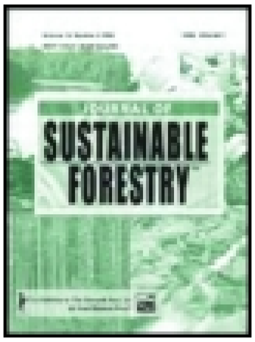

Journal of Sustainable Forestry

ISSN: 1054-9811 (Print) 1540-756X (Online) Journal homepage: http://www.tandfonline.com/loi/wjsf20

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JOURNAL OF SUSTAINABLE FORESTRY
https://doi.org/10.1080/10549811.2018.1433047

Predicting abundance and productivity of blueberry plants under insect defoliation in Alaska

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ABSTRACT

Unprecedented outbreaks of defoliating insects severely damaged blueberry crops near Port Graham on the Kenai Peninsula in Alaska from 2008-2012. The Native people in this region rely heavily on gathered blueberries and other foods for sustenance and nourishment. Influences of topography and stand structure on blueberry abundance and fruiting were examined and used to develop spatial models to predict abundance and productivity of blueberry plants. Fruiting was associated with decreased canopy density, a low basal area and southwesterly aspects. Stands with relatively high site indices have greater abundance of blueberry plants, while the opposite trend was observed with productivity. Results demonstrate the feasibility of modeling the abundance and productivity of blueberry plants using easily obtained satellite imagery in conjunction with a well-organized field data collection system.

KEYWORDS

Epirrita undulata; Operophera bruceata; subsistence food; blueberry; Alaska; Port Graham

Introduction

The seven tribes of the Chugach Region of Alaska (Chenega Bay, Eyak, Nanwalek, Port Graham, Qutekcak, Tatitlek, and Valdez) rely heavily on subsistence gathered food for sustenance and nourishment. Studies by the Alaska Department of Fish and Game show that a significant portion of the total foods consumed, 375 pounds per person per year, is from subsistence hunting and gathering. In the traditional Native diet, fruits from the Alaska blueberry (*Vaccinium alaskensis* Howell) plant and the salmonberry (*Rubus spectabilis* Prush) are major sources of sweet food; hence are culturally and nutritionally important (Figure 1; Viereck & Little, 1972).

Alaska blueberry fruits are also an important source of food for many species of wildlife, including songbirds, game birds, mice, chipmunks, squirrels, raccoons, and black bears (Viereck & Little, 1972). Twigs and foliage are used as browse by rabbit, snowshoe hare, bear, goat, elk, and deer (Hanley, Cates, Van Horne, & McKendrick, 1987). Alaska blueberry plants are an important source of winter browse because they are often found in older stands with shallow snowpack, making them more accessible to wildlife. Utilization may also increase in early winter in open areas when lower growing vegetation becomes covered with snow (Matthews, 1992).

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Color versions of one or more of the figures in the article can be found online at www.tandfonline.com/wjsf.

Figure 1. Alaska blueberry (Vaccinium alaskensis Howell) plant.

The Alaska blueberry occurs as an understory species in many forest community types throughout the Cascade Range in northern Oregon and Washington to Prince William Sound, Alaska (Matthews, 1992). It is most often associated with Pacific silver fir (*Abies amabilis* Douglas ex. Loud), western hemlock (*Tsuga heterophylla* (Raf.) Sarg.), mountain hemlock (*T. mertensiana (*Bong.) Carrière), and Sitka spruce (*Picea sitchensis* (Bong.) Carr.). The blueberry plant rapidly sprouts from underground stems or establishes by seed within three years of disturbance from clearcutting, burning, and windthrow (Alaback, 1984). However, as the forest overstory becomes dense (stand age 25–150 years), blueberry plants decrease drastically in frequency and abundance. As stands continue to mature (stand age 150–250 years) and begin to self-thin, the frequency and abundance of blueberry plants increase again (Alaback, 1984).

Beginning in 2008, an outbreak of native Geometrid moths (*Geometridae: Epirrita undulata* (Harrison, 1942) *and Operophtera bruceata* (Hulst, 1886)) caused widespread defoliation of salmonberry and blueberry plants in many Native communities in the Chugach Region, resulting in major berry failures. The outbreak was particularly severe in Port Graham, Nanwalek, and Seldovia, three villages located in the southern Kenai Peninsula in Southcentral Alaska (Figure 2). In Seldovia, a tribal for-profit enterprise based on blueberries was placed in jeopardy because of successive failure of their blueberry crops. This outbreak continued through 2012 when moth populations collapsed and berry yields recovered. Although this is the first known Geometrid outbreak in this region, in other areas of the world where closely related species (e.g., *Epirrita autumnata* (Borkhausen, 1794)) are native, outbreaks return in cycles of approximately 10 years (Berryman, 2002). Future outbreaks of the Geometrid moths are expected in the Chugach Region.

In this study, we use statistical analysis and spatial modeling to determine how blueberries are influenced by topography and forest stand structure. The models are designed

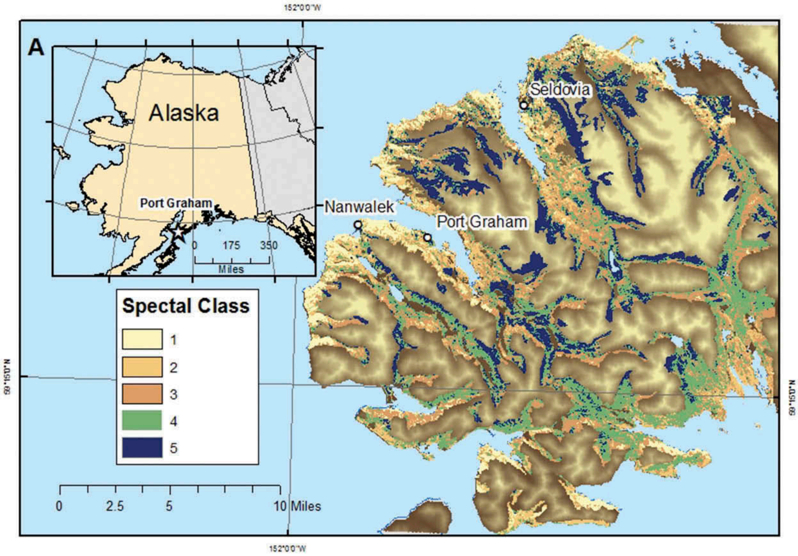

Figure 2. Location of the study area and five spectral classes derived from March 2013 LandSat-8 OLI used to characterize forest stand structure in the study area.

to facilitate and support tribal communities and their preparation for potential future impacts from these damaging insects on subsistence berries by suggesting silvicultural prescriptions aimed at maintaining the health and productivity of blueberry plants.

Methods

Spatial data

Information on the spectral variability of forested vegetation and topography were taken from satellite imagery and Digital Elevation Model (DEM, 30-m spatial resolution) of the area surrounding Port Graham, Alaska, which is located at latitude 59°20′52″N and longitude 151°50′0″W (Figure 2). Two cloud-free Landsat-8 Operational Land Imager (OLI, 30-m resolution) obtained during March in 2013 and 2014 were obtained from EROS Data Center (Sioux Falls, South Dakota). The satellite imagery consisted of 11 spectral bands (Table 1). Since band 8 was a panchromatic image at 15-m resolution, this band was resampled to a 30-m spatial resolution using nearest neighbor techniques (Muukkonena & Heiskanenb, 2005).

The DEM and all spectral bands associated with the two LandSat-8 OLI were resampled to a 10 m spatial resolution using a three-step process. First, each band was resampled to a 10 m spatial resolution using nearest neighbor techniques (Muukkonena & Heiskanenb, 2005). A 3 × 3 window was passed over each of the resampled bands generating a surface of average reflectance values. Each 10-m pixel thus represents the average reflectance of the surrounding 30 m x 30 m area. Finally, all pixel values were converted to integers for further processing and analysis.

Proper classification of the variability in forest stand structure is an essential requirement for designing an efficient sampling method to collect field data for the purpose of modeling forest stand structure and blueberry plant productivity and abundance (Engman

Table 1. Description of the Landsat 8 spectral bands.†

Band	Wavelength	Pixel Size	Application
Band 1 – coastal aerosol	0.43–0.45	30	Coastal and aerosol studies
Band 2 – blue	0.45–0.51	30	Bathymetric mapping, distinguishing soil from vegetation and deciduous from coniferous vegetation
Band 3 – green	0.53–0.59	30	Emphasizes peak vegetation, which is useful for assessing plant vigor
Band 4 – red	0.64–0.67	30	Discriminates vegetation slopes
Band 5 - Near Infrared (NIR)	085.-0.88	30	Emphasizes biomass content and shorelines
Band 6 - Short-wave Infrared (SWIR) 1	1.57–1.65	30	Discriminates moisture content of soil and vegetation; penetrates thin clouds
Band 7 - Short-wave Infrared (SWIR) 2	2.11–2.29	30	Improved moisture content of soil and vegetation and thin cloud penetration
Band 8 – Panchromatic	.50-.68	15	15-meter resolution, sharper image definition
Band 9 – Cirrus	1.36–1.38	30	Improved detection of cirrus cloud contamination
Band 10 – Thermal Infrared (THIR) 1	10.60 – 11.19	30	100-meter resolution, thermal mapping and estimated soil moisture
Band 11 – Thermal Infrared (THIR) 2	11.5–12.51	30	100-meter resolution, Improved thermal mapping and estimated soil moisture

†Source: http://landsat.usgs.gov/best_spectral_bands_to_use.php

& Gurney, 1991). However, in remote areas surrounding Port Graham, this type of information is difficult to obtain due to a lack of detailed forest inventories and inaccessibility of some areas. Based on previous work that revealed the variability in forest stand structure as reflected in the spectral variability observed on the LandSat-8 OLI (Reich, Aguirre-Bravo, & Mendoza-Briseño, 2008), an unsupervised classification method was used to identify five spectral classes characterizing the forested areas identified on the resampled 2013 LandSat-8 OLI (Figure 2, Al-Ahmadi & Hames, 2009). The resulting spectral classes were treated as strata in the field sampling phase of the project. Histogram equalization, an image enhancement technique (Garg, Mittal, & Garg, 2011), was applied to individual bands of the resampled 2014 LandSat-8 OLI. A histogram is a graphical representation of the brightness values that comprise an image. Histogram equalization is a method that redistributes the image's intensity distributions in order to produce a uniform histogram for the image. All negative values in the final predicted surface were set to zero.

Field data

The data used in this study are from an inventory designed to provide local estimates of forest stand structure and blueberry plant abundance and productivity in the Port Graham area. A total of 111 variable radius plots were visited during periods of peak fruit yields (mid-August) throughout the area using a stratified design that took into consideration the spectral variability in forest stand structure (Figure 2). At preselected locations along the main access road, 37 sets of three plots (37 x 3 = 111) were established on each side of the road. The first plot of each set was established within 15-m of the road and each subsequent plot was located 30-m apart running perpendicular to the road, if possible. Plot locations were verified using a Global Positioning System (GPS) with an estimated accuracy of ± 3 meters.

At the center of each plot, a prism (with basal area factor of 40) was used to estimate the average tree basal area per acre (m^2/ha) of the plot. Plots fell in pure Sitka spruce stands with insignificant basal area contributions from other species (unpublished data from Chugachmiut). A spherical densiometer was used to estimate the average percent tree canopy closure on each sample plot. Readings were recorded for the four major cardinal directions and then averaged. A representative tree on each sample plot was measured for total tree height and height to the base of the live crown. Height measurements were obtained using both optical and laser-based hypsometers.

Each variable radius sample plot was divided into four quadrants using the four major cardinal directions. In each quadrant, the presence (1) or absence (0) of blueberry plants within 3-m of the center were noted and summed creating five classes of abundance: 0 – trace to none, 1 – low, 2 – medium, 3 - high, and 4 – very high. All counts were converted to a proportion by dividing the counts by four. Representative blueberry plants were selected in each of the four quadrants and rated in terms of the amount of blueberry fruits found on the plant (e.g., productivity) using a five-point scale: 0 – trace, 1 – below average, 2 – average, 3 – above average, and 4 – bumper crop. Ratings of plant productivity were averaged across the four quadrants.

Model development

For each component of forest structure and blueberry productivity and abundance, a stepwise Akaike information criterion (AIC) procedure (Venables & Ripley, 2002) was used to identify a subset of independent variables to include in the regression model that minimized the AIC (Akaike, 1973). Independent variables considered for inclusion in the regression models included elevation, slope, the sine and cosine of aspect, LandSat-8 OLI bands, and the spectral classes used to design the field sampling. Regression coefficients and variances were estimated using generalized linear model theory (McCullagh & Nelder, 1989).

The regression models were developed sequentially starting with percent tree canopy closure, then tree basal area, followed by the models for total tree height and height to the base of the live crown, and finally, models for the abundance and productivity of blueberry plants (Figure 3). Canopy closure was allowed to enter the basal area model as a predictor. Likewise, in the model for total tree height, both canopy closure and basal area could potentially enter the models as predictor variable(s). Thus, each subsequent model builds upon previously developed models. The model for the productivity of blueberry plants was the last model developed in the sequence, and variables such as percent canopy closure, basal area, total tree height, height to the base of the live crown and predicted abundance of blueberry plants were allowed to enter the model as potential predictors.

The small-scale variability (i.e., estimated errors from the regression models) in forest structure and the abundance and productivity of blueberry plants was modeled using a regression tree-based stratified design (Reich, Aguirre-Bravo, Bravo, & Mendoza-Briseño, 2011). Independent variables considered in the stratification included elevation, slope, the cosine and sine of aspect, LandSat-8 OLI bands, the spectral classes or strata used in developing the field sampling, the predicted values from the linear regression model associated with the regression tree, as well as the predicted values of dependent variables

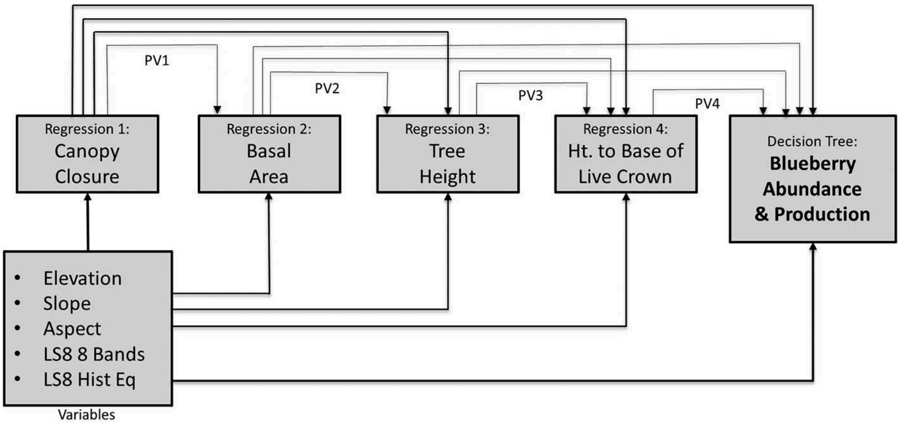

Figure 3. The sequential approach using regression models of forest structure as potential predictor variables for each succeeding metric. The regression models were developed sequentially starting with percent canopy closure, then basal area, followed by the models for total tree height and height to the base of the live crown, and finally, models for the abundance and productivity of blueberry. (PV = Predictor Variable).

developed in previous steps. A 10-fold cross-validation was performed on each regression tree to identify the regression tree size that minimized the mean squared error of prediction. The regression trees were then pruned to the appropriate size. The FIT statistic, which is defined as the correlation between the observed and predicted values squared, was used to assess the goodness-of–fit of the final models.

Maps representing the components of forest structure and the productivity and abundance of blueberry plants were generated for the models selected to minimize the error in estimating the uncertainty in the spatial estimates (Figure 4). This was accomplished by passing the various spatial layers through the linear regression models and binary regression trees to produce two new spatial layers representing the large-scale (linear regression) and small-scale (binary regression tree) spatial variability. These two surfaces were then added together to produce the final predicted surface. All negative values were set to zero due to the linear models producing positive as well as negative estimates. Since the linear regression models cannot avoid negative estimates any negative estimates were set to zero, while any extreme values were set to the 95th percentile of the estimated values

Results

The abundance of blueberry plants showed a positive relationship with total tree height and a negative relationship with basal area and height to the base of the live crown, while blueberry plant productivity showed a negative relationship with total tree height. Stands with high site indices had significantly greater abundance of blueberry plants than stands with low site indices, while the opposite trend was observed with respect to the productivity of the blueberry plants.

Canopy closure, basal area, total tree height, height to the base of live crown, blueberry abundance, and blueberry production were accurately modeled using remotely sensed data (Table 2). Some of the distributions for these values were skewed and had no influence on

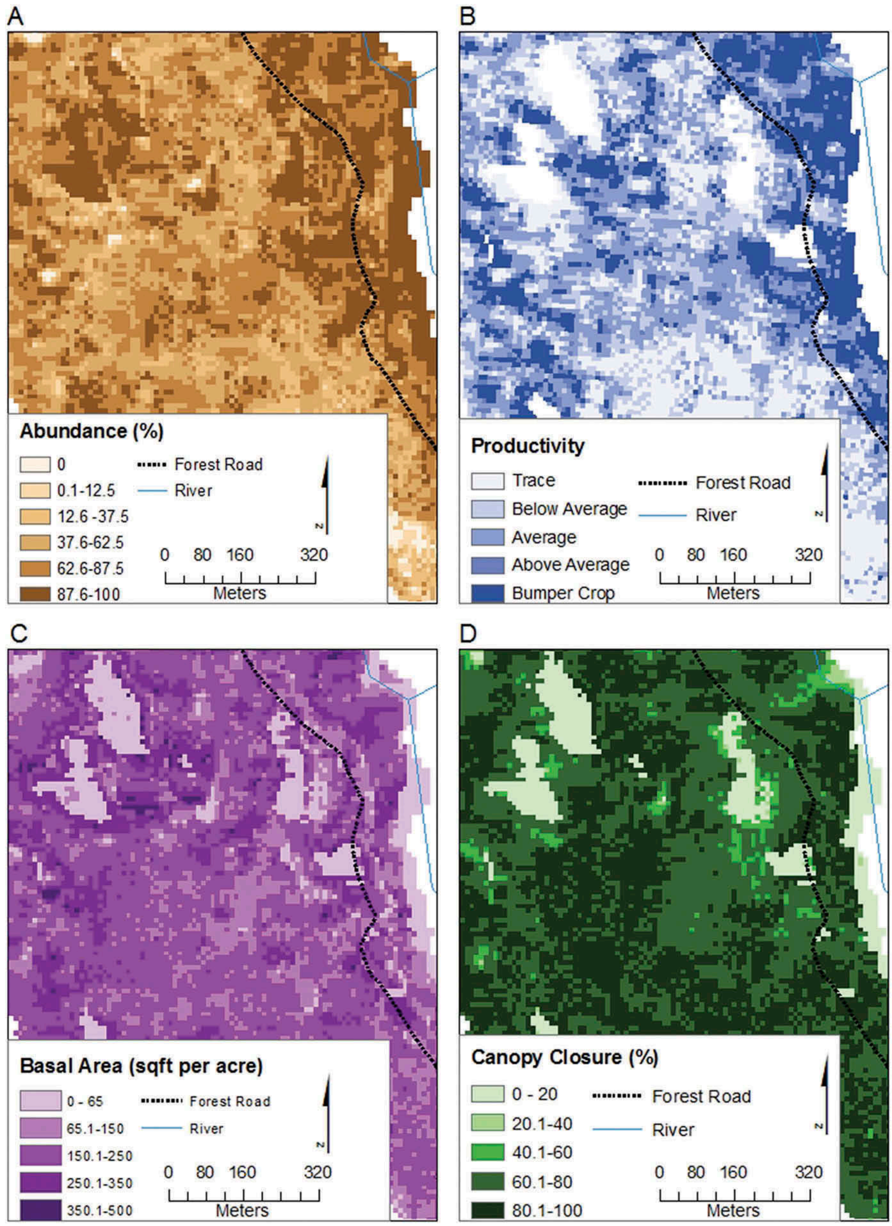

Figure 4. Predictive model of the a) abundance and b) productivity of blueberry plants as an influence by forest stand structure and elevation; and model predicted stand structure attributes c) basal areas and d) canopy closure at an undisclosed location in Port Graham.

the final fit of the models. It was not possible to transform the data to sufficiently remove this skewness. However, residuals plots, plots of predicted v. observed values, showed no trends and therefore demonstrated the models to be free of bias.

Forest stand structure, blueberry plant abundance, and productivity of blueberries were linearly correlated with the topographical, land classification and LandSat-8 OLI data, and these linear relationships varied significantly among the various models (Table 3). Unlike

Table 2. Summary statistics of observed and predicted forest stand structure and the abundance and productivity of blueberry plants on variable radius sample plots around Port Graham, Alaska.

	Canopy Closure (%)		Basal Area(ft^2/ac)		Total Tree Height (ft)		Height Base Live Crown (ft)		Abundance (Scale 0–4)		Productivity (Scale 0–4)	
Variable	Obs	Pred	Obs	Pred	Obs	Pred	Obs	Pred	Obs	Pred	Obs	Pred
N	111		111		111		111		111		111	
Mean	61.3	61.3	158.2	160.5	71.7	71.8	16.6	16.6	2.2	2.2	1.2	1.2
s.d.	36.0	33.9	119.1	98.3	39.6	37.3	14.1	11.1	1.5	1.2	1.2	1.0
CV%	58.7	55.2	75.3	61.3	55.3	52.0	84.9	66.7	68.7	53.5	103.8	85.2
Minimum	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
First Quantile	21.65	26.4	40.0	52.0	49.5	59.1	3.5	8.6	1.0	1.6	0.0	0.4
Median	82.3	76.7	200	194.2	85.0	88.5	17.0	18.3	2.0	2.5	1.0	1.1
Third Quartile	86.5	85.5	240.0	235.4	100.0	96.5	23.5	23.3	4.0	3.1	2.0	1.9
Maximum	93.8	96.4	360.0	316.8	126.0	121.4	60.0	42.6	4.0	4.4	4.0	3.8
%Bias	0.0		1.45		0.1		0.0		0.0		0.0	

the models developed for modeling the coarse-scale variability, not all the topographic, LandSat-8 OLI, and land classifications data were used to describe the small-scale variability in one or more of the regression models.

The overall contribution of forest stand structure and blueberry plant abundance and productivity varied among models (Table 3). The influence of topography and forest stand structure on the abundance and productivity of blueberry plants are displayed in Figure 4. The regression models alone explained 61% (abundance) to 89% (canopy closure) of the variability observed in the field data. The regression trees accounted for an additional 2% (height base live crown) to 10% (productivity) of the unexplained variability observed in the field data (Table 4). Overall model performance ranged from a low of 0.73 (productivity) to a high of 0.96 (canopy closure). The remaining four models had R^2 ranging from 0.73 to 0.84.

Prediction bias was nominal (Table 2) for all models. Minimum, maximum and quartiles showed that estimated and observed value distribution were similar for all models. The mean estimation errors did not differ significantly from zero (p-value $\geq$ 0.05). The mean absolute errors were smaller than the root mean squared error for all models indicating that, in general, the models are more accurate in predicting regional or global means than on a point-by-point basis.

Discussion

This study aims at developing a way to describe where blueberry production could be enhanced by manipulating forest stand conditions. Predictive models are used to characterize and quantify stand components associated with blueberry plant abundance and fruit production. Tribal land managers could use these observations to guide silvicultural treatments. Results indicate that reduced tree density and low tree basal area are associated with forested locations that produce abundant berry crops. This suggests that the abundance and productivity of blueberry plants have an opposite relationship with the site productivity of the Sitka spruce stands in which they are established. More berries develop where more light and less competition from

Table 3. Variables used in describing the large-scale variable in forest stand structure and the abundance and productivity of blueberry plants around Port Graham, Alaska.

	Dependent Variable†					
Independent Variable	PROD	PROD	PROD	PROD	PROD	PROD
			Predicted Variables (RG+RT)			
CNPY_ RGRT §		+	+			
BA_ RGRT				+	-	
THT_ RGRT					+	-
HBLC_ RGRT					-	
ABUND_ RGRT						+
			Topography			
ELEV		+	-	-		-
SLP			+	+	-	
COS(ASP)	+			+	-	-
SIN(ASP)		-	+		-	-
STRATA	**X**		**X**		**X**	
			Landsat 8 Satellite Bands			
BND1		-	+		-	
BND2	+	+				
BND3				-		+
BND4	-		-	+	+	-
BND5		-	+			-
BND6			+	-		+
BND7	+			+	-	-
BND8	-	-	+			
BND10	-		-	+		-
BND11	+		+	-	-	+
BND1H	+	+	-			
BND2H		-	+		-	
BND3H		-			+	
BND4H	-	+	+		-	
BND5H	-	+			-	
BND6H	+	-	-	+	+	+
BND7H	–	+	+	-	-	-
BND8H	+	+				
BND10H		+		-	+	+
BND11H				+		-
R^2_RG	**0.886**	**0.745**	**0.866**	**0.618**	**0.607**	**0.674**
R^2_RGRT	**0.957**	**0.839**	**0.897**	**0.734**	**0.802**	**0.771**

The plus (+) or minus (-) sign indicates the direction of the relationship between the independent and dependent variables while an X indicates the presence of categorical variable in the model.

† CNPY - canopy closure (%); BA - basal area per acre (ft2/acre), THT - total tree height (ft); HBLC - height to base of live crown (ft); ABUND - blueberry abundance 0- trace to 4 - very high); PROD - blueberry productivity (0 – trace to 5 - bumper crop); Elev - elevation (m); Slope (%); ASP - aspect (degrees); STRATA -;BND*X*/BND*X*H- Landsat 8 band, where *X* represents the band number (1–11) and the H after the band number indicates the Landsat band was histogram equalized.

§RGRT – Predicted values based on the regression model (RG) describing the large-scale variability plus binary regression tree (RT) describing the small-scale variability.

overtopping trees occur. This relationship suggests that a forest manager would thin trees to enhance blueberry fruit productivity.

Blueberry plants are unevenly distributed in forests surrounding the village of Port Graham and are more abundant in some locations than others. Traditionally, locations where berries are abundant have been determined by casual field observations. In recent years, plants growing in several of these locations have been damaged by insect defoliators. During years of heavy defoliation, berry crops have nearly been eliminated. The models developed in this study predict the spatial distribution of blueberry plant abundance and

Table 4. Variables used in describing small-scale variability in forest stand structure and the abundance and productivity of blueberry plants around Port Graham, Alaska.

	Dependent Variable†[1]					
Independent Variable †	CNPY	BA	THT	HBLC	ABUND	PROD
			Predicted Residuals from Regression Model (RG)			
CNPY_R [§]	x				x	
BA_R				x	x	
THT_R			x			
HBLC_R				x		
PROD_R						x
			Topography			
SIN(ASP)						x
STRATA						x
			Landsat 8 Satellite Bands			
BND1					x	
BND2		x				
BND4	x	x				
BND5	x	x			x	
BND6		x				
BND8			x	x		
BND10				x		
R^2_RT	**0.071**	**0.094**	**0.031**	**0.016**	**0.195**	**0.097**
R^2_RGRT	**0.957**	**0.839**	**0.897**	**0.734**	**0.802**	**0.771**

†CNPY - canopy closure (%); BA - basal area per acre (ft2/acre), THT - total tree height (ft); HBLC - height to base of live crown (ft); ABUND - blueberry abundance 0- trace to 4 - very high); PROD - blueberry productivity (0 – trace to 5 - bumper crop); Elev - elevation (m); Slope (%); ASP - aspect (degrees); BND*X*- - Landsat 8 band, where *X* represents the band number (1–11

§ _R – Predicted residuals from the regression model (RG) describing the large-scale variability.

the productivity of berries in a continuous layer across the entire forest. A complete knowledge of the spatial distribution of berry plants and their abundance and productivity would offer a potential hedge against future defoliation and other disturbance events by specifying alternative harvest locations that might not have been affected.

This modeling approach has several advantages to resource users and managers. It is more cost-efficient than estimates based solely on field sampling where frequency and geographic distribution of plots may be limited, especially if stands are difficult to reach, small in size or irregularly shaped. Furthermore, evaluation of the models indicates that the estimated variances associated with the point estimates could be used to assess estimates of uncertainty when applied to non-sampled plot locations. The ability to calculate estimation uncertainties allows one to develop GIS layers showing the computed estimation errors and to place confidence intervals around these estimates.

The models assume that similar stands have similar characteristics with respect to stand structure and berry production. The variable R^2-values for some of the models may be due, in part, to differences in stand structure resulting from past management activities or weather-related damage. To account for this variability and to improve their overall predictive accuracy, it may be possible to include past disturbances from both anthropogenic land management effects (e.g., forest extraction and/or thinning) and other natural disturbances (e.g., storm damage), or similar sources of error. Other sources of error that could have influenced the performance of the models include the sparseness of the field data, errors in stratifying the forest, and errors associated with registration of the field plots and satellite imagery.

Inferences from the models developed in this study suggest that silvicultural thinning may enhance the abundance and productivity of blueberry plants in young even-aged (<100 years old) stands by opening up the canopy to allow more light to penetrate the forest floor. The models, however, provide no evidence that would suggest that silivicultural thinnings or timber harvesting would measurably increase either the abundance or productivity of blueberry plants more than that found in old-growth forests. Repeated tree thinning may be necessary to maintain a high rate of productivity of blueberries in young, even-aged stands, but collateral damage to the understory would require recovery time. Such activity may increase wind damage and other associated disturbances by opening the canopy too quickly. More research would help understand how silvicultural manipulations might create conditions of health for blueberry assemblages found in unmanaged old growth.

Management implications

During this research, two key pieces of information were generated that are directly applicable to management activities. First, significant blueberry resources are available in clear cuts prior to canopy closure, but many of these areas are brushy and access is extremely difficult. A tribal vegetation management program could open up large areas of high-quality berry harvesting ground by facilitating access. Second, blueberry plants are abundant in high site index mature stands, but productivity is relatively low. Blueberry production tends to be higher in low site index stands with open canopies. A vegetation management program could open the canopy of high site index even-aged stands to increase blueberry yields and maintain canopy openings in lower site index stands to sustain blueberry yield.

Acknowledgments

In order to conduct this research, we had to be sensitive to the proprietary nature of the traditional ecological knowledge we utilized to inform our models, specifically the location of traditional berry harvesting areas. The tribe was very concerned with blueberry resource data becoming available outside of the tribe and would not agree to the research without guarantees to the confidentiality of the data and modeling products. The Tribe felt comfortable sharing their traditional ecological knowledge with the research team because of trust built between the tribe and the research team on past collaborative projects. This trust was critical to the success of this project.

We would like to thank the Elders from Port Graham, the Port Graham Tribal Council, and landowners near Port Graham for their support of this project for without their support this project would not have been possible.

Funding

This project was funded by a grant from the North Pacific Landscape Conservation Cooperative through the United States Fish and Wildlife Service award F13AP00533.

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