Integration of proximal and remote sensing data for site-specific management of wild blueberry

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Abstract. *In Saguenay-Lac-St-Jean, there are nearly 27,000 ha of wild blueberries (Vaccinium angustifolium Ait.). This production is carried out in fields with heterogeneous growing conditions due to the local changes in topography, key soil properties, and crop density. The main objective of this study was to develop a regression-based approach to site-specific management (SSM) by integrating proximally and remotely sensed data layers, namely, apparent soil electrical conductivity (EC_a), field elevation, and multi-spectral satellite imagery. The study sites were an 11.3-ha flat field ($Field_{Flat}$) and a 13.2-ha undulating field ($Field_{Und}$) from Normandin, QC. Soil samples were collected at 5 - 15 cm depth using a 33-m grid sampling strategy and then analyzed for a range of chemical and physical properties. A vegetation index (VI) based on the second principal component in principal components analysis (PCA) was generated from a four-band SPOT satellite image (pan-sharpened to 1.5-m resolution). VI correlation with yield was calculated using Pearson's correlation test ($p < 0.05$). Four distinct areas based on combinations of elevation and EC_a were defined to signify the most diverse growing conditions in terms of the soil's potential to store water and nutrients and the landscape's susceptibility to run-off. Soil characteristics as well as crop performance in these areas were compared using Analysis of Variance (ANOVA) and Tukey's post-hoc test ($\alpha = 0.05$). Though neither field showed significant differences in yield among the four growing conditions, several yield-limiting soil properties were significantly different. In both fields, the greatest contrast in soil properties was between high elevation areas* *with low EC_a and low elevation with high EC_a. The VI was not strongly correlated with yield (r_{und}=-0.41, r_{flat}=-0.36). However, the VI successfully classified large, contiguous bare spots in the undulating field (r_{und}=0.68). Our findings indicate satellite imagery supplements yield estimation and captures greater crop density variation than the sampled yield. Furthermore, the results indicate an integration of elevation and EC_a data targets within-field contrasts effectively for SSM. By combining satellite, elevation and EC_a data, our proposed methodology captures diverse field conditions.*

Keywords.

Precision Horticulture, Vaccinium angustifolium Ait., Apparent soil electrical conductivity, SPOT satellite image.

Introduction

Wild blueberry (*Vaccinium angustifolium* Ait.) cultivation generates a business value of over $45 million annually in Quebec (Gagnon 2013). Specialty crop such as wild blueberry potentially benefits from site-specific management (SSM) due to its relatively high price of yield and cost of production. Efficient N fertilization of wild blueberry benefits both producers and the environment. Excessive N will cause an overgrowth of leaves, stunted fruiting, and heightened disease susceptibility (Percival and Sanderson, 2004), while mis-application of N threatens the ecological activity in the region through ammonia volatilization and nitrate leaching (Thyssen et al. 2006; Istas 1988). An additional challenge to wild blueberry cultivation is variation in crop density. Bare spots commonly occur in young and/or mismanaged fields. Previous studies have developed SSM strategies based on management zone (MZ) delineation of either topography or EC_a in conjunction with mapping and excluding bare spots (Saleem et al. 2013, Farooque et al. 2012). However, MZs rely on categorical prescriptions, treating sub-field classes with uniform rates. Alternatively, a regression-based approach applies treatment at a continuously changing rate, relative to changing field conditions. The goal of this study was to illustrate how proximal EC_a and elevation data might be integrated with remotely sensed imagery to develop a regression-based SSM strategy for the specialty crop wild blueberries. A simple data separation method on which to base the regression was suggested. The facility of this method may provide future decision support systems for widespread adoption of regression-based SSM.

Materials & Methods

Experimental sites

Two commercial fields were selected (**Fig. 1**). The experimental blueberry fields lay 6 km southwest of Normandin, QC (48.8369° N, 72.5279° W) north of the Chamouchouane River. Soil here was primarily podzolic, mixed with finer eolian deposits. Drainage varied from moderate to good. The site was generally flat with some undulation. $Field_{Flat}$ (11.3 ha) represented a uniform low-lying topography ranging from 123 – 125 m elevation and $Field_{Und}$ (13.2 ha) represented a more heterogeneous topography with elevation ranging from 127 – 136 m.

Data layers were divided into proximally and remotely sensed data, soil samples analyzed in the lab, and sampled yield. The selected data layers were meant to encompass the various properties and processes which affect yield.

Soil sampling and analysis

Soil and yield samples were obtained in both fields with a 33-m grid sampling scheme for a total of 136 points in $Field_{Und}$ and 116 points in $Field_{Flat}$. Soil samples were collected in October 2016 at 5-15 cm depth. Yield samples were collected over two days in August 2016 before the fields were harvested for commercial sale. Blueberries were combed from a square meter of blueberry bush at each point. The weight of the fresh blueberries was measured and recorded on site for every sample.

Soil samples were dried and ground to 2 mm for textural and chemical laboratory analysis. A Mehlich-III soil extractant was used to extract key nutrients (Ziadi and Tran 2007). Phosphorus (P) content was determined by colorimetry (Lachat Instruments, model 8500, series 2) (Murphy and Riley 1962). Potassium (K) content was determined with spectrophotometry flame emission (Lachat Instruments, model 8500, series 2). Total Carbon (C) and Nitrogen (N) content were evaluated with the Elementar vario MAX CN analyzer (Elementar Analysensysteme GmbH, Hanau, Germany). Soil texture was analyzed for soil samples using the pipette method (Day 1965). Texture was categorized in terms of grams per kilogram total sand, total silt, and total clay according to the Canada Soil Survey Committee standards (Sheldrick, 1984). Descriptive statistics on all attribute data were calculated. Laboratory analysis methods are summarized in

The ECa was collected with the Veris 3100 sensor. The Veris 3100 was configured with six roller coulter electrodes pulled by a truck. Sample transects were 3 m apart, and measurements were received at a density of one sample per meter. Elevation was collected with a GNSS receiver mounted on a gator. Data was collected at 5 samples per second. Transects were spaced 10 meters apart, guided with a GPS steering guidance system.

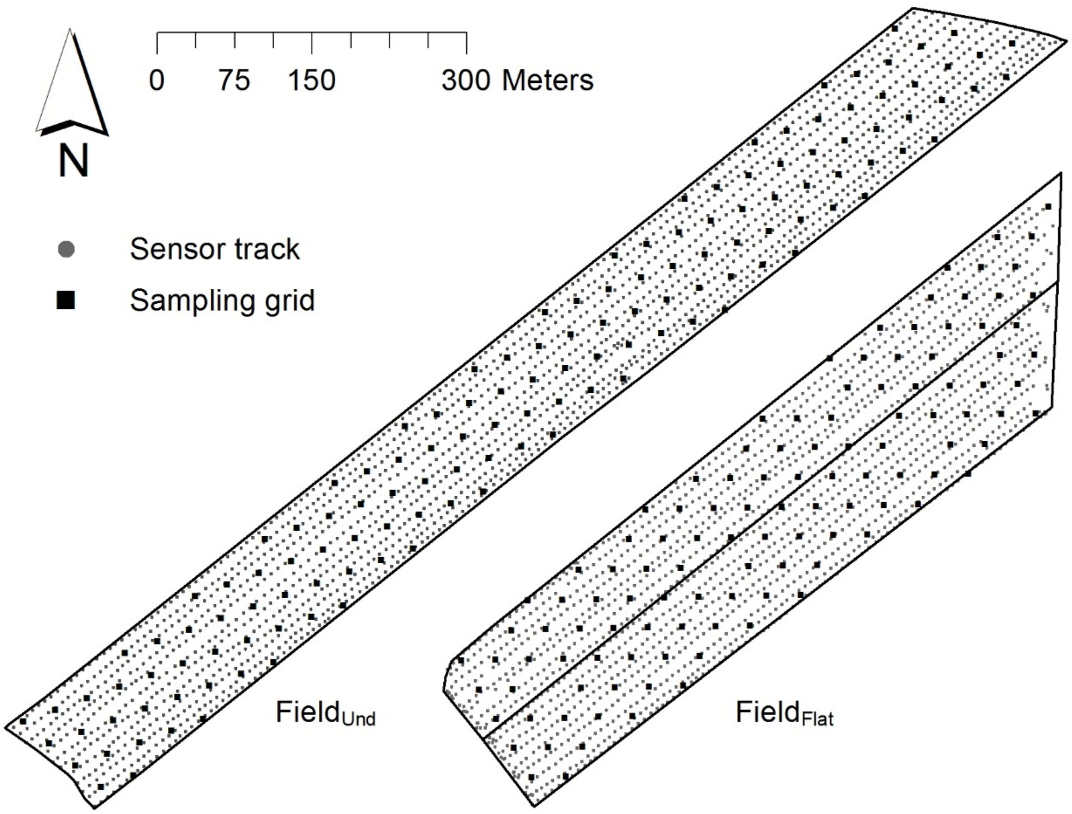

Fig. 1: Experimental sites.

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Table 1: Summary of field sensor and laboratory analysis methods.

Property	Method	Reference
Granulometry	Pipette	Day (1965)
P, K	Mehlich-III	Ziadi and Tran (2007)
pH	Water	Hendershot *et al.* (2007)
Total C, Total N	Elementar vario MAX CN analyzer[x]	Elementar Analysensysteme GmbH, Hanau, Germany
EC_a	Veris 3100[x]	Veris Technologies, Salina, KS
Elevation	Real-time-kinematic GPS[x]	Trimble Navigation Inc., Sunnyvale, CA

[x]Mention of a trade name, proprietary product, or company name is for presentation clarity and does not imply endorsement by the author or McGill University, nor does it imply exclusion of other products that may also be suitable.

Proximal soil sensing

The EC_a was collected with the Veris 3100 sensor. The Veris 3100 was configured with six roller coulter electrodes pulled by a truck. Sample transects were 3 m apart, and measurements were received at a density of one sample per meter. Elevation was collected with a GNSS receiver mounted on a gator. Data was collected at 5 samples per second. Transects were spaced 10 meters apart, guided with a GPS steering guidance system.

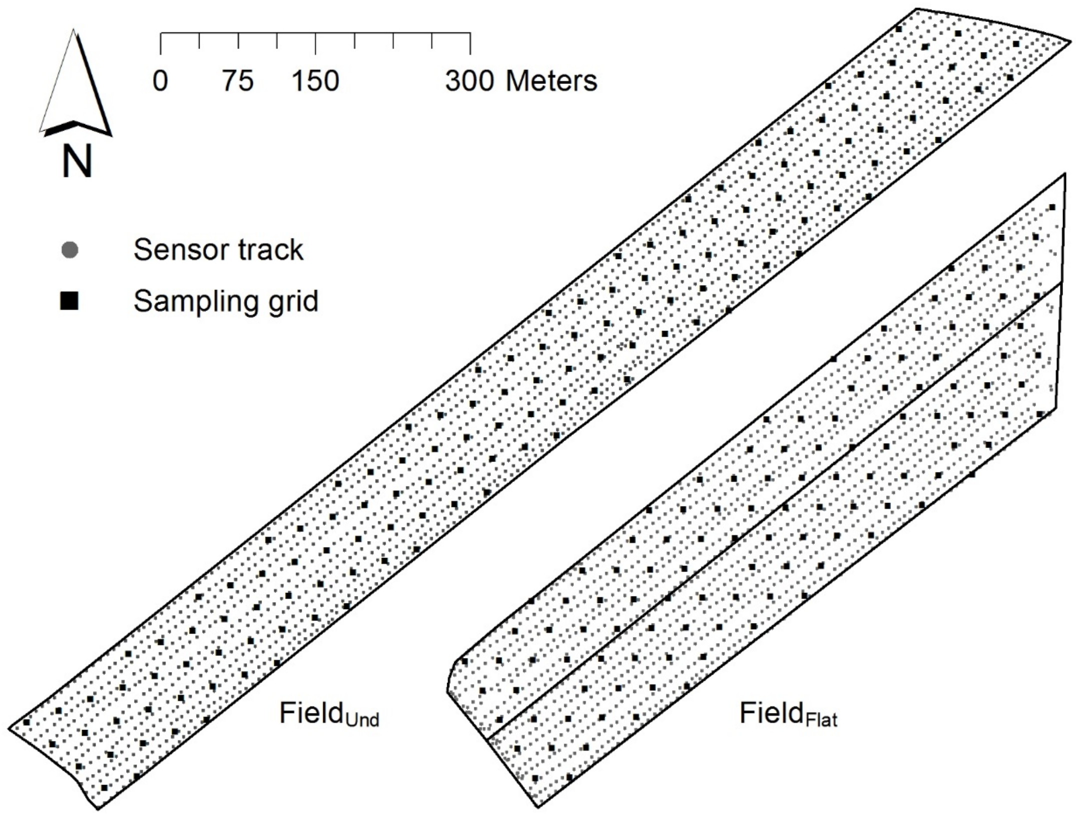

Fig. 1: Experimental sites.

Remote sensing

A multi-spectral (MS) satellite image of the fields during August 2017 was obtained from Airbus's SPOT-6 satellite archive. The SPOT-6 image was delivered georeferenced, corrected for off-nadir acquisition and terrain effects using the standard Reference3-D model for ground corrections (SPOT User Guide). The image included red, green, blue, and NIR bands at 5 m^2 resolution, as well as a panchromatic band at 1.5 m^2 resolution. The panchromatic and MS images were simultaneously acquired, allowing for geospatially accurate pan-sharpening of the MS image to 1.5 m resolution. The pansharpened image was radiometrically and atmospherically corrected in ENVI image analysis software (Exelis Inc., Boulder, Colorado). PCA reduced the MS image to principal components which maximized variation and reduced noise. The second principal component was used as a VI per published recommendations (Eklundh and Singh 1993; Townshend 1985).

Pearson's correlation coefficient was calculated for the VI and yield to assess how well the VI predicted yield. The VI was classified by the Jenks optimization method to delineate bare spots within the field (Jenks 1967). The effectiveness of bare spot prediction was assessed by calculating Pearson's correlation with a binary classification of sampled yield where yield values of 0 kg ha^{-1} were assigned a 0 and all other values were assigned a 1.

Data processing

Elevation and EC_a data were filtered to one value per five seconds. Data distribution was examined for normality and values outside of two standard deviations were removed. Slope and topographic wetness index (TWI) were calculated from the elevation data using SAGA GIS (Beven and Kirkby 1979). Elevation and EC_a data were interpolated to continuous surfaces using the Ordinary kriging (OK) method with R statistical software (R Foundation for Statistical Computing, Vienna, Austria).

Topographic attributes and EC_a were extracted from their raster grids by the yield/soil sample points so they could be compared with other sampled attributes. Elevation *vs.* EC_a values were then projected onto a scatter plot, and ten points in the four corners of the scatter plot – with the exclusion of outliers – were sub-set to represent four extreme growing conditions of EC_{Low} $Elev_{Low}$, EC_{Low} $Elev_{High}$, EC_{High} $Elev_{Low}$, and EC_{High} $Elev_{High}$. Veris Shallow EC_a was selected because its depth of response (0.3 m) most closely corresponded with the depth of soil samples. ANOVA and Tukey's post-hoc test were used to compare the significant difference of the means of individual soil properties in the four scenarios (locations with extreme soil conditions).

Results & Discussion

Lab analysis showed both fields with sandy, acidic soil. Average yield in $Field_{Und}$ was higher than the $Field_{Flat}$ (6432 kg ha^{-1} *vs.* 3985 kg ha^{-1}). $Field_{Und}$ also had higher silt content and less sand than $Field_{Flat}$ (**Table 2**). The average pH in both fields was within the range of 4.6 to 5.2, which was appropriate for wild blueberry production according to NBDAAF (1998). Nutrient levels were similar in both fields except for the P content, which was higher in $Field_{Und}$. Sampled yield was highly variable, and correlation was difficult to establish. In $Field_{Und}$, a significant negative correlation existed between yield and elevation (

		$Field_{Und}$						$Field_{Flat}$					
	Unit	**N**	**Min**	**Max**	**Mean**	**STD**	**CV %**	**N**	**Min**	**Max**	**Mean**	**STD**	**CV %**
Yield	kg ha^{-1}	136	0	16080	6432	3499	54.4	116	0	10740	3985	2253	56.5
Total C	%	136	0.64	3.88	1.29	0.53	40.9	116	0.20	4.12	1.17	0.57	48.8
Total N	%	136	0.04	0.17	0.07	0.02	35.5	116	0.02	0.22	0.08	0.03	35.0
Soil pH_{water}	--	136	4.5	6.5	5.1	0.3	6.0	116	4.6	5.8	5.0	0.2	3.5
P	mg kg^{-1}	136	1.1	249.1	67.0	48.5	72.3	116	1.1	134.3	24.3	21.4	88.0
K	mg kg^{-1}	136	8.1	256.8	38.7	25.0	64.4	116	3.4	95.2	40.4	18.4	45.6
Sand	g kg^{-1}	136	636.4	948.1	856.8	74.1	8.6	116	718.9	968.4	896.0	30.2	3.4
Silt	g kg^{-1}	136	35.4	345.8	119.7	75.6	63.1	116	19.2	257.6	77.5	30.5	39.3
Clay	g kg^{-1}	136	12.0	37.3	23.5	5.2	22.1	116	9.9	38.1	26.5	6.1	23.1

Table 3). There was also a positive correlation between yield and silt in the undulating field. Texture and topography appeared to be more yield-determining in $Field_{Und}$. In $Field_{Flat}$, yield was significantly correlated with total C and extractable K.

Table 2: Statistical summary of yield and soil samples.

		$Field_{Und}$						$Field_{Flat}$					
	Unit	**N**	**Min**	**Max**	**Mean**	**STD**	**CV %**	**N**	**Min**	**Max**	**Mean**	**STD**	**CV %**
Yield	kg ha^{-1}	136	0	16080	6432	3499	54.4	116	0	10740	3985	2253	56.5
Total C	%	136	0.64	3.88	1.29	0.53	40.9	116	0.20	4.12	1.17	0.57	48.8
Total N	%	136	0.04	0.17	0.07	0.02	35.5	116	0.02	0.22	0.08	0.03	35.0
Soil pH_{water}	--	136	4.5	6.5	5.1	0.3	6.0	116	4.6	5.8	5.0	0.2	3.5
P	mg kg^{-1}	136	1.1	249.1	67.0	48.5	72.3	116	1.1	134.3	24.3	21.4	88.0
K	mg kg^{-1}	136	8.1	256.8	38.7	25.0	64.4	116	3.4	95.2	40.4	18.4	45.6
Sand	g kg^{-1}	136	636.4	948.1	856.8	74.1	8.6	116	718.9	968.4	896.0	30.2	3.4
Silt	g kg^{-1}	136	35.4	345.8	119.7	75.6	63.1	116	19.2	257.6	77.5	30.5	39.3
Clay	g kg^{-1}	136	12.0	37.3	23.5	5.2	22.1	116	9.9	38.1	26.5	6.1	23.1

Table 3: Pearson's correlation coefficients, *p < 0.05, **p < 0.001, ***p < 0.0001.

	Field Und	Field Flat

	Yield	Elevation	EC_a	Yield	Elevation	EC_a
Yield	1.00	-0.22*	-0.02	1.00	-0.06	0.18
Elevation	-0.22*	1.00	-0.50***	-0.06	1.00	-0.28*
EC_a	-0.02	-0.50***	1.00	0.18	-0.28**	1.00
Total C	0.10	-0.02	0.16	0.25*	0.00	0.28*
Total N	0.08	-0.04	0.14	0.23	-0.14	0.36***
Soil pH_{water}	-0.04	-0.50***	0.38***	-0.18	-0.46***	0.25*
P	-0.02	-0.11	0.04	0.02	-0.31**	0.17
K	0.25*	0.22**	-0.07	0.25*	0.04	0.16
Sand	-0.16	0.60***	-0.34***	-0.20	0.12	-0.31**
Silt	0.19*	-0.69***	0.38	0.12	-0.06	0.25*
Clay	-0.14	0.55***	-0.28*	-0.02	0.15	0.12

In addition, it was observed that EC_a correlated with pH (r_{Und} = 0.38, r_{Flat} = 0.25). In both fields, EC_a was significantly correlated with the results of particle size analysis, particularly for total sand (r_{Und} = -0.34, r_{Flat} = -0.31) indicating sandier soil is negatively correlated with EC_a. EC_a was not significantly correlated with TWI in $Field_{Und}$ but was correlated in $Field_{Flat}$ (r_{Flat} =0.25). In $Field_{Und}$, physical soil characteristics were more correlated with EC_a while in the $Field_{Flat}$, chemical and physical soil characteristics were correlated with EC_a. In $Field_{Und}$, total silt was negatively correlated with elevation while total clay was positively correlated with elevation. Elevation showed a significant correlation with pH in both fields with higher elevations corresponding to lower pH (r_{Und} = - 0.50, r_{Flat} = - 0.46).

Extreme cases

The scatter plots in **Fig. 2** and **Fig. 3** illustrate the relationship between EC_a and elevation data used to identify contrasting field conditions on which to base the regression. The two distinct clusters in **Fig. 2** show the bimodal distribution of elevation in $Field_{Und}$. The red points highlighted in the scatterplot represent occurrences of zero yield. They all occur in the high elevation cluster and are mostly distributed among higher EC_a. Tukey's post-hoc test revealed slope to be significantly higher in the $Elev_{High}$ EC_{High} scenario indicating that high slope and bare spots coincide. In $Field_{Flat,}$ elevation varies less, but EC_a was also slightly lower in high elevation areas (**Fig. 3**).

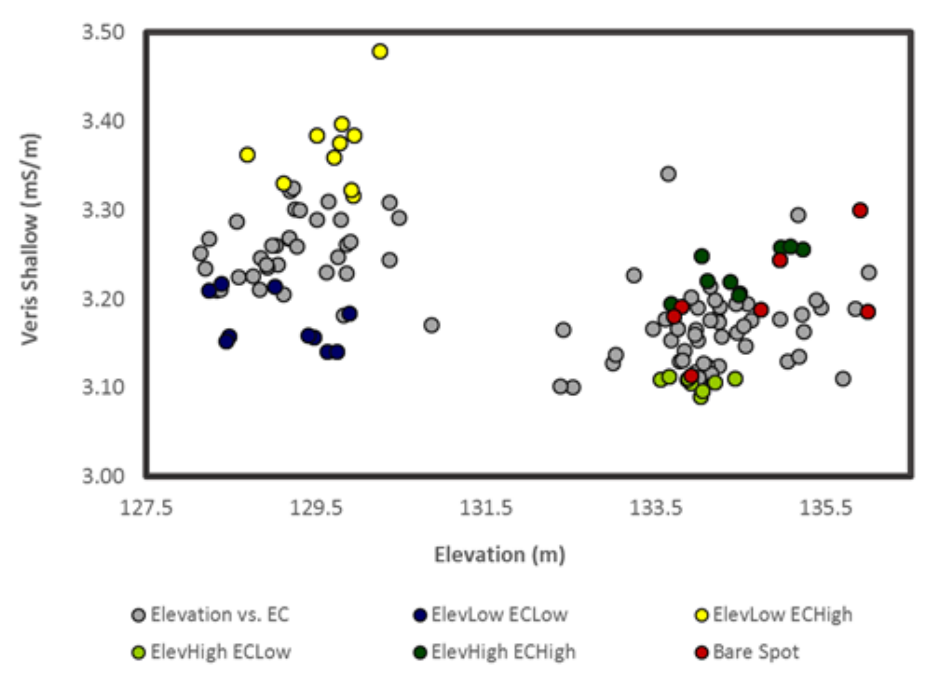

Fig. 2: Field$_{Und}$ scatter plot of Elevation *vs.* ECa values. Bare spots are highlighted in red. Bare spots are highlighted in red and correspond with higher elevation.

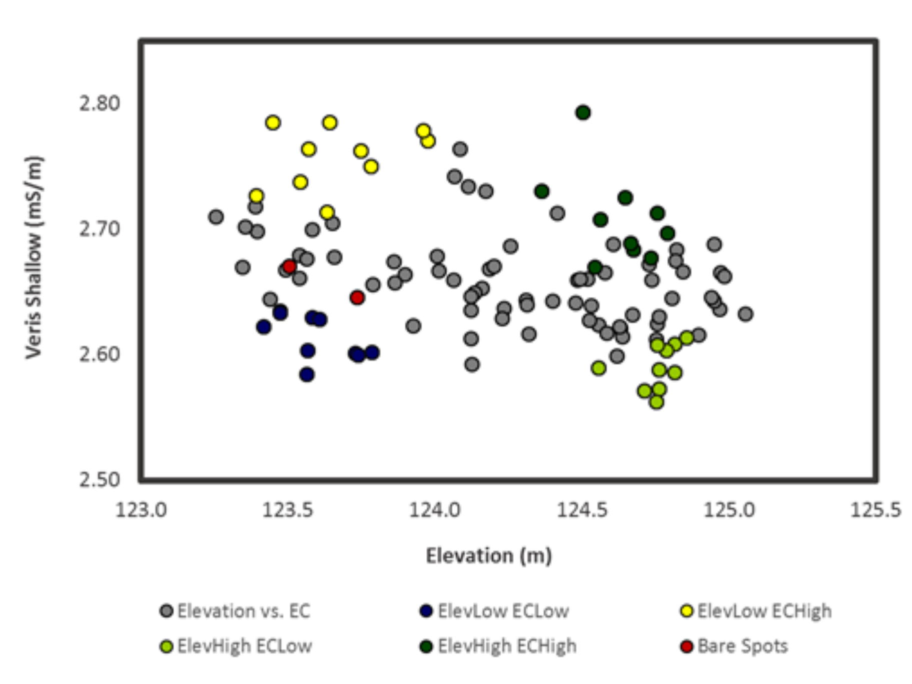

Fig. 3: Field$_{Flat}$ scatter plot of Elevation *vs.* ECa values. Bare spots are highlighted in red.

Tukey results showed a significant difference in soil texture among high and low elevation scenarios. Total silt was separated by elevation, but not distinguished by EC$_a$ (**Fig. 4**). The combination of EC$_a$ and elevation distinguished other physical and chemical attributes (sand, slope, Fe, and pH). Average pH was significantly higher in Elev$_{Low}$ EC$_{High}$ and slightly above the optimal range.

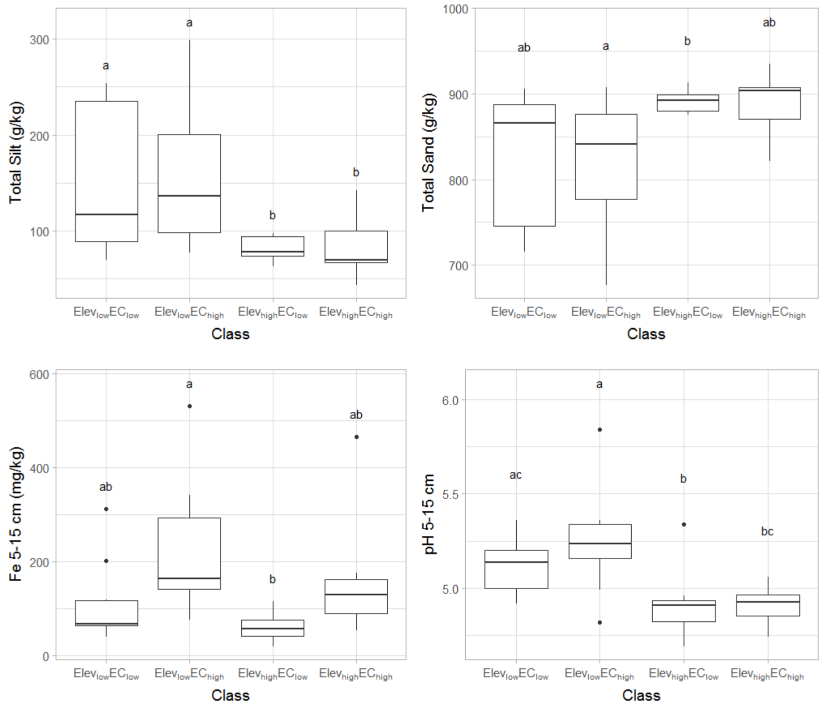

Fig. 4: Field$_{Und}$ total silt separated by high *vs.* low elevation and other chemical and physical soil properties separated by the combination of high *vs.* low elevation and EC$_a$.

Like Field$_{Und}$, the greatest distinction in Field$_{Flat}$ was between scenarios Elev$_{Low}$ EC$_{High}$ and Elev$_{High}$ EC$_{Low}$ (**Fig. 5**). Elevation was less variable in Field$_{Flat}$, so EC$_a$ was more useful in separating data.

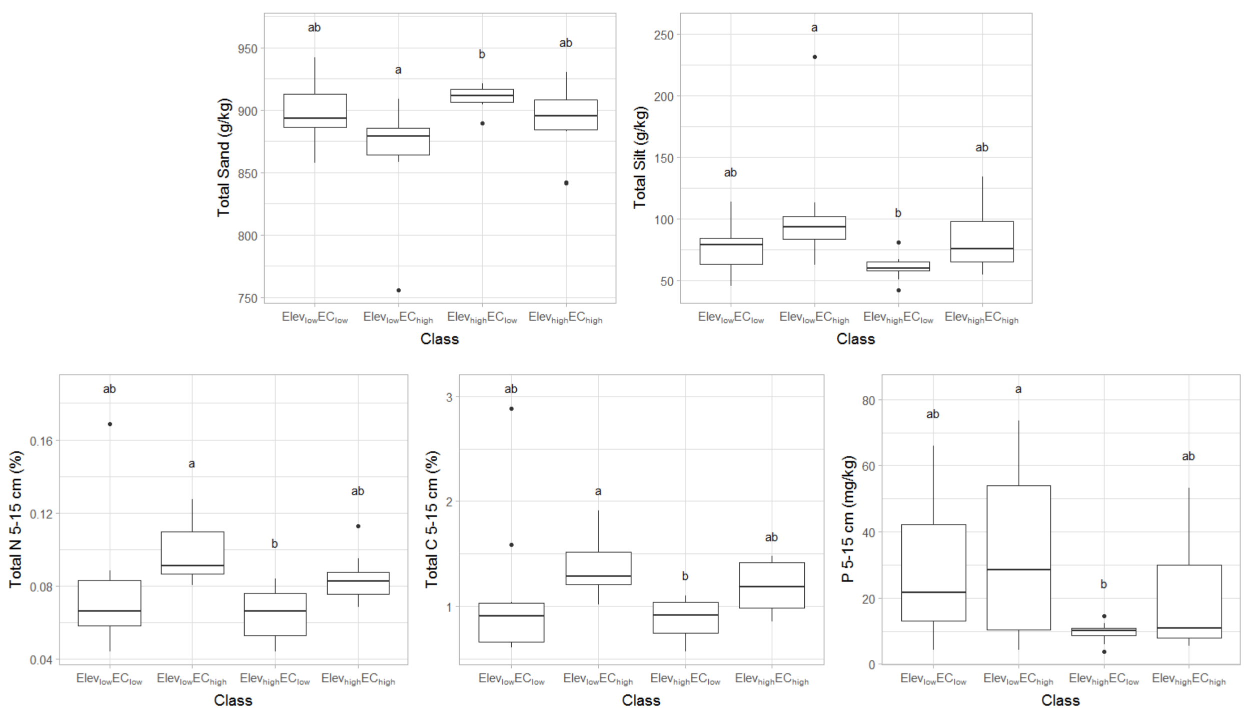

Fig. 5: Field$_{Flat}$ physical and chemical properties separated by combining high *vs.* low elevation and EC$_a$.

Remote Sensing

The VI derived from the second principal component (PC2) using PCA improved the classification of bare soil *vs.* vegetation. Correlation with yield in Field$_{Und}$ was higher than in Field$_{Flat}$ (r_{Und}=0.-41,

r_{Flat}=-0.36). Low correlation coefficients suggest the VI alone could not capture yield patterns in the field – in part, because greener and denser growth did not necessarily indicate higher blueberry yield but may have represented weed patches or more excessive leaf growth.

Based on the VI classification, bare spots comprised 75.5 m^2 or 8.5% of $Field_{Und}$ and 29.3 m^2 or 10.7% of $Field_{Flat}$. Results showed the VI better identified bare spots in $Field_{Und}$ (r=0.68) than in $Field_{Flat}$ (r=0.40), likely because the incidence of bare spots was more contiguous in the undulating field (**Fig. 6**). Validating the VI with sampled yield proved challenging because SPOT imagery pixels were pansharpened to 1.5 m^2 resolution while ground-truth yield was sampled at 1 m^2. Smaller and less contiguous bare spots did not appear on the satellite image.

Larger classified spots could be used to identify areas of the fields to be excluded from the regression approach. The average soil conditions in bare spots were found to have only a slightly lower EC_a (z_{Und} = -0.143 z_{Flat} = -0.090), yet soil showed higher than average pH (z_{Und} = 0.33, z_{Flat} = 2.53) and lower than average total C (z_{Und} = -0.27, z_{Flat} = -1.19) and K (z_{Und} =-0.59, z_{Flat} = -1.347). This suggests soil conditions in bare spots differ dramatically from average field conditions, despite little change in EC_a. The large bare spots classified in $Field_{Und}$ will be separated for tailored management.

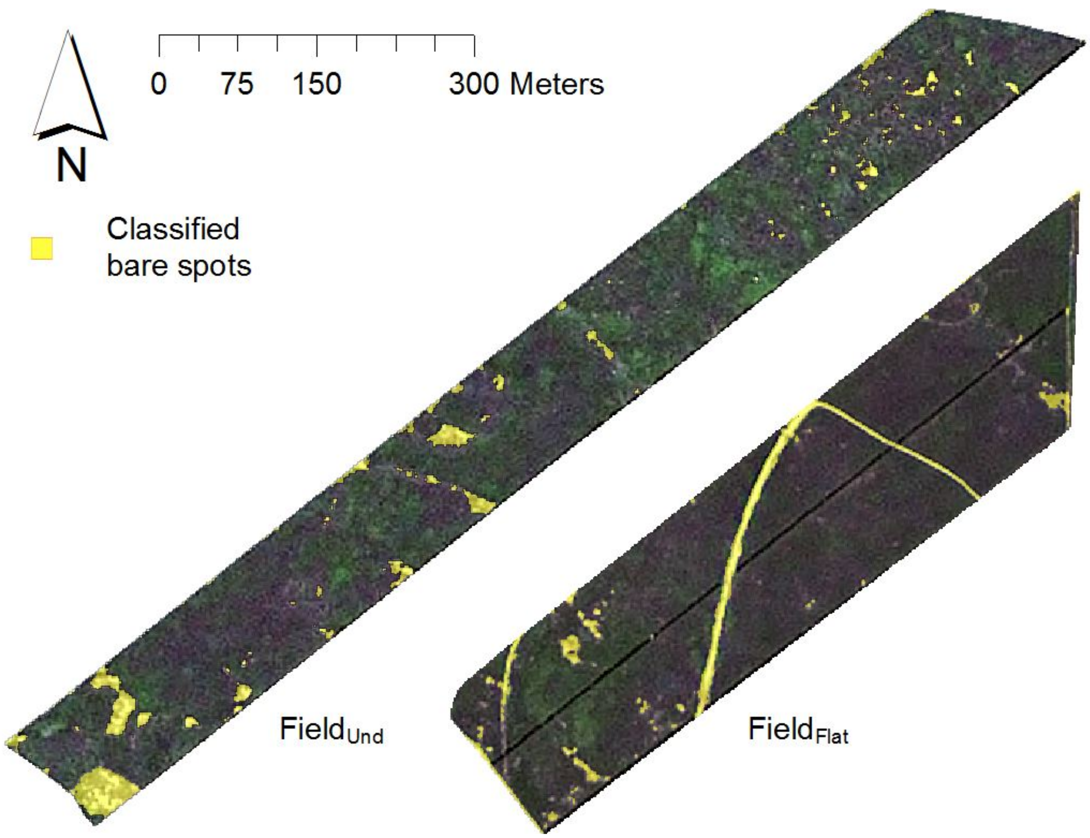

Fig. 6: Classification of bare spots based on PCA-derived VI. The VI performs especially well when classifying large contiguous bare spots.

Conclusion

In this study spatial heterogeneity of the growing environment was analyzed in two wild blueberry production fields using proximally-sensed elevation and EC_a data combined with remotely-sensed satellite data. We found the VI generated from satellite imagery was limited in mapping yield in part because ground-truth data could not appropriately validate the VI and in part because measuring vigor in fruiting crops presented new challenges when compared to green crops.

However, where large, contiguous bare spots occurred, the VI satisfactorily identified them. Satellite imagery proved to be a simple method for mapping large bare spots to be separated from the rest of the field for SSM. Future studies should investigate how this method can be scaled to cover an entire producer's site for rapid assessment of bare spots.

The two experimental fields showed contrasting field conditions with one field topography-driven and with larger bare spots than the other. Yet, the integration of elevation and EC_a data effectively separated within-field contrasting field conditions in both fields – the greatest contrast occurring between $Elev_{Low}$ EC_{High} *vs*. $Elev_{High}$ EC_{Low}. With the inclusion of bare spot delineation from satellite imagery, a host of field conditions may be separated with our methodology.

Future studies should address the question of scalability of SSM strategies on this specialty crop in this region. Furthermore, this regression-based fertilization strategy lends itself to the development of a decision support system for determining fertilization levels based on sampled EC_a and elevation data. When combined with satellite imagery for mapping bare spots, this methodology encompasses the main challenges of wild blueberry production.

Acknowledgements

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Appendix

Appendix A: Standard score of soil variables in bare spots. The score represents distance from the field average. A value close to 0 has little difference from field average. N_{Und} = 8 and N_{Flat}=2.

Soil Particle size	z_{Und}	z_{Flat}
Clay	0.329	-1.570
Silt	-0.594	-1.124
Sand	0.583	1.453
Chemical analysis		
Total N	0.087	-1.239
Total C	-0.266	-1.186
Soil pH_{water}	0.329	2.530
P	-0.297	1.478
K	-0.587	-1.347
Sensor + Yield		
Veris Shallow	-0.143	-0.090
Veris Deep	0.077	-1.245
Elevation	1.090	-1.159
Yield	-1.838	-1.768
Slope	0.676	0.471
TWI	-0.371	0.140