Project Title: Improving Regional and Block-Level Concord Crop Estimation

Report to the New York Wine and Grape Foundation

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New Research

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Project Summary Impact Statement: In 2021, activities were conducted to address crop estimation in Concord vineyards at both the vineyard block level and the regional industry level. At the block level, ancillary spatial NDVI mapping was used to improve vineyard crop estimation sampling locations and inform variable-rate mechanical fruit thinning for vineyard balance. At the regional level, historical viticulture and weather information is being used to build a prediction model for next season's average crop yield.

Block Level Crop Estimation

The general approach to block level crop estimation is to sub-sample the vineyard at approximately 30 days after bloom and "estimate" the current fruit yield. Then the final crop size is "predicted" by comparing the fresh berry weight at crop estimation time and the fresh berry weight at harvest time and applying that multiplication factor to the estimate. Our current goal is to improve this process by (1) using NDVI spatial data to direct crop estimation sample locations which better represent the variation in vineyard yield and (2) use weather and berry growth information to predict harvest berry weight more accurately.

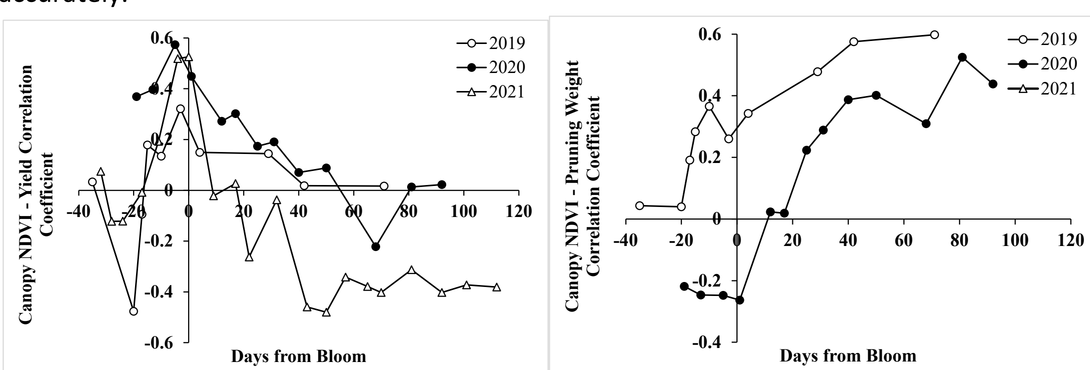


Figure 1: Correlation coefficients between NDVI and harvest yield (left) or NDVI and vine pruning weight (right) in a six-acre Concord block at CLEREL. For these data, vineyard NDVI (side canopy facing

CropCircle sensor) was collected throughout the growing season and compared to harvest yield data (OXBO Yield Tracker) or vine pruning weight (manually collected). The highest correlation between NDVI and yield over three years was at the immediate pre-bloom NDVI scan; therefore, this timing was used to inform crop estimation sample locations in subsequent work. The highest correlation between NDVI and vine pruning weight was at the veraison, or other late-season, NDVI scans.

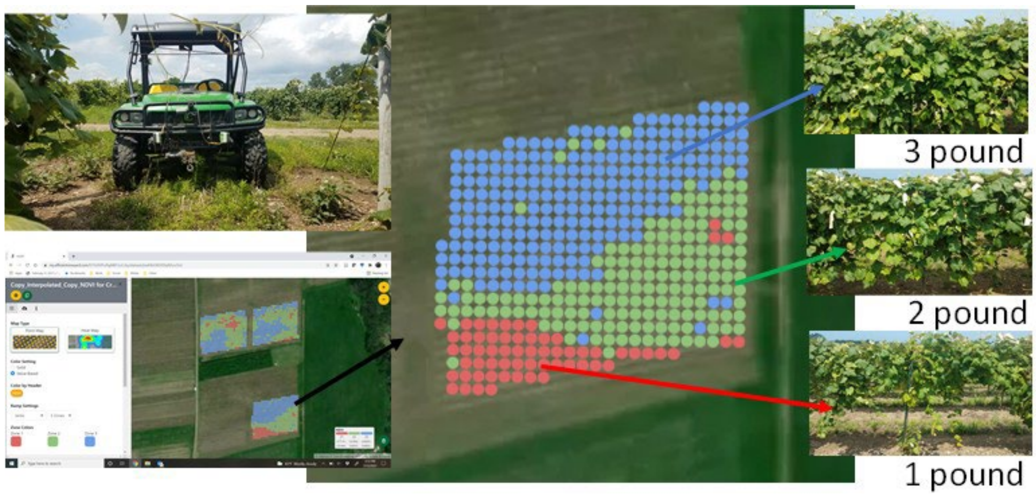
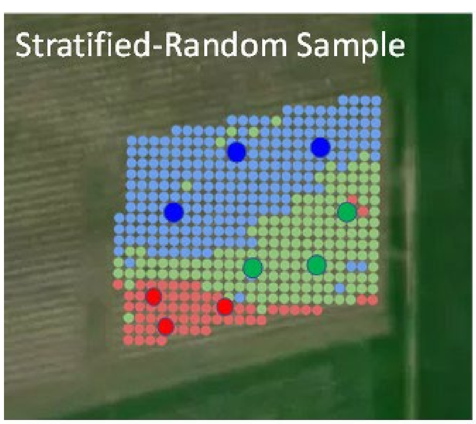


Figure 2: NDVI spatial vineyard mapping in a one-acre Concord vineyard at CLEREL. Prior to crop estimation, the vineyard was scanned with a CropCircle (Holland Scientific) sensor to collect red, red-edge, and near infra-red canopy reflectance. With each scan, the position of the sensor is adjusted to capture the active growing region of the canopy to reflect the differences in vine growth but to also avoid saturation of the sensor signal. Raw sensor NDVI data was imported into MyEV software platform, IDW interpolated to a 3m x 3m vineyard grid, and broken into NDVI management classifications. Similar data could also be collected visually (without a sensor) using the MyEV data collector function and a smart phone or tablet in the field.



Dr. Terry Bates: Crop Estimation and Thinning Table: 7/16/2003

Time of Season	20DAB			25DAB			30DAB		40DAB	50DAB		Veraison			Harvest
Pounds of Fruit Removed in 1/100th of an Acre \ % of Final Berry Weight	20	25	30	35	40	45	50	55	60	65	70	75	80	90	100
10	2.5	2.0	1.7	1.4	1.3	1.1	1.0	0.9	0.8	0.8	0.7	0.7	0.6	0.6	0.5
20	5.0	4.0	3.3	2.9	2.5	2.2	2.0	1.8	1.7	1.5	1.4	1.3	1.3	1.1	1.0
30	7.5	6.0	5.0	4.3	3.8	3.3	3.0	2.7	2.5	2.3	2.1	2.0	1.9	1.7	1.5
40	10.0	8.0	6.7	5.7	5.0	4.4	4.0	3.6	3.3	3.1	2.9	2.7	2.5	2.2	2.0
50	12.5	10.0	8.3	7.1	6.3	5.6	5.0	4.5	4.2	3.8	3.6	3.3	3.1	2.8	2.5
60	15.0	12.0	10.0	8.6	7.5	6.7	6.0	5.5	5.0	4.6	4.3	4.0	3.8	3.3	3.0
70	17.5	14.0	11.7	10.0	8.8	7.8	7.0	6.4	5.8	5.4	5.0	4.7	4.4	3.9	3.5
80	20.0	16.0	13.3	11.4	10.0	8.9	8.0	7.3	6.7	6.2	5.7	5.3	5.0	4.4	4.0
90	22.5	18.0	15.0	12.9	11.3	10.0	9.0	8.2	7.5	6.9	6.4	6.0	5.6	5.0	4.5
100	25.0	20.0	16.7	14.3	12.5	11.1	10.0	9.1	8.3	7.7	7.1	6.7	6.3	5.6	5.0
110	27.5	22.0	18.3	15.7	13.8	12.2	11.0	10.0	9.2	8.5	7.9	7.3	6.9	6.1	5.5
120	30.0	24.0	20.0	17.1	15.0	13.3	12.0	10.9	10.0	9.2	8.6	8.0	7.5	6.7	6.0
130	32.5	26.0	21.7	18.6	16.3	14.4	13.0	11.8	10.8	10.0	9.3	8.7	8.1	7.2	6.5
140	35.0	28.0	23.3	20.0	17.5	15.6	14.0	12.7	11.7	10.8	10.0	9.3	8.8	7.8	7.0
150	37.5	30.0	25.0	21.4	18.8	16.7	15.0	13.6	12.5	11.5	10.7	10.0	9.4	8.3	7.5
160	40.0	32.0	26.7	22.9	20.0	17.8	16.0	14.5	13.3	12.3	11.4	10.7	10.0	8.9	8.0
170	42.5	34.0	28.3	24.3	21.3	18.9	17.0	15.5	14.2	13.1	12.1	11.3	10.6	9.4	8.5
180	45.0	36.0	30.0	25.7	22.5	20.0	18.0	16.4	15.0	13.8	12.9	12.0	11.3	10.0	9.0
190	47.5	38.0	31.7	27.1	23.8	21.1	19.0	17.3	15.8	14.6	13.6	12.7	11.9	10.6	9.5
200	50.0	40.0	33.3	28.6	25.0	22.2	20.0	18.2	16.7	15.4	14.3	13.3	12.5	11.1	10.0

Row Spacing determines length of 1/100th of an acre
10.0 feet row spacing = 43.5 feet = 1/100th of an acre
9.5 feet = 45.9 feet = 1/100th of an acre
9.0 feet = 48.4 feet = 1/100th of an acre
8.5 feet = 51.2 feet = 1/100th of an acre
8.0 feet = 54.45 feet = 1/100th of an acre
7.5 feet = 58.1 feet = 1/100th of an acre

Calculation
43, 560 square feet per acre
Divide by row spacing and then
divide by 100 to get 1/100th of an acre

Example:
A grower has 9 foot row spacing and clean picks 48.4 feet at 25 days after bloom. The fruit weighs 80 pounds and the grower estimates that the berries are between 35% and 40% of final berry weight. According to the table, the crop estimate is between 10.0 and 11.4 tons per acre.

Disclaimer:
This table gives the relationship between time of season and % final berry weight on an average year. Year to year variability in weather related berry growth adds error to this table. Information on current year berry growth can be obtained from the Fredonia Vineyard Lab (or) it is strongly suggested that individual growers start collecting berry weight information from their own individual vineyard blocks.

Figure 3: Stratified-Random sampling for crop estimation. Using the identified vineyard management classifications (or zones), nine crop estimation sample locations were stratified across three zones with three random locations within each zone. Fruit was clean picked and weighed at 30 days after bloom

from 1% of an acre with a mechanical grape harvester (the standard practice). The final harvest weight at each location was predicted using the 2003 fresh berry weight table (right).

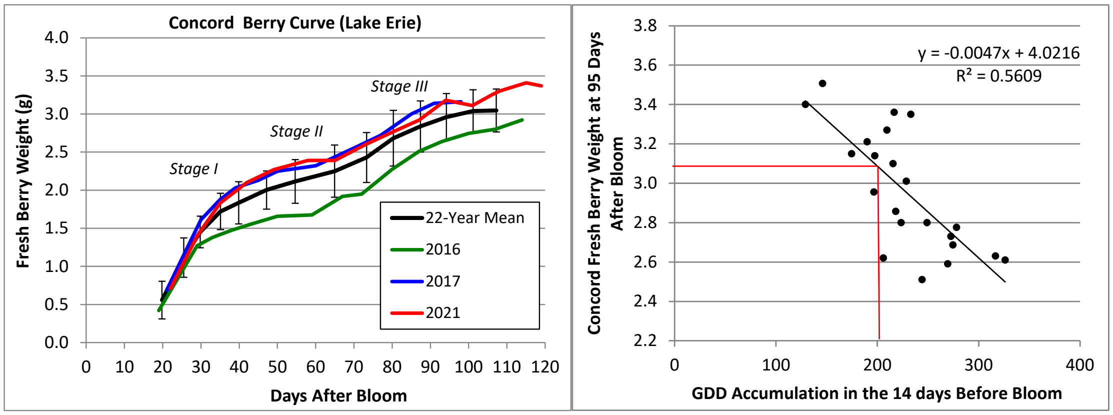


Figure 4: Predicting harvest berry weight. Traditionally, predicted final fresh berry weight is derived from the fresh Concord berry weight curve (left, also depicted in Fig 3 table). The most common use statement is to say that Concord fresh berry weight is 50% of the final weight at 30 days after bloom. However, the percent of final can be calculated at any point along the curve. It is also important to add that "final" fresh berry weight should be defined as "berry weight at 100 days after bloom." Beyond this time, berries can increase or decrease in fresh weight in an unpredictable manner. Interestingly, growing degree day accumulation in the two-weeks prior to bloom has a negative linear relationship with berry weight at 100 days after bloom (i.e. final weight, right chart). The warmer it is in the two weeks prior to bloom, the smaller the final berry weight. In the future, the pre-bloom GDD information and fresh berry weight information can be used together to strengthen the final berry weight prediction.

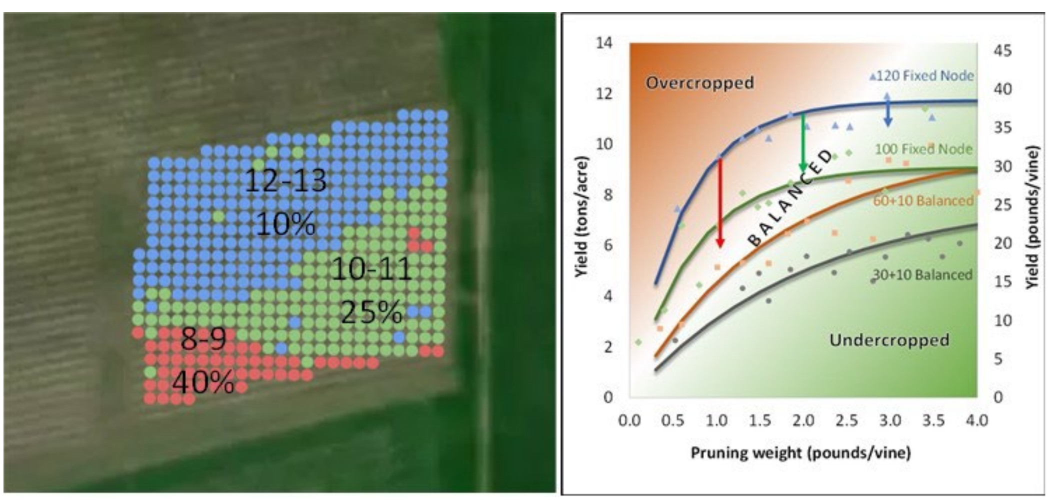


Figure 5: Crop estimation, Concord crop load balance, and the variable-rate thinning decision. Using the method described above, the 2021 crop was predicted to be between 8-13 tons/acre depending on management classification (numbers on left map). Using the published Concord crop load model, the amount of crop reduction needed to bring the vines into balance was determined and indicated by the arrows in the right chart and percent crop reduction indicated on the left map.

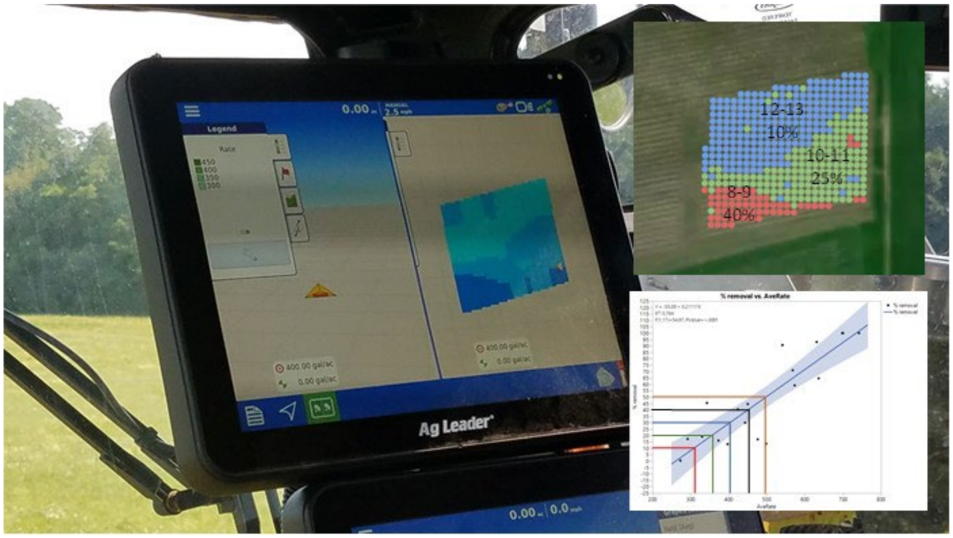


Figure 6: Variable-rate mechanical fruit thinning. Mid-season mechanical fruit thinning in Concord is typically done by adjusting the shaker head speed on a mechanical grape harvester to gently shake the canopy and remove the desired fruit amount. To adjust the shaker head speed for different thinning amounts in the different zones, AgLeader equipment and flow control was used to control the hydraulic flow rate to the shaker head through a hydraulic PWM valve. Two vineyard test rows were used to measure the amount of fruit removal at different flow rates (inset, bottom right). Once the desired flow rates and fruit removal levels were determined, the rates were programmed into the prescription map and the variable rate fruit thing was performed on-the-fly. An educational video on this process: https://www.efficientvineyard.com/blog/variable-rate-fruit-thinning-for-concord-crop-load-balance

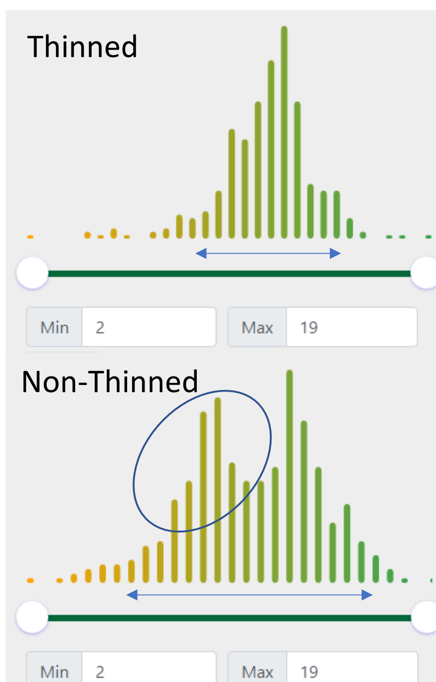


Figure 7: Comparison of thinned and non-thinned rows. In the VR thinning trial, even rows received the VR thinning treatments. Odd rows received no thinning. At the end of the season, odd and even rows

were harvested separately, and the resulting yield maps were generated. VR thinning only slightly decreased the mean block yield, primarily because the large vines with large crops were already balanced and received little thinning. Arguably, if one thinning rate (uniform thinning) were conducted, the large vines would have been over-thinned, leading to unneeded revenue loss. The smaller vine zone, although it set lower yield, was still much more overcropped at 8-10 tons/acre. Applying higher thinning rates to the small vine zone eliminated the overcropping (indicated by the circle in the non-thinned vines) and reduced the overall variation in block yield (indicated by the double headed arrows).

Regional Crop Estimation

We continue to pursue a collaborative effort with Justine VandenHeuvel (Cornell), Guiping Hu and Luning Bi (RIT) on using historical viticultural and environmental data to model yield prediction. Current inputs into the model include:

- Historical Weather Data: Daily Max/Min Temp, Precipitation, and Growing Degree Days, 1926-2021
- Phenology Dates: Bud Break, Bloom, Veraison, 1965-2021
- Industry Yield Component Data, 1975-2021
- Cornell small plot viticulture data 1974-2021
- Cornell Fresh Berry Weight Curves, 1999-2021
- Cornell Juice Soluble Solids Curves, 1999-2021

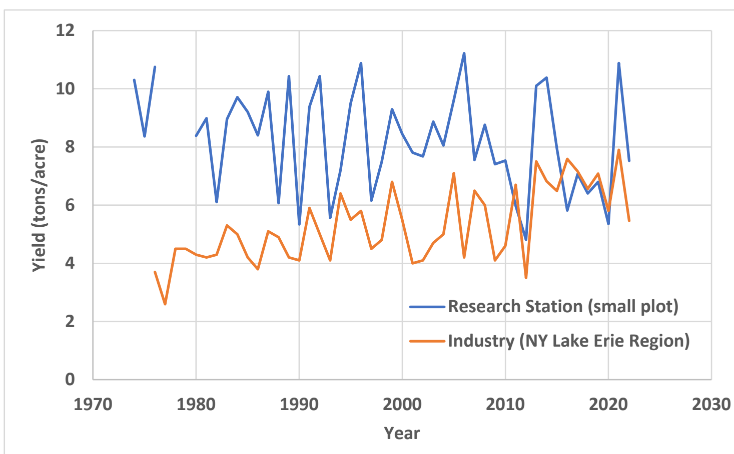


Figure 8: Comparative data sets. In addition to long term weather and phenology data, effort was put toward compiling comparative university and industry data sets with respect yield and yield components from 1975-2021. The university data comes from Cornell small plot viticulture field trials with comparable parameters (same spacing, pruning, training, rootstock, and general soil type/location – either the Fredonia Vineyard Lab or the Cornell Lake Erie Research and Extension Lab). The industry data comes from processor collected data in western New York region. This graphic illustrates that the small plot data tends to have higher yield and higher variation than the composite region-wide data. The "relative" yield change between the two data sets, however, tends to be more similar and can be leveraged in the crop prediction model.

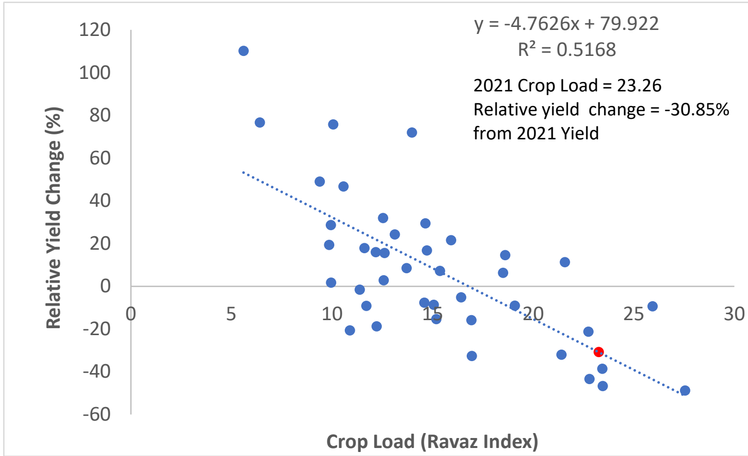


Figure 9: Crop load in the crop prediction model. Crop load is an indicator of the relative balance between vine vegetative and reproductive growth. The indicator measurement of crop load is the yield to pruning ratio (or Ravaz Index). The Concord crop load model is represented in Figure 5. In relation to crop prediction, undercropped vines gain pruning weight and crop potential for the next season. Overcropped vines lose pruning weight and crop potential. This relationship is measured at CLEREL and can potentially be used as a starting point to predict yield potential for next season. This graphic shows the effect of crop load on the relative yield change from the previous season. (It is important to note that this is the yield change from the previous season and not from the long-term mean.) For example, the 2021 Ravax Index from CLEREL was approximately 23, which predicts a 30% reduction in yield potential for 2022. Therefore, if the region-wide 2021 yield was 7.9 tons/acre with a Ravaz Index of 23, then the initial yield prediction for 2022 will be 30% less at 5.5 tons/acre.

Ongoing work: Guiping Hu and Luning Bi (RIT data scientists) are developing and testing different crop prediction models which include both crop load and other weather data. We have not requested additional funds for 2022 but will continue to validate potential models and re-visit a new funding request, if warranted.