Remote sensing of vineyard FPAR, with implications for irrigation scheduling

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Abstract

Normalized difference vegetation index (NDVI) data, acquired at two-meter resolution by an airborne ADAR System 5500, were compared with fraction of photosynthetically active radiation (FPAR) absorbed by commercial vineyards in Napa Valley, California. An empirical line correction was used to transform image digital counts to surface reflectance. "Apparent" NDVI (generated from digital counts) and "corrected" NDVI (from reflectance) were both strongly related to FPAR of range 0.14-0.50 (both $r^2 = 0.97$, $P < 0.01$). By suppressing noise, corrected NDVI should form a more spatially and temporally stable relationship with FPAR, reducing the need for repeated field support. Study results suggest the possibility of using optical remote sensing to monitor the transpiration crop coefficient, thus providing an enhanced spatial resolution component to crop water budget calculations and irrigation management.

Keywords: Grape, vineyard, FPAR, ADAR, NDVI, transpiration, irrigation

1. Introduction

Premium wine production is an intricate fusion of viticulture and enology. The viticultural aspect is becoming increasingly knowledge-based as viticulturists seek to maximize the potential of their lands, and enologists seek to optimize fruit sampling strategies with regard to vineyard variability. California winegrapes are a high-value, irrigated crop, and investments that boost fruit quality or yield can provide substantial economic returns.

One such technology development involves multispectral remote sensing. Remotely sensed NDVI imagery has been used in commercial settings to map *relative* variations in vineyard vigor, enact sampling strategies, establish management zones, and conduct harvest (Johnson et al., 2001; Hall et al., 2002). More recently, NDVI has been related to various *absolute* measures of vineyard leaf area (Dobrowski et al., 2002; Johnson et al., 2003a) that are of agronomic relevance and can provide a basis for multitemporal monitoring (Johnson, 2003b).

As a consequence of sensitivity to canopy size, the NDVI also tends to be related to canopy FPAR (Asrar et al., 1984; Myneni and Williams, 1994). Related research has shown that FPAR, measured as the percent of land surface shaded by a canopy near solar noon, is related to the transpiration crop coefficient in grape (Peacock et al., 1987;

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Williams, 2001; Prichard et al., 2003) and other row crops (Grattan et al., 1998). The crop coefficient (K_c) is the ratio of actual to potential evapotranspriation (Doorenbos and Pruitt, 1977), and can be used to track water budget for operational irrigation management (Goldhamer and Snyder, 1989; Hatfield and Fuchs, 1990). A theoretical basis for linkage between spectral vegetation indices and K_c has been established (Choudhury et al., 1994) and demonstrated empirically in agricultural settings with *in-situ* radiometers (Heilman et al., 1982; Bausch and Neale, 1987)

In vineyards, water balance affects ripening rate (Winkler, 1958), fruit yield and composition (Smart, 1985; Williams and Matthews, 1990), and susceptibility to infestation and disease (English et al., 1989). Water deficits have neutral to negative impact on yield but, if strategically imposed by deficit irrigation, can be used for grape quality enhancement, canopy regulation and water conservation (Goodwin, 1995; Williams, 2001; Prichard et al., 2003). Accurate water budget characterization is perhaps especially crucial under deficit irrigation, as excessive stress can diminish or destroy fruit quality.

Crop water use estimation, as supplied by remote sensing, might then support the formulation of effective irrigation management decisions. Optical remote sensing and *in-situ* spectral studies have shown positive results for FPAR estimation in relatively continuous canopy annuals. This study extends these prior results to the discontinuous canopy, perennial vineyard setting. Supporting ground measurements were made by a simple and quick ground-based canopy evaluation method as currently recommended to growers by agricultural extension agents.

2. Methods

2.1 *Study area*

Five relatively small commercial vineyard fields were examined. All were situated in close proximity on a 1.5 ha parcel, within the 400 ha To-Kalon vineyard property (Robert Mondavi Winery, Inc.). To-Kalon is located in California's Napa Valley at 38°26'N latitude, 122°24'W longitude. All vines in this study were *Vitis vinifera* L. (cultivar Cabernet Sauvignon). The study fields were planted in 1989 with NE-SW row orientation. Additional details are provided in table 1.

2.2 *FPAR estimation*

The procedure described here offers a practical means of measuring instantaneous PAR interception. This measurement, absent consideration of photon scatter, serves as a first approximation of FPAR.

A steel tape was used to measure the width of the shade zone, perpendicular to the row direction, at ten random locations along one 50 m transect per field (after Grattan et al., 1998). A consumer-grade, three megapixel digital camera was immediately used to capture a nadir-view photograph of a 46x46 cm white board placed within the shade zone at three random locations per transect (figure 1). To avoid observer bias, one investigator performed all of the tape measurements, while another performed the photography. All

observations were made under clear sky near solar noon on 18-July-2003. All measurements were taken under nearly constant solar elevation (72.3-72.6°).

The photographs were post-processed with Photoshop software (Adobe Systems, Inc.) to estimate and correct for sunflecks within the shade zone. A threshold brightness level was applied to force darker areas (shade) to black, and brighter areas (sunflecks) to white. A histogram was then used to derive sunfleck proportion per photograph.

Estimates of FPAR were then obtained per field as:

$$\text{FPAR} = z / r * (1 - s), \qquad (1)$$

where z was mean shade zone width, r was between-row spacing, and s was mean sunfleck proportion.

2.3 *Multispectral image collection*

A multispectral image of the study area was acquired under clear sky near solar noon on 8-August-2003 with a commercial ADAR System 5500 (Positive Systems, Inc.). The system included four approximately boresighted Kodak DCS 420 monochrome cameras, respectively fitted with blue, green, red, and NIR filters. Gains were set by shutter speed, which can be independently modified on each spectral band based upon brightness histogram output from the corresponding camera. The spectral bands were precisely co-registered by routine pre-processing conducted by the image provider. Aircraft flight altitude was ca. 4000 m above ground level, yielding nominal 2 m spatial resolution. Data from the blue and green channels were not used in this study.

2.4 *Image calibration*

A GER Model 1500 field spectroradiometer (Spectra Vista Corp.) was used to develop an empirical basis for conversion of raw image digital counts to surface reflectance (after Schott et al., 1988; Stow et al., 1996). Spectroradiometer data, normalized to a 46x46 cm Spectralon™ reference panel (Labsphere, Inc.), were used to measure reflectance of spectrally flat ground targets of varying brightness located within the ADAR scene. These targets included an unlined asphalt road, a gravel parking lot, and two concrete surfaces. All targets were large relative to the ADAR pixel size. Reflectance was derived as the mean of ten or more GER measurements taken at different locations within each target. Corresponding panel measurements were taken within five minutes of any target reading. Mean reflectance of the various targets ranged from 8.9-56.2% in red, and 10.5-59.5% in the NIR. A reservoir provided an additional, dark target, with assumed brightness of 2% in red and zero percent in NIR (after Lillesand and Kiefer, 1994). The data were taken under clear sky near solar noon on 26-August-2003.

Mean ADAR red and NIR digital counts corresponding to each target were calculated from nine "pure" pixels (*i.e.,* containing spectral contribution only from within the target of interest), arranged as a 3x3 box in the target center. The black asphalt road was too narrow to support such a scheme without introduction of "mixed" pixels (contaminated by spectral contributions from areas external to the target). Thus, for this case, pure pixels were extracted in essentially linear fashion from along the road center.

2.5 *Image data extraction*

Mean red and NIR digital counts were calculated for each study field using the area-of-interest tool in the Imagine software package (ERDAS, Inc.). In specifying the area of interest for these calculations, care was taken to avoid pixels located near any of the study field boundaries. "Apparent" NDVI was calculated from the digital counts. For additional reference, digital counts were extracted and apparent NDVI calculated for bare soil adjacent to the study fields.

3. Results and discussion

Measurement means from the field procedure are summarized in table 2. Study field FPAR ranged from 0.14-0.50. These values are believed to approach the full range of canopy development that is encountered in mature (fruit-producing) California coastal vineyards under typical management practice.

Strong linear relationships were observed between target percent reflectance (R) and digital count (DC) in the red and NIR channels (both $r^2 > 0.99$). The red channel was set to higher instrument gain (Δ DC / Δ R) than the NIR, to compensate for the relative darkness of vegetation in the red spectral region. As a result, red channel response was saturated on the brightest target (56.2%). Red calibration thus involved four targets, and NIR five. Reflectance was related to digital count as:

$$R_{red} = 0.1621 * DC_{red} - 2.6648, \text{ and} \quad (2)$$
$$R_{NIR} = 0.3547 * DC_{NIR} - 9.2643 \quad (3)$$

Equations (2,3) were used to convert mean digital counts from each field to reflectance, and subsequently to "corrected" NDVI.

Apparent and corrected NDVI were both strongly related to FPAR within the study fields (both $r^2 = 0.97$, $P < 0.01$) (figure 2). The regression lines were of similar slope and differed primarily in y-intercept, which in both cases approximated bare soil NDVI. Both NDVI forms should then be equally useful for discriminating relative FPAR differences within a given scene, or mapping absolute FPAR in the event that field data are taken as in this study. The extra effort involved in data calibration provides resistance to noise introduced by such factors as instrument gain setting(s), atmospheric loading, and sun-view angle, therefore possibly alleviating the need for repeated fieldwork. Corrected NDVI should thus form a more spatially and temporally stable relationship with FPAR, as compared to apparent NDVI.

Despite the relatively high degree of pixel heterogeneity ("clumpiness") caused by vineyard row structure and foliage training, the corrected NDVI-FPAR relationship found here was similar to relationships observed in wheat (Asrar et al., 1984), corn/soybeans (Daughtry et al., 1992), and cotton (Pinter et al., 1994). This finding is consistent with a theoretically based prediction of Myneni and Williams (1994), who proposed that the NDVI-FPAR relationship is independent of clump factor.

Published crop coefficients are generally expressed for a particular crop as a crude function of time from planting date or budbreak (e.g., Doorenboos, 1977; Goldhamer and

Snyder, 1989). This simplification is convenient and useful for many irrigation scheduling needs. However, as an idealized canopy is assumed and time periods are fairly broad, the coefficients may misrepresent actual conditions due to effects of site favorability, crop management practice, and subtleties of phenological development (Grattan et al., 1998; Pinter et al., 2003). Thus, there is motivation to derive crop coefficients from biophysical observations of the crop at hand.

For larger farms, or those with highly variable growing conditions, it may be impractical to collect sufficient point-based field data to support operational irrigation scheduling needs. Insofar as spectral vegetation indices respond to canopy size expressed terms of leaf area index or FPAR, remote sensing could potentially be used to map crop coefficients. The result might be an improved accounting for within-field variability and deviations from idealized, average conditions. Viticulturists are making increased use of commercial NDVI-based products for various aspects of decision support (e.g., Penn, 1999), and the improved ability to extract water budget information would add value to this existing agribusiness investment. For instance, a process model can be used to predict crop water balance on a daily basis by integrating imagery with weather and soil texture data (Johnson et al., 2003c).

4. Conclusion

Optical remotely sensed data are becoming increasingly available worldwide for support of agricultural planning and operation. This study and others have shown the feasibility of evaluating a key agronomic variable, FPAR, by a simple vegetation index approach. In turn, FPAR is related to crop water demand through K_c. It is notable that water budget calculations involving K_c apply to well watered canopies. Under stress conditions such as imposed by deficit irrigation, computations must be corrected for the effect of stomatal regulation (Allen et al., 1998). Additional remote sensing study is recommended to explore the relationship of spectral vegetation indices directly with K_c, and hence the potential for improved water-budget based irrigation scheduling in grape and other high-value crops.

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Table 1. Study field characteristics. Fields are listed by ascending FPAR as per table 2. All fields are *Vitis vinifera* L. (cultivar Cabernet Sauvignon), planted in 1989 along NE-SW rows.

Field	Clone	Rootstock	Trellis[a]	Within-row spacing (m)	Between-row spacing (m)	Plot size (ha)
a	04	5C	VSP	1.5	2.7	0.20
b	07	110R	VSP	1.5	2.7	0.28
c	06	110R	VSP	1.5	2.7	0.16
d	07	110R	VSP	1.0	1.0	0.13
e	07	110R	S	1.5	2.7	0.12

[a] VSP = vertically shoot positioned; S = split canopy

Table 2. Mean data from FPAR estimation procedure.

Field	Shade zone width (m)	Sunfleck proportion	FPAR
a	0.44	0.10	0.14
b	0.62	0.07	0.25
c	0.69	0.08	0.26
d	0.34	0.09	0.32
e	1.55	0.12	0.50

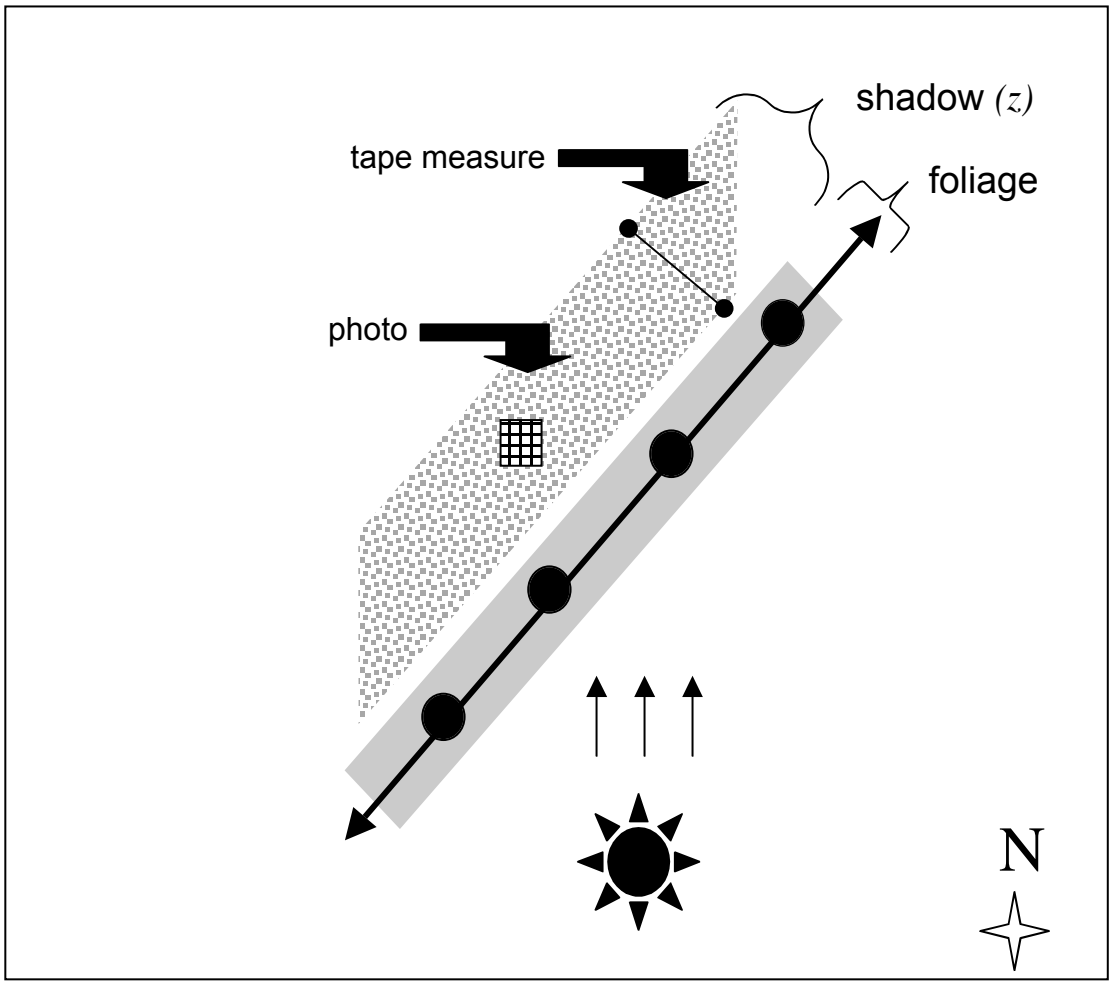

Fig 1. Top view schematic of measurement transect used for FPAR estimation within each study field. Ten measurements of shadow width (*z*) were made with a steel tape, and three digital photographs were taken of a white board, at random locations along each transect.

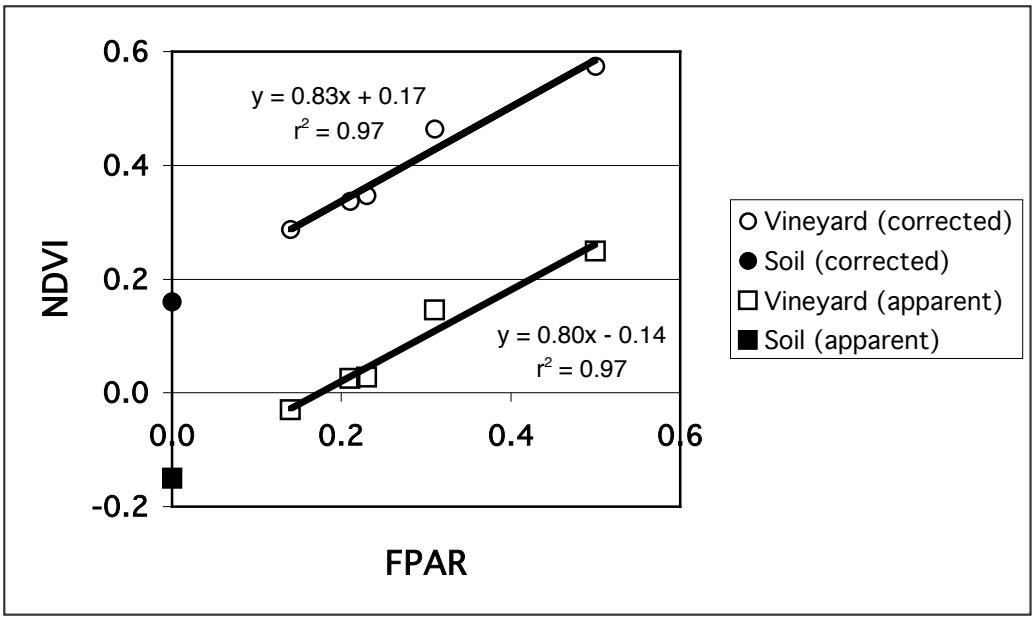

Fig 2. Relationship between FPAR and NDVI (both unitless) for five study fields. Upper data grouping - "corrected" NDVI from reflectance-calibrated digital counts. Lower grouping - "apparent" NDVI generated from raw digital counts. Soil NDVI shown in each case for reference, excluded from regression computations.