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Analysis of Environmental Factors Affecting Fruit Quality for the 2007 Growing Season in a California Vineyard

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ANALYSIS OF
ENVIRONMENTAL FACTORS AFFECTING FRUIT QUALITY FOR THE 2007 GROWING SEASON IN A CALIFORNIA VINEYARD

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Sean Castorani

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ANALYSIS OF
ENVIRONMENTAL FACTORS AFFECTING FRUIT QUALITY FOR THE 2007 GROWING SEASON IN A CALIFORNIA VINEYARD

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ABSTRACT

Wine grape quality is heavily influenced by a combination of soil properties and site topography. We used anthocyanin content and yield data from *Vitis vinifera* L. cv. Cabernet Sauvignon from a vineyard near Madera, California collected during the 2007 growing season. We compared sets of hypotheses regarding the anthocyanin content of winegrapes and vineyard yields as a function of vineyard soil and topographic properties. Each hypothesis was expressed as a regression model predicting a response variable (yield or anthocyanin content) from one or more predictor variables. We used a multiple working hypotheses approach to compare these models using information theoretic criteria (AIC). There was substantial evidence that soil properties affected both anthocyanin content and yield. The top four anthocyanin models received 94% support while the top yield model received 68% support of all models considered. The null models received no support (AICw = 0.00). The predictive power of both the model-averaged anthocyanin content and yield was relatively small (R^2 = 0.04, R^2 = 0.07, respectively). It is likely that greater predictive power could be achieved through the use of more finely-detailed spatial maps and data from additional vineyards.

Key Words: Winegrape quality modeling, anthocyanin, yield, AIC, precision viticulture.

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Introduction

Success in the production of high-yield and high-quality grapes depends on the understanding of soil and site variability (White 2009). The complex relationship between this variability and fruit quality is not completely understood (Copiel et al. 2006, Keller 2010). Despite extensive research in this area it is unclear exactly what contribution climate, vineyard sites, and viticultural practices make on wine quality (Keller 2010). The majority of studies detailing environmental effects on grape quality have focused on a single variable or a small set of properties (Tesic et al. 2001, Xoné et al. 2001, Van Leeuwen et al. 2004, Copiel et al. 2006, Santesteban and Royo, 2006). To date there have been few detailed studies into the spatial variability of wine grapes within vineyards (Taylor et al. 2005). While single-variable studies on grape and wine quality are well-known, knowledge of the complexity of the vineyard system is not extensive because most factors are studied separately (Scienza and Bogoni 1996).

Spatial variability of biological, chemical, and physical soil properties as well as site topography affects fruit quality and fruit yield in vineyards (Zsófi et al 2007, Hall 2002, Bramely 2004 and 2005). Furthermore, single vineyard blocks are generally subject to uniform management approaches, which ignore this variability (Hall, Louis, and Lamb 2003). Ultimately, the ability to assess and augment the yield and ripening patterns within vineyard blocks will enable growers to implement differential or zonal management systems (precision viticulture).

More complete knowledge of the relationships between soil conditions and grape quality would allow for targeted cultural practices that would promote uniformity in grape yield and color (anthocyanin) development (Bramely 2001), a key indicator of red grape quality. Through these targeted cultural practices, growers would be able to farm more effectively (Bramley 2005, Taylor et al. 2005) by reducing variability and ultimately cost.

We postulated berry anthocyanin content and yield are influenced by one or more of a range of predictors (calcium, depth to root restriction, hardpan restriction, potassium, saturated hydraulic conductivity, nitrates, organic matter, observed moisture status, soil pH, root limiting field content, root limiting moisture, root limiting plant available water, root limiting permanent wilting point, root limiting saturation, soluble salts, slope, solar radiation, and soil texture), addressing the lack of multi-variable studies of grape quality and site variability. We examined these postulates using hypotheses represented by statistical models (linear regressions). Our objectives were twofold, first to determine if relationships exist between predictors and response variables within our dataset, and second to create models that can be used to predict relative anthocyanin content and yield patterns given differing soil and topographic conditions.

Materials and Methods

Study Area Description. The Merjan vineyard (Figure 1), located outside Madera, California was used for this study. The vineyard was planted to *Vitis vinifera* L. cv. Cabernet Sauvignon clone 8, without integration of a root stock (own-rooted). The area of the vineyard was approximately 162 acres and the calculated number of vines was 95,172. The vines were planted in a north-south orientation with spacing of 3.048 m x 2.26 m (10 ft x 7.5 ft). The Merjan Vineyard is a mechanically pruned vineyard and is cut to a 'tight box' of approximately 0.46 square meters (60 square inches) in size. Unlike hand pruned vines, mechanically pruned vines begin the growing season with an indeterminate number of buds which increases vine to vine variability and, as a whole, make the vineyard much more susceptible to spatial variation.

Sampling Techniques. Vines were sampled within the Merjan vineyard beginning in the northeast corner and working north to south. This resulted in a sampling grid of 20.6m x 27m (average distance between data rows and data vines). Sampling locations were measured using a Trimble GeoXT Geoexplorer 2005 series receiver. Ten grape clusters from each vine sampled were collected two weeks prior to the 2007 harvest. Cluster samples were taken in a deliberate and uniformed manner, with five clusters sampled from the upper 50% of the canopy, while five others were sampled from the bottom 50%. This sampling scheme ensured that an equal distribution of clusters was sampled at each vine location. Yield estimates were calculated by weighing each cluster on an electronic scale and obtaining an average cluster weight for each vine. Anthocyanin content was measured with a Zeiss Corona 45 VISNIR 1.7 spectrometer. Total anthocyanin measurements resulted in $N_a = 581$ samples. Total sample size for yield measurements resulted in $N_y = 631$ samples.

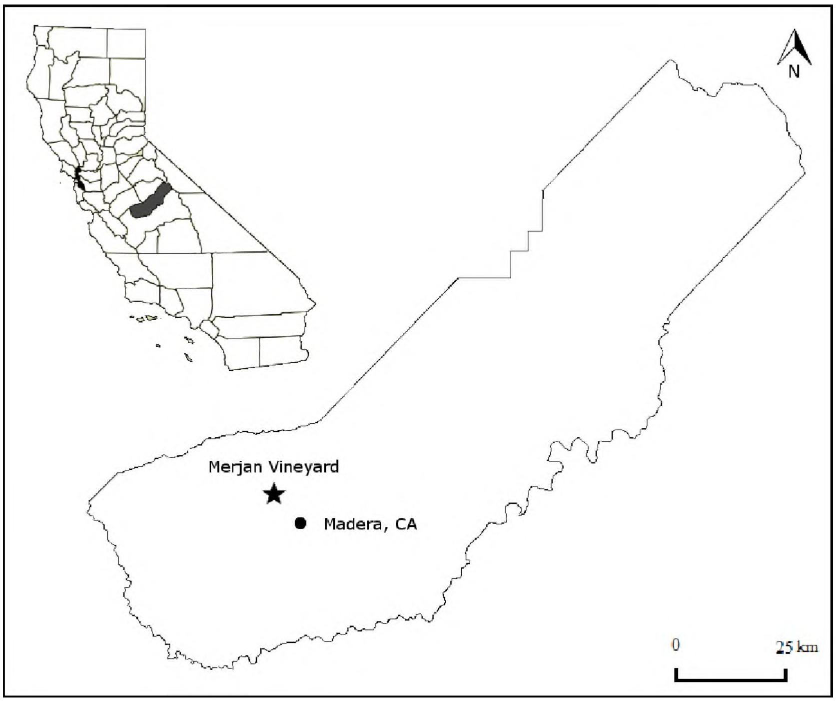

Figure 1. Merjan Vineyard, 12 km northwest of Madera, Madera County, CA

Ground penetrating radar, electromagnetic induction, electrical conductivity, and soil probing and boring equipment were used to determine the spatial variability of physical, chemical, and biological soil properties. These resulting measurements were spatially interpolated to obtain a raster model of continuous properties over the vineyard site (unpublished data, R. Wample, Fresno State University and D. Rooney, Soil and Topography Information LLC, Madison, WI), Hawth's Analysis Tools for ArcGIS (Beyer, 2004) in ESRI ArcGIS to extract interpolated topographic and soil data. This interpolated data was then paired with measured anthocyanin and yield data from each vine location for analysis.

Climate. The 2007 growing season was marked by a mild winter with below average rainfall and a warmer than average growing season (4448 GDD {CIMIS}). The average high temperature in July 2007 was 35.8 degrees Celsius, with the average daily low being 16.5 degrees Celsius. Rainfall for the 2007 water year (October 2006 through September 2007) was 15.2 cm. Historic average rainfall for the Madera area is 30.33 cm/year with the majority of rainfall occurring between October and April (NOAA, 2012). While this study only focused on one growing season, spatial variation of winegrape quality within vineyards are broadly consistent from year to year (Bramley 2005).

Model Comparison Approach.

We used an information theoretic approach to model selection because this approach has advantages over traditional hypothesis testing (Burnham and Anderson 2002, Mazerolle 2006). Sets of hypotheses about anthocyanin content and yield were compared. Each hypothesis was expressed as a regression model predicting a response variable (yield or anthocyanin content) from one or more predictor variables (Table 1).

The regression models were structured such that the response variable Y is a function of r explanatory variables X_j ($j = 1, 2\ldots, r$):

$$Y_i = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_r X_r + \rho W_y + \varepsilon_i, \quad i = 1,\ldots,n.$$

Each model was constructed *a-priori* (Table 2) and comparisons were made using Akaike's Information Criterion (AIC), with inferences about which predictors are important being derived from the results of these comparisons. The idea behind AIC is the best model represents natural variation in the data using the fewest number of independent variables. Represented mathematically:

$$\text{AIC} = -2 \log(\text{L}) + 2\text{K}$$

where L is the maximized likelihood function and K is the number of parameters in a given model. The model with the lowest AIC value provides the strongest prediction of patterns in a data set given the suite of predictor variables and the set of candidate models from which the best model was chosen. All analyses were conducted using R statistical software (R Development Core Team 2011). Variables were assumed to be independent of one another.

Selection of Candidate Models.

We identified eighteen environmental variables that the literature suggested would affect berry quality in terms of anthocyanin content and yield (Table 1). In addition to the global model (a model inclusive of all possible variables), we constructed forty-two candidate models to compare (twenty-one each for anthocyanin and yield), with the number of variables and parameters in each model ranging from two to ten.

Table 1. List of explanatory variables with units and model abbreviations.

Variable	Variable Name	Variable Type
Slope (%)	SLOPE	Continuous
Solar Radiation (kWH/m^2)	SOLAR	Continuous
Calcium (ppm)	CA	Continuous
Nitrate (ppm)	N	Continuous
Organic Matter (%)	OM	Continuous
pH (pH units)	PH	Continuous
Potassium (ppm)	K	Continuous
Soluble Salts (dS/m)	SALT	Continuous
Hardpan Restriction (dimensionless index)	HARD	Continuous
Depth to Root Restriction (cm)	DPRR	Continuous
Observed Moisture Status (dimensionless index)	OMS	Continuous
Saturated Hydraulic Conductivity (cm/hr)	KUSAT	Continuous
Texture: USDA Texture Class 4 – Clay Loam	TEX	Factor
USDA Texture Class 6 – Sandy Clay Loam		
USDA Texture Class7 – Loam		
USDA Texture Class 8 – Sandy Loam		
Root Limiting Field Capacity (cm)	RLFC	Continuous
Root Limiting Field Moisture (cm)	RLM	Continuous
Root Limiting Field Permanent Wilting Point (cm)	RLPWP	Continuous
Root Limiting Plant Available Water (cm)	RLPAW	Continuous
Root Limiting Saturation (cm)	RLSAT	Continuous

Models (Tables 2 and 3) were compiled based on several characteristics. Several of the models composed were based on published research, such as model A20 (Table 2, K+N) from Delgado et al. (1996) and models A21 (Table 3, DPRR+TEX) and Y21 (DPRR+TEX) from Morlat and Bodin (2006), which is also similar to Tesic et al. (2004) and Van Leeuwen et al. (2004). Some reflect combinations of prior published experiments such as model A15 (TEX+SOLAR+RLPAW), a combination of Tesic et al. (2004), Lamb et al. (2004), and Zsófi et al. (2007) and model Y16 (RLSAT+TEX+CA), a combination of Santesteban and Royo (2006), Van Leeuwen et al. (2004) and Yokotsuka et al. (1999). Other models were determined from an extensive literature review, personal communications, and inferential approaches.

We deliberately attempted to exclude variable interactions that may have been potentially correlated. Soil structure influences movement and storage of ground water as well as root development (Wilson 1999). Variables such as soil texture (TEX) and slope (SLOPE) influence variables related to water availability, such as root limiting field capacity (RLFC). Due to the complex nature of soil systems it was not possible to separate all possible interacting factors. A statistical analysis of potentially correlated predictors was completed using Pearson's correlation coefficient. The resulting correlation analysis showed little correlation among the variables with the exception of all root limiting factors (RLFC, RLMOIST, RLPAW, RLPWP) being positively correlated with themselves as well as depth to root restriction (DPRR), $\bar{r} = 0.958$. Their occurrence together in the models was minimal and no further action was taken.

The list of candidate models for anthocyanin content and yield modeling are presented in Tables 2 and 3, respectively. Prior to modeling, both predictor and response variables were standardized to be dimensionless variables with zero mean and unit standard deviation, in order to facilitate comparison of effects between predictors by virtue of their coefficients being dimensionless and on a unit scale.

Table 2. Selection of candidate a-priori models to predict grape anthocyanin content. n = number of predictor variables (k = n+1)

Name	n	Model
A0	0	β_0
A1	9	CA + DPRR + HARD + K + N + PH + RLMOIST + SOLAR + TEX
A2	8	K + N + RLFC + RLPAW + SALT + SOLAR + SLOPE + TEX
A3	7	HARD + K + N + PH + RLMOIST + SOLAR + TEX
A4	7	HARD + PH + RLSAT + SALT + SOLAR + SLOPE + TEX
A5	6	CA + HARD + OM + PH + SOLAR + TEX
A6	5	N + PH + RLPWP + SOLAR + TEX
A7	5	HARD + KUSAT + OM + RLPAW + SALT
A8	5	CA + OMS + RLFC + SLOPE + SOLAR
A9	4	K + HARD + RLFC + SOLAR
A10	4	OM + PH + RLSAT + SLOPE
A11	4	PH + RLFC + SLOPE + SOLAR
A12	4	KUSAT + OMS + RLPWP + TEX
A13	4	K + OM + RLPAW + SLOPE
A14	4	KUSAT + OM + RLMOIST + SALT
A15	3	RLPAW + SOLAR + TEX
A16	3	PH + SOLAR + TEX
A17	3	PH + RLSAT + TEX
A18	3	OM + RLPAW + SOLAR
A19	3	CA + K + N
A20	2	N + TEX
A21	2	DPRR + TEX
A99	18	CA+DPRR+HARD+K+KUSAT+N+OM+OMS+PH+RLFC+RLMOIST+RLPAW +RLPWP+RLSAT+ SALT+SLOPE+SOLAR +TEX

Table 3. Selection of candidate a-priori models to predict grapevine yield

Name	n	Model
Y0	0	β_0
Y1	10	CA + DPRR + HARD +K+N+OMS+ PH + RLMOIST+SOLAR+ TEX
Y2	9	DPRR + HARD + K + N + PH + RLFC + RLMOIST + SOLAR+TEX
Y3	7	K + N + RLFC + RLPAW + SALT + SOLAR + TEX
Y4	7	HARD + KUSAT + PH + RLSAT + SOLAR + SLOPE + TEX
Y5	6	CA + HARD + OM + PH + SOLAR + TEX
Y6	6	K + KUSAT + N + RLPAW + SOLAR + TEX
Y7	5	DPRR + PH + RLFC + SOLAR + TEX
Y8	5	CA + HARD + RLFC + SALT + SOLAR
Y9	5	CA + K + OM + RLFC + SLOPE
Y10	4	N + PH + RLSAT + SOLAR
Y11	4	CA + RLFC + SLOPE + SOLAR
Y12	4	KUSAT + OMS + RLPWP + TEX
Y13	4	KUSAT + RLMOIST + RLPWP + SALT
Y14	3	CA + RLPAW + SLOPE
Y15	3	CA + SALT + SOLAR
Y16	3	CA + RLSAT + TEX
Y17	3	CA + RLPAW + SOLAR
Y18	3	HARD + OM + RLPAW
Y19	3	CA + K + N
Y20	2	HARD + TEX
Y21	2	DPRR + TEX
Y99	18	CA+DPRR+HARD+K+KUSAT+N+OM+OMS+PH+RLFC+RLMOIST+RLPAW +RLPWP+RLSAT+ SALT+SLOPE+SOLAR +TEX

Resulting statistical inference was derived from Akiake weights (w_i) and evidence ratios (ER). Akiake weights are a normalization of the log likelihood of a given model compared to the entire set of models; $\sum w_i = 1$. A given w_i denotes the strength of support of model *i* given the set. Evidence ratios further aid in the model selection process. Evidence ratios are relative measures of strength of support for one model as compared with another (w_i / w_j).

Spatial autocorrelation, or the degree to which variables are correlated with themselves, was accounted for by the inclusion of the term ρW_y, to account for possible spatial dependence within the dataset. The error distribution ε_i was initially be specified to be normal with constant variance, and the errors were assumed to be independent (after accounting for spatial dependence). AIC was used to select the best approximating model.

Results

A sample size of N = 1212 independent anthocyanin and yield measurements were taken during the 2007 growing season and used for our analysis. The distribution of the data can be seen in Figure 2.

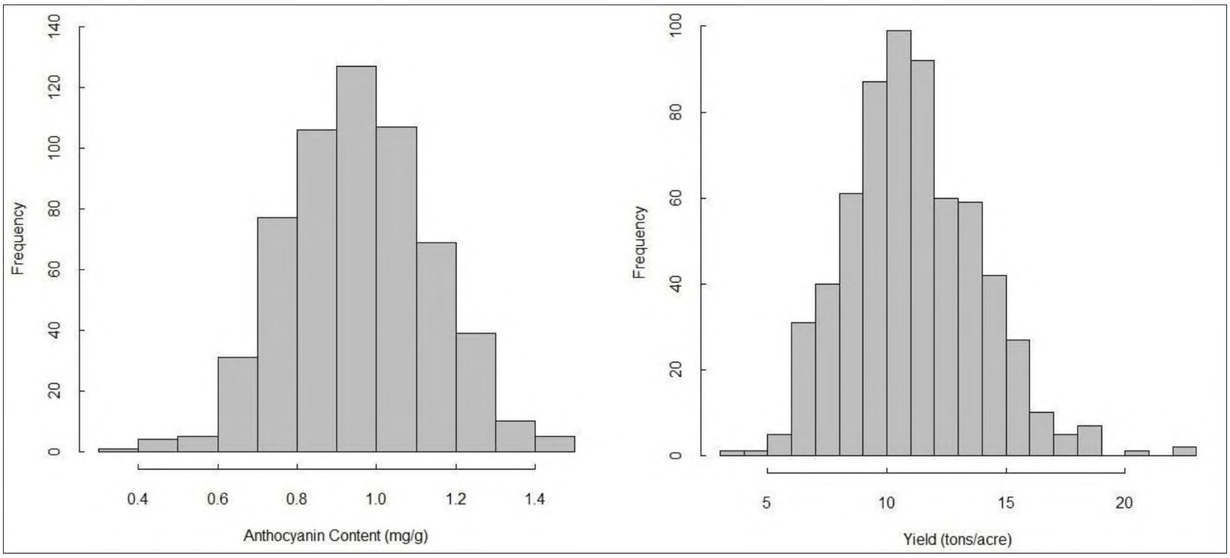

Figure 2. Histogram of Anthocyain Content and Yield

Both predictor and response variables were standardized prior to modeling. The analysis showed substantial evidence soil properties affected both anthocyanin content (Table 4) and yield (Table 5). Both the null models received no support (AICw = 0.00). For anthocyanin content modeling, four models (A1,A3, A4, A5) garnered 94% of support given the entire set (Table 4). These models all shared the predictors HARD, PH, SOLAR, and TEX. The best model, A4, received 35% support and also included the predictors RLSAT, SALT, and SLOPE. Model A4 was the only highly supported model which included these variables. The second and third best models, A1 (AICw=0.25) and A5 (AICw=0.22) represented a combined 47% support. These models also shared the predictor CA. Model A1 and A3 (AICw=0.12) were the most similar in structure and shared the predictors K, N, and RLMOIST, in addition to the four predictors shared by all top models. There was no support for the remaining models (AICw < 0.02). For estimation of the importance of each predictor (below), a model averaging approach was taken for anthocyanin content due to the lack of a dominant model from the results. This averaged model was named A_{avg}.

The yield model with overwhelming statistical support was Y5, which garnered 68% support (Table 5). Individual support for any individual remaining yield model was very small (AICw ≤ 0.07). The model with the greatest predictive power was Y5 which contained the predictors CA, HARD, OM, PH, SOLAR, and TEX. This model was identical to model A5, which received 22% support within anthocyanin content modeling. These results suggest that many of the factors which affect anthocyanin production may also contribute to grapevine yield as well.

Table 4. Model selection using Akiake information criterion (AIC) of 23 linear regression models used to predict vineyard anthocyanin content. ΔAIC = change in AIC score from top model; AICw = model weight. Winning models highlighted.

Model	n	AIC	ΔAIC	AICw
A0	0	1651.81	13.98	0.00
A1	9	1638.47	0.65	0.25
A2	8	1645.73	7.91	0.01
A3	7	1639.89	2.07	0.12
A4	7	1637.82	0.00	0.35
A5	6	1638.70	0.88	0.22
A6	5	1647.58	9.75	0.00
A7	5	1649.65	11.83	0.00
A8	5	1652.28	14.46	0.00
A9	4	1656.69	18.86	0.00
A10	4	1652.04	14.21	0.00
A11	4	1652.04	14.21	0.00
A12	4	1649.26	11.43	0.00
A13	4	1654.82	17.00	0.00
A14	4	1652.06	14.24	0.00
A15	3	1647.40	9.58	0.00
A16	3	1644.07	6.25	0.02
A17	3	1646.12	8.29	0.01
A18	3	1656.10	18.28	0.00
A19	3	1657.26	19.43	0.00
A20	2	1646.76	8.94	0.00
A21	2	1647.69	9.86	0.00
A99	18	1644.90	7.08	0.01

Table 5. Model selection using Akiake information criterion (AIC) of 23 linear regression models used to predict vineyard yield. Winning model highlighted

Model	n	AIC	ΔAIC	AICw
Y0	0	1793.70	29.72	0.00
Y1	10	1764.47	4.46	0.07
Y2	9	1779.15	18.98	0.00
Y3	7	1786.76	24.82	0.00
Y4	7	1780.94	20.96	0.00
Y5	6	1761.12	0.00	0.68
Y6	6	1782.82	22.21	0.00
Y7	5	1793.78	32.93	0.00
Y8	5	1768.87	4.89	0.06
Y9	5	1770.55	6.57	0.03
Y10	4	1792.09	28.12	0.00
Y11	4	1771.54	7.56	0.02
Y12	4	1791.86	31.83	0.00
Y13	4	1789.85	25.87	0.00
Y14	3	1769.02	5.04	0.05
Y15	3	1771.86	7.88	0.01
Y16	3	1766.63	6.21	0.03
Y17	3	1770.14	6.16	0.03
Y18	3	1781.56	17.58	0.00
Y19	3	1771.84	7.87	0.01
Y20	2	1789.22	28.57	0.00
Y21	2	1791.40	31.01	0.00
Y99	18	1773.65	13.60	0.00

Note: See table 4 for descriptions of abbreviations.

Within the model averaged anthocyanin response A_{avg}, the greatest effects were driven by sandy loam (TEX=8, $\beta_i = 0.76$), and loam (TEX=7, $\beta_i = 0.56$) soil texture (Table 6). Soil pH ($\beta_i = -0.12$) had the second greatest effect, followed by hardpan restriction ($\beta_i = 0.10$). Other physical soil properties such as depth to root restriction (β_i = -0.06), root limiting moisture (β_i = 0.07), and root limiting saturation (β_i = -0.03) had weaker effects. Similarly, some chemical soil predictors such as nitrogen (β_i = -0.06), potassium (β_i = 0.03), and salt (β_i = 0.03) had a modest impact while the effect of calcium (β_i = -0.01) and organic matter (β_i = 0.00) were negligible. Additionally, the topographic variables of solar radiation (β_i = -0.04) and slope (β_i = 0.00) contributed little to the model.

Similar to A_{avg}, the strongest effect on the winning yield model Y5 was soil texture, specifically sandy loam (β_i = -0.43) and loam (β_i = -040). The second strongest effect was calcium (β_i = -0.27). Soil pH was also important (β_i = 0.12) as was hardpan restriction (β_i = - 0.07). The predictors of relatively little significance were organic matter (β_i = 0.05) and solar radiation (β_i = 0.01). Comprehensive explanations of soil and topographic influences on the response variables for both anthocyanin content and yield can be found below in the discussion section.

Models Y5 and A_{avg} shared coefficients HARD, SOLAR, PH, TEX, CA, and OM. However, the effect of these variables on yield was opposite to their effect on anthocyanin i.e. the coefficients had opposite signs. The predictor with the greatest difference in influence between anthocyanin content and yield was calcium, which had a much larger effect on yield (β_i = -0.27) than anthocyanin content (β_i = 0.06).

An exploratory analysis was conducted to assess the importance of the predictors with very small contributions to the highest supported anthocyanin models. Two additional models, A22 (predictor: TEX) and A23 (predictors: HARD+PH+TEX) were compared with the winning anthocyanin model, A4. With the three models analyzed together (Table 6), we found relatively little support for model A22 (2.0%) while model A23 received a fair amount (18.0%). This indicates that the additional predictors from model A4

(RLSAT + SALT + SOLAR + SLOPE) are important in capturing variation in combination, even though their individual influence was rather weak.

Table 6. Exploratory model comparison including two additional anthocyanin models (A22 and A23). AIC weights in this table were computed relative to just the three models compared in the table.

Model	Predictor	n	AIC	ΔAIC	AICw
A4	HARD + PH + RLSAT + SALT + SOLAR + SLOPE + TEX	7	1637.82	0.00	0.81
A22	TEX	1	1645.77	7.95	0.02
A23	HARD + PH + TEX	3	1640.86	3.04	0.18

There was no significant predictive power for either best model. Spatial representations of the best models projected onto a vineyard layout are found in Figures 2 and 3. Normalized yields were measured between -3.98 and 4.09, model Y5 predictions ranged between -0.96 and 0.616. This loss of variation was also seen in anthocyanin content modeling, where the range of modeled anthocyanin content was recorded between -3.39 and 2.95 and our best model estimated between -0.52 and 0.53. The models appear to reproduce some aspects of the overall spatial pattern of variation within the vineyard, but there is substantial unexplained variation.

Table 7. Standardized coefficient values from best approximating anthocyanin and yield models. The coefficient values for A_{avg} are an AIC-weighted average of the four models representing 94% support of all anthocyanin models. Model Y5 represents 68% support of all yield models. Weighted averages of coefficients were calculated using Burnham and Anderson 2002. See Table 1 for explanations of covariates.

		Coefficient																
Model	AICw	β_o	CA	DPRR	HARD	K	N	OM	PH	RLMOIST	RLSAT	SALT	SLOPE	SOLAR	TEX=4	TEX=6	TEX=7	TEX=8
															Clay Loam	Sandy Clay Loam	Loam	Sandy Loam
A1	0.25	-0.63	0.10	-0.21	0.08	0.05	-0.14	0.00	-0.18	0.24	0.00	0.00	0.00	-0.04	0.00	0.09	0.60	0.86
A3	0.12	-0.56	0.00	0.00	0.08	0.15	-0.17	0.00	-0.15	0.03	0.00	0.00	0.00	-0.06	0.00	0.04	0.55	0.73
A4	0.35	-0.51	0.00	0.00	0.13	0.00	0.00	0.00	-0.07	0.00	-0.02	0.08	-0.07	-0.02	0.00	-0.01	0.50	0.68
A5	0.22	-0.6	0.12	0.00	0.08	0.00	0.00	0.00	-0.11	0.00	0.00	0.00	0.00	-0.04	0.00	0.02	0.60	0.79
A_{vvg}^{a}	0.94	-0.57	0.06	-0.06	0.10	0.03	-0.06	0.00	-0.12	0.07	-0.01	0.03	-0.03	-0.04	0.00	0.03	0.56	0.76
Y5	0.68	0.38	-0.27	0.0	-0.07	0.0	0.0	0.05	0.12	0.0	0.0	0.0	0.0	0.01	0.00	-0.15	-0.40	-0.43

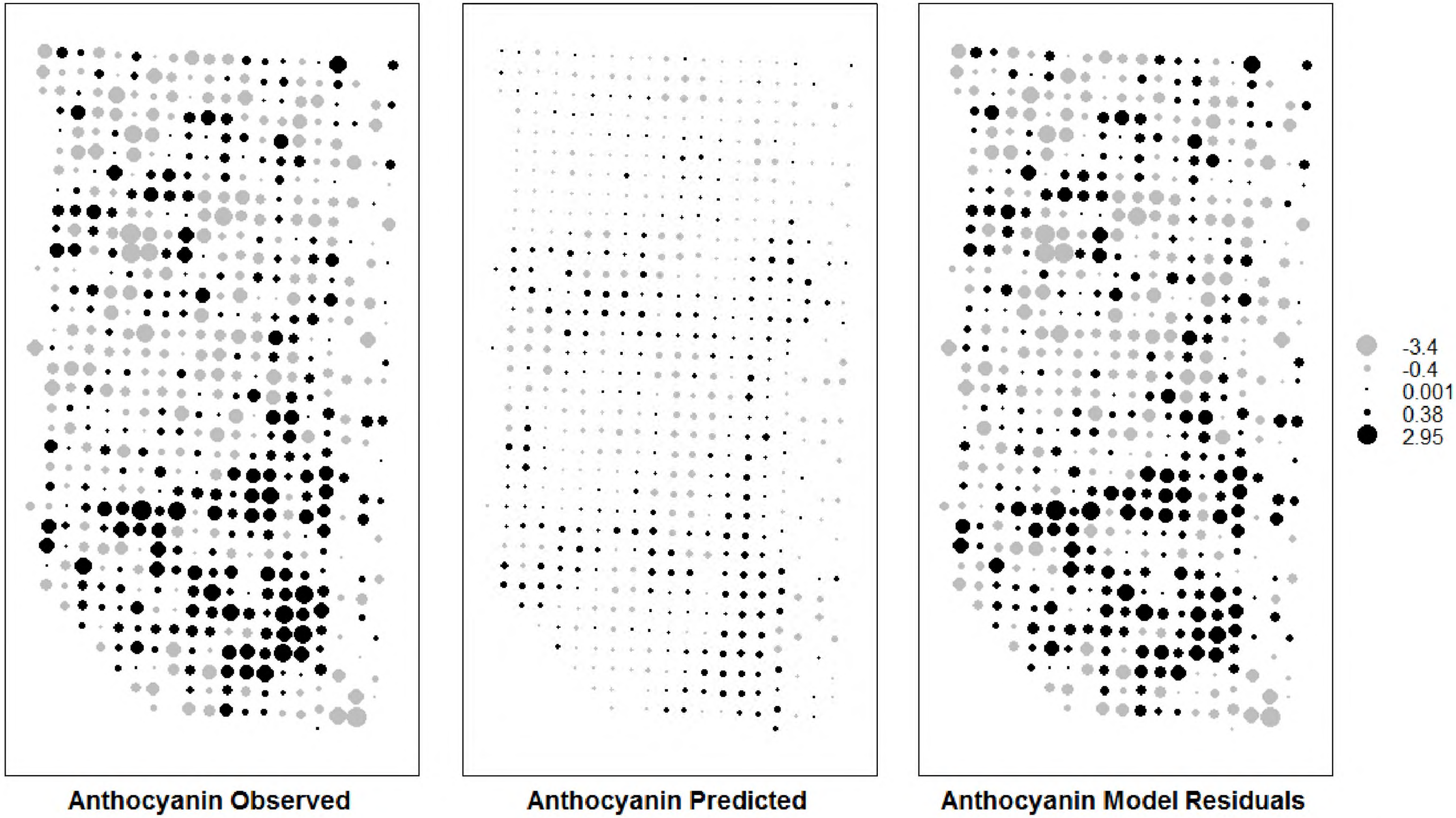

Figure 3. Spatial representation of standardized observed, Model A_{avg} predicted, and residual (i.e. unaccounted) variation in anthocyanin in the Merjan Vineyard.

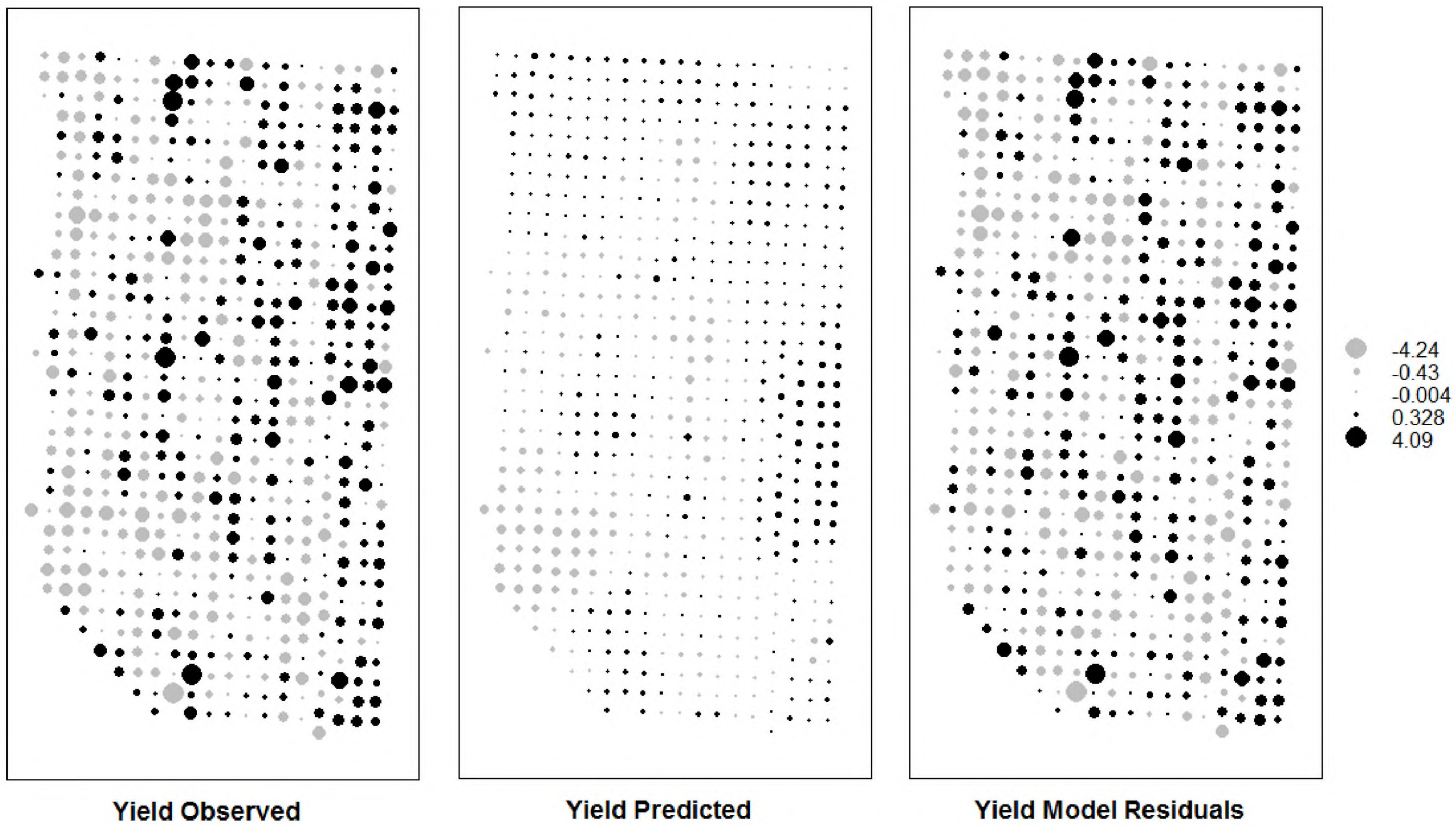

Figure4. Spatial representation of standardized observed, model Y5 predicted, and residual variation of vineyard yield.

Discussion

This research represents a novel approach to the synthesis of complex soils data and fruit quality within the vineyard system. While the non-null models out-performed the null, the predictive power of the winning models was low for both anthocyanin (R^2 = NS) and yield (R^2 = NS). Because predictor measurement was conducted independently and at a somewhat coarse scale relative to sampled grapevine data, these data were interpolated in order to provide coverage of the entire vineyard. Point data was then taken from the interpolated maps corresponding to the location of grapevine response data. This results in a loss of spatial detail and could explain the low predictive ability of the models. However, the strong support for non-null models demonstrates the importance of predictor variables on anthocyanin content and yield in the vineyard. The directionality of coefficients of the winning models was consistent with recently published literature, with the exception of soil pH.

The soil texture of the Merjan vineyard was overwhelmingly loam (USDA class 7) with a small amount sandy loam (USDA class 8) and a small amount trending towards clay loam (USDA class 4-6). Soil structure affects the movement and storage of water as well as root penetration. From our results, we found soil texture to be the greatest contributor to both the winning anthocyanin and yield models. The winning anthocyanin model, A_{avg}, suggests that loam (β_i=0.56) and sandy loam (β_i=0.76) positively affect anthocyanin content. Soils comprised of more loam and sandy loam contribute to better drainage and reduce the water availability to the root zone. Copiel and Van Leeuwen (2006) found reduced water availability leads to higher anthocyanin content. Furthermore, while the influence of root-limiting saturation (RLSAT) and depth to root restriction (DPRR) on anthocyanin content were minimal (β_i= - 0.03, β_i= 0.06, respectively) the directionality of the predictors is consistent with expectations based on the literature. The positive influence of root-limiting moisture (RLMOIST) on anthocyanin content (β_i= 0.07) is similarly weak and inconsistent with expected results.

The winning yield model Y5, predicted loamy (TEX=7) and sandy loamy (TEX=8) soils negatively impacted yield (β_i= - 0.40 and β_i= - 0.43 respectively). We attribute this to decreased water availability due to better soil drainage. Copiel and Van Leeuwen (2006) found shallow soils, resulted in early shoot growth, moderate yield as well as high anthocyanin content. This was due to low nitrogen status and water availability.

The second largest contributor to anthocyanin content, and to a lesser extent yield, was found to be soil pH (pH 5– pH 7). Our findings diverge from previously published literature. The results indicate a negative response of anthocyanin to increasing soil pH (β_i= - 0.12, R^2=NS). In contrast, Yokotsuka et al. (1999) found increasing the alkalinity of the soil significantly increased anthocyanin content of berry skins. Our results also identify an equally positive response of grape yield to increased soil pH (β_i= 0.12, R^2=NS). Wooldridge (2010) found soil pH to have an inverse relationship with grape yield, higher soil pH increased carbohydrate translocation to vegetative growth rather than the fruiting zones.

Hardpan restriction was a lessor contributor to both anthocyanin content and yield. Our results indicate that greater hardpan restriction positively affects anthocyanin production (β_i= 0.10) and negatively impacts yield (β_i= - 0.7). Hardpan restriction is a major factor in vine rooting depth as well as water holding capacity and acts in a similar fashion as soil texture by limiting water and nutrient availability (Tesic et al. 2001 and Copiel and Van Leeuwen 2006).

The weight of evidence suggests the remaining predictors had relatively minimal influence on grapevine anthocyanin content and yield. The winning models indicate that nitrogen had a small but inhibiting effect on anthocyanin formation (β_i= - 0.06) while potassium had a lesser but positive effect (β_i= 0.03). Hilbert (2003) and Keller (1999) found similar results in which high nitrogen inhibited and impaired the development and synthesis of anthocyanins in wine grapes. Excessive nitrogen delays sugar accumulation and causes vegetative growth which competes with pigment accumulation in grape skins while adequate potassium nutrition results in increased color and phenolic content of berries due to the stimulative effect on photosynthetic activity (Delgado 2004). For vineyard yield, organic matter had a small, but positive effect (β_i= 0.05), as expected.

Solar radiation had a very small negative effect on anthocyanin content (β_i= - 0.04), and a very slight, positive effect on grape yield (β_i= 0.01). Cortell (2007) and Mori (2007) also found high temperatures and increased solar radiation reduce berry anthocyanin content. Conversely, Spayd et al. (2002) while trying to separate temperature from solar radiation, found anthocyanin increased as a function of solar radiation, not temperature. For yield, our results remain consistent with the literature. Smart et al. (1990) found increased solar radiation on the canopy increases yield potential, although its effect within our model may be negligible.

Conclusion

We found both grapevine anthocyanin content and yield to be primarily influenced by soil texture, specifically loam (40% sand, 40% silt, 20% clay) and sandy loam (60% sand, 30% silt, 10% clay), relative to sandy clay loam (60% sand, 30% clay, 10% silt). We attributed this to the influence of soil texture on soil water holding capacity. For anthocyanin content, soil pH had the next greatest influence followed by hardpan restriction, and to a lesser and less-certain extent, root limiting moisture, depth to root restriction, nitrogen content, solar radiation, salt content, and finally, potassium. Vineyard yield was also found to be primarily influenced by soil texture and to a lesser extent by calcium, pH, hardpan restriction, organic matter, and, solar radiation. Our conclusions about the relative importance of these effects are conditional by the variation they happened to exhibit within the particular vineyard we studied.

While the results were consistent with previously published literature and tended to recreate the overall spatial pattern (Fig. 3 and 4), the models lacked predictive ability. We believe this was due to the predictor point data taken from interpolated maps which were at a coarser scale than grapevine data. We investigated only a subset of all possible models one might conceive in order to predict anthocyanin and yield; it is possible that better models could be developed using additional predictor variables, non-linear terms, interaction terms, or different types of models. Furthermore, a multivariate modeling approach for yield and anthocyanin may provide additional insight. This approach could assist the goal of farming or identifying potential vineyard sites that would fit a high yield and high anthocyanin model.

More fine-scaled soils maps or non-interpolated soils data might facilitate greater model predictive power. Vineyards with more diverse soil and topographic conditions could provide a clearer response signature in terms of relative anthocyanin content and yield. Incorporating these multiple vineyard sites within the model would further aid in refinement.

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