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Towards meaningful geographical indications: Validating terroirs on a 200 km^2 scale in Australia's lower Hunter Valley

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ABSTRACT

Terroir can be loosely defined as the 'taste of place'. Our ability to create meaningful geographical indications (GIs) is limited by our inability to establish terroirs on a large spatial extent (>100 km^2). We performed an investigation to build on previous efforts to quantitatively establish terroirs for Semillon grapes grown in Australia's Lower Hunter Valley (Area ~200 km^2). We mapped 10 soil variables, six terrain variables and three climate variables across the entire region to a resolution of 25 m. We clustered these variables, using fuzzy-k-means, to create a single 'Terron map' that parsimoniously divided the Lower Hunter Valley into six distinct environments (Terrons). The addition of climate variables and new soil data enabled an improvement on the previously created Lower Hunter Valley Terron map. Moreover, preliminary analysis indicated substantial variation in Semillon grape juice characteristics across the Lower Hunter Valley. We concluded the region covered by the 'Hunter Valley' Geographical Indication is more than two orders of magnitude too large to meaningfully reflect terroir. The methodologies discussed in this report could be reapplied to establish terroir and thus GIs for other perennial crops.
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1. Introduction

Standardization suppresses the diversity of agricultural systems. Agricultural commodity standards standardize products (Galtier et al., 2013). Similarly, eco-label standards (e.g. organic, fair trade and rainforest friendly) standardize production methods (Daviron and Vagneron, 2011). These mainstream agricultural marketing tools do not reward agricultural systems for unique practices or produce (Mancini, 2013). In general terms, this compromises the diversity of agricultural systems and thus human nutrition (Arsenault et al., 2015), human culture (Maat and Hazareesingh, 2016) and the resilience of agricultural systems (Herrero et al., 2017).

Geographical indications (GIs) provide a mechanism to conserve the diversity of agricultural systems. Established by the World Trade Organization in 1994, GIs are defined as "a sign used on products that have a specific geographical origin and possess qualities or a reputation that are due to that origin" (World Intellectual Property Organization, 2018). GIs are administered differently in different countries but essentially provide regions with intellectual property rights for the branding of unique food production systems (Marie-Vivien and Bienabe, 2017). GIs present opportunities to diversify consumer choices, conserve human culture and boost sustainable rural development (Bramley and Bienabe, 2012; Mancini, 2013).

Geographical indications generally derive their meaning from the concept of terroir (Tashiro et al., 2018; Clark and Kerr, 2017). Terroir can be loosely defined as the 'taste of place' (understanding that the specific natural, anthropogenic and/or mystical variables supposed to influence terroir is a point of contention) (Spielmann and Gélinas-Chebat, 2012). Failure to valorize the terroir(s) underpinning a GI can undermine the benefits GIs are designed to deliver (Besky, 2014; Josling, 2006). For example, Mexican GI legislation explicitly requires GI products to be linked to terroir. However, lack of enforcement in the agave-tequila industry led to reduced product quality as well as accelerated cultural and environmental degradation (Bowen and Zapata, 2009).

Our ability to create meaningful Geographical indications is often limited by our ability to validate terroirs on a large spatial extent (>100 km^2). The rapid development of pedometrics and remote sensing sparked growth in the number of terroir-related journal publications over the past 10 years (Fig. 1). However, only a small number of studies analyzed terroir on a district scale (e.g. Bonfante et al., 2011; Meggio et al., 2010; Martín et al., 2007) and regional scale (e.g. Priori et al., 2014; Vaudour et al., 2010; Carey et al., 2008). Terroir-zoning studies published between 2002 and March 2014 had a median study area of just 0.12 ha (Vaudour et al., 2015). This highly localized understanding of terroir is relevant to precision agriculture but less so to GIs, which are typically established on a large spatial extent. For example, the establishment of a GI for 'Basmati' rice was delayed for many years due to the complexity involved in characterizing rice grown over such a large area (Das, 2006).

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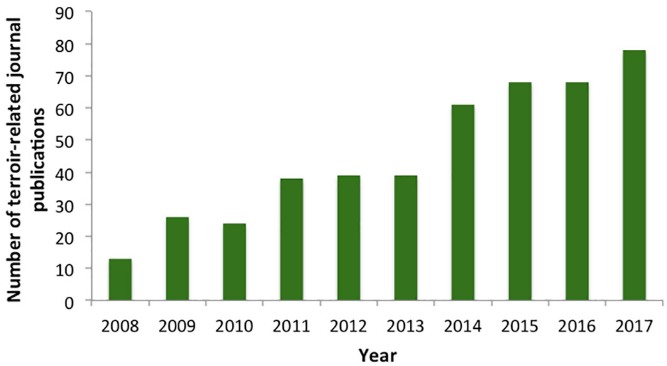

Fig. 1. Number of peer-reviewed journal publications indexed under the keyword "terroir" published every year from 2008 to 2017. Source: Web of Science Core Collections. (Single column, no column required).

Malone et al. (2014) attempted to validate terroirs on a 200 km^2 extent in the Lower Hunter Valley of New South Wales. Carré and McBratney (2005) developed a methodology for mapping Terrons, basic bricks of viticultural terroirs defined as "soil-landscape entit[ies] which combines soil and landscape at the same time". Malone et al. (2014) applied this methodology to divide the Lower Hunter Valley into twelve Terrons. The Malone et al. (2014) Terron map has three limitations that must be addressed to valorize terroirs on this large spatial extent:

1. The Terron map captured only some of the soil variation and none of the climate variation across the Lower Hunter Valley.
2. Dividing the Lower Hunter Valley into 12 distinct environments may have made the Terron map unnecessarily complicated.
3. The Terron map has not been linked to the spatial variation of grape characteristics in the Lower Hunter Valley.

We performed an investigation with three aims designed to address the three limitations of the Terron map created by Malone et al. (2014). First, map 19 soil, terrain and climate variables across the Lower Hunter Valley. Second, combine these 19 maps to create a parsimonious Terron map of the Lower Hunter Valley. Third, link this Terron map to the spatial variation of Semillon grapes in the Lower Hunter Valley. Ultimately, our goal was to improve quantitative methodologies for establishing terroir on a large spatial extent.

2. Materials and methods

The Lower Hunter Valley is a 200 km^2 area situated approximately 140 km north of Sydney (Fig. 2). The region is in a temperate climate zone that experiences warm humid summers, cool humid winters and an average rainfall of 780 mm per year (Bureau of Meteorology, 2017). The geology of the Lower Hunter Valley is mainly composed of Early Permian siltstones, marl and minor sandstone (Hawley et al., 1995). The dominant land use is viticulture, followed by dryland grazing systems.

2.1. Soil, terrain and climate mapping (aim 1)

2.1.1. Create new soil maps

Top-soil pH (0–10 cm), sub-soil pH (40–50 cm), Australian Soil Classification soil class (Isbell, 2016) and presence of marl (lime-infused clay) was measured at >1800 locations in the Lower Hunter Valley between 2001 and 2016. 70% of this dataset was randomly selected to calibrate predictive models for the four soil variables using 14 environmental predictor variables and a variety of statistical methods (Table 1).

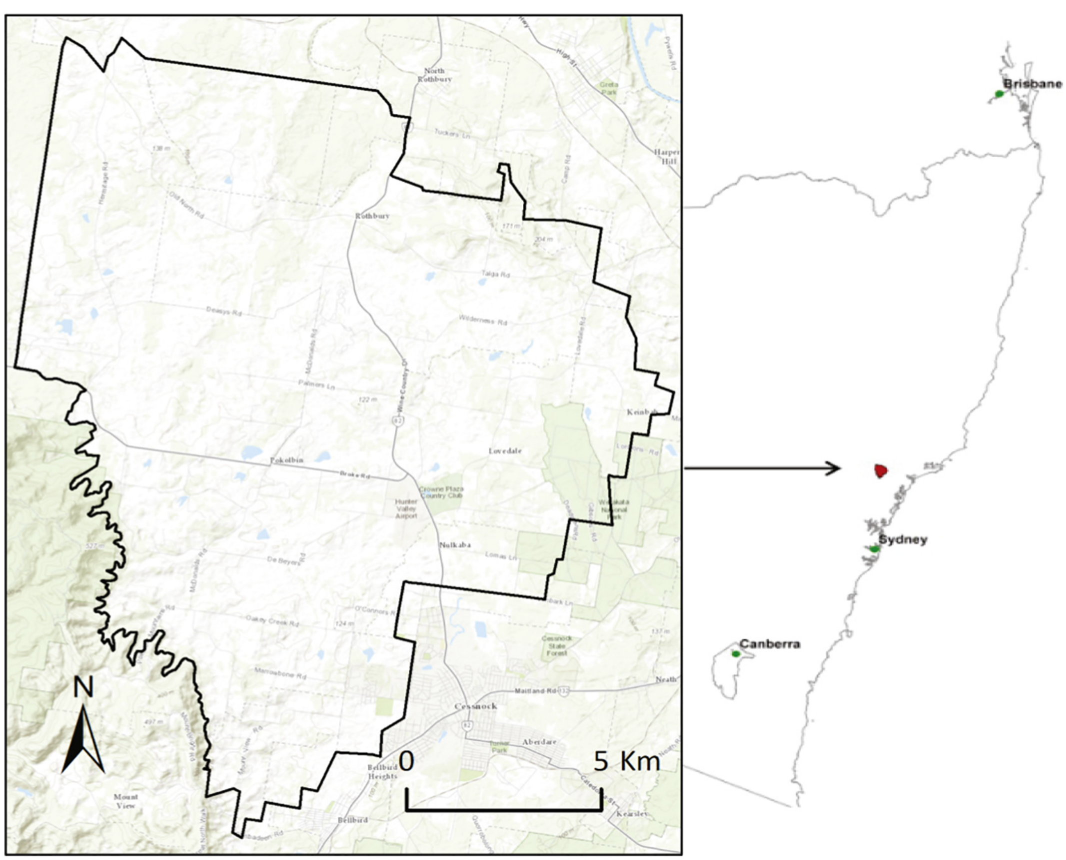

Fig. 2. Location of the Lower Hunter Valley with reference to the eastern coastline of Australia and associated capital cities. (Single column, no colour required).

Table 1
Statistical methods and environmental predictor variables used to create predictive models for continuous soil class, presence of marl, top-soil pH (0–10 cm) and sub-soil pH (40–50 cm) in the Lower Hunter Valley. Data for the 10 terrain predictor variables was extracted from a 25 m digital elevation model acquired from NSW Department of Lands using the SAGA GIS software (http://www.saga-gis.org/en/index.html). Data for the four radiometric predictor variables was extracted from a 100 m resolution radiometric map of Australia created by Minty et al. (2009). See Appendix 1 for predictor variable definitions.

Modelled soil variable	Statistical model	Terrain predictor variables	Radiometric predictor variables
Continuous soil class (fuzzy soil classification - McBratney et al., 1992)	Multinomial logistic regression	Altitude above channel network, Filled digital elevation model, Hill shading, Light insolation, Mid-slope position, Multi-resolution ridge top flatness, Multi-resolution valley bottom flatness, SAGA wetness index, Slope angle, Terrain ruggedness index	Radioelement concentration (total, Ur, K and Th)
Presence of Marl	Binomial logistical regression		
Top-soil pH (0–10 cm)	Cubist regression and residual kriging		
Sub-soil pH (40–50 cm)			

Table 2
Pre-existing soil and terrain map sources. See Appendix 1 for variable definitions.

Map type	Variable	Source
Soil	Total Ti/Zr (30–60 cm)	Unpublished maps created by Boquillon (2017)
	Total Ti content (30–60 cm)	Unpublished maps created from point data published by Odgers et al. (2011)
	Total Fe content (30–60 cm)	
	K radioelement concentration	Minty et al., (2009)
	Th radioelement concentration	
	Soil drainage potentiel index	Malone et al. (2012)
Terrain	Mid-slope position	Derivatives of digital elevation model (DEM) acquired from NSW Department of Lands.
	Altitude above channel network	
	Light Insolation	
	Multi-resolution Valley Bottom Flatness	
	Slope angle	
	SAGA wetness index	

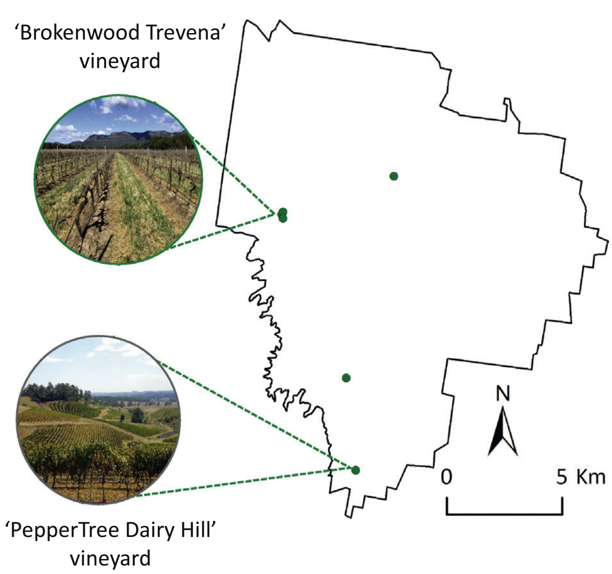

Fig. 3. Locations of the six sampled Semillon vineyards in the Lower Hunter Valley. Photographs of the 'Brokenwood Trevena' vineyard (taken August 2017) and the 'PepperTree Dairy Hill' vineyard (taken January 2017) illustrate the considerable spatial variability within the Lower Hunter Valley (Single column, colour required).

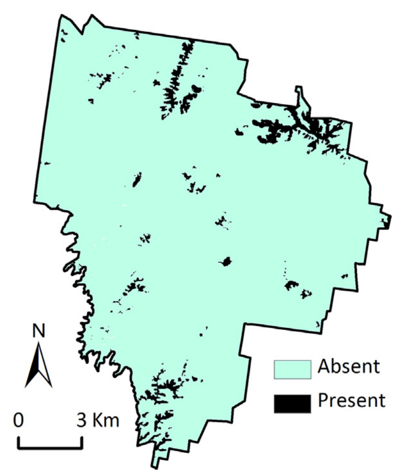

Fig. 4. New marl map of the Lower Hunter Valley. (single column, no colour required).

The 30% subset of the data that was withheld from the calibration of the models was used to independently validate all of them.

The validated predictive models were applied to the entire dataset to map soil class, presence of marl, top-soil pH and sub-soil pH at 25 m resolution across the Lower Hunter Valley. For the soil class maps, the predicted probabilities for each of the 14 continuous soil classes were centred, scaled and then generalized using principal component analysis (PCA) and the first four principal components were mapped. For the presence of marl map, pixels where the probability of containing marl exceeded 0.25 were mapped to have marl present.

Table 3
The new Lower Hunter Valley marl model compared to the original model created by Malone et al. (2014). The overall accuracy statistics for the models were obtained using validation data.

Marl model	Number of raw observations	Overall Accuracy
Original	1399	92%
New	2103	94%

Table 4
The new Lower Hunter Valley continuous soil class model compared to the original model created by Malone et al. (2014). The overall accuracy statistics for the models were obtained using validation data.

Soil class model	Number of observations	Overall Accuracy
Original	1399	38%
New	2247	29%

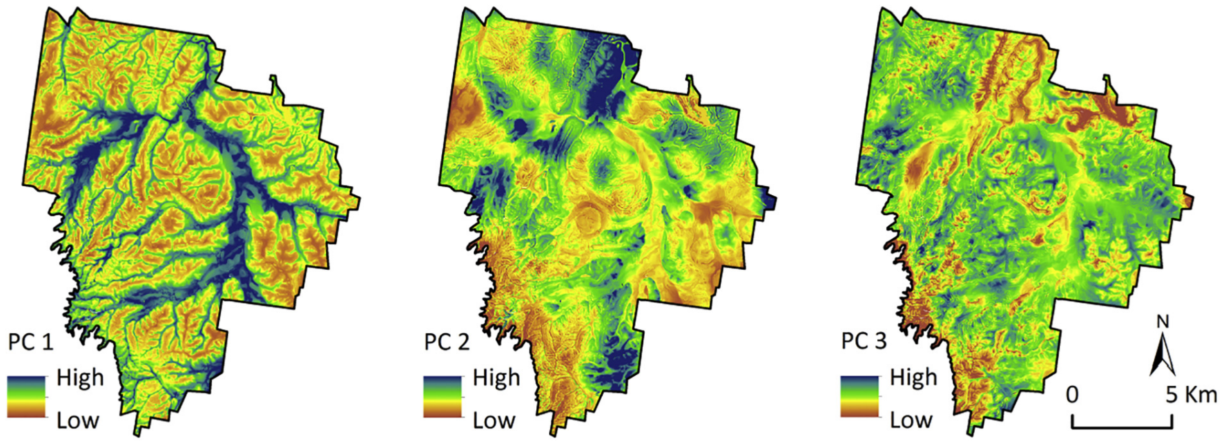

Fig. 5. The first three principal components of the Australia Soil Classification continuous soil class mapped across the Lower Hunter Valley (resolution 25 m) using the new soil class predictive model. (Double column, colour required).

2.1.2. Use of pre-existing soil and terrain maps

Pre-existing soil and terrain maps were also utilized (Table 2). K and Th radioelement concentration maps were resampled from a resolution of 100 m to 25 m. All other soil and terrain maps had an original resolution of 25 m.

2.1.3. Climate mapping

Climate raster data (1000 m resolution) for monthly rainfall, minimum daily temperature, maximum daily temperature across the Lower Hunter Valley from 1970 to 2016 was accessed from the Australian National Computing Infrastructure data repository (Jones et al., 2009). The data for each of the three climate variables was averaged from 1970 to 2016. The mean monthly rainfall, mean daily minimum temperature and mean daily maximum temperature maps were downscaled to a resolution of 25 m using linear regression models. Latitude, longitude and the 10 terrain predictor variables in Table 1 were used as predictors to calibrate the models, which were optimized using stepwise (forward and backward) selection.

Table 5
The sample size and root mean square error of the new pH model as well as the original whole-soil pH model created by Malone et al. (2014). The root mean square statistics for the models were obtained using validation data.

pH model	Number of observations	Root mean square error (pH units)
Original whole-soil	1399	0.76
New top-soil	1958	0.69
New sub-soil	1968	0.93

2.2. Terron mapping (aim 2)

The newly created soil maps (2.2.1), pre-existing soil and terrain maps (2.2.2.) and newly created climate maps (2.2.3.) were screened for accuracy, re-projected to the same extent and stacked. Pixels mapped to contain marl were removed from the stack and collated to form a 'marl cluster'. The environmental variables in the stack were centred, scaled and then generalized using PCA. A random sub-sample of 10,000 pixels (of the 318,709 remaining in the stack) were clustered using fuzzy-k-means based on the principal components that cumulatively explained >80% of the variation in the stack. The fuzzy-k-means clustering was iterated 13 times to test different numbers of classes ranging from two to 15. The fuzzy exponent value was held constant at 1.3. The optimal number of classes was determined on the basis the fuzzy performance index and the relative Mahalanobis distances

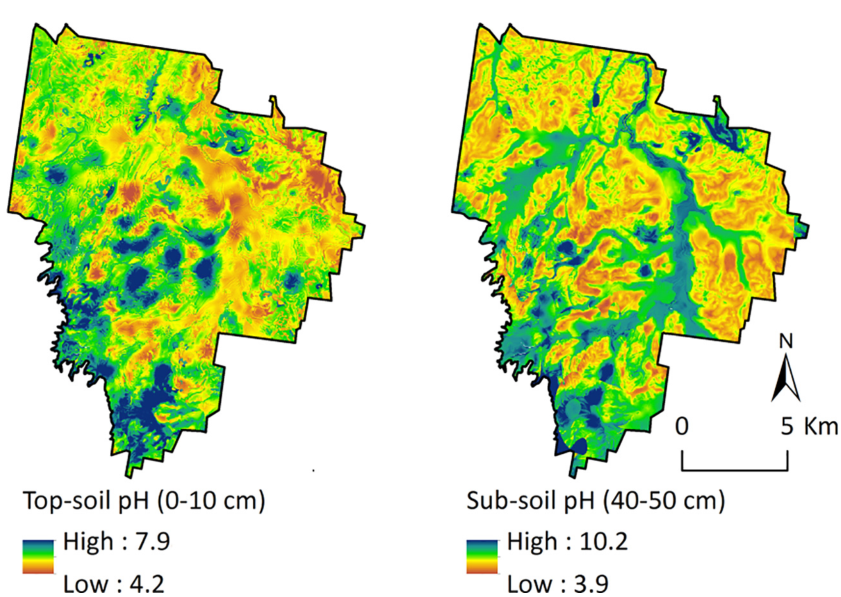

Fig. 6. New top-soil pH map and sub-soil pH map of the Lower Hunter Valley. (Double column, colour required).

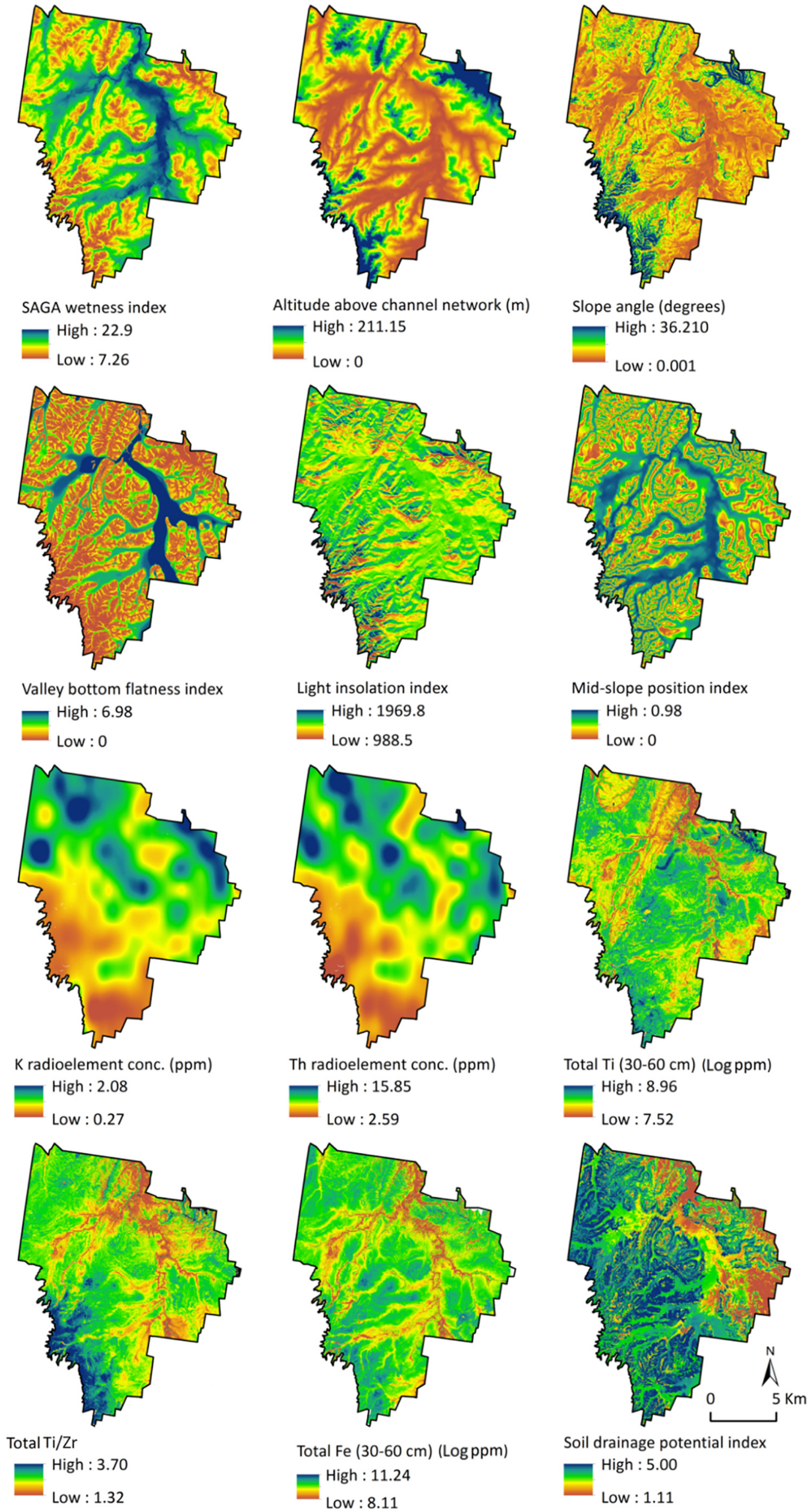

Fig. 7. Collated pre-existing soil and terrain maps for the Lower Hunter Valley. See Appendix 1 for variable definitions and Table 2 for map sources. (Double column, colour required).

Table 6
Linear regression models used to downscale climate maps.

Climate model	Predictors	P-value	Adj. R^2
Mean Minimum Temperature (1970–2016)	Longitude, Latitude, Altitude Above Channel Network, Filled Digital Elevation Model, Multi-resolution ridge top flatness, Light Insolation, Hill shading	$<10^{-3}$ for all predictors	0.91
Mean Maximum Temperature (1970–2016)	Longitude, Latitude, Altitude Above Channel Network, Filled Digital Elevation Model, Multi-resolution ridge top flatness, SAGA wetness index	$< 10^{-4}$ for all predictors	0.95
Mean Annual Rainfall (1970–2016)	Longitude, Altitude Above Channel Network, Filled Digital Elevation Model, Hill shading, SAGA wetness index	$< 10^{-5}$ for all predictors	0.91

between centroids. The optimal fuzzy-k-means algorithm was applied to all pixels remaining in the stack so that each pixel was allocated to the centroid it was closest to. The resultant clusters were mapped along with the marl cluster to create a Terron map of the Lower Hunter Valley. All soil, climate, terrain and Terron mapping was conducted using R and ArcGIS (R Core Team 2018; ESRI, 2011).

2.3. Exploratory analysis: linking grape variation to the Terron map (aim 3)

'PepperTree Dairy Hill' (1.2 ha), 'Brokenwood Oakey Creek' (1.2 ha), 'Brokenwood Latara' (1.3 ha), 'Brokenwood Trevena' (5.2 ha), 'PepperTree Trevena' (3.4 ha) and 'PepperTree Braemore' (1.6 ha) are commercial Semillon vineyards in the Lower Hunter Valley (Fig. 3). These vineyards were targeted because the Hunter Valley is famous for Semillon wines. Grapevine age, management (including irrigation and harvest date) and genetics varied between the vineyards but not within the vineyards. All grapes from the same vineyard were pooled and machine crushed on the day they were harvested in January 2017. Immediately after the crushing, 300 ml of grape juice from each vineyard was sampled and stored at −12 °C.

All grape juice samples were thawed at room temperature and analyzed. The Brix (a measure of sugar content) was measured using a portable refractometer and the pH was measured using a pH meter. The three CIE colour space variables (Smith and Guild, 1931) were measured using a portable colorimeter, centred, scaled and then generalized using PCA. Finally, the juice samples were analyzed using gas chromatography–mass spectrometry (GC–MS). Compounds and artefacts were identified in the GC–MS output using the NIST MS Search Program (Version 2.0). The peak areas of identified compounds were centred, scaled and then generalized using PCA. The pH and Brix principal components that explained >80% of the variation in the colour variables and principal components that explained >80% of the variation in the GC–MS peak areas were centred, scaled and then generalized using another PCA. All grape juice statistical analysis was conducted using R (R Core Team, 2018).

3. Results and discussion

3.1. Soil, terrain and climate mapping (aim 1)

3.1.1. Newly created soil maps

The addition of approximately 7000 new observations improved the marl map. The marl model predicted the absence of marl very accurately (94% user's accuracy, 100% producer's accuracy) but generally underestimated the presence of marl (67% user's accuracy, 5% producer's accuracy). Indeed, the new marl map identified the presence of marl in fewer locations than the original marl map (Fig. 4). Notwithstanding this, the new marl model had a higher overall accuracy than the original model (Table 3) and thus the new marl map was an improvement on the original map created by Malone et al. (2014).

An improvement in the soil class map was not observed. The new continuous soil class model was calibrated with approximately 60% more raw observations than the original model (Table 4). However, the overall accuracy of the new soil class model was lower (Table 4). Perhaps this was because the addition of new soil data captured new soil variability that was not reciprocated by the environmental covariates used as predictor variables. The accuracy may have also been reduced because the new soil class map predicted 14 continuous soil classes, whereas the original map only predicted 12 continuous soil classes. Nevertheless, only the first three principal components of the predicted soil class probabilities were included in the Terron model to account for the relatively low accuracy (Fig. 5). These three principal components explained 51% of the variation in the 14 continuous soil class probabilities.

The top-soil and sub-soil pH models were an improvement on the singular whole-soil pH map created by Malone et al. (2014). The

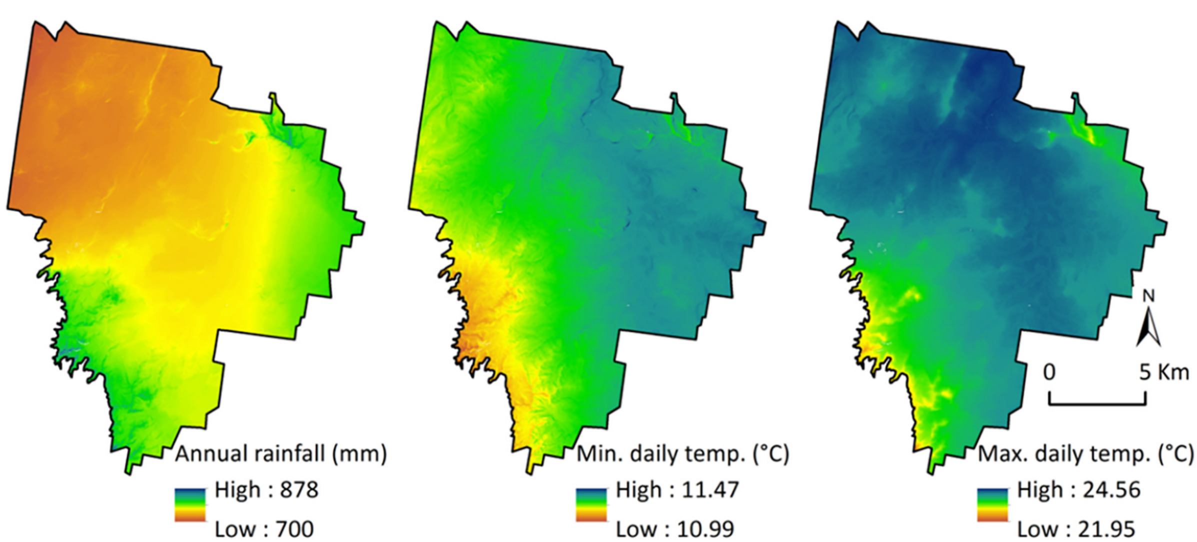

Fig. 8. Annual rainfall, minimum daily temperature, maximum daily temperature (all averaged from 1970 to 2016) downscaled from 1 km resolution to 25 m resolution. (Double column, colour required).

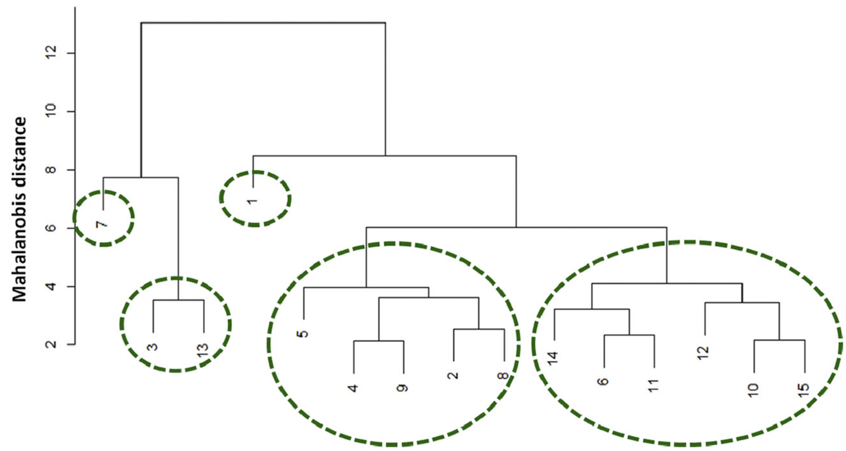

Fig. 9. Dendrogram depicting the relative Mahalanobis distance between 15 centroids generated by fuzzy-k-means clustering of the Lower Hunter Valley environmental variables. The five green ovals demonstrate how five clusters could delineate the Lower Hunter Valley environmental variation. Centroids are numbered arbitrarily. (Single column, colour required). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

whole-soil pH model's root mean square error (RMSE) was higher than the top-soil pH model's RMSE but lower than the sub-soil pH model's RMSE (Table 5). All the same, delineating the top-soil and sub-soil pH added an important dimension to our understanding of the Lower Hunter Valley soil. For example, the range of pH values mapped in the sub-soil pH map was greater than in the original whole-soil pH map (Fig. 6).

3.1.2. Other soil and terrain maps

Pre-existing maps for other soil and terrain variables were successfully accessed and systematic spatial variation was observed in all of them (Fig. 7). The total Ti content (30–60 cm) map was excluded from the Terron mapping analysis because artefacts were observed in the northwestern section of the map (Fig. 7).

3.1.3. Climate mapping

Maps for daily minimum temperature (1970–2016), daily maximum temperature and monthly rainfall (all averaged from 1970 to 2016) were successfully downscaled to 25 m resolution using predictive linear regression models (Table 6; Fig. 8). Assumptions were met for all three linear regression models, even though the daily maximum temperature model residuals were slightly skewed.

We observed systematic variation in mean minimum temperature, mean maximum temperature and mean annual rainfall across the Lower Hunter Valley (Fig. 8). The range of mean minimum temperature across the study area was only 0.5 °C. The variable was still included in the Terron mapping analysis because a clear gradient was observed across the Lower Hunter Valley and climate variables were arguably already underrepresented in the Terron mapping analysis (Fig. 8).

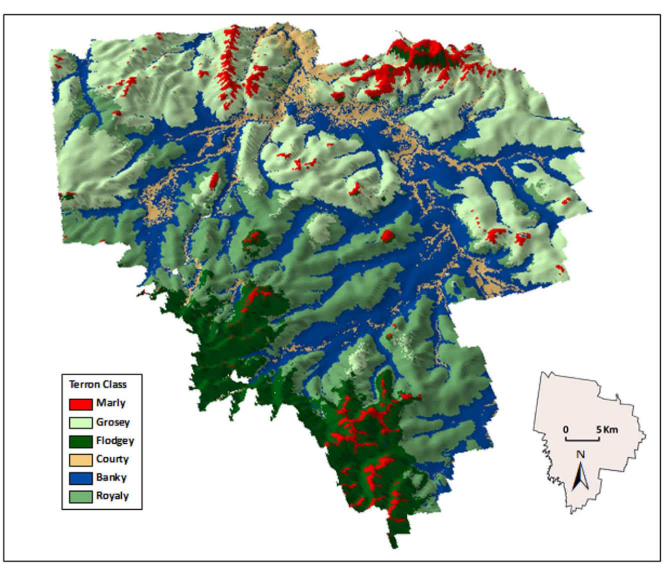

Fig. 10. Final Terron map of the Lower Hunter Valley depicted in 'two and a half' dimensions and superimposed over the digital elevation model with hill shading. The Terron with higher probability of presence of marl was named 'Marly'. (Double column, colour required).

3.2. Terron mapping (aim 2)

Gridded values for all soil, terrain and climate variables (excluding total Ti content) across the Lower Hunter Valley were successfully collated. All pixels where marl could be present ($P > .25$) were removed from the stack and aggregated to create a marl Terron. Like in Malone et al. (2014) Terron map, this was done because soil containing marl is highly desirable for viticulture (White et al., 2007). The remaining data was clustered to classify other Terrons in the Lower Hunter Valley. Variables were included in the Terron map calibration if they had a strong influence on grape juice characteristics according to White et al. (White, 2009), and if there was sufficient high-quality data to map the variable across the Lower Hunter Valley.

The optimal number of Terron classes was determined on the basis the fuzzy performance index (FPI) and the relative Mahalanobis distances between cluster centroids. The FPI measures the degree of fuzziness created by a specific number of classes - the smaller the FPI, the more suitable is the specified number of classes (McBratney and Moore, 1985). The FPI was lowest with three classes and second lowest with five classes. Additionally, the relative Mahalanobis distances between centroids in the 15-class model indicated that five clusters would classify the Lower Hunter Valley environmental variability most effectively (Fig. 9). On the basis of these two factors, we concluded that five Terrons (six including the marl Terron) would create the most parsimonious Lower Hunter Valley Terron map.

A Lower Hunter Valley Terron map with six Terron classes was successfully created (Fig. 10). All delineated Terrons featured unique characteristics (Table 7; Table 8). For example, the 'Flodgey' Terron, situated in the mountainous southern parts of the study area, was characterized by high rainfall, lower temperatures, high soil pH and steep slopes (Table 7; Table 8). Contrastingly, the 'Courty' Terron, situated on the valley floor, was defined by low rainfall, low sub-soil Fe and gentle slopes (Table 7; Table 8).

Table 7
Mean, median and interquartile range for all soil and climate variables included in the Terron map for each of the Terrons.

	Soil variables									Climate variables		
Terron class	Topsoil pH (0-10 cm)	Subsoil pH (40-50 cm)	Continuous soil class principal components			Presence of marl (p > .25)	Soil drainage potential index	Total Fe (30-60 cm) (log ppm)	Total Ti/Zr	Mean annual rainfall (mm)	Mean min. Daily temp. (°C)	Mean max. Daily temp. (°C)
			PC1	PC2	PC3							
Mean												
Royaly	6.0	5.7	−0.9	0.6	0.4	0.0	4.6	10.5	2.6	760	11.27	24.01
Banky	5.9	6.2	2.1	−0.1	0.4	0.0	3.8	10.3	2.5	758	11.33	24.19
Courty	5.7	6.4	2.8	0.6	−0.4	0.0	3.5	9.5	2.1	750	11.36	24.30
Flodgey	6.4	6.7	0.2	−1.4	−1.2	0.0	4.4	10.6	2.9	798	11.17	23.36
Grosey	5.8	5.5	−1.4	−0.1	0.2	0.0	4.0	10.5	2.6	751	11.32	24.18
Marly	6.1	6.5	−1.3	−0.3	−2.3	0.9	3.8	10.6	2.7	776	11.29	23.79
Median												
Royaly	6.0	5.6	−1.0	0.5	0.4	0.0	4.8	10.5	2.6	766	11.26	24.04
Banky	5.8	6.3	2.2	−0.2	0.5	0.0	4.0	10.3	2.5	763	11.34	24.23
Courty	5.7	6.5	3.2	0.3	−0.4	0.0	3.6	9.6	2.1	744	11.38	24.34
Flodgey	6.4	6.6	0.0	−1.4	−1.0	0.0	4.5	10.7	2.9	796	11.16	23.37
Grosey	5.8	5.5	−1.6	−0.3	0.2	0.0	4.3	10.5	2.6	744	11.34	24.19
Marly	6.1	6.3	−1.2	−0.5	−1.9	1.0	4.0	10.7	2.7	784	11.31	23.90
IQR												
Royaly	0.4	0.7	1.8	1.7	1.0	0.0	0.6	0.18	0.14	32	0.08	0.30
Banky	0.4	0.6	1.8	1.6	1.3	0.0	1.0	0.20	0.19	34	0.11	0.20
Courty	0.3	0.9	2.4	2.3	1.4	0.0	1.3	0.62	0.23	30	0.04	0.19
Flodgey	0.5	0.8	2.4	1.3	1.6	0.0	0.9	0.21	0.19	17	0.07	0.37
Grosey	0.3	0.4	1.6	1.6	1.2	0.0	1.3	0.17	0.16	50	0.10	0.18
Marly	0.6	1.1	1.4	2.3	2.0	0.0	1.6	0.20	0.35	51	0.13	0.69

3.3. Linking grape variation to environmental variation (aim 3)

There was substantial variation in the grape juice chemical content, pH, colour and Brix across six Lower Hunter Valley Semillon vineyards (Fig. 11; Fig. 12). It must be noted that this was only an exploratory analysis. Rigorous statistical analysis with a much larger sample size and precise meta-data (grapevine age, management and genetics) will be required to link grape juice spatial variation to the Terron map.

4. General discussion

Terroir can vary significantly over short distances. Our study demonstrated that the Lower Hunter Valley (a region of just 200 km^2) can be cleanly divided into six Terrons. However, the number of Terrons identified was low considering the size of the study area. Based exclusively on a weak trend observed in recently published terroir-zoning studies, we would expect the Lower Hunter Valley to be divided into 14 Terrons (Fig. 13).

Table 8
Mean, median and interquartile range for all terrain variables included in the Terron map for each of the Terrons.

	Terrain variables							
Terron class	Altitude above channel network (m)	Mid-slope position index	Multi-resolution valley bottom flatness	Slope angle (degrees)	Light insolation index	SAGA wetness index	K radioelement concentration (ppm)	Th radioelement concentration (ppm)
Mean								
Royaly	13.9	0.41	1.0	3.1	1710	14.7	0.82	7.90
Banky	5.1	0.76	3.9	1.4	1704	18.3	0.99	9.07
Courty	7.1	0.78	4.0	1.6	1698	19.2	1.01	9.05
Flodgey	40.7	0.52	0.4	8.8	1684	11.7	0.62	5.73
Grosey	28.7	0.36	1.1	3.4	1698	13.7	1.35	11.61
Marly	63.3	0.55	0.3	7.5	1715	10.1	1.13	9.37
Median								
Royaly	12.9	0.41	0.7	2.9	1713	14.8	0.83	7.90
Banky	3.4	0.79	3.9	1.2	1705	18.3	0.98	8.99
Courty	2.7	0.85	4.2	1.2	1701	19.6	0.98	8.92
Flodgey	37.4	0.55	0.2	7.5	1708	11.2	0.56	5.70
Grosey	26.9	0.35	0.6	3.0	1701	13.7	1.35	11.51
Marly	57.5	0.61	0.1	6.6	1723	9.8	1.21	10.02
IQR								
Royaly	10.1	0.38	1.2	1.9	53	2.4	0.30	2.45
Banky	5.6	0.18	1.9	1.1	22	2.0	0.27	2.39
Courty	9.4	0.18	3.3	1.5	22	2.5	0.22	1.99
Flodgey	29.0	0.47	0.6	6.0	146	3.4	0.21	1.73
Grosey	16.5	0.36	1.3	2.3	58	2.8	0.35	2.23
Marly	32.2	0.38	0.3	5.6	114	1.3	0.67	4.65

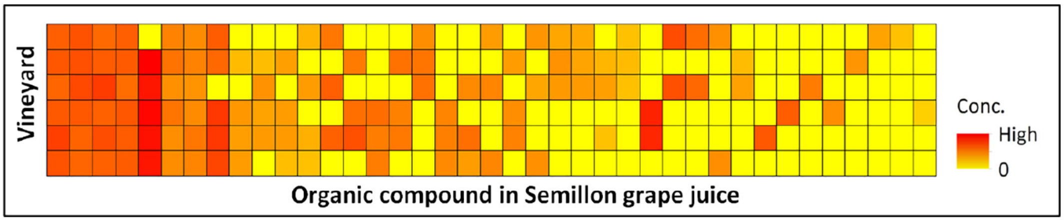

Fig. 11. Depiction of the variability in chemical content (captured by GC–MS) between the grape juice samples collected from the six Semillon vineyards. Each row represents a single grape juice sample and each column represents an organic compound identified in at least one of the six juice samples. The relative concentration of each compound in each sample is represented by a colour hue spectrum. (Double column, colour required).

The Australian 'Hunter Valley' GI (which contains three sub-regions with their own GIs) has an area of 200,000 km^2. This is two orders of magnitude larger than our area of study, in which we observed six distinct Terrons and substantial grape juice variability (albeit with a very low sample size) (Fig. 14). Therefore, we conclude that the "Hunter Valley" GI is not a meaningful reflection of terroir.

Further research must investigate terroirs on a larger spatial extent to bridge the gap between science and policy. The spatial resolution of the 'Hunter Valley' GI is too coarse to meaningfully reflect terroir. However, creating and validating a GI for every vineyard in the Hunter Valley would be impractical. For example, it currently costs 27,500 AUD to lodge an application to add, omit or change a GI in Australia (Wine Australia, 2016). In view of this, further research will be needed to parsimoniously establish terroirs on a large spatial extent and thus make terroir-zoning studies actionable for GI policy makers.

A more direct approach may be required to establish terroirs on a large spatial extent. Terroir imposes a simple concept on a complex system. We attempted to validate terroirs using 'Digital Terron Mapping' - a bottom up approach. We clustered environmental variables and attempted to link grape juice characteristics to the clusters. This approach has two limitations:

1. The selection of environmental variables for the Terron map is not directly data driven. The Terron map relies on the assumption that all included soil, climate and terrain variables influence wine characteristics. Conversely, the map assumes that all excluded soil, climate and terrain variables do not influence wine characteristics.
2. The Terron map does not account for non-environmental influences on wine characteristics. For example, the Terron map does not account for the effect of variability in viticulture practices, winemaking techniques and grapevine genetics (Fig. 15).

Perhaps 'Digital Terroir Mapping' (a top down approach) would be a more effective strategy for validating terroirs on a large spatial extent. Digital Terroir Mapping would be a reversal of the Digital Terron Mapping process. Similar to the method implemented by Vaudour et al. (2010), we would create spatial clusters of wine quality variables (e.g. alcohol content, colour, phenolic content, tannin content, pH, titratable acidity, sensory evaluations). This would enable a direct validation of terroir for the consumable product and hence all factors that influence terroir would be captured (Fig. 15). Moreover, Digital Terroir Mapping would support the data driven delineation of what causes terroir. We could quantify the effect of specific environmental, anthropogenic and genetic variables on wine characteristics by linking the spatial variation of individual variables to the digital terroir map. Ultimately, this approach may facilitate a systems model for terroir.

Digital Terroir Mapping would have its own challenges. First, the clustered wine quality variables may not capture all variability in wine quality. Second, there is less pre-existing data available to create and downscale a digital wine map of the Lower Hunter Valley. Third, Digital Terroir Mapping may not be able to account for terroir's temporal variability, which is becoming increasingly significant due to climate change (Clark and Kerr, 2017). Even so, Digital Terron Mapping and Digital Terroir Mapping are transferrable methodologies with potential to quantitatively validate terroirs on a large spatial extent.

5. Conclusions

Our analysis arrived at five conclusions:

1. There is systematic spatial variation in soil, climate and terrain variables across the Lower Hunter Valley. These variables included top-

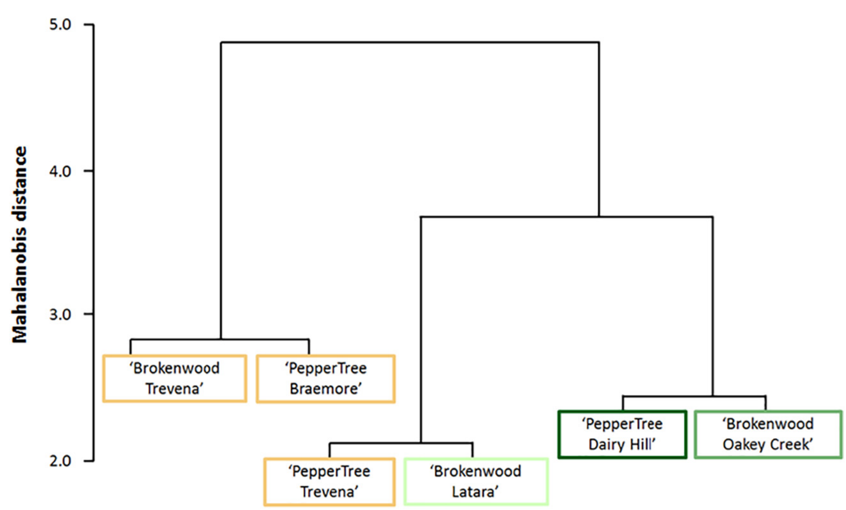

Fig. 12. Comparison of six Semillon grape juice samples with reference to the Terron map. The six samples are clustered based on principal components that explained 95% of the variation in the colour, pH, Brix and GC–MS data. The six samples are colour-coded based on their Terron class (yellow = 'Courty', light green = 'Grosey', dark green = 'Flodgey', mid-green = 'Royaly'). (Single column, colour required). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

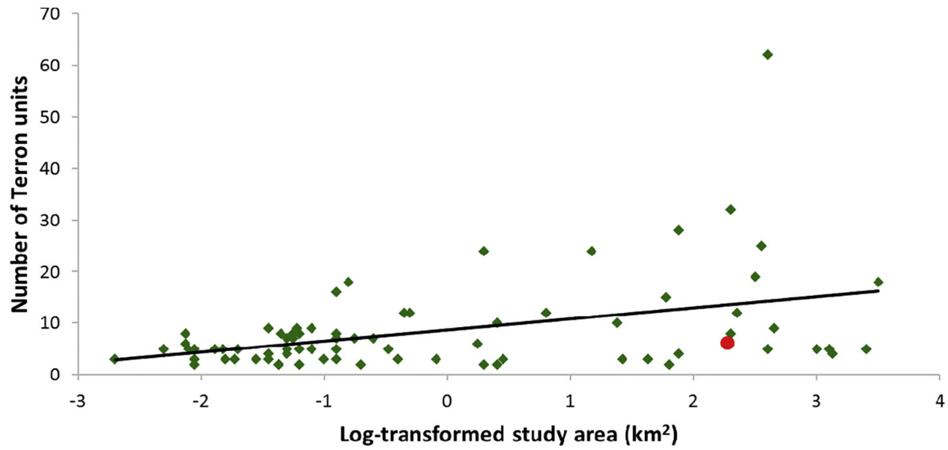

Fig. 13. Number of Terron units versus the log-transformed study area for Terron maps generated by this study (circle) and 73 other studies (green diamonds) published in peer-reviewed journals between 2002 and March 2014. Data was obtained from Vaudour et al., (Vaudour et al., 2015). The equation of the trend line is $y = 2.15\times + 8.69$ ($R^2 = 0.17$). (Single column, colour required). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

soil pH, sub-soil pH, Australian Soil Classification soil class, presence of marl, rainfall, maximum temperature and minimum temperature.

2. The Lower Hunter Valley can be parsimoniously divided into six distinct Terrons. These Terrons were mapped to a resolution of 25 m.
3. There appears to be substantial spatial variation in grape juice characteristics within the Lower Hunter Valley. However, a much greater number of grape juice samples will be required to validate the Terron map.
4. The region covered by the 'Hunter Valley Geographic Indication' is more than two orders of magnitude too large to meaningfully reflect terroir.
5. Digital Terron Mapping and Digital Terroir Mapping methodologies could be applied to validate terroirs in other regions, create meaningful GIs for them and thus support the diversity of agricultural systems.

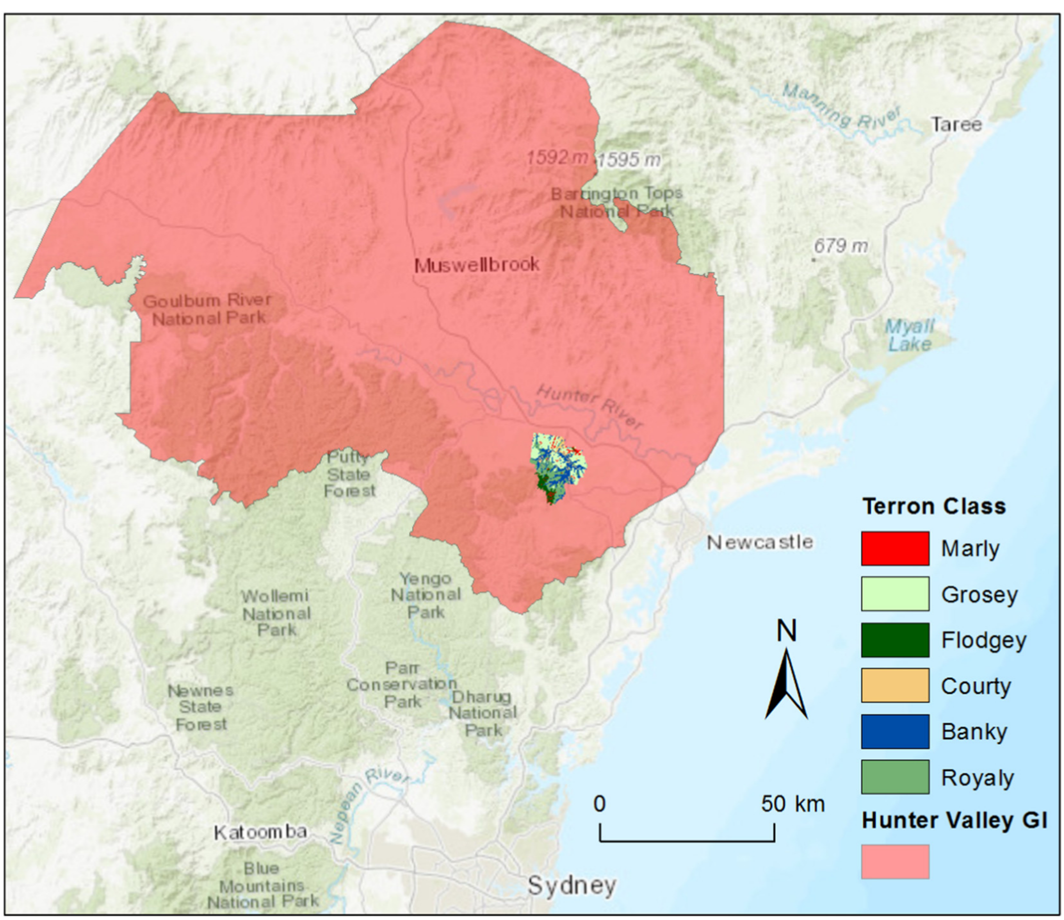

Fig. 14. The 'Hunter Valley' Geographical Indication (GI) region relative to the Terron map. (Single column, colour required).

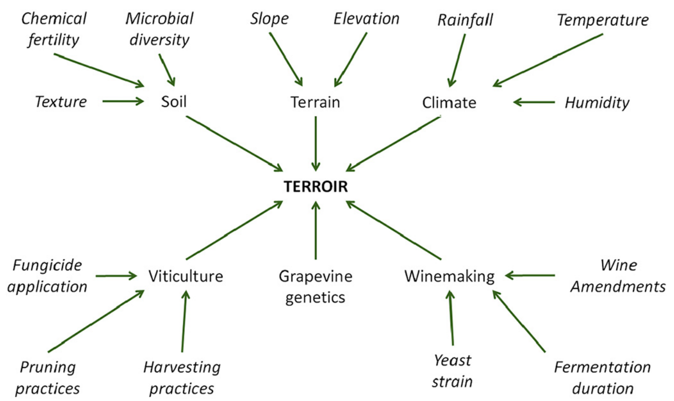

Fig. 15. A non-exhaustive list of factors that may influence terroir. (Single column, no colour required).

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Appendix 1. Definitions

Terrain variables:

- Altitude above channel network: difference between the elevation and an interpolation of a channel network base elevation.
- Filled digital elevation model: original digital elevation model but with all sinks filled.
- Hill shading: solar radiation taking into account the slope aspect and digital elevation of surrounding cells.
- Light insolation: measure of potential incoming solar radiation.
- Mid-slope position: a relative slope position parameter which gives a classification of the slope position in both valley and crest positions.
- Multi-resolution ridge top flatness: a topographic index designed to identify high flat areas at a range of scales.
- Multi-resolution valley bottom flatness: a topographic index derived using slope and elevation to classify valley bottoms as flat, low areas.
- SAGA wetness index: wetness index computed as a tangent function of slope angle and specific catchment area.
- Slope angle: measured in degrees, is the first derivative of the elevation of the digital elevation model in the direction of the greatest slope.
- Terrain ruggedness index: the mean difference between a central pixel in the digital elevation model and its surrounding cells.

Soil variables:

- Electrical conductivity (0–0.5 m, 0–1 m, 0–1.6 m, 0–3.2 m): integrated soil conductivity measurements (in mS m^{-1}) for depths 0–0.5 m, 0–1 m, 0–1.6 m and 0–3.2 m obtained using a DUALEM-21S (Dualem, Milton, ON, Canada) sensor.
- Radioelement concentration (total, Ur, K and Th): estimated concentrations (in ppm) for the total radioelement concentration in the soil as well as the concentrations for radioelements of Ur, K and Th. Estimations were derived from gamma-ray spectrometric surveys (Minty et al., 2009).
- Soil drainage potentiel index: soil drainage potential estimated from soil colour dataset (Malone et al., 2012).
- Total Fe content (30–60 cm): total Fe content (in ppm) at depths 30–60 cm and log-transformed.
- Total Ti content (30–60 cm): total Ti content (in ppm) at depths 30–60 cm and log-transformed.
- Total Ti/Zr (30–60 cm): ratio of total Ti content and total Zr content at depths 30–60 cm.

Appendix A. Supplementary data

Supplementary data associated with this article can be found in the online version, at https://doi.org/10.1016/j.geodrs.2019.e00209. These data include the Google map of the most important areas described in this article.

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