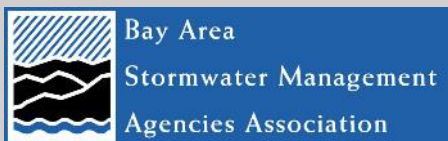


# BASMAA Regional Monitoring Coalition Five-Year Bioassessment Report

Water Years 2012 - 2016



Prepared for:



Prepared by:



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## Executive Summary

Biological assessment (bioassessment) is an evaluation of the biological condition of a water body based on the organisms living within it. In 2009, the Bay Area Stormwater Management Agencies Association's (BASMAA) Regional Monitoring Coalition (RMC) developed a bioassessment monitoring program to answer management questions identified in the Municipal Regional Stormwater National Pollutant Discharge Elimination System (NPDES) Permit (referred to as the Municipal Regional Permit or MRP):

- *Are water quality objectives, both numeric and narrative, being met in local receiving waters, including creeks, rivers and tributaries?*
- *Are conditions in local receiving waters supportive or likely to be supportive of beneficial uses?*

Bioassessment data collected over the first five years of RMC monitoring (2012-2016) are included in this report. The RMC's monitoring design addresses these management questions on a regional (Bay Area) scale to monitoring results across the five participating Bay Area counties (Alameda, Contra Costa, San Mateo, Santa Clara and Solano). Three study questions, developed to assist with addressing the management questions described above, including:

- 1) What is the biological condition of perennial and non-perennial streams in the region?
- 2) What stressors are associated with poor condition?
- 3) Are conditions changing over time?

The findings of this study are intended to help stormwater programs better understand the current condition of these water bodies and identify stressors that are likely to pose the greatest risk to the health of streams in the Bay Area. The report evaluates the existing RMC monitoring design and identifies a range of potential options for revising the design (if desired) to better address the questions posed. These options are intended to provide considerations for discussion during the planning for reissuance of the Municipal Regional Permit, which is likely to be adopted in 2020 or 2021.

### KEY FINDINGS

- **Most streams in the region are in poor biological condition.** The biological conditions of streams in the RMC area are assessed using two ecological indicators: benthic macroinvertebrates (BMIs) and algae. Results from 2012 through 2016 study period indicate that streams in the RMC area are generally in poor biological condition. Based on BMIs, over half (58%) of stream length was ranked in the lowest condition category of the California Stream Condition Index (CSCI). For algae indices (D18 and S2), stream conditions appear slightly less degraded, with approximately 40% of the streams ranked in lowest condition category. These findings should be interpreted with the understanding that the survey focused on urban stream conditions, and that these data represent current (baseline) conditions.
- **Poor biological conditions are strongly associated with physical habitat and landscape stressors.** The associations between biological indicators (CSCI and D18) and stressor data were evaluated using random forest and relative risk analyses. The study results showed that different biological indicators responded to different types of stressors. CSCI scores were strongly influenced by

physical habitat variables (e.g., level of human disturbance at a site) and land use factors (e.g., level of impervious surfaces near the site), while D18 scores were moderately influenced by water quality variables (e.g., dissolved oxygen and conductivity). Together, BMI and algae indices can be used to assess the overall biological condition of water bodies and potentially identify the causes of poor (or good) conditions. In general, CSCI scores at urban sites were consistently low, indicating that degraded physical habitat conditions common in urban settings are impacting biological conditions in streams. In contrast, D18 scores at urban sites were more variable, indicating that healthy diatom (algae) assemblages can occur at sites with poor physical habitat, which may provide valuable information about the overall water quality conditions in urban streams.

- **No changes in biological conditions are evident over the 5-year survey.** The short time frame of the survey (five years) limited the ability to detect trends. The variability in biological condition observed over the five years of the current analysis may have been associated with annual variation in precipitation, which included drought conditions during the first four years of the survey. A longer time period may be needed to detect trends in biological condition at a regional scale.
- **Baseline biological assessment data can assist Bay Area stormwater managers in evaluating the long-term effectiveness of ongoing or planned management actions.** Baseline bioassessment monitoring data collected by the RMC provides valuable information about the current status of aquatic life uses in the Bay Area and how RMC streams compare to other regions in the State of California. The baseline dataset provides context for potential future biological integrity policies being developed by the State Water Resources Control Board (State Water Board) and serves as a foundation for evaluating on-going and future watershed management actions that attempt to reduce the impacts of urbanization on creeks and channels. Future creek status monitoring may provide additional insight into the potential positive impacts of actions, such as green stormwater infrastructure and creek restoration, that improve water quality and address other needs of aquatic life uses in urban creeks.
- **The RMC monitoring design provides estimates for overall stream conditions in RMC area and urban stream conditions for each county.** Because participating municipalities are primarily concerned with stormwater runoff from urban areas, the RMC focused sampling efforts on urban sites (approximately 80%) over non-urban sites (approximately 20%). As a result, non-urban sites are under-represented in the dataset, resulting in lower overall biological condition scores than would be expected for a spatially balanced dataset. Depending on the goals for the RMC moving forward, consideration should be given to developing a new sample draw that establishes a new list of assessment sites that are weighted for specific land uses categories and Program areas of interest. Based on evaluation of data collected during the first five years of the survey, several options to revise the RMC Monitoring Design are presented in the report.

# 1 INTRODUCTION

## 1.1 BACKGROUND

The Bay Area Stormwater Management Agencies Association (BASMAA) Regional Monitoring Coalition (RMC) is a consortium of six San Francisco Bay Area municipal stormwater programs that joined together in 2010 to coordinate and oversee water quality monitoring required by the Municipal Regional Stormwater National Pollutant Discharge Elimination System (NPDES) Permit (referred to as the Municipal Regional Permit or “MRP”). The MRP was first adopted in 2009 (Order R2-2009-0074) by the San Francisco Bay Regional Water Quality Control Board (SFBRWQCB). The MRP was reissued in 2015 through Order R2-2015-1049. The 2009 and 2015 versions of the MRP are referred to as MRP 1.0 and MRP 2.0, respectively. Both versions of the MRP require bioassessment monitoring in accordance with Standard Operating Procedures (SOPs) established by the California Surface Water Ambient Monitoring Program (SWAMP), including sampling of benthic macroinvertebrates (BMIs), benthic algae (i.e., diatoms and soft algae), and water chemistry, and the characterization of physical habitat.

The MRP identifies two broad management questions that required bioassessment monitoring (and other creek status monitoring requirements) is intended to address:

- *Are water quality objectives, both numeric and narrative, being met in local receiving waters, including creeks, rivers and tributaries?*
- *Are conditions in local receiving waters supportive or likely to be supportive of beneficial uses?*

Consistent with the requirements of the MRP, the RMC developed a probabilistic monitoring design to address the management questions on a regional scale and compare monitoring results across stormwater programs. The probabilistic design is based on the Generalized Random Tessellation Stratified (GRTS) approach (Stevens and Olson 2004) for evaluating and selecting sampling stations in perennial and nonperennial streams. A power analysis estimated a minimum sample size of 30 sites to evaluate the condition of aquatic life within a confidence interval of approximately 12%. This was considered sufficient for decision-making in the RMC area. Under the MRP, each municipal Stormwater Program is required to assess a minimum number of stream/channel sites based on their relative population. As a result, the number of sites required each year varies by county: 20 sites for Santa Clara and Alameda counties and 10 sites for San Mateo and Contra Costa counties. Fairfield-Suisun and Vallejo are required to sample 8 and 4 sites, respectively, during each five-year period. In addition, the San Francisco Bay Regional Water Quality Control Board (SF Bay Water Board) collaborated with the RMC by monitoring additional sites in non-urban areas in each of the counties.

## 1.2 PROJECT GOAL

This goal of this project was to compile and evaluate bioassessment data collected over the first 5-years of bioassessment monitoring conducted by the RMC (2012 – 2016). The evaluation was designed to address three main questions, consistent with the overarching questions in the MRP:

- 1) What is the biological condition of perennial and non-perennial streams in the region?

- 2) What stressors are associated with poor condition?
- 3) Are conditions changing over time?

The findings of this report are intended to help stormwater programs better understand the current condition of these water bodies, prioritize stream reaches in need of protection or restoration, and identify stressors that are likely to pose the greatest risk to the health of streams in the Bay Area.

This report also provides an evaluation of the existing RMC monitoring design and identifies a range of potential options for revising the design (if desired) in anticipation of the next version of the MRP, which is likely to be adopted in 2020 or 2021. These options can inform the monitoring re-design process as part of a future BASMAA Regional Project.

This project was implemented by a Project Team comprised of EOA, Inc. and Applied Marine Sciences, Inc. (AMS) with technical review provided by the Southern California Coastal Water Research Project (SCCWRP). A BASMAA Project Management Team (PMT) consisting of representatives from BASMAA stormwater programs and municipalities provided oversight and guidance to the Project Team.

Sections of this report are organized according to the following topics:

- **Section 1.0** – Introduction including summary of other Regional Monitoring Programs using biological assessments, development of State policies that are relevant to bioassessment data collection, and description of the goals for this report;
- **Section 2.0** – Methods including monitoring survey design, site evaluation procedures, field sampling and data analyses;
- **Section 3.0** – Results summarizing biological conditions, stressor association with conditions, and trends;
- **Section 4.0** – Discussion organized by the management questions and goals; and
- **Section 5.0** – Conclusions and recommendations.

### 1.3 BIOASSESSMENTS PROGRAMS IN CALIFORNIA

Bioassessment programs are currently implemented on a statewide and regional basis in California. The RMC's monitoring design is consistent with the design used by the statewide Perennial Streams Assessment (PSA) program and is specifically intended to allow for future integration of data between the two monitoring programs. The RMC has also integrated lessons learned from the Stormwater Monitoring Coalition (SMC), which spearheads a similar collaborative monitoring effort in Southern California, in the development of alternatives for potential re-design of the RMC monitoring survey described at the end of this report.

Since 2000, the State of California has conducted probability surveys of its perennial streams and rivers with a focus on biological endpoints. These surveys are managed collectively by the Surface Water Ambient Monitoring Program (SWAMP) under its PSA program. The PSA collects samples for biological indicators (BMIs and algae), chemical constituents (nutrients, major ions, etc.), and physical habitat assessments for both in-stream and riparian corridor conditions. As of 2012, over 1300 unique perennial



stream sites have been monitored by PSA and its partner programs.<sup>1</sup> In 2015, the PSA developed a management memorandum summarizing biological conditions (based on California Stream Condition Index score) and associated stressor data collected at probabilistic sites over a 13-year time period (2000 – 2012) (SWRCB 2015).

The SMC, a coalition of multiple state, federal, and local agencies, initiated a regional monitoring program in 2009. The SMC uses multiple biological indicators to assess ecological health of streams, including BMIs, benthic algae (diatoms and soft algae) and riparian wetland condition. The SMC also collects water chemistry, water column toxicity, and physical habitat data to evaluate potential stressors to biological health. During the first five years of the program (2009 to 2013), the SMC monitored more than 500 probabilistic sites in 15 major watersheds in California’s South Coast region, with a focus on perennial streams (Mazor 2015). Evolution of those data suggested that few perennial, wadeable streams in the SMC study area are in good biological condition (Mazor 2015a). Recognizing that perennial streams account for only 25% of stream-miles in the region, in 2015, the SMC expanded its monitoring program to include nonperennial streams, which account for approximately 59% of stream-miles (Mazor 2015b). The SMC program also focused about 30% of the monitoring effort towards revisiting probabilistic sites to provide an estimate of change in condition (Mazor 2015b). The next iteration of the SMC monitoring program will likely include a larger focus on trends monitoring (Rafael Mazor, SCCWRP, personal communication, 2018).

#### 1.4 BIOSTIMULATORY/BIOINTEGRITY POLICY DEVELOPMENT

Bioassessment monitoring conducted by the RMC not only provides information about the condition of aquatic life uses in Bay Area streams and how they compare to other regions (i.e., SMC), it also generates a significant baseline dataset that provides context for potential future biological integrity and biostimulatory policies that are currently under development by the State Water Resources Control Board (State Water Board). The biostimulatory policy will likely develop water quality objectives for biostimulatory substances (e.g., nutrients) along with an implementation program as an amendment to the Water Quality Control Plan for Inland Surface Water, Enclosed Bays and Estuaries of California (ISWEBE Plan).<sup>2</sup> The biostimulatory substances policy may include a numeric and/or narrative objective(s) that will be applicable to streams in California. The State Water Board plans is expected to establish the implementation plan for the biostimulatory substances policy in three phases, with each phase including a plan that would be unique for each of the three different water body types. The first phase of the Biostimulatory Amendment would be applicable to wadeable streams.

The biostimulatory policy will also include a water quality control policy (i.e., Biointegrity Policy) to establish and implement biological condition assessment methods, scoring tools, and targets aimed at protecting the biological integrity in wadeable streams. The policy will utilize a multi-indicator approach that includes the California Stream Condition Index (CSCI) for benthic macroinvertebrates and statewide

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<sup>1</sup> The Stormwater Monitoring Coalition has collected a majority of samples at probabilistic sites in Coastal Southern California watersheds and the US Forest Service has collected PSA-comparable data from sites in National Forests of the Sierra Nevada.

<sup>2</sup> Information obtained from: [https://www.waterboards.ca.gov/water\\_issues/programs/biostimulatory\\_substances\\_biointegrity](https://www.waterboards.ca.gov/water_issues/programs/biostimulatory_substances_biointegrity)

algal stream condition index (ACSI), which is currently under development. The State Water Board's plan is to establish "assessment endpoints" as primary lines of evidence to assess beneficial use support in wadeable streams. These endpoints may be used to establish default nutrient objectives or thresholds for California streams, with potential option to refine the thresholds under a "watershed approach."

The State Water Board's biostimulatory/biointegrity project has been delayed due to several unresolved policy issues that need to be addressed prior to development of the policy, including<sup>3</sup>:

- 1) Consideration of channels in highly developed landscapes (i.e., where assessment endpoints may not be achieved);
- 2) Identify Beneficial Uses;
- 3) Relationship between established biological assessment endpoints and nutrient endpoints; and
- 4) Define process for coordinated watershed approach.

The State Water Board is currently planning to develop draft policy options to present to Stakeholder Advisory and Regulatory Groups in 2019.

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<sup>3</sup> Information obtained from presentation by Jessie Maxfield, California State Water Board, given at the 2017 California Aquatic Bioassessment Workgroup conference in Davis, California.

## 2 METHODS

### 2.1 STUDY AREA

The study area for RMC creek status monitoring consists of the perennial and non-perennial streams, channels and rivers within the portions of the five participating counties (San Mateo, Santa Clara, Alameda, Contra Costa, Solano) that overlap with the San Francisco Bay Regional Water Quality Control Board (Region 2) boundary, and the eastern portion of Contra Costa County that drains to the Central Valley region (Region 5). The RMC creek status sample frame consists of the urban and non-urban portions of the stream network flowing through the RMC area. The source dataset used to create the sample frame was the 1:100,000 National Hydrography Dataset (NHD).

### 2.2 SURVEY DESIGN AND SAMPLING SITES

Creek status monitoring sites were selected based on a probabilistic survey design consisting of a master draw of 5,740 sites (approximately one site for every stream kilometer in the sample frame). The selection procedure employed the U.S. EPA's Generalized Random Tessellation Stratified (GRTS) survey design methodology (Stevens and Olson, 2004). The GRTS approach generated a spatially-balanced distribution of sites covering the majority of the San Francisco Bay Area. It should be noted that the sample draw of 5,740 sites did not account for land use designations or other emphases (i.e., County) and therefore, the master draw of sample sites was weighted towards commonly occurring conditions (i.e., non-urban sites), with less common conditions (i.e., reference and urban sites) being less represented due to their lower relative abundance in the sample frame.

The RMC sampling design targeted the population of accessible streams with flow conditions suitable for sampling (i.e., adequate flow during spring index period). A random set of potential monitoring sites (i.e., the master draw) was established, with each site having an equal, non-zero weight, proportional to the inverse of its selection probability. Thus, all sites were assumed to have an equal probability of selection throughout the sample frame. The weights represent the amount of stream length encompassed by each site in the overall target population.

Once the master draw was established, the list of monitoring sites was separated into 19 categories to facilitate site evaluations and implement creek status monitoring, including bioassessment (Table 1). The following attributes were used to generate the categories:

- County (n=5): San Mateo, Santa Clara, Alameda, Contra Costa, Solano (source: California Department of Forestry and Fire, 2009);
- Water Quality Control Board Region (n=2): Region 2, Region 5 (source: San Francisco Regional Water Quality Control Board, undated);
- Land use Category (n = 4): Urban or nonurban in all counties, except Solano ('urban\_V' and 'urban\_FS' in Solano County). Urban land use was defined as a combination of US Census (2000) areas classified as urban, and areas within Census City boundaries. This definition of urban land use results in some relatively undeveloped areas and parks along the fringes of cities to be

classified as urban. Urban sites therefore represent a broad range of developed (i.e., impervious surface) conditions. Non-urban area was defined as all remaining area in the RMC boundary not classified as urban.

**Table 1. Number of sites and stream length from the master draw in each post-stratification category.**

County	Urban		Non-Urban		Total	
	Sites	Stream Length (km)	Sites	Stream Length (km)	Sites	Stream Length (km)
San Mateo	222	233.8	528	556.0	750	789.8
Santa Clara	542	570.8	1376	1449.1	1918	2019.8
Alameda	454	478.1	842	886.7	1296	1364.8
Contra Costa (Region 2)	587	618.2	363	382.3	845	889.9
Contra Costa (Region 5)			349	367.5	454	478.1
Solano (Vallejo)	12	12.6	386	406.5	477	502.3
Solano (Fairfield-Suisun)	79	83.2				
<b>Overall Total</b>					<b>5740</b>	<b>6,044.7</b>

To maintain a spatially-balanced pool of monitoring sites, sites were evaluated in the order that they appeared in the master draw list (with a few exceptions). Sites were evaluated for sampling using both desktop and field reconnaissance. Field crews attempted to locate a reach suitable for sampling within 300 m of the target coordinates. Sites without a suitable reach were rejected for sampling. Reasons for rejection included physical barriers, lack of flowing water, refusal or lack of response from landowners, unwadeable (i.e., >1 m deep for at least 50% of the reach) and inappropriate waterbody types (e.g., tidally influenced). Sites with temporary inaccessibility, unsafe/hazardous or permission issues (e.g., construction, lack of response from landowners) were re-evaluated for sampling in subsequent years. All program participants were instructed to use a standard set of codes to identify the reason behind exclusion of sites.

In contrast to the PSA and SMC regional monitoring designs, which targeted perennial streams, the RMC sampled both perennial and non-perennial streams. Additionally, at the outset, each countywide Program agreed they would attempt to assess up to 20% of their required sites in non-urban areas.

### 2.3 SAMPLING PROTOCOLS/DATA COLLECTION

Biological sample collection and processing was consistent with the BASMAA RMC Quality Assurance Project Plan (QAPP)<sup>4</sup> (BASMAA 2016a) and Standard Operating Protocols (SOPs) (BASMAA 2016b) which

<sup>4</sup> The RMC QAPP and SOP documents were initially developed in 2012 (Version 1.0), revised in 2013 (Version 2.0) and 2016 (Version 3.0)

were developed to be consistent with the current SWAMP Quality Assurance Program Plan (QAPrP) and SOPs. Bioassessments were conducted during the spring index period (approximately April 15 – June 30) with the goal to sample a minimum of 30 days after any significant storm (defined as at least 0.5-inch of rainfall within a 24-hour period). A 30-day grace period allows diatom and soft algae communities to recover from peak flows that may scour benthic algae from the bottom of the stream channel.

### 2.3.1 Biological Indicators

Each monitoring site consisted of an approximately 150-meter stream reach that was divided into 11 equidistant transects placed perpendicular to the direction of flow. Benthic macroinvertebrate (BMI) and algae (i.e., diatom and soft algae) samples were collected at each transect using the Reach-wide Benthos (RWB) method described in Ode et al. (2016). The algae composite sample was also used to collect chlorophyll a and ash free dry mass (AFDM) samples following methods described in Ode et al. (2016).

Biological samples were sent to laboratories for analysis. The laboratory analytical methods used for BMIs followed Woodward et al. (2012), using the Southwest Association of Freshwater Invertebrate Taxonomists (SAFIT) Level 1a Standard Taxonomic Level of Effort, with the additional effort of identifying chironomids (midges) to subfamily/tribe instead of family (Chironomidae). Soft algae and diatom samples were analyzed following SWAMP protocols (Stancheva et al. 2015). The taxonomic resolution for all data was standardized to the SWAMP master taxonomic list.

### 2.3.2 Physical Habitat

Both quantitative and qualitative measurements of physical habitat structure were taken at each of the 11 transects and 10 inter-transects at each monitoring site. At the outset of the monitoring program in 2012, Physical habitat measurements followed procedures defined in the “BASIC” level of effort (Ode 2007), with the following exceptions as defined in the “FULL level of effort: stream depth and pebble count + coarse particulate organic matter (CPOM), cobble embeddedness, and discharge measurements. In 2016, the entire “FULL” level of effort for the characterization of physical habitat described in Ode et al. (2016) was adopted, consistent with the reissued MRP 2.0 (SFBRWQCB 2015). Physical habitat measurements include channel morphology (e.g., channel width and depth), habitat features (e.g., substrate size, algal cover, flow types, and in-stream habitat diversity) and human disturbance in the riparian zone (e.g., presence of buildings, roads, vegetation management). In addition, a qualitative Physical Habitat Assessment (PHAB) score was assessed for the entire bioassessment reach. The PHAB score is composed of three characteristics for the reach, including channel alteration, epifaunal substrate, and sediment deposition. Each attribute is individually scored on a scale of 0 to 20, with a score of 20 representing good condition.

### 2.3.3 Water Quality

Immediately prior to biological and physical habitat data collection, general water quality parameters (dissolved oxygen, pH, specific conductance and temperature) were measured at each site, at or near the centroid of the stream flow using pre-calibrated multi-parameter probes. In addition, water samples were collected for nutrients and conventional analytes analysis using the Standard Grab Sample Collection Method as described in SOP FS-2 (BASMAA 2016b).

### 2.3.4 Stressor Variables

Physical habitat, land-use, and water quality data were compiled and evaluated as potential stressor variables for biological condition. Land-use variables were calculated in GIS by overlaying the drainage area for sample locations with land use and road data. The variables included percent urbanization, percent impervious, total number of road crossings and road density at three different spatial scales (1 km, 5 km and entire watershed).

Physical habitat metrics were calculated using the SWAMP Bioassessment Reporting Module (SWAMP RM). The SWAMP RM output includes calculations based on parameters that are measured using EPA's Environmental Monitoring and Assessment Program (EMAP) for freshwater Wadeable Streams (Kaufmann et al. 1999), as well as parameters collected under the SWAMP protocol (Marco Sigala, personal communication, 2017). The RM produces a total of 176 different metrics based on data collected using the SWAMP "FULL" habitat protocol. Ten of the best performing metrics (Andy Rehn, CDFW, personal communication) were selected based on best professional judgment from the SWAMP RM output to analyze physical habitat data collected by the RMC.

General water quality (e.g., DO, SpCond) and chemistry (e.g., nitrate and phosphorus) data collected at the bioassessment sites were also included. Some of the water chemistry variables were calculated from the analytes that were measured. These include Total Nitrogen (sum of Nitrate, Nitrite and Total Kjeldahl Nitrogen) and Unionized Ammonia (calculated using pH and temperature).

### 2.3.5 Rainfall Data

For evaluation of trends, a representative rainfall dataset was collated for San Mateo, Santa Clara, Contra Costa, and Alameda counties. The total accumulated rainfall in each water year during the period of 2012-2016 was calculated. The rainfall dataset assembled was derived from: San Jose Airport (Santa Clara), San Francisco Airport (San Mateo), Oakland Airport (Alameda), and Walnut Creek (Contra Costa).

## 2.4 DATA ANALYSES

All statistical, tabular, and graphical analyses were conducted in R Studio, running R version 3.4.3 (R Core Team 2016). For analyses involving water quality data, censored results (i.e., below the method detection limit) were substituted with 50% of the method detection limit (MDL). Generally, analytical sensitivity was good, with only three variables having > 30% non-detects (Suspended Sediment Concentration, Nitrite, Ammonia). To facilitate use of the data for random forest and relative risk analyses, missing values were subject to an imputation method to fill in data gaps. Seven variables were found to have missing values. Three of these, Suspended Sediment Concentration (SSC), Dissolved Organic Carbon (DOC), and Alkalinity<sup>5</sup>, consisted of more than 50 missing values, and were excluded from further analysis. The remaining four variables (Silica, Ash Free Dry Mass, Chlorophyll a, Nitrate) were subject to imputation using the R-package *mice* (van Buuren and Groothuis-Oudshoorn, 2011). In this method, replacement values were randomly selected from the distribution of observed data. Overall, fewer than 25 values were

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<sup>5</sup> Suspended Sediment Concentration (SSC), Dissolved Organic Carbon (DOC) and alkalinity were not monitored in 2016, due to the removal of these parameters in Provision C.8.c of the reissued MRP.

imputed for any variable (Silica, n = 24; AFDM, n = 4; Nitrate, n = 1; Chl a, n = 1), and thus their influence on the analysis is assumed to be minor.

#### 2.4.1 Biological Condition Indices

The California Stream Condition Index (CSCI) was developed by the State Water Board as a standardized measure of benthic macroinvertebrate assemblage condition in perennial wadeable rivers and streams. The CSCI was developed using a large reference data set representing the range of natural conditions in California (Ode et al. 2016). The CSCI tool (Mazor et al. 2016) translates BMI data into an overall measure of stream health by combining two types of indices: 1) ratio of observed-to-expected taxa (O/E) (used as a measure of taxonomic completeness), and 2) a predictive multi-metric index (pMMI) for reference conditions (used as a measure of ecological structure and function). The CSCI score is computed as the average of the sum of O/E and pMMI.

The CSCI scoring tool was used to assess BMI data collected at both perennial and non-perennial sites in the RMC area. The CSCI scores for RMC sites should be interpreted with caution, as the CSCI tool has not been fully validated at non-perennial sites. Preliminary analyses suggest that the CSCI is valid in certain types of nonperennial streams in southern California, but its validity in nonperennial streams in other regions, such as the Bay Area, remains unknown.

The algae data were analyzed using algal indices of biological integrity (IBIs) that were developed for streams in Southern California (Fetscher 2014). These include a soft algae index (S2), diatom index (D18) and soft algae-diatom hybrid index (H20). The algal indices were calculated using the SWAMP Algae Reporting Module (Algae RM). The interpretation of algae data collected in San Francisco Bay area using IBIs developed in Southern California (SoCal) should be considered preliminary. The State Board and SCCWRP are currently developing and testing a statewide index using benthic algae data as a measure of biological condition for streams in California. The statewide Algae Stream Condition Indices (ASCIs) were not available at the time this project was conducted, but are expected to be available in late 2018 (personal communication, Jessie Maxfield, SWRCB).

#### 2.4.2 Biological Indicator Thresholds

Existing thresholds for biological indicator scores (CSCI, D18, S2) defined in Mazor (2015) were used to evaluate bioassessment data compiled and analyzed in this report (Table 2, Figure 1). The thresholds for each index were based on the distribution of scores for data collected at reference calibration sites in California (BMI) or in Southern California (algae). Four condition categories are defined by these thresholds: “likely intact” (greater than 30<sup>th</sup> percentile of calibration reference site scores); “possibly altered” (between the 10<sup>th</sup> and the 30<sup>th</sup> percentiles); “likely altered” (between the 1<sup>st</sup> and 10<sup>th</sup> percentiles); and “very likely altered” (less than the 1<sup>st</sup> percentile). The probability-based approach to develop the threshold classes was consistent across indices, allowing comparison for all indicators across sites.

The performance of CSCI on a statewide basis is the subject of ongoing review by the State Water Board. In the current MRP, the SF Bay Water Board defined a CSCI score of 0.795 as a threshold for identifying sites with degraded biological condition that should be considered candidates for Stressor Source Identification (SSID) projects. No MRP threshold has been established for any of the algae indices.

Table 2. Biological condition indices, categories and thresholds.

Index	Likely Intact	Possibly Altered	Likely Altered	Very Likely Altered
<i>Benthic Macroinvertebrates (BMI)</i>				
CSCI Score	≥ 0.92	≥ 0.79 to < 0.92	≥ 0.63 to < 0.79	< 0.63
<i>Benthic Algae</i>				
S2 Score	≥ 60	≥ 47 to < 60	≥ 29 to < 47	< 29
D18 Score	≥ 72	≥ 62 to < 72	≥ 49 to < 62	< 49

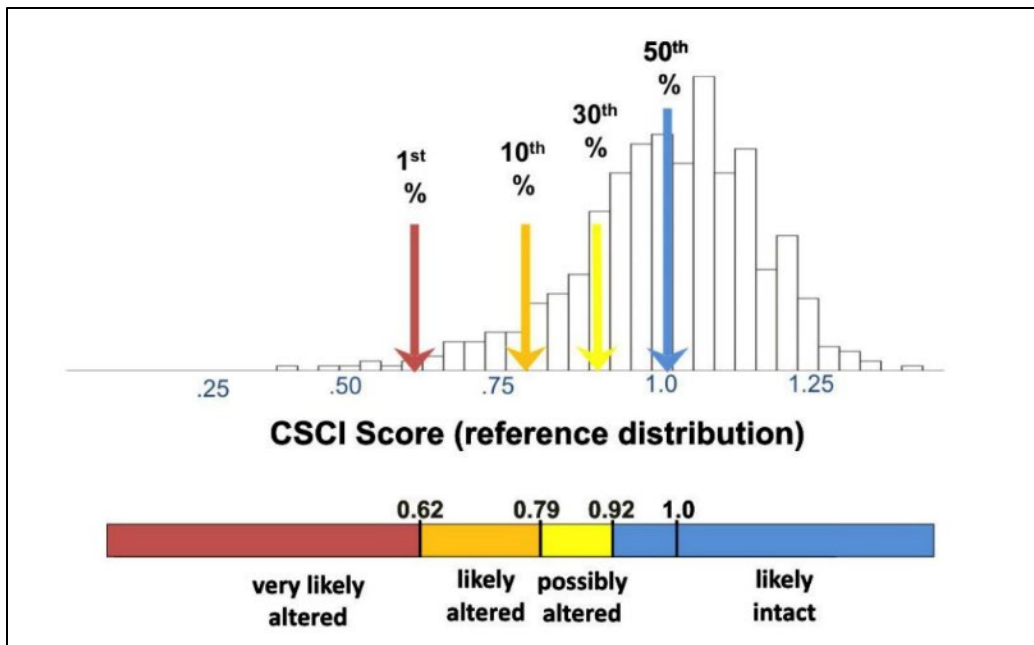


Figure 1. Distribution of CSCI scores at reference sites with thresholds and condition categories used to evaluate CSCI scores (from Rehn et al. 2015). Note: colors in this figure differ from other figures in this report.

### 2.4.3 Estimating Extent of Healthy Streams in SF Bay Area

To estimate overall extent of biological conditions in streams within the RMC area, cumulative distribution functions (CDFs) of biological condition scores were generated. Because the survey focused significantly more effort in urban areas compared to non-urban areas, sample weights were re-calculated as the total stream length in the sample frame, and divided by the stream length evaluated in each land use category. Therefore, sites contribute a proportional amount of stream length to the extent estimates, based on the number of sites assessed in each land use category. Sites without evaluations (6%), primarily non-urban sites, were excluded from the analysis. The adjusted sample weights were used to estimate the proportion of stream length represented by CSCI, D18, and S2 scores both regionwide and for urban



sites only. Estimates for non-urban streams were not calculated separately due to the lower number of monitoring events at non-urban sites and greater width of confidence intervals. Condition estimates and 95% confidence intervals were calculated for all sampled sites in the RMC sample frame and for urban sites only. Post-stratification of the urban sites by County was also performed. However, Solano County was excluded from this assessment, due to the relatively low sample size compared to the other areas. All calculations were conducted using the R-package *spsurvey* (Kincaid and Olsen 2016). See Section 4.4 for further discussion of the RMC sample design.

## 2.4.4 Evaluating the Importance of Stressors

### 2.4.4.1 Random Forest Analyses

Stressor association with biological condition scores was evaluated using random forest statistical analyses. Random forest analysis is a non-parametric classification and regression tree (CART) method commonly applied to large datasets of multiple explanatory variables. Recent papers describe their use for stressor identification in stream bioassessment studies (e.g., Maloney et al. 2009, Waite et al. 2012, Mazor et al. 2016). Random forest models use bootstrap averaging to determine splits of numerous trees (Elith et al. 2008) for reducing error and optimizing model predictions. Model outputs provide an ordered list of importance of the explanatory variables that can be applied to a new or validation dataset for prediction.

Random forest models were developed using the R-package *randomForest* to determine a list of explanatory variables related to biological condition scores (CSCI or D18 score). The stressor data consisted of 49 variables, related to (1) water quality; (2) habitat; and (3) land use factors that could potentially influence condition scores (Appendix 1, Table A). Subsequently, the data were partitioned into training (80%) and validation (20%) sets for model testing. A random selection of samples was generated by sub-sampling from within each RMC County to maintain a regional balance of samples within the partitioned datasets. The training dataset had 278 sites, while the validation data encompassed 76 sites across all counties.

First, several iterations of the model procedure were performed with the training data set to optimize the random forests, including tuning the model to the maximum number of predictors per branch, the number of trees to build, and validation of the predictions. Appendix 1 presents the results of initial steps to optimize the random forest model outputs. The final set of models evaluated a maximum of 6 predictor interactions, and 1000 trees. Two variable importance statistics were used to estimate the relative influence of predictor variables: (1) % Increase in MSE = percent increase in mean-square-error of predictions as a result of variable values being permuted; (2) Increase in Node Purity = difference between the residual sum-of-squares before and after a split in the tree. More important variables achieve larger changes in MSE and node purity. K-fold cross validation of the selected models was performed to assess prediction error, by evaluating residual error and R-squared differences.

Random forest models were developed in two steps: (1) random forest models were run with all variables included ( $N = 49$ ), retaining the top 10 variables in the variable relative importance list ranked by % increase in MSE, and (2) random forest models were re-run with just the top 10 variables from step 1. Subsequently, the variable list was further trimmed by evaluating the corresponding variable importance scores, partial dependency plots, and the change in  $R^2$  once the variable was excluded. Partial

dependency plots show the predicted biological response based on an individual explanatory variable with all other variables removed. No variable with less than 10% influence on CSCI or D18 predictions was retained in the final models. Finally, random forest models were used to predict biological condition scores for the validation data set. Appendix 1, Figure B presents the observed and predicted values for the validation models with CSCI and D18 in Steps 1 and 2 of the model development.

**2.4.4.2 Stressor Thresholds and Relative Risk Assessment**

Relative risk analyses were also conducted to evaluate associations between stressors with biological condition scores. From the list of potential stressors discussed in Section 2.3.4, eight variables were selected to conduct a relative risk analyses (Table 3). Six of the stressor thresholds were derived from statewide data collected for the Perennial Streams Assessment (SWAMP 2015). The thresholds were based on the 90<sup>th</sup> percentile of data collected at bioassessment sites that exhibited good biological condition (i.e., CSCI scores > 0.92, likely intact). The 90<sup>th</sup> percentile of stressor values at these sites was used to define the most-disturbed thresholds for variables where higher values indicate more disturbance (SWRCB 2015). Similarly, the chlorophyll a threshold (100 mg/m<sup>2</sup>) used for this report (Table 3) was based on 90<sup>th</sup> percentile of data that was collected at all RMC sites that had CSCI scores > 0.92 (Figure 2). The threshold for Dissolved Oxygen (7.0 mg/l) was based on Water Quality Objectives (WQOs) for COLD Freshwater Habitat Beneficial Use in the Water Quality Control Plan for the San Francisco Basin (SFBRWQCB 2017).

**Table 3. Biological condition and stressor variable thresholds used for relative risk assessment.**

Variables	Thresholds		Units	Reference	Criteria
	Poor	Good			
<i>Biological Condition</i>					
CSCI Score	< 0.625	≥ 0.925		Mazor et al. 2016	
<i>Stressor Condition</i>	<i>High</i>	<i>Low</i>			
Dissolved Oxygen (DO)	<7.0	≥ 7.0	mg/L	SF Bay Water Quality Control Plan	WQO
Specific Conductivity (SpCon)	> 1460	≤ 1460	us/cm	SWAMP 2015	90 <sup>th</sup> Percentile of sites with CSCI score > 0.925
Chloride	> 122	≤ 122	mg/L		
Total Nitrogen (TotN)	> 2.3	≤ 2.3	mg/L		
Total Phosphorus (TotP)	> 0.122	≤ 0.122	mg/L		
Chlorophyll a (Chla)	> 100	≤ 100	mg/m <sup>2</sup>	RMC data	
Sand and Fines (SaFn)	> 69	≤ 69	%	SWAMP 2015	
Human Disturbance Index (HDI)	> 1.3	≤ 1.3			

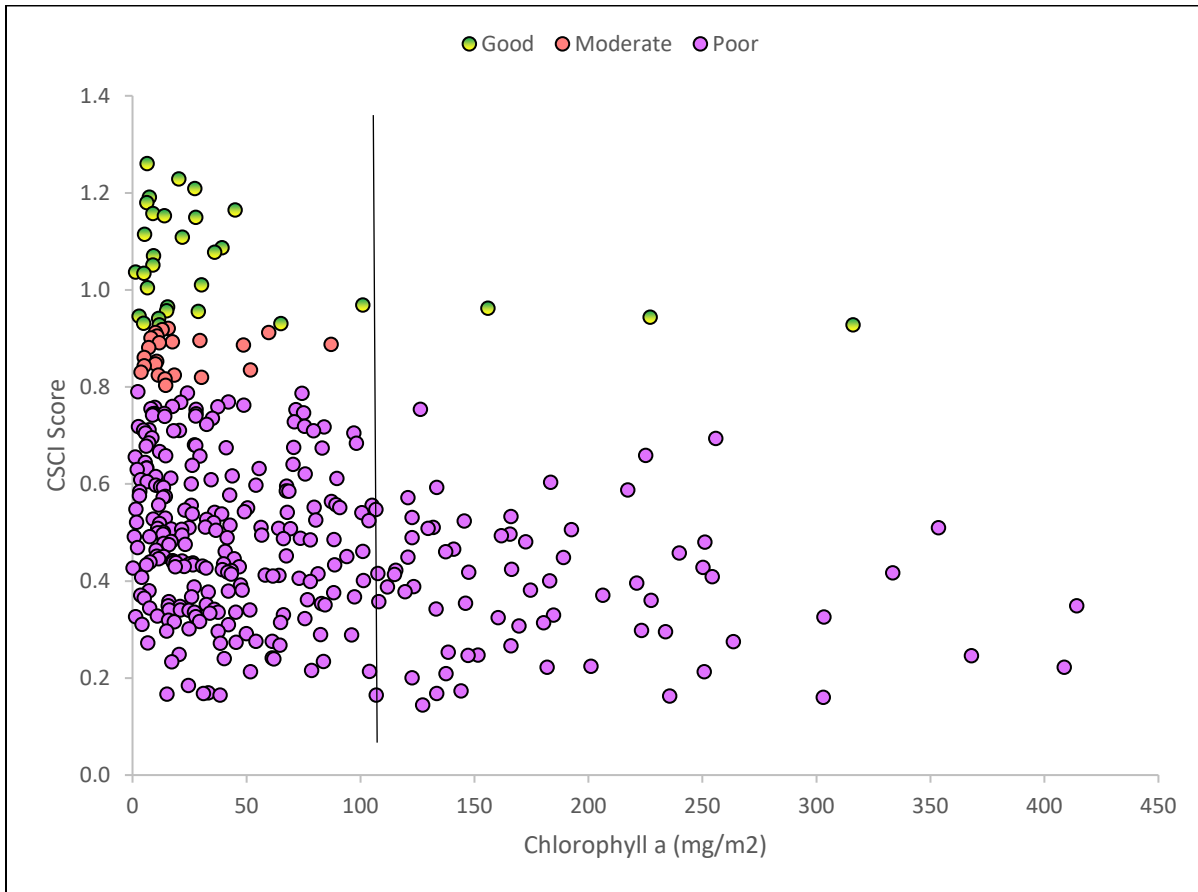


Figure 2. Plot of CSCI score and *chlorophyll a* concentration at RMC sites. Threshold for *chlorophyll a* used for relative risk assessment is shown. Sites classified as “good” include the two highest CSCI condition categories.

The relative risk approach was used to evaluate the association between stressors and biological condition (Van Sickle et al., 2008). The relative risk is a conditional probability representing the likelihood that poor biological condition is associated with high stressor levels and is calculated as follows:

$$\text{Relative Risk} = \frac{\text{Pr}(CSCI_p)/S_h}{\text{Pr}(CSCI_p)/S_l}$$

The numerator is the probability of finding poor biological condition ( $CSCI_p$ ) given high stressor scores ( $S_h$ ) and denominator is the probability of finding poor biological condition given low stressor scores ( $S_l$ ). Poor biological conditions were defined as CSCI scores < 0.625. High and low stressor levels are defined in Table 3. In cases where RR is equal to 1, there is no association between stressor and biological indicator score. Where  $RR > 1$ , the higher the value, the more likely poor biological condition would occur given high stressor levels.

### 3 RESULTS

#### 3.1 SITE EVALUATION RESULTS

A total of 354 monitoring sites were sampled in the RMC region between 2012 and 2016. These are identified as “target” sites in Figure 3 and Table 4. Samples were collected at 284 urban sites (80%) and 70 non-urban sites (20%) (Table 4). The greatest number of non-urban sampling locations were in Santa Clara (n=25) and San Mateo Counties (n=19). Samples were collected at 8 or 9 non-urban sites for each of the other counties.

The population of 354 monitored sites was obtained through the evaluation of 1,455 unique sites, which equate to a rejection rate of 76% for entire RMC area over the 5-year period. Solano County had the highest rejection rate (90%) and San Mateo County had the lowest (65%). The most common reason for site rejection (55% of all evaluated sites) was that a site did not present the physical requirements to support monitoring within a 300-meter radius of target coordinates. These “non-target sites” were rejected for several reasons, including lack of flowing water, site was not a stream (e.g., aqueduct or pipeline), tidally influenced, or non-wadeable. The lack of flow was the most common reason for rejection. The extended drought period between 2012 and 2014 may have resulted in an unusually high number of sites with no or low flow conditions during the target index period.

Another reason for site rejection was the inability to obtain access to conduct the sampling (e.g., physical access or obtain private land/permission). These “target non-sampleable” sites comprised 21% of sites that were rejected. These sites were often located on private land in non-urban areas where permissions were not granted and/or where steep, highly-vegetated conditions prevented access. Obtaining access to sites in urban areas was variable by county. For example, most of the streams in the urban area of San Mateo County are privately owned, while most of the urban sites in Santa Clara County are owned by municipal jurisdictions and water district agencies, making permissions more easily obtained.

**Table 4. Number of sites per county in each site evaluation class.**

County	Target Not-Sampleable		Non-Target		Target		Total by County
	Non-Urban	Urban	Non- Urban	Urban	Non- Urban	Urban	
Alameda	12	74	162	91	9	96	444
Contra Costa	12	34	32	89	9	48	224
San Mateo	21	42	9	37	19	41	169
Santa Clara	37	24	74	161	25	87	408
Solano	44	3	109	34	8	12	210
Total RMC	126	177	386	412	70	284	1,455
% of Total RMC	9%	12%	27%	28%	5%	20%	-

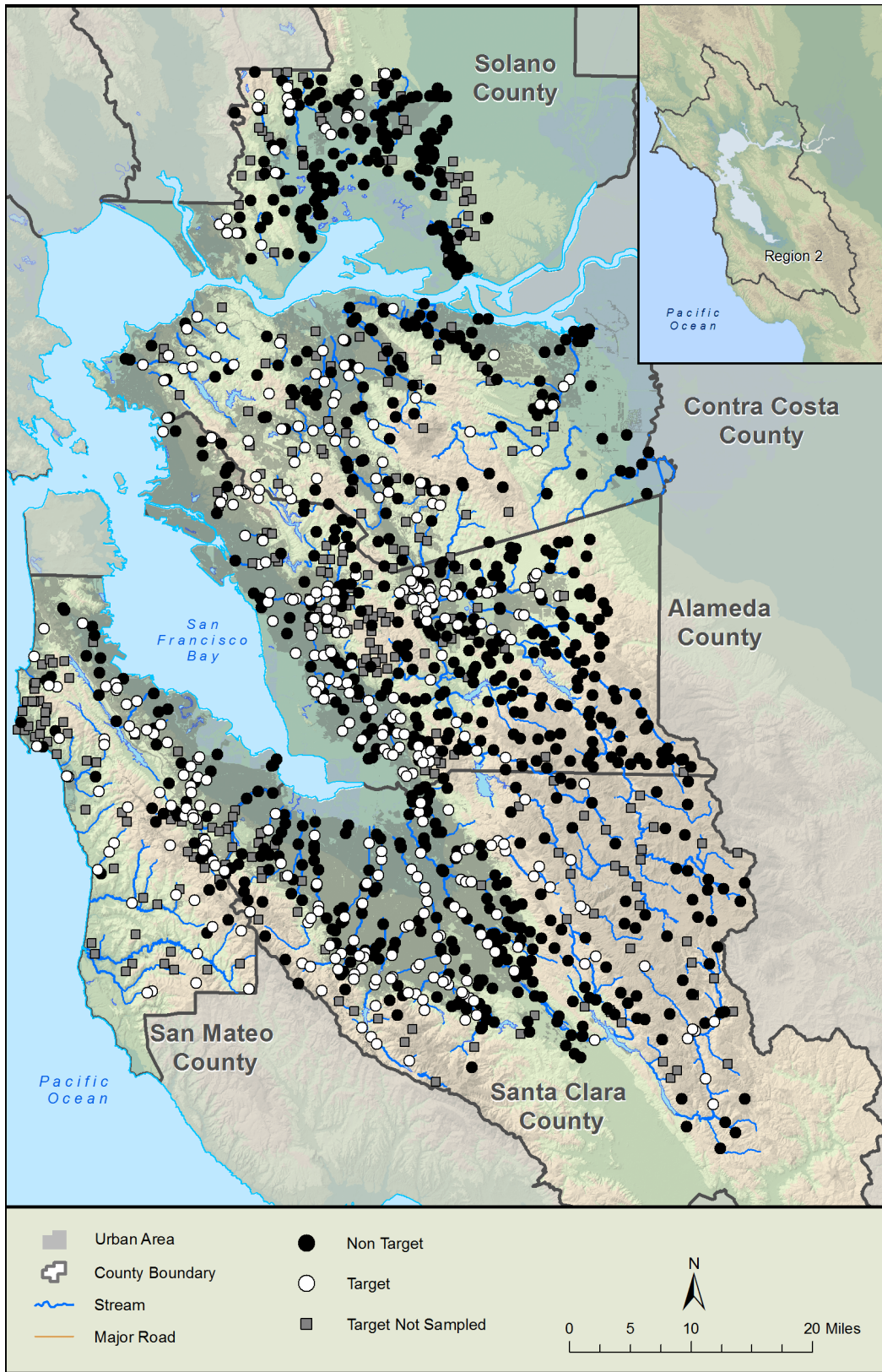


Figure 3. RMC sites evaluated by evaluation class.

Figure 4 presents rainfall for the 2000-2017 time period at the San Francisco Airport. Rainfall was generally below average during the 2012-2016 period, especially in 2014, and therefore, the RMC monitoring occurred in a drier-than-normal period. Because biological condition index scores can vary natural due to multi-year climatic patterns, it is important to note that the 5-year period of monitoring may not be representative of the long-term condition.

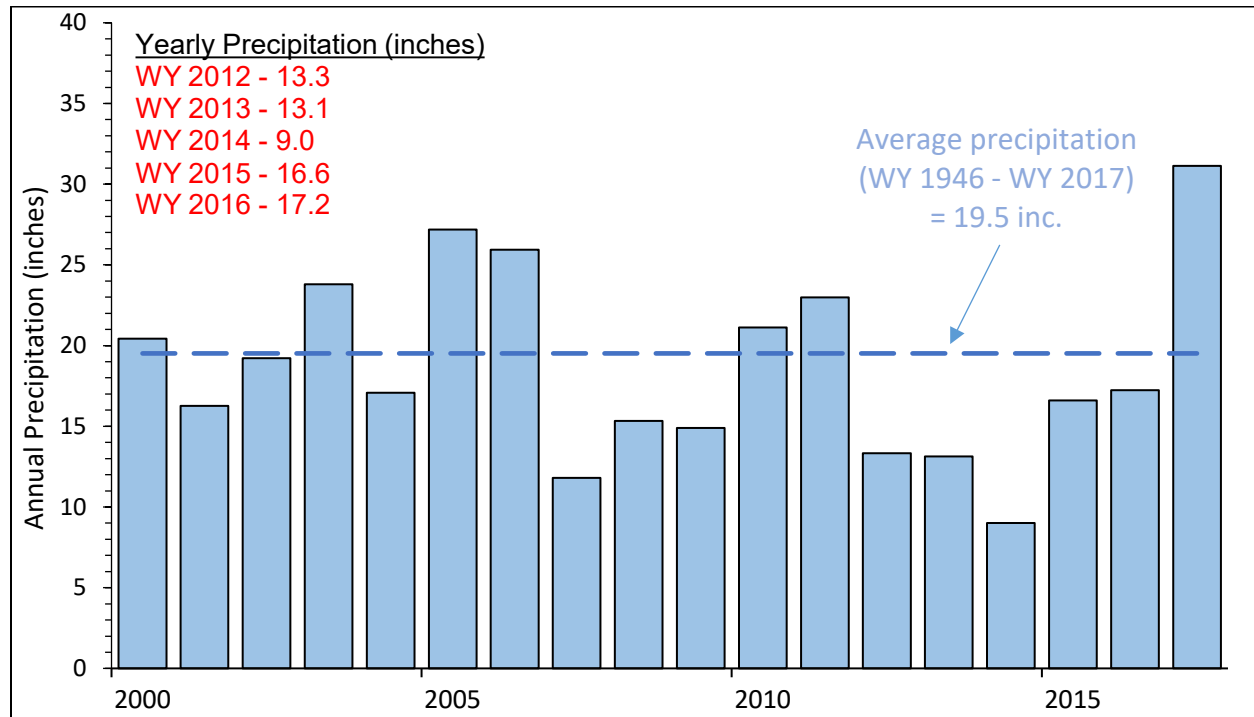


Figure 4. Annual precipitation at San Francisco Airport (2000-2017)

### 3.2 BIOLOGICAL CONDITION OF BAY AREA STREAMS

#### 3.2.1 Regional Assessment

The distribution of BMI and algae index scores observed during 2012-2016 suggests that the majority of streams in the RMC sample area do not exhibit healthy biological conditions. Figures 5, 6 and 7 show cumulative distribution functions of the biological index scores for the entire regional dataset (i.e., urban and non-urban sites) and the urban dataset. Across all sites, over half (58%) of the stream-length was in the lowest condition class for CSCI (Very Likely Altered) and 15% of the stream-length was in the highest condition class (Likely Intact) (Figure 5).

Both of the algae index scores (D18 and S2) exhibited higher condition scores than CSCI regionally. For D18 (diatoms), 41% of the stream-length in the Bay Area was in the Very Likely Altered condition class and 19% of the stream-length was in the Likely Intact condition class (Figure 6). Similar distribution of

scores was evident with S2 (soft-algae), where less than half (44%) of the stream-length was in the Very Likely Altered condition class and 21% of the stream-length was in the Likely Intact condition class (Figure 7). The higher proportion of sites in the Likely Intact condition for algae indices compared to CSCI suggest that the algae communities in streams may be less degraded than BMI assemblages.

Bay Area wide, urban sites were responsible for the majority of poor CSCI scores. Seventy-nine percent (79%) of the stream length in urban areas was in the Very Likely Altered condition category for CSCI, while only 3.5% was in the Likely Intact class (Figure 5). Additionally, over 80% of the sampled stream length in urban areas was below the MRP trigger for CSCI scores (0.795), where potential follow-up source/stressor identification studies should be considered.

The influence of urban sites on the stream condition of all sites was also apparent for algae scores, although to a lesser degree than for CSCI. For D18, just over half (53%) of the stream length in urban areas was in the Very Likely Altered condition class, compared to 9% in the Likely Intact class (Figure 6). For S2 scores, 65% of stream length in urban areas was in the Very Likely Altered class, and only 7% in the Likely Intact class (Figure 7). These patterns suggest that stressors in the urban landscape may still exert influence on algae condition. Section 4.0 provides additional discussion about the results presented here.

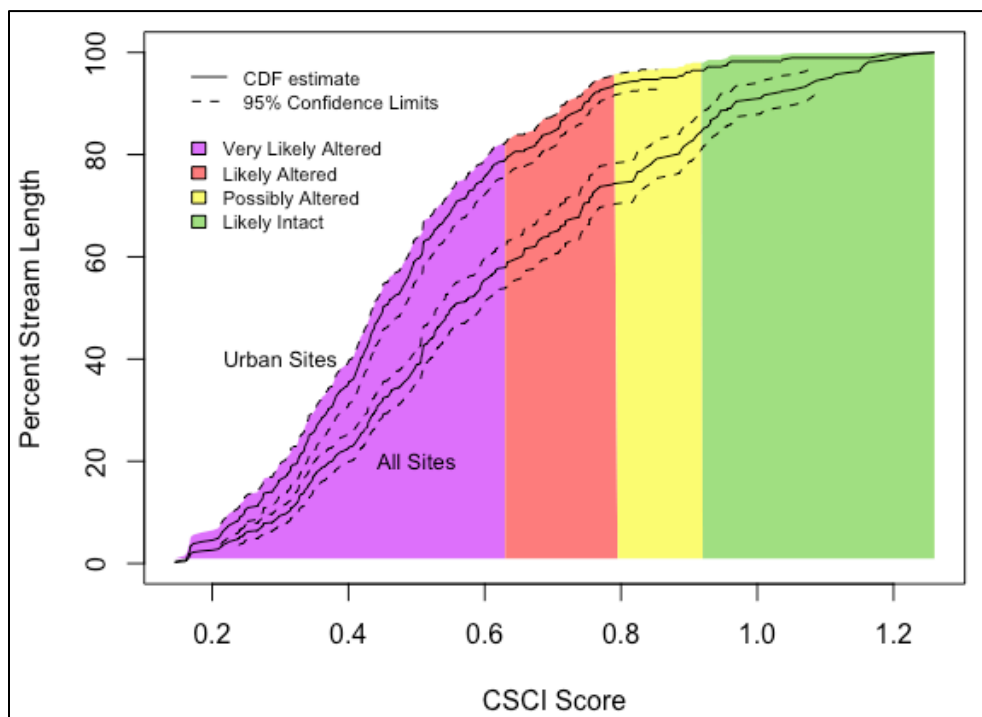


Figure 5. Cumulative distribution function (CDF) of CSCI scores at all RMC sites and urban sites.

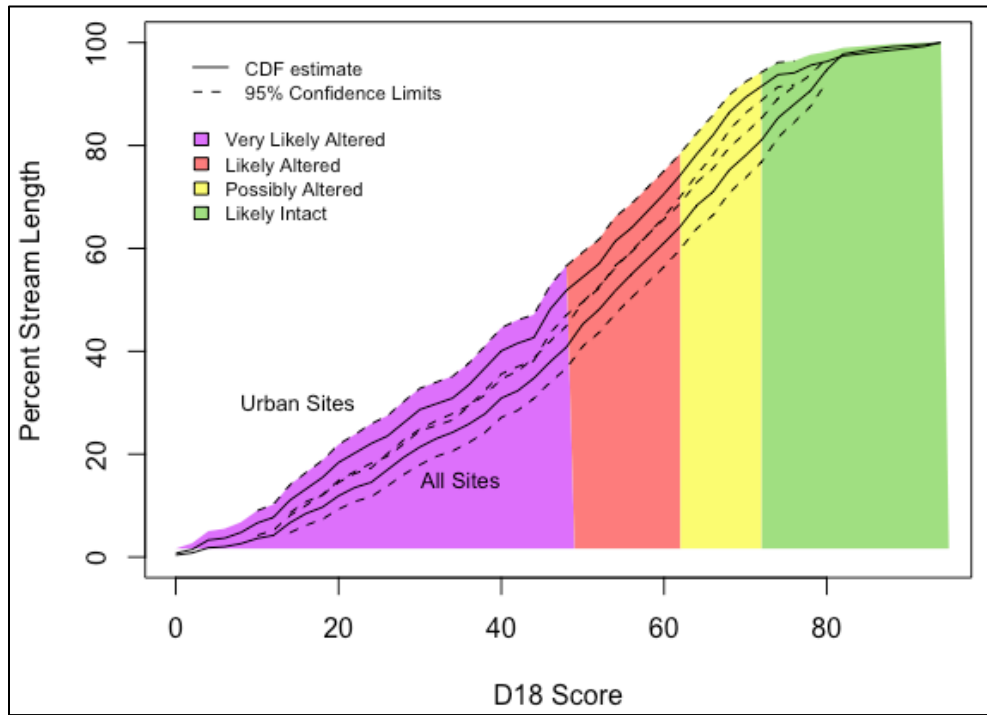


Figure 6. Cumulative distribution function (CDF) of D18 scores at all RMC sites and urban sites.

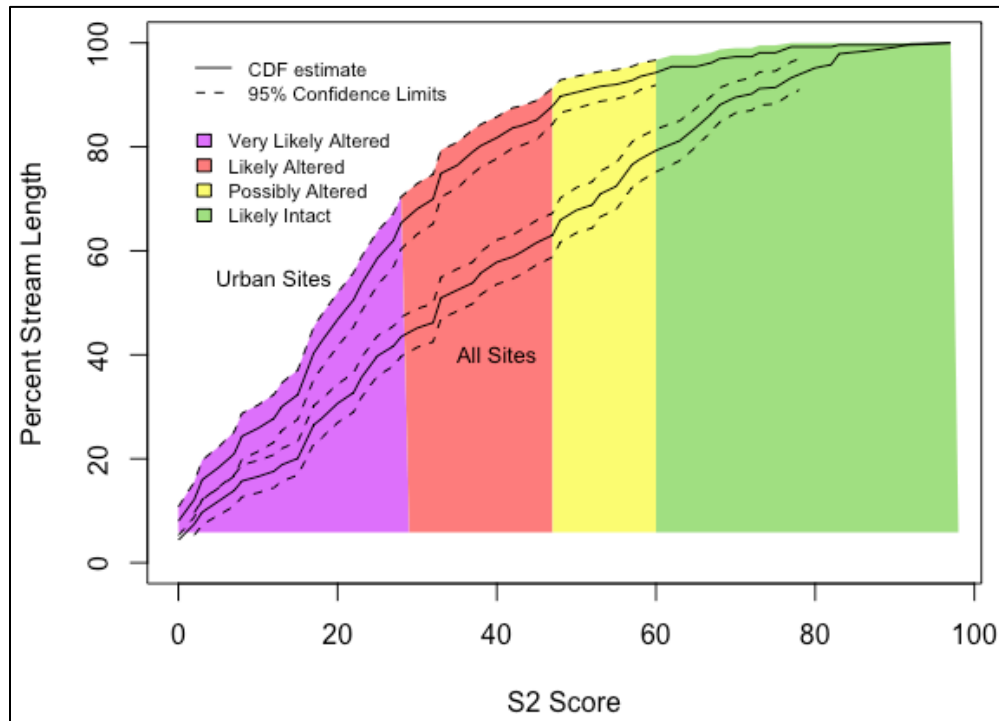


Figure 7. Cumulative distribution function (CDF) of S2 scores at all RMC sites and urban sites.



### 3.2.2 County Assessment

In addition to Bay Area wide biological condition estimates of streams, post-stratification of the CSCI condition estimates for urban sites in each County (excluding Solano County due to low sample size) suggests that poor condition scores are widespread in each Bay Area county. The proportion of urban stream length in the Very Likely Altered condition class was highest for Contra Costa (96%), followed by Alameda County (83%), San Mateo County (73%), and Santa Clara County (64%) (Figure 8). Less than 10% of the urban stream length in each of the counties was in the Likely Intact condition class. The highest proportion of Likely Intact BMI communities occurred in San Mateo and Santa Clara counties (7% each), followed by Alameda (1%) and Contra Costa (0%) counties. In comparison to the MRP threshold of 0.795, the vast majority of urban streams in each county fall below this threshold.

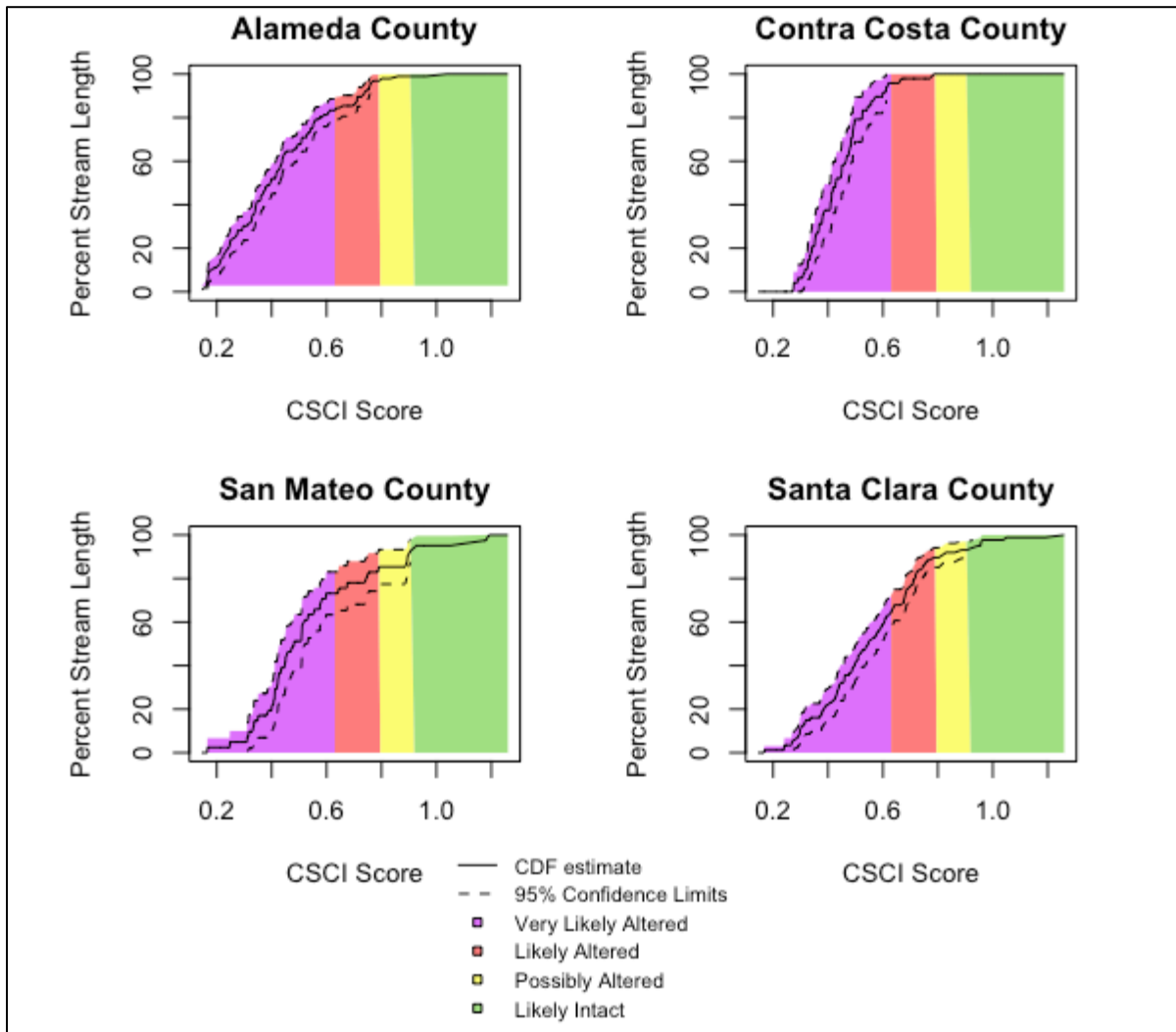


Figure 8. Cumulative distribution functions of CSCI scores at RMC urban sites in each participating Bay Area County.

### 3.2.3 Biological Condition of Urban and Non-Urban Streams

Figure 9 illustrates CSCI scores (by condition category) for the region and includes county boundaries and urban areas for reference. Maps illustrating the biological condition of stream in each county based on CSCI and D18 scores are included in Appendix 4.



Figure 9. Biological condition of streams in the RMC area based on CSCI scores.

CSCI scores grouped by land use class (urban vs. non-urban) showed that all counties, with the exception of Solano, exhibit higher scores in non-urban areas (Figure 10), which generally span a narrower scoring range than urban sites. Santa Clara and San Mateo counties had the highest median CSCI scores compared to other counties, with several sites in both counties receiving scores greater than 1.0, which typically represent reference conditions. However, non-urban sites for all five counties had CSCI scores below the MRP trigger (0.795), indicating that some sites non-urban areas have degraded biological condition.

Stratification of D18 and S2 scores by land use (urban vs non-urban; Figures 11 and 12) suggests that biological condition scores based on algae metrics generally mirror CSCI scores, which are based on BMIs. Generally, algae scores in the non-urban area were higher than scores for sites in urban areas within each county. The low sample sizes of the non-urban population preclude making any definitive comparisons, however, it was noteworthy that sites in the urban areas may receive similar or higher algae index scores than sites non-urban areas.

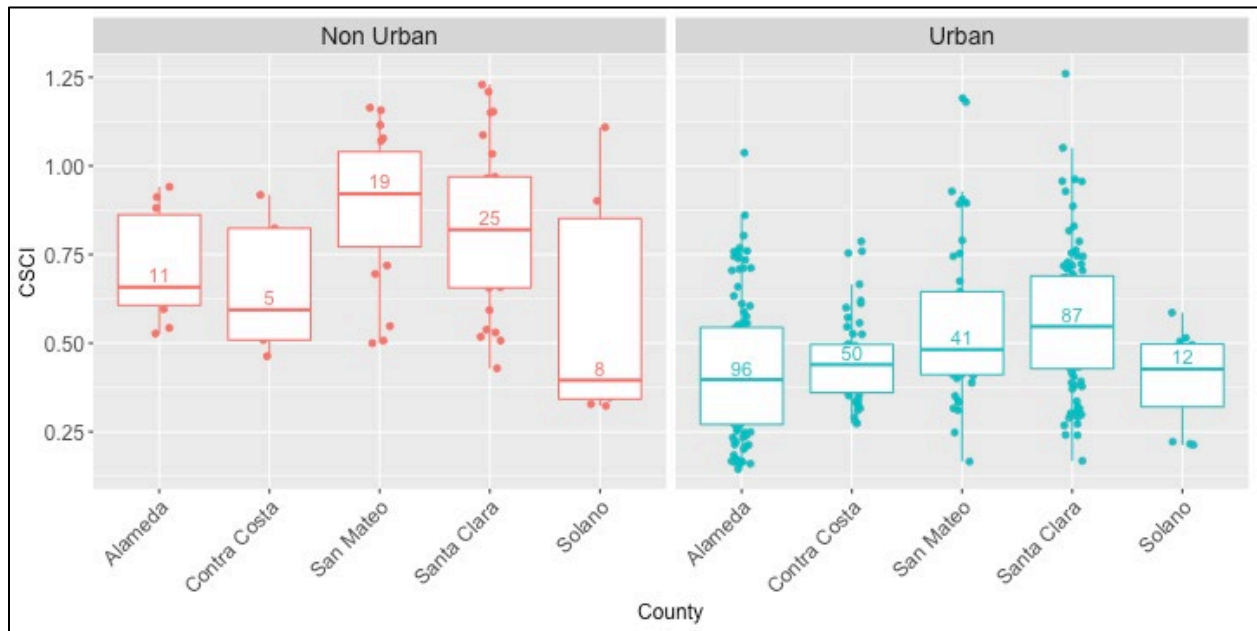


Figure 10. CSCI scores for urban and non-urban sites in each County. Sample sizes for each county are included in each boxplot.

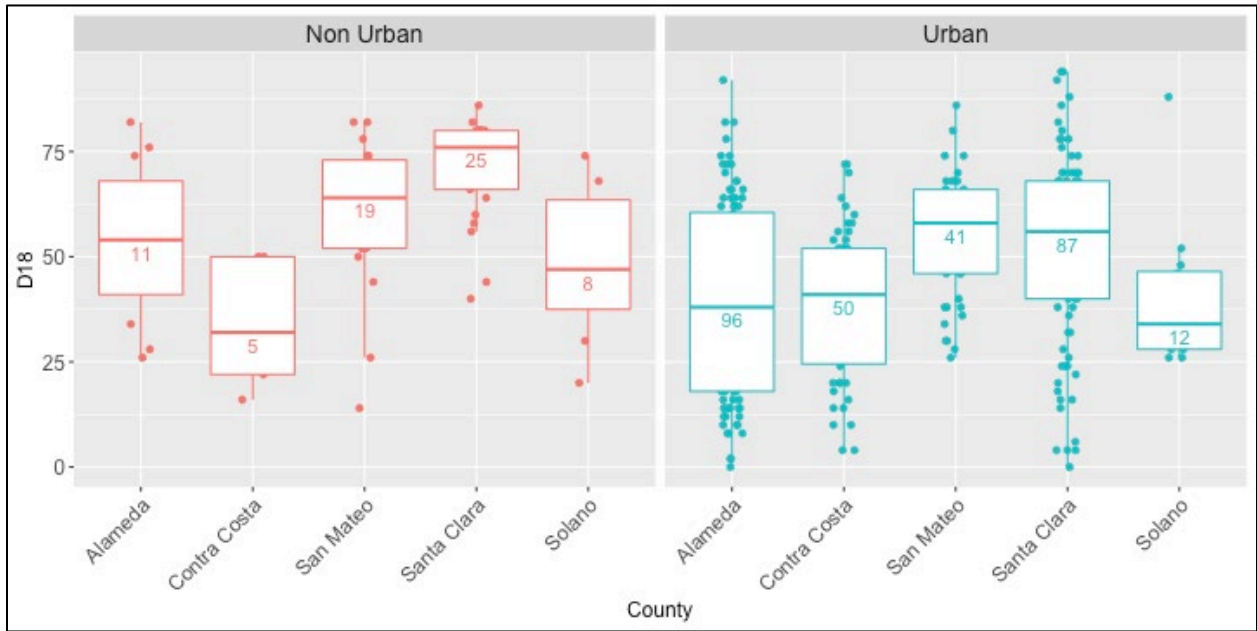


Figure 11. D18 scores for urban and non-urban sites in each County. Sample sizes for each county are included in each boxplot.

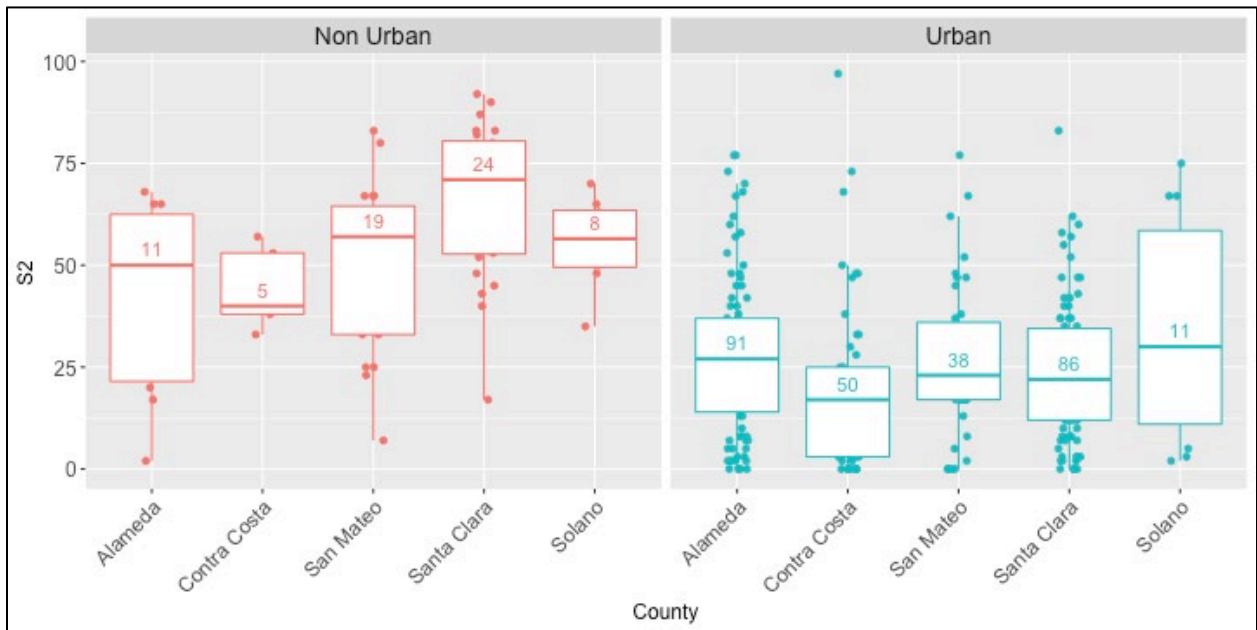


Figure 12. S2 scores for urban and non-urban sites in each County. Sample sizes for each county are included in each boxplot.

### 3.3 STRESSORS ASSOCIATED WITH BIOLOGICAL CONDITION

#### 3.3.1 Random Forest Model Outputs

To evaluate stressors associated with biological condition within the RMC area, random forest models were developed using the CSCI and D18 index results. A parallel analysis was not performed for the S2 indicator due to the lack of soft algae at many of the assessment sites. Stressor data consisted of 49 variables grouped into three types: (1) water quality; (2) habitat; and (3) land use (Appendix 1, Table A). Model results clearly indicated better relationships between stressors and the CSCI, versus the D18 index. Validation of the final random forest models showed that the CSCI model explained 61% of the variance using eight predictor (stressor) variables, while the D18 model only explained 34% of the variance using six predictors.

The CSCI random forest model indicated that land use and physical habitat variables were most influential to most biological condition (Table 5). Of the eight variables in the final CSCI model, four were landscape-based (HDI, PctImp\_5K, PctImp\_1K, PctImp), three were habitat associated (PctFines, PctGra, PctFstH2O), and one was a water quality variable (Dissolved Oxygen, DO). There was general consistency amongst the individual variables within each of the landscape and habitat groups. The landscape variables that were most influential to CSCI scores were associated with the degree of human impact/imperviousness and the habitat variables were associated with the characteristics of the sediment substrate and water flow. Overall, the largest influence on the CSCI random forest model was percent impervious area within a 5 km radius (35.2%) of the site. The other seven variables in the final model exerted a lesser, but similar degree of influence (18.8 – 25.3%) on CSCI scores. It was notable that none of the nutrient variables were identified as indicators of biological condition scores using the CSCI model (Appendix 3 Figure A). The same may be true for DO, where the apparent relationship was driven by a few high values (Appendix 3 Figure B).

**Table 5. Summary statistics for the CSCI random forest model. Rank of importance of selected stressor variables are colored according to categories: physical habitat (green), land use (brown), and water quality (blue). The correlation coefficient (rho) for each stressor variable is also presented.**

Stressor Variable	% Increase MSE	Increase Node Purity	Rank Correlation Coefficient (Rho)
Percent Impervious Area in 5km (PctImp_5K)	35.21	4.74	-0.62
Percent Impervious Areas of Reach (PctImp)	25.37	1.03	-0.59
Dissolved Oxygen (DO)	24.43	1.60	0.24
Percent Fast Water of Reach (PctFstH2O)	22.52	1.62	0.51
Percent Fines (PctFin)	20.73	1.13	-0.36
Percent Substrate Smaller than Sand (PctSmalSnd)	20.64	1.36	-0.46
Percent Impervious Area in 1km (PctImp_1K)	20.64	2.26	-0.61
Human disturbance Index (HDI)	18.81	1.45	-0.62

The results of the random forest model for D18 indicated that different variables explained biological condition than the CSCI model. Water quality variables exerted greater influence in the D18 model (Table 6). Of the six variables in the final D18 model, four were water quality variables (SpCond, Chloride, AFDM, Phosphorus), one was a habitat variable (PctSmalSnd), and one was a landscape variable (RdDen\_1k). Overall, the variable with the largest influence on the random forest model was specific conductivity (29.5%). The remaining five variables exerted a lesser, but similar influence (12.5% – 22.0%) on the model. The importance of water quality variables in the model suggests that general water quality conditions (e.g., conductivity) likely influence algae condition scores. Specific types of water quality stress, such as from nutrients, however, appear to be less important to algal community condition on a regionwide scale.

**Table 6. Summary statistics for the D18 random forest model. Rank of importance of selected stressor variables are colored according to categories: physical habitat (green), land use (brown), and water quality (blue). The correlation coefficient (rho) for each stressor variable is also presented.**

Stressor Variable	% Increase MSE	Increase Node Purity	Rank Correlation Coefficient (Rho)
Specific Conductivity (SpCond)	29.55	35357.81	-0.49
Percent Substrate Smaller than Sand (PctSmalSnd)	21.99	24671.80	-0.46
Phosphorus	21.93	17465.87	-0.33
Chloride	18.53	18873.52	-0.51
Ash Free Dry Mass (AFDM)	15.09	21937.23	-0.44
Road Density in 1km (RdDen_1k)	12.51	16383.17	-0.33

Using the random forest model outputs, plots of individual stressor variables versus observed response values (i.e., CSCI and D18 scores) were developed to illustrate relationships between stressors and biological condition (Figures 13 to 18 and Appendix 2). For the CSCI model output, the plots of habitat and landscape variables indicate patterns of dose-response. For example, the Human Disturbance Index (HDI) stressor variable indicated that poor condition scores are observed when HDI exceeds a value of 2. This pattern was also evident in the regressions of observed CSCI values, relative to HDI and separating out HDI scores by their condition class (Figure 13). It is worth noting that Ode et al. (2016) identified a cutoff of HDI = 1.5 for reference sites (Ode et al. 2016). Based on the analysis conducted on this five-year Bay Area dataset, the range between 1.5 and 2.0 appeared to separate out the urban and non-urban sites, supporting the previous authors’ assertion that sites with HDI values below this range exhibit reference conditions.

Similar to HDI, the stressor variables related to imperviousness indicated a threshold-style response with CSCI scores. For the variable ‘percent imperviousness in 5km’, a value above 10% appeared to correspond to poor CSCI condition scores (Figure 14). All sites that had less than 10% impervious area within 5km were classed as either Possibly Intact or Likely Intact condition. In the case of the habitat variables included in the final model, response patterns were less pronounced than for the landscape variables (Figure 15). For example, the variable ‘percent reach habitat smaller than sand’, indicated that poor sites spanned a wide-range in stressor values, while sites in the top three condition classes had a much

narrower range in this metric. Biological condition at sites where more than 50% of the stream reach had substrate smaller than sand appeared to be a line of demarcation between the bottom two and top three condition categories.

The results of the D18 model indicated dose-response relationships between biological condition and all four water quality variables (i.e. SpCond, Chloride, AFDM, Phosphorus), however there were less obvious patterns delineating biological condition. For example, the partial dependency plots for D18 scores indicated that poor condition (i.e., bottom two condition categories) was evident when chloride was above 200 mg/L (Figure 16) and specific conductivity was above 1200  $\mu\text{S}/\text{cm}^6$  (Figure 17). However, the plots of observed D18 values relative to these variables suggested that only some of the lowest scoring sites could be delineated using these threshold values. Similarly, response patterns of the habitat variables were inconclusive for delineating biological condition. A value of approximately 60% or greater of the stream habitat 'smaller than sand' corresponded to lower D18 scores (Figure 18), but there was considerable variability to this signal.

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<sup>6</sup> This corresponds well with the MRP threshold of 2000  $\text{uS}/\text{cm}^2$  for evaluating continuous monitoring data. Sites with 20% or more of instantaneous specific conductance results greater than 2000  $\text{uS}/\text{cm}^2$  are considered as candidates for SSID projects.

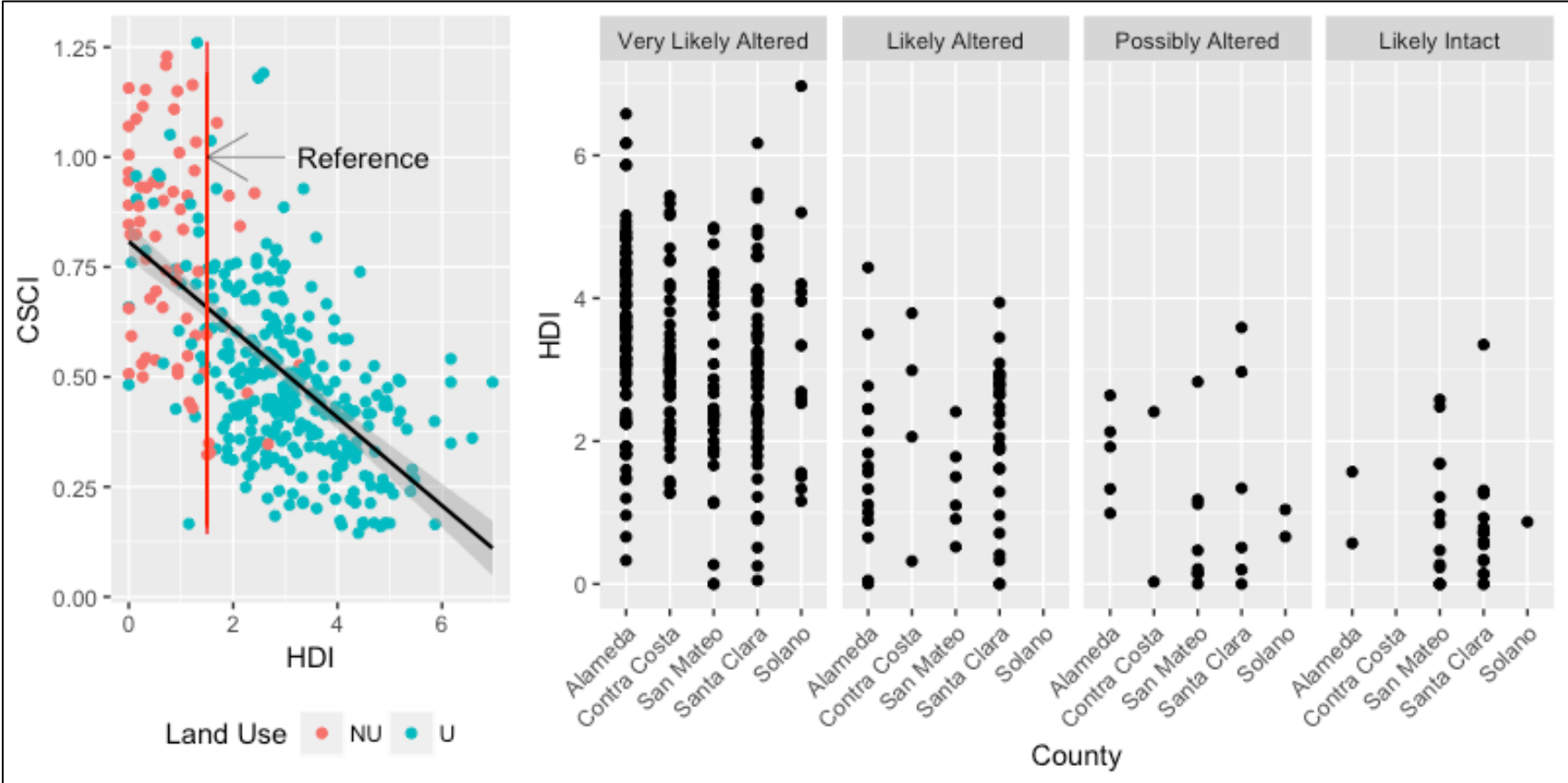


Figure 13. Relationship of CSCI scores to the Human Disturbance Index (HDI) stressor indicator. Red line indicates a reference condition cutoff of 1.5 (Ode et al. 2016).



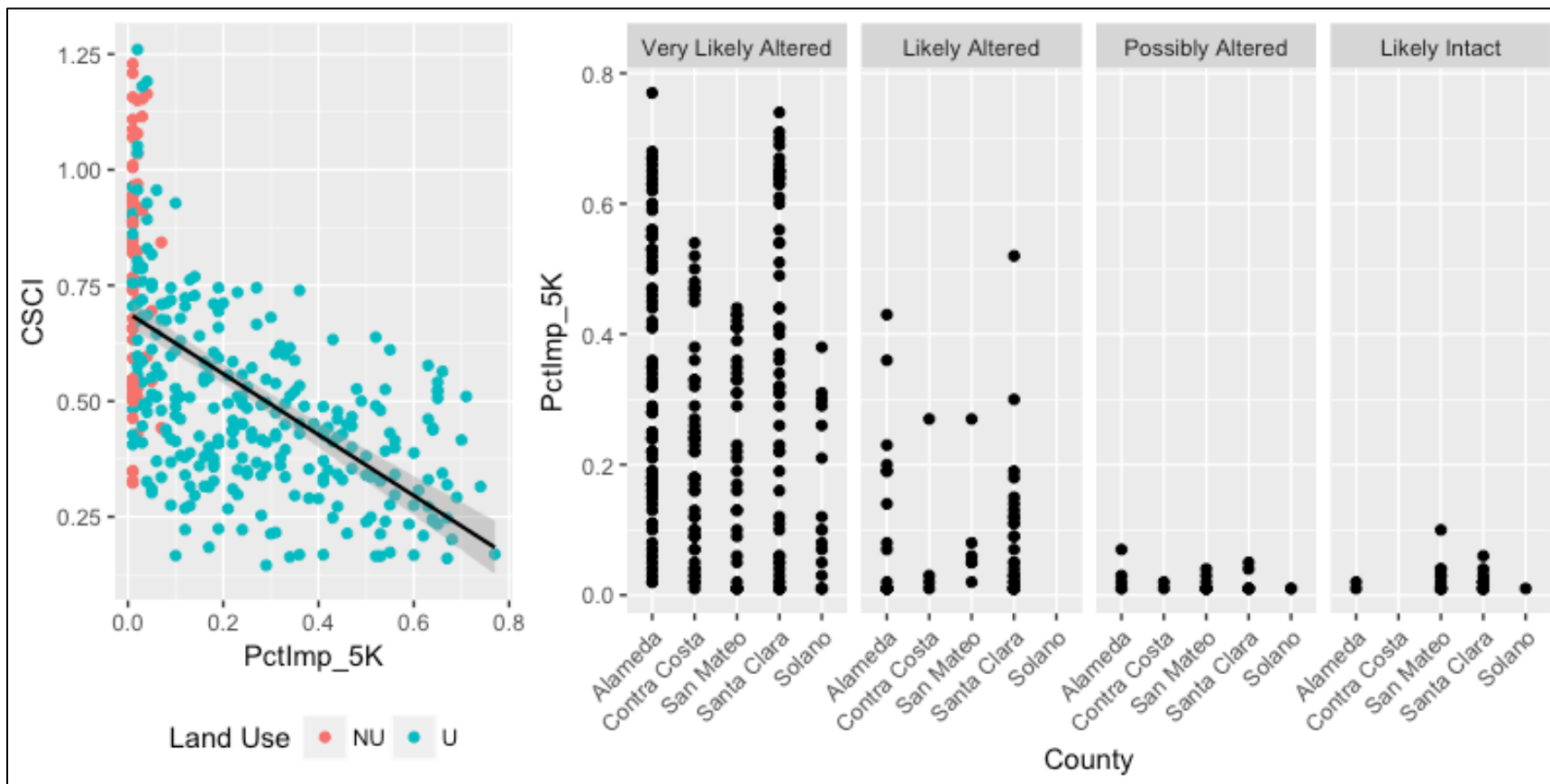


Figure 14. Relationship of CSCI scores to the percentage of land area in a 5 km radius (km<sup>2</sup>) around the site that is impervious.

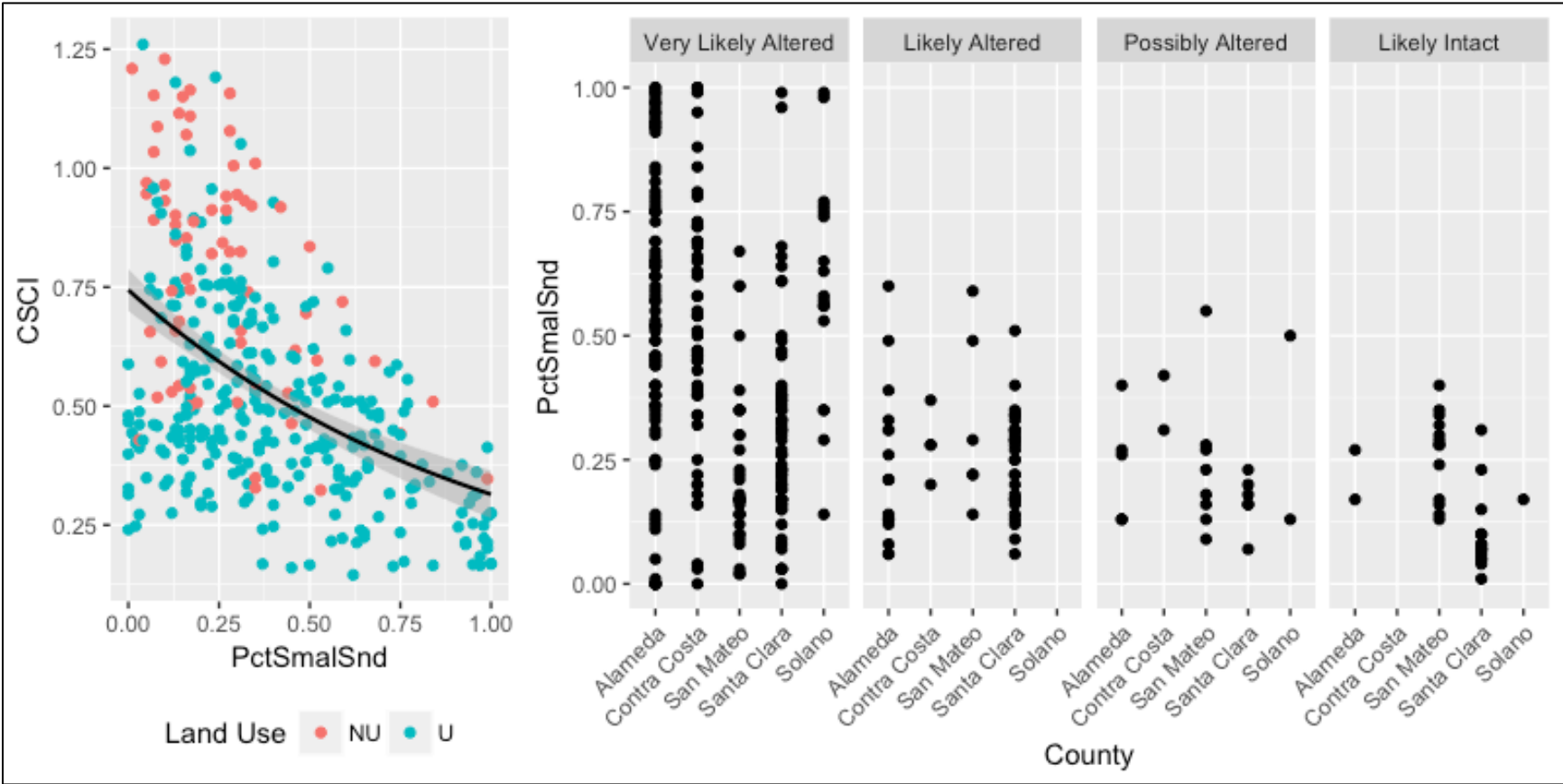


Figure 15. Relationship of CSCI score to the percent of substrate in the stream reach that was smaller than sand.

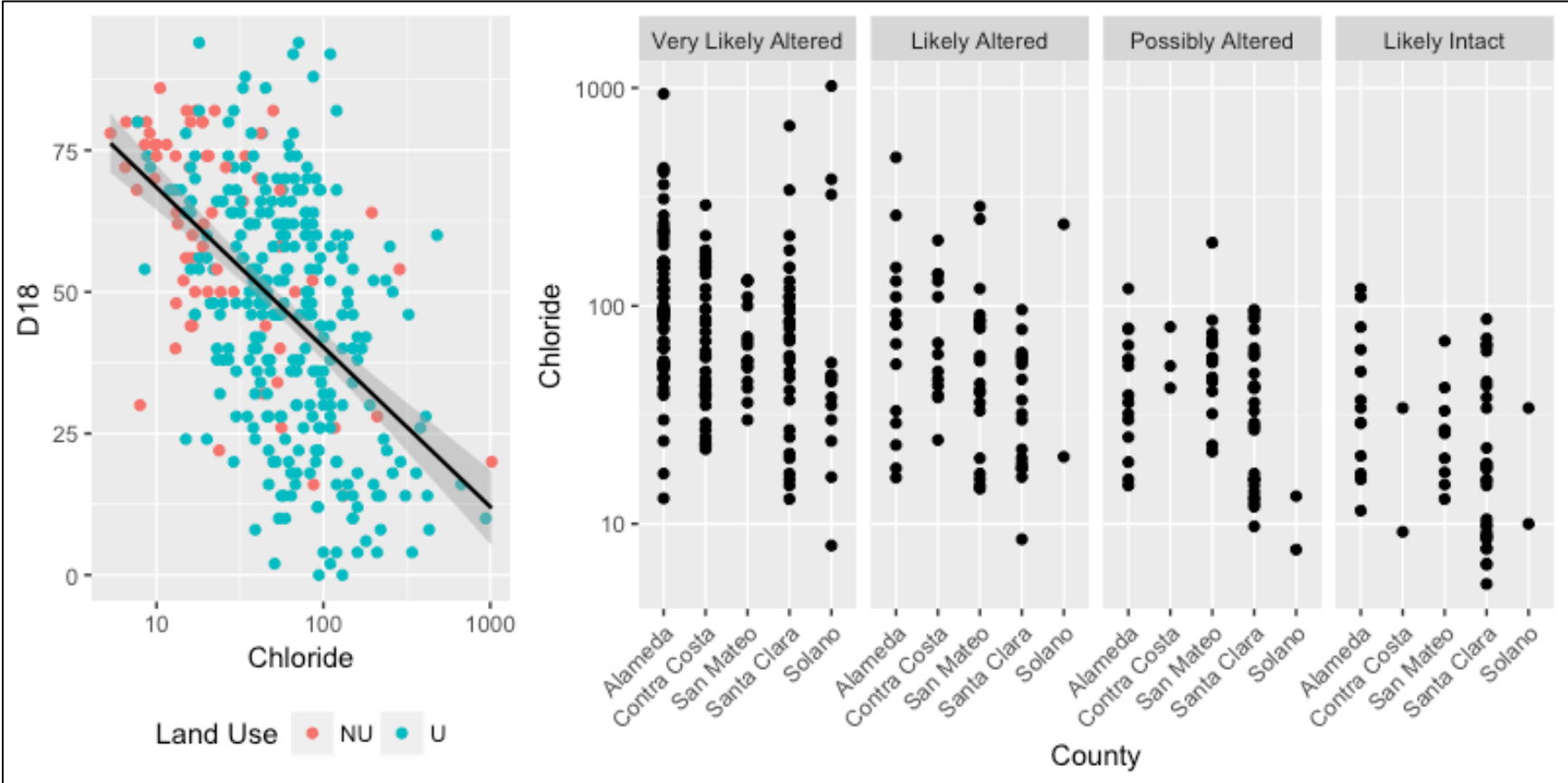


Figure 16. Relationship of D18 score to chloride concentration (mg/L). Note the chloride concentration scale is displayed in log units.

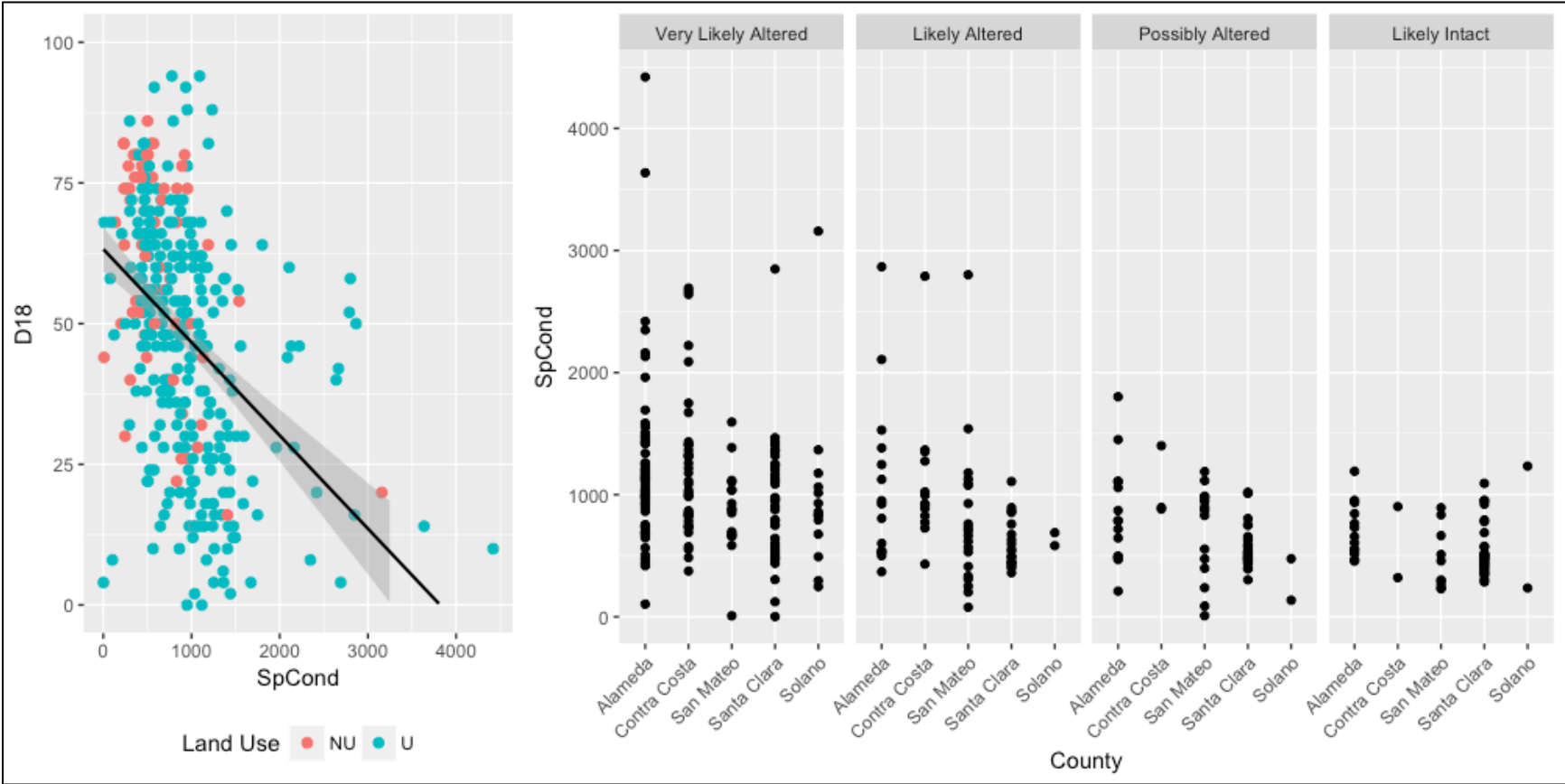


Figure 17. Relationship of D18 score to specific conductivity ( $\mu\text{S}/\text{cm}$ ).

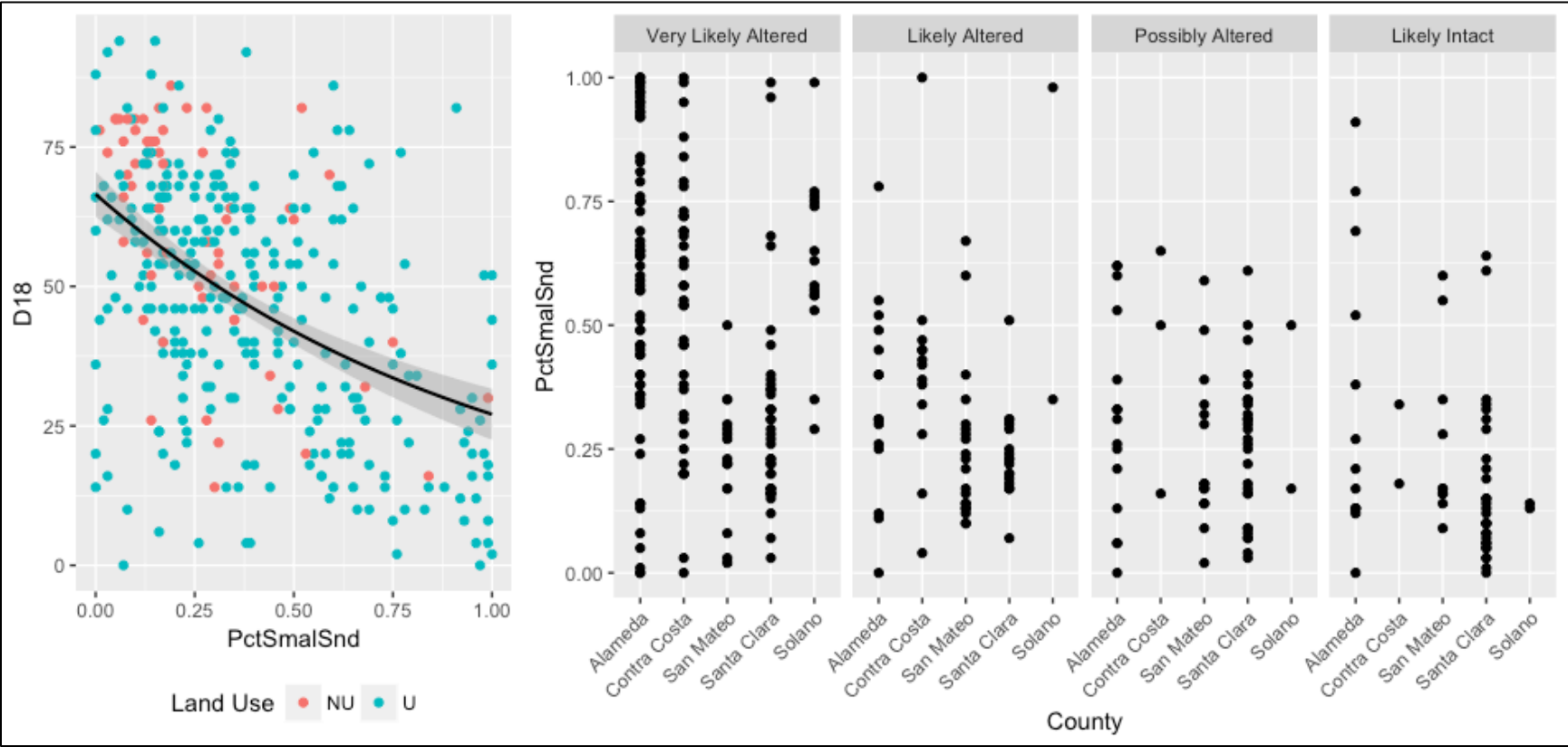


Figure 18. Relationship of D18 score to the percent of substrate in the stream reach that was smaller than sand.

### 3.3.2 Relative Risk Outputs

The relative risk of several stressors that may impact biological condition (based on CSCI scores) is shown in Figure 19. Definitions of abbreviations and threshold values for relative risk are described in Section 2.4.5. The Human Disturbance Index (HDI) stressor had the strongest relationship (> 3.0) with poor biological condition observed in the RMC dataset. Of the remaining physical habitat stressor variables, percent substrate smaller than sand (SmaISnd) had the strongest relationship (1.56) with poor biological condition. The remaining six stressors evaluated were associated with water quality and water chemistry and had Relative Risk values ranging between 1.26 and 1.51. These results are consistent with the random forest model results presented in the previous section, suggesting that physical habitat variables are more strongly associated with biological condition (based on CSCI scores) in the Bay Area, compared to water quality variables.

The relative risk for the eight stressors evaluated for RMC study were consistent with the results of the relative risk analysis of the same stressors that was conducted by the SMC (Mazor 2015a), with the exception of nutrients. The SMC study showed that relative risk for both Total Nitrogen and Phosphorus slightly under 3.0, while the RMC analysis indicated a much lower relative risk for each of these water quality parameters. The differences in relative risk of nutrients in Northern and Southern California suggest that there may be regional differences in the effects of these water quality parameters on biological condition (based on CSCI). However, it is important to note that the threshold values used by the SMC for Total Nitrogen and Phosphorus were lower than those used in the RMC data analyses.

Please note that the relative risk estimates for the eight stressors illustrated in Figure 19 could not be compared among RMC counties due to the insufficient number of sites with biological conditions above and below stressor thresholds in some counties.

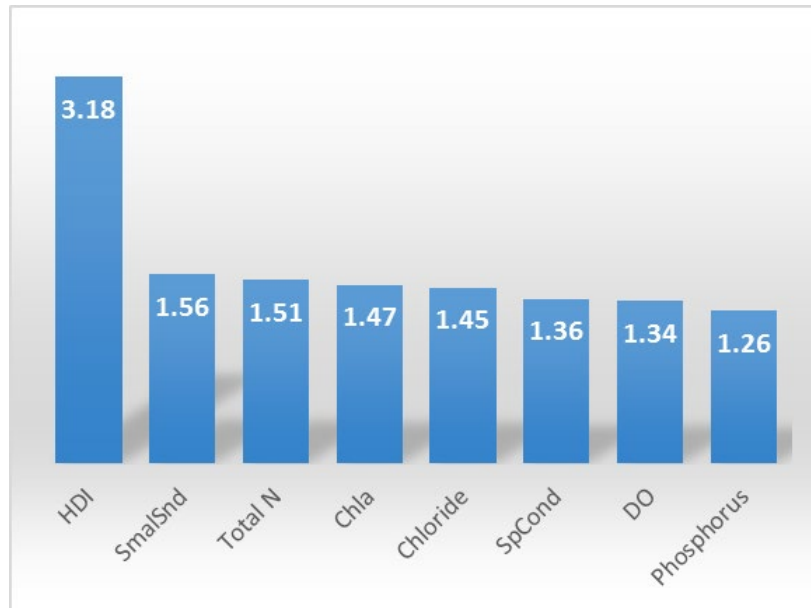


Figure 19. Relative risk of poor biological condition (i.e., scores in the lowest two CSCI condition categories) for sites that exceed stressor disturbance thresholds.

### 3.4 TRENDS

During the 2012-2016 monitoring period, there was no obvious temporal trend in biological condition, using either the CSCI, D18 or S2 indices. The median annual CSCI score for non-urban sites fluctuated between 0.518 and 0.931, but estimates in three of five years (2012, 2015, 2016) were only based on data collected at ten sites or less. Estimates were particularly imprecise for 2016, where only five non-urban sites were sampled. In urban areas, the median scores for CSCI had a much smaller range (0.408 to 0.510) than scores at non-urban sites. For urban sites, there was a clear lack of temporal trend, with 2016 exhibiting the highest median of the five years monitored (Figure 20).

D18 and S2 scores in each of the water years followed a similar pattern to CSCI scores. Scores in non-urban areas tended to vary widely depending on the water year and number of sites assessed (Figures 21 and 22). However, the urban sites tended to be relatively consistent, with scores generally being within a similar range each year. One observation to note was that S2 scores at urban sites were generally lower in 2016, compared to the preceding years of the survey, while CSCI scores were higher in 2016.

A comparison of median scores for CSCI each year and accumulated rainfall in each County did not reveal clear patterns on a county-by-county basis (Figure 23). Annual rainfall, as measured at San Francisco International Airport, during the five-year survey period was generally below the long-term average (Figure 5). Regional differences in accumulated rainfall additionally contribute to the lack of discernible changes in condition over time at a regional scale.

Contra Costa exhibited the highest range in accumulated rainfall during the monitoring period (10-20 inches) and generally had consistently low median CSCI scores. Alameda and Santa Clara counties, however, experienced a similar range in accumulated rainfall (5-16 inches), but had very different median CSCI scores in each water year. Given the variations in CSCI scores during different water years in some counties, future analyses to evaluate temporal trends in biological conditions will likely need to consider the influence of climatic variation at the county and regional-scales.

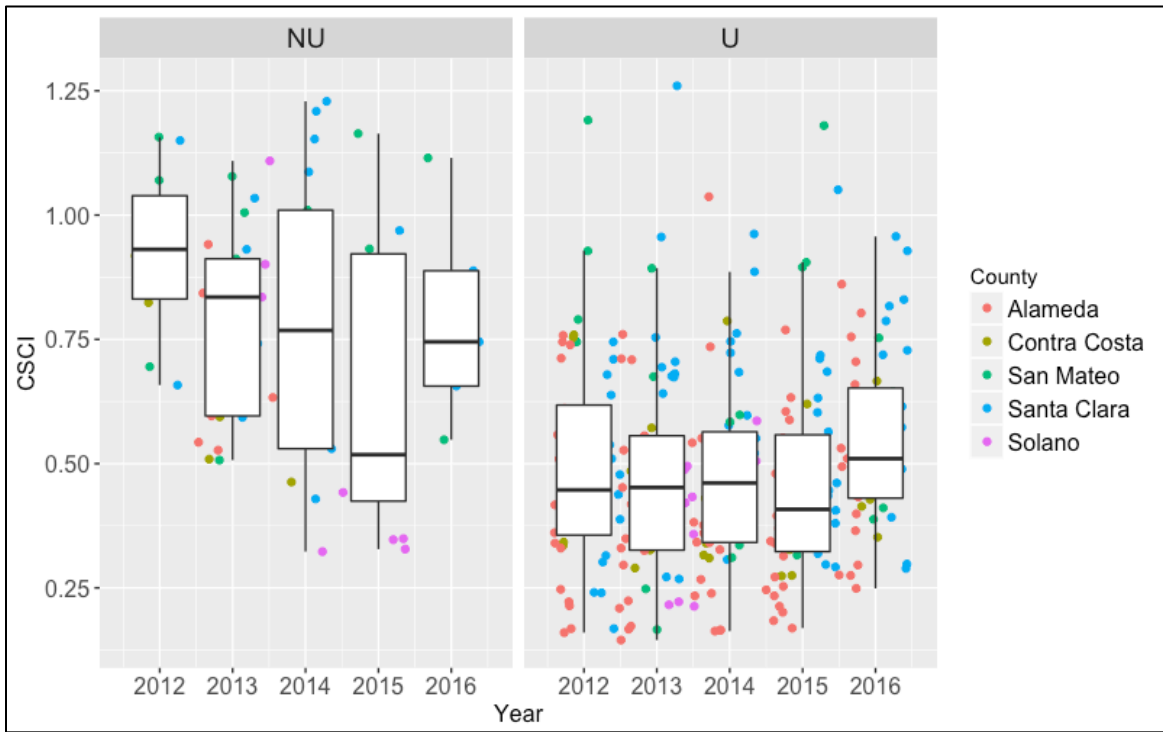


Figure 20. Distribution of CSCI scores during water years 2012-2016. NU = non-urban, U= urban.

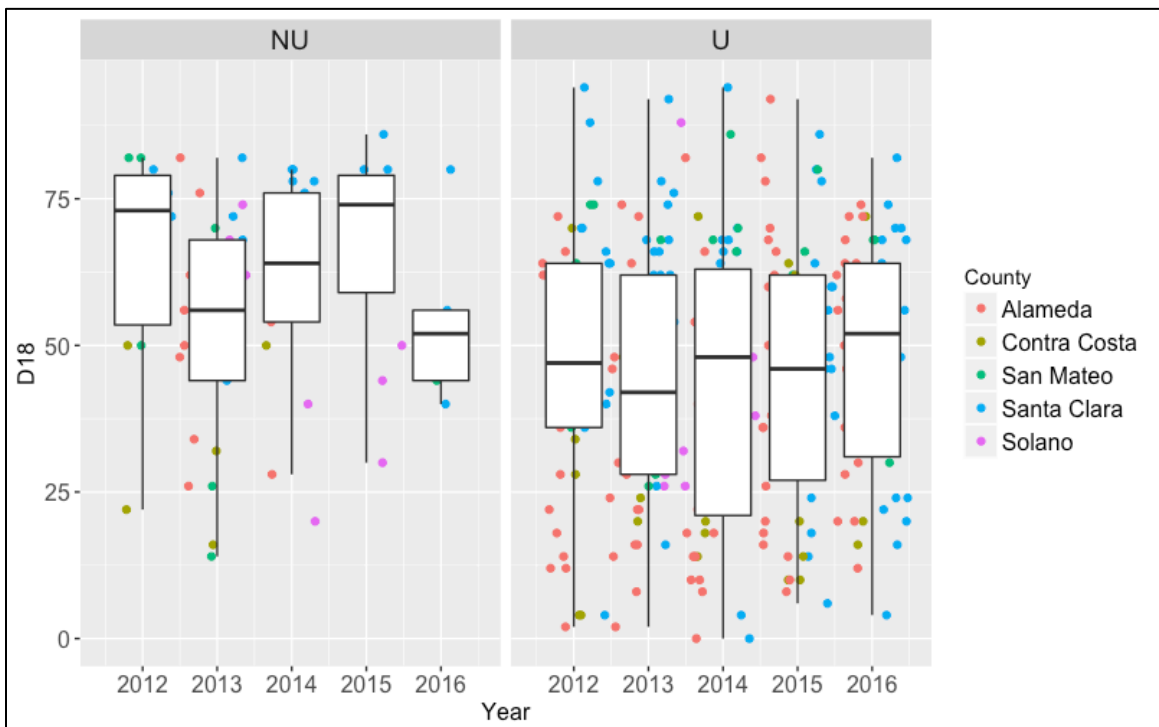


Figure 21. Distribution of D18 scores during water years 2012-2016. NU = non-urban, U= urban.



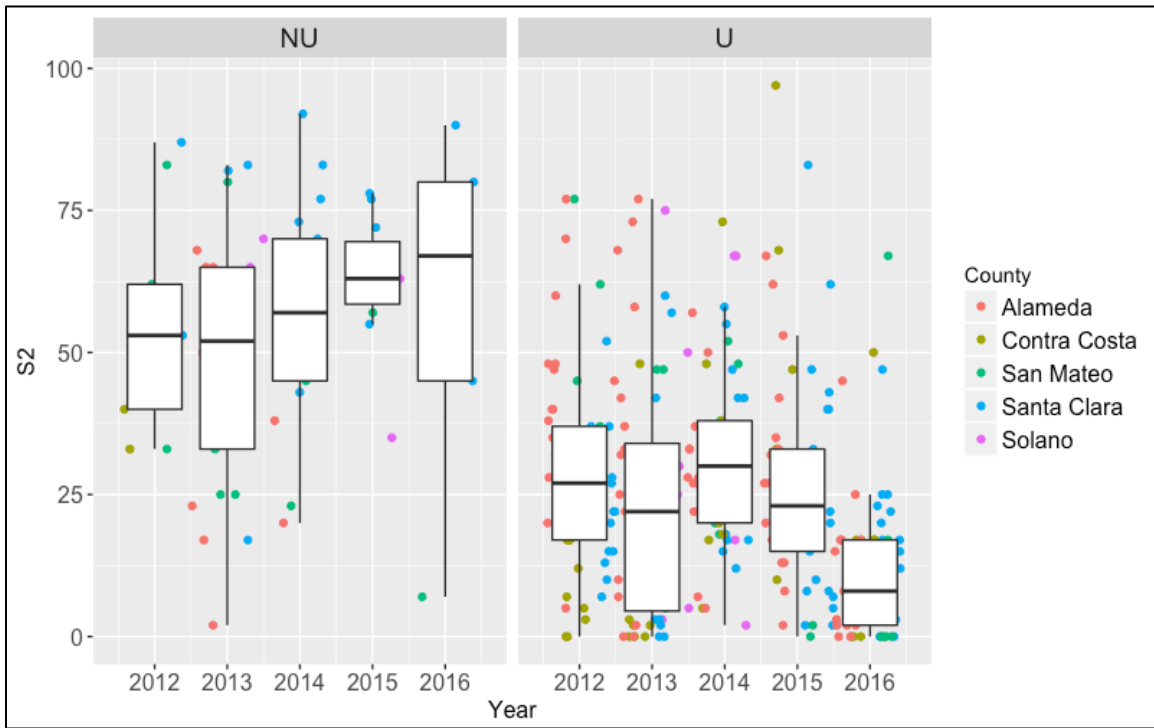


Figure 22. Distribution of S2 scores during water years 2012-2016. NU = non-urban, U= urban.

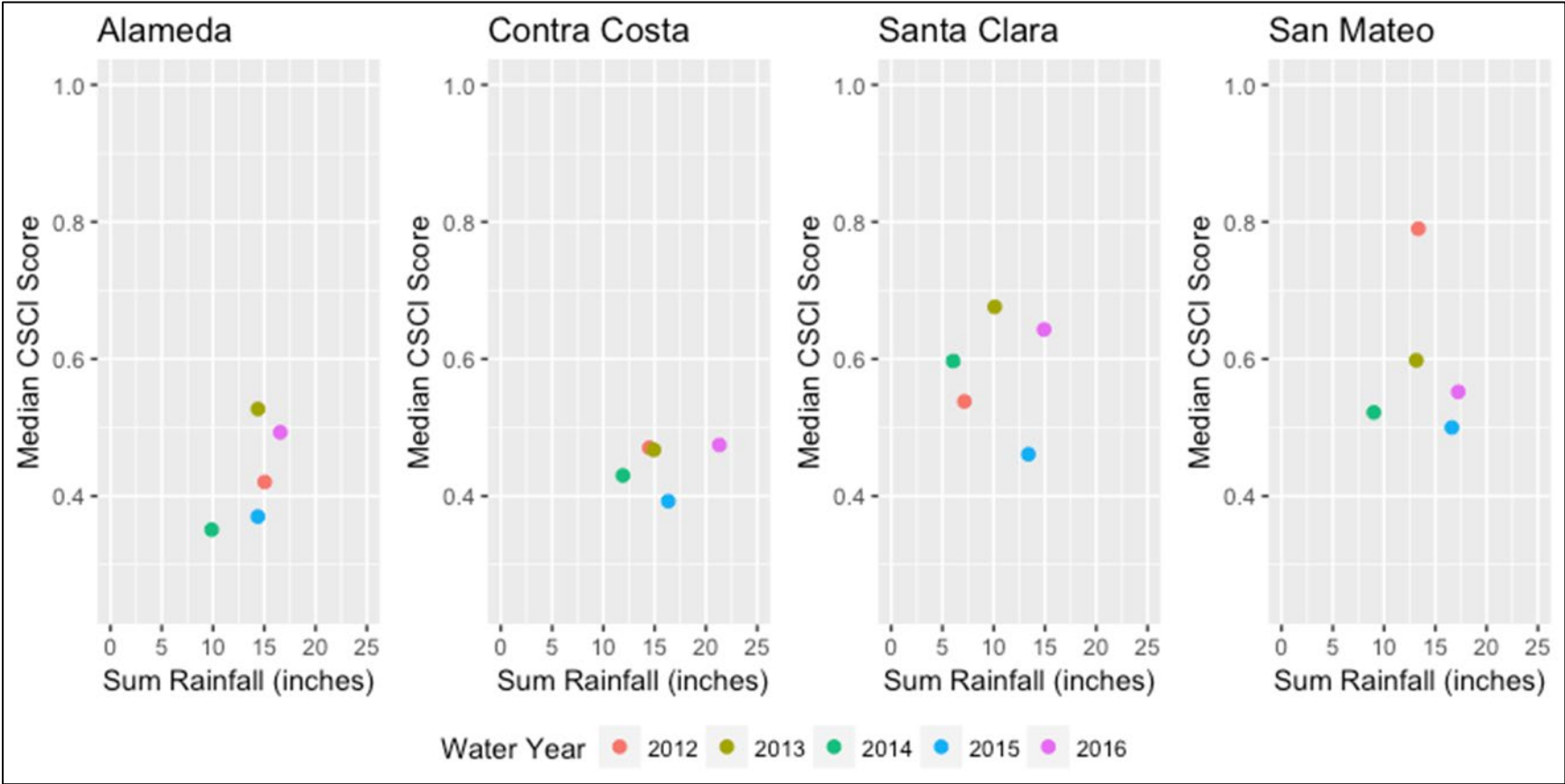


Figure 23. Relationship between median CSCI scores and accumulated annual rainfall in each County during water years 2012-2016. Includes urban and non-urban sites.

## 4 FINDINGS AND NEXT STEPS

The results and conclusions of the RMC's five-year bioassessment data evaluation are discussed below as they relate to the management questions and goals identified for the project.

### 4.1 WHAT ARE THE BIOLOGICAL CONDITIONS OF STREAMS IN THE RMC AREA?

#### *Regional Conditions*

The biological conditions of streams in the RMC area were assessed using two ecological indicators: BMIs and algae. The probabilistic survey design was developed to provide an objective estimate of biological condition of sampleable streams (i.e., accessible streams with suitable flow conditions) at both the RMC area and countywide scale.<sup>7</sup> Results of the survey indicate that streams in the RMC area are generally in poor biological condition:

- The CSCI for benthic macroinvertebrates (BMIs) indicates that 58% of stream length in the region are in the lowest CSCI condition category (Very Likely Altered); 74% of the of the sampled stream length exhibited CSCI scores below 0.795, the MRP trigger for potential follow-on activity.
- Using both algae indices (D18 and S2), stream conditions regionwide appear slightly less degraded than when using CSI, with approximately 40% of the streams ranked in the lowest algae condition category (Very Likely Altered). The algal indices also indicate that greater stream lengths (19-21%) are in the highest condition category (Likely Intact) compared to lengths in this category when the CSCI is used (15%).

These findings should be interpreted with the understanding that the survey focused on urban stream conditions. Approximately 80% of the samples (284 of 354) were collected at urban sites. As a result, the overall condition assessment represents the range of conditions found in the urban area, which is defined in the sample frame as areas classified as "urban" in the US Census (2000), plus all areas within city boundaries. Although the low non-urban sample size precludes making any definitive comparisons, bioassessment scores in the non-urban area were higher than scores in the urban area for each of the RMC counties. In general, the biological condition assessment for the RMC area (with a focus on urban sites) was consistent with the statewide assessment of biological conditions at sites located within urban land uses (PSA 2015), which resulted in more than 90% of urban streams rated in the two lowest biological condition categories using CSCI.

#### *Differences Across Counties*

One of the goals for the RMC monitoring design was to compare biological conditions of streams between counties. In general, biological conditions, based on CSCI and D18 scores, appeared better in streams located in Santa Clara and San Mateo counties, compared others. However, Santa Clara and San Mateo counties had proportionally more non-urban sites (with higher CSCI and D18 scores) compared to other

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<sup>7</sup> More samples are needed to estimate condition for non-urban land use areas and finer spatial scales (i.e., watersheds).

counties. All counties exhibit higher biological condition scores in the non-urban area compared to the urban area. The difference between urban and non-urban median scores is lower for the D18 index, suggesting that diatoms may respond less to the habitat degradation commonly found at urban sites and may therefore provide better response to changes in water quality conditions.

Higher overall scores in Santa Clara and San Mateo may also be associated with regional differences in rainfall and flow duration. For example, San Mateo County and western Santa Clara County watersheds drain the Santa Cruz mountains, which typically receive higher rainfall, in contrast to Alameda and Contra Costa counties, which primarily contain watersheds that drain the western slopes of the drier Diablo range.

### *Indicator Tools*

The use of multiple indicators provides a broad assessment of ecosystem functions. Streams that show degraded conditions for a single indicator may provide opportunities to identify the stressor and potentially implement management controls to reduce impacts. Alternatively, streams with poor conditions for both indicators (BMI and algae) may have multiple stressors that might be more challenging to address. Watershed managers may also choose to prioritize streams that are in good biological condition, based on both biological indicators, for protection of beneficial uses.

The RMC used existing tools to assess biological condition (CSCI and SoCal Algal IBIs). Although these tools were also used in the regional assessments conducted by the SMC, uncertainty remains as to how well these indices perform for streams within the San Francisco Bay Region:

- The CSCI is a statewide index that was developed for perennial streams. For the RMC project, however, the CSCI was used to evaluate BMI data collected in both perennial and non-perennial streams (note: the RMC assessed flow status by conducting site visits at all sampled sites during the dry season). In addition, CSCI scores appear highly sensitive to physical habitat degradation, which occurs frequently in the many highly modified urban streams monitored by the RMC. It is not clear how well the CSCI tool can show response to stressors associated with water quality, when physical habitat is the primary factor affecting the BMI community.
- For this report, the RMC evaluated algae data using SoCal Algae IBIs for diatoms (D18) and soft algae (S2). The D18 was more responsive to stressor gradients associated with water quality, however, high scores were often found in urban sites with highly degraded physical habitat. The soft algae index (S2) was not a reliable indicator of condition due to overall low taxa richness observed at both disturbed and undisturbed sites throughout the RMC area. In many cases, there was insufficient number of soft algae taxa to calculate S2, resulting in data gaps and lack of utility of the S2 index. Additional testing of soft algae indices is needed to assess the utility of this indicator in the RMC area.

The State Water Board and Southern California Coastal Water Research Project are currently developing and testing a set of statewide indices using benthic algae data as a measure of biological condition for streams in California. The statewide Algae Stream Condition Indices (ASCIs) are expected to be finalized in 2019. It is anticipated that the RMC will apply the ASCIs to analyze algae data when they become available.

## 4.2 *WHAT STRESSORS ARE ASSOCIATED WITH BIOLOGICAL CONDITIONS?*

This question was addressed by evaluating the relationships between biological indicators (CSCI and D18) and stressor data through random forest and relative risk analyses. The study results indicate that each of the biological indicators responded to different types of stressors and therefore the two may be best used in combination to assess potential causes of poor (or good) biological conditions in streams:

- Biological condition, based on CSCI scores, is strongly influenced by physical habitat variables and land use within the vicinity of the site. The percent of the land area within a 5 km radius of a site that is impervious appears to have the largest influence on CSCI scores based on the random forest model results. Based on the relative risk analysis, the degree of human disturbance near a site, as observed via the Human Disturbance Index (HDI), appears to have the greatest relationship with poor biological condition of streams.
- Biological condition, based on D18 scores, is moderately correlated with water quality variables and less associated with physical or landscape variables, such as imperviousness or HDI.

In general, CSCI scores at urban sites were consistently low in all RMC counties, indicating that degraded physical habitat conditions in and around streams do not support healthy in-stream biological communities. D18 scores at urban sites were more variable, indicating that healthy diatom assemblages can occur at sites with poor physical habitat and may be important water quality indicator these sites.

No nutrient variables (e.g., nitrate, total nitrogen, orthophosphate, phosphorus) correlated strongly with CSCI scores in the Bay Area, nor were nutrients ranked as important variables explaining CSCI scores via the random forest model. Phosphorus and ash-free dry mass, which increase in response to biostimulation, were important in predicting algae (D18) index scores, although no statistically significant relationships were observed. This finding suggests that nutrient targets currently under development by the State Water Board as part of their Biostimulatory/Biointegrity Project, should be applied in the context of observed biological conditions, not uniformly based solely on broad relationships that may not apply to the Bay Area streams.

Although results show associations between some stressors and biological condition, they do not establish causation. There are several factors that may affect the strength of the correlation between stressors and biological condition:

- Stressors are not independent of one another and may have synergistic or mediating effects on condition. For example, elevated temperatures reduce the amount of oxygen that can be dissolved in the water column and both stressors may result in adverse effects to aquatic biota.
- Potential variability of stressor concentrations over time may not be represented in a single grab sample. For example, dissolved oxygen can have a wide range of concentrations over a 24-hour period. Drops in DO concentrations typically occur in early morning hours, potentially well prior to the timing of measurements during bioassessment events.
- Many of the physical habitat variables can be highly variable throughout the sample reach. For example, a wide range of substrate grain sizes can occur within a single transect. Thus, degraded habitat conditions that may exist at selected transect(s) of the assessment reach may not be well represented in reach-wide averages used as endpoints for the stressor analysis.

- Stressor impacts may be dependent on other factors (possibly not measured) for negative effects to occur. For example, elevated nutrient concentrations do not necessarily result in eutrophication (i.e., excessive plant and algal growth, reduced oxygen levels). Stream locations that have minimal exposure to sunlight, cooler water and higher flow rates may not develop eutrophic conditions, despite presence of elevated concentrations of nutrients.
- Stressors may have natural sources; prevalence and magnitude may vary by watershed or regionally. For example, naturally occurring nitrogen or phosphorus concentrations may be present in minimally disturbed upper watershed areas.

### 4.3 *ARE BIOLOGICAL CONDITIONS CHANGING OVER TIME?*

The short timeframe of the survey (five years) limited the ability to detect temporal trends in bioassessment data. Since new sites are surveyed each year, it is expected that a much longer time period is needed to detect trends at a regional scale over time. The variability in biological condition observed over the five years of the current analysis may have been associated with annual variation in precipitation or other factors. Drought conditions were present during the first four years of the survey. Trends in biological condition are more likely to occur on the decadal timescale. That said, the PSA evaluated trends for unique probabilistic sites sampled over a 13-year period and observed no trends (i.e., consistent directional change over time) (PSA 2015).

It is also important to consider these results within the broader context of the progress made over the past decade to reduce the effects of urbanization on creeks and channels through the mandatory treatment of stormwater and reduction of impervious areas via applicable new and redevelopment projects, and the numerous stream restoration projects that have been put into place. The implementation of mandatory stormwater treatment via green stormwater infrastructure (GSI) and low impact development (LID) began prior to the adoption of the MRP in 2005. These requirements reduce the effects of stormwater from impervious surfaces created via new and redevelopment and likely have positive effects on biological condition in streams, although the responses may be delayed. Bay Area municipalities are currently developing GSI Plans, which will result in the strategic and widespread integration of GSI into Capital Improvement Projects and other co-benefit projects like regional stormwater capture projects, creek restoration and flood control and resiliency projects. These efforts are anticipated to further reduce the impacts of stormwater on local streams. Future creek status monitoring may provide additional insight into the potential positive impacts of GSI and creek restoration on water quality and beneficial uses in urban creeks.

The ability to detect trends would be increased if the sample design included re-visiting sites over multiple years. Multiple surveys at individual sites would provide more site-specific detection of changing biological conditions over time. Should RMC participants intend to use BMIs and algae as long-term indicators, analyses should be conducted to identify the minimum number of samples needed over a specified timeframe to detect trends at a site or within a watershed or county, with a specified level of confidence. The analysis could also be used to optimize the monitoring program by evaluating appropriate sample sizes for detecting trends when considering expected variability in condition for different groups of sites, land use types, or areas where management actions are being implemented.

## 4.4 EVALUATION OF MONITORING DESIGN

The information presented below is intended to provide recommendations on potential revisions RMC monitoring procedures that should be considered for future implementation of bioassessment programs in the Bay Area.

### 4.4.1 Site Evaluations

Over the first five years of monitoring, the RMC evaluated about 25% (1455 out of 5740) of the sites in the sample frame to assess 354 sites. Approximately 46% (873 out of 1896) of the total number of urban sites in the sample frame were evaluated during that time. Additional sites have subsequently been selected from the sample frame and evaluated for sampling in 2017 and 2018. The number of remaining sites for evaluation in the RMC Sample Frame for each county is presented in Table 7.

**Table 7. Sites remaining in RMC sample frame before site evaluation in water year 2019.**

County	Urban	Non-urban
Alameda	124	797
Contra Costa (R2)	348	307
Contra Costa (R5)		331
Santa Clara	143	1189
San Mateo	67	469
Fairfield-Suisun	37	208
Vallejo	4	

Based on rejection rates from previous years, the sample frame is anticipated to only last two to three years at which time the urban sites in the frame will be exhausted. Revision of the RMC monitoring design could seek to reduce the future rejection rate through re-evaluation of the sample frame to exclude areas of low management interest or regions that would not be candidates for sampling (such as due to lack of permissions or physical barriers to access). This would improve the spatial balance of samples that more closely represents the proportion of the sample frame that can be reliably assessed.

Each countywide stormwater program managed their site evaluation information independently using a standardized database. The site evaluation data were then compiled to conduct the spatial analysis needed to calculate the regional biological condition estimates presented in this report. During the compilation process, inconsistencies in procedures used to conduct site evaluation (BASMAA 2016a) were identified that affect the statistical certainty of the regional estimates. Some sites in the sample draw were skipped over (e.g., challenges in obtaining permissions from private land owners, lack of flow during period of drought) with the intention to re-evaluate the sites at a future date. The skipped sites created sampling bias that affects the spatial balance of the draw and reduces certainty in the condition estimates.

Another issue was the disproportionate sampling of non-urban sites among the counties. The RMC intended to sample twenty percent of the targeted sites each year. Some Programs had difficulty getting

access to non-urban sites, or decided to focus on urban sites, resulting in a wide range in number of samples collected at non-urban sites across the counties. As a result, biological condition scores at the county-scale tended to be higher in counties that sampled more non-urban sites.

#### 4.4.2 RMC Sample Frame

Consistent with the PSA, the RMC sample design was created to probabilistically sample all streams within the RMC area, which resulted in a master list of 33% urban sites and 67% non-urban sites. However, because participating municipalities are primarily concerned with runoff from urban areas, the RMC focused sampling efforts on urban sites (80%) over non-urban sites (20%). As a result, non-urban samples are under-represented in the dataset resulting in much lower overall biological condition scores than would be expected for a spatially balanced dataset. In addition, the limited number of non-urban samples (2% sample frame assessed thru-2016) prevented statistical confidence in estimates of biological condition for non-urban land use at the regional scale.

Depending on the goals for the RMC moving forward, the RMC may want to consider developing a new sample draw that establishes a new list of sites that is weighted for specific land uses categories and Program areas of interest. Development of a revised sample frame would result in a new list of sites, associated with different length weights for each land use category. The sample draw could also include a list of sites for oversampling (replacements for sites not sampled) to maintain the spatial balance throughout any timeframe of the draw and allow for a much longer time frame before the list is exhausted.

Re-design of the RMC sample frame could also include new strata based on developed channel classifications created by SCCWRP. The classifications are created using a statistical model that predicts likely ranges of CSCI scores based on landscape characteristics (Mazor et al. 2018). These channel classifications could be integrated as strata into the RMC sample frame to allow varying sampling efforts for urbanized streams.

## 4.5 POSSIBLE NEXT STEPS FOR THE RMC BIOASSESSMENT MONITORING

Based on evaluation of data collected during the five years of the survey, several options to revise the RMC Monitoring Design are presented below:

- 1) Continue to sample new probabilistic sites until the draw is exhausted;
- 2) Re-visit probabilistic sites in support of assessing temporal trends;
- 3) Monitor targeted sites for special studies; or
- 4) Combination of two or more of the above.

Each of these options is discussed in more detail below.

### Continue Sampling New Probabilistic Sites

The RMC could continue to sample new probabilistic sites from the current sample frame with the goal to establish baseline conditions over smaller spatial scales. Eventually, statistically significant datasets would be obtained to estimate biological condition for all strata previously considered (i.e., non-urban and countywide), as well as finer scales (e.g., watersheds). Smaller geographic scales of assessments may



provide stronger associations between biological conditions and stressor levels. Watershed-level assessments may provide managers more opportunities to evaluate spatial patterns and temporal trends for specific watersheds.

Exclusively sampling new sites would exhaust sites in the current sample draw. It is anticipated that at the current rate of sampling (at same proportion of urban/non-urban sites), some of the Programs would run out of urban sites in two to three years. Solano County has already depleted urban sites from their sample frame. Sampling effort at new non-urban sites should also be evaluated. Resources to conduct site evaluations (e.g., permission to access private property) are typically much higher at non-urban sites. In addition, the access to non-urban sites appears to be highly variable by county.

If this option is desired, the RMC could develop a new probabilistic sample draw with a list of oversample sites.

#### Re-visit Probabilistic Sites to Assess Temporal Trends

Re-visiting probabilistic sites previously sampled may provide trend estimates and more refined information to potentially explain causes of observed trends. The most robust trends scenario would involve sampling the same sites each year; however, given the current level-of-effort, this would only be possible at a relatively small number of sites in each county. Thus, the resulting trends assessment could only answer regional questions. Some sites could be sampled for multiple years to evaluate potential variability related to changes in precipitation; non-urban sites may be particularly sensitive to annual variation in precipitation. Integrating site re-visits into the sample design would have the advantage of extending the life of the sample frame (i.e., reduce number of new sites each year).

#### Targeted Studies

There are several potential objectives for conducting biological assessments at targeted sites, including:

- 1) Evaluate effectiveness of stream restoration/BMP implementation projects;
- 2) Determine source/stressor at impaired site (i.e., causal assessment);
- 3) Evaluate conditions in selected watersheds;
- 4) Study trends at minimally disturbed sites (e.g., climate change);
- 5) Assess validity of CSCI in nonperennial streams in the Bay Area;
- 6) Investigate variability in biological indicator scores within sampling index period.

Targeted studies could be coordinated among RMC participants to evaluate similar objectives at regional scale or could be done independently by each Program. It is anticipated that targeted studies may require more resources with regards to site selection, data needs, detailed analyses, and reporting. However, targeted monitoring could also leverage requirements that Permittees have for other projects.

#### Combined Approaches

The RMC may consider implementing a combination of all the approaches described above for the future monitoring design.

## 5 REFERENCES

- Bay Area Stormwater Management Agencies Association (BASMAA). 2016a. Regional Monitoring Coalition Creek Status Monitoring Standard Operating Procedures. Version 3, March 2016.
- Bay Area Stormwater Management Agencies Association (BASMAA). 2016b. Regional Monitoring Coalition Creek Status Monitoring Program Quality Assurance Project Plan. Version 3, March 2016.
- Elith, J., Leathwick, J. R. and Hastie, T. 2008. A working guide to boosted regression trees. *Journal of Animal Ecology* 77.4: 802-813.
- Fetscher, A. E., Stancheva, R., Kociolek, J. P., Sheath, R. G., Stein, E. D., Mazor, R. D., & Busse, L. B. 2014. Development and comparison of stream indices of biotic integrity using diatoms vs. non-diatom algae vs. a combination. *Journal of applied phycology*, 26(1), 433-450.
- Kincaid, T. M. and Olsen, A. R. 2016. spsurvey: Spatial Survey Design and Analysis. R package version 3.3.
- Maloney, K., Weller, D., Russell, M., Hothorn, T. 2009. Classifying the biological condition of small streams: an example using benthic macroinvertebrates. *J North Am Benthol Soc* 28(4): 869–884.
- Mazor, R.D. 2015a. Bioassessment of Perennial Streams in Southern California: A Report on the First Five Years of the Stormwater Monitoring Coalition’s Regional Stream Survey. SCCWRP Technical Report #844. May 2015.
- Mazor, R.D. 2015b. Bioassessment Survey of the Stormwater Monitoring Coalition. Workplan for Years 2015 through 2019. Version 1.0. SCCWRP Technical Report #849. February 2015.
- Mazor R.D., Rehn A.C., Ode P.R., Engeln M., Schiff K.C., Stein E.D., Gillett DJ, Herbst D.B., Hawkins C.P. 2016. Bioassessment in complex environments: designing an index for consistent meaning in different settings. *Freshwater Science* 35(1):249-71.
- Mazor, R., Ode, P.R., Rehn, A.C., Engeln, M., Boyle, T., Fintel, E., Verbrugge, S., and Yang, C. 2016. The California Stream Condition Index (CSCI): Interim instructions for calculating scores using GIS and R. SWAMP-SOP-2015-0004. Revision Date: August 5, 2016.
- Mazor, R., M. Beck, and J. Brown. 2018. 2017 Report on the Stormwater Monitoring Coalition Regional Stream Survey. SCCWRP Technical Report #1029. Southern California Coastal Water Research Project. Costa Mesa, CA.
- Ode, P.R., Fetscher, A.E. and Busse, L.B. 2016. Standard Operating Procedures for the Collection of Field Data for Bioassessments of California Wadeable Streams: Benthic Macroinvertebrates, Algae, and Physical Habitat. California State Water Resources Control Board Surface Water Ambient Monitoring Program (SWAMP) Bioassessment SOP 004.
- R Core Team. 2016. R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. <https://www.R-project.org/> (<https://www.R-project.org/>).
- Rehn, A.C., Mazor, R.D. and Ode, P.R. 2015. The California Stream Condition Index (CSCI): A new statewide biological scoring tool for assessing the health of freshwater streams. California State Water Resources Control Board Surface Water Ambient Monitoring Program (SWAMP) TM-2015-0002. September 2015.
- State Water Resources Control Board (SWRCB). 2015. Surface Water Ambient Monitoring Program (SWAMP) Perennial Stream Assessment Management Memo. SWAMP-MM-2015-0001. June 2015.
- Stevens, D.L., Jr., and Olsen, A.R. 2004. Spatially-balanced sampling of natural resources. *Journal of the American Statistical Association* 99: 262-278.

- San Francisco Bay Regional Water Quality Control Board (SFBRWQCB). 2017. San Francisco Bay Basin (Region 2) Water Quality Control Plan (Basin Plan). Incorporating all amendments approved by the OAL as of May 4, 2017.
- San Francisco Bay Regional Water Quality Control Board (SFBRWQCB). 2015. California Regional Water Quality Control Board San Francisco Bay Region Municipal Regional Stormwater NPDES Permit (MRP 2.0). Order No. R2-2015-0049. NPDES Permit No. CAS612008. November 19, 2015.
- San Francisco Bay Regional Water Quality Control Board (SFBRWQCB). 2009. California Regional Water Quality Control Board San Francisco Bay Region Municipal Regional Stormwater NPDES Permit (MRP 1.0). Order No. R2-2009-0049. NPDES Permit No. CAS612008. October 14, 2009.
- van Buuren, S. and Groothuis-Oudshoorn, K. 2011. mice: Multivariate Imputation by Chained Equations in R. *Journal of Statistical Software*, 45(3), 1–67.
- Waite, I. R., Kennen, J. G., May, J. T., Brown, L. R., Cuffney, T. F., Jones, K. A. and Orlando, J. L. 2012. Comparison of Stream Invertebrate Response Models for Bioassessment Metrics. *JAWRA Journal of the American Water Resources Association*, 48: 570-583.

## APPENDICES

1. Random Forest Analysis
2. Partial Dependency Plots
3. CSCI-Stressor Plots
4. Additional Figures

## APPENDIX 1 RANDOM FOREST ANALYSIS

**Table 1-A. Variable group, variable code, and description of response variables (condition indices) and explanatory environmental variables (landscape, habitat, and water quality) used for random forest model development.**

Variable Group	Variable Code	Description
Response	CSCI	California Stream Condition Index
Response	D18	Soft algae condition score
Habitat	AvAlgCov	Mean Filamentous Algae Cover
Habitat	AvBold	Mean Boulders cover
Habitat	AvWetWd	Mean Wetted Width/Depth Ratio
Habitat	AvWoodD	Mean Woody Debris <0.3m cover
Habitat	ChanAlt	Channel Alteration Score
Habitat	EpiSub	Epifaunal Substrate Score
Habitat	FlowHab	Evenness of Flow Habitat Types
Habitat	NatShelt	Natural Shelter cover - SWAMP
Habitat	NatSub	Evenness of Natural Substrate Types
Habitat	PctBold_L	Percent Boulders - large
Habitat	PctBold_LS	Percent Boulders - large & small
Habitat	PctBold_S	Percent Boulders - small
Habitat	PctFin	Percent Fines
Habitat	PctFstH2O	Percent Fast Water of Reach
Habitat	PctGra	Percent Gravel - coarse
Habitat	PctSlwH2O	Percent Slow Water of Reach
Habitat	PctSmalSnd	Percent Substrate Smaller than Sand (<2 mm)
Habitat	PctSnd	Percent Sand
Habitat	ShD.AqHab	Shannon Diversity (H) of Aquatic Habitat Types
Habitat	ShD.NatSub	Shannon Diversity (H) of Natural Substrate Types

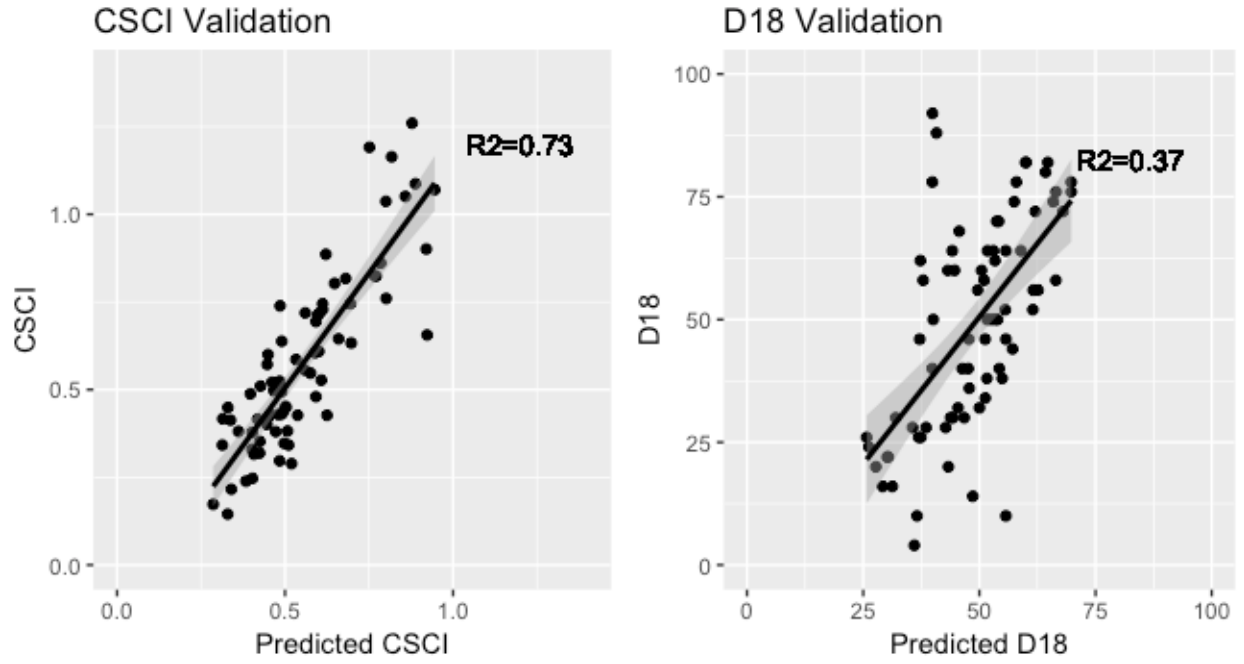
Variable Group	Variable Code	Description
Land Use	HDI	Combined Riparian Human Disturbance Index - SWAMP
Land use	PctImp	Percent Impervious Area of Reach
Land use	PctImp_1K	Percent Impervious Area in 1km
Land use	PctImp_5K	Percent Impervious Area in 5km
Land use	PctUrb	Percent Urban Area of Reach
Land use	PctUrb_1K	Percent Urban Area in 1km
Land use	PctUrb_5K	Percent Urban Area in 5km
Land use	RdCrs_5K	Number Road Crossings in 5km
Land use	RdCrs_W	Number Road Crossings in watershed
Land use	RdDen_1K	Road Density in 1km
Land use	RdDen_5K	Road Density in 5km
Land use	RdDen_W	Road Density in watershed
Land use	RoadCrs_1K	Number Road Crossings in 1km
Water Quality	AFDM.sub	Ash Free Dry Mass
Water Quality	Ammonia.sub	Ammonia
Water Quality	Chla.sub	Chlorophyll a
Water Quality	Chloride	Chloride
Water Quality	DO	Dissolved oxygen
Water Quality	Nitrate.sub	Nitrate
Water Quality	Nitrite.sub	Nitrite
Water Quality	OP.sub	Orthophosphate
Water Quality	pH	pH
Water Quality	Phosphorus.sub	Phosphorus
Water Quality	Silica	Silica
Water Quality	SpCond	Specific conductivity
Water Quality	Temp	Temperature
Water Quality	TKN.sub	Total Kjeldahl Nitrogen

Variable Group	Variable Code	Description
Water Quality	Total N	Total Nitrogen
Water Quality	UIA.sub	Unionized Ammonia

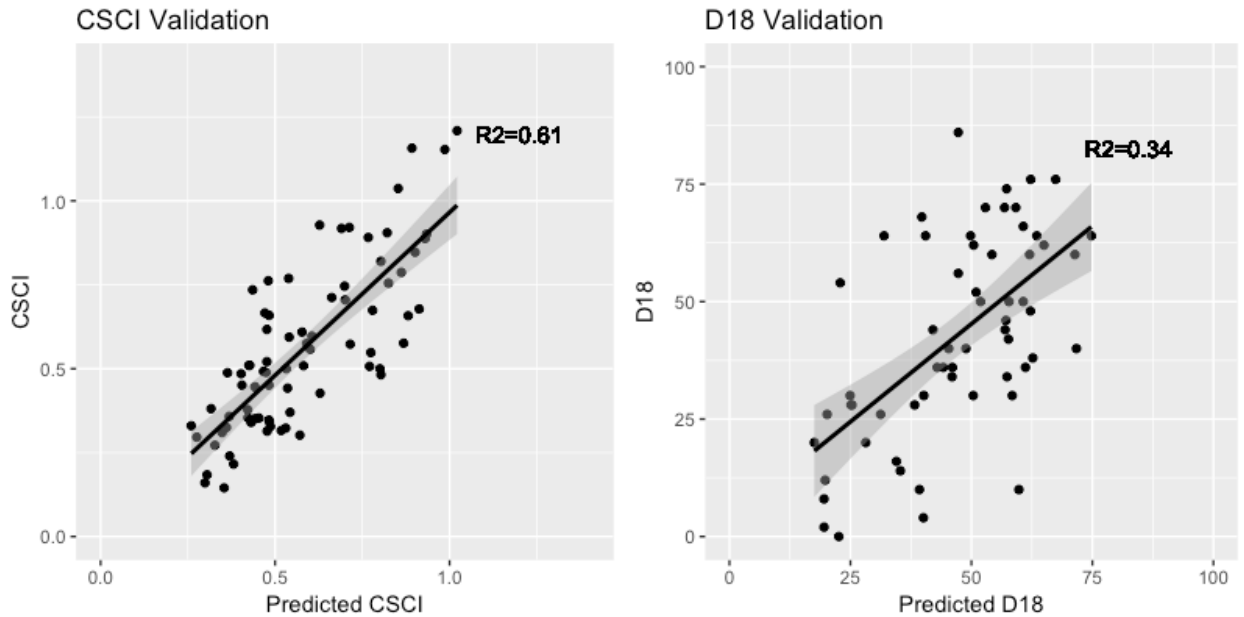
**Table 1-B. Model and cross-validation statistics for random forest models with CSCI and D18 scores using the final set of model variables (Table 2, Table 3)**

Index	Model Dataset	Model Statistic	
CSCI	Training	R <sup>2</sup>	0.95
	Validation	R <sup>2</sup>	0.61
CSCI	Training	CV R <sup>2</sup>	0.66
	Validation	CV R <sup>2</sup>	0.52
D18	Training	R <sup>2</sup>	0.92
	Validation	R <sup>2</sup>	0.34
D18	Training	CV R <sup>2</sup>	0.35
	Validation	CV R <sup>2</sup>	0.33

Training and validation models run with the same variables, \*R<sup>2</sup> = adjusted R-squared, CV R<sup>2</sup> = Cross validation R<sup>2</sup>

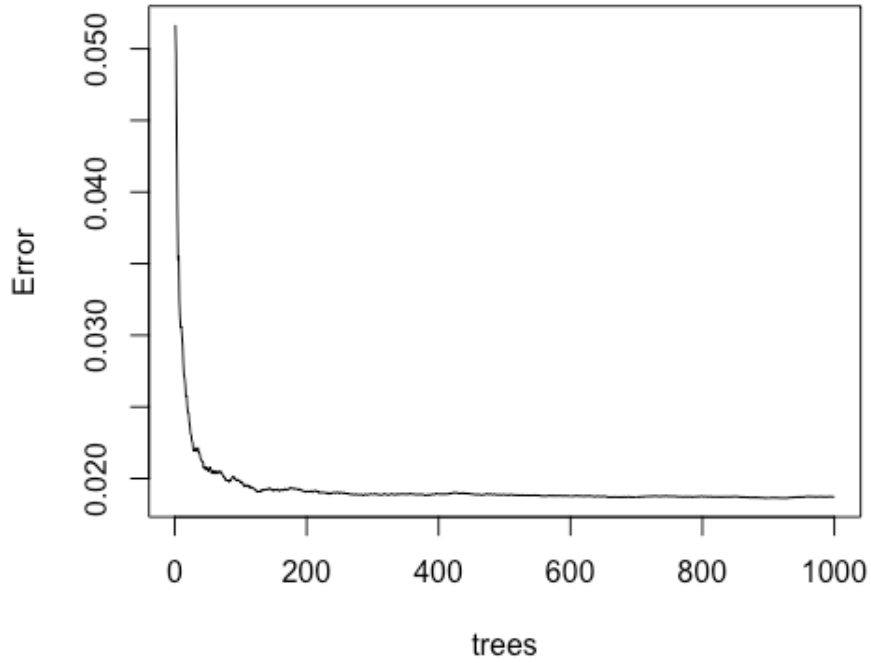


**Figure 1-A. Relationship of observed to predicted CSCI and D18 scores in the validation dataset using all 49 explanatory variables in Step 1 of the random forest trial**



**Figure 1-B. Relationship of observed to predicted CSCI and D18 scores in the validation dataset using the final, selected list of explanatory variables in Step 2 of the random forest trial**





**Figure 1-C. Prediction error vs. number of trees in the CSCI model with 49 stressor variables**

APPENDIX 2 PARTIAL DEPENDENCY PLOTS

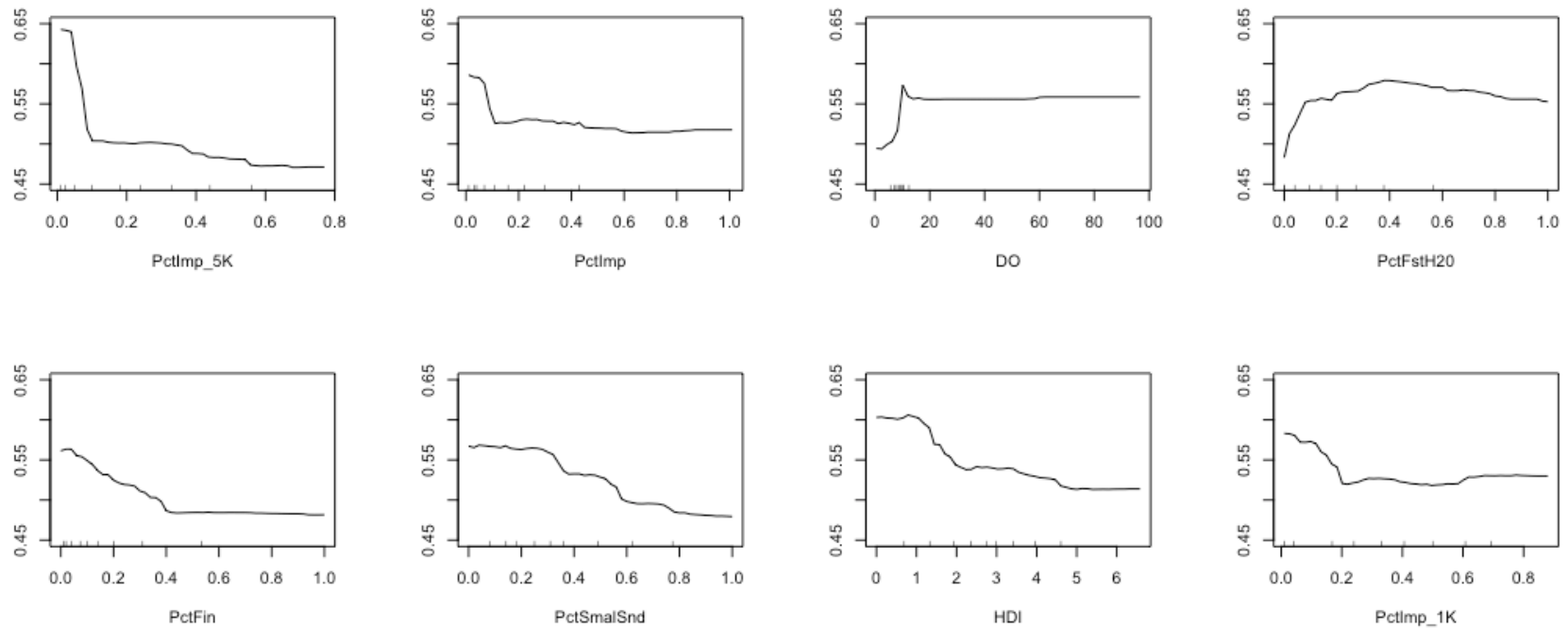
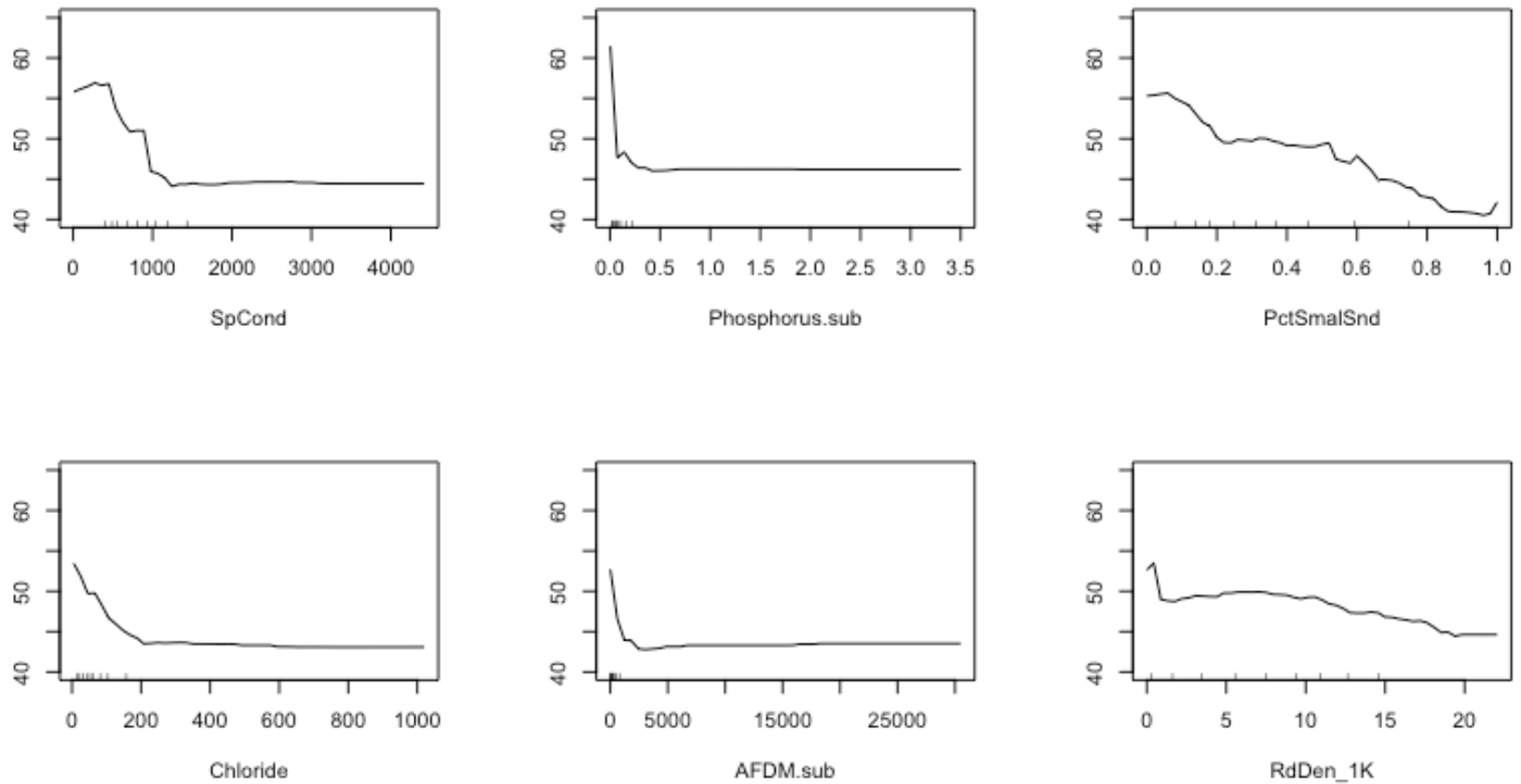


Figure 2-A. Partial dependency plots for stressor variables in random forest model of CSCI condition. Plots show the predicted response of CSCI (y-axis) based on the effect of individual explanatory variables (x-axis) with the response of all other variables removed in the training data set.



**Figure 2-B. Partial dependency plots for stressor variables in random forest model of D18 condition. Plots show the predicted response of D18 (y-axis) based on the effect of individual explanatory variables (x-axis) with the response of all other variables removed in the training data set.**

APPENDIX 3 CSCI-STRESSOR PLOTS

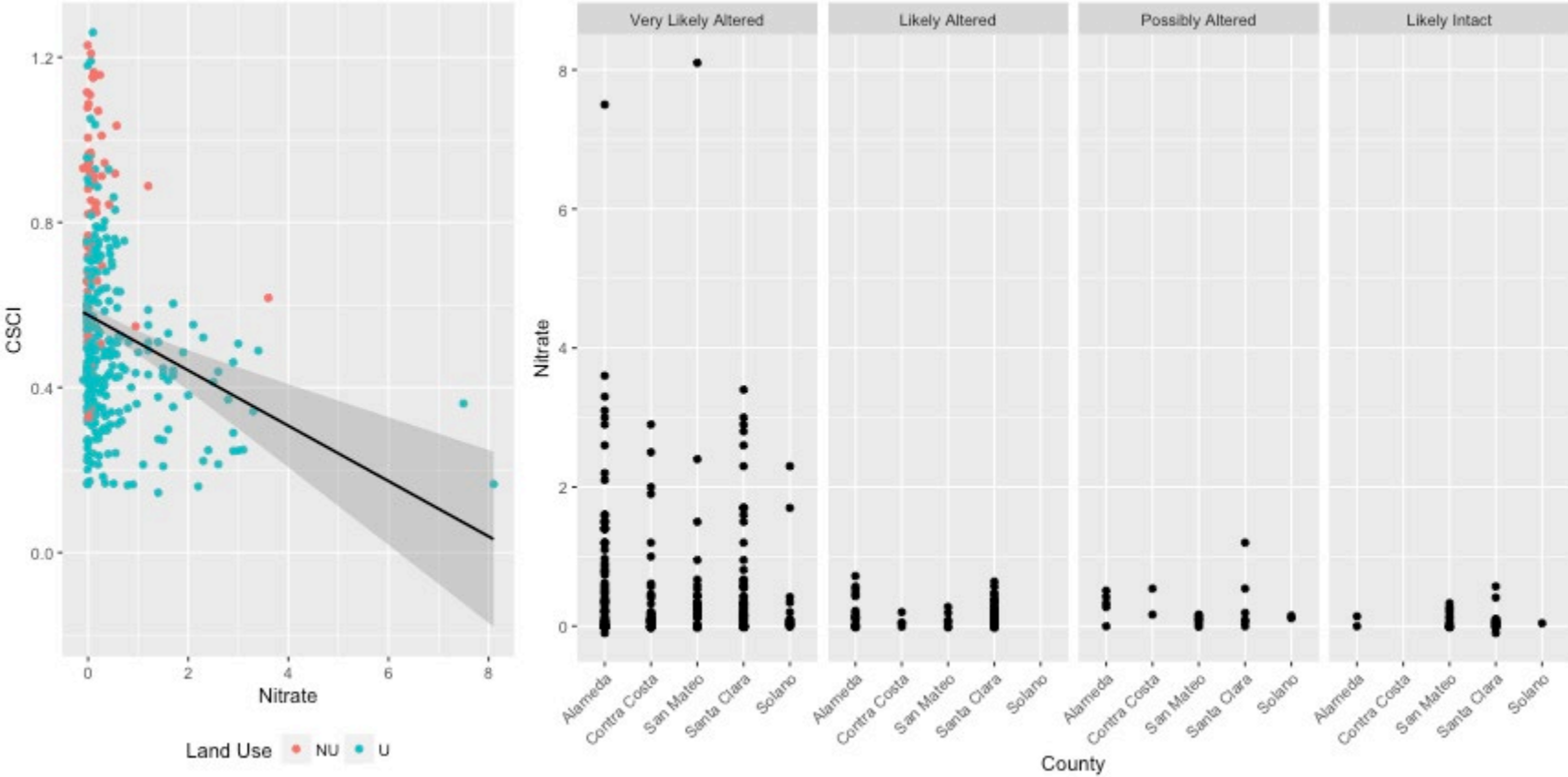


Figure 3-A. Relationship of Nitrate concentration to CSCI scores

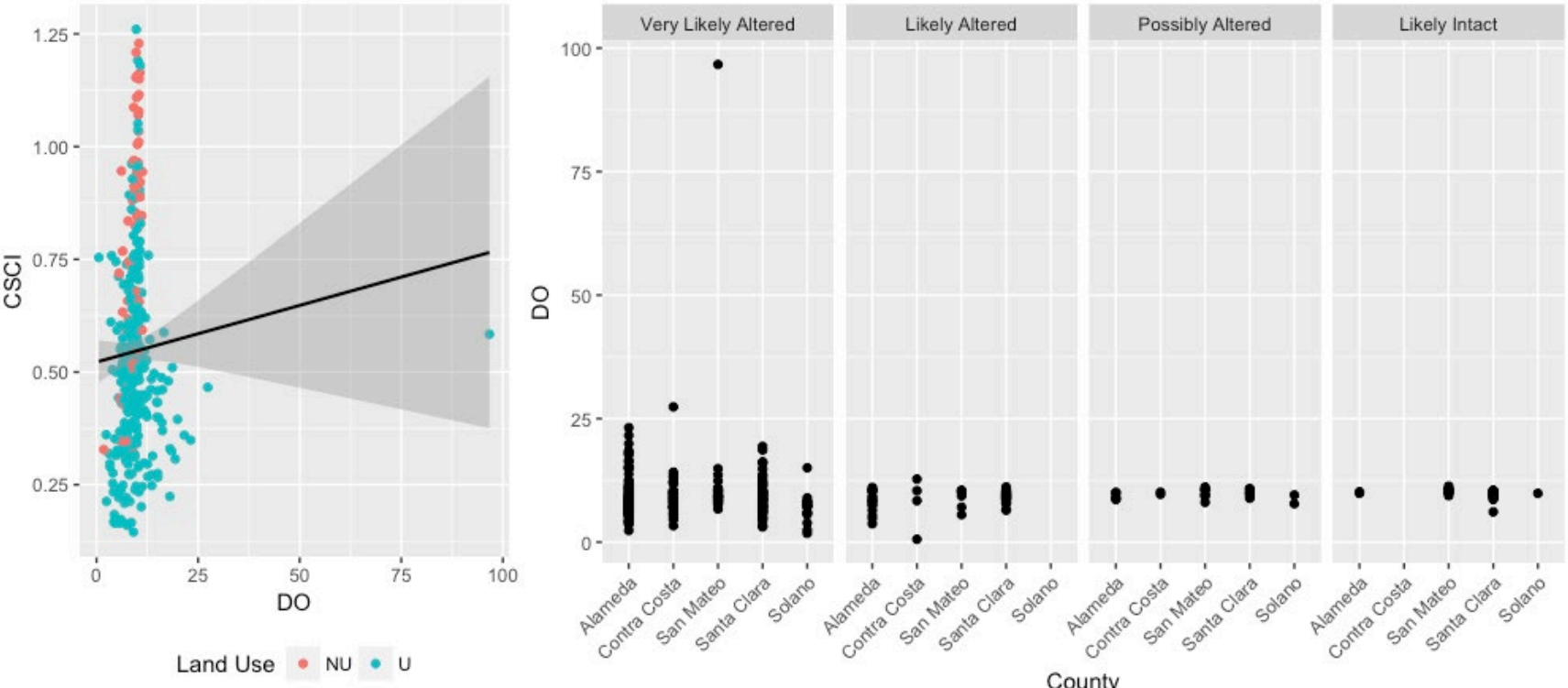


Figure 3-B. Relationship of Dissolved Oxygen values to CSCI scores

APPENDIX 4 ADDITIONAL FIGURES

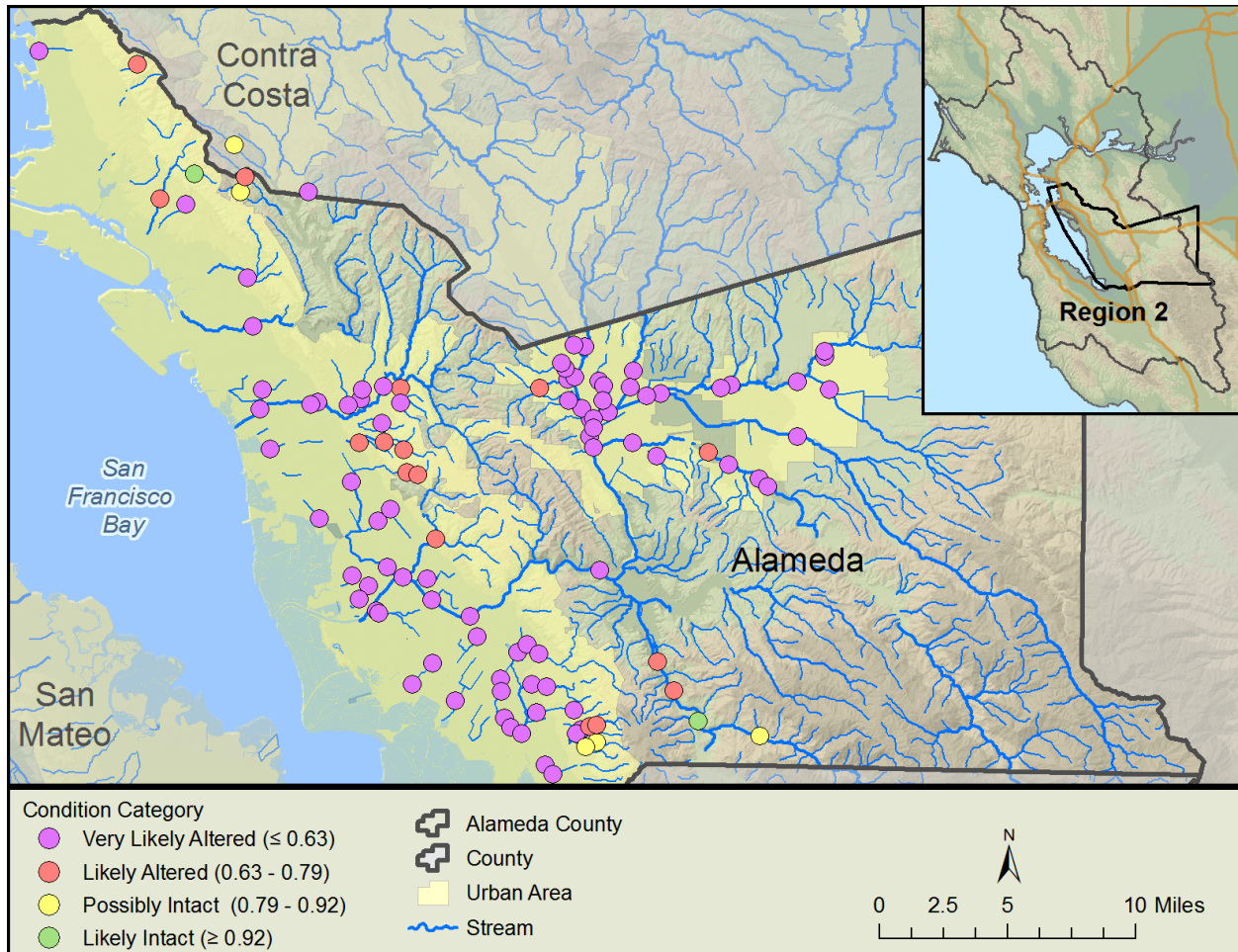
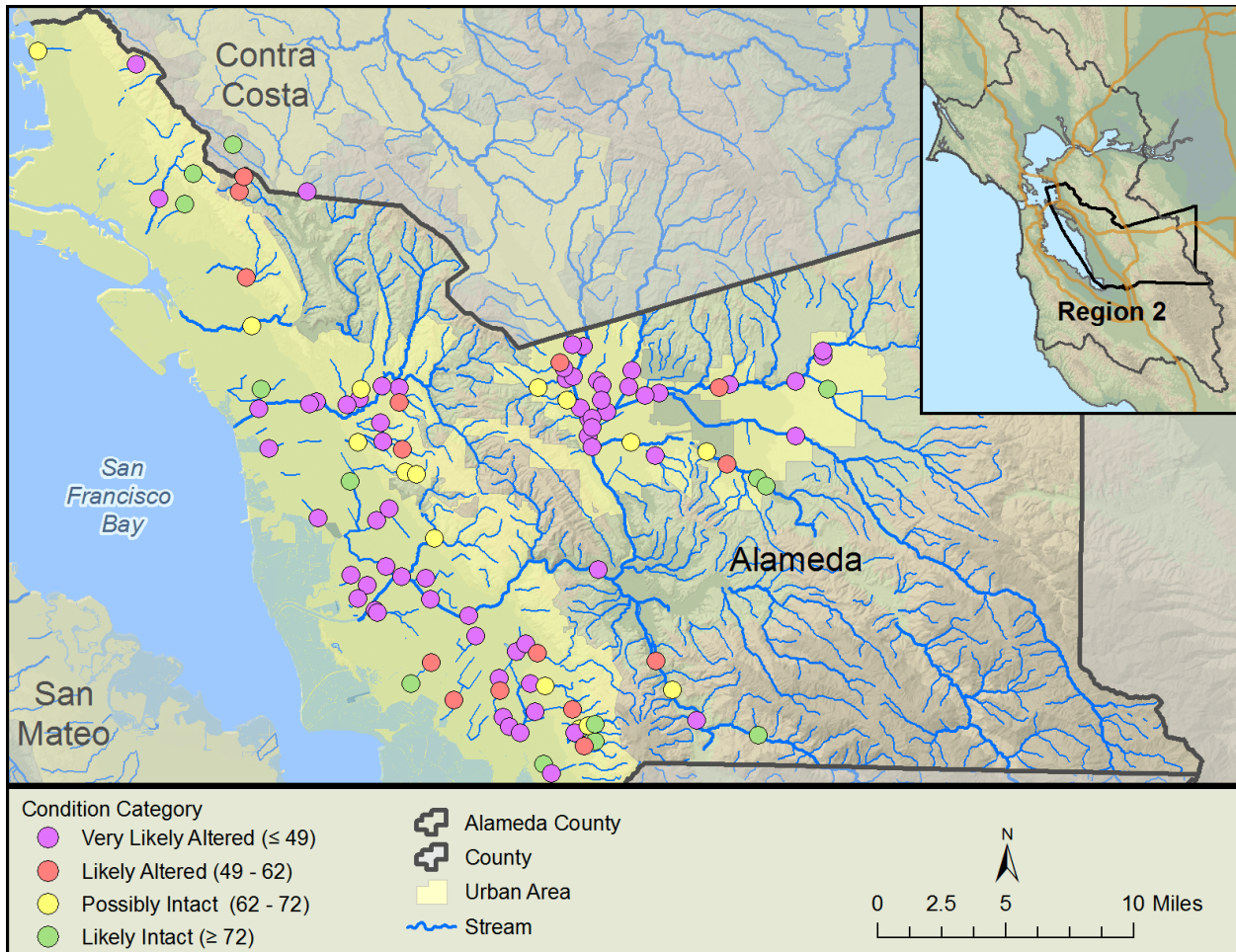


Figure 4-A. Biological condition based on CSCI scores in Alameda County.



**Figure4-B. Biological condition based on D18 scores in Alameda County.**

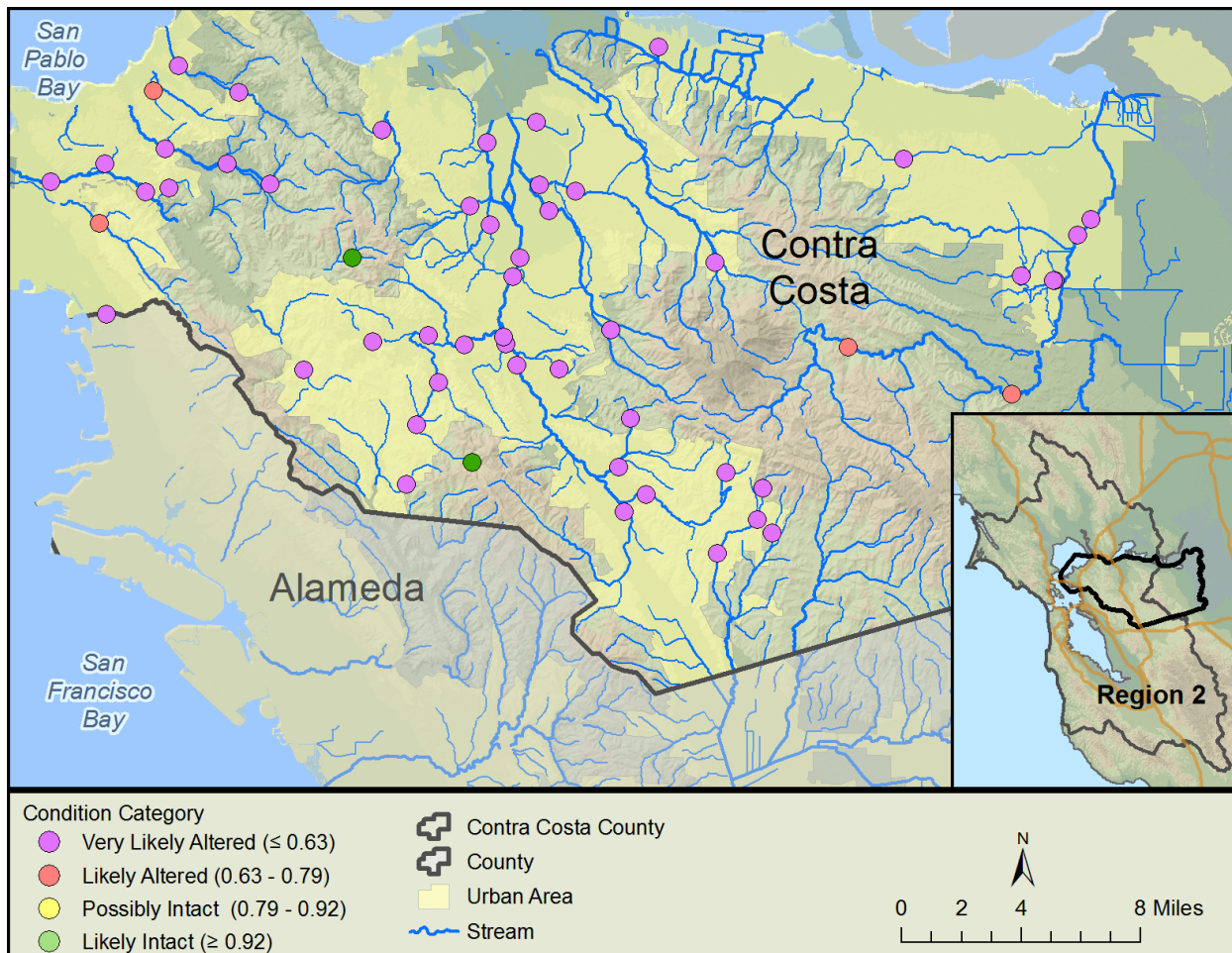


Figure 4-C. Biological condition based on CSCI scores in Contra Costa County.



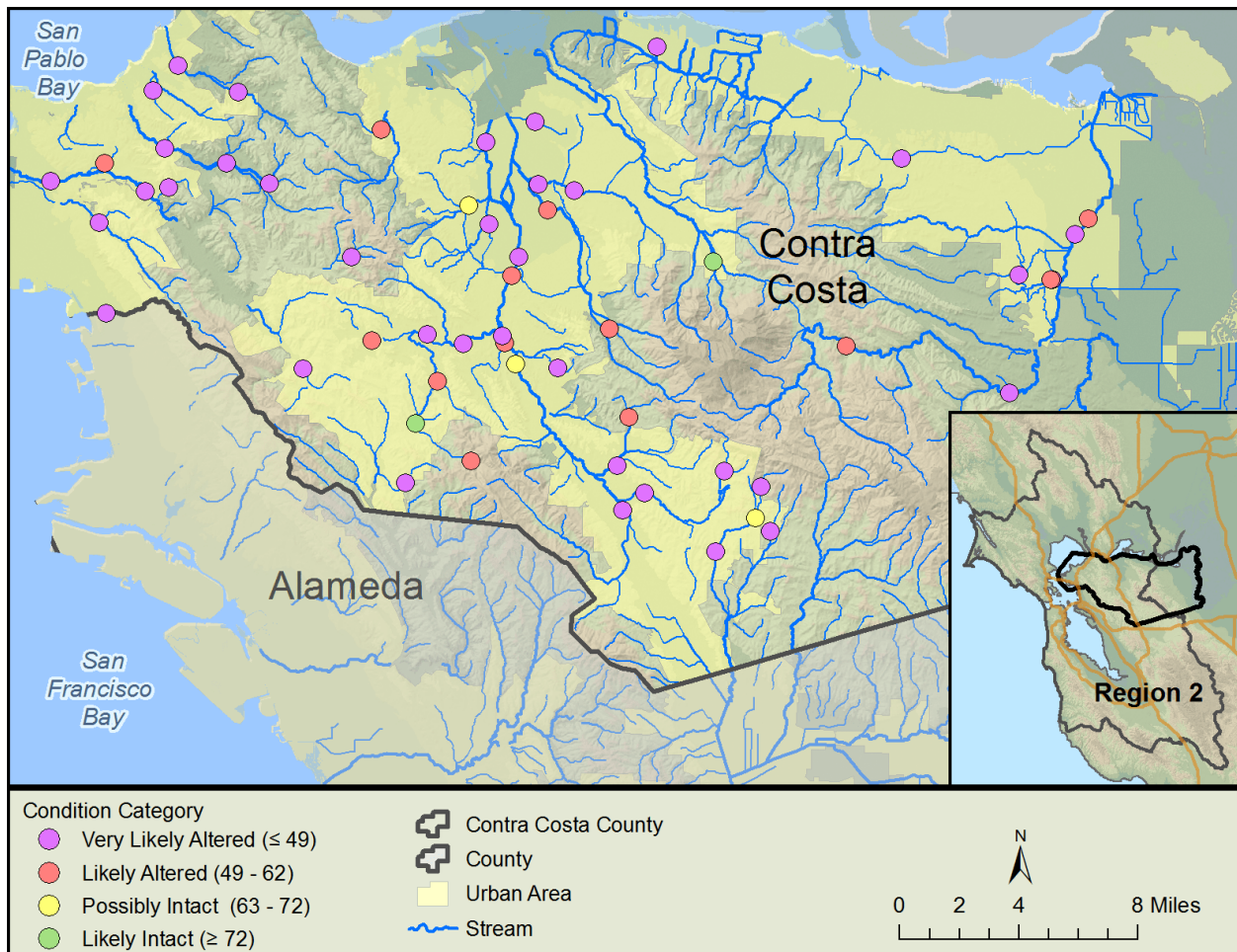


Figure 4-D. Biological condition based on D18 scores in Contra Costa County.



Figure 4-E. Biological condition based on CSCI scores in San Mateo County.

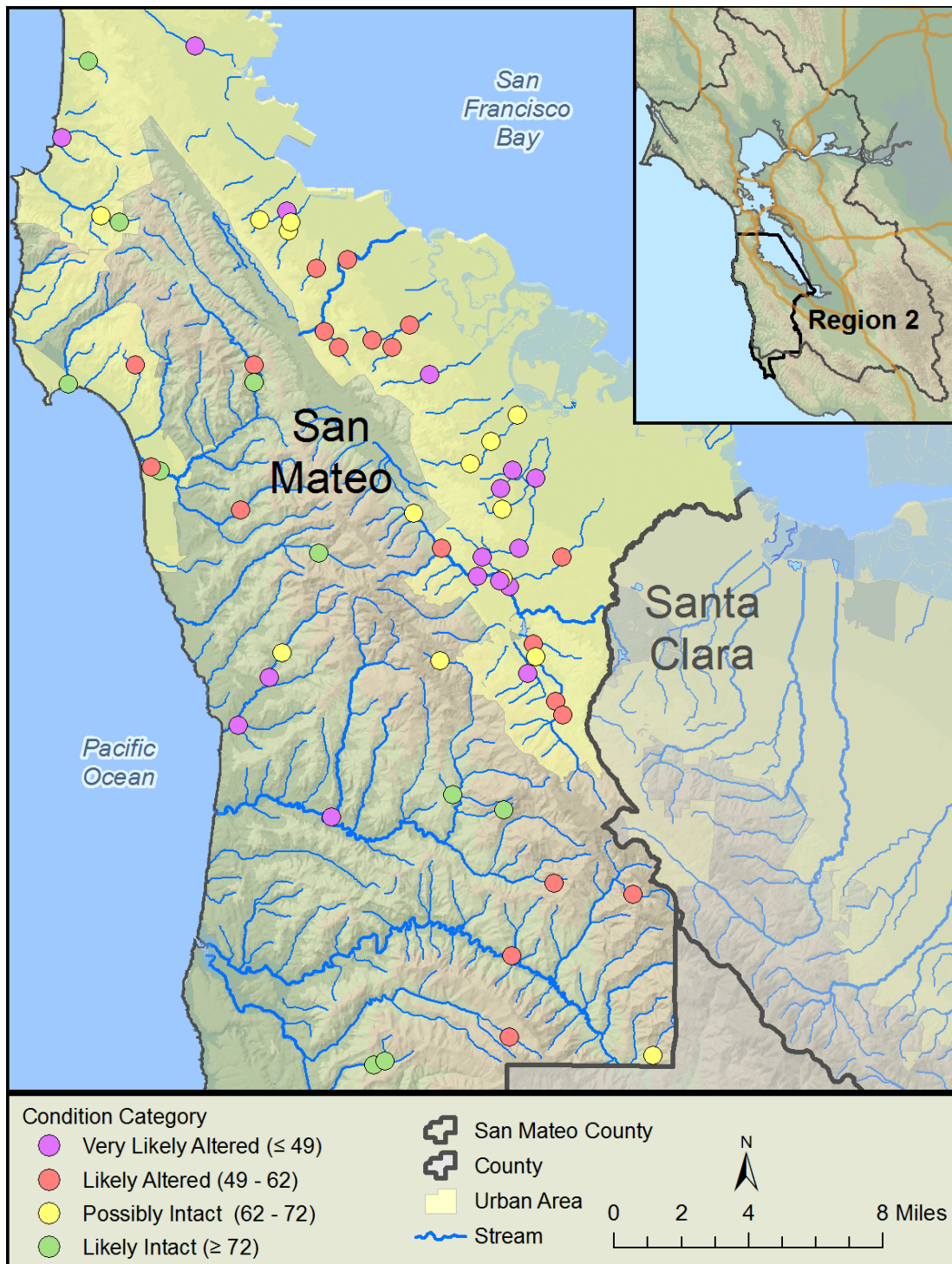


Figure 4-F. Biological condition based on D18 scores in San Mateo County.

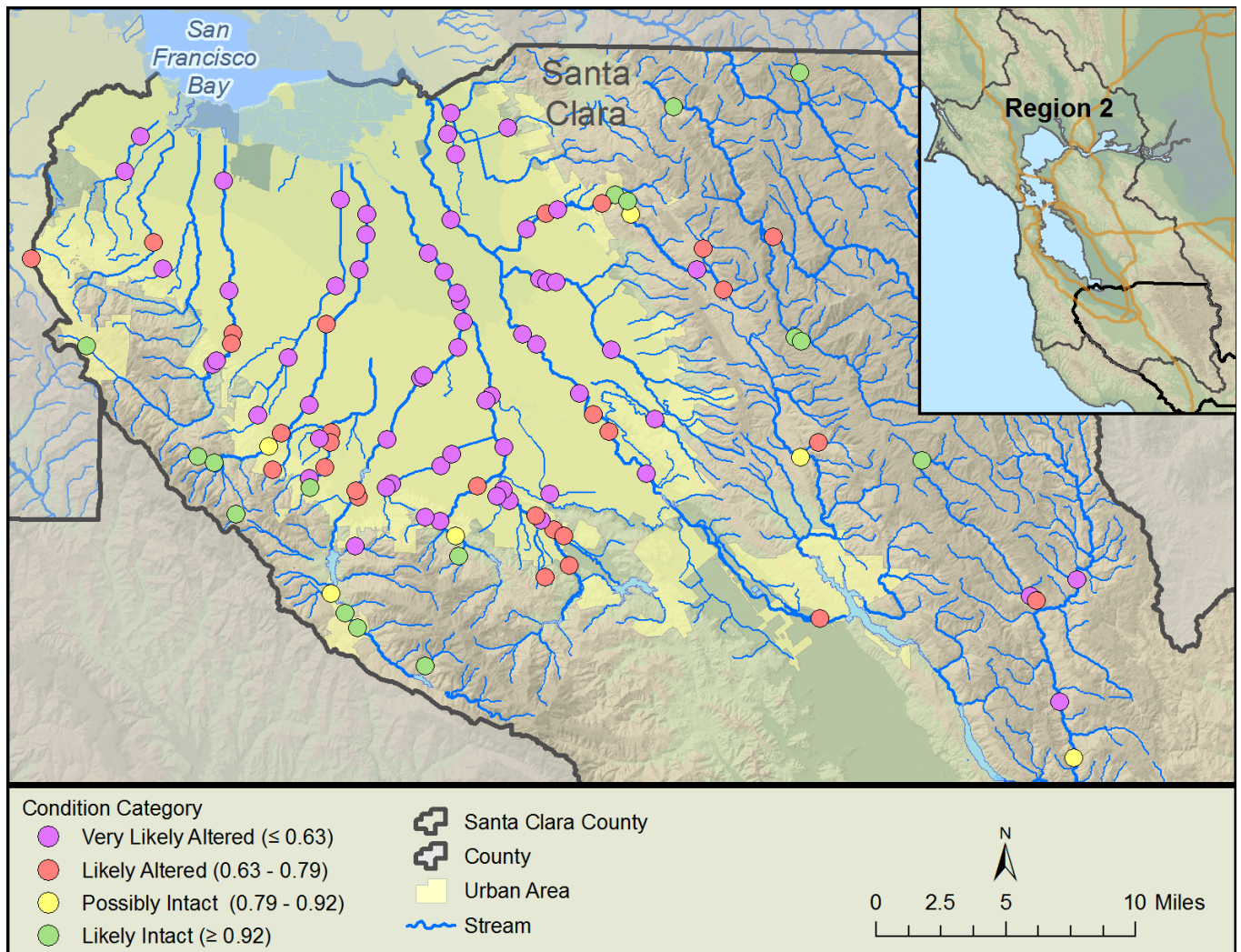


Figure 4-G. Biological condition based on CSCI scores in Santa Clara County.

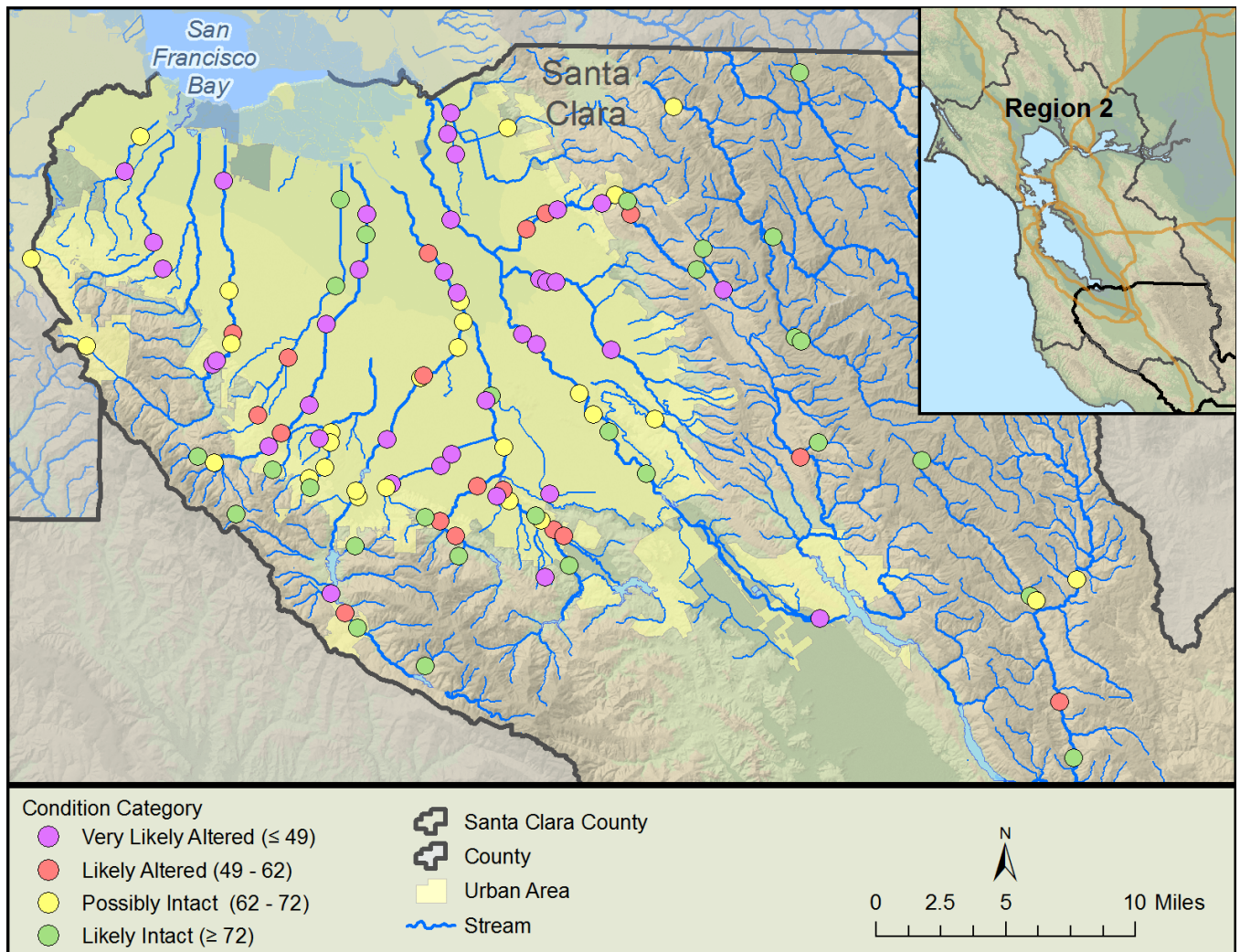


Figure 4-H. Biological condition based on D18 scores in Santa Clara County.

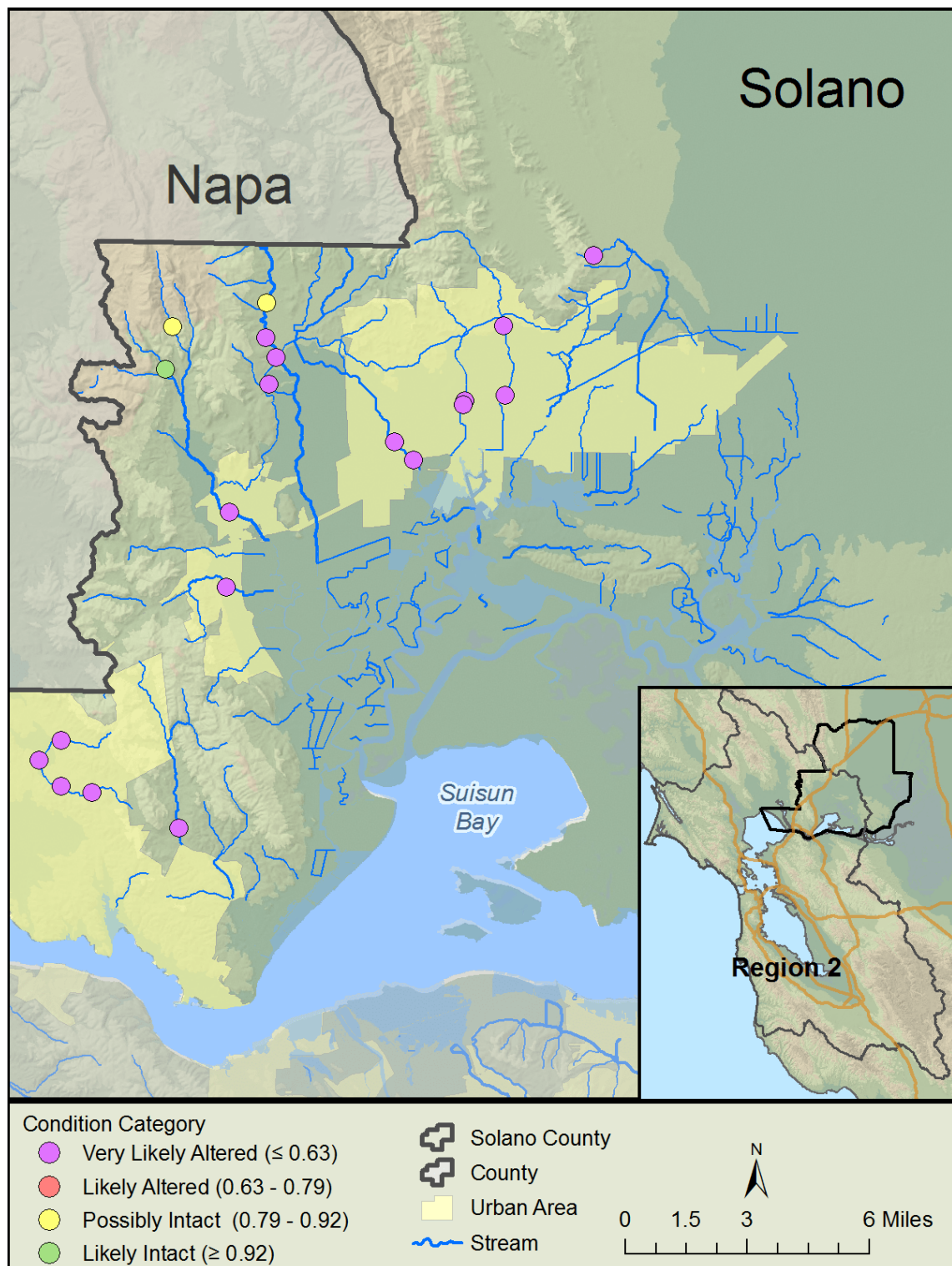


Figure 4-I. Biological condition based on CSCI scores in Solano County.

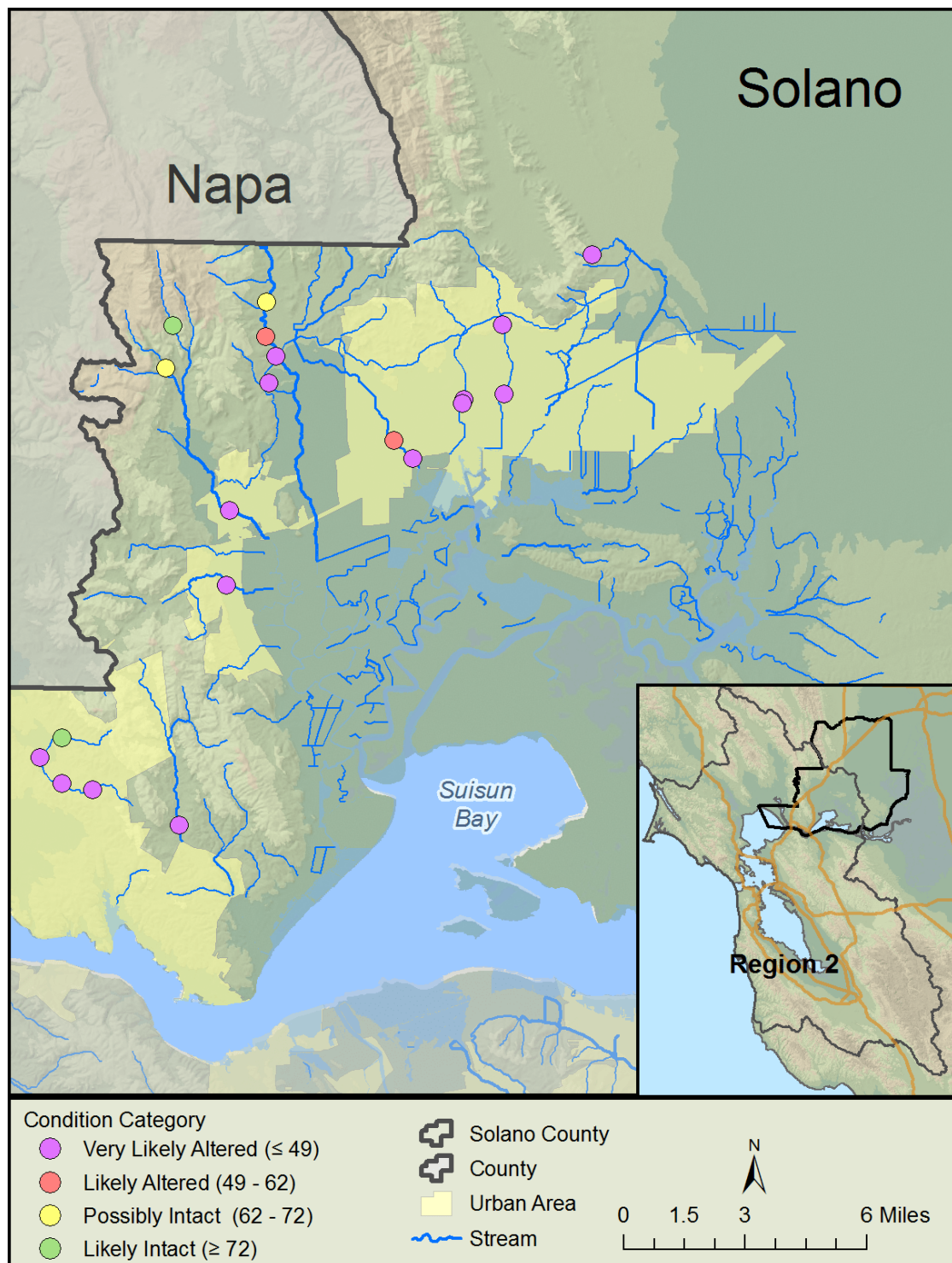


Figure 4-J. Biological condition based on D18 scores in Solano County.