REMOTE SENSING APPLICATIONS IN VITICULTURE: RECENT ADVANCES AND NEW OPPORTUNITIES

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Abstract

Remote sensing applications in viticulture have been a research theme now for nearly two decades, becoming a valuable tool for vineyard management. Metrics produced using remotely sensed images of vineyards have yielded relationships with grape quality and yield that can help optimise vineyard performance. While valuable at the scale of precision viticulture, opportunities for spatial applications at the terroir scale are yet to be fully explored. The spatial scale of terroir analysis is different to precision viticulture and requires adaptation and new models of analysis. With the rising availability of high spatial and temporal resolution datasets, increasing computing power and advances in image processing software, the opportunities for vineyard interrogation through spatial analysis are increasing. Remote sensing and image analysis techniques that are becoming more accessible include: object based image analysis, spatiotemporal analysis, hyperspectral analysis and topoclimatology. Each of these techniques has potential for development within a viticulture and terroir context. This paper investigates the use of these techniques in a spatial science framework at various scales and identifies potential opportunities for their application in a terroir context, particularly in terms of terroir zoning.

Keywords: terroir zoning, remote sensing, phenology, OBIA, topoclimate

1 INTRODUCTION

The concept of terroir can be thought of in terms of interactions between the environment and cultural practices in wine production (Deloire et al. 2005). Cultural practices are highly influential on the characteristics of wine, but they are ultimately dependent on the local environment to which the viticultural practices interact over time in adapting to the local environment (Van Leeuwen and Seguin 2006). Climate, soil characteristics and topography are the environmental determinants of terroir and many characteristics of their physical properties can be quantified and mapped (Bonfante et al. 2011). By typifying the environmental determinants of high quality wine, suitable viticultural techniques may be identified based on the practices of regions with similar environmental characteristics. A key step in identifying the factors that influence terroir is making a link between wine attributes and the environment (e.g. Ubalde et al. 2010, Zsófi et al. 2011). Characterisation of the physical elements of terroir is required for this step to be realised. High quality spatial data of the physical elements must be collected and appropriately analysed in order to understand the influence of terroir on wine.

Remote sensing techniques are becoming more accessible as tools to acquire the data required for terroir investigations. While remote sensing hardware has recently become more readily available, analytical techniques to interrogate the acquired data may not be keeping pace. In addition, while progress in remote sensing applications in precision agriculture has been strong over the last 20 years, the scale of analysis for terroir applications is very different. While there is a degree of common ground in precision viticulture and terroir, much larger areas are subject to analysis in a terroir context, and spatial analysis at this scale differs in many ways. Some of the techniques developed from precision viticulture research can be adapted to a larger scale of analysis, and remote sensing products suited to larger scales of analysis are available (e.g. Vaudour et al. 2010). Climate data is a much more important element within terroir research compared to precision viticulture; climate varies only a little due to minor topographical variation at the precision viticulture scale but is a key determinant in spatial variability at the terroir scale. Topoclimate mapping relevant to terroir research relies on accurate digital terrain models (DTMs), which, being acquired by remote sensing and inherently spatial, places climatic analysis firmly within the subject matter of this discussion.

There are two interrelated objectives of terroir spatial analysis: identifying similar management units that have spatially homogeneous production characteristics; and making spatial based predictions of the quality of wine production. Both objectives require spatially continuous data describing the environment, i.e. digital images, where each individual pixel of the image is the smallest resolvable spatial unit of a data acquisition device, commonly raster maps derived from remote sensing devices. While new data acquisition techniques are rapidly developing in the field of remote sensing, the technical development of such tools is common across a number of fields, and it is therefore not the purpose of this paper to go into detail about these devices. Instead, this paper focusses in on data processing techniques that will provide meaningful data for terroir scale analysis in the context of the two above objectives. Essentially, this paper examines spatial science techniques that can potentially add value to spatial data for informing studies in terroir.

2 IMAGE CLASSIFICATION

Image classification techniques address the first objective of identifying similar management units that have spatially homogeneous winegrape production characteristics. Image classification is a process whereby raster data are classified into a number of classes with each of those classes having similar characteristics. At the simplest level, a single data value (data with one dimension) for each pixel in an image can be classified based on its magnitude, and the simplest of all classifications is for the pixels with the highest values to be classified as class 1 and the pixels with the lowest values be classified as class 2 with the median value pixel being the point of separation. Combining many layers of image data, where each image describes a characteristic of the environment can be similarly classified in a multi-dimensional space where the number of dimensions is equal to the number of layers. To understand, it can be helpful to imagine three layers of spatial data with spatially coincident pixels being plotted in a 3-dimenstional space where the axes of that space are the data values of each of the three layers. Where pixels cluster within this multi-dimensional space, a class can be identified. The ranges of the values of pixels in each layer that are within the cluster can then be used to assign classes to every pixel location in the data set. A single layer classification image is then produced. In a terroir context the spatial data is not necessarily simple remote sensing data, but can be any environmental metric that be quantified and mapped including climate, soil and topography (Vaudour et al. 2015).

3 OBJECT BASED IMAGE ANALYSIS IN VITICULTURE

Image classification procedures can be performed using various algorithms within geographic information system (GIS) software, and have, until recently, been performed at a pixel by pixel basis. However, with improved data acquisition technology, high spatial resolution remotely sensed imagery is becoming more widely available, and pixel based classification methods when applied at this very high spatial resolution may often no longer be the best choice. A new paradigm of image analysis, based on groupings of spatially contiguous pixels with similar characteristics, is object based image analysis (OBIA) (Blaschke 2010), which is appropriate to high spatial resolution data and is potentially highly applicable to terroir analyses. The contiguous areas of pixels identified as being similar are known as objects, which can be various shapes and sizes. An object can be quantified in terms of the characteristics used to define it, such as the mean value or variance of a remotely sensed vegetation index or the mean July temperature, for example. Object based image analysis at the precision viticulture scale can be based on the regular layout of a vineyard: row and vine spacing. The location coordinates of each vine trunk in a vineyard can be easily produced using a simple algorithm. Thiessen polygons (Brassel and Reif 1979) can then be used to assign each pixel in a vineyard image to each grapevine object (Figure 1). The values from the data layers of the pixels associated with each grapevine can then be used to quantify its vegetative canopy using summary descriptive statistics, e.g. density (mean vegetation index), size (count above threshold), variability (vegetation index standard deviation), shape (kurtosis, skew) (Hall et al. 2003). Such a procedure enables a high level of metric precision and spatial accuracy. At the regional scale, where macroscale climate features are relevant to characterising terroir, quantification of viticulture climate metrics and grapevine phenology, as produced for example by Hall et al. (2016), is somewhat analogous to OBIA in terms of characterising the values of pixels within a region. At this larger scale, variability within regions is a function of macroclimate determinants, such as distance to the coast, latitude and elevation. Phenological modelling of climate data can proceed for each pixel within a region to characterise viticulture conditions. Summary statistics of spatial variability within regions, being an important product of such an analysis, enable informed comparisons of the climatic characteristics of different regions (e.g. Hall and Jones 2010).

At the precision viticulture scale, OBIA has enabled exploration of metrics of vine objects and their relationship with on-ground measures of production and fruit quality (e.g. Hall et al. 2011). An important outcome of some of this work has been to show that relationships of on-ground measures of quality and yield with remotely sensed descriptors of grapevine canopy vary at the terroir scale. While some stability over time in such relationships have been shown (Bramley and Hamilton 2004), those vineyards more sensitive to year-to-year climatic variability may exhibit some degree of temporal inconsistency in the strength of such relationships (Hall and Wilson 2013). In a spatial context, at a large distance apart, climate and cultural adaptations to the climate result in very different vineyards. For two vineyards with the same variety, relationships with remotely sensed metrics were found for different quality and yield descriptors. The reasons for inconsistent relationships and their variability over space and time is yet to be fully explained. Small differences in topography and soil characteristics within the vineyard likely affect grapevine development and resulting differences in grapevine size across a vineyard. Additionally, root-zone temperature variability across a vineyard (Clarke et al. 2015), engendered by spatial variability in soil physical properties such as water holding capacity, soil depth and minor topographical differences, may effect a spatial variability in phenology. With key reproductive stages occurring at different times, being affected by different weather at those times, spatial differences in productivity and quality a likely.

Through OBIA, an investigation of various remote sensing derived metrics of grapevine characteristics is possible. While the normalised difference vegetation index (NDVI) is very commonly used, the index has limited capacity to distinguish between relative levels of vegetation density where that vegetation is dense. The NDVI was originally used by Rouse et al. (1973) to investigate variability of grasses in the Great Plains Corridor using ERTS-1 (renamed Landsat in 1975). The NDVI is effective at large spatial scales (pixel size of ERTS-1 was about 80 m) for relatively low levels of vegetation density (e.g. grasses), but it less suited to distinguishing between levels of dense vegetation (Huete et al. 2002). With very high resolution imagery of vineyards now including pixels that are all taken up with vineyard canopy that can be several layers of leaves thick (Hall et al. 2008), the precision provided by the NDVI is not as suitable for vineyard analysis as other vegetation indices. Grapevine canopy metrics derived from vegetation indices more sensitive to differences in dense vegetation have been demonstrated to have stronger relationships with measures of grapevine yield and quality (Hall and Wilson 2013). The increasing availability of hyperspectral imaging devices, may reveal particular bands of the spectrum and indices derived from such that are again more suitable in a terroir context (Cemin and Ducati 2011).

4 SPATIAL ANALYSIS AT THE TERROIR SCALE

Revisiting the paper by Rouse et al. (1973) is informative as it concentrates on temporal differences and the consequent phenological analysis that was enabled by ERTS-1 being able to revisit the same location every 18 days. Through the availability of inexpensive remotely piloted aircraft, frequent remote sensing monitoring of vineyards at a high spatial resolution can be achieved at a much lower cost and offers a mechanism for validation of climatic predictions at the terroir scale (Corbane et al. 2012). Tracking phenology through remote sensing, by recording budbreak, veraison (when canopy development greatly slows) and leaf-fall have potential for making predictions about fruit quality and yield by identifying the timing of important events such as fruit set, ripening period or post-harvest (Hall et al. 2011, Hall and Wilson 2013); weather events known to effect production during these times can then be studied. Remote sensing also enables monitoring of spatial variability in phenology.

Terroir scale analysis, except in cases where vineyards are ubiquitous and extensive, is likely to be more informed by topoclimatic data. Spatial non-continuity of vineyard areas, varietal variation, differences in management practices and a large spatial scale often make canopy remote sensing not especially suited to providing baseline spatial data required for terroir analysis. Topoclimatic based analysis based on digital terrain models (e.g. Hall and Jones 2010) is likely much more informative. Topoclimate can be defined as a continuous raster map of climatic variabilities at a fine spatial scale informed by topographic data. Weather station data provide spatially extensive coverage of an area but is confined to points that may be irregular. Spatial interpolation of these data (e.g. Webb et al. 2016) is required to produce continuous maps. Fine spatial resolution digital terrain models provide the topographical data, which can be produced at a relatively fine spatial scale using digital elevation data derived from the shuttle radar topography mission (SRTM) (Farr et al. 2007) products (e.g. Gallant et al. 2011). In addition, topography specific remote sensing devices (light distancing and ranging, LiDAR) can produce finer scale products for smaller areas through the use of airplane mounted systems and remotely piloted aircraft (RPA) mounted systems. Progress in structure-from-motion may also provide finer scale topographic information and may even provide data on grapevine canopy structure (Mathews and Jensen 2013). Topoclimatic interpolation is derived through the use of topographic based variables that can be used to predict climate variables. Descriptors of topoclimate derived from DTMs include elevation, exposure, solar radiation exposure, aspect and cold air hollows. A predictive model for particular areas can be calculated using derived raster maps of these descriptors to produce high resolution topoclimate maps. Viticulture related metrics, such as growing degree days (GDD) (Winkler et al. 1974) or the Huglin Index (HI) (Huglin 1978), to model phenology, and cold and heat indexes to model specific weather events can then be derived to inform spatial variability in a terroir scale context. Relationships based on these metrics with fruit yield and quality metrics can then be made. The aim is to determine the key factors that produce high quality fruit production.

With knowledge of the important aspects of climate and phenological response in the form of high spatial resolution raster maps, the base data required for zoning areas at a terroir scale are available. There are several spatial classification techniques that can be applied, e.g. support vector networks (Cortes and Vapnik 1995), random forests (Bosch et al. 2007), maximum likelihood classifications (Strahler 1980) and ISO-cluster classifications (Ball and Hall 1965). Each classification algorithm produces data describing a classification definition to assign categories to each pixel of an image. Image classification is also a feature of object-based image analysis. Image classification with an OBIA framework is appropriate as a classification technique for high-spatial resolution imagery (Figure 2). The starting point for OBIA classification is seed generation, whereby points in an image are identified that have similar levels of total variability in the spatial data surrounding them. Polygons derived from the seed points, with their edges being equidistant from the seed points, produces the initial set of objects. Classification through OBIA can be applied in various ways in a viticultural context. At the precision viticulture scale classification can be performed based on physical environmental properties, such as soil electrical conductivity, topography and remotely sensed imagery, to identify management zones which can then be used to inform vineyard sampling protocols or segmented harvests. At the terroir scale, topoclimate and phenological metrics are likely to be more informative, but significant work to validate the basis for such an analysis is required. Links at the terroir scale between spatial data products and on-ground measures of yield and fruit quality metrics are key.

5 CONCLUSION

Spatial data products are becoming more available at higher spatial resolutions that are suitable for analyses in viticulture terroir research. Raster data classification techniques are readily available and easy to apply to these data using geographic information system software, and object based image analysis (OBIA) provides a potentially valuable framework for such analyses, being suited to high spatial resolution or spatially extensive raster data sets prevalent at the terroir scale. Object-based image analysis has been shown to be a valuable tool at the precision viticulture scale, whereby groups of pixels can be analysed to produce accurate metrics of vineyard characteristics. At the terroir scale, spatial classification performed within an OBIA framework is a potentially valuable zoning tool. In contrast to the precision viticulture spatial scale, the type of spatial data of relevance is likely to be topoclimate based, derived from high-quality digital terrain models. Derived phenological metrics, coupled with temporal remote sensing analysis are likely key to successful studies linking physical characteristics of the environment with descriptors of winegrape quality and yield components at a regional scale.

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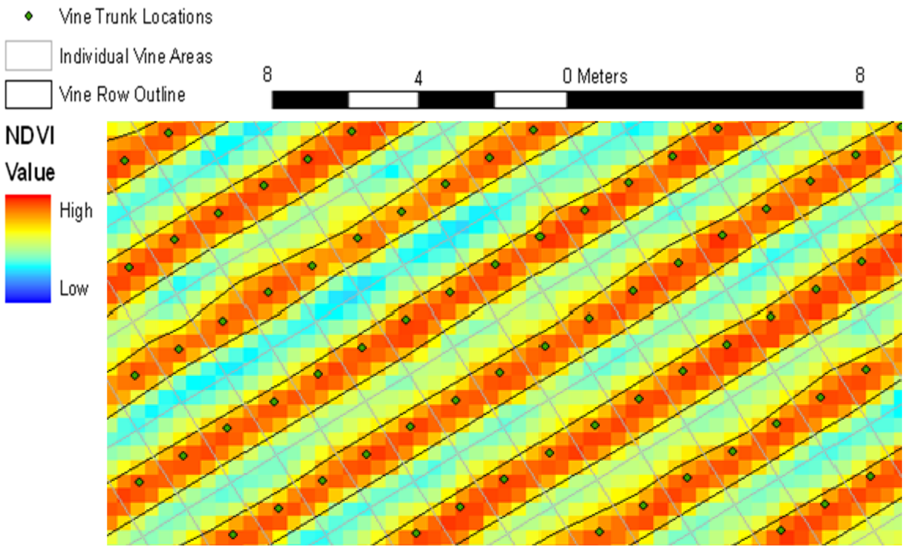

Figure 1 Object based image analysis of a section of a high spatial resolution (0.25 m) vegetation index image of a vineyard. Objects are based on regular vine and row spacing of grapevine trunk locations. Metrics describing vine objects are derived from pixels within individual vine areas.

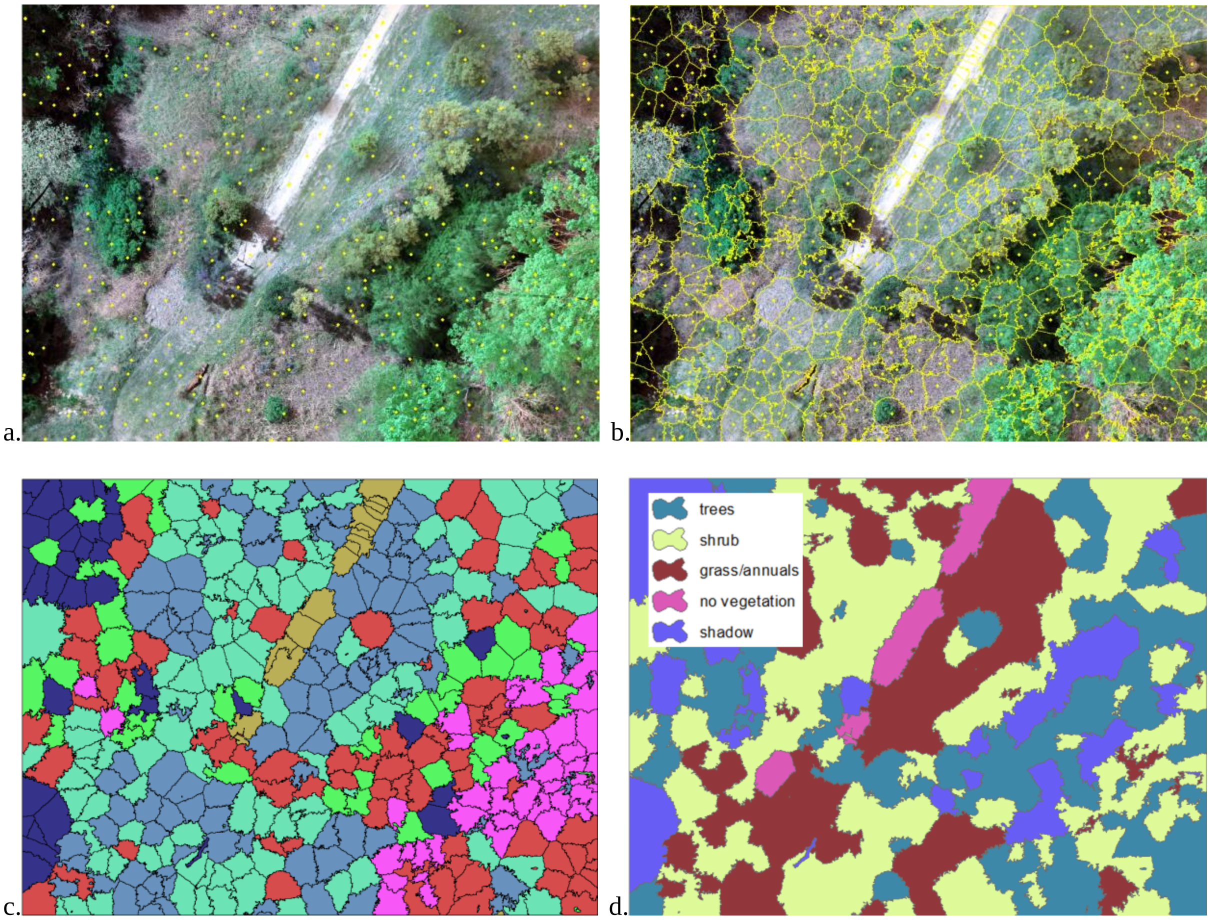

Figure 2 Classification process in an object based image analysis framework for an ultra-high spatial resolution (0.02 m) RGB image of an area of variable vegetation. (a) seed points generated based on local spatial variability (b) polygons with vertices equidistant from seed points (c) unsupervised classification of polygons based on RGB reflectance data (d) user post-classification result with combined classes