Mitigating Nonpoint Source Pollution Across Oahu with Geographic Information Systems

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ABSTRACT

Nonpoint source pollution (NSP) is often difficult to manage because of the large amount of pollution sources spread out over a wide area. Nutrient NSP runoff in particular poses a significant risk in damaging surrounding aquatic ecosystems through eutrophication. In this paper, I modeled and analyzed NSP nutrient runoff for phosphorus and nitrogen within the Ala Wai watershed on the island of Oahu, Hawaii by creating a weighted risk map with Geographic Information Systems (GIS) and by performing a statistical analysis on water quality data. I then suggested potential control and remediation measures. I found that there were no exceedances in the acceptable water parameters for average values of total nitrogen (≥ .15 mg/L) or total phosphorus (≥ 0.02 mg/L) across the study period. However, the average values for chlorophyll a exceeded acceptable levels (≥ 0.3 mg/L) for both years of the study period (2018-2019). Using the water parameter data in conjunction with the weighted risk map, I identified 3 neighborhoods with a high risk of producing high levels of nutrient NSP within the Ala Wai watershed: the Makiki, Manoa, and Palolo neighborhoods. Overall, I found to most effectively reduce nonpoint source runoff in these high risk neighborhoods, a multidimensional approach that combined policy, increased public education, and engineering controls was needed.

KEYWORDS

runoff, eutrophication, GIS, nitrogen, phosphorus, chlorophyll *a*

INTRODUCTION

As the global population and overall standard of living increases, so do human activities and resources required to sustain such growth. These activities often produce pollution as a byproduct that due to factors such as improper storage, leakage over time, accidents, and negligence, contaminates the surrounding environment (Ballo et al. 2009). Remediating the damage to the environment and public health caused by pollution comes with a steep economic cost; it is estimated that pollution generated by the combined sectors of the United States economy accounts for about $184 billion worth of damages every year (Muller et al. 20011). Furthermore, anthropogenic pollution is a significant threat to public health and important natural resources such as potable water in developing and developed countries (Wang et al. 2019).

Pollution is classified into two distinct classes based on origin. Point source pollution (PSP) is defined as pollution that can be traced to a single or clustered source while nonpoint source pollution (NSP) is defined as pollution that stems from diffuse sources over a wide area (Taebi et al. 2009). A classic example of point source pollution is an oil spill from a petroleum tanker sinking as the spill can be traced back to a single source. An example of nonpoint source pollution and the focus of this study is stormwater runoff, where pollutants originate from a wide area and many sources. Although governmental organizations can identify and penalize individual violators of environmental regulation, the dispersed nature of NSP makes it a challenge to regulate as it is difficult to assign liability to a specific party (Wang et al. 2019). Stormwater runoff from agricultural and urban areas are forms of NSP that are particularly detrimental to the environment. Because runoff pollutants such as nitrogen, phosphorus, and heavy metals can pollute groundwater used for drinking and bodies of water used for recreational activities, high levels of stormwater runoff pose a significant risk to the environment (Dillaha et al. 1989, Dwight et al. 2004).

As the diffuse nature of NSP runoff also makes identifying and assessing the source of pollution in areas difficult, remote sensing and GIS can be used in conjunction with pollution runoff estimate models to assess high risk areas (Engel et al. 1993). For example, remote sensing images can be used to locate and identify agricultural zones and their proximity and elevation relative to surface water to predict pollutant concentrations (Wang et al. 2019). Likewise, in urban areas, remote sensing images can be used to classify urban infrastructure material and age, both of which are important factors in determining the concentration and type of urban runoff (Gromaire-

Mertz et al. 1999). GIS software can use this geospatial data from remote sensing to generate a model that can identify areas that are likely to produce a large amount of NSP through a weighted risk analysis. The risk maps generated by this weighted risk analysis can be used to better inform policy decisions and remediation measures that target NSP.

One form of NSP that GIS and remote sensing can be used to assess is nutrient runoff, which is a particular environmental issue on the island of Oahu. Nutrients from runoff leaches into bodies of water and damages the unique aquatic ecosystems of the island (Glenn et al. 1995). The primary objective of this study is to delineate the best approaches to prevent nutrient runoff in Oahu from spreading throughout watersheds and into coastal waters. Currently, there is no modern geospatial model based on land use for Oahu that identifies areas with high amounts of NSP from stormwater runoff. With GIS, the data from the runoff model for the Oahu study site can be integrated with publicly available geospatial data such as land use boundaries and remote sensing data. I collected geospatial and water quality data from my subject areas to add to my risk map model. To do this, I identified areas and land uses that pose the largest risk for nitrogen and phosphorus runoff. I then used these classifications to generate a weighted risk map based on existing literature and data on the runoff risk of the respective areas. Finally, I used this risk map to locate areas within the study area that posed a high likelihood of producing large amounts of NSP. The risk maps and NSP runoff model from this study can play an important role in protecting Hawaii's unique marine ecosystems from issues caused by NSP such as eutrophication and ocean acidification.

METHODS

Study site

The study area chosen for this research project is the Ala Wai (Hawaiian meaning "freshwater way") watershed on the island of Oahu, Hawaii. The hydraulic boundaries for the Oahu watersheds were determined by the Division of Aquatic Resources (DAR) of the Hawaii Department of Land and Natural Resources. The Ala Wai watershed has a total area of 49.1 square kilometers and a maximum elevation of 930 meters. The Ala Wai watershed is primarily made up of urban districts, with a land use breakdown of 59.1% urban, 40% conservational, and 0.9%

agricultural (Hawai'i Division of Aquatic Resources, 2008) (Figure 2). There are approximately 181,288 residents living within the watershed area, according to data provided by the US Census Bureau in 2015.

Geospatial data collection

For the geospatial data, I collected data on variables that I found through existing literature that had a significant impact on nutrient NSP runoff: precipitation, land use/land cover, stream proximity, slope steepness, and runoff curve data (Hobbie et al., 2017; Evans et al., 2002). I collected the necessary geospatial data from the State of Hawaii Office of Planning GIS program (Data Source 2), and obtained the curve numbers for each parcel from the USDA tables land use curve number table (USDA, 1986). This geospatial data was used as the basis for generating my risk assessment maps and creating the final weighted risk analysis and resulting map.

Water quality data collection

For water quality data, I focused on the two types of nutrient runoff that primarily causes eutrophication phosphorus and nitrogen. As my study is focused on how land use affects runoff pollutant concentrations, the geospatial and water quality data needed to be relatively recent: I collected data within 2 years of the start of my study. I collected total nitrogen, total phosphorus, oxygen concentration and chlorophyll a concentrations for coastal water quality data in my study area across a two year time period (2018-2019). The State of Hawaii's Clean Water Branch provided the available data and the data is available for download on Hawaii's Department of Health website.

Site chemistry

To understand the risk nutrient runoff posed for eutrophying coastal waters, I looked at the primary nutrients responsible for eutrophication: total phosphorus and total nitrogen concentrations (Ballo et al., 2009; Yang et al., 2018) . I then analyzed the relationship between the nutrients and chlorophyll a concentrations. To do this, I gathered publicly available coastal water chemistry data from across 15 sampling points across the study site from 2018-2019, provided by Hawaii's Clean Water Branch. I refined the raw data by organizing the available data, specifically for the total nitrogen, total phosphorus, and chlorophyll a values. I then performed a descriptive statistical analysis to gauge if there were any exeedences in acceptable coastal water quality parameters for the three variables (Hobbie et al., 2017). These water quality parameter exceedances were set by the State of Hawaii's Clean Water Branch. Due to the non-parametric nature of the data, I then used Spearman's rank-order correlation between the total nitrogen and chlorophyll a and between total phosphorus and chlorophyll a (Sánchez-Carrillo et al., 2006). I used the rho and p values generated from the analysis to measure if the monotonic relationships were statistically significant, and the gauge the strength between the relationships.

Runoff pollution risk variables

The geospatial analysis and mapping for this project was done using ArcMap 10.7.1 (Esri 2020). I then input the risk variables: precipitation, slope, stream proximity, and land use/runoff data. For the precipitation risk map, I loaded the precipitation contour shapefile into ArcMap. Then, using the "Feature to Raster" tool (Esri 2020), I converted the precipitation contour into a raster. I added risk weight values to the precipitation raster by using the "Reclassify" tool (Esri 2020) and generated the precipitation risk map using the original precipitation values. For the slope data, I loaded a digital elevation model (DEM) of Oahu and created a slope raster using the "Slope" tool (Esri 2020) (Ghuman et al., 2017). I then used the "Reclassify" tool to assign risk weight values to areas based on steepness: I assigned slopes less than 30 degrees a weight of 0, slopes between 30 and 50 degrees were a weight of 1, and slopes greater than 50 degrees a weight of 2. For stream proximity, I used the "Euclidean Distance" tool (Esri 2020) to generate a 300 meter buffer around the stream polygon. I then assigned risk weights using the Reclassify tool based on equal interval (50 meter) proximity to streams within the 300 meter buffer. For the land use risk map, I subdivided the watershed into parcels based on land use using the Clip Analysis tool in ArcGIS (Esri, 2020) and assigned each parcel a risk weight based on the Soil Concentration Survey's (SCS) distributed surface runoff model for each parcel (Weng, 2001; Zheng et al., 2021).

Weighted risk analysis

Using the rasters generated from these risk maps, I created a compound weighted risk map to model and predict which areas would produce the greatest amount of nutrient (nitrogen and phosphorus) runoff that would reach the surrounding coastal waters (Gromaire-Mertz et al., 1999; Lee and Bang, 2000; Taebi and Droste, 2004). This was done by using the Map Algebra "Raster Calculator" function (Esri, 2020) to combine the individual risk rasters into a single weighted risk map (Evans et al., 2002). I then used the results of the weighted risk analysis to identify neighborhoods within the watershed that pose a high likelihood of contributing a large amount of nutrient runoff to the surrounding watershed and coast (De Carlo et al., 2007). The resulting weighted risk analysis was then used to propose and discuss potential NSP runoff mitigation strategies suitable for the identified areas.

RESULTS

Site Chemistry

I found that throughout the two year period, there were no exceedances in the average levels of total nitrogen or total phosphorus (Table 1,2). However, I found that the average levels of total nitrogen, total phosphorus, and chlorophyll a in the coast of the Ala Wai watershed were generally higher in the 2018 period than the 2019 period and the average total nitrogen level in 2018 was not far from meeting the exceedance criteria (Table 1,2). Furthermore, the average chlorophyll a levels exceeded the set exceedance criteria for both years ($\geq$ 0.3 mg/L) (Table 1,2,3). Using Spearman's rank correlation, I also found that there was a statistically significant weak positive correlation between total nitrogen levels and chlorophyll a levels (rho = 0.26411, p = 0.00032) (Table 4). I also found that there was a significant very weak positive correlation between total phosphorus levels and chlorophyll a levels (rho = 0.16102, p =0.03034) (Table 5).

Table 1. Water quality sample results, 2018. I took a basic statistical analysis of the total nitrogen, total phosphorus, and total chlorophyll a levels along the coast of the Ala Wai watershed from 2018.

2018 Samples	Total N	Total P	Chlorophyll a
	mg/L		
Mean	0.1459	0.0106	0.5632
Minimum	0.037	0.005	0.12
Maximum	0.487	0.038	2.61
Standard Deviation	0.0758	0.0075	0.4780

Table 2. Water quality sample results, 2019. I took a basic statistical analysis of the total nitrogen, total phosphorus, and total chlorophyll a levels along the coast of the Ala Wai watershed from 2019.

2019 Samples	Total N	Total P	Chlorophyll a
	mg/L		
Mean	0.1191	0.0062	0.34222
Minimum	0.025	0.005	0.05
Maximum	0.229	0.034	1.69
Standard Deviation	0.0406	0.0032	0.2329

Table 3. Water Quality Parameters, Clean Water Branch. Acceptable water quality parameters for coastal waters provided by the Clean Water Branch of Hawaii.

Water Quality Criteria	Average Total N	Average Total P	Average Chlorophyll a
	mg/L		
Exceedance Level	0.15	0.02	0.3

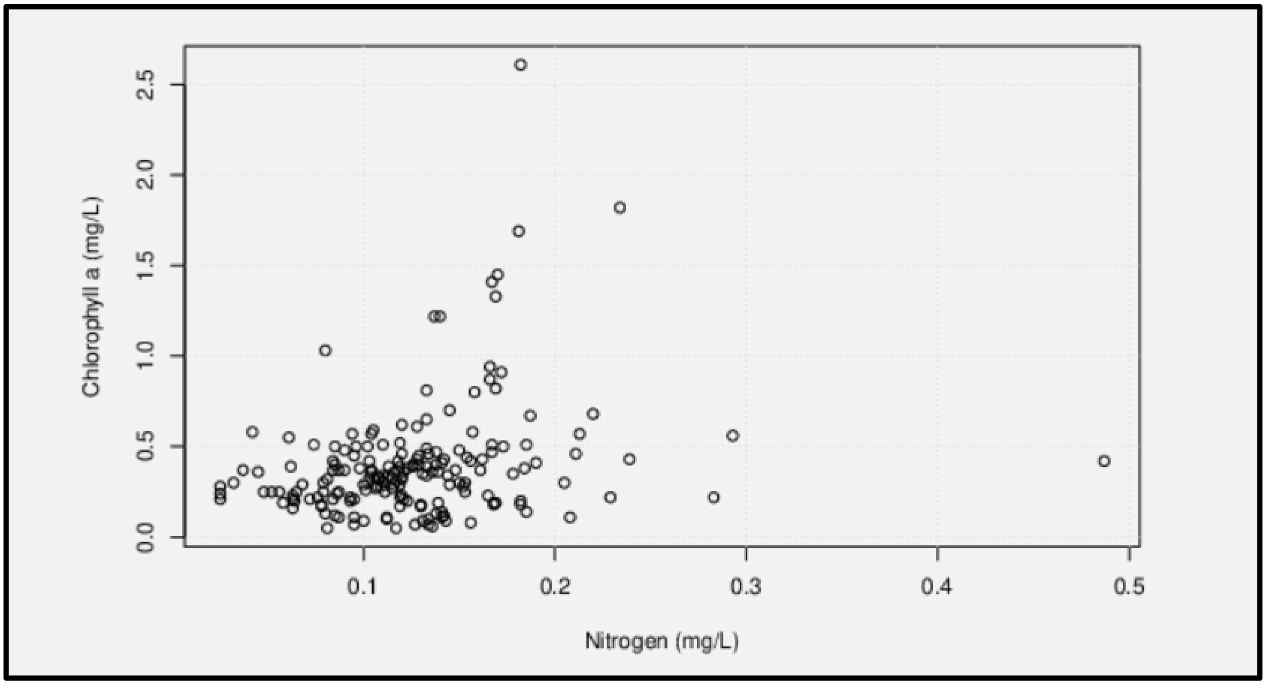

Figure 1. Nitrogen and Chlorophyll a scatter plot (Spearman's rank correlation). I used Spearman's rank order correlation to gauge the correlation between and significance of total nitrogen levels and total chlorophyll a levels.

Table 4: Nitrogen and Chlorophyll a Spearman's rank correlation. Correlation value and significance of total nitrogen compared with chlorophyll a in coastal waters.

Spearman's Rank Correlation	Total N vs. Chlorophyll a
ρ (rho)	0.26411
p value	0.00032

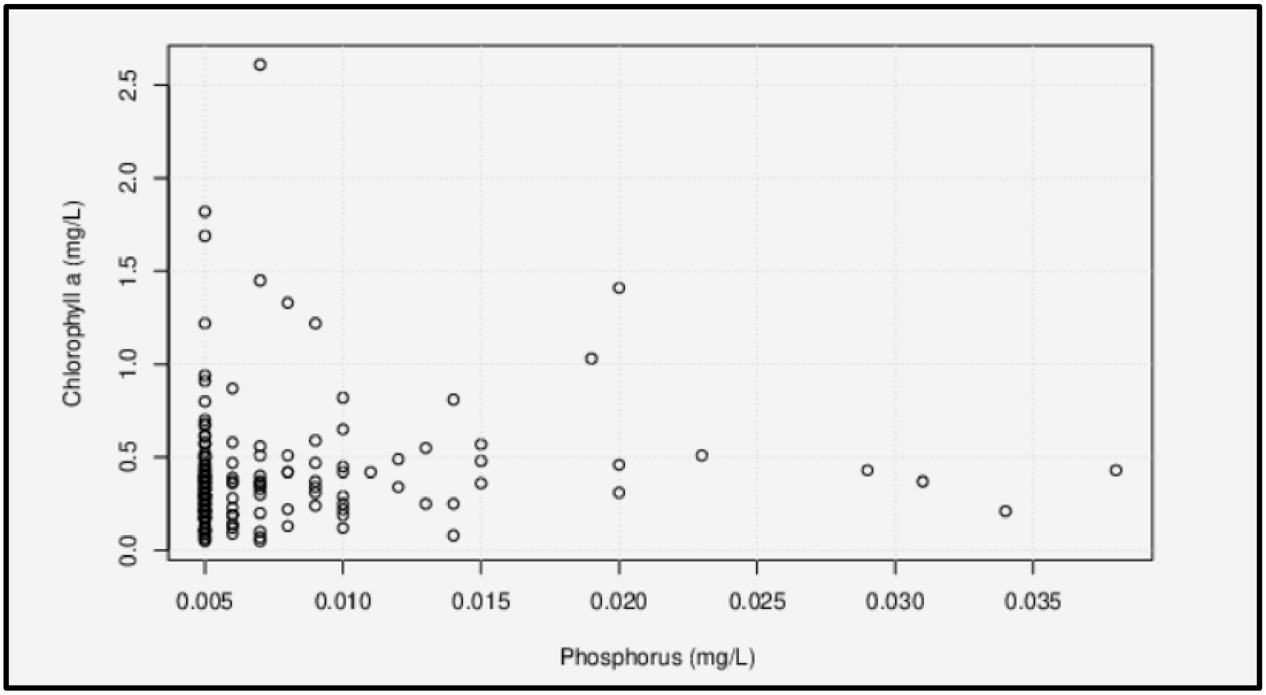

Figure 2: Phosphorus and Chlorophyll a scatter plot (Spearman's rank correlation). I used Spearman's rank order correlation to gauge the correlation between and significance of total phosphorus levels and total chlorophyll a levels.

Table 5: Phosphorus and Chlorophyll a Spearman's rank correlation. Correlation value and significance of total phosphorus compared with chlorophyll a in coastal waters.

Spearman's Rank Correlation	Total P vs. Chlorophyll a
ρ (rho)	0.16102
p value	0.03034

Risk maps and weighted risk analysis

For the land use risk map, I assigned risk weights based on USGS provided curve numbers and land cover (Figure 3) (Appendix 1). I found that highways were highly significant in allowing NSP runoff to diffuse through the watershed and into the oceans and therefore assigned a proportionally high risk weight (w = 8) based on the curve numbers. Likewise, I assigned a relatively high risk weight for urban developed and residential areas based on these curve numbers (w = 5, 6). Conservational and undeveloped land posed little to no significant risk of nutrient NSP according to the curve numbers so I assigned a low weight (w = 0). For the precipitation risk map, I assigned risk weights based on the amount of precipitation within each parcel. I found that the amount of precipitation increased toward the mountains and steadily decreased toward the coast (Figure 4). I found through the slope risk map that while high slope areas pose a greater risk for increasing NSP runoff, due to the difficulty of developing or farming on steep areas, the high slope areas also tended to be conservation areas (Figure 5). Finally, I assigned risk weights based on proximity to streams within a 300 meter buffer (within 50 meters, w = 5; 50 - 100 meters, w = 4; 100 - 150 meters, w = 3; 150-200 meters, w = 2; 200-250 meters, w = 1; 250 - 300 meters, w = 0) (Figure 6). Based on the risk factors, the completed weighted risk analysis, my model identified areas within the watershed that were highly likely to produce nutrient NSP from runoff (Figure 7). I noticed three neighborhoods within the watershed had particularly high risk weights (≥17), these were the Makiki, Manoa, and Palolo neighborhoods (Figure 8).

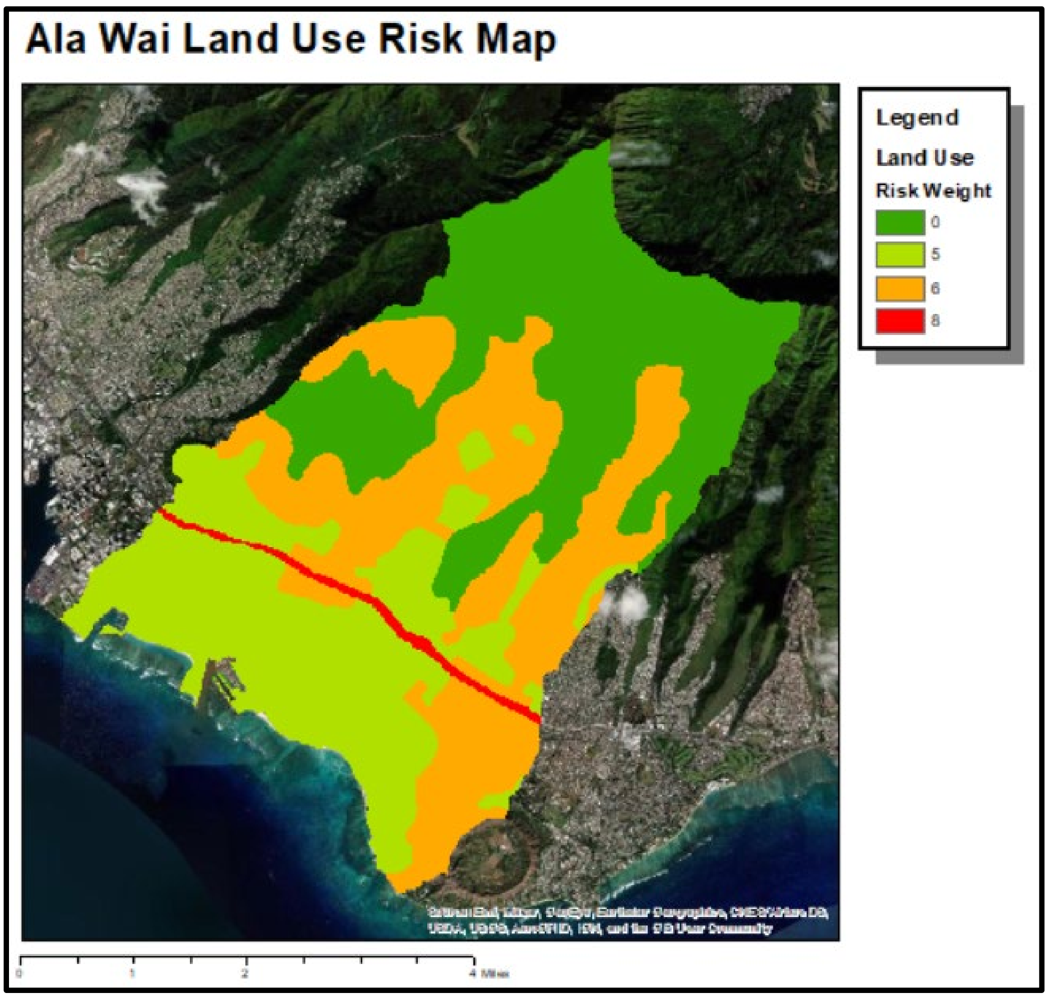

Figure 3. Land use risk map. I determined the risk weights for each parcel based on land use and runoff curve numbers.

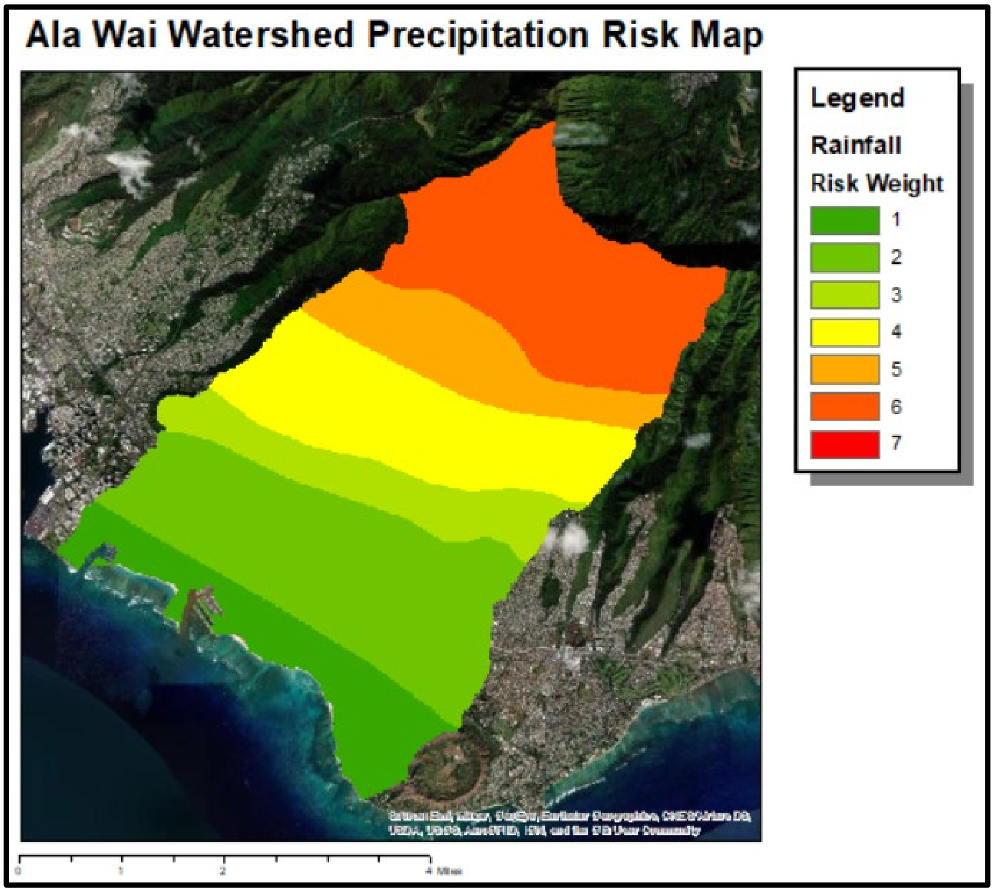

Figure 4. Precipitation Risk Map. I determined the risk weights based on precipitation curves and data provided by the State of Hawaii's Office of Planning.

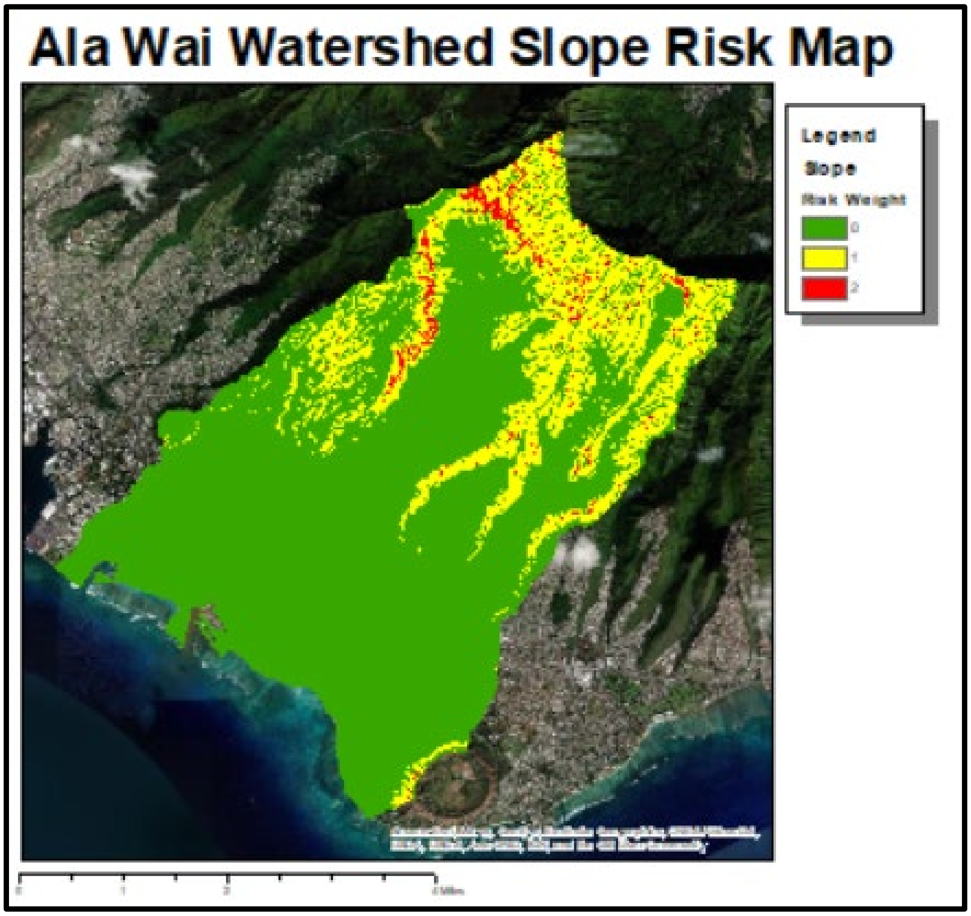

Figure 5. Slope Risk Map. I created a 10m resolution DEM slope model and added risk values corresponding to slope. 0-30 degree slopes were classified with a risk weight of 0, 30-50 were classified with a risk weight of 1, and slopes over 50 degrees were classified with a risk weight of 2.

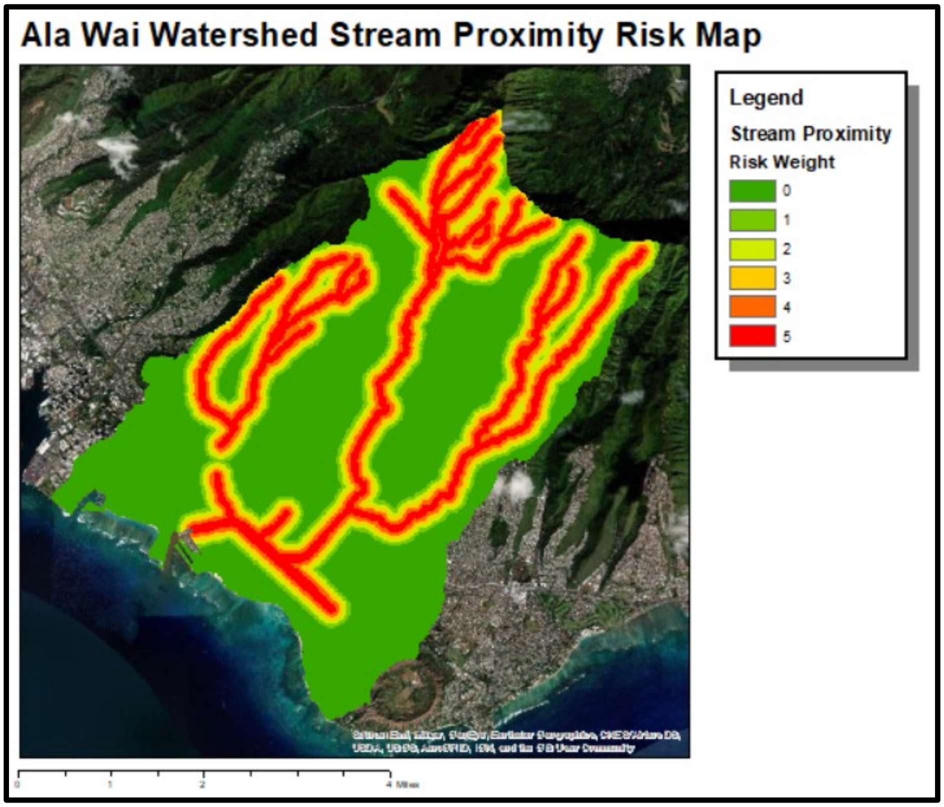

Figure 6. Stream Proximity Risk Map. I generated a 300 meter buffer around existing streams within the Ala Wai watershed. I added risk weights based on stream proximity within this buffer: within 50 meters, w = 5; 50 - 100 meters, w = 4; 100 - 150 meters, w = 3; 150-200 meters, w = 2; 200-250 meters, w = 1; 250 - 300 meters, w = 0.

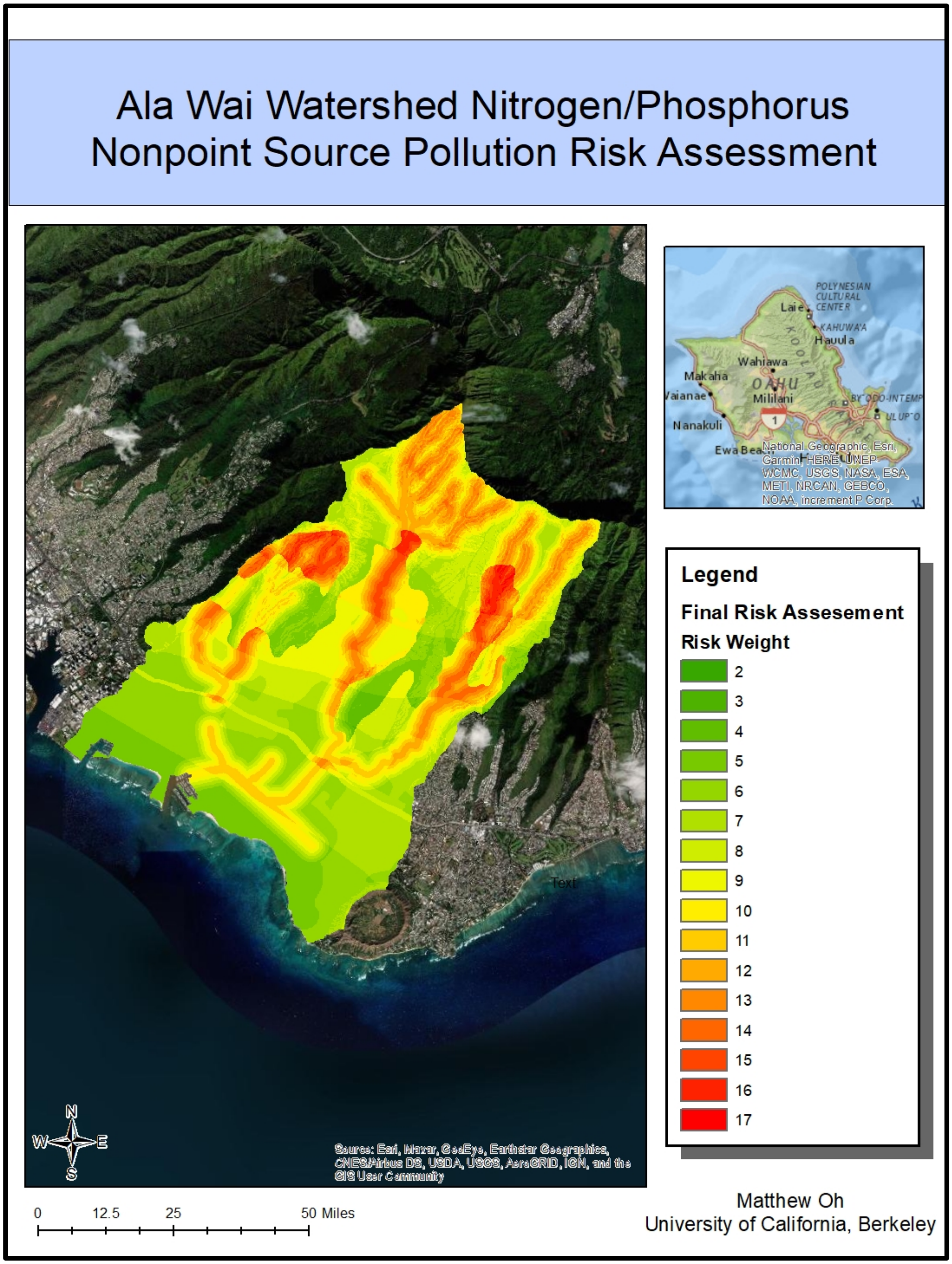

Figure 7. Final weighted risk analysis. I combined all risk variables into one weight classified raster. I identified the Manoa, Palolo, and Makiki neighborhoods as the highest risk for nonpoint source nutrient runoff.

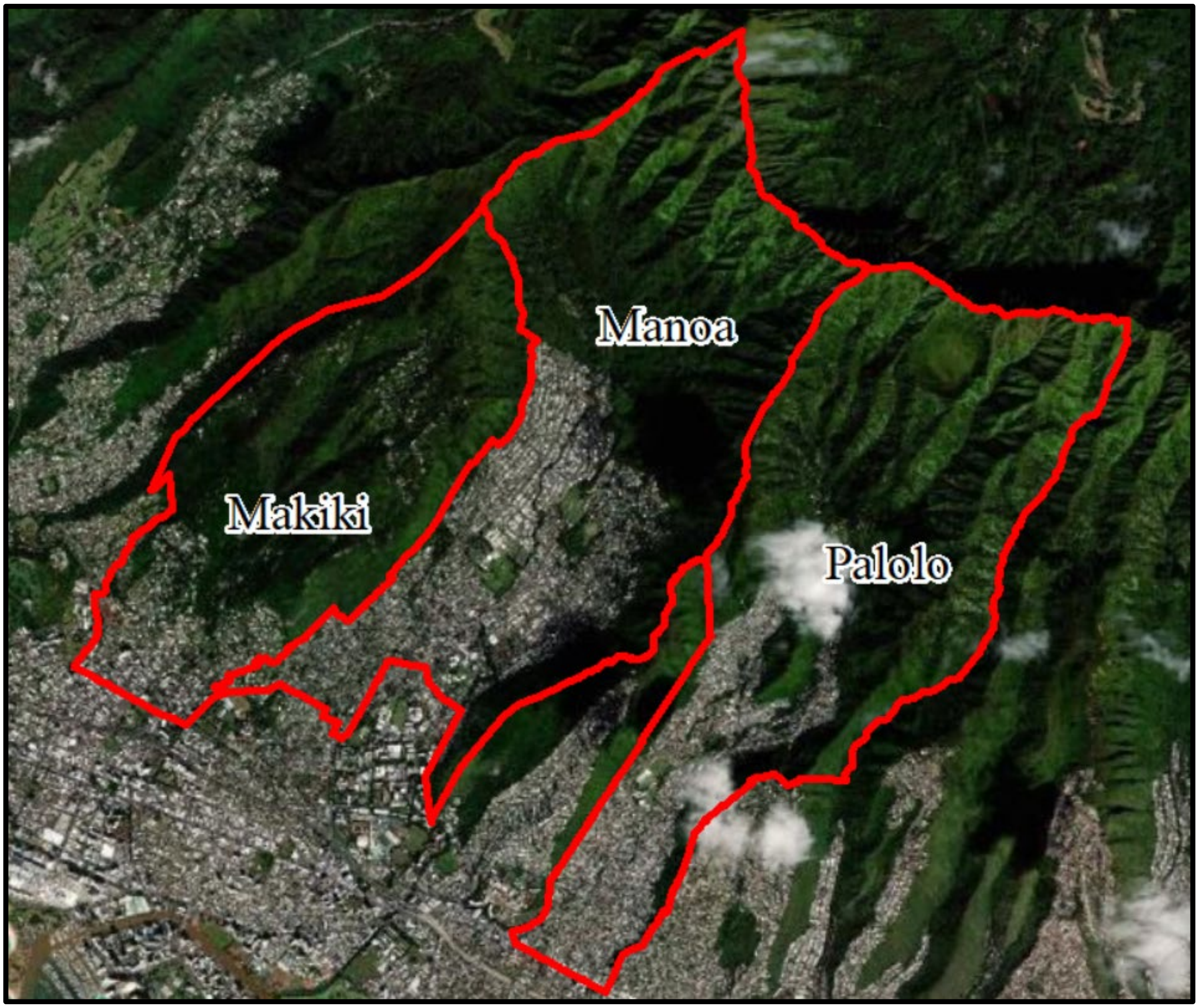

Figure 8. Manoa, Makiki, and Palolo neighborhood boundaries.

DISCUSSION

These results indicate that managing NSP runoff in Oahu is a multifaceted, but critical challenge to overcome to keep coastal ecosystems healthy. The results of my water parameter data analysis of the Ala Wai revealed that NSP runoff in Oahu is an urgent matter of importance for maintaining the health and biodiversity of the surrounding coastal ecosystems. My risk analysis identified high priority neighborhoods within the Ala Wai watershed that would need a thorough and comprehensive NSP runoff management plan. I determined that the best NSP runoff mitigation plan required a varied approach of managing stormwater, building infrastructure, and educating stakeholders rather than any individual approach.

Water Quality Parameters

Total nitrogen and total phosphorus levels were shown to be weak (N_{rho} = 0.26411) and very weak (P_{rho} = 0.16102) predictors of chlorophyll a levels (Tables 4, 5). However, given the p values (p_n = 0.00032, p_p = 0.03034) along with the statistically large sample size for Spearman's Rank Correlation (n > 20), this positive monotonic relationship between the nutrient loads and chlorophyll a levels cannot be attributed to sheer chance. This suggests that total nutrient concentrations are linked to the amount of chlorophyll a in water, which indicates the level of eutrophication. Furthermore, while the data shows that average nutrient loads found in coastal waters along the Ala Wai watershed do not currently exceed the State of Hawaii's Clean Water Branch's acceptable coastal water quality parameters, consistent average chlorophyll a exceedances indicate a present threat for the surrounding coastal ecosystems (Tables 2, 3) (De Carlo et al., 2007).

Considering anthropogenic activities and urban development have been shown to be directly related to increased nutrient release into coastal waters, it is critical to assess the effect nutrient NSP has on the coastal ecosystems in islands like Oahu that are seeing increasing development (Weng, 2001; Lewis, 2002; Zhou et al., 2020). Coastal ecosystem diversity is threatened by increased nutrient loads from stormwater, which have been shown to fuel the growth and spread of non native algae while decreasing the abundance and diversity of native algae in Hawaiian coastal waters. This in turn threatens native endemic aquatic species which depend on the native algae. (Lapointe and Bedford, 2010).

Furthermore, eutrophication has been shown to compound the effects of other threats to coastal ecosystems.Ocean acidification and increased coral reef vulnerability to acidic conditions have shown to be linked to nutrient pollution and eutrophication (Laurent et al., 2018; Silbiger et al., 2018). Coupled with rising greenhouse gas emissions even further acidifying the oceans, these related issues underscores the need for the increased regulation of and careful monitoring of NSP nutrient pollution now more than ever.

Nutrient Runoff Controls

The three high risk neighborhoods (Makiki, Manoa, and Palolo) within the Ala Wai watershed identified by the weighted risk analysis are all known to be elevated residential neighborhoods with a greater than average amount of rainfall and a multitude of streams, variables that I identified that have a significant impact on the generation of nutrient nonpoint source pollution (Figures 7, 8). My risk weightings created a decently accurate map of critical nonpoint source pollution risk areas, but had trouble accurately mapping risk weights of minimally disturbed elevated watersheds, such as those near mountain streams. I believe this to be a result of streams being overvalued in areas minimally disturbed by anthropogenic activities. To better account for this I would need to create separate risk weights for streams based on the type of land use surrounding them. Furthermore, my risk weight model had some trouble with underweighting some mid risk urban areas such as those near the Ala Wai canal as lower risk. This is likely due to the underweighting of the precipitation risk variables in these areas.

Reducing NSP runoff from these neighborhoods therefore, is critical and my analyses and suggested nutrient runoff management practices are designed specifically with these neighborhoods in mind. Because these neighborhoods are predominantly suburban, the majority of nutrient NSP runoff stems from anthropogenic sources (Gromaire-Mertz et al., 1999; Lee and Bang., 2000). The primary sources for nutrient NSP identified for residential areas include chemical fertilizers used in lawns and gardens, leaf litter and other decomposing vegetation, and human waste leaking from faulty sewage and septic systems (Xia et al., 2020; Yang and Lusk, 2018; Kris et al., 2017). Because of the highly different natures of these sources, an optimal NSP runoff management plan for these neighborhoods will need to incorporate policy/regulation and public awareness along with engineering controls (Xia et al., 2020).

Across the Makiki, Manoa, and Palolo watersheds, increased regulation and maintenance of sewage and septic systems is needed to reduce nutrient NSP from these sources. Street sweeping programs that reduce the amount of dead vegetation and leaf litter should also be implemented to reduce nutrient runoff from those pathways (Yang and Lusk, 2018). To implement these programs and regulations, state policies specifically addressing NSP runoff should be created or updated. On the other hand, managing nutrient NSP from individual lawns and gardens would likely prove too challenging to regulate or enforce, public education in such issues has been proven to be more effective (Yang and Lusk, 2018). Furthermore, while engineering controls such as vegatative strip filters and porous pavement have been proven to be effective to reduce nutrient NSP from entering streams and the ocean, because of the wide area the watershed encompasses and to keep costs relatively low they should be used sparingly across areas that pose the greatest amount of risk such as near streams in a residential neighborhood (Dillaha et al., 1988 Prosser et al., 2020; Zhou et al., 2020)).

Limitations and future directions

Although my weighted risk analysis models areas that pose a high risk for NSP nutrient runoff within the Ala Wai watershed, my model is restricted by the limitations of a land based weighted risk analysis. One such limitation is representational accuracy: how accurate my maps and models are at representing real world problems through the use of objective data and my own subjective biases as a researcher (Malczewski, 2004). Ideally, any model would present objective information and data in a way that is both accurate and free of subjectivity. However, weighted risk analysis maps done through GIS are often intrinsically tied to the researcher's subjectivity: from choosing which variables and data to include to deciding how to weigh risk variables it is difficult, if not impossible, to completely remove subjective bias from GIS based weighted risk analysis. Another limitation in my risk model is the lack of other watersheds with different land usage across the island. While the Ala Wai watershed is predominantly developed and residential areas, I would have liked to have seen how my weighted risk analysis modeled watersheds with different/minimally disturbed land cover. This was not possible in this study because of the lack of available coastal water quality data from other watersheds. Furthermore, as the only consistent and publicly available water chemistry data was for coastal water within the Ala Wai watershed, my weighted risk analysis and water quality analysis was limited by a lack of water quality data from along streams or from runoff during stormwater events within the watershed. Therefore, to further this study, a more in depth analysis on the nutrient runoff process in the Ala Wai watershed is necessary which could be done by taking regular water quality samples along streams within the watershed and analyzing the data would give a more accurate picture of how and where nutrient NSP travels throughout watersheds in Oahu. Moreover, based on the risk maps generated by the current weighting systems further optimization in risk weighting each variable is necessary,

Broader implications

Using GIS to create weighted risk maps can be extremely powerful tools in modeling and analyzing complex pollution systems. Because the risk weight model is designed to map areas that pose a significant risk of producing a large amount of nutrient NSP, it is well suited to inform general policy decisions and management plans over a wide area rather than for estimating pollutant loads. Overall, my research on NSP runoff in the Ala Wai watershed shows that there is currently a significant opportunity for more GIS based analysis and models when discussing and creating environmental policies not only in Oahu, but around the world.

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