Santa Cruz and Santa Clara Fine Scale Vegetation Map

Final Report

Prepared by Tukman Geospatial & Aerial Information Systems for the Santa Cruz Mountains Stewardship Network

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1. Executive Summary

This report documents the methods and results of the fine-scale, countywide vegetation map of Santa Cruz and Santa Clara Counties. The map represents the state of the landscape in summer, 2020, when the high-resolution imagery for the two counties was collected.

In 2020 the Santa Cruz Mountains Stewardship Network (SCMSN or the Network), initiated a fine scale vegetation mapping project in Santa Cruz and Santa Clara counties . The Network is a region-wide and cross-sector collaboration of independent individuals and organizations who are committed to practicing effective stewardship on their own lands and coordinating their efforts with other land stewards to enhance stewardship on a regional level. The Network facilitated multiple meetings with potential project stakeholders and, with support from the San Mateo Resource Conservation District, was able to build a consortium of funders to map all of Santa Cruz and Santa Clara counties. The consortium included Big Creek Lumber, CALFIRE - Santa Clara Unit, CALFIRE - Santa Cruz/San Mateo Unit, California Department of Fish and Wildlife, California Department of Parks and Recreation, California State Coastal Conservancy, County of Santa Cruz, County of Santa Clara Technology Services and Solutions, Gordon and Betty Moore Foundation, Midpeninsula Regional Open Space District, National Oceanic and Atmospheric Administration - Coastal Change Analysis Program (C-CAP), Peninsula Open Space Trust, Resources Legacy Fund, San Francisco Public Utilities Commission, Santa Clara Valley Open Space Authority, Santa Clara Valley Water District, Save the Redwoods League, UC Santa Cruz Natural Reserves, and United States Geological Survey, 3D Elevation Program. Over a 3-year period, the project, collectively referred to as the "Santa Cruz and Santa Clara Fine Scale Veg Map", produced numerous environmental GIS products including impervious surfaces, wildland fuels, orthophotography, and other land cover maps. A 121-class fine-scale vegetation map was completed in June 2023 that details vegetation communities and agricultural land cover types, including forests, grasslands, riparian vegetation, wetlands, and croplands.

The environmental data products from the Santa Cruz and Santa Clara County Fine Scale Veg Map are foundational and can be used by organizations and government departments for a wide range of purposes, including planning, conservation, and to track changes over time to the two counties' habitats and natural resources.

Development of the Santa Cruz and Santa Clara fine-scale vegetation map was managed by the Santa Cruz Mountains Stewardship Network with support from the Golden Gate National Parks Conservancy, and staffed by personnel from [Tukman Geospatial](), [Aerial Information Systems]() (AIS), and Kass Green and Associates. The fine-scale vegetation map effort included field surveys by a team of trained botanists including Lucy Ferneyhough (UCSC Arboretum), Brett Hall (UCSC Arboretum), Alex Hubner (UCSC Arboreturm), Emma Wheeler (SCMSN), Kendra Sikes (CNPS), Jennifer Buck-Diaz (CNPS), Julie Evens (CNPS), Kelse Guest (CNPS), Alexis LaFever-

Jackson (CNPS), Savannah Vu (CNPS), and others. Data from these surveys, combined with older surveys from previous efforts, were analyzed by the California Native Plant Society (CNPS) Vegetation Program, with support from the California Department of Fish and Wildlife Vegetation Classification and Mapping Program (VegCAMP) to develop a Santa Cruz and Santa Clara County-specific vegetation classification. For more information on the field sampling and vegetation classification work, refer to the final report issued by CNPS and corresponding floristic descriptions.

Existing lidar data, collected in 2020 in collaboration with the USGS 3D Elevation Program, County of Santa Cruz, and County of Santa Clara, was used to support the project. The lidar point cloud, and many of its derivatives, were used extensively during the process of developing the fine-scale vegetation and map. The lidar data was used in conjunction with optical data. Optical data used throughout the project included 6-inch resolution airborne 3-band imagery collected in the summer of 2020 for Santa Cruz County, 3 and 9-inch resolution airborne 3-band imagery for Santa Clara County collected in early fall, as well as various dates of National Agriculture Imagery Program (NAIP) imagery.

In late 2021, an enhanced lifeform map was produced with funding from the CALFIRE Fire Prevention Grants Program to support the development of wildfire hazard and risk maps, which also serves as the foundation for the much more floristically detailed fine-scale vegetation and habitat map. The lifeform map was developed using expert systems rulesets in Trimble Ecognition®, followed by manual editing. Refinements to the lifeform map were completed in 2022 and 2023 concurrently with fine scale vegetation map finalization.

In 2021, Tukman Geospatial and AIS staff conducted countywide reconnaissance field work to support fine-scale mapping. Field-collected data were used to train automated machine learning algorithms, which produced a fully automated countywide fine-scale vegetation and habitat map. Throughout 2022, Tukman Geospatial and AIS manually edited the fine-scale maps, and Tukman Geospatial and AIS went to the field for validation trips to inform and improve the manual editing process. In March of 2023, draft maps were distributed and reviewed by Santa Cruz and Santa Clara counties' community of land managers and by the funders of the project. Input from these groups was used to further refine the map. The countywide fine-scale vegetation map and related data products were made public in late June 2023. In total, 121 vegetation classes were mapped with a minimum mapping size of one fifth to one acre, varying by class.

Accuracy assessment plot data were collected in 2023. Accuracy assessment results were compiled and analyzed May and June of 2023. The overall accuracy of the by lifeform is 97%. The overall accuracy of the vegetation map by fine-scale vegetation map class is 82.3%, with an overall 'fuzzy' accuracy of 92.0%.

The Santa Cruz and Santa Clara fine-scale vegetation map was designed for a broad audience for use at many floristic and spatial scales. At its most floristically resolute scale, the fine-scale vegetation map depicts the landscape at the National Vegetation Classification alliance level – which typically characterizes stands of vegetation by the dominant species present. This product is useful to managers interested in specific information about vegetation composition. For those interested in general land use and land cover, the enhanced lifeform map may be more appropriate. To make the information in the map accessible to most users, the vegetation map is published as a suite of GIS deliverables available in many formats. Map products are being made available wherever possible by the project stakeholders, including the regional data portal Pacific Veg Map.

In addition to the numerous data products, the fine-scale vegetation map contains several attributes that provide utility to the end user beyond vegetation type information. The map contains lidar-derived information about stand height, stand canopy cover, and the percentage of impervious cover in each vegetation and habitat map polygon.

The fine scale vegetation map also provides information relevant to forest health for the Santa Cruz Mountains ecoregion of the two counties. Specifically, the map includes stand-by-stand attribution about canopy mortality (percent standing dead in 2020), created with support from the Santa Clara County Firesafe Council. The standing dead information will be useful for tracking the spread of pathogens such as sudden oak death and pitch pine canker in the Santa Cruz mountains' forests and woodlands.

This report details the methods used to develop the fine-scale vegetation map and its derivative products.

This report is organized into the following sections:

- **Section 2. Acknowledgements**
- **Section 3. Mapping Methods** – details methods used to create the final map classes and rules, the enhanced lifeform map, and the fine-scale vegetation and map
- **Section 4. Accuracy Assessment Methods and Results** – provides information on the accuracy of the vegetation map overall, the accuracy by map class, and discussion of the major sources of confusion.
- **Section 5. Vegetation Map Data Products** – provides a list of the vegetation map data products, instructions for obtaining the data products and specifications of the map products including minimum mapping units.
- **Section 6. References**

2. Acknowledgements

The Santa Cruz and Santa Clara County fine scale vegetation map was a multi-year effort made possible with financial support from the following agencies and organizations:

- Big Creek Lumber
- CALFIRE - Santa Clara Unit
- CALFIRE - Santa Cruz/San Mateo Unit
- California Department of Fish and Wildlife
- California Department of Parks and Recreation
- California State Coastal Conservancy
- County of Santa Cruz
- County of Santa Clara, Technology Services and Solutions
- Gordon and Betty Moore Foundation
- Midpeninsula Regional Open Space District
- National Oceanic and Atmospheric Administration - Coastal Change Analysis Program (C-CAP)
- Peninsula Open Space Trust
- Resources Legacy Fund
- San Francisco Public Utilities Commission
- Santa Clara County Firesafe Council
- Santa Clara Valley Open Space Authority
- Santa Clara Valley Water District
- Santa Cruz Mountains Stewardship Network
- Save the Redwoods League
- UC Santa Cruz Natural Reserves
- United States Geological Survey, 3D Elevation Program

Additional support including existing vegetation data, local knowledge, review of draft map products, guidance on floristic characteristics of region, advocacy, and access for field crews was provided by the following agencies and organizations:

- Auten Resource Consulting
- Blue Oak Ranch Reserve, UC Berkeley
- Bureau of Land Management
- California Department of Conservation
- California Department of Fish and Wildlife
- California Native Plant Society (CNPS)
- City of Santa Cruz
- Consortium of California Herbaria
- Digital Mapping Solutions
- Don Edwards National Wildlife Refuge

- Dylan Neubauer
- Elkhorn Slough Foundation
- Fire Safe Santa Cruz County
- Golden Gate National Parks Conservancy
- Jasper Ridge Biological Preserve
- Jodi McGraw Consulting
- Kass Green and Associates
- Karen Thorne, PhD, Research Ecologist, USGS Western Ecological Research Center
- Land Trust of Santa Cruz County
- Lick Observatory UCSC
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- Nadia Hamey, Hamey Woods
- NatureServe
- Point Blue Conservation Science
- Quantum Spatial/NV5
- Quail Hollow Conservation Areas
- San Lorenzo Valley Water District
- San Mateo Resource Conservation District
- Santa Clara County Fire
- Santa Clara County Parks
- Santa Clara Valley Habitat Agency
- Santa Cruz Resource Conservation District
- Sempervirens Fund
- Soquel Demonstration State Forest
- Stuart Weiss, Creekside Science
- Together Bay Area
- UC Santa Cruz Arboretum
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- Vollmar Natural Lands Consulting
- Wildland Resource Management

We would like to extend our gratitude to those private landowners who provided access to their land for field work.

Thanks to the Midpeninsula Regional Open Space District for providing access to their ArcGIS Online account to host many of the datasets produced in this project. Finally, thanks to Dr. Mike Vasey, who provided pro-bono support throughout this project to share his deep knowledge of San Mateo County's vegetation communities and their distributions.

3. Mapping Methods

3.1. Introduction

As summarized by Green, Congalton, & Tukman (2017), using remotely sensed data and ancillary information to map vegetation type is effective because there is a high correlation between variation in the imagery and ancillary data and variation in vegetation as specified by the classification scheme. In other words, when the vegetation on the ground changes, the spectral response of the imagery and/or the classes of ancillary data also change. Using remotely sensed data and ancillary information to map land cover and land use requires an understanding of the factors that cause variation on the ground and how the imagery and ancillary information represent those variations. Therefore, vegetation mapping requires completion of three basic steps:

- Developing a classification scheme to specify the type of land cover and land use characteristics to be detected and mapped
- Controlling variation in the imagery and ancillary information that is not related to variation in the classification scheme
- Capturing the variation in the imagery and ancillary data related to the variation in the classification scheme.

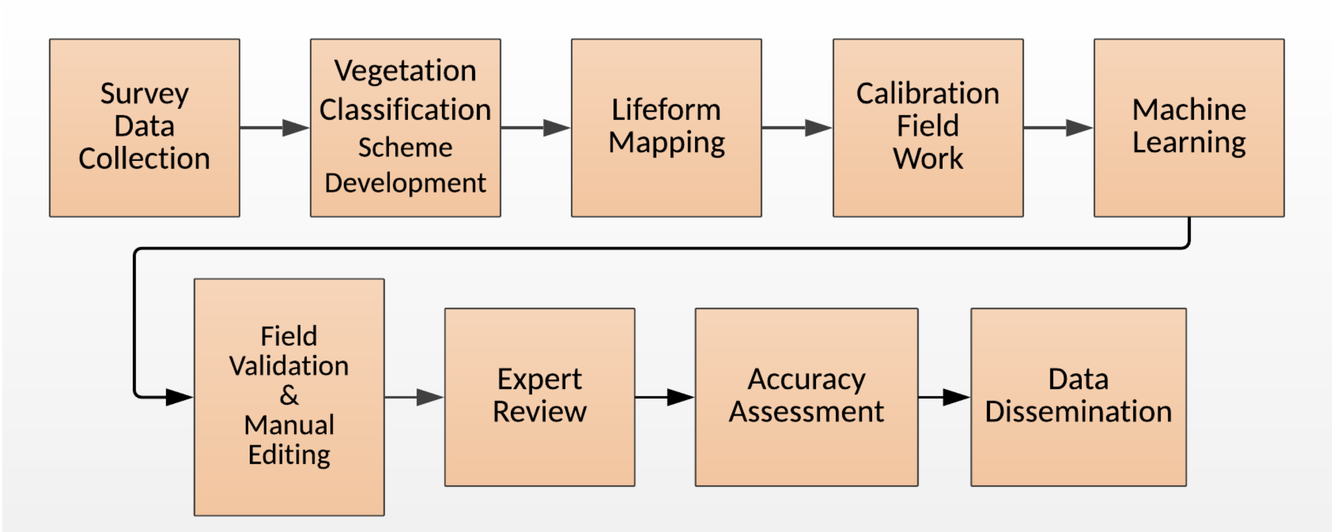
Since the early 1900s, these steps have been completed through the manual interpretation of remotely sensed data to delineate and identify vegetation using seven indicators of vegetation type; color, tone, texture, location, context, height, and shape of the feature of interest (Spurr, 1960). While a mainstay for decades, manual interpretation can be extremely time consuming, costly, and inconsistent. Semi-automated classification involves machine learning to establish relationships between the imagery, ancillary information, and features on the ground. Semi-automated methods can be more cost effective and consistent than manual interpretation by allowing computer data analysis to label the easily identified features, thereby focusing the skilled remote sensing analysts' efforts on difficult and complex features. This project employed semi-automated techniques.

Innovations over the last decade have resulted in the development of the semi-automated classification method of object-oriented classification. Object-oriented image classification classifies image objects (image segments) instead of single pixels, allowing for the incorporation of not only texture, tone, and color, but also shape and context into the creation of vegetation data. Object-oriented classification closely mimics manual interpretation by creating vegetation polygons yet brings substantial increase to the speed of map production, consistency, accuracy, and detail. While powerful in the classification of medium resolution data (e.g., Landsat), object-oriented classification is pivotal for semi-automated classification of high-resolution airborne imagery because of the mixture of shadow and illuminated features in the imagery and the need to group pixels together to map vegetation classes instead of vegetation features such as individual trees.

This project's semi-automated techniques combine the computer automation of object-oriented image segmentation and machine learning with the human work of field data collection, vegetation classification development, manual image interpretation and editing to create Santa Cruz and Santa Clara Counties' vegetation map products.

This section provides an overview of the methods – both automated and non-automated – and data used to make the fine-scale vegetation and habitat map. There were nine overall steps in the mapping team's methods (see Figure 1).

Figure 1. *Fine-scale mapping steps*



3.2. Plot Data Collection and Classification Development

The fine-scale mapping effort began with countywide vegetation survey data collection by a team of trained botanists. These data were combined with surveys from previous efforts by the California Native Plant Society (CNPS). The collective body of new and older surveys was analyzed by CNPS to create a comprehensive classification, a dichotomous key that provides decision rules for labeling fine-scale vegetation classes, and vegetation descriptions for each fine-scale vegetation class in Santa Cruz and Santa Clara County (see Table 1). These products follow the same standards, framework, and hierarchy used by both the Manual of California Vegetation (Sawyer, Keeler-Wolf, & Evens, 2009) and the National Vegetation Classification System.

Table 1. *Table of classification related data products*

Data Product	Description	Download URL
CNPS Vegetation Classification of Alliances and Associations	Main body of classification document. Includes a floristic key.	https://vegmap.press/cruz_clara_descriptions
Alliance and Associations Vegetation Descriptions	Appendix D of classification document (detailed descriptions of alliances)	https://vegmap.press/cruz_clara_classification_report
Santa Cruz – Santa Clara County Fine-scale Mapping Key	Key used for lifeform mapping and fine-scale vegetation mapping	https://vegmap.press/cruz_clara_mapping_key

During the classification development phase, minimum mapping units (MMUs) were established for the vegetation mapping project. An MMU is the smallest area to be mapped on the ground. Many mapping projects have a single MMU; for this project, the mapping team chose to map different features at different MMUs. For example, riparian vegetation had a smaller MMU than upland vegetation types because riparian vegetation is a sensitive habitat, is uncommon on the landscape, and very important from a land manager's perspective. Table 2 shows the MMUs for the various features mapped in the Santa Cruz and Santa Clara fine scale vegetation map.

Table 2. *Minimum mapping units by feature type*

Feature Type	**Minimum Mapping Unit**
Agricultural Classes	1/4 Acre
Woody Upland Classes	1/2 acre for contrasting lifeforms (e.g., forest surrounded by non-forest); 1 acre for different alliances in the same lifeform
Woody Riparian Classes	1/4 acre for contrasting lifeforms; 1 acre for different alliances in the same lifeform
Upland Herbaceous Classes	1/2 acre for contrasting lifeforms; 1 acre for different alliances in the same lifeform
Wetland Herbaceous Classes	1/4 acre for contrasting lifeforms; 1 acre for different alliances in the same lifeform
Bare Land	1/2 Acre
Impervious Features (in the impervious surfaces map)	1000 square feet; 200 square feet for buildings*
Developed (in the vegetation and habitat map)	1/5 Acre
Water	400 square feet

*These numbers apply to the Santa Cruz and Santa Clara impervious surfaces map, which is referenced in this report but is not a vegetation map product. The lifeform map and fine-scale vegetation map show major road polygons and impervious features that have contiguous impervious areas (not including roads) of .2 acres or more.

It is important to note that in the fine scale vegetation map, upland shrub and upland forest patches between ½ and one acre and not touching adjacent shrub or forest are mapped as 'Shrub Fragments' and 'Forest Fragments' respectively. This was done so that the map has smaller MMUs for upland forest and shrubs (the typical MMU for fine scale maps in California is one acre for upland woody types) without having to assign fine scale map class, which becomes more and more difficult as patch size decreases. Keeping forest and shrub fragments in the map provides utility for habitat analysis and modeling, carbon mapping, and fuels mapping.

3.3. Lifeform Mapping

3.3.1. Lifeform Mapping Overview

The lifeform and the enhanced lifeform maps depict land cover in a floristically general way and serve as the foundation for subsequent fine-scale mapping. This section describes the creation of the lifeform and enhanced lifeform maps, the methods used to map the built and agriculture lifeform classes, and the process of manually editing the lifeform and enhanced lifeform maps.

The mapping process begins with lifeform mapping, which is conducted using Trimble® Ecognition® followed by manual image interpretation. Lifeform mapping results in a map of very general lifeform classes. The lifeform map serves as the foundation for the enhanced lifeform map, which adds more classification detail in forested areas. The enhanced lifeform mapping process combines fine scale segmentation in Trimble® Ecognition® with machine learning and further manual image interpretation. The enhanced lifeform map is produced and published as an interim draft map while the mapping team creates the final, fine scale vegetation map. The overall mapping workflow is shown in Figure 2. After the fine scale vegetation map is produced, a final version of the enhanced lifeform map is 'spun off' from the fine scale vegetation map.

Figure 2. *Lifeform mapping, fine scale segmentation and fine scale vegetation mapping workflow*

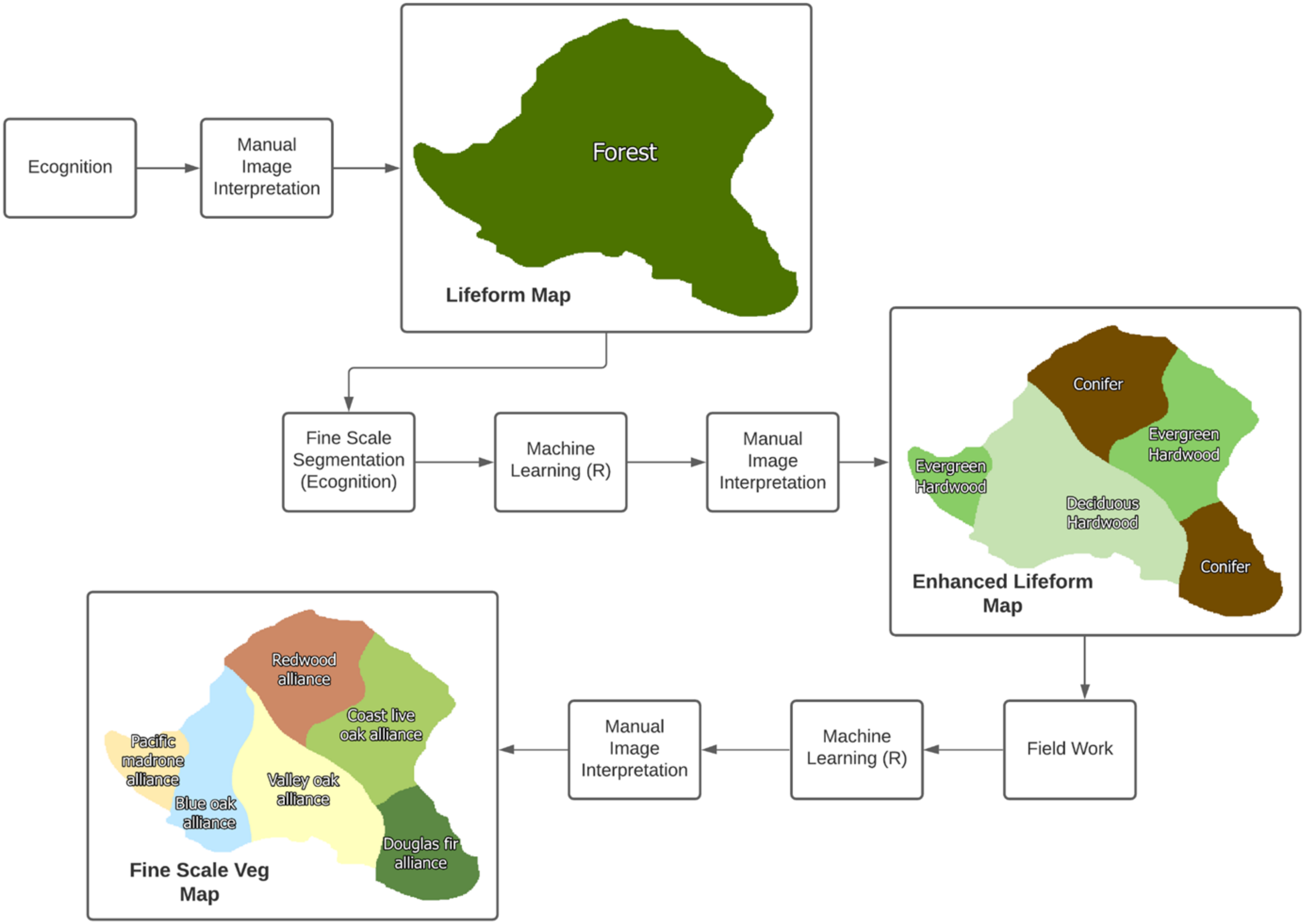


Table 3. *Enhanced lifeform classes and acreages, Santa Cruz and Santa Clara Counties*

Class	**Description**	**Acres**
Barren and Sparsely Vegetated	Areas where shrub, forest, and herbaceous cover are each less than 10% absolute cover and the area is best characterized as bare land.	4,138
Deciduous Hardwood	Areas mapped as deciduous hardwood types in the fine scale vegetation map, such as blue oak, valley oak, black oak, buckeye, etc. Does not include riparian hardwood types. Refer to the fine scale mapping key for decision rules.	123,846
Developed	Human-caused developed areas greater than 0.2 acres; areas include irrigated lawns, heavily landscaped garden and patio areas, bocce courts, tennis courts, sport courts, developed horse riding arenas, baseball fields, soccer fields, golf courses, swimming pools, and playground areas.	174,932
Eucalyptus	Areas where tree species are at least 10% absolute cover and *Eucalyptus spp.* dominates tree cover (>50% relative tree cover).	3,897
Evergreen Hardwood	Areas mapped as evergreen hardwood types in the fine scale vegetation map, such as tanoak, madrone, live oak, etc. Does not include riparian hardwood types. Refer to the fine scale mapping key for decision rules.	202,190
Forest	Areas of forest between ½ acre and 1 acre (*forest fragments*, see discussion above in section 3.2). Mapping these small stands to their enhanced lifeform and fine scale class would result in low accuracies. They are included in the map because these areas are mappable at the lifeform level and because they are important for fuels mapping and other use cases.	3,904
Freshwater Wetland	Areas that are depressional, wet all year long, and/or exhibit obvious herbaceous wetland vegetation in the 2020 imagery; absolute tree and shrub cover are both less than 10%.	1,236
Herbaceous	Areas where upland herbaceous vegetation is at least 10% absolute cover; absolute tree and shrub cover is less than 10%.	207,695
Intensively Managed Hayfield	Area is an intensively managed hayfield that is mechanically turned over every year.	2,815
Irrigated Pasture	Area is an irrigated pasture.	178
Major Road	Area is a major road.	3,817
Non-native Forest	Areas where tree species are at least 10% absolute cover; tree cover dominated by ornamental non-native species (>50% relative tree cover).	23,776
Non-native Herbaceous	Areas where herbaceous vegetation is at least 10% absolute cover; non-native herbaceous species dominate the herbaceous stratum; absolute tree and shrub cover are both less than 10%.	2,837

Class	Description	Acres
Non-native Shrub	Areas where shrub species are at least 10% absolute cover; absolute tree cover is less than 10%; relative shrub cover is dominated by non-native species.	810
Nursery or Ornamental Horticulture Area	Area is a nursery or horticultural area.	1,826
Orchard or Grove	Area is an orchard or grove of fruit or nut trees.	5,590
Pine/Cypress	Areas mapped as pine and cypress types in the fine scale vegetation map. Refer to the [fine scale mapping key]() for decision rules.	19,592
Redwood/Douglas fir	Areas mapped as redwood and or Douglas fir types in the fine scale vegetation map. Refer to the [fine scale mapping key]() for decision rules.	146,046
Riparian Forest	Areas where tree species are at least 10% absolute cover; obligate riparian tree genera (alder, willow, cottonwood, ash, sycamore) dominate tree cover (>50% relative tree cover).	10,233
Riparian Shrub	Areas where woody riparian shrub species are at least 10% absolute cover; obligate riparian genera (e.g., shrubby willow trees) dominate shrub cover (>50% relative shrub cover).	2,228
Row Crops	Areas that are either active annual or perennial row crops or are tilled and prepped for planting of row crops or are in between plantings. Row crops include annual crops like lettuce, spinach, corn, etc. and perennial crops such as strawberries, raspberries, lavender, or actively managed Christmas tree farms. Temporary greenhouses should be classified as Row Crops.	29,576
Salt Marsh	Salt marsh areas dominated by salt-tolerant wetland species.	2,291
Shrub	Area where native upland woody shrubs are at least 10% absolute cover; absolute tree cover is less than 10%.	135,136
Tidal Mudflat	Areas in the intertidal zone that are unvegetated and exposed during low tide.	856
Vineyard	Area is a vineyard.	2,781
Water	Water covers the area.	20,879
	Total:	1,133,106

3.3.2. Lifeform and Enhanced Mapping Methods

The lifeform map and enhanced lifeform map are created using Trimble® Ecognition®, machine learning and manual image interpretation.

The initial lifeform map, a 13-class vegetation map, is created using an Ecognition® rule set that combines automated image segmentation with object-based image classification. The rule set is developed heuristically based on the knowledge of experienced image analysts and is based on the rulesets used in previous mapping efforts. After Ecognition is run, an automated, countywide lifeform map is created. In this automated map, 'native forest' is mapped as a single class. The automated countywide map is edited by image interpreters (see Section 3.4.3).

After a round of editing on the initial countywide map (with 'Native Forest' as a single class), a second round of image segmentation is used to divide the broad 'Native Forest' class into smaller forested segments that are compositionally and structurally homogenous (see Section 3.3.7). Fine-scale segmentation divides the large and floristically broad native forest and shrub areas into much smaller image segments suitable for fine-scale mapping. There are 26 unique classes in the enhanced lifeform map (see Table 3 above).

Once fine scale segmentation is completed, a round of machine learning is used to classify native forest areas to their enhanced lifeform labels, which include 'Evergreen Forest,' 'Deciduous Forest,' 'Redwood and/or Douglas Fir' and 'Pine and/or Cypress.' Machine learning is discussed in more detail in Section 3.4.2. Table 3 shows the list of enhanced lifeform classes and their definitions.

Key data sets used in the lifeform and the enhanced lifeform mapping process include high resolution aerial imagery from 2020, the lidar-derived Canopy Height Model (CHM), and several other lidar-derived raster and vector datasets. In addition, several forest structure lidar derivatives are used in the machine learning portion of the enhanced lifeform workflow. See Table 4 for a summary of datasets used in lifeform and enhanced lifeform mapping.

Table 4. *Imagery and ancillary datasets used in lifeform and enhanced lifeform and mapping*

Layer	Roles in Lifeform Mapping	Source
Summer/Fall 2020 County Orthoimagery	Used for reference for manual editors.	Various
NDVI from Summer 2020	Used as the primary spectral input for lifeform mapping in Ecognition® and used in Ecognition® decision rules for discriminating between vegetated and non-vegetated areas.	Tukman Geospatial, NV5
2020 lidar Derived Canopy Height Model (CHM)	Represents height of vegetation. The CHM was used widely as an input to the Ecognition® rule set, especially for mapping the natural lifeform classes.	Tukman Geospatial, Sanborn, NV5
Road Centerlines	The Santa Cruz and Santa Clara County Road Centerlines datasets were used to include major roads in the lifeform map.	Open Street Map, CAL FIRE, Santa Cruz and Santa Clara County

Layer	Roles in Lifeform Mapping	Source
lidar-derived DEM, Slope and Aspect	Used for various Ecognition® decision rules.	Tukman Geospatial, Sanborn
Sentinel-2 Data	Multi-temporal Sentinel data from the past 3 years was used as a predictor variable in the machine learning phase of enhanced lifeform mapping.	European Space Agency / Google Earth Engine
Lidar percentile heights	Percentile heights derived from 2020 lidar data was used in the machine learning part of the enhanced lifeform workflow.	Tukman Geospatial
Lidar canopy volume profiles	Canopy volume profiles derived from 2020 lidar data were used in the machine learning part of the enhanced lifeform workflow.	Tukman Geospatial
Other lidar derivatives	Other lidar derivatives, such as rumple and highest hit slope, were used in the machine learning part of the enhanced lifeform workflow.	Tukman Geospatial

3.3.3. Lifeform Map - Built Classes

While the natural classes in the lifeform and enhanced lifeform maps are mapped by Ecognition® using rules developed solely from the imagery and the lidar data (except for wetlands, which are discussed below), classes depicting the built landscape are mapped by Ecognition® using additional data sources and workflows. This section describes how the built classes will be mapped.

Developed areas – such as rural residential developments – are assigned the ‘developed’ class. Developed areas are included in the lifeform map if they exceed 0.2 acres in size and contain significant human-caused impervious cover or are highly altered by man.

Major paved road polygons (highways and some major arterial roads) are included in the lifeform map and the fine-scale map as major roads, but minor paved roads and dirt roads are not included.

Minor roads and individual building footprints are omitted from both the lifeform and fine-scale vegetation maps intentionally since these maps are meant to focus on the natural landscape. A separate product – the Santa Cruz impervious surfaces map and the Santa Clara impervious surfaces map – provide very detailed polygons for all vehicle roads (paved and dirt), as well as all impervious surfaces such as parking lots, buildings, etc. It should be noted that the fine-scale vegetation map contains attributes for each fine scale map polygon about percent imperviousness (from the impervious map) by impervious cover type. As such, the fine-scale detail regarding the built environment that exists in the impervious map is embedded in the fine-scale map polygons. The work to embed information about imperviousness into the fine scale vegetation map occurred during final processing (see section 3.6).

3.3.4. The 'Urban Window'

The 'urban window' layer represents large, contiguous areas of urban landscape. This class was modeled after the approach used for Northern Sierra Nevada Foothills Mapping Project (Menke et al., 2011).

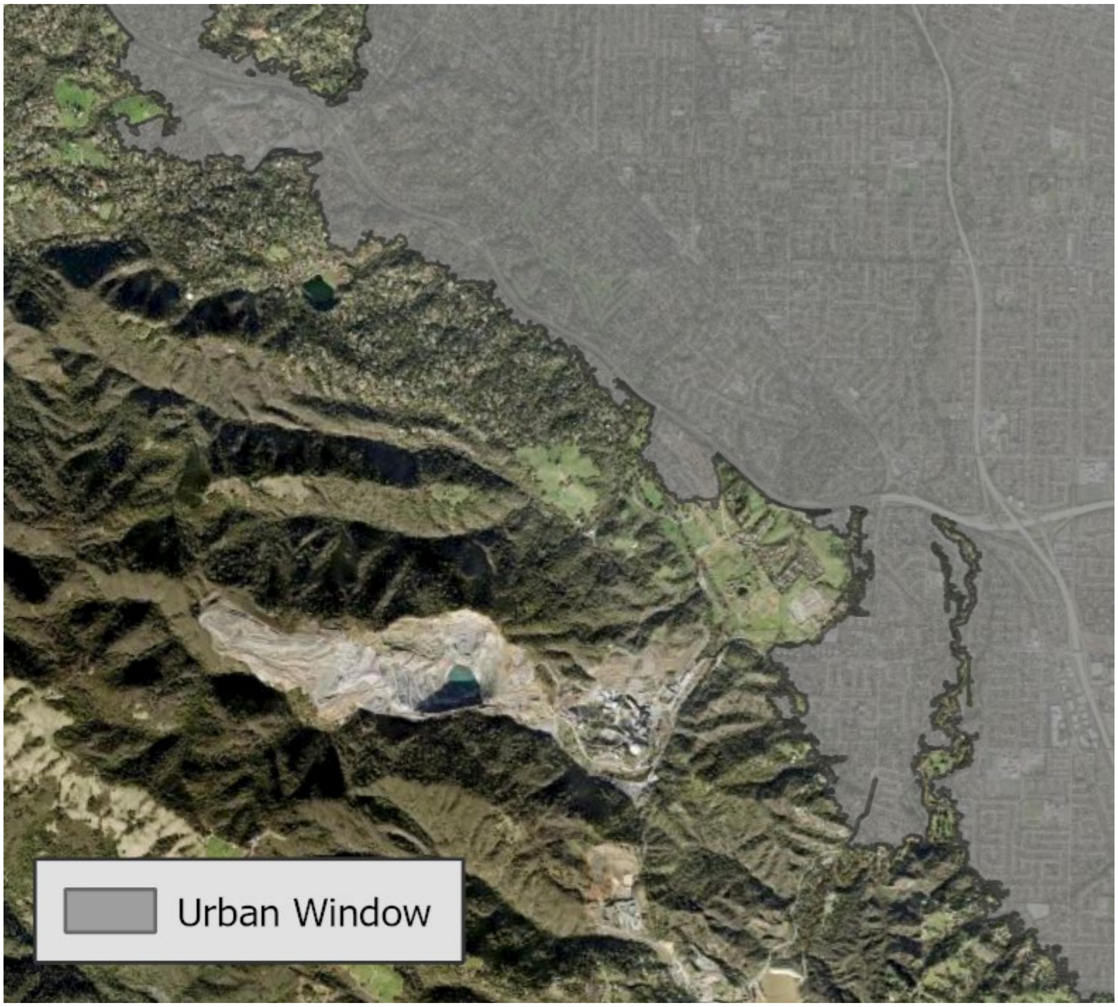
Inside the urban window, which for this project we limited to the massive urban core area of Santa Clara County, fine scale map classes are less scrutinized during manual editing than in the non-urban core areas. In addition, relative conifer cover, relative hardwood cover, absolute conifer cover, and absolute hardwood cover are not assigned inside of the urban window for 'Non-native Forest,' 'Forest Fragment,' and for 'Eucalyptus' stands. Furthermore, shrub cover and % standing dead (see section 3.7) are not assigned inside the urban window. Otherwise, attribution and classification are the same inside and outside of the urban window.

The following criteria were used to create the 'urban window' area:

1. The urban window represents contiguous and adjacent developed and/or major roads areas. For this project, the urban window was limited to the large, urbanized area of central Santa Clara County.
2. The urban window can finger out into adjacent natural areas if it has >30% impervious land cover.
3. Natural areas can extend into the urban window if they have <= 30% impervious land cover.
4. The urban window does not include lower density rural residential areas on the edge of the natural landscape.

Figure 3 shows an example of the urban window for an area of northern Santa Clara County.

Figure 3. *The urban window in northern Santa Clara County*



3.3.5. Agriculture

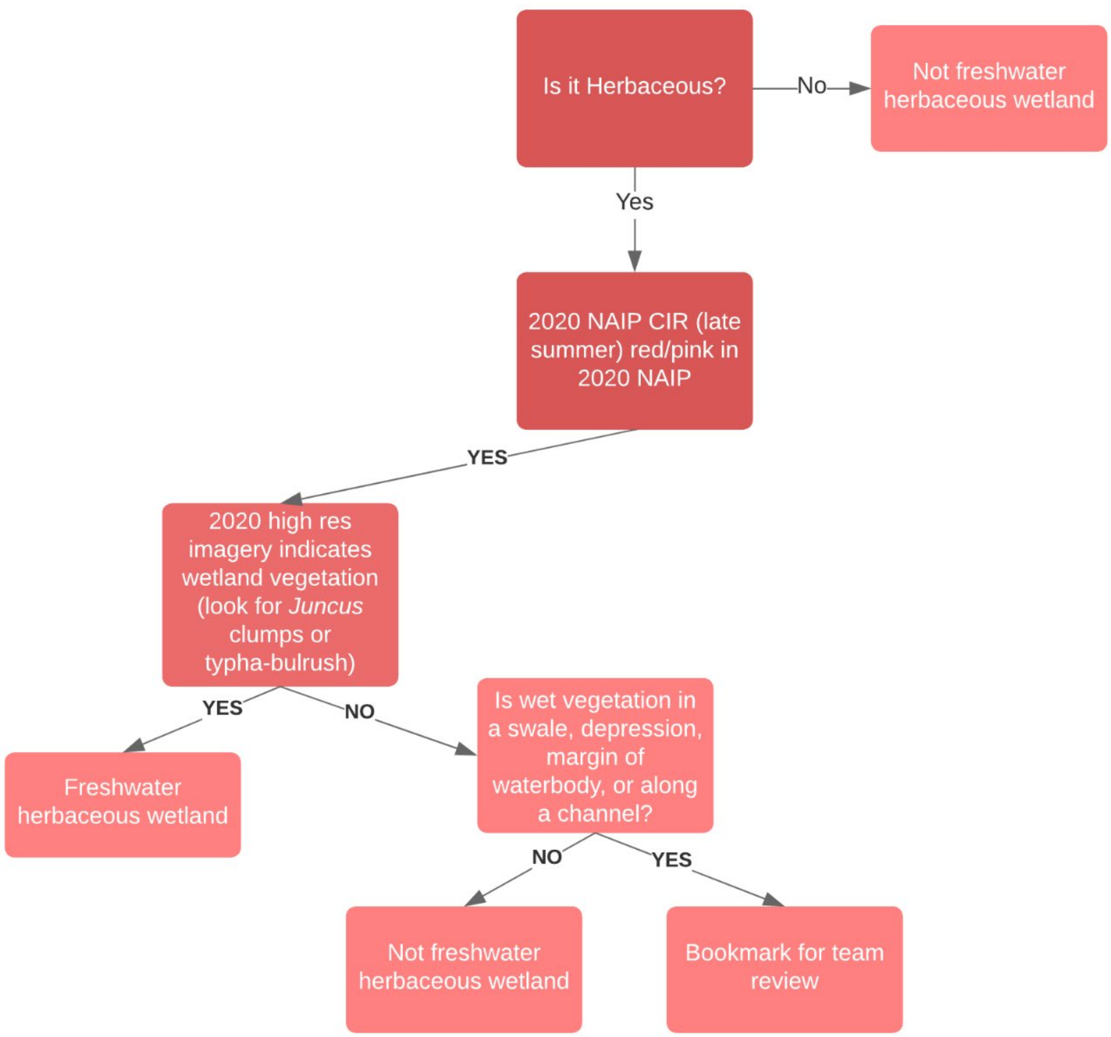
Agriculture was mapped during lifeform and enhanced lifeform mapping as several classes, at a ¼ acre minimum mapping unit. Agriculture classes included row crops, intensively managed hayfield, irrigated pasture, orchard or grove, and vineyard. Agriculture fields were not mapped using Ecognition®, but entirely by manual editing.

3.3.6. Tidal and Freshwater Wetlands

Tidal and freshwater wetlands are mapped initially in the lifeform and enhanced lifeform maps and refined during fine scale map editing. Tidal marshes are extracted from the SFEI's BAARI Baylands dataset where the class label in that dataset is 'Tidal Vegetation'. These representative polygons were integrated into the lifeform dataset during the Ecognition® processing. During lifeform and enhanced lifeform manual editing, the tidal marsh polygons integrated from SFEI (San Francisco Estuary Institute) were assessed and edited significantly. Additional tidal marsh (that was not included in SFEI's layer) was added manually through photo-interpretation. In the fine scale vegetation map, tidal marsh areas were mapped to the alliance level. See Section 3.4.5 for details.

Freshwater wetlands were identified and delineated manually during lifeform and enhanced lifeform mapping; existing freshwater wetlands datasets were not of high enough accuracy for direct integration into the map. Lifeform editors used the decision rules shown in Figure 4 for manually editing freshwater wetlands into the enhanced lifeform map. The rules are based on the appearance of the 2020 NAIP, while viewed in color infrared (CIR). Freshwater wetlands were further refined during fine scale map editing.

Figure 4. *Rules for editing freshwater wetlands in the lifeform map*

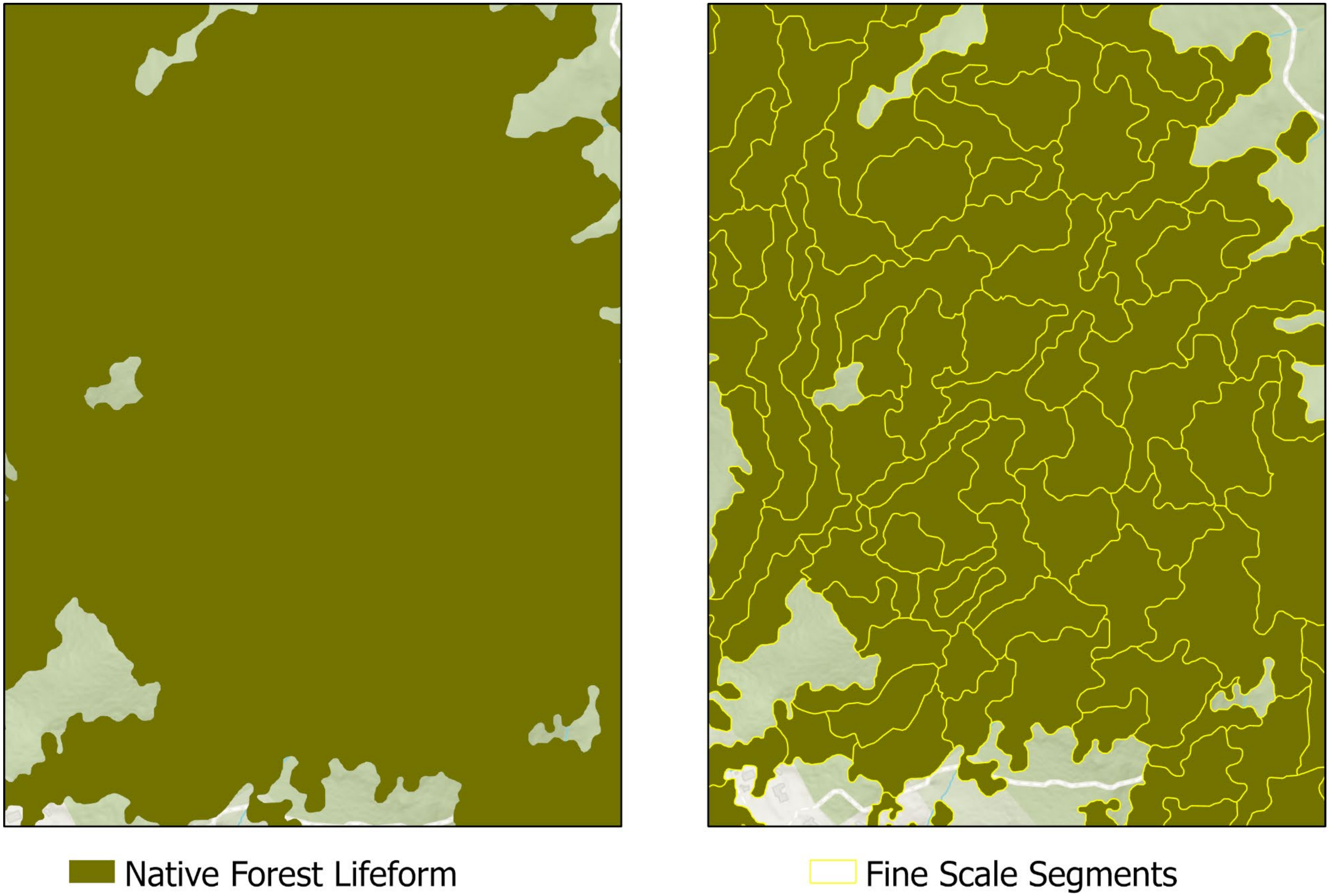


3.3.7. Fine Scale Segmentation

After the lifeform map was completed, and before the enhanced lifeform work began, a second round of image segmentation was performed to divide the broad 'Native Forest' and 'Native Shrub' classes into smaller forested segments that are spectrally and structurally homogenous. Fine-scale segmentation divides the large and floristically broad native forest and shrub areas into much smaller image segments that are more suitable for fine-scale mapping. Fine-scale segmentation was conducted using Trimble Ecognition® and relies on summer 2020 4-band NAIP, the 2020 lidar-derived canopy height model, and a suite of spectral indices derived from the NAIP. Fine scale segments were created so that they had spectral homogeneity (from the high-resolution imagery) but also had structural homogeneity, meaning uniform within-segment canopy height and canopy density. Figure 5 shows an example of the fine scale segments versus the much larger polygons of the lifeform map.

Fine-scale segments are used as the basis for the enhanced lifeform and fine-scale vegetation mapping. They serve as the units of analysis for enhanced lifeform and fine scale vegetation map machine learning and as mapping units for enhanced lifeform and fine scale vegetation map manual editing.

Figure 5. *Native forest polygon in lifeform map (left) and same area showing fine scale segments fine-scale segments (right)*



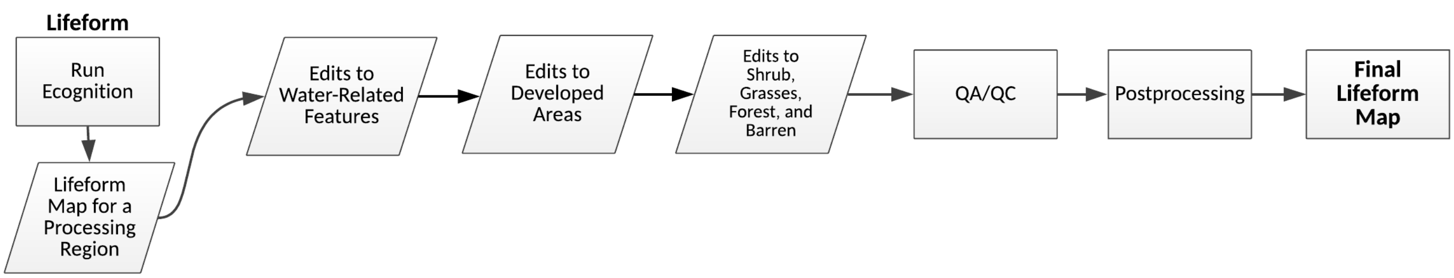
3.3.8. Lifeform and Enhanced Lifeform Map Manual Editing

After it was produced using Ecognition®, the preliminary lifeform and enhanced lifeform maps were manually edited by photo-interpreters. Edits were made to accomplish the following:

- Splitting of map polygons that are not compositionally homogenous as per the lifeform or enhanced lifeform mapping rules
- Addition of non-native forest and non-native shrub polygons where appropriate
- Edits to the lifeform and enhanced lifeform labels (e.g., changes from a forested lifeform to a shrub lifeform for lifeform, or from 'Evergreen Hardwood' to 'Redwood-Douglas fir' for enhanced lifeform)

Figure 6 shows a schematic of the lifeform editing workflow. The workflow for enhanced lifeform editing is more focused on splitting the lifeform 'Forest' class into the more floristically detailed enhanced lifeform classes such as 'Evergreen Hardwood Forest,' 'Deciduous Hardwood Forest,' 'Pine/Cypress' and 'Redwood - Douglas fir.'

Figure 6. *Lifeform editing workflow*



3.4. Fine Scale Mapping

3.4.1. Fine-scale Map Calibration Field Work

Calibration field work is a critical step in the mapping workflow, providing training data for machine learning (see Section 3.4.2) as well as visual reference for analysts conducting manual editing of the fine-scale vegetation map. The objectives of calibration field work are 1) to collect observations of all fine scale map classes (as defined in the Santa Cruz-Santa Clara fine scale mapping key) across their range of structural and compositional conditions and 2) to collect observations across the entire geography of the county, providing mappers with on-the-ground knowledge of the distribution of, and variation within, the fine scale map classes.

Calibration field data collection occurred in 2022 with a kick-off meeting to review methods and protocols and to calibrate optical percent cover estimates to ensure that different field crews consistently assigned fine-scale map classes.

Teams from Tukman Geospatial and AIS collected calibration field data. AIS field teams were joined by Todd Keeler Wolf in Santa Clara County. Existing and new field survey data collected for floristic classification was also used for map calibration.

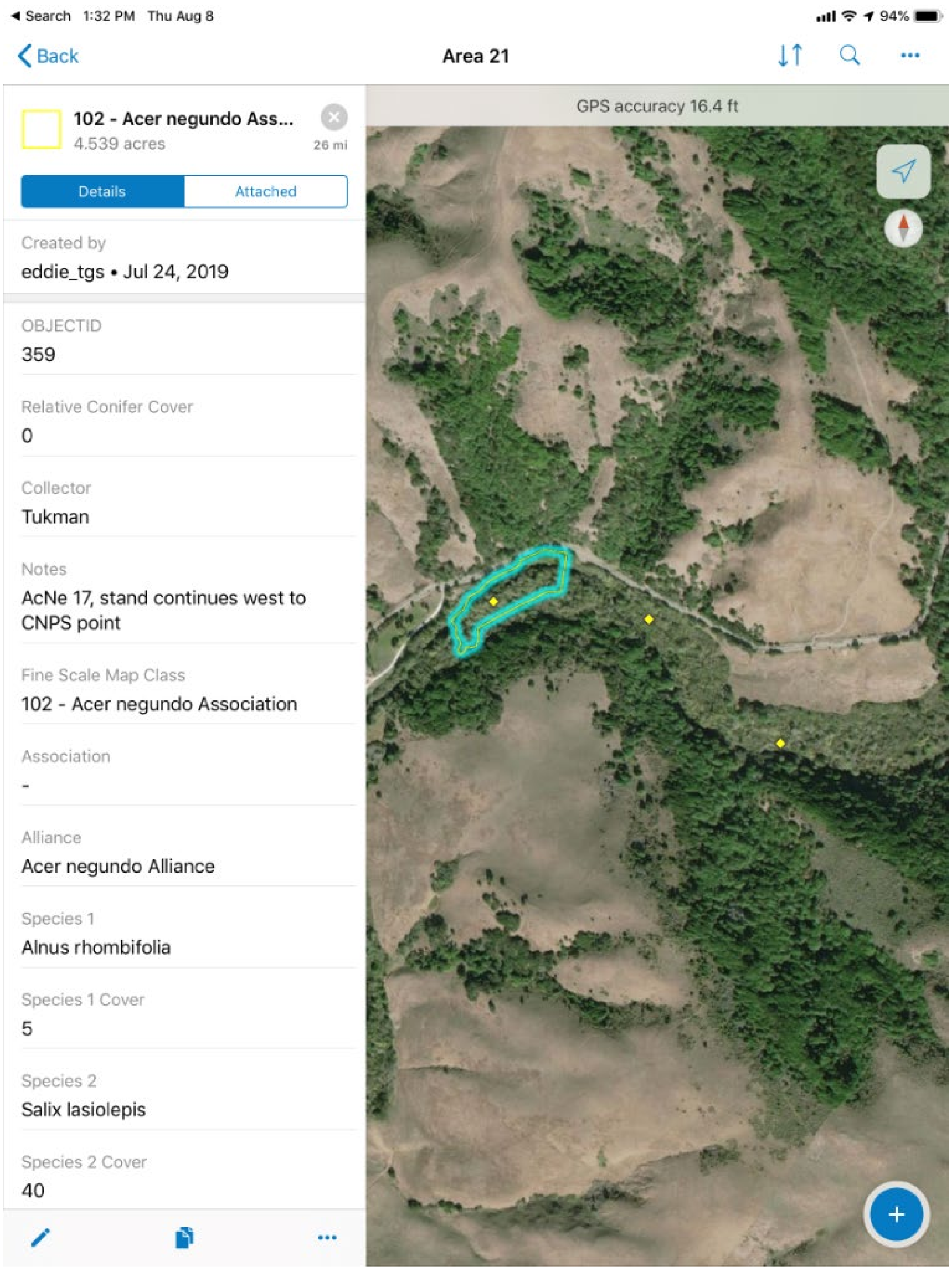
Calibration data collection teams use tablets running ESRI's Field Maps (see Figure 7) to delineate and attribute polygons (or label image segments) representing shrub, forest and herbaceous stands observed in the field. Field Maps uses an ArcGIS Online web map with syncable feature services.

Data collected by field crews was synchronized up at the end of each day and more frequently where cell service and WIFI coverage permitted. Field crews assigned the following to each of the field-collected calibration sites:

- Vegetation map class (from the fine scale mapping key)
- Field team names
- Notes
- Photos (as feature attachments)

Calibration field work resulted in hundreds of sites labeled countywide with their field-verified fine-scale map class. GPS-tagged photos were also taken at many locations for reference. After field visits, analysts reviewed the field-validated calibration sites with the dual aims of correcting data entry errors and performing QA/QC on field classifications. Data entry errors included assignment of incorrect map classes from the pick lists (usually this was the mis-assignment of the class falling before or after the intended class in the pick list). QA/QC resulted in throwing out or modifying field validated sites where in-office review showed inconsistencies between the field crew's map class assignment and what aerial imagery showed. When field labeled sites could not be reconciled with labels based on aerial imagery interpretation, they were removed as calibration candidates.

Figure 7. *Collector App for field calibration data collection*



3.4.2. Fine-scale Map Machine Learning

3.4.2.1. Overview

The Santa Cruz – Santa Clara Veg Map Team utilized a type of algorithmic data modeling known as machine learning to automate the classification of fine-scale segments into one of Santa Cruz and Santa Clara Countys' 121 fine-scale map classes. A form of supervised machine learning was adopted, whereby areas of known classification (training sites) are used to predict the map class for unknown areas through modeling techniques.

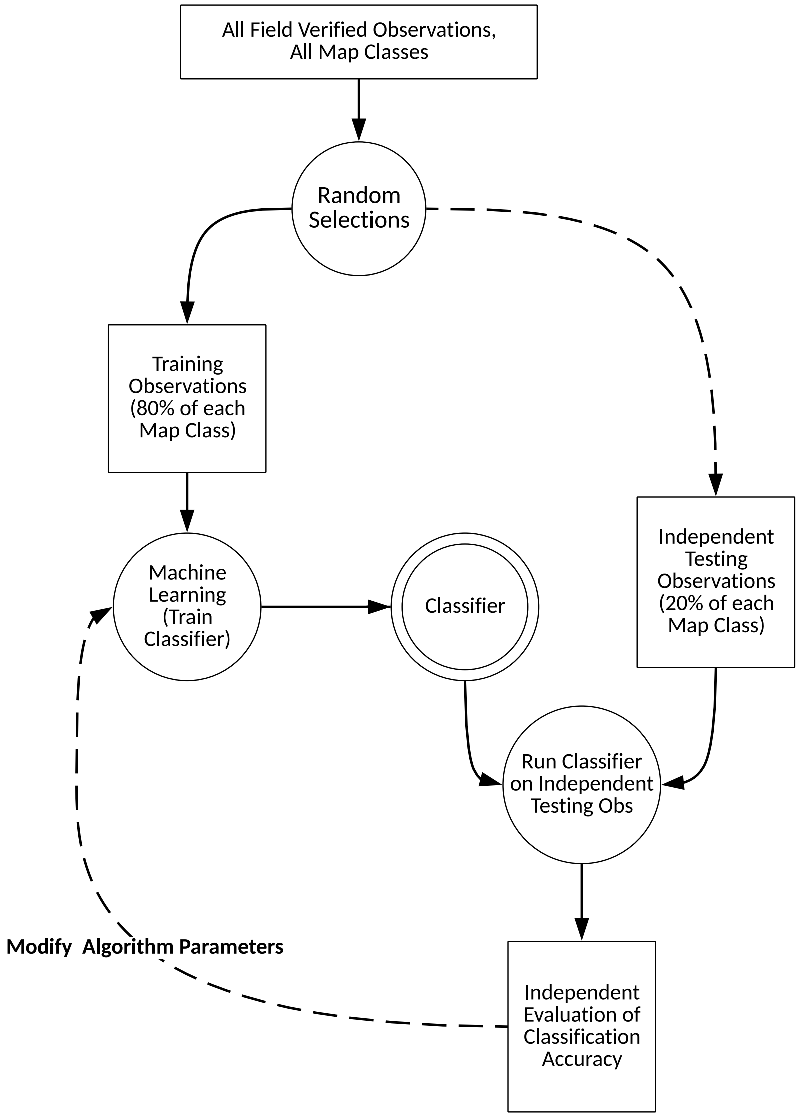
Field-calibrated sites discussed in the previous section were used as training data for machine learning, with their fine scale map class label serving as the dependent variable. The independent variables (referred to in this discussion as *predictor variables*) number over 300 and include variables that characterize the physical landscape and a wide variety of remotely sensed data to represent spectral reflectance of vegetation and forest structure. The predictor variables are discussed in detail in the next section.

Two machine learning algorithms were chosen to predict fine-scale vegetation class:

- Random Forests (Breiman, 2001) (section 3.4.2.3)
- Support Vector Machines (Meyer at al., 2018) (section 3.4.2.4)

Machine learning is an iterative process that requires trial and error to fine-tune algorithm parameters and inputs to maximize model accuracy. The Santa Cruz and Santa Clara Veg Map team employed the workflow shown in Figure 8. At the beginning of the machine learning process, 20% of the calibration sites were randomly selected for use as independent testing observations. These sites were not used to train the algorithm. The machine learning algorithms (random forests and support vector machines) were run on the remaining 80% of the calibration sites to create the classifying model. The classifying model was then applied to the calibration sites reserved for independent testing, resulting in map class predictions for those sites. The predicted map class for each site was compared to the field-verified map class and accuracy numbers were generated. Changes to parameters and training sites were applied, and each change was evaluated in the context of its effect on the model accuracy of the independent testing group of sites. The final parameters chosen for both random forests and support vector machines were those that maximized model accuracy for the independent testing group.

Figure 8. *Workflow for machine learning*



3.4.2.2. Random Forests and Support Vector Machines

Random forests and support vector machines (SVMs) were used in tandem in an ensemble approach. The two algorithms were implemented as a script using the R statistical computing package (R Core Team, 2013). Dr. Matt Clark, professor at Sonoma State University, wrote the script. The script was originally used for the Sonoma Veg Map and adapted for use in Santa Cruz and Santa Clara Counties.

The ensemble approach uses random forests and SVMs so that both algorithms predict fine-scale map class labels for each unlabeled fine scale segment across the landscape. The script then compares the predictions against each other – if the prediction from the two algorithms is the same, the segment is labeled with that fine-scale map class. If the predictions are different, the fine-scale map class from the algorithm with the higher confidence is used (both random forest and SVMs provide metrics for confidence or probability of correctness). Both algorithms produced a primary fine-scale map class label – the algorithm's first choice for a segment – and a secondary class label – the algorithm's second choice. These primary and secondary labels and their associated confidence values were used by manual editors as reference information.

In addition to predicting fine-scale map class for each segment, machine learning was also used to predict relative hardwood versus conifer cover. This was done using relative cover calibration sites collected during calibration field work and supplemented by photo interpreted sites.

3.4.2.3. Random Forests

Random forests "mines" the field-labeled training data and a stack of independent predictor variables and builds rules (if-then statements) in a decision tree to predict the fine-scale map class for all unlabeled segments across landscape. Random forest is a powerful modeling approach because:

- it can accept both continuous and categorical data inputs,
- the results are easy to interpret,
- unlike a maximum likelihood classifier, no assumptions are required concerning the distributions of the independent variables,
- it identifies simple and complex relationships between variables that other techniques might not uncover, and
- it forces consistency and analytical rigor into the segment labeling process.

Dr. Clark's R code included several analytical tools that were helpful in interpreting the results of the random forest model and in providing information to help refine and improve model results. These items included – for each run of random forests – an importance matrix for assessing predictor variable importance (as an example, Table 6 in section 3.4.2.5 shows the importance matrix for the *Umbellularia californica Mapping Unit*. In addition, Dr. Clark's code automatically created error matrixes for each run of random forests, providing user's accuracy, producer's accuracy, and overall accuracy for the independent testing sites. Lastly, for each fine scale segment on the landscape, the R code provided two votes – a first vote and a second vote. For both the first and second votes, Dr. Clark's R code provided a confidence value (0 to 1) for its fine-scale vegetation class prediction for the segment. Random forests bases its confidence values on the percentage of individual trees (i.e., set of rules) that predict the class.

For random forests, analysts did not do any predictor variable selection or winnowing – the entire stack of predictor variables was used for each run and the model assessed their importance.

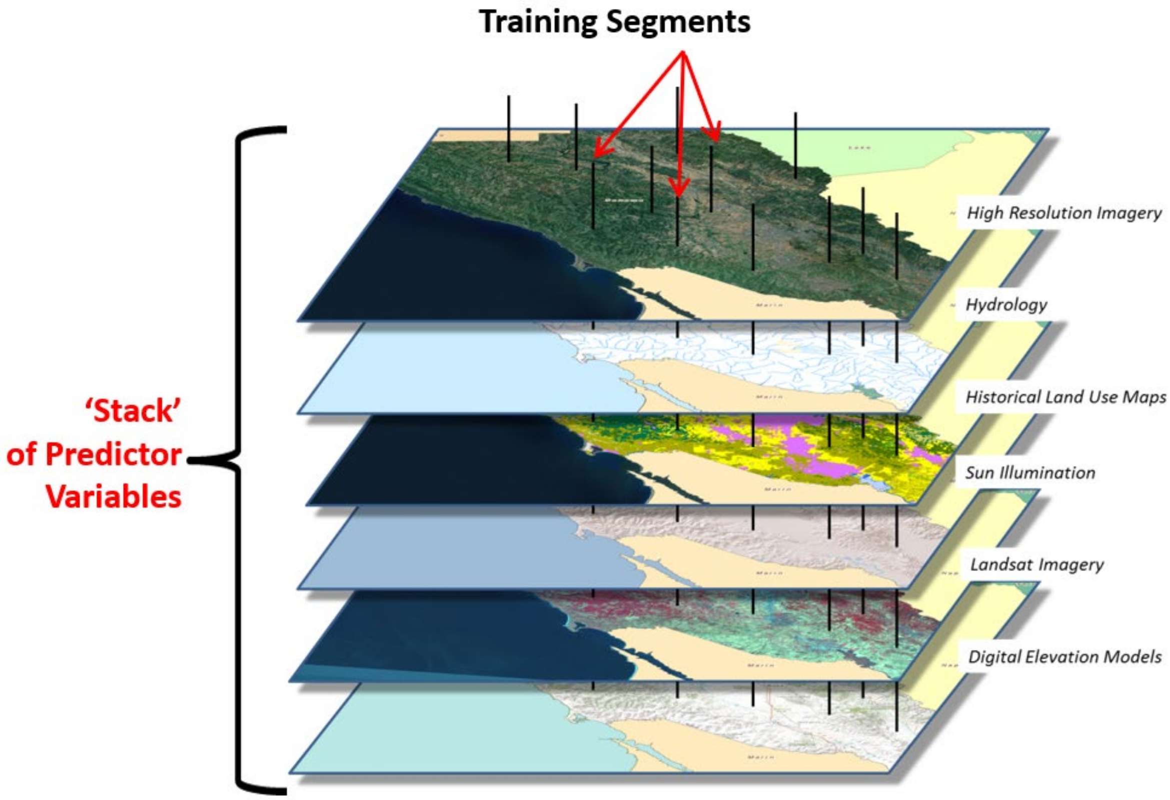
3.4.2.4. Support Vector Machines

Like Random Forests, SVMs are nonparametric supervised classifiers (Congalton, 2010). SVMs perform very well as a machine learning algorithm for vegetation mapping and have been widely adopted in the past few years. Like random forests, SVMs were used to assign each segment a predicted fine-scale map label, as well as a second label with lower confidence. As was done for random forests, Dr. Clark's R code provided error matrixes for SVMs' predictions for the independent testing sites.

3.4.2.5. Independent Variables

Both random forests and support vector machines require a "stack" of predictor variables for each training site and for each fine scale segment. Figure 9 illustrates the concept of the predictor variable stack. The stack of predictor variables was created by running ESRI's zonal statistics tool iteratively in a python script to create a table with the rows representing the training sites or fine scale segments and the columns representing the predictor variables.

Figure 9. *The concept of the “stack” of machine learning predictor variables*



Over 300 predictor variables were used, including high and medium resolution spectral information, spectral and hyperspectral indices derived from AVIRIS data from Dr. Clark, landscape characteristics such as slope, and other variables. Table 5 shows the list of predictor variables. Note that the Sentinel-derived variables at the bottom of the table represent over 100 individual predictor variables, and other rows in Table 5 represent more than one individual variable.

Table 5. *Predictor variables used in machine learning*

Machine Learning Predictor Variable	Data Source
% canopy density in the 15-to-60-foot range	2020 QL1 (Quality Level 1) lidar
% canopy density in the 60-to-100-foot range	2020 QL1 lidar
% canopy density in the 100-to-150-foot range	2020 QL1 lidar
% canopy density in the 150-to-200-foot range	2020 QL1 lidar
% canopy density in the 200-to-250-foot range	2020 QL1 lidar
Average lidar height from lascanopy	2020 QL1 lidar
Lidar kurtosis for height from lascanopy	2020 QL1 lidar
Lidar quadratic average height from lascanopy	2020 QL1 lidar

Machine Learning Predictor Variable	Data Source
Lidar skewness for height from lascanopy	2020 QL1 lidar
% lidar returns between 0-4 meters above ground	2020 QL1 lidar
Absolute canopy cover	2020 QL1 lidar
Relative cover of trees taller than 60 feet	2020 QL1 lidar
Lidar 5th percentile height from lascanopy	2020 QL1 lidar
Lidar 10th percentile height from lascanopy	2020 QL1 lidar
Lidar 25th percentile height from lascanopy	2020 QL1 lidar
Lidar 50th percentile height from lascanopy	2020 QL1 lidar
Lidar 75th percentile height from lascanopy	2020 QL1 lidar
Lidar 90th percentile height from lascanopy	2020 QL1 lidar
Lidar canopy height from lascanopy	2020 QL1 lidar
Ladder Fuels 1-4m	2020 QL1 lidar
Ladder Fuels 4-8m	2020 QL1 lidar
Eastness	2020 QL1 lidar
Northness	2020 QL1 lidar
Bare earth DEM	2020 QL1 lidar
Terrain slope (from bare earth DEM)	2020 QL1 lidar
Canopy slope (slope derived from the canopy height model)	2020 QL1 lidar
Canopy height model (a.k.a. normalized digital surface model)	2020 QL1 lidar
Distance from nearest stream	2020 QL1 lidar
Height above nearest stream	2020 QL1 lidar
2020 NAIP image indices (DVI, GDVI, GNDVI, VARI, OVB)	USDA Farm Service Agency (NAIP)
Loudon Index: (green band*2)/(red band + blue band) from NAIP 2009	USDA Farm Service Agency (NAIP)
2020 NAIP bands (Red, Green, Blue, Near Infrared)	USDA Farm Service Agency (NAIP)
2012 NAIP bands (Red, Green, Blue, Near Infrared)	USDA Farm Service Agency (NAIP)
AVIRIS indexes (EWT_AV, NDWI_AV, Wtr1AbAr_AV)	Dr. Matthew Clark, NASA (National Aeronautics and Space Administration)
Sentinel 2019 bands (Red, Green, Blue, NIR, Red-Edge) for multiple months (Jan, March, April, May, July, Oct, Nov)	The European Space Agency, Google Earth Engine
Sentinel 2019, band differences (Red, Green, Blue, NIR, Red-Edge), between months (Jan, March, April, May, July, Oct, Nov)	The European Space Agency, Google Earth Engine

Machine Learning Predictor Variable	Data Source
Sentinel 2019, indices (DVI, GNDVI, GRVI, VARI, NDVI) for multiple months (Jan, March, April, May, July, Oct, Nov)	The European Space Agency, Google Earth Engine
Sentinel 2019 index differences (DVI, GNDVI, GRVI, VARI, NDVI), between months (Jan, March, April, May, July, Oct, Nov)	The European Space Agency, Google Earth Engine
Average annual precipitation	PRISM, Oregon State University

To illustrate how predictor variables are used by the machine learning algorithms, Table 6 shows an importance matrix from random forests for the Umbellularia californica Alliance. Table 6 shows the most important predictor variables to classify the *Umbellularia californica Mapping Unit*. They include variables derived from 2018 Sentinel satellite imagery (which top the list in terms of importance), indices derived from AVIRIS (a hyperspectral sensor), and lidar derived canopy slope.

Table 6. *Top 10 most important predictor variables for the Umbellularia californica Mapping Unit*

Predictor Variable Importance Rank	Description of Predictor Variable	Data Source
1	March May NDVI Difference	Sentinel Imagery
2	April May NDVI Difference	Sentinel Imagery
3	July October NDVI Difference	Sentinel Imagery
4	SWIR1 Ligno-Cellulose Absorption Asym Canopy	AVIRIS hyperspectral data
5	April May VARI Difference	Sentinel Imagery
6	SWIR1 Ligno-Cellulose Absorption Asym	AVIRIS hyperspectral data
7	SWIR1 Ligno-Cellulose Absorption Width Canopy	AVIRIS hyperspectral data
8	Canopy Slope Mean	2020 QL1 countywide lidar
9	March July NDVI Difference	Sentinel Imagery
10	March July GNDVI Difference	Sentinel Imagery

3.4.3. Fine-scale Manual Editing & Map Field Validation

3.4.3.1. Fine-scale Map Manual Editing

Manual editing allowed Tukman Geospatial and AIS image analysts to improve the detail and accuracy of machine learning model predictions. Editors used a variety of supporting datasets and best practice protocols to standardize and maintain high quality edits.

Editing is an individual endeavor, and because of the difficulty of precisely interpreting vegetation type and cover from imagery, different humans may assign different labels to the same segment. To minimize inconsistencies among the numerous editors working on the map, protocols were followed to standardize the editing approach. All members of the mapping team worked with the same map document format, loaded with the same image and ancillary datasets.

Editors were assigned specific production modules based on the USGS topographic quadrangle boundaries. Fine-scale map class edits were conducted at various scales, depending upon the complexity of the boundary adjustments; for example, discerning differences between intermixing shrub species requires a different level of scrutiny than boundaries between grass and forest lands. Editors worked module-by-module, completing one module, and moving on to the next, edge matching the data across boundaries to ensure the seamless continuity of information. Edits resulted in the following types of changes to the fine-scale map:

- Changes to fine-scale map class where the editor noted a different map class than what was assigned by machine learning
- Changes to polygon shapes where a polygon was not compositionally homogenous
- Changes to relative hardwood versus conifer class

Editors relied on a wide variety of imagery and other data sources during editing (see Table 7). High resolution imagery was the most important dataset for editing, but different imagery or combinations of imagery were used to interpret different types of vegetation.

Table 7. *Datasets used as reference in fine-scale map class manual editing*

Raster Datasets	Vector Datasets
2009, 2012, 2016 and 2018 and 2020 NAIP imagery, displayed as an RGB and as CIR composites	Production modules (editing units) for tracking editing progress
2020 high resolution RGB imagery	Roads and trails
2020 lidar derived bare earth DEM	Field photos
2020 lidar derived bare earth hillshade	CNPS survey points
2020 lidar derived canopy height	Field calibration polygons
USGS 7.5-minute topography	Soils (NRCS)
	Ultramafic layer (BLM)
	Existing vegetation maps
	Fire history and burn severity
	Field survey data from past vegetation mapping projects

Online image sources, such as Google Maps and Google Earth Engine were also used to assist the editors. Winter imagery from Google Earth Engine was used to help discern deciduous tree and shrub species, as the vegetation was in “leaf-off” condition, making it easier to distinguish between evergreen and deciduous types. On some Google Earth Engine imagery, it was possible to see vegetation in bloom, providing a good correlation to species signature on the base imagery.

Environmental factors, such as slope, aspect, elevation, soils, and geology, were also assessed by the analysts. Mental models correlating the environmental factors to vegetation types were developed based on patterns observed on the ground during calibration and validation field work. These proved useful, especially where the imagery did not provide sufficient information to discern the vegetation type.

In addition to the pre-loaded raster and vector datasets, the map document used by the map editors contained a project specific coding menu to facilitate consistent fine-scale map class editing among the team of analysts working on the map. The map document contained the following:

- Labels that show the polygon’s fine scale map class and associated attributes, such as relative conifer cover and standing dead (where applicable)
- For edited polygons, dynamically rendered symbology (or tracking tiles) to inform the editor that they have already been edited
- The coding menu displayed error flags that automatically turned on if the relative cover was incompatible with the map class (e.g., if a redwood classified polygon was assigned very low conifer relative cover)
- The coding menu displayed error flags that automatically turned on if an invalid vegetation type was assigned.

Map editors had weekly calls to review challenging areas. Areas that were difficult to map were labeled by group consensus or prioritized for field review.

3.4.4. Fine-scale Map Validation Field Work

Validation field work occurred during 2022. Validation field work provided the mapping team with an opportunity to review the manually edited map in the field and perform quality control on the map. The mapping team also relied on field validation for difficult-to-map areas to inform additional map refinement and manual editing.

During manual editing, analysts targeted areas where uncertainty in the fine-scale map class was high. These areas were prioritized and visited by field crews where access was possible. Validation field work – like calibration field work – results in field verified fine-scale map class labels for all areas visited. During validation field work, polygons and points were labeled with their fine-scale map class using ESRI's collector app running on iPads by field teams in vehicles and on foot. See section 3.4.1 for more on how crews conducted this type of field work.

3.4.5. Tidal Wetlands Mapping

Most fine scale vegetation maps map tidal wetlands only to the macrogroup level, which results in a map of tidal wetlands as a single class. For this project, separate NOAA funding allowed the mapping team to map tidal wetlands to the alliance level. The resulting fine scale tidal wetlands map was completed in 2022 and 'burned in' to this fine scale 2-county map. The result is that tidal wetlands in the fine scale vegetation map include the following alliances and associations in areas of tidal wetlands, each one mapped as its own fine scale map class:

- *Bolboschoenus maritimus* Alliance
- *Distichlis spicata* Alliance
- *Sarcocornia pacifica* (*Salicornia depressa*) Alliance
- *Grindelia stricta* Provisional Association
- *Spartina foliosa* Association
- *Atriplex prostrata – Cotula* coronopifolia Semi-Natural Alliance
- Mudflat/Dry Pond Bottom Mapping Unit

These alliances and associations were mapped in a separate workflow from the rest of the vegetation map. Field calibration data was collected in the tidal wetlands, and fine scale segmentation was conducted with separate setting than for the rest of the vegetation map. During the classification development phase of this project, minimum mapping units (MMUs) were established. Minimum mapping units in the tidal wetlands were much smaller than for uplands and freshwater wetlands, with vegetated polygons in the tidal wetlands as small as 600 square feet, and water polygons as small as 400 square feet. This allowed for the fine scale delineations required to map narrow features such as mud bottomed channels, gumplant (*Grindelia stricta*) polygons along channels, and long linear areas of cord grass (*Spartina foliosa*) and saltgrass (*Distichlis spicata*) at interfaces between different areas of the tidal wetlands. Note that these small MMUs should not imply that every distinct patch of vegetation greater than 600 square was mapped. Instead, 600 square feet was used as the minimum size for image segmentation, object-based image analysis, and manual editing.

Accuracy was not assessed for the individual tidal wetland alliances and associations. However, map accuracy for alliance level mapping of tidal marshes is expected to be significantly lower than map accuracies for fine scale vegetation maps of woody upland vegetation. The difficulty of mapping the tidal marsh herbaceous communities at high accuracy results from many factors. The following bullets includes some of the primary factors that drive the confusion between tidal marsh classes:

- **The tidal marsh alliances/associations have a wide range of appearances in the imagery**. For example, young pickleweed is very reflective of near infrared light, but older pickleweed does not reflect near infrared light as readily. Young, vigorous pickleweed has bright infrared reflectance and a smooth texture that is very similar to salt grass.
- **The alliances/associations mix and intergrade in ways that are difficult to interpret in the imagery**. For example, pickleweed (Sarcocornia pacifica) and salt grass (Distichlis spicata) often co-dominate in equal covers, making it hard to assign the correct class. These two alliances also can appear the same in the high resolution 4-band imagery.
- **Non-native herbaceous and ruderal species intermix in the tidal marsh, further confounding interpretation of the tidal marsh alliance/association.**
- **The appearance in the imagery of the tidal marsh alliances and associations varies across space and time in unpredictable ways.** These variations are driven by many factors including salinity, inundation, mortality, and a wide range of other factors.
- **The salt marsh alliances and associations often occur in very narrow, linear patches that are inherently difficult to map due to their shape.**

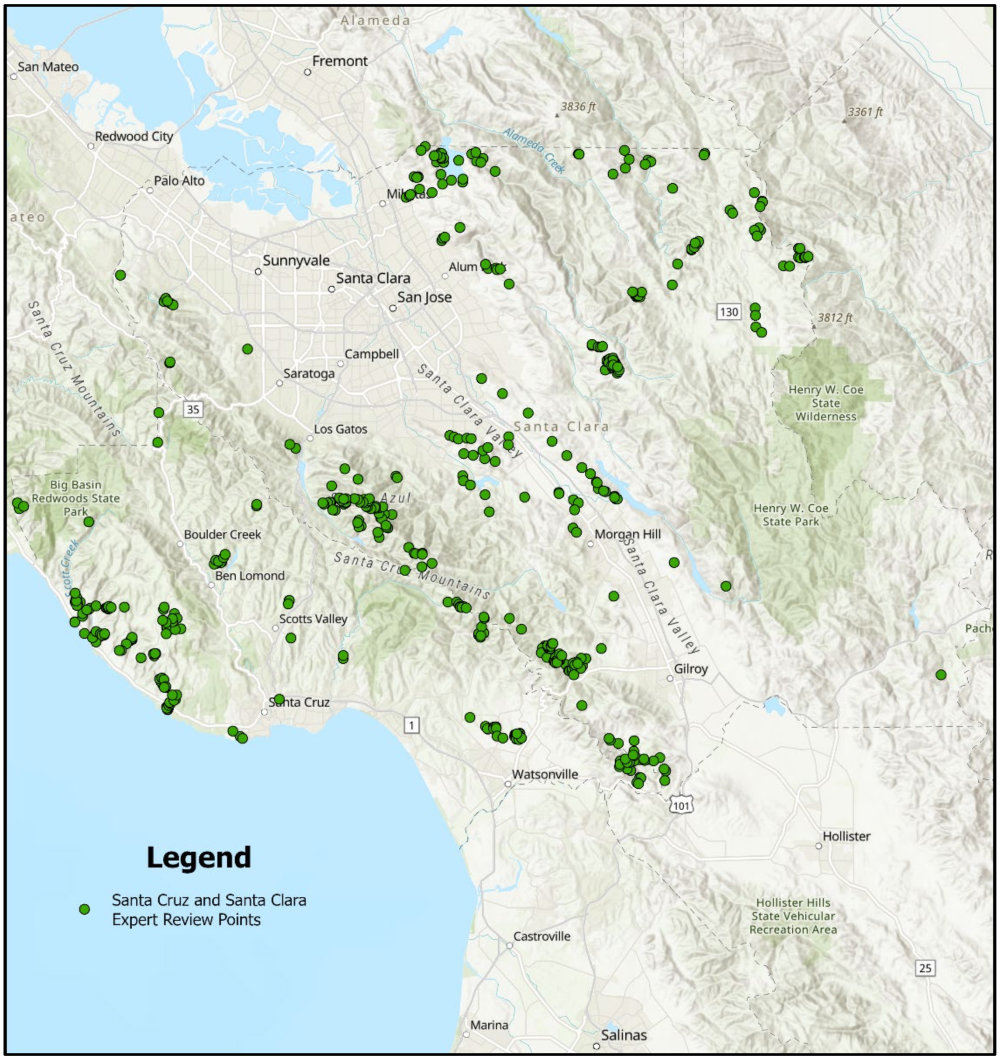
3.5. Fine-scale Map Expert Review

After the fine-scale vegetation map was manually edited and field validation work was completed, the fine-scale vegetation map was distributed to dozens of Santa Cruz and Santa Clara County land managers, ecologists, and interested parties. The vegetation map was also submitted to the California Native Plant Society's Vegetation Program and the Department of Fish and Wildlife's Vegetation Classification and Mapping Program (VegCAMP). The purposes of expert map review were as follows:

1. For land managers who are intimately familiar with a parcel or set of parcels to impart their local knowledge into the vegetation and habitat map.
2. For local land managers, ecologists, botanists, and the map's end users to provide comments on geographic areas that they are familiar with or suggestions on ways to improve the map for their end uses.

Input from land managers was obtained through a publicly shared webmap, where stakeholders dropped points and entered for each point text about the issue or concern associated with that location. After the input period ended, Tukman Geospatial compiled the collected input and provided it to AIS and Tukman Geospatial mappers. The mappers reviewed the input and took appropriate action to refine the map. If mappers had questions about a reviewer's concern, Tukman Geospatial and/or AIS contacted the reviewer to discuss the question. In all, there were 494 points provided to the mapping team. The expert review points are shown in Figure 10.

Figure 10. *Expert review points provided for the Santa Cruz and Santa Clara fine scale vegetation map*



3.6. Post-processing

After final review and a final round of manual editing was completed, post-processing was conducted to prepare the fine-scale vegetation map for publishing. Post-processing included the following steps:

- *Topology Checks*: Topology checks and topology edits ensure that there are no gaps and no overlaps in the fine scale vegetation map.
- *Adding the suite of attributes for percent imperviousness, carbon & biomass, and forest structure* (see section 5.4 for a complete list of all fine-scale map attributes).
- *QA/QC to ensure valid and complete data:* This step entailed review of all vegetation map polygons to ensure that each map polygon had complete and valid data. For

example, each attribute of each polygon was checked for missing data, out-of-range, or inappropriate values, etc.

- *Burn in AA sites:* In stands where the accuracy assessment revealed an incorrect map label, the stand label was modified to the field validated call.

Attributes delivered in the final, countywide map are shown in Section 5.4, Table 15.

3.7. Forest Health Mapping (standing dead)

For forested areas, Tukman Geospatial mapped standing dead vegetation and included this information as attributes in the fine scale vegetation map. Standing dead was mapped as a percentage of the woody canopy over 7 feet tall that appeared to be dead in the 2018 imagery. Standing dead areas were mapped in Trimble® Ecognition® using a high-resolution imagery from 2018, as well as countywide 2017 lidar data. The discussion below provides more detail on standing dead mapping.

3.7.1. Standing Dead

The mapping team mapped standing dead vegetation over 7 feet for forested stands in the Santa Cruz Mountains regions of Santa Cruz and Santa Clara County. The areas where standing dead vegetation was mapped are shown in Figure 11. Note that stands within the Santa Clara County Urban Window were not assigned standing dead.

Figure 11. *Mapping area for standing dead vegetation*

Standing dead vegetation was mapped using semi-automated techniques that combine automated object-based image analysis with manual photointerpretation. Standing dead forest areas were mapped using 2020 high-resolution countywide imagery and the 2020 QL1 lidar data. Object based image analysis resulted in a 1-meter raster of living v. dead areas. The resulting map of standing dead was integrated into the forested stands of the fine scale vegetation map, and each forested stand was assigned a value representing the percentage of the woody canopy over 7 feet tall that was standing dead in 2020. Tukman Geospatial analysts manually edited the percent dead assignments up or down based on image interpretation, adjusting the attribute upward where automated techniques underestimated standing dead and adjusting the attribute downward where automated techniques overestimated standing dead area. This product reflects the state of the landscape in summer 2020. Some qualifications and specifications for the standing dead data product are listed below:

- Standing dead mortality applies to woody vegetation greater than or equal to 7 feet in height. Standing dead areas include entire tree crowns and parts of tree crowns that have died back.
- Each vegetation map polygon receives a percent of the polygon that is standing dead. This number was calculated as the area of the polygon over 7 feet in height that is dead, divided by the total area of the polygon over 7 feet in height.
- Living v. dead is defined by the presence of green leaves as viewed from above in the summer, 2020 high resolution imagery.
- Note that this product does not provide species-specific mortality information. In a stand with 5% mortality labeled Sequoia sempervirens alliance in the vegetation map, for example, the dead trees may include a mix of hardwoods and this product does not include details on the species of the dead trees.
- Areas within the 2020 CZU Lightning Complex fire were minimally manually edited for standing dead. As a result, these areas have significantly lower accuracies for standing dead than the unburned areas. Editing of these areas was kept to a minimum so that the limited standing dead budget focused editors' time on the unburned areas, where accurate pre-fire standing dead estimates are useful to land managers.

Standing dead was assigned to forested stands in increments of 1%.

3.7.2. Shrub % Cover

Percent shrub cover was mapped for shrub and herbaceous stands in Santa Cruz and Santa Clara Counties, except for those inside of the Santa Clara urban window. Countywide shrub cover was mapped using semi-automated techniques that combined automated object-based image analysis with manual photointerpretation.

4. Accuracy Assessment

Accuracy assessment entails collecting representative samples of the map and comparing the reference label of the sample to its map label. The reference labels are assumed to be the "true" label and are usually derived from a source of higher accuracy than the map (e.g., field plot samples). This section of the report reviews the accuracy assessment methods and results for the lifeform map and the fine-scale vegetation map. The first section describes how the accuracy assessment samples were selected and labeled. Next, analysis procedures are explained, and the resulting error matrices are presented. The last section details the causes of the most significant confusion in the maps.

Map accuracy was assessed for fine scale map classes that cover a significant portion of the landscape (more than 1,000 acres). Accuracy was not assessed for the tidal wetland alliances.

The accuracy assessment for this project was conducted as a single accuracy assessment for the 2-county map.

4.1. Sample Design

Final draft map polygons were used as the spatial units for assessing map accuracy. Sample polygons were constrained so that only those greater than the project minimum map units were used to avoid sampling sub-minimum mapping unit islands of vegetation.

Two types of samples were collected:

- **Non-Forested, Non-Shrub Types**: Manual labelling (using air photo interpretation) of sites for assessment of non-forested, non-shrub classes in the vegetation map. These types include agriculture, bare land, developed areas, herbaceous areas, major roads, water, and tidal wetlands. These non-woody classes are easy to interpret from imagery and do not require field verification.
- **Forest and Shrub Types**: Field verification of sites for assessment of the shrub and forest fine-scale vegetation map classes. These woody classes require field verification to accurately assign a verified fine scale map class.

4.1.1. Manually Interpreted Samples (non-forest, non-shrub)

Manually interpreted samples were collected using aerial image interpretation of randomly selected map polygons. The reference data used by image analysts was 2020 high resolution imagery. To select the manually interpreted sites (the classes are listed in the first bullet in section 4.1), a random number generator was used to select between 10 and 45 sample segments from the draft fine scale vegetation map for each of the non-forest, non-shrub classes (the number varies according to acreage mapped for the lifeform class).

4.1.2. Field-Verified Samples (shrub and forest types)

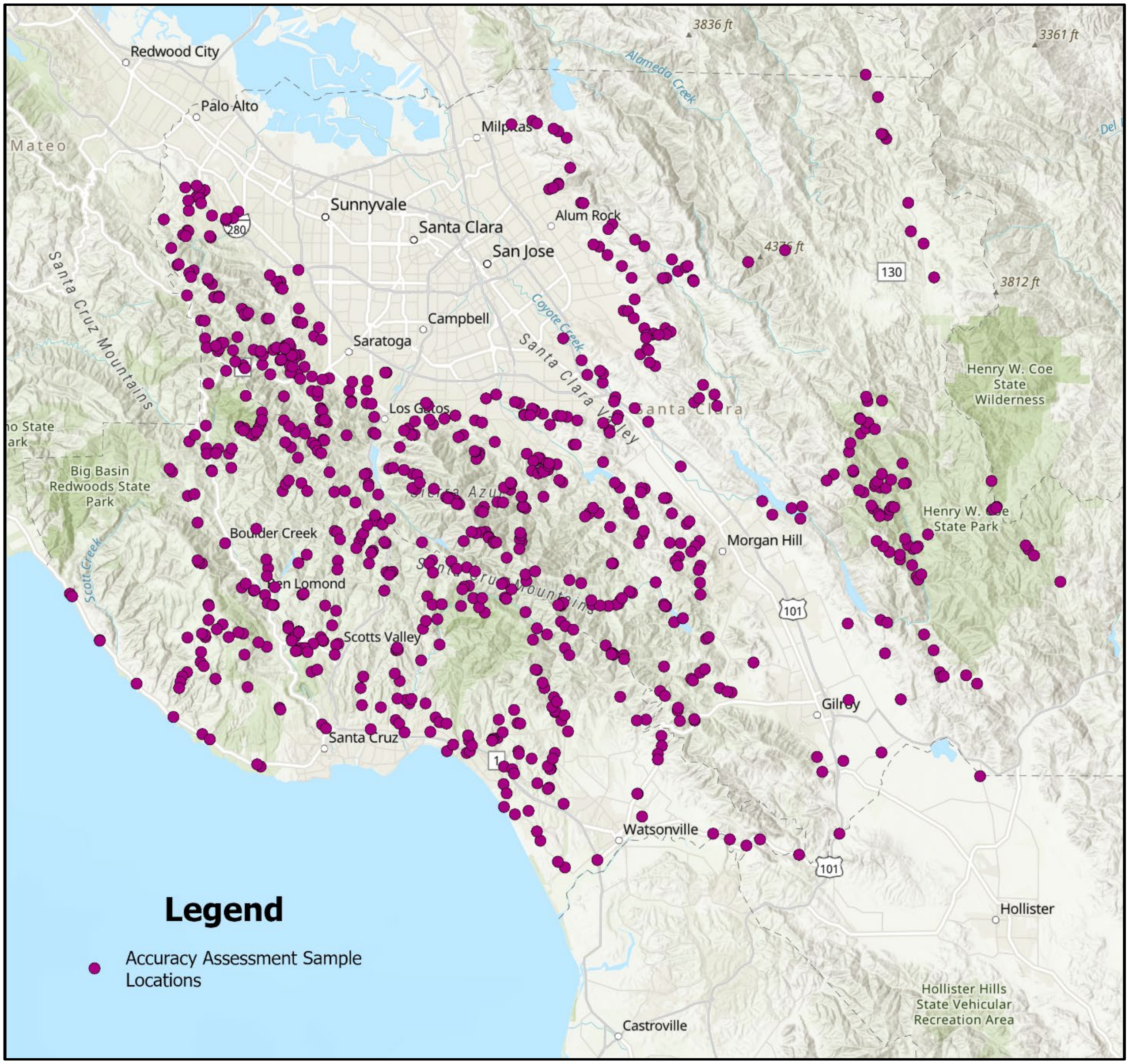
Field-verified accuracy assessment samples were chosen across the two-county area using a combined stratified random/cluster sampling approach after the final draft of the fine scale vegetation map was completed. To select the field sites, all access-restricted areas were masked out of the draft fine scale vegetation map, which focused the field sampling on public lands, conservation lands, and private lands whose landowners were willing to provide access. Next, areas with difficult access were masked out. These 'high travel cost' areas were defined by a cost surface that identified areas far from accessible roads and trails, as well as areas inaccessible due to steep terrain. Analysts also excluded from the allocation areas that overlapped or were near to areas where mappers or CNPS survey crews had visited a site in the field during mapping calibration, validation, or survey data collection. Within the remaining areas, fine-scale map stands were randomly selected per fine-scale map class to serve as the feasible set of field-verified accuracy assessment samples. To ensure that samples were not spatially autocorrelated, a minimum distance of 1,500 feet between targeted stands of the same map class was required. Random allocations were performed to target stands for accuracy assessment sampling such that:

- 25 accuracy assessment samples were targeted for collected for fine scale map classes in the draft map that encompassed more than 2,500 acres
- 15 accuracy assessment samples were targeted for collected for fine scale map classes in the draft map that encompassed more than 1,000 acres and less than 2,500 acres
- 5 accuracy assessment samples were targeted for collected for fine scale map classes in the draft map that encompassed more than 500 acres and less than 1,000 acres

Field crews were made up of experienced botanists who did not begin data collection work until the fine scale draft map was completed. Crews visited the randomly selected target sample stands with no indication of the stand's mapped label. To reduce travel costs, field personnel were encouraged to choose and collect AA data for two additional stands that were adjacent or nearby the randomly selected target sample stand but *with different fine-scale map classes than the randomly selected target sample stand*. At the selected target sample stand, field personnel viewed the entire area before assigning a reference map class for the stand. If the entire target sample stand was not visible from a vantage point, the crew walked or drove through the remaining area of the stand. Following inspection of the target sample stand, field personnel completed the accuracy assessment form using Field Maps and Survey123. Field personnel estimated the percent cover of each vegetative species visible in the imagery and used the mapping key to label the stand with its appropriate fine scale map class. Estimates of cover by species were determined through manual interpretation of the imagery to ensure that estimates were made from above, rather than below the canopy. Accuracy assessment field crews were also permitted to take opportunistic samples (that were not allocated or near allocated sites) as long as these areas were not nearby areas that had been visited in the field previously by mappers or CNPS survey crews.

981 total accuracy assessment samples (210 manually interpreted and 771 in the field) were collected, representing 61 of the 121 fine-scale vegetation map classes. Those 62 classes represent 98% of the area mapped. Some classes were not sampled or lightly sampled because the class was extremely rare. Other classes were not assessed because there were an insufficient number of accessible areas representing the class to sample, or because all accessible areas where the type occurs had been visited by mappers or by CNPS surveyors.

Figure 12. *Field verified accuracy assessment sample locations in Santa Cruz and Santa Clara Counties*



4.2. Analysis

Once the accuracy assessment reference data were collected, the map labels (assigned during the mapping process) for each sample were compared to the reference labels (assigned from manual interpretation or field validated samples). Extensive quality control was performed to ensure that reference labels and map labels were accurate, and that spatial autocorrelation did not exist between sample segments. As a result, reference polygons were removed from the data set for one or more of the following reasons:

- The reference label (or a part of it) was not representative of the stand. This condition often applied to a part of a reference sample polygon that contained areas that did not represent the reference class. For example, if a 2-acre reference stand collected by AA crews as *Quercus agrifolia* contained .6-acre inclusion of *Bacharris pilularis* shrubland (evident in the imagery), the shrubland was omitted from the AA reference sample.
- The reference sample was below MMU.
- Upon review by photo-interpreters and AA data field crews, it was found that the reference sample was incorrect because of data entry errors, horizontal accuracy errors, species misidentification errors, or failure to assess accuracy across the entire reference polygon.
- The accuracy assessment polygon was visited in the field by mapping field crews (or CNPS surveyors) and collected by AA field crews.

Following quality control, the error matrices were created, and analysis was performed. The matrices can be found in Tables 8 (lifeform) and 11 (fine-scale vegetation). Error matrices provide a wealth of information about the map by indicating how many samples have agreement between the reference and map labels, and what classes are confused with one another. Samples with matching reference and map labels fall along the diagonal of the matrices, with cells shaded in green.

Two types of accuracy assessment analysis are typically done – deterministic and fuzzy (Green and Congalton, 2019). Overall deterministic accuracy is calculated by dividing the total number of samples on the diagonal by the total number of samples in the matrix. Samples off the diagonal indicate confusion between the map and the reference labels. Confused samples indicate not only that error exists in the map, but which classes are confused with one another. Several samples falling in an off-diagonal cell indicated a pattern of confusion which may exist throughout the map.

Useful additional measures for each class are the user’s and producer’s accuracies because they measure the proportion of errors of commission and omission in each class, respectively. User’s accuracy is the total number of samples in agreement divided by the number of map samples in a class and indicates the errors of commission in each class. Producer’s accuracy is the total number of samples in agreement divided by the number of reference samples in a class and indicates the level of errors of omission of each class.

Map producers and users have long recognized that there is a certain amount of “fuzziness” in vegetation mapping because:

- Humans are incapable of precisely estimating percent cover, resulting in an average variance in estimates of +/- 10% (Congalton and Green, 2019). While this will have little impact in a simple map such as the lifeform map, it can have significant impact on a map

as detailed as the fine-scale map, with numerous classes that are often distinguished from one another in the key based on small species percent cover differences.
- Classification schemes impose boundaries between vegetation types. However, vegetation usually exists along a continuum of vegetation cover. If the composition of a sample meets the condition for two or even more different map classes, then those labels should be considered acceptable.

Many map users and producers implement fuzzy accuracy assessment to deal with the ambiguity in a map. Usually this is implemented when the reference sample is being assessed by choosing a second acceptable reference label for a sample if the person collecting the data believes that more than one label would be acceptable (Congalton and Green, 2019). Rather than evaluating every sample for variation in interpretation, an alternative approach has been adopted by the California Department of Fish and Wildlife that applies a ruleset to the entire sample dataset as defined in Table 10. (CDFW (California Department of Fish and Wildlife) & Aerial Information Systems, 2013; Menke et al., 2011). This is the form of fuzzy analysis chosen for the Santa Cruz and Santa Clara County fine scale vegetation map assessment.

4.3. Results

4.3.1. Lifeform Map AA Results

Table 8 is the error matrix for the lifeform map. Lifeform classes are simple to discern and are also homogeneous, which reduces any ambiguity in labeling. Overall lifeform accuracy is 98 percent, indicating that there is minimal confusion in the lifeform map. Table 9 shows user's and producer's accuracies for the lifeform map. Note that freshwater herbaceous wetlands require field collection and because of limitations of time, accessibility, previous visits by mappers, and the small footprint of herbaceous non-tidal wetlands on the two-county landscape, the AA crews did not succeed in collecting a robust sample of herbaceous non-tidal wetlands.

Table 8. *Lifeform error matrix with deterministic accuracy along the diagonal and user's accuracy (errors of commission) and producer's accuracy (errors of omission) along the vertical and horizontal axes. Note that the sample size for freshwater herbaceous wetlands (1) is too low to reliably access that type's accuracy.*

MAP \ REFERENCE	Ag	Barren and Sparsely Vegetated	Developed	Forest	Freshwater Herbaceous Wetland	Herbaceous	Major Road	Riparian Forest and Riparian Shrub	Shrub	Tidal Wetland	Water	Grand Total	User's Accuracy
Ag	35	0	1	0	0	2	0	0	0	0	0	38	92%
Barren and Sparsely Vegetated	0	9	0	0	0	0	0	0	0	0	0	9	100%
Developed	0	1	23	0	0	0	0	0	0	0	0	24	96%
Forest	0	0	0	491	0	0	0	6	3	0	0	500	98%
Freshwater Herbaceous Wetland	0	0	0	0	1	0	0	0	0	0	0	1	100%
Herbaceous	0	0	1	0	0	42	0	0	0	0	0	43	98%
Major Road	0	0	0	0	0	0	10	0	0	0	0	10	0%
Riparian Forest and Riparian Shrub	0	0	0	7	0	0	0	72	0	0	0	79	91%
Shrub	0	0	0	1	0	0	0	0	221	0	0	222	100%
Tidal Wetland	0	0	0	0	0	0	0	0	0	24	0	24	100%
Water	0	0	0	0	0	0	0	0	0	1	30	31	97%
Grand Total	35	10	25	499	1	44	10	78	224	25	30	981	
Producer's Accuracy	100%	90%	92%	98%	100%	95%	100%	92%	99%	96%	100%		**97%** Overall Lifeform Accuracy

Table 9. *Lifeform user's and producer's accuracies*

Lifeform	User's Accuracy	Producer's Accuracy
Agriculture	92%	100%
Barren	100%	90%
Developed	96%	92%
Forest	98%	98%
Herbaceous	98%	95%
Riparian Forest and Riparian Shrub	91%	92%
Shrub	100%	99%
Tidal Wetland	100%	96%
Water	97%	100%

4.3.2. Fine Scale Vegetation Map AA Results

The error matrix in Table 12 (fine-scale vegetation) is a deterministic accuracy matrix (it does not implement fuzzy accuracy assessment) developed using the approach suggested by Congalton and Green (2019) in their widely accepted accuracy assessment textbook.

Table 12 can be interpreted as follows:

- Classes with map and primary reference labels in agreement fall on the diagonal with cells shaded in green.
- Confused classes fall off the diagonal.

Overall deterministic accuracy of the fine-scale vegetation map is 82.3%.

Fuzzy accuracy assessment for the fine scale vegetation map was implemented as per state of California standards. The state standard was developed by the California Department of Fish and Wildlife in several mapping projects (CDFW & Aerial Information Systems, 2013; Menke et al., 2011). The CDFW state standard approach to fine scale vegetation map accuracy assessment applies a set of evaluation criteria to the entire accuracy assessment sample dataset. For accuracy assessment samples where the reference label is similar but not identical to the map label, partial credit is given. The criteria for partial credit are shown in Table 10. **Applying this approach to the Santa Cruz and Santa Clara County fine scale vegetation map results in an overall fuzzy accuracy of 92.0%.**

Table 11 summarizes the user's accuracy, producer's accuracy, and fuzzy accuracies for all map classes that had greater than one accuracy assessment stand collected by field crews or manually by analysts.

Table 10. *CDFW evaluation criteria for fuzzy accuracy assessment*

Code	Reason For Score	Score
A	PI completely correct.	5
B	The PI chose the correct Group OR the next level up in the hierarchy.	4
C	Threshold/transition between PI call and Final call. This was used when cover values of the dominant or indicator species were close to the values that would key to the PI's type (e.g., an AAP call of *Yucca brevifolia* Alliance for a stand with 1% evenly distributed *Yucca brevifolia* over *Larrea tridentata-Ambrosia dumosa* would get this score if the PI call was *Larrea tridentata-Ambrosia dumosa* Alliance with <1% *Yucca brevifolia*).	4
D	Correct Macrogroup OR next level up in hierarchy.	3
E	Based on close ecological similarity. Ecological similarity addresses assessed and mapped calls that contained vegetation with overlapping diagnostic species but were not technically closely related in the NVCS hierarchy. This was common in stands that contain a mix of species of late and early seral vegetation types and also common in zones of overlap between ecoregions.	3
F	Correct Division.	2
G	Some floristic/hydrologic similarity. This addresses cases in which the mapped and the assessed vegetation type had different diagnostic species, but bore some similarity in ecological traits based on predicted and actual setting such as hydrologic regime, overall climate, or successional state.	2
H	Correct only at Lifeform.	1
I	No similarity above Formation and incorrect life form.	0
J	Survey removed because there was a significant change in the polygon (e.g., the stand was burned, developed, or cleared since the date of the base imagery).	no score
K	Survey removed because inadequate portion (<10%) of the polygon was viewed by the field crew.	no score
L	Survey removed because field/PI data are incomplete, inadequate or confusing (e.g., cover values were not provided for key species in the stand).	no score
M	Supplementary record not scored (for multiple point assessments within a polygon where the AA call was the same).	no score

Table 11. *Producer's and user's accuracies for the fine-scale vegetation map*

Fine Scale Map Class	Acres in Veg Map	# of Map Sites	Deterministic User Accuracy	Fuzzy User Accuracy	# of Reference Sites	Deterministic Producer Accuracy	Fuzzy Producer Accuracy
Sequoia sempervirens Alliance	115,456	45	84%	89%	42	90%	93%
Californian Annual & Perennial Grassland Macrogroup	207,495	39	97%	97%	40	95%	95%
Quercus agrifolia Alliance	107,864	45	80%	90%	38	95%	98%
Umbellularia californica Mapping Unit	48,891	42	83%	93%	36	97%	99%
Non-native Forest	23,454	40	88%	89%	36	97%	98%
Ag	42,778	38	92%	92%	35	100%	100%
Quercus douglasii Alliance	85,101	39	87%	96%	34	100%	100%
Quercus lobata Mapping Unit	12,183	22	91%	95%	33	61%	90%
Pseudotsuga menziesii – Notholithocarpus densiflorus / Vaccinium ovatum Associa	30,592	28	89%	92%	31	81%	87%
Water	20,880	31	97%	97%	30	100%	100%
Adenostoma fasciculatum Alliance	33,532	35	66%	89%	28	82%	95%
Arbutus menziesii Alliance	7,555	27	96%	97%	28	93%	99%
Quercus wislizeni – Quercus parvula (tree) Alliance	9,915	22	100%	100%	27	81%	96%
Toxicodendron diversilobum – (Baccharis pilularis) Association	3,592	21	95%	99%	27	74%	89%
Baccharis pilularis Alliance	11,021	29	76%	91%	26	85%	94%
Notholithocarpus densiflorus Alliance	7,577	24	100%	100%	26	92%	94%
Developed	174,922	24	96%	96%	25	92%	92%
Platanus racemosa – Quercus agrifolia Alliance	4,176	27	81%	89%	25	88%	94%
Tidal Wetland	3,147	24	100%	100%	25	96%	96%
Quercus kelloggii Alliance	17,430	38	58%	86%	24	92%	98%
Arctostaphylos (crustacea, tomentosa) Alliance	7,190	17	76%	92%	24	54%	82%
Quercus chrysolepis (tree) Alliance	20,399	24	83%	97%	23	87%	97%
Aesculus californica Alliance	4,363	24	96%	99%	23	100%	100%
Artemisia californica – (Salvia leucophylla) Alliance	9,723	22	86%	95%	22	86%	96%
Arctostaphylos glauca Alliance	7,916	19	89%	96%	21	81%	92%
Quercus (agrifolia, douglasii, garryana, kelloggii, lobata, wislizeni) Alliance	4,175	10	50%	90%	18	28%	86%
Salvia mellifera - Artemisia californica Alliance	3,634	21	71%	87%	17	88%	95%
Pinus sabiniana Woodland Alliance	6,888	16	75%	88%	15	80%	83%
Acer macrophyllum Mapping Unit	577	7	86%	97%	15	40%	57%
Pinus attenuata Alliance	6,086	14	79%	86%	14	79%	91%
Populus trichocarpa Alliance	1,249	9	89%	96%	14	57%	89%
Pinus ponderosa – (Quercus agrifolia – Arbutus menziesii) Provisional Association	990	14	86%	93%	14	86%	90%
Salix lasiolepis Alliance	2,039	16	63%	75%	13	77%	83%
Cercocarpus montanus Alliance	1,376	7	57%	89%	12	33%	80%
Pinus radiata Plantation Provisional Semi-Natural Association	1,005	10	100%	100%	12	83%	90%
Ceanothus cuneatus Alliance	23,907	13	23%	77%	10	30%	78%
Quercus berberidifolia Alliance	19,389	15	60%	88%	10	90%	98%
Barren and Sparsely Vegetated	4,082	9	100%	100%	10	90%	90%
Major Road	3,817	10	100%	100%	10	100%	100%
Salix gooddingii – Salix laevigata Alliance	1,698	9	44%	76%	9	44%	62%
Prunus ilicifolia – Heteromeles arbutifolia – Ceanothus spinosus Alliance	5,418	9	56%	82%	7	71%	83%
Hesperocyparis macrocarpa Ruderal Semi-Natural Association	372	7	100%	100%	7	100%	100%
Alnus rhombifolia Alliance	982	10	40%	88%	6	67%	80%
Adenostoma fasciculatum – Salvia spp. Alliance	624	2	50%	70%	6	17%	57%
Arctostaphylos silvicola Association	500	4	100%	100%	4	100%	100%
Mesembryanthemum spp. – Carpobrotus spp. Semi-Natural Alliance	212	4	100%	100%	4	100%	100%
Populus fremontii – Fraxinus velutina – Salix gooddingii Alliance	989	2	50%	50%	3	33%	80%
Acer macrophyllum – Alnus rubra Alliance	520	4	25%	85%	3	33%	87%
Quercus durata Alliance	792	3	0%	60%	2	0%	70%
Arctostaphylos (canescens, manzanita, stanfordiana) Provisional Alliance	411	2	50%	80%	2	50%	90%
Pinus ponderosa / Chorizanthe pungens Association	393	1	100%	100%	2	50%	90%
Salix lucida ssp. lasiandra Association	233	1	100%	100%	2	50%	50%
Juglans hindsii and Hybrids Special Stands and Semi-Natural Alliance	102	1	100%	100%	2	50%	50%
Quercus wislizeni – Quercus chrysolepis (shrub) Alliance	96	0	0%	0%	2	0%	30%

Table 12. *Fine-scale deterministic map error matrix. (See https://vegmap.press/cruz_clara_fs_error_matrix for a larger-scale zoomable version of the error matrix)*

REFERENCE

MAP	Acer macrophyllum Mapping Unit	Acer macrophyllum – Alnus rubra Alliance	Adenostoma fasciculatum Alliance	Adenostoma fasciculatum – Salvia spp. Alliance	Aesculus californica Alliance	Ag	Alnus rhombifolia Alliance	Arbutus menziesii Alliance	Arctostaphylos (canescens, manzanita, stanfordiana) Provisional Alliance	Arctostaphylos (crustacea, tomentosa) Alliance	Arctostaphylos (nummularia, sensitiva) – Chrysolepis chrysophylla Alliance	Arctostaphylos glauca Alliance	Arctostaphylos silvicola Association	Artemisia californica – (Salvia leucophylla) Alliance	Baccharis pilularis Alliance	Barren and Sparsely Vegetated	Californian Annual & Perennial Grassland Macrogroup	Ceanothus cuneatus Alliance	Ceanothus papillosus Alliance	Cercocarpus montanus Alliance	Cornus sericea – Salix (lasiolepis, exigua) Association	Cytisus scoparius – Genista monspessulana – Cotoneaster spp. Semi-Natural Alliance	Developed	Ericameria nauseosa Alliance	Frangula californica – Rhododendron occidentale – Salix breweri Alliance	Hesperocyparis macrocarpa Ruderal Semi-Natural Association	Juglans hindsii and Hybrids Special Stands and Semi-Natural Alliance	Lotus scoparius – Lupinus albifrons – Eriodictyon spp. Alliance	Major Road	Mesembryanthemum spp. – Carpobrotus spp. Semi-Natural Alliance	Non-native Forest	Notholithocarpus densiflorus Alliance	Pinus attenuata Alliance	Pinus muricata – Pinus radiata Alliance	Pinus ponderosa / Chorizanthe pungens Association	Pinus ponderosa – (Quercus agrifolia – Arbutus menziesii) Provisional Association	Pinus radiata Plantation Provisional Semi-Natural Association	Pinus sabiniana Woodland Alliance	Platanus racemosa – Quercus agrifolia Alliance	Populus fremontii – Fraxinus velutina – Salix gooddingii Alliance	Populus trichocarpa Alliance	Prunus ilicifolia – Heteromeles arbutifolia – Ceanothus spinosus Alliance	Pseudotsuga menziesii – Notholithocarpus densiflorus / Vaccinium ovatum Association	Quercus (agrifolia, douglasii, garryana, kelloggii, lobata, wislizeni) Alliance	Quercus agrifolia Alliance	Quercus berberidifolia Alliance	Quercus chrysolepis (tree) Alliance	Quercus douglasii Alliance	Quercus durata Alliance	Quercus kelloggii Alliance	Quercus lobata Mapping Unit	Quercus wislizeni – Quercus chrysolepis (shrub) Alliance	Quercus wislizeni – Quercus parvula (tree) Alliance	Rubus spectabilis – Morella californica Alliance	Salix gooddingii – Salix laevigata Alliance	Salix lasiolepis Alliance	Salix lucida ssp. lasiandra Association	Salvia mellifera – Artemisia californica Alliance	Sequoia sempervirens Alliance	Tidal Wetland	Toxicodendron diversilobum – (Baccharis pilularis) Association	Umbellularia californica Mapping Unit	Vancouverian Lowland Marsh, Wet Meadow & Shrubland Group	Water	Total	Deterministic User's Accuracy
Acer macrophyllum Mapping Unit	6	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	7	86%
Acer macrophyllum – Alnus rubra Alliance	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4	25%
Adenostoma fasciculatum Alliance	0	0	23	1	0	0	0	0	0	7	0	0	0	0	0	0	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	35	66%
Adenostoma fasciculatum – Salvia spp. Alliance	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	2	50%
Aesculus californica Alliance	0	0	0	0	23	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	24	96%
Ag	0	0	0	0	0	35	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	38	92%
Alnus rhombifolia Alliance	2	2	0	0	0	0	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	10	40%
Arbutus menziesii Alliance	1	0	0	0	0	0	0	26	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	27	96%
Arctostaphylos (canescens, manzanita, stanfordiana) Provisional Alliance	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	50%
Arctostaphylos (crustacea, tomentosa) Alliance	0	0	0	0	0	0	0	0	0	13	1	0	0	0	0	0	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	17	76%
Arctostaphylos (nummularia, sensitiva) – Chrysolepis chrysophylla Alliance	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0%
Arctostaphylos glauca Alliance	0	0	0	0	0	0	0	0	0	0	0	17	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	19	89%
Arctostaphylos silvicola Association	0	0	0	0	0	0	0	0	0	0	0	0	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4	100%
Artemisia californica – (Salvia leucophylla) Alliance	0	0	0	0	0	0	0	0	0	0	0	0	0	19	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	22	86%
Baccharis pilularis Alliance	0	0	1	0	0	0	0	0	0	0	0	0	0	1	22	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	4	0	0	0	29	76%
Barren and Sparsely Vegetated	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	9	100%
Californian Annual & Perennial Grassland Macrogroup	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	38	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	39	97%
Ceanothus cuneatus Alliance	0	0	4	0	0	0	0	0	1	2	0	0	0	0	0	0	0	3	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	13	23%
Ceanothus papillosus Alliance	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0%
Cercocarpus montanus Alliance	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	7	57%
Cornus sericea – Salix (lasiolepis, exigua) Association	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0%
Cytisus scoparius – Genista monspessulana – Cotoneaster spp. Semi-Natura	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0%
Developed	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	23	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	24	96%
Ericameria nauseosa Alliance	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0%
Frangula californica – Rhododendron occidentale – Salix breweri Alliance	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0%
Hesperocyparis macrocarpa Ruderal Semi-Natural Association	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	7	100%
Juglans hindsii and Hybrids Special Stands and Semi-Natural Alliance	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	100%
Lotus scoparius – Lupinus albifrons – Eriodictyon spp. Alliance	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0%
Major Road	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	10	100%
Mesembryanthemum spp. – Carpobrotus spp. Semi-Natural Alliance	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4	100%
Non-native Forest	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	35	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	3	0	0	0	0	0	40	88%
Notholithocarpus densiflorus Alliance	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	24	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	24	100%
Pinus attenuata Alliance	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	11	0	0	1	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	14	79%
Pinus muricata – Pinus radiata Alliance	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	100%
Pinus ponderosa / Chorizanthe pungens Association	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	100%
Pinus ponderosa – (Quercus agrifolia – Arbutus menziesii) Provisional Asso	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	12	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	14	86%
Pinus radiata Plantation Provisional Semi-Natural Association	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	10	100%
Pinus sabiniana Woodland Alliance	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	3	0	0	0	0	12	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	16	75%
Platanus racemosa – Quercus agrifolia Alliance	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	22	1	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	27	81%
Populus fremontii – Fraxinus velutina – Salix gooddingii Alliance	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	2	50%
Populus trichocarpa Alliance	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	9	89%
Prunus ilicifolia – Heteromeles arbutifolia – Ceanothus spinosus Alliance	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	9	56%
Pseudotsuga menziesii – Notholithocarpus densiflorus / Vaccinium ovatum	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	25	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	28	89%
Quercus (agrifolia, douglasii, garryana, kelloggii, lobata, wislizeni) Alliance	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	5	0	0	0	0	0	1	4	0	0	0	0	0	0	0	0	0	0	0	0	0	10	50%
Quercus agrifolia Alliance	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	36	0	0	0	0	0	1	0	3	0	1	1	0	0	0	0	0	1	0	0	45	80%
Quercus berberidifolia Alliance	0	0	0	0	0	0	0	0	0	2	0	1	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	9	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	15	60%
Quercus chrysolepis (tree) Alliance	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	20	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	24	83%
Quercus douglasii Alliance	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	2	0	0	0	34	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	39	87%
Quercus durata Alliance	0	0	0	0	0	0	0	0	0	0	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0%
Quercus kelloggii Alliance	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	9	0	0	0	0	0	22	4	0	0	0	0	0	0	0	0	0	0	0	0	0	38	58%
Quercus lobata Mapping Unit	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	20	0	0	0	0	0	0	0	0	0	1	0	0	0	22	91%
Quercus wislizeni – Quercus chrysolepis (shrub) Alliance	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0%
Quercus wislizeni – Quercus parvula (tree) Alliance	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	22	0	0	0	0	0	0	0	0	0	0	0	22	100%
Rubus spectabilis – Morella californica Alliance	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0%
Salix gooddingii – Salix laevigata Alliance	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4	2	0	0	0	0	0	0	0	0	9	44%
Salix lasiolepis Alliance	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	4	10	0	0	0	0	0	0	0	0	16	63%
Salix lucida ssp. lasiandra Association	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1	100%
Salvia mellifera - Artemisia californica Alliance	0	0	0	4	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	15	0	0	0	0	0	0	21	71%
Sequoia sempervirens Alliance	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	38	0	0	0	0	0	45	84%
Tidal Wetland	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	24	0	0	0	0	24	100%
Toxicodendron diversilobum – (Baccharis pilularis) Association	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	20	0	0	0	21	95%
Umbellularia californica Mapping Unit	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	0	1	0	1	0	0	0	0	0	0	0	0	0	35	0	0	42	83%
Vancouverian Lowland Marsh, Wet Meadow & Shrubland Group	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	100%
Water	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	30	31	97%
Total	15	3	28	6	23	35	6	28	2	24	1	21	4	22	26	10	40	10	1	12	1	0	25	0	0	7	2	1	10	4	36	26	14	1	2	14	12	15	25	3	14	7	31	18	38	10	23	34	2	24	33	2	27	1	9	13	2	17	42	25	27	36	1	30		
Deterministic Producer's Accuracy	40%	33%	82%	17%	100%	100%	67%	93%	50%	54%	0%	81%	100%	86%	85%	90%	95%	30%	0%	33%	0%	0%	92%	0%	0%	100%	50%	0%	100%	100%	97%	92%	79%	100%	50%	86%	83%	80%	88%	33%	57%	71%	81%	28%	95%	90%	87%	100%	0%	92%	61%	0%	81%	0%	44%	77%	50%	88%	90%	96%	74%	97%	100%	100%		
																																																																	Overall Accuracy	82.3%

4.4. Discussion

As indicated by the lifeform error matrix, there is very little confusion in the lifeform map. All lifeform classes have user's and producer's accuracies greater than or equal to 90%. In the fine scale vegetation map, confusion between alliances within the same lifeform followed the trends seen in recent similar mapping efforts in Sonoma, Marin, and San Mateo Counties.

Most of the confusion in the fine-scale vegetation map error matrix consists of scattered confusion of 1 or 2 sites in various cells across the matrix. When confusion does occur it is typically within lifeform and tends to be between map classes that commonly occur together and are difficult to distinguish from each other using machine learning and manual image interpretation. The following two subsections discuss the confusion in selected lower accuracy forest and shrub types in the Santa Cruz and Santa Clara fine scale vegetation map.

4.4.1. Confusion in Forest Classes

For the upland forests, accuracies are high, with the lowest accuracies occurring in the oak alliances. Oak stands are sometimes difficult to map to the alliance level because trees of different oak species intermix in stands, hybridize with one another, and are sometimes difficult to distinguish from one another in the imagery. Among the oak types, deterministic accuracies were lowest for the *Quercus kelloggii Alliance,* the *Quercus lobata Mapping Unit*, and the Quercus *(agrifolia, douglasii, garryana, kelloggii, lobata, wislizeni) Alliance*. The confusion in these types is illustrated by looking at the accuracy assessment results for the Quercus *Kelloggii Alliance,* which had 16 errors of commission, resulting in a deterministic user's accuracy of only 58% (it had a much higher deterministic producer's accuracy of 92%). Four of these errors of commission were to the *Quercus lobata Mapping Unit* (another deciduous *Quercus* alliance), and two of the four had *Quercus kelloggii* present at greater than 20% absolute canopy cover. Nine of 16 of the *Quercus kelloggii* errors of commission were to the Quercus *(agrifolia, douglasii, garryana, kelloggii, lobata, wislizeni) Alliance.* In these field verified mixed oak stands that were mapped to the *Quercus kelloggii Alliance*, all had *Quercus kelloggii* present according to the AA crew's field data, and *Quercus kelloggii* had the highest or second highest tree cover of all the species in the stand in seven out of nine of these stands. Because the *Quercus Kelloggii Alliance* is in the same National Vegetation Classification Group as the Quercus lobata Mapping Unit and the *Quercus (agrifolia, douglasii, garryana, kelloggii, lobata, wislizeni) Alliance,* it received high fuzzy accuracies despite lower deterministic accuracies. Fuzzy accuracies for the *Quercus kelloggii Alliance* were high: 86% for fuzzy user's accuracy (v. 58% for deterministic user's accuracy) and 98% for fuzzy producer's accuracy (v. 92% for deterministic producer's accuracy).

Errors in the riparian forest types were higher than for upland forests. Riparian forest alliances are difficult to map because they often are hard to distinguish in machine learning and in human aerial image interpretation. The confusion in the riparian forests is illustrated by looking at the accuracy assessment results for the *Salix lasiolepis Alliance.* The *Salix lasiolepis Alliance* had a deterministic user's accuracy of only 63%, and a deterministic producer's accuracy of 77%. This riparian alliance had eight errors of commission, four of these were to the *Salix gooddingii – Salix laevigata Alliance*, one to the *Populus fremontii – Fraxinus velutina – Salix gooddingii Alliance*, and one to the *Juglans hindsii and Hybrids Special Stands and Semi-Natural Alliance*. In summary, the Salix lasiolepis Alliances' six errors of commission were all with similar types that all contain species of *Salix* and can be difficult to distinguish from one another using machine learning and aerial image interpretation.

4.4.2. Confusion in Shrub Classes

The highest level of confusion in the two-county fine scale vegetation map is in the shrublands. Shrublands often contain a mix of species of short, woody vegetation where individual species can be difficult to interpret from the imagery with confidence. Machine learning is much less effective for shrubs than for tree types. Field validation of shrubs in Santa Cruz and Santa Clara Counties was also difficult because many of the shrublands burned in the 2020 fires and much of the unburned shrubland occurs on private lands or on steep, inaccessible public lands.

The *Ceanothus cuneatus alliance* is an example of a lower accuracy shrub type and illustrates the confusion between some shrub types. The *Ceanothus cuneatus alliance* had 10 errors of commission resulting in a user's accuracy of only 23%. Of the 10 errors of commission, four were to the *Adenostoma fasciculatum Alliance.* In the *Adenostoma fasciculatum Alliance, Ceanothus cuneatus* often codominates with chamise, making the distinction between these two similar shrub types a difficult one to make from the mapping perspective. The rest of the errors of commission were to two *Arctostaphylos* alliances and to the *Cercocarpus montanus Alliance*. The *Ceanothus cuneatus alliance* had seven errors of omission, three to the *Adenostoma fasciculatum Alliance*, three to the *Arctostaphylos (crustacea, tomentosa) Alliance*, and one to the *Cercocarpus montanus Alliance.* These errors between *Ceanothus cuneatus alliance* and similar shrub map classes that often contain *Ceanothus cuneatus* as a component are expected (and inevitable) errors. Fuzzy accuracies for the *Ceanothus cuneatus alliance* came in at 77% (user's accuracy) and 78% (producer's accuracy).

5. Santa Cruz and Santa Clara County Vegetation Map Data Products

5.1. Introduction

One of the aims of this program is to provide well-documented fine-scale vegetation data to the public in a way that makes the data easily accessible and easy to use. This section provides an overview of the data products. Section 5.2 provides an overview of obtaining the data products and section 5.3 provides the datasheets for each of the data products.

5.2. Obtaining Data Products

The vegetation map and related products are available for download from https://pacificvegmap.org. There are numerous ways of obtaining data from the web site. Table 13 provides an overview of available formats for each data product. The formats for the available products are listed and described as follows:

- **Feature Service**: Streaming data from ArcGIS Online to GIS software or webmaps. Feature services are queryable (attributes are exposed to the end user) and their symbology can be changed.
- **Tile Service**: Streaming data layer from ArcGIS Online where the polygons are turned into vector tiles that draw quickly and use less bandwidth than a feature service. Tile services are not queryable and their symbology is immutable to the end user.
- **File Geodatabase**: ESRI proprietary data format containing feature classes, for use with ArcGIS Desktop products (ArcMap and ArcGIS Pro). File geodatabases are also readable by open-source mapping software packages like QGIS.
- **Layer File**: ESRI proprietary file type which can be applied to a specific layer in a map and will apply pre-defined symbology and labels to that layer.
- **Datasheet**: Text descriptions of a data product.

Table 13. *Available formats for vegetation map data products from pacficvegmap.org*

Data Product	Feature Service	Tile Service	Countywide Geodatabase	Countywide Layer Package	Layer File	Datasheet
Santa Cruz – Santa Clara County Fine-Scale Veg Map	✓		✓	✓	✓	✓
Santa Cruz-Santa Clara Enhanced Lifeform Map	✓		✓		✓	✓
Santa Cruz-Santa Clara County Impervious Surfaces		✓	✓	✓		✓

5.3. Data Product Specifications (Datasheets)

In addition to metadata for each spatial data product, datasheets were created and made available for each of the Santa Cruz – Santa Clara data products. Links to the datasheets for the vegetation map and its derivatives are provided in Table 14.

Table 14. *Datasheets for vegetation map products*

Product	Datasheet Link
Santa Cruz-Santa Clara County Fine Scale Vegetation Map	https://vegmap.press/cruz_clara_vegmap_datasheet
Santa Cruz-Santa Clara County Enhanced Lifeform Map	https://vegmap.press/cruz_clara_elf_datasheet
Santa Cruz-Santa Clara County Impervious Surfaces Map	Santa Cruz Impervious Datasheet: https://vegmap.press/Santa_Cruz_Impervious_Datasheet Santa Clara Impervious Datasheet: https://vegmap.press/Santa_Clara_Impervious_Datasheet

5.4. Attributes of the Fine-scale Vegetation Map

The fine-scale vegetation map has 309,785 polygons across the two-county area. Each polygon includes its fine-scale map class and a suite of information about the polygon. Information is included in the form of numerous attributes that characterize the polygon’s forest structure, its impervious composition, its relative hardwood versus conifer cover, and others. Table 15 includes a list and description of the numerous fine-scale vegetation map attributes.

Table 15. *Fine-scale vegetation map attributes*

Fine Scale Map Attributes (Name/Alias)	Description
OID_COPY/ OID_COPY	Index for internal use
MAP_CLASS/Fine Scale Map Class in 2020	National Vegetation Classification (NVCS) map class label for all stands.
ABBRV/Fine Scale Map Class Abbreviation	Map class abbreviations for use in cartography and visualization. A key to abbreviations is available here: https://vegmap.press/cruz_clara_vegmap_abbrevs
ENHANCED_LIFEFORM/Enhanced Lifeform in 2020	27-class lifeform label for all stands. Labels are floristically more general than the fine scale map class.
ABS_COVER/% Veg Returns > 15 Feet in 2020	Absolute cover of trees greater than 15 feet in height. Derived from 2020 lidar data.
REL_CON_COV/Relative % Conifer Cover in 2020	Relative conifer cover, estimating the percent of tree canopy >= 15 ft. is conifer. Derived from machine learning on lidar-derived tree approximate objects combined with manual image interpretation of 2020 imagery.
REL_HDW_COV/Relative % Hardwood Cover in 2020	Relative hardwood cover, estimating the percent of tree canopy >= 15 ft. is hardwood. Derived from machine learning on lidar-derived tree approximate objects combined with manual image interpretation of 2020 imagery.
CON_COVER/Absolute % Conifer Cover in 2020	Absolute conifer cover, derived as: ((relative % conifer cover/100) x (absolute % cover/100)) * 100
HDW_COVER/Absolute % Hardwood Cover in 2020	Absolute hardwood cover, derived as: ((relative % hardwood cover/100) x (absolute % hardwood/100)) * 100
SHB_COVER/Absolute % Shrub Cover in 2020	Absolute shrub cover for herbaceous and shrub stands. Derived from manual image interpretation of 2020 imagery.
STAND_HT_MN/Mean lidar Stand Height in 2020 (ft.)	Mean stand height from lidar-derived canopy height model (CHM).
STAND_HT_MX/Maximum lidar Stand Height in 2020 (ft.)	Maximum stand height from lidar-derived canopy height model (CHM). Calculated for areas of the stand greater than or equal to 15 feet tall.
STAND_HT_MD/Median lidar Stand Height in 2020 (ft.)	Median stand height from lidar-derived canopy height model (CHM). Calculated for areas of the stand greater than or equal to 15 feet tall.
STAND_HT_SD/Standard Deviation lidar Stand Height in 2020 (ft.)	Standard deviation of stand height from lidar-derived canopy height model (CHM). Calculated for areas of the stand greater than or equal to 15 feet tall.
IMPERVIOUS/% Impervious in 2020	Percent of stand that was impervious in 2020. Integrated from the Santa Cruz and Santa Clara impervious surface maps.
PERVIOUS/% Pervious in 2020	Percent of stand that was pervious in 2020. Integrated from the Santa Cruz and Santa Clara impervious surface maps.
PAVED_RD/% Paved Road in 2020	Percent of stand that was paved road in 2020. Integrated from the Santa Cruz and Santa Clara County impervious surface map.
DIRT_RD/% Dirt and Gravel Road in 2020	Percent of stand that was dirt or gravel road in 2020. Integrated from the Santa Cruz and Santa Clara County impervious surface map.
OTHER_IMPERVIOUS/% Other Impervious in 2020	Percent of stand that was paved or unpaved, non-road surface (such as a paved or unpaved parking lot) in 2020. Integrated from the Santa Cruz and Santa Clara County impervious surface map.
BUILDINGS/% Buildings in 2020	Percent of stand that was a building in 2020. Integrated from the Santa Cruz and Santa Clara County impervious surface map.

Fine Scale Map Attributes (Name/Alias)	Description
STAND_DEAD/% Standing Dead 2020	Estimate of percent standing dead vegetation in forested stands. Estimates the percent of the woody canopy > 7 feet tall that did not have a living crown in 2020. Mapped only for forest stands in the Santa Cruz Mountains.
URB_WINDOW/Santa Clara County Urban Window	Core urban areas of Santa Clara County, where conifer and hardwood cover attributes were not assigned to non-native forest types or to forest fragments.
COUNTY/County	Indicates whether the stand was in Santa Clara, Santa Cruz or San Mateo County (border polygons only).
SOURCE/Fine Scale Map Label Source	Indicates whether stand's fine scale map class was validated during field work, or if the map label was assigned based on remote sensing methods.
ACRES/ Acres	Acres of land encompassed by the stand.
ULT_MAFIC_OVERLAP/% Ultramafic Overlap	% of the stand that overlaps with layer depicting ultramafic substrate provided by Ryan E. O'Dell, from the Bureau of Land Management.
OID_COPY/ OID_COPY	Index for internal use.

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