Remotely Sensed Determination of Orchard Removal Biomass - Assess Carbon Sequestration Potential of Applying Chipped Almond Prunings to the Orchard Floor

Project No.: **11-STEWCROP4-Kimmelshue**

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Objectives:

The overall objective of this on-going project is to improve the industry understanding of how pruning management and tree removal techniques impact soil carbon stocks, air quality and greenhouse gas emissions. To serve this purpose, the project includes development of various input data sets to incorporate into the DeNitrification-DeComposition (DNDC) model. The DNDC model is a soil biogeochemical model used to estimate greenhouse gas flux from natural systems. The model results were used to quantify how pruning management, tree removal and other factors influence soil C and N cycling, soil C stocks and production of nitrous oxide (N_2O). This work satisfies many of the Areas of Interest within Environmental Stewardship that the Almond Board has defined for 2011/2012. More specifically, this work has achieved the following objectives:

1. Support a larger 2-year CDFA Specialty Crop Block Grant where funding was made available beginning in November of 2010. Some of the resources were used for continued investigation, understanding and ultimate integration of data acquisition for an almond-specific plant physiological model to enhance inputs to the DNDC model.
2. Leverage existing ABC and CDFA funding for calibration and validation of a new version of the DNDC model for almond systems in California.
3. Increase collaboration with Dr. Ted DeJong at UC Davis on model calibration and validation.
4. Improve a spatial database of almond acreage and biomass determinations across the California by incorporating remote sensing techniques.

The remainder of this report focuses on this last specific objective. The incorporation of remote sensing into the project work as a whole is integral to successfully understanding and managing the diversity of almond production systems within the state.

The main purpose of this effort was to determine if almond orchard biomass can be estimated using remote sensing techniques, specifically correlating the amount of biomass hauled (green chip weight) during orchard removal to canopy coverage in remotely sensed imagery. The following objectives were also an initial part of this investigation:

1. Identify imagery sources that are the most suited to analyzing almond orchard characteristics
2. Use remotely sensed imagery to determine orchard age
3. Determine if orchard age is correlated to orchard biomass in remote sensing analysis
4. Explore the statistical relationship between various remotely sensed image texture characteristics and almond orchard biomass
5. Begin to establish a statistically valid method to predict carbon stocks in almond orchards
6. Demonstrate the use of LiDAR in determining variability in orchard height

Interpretive Summary:

Two sources of remotely sensed imagery (available to public at no cost) and the remote sensing analytical technique called object-based identification analysis (OBIA) were used to explore the relationship between measured biomass, orchard age, and vegetative (canopy) cover in 36 almond orchards in California. The orchards were in five counties that produce a major proportion of the California almond crop. Results indicated that green chipped weight measured during orchard removal was correlated to canopy cover as determined using remote sensing analytical techniques. Certain remotely sensed image texture characteristics also correlated well with vegetative cover. Orchard age, determined by remote sensing image analysis, was not a good predictor of orchard biomass. In an additional effort to use remote sensing to acquire information about almond orchards, LiDAR was used to determine orchard height on one orchard to demonstrate the value of the LiDAR image resource.

The significance of these findings is that remote sensing imagery and analytical techniques can be used to estimate almond orchard biomass, as well as other almond orchard characteristics, eliminating the need to acquire costly and time-consuming field data to provide this information over a large extent of almond acreage. This information can be used to improve the spatial database of almond acreage statewide, and provide valuable inputs for the DNDC model to estimate the effects of management practices on carbon flux in orchard soils.

The following accomplishments resulted from this work:

1. Developed relationships with industry and academic personnel who can provide biomass removal data.
2. Developed a method to evaluate vegetative coverage, using remote sensing analytical techniques, in almond orchards and correlate it to biomass.
3. Demonstrated that LiDAR can be used to determine individual tree height determination within almond orchards.
4. Advanced continuing work on identifying orchard age using remote sensing.

Materials and Methods:

Study Site

The project study site spans five counties in the California Central Valley (**Figure 1**) which produces approximately 450 million pounds of almonds annually. The climatic conditions across this study area are relatively uniform: hot dry summers and cool rainy winters. Soil types vary but generally comprise moderate to coarse-textured soils. The dominant almond species for the study area are *Amygdalus communis L. var. dulcis*. Throughout this extent, 36 fields in five counties (**Figure 1**) comprise the study fields. Within these orchards, all of the trees within the orchards were removed, chipped, hauled, and weighed offsite in 2010.

Field Data

Biomass data were available for 40 orchards that were removed and chipped between February 2010 and early 2011. Out of these 40 orchards, 36 had been vegetatively classified during previous efforts for this project. These 36 orchards that had both vegetative classification and chipped weight data from orchard removal were used in this study.
The number of loads of green chippings hauled offsite was recorded for each field. Loads per acre were calculated using the number of loads and the acreage of each field. This value was multiplied by 25 to estimate green tons of biomass per acre. Lastly, a multiplier of 17 was used to estimate dry material from green material, resulting in dry tons per acre. This set of conversion factors are based on experience of the contractors performing the orchard removal. For these fields the chipper data was summarized at the field level.

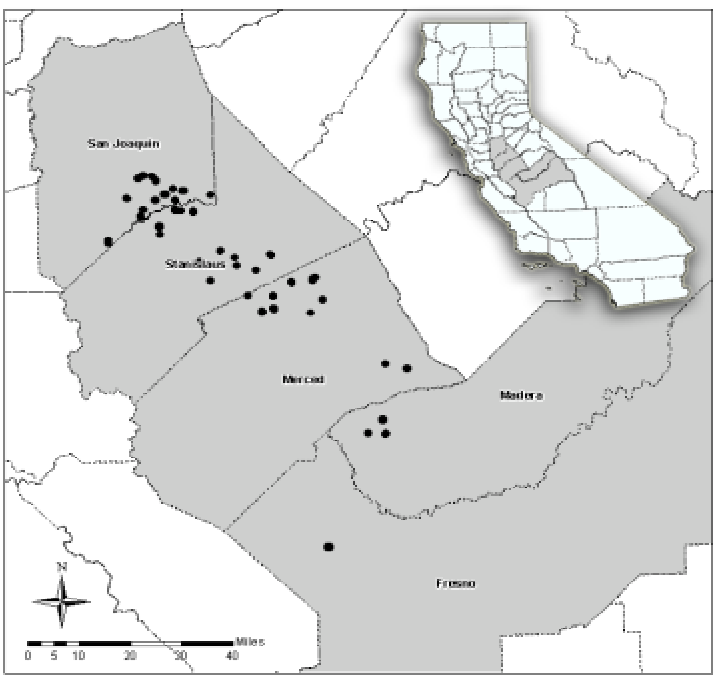

Figure 1. Study Sites in Central California

Subsequent to field data collection, additional variables were measured from high-resolution imagery for the study fields. These included tree canopy width by row and width between rows, both of which were averaged to the field level. Lastly, the planting orientation (diamond, square, etc.) was attributed to each field based on visual assessment.

The traditional method for estimating biomass is to measure a selected sample of tree trunk diameter at breast height (DBH). This relationship is well-published in biomass studies, especially for the forestry industry. However, equations that describe the correlation between DBH and biomass are specific to region, climate and tree type categorizations. Estimating biomass in almond orchards using a DBH correlation is challenging because of the logistics, time, and cost of acquiring data. Also, there would still be a need to evaluate if DBH correlates to biomass successfully as it does for forest stands. Orchard management, irrigation/drainage management, climate, variety, planting density, and soil conditions would likely impact the effectiveness and ability to derive a DBH average value for orchards statewide.

Aerial and Satellite Imagery

Remote sensing analytical techniques are used frequently to extend field-level assessments over large regions in a cost-effective manner. Two types of imagery were used in this study for two different purposes:

1. Imagery from the National Agriculture Imagery Program (NAIP) program collected in 2010 was used to determine canopy cover on almond orchards. Its characteristics are as follows:
   a. Available to public at no cost
   b. Complete statewide coverage
   c. High temporal frequency
   d. Relatively high spatial resolution
   e. Inconsistent properties that make traditional remote sensing analysis difficult
2. Landsat5 imagery (path43row34) acquired on one date per year in the month of June from 1985 to 2011 was used to determine orchard age.
   a. Available to public at no cost
   b. Extensive archive
   c. Relatively low spatial resolution

Results and Discussion:

Image Analysis

The results of the image analysis include vegetative cover delineation, orchard age determination, and textural analysis.

Vegetative Cover within Fields

Almond orchard vegetative (canopy) coverage was determined on the 36 study fields for the 2010 growing season. This analysis was performed on NAIP imagery using advanced remote sensing analysis techniques that shift the analytical focus from pixels to objects. Objects are polygons of similar pixels. The degree of similarity between pixels grouped in one object can be set, and determines the granularity or level of detail of the resulting data. Objects become the input into subsequent analysis procedures. **Figure 2** illustrates the object concept used in OBIA.

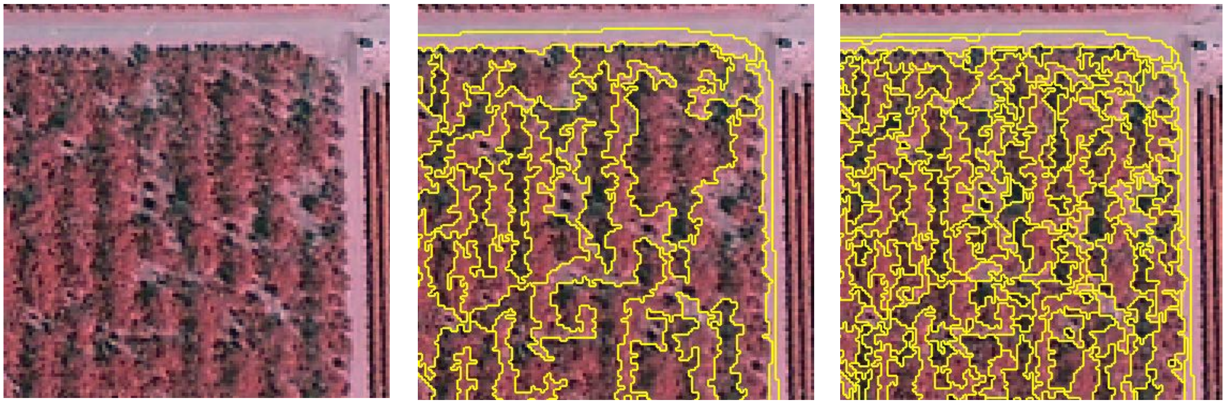

Figure 2. NAIP imagery pixels (left); low homogeneity (higher variance) objects (center); high homogeneity (lower variance) objects (right)

Utilizing a series of OBIA-based procedures, a classification of “Canopy Vegetation” and “Ground” was produced for the 36 orchards. **Figure 3** illustrates the result of the almond orchard vegetation/canopy delineation for two fields of differing canopy extent.

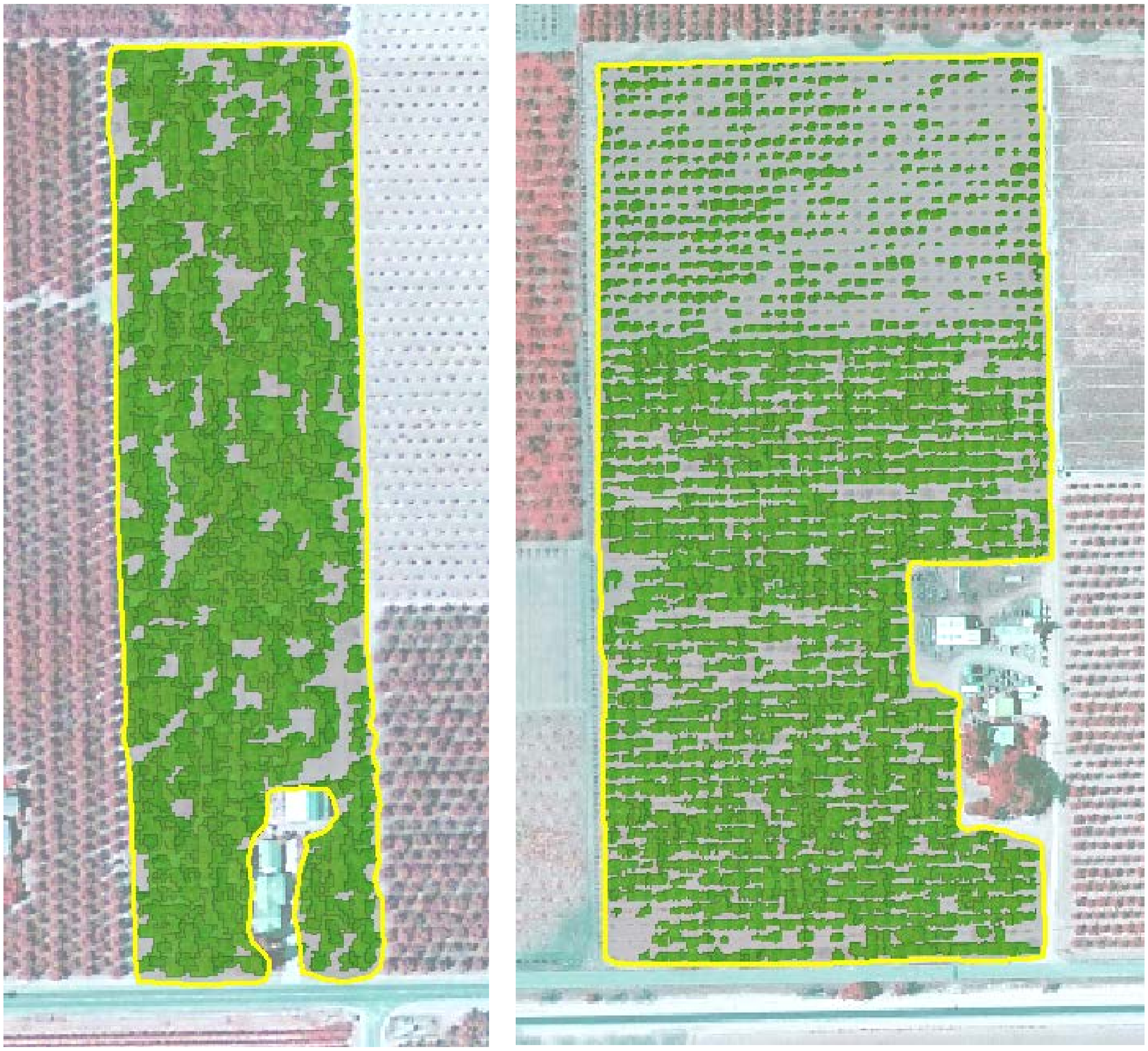

Figure 3. Relatively uniform canopy (left) and a less uniform canopy (right)

NAIP imagery is a valuable resource because of its vast archive. However, NAIP images are mapping products, often treated simply as a visual and are typically not well suited to advanced remote sensing analysis. The properties of NAIP imagery would likely preclude analysis with traditional pixel-based analysis, but with use of OBIA, these properties become much less significant and their effects are minimized. For this reason, NAIP imagery is sufficient for this application with proper processing techniques, and OBIA is a useful tool to leverage the NAIP resource.

Orchard Age by Field

Orchard age was considered as an additional factor that might improve the correlation between vegetative cover and biomass. Orchard age is considered important because of the relationship of age to biomass. However, the relationship between age and vegetative cover was uncertain. For the fields in the project area, the planting dates are depicted in **Figure 4**.

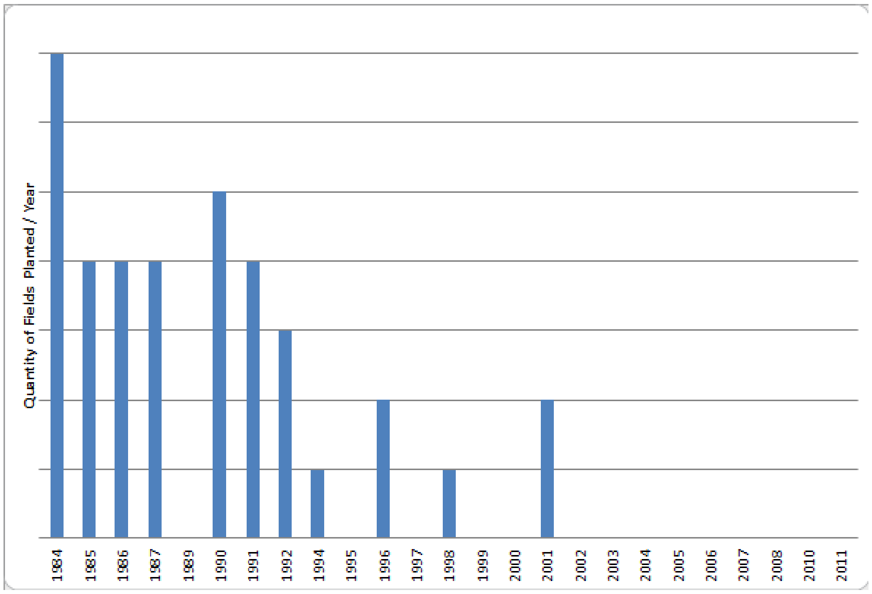

Figure 4. Study fields - derived planting years

Historical Landsat5 satellite imagery was analyzed to determine orchard age. A single image was selected representing every June from 1985 to 2011. These images were analyzed beginning with the present and proceeding back in time. When an orchard was planted, a significant drop in vegetative activity was evident. **Figure 5** illustrates two of the analyzed fields that depict this expectation. Both fields were removed in 2010, with Field 16 planted in 1991 and Field 20 planted in 1992. These fields are examples of consistent vegetative cover with the minor vegetative variation between 1995 – 2010 likely representing changing orchard conditions that results from environmental variability and management practices such as pruning.

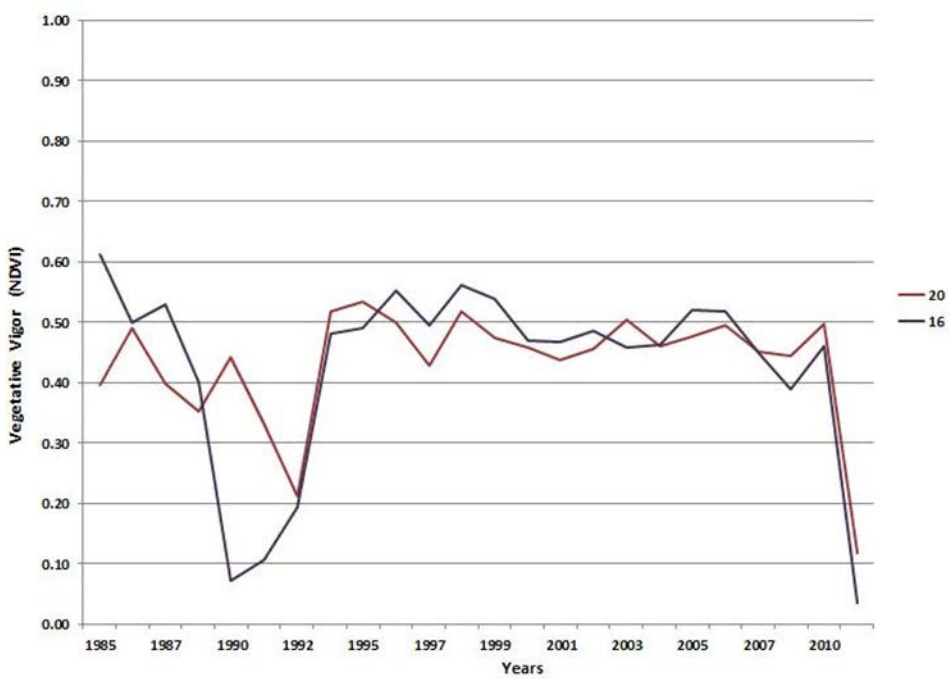

Figure 5. Examples of fields with relatively consistent vegetative cover (1995 – 2010)

Figure 6 illustrates the orchards which had much greater variability both through time and within the field during any given year. Field 5 had almonds planted in 2001 and appears previously to have been farmed as a variety of different crops based on wide-variation in vegetative activity and duration of cycles. Field 60, planted as almonds in 1987, shows a less dense planting evident by the low vegetative activity values.

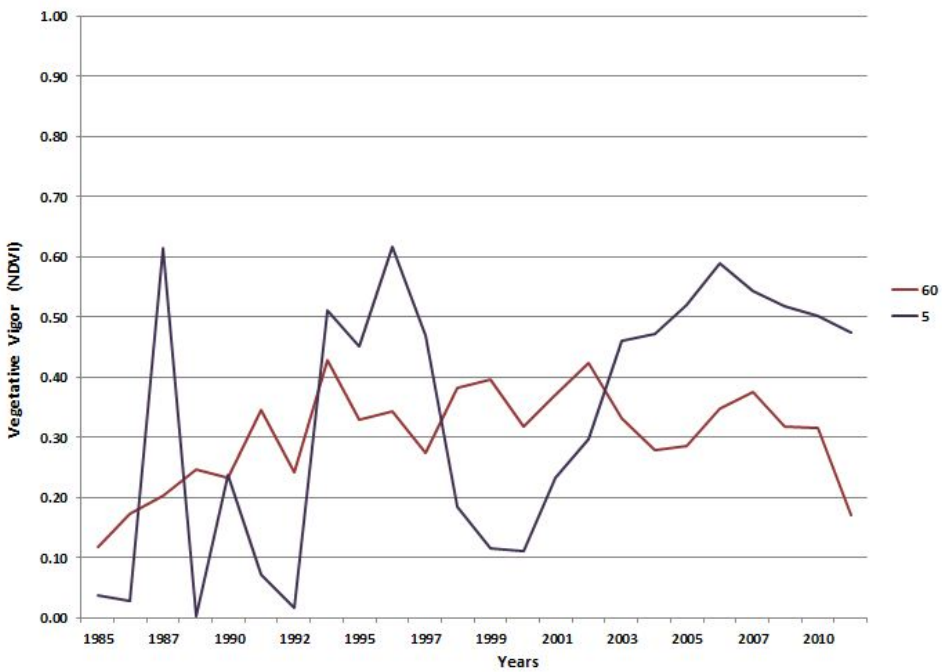

Figure 6. Examples of fields with highly variable vegetative cover (1995 – 2010)

<u>Imagery Texture Analysis</u>

Imagery texture, both NAIP and LandSat5, were explored as part of this project. Kajisa et al. (2009), Chen et al. (2009), and Lu (2005) cite use of imagery texture as a variable of Landsat satellite imagery that can be used to estimate forestry biomass at a regional scale. This relationship of imagery texture to biomass estimation is explored in this effort at both the coarse level of Landsat imagery and at the detailed level of NAIP imagery. This relationship is of special interest because it presents the potential to determine biomass on a regional level, rather than determining vegetative cover on individual fields.

Textural analysis was most successful with the NAIP imagery. The spatial resolution of the Landsat imagery (30 m) was too coarse relative to almond orchard field size to produce a good correlation to field biomass data. The results based on the 36-field population show a high correlation between biomass (green chip weight) and several textural measures, especially the Grey Level Co-occurrence Matrix (GLCM) texture measure of entropy. GLCM measures considered include those listed below, and are discussed later in this report:

1. Entropy
2. Angular
3. Contrast
4. Correlation.

5. Dissimilarity
6. Homogeneity

Statistical Analysis

Statistical analysis included linear relationships and multiple linear relationships between and among the following variables:

1. Biomass (green chipped weight) – field data
2. Vegetative cover – delineated using remote sensing analysis
3. Orchard age – determined using remote sensing analysis
4. Various image texture characteristics – remotely sensed image characteristic

Linear Relationships

Data was initially evaluated by developing a correlation matrix and deriving Pearson product-moment correlation coefficients (Pearson r) for all variables. The correlation matrix provides a means to visually inspect the pattern of correlation among variables and determine if a relationship between the independent and dependent variables exists. In addition, the Pearson r matrix provides a numeric assessment of the measure of the correlation (linear dependence) between the independent and dependent variables. The Pearson r matrix for considered variables is presented in **Table 1**.

Table 1. Pearson r Matrix

	GRNTOTAL	VEGACRE	AGE	AVG_WITHIN	AVG_BETWEE	ACREAGE	MIN_TXENTP	MAX_TXENTP	AVE_TXENTP	SUM_TXENTP	SD_TXENTPC	VAR_TXENTP
GRNTOTAL	1											
VEGACRE	0.911	1										
AGE	0.106	0.023	1									
AVG_WITHIN	-0.105	-0.243	0.021	1								
AVG_BETWEE	0.084	0.1	-0.05	0.15	1							
ACREAGE	0.913	0.967	0.002	-0.25	0.063	1						
MIN_TXENTP	-0.058	-0.084	0.002	0.003	-0.17	-0.105	1					
MAX_TXENTP	0.177	0.278	-0.171	-0.375	-0.024	0.38	0.12	1				
AVE_TXENTP	-0.185	-0.183	0.195	-0.168	-0.268	-0.202	0.278	-0.419	1			
SUM_TXENTP	0.924	0.953	-0.023	-0.203	0.09	0.981	-0.137	0.361	-0.302	1		
SD_TXENTPC	0.07	0.167	-0.178	-0.206	-0.022	0.197	-0.191	0.653	-0.667	0.217	1	
VAR_TXENTP	0.059	0.157	-0.175	-0.203	-0.026	0.185	-0.208	0.632	-0.664	0.205	0.998	1

Several variables were strongly correlated with green weight. However, this analysis does not indicate which variables may work well together to predict green chip weight. A stepwise regression technique was used to select a subset of statistically significant variables that could be used to predict green chip weight. Variables that worked well together to predict green chip weight include imagery texture variables calculated and summarized at the field level. Minimum, maximum and summed entropy texture variables provided an R2 of 0.89 and a standard error of 338 Tons.

Further analysis was conducted on the highly-correlated variables. For the 36 study fields, the vegetative canopy extent was summarized by field. **Figure 7** expresses this foundational relationship of collected field data, chip weight (tons), to vegetative canopy extent (acres).

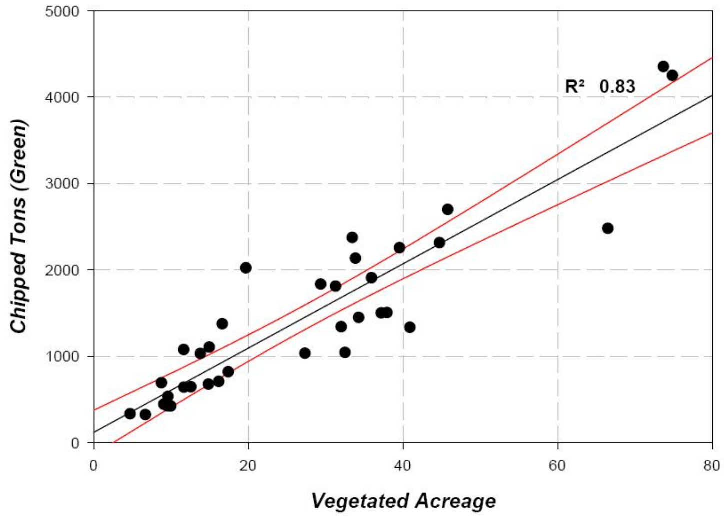

Figure 7. Linear regression - chipped tons (green) to vegetative canopy extent (acres/field)

Textural measures derived from NAIP-based objects in the study fields were found to have an even greater relationship with chipped weight (tons), though the data distribution is more clumped, putting significant importance on the two fields. **Figure 8** illustrates this relationship.

The population from which the texture characteristic, Sum of Entropy, was calculated includes *all* objects within a given almond orchard field, thus alleviating the need to a prior classification of vegetation and bare ground. The removal of this step offers significant cost savings if the relationship proves robust in a larger, more diverse field population.

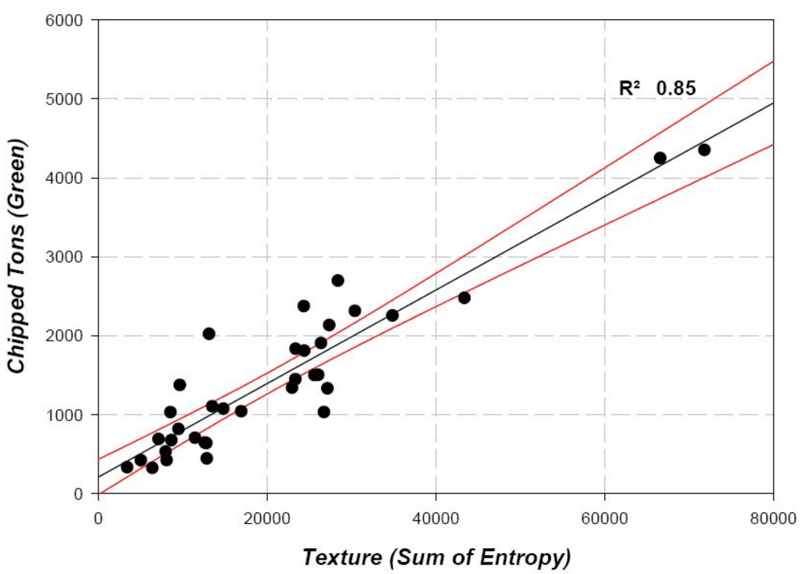

Figure 8. Linear regression - chipped tons (green) to texture (sum of entropy)

It was hypothesized that orchard age may have significant influence on the amount of material chipped. **Figure 9** illustrates the inclusion of orchard age by field as a variable, in addition to

Vegetation Acreage as related to Chipped Tons (Green). As this relationship illustrates, the addition of orchard age has little effect on the relationship. The 3-axis graph indicates the vegetation acres to chipped tons (green) relationship clearly indicates the lack of influence of the orchard age variable.

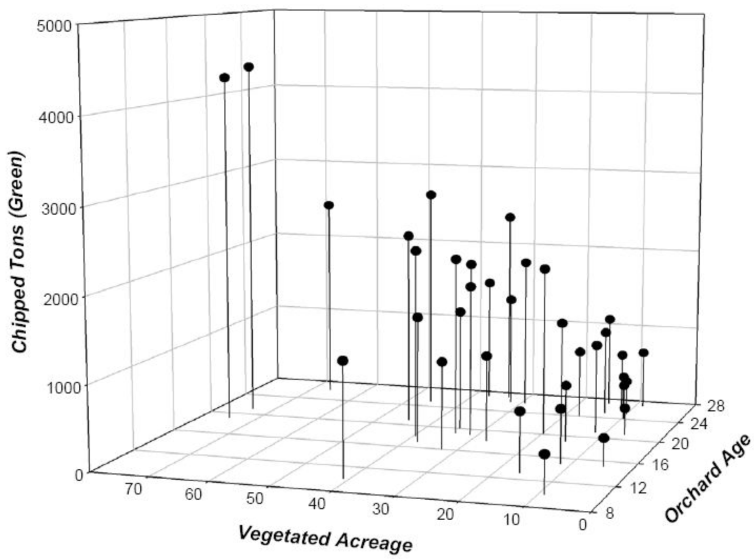

Figure 9. Regression with addition of orchard age

Even though orchard age shows little benefit to estimating biomass for almond orchards, the methodology of determining orchard age and benefits to other crop forecasting applications remain strong. Such applications include estimating age-related bearing and non-bearing acreage, or predicting loss of production due to age-related decline or forecasting orchard replacement by field.

The linear relationship of chipped tons (green) compared to field acreage was evaluated. This relationship also shows strong promise (**Figure 10**), with the least analysis effort required. This relationship would prove less successful as a field extent is more highly variable in canopy extent or with varied size (age) trees within a single field. As a high-level estimation, this relationship would offer the opportunity to perform a rapid assessment with minimal effort and cost.

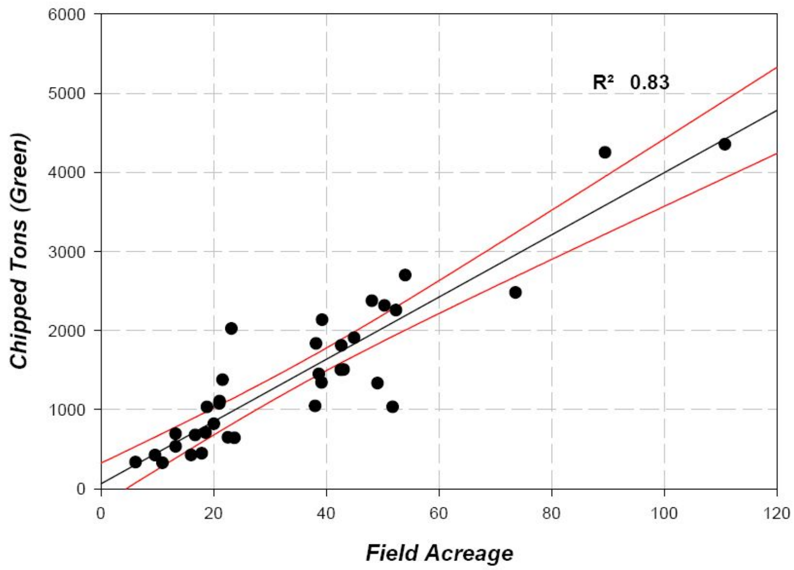

Figure 10. Linear regression - chipped tons (green) to field size (acres/field)

<u>Multiple Linear Relationships</u>

Subsequent to evaluation of linear relationships, a step-wise multiple linear regression was performed. The combination of variables that offer the best explanation of the data relationship to green chipped weight are minimum texture entropy, maximum texture entropy, and sum texture entropy – all textural characteristics. This texture-based multiple linear regression is not fully understood at this time. Further investigation would be necessary to develop this relationship.

Conclusions:

Advanced remote sensing analytical techniques, especially OBIA, can be used to leverage no-cost sources of imagery for improving the type, amount, and level of detail of information in the spatial database of almond acreage in California. Landsat and NAIP are two no-cost sources of imagery that are suitable for determining vegetative cover and orchard age, respectively.

Biomass in almond orchards can be estimated from vegetative cover determined by remotely-sensed image analysis. The correlation established in 36 orchards is very strong (r=0.92), and is potentially a better alternative to estimating biomass using field methods, which is costly, time-consuming, and labor intensive.

A larger ground truth dataset and the use of non-parametric classification and regression techniques would further benefit an investigation of remote sensing techniques to analyze various characteristics of almond orchards. These techniques may provide better statistical fit because they can simultaneously take advantage of continuous and categorical data (e.g. soil survey data) in the same model.

Additional Research: Incorporation of LiDAR Mass Point Data in Orchard Evaluation
For one of the 36 fields evaluated in this study, LiDAR data was available from NOAA. LiDAR is valuable in quantifying the height of vegetation as well as roughly estimating the canopy complexity. Because LiDAR data was only available for a single field, there was no statistical evaluation performed. The vegetative canopy, almond tree height, and a rough canopy complexity estimate were calculated for this field. **Figure 11** illustrates the difference in tree height within the orchard. Interplanting at different times, soil conditions, wind events, or other reasons could be the cause.

The potential value of inclusion of LiDAR mass point multi-return data is the ability to determine tree height as well as canopy extent. As multi-return LiDAR, as well as waveform LiDAR, is more widely collected, this data source may be a cost-effective option.

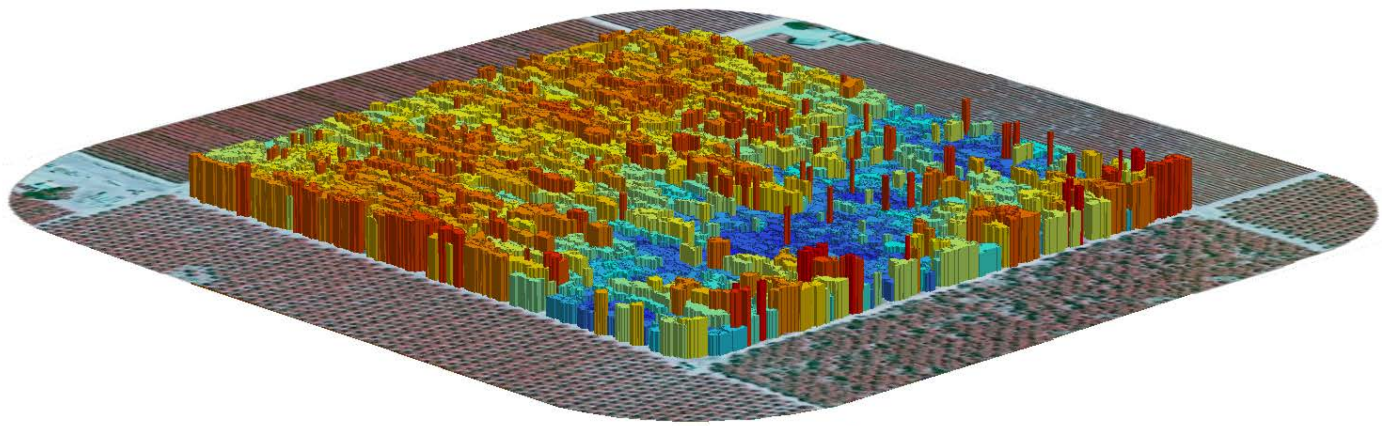

Figure 11. Almond orchard tree height as derived from multi-return LiDAR

Research Effort Recent Publications:

None

References:

Chen, Wenjun, D. Blain, Junhua Li, K. Keohler, R. Fraser, Yu Zhang, S. Leblanc, I. Olthof, Jixin Wang, and M. McGovern. 2009. "Biomass Measurements and Relationships with Landsat-7/ETM+ and JERS-1/SAR Data over Canada's Western Sub-arctic and Low Arctic." *International Journal of Remote Sensing* 30 (9) (May): 2355–2376. doi:10.1080/01431160802549401. http://www.tandfonline.com/doi/abs/10.1080/01431160802549401.

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