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IDENTIFICATION OF AGRICULTURAL LAND USE IN CALIFORNIA THROUGH REMOTE SENSING

A Thesis

presented to

the Faculty of California Polytechnic State University,

San Luis Obispo

In Partial Fulfillment

of the Requirements for the Degree

Master of Science in Engineering

by

Todd Allen Robinson

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COMMITTEE MEMBERSHIP

TITLE:	Identification of Agricultural Land Use in California Through Remote Sensing
AUTHOR:	Todd Allen Robinson
DATE SUBMITTED:	September 2016
COMMITTEE CHAIR:	Daniel J. Howes, Ph.D., P.E. Associate Professor of BioResource and Agricultural Engineering
COMMITTEE MEMBER:	Franklin Gaudi, Ed.D. Lecturer of BioResource and Agricultural Engineering
COMMITTEE MEMBER:	Rebekah Oulton, Ph.D., P.E. Assistant Professor of Civil and Environmental Engineering

ABSTRACT

Identification of Agricultural Land Use in California Through Remote Sensing

Todd Allen Robinson

Ground truthing actual crop types in an area can be expensive and time-consuming. The California Department of Water Resources attempts to ground truth land use in each county in California every five years. However, this is limited by budgetary constraints and often results in infrequent (more than every ten years) surveying of many counties. An accurate accounting of crops growing in a region is important for a variety of purposes including farm production estimates, groundwater and surface water modeling, evapotranspiration estimation, water planning, research applications, etc. Agricultural land use is continually changing due to development and environmental factors.

Currently, USDA NASS provides georeferenced land use maps of regions throughout the U.S. While these are beneficial, the accuracy is not very high for California due to the wide variety of crops grown throughout the state. California has an increasingly complex agricultural system which includes multi-crops changing on an annual and even semiannual basis, long growing seasons, and complex and flexible irrigation schedules.

Remotely sensed data from available satellites are used to more accurately classify crop types within the Madera and Merced Counties of California's Central Valley. An initial classification approach utilizing a simplified decision tree for a data subset of the area considered is presented. In order to accommodate the larger dataset at hand, a computer based approach is applied using the Nearest Neighbor classification algorithm in the computer program eCognition. Iterative analyses were performed to consider a range of scenarios with varying spectral inputs. The results show the methods presented can be beneficial in discriminating 24 of the major crop types from multi-temporal spectral data.

Keywords: remote sensing, land classification, decision tree, eCognition, Phenology, object-based classification

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1. INTRODUCTION

The following presents the objective of this research and a brief summary of the general layout of the thesis.

1.1 Research Objective

The purpose of this research is to develop a simple and repeatable crop classification methodology that can be used in the Central Valley of California. While cataloging California's crop inventory for policy and environmental necessity is important; there is a clear need for the proposed methodology to be relatively inexpensive and minimize future work during implementation.

It has been shown that object-based analysis has advantages over pixel-based analysis as the spatial resolutions increase (Blaschke 2010). In order to improve the accuracy of the classification, various classification methods that include object-based analysis, segmentation, curve fitting (phenology), ancillary spatial data, and Actual Crop Coefficient data were reviewed.

To simplify the analysis, the research concentrated on available data from two Central Valley counties, Merced and Madera. The base data utilized included available publicly disseminated satellite imagery and Actual Crop Coefficient data acquired through the Irrigation Training Research Center (ITRC) at California Polytechnic State University San Luis Obispo (Cal Poly). This research focused

on the applicability of two separate approaches to classify land crop types for the subject areas including:

1) a simplistic manual hybrid decisions tree capable of classifying crop types based on user thresholds; and
2) a computer-assisted algorithm using the object-based image analysis software Trimble® eCognition.

1.2 Thesis Structure

This thesis has been broken into six chapters for clarity purposes. Chapter 1 provides the research objective and outline of the thesis.

Background information regarding the importance of land classification, various datasets and typical classification methods used in current practice are summarized in Chapter 2.

Chapter 3 introduces the study area of this research as well as the collated data available in the area of focus. Data processing was then performed in order to achieve a simplified dataset for analyses.

Chapter 4 demonstrates the use of a simplified decision tree classification system in land crop classification for a subset of data from one of the subject areas. The results are summarized with respect to strengths and shortcomings of this

classification method and the ultimate need for further classification techniques such as computer-assisted algorithms.

As described in Chapter 5, the object-based image analysis software Trimble® eCognition was used to develop a crop classification system for the relative datasets used for this research. A description of the methodology employed and findings are provided.

Lastly, Chapter 6 includes a summary of the research performed for this study. Findings are highlighted with respect to the contribution of this research, limitations of the methods employed, and future work.

2. BACKGROUND

This chapter serves to provide the reader with background information regarding crop classification and remote sensing techniques, as well as introduce terminology to be used throughout the thesis. Upon review of methods used in current practice, there is a clear need for an improved classification system, particularly with respect to the complex agriculture in the Central Valley, California.

2.1 Importance of Crop Classification

Due to its long growing seasons and economic strength, California has one of the most productive and varied agricultural industries in the world. As a result, agricultural awareness and land use classification is becoming ever more important. Population increase strains food demand on all scales making crop assessment and yield calculation critical in order to effectively maintain a balance between the two (Toan et al. 1997, Doraiswamy et al. 2004). Continually changing climatic conditions provide periods of limited water supplies and further emphasize the importance of accurate assessments of consumptive crop water use, making the necessity for accurate land use classification a key component for on-farm decision-making, economical assessment, land use change monitoring (Vogelmann et al. 1998), and policy development (Zilberman et al. 1994).

Although the California Central Valley is a highly dynamic and productive agricultural region, the semi-arid/arid environment generally results in water scarcity during summer months as well as long periods of low precipitation during

winter months, making irrigation scheduling difficult (Dinar and Zilberman 1991). Accurate annual crop classification can help in understanding agricultural consumptive requirements which are a key parameter in water balance equations. Prudent decision making on farm and district levels require water balance analysis for conservation and water management (Burt 1999).

2.2 Available Resources

Since the late 1940's the California Department of Water Resources (DWR) has continually surveyed and monitored land use changes (Wall et al. 1984). DWR attempts to ground truth land use in each county in California every five years through ground surveying. However, due to budget constraints, some counties are only examined once every ten years at best. The disseminated land use information is publically available for download from DWR as parcel shape files for select counties. This data can be used as ground truthing to verify known data points and also as "training data" when developing alternative supervised classification methods.

The U.S. Department of Agricultural (USDA), National Agricultural Statistics Service (NASS) provides crop land classification via a web-based application called CropScape. CropScape is a user-friendly platform capable of customizing, downloading, analyzing and broadcasting geospatial data for agricultural applications (Han et al. 2012). The program has expanded over the years with

funding from outside sources. USDA NASS also provides georeferenced land use maps at 30- to 56-meter resolution throughout the U.S.

Since the CropScape program's beginning in 1997, Cropland Data Layer (CDL) datasets have been processed by NASS field offices and analyzed by the Spatial Analysis Research Section (SARS), a subset of NASS. The CDL dataset primarily utilizes satellite imagery to provide acreage estimates for the Agricultural Statistics Board (ASB). ASB uses a supervised classification of the cropland cover with training sample points from the Farm Service Agency (FSA) and National Land Cover Data (NLCD) for the See5 decision tree (DT) classifier. Users can download georeferenced tiff images directly. Shortcomings of the dataset include the exclusion of double crops or areas that include more than one crop type, which can limit the accuracy of the data in agricultural areas where crop rotation is common (Boryan and Craig 2005).

2.3 Review of Crop Classification Methods

With the increase in common computing power, accessing and processing agro-geoinformation is not only viable but also extensively used. The past several decades have presented extensive literature discussing land cover classification products and procedures. Some examples include discrimination of forest types (Vieira et al. 2003), crop field types (Price et al. 1997, Kandrika and Roy 2008, Yan and Roy 2014), and land cover characterization on a global scale (Townshend et al. 1991, Running et al. 1995, De Fries et al. 1998, Vogelmann et al. 1998, Hansen

and Loveland 2012). Further, research has been performed utilizing multi-spectral satellite data to increase accuracy in urban land use classification through the use of vegetative indices (Yuan and Bauer 2007) and impervious identification to map urban spread (Ridd 1995, Lu and Weng 2006). Remote sensing has been utilized extensively for classification of crop types in California but it has been proven to be difficult as season lengths in California often exceed 280 days (Wall et al. 1984) allowing for multiple crop rotations and varied irrigation methodologies.

Review of global and regional land cover methods reveals the importance of consistency and reliability of sensors (Townshend et al. 1991). The recent increase in sensor resolution and availability of various spectral bands has presented an opportunity for the remote sensing community to develop a plethora of models and approaches to land cover classification. A broad range of methods and approaches have been reviewed and range anywhere from utilization of human expertise and traditional methods to newer computer-assisted and algorithm-based predictor models.

Systematic repetitive collection of data from satellites can provide insight from multi-year analysis to determine cropping patters (Martínez-Casasnovas et al. 2005). Ample literature available provides insights to the benefits of multi-temporal analysis for crop discrimination (Murakami et al. 2001) (Turker and Arikan 2005) (De Santa Olalla et al. 2003). Analysis based on image object classification rather

than a pixel-based level, can contribute to higher accuracy reducing noise (Tso and Mather 1999).

As land cover mapping and assessment are key elements in remote sensing data analysis and application (Foody 2002), derivation of applicable classification techniques is critical to successful application to land cover discrimination. A detailed review and survey of common land use classification methods and techniques developed is provided by Lu and Weng (2007) and Nath et al. (2014). Otukei and Blaschke (2010) identified that methods for classification can be divided into common or advanced schemes. A few of the more common methodologies applicable to this study are discussed below.

2.4 Decision Tree (DT) Method

The Decision Tree (DT) methodology is a relatively simplistic approach which uses a flowchart to narrow down the appropriate crop classification based on thresholds determined from imagery data for a particular crop type. Considered a common scheme, Friedl and Brodley (1997) determined that DT classification outperformed other advanced classification methods when evaluated on three different sets of remote sensing data. Based on initial review, this method appears to be straight forward allowing direct user input. Algorithms created by the decision tree can be easily reviewed and adjusted as needed based on user experience. Hansen et al. (1996) provided insight to pre-processing methods and the use of vegetation indices which give DTs several advantages over other methods, including the

flexibility for users to define thresholds manually based solely on professional expertise. Other researchers have found similar conclusions (Running et al. (1995), De Fries et al. (1998)).

The DT method can be readily expanded to incorporate more advanced schemes that may increase accuracy. Various algorithms including neural networks and fuzzy classifiers can be incorporated into the decisions trees (Wang 1990, Shimabukuro and Smith 1991, Bischof et al. 1992, De Fries et al. 1998, DeFries and Chan 2000, Huang et al. 2002, Mountrakis et al. 2011). Definition of DT's using more complex computer-assisted algorithms such as s-plus statistical software (Hansen et al. 2000), C5.0 software (Friedl et al. 1999) or regression tree analysis (Michaelsen et al. 1994) have shown acceptable results. Increased accuracy in machine learning algorithms have been seen with the inclusion of methods such as boosting, Bootstrap Aggregation (bagging) or pruning (Pal and Mather 2001). These approaches are techniques added to algorithms the decrease the variability, bias, or improved predictive force of a data set.

Although simplistic and with several advantages, the DT approach does have its limitations. For example, variability in spectral data can make it difficult to determine appropriate user thresholds, particularly as the DT grows and crops become more alike in spectral signatures. In addition, image discrimination is complex and paramount importance is placed on the selection of appropriate ground survey data used to determine the classification thresholds. The common

DT method may prove to be most beneficial to classify more global classifications such as crop vs. non-crop or trees vs. ground crops classes rather than final crop classification on a micro scale.

2.5 Phenology-based Approach

Multi-temporal images can add to the computing complexity of the analysis by attributing to larger data volume. An alternative approach to analyzing these multi-temporal datasets incorporates a phenology-based approach, similar to that described by Zhong et al. (2012). Based on physical and physiological data captured by satellite imagery, it is possible to create a phenology-based curve from spectral indexes. For example, Van Dijk et al. (1987) designed a polynomial function to smooth composite VI values and Zhong et al. (2012) and Soudani et al. (2008) present the use of a piecewise logistic function modified using an asymmetric double-sigmoid function for determining phenology thresholds.

An alternative classification approach involves the use of logistic functions (e.g. (Zhang et al. 2003, Soudani et al. 2008)). Similar to Zhong et al. (2012) and Shimabukuro and Smith (1991), curve-fitting has been used to detect phenological stages through the use of double sigmoid functions. For example, Zhong et al. (2012) developed the asymmetric double sigmoid function provided in equation (2-1) to fit a curve to the vegetation index, Normalized Difference Vegetation Index (NDVI).

$$V(t) = V_b + \frac{1}{2} V_a[\tanh(p(t - D_i)) - \tanh(p(t - D_d))] \quad (2\text{-}1)$$

Where:
$V(t)$ = NDVI at time t
t = Day of Year (DOY)
V_b = base NDVI value related to the non-leaf season
V_a = amplitude of NDVI within the growing season
D_i = DOY with the highest increasing rates of NDVI
D_d = DOY with the highest decreasing rates of NDVI
p = increasing rate change
q = decreasing rate change

The double asymmetric sigmoid function can be fit to the data points utilizing the solver function in excel by changing the variables on the right hand side of equation to better fit the curve. Figure 2-1 illustrates a typical phonological cycle expected for a single crop, considering the NDVI parameter. Creating a metric using the curve-fitting method can reduce computational complexity in crop classification (Zhong et al. 2012) and ultimately user cost.

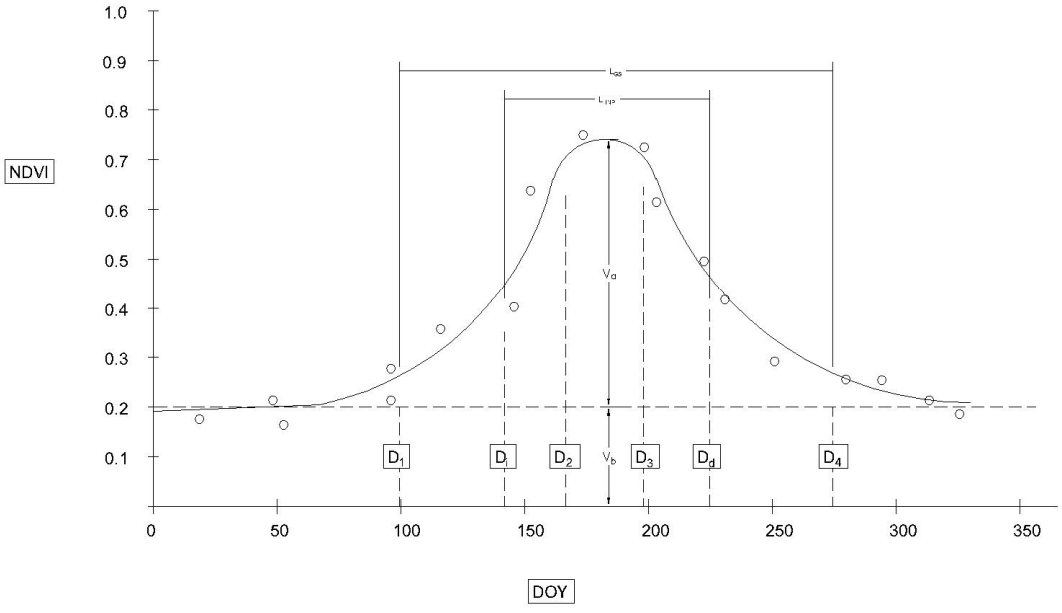

Figure 2-1. Sample NDVI temporal series showing fitted double-sigmoid curve

A phenology-based approach may be a successful classification scheme for crops with discernable cropping calendars. It is anticipated that this method would likely perform better on classifying single crops with consistent, well defined spectral patters (e.g. NDVI), as shown in Figure 2-1. However, the method requires the user to have an understanding of local cropping practices. Furthermore, this method relies on user expertise as threshold levels may require continual adjustment based on changes in agricultural practices or climatic conditions within regions or time under consideration (year of data collection). The Central Valley's immense variety of crop types and multiple crop rotations would prove the phenology-based approach to be computationally difficult and was not considered in this analysis.

2.6 Computer-assisted Algorithms

This approach utilizes a computer to run more complex classification algorithms. The benefit of a computer-assisted algorithm is its ability to handle large data sets and efficiently reduce computation time compared to manual approaches. The more common algorithms are reviewed in this section.

The Maximum Likelihood Classification (MLC) utilizes a supervised or unsupervised classification approach, i.e. with or without training data, as described by Otukei and Blaschke (2010). Computer based algorithms have been applied to include other methodologies such as: decisions trees e.g. Quinlan (1993); support vector machines (SVMs); e.g. Melgani and Bruzzone (2004) and

Mountrakis et al. (2011); neural networks, e.g. Gopal and Woodcock (1996); and least-squares mixing, e.g. Shimabukuro and Smith (1991), to name a few. Improved spatial and spectral resolution has made the algorithm training processes and classification approach more complex. Additional Improvement of sensor resolution has increased the data size which requires more computing power.

A computer program that is widely used in the remote sensing community, eCognition, has been shown to be a powerful tool with many applications for classification and change detection using remote sensing applications. Recent advances in object-based analysis and complex computer algorithms can be incorporated into eCognition through image segmentation, feature space and data extraction applied to built-in classification schemes. Previous work by Stumpf and Kerle (2011) in eCognition has shown good results detecting landslides using the Random Forests algorithm. Recursive fuzzy classification logic has been used in eCognition to classify rangeland at 87% accuracy (Laliberte et al. 2011). Laliberte et al. (2004) mapped shrub encroachments in southern New Mexico using the Nearest Neighbor (NN) algorithm in eCognition to accuracies of about 87%.

The NN algorithm relates how close an object is to the defined feature space and ultimately assigns values of 1.0 if the object is an exact match or if an object is not related to the feature set it is assigned a value of 0.0 and remains unclassified. For objects that fall in between 1.0 and 0.0 in the feature space, fuzzy logic is

applied to find the nearest distance to a feature space. For example, eCognition computes a distance (d), standardized by the standard deviation, as shown equation 2-2 below (Geospatial 2016):

$$d = \sqrt{\sum_f \left(\frac{V_f(s) - V_f(o)}{\sigma_f}\right)^2} \qquad (2\text{-}2)$$

Where: $V_f(s)$ = the feature value of sample object for feature f,
$V_f(o)$ = feature value of image object for feature f, and
f = the standard deviation

An exponential membership function z(d) is calculated. The membership value k determines the change in z(d) and can be changed by the user. Based on sensitive analysis performed, the value of k used was 0.1 and can range from 0 to 1:

$$z(d) = c^{-kd^2} \qquad (2\text{-}3)$$

k can be defined further by:

$$k = ln\left(\frac{1}{function\ slope}\right) \qquad (2\text{-}4)$$

Once the NN features are defined for the subject classes it can be applied to a classification algorithm. This approach was applied to the analysis for this study, as discussed in Chapter 5.

As discussed above the computer-assisted algorithm approach has many benefits, including decreased computation time, ability to handle higher imagery resolution

and larger data sets. Some statistical software programs provide a “black box” computational method, which doesn’t allow users to review the end classification algorithm and therefore makes it difficult for calibration or trouble shooting. In order to be successful, it is critical that the user maintains full understanding of the algorithms utilized in the analysis and the effects of each variable considered in the process.

2.7 Project Justification

While numerous approaches have been developed for crop classification, there still exists a need for a rapid, inexpensive crop classification system. In particular, the complexity of Central Valley, California, agriculture presents challenges and shortcomings for current classification methods. Parcel size, repeatability, labor costs and computing time all are contributing factors. The limitations of available methodologies combined with the complex agriculture of the area has resulted in a quest for a new, innovative approach to classify crop data.

Little research has been found that utilizes common or advanced classification schemes on complex land types such as those found in the California Central Valley. California’s large variety of crops, extended cropping calendars, and unique farming methods all contribute to the difficulty in accurate classification of crop types using remote sensing. The research presented in this paper reviews the applicability of two classification approaches in hopes to understand their individual performance in classifying Central Valley crop types. First, a manual

approach is reviewed for a subset of crop types that uses a common DT method. A more complex approach is analyzed using the Nearest Neighbor (NN) classification scheme within Trimble's eCognition computer program.

3. STUDY AREA

This research focused on the Madera and Merced Counties in California in hopes of developing an innovative approach to classify crop data through remote sensing techniques. This chapter provides an introduction to the study area and relevant data sets used for analyses. In order to develop a more simplistic and accurate approach, the data sets were corrected and reduced prior to analysis, as described herein.

3.1 Madera and Merced Counties

The research focused on available data from the Madera and Merced Counties of the Central Valley, California. The approximate locations of these counties within the Central Valley are provided in Figure 3-1. The scrutinized data included Landsat and DWR data in Madera County from 2001 and 2011, and in Merced County from 2002.

Figure 3-1. Location of Merced and Madera County datasets

The Madera and Merced County data sets were selected for this study because:

- The areas have been ground surveyed by the DWR.
- The Landsat data scenes have been pre-adjusted in-house for atmospheric effects and pre-processed using the ITRC-METRIC.
- Actual evapotranspiration and Actual Crop Coefficients by pixel have been preprocessed by ITRC.

A discussion of the respective data sets used to develop the proposed crop classification methods is provided in the subsequent sections.

3.2 Landsat Data

Two sets of Landsat data were available within the study area: (1) Landsat 5 Thematic Mapper (TM) for path/row 43/34 and (2) Landsat 7 TM for path/row 43/34. Table 3-1 illustrates the band identification and wavelengths available from Landsat 5 – TM and Landsat 7 ETM+ respectively.

Table 3-1.Landsat band identification

Band	**Description**
Band 1	Blue
Band 2	Green
Band 3	Red
Band 4	Near infrared
Band 5	Short-wave infrared
Band 6	Thermal Infrared
Band 7	Short Wave infrared

Landsat 7 - Enhanced Thematic Mapper Plus (ETM+)			
Band	**Wavelength (micrometers)**	**Resolution (meters)**	**Description**
Band 1	0.45-0.52	30	Blue
Band 2	0.52-0.60	30	Green
Band 3	0.63-0.69	30	Red
Band 4	0.77-0.90	30	Near infrared
Band 5	1.55-1.75	30	Short-wave infrared
Band 6	10.40-12.50	60	Thermal Infrared
Band 7	2.09-2.35	30	Short Wave infrared
Band 8	0.52-.90	15	Panchromatic (Landsat 7 only)

3.3 Vegetation Indices

As mentioned previously, vegetation indices can be extracted from Landsat data and used for parametric analyses (Tucker 1979). Vegetation indices were developed from spectral bands of available scenes in-house by the ITRC during the subject year. Maximum, minimum, mean and amplitude values were imported

from the index datasets in raster format. Table 3-2 summarizes the indices considered for this study which included: Albedo, Emissivity, Leaf Area Index (LAI), Normalized Difference Vegetation Index (NDVI), surface temperature adjusted for elevation (T_{s_dem}), humidity (H), Actual Crop Coefficient (EToF), reflectance (bands 1-7), and radiance (bands 1-7). A brief discussion of each of these variables is provided below.

Table 3-2. Description of indices

Index	**Description**
Albedo	Measure of reflectivity (short wave radiation) that is reflected from the earth's surface
Emissivity	Measure of the efficiency in which a surface emits thermal energy
LAI	(Leaf Area Index) is a dimensionless quantity that characterizes plant canopies
NDVI	(Normalized Difference Vegetation Index) assesses whether the target being observed contains live green vegetation or not
NDWI	(Normalized Difference Water Index) measures the amount of water present in a leaf internal structure
$T_{s\ dem}$	Measure of surface temperature accounting elevation
H	(Sensible Heat Flux) measures the transfer of heat energy from the Earth's surface to the atmosphere
EToF	Actual Crop Coefficient (computed from the ITRC-METRIC)
Reflectance	Fraction of incident radiant flux at a given wavelength reflected by a material (bands 1-7)
Radiance	Flux of radiation emitted per unit solid angle in a given direction by a unit area of a source (light or heat as emitted of reflected by an object) (bands 1-7)

Albedo: Albedo is the measurement of the sun's radiation that is reflected back from the surface. Typically, this is expressed as a percentage of wavelength. An example of 0% albedo would be a black object (e.g. wavelengths are absorbed and not reflected back) versus a true white object would where the albedo value

could be at 100%. Albedo used in land classification can be useful as the vegetative leafs, plan color, soil color impact this value.

Leaf Area Index (LAI): Leaf area index is a ratio between 0 and 10 that measures the area of leaf per a unit of ground surface.

Normalized Vegetation Index (NDVI): NDVI can indicate the amount of dry biomass above ground through the ratio of visible red (VIS) and near infrared (NIR) channels captured by Landsat spectral imagery (Tucker 1979). A key concept is that this index can sense multiple layers within a crops biomass. For example, the NIR can sense approximately eight leaf layers while the VIS sees only one leaf layer or less (Lillesaeter, 1982).

Chlorophyll on the plant absorbs light in the red channel (0.58-0.68 microns) and foliage reflects light in the near infrared channel (0.72-1.10 microns). The ratio of the reflected light (NIR) less the absorbed light (VIS) to the reflected light plus the absorbed light yields the NDVI, as shown in equation (3-1) below.

$$NDVI = \frac{NIR - VIS}{NIR + VIS} \qquad (3\text{-}1)$$

The values of NDVI can range between -1.0 and 1.0 (Myneni et al. 1995). The NDVI on farmed land generally increases during leaf development stages and declines after harvest and bare soil generally have larger NIR than VIS values and

therefore generate small positive NDVI values ranging from about 0 to 0.2. In contrast, areas covered by vegetation usually correspond to an NDVI of 0.2 or greater. Water areas typically have low NIR and VIS values which result in a very low positive or slightly negative NDVI. Table 3-3 summarizes typical ranges of VIS, NIR and NDVI values for common types of cover (Holben 1986).

Table 3-3. Typical NDVI values for various cover types (Holben 1986)

Cover Type	**VIS**	**NIR**	**NDVI**
Dense vegetation	0.1	0.5	0.7
Bare soil (dry)	0.69	0.283	0.025
Clouds	0.227	0.228	0.002
Snow and ice	0.375	0.342	-0.046
Water	0.022	0.013	-0.257

It is important to understand that the NDVI pixel rarely covers a single homogeneous area of one land cover type. It can encompass many types such as road, vegetation and water all in one. The calculated NDVI is the sum of all the types within the pixel and is considered to look at a general condition more accurately than a crop specific condition.

Normalized water index (NDWI): NDWI is the normalized water index (NDWI) based on the formula originally published by McFeeters (1996) and shown in equation (3-2) below, where X_{green} and X_{nir} are the green band (Band 2) and near infrared (nir) band (Band 4), respectively.

$$NDWI = \frac{X_{green} - X_{nir}}{X_{green} + X_{nir}} \quad (3\text{-}2)$$

Similar to NDVI, the NDWI can range from -1 to +1 and general a positive NDWI values indicate open water surfaces while negative values indicate a non-water surface feature.

Tasseled Cap Transformations: Tasseled Cap Transformations developed by Kauth and Thomas (1976) involve converting a set of readings from the raw data into composite values to indicate brightness greenness and wetness. Crist (1985) used top of atmosphere reflectance bands to calculate Tasseled Cap Transformations including brightness, greenness, wetness, and fourth, fifth and sixth indices, using coefficients presented by Huang et al. (2002) for the Landsat data.

Actual Crop Coefficient, EToF: The Actual Crop Coefficient (ITRC-Metric output), EToF, was developed in-house by the Irrigation Training and Research Center (ITRC). This metric is produced through ITRC modified mapping evapotranspiration at high resolution with internal calibration process.

3.4 DWR Data

Land use ground survey data classifying crop types were downloaded from DWR for the Madera and Merced Counties for the respective years of interest (2001,

2011 Madera and 2002 Merced). DWR descriptors were matched to NASS descriptors for the year of the respective data set in order to identify approximately 80 land cover classifications. The classifications included crop types and non-crop areas, impervious areas and water areas. Refer to Appendix C for a full list of NASS identifications and classification descriptions. Appendices A and B provide a full list of DWR crops and equivalent NASS identifications/descriptors.

3.5 Data Processing

Within the DWR data sets, non-crops and unknown crops such as “miscellaneous vegetables and fruits” (NASS ID 47) and “other tree crops” (NASS ID 71) were removed in order to avoid confusion for classification during the study. In addition, crops with less than 10 fields in the county were also removed to avoid classification bias based on a single crop field. Reducing the data to only NASS identifications present within each county and removing non-crops and unknowns, decreased the total classes reviewed for the study and allowed for more accurate analysis. In Madera County approximately 12,350 and 14,700 fields (agriculture and non-agriculture) were defined for the 2001 and 2011 data sets, respectively, and 13,270 fields were defined in the Merced 2002 data set.

The specified vegetation indices as well as a DWR shapefile identifying parcels and crop type were imported into an ArcGIS computer program and re-projected into the Universal Transverse Mercator coordinate system (zone 10) and the WGS

84 datum. The collective data was then processed in ArcGIS and/or imported into alternative programs as discussed below.

Within ArcGIS, the raster data was extracted for analysis by applying a buffer of 45 meters to each of the parcels/fields. Buffered areas less than 1 acre in size were eliminated. It was discovered that the buffer eliminated noise that may be associated with items such as roads, poor crop uniformity, etc. typically located at the edge of field. Cloud cover was analyzed for both years and it was concluded that the occurrence of clouds in the scenes had a negligible effect in the areas of interest during the time period analyzed. Therefore, no adjustments were made to the data for cloud cover. The processed and reduced data sets were then used in the subsequent analyses presented in Chapters 4 and 5.

4. SIMPLIFIED DECISION TREE CLASSIFICATION

A simplified decision tree (DT) classification approach was developed using the 2002 Merced data (Landsat and DWR). The following presents a discussion of the methods used to develop the decision tree, findings, and the pros and cons of this type of classification method.

4.1 Methodology

As described in Chapter 3, the raster data used for this research was corrected for noise, etc. The data reduction lead to a subset of 11 land type classifications for the 2002 Merced data set. Thus, the DT analysis considered the following land types: asparagus, beans (dry), broccoli, cotton, onions and garlic, peppers, sugar beets, sweet potatoes, table grapes, unknown grapes, and unknown rice.

The objective of the proposed scheme was to produce a model that was simple, observable and repeatable. Previous studies have shown a decision tree (DT) can be an effective tool for crop classification due to its non-parametric nature and ability to effectively handle non-linear relations and non-homogenous inputs (Quinlan 1993). A schematic diagram of the DT process developed for this study is shown in Figure 4-1.

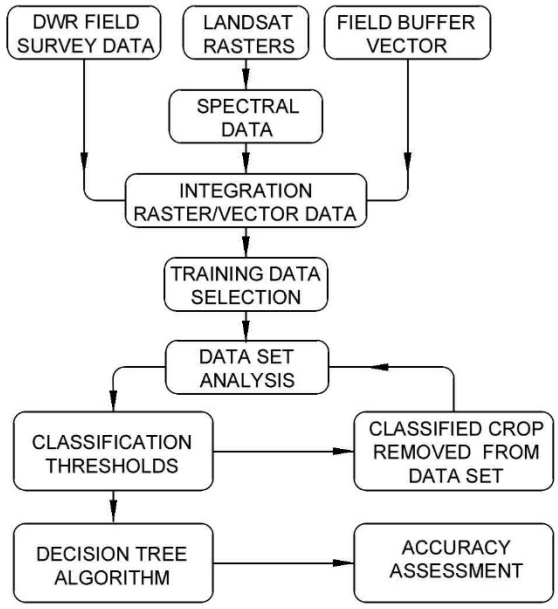

Figure 4-1. Schematic DT diagram

Available spectral data for the subset was scrutinized in hopes of creating a DT model for effectively identifying ground crops. Upon initial review of the data, observable trends were identified for certain crops throughout the year. The observed trends provided relative certainty that the crop type, as identified by DWR, were present in the field during the analysis. Because crop planting and harvest dates varied, the initial DT was created based on multi-temporal spectral data between the dates of March and September 2002.

The first step for land classification involved experience and expertise in identifying temporal trends and vegetation index thresholds for each of the classifications. Initial thresholds for the DT were created using average values from single indices

for one or more image dates. Once a crop type was classified based on a particular index, it was removed from the subset and the remaining data was re-analyzed.

For example, Figure 4-2 shows average albedo and reflectance 5 values for the various crop types on August 25, 2002. Error bars were used to show +/- two times the standard deviation. Onions and garlic can easily be identified in the figure as the upper bound in both plots. Thus, the use of a threshold value for either albedo or reflectance band 5 can be applied to the data to discriminate this crop type from the remaining subset. Onions and garlic were then removed from the analysis and each of the indices were visually re-scrutinized for further classification.

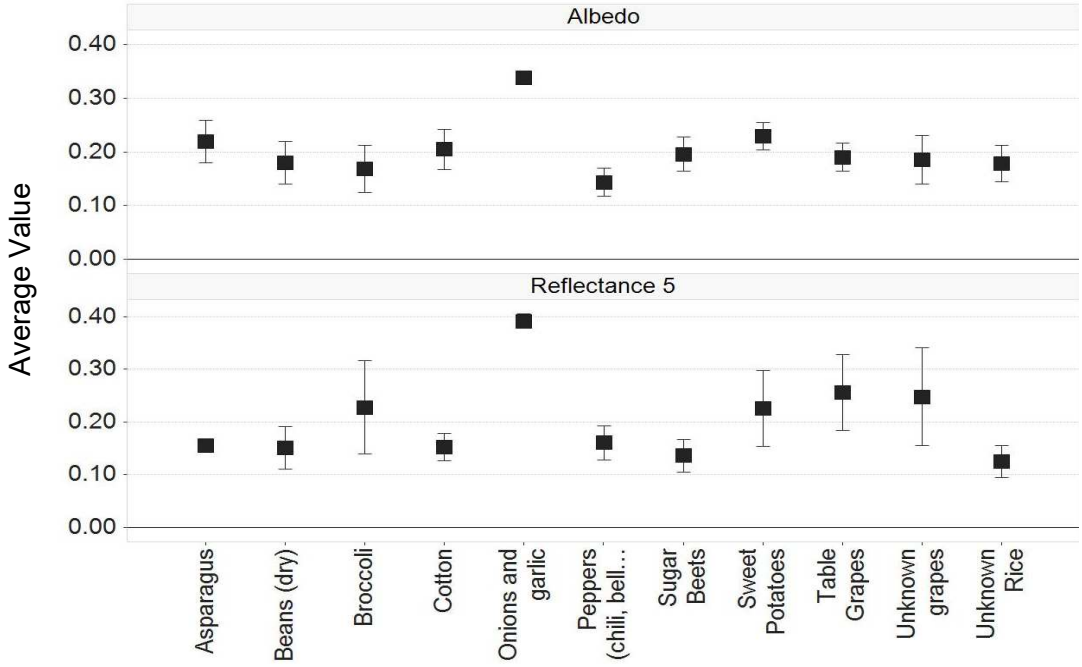

Figure 4-2. Average albedo and reflectance band 5 values for selected crops on 8/25/2002 (vertical error bars represent +/- 2 б)

After removing onion and garlic crop from the data set, additional thresholds were determined from the average net radiation and LAI parameters which led to the discrimination of asparagus and unknown rice crops. As shown in Figure 4-3, using the ten crop subset (onions and garlic omitted) and considering average LAI and net radiation, respectively asparagus and unknown rice plot distinctively above the remaining data. This approach was applied to 21 indices for each month of the year and resulted in thresholds or discrimination of the data subset.

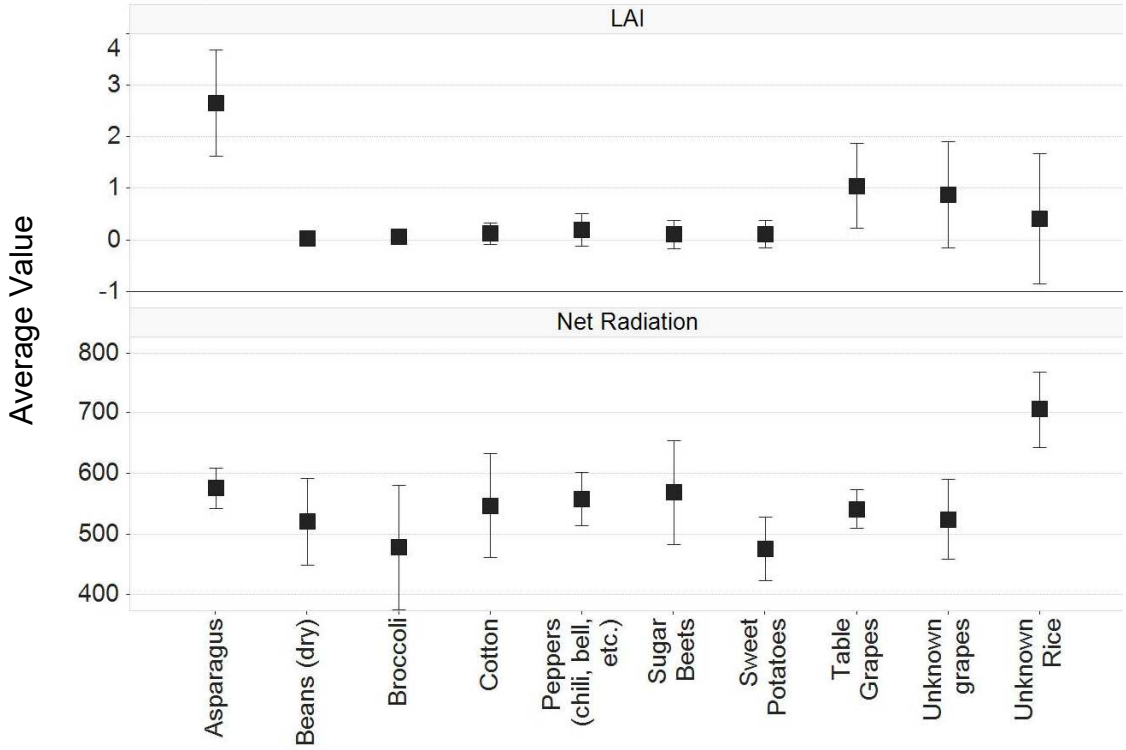

Figure 4-3. Average LAI and net radiation values for selected crop subsets on 6/6/2002 (vertical error bars represent +/- 2 σ)

4.2 Results

The results of the analysis led to the simplified decision tree provided in Figure 4-4 for the Merced 2002 data set. As indicated in the decision tree, (9) levels or thresholds were used to help discriminate crop types. At the first level, (1), the use of the albedo spectral index from August 25, 2002 was used to evaluate crop ID's 1 through 11. As described earlier in this section onions and garlic (Crop Type ID = 5) were easily discernable from the remaining crop types when comparing Albedo spectral value. The onions and garlic crop was then removed from the data set and the remaining crop types (ID's 1 through 4 and 6 through 11) were reevaluated at the second level. In level (2) the June 22, 2002 LAI spectral index scene was used as a threshold (LAI > 1.8) to discriminate asparagus from the other crop types, at which time it was removed from the data set. This approach was continued in a similar fashion through the 9 levels.

Note that in some cases it was necessary to utilize more than one spectral scene to discriminate a crop. For example, in level (5) the LAI and Net Radiance were used to identify broccoli (Crop Type ID = 5) within the data set. It was observed that as the decision tree grew the spectral signatures became more similar which made them more difficult to classify. Some spectral overlap was then required to determine the appropriate thresholds.

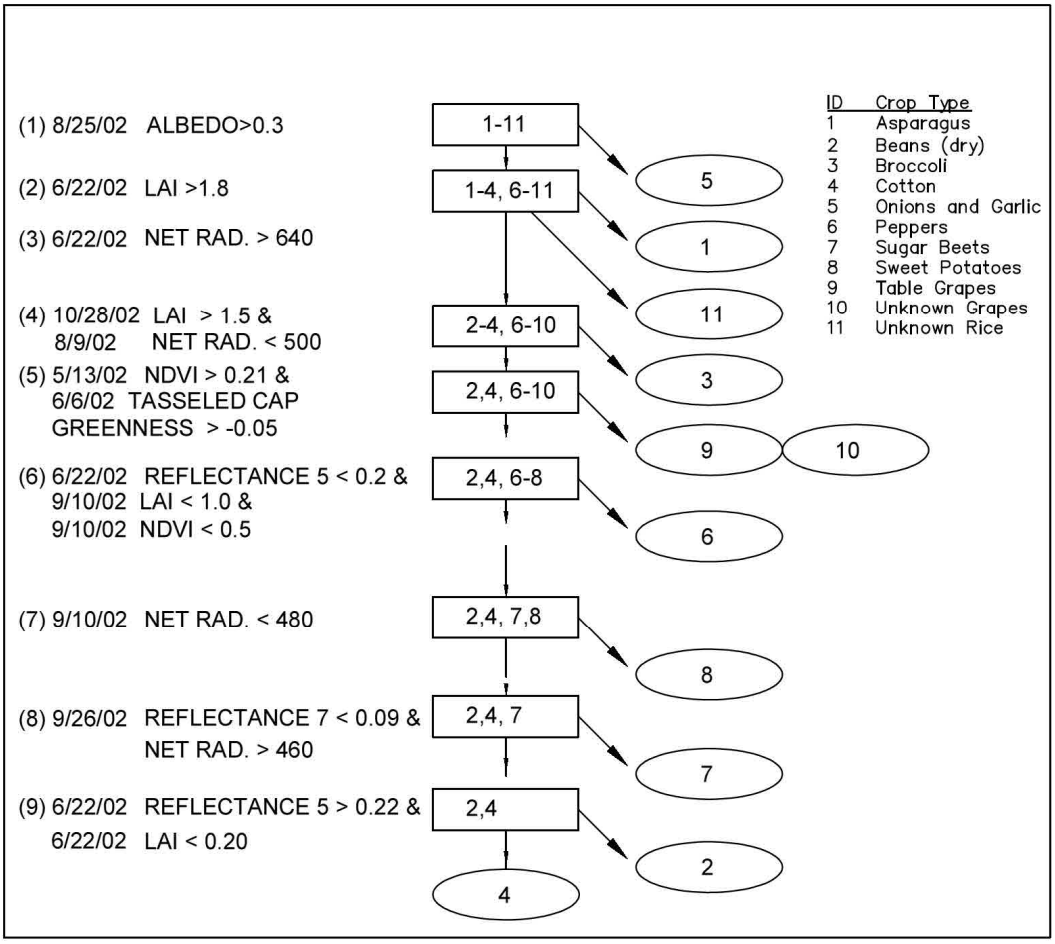

Figure 4-4. Merced 2002 Decision Tree Schematic

4.3 Conclusions

A supervised hybrid DT was created using the initial 2002 Merced data subset to discriminate 11 crops types from multi-temporal spectral data. Discrimination of crops grew more difficult further down the decision tree as spectral overlap increased.

The decision tree was shown to be successful in classifying the select subset (11 crops) through discrimination of various indices. However, when attempting to

apply the method to a larger dataset, several shortcomings were encountered due to the complexity and volume of the data. The accuracy of the decision tree significantly decreased when other crops outside the 11 crop subset are introduced into the analysis. This may be due to the quality of the training data and therefore could be improved in the future. In addition, crops with more variable spectral signatures, i.e. evergreens, alfalfa, or fields with crop rotation, led to misclassification within the specified decision tree. Additional, complex analysis would be required to try and better define the selected thresholds in order to segregate these more diverse signatures. Thus, this type of approach would likely yield unreasonable computation time and costs when assessing larger regions and the complex cropping scenes such as those found in California.

The use of a computer-assisted classification tool may be beneficial to further discriminate the results. Some of the thresholds determined in the manual method could be utilized with computer-assisted programs like eCognition to create an object-based classification regime. The application of computer-assisted classification tools using eCognition is presented in the following chapter.

5. COMPUTER-ASSISTED CLASSIFICATION USING ECOGNITION

Computer-assisted algorithms can likely decrease the computing time and increase accuracy of classification when compared to a manual method such as the simplified decision tree discussed in Chapter 4. A method that is not only repeatable but also can be performed without a large amount of labor and cost for future classification is highly desirable. This chapter aims to determine the applicability and viability of eCognition as a global classification engine for California crops and its capability to provide a simplistic, user friendly platform for classification.

5.1 Data Extraction

As mentioned previously, it is important that the selected training data is representative of the actual crop present so that the classification analysis will be accurate. Chapter 3 provided details regarding data processing and reduction for the Madera (2001 and 2011) and Merced (2002) data sets performed to eliminate bias and erroneous data. The resultant lead to a total crop list of 24 land type classifications (considering the three data sets) which could then be analyzed using the eCognition program. The crop class subset is summarized in Table 5-1. Considering these classes, the refined data set consisted of 8,358 crop fields for the 2001 data (Madera); 5,935 crop fields for the 2011 data (Madera); and 9,959 crop fields for the 2002 data (Merced). A summary of the ground survey data sets for these classes is shown in Table 5-2 with percentage of overall crop types shown in Table 5-3.

Table 5-1. Crop types used in analysis

Crop Type			
Alfalfa	Fallow/Idle cropland	Pasture/Grass	Sudan
Almond	Grapes	Peaches	Sugarbeets
Apples	Olives	Pistachio	Corn
Christmas Trees	Onions	Plums	Tomatoes
Cotton	Orange	Prunes	Walnuts
Dry Beans	Other Hay/Non Alfalfa	Sod/Grass Seed	Watermelons

Table 5-2. Field count ground surveyed by DWR

Crop Type	Count of 2001 DWR Ground Survey	Count of 2002 DWR Ground Survey	Count of 2011 DWR Ground Survey
Alfalfa	682	1810	497
Almond	1487	2774	2079
Apples	73	18	66
Christmas Trees	25	47	24
Cotton	466	1503	235
Dry Beans	10	21	24
Fallow/Idle Cropland	108	125	154
Grapes	3218	108	1683
Olives	42	319	49
Onions	10	3	4
Oranges	153	4	152
Other Hay/Non Alfalfa	399	3	219
Pasture/Grass	383	1269	49
Peaches	143	351	1
Pistachios	428	1	420
Plums	115	4	20
Prunes	37	77	20
Sod/Grass Seed	37	36	n/a
Sudan	40	34	n/a
Sugarbeets	13	87	n/a
Sweet Corn	383	408	129
Tomatoes	41	537	52
Walnuts	52	310	48
Watermelons	13	110	10
Total	8358	9959	5935

Table 5-3. Percent of total crops analyzed for 2001 Madera, 2002 Merced, and 2011 Madera Data Sets

Crop Type	Percent of Crop Types in 2001 DWR Ground Survey	Percent of Crop Types in 2002 DWR Ground Survey	Percent of Crop Types in 2011 DWR Ground Survey
Alfalfa	8.2%	18.2%	8.4%
Almond	17.8%	27.9%	35.0%
Apples	0.9%	0.2%	0.0%
Christmas Trees	0.3%	0.5%	0.4%
Cotton	5.6%	15.1%	4.0%
Dry Beans	0.1%	0.2%	0.4%
Fallow/Idle Cropland	1.3%	1.3%	2.6%
Grapes	38.5%	1.1%	28.4%
Olives	1.5%	3.2%	0.8%
Onions	0.1%	0.0%	0.1%
Oranges	1.8%	0.0%	2.6%
Other Hay/Non Alfalfa	4.8%	0.0%	n/a
Pasture/Grass	4.6%	12.7%	3.7%
Peaches	1.7%	3.5%	0.8%
Pistachios	5.1%	0.0%	7.1%
Plums	1.4%	0.0%	0.3%
Prunes	0.4%	0.8%	0.3%
Sod/Grass Seed	0.4%	0.4%	n/a
Sudan	0.5%	0.3%	n/a
Sugarbeets	0.2%	0.9%	n/a
Sweet Corn	4.6%	4.1%	2.2%
Tomatoes	0.5%	5.4%	0.9%
Walnuts	0.6%	3.1%	0.8%
Watermelons	0.2%	1.1%	0.2%
Total	100%	100%	100%

5.2 Methodology

Pattern recognition seems to be a combination of art and science: science, in the sense that computer algorithms are utilized to assist classification procedures and art, in that interpretation and training sites are based on user experience and knowledge. Both aspects can greatly affect the outcome of the results. An unsupervised classification model allows for a strictly science analysis determining patterns and classes without any prior user input but will require user analysis to properly interpret the results. A supervised system uses training data based on input from the user and known classes which may narrow the results of the classification test and may be subject to user bias.

5.2.1 eCognition Analyses

The computer program eCognition, discussed in Chapter 2, has the capability for supervised or unsupervised models with a set of spectral features as inputs. The spectral signatures can be based on a parametric (statistical parameters) or non-parametric (discrete objects) as the basis or a combination of both (Kloer 1994). The focus of this paper is a supervised model using the Nearest Neighbor (NN) method uses a set of training data (objects with known classes) as a base. The NN method was utilized because the approach is computationally simple (Laliberte et al. 2004). Details of the NN method are provided in Chapter 2. The training samples consisted of sites with known crops based on DWR field survey used as ground truthing.

A classification algorithm was created with Trimble's eCognition© Developer program which utilizes image layers (such as spectral data), thematic layers (such as parcel shape files) and incorporates the Nearest Neighbor algorithm which has been pre-programed within the software package. The user can provide direct input through parent/child process tree organization where results can easily be interrogated and reviewed by the end user. A sample process tree layout in eCognition is provided in Figure 5-1.

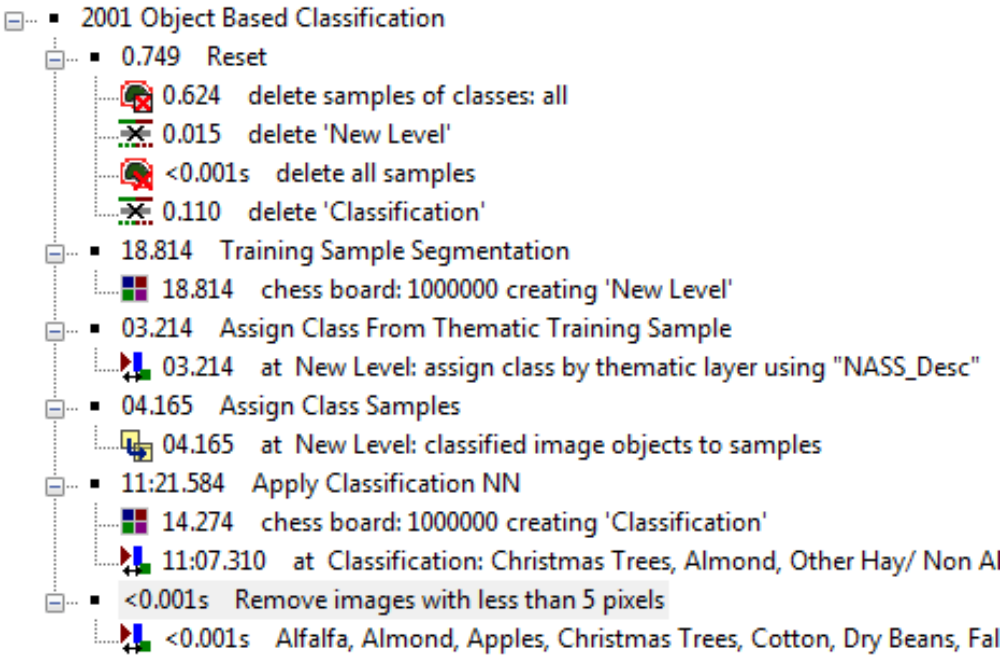

Figure 5-1. eCognition Process Tree Sample

5.2.2 Scenarios Considered

Using the NN classification algorithm in eCognition, a series of four scenarios were analyzed. The four scenarios considered are described below:

Scenario 1: The 2001 Madera, 2002 Merced, 2011 Madera were analyzed using 5%, 10%, 20% of the DWR ground survey data as training data for each of the respective years. For example, 2001 Madera analysis utilizes 10% of the 2001 (Madera) DWR ground survey as ground truthing to create training data for use in the classification algorithm. This scenario reviews the effects of using various percentages of ground truthing as training data used in subsequent analysis. Due to the high cost and labor that may be involved with acquisition of ground survey for future data sets, users should understand the effects of the percentage of training data used. Each county should be re-assessed as they vary in size and quantity of field. For example a field survey aiming to ground truth 20% of field in a small county may be more feasible than a larger county.

Scenario 2: Scenario 2 reviews the applicability of utilizing the DWR existing ground survey data as a basis to create a comprehensive training sample set from one county that can be applied to a future site for use in the classification algorithm. In this scenario, 90% of the Madera 2001 ground survey data is used to create a comprehensive training set that is applied to the Merced 2002 and the Madera 2001 study areas.

Scenario 3: Utilizing the methods and results from Scenario 2, this scenario reviews the effect of adding an additional 10% of the respective DWR ground survey data (from the subject area and year) to the existing training sample set. For example, 90% of the 2001 Madera County ground survey is used to create a training sample set as described in scenario 2 and an additional 10% of DWR ground survey from Merced 2002 data set is applied on the 2002 Merced classification algorithm. The change in accuracy associated with updating a base training sample set (from 2001 Madera) with additional training data points of a subject year is reviewed.

Scenario 4: The vegetation indices presented in the previous sections and utilized for the analysis have all been pre-processed in house by the ITRC. With the dissemination of Landsat data, corrected spectral data are relatively common practice and can be obtained without much effort. The EToF utilized in the analysis is produced by a METRIC created by the ITRC in house. Scenario 4 reviews the effects of the Actual Crop Coefficient feature space on the classification accuracy. For simplicity, only the Madera 2011 data set used in scenario 3 was considered.

5.2.3 Data Input

The satellite data dates used for the algorithm feature set are listed in the Table 5-4. During early and late 2011 the land satellite experienced a failure in one of its sensors creating a band gap in the produced data. Interpolation could be applied to compensate the data gap; however, since the interpolated data would

not be actual data, the satellite dates for early March and late December were omitted from the analysis.

Table 5-4. Satellite dates used for multi-temporal analysis

2001 Madera	10-May	19-Jul	13-Jul	14-Aug	1-Oct
2002 Merced	5-May	22-June	8-July	9-Aug	4-Oct
2011 Madera	6-May	23-Jul	9-Jul	10-Aug	27-Sep

It is important to note that the two data sets data sets from Madera are 10 years apart and that selection of the appropriate satellite acquisition dates greatly affected the accuracy results. It was found that analysis dates (time of year satellite image was taken) needed to match relatively closely for all three data sets. In general, if the dates between the respective satellite data sets were not within 2-5 days of each other, they were removed for analysis.

Feature spaces have been defined in order to create the class hierarchy to be used with the NN algorithm. Initial trials attempted to utilize all the available indices available for the subject data set within eCognition - approximately 14 indices and 14 dates including reflectance and radiance which resulted in approximately 400+ image layers resulting in the program becoming unstable and having unreasonable processing times.

It is important to note that a feature space can be reviewed and optimized within the eCognition program. Thus, feature space combinations were then analyzed through trial iterations. It was found that a combination of spectral indices and bands including NDVI, NDWI, Albedo, Actual Crop Coefficient, and Radiance

bands 1 through 7, resulted in the highest classification accuracy. The combination of these feature spaces for the dates considered (Table 5-4) created a final multi-temporal feature space of 55 images.

Once the final feature space was defined, training samples were extracted and a class hierarchy was defined in eCognition. The class hierarchy used in analysis is presented in Figure 5-2.

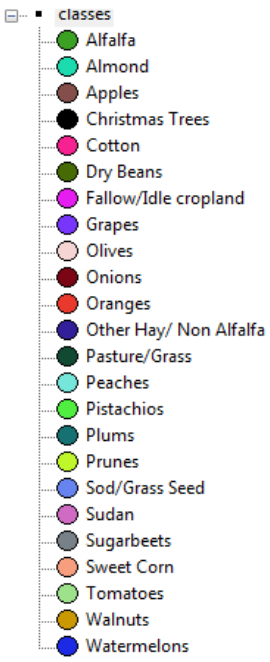

Figure 5-2. eCognition class hierarchy

Figure 5-3 below shows an example from eCognition where 10% of 2001 Madera data were used as training samples, i.e. Scenario 1. The colored areas correspond to the class symbols lists in Figure 5-2 and represent the 10% DWR ground surveyed parcels that were used as training data for the NN algorithm.

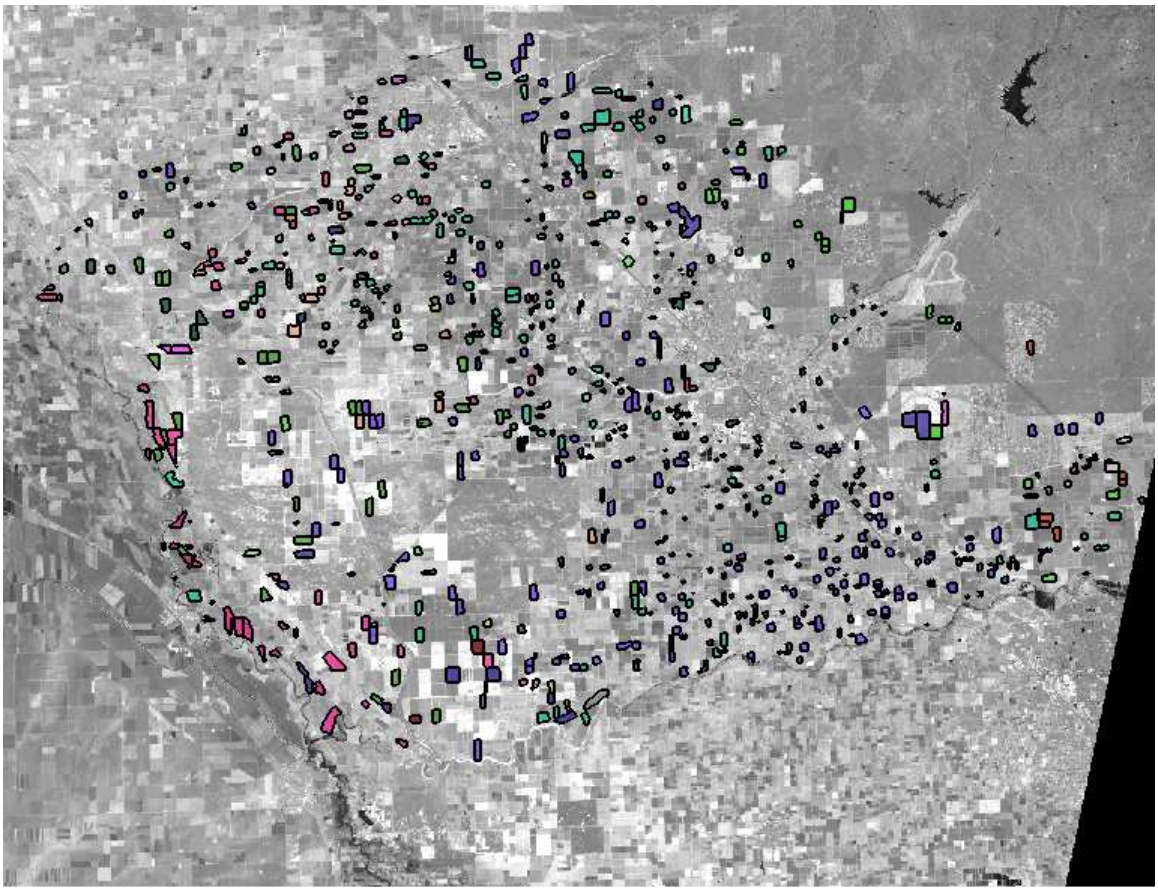

Figure 5-3. 10% training sample sites for Madera 2001

Once 10% training data has been input into eCognition, the program then creates a unique spectral signature for each class within the feature space. The sample editor within the program can then be used to compare different spectral signatures. An example of the sample editor is shown in the Figure 5-4 and illustrates the comparison of several different layers that help the NN algorithm discriminate between Cotton (shown in black) and Alfalfa (shown in blue).

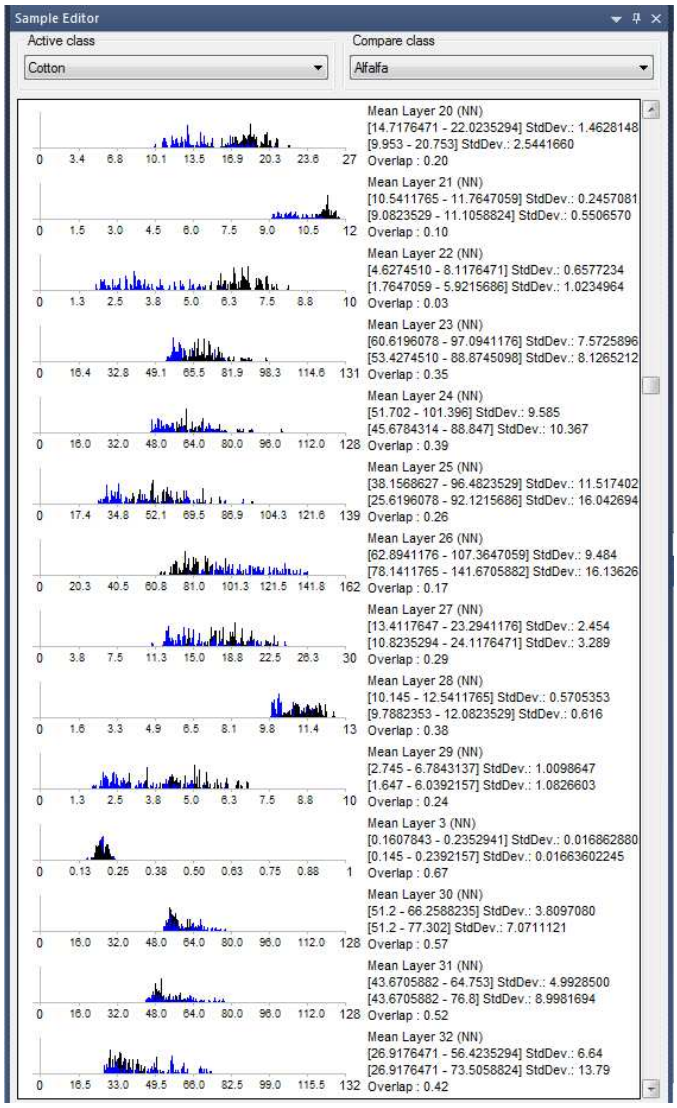

Figure 5-4. Sample editor comparing class feature space created for Cotton (black) and Alfalfa (blue)

Once the samples are populated with a feature space from the imported image data, the program can run the NN classification algorithm. The analysis results in a final classification image, similar to that presented in Figure 5-5. This process was applied to the four scenarios and the results are discussed in the subsequent section.

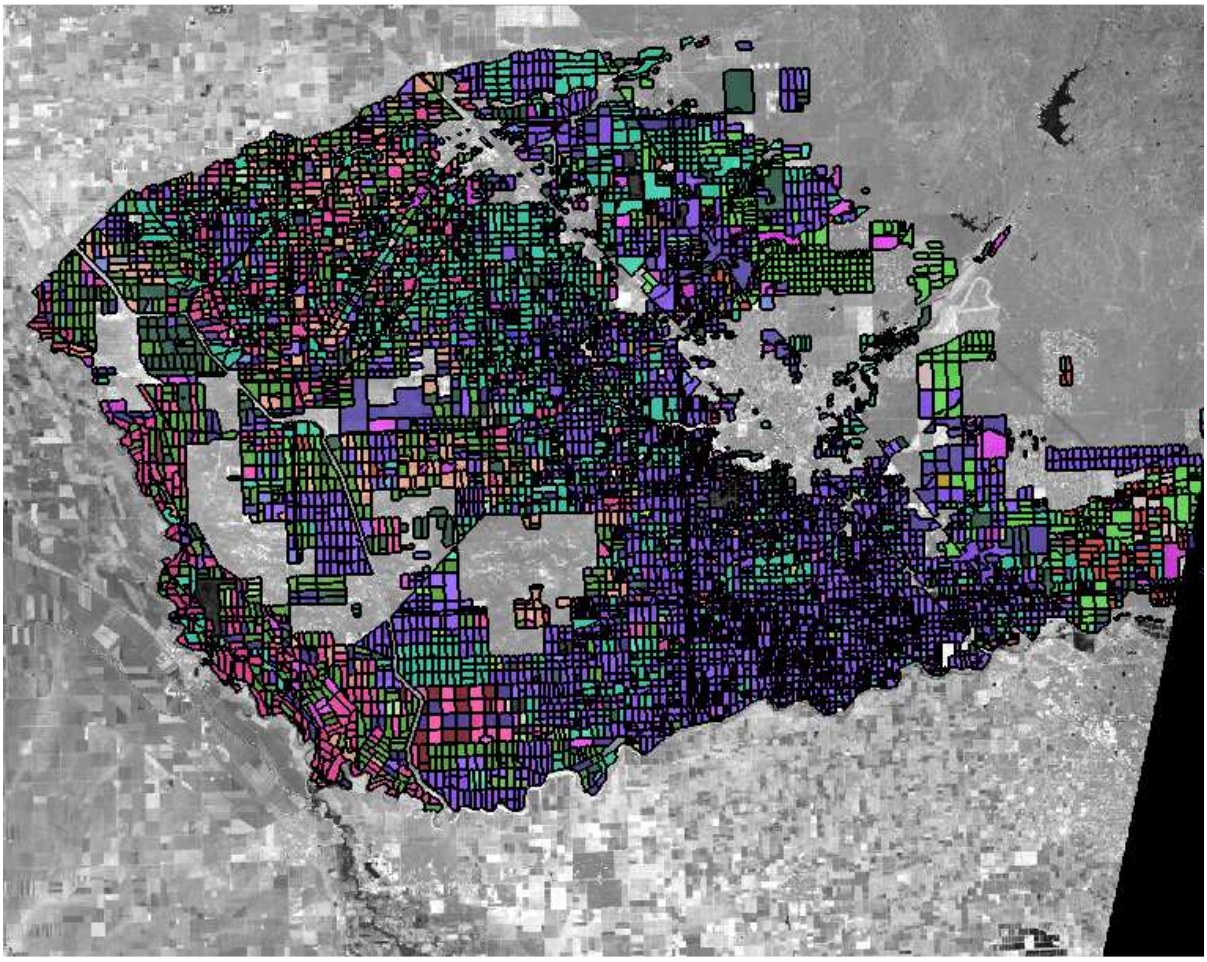

Figure 5-5. Example of final classification results using the NN algorithm in eCognition

5.3 Results

Accuracy is essential in determining the performance of a classification scheme and identifying areas where improvements may be required within certain classes. Thus, the results from each scenario are discussed in terms of the accuracy of the algorithm to classify crops according to the DWR ground survey data.

Individual tables reporting each class (crop type) accuracy are presented in Appendix D for each of the scenarios considered. Confusion matrices of the resulting classifications for each of the four scenarios considered are provided in Appendix E. The overall accuracies (calculated based on field areas) of each of the analyses performed for the respective scenarios are summarized in Table 5-5, followed by a discussion of each. The overall accuracies are based on area.

Table 5-5. Summary of results from eCognition analyses

Scenario	Overall Accuracy		
	2001 Madera	**2002 Merced**	**2011 Madera**
1A	77 %	69 %	74 %
1B	79 %	73 %	77 %
1C	84 %	78 %	83 %
2	-	60 %	70 %
3	-	75 %	78 %
4	-	-	75 % (no EToF)

Scenario 1 involved using a percentage (5%, 10%, and 20% for 1A, 1B, and 1C respectively) of the DWR ground survey data to define training samples and a class hierarchy feature set to be used on the same year with the NN algorithm for 2001 Madera, 2002 Merced, and 2011 Madera data sets. The overall accuracies are summarized in Table 5-5 for the 2001 Madera, 2002 Merced, and 2011 Madera data sets respectively. Individual class accuracies tended to be greater for crops that had a higher percentage of field area present in the county and increased as the percentage of training samples utilized increased.

In Scenario 2, the 2002 Merced and 2011 Madera data sets were analyzed using training data compiled from 90% of the 2001 Madera DWR ground survey data imported into the two subject data sets and the NN classification algorithm was applied. Merced 2002 and Madera 2011 showed a decrease in overall accuracy from the first scenario, resulting in an overall user class accuracy of 60% and 70% respectively. This reduction in overall accuracy is believed to be due to the large date gap between the two data sets (10 years) in the same county and spatial differences between the two counties for years with close proximity. Factors that may affect cropping calendars and phenology include: changes in climate, irrigation technology, farming methods, and sensor accuracy.

In an effort to improve the overall accuracy of the 2002 Merced and 2011 Madera data, additional training samples from the respective DWR ground survey data sets were added into the compiled 2001 Madera training samples in Scenario 3. For example, 10% of the 2011 DWR ground survey data was used to create training data and added to the imported (90%) 2001 Madera training sample set, resulting in an overall user classification improved accuracy of 78%. With a similar application to the 2002 Merced data set, the overall user classification accuracy increased to 75%. The increase in performance is likely because the additional training data allows the algorithm to overcome changes in phenology and agricultural practices resulting from a large date gap or change in area use.

The last scenario (Scenario 4) analyzed the overall effect of including the Actual Crop Coefficient, EToF, within the algorithm feature space. It was found the inclusion of the EToF boosted overall user class results by approximately 3.0%, as shown by comparing the results from Scenario 3 (78%) to the overall accuracy with the removal of EToF in Scenario 4 (75%).

5.4 Discussion

It is understood that selection of appropriate training samples, suitability of classification algorithm and selection of spectral inputs used for analysis is critical for successful classification (Lu and Weng 2007). Although the DWR assure high accuracy on ground survey data, it is noted that errors in field verifications are inevitable and likely present in the data sets used for the analyses presented. Since the ground truthing data was performed by the DWR separately, quality control for training samples was not performed and may be a source of error in the crop classification. Further double cropping was not considered and could expand the potential for increase error.

As mentioned previously, it was found that it was incredibly important that the dates input into eCognition that make up the feature space be similar across the data sets considered. For example, if a spectral image for NDVI during May 5th was used for sampling in the 2001 Madera data set, it was critical that a similar date (generally found with 4-5 days) was used for the 2011 Merced analysis. Since it is likely that cropping calendars for a specific crop type may not change

significantly, similar dates improved results likely because the growth and harvest cycles were captured at similar times. Factors such as irrigation practice, farming methods, technological advancement, and changes in climate, may vary greatly between time of data acquisition for a given area (i.e. 2001 Madera versus 2011 Madera). Thus, if the time between data sets for a given area were closer together, the overall accuracy of the tested algorithms would likely increase.

5.5 Conclusion

A large crop list in California makes it very difficult to create a classification scheme that can identify all crop types with confidence. Much effort is required to acquire quality training data for use in supervised classification algorithms since crops can vary greatly geographically within California. The acquisition of highly accurate ground truthing would likely be labor intensive and expensive.

As mentioned previously, DWR ground survey is only available for each county in California every 5-10 years, at best, which presents a gap in cataloging of crop types in the region. The research presented in this chapter utilized DWR ground survey as training samples for input into the NN algorithm within the program eCognition. The program is capable of handling large image data sets.

Madera County 2001 and 2011 and Merced County 2002 data were analyzed because the DWR has ground survey available and the ITRC has pre-processed

Landsat images for the subject years. The subject data set was reduced to agricultural crops that were present in the County and non-agriculture land types were removed, as discussed in Chapter 3.

When the NN algorithm was applied using 5%, 10%, and 20% of each crop type as training data for the respective data set, overall user classification accuracies ranged between 77% to 83% depending on the percentage of training samples used in the analysis. It was found that an increase in training samples generally increase the overall accuracy of the analysis. When applying only 90% 2001 Madera training data to the 2011 Madera and 2002 Merced data sets resulted in a decreased overall accuracy. However, coupling the 90% 2001 Madera training data with 10% training data from the respective data sets, resulted to improved classification accuracies of 75% (2002 Merced) and 78% (2011 Madera). Lastly, the exclusion of the Actual Crop Coefficient, ETоF, was found to decrease the overall accuracy by 3% when considering the 2011 Madera data set in the scenario 3 analysis.

In conclusion, the results show there are clear advantages of using an algorithm-based approaches to classify crop types. It was demonstrated that historical ground survey data provided by DWR can be used with future imagery datasets to obtain reasonable classification results. Crops types with larger population within a county had the highest classification accuracy. This is likely due to the larger

sample number within the dataset overcoming small biases associated with poor training data.

6. CONCLUSIONS

With the high cost of physical ground survey there is an absolute need for an accurate, inexpensive methodology to identify crop types in California through remote sensing. This research has focused on an area of the Central Valley, the Madera and Merced Counties, in an effort to develop an improved approach to crop classification using available Landsat and DWR data.

The results of this study have shown the use of a manual simplified decision tree approach (DT) or computer-assisted approach, using the Nearest Neighbor (NN) algorithm within eCognition, may be sufficient in the classification of certain crops. However, both methods presented have associated shortcomings and when considered individually, each have difficulty in classifying *all* of the crop types within the areas considered.

It is hypothesized that a combination of multiple approaches discussed and/or presented in this research such as classical decision trees, phenology-based approach, or computer-assisted algorithms could result in an improved overall classification of crop types. For example, the use of the NN algorithm within eCognition resulted in acceptable results for major crops types present within the subject data sets and it is suggested that alternate methods such as manual classification, phonology based, or SVM (to name a few) be incorporated into the classification scheme to better discriminate among all the remaining crop types. Ultimately, the hybrid approach will need to be capable of capturing single and

multiple crop rotation within a field and be diverse enough to capture the constantly changing climate conditions and farming practices.

As accuracy, resolution and confidence in Landsat imagery increases, a method to comprehensively classify and catalog crops in California at any time can provide many uses. In California, during times of drought, groundwater basins are being over drafted. Accurate crop classification can help improve water balance calculations for agricultural and environmental habitat and contribute to planning and policy decision making. Further use of an improved classification system can be applied on a global scale to land use changes and assessment of non-point source contamination loading.

6.1 Comparison to CDL

The United States Department of Agriculture (USDA) National Agricultural Statistics Service (NASS) provides a geo-referenced, crop-specific land cover data product called the Cropland Data Layer (CDL). The main goals of the CDL are to provide 1) supplemental acreage estimates and 2) produce geo-referenced crop specific products on an annual basis. The product is a pixel-based raster image processed and analyzed by the Spatial Analysis Research Section (SARS) and is available for the State of California after 2007.

CDL accuracies tend to be higher in areas where only a few crops are dominant and in areas such California where crop types are diverse and complex,

classification accuracies of the CDL would likely be much lower. Reitsma et al. (2016) reported CDL accuracies in South Dakota that ranged from 38.9% to 95.2% for an analysis classifying grasslands. They attributed the wide range of accuracy to the intrinsic errors associated within CDL and noted that the highest accuracies occurred when the subject fields were dominantly present and conversely, lower accuracy's occurred when a single crop was less dominantly practiced. Similarly Larsen et al. (2015) compared area estimates for major US crops in 2012 and found that accuracy of the CDL is extremely variable and influenced greatly by the variability of crops present.

The 2011 Madera CDL raster image was downloaded from the CropScape web interface for comparison against the 2011 Madera County DWR ground survey. The CDL was pre-processed within the ArcGIS computer program and reduced to a similar 24 crop type subset of as described in section 5. The 2011 Madera County CDL resulted an overall accuracy of 67.1% when compared against the 2011 Madera County DWR ground survey as summarized in Table 6-1. The 2011 Madera (scenario 3) accuracies determined from eCognition's Nearest Neighbor algorithm and the quantity of fields utilized as training data in the 2011 Madera (scenario 3) analysis are included in for reference.

Table 6-1. Accuracy comparison of 2011 Madera CDL versus 2011 Madera (scenario 3) analysis

Crop Type	2011 Madera (scenario 3) Accuracy	Qty of fields used as training data in 2011 Madera (scenario 3) Analysis	2011 Madera Cropscape CDL Accuracy
Alfalfa	86.5%	663	94.3%
Almond	85.5%	1548	85.6%
Apples	7.7%	72	0.0%
Christmas Trees	7.5%	24	0.0%
Corn	89.4%	357	54.6%
Cotton	69.9%	443	57.8%
Dry Beans	4.2%	11	0.0%
Fallow/Idle cropland	31.7%	113	69.0%
Grapes	84.1%	3064	77.3%
Olives	3.5%	42	25.9%
Onions	15.0%	10	0.0%
Oranges	56.6%	153	52.7%
Pasture/Grass	59.1%	367	0.0%
Peaches	0.0%	134	0.0%
Pistachios	63.2%	427	63.3%
Plums	29.6%	105	0.0%
Prunes	24.1%	35	0.0%
Sod/Grass Seed	n/a	39	0.0%
Sudan	n/a	0	n/a
Sugarbeets	n/a	0	n/a
Tomatoes	69.4%	42	63.3%
Walnuts	27.9%	52	21.0%
Watermelons	12.5%	12	0.0%
Overall Accuracy	78.0%		74.7%

The overall accuracy determined for the 2011 Madera County CDL is approximately 3.3% lower than the accuracy for the Scenario 3 analysis. Further, the CDL tends to have similar accuracies for the five dominant crop types (grapes, almond, alfalfa, cotton and pistachios) when compared to the Scenario 3 analysis. It is thought that because these five crops had some of the highest acreage and field presence in Madera County during 2011, the CDL is able to provide an acceptable classification accuracy. Other crops reviewed that do not have dominating field presence tended to show highly variable accuracies and it is hypothesized that in general, the CDL is more appropriate for identifying crop types with large dominance within a study area; however, in California the overall accuracy remains low due to the large diversity of crop types in the Central Valley.

6.2 Future Work

Largely due to the complexity of California crop types, future improvement to the presented classification schemes could incorporate a hybrid approach which combines the power of the computer based analysis with alternative methods, such as those discussed in this thesis: decision tree, phenology-based approach, and computer-assisted algorithms.

The decisions tree approach would may be more applicable to classifying general crop types at initial levels such as a crop versus non crop or tree crop versus ground crop level of analysis. As discussed in Chapter 4, as the decision tree grows spectral signatures of crop types become more similar making this approach

less effective. At this stage the use of a computer-assisted algorithms such as eCognition could be applied in an attempt to classify crop types with a large field presence within the data set. Further, since the phenology-based classification approach is less reliant on training data and more reliant on cropping calendars, the inclusion this algorithm may be used to help discriminate crops with less fields present in a study area and that have defined cropping calendars.

This research suggests that eCognition could provide a promising platform for future analysis. Continued iterations of the algorithms within eCognition may lead to even better accuracy but this was considered beyond the scope of the thesis. The suggested hybrid approach combined with future efforts should further evaluate other methods not considered in this research such as CART, SVM, and Neural Networks.

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Appendix A. Madera 2001 DWR to NASS ID conversion

CLASS 1	SUBCLASS 1	Lookup ID	DWR Description	NASS Description	NASS ID Value
G	1	G1	Barley	Barley	21
G	2	G2	Wheat	Spring Wheat	23
G	3	G3	Oats	Oats	28
G	6	G6	Misc and mixed grain and hay	Other Hay/Non Alfalfa	37
G	99	G99	Unknown mixed grain and hay	Other Hay/ Non Alfalfa	37
R	1	R1	Rice	Rice	3
F	1	F1	Cotton	Cotton	2
F	2	F2	Safflower	Safflower	33
F	3	F3	Flax	Flaxseed	32
F	4	F4	Hops	Hops	56
F	5	F5	Sugar Beets	Sugar beets	41
F	6	F6	Corn (field and sweet)	Corn	12
F	7	F7	Grain sorghum	Sorghum	4
F	8	F8	Sudan	Sorghum	4
F	9	F9	Castor Beans	Dry Beans	42
F	10	F10	Beans (dry)	Dry Beans	42
F	11	F11	Miscellaneous field	Pasture/Grass	62
F	12	F12	Sunflowers	Sunflower	6
F	99	F99	Unknown Field Crop	Safflower	33
P	1	P1	Alfalfa & alfalfa mixtures	Alfalfa	36
P	2	P2	Clover	Clover/Wildflower	58
P	3	P3	Mixed pasture	Pasture/Grass	62
P	4	P4	Native Pasture	Pasture/Grass	62
P	5	P5	Induced high water table native pasture	Pasture/Grass	62
P	6	P6	Misc. grasses (normally grown from seed)	Pasture/Grass	62
P	7	P7	Turf farm	Sod/Grass Seed	59
P	99	P99	Unknown Pasture	Pasture/Grass	62
T	1	T1	Artichokes	Asparagus	207
T	2	T2	Asparagus	Asparagus	207
T	3	T3	Beans (green)	Dry Beans	42
T	4	T4	Cole crop (when further breakdown is not needed)	Pasture/Grass	62
T	5	T5	Unknown	Misc. Vegs & Fruits	47
T	6	T6	Carrots	Carrots	206
T	7	T7	Celery	Celery	245
T	8	T8	Lettuce (all types)	Lettuce	227
T	9	T9	Melons, squash, and cucumbers (all types)	Watermelons	48
T	10	T10	Onions and garlic	Onions	49
T	11	T11	Peas	Peas	53
CLASS 1	**SUBCLASS 1**	**Lookup ID**	**DWR Description**	**NASS Description**	**NASS ID Value**

T	12	T12	Potatoes	Potatoes	43
T	13	T13	Sweet Potatoes	Sweet Potatoes	46
T	14	T14	Spinach	Greens	219
T	15	T15	Tomatoes	Tomatoes	54
T	16	T16	Flowers, nursery & Christmas tree farms	Christmas Trees	70
T	17	T17	Mixed (four or more)	Misc. Vegs & Fruits	47
T	18	T18	Miscellaneous truck	Misc. Vegs & Fruits	47
T	19	T19	Bush berries	Blueberries	242
T	20	T20	Strawberries	Strawberries	221
T	21	T21	Peppers (chili, bell, etc.)	Peppers	216
T	22	T22	Broccoli	Broccoli	214
T	23	T23	Cabbage	Cabbage	243
T	24	T24	Cauliflower	Cauliflower	244
T	25	T25	Brussels Sprouts	Asparagus	207
T	99	T99	Unknown truck, nursery, and berry crops	Misc. Vegs & Fruits	47
D	1	D1	Apples	Apples	68
D	2	D2	Apricots	Apricots	223
D	3	D3	Cherries	Cherries	66
D	5	D5	Peaches and nectarines	Peaches	67
D	6	D6	Pears	Pears	77
D	7	D7	Plums	Plums	220
D	8	D8	Prunes	Prunes	210
D	9	D9	Figs	Other Tree crop	71
D	10	D10	Miscellaneous deciduous	Deciduous Forest	141
D	12	D12	Almonds	Almond	75
D	13	D13	Walnuts	Walnuts	76
D	14	D14	Pistachios	Pistachios	204
D	99	D99	Unknown tree crop	Other Tree Crop	71
C	1	C1	Grapefruit	Cantaloupes	209
C	2	C2	Lemons	Citrus	72
C	3	C3	Oranges	Oranges	212
C	4	C4	Dates	Other	71
C	5	C5	Avocados	Other	71
C	6	C6	Olives	Olives	211
C	7	C7	Miscellaneous subtropical fruits	Citrus	72
C	8	C8	Kiwis	Citrus	72
C	9	C9	Jojoba	Other	71
C	10	C10	Eucalyptus	Other	71
C	99	C99	Unknown citrus or subtropical	Other	71
V	1	V1	Table Grapes	Grapes	69
V	2	V2	Wine Grapes	Grapes	69
V	3	V3	Raisin Grapes	Grapes	69
V	99	V99	Unknown grapes	Grapes	69

CLASS 1	**SUBCLASS 1**	**Lookup ID**	**DWR Description**	**NASS Description**	**NASS ID Value**

I	1	I1	Land not cropped the current or previous crop season, but cropped within the past three years	Fallow/Idle cropland	61
I	2	I2	New lands being prepared for crop production	Fallow/Idle cropland	61
S	1	S1	Farmsteads	Developed/Low Density	122
S	2	S2	Livestock feed lots	Developed/Low Density	122
S	3	S3	Dairies	Developed/Low Density	122
S	4	S4	Poultry Farms	Developed/Low Density	122
U	1	U1	generic nomenclature with no subclass	Developed/Low Density	122
U	99	U99	Urban	Developed/Low Density	122
UR	1	UR1	Single family dwelling with lot sizes greater than 1 acre up to 5 acres	Developed/Low Density	122
UR	11	UR11	Single family dwelling with lot sizes greater than 1 acre up to 5 acres - 0%-25% area irrigated	Developed/Low Density	122
UR	12	UR12	Single family dwelling with lot sizes greater than 1 acre up to 5 acres - 26%-50% area irrigated	Developed/Low Density	122
UR	13	UR13	Single family dwelling with lot sizes greater than 1 acre up to 5 acres - 51%-75% area irrigated	Developed/Low Density	122
UR	14	UR14	Single family dwelling with lot sizes greater than 1 acre up to 5 acres - >76% area irrigated	Developed/Low Density	122
UR	2	UR2	Single family dwelling with a density of 1 unit/acre up to 8+ units/acre	Developed/Med Density	123
UR	21	UR21	Single family dwelling with a density of 1 unit/acre up to 8+ units/acre - 0%-25% area irrigated	Developed/Med Density	123
CLASS 1	**SUBCLASS 1**	**Lookup ID**	**DWR Description**	**NASS Description**	**NASS ID Value**

UR	22	UR22	Single family dwelling with a density of 1 unit/acre up to 8+ units/acre - 26%-50% area irrigated	Developed/Med Density	123
UR	23	UR23	Single family dwelling with a density of 1 unit/acre up to 8+ units/acre - 51%-75% area irrigated	Developed/Med Density	123
UR	24	UR24	Single family dwelling with a density of 1 unit/acre up to 8+ units/acre - >76% area irrigated	Developed/Med Density	123
UR	3	UR3	Multiple family (apartments, condos, townhouses, etc.)	Developed/High Density	124
UR	31	UR31	Multiple family (apartments, condos, townhouses, etc.) - 0%-25% area irrigated	Developed/High Density	124
UR	32	UR32	Multiple family (apartments, condos, townhouses, etc.) - 26%-50% area irrigated	Developed/High Density	124
UR	33	UR33	Multiple family (apartments, condos, townhouses, etc.) - 51%-75% area irrigated	Developed/High Density	124
UR	34	UR34	Multiple family (apartments, condos, townhouses, etc.) - >76% area irrigated	Developed/High Density	124
UR	4	UR4	Trailer courts	Developed/Med Density	123
UR	41	UR41	Trailer courts - 0%-25% area irrigated	Developed/Med Density	123
UR	42	UR42	Trailer courts - 26%-50% area irrigated	Developed/Med Density	123
UR	43	UR43	Trailer courts - 51%-75% area irrigated	Developed/Med Density	123
UR	44	UR44	Trailer courts - >76% area irrigated	Developed/Med Density	123
CLASS 1	**SUBCLASS 1**	**Lookup ID**	**DWR Description**	**NASS Description**	**NASS ID Value**

UR	99	UR99	Residential	Developed/Med Density	123
UC	1	UC1	Offices, retailer, etc.	Developed/Med Density	123
UC	2	UC2	Hotels	Developed/High Density	124
UC	3	UC3	Motels	Developed/High Density	124
UC	4	UC4	Recreation vehicle parking, camp sites	Developed/Open Space	121
UC	5	UC5	Institutions (hospitals, prisons, reformatories, asylums, etc.)	Developed/High Density	124
UC	6	UC6	Schools	Developed/High Density	124
UC	7	UC7	Municipal auditoriums, theaters, churches, buildings, etc	Developed/High Density	124
UC	8	UC8	Miscellaneous high water use	Developed/Open Space	121
UI	1	UI1	Manufacturing, assembly, and general processing	Developed/High Density	124
UI	2	UI2	Extractive industries (oil fields, rock quarries, etc.)	Developed/High Density	124
UI	3	UI3	Storage and distribution (warehouses, substations, etc)	Developed/High Density	124
UI	6	UI6	Saw mills	Developed/High Density	124
UI	7	UI7	Oil refineries	Developed/High Density	124
UI	8	UI8	paper mills	Developed/High Density	124
UI	9	UI9	Meat packing plants	Developed/High Density	124
UI	10	UI10	steel and aluminum mills	Developed/High Density	124
UI	11	UI11	Fruit and vegetable canneries and general food processing	Developed/High Density	124
UI	12	UI12	Miscellaneous high water use	Developed/Open Space	121
UI	13	UI13	Sewage treatment plant including ponds	Developed/Open Space	121
UI	14	UI14	Waste accumulation sites	Developed/Open Space	121
UI	15	UI15	Wind farms, solar collector farms	Developed/Low Density	122
UL	1	UL1	Lawn area - irrigated	Sod/Grass Seed	59
UL	2	UL2	Golf course - irrigated	Sod/Grass Seed	59

CLASS 1	**SUBCLASS 1**	**Lookup ID**	**DWR Description**	**NASS Description**	**NASS ID Value**

UL	3	UL3	Ornamental landscape (excluding lawns) - irrigated	Sod/Grass Seed	59
UL	4	UL4	Cemeteries - irrigated	Sod/Grass Seed	59
UL	5	UL5	Cemeteries - not irrigated	Non ag/Undefined	88
UV	1	UV1	Unpaved areas	Barren	65
UV	3	UV3	Railroad right of way	Developed/Low Density	122
UV	4	UV4	Paved areas	Developed/High Density	124
UV	6	UV6	Airport runways	Developed/High Density	124
UV	99	UV99	Vacant	Developed/High Density	124
NC	1	NC1	Native Classes Unsegregated	Grassland Herbaceous	171
NV	1	NV1	Grass land	Grassland Herbaceous	171
NV	2	NV2	Light brush	Shrubland	152
NV	3	NV3	Medium brush	Shrubland	152
NV	4	NV4	Heavy Brush	Shrubland	152
NV	5	NV5	Brush and timber	Mixed Forest	143
NV	6	NV6	Forest	Mixed Forest	143
NV	7	NV7	Oak woodland	Deciduous Forest	141
NV	99	NV99	Native Vegetation	Mixed Forest	143
NR	1	NR1	Marsh Lands, tules, and sedges	Herbaceous Wetlands	195
NR	2	NR2	Natural high water table meadow	Herbaceous Wetlands	195
NR	3	NR3	Trees, shrubs or other larger streams side or watercourse vegetation	Woody Wetlands	190
NR	4	NR4	Seasonal duck marsh, dry or only partially wet during summer	Herbaceous Wetlands	195
NR	5	NR5	Permanent duck marsh, flooded during summer	Herbaceous Wetlands	195
		NR99	Riparian Vegetation	Herbaceous Wetlands	196
NW	1	NW1	Lakes, Reservoirs, rivers, canals, etc	Open Water	111
NW	99	NW99	Water Surface	Open Water	111
NB	1	NB1	Dry streams channels	Open Water	111
NB	2	NB2	Mine tailings	Barren	131
NB	3	NB3	Barren land	Barren	131
NB	4	NB4	Salt flats	Barren	131
NB	5	NB5	Sand dunes	Barren	131
NB	99	NB99	Riparian Vegetation	Barren	131
NS	1	NS1	Not surveyed	Barren	131
E	1	E1	Entry denied	Barren	131
Z	1	Z1	Outside area of study	Background	0
Z	99	Z99	Outside area of study	Background	0

Appendix B. Merced 2002 DWR to NASS ID conversion

CLASS 1	SUBCLASS1	Lookup ID	DWR Description	NASS Description	NASS ID Value
G	1	G1	Barley	Barley	21
G	2	G2	Wheat	Spring Wheat	23
G	3	G3	Oats	Oats	28
G	6	G6	Misc and mixed grain and hay	Other Hay/Non Alfalfa	37
G	99	G99	Unknown mixed grain and hay	Other Hay/ Non Alfalfa	37
R	1	R1	Rice	Rice	3
R	99	R99	Unknown Rice	Rice	
F	1	F1	Cotton	Cotton	2
F	2	F2	Safflower	Safflower	33
F	3	F3	Flax	Flaxseed	32
F	4	F4	Hops	Hops	56
F	5	F5	Sugar Beets	Sugar beets	41
F	6	F6	Corn (field and sweet)	Corn	12
F	7	F7	Grain sorghum	Sorghum	4
F	8	F8	Sudan	Sorghum	4
F	9	F9	Castor Beans	Dry Beans	42
F	10	F10	Beans (dry)	Dry Beans	42
F	11	F11	Miscellaneous field	Pasture/Grass	62
F	12	F12	Sunflowers	Sunflower	6
F	99	F99	Unknown Field Crop	Safflower	33
P	1	P1	Alfalfa & alfalfa mixtures	Alfalfa	36
P	2	P2	Clover	Clover/Wildflower	58
P	3	P3	Mixed pasture	Pasture/Grass	62
P	4	P4	Native Pasture	Pasture/Grass	62
P	5	P5	Induced high water table native pasture	Pasture/Grass	62
P	6	P6	Misc. grasses (normally grown from seed)	Pasture/Grass	62
P	7	P7	Turf farm	Sod/Grass Seed	59
P	99	P99	Unknown Pasture	Pasture/Grass	62
T	1	T1	Artichokes	Asparagus	207
T	2	T2	Asparagus	Asparagus	207
T	3	T3	Beans (green)	Dry Beans	42

T	4	T4	Cole crop (when further breakdown is not needed)	Pasture/Grass	62
T	5	T5	Unknown	Misc. Vegs & Fruits	47
T	6	T6	Carrots	Carrots	206
T	7	T7	Celery	Celery	245
T	8	T8	Lettuce (all types)	Lettuce	227
T	9	T9	Melons, squash, and cucumbers (all types)	Watermelons	48
T	10	T10	Onions and garlic	Onions	49
T	11	T11	Peas	Peas	53
T	12	T12	Potatoes	Potatoes	43
T	13	T13	Sweet Potatoes	Sweet Potatoes	46
T	14	T14	Spinach	Greens	219
T	15	T15	Tomatoes	Tomatoes	54
T	16	T16	Flowers, nursery & Christmas tree farms	Christmas Trees	70
T	17	T17	Mixed (four or more)	Misc. Vegs & Fruits	47
T	18	T18	Miscellaneous truck	Misc. Vegs & Fruits	47
T	19	T19	Bush berries	Blueberries	242
T	20	T20	Strawberries	Strawberries	221
T	21	T21	Peppers (chili, bell, etc.)	Peppers	216
T	22	T22	Broccoli	Broccoli	214
T	23	T23	Cabbage	Cabbage	243
T	24	T24	Cauliflower	Cauliflower	244
T	25	T25	Brussels Sprouts	Asparagus	207
T	99	T99	Unknown truck, nursery, and berry crops	Misc. Vegs & Fruits	47
D	1	D1	Apples	Apples	68
D	2	D2	Apricots	Apricots	223
D	3	D3	Cherries	Cherries	66
D	5	D5	Peaches and nectarines	Peaches	67
D	6	D6	Pears	Pears	77
D	7	D7	Plums	Plums	220
D	8	D8	Prunes	Prunes	210
D	9	D9	Figs	Other Tree crop	71
D	10	D10	Miscellaneous deciduous	Deciduous Forest	141
D	12	D12	Almonds	Almond	75
D	13	D13	Walnuts	Walnuts	76

D	14	D14	Pistachios	Pistachios	204
D	99	D99	Unknown tree crop	Other Tree Crop	71
C	1	C1	Grapefruit	Cantaloupes	209
C	2	C2	Lemons	Citrus	72
C	3	C3	Oranges	Oranges	212
C	4	C4	Dates	Other	71
C	5	C5	Avocados	Other	71
C	6	C6	Olives	Olives	211
C	7	C7	Miscellaneous subtropical fruits	Citrus	72
C	8	C8	Kiwis	Citrus	72
C	9	C9	Jojoba	Other	71
C	10	C10	Eucalyptus	Other	71
C	99	C99	Unknown citrus or subtropical	Other	71
V	1	V1	Table Grapes	Grapes	69
V	2	V2	Wine Grapes	Grapes	69
V	3	V3	Raisin Grapes	Grapes	69
V	99	V99	Unknown grapes	Grapes	69
I	1	I1	Land not cropped the current or previous crop season, but cropped within the past three years	Fallow/Idle cropland	61
I	2	I2	New lands being prepared for crop production	Fallow/Idle cropland	61
S	1	S1	Farmsteads	Developed/Low Density	122
S	2	S2	Livestock feed lots	Developed/Low Density	122
S	3	S3	Dairies	Developed/Low Density	122
S	4	S4	Poultry Farms	Developed/Low Density	122
U	1	U1	generic nomenclature with no subclass	Developed/Low Density	122
U	99	U99	Urban	Developed/Low Density	122
UR	1	UR1	Single family dwelling with lot sizes greater than 1 acre up to 5 acres	Developed/Low Density	122
UR	11	UR11	Single family dwelling with lot sizes greater	Developed/Low Density	122

			than 1 acre up to 5 acres - 0%-25% area irrigated		
UR	12	UR12	Single family dwelling with lot sizes greater than 1 acre up to 5 acres - 26%-50% area irrigated	Developed/Low Density	122
UR	13	UR13	Single family dwelling with lot sizes greater than 1 acre up to 5 acres - 51%-75% area irrigated	Developed/Low Density	122
UR	14	UR14	Single family dwelling with lot sizes greater than 1 acre up to 5 acres - >76% area irrigated	Developed/Low Density	122
UR	2	UR2	Single family dwelling with a density of 1 unit/acre up to 8+ units/acre	Developed/Med Density	123
UR	21	UR21	Single family dwelling with a density of 1 unit/acre up to 8+ units/acre - 0%-25% area irrigated	Developed/Med Density	123
UR	22	UR22	Single family dwelling with a density of 1 unit/acre up to 8+ units/acre - 26%-50% area irrigated	Developed/Med Density	123
UR	23	UR23	Single family dwelling with a density of 1 unit/acre up to 8+ units/acre - 51%-75% area irrigated	Developed/Med Density	123
UR	24	UR24	Single family dwelling with a density of 1 unit/acre up to 8+ units/acre - >76% area irrigated	Developed/Med Density	123
UR	3	UR3	Multiple family (apartments, condos, townhouses, etc.)	Developed/High Density	124
UR	31	UR31	Multiple family (apartments, condos, townhouses, etc.) - 0%-25% area irrigated	Developed/High Density	124
UR	32	UR32	Multiple family (apartments, condos, townhouses, etc.) - 26%-50% area irrigated	Developed/High Density	124
UR	33	UR33	Multiple family (apartments, condos, townhouses, etc.) - 51%-75% area irrigated	Developed/High Density	124

UR	34	UR34	Multiple family (apartments, condos, townhouses, etc.) - >76% area irrigated	Developed/High Density	124
UR	4	UR4	Trailer courts	Developed/Med Density	123
UR	41	UR41	Trailer courts - 0%-25% area irrigated	Developed/Med Density	123
UR	42	UR42	Trailer courts - 26%-50% area irrigated	Developed/Med Density	123
UR	43	UR43	Trailer courts - 51%-75% area irrigated	Developed/Med Density	123
UR	44	UR44	Trailer courts - >76% area irrigated	Developed/Med Density	123
UR	99	UR99	Residential	Developed/Med Density	123
UC	1	UC1	Offices, retailer, etc.	Developed/Med Density	123
UC	2	UC2	Hotels	Developed/High Density	124
UC	3	UC3	Motels	Developed/High Density	124
UC	4	UC4	Recreation vehicle parking, camp sites	Developed/Open Space	121
UC	5	UC5	Institutions (hospitals, prisons, reformatories, asylums, etc.)	Developed/High Density	124
UC	6	UC6	Schools	Developed/High Density	124
UC	7	UC7	Municipal auditoriums, theaters, churches, buildings, etc	Developed/High Density	124
UC	8	UC8	Miscellaneous high water use	Developed/Open Space	121
UC	99	UC99	Unknown Developed/Open Space	Developed/Open Space	121
UI	1	UI1	Manufacturing, assembly, and general processing	Developed/High Density	124
UI	2	UI2	Extractive industries (oil fields, rock quarries, etc.)	Developed/High Density	124
UI	3	UI3	Storage and distribution (warehouses, substations, etc)	Developed/High Density	124
UI	6	UI6	Saw mills	Developed/High Density	124

UI	7	UI7	Oil refineries	Developed/High Density	124
UI	8	UI8	paper mills	Developed/High Density	124
UI	9	UI9	Meat packing plants	Developed/High Density	124
UI	10	UI10	steel and aluminum mills	Developed/High Density	124
UI	11	UI11	Fruit and vegetable canneries and general food processing	Developed/High Density	124
UI	12	UI12	Miscellaneous high water use	Developed/Open Space	121
UI	13	UI13	Sewage treatment plant including ponds	Developed/Open Space	121
UI	14	UI14	Wast accumulation sites	Developed/Open Space	121
UI	15	UI15	Wind farms, solar collector farms	Developed/Low Density	122
UI	99	UI99	Unknown Develped/Open Space	Developed/Low Density	122
UL	1	UL1	Lawn area - irrigated	Sod/Grass Seed	59
UL	2	UL2	Golf course - irrigated	Sod/Grass Seed	59
UL	3	UL3	Ornamental landscape (excluding lawns) - irrigated	Sod/Grass Seed	59
UL	4	UL4	Cemeteries - irrigated	Sod/Grass Seed	59
UL	5	UL5	Cemeteries - not irrigated	Nonag/Undefined	88
UL	99	UL99	Unknown non-crop	Nonag/Undefined	88
UV	1	UV1	Unpaved areas	Barren	65
UV	3	UV3	Railroad right of way	Developed/Low Density	122
UV	4	UV4	Paved areas	Developed/High Density	124
UV	6	UV6	Airport runways	Developed/High Density	124
UV	99	UV99	Vacant	Developed/High Density	124
NC	1	NC1	Native Classes Unsegregated	Grassland Herbaceous	171
NV	1	NV1	Grass land	Grassland Herbaceous	171
NV	2	NV2	Light brush	Shrubland	152
NV	3	NV3	Medium brush	Shrubland	152
NV	4	NV4	Heavy Brush	Shrubland	152

NV	5	NV5	Brush and timber	Mixed Forest	143
NV	6	NV6	Forest	Mixed Forest	143
NV	7	NV7	Oak woodland	Deciduous Forest	141
NV	99	NV99	Native Vegetation	Mixed Forest	143
NR	1	NR1	Marsh Lands, tules, and sedges	Herbaceous Wetlands	195
NR	2	NR2	Natural high water table meadow	Herbaceous Wetlands	195
NR	3	NR3	Trees, shrubs or other larger streams side or watercourse vegetation	Woody Wetlands	190
NR	4	NR4	Seasonal duck marsh, dry or only partially wet during summer	Herbaceous Wetlands	195
NR	5	NR5	Permanent duck marsh, flooded during summer	Herbaceous Wetlands	195
		NR99	Riparian Vegetation	Herbaceous Wetlands	196
NW	1	NW1	Lakes, Reservoirs, rivers, canals, etc	Open Water	111
NW	99	NW99	Water Surface	Open Water	111
NB	1	NB1	Dry streams channels	Open Water	111
NB	2	NB2	Mine tailings	Barren	131
NB	3	NB3	Barren land	Barren	131
NB	4	NB4	Salt flats	Barren	131
NB	5	NB5	Sand dunes	Barren	131
NB	99	NB99	Riparian Vegetation	Barren	131
NS	1	NS1	Not surveyed	Barren	131
E	1	E1	Entry denied	Barren	131
Z	1	Z1	Outside area of study	Background	0
Z	99	Z99	Outside area of study	Background	0

Appendix C. Full list of NASS ID and Classifier descriptions

NASS ID Value	Class Name	NASS ID Value	Class Name
0	Background	81	Clouds/No Data
1	Corn	82	Developed
2	Cotton	83	Water
3	Rice	87	Wetlands
4	Sorghum	88	Non ag/Undefined
5	Soybeans	92	Aquaculture
6	Sunflower	111	Open Water
10	Peanuts	112	Perennial Ice/Snow
11	Tobacco	121	Developed/Open Space
12	Corn	122	Developed/Low Intensity
13	Pop or Orn Corn	123	Developed/Med Intensity
14	Mint	124	Developed/High Intensity
21	Barley	131	Barren
22	Durum Wheat	141	Deciduous Forest
23	Spring Wheat	142	Evergreen Forest
24	Winter Wheat	143	Mixed Forest
25	Other Small Grains	152	Shrubland
26	Dbl Crop WinWht/Soybeans	171	Grassland Herbaceous
27	Rye	181	Pasture/Hay
28	Oats	190	Woody Wetlands
29	Millet	195	Herbaceous Wetlands
30	Speltz	204	Pistachios
31	Canola	205	Triticale
32	Flaxseed	206	Carrots
33	Safflower	207	Asparagus
34	Rape Seed	208	Garlic
35	Mustard	209	Cantaloupes
36	Alfalfa	210	Prunes
37	Other Hay/Non Alfalfa	211	Olives
38	Camelina	212	Oranges
39	Buckwheat	213	Honeydew Melons
41	Sugarbeets	214	Broccoli
42	Dry Beans	216	Peppers
43	Potatoes	217	Pomegranates
44	Other Crops	218	Nectarines
45	Sugarcane	219	Greens
46	Sweet Potatoes	220	Plums
47	Misc Vegs & Fruits	221	Strawberries
48	Watermelons	222	Squash
49	Onions	223	Apricots
50	Cucumbers	224	Vetch
51	Chick Peas	225	Dbl Crop WinWht/Corn
52	Lentils	226	Dbl Crop Oats/Corn
53	Peas	227	Lettuce
54	Tomatoes	229	Pumpkins

NASS ID Value	Class Name	NASS ID Value	Class Name
55	Cranberries	230	Dbl Crop Lettuce/Durum Wht
56	Hops	231	Dbl Crop Lettuce/Cantaloupe
57	Herbs	232	Dbl Crop Lettuce/Cotton
58	Clover/Wildflowers	233	Dbl Crop Lettuce/Barley
59	Sod/Grass Seed	234	Dbl Crop Durum Wht/Sorghum
60	Switchgrass	235	Dbl Crop Barley/Sorghum
61	Fallow/Idle Cropland	236	Dbl Crop WinWht/Sorghum
62	Pasture/Grass	237	Dbl Crop Barley/Corn
63	Forest	238	Dbl Crop Win Wht/Cotton
64	Shrubland	239	Dbl Crop Soybeans/Cotton
65	Barren	240	Dbl Crop Soybeans/Oats
66	Cherries	241	Dbl Crop Corn/Soybeans
67	Peaches	242	Blueberries
68	Apples	243	Cabbage
69	Grapes	244	Cauliflower
70	Christmas Trees	245	Celery
71	Other Tree Crops	246	Radishes
72	Citrus	247	Turnips
74	Pecans	248	Eggplants
75	Almonds	249	Gourds
76	Walnuts	250	Cranberries
77	Pears	254	Dbl Crop Barley/Soybeans

Appendix D. Individual Field Crop Accuracy Results from eCognition Analyses

(based on field counts)

(Scenarios 1 through 4)

Scenario 1a - overall class accuracies on a per field basis for 2001 Madera, 2002 Merced, 2011 Madera Data sets using 5% training from the respective DWR ground survey for each data set.

Crop Type	2001 Madera	2002 Merced	2011 Madera
Alfalfa	73.2%	79.5%	74.3%
Almond	77.3%	83.2%	85.5%
Apples	26.2%	0.0%	6.6%
Christmas Trees	0.0%	16.9%	30.6%
Corn	77.0%	48.3%	53.0%
Cotton	96.2%	74.9%	66.6%
Dry Beans	71.9%	49.3%	48.7%
Fallow/Idle cropland	22.1%	0.6%	14.9%
Grapes	90.7%	44.5%	82.4%
Olives	36.5%	11.2%	28.4%
Onions	0.0%	0.0%	15.8%
Oranges	29.3%	0.0%	55.0%
Other Hay/ Non Alfalfa	79.4%	n/a	0.0%
Pasture/Grass	64.8%	62.0%	55.6%
Peaches	23.2%	62.2%	0.0%
Pistachios	65.0%	0.0%	56.2%
Plums	28.4%	42.5%	0.0%
Prunes	0.0%	49.9%	8.3%
Sod/Grass Seed	13.3%	0.0%	n/a
Sudan	63.0%	n/a	n/a
Sugarbeets	7.8%	34.1%	n/a
Tomatoes	33.8%	54.7%	0.0%
Walnuts	9.4%	20.5%	11.8%
Watermelons	0.0%	20.0%	0.0%

Scenario 1b - overall class accuracies on a per field basis for 2001 Madera, 2002 Merced, 2011 Madera Data sets using 10% training from the respective DWR ground survey for each data set.

Crop Type	2001 Madera	2002 Merced	2011 Madera
Alfalfa	84.5%	78.6%	80.8%
Almond	84.1%	83.6%	85.0%
Apples	28.4%	29.1%	8.1%
Christmas Trees	11.0%	15.3%	7.5%
Corn	77.3%	56.3%	77.0%
Cotton	97.4%	85.6%	74.0%
Dry Beans	60.4%	49.2%	52.6%
Fallow/Idle cropland	63.7%	16.3%	34.1%
Grapes	89.3%	65.0%	81.6%
Olives	46.5%	29.9%	1.4%
Onions	95.2%	0.0%	15.0%
Oranges	59.9%	0.0%	57.8%
Other Hay/ Non Alfalfa	62.7%	n/a	0.0%
Pasture/Grass	58.8%	62.4%	57.5%
Peaches	24.5%	53.1%	0.0%
Pistachios	68.5%	0.0%	66.9%
Plums	30.8%	33.9%	29.0%
Prunes	4.6%	23.2%	24.1%
Sod/Grass Seed	40.9%	0.0%	n/a
Sudan	45.7%	n/a	n/a
Sugarbeets	53.0%	69.1%	n/a
Tomatoes	41.5%	61.5%	89.6%
Walnuts	17.3%	29.8%	16.9%
Watermelons	0.0%	51.3%	0.0%

Scenario 1c - overall class accuracies on a per field basis for 2001 Madera, 2002 Merced, 2011 Madera Data sets using 20% training from the respective DWR ground survey for each data set.

Crop Type	2001 Madera	2002 Merced	2011 Madera
Alfalfa	88.6%	85.6%	87.3%
Almond	86.5%	89.2%	89.3%
Apples	53.9%	3.0%	33.4%
Christmas Trees	45.0%	26.8%	21.1%
Corn	87.5%	72.4%	72.6%
Cotton	94.0%	88.3%	74.0%
Dry Beans	69.8%	62.2%	89.5%
Fallow/Idle cropland	36.9%	11.7%	45.6%
Grapes	91.8%	66.0%	87.8%
Olives	71.8%	11.2%	33.7%
Onions	72.2%	0.0%	69.2%
Oranges	60.5%	10.7%	62.9%
Other Hay/ Non Alfalfa	80.8%	n/a	0.0%
Pasture/Grass	60.1%	71.0%	77.7%
Peaches	37.1%	73.1%	0.0%
Pistachios	82.5%	0.0%	75.6%
Plums	52.4%	20.6%	43.4%
Prunes	21.0%	68.8%	41.7%
Sod/Grass Seed	52.3%	0.0%	n/a
Sudan	66.7%	n/a	n/a
Sugarbeets	20.1%	80.2%	n/a
Tomatoes	30.7%	67.4%	78.8%
Walnuts	12.3%	35.6%	49.9%
Watermelons	42.1%	72.8%	67.4%

Scenario 2 - Overall Class Accuracies for 2002 Merced and 2011 Madera Data sets using 90% training date from 2001 DWR ground survey

Crop Type	2002 Merced	2011 Madera
Alfalfa	80%	84%
Almond	83%	78%
Apples	0%	0%
Christmas Trees	29%	0%
Corn	58%	89%
Cotton	67%	49%
Dry Beans	1%	4%
Fallow/Idle cropland	5%	12%
Grapes	75%	83%
Olives	30%	2%
Onions	0%	0%
Oranges	0%	35%
Other Hay/ Non Alfalfa	n/a	0%
Pasture/Grass	33%	43%
Peaches	25%	0%
Pistachios	0%	39%
Plums	3%	1%
Prunes	0%	0%
Sod/Grass Seed	0%	n/a
Sudan	n/a	n/a
Sugarbeets	16%	n/a
Tomatoes	4%	62%
Walnuts	1%	13%
Watermelons	2%	12%

Scenario 3 - Overall Class Accuracies for 2002 Merced and 2011 Madera Data sets using 90% training date from 2001 DWR ground survey and 10% from the respective DWR Ground Survey for each data set

Crop Type	2002 Merced	2011 Madera
Alfalfa	80.9%	86.5%
Almond	85.3%	85.5%
Apples	29.1%	7.7%
Christmas Trees	10.5%	7.5%
Corn	63.3%	89.4%
Cotton	86.0%	69.9%
Dry Beans	56.3%	4.2%
Fallow/Idle cropland	12.5%	31.7%
Grapes	66.4%	84.1%
Olives	29.9%	3.5%
Onions	0.0%	15.0%
Oranges	73.5%	56.6%
Other Hay/ Non Alfalfa	n/a	0.0%
Pasture/Grass	68.2%	59.1%
Peaches	59.5%	0.0%
Pistachios	57.7%	63.2%
Plums	30.7%	29.6%
Prunes	45.2%	24.1%
Sod/Grass Seed	0.0%	n/a
Sudan	n/a	n/a
Sugarbeets	60.2%	n/a
Tomatoes	61.3%	69.4%
Walnuts	31.3%	27.9%
Watermelons	43.8%	12.5%

Scenario 4 - Overall Classification Results for 2011 Madera data analysis using 90% of 2001 DWR ground survey and 10% 2011 DWR ground survey as training data. Comparison of results with and without the feature space of Actual Crop Coefficient (EToF)

	2011 Madera	
Crop Type	EtoF	No EtoF
Alfalfa	86.5%	76.3%
Almond	85.5%	83.7%
Apples	7.7%	4.5%
Christmas Trees	7.5%	7.7%
Corn	89.4%	69.7%
Cotton	69.9%	72.5%
Dry Beans	4.2%	0.0%
Fallow/Idle cropland	31.7%	32.6%
Grapes	84.1%	77.3%
Olives	3.5%	5.1%
Onions	15.0%	15.0%
Oranges	56.6%	66.0%
Other Hay/ Non Alfalfa	0.0%	0.0%
Pasture/Grass	59.1%	40.6%
Peaches	0.0%	0.0%
Pistachios	63.2%	63.7%
Plums	29.6%	25.7%
Prunes	24.1%	19.9%
Sod/Grass Seed	n/a	n/a
Sudan	n/a	n/a
Sugarbeets	n/a	n/a
Tomatoes	69.4%	92.8%
Walnuts	27.9%	18.4%
Watermelons	12.5%	0.0%

Appendix E. Crop Confusion Matrices Resulting from eCognition Analyses

(based of field count)

(Scenarios 1 through 4)

2001 Confusion Matrix – Utilizing 5% of DWR ground survey data from 2001.

			User Classification																								
	Crop Type	Alfalfa	Almond	Apples	Christmas Trees	Cotton	Dry Beans	Fallow/Idle cropland	Grapes	Olives	Onions	Oranges	Other Hay/ Non Alfalfa	Pasture/Grass	Peaches	Pistachios	Plums	Prunes	Sod/Grass Seed	Sudan	Sugarbeets	Corn	Tomatoes	Walnuts	Watermelons	Unclassified	Grand Total
DWR Ground Survey	Alfalfa	554	11			10		2	30	1	2	1	2	50			1		12	4		1				1	682
	Almond	2	1202	3		6		20	135	1		11	2	25	11	52	6	1			6	1				3	1487
	Apples		14	22					21			1	1	3	3	4	2	1						1			73
	Christmas Trees		3		4	1		1	7			2		2		4						1					25
	Cotton		3			447		1	7			1	2	1								3	1				466
	Dry Beans		1				5															4					10
	Fallow/Idle cropland		4			1		61	8	1			11	15		6										1	108
	Grapes	10	153	2	5	7		29	2814			13	10	45	10	48	18		3		3	7		14	3	24	3218
	Olives		9						6	11		9				4								1		2	42
	Onions		1								8		1														10
	Oranges		15	2				5	15	2		85	2	9	1	16										1	153
	Other Hay/ Non Alfalfa	2	23			2		40	12	3	10		232	62		4			1			5				3	399
	Pasture/Grass	18	33		1	1		27	36	3			24	194		11	4		21			3		1	1	5	383
	Peaches		33	5				2	38			2	1	2	36	1	3	13			1	1		4	1		143
	Pistachios		61	2				13	18	3		13	4	7		292								10	3	2	428
	Plums		26	3		2			24			1	1	1	2	13	33	3						3		3	115
	Prunes		18	2					8			2		1	2	1		3									37
	Sod/Grass Seed	1	3						2			4		6		11			9							1	37
	Sudan	6	1			1		2	7				1	1					1	19		1					40
	Sugarbeets		1			2			4												6						13
	Corn	12	1			25		3	39				1	7	2	2						283	5			3	383
	Tomatoes		2			5	1		8				1	1								10	13				41
	Walnuts		13		1			3	10					1	3	10	2							8		1	52
	Watermelons		2			3		3	2				1										1			1	13
	Grand Total	605	1633	41	11	513	6	212	3251	25	20	145	297	433	70	479	69	21	47	23	16	320	20	42	8	51	8358

2002 Merced Confusion Matrix – Utilizing 5% of DWR ground survey data from 2002 Merced.

			User Classification																								
	Crop Type	Alfalfa	Almond	Apples	Christmas Trees	Cotton	Dry Beans	Fallow/Idle cropland	Grapes	Olives	Onions	Oranges	Other Hay/ Non Alfalfa	Pasture/Grass	Peaches	Pistachios	Plums	Prunes	Sod/Grass Seed	Sudan	Sugarbeets	Corn	Tomatoes	Walnuts	Watermelons	Unclassified	Grand Total
DWR Ground Survey	Alfalfa	1374	99	1		58	4	5	6	5				165	13		9	1				20	27	7	1	15	1810
	Almond	22	2224	1	3	52	1	2	46	1		6		148	68	23	25					24	7	94		27	2774
	Apples	1	4	2		2			1					3	4							1					18
	Christmas Trees		7		7	3			1	6				7	1	2	2						1	7		3	47
	Cotton	48	37		6	1042	15	7	17	19				54	13	1	6					67	111	29	10	21	1503
	Dry Beans	1	4				8	1						5	1											1	21
	Fallow/Idle cropland	7	3			13	66	1	1					6	1		3					3	17	2	1	1	125
	Grapes	1	3			5		1	66	1				3	3							10	3	7	2	3	108
	Olives	10	56			6		2	103	33				43	38	1	3					4		17		3	319
	Onions									1														2			3
	Oranges					1																				3	4
	Other Hay/ Non Alfalfa	1	1											1													3
	Pasture/Grass	97	218	1	1	37		1	22	1				751	30	6	23				1	9	9	45	2	15	1269
	Peaches	4	78			3		1	12			1		19	196		7					2		24		4	351
	Pistachios														1												1
	Plums																3	1								0	4
	Prunes		16			2			1	4		4		4		1	1	41						3		0	77
	Sod/Grass Seed	1	6			1								4	5	1	15					2		1		0	36
	Sudan		13		1				1					1			2	14						2		0	34
	Sugarbeets	26	3			20		1						3	1		1				30	1		1		0	87
	Corn	28	31		1	44	13		9	2				18	2	3	2					160	78	3	5	9	408
	Tomatoes	12	24		2	85	21	2	9	1				10		1	7				2	48	281	9	8	15	537
	Walnuts	4	130			4	1		9			1		34	44	4	8					4	1	63		3	310
	Watermelons	2	13		2	15	14	1	2	1				11	3		2					3	15	5	21		110
	Grand Total	1639	2970	5	23	1393	143	25	306	75	0	12	0	1290	424	43	119	57	0	0	33	358	550	321	50	144	9959

2011 Confusion Matrix – Utilizing 5% of DWR ground survey data from 2011.

			User Classification																								
	Crop Type	Alfalfa	Almond	Apples	Christmas Trees	Cotton	Dry Beans	Fallow/Idle cropland	Grapes	Olives	Onions	Oranges	Other Hay/ Non Alfalfa	Pasture/Grass	Peaches	Pistachios	Plums	Prunes	Sod/Grass Seed	Sudan	Sugarbeets	Corn	Tomatoes	Walnuts	Watermelons	Unclassified	Grand Total
DWR Ground Survey	Alfalfa	355	33			5		5	31		4			50		1						12		1			497
	Almond	15	1719	6	6	35		57	127	5	7	28		9		51								1		13	2079
	Apples	2	26	3	1	4		7	8			3		4		3						1		1		3	66
	Christmas Trees		4		6	2			6			1														5	24
	Cotton	10	32		6	128		11	30	1	4	4		4								2				3	235
	Dry Beans		1				11		3							1						8					24
	Fallow/Idle cropland	8	33		1	43		33	22		2	2		2		6								2			154
	Grapes	12	182	12	24	25		20	1305	2		29		7		32										33	1683
	Olives		6		3	2		15	8	6		4				3										2	49
	Onions		1			1			1		1																4
	Oranges	2	31	1	2				10	1		74				26						1				4	152
	Other Hay/ Non Alfalfa	15	47			11		4	46	4		4		69		4								1		14	219
	Pasture/Grass		27	1		1						2		14		2										2	49
	Peaches		1																								1
	Pistachios	16	84	2	3	10		26	37	6		25		4		194								1		12	420
	Plums		14			1			2					1		2											20
	Prunes		14			1			1							1		2								1	20
	Sod/Grass Seed																										0
	Sudan																										0
	Sugarbeets																										0
	Corn	4	7		1	9			34			1		2								66				5	129
	Tomatoes	1	1			5	3	2	5													24				11	52
	Walnuts		30			5			3					3		1								5		1	48
	Watermelons		3	1	1	1			3																	1	10
	Grand Total	440	2296	26	54	289	14	180	1682	25	18	177	0	169	0	327	0	2	0	0	0	114	0	12	0	110	5935

2001 Confusion Matrix – Utilizing 10% of DWR ground survey data from 2001.

			User Classification																								
	Crop Type	Alfalfa	Almond	Apples	Christmas Trees	Cotton	Dry Beans	Fallow/Idle cropland	Grapes	Olives	Onions	Oranges	Other Hay/ Non Alfalfa	Pasture/Grass	Peaches	Pistachios	Plums	Prunes	Sod/Grass Seed	Sudan	Sugarbeets	Corn	Tomatoes	Walnuts	Watermelons	Unclassified	Grand Total
DWR Ground Survey	Alfalfa	554	11			10		2	30	1	2	1	2	50			1		12	4		1				1	682
	Almond	2	1202	3		6		20	135	1		11	2	25	11	52	6	1			6	1				3	1487
	Apples		14	22					21			1	1	3	3	4	2	1						1			73
	Christmas Trees		3		4	1		1	7			2		2		4						1					25
	Cotton		3			447		1	7			1	2	1								3	1				466
	Dry Beans		1				5															4					10
	Fallow/Idle cropland		4			1		61	8	1			11	15		6										1	108
	Grapes	10	153	2	5	7		29	2814			13	10	45	10	48	18		3		3	7		14	3	24	3218
	Olives		9						6	11		9				4								1		2	42
	Onions		1								8		1														10
	Oranges		15	2				5	15	2		85	2	9	1	16										1	153
	Other Hay/ Non Alfalfa	2	23			2		40	12	3	10		232	62		4			1			5				3	399
	Pasture/Grass	18	33		1	1		27	36	3			24	194		11	4		21			3		1	1	5	383
	Peaches		33	5				2	38			2	1	2	36	1	3	13			1	1		4	1		143
	Pistachios		61	2				13	18	3		13	4	7		292								10	3	2	428
	Plums		26	3		2			24			1	1	1	2	13	33	3						3		3	115
	Prunes		18	2					8			2		1	2	1		3									37
	Sod/Grass Seed	1	3						2			4		6		11			9							1	37
	Sudan	6	1			1		2	7				1	1					1	19		1					40
	Sugarbeets		1			2			4												6						13
	Corn	12	1			25		3	39				1	7	2	2						283	5			3	383
	Tomatoes		2			5	1		8				1	1								10	13				41
	Walnuts		13		1			3	10					1	3	10	2							8		1	52
	Watermelons		2			3		3	2				1										1			1	13
	Grand Total	605	1633	41	11	513	6	212	3251	25	20	145	297	433	70	479	69	21	47	23	16	320	20	42	8	51	8358

2002 Merced Confusion Matrix – Utilizing 10% of DWR ground survey data from 2002 Merced.

			User Classification																								
	Crop Type	Alfalfa	Almond	Apples	Christmas Trees	Cotton	Dry Beans	Fallow/Idle cropland	Grapes	Olives	Onions	Oranges	Other Hay/ Non Alfalfa	Pasture/Grass	Peaches	Pistachios	Plums	Prunes	Sod/Grass Seed	Sudan	Sugarbeets	Corn	Tomatoes	Walnuts	Watermelons	Unclassified	Grand Total
DWR Ground Survey	Alfalfa	1352	78	1		63	4	1	15	2				194	14	4		1			2	21	29	12	4	13	1810
	Almond	15	2229	1	8	40		45	52	6		6		130	53	40	1	3			2	9	5	88	8	33	2774
	Apples		6	2		1			2					1	4							1		1			18
	Christmas Trees	2	11		10	3		1	3					6	2	1	1						3	3		1	47
	Cotton	25	51		2	1166	8	32	10	1				47	6	8		1			3	23	69	22	16	13	1503
	Dry Beans		2		1		12	1	2					2	1												21
	Fallow/Idle cropland	5	5		2	23	31	31						2		1						4	10	5	5	1	125
	Grapes	2	6			18		5	54					5	2	3		1			2	2	4	1		3	108
	Olives	6	39			4		3	112	62				33	31	9						1	2	9	2	6	319
	Onions				1					1						1											3
	Oranges																					1	1			2	4
	Other Hay/ Non Alfalfa		1									1		1													3
	Pasture/Grass	85	179	1	4	40	2	8	34	1				776	29	12		2			15	18	11	33	6	13	1269
	Peaches	1	83		2	2		2	17	4		1		23	172	3		1						35		5	351
	Pistachios														1												1
	Plums																1						3				4
	Prunes		20			4				2		2				21		24					1	2		1	77
	Sod/Grass Seed		17			1								1	3	2	9	2						1			36
	Sudan		6		3	1			1							5	8	10									34
	Sugarbeets	1	1			18	1	1													54	6	1		4		87
	Corn	20	29		1	58	8	1	6					28	5						1	205	30	8	3	5	408
	Tomatoes	6	12			96	8	2	1					15	1	3		3				22	316	5	36	11	537
	Walnuts	2	127		1	8	1	3	8	1		1		32	31	5		1						85		4	310
	Watermelons	1	2		2	8	9		1					6	1								17	3	60		110
	Grand Total	1523	2904	5	37	1554	84	136	318	80	0	11	0	1302	356	118	20	49	0	0	79	313	502	313	144	111	9959

2011 Confusion Matrix – Utilizing 10% of DWR ground survey data from 2011.

			User Classification																							
	Crop Type	Alfalfa	Almond	Apples	Christmas Trees	Cotton	Dry Beans	Fallow/Idle cropland	Grapes	Olives	Onions	Oranges	Other Hay/ Non Alfalfa	Pasture/Grass	Peaches	Pistachios	Plums	Prunes	Sod/Grass Seed	Sudan	Sugarbeets	Corn	Tomatoes	Walnuts	Watermelons	Unclassified	Grand Total
DWR Ground Survey	Alfalfa	384	20	2	1			4	37					36		10						1	2				497
	Almond	6	1712	8	2	33		23	97		2	22		10	4	141		7				1		1		10	2079
	Apples	4	22	9		4		7	9						1	4						1		2		3	66
	Christmas Trees		5		2	3			5							2		2								5	24
	Cotton	3	19	6	4	142		14	22		2			3	1	12		1					2	2		2	235
	Dry Beans		1			9			7													5	2				24
	Fallow/Idle cropland	3	9	11		17		56	10		2			6	9	17						2		12			154
	Grapes	6	208	10	8	12		17	1290	1	1	11		9	18	47		12						8		25	1683
	Olives		11	11	3	1		2	5	1		1				11		1								2	49
	Onions		1		1			1			1																4
	Oranges		28	2	1	1		2	15			77			1	21										4	152
	Other Hay/ Non Alfalfa	23	42		1	5		11	31	1		3		66	1	14						1		3		17	219
	Pasture/Grass		12	2				1	7			1		16			7							1		2	49
	Peaches		1																								1
	Pistachios	3	38	5	4	20		20	26		1	27			1	262								2		11	420
	Plums		7			1			2						2		7	1									20
	Prunes		7			1										1	4	6								1	20
	Sod/Grass Seed																										0
	Sudan																										0
	Sugarbeets																										0
	Corn	3	6			7			13		1				1	2						87	4			5	129
	Tomatoes		1			1			3													6	36			5	52
	Walnuts	3	18	1		1		1	5		1				3	4	1							9		1	48
	Watermelons		1		1				5		1					1										1	10
	Grand Total	438	2169	67	28	258	0	159	1589	3	12	142	0	146	42	549	19	30	0	0	0	104	46	40	0	94	5935

2001 Confusion Matrix – Utilizing 20% of DWR ground survey data from 2001.

			User Classification																								
	Crop Type	Alfalfa	Almond	Apples	Christmas Trees	Cotton	Dry Beans	Fallow/Idle cropland	Grapes	Olives	Onions	Oranges	Other Hay/ Non Alfalfa	Pasture/Grass	Peaches	Pistachios	Plums	Prunes	Sod/Grass Seed	Sudan	Sugarbeets	Corn	Tomatoes	Walnuts	Watermelons	Unclassified	Grand Total
DWR Ground Survey	Alfalfa	588	10			5		1	36			1	9	28					2	1						1	682
	Almond		1261	6	1	2		9	92	5		12	13	16	4	44	9	3						3	4	3	1487
	Apples	1	14	35					8	1		6			1	4	2							1			73
	Christmas Trees		2	1	8				6	2		1		1		3	1										25
	Cotton	9	2			433		1	7	1			1									12					466
	Dry Beans						5															4				1	10
	Fallow/Idle cropland	1	9					32	15				23	15		5	2				2	1		1	1	1	108
	Grapes	11	107	17				12	2894	2		16	11	28	10	51	27	1			1	5	1	3	2	19	3218
	Olives		3						2	27			1	2		7											42
	Onions										7		2									1					10
	Oranges		15	2					12	6		89	3	5		19	1		1								153
	Other Hay/ Non Alfalfa	8	8	1		1		18	21		3	2	295	30		6						4				2	399
	Pasture/Grass	8	35	6		1		18	37	2		5	38	197	1	11	3		8					7	1	5	383
	Peaches		20	5	1				33	3		5		5	48	7	13				1	1			1		143
	Pistachios		22	1				1	10	6		6	14	9		351	3							3		2	428
	Plums		15	3					15	1		5		2	3	14	52	2								3	115
	Prunes		16	2					6						1	1	3	8									37
	Sod/Grass Seed	1	2	1				1	10			2		1		12			6							1	37
	Sudan	2							4				2	3		1				26		2					40
	Sugarbeets		2			3			2					1							4	1					13
	Corn		4			12			27	1			5	4								322	3	1		4	383
	Tomatoes			1		3			7													17	13				41
	Walnuts		14	1					4	1				2		16	4				1			8		1	52
	Watermelons	1	1						3				1								1		1		4	1	13
	Grand Total	630	1562	82	10	460	5	93	3251	58	10	150	418	349	68	552	120	14	17	27	10	370	18	27	13	44	8358

2002 Merced Confusion Matrix – Utilizing 20% of DWR ground survey data from 2002 Merced.

			User Classification																								
	Crop Type	Alfalfa	Almond	Apples	Christmas Trees	Cotton	Dry Beans	Fallow/Idle cropland	Grapes	Olives	Onions	Oranges	Other Hay/ Non Alfalfa	Pasture/Grass	Peaches	Pistachios	Plums	Prunes	Sod/Grass Seed	Sudan	Sugarbeets	Corn	Tomatoes	Walnuts	Watermelons	Unclassified	Grand Total
DWR Ground Survey	Alfalfa	1489	56		1	37	21	5	8			1		118	9	2	2				3	22	14	7	4	11	1810
	Almond	13	2395	3	4	39		13	39					73	74	17	7	1				9	4	50		33	2774
	Apples		9	1	2	3		1	1															1		0	18
	Christmas Trees		13		15	1			2	3				1	1	5	1					1		1		3	47
	Cotton	35	69		6	1201	15	19	11	4				37	6	6	1				3	9	52	7	10	12	1503
	Dry Beans	1			2		13	2	1						2												21
	Fallow/Idle cropland		3			10	67	16	2					2	2							7	11		4	1	125
	Grapes	5	9		1	4		7	66	1				3	2	3					1	1		2	1	2	108
	Olives	5	47		1	3	1	3	144	37				33	29	2						1		7		6	319
	Onions	1								1														1		0	3
	Oranges											1														3	4
	Other Hay/ Non Alfalfa		2									1														0	3
	Pasture/Grass	83	172		2	24	1	10	18					851	41	6	2					8	5	29	4	13	1269
	Peaches	1	44	1		3		4	12					4	242	1	4					1		29		5	351
	Pistachios														1											0	1
	Plums					1											1						2			0	4
	Prunes	4	26											1	1			39						5		1	77
	Sod/Grass Seed		5			1								1	6	2	8	7				1		4	1	0	36
	Sudan	1	10		1													22								0	34
	Sugarbeets		3			16	2			1				3							62					0	87
	Corn	15	22			43	5		5					14	5	1	2				1	263	18	6	4	4	408
	Tomatoes	13	4		2	99	3	4	1					9	1	1						21	357	2	9	11	537
	Walnuts	4	97		2	11		3	8					14	49	2	3	1				4	1	106	1	4	310
	Watermelons		4			8	6		2					7	1							3	12		67	0	110
	Grand Total	1670	2990	5	39	1504	134	87	320	47	0	3	0	1171	472	48	31	70	0	0	70	351	476	257	105	109	9959

2011 Confusion Matrix – Utilizing 20% of DWR ground survey data from 2011.

			User Classification																							
	Crop Type	Alfalfa	Almond	Apples	Christmas Trees	Cotton	Dry Beans	Fallow/Idle cropland	Grapes	Olives	Onions	Oranges	Other Hay/ Non Alfalfa	Pasture/Grass	Peaches	Pistachios	Plums	Prunes	Sod/Grass Seed	Sudan	Sugarbeets	Corn	Tomatoes	Walnuts	Watermelons	Unclassified	Grand Total
DWR Ground Survey	Alfalfa	417	26	2		2		5	17	1				22		2									1	2	497
	Almond	2	1818	5	3	10		20	69	11		9		4	5	88	6							5		24	2079
	Apples	1	10	18		2		8	13	1		1			3	4								2		3	66
	Christmas Trees		2		4				8	2					2	1										5	24
	Cotton	2	33	5		134		14	25	6				3		8						2				3	235
	Dry Beans						21		2														1				24
	Fallow/Idle cropland	10	18	7		9		53	25	6				8		12								3		3	154
	Grapes	2	143	3	4	7		16	1398	5		9		9	1	39		1						3	1	42	1683
	Olives		6	1		1			6	22		1				9										3	49
	Onions		1					1			2																4
	Oranges		36		1			1	7			85				18										4	152
	Other Hay/ Non Alfalfa	13	39	1	1			5	19	1				113		9								1		17	219
	Pasture/Grass		6					2	7			1		25		1	1							4		2	49
	Peaches		1																								1
	Pistachios	1	61	1		7		11	16	4		7		3	1	295	1									12	420
	Plums		4			1				1					5	1	7	1									20
	Prunes		12						1									5						1		1	20
	Sod/Grass Seed																										0
	Sudan																										0
	Sugarbeets																										0
	Corn	3	8			9	3	1	13					1	1	4						80	1			5	129
	Tomatoes	1	1			4	1		4													2	36		1	2	52
	Walnuts		8	1				1	6					1	3	6								21		1	48
	Watermelons		3						2																4	1	10
	Grand Total	452	2236	44	13	186	25	138	1638	60	2	113	0	189	21	497	15	7	0	0	0	84	38	40	7	130	5935

2002 Merced Confusion Matrix – Utilizing 90% of DWR ground survey data from 2001.

			User Classification																							
	Crop Type	Alfalfa	Almond	Apples	Christmas Trees	Cotton	Dry Beans	Fallow/Idle cropland	Grapes	Olives	Onions	Oranges	Other Hay/ Non Alfalfa	Pasture/Grass	Peaches	Pistachios	Plums	Prunes	Sod/Grass Seed	Sudan	Sugarbeets	Corn	Tomatoes	Walnuts	Watermelons	Unclassified	Grand Total
DWR Ground Survey	Alfalfa	1391	103	4	6	27		1	133	3	1	4	20	73	1	7	8		1	3		17	3	3	1		1810
	Almond	23	2268	7	7	3		6	299	4		9	15	37	7	60	5	2	3		1	4	1	12	1		2774
	Apples		7			1		2	5				1	1		1											18
	Christmas Trees	1	7	1	4				20	1		1	3			4	1		1					1		2	47
	Cotton	22	132	2	19	872	2	19	220	15		7	78	42	3	13	6	2			1	21	8	7	12		1503
	Dry Beans	1			2		13	2	1						2												21
	Fallow/Idle cropland	1	36				1	9	30	1		1	14	6		5		2	2			2		2		13	125
	Grapes	10	8	1					68			1	6	5		7			1						1		108
	Olives	5	53		1		1	3	144	37				30	29	2						1		7	6		319
	Onions																					1				2	3
	Oranges	1	1																					1		1	4
	Other Hay/ Non Alfalfa																									3	3
	Pasture/Grass	204	371	7	3	4		4	176	3			27	404	2	19		11	12	2		7		12	1		1269
	Peaches	5	105	11				1	121	2		1	3	4	72	2	22	1				1					351
	Pistachios														1												1
	Plums									2							1									1	4
	Prunes		10				8		15	1		13				8				15						7	77
	Sod/Grass Seed		5			1								1	6	2	8	7				1		4	1		36
	Sudan	1	10		1													22									34
	Sugarbeets	2	11		1	10			22	3			2	1		18			8		9						87
	Corn	27	44		2	22	2		61	1		1	14	18	2	8	5	1	1	4		186	6	1		2	408
	Tomatoes	14	48	2	13	104	3	1	176	4	3		14	15	1	28	5	1	5			67	17	5	11		537
	Walnuts	4	172	11	1			1	73	2		2	3	3	20	9	7							2			310
	Watermelons	5	20		1	18		1	34	2			1			2	1			3		15	6		1		110
	Grand Total	1717	3411	46	61	1062	30	50	1598	81	4	40	201	640	146	195	69	49	34	27	11	323	41	57	35	31	9959

2011 Confusion Matrix – Utilizing 90% of DWR ground survey data from 2001.

			User Classification																								
	Crop Type	Alfalfa	Almond	Apples	Christmas Trees	Cotton	Dry Beans	Fallow/Idle cropland	Grapes	Olives	Onions	Oranges	Other Hay/ Non Alfalfa	Pasture/Grass	Peaches	Pistachios	Plums	Prunes	Sod/Grass Seed	Sudan	Sugarbeets	Corn	Tomatoes	Walnuts	Watermelons	Unclassified	Grand Total
DWR Ground Survey	Alfalfa	402	13	1					27			1	10	25	4	1		1	1	1		9		1			497
	Almond	6	1546	17	8			29	196			11	20	33	21	61	62	27	1	1	1	5		10	1	23	2079
	Apples	1	18		1	1		5	11		2	1	6	1	3	4	4			1		2		2		3	66
	Christmas Trees	1	2			2			9	1						3					2					4	24
	Cotton	4	27	2		81		12	44		1		22	11	1	3						21	1		2	3	235
	Dry Beans	1	2			12	1	1	1													5	1				24
	Fallow/Idle cropland	3	34	2	1			25	30				12	33	3	10				1							154
	Grapes	47	105	17	7	1		13	1313	3	1	9	15	24	30	27	25	5	3					6		32	1683
	Olives		3					2	15	1		1	6			18								1		2	49
	Onions		1						1				1	1													4
	Oranges		37	3	1				23	2		41		1	8	26	5		1							4	152
	Other Hay/ Non Alfalfa	21	42	4		1		3	23			1		86	3	4	5		6					3		17	219
	Pasture/Grass		14	3					6					18		3	1	1						1		2	49
	Peaches		1																								1
	Pistachios	1	91	16	7	1		15	62			10	8	10	4	156	22					3		4		10	420
	Plums		8	2					2						4	1	2	1									20
	Prunes		13						3					1		2										1	20
	Sod/Grass Seed																										0
	Sudan																										0
	Sugarbeets																										0
	Corn	2	1			1		1	12	1			2	3			2					98		1		5	129
	Tomatoes	1				1			2							1						22	23			2	52
	Walnuts		15	2					9					5	5	4	3							4		1	48
	Watermelons	1	1						6																1	1	10
	Grand Total	491	1974	69	25	101	1	106	1795	8	4	75	102	252	86	324	131	35	12	4	3	165	25	33	4	110	5935

2002 Merced Confusion Matrix – Utilizing 90% of DWR ground survey data from 2001 plus 10% 2002 Merced DWR ground survey added to the Training Data set.

			User Classification																							
	Crop Type	Alfalfa	Almond	Apples	Christmas Trees	Cotton	Dry Beans	Fallow/Idle cropland	Grapes	Olives	Onions	Oranges	Other Hay/ Non Alfalfa	Pasture/Grass	Peaches	Pistachios	Plums	Prunes	Sod/Grass Seed	Sudan	Sugarbeets	Corn	Tomatoes	Walnuts	Watermelons	Unclassified	Grand Total
DWR Ground Survey	Alfalfa	1409	60		1	69	4	5	14	1	1		4	168	5	1		2		1	3	15	25	9	3	10	1810
	Almond	11	2298	1	6	51		35	64	5		1		99	48	29	3	1				10		81	7	24	2774
	Apples		3	2		4			4					1	2									2			18
	Christmas Trees		8		10	4		1	3					5		5	1						1	6		3	47
	Cotton	27	53		5	1170	7	28	11	4			3	55	4	7					5	16	66	17	15	10	1503
	Dry Beans		1				9		5																	6	21
	Fallow/Idle cropland	7	4			17	70	3	1				2	7	1							6	2	1	4		125
	Grapes		7		1	6	1	14	63	1			1	4		3		1				2	1	2		1	108
	Olives	1	36			4		6	158	34				16	28	14						1		16		5	319
	Onions		1			1				1																	3
	Oranges											3												1			4
	Other Hay/ Non Alfalfa				1							1		1													3
	Pasture/Grass	73	148		3	47	2	13	41	3			2	840	11	5	1	1			24	10	8	20	2	15	1269
	Peaches		70		2	5		4	18					12	193	3		1						40		3	351
	Pistachios														1												1
	Plums					1											1						2				4
	Prunes		29		3	2				1				1		14		24						2		1	77
	Sod/Grass Seed		10		1	1								1	5	3	8	3						4			36
	Sudan		12		1	1		1								3	2	14									34
	Sugarbeets	2	1			21	1		1					2							48	8	2		1		87
	Corn	20	27			61	8	3	7				4	18	1					2		218	26	4	4	5	408
	Tomatoes	8	14			81	9	3	14		3		7	11	2	5					1	17	311	9	29	13	537
	Walnuts	1	113		2	10		12	11			2		20	36	6								93	1	3	310
	Watermelons	1	8			6	9							10	1							2	18	2	53		110
	Grand Total	1560	2903	3	36	1562	120	128	415	50	4	7	23	1271	338	98	16	47	0	3	81	305	462	309	119	99	9959

2011 Confusion Matrix – Utilizing 90% of DWR ground survey data from 2001 plus 10% 2011 DWR ground survey added to the Training Data set.

			User Classification																								
	Crop Type	Alfalfa	Almond	Apples	Christmas Trees	Cotton	Dry Beans	Fallow/Idle cropland	Grapes	Olives	Onions	Oranges	Other Hay/ Non Alfalfa	Pasture/Grass	Peaches	Pistachios	Plums	Prunes	Sod/Grass Seed	Sudan	Sugarbeets	Corn	Tomatoes	Walnuts	Watermelons	Unclassified	Grand Total
DWR Ground Survey	Alfalfa	1409	60		1	69	4	5	14	1	1		4	168	5	1		2		1	3	15	25	9	3	10	1810
	Almond	11	2298	1	6	51		35	64	5		1		99	48	29	3	1				10		81	7	24	2774
	Apples		3	2		4			4					1	2									2			18
	Christmas Trees		8		10	4		1	3					5		5	1						1	6		3	47
	Cotton	27	53		5	1170	7	28	11	4			3	55	4	7					5	16	66	17	15	10	1503
	Dry Beans		1				9		5																	6	21
	Fallow/Idle cropland	7	4			17	70	3	1				2	7	1							6	2	1	4		125
	Grapes		7		1	6	1	14	63	1			1	4		3		1				2	1	2		1	108
	Olives	1	36			4		6	158	34				16	28	14						1		16		5	319
	Onions		1			1				1																	3
	Oranges											3												1			4
	Other Hay/ Non Alfalfa				1							1		1													3
	Pasture/Grass	73	148		3	47	2	13	41	3			2	840	11	5	1	1			24	10	8	20	2	15	1269
	Peaches		70		2	5		4	18					12	193	3		1						40		3	351
	Pistachios														1												1
	Plums					1											1						2				4
	Prunes		29		3	2				1				1		14		24						2		1	77
	Sod/Grass Seed		10		1	1								1	5	3	8	3						4			36
	Sudan		12		1	1		1								3	2	14									34
	Sugarbeets	2	1			21	1		1					2							48	8	2		1		87
	Corn	20	27			61	8	3	7				4	18	1					2		218	26	4	4	5	408
	Tomatoes	8	14			81	9	3	14		3		7	11	2	5					1	17	311	9	29	13	537
	Walnuts	1	113		2	10		12	11			2		20	36	6								93	1	3	310
	Watermelons	1	8			6	9							10	1							2	18	2	53		110
	Grand Total	1560	2903	3	36	1562	120	128	415	50	4	7	23	1271	338	98	16	47	0	3	81	305	462	309	119	99	9959

2011 Confusion Matrix – Utilizing 90% of DWR ground survey data from 2001 plus 10% 2011 DWR ground survey added to the Training Data set (EToF omitted)

			User Classification																								
	Crop Type	Alfalfa	Almond	Apples	Christmas Trees	Cotton	Dry Beans	Fallow/Idle cropland	Grapes	Olives	Onions	Oranges	Other Hay/ Non Alfalfa	Pasture/Grass	Peaches	Pistachios	Plums	Prunes	Sod/Grass Seed	Sudan	Sugarbeets	Corn	Tomatoes	Walnuts	Watermelons	Unclassified	Grand Total
DWR Ground Survey	Alfalfa	411	15	1	1			5	22					25	2	3			1			11					497
	Almond	3	1721	7	12	17		16	122	3	4	22	6	12	5	98	2	6		1	1			4		17	2079
	Apples	3	21	7		3		9	7		1	1	2	1		4	1	1						2		3	66
	Christmas Trees	1	3		2	2			8		1					2		1								4	24
	Cotton	3	25	3	4	125		10	31		3		3	3	2	13		1		1		5		1		2	235
	Dry Beans		4			14		4														1	1				24
	Fallow/Idle cropland	2	13	7		20		53	10	1	3		1	15	5	9						3		11		1	154
	Grapes	10	156	18	10	6		12	1339	2	1	17	1	18	16	34	5					1	1	7	1	28	1683
	Olives		7	5	2	1		3	8	3		2	1			14		1								2	49
	Onions		1					1	1		1																4
	Oranges		28	2	1			1	13	1		81	1		3	17								1		3	152
	Other Hay/ Non Alfalfa	19	45	1		1		10	28	1		2		82	1	7			3					2		17	219
	Pasture/Grass		14	1					7					20			3	1						1		2	49
	Peaches		1																								1
	Pistachios	2	49	5	4	8		21	28		4	29	1	1	5	248	1	1				2	1	1		9	420
	Plums		6	1		1			1						2		7	2									20
	Prunes		7			1			1					1		1	4	5									20
	Sod/Grass Seed																										0
	Sudan																										0
	Sugarbeets																										0
	Corn	2	2			4			11		1		1		2							94	1	1		10	129
	Tomatoes	1					1		2													12	34			2	52
	Walnuts	3	12			1		1	7		1			1	7	2	1							11		1	48
	Watermelons		1						7		1															1	10
	Grand Total	460	2131	58	36	204	1	146	1653	11	21	154	17	179	50	452	24	19	4	2	1	129	38	42	1	102	5935