral reflectance (Equation 1), will be used as the spectral variance metric for this study (Wang, et al., 2018). Here the average between image variance for each spectral band is calculated.

**(2)**

*ρλ is the reflectance at wavelength λ=n.* σ*(ρλ) and μ(ρλ) are the standard deviation and mean value of reflectance at wavelength λ=n across measurands in one band, respectively. (Wang, Gamon, Cavender-Bares, et al., 2018b)*

1. Spectral diversity (coefficient of variance(CV)): CV of spectral reflectance (equation 2), will be used as the spectral diversity metric for this study (Wang, et al., 2018). Here the average variation between all spectral bands is calculated for the pixels within an image.

**(3)**

*ρλ is the reflectance at wavelength λ.* σ*(ρλ) and μ(ρλ) are the standard deviation and mean value of reflectance at wavelength λ across all the pixels in one plot, respectively. (Wang, Gamon, Cavender-Bares, et al., 2018b).*

1. Instability index (ISI): Used to identify discriminative wavelengths used for the stable zone unmixing method (SZU) of optimal band selection (Beamish et al., 2017; Somers et al., 2010) .

**(4)**

*Rmean,1,i and Rmean,2,i are the mean reflectance values of each vegetation type and σmean,1,i and σmean,2,i are the standard deviations of the reflectance values.*

1. Spectral normalization (Rnorm): Used to identify the difference between field and plane spectral measurements (Beamish et al., 2018).

**(5)**

*Rj is the reflectance of remotely sensed plane data at wavelength λ and Rj is the reflectance field measured data at wavelength λ. (Rj may be subject to resolution rescaling to match remotely sensed plane data and then normalisation)*

### Analysis Plan

You may describe one or more confirmatory analysis in this preregistration. Please remember that all analyses specified below must be reported in the final article, and any additional analyses must be noted as exploratory or hypothesis generating.

A confirmatory analysis plan must state up front which variables are predictors (independent) and which are the outcomes (dependent), otherwise it is an exploratory analysis. You are allowed to describe any exploratory work here, but a clear confirmatory analysis is required.

1. Statistical models (required)

I will use R (v 3.5.2) to conduct general linear modeling and ordinations.

**1: Can Arctic Vegetation types be identified based on the mean and variance of hyperspectral signatures?**

Multiple linear regressions will be run to test if hyperspectral signatures of different vegetation types differ significantly from each other.

*Spectral mean ~ vegetation type + plot + year*

*Spectral variance (CVb) ~ vegetation type + plot + year*

Both spectral mean and spectral variance will be used as response variables of hyperspectral signatures.

**2: How does spectral diversity relate to species richness, evenness, canopy cover, and soil-background?**

The following model will be run to quantify relative contribution species richness, evenness, and soil-background on spectral diversity.

*Spectral diversity (CV) ~ vegetation type + richness + evenness + Soil-background*

Spectral diversity will be ordinated using PCA, to identify which components best explain the variation in spectral diversity.

One ordination plot will then be produced and points will be discriminated by each variable.

**3: What parts of the full spectrum best discriminate vegetation types?**

The band selection methods of using a defined subset of spectral bands and spectral band unmixing will be used to reduce dimensionality of spectral data. Spectral variance will be re-calculated, based on these new subsets and spectral data, the same model as question 1 will be used to assess how band selection affects correspondence between spectral variance and vegetation type.

*Spectral variance (CVb) ~ vegetation type + plot + year*

**4: Are closer measurements more similar than more distant measurements?**

This will be assessed

**5: Do plot and airborne spectra differ? Do plot or airborne spectra show more variation among vegetation types?**

**6: Can airborne remotely-sensed spectral diversity be used to identify vegetation types at the island scale?**

1. Transformations (optional)

During ordination, variables will be standardized to zero mean and unit variance.

1. **Inference criteria (optional)**

Variables in linear models will be considered to be significant, if the upper and lower bounds of the 95 percent credible interval do not cause the estimated effect size to cross zero. The results of all statistical tests will be reported, even if these contradict hypothesized direction or are non-significant.

1. Data exclusion (optional)

All relevant available field data will we used in data analysis, with additional meta-data such as year being used when appropriate. Extreme outliers in measurement data, that are resultant of spectrometer malfunctioning will be excluded.

1. Missing data (optional)
   1. How will you deal with incomplete or missing data?
   2. **Example**: If a subject does not complete any of the three indices of tastiness, that subject will not be included in the analysis.
   3. **More information**: Any relevant explanation is acceptable. As a final reminder, remember that the final analysis must follow the specified plan, and deviations must be either strongly justified or included as a separate, exploratory analysis.
2. Exploratory analysis (optional)

A spectral comparison of normalized plot and plane data will be conducted to check the variance between plot level and remotely sensed data.

Band selection using spectral zone unmixing (SZU) will be conducted to identify which wavelength bands are the most discriminative for differentiating vegetation types/soil cover. This will be done using a inStability index (ISI) (Beamish et al., 2017; Somers et al., 2010).

Categorical spectral classifications will be created and applied to remotely sensed spectral data to create a predictive map of the spatial distributions of vegetation types across Qikiqtaruk- Herschel Island.

Other

1. Other (Optional)

References:

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* 1. If there is any additional information that you feel needs to be included in your preregistration, please enter it here. Literature cited, disclosures of any related work such as replications or work that uses the same data, or other context that will be helpful for future readers would be appropriate here.

**Instructions**:

* Under the “File” menu, select “Make a copy…” or “Download As” to make your own preregistration document.
* Preregister your study by either 1) attaching the document to an OSF project and registering with the “OSF Standard pre-data collection” form or 2) use the “OSF Prereg” form available here: (<https://osf.io/prereg>) (option 2 provides a better formated, final preregistration)
* Information on registering OSF projects and the different forms is available [on the OSF help docs](https://help.osf.io/hc/en-us/categories/360001550953-Registrations).
* General information about preregistration is available at <https://cos.io/prereg> and you can reach out to [prereg@cos.io](mailto:prereg@cos.io) or [@OSFprereg](https://twitter.com/osfprereg?lang=en). A preprint of this template is available at <https://osf.io/preprints/metaarxiv/epgjd/>