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Advanced datasets guide vineyard development

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Precision viticulture strategies that focus on promoting uniformly high winegrape quality throughout vineyard blocks require information about the distribution of elements that can impact grape quality, such as micrometeorological and soil properties.

Although airborne remote sensing and surface-based geophysical datasets are now available to provide information about vegetation and soil variability, the industry is still at an early stage in using these advanced datasets to guide development of new vineyards or management of existing vineyards.

One of the reasons for the lag between the availability of the technology and its adaptation is the difficultly involved in interpreting the remote datasets in terms of parameters that are meaningful for guiding vineyard development and management. Although the airborne and surface-based geophysical datasets provide spatially extensive information in a non-invasive manner, they provide only indirect information about the parameters that control wine grape growth.

Interpretation of the remote datasets in terms of meaningful parameters requires comparison with direct measurements obtained using conventional approaches, such as from well borings, backhoe pits, or meteorological stations. This comparison is exacerbated by the scale disparity between spatially extensive yet indirect measurements and sparse, yet direct measurements of vegetation vigor, soil texture, and soil moisture, for example.

In this study of a potential 28-acre Sonoma County vineyard site in California, a variety of airborne, surface geophysical, wellbore, and land surface methods were used to characterize the site. Conventional characterization approaches were used (soil pits, time domain reflectometer, digital elevation, micrometeorology), and analysis was performed on soil samples or neutron probe readings that were collected through vertical access tubes (wellbores installed in the ground). Less conventional approaches included cone penetrometer, surface ground penetrating radar, surface electromagnetic induction, and Normalized Difference Vegetation Difference [NDVI] remote sensing information. Many of these datasets were collected several times over 1.5 years to capture natural temporal and spatial trends prior to determining potential vineyard blocks.

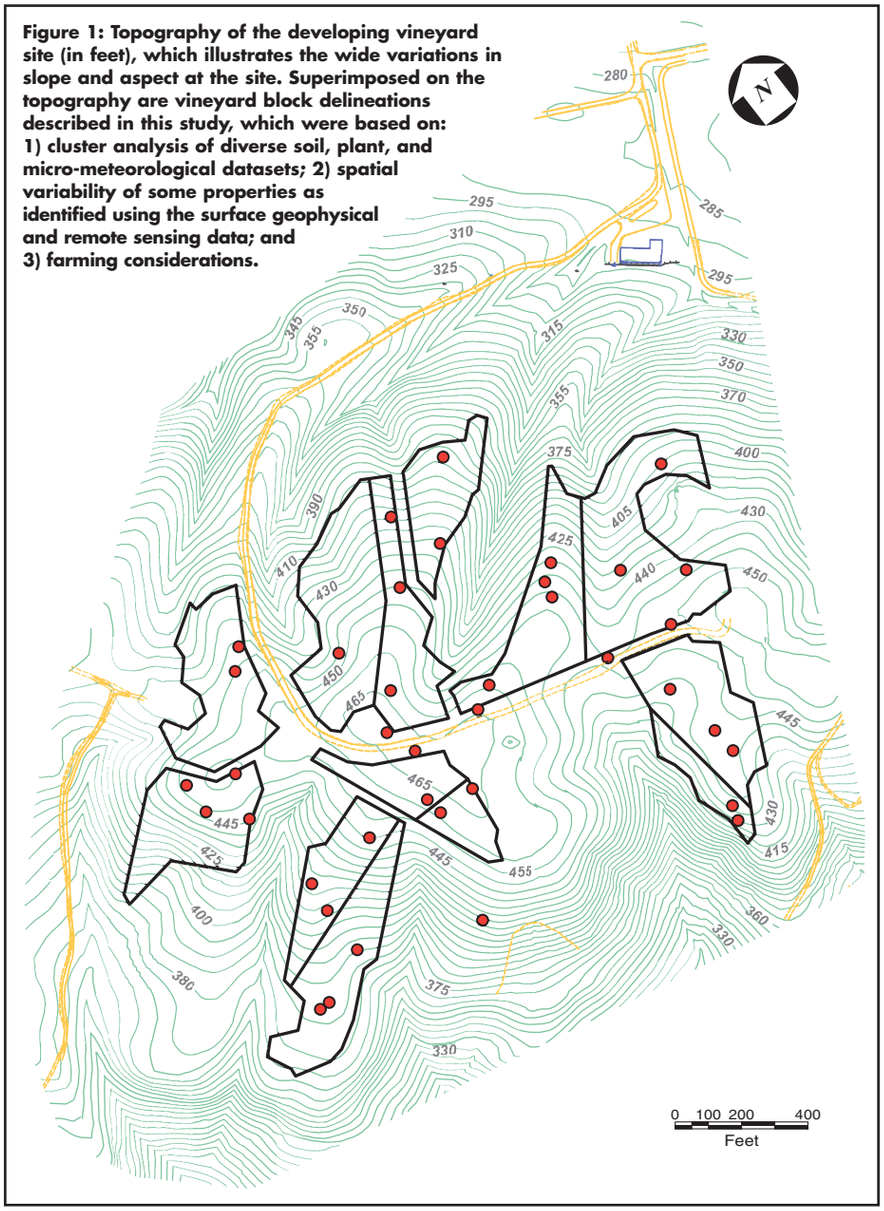

Figure 1: Topography of the developing vineyard site (in feet), which illustrates the wide variations in slope and aspect at the site. Superimposed on the topography are vineyard block delineations described in this study, which were based on: 1) cluster analysis of diverse soil, plant, and micro-meteorological datasets; 2) spatial variability of some properties as identified using the surface geophysical and remote sensing data; and 3) farming considerations.

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The study consisted of four key components:
1) data acquisition and interpretation of the datasets in terms of key soil, vegetation, or micrometeorological properties;
2) cluster analysis to define vineyard zones that are characterized by a unique combination of soil, vegetation, and topographic elements;
3) delineation of vineyard blocks based on natural site variability, with an objective to identify blocks that have fairly uniform soil, vegetation, and micrometeorological parameters; and
4) use of obtained mean block-specific parameters within water balance numerical models to develop block-specific irrigation strategies.

This study highlights how straightforward statistical and analysis approaches can be used with advanced datasets to optimize block layout and to develop precision irrigation strategies that respect natural site variability. Such approaches are expected to lead to more uniform vegetation and winegrape characteristics within vineyard blocks while potentially reducing water and energy use.

Sonoma County vineyard study site

The site in Alexander Valley is approximately five miles northeast of Healdsburg, CA. The mean January temperature at the site is 39ºF and annual precipitation can be up to 40 inches with most precipitation occurring during the winter.

The center of the site is delineated by an access road and is situated on a hilltop. The elevation varies from 465 feet down to 375 feet. Slopes range from 0 to 40% (average of 10%), with predominant slopes to the northeast and southwest.

Many of the elements that control wine grape growth, such as soil depth, drainage characteristics, and solar aspect ratio vary substantially over the site due to the variable site topography.

Characterization approach

Several different airborne, point, wellbore, and surface geophysical datasets were collected at the nascent vineyard site to assess spatial and temporal variations of site properties.

Many of the approaches that were employed are relatively new for use within vineyards. For example, a Cone Penetrometer (CPT), which is commonly used in civil engineering to characterize soil strength as needed for construction was used to assess soil texture variability and to identify the location of resistive layers. Surface-based Ground Penetrating Radar (GPR; Figure 2), and electromagnetic (EM) induction geophysical techniques have been tested for use in viticulture, but have not yet been widely

Table I. Different datasets collected at study site to characterize soil, vegetation, and micrometerological parameters that influence wine grape growth.

Method	Spatial Distribution of Measurements	Characterization Objective	Reference
Digital Elevation data and cultural boundary outlines	2D measurements of land surface	Elevation and property locators and extraction of slope and aspect.	*1
Soil Pit data	Point samples to depths of 2 meters	Soil Chemistry (Mg, Ca), qualitative soil texture and moisture descriptions	*2
Borehole soil samples	1D vertical series of point measurements to 4 meters	Gravimetric and soil textural analysis, development of site-specific neutron probe calibration curve	Lunt et al., 2005
Borehole neutron probe logs	1D vertical series of point measurements to 4 meters	Soil water content	Lunt et al., 2005
Cone Penetrometer (CPT)	1D vertical series of point measurements to 4 meters	Soil behavior type and depth to resistive layer	Lunne et al., 1997
Time Domain Reflectometer (TDR)	Point samples in upper 15 cm	Soil water content estimated from electromagnetic wave velocity	Topp et al., 1980
Ground Penetrating Radar (GPR) using sensors and software 900MHz groundwave	Integrated point measurements interpreted in term of 3D property distribution in upper ~20 cm of soil layer	Soil water content estimated from electromagnetic wave velocity	Grote et al., 2003; Lunt et al., 2005
Surface Electromagnetic (EM) Induction using Geonix EM-38 meter	Integrated point measurements interpreted in terms of 3D property distributions in upper 0.5 meters (horizontal dipole orientation) and 1.25 meters (vertical orientation) of soil layer	Soil property (texture/moisture variations) estimated from electrical conductivity	Lamb et al., 2004
NDVI	2D vegetation canopy measurements at 1m x 1m resolution.	Vegetation density	*3 Johnson et al., 1996
Weather station	Point micrometeorological measurements	Precipitation, ETo	CIMIS Santa Rosa station #42

*1 Digital Elevation Data provided by Erickson Engineering
*2 Soil pit data provided by Bryan Rahn, Coastalvit
*3 NDVI data provided by Jay Hutton, Grayhawk

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Figure 2: Obtaining data with ground-penetrating radar (GPR).

adopted nor jointly used for site characterization.

The locations of 29 soil pits (up to 4 feet in depth) were chosen based on the variability observed in the surface geophysical and remote sensing imagery.

Table I lists the different types of data collected at the site, the spatial sampling and characterization approach associated with different measurements, and references for details on data acquisition and inversion approaches. Figure 3 illustrates the dates of four different rounds of data collection (field campaigns) that were performed seasonally prior to block delineation as the site was wetting up and drying down.

The combined datasets (Table I) revealed spatial and temporal variations in soil and vegetation properties across the site. Figure 4 is an example of co-located wellbore datasets: volumetric water content (measured using neutron probe datasets collected over time and a site-specific calibration curve) is shown on the top and soil texture (inferred using CPT datasets collected directly adjacent to the neutron probe access tube) is shown on the bottom. At this location, the CPT dataset suggests the presence of a restrictive layer at about 3.75 meters below ground surface.

The soil moisture curves obtained from the neutron probe data reveal that the moisture content varies seasonally above this restrictive layer, but is constant below it. This suggests that the restrictive layer, identified using CPT data, is likely acting as a hydraulic control.

Dense surface geophysical and remote sensing datasets were used to assess property variations over space and time. Figure 5 (left and center) illustrates variations in electrical conductivity in the top ~1.25 meters of the soil during two different seasons, obtained using the surface-based electromagnetic method. Electrical conductivity measurements often respond to various elements: saturated, clay-rich soils will lead to higher values of electrical conductivity relative to dryer, sandier soils. Soils with saline-pore waters are more conductive than similar soils with fresh pore waters.

Because some soil properties (such as texture and possibly salinity) do not change over short periods of time, use of time-lapse measurements helps to reduce some ambiguity associated with interpretation of geophysical measurements that are sensitive to different properties. For example, by examining spatial variations in seasonal differences in electrical conductivity (Figure 5 right), we can investigate areas that tend to preferentially retain moisture or drain more readily over time.

Time-lapse NDVI data were also used to explore spatiotemporal variations in natural vegetative growth. By examining the NDVI data over time we were able to assess the influence of aspect on vegetative growth. For example, the time-lapse NDVI data suggested that the south- and southwest-facing slopes experience an increase in vegetation relative to other areas during the early part of the growing season where as north-facing slopes experienced a later increase in vegetation.

Optimal block delineation using cluster analysis and spatially-extensive datasets — Several elements varied significantly over space and time at the site, and there are interdependencies between elements. Examples include: soil texture and associated soil moisture; topography and associated slope and aspect; propensity toward vigorous vegetation; rooting depth

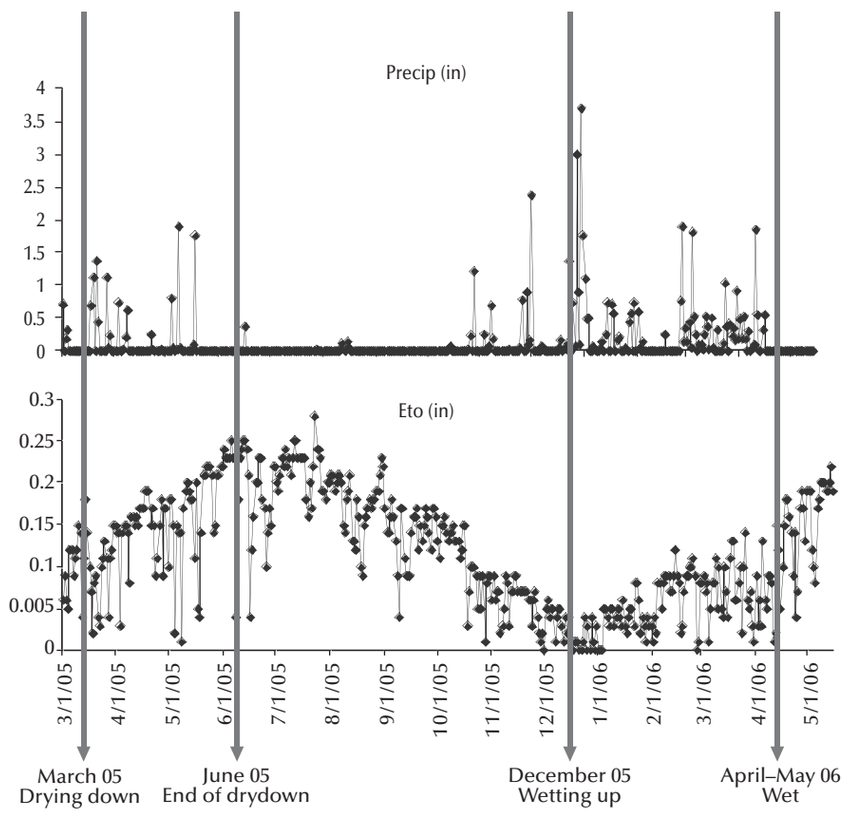

Figure 3: Timetable of four major field measurement campaigns at the vineyard site as a function of precipitation (top) and reference evapotranspiration (bottom).

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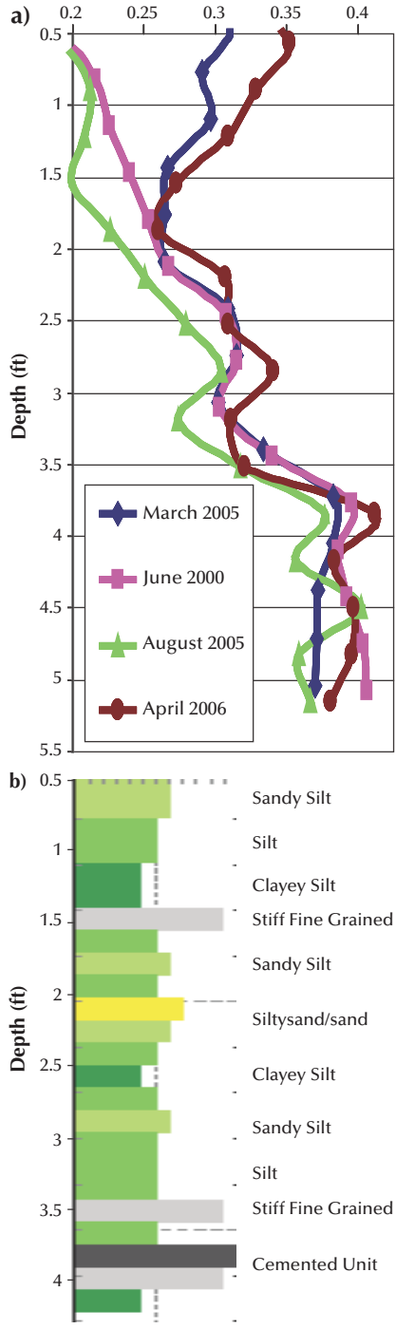

Figure 4: (a) Neutron probe measurements of volumetric water content as a function of season and (b) CPT estimates of lithology at the same location. These datasets illustrate seasonal shallow soil moisture variations and the control of a resistive unit on water content. Such wellbore-based datasets complement the spatially extensive datasets (obtained using surface geophysical and remote sensing methods) because they provide detailed information about subsurface variability at one location as a function of depth.

and associated depth to the restrictive layer.

Ideally, our extensive database could be used to parameterize numerical models that could, in turn, be used to simulate the cycling of water and nutrients through the soil, grapevines, and atmosphere.

However, accurate simulation of these dynamic biophysical-hydrological interactions is still at a very early research stage and would require model development, biophysical measurements, process investigations, and model calibration that are beyond the scope of most practical vineyard development efforts.

Instead, a cluster analysis approach was utilized to delineate statistically significant regions within the developing vineyard site that had a unique and meaningful combinations of soil, plant, and micrometerological parameters that are expected to influence grapevine growth (and eventually, fruit quality).

We relied on a relatively new hybrid clustering algorithm developed at University of California, Berkeley by M. van der Laan and K.S. Pollard in 2003. This procedure optimizes the number of parameter groupings such that they are distinct from one another and so that the parameter values within the groups are relatively homogeneous.

The dataset for the cluster analysis consisted of 14 variables, including the key soil, vegetation, and elevation-related parameters shown in Table I and changes in some of those variables as a function of season. The dataset was compiled by extracting measurements from the dense geophysical, vegetation, remote-sensing micrometerological, and soil-based datasets at the locations of soil pits and wellbores. Dots in Figure 1 indicate the location of the soil pits and wellbores that were used for the cluster analysis.

The cluster analysis indicated that there were six distinct clusters, each of which were constrained to a particular geographic region and could be described by a unique combination of soil, vegetation, and micrometeorological-based parameters (or change in those parameters over time).

Cluster distribution was used together with the spatially distributed (2D or 3D) datasets and site cultural features (existing roads, natural gulleys, extreme topography) to delineate vineyard blocks in Figure 1. These blocks represent delineation of regions that have a unique combination of elements that influence grapevine growth and that are practical to manage from a farming perspective.

For example, the northern-most delineated block is characterized as being primarily north-facing with a rooting depth of about 35 inches and relatively low vegetation, and composed of sandy, gravelly loam soils that were subject to drainage above but were consistently moist below a 4-foot deep restrictive layer. In addition to using these gross characteristics to define the block, the higher resolution remote sensing datasets can be used to explore more subtle within-block variability, which can be used to guide vineyard planting.

Development of precision irrigation schedules using block-specific information — Once the vineyard blocks were delineated, the associated soil, vegetation, and climate-based parameters of the individual blocks can be used to guide further vineyard development or management strategies, such as choice of rootstocks, grape variety scions, spacing, and orientation of vine rows, and irrigation scheduling.

Such zonal-based management strategies can be developed using expert viticulture knowledge or with the help of numerical modeling approaches that take into account several identified block-specific elements.

An example of the potential use of the obtained information for guiding block-specific management strategies is the use of a simple water balance model to simulate irrigation needs for each block based on obtained mean values of key parameters associated with that block (such as soil depth and texture, elevation and aspect ratio, etc.) and as a function of tractor row and vine spacing.

For this simulation, the Vineyard Soil Irrigation Model (VSIM: Pierce, 2006) was used. This simple Excel

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spreadsheet-based simulation tool can be used to calculate water balance over the entire root zone of the plant using $\Delta S = P + I - ET - R$, where ΔS is the change in soil water storage over the root zone, P is precipitation, ET is the evapotranspiration of the soil-plant system, R is the surface water runoff, and I represents irrigation water input to the system.

Evapotranspiration is based on reference evapotranspiration (ETo) and a crop coefficient (k_c), where crop ET (ETc) = ETo * k_c. VSIM utilizes the California Irrigation Management Information System (CIMIS) meteorological station network to quantify daily and seasonal variations in climate, and these "average" ET_0 values can be modified to account for expected changes in micrometeorology of different blocks as a function of latitude, slope, and aspect.

In VSIM, daily ETc and runoff are subtracted from soil moisture, while irrigation and rainfall (if any) are added to soil moisture to keep a daily running calculation of soil moisture. The soil/leaf water potential is then obtained from the calculated soil moisture using relationships based on site-specific soil texture and depth.

Figure 6 is an example of a block-specific irrigation simulation, which was simulated using VSIM with: 2004 meteorological data from the Santa Rosa CIMIS station; ETo values corrected for block-specific latitude, mean slope and mean aspect; initial soil moisture at beginning of growing season calculated based on block-specific soil texture; regional growing degree day values for bud break; and peak leaf area index.

Parameters that can be varied within the simulation include crop cover, target midday stem water potential, and tractor row and vine row spacing. For choices of 75% crop cover, a mid-day stem water potential target for developing vines during the growing season of –9 bars, and four feet by four feet vine and tractor row spacing, Figure 6 shows that this particular block should be given 10 mm of irrigation water every two weeks.

Summary

Precision viticulture strategies that focus on promoting uniformly high wine grape quality throughout vineyard blocks require information about the distribution of elements that can impact grape quality. Although advanced remote sensing and surface geophysical datasets can provide indirect information about such elements, they are not routinely used to guide vineyard development because of the cost and effort involved in acquisition and challenges involved in interpretation.

This study illustrated how advanced characterization datasets can be used to guide block delineation and irrigation scheduling. In particular, we found that:

- Statistical clustering approaches facilitated the interpretation of multi-scale and multi-variable vineyard characterization datasets in terms of vineyard regions that have fairly unique and uniform properties. The clustering and spatially extensive datasets were useful in delineating vineyard blocks.
- The obtained cluster properties within each block could then be used to develop zonal vineyard management strategies that honor natural site variability, such as block-specific irrigation schedules.

In addition to illustration of a characterization strategy for delineating vineyard blocks and associated management strategies, we found that:

- Time-lapse NDVI and surface geophysical datasets (collected prior to planting), provided good information about soil drainage and propensity for vigorous vegetation growth over space and time;
- Although the GPR dataset provided a more unique signature of soil moisture variation than did the surface EM

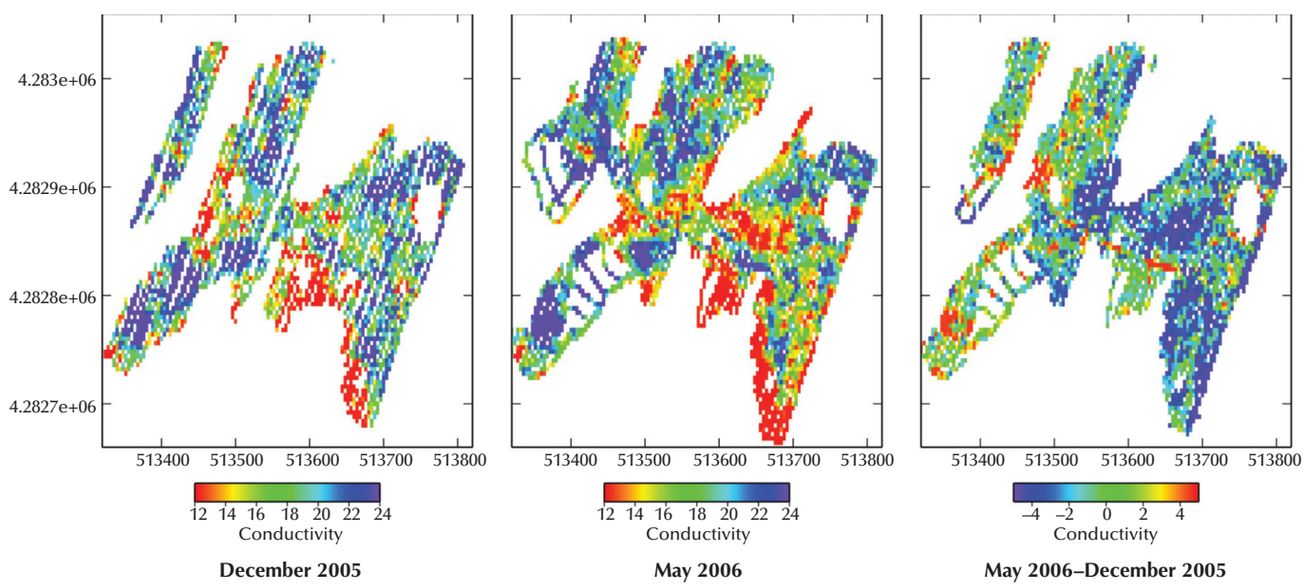

Figure 5: Electrical conductivity measurements obtained over the field site during two different seasons (left and middle), and difference between those datasets (right).

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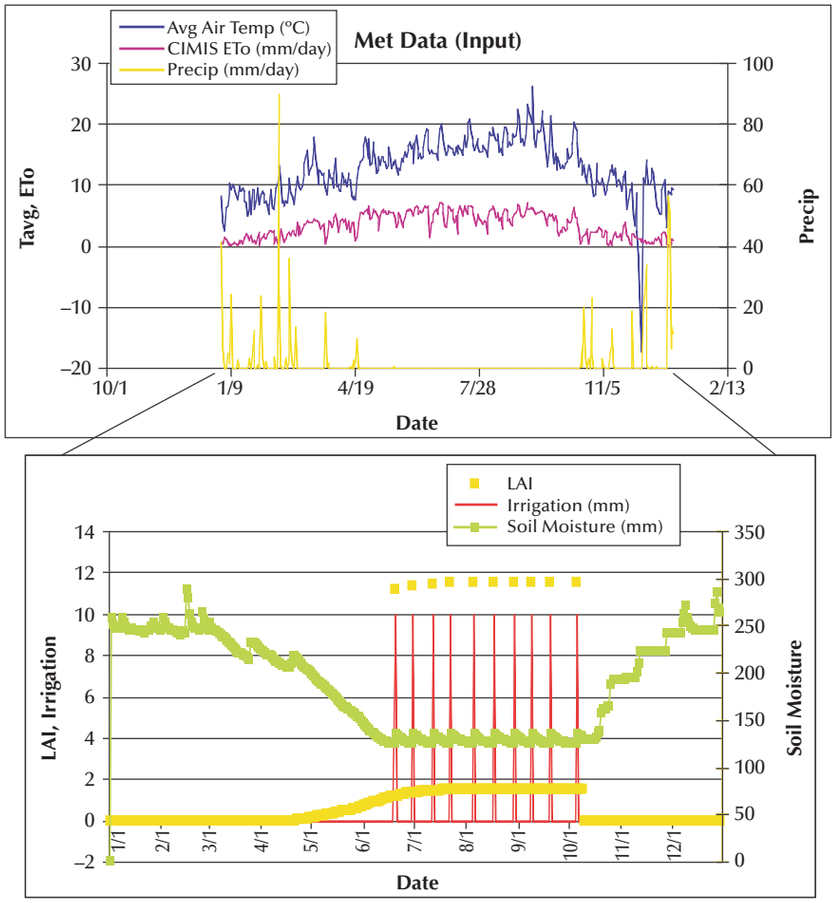

Figure 6: Example of an irrigation schedule obtained using CIMIS and block-specific parameters within a simple water balance numerical model.

dataset, the surface EM geophysical datasets were easier to collect and process than surface GPR datasets and thus offered more a more cost-effective characterization approach.

CPT datasets were useful for delineating the distribution of a resistive layer that prohibited root growth, but provided only marginally useful information about other soil properties that influence drainage. Neutron probe data, combined with surface geophysical datasets, were most useful for understanding spatial and temporal soil water dynamics.

Although we focus here on developing vineyard blocks that should lead to uniform within-block vegetation, we anticipate that zonal-based vineyard development and management strategies should also lead to more uniform winegrape characteristics that reflect natural site conditions. However, because the vineyard is still in the planing stage, we leave assessment of the impact of advanced characterization on fruit quality for future studies.

We recognize it would be impractical to undertake the effort described here in the development of many vineyards. However, we provide a reasonable strategy for using multiple datasets and simple analysis approaches, which we feel renders vineyard characterization effort quite useful.

As available land and water resources continue to decrease, as advanced datasets become less costly to collect and interpret, and as the public demand for high-quality wine increases, we anticipate that strategies and datasets such as the one presented herein will become cost-effective for wineries targeting balanced vineyards and high-quality winegrapes. ■

Additional Information

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