GigaScience

Multi-dimensional leaf phenotypes reflect root system genotype in grafted grapevine over the growing season --Manuscript Draft--

Manuscript Number:	GIGA-D-21-00137R1	
Full Title:	Multi-dimensional leaf phenotypes reflect roover the growing season	oot system genotype in grafted grapevine
Article Type:	Research	
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Abstract:	Background: Modern biological approaches data, offering unprecedented opportunities beyond reach due to small or subtle effects the extent to which below-ground activity in phenotypes expressed in the shoot system. that fuses the root system of one individual second, genetically distinct individual (the s understand below-ground effects on above- grafted grapevines have detected rootstock physiology and berry chemistry. However, t leaves, the photosynthetic engines of the vi course of a growing season, are still largely Results: Here, we investigate associations is system phenotypes using five multi-dimensi in a common grafted scion: ionomics, metal and physiology. Rootstock influence is ubiq strongest signature of rootstock observed in the extent of rootstock influence on scion ph covariation are highly dynamic across the s Conclusions: These findings substantially e demonstrate that rootstock influence on scion underscore that broad understanding neces previously unmet.	a generate volumes of multi-dimensional to address biological questions previously . A fundamental question in plant biology is the root system influences above-ground . Grafting, an ancient horticultural practice (the rootstock) with the shoot system of a cion), is a powerful experimental system to -ground phenotypes. Previous studies on . influence on scion phenotypes including he extent of the rootstock's influence on ne, and how those effects change over the nuknown. between rootstock genotype and shoot ional leaf phenotyping modalities measured bolomics, transcriptomics, morphometrics, uitous but subtle across modalities with the n the leaf ionome. Moreover, we find that henotypes and patterns of phenomic eason. xpand previously identified patterns to on phenotypes is complex and dynamic and asitates volumes of multi-dimensional data
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Response to Reviewers:	Editor Comments: Overall, the reviewers have highlighted that in its current form, the manuscript requires more biological validation and more detailed methods to ensure reproducibility of the work presented. Limitations on the study should be discussed and how they may impact the results; and more data should be provided to understand the reliability of the RNA-seq experiment. Furthermore, RNA-seq methods are incomplete - we strongly encourage all authors to add their detailed methods to protocols.io (if not already open in protocols.io and cite the protocol DOI in the paper. -Response: Thank you for this. We have added all details that have been requested on L191-195. In addition, we added a supplemental figure (Supplemental Figure 2) showcasing our analysis for gene expression validity. A summary of this analysis is on L207-210.
	We also see reviewer #4 suggests to use Figshare - but this is not an appropriate database to share large-scale data, such as this work presents. Github is still the most appropriate place to share scripts and associated documentation, and our open repository, GigaDB can host the other metadata not already open in other community approved repositories; we will also host snapshots of your scripts in GitHub. -Response: In addressing Reviewer #4's specific recommendation, we have moved the document in question from GitHub to a Supplementary Note in the manuscript. In line with previous communications, we are also in the curation process of metabolomics data uploaded to Metabolights. We are happy to jointly upload other data sets to preferred repositories and databases, we just need guidance on the preferred locations for those data. As of today, we are unaware of standard databases for ionomics and leaf shape data. Scripts used for analysis are still available on GitHub, but can be hosted elsewhere if this is of concern.
	Reviewer #1
	The manuscript by Harris and co-workers presents a characterization of rootstock genotype effects on multilevel leaf phenotypes of one grafted grapevine scion cultivar. Three rootstock genotypes along with the ungrafted cultivar were compared for ionomics, transcriptomics, metabolomics, leaf morphology and physiology in three phenological stages. Analytical and statistical analyses applied were generally sound. While authors identify larger effects in most cases for stage and vineyard position/sampling time, ionic composition was the phenotype most significantly affected by rootstock genotype. Co-variance among multilevel phenotypes is also presented.
	Major issues 1. The study comprises a vast dataset, with a total of 288 plants independently analyzed for two phenotypes (morphometry and ionomics) and 72 plants were used for the rest of phenotypes. Nevertheless, the experiment is limited in terms of genotypes tested and reproducibility. Only one year of study and under the specific soil and climate conditions of a single field plot. Moreover, the effects were only tested on a single scion genotype, a bred interspecific hybrid including Vitis riparia and V. rupestris in its pedigree. At least one of these species is also in the pedigree of the three rootstocks tested, which might involve lower diversity than in common interactions between rootstocks and V. vinifera cultivars. These limitations should at least be considered when discussing the results. -Response: The comments provided by the reviewer are all excellent observations that were clearly missing from the discussion of our work. We have added a paragraph to

the Discussion (L544 - L559) to better couch how our work should be compared to other studies and the considerations that may account for those differences.

2. The RNA-seq assay did not identify differentially expressed genes (DEGs) in response to rootstock genotype, which disagrees with previous reports. While the origin of the lack of effects here is unclear, further data should be provided to understand the reliability of the RNA-seq experiment:

-Response: We thank the reviewer for this comment. We were similarly interested to see that our results differ from previously published analyses in similar systems. We added comments to the discussion to clarify why we think these differences might be present. To ensure such reliability, we confirmed in our data that previously established patterns of house-keeping and circadian phased genes were behaving as expected. The following has been added to the manuscript:

-Added to data description L208-210, "To check the validity of our expression results, we assayed two classes of housekeeping gene (Ubiquitin-domain and actin-family) and eight previously annotated circadian genes (Carbonell-Bejerano et al. 2014)" -Added to Analyses, L339 - 345, "We computed the expression of two classes of housekeeping genes, and showed that they are generally stable across samples over phenological time (Supplemental Figure 2). We noted that some variation is expected for housekeeping genes; see, for example, [49]. Moreover, we showed that patterns of previously annotated circadian genes conform to expected results over the sampling window. For example, predicted orthologs of LHY and RVE1 are correlated and decreasing over our sampling window, and a predicted TOC1 ortholog is invariant. The results of these analyses provide general confidence in the gene expression data presented here."

-Created and added Supplemental Figure (now supplemental Figure 2) showing these patterns.

2.1. Which was the timing of sample collection for RNA-seq samples? Was the same sampling order followed for the three phenological stages? Which were the weather conditions on each of the three sampling dates? It is relevant to describe that information since environmental and circadian changes between and within days can alter gene expression.

-Response: We added the following to the section describing the gene expression data set (L187-190): "Leaves were sampled by a single team near midday between 10AM and 2PM in row order ensuring that 'block' and 'row' accounted for unmeasured environmental variation and temporal variation over the sampling window." A statement was added on L637-638 that "At each phenological stage, effort was made to sample on days with full to partial sun and minimal precipitation."

2.2. Data on RNA sequencing depth should be provided to understand the resolution of the transcriptomics experiment. For instance, how many bases/reads per sample were produced? How many genes per sample were called as expressed (DESeq2-norm counts >2 according to authors own threshold)?

-Response: Information on sequencing depth and genes per sample were added to the Analyses section. Specifically, we added the following to L337-338: "On average, each sample contained 4.1 million 3'-reads and showed the expression of 17,852 genes."

3. The interpretation of the origin of the results is generally shallow and several questions or limitations are overlooked. For instance:

3.1. It is described that physiological parameters were measured from 10 am to 1 pm, a wide interval with expected changes in environmental conditions affecting these measurements. To understand for possible covariances, it should be indicated if these measurements were carried out simultaneously and following the same order than that of leaf sample collection for the other phenotyping.

-Response: We agree that we missed crucial details about the timing of this sampling. To fix this, we included the clarifications that (on L241) all physiology measurements were being taken simultaneously by different groups moving though the vineyard and (on L243-245) the measurements were all taken in row order ensuring that the vineyard blocking factor captured temporal variation. SImilar notes were added for the other phenotypes to better explain sampling. As was noted in the next reviewer comment, block is missing from Figure 5 which means it was not significant as a main effect.

3.2. Related to the previous, why block effect alone was not considered for physiological measurements in Figure 5?

-Response: Thank you for this comment. Block (or row for gene expression) was included in the models as a main effect for every modality (see analysis section). Non-significant factors were dropped from figures summarizing linear models; because the block main effect was not significant, it was not included in Figure 5.

3.3. Did the horseshoe shape for row effect on the transcriptome correlate with oscillation of environmental/circadian clock conditions during the sampling interval or with vineyard heterogeneity? Functional analysis of the genes contributing to row effect could be informative on the origin of these effects that might have hindered the identification of rootstock effect on the transcriptome.

-Response: This is a really interesting comment. We agree with the reviewer that the horseshoe shape in LDA space is either a function of circadian conditions or spatial heterogeneity. We have added to the Data Description section a comment on assaying genes with known circadian topology (L207-210) and show in Supplemental Figure 2 that those genes are variable over our sampling window. In addition, we commented on this outcome in the Analyses section on L360-362. We show that the impact of vineyard position/spatial variation is weak in other measured phenotypes (captured by the 'block' model term; see, for example, Figure 1A and Supplemental Figure 5A). Future studies should assess potential intra-vineyard variation either through blocking (as we did here) or explicit measurement (for example, soil composition) and control for that variation.

3.4. Is there a rootstock effect on vigor, biomass, fruit fertility and production that could explain or condition the effects in leaf phenotypes that were measured? Were these factors normalized in any way, either by agronomic practices or statistical treatment?

-Response: This is an excellent question that is perhaps beyond the scope of this comprehensive analysis of leaf phenotypes, but one that is certainly an important next step in our research trajectory. Conditioning or normalizing on aspects of vigor or yield or looking for correlates of those traits in early season leaf phenotypes would be immensely valuable to viticulture and a general understanding of grapevine biology. To explore this idea, we have amended the language of the Potential Implications section on L588-608. In addition, some of these data were collected and are being prepared for papers focused toward berry phenotypes. In the meantime, we point to (https://doi.org/10.1002/pld3.324) to show that this is absolutely a valid direction of inquiry for future work and data integration efforts.

4. This study comprises similar experiments to these already published by the same group in the same set of plants (Migicovsky et al., Hort Res 2019), although extended to include metabolomics and physiology data and two additional phenologcal stages. While the effect of phenology is clearly presented here, the addition of the metabolite data is undermined. What are the metabolites determining rootstock effect in Figure 2C? What about metabolites determining a rootstock effect depending on phenology that could be inferred from PC10?

-Response: We thank the reviewer for this comment and appreciate the careful consideration of this manuscript in the context of the Migicovsky et al, 2019 manuscript. We completely agree that the value of the metabolomics data is undermined in the manuscript. This is primarily the result of current challenges in mapping peaks from LC-MS onto named metabolites. The current state of untargeted metabolomics from LC-MS would require significant chemical laboratory work to narrow down the space of potential metabolites. While we believe this work should absolutely be done, our goal with this study was not necessarily to identify specific metabolites but to determine if the metabolome was a potential avenue through which the rootstock is influencing scion phenotypes. To address this, we used only a portion of the runs available to show there is a signal. Future work will focus on merging the various additional LC-MS runs (not presented here) and chemical experimentation to uncover the full scope of this effect. We note that we are uploaded raw data to Metabolights, QC/filtered data to FigShare, and reported the retention times and m/z ratios for the compounds of putative interest in the manuscript. We hope that these data may be useful in future analyses of grapevine metabolites, either by our group or others.

Minor revisions

1. "Ubiquitous" effects of rootstock genotype are described along the MS. However, since only one location was analyzed (leaves), would "pleotropic" be more appropriate to define the different phenotypes affected by rootstock-scion genotype interaction in this study?

-Response: This is a great point. We clarified our usage of the word "ubiquitous" to ensure its intended meaning (across modalities within leaves, not as an inherent feature of grapevine) was clear (for example, on L514) throughout the manuscript. Supporting the reviewer's observation that this study only included one environment, we are hesitant to use the word "pleiotropy", though we are interested in the implication that the different rootstock/scion pairs create different local environments and will consider this idea in future works.

2. Methods on RNA-seq procedures are incomplete. Which sequencing technology was used? Which type and length of reads? Etc.

-Response: Good catch. We added the following to the L194-195: "Sequencing was conducted using the Illumina NextSeq500 platform which returned single-end 86 bp reads."

Inter-annual comparison for anthesis ionomics, transcriptomics and morphology 3. between this study and their previous publication (Migicovsky et al., Hort Res 2019) could enable a broader interpretation of rootstock effects, overcoming the reproducibility limitation of considering only a single season here. -Response: We absolutely agree that interannual analyses are required for a detailed understanding of the root system influence on shoot phenotypes and these analyses are underway. Our goal with this manuscript was to carefully quantify different phenotyping modalities and to understand how they relate to one another. The results from this study have helped us consider what is worth more detailed investigations. and analyses that address longer (multi-year) studies for those phenotypes are currently in the works. Given the magnitude of the data presented here and the extent of analyses conducted, we struggled to fit this detailed work in a single manuscript that also covered inter-annual variation as well as additional phenotypes (berry chemistry, etc.). As a result of work presented here, we are currently exploring tradeoffs between deep analyses of individual phenotypes and shallower analyses of more modalities over longer time periods, additional scions, and multiple sites. In the meantime, wherever possible we note some comparisons to the Migicovsky 2019 study where appropriate. The Migicovsky 2019 pilot study used considerably different methods for many phenotypes, which preclude direct comparisons.

4. L426. The sentence might not be completely fair as no DEG was identified for rootstock effect (transcriptome phenotype would therefore be mostly unaffected) and developmental stage-specific could be more adequate than season-specific. -Response: Thank you for this. We agree with the suggested change in language for the effect of phenology and changed "season specific" to "specific to the vine's developmental stage" on L468. On gene expression, while no DEGs were identified, we were able to identify latent combinations of genes that were responsive to rootstock treatment. While this effect is subtle, it was nonetheless detectable.

5. Any biological interpretation of the specific metabolites, genes, iones, shapes determining the resulting PC covariation networks? While it can be interesting to add to covariation networks additional levels of phenomics as authors propose (IcRNA, micorobiome, epigenetics), it would also be informative to exploit the interpretation of the dataset that they have already produced.

-Response: Excellent suggestion. Unfortunately, after much consideration, at this point we do not feel comfortable with detailed biological interpretations based on specific metabolites or genes that underlie PC covariation networks shown here. Some of the limitations of our dataset, and why we are unable to make these mechanistic connections with data presented here, are detailed in the discussion. We note that the ionome offers a very rich source of data ripe for deep analysis, and that an additional manuscript describing a deep dive into multi-year, multi-time point ionomic dataset is in preparation now. We agree that future work should be targeted toward biological understanding of these relationships. On suggesting inclusion of other phenotypes, this comment reflects our enthusiasm for other existing approaches and exciting areas of

research that might further uncover mechanistic understanding of the effects we are seeing from grafting and over time. The analysis presented in the paper, unfortunately, does little to advance us toward the goal of mechanistic understanding, but it does help us see where future studies could be targeted. To this end, we added language to clarify this point on L573-578.

6. L470, If the lack of rootstock effect on the transcriptome was due to the phenology effect, specific analysis at each phenology stage would identify rootstock genotype factor significant DEGs. Is it the case? Would there be any rootstock effect detected on transcriptome if the analysis was restricted to single blocks at specific phenological stages?

-Response: We thank the reviewer for this comment. This is certainly something we are trying to wade through as our results suggest that the rootstock influence on our vines is incredibly complex and works through interaction with other factors of the experimental design. Ongoing work is focused on identifying these complex effects, in a statistically robust way. We are also currently working with collaborators to identify genes and gene regions worth further exploration. Moreover, we are seeking to use results from other phenotypes to focus on genes in a more 'hypothesis-driven' approach that can further the 'discovery-driven' results observed here.

7. Apart from the seasonal effect, the "Potential implications" presented are not directly inferred from the Results obtained here but from the potential of the approach used. Any other potential implication of the specific results?

-Response: This is a very helpful suggestion. In response to this and comments from other reviewers we have re-worked the potential implications section. Other reviewers called for an enhanced focus on yield/viticultural implications, while others have asked us to minimize such speculation. Consequently, we have attempted to carefully place this work in the context of both basic plant biology and viticulture. If the current revision does not meet the expectations of the reviewer(s) or editors we would be happy to revise further.

8. Is there any data available for the distribution of soil properties across the experimental plot that could be considered to discuss the origin of block effects? Could the human factor during that extensive sampling be another variable accounting for block effect?

-Response: Thank you for this excellent observation. For the data presented here, we do not have paired soil samples. We anticipate some heterogeneity in soil properties across the experimental plot; however it is unclear how strongly this would correspond directly to block effect. Regarding the human factor, we have added a sentence into each data modality clarifying what variation is captured by the blocking factor. See each addition below:

-L136-138 added, "Teams were deployed in the vineyard so that multiple vineyard rows were being sampled concurrently. As such, 'block' represented unmeasured spatial variation, but did not strictly correlate with time of sampling due to the nature of sampling (see Methods)."

-L155 - 157 added, "ensuring that 'block' captured both unmeasured environmental variation and temporal variation over the sampling window".

-L187-190 added, "Leaves were sampled by a single team near midday between 10AM and 2PM in row order ensuring that 'block' and 'row' accounted for unmeasured spatial variation and temporal variation over the sampling window (see Methods)" -Overall, block is not a large descriptor of variation in our study except for the phenotypes for which block is collinear with time of day. In these phenotypes (the metabolome and the transcriptome) there is a noted circadian topology. The other phenotypes (ionomics, leaf shape, and physiology) see little effect from block suggesting there is little spatial variation (or at least that the spatial variation is unimportant for those phenotypes).

9. Because half of 3309C reps would have been collected before any ungrafted rep was taken, could the LD2 effect in discriminating 3309C and ungrafted from RNA-seq data be related with sampling times? What are the genes involved in this effect? -Response: We thank the reviewer for this comment. While it is always possible that results correlate with unmeasured confounders, rootstock genotype was not

confounded with any of the terms in our model (including time of sampling, which was a correlate for row in our study; L653-655). Each rootstock was present in each row of the vineyard in cells of four replicated vines (See supplemental Figure 1A). For the transcriptome sample, we sampled leaves from the middle two vines in each cell. While it certainly takes time to sample in a vineyard, each rootstock in each row would have been sampled within minutes of one another. Due to this, the grouping we report in LD space is not confounded with time. The current results suggest that this effect is driven by complex combinations of genes (from the PCA results) and not any particular genes being strongly affected (from the traditional DGE results). We are currently working on exploring these subtle effects in more statistically robust ways in a multi-year study.

10. Any discussion on the origin of leaf position effects in specific ions? -Response: Thank you for this comment, and this is something we think about often. Leaf position was added to this study on the ionome because it is known that leaves vary in their elemental composition over development. The major question here was whether or not rootstock would influence the elemental composition of those leaves in such a way that the known patterns might be interrupted. While we observed significant variation in ion concentrations as a function of leaf position, it did not strongly interact with rootstock genotype. In other words, the rootstock effect was present in all leaves, not just leaves of a particular age. As such, we struggled to fit a detailed description of the effect of leaf position in the current paper. However, we have made all data from this analysis publicly available if there exists specific interest for the leaf position. Ongoing work focused explicitly on the leaf ionome will provide a deep dive on how ion concentrations vary by rootstock, over development, across seasons, and across multiple years.

11. L556. Indicating in there that "only the middle two vines of the four cells in the front half of the vineyard were included in the 72-vine set" would be handy to understand the distribution of this set.

-Response: Thank you for this comment. We have clarified the description of the experimental vine throughout the manuscript. The experimental design of the vineyard included groups of four identical vines (e.g., Chambourcin grafted to 3309C) that are distributed in a randomized block experimental design throughout the vineyard. For some data modalities we were unable to process samples from all four vines per cell. In these circumstances, we opted to collect samples from the middle two vines of the four vine set. We collected from the middle two vines from a total of 36 cells for the 72 vine set. To improve the understanding of this section, we have amended the text to point to more appropriate sections of Supplemental Figure 1. In addition, we have improved the Figure Legend for this figure so it is more clear what each panel is showing with explicit descriptions for Supplemental Figure 1B, which should improve the clarity of this section. Finally, we clarified that this description only applied to the front half of the vineyard which was missing from the previous draft. We would be happy to make additional edits to the text if this description does not provide sufficient clarification.

Reviewer #2

The manuscript by Harris et al investigates the effect of grafting on a number of physiological and molecular phenotypes within grapevine (Vitis spp.) scions. The hybrid Vitis cultivar Chambourcin was compared when grown on its own-roots, or when grafted to three different commercial hybrid rootstocks: 1103P, 3309C, and SO4. The vines were grown in the field, irrigated with different volumes of water, and sampled over a single growing season. Large data sets have been generated for leaf metabolites, solutes (ions), transcripts, shape, and physiology (stomatal conductance, transpiration). As such, the manuscript fits the scope of Gigascience well. The manuscript is well written, however I found it was very statistical and would benefit from additional biological analyses to confirm and validate the findings. The methods section is lacking some details that would enable reproducibility. Some of the figures could be improved for readability. My comments and suggestions are detailed below:

Major comments

1. There is no information on the age of the vines at the time of the experiments.

-Response: This is a great observation of information we overlooked. The vineyard had been in the ground for eight years at the time of sampling. The age of the vineyard has been added to L538 and commented on in the discussion.

2. A quantitative analysis of the elemental content of the irrigation water by ICP-MS would be beneficial. In this study, it is unknown whether the irrigation treatments contained varying levels of the elements that were measured in leaves. To this end, it is perhaps not surprising that rootstocks had minimal effect on, for example, the Na+ content of grafted scions. However, it has been demonstrated previously that own-rooted vines cannot efficiently exclude Na+ compared to grafted vines when irrigated with 100 mM NaCl (see Fisarakis el al (2001) Agricultural Water Management 51 13-27).

-Response: This is a really intriguing suggestion, and one we wish we would have thought of in 2017. Regrettably, it was not something that was considered for this study at the time. However, we can be confident that irrigation was not significantly altering the findings of our study due to the weak nature of the irrigation effect (See Supplemental Note 1). Had there been variation in the ionome of the irrigation water, we would have expected to see a stronger irrigation or irrigation by phenology effect, neither of which were strongly observed in this study. We thank the reviewer for pointing us to this helpful article.

3. The manuscript would be more useful to the plant science community if a subset of the actual metabolites and genes identified within the principle components were named and confirmed using a second method. It would then be possible to discuss which physiological, metabolic, and molecular processes within Vitis scions are impacted by rootstock selection.

-Response: We absolutely agree gene-level and metabolite-level understanding of the root system influence on shoot system phenotypes is the direction this work needs to head. This is perhaps one of the biggest limitations of large-scale analyses of multidimensional phenotypes: it is sometimes hard to narrow in on individual phenotypes for some systems. We acknowledge that there is a trade-off between large-scale analyses like the one presented here and identification of actual metabolites/genes and their functional role in the vine. We see these as very complimentary approaches that illuminate different aspects of vine biology; however, we were unable to do both in this study. Ongoing work is attempting to, in a statistically robust way, uncover those subtle effects from even deeper sampling of the transcriptome. The metabolome as described using the untargeted approach here is a whole different monster. We were able to show that some metabolites are responding to the rootstock treatment and even to the rootstock by season interaction. The current nature of LC-MS and untargeted metabolomics in Vitis generally make it incredibly non-trivial to map these metabolites. Here we sought to catalog the basic responses of multiple phenotypes to help guide more targeted analyses and guide us toward studies that could produce mechanistic understanding.

4. Similar to my comment above, some of the data could be integrated. For example, transpiration was increased for scions grafted to 1103P (Fig 5B). Were genes or metabolites involved in the regulation of stomatal aperture differentially abundant when grafted to 1103P?

-Response: This kind of data integration is an excellent suggestion. While such analyses would require work beyond the scope of this paper, we think that this comment is exactly in line with how we should be guiding future work. We proposed in the previous comment that this work was meant as a foundation on which we establish the basic responses of many complex phenotypes over the growing season with respect to the rootstock genotype. The PCA-based integration was to help us narrow down which types of data modalities warrant future integrative work. As we move toward identifying and annotating individual genes and metabolites, these suggestions will certainly help in that future planning.

5. The ionomics data in Fig 1B and C would be easier to interpret if presented as a percentage - for example, % DW, % FW, or mM of tissue water. Currently, there are no units on the Y-axis.

-We agree that z-scores were not the ideal choice for this figure. To address this, we remade this portion of this figure to show the elements as concentrations in parts per million of acid-digested dried leaves. We have updated the Figure Legend L706 and

L710 to reflect this change.

6. There is no mention of how the RNA was extracted from plant tissues. Further, a quality control would normally be performed, e.g. by measuring the 260/280 ratios at the very least. Was any quality control performed on these RNA samples? How do we know the samples were pure and not degraded?

-Response: Excellent point that was also noted by Reviewer 1. The information requested has been added to the Data Description section, L191 - 193: "Total RNA was extracted from plant tissues using the Sigma Spectrum Plant Total RNA kit with modification of the addition of 2% PVP40 to the extraction buffer to decrease phenolic inhibitors. All RNA extractions were checked for quality control using a Nanodrop. Sequencing was conducted using the Illumina NextSeq500 platform which returned single-end 86 bp reads."

7. It is unclear how many biological replicates were used for the RNAseq experiments.

-Response: Good catch- thank you for this. Language changes were made throughout the manuscript (in conjunction with other review comments in the section "Study Design" and within the Data Description for each modality to improve clarity. In short, each modality was sampled from either a 72-vine set (metabolomics, gene expression, physiology) or a 288-vine set (ionomics, leaf shape). In the 72-vine set, we only sampled the middle two vines from each four-vine cell in the vineyard (shown in Supplemental Figure 1B-C). At the highest order interaction for gene expression (rootstock:row:phenology), the number of biological replicates would be two. Since this is clearly underpowered, we put little effort into estimating or interpreting those effects. However, lower order interactions (like rootstock:row or rootstock:phenology) are averaged over the remaining samples. For example, the rootstock:row effect is estimated from 6 samples (averaged over phenology). Similarly, main effects are averaged over all other terms, so the rootstock effect would be estimated from 18 samples.

8. Usually, for genome-wide transcriptional studies, the expression patterns of a subset of genes are confirmed using another method (e.g. quantitative real-time PCR). This has not been performed in this manuscript. Authors need to confirm the validity of the RNA seq dataset.

- Response: Thank you for this comment. We agree that for studies focused on identifying genes associated with specific phenotypes, that the gold standard for genome-wide transcriptional studies is cross-validation using qPCR. The goal of this study is to understand the influence of root system genotypes on shoot system phenotypes, and here we are treating gene expression in the leaves as a shoot system phenotype. Because we are not testing explicit hypotheses about any particular gene or pathway, we determined that PCR-based confirmation would not add value. This decision was not made lightly, and was done following consideration of other recent work that applied various RNAseq platforms to address structurally similar questions, including:

1) Griffith M, Griffith OL, Mwenifumbo J, Goya R, Morrissy a S, et al. (2010) Alternative expression analysis by RNA sequencing. Nat Methods 7: 843–847. Doi:10.1038/nmeth.1503.

2) Asmann YW, Klee EW, Thompson EA, Perez E a, Middha S, et al. (2009) 3' tag digital gene expression profiling of human brain and universal reference RNA using Illumina Genome Analyzer. BMC Genomics 10: 531. Doi:10.1186/1471-2164-10-531.
3) Wu AR, Neff NF, Kalisky T, Dalerba P, Treutlein B, et al. (2014) Quantitative assessment of single-cell RNA-sequencing methods. Nat Methods 11: 41–46. Doi:10.1038/nmeth.2694.

4) Shi Y, He M (2014) Differential gene expression identified by RNA-Seq and qPCR in two sizes of pearl oyster (Pinctada fucata). Gene 538: 313–322. Doi:10.1016/j.gene.2014.01.031.

-Moreover, we point to an excellent blogpost on the same validation-discussion that goes further in to this debate:

http://dave-bridges.blogspot.no/2014/11/validation-of-rnaseq-experiments-byqpcr.html?m=1

-We agree that it adds value to ensure that our data show previously established patterns of house-keeping and circadian-phased genes relevant to our sampling

paradigm. As such, the following have been added to the manuscript: -Added to data description L207 - 210, "To check the validity of our expression results, we assayed two classes of housekeeping gene (Ubiquitin-domain and actin-family) and eight previously annotated circadian genes (Carbonell-Bejerano et al. 2014)" -Added to Analyses, L339 - 341, "We computed the expression of two classes of housekeeping genes, and show that they are generally stable (Supplemental Figure 2). We note that some variation is expected for housekeeping genes; see, for example, (Liang et al. 2018). Moreover, we show that patterns of previously annotated circadian genes show expected results over the sampling window. For example, predicted orthologs of LHY and RVE1 are correlated and decreasing over our sampling window, and a predicted TOC1 ortholog is invariant. That our samples showed such patterns suggested the gene expression data presented here were valid." -Created and added Supplemental Figure (now supplemental Figure 2) showing these

patterns.

9. The effect of the different irrigation regimes is not adequately discussed in this manuscript.

-Response: Thank you for this note - good catch. Effects of different irrigation regimes were originally presented in a Supplemental Note hosted on GitHub. To increase accessibility, we moved Supplemental Note 1 from GitHub so that it is now a Supplemental Note to the manuscript.

-Some additional notes: our study site is located in southwestern Missouri where it can be quite rainy. In 2017, the year in which samples were collected for this study, it rained a lot, essentially rendering the vines all properly irrigated despite the amount of irrigation applied as part of the study. Not surprisingly, our physiological metrics showed little/no evidence of stress. As such, we opted to include irrigation as a term in the model that is there and could impart variation into some phenotypes, but those effects are very small.

10. The Abstract must be structured into three separate sections: Background; Results; Conclusions.

-Response: The abstract has been restructured to meet the suggested format. We thank the reviewer for catching this oversight.

Minor comments

1. A lot of the information under "data description" should be moved to the methods section. For me, the data description should provide more of a background and rationale of the work, while the methods should provide the actual steps that were taken.

-Response: Thank you for this note. We struggled to balance the need to provide enough information for readers to understand the work up front, while saving the majority of methodological details for the methods section. In its current version, we hope that we have provided the appropriate information in the approximately preferred locations according to the journal's instructions. If there are persistent issues with information placement in the current version of the manuscript, we would be happy to address those in whatever way the editor/reviewers request.

2. Although it is alluded to in the introduction and data description, the tissue type that was harvested and used for the RNAseq experiments is not mentioned in the methods or analyses sections.

-Response: Good catch, and we regret this omission. The tissue type used for RNAseq experiments were young, fully opened leaves. We added information about the tissue type in the analysis section, and assured it was explicitly mentioned in the data description.

-L185 starts "The youngest fully-opened leaves" -L336 added "youngest fully-opened leaves"

The Figure 1B legend should denote what Y, M, and O mean. I realise that it is young, middle and old, but the legend should stand alone.
 Response: Another good catch. We added a short key to L705 - 706 indicating Y (young), M (middle), and O (old).

4. Significant differences in Fig 1B and Fig 5 B&C could be annotated within the

Figure, for example with an asterisk.

-Response: Excellent suggestion. Significant comparisons have been labelled with letters in the identified figures, and the figure legends have been edited to explain them.

5. Please be careful to use the past tense consistently, for example P16, L403 "correlation between gPC4 and pPC3 is similar" should be 403 "correlation between gPC4 and pPC3 was similar".

-Response: Thank you for this important catch. Tense was changed in the cited examples and edited throughout the manuscript.

P19, L472 "stomatal conductance were higher vines" should be "stomatal conductance were higher in vines".
-Response: Added 'in' to L512

7. P19, L475 "Understanding of rootstock genotype influence shoot system phenotypes" should be "Understanding of how rootstock genotype influence shoot system phenotypes".

-Response: Edited L516 to read, "Understanding rootstock genotype influence on shoot system phenotypes"

8. Perhaps consider re-writing the title to the Fig 5 legend. "Vine physiology measurements show signal from most experimental manipulation" does not make sense to me.

-Response: Edited title on L746 to "Vine physiology varies with rootstock and the rootstock by phenology interaction"

Nice work.

Thank you for this. We appreciate the detailed review.

Reviewer #3

This study investigate associations between rootstock genotype and shoot system phenotypes using five multi-dimensional approaches contributing to elucidate how root systems influence vine phenotype.

the influence of rootstock on the traits analyzed are roughly well documented in literature and authors are aware about this since they very often commented that results are consistent with previous study. Hence the reader might question about the limited new information provided. I would recommend the authors at the "potential implications" paragraph to avoid speculation on "yield" and to emphasis the novelty of engaging a simultaneously analysis as they did in order to speed up comparative studies.

-Response: This is a very helpful suggestion. In response to this and comments from other reviewers we have re-worked the potential implications section. Other reviewers called for an enhanced focus on yield/viticultural implications; however, we agree with this reviewer's request to minimize speculation. Consequently, we have attempted to carefully place this work in the context of both basic plant biology and viticulture. If the current revision does not meet the expectations of the reviewer(s) or editors we would be happy to revise further.

Minor comments

1.At line 226-227, check "umol/s" replace with [?]mol s-1 ? -Response: Unfortunately the symbol the reviewer suggested did not render in the communications (we can't see it). We have replaced the umol with the more commonly accepted µmol where appropriate. If another symbol is preferred or a different symbol was meant, please let us know and we would be happy to make the requested change.

2.At line 231, is 15 min interval time enough to equilibrate? Considering that usually 30 or 60 min are required (e.g., J.Int.Sci.VigneVin, 2012, 46, n°3, 207-219, See https://urldefense.com/v3/__https://doi.org/10.20870/IVES-TR.2020.3620__;!!K543PA!bnhJBaYGb-608nkV-F90Yallxoa2UGVyHkLiToTGXSjDbduO2MrZFPISJayIAoKRcnAWzw\$See ISBN 978-90-481-9282-3 at pag 89), please justify your 15 min interval.

-Response: We thank the reviewer for this thoughtful comment. We acknowledge that this is a topic of much debate. A 15 minute equilibration has been used in the past to measure midday stem water potential for tree species, and explicit testing showed that there was little difference between a 10-15 equilibration and a >1hr equilibration in oak trees

(https://www.fs.fed.us/psw/publications/documents/psw_gtr184/psw_gtr184_035_Shac kelGross.pdf). A more recent study (published after our work was completed) suggests that there is a small effect from different equilibration times in grapevine, but that effect is smaller than the effect from the person operating the pressure chamber (https://doi.org/10.1016/j.agwat.2019.03.026). We have amended the section of the manuscript to include these references for future readers (L254-255).

3.Please note that "old" and "young" communicate leaf age rather than leaf position, what's about top, middle, bottom?

-Response: This has been a topic of much debate on our team and we really appreciate this comment. The designation of "old", "middle" and "young" stem essentially reflect terminology used by our team since the inception of the project. We totally agree that these terms reflect leaf age rather than position. However, in grapevines these are equivalent because the oldest leaf along a vine is at the bottom of the shoot and the youngest leaves are at the top of the shoot. All things being equal we would readily make this change; however, the current terminology is used in this paper and in many other completed or ongoing manuscripts being carried out by members of our team. If it is amenable to the editor and the reviewer, we would prefer to retain the "old" "middle" and "young" designation. However, if this is unworkable we will make changes to the language.

4.It is not clear why 1103 P had a very little variability of gs at anthesis compared to other rootstocks, for these plant water status seems to range from well irrigated to deep stressed vines while 1103P vines seem to be all roughly well irrigated. -Response: We appreciate this observation. It is not immediately clear why vines grafted to 1103P showed such little variation in stomatal conductance at anthesis. Unfortunately we don't think we can test this with the current study. To investigate this and related questions we completed a greenhouse study with 1103P and other rootstocks grafted with a common scion with an irrigation treatment. This work is in preparation now.

5.Providing VPD data might help to explain why transpiration is low at anthesis (approx. 2.5 mmol m-2 s-1) while gs at anthesis is comparable to that of other sampling time.

-Response: Thank you for this interesting point. We agree that features of the environment (like VPD) will partially explain the differences we see across the time point in this and future studies. Ongoing work is attempting to identify features of the environments that correlate and can explain some of the variation we see in these traits. This is partially undermined by natural season changes, so these relationships are hard to untangle and require a substantial amount of data, much beyond the three time points presented here. However, we appreciate this comment and hope to address this in future works.

6. "leaf position" should also be discussed against "leaf angle" (e.g., https://urldefense.com/v3/__https://doi.org/10.3389/fpls.2020.00595__;!!K543PA!bnhJB aYGb-6O8nkV-F90Yallxoa2UGVyHkLiToTGXSjDbduO2MrZFPISJayIAoLo-b4lwA\$) which likely change across the season due to change of soil water availability. was leaf angle accounted for image analysis? Considering that soil moisture reasonably differed at the three stages considered (Fig. 5).

-Response: Thank you for this insightful comment. We agree that leaf angle is important for physiology, and would likely correlate with some of the traits we measured. Unfortunately, leaf angle was not quantified at the time of collection in the field. Leaves were simply chosen from vines that emerged directly from the cordon and had intact young, middle, and old leaves. Leaf scans were completed in the lab after leaves had been removed from the vine, and it was not possible to quantify leaf angle at this time. Having said that, this is an important consideration for future studies and we very much appreciate this observation.

7.Please add the mean leaf water potential and soil moisture values directly in the Fig. 5 panels to help the readers.

-Response: We thank the reviewer for this suggestion on improving our figures. We have added the mean value for reach rootstock/phenology combination in Figure 5 and, for consistency, to Figure 1. Figurel legends have been edited to address these changes on L712 and L751.

Reviewer #4

This 'big data' manuscripts offers a comprehensive snapshot of the grape phenome as influenced by several factors, including ionomics, leaf morphology, physiological data, metabolomics and transcriptomics. The overall scope is ambitious and a step forward for the phenomics community. Overall the paper was well-written and the design and analysis are sound, though I had a few questions below.

Response: Thank you for these very kind and encouraging words.

I had a few suggestions.

1.Phenomic and phenotypic are used interchangeably, and I would ask they be clearly defined - should they really mean the same thing? What's the difference between a phenome and a phenotype?

-Draft response: Thank you for this important observation. We define "phenomics" to be a "field characterized as the acquisition and analysis of high-dimensional phenotypic data at hierarchical levels, often with an eye toward multiscale data integration" in the introduction. We define a phenotype as a single particular trait (e.g., calcium concentration). As such, we have amended usages of these words to comport with this definition: phenomic (and phenomics) now refer to the joint analysis of multiple data modalites, each of which contain several phenotypes (or a single multi-dimensional phenotype). In addition, we recognize that we were being imprecise with language here, so we have fixed this and other terms used interchangeably (trait/phenotype, phenotypic/phenomic, and data type/modality) throughout the manuscript.

2.Is the paper considering transcriptomics as phenomics? I know it's a debated issue really, but would be good to state so and why.

-Draft response: Thanks for this comment, like many groups we have spent a lot of time thinking about the question of whether or not the transcriptome is a phenomic modality. In the introduction of this manuscript, we loosely acknowledge phenomics as the field of study concerned with high-throughput data acquisition through multiple simultaneous trait measurements, often requiring advanced computation to analyze and integrate L62-63. Following this definition, we treat the transcriptome as a multi-dimensional phenotype (or that the extent to which a particular gene is expressed at a particular time in a particular place is a measurable trait/phenotype). In the analysis and interpretation of the data in this manuscript, we treat the transcriptome like the other data modalities presented here.

3.Related, phenotype and trait are inconsistently used as detailed below. I recommend to define them and use consistently. This is a huge problem for phenomics and I think prevents clear discussion of the topic.

-Response: We thank the reviewer for this comment on clarity. Throughout the manuscript we have edited the language we used to describe phenotypes to be consistent. In particular, we have edited each usage of 'trait' to 'phenotype. As above, we recognize that we were being imprecise with language, so we have fixed this and other terms used interchangeably (trait/phenotype, phenotypic/phenomic, and data type/modality) throughout the manuscript.

4.I had some questions about the experimental design and randomization, detailed in line comments. I'm not sure about the claim of 72 replicates. Maybe it's a question of what should be considered an experimental unit.

-Response: Other reviewers also noted lack of clarity with respect to experimental design, and we appreciate this observationt. A full response to this concern can be found in our response to your comment on L561 (below); which is partially copied here: I think some additional confusion may stem from us using "replicate" as a vague stand-in for both clonal replicates and statistical replicates. To address this, we have

amended the language about the four rootstock scion combinations as follows on L617: "Clonal replicates of each of the four rootstock-scion combinations were planted 72 times for a total of 288 vines planted in nine rows". In addition, we included the specific type of design (split-plot) to this section. Finally, we addressed the number of true replicates in a comment by reviewer 2 concerning RNAseq. The same logic can be used to derive the total number of biological replicates for leaf shape and ionomics at the highest order interactions (4) and for all other phenotypes (2). In the case where the number of biological replicates is two, the estimation and interpretation of effects is minimized due to lack of power.

5. The analysis of individual datasets (or modalities, good word) seems good, and I think the approach to combine into a larger set using the PCA is pretty clever. I still wondered how 'fused' the data really is but can't really think of a better way other than combining all the raw data except then the number of genes and metabolites would just swamp the analysis I guess. Perhaps the authors could articulate why this is a good fusion approach they've used, and perhaps what could be done in the future. -Response: Thank you for this kind observation and really insightful comment. We considered a larger integrative framework that would include all phenotypes measured in the study. However, as the reviewer identified, this would include a heavy bias toward gene expression (expression data for 24,000+ transcripts) and metabolomics (600+ different features measured) which would likely overpower leaf shape (17 x,y coordinates) and jonomics (20 jons). We felt that the PCA approach allowed us to weigh each modality more evenly in order to see if further integrative efforts were warranted. Based on these high-level results, it looks like integration among modalities is a warranted effort, especially if we could collect more targeted data that could expand mechanistic understanding of observed patterns. However, the scope of these integrative techniques is broad and several papers could likely be written just exploring differences in integration techniques with just a single phenotype, for example, gene expression. We have edited the sentence on L430-431 to reflect this logic: "Within each phenotyping modality, we summarized the primary dimensions of phenotypic variation using PCA (see Methods), so as to not weigh any modality too heavily."

6.I Biologically, I'd like to see more insights to why these traits matter. How could understanding that these traits change help production? I think some arm waving is warranted. Especially, how is understanding the correlation among modalities important? One idea is to identify trade-offs and synergisms? -Response: We thank the reviewer for this suggestion. We modified the language of the potential implications to suggest some ways in which this kind of work could balloon into other phenotypes (not measured for this study) that are more useful to breeding through synergistic relationships (enhancement), trade-offs (constraint), or just simply predictability. Moreover, we maintain that the broadest implication is the notion that there is a strong temporal component to phenotypic expression in long-lived perennial plants and that grafting and rootstock genotype add another dimension to it.

7.Last, I'm happy to see how much data is shared. However, GitHub is not appropriate for sharing data, which should all be on a public repository, including the analysis scripts. I think FigShare has been used for other permanent data, so I recommend to share the scripts there.

-Response: We thank the reviewer for this insight. The note on irrigation, which was initially uploaded to GitHub, has been added as a Supplemental Note to this manuscript. This note will additionally stay on github for easy access. All phenotypic data from the ionome, metabolome, leaf shape, and physiology are on Figshare and the gene expression are on the SRA. In addition, we are in the process of submitting raw metabolomics data to the Metabolights database, as requested by GigaScience. Line comments and other details follow:

39: In my opinion, the 'hyphens' are not needed in belowground and aboveground. -Response: From what I can gather, above-ground and aboveground are considered to have the same meaning. We leave this stylistic choice up to the editor.

45: "change" -Response: L46: changes -> change 46: long sentence with semicolon, consider making that a period, but the use of many interjections make it a little hard to parse still

-Response: Good catch. This sentence has been split into two (now L44).

99: are phenotypes and traits taken to be completely synonymous in this paper? Given that many definitions are used of each, it would be helpful to define. For example, both can be used to describe the 'general' properties like 'eye color' or the specific like 'blue eyes.' Phenotype, in addition, is sometimes used to describe the totality of all trait values in an organism. More careful and exact usage would benefit the paper. For example, trait value can also describe the specific like 'blue eyes' while trait the general 'eye color.' The title of your paper suggests that you additionally consider the phenotype as all traits (or trait values?). Leaf shape is referred to as a phenotype at line 439, so consistent with the 'general trait' definition.

-Response: We agree this was a persistent problem in the initial version of the manuscript. As above, we recognize that we were being imprecise with language, so we have fixed this and other terms used interchangeably (trait/phenotype, phenotypic/phenomic, and data type/modality) throughout the manuscript.

111: what would the difference bet tween phenomic and phenotypic variation? what is the definition of the phenome? phenotypic variation is also used at line 434 -Response: Another good catch. We have edited the language throughout the text so that it is now consistent. We did not actually mean to distinguish between these two things in the highlighted example. As above, we recognize that we were being imprecise with language, so we have fixed this and other terms used interchangeably (trait/phenotype, phenotypic/phenomic, and data type/modality) throughout the manuscript.

115: Were there any hypotheses? Is the intent to be descriptive? -Response: The goals of this study were to address three questions: 1) what is the influence of root system genotype on shoot system phenotype? 2) How do systems of plant phenotypes vary over the growing season and does rootstock genotype influence this variation? And 3) how do phenotypes covary within and between phenotyping modalities? For clarity, we have enumerated these questions in the Study Design section. L639 - 642.

118: Are the details of the experimental design needed here because of the wonky format of a GigaScience paper with methods at the end? Not your fault, but I find these formats so confusing and redundant since authors try to move methods into other sections to make up for it.

-Response: We appreciate this comment. This was certainly a design choice by us so that the paper could be understood linearly.

139: if this pipeline is capitalized and sort of 'official' - is there a citation or access to details of it?

-Response: This is a standardized pipeline at the Donald Danforth Plant Science Center. The sentences surrounding this line (now L140-146) have been restructured to make this more clear: "Between 20 and 100 mg of leaf tissue was acid digested and 20 ions were quantified using inductively coupled plasma mass spectrometry (ICP-MS) following standard protocol of the Donald Danforth Plant Science Center (DDPSC) lonomics Pipeline [30,31]. Ion quantifications were corrected for internal standard concentrations, instrument drift and by initial sample mass. The output of the Pipeline contained measures for each of the following 20 elements: AI, As, B, Ca, Cd, Co, Cu, Fe, K, Mg, Mn, Mo, Na, Ni, P, Rb, S, Se, Sr, and Zn."

140: Why the difference for ML?

-Response: Z-scores were used in the linear models for ion concentrations so that models could be compared. However, the random forest is a single model that needs no adjustment on the input space. We included a small comment that non-standardized input is the convention for random forests (however many ML models do need to be standardized to equally weight each feature).

141: This Leaf Ionomics section, to me, describes the method to sample and measure, but fails to describe the final output? How many ions? which? I don't fully understand

why GigaScience requests this format, but it does mention the background should be given. SO, I think you should say why the ionome is important, and the same for other trait conglomerates mentioned in the paper.

-Response: This is helpful - thank you. We have added the following:

- to L145-146 to explain the ionomics data set, "The output of the Pipeline contained measures for each of the following 20 elements: Al, As, B, Ca, Cd, Co, Cu, Fe, K, Mg, Mn, Mo, Na, Ni, P, Rb, S, Se, Sr, and Zn."

-To L179 to explain the metabolomics data set, "The 661 identified metabolomic features..."

143: carbon-based molecules? For example, not nutrient ions? -Response: Added "mostly organic" to enhance description of the metabolome

144: I had to look up 'veraison' - could you put 'ripening' in parentheses if that captures that idea?

-Response: Clarified as the "onset of fruit ripening" on L153

210: scanning details? background, color, DPI, image format? -Response: L228 - 229: added "in color against a white background at 1200 DPI and written as JPEG formatted images".

236: recommend to again announce the number of ions analyzed -Response: Added "and measured the concentrations of 20 ions" to L262

244: It's not clear what the percentage refers to, I imagine percentage of total variation accounted for by that factor, ie the effect size. recommend to include 'effect size' -Response: Added variation explained to first usage

249: Giving the effect sizes is a reasonable summary given your multiple factors, however I think giving some indication of absolutely changes is also relevant? Like, what type of percent changes were observed across all the samples in absolute terms, or give the min and max for some ions? Obviously you can't be exhaustive, but this would put the effect size in some type of context of biological influence, like rootstock explaining 10% of variation in a 1% change in Ca vs a 100% change in in Ca. Hope that's understandable. Perhaps these absolute changes would be most relevant where you highlight the influence of rootstocks?

-Response: Thanks for this thoughtful comment. The value of effect sizes like percent variation explained are that they can be directly compared if the models are parameterized in an identical manner. However, I think this confusion could be clarified by projecting samples back into a real concentration space which has now been done for the figure.

267: Could MDA be spelled out on first mention? -Response: L293 now includes Mean Decrease in Accuracy. It is also defined in the methods.

350: personal placeholder to check discussion for how so much variation isn't accounted for - seems surprising!

-Response: We agree that the lack of variation explained in the models for leaf shape is quite interesting. Future work will certainly explore factors such as variation imparted from individual vine and environmental variation to attempt to explain this.

400: I'm confused that the PCs should correlate from the same modality, something which I thought didn't usually happen?

-Response: There is statistical literature on this topic. In short, principal components are orthogonal, however orthogonal does not always mean uncorrelated. See Rodgers, Nicewander, and Toothaker, 1984.

462: Good to bring up the biological implications - what are they? Are these changes relevant for growth, taste, etc?

-Response: We agree that the earlier version of this manuscript was missing key information about why the ionome is important. Unfortunately, there is not a lot of work tying together the elements of the ionome that we identified as responsive to rootstock genotype. Traits of biological interest, features that are known to be influenced by ion

uptake by the root system (rootstock) are now mentioned in the manuscript, including vine growth and fruit/wine quality. We have added a comment on this in the discussion to address that there is a known connection between macronutrients and these traits, but more work is needed is to uncover these connections with micronutrients in grapevine. To this end, we added the following to L518 - 520: "To our knowledge, there is not yet a strong causal link between the micronutrient component of the ionome and factors of vine growth or development that might influence traits like wine quality. However, it is noted that macronutrient deficiencies can have negative effects on such traits (Bravdo 2000; Brunetto et al. 2015) and can be mediated by rootstock (Gautier et al. 2018). This suggests a strong understanding of the rootstock influence on the vine's ionome is warranted, and more work needs to be done to establish these relationships"

474: Can stomatal conductance be limited by flow in the roots? Do you think it's more likely such an indirect effect, or a direct effect such as signals from the rootstock actually change the rates by stomatal closure, etc?

-Response: This is a really good question that is particularly challenging to fully address. We would wager that root architecture is a key driver of physiological variation, and we tested this in a greenhouse study the results of which are in preparation now. However, it is worth noting signals could be passed from the rootstock, but the space of signal passing through graft junctions is complex and this work was not designed to address anything to that end.

501: I think here, rather than 'phenotype' as 'traits' you meant to say something about the 'data types,' which you referred to as modalities before and would be appropriate to use here. 'traits of different modalities'. I would suggest this instead of 'data types' perhaps for consistency. Definitely it would be a benefit to the field to have ways to describe these 'groups' of traits from the same instrument, my lab also runs into this with fused, multi-dimensional data.

-Response: Great observation, and we agree. We have fixed this instance of improper usage and we have clarified the language in the discussion (and the rest of the manuscript) to be more consistent. Specific to this comment, 'data type' has been replaced with modality/ies throughout the piece. As above, we recognize that we were being imprecise with language, so we have fixed this and other terms used interchangeably (trait/phenotype, phenotypic/phenomic, and data type/modality) throughout the manuscript.

502: latent phenotypes were mentioned in the definition of phenomics (where I only see them as one possibility, not a defining feature). Some definition would be useful. -Response: This is a good catch. We did not mean to imply latent phenotypes were the only possible outcome of this work. This sentence was expanded a bit to include that idea that latent structure is one possibility, but using this to target integrative analysis is also a strong possibility. (L565)

510: back to phenomic correlation - what's the difference with phenotypic correlation? -Response: Good catch of this persistent issue in the earlier version of the manuscript. We did not mean to imply there was a difference, or to make any kind of statement on this distinction. As above, we recognize that we were being imprecise with language, so we have fixed this and other terms used interchangeably (trait/phenotype, phenotypic/phenomic, and data type/modality) throughout the manuscript.

533: Very little information was provided about how the changes measured here in traits would affect yield or other consumer-facing traits. Not only that, but why is the multi-dimensionality important? Does it reveal trade-offs in traits, for example? I'm trying to help you improve the biological impact component. Some arm waving may be warranted.

-Response: We very much appreciate the direction the reviewer is going here, and we have attempted to address this in the potential implications section of the manuscript and elsewhere. Multi-dimensional data are data that consist of many different observations (for example, the ionome which includes measurements of 20 different ions). Multi-dimensional data offer more robust, approaching comprehensive observations of plant phenotypes. They offer a rich source of information that can be used to more comprehensively understand the basic biology of the organism - for example, how root systems influence features of shoot systems in grafted plants. This is described in, for example, L94-100 of the introduction. The influence of the

	phenotypes we measured on yield or other consumer facing traits are under active investigation. For example, ongoing work by others members of our project team describes berry chemistry and wine volatiles for the experimental vineyard described here. The volume of data was so large; this manuscript represents the first step in processing and interpreting multiple multi-dimensional phenotypes and trying to understand what approaches can be used to understand how they relate to one another. The next steps will be to connect these data with observations that might be more directly relevant to viticulturists. Our hope is that this manuscript will provide the foundation for those analyses that integrate multi-dimensional data from different organ systems, such as leaves and berries.
	permanent and therefore I suggest to include as supplemental to this paper or else place on a 'permanent' public repository such data dryad, Zenodo, etc. If the irrigation factor was ignored, you should say so. -Response: Good point. The note on irrigation has been added as a Supplemental Note to this manuscript. Irrigation was treated as an additional blocking factor in the analyses done here. While we will keep the other data available on Figshare, we are exploring other homes for the data that are in line with GigaScience's preferences.
	561: After reading this section, I wasn't sure about the experimental design, especially what type of randomization was used. I would guess that an appropriate design here would have been split plot block design taking into account irrigation (which I guess you are saying you ignored in the end). Were genotype randomized? the groups of 4 are mentioned, should that be taken as the experimental unit? I'm not super picky about stats, but some might say there are flaws here, and perhaps the 72 should be divided by 4 as as far as complete replicates? In Supp Fig 1 in the map, I see up to Block F - so should it be 6 true replicates? In cases likes this, I usually think of the additional plants as subreplicates. Your design seems basically just like a annual crop field trial with small plots with multiple plants. We usually measure a trait on those subreps then average it to the plot level for further analysis. In that case, the subreplication isn't used in stats directly, but does allow a better approximation of the value for each plot and decrease overall 'random' or 'environmental' errorResponse: This is a great catch by the reviewer. We regret that the earlier version of this manuscript did not fully explain the experimental design of the research vineyard used in this study. These details have been filled in in section Study Design of the manuscript. Further, I think some additional replicates and statistical replicates. To address this, we have amended the language about the four rootstock scion combinations were planted 72 times for a total of 288 vines planted in nine rows". In addition, we included the specific type of design (split-plot) to this section. Finally, we addressed the number of true replicates in a comment by reviewer 2 concerning RNAseq. The same logic can be used to derive the total number of biological replicates for leaf shape and ionomics at the highest order interactions (4) and for all other phenotypes (2). In the case where the number of biological replicates is two, the estimation and
Additional Information:	D
QUESTION	Kesponse
Are you submitting this manuscript to a special series or article collection?	No
Experimental design and statistics	Yes
Full details of the experimental design and statistical methods used should be given in the Methods section, as detailed in our <u>Minimum Standards Reporting Checklist</u> . Information essential to interpreting the	

data presented should be made available in the figure legends.	
Have you included all the information requested in your manuscript?	
Resources	Yes
A description of all resources used, including antibodies, cell lines, animals and software tools, with enough information to allow them to be uniquely identified, should be included in the Methods section. Authors are strongly encouraged to cite <u>Research Resource</u> <u>Identifiers</u> (RRIDs) for antibodies, model organisms and tools, where possible.	
Have you included the information requested as detailed in our <u>Minimum</u> <u>Standards Reporting Checklist</u> ?	
Availability of data and materials	Yes
All datasets and code on which the conclusions of the paper rely must be either included in your submission or deposited in <u>publicly available repositories</u> (where available and ethically appropriate), referencing such data using a unique identifier in the references and in the "Availability of Data and Materials" section of your manuscript.	
Have you have met the above requirement as detailed in our <u>Minimum</u> <u>Standards Reporting Checklist</u> ?	

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1	Multi-dimensional leaf phenotypes reflect root system genotype in grafted
2	grapevine over the growing season
3	
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36 Abstract

37	Background: Modern biological approaches generate volumes of multi-dimensional data, offering
38	unprecedented opportunities to address fundamental biological questions previously beyond reach due to
39	small or subtle effects. A fundamental question in plant biology is the extent to which below-ground
40	activity in the root system influences above-ground traits (phenotypes) expressed in the shoot system.
41	Grafting, an ancient agricultural horticultural practice that fuses the root system of one individual (the
42	rootstock) with the shoot system of a second, genetically distinct individual (the scion), is a powerful
43	experimental system to understand below-ground effects on above-ground phenotypes. Previous studies
44	on grafted grapevines have detected rootstock influence on scion phenotypes including physiology and
45	berry chemistry; however. However, the extent of the rootstock's influence on leaves, the photosynthetic
46	engines of the vine, and how those effects changeschange over the course of a growing season, are still
47	largely unknown.
48	Results: Here, we investigate associations between rootstock genotype and shoot system phenotypes
49	using five multi-dimensional leaf phenotyping modalities measured in a common grafted scion: ionomics,
50	metabolomics, transcriptomics, morphometrics, and physiology. Rootstock influence is ubiquitous but
51	subtle across modalities with the strongest signature of rootstock observed in the leaf ionome. Moreover,
52	we find that the extent of rootstock influence on scion phenotypes and patterns of phenotypiephenomic
53	covariation are highly dynamic across the season.
54	Conclusions: These findings substantially expand previously identified patterns to suggestdemonstrate
55	that rootstock influence on scion phenotypes is complex and dynamic and underscore that broad
56	understanding necessitates volumes of multi-dimensional data previously unmet.
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58	Background
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- High-throughput data acquisition has afforded unprecedented capacity to quantify and understand
 plant form and function. Recent advances in imaging and computation have expanded our ability to

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62	measure plant structures [1,2]traits or phenotypes [1,2], and to extend those comprehensive measurements
63	into latent space phenotypes [3]. Now broadly known as phenomics, this burgeoning field is
64	characterized as the acquisition and analysis of high-dimensional phenotypic data at different hierarchical
65	levels [4,5][4,5], often with an eye toward multiscale data integration. A holistic and hierarchical
66	approach to plant phenotypic variation affords unique insights into plant evolution, and how plants
67	change over development and in response to environmental cues and horticultural manipulation.
68	A fundamental question in plant biology is how root systems influence phenotypicphenomic
69	variation in above-ground shoot systems including leaves, flowers, and fruits. Grafting, a common
70	horticultural manipulation that joins the shoot system of one individual (the scion) with the root system of
71	another individual (the rootstock), is commonly used in crop species to confer favorable phenotypes to
72	commercial scions [6][6], including enhanced disease resistance [7,8][7,8], fruit quality, plant form [9][9],
73	response to water stress [10][10], and growth on particular soils [11,12][11,12]. Because grafting often
74	uses clonally propagated materials, it is possible to manipulate and replicate different combinations of
75	root systems and shoot systems, offering a valuable experimental system in which root system impacts on
76	shoot system phenotypes can be evaluated.
77	The European grapevine (Vitis vinifera) is among the most economically important grafted crops
78	in the world. Grapevines are cultivated primarily for fruits used to make wine and juice, as well as for
79	table grape and raisin production. Grafting in grapevines became widespread in the mid-1800's following
80	the accidental introduction of the root-feeding aphid phylloxera from its native North America into
81	Europe, where it began attacking the roots of European grapevines [13].[13]. Because European
82	grapevines often diddo not survive phylloxera infestation, in regions where phylloxera has been
83	introduced most grapevine cultivation now consists of European grapevines grafted to rootstocks derived
84	from phylloxera-resistant North American Vitis species including V. berlandieri, V. riparia, and V,
85	rupestris, and their hybrid derivatives. In addition to grapevines, more than 70 major perennial crops are
86	grafted including many fruit trees and vines [9]. In these crops, grafting[9]. Grafting decouples the
87	breeding of shoot systems and root systems, with selection in plants targeted for use as scions focusing

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88	primarily on fruit traitsphenotypes, and selection in plants targeted for use as rootstocks focused on
89	below-ground biotic and abiotic stress resistance, as well as their impacts on shoot system phenotypes.
90	The effects of grafting in grapevine show a remarkable breadth of scion response patterns. For
91	example, a study of Vitis vinifera cv. 'Cabernet Sauvignon' grafted to different rootstocks identified
92	transcriptome reprogramming in the scion of grafted plants; this appeared to be a general effect of
93	grafting to a rootstock and was not rootstock-specific [14].[14]. In contrast, other studies have found
94	signatures of rootstock genotype in the transcriptome in early berry development, although this distinction
95	was lost in later development [15,16], but see [17].[15,16], but see [17]. Comprehensive phenomic
96	analyses, including those that link transcriptome data with other high-throughput phenotyping
97	assays, offer an opportunity to expand understanding of rootstock effects on grapevine shoots. In one
98	study, leaves of the V. vinifera cultivar 'Gaglioppo' showed variation in stilbene and abscisic acid
99	concentrations due to rootstock genotype, as well as differences in transcriptional profiles [18].[18].
100	Likewise, gene expression, ion concentrations, and leaf shape in the cultivar 'Chambourcin' varied in
101	response to rootstock genotype [18,19].[18,19]. Collectively, these studies suggest the impacts of grafting
102	are diverse and may vary over the course of vine development. However, to date few studies have
103	surveyed multiple high-dimensional scion phenotypes to understand the rootstock influence on shoot
104	system traitsphenotypes over the course of the growing season or the extent to which grafting effects on
105	the scion covary with one another.
106	Grapevine leaves Leaves are the photosynthetic engine of the organism and a primary site
107	for perception and response to environmental change. Leaves present a wide variety of highly variable
108	and readily assayable phenotypes, providing an important opportunity for phenomic assessment.
109	Grapevine leaves have been used for centuries as markers of species and cultivar delimitation,
110	developmental variation, disease presence, and nutrient deficiency [20,21]. [20,21]. More recently,
111	analysis of grapevine leaf morphology has identified genetic architecture of leaf shapes [22][22],
112	developmental patterns across the season $\frac{23}{23}$, and signatures of evolution in the grapevine genus
113	[24]-[24]. Grapevine leaves respond to stress through gas and water exchange with the atmosphere
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114	[25,26][25,26] and have been shown to differentially partition the ionome depending on their position on
115	the shoot [19][19] and their rootstock genotype [19,27,28][19,27,28]. The volume of work on grapevine
116	leaves provides a foundation for the analysis of phenomic variation in a vineyard over a season in
117	response to grafting.
118	In this study, we investigate effects of grafting on high dimensional leaf phenotypes of the hybrid
119	cultivar 'Chambourcin' over the course of the growing season. We quantify leaf elemental (ion)
120	concentrations, metabolite abundance, gene expression, shape, and vine physiology in a replicated
121	rootstock trial where the hybrid grapevine cultivar 'Chambourcin' is growing ungrafted and grafted to
122	three different rootstocks. The four root-shoot combinations ('Chambourcin' ungrafted, 'Chambourcin'
123	grafted to three different rootstocks) are replicated 72 times in a randomized block experimental design
124	with an irrigation treatment (Supplemental Figure 1). DataPhenotypic data, data that describe variation for
125	a particular trait within a particular modality, were collected either on the full 288-vine set (ion
126	concentrations, leaf shape) or on a subset of 72 vines (the 72-vine set; metabolite abundance, gene
127	expression, vine physiology). Using data collected at three time points that span the growing season
128	(anthesis, veraison, and harvest), we show that <u>all phenotyping modalities (</u> ionomic, metabolomic,
129	transcriptomic, morphometric, and physiology phenotypes) reflect subtle but ubiquitous responses to
130	grafting and rootstock genotype. Rootstock effects on shoot system phenotypes were often dynamic
131	across the season, suggesting that accounting for seasonal variation could alterenhance our understanding
132	of grafting <u>effects</u> in viticulture.
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134	Data Description
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136	Leaf Ionomics
137	The ionome describes elemental composition of a tissue at a particular time point [29].[29]. Three
138	leaves per vine were collected from the 288-vine set- <u>at three seasonal time points: anthesis (~mid May).</u>
139	veraison (~late July), and harvest ~mid September). Leaves were sampled from a single shoot and

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140	included the youngest fully opened leaf at the shoot tip, the approximate middle leaf, and the oldest leaf at
141	the shoot base. Teams were deployed in the vineyard so that multiple vineyard rows were being sampled
142	concurrently. As such, 'block' represented unmeasured spatial variation, but did not strictly correlate with
143	time of sampling due to the nature of sampling (see Methods). Whole leaves were placed in zip-lock bags
144	in the field and stored in a cooler on ice packs, scanned for leaf shape analysis in the lab (see Leaf Shape)
145	and then dried in coin envelopes at 50° C for one to three days for elemental analysis. Between 20 and 100
146	mg of leaf tissue was acid digested and 20 ions were quantified using inductively coupled plasma mass
147	spectrometry (ICP-MS) following standard protocol [30,31] atof the Donald Danforth Plant Science
148	Center (DDPSC)) Ionomics Pipeline [30,31]. Ion quantifications were corrected for internal standard
149	concentrations, instrument drift and by initial sample mass-as part of the DDPSC Ionomies Pipeline. The
150	output of the Pipeline contained estimated concentrations of each of the following 20 elements: Al, As, B,
151	Ca, Cd, Co, Cu, Fe, K, Mg, Mn, Mo, Na, Ni, P, Rb, S, Se, Sr, and Zn. For each ion concentration, we
152	computed z-score distributions and used those values as the basis for linear models. NonFollowing
153	convention, non-standardized values were used for machine learning analysis.
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155	Leaf Metabolomics
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156	The metabolome comprises small mostly organic molecules present in a tissue, representing and
157	represents a catalogue of the products of metabolic processes [32,33].[32,33]. Metabolomic analysis was
158	completed at veraison and (the onset of fruit ripening) and immediately prior to harvest for the 72-vine set.
159	For each vine, three mature leaves were sampled from the middle of a single shoot and immediately flash
160	frozen in liquid nitrogen in the field to capture the metabolic state of the leaves when attached to the vine.
161	Leaves were sampled by a single team near midday in row and block order-, ensuring that 'block'
162	captured both unmeasured spatial variation and temporal variation over the sampling window (see
163	Methods). Frozen leaves were transported to the University of Missouri Enology labLab on dry ice and

stored at -80°C. Following the protocol of [34][34], whole leaves were manually ground in liquid nitrogen

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165	with a mortar and pestle, 0.5g of powder was weighed into a centrifuge tube, 1.5ml of 1:1 MeOH: ACN
166	was added. Samples were vortexed to suspend leaf particles and sonicated for 20 minutes in an ice bath.
167	FollowingAfter extraction, samples were centrifuged for 10 minutes at 3,000 g and filtered with a 0.22
168	PTFE syringe filter into a 1.5ml sample vial before injecting into a Waters XEVOTM QToF LCMS
169	system (Waters Corporation, Milford, MA, USA). Chromatographic separation was achieved using a
170	Waters Acquity TM Ultra Performance LC H-Class system (Waters Corporation, Milford, MA, USA)
171	equipped with Waters Acquity BEH C18 column (2.1mmx150mm and 1.7um particle size) and a diode
172	array detector. Samples were injected in random order across the sampling periods. The injection volume
173	was set at 2.5ul and the flow rate was set at 0.4 ml/min. The mobile phase consisted of 0.1% formic acid
174	in water (solvent A) and 0.1% formic acid and 5% water in acetaldehyde (solvent B) and the gradient was
175	as follows: 100% A for 0.5 min; 0.5-18min increased to 99% B; 18-19 min. held at 99% B; mobile phase
176	was re-equilibrated for 2 min between runs. Diode array was monitored at 225-500nm. Mass spectrometry
177	was performed on a XevoTM QTof (Waters Corporation, Milford, MA, USA). The electrospray
178	ionization (ESI) was operated in both positive or negative ionization modes in separate runs. The scan
179	range was set as m/z 50-1500 with 0.2 sec accumulation time. MS settings were as follows: capillary
180	voltage was 2.5kV; cone voltage ramped from 20-40V; collision energy was set to 6V; detector voltage
181	was set to 1950V; desolvation gas was set to 1000 L/hour; cone gas was set to 50 L/hr; source
182	temperature was 120 °C and desolvation temperature was set at 550 °C.
183	LC-MS instrument files were converted to .cdf format and uploaded to XCMS online [35][35] for
184	chromatogram normalization and feature detection via "single job" parameters. Identified The 661
185	identified metabolomic features were used as the basis of a principal components (PC) analysis. The top
186	20 PCs were treated as distinct phenotypes to model according to the experimental design. In PCs that
187	varied significantly by rootstock, features that loaded more than 1.96 standard deviations above or below
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188 the mean were fit independently with the same model design.

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189 Leaf Gene Expression

190	The youngest fully-opened leaves on two shoots were collected from each plant of the 72-vine set
191	(see Study Design). The two leaves, which were distinct from leaves used for ionomics, leaf shape,
192	metabolomics and physiology data collection, were pooled for RNA sequencing. Leaves were sampled by
193	a single team near midday between 10AM and 2PM in row order ensuring that 'block' and 'row'
194	accounted for unmeasured spatial variation and temporal variation over the sampling window (see
195	Methods). Samples were sequenced using 3'-RNAseq, a method ideal for organisms with reasonably
196	characterized reference genomes [36]. Total RNA was extracted from plant tissues using the Sigma
197	Spectrum Plant Total RNA kit with modification of the addition of 2% PVP40 to the extraction buffer to
198	decrease phenolic inhibitors. All RNA extractions were checked for quality control using a Nanodrop.
199	Sequencing was conducted using the Illumina NextSeq500 platform which returned single-end 86 bp
200	reads. The first 12 nucleotides from each read were trimmed to remove low-quality sequences using
201	Trimmomatic (options: HEADCROP:12; [37]). Low quality trimmed reads were additionally
202	identified based on overrepresentation of kmers and removed using BBduk (April 2019 release) [38].[38].
203	Trimmed and QC-controlled reads were mapped to the 12Xv2 reference Vitis vinifera genome
204	[39,40][39,40] using STAR (v2.7.2b) [41][41] with default alignment parameters. RNAseq read
205	alignments were quantified using HTSeq-count (v0.11.2) $\frac{42}{42}$ and a modified version of the VCost.v3
206	reference V. vinifera genome annotation [40].[40]. To capture mis-annotated gene body boundaries in the
207	genome, all gene boundaries in the annotation were extended 500 bp.
208	Variation in gene expression was assessed using two methodologies. First, we identified
209	individual genes which responded to specific factors in the experimental design using DESeq2 (v1.24.0)
210	[43].[43]. Each gene was fit with the model "~ Block + Irrigation + Phenology_Rootstock" where the
211	'Phenology_Rootstock' model term was used to understand the potential interaction of phenology and
212	rootstock. Differentially expressed genes were identified for each pairwise contrast in the modelGenes
213	were filtered to a gene set that included only genes with a normalized count greater than or equal to two in
214	at least five samples. To check the validity of our expression results, we assayed two classes of
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215	housekeeping gene (Ubiquitin-domain and actin-family) and eight previously annotated circadian genes
216	[44] (Supplemental Figure 2). Differentially expressed genes were identified for each pairwise contrast in
217	the model. Second, we used principal component analysis (PCA) to collapse variation in co-expressed
218	genes into fewer dimensions. Normalized count-filtered genes from DESeq2 were transformed using the
219	variance stabilizing transformation (VST; [44][45]) and input into a PCA. We then analyzed the top 100
220	PCs in the context of the broader experimental design. We previously showed that the transcriptome
221	varied by the time of collection and was potentially interacting with the rootstock effect [19].[19].
222	Moreover, the other modalities in this study point to weak if any effects from the irrigation treatment- <u>(see</u>
223	Supplemental Note 1). Due to the nature of the vineyard design, we could not identify both irrigation and
224	time effects (marked by row) in a single model (irrigation and row are collinear; see Study Design). To
225	approximate the impact from time of collection (row) in the vineyard on gene expression, linear models
226	were first fit to remove variation imparted by irrigation from each of the top 100 PCs. The residuals were
227	then used as the basis for linear models and machine learning analysis.
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229	Leaf Shape
230	All leaves from a single shoot directly emerging from a trained cordon were collected from each
231	vine in the 288 vine set at 80%-anthesis and veraison. At harvest, we collected only the oldest (first
232	emerging leaf), middle (estimated from the middle of a whole shoot), and youngest (smallest fully
233	emerged leaf at the shoot tip, >1cm). Leaves were collected approximately in row order (from south to
234	north) and stored in a cooler. Each leaf was imaged using an Epson DS-50000 scanner- in color against a
235	white background at 1200 DPI and written as JPEG formatted images. Following scanning of leaves for
236	leaf shape analysis, the oldest, middle, and youngest leaves were dried and used to estimate leaf elemental
237	composition (see Ionomics). As the leaf shape samples and ionomics samples were identical, 'block'

- 238 represented unmeasured spatial variation, but did not strictly correlate with time of sampling (see
- <u>Methods</u>). While all leaves were collected from a single shoot, only the oldest, middle, and youngest
 <u>leaves</u> were used in this analysis.

241 We assessed leaf shape using generalized procrustes analysisGeneralized Procrustes Analysis 242 (GPA) of landmarks. For the three leaves per vine used in leaf shape analysis, 17 homologous landmark 243 features were identified [22].[22]. The GPA-rotated coordinate space was used for all subsequent 244 statistical analysis including PCA in order to summarize variation in leaf shape [45].[46]. From the PCA, 245 we extracted the top 20 PCs and fit linear models and machine learning models to describe variation. 246 247 Vine physiology 248 Intracellular CO₂ concentration, stomatal conductance and leaf transpiration rate were measured 249 at midday (each measured simultaneously between 10am to 1pm) on one fully expanded sun-exposed leaf for each of the vines in the 72-vine set. Physiology measurements were taken in row order ensuring that 250 251 'block' correlated with temporal variation over the sampling window. Measurements were taken using an 252 LI-6400XT Portable Photosynthesis system coupled with a pulse amplitude-modulated (PAM) leaf 253 chamber fluorometer (Li-Cor, Inc., Lincoln, NE, USA) with the following parameters: incident 254 photosynthetic photo flux density level of 1000 µmol m-2 s-1 generated by a red LED array and 10% Formatted: Font: Times New Roman 255 blue light to maximize stomatal opening, CO2 mixer of 400 umolumol/s, fixed flow of 300 umolumol/s, 256 and ambient leaf and block temperature. Soil moisture was measured for each plant in the 72-vine set 257 using a fieldScout TDR 300 Moisture meter equipped with 20 cm rods (Spectrum Technologies, Inc. 258 Aurora, IL, USA). Midday stem water potential was measured using a pressure bomb/chamber (PMS 259 Instrument Co., Albany, OR, USA) after enclosing the leaves in an aluminum foil bag for at least 15 260 minutes to equilibrate the water potential of the xylem in the stem to that attached leaf-(for a discussion 261 on equilibration time, see [47,48]). 262

263 Analyses

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265 Leaf ionome

266 To characterize the leaf ionome over the growing season, we sampled the youngest, middle, and 267 oldest leaf from a single shoot from each of the vines within the 288-vine set at three phenological stages 268 (Figure 1).and measured the concentrations of 20 ions in each leaf individually. Bivariate correlations 269 showed that ion concentrations are not independent of each other, but that the strength and direction of 270 relationships between ions vary with respect to phenological stage and leaf position (Supplemental Figure 271 23). As such, we fit independent linear models to each ion. Leaf position, phenological stage, or the 272 interaction of phenological stage and leaf position explained the highest amount of variation for most ions 273 (Figure 1A-B). Many ions significant for the interaction showed a clear signal of leaf position at anthesis 274 and veraison, and either no explainable variation or muted variation at harvest. For example, calcium 275 (Figure 1B) varied with leaf position ($22.7\frac{\%}{2}$ variation explained; p < 1e-05), phenology (24.0%; p < 276 1e-05), and their interaction (7.4%, p < 1e-05). All possible pairwise combinations of leaf position were 277 significantly different at anthesis, and both the youngest and middle leaves were different from the oldest 278 leaves at veraison and harvest. In the case of potassium (Figure 1B), significant variation was explained 279 by leaf position (16.1%; p < 1e-05), phenology (19.6%; p < 1e-05), and their interaction (10.6%; p < 1e-05) 28005). However, post-hoc comparisons of phenology-wise mean calcium concentrations showed that 281 differences were present only at anthesis and veraison. 282 The rootstock Rootstock genotype showed remarkable influence on the composition of the leaf 283 ionome. All ions except aluminum, sodium, and zinc were significant for rootstock as a single fixed effect 284 (Figure 1A). Rootstock explained between 0.4% (rubidium; p = 3.2e-05) and 14.3% (nickel; p < 1e-05) of variation in each ion concentrations (Figure 1A). Ions that responded weakly to the interaction of leaf 285 286 position and phenology tended to show For some ion concentrations (such as cobalt and nickel), 287 significant variation was explained by the interaction of rootstock and phenology; this pattern was 288 observed mostly in ions that responded weakly to the interaction of leaf position and phenology. These 289 ions showed similar patterns to the leaf position by phenology interaction where clear signal was 290 exhibited at anthesis and veraison then is either absent or muted at harvest. For example, cobalt was most

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291	abundant in '1103P'-grafted vines at anthesis (Figure 1C). At veraison, both '1103P'-grafted and 'SO4'-
292	grafted had elevated concentrations compared to Ungrafted and '3309'-grafted vines. However, by
293	harvest, cobalt concentration variation was muted and only 'SO4'-grafted vines showed evidence of
294	elevated concentration. Similarly, nickel showed significant variation partitioned into the rootstock by
295	phenology effect (Figure 1C). Both anthesis and veraison show reduced nickel concentration in '1103P'-
296	grafted vines and elevated concentrations in 'SO4'-grafted vines. However, at harvest, no comparisons
297	are significant.
298	Machine learning on ion concentrations confirms that the leaf ionome contains a signature from
299	the rootstock genotype and the interactions of rootstock genotype with phenology and leaf position. A
300	random forest model trained to predict rootstock showed an overall accuracy of 75.2% (Figure 1D). Ions
301	important for this classification were nickel (MDA=Mean Decrease in Accuracy (MDA)=0.089),
302	molybdenum (MDA=0.058), and magnesium (MDA=0.054), corroborating the rootstock term's
303	significance in the linear models. Notably, when we trained a model to simultaneously predict rootstock
304	and phenological stage, rootstock prediction accuracy increased appreciably (Figure 1E). For example,
305	the ability of the model to detect ungrafted vines (the balanced accuracy of ungrafted predictions)
306	improved from 81.7% accuracy overall to 91.1% accuracy at anthesis and 85.9% at harvest. Generally,
307	performance at veraison matched the rootstock-only model performance. The ions most important for this
308	joint (rootstock/phenological stage) prediction were nickel (MDA=0.167), phosphorus (MDA=0.110),
309	and strontium (MDA=0.065). The rootstock by phenology model term was significant in the linear
310	models for these ions, but was not a largest descriptor of variation. The joint prediction of rootstock and
311	leaf position performed substantially better than chance ($p < 1e-05$), but accounting for leaf position did
312	not improve rootstock prediction as was the case in the joint prediction of rootstock and phenology
313	(Figure 1F). Ions important for this classification were sulfur (MDA = 0.051), rubidium (MDA = 0.051),
314	and nickel (MDA = 0.049).

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316	Leaf metabolomics	
510	Leaj metabolomics	

317	We performed untargeted metabolomics on leaves from the 72-vine set at veraison and harvest,
318	quantifying the concentrations of 661 metabolites (Figure 2). The top 20 PCs accounted for a total of
319	67.3% of the total metabolomic variation, with the top three capturing 23.1%, 9.2%, and 6.2%,
320	respectively. Individual PCs after the top 20 explained less than 0.82% of the metabolome. Linear models
321	for each of the top 20 PCs found that the strongest drivers of variation in leaf metabolomics were
322	phenology and temporal blocking factor. For example, 90.6% of variation on PC1 was due to phenology
323	(p < 1e-05; Figure 2A). PC2 primarily reflected the interaction of phenology and temporal block (26.4%,
324	p < 1e-05) and temporal block as a main effect (18.9%, $p < 1e-05$). The patterns of variation attributable
325	to PC2 were similar in PCs 3-10 (Figure 2A).
326	PC17 was controlled by rootstock as a main effect (18.5%, p < 1e-03; Figure 2B). On PC17,
327	ungrafted vines were significantly different from vines grafted to '3309C' ($p = 0.02$) and 'SO4' ($p < 1e$ -
328	05). Vines grafted to '1103P' were also significantly different from vines grafted to 'SO4' ($p = 0.009$).
329	Metabolites that loaded more than 1.96 sd from the mean loading on PC17 were extracted and
330	independently fit to additional linear models. We identified four metabolite features (M374T1 [$rt = 1.33$,
331	$m/z = 374.1146$], M117T1 [rt = 0.61, $m/z = 117.0583$], M175T1_1 [rt = 0.87, $m/z = 175.1269$], and
332	M333T1_3 [rt = 0.71; $m/z = 333.1582$]) which were influenced by rootstock as a main effect and the
333	metabolite (M112T1 [$rt = 1.48$, m/z = 112.0061]) which was influenced by the interaction of rootstock
334	genotype and phenological stage. At this time, the identification of these features remains unknown.
335	Linear discriminant analysis confirmed that many experimental factors likely influence the
336	metabolome. For example, when trained to maximize variation between classes of rootstocks, the model
337	identified a space that weakly separates '1103P'-grafted and 'SO4'-grafted vines from
338	Ungrafted <u>ungrafted</u> and '3309C'-grafted vines (LD1) and separates '3309C'-grafted vines from other
339	classes (on LD2) (Figure 2C). Despite this, machine learning showed minimal predictability for any class
340	other than phenology, which was predictable with an accuracy of 100% for withheld samples. Rootstock

341 genotype based on the metabolome was not predictable with accuracy only marginally better than chance 342 (34.6%). 343 Gene Expression 344 345 We performed 3'-RNAseq on the youngest fully-opened leaves of the 72--vine set at three time 346 points (Figure 3). WeOn average, each sample contained 4.1 million 3'-reads and measured the 347 expression of 17,852 genes. Overall, we identified variation in 23,460 genes that had a DESeq2-348 normalized count greater than two in at least five samples. We computed the expression of two classes of 349 housekeeping genes, and showed that they are generally stable across samples over phenological time 350 (Supplemental Figure 2). We noted that some variation is expected for housekeeping genes; see, for 351 example, [49]. Moreover, we showed that patterns of previously annotated circadian genes conform to 352 expected results over the sampling window. For example, predicted orthologs of LHY and RVE1 are 353 correlated and decreasing over our sampling window, and a predicted TOC1 ortholog is invariant. The 354 results of these analyses provide general confidence in the gene expression data presented here. 355 Using a traditional differential expression analysis framework, based on established DGE 356 software (Deseq2), all genes returned as significantly differentially expressed by rootstock appeared to be 357 false positives, evidenced by a single extreme outlier altering group means. Hierarchical clustering of the 358 500 most variable genes after variance stabilizing transformation (VST) showed strong latent structure in 359 the transcriptome and that most variation in the transcriptome was explained by phenological stage (Figure 3A). The top 100 PCs on the VST-transformed gene counts accounted for nearly 92.3% of 360 361 variation in the transcriptome. Linear models on each of the top 100 PCs indicated that 82.4% and 61.4% 362 of the variation on PC1 and PC2 respectively were attributable to the phenological stage (Figure 3B-C). 363 Row was also a significant descriptor of variation as a single, fixed effect and in interactions with 364 rootstock and phenological stage. For example, row accounted for 36.0% and 43.3% of the variation on PC4 and PC6, respectively. Interacting with phenological stage, row accounted for >10% of variation on 365 17 additional PCs. 366

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367	Patterns of gene expression identified through LDA corresponded to phenological stage, vine
368	row, and rootstock. LDA separated phenological stages into three distinct, non-overlapping groups in the
369	space spanning LD1 and LD2 (Supplemental Figure 34). When trying to separate rows into distinct
370	classes, the model converged on a 'horseshoe' shape in the LD1- LD2 space (Figure 3D). suggesting
371	either a circadian topology to the transcriptome or continuous spatial variation over the vineyard [50].
372	LD1 maximized the variation between row 8 (sampled early in the day) and row 16 (sampled a few hours
373	later). LD2 maximized the separation of both rows 8 and 16 with row 12 (the row sampled in the middle
374	of the sampling window). A model trained to separate rootstock classes (Figure 3E) showed that LD1
375	separated the rootstock 1103P from other rootstock genotypes, and LD2 primarily separated the rootstock
376	'3309C' from ungrafted vines (Supplemental Figure <u>34</u>).
377	Formal machine learning on gene expression PCs largely supported the linear models. A random
378	forest trained to predict phenological stage classified testing samples with 92.9% accuracy. Anthesis was
379	the most predictable class with a balanced accuracy of 100%; veraison and harvest displayed balanced
380	accuracies of 92.7% and 92.4%, respectively. The PCs most important in phenology prediction were PC1
381	(MDA = 0.16) and PC2 $(MDA = 0.12)$. Gene expression PCs were unable to predict rootstock, with a
382	total prediction accuracy of 23.4%. While no features were especially important in the prediction
383	processes, PC44 showed the largest mean decrease in Gini impurity corroborating its signal in the linear
384	models.
385	
386	Leaf shape
387	We collected leaves from the 288-vine set at three time points and landmarked a total of 2,422
388	leaves (Figure 4). Homologous leaf landmarks were used for generalized procrustes analysisGeneralized
389	Procrustes Analysis (GPA). PCA on the GPA-rotated coordinates revealed ~97.2% of the total shape
390	variation was captured by the top 20 principal components with PC1, PC2, and PC3 explaining 24.1%,
391	19.0%, and 13.3% of the variation respectively. Lower values on PC1 primarily capture leaves with
392	shallow petiolar sinuses and short midvein distance from the depth of the superior sinus to the top of the

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393	midvein, whereas higher values on PC1 capture the opposite (Figure 4A). Similarly, lower values on PC2
394	capture deep petiolar sinuses combined with very shallow superior sinuses, and vice versa for higher
395	values. PC3 primarily captures asymmetry (Figure 4A).
396	In total, only 5.76% of variation on PC1 was explained by the experimental design, with most. Of
397	this, variation in leaf shape was explained by phenology (2.63%; padj < 1e-05), then rootstock (0.95%;
398	padj < 0.001), leaf position (2.61%; padj = 0.03), and the interaction of phenology and leaf position
399	(0.62%; padj = 0.009) (Supplemental Figure 4A-5A). Post-hoc mean comparisons on PC1 showed that
400	shapes of leaves from ungrafted vines were significantly different from leaves of vines grafted to 1103P
401	(p < 0.001), 3309C $(p < 0.001)$ and SO4 $(p < 0.001)$ (Supplemental Figure 4 <u>B5B</u>). Moreover, PC1
402	captured subtle variation in the leaf position by phenological stage interaction where middle leaves
403	showed significant differences between anthesis and veraison ($p < 1e-03$), and the oldest leaves showed
404	significant differences when comparing anthesis to versison ($p < 1e-05$) and anthesis to harvest ($p < 1e-05$)
405	03).
406	For PC2, 61.4% of variation could be assigned to an experimental factor. This included
407	significant variation from leaf position (46.9%, padj < 1e-05), phenology (1.4%; padj < 1e-05), and the
408	interaction of leaf position and phenology (12.05%; padj < 1e-05; Figure 4D). Specifically, younger
409	
	leaves tended to have shallower sinuses and exaggerated superior sinus depths (higher values on PC2),
410	leaves tended to have shallower sinuses and exaggerated superior sinus depths (higher values on PC2), whereas older leaves tended to develop deeper petiolar sinuses and more shallow superior sinuses (lower
410 411	leaves tended to have shallower sinuses and exaggerated superior sinus depths (higher values on PC2), whereas older leaves tended to develop deeper petiolar sinuses and more shallow superior sinuses (lower values on PC2). The degree of this separation decreased across the season, and the shapes converged on
410 411 412	leaves tended to have shallower sinuses and exaggerated superior sinus depths (higher values on PC2), whereas older leaves tended to develop deeper petiolar sinuses and more shallow superior sinuses (lower values on PC2). The degree of this separation decreased across the season, and the shapes converged on the mean leaf shape on PC2, consistent with the middle leaf at all three phenological stages. PC2
410411412413	leaves tended to have shallower sinuses and exaggerated superior sinus depths (higher values on PC2), whereas older leaves tended to develop deeper petiolar sinuses and more shallow superior sinuses (lower values on PC2). The degree of this separation decreased across the season, and the shapes converged on the mean leaf shape on PC2, consistent with the middle leaf at all three phenological stages. PC2 additionally reflected the interaction of leaf position and rootstock (0.22%; $p = 0.04$; Supplemental Figure
 410 411 412 413 414 	leaves tended to have shallower sinuses and exaggerated superior sinus depths (higher values on PC2), whereas older leaves tended to develop deeper petiolar sinuses and more shallow superior sinuses (lower values on PC2). The degree of this separation decreased across the season, and the shapes converged on the mean leaf shape on PC2, consistent with the middle leaf at all three phenological stages. PC2 additionally reflected the interaction of leaf position and rootstock (0.22%; $p = 0.04$; Supplemental Figure 4B5B), but post-hoc comparisons did not find any significant pairwise comparisons.
 410 411 412 413 414 415 	leaves tended to have shallower sinuses and exaggerated superior sinus depths (higher values on PC2), whereas older leaves tended to develop deeper petiolar sinuses and more shallow superior sinuses (lower values on PC2). The degree of this separation decreased across the season, and the shapes converged on the mean leaf shape on PC2, consistent with the middle leaf at all three phenological stages. PC2 additionally reflected the interaction of leaf position and rootstock (0.22%; p = 0.04; Supplemental Figure 4B5B), but post-hoc comparisons did not find any significant pairwise comparisons. Machine learning on the GPA-rotated coordinate space identified moderate division of
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421	28.1% accuracy.
422	
423	Vine physiology
424	For the 72 vine set, we We measured intracellular CO_2 concentration (C _i), stomatal conductance
425	(g _s), leaf transpiration, water potential (ψ), and soil moisture <u>for the 72-vine set</u> (Figure 5). Each
426	physiological traitphenotype varied significantly across phenology and the block by phenology interaction
427	(Figure 5A). For example, at harvest, we observed specific differences in leaf CO ₂ concentration (A vs C:
428	p=0.003; B vs C: p=0.002) and leaf transpiration (A vs B: p < 1e-03; A vs C: p < 1e-05; B vs C: p < 1e-05;
429	05). Leaf transpiration and stomatal conductance varied significantly with the interaction of rootstock and
430	phenology. A post-hoc comparison of means showed that leaf transpiration and stomatal conductances
431	were elevated in 'Chambourcin' vines grafted to '1103P' at veraison as compared to leaves of ungrafted
432	vines (leaf transpiration: $p = 0.001$; stomatal conductance: $p = 0.002$ Figure 5B-C).
433	
434	
435	Phenomic trait-covariation
436	Four leaf dataphenotyping modalities consisted of at least-10 traitsor more measured phenotypes
437	and were measured for all plants in the 72-vine set (leaf ionome, leaf metabolomics, gene expression, leaf
438	shape). Using these data, we explored the extent to which different phenotypes (within and between
439	modalities) covaried over phenology and rootstock genotype (Figure 6; Supplemental Figure 56;

components of the points corresponding to superior sinus depth (left sinus MDA = 0.030, right sinus MDA = 0.019). A model trained to predict rootstock performed only marginally better than chance at

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440 Supplemental Figure 67). Within each phenotyping modality, we summarized the primary dimensions of

441 <u>phenotypic</u> variation using PCA (see Methods)., so as to not weigh any modality too heavily. From each

442 PCA, we extracted the top 10 PCs, which explained a total of 88.9% of variation in the ionomics PCA

443 (iPCA), 55.9% of the variation for the metabolomics PCA (mPCA), 74.8% of the variation in the gene

444 expression PCA (gPCA) and 87.9% of the variation in the leaf shape PCA (sPCA).
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445	Pairwise correlations of each PC within each phenological stage showed diverse correlation
446	magnitudes and directions both within a phenotyping modality and between phenotyping modalities
447	(Figure 6A-C; Supplemental Figure 56). Generally, the strongest relationships were between PCs within
448	phenotypiephenotyping modalities. For example, the strongest correlations identified were between gene
449	expression PCs gPC1 and gPC2 at anthesis (r = 0.85, CI = [0.81, 0.87]; Supplemental Figure $\frac{5A_{6A}}{2}$, and
450	metabolomics PCs mPC1 and mPC2 at harvest (r = -0.78, CI = [-0.820.76]). Correlations between
451	modalities represented a diversity of responses across phenological stages. For example, the correlation
452	between gene expression gPC4 and shape sPC3 is was similar across the phenological stages, but only the
453	correlation at veraison $\frac{1}{100}$ significant (r = 0.41, CI = [0.34, 0.47]; Supplemental Figure $\frac{5B6B}{0}$).
454	Correlations such as between metabolomics mPC3 and gene expression gPC6 were similar and significant
455	at both version (r = -0.44, CI = [-0.50, -0.37]; Supplemental Figure $\frac{5-6C}{2}$ and harvest (r = -0.37, CI = [-
456	0.45, -0.28]; Supplemental Figure 5C). While many correlations varied over the course of the season,
457	some relationships entirely shifted in direction. For example, the correlation between metabolomics
458	mPC3 and mPC6 shifted from a positive significant relationship ($r = 0.58$, $CI = [0.52, 0.63]$) at veraison
459	to a negative significant relationship at veraison ($r = -0.66$, $CI = [-0.73, -0.59]$) (Supplemental Figure
460	5D 6D).
461	Pairwise comparisons of PCs within each rootstock genotype show a suite of traitslatent
462	phenotypes with significant presence/absence variation in significant correlations. Where each
463	phenological stage showed modularity by phenotyping modality, variation over rootstock genotype shows
464	a strong ionomics module with latent combination of other modalities interspersed (Supplemental Figure
465	67). For example, in ungrafted vines, <u>metabolomics</u> mPC1 was correlated with four PCs from the ionome
466	(Supplemental Figure 6A7A). Each of the other rootstock genotypes havehad dramatically different
467	topologies with the ionome tending to be more connected within the ionome and connected to other
468	modalities only on the periphery (Supplemental Figure 68-7B-D). Examples of presence/absence variation
469	arewere shown in small modules of two latent phenotypes that arewere present in only one rootstock
470	genotype. For example, in the ungrafted vines, the correlation between gene expression gPC4 and
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471	metabolomics mPC3 was significant (r = -0.58, CI = [-0.65, -0.51]) and, in '1103P'-grafted vines, the
472	correlation between <u>metabolomics</u> mPC3 and <u>shape</u> sPC6 ($r = 0.59$, CI = [0.53, 0.70]) was significant.
473	
474	Discussion
475	
476	In this study, we used grafted grapevines as an experimental system for characterizing root system
477	impacts on high-multi-dimensional leaf phenotypes over the course of a growing season. We detected
478	ubiquitous but subtle effects of the root system on all assayed phenotypesmodalities, and demonstrated
479	that rootockrootstock influences on leaf phenotypes can be season-specific to the vine's developmental
480	stage. The strongest signals of rootstock influences on leaves were observed in the ionomics dataset,
481	phenotypes for which the root systems havesystem has a noted and well-understood role.
482	
483	Phenology explains significant variation in all leaf phenotypes
484	The timing of sampling or phenological stage of the vines (anthesis, veraison, harvest) was the
485	strongest driver of phenotypicphenomic variation for most leaf phenotypes. For example, all 20 ions
486	varied with phenology and most ions showed that phenology, or the interaction of phenology with leaf
487	developmental position, was the strongest source of variation (Figure 1). Nearly one third of all measured
488	transcripts responded to seasonal variation, and the strongest effects on the transcriptome were phenology
489	and row, a correlate for the time within a three-hour sampling window. The only phenotype for which
490	phenology was not the most explanatory factor is leaf shape. Consistent with previous studies [23][23].
491	we confirm that most of the leaf shape variation-measured reflects development along a single shoot, but
492	much of this variation is explained via interaction with phenology. These data highlight the dynamic
493	nature of biological processes taking place within grapevines over the course of a season.
494	The seasonal component to grapevine phenotypicphenomic variation is a subject of much
495	research, especially in the berry. In studies designed to quantify molecular underpinnings of terroir,
496	seasonal variation was identified as the strongest signal in the metabolome [46-49].[51-54]. Several
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497	studies have characterized transcriptomic variation over the course of the season. For example, in
498	conjunction with metabolomics, seasonal variation of berry development was used to identify
499	transcriptomic and metabolomic developmental markers in 'Corvina' [50]. Follow-up analysis
500	showed that nearly 18% of transcripts varied seasonally [51]-[56]. Grapevine leavesleaf shape also
501	varyvaries tremendously in shape over the growing season [23][23] and areis stable over multiple
502	growing seasons; interestingly, grapevine leaves are patterned in the previous year, and the climate of the
503	season in which the leaves were patterned influence aspects of leaf shape [52,53].[57,58].
504	
505	Grafting and rootstock genotype exhibit a complex and subtle signal on leaf phenotypes
506	Consistent with previous studies, we confirm that grafting, as well as rootstock genotype, has a
507	complex effect on phenotypiephenomic variation in the scion (the grafted shoot system). Most notably,
508	we show that the rootstock to which a scion is grafted influences ion concentrations in leaves. Rootstock
509	genotype is predictable from ion concentrations in the leaves; further, and this signal is strengthened
510	when phenological stage is included in the model. For example, we previously showed that nickel
511	concentration was elevated in vines grafted to the rootstock 'SO4' [19]. At a similar point in the
512	season, we observe the same pattern, but by harvest, nickel was almost entirely excluded from the leaf.
513	This suggests that the biological implications of this differential uptake could be missed if not surveyed
514	across the season. We also confirm that rootstock genotype influences the metabolome of grafted
515	grapevine, in some cases in a season-specific manner. In the transcriptome, PCA was able to identify
516	dimensions of variation that were significantly described by rootstock and the interaction of rootstock and
517	time of day, confirming prior observations [19].[19]. Patterns of gene expression were associated with
518	rootstock in some analyses; for example, supervised methodologies identified linear discriminants in the
519	PC space that separated gene expression patters of some rootstock genotypes. However, gene-by-gene
520	analysis found no genes modulated by rootstock genotype, or even just from the act of grafting that were
521	not driven entirely by a single outlier. We suspect these results are due, at least in part, to the strength of
522	the phenology effect overpowering more subtle variation imparted by rootstock genotype. Finally, of the

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523	physiology traitsphenotypes we measured, leaf transpiration and stomatal conductance were higher in
524	vines grafted to '1103P' in the middle of the season. Thus, the impact of grafting on leaf phenotypic
525	variation varies by phenotype. Regardless, Through these analyses we identify have identified subtle but
526	ubiquitous effects from of rootstock genotype on shoot system phenotype across modalities, and have
527	shown that the impact of grafting on leaf phenomic variation varies from one phenotype to the next.
528	Understanding of rootstock genotype influence on shoot system phenotypes is a growing area of
529	research, especially in grapevine. For example, in 'Cabernet Sauvignon', grafting increased ion uptake
530	globally and some rootstock genotypes provide a clear signal in the scion [28,54]. Also[28,59]. To our
531	knowledge, there is not yet a strong causal link between the micronutrient component of the ionome and
532	factors of vine growth or development that might influence traits like wine quality. However, it is noted
533	that macronutrient deficiencies can have negative effects on such traits [60,61] and can be mediated by
534	rootstock [62]. This suggests a strong understanding of the rootstock influence on the vine's ionome is
535	warranted, and more work needs to be done to establish these relationships. Similarly, the metabolome is
536	a key driver of the formation of the graft junction and some key metabolites could be responsible for graft
537	incompatibility [55].[63]. Building on this work, targeted metabolomics showed two classes of
538	metabolites, flavanols and stilbenes, were differentially abundant at graft junctions and in the rootstocks
539	of 'Cabernet Sauvignon' vines one month after grafting [56].[64]. However, flavanols were not
540	differentially abundant in the scion, but scion stilbene concentrations were apparently controlled by
541	rootstock genotype. The effect of rootstock genotype on the scion transcriptome is perhaps the most
542	varied. For example, 'Cabernet Sauvignon' shoot apical meristems show no effects by rootstock genotype
543	[14][14], but berries of the same cultivar do, although the effect is tempered by seasonal variation
544	[15].[15]. Variation in 'Chambourcin' leaf shape iswas also driven by rootstock genotype, especially in
545	conjunction with differences in irrigation [19]. [19]. Collectively, these studies all suggest that rootstock
546	genotype influences scion phenotypes, but those effects will vary by phenotype, scion genotype, and
547	perhaps other experimental conditions.

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548	Data presented here confirm and expand upon previous observations of rootstock effects on scion
549	phenotypes. Notably, the this study was carried out using a robust experimental design (288 vine set and
550	72 vine set comprising replicates of three rootstocks grafted with a common scion and an ungrafted
551	control), a vineyard that had been in the ground for eight years at the time of sampling. Our coordinated
552	collection of five multi-dimensional leaf phenotypes, and inclusion of three sampling points spanning the
553	growing season allowallowed us to honeinvestigate in on the comprehensive nature of rootstock
554	influences on the scion. Further, this thorough analysis demonstrates that rootstock effects on scion
555	phenotypes shift in magnitude over the course of the season, indicating that aspects of time are
556	tremendously influential to the observed results regardless of phenotype.
557	While the results of previous studies on grafted grapevine are worthy of comparison, the work
558	presented here has a few limitations that render comparisons with other studies challenging for a variety
559	of reasons. One novelty in our study is the exploration of a hybrid grapevine system, 'Chambourcin'.
560	'Chambourcin' has a complex pedigree, including contributions from Vitis riparia and V. rupestris,
561	species which are each parent to two of the rootstocks used in this study [65]. Many of the significant
562	effects we observed in this study were subtle, which could reflect the genomic similarity between shoot
563	and root systems. It might be expected that rootstocks derived from V. riparia, V. rupestris and other
564	North American species might prompt more pronounced responses in European scions that lack North
565	American Vitis in their pedigrees . Moreover, our results were derived from data collected in a single year
566	at a single location. The phenotypes we measured are known to be heavily influenced by the environment,
567	and we expect some inter-annual variation in rootstock influences on shoot system phenotypes. This study
568	focused on a single scion, and as a result we are unable to explore how rootstock effects on shoot system
569	phenotypes vary across scions. To our knowledge, this is among the largest populations to have been
570	surveyed for such phenotypes in a decade old established vineyard. While many studies have been
571	conducted in green houses or recently planted vineyards, the juxtaposition of our results and those
572	previously established serve as a powerful foundation for the generation of hypotheses for future studies.
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574 Phenomic covariation warrants work toward latent phenotypes 575 In the present study, we assess the extent of covariation among leaf phenotypes. For the primary 576 dimensions of variation in each data typemodality, within-data-typemodality correlations are strongest 577 when accounting for phenological timing. Correlations also exist between phenotypesmodalities, 578 suggesting room for the analysis of latent phenotypiephenomic structure or targeted integrative analyses 579 for experimental questions. For example, aspects of the metabolome were frequently correlated with the 580 transcriptome and leaf shape when accounting for both phenological stage and rootstock genotype. 581 Interestingly, correlations within and between data types are modalities were highly dynamic over a 582 growing season and across rootstock genotype. For example, several correlations with leaf shape were 583 present at veraison, but were not detected at anthesis and harvest. Moreover, the topology of connections 584 in the ionomic network was variable over the rootstock genotype (Supplemental Figure 6). This variation 585 in topology confirms that root system genotype has a strong influence on shoot system elemental 586 composition, and suggests that root system genotype can alter correlative patterns in the ionome. We 587 believe the work of understanding phenomic covariation warrants further investigation, specifically, by 588 further including additional phenotypes such as lncRNA expression [57,58], epigenetics [59], and 589 microbiomes [60,61]. Much[66,67], epigenetics [68], and microbiomes [69,70] which could yield more 590 mechanistic understandings of the influence of root systems on shoot systems and how plants interact 591 with their environments through their root systems. These mechanistic understandings could be used to 592 further understand and optimize consumer-facing traits such as fruit quality and yield. To date, much of 593 the work constituting phenomics in grapevine has addressed how berries develop over the growing 594 season, how cultivars differ from one another, and how the concept of terroir influences wine 595 [46,47,50,62-64].[51,52,55,71-73]. Despite data integration techniques becoming more popular, there are 596 still many open questions as to what analytical methods are most appropriate and how to most effectively 597 utilize them (reviewed for grapevine in [65,66][74,75]; reviewed broadly in [67,68]).[76,77]). Ongoing 598 work attempts to integrate high-dimensional phenotypicphenomic datasets generated within a single

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599	organ system (e.g., leaves); and future studies will expand this to explore phenomic covariation in and
600	among organs, over time, and across space.
601	
602	Potential Implications
603	Our work on the influence of root system genotype on shoot system phenotype has broad
604	implications for a holistic understanding of how plants detect and respond to changing environmental
605	conditions. In particular, this study highlights the influence of root system genotype and its interaction
606	with phenology on shoot system phenotype: there is a seasonal component to the extent to which
607	rootstock shapes phenotypic variation in the scion. Expanding this multi-dimensional understanding of
608	phenotypic variation over time to include different tissues (e.g., root architecture, floral and fruit
609	development), and different spatial scales (replicated root shoot combinations located in geographically
610	distinct vineyards) presents a challenging but exciting next frontier. Of particular note, patterns of
611	phenomic covariation derived from complex datasets have implications for understanding how
612	individuals perceive and respond to their environments, and how that response is coordinated throughout
613	the plant body. This work is relevant for breeding efforts aimed at optimizing yield and other desired
614	traits that can be optimized, or constrained by, phenotypic variation elsewhere in the plant, and how this
615	response is coordinated among different organ systems. Data presented here demonstrate that root
616	systems that are genetically distinct from the scion exert influence on the scion, leading to statistically
617	significant differences in scion phenotypes based on the identity of their root systems. This observation
618	suggests that the above-ground phenotype of plants results, at least in part, from below-ground activity of
619	the root system. Further, these data highlight the value of coordinated collection of different multi-
620	dimensional phenotypes for comparative studies, and for describing whole-plant phenotypic shifts over
621	seasons and in response to horticultural manipulations.
622	Beyond its use as an experimental model that is ideal for studying root/shoot interaction, grafting
623	is an important horticultural technique that is used in over 70 major crops. In grapevines, grafting was
624	developed primarily to combat the below-ground pest phylloxera, and grapevine rootstocks were selected

625	initially based on their resistance to this pest. Results presented here indicate that beyond phylloxera				
626	resistance, grafting to genetically distinct rootstocks is a potential source of variation for the scion.				
627	Ongoing work explores how root system impacts on shoot system phenotypes vary across scion				
628	genotypes, and how the rootstock \times scion interaction changes over space. The long-term implications of				
629	this study are the potential honing of viticulture for future climates including the optimization of				
630	rootstock-scion combinations based in part on an understanding of how rootstock effects on scion				
631	phenotypes change over the course of the season. This work is relevant for breeding efforts, and may play				
632	a role in the optimization of quantitative phenotypes such as vigor, fruit quality, and yield that may be				
633	enhanced by, constrained by, or partially predicted from phenotypic variation elsewhere in the plant.				
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635	Methods				
636					
637	Study Design				
638	Data were collected in 2017 in anfrom a split-plot experimental rootstock trial established in 2009				
639	at the University of Missouri's Southwest Research Center near Mount Vernon, MO (37.074167 N;				
640	93.879167 W; Supplemental Figure 1). The rootstock trial includes the interspecific hybrid cultivar				
641	'Chambourcin' growing ungrafted (own-rooted) and grafted to three rootstocks: '1103P', '3309C', and				
642	'SO4' (Supplemental Figure 1D). EachClonal replicates of each of the four rootstock-scion combinations				
643	was replicated were planted 72 times for a total of 288 vines planted in nine rows. Each row was treated				
644	with one of three irrigation treatments: full evapotranspiration replacement, partial (50%)				
645	evapotranspiration replacement (reduced deficit irrigation; RDI), or no evapotranspiration replacement				
646	(Supplemental Figure 1A). However, rainfall in 2017 likely mitigated the applied irrigation treatment (see				
647	Supplemental Note at:				
648	https://github.com/PGRP1546869/mt_vernon_2017_leaf/blob/main/On_the_irrigation_treatment.pdf).1).				
649	Vine position in the vineyard corresponded to time of sampling for some phenotypes, (metabolomics,				
650	gene expression, and physiology), as samples were taken from one end of the vineyard to the other over				
I					

651	the course of two to three hours. Because vineyard microclimates and sampling time may be associated
652	with phenotypiephenomic variation, we defined 'temporal block' as a factor that captures this spatial and
653	temporal variation inherent in sampling for those phenotypes. In the other phenotypes (ionomics and leaf
654	shape), neither row nor block correlated with time, so 'block' was simply a spatial covariate. Unique
655	rootstock-scion combinations were planted in cells of four adjacent replicated vines (Supplemental Figure
656	1B1A-B), with rows consisting of eight cells (32 vines/row). To our knowledge, a field-planted rootstock
657	experimental vineyard of this size and age is rare. For some phenotypes (leaves for ionomeionomics and
658	leaf shape-analysis), it was possible to collect samples from all vines in the experimental vineyard (the
659	288-vine set; Supplemental Figure 1C<u>1A-B</u>). For other phenotypes (physiology, metabolomics, and gene
660	expression, and physiology), time and/or expense associated with the phenotyping process required that
661	we reduce sampling to a nested set of 72 vines representing the middle two vines in each four-vine cell \underline{in}
662	the front half of the vineyard (the 72-vine set; Supplemental Figure 1-C1B-C). All phenotypes were
663	assayed hat three phenological stages: anthesis (~80% of open flowers; 22 May 2017); veraison (~50% of
664	berries had transitioned from green to red; 30 July 2017); and immediately prior to harvest (25 September
665	2017). At each phenological stage, effort was made to sample on days with full to partial sun and minimal
666	precipitation.
667	This design was used to assess the following questions: 1) What is the influence of root system
668	genotype on shoot system phenotype? 2) How do systems of plant phenotypes vary over the growing
669	season and does rootstock genotype influence this variation? And 3) how do phenotypes covary within
670	and between phenotyping modalities?
671	
672	Linear Models
673	Linear models were fit to the 20 measured ion concentrations, the top 20 PCs of the leaf
674	metabolome, the top 100 PCs of the leaf transcriptome, the top 20 PCs of leaf morphospace, and each

- 675 measured physiological trait. Outliers were detected using the R function 'anomalize' (options:
- alpha=0.03, max_anoms=0.1). Each model was fit with fixed effect factors representing phenological

677	stage (anthesis, veraison, or harvest), rootstock (Ungrafted, '1103P', '3309C', or 'SO4'), leaf position
678	(youngest, middle, or oldest; only used in leaf morphology and leaf ion concentration models), and all
679	pairwise interactions of those terms. Both irrigation and block were included as fixed, non-interacting
680	effects with the exceptions of physiology and metabolomics, for which we allowed the interaction of
681	'Block' as it correlates with the time of sampling, potentially capturing temporal variation. Row, an
682	additional correlate for time and spatial variation, was included in place of a temporal block for the gene
683	expression models after removal of the variation attributable to irrigation, a factor collinear with row. All
684	linear models were interpreted using a type-3 sum of squares computation using the R package 'car'
685	[69].[78]. Estimated p-values for each term in the models were corrected for multiple tests (within
686	phenotype) using FDR correction as implemented by the R package 'stats' [70]. Results from the
687	models are reported as the variation explained by a particular term in the model and the estimated p-value.
688	When appropriate, post-hoc mean comparisons were computed using the package 'emmeans' [71].[80].
689	Where multiple linear models were being simultaneously interpreted, we applied a Bonferonni correction
690	to reduce the number of false positives.
691	
692	Machine Learning to Identify Rootstock Effects
693	For visualization of between-class variation, we fit linear discriminant analysis models (LDA) to
694	the full phenotypic data sets of each modality (ionomics, metabolomics, gene expression, and leaf
695	morphology) using the 'lda' function of the R package 'MASS' [72][81]. Projections of all samples into
696	the LD space were plotted using ggplot2 [73].[82]. In addition, we employed machine learning to capture
697	subtle experimental effects. We partitioned phenotypic data sets from each modality into 80% training
698	partitions and 20% testing partitions. Models were fit to predict the phenological stage from which a

sample was taken, the rootstock to which the scion was grafted, and the joint prediction of phenology and

700 rootstock. We also tested the predictability of leaf position for ionomics and leaf shape, and the

interaction of rootstock and leaf position for ionomics. We used the 'randomForest' [74][83]

702 implementation of the random forest algorithm. Models were fit and tuned using the R package 'caret'

703	[75].[84]. Each performance was assessed using accuracy, with performance on each class being assessed
704	using the balanced accuracy, the midpoint of class-wise sensitivity and specificity. Where appropriate,
705	models were compared to 'chance', or the occurrence frequency of each class. Confusion matrices were
706	visualized from the out-of-bag predictions using ggplot2. Important features were identified from the
707	randomForest object based on a phenotype-specific mean decrease in model accuracy (MDA).

708

709 Phenomic trait covariation

710 We extracted ionomics, metabolomics, gene expression, and leaf shape data for the youngest 711 available leaf from the 72 vine-set. Each elass of phenotypic data modality was summarized along the 712 primary dimensions of variation using PCA. For each class, we extracted the top 10 PCs and fit Pearson's 713 correlations across all pairs of PCs at each phenological stage. P-values from computed correlations were 714 corrected using the FDR method from the package 'stats' [76].[85]. Correlations and their strengths were 715 visualized using the R package 'igraph' [77]-[86]. Example correlations were reported after running 716 10,000 bootstrapped subsamples of 90% of data for paired traitsphenotypes. From the distribution of 717 estimated correlation coefficients, confidence intervals were computed from the 0.025 and 0.975 718 quantiles. A subset of example correlations were plotted using the R package 'ggplot2' [7382]. 719

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729	Figure Legends:	
730	Figure 1: The ionome shows strong signal from rootstock genotype, leaf position, and phenological stage	 Formatted: Font color: Black
731	(A) Percent variation captured in linear models fit to each of 20 ions measured in the ionomics pipeline.	
732	Presence of a cell indicates the model term (top) was significant (FDR; p.adj < 0.05) for that ion (left).	
733	(B) Example ions shown to vary significantly by the interaction of leaf position $(Y=Youngest,$	
734	<u>M=Middle, O=Oldest)</u> and phenological stage- <u>in parts per million</u> . Boxes are bound by 25th and 75th	
735	percentile with whiskers extending 1.5 IQR from the box. Significant changes are indicated by letters	
736	above boxes, and are only meant for comparison within each phenological stage. Group means are	
737	displayed with black squares. (C) Example ions shown to vary significantly by the interaction of	
738	rootstock genotype and phenological state.stage in parts per million. Significant changes are indicated by	
739	letters above boxes, and are only meant for comparison within each phenological stage. Boxes are bound	
740	by 25th and 75th percentile with whiskers extending 1.5 IQR from the box. Group means are displayed	
741	with black squares. (D) Standardized heatmap for out-of-bag (OOB) predictions by a random forest	
742	trained to predict rootstock genotype, (E) the interaction between rootstock genotype by phenology, and	
743	(F) the interaction between rootstock genotype and leaf position.	
744		
745	Figure 2: The metabolome is influenced by rootstock genotype, phenological stage, and time of sampling.	 Formatted: Font color: Black
746	(A) Percent variation captured in linear models fit to each of the top 20 principal components of the	
747	metabolome (661 measured metabolites). Presence of a cell indicates the model term (top) was significant	
748	for that PC (left, percent variation explained by the PC in parentheses). (B) The distribution of projections	
749	onto PC17, the strongest captured rootstock effect in the metabolome. Boxes are bound by the 25th and	
750	75th percentiles with whiskers extending 1.5 IQR from the box. (C) Projections of all samples into the	
751	first two dimensions of a linear discriminant space trained to maximize variation between rootstock	
752	genotypes.	
753		
754	Figure 3: Gene expression primarily responds to time of season and circadian correlates	 Formatted: Font color: Black

755 (A) Heatmap showing 500 genes with the highest variance following the filtering of lowly expressed 756 genes and gene-by-gene variance stabilizing transformations (VST) ordered by example model factors 757 (below). (B) Percent variation captured in linear models fit to the top 100 Principal Components of the 758 VST-transformed gene-expression space. Presence of a cell indicates the model term (top) was significant 759 for that PC (left, percent variation explained by the PC in parentheses). (C) Projections of all samples into 760 the first two principal component dimensions to show that the largest descriptors of variation are due to 761 phenology. (D) Projections of all samples into the first two dimensions of the linear discriminant space trained to maximize variation between the rows of the vineyard, and (E) rootstock genotype. 762 763 Figure 4: Leaf shape variation is primarily determined by shoot position but changes over the season 764 Formatted: Font color: Black 765 (A) Representative shapes showing leaf variation (-3 sd, mean, +3 sd) captured in each of the top 4 766 principal components of the Generalized Procrustes Analysis-rotated leaf shapes. (B) Projections of all 767 leaves into the first two dimensions of principal component space colored by the strongest determinant of 768 variation in the top two PCs. (C) Projections of all leaves into the first two dimensions of a linear 769 discriminant space trained to maximize variation between phenological stages. (D) Variation in leaf shape 770 captured on PC2 shown by leaf position and phenological stage. Large points represent the mean of the 771 group when projected onto PC2. Bars surrounding the mean show one standard deviation. Variation in 772 each group is shown as a composite leaf trace scaled to a standard size and centered over the mean. 773 774 Figure 5: Vine physiology measurements show signal from most experimental manipulation varies with Formatted: Font color: Black 775 rootstock and the rootstock by phenology interaction 776 (A) Percent variation explained by model terms (top) from linear models fit to each of four physiology 777 traits (left). (B) Variation in leaf transpiration rate for each rootstock genotype over the course of the 778 season. Boxes are bound by the 25th and 75th percentiles with whiskers extending 1.5 IQR from the box. 779 Significant changes are indicated by letters above boxes, and are only meant for comparison within each 780 phenological stage. Group means are displayed with black squares. (C) Variation in stomatal conductance

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781	for each rootstock genotype over the course of the season. Boxes are bound by the 25th and 75th	
782	percentiles with whiskers extending 1.5 IQR from the box. Group means are displayed with black	
783	squares. Significant changes are indicated by letters above boxes, and are only meant for comparison	
784	within each phenological stage.	
785		
786	Figure 6: TraitPhenomic covariation varies over the course of the season	Formatted: Font color: Black
787	Correlation networks showing patterns of covariation within and between phenotyping modalities. Nodes	
788	of the network are connected if they are significantly correlated (Pearson, FDR; $p.adj < 0.05$). Edge	
789	thickness is proportional to the strength of correlation (multiplied by 16 for visibility). Edge color reflects	
790	the direction of the correlation where blue edges indicate positive correlations and orange edges indicate	
791	negative correlations. Modalities are indicated by a leading character and node color: ionomics (iPCs;	
792	purple), metabolomics (mPCs; pink), gene expression (gPCs; yellow), leaf shape (sPCs; green). Network	
793	topologies are shown for (A) anthesis, (B) veraison, and (C) harvest.	
794		
795	Figure Supplement Legends:	
796	Supplemental Figure 1: Experimental Design	Formatted: Font color: Black
797	(A) Vineyard Map. The vineyard features a randomized block design where 'Chambourcin' is grown	
798	ungrafted and grafted to three rootstock genotypes: '1103P', '3309C', and 'SO4'. Each row is treated	
799	with one of three irrigation treatments: full replacement of ET, reduced-deficit, no replacement of ET.	
800	Each cell of the vineyard contains four replicate grafts. (B) Phenotype sampling scheme across the four	
801	replicates in a cell. For example, the top panel (purple) shows all four vines in the first cell of Row 8 in	
802	Block D. From each vine in that cell, ionomics and leaf shape were sampled. In contrast, the lower panel	
803	shows the first cell in Row 8 in Block A. Here, the first and fourth replicates were sampled for ionomics	
804	and leaf shape while the second and third replicates were sampled for all phenotypes. All vines (288)	
805	were sampled for ionomics and leaf shape. The middle two vines in the front half of the vineyard (72)	
806	were additionally sampled for metabolomics, gene expression, and physiology. (C) Phenotype sample	

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807	scheme within a vine (along a shoot). For each plant, young leaves were sampled for ionomics, leaf	
808	shape, and gene expression. Middle leaves were sampled for ionomics, leaf shape, metabolomics, and	
809	nhysiology. Older leaves were sampled for ionomics and leaf shape. Samples for ionomics and leaf shape	
810	were taken from the same sharet. All other phoneteries user sampled from independent sharets.	
810	were taken from the same shoot. All other phenotypes were sampled from independent shoots. (D)	
811	Rootstock relatedness. Each of the rootstocks in this trial shares a parent species with a different	
812	rootstock. '1103P' is a cross between <i>Vitis rupestris</i> and <i>V. berlandieri</i> . '3309C' is a cross between <i>V</i> .	
813	rupestris and V. riparia. 'SO4' is a cross between V. riparia and V. berlandieri. The parent that is shared	
814	between each pair of rootstocks is highlighted. This figure is partially reproduced from [19] available	Formatted: Font color: Black
815	under a Creative Common license (CC BY 4.0).	Field Code Changed
816		
817	Supplemental Figure 2 Supplemental Figure 2: Quality and validity assessment of 3' RNAseq data. (A)	
818	A survey of recently annotated circadian clock orthologs from the grapevine genome annotation [44].	
819	Orthologs surveyed included the morning-phased RVE1 and LHY, evening-phased LUX and ELF4, and	
820	the nigh-phased TOC1 (B) A survey of genes with housekeeping domains related to IPR000626	
821	(ubiquitin) and IPR004000 (actin).	
822		
823	Supplemental Figure 3: Patterns of ion covariation change over experimental treatments	
824	Correlation networks showing patterns of ion covariation across phenological stages and shoot position.	
825	Nodes of the network are connected if they are significantly correlated (Pearson, FDR; $p.adj < 0.05$).	
826	Edge thickness is proportional to the strength of correlation (multiplied by 16 for visibility). Edge color	
827	reflects the direction of the correlation where blue edges indicate positive correlations and orange edges	
828	indicate negative correlations.	
829		
830	Supplemental Figure 34: Patterns of variation contributing to gene expression linear discriminants	 Formatted: Font color: Black
831	(A) Projections of leaf gene expression samples into the first two dimensions of a linear discriminant	
832	space trained to maximize variation between phenological stages, rows in the vineyard, and rootstock	

833	genotype. For each LD, the PCs that loaded significantly (>1.96 sd from the mean loading) are listed in		
834	order of loading magnitude. (B) Distribution of the top loading PCs onto LD1 and LD2 for each of the		
835	trained models.		
836			
837	Supplemental Figure 45: Patterns of variation in leaf shape are subtle		Formatted: Font color: Black
838	(A) Percent variation captured in linear models fit to each of the top 20 principal components of leaf	$\overline{\langle}$	Formatted: Font color: Black
839	morphology. Presence of a cell indicates the model term (top) was significant for that PC (left_percent		Formatted: Font color: Black
057	inorphology. Thesence of a cert indicates the model term (top) was significant for that i e (tert, percent		
840	variation explained by the PC in parentheses). (B) Composite leaf traces for the main rootstock genotype		
841	effect identified on PC1.		
842			
843	Supplemental Figure 56: Example correlations within and between dataphenotyping modalities over the		Formatted: Font color: Black
844	course of the season		Formatted: Font color: Black
845	(A) Example correlation showing a strong within-modality correlation between the ionomics gPC1 and		
846	gPC2 at anthesis. Pearson correlations by phenological stage and CIs derived from 10000 random 90%		
847	draws are shown for each panel. Generally speaking, CIs overlapping with 0 were not accepted as		
848	significant. (B) Example correlation showing one of the stronger between-modality correlations between		
849	the gene expression gPC4 and morphology (shape) sPC3 at version. (C) Example correlation of a		
850	relationship that is present multiple times over the course of the season between metabolomics mPC3 and		
851	gene expression gPC6 at both veraison and harvest. (\mathbf{D}) Example correlation that is dynamic over the		
852	course of the growing season between the ionomics mPC3 and mPC6.		
853			
854	Supplemental Figure 6: Trait7: Phenomic covariation varies over rootstock genotype		Formatted: Font color: Black
855	Correlation networks showing patterns of covariation within and between phenotyping modalities. Nodes		
856	of the network are connected if they are significantly correlated (Pearson, FDR; p.adj < 0.05). Edge		
857	thickness is proportional to the strength of correlation (multiplied by 16 for visibility). Edge color reflects		

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858	the direction of the correlation where blue edges indicate positive correlations and orange edges indicate
859	negative correlations. Modalities are indicated by a leading character and node color: ionomics (iPCs;
860	purple), metabolomics (mPCs; pink), gene expression (gPCs; yellow), leaf shape (sPCs; green). Network
861	topologies are shown for (A) Ungrafted, (B) '1103P'-grafted vines, (C) '3309C'-grafted vines, and (D)
862	'SO4'-grafted vines.
863	
864	Availability of Data:
865	Ionomics data are available at https://dx.doi.org/10.6084/m9.figshare.13200980 . Metabolomics data are
866	available at https://dx.doi.org/10.6084/m9.figshare.13201043. Gene expression data are available in the
867	Sequence Read Archive under BioProject PRJNA674915. Leaf scans and leaf landmarks are available at
868	https://dx.doi.org/10.6084/m9.figshare.13200953. Weather and physiology data are available at
869	https://dx.doi.org/10.6084/m9.figshare.13198682 and https://dx.doi.org/10.6084/m9.figshare.13201016,
870	respectively.
871	
872	Availability of Code:
873	All code for this paper including shell scripts for RNAseq analysis and Jupyter Notebooks for data
874	analysis in R can be found on the Vitis Underground GitHub
875	(https://github.com/PGRP1546869/mt_vernon_2017_leaf).
876	
877	Author Contributions:
878	AJM, DHC, AF, LGK, MK, JPL, and QM designed the experiment. ZNH, LLK, MA, JFS, ZM, NB, EF,
879	and JPL contributed to sample collection and sample processing. ZNH, LLK, JFS, and MA contributed to
880	data analysis. ZNH and AJM contributed to the writing of the manuscript. All authors contributed to

- 881 manuscript editing.
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933 ROOTSTOCKS FOR RESISTANCE TO PHYLLOXERA AND NEMATODES - IT'S NOT ALWAYS

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Rootstock

Rootstock






Gene Expression (g)

Morphometrics (s)

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Dr. Nicole Nogoy,

We are happy to submit our revised manuscript (GIGA-D-21-00137) for review. We would like to start by thanking the reviewers for their robust, extremely careful and thorough consideration of our manuscript. The suggestions made by the reviewers were invaluable, and addressing them has led to a stronger manuscript and a more complete and reproducible analysis.

The largest changes to the manuscript address the issues of validation of RNAseq data, more detailed descriptions of RNAseq methods, changes to language for the sake of clarity, and a discussion on the limitations of our work. Every change made to the manuscript is addressed and summarized in the attached (and pasted below) point-by-point response to the reviewers.

In addition to the changes made at the request of the reviewers, we made changes to the manuscript based on editor comments. Primarily, we agree with your summary on the appropriateness of data placement. As such, we have moved a supplemental note on this manuscript from GitHub to a Supplemental Note in the manuscript. Following previous correspondence, we are in the process of uploading the metabolomics data to Metabolights. There is currently an extended waiting period for review of Metabolights submissions, but we have been given a temporary accession (MTBLS2831), and we will update you when this review is complete.

We deeply appreciate the time that everyone has spent on this manuscript, and we look forward to hearing back soon.

Best,

Zachary N Harris and Allison J Miller

Black Text = Reviewer Comments

Grey Text = Author Response

Note to all: Microsoft Word on macOS does not allow correct continuous line numbering with "track changes" on. All referenced line numbers were identified such that they were continuous. If line numbers appear way off, try changing "All Markup" to "Simple Markup" under the Review tab to align the line numbers.

Editor Comments

Overall, the reviewers have highlighted that in its current form, the manuscript requires more biological validation and more detailed methods to ensure reproducibility of the work presented. Limitations on the study should be discussed and how they may impact the results; and more data should be provided to understand the reliability of the RNA-seq experiment. Furthermore, RNA-seq methods are incomplete - we strongly encourage all authors to add their detailed methods to protocols.io (if not already open in protocols.io and cite the protocol DOI in the paper.

 Response: Thank you for this. We have added all details that have been requested on L191-195. In addition, we added a supplemental figure (Supplemental Figure 2) showcasing our analysis for gene expression validity. A summary of this analysis is on L207-210.

We also see reviewer #4 suggests to use Figshare - but this is not an appropriate database to share large-scale data, such as this work presents. Github is still the most appropriate place to share scripts and associated documentation, and our open repository, GigaDB can host the other metadata not already open in other community approved repositories; we will also host snapshots of your scripts in GitHub.

- Response: In addressing Reviewer #4's specific recommendation, we have moved the document in question from GitHub to a Supplementary Note in the manuscript. In line with previous communications, we are also in the curation process of metabolomics data uploaded to Metabolights. We are happy to jointly upload other data sets to preferred repositories and databases, we just need guidance on the preferred locations for those data. As of today, we are unaware of standard databases for ionomics and leaf shape data. Scripts used for analysis are still available on GitHub, but can be hosted elsewhere if this is of concern.

Reviewer #1

The manuscript by Harris and co-workers presents a characterization of rootstock genotype effects on multilevel leaf phenotypes of one grafted grapevine scion cultivar. Three rootstock genotypes along with the ungrafted cultivar were compared for ionomics, transcriptomics, metabolomics, leaf morphology and physiology in three phenological stages. Analytical and statistical analyses applied were generally sound. While authors identify larger effects in most

cases for stage and vineyard position/sampling time, ionic composition was the phenotype most significantly affected by rootstock genotype. Co-variance among multilevel phenotypes is also presented.

Major issues

1. The study comprises a vast dataset, with a total of 288 plants independently analyzed for two phenotypes (morphometry and ionomics) and 72 plants were used for the rest of phenotypes. Nevertheless, the experiment is limited in terms of genotypes tested and reproducibility. Only one year of study and under the specific soil and climate conditions of a single field plot. Moreover, the effects were only tested on a single scion genotype, a bred interspecific hybrid including Vitis riparia and V. rupestris in its pedigree. At least one of these species is also in the pedigree of the three rootstocks tested, which might involve lower diversity than in common interactions between rootstocks and V. vinifera cultivars. These limitations should at least be considered when discussing the results.

 Response: The comments provided by the reviewer are all excellent observations that were clearly missing from the discussion of our work. We have added a paragraph to the Discussion (L544 - L559) to better couch how our work should be compared to other studies and the considerations that may account for those differences.

2. The RNA-seq assay did not identify differentially expressed genes (DEGs) in response to rootstock genotype, which disagrees with previous reports. While the origin of the lack of effects here is unclear, further data should be provided to understand the reliability of the RNA-seq experiment:

- Response: We thank the reviewer for this comment. We were similarly interested to see that our results differ from previously published analyses in similar systems. We added comments to the discussion to clarify why we think these differences might be present. To ensure such reliability, we confirmed in our data that previously established patterns of house-keeping and circadian phased genes were behaving as expected. The following has been added to the manuscript:
 - Added to data description L208-210, "To check the validity of our expression results, we assayed two classes of housekeeping gene (Ubiquitin-domain and actin-family) and eight previously annotated circadian genes (Carbonell-Bejerano et al. 2014)"
 - Added to Analyses, **L339 345**, "We computed the expression of two classes of housekeeping genes, and showed that they are generally stable across samples over phenological time (Supplemental Figure 2). We noted that some variation is expected for housekeeping genes; see, for example, [49]. Moreover, we showed that patterns of previously annotated circadian genes conform to expected results over the sampling window. For example, predicted orthologs of LHY and RVE1 are correlated and decreasing over our sampling window, and a predicted TOC1 ortholog is invariant. The results of these analyses provide general confidence in the gene expression data presented here."
 - Created and added Supplemental Figure (now supplemental Figure 2) showing these patterns.

2.1. Which was the timing of sample collection for RNA-seq samples? Was the same sampling order followed for the three phenological stages? Which were the weather conditions on each of the three sampling dates? It is relevant to describe that information since environmental and circadian changes between and within days can alter gene expression.

Response: We added the following to the section describing the gene expression data set (L187-190): "Leaves were sampled by a single team near midday between 10AM and 2PM in row order ensuring that 'block' and 'row' accounted for unmeasured environmental variation and temporal variation over the sampling window." A statement was added on L637-638 that "At each phenological stage, effort was made to sample on days with full to partial sun and minimal precipitation."

2.2. Data on RNA sequencing depth should be provided to understand the resolution of the transcriptomics experiment. For instance, how many bases/reads per sample were produced? How many genes per sample were called as expressed (DESeq2-norm counts >2 according to authors own threshold)?

 Response: Information on sequencing depth and genes per sample were added to the Analyses section. Specifically, we added the following to <u>L337-338</u>: "On average, each sample contained 4.1 million 3'-reads and showed the expression of 17,852 genes."

3. The interpretation of the origin of the results is generally shallow and several questions or limitations are overlooked. For instance:

3.1. It is described that physiological parameters were measured from 10 am to 1 pm, a wide interval with expected changes in environmental conditions affecting these measurements. To understand for possible covariances, it should be indicated if these measurements were carried out simultaneously and following the same order than that of leaf sample collection for the other phenotyping.

Response: We agree that we missed crucial details about the timing of this sampling. To fix this, we included the clarifications that (on 241) all physiology measurements were being taken simultaneously by different groups moving though the vineyard and (on 243-245) the measurements were all taken in row order ensuring that the vineyard blocking factor captured temporal variation. SImilar notes were added for the other phenotypes to better explain sampling. As was noted in the next reviewer comment, block is missing from Figure 5 which means it was not significant as a main effect.

3.2. Related to the previous, why block effect alone was not considered for physiological measurements in Figure 5?

- Response: Thank you for this comment. Block (or row for gene expression) was included in the models as a main effect for every modality (see analysis section). Non-significant factors were dropped from figures summarizing linear models; because the block main effect was not significant, it was not included in Figure 5.

3.3. Did the horseshoe shape for row effect on the transcriptome correlate with oscillation of environmental/circadian clock conditions during the sampling interval or with vineyard

heterogeneity? Functional analysis of the genes contributing to row effect could be informative on the origin of these effects that might have hindered the identification of rootstock effect on the transcriptome.

- Response: This is a really interesting comment. We agree with the reviewer that the horseshoe shape in LDA space is either a function of circadian conditions or spatial heterogeneity. We have added to the Data Description section a comment on assaying genes with known circadian topology (L207-210) and show in Supplemental Figure 2 that those genes are variable over our sampling window. In addition, we commented on this outcome in the Analyses section on L360-362. We show that the impact of vineyard position/spatial variation is weak in other measured phenotypes (captured by the 'block' model term; see, for example, Figure 1A and Supplemental Figure 5A). Future studies should assess potential intra-vineyard variation either through blocking (as we did here) or explicit measurement (for example, soil composition) and control for that variation.

3.4. Is there a rootstock effect on vigor, biomass, fruit fertility and production that could explain or condition the effects in leaf phenotypes that were measured? Were these factors normalized in any way, either by agronomic practices or statistical treatment?

Response: This is an excellent question that is perhaps beyond the scope of this comprehensive analysis of leaf phenotypes, but one that is certainly an important next step in our research trajectory. Conditioning or normalizing on aspects of vigor or yield or looking for correlates of those traits in early season leaf phenotypes would be immensely valuable to viticulture and a general understanding of grapevine biology. To explore this idea, we have amended the language of the Potential Implications section on 1588-608. In addition, some of these data were collected and are being prepared for papers focused toward berry phenotypes. In the meantime, we point to (https://doi.org/10.1002/pld3.324) to show that this is absolutely a valid direction of inquiry for future work and data integration efforts.

4. This study comprises similar experiments to these already published by the same group in the same set of plants (Migicovsky et al., Hort Res 2019), although extended to include metabolomics and physiology data and two additional phenologcal stages. While the effect of phenology is clearly presented here, the addition of the metabolite data is undermined. What are the metabolites determining rootstock effect in Figure 2C? What about metabolites determining a rootstock effect depending on phenology that could be inferred from PC10?

Response: We thank the reviewer for this comment and appreciate the careful consideration of this manuscript in the context of the Migicovsky et al, 2019 manuscript. We completely agree that the value of the metabolomics data is undermined in the manuscript. This is primarily the result of current challenges in mapping peaks from LC-MS onto named metabolites. The current state of untargeted metabolomics from LC-MS would require significant chemical laboratory work to narrow down the space of potential metabolites. While we believe this work should absolutely be done, our goal with this study was not necessarily to identify specific metabolites but to determine if the metabolome was a potential avenue through which the rootstock is influencing scion phenotypes. To address this, we used only a portion of the runs available to show there

is a signal. Future work will focus on merging the various additional LC-MS runs (not presented here) and chemical experimentation to uncover the full scope of this effect. We note that we are uploaded raw data to Metabolights, QC/filtered data to FigShare, and reported the retention times and m/z ratios for the compounds of putative interest in the manuscript. We hope that these data may be useful in future analyses of grapevine metabolites, either by our group or others.

Minor revisions

1. "Ubiquitous" effects of rootstock genotype are described along the MS. However, since only one location was analyzed (leaves), would "pleotropic" be more appropriate to define the different phenotypes affected by rootstock-scion genotype interaction in this study?

- Response: This is a great point. We clarified our usage of the word "ubiquitous" to ensure its intended meaning (across modalities within leaves, not as an inherent feature of grapevine) was clear (for example, on 1514) throughout the manuscript. Supporting the reviewer's observation that this study only included one environment, we are hesitant to use the word "pleiotropy", though we are interested in the implication that the different rootstock/scion pairs create different local environments and will consider this idea in future works.

2. Methods on RNA-seq procedures are incomplete. Which sequencing technology was used? Which type and length of reads? Etc.

- Response: Good catch. We added the following to the L194-195: "Sequencing was conducted using the Illumina NextSeq500 platform which returned single-end 86 bp reads."

3. Inter-annual comparison for anthesis ionomics, transcriptomics and morphology between this study and their previous publication (Migicovsky et al., Hort Res 2019) could enable a broader interpretation of rootstock effects, overcoming the reproducibility limitation of considering only a single season here.

Response: We absolutely agree that interannual analyses are required for a detailed understanding of the root system influence on shoot phenotypes and these analyses are underway. Our goal with this manuscript was to carefully quantify different phenotyping modalities and to understand how they relate to one another. The results from this study have helped us consider what is worth more detailed investigations, and analyses that address longer (multi-year) studies for those phenotypes are currently in the works. Given the magnitude of the data presented here and the extent of analyses conducted, we struggled to fit this detailed work in a single manuscript that also covered inter-annual variation as well as additional phenotypes (berry chemistry, etc.). As a result of work presented here, we are currently exploring tradeoffs between deep analyses of individual phenotypes and shallower analyses of more modalities over longer time periods, additional scions, and multiple sites. In the meantime, wherever possible we note some comparisons to the Migicovsky 2019 study where appropriate. The Migicovsky 2019 pilot study used considerably different methods for many phenotypes, which preclude direct comparisons.

4. L426. The sentence might not be completely fair as no DEG was identified for rootstock effect (transcriptome phenotype would therefore be mostly unaffected) and developmental stage-specific could be more adequate than season-specific.

- Response: Thank you for this. We agree with the suggested change in language for the effect of phenology and changed "season specific" to "specific to the vine's developmental stage" on L468. On gene expression, while no DEGs were identified, we were able to identify latent combinations of genes that were responsive to rootstock treatment. While this effect is subtle, it was nonetheless detectable.

5. Any biological interpretation of the specific metabolites, genes, iones, shapes determining the resulting PC covariation networks? While it can be interesting to add to covariation networks additional levels of phenomics as authors propose (IcRNA, micorobiome, epigenetics), it would also be informative to exploit the interpretation of the dataset that they have already produced.

Response: Excellent suggestion. Unfortunately, after much consideration, at this point we do not feel comfortable with detailed biological interpretations based on specific metabolites or genes that underlie PC covariation networks shown here. Some of the limitations of our dataset, and why we are unable to make these mechanistic connections with data presented here, are detailed in the discussion. We note that the ionome offers a very rich source of data ripe for deep analysis, and that an additional manuscript describing a deep dive into multi-year, multi-time point ionomic dataset is in preparation now. We agree that future work should be targeted toward biological understanding of these relationships. On suggesting inclusion of other phenotypes, this comment reflects our enthusiasm for other existing approaches and exciting areas of research that might further uncover mechanistic understanding of the effects we are seeing from grafting and over time. The analysis presented in the paper, unfortunately, does little to advance us toward the goal of mechanistic understanding, but it does help us see where future studies could be targeted. To this end, we added language to clarify this point on L573-578.

6. L470, If the lack of rootstock effect on the transcriptome was due to the phenology effect, specific analysis at each phenology stage would identify rootstock genotype factor significant DEGs. Is it the case? Would there be any rootstock effect detected on transcriptome if the analysis was restricted to single blocks at specific phenological stages?

- Response: We thank the reviewer for this comment. This is certainly something we are trying to wade through as our results suggest that the rootstock influence on our vines is incredibly complex and works through interaction with other factors of the experimental design. Ongoing work is focused on identifying these complex effects, in a statistically robust way. We are also currently working with collaborators to identify genes and gene regions worth further exploration. Moreover, we are seeking to use results from other phenotypes to focus on genes in a more 'hypothesis-driven' approach that can further the 'discovery-driven' results observed here.

7. Apart from the seasonal effect, the "Potential implications" presented are not directly inferred from the Results obtained here but from the potential of the approach used. Any other potential implication of the specific results?

- Response: This is a very helpful suggestion. In response to this and comments from other reviewers we have re-worked the potential implications section. Other reviewers called for an enhanced focus on yield/viticultural implications, while others have asked us to minimize such speculation. Consequently, we have attempted to carefully place this work in the context of both basic plant biology and viticulture. If the current revision does not meet the expectations of the reviewer(s) or editors we would be happy to revise further.

8. Is there any data available for the distribution of soil properties across the experimental plot that could be considered to discuss the origin of block effects? Could the human factor during that extensive sampling be another variable accounting for block effect?

- Response: Thank you for this excellent observation. For the data presented here, we do not have paired soil samples. We anticipate some heterogeneity in soil properties across the experimental plot; however it is unclear how strongly this would correspond directly to block effect. Regarding the human factor, we have added a sentence into each data modality clarifying what variation is captured by the blocking factor. See each addition below:
 - L136-138 added, "Teams were deployed in the vineyard so that multiple vineyard rows were being sampled concurrently. As such, 'block' represented unmeasured spatial variation, but did not strictly correlate with time of sampling due to the nature of sampling (see Methods)."
 - **L155 157** added, "ensuring that 'block' captured both unmeasured environmental variation and temporal variation over the sampling window".
 - L187-190 added, "Leaves were sampled by a single team near midday between 10AM and 2PM in row order ensuring that 'block' and 'row' accounted for unmeasured spatial variation and temporal variation over the sampling window (see Methods)"
- Overall, block is not a large descriptor of variation in our study except for the phenotypes for which block is collinear with time of day. In these phenotypes (the metabolome and the transcriptome) there is a noted circadian topology. The other phenotypes (ionomics, leaf shape, and physiology) see little effect from block suggesting there is little spatial variation (or at least that the spatial variation is unimportant for those phenotypes).

9. Because half of 3309C reps would have been collected before any ungrafted rep was taken, could the LD2 effect in discriminating 3309C and ungrafted from RNA-seq data be related with sampling times? What are the genes involved in this effect?

- Response: We thank the reviewer for this comment. While it is always possible that results correlate with unmeasured confounders, rootstock genotype was not confounded

with any of the terms in our model (including time of sampling, which was a correlate for row in our study; L653-655). Each rootstock was present in each row of the vineyard in cells of four replicated vines (See supplemental Figure 1A). For the transcriptome sample, we sampled leaves from the middle two vines in each cell. While it certainly takes time to sample in a vineyard, each rootstock in each row would have been sampled within minutes of one another. Due to this, the grouping we report in LD space is not confounded with time. The current results suggest that this effect is driven by complex combinations of genes (from the PCA results) and not any particular genes being strongly affected (from the traditional DGE results). We are currently working on exploring these subtle effects in more statistically robust ways in a multi-year study.

10. Any discussion on the origin of leaf position effects in specific ions?

- Response: Thank you for this comment, and this is something we think about often. Leaf position was added to this study on the ionome because it is known that leaves vary in their elemental composition over development. The major question here was whether or not rootstock would influence the elemental composition of those leaves in such a way that the known patterns might be interrupted. While we observed significant variation in ion concentrations as a function of leaf position, it did not strongly interact with rootstock genotype. In other words, the rootstock effect was present in all leaves, not just leaves of a particular age. As such, we struggled to fit a detailed description of the effect of leaf position in the current paper. However, we have made all data from this analysis publicly available if there exists specific interest for the leaf position. Ongoing work focused explicitly on the leaf ionome will provide a deep dive on how ion concentrations vary by rootstock, over development, across seasons, and across multiple years.

11. L556. Indicating in there that "only the middle two vines of the four cells in the front half of the vineyard were included in the 72-vine set" would be handy to understand the distribution of this set.

Response: Thank you for this comment. We have clarified the description of the experimental vine throughout the manuscript. The experimental design of the vineyard included groups of four identical vines (e.g., Chambourcin grafted to 3309C) that are distributed in a randomized block experimental design throughout the vineyard. For some data modalities we were unable to process samples from all four vines per cell. In these circumstances, we opted to collect samples from the middle two vines of the four vine set. We collected from the middle two vines from a total of 36 cells for the 72 vine set. To improve the understanding of this section, we have amended the text to point to more appropriate sections of Supplemental Figure 1. In addition, we have improved the Figure Legend for this figure so it is more clear what each panel is showing with explicit descriptions for Supplemental Figure 1B, which should improve the clarity of this section. Finally, we clarified that this description only applied to the front half of the vineyard which was missing from the previous draft. We would be happy to make additional edits to the text if this description does not provide sufficient clarification.

Reviewer #2

The manuscript by Harris et al investigates the effect of grafting on a number of physiological and molecular phenotypes within grapevine (Vitis spp.) scions. The hybrid Vitis cultivar Chambourcin was compared when grown on its own-roots, or when grafted to three different commercial hybrid rootstocks: 1103P, 3309C, and SO4. The vines were grown in the field, irrigated with different volumes of water, and sampled over a single growing season. Large data sets have been generated for leaf metabolites, solutes (ions), transcripts, shape, and physiology (stomatal conductance, transpiration). As such, the manuscript fits the scope of Gigascience well. The manuscript is well written, however I found it was very statistical and would benefit from additional biological analyses to confirm and validate the findings. The methods section is lacking some details that would enable reproducibility. Some of the figures could be improved for readability. My comments and suggestions are detailed below:

Major comments

- 1. There is no information on the age of the vines at the time of the experiments.
 - Response: This is a great observation of information we overlooked. The vineyard had been in the ground for eight years at the time of sampling. The age of the vineyard has been added to **L538** and commented on in the discussion.

2. A quantitative analysis of the elemental content of the irrigation water by ICP-MS would be beneficial. In this study, it is unknown whether the irrigation treatments contained varying levels of the elements that were measured in leaves. To this end, it is perhaps not surprising that rootstocks had minimal effect on, for example, the Na+ content of grafted scions. However, it has been demonstrated previously that own-rooted vines cannot efficiently exclude Na+ compared to grafted vines when irrigated with 100 mM NaCl (see Fisarakis el al (2001) Agricultural Water Management 51 13-27).

Response: This is a really intriguing suggestion, and one we wish we would have thought of in 2017. Regrettably, it was not something that was considered for this study at the time. However, we can be confident that irrigation was not significantly altering the findings of our study due to the weak nature of the irrigation effect (See Supplemental Note 1). Had there been variation in the ionome of the irrigation water, we would have expected to see a stronger irrigation or irrigation by phenology effect, neither of which were strongly observed in this study. We thank the reviewer for pointing us to this helpful article.

3. The manuscript would be more useful to the plant science community if a subset of the actual metabolites and genes identified within the principle components were named and confirmed using a second method. It would then be possible to discuss which physiological, metabolic, and molecular processes within Vitis scions are impacted by rootstock selection.

- Response: We absolutely agree gene-level and metabolite-level understanding of the root system influence on shoot system phenotypes is the direction this work needs to head. This is perhaps one of the biggest limitations of large-scale analyses of multi-

dimensional phenotypes: it is sometimes hard to narrow in on individual phenotypes for some systems. We acknowledge that there is a trade-off between large-scale analyses like the one presented here and identification of actual metabolites/genes and their functional role in the vine. We see these as very complimentary approaches that illuminate different aspects of vine biology; however, we were unable to do both in this study. Ongoing work is attempting to, in a statistically robust way, uncover those subtle effects from even deeper sampling of the transcriptome. The metabolome as described using the untargeted approach here is a whole different monster. We were able to show that some metabolites are responding to the rootstock treatment and even to the rootstock by season interaction. The current nature of LC-MS and untargeted metabolomics in Vitis generally make it incredibly non-trivial to map these metabolites. Here we sought to catalog the basic responses of multiple phenotypes to help guide more targeted analyses and guide us toward studies that could produce mechanistic understanding.

4. Similar to my comment above, some of the data could be integrated. For example, transpiration was increased for scions grafted to 1103P (Fig 5B). Were genes or metabolites involved in the regulation of stomatal aperture differentially abundant when grafted to 1103P?

- Response: This kind of data integration is an excellent suggestion. While such analyses would require work beyond the scope of this paper, we think that this comment is exactly in line with how we should be guiding future work. We proposed in the previous comment that this work was meant as a foundation on which we establish the basic responses of many complex phenotypes over the growing season with respect to the rootstock genotype. The PCA-based integration was to help us narrow down which types of data modalities warrant future integrative work. As we move toward identifying and annotating individual genes and metabolites, these suggestions will certainly help in that future planning.

5. The ionomics data in Fig 1B and C would be easier to interpret if presented as a percentage - for example, % DW, % FW, or mM of tissue water. Currently, there are no units on the Y-axis.

We agree that z-scores were not the ideal choice for this figure. To address this, we remade this portion of this figure to show the elements as concentrations in parts per million of acid-digested dried leaves. We have updated the Figure Legend L706 and L710 to reflect this change.

6. There is no mention of how the RNA was extracted from plant tissues. Further, a quality control would normally be performed, e.g. by measuring the 260/280 ratios at the very least. Was any quality control performed on these RNA samples? How do we know the samples were pure and not degraded?

 Response: Excellent point that was also noted by Reviewer 1. The information requested has been added to the Data Description section, <u>L191 - 193</u>: "Total RNA was extracted from plant tissues using the Sigma Spectrum Plant Total RNA kit with modification of the addition of 2% PVP40 to the extraction buffer to decrease phenolic inhibitors. All RNA extractions were checked for quality control using a Nanodrop. Sequencing was conducted using the Illumina NextSeq500 platform which returned single-end 86 bp reads."

7. It is unclear how many biological replicates were used for the RNAseq experiments.

Response: Good catch- thank you for this. Language changes were made throughout the manuscript (in conjunction with other review comments in the section "Study Design" and within the Data Description for each modality to improve clarity. In short, each modality was sampled from either a 72-vine set (metabolomics, gene expression, physiology) or a 288-vine set (ionomics, leaf shape). In the 72-vine set, we only sampled the middle two vines from each four-vine cell in the vineyard (shown in Supplemental Figure 1B-C). At the highest order interaction for gene expression (rootstock:row:phenology), the number of biological replicates would be two. Since this is clearly underpowered, we put little effort into estimating or interpreting those effects. However, lower order interactions (like rootstock:row or rootstock:phenology) are averaged over the remaining samples. For example, the rootstock:row effect is estimated from 6 samples (averaged over phenology). Similarly, main effects are averaged over all other terms, so the rootstock effect would be estimated from 18 samples.

8. Usually, for genome-wide transcriptional studies, the expression patterns of a subset of genes are confirmed using another method (e.g. quantitative real-time PCR). This has not been performed in this manuscript. Authors need to confirm the validity of the RNA seq dataset.

- Response: Thank you for this comment. We agree that for studies focused on identifying genes associated with specific phenotypes, that the gold standard for genome-wide transcriptional studies is cross-validation using qPCR. The goal of this study is to understand the influence of root system genotypes on shoot system phenotypes, and here we are treating gene expression in the leaves as a shoot system phenotype. Because we are not testing explicit hypotheses about any particular gene or pathway, we determined that PCR-based confirmation would not add value. This decision was not made lightly, and was done following consideration of other recent work that applied various RNAseq platforms to address structurally similar questions, including:

1) Griffith M, Griffith OL, Mwenifumbo J, Goya R, Morrissy a S, et al. (2010) Alternative expression analysis by RNA sequencing. Nat Methods 7: 843–847. Doi:10.1038/nmeth.1503.

2) Asmann YW, Klee EW, Thompson EA, Perez E a, Middha S, et al. (2009) 3' tag digital gene expression profiling of human brain and universal reference RNA using Illumina Genome Analyzer. BMC Genomics 10: 531. Doi:10.1186/1471-2164-10-531.

3) Wu AR, Neff NF, Kalisky T, Dalerba P, Treutlein B, et al. (2014) Quantitative assessment of single-cell RNA-sequencing methods. Nat Methods 11: 41–46. Doi:10.1038/nmeth.2694.

4) Shi Y, He M (2014) Differential gene expression identified by RNA-Seq and

qPCR in two sizes of pearl oyster (Pinctada fucata). Gene 538: 313–322. Doi:10.1016/j.gene.2014.01.031.

 Moreover, we point to an excellent blogpost on the same validation-discussion that goes further in to this debate: http://dave-bridges.blogspot.no/2014/11/validation-of-rnaseq-experiments-by-

qpcr.html?m=1

- We agree that it adds value to ensure that our data show previously established patterns of house-keeping and circadian-phased genes relevant to our sampling paradigm. As such, the following have been added to the manuscript:
 - Added to data description L207 210, "To check the validity of our expression results, we assayed two classes of housekeeping gene (Ubiquitin-domain and actin-family) and eight previously annotated circadian genes (Carbonell-Bejerano et al. 2014)"
 - Added to Analyses, <u>L339 341</u>, "We computed the expression of two classes of housekeeping genes, and show that they are generally stable (Supplemental Figure 2). We note that some variation is expected for housekeeping genes; see, for example, (Liang et al. 2018). Moreover, we show that patterns of previously annotated circadian genes show expected results over the sampling window. For example, predicted orthologs of LHY and RVE1 are correlated and decreasing over our sampling window, and a predicted TOC1 ortholog is invariant. That our samples showed such patterns suggested the gene expression data presented here were valid."
 - Created and added Supplemental Figure (now supplemental Figure 2) showing these patterns.

9. The effect of the different irrigation regimes is not adequately discussed in this manuscript.

- Response: Thank you for this note good catch. Effects of different irrigation regimes were originally presented in a Supplemental Note hosted on GitHub. To increase accessibility, we moved Supplemental Note 1 from GitHub so that it is now a Supplemental Note to the manuscript.
- Some additional notes: our study site is located in southwestern Missouri where it can be quite rainy. In 2017, the year in which samples were collected for this study, it rained a lot, essentially rendering the vines all properly irrigated despite the amount of irrigation applied as part of the study. Not surprisingly, our physiological metrics showed little/no evidence of stress. As such, we opted to include irrigation as a term in the model that is there and could impart variation into some phenotypes, but those effects are very small.

10. The Abstract must be structured into three separate sections: Background; Results; Conclusions.

- Response: The abstract has been restructured to meet the suggested format. We thank the reviewer for catching this oversight.

Minor comments

1. A lot of the information under "data description" should be moved to the methods section. For me, the data description should provide more of a background and rationale of the work, while the methods should provide the actual steps that were taken.

- Response: Thank you for this note. We struggled to balance the need to provide enough information for readers to understand the work up front, while saving the majority of methodological details for the methods section. In its current version, we hope that we have provided the appropriate information in the approximately preferred locations according to the journal's instructions. If there are persistent issues with information placement in the current version of the manuscript, we would be happy to address those in whatever way the editor/reviewers request.

2. Although it is alluded to in the introduction and data description, the tissue type that was harvested and used for the RNAseq experiments is not mentioned in the methods or analyses sections.

- Response: Good catch, and we regret this omission. The tissue type used for RNAseq experiments were young, fully opened leaves. We added information about the tissue type in the analysis section, and assured it was explicitly mentioned in the data description.
 - L185 starts "The youngest fully-opened leaves"
 - L336 added "youngest fully-opened leaves"

3. The Figure 1B legend should denote what Y, M, and O mean. I realise that it is young, middle and old, but the legend should stand alone.

Response: Another good catch. We added a short key to <u>L705 - 706</u> indicating Y (young), M (middle), and O (old).

4. Significant differences in Fig 1B and Fig 5 B&C could be annotated within the Figure, for example with an asterisk.

- Response: Excellent suggestion. Significant comparisons have been labelled with letters in the identified figures, and the figure legends have been edited to explain them.

5. Please be careful to use the past tense consistently, for example P16, L403 "correlation between gPC4 and pPC3 is similar" should be 403 "correlation between gPC4 and pPC3 was similar".

- Response: Thank you for this important catch. Tense was changed in the cited examples and edited throughout the manuscript.

6. P19, L472 "stomatal conductance were higher vines" should be "stomatal conductance were higher in vines".

Response: Added 'in' to L512

7. P19, L475 "Understanding of rootstock genotype influence shoot system phenotypes" should be "Understanding of how rootstock genotype influence shoot system phenotypes".

- Response: Edited **L516** to read, "Understanding rootstock genotype influence on shoot system phenotypes"

8. Perhaps consider re-writing the title to the Fig 5 legend. "Vine physiology measurements show signal from most experimental manipulation" does not make sense to me.

 Response: Edited title on L746 to "Vine physiology varies with rootstock and the rootstock by phenology interaction"

Nice work.

Thank you for this. We appreciate the detailed review.

Reviewer #3

This study investigate associations between rootstock genotype and shoot system phenotypes using five multi-dimensional approaches contributing to elucidate how root systems influence vine phenotype.

the influence of rootstock on the traits analyzed are roughly well documented in literature and authors are aware about this since they very often commented that results are consistent with previous study. Hence the reader might question about the limited new information provided. I would recommend the authors at the "potential implications" paragraph to avoid speculation on "yield" and to emphasis the novelty of engaging a simultaneously analysis as they did in order to speed up comparative studies.

- Response: This is a very helpful suggestion. In response to this and comments from other reviewers we have re-worked the potential implications section. Other reviewers called for an enhanced focus on yield/viticultural implications; however, we agree with this reviewer's request to minimize speculation. Consequently, we have attempted to carefully place this work in the context of both basic plant biology and viticulture. If the current revision does not meet the expectations of the reviewer(s) or editors we would be happy to revise further.

Minor comments

- 1. At line 226-227, check "umol/s" replace with [?]mol s-1 ?
- Response: Unfortunately the symbol the reviewer suggested did not render in the communications (we can't see it). We have replaced the umol with the more commonly accepted µmol where appropriate. If another symbol is preferred or a different symbol was meant, please let us know and we would be happy to make the requested change.
- At line 231, is 15 min interval time enough to equilibrate? Considering that usually 30 or 60 min are required (e.g., J.Int.Sci.VigneVin, 2012, 46, n°3, 207-219, See https://urldefense.com/v3/__https://doi.org/10.20870/IVES-TR.2020.3620__;!!K543PA!bnhJBaYGb-608nkV-F90Yallxoa2UGVyHkLiToTGXSjDbduO2MrZFPISJayIAoKRcnAWzw\$See ISBN 978-90-481-9282-3 at pag 89), please justify your 15 min interval.

 Response: We thank the reviewer for this thoughtful comment. We acknowledge that this is a topic of much debate. A 15 minute equilibration has been used in the past to measure midday stem water potential for tree species, and explicit testing showed that there was little difference between a 10-15 equilibration and a >1hr equilibration in oak trees

(https://www.fs.fed.us/psw/publications/documents/psw_gtr184/psw_gtr184_035_ShackelGro ss.pdf). A more recent study (published after our work was completed) suggests that there is a small effect from different equilibration times in grapevine, but that effect is smaller than the effect from the person operating the pressure chamber (https://doi.org/10.1016/j.agwat.2019.03.026). We have amended the section of the manuscript to include these references for future readers (L254-255).

- 3. Please note that "old" and "young" communicate leaf age rather than leaf position, what's about top, middle, bottom?
- Response: This has been a topic of much debate on our team and we really appreciate this comment. The designation of "old", "middle" and "young" stem essentially reflect terminology used by our team since the inception of the project. We totally agree that these terms reflect leaf age rather than position. However, in grapevines these are equivalent because the oldest leaf along a vine is at the bottom of the shoot and the youngest leaves are at the top of the shoot. All things being equal we would readily make this change; however, the current terminology is used in this paper and in many other completed or ongoing manuscripts being carried out by members of our team. If it is amenable to the editor and the reviewer, we would prefer to retain the "old" "middle" and "young" designation. However, if this is unworkable we will make changes to the language.
- 4. It is not clear why 1103 P had a very little variability of gs at anthesis compared to other rootstocks, for these plant water status seems to range from well irrigated to deep stressed vines while 1103P vines seem to be all roughly well irrigated.
- Response: We appreciate this observation. It is not immediately clear why vines grafted to 1103P showed such little variation in stomatal conductance at anthesis. Unfortunately we don't think we can test this with the current study. To investigate this and related questions we completed a greenhouse study with 1103P and other rootstocks grafted with a common scion with an irrigation treatment. This work is in preparation now.
- Providing VPD data might help to explain why transpiration is low at anthesis (approx.
 2.5 mmol m-2 s-1) while gs at anthesis is comparable to that of other sampling time.
- Response: Thank you for this interesting point. We agree that features of the environment (like VPD) will partially explain the differences we see across the time point in this and future studies. Ongoing work is attempting to identify features of the environments that correlate and can explain some of the variation we see in these traits. This is partially undermined by natural season changes, so these relationships are hard to untangle and require a substantial amount of data, much beyond the three time points

presented here. However, we appreciate this comment and hope to address this in future works.

- "leaf position" should also be discussed against "leaf angle" (e.g., https://urldefense.com/v3/__https://doi.org/10.3389/fpls.2020.00595__;!!K543PA!bnhJBa YGb-6O8nkV-F90YalIxoa2UGVyHkLiToTGXSjDbduO2MrZFPISJayIAoLo-b4lwA\$) which likely change across the season due to change of soil water availability. was leaf angle accounted for image analysis? Considering that soil moisture reasonably differed at the three stages considered (Fig. 5).
- Response: Thank you for this insightful comment. We agree that leaf angle is important for physiology, and would likely correlate with some of the traits we measured. Unfortunately, leaf angle was not quantified at the time of collection in the field. Leaves were simply chosen from vines that emerged directly from the cordon and had intact young, middle, and old leaves. Leaf scans were completed in the lab after leaves had been removed from the vine, and it was not possible to quantify leaf angle at this time. Having said that, this is an important consideration for future studies and we very much appreciate this observation.
- 7. Please add the mean leaf water potential and soil moisture values directly in the Fig. 5 panels to help the readers.
- Response: We thank the reviewer for this suggestion on improving our figures. We have added the mean value for reach rootstock/phenology combination in Figure 5 and, for consistency, to Figure 1. Figurel legends have been edited to address these changes on L712 and L751.

Reviewer #4

This 'big data' manuscripts offers a comprehensive snapshot of the grape phenome as influenced by several factors, including ionomics, leaf morphology, physiological data, metabolomics and transcriptomics. The overall scope is ambitious and a step forward for the phenomics community. Overall the paper was well-written and the design and analysis are sound, though I had a few questions below.

Thank you for these very kind and encouraging words.

I had a few suggestions.

- 1. Phenomic and phenotypic are used interchangeably, and I would ask they be clearly defined should they really mean the same thing? What's the difference between a phenome and a phenotype?
- Draft response: Thank you for this important observation. We define "phenomics" to be a "field characterized as the acquisition and analysis of high-dimensional phenotypic data at hierarchical levels, often with an eye toward multiscale data integration" in the introduction. We define a phenotype as a single particular trait (e.g., calcium concentration). As such, we have amended usages of these words to comport with this

definition: phenomic (and phenomics) now refer to the joint analysis of multiple data modalites, each of which contain several phenotypes (or a single multi-dimensional phenotype). In addition, we recognize that we were being imprecise with language here, so we have fixed this and other terms used interchangeably (trait/phenotype, phenotypic/phenomic, and data type/modality) throughout the manuscript.

- 2. Is the paper considering transcriptomics as phenomics? I know it's a debated issue really, but would be good to state so and why.
- Draft response: Thanks for this comment, like many groups we have spent a lot of time thinking about the question of whether or not the transcriptome is a phenomic modality. In the introduction of this manuscript, we loosely acknowledge phenomics as the field of study concerned with high-throughput data acquisition through multiple simultaneous trait measurements, often requiring advanced computation to analyze and integrate 62.
 63. Following this definition, we treat the transcriptome as a multi-dimensional phenotype (or that the extent to which a particular gene is expressed at a particular time in a particular place is a measurable trait/phenotype). In the analysis and interpretation of the data in this manuscript, we treat the transcriptome like the other data modalities presented here.
- 3. Related, phenotype and trait are inconsistently used as detailed below. I recommend to define them and use consistently. This is a huge problem for phenomics and I think prevents clear discussion of the topic.
- Response: We thank the reviewer for this comment on clarity. Throughout the manuscript we have edited the language we used to describe phenotypes to be consistent. In particular, we have edited each usage of 'trait' to 'phenotype. As above, we recognize that we were being imprecise with language, so we have fixed this and other terms used interchangeably (trait/phenotype, phenotypic/phenomic, and data type/modality) throughout the manuscript.
- -
- 4. I had some questions about the experimental design and randomization, detailed in line comments. I'm not sure about the claim of 72 replicates. Maybe it's a question of what should be considered an experimental unit.
- Response: Other reviewers also noted lack of clarity with respect to experimental design, and we appreciate this observationt. A full response to this concern can be found in our response to your comment on L561 (below); which is partially copied here: I think some additional confusion may stem from us using "replicate" as a vague stand-in for both clonal replicates and statistical replicates. To address this, we have amended the language about the four rootstock scion combinations as follows on L617: "Clonal replicates of each of the four rootstock-scion combinations were planted 72 times for a total of 288 vines planted in nine rows". In addition, we included the specific type of design (split-plot) to this section. Finally, we addressed the number of true replicates in a comment by reviewer 2 concerning RNAseq. The same logic can be used to derive the total number of biological replicates for leaf shape and ionomics at the highest order

interactions (4) and for all other phenotypes (2). In the case where the number of biological replicates is two, the estimation and interpretation of effects is minimized due to lack of power.

- 5. The analysis of individual datasets (or modalities, good word) seems good, and I think the approach to combine into a larger set using the PCA is pretty clever. I still wondered how 'fused' the data really is but can't really think of a better way other than combining all the raw data except then the number of genes and metabolites would just swamp the analysis I guess. Perhaps the authors could articulate why this is a good fusion approach they've used, and perhaps what could be done in the future.
- Draft response: Thank you for this kind observation and really insightful comment. We considered a larger integrative framework that would include all phenotypes measured in the study. However, as the reviewer identified, this would include a heavy bias toward gene expression (expression data for 24,000+ transcripts) and metabolomics (600+ different features measured) which would likely overpower leaf shape (17 x,y coordinates) and ionomics (20 ions). We felt that the PCA approach allowed us to weigh each modality more evenly in order to see if further integrative efforts were warranted. Based on these high-level results, it looks like integration among modalities is a warranted effort, especially if we could collect more targeted data that could expand mechanistic understanding of observed patterns. However, the scope of these integrative techniques is broad and several papers could likely be written just exploring differences in integration techniques with just a single phenotype, for example, gene expression. We have edited the sentence on 1430-431 to reflect this logic: "Within each phenotyping modality, we summarized the primary dimensions of phenotypic variation using PCA (see Methods), so as to not weigh any modality too heavily."
- 6. I Biologically, I'd like to see more insights to why these traits matter. How could understanding that these traits change help production? I think some arm waving is warranted. Especially, how is understanding the correlation among modalities important? One idea is to identify trade-offs and synergisms?
- Response: We thank the reviewer for this suggestion. We modified the language of the potential implications to suggest some ways in which this kind of work could balloon into other phenotypes (not measured for this study) that are more useful to breeding through synergistic relationships (enhancement), trade-offs (constraint), or just simply predictability. Moreover, we maintain that the broadest implication is the notion that there is a strong temporal component to phenotypic expression in long-lived perennial plants and that grafting and rootstock genotype add another dimension to it.
- 7. Last, I'm happy to see how much data is shared. However, GitHub is not appropriate for sharing data, which should all be on a public repository, including the analysis scripts. I think FigShare has been used for other permanent data, so I recommend to share the scripts there.

Response: We thank the reviewer for this insight. The note on irrigation, which was
initially uploaded to GitHub, has been added as a Supplemental Note to this manuscript.
This note will additionally stay on github for easy access. All phenotypic data from the
ionome, metabolome, leaf shape, and physiology are on Figshare and the gene
expression are on the SRA. In addition, we are in the process of submitting raw
metabolomics data to the Metabolights database, as requested by GigaScience.

Line comments and other details follow:

39: In my opinion, the 'hyphens' are not needed in belowground and aboveground.

- Response: From what I can gather, above-ground and aboveground are considered to have the same meaning. We leave this stylistic choice up to the editor.

45: "change"

- Response: L46: changes -> change

46: long sentence with semicolon, consider making that a period, but the use of many interjections make it a little hard to parse still

- Response: Good catch. This sentence has been split into two (now <u>L44</u>).

99: are phenotypes and traits taken to be completely synonymous in this paper? Given that many definitions are used of each, it would be helpful to define. For example, both can be used to describe the 'general' properties like 'eye color' or the specific like 'blue eyes.' Phenotype, in addition, is sometimes used to describe the totality of all trait values in an organism. More careful and exact usage would benefit the paper. For example, trait value can also describe the specific like 'blue eyes' while trait the general 'eye color.' The title of your paper suggests that you additionally consider the phenotype as all traits (or trait values?). Leaf shape is referred to as a phenotype at line 439, so consistent with the 'general trait' definition.

 Response: We agree this was a persistent problem in the initial version of the manuscript. As above, we recognize that we were being imprecise with language, so we have fixed this and other terms used interchangeably (trait/phenotype, phenotypic/phenomic, and data type/modality) throughout the manuscript.

111: what would the difference bet tween phenomic and phenotypic variation? what is the definition of the phenome? phenotypic variation is also used at line 434

- Response: Another good catch. We have edited the language throughout the text so that it is now consistent. We did not actually mean to distinguish between these two things in the highlighted example. As above, we recognize that we were being imprecise with language, so we have fixed this and other terms used interchangeably (trait/phenotype, phenotypic/phenomic, and data type/modality) throughout the manuscript.

115: Were there any hypotheses? Is the intent to be descriptive?

Response: The goals of this study were to address three questions: 1) what is the influence of root system genotype on shoot system phenotype? 2) How do systems of plant phenotypes vary over the growing season and does rootstock genotype influence this variation? And 3) how do phenotypes covary within and between phenotyping modalities? For clarity, we have enumerated these questions in the Study Design section. L639 - 642.

118: Are the details of the experimental design needed here because of the wonky format of a GigaScience paper with methods at the end? Not your fault, but I find these formats so confusing and redundant since authors try to move methods into other sections to make up for it.

- Response: We appreciate this comment. This was certainly a design choice by us so that the paper could be understood linearly.

139: if this pipeline is capitalized and sort of 'official' - is there a citation or access to details of it?

 Response: This is a standardized pipeline at the Donald Danforth Plant Science Center. The sentences surrounding this line (now L140-146) have been restructured to make this more clear: "Between 20 and 100 mg of leaf tissue was acid digested and 20 ions were quantified using inductively coupled plasma mass spectrometry (ICP-MS) following standard protocol of the Donald Danforth Plant Science Center (DDPSC) lonomics Pipeline [30,31]. Ion quantifications were corrected for internal standard concentrations, instrument drift and by initial sample mass. The output of the Pipeline contained measures for each of the following 20 elements: Al, As, B, Ca, Cd, Co, Cu, Fe, K, Mg, Mn, Mo, Na, Ni, P, Rb, S, Se, Sr, and Zn."

140: Why the difference for ML?

- Response: Z-scores were used in the linear models for ion concentrations so that models could be compared. However, the random forest is a single model that needs no adjustment on the input space. We included a small comment that non-standardized input is the convention for random forests (however many ML models do need to be standardized to equally weight each feature).

141: This Leaf Ionomics section, to me, describes the method to sample and measure, but fails to describe the final output? How many ions? which? I don't fully understand why GigaScience requests this format, but it does mention the background should be given. SO, I think you should say why the ionome is important, and the same for other trait conglomerates mentioned in the paper.

- Response: This is helpful thank you. We have added the following:
 - to L145-146 to explain the ionomics data set, "The output of the Pipeline contained measures for each of the following 20 elements: Al, As, B, Ca, Cd, Co, Cu, Fe, K, Mg, Mn, Mo, Na, Ni, P, Rb, S, Se, Sr, and Zn."
 - To L179 to explain the metabolomics data set, "The 661 identified metabolomic features..."

143: carbon-based molecules? For example, not nutrient ions?

- Response: Added "mostly organic" to enhance description of the metabolome

144: I had to look up 'veraison' - could you put 'ripening' in parentheses if that captures that idea?

- Response: Clarified as the "onset of fruit ripening" on L153

210: scanning details? background, color, DPI, image format?

- Response: L228 - 229: added "in color against a white background at 1200 DPI and written as JPEG formatted images".

236: recommend to again announce the number of ions analyzed

Response: Added "and measured the concentrations of 20 ions" to L262

244: It's not clear what the percentage refers to, I imagine percentage of total variation accounted for by that factor, ie the effect size. recommend to include 'effect size'

- Response: Added variation explained to first usage

249: Giving the effect sizes is a reasonable summary given your multiple factors, however I think giving some indication of absolutely changes is also relevant? Like, what type of percent changes were observed across all the samples in absolute terms, or give the min and max for some ions? Obviously you can't be exhaustive, but this would put the effect size in some type of context of biological influence, like rootstock explaining 10% of variation in a 1% change in Ca vs a 100% change in in Ca. Hope that's understandable. Perhaps these absolute changes would be most relevant where you highlight the influence of rootstocks?

- Response: Thanks for this thoughtful comment. The value of effect sizes like percent variation explained are that they can be directly compared if the models are parameterized in an identical manner. However, I think this confusion could be clarified by projecting samples back into a real concentration space which has now been done for the figure.

267: Could MDA be spelled out on first mention?

 Response: L293 now includes Mean Decrease in Accuracy. It is also defined in the methods.

350: personal placeholder to check discussion for how so much variation isn't accounted for - seems surprising!

- Response: We agree that the lack of variation explained in the models for leaf shape is quite interesting. Future work will certainly explore factors such as variation imparted from individual vine and environmental variation to attempt to explain this.

400: I'm confused that the PCs should correlate from the same modality, something which I thought didn't usually happen?

- Response: There is statistical literature on this topic. In short, principal components are orthogonal, however orthogonal does not always mean uncorrelated. See Rodgers, Nicewander, and Toothaker, 1984.

462: Good to bring up the biological implications - what are they? Are these changes relevant for growth, taste, etc?

Response: We agree that the earlier version of this manuscript was missing key information about why the ionome is important. Unfortunately, there is not a lot of work tying together the elements of the ionome that we identified as responsive to rootstock genotype. Traits of biological interest, features that are known to be influenced by ion uptake by the root system (rootstock) are now mentioned in the manuscript, including vine growth and fruit/wine quality. We have added a comment on this in the discussion to address that there is a known connection between macronutrients and these traits, but more work is needed is to uncover these connections with micronutrients in grapevine. To this end, we added the following to **1518 - 520**: "To our knowledge, there is not yet a strong causal link between the micronutrient component of the ionome and factors of vine growth or development that might influence traits like wine quality. However, it is noted that macronutrient deficiencies can have negative effects on such traits (Bravdo 2000; Brunetto et al. 2015) and can be mediated by rootstock (Gautier et al. 2018). This suggests a strong understanding of the rootstock influence on the vine's ionome is warranted, and more work needs to be done to establish these relationships"

474: Can stomatal conductance be limited by flow in the roots? Do you think it's more likely such an indirect effect, or a direct effect such as signals from the rootstock actually change the rates by stomatal closure, etc?

- Response: This is a really good question that is particularly challenging to fully address. We would wager that root architecture is a key driver of physiological variation, and we tested this in a greenhouse study the results of which are in preparation now. However, it is worth noting signals could be passed from the rootstock, but the space of signal passing through graft junctions is complex and this work was not designed to address anything to that end.

501: I think here, rather than 'phenotype' as 'traits' you meant to say something about the 'data types,' which you referred to as modalities before and would be appropriate to use here. 'traits of different modalities'. I would suggest this instead of 'data types' perhaps for consistency. Definitely it would be a benefit to the field to have ways to describe these 'groups' of traits from the same instrument, my lab also runs into this with fused, multi-dimensional data.

- Response: Great observation, and we agree. We have fixed this instance of improper usage and we have clarified the language in the discussion (and the rest of the manuscript) to be more consistent. Specific to this comment, 'data type' has been replaced with modality/ies throughout the piece. As above, we recognize that we were being imprecise with language, so we have fixed this and other terms used interchangeably (trait/phenotype, phenotypic/phenomic, and data type/modality) throughout the manuscript.

502: latent phenotypes were mentioned in the definition of phenomics (where I only see them as one possibility, not a defining feature). Some definition would be useful.

- Response: This is a good catch. We did not mean to imply latent phenotypes were the only possible outcome of this work. This sentence was expanded a bit to include that idea that latent structure is one possibility, but using this to target integrative analysis is also a strong possibility. (L565)

510: back to phenomic correlation - what's the difference with phenotypic correlation?

- Response: Good catch of this persistent issue in the earlier version of the manuscript. We did not mean to imply there was a difference, or to make any kind of statement on this distinction. As above, we recognize that we were being imprecise with language, so we have fixed this and other terms used interchangeably (trait/phenotype, phenotypic/phenomic, and data type/modality) throughout the manuscript.

533: Very little information was provided about how the changes measured here in traits would affect yield or other consumer-facing traits. Not only that, but why is the multi-dimensionality important? Does it reveal trade-offs in traits, for example? I'm trying to help you improve the biological impact component. Some arm waving may be warranted.

Response: We very much appreciate the direction the reviewer is going here, and we have attempted to address this in the potential implications section of the manuscript and elsewhere. Multi-dimensional data are data that consist of many different observations (for example, the ionome which includes measurements of 20 different ions). Multi-dimensional data offer more robust, approaching comprehensive observations of plant phenotypes. They offer a rich source of information that can be used to more comprehensively understand the basic biology of the organism - for example, how root systems influence features of shoot systems in grafted plants. This is described in, for example, L94-100 of the introduction. The influence of the phenotypes we measured on yield or other consumer facing traits are under active investigation. For example, ongoing work by others members of our project team describes berry chemistry and wine volatiles for the experimental vineyard described here. The volume of data was so large; this manuscript represents the first step in processing and interpreting multiple multi-dimensional phenotypes and trying to understand what approaches can be used to understand how they relate to one another. The next steps will be to connect these data with observations that might be more directly relevant to viticulturists. Our hope is that this manuscript will provide the foundation for those analyses that integrate multi-dimensional data from different organ systems, such as leaves and berries.

457: This note is very thorough and appreciated, however a github link is not permanent and therefore I suggest to include as supplemental to this paper or else place on a 'permanent' public repository such data dryad, Zenodo, etc. If the irrigation factor was ignored, you should say so.

- Response: Good point. The note on irrigation has been added as a Supplemental Note to this manuscript. Irrigation was treated as an additional blocking factor in the analyses done here. While we will keep the other data available on Figshare, we are exploring other homes for the data that are in line with GigaScience's preferences.

561: After reading this section, I wasn't sure about the experimental design, especially what type of randomization was used. I would guess that an appropriate design here would have been split plot block design taking into account irrigation (which I guess you are saying you ignored in the end). Were genotype randomized? the groups of 4 are mentioned, should that be taken as the experimental unit? I'm not super picky about stats, but some might say there are flaws here, and perhaps the 72 should be divided by 4 as as far as complete replicates? In Supp Fig 1 in the map, I see up to Block F - so should it be 6 true replicates? In cases likes this, I usually think of the additional plants as subreplicates. Your design seems basically just like a annual crop field trial with small plots with multiple plants. We usually measure a trait on those subreps then average it to the plot level for further analysis. In that case, the subreplication isn't used in stats directly, but does allow a better approximation of the value for each plot and decrease overall 'random' or 'environmental' error.

- Response: This is a great catch by the reviewer. We regret that the earlier version of this manuscript did not fully explain the experimental design of the research vineyard used in this study. These details have been filled in in section Study Design of the manuscript. Further, I think some additional confusion may stem from us using "replicate" as a vague stand-in for both clonal replicates and statistical replicates. To address this, we have amended the language about the four rootstock scion combinations as follows on 1617: "Clonal replicates of each of the four rootstock-scion combinations were planted 72 times for a total of 288 vines planted in nine rows". In addition, we included the specific type of design (split-plot) to this section. Finally, we addressed the number of true replicates in a comment by reviewer 2 concerning RNAseq. The same logic can be used to derive the total number of biological replicates for leaf shape and ionomics at the highest order interactions (4) and for all other phenotypes (2). In the case where the number of biological replicates is two, the estimation and interpretation of effects is minimized due to lack of power.