Article

Adjusting Mineral Nutrition of Lowbush Blueberry to Agroecosystem Conditions

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Abstract: Nutrient management of lowbush blueberry (*Vaccinium angustifolium* Ait.) depends on several yield-limiting features. Machine learning models can process such yield-impacting variables to predict berry yield. We investigated the effects of local variables on yields and nutrient management of lowbush blueberry. We collected 1504 observations from N-P-K fertilizer trials conducted in Quebec, Canada. Meteorological indices at various phenological stages showed the greatest impact on yield. High mean temperature at flower bud opening and after fruit maturation, and total precipitation at flowering showed positive effects. Low mean temperature and low total precipitation before bud opening, at flowering, and by fruit maturity, as well as number of freezing days (< -5ºC) before flower bud opening, showed negative effects. Soil fertility variables, leaf nutrient compositions and N-P-K fertilization showed smaller effects. Gaussian processes predicted berry yields from historical weather data, soil analysis, fertilizer dosage, and leaf nutrients with a root-mean-square-error of 1447 kg ha^{-1} on the testing data set. An in-house Markov chain algorithm optimized yields modelled with Gaussian processes from leaf nutrient composition, soil test value, and fertilizer dosage conditioned to specified historical weather features. We propose to use conditioned machine learning models to manage nutrients of lowbush blueberry at local scale.

Keywords: blueberry; crop modeling; plant nutrition; machine learning

1. Introduction

Lowbush blueberry species (*Vaccinium angustifolium* Ait. and, to some extent, *V. myrtilloides* Michx.) are North American wild ericaceous species growing in upland acid sandy soils. The province of Québec, Canada, is among the world leaders in the production of lowbush blueberry [1]. Berry yields vary widely between 0.6 [2] and 8.9 Mg ha-1 [3], indicating high risk of production failure in that area. Lowbush blueberry is managed over 2-year cycles where vegetative (or pruning) and fruit-bearing (or fruit-harvesting) years alternate. Flower bud initiation occurs during the vegetative year and impacts on crop productivity during the fruit-bearing year [4]. Fruit set depends on the number of flowers, pollination success, edaphic and managerial conditions, year, and clone [5], as well as nesting habitats of pollinators [6].

During the 2004-2009 period, low average yield of 1.9 Mg ha-1 impacted by adverse weather conditions affected the economic viability of most Quebec lowbush blueberry farms [7]. Snow cover, frost frequency, defrost and drought periods, flowering, weather variations, pollination, diseases and

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maturation dates impact on lowbush blueberry productivity. Meteorological models have been developed to predict yields of lowbush blueberry and scout fields for pests [8].

Lowbush blueberry is fertilized during the spring of the vegetative year to stimulate and support plant regrowth after pruning [9]. Almost all fertilizer trials on lowbush blueberry have been conducted as single nutrient N, P, and K experiments [3,9–13] as well as factorial N-P [14] and N-P-K combinations [2,15–17]. While ammonium-phosphate interaction may promote yields, lowbush blueberry appeared little responsive to added K [18]. Large variation in fertilizer dosage from 0.50 to 0.75 grower's rate showed small impact on berry yield [19]. Little attention has been given to other elements [20]. Fertilization dosage and timing of application have not yet been optimized [9].

Where soil and tissue tests return opposite nutrient diagnoses, tissue tests generally appeared preferable [18]. Fertilization guidelines for lowbush blueberry are thus based on tissue tests: soil tests are complementary. Tissue diagnosis as nutrient deficiency, sufficiency or toxicity is conducted by comparing each element to selected nutrient concentration ranges where crop productivity has been found to be adequate [21]. The selection of regional standards using univariate descriptive statistical tests [22–25] may be hazardous because,

1. nutrient variables are intrinsically multivariate — compositions should be interpreted as a whole, not as a collection of parts (26),
2. regional standards disregard local conditions of lowbush blueberry agroecosystems [18,26–29],
3. descriptive statistical tests compare the nutrient status of high and low yielders based on arbitrary yield threshold and are designed to test differences, not to predict optimal nutrient combinations of compositional entities.

Machine learning can process yield-impacting variables to predict yields at production sites (31). Markov chain random walk can optimize features at local scale. Machine learning models coupled with Markov chain optimization could help to find optimal sets of manageable features such as leaf and soil nutrient status as well as fertilizer dosage of lowbush blueberry under site-specific agroecosystem conditions.

Our objective was to predict yield of lowbush blueberry from a set of investigated feature-specific conditions. We hypothesized that (1) soil chemistry, tissue nutrients, weather indices, and N-P-K fertilization affect berry yields, and (2) predictive models could optimize leaf nutrient combinations under assigned specific weather and soil conditions.

2. Materials and Methods

2.1 Experimental setup

Experimental sites were located in Normandin (48°50′N, 72°32′W), Saint-Eugène d'Argentenay (48o59′N, 72o17′W) and Labrecque (48°40′N, 71°32′W) in the Saguenay-Lac-Saint-Jean region, north-central Québec, Canada. The regional climate is at the edge between Dfb (warm summer continental or hemiboreal) and Dfc (subartic) [30]. Soils were sandy to sandy loam Spodosols developed on deltaic and eolian deposits [31]. There were 1504 observations collected from fertilizer trials conducted during the 2001 – 2011 period. The N, P, and K doses varied in the range of 0-90 kg N ha-1, 0-39 kg P ha-1, and 0-75 kg K ha-1. Because weeds strongly impact leaf nutrient concentrations and fruit yield of lowbush blueberry [32], all trials were realized in weed-controlled environments according to local recommendations [33].

2.2 Soil and tissue analyses

Diagnostic tissues were collected at tip-dieback stage during the vegetative year [13,26,27,29,34]. Tissues were sampled in 50 m2 plot by combining the leaves of 25 randomly collected stems. Leaf samples were dried at 55oC, ground to less than 1 mm using a Wiley mill, and digested in a solution of H2SO4 and H2O2 [35]. Digests were analyzed for total N, P, K, Ca, Mg, B, Cu, Zn, Mn, Fe, and Al. The N and P concentrations in leaf tissues were quantified by automated colorimetry [Lachat Instruments (2005), QuickChem Method 13-107-06-2-E and QuickChem Method 15-501-3], and ICP-OES for other elements. Soil samples (0-20 cm), collected at the same time as tissue samples, were air-

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dried, 2-mm sieved, extracted using the Melhlich3 method [36], and analyzed for P, K, Ca and Mg using ICP-OES. The pH was measured in water (1: 1, v: v).

2.3 Meteorological indices

Site weather data were downloaded from the closest (< 50 km) Environment Canada meteorological stations using the weathercan R package version 0.3.4 [37]. Monthly weather indices computed from downloaded data are presented in **Figure 1**.

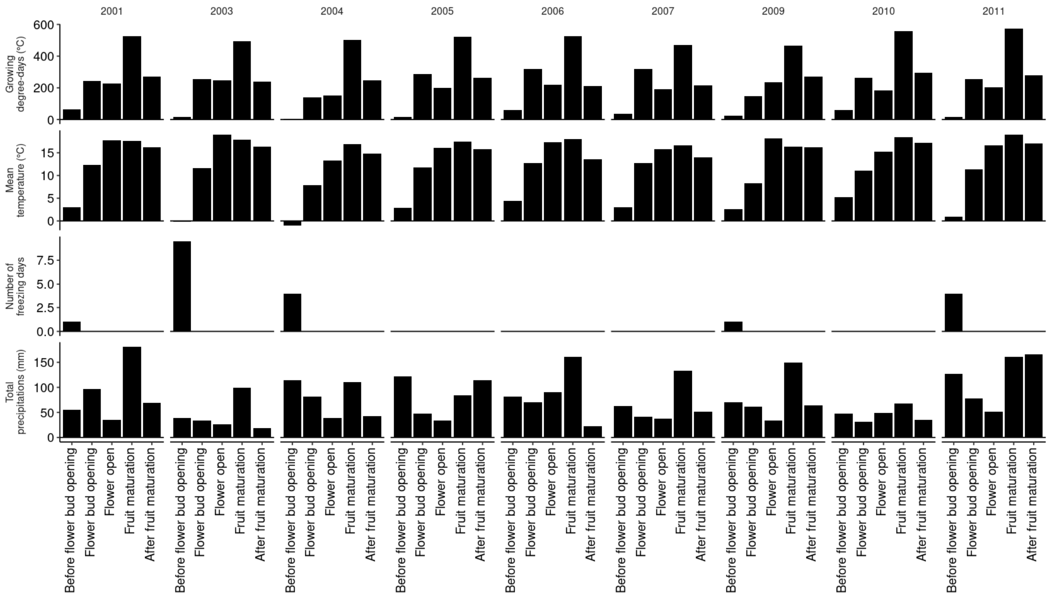

Figure 1. Mean weather indices computed across sites from 2001 to 2011, excepting 2002 and 2008 when no data have been collected.

2.4 Investigative models

We conducted exploratory analyses using two investigative models. The first investigative model considered seasonal mean temperature, total precipitations, and number of freezing days – days with minimum mean temperature < -5ºC [38] – between April and August inclusively in vegetative and fruit-bearing years. The second investigative model considered mean temperatures and total precipitations for phenological stages described by Fournier et al. [39] and presented in Table 1.

Table 1. Wild blueberry phenological stages [39]

Phenological stage	Julian day	Calendar dates
Before flower bud opening	[92 to 125]	April 1st to May 5th
Flower bud opening	[126 to 163]	May 5th to June 11th
Flower open (Pollination period)	[164 to 180]	June 12th to June 28th
Fruit maturation	[181 to 220]	June 29th to August 7th
After fruit maturation (Harvests)	[221 to 244]	August 7th to August 31st

When conducting predictive model, future weather is unknown. Thus, we fitted the predictive model to mean temperature and total precipitation data for phenological stages averaged over the six years (or three cycles) preceding the season of the observation. Commercial stands of lowbush blueberry included phenotypically and genotypically variable clones [40]. The phenology of *Vaccinium angustifolium* Ait. has been predicted from growing degree-days (GDD) using 0°C [4] or 4.4°C [5] as base air temperature from April 1st (day of the year 91). The GDD is commonly used in relation with pest management [7]. In this study, we tested mean temperatures and growing degree days (4.4°C). After running preliminary models, we concluded that, compared to phenological stages and GDD, seasonal mean temperatures offered more meaningful gradients across the whole season.

2.5 Statistical analysis

2.5.1 Isometric log-ratio

Raw concentration values were transformed into isometric log-ratios (*ilr*) to free compositional data from their total sum constraint (closure to measurement unit), and offer a sound framework to interpret tissue nutrient compositions [41]. Such framework is presented as a bifurcating tree or a mobile-and-fulcrum diagram based on nutrient interactions in living tissues [42] and soils [43]. Groups of variables were sequentially split until each group contain a single part (**Figure 2**). A filling value (Fv), computed by subtracting the sum of tissue elements from the total sum constrain (e.g. 100%), is included in balance diagrams to back-transform *ilr* balances to more familiar concentration domain. Concentration values are shown at the bottom and the balances at the fulcrums of the bifurcating trees.

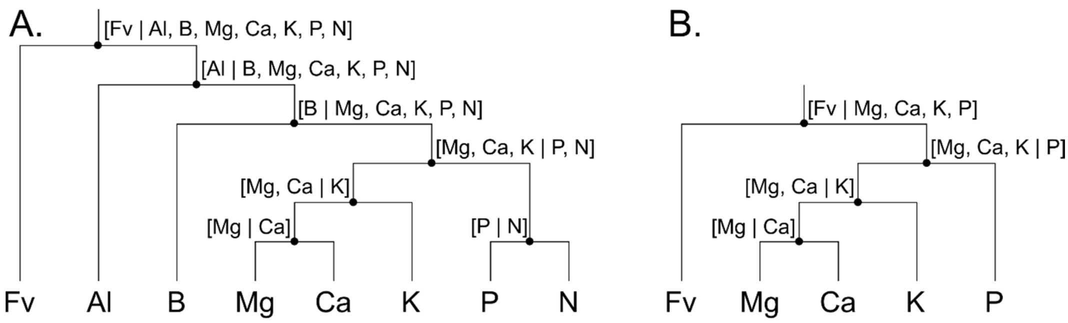

Figure 2. Balance diagram for used to transform (A) nutrients to nutrient balances and (B) soil nutrients to soil balances. Fv is the filling value.

There are D-1 balances in a D-part composition [44], each balance representing one degree of freedom [45]. Redundancy is accounted for by removing one degree of freedom attributable to interaction producing resonance by altering proportions of components within a closed system. At one extreme, if two nutrients are fully synergistic or antagonistic, they carry the same information and one of them is thus redundant. However, no such nutrients exist as fully replaceable. One degree of freedom is removed to handle myriads of interactions among components in the tissue dry mass to yield linear independence among orthogonally arranged subsets of interacting components. The isometric log-ratios or log-contrasts between two subsets of components are computed as follows (1):

$$ilr_j = \sqrt{\frac{r_j s_j}{r_j + s_j}} \, ln\left(\frac{g(c_j^+)}{g(c_j^-)}\right), \tag{1}$$

where, for the j^{th} balance in [1...D−1], D is the number of components, r_j and s_j are the number of parts on the left-hand- and right-hand side of the log contrast, respectively, c_j^- and c_j^+ are the compositional vectors at the left-hand- and right-hand-side, respectively, and g() is the geometric mean function. Computations were performed using the R 4.0.2 package [46]. Leaf and soil nutrient concentrations were transformed into orthonormal nutrient balances or isometric log ratios [47] using the compositions R package version 2.0-0 [48].

The Aitchison distance between a given nutrient composition and its target is a metric of interest to measure nutrient imbalance [41]. The Aitchison distance is a distance in the compositional space computed as the Euclidean distance between two equal-length compositional vectors transformed into *ilr* variables. The Aitchison distance depends on the number of components in the compositional vector and should be interpreted as a misbalance index compared to other distances computed from compositions with equal number of parts. Also, the ratio between each nutrient of an observation and its target indicates the direction of the misbalance.

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2.5.2 Analysis and modelling

Investigative and predictive models relate yield to uncontrollable and controllable yield-impacting features. Yield variation could be explained by large differences in fertilization regimes, meteorological indices, as well as soil and tissue tests. Investigative models were fitted by Bayesian linear regression with vague priors using the rstanarm R package version 2.21.1 [49]. No model hierarchy (or random effects) was included to avoid over-fitting. All explanatory variables were centered at 0 mean and scaled to unit variance, allowing comparing slope coefficients on a common scale.

For the predictive model, the data set was split into 70% training and 30% testing subsets. All variables (outcomes and predictors) were centered to zero mean and scaled to unit variance based on the training set. To predict yield, a Gaussian process model was fitted to data using the kernlab package version 0.9-29 [50] with the caret modelling interface version 6.0-86 for R [51] with optimized hyper-parameters.

The model fitted to training data was used to predict yield from features, some selected as varying and some selected as fixed, a process known as conditioning. We fixed historical weather conditions while sequentially extracted the combination of randomly generated leaf nutrients, soil chemistry features and N-P-K dosages returning the highest yield in the neighborhood of the optimal vector obtained from the previous sequence. This process is a Markov-chain random walk:

1. use the model to predict yield from initial conditions,
2. generate *n* random samples within a fixed *radius* around the point,
3. to avoid extrapolations, compute the Mahalanobis distance between each random sample and the center and covariance of the training data set, then filter out random samples where the Mahalanobis distance is higher than a critical distance,
4. use the model to predict yields from the remaining samples,
5. extract the sample returning the highest yield,
6. if yield is increased compared to the previous value, retain the vector for the next round and shorten the *radius* by a *factor* - else, keep the previous vector for the next round, then increase the *radius* by a *factor*.

To show how this algorithm scans the multivariate space in search for higher yields, we used the R volcano data set [52] to generate a simplistic 2D space were the highest topography, modelled by a Gaussian process on a random sample of the data set, is approached from a starting point (white circle), as shown in **Figure 3**.

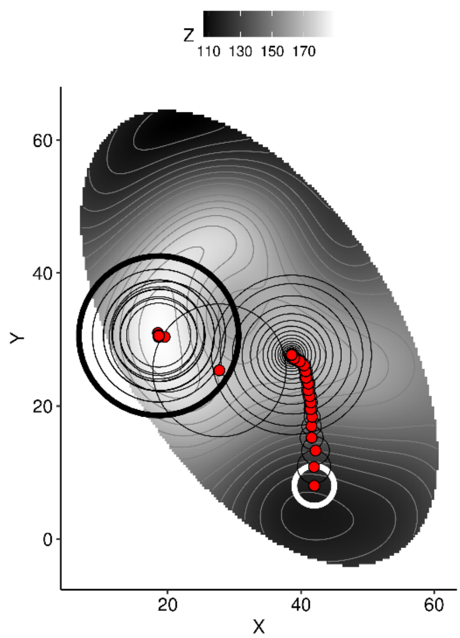

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Figure 3. Two-dimensional representation of the algorithm scanning XY coordinates to draw the path to higher Z topography as a metaphor for scanning tissue nutrient balances that augment yields. The red dot started at (42, 8) with a radius of 3 (thick white circle), moved with a decreasing radius to reach a local optimum where radius was increased until finding another point from which it continued scanning until the maximum of iterations was reached (thick black circle).

The optimization of leaf nutrient status was performed for each observation in our database. We also randomly selected a sample from our database and looked for optimal leaf nutrient status, soil chemistry and fertilizer dosage under given weather conditions. Codes and data are available at git.io/JvQOa.

3. Results

3.1 Variability of tissue and yield data at regional state

Berry yields from experimental plots ranging between 0.6 and 13.8 Mg ha^{-1} in our data set was wider than the ranges of lowbush blueberry yields published in other studies in Maine, Québec, the Canadian Atlantic provinces, and Estonia (**Figure 4**).

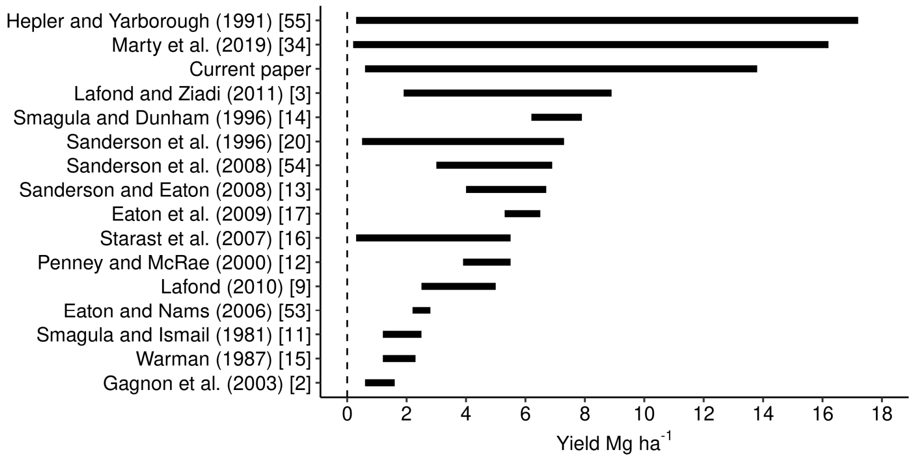

Figure 4. Yield ranges of lowbush blueberry reported in the literature compared to yield range in the present study [2,3,9,11–17,20,32,53–55].

3.2 Investigative models at regional scale

3.2.1 Effects over 2-years cropping cycles

The first Bayesian linear regression investigated the effects of leaf nutrients, soil nutrients, soil pH, NPK dosage and seasonal weather indices over 2-years on yields of lowbush blueberry. Posterior distributions of effects are shown in **Figure 5**. While interactions between variables were likely to occur, they were not addressed in the present study to avoid over-fitting.

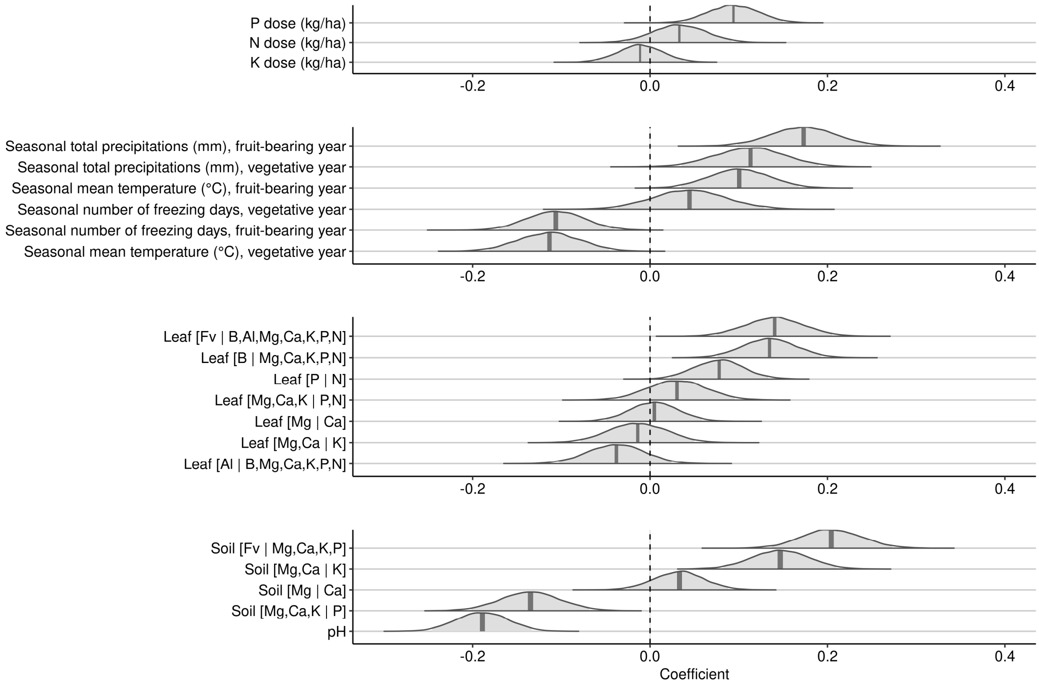

Figure 5. Posterior distributions of coefficients of scaled variables against berry yield for the 2-year cycle model.

The N and P fertilization averaged small positive effects, while K fertilization averaged marginal negative effects on berry yield. Seasonal total precipitations during both *fruit-bearing* and *vegetative* years increased berry yield. Seasonal mean temperatures showed positive effect during the *fruit-bearing* year, but negative effect during the *vegetative* year. The number of freezing days during the *fruit-bearing* year decreased markedly yield but showed a small and uncertain effect on yield during the *vegetative* year.

The most impacting leaf nutrient balances were (1) the [B | Mg, Ca, K, P, N] balance, where higher concentrations of boron compared to macronutrients slightly decreased yield and (2) the [Fv | B, Mg, Ca, K, P, N] balance, where nutrient accumulation in tissues increased berry yield. Soil [Fv | Mg, Ca, K, P] and [Mg, Ca, K | P] were the most yield-impacting soil nutrient balances. The positive slope on the soil [Fv | Mg, Ca, K, P] balance indicated that greater yields were associated with higher nutrient levels in the soil. The negative slope of the soil [Mg, Ca, K | P] balance indicated that lower yields were associated with higher P concentrations relatively to cations K, Ca and Mg in the soil. Low yields were associated with high soil pH.

3.2.2 Effects during the *fruit-bearing* year

A second investigative model substituted seasonal weather indices by weather indices at phenological stages for the year of experimentation (**Figure 6**).

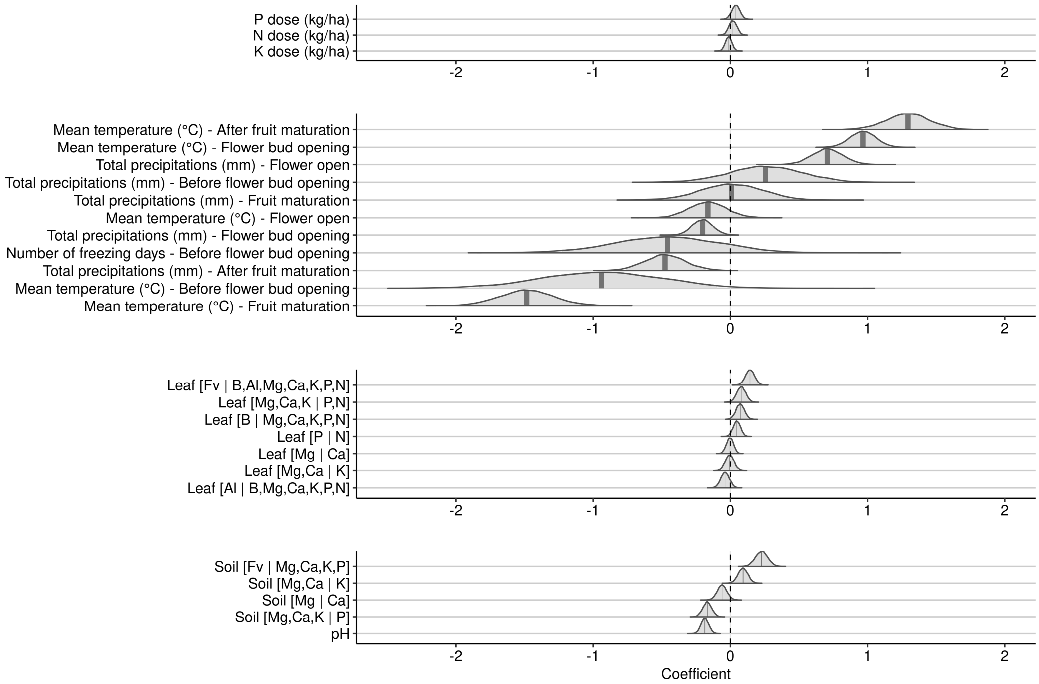

Figure 6. Posterior distributions of coefficients of scaled variables against berry yield for the fruit-bearing year model.

As it is the case of the 2-years cropping model, the effects of N-P-K fertilization in the fruit-bearing model were small compared to weather variables.

Mean temperature effects varied with developmental stage. Indeed, higher mean temperatures increased yields during the *after fruit maturation* and the *flower bud opening* stages, but decreased yields through the *before bud opening* and the *fruit maturation* stages, with uncertain effects during the *flower open* stage. Precipitation effects also varied with the developmental stage. Higher precipitations increased yields during the *flower open* stage, but decreased yields during the *flower bud opening* and the *after fruit maturation* stages, with small and variable effects during the *flower bud opening* and *fruit maturation* stages. The number of freezing days, recorded only for the earliest development stage, showed a negative but uncertain effect on yield.

The [Fv | B,Al,Mg,Ca,K,P,N] leaf nutrient balance showed the most important positive effect among leaf nutrient balances, indicating that greater proportions of nutrients increased yield. The effect of the [B | Mg,Ca,K,N,P] balance was also positive, indicating that yield decreased with higher proportions of B. The [Mg,Ca,K | N,P] balance also showed a positive effect, indicating that higher N and P compared to K, Ca and Mg increased yield. While the Redfield ratio [P | N] showed positive effect, the effects of [Mg,Ca | K], [Mg | Ca] and [Al | B,Mg,Ca,K,N,P] were small and uncertain.

The effects of soil nutrient balances were also smaller than meteorological features. The most positive balances were soil nutrient supply capacity expressed as the [Fv | Mg,Ca,K,P], and higher K level in the cationic balance expressed as [Mg, Ca | K]. The most negative soil balance was [Mg,Ca,K | P], indicating excessive P level in the soil or insufficient concentrations of K, Ca and Mg cations. Low yields were also associated with high soil pH.

3.3 Predictive model at local scale

While freezing days appeared important in both investigative models, they were not informative in the predictive model. Indeed, data exploration in Supplementary material 1 shows that the number of freezing days was inconsistent from year to year, making the 6-year average unreliable for yield prediction. The number of freezing days in April and May were thus removed from the predictive model.

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The Gaussian process regression model returned root-mean-square-errors (RMSEs) of 1047 kg ha^{-1} in training and 1447 kg ha^{-1} in testing (**Figure 7**). Lower yields were predicted accurately while higher yields showed systematic deviation from the straight line. Although we used a regression, a classification aiming at reaching a minimum yield could be useful to secure profitability. When the regression model is used as a classifier with yield cut-off of 5000 kg ha^{-1}, model accuracy reached 83% on the testing set. The detection of low yielders was 91% accurate (positive predictive rate) and the detection of high yielders was 53% accurate (negative predictive rate).

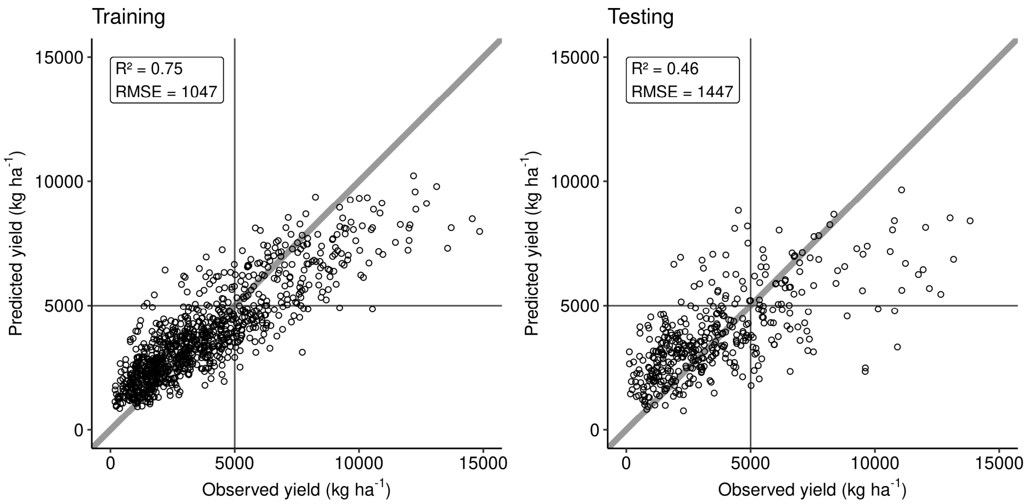
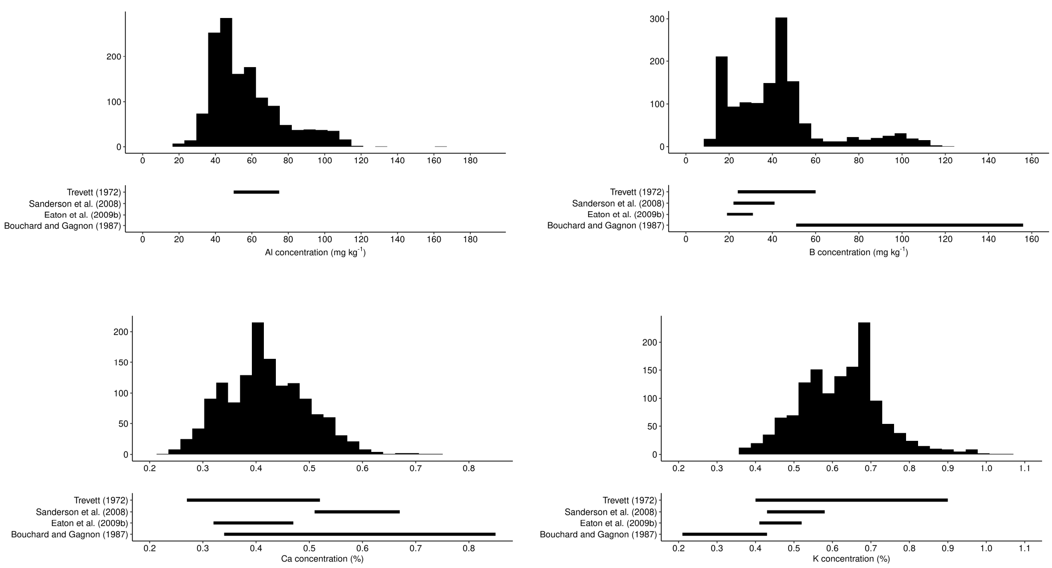


Figure 7. Performance of the predictive Gaussian process model shown as prediction against observed in training and testing data sets.

3.4 Portrait of optimal leaf nutrients at regional scale

Because nutrient balances are feature-specific, we fixed no *a priori* optima for soil and tissue nutrient levels and looked for feature-specific optima. The Markov-chain algorithm applied to all weather conditions in the data set provided an overall portrait of predicted optimal leaf nutrient concentrations that differed from concentration ranges suggested in the Canadian literature [13,17,27,28] (**Figure 8**). Note that the K range reported by Bouchard and Gagnon [28] for the same region was much lower than the distribution modelled from our data set.



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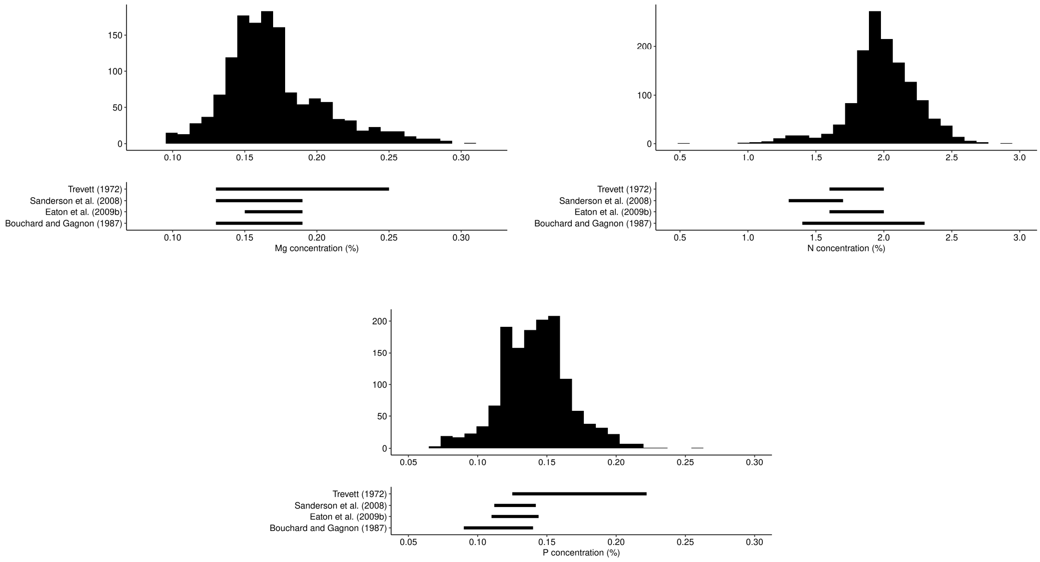

Figure 8. Distributions of optimal concentrations in the tissue ionome of blueberry compared to ranges reported in the Canadian literature [13,17,27,28].

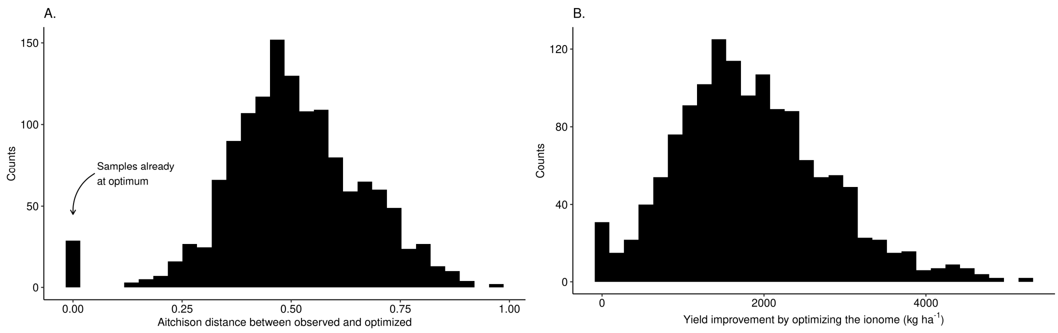

Figure 9. Distributions of optimal Aitchison distances and computed yield improvements by optimizing the leaf nutrients.

Distributions of Aitchison distances and expected yield improvements by optimizing leaf nutrient levels are shown in **Figure 9**. The median Aitchison distance between *ilr* variables of diagnosed tissue nutrient composition to reach optimal nutrient status was 0.50. Yield difference (potential yield minus initial yield) obtained where leaf nutrient compositions were perturbed from the initial composition to their optimal status varied widely with median value of 1773 kg ha^{-1}, 1.5 times the yield of the diagnosed specimen for the specified combination of features. Expected yields reported in the data set for the specified feature combinations were locally realistic compared to arbitrarily expected yield at regional scale.

The path to controllable features returning the highest yield given a fixed set of local features was initiated by randomly sampling a low yielder (yield < 3000 kg ha^{-1}, sample no 1269), fixing weather features, then sequentially altering leaf nutrients, soil nutrients, pH and N-P-K dosage using the Markov chain algorithm. At each iteration of the Markov chain, we back transformed leaf and soil nutrients from *ilr* variables to raw concentration values. We followed an optimal multivariate path towards optimum yield considering the fixed historical weather conditions (**Figure 10**).

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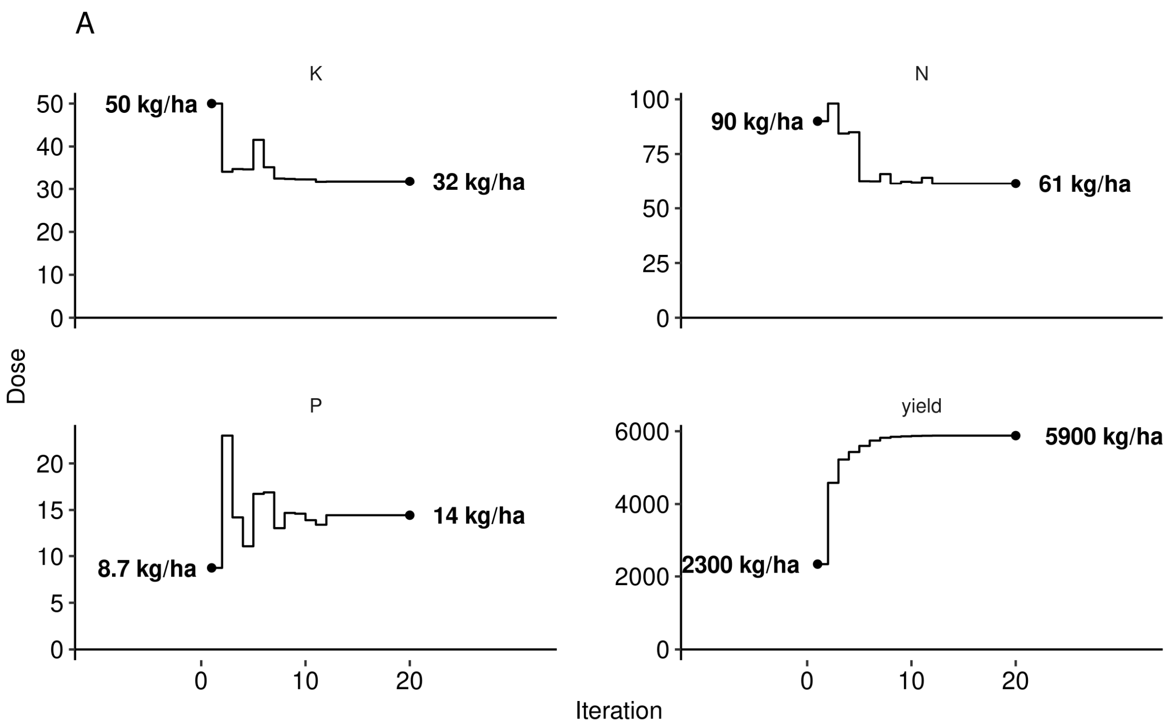

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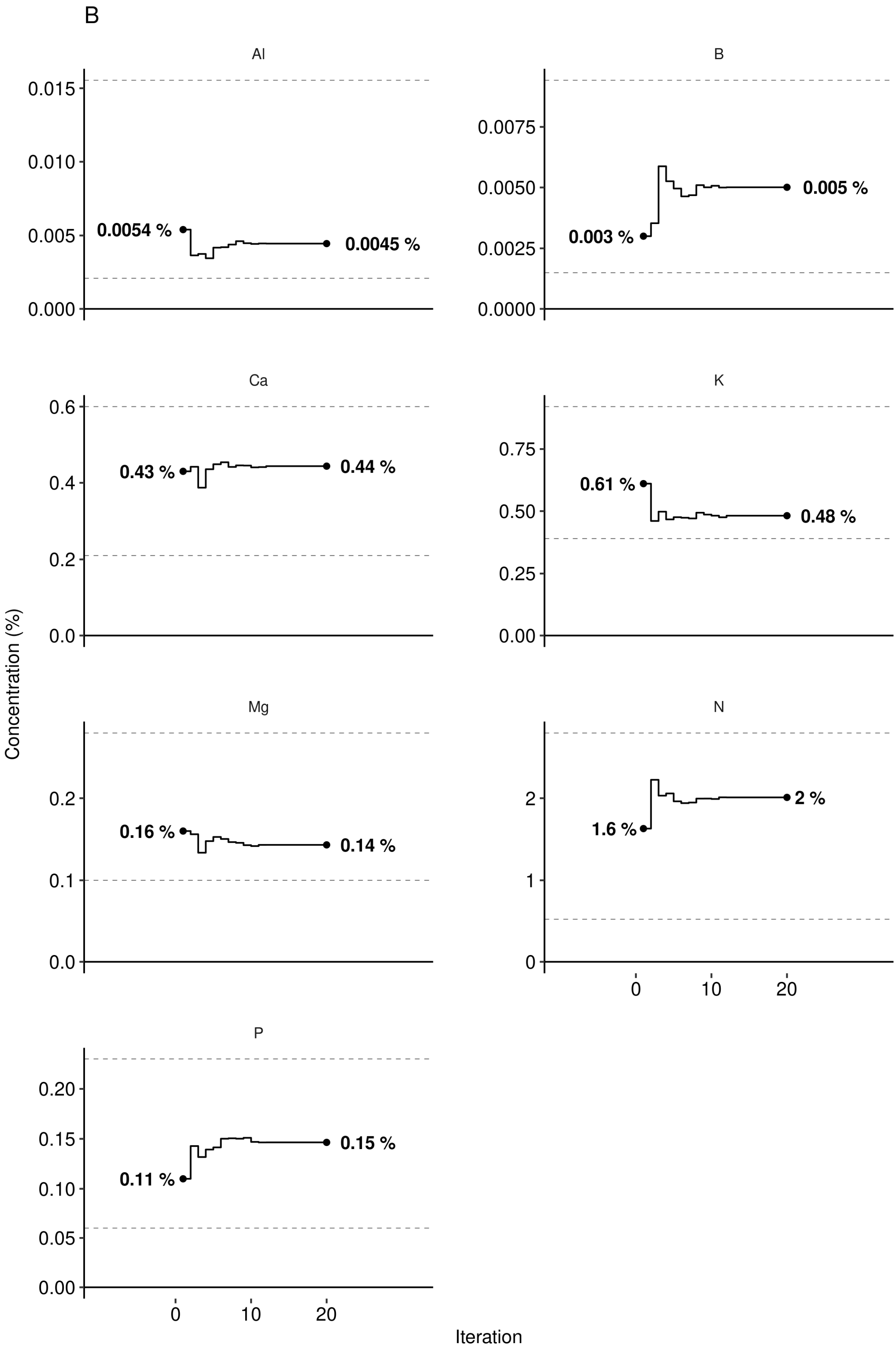

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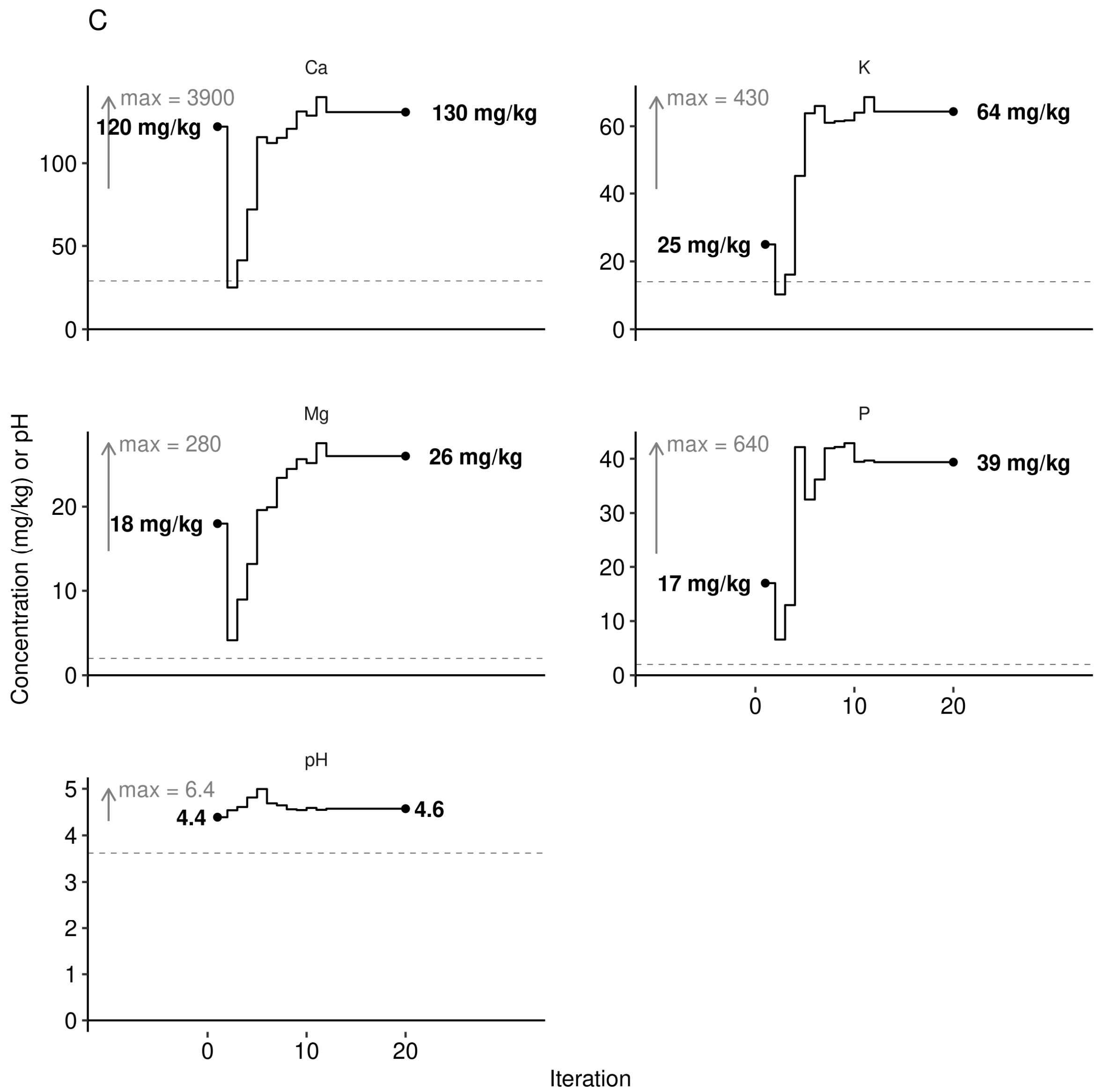

Figure 10. Markov chain searching for (A) N-P-K dosage (B) tissue concentration ranges and (C) soil chemistry matching the highest yield (shown in A) under given historical weather conditions of the randomly selected sample no 1269. Constrained paths represent minimum and maximum values in the training data set and avoid modelling extrapolations.

The Aitchison distance between the observed composition and the targeted composition obtained at the end of the Markov chain was 0.68 for leaf nutrients and 0.87 for soil nutrients. We also measured the size of the perturbation of nutrient composition between the observed leaf and soil nutrient compositions and the reference composition provided by the Markov chain algorithm as ratios their respective concentrations. The observed/target concentration ratios in

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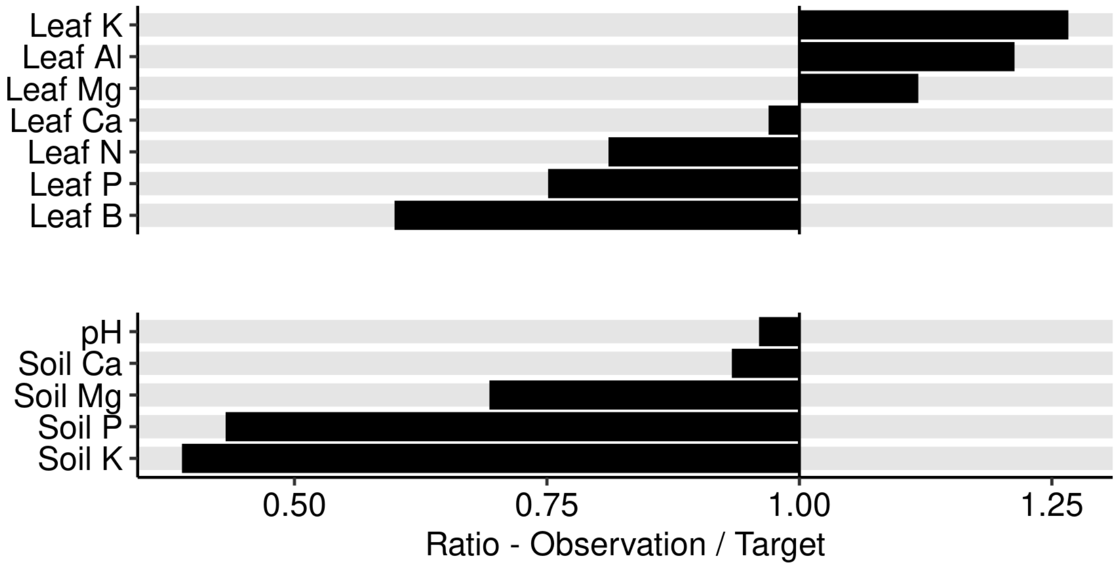

Figure 11 showed that leaf K, Al and Mg concentrations appeared in relative excess in the diagnosed specimen compared to the successful Markov specimen, while B, P and N appeared in relative shortage. Soils nutrients K, P and Mg were in relative shortage while soil Ca and soil pH were near optimum.

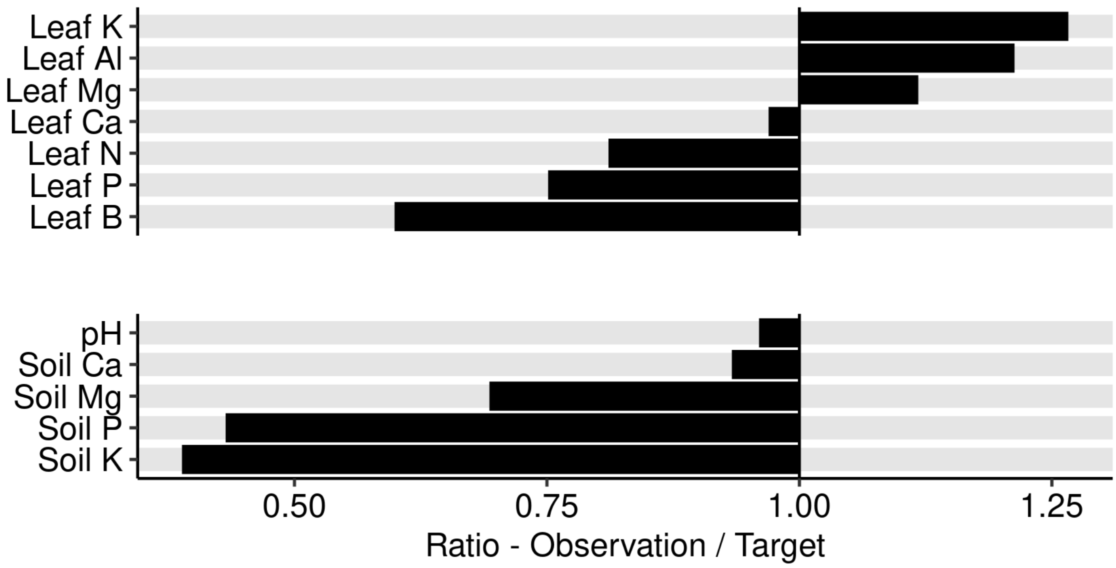

Figure 11. Ratio between leaf nutrients in sample no 963 and the optimal composition found at the end of the Markov chain algorithm.

4. Discussion

4.1 Model features

Agroecosystems viewed as Humboldtian agricultural production units [56] requires assembling local agroecosystem features to make predictions on system's performance. Indeed, the concept of optimum fertilization may fail at local scale where genetic and environmental conditions may vary widely [57]. We used leaf nutrients, soil nutrients, pH, and weather data as features to predict yields of lowbush blueberry across *Vaccinium angustifolium* and *V. myrtilloides* stand mixtures, using a Gaussian process machine learning model. By conditioning the model on the selected uncontrollable features such as weather historical data, and allowing other features related to plant nutrition management to vary, we could assess corrective measures at local scale. Where the model was

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conditioned on weather features, the localized model predicted that optimized nutrition and soil chemistry at local scale could increase berry yields substantially (Figure 9B).

4.2 Weather indices

In the 2-year cycles and fruit-bearing year models (results presented in Figure 5 and Figure 6), weather features dominated largely yield potential of lowbush blueberry in Quebec.

Developmental stages were sensitive to precipitations. The plant-pollinator networks are also affected by rainfall patterns (59). Heavy precipitations can impact decrease pollination activities and increase the incidence of plant fungal diseases [58]. Heavy precipitations also affect pollinators success through nectar dilution, pollen degradation, volatile removal, etc. At the other extreme, where precipitations are too low, irrigation is required to avoid shifting from reproductive to vegetative growth [59]. Lowbush blueberry stands were not irrigated in experimental areas as in most commercial fields in Quebec.

While favorable weather conditions for pollination activities during the month following pollination (July) are critical to reach maximum yield of lowbush blueberry, yield predictions were inconsistent based on meteorological features alone [58]. Adding soil and tissue nutrient features and phenological stages, the classification models reached an accuracy of 82% about yield cutoff of 5000 Mg ha^{-1}, similar to model accuracy for several fruit crops [60].

4.3 Fertilization

As wild species, lowbush blueberry responds slowly to nutrient supply [29] and may constrain its growth rate to available resources [61]. Moreover, nutrient accumulations in reserve tissues can be remobilized during the following years, as for fruit trees [62] and vines [63]. While fertilization features appeared to impact yield less than meteorological features. Lowbush blueberry may respond positively to added N and P over 2-years cropping cycles [14,64–66].

While regional N recommendation is 45 kg N ha^{-1} [32], nitrogen dosage appeared to be highly site-specific. Predicted fertilizer dosage in the low-fertility soil of our case-study (Figure 10A, 61 N ha^{-1}, 14 kg P ha^{-1} and 32 kg K ha^{-1}) departed from current ranges of 25-60 kg N ha^{-1}, 7 to 9 kg P ha^{-1} and 16-20 kg K ha^{-1} [67]. In comparison, a fertilizer trial in Nova Scotia, Canada, indicated optimum levels of 35 kg N ha^{-1}, 40 kg P ha^{-1}, and 30 kg K ha^{-1} [66].

In our case study, N requirement up to 61 kg N ha^{-1} could be split between the spring of the vegetative year and the spring of the fruit-bearing year [67]. The response to added N may be strong as modulated by competition with weeds [32]. Nevertheless, it should be emphasized that N fertilization may decrease berry quality, as shown by linear decrease of total polyphenols upon N additions of 0, 30 and 60 kg ha^{-1} to highbush blueberry [68].

In contrast with N, the response to P fertilization was found to be generally small [69]. The fact that the soil [Mg,Ca,K | P] balance impacted negatively on berry yield indicated that feature-specific corrective measures should be adopted to re-established soil P balance and avoid excessive soil P accumulation. The P fixation by oxy-hydroxides of Fe and Al at low pH values reduces P fertilizer-use efficiency in the acidic P-fixing podzolic soils used for lowbush blueberry production [70]. However, making P fertilizer applications based on solely soil P fixing capacity can result in wrong decisions [71]. Soil pH values exceeding 5.2 can decrease the yield of lowbush blueberry [51].

Leaf B concentration may increase by 4-5 folds with B application over control [72]. Such boost may affect the leaf [B | Mg,Ca,K,P,N] nutrient balance. Boron applications have been recommended to avoid boron shortage in lowbush blueberry stands [73]. Since 2000 in Quebec, shoot tip abortion is prevented by applying 0.7 kg of B ha-1 at each crop cycle [67]. In our study, the [B | Mg,Ca,K,P, N] tissue balance increased yields (Figure 5 and Figure 6). Boron being on the denominator of the balance, a positive slope coefficient indicates that boron over-fertilization possibly leaded to boron toxicity. As a result, boron should be managed to reach optimal growth conditions based on leaf analysis and proper nutrient balances to avoid excessive B applications.

The Al concentration in plant tissues may be problematic in acid soils due to high Al toxicity [74]. The leaf Al concentrations depend largely on soil pH. The effect of soil pH on blueberry yield ans Al levels is complex because (1) lower pH is associated with higher berry yields and (2) Al tends to be mobilized in soils at pH lower than 5.5 [74,75] and even more at pH values less than 5.0 [76]. Foliar tissues of lowbush blueberry normally contains 50-110 [27], up to 400 [77] mg Al kg^{-1} compared to 400-760 mg Al kg^{-1} in rhizomes [77]. In our study, the Markov chain random walk indicated optimum foliar Al concentration of 45 mg Al kg^{-1} (Figure 10B) in a locally diagnosed specimen – which is close to the median of its distribution in our data set (51 mg Al kg^{-1}, **Figure 8**) – with an optimal pH of 4.6.

4.4 Agronomic features optimisation

Open ecosystems have numerous sources of unexplained variations. While the R^2 of the regression on the testing set can be seen as rather low at 0.46 (root-mean-square-error of 1447 kg ha^{-1}), its exploratory use for classification reached 82% accuracy, a fair value compared to other crops [42,78–81]. However, using regression instead of classification models can avoid selecting arbitrary yield thresholds to delineate low-yielding and high-yielding specimens and allows comparing current yields to modelled yields under optimized nutrient management. In this paper, we challenged regional tissue nutrient ranges for the following reasons.

1. Regional guidelines deny the importance of local conditions on plant epigenetics.
2. A collection of reference ranges relies on the assumption that the healthy spaces of nutrient dosage and leaf and soil compositions have the shape of hypercubes. As illustrated by Parent [41], the shape of such space is more likely to be irregular [41].
3. Arbitrary delimiters defining a healthy region should be avoided.
4. According to Parent [41], interpreting a perturbation between a nutritionally misbalanced specimen and its optimum target "*should be done with a multivariate and compositional data perspective in mind. This implies that (1) a univariate or an incomplete multivariate perspective (e.g. focusing on extreme excesses and deficiencies) could miss a high yield region (a parachutist adjusting her fall following only one axis will likely miss the enchanting island and fall into the sea) and (2) changes of concentrations in a closed system are relative, i.e. increasing the concentration of a component will inevitably decrease the concentration of at least another one*".

Instead of presenting leaf nutrient, soil chemistry and dosage ranges at high-yield level, as is the case for common agronomic interpretation methods developed so far, we followed a Markov chain towards optimal values conditioned to local weather. Those results emphasize the need to monitor nutrient management locally, regularly updating the data set with both experimental and observational data.

5. Conclusions

Our investigative models related berry yields to soil and tissue tests, weather indices and, to a smaller extent, to N-P-K fertilization. Relative P excess in the soil, too high soil pH, and relative B excess in the tissue mass impacted negatively on berry yield.

We used a Gaussian processes model to predict yield from leaf nutrient composition, soil tests, fertilizer dosage, and weather conditions. We also elaborated an in-house Markov chain algorithm to draw a path from current observations to maximal yields along steadily improved leaf nutrient composition, soil chemistry and fertilizer dosage for given historical weather indices. Such modelling approach is the first one ever to simultaneously optimize soil and tissue diagnoses and recommend fertilizer dosage and provide realistic yield expectations at local scale. Obviously, present nutrient management approaches, based on general concepts of nutrient buildup and maintenance, cation saturation ratios, or nutrient sufficiency levels (82), should be revisited to better guide economically and environmentally wise fertilization decisions at local scale.

Unlike tissue concentration ranges and soil fertility classification based on descriptive statistics and dichotomous decisions, machine learning models can predict yield from specific combinations of features documented in large data sets. The lowbush blueberry data set could be augmented and updated regularly to tackle the source of yield variations and implement means to sustain production of lowbush blueberry by rebalancing nutrients at local scale. Because growers collect large amounts of local data such as soil and tissue tests and berry yield and quality data, and because more soil and climatic data become accessible, the lowbush blueberry data sets can grow rapidly. Moreover, big data sets can be processed by machine learning and Markov-chain optimization methods to develop solutions at local scale under various scenarios of climate change. Where sufficient data are available, critical concentration ranges should be abandoned for diagnostic purposes, and predictive feature-specific approaches be adopted.

Supplementary Materials: Codes and data are available at git.io/JvQOa.

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