Underpinning terroir with data: rethinking the zoning paradigm

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Abstract:

Terroir zoning has traditionally relied on a mixture of classical approaches to land classification and thematic mapping, coupled to various heuristics, 'expert' opinions and the whims of marketers and wine writers. Here, we show how, by using data-driven methods and focussing just on the land which supports grape production, rather than on all of the land within a winegrowing region, we might move towards a more robust terroir zoning. By using data to provide an improved understanding of terroir, such methods should also promote improved management of the entire wine value chain, offering quantitative indications of the impact of the biophysical characteristics of the places where grapes are grown on the chemical and sensory attributes of the wines derived from them.

Introduction:

Agriculture, natural resource management and the production and sale of products such as wine are increasingly data-driven activities. Thus, the use of remote and proximal crop and soil sensors to aid management decisions is becoming commonplace and 'AgTech' is proliferating commercially; mapping, underpinned by geographical information systems and complex methods of spatial analysis, is becoming widely used. Likewise, the chemical and sensory analysis of wines draws on multivariate statistics; the efficient winery intake of grapes, subsequent production of wines and their delivery to markets relies on logistics; whilst the sale and marketing of wines is increasingly driven by artificial intelligence linked to the recorded purchasing behaviour of consumers. In brief, there are data everywhere!

Opinions will vary on whether these developments are a good thing. Those concerned with the 'mystique' of wine, or the historical aspects of terroir and its preservation, may find them confronting, especially in cases where quantitative analysis is used to challenge historical norms (e.g. Ballester, 2020). However, the abundance of data offers opportunities to those interested in how soil, climate, landscape and management factors impact on vineyard performance and the chemical and sensory attributes of resultant wines. It may therefore enable a better understanding of terroir.

At the previous Terroir Congress, we demonstrated the potential of analytical methods used at the within-vineyard scale, in the development of Precision Viticulture, for contributing to a quantitative understanding of regional terroir (Bramley et al., 2020). Here, we review recent examples from contrasting locations in Australia (Bramley and Gardiner, 2021; Bramley and Ouzman, 2022), New Zealand and the USA, in which this approach is refined. A key aspect of this work is confining data analysis in any given region to just that land which supports wine production, rather than to the region as a whole. In Australia and the USA, it leads to some accepted norms being challenged and questioned, whereas the NZ example illustrates how data that are routinely collected can be used to inform the regional terroir.

Materials and methods:

Detailed descriptions of the methods used in this work are given in the source papers, where available. In brief, the details are as follows:

Australia – The Margaret River and Barossa Zone geographical indications

Boundaries for each geographical indication (GI) were used to generate raster grids comprised of 1 ha pixels (100 m x 100m) onto which all map layers were interpolated; in the case of the Barossa, the GI boundary was modified to better reflect the vineyard area (Bramley and Ouzman, 2022). Land under vineyard was delineated from map data kindly provided by the Western Australian Department of Primary Industries and Regional Development (DPIRD; Margaret River) and Vinehealth Australia (Barossa).

A range of climate data (averages based on at least 30 years) were obtained from the 'SILO' dataset (https://www.longpaddock.qld.gov.au/silo/), a national database maintained by the Queensland government in collaboration with the Australian Bureau of Meteorology (BOM). Here, we focus on season growing degree days (GDD) and growing season rainfall (GSR), with 'season' defined as September to April in Margaret River, and September to March in the Barossa. Soil data were obtained from the soil and landscape grid of Australia (SLGA; Grundy et al. 2015); SLGA makes individual soil property data available in raster format at a resolution of 90 m in a range of increments to 2 m depth. In both Margaret River and the Barossa, we generated profile-weighted means for the 5-60 cm depth increment for the soil properties of interest. In the Barossa, these were the soil available water capacity (AWC) and cation exchange capacity (CEC) which is inferred to be a surrogate indicator of fertility. In Margaret River, neither CEC nor soil clay content proved to be useful discriminators of vineyard soils when examined at regional scale, but the content of coarse fragments (> 2mm; CFG) was included given the local viticultural importance attached to gravelly soils; AWC was also considered important. The hydrologically enforced digital elevation model (DEM-H; Gallant et al., 2011) derived from the 1s Shuttle Radar Topography Mission (SRTM) was used for both regions (https://elevation.fsdf.org.au/).

The above data were either resampled (soil properties) or interpolated using global point kriging (climate) onto the 1 ha raster defined by the regional boundary. For whole-of region analysis, the resulting map layers were clustered using *k*-means. For the analysis focussed solely on land under vineyards, vineyard-specific data layers were extracted from whole-of region map layers for each attribute using the vineyard coverage as a template. These vineyard-only data were also clustered using *k*-means. In both cases, the cubic clustering criterion (SAS Institute, 1983) was used to identify the optimum cluster number. Further details are given for Margaret River by Bramley and Gardiner (2021) and for the Barossa by Bramley and Ouzman (2022).

USA – The Lodi region of California

Similar methods to those used in the above Australian examples were used to examine biophysical variation in the American Viticultural Area (AVA) of Lodi in California's Central Valley. Annual rainfall and mean July temperature (30 year averages) were obtained from the PRISM database (Daly et al., 2001; see also https://prism.oregonstate.edu/) in raster format comprised of 800 m (½ mile) pixels. Soil CEC (15-30 cm depth) and a profile-weighted average of AWC (0-100 cm depth) were obtained from the USDA SSURGO database (https://sdmdataaccess.sc.egov.usda.gov) and sampled to the same raster as the climate data. Note that these data derive from reconnaissance soil survey at 1:24,000. Elevation data were obtained from the United States Geological Survey (USGS) 3D Elevation Program (3DEP; Thatcher et al., 2020; see also https://apps.nationalmap.gov/). A shapefile of vineyard locations was obtained from the California Natural Resources Agency (https://data.cnra.ca.gov/dataset/statewide-crop-mapping). The latter was used as the basis for extracting vineyard only data from the climate and soil rasters. It was also used to generate a modified AVA boundary which better reflects the vineyard area (Figure 3e). The resulting data (Figure 3a-d) were analysed using *k*-means as in the Australian examples, with the exception that the optimum cluster number was determined using the Akaike information criterion (AIC).

New Zealand - Marlborough

The methods used in this work are exactly as described by Bramley et al. (2020) with the exception that here we include data for vintage 2019 in addition to 2014-2018, and for all years, include data for vineyards additional to those canvassed in the earlier work; in 2019, yield data for 1083 vineyards were available. In brief, a 1 ha raster was generated from a 'regional grapegrowing boundary' which, in turn, derived from a coverage of land under vineyard supplied by the Marlborough Regional Council (Figure 4a). Various indices of vineyard performance were then collected, by request and in confidence, from local grapegrowers and wine companies; the data were those that are typically collected for the purposes of yield estimation, harvest record keeping and payments to growers. Here, we focus just on yield and harvest date. For mapping, harvest dates were converted to Julian numbers (where 1 and 31= 1st and 31st January, etc). In the case of yield, the effects of different row spacings were removed by expressing the data as kg/m and the effects of seasonal variation were removed by normalising all data on an annual basis to a mean (μ) of zero and standard deviation (σ) of one; the latter normalisation was also considered useful in protecting grower privacy. Only data from blocks planted to Sauvignon Blanc at least three years prior were included. All data were georeferenced to the centroid of the vineyard block from which they derived and were then interpolated into maps of yield and harvest data using local point kriging with a data cloud of 100 data points.

Results and discussion:

In both the Margaret River and Barossa GIs, clustering data pertaining solely to land under vineyard led to different characterisations of regional-scale biophysical variation compared to when data for the whole region were used for the analysis (Figures 1 and 2). Since less than 3 and 11 % of the land area is planted to vineyards in the Margaret River and Barossa GIs, these different results are considered important to the understanding of terroir and to terroir zoning more broadly, given that terroir is the expression of a wine's 'sense of place' (Goode, 2005). Clearly, if we want to understand how a wine reflects the land from whence it came, including other land in the analysis seems both counter-intuitive and counter-productive to the rigour of that understanding. In both Margaret River and the Barossa, local winemakers are interested in the pursuit of so-called 'subregionalisation' as a means of promoting the distinctiveness of wines and using this as a marketing tool. Margaret River is presently a single GI with no defined subregions, albeit with a small group of winemakers currently seeking to gain certification for a subregion towards the northern part of the GI. Yet neither of two previously proposed divisions of the GI into subregions (Gladstones, 1999; Lacorde, 2017), nor this current attempt at establishing a subregion are supported by the results shown in either Figures 1b or 1c.

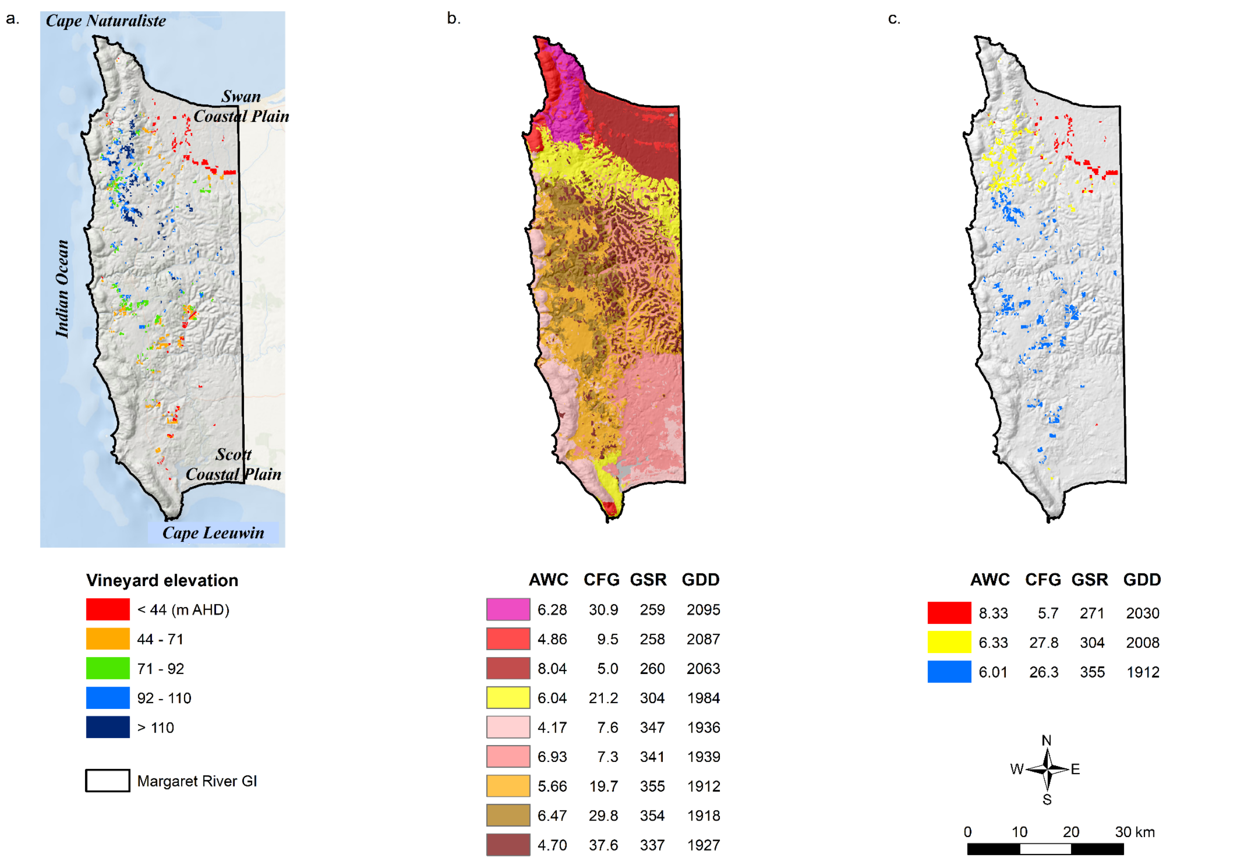

Figure 1. Variation in (a) elevation, and (b, c) soil properties and climate indices in the Margaret River geographical indication of Western Australia.
In (a), the data have been classified into 20th percentiles; in (b, c) the numbers in the legends are cluster means when map layers for the individual attributes are analysed using *k*-means for either (b) the entire region, or (c) just the land under vineyard. The hillshade derives from the elevation model (not shown). AWC, soil available water capacity; CFG, soil coarse fragment content; GSR, growing season rainfall; GDD, season growing degree days. Data of Bramley and Gardiner (2021).

Figure 1b shows that when the analysis was conducted for the entire region, nine clusters were identified; interpreting these proved to be very difficult (Bramley and Gardiner, 2021). Preliminary clustering of just the temperature indices indicated a temperature gradient running through the GI in an approximately northeast-southwest direction. The Swan Coastal Plain, to the north, was identified as markedly warmer than the coastal area to the southwest of the GI. Likewise, the north is drier than the south in both annual and growing season rainfall. Clustering of soil data alone also identified the Swan Coastal Plain as distinct from the rest of the GI, but the patterns of soil variation in the remainder were seen to be both highly complex and to occur over short distances, reflecting the impact of drainage and elevation on the patterns of variation in this ancient landscape (Figure 1a,b). However, as can be seen in Figure 1a, except for vineyards on the Swan Coastal Plain, Margaret River vineyards do not occupy locally characteristic elevations and none of the soil clusters identified by Bramley and Gardiner (2021) aligned closely with sub-regions that had previously been proposed by either Gladstones (1999) or Lacorde (2019). Overall, as can be seen from Figure 1b, Margaret River is a highly complex landscape in terms of its patterns of variation.

When the cluster analysis was repeated for just the land under vineyard, a somewhat simpler picture emerged. Again, the Swan Coastal Plain vineyards appear distinct (Figure 1c). Otherwise, it is clear that Margaret River vignerons have a preference for more gravelly soils. However, because these gravelly soils occur throughout the GI, the main separation identified by the cluster analysis is one based on growing season temperature and rainfall. This finding should not be used to infer that soil variation is not important in Margaret River; indeed, there is good evidence in support of the view that it is critical to vineyard-scale management. But in terms of sub-regional terroir, it appears that its short-range variation is too complex to enable readily identifiable and locally distinct sub-regions to be delineated. Figure 1c was therefore proposed as a sensible basis for a chemical and sensory analysis of Margaret River wines with a view to further understanding distinctiveness within the region (Bramley and Gardiner 2021).

In the Barossa GI, the whole-of-region analysis clearly separates the cooler, wetter Eden Valley from the Barossa Valley whose soils are also more fertile than in Eden Valley (Figure 2a). When the analysis was repeated on a vineyard-only basis (Figure 2b), a more substantial separation within the GI was seen – seven clusters (Figure 2b) instead of just two (Figure 2a). The two valleys were again separated, but some subdivision

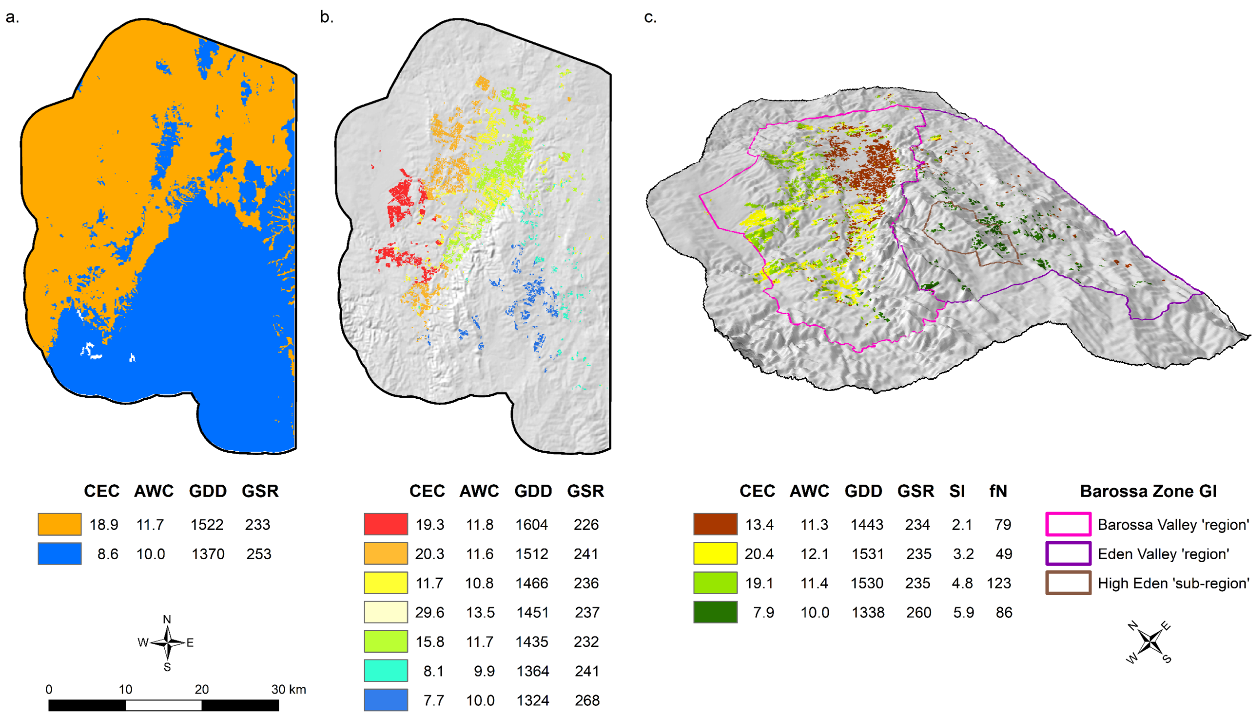

Figure 2. Variation in soil properties, climate indices and topography in the Barossa Zone geographical indication of South Australia.
The numbers in the legends are cluster means when map layers for the individual attributes are analysed using *k*-means for either (a) the entire region, or (b, c) just the land under vineyard. CEC, soil cation exchange capacity; AWC, soil available water capacity; GSR, growing season rainfall; GDD, season growing degree days. In (c), slope (Sl) and aspect (degrees from north; fN), are included in the cluster analysis. (b,c) data of Bramley and Ouzman (2022).

within the Barossa Valley was also seen. In particular, the northwesternmost areas appeared to separate largely on temperature, but in the strip of land lying immediately to the west of the hills which separate the Barossa and Eden Valleys, there was greater delineation; this strip of land was consistently identified across various analyses involving different combinations of soil and climate attributes (Bramley and Ouzman, 2022).

Because it seemed likely that topography might be important to the variation within the Barossa GI, a further analysis is shown in Figure 2c in which, in addition to the attributes used in Figure 2b, slope (Sl) and aspect (fN) were also included; these are readily determined from the DEM. The result again clearly separates the cooler, wetter Eden Valley, whose vineyards tend to have steeper slopes and aspects within 90° of north, from the rest of the GI. But within the Barossa Valley there are three clusters of vineyards in which slope and aspect are important; the yellow and green clusters in Figure 2c appear to separate only on slope, aspect and AWC, whilst the vineyards on the flattest land immediately to the west of the hills which divide the Barossa and Eden Valleys are the least fertile (based on CEC as a surrogate for fertility) and also experience a cooler season than the remainder of the Barossa Valley. Figure 2c was proposed as a useful starting point for examining differences in grape and wine chemistry and wine sensory characteristics as a basis for gaining a better understanding of the terroir of the Barossa Zone GI (Bramley and Ouzman 2022). Note that Figure 2c contrasts somewhat with the ‘Barossa Grounds’ proposed by the Barossa Grape and Wine Association (BGWA, 2017).

The Lodi AVA in California comprises 7 sub-AVAs in addition to two areas to the south and southwest which are not separately identified. Interestingly, the establishment of these AVAs appears to have derived solely from consideration of apparent differences between them in terms of climate, soils and topography; no mention is made in either the document through which the AVAs were established (ATTTB, 2005), or a local commentary on them (Caparoso, 2018), of the sensory or chemical attributes of their wines. When a vineyard-only mapping and cluster analysis is undertaken using the data in Figure 3a-d, the various sub-AVAs are not seen to be distinct with respect to their biophysical characteristics (Figure 3e). Indeed, none of the sub-AVAs

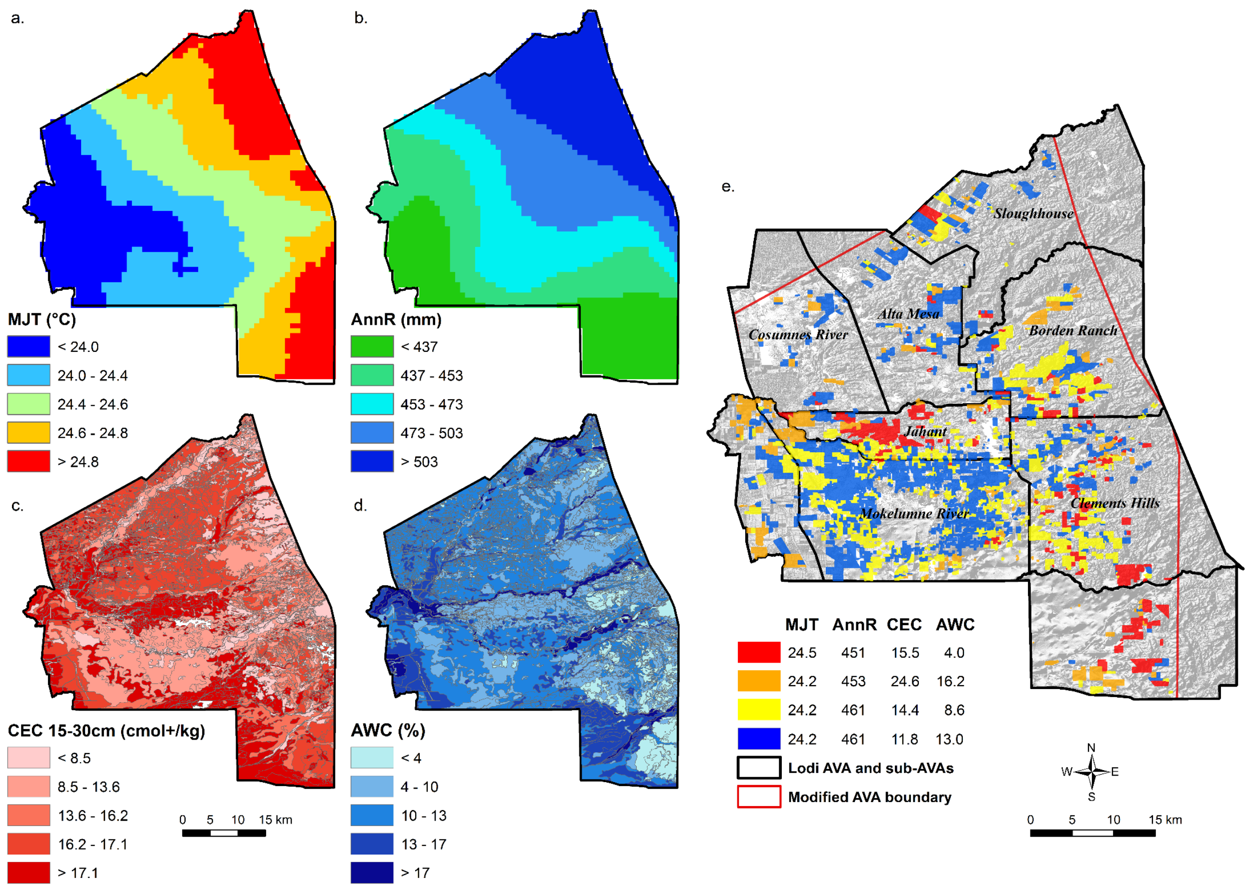

Figure 3. Biophysical variation in the Lodi AVA, California.
(a) Mean July temperature (MJT); (b) annual rainfall (AnnR); (c) soil cation exchange capacity (CEC); (d) soil available water capacity (AWC); and (e) the result of clustering the data layers in (a-d) on a vineyard-only basis using *k*-means. Also shown in (e) are the boundaries of the AVA and sub-AVAs, the modified boundary used for this analysis and a hillshade derived from the DEM. Numbers in the legend to (e) are cluster means.

are characterised by a single vineyard cluster; Cosumnes River and the un-named westernmost region are the only areas which do not contain vineyards from all four clusters. Mokelumne River is arguably the most uniform sub-AVA based on this simple biophysical classification, with soil properties nevertheless a key discriminator *within* this area. Neither temperature nor rainfall appear to be important discriminators between the clusters in spite of these being the justification for their establishment (ATTTB, 2005; Caparoso, 2018). Thus, the present analysis suggests that some re-examination of boundaries between the sub-AVAs may be warranted. It is accepted that, following the principal of parsimony, the present analysis involved a much reduced suite of climate, soil and topographic variables than those used to underpin the establishment of the AVAs, but nonetheless, it tends to suggest the possibility of a different outcome if solely the land under vine is considered. Inclusion of wine sensory and chemical analysis would no doubt promote an improved basis for any sub-AVA discrimination. Meanwhile, it appears that the primary driver for establishing these subregions within the Lodi AVA was simply that, if *Appellations*, *Villages* and *Climats* are good for the French, the sub-AVAs ought to be good for Lodi, even if their establishment is unlikely to deliver a marketing benefit (Caparaso, 2018). On the other hand, knowing that any differences between the sub-AVAs in wine chemical or sensory attributes can be related to the biophysical variation is presumably of potential importance to Lodi wine production systems. Interestingly, the sub-AVAs have no impact on the prices paid by wineries for grapes since Californian grape pricing is determined largely by 'district' (CDFA, 2022); all of the area in Figure 3 falls within the same pricing district.

Consistent with the previous analysis of Bramley et al. (2020) interpolation of vineyard performance data in the Marlborough region of New Zealand is strongly suggestive of both a clear distinction between the Wairau Valley to the north (warmer, higher yielding) and Awatere Valley to the south (cooler, lower yielding and with a later season) in addition to some separation within the two Valleys. Importantly, Figure 4 highlights the potential for using shared vineyard performance metrics for improved understanding of regional scale variation. When these are analysed using the same geostatistical methods as are used in Precision Agriculture at the vineyard or field scale to inform understanding of within-vineyard variation (e.g. Bramley, 2022; Sams et al., 2022) such data can provide valuable insight in relation to terroir. In the case of yield, what we have effectively done here is to use wineries as though they were harvester-mounted yield monitors. Grapegrowers and winemakers already collect a lot of such data to support various tasks aimed at facilitating management of winery intake and other elements of production; indeed, no data were collected to underpin Figure 4 that were not already collected routinely for other purposes. Note that whilst some of the between-cluster differences (Figure 4) may appear minor, when the raw vineyard data are analysed to test for between-cluster differences (i.e. 'cluster' used as a treatment), the majority are seen to be consistently and significantly different (not shown). Furthermore, ignoring the clusters and testing for differences between the Wairau and Awatere Valleys also shows these to be different in terms of both yield and harvest date.

A number of contrasts and similarities exist between these four studies, each of which point to obvious ways of taking them forward. So far, none of them have included wine chemical or sensory analysis. However, the various cluster solutions (Figures 1c, 2c, 3e and 4d) offer an obvious basis for examining differences in the chemical and sensory properties of wines produced in these different GIs and integrating these into the analysis. In the case of the Barossa, a current Wine Australia-funded project is doing just that, with the results to be reported presently. Analysis of the wine sensory and chemical data independently of other attributes will also enable assessment of the degree to which any identification of sub-regions based solely on wine attributes aligns with the one shown here (Figure 2c) based on soil, climate and topographic data. Likewise, the Margaret River Wine Association will be pursuing similar investigations of wine sensory and chemical alignment to the biophysical variation in their region. In Lodi, the opportunity exists to examine a large database of grape chemical data in terms of alignment with Figure 3e and a re-working of the cluster analysis to better understand the regional scale variation in the Lodi AVA and the separation between the sub-AVAs.

Further, whereas the Margaret River, Barossa and Lodi studies presently rely solely on biophysical data that are publicly available, they do not incorporate any measures of vineyard performance such as those which underpin the Marlborough study. Collecting these kinds of data is a large and complex task which also requires careful management of grower privacy issues. On the other hand, as the Marlborough example shows, it can be done, not least because most of the required data are routinely collected anyway. Whether there would be an appetite amongst Australian and Californian producers for contributing such data remains to be tested, but a possible avenue in Australia would be to use the various vintage surveys that are currently conducted, along with the national vineyard scan (Wine Australia, 2021) as a means of facilitating this. Such a strategy, together with expansion of the data collected to include indices of fruit quality or value of production, could potentially inform various decisions aimed at optimising wine production systems, including what variety to grow where.

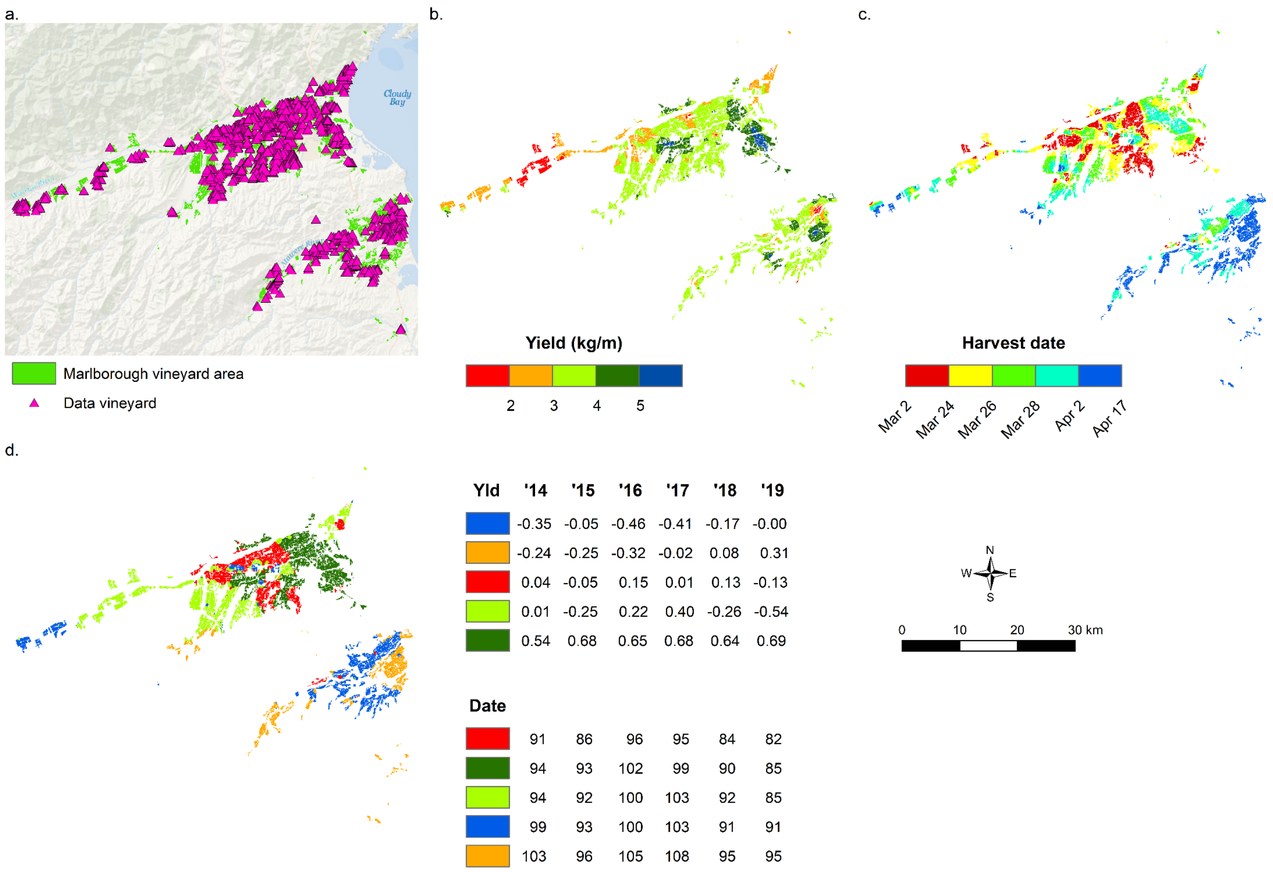

Figure 4. Variation in vineyard performance in the Marlborough region of New Zealand assessed either at (a-c) vintage 2019, or (d) over the six vintages from 2014-2019.
Data were collected from (a) 1083 individual vineyards planted to Sauvignon Blanc and used to interpolate maps of (b) yield and (c) harvest date. In (d) similar maps layers produced in the 2014-2019 period were analysed using *k*-means clustering. The numbers in the legends to (d) are cluster means when yield is normalised ($\mu = 0$, $\sigma = 1$) and harvest date is expressed in Julian days.

In Australia, alignment of such analyses with data available in the Australian Climate Atlas (Remenyi et al. 2019) may also promote consideration of the climate change impact on terroir (Brillante et al. 2020). Similarly, incorporation of soil and climate data into the Marlborough analysis (currently underway) seeks to enable the yield and harvest date variation (Figure 4) to be more meaningfully understood in the context of the Marlborough terroir.

Whichever way these studies evolve, by utilising modern methods of spatial analysis, all of them provide data-driven platforms which are free of heuristics, constraints imposed by historical appellation boundaries and the effects of prior perceptions of our vineyard regions and the boundaries of their GIs, to promote a better understanding of terroir and regional wine distinctiveness. Ballester (2020) provides a valuable cautionary tale in regard to reliance on historical appellation boundaries, or boundaries that are otherwise not robustly defined, in claiming distinctiveness. Furthermore, as discussed by both Bramley and Gardiner (2021) and Bramley and Ouzman (2022), there are good reasons why the marketing benefits of all this may be minor, albeit that work such as that reported here may allow us to tell stories about wine that are true and based on science rather than mythology. The real value in truly understanding terroir from a data-driven perspective therefore lies in the opportunity it generates for optimising our winegrowing management systems – at both vineyard and regional scales (Bramley 2022; Brillante et al. 2020) based on understanding the soil, landscape and climate factors which, at subregional scale, drive terroir expression and wine distinctiveness.

Conclusion:

Quantitative, data-driven methods of spatial analysis provide a robust basis for characterising biophysical variation and so may usefully underpin sensory and chemical analysis of wines, leading to an improved understanding of terroir and regional/subregional distinctiveness. Such methods are free of any bias introduced to studies of terroir zoning arising from adherence to historical or geopolitical boundaries. Confining the analysis to land under vine contributes to the robustness of the approach.

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