PREDICTING GARRY OAK DISTRIBUTION IN THE SOUTHERN GULF ISLANDS, CANADA, USING SPECTRORADIOMETER, AIRBORNE HYPERSPECTRAL AND LIDAR DATA

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ABSTRACT:

Characterizing tree species distribution is a fundamental requirement for sustainable ecosystem management. Within British Columbia, Canada, the Gulf Islands National Park Reserve (GINPR) represents one of Canada's most diverse yet threatened ecosystem assemblages. Of particular concern are Garry oak ecosystems. To predict Garry oak distribution, Park managers rely on 1:5000 scale aerial photographs. New state-of-the-art methodologies involve a combination of lab-based and airborne hyperspectral remotely sensed data supplemented by light detection and ranging (LiDAR) data. The spectral reflectance of dominant overstory tree species in the GINPR was retrieved from leaf samples using an Analytical Spectral Devices (ASD) spectroradiometer and curves and derivatives were used in forward stepwise discriminant analysis to select key wavelengths that minimize within species variance while maximizing between species variance. Key wavelengths were used in normal discriminant analysis to test between species seperability. Once leaf-level lab-based relationships were identified in ASD data sets, wavelengths important for species differentiation were used to classify Airborne Imaging Spectrometer for Applications (AISA) imagery. Prior to classification a LiDAR derived canopy height model was used to isolate AISA pixels containing sunlit tree crown. Image classification was undertaken to predict the distribution of 9 species including Garry oak using Support Vector Machine (SVM) classification. SVM classification resulted in overall accuracy of >86 % and Garry oak Producer's and User's accuracies of 81.7 % and 92.1 % respectively. All three Garry oak ecosystem variants found within this region were mapped with more accuracy and detail as compared with distributive information offered through conventional methods.

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1.0 INTRODUCTION

Managers often rely on aerial photograph interpretation for species distributive information. However, this approach lacks spatial detail and accuracy. Hyperspectral remotely sensed data can be used as an alternative for species distributive mapping. Species can be differentiated in hyperspectral imagery as these sensors measure subtle absorption features related to biogeochemical constituents (Martin et al. ,1998; Cochrane ,2000; Ustin et al. ,2004; Clark et al. ,2005; Carlson et al. ,2007). However, hyperspectral data are highly correlated (Smith ,2006). To reduce redundancy, ground-based spectroradiometers target wavelengths where leaf-level species reflectance differences exist. Optimal wavelengths can then be employed in airborne hyperspectral data sets to predict species distribution.

In the Canadian Gulf Islands National Park Reserve (GINPR), in south-western British Columbia (BC), managers lack detailed and accurate species distributive information. Of all tree species found on GINPR lands, Garry oak is the most ecologically important. According to Fuchs (2001), in Canada, Garry oak occurs only in BC where it is the only native oak species. In BC, the GINPR and its surrounding lands are one of few places where near-natural Garry oak ecosystems still exist (Fuchs ,2001). This research employs ground-based spectroradiometer data and hyperspectral imagery supplemented by LiDAR data to predict the distribution of Garry oak in the northeast section of the GINPR and its surrounding lands.

2.0 METHODS

2.1 Study area

The GINPR encompasses 2832 hectares (ha) of terrestrial lands distributed across 16 islands and in the southern Gulf Islands (SGI), 50 km south of Vancouver, BC, Canada (lat 48.76, long -123.18). Although once common in coastal areas of south-western BC, the range of near-natural Garry oak ecosystems has been reduced to 5 % of its pre-European settlement range (Fuchs ,2001). Within Garry oak ecosystems an estimated 118 species of flora and fauna are at-risk (GOERT ,2003). The geographical focal point of this research is two islands in the northeast SGI for which hyperspectral and LiDAR transects were collected. Three variants of Garry oak ecosystems exist in this area: rocky bluff with woodland patches; field with woodland patches; and steep slope woodland (Green ,2007).

2.2 Sampling Protocol

In July 2006, within 26 plots, 2-5 tree branches were collected from trees using clippers attached to a 6 m long pole representing samples for 9 species. Samples were collected for all species to ensure the full range of spectral variability would be captured. In accordance with Foley et al. (2006) leaves were removed and placed in sealed plastic freezer bags.

2.2 Ground-based spectra collection, processing and analysis

Spectral response curves were retrieved from 350-2500 nanometres for all species (nm) in a controlled indoor setting using an Analytical Spectral Devices (ASD) Full Range spectroradiometer. To approximate infinite optical thickness and the maximum of NIR reflectance leaves were stacked six layers deep (Datt ,1998).

Slope and the slope of the slope (i.e., first and second derivatives) were calculated for baseline ASD data resulting in 3 data sets. Wavelength regions 1350-1416 and 1796-1970 nm; 350-429 and 2401-2500 nm; and 998-1002 and 1798-1802 nm were removed due to water absorption regions (van Aardt and Wynne 2001); sensor extremes; and sensor transitional zones respectively.

Forward stepwise discriminant analysis (FSDA) selected 40 key wavelengths that minimized within species variance while maximizing between species variance. Key wavelengths were compartmentalized within 400-500 nm (pigment absorption), 501-550 nm (chlorophyll absorption), 551-680 nm (pigment absorption), 681-740 nm (red edge transition), 741-1100 nm (biogeochemical), 1101-1400 nm (transitional) and 1401-2400 nm (biogeochemical) (Jensen ,2007). Significant wavelengths were input in normal discriminant analysis (NDA) and accuracy was tested using cross validation.

2.3 Airborne remotely sensed data acquisition, processing and classification

Airborne hyperspectral and LiDAR data were collected by Terra Remote Sensing Inc. (Sidney, BC), in July 2006 using an AISA Dual sensor and a Mark II two-return sensor respectively, flown simultaneously on a fixed-wing platform.

Ground return elevation values were subtracted from non-ground height values to produce a canopy height model (CHM), which was used to mask out (i.e., spatially subset) AISA pixels below 5m as this height represented shortest sunlit canopy height recorded in plots.

A non-parametric support vector machine (SVM) classifier was used to separate continuous predictor variables (i.e., spectral values) into a predefined categorical target variable (i.e., tree species) (Wu et al. ,2004; Hsu et al. ,2007).

3.0 RESULTS

3.1 FSDA and NDA results

Using baseline reflectance and its derivatives as input (**Figure 1**) FSDA indicated 40 wavelengths could discriminate between all species for all three data sets (**Table 1**). The region containing the largest number of significant wavelengths is 1401-2400 nm, whereas 1101-1400 nm contains the least. Wavelength range 501-550 nm contained the highest occurrence of wavelengths selected more than once. Consecutive wavelengths were selected multiple times (± 5 nm) in 501-500 nm and 681-740 nm. NDA confirmed all species could be differentiated using all data sets with overall accuracies ≥ 98 %. Baseline data performed marginally better then derivatives.

3.2 Classification results

The overall accuracy of hyperspectral SVM classification was 86.4 %. For Garry oak Producer's accuracy was 81.7 % and User's accuracy of 92.1 %. Lodgepole pine and Arbutus were responsible for Garry oak commission error and Douglas-fir and Red alder for omission error. Accurate results applied to all three Garry oak ecosystem variant types.

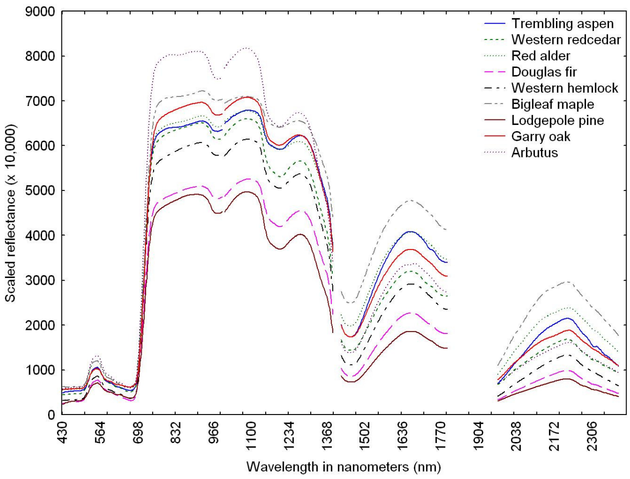
4.0 DISCUSSION

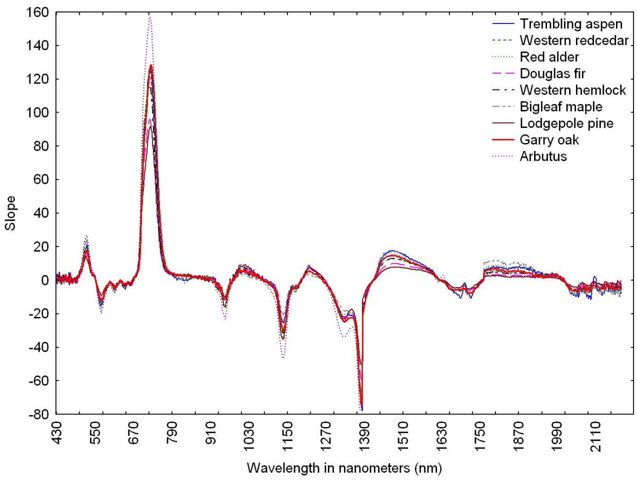
4.1 Comparison to Existent Ecological Data

Classification results provide spatially explicit locations for Garry oak at the fine spatial resolution of 2 m pixels. Increased detail and accuracy is apparent for all Garry oak ecosystem variant types (i.e., rocky bluff with woodland patches; field with woodland patches; and steep slope woodland).

5.0 CONCLUSION

Conventional aerial photograph interpretation yields products which lack spatially explicit and accuracy needed by managers for a wide variety of applications. Employing optimal airborne hyperspectral bands to predict species distribution, aided by LiDAR height data, results in increased accuracy and detail. Discriminating between all species found in the study area allowed for spectral variability to be captured, and ensured representative distributive classification. The resulting map provides managers with information on not only where sensitive and at-risk Garry oak ecosystems are, but also, where they are not and what species occur in these areas.





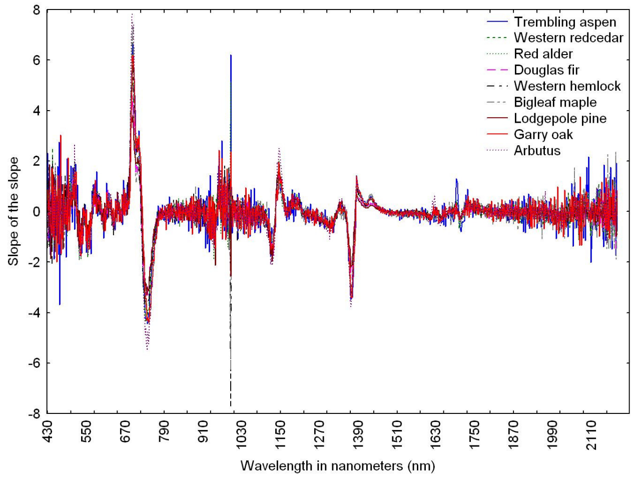


Figure 1. Baseline reflectance and its derivatives.

Table 1. Significant discriminatory wavelengths.

	baseline	1st derivative	2nd derivative
400-500	460	438	442
pigment	482	452	452
absorption	494	480	478
		498	
501-550	504	502	546
chlorophyll	514	514	550
reflection	516	522	
	520	528	
	522	530	
	528		
	530		
	534		
	546		
	550		
551-680	564	584	552
pigment	572	634	556
absorption	618	648	562
	642	666	628
		678	636
			646
681-740	692	692	684
red edge	694	702	690
transition	696	708	694
	706	720	696
	710	730	702
	714		704
	720		712
			724
			728

	baseline	1st derivative	2nd derivative
741-1100	960	754	816
biogeochemical	1020	764	988
	1050	796	
		884	
		904	
		974	
		1044	
		1094	
		1096	
1101-1400	1272	1328	1146
transition zone	1358	1388	1152
	1388		1376
1401-2400	1418	1516	1650
biogeochemical	1656	1520	1652
	1674	1644	1654
	1718	1648	1656
	1730	1664	1658
	1780	1668	1660
	1794	1706	1662
	2106	1722	1728
	2196	1726	1730
	2274	1736	1732
			1734
			1736
			1738
			1740
			1742

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