2009

Comparison of passive and active canopy sensors for the estimation of vine biomass production

Stamatis Stamatiadis
Goulandris Natural History Museum, stam@gnhm.gr

Dimitris Taskos
Goumenissa Winery

Eleftheria Tsadila
Goulandris Natural History Museum

Calliopi Christofides
Goulandris Natural History Museum

Christos Tsadilas
Institute of Soil Classification and Mapping

See next page for additional authors

Authors
Stamatis Stamatiadis, Dimitris Taskos, Eleftheria Tsadila, Calliopi Christofides, Christos Tsadilas, and James S. Schepers

Precision Agric
DOI 10.1007/s11119-009-9131-3

Comparison of passive and active canopy sensors for the estimation of vine biomass production

Stamatis Stamatiadis · Dimitris Taskos · Eleftheria Tsadila · Calliopi Christofides · Christos Tsadilas · James S. Schepers

Abstract Recent advances in optical designs and electronic circuits have allowed the transition from passive to active proximal sensors. Instead of relying on the reflectance of natural sunlight, the active sensors measure the reflectance of modulated light from the crop and so they can operate under all lighting conditions. This study compared the potential of active and passive canopy sensors for predicting biomass production in 25–32 randomly selected positions of a Merlot vineyard. Both sensors provided estimates of the normalized difference vegetation index (NDVI) from a nadir view of the canopy at veraison that were good predictors of pruning weight. Although the red NDVI of the passive sensors explained more of the variation in biomass ($R^2 = 0.82$), its relationship to pruning weight was nonlinear and was best described by a quadratic regression ($\text{NDVI} = 0.55 + 0.50\ \text{wt} - 0.21\ \text{wt}^2$). The theoretically greater linearity of the amber NDVI-biomass relationship could not be verified under conditions of high biomass. The linear correlation to stable isotope content in leaves (^{13}C and ^{15}N) provided evidence that canopy reflectance detected plant stresses as a result of water shortage and limited fertilizer N uptake. Thus, the canopy reflectance data provided by these mobile sensors can be used to improve site-specific management practices of vineyards.

Keywords Ground sensors · NDVI · Stable isotopes · Leaf $\delta^{13}C$ · Leaf $\delta^{15}N$ · Leaf nitrogen

S. Stamatiadis (✉) · E. Tsadila · C. Christofides
Soil Ecology and Biotechnology Laboratory, Gaia Environmental Research and Education Center, Goulandris Natural History Museum, 13 Levidou Street, 14562 Kifissia, Greece
e-mail: stam@gnhm.gr

D. Taskos
Boutari S.A., Goumenissa Winery, 61300 Goumenissa, Greece

C. Tsadilas
National Agricultural Research Foundation, Institute of Soil Classification and Mapping, 1 Theophrastou Street, 41335 Larissa, Greece

J. S. Schepers
USDA-ARS, University of Nebraska, 120 Keim Hall, Lincoln, NE 68583-0915, USA

Published online: 23 August 2009

Introduction

Information about spatial variation and the timeliness of data acquisition are key to helping producers make management decisions that have the potential to increase profitability. Advanced electronics and optics for measuring reflectance and computer technologies for recording, storing and processing large amounts of temporal and spatial data often move into production agriculture and speciality crops from military and sophisticated engineering applications. Vineyard management is one such application because management decisions are readily linked to the quantity and quality of the wine produced. Recent studies with optical remote sensing have demonstrated the relationship between canopy reflectance and biomass production in vineyards (Dobrowski et al. 2003; Johnson 2003; Johnson et al. 2003). This relationship was obtained despite peculiarities in vine growth patterns such as discontinuous canopies, low ground cover, understory foliage and differing trellis systems. Long-range canopy reflectance data are typically derived from aircraft or satellite images in the visible near infrared (NIR) regions of the spectrum and are transformed subsequently into vegetation indices, such as the normalized difference vegetation index (NDVI). Since NDVI is related to plant canopy leaf area index (LAI) and the amount of photosynthetically active radiation absorbed by the canopy, maps of NDVI can be used to interpret spatial patterns of pest and disease infestation, water status, fruit characteristics and wine quality (Johnson et al. 2003). Specific interpretation of the reflectance features and patterns requires ground-truthing to account for the spatial distribution of plant and soil properties.

Mobile proximal sensors are an emerging technology designed to overcome many of the limitations associated with satellite- or aircraft-based remote sensing systems (Bausch and Delgado 2003). Although airborne platforms have the advantage of delivering spectral information rapidly over relatively large areas of the landscape, this information might not be available in time to implement critical management decisions. This is because the availability of airborne sensor data is constrained by weather conditions, the frequency of revisiting the site and elaborate data processing. These problems are further complicated by peculiarities in vine canopy architecture, such as inter-row soil and shadow interference that require additional processing steps to produce realistic maps of spectral reflectance. Proximal sensors overcome issues with timeliness and the need for image processing, but time of day and cloud cover can still be problematic for ground-based passive sensors. Passive sensors detect the canopy radiance (reflected radiation) of natural sunlight with a down-facing sensor. Canopy reflectance is electronically calibrated by monitoring the irradiance (incoming radiation) with an up-facing sensor. In this way, passive sensors effectively eliminate issues with differential and changing cloud cover, but do not address the problem of shadows. A recent study demonstrated the value of passive proximal sensors for predicting the spatial variation of biomass production in a Merlot vineyard with measurements taken at midday over clear skies (Stamatiadis et al. 2006).

Recently commercialized active ground-based sensors eliminate the need for frequent calibration and overcome the problems of cloud cover and limitations of the time of day when measurements are made (i.e. natural illumination and shadows). This is achieved by generating modulated (pulsed) light from an auxiliary light source so that the active sensors can operate equally well under all lighting conditions. The polychromatic bank of light emitting diodes (LEDs) used in the Crop Circle ACS-210 (Holland Scientific, Lincoln, NE) sensor emits light in two wavebands, visible (595 nm) and NIR (880 nm). Natural light is not modulated, so with sophisticated electronics the detection circuitry of the sensor is able to differentiate between the radiance (reflectance) generated by natural and modulated light. The close proximity of active sensors to the vine canopy greatly reduces or eliminates interference from soil reflectance because the light source can be directed towards the desired part of the canopy. It is important to note that the sensing capability of active sensors decreases with distance between the light source and target. For example, the intensity of reflectance for a given target will be four times greater at a 1 m distance than at 2 m. Therefore, the influence of soil background can be minimized if the target is closer than the soil or by directing the sensor strategically towards the target (i.e. non-nadir). When coupled to a differential GPS, these ground sensors can provide data of high spatial resolution (10 readings per second adjusted for movement of the sensor footprint) that can be integrated with fertilizer applicators and sprayers to facilitate real-time applications (Holland et al. 2006). This study compared the potential of active and passive canopy sensors for predicting the spatial variation of biomass production in a Merlot vineyard in northern Greece. The vineyard displayed sufficient spatial heterogeneity in terms of topography and growth patterns to facilitate a comparison between the sensors.

Materials and methods

Site description

This study was undertaken in a commercial Merlot vineyard block (0.5 ha) in the municipality of Goumenisa (northern Greece) during the summers of 2003, 2004, 2005 and 2006. Vines were trained on a bilateral cordon with two fixed pairs of foliage wires and were spur-pruned. Vine spacing was 2.2 m between rows and 1.3 m within rows. The field has a soil with coarse texture and an 11% inclination with associated erosion problems. Shoot growth ceased before the stage of color change of grapes (veraison) during all growing seasons. A single topping took place in the last week of June. The soil was surface-tilled for weed removal.

Fertilizer was applied before the growing season in February or March. As a common practice by the local producers, the field received 31.5 kg N ha^{-1}, 75 kg K ha^{-1} and 25 kg Mg ha^{-1} in the form of ammonium sulfate and K–Mg sulfate every year except for 2004. In 2004 the rates of N and K application were increased by 50% at the eroded top of the field and P was also added in an attempt to increase vine productivity. The mean vine size of the upland positions was small ($\sim$60% of those at the foot of the slope), which appeared to be caused by a shallow soil and limited root depth (0–30 cm) resulting from a deep calcic horizon (30–100 cm depth). Other management practices that were applied uniformly in the field included drip irrigation and products to protect the plants, such as $CuSO_4$, S and organic fungicides.

Field sampling and analysis

Thirty-two sampling sites were selected randomly in 2003 to represent the entire field and each location consisted of four consecutive vines along the rows (Fig. 1). The number of sampling locations was reduced in the following 3 years of the experiment (2004–2006) by retaining the first 25 only. Leaf samples (20–25 leaves) were taken at random from the basal shoot nodes at each sampling location at veraison (August). All bunches and canes from the same sampling locations were collected and weighed in September and December, respectively. The biomass units were expressed in kg plant^{-1} by dividing the total wet weight with the number of plants (4) at each location.

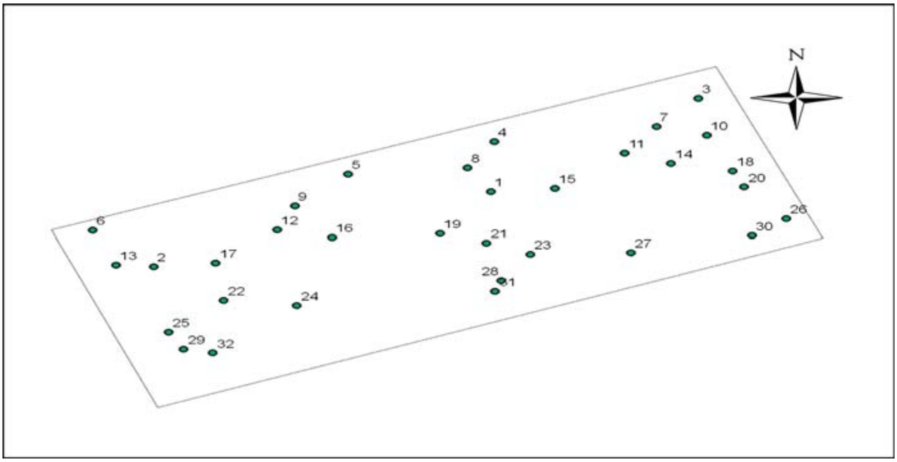

Fig. 1 Spatial distribution of the 32 sampling locations within the vineyard in 2003

Leaf samples were dried at 65°C and ground to a fine powder in the laboratory. Total nitrogen and carbon content, and isotope composition (δ^{15}N, δ^{13}C) of the leaf samples were measured by an automated combustion elemental analyzer interfaced with a continuous-flow isotope ratio mass spectrometer (PDZ Europa). Samples were prepared as described by Schepers et al. (1989) and 2.8 ± 0.1 mg of each was used for the analysis. The isotopic signature of the leaves provided information on plant stress relative to water shortage (δ^{13}C) and fertilizer N uptake (δ^{15}N).

Multi-spectral readings of the vine canopy were taken along the rows and at the sampling locations in the field at veraison (August). Multi-spectral Crop Circle passive sensors were calibrated to measure absolute reflectance to a Spectralon panel (~99.9% reflectance) before being mounted at the front of a tractor (Fig. 2). The vehicle travelled forward at a constant speed of 3.5 km h^{-1} at midday under clear skies and measured reflectance was integrated over intervals of 250 ms at four wavelengths (blue at 460 ± 10 nm, green at 550 ± 10 nm, red at 680 ± 10 nm and NIR at 800 ± 65 nm). One passive sensor viewed the top of the vine canopy from a near-vertical position (Fig. 2) and from a distance of ~0.5 m through a mask over the optics that reduced the view area to 0.25 m diameter. Canopy reflectance measurements for the vertical view area were compared to unmasked measurements with an oblique side view of the canopy (~30° off-nadir) from the same distance (Fig. 2). A third up-facing sensor was electronically coupled with the down-facing sensors to compensate for changes in irradiance. In a similar manner, a differential GPS (AG114 Trimble) was coupled to provide coordinates for the sensor readings with a precision of ± 50 cm (Fig. 2). The same procedure was repeated with an active ACS-210 Crop Circle sensor from the same distance and viewing angles at two wavelengths (amber at 595 ± 10 nm and NIR at 880 ± 65 nm) in 2005 and 2006. Active sensors measure relative reflectance by calibrating reflectance of modulated light to a grey standard. Both passive and active sensors can detect radiance from soil or adjoining rows, but the portion of signal attributed to objects further away from the target is small because reflectance follows the inverse square of the distance rule. In the case of the amber version of the ACS-210 sensor, data generated by reflectance from turf followed the inverse square of the distance rule, but the normalized difference vegetation index (NDVI) was constant beyond 40 cm (Fig. 3). The effect of distance between the passive sensor and the target on

Fig. 2 Configuration of the mobile system with two down-facing passive sensors (near-vertical and oblique viewing angles) coupled with an up-facing sensor and a differential GPS

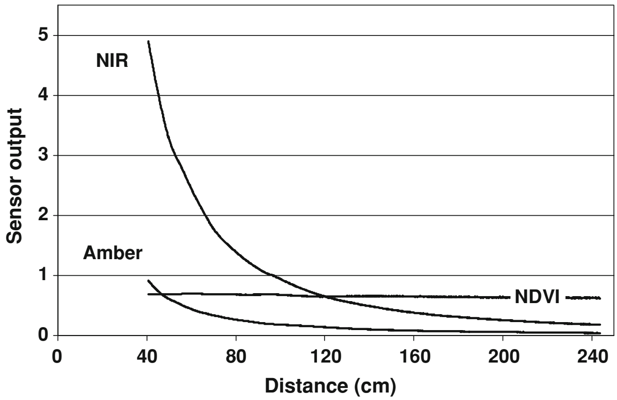

Fig. 3 Influence of distance between the Crop Circle ACS-210 sensor and turf on NIR and amber reflectance and calculated NDVI ($n = 1774$ readings)

reflectance is unknown because a mask was placed over the sensor to collimate the reflected light and define the footprint. The data were recorded in a portable PC inside the vehicle. The NDVI was computed as:

$$\mathrm{NDVI} = [\mathrm{NIR} - \mathrm{red}]/[\mathrm{NIR} + \mathrm{red}] \text{ for the passive sensor.} \quad (1)$$

$$\mathrm{NDVI} = [\mathrm{NIR} - \mathrm{amber}]/[\mathrm{NIR} + \mathrm{amber}] \text{ for the active sensor.} \quad (2)$$

For direct comparison of spectral reflectance, NDVI was further standardized by the mean of each sensor for each year as follows:

$$\mathrm{NDVI}_{\mathrm{norm}} = [\mathrm{NDVI}_{\mathrm{i}} - \mathrm{NDVI}_{\mathrm{mean}}]/\mathrm{NDVI}_{\mathrm{mean}}. \quad (3)$$

Data analyses included the analysis of variance (general linear models) and correlation analysis. In the analysis of variance, the least significant difference (LSD) test was used to detect differences between year means at $p < 0.05$. Data analysis was done using Statistical Analysis System software, version 6 (SAS Institute 1990).

Results and discussion

All measured vine properties show significant year-to-year variability except for leaf $\delta^{13}C$ (Table 1). Pruning weight, as an indicator of annual biomass production, was largest in 2004 and this was probably the result of increased fertilizer application early in that year. Annual variation in bunch weight followed a different pattern; it was largest in 2006. Leaf C content was less in the years of greater biomass production, but the C:N ratio was inversely related to leaf N content (Table 1). The low $\delta^{15}N$ signal in 2004 indicated increased fertilizer uptake and coincided with the increased fertilizer application and biomass production of that year.

Sensor NDVI values at veraison are linearly correlated to several vine properties for single years (Table 2). The NDVI is known to be related to plant canopy leaf area index

Table 1 Annual variability of vine properties

Year	Productivity at harvest		Leaf composition at veraison				
	Pruning wt. (kg plant^{-1})	Bunch wt. (kg plant^{-1})	C (%)	N (%)	C:N	$\delta^{15}N$ (‰)	$\delta^{13}C$ (‰)
2003	0.72 c†	2.88 c	46.9 a	2.70 a	17.5 d	4.86 a	−25.89
2004	0.96 a		45.3 b	2.23 bc	20.6 b	2.73 c	−26.03
2005	0.69 c	4.37 b	47.6 a	2.15 c	22.3 a	3.48 b	−26.01
2006	0.81 b	5.72 a	43.7 c	2.28 b	19.3 c	3.14 b	−26.05

† Within columns, means followed by different letters are significantly different whereas those with the same letter are not according to LSD ($p < 0.05$)

Table 2 Pearson correlation coefficients (r) between vine properties and canopy NDVI at veraison

Sensor type	Year	Viewing angle	n	Productivity at harvest		Leaf composition at veraison		
				Pruning wt. kg plant^{-1})	Bunch wt. (kg plant^{-1})	N (%)	$\delta^{15}N$ (‰)	$\delta^{13}C$ (‰)
Passive	2003	Nadir	25–31	**0.88**	0.47	(−0.10)	**−0.84**	*−0.68*
		Off-nadir	25–31	**0.91**	0.49	(−0.08)	**−0.81**	**−0.74**
	2004	Nadir	25	**0.80**	–	(0.34)	−0.47	−0.50
		Off-nadir	25	*0.64*	–	0.44	(−0.02)	−0.46
Active	2005	Nadir	22	**0.77**	(0.41)	(−0.12)	−0.50	−0.58
		Off-nadir	24	0.56	(0.28)	(0.23)	−0.45	−0.43
	2006	Nadir	18–19	0.65	(−0.24)	(−0.01)	−0.57	(−0.45)
		Off-nadir	20–21	0.59	(−0.15)	(−0.24)	−0.64	(−0.38)

Non-significant correlations in parentheses

Significant correlation coefficients at $p < 0.05$ in roman

Significant correlation coefficients at $p < 0.001$ in italics

Significant correlation coefficients at $p < 0.0001$ in bold

– Missing data

(LAI) and amount of photosynthetically active radiation absorbed by the canopy (Johnson et al. 2003). Hall et al. (2008) found that grapevine NDVI derived from multispectral airborne images was related to planimetric canopy area, rather than LAI, in a minimally pruned and unconfined vineyard of Cabernet Sauvignon in South Wales (Australia). This relationship is yet to be demonstrated in trellis-trained and trimmed vineyards with smaller variations in canopy area. Whether the primary predictive variable is LAI or canopy area, spectral reflectance measured using airborne platforms has been correlated to vine biomass in Californian and Australian red wine vineyards (Lamb 2004; Johnson 2003; Dobrowski et al. 2003). Our data agree with these studies in that pruning weight has the largest correlation coefficients with NDVI independent of sensor type and viewing angle (Table 2). These correlations were obtained despite the fact that a single topping before veraison reduced differences in leaf area between the sampling positions. By comparison to the off-nadir view, the nadir view of the canopy produced NDVI values that have larger linear correlations to pruning weight with the exception of 2003 (Table 2). In contrast, the correlation between NDVI and bunch weight was significant only in the first year of the experiment.

The correlation between sensor NDVI and leaf stable isotopes is inverse and significant for almost all years (Table 2). Smaller canopy NDVI values coincide with larger leaf δ^{15}N values for the low-biomass plants in the eroded upland positions of the field. Larger δ^{15}N values indicate reduced fertilizer uptake or increased uptake of soil-derived N assuming that the isotopic signal of fertilizer N was distinctly less than that of soil-derived nitrates (Shearer and Legg 1975; Bort et al. 1998). Similarly, the larger δ^{13}C values in the upland positions are probably a sign of water stress and, consequently, reduced growth. This is because leaf δ^{13}C is a long-term indicator of water use efficiency (Farquhar et al. 1989; O'Leary 1993). Strong negative correlations were also obtained between these stable isotopes and pruning weight in the same vineyard for the first two years of the experiment (Stamatiadis et al. 2007).

Contrary to the correlations with stable isotopes, nadir canopy NDVI is not significantly correlated to leaf N content in any single year (Table 2). Schepers et al. (1996) raised concerns about the reliability of using reflectance measurements from water-stressed corn to characterize crop N status in a greenhouse experiment of variable N and water regimes. It is likely that this was also the case in this vineyard where water stress was evident from the significant correlations between leaf δ^{13}C and pruning weight.

Although the linear correlations of Table 2 are presented for comparison, the NDVI-biomass relationship is nonlinear for other crops when derived from satellite images (Gitelson et al. 2002; 2003). Indeed, the relationship between pruning weight and NDVI of both sensors is described best by a quadratic regression for nadir-view data recorded over two growing seasons (Fig. 4a, open circles). In this experiment, the passive sensors used red reflectance to calculate NDVI. Under field conditions with even modest amounts of vegetation, red reflectance approaches zero and typically reaches 2–3% with a full canopy. This situation corresponds to a LAI of $\sim$2.0 and causes vegetation indices, such as NDVI, to approach a plateau because they are controlled by NIR reflectance (amount of living biomass) at that point. Amber light is not used efficiently by photosynthesis and therefore its reflectance remains responsive to changes in canopy chlorophyll content to much larger LAI values ($\sim$6.0).

The slope of the relationship between NDVI and pruning weight is similar for the active and passive sensors, but the scattering of values is greater for the active sensor (Fig. 4a). This observation may be related to differences in the shape of the footprint for the passive sensor (25 cm diameter, 491 cm^2) and the active sensor (10 $\times$ 50 cm, 500 cm^2) although

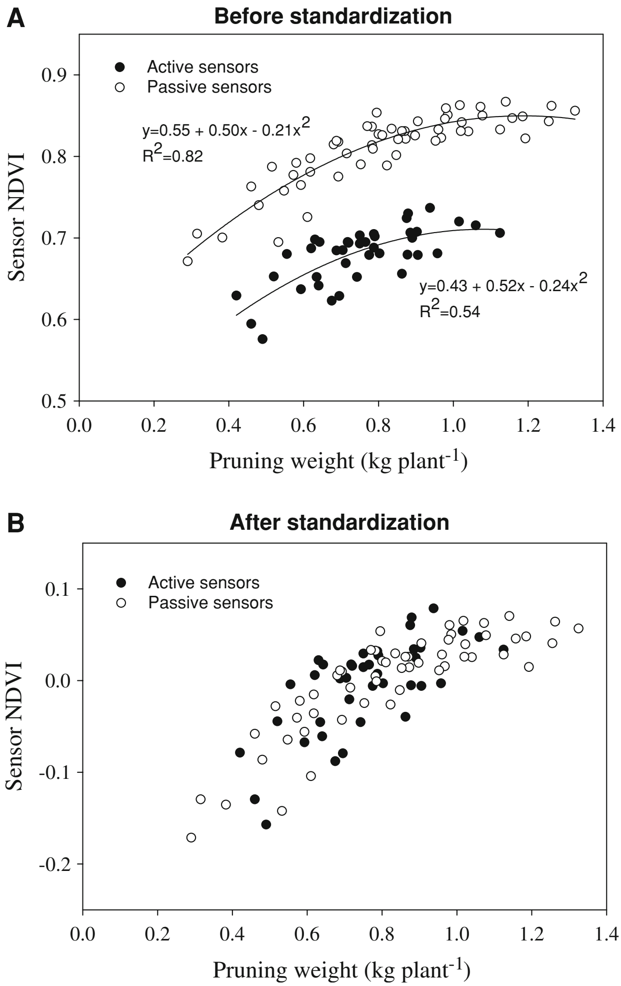

Fig. 4 Comparison of passive and active sensor NDVI (nadir view) with pruning weight before and after standardization

the area monitored by each sensor was similar. Even if the footprints were the same, the active sensor might be expected to be more variable because the output is reported at 10 Hz (every 100 ms representing ~4000 pulses of modulated light) rather than 4 Hz (continuous integration over 250 ms) for the passive sensor. Even though the sensors are operationally different, they both provide multiple recorded values per plot (~21 and 54 readings per plot for the passive and active sensors, respectively) that should represent the vegetative characteristics adequately for each group of four plants. The NDVI values of the active sensor were distinctively smaller than those of the passive sensors for the same pruning weights. This difference was caused by the unique operational characteristics of the active sensor (auxiliary light source, amber waveband). Similar regression slopes resulted after merging the standardized NDVI data from the two sensors to allow a direct comparison of their relationship to pruning weight (Fig. 4b). The quadratic nature of the relationship indicates the saturation effect of red NDVI when the biomass is large. This is a limitation of the passive sensors that does not enable differences to be distinguished in canopy NDVI under conditions of excessive growth (pruning weights >1.3 kg per plant or 1 kg m^{-1} row, Dobrowski et al. 2003). The relationship between active sensor NDVI and pruning weight would be expected to be more linear than that of the passive sensors because the amber reflectance of the active sensor does not tend to saturate (i.e. reach an NDVI plateau) until the LAI is large (Fig. 4b). Gitelson and Merzlyak (1996) demonstrated this phenomenon by comparing the green (slightly curvilinear relationship between LAI and NDVI) and red (near quadratic-plateau) methods of calculating NDVI. The amber version of NDVI would be intermediate to the green and red responses to LAI. More data are needed with the active sensors under conditions of large biomass to confirm this hypothesis.

Since NDVI explained most of the spatial variation in pruning weight, the use of proximal sensors for site-specific management is possible by estimating plant properties and needs in this Merlot vineyard. The reflectance data obtained at veraison may be used to define better management practices for the next growing season, i.e. crop thinning strategies that optimize vegetative and reproductive balance to produce a higher-value product (Dobrowski et al. 2003), provided that grape yield estimates are known. If the nature and strength of the relationship between sensor reflectance and pruning weight holds before veraison, it will be possible to implement real-time spatial management of vineyards within the same growing season. A standardization of the relationship between sensor reflectance and canopy biomass over a range of vine varieties, soil types and wider geographical areas will be necessary before this technology finds wider application in the site-specific management of vineyards. It may also be worth considering the use of vegetation index data to determine where and how much to top the vineyard to improve production and fruit quality. As shown in this study, sensor data clearly quantified leaf biomass which can be used to target soil sampling and remedial treatments.

Conclusion

Canopy NDVI determined with both passive and active sensors at veraison provided reasonable predictions of biomass production. The linear correlation between NDVI and leaf stable isotopes provided evidence that canopy reflectance detected plant stress as a result of water shortage and limited N uptake. The red NDVI-biomass relationship was nonlinear and was described best by a quadratic regression. The theoretically more linear relationship between amber NDVI and biomass could not be verified under high biomass conditions. Nevertheless, the canopy reflectance data provided by these mobile sensors can be used to improve site-specific management practices of vineyards. Much is yet to be learned about how to extend these findings to recently introduced multiband active sensors that might be able to differentiate between water and N stresses. Our results might encourage the knowledge base about the attributes and capabilities of active sensors to be extended to other crops.

Acknowledgments This project was carried out jointly by USDA-ARS and the Gaia Environmental Research and Education Center of the Goulandris Natural History Museum (Specific Cooperative Agreement # 58-4012-0-F169) together with the Institute of Soil Mapping and Classification of the National Agricultural Research Foundation.

References

Bausch, W. C., & Delgado, J. A. (2003). Ground-based sensing of plant nitrogen status in irrigated corn to improve nitrogen management. In T. VanToai et al. (Eds.), *Digital imaging and spectral techniques: Applications to precision agriculture and crop physiology* (pp. 145–157). ASA Special Publication 66. Madison, WI: ASA, CSSA, SSSA.

Bort, J., Araus, J. L., Hazzam, H., Grando, S., & Ceccarelli, S. (1998). Relationships between early vigour, grain yield, leaf structure and stable isotope composition in field grown barley. *Plant Physiology and Biochemistry, 36*, 889–897.

Dobrowski, S. Z., Ustin, S. L., & Wolpert, J. A. (2003). Grapevine dormant pruning weight prediction using remotely sensed data. *Australian Journal of Grape and Wine Research, 9*, 177–182.

Farquhar, G. D., Ehleringer, J. R., & Hubick, K. T. (1989). Carbon isotope discrimination and photosynthesis. *Annual Review of Plant Physiology and Plant Molecular Biology, 40*, 503–537.

Gitelson, A. A., Kaufman, Y. J., Stark, R., & Rundquist, D. C. (2002). Novel algorithms for remote estimation of vegetation fraction. *Remote Sensing of Environment, 80*, 76–87.

Gitelson, A., & Merzlyak, M. N. (1996). Signature analysis of leaf reflectance spectra: Algorithm development for remote sensing of chlorophyll. *Journal of Plant Physiology, 148*, 494–500.

Gitelson, A. A., Vina, A., Arkebauer, T. J., Rundquist, D. C., Keydan, G. P., & Leavitt, B. (2003). Remote estimation of leaf area index and green leaf biomass in maize canopies. *Geophysical Research Letters, 30*, 1248.

Hall, A., Louis, J. P., & Lamb, D. W. (2008). Low-resolution remotely sensed images of winegrape vineyards map spatial variability in planimetric canopy area instead of leaf area index. *Australian Journal of Grape and Wine Research, 14*, 9–17.

Holland, K. H., Schepers, J. S., & Shanahan, J. F. (2006). Configurable multi-spectral active sensor for high-speed plant canopy assessment. In D. J. Mulla (Ed.), *Proceedings of the 8th international conference on precision agriculture (CD)*. Minneapolis, MN: University of Minnesota.

Institute, S. A. S. (1990). *SAS/STAT User's guide, version 6* (4th ed.). Cary, NC, USA: SAS Institute Inc.

Johnson, L. F. (2003). Temporal stability of an NDVI-LAI relationship in a Napa Valley vineyard. *Australian Journal of Grape and Wine Research, 9*, 96–101.

Johnson, L. F., Roczen, D. E., Youkhana, S. K., Nemani, R. R., & Bosch, D. F. (2003). Mapping vineyard leaf area with multispectral satellite imagery. *Computers and Electronics in Agriculture, 38*, 33–44.

Lamb, D. W. (2004). Remote sensing technologies for the grape and wine industry. In S. Stamatiadis & J. S. Schepers (Eds.), *Remote sensing for agriculture and the environment* (pp. 226–236). Larissa, Greece: Peripheral Publications "ella".

O'Leary, M. H. (1993). Biochemical basis of carbon isotope fractionation. In J. R. Ehleringer, A. E. Hall, & J. D. Farquhar (Eds.), *Stable isotopes and plant carbon–water relations* (pp. 19–26). San Diego: Academic Press.

Schepers, J. S., Blackmer, T. M., Wilhelm, W. W., & Resende, M. (1996). Transmittance and reflectance measurements of corn leaves from plants with different nitrogen and water supply. *Journal of Plant Physiology, 148*, 523–529.

Schepers, J. S., Francis, D. D., & Thompson, M. T. (1989). Simultaneous determination of total C, total N, and ^{15}N on soil and plant material. *Communications in Soil Science and Plant Analysis, 20*, 949–959.

Shearer, G. B., & Legg, J. O. (1975). Variations in the natural abundance of ^{15}N of wheat plants in relation to fertilizer nitrogen applications. *Soil Science Society of America, Proceedings, 39*, 896–901.

Stamatiadis, S., Christofides, C., Tsantila, E., Taskos, D., Tsadilas, C., & Schepers, J. S. (2007). Relationship of leaf stable isotopes (δ^{13}C and δ^{15}N) to biomass production in two fertilized Merlot vineyards. *American Journal of Enology and Viticulture, 58*, 67–74.

Stamatiadis, S., Taskos, D., Tsadilas, C., Christofides, C., Tsadila, E., & Schepers, J. S. (2006). Relation of ground-sensor canopy reflectance to biomass production and grape color in two Merlot vineyards. *American Journal of Enology and Viticulture, 5*, 415–422.