Alameda and Contra Costa Fine Scale Vegetation Map

Final Report

Prepared by Tukman Geospatial for East Bay Regional Parks

Recommended Citation: Tukman Geospatial. (2025). *2020 Alameda and Contra Costa county fine scale vegetation map* [final report].

https://vegmap.press/alcc_finescale_final_report

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1. Executive Summary

This report documents the methods and results of the fine scale, countywide vegetation map of Alameda and Contra Costa Counties. The map represents the state of the landscape in summer, 2020, when National Aerial Imagery Program (NAIP) data was collected.

In 2020 East Bay Regional Parks District (EBRPD) initiated a fine scale vegetation mapping project in Alameda and Contra Costa counties. EBRPD manages thousands of acres of land, balancing habitat conservation, wildfire risk reduction, and sustainable public recreation. Modern fine scale datasets, derived from lidar and high-resolution data, and field work, were identified as an important data gap to fill. EBRPD facilitated multiple meetings with potential project stakeholders and was able to build a consortium of funders to map all of Alameda and Contra Costa counties. The consortium included CALFIRE, California Department of Fish and Wildlife, and the California State Coastal Conservancy, and United States Geological Survey, 3D Elevation Program. Over a 3-year period, the project, collectively referred to as the "Alameda and Contra Costa Fine Scale Veg Map", produced numerous environmental GIS products including an impervious surfaces map, a wildland fuels map, a wildfire hazard map, a wildfire risk to structures map, and other land cover maps. A 115-class fine scale vegetation map was completed in May 2025 that details vegetation communities and agricultural land cover types, including forests, grasslands, riparian vegetation, wetlands, and croplands.

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

Development of the Alameda and Contra Costa fine scale vegetation map was managed by the East Bay Regional Park District and staffed by personnel from Tukman Geospatial. The fine scale vegetation map effort included field surveys by a team of trained botanists from CNPS, who were assisted by botanists from Nomad Ecology Consulting. Data from these surveys, combined with older surveys from previous efforts, were analyzed by the California Native Plant Society (CNPS) Vegetation Program, with support from the California Department of Fish and Wildlife Vegetation Classification and Mapping Program (VegCAMP) to develop an Alameda and Contra Costa County-specific vegetation classification. For more information on the field sampling and vegetation classification work, refer to the final report issued by CNPS and corresponding floristic descriptions.

As part of this effort, the project team assembled, harmonized and created lidar derivatives from the most recent/best available lidar data in the two-county area. The harmonized lidar point cloud, and many of its derivatives, were used extensively during the process of developing the fine scale vegetation map. The lidar data was used in conjunction with the optical NAIP data. Optical data used throughout the project included 2020 NAIP as well as various dates of earlier NAIP imagery. 2022 NAIP was released during map production too late to be the authoritative imagery for mapping but was used for the mapping of standing dead trees which occurred at the end of the mapping process.

In late 2023, an enhanced lifeform map was produced with funding from CAL FIRE to support the development of wildfire hazard and risk maps. The enhanced lifeform map also serves as the foundation for the much more floristically detailed fine scale vegetation map. The lifeform map was developed using expert systems rulesets in Trimble Ecognition®, followed by manual editing. Refinements to the lifeform map were completed in 2024 and 2025 concurrently with fine scale vegetation map finalization.

In 2023-2025, Tukman Geospatial and Nomad Ecology staff conducted countywide reconnaissance field work to support fine scale mapping. Field-collected data were used to train automated machine learning algorithms, which produced a semi-automated countywide fine scale vegetation and habitat map. Throughout 2024 and 2025, Tukman Geospatial manually edited the fine scale maps, and Tukman Geospatial and Nomad Ecology went to the field for validation trips to inform and improve the manual editing process. In January of 2025, draft maps were distributed and reviewed by Alameda and Contra Costa counties' community of land managers and by the funders of the project. Input from these groups was used to further refine the map. The countywide fine scale vegetation map and related data products were made public in May 2025. In total, 115 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 2025. Accuracy assessment results were compiled and analyzed May of 2025. **The overall accuracy of the vegetation map by lifeform is 97%. The overall accuracy of the vegetation map by fine scale vegetation map class is 80.8%, with an overall 'fuzzy' accuracy of 93.1%.**

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

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

The fine scale vegetation map also provides information relevant to forest health for the two counties. Specifically, the map includes stand-by-stand attribution about canopy mortality (percent standing dead in 2022). The standing dead information will be useful for tracking the spread of pathogens in the area.

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

This report is organized into the following sections:

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

2. Acknowledgements

The Alameda and Contra Costa Fine Scale Vegetation map was made by a team of professionals led by Eddie Fitzsimmons and Julia Murphy. Others who contributed to the effort include Elliot Kuskulis, Brittany Burnett, Dylan Loudon, and Mark Tukman.

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

- CAL FIRE - Santa Clara Unit
- California Department of Fish and Wildlife
- California State Coastal Conservancy
- East Bay Regional Park District
- United States Geological Survey, 3D Elevation Program

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

- Alameda County Fire Department
- Applied Technology & Science
- California Department of Fish and Wildlife, VegCAMP
- California State Parks
- California Native Plant Society (CNPS)
- Consortium of California Herbaria
- Diablo Firesafe Council
- Digital Mapping Solutions
- East Bay Municipal Utility District (EBMUD)
- Golden Gate National Parks Conservancy
- Karen Thorne, PhD, Research Ecologist, USGS Western Ecological Research Center
- Kass Green and Associates
- National Park Service (NPS)
- Nomad Ecology Consulting, with special extra thanks to Heath Bartosh and Erin McDermott
- Quantum Spatial/NV5
- San Francisco Public Utilities Commission
- Sequoia Ecological Consulting
- Shelly Benson of Benson Bio Consulting
- Tobias Rohmer of the San Francisco Estuary Invasive Spartina Project
- Together Bay Area
- Vollmar Natural Lands Consulting
- Wildland Res. Mgt

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

3. Mapping Methods

3.1. Introduction

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

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

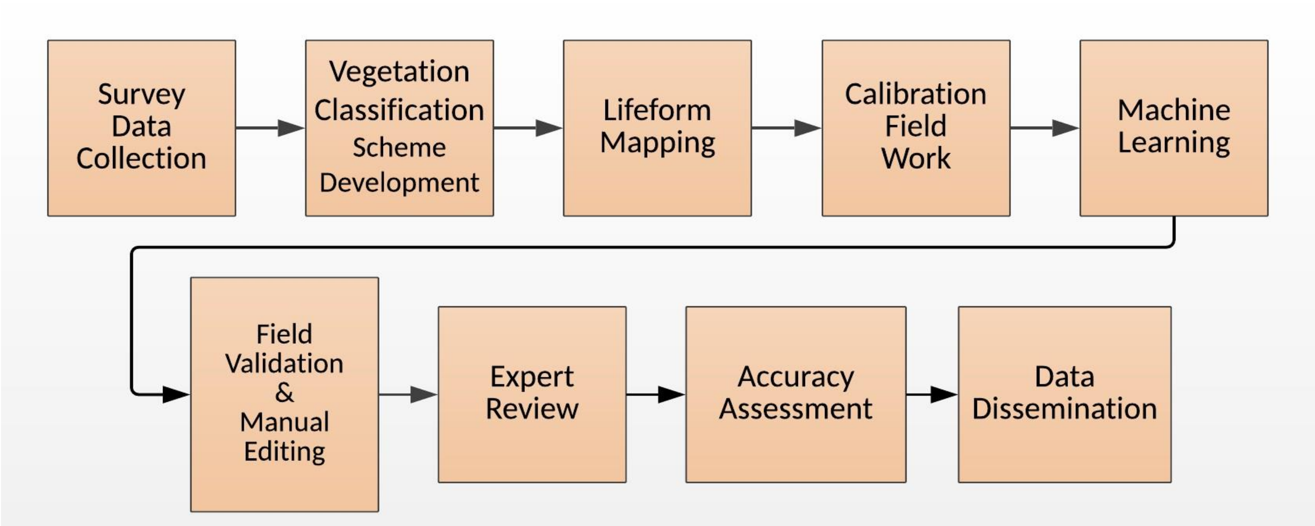
Since the early 1900s, these steps have been completed through the manual interpretation of remotely sensed data to delineate and identify vegetation using seven indicators of vegetation type; color, tone, texture, location, context, height, and shape of the feature of interest (Spurr, 1960). While a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

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

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

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

Figure 1. *Fine scale mapping steps*



3.2. Plot Data Collection and Classification Development

The fine scale mapping effort began with countywide vegetation survey data collection by a team of trained botanists. These data were combined with surveys from previous efforts by the California Native Plant Society (CNPS). The collective body of new and older surveys was analyzed by CNPS to create a comprehensive classification, a dichotomous key that provides decision rules for labeling fine scale vegetation classes, and vegetation descriptions for each fine scale vegetation class in Alameda and Contra Costa 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 US National Vegetation Classification system.

Table 1. *Table of classification related data products*

Data Product	Description	Download URL
CNPS Vegetation Classification of Alliances and Associations	Main body of classification document. Includes a floristic key.	https://vegmap.press/alcc_descriptions
Alliance and Associations Vegetation Descriptions	Appendix D of classification document (detailed descriptions of alliances)	https://vegmap.press/alcc_classification_report

Data Product	Description	Download URL
Alameda – Contra Costa Fine scale Mapping Key	Key used for lifeform mapping and fine scale vegetation mapping	https://vegmap.press/alcc_mapping_key

During the classification development phase, minimum mapping units (MMUs) were established for the vegetation mapping project. An MMU is the smallest area to be mapped on the ground. Many mapping projects have a single MMU; for this project, the mapping team chose to map different features at different MMUs. For example, riparian vegetation had a smaller MMU than upland vegetation types because riparian vegetation is a sensitive habitat, is uncommon on the landscape, and very important from a land manager's perspective. Table 2 shows the MMUs for the various features mapped in the Alameda and Contra Costa 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
Upland Herbaceous Classes	1/2 acre for contrasting lifeforms; 1 acre for different alliances in the same lifeform
Wetland Herbaceous Classes	1/4 acre
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 Alameda and Contra Costa impervious surfaces map, which is referenced in this report but is not a vegetation map product. The lifeform map and fine scale vegetation map show major road polygons and impervious features that have contiguous impervious areas (not including roads) of .2 acres or more.

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

3.3. Lifeform Mapping

3.3.1 Lifeform Mapping Overview

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

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

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

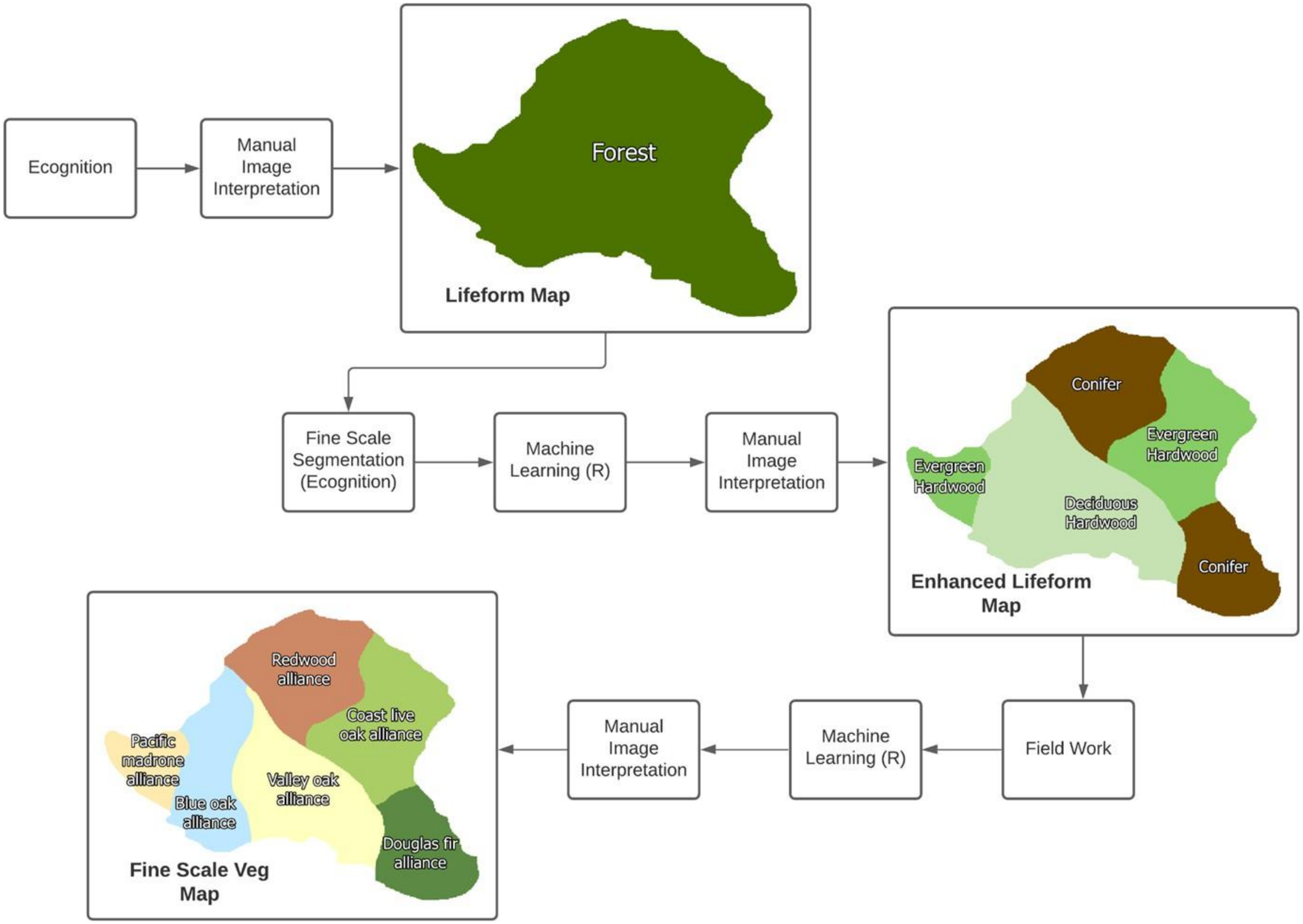


Table 3. *Enhanced lifeform classes and acreages, Alameda and Contra Costa Counties*

Class	Description	Acres
Alkali Grasses and Forbs	Areas mapped as alkaline types in interior settings (saline or alkali sinks and soils) in the fine scale vegetation map; absolute tree and shrub cover is less than 10%. Refer to the fine scale mapping key for decision rules.	454
Aquatic Vegetation	Freshwater stands dominated by aquatic, floating or submerged plants.	939
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.	6,397
Deciduous Hardwood	Areas mapped as deciduous hardwood types in the fine scale vegetation map, such as blue oak, valley oak, black oak, buckeye, etc. Does not include riparian hardwood types. Refer to the fine scale mapping key for decision rules.	68,783
Developed	Human-caused developed areas greater than 0.2 acres; areas include irrigated lawns, heavily landscaped garden and patio areas, bocce courts, tennis courts, sport courts, developed horse riding arenas, baseball fields, soccer fields, golf courses, swimming pools, and playground areas.	237,107
Eucalyptus	Areas where tree species are at least 10% absolute cover and *Eucalyptus spp.* dominates tree cover (>50% relative tree cover).	6,698
Evergreen Hardwood	Areas mapped as evergreen hardwood types in the fine scale vegetation map, such as tanoak, madrone, live oak, etc. Does not include riparian hardwood types. Refer to the fine scale mapping key for decision rules.	87,333
Forest	Areas of forest between ½ acre and 1 acre (*forest fragments*, see discussion above in section 3.2). Mapping these small stands to their enhanced lifeform and fine scale class would result in low accuracies. They are included in the map because these areas are mappable at the lifeform level and because they are important for fuels mapping and other use cases.	6,106
Freshwater Wetland	Areas that are depressional, wet all year long, and/or exhibit obvious herbaceous wetland vegetation in the 2020 imagery; absolute tree and shrub cover are both less than 10%.	11,668
Herbaceous	Areas where upland herbaceous vegetation is at least 10% absolute cover; absolute tree and shrub cover is less than 10%.	348,565
Intensively Managed Hayfield or Irrigated Pasture	Area is an intensively managed hayfield that is mechanically turned over every year or it is an irrigated pasture	16,639
Major Road	Area is a major road.	5,482

Class	Description	Acres
Non-native Forest	Areas where tree species are at least 10% absolute cover; tree cover dominated by ornamental non-native species (>50% relative tree cover).	14,817
Non-native Herbaceous	Areas where herbaceous vegetation is at least 10% absolute cover; non-native herbaceous species dominate the herbaceous stratum; absolute tree and shrub cover are both less than 10%.	5,177
Non-native Shrub	Areas where shrub species are at least 10% absolute cover; absolute tree cover is less than 10%; relative shrub cover is dominated by non-native species.	1,487
Nursery or Ornamental Horticulture Area	Area is a nursery or horticultural area.	233
Orchard or Grove	Area is an orchard or grove of fruit or nut trees.	6,918
Pine/Cypress	Areas mapped as pine and cypress types in the fine scale vegetation map. Refer to the fine scale mapping key for decision rules.	8,475
Redwood/Douglas fir	Areas mapped as redwood and or Douglas fir types in the fine scale vegetation map. Refer to the fine scale mapping key for decision rules.	3,394
Riparian Forest	Areas where tree species are at least 10% absolute cover; obligate riparian tree genera (alder, willow, cottonwood, ash, sycamore) dominate tree cover (>50% relative tree cover).	6,573
Riparian Shrub	Areas where woody riparian shrub species are at least 10% absolute cover; obligate riparian genera (e.g., shrubby willow trees) dominate shrub cover (>50% relative shrub cover).	2,523
Row Crop	Areas that are either active annual or perennial row crops or are tilled and prepped for planting of row crops or are in between plantings. Row crops include annual crops like lettuce, spinach, corn, etc. and perennial crops such as strawberries, raspberries, lavender, or actively managed Christmas tree farms. Temporary greenhouses should be classified as Row Crops.	17,645
Tidal Wetland	Salt marsh areas dominated by salt-tolerant wetland species.	10,413
Shrub	Area where native upland woody shrubs are at least 10% absolute cover; absolute tree cover is less than 10%.	39,130
Tidal Mudflat	Areas in the intertidal zone that are unvegetated and exposed during low tide.	1,367
Vineyard	Area is a vineyard.	5,118
Water	Water covers the area.	67,236
	Total:	986,667

3.3.2 Lifeform and Enhanced Mapping Methods

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

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

After a round of editing on the initial countywide map (with 'Native Forest' as a single class), a second round of image segmentation is used to divide the broad 'Native Forest' class into smaller forested segments that are compositionally and structurally homogenous (see Section 3.3.7). Fine scale segmentation divides the large and floristically broad native forest and shrub areas into much smaller image segments suitable for fine scale mapping. There are 27 unique classes in the enhanced lifeform map (see Table 3 above).

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

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

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

Layer	Roles in Lifeform Mapping	Source
Summer 2020 4-band NAIP Imagery	Used for reference for manual editors.	Various
NDVI from 2020 NAIP	Used as the primary spectral input for lifeform mapping in Ecognition® and used in Ecognition® decision rules for discriminating between vegetated and non-vegetated areas.	Tukman Geospatial, NV5

Layer	Roles in Lifeform Mapping	Source
2017-2022 lidar Derived Canopy Height Model (CHM) *See Figures 3 + 4*	Represents height of vegetation. The CHM was used widely as an input to the Ecognition® rule set, especially for mapping the natural lifeform classes.	Tukman Geospatial, Sanborn, NV5
Road Centerlines	The Alameda and Contra Costa County Road Centerlines datasets were used to include major roads in the lifeform map.	Open Street Map, CAL FIRE, Alameda and Contra Costa County
lidar-derived DEM, Slope and Aspect	Used for various Ecognition® decision rules.	Tukman Geospatial, Sanborn
Sentinel-2 Data	Multi-temporal Sentinel data from the past 3 years was used as a predictor variable in the machine learning phase of enhanced lifeform mapping.	European Space Agency / Google Earth Engine
Lidar percentile heights	Percentile heights derived from 2017-2022 lidar data were used in the machine learning part of the enhanced lifeform workflow.	Tukman Geospatial
Lidar canopy volume profiles	Canopy volume profiles derived from 2017-2022 lidar data were used in the machine learning part of the enhanced lifeform workflow.	Tukman Geospatial
Other lidar derivatives	Other lidar derivatives, such as highest hit slope, were used in the machine learning part of the enhanced lifeform workflow.	Tukman Geospatial

Note that the lidar data used for the vegetation map was an assemblage of the most recent, best available existing lidar data in the two-county area. As such the data varies in USGS quality level and date of acquisition. Although the vegetation map classes in the fine scale map reflect the ground conditions as of the 2020 NAIP imagery, the lidar attributes in the fine scale vegetation map (e.g., canopy height) reflect a variety of ground condition dates (ranging from 2017-2022). Figure 3 shows the lidar collection year for the lidar used in the fine scale vegetation map. Figure 4 shows the USGS quality level of the lidar used. A suite of lidar data products produced by this project, including a canopy height model, are available at pacificvegmap.org.

Figure 3. *Lidar collection year for lidar used in the fine scale vegetation map*

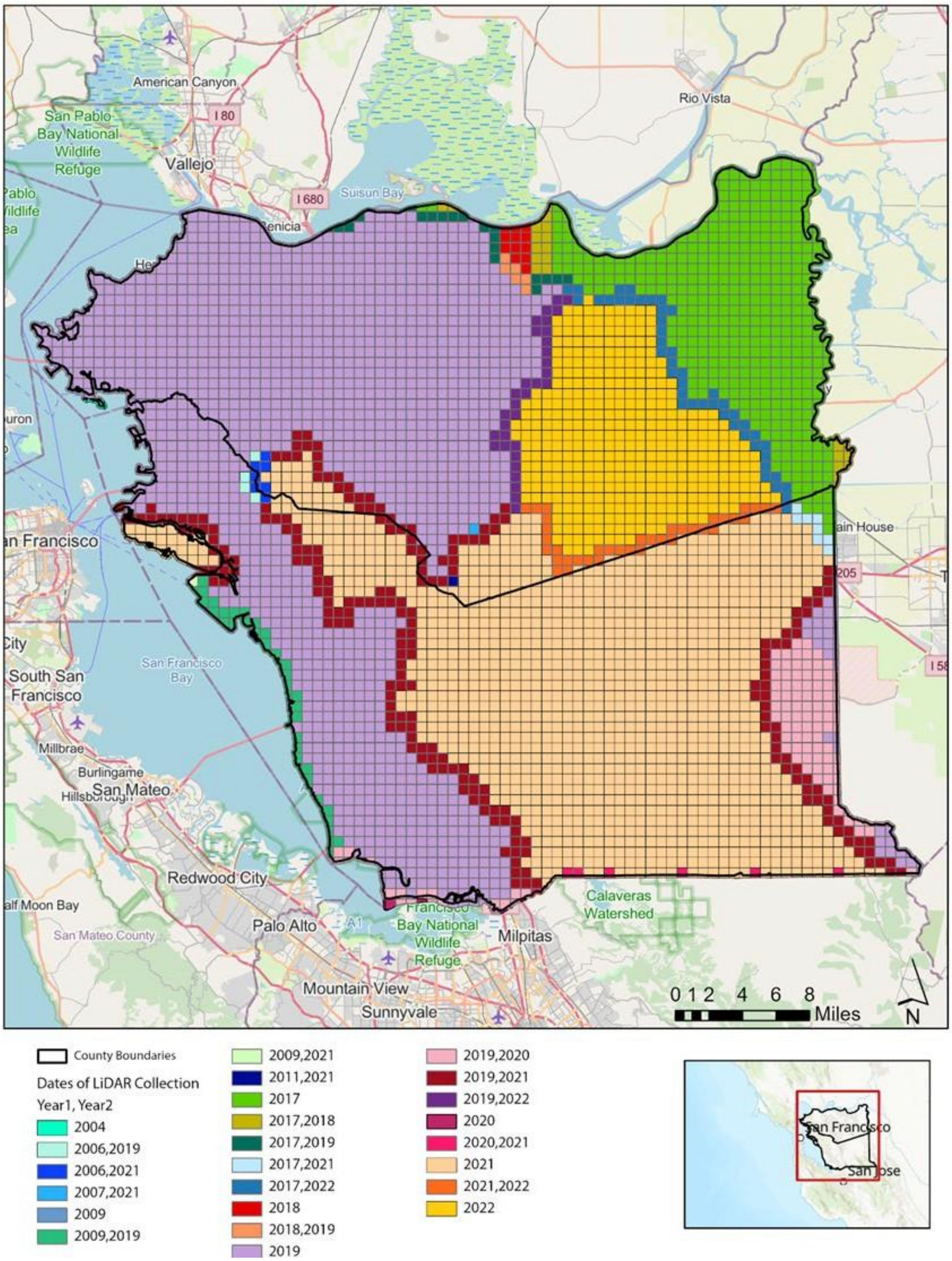
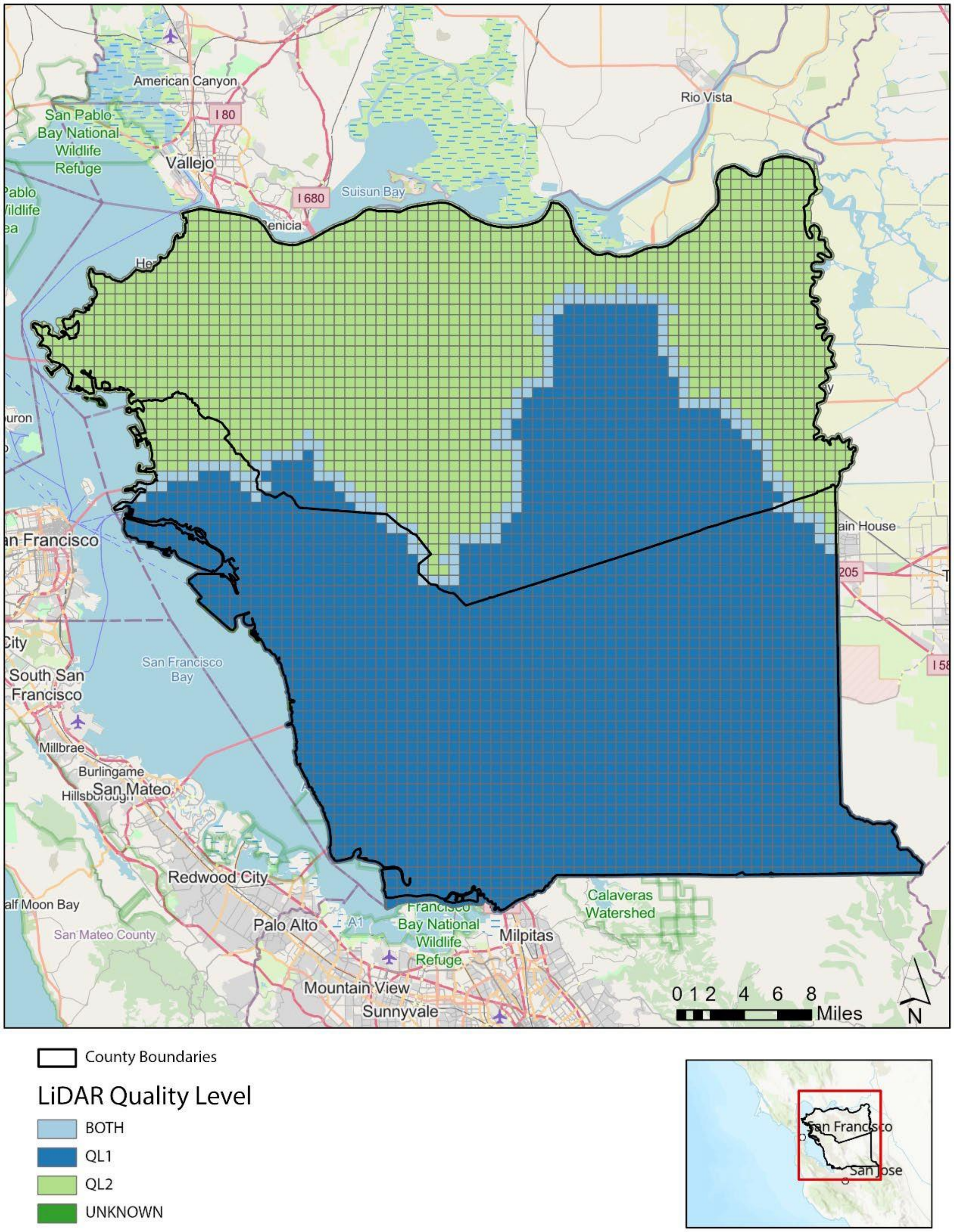


Figure 4. *Lidar quality level for lidar used in the fine scale vegetation map*



3.3.3 Lifeform Map - Built Classes

While the natural classes in the lifeform and enhanced lifeform maps are mapped by Ecognition® using rules developed solely from the imagery and the lidar data (except for wetlands, which are discussed below), classes depicting the built landscape are mapped by

Ecognition® using additional data sources and workflows. This section describes how the built classes are mapped.

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

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

Minor roads and individual building footprints are omitted from both the lifeform and fine scale vegetation maps intentionally since these maps are meant to focus on the natural landscape. A separate product – the Alameda and Contra Costa impervious surfaces map – provides 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 very fine scale detail regarding the built environment that exists in the impervious map is embedded in the fine scale map polygons. The work to embed information about imperviousness into the fine scale vegetation map occurred during final processing (see section 3.6).

3.3.4 Mapping Inside the Urban Core

In past fine scale vegetation mapping projects, Tukman Geospatial created an 'Urban Window,' to define the urban core. Inside the urban window, mapping was typically performed at larger minimum mapping units (MMUs) and/or a lower floristic resolution. This was done to focus the mapping on the natural landscape.

However, because end users find value in vegetation mapping inside urban areas, especially with regards to mapping the location of fuels, Tukman Geospatial is mapping to the same MMUs inside of the urban core as outside of the urban core.

However, certain structural vegetation map attributes – namely hardwood cover, conifer cover, and standing dead cover – were not assigned to forested stands with a 'Non-native Forest' fine scale vegetation map classification. This was done to reduce manual editing workloads in the core urban areas where it is often difficult to discern hardwood versus conifer composition in mixes of non-native and native trees, often of various sizes, and intermixed with buildings and other human-made features.

3.3.5 Agriculture

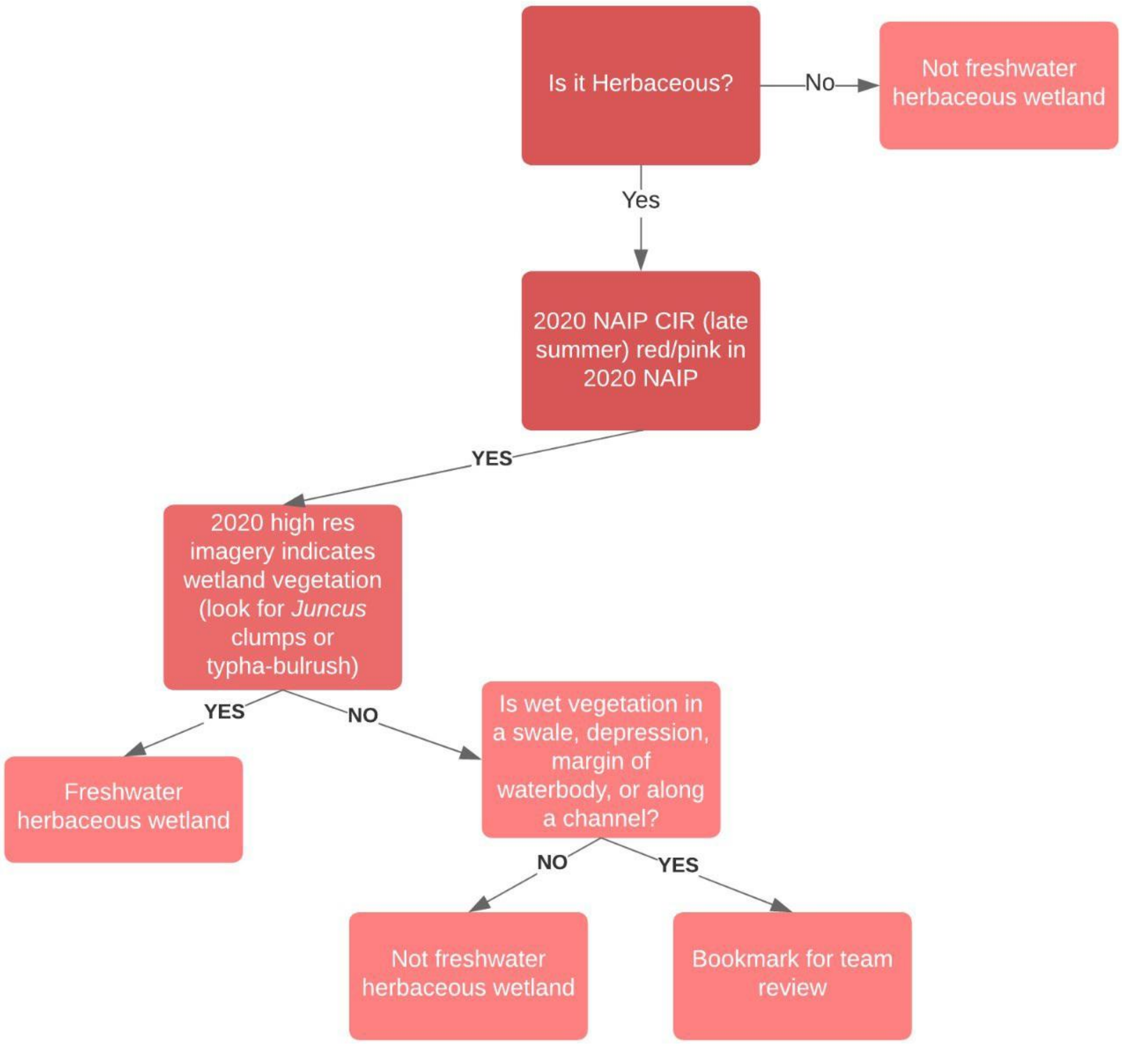
Agriculture was mapped during lifeform and enhanced lifeform mapping as several classes, at a ¼ acre minimum mapping unit. Agriculture classes included row crops, intensively managed hayfield, irrigated pasture, orchard or grove, and vineyard. Agriculture fields were not mapped using Ecognition®, but entirely by manual editing using the 2020 Statewide Crop Mapping Dataset from the California Department of Water Resources (DWR) to guide agricultural type calls.

3.3.6 Tidal and Freshwater Wetlands

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

Freshwater wetlands were identified and delineated manually during lifeform and enhanced lifeform mapping; existing freshwater wetlands datasets were not of high enough accuracy for direct integration into the map. Lifeform editors used the decision rules shown in Figure 5 for manually editing freshwater wetlands into the enhanced lifeform map. The rules are based on the appearance of the 2020 NAIP, while viewed in color infrared (CIR). Freshwater wetlands were further refined during fine scale map editing.

Figure 5. *Rules for editing freshwater wetlands in the lifeform map*

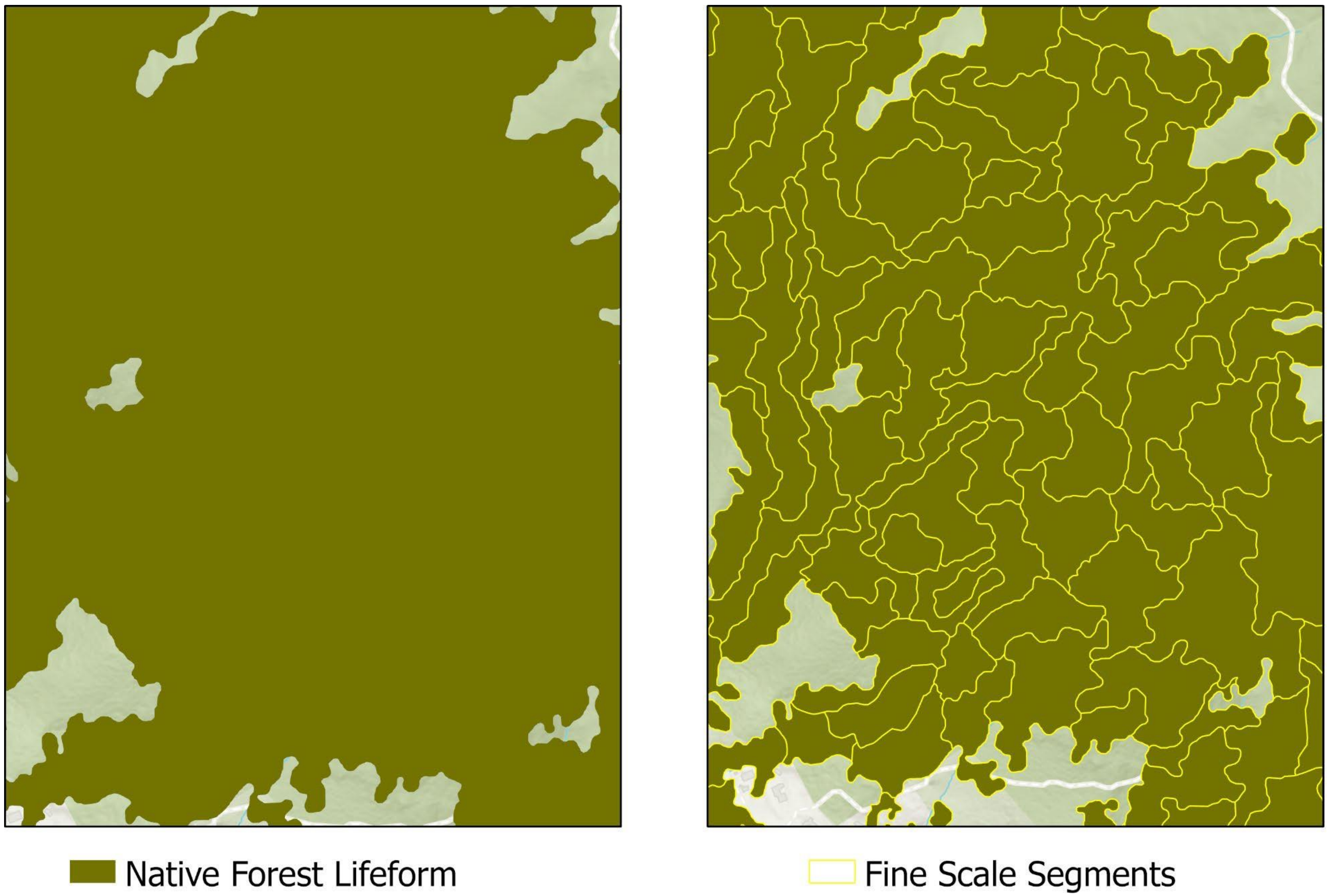


3.3.7 Fine Scale Segmentation

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 'Shrub' classes into smaller segments that are spectrally and structurally homogenous. Fine scale segmentation divides the large and floristically broad native forest and shrub areas into much smaller image segments that are more suitable for fine scale mapping. Fine scale segmentation was conducted using Trimble Ecognition® and relies on summer 2020 4-band NAIP, the lidar-derived canopy height model, and a suite of spectral indices derived from the NAIP. Fine scale segments were created so that they had spectral homogeneity (from the high-resolution imagery) but also had structural homogeneity, meaning uniform within-segment canopy height and canopy density. Figure 6 shows an example of the fine scale segments versus the much larger polygons of the lifeform map.

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

Figure 6. *Native forest polygon in lifeform map (left) and same area showing fine scale segments fine scale segments (right)*



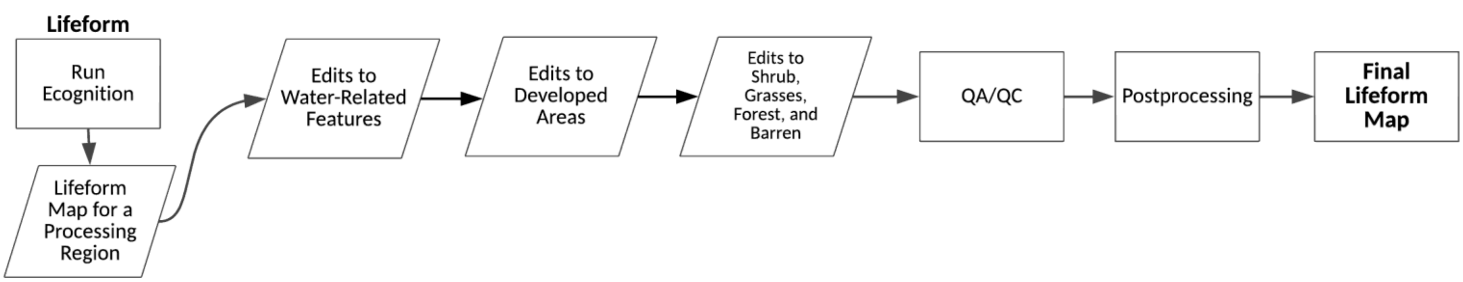
3.3.8 Lifeform and Enhanced Lifeform Map Manual Editing

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

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

Figure 7 shows a schematic of the lifeform editing workflow. The workflow for enhanced lifeform editing is more focused on splitting the lifeform 'Forest' class into the more floristically detailed enhanced lifeform classes such as 'Evergreen Hardwood Forest,' 'Deciduous Hardwood Forest,' 'Pine/Cypress' and 'Redwood/ Douglas fir.'

Figure 7. *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 Alameda-Contra Costa fine scale mapping key) across their range of structural and compositional conditions and 2) to collect observations across the entire geography of the county, providing mappers with on-the-ground knowledge of the distribution of, and variation within, the fine scale map classes.

Calibration field data collection occurred in 2022 and 2023 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 collected calibration field data. Existing and new field survey data collected for floristic classification by CNPS was also used by the mapping team for map calibration.

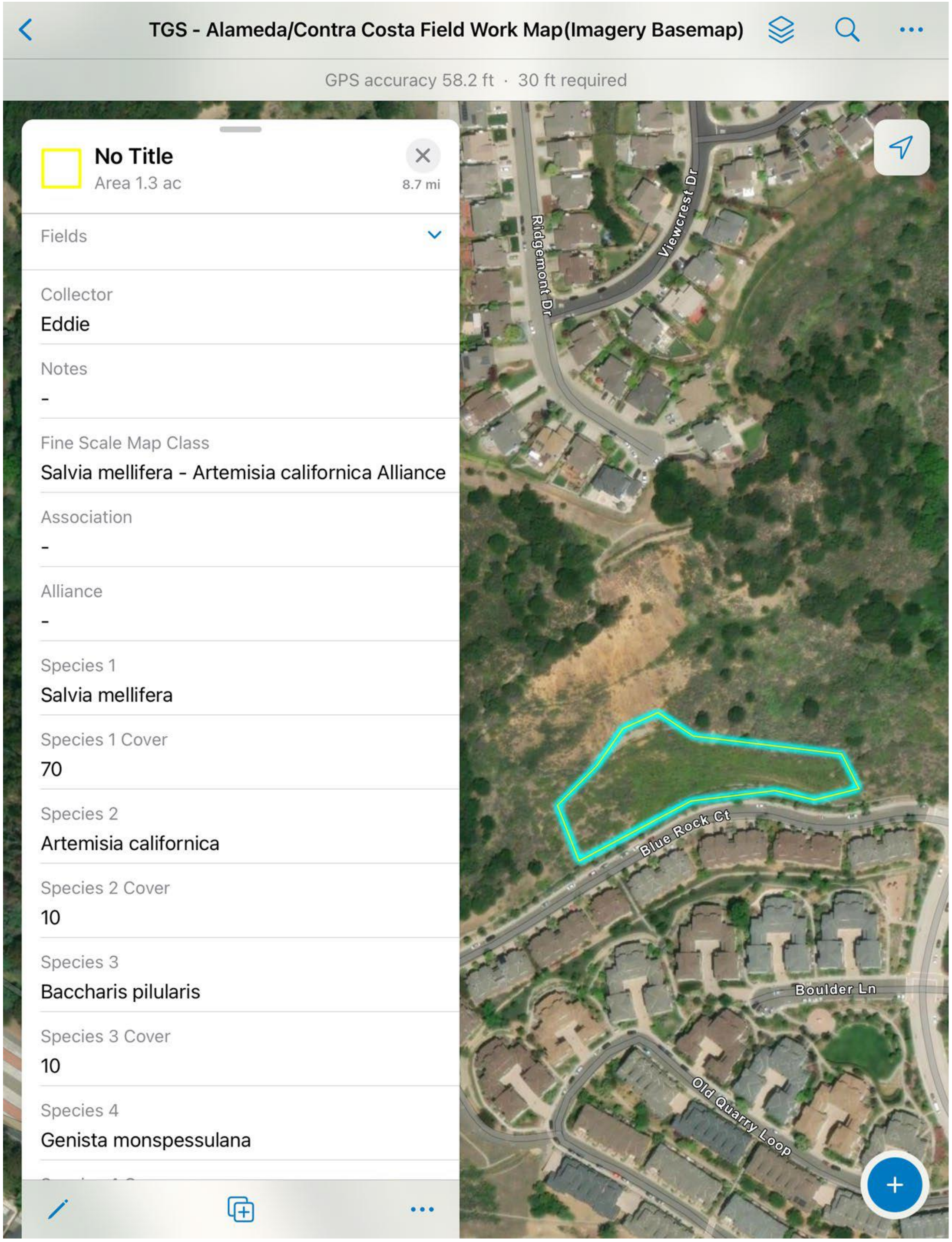
Calibration data collection teams use tablets running ESRI's Field Maps (see Figure 8) to collect and attribute points representing shrub, forest and herbaceous stands observed in the field. Field Maps uses an ArcGIS Online web map with syncable feature services.

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

- Vegetation map class (from the fine scale mapping key)
- Field team names
- Notes
- Percent cover for more detailed polygons (a subset of the total number of field observations)
- Photos (as feature attachments)

Calibration field work resulted in hundreds of points labeled 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 8. *Collector App for field calibration data collection*



3.4.2 Fine Scale Map Machine Learning

3.4.2.1. Overview

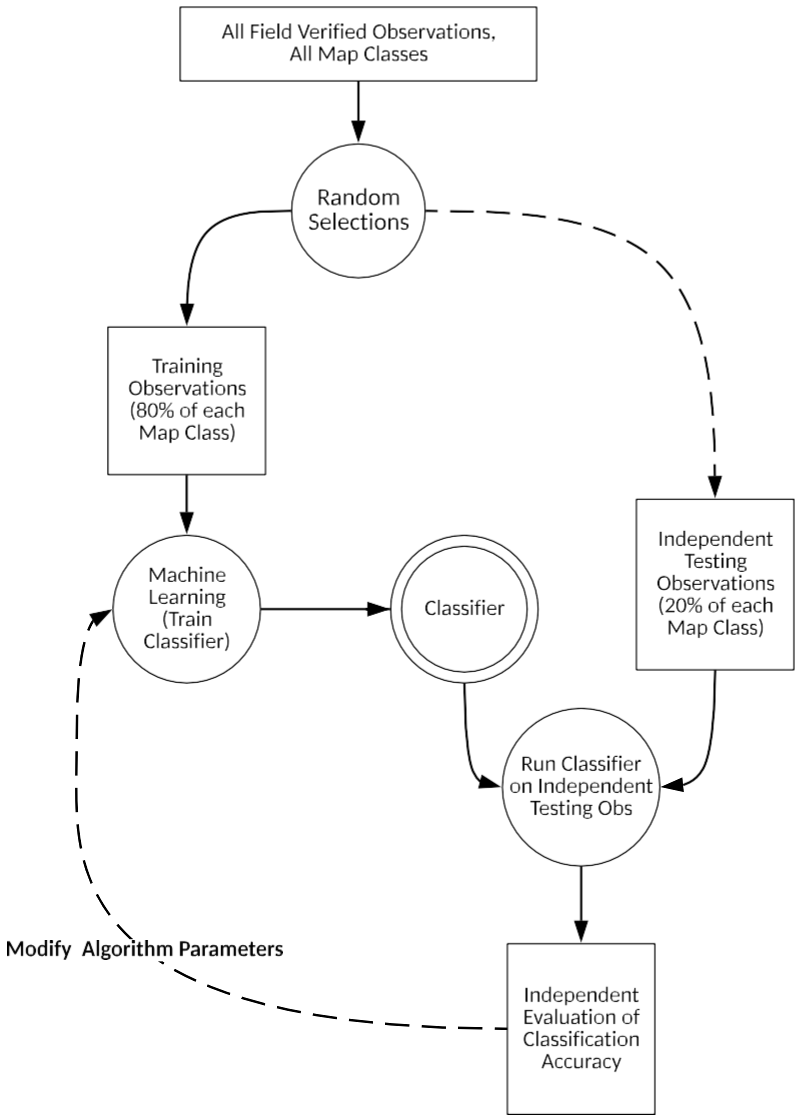
The Alameda and Contra Costa Veg Map Team utilized a type of algorithmic data modeling known as machine learning to help automate the classification of forested fine scale segments into one of the project's fine scale map classes. A form of supervised machine learning was adopted, whereby areas of known classification (training sites) are used to predict the map class for unknown areas through modeling techniques. Machine learning was used to classify evergreen hardwood segments into one of three common alliances (*Quercus agrifolia, Quercus chrysolepis, Umbellularia californica*) and to classify deciduous hardwood segments into one of four common alliances (*Quercus douglasii, Quercus lobata, Quercus kelloggii*, and *Aesculus californica*).

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.

Random Forests (Breiman, 2001) was the machine learning algorithm used to predict fine scale vegetation type for this project (see section 3.4.2.3).

Machine learning is an iterative process that requires trial and error to fine-tune algorithm parameters and inputs to maximize model accuracy. The Alameda and Contra Costa Veg Map team employed the workflow shown in Figure 9. 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. Random Forests was 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 Random Forests were those that maximized model accuracy for the independent testing group.

Figure 9. *Workflow for machine learning*



3.4.2.2. Random Forests

Random Forests was 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 Alameda and Contra Costa Counties. The script assigns a primary predicted fine scale map class to each stand as well as a secondary fine scale map class – the algorithm's 'second choice'. Both the primary and secondary class predictions are accompanied by metrics for Random Forest's confidence in the assignment (expressed as probability). These primary and secondary map class assignments and their associated confidence values are used by manual editors as reference information.

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.

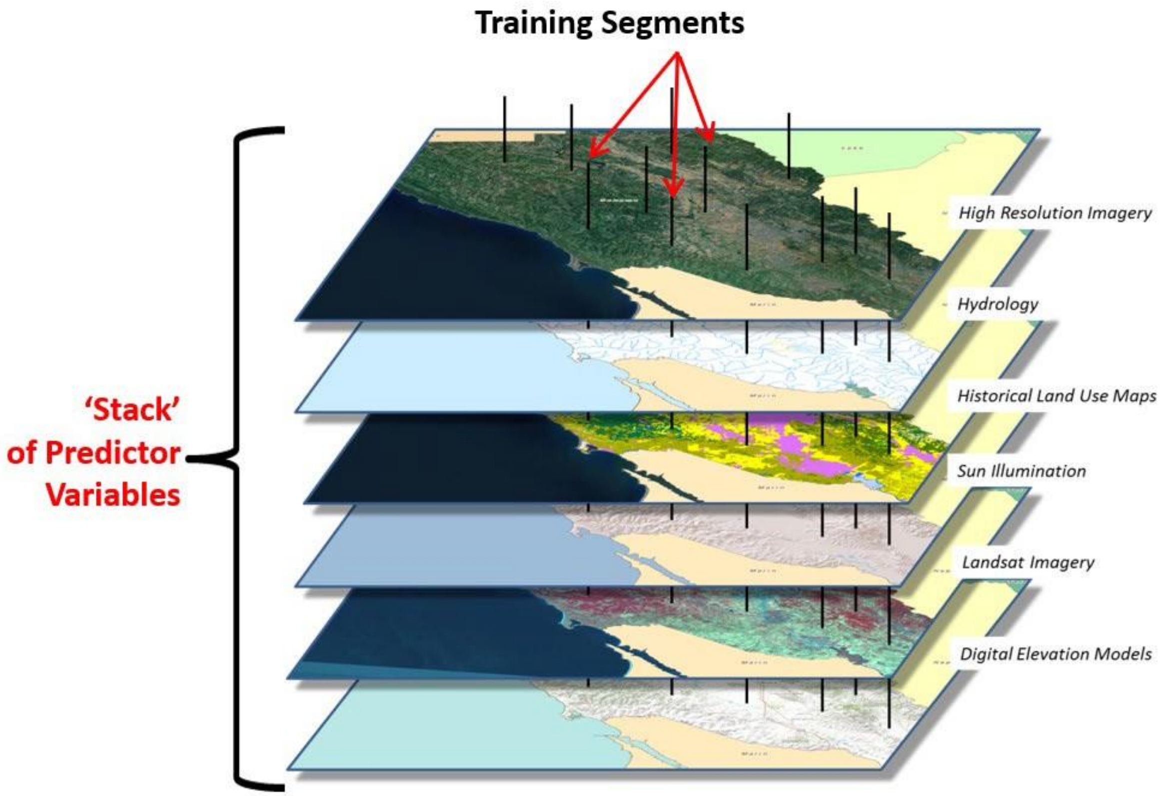
Dr. Clark's R code included several analytical tools that were helpful in interpreting the results of the Random Forests model and in providing information to help refine and improve model results. These items included – for each run of Random Forests – an importance matrix for assessing predictor variable importance. In addition, Dr. Clark's code automatically creates error matrixes for each run of Random Forests, providing user's accuracy, producer's accuracy, and overall accuracy for independent testing sites. Lastly, for each fine scale stand, the R code provides two votes – a first vote and a second vote – each with a confidence value (0 to 1) for its fine scale vegetation class prediction for the stand. Random Forests bases its confidences 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.

3.4.2.3. Independent Variables

Random Forests requires a "stack" of predictor variables for each training site and for each fine scale segment. Figure 10 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 10. *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	2017-2022 lidar
% canopy density in the 60-to-100-foot range	2017-2022 lidar
% canopy density in the 100-to-150-foot range	2017-2022 lidar
% canopy density in the 150-to-200-foot range	2017-2022 lidar
% canopy density in the 200-to-250-foot range	2017-2022 lidar
Average lidar height from lascanopy	2017-2022 lidar
Lidar kurtosis for height from lascanopy	2017-2022 lidar

Machine Learning Predictor Variable	Data Source
Lidar quadratic average height from lascanopy	2017-2022 lidar
Lidar skewness for height from lascanopy	2017-2022 lidar
% lidar returns between 0-4 meters above ground	2017-2022 lidar
% lidar returns over 15 feet (normalized to ground)	2017-2022 lidar
Relative cover of trees taller than 60 feet	2017-2022 lidar
Lidar 5th percentile height from lascanopy	2017-2022 lidar
Lidar 10th percentile height from lascanopy	2017-2022 lidar
Lidar 25th percentile height from lascanopy	2017-2022 lidar
Lidar 50th percentile height from lascanopy	2017-2022 lidar
Lidar 75th percentile height from lascanopy	2017-2022 lidar
Lidar 90th percentile height from lascanopy	2017-2022 lidar
Lidar canopy height from lascanopy	2017-2022 lidar
Lidar intensity	2017-2022 lidar
Ladder Fuels 1-4m	2017-2022 lidar
Ladder Fuels 4-8m	2017-2022 lidar
Eastness	2017-2022 lidar
Northness	2017-2022 lidar
Bare earth DEM	2017-2022 lidar
Terrain slope (from bare earth DEM)	2017-2022 lidar
Canopy slope (slope derived from the canopy height model)	2017-2022 lidar
Canopy height model (a.k.a. normalized digital surface model)	2017-2022 lidar
Distance from nearest stream	2017-2022 lidar
Height above nearest stream	2017-2022 lidar
2020 NAIP image indices (DVI, GDVI, GNDVI, VARI, OVB, NDVI, Classified Low/High NDVI)	USDA Farm Service Agency (NAIP)
Loudon Index: (green band*2)/(red band + blue band) from NAIP 2009	USDA Farm Service Agency (NAIP)
2020 NAIP bands (Red, Green, Blue, Near Infrared)	USDA Farm Service Agency (NAIP)
2012 NAIP bands (Red, Green, Blue, Near Infrared)	USDA Farm Service Agency (NAIP)
AVIRIS indexes (EWT_AV, NDWI_AV, Wtr1AbAr_AV)	Dr. Matthew Clark, NASA (National Aeronautics and Space Administration)

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

3.4.3 Fine Scale Manual Editing & Map Field Validation

3.4.3.1. Fine Scale Map Manual Editing

Manual editing allowed Tukman Geospatial analysts to improve the detail and accuracy of machine learning model predictions, as well as to classify all segments that were not machine-learned, including all pine, shrub, riparian forest and shrub, wetland herbaceous, alkali herbaceous lifeforms, as well as the less common deciduous and evergreen hardwood classes not used in machine learning. 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. 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
- Assignments of fine scale map class to lifeforms not machine learned
- Changes to polygon shapes where a polygon was not compositionally homogenous

Editors relied on a wide variety of imagery and other data sources during editing (see Table 6). 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 6. *Datasets used as reference in fine scale map class manual editing*

Raster Datasets	Vector Datasets
2012, 2014, 2016, 2018, 2020, and 2022 NAIP imagery, displayed as an RGB and as CIR composites	Production modules (editing units) for tracking editing progress
2020 Winter 3- and 9- inch RGB imagery	Roads and trails
2017 3- and 9- inch RGB imagery	CNPS survey points
2020 lidar derived bare earth DEM	iNaturalist Research-grade Observation points, exported 2022.
2020 lidar derived bare earth hillshade	CNDDB point layer
2020 lidar derived canopy height	Field Observation Points (Tukman)
USGS 7.5-minute topography	Field calibration polygons (Tukman)
Google Earth Historical Imagery	Ultramafic layer (USGS 2009)
Bing Bird's Eye Imagery	Soils (NRCS)
	Fire history perimeters (CALFIRE)
	California Protected Areas Database, CPAD (Greeninfo Network)
	NHD flowlines of rivers, streams, etc (USGS)
	2020 Statewide Crop Mapping (DWR)
	Historical Habitats (SFEI, 2011)
	Carnegie Hollister Hills Points (State Parks, 2022)
	Existing vegetation maps, including the following: • Springtown Alkali Sink (UCB Herbarium/AIS, 2008) • Delta Vegetation and Land Use Update (CDFW, 2016) • Carnegie SVRA / Alameda Tesla Veg Polys (State Parks, 2022) • Central Valley Riparian Project Veg Map (GIC, 2009) • Bay Area Aquatic Resource Inventory (SFEI, 2017) • Weislander Vegetation Type Mapping (Kelly, M., B. Allen-Diaz, and N. Kobzina, 2005) • Alameda Watershed Vegetation Communities (SFPUC/Jones & Stokes, 2003) • Various internal polygon and point datasets provided by EBRPD

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

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

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

- Labels that show the polygon’s fine scale map class
- For edited polygons, dynamically rendered symbology (or tracking tiles) to inform the editor that they have already been edited
- The coding menu displayed error flags that automatically turned on if an invalid vegetation type was assigned.

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

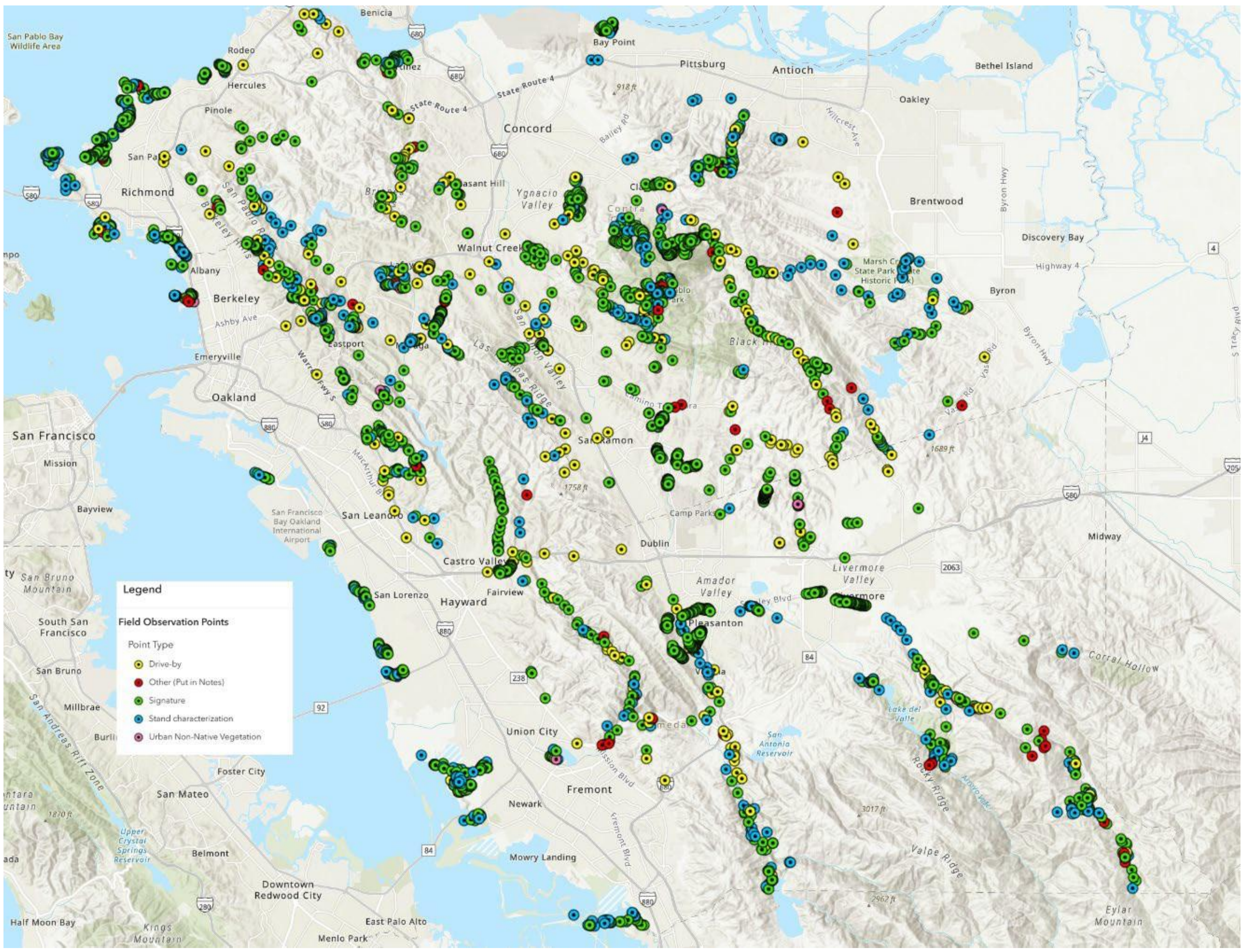
3.4.4 Fine Scale Map Validation Field Work

Validation field work occurred between 2022 and 2024. Validation field work provided the mapping team with an opportunity to review the manually edited map in the field and perform quality control on the map. The mapping team also relied on field validation for difficult-to-map areas to inform additional map refinement and manual editing.

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

In addition to collecting polygons as described in section 3.4.1, crews also collected hundreds of observational points to record observations and signatures of specific plant species or alliances, to note areas of native vegetation in urban areas, and to otherwise enrich and inform the manual editing process. The 2795 observation points collected for Alameda and Contra Costa Counties are shown in Figure 11.

Figure 11. *Field Observation Points gathered between 2022-2024 by Tukman Geospatial and Nomad Ecology Consulting crews.*



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, California Department of Fish and Wildlife funding allowed the mapping team to map tidal wetlands to the alliance level. 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 spp.* Mapping Unit
- *Atriplex prostrata – Cotula* coronopifolia Semi-Natural Alliance
- Ruppia (cirrhosa, maritima) Alliance
- Mudflat/Dry Pond Bottom Mapping Unit

These alliances and associations were mapped in a separate workflow from the rest of the vegetation map. Field calibration data was collected in the tidal wetlands, and fine scale segmentation was conducted with separate setting than for the rest of the vegetation map. During the classification development phase of this project, minimum mapping units (MMUs) were established. Minimum mapping units in the tidal wetlands were ¼ acre for tidal vegetation assemblages (our herbaceous wetland mapping MMU).

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

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

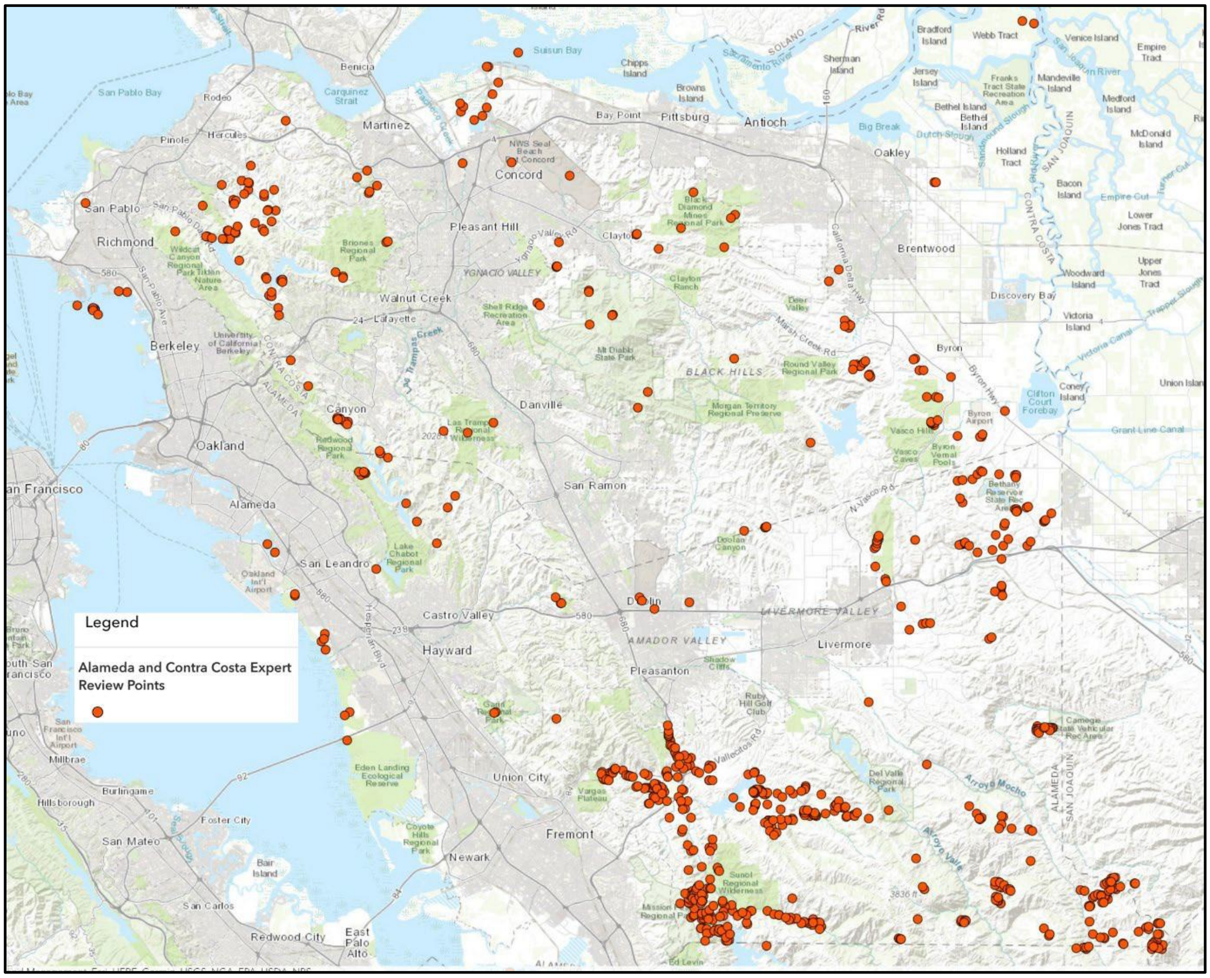
After the fine scale vegetation map was manually edited and field validation work was completed, the fine scale vegetation map was distributed to dozens of Alameda and Contra Costa County land managers, ecologists, and interested parties. The vegetation map was also submitted to the California Native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

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

Input from land managers was obtained through a publicly shared webmap, where stakeholders dropped points and entered for each point text about the issue or concern associated with that location. After the input period ended, the mappers reviewed the input and took appropriate action to refine the map. In many cases, the map was corrected to address the review point. In some cases, the map was not changed – for instance, when the review point identified a sub-MMU stand, or referenced changes that occurred on the landscape after the 2020 reference period of the map. If mappers had questions about a reviewer's concern, Tukman Geospatial contacted the reviewer to discuss the question. Each review point was attributed with the action that the mappers took and the reasoning behind the action.

In all, there were 735 points provided to the mapping team. The expert review points are shown in Figure 12.

Figure 12. *Expert review points provided for the Alameda and Contra Costa 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 and forest structure* (see section 5.4 for a complete list of all fine scale map attributes).
- *QA/QC to ensure valid and complete data:* This step entailed review of all vegetation map polygons to ensure that each map polygon had complete and valid data. For example, each attribute of each polygon was checked for missing data, out-of-range, or inappropriate values, etc.

- *Correct labels of AA sites:* After AA analysis was complete, stands where the accuracy assessment revealed an incorrect map label were modified to the field validated label.

Attributes delivered in the final, countywide map are shown in Section 5.4, Table 14.

3.7. Structural Attribute and Forest Health Mapping

All native forest stands were attributed with percent conifer and hardwood covers (relative and absolute) as well as percent standing dead – attributes derived from a combination of machine learning and manual editing. This process was also used to give all shrub and herbaceous stands a percent shrub cover attribute.

3.7.1 Standing Dead

Standing dead vegetation was mapped as a percentage, in 1% increments, of the woody canopy over 15 feet tall that appeared to be dead in the 2022 imagery.

Though the fine scale vegetation map classes were mapped to 2020 imagery, the standing dead attribute was mapped using 2022 NAIP imagery per a request from EBRPD for the standing dead attribute to reflect a more recent landscape. In some cases, such as in areas that burned at high severity between 2020 and 2022, this resulted in standing dead levels that appear to contradict the map class (e.g. 100% standing dead canopy in forested map classes). These areas were flagged with the *FIRE_FLAG_20_25* attribute by assigning 'yes' if the majority of a polygon experienced fire between 2020-2025, to indicate that the landscape has potentially changed since the 2020-based map class assignment.

Standing dead areas were mapped in Trimble® Ecognition® with high-resolution 2022 countywide imagery and 2017-2022 lidar data, using semi-automated techniques that combine automated object-based image analysis with manual photointerpretation. Object-based image analysis resulted in a 1-meter raster of living vs 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 15 feet tall that was standing dead in 2022.

Volmar Natural Lands Consulting analysts manually edited the percent dead assignments up or down based on image interpretation, adjusting the attribute upward where automated techniques underestimated standing dead and adjusting the attribute downward where automated techniques overestimated standing dead area. This product reflects the state of the landscape in summer 2022. 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 15 feet in height. Standing dead areas include entire tree crowns and parts of tree crowns that have died back.
- The percent standing dead attribute was calculated as the area of the polygon over 15 feet in height that is dead, divided by the total area of the polygon over 15 feet in height. It reflects the percentage of the canopy area that is dead, not of the entire area of the polygon.
- Living v. dead is defined by the presence of green leaves as viewed from above in the summer, 2022 high resolution imagery. Summer deciduous species such as *Aesculus californica* that do not appear green, but are still alive, were flagged for manual attention to limit overestimation of standing dead.
- 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.

3.7.2 Conifer and Hardwood Percent Cover

For all native forest segments, machine learning was 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. These sites were used as training for lidar-derived "tree approximate objects", designating the objects as either conifer or hardwood. Based on this model, the area of each polygon that was greater than or equal to 15 feet (assumed to be the area of the tree canopy) was then assigned a relative conifer cover.

Volmar Natural Lands Consulting analysts manually edited the relative conifer up or down based on image interpretation, with special attention to polygons that violated the map class rules (e.g., if a redwood classified polygon was assigned very low conifer relative cover).

Conifer relative cover was used as the basis for calculating the rest of the compositional attribute values: hardwood relative cover, conifer absolute cover, and hardwood absolute cover. Hardwood relative cover is the area of the tree canopy occupied by hardwood canopy, and was calculated by subtracting the relative conifer cover from 100. Absolute conifer cover is the percent of the entire polygon area (not simply the canopy area) that is occupied by conifer canopy, and was calculated by taking the absolute cover of lidar returns over 15 feet and multiplying by the relative conifer cover. Absolute hardwood cover was calculated in the same way.

3.7.3 Shrub Percent Cover

Percentage shrub cover was mapped for shrub and herbaceous stands in Alameda and Contra Costa Counties. Countywide shrub cover was mapped using semi-automated techniques that combined automated object-based image analysis with manual photointerpretation conducted by Vollmar Natural Lands Consulting. The resulting attribute is the percentage of each polygon area occupied by shrubs, as viewed from above in the 2020 NAIP imagery.

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 and accuracy assessment tables 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. Accuracy was not assessed for the tidal wetland alliances – only for tidal wetlands as a single class.

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

4.1. Sample Design

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

Two types of samples were collected:

- **Manually Interpreted (Office) AA Sites**: Manual labelling (using aerial photointerpretation) of stands for accuracy assessment in the vegetation map. Fine scale map classes that were targeted for manual assessment are:
    - Agriculture
    - Barren and Sparsely Vegetated
    - Developed
    - Water
    - Non-native Forest

  These classes are easy to interpret from imagery and Google Street View and do not require field verification.

- **Field Surveyed AA Surveys** Field verification of surveys was performed for the majority of shrub and native forest fine scale vegetation map classes. These woody classes require field verification to accurately assign a verified fine scale map class.

4.1.1 Manually Interpreted Sites

Manually interpreted samples were collected using aerial image interpretation of randomly selected map polygons. The reference data used by image analysts was 2020 high resolution imagery, which was augmented by Google Street View where available. To select the manually interpreted sites (the classes are listed in the first bullet in section 4.1), a random selection was used to select between 5 and 40 sample stands (target size was based on the class's acreage in the draft map) from the draft fine scale vegetation map. The selection was performed using python code that ensured that randomly selected stands of the same map label were at least 500 feet apart.

4.1.2 Field-Verified Surveys

Field-verified accuracy assessment samples were chosen across the two-county area using a combined stratified random/cluster sampling approach after the final draft of the fine scale vegetation map was completed. To select the field surveys, all access-restricted areas were masked out of the draft fine scale vegetation map, which focused the field sampling on public lands, conservation lands, and private lands whose landowners were willing to provide access. Next, areas with difficult access were masked out. These 'high travel cost' areas were defined by a cost surface that identified areas far from accessible roads and trails, as well as areas inaccessible due to steep terrain. Analysts also excluded from the allocation stands that touched CNPS relevés and rapid assessment points, or field observation points collected by the mapping crews doing field calibration or field validation work. Within the remaining areas, 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 500 feet between targeted stands of the same map class was required. The number of stands chosen randomly as targets to visit in the field was based on the number of stands of that map class on accessible lands, which were also within 750 feet of an accessible road or trail. Target allocations (those shown below) were multiplied by 1.5x so that there were more targeted, allocated stands than actually needed for each map class.

Target allocations were made with the following accessible stand number breaks:

- **40** target samples allocated if accessible stand count for the map class were greater than 2,500 stands across the two-county area. With the 1.5x multiplier, 60 stands of these map classes would actually be allocated.
- **30** target samples allocated if accessible stand count was between 500-2,500 stands
- **25** target samples allocated if accessible stand count was between 400-500 stands
- **20** target samples allocated if accessible stand count was between 320-400 stands

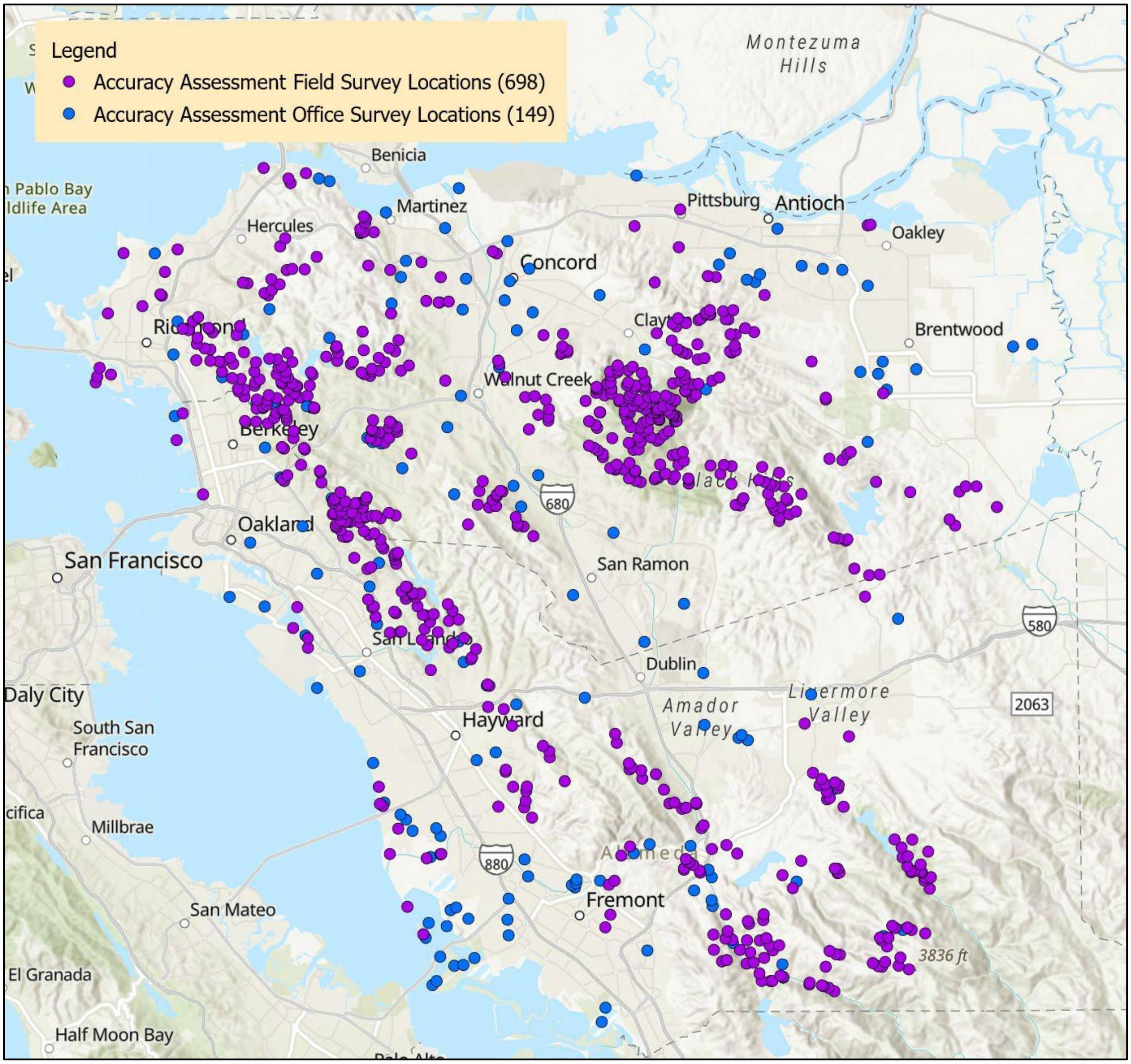
- **15** target samples allocated if accessible stand count was between 210-320 stands
- **10** target samples allocated if accessible stand count was between 180-210 stands
- **5** target samples allocated if accessible stand count was between 100-180 stands
- **4** target samples allocated if accessible stand count was between 70-100 stands
- **3** target samples allocated if accessible stand count was between 50-70 stands
- **2** target samples allocated if accessible stand count was between 30-50 stands
- **0** target samples allocated if accessible stand count was less than 30

Field crews were made up of experienced botanists who did not begin data collection work until the fine scale draft map was completed. Field crews were not involved with the vegetation mapping. Crews visited the randomly selected target sample stands with no indication of the stand's mapped label. At the selected target sample stand, field personnel viewed at least 50% of the entire allocated stand before assigning a reference map class for the stand. If the entire target sample stand was not visible from a vantage point, the crew attempted to walk or drive to the remaining area of the stand. Following inspection of the target sample stand, field personnel completed the accuracy assessment form using Field Maps and Survey123. Field personnel estimated the percent cover of each vegetative species visible in the imagery and used the mapping key to label the stand with its appropriate fine scale map class. If a second map class was also an acceptable call for the stand, mappers were allowed to assign a secondary 'acceptable' fine scale class to the stand. Secondary labels were assigned to 183 of the 698 field visited AA surveys, or 26% of the surveys.

Accuracy assessment field crews were not permitted to collect opportunistic samples (surveys were generally required to be in allocated stands), although 4 out of the 698 AA surveys were opportunistically collected. For a more detailed accuracy assessment protocol, view this link: vegmap.press/alcc_protocols.

847 total accuracy assessment samples (149 manually interpreted and 698 in the field) were collected, representing 61 of the 115 fine scale vegetation map classes. Those 61 classes (across the final two-county map) represent 94% of the area mapped. Some classes were not sampled or lightly sampled because the class was extremely uncommon. Other classes were not assessed because there were an insufficient number of accessible areas representing the class to sample, or because all accessible areas where the type occurs had been visited by mappers or by CNPS surveyors. Figure 13 shows the locations of the accuracy assessment surveys collected.

Figure 13. *Field and office-collected accuracy assessment survey locations in Alameda and Contra Costa Counties*



4.2. Analysis

Once the accuracy assessment reference data were collected, the map labels (assigned during the mapping process) for each sample were compared to the reference labels (assigned from manual interpretation or field validated samples). Extensive quality control was performed to ensure that reference labels and map labels were accurate, and that spatial autocorrelation did not exist between sample segments. As a result, a small number of reference polygons (<10) were removed from the data set with the consultation of the AA field crew supervisor for one or more of the following reasons:

- Upon review by photo-interpreters and AA data field crews, it was found that the reference sample was incorrect or a failure to assess accuracy across the entire reference polygon, or a large enough portion of it for a correct survey.
- The reference polygon included surveys for two sub-MMU types (e.g. ½ acre of one shrub type and ½ acre of a different shrub type in a one acre polygon), which could not have been split during mapping due to MMU rules
- The reference polygon was noted by surveyors to have been significantly altered between the mapped date of 2020 and the survey date in 2025. For example, stands mapped as *Pinus radiata* had significant numbers of *Pinus radiata* trees removed, which were noted as recent stumps by AA field crews.

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

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

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

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

- Humans are incapable of precisely estimating percent cover, resulting in an average variance in estimates of +/- 10% (Congalton and Green, 2019). While this will have little

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

Many map users and producers implement fuzzy accuracy assessment to deal with the ambiguity in a map. Usually this is implemented when the reference sample is being assessed by choosing a second acceptable reference label for a sample if the person collecting the data believes that more than one label would be acceptable (Congalton and Green, 2019). This was done for Alameda and Contra Costa's field surveyed AA sites, resulting in 26% of the field surveys receiving a secondary 'acceptable' label. The secondary label was used in fuzzy accuracy assessment for Alameda and Contra Costa County and was integrated into the California Department of Fish and Wildlife's fuzzy scoring rubric (CDFW (California Department of Fish and Wildlife) & Aerial Information Systems, 2013; Menke et al., 2011). See Table 7 for details.

CDFW's fuzzy scoring rubric was developed during several mapping projects (CDFW & Aerial Information Systems, 2013; Menke et al., 2011). The approach 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. CDFW's criteria for partial credit are shown in the second column of Table 7.

For our work, scoring is fully automated, which likely reduces the leniency of fuzzy scoring and produces lower fuzzy accuracies. For this project, the fuzzy scoring protocols developed by CDFW are implemented as outlined and described in the third column of Table 7.

Table 7. *CDFW evaluation criteria for fuzzy accuracy assessment*

CDFW Code	CDFW Scoring Method	Implementation for ALCC Fine Scale Mapping	Score
A	PI completely correct.	Implemented in automated scoring. The *primary* surveyed AA map class must match the map.	5
B	The PI chose the correct Group OR the next level up in the hierarchy.	Implemented in automated scoring. The Group that the primary surveyed AA map class is in must match the Group that mapped map class is in.	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).	Not implemented through manual scoring. Instead, if the secondary map class existed (it did for 26% of field surveyed AAs) we gave four points if the secondary map class matched the map when the primary class did not match the map. This is the *only way* we used the secondary field surveyed AA map class in scoring.	4
D	Correct Macrogroup OR next level up in hierarchy.	Implemented in automated scoring. The Macrogroup that the primary surveyed AA map class is in must match the Macrogroup that mapped map class is in.	3

CDFW Code	CDFW Scoring Method	Implementation for ALCC Fine Scale Mapping	Score
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.	Implemented (assigned 3 points) *only* if the reference class and map class were different but both were in one of the following groups: 1. 'Salix gooddingii - Salix laevigata Alliance', 'Salix lucida ssp. lasiandra Association', 'Salix lasiolepis Alliance' 2. 'Quercus chrysolepis (tree) Alliance', 'Quercus wislizeni - Quercus chrysolepis (shrub) Alliance'	3
F	Correct Division.	Implemented in automated scoring. The Division that the primary surveyed AA map class is in must match the Division that mapped map class is in.	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.	Did not implement.	2
H	Correct only at Lifeform.	Implemented in automated scoring. The Lifeform that the primary surveyed AA map class is in must match the Lifeform that mapped map class is in.	1
I	No similarity above Formation and incorrect life form.	Implemented.	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).	Implemented.	no score
K	Survey removed because inadequate portion (<10%) of the polygon was viewed by the field crew.	Implemented.	no score

CDFW Code	CDFW Scoring Method	Implementation for ALCC Fine Scale Mapping	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).	Implemented.	no score
M	Supplementary record not scored (for multiple point assessments within a polygon where the AA call was the same).	Implemented.	no score

4.3. Results

4.3.1 Lifeform Map AA Results

Table 8 is the error matrix for the lifeform map. Lifeform classes are simple to discern and are also homogeneous, which reduces any ambiguity in labeling. Overall lifeform accuracy is 97 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 \ REFERENCE	Agriculture	Barren and Sparsely Vegetated	Developed	Forest	Freshwater Herbaceous Wetland	Upland Herbaceous	Riparian Forest and Riparian Shrub	Shrub	Temperate Pacific Salt Marsh Group	Water	Grand Total	User's Accuracy
Agriculture	5	0	0	0	0	0	0	0	0	0	**5**	**100%**
Barren and Sparsely Vegetated	0	14	0	0	2	0	0	0	0	0	**16**	**88%**
Developed	0	0	40	0	0	1	0	0	0	0	**41**	**98%**
Forest	0	0	0	398	0	0	3	4	0	0	**405**	**98%**
Freshwater Herbaceous Wetland	0	0	0	0	32	4	0	0	0	0	**36**	**89%**
Upland Herbaceous	0	0	0	0	0	43	0	0	0	0	**43**	**100%**
Riparian Forest and Riparian Shrub	0	0	0	8	1	0	66	1	0	0	**76**	**87%**
Shrub	0	0	0	3	0	2	0	167	0	0	**172**	**97%**
Temperate Pacific Salt Marsh Group	0	0	0	0	0	0	0	0	13	0	**13**	**100%**
Water	0	0	0	0	0	0	0	0	0	40	**40**	**100%**
Grand Total	**5**	**14**	**40**	**409**	**35**	**50**	**69**	**172**	**13**	**40**	**847**	
Producer's Accuracy	**100%**	**100%**	**100%**	**97%**	**91%**	**86%**	**96%**	**97%**	**100%**	**100%**		

97% Overall Lifeform Accuracy

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

Lifeform	User's Accuracy	Producer's Accuracy
Agriculture	100%	100%
Barren	88%	100%
Developed	98%	100%
Forest	98%	97%
Freshwater Herbaceous Wetland	89%	91%
Upland Herbaceous	100%	86%
Riparian Forest and Riparian Shrub	96%	87%
Shrub	97%	97%
Temperate Pacific Salt Marsh Group	100%	100%
Water	100%	100%

4.3.2 Fine scale Vegetation Map AA Results

The error matrix in Table 11 (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. A link is provided in the Table 11 heading to a large format version of the error matrix.

Table 11 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 80.8%. For these stands, the primary field surveyed AA label matches the map.

Fuzzy accuracy of the fine scale vegetation map is 93.1% (see the end of section 4.2 above for the fuzzy methods).

Table 10 summarizes the user's accuracy, producer's accuracy, and fuzzy accuracies for all fine scale map classes that had any accuracy assessment surveys collected to represent them.

Table 10. *Producer's and user's accuracies for the fine scale vegetation map by map class*

Fine Scale Map Class	Acres in Veg Map	# of Map Sites	Deterministic User Accuracy	Fuzzy User Accuracy	# of Reference Sites (n=847)	Deterministic Producer Accuracy	Fuzzy Producer Accuracy
Californian Annual & Perennial Grassland Mapping Unit	348,554	33	100%	100%	40	83%	89%
Developed	237,107	41	98%	98%	40	100%	100%
Water	67,236	40	100%	100%	40	100%	100%
Quercus agrifolia Alliance	47,894	32	69%	91%	40	55%	86%
Quercus douglasii Alliance	47,309	39	92%	98%	43	84%	94%
Umbellularia californica Mapping Unit	34,289	23	91%	98%	46	46%	79%
Non-native Forest	14,181	41	98%	99%	40	100%	100%
Baccharis pilularis Alliance	11,660	37	76%	90%	33	85%	94%
Quercus lobata Mapping Unit	10,615	26	73%	90%	29	66%	88%
Temperate Pacific Salt Marsh Group	10,302	13	100%	100%	13	100%	100%
Adenostoma fasciculatum Alliance	7,343	34	53%	89%	29	62%	90%
Orchard or Grove	6,918	4	100%	100%	4	100%	100%
Eucalyptus (globulus, camaldulensis) Semi-Natural Association	6,698	32	97%	99%	31	100%	100%
Barren and Sparsely Vegetated	6,400	16	88%	88%	14	100%	100%
Quercus (agrifolia, douglasii, garryana, kelloggii, lobata, wislizeni) Alliance	5,981	27	52%	90%	20	70%	94%
Vineyard	5,118	1	100%	100%	1	100%	100%
Arid West Interior Freshwater Marsh Group	5,025	16	88%	93%	16	88%	94%
Pinus sabiniana Woodland Alliance	4,194	37	86%	96%	34	94%	98%
Adenostoma fasciculatum - Salvia spp. Alliance	3,770	19	53%	86%	17	59%	92%
Artemisia californica - (Salvia leucophylla) Alliance	3,570	23	87%	96%	23	87%	96%
Sequoia sempervirens Alliance	3,399	33	88%	92%	30	97%	99%
Quercus chrysolepis (tree) Alliance	3,242	27	67%	93%	20	90%	98%
Platanus racemosa - Quercus agrifolia Alliance	3,110	28	82%	88%	25	92%	95%
Quercus kelloggii Alliance	2,754	18	72%	94%	13	100%	100%
Vancouverian Lowland Marsh, Wet Meadow & Shrubland Macrogroup	2,427	11	73%	89%	9	89%	91%
Mudflat/Dry Pond Bottom Mapping Unit	2,358	6	100%	100%	8	75%	75%
Salix lasiolepis Alliance	2,028	24	71%	85%	18	94%	94%
Pinus radiata Plantations Semi-Natural Association	1,982	22	100%	100%	24	92%	98%
Aesculus californica Alliance	1,609	17	82%	96%	16	88%	98%
Salix gooddingii - Salix laevigata Alliance	1,605	2	0%	40%	5	0%	68%
Arctostaphylos glauca Alliance	1,452	3	100%	100%	5	60%	92%
Conium maculatum - Foeniculum vulgare Semi-Natural Alliance	1,333	7	71%	86%	6	83%	83%
Quercus wislizeni - Quercus parvula (tree) Alliance	1,327	14	79%	96%	11	100%	100%
Salvia mellifera - (Artemisia californica) Alliance	1,327	2	50%	70%	5	20%	60%
Populus fremontii - Fraxinus velutina - Salix gooddingii Alliance	1,264	5	80%	80%	6	67%	80%
Ceanothus cuneatus Alliance	1,144	3	67%	93%	11	18%	84%
Prunus ilicifolia - Heteromeles arbutifolia - Ceanothus spinosus Alliance	1,035	12	58%	85%	9	78%	96%
Toxicodendron diversilobum Alliance	939	24	67%	88%	18	89%	98%
Juniperus californica Alliance	769	4	100%	100%	4	100%	100%
Pinus coulteri Alliance	623	1	0%	80%	0	0%	0%
Lepidium latifolium - Lactuca serriola Semi-Natural Alliance	584	0	0%	0%	1	0%	80%
Arbutus menziesii Alliance	552	4	50%	75%	2	100%	100%
Arctostaphylos (canescens, manzanita, stanfordiana) Alliance	519	6	67%	93%	6	67%	93%
Acer macrophyllum Mapping Unit	492	2	0%	50%	2	0%	40%
Seasonally Saturated Herbaceous	458	3	0%	7%	1	0%	80%
Distichlis spicata - (Juncus cooperi - Frankenia salina) Interior Alliance	434	3	100%	100%	4	75%	95%
Quercus wislizeni - Quercus chrysolepis (shrub) Alliance	425	7	43%	83%	4	75%	90%
Ericameria linearifolia - Cleome isomeris Alliance	403	0	0%	0%	2	0%	50%
Hesperocyparis macrocarpa Ruderal Semi-Natural Association	370	4	50%	90%	2	100%	100%
Alnus rhombifolia Alliance	263	6	83%	97%	5	100%	100%
Cytisus scoparius - Genista monspessulana - Cotoneaster spp. Semi-Natural Alliance	262	0	0%	0%	2	0%	80%
Salix exigua Alliance	254	4	75%	95%	3	100%	100%
Juglans hindsii and Hybrids Alliance	245	4	75%	95%	3	100%	100%
Pinus attenuata Alliance	187	2	50%	90%	1	100%	100%
Baccharis salicifolia Alliance	175	3	100%	100%	4	75%	95%
Cercocarpus montanus Alliance	166	1	100%	100%	1	100%	100%
Ribes quercetorum - Rhus trilobata - Frangula californica Alliance	161	1	100%	100%	1	100%	100%
Lotus scoparius - Lupinus albifrons - Eriodictyon spp. Alliance	79	0	0%	0%	2	0%	60%
Arctostaphylos (crustacea, tomentosa) Alliance	74	0	0%	0%	1	0%	80%
Ceanothus (oliganthus, leucodermis, tomentosus) Alliance	51	0	0%	0%	2	0%	70%
Gaultheria shallon - Rubus (ursinus) Alliance	20	0	0%	0%	1	0%	20%
Robinia pseudoacacia Semi-Natural Association	13	0	0%	0%	1	0%	40%

Table 11. *Fine scale deterministic map error matrix. (See https://vegmap.press/alcc_fs_error_matrix for a larger-scale zoomable version of the error matrix)*

Alameda and Contra Costa Fine Scale Vegetaion Map Accuracy Assessment - May 15, 2025

REFERENCE (columns 1–21)

MAP	Acer macrophyllum Mapping Unit	Adenostoma fasciculatum - Salvia spp. Alliance	Adenostoma fasciculatum Alliance	Aesculus californica Alliance	Alnus rhombifolia Alliance	Arbutus menziesii Alliance	Arctostaphylos (canescens, manzanita, stanfordiana) Alliance	Arctostaphylos (crustacea, tomentosa) Alliance	Arctostaphylos glauca Alliance	Arid West Interior Freshwater Marsh Group	Artemisia californica - (Salvia leucophylla) Alliance	Baccharis pilularis Alliance	Baccharis salicifolia Alliance	Barren and Sparsely Vegetated	Californian Annual & Perennial Grassland Mapping Unit	Ceanothus (oliganthus, leucodermis, tomentosus) Alliance	Ceanothus cuneatus Alliance	Cercocarpus montanus Alliance	Conium maculatum - Foeniculum vulgare Semi-Natural Alliance	Cytisus scoparius - Genista monspessulana - Cotoneaster spp. Semi-Natural Alliance	Developed
Acer macrophyllum Mapping Unit	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Adenostoma fasciculatum - Salvia spp. Alliance	0	10	6	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0
Adenostoma fasciculatum Alliance	0	7	18	0	0	0	2	0	0	0	0	0	0	0	0	1	5	0	0	0	0
Aesculus californica Alliance	0	0	0	14	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Alnus rhombifolia Alliance	0	0	0	0	5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Arbutus menziesii Alliance	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Arctostaphylos (canescens, manzanita, stanfordiana) Alliance	0	0	1	0	0	0	4	0	1	0	0	0	0	0	0	0	0	0	0	0	0
Arctostaphylos (crustacea, tomentosa) Alliance	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Arctostaphylos glauca Alliance	0	0	0	0	0	0	0	0	3	0	0	0	0	0	0	0	0	0	0	0	0
Arid West Interior Freshwater Marsh Group	0	0	0	0	0	0	0	0	0	14	0	0	0	0	0	0	0	0	1	0	0
Artemisia californica - (Salvia leucophylla) Alliance	0	0	0	0	0	0	0	0	0	0	20	1	0	0	0	0	0	0	0	0	0
Baccharis pilularis Alliance	0	0	0	0	0	0	0	0	0	0	1	28	0	0	1	0	0	0	0	2	0
Baccharis salicifolia Alliance	0	0	0	0	0	0	0	0	0	0	0	0	3	0	0	0	0	0	0	0	0
Barren and Sparsely Vegetated	0	0	0	0	0	0	0	0	0	0	0	0	0	14	0	0	0	0	0	0	0
Californian Annual & Perennial Grassland Mapping Unit	0	0	0	0	0	0	0	0	0	0	0	0	0	0	33	0	0	0	0	0	0
Ceanothus (oliganthus, leucodermis, tomentosus) Alliance	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Ceanothus cuneatus Alliance	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0
Cercocarpus montanus Alliance	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0
Conium maculatum - Foeniculum vulgare Semi-Natural Alliance	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	5	0	0
Cytisus scoparius - Genista monspessulana - Cotoneaster spp. Semi-Natural Alli	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Developed	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	40
Distichlis spicata - (Juncus cooperi - Frankenia salina) Interior Alliance	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Ericameria linearifolia - Cleome isomeris Alliance	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Eucalyptus (globulus, camaldulensis) Semi-Natural Association	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Gaultheria shallon - Rubus (ursinus) Alliance	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Hesperocyparis macrocarpa Ruderal Semi-Natural Association	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Juglans hindsii and Hybrids Alliance	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Juniperus californica Alliance	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Lepidium latifolium - Lactuca serriola Semi-Natural Alliance	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Lotus scoparius - Lupinus albifrons - Eriodictyon spp. Alliance	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Mudflat/Dry Pond Bottom Mapping Unit	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Non-native Forest	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Orchard or Grove	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Pinus attenuata Alliance	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
Pinus coulteri Alliance	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Pinus radiata Plantations Semi-Natural Association	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Pinus sabiniana Woodland Alliance	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0
Platanus racemosa - Quercus agrifolia Alliance	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Populus fremontii - Fraxinus velutina - Salix gooddingii Alliance	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Prunus ilicifolia - Heteromeles arbutifolia - Ceanothus spinosus Alliance	0	0	1	0	0	0	0	0	0	0	1	0	0	0	0	0	2	0	0	0	0
Quercus (agrifolia, douglasii, garryana, kelloggii, lobata, wislizeni) Alliance	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Quercus agrifolia Alliance	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
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
Quercus douglasii Alliance	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Quercus kelloggii Alliance	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Quercus lobata Mapping Unit	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Quercus wislizeni - Quercus chrysolepis (shrub) Alliance	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0
Quercus wislizeni - Quercus parvula (tree) Alliance	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Ribes quercetorum - Rhus trilobata - Frangula californica Alliance	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Robinia pseudoacacia Semi-Natural Association	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Salix exigua Alliance	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
Salix gooddingii - Salix laevigata Alliance	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Salix lasiolepis Alliance	1	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0	0	0	0	0
Salvia mellifera - (Artemisia californica) Alliance	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Seasonally Saturated Herbaceous	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0
Sequoia sempervirens Alliance	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Temperate Pacific Salt Marsh Group	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Toxicodendron diversilobum Alliance	0	0	1	0	0	0	0	0	0	0	1	3	0	0	1	0	0	0	0	0	0
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
Vancouverian Lowland Marsh, Wet Meadow & Shrubland Macrogroup	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0
Vineyard	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Water	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Total	2	17	29	16	5	2	6	1	5	16	23	33	4	14	40	2	11	1	6	2	40
Deterministic Producer's Accuracy	0%	59%	62%	88%	100%	100%	67%	0%	60%	88%	87%	85%	75%	100%	83%	0%	18%	100%	83%	0%	100%

REFERENCE (columns 22–42)

MAP	Distichlis spicata - (Juncus cooperi - Frankenia salina) Interior Alliance	Ericameria linearifolia - Cleome isomeris Alliance	Eucalyptus (globulus, camaldulensis) Semi-Natural Association	Gaultheria shallon - Rubus (ursinus) Alliance	Hesperocyparis macrocarpa Ruderal Semi-Natural Association	Juglans hindsii and Hybrids Alliance	Juniperus californica Alliance	Lepidium latifolium - Lactuca serriola Semi-Natural Alliance	Lotus scoparius - Lupinus albifrons - Eriodictyon spp. Alliance	Mudflat/Dry Pond Bottom Mapping Unit	Non-native Forest	Orchard or Grove	Pinus attenuata Alliance	Pinus coulteri Alliance	Pinus radiata Plantations Semi-Natural Association	Pinus sabiniana Woodland Alliance	Platanus racemosa - Quercus agrifolia Alliance	Populus fremontii - Fraxinus velutina - Salix gooddingii Alliance	Prunus ilicifolia - Heteromeles arbutifolia - Ceanothus spinosus Alliance	Quercus (agrifolia, douglasii, garryana, kelloggii, lobata, wislizeni) Alliance	Quercus agrifolia Alliance
Acer macrophyllum Mapping Unit	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0
Adenostoma fasciculatum - Salvia spp. Alliance	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Adenostoma fasciculatum Alliance	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Aesculus californica Alliance	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	2
Alnus rhombifolia Alliance	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Arbutus menziesii Alliance	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Arctostaphylos (canescens, manzanita, stanfordiana) Alliance	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Arctostaphylos (crustacea, tomentosa) Alliance	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Arctostaphylos glauca Alliance	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Arid West Interior Freshwater Marsh Group	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
Artemisia californica - (Salvia leucophylla) Alliance	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0
Baccharis pilularis Alliance	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0
Baccharis salicifolia Alliance	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Barren and Sparsely Vegetated	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0
Californian Annual & Perennial Grassland Mapping Unit	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Ceanothus (oliganthus, leucodermis, tomentosus) Alliance	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Ceanothus cuneatus Alliance	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Cercocarpus montanus Alliance	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Conium maculatum - Foeniculum vulgare Semi-Natural Alliance	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Cytisus scoparius - Genista monspessulana - Cotoneaster spp. Semi-Natural Alli	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Developed	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Distichlis spicata - (Juncus cooperi - Frankenia salina) Interior Alliance	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Ericameria linearifolia - Cleome isomeris Alliance	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Eucalyptus (globulus, camaldulensis) Semi-Natural Association	0	0	31	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
Gaultheria shallon - Rubus (ursinus) Alliance	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Hesperocyparis macrocarpa Ruderal Semi-Natural Association	0	0	0	0	2	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0
Juglans hindsii and Hybrids Alliance	0	0	0	0	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Juniperus californica Alliance	0	0	0	0	0	0	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Lepidium latifolium - Lactuca serriola Semi-Natural Alliance	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Lotus scoparius - Lupinus albifrons - Eriodictyon spp. Alliance	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Mudflat/Dry Pond Bottom Mapping Unit	0	0	0	0	0	0	0	0	0	6	0	0	0	0	0	0	0	0	0	0	0
Non-native Forest	0	0	0	0	0	0	0	0	0	0	40	0	0	0	0	0	0	0	0	0	1
Orchard or Grove	0	0	0	0	0	0	0	0	0	0	0	4	0	0	0	0	0	0	0	0	0
Pinus attenuata Alliance	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
Pinus coulteri Alliance	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0
Pinus radiata Plantations Semi-Natural Association	0	0	0	0	0	0	0	0	0	0	0	0	0	0	22	0	0	0	0	0	0
Pinus sabiniana Woodland Alliance	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	32	0	0	0	0	2
Platanus racemosa - Quercus agrifolia Alliance	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	23	0	0	0	0
Populus fremontii - Fraxinus velutina - Salix gooddingii Alliance	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4	0	0	0
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	7	0	0
Quercus (agrifolia, douglasii, garryana, kelloggii, lobata, wislizeni) Alliance	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	14	3
Quercus agrifolia Alliance	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	22
Quercus chrysolepis (tree) Alliance	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	3
Quercus douglasii Alliance	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1	0
Quercus kelloggii Alliance	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	1
Quercus lobata Mapping Unit	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1
Quercus wislizeni - Quercus chrysolepis (shrub) Alliance	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0
Quercus wislizeni - Quercus parvula (tree) Alliance	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2
Ribes quercetorum - Rhus trilobata - Frangula californica Alliance	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Robinia pseudoacacia Semi-Natural Association	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Salix exigua Alliance	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Salix gooddingii - Salix laevigata Alliance	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1
Salix lasiolepis Alliance	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Salvia mellifera - (Artemisia californica) Alliance	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Seasonally Saturated Herbaceous	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Sequoia sempervirens Alliance	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
Temperate Pacific Salt Marsh Group	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Toxicodendron diversilobum Alliance	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
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
Vancouverian Lowland Marsh, Wet Meadow & Shrubland Macrogroup	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Vineyard	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Water	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Total	4	2	31	1	2	3	4	1	2	8	40	4	1	0	24	34	25	6	9	20	40
Deterministic Producer's Accuracy	75%	0%	100%	0%	100%	100%	100%	0%	0%	75%	100%	100%	100%	0%	92%	94%	92%	67%	78%	70%	55%

REFERENCE (columns 43–62)

MAP	Quercus chrysolepis (tree) Alliance	Quercus douglasii Alliance	Quercus kelloggii Alliance	Quercus lobata Mapping Unit	Quercus wislizeni - Quercus chrysolepis (shrub) Alliance	Quercus wislizeni - Quercus parvula (tree) Alliance	Ribes quercetorum - Rhus trilobata - Frangula californica Alliance	Robinia pseudoacacia Semi-Natural Association	Salix exigua Alliance	Salix gooddingii - Salix laevigata Alliance	Salix lasiolepis Alliance	Salvia mellifera - (Artemisia californica) Alliance	Seasonally Saturated Herbaceous	Sequoia sempervirens Alliance	Temperate Pacific Salt Marsh Group	Toxicodendron diversilobum Alliance	Umbellularia californica Mapping Unit	Vancouverian Lowland Marsh, Wet Meadow & Shrubland Macrogroup	Vineyard	Water	Total	Deterministic User's Accuracy
Acer macrophyllum Mapping Unit	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	2	0%
Adenostoma fasciculatum - Salvia spp. Alliance	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	19	53%
Adenostoma fasciculatum Alliance	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	34	53%
Aesculus californica Alliance	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	17	82%
Alnus rhombifolia Alliance	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	6	83%
Arbutus menziesii Alliance	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	4	50%
Arctostaphylos (canescens, manzanita, stanfordiana) Alliance	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	6	67%
Arctostaphylos (crustacea, tomentosa) Alliance	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0%
Arctostaphylos glauca Alliance	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	100%
Arid West Interior Freshwater Marsh Group	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	16	88%
Artemisia californica - (Salvia leucophylla) Alliance	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	23	87%
Baccharis pilularis Alliance	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	2	0	0	0	37	76%
Baccharis salicifolia Alliance	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	100%
Barren and Sparsely Vegetated	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	16	88%
Californian Annual & Perennial Grassland Mapping Unit	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	33	100%
Ceanothus (oliganthus, leucodermis, tomentosus) Alliance	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0%
Ceanothus cuneatus Alliance	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	67%
Cercocarpus montanus Alliance	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	100%
Conium maculatum - Foeniculum vulgare Semi-Natural Alliance	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	7	71%
Cytisus scoparius - Genista monspessulana - Cotoneaster spp. Semi-Natural Alli	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0%
Developed	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	41	98%
Distichlis spicata - (Juncus cooperi - Frankenia salina) Interior Alliance	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	100%
Ericameria linearifolia - Cleome isomeris Alliance	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0%
Eucalyptus (globulus, camaldulensis) Semi-Natural Association	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	32	97%
Gaultheria shallon - Rubus (ursinus) Alliance	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0%
Hesperocyparis macrocarpa Ruderal Semi-Natural Association	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4	50%
Juglans hindsii and Hybrids Alliance	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4	75%
Juniperus californica Alliance	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4	100%
Lepidium latifolium - Lactuca serriola Semi-Natural Alliance	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0%
Lotus scoparius - Lupinus albifrons - Eriodictyon spp. Alliance	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0%
Mudflat/Dry Pond Bottom Mapping Unit	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	6	100%
Non-native Forest	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	41	98%
Orchard or Grove	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4	100%
Pinus attenuata Alliance	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	50%
Pinus coulteri Alliance	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0%
Pinus radiata Plantations Semi-Natural Association	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	22	100%
Pinus sabiniana Woodland Alliance	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	37	86%
Platanus racemosa - Quercus agrifolia Alliance	0	0	0	3	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	28	82%
Populus fremontii - Fraxinus velutina - Salix gooddingii Alliance	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	5	80%
Prunus ilicifolia - Heteromeles arbutifolia - Ceanothus spinosus Alliance	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	12	58%
Quercus (agrifolia, douglasii, garryana, kelloggii, lobata, wislizeni) Alliance	0	2	0	5	0	0	0	0	0	0	0	0	0	0	0	0	3	0	0	0	27	52%
Quercus agrifolia Alliance	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	7	0	0	0	32	69%
Quercus chrysolepis (tree) Alliance	18	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	3	0	0	0	27	67%
Quercus douglasii Alliance	0	36	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	39	92%
Quercus kelloggii Alliance	0	0	13	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	18	72%
Quercus lobata Mapping Unit	0	1	0	19	0	0	0	1	0	0	0	0	0	0	0	0	2	0	0	0	26	73%
Quercus wislizeni - Quercus chrysolepis (shrub) Alliance	0	0	0	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	7	43%
Quercus wislizeni - Quercus parvula (tree) Alliance	0	1	0	0	0	11	0	0	0	0	0	0	0	0	0	0	0	0	0	0	14	79%
Ribes quercetorum - Rhus trilobata - Frangula californica Alliance	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	100%
Robinia pseudoacacia Semi-Natural Association	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0%
Salix exigua Alliance	0	0	0	0	0	0	0	0	3	0	0	0	0	0	0	0	0	0	0	0	4	75%
Salix gooddingii - Salix laevigata Alliance	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0%
Salix lasiolepis Alliance	0	0	0	0	0	0	0	0	0	4	17	0	0	0	0	0	0	0	0	0	24	71%
Salvia mellifera - (Artemisia californica) Alliance	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	2	50%
Seasonally Saturated Herbaceous	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	3	0%
Sequoia sempervirens Alliance	0	0	0	0	0	0	0	0	0	0	0	0	0	29	0	0	3	0	0	0	33	88%
Temperate Pacific Salt Marsh Group	0	0	0	0	0	0	0	0	0	0	0	0	0	0	13	0	0	0	0	0	13	100%
Toxicodendron diversilobum Alliance	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	16	0	0	0	0	24	67%
Umbellularia californica Mapping Unit	1	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	21	0	0	0	23	91%
Vancouverian Lowland Marsh, Wet Meadow & Shrubland Macrogroup	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	8	0	0	11	73%
Vineyard	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	100%
Water	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	40	40	100%
Total	20	43	13	29	4	11	1	1	3	5	18	5	1	30	13	18	46	9	1	40		
Deterministic Producer's Accuracy	90%	84%	100%	66%	75%	100%	100%	0%	100%	0%	94%	20%	0%	97%	100%	89%	46%	89%	100%	100%		

Overall Accuracy 80.8%

4.4. Discussion

As indicated by the lifeform error matrix, there is very little confusion in the lifeform map. In the fine scale vegetation map, confusion between alliances within the same lifeform followed the trends seen in recent similar mapping efforts in Sonoma, Marin, and San Mateo Counties.

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

4.4.1 Confusion in Forest Classes

For the upland forests, accuracies are high, with the lowest accuracies occurring in the oak alliances, and between the *Quercus agrifolia* Alliance and the *Umbellaria californica* Mapping Unit. Oak stands are sometimes difficult to map to the alliance level because trees of different oak species intermix in stands, hybridize with one another, and are sometimes difficult to distinguish from one another in the imagery. In addition, live oak often co-dominates with California bay, resulting in confusion between live oak and bay alliances.

Among the common oak types, deterministic accuracies were lowest for the *Quercus agrifolia* Alliance, the *Quercus lobata* Mapping Unit, and the Quercus *(agrifolia, douglasii, garryana, kelloggii, lobata, wislizeni)* Alliance. The confusion in these types is illustrated by looking at the accuracy assessment results for the *Quercus agrifolia* Alliance, which had 10 errors of commission, resulting in a deterministic user's accuracy of only 69%. Seven of these errors of commission were assigned by surveyors to the *Umbellaria californica* Mapping Unit. Of these seven, five received a secondary 'acceptable' assignment of *Quercus agrifolia*, and the other two stands had co-dominant *Quercus agrifolia*.

Ten of the 13 of the Quercus *(agrifolia, douglasii, garryana, kelloggii, lobata, wislizeni)* Alliance errors of commission were to other oak alliances (*Quercus lobata*-5, *Quercus agrifolia*-3, *Quercus douglasii*-2) and the other 3 were to *Umbellaria* (the three errors of commission to *Umbellaria* all had secondary AA labels of some kind of *Quercus*). These errors typically resulted when multiple oak species mixed in a stand, but there were differences in the assessment of cover of each species between the mappers and the field. Because many of the *Quercus* alliances are in the same National Vegetation Classification Group, they receive high fuzzy accuracies despite lower deterministic accuracies. For example, fuzzy accuracies for the Quercus *(agrifolia, douglasii, garryana, kelloggii, lobata, wislizeni)* Alliance were high: 90% for fuzzy user's accuracy (v. 52% for deterministic user's accuracy) and 94% for fuzzy producer's accuracy (v. 70% for deterministic producer's accuracy).

Lifeform errors between riparian ('Riparian Forest and Shrub') and upland forests ('Forest') can be largely attributed to the grouping of riparian and upland alliances into generalized Mapping Units in the mapping key. Of the 7 AA surveys where the map lifeform was 'Riparian Forest' and the reference lifeform was 'Forest', 6 were given a riparian field alliance, e.g. the *Quercus lobata* Riparian Alliance. But because that alliance keys to the all-inclusive *Quercus lobata* Mapping Unit, it is assigned the Forest lifeform for the purposes of the AA analysis. Four of the 7 were surveyed as riparian field alliances within the *Quercus lobata* Mapping Unit, 1 to a riparian field alliance witin the *Umbellularia californica* Mapping Unit, and 1 to a riparian field alliance within the *Acer macrophyllum* Mapping Unit.

Errors in the riparian forest types were higher than for upland forests. Riparian forest alliances are difficult to map because they often are hard to distinguish via aerial image interpretation, and it can be difficult even in the field to determine stand boundaries between different riparian alliances.

The confusion in the riparian forests is illustrated by looking at the accuracy assessment results for the *Salix lasiolepis* Alliance. The *Salix lasiolepis* Alliance had a deterministic user's accuracy of only 71%, and a deterministic producer's accuracy of 94%. This riparian alliance had seven errors of commission, four of these were to the *Salix gooddingii – Salix laevigata* Alliance, one to the *Acer macrophyllum* Mapping Unit (*Salix lasiolepis* was codominant in this stand), one to the Arid West Interior Freshwater Marsh Group (this AA survey had a secondary 'acceptable' map class of *Salix lasiolepis* Alliance), and one to the *Baccharis pilularis* Alliance. In summary, six of the *Salix lasiolepis* Alliance surveys' seven errors of commission were confused with other *Salix* types or had significant amounts of *Salix spp*. present in the stand.

4.4.2 Confusion in Shrub Classes

Shrublands often contain a mix of species of short, woody vegetation where individual species can be difficult to interpret from the imagery with confidence. Field validation of shrubs in Alameda and Contra Costa Counties was also difficult because large areas of shrublands burned in the 2020 fires and much of the unburned shrubland occurs on private lands or on steep, inaccessible public lands.

The *Adenostoma fasciculatum* Alliance is an example of a lower accuracy shrub type and illustrates the confusion between some shrub types. The *Adenostoma fasciculatum* Alliance had

16 errors of commission resulting in a user's accuracy of only 53%. Of the 16 errors of commission, seven were to the *Adenostoma fasciculatum - Salvia spp.* Alliance, an alliance with very similar composition and diagnostic species. Five of the errors of commission were to the *Ceanothus cuneatus* Alliance – in four out of five of these, *Adenostoma fasciculatum* Alliance was assigned as a secondary label. When *Ceanothus cuneatus* and *Adenostoma fasciculatum* codominate (both with relative shrub cover values between 30-60%), the map class keys to the *Ceanothus cuneatus* Alliance, often making the distinction between these similar shrub types a difference of estimated covers from the mapping and AA perspectives. The rest of the errors of commission were to the *Arctostaphylos (canescens, manzanita, stanfordiana)* Alliance (2), the *Salvia mellifera - (Artemisia californica)* Alliance (1), and the *Ceanothus (oliganthus, leucodermis, tomentosus)* Alliance (1). For three of these four, the *Adenostoma fasciculatum* Alliance was assigned as secondary 'acceptable' map class. These errors between *Adenostoma fasciculatum* Alliance and similar shrub map classes that often contain *Adenostoma fasciculatum* as a codominant or component are expected (and inevitable) errors. Fuzzy accuracies for the *Adenostoma fasciculatum* Alliance came in at 89% (user's accuracy) and 90% (producer's accuracy).

5. Alameda and Contra Costa County Vegetation Map Data Products

5.1. Introduction

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

5.2. Obtaining Data Products

The vegetation map and related products are available for download from pacificvegmap.org. There are numerous ways of obtaining data from the web site. Table 12 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 12. *Available formats for vegetation map data products from pacficvegmap.org*

Data Product	Feature Service	Tile Service	Countywide Geodatabase	Countywide Layer Package	Layer File	Datasheet
Alameda-Contra Costa County Fine scale Veg Map	*Y*	*Y*	*Y*	*Y*	*Y*	*Y*
Alameda-Contra Costa Enhanced Lifeform Map			*Y*		*Y*	*Y*
Alameda-Contra Costa County Impervious Surfaces		*Y*	*Y*	*Y*		*Y*

5.3. Data Product Specifications (Datasheets)

In addition to metadata for each spatial data product, datasheets were created and made available for each of the Alameda and Contra Costa County data products. Links to the datasheets for the vegetation map and its derivatives are provided in Table 13.

Table 13. *Datasheets for vegetation map products*

Product	Datasheet Link
Alameda-Contra Costa County Fine Scale Vegetation Map	https://vegmap.press/alcc_fine_scale_datasheet
Alameda-Contra Costa County Enhanced Lifeform Map	https://vegmap.press/alcc_elf_datasheet
Alameda-Contra Costa County Impervious Surfaces Map	https://vegmap.press/alcc_impervious_datasheet

5.4. Attributes of the Fine scale Vegetation Map

The fine scale vegetation map has 140,442 polygons across the two-county area. Each polygon includes its fine scale map class and a suite of information about the polygon. Information is included in the form of numerous attributes that characterize the polygon's forest structure, its impervious composition, its relative hardwood versus conifer cover, and others. Table 14 includes a list and description of the numerous fine scale vegetation map attributes.

Table 14. *Fine scale vegetation map attributes*

Fine Scale Map Attributes (Name/Alias)	Description
FINESCALE/Fine Scale Map Class in 2020	U.S. National Vegetation Classification (USNVC) map class label for all stands.
FSMC_ABBRV/Fine Scale Map Class Abbreviation in 2020	Map class abbreviations for use in cartography and visualization. A key to abbreviations is available here: https://vegmap.press/alcc_vegmap_abbrevs
FSMC_DESCRIPTION/Map Class Description in 2020	Map class descriptions as defined in the mapping key. The key is available here: https://vegmap.press/alcc_mapping_key
LIFEFORM/Lifeform in 2020	15-class lifeform label for all stands. Floristically more general than the fine scale map class.
ENHANCED_LIFEFORM/Enhanced Lifeform in 2020	27-class lifeform label for all stands. Forest and shrub class labels have more floristic definition than the lifeform map. Floristically more general than the fine scale map class.
ABS_COVER % lidar Returns > 15 Feet (2017-2022)[1]	Absolute cover of lidar returns greater than 15 feet in height. Derived from 2017-2022 lidar data.[1]
REL_CON_COV/Relative % Conifer Cover in 2020	Relative conifer cover, estimating the percent of tree canopy >= 15 ft. is conifer. Derived from machine learning on lidar-derived tree approximate objects combined with manual image interpretation of 2020 imagery.
REL_HDW_COV/Relative % Hardwood Cover in 2020	Relative hardwood cover, estimating the percentage of tree canopy >= 15 ft. is hardwood. Derived from relative conifer cover. (100-REL_CON_COV)
CON_COVER/Absolute % Conifer Cover in 2020	Absolute conifer cover, calculated as: ((relative % conifer cover/100) x (absolute % cover/100)) * 100
HDW_COVER/Absolute % Hardwood Cover in 2020	Absolute hardwood cover, calculated as: ((relative % hardwood cover/100) x (absolute % hardwood/100)) * 100

[1] 2017-2022 date range for all lidar attributes refers to the different collection dates of lidar across different areas of the two counties. See Figures 3 and 4 in Section 3.2.2.

Fine Scale Map Attributes (Name/Alias)	Description
SHB_COVER/Absolute % Shrub Cover in 2020	Absolute shrub cover for herbaceous and shrub stands. Derived from machine learning combined with manual image interpretation of 2020 imagery.
STAND_HT_MN/ Mean lidar Stand Height (ft.) (2017-2022)	Mean stand height from lidar-derived canopy height model (CHM).
STAND_HT_MX/ Maximum lidar Stand Height (ft.) (2017-2022)	Maximum stand height from lidar-derived canopy height model (CHM). Calculated for areas of the stand greater than or equal to 15 feet tall.
STAND_HT_MD/ Median lidar Stand Height (ft.) (2017-2022)	Median stand height from lidar-derived canopy height model (CHM). Calculated for areas of the stand greater than or equal to 15 feet tall.
STAND_HT_SD/ Standard Deviation lidar Stand Height (ft.) (2017-2022)	Standard deviation of stand height from lidar-derived canopy height model (CHM). Calculated for areas of the stand greater than or equal to 15 feet tall.
IMPERVIOUS/% Impervious in 2020	Percent of stand that was impervious in 2020. Integrated from the Alameda and Contra Costa impervious surface maps.
PERVIOUS/% Pervious in 2020	Percent of stand that was pervious in 2020. Integrated from the Alameda and Contra Costa impervious surface maps.
PAVED_RD/% Paved Road in 2020	Percent of stand that was paved road in 2020. Integrated from the Alameda and Contra Costa County impervious surface map.
DIRT_RD/% Dirt and Gravel Road in 2020	Percent of stand that was dirt or gravel road in 2020. Integrated from the Alameda and Contra Costa County impervious surface map.
OTHER_IMPERVIOUS/% Other Impervious in 2020	Percent of stand that was a paved or unpaved, non-road surface (such as a paved or unpaved parking lot) in 2020. Integrated from the Alameda and Contra Costa County impervious surface map.
BUILDINGS/% Buildings in 2020	Percent of stand that was a building in 2020. Integrated from the Alameda and Contra Costa County impervious surface map.
SLOPE_MN/Mean Bare Earth Slope (2017-2022)	Mean bare-earth slope (degrees) derived from 2017–2022 lidar.
SLOPE_MX/Maximum Bare Earth Slope (2017-2022)	Maximum bare-earth slope (degrees) derived from 2017–2022 lidar.
SLOPE_SD/Standard Deviation Bare Earth Slope (2017-2022)	Standard deviation of the bare-earth slope (degrees) derived from 2017–2022 lidar.

Fine Scale Map Attributes (Name/Alias)	Description
STAND_DEAD/% Standing Dead Over 15ft. in 2022	Estimate of percent standing dead vegetation in forested stands. Estimates the percent of the woody canopy > 15 feet tall that did not have a living crown in 2022.
SOURCE/Fine Scale Map Label Source	Indicates whether stand's fine scale map class was validated during field work, or if the map label was assigned based on remote sensing methods.
ACRES/Acres	Acres of land encompassed by the stand.
FIRE_FLAG_20_25/Experienced Fire Between 2020-2025	Yes/No attribute, assigned yes when >50% of a stand overlapped with a fire that occurred between 2020-2025, based on published FRAP (CAL FIRE) perimeters.
OID_COPY/ OID_COPY	Index for internal use.

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