SAN MATEO COUNTYWIDE FINE SCALE VEGETATION MAP

Final Report

Prepared by Tukman Geospatial & Aerial Information Systems for the Golden Gate National Parks Conservancy

October 21, 2022

Recommended Citation: 2018 San Mateo Countywide Fine Scale Vegetation Map, Golden Gate National Parks Conservancy et al.

Contents

LIST OF TABLES

LIST OF FIGURES

1. Executive Summary

This report documents the methods and results of the fine-scale, countywide vegetation map of San Mateo County, CA. The map represents the state of the landscape in summer, 2018, when the high-resolution imagery for the county was collected (https://vegmap.press/marin_imagery_report).

In 2018, the Golden Gate National Parks Conservancy (Parks Conservancy) (https://parksconservancy.org), non-profit support partner to the National Park Service (NPS) Golden Gate National Recreation Area (GGNRA), initiated a fine scale vegetation mapping project in Marin County. The GGNRA includes lands in San Francisco and San Mateo counties, and NPS expressed interest in pursuing fine scale vegetation mapping for those lands as well. The Parks Conservancy facilitated multiple meetings with potential project stakeholders and was able to build a consortium of funders to map all of San Mateo County (and NPS lands in San Francisco). The consortium included the San Francisco Public Utilities Commission (SFPUC), Midpeninsula Regional Open Space District (MROSD), Peninsula Open Space Trust (POST), San Mateo City/County Association of Governments, and various County of San Mateo departments including Parks, Agricultural Weights and Measures, Public Works/Flood Control District, Office of Sustainability, and Planning and Building. Over a 3-year period, the project, collectively referred to as the “San Mateo Fine Scale Veg Map”, has produced numerous environmental GIS products including 1-foot contours, orthophotography, and other land cover maps. A 106-class fine-scale vegetation map was completed in April 2022 that details vegetation communities and agricultural land cover types, including forests, grasslands, riparian vegetation, wetlands, and croplands. The environmental data products from the San Mateo 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 San Mateo County’s habitats and natural resources.

Development of the San Mateo fine-scale vegetation map was managed by the Golden Gate National Parks Conservancy and staffed by personnel from Tukman Geospatial (https://tukmangeospatial.com/), Aerial Information Systems (AIS; http://www.aisgis.com/), and Kass Green and Associates. The fine-scale vegetation map effort included field surveys by a team of trained botanists including Neal Kramer, Brett Hall, Lucy Ferneyhough, Brittany Burnett, Patrick Furtado, and Rosie Frederick. Data from these surveys, combined with older surveys from previous efforts, were analyzed by the California Native Plant Society (CNPS) Vegetation Program (https://www.cnps.org/vegetation), with support from the California Department of Fish and Wildlife Vegetation Classification and Mapping Program (VegCAMP; https://wildlife.ca.gov/Data/VegCAMP) and ecologists with NatureServe (https://www.natureserve.org/) to develop a San Mateo County-specific vegetation classification. For more information on the field sampling and vegetation classification work refer to the final report (https://tukmangeospatial.egnyte.com/dl/j2aU0OaBZZ) issued by CNPS and corresponding floristic descriptions (https://tukmangeospatial.egnyte.com/dl/LsAJ4YA6tg).

Existing lidar data, collected in 2017 by San Mateo County 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 habitat map. The lidar data was used in conjunction with optical data. Optical data used throughout the project included 6-inch resolution airborne 4-band imagery collected in the summer of 2018, as well as various dates of National Agriculture Imagery Program (NAIP) imagery.

In 2020, an enhanced lifeform map was produced which 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.

In 2020, Tukman Geospatial staff and partners 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 2021, 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 early January of 2022, draft maps were distributed and reviewed by San Mateo County's 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 April 2022. In total, 106 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 2021 and 2022. Accuracy assessment results were compiled and analyzed in the April of 2022. Overall accuracy of the lifeform map is 98%. Overall accuracy of the fine-scale vegetation map is 83.5%, with an overall 'fuzzy' accuracy of 90.8%.

The San Mateo County 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 characterizes stands of vegetation generally 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 contained in the map accessible to the most users, the vegetation map is published as a suite of GIS deliverables available in a number of formats.

Map products are being made available wherever possible by the project stakeholders, including the regional data portal Pacific Veg Map (http://pacificvegmap.org/data-downloads/).

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 percent of impervious cover in each vegetation and habitat map polygon.

The fine scale vegetation map also provides information relevant to forest health. Specifically, the map includes stand-by-stand attribution about canopy mortality (percent standing dead in 2018). The standing dead information will be useful for tracking the spread of pathogens such as sudden oak death and pitch pine canker in San Mateo's 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 lifeform map, and the fine-scale vegetation and habitat maps
- **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. Discussion of the Veg Map and the State Standard** – provides a short discussion on how the San Mateo fine scale vegetation map differs from the California Department of Fish and Wildlife's state standard for vegetation mapping.
- **Section 8**. **Additional Documentation on San Mateo's Vegetation Communities**
- **Section 7. References**

2. Acknowledgements

The San Mateo County fine scale vegetation map was a multi-year effort made possible with support from the following agencies and organizations:

- Aerial Information Systems Inc.
- California State Parks – Santa Cruz District
- CAL FIRE
- California Department of Fish and Wildlife, Vegetation Classification and Mapping Program
- California Native Plant Society, Vegetation Program
- Golden Gate National Parks Conservancy
- Jasper Ridge Biological Preserve

- Kass Green & Associates
- Midpeninsula Regional Open Space District
- Dr. Mike Vasey
- Nate Herold – NOAA Office for Coastal Management
- National Park Service - GGNRA
- Neal Kramer - Kramer Botanical
- Peninsula Open Space Trust
- Point Blue Conservation Science
- Quantum Spatial/NV5
- San Mateo County Parks, ISD, C/CAG, Ag. Weights and Measures, DPW, Office of Sustainability, Planning and Building, and the Board of Supervisors
- San Mateo FireSafe Council
- San Mateo RCD
- Santa Cruz Mountains Stewardship Network
- San Francisco Bay Area Network of National Parks
- San Francisco Public Utilities Commission
- Sonoma Ag + Open Space
- Toni Corelli
- Tukman Geospatial
- UC Santa Cruz Arboretum
- USGS 3D Elevation Program

We would like to extend our gratitude to those private landowners who provided access to their land for field work, and to the San Mateo Resource Conservation District for facilitating access. Thanks also to San Francisco Public Utilities Commission (SFPUC), San Mateo County Parks, the Midpeninsula Regional Open Space District (MROSD), the National Park Service (NPS), California Department of Parks and Recreation (CDPR), Peninsula Open Space Trust (POST), and Jasper Ridge Biological Preserve, for providing full access to their properties for field crews as well as access to existing vegetation information.

Thanks to the Santa Cruz Mountains Stewardship Network (http://scmsn.net/) for advocating for the project and providing datasets. 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 that is related to the variation in the classification scheme.

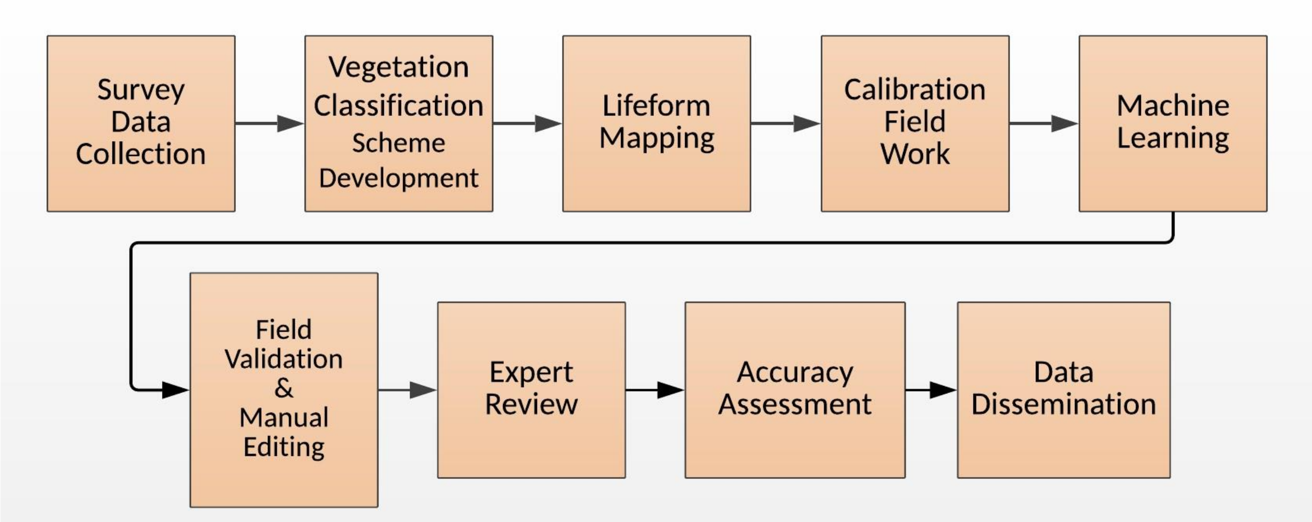
Since the early 1900s, these steps have been completed through the manual interpretation of remotely sensed data to delineate and identify vegetation using seven indicators of vegetation type; color, tone, texture, location, context, height, and shape of the feature of interest (Spurr, 1960). While a 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 San Mateo County's 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-fine-scale vegetation class in San Mateo 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	https://vegmap.press/san_mateo_classification
Alliance and Associations Vegetation Descriptions	Appendix D of classification document (detailed descriptions of alliances)	https://vegmap.press/san_mateo_descriptions
San Mateo County Fine-scale Mapping Key	Key used for lifeform mapping and fine-scale vegetation mapping	https://vegmap.press/sm_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 relatively 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 San Mateo 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 San Mateo 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.

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*

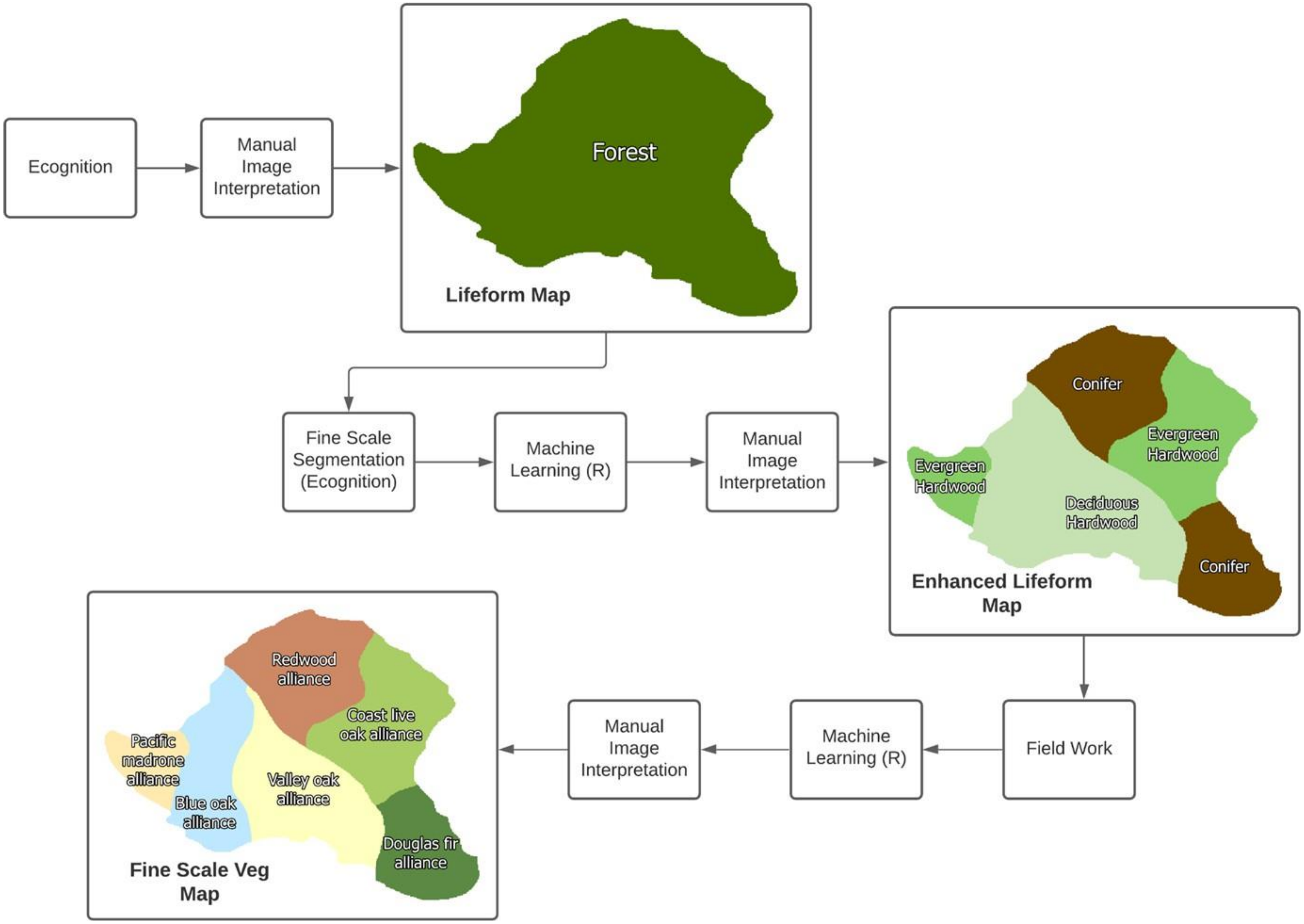


Table 3. *Enhanced lifeform classes and acreages, San Mateo County*

Class	Description	Acres
Annual Cropland	Area is an irrigated annual cropland (e.g., vegetable crops)	2,901
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	3,243
Conifer	Areas where trees are at least 10% absolute cover; fine scale map class is a conifer type (e.g., coast redwood)	69,768
Deciduous Hardwood	Areas where trees are at least 10% absolute cover; fine scale map class is a non-riparian deciduous hardwood type (e.g., buckeye).	2,573
Developed	Manmade developed areas greater than 0.2 acres	62,013
Eel Grass	Areas where eel grass is dominant	8
Evergreen Hardwood	Areas where trees are at least 10% absolute cover; fine scale map class is a non-riparian evergreen hardwood type (e.g., oaks, madrone, tanoak)	30,468
Forest	'Forest fragment' Areas, 1/2 acre to <1 acre, where woody vegetation >15 feet is at least 10% absolute cover, surrounded by a contrasting lifeform (e.g., 'Evergreen Hardwood' surrounded by 'Herbaceous')	1,321
Freshwater Herbaceous Wetland	Areas that are depressional, wet all year long, and/or exhibit obvious herbaceous wetland vegetation in the 2018 imagery; absolute tree and shrub cover is less than 10%	663
Herbaceous	Areas where herbaceous vegetation is at least 10% absolute cover; absolute tree and shrub cover is less than 10%	31,087
Intensively Managed Hayfield	Area is an intensively managed hayfield that is mechanically turned over every year.	53
Irrigated Pasture	Area is an irrigated pasture that appears green in the June 2018 imagery	34
Major Roads	Area is a major road	2,023
Mud Flat	Areas in the intertidal zone that are unvegetated and exposed during low tide	2,916
Non-native Forest	Areas where trees are least 10% absolute cover; tree cover dominated by ornamental non-native species (>50% relative tree cover)	11,687
Non-native Herbaceous	Areas where non-native herbaceous vegetation is at least 10% absolute cover; non-native herbaceous species dominate the herbaceous stratum; absolute tree and shrub cover is less than 10%	764

Non-native Shrub	Areas where non-native, ornamental, or landscaping woody shrubs are at least 10% absolute cover; absolute tree and shrub cover is less than 10%	265
Nursery or Ornamental Horticulture Area	Area is a nursery or horticultural area	437
Orchard or Grove	Area is an orchard or grove of fruit or nut trees	102
Perennial Agriculture	Area is a perennial cropland (e.g., lavender, berries, Christmas trees, rhododendron)	217
Riparian Forest	Areas where tree cover at least 10% absolute cover; obligate riparian tree genera (alder, willow, cottonwood, ash) dominate tree cover (>50% relative tree cover)	7,838
Shrub	Areas where native woody shrubs are at least 10% absolute cover; absolute tree cover is less than 10%	60,994
Tidal Marsh	Salt marsh areas dominated by salt-tolerant wetland species	3,519
Vineyard	Area is a vineyard	231
Water	Water covers the area	15,003

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 3.4.4).

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 25 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 3.4.3. 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 2018, the lidar-derived Canopy Height Model (CHM), and several other lidar-derived raster and vector datasets. In addition, a number of 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 2018 Orthoimagery	Used as the primary spectral input for lifeform mapping in Ecognition®.	NV5
NDVI from Summer 2018	Used in Ecognition® decision rules for discriminating between vegetated and non- vegetated areas.	Tukman Geospatial, NV5
2017 lidar Derived Canopy Height Model (CHM)	Represents height of vegetation. The CHM will be used widely as an input to the Ecognition® rule set, especially for mapping the natural lifeform classes.	Tukman Geospatial, Sanborn
Road Centerlines	The Santa Cruz and Santa Clara County Road Centerlines dataset will be used to include major roads in the lifeform map.	Open Street Map
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 is 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 2017 lidar data are used in the machine learning part of the enhanced lifeform workflow.	Quantum Spatial, Sanborn

Layer	Roles in Lifeform Mapping	Source
Lidar canopy volume profiles	Canopy volume profiles derived from 2017 lidar data are used in the machine learning part of the enhanced lifeform workflow.	Tukman Geospatial, Sanborn
Other lidar derivatives	Other lidar derivatives, such as rumple and highest hit slope, are used in the machine learning part of the enhanced lifeform workflow.	Tukman Geospatial, Sanborn

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 (with the exception of 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 man-made 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 impervious surfaces map (https://tukmangeospatial.egnyte.com/dl/STL9Blh0f6) - includes 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 will 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 of the urban window, vegetation was generally less scrutinized during manual editing than in the non-urban core areas.

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 larger than approximately one square mile.
2. The urban window can finger out into adjacent natural areas if it has >30% impervious coverage.
3. Natural areas (e.g., riparian corridors) can extend into the urban window.
4. “Islands” of predominately natural land cover surrounded by urban core areas are mapped as part of the urban window if they are less than 10 acres. The MMU for natural vegetation within the urban core is 10 acres. If a natural area is greater than 10 acres (e.g., a large urban park), it is not considered part of the urban window and is mapped as natural vegetation.
5. Agriculture islands that exceed ¼ acre (the minimum mapping unit for agriculture) are preserved with their respective agricultural label inside the urban window.
6. Golf courses and playing fields are considered urban land cover and included as part of the urban window.
7. Forested riparian stands are mapped as natural vegetation within the urban window if they exceed 1/4 acre.

Figure 3 shows an example of the urban window for an area of northwestern San Mateo County near Pacifica.

Figure 3. *The urban window in west central San Mateo County*

3.3.5. Agriculture

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

3.3.6. Tidal and Freshwater Wetlands

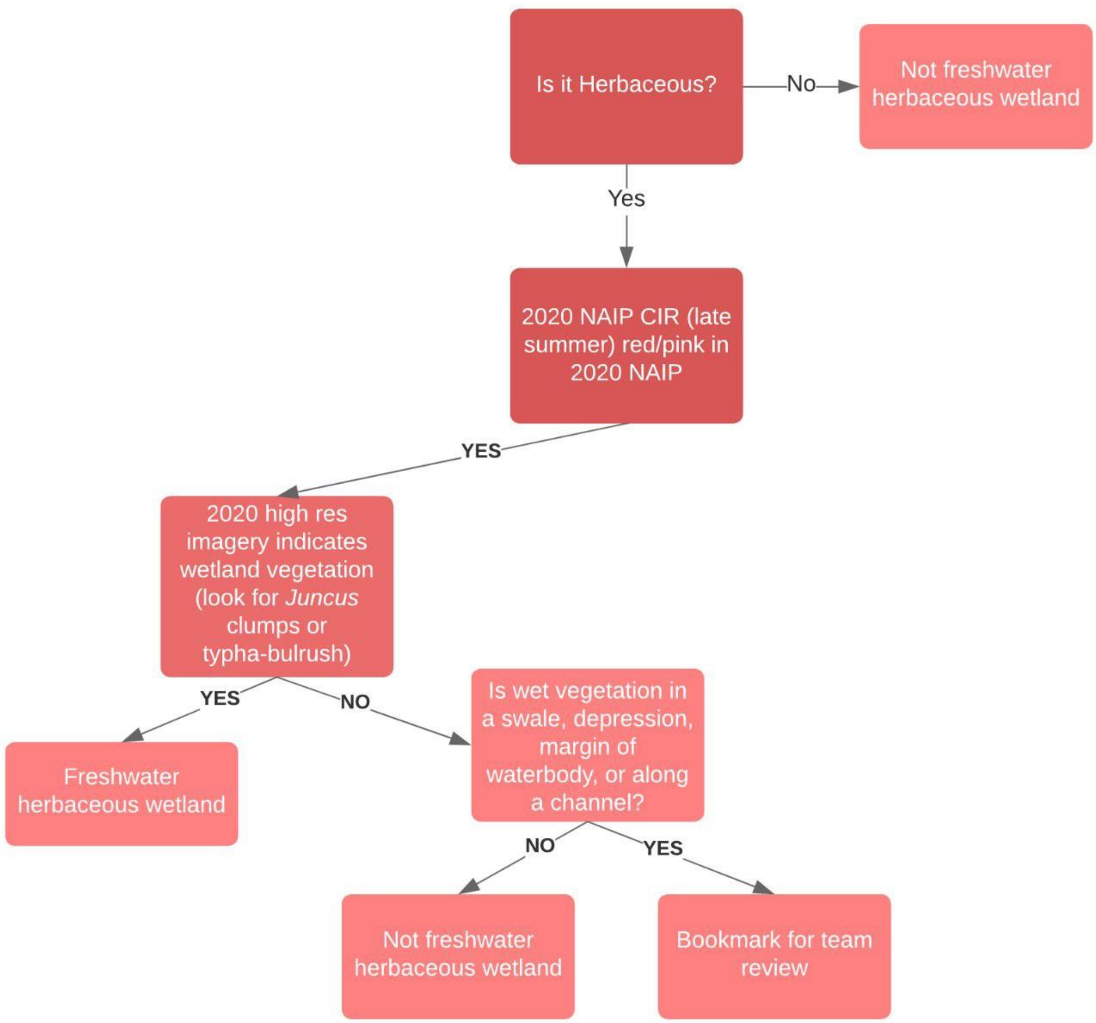
Tidal and freshwater wetlands are mapped initially in the lifeform and enhanced lifeform maps and refined during fine scale map editing. Tidal marshes are extracted from the SFEI's BAARI Baylands dataset where the class label in that dataset is 'Tidal Vegetation'. These representative polygons were integrated into the lifeform dataset during the Ecognition processing. During lifeform and enhanced lifeform manual editing, the tidal marsh polygons integrated from SFEI 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 3.4.6 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 2018 countywide orthoimagery, while viewed in color infrared (CIR).

Freshwater wetlands were further refined during fine scale map editing.

Existing freshwater wetland layers provided by the National Park Service for Pt. Reyes National Seashore were used to inform herbaceous wetland mapping during manual editing of the lifeform map.

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

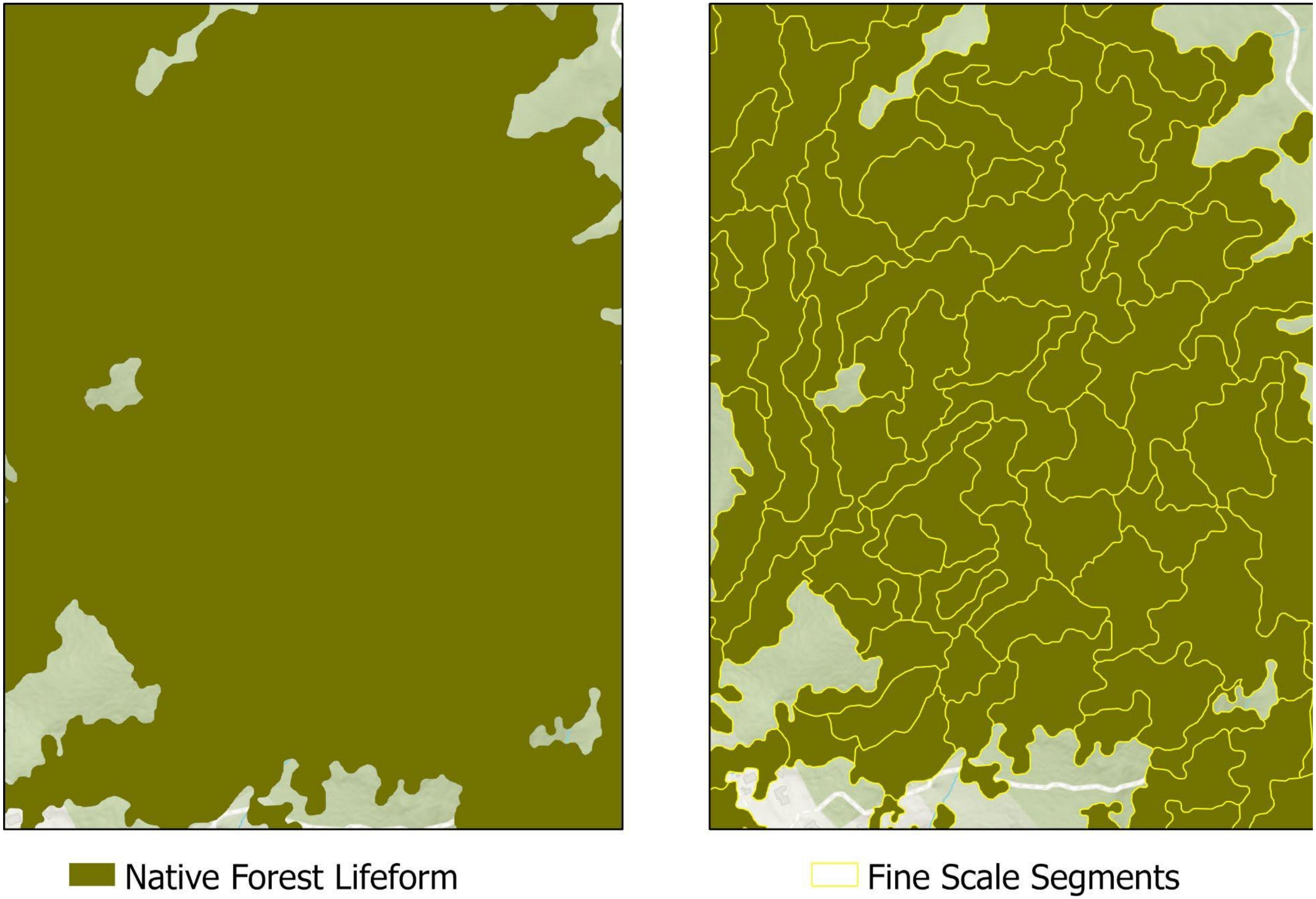


3.3.7. Fine Scale Segmentation

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 2018 high resolution imagery, the 2017 lidar-derived canopy height model, and a suite of spectral indices derived from the high-resolution imagery. Fine scale segments were created so that they had spectral homogeneity (from the high-resolution imagery) but also had structural homogeneity, meaning relatively 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 mapping as well as for the fine scale vegetation mapping. They serve as the units of analysis for enhance 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)*



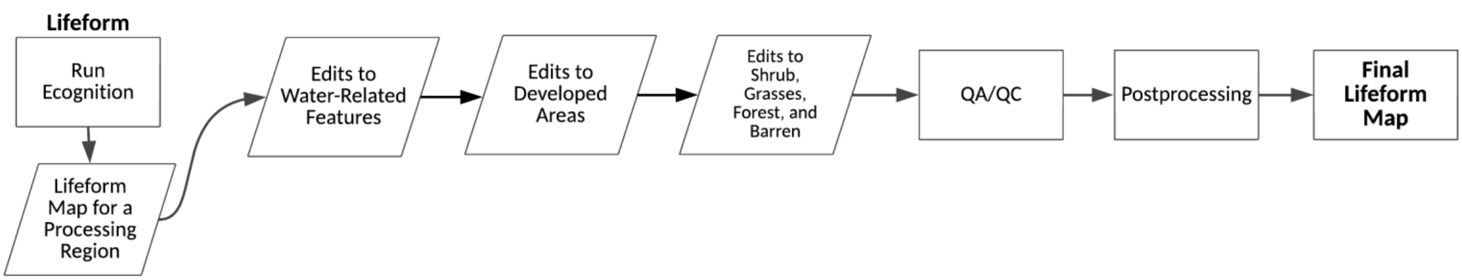
3.3.8. Lifeform and Enhanced Lifeform Map Manual Editing

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 'Conifer' 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 of 'Evergreen Hardwood Forest,' 'Deciduous Hardwood Forest,' and 'Conifer Forest'.

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 San Mateo County 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 2021 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. Field teams were joined frequently by Neal Kramer (Kramer Botanical) and for three days by CNPS (Julie Evens and Jennifer Buck Diaz). Existing and new field survey data collected for floristic classification was also used for map calibration.

Tukman Geospatial developed a San Mateo County Veg Map Field Book that contains comprehensive information about identifying and keying out map classes, field data collection protocols, and detailed vegetation summaries for the fine-scale map classes. The field book was used by field data collection teams to standardize data collection and apply fine scale map class labels consistently in the field.

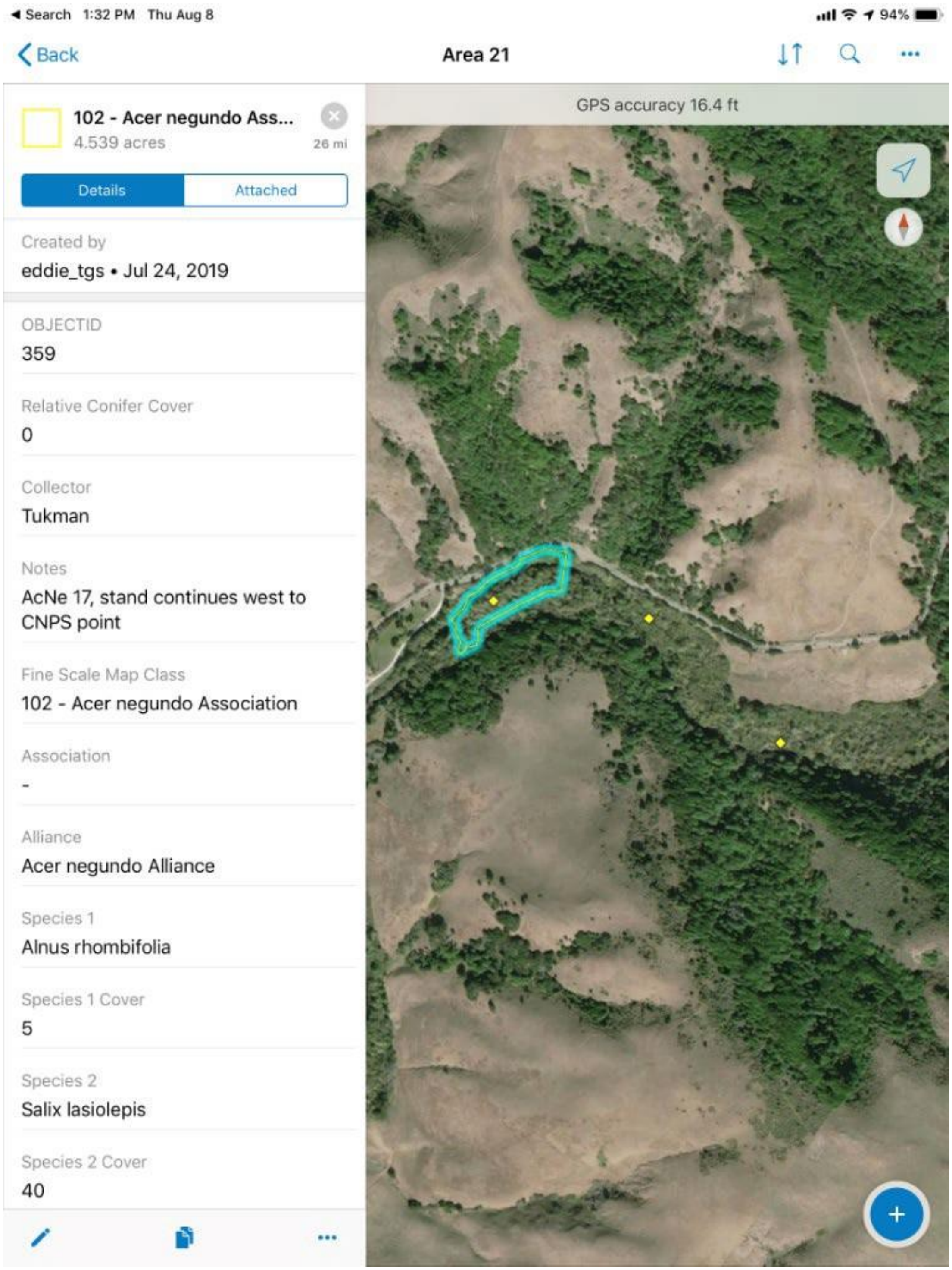
Calibration data collection teams use tablets running ESRI's Collector App (see Figure 7) to delineate and attribute polygons (or label image segments) representing shrub, forest and herbaceous stands observed in the field. The Collector App uses an ArcGIS Online web map with syncable feature services.

Data collected by field crews was synced 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
- Species and species cover for the 10 highest cover species in the stand
- 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 San Mateo 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 San Mateo County's 106 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.

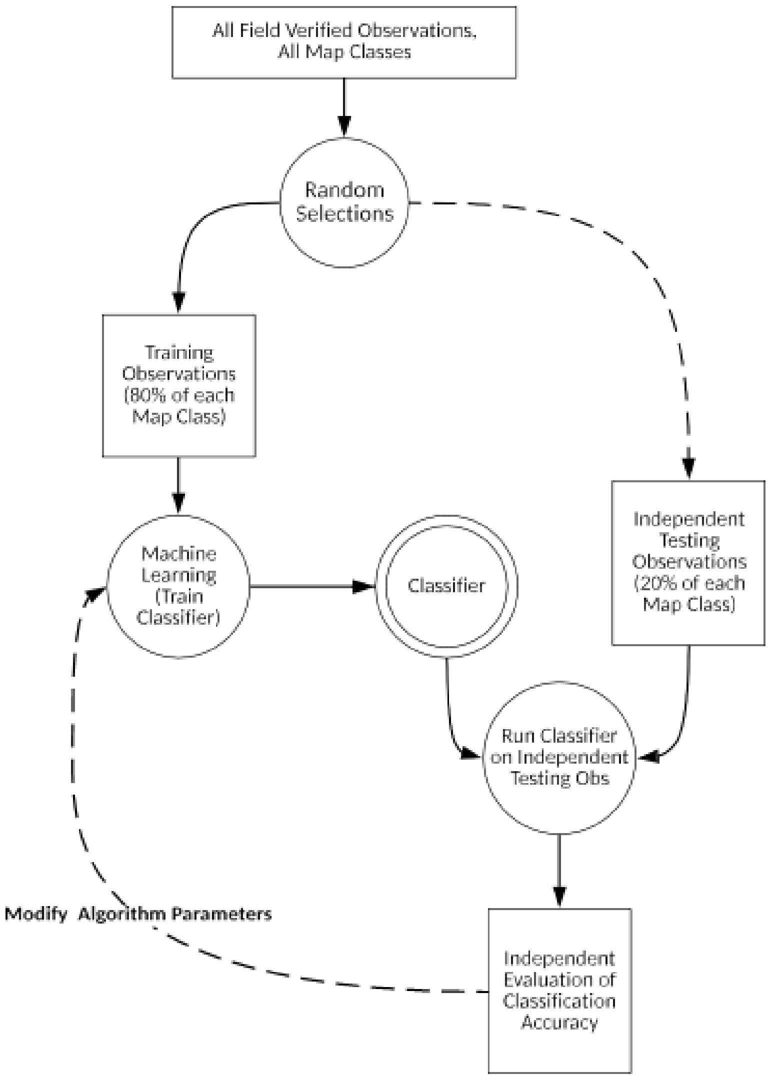
Field-calibrated sites discussed in the previous section were used as training data for machine learning, with their fine scale map class label serving as the dependent variable. The independent variables (referred to in this discussion as *predictor variables*) number over 300 and include variables 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 3.5.2.1)
- Support Vector Machines (Meyer at al., 2018) (section 3.5.2.2)

Machine learning is an iterative process that requires trial and error to fine-tune algorithm parameters and inputs to maximize model accuracy. The San Mateo 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 San Mateo.

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 3.4.3.5 shows the importance matrix for the *Pseudotsuga menziesii – (Notholithocarpus densiflorus – Arbutus menziesii)* Alliance. 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.

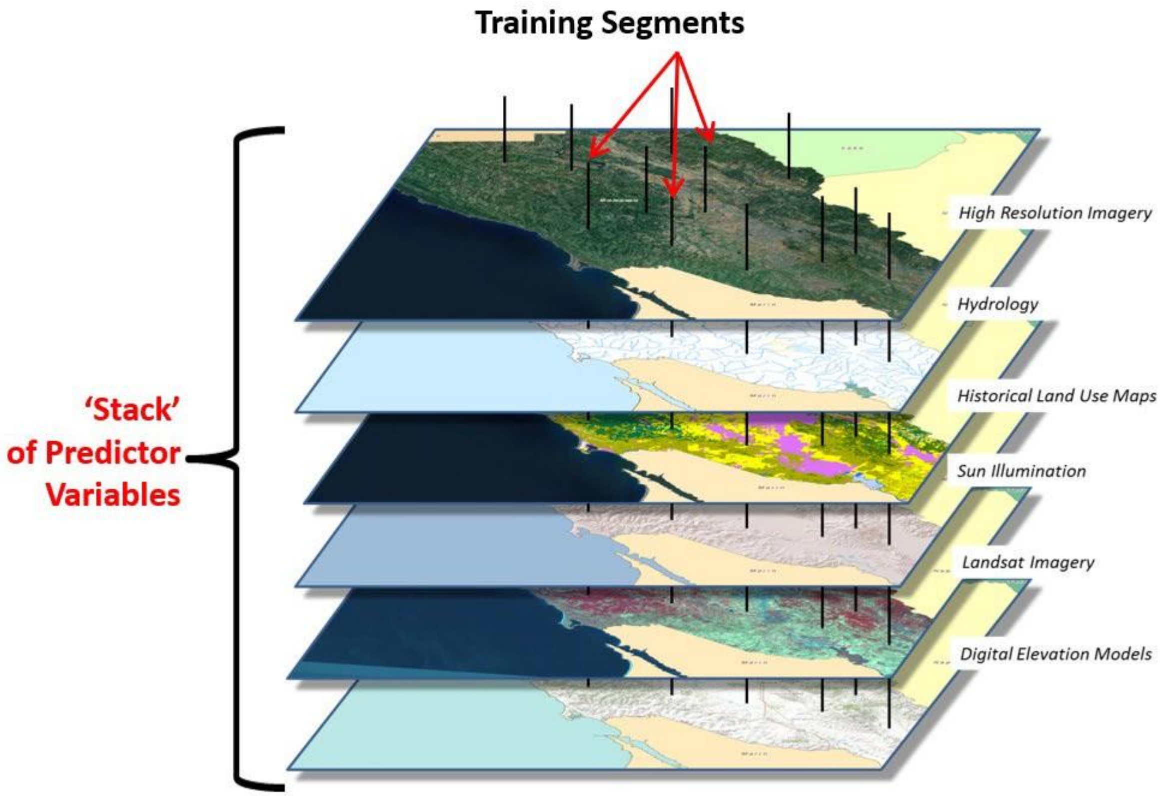
3.4.2.4. Support Vector Machines

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	2017 QL1 countywide lidar
% canopy density in the 60 to 100 foot range	2017 QL1 countywide lidar
% canopy density in the 100 to 150 foot range	2017 QL1 countywide lidar
% canopy density in the 150 to 200 foot range	2017 QL1 countywide lidar
% canopy density in the 200 to 250 foot range	2017 QL1 countywide lidar
Average lidar height from lascanopy	2017 QL1 countywide lidar
Lidar kurtosis for height from lascanopy	2017 QL1 countywide lidar
Lidar quadratic average height from lascanopy	2017 QL1 countywide lidar

Machine Learning Predictor Variable	Data Source
Lidar skewness for height from lascanopy	2017 QL1 countywide lidar
% lidar returns between 0-4 meters above ground	2017 QL1 countywide lidar
Absolute canopy cover	2017 QL1 countywide lidar
Relative cover of trees taller than 60 feet	2017 QL1 countywide lidar
Lidar 5th percentile height from lascanopy	2017 QL1 countywide lidar
Lidar 10th percentile height from lascanopy	2017 QL1 countywide lidar
Lidar 25th percentile height from lascanopy	2017 QL1 countywide lidar
Lidar 50th percentile height from lascanopy	2017 QL1 countywide lidar
Lidar 75th percentile height from lascanopy	2017 QL1 countywide lidar
Lidar 90th percentile height from lascanopy	2017 QL1 countywide lidar
Lidar canopy height from lascanopy	2017 QL1 countywide lidar
Terrain slope (from bare earth DEM)	2017 QL1 countywide lidar
Canopy slope (slope derived from the canopy height model)	2017 QL1 countywide lidar
Canopy height model (a.k.a. normalized digital surface model)	2017 QL1 countywide lidar
2018 image indices (DVI, GDVI, GNDVI, VARI)	2018 6-inch countywide imagery
2018 high resolution imagery bands (Red, Green, Blue, Near Infrared)	2018 6-inch countywide imagery
Percentage of stand’s canopy that is low NDVI (not including non-veg areas)	2018 6-inch countywide imagery
Loudon Index: (green band*2)/(red band + blue band) from NAIP 2009	USDA Farm Service Agency (NAIP)
2018 NAIP bands (Red, Green, Blue, Near Infrared)	USDA Farm Service Agency (NAIP)
AVIRIS indexes (EWT_AV, NDWI_AV, Wtr1AbAr_AV)	Dr. Matthew Clark, NASA
Sentinel 2018 bands (Red, Green, Blue, NIR, Red-Edge) for multiple months (Jan, Feb, Mar, July, Oct)	The European Space Agency, Google Earth Engine
Sentinel 2018, band differences (Red, Green, Blue, NIR, Red-Edge), between months (Jan, Feb, Mar, July, Oct)	The European Space Agency, Google Earth Engine
Sentinel 2018, indices (DVI, GNDVI, GRVI, VARI, NDVI) for multiple months (Jan, Feb, Mar, July, Oct)	The European Space Agency, Google Earth Engine
Sentinel 2018 index differences (DVI, GNDVI, GRVI, VARI, NDVI), between months (Jan, Feb, Mar, July, Oct)	The European Space Agency, Google Earth Engine
Distance from coast	Tukman Geospatial
Average annual precipitation	PRISM, Oregon State University
Summer fog frequency	The Pacific Coast Fog Project, USGS

Machine Learning Predictor Variable	Data Source
Mean annual maximum temperature, 1981-2010	Basin Characterization Model, USGS
Climatic water deficit, 1981 - 2010	Basin Characterization Model, USGS
Evapotranspiration, 1981 - 2010	Basin Characterization Model, USGS

To illustrate how predictor variables are used by the machine learning algorithms, Table 6 shows an importance matrix from random forests for the *Pseudotsuga menziesii – (Notholithocarpus densiflorus – Arbutus menziesii)* Alliance. Table 6 shows the most important predictor variables to predict the presence of the *Pseudotsuga menziesii – (Notholithocarpus densiflorus – Arbutus menziesii)* Alliance are varied. They include a number of variables derived from the 2018 high resolution imagery (which top the list in terms of importance), indices derived from AVIRIS (a hyperspectral sensor), and a number of lidar forest structure derivatives, such as, and the percent of lidar returns between 15 and 60 feet above the ground.

Table 6. *Top 10 most important predictor variables for the Pseudotsuga menziesii – (Notholithocarpus densiflorus – Arbutus menziesii) Alliance*

Predictor Variable Importance Rank	Description of Predictor Variable	Data Source
1	Standard deviation of the ortho green band	2018 Ortho Imagery
2	Standard deviation of the ortho red band	2018 Ortho Imagery
3	AVIRIS Index 1	AVIRIS hyperspectral data
4	AVIRIS Index 2	AVIRIS hyperspectral data
5	Percent of lidar returns between 15-60 feet above the ground	2017 QL1 countywide lidar
6	Standard deviation of the ortho blue band	2018 Ortho Imagery
7	Percentile height from lascanopy	2017 QL1 countywide lidar
8	Mean precipitation	Basin Characterization Model
9	Mean canopy height	2017 QL1 countywide lidar
10	AVIRIS Index 3	AVIRIS hyperspectral data

3.4.3. Fine-scale Manual Editing & Map Field Validation

3.4.3.1. Fine-scale Map Manual Editing

Manual editing allowed experts 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 wasn't 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 NAIP imagery, displayed as an RGB and CIR composite	Production modules (editing units) for tracking editing progress
2018 San Mateo County imagery (6-inch, 4-band), displayed as an RGB and CIR composite	Roads and trails
2017 lidar derived bare earth DEM	Field photos
2017 lidar derived bare earth hillshade	CNPS survey points
2017 lidar derived canopy height	Field calibration polygons
USGS 7.5-minute topography	Soils (NRCS)
	Ultramafic layer (CNPS)
	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.

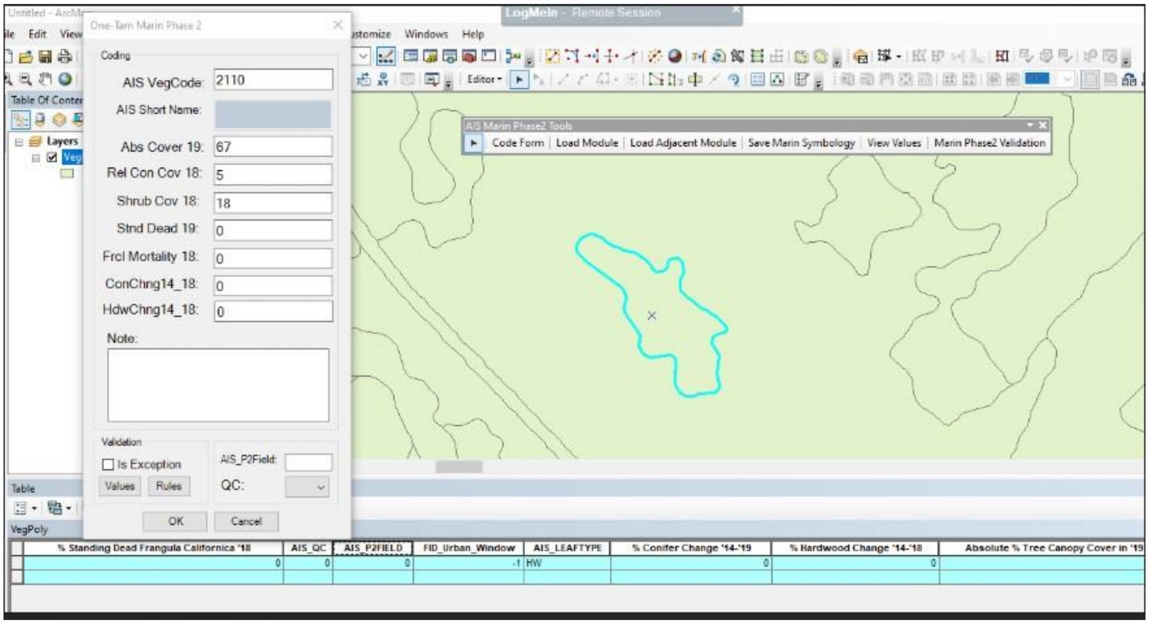
Environmental factors, such as slope, aspect, elevation, soils, and geology, were also assessed by the analysts. "Mental" models correlating the environmental factors to vegetation types were developed based on known correlations in the county. These proved useful, especially where the imagery did not provide sufficient information to discern the vegetation type.

In addition to the pre-loaded raster and vector datasets, the map document 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 map class with a unique numeric code assignment and associated attributes, such as cover class and relative conifer cover
- For edited polygons, dynamically rendered symbology 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.

Figure 10 shows an image of the map used for fine scale manual editing.

Figure 10. *Fine scale editing in ArcMap*



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 2020 and in early 2021. 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 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 3.4.2 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, the stakeholders were interested in a floristically more detailed map of tidal wetlands. As a result, the mapping team conducted alliance level mapping for the tidal wetlands. 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
- *Zostera* (marina, pacifica) Pacific Aquatic Alliance

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 allowed to be 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 on the imagery**. For example, young pickleweed is very reflective of near infrared light, but older pickleweed doesn't 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 occur in nearly the same percent cover, making it hard to assign the correct class. These two alliances also can appear nearly 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.**

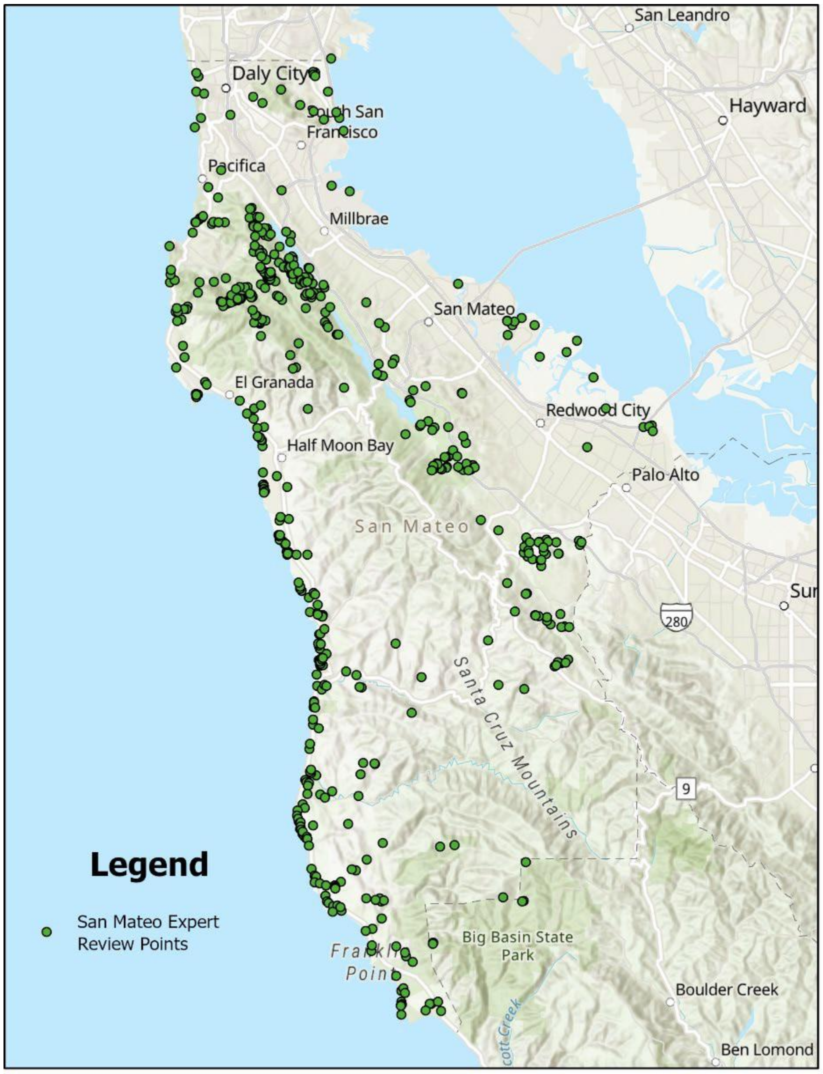
3.5. Fine-scale Map Expert Review

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 San Mateo County land managers, ecologist, 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. Other reviewers chose not to use the webmap but instead provided standalone spatial data (points) of the issues that they observed – these points were combined with those in the webmap. After the input period ended, Tukman Geospatial compiled the collected input and provided it to AIS. AIS reviewed the input and took appropriate action to refine the map. If AIS had questions about a reviewer's concern, Tukman Geospatial and/or AIS contacted the reviewer to discuss the question. In all, there were 580 points provided to the mapping team. The expert review points are shown in Figure 11.

Figure 11. *Expert review points provided for the San Mateo 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 6.4 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 6.4, Table 16.

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 all areas of San Mateo County. Countywide 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 2018 high resolution countywide imagery and the 2017 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 2018. AIS 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 2018. 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, 2018 high resolution imagery. It is possible that some areas mapped as dead could be trees defoliated by insects or fire in 2018 that regrew their leaves in the summer 2019 growing season.

- 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.

Standing dead was assigned to forested stands in increments of 1%. For stands where one or more standing dead canopy tree was present, but the standing dead was less than 0.5 percent, the stand was assigned a value of ‘Present’ for the attribute called SD_PRESENCE. This attribute is meant to capture stands where standing dead trees were present but represented less than 0.5 percent of the canopy over 7 feet.

3.7.2. Shrub % Cover

Percent shrub cover was be mapped for all non-forested, non-developed, and non-water vegetation map stands in San Mateo. 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 (generally more than 1,000 acres). Accuracy was not assessed for the tidal wetland alliances or for the small area of fine scale vegetation mapping conducted in San Francisco County.

4.1. Sample Design

Final draft map polygons, as well as field crew created calibration 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:

- Manual labelling of sites from the imagery for assessment of classes other than shrub and native forest
- Field verification of sites for assessment of the shrub and forest fine-scale vegetation map and lifeform classes

4.1.1. Manually Interpreted Samples

Lifeform map accuracy was assessed using both the lifeform map class assigned to field-verified samples (see below) and the lifeform map class manually interpreted from imagery. Unlike fine-scale vegetation labels, non-shrub and non-native forest lifeform classes are easy to interpret from imagery and do not require field verification. Therefore, accuracy assessment reference samples for the non-native forest and non-shrub lifeforms were labeled using manual image interpretation in the office. Tidal wetlands were also assessed using manual interpretation because these areas are similarly readily identifiable on the imagery. For the manually interpreted sites, a random number generator was used to select approximately 30 sample segments for each class in the final draft fine scale vegetation map. Not all lifeform classes were assessed for accuracy. For example, the 'Major Road' class was not assessed because 1) it was developed from very high accuracy inputs (road centerlines and the impervious surface map) and 2) the build landscape is not the primary focus of this project.

4.1.2. Field-Verified Samples

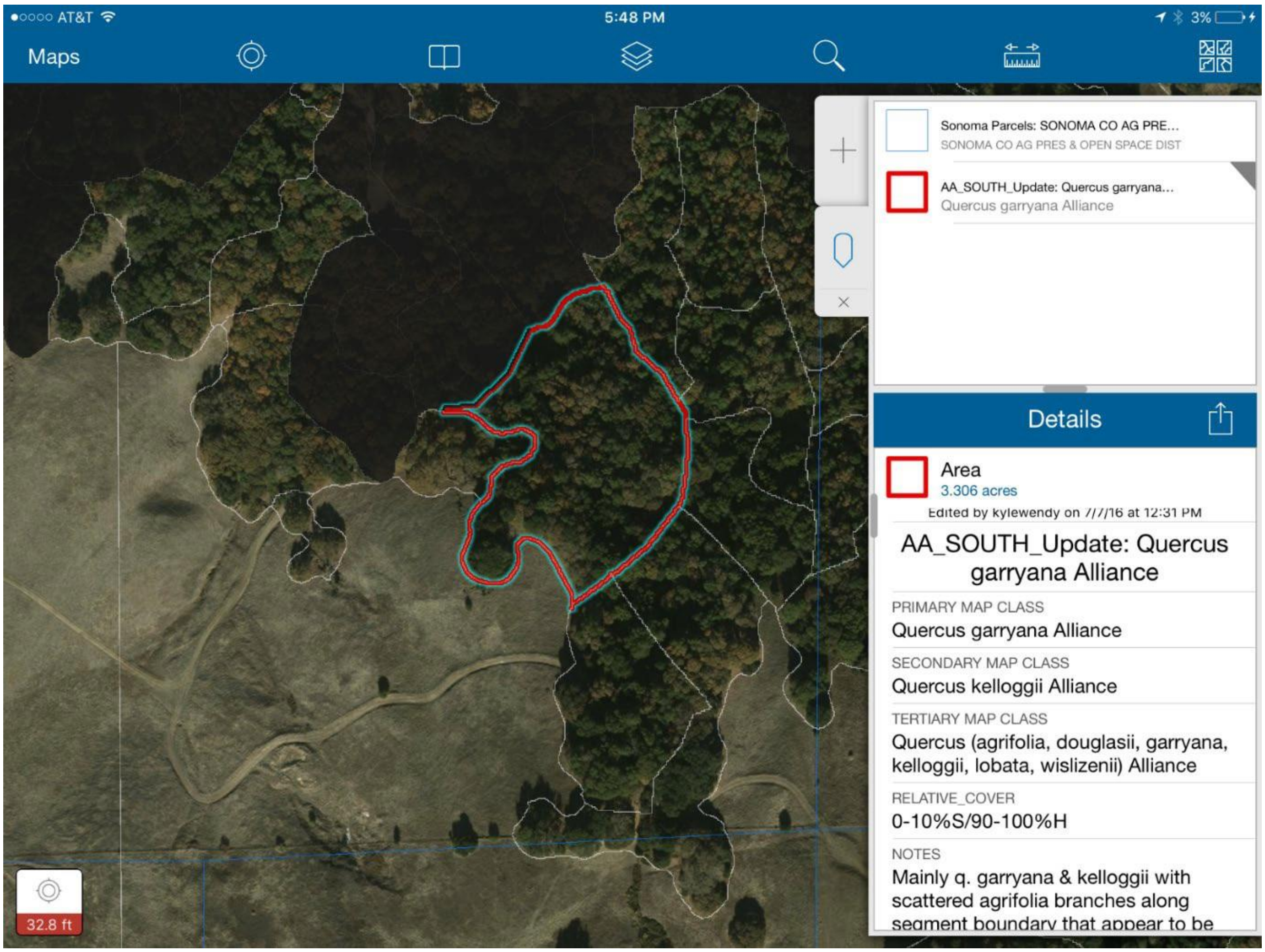
Two sources were used for field-verified accuracy assessment samples – field-collected calibration sites (see Section 3.4.2) that were not used in the development of the lifeform and fine-scale vegetation maps, and newly established field sites that were chosen using a combined stratified random/cluster sampling approach after the final draft of the fine scale vegetation map was completed. To select the new field sites, all access-restricted areas were masked out of the 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. 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 2000 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
- 10 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 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 2,500 acres

Field crews were made up of experienced botanists who had no role in creating or editing the fine scale map. 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 on an iPad (see Figure 12). 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.

A total of 553 total accuracy assessment samples were collected for 42 of the 106 fine-scale map classes. Those 42 classes represent 94% 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.

Figure 12. *Accuracy assessment form on iPad (ESRI Collector App)*



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 didn't 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 as well as 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 12 (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 provides an indication of 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 & Aerial Information Systems, 2013; Menke et al., 2011). This is the form of fuzzy analysis chosen for the San Mateo 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 relatively simple to discern and are also homogeneous, which greatly 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.

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.*

MAP	Ag	Barren and Sparsely Vegetated	Developed	Forest	Freshwater Herbaceous Wetland	Herbaceous	Riparian Forest	Shrub	Tidal Wetland	Water	Grand Total	User's Accuracy
Ag	28	0	0	0	0	2	0	0	0	0	30	93%
Barren and Sparsely Vegetated	0	28	0	0	0	0	0	0	0	0	28	100%
Developed	0	0	30	0	0	0	0	0	0	0	30	100%
Forest	0	0	0	203	0	0	0	0	0	0	203	100%
Freshwater Herbaceous Wetland	0	0	0	0	3	0	0	0	0	0	3	100%
Herbaceous	0	1	0	0	0	35	0	0	2	0	38	92%
Riparian Forest	0	0	0	1	0	0	37	2	0	0	40	93%
Shrub	0	0	0	0	0	1	1	118	0	0	120	98%
Tidal Wetland	0	0	0	0	1	1	0	0	29	0	31	94%
Water	0	0	0	0	0	0	0	0	0	30	30	100%
Grand Total	**28**	**29**	**30**	**204**	**4**	**39**	**38**	**120**	**31**	**30**	**553**	
Producer's Accuracy	**100%**	**97%**	**100%**	**100%**	**75%**	**90%**	**97%**	**98%**	**94%**	**100%**		**98%** Overall Lifeform Accuracy

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

Lifeform	**User's Accuracy**	**Producer's Accuracy**
Agriculture	93%	100%
Barren	100%	97%
Developed	100%	100%
Forest	100%	100%
Freshwater Herbaceous Wetland	100%	75%
Herbaceous	92%	90%
Riparian Forest	93%	97%
Shrub	98%	98%
Tidal Wetland	94%	94%
Water	100%	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 83.5%.

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 San Mateo County fine scale vegetation map results in an **overall fuzzy accuracy of 90.8%.**

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

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	User Accuracy	Fuzzy User Accuracy	# of Reference Sites	Producer Accuracy	Fuzzy Producer Accuracy
Developed	60,351	30	100%	100%	30	100%	100%
Sequoia sempervirens Alliance	47,347	17	82%	93%	15	93%	95%
Baccharis pilularis Alliance	43,319	46	37%	76%	23	74%	91%
Californian Annual & Perennial Grassland Mapping Unit	30,432	28	89%	89%	28	89%	89%
Quercus agrifolia Alliance	20,786	23	83%	89%	23	83%	88%
Pseudotsuga menziesii – Notholithocarpus densiflorus / Vaccinium ovatum Associa	19,725	13	100%	100%	17	76%	86%
Water	14,055	30	100%	100%	30	100%	100%
Eucalyptus (globulus, camaldulensis) Provisional Semi-Natural Assocation	4,924	27	100%	100%	27	100%	100%
Umbellularia californica Mapping Unit	4,888	20	100%	100%	23	87%	92%
Salix lasiolepis Alliance	4,634	24	83%	85%	21	95%	96%
Agriculture	3,978	30	93%	93%	28	100%	100%
Pinus radiata Plantation Provisional Semi-Natural Association	3,668	25	92%	96%	26	88%	98%
Tidal Wetland	3,516	31	94%	94%	31	94%	94%
Toxicodendron diversilobum – (Baccharis pilularis) Association	3,503	11	64%	69%	23	30%	79%
Frangula californica ssp. californica – Baccharis pilularis / Scrophularia californica	2,982	19	58%	82%	16	69%	94%
Barren and Sparsely Vegetated	2,756	27	100%	100%	29	93%	94%
Mesic Coastal Scrub Mapping Unit	2,573	14	71%	77%	19	53%	61%
Acer macrophyllum – Alnus rubra Alliance	2,467	15	93%	95%	16	88%	90%
Notholithocarpus densiflorus Alliance	2,286	14	100%	100%	15	93%	97%
Quercus chrysolepis (tree) Alliance	1,931	14	93%	99%	13	100%	100%
Hesperocyparis macrocarpa Ruderal Provisional Semi-Natural Association	1,410	11	64%	87%	8	88%	98%
Gaultheria shallon – Rubus (ursinus) Alliance	1,259	4	75%	80%	8	38%	50%
Artemisia californica – (Salvia leucophylla) Alliance	1,184	11	64%	84%	8	88%	95%
Adenostoma fasciculatum Alliance	969	4	75%	90%	4	75%	85%
Quercus (agrifolia, douglasii, garryana, kelloggii, lobata, wislizeni) Alliance	947	11	82%	91%	12	75%	90%
Arctostaphylos (crustacea, tomentosa) Alliance	907	0	0%	0%	1	0%	60%
Corylus cornuta / Polystichum munitum Association	723	4	75%	80%	4	75%	95%
Aesculus californica Alliance	569	6	83%	97%	6	83%	97%
Arbutus menziesii Alliance	564	5	60%	68%	3	100%	100%
Quercus lobata Mapping Unit	501	9	78%	82%	10	70%	76%
Ceanothus thyrsiflorus Alliance	470	3	100%	100%	6	50%	90%
Prunus ilicifolia – Heteromeles arbutifolia – Ceanothus spinosus Alliance	436	2	100%	100%	2	100%	100%
Arid West Freshwater Emergent Marsh Group	396	3	100%	100%	4	75%	75%
Quercus douglasii Alliance	390	7	86%	97%	6	100%	100%
Rubus spectabilis – Morella californica Alliance	273	1	100%	100%	4	25%	35%
Mesembryanthemum spp. – Carpobrotus spp. Semi-Natural Alliance	265	7	100%	100%	9	78%	82%
Cornus sericea – Salix (lasiolepis, exigua) Association	238	0	0%	0%	1	0%	0%
Eriophyllum staechadifolium – Erigeron glaucus – Eriogonum latifolium Alliance	218	2	50%	70%	1	100%	100%
Non-native Shrub	205	0	0%	0%	1	0%	20%
Cortaderia (jubata, selloana) Semi-Natural Alliance	161	0	0%	0%	1	0%	80%
Quercus durata Alliance	56	1	100%	100%	1	100%	100%

Table 12. *Fine-scale deterministic map error matrix. (See [https://vegmap.press/San Mateo_error_matrix](https://vegmap.press/San_Mateo_error_matrix) for a larger-scale version of the error matrix)*

REFERENCE

MAP	Acer macrophyllum – Alnus rubra Alliance	Adenostoma fasciculatum Alliance	Aesculus californica Alliance	Ag	Arbutus menziesii Alliance	Arctostaphylos (crustacea, tomentosa) Alliance	Arid West Freshwater Emergent Marsh Group	Artemisia californica – (Salvia leucophylla) Alliance	Baccharis pilularis Alliance	Barren and Sparsely Vegetated	Californian Annual & Perennial Grassland Mapping Unit	Ceanothus thyrsiflorus Alliance	Cornus sericea – Salix (lasiolepis, exigua) Association	Cortaderia (jubata, selloana) Semi-Natural Alliance	Corylus cornuta / Polystichum munitum Association	Developed	Eriophyllum staechadifolium – Erigeron glaucus – Eriogonum latifolium Alliance	Eucalyptus (globulus, camaldulensis) Provisional Semi-Natural Association	Frangula californica ssp. californica – Baccharis pilularis / Scrophularia californica Association	Gaultheria shallon – Rubus (ursinus) Alliance	Hesperocyparis macrocarpa Ruderal Provisional Semi-Natural Association	Mesembryanthemum spp. – Carpobrotus spp. Semi-Natural Alliance	Mesic Coastal Scrub Mapping Unit	Non-native Shrub	Notholithocarpus densiflorus Alliance	Pinus radiata Plantation Provisional Semi-Natural Association	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 chrysolepis (tree) Alliance	Quercus douglasii Alliance	Quercus durata Alliance	Quercus lobata Mapping Unit	Rubus spectabilis – Morella californica Alliance	Salix lasiolepis Alliance	Sequoia sempervirens Alliance	Tidal Wetland	Toxicodendron diversilobum – (Baccharis pilularis) Association	Umbellularia californica Mapping Unit	Water	Total	User's Accuracy
Acer macrophyllum – Alnus rubra Alliance	14	0	0	0	0	0	0	0	0	0	0	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	15	93%
Adenostoma fasciculatum Alliance	0	3	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	4	75%
Aesculus californica Alliance	0	0	5	0	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	6	83%
Ag	0	0	0	28	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	30	93%
Alnus rhombifolia 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	1	0	0	0	0	0	0	0	0	0	0	0	1	0%
Arbutus menziesii Alliance	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	1	0	0	0	0	0	0	0	0	0	1	0	5	60%
Arid West Freshwater Emergent Marsh Group	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	3	100%
Artemisia californica – (Salvia leucophylla) Alliance	0	1	0	0	0	0	0	7	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	2	0	0	11	64%
Baccharis pilularis Alliance	0	0	0	0	0	0	0	1	17	0	1	3	0	0	1	0	0	0	5	1	0	0	5	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	11	0	0	46	37%
Barren and Sparsely Vegetated	0	0	0	0	0	0	0	0	0	27	0	0	0	0	0	0	0	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	100%
Californian Annual & Perennial Grassland Mapping Unit	0	0	0	0	0	0	0	0	0	1	25	0	0	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	28	89%
Californian Cliff, Scree & Rock Vegetation Group	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	1	0%
Ceanothus thyrsiflorus 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	3	100%
Conium maculatum – Foeniculum vulgare Semi-Natural Alliance	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	1	0%
Corylus cornuta / Polystichum munitum Association	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	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	4	75%
Developed	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	30	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	30	100%
Eriophyllum staechadifolium – Erigeron glaucus – Eriogonum latifolium Alliance	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	50%
Eucalyptus (globulus, camaldulensis) Provisional Semi-Natural Assocation	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	27	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	27	100%
Frangula californica ssp. californica – Baccharis pilularis / Scrophularia californica Associati	0	0	0	0	0	0	0	0	4	0	0	0	0	0	0	0	0	0	11	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1	0	0	19	58%
Gaultheria shallon – Rubus (ursinus) Alliance	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	1	0	0	4	75%
Hesperocyparis macrocarpa Ruderal Provisional Semi-Natural Association	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	3	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	11	64%
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	7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	7	100%
Mesic Coastal Scrub Mapping Unit	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	1	0	0	10	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1	0	0	14	71%
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	1	0	0	0	0	0	0	0	0	0	0	0	1	0%
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	14	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	14	100%
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	1	0	0	0	0	23	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	25	92%
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	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	100%
Pseudotsuga menziesii – Notholithocarpus densiflorus / Vaccinium ovatum 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	13	0	0	0	0	0	0	0	0	0	0	0	0	0	13	100%
Quercus (agrifolia, douglasii, garryana, kelloggii, lobata, wislizeni) Alliance	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	9	0	0	0	0	1	0	0	0	0	0	0	0	11	82%
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	19	0	0	0	2	0	0	1	0	0	1	0	23	83%
Quercus chrysolepis (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	1	13	0	0	0	0	0	0	0	0	0	0	14	93%
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	1	0	0	6	0	0	0	0	0	0	0	0	0	7	86%
Quercus durata 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	1	0	0	0	0	0	0	0	0	1	100%
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	1	0	0	0	0	7	0	0	0	0	0	1	0	9	78%
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	1	0	0	0	0	0	0	1	100%
Salix lasiolepis Alliance	2	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	1	20	0	0	0	0	0	24	83%
Sequoia sempervirens 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	1	0	0	2	0	0	0	0	0	0	0	0	14	0	0	0	0	17	82%
Tidal Wetland	0	0	0	0	0	0	1	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	29	0	0	0	31	94%
Toxicodendron diversilobum – (Baccharis pilularis) Association	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	2	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	7	0	0	11	64%
Umbellularia californica 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	20	0	20	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	30	30	100%
Total	16	4	6	28	3	1	4	8	23	29	28	6	1	1	4	30	1	27	16	8	8	9	19	1	15	26	2	17	12	23	13	6	1	10	4	21	15	31	23	23	30		
Producer's Accuracy	88%	75%	83%	100%	100%	0%	75%	88%	74%	93%	89%	50%	0%	0%	75%	100%	100%	100%	69%	38%	88%	78%	53%	0%	93%	88%	100%	76%	75%	83%	100%	100%	100%	70%	25%	95%	93%	94%	30%	87%	100%		
																																										Overall Accuracy	**83.5%**

4.4. Discussion

As indicated by the lifeform error matrix, there is very little confusion in the lifeform map. Only one lifeform class, freshwater herbaceous wetland, has a user or producer accuracies below 80%. **19 map classes representing 68% of the county acreage have both producer's and user's accuracies above 80%.**

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. For example, the *Baccharis pilularis Alliance* contains significant errors of commission (11) to *Toxicodendron diversilobum – (Baccharis pilularis) Association.*

The highest level of confusion in the map is in the shrublands, particularly between *Bacharris* and closely related shrub map classes. *Baccharis* is ubiquitous throughout San Mateo County, comprising 14% of the county and, therefore, is heavily sampled. *Bacharis* has 29 errors of commission, resulting in a deterministic user's accuracy of only 37%. Most of the errors of commission are to classes that contain *Baccharis pilularis* such as the *Toxicodendron diversilobum* – (*Baccharis pilularis*) Association, *Artemisia californica* – (*Salvia leucophylla*) Alliance, or the *Frangula californica* ssp. *californica – Baccharis pilularis* / *Scrophularia californica* Association. In these reference samples where, a significant amount of *Baccharis pilularis* was present. These errors between *Bacharris* and similar shrub map classes that contain *Bacharris* are acceptable (and inevitable) errors. As a result, *Baccharis* has reasonably high fuzzy producer's (76%) and user's (91%) accuracies.

4.5. Standing Dead Accuracy Assessment

A separate accuracy assessment was conducted to assess the accuracy of standing dead. Percent standing dead was assigned to each forested stand of the fine scale vegetation map. The mapping team performed an accuracy assessment on the standing dead attribute.

Selection of sites for AA was done using a stratified random sample of 90 forested fine scale map polygons, stratified by ranges of percent dead. Fifteen sites were selected from each of the following classes:

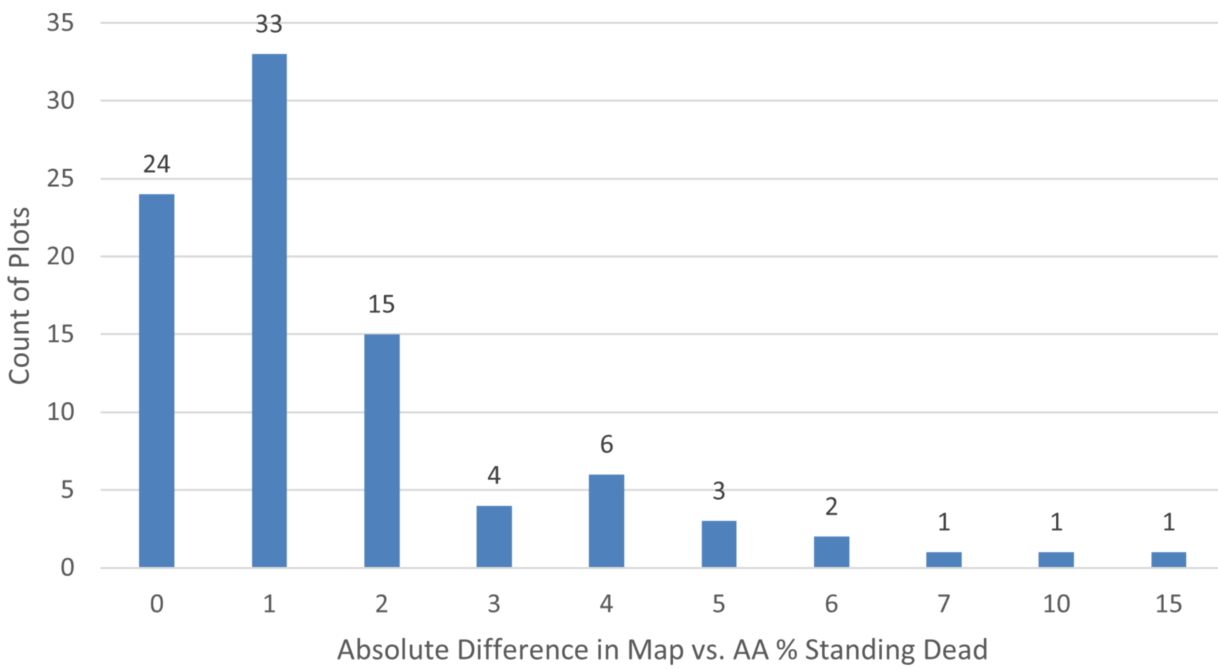
- 0% Standing Dead
- 1% Standing Dead
- 2% Standing Dead
- 3% Standing Dead
- 4-7% Standing Dead
- 7%+ Standing Dead

Only stands outside of the core urban areas were allowed to be randomly selected for AA. For each of the 90 polygons, analysts carefully digitized standing dead vegetation over 7 feet, using the 2018 high resolution imagery as visual reference. Very small areas of standing dead (less than 16 square feet) were not digitized. These analyst-validated areas of standing dead were used as a proxy for field validation of the standing dead mapping.

When the standing dead areas were completely digitized for the 90 polygons, the area of standing dead within each polygon was summed up and divided by the area of the stand with vegetation over 7 feet in height to calculate the percentage of standing dead over 7 feet in height. This number wa s compared to the value for mapped % standing dead over 7 feet.

Figure 13 shows the count of stands by absolute difference between mapped and validated % standing dead over 7 feet. The plot demonstrates that 71 of the 90 polygons that were assessed had analyst-validated standing dead that was within 2% of the mapped standing dead. This indicates that the mapping of standing dead is generally consistent with the standing dead on the landscape.

Figure 13. *Count of stands by absolute difference between mapped and validated % standing dead (n=90)*



Because humans are incapable of precisely estimating percent cover, resulting in an average variance in estimates of +/- 10% (Congalton and Green, 2019), we performed a fuzzy accuracy assessment of standing dead. For areas with very little standing dead, we allowed for much less fuzziness. For areas with greater standing dead, we allowed for more fuzziness. The reason for the ‘sliding scale’ of allowed fuzziness is that it is that image interpretation of standing dead should be within 1-2% if there is very little standing dead, with acceptable error increasing as the percent standing dead increases. Stands with very high standing dead are the most difficult to assign percent standing dead with high accuracy. Table 13 below shows the accepted fuzziness that was allowed in the accuracy assessment. To demonstrate how to interpret Table 13, if a stand was assigned 2% standing dead during analyst validation and the stand was mapped with 3% standing dead, the stand would be considered ‘Correct’ in the fuzzy accuracy assessment, since the mapped standing dead (3%) is +/- 1% of the analyst-validated standing dead (2%).

Table 13. *Accepted fuzziness in standing dead accuracy assessment*

Validated Percent Standing Dead %	**Acceptable Fuzzy Range for Map**
0-2%	+/- 1%
3-5%	+/- 2%
6-7%	+/- 3%
8-9%	+/- 4%
10-12%	+/- 5%
12-20%	+/- 7%
20% +	10%

Overall accuracy in standing dead, using the fuzzy rules defined above, was 74.4%.

5. The San Mateo Fine Scale Vegetation Map and the State Standard

The San Mateo fine scale vegetation map specifications were designed to meet the needs of the project funders and stakeholders within the available project budget. Though similar to the fine scale vegetation maps produced by the Department of Fish and Wildlife’s Vegetation

Mapping Program standards,[1] there are several important differences. CDFW VegCAMP (https://wildlife.ca.gov/Data/VegCAMP) reviewed the final San Mateo Fine Scale Vegetation Map, and key differences are summarized below:

> **San Mateo fine scale vegetation map stands are not aggregated by California Wildlife Habitat Relationship (CWHR) System cover classes**: The result is a map that is more finely segmented. The justification for keeping it this way is that the cover values in the map are very accurately derived from lidar and some people might find the fine divisions useful.
>
> *CDFW Assessment:* Stands of the same community type are broken out by cover in a way that we would consider ecologically insignificant. However, the information is all there to collapse by cover classes if the desired. There is no "loss" of information here but the user would need GIS skills to simplify the map to state standard which most users do not have.
>
> **Tree cover is really "vegetation cover that is taller than 15ft"**: Tall shrub stands (>15ft) will have high cover for this attribute and emergent tree cover would not be noted**. Shrub cover** is estimated using our standards. The process for deriving tree cover is based solely on vegetation height above 15ft rather than lifeform.
>
> *CDFW Assessment*: We are losing some information on habitat value with this approach by losing the ability to easily identify stands where there is emergent tree cover (an important wildlife habitat feature). In addition, this will make attribution for FVeg difficult because for CalFire standards, if trees are dominant (10% or more) then the tree cover should be based on the *tree cover* only. VegCAMP suggests future mapping efforts to consider breaking the height into 2 categories: 15-25ft for tall shrub/low trees and >25ft for emergent trees to better capture the tree vs. shrub strata.
>
> **Herbaceous cover is not estimated, and shrub cover is not estimated for forested stands:**
>
> *CDFW Assessment:* CDFW VegCAMP recommends estimating shrub, herbaceous cover, and non-native species (exotics) cover to support habitat conservation and restoration planning. For future maps we suggest estimating shrub and herbaceous cover in broad cover classes as we define in our standards.
>
> **Herbaceous classification is very broad:**

[1] chrome-extension://efaidnbmnnnibpcajpcglclefindmkaj/https://nrm.dfg.ca.gov/FileHandler.ashx?DocumentID=102342&inline.

CDFW Assessment: Coastal prairie vs. CA annual grassland could generally be derived by users by doing a spatial analysis on herb polygons by applying distance from coast, fog, etc. This is an acceptable limitation of the map given the additional time and effort it would require to accurately differentiate these types.

6. San Mateo County Vegetation Map Data Products

6.1. 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 6.2 provides an overview of obtaining the data products and section 6.3 provides the datasheets for each of the data products.

6.2. Obtaining Data Products

The vegetation map and related products are available for download from https://pacificvegmap.org. There are numerous ways of obtaining the data products 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 14. *Available formats for vegetation map data products from pacficvegmap.org*

Data Product	**Feature Service**	**Tile Service**	**Countywide Geodatabase**	**Countywide Layer Package**	**Layer File**	**Datasheet**
San Mateo County Fine-Scale Veg Map	✓		✓	✓	✓	✓
San Mateo County Enhanced Lifeform Map	✓		✓		✓	✓
San Mateo County Impervious Surfaces		✓	✓	✓		✓

6.3. Data Product Specifications (Datasheets)

In addition to metadata for each spatial data product, datasheets were created and made available for each of the San Mateo Veg Map data products. Links to the datasheets for the vegetation map and its derivatives are provided in Table 14.

Table 15. *Datasheets for vegetation map products*

Product	Datasheet Link
San Mateo County Fine Scale Vegetation Map	https://vegmap.press/San_Mateo_vegmap_datasheet
San Mateo County Enhanced Lifeform Map	https://vegmap.press/san_mateo_lifeform_datasheet
San Mateo County Impervious Surfaces Map	https://vegmap.press/San_Mateo_impervious_datasheet

6.4. Attributes of the Fine-scale Vegetation Map

The fine-scale vegetation map has 97,580 polygons countywide. 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 16 includes a list and description of the numerous fine-scale vegetation map attributes.

Table 16. *Fine-scale vegetation map attributes*

Fine Scale Map Attributes (Name/Alias)	**Description**
OID_COPY/ OID_COPY	Index for internal use
MAP_CLASS_18/Fine Scale Map Class in '18	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/San Mateo_vegmap_abbrevs](https://vegmap.press/SanMateo_vegmap_abbrevs)
LIFEFORM_18/Lifeform in '18	13-class lifeform label for all stands. Labels are floristically more general than the fine scale map class and forest lifeform.
ENHANCED_LIFEFORM_18/Enhanced Lifeform in '18	19-class enhanced lifeform label for all stands. Labels are floristically more general than the fine scale map class.
ABS_COVER_17/% Veg Returns Over 15 ft. in '17	Absolute cover of trees greater than 15 feet in height. Derived from 2019 lidar data.
REL_CON_COV_18/Relative % Conifer Cover in '18	Relative conifer cover, estimating the percent of tree canopy >= 15 ft. is conifer. Derived from manual image interpretation of '18 imagery.
REL_HDW_COV_18/Relative % Hardwood Cover in '18	Relative hardwood cover, estimating the percent of tree canopy >= 15 ft. is hardwood. Derived from manual image interpretation of '18 imagery.
HDW_COVER_18/Absolute % Hardwood Cover in '18	Absolute hardwood cover, derived as: ((relative % hardwood cover/100) x (absolute % hardwood/100)) * 100
CON_COVER_18/Absolute % Conifer Cover in '18	Absolute conifer cover, derived as: ((relative % conifer cover/100) x (absolute % cover/100)) * 100
SHB_COVER_18/Absolute % Shrub Cover in '18	Absolute shrub cover for herbaceous and shrub stands. Derived from manual image interpretation of '18 imagery.
STAND_HT_MN_17/Mean LiDAR Stand Height in '17 (ft.)	Mean stand height from LiDAR-derived canopy height model (CHM).
STAND_HT_MN_17/Median LiDAR Stand Height in '17 (ft.)	Median stand height from LiDAR-derived canopy height model (CHM).
STAND_HT_MX_17/Maximum LiDAR Stand Height in '17 (ft.)	Maximum stand height from LiDAR-derived canopy height model (CHM).
STAND_HT_SD_17/Standard Deviation LiDAR Stand Height in '17 (ft.)	Standard deviation stand height from LiDAR-derived canopy height model (CHM).

Fine Scale Map Attributes (Name/Alias)	Description
STANDING_DEAD_19/% Standing Dead 2018	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 2018.
SD_PRESENCE/Standing Dead Presence in 2018	Indicates the presence of standing dead vegetation at under .5% of the stand's cover above 7 ft. (trace amount of standing dead).
LADDER_FUELS_17/Mean Ladder Fuels 1-4 Meters (0-1)	Mean lidar derived 'ladder fuels' for forested stands. Represents density of lidar returns between 1-4 meters above ground. Integrated from the 2017 lidar derived ladder fuels raster (https://onetam.maps.arcgis.com/home/item.html?id=9bb7e5236660 4d2ea9ecacaf95c318df)using the zonal statistics function. The ladder fuel metric is a 0-1 metric; 0 is lowest, 1 is highest.
SLOPE_MEAN/Mean Slope Degrees	Mean slope degrees, derived from the 2017 lidar data.
SLOPE_STD/Standard Deviation Slope Degrees	Standard deviation slope degrees, derived from the 2017 lidar data.
SLOPE_MAX/Maximum Slope Degrees	Maximum slope degrees, derived from the 2017 lidar data.
PERVIOUS_18/% Pervious in '18	Percent of stand that was pervious in 2018. Integrated from the San Mateo County impervious surface map.
IMPERVIOUS_18/% Impervious in '18	Percent of stand that was impervious in 2018. Integrated from the San Mateo County impervious surface map.
PAVED_RD_18/% Paved Road in '18	Percent of stand that was paved road in 2018. Integrated from the San Mateo County impervious surface map.
DIRT_RD_18/% Dirt and Gravel Road in '18	Percent of stand that was dirt or gravel road in 2018. Integrated from the San Mateo County impervious surface map.
OTHER_IMPERVIOUS_18/% Other Impervious in '18	Percent of stand that was a paved or unpaved, non-road surface (such as a paved or unpaved parking lot) in 2018. Integrated from the San Mateo County impervious surface map.
BUILDING_18/% Buildings in '18	Percent of stand that was a building in 2018. Integrated from the San Mateo County impervious surface map.
ACRES/ Acres	Acres of land encompassed by the stand.
SOURCE/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.
URBAN_WINDOW/Urban Window Flag	A flag that indicates if the stand was in a core urban area (the 'urban window').

Fine Scale Map Attributes (Name/Alias)	Description
COUNTY/County	Indicates whether the stand was in San Francisco or San Mateo County.

7. References

CDFW & Aerial Information Systems, Inc. (2013). *2013 California Desert Vegetation Map and Accuracy Assessment in Support of the Desert Renewable Energy Conservation Plan*. https://nrm.dfg.ca.gov/FileHandler.ashx?DocumentID=62825&inline

Congalton, R.G. (2010). Remote Sensing: An Overview. *GIS Science and Remote Sensing*. 47 (4): 443-59.

Congalton, R.G. & Green, K. (2019). *Assessing the Accuracy of Remotely Sensed Data: Principles and Practices*, *Third Edition*. Boca Raton, FL: CRC/Taylor & Francis.

Dilts, T., Yang, J., & Weisberg, P. (2010*). ArcUser Magazine. Mapping Riparian Vegetation with lidar Data: Predicting Plant Community Distribution Using Height Above River and Flood Height*. 13 (1): 18-21.

Green, K., Cogalton, R.G., & Tukman, M. (2017). *Imagery and GIS: Best Practices for Extracting Information from Imagery*. Redlands, CA: ESRI Press.

Breiman, L. (2001). Random Forests*. Machine Learning.* 45(1), 5-32.

Menke, J., Reyes, E., Johnson, D., Evens, J., Sikes, K., Keeler-Wolf, T., & Yacoub, R. (2011). *Northern Sierra Nevada Foothills Vegetation Project: Vegetation Mapping Report*. https://nrm.dfg.ca.gov/FileHandler.ashx?DocumentID=31346&inline

Meyer, D., Dimitriadou, E., Hornik, K., Weingessel, A., & Leisch, F. (2018). *e1071: Misc Functions of the Department of Statistics, Probability Theory Group* (Formerly: E1071), TU Wien. R package version 1.7-0. https://CRAN.R-project.org/package=e1071

R Core Team. (2013). *R: A language and environment for statistical computing.* R Foundation for Statistical Computing. Vienna, Austria. URL http://www.R-project.org/

Sawyer, J.O., Keeler-Wolf, T., & Evens, J.M. (2009). *A Manual of California Vegetation, Second Edition*. Sacramento, CA: California Native Plant Society.

San Francisco Estuary Institute and Aquatic Science Center (SFEI ASC). (2015). Bay Area Aquatic Resource Inventory (BAARI) Version 2 GIS Data.

San Francisco Estuary Institute (SFEI). (2017). California Aquatic Resource Inventory (CARI) Version 0.3.

Spurr, S. (1960). *Photogrammetry and Photo-Interpretation*. New York: The Ronald Press Company.