Pesticide Application and Water Quality in the Central Valley: Calculating Sensitivity of CSCI scores to Pesticide Toxic Units and Visualizing Applied Pesticide and Ecosystem Health Data

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ABSTRACT

Pesticides runoff from agricultural fields introduces toxins into freshwater aquatic ecosystems. California's Central Valley is vulnerable to pesticide pollution from extensive agricultural land use in areas where runoff contaminates the Sacramento-San Joaquin watershed harming ecosystems and limiting California's freshwater supply. I studied which pesticides were detected at the greatest concentrations and in the greatest toxic units. Diuron, an herbicide, was detected at the highest concentration and highest TU over all my study sites. To understand the biological implications of chemicals entering the watershed I calculated correlations between the California Stream Condition Index and Toxic Units of pesticides groups appearing in the water. Total TU of all pesticides had a weak negative correlation of -0.13 (p=.28) with CSCI scores. Insecticide TU and CSCI scores had the highest correlation with -0.33 (p=.228). Poor ecosystem health, low CSCI scores, is correlated with higher levels of Toxic Units of pesticides. However, more Central Valley datapoints are required to evaluate statistically significant correlations. Additionally, I produced an interactive map to communicate pesticide application and biological health of aquatic ecosystems in the Central Valley. Data communication will help draw more definitive conclusions and sharing these findings with the public is important to increase engagement in this issue and encourage policy change to reduce pesticide use.

KEWORDS

Toxic Units, Biological Index, EC50, Environmental Pollutants, Interactive Visualization

INTRODUCTION

California water management and conservation is an increasingly important issue in today's changing climate. Climate change is enhancing California's natural drought conditions and making fresh water harder to come by (Kiparsky and Gleick 2005). Protecting clean water across California is important for environmental and human health. Natural events that shift the hydraulic conditions in an area can lead to contaminated water but human development is a much greater cause of water pollution in California (Inyinbor et al. 2018). Agricultural contaminants and urban contaminants make up the top two sources of pollutants in freshwater ecosystems today (Paul et al. 2001). Polluted water harms both humans and the natural ecosystems around a pollutant sources (Vörösmarty et al. 2010). Contaminated water not only harms hydraulic ecosystems but also is harder to clean and filter properly to convert to drinking water, which is problematic in a world where water is already hard to come by (Price and Heberlin 2018). In both urban and rural areas human chemical use of agricultural pesticides and urban pollutants harm our natural hydraulic ecosystems.

Land use changes and applications of chemicals onto land influence water quality in urban and rural areas in the state of California. Pesticides are shown to be a source of water pollutants in agricultural areas (Agrawal et al. 2010, Chiu et al. 2016) and agricultural runoff is the main source of nonpoint water pollution in the United States (Luo et al. 2008). All agricultural pesticides applied in the state of California are required be recorded as part of the Pesticide Use Reporting (PUR) database (PUR 2019). Similarly, in urban areas chemicals enter into the water system from landscaping pesticide use as well as from other sources (Rezaei et al. 2010). Chemicals in both urban and rural areas affect water quality yet, much remains to determine quantitatively how of specific point pollutants are entering hydraulic ecosystems, how these pollutants are shifting with different management techniques and in different areas, and ultimately the ecosystem harms that they are causing.

Current research on chemicals and polluted water mainly emphasize human health and human interactions but these pollutants also carry serious ecological effects on ecosystems. Pesticide contamination can change entire benthic macroinvertebrate communities and may be the only variable to explain this variation (Scheafer et al. 2011, Chiu et al. 2016). For water quality in California 37% of streams in the San Joaquin Valley exceed the threshold of pesticides that aquatic communities can survive in (Luo et al. 2008). Biological indices like the California Stream Condition Index (CSCI) communicate how similar biological communities are to the expected macroinvertebrate community without impairment. CSCI scores are calculated using holistic factors of ecosystem health. Macroinvertebrate samples from the stream, water quality samples, and statewide geography and climate factors are all combined to make up one overall score representing ecosystem health. These inputs create a standard for the whole state that can be compared across climates (Tang 2015). However, it is not yet identified if CSCI scores are correlated with pesticide concentrations throughout California. Analyzing CSCI scores helps us to identify if there is any indication of pesticide pollution affecting ecosystem health. Then I can determine which pesticide groups may be more correlated to CSCI scores and thus biological ecosystems.

To better understand pesticide effects on aquatic ecosystems, I used the PUR database to examine the use of pesticides across the Central Valley, the appearance of specific pesticides in surface water samples in the Central Valley, and the correlation of these pesticide groups with CSCI scores. I examine herbicides and insecticides to identify which one has a larger impact on CSCI scores. The correlation of CSCI scores and herbicide or insecticide concentrations may indicate how sensitive CSCI scores are to pesticide application, if at all, and if they are a good indicator of chemical concentration of harmful toxins in surface waters in California.

I also created an interactive map to communicate pesticide use, land use, and water quality in California. Ultimately this map will help investigate how pesticide applications affect water quality and hydraulic ecosystems in California as well as understanding how visualizing this data helps improve understanding of the environmental implications of human development. This map along with my analysis will clarify the harm that pesticide application is having on the environment by looking into how well the tools that we already have, CSCI scores, show pesticide harms and if this varies with different types of pesticides. The map will provide information on pesticide application throughout the Central Valley and interactive features will assist the user in narrowing down areas of concern by filtering through CSCI scores and pounds of pesticides applied. Through effective visual communication and analysis I hope to emphasis the ecological implications of land use change and ultimately reach a variety of audiences who can use this information to make better-informed policy decisions.

METHODS

Study system

The extensive agricultural land-use of the Central Valley in conjunction with the existing relevant data on pesticide application and ecosystem health made the Central Valley an optimal study site. The Central Valley includes the Sacramento and San Joaquin River watersheds, the two largest rivers in California (Carter and Resh 2005). At a 160,000 square kilometer area it includes 1/3 of the area of the state of California that drains into the Central Valley.

Agricultural land use covers 15% of the Sacramento Valley and 60% of the San Joaquin Valley with very few urban areas that are instead concentrated around San Francisco, Sacramento, Fresno, Stockton, and Modesto (Carter and Resh 2005). The majority of the farming occurs in the Valley leaving the upper portion of the watershed free from agricultural runoff.

The Central Valley has a Mediterranean Climate with cool wet winters and warm hot summers (Bonada and Resh 2013) and rainfall can be highly variable from year to year. Water flows from mountain tributaries down through the Sacramento and San Joaquin Rivers and into the Sacramento-San Joaquin Delta. The watershed extends as high as 4,000 meters in the Sierra Nevada and ends at Sea Level where the Delta intersects with the San Francisco Bay (Carter and Resh 2005). The streams in the Sacramento and San Joaquin watershed are characterized by high variation in stream flow. Snowmelt and rainfall in the spring cause seasonal flooding events while dry hot summers lead to drought conditions. Flow regimes are additionally altered by human alterations providing water for drinking and irrigation (Carter and Resh 2005).

Dataset description

I used publically accessible Pesticide data from the California Pesticide Use Reporting Database (PUR 2017). PUR is the most comprehensive database of pesticide use in California with data starting in 1970 through present day. This data resource reports pesticide use by townships and is separated into different series of records for every year and every county.

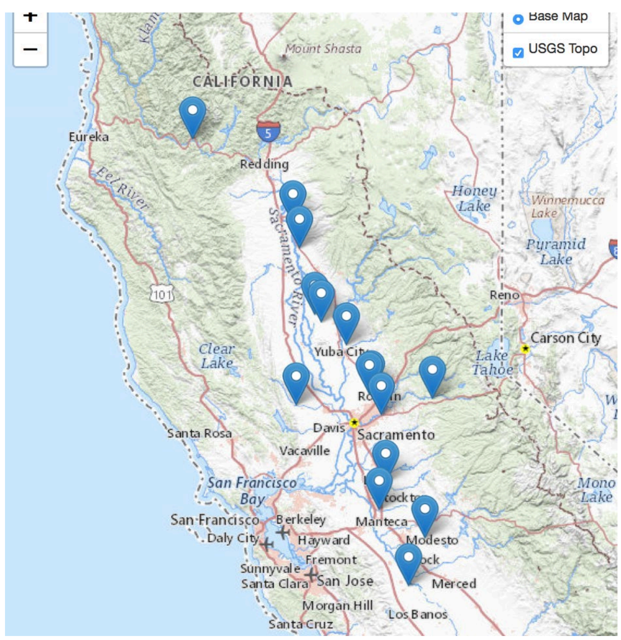
For water quality data I used the California Environmental Data Exchange Network (CEDEN 2019) database that is compiled from the San Francisco Estuary Institute (https://www.sfei.org/projects/california-environmental-data-exchange-network-ceden). The CEDEN surface water database is a compilation of data collected from USGS, SURF, and other surface water quality monitoring programs.

I also used CSCI scores. CSCI scores are a biological assessment score that rates overall ecosystem health. CSCI scores are calculated using statewide data of macro invertebrate samples and environmental geographic variability of stream types to give a score between 0-1.4 that indicates how close the ecosystem is to the expected ecosystem at the site studied (Tang 2015). A score of 1 indicates that the ecosystem health is normal in that area. Any score above one is better than expected ecosystem health for a stream of that type. Scores below one show diminished ecosystem health.

Site selection and pesticide selection

To select sites I filtered through CSCI scores and CEDEN data to find water quality testing sites that had both pesticide concentration data and CSCI scores for the same month and year (Figure 1). Of the sites, 15 sites from 2004 to 2010 matched CSCI and concentration criteria (Table 2).

Figure 1: 15 Study Sites Selected in The Central Valley. Sites taken from CEDEN (https://www.sfei.org/projects/california-environmental-data-exchange-network-ceden) and map made using leaflet (Joe Chang et al. 2019)



Two commonly used types of pesticides in California are Insecticides and Herbicides. There are many chemicals encompassed within these two groups categorized based on the target organism that they are attempting to harm. Insecticides mainly target nerves and muscles, growth and development, and energy production because they are trying to target insect pests that will forage on crops. Herbicides target plant specific pathways acting as growth regulators, seedling and photosynthesis inhibitors, and cell membrane disrupters (Lushchak 2018). Both groups can cause damage to aquatic ecosystems by disrupting the life cycles of plants and insects.

Pesticide selection was based on occurrence of pesticides in nature, detrimental effects of pesticides, available data on pesticides, and selection of both herbicides and insecticides. I collected data from CEDEN of 5 different pesticides. Diuron, Simazine, and Atrazine were the three Sulfonylurea Herbicides studied and Chlorpyrifos and Diazinon were the two Organophosphorous Insecticides studied (Table 1). These were reported as 5 of the most common pesticides detected in water by studies and are all soluble in water (Mullins 2015, Green 2006).

Toxic unit calculation

For each site with CSCI and concentration data I calculated average toxic units present (Table 1). To find the average TU score I first had to calculate the TU for each simulated pesticide using $TU = C_i / EC50_i$. C_i is the concentration of both dissolved and suspended pesticides in the water. $EC50_i$ is determined from the ECOTOX database (https://cfpub.epa.gov/ecotox/) and is the 48-hr median effects concentration that causes the immobilization or mortality of *Daphnia magna*. This calculation methodology was derived from Chiu et al. (2016).

Table 1: **Pesticide $EC50_i$'s from ECOTOX database.** All $EC50_i$ came from the ECOTOX database (https://cfpub.epa.gov/ecotox/)

Pesticide Type	Chemical Name	$EC50_i$ (mg/L)	TU Calculation
Sulfonylurea Herbicide	Atrazine	50.4	$TU = C_i / 50.4$
Sulfonylurea Herbicide	Simazine	3.5	$TU = C_i / 3.5$
Sulfonylurea Herbicide	Diuron	7.2	$TU = C_i / 7.2$
Organophosphorous Insecticide	Chlorpyrifos	3.17	$TU = C_i / 3.17$
Organophosphorous Insecticide	Diazinon	6.1	$TU = C_i / 6.1$

Total concentration and total TU of pesticides types Calculations

I calculated the total concentration and total TU of each type of pesticide found throughout all my study sites by summing up TU and concentration at each site. Using total concentration and total TU, I compared which pesticides were detected at the highest concentration in surface water and then corrected the concentrations by toxicity of pesticides by doing a second comparison with total TU values of all the pesticides. I also calculated average TU across all sites as another measure to compare quantities across pesticides.

Types of pesticides and correlation with CSCI scores

To determine the relationship between average pesticide Toxic Unit (TU) values and CSCI values, I used a correlation test. I calculated the correlation coefficient of total TU values of each pesticide type and CSCI scores, one for all overall TU values and CSCI scores, one for herbicide TU values and CSCI scores, and one for insecticide TU values and CSCI scores. I calculated these first using a Pearson correlation in R and then a Spearman rank correlation to examine what a non-parametric correlation looked like. I calculated Spearman rank correlation in addition to Pearson correlation to see if either model gave statistically significant results. Spearman's correlation calculates relationship based on ranked values of variables not raw data so the data does not need to satisfy the assumption of normality.

Interactive map of pest application and water quality

To create a web map, I used Shiny (Chang et al. 2019) with leaflet (Cheng et al. 2019) to map pesticide application data and water quality data that indicates biological harm. I concatenated the data for township to combine with identical township column for shape files from the CA state website California Department of Regulation (https://www.cdpr.ca.gov/docs/emon/grndwtr/gis_shapefiles.htm). I merged these two data frames and then applied this method for each of the counties in the Sacramento Watershed. I then combined the merged tables for all of these counties to get an all_counties data frame. Using shiny and leaflet I mapped the all_counties frame on a USGS base map and included a US hydrography layer.

Once I had total pesticide application per township mapped I added water quality data and biological measures onto the map. I used color-coded CSCI scores to highlight biologically at risk areas.

The map is designed to be interactive so it is more engaging to the user. A slider bar was designed to be able to filter through different CSCI scores and only visualize the desired ecosystem health. Interactive filtering allows areas of concerning toxic levels and altered ecosystem health, low CSCI scores and high pesticide application, to be visualized. CSCI scores are color coded with the 0-.55 range are displayed red and indicate the worst ecosystem impairment, .55 – 0.99 are yellow for intermediate ecosystem health, and 1 and above are green for expected or above expected ecosystem health The coloration of CSCI scores overlaid with the heat map that indicates pounds of pesticide applied allows for visual comparisons to be made across areas.

RESULTS

Concentration and toxic unit by pesticide category

The greatest concentration of pesticide detected in total water quality samples was for the herbicide Diuron (Table 2). Diuron also had the highest total TU and highest average TU detected in samples followed by Simazine (Table 3). Because Simazine has a lower EC50 than Diuron the difference between Diuron and Simazine TU is smaller than the difference in concentration between the two pesticides.

Table 2: TU of Pesticide Type by Station Code with Average TU and SD TU Detected. Data of Pesticides found as concentrations from CEDEN database (https://www.sfei.org/projects/california-environmental-data-exchange-network-ceden) and then converted to TU using EC 50 (Table 1).

Station Code	Atrazine TU	Diuron TU	Simazine TU	Chlorpyrifos TU	Diazion TU	Total TU
520XXCS31	0	3.88889×10^{-4}	0	2.2082×10^{-6}	1.14754×10^{-5}	0.000402573
PGC030	0	0	0	3.91167×10^{-6}	0	3.91167×10^{-6}
504XXNS07	0	0	1.1143×10^{-4}	0	0	1.11429×10^{-4}
504XXNS04	0	0	0	4.4164×10^{-6}	1.04918×10^{-5}	1.49082×10^{-5}
520XXCS37	0	0	0	0	0	0
515XJSNKL	0	0	0	0	1.21311×10^{-5}	1.21311×10^{-5}
511XCCCPY	0	0	5.45714×10^{-6}	0	0	5.45714×10^{-6}
Nimbus	9.54365×10^{-7}	1.875×10^{-5}	1.61143×10^{-5}	7.88644×10^{-6}	4.59016×10^{-6}	4.82953×10^{-5}
106NF0015	0	0	0	0	1.96721×10^{-6}	1.96721×10^{-6}
PGC010	0	0	0	0	0	0
531SJC504	0	4.16667×10^{-5}	2.3429×10^{-4}	1.04101×10^{-4}	0	3.80053×10^{-4}
531XNSJ34	0	0	0	0	0	0
535XNSJ24	0	0	1.0×10^{-5}	1.76656×10^{-5}	0	2.76656×10^{-5}
541MER554	0	7.22222×10^{-5}	0	9.77918×10^{-5}	0	1.70014×10^{-4}
514XNRTCN	0	0	0	0	0	0
Average TU	6.36243×10^{-8}	3.7252×10^{-5}	2.51524×10^{-5}	1.58654×10^{-5}	2.7104×10^{-6}	7.85603×10^{-5}
SD TU	2.46416×10^{-7}	1.03445×10^{-4}	6.44792×10^{-5}	3.48861×10^{-5}	4.6574×10^{-6}	1.35953×10^{-4}

Table 3: Concentrations and TU by Pesticide Type Detected. Pesticide data found as concentrations from CEDEN database (https://www.sfei.org/projects/california-environmental-data-exchange-network-ceden) and then converted to TU using EC 50 (Table 1). Total concentration and TU are calculated over all sites to look at overall abundance of pesticide in the ecosystem. Mean TU across all sites is included which down weights in comparison to total TU because it includes sites with 0 TU of pesticides present.

Pesticide Type	Total Concentration across all sites (ug/L)	Total TU across all Sites	Mean TU across all sites
Atrazine	0.0481	9.54365×10^{-7}	6.36243×10^{-8}
Diuron	3.755	5.21528×10^{-4}	3.7252×10^{-5}
Simazine	1.3205	3.77286×10^{-4}	2.51524×10^{-5}
Chloropyrifos	0.7474	2.35773×10^{-4}	1.58654×10^{-5}
Diazion	0.248	4.06557×10^{-5}	2.7104×10^{-6}

Pesticide application and biological index results (CSCI)

Pesticide TU values and CSCI index scores were negatively correlated (Table 4). A negative correlation was anticipated because the higher the toxic unit the less likely that an ecosystem is maintaining its natural form. The correlation for TU and CSCI scores was not statistically significant with a correlation coefficient of -0.1263 and a p-value of 0.28 (Table 4, Figure 2).

Table 4: Correlation of CSCI and TU for Different Groupings of Pesticides. Pesticide data found as concentrations from CEDEN database (https://www.sfei.org/projects/california-environmental-data-exchange-network-ceden) and then converted to TU using EC 50 (Table 1), CSCI scores from (Tang, 2015), and Pearson calculated in R.

Group	Pearson Correlation Coefficient	Pearson p-value	Statistically Significant
Total	-0.1263	0.28	No
Herbicides	-0.2125	0.448	No
Insecticides	-0.3319	0.228	No

Figure 2: CSCI Scores and Total TU Correlation. Pesticide data found as concentrations from CEDEN database (https://www.sfei.org/projects/california-environmental-data-exchange-network-ceden) and then converted to TU using EC 50 (Table 1), CSCI scores from (Tang, 2015), and correlation calculated in R.

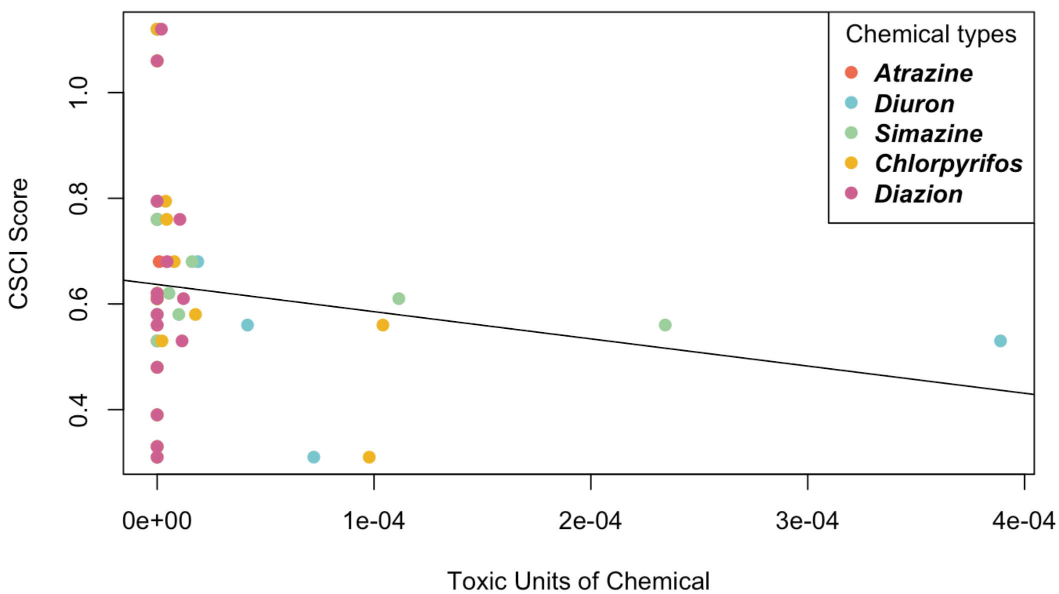


Figure 3: CSCI Scores and Herbicide TU Correlation. Pesticide data found as concentrations from CEDEN database (https://www.sfei.org/projects/california-environmental-data-exchange-network-ceden) and then converted to TU using EC 50 (Table 1), CSCI scores from (Tang, 2015), and correlation calculated in R.

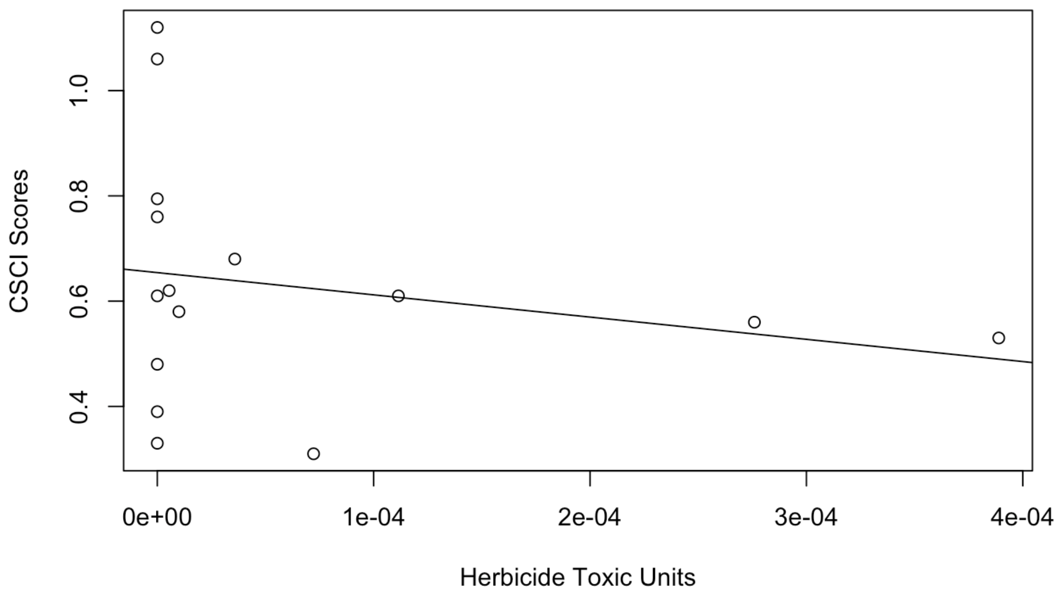
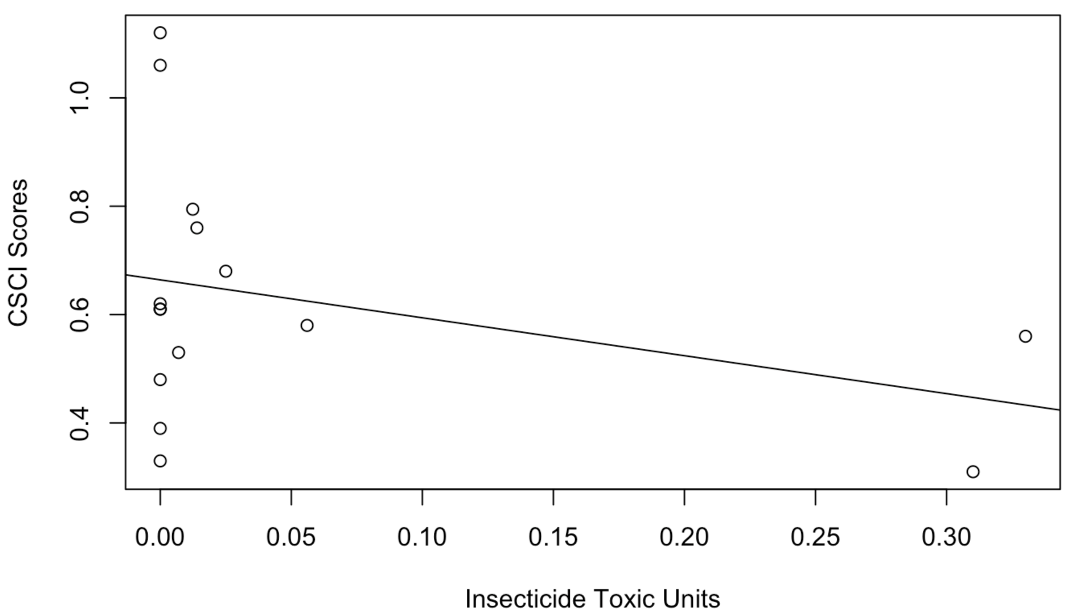


Figure 4: CSCI Scores and Insecticide TU Correlation. Pesticide data found as concentrations from CEDEN database (https://www.sfei.org/projects/california-environmental-data-exchange-network-ceden) and then converted to TU using EC 50 (Table 1), CSCI scores from (Tang, 2015), and correlation calculated in R.



Insecticide TU values and CSCI scores has the strongest negative correlation of 0.3319 (p-value = .228) (Figure 4). Herbicide TU and CSCI scores also had a stronger correlation than the total TU and CSCI scores but it was only -0.2125 (p-value = .448) (Figure 3), which is still less than the insecticide correlation.

There are two herbicides and two insecticide points that have very high TU and are outliers. These are from high TU of Diazon, Simazine, and Chlorpyrifos. These points have low CSCI scores but are still outliers and may be overly influential in the Pearson correlation because the TU are much higher than the other results. I calculated Spearman rank correlation in addition to Pearson correlation to see if this gives statistically significant results (Table 5). The Spearman's had very high p-values for total TU CSCI correlation and insecticide CSCI correlation and all groups were still not statistically significant. Spearman rank correlation did not appear to preform better than Pearson correlation for the total group and the Insecticide group.

Table 5: Spearman Correlation of CSCI and TU for Different Groupings of Pesticides. Pesticide data found as concentrations from CEDEN database (https://www.sfei.org/projects/california-environmental-data-exchange-network-ceden) and then converted to TU using EC 50 (Table 1), CSCI scores from (Tang, 2015), and spearman correlation calculated in R.

Group	Spearman Correlation Coefficient	Spearman p-value	Statistically Significant
Total	-0.1388684	0.6216	No
Herbicides	-0.2936995	0.288	No
Insecticides	-0.1298869	0.6445	No

At sites with high TU and low CSCI scores there are more contaminants entering the water and impaired ecosystems (Figure 2-4). However, some sites have no TU of chemicals and still have very low CSCI scores. Other factors, besides specific chemical TU that were calculated in this study, must account for ecosystem impairment in these cases. The two sites with a CSCI score at or above 1, with ecosystem at normal or above normal health, have 0 TU of pesticide (Figure 2-4).

MAP Visualization

I made an interactive map of water quality and pesticide application. This map has layers that show topography, hydrography, and pesticide application throughout California. Layers can be included or excluded with a click of the mouse to simplify the graphics or add more information. Additionally, an interactive slider allows the user to control what CSCI scores appear on the map. Filtering through CSCI scores shows what areas have better or worse CSCI scores and ecosystem health.

Poor ecosystem health or CSCI scores (0-.55) are mainly in urban areas and in the Central Valley. Good ecosystem health or CSCI scores (>1) are mainly in the Sierra and Costal Ranges.

Figure 5: Overview of web map. This overview of web map shows map with heat map of pesticides in the central valley, legend in bottom right, and interactive features in the top right. The top right interactive features include layers to include or exclude topography, hydrology, and pesticide application data. There is also an interactive slider that controls the CSCI scores that appear on the map. These CSCI scores are grouped by area in the screenshot below so that the map is not overcrowded with scores. In the map below scores are shown as water droplet or grouped circles.

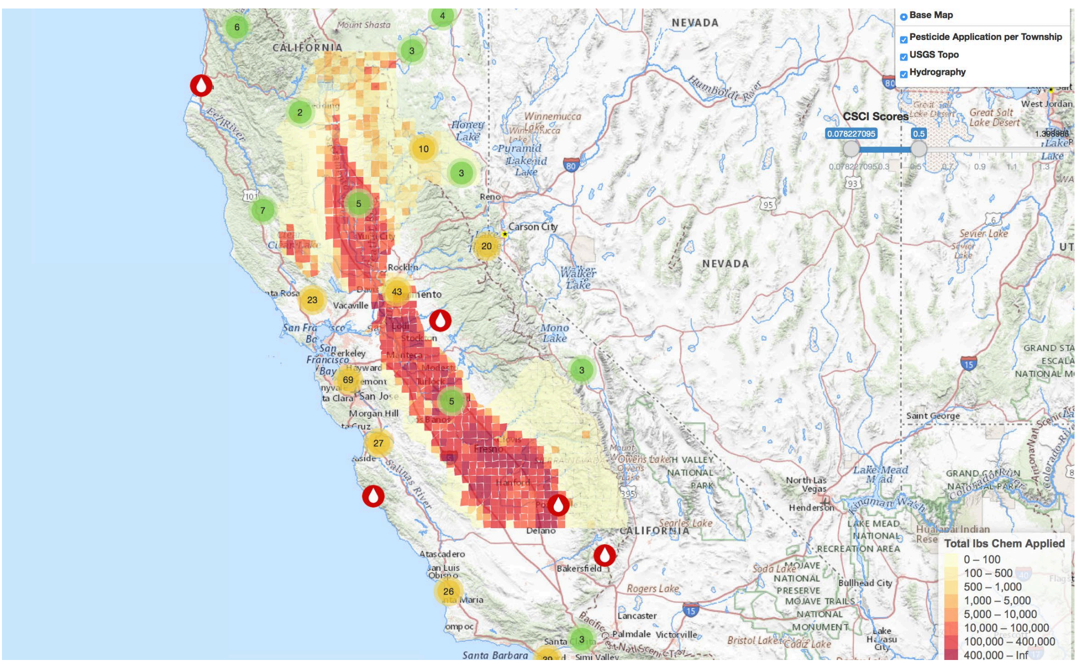


Figure 6: Web map with high CSCI scores. High CSCI scores are any scores above 1. To view only high CSCI scores on the map more the interactive slider so that it highlights scores from 1 to the end of the slider bar.

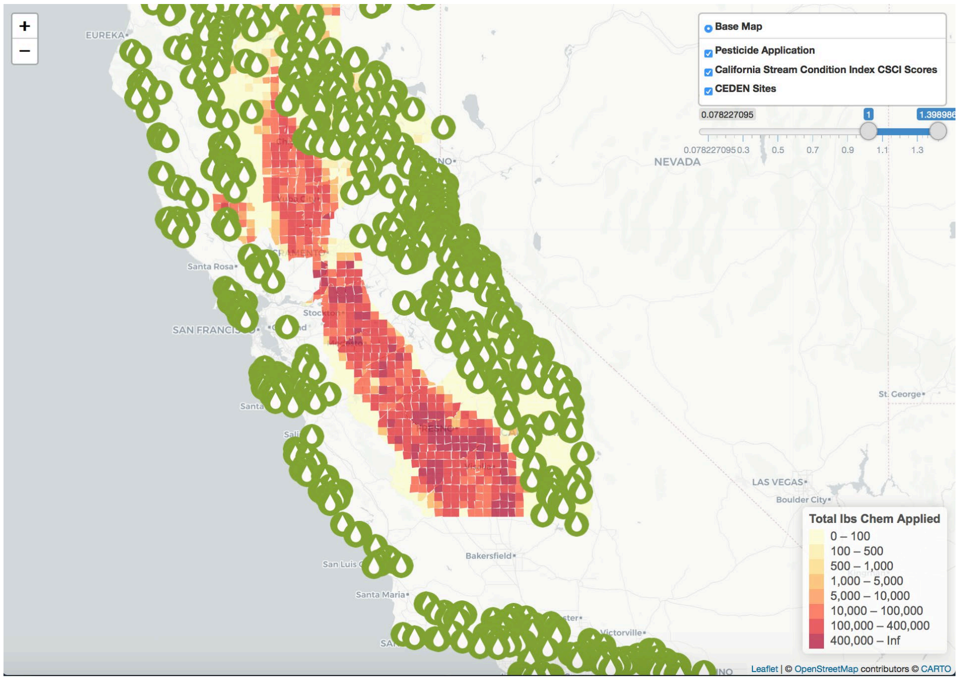
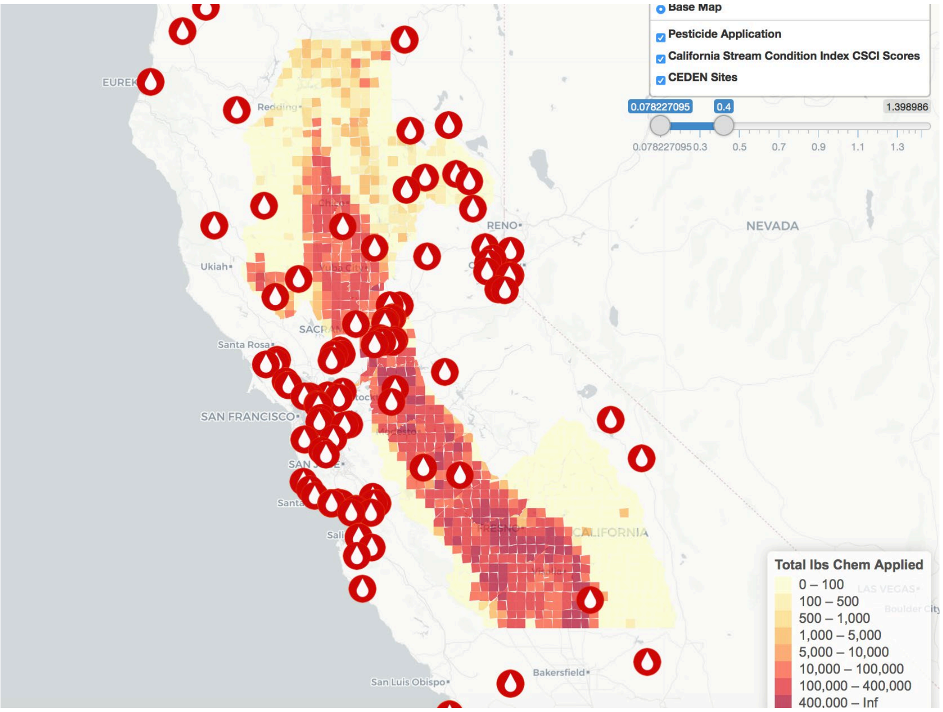


Figure 7: Web map with low CSCI scores. Low CSCI scores are any scores below .55. This map screenshot only shows below .4 so does not include all low values. To look at low scores set the slider on the map from 0 to .55



DISCUSSION

Understanding pesticide impacts on aquatic ecosystems can indicate potential harms to human health and can help to target preventative measures to improve the health of humans and the environment. To gain a better understanding of pesticide use and ecosystem health I first examined which pesticide types are most commonly applied and their concentrations in the surface water. Toxic Units (TU) of pesticides detected in the water had a non-significant negative correlation to biological measures of ecosystems health indicating that more contaminants lead to poor ecosystem health. More herbicide TU were detected in water quality samples but insecticides and TU has a higher negative correlation. Identifying if CSCI scores were reflecting pesticide load in surface water identified where chemicals in water impair freshwater ecosystems, where chemicals are potentially dangerous to humans, and areas where water quality remains high despite TU at a site. Using this information we can target pesticides and make better-informed policy decisions for healthier ecosystems.

Detected pesticide concentrations

Concentration measures of pesticide groups in water downstream of pesticide application in agricultural areas indicate that pesticides are entering the water supply. Diuron was found at the highest concentration and had the highest TU out of the 5 pesticides at the 15 study sites (Table 2). There were higher concentrations of herbicides at our sites and higher Toxic Units of herbicides. On average there are more insecticides applied each year in California (PUR 2017). In California historically, Atrazine has been found in the most streams, with 80% occurrence in major rives with mixed land use, followed by Simazine, with 65% occurrence (Mullins 2015). Diuron is also identified as the most commonly occurring herbicides found in California with 680 kg found at their study site in the Central Valley (Green 2006). These past findings were semi consistent with my findings of high occurrences of Diuron and Simazine, which were both found at 33% of my study sites, but were in contrast with the low occurrences of Atrazine and high occurrences of Chlorpyrifos in my study. I found Chlorpyrifos at 47% of the sites I sampled, a greater occurrence than the 10% found by past studies (Mullins 2015). Atrazine is only present at one of the sites making it under detected in the sites that I sampled. I sampled fewer sites and selectively picked sites with CSCI scores present which may not be a representative sample of the total sites that were used in Mullins.

TU correlation with CSCI scores

A negative correlation between TU in watershed and CSCI scores indicated pesticides may be contributing to harm of ecological communities. Increasing TU correlates negatively to increasing CSCI scores, which is interpreted as an increase in toxic units linked with a decreases in ecosystem health. Overall throughout all the sites and all pesticide types TU and CSCI scores had a correlation of -0.13 (p-value = .28). TU of Chlorpyrifos and Simazine in freshwater ecosystems significantly contribute to the toxic exposure and impairment of stream macro invertebrates but no specific values are given for correlation of these individual pesticides (Rasmussen 2015). Additional evidence found that Diuron and Atrazine cause phototoxicity in non-target plants effecting ecosystem health, therefore impacting CSCI scores (Wilkenson et al. 2015). These results indicate that a high TU of pesticides in freshwater ecosystems should correlate to high toxic exposure and impartment of macro invertebrates or high phototoxicity in plants and therefore a low CSCI score. High pesticide TU correlating with poor ecosystem health was shown in correlations of SPEAR scores, a different biological index, and pesticide TU. TU of pyrethroid insecticides had a correlation of .17 to SPEAR scores (Chiu et al. 2016). The .17 correlation found using SPEAR scores was lower than the -.33 correlation to CSCI scores, although my results were not statistically significant. Sites with low TU and low CSCI scores were not anticipated but occurred in this study. Low TU and low CSCI scores indicate that a factor other than TU of specific chemicals studied are contributing to low ecosystem health. 2 sites had a CSCI score of 1 or more, at or above normal ecosystem health, and both had no TU of pesticides detected at the site. No TU present at sites with above 1 CSCI scores is consistent with our expectation that TU contamination is contributing to ecosystem impairment and low CSCI scores.

Insecticides vs. herbicides

Both insecticides and herbicides have been linked to human health problems such as increased cancer risk and reproductive impairment. Here insecticides correlate more strongly with biological indices values than herbicides. There is a non-significant correlation of -0.2125 between TU of herbicides and CSCI scores. This differs from the non-significant -0.3319 correlation of TU of insecticide and CSCI scores. This difference in correlation of insecticides vs. herbicides may stem from properties of these chemicals. Herbicides are meant to target plants and not insects so they may have a lower impact on macroinvertebrate communities in aquatic ecosystems (Lushchak 2018). However although there is a lower correlation between herbicides and CSCI scores herbicides can be incredibly detrimental to human health (Joshi et al. 2007) so they shouldn't be allowed in high volumes even if they aren't affecting the biological indicators. Both the insecticides and herbicides have detrimental health affects on humans. Chloropyrifos insecticides decrease fertility. Simazine and Atrazine disrupt the human reproductive system and are carcinogens in rats but have not yet been proven carcinogenic in humans (Lubow and Howd 2011). Diuron another herbicide is harmful to fetal development and can increase risk of cancer in certain tissues (Huovinen et al. 2015). Additionally, Atrazine has negative effects on frog reproduction in multiple studies, causing both decrease in testosterone and increase in hermaphroditism, potentially diminishing frog populations (Rosenfeld et al. 2011). Evidence of ecosystem harms of herbicides on frogs and other specific non-macro invertebrate species may not be detected by the CSCI and TU correlation but are still important. Making use of research on specific organisms that are harmed by specific pesticides or using a biological index that takes into account pesticides in calculating ecosystem health, like the SPEAR index (Chui et al. 2016), may give better insights into the ecosystem effects of pesticides.

Map visualization

CSCI scores are lower in townships with high pesticide application because agricultural activity is affecting aquatic ecosystem heath, regardless on whether or not specific pesticide TU are high (Rasmussen 2015). Geographical factors that describe landscapes are key to understanding why some areas may experience higher pesticide contamination than others (Luo et al. 2010). Soil characteristics, topography, and climatic factors all play a role in pesticide transport from fields to water systems (Rasmussen 2015). CSCI scores already use geographical considerations when calculating ecosystem health but by visualizing the sites that have low water quality we can identify what factors are causing the impairment (Tang 2015). In some cases impaired sites may be directly next to or downstream from a field with large quantities of pesticides applied. Visualizing pesticide application and CSCI scores with emphasis on areas in which toxins are present and contributing to biological harm can alert managers of problem areas and encourage solutions to these problems.

Mapping tools have improved to enable researchers and managers to more quickly and effectively convey information (Kyle 2012) In today's world information is consumed in headlines and flashy visuals, not long-winded articles and scientific papers. To communicate, scientists must adapt to these changing trends to convey scientific insights to non-experts (Trilles 2020). Current scientific data communication calls for new use of new interactive visualization tools to communicate data to the public. In urban planning these tools have been used extensively to communicate current data and development scenarios. Testing has shown that public engagement in data increases when interactive tools are used (Trilles 2020). Shifts in the environmental data are moving towards effective data communication but more needs to be done to adapt interactive visuals as a means of inclusive and open data sharing to fuel public interest and create change.

Pesticide impacts on freshwater systems

Pesticide application in the Central Valley likely impacts freshwater ecosystems as measured using CSCI and TU correlation. Four out of fifteen studied sites have no detected pesticides indicating that these sites are protected from pesticide contamination, however not all of these sites had high water quality indicating that other factors such as water velocity or natural disturbances can also impact water quality (Inyinbor et al. 2018). More work is required to understand the dynamics in non-contaminated sites, to understand both why pesticides are not observed at these sites and what other factors could be impacting ecosystem health. Total herbicides quantities found at the study sites were greater than insecticide totals. However, insecticide TU are more closely correlated to CSCI scores than both herbicides and total pesticides indicating that insecticides may have a more negative impact on ecosystem health than herbicides (Lushchak 2018). Insecticides are also more heavily applied in the Central Valley than herbicides (PUR 2017, Lushchak 2018). Visualizing this data on a map can give a better understanding of the geographical and landscape factors influencing the system and provide a platform for further geographical analysis as well as engage the public to advocate for policy change (Trilles 2020).

Limitations and future directions

To fully access and communicate health to a larger community this study needs a larger geographical coverage, more chemical groups, and better understanding of visualizations. This model is only looking at the Central Valley and to be more generalizable should be expanded to look at all of California. It also only looks at 3 insecticides and 2 herbicides out of the hundreds of pesticides that can be used. I could take more pesticides into account to better understand the totality of the effects that pesticide application by humans has to aquatic ecosystems.

Finally, this projects attempts to engage a broader audience by making a more accessible visualization tool however to really work to communicate this science better we can do better to learn what communication techniques are and find better ways to measure how affective these visuals are. Expanding on this research to better understand how to communicate this data affectively to the general public and people in power we can use data to make more informed policy decisions and encourage more sustainable environmental practices in agriculture. Our abilities to show data in effective visualizations and principles to make effective visualizations are growing rapidly and we must use these tools to communicate science in a more engaging and inclusive way. Visualizations have been used for thousands of years and are useful to communicate data trends quickly and efficiently (Krum 2013).

Broader implications

Using this research to make better policy decisions on what pesticides to ban and better regulate will decrease pesticide concentrations in water which may increase aquatic ecosystem health, human health, and water quality (Mahmood 2016). The external costs of pesticide application on the environment are 4-19$ for every pound of pesticide applied (Pretty and Bharucha 2015). Communicating the harms of pesticides to aquatic ecosystems and communities that may be exposed to these contaminants is the first step to getting the conversation growing to encourage policy change around regulation of these toxic chemicals. Important steps to improving aquatic ecosystem health are increased cohesive eco-toxicity studies that inform decreased use of pesticides and banning the most toxic ones (Brock 2006). Pest control is an important factor in food production but does not need to rely fully on conventional chemicals; integrative pest management techniques have proven to be effective (Pretty and Bharucha 2015). In addition if data on the use of pesticides and the affects that they have on the environment is more readily available then the public can be educated and can help to motivate future change of government policies and corporations.

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