IDENTIFYING VITICULTURAL FACTORS THAT DIRECTLY INFLUENCE ACIDITY IN WINEGRAPES

A Thesis

by

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ABSTRACT

High wine pH is an important challenge in hot climates due to pH's influence on red wine color, oxidation, flavor, and cold and microbial stability. In order to increase grape acidity in the vineyard and decrease the pH, viticultural factors that directly influence grape berry acidity need to be determined. For this purpose, a two-year field study was conducted in seven commercial *V. vinifera* cv. 'Tempranillo' vineyards located in the Texas High Plains and North Texas regions. Data on cultivar, canopy architecture, soil and vine nutrition, climate, harvest yield, and berry composition were collected from twenty consecutive vines from each vineyard site. Partial least squares regression (PLSR) models were constructed to predict factors that influence acidity at individual vineyard sites and across all vineyard sites by year and collectively. The variance in juice pH observed across sites and within individual sites was best explained by juice potassium (K). Juice pH increased with the increase in total K concentrations in the berry. Rootstock selection and vine water status were also important factors to the models. Results from the study indicate that proper rootstock selection and water management are important factors for reducing K and pH in grape juice. The strong correlation between K and juice pH was further investigated in four additional *V. vinifera* cultivars. 'Malbec', 'Grenache' and 'Carnelian' also showed a strong positive correlation between K and juice pH.

Key words: Grapevine, pH, acidity, controls, potassium, rootstock, water management.

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NOMENCLATURE

AVR	Acid variables removed
AVA	American Viticultural Area
Ca	Calcium
CEFA	Cluster exposure flux availability
DAA	Days After Anthesis
EC	Electrical conductivity
Ep1	Canopy calibration coefficient
FW	Fresh weight
H	Harvest
K	Potassium
KHT	Potassium bitartrate
LEFS	Leaf exposure flux symmetry
NOAA	National Oceanic and Atmospheric Administration
OLSR	Ordinary least squares regression
PLSR	Partial least squares regression
TA	Titratable Acidity
VIP	Variable of importance in projection
YC	Years combined
TA	Titratable Acidity
50V	50% veraison

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CHAPTER I
INTRODUCTION

The production of wine dates back 8,000 years to modern-day Georgia (Curry, 2017). Since that time winemaking has spread throughout the world by means of religion and culture, with the United States being no exception. The United States produces 6.9 million tons of grapes annually, with 65.6% of that for wine production. In 2018, the US produced 624 gallons of wine (OIV, 2019). In wine production by state, Texas is the fifth leading wine producer in United States, producing 4.2 million gallons in 2018 (WineAmerica, 2019). Grape and wine production in Texas does not come without challenges. Aside from domestic and global competition, the hot climate of Texas has shown to be less conducive for grape growing compared to well-known regions with cooler climates such as California, France or Italy. Hot climates tend to produce grapes with relatively low acidity and high pH, causing problems for wine making (Jones et al., 2005; Neethling et al., 2012; Ramos et al., 2008; Webb et al., 2007). With the immense national increase in demand for wine, and the economic incentive for Texas to increase production, it is important to assess and overcome the pitfall of relatively low acidic grapes and resulting wine produced in the hot climate of Texas.

Acidity in Grapes and Wine

It is widely recognized that wine quality is inextricably correlated with the quality of the grapes used. Acidity is an important parameter to monitor in the vineyard as a proxy for grape maturity and potential quality of the wine. Acidity impacts the aroma (Jackson, 2014), color (Kodur, 2011; Poni et al., 2018), taste (Poni et al., 2018), chemical and microbiological stability (Boulton, 1980), and ageing potential (Boulton, 1980; Poni et al., 2018) of wine. The rate of fermentation is affected by acid levels in the grape. The three predominate organic acids present in grapes are tartaric, malic, and citric acid. Three additional acids, lactic, succinic, and acetic, are formed during the winemaking process (Waterhouse et al., 2016).

The organic acids found in grapes are considered weak acids, because they partially dissociate hydrogen ions (protons) in solution. Grape acidity is routinely quantified in two ways: pH and titratable acidity (TA). pH represents the negative log (base 10) of dissociated (free) protons in solution. pH is measured to determine microbial stability of wine (Boulton, 1980), precipitation of potassium bitartaric acid during winemaking (Berg & Keefer, 1958), and malolactic acid fermentation potential (Fornachon, 1957). Grape juice pH is primarily the result of anionic forms of malic and tartaric acids, and potassium interacting in the juice (Boulton, 1980). Changes in the concentration of any of these three factors, whether in the vineyard or winery, can affect pH. A maximum pH of 3.7 is considered ideal for inhibiting unwanted microbial growth in the wine, thus preventing spoilage. Sulfur dioxide (SO_2) is an additive often used in winemaking to provide additional protection from spoilage microbes and oxidation in wine. SO_2 exists as both free SO_2 and

bound SO_2 in wine. Free SO_2 exists as molecular SO_2 (the form effective against wine microbes and oxidation), bisulfite and sulfite. The wine pH determines how free SO_2 is distributed between these three forms. When wine pH is low, small amounts of free SO_2 can be effective in controlling wine microbes. When wine pH is high, excessive additions of free SO_2 may not produce enough molecular SO_2 to effectively control microbes.

In contrast, titratable acidity (TA) is a measure of both free and undissociated protons using an acid-base titration, most commonly with an endpoint of pH 8.2. TA is more strongly correlated with consumer perception of acidity and taste (Rühl et al., 1992), but does not contribute to wine stability and is a poor indicator of organic acid content (Boulton, 1980). TA values vary by grape cultivar, climate, vineyard practices, and preference of the winemaker. In developing grape berries, TA increases from berry set to véraison, and then declines throughout maturation.

Tartaric Acid

Tartaric acid, or 2,3-dihydroxybutanedioic acid, is a carbon-based compound found in various plant species, including grapes. Tartaric acid is diprotic. Tartrate is the predominant acid at all stages of grape berry development (Morris et al., 1983), commonly present in mature grapes at an average concentration of 5 to 10 g/L (Ruffner, 1982). It is also predominant in all the parts of the vine, except for the roots (Ruffner, 1982). Tartaric acid is not metabolized during fermentation, so it is often used to adjust the pH of the juice in the winery (Keller, 2015). In mature grapes, tartaric acid concentrations are often higher than malic acid, and are relatively constant. It is the primary acid perceived in all wine that attributes to the body and balance of flavors (Ruffner, 1982).

Malic Acid

Like tartaric acid, malic acid is also diprotic. Malic acid is derived from a succinic acid via glycolysis and the TCA cycle (Volschenk et al., 2006) in which a hydrogen attached to a carbon is replaced by a hydroxyl group. Along with tartaric acid, malic acid is a major organic acid found in all the parts of the vine (Ruffner, 1982) and is predominant at all stages of grape berry development, resulting in a significant influence on the acidity in mature grapes (Morris et al., 1983). Combined, tartaric acid and malic acid represent up to 90% of total organic acids present in mature grape berries (Hale, 1977; Ibrahim, 2001; Ruffner, 1982). Malic acid contributes to the tartness in wine, and can be converted into the weaker acid, lactic acid, in the presence of lactic bacteria during fermentation. Malic acid is present in mature grapes at an average concentration of 2 to 6.5 g/L (Boulton et al., 1996). The concentration of malic acid in mature grapes commonly fluctuates and declines more rapidly from véraison to maturation than tartaric acid, posing challenges to winemakers (Margalit, 1997). The degradation of malic and tartaric acids occurs from an increase in membrane permeability in the cell vacuole, causing stored acids to respire and reducing the amount of acids being transported from the leaves. Potassium from within the berries bind to the leaked acids and form salts that reduce berries ability to synthesize organic acids as the berry matures, leading to a dilution effect of acid to sugar ratio in the berries (Winkler et al,. 1974). Malic acid levels are a function of temperature, and generally decrease as a result of high respiration rates of the berry during maturation (Jackson & Lombard, 1993).

Citric Acid

Citric acid is produced directly by grapevines, but in significantly lower concentrations than tartaric and malic acids (Mato et al. 2005). It is a tricarboxylic acid commonly present in concentrations of ≤1 g/L in mature grapes (Jackson, 2014). Additions of citric acid are often made to white wines to impart citric character. Citric acid can be converted into acetic acid by lactic bacteria during fermentation, resulting in an unpleasant vinegar taste. Additionally, *Oenococcus oeni* bacteria can convert citric acid into diacetyl during malolactic fermentation which may not be desirable depending on concentration and wine style. To avoid unwanted flavor profiles, tartaric acid adjustments may be made instead of citric acid (Jackson, 2014).

Potassium

Potassium (K) ion is estimated to make up 80% of the total cations in mature grape, and is the most abundant cation in all developmental stages of the berry (Rogiers et al. 2006). K in the plant is a function of available soil K and the capacity of uptake by the host plant roots (Ruhl, 1989). The accumulation of K in the plant is equal to the K net uptake by the roots (Mpelasoka, et al., 2003). Mobilization of K from root to shoot is hypothesized to be regulated by the xylem loading capacity (Tanner and Beevers, 2001), and storage sinks within developing tissues (Mengel and Kirkby, 1987). As an essential plant nutrient, K is an important mineral for stomatal regulation and ATP synthesis in plants (Boulton, 1980; Daverède, 1996; Gawel et al., 2000**;** Iland, 1987). K also facilitates amino acid, sugar, and water transport during the onset of berry ripening (Marten et al., 1999). High accumulation of K increases the neutralization of organic acids (Kodur, 2010) and has been linked to

changes in berry pH (Hafke et al., 2007). Alongside sugar accumulation, K accumulates rapidly in the berry during ripening. In wine, K and tartaric acid can form a salt, potassium bitartrate (KHT), which can precipitate resulting in changes to wine pH. Additions of K and calcium (Ca) salts during winemaking may also cause precipitations of potassium bitartrate (KHT) or calcium tartarate (CaT). The precipitation of KHT will further decrease TA of the wine because KHT yields a titratable proton that contributes to TA. The shift in pH is dependent on the pH prior to precipitation (Waterhouse, et al. 2016).

Acidity Adjustments in the Winery

Without acid additions, high pH, low acid wines are commonly made from grapes grown in warm climates, such as Texas, resulting in wines described as low bodied or flat. Adjustments by adding tartaric, malic, and citric acids or their mixtures can help reduce the low acidity attributes of high pH wines, but pH adjustments are limited by the concomitant increase in TA (Jackson & Lombard, 1993; Waterhouse et al. 2016). The addition of tartaric, malic, or citric acids will result in an increase of TA.

Cultural Practices and Environmental Impacts on Acidity

Vine Nutrition

K is the predominate cation in leaves, must, and wine, and is recognized as an important factor in controlling must and wine acidity (Champagnol, 1986; Daverède, 1996; & Garcia et al., 2001). This cation varies considerably in concentration among grape cultivars and climate conditions.

Gawel et al. (2000) observed a decrease of tartaric acid in grape juice in response to increasing concentrations of juice K. The change in free acids resulted in an overall increase in the juice pH. Similar results were observed in a hydroponics study conducted by Daverède (1996). The study indicated that acid levels in the must and wine of *Vitis vinifera* L. cv. 'Negrette' decreased when K levels were high. The study also determined a positive correlation between the concentrations of K in leaves at veraison and in the must of mature grapes. These results are supported by an additional hydroponic study conducted by C. Daverède and Garcia (2000). The titratable acidity of must and wine obtained from *Vitis vinifera* L. cv. 'Negrette' increased as the K concentration in the nutrient solution decreased. Boulton (1980) proposed that membrane-bound enzymes with high affinity for K causes a stoichiometric exchange for protons originating from endogenous plant acids to accumulate K in grapevines and berries resulting in a net loss of free protons.

With many studies determining that high accumulation of K (e.g. > 50mM) in the juice of grape berries can result in high juice pH, there is an apparent need to determine the appropriate combination of scion/rootstock, and/or environmental factor(s) in order to lessen high pH outcomes in wine (Cirami et al. 1993, Kodur et al., 2010; Kodur, 2011; Rühl, 1989; Whiting, 2003).

Plant Genotype

More than 30 grape cultivars are commercially grown in Texas, including cultivars of *Vitis vinifera*, interspecific hybrids, and muscadine grapes (*Vitis rotundifolia*) (USDA, 2019). Plant genotype heavily influences nutrient absorption and accumulation in vegetative

tissues. Various studies have evaluated nutrient and cation content of the plant, must, and wine, predominately K, to determine the scions influence on nutrient uptake.

A two-year study on *Vitis vinifera* scion on 3309 Couderc rootstock reported that K absorption and storage in leaf and berry tissues varied depending on scion cultivar (Attia et al., 2004). 'Negrette' showed the highest accumulation of K in leaf tissues at bloom and veraison in the two seasons, and the highest accumulation of K in the must in the first season. Similar results were observed in studies conducted by Garcia et al. (2001) and Ibrahim et al. (2001). In contrast, 'Malbec' presented the lowest levels of K in leaf tissues at bloom and veraison in both seasons, and the lowest accumulation of K in the must in the first season. The data also showed a linear correlation between K content of the must and leaves, with a less considerable correlation observed with K level in the wine. Over extraction of K from leaf tissue to berry tissue has been suggested to cause an increase in juice pH due to the binding of K to tartaric acid (Hale, 1977; Boulton, 1980; Walker and Blackmore, 2012).

Ca content was the highest in leaf tissues at bloom and véraison and in the must of 'Malbec' and the lowest in 'Négrette' for the two consecutive seasons. The antagonistic relationship of K to Ca reported in 'Négrette' and 'Malbec' cultivars supports previous data findings by Daverède (1996), Garcia et al. (1999), Gallego (1999) and Ibrahim et al. (2001). No significant difference was observed for magnesium (Mg) content in leaves and grape must for all cultivars.

Organic acid concentrations from véraison to harvest were also analyzed by Attia et al. (2004). Malic acid showed a greater decline in all cultivars tested from véraison to harvest than tartaric acid. Cultivars 'Tannat' and 'Fer Servadou' had the highest levels of

malic acid, and ‘Malbec’ had the highest levels of tartaric acid compared to the other cultivars. Negative correlations were observed between the tartaric acid concentration and the pH levels in musts and wines of all cultivars. Overall organic acid data collected from the five cultivars indicate a similar evolution of tartaric and malic acids from véraison to harvest.

The use of rootstocks to control scion vigor or to overcome specific soil and climate limitations is a common practice in viticulture. The effect of the rootstock on scion nutrition and growth has been well documented in the literature (Delas & Pouget, 1979; Kodur, 2011; Loué et al. 1984; Valcheva et al. 2012), but with many studies analyzing acid accumulation. S. Kodur (2011) suggests that plant genotype, in respect to root morphology and rooting pattern, can impact K uptake, thus, the pH in the berry or wine. Garcia et al. (2001) analyzed the effect of three commercially used rootstocks, 101-14 Mgt (*Vitis riparia* x *Vitis rupestris*), 3309 C (*Riparia tomenteux* x *Rupestris martin*), and SO4 (*Vitis Berlandieri* x *Vitis riparia*) grown under identical conditions on acid content in grape must. The study reported that K concentrations in the must and wine were the highest for the SO4 rootstock and the lowest for the 3309 C rootstock. The opposite was observed for calcium and magnesium concentrations in the must and leaves. Must pH was the highest in the SO4 and the lowest in 3309 C rootstock, whereas TA of musts was not significantly different among the three rootstocks. Tartaric acid concentrations in the must were significantly higher in the SO4 rootstock. No significant difference was measured for malic acid across all three rootstocks. Results from the study suggest that 3309 C rootstock is the ideal choice to combat high pH conditions often observed in warm climates (Garcia et al. 2001).

Canopy Microclimate

Sunlight is an important component to physiological processes of grapes because it is required for photosynthesis, sugar accumulation, and can influence grape berry temperature. Changes in sunlight exposure and temperature have been observed to influence biochemical components in the berry such as organic acids and phenolic compounds (Price et al., 1995; Reynolds et al., 1986), leading many to suggest that sunlight and berry temperature are two of the most important microclimate factors impacting berry acid content (Jogaiah, et al. 2012; Kliewer, 1973; Spayd et al. 2002). Consequently, a considerable number of studies have been conducted to determine the effect of sunlight and temperature on berry acidity and pH.

In 1976, Smart and Sinclair noted a significant effect of canopy density on grape berry temperature. Shaded berries were reported 2.4°C above the ambient temperature, whereas clusters exposed to solar radiation were up to 12.4°C above the ambient temperature. Smart (1976) also observed delays in sugar accumulation and acid degradation under densely shaded berries. Findings from a field trail by Jogaiah et al. (2012) stated that TA was the highest in shaded berry clusters compared to fully exposed or partly exposed clusters, agreeing with R.E. Smart observations. Jogaiah et al. (2012) suggested that the increased TA and pH in shaded clusters may be attributed to greater accumulation of malic acid and K. Additional studies agree with the relationship between berry temperature and malic acid content (Buttrose et al. 1971; Sepu´lveda and Kliewer 1986; Smart et al., 1985). It has also been observed that reduced malic acid accumulation and increased pH of grape

berries is the result of night time heating between véraison and ripening, and inverse relationship with shading during day time (Sweetman, et al. 2014).

An additional sunlight exposure study conducted by Morrison and Noble reported that shaded 'Cabernet-Sauvignon' clusters accumulated more K from véraison to harvest compared to sunlight exposed clusters, increasing juice pH (1990). The study suggested that temperature may have a greater influence on berry acidity than sunlight exposure. A previous study by Crippen and Morrison reported similar patterns of sugar accumulation and acid metabolism in shaded and exposed berry clusters when the cluster-bearing shoots were exposed to the same amount of sunlight (1986). These findings are in conjugation with Morrison and Noble's claim on K accumulation. An additional study conducted in Washington to assess 'Merlot" berries composition by separating the effects of sunlight and temperature determined the overall temperature of the berry is inversely related to berry TA (Spayd et al., 2002).

Row orientation has also shown to impact acid content in grape berries as a function of sunlight exposure and temperature. In a sun exposure field trail, *Vitis aestivalis* c.v 'Norton' grapes oriented from east-west had higher levels of tartaric acid, glucose, and fructose, and lower levels of citric acid, malic acid, titratable acidity, and juice K compared to vines oriented from north-south (Jogaiah, et al., 2012). In the same study, grape clusters on the south and west sides of the canopy were recorded to have higher juice pH compared to clusters on the north or east sides.

Soil Nutrients

The importance of soil conditions for plant nutrient uptake is well known. The accumulation of K in grapevines is a function of the availability of K in the soil (Ruhl, 1989). Soil electrical conductivity (EC), the measure of the amount of salts in a solution, can affect the plants ability to take up available nutrients in the soil. Low soil EC limits the plants growth due to nutrient deficiency, while too high soil EC inhibits plant growth due to salinity stress (Ding, et al., 2018). High levels of Ca and Mg uptake by plants in alkaline soils (pH > 7.0) has been associated with reduced K availability (Hannan, 2011). Remobilization of K from other plant tissues to the grape berry may depend on soil K availability, K uptake capacity of the roots, and rates of K translocation from root to shoot to meet the berry demand for K (Mpelasoka, et al., 2003).

Water Status

Crop yield and grape berry compositional traits that influence the quality of a wine can be highly influenced by water status during the growing season. The effect of water deficit irrigation on grape berry acidity has been studied extensively. As mentioned previously, many studies have suggested that malic acid concentration in grape berries and must is a function of temperature. Grape berry temperature can be considered a function of water status as demonstrated in a 5-year irrigation treatment study conducted by Intrigliolo and Castel (2010). Moderate to heavily irrigated *V. vinifera* cv. 'Tempranillo' vines had higher malic acid concentration in the must and wine compared to non-irrigated vines. This result is attributed to the greater vegetative growth of the irrigated vines reducing sunlight exposure, thus, lowering berry cluster temperature. Additional studies reported that reduced

canopy shading from non-irrigated vines resulted in a higher rate of malic acid degradation (Buttrose et al. 1971; Sepu´lveda & Kliewer 1986; Smart et al., 1985). A significant difference in wine pH was also reported in wines from grapes grown under different irrigation practices (Intrigliolo and Castel, 2010). Wine pH was higher in irrigated vines compared to non-irrigated vines. In contrast, tartaric acid concentrations were lower in the must and wine of irrigated grapes compared to non-irrigated grapes. No significant difference was reported for titratable acidity. Another water status study conducted by Phogat et al. (2017) reported contrasting results. In the two-year study, a decrease in must pH and an increase in must TA were observed in the must of increased irrigated *Vitis vinifera* cv. 'Chardonnay' vines, suggesting that quality component responses to water status could be cultivar dependent.

Climate Change

Within the past few decades, researchers have begun investigating the impact of climate change on grapevine, and multiple studies have determined that climate change is significantly impacting grape berry acidity (Jones et al., 2005; Neethling et al., 2012; Ramos et al., 2008; Webb et al., 2007). Studies have shown grapevines to begin key phenological stages such as bud break and fruit maturity earlier than average dates in response to increased temperatures (Petgen, 2007; Nemani et al., 2001; Ramos et al., 2008: Sigler, 2008;). TA reduction at harvest has been observed in regions experiencing warmer annual temperatures (Barnuud et al., 2014), thus resulting in a decline of malic acid concentration at harvest (Sweetman et al. 2014). Grapes are being harvested with lower acidity and higher sugar

levels (Duchêne & Schneider 2005). Subsequently, growers are harvesting lower quality fruit that will require additional adjustments in the winery or be market at a lower cost.

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CHAPTER II
IDENTIFYING PREDICTOR VARIABLES OF PH AND K IN GRAPE BERRY

Abstract

High wine pH is an important challenge in hot climates due to pH's influence on red wine color, oxidation, flavor, and cold and microbial stability. In order to increase grape acidity in the vineyard, viticultural factors that directly influence berry acidity need to be determined. For this purpose, a two-year field study was conducted in seven commercial *V. vinifera* cv. 'Tempranillo' vineyards located in the Texas High Plains and North Texas regions. Data on cultivar, canopy architecture, soil and vine nutrition, climate, harvest yield, and berry composition were collected from twenty consecutive vines from each vineyard site. Partial least squares regression (PLSR) models were constructed to predict factors that influence acidity at individual vineyard sites and across all vineyard sites by year and collectively. The variance in juice pH observed across sites and within individual sites was best explained by juice potassium (K). Juice pH increased with the increase in total K concentrations in the vine. Rootstock selection and the amount of water received by the vines were also important factors to the models. Results from the study indicate that proper rootstock selection and water management are important factors for reducing K and pH in grape juice.

Key words: Grapevine, pH, acidity, controls, potassium, rootstock, water management.

Introduction

High wine pH is a serious challenge for warm and hot climate wine regions. *V. vinifera* cv. Tempranillo is the second most cultivated grape cultivar in Texas (USDA, 2020), and often has high juice pH at harvest. Grape juice and wine pH influence the microbial stability of wine (Boulton, 1980b), consumer perception of acidity, taste, and balance (Ruhl et al., 1992), precipitation of potassium bitartaric acid during winemaking (Berg & Keefer, 1958), and malolactic acid fermentation potential (Fornachon, 1957). The pH of juice or wine may be managed in the winery, but techniques are limited and may be cost prohibitive. Organic acid additions may be made to lower the pH, but will increase the perception of acidity (Jackson & Lombard, 1993; Waterhouse et al. 2016). Other techniques such as electrodialysis and cation exchange may also be employed to lower wine pH, but may result in unwanted changes to wine flavor or may be cost prohibitive (Ponce, et al., 2018). Therefore, managing acidity should begin in the vineyard. A large number of viticultural factors are shown to influences acidity including vine nutrition (Champagnol, 1986; Ruhl, 1989; Kodur, 2011), plant genotype (Hale, 1977; Boulton, 1980b; Garcia et al., 2001; Attia et al., 2004), canopy microclimate (Reynolds et al., 1986; Kliewer, 1973; Spayd et al. 2002), soil nutrients (Ruhl, 1989; Mpelasoka, et al., 2003; Hannan, 2011), water status (Buttrose et al. 1971; Sepu´lveda & Kliewer, 1986; Smart et al. 1985b), and climate change (Jones et al., 2005; Neethling et al., 2012; Ramos et al., 2008). However, most studies only measure a limited number of parameters making it difficult to determine what factors directly influences acidity in grapes. The objective of this study was to identify factors that

directly correlate with grape juice acidity in Tempranillo by evaluating relationships between dependent and independent variables using ordinary least squares regression (OLSR) and developing predictive models with partial least squares regression (PLSR). This may lead to new and improved vineyard management practices to address the challenge of high pH in vineyards grown in warm and hot climates.

Materials And Methods

Experimental Design

This study was conducted in 2019 and 2020 in seven commercial vineyards located in the Texas High Plains American Viticultural Area (AVA) and North Texas Growing Region (Table 2.1) Twenty mature (three years or older) *V. vinifera* cv. Tempranillo vines were selected at each site for the study. Ten additional vines were selected from Site 6. When possible, vines were consecutive in a single row. All vines were located in the same block in close proximity. Standard cultural practices for the respective growing region were implemented at all vineyard sites. Experimental units consisted of single vines and all data were collected on individual experimental units (Table 2.2). In 2019, anthesis measurements were not recorded at all study sites. Site 7 did not participate in the 2020 study.

Vine Characterization

Grapevine canopy was characterized using enhanced point quadrant analysis as described by Meyers and Vanden Heuvel (2008). Measurements were taken at 20cm intervals at anthesis, 30 days after anthesis (DAA), and at harvest. The number of count and

non-count shoots were determined at 30 DAA and harvest, and canopy density was determined as the number of shoots per vine divided by in-row vine spacing. Measurements of photosynthetically active radiation (PAR, 400 - 700 nm) were taken in the fruiting zone with a AccuPAR LP-80 ceptometer (Decagon Devices, Cambridge, UK) on cloudless days between 10:00 am and 3:00 pm at anthesis, 30 DAA and harvest. The probe was inserted parallel to the row in the interior of the canopy at the fruiting zone and mid canopy and the mean of 2 readings of Ambient Flux and OLN/2 Flux were recorded.

Vine vigor was measured as shoot diameter using a digital caliper (IP54 Digital Caliper, EAGems, Los Angeles, California) between nodes 1 and 2 at the base of shoots from ten randomly selected shoots per vines at 30 DAA and harvest. For the first year of the study, dormant cane pruning weights were recorded during winter pruning in January of 2020. The dormant canes were pruned above node 5 from the base of each shoot and weighed per vine to determine total pruning weight. Pruning weight data were not collected in the second year of the study.

Climatic Measurements

Weather data is presented in Table 2.3. Mean monthly temperatures for 2019 and 2020 during the April-August growing seasons were obtained from local weather stations (WatchDog 1650 Micro, Spectrum Technologies, Inc., Dallas/Fort Worth, TX) at Sites 1, 2, 3, and 4. Mean monthly temperatures for Sites 5, 6, and 7 were obtained by regional weather stations recorded by the National Oceanic and Atmospheric Administration (NOAA) National Centers for Environmental Information (NOAA, 2020). Monthly precipitation means for 2019 and 2020 during the April-August growing seasons were obtained by

regional weather stations recorded by the NOAA National Centers for Environmental Information at all research sites. Growing degree days (GDD) were determined as GDD = [(maximum daily temperature + minimum daily temperature) / 2] – 10 from 1 April to harvest.

Vine Nutrient Status

Whole leaf samples were collected at 30 DAA and 50% veraison to assess vine nutrient status. One recently matured leaf (corresponding to nodes 5 to 7 from the apical shoot tip) per primary fruit bearing shoot that were well exposed to sunlight were selected. Five leaves per vine were collected. The samples were stored in paper bags during field collection. Whole leaf samples were washed in a mild, phosphorus-free soap water solution, rinsed with distilled water, and then dried for 72 hours in a drying oven at 60°C. Samples were analyzed by the Texas A&M AgriLife Extension Soil, Water and Forage Testing Laboratory for P, K, Ca, Mg, Na, S, Fe Cu, Mn, Zn, and B analysis.

Soil Sampling

Soil sampling was performed in July 2020 using a spade as described by Soil, Water and Forage Testing Laboratory, Department of Soil and Crop Sciences, Texas AgriLife Extension Service. A homogenous soil sample consisting of 4 subsamples at vines 3, 8, 13, and 18 were taken per site and submitted to the Texas AgriLife Extension Soil, Water and Forage Testing Laboratory for pH, NO3-N, soil electrical conductivity, P, K, Ca, Mg, Na, and S analysis.

Berry Sampling And Analyses for Chemical Composition

Twenty berries were randomly sampled per vine at 30 DAA and 50% veraison, and 200 berries were randomly sampled per vine at harvest for chemical analyses. Whole berry samples were immediately frozen at -23ºC for preservation until processing. For sample preparation, the frozen berries were placed in a beaker and heated to 65ºC for one hour in a water bath (DSB-500D, LW Scientific, Inc., Atlanta, Georgia) to re-dissolve tartrates. The warmed samples were homogenized in a commercial blender (GB26-b, Hamilton Beach, Glen Allen, VA) for 3 minutes and transferred to 50ml polypropylene tubes. The sample tubes were centrifuged for 5 minutes at 4000 rpm. The supernatant was transferred into 57 grams wide-mouth plastic jars for carbon isotope analysis, and the juice was centrifuged an additional 5 minutes at 4000 rpm. Remaining supernatant was discarded and the must samples were immediately frozen at -23ºC until analyses.

For must analysis, the samples were thawed for 48 hours at 4ºC. The samples were analyzed with a FOSS WineScan (WineScan™, Foss, Denmark) for soluble solids (ºBrix), pH, K, TA, malic acid, tartaric acid, fructose, and glucose using Fourier Transform Infrared analysis as described by Musingarabwi, et al. (2015). To validate chemical analysis methodology, 20 must samples from the 2020 harvest were selected at random for soluble solids (ºBrix), pH, K, TA, malic acid, tartaric acid, fructose, and glucose analysis by ETS Laboratories in St. Helena, CA for correlation comparison with the Fourier Transform Infrared analysis.

Harvest Parameters

At harvest, cluster counts were recorded and yield per vine was measured with a digital hanging scale (FG007750000000 Pelouze, Rubbermaid, Atlanta, GA). Mean cluster weight was calculated as yield divided by the number of clusters. Mean fresh berry weight was determined by weighing the 200-berry harvest samples. Crop load was calculated in 2019 as vine yield divided by dormant pruning weight.

Statistical Analysis

To evaluate relationships between dependent and independent variables and to develop predictive models, partial least squares regression (PLSR) and ordinary least squares (OLS) regression were conducted with JMP Version Pro 15 Statistical Software (SAS Institute, Cary, NC). The method of validation carried out was the leave one out cross-validation. Data was normalized and the number of latent vectors in each PLS model was determined by the lowest predicted residual sum of squares (PRESS). When building models, all variables were included in the initial models and independent variables were removed in an iterative process based on low regression coefficients and variable importance factors until the strength of the model could no longer be improved. To determine the variables most significant to the models, a variable of importance coefficient (VIP) of 0.8 was used as the threshold. All variables below the threshold were removed before each model was reconstruction. One-way analysis of variance (ANOVA) and Welch's t-test, followed by means separation using Games-Howell test at the 5% significance level was used to compare data on juice pH across research sites and years.

Results And Discussion

This study was conducted in seven commercial Tempranillo vineyards located in two separate grape production regions in Texas that represent different climatic and soil conditions. Tempranillo was selected for the study because it is the second most cultivated grape cultivar in Texas (USDA, 2019), and often has high juice pH at harvest. With high juice pH being problematic in winemaking by reducing the microbial stability of wine and lowering wine quality, it is important to understand the variables that influence pH in Tempranillo grown in Texas. In this study, berry acidity was evaluated because pH is the measure of free acid in solution, primarily tartaric acid, malic acid, and K in grape juice (Boulton, 1980b). The variability in vine growth, yield components, nutritional status, and weather was used to explain differences in grape acidity over two growing seasons.

Grape berries were collected 30 days after anthesis (30 DAA), at 50% veraison (50V), and at harvest for berry composition analysis. Mean pH by site data are displayed in Table 2.4. A significant difference in mean pH at p-value <0.0001 was found among sites in the 2019 and 2020 growing seasons at 30 DAA and at harvest. At harvest in 2019, sites 1 and 5 had the highest mean pH of 4.493 and 4.623, respectively, and site 7 had the lowest mean pH of 4.094. In 2020, harvest data was not collected for sites 5 and 7 due to crop loss. At harvest in 2020, sites 1, 3, and 4 had the significantly highest mean pH of 4.402, 4.314, and 4.286 respectively, and site 2 had the significantly lowest mean pH of 3.952. Across all years and years combined, sites 1 and 5 had the highest juice pH. Site 2 had lowest mean pH across all years and years combined.

Important Predictors of pH

To determine the correlation between grape juice pH and key vine physiological attributes and environmental factors, PLSR analysis was performed to construct best fit predictive models (Table 2.5). Models were constructed for data collected in 2019, 2020, and for data from both years combined at 30 DAA, 50V, and harvest. PLSR analysis was performed using a total of 69 acidity predictor variables (APV), and with measures of acidity (tartaric acid, malic acid, and total acidity) removed (AVR) due to their strong, well-known relationship with pH. The goal of the study was to identify viticultural factors that influence pH that may be manipulated through vineyard practices.

PLSR Analysis with All Acidity Predictive Variables

The PLSR analysis with all 69 predictor variables included was performed to test the expected strong correlations between pH and tartaric acid, malic acid, and total acidity. A mean of 9 variables (berry composition and yield components) explained the greatest variance in predictor variables and grape juice pH (Table 2.5). The six most important variables to each model are provided in Table 2.6.

At all collection timings, berry composition indices of K, tartaric acid, malic acid, and °Brix show the greatest importance (VIP $\geq$ 1.077; coefficients $\geq \pm$ 0.0298). Of those variables, juice K had the highest model correlation coefficient with pH (VIP $\geq$ 1.483; coefficients $\geq \pm$ 1.1695) at the three collection timings (Table 2.6). The correlation between K and juice pH has been reported previously (Boulton 1980a; Hepner and Bravado, 1985; Gawel et al., 2000; Rogiers, et al., 2017). Ordinary Least Squares Regression (OLSR) analysis was conducted to further understand this positive correlation (Figure 2.1). In the

2019 fitted regression, K accounted for 48% of the variation in berry pH at 30 DAA, 68% of the variation at 50V, and 84% of the variation at harvest. A similar increase in the percent of variation of pH through berry development was observed in the 2020 growing season. These results indicate that the proportion of the variance in juice pH explained by juice K increases with grape berry growth and development. Mean K concentration from all sites increase by 58.5% from 30DAA to 50V and 65.5% from 50V to harvest in 2019. Mean K concentrations from all sites increase by 34.06% from 30DAA to 50V and 73.89% from 50V to harvest in 2020. Similar results were found in a study on Carignane grapevines, where K concentration accumulated rapidly until the berries reached 10°Brix, followed by relatively slow accumulation between 10° and 17°Brix, and then a second rapid period of accumulation during the final stages of ripening (Freeman and Kliewer, 1983).

The proportion of major organic acids (VIP ≥ 1.0435; coefficients ≥ ± 0.0348) and dissolved sugars (VIP ≥ 1.0504; coefficients ≥ ± 0.0145) are also high in importance for predicting pH (Table 2.6). An order of variable importance cannot be easily defined between organic acids and major sugars because of fluctuation in coefficient values by year and timing, but tartaric acid, malic acid, glucose, fructose, and °Brix all lie within the number of latent vectors in each PLSR model. Notwithstanding the fluctuation in variables of importance, tartaric acid followed juice K for variable of importance in four of the models (VIP ≥ 1.1745; coefficients ≥ ± 0.0229). OLSR analysis showed tartaric acid to account for 17% of the variation in juice pH, 11% of the variation at 50V, and 48% of the variation at harvest (Table 2.11). °Brix followed K in three of the models (VIP ≥ 1.1113; coefficients ≥

± 0.1147) (Table 2.6). OLSR analysis showed °Brix to account for 31 – 34% of the variation in berry pH between all collection timings (Table 2.11).

Results from the PLSR analysis showed cluster number and crop load to be important predictors of the models at timings 30 DAA and 50V in both growing seasons (VIP ≥ 1.0124; coefficients ≥ ± 0.0001). The correlation between cluster number and juice pH was inconsistent between timings. A slightly negative correlation coefficient of -0.0443 between crop load and berry pH was observed at 50V in years combined. OLSR analysis at the three collection timings in years combined revealed relatively no relationship between juice pH and cluster number or crop load (Table 2.11). OLSR analysis by site and year revealed strong correlations between crop load and pH in 2019. Sites 1 and 4 showed strong negative correlations of 14% and 40%, respectively, between crop load and pH at 30 DAA. Sites 1, 2, and 4 showed strong negative correlations of 20%, 14%, and 22%, respectively, between crop load and pH at 50V. Sites 1, 2, and 6 showed strong negative correlations of 12%, 17%, and 15%, respectively, between crop load and pH at harvest. Measurements of cluster number and crop load may not have accounted for intentional fruit thinning or shoot hedging over the growing season, which could have contributed to the varying correlations. Research conducted on the effects of crop load on juice pH and K have been conflicting. One study that compared juice quality from Carignane vines not thinned and thinned to one cluster per shoot observed no effect on grape juice pH, titratable acidity and K between the treatment and control (Freeman and Kliewer, 1983). Another study observed an increase in juice K when crop load decreased in Carignane and Cabernet-Sauvignon (Hepner and Bravdo 1985). The researches partially accredited the increase in juice K in Cabernet-

Sauvignon to crop load reduction by frequent irrigation. The variation in crop load effect on K and juice pH may indicate an indirect effect dependent on source/sink relationships with K concentration and water availability.

PLSR Analysis with Acid Variables Removed

PLSR analysis with acid variables removed was performed to predict pH by the environmental and cultural predictor variables without interference of tartaric acid, malic acid, or total acidity as pH is a measure of free acid (Table 2.5). These models provide variables of importance for pH that may be manipulated through vineyard management practices. The models predict that a mean of 11 factors (berry composition, nutritional status, and climate) explain the greatest variance in predictor variables and grape juice pH. The six most important variables to each model are provided in Table 2.7.

Consistent with the models constructed with all predictor variables, juice K had the highest correlation to juice pH at the three collection timings (VIP $\geq$ 1.4867; coefficients $\geq \pm$ 0.6724), followed by dissolved sugars (VIP $\geq$ 0.9953; coefficients $\geq \pm$ 0.0167). Cluster count and crop load variables also showed importance at 30 DAA and 50V (VIP $\geq$ 1.0357; coefficients $\geq \pm$ 0.0074) as seen in models constructed including acid variables.

Growing degree days (GDD) were determined by month at each site to provide an additional temperature variable in the PLSR models. Results from the PLSR analysis show GDD in June and July to be important predictors of the models at timings 30 DAA and 50V depending on growing season (VIP $\geq$ 0.9739; coefficients $\geq \pm$ 0.0074; Table 2.11). OLSR analysis showed GDD in June accounted for 58% of the variation in juice pH at 30 DAA in 2019. In years combined, GDD in July accounted for 43% of the variation in juice pH at 30

DAA. These findings agree with the study by Spayd et al. that determined the overall temperature of the berry is inversely related to berry TA (2002).

The PLSR models with acid variables removed also revealed soil parameters to be of lesser, but significant importance to berry pH at harvest in both growing seasons (VIP ≥ 0.9935; coefficients ≥ ± 0.0081; Table 2.7). Soil K at harvest in years combined had a model coefficient of -0.0553, suggesting a slightly negative relationship with juice pH. OLSR analysis confirmed the negative relationship between soil K and juice pH, but soil K does not show to be highly influential, accounting for only 1% of the variance in juice pH (Table 2.11). The amount of K in the plant being a function of the vines capacity to uptake nutrients from the soil may contribute to the low correlation between soil K and juice pH at harvest. The PLSR model at harvest in 2020 suggests soil Ca as an important variable in the models (VIP = 1.0391; coefficient = 0.0105), however OLSR analysis indicated a minor positive relationship between the two variables. In years combined, soil electrical conductivity (EC) variables lie within the number of latent vectors in each PLSR model (VIP = 0.9935; coefficients = 0.3096). OLSR analysis indicated a positive relationship between pH and soil EC in years combined, accounting for 26% of the variation in berry pH at harvest. The significance of soil nutrient content to juice acidity has been researched with varying effects. In a study by Downton and Loveys to assess the effects of salinity in grape development, vines grown under high salinity irrigation produced fruit with higher juice acid than the control throughout pre-veraison (1978). The authors attributed the high juice acidity in salt-treated plants to an increase in osmotic pressure of the juice from the accumulation of

reducing sugars. After veraison, a degradation of malate and tartrate were observed as K concentrations increased in the juice, resulting in a decrease in juice acidity.

Important Predictors of K

In accordance with previous reports (Boulton 1980a; Gawel et al. 2000)**,** the PLSR analysis to predict juice pH indicated that juice K is highly correlated with juice pH across sites. Therefore, identifying variables that directly affect juice K may provide management solutions to control grape juice pH in the vineyard. To determine the correlation between K and key physiological and environmental attributes in grapevine, PLSR analyses were performed to construct best fit predictive models (Table 2.8). Models were constructed for the 2019, 2020, and years combined to predict K in berries at 30 DAA, 50V, and harvest. PLSR analysis was performed using a total of 69 acidity predictor variables (APV), and with measures of acidity (tartaric acid, malic acid, and total acidity) removed (AVR). The acid variables were removed from the second analysis due to the evidently strong relationship between acidity parameters and pH and K that may prevent the models ability to predict important environmental or cultural factors.

PLSR Analysis with All Acidity Predictive Variables

The models conducted with all predictor variables present predict that a mean of seven factors (berry composition, nutritional status, and climate) explain the greatest variance in juice K (Table 2.8). A maximum of the six most important variables to each model are provided in Table 2.9. The significance of the predictive variables lying within the number of latent vectors in each PLSR model for K varied greatly by collection timing.

At 30 DAA, °Brix and total acidity were the two most important variables to explain the greatest variance in juice K, dependent on growing season (VIP ≥ 1.146; coefficients ≥ ± 0.2427). At 50V and harvest, juice pH had the highest correlation to juice K in both growing seasons (VIP ≥ 1.4089; coefficients ≥ ± 0.3255). An apparent difference in the types of important variables following the main variable is present at 30 DAA from 50V and harvest. At 30 DAA, fruit maturity indices, organic acids, and dissolved sugars were the variables with the greatest importance to the models. At 50V and harvest, soil variables and leaf nutrition become prominent in the models. This change in variables of importance as the fruit matures suggests that K content in the juice may be dependent on nutrient remobilization from source to sink relations in the grapevine. It had been previously identified that K accumulation is most rapid after the onset of ripening (Hale, 1977; Possner and Kliewer, 1985; Ramos and Romero, 2017). The process of K uptake and accumulation in grapevine has been explored and defined with limitations. K from the soil is taken up through the roots by membrane transporters and channel proteins and stored in woody plant structures for remobilization to new shoots and leaves during the growing season (Cherel et al., 2014). The amount of K remobilized from long-term storage structures to fruit has not been determined, however, the majority of K within growing shoots and inflorescences comes from woody storage areas (Clarke et al., 2015). Drivers of K accumulation after veraison have been attributed to a change from symplastic to apoplastic phloem loading of K and the decline in xylem flow (During et al., 1987; Findlay et al., 1987).

Leaf nutrient variables K, Cu, and Ca were important in the models for predicting juice K at 50V in the 2019 and 2020 growing seasons (VIP ≥ 0.9596; coefficients ≥ ±

0.0310). OLSR analysis was conducted to further understand the significance of leaf nutrients at these timings (Table 2.12). The results indicate that leaf K at 50V accounted for 35% of the variation in juice K in 2019, and 39% of variation in 2020. Leaf Cu at 50V in growing seasons combined accounted for 19% of the variation in juice K. A negative relationship between leaf Ca and juice K in years combined was observed at 50V (22%). Leaf nutrient analysis by site showed mean leaf K concentrations at 50V were lower at sites 2, 3, 5, and 7 (Range: 8,601 – 11,838 ppm) than sites 1, 4, and 6 (Range: 14,090 – 18,238 ppm) in 2019 and 2020. Mean leaf K concentrations in 2019 at harvest were lower at sites 5, 6, and 7 (Range: 5,563 – 6,776 ppm) than sites 1, 2, 3, and 4 (Range: 9,032 – 18,276 ppm). Mean leaf K concentrations at 50V were lower at sites 2, 3, and 5 (Range: 8,601 – 10,957 ppm) than sites 1, 4, and 6 (Range: 14,398 – 18,381 mg/kg) in 2020. As mentioned previously, site 1 had the highest mean K and juice pH at all collection timings in both years, with the exception of 30 DAA in 2020. In contrast, Site 2 had the significantly lowest mean pH at all collection timings in both years, with the exception of harvest in 2019. At 50V and harvest in both growing seasons, leaf K concentration at site 1 was in the higher range and leaf K concentration at site 2 was in the lower range, suggesting the concentrations of juice K during ripening is partially dependent on K concentrations in the leaves. This phenomenon has been previously identified. Remobilization of K from other plant tissues to the grape berry may depend on soil K availability, K uptake capacity of the roots, and rates of K translocation from root to shoot to meet the berry demand for K (Mpelasoka, et al., 2003). The roles of K in sucrose phloem loading and stomatal regulation may contribute to the positive correlation between leaf K and juice K during ripening. K assistance in re-

energizing the transmembrane phloem loading process has been observed in *Arabidopsis* (Wolf et al., 2008). This process occurs if excess K is available after it has been transported along the phloem stream to K deficient areas of the plant.

Soil variables were also prominent in the models for predicting juice K at 50V and harvest in the years combined data (VIP ≥ 0.9447; coefficients ≥ ± 0.006). OLSR analysis was conducted to further understand the significance of soil nutrients at these timings (Table 2.12). The results indicate that soil K at 30 DAA accounted for 35% of the variation. Soil EC at 50V and harvest accounted for 74% and 65%, respectively, of the variation in juice K. Soil Ca at harvest accounted for 29% of the variation in juice K. At harvest, soil EC was the most important soil parameter. The degree of salinity in the soil measured as soil EC_e (dS/m) was determined for each site according to Michael Cahn (n.d.). All sites were considered non-saline (< 4 dS/m). Sites 1 and 4 had the lowest soil EC at 0.07 and 0.16 dS/m, respectively, and site 7 had the highest at 0.4 dS/m. The remaining sites had a soil EC range of 0.2 – 0.25 dS/m.The sufficiency ranges for soil pH, phosphorous (P), potassium (K), calcium (Ca), and magnesium (Mg) concentrations were determined for each site according to the Wolf, et al. (2008). Site 1 had a soil pH within the sufficient range for growing *Vitis vinifera*, and all other sites were above the sufficient range for soil pH. P deficiency (< 20 ppm) was present at sites 1, 2, 3, and 6. Site 1 was deficient in soil K (<75 ppm), and all other sites were high in soil K (>100 ppm). Ca was high at sites 2 and 3 (>2,000 ppm). Site 1 was deficient in Mg (<100 ppm), and sites 5, 6, and 7 were high in Mg (>250 ppm). The soil conditions at site 1 appear contradictory to the juice pH and K concentrations at harvest in both growing seasons. Site 1 had the significantly highest mean

pH at all collection timings in both years, with the exception of 30 DAA in 2020 (Table 2.4). Mean K concentrations at site 1 were also the highest at all collection timings in both years, with the exception of 30 DAA in 2020 (Range: 687.45 – 2797.75 mg/L). Conversely, the soil pH at site 1 was slightly acidic (6.5) and the soil was deficient in K (56 ppm) and Mg (83 ppm). In contrast, Site 2 had the significantly lowest mean pH at all collection timings in both years, with the exception of harvest in 2019 (Table 2.4). Mean K concentration at site 2 was lower than the mean K concentration at site 1 by collection timing and year (Range: 635.06 – 1348.70 mg/L). Mean K concentration of all collection timings in growing seasons combined was 42% less at site 2 than at site 1. The soil pH at site 2 was the highest of all sites (7.8) and high in K (157 ppm). These contradicting measures suggest another variable is responsible for juice pH and K concentrations. Previous research has shown inconsistent responses in grapevine to soil conditions. Morris et al. (1983) observed an increase in petiole K from 1.24% (dry weight basis) in control plants to 6.07% in plants grown under high K fertilizers. In addition, an increase in juice K was also observed with high levels of K fertilization, resulting in pH increases and titratable acidity reductions in the juice. In another study, K fertilization had no effect on grape juice pH, titratable acidity and K (Freeman and Kleiwer, 1983). The variation in grapevine response to soil K concentrations may be attributed to the complexities of soil nutrient chemical reactions (Mpelasoka et al., 2003).

The results shown in Table 2.9 also indicate that rainfall in 2020 was of importance at 30 DAA and harvest (VIP $\geq$ 1.0991; coefficients $\geq \pm$ 0.0004). OLSR analysis showed rainfall in April accounted for 70% of the variation in juice K at 30 DAA. At harvest,

rainfall in June and July accounted for 83% and 66% of the variation in juice K. Rainfall data by site are displayed in Table 2.3. The mean amount of rainfall received in 2020 was 38% less than the rainfall received in 2019 (Table 2.3). In 2020, site 1 had the mean highest pH (4.4) at harvest, and site 2 had the lowest mean pH (3.95) at harvest (Table 2.4) Rainfall in June of 2020 at site 1 was 64% greater than rainfall at site 2. Rainfall in July of 2020 at site 1 was 72% greater than rainfall at site 2. K concentration at site 1 was also higher than site 2 by 62% at harvest that year. These findings, parallel to the high positive linear correlation between monthly rainfall and juice K, suggest that an increase in rainfall or irrigation during mid-to-late-veraison will result in an increase in juice K, thus an increase in juice pH. Previous studies corroborate these findings. Hepner and Bravdo (1985) observed frequent irrigation to be partially responsible for a reduction in crop load, and thus an increase in juice K in Cabernet-Sauvignon. Another study observed this same relationship, in that an increase in pH and K was observed in vines grown under high irrigation (Freeman and Kleiwer, 1983). K uptake by plants is often escalated in by surplus of water due to increased mobility in the soil and rapid root uptake (Tazawa et al., 2001).

PLSR Analysis with Acid Variables Removed

The PLSR analysis with acidity variables removed (AVR) was performed to predict K by the environmental and cultural predictor variables without interference of tartaric acid, malic acid, total acidity, or pH (Table 2.5). These models provide variables of importance for K that may be manipulated through vineyard management practices. These models predicted a mean of 4 factors (nutritional status and rootstock) explain the greatest

variance in predictor variables and grape juice K. A maximum of the six most important variables to each model are provided in Table 2.8.

With acidity variables removed, the variables of greatest importance were leaf and soil nutrition (VIP ≥ 0.8672; coefficients ≥ ± 0.1145), followed by rootstock (VIP ≥ ; coefficients ≥ ±), and rainfall and temperature (VIP ≥ 1.1855; coefficients ≥ ± 0.034). Leaf P (VIP ≥ 1.3229; coefficients ≥ ± 0.1743) and soil EC (VIP ≥ 1.3044; coefficients ≥ ± 0.0392) were modeled as important predictors of K at 30 DAA in both growing seasons. OLSR analysis indicated 25% of the variation in juice K was explained by leaf P, and 14% of the variation in juice K was explained by soil EC (Table 2.12). At 50V and harvest, leaf K (VIP ≥ 0.9752; coefficients ≥ ± 0.0126), soil EC (VIP ≥ 1.2894; coefficients ≥ ± 0.4779), soil K (VIP = 1.2496; coefficients = -0.0472), and soil Ca (VIP ≥ 1.3914; coefficients ≥ ± 0.1439) were the most important variables, dependent on growing season. At 30 DAA in 2019, cluster exposure flux availability (CEFA) had the greatest variable of importance of 1.3936 with a correlation coefficient of 0.2604, however, OLSR analysis showed only a 2% predictivity of variation in juice K, suggesting CEFA to be of lesser importance than determined by PLSR analysis (Table 2.12).

With acidity variables removed, PLSR analysis modeled rootstock to be a variable of importance in predicting K (VIP ≥ 1.3882; coefficients ≥ ± 0.1173). In the years combined data, rootstock accounted for 25% of the variability in K at 50V and 33% of the variability in K at harvest (Table 2.12). A comparison of rootstocks to mean pH by site at 50V and harvest in growing seasons combined suggests that own-rooted and 101-14 Mgt grafted vines produced the lowest juice pH, 3309 Couderc grafted vines produced moderate juice

pH, and 1103 Paulsen vines produced the highest juice pH. Previous studies showed similar results for rootstock 101-14 Mgt and contrasting results for 1103 Paulsen. The effect of the rootstock on scion nutrition and growth has been well documented in the literature (Delas & Pouget, 1979; Kodur, 2011; Garcia et al. 2001; Loue et al. 1984; Valcheva et al. 2012). In a rootstock trial by Ruhl, the scion variety Sultana was grafted to six different rootstock varieties and the juice acidity was analyzed (1989). Rootstocks 1103P (*V. berlandieri* X *V. rupestris*), 110R (*V. berlandieri* x *V. rupestris*), and 1202 (*V. vinifera* x *V. rupestris*) had the lowest pH and lowest concentrations of K. In another study, rootstock SO4 (*Vitis Berlandieri x Vitis riparia*) had greater K concentrations and higher pH in the must than 3309 C (*Riparia tomenteux x Rupestris martin*) and 101-14 Mgt (*Vitis riparia x Vitis rupestris*) when grown under identical conditions (Garcial, et al., 2001). Mg and Ca concentrations were also lower in SO4 than 3309 C and 101-14 Mgt.

Summary

Results from the Partial Least Squares Regression (PLSR) analyses identified twenty predictive variables to be of the greatest importance in predicting grape juice pH. The twenty variables are categorized as berry maturity indices, temperature, water status, soil conditions, rootstock genotype, leaf nutrition, and crop load. As observed in previous studies (Boulton 1980a; Gawel et al. 2000)**,** grape juice K concentration had the highest model correlation coefficient with pH (VIP $\geq$ 1.483; coefficients $\geq \pm$ 1.1695) at all collection timings in 2019 and 2020. This strong correlation indicates that K is the key variable for

manipulating grape juice pH. Therefore, identifying variables that directly affect juice K may provide management solutions to control grape juice pH in the vineyard. PLSR analyses determine twelve latent vectors to be of the greatest importance in predicting grape juice K. The twelve latent vectors are categorized as temperature, water status, soil conditions, rootstock genotype, and leaf nutrition. The variation in juice K in grapevine appears to be a function of the rootstocks ability to take up the nutrients available in the soil. Increased ambient temperatures and increased water status from the onset of berry ripening to mid-ripening correlated to an increase in K concentrations in the leaves, and thus in the berries at harvest. Future research should consider the importance of potassium, plant nutrient availability, soil nutrient availability, rootstock cultivar, and vine water status as viticulture factors important in directly influencing juice acidity. By focusing on these five variables, future research may determine a precise vineyard management approach to decrease berry pH and thus, increase berry acidity.

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Table 2.1 Research sites characteristics

Site ID	Location	Site Coordinates	Regional Weather Station Coordinates	Soil series	Scion	Rootstock	Year Planted	Number of vines	
								2019	2020
Site 1	Southlake, TX	32°57'06.8"N -97°09'58.9"W	32.8978° N -97.0189° W	Vertisols	Tempranillo clone 11.1	1103 Paulsen	2018	20	20
Site 2	Weatherford, TX	32°50'49.4"N -97°39'26.8"W	32.7816° N -98.0602° W	Vertisols	Tempranillo clone 11	101-14 Mgt	2015	20	20
Site 3	Mingus, TX	32°27'12.3"N -98°27'27.3"W	32.4444° N -97.8169° W	Mollisols	Tempranillo clone 05	3309 Couderc	2008	20	20
Site 4	Edna Hill, TX	31°58'09.0"N -98°21'55.8"W	32.2153° N -98.1775° W	Mollisols	Tempranillo	1103 Paulsen	2015	20	20
Site 5	Brownfield, TX	33°11'18.5"N -102°14'08.9"W	33.1713°N -101.7980° W	Alfisols	Tempranillo	1103 Paulsen	2014	20	20
Site 6	Brownfield, TX	33°09'05.1"N -102°13'13.5"W	33°10'30.8"N -102° W	Alfisols	Tempranillo clone 02	Ownrooted	2007	30	20
Site 7	Tokio, TX	33°08'24.1"N -102°34'50.7"W	33.1869°N -102.8281° W	Alfisols	Tempranillo	101-14 Mgt	2015	20	0

Table 2.2 Date of data collection by site in 2019 and 2020 at anthesis[a], 30 DAA, 50% veraison, harvest and rough pruning[b]

	2019					2020				
Site	Pruning	Anthesis	30 DAA	50% veraison	Harvest	Pruning	Anthesis	30 DAA	50% veraison	Harvest
1	-	-	20-Jun	19-Jul	31-Jul	15-Jan	1-May	15-Jun	19-Jul	9-Aug
2	-	-	20-Jun	19-Jul	31-Jul	16-Jan	1-May	15-Jun	19-Jul	4-Aug
3	-	-	21-Jun	19-Jul	17-Aug	8-Mar	1-May	15-Jun	19-Jul	15-Aug
4	-	-	21-Jun	19-Jul	31-Jul	1-Feb	1-May	15-Jun	19-Jul	8-Aug
5	-	-	26-Jun	30-Jul	6-Sep	-	24-May	29-Jun	13-Jul	-
6	-	-	25-Jun	30-Jul	6-Sep	1-Feb	24-May	29-Jun	13-Jul	16-Aug
7	-	-	25-Jun	30-Jul	19-Aug	-	-	-	-	-

[a]Anthesis data was not collected in 2019

[b] Pruning data was not collected in 2019

Table 2.3 Temperature, rainfall, and GDD by site from April to August in 2019 and 2020

	2019				2020		
Site	Month	Temperature[b]	Rainfall	GDD[c]	Month	Temperature	Rainfall	GDD
		---- °C ----	---- mm ----			---- °C ----	---- mm ----	
1	Apr	18.89	171.45	162	Apr	18.11	48.26	151
	May	23.00	207.01	367	May	23.22	191.52	367
	Jun	26.9844[a]	104.90	479	Jun	26.01[a]	135.89	516
	Jul	37.98[a]	19.81	595	Jul	28.51[a]	58.67	595
	Aug	42.21[a]	61.98	624	Aug	28.59[a]	32.26	599
2	Apr	18.17	146.05	282	Apr	17.11	24.89	119
	May	21.83	267.97	453	May	22.61	100.08	338
	Jun	26.00[a]	85.09	623	Jun	25.79[a]	48.51	495
	Jul	26.90[a]	32.51	604	Jul	29.05[a]	16.26	590
	Aug	29.53[a]	130.56	526	Aug	28.31[a]	11.94	599
3	Apr	25.00	224.54	0	Apr	19.44	15.49	158
	May	23.33	161.80	26	May	23.33	107.44	378
	Jun	27.22	135.13	21	Jun	27.05[a]	93.73	528
	Jul	31.11	47.50	287	Jul	30.12[a]	45.47	637
	Aug	27.22	48.26	204	Aug	28.55[a]	9.65	602
4	Apr	23.33	9.65	153	Apr	18.89	4.06	121
	May	22.78	10.41	313	May	23.89	75.95	344
	Jun	26.11	69.09	456	Jun	25.74[a]	73.41	475
	Jul	29.44	1.27	553	Jul	28.69[a]	37.85	599
	Aug	27.22	55.12	609	Aug	28.74[a]	0.00	541
5	Apr	16.39	85.60	50	Apr	15.56	0.51	63
	May	19.72	84.33	116	May	22.50	65.02	313
	Jun	24.44	41.40	413	Jun	25.83	58.93	465
	Jul	27.78	1.27	545	Jul	29.17	14.73	593
	Aug	28.89	25.91	584	Aug	28.06	13.97	560

Table 2.3 Continued

6	Apr	16.72	44.45	213	Apr	15.83	0.51	289
	May	19.89	100.58	324	May	21.11	52.32	311
	Jun	24.94	52.32	537	Jun	25.28	46.99	496
	Jul	27.78	0.00	579	Jul	26.39	46.99	592
	Aug	29.11	54.36	459	Aug	25.83	13.72	554
7	Apr	15.00	22.35	34	Apr	-	-	-
	May	18.89	33.78	144	May	-	-	-
	Jun	23.61	73.15	376	Jun	-	-	-
	Jul	28.06	8.64	520	Jul	-	-	-
	Aug	26.11	55.12	555	Aug	-	-	-

[a]Data collected on-site by WatchDog 1650 Micro Station weather stations

[b]Temperature values determined as a total mean of the daily temperature means recorded by month

[c]GDD: growing degree days. Determined as GDD = [(maximum daily temperature + minimum daily temperature) / 2] – 10_{base}

Table 2.4 Mean (+ SD) pH in Tempranillo by site in 2019, 2020, and years combined at 30 DAA, 50% veraison, and harvest

	2019						2020					
Site	30 DAA[b]	SD	50% veraison	SD	Harvest	SD	30 DAA	SD	50% veraison	SD	Harvest	SD
1	3.385a[c]	0.075	3.934a	0.117	4.493ab	0.130	3.332c	0.055	3.849a	0.106	4.402a	0.189
2	3.298bcd	0.063	3.71b	0.139	4.237c	0.099	3.323c	0.091	3.717b	0.147	3.952c	0.137
3	3.307bcd	0.070	3.828ab	0.120	4.246c	0.143	3.449ab	0.072	3.842a	0.063	4.314ab	0.226
4	3.261d	0.043	3.761b	0.113	4.094c	0.132	3.344c	0.046	3.845ab	0.130	4.286ab	0.131
5	3.324abc	0.054	3.937a	0.136	4.623a	0.131	3.487a	0.080	3.909a	0.172	-	-
6	3.361ab	0.091	-	-	4.438b	0.194	3.403b	0.054	3.8ab	0.121	4.171b	0.254
7	3.275cd	0.068	3.753b	0.162	4.094d	0.149	-	-	-	-	-	-
p[a]	< 0.0001		< 0.0001		< 0.0001		< 0.0001		< 0.0143		< 0.0001	

	Years Combined						p-value (year)[d]			
Site	30 DAA	SD	50% veraison	SD	Harvest	SD	Site	30 DAA	50% veraison	Harvest
1	3.358ab	0.070	3.893a	0.118	4.448b	0.167	1	< 0.0026	< 0.0204	< 0.0907
2	3.310bc	0.078	3.714c	0.141	4.094d	0.187	2	< 0.1296	< 1.0000	< 0.9043
3	3.378a	0.100	3.834ab	0.098	4.28c	0.190	3	< 1.0000	< 1.0000	< 0.0001
4	3.303c	0.061	3.803b	0.127	4.279c	0.130	4	< 1.0000	< 1.0000	< 0.0819
5	3.394a	0.105	3.925a	0.152	4.623a	0.131	5	< 0.9888	< 0.0001	< 1.0000
6	3.374a	0.084	3.8abc	0.121	4.345bc	0.250	6	< 0.0223	< 1.0000	< 0.9505
7	3.275c	0.068	3.753bc	0.162	4.094d	0.149	7	< 1.0000	< 1.0000	< 1.0000
p[a]	< 0.0001		< 0.07		< 0.0001					

[a]p-value, comparison of mean pH by research site.
[b]DAA: days after anthesis.
[c]Means within a column followed by the same letter are not significantly different at the 0.05 level of probability (Games-Howell).
[d]Comparison of mean pH by year (Welch's test).

Table 2.5 Best fit predictive models[a] for grape juice pH in 2019, 2020, and years combined at 30 DAA, 50% veraison, and harvest[b]

Year	Data Type	Collection Timing	Number of factors	Root Mean PRESS	Cumulative Q^2	Cumulative R^2X	Cumulative R^2Y
2019	APV	30 DAA	10	0.3960	1.0000	0.9513	0.8893
2019	AVR	30 DAA	11	0.4119	1.0000	0.9430	0.8872
2019	APV	50V	8	0.3089	1.0000	0.8860	0.9560
2019	AVR	50V	9	0.3312	1.0000	0.8885	0.9732
2019	APV	Harvest	9	0.3336	1.0000	0.8791	0.9721
2019	AVR	Harvest	9	0.2773	1.0000	0.9208	0.9609
2020	APV	30 DAA	10	0.4983	1.0000	0.9123	0.8639
2020	AVR	30 DAA	12	0.5203	1.0000	0.9526	0.8294
2020	APV	50V	10	0.3659	0.9999	0.9648	0.9151
2020	AVR	50V	6	0.3634	1.0000	0.9146	0.9058
2020	APV	Harvest	10	0.2845	1.0000	0.9660	0.9585
2020	AVR	Harvest	12	0.2728	1.0000	1.0000	0.9529
YC	APV	30 DAA	9	0.3982	1.0000	0.9303	0.8877
YC	AVR	30 DAA	15	0.3906	1.0000	0.9659	0.9081
YC	APV	50V	8	0.2645	1.0000	0.9414	0.9587
YC	AVR	50V	8	0.3255	1.0000	0.9497	0.9360
YC	APV	Harvest	9	0.2790	1.0000	0.9140	0.9584
YC	AVR	Harvest	13	0.2608	1.0000	0.9872	0.9592

[a]Models conducted with JMP Pro 15 Statistical Software using Leave-One-Out Cross Validation with NIPALS method

[b]Abbreviatons: DAA, days after anthesis; 50V, 50% veraison; YC, years combined; APV, all acidity predictive variables; AVR, acid variables removed

Table 2.6 Variable of importance coefficients and model coefficients from best fit predictive models[a] for grape juice pH in 2019, 2020, and years combined at 30 DAA, 50% veraison, and harvest[b]

	30 DAA			50V			Harvest		
	Variable of Importance	VIP coefficient	Model coefficient	Variable of Importance	VIP coefficient	Model coefficient	Variable of Importance	VIP coefficient	Model coefficient
2019	Juice K- 1[c]	1.616	1.2012	Juice K- 2[d]	1.8205	0.801	Juice K- 3[e]	1.7048	0.7116
	Tartaric Acid- 1	1.531	-0.2201	°Brix- 2	1.5869	0.1212	Tartaric Acid- 3	1.3822	0.0298
	°Brix- 1	1.189	0.3267	Glucose- 2	1.5517	0.0955	°Brix- 3	1.2686	0.1147
	Total Acidity- 1	1.153	-0.3468	Fructose- 2	1.5499	0.076	Malic Acid- 3	1.22	0.039
	Malic Acid- 1	1.077	-0.2214	Crop load- 3	1.2205	0.0001	Fructose- 3	1.2144	0.0535
	Cluster number- 1	1.049	0.0656	Soil pH	1.0707	-0.021	Glucose- 3	1.1989	0.0145
2020	Juice K- 1	1.7669	1.1695	Juice K- 2	1.6956	0.8001	Juice K- 3	1.483	0.9732
	Yield per Vine- 1	1.2906	-0.3283	°Brix- 2	1.4188	0.3432	Malic Acid- 3	1.2175	0.3002
	Cluster number- 1	1.1557	0.05	Fructose- 2	1.3453	0.1254	Tartaric Acid- 3	1.1745	-0.1692
	Mean cluster weight- 1	1.1521	-0.0637	Glucose- 2	1.2929	-0.0834	Rainfall (Jul)	1.1451	-0.0385
	Leaf Cu- 1	1.1047	0.0462	Cluster number- 3	1.1393	-0.0994	Soil Ca	1.1264	0.0948
	Nitrate-N- 1	1.1032	0.0578	GDD (Jul)	0.9572	0.0726	Juice K- 2	1.0911	0.0928
Years Combined	Juice K- 1	1.5802	1.1886	Juice K- 2	1.5613	0.8233	Juice K- 3	1.6126	0.7883
	Tartaric Acid- 1	1.4816	-0.1988	°Brix- 2	1.335	0.1261	Tartaric Acid- 3	1.4627	0.0229
	°Brix- 1	1.1671	0.3263	Fructose- 2	1.3021	0.0666	Malic Acid- 3	1.1382	0.4312
	Total Acidity- 1	1.115	-0.35	Glucose- 2	1.2973	0.0989	°Brix- 3	1.1113	0.1385
	Malic Acid- 1	1.0435	-0.2278	Crop load- 3	1.0512	-0.0443	Juice K- 2	1.0687	0.0565
	Cluster number- 1	1.0124	0.1105	GDD (Jun)	0.9641	0.0087	Fructose- 3	1.0504	0.0348

[a]Models conducted with JMP Pro 15 Statistical Software using Leave-One-Out Cross Validation with NIPALS method
[b]Abbreviatons: DAA, days after anthesis; 50V, 50% veraison; YC, years combined; VIP, variable of importance; GDD, growing degree days
[c] Variables followed by 1 indicate collection timing at 30 DAA
[d]Variables followed by 2 indicate collection timing at 50% veraison
[e]Variables followed by 3 indicate collection timing at harvest

Table 2.7 Variable of importance coefficients and model coefficients from best fit predictive models[a] with acid variables removed for grape juice pH in 2019, 2020, and years combined at 30 DAA, 50% veraison, and harvest[b]

	30 DAA			50V			Harvest		
	Variable of Importance	VIP coefficient	Model coefficient	Variable of Importance	VIP coefficient	Model coefficient	Variable of Importance	VIP coefficient	Model coefficient
2019	Juice K- 1[c]	1.7778	0.9097	°Brix- 2[d]	1.7594	0.118	Juice K- 3[e]	1.8523	1.0704
	°Brix- 1	1.3395	0.3805	Juice K- 2	1.7369	0.7527	Juice K- 2	1.2135	-0.0173
	Cluster number- 1	1.152	0.1309	Glucose- 2	1.7361	0.0896	°Brix- 3	1.2045	0.1414
	GDD (Jul)	1.14	0.0302	Fructose- 2	1.7201	0.067	Fructose- 3	1.1484	0.0237
	Temperature °C (Aug)	1.1128	-0.0435	Crop load- 3	1.1163	0.0337	Glucose- 3	1.1292	-0.0167
	GDD (Jun)	1.055	0.0493	Leaf Mn- 1	1.0668	-0.1467	Soil K	1.0284	-0.0081
2020	Potassium- 1	1.7562	0.8528	Juice K- 2	1.7084	0.6724	Juice K- 3	1.4867	0.9861
	Yield per Vine- 3	1.1192	-0.2952	°Brix- 2	1.4016	0.1907	Juice K- 2	1.0998	0.0087
	Soil nitrate-N	1.1141	-0.131	Fructose- 2	1.3271	0.1288	Rainfall (Jul)	1.085	-0.1112
	GDD (Jul)	1.0804	0.7013	Glucose- 2	1.2728	0.0857	Soil Ca	1.0391	0.0105
	Leaf N- 1	1.0464	0.0901	Cluster number- 3	1.0847	-0.1543	Soil nitrate-N	0.9956	0.0746
	Ep1- 1	1.015	0.0704	GDD (Jul)	0.9425	0.0841	°Brix- 3	0.9915	0.1712
Years Combined	Juice K- 1	1.8332	0.5759	Juice K- 2	1.6056	0.7725	Juice K- 3	1.7073	1.0387
	°Brix- 1	1.4203	1.2442	°Brix- 2	1.3676	0.0908	Juice K- 2	1.151	-0.0171
	GDD (Jul)	1.1664	0.0418	Fructose- 2	1.329	0.0918	°Brix- 3	1.0628	0.6961
	Cluster number- 1	1.1577	0.0074	Glucose- 2	1.3278	0.1014	Soil K	1.0166	-0.0553
	Temperature °C (Aug)	1.1524	-0.1076	Crop load- 3	1.0357	-0.0275	Fructose- 3	0.9953	-0.3486
	GDD (Jun)	1.08	-0.0356	GDD (Jun)	0.9739	0.0312	Soil EC	0.9935	0.3096

[a]Models conducted with JMP Pro 15 Statistical Software using Leave-One-Out Cross Validation with NIPALS method
[b]Abbreviatons: DAA, days after anthesis; 50V, 50% veraison; YC, years combined; VIP, variable of importance; Ep1, canopy calibration coefficient; EC, electrical conductivity
[c] Variables followed by 1 indicate collection timing at 30 DAA
[d]Variables followed by 2 indicate collection timing at 50% veraison
[e]Variables followed by 3 indicate collection timing at harvest

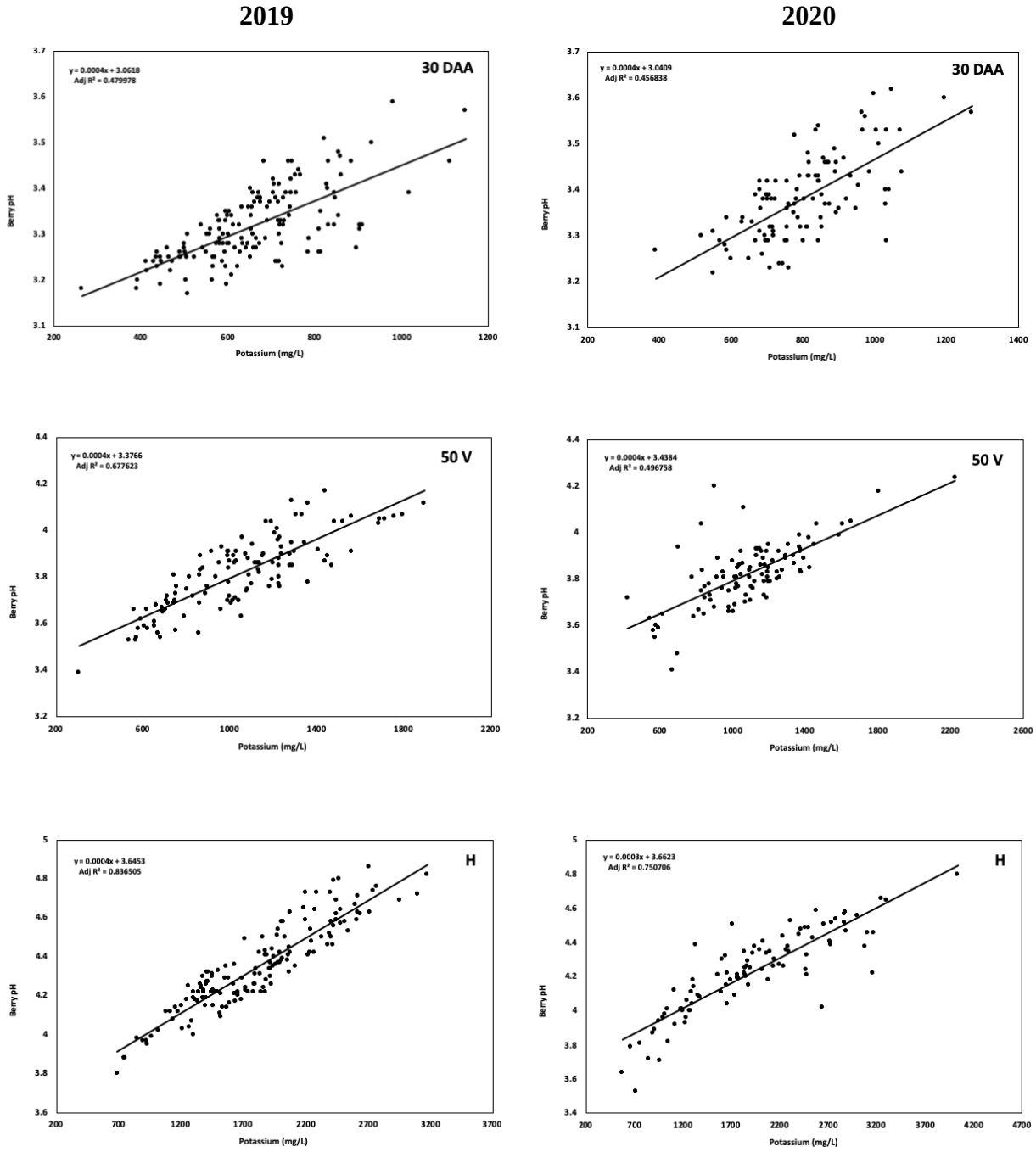

Figure 2.1 Ordinary Least Squares Regression of pH by potassium (K) in the 2019 and 2020 growing seasons. There is a significant correlation between pH and K at p-value <0.0001 for all timings. Abbreviations for collection timings: 30 DAA, 30 days after anthesis; 50V, 50% veraison; H, harvest.

Table 2.8 Best fit predictive models[a] for grape juice potassium in 2019, 2020, and years combined at 30 DAA, 50% veraison, and harvest[b]

Year	Data Type	Collection Timing	Number of factors	Root Mean PRESS	Cumulative Q^2	Cumulative R^2X	Cumulative R^2Y
2019	APV	30 DAA	9	0.1907	1.0000	1.0000	0.9695
2019	AVR	30 DAA	5	0.7877	0.8773	0.7342	0.5776
2019	APV	50V	9	0.2505	1.0000	0.9009	0.9796
2019	AVR	50V	1	0.6243	0.6103	0.5499	0.6540
2019	APV	Harvest	15	0.1341	1.0000	0.9635	0.9931
2019	AVR	Harvest	3	0.6459	1.0000	0.6051	0.7054
2020	APV	30 DAA	4	0.3015	0.9985	0.5985	0.9408
2020	AVR	30 DAA	2	0.8456	0.4541	0.5992	0.3875
2020	APV	50V	7	0.2598	1.0000	0.8723	0.9580
2020	AVR	50V	4	0.5387	0.9892	0.6745	0.8504
2020	APV	Harvest	8	0.1433	1.0000	0.9434	0.9887
2020	AVR	Harvest	2	0.5948	0.8711	0.7051	0.6845
YC	APV	30 DAA	6	0.2818	0.9999	0.9997	0.9271
YC	AVR	30 DAA	6	0.7787	0.9250	0.7569	0.6090
YC	APV	50V	5	0.3318	0.9999	0.7032	0.9668
YC	AVR	50V	7	0.6295	0.9978	0.8640	0.7466
YC	APV	Harvest	4	0.1883	1.0000	0.8829	0.9750
YC	AVR	Harvest	4	0.6798	0.9414	0.5251	0.8009

[a]Models conducted with JMP Pro 15 Statistical Software using Leave-One-Out Cross Validation with NIPALS method

[b]Abbreviatons: DAA, days after anthesis; 50V, 50% veraison; YC, years combined; APV, all acidity predictive variables; AVR, acid variables removed

Table 2.9 Variable of importance coefficients and model coefficients from best fit predictive models models[a] for grape juice K in 2019, 2020, and years combined at 30 DAA, 50% veraison, and harvest[b]

	30 DAA			50V			Harvest		
	Variable of Importance	**VIP coefficient**	**Model coefficient**	**Variable of Importance**	**VIP coefficient**	**Model coefficient**	**Variable of Importance**	**VIP coefficient**	**Model coefficient**
2019	°Brix- 1[c]	1.233	-0.0337	pH- 2[d]	1.6245	0.5960	pH- 3[e]	1.6435	0.3255
	Total Acidity- 1	1.212	-1.7085	Malic Acid- 2	1.2639	0.3031	Tartaric Acid- 3	1.4429	0.2531
	Malic Acid- 1	1.196	1.9378	Soil K	1.0976	0.0134	Malic Acid- 3	1.3533	0.6396
	Tartaric Acid- 1	1.026	0.5525	Soil Mg	1.0768	0.0236	Soil EC	1.1767	-0.0674
	pH- 1	1.009	0.2703	Soil EC	1.0745	-0.0571	Soil S	1.0783	-0.0481
	Glucose- 1	0.930	0.0236	Leaf K- 2	1.0671	0.0015	GDD (Jun)	1.0718	0.0381
2020	Total Acidity- 1	1.922	0.2427	pH- 2	1.6938	0.4415	pH- 3	1.4089	0.3818
	Malic Acid- 1	1.793	0.2086	Tartaric Acid- 2	1.1971	0.2953	Malic Acid- 3	1.2932	0.2836
	pH- 1	1.742	0.2967	Soil Ca	1.1765	-0.1342	Rainfall (Jul)	1.1638	-0.0185
	Tartaric Acid- 1	1.576	0.2758	Malic Acid- 2	1.1685	0.1738	Tartaric Acid- 3	1.1345	0.2787
	°Brix- 1	1.5201	0.1629	Leaf K- 2	1.1628	0.0374	Rainfall (Jun)	1.0991	-0.0004
	Rainfall (Apr)	1.2165	-0.0327	Leaf Ca- 2	1.1623	0.0310	Soil EC	1.0985	0.0060
Years Combined	°Brix- 1	1.146	-0.6323	pH- 2	1.6845	0.2937	pH- 3	1.4875	0.4398
	pH- 1	1.112	0.3395	Malic Acid- 2	1.3456	0.1606	Tartaric Acid- 3	1.2495	0.2719
	Malic Acid- 1	1.0766	1.1078	Soil K	1.2167	-0.0080	Malic Acid- 3	1.1675	0.2280
	Total Acidity- 1	1.0604	-0.3490	Leaf Cu- 2	1.2045	0.0534	Soil EC	1.0356	-0.0458
	Glucose- 1	0.8775	-0.5613	Soil EC	1.1875	-0.0341			
	Tartaric Acid- 1	0.8704	0.3230						

[a]Models conducted with JMP Pro 15 Statistical Software using Leave-One-Out Cross Validation with NIPALS method
[b]Abbreviatons: DAA, days after anthesis; 50V, 50% veraison; YC, years combined; VIP, variable of importance; EC, electrical conductivity

[c] Variables followed by 1 indicate collection timing at 30 DAA

[d]Variables followed by 2 indicate collection timing at 50% veraison
[e]Variables followed by 3 indicate collection timing at harvest

Table 2.10 Variable of importance coefficients and model coefficients from best fit predictive models[a] with acid variables removed for grape juice K in 2019, 2020, and years combined at 30 DAA, 50% veraison, and harvest[b]

	30 DAA			50V			Harvest		
	Variable of Importance	VIP coefficient	Model coefficient	Variable of Importance	VIP coefficient	Model coefficient	Variable of Importance	VIP coefficient	Model coefficient
2019	CEFA- 2[d]	1.3936	0.2604	Soil K	1.2496	-0.0472	Leaf K- 1	1.6527	0.0945
	Leaf P- 1[c]	1.3229	0.1743				GDD (Jun)	1.6509	0.0405
	Soil EC	1.3044	-0.0392				Leaf Na- 1	1.6195	0.1194
	LEFS- 2	1.2748	-0.3365						
	GDD (Aug)	1.2029	-0.0340						
2020	PIC- 2	1.2912	-0.1145	Rootstock	1.6628	-0.1730	Rainfall (Jul)	1.2894	1.2894
	Rainfall mm (Apr)	1.252	-0.0531	Soil Ca	1.6543	-0.1694	Soil EC	1.2712	1.2712
Years Combined	CEFA- 2	1.3997	1.3997	Leaf K – 2	1.6174	0.0833	Soil Ca	1.3914	-0.1439
	Leaf P- 1	1.3596	1.3596	Leaf Ca – 2	1.5221	-0.0793	Soil EC	1.3882	-0.4779
	Soil EC	1.3367	1.3367				Rootstock	1.3493	-0.1173
	GDD (Aug)	1.2055	1.2055				GDD (Jun)	1.1855	0.1577
	LEFS- 2	1.1994	1.1994				Leaf K -1	0.9752	0.0126
	Leaf Cu- 1	1.1990	1.1990				Leaf Zn -2	0.8672	-0.2182

[a]Models conducted with JMP Pro 15 Statistical Software using Leave-One-Out Cross Validation with NIPALS method
[b]Abbreviatons: DAA, days after anthesis; 50V, 50% veraison; YC, years combined; VIP, variable of importance; EC, electrical conductivity; LEFS, leaf exposure flux symmetry, CEFA, cluster exposure flux availability

[c] Variables followed by 1 indicate collection timing at 30 DAA

[d]Variables followed by 2 indicate collection timing at 50% veraison

[e]Variables followed by 3 indicate collection timing at harvest

Table 2.11 Ordinary Least Squares regression of pH by predictor variables identified as important in PLSR models in (list year)[a]

Response variable	Predictor variable	Collection timing	Growing season	Equation	Adjusted R-square
pH- 1	K- 1[b]	30 DAA	Years combined	y = 0.00041x + 3.04775	0.544352
pH- 2	K- 2[c]	50V	Years combined	y = 0.000392x + 3.4034	0.601285
pH- 3	K- 3[d]	Harvest	Years combined	y = 0.0003256x + 3.6964	0.696411
pH- 1	Cluster number- 1	30 DAA	Years combined	y = -0.0007x + 3.3574	0.02273
pH- 2	Cluster number- 2	50V	Years combined	y = 4E-05x + 3.8135	-0.00495
pH- 3	Cluster number- 3	Harvest	Years combined	y = 0.0015x + 4.2557	0.013478
pH- 1	Crop load- 1	30 DAA	Years combined	y = 0.0028x + 3.3043	0.085883
pH- 2	Crop load- 2	50V	Years combined	y = -0.018x + 3.9016	0.340724
pH- 3	Crop load- 3	Harvest	Years combined	y = -0.0005x + 4.3501	-0.00852
pH- 3	Malic acid- 3	Harvest	Years combined	y = 0.1447x + 3.9841	0.285631
pH- 1	Tartaric acid- 1	30 DAA	Years combined	y = 0.05x + 3.1466	0.170121
pH- 2	Tartaric acid- 2	50V	Years combined	y = 0.0879x + 3.5508	0.112098
pH- 3	Tartaric acid- 3	Harvest	Years combined	y = 0.1807x + 3.5544	0.48296
pH- 1	°Brix- 1	30 DAA	Years combined	y = 0.0536x + 3.1915	0.326229
pH- 2	°Brix- 2	50V	Years combined	y = 0.0316x + 3.456	0.314158
pH- 3	°Brix- 3	Harvest	Years combined	y = 0.039x + 3.6296	0.335536
pH- 1	Fructose- 1	30 DAA	Years combined	y = 0.0079x + 3.30675	0.185455
pH- 2	Fructose- 2	50V	Years combined	y = 0.0067x + 3.4192	0.407625
pH- 3	Fructose- 3	Harvest	Years combined	y = 0.007x + 3.6654	0.319253
pH- 1	Glucose- 1	30 DAA	Years combined	y = 0.006197x + 3.5132	0.163133
pH- 2	Glucose- 2	50V	Years combined	y = 0.0055x + 3.6129	0.388636
pH- 3	Glucose- 3	Harvest	Years combined	y = 0.0058x + 3.8774	0.279118
pH- 1	Soil K	30 DAA	Years combined (m)[e]	y = 2.3324E-6x + 3.3494	-0.0909
pH- 2	Soil K	50V	Years combined (m)	y = -0.00038x + 3.8871	-0.01779
pH- 3	Soil K	Harvest	Years combined (m)	y = -0.00089X + 4.4435	-0.01048
pH- 1	Soil Ca	30 DAA	Years combined (m)	y = -2.205E-6x + 3.3597	-0.02402
pH- 2	Soil Ca	50V	Years combined (m)	y = -6.665E-6x + 3.8554	0.370182
pH- 3	Soil Ca	Harvest	Years combined (m)	y = -1.225E-5x + 4.3511	0.202058
pH- 1	Soil EC	30 DAA	Years combined (m)	y = -0.000207x + 3.3909	-0.0208
pH- 2	Soil EC	50V	Years combined (m)	y = -0.000506x + 3.9241	0.230642
pH- 3	Soil EC	Harvest	Years combined (m)	y = -0.00122x + 4.53568	0.261449

Table 2.11 Continued

pH- 1	GDD June	30 DAA	2019 (m)	y = 0.0260281x + 1.5253	0.580628
pH- 2	GDD June	50V	2020 (m)	y = 0.0631893x + -0.5134	0.784431
pH- 1	GDD July	30 DAA	Years combined (m)	y = 0.01142x + 2.4984568	0.429271
pH- 2	GDD July	50V	Years combined (m)	y = 0.00323x + 3.581892	-0.06958

[a]Abbreviatons: DAA, days after anthesis; 50V, 50% veraison; EC, electrical conductivity; GDD, growing degree days

[b]Variables followed by 1 indicate collection timing at 30 DAA

[c]Variables followed by 2 indicate collection timing at 50% veraison

[d]Variables followed by 3 indicate collection timing at harvest

[e]Growing season followed by (m) indicate that mean data was analyzed

Table 2.12 Ordinary Least Squares regression of K by predictor variables identified as important in PLSR models in (list year)[a]

Response variable	Predictor variable	Collection timing	Growing season	Equation	Adjusted R-square
K- 1	pH- 1[b]	30 DAA	Years combined	y = 1320.1662x + -3696.131	0.544352
K- 2	pH- 2[c]	50V	Years combined	y = 1538.8219x + -4811.143	0.601285
K- 3	pH- 3[d]	Harvest	Years combined	y = 2142.4107x + -7358.509	0.696411
K- 1	Malic acid- 1	30 DAA	Years combined	y = 55.0218x + 391.9869	0.528908
K- 2	Malic acid- 2	50V	Years combined	y = 179.0233x + 578.3215	0.383542
K- 3	Malic acid- 3	Harvest	Years combined	y = 485.145x + 794.0618	0.491231
K- 1	Tartaric acid- 1	30 DAA	Years combined	y = 125.271x + 221.588	0.338158
K- 2	Tartaric acid- 2	50V	Years combined	y = 282.733x + 198.297	0.301838
K- 3	Tartaric acid- 3	Harvest	Years combined	y = 531.725x + -340.142	0.63685
K- 1	°Brix- 1	30 DAA	Years combined	y = 129.272x + 348.075	0.5987
K- 2	°Brix- 2	50V	Years combined	y = 52.9975x + 455.04	0.224655
K- 3	°Brix- 3	Harvest	Years combined	y = 104.356x + 58.0131	0.366042
K- 1	Fructose- 1	30 DAA	Years combined	y = 16.8149x + 637.527	0.264614
K- 2	Fructose- 2	50V	Years combined	y = -1.82116x + 837.523	0.0191
K- 3	Fructose- 3	Harvest	Years combined	y = 1.06539x + 610.98	0.013522
K- 1	Glucose- 1	30 DAA	Years combined	y = 15.535x + 1140.066	0.325025
K- 2	Glucose- 2	50V	Years combined	y = -1.4999x + 786.173	0.01871
K- 3	Glucose- 3	Harvest	Years combined	y = 1.034397x + 632.8662	0.016728
K- 1	Soil K	30 DAA	Years combined (m)[e]	y = -2.39531x + 1469.18	0.353598
K- 2	Soil K	50V	Years combined (m)	y = -2.489x + 1476.785	0.202537
K- 3	Soil K	Harvest	Years combined (m)	y = -4.58388x + 2630.567	0.238388
K- 1	Soil Ca	30 DAA	Years combined (m)	y = -0.00273x + 743.793	-0.05974
K- 2	Soil Ca	50V	Years combined (m)	y = -0.01577x + 1146.69	0.269516
K- 3	Soil Ca	Harvest	Years combined (m)	y = -0.03996x + 2027.24	0.292538
K- 1	Soil EC	30 DAA	Years combined (m)	y = -0.6862x + 867.95	0.144171
K- 2	Soil EC	50V	Years combined (m)	y = -2.1532x + 1498.63	0.739584
K- 3	Soil EC	Harvest	Years combined (m)	y = -5.02415x + 2836.737	0.648837
K- 2	Leaf K- 1	50V	Years combined	y = 0.035198x + 619.169	0.200581
K- 2	Leaf K- 2	50V	2019	y = 0.03696x + 672.6961	0.345415
K- 2	Leaf K- 2	50V	2020	y = 0.04185x + 566.381	0.39432
K- 2	Leaf K- 2	50V	Years combined	y = 0.03755x + 645.2955	0.363921
K- 3	Leaf K- 1	Harvest	Years combined	y = 0.06792x + 918.94753	0.18457

Table 2.12 Continued

K- 3	Leaf K- 2	Harvest	Years combined	y = 0.0531 + 1279.976	0.187907
K- 1	Leaf P- 1	30 DAA	2019	y = 0.10679x + 443.3319	0.246817
K- 2	Leaf Ca - 2	50V	Years combined	y = -0.0216x + 1625.419	0.218416
K- 2	Leaf Cu - 2	50V	Years combined	y = 4.0454x + 998.6694	0.189151
K- 1	Rainfall (Apr)	30 DAA	2020 (m)	y = -4.4014x + 881.39166	0.695119
K- 2	Rainfall (Jun)	50V	2020 (m)	y = 3.884x + 793.31336	0.408244
K- 2	Rainfall (Jul)	50V	2020 (m)	y = 7.1428x + 827.59798	0.351974
K- 3	Rainfall (Jun)	Harvest	2020 (m)	y = 16.3701x + 595.8793	0.833271
K- 3	Rainfall (Jul)	Harvest	Years combined (m)	y = 35.339x + 450.125	0.657144
K- 1	CEFA- 1	30 DAA	2019	y = 268.774x + 633.139	0.019837
K- 2	Rootstock	50V	Years combined	y = -0.0408x + 1230.218	0.253728
K- 3	Rootstock	Harvest	Years combined	Y = -0.09549x + 2193.014	0.332835

[a]Abbreviatons: DAA, days after anthesis; 50V, 50% veraison; EC, electrical conductivity; GDD, growing degree days; CEFA, cluster exposure flux availability

[b]Variables followed by 1 indicate collection timing at 30 DAA

[c]Variables followed by 2 indicate collection timing at 50% veraison

[d]Variables followed by 3 indicate collection timing at harvest

[e]Growing season followed by (m) indicates that mean data was analyzed

CHAPTER III
INVESTIGATING THE RELATIONSHIP BETWEEN PH AND K IN RED GRAPE VARIETALS

Abstract

High wine pH is an important challenge for growing red grape cultivars in hot climates due to pH's influence on red wine color, oxidation, flavor, and cold and microbial stability. In grape berries, potassium (K) is the most abundant cation. A positive correlation between grape juice and wine pH and potassium has been reported in grape cultivars Cabernet-Sauvignon, Syrah, and Chardonnay. This study evaluated the relationship between K and juice pH in five additional *Vitis vinifera* cultivars. During harvest in 2020, twenty vines of Carnelian (ownrooted), Grenache (**TBD*), Malbec (1103 Paulsen), and Tempranillo clone 05 (3309 Couderc) and 50 vines Malbec clone 04 (ownrooted) and Sangiovese (ownrooted) were harvested and analyzed for pH and K content. Strong correlation between K and juice pH was observed in Carnelian (R^2 = 0.88), Grenache (R^2 = 0.8), Malbec (R^2 = 0.92) and Tempranillo (R^2 = 0.88). The strong positive correlations observed at in these cultivars across multiples vineyard sites highlights the strength of this relationship irrespective of cultivar.

Key words: Grapevine, *Vitis vinifera*, pH, acidity, potassium.

Introduction

As a macronutrient, potassium (K) serves a large number of roles in plants including cell expansion and growth, phloem sucrose loading, long-distance phloem transport, and berry stomatal control (Rogiers, et al., 2017). In grape berries, K is the most abundant cation with concentrations reported over 5 mg per berry. The berry mesocarp is reported to contain the highest proportion of K followed by the exocarp and seeds. However, the exocarp contains higher concentrations on a fresh weight basis. Boulton (1980b) was the first to report on the relationship between grape juice and wine pH and potassium, and other researchers have since reported similar positive correlations in several grape cultivars. Because pH plays an important role in wine microbial stability, oxidation, color, and flavor, controlling K in juice and wine may be desirable. K content of the berry may be a particularly important consideration during red wine maceration because K concentration is generally the highest (4.76 – 8.82 mg K/g FW) in berry skins, and therefore may also be extracted in the juice during skin contact (Mpelasoka, et al., 2003). The results from the Chapter II PLSR analysis to identify predictor variables of pH in grape berries indicated that juice K had the highest correlation to pH than all other variables at 30 days after anthesis, veraison, and harvest. Due to these findings and corroborating results from previous studies (Boulton, 1980a; Gawel et al., 2000; Hepner and Bravado, 1985; Rogiers, et al., 2017), this project evaluated the relationship between K and juice pH in five *Vitis vinifera* cultivars. Identifying a strong relationship would further support the need to development management practices to control K in the vineyard.

Materials And Methods

Experimental Design

In 2020, berries from five *V. vinifera* cultivars were collected at harvest from the Texas High Plains and North Texas regions and analyzed for berry composition to assess the correlation between K and juice pH. Twenty mature grape vines (three years or older) of scion variety *V. vinifera* cv. Carnelian (ownrooted), Grenache (**TBD*), Malbec (1103 Paulsen), and Tempranillo clone 05 (3309 Couderc) and 50 mature grape vines of scion variety *V. vinifera* cv. Malbec clone 04 (ownrooted) and Sangiovese (ownrooted) were selected for the study. The Carnelian vines and Tempranillo vines were located in the same vineyard. Berry sampling was performed on individual vines.

Berry Sampling and Analyses for Chemical Composition

200 berries were randomly sampled per vine at harvest for chemical analyses. Sites 1, 2, 3, and 6 were processed different from sites 4 and 5. Whole berry samples from sites 1, 2, 3 and 6 were immediately frozen at -23ºC for preservation until processing. Samples from sites 5 and 6 were processed immediately after collection.

For sample preparation, the frozen berries from sites 1, 2, 3 and 6 were placed in a beaker and heated to 65 ºC for one hour in a LW Scientific 115V water bath to re-dissolve tartrates. The warmed samples were blended in a commercial blender (GB26-b, Hamilton Beach, Glen Allen, VA) for 3 minutes and transferred to 50ml polypropylene tubes. The sample tubes were centrifuged for 5 minutes at 4000 rpm. After, the supernatant was discarded, the remaining juice were centrifuged for an additional 5 minutes, and then

immediately frozen at -23ºC until analyses. The samples from sites 4 and 5 were crushed). The juice was centrifuged for 5 minutes at 4000 rpm. After, the supernatant was discarded, and the remaining juice was centrifuged for an additional 5 minutes then immediately analyzed.

For must analysis, the samples from sites 1, 2, 3 and 6 were thawed for 48 hours at 4 ºC. All samples were analyzed with a FOSS WineScan (WineScan™, Foss, Denmark) for soluble solids (ºBrix), pH, K, TA, malic acid, tartaric acid, fructose, and glucose using Fourier Transform Infrared analysis as described by Musingarabwi, et al. (2015).

Statistical Analysis

To evaluate relationships between grape berry K and pH at harvest, ordinary least squares (OLS) was conducted with JMP Statistical Software Version Pro 15 (SAS Institute, Cary, NC).

Results And Discussion

The results of Chapter II indicate that potassium plays a strong role in juice pH of Tempranillo berries relative to other viticultural and environmental factors. These results are supported by previous research that found correlations between grape berry pH and potassium (K) concentrations in Cabernet-Sauvignon and Syrah (Ramos and Romero, 2017) and Chardonnay (Walker and Blackmore, 2012). OLSR analysis was conducted to assess the correlation between K and juice pH in mature red grape cultivars Carnelian (ownrooted), Grenache (unknown), Malbec (1103 Paulsen), Malbec clone 04 (ownrooted), Sangiovese

(ownrooted) and Tempranillo clone 05 (3309 Couderc) (Figure 3.1). There was a very strong correlation between K and juice pH in Carnelian (R^2 = 0.88), Grenache (R^2 = 0.8), Malbec (R^2 = 0.92) and Tempranillo (R^2 = 0.88) at harvest. A weaker relationship was observed between K and pH in Malbec clone 04 (R^2 = 0.4) and Sangiovese (R^2 = 0.3).

Summary

Juice and wine pH play an important role in wine quality and previous research suggests that K plays an important role in determining pH. This project evaluated the relationship between K and juice pH in mature Malbec, Tempranillo, Sangiovese, and Carnelian grapes. The strong positive correlations observed at in these cultivars across multiples vineyard sites highlights the strength of this relationship irrespective of cultivar.

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Table 13.1 Research sites characteristics

Site ID	Location	Site Coordinates	Soil series	Scion	Rootstock	Year Planted	Number of vines
Site 1	Mingus, TX	32°27'12.3"N -98°27'27.3"W	Mollisols	Carnelian	Ownrooted	2008	20
Site 2	Weatherford, TX	32°50'49.4"N -97°39'26.8"W	Vertisols	Grenache	-[a]	-	20
Site 3	Southlake, TX	32°57'06.8"N -97°09'58.9"W	Vertisols	Malbec	1103 Paulsen	2018	20
Site 4	Brownfield, TX	33°09'05.1"N -102°13'13.5"W	Alfisols	Malbec clone 04	Ownrooted	2011	50
Site 5	Brownfield, TX	33°09'32.7"N 102°15'24.5"W	Alfisols	Sangiovese VCR 06 and 23	Ownrooted	2015	50
Site 6	Mingus, TX	32°27'12.3"N -98°27'27.3"W	Mollisols	Tempranillo clone 05	3309 Couderc	2008	20

[a]Data unavailable.

Table 14 Mean **(**+SD) pH and K by cultivar at 2020 harvest

Cultivar	pH	SD	K (mg/l)	SD
Tempranillo clone 05	4.314a	0.226	2055.9b	527.9
Malbec clone 04	4.216a	0.107	2738.4a	229.8
Grenache	4.064b	0.180	1269.6c	285.8
Malbec	4.064b	0.169	1890.7b	388.3
Carnelian	3.952b	0.160	1397.9c	276.0
Sangiovese VCR 06 and 23	3.758c	0.111	1813.1b	199.0
p[a]	< 0.0001		< 0.0001	

[a]p-value, comparison of mean data by research site.
[b]Means within a column followed by the same letter are not significantly different at the 0.05 level of probability (Games-Howell).

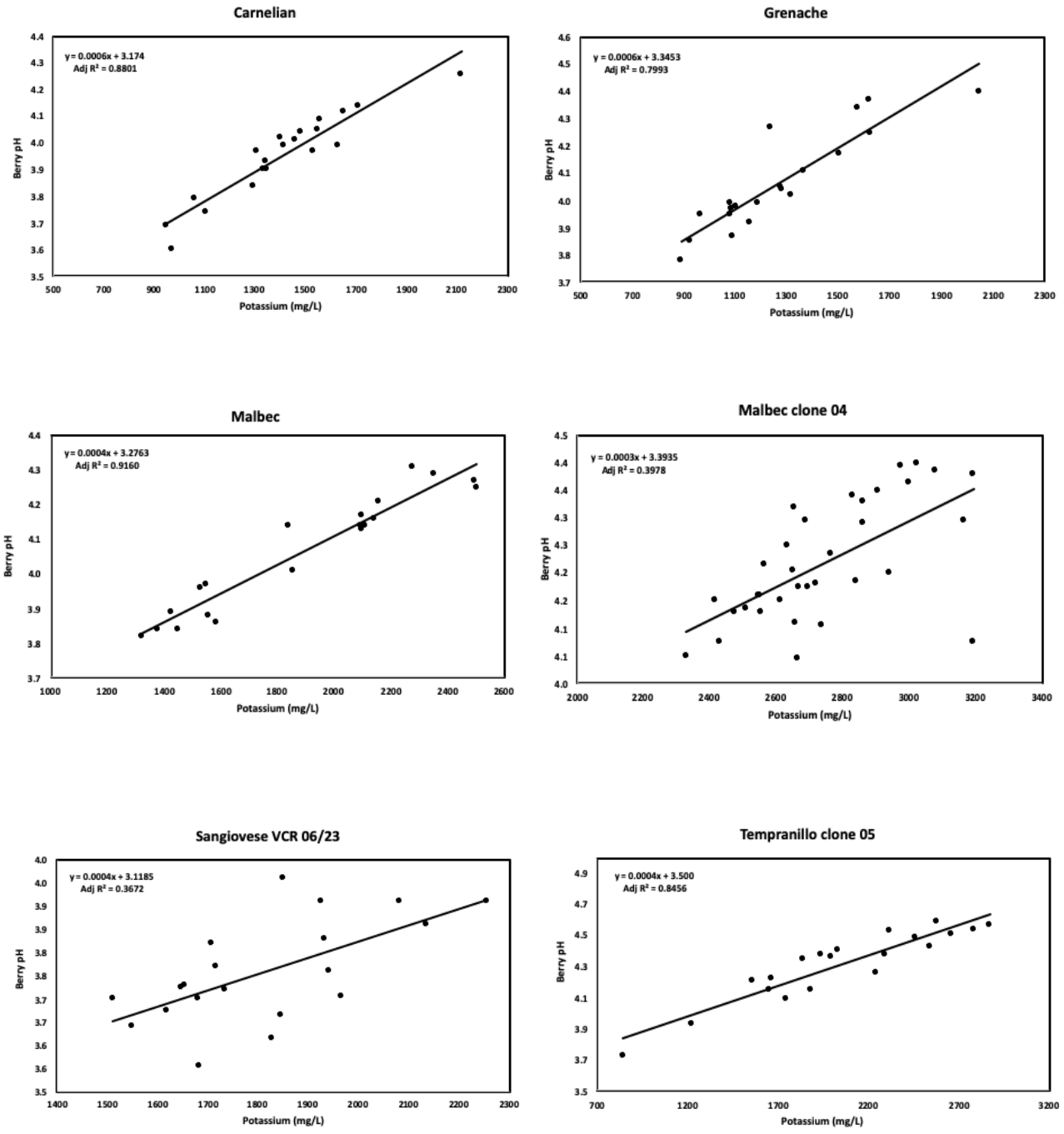

Figure 3.1 Ordinary Least Squares Regression of grape berry pH by K at harvest in 2020**.** There is a significant correlation between pH and K at p-value <0.0001 for Carnelian, Grenache, Malbec, Malbec clone 04, and Tempranillo clone 05. There is a significant correlation between pH and K at p-value <0.0027 for Sangiovese. Abbreviations for collection timings: 30 DAA, 30 days after anthesis; 50V, 50% veraison; H, harvest.

CHAPTER IV
CONCLUSIONS

Results from the Partial Least Squares Regression (PLSR) analyses identified potassium, plant nutrient availability, soil nutrient availability, rootstock cultivar, and vine water status as the viticulture factors with the greatest importance in predicting berry K in *V. vinifera* cv. Tempranillo, and in accordance to previous studies (Hafke et al., 2007**;** Ramos and Romero, 2017; Walker and Blackmore, 2012; Waterhouse, et al., 2016), will have similar influences with the berry pH. The variation in juice K in grapevine appears to be a function of the rootstocks ability to take up the nutrients available in the soil, subsequently controlling the nutrient status of the grapevine. The physiological demands of the vine at the onset of berry ripening drives the transport of potassium from vegetative tissues to the berry (Rogiers, et al., 2006), resulting in an accumulation of K in the berry after veraison. An increase in ambient temperatures and water status from the onset of berry ripening to mid-ripening also appear to correlate to an increase in K concentrations in the leaves and berries. Results from the study also identified strong positive correlations between K and juice pH in three additional red cultivars, *V. vinifera* cv. Carnelian (ownrooted), Grenache (unknown), Malbec (1103 Paulsen), across different vineyard sites. The strong positive correlations observed at in these cultivars across multiples vineyard sites highlights the strength of this relationship irrespective of cultivar.

The ability of *V. vinifera* cv. Tempranillo to thrive in warm climate such as Texas makes it an attractive cultivar to grow in warm to hot climates. Producing quality wines from Tempranillo can be problematic for winemakers due to its low total acidity and its high

pH. The results obtained in this work indicate that future studies should consider potassium, plant nutrient availability, soil nutrient availability, rootstock cultivar, and vine water status as variables to control to manipulate acidity in the grape berry.

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APPENDIX A

Appendix A. Predictor variables in Partial Least Squares Regression (PLSR) analyses for berry pH and berry potassium content

	BERRY COMPOSITION
1	Total soluble solids (°Brix)
2	Fructose (g/l)
3	Glucose (g/l)
4	Malic acid (g/l)
5	Tartaric acid (g/l)
6	pH[a]
7	Potassium[b] (mg/l)
8	Total acidity (g/l)

	GENOTYPE
9	Scion clone cultivar
10	Rootstock cultivar

	VINE CHARACTERIZATION
11	Dormant pruning weight (kg)
12	Percent gaps (PG)
13	Leaf layer number (LLN)
14	Percent Interior Leaves (PIL)
15	Percent Interior Clusters (PIC)
16	Occlusion layer number (OLN)
17	Cluster exposure layer (CEL)
18	Canopy calibration coefficient (CCS)
19	Leaf exposure layer (LEL)
20	Canopy calibration coefficient (EP1)
21	Cluster exposure flux availability (CEFA)
22	Cluster exposure flux symmetry (CEFS)
23	Leaf exposure flux availability (LEFA)
24	Leaf Exposure Flux Symmetry (LEFS)
25	Leaf contacts
26	Cluster contacts
27	Shoot diameter (mm)

	VINE NUTRIENTS
28	Nitrogen (%)
29	Phosphorous (ppm)
30	Potassium (ppm)
31	Calcium (ppm)
32	Magnesium (ppm)
33	Sodium (ppm)
34	Zinc (ppm)
35	Copper (ppm)
36	Manganese (ppm)
37	Sulfur (ppm)
38	Boron (ppm)

	CLIMATIC MEAUREMENTS
39	GDD in April
40	GDD in May
41	GDD in June
42	GDD in July
43	GDD in August
44	Rainfall average in April (mm)
45	Rainfall average in May (mm)
46	Rainfall average in June (mm)
47	Rainfall average in July (mm)
48	Rainfall average in Aug (mm)
49	Temperature average in April (°C)
50	Temperature average in May (°C)
51	Temperature average in June (°C)
52	Temperature average in July (°C)
53	Temperature average in August (°C)

	SOIL COMPOSITION
54	pH
55	Electrical conductivity (dS/m)
56	Nitrate-N (ppm)
57	Phosphorous (ppm)
58	Potassium (ppm)
59	Calcium (ppm)
60	Magnesium (ppm)
61	Sulfur (ppm)
62	Sodium (ppm)
63	Sulfur (ppm)
64	Boron (ppm)

	HARVEST PARAMETERS
65	Cluster number per vine
66	Yield per vine (kg)
67	Average cluster weight (g)
68	Average fresh berry weight (mg)
69	Crop load (vine yield/dormant pruning weight)

	AGE
70	Age of vine (years)

[a]Predictor variable not used in PLSR models to predict berry pH

[b]Predictor variable not used in PLSR models to predict berry potassium