

¹ Graphical Abstract

² **Resource-use and the Value-Productivity Tradeoff in Australian**
³ **Winegrowing Regions**

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5 Highlights

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10 • Research highlight 2

Resource-use and the Value-Productivity Tradeoff in Australian Winegrowing Regions

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Abstract

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1. Introduction

The global focus on sustainability in agronomic industries has changed the way in which these enterprises do business. When strategies for a sustainable winegrowing industry are assessed, there is a trade-off between balancing the amount of resources invested and the resultant yield verses quality produced. This dilemma exists across agriculture through shared fundamental considerations such as water use and nitrogen levels (Hemming et al., 2020; Kawasaki

25 and Uchida, 2016; ZHU et al., 2017). Quality in viticulture (the cultivation
 26 of grapes for wine production) is driven through its integration within the
 27 wine industry; with a wine’s potential quality being initially defined through
 28 the chemical makeup of the grapes used in its production. The consideration
 29 of sustainability within viticulture is further complicated by environmental
 30 and socio-demographic pressures. In the Australian context, these include:
 31 biosecurity, climate and international market demands.

32 In this analysis we observe relationships between yield and quality through
 33 the use of linear models. Although an extensive amount of research into a
 34 variety of factors’ effect on grape quality and yield exists; due to the lack
 35 of long-term and in-depth data, individual effects are often studied in isola-
 36 tion (Abbal et al., 2016). The lack of consolidated datasets also restricts the
 37 ability to gain statistical insights at large scales and across multiple regions
 38 (Keith Jones, 2002; Knight et al., 2019). The dataset used for this analysis
 39 includes data collected for the past 10 years from a multitude of vineyards
 40 located over a diverse range of Australian winegrowing regions.

41 We aim to use this broad dataset to confirm the existence of a yield verse
 42 quality trade off within Australian winegrowing; one not prior confirmed ex-
 43 plicitly across such extensive diversities. In achieving this, the context of
 44 how resource-use relates to yield and quality will also be described. We link
 45 these relations to the potential for improvement through decision-making
 46 processes, whilst highlighting that the way moving forward will require the
 47 optimisation of these processes. The practical addition of these aims is a
 48 baseline for comparison - given a vineyard within Australia, one could ex-
 49 trapolate their comparative efficiency with regard to the tradeoff between

Table 1: Summary of models; their predictors, covariates and variable interactions.

	Response	Predictors	Covariates
Model 1	Yield	Water Used, Scope 1 Emissions	Area Harvested, Year, G
Model 2	$\frac{\text{Yield}}{\text{Area Harvested}}$	Water Used, Scope 1 Emissions	Area Harvested, Year, G
Model 3	Yield \times Average Sale Price	Water Used, Scope 1 Emissions	Area Harvested, Year, G
Model 4	$\frac{\text{Yield} \times \text{Average Sale Price}}{\text{Area Harvested}}$	Water Used, Scope 1 Emissions	Area Harvested, Year, G

invested resources, yield and quality.

2. Methods

We created four linear models to explore relationships between resource-use and vineyard outputs (see Table 1). The data was sourced from Sustainable Winegrowing Australia and Wine Australia. Variables used included: yield, average sale price, region, water use, emissions, area harvested and year. After fitting to the data, each model was validated using k-fold cross validation.

2.1. Analysis

Before models were fit to the data, Pearson Correlation Coefficients were used to look at the existence of linear relationships between predictor variables. These relationships were summarised in correlation matrices to compare levels of interaction present between predictor variables. The relationships between the predictors and response variables were then modelled using General Linear Models. Both the Pearson Correlation Coefficients and

65 General Linear Models were created using the R statistical programming lan-
66 guage (R Core Team, 2021). General Linear Models were chosen as they offer
67 the ability to produce statistical models that are explicit in the relationships
68 between predictors and response variables. General Linear Models also al-
69 low the exploration of interactions between predictors and easily comparable
70 differences in the influence and magnitude of relationships. A variety of alter-
71 nate methods to General Linear Models was also explored, including: Splines,
72 hierarchical regression, Additive and Generalised Linear Models. These al-
73 ternative approaches were not used as final models due to offering no further
74 improvements or to producing inaccurate models.

75 The response variables of the models were yield and quality. The definition
76 of quality was an important consideration, as quality can be defined in a
77 variety of ways, for example analysing grapes': aroma, chemical composition
78 and color. For the purpose of this study, quality was defined by the financial
79 value of winegrape crops' average sale price per tonne. This definition was
80 used due to the market value of winegrapes being reliant on grape quality
81 and because Wine Australia explicitly defines grape quality through the use
82 of discrete price brackets in their annual reports ; the generalisation made to
83 reflect quality through using average price assumed a due diligence of those
84 who purchased the grapes (Yegge, 2001). Yield was defined as the total
85 tonnes of grapes harvested. Both response variables were examined as totals
86 and as scales of area harvested. Values were compared in this manner to
87 observe how economies of scale affect the use of resources.

88 2.2. Data

89 Data used in this analysis was sampled by Sustainable Winegrowing Aus-
90 tralia and Wine Australia. Sustainable Winegrowing Australia is Australia’s
91 national wine industry sustainability program, which aims to facilitate grape-
92 growers and winemakers in demonstrating and improving their sustainability
93 (SWA, 2022). Wine Australia is an Australian Government statutory author-
94 ity governed by the Wine Australia Act 2013 (Win, 2019).

95 Data sampled by Wine Australia was collected via phone surveys and in-
96 cluded: summary statistics such as yield and average price of sale per tonne;
97 these values were summarised by region and grape varietal. Data recorded
98 by Sustainable Winegrowing Australia was entered manually by winegrowers
99 using a web based interface with some fields being optional, variables in-
100 cluded: region, harvest year, yield, area harvested, water used and fuel used
101 (diesel, petrol, biodiesel and LPG). To enable direct comparisons between
102 fuels, they were converted to tonnes of Carbon Dioxide equivalent.

103 The inclusion of Wine Australia data was due to average sale price being
104 an optional field in Sustainable Winegrowing Australia’s dataset. Regional
105 average prices from Wine Australia were filled into values that were missing
106 from the Sustainable Winegrowing Australia data; the common practice of
107 purchasing grapes at regional prices was an important consideration in this
108 decision. Two subsets of data were then created for the analysis. The first
109 subset contained all vineyards and was used for Models 1 and 3. The second
110 subset contained vineyards which either recorded a value for average price of
111 sale per tonne through Sustainable Winegrowing Australia, or were within a
112 region with an average price of sale recorded by Wine Australia; this subset

113 was used for Models 2 and 4. These subsets meant that the data would be
114 limited to samples which had recorded values for the response variables (see
115 Table 1), where every sample had a recorded value for yield but not average
116 price of sale per tonne.

117 The first subset of data was used for Model 1 and Model 2 (see Table 1).
118 This subset contained 5298 samples spanning the period from 2012 to 2022,
119 covering 57 GI Regions and 1432 separate vineyards.

120 The second subset of data, was limited to vineyards that recorded a value
121 for their average sale price of grapes per tonne. This subset was used for
122 Model 3 and Model 4 (see Table 1); and contained 2878 samples spanning
123 the period from 2015 to 2022, covering 51 GI Regions and 944 separate vine-
124 yards. 1842 of the values for average price of sale per tonne were extracted
125 from Wine Australia surveys with the remaining 1036 being from Sustainable
126 Winegrowing Australia’s dataset.

127 Additional variables were considered for analysis but were excluded due to
128 being either underreported or had insignificant contributions to model accu-
129 racies. Variables explored but not used due to low reporting values included:
130 fertiliser, tractor and contractor use, and scope 2 emissions. Variables con-
131 sidered but ultimately removed due to a lack of significant contributions to
132 models, included: the use of renewable energy, contractors, and pressures
133 such as frost, fire and disease.

134 Data preprocessing was conducted prior to analysis using the Python pro-
135 gramming language (G. van Rossum, 1995). Preprocessing included logarith-
136 mic transformations, centring and scaling by standard deviation. Variables
137 such as scope 1, which required prior calculations were also computed using

138 Python.

139 2.3. Total Emissions

140 The equation given from the Australian National Greenhouse Accounts
141 Factors, shown as

$$142 \quad tCO_2e = \frac{Q \times EC \times EF1 + EF3}{1000}, \quad (1)$$

143
144 was used to convert the quantity of fuel in litres, Q , using a prescribed
145 Energy Content, EC , and emission factors of scope one, $EF1$, and scope
146 three, $EF3$, to tonnes of Carbon Dioxide equivalent, tCO_2e (Department
147 of Climate Change, Energy, the Environment and Water, 2022). Emissions
148 were calculated for total diesel, petrol, bio-diesel and LPG used.

149 2.4. Region

150 Differences in vineyard locations were captured through the use of Ge-
151 ographical Indicator Regions (GI Regions). Each GI Region has its own
152 unique mixture of climatic and geophysical properties that describes a unique
153 winegrowing region within Australia; these regions were predefined by Wine
154 Australia (Halliday, 2009; Oliver et al., 2013; SOAR et al., 2008). Both Wine
155 Australia and Sustainable Winegrowing Australia used the same GI Region
156 format to describe location.

157 The site of a vineyard predetermines several physical parameters such as cli-
158 mate, geology and soil; making location a widely considered key determinant
159 of grape yield and quality (Abbal et al., 2016; Agosta et al., 2012; Fraga
160 et al., 2017). The climatic properties of each GI Region were summarised by

161 using predefined classifications as per the SWA (2021) user manual. The user
162 manual describes climates by rainfall and temperature, creating supersets of
163 Regions of similar climatic properties. The climatic groups were used to il-
164 lustrate similarities and differences occurring in areas larger than GI Regions.

165

166 *2.5. Model Validation*

167 Models were validated using K-fold cross validation calculated through
168 the R Caret Package (Kuhn, 2008). K-fold cross validation works by remov-
169 ing a subset of data from the sample used to train models and then predicts
170 those variables to determine how sensitive the model is to changes in the sam-
171 ple data. For this analysis each model was validated using 10 folds, repeated
172 100 times.

173 **3. Results**

174 *3.1. Exploratory Analysis*

175 Linear relationships between variables were explored using Pearson Cor-
176 relation Coefficients. Values for these coefficients are a measure of the lin-
177 ear relation between two variables; this measure is scale between -1 and 1,
178 indicating the strength of the relationship. Transforming the data prior to
179 calculating these values changes several things: The logarithmic transform of
180 the data changes the interpretation of the coefficients to percentage changes,
181 such that a coefficient will be indicative of the ratio a variable will change
182 in percentage compared to a one percent increase in the other; being scaled
183 by standard deviation this increase will be relative to the standard devia-
184 tion, making it a percent of that variables standard deviation. Scaling by

Table 2: Summary of models, their predictors, covariates and variable interactions.

Variable	Yield	Area	Water Used	Scope One Emissions	$\frac{Yield}{Area}$
Yield	1.000E+00	7.440E-01	-4.309E-03	7.290E-01	3.500E-01
Area	7.440E-01	1.000E+00	-5.331E-03	8.921E-01	7.854E-02
Water Used	-4.309E-03	-5.331E-03	1.000E+00	-1.929E-03	-5.600E-03
Scope One Emissions	7.290E-01	8.921E-01	-1.929E-03	1.000E+00	9.357E-02
$\frac{Yield}{Area}$	3.500E-01	7.854E-02	-5.600E-03	9.357E-02	1.000E+00
Average Price Per Tonne	-2.262E-01	-1.178E-01	-3.562E-02	-9.422E-02	-4.849E-02
<u>Average Price per tonne</u> Area	-1.644E-01	-2.042E-01	-2.669E-02	-1.933E-01	-1.698E-01

standard deviation also makes the Pearson Correlation Coefficient equal to the covariance of the two variables. This was undertaken for data on the original scale (see Table 2) and for data as a logarithmic transform (see Table 3). Strong relationships were found to be present, as all P-values were considered significant ($p < 2.200E-16$, see Tables 2 and 3), except for the non-transformed values for water used (see Table 4). The logarithmic transforms showed the strongest correlations, this was likely due to a skew caused by a greater number of smaller vineyards within the dataset (see Table 5).

3.2. General Linear Models

Models 1 and 2 showed significant relationships between each of the predictors and their response variables (see Tables 6 and 7). Variables in models 3 and 4 reported similar significance; except for scope 1 emissions (see Tables 8 and 9). Scope one emissions was included in all models to directly compare the response variables as ratios of vineyard size to raw values. Even though not significant within models 3 and 4, when using the Pearson Correlation

Table 3: Pearson correlation coefficients for each logarithmically transformed variable.

Variable	Yield	Area	Water Used	Scope One Emissions	$\frac{Yield}{Area}$
Yield	1.000E+00	8.822E-01	8.245E-01	7.617E-01	9.353E-01
Area	8.822E-01	1.000E+00	7.750E-01	8.311E-01	6.742E-01
Water Used	8.245E-01	7.750E-01	1.000E+00	6.668E-01	7.292E-01
Scope One Emissions	7.617E-01	8.311E-01	6.668E-01	1.000E+00	6.086E-01
$\frac{Yield}{Area}$	9.353E-01	6.742E-01	7.292E-01	6.086E-01	1.000E+00
Average Price Per Tonne	-4.591E-01	-1.911E-01	-4.881E-01	-1.559E-01	-5.625E-01
$\frac{Average Price per tonne}{Area}$	-8.918E-01	-8.474E-01	-8.300E-01	-7.063E-01	-8.070E-01

Table 4: P-values for the non-transformed water used variable's Pearson correlation coefficients.

Variable	Water Used
Yield	7.538E-01
Area	6.981E-01
Scope One Emissions	8.883E-01
$\frac{Yield}{Area}$	6.836E-01
Average Price Per Tonne	5.600E-02
$\frac{Average Price per tonne}{Area}$	1.522E-01

Table 5: Summary statistics for each variable on the original scale..

Variable	Yield	Area	Water Used	Scope One Emissions	$\frac{Yield}{Area}$
Yield	1.000E+00	8.822E-01	8.245E-01	7.617E-01	9.353E-01
Area	8.822E-01	1.000E+00	7.750E-01	8.311E-01	6.742E-01
Water Used	8.245E-01	7.750E-01	1.000E+00	6.668E-01	7.292E-01
Scope One Emissions	7.617E-01	8.311E-01	6.668E-01	1.000E+00	6.086E-01
$\frac{Yield}{Area}$	9.353E-01	6.742E-01	7.292E-01	6.086E-01	1.000E+00
Average Price Per Tonne	-4.591E-01	-1.911E-01	-4.881E-01	-1.559E-01	-5.625E-01
$\frac{Average Price per tonne}{Area}$	-8.918E-01	-8.474E-01	-8.300E-01	-7.063E-01	-8.076E-01

Table 6: Model 1 ANOVA summarising variable significance at the .5 level.

Variable	Df	Sum Sq	Mean Sq	F Value	Pr(>F)
Year	9	7.060E+01	7.800E+00	8.353E+01	<2.20E-16 ***
GI Region	54	1.507E+03	2.790E+01	2.972E+02	<2.20E-16 ***
Area Harvested	1	3.211E+03	3.211E+03	3.419E+04	<2.20E-16 ***
Water Used	1	1.040E+01	1.040E+01	1.103E+02	<2.20E-16 ***
Scope One Emissions	1	6.600E+00	6.600E+00	7.056E+01	<2.20E-16 ***

200 Coefficients, scope one emissions was strongly correlated to every Model's re-
201 sponse variable; this was especially so for Model 1 and 4 (Yield and average
202 price per tonne as a ratio to area harvested, respectively).

203 The comparison of models performance shows that the average price per
204 tonne of grapes describes a great deal of the relationship between predic-
205 tor and response when comparing model 2 to model 4 (see Table 10). This
206 relationship between yield and average price was also illustrated in the cor-
207 relation values between them (see Table 2).

Table 7: Model 2 ANOVA summarising variable significance at the .5 level.

Variable	Df	Sum Sq	Mean Sq	F Value	Pr(>F)
Area Harvested	1	2.407E+03	2.407E+03	1.080E+04	<2.20E-16
Scope One Emissions	1	3.989E+01	3.989E+01	1.789E+02	<2.20E-16
Water Used	1	5.500E+02	5.500E+02	2.467E+03	<2.20E-16
Area Harvested*Scope One Emissions	1	6.921E+01	6.921E+01	3.104E+02	<2.20E-16
Area Harvested * Water Used	1	1.040E+00	1.040E+00	4.686E+00	3.045E-02 *
Year * GI Region	424	1.144E+03	2.700E+00	1.210E+01	<2.20E-16

Table 8: Model 3 ANOVA summarising variable significance at the .5 level.

Variable	Df	Sum Sq	Mean Sq	F Value	Pr(>F)
Year	6	1.324E+01	2.210E+00	8.748E+01	<2.20E-16 ***
GI Region	50	6.498E+02	1.300E+01	5.151E+02	<2.20E-16 ***
Area Harvested	1	2.142E+03	2.142E+03	8.491E+04	<2.20E-16 ***
Water Used	1	3.200E-01	3.200E-01	1.259E+01	3.947E-04 **
Scope One Emissions	1	4.000E-02	4.000E-02	1.492E+00	2.221E-01

Table 9: Model 4 ANOVA summarising variable significance at the .5 level.

Variable	Df	Sum Sq	Mean Sq	F Value	Pr(>F)
Area Harvested	1	2.066E+03	2.066E+03	5.700E+04	<2.20E-16
Scope One Emissions	1	6.000E-02	6.000E-02	1.569E+00	2.105E-01
Water Used	1	2.014E+02	2.014E+02	5.557E+03	<2.20E-16
Area Harvested*Scope One Emissions	1	5.246E+01	5.246E+01	1.448E+03	<2.20E-16
Area Harvested * Water Used	1	7.270E+00	7.270E+00	2.005E+02	<2.20E-16
Year * GI Region	243	4.546E+02	1.870E+00	5.162E+01	<2.20E-16

Table 10: Comparison of Model Residuals

	Df	Sum Sq	Mean Sq
Model 1	5231	4.913E+02	1.000E-01
Model 2	4868	1.085E+03	2.200E-01
Model 3	2818	7.111E+01	3.000E-02
Model 4	2629	9.528E+01	4.000E-02

Table 11: Comparison of Model performance.

	RSE	R2	Adjusted R2	F-statistic	P-Value
Model 1	3.065E-01	9.072E-01	9.061E-01	7.753E+02	<2.2e-16
Model 2	4.722E-01	7.951E-01	7.770E-01	4.403E+01	<2.2e-16
Model 3	1.589E-01	9.753E-01	9.748E-01	1.885E+03	<2.2e-16
Model 4	1.904E-01	9.669E-01	9.638E-01	3.095E+02	<2.2e-16

208 Limitations included overestimating yield for models 1 and 2, (see Figures
 209 1 and 2) and underestimating crop value in models 3 and 4 (see Figures 3 and
 210 4). Reviewing the data to uncover reasons for this included the use of binary
 211 variables such as the utilisation of renewable energy, contractors, and the
 212 occurrence of disease, fire and frost; however none of these variables were able
 213 to explain why some vineyards produced less, or why other vineyards sold at
 214 higher prices than predicted. A wide variety of these influences were likely
 215 already explained within the use of year and GI Region, or the interaction
 216 of both variables. The change between some regions was dramatic, with
 217 particularly warmer and drier regions producing much higher volumes of
 218 grapes at lower prices (See Figures 5 and 6). The use of other variables and
 219 methods, specifically splines, were able to create a more normally distributed

220 set of residuals but at a drastically reduced accuracy when comparing R2 and
221 RSE. The introduction of known average prices per tonne also helped increase
222 R2 values a small amount; it is important to not that it is common practice
223 for wineries to purchase grapes at a regional average rate, likely resulting in
224 much less variance within a region.

225 The correlation between average sales price and yield was a negative trend
226 (see table 2); the contributing factors to yield and average sales price was ???.
227 Correlation values showed that water and emissions increased with yield but
228 decreased with average sale price (see Table 4). In alternative attempts at
229 models it was found that without the incorporation of GI Region or year the
230 predictions greatly under performed. The possible reason behind this effect
231 was that different strategies are likely employed between different regions,
232 where some regions target the mass production of cheaper grapes over qual-
233 ity. This is most notable when grouping regions by climate, especially when
234 considering GI Regions in the 'Hot Very Dry' climate (see Figure 7). The
235 effect of climate in the models was not more significant than the more gran-
236 ular use of GI regions. The interaction between year and GI Region likely
237 accounted for localised events such as bushfires, which would be impactful,
238 but only at a local level in both time and space.

239 *3.3. Model Validation*

240 To validate the performance of these models k-fold cross validation was
241 used. This was done using 10 folds, k=10, repeated 100 times. The models
242 performed similarly to their original counter parts (see Table 11).

Table 12: Model validation using k-fold cross validation, for 10 folds repeated 100 times.

	RMSE	R2	MAE
Model 1	3.087E-01	9.045E-01	2.165E-01
Model 2	5.104E-01	7.409E-01	3.493E-01
Model 3	1.652E-01	9.723E-01	1.008E-01
Model 4	2.235E-01	9.500E-01	1.279E-01

243 4. Discussion

244 This study investigated the general relationships between input resources
245 of a vineyard, including fuel and water, and the outputs including yield
246 and value. Some regions appeared to produce many low quality grapes at
247 scale compared to attempting to produce fewer higher quality grapes. This
248 behaviour can be observed when reviewing Wine Australia’s annual reports,
249 where it is apparent that warm inland regions such as the Riverland are
250 known to only produce large amounts of lower graded grapes Wine Australia
251 (2022); Winemakers’ Federation of Australia (2017). Comparatively, regions
252 such as Tasmania only produce A grade grapes but in much smaller quantities
253 than the Riverland. Knowing that the difference in pricing per tonne can
254 exceed a magnitude of 10 between grades E and A, the operations in regions
255 that target different grades would have varied priorities. However, some
256 regions such as the Yarra Valley produce a Variety of different grades of
257 grapes, from C to A, highlighting that vineyard priorities, although may be
258 somewhat present within regional classifications, are not necessarily aligned
259 within a given region.

260 The opportunity to target different grades of grapes may not always be

261 available, with some regions being more renowned than others, and likely to
262 be sought after regardless (Halliday, 2009). The Barossa is an example of
263 this, known for its quality could also lend itself to a bias in purchasers not
264 considering other regions that may be capable of similar quality. This effect
265 could stifle the potential for market opportunities within these lesser known
266 regions. A further possibility is that there may be regional upper limits with
267 the relationship between resource input and the value gained becoming no
268 longer proportional due to diminishing returns. Climate was considered to be
269 a large determinant of the ability to grow a larger quantity of grapes, as well
270 as a determinant in grape quality (Agosta et al., 2012); however there were
271 vineyards in similar regions that were able to produce exceptionally better
272 results than others (See Figure 7).

273 The issue of model 1 and 2 over predicting yield, may have been due to
274 preventative measures brought on by regional pressures such as fire, frost and
275 disease. Where, more resources were required to prevent these issues from
276 spreading within a region, thus disproportionately effecting some vineyards
277 compared to others locally. This type of maintenance is not well captured
278 especially when considering that some regions, those in warmer areas are
279 not as prone to disease as cooler climates and could potentially have lower
280 operating costs per hectare. This could create a discrepancy in vineyards that
281 utilise preventative measures in wetter regions, as opposed to those who do
282 not, and thus expend less fuel and energy but risk disease. When reviewing
283 the differences between regions it is important to consider that vineyards
284 in Hot Very Dry areas can be hundreds of times the size of those in other
285 regions. It is interesting that while area, although significantly correlated to

286 the ratio of yield to area, was still lower than water and about the same as
287 emissions. This points to economies of scale playing a role but still being
288 only one consideration alongside the potential resources that can be used.
289 The negative trend between size and average sales price could also be a side
290 effect of mass supply verse demand, especially when looking at the level of
291 difference in production of some vineyards (see Table 4). The relationships
292 between yield, value and area are not simply about efficiently producing the
293 most grapes; sales price and by association grape quality, are integral to the
294 profitability, and this is strongly linked to resource-use and thus the longevity
295 and sustainability of a vineyard.

296 Literature shows that there are many on-the-ground decisions that in-
297 fluence both quality and yield. Where these decisions are governed by com-
298 plex physical and social forces such as international market demands, disease
299 pressures and natural disasters (Abad et al., 2021; Cortez et al., 2009; Hall
300 et al., 2011; I. Goodwin, et al., 2009; Kasimati et al., 2022; Oliver et al.,
301 2013; Srivastava and Sadistap, 2018). Many of these occurrences being high-
302 lighted throughout the past decades vintage reports (Wine Australia, 2019,
303 2021, 2022; Winemakers' Federation of Australia, 2013, 2014, 2015, 2016,
304 2017, 2018). It is also important to consider that these reports show that
305 the warm inland regions have seen a decline in profit during this period, as
306 they were often compared to other regions that focused more on quality than
307 quantity. This is an important consideration, as the size of some of these
308 vineyards when considering their ratio of value to area would only require a
309 marginal increase to out compete other regions. There are also differences
310 when comparing winegrowers to other agricultural industries as they are ver-

311 tically integrated within the wine industry, tying them to secondary and
312 tertiary industries, such as wine production, packaging, transport and sales.
313 This results in unique issues and considerations for each vineyard, where these
314 on-the-ground decisions may be influenced by other wine industry’s choices,
315 such as the use of sustainable practices in vineyards as a requirement for sale
316 in overseas markets; notably these interactions are further complicated by
317 some winegrowers being totally integrated into wine companies, while others
318 are not (Knight et al., 2019). Incorporating such decisions into the model
319 could help describe the contributing factors to regional differences beyond
320 resource consumption and regional differences.

321 Having more data for each region would also be an improvement, allowing
322 greater comparison between regions. More variables may also help to discern
323 vineyards that can produce larger volumes of grapes at higher prices. The use
324 of semi transparent tools such as random forests and decision trees alongside
325 more variables and data may help to uncover the reasons for values that
326 were under or over estimated. These differences could be caused by the use
327 of alternative sustainable practices in the field. While there is evidence to
328 suggest that environmentally sustainable practices can reduce costs, increase
329 efficiency, whilst improving the quality of grapes, more research is needed
330 to link these benefits across different regions and climates (Baiano, 2021;
331 Mariani and Vastola, 2015; Montalvo-Falcón et al., 2023).

332 The relationship between scope one emissions and the response variables
333 that included average sales price

334 It is possible that the relationships between scope one emissions and the
335 response variables were closely tied to a vineyards area. This possibility could

336 be explained through the emissions

337 Noting that irrigation systems use fuel and that the application of water
338 was a significant variable in each model scope one emissions' lack of signifi-
339 cance and contribution given its F-statistics (See Tables 7 and 8), indicated
340 that it is possible other vineyard activities requiring fuel are not as deter-
341 mining factors for a vineyards grape quality.

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