Wildfire vulnerability assessment for Marin County *Bay Area, California*

Matthew Price

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Introduction

The landscape of the Marin County of the Bay Area in Northern California is an environment rich in hills and mountains, hosting a part of a metropolitan city along the coast of the Pacific Ocean. This mountainous region is covered by native forests, farmland and National parks and shrubland, all of which are susceptible to the environmental effects of climate change and other compounding effects. Due to our world warming, the environment has reached historical surface temperature limits, wildfires therefore occur more frequently and with increased intensity. Over the past two decades, wildfires around the world have increasingly affected human values (lives, views, sacred environments), assets (home or public infrastructure) and ecosystem services (air quality, long term carbon storage) (Batllori, E., et al, 2014), (Alexandre, P. M., et al, 2018), (Butry, D., et al, 2010), (Westerling, A. L., et al, 2011), (Abatzoglou, J. T., et al, 2021).

The fluctuations of wildfire frequency and intensity are due to environmental factors (precipitation, temperature fluctuations, drought, soil moisture) and partly due to repercussions of accumulation of fuel-loads due to years of fire management methods. In this paper I review environmental variables that could explain the fire behavior, the adaptive capacity and vulnerability that the Marin County has in the face of a wildfire event(s) and possible alternative methods that could improve existing emergency management.

Hypothesis Questions:

1. Which environmental factors within the Marin County region are associated with and contribute to wildfire occurrence?

    - Low Precipitation rates
    - High Drought index for Marin County
    - Low Soil moisture for Marin County
    - High-low Elevation
    - Landscape structure of Marin County

2. How well does the National Risk Index (NRI) predict historical fire occurrence (based on where fires have occurred historically) and what does it predict for the future? Are these spatial patterns associated with the same environmental variables as in Q1?

3. How can the risk-response coordination be enhanced based on Q1 & Q2 in the Marin County?

Background Research

Local government

For research into the preparedness of Marin County, I have reviewed the Marin County fire department protocols on wildfire/fire events. Based on an overview of the local fire department for Marin County emergency management, it involves data-driven decision making and utilizes statistical analytics to enhance their strategies for future use. Communication for fire hazards is well-developed and is accessible through the website platforms, Firesafe Marin and Alert Marin, which provides notifications and information to the public on what to do in the event of a wildfire. Different instructions are used based on the level of urgency and time for evacuation involved. There are three modes of fire hazard status: evacuation order, evacuation warning and shelter in place (FireSafe Marin, 2019). *Evacuation order* is the fire department instructing the public to, "Leave now & evacuate immediately" (FireSafe Marin, 2019). *Evacuation warning* is a preliminary warning that permits time for the public to prep for evacuations and eventually leave (FireSafe Marin, 2019). *Shelter-in-place* orders for citizens to stay in current locations or nearest building, as evacuation might be impossible, too dangerous or unnecessary (FireSafe Marin, 2019). The website for the fire department of Marin County gives a checklist of instructions before a citizen leaves a household for :

- *Communications*
- *On your person items*
- *Pets & Animals*
- *Outside & in Neighborhood*
- *Inside the house*
- *Evacuation*

The Marin County Strategic plan for 2017-2020, outlines workload metrics for their employees, recording over 67,000 hours of fire training in 2016 and a breakdown of fire department assets (County of Marin, 2017). As it stands, Marin County, has just 6 fire stations that that are responsible for wildland fire prevention & protection of 340,000 acres of Federal, State, Local and private land: *Point Reyes, Tomales, Hicks Valley, Woodacre, Throckmorton Ridge, Marin City fire station,* refer to *figure 2* located in *appendix*. Supporting these fire stations is a vast network of fire lookouts, 17 fire Engines, 5 Rescue Vehicles, 5 Water Rescue Vehicles, and 2 Ambulances, along with a supplementary fire detection camera network that monitors the county 24/7 for wildfires threats (County of Marin, 2017). Evacuations for the Marin County are mapped out by the County government, providing PDF maps of planned evacuation zones and routes for each district. This effectively organizes the public evacuation and controls the rate of traffic to and from planned evacuation zones and allows for increased mobility for firefighter personnel to respond to fire hazard reports. The evacuations in the Marin County are further supported and coordinated by various agencies for water rescue operations, adopting the Coastal Incident Response Plan, as a means for seamless and safe responses to emergency situations.

National government

Natural hazards, such as wildfires, are constantly monitored by other various governmental agencies, such as the Federal Emergency Management Agency (FEMA), Fire Information for Resource Management System (FIRMS), National Wildfire Coordinating Group (NWCG) and U.S. Fire Administration. Agencies, such as FEMA, routinely conduct a National Risk Index (NRI) for the entire nation for various natural disasters: wildfires, earthquakes, tsunami, etc. The NRI uses data from several national and state datasets to create an overall risk assessment and vulnerability identification for the individual hazards and the combined relative hazards that a region is likely to have. There are three scopes of data that represents the NRI: census block, census tract, and county (FEMA,2021). In this case study for wildfire hazards, the NRI is constructed in census tract format via vector layer for Marin County, giving a general “Big picture” of the susceptibility the region has to wildfire events. With this said it is good to note that the NRI does not consider the intricate economic and physical interdependencies that exist across geographic regions (FEMA, 2021).

The NRI considers three components: expected annual loss, social vulnerability, and community resilience (FEMA, 2021).The *Expected Annual Loss* represents a risk component measuring building value, population, and /or agriculture value each year due to natural hazards (FEMA, 2021), refer to *figure 3* located in *appendix*. *Social Vulnerability* represents a consequence enhancing component and analyzes demographic characteristics to measure the susceptibility of social groups to the adverse impacts of natural hazards (FEMA, 2021), refer to *figure 3* located in *appendix*. *Community Resilience* is a reduction component and uses the demographic characteristics to measure a community’s ability to prepare for, adapt to, withstand and recover from the effects of a natural disaster (FEMA, 2021), refer to *figure 3* located in *appendix*. These three components are used in an equation, seen in *figure 1*, to estimate overall risk level for counties or local communities.

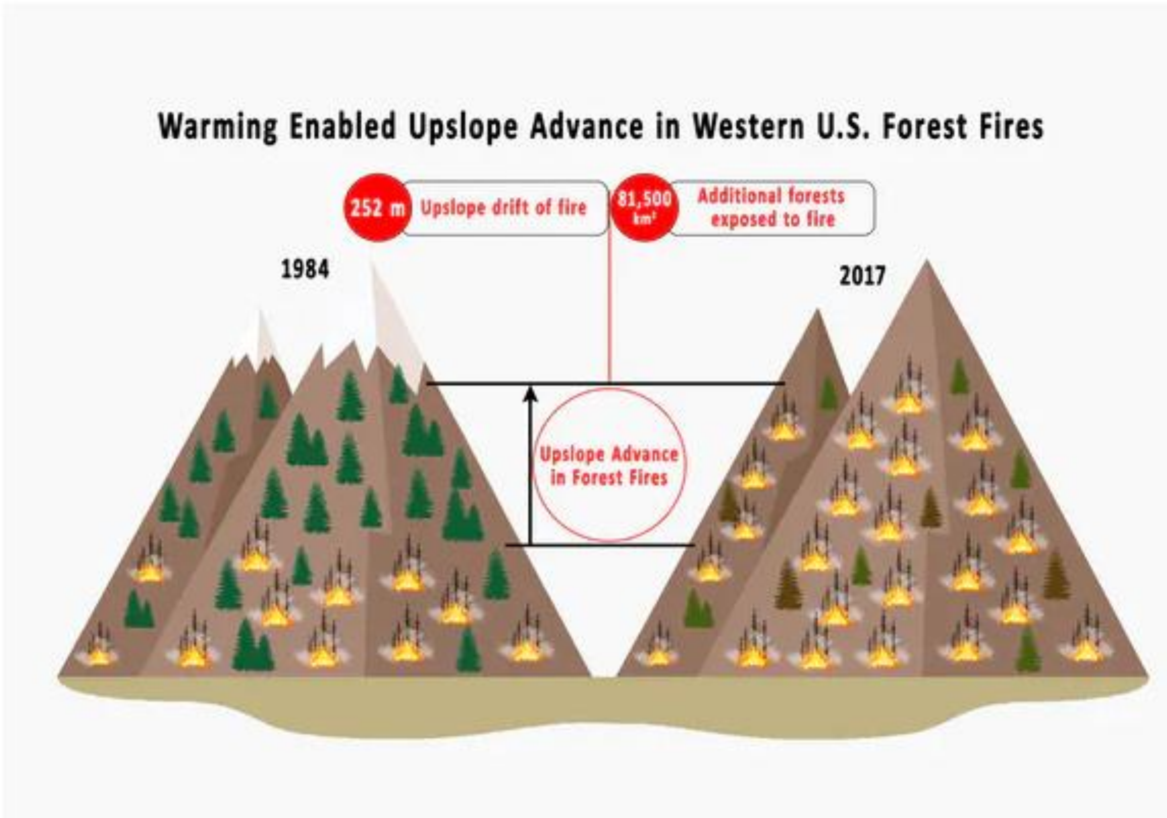
Overall Risk = *Expected Annual Loss* x *Social Vulnerability* x *1/ Community Resilience*

Figure 1: This is an equation that the FEMA agency has constructed to calculate the Nation Risk Index, constructed with three components that are provided by analyzing the census block/tracts for each county within each state of the nation, refer to *figure 3* located in *appendix*.

As seen in *table 1* located in *appendix* , the social vulnerability component has a recorded 29 socioeconomic variables that contribute to the social vulnerability score to wildfire events in the Marin County (FEMA, 2016). These variables are then averaged out to show the high-low impacts for each district toward a wildfire event and displays of how fragile the region’s population is towards wildfires. The Community Resilience is another index that consists of 59 variables that are averaged out to gauge the overall community resilience toward wildfire events and the propensity to recovery from such a natural disaster, refer to *table 2* located in *appendix for* resilience variables.

Natural environment

The western US forests is comprised of high-elevation and low-elevation subalpine environments and mid-montane forests (Batllori, E., et al, 2014). About 30% of the western US forest are dominated by high-severity fires and mixed together with ~45% of low-severity fires (Batllori, E., et al, 2014). Normally, the high-elevation forests would be considered too wet to burn, but with the climate change affecting general temperatures in higher elevation areas, more forested areas are at higher risk (John Abatzoglou, et al, 2021). Recent research from the Proceedings of the National Academy of Sciences of the US, found that forest fires are now reaching higher, normally wetter elevations, and at a rate that in unprecedented in fire history (John Abatzoglou, et al, 2021), (Alizadeh, M. R., et al, 2021), (Abatzoglou, J. T., et al, 2021). Results show that climate warming has diminished the natural high-elevation flammability barrier, a point where forests were wet from the lingering snowmelt lasting from summer to the fall (John Abatzoglou, et al, 2021), (Alizadeh, M. R., et al, 2021), (Abatzoglou, J. T., et al, 2021). This diminished barrier has led to high-elevation forests experiencing wildfires and subsequently covered in burn scars that affect how much snow can be accumulated at high-elevations in the future (John Abatzoglou, et al, 2021), (Alizadeh, M. R., et al, 2021). The wildfire events on the high-elevation forests, remove natural standing trees that would act as an anchor of the snow and stabilize it throughout the seasons, ultimately influencing quality and quantity of water that reaches the reservoirs for the region (John Abatzoglou, et al, 2021), (Abatzoglou, J. T., et al, 2021).



This gradual increase in climate change (drought, air temp., soil moisture, and precipitation, etc.), see *figure 4-6*, has encouraged fires to advance about 826 feet (252 meters) uphill in the western mountains over three decades (John Abatzoglou, et al, 2021). These high-elevation forested areas are now typically susceptible to high-severity fires, key controlling elements of this regime are extreme drought, high winds and local influences (topography). Low-elevation forested areas are mainly susceptible to ignition patterns, vegetation structure and fuel amount(s) as the key controllers on low-severity fires regimes (Batllori, E., et al, 2014). The low-severity contributing control factors make low-elevation fire incidents sensitive to modern human activity and amenable to fuel-management techniques (Batllori, E., et al, 2014). Mechanical fuel-reduction treatments are most suited to dry and fire-prone mesic forests, but ‘thinning’ techniques on fuel loads over smaller understory trees and the by-product surface fuels (nonmerchantable treetops and limbs) created by the treatments will reduce fire intensities and rates of spread while promoting vegetation regeneration (Batllori, E., et al, 2014). Under extreme but not infrequent conditions fire suppression is less successful particularly where fuels have accumulated causing increased impacts to nature and developed resources (Calkin, D. E., et al, 2015).

Fire Management Methodology

General consensus regarding prescribed burning methods utilized in fire management methods is favored, as prescribed burnings maintain native grasslands and open woodlands (Batllori, E., et al, 2014). Despite the human natural reaction to wildfires as a catastrophe, it is a natural cycle in the ecosystem that stimulates vegetation regeneration and maintains the natural biodiversity within the Marin County. As a consequence, the fire suppression methods and the Wildland-Urban Interface (WUI) rising development, results in a nonnative and fire-intolerant plant species incursion over native plant species. Recent research in Fire Ecology show that invasive grasses cause very frequent and often large fires across the western US (Batllori, E., et al, 2014). The increase of fire frequencies, due to abundant human ignitions and non-native grasses that support rapid burning, threaten to convert many native shrublands to degraded habitats (Batllori, E., et al, 2014). This points out that the current policies that govern over fire management do not recognize the cultural, environmental and economic dimensions of wildfire to Marin County.

Prevention strategies, such as fire suppression methods, are imposed to help slow the spread of fire before it happens and allows firefighters to easily manage the potential extent of damage from wildfires. Historically speaking, fire suppression methods have had a pivotal role over wildfire occurrences, leading to increased fuel loading and continuity on most forest landscapes in the western US (Calkin, D. E., et al, 2015). Moreover, not treating the additional surface fuel by-products can actually increase the fire intensity and severity when a wildfire does occur (Batllori, E. et al, 2014). The fire hazard within Marin County has been a growing environmental concern for decades due to climate change, even more so as the growing housing development in the WUI greatly exacerbates wildfire problems and other environmental issues (Alexandre, P. M., et al, 2018). Areas known as the WUI are houses that are in or near natural vegetation, and approximately one in three houses and one in ten hectares are now in the WUI for the western US (Alexandre, P. M., et al, 2018). The WUI is used by various government agencies to identify those homes within the county that most likely will be affected by wildland fire (Hammer, R. B., et al, 2007). The WUI comprises of three components: human presence, wildland vegetation and a distance that represents the potential for effects to extend beyond boundaries and impact neighboring lands (Hammer, R. B., et al, 2007). Characterized with two types of WUI, in locations of houses that exists, > 1 housing unit per 40 acre and (Hammer, R. B., et al, 2007):

1. Wildland vegetation covers > 50% of the land area (*Intermix WUI*) (Hammer, R. B., et al, 2007).

   OR

2. Is within 1.5 miles of large area with >75% wildland vegetation (*Interface WUI*) (Hammer, R. B., et al, 2007).

Establishing the Home Ignition Zone (HIZ), which is a 30-60m perimeter around any housing structure (Calkin, D. E., et al, 2015). The WUI serves a valuable purpose for strategic planning by providing consistency and credibility to estimates of the scope of the WUI nationwide (Hammer, R. B., et al, 2007). The WUI is supported by the Healthy Forest Initiative (2002) and the Healthy Forest Restoration Act (2003), which reiterate the need for resource managers to work with communities and homeowners in the WUI to reduce the risks associated with wildfire (Hammer, R. B., et al, 2007). Methods using the WUI have shown that prioritizing public investments of fuel-reduction efforts and wildfire suppression in and around the HIZ. This essentially reduces the true costs of housing location decisions, thus incentivizing development in high wildfire hazard areas (Calkin, D. E., et al, 2015). Houses built close to forests or other natural vegetation, cause two problems to arise (Alexandre, P. M., et al, 2018):

1. More wildfires due to human ignition

2. Greater risk to lives and homes, resulting in increased difficulty in fight off wildfires and letting natural fire burn methods become impossible.

The annual review has stated that the area burned, and fire suppression costs have rapidly increased in the US (Alexandre, P. M., et al, 2018). The area burned annually nearly doubled and from an average of *18,000* km^2/y in 1985-94 to *33,000* km^2/y in 2005-14 (Alexandre, P. M., et al, 2018). Federal wildfire suppression expenditures tripled from *$0.4 Billion/*y to *$1.4 Billion/y* and has exceeded $*2 Billion* in 2017 (Alexandre, P. M., et al, 2018). Although federal policy on fires is focused on fighting, prevention methods and fuel-reduction and public outreach campaigns, they will be unsuccessful by themselves (Alexandre, P. M., et al, 2018). Factors such as socio-political influences from politicians, landowners and public increase the gravity and cost of fire suppression costs (Calkin, D. E., et al, 2015). Due the housing growth rate being unchecked it has become the leading growth factor of the WUI, thus contributing as a major factor to wildfire occurrence and cost (Alexandre, P. M., et al, 2018). If the WUI growth is unchecked and housing unable to adjust to environmental needs, it is likely that wildfire problems will worsen in the near future.

Methods

Research Question 1 *: Which environmental factors within the Marin County region are associated with and contribute to wildfire occurrence?*

Regarding my first hypothesis on the environmental factors that contribute to wildfire occurrences, I would need to conduct a regression model analysis using the various compiled environmental datasets (drought, soil moisture, precipitation, thermal anomalies). Using the thermal datasets, sourced from FIRMS via Terra satellite and captured by MODIS instruments, as the dependent variable against the various environmental factors as the independent variable(s). I would be able to reveal the possible negative or positive relationships for each environmental variable(s) contributing to the wildfire occurrence. To conduct this analysis, I am utilizing the “GeoDa” program to process the raw data into CSV formats to accomplish the regression analysis. To visualize these variables for the Marin County I have acquired and edited the raster and vector datasets that display the regions: precipitation data sourced from PRISM climate group, soil moisture data sourced from ArcGIS Online and Department of Conservation, drought index sourced from FIRMS & FEMA, thermal points sourced from the Fire Information for resource Management System (FIRMS) & Federal Emergency Management Agency

(FEMA), National Risk Index sourced from FEMA, and DEM sourced from USGS: The National Map , and land cover data from the Golden Gate National Parks Conservancy.

Thermal anomalies

Starting with the FIRMS thermal data, which was sourced from the Terra satellite using the MODIS instruments to record thermal anomalies as "brightness" values to represent the fires on the earth's surface. I separated the point features by individual year for 2018-2021, and by level of "Brightness" value (high-ed-low). I will be able to accomplish this by manipulating the attribute tabular data via the "Select by attribute" tool, showing only the thermal anomalies within the Marin County region and the targeted time period(s) 2018-2021. After which everything has been processed, I will be using these three layers in a "table join" operation with the following other environmental layers to create a CSV file that I can utilize in a regression analysis from the "GeoDa" program.

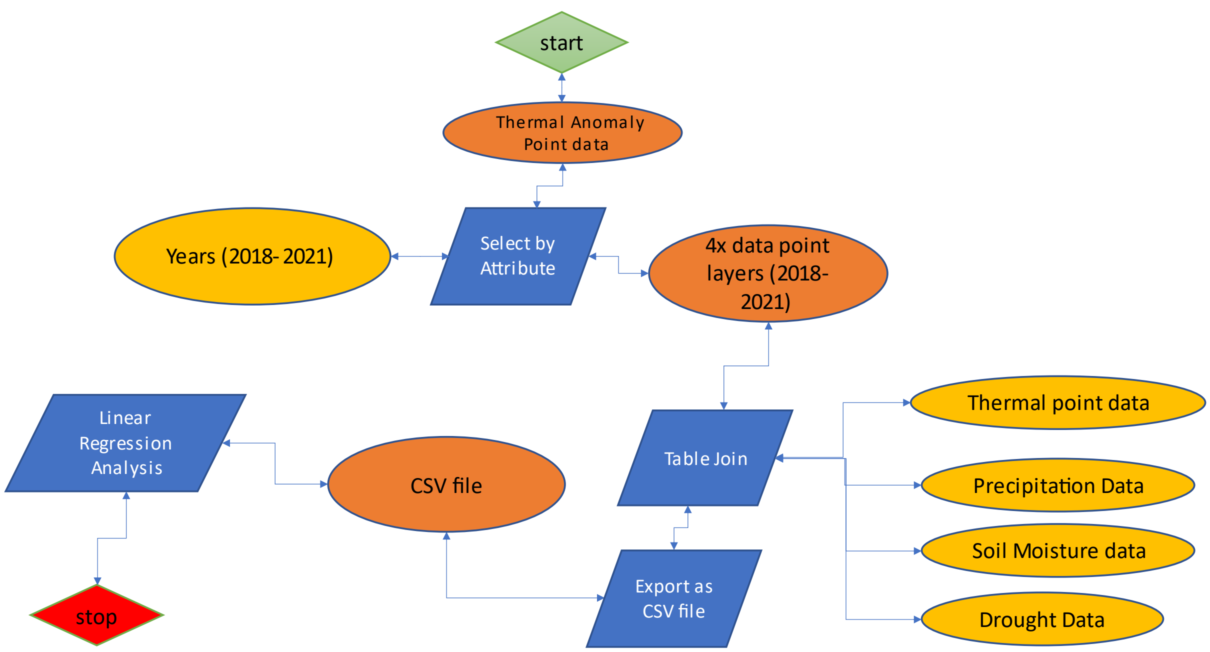


Figure 9.

Drought Dataset

For the drought vector datasets, sourced from FEMA, I had used an "Intersect" operation with the Californian boundary polyline layer to focus the drought information onto only the

California state. Narrowing this even further I had utilized the Marin County boundary layer to pinpoint the drought index for the corresponding years, 2018-2021, utilizing the “Intersect” operation once again. Then using the three sets of drought polygon datasets with the correlating fire point datasets in an “Intersect” operation I will be able to combine the attributes of the two sets of vector layers. Successfully concatenating the point fire data to have the drought data, represented by the “DM” value. The “DM” value ranges from D0-D4 (D0= Abnormally Dry, D1=Moderate Drought, D2=Severe Drought, D3=Extreme Drought, D4=Exceptional Drought), which is the Ca Drought Monitors index of drought intensity. This step further builds the required CSV file needed for the regression analysis of environmental independent variables to reveal the positive or negative relationships for the dependent variable (thermal anomalies).

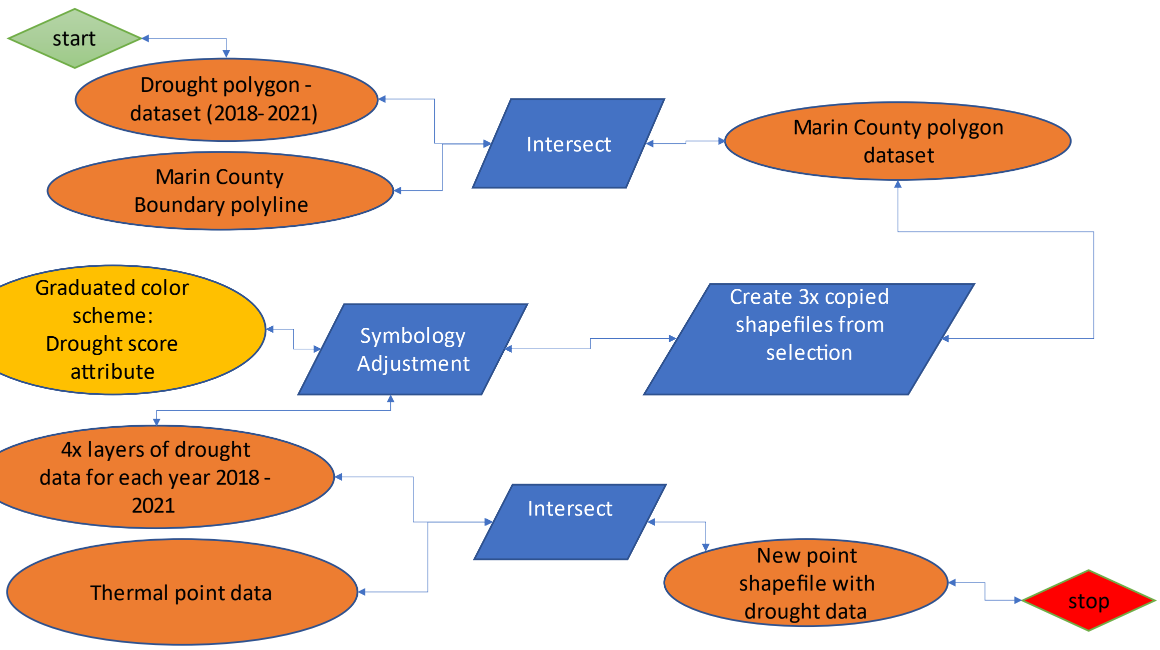


Figure 10.

Precipitation Dataset

The process for the “Clip Raster” operation will be repeated for the three precipitation raster datasets, acquired from NOAA at 4km resolution, and the Marin County boundary polyline. By manipulating the attribute table and a “Intersect” operation I can concatenate the precipitation data with the following corresponding fire points for each year. Further building the CSV files that are needed for the regression analysis.

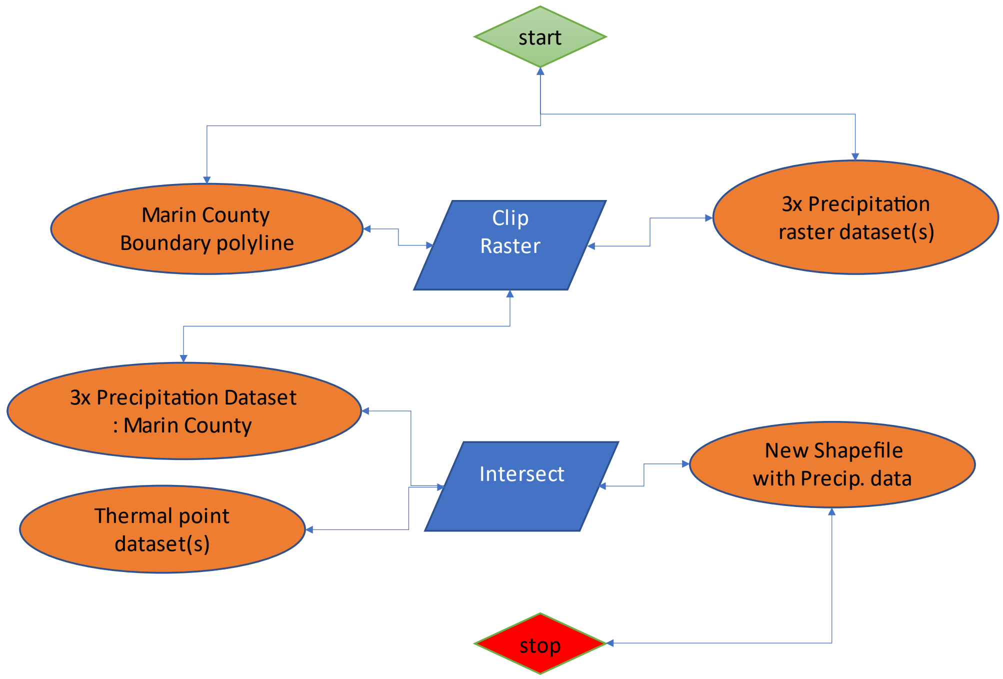


Figure 11.

Soil Moisture Dataset

The soil moisture vector data , acquired from ArcGIS and the Department of Conservation, will be used in a "Select by Location" to narrow the focus of the dataset to only Marin County. After narrowing down the scope of this dataset I then can adjust the 'Primary symbology' of the layer to 'Graduated Colors' and utilize the "*Available water storage 0-100cm*" attribute to visualize the levels of soil moisture within the Marin County. Next will be an "Intersect" operation to the fire points and spoil moisture layers, successfully concatenating the soil moisture data and fire data to create the required CSV file for the regression analysis.

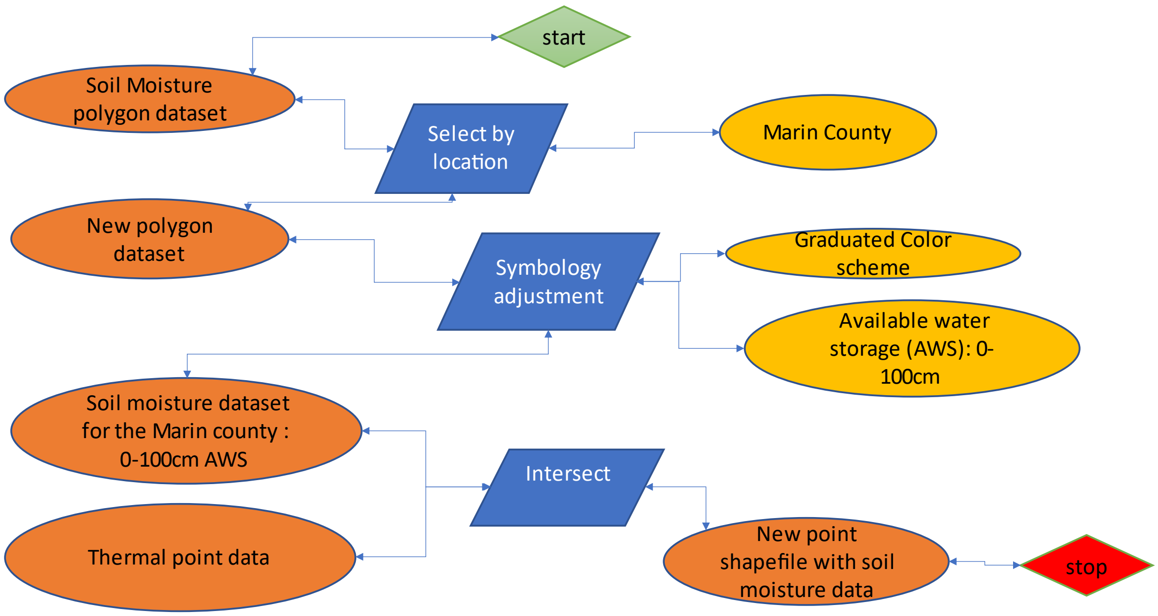


Figure 12.

Research Question 2: How well does the National Risk Index (NRI) predict historical fire occurrence (based on where fires have occurred historically) and what does it predict for the future? Are these spatial patterns associated with the same environmental variables as in Q1?

National Risk Index (NRI)

The NRI overall risk, sourced from FEMA, has been created for the entire United States nation utilizing their own proprietary algorithm, refer to *figure 1*. The NRI overall risk layer represents the census tract files, representing each district within the nation. Each district within the NRI displays different values for the three components, seen in *figure 3* located in the *appendix*. To narrow down the NRI shapefile to only the districts within the Marin County, I will utilize a “Select by attribute“ operation selecting Marin County ID value. Afterward I will create three separate selection layers from this main NRI layer, each one adjusted with the symbolism pane to emphasize one of the three main components of the “Overall Risk” NRI. The “Overall Risk” layer of the NRI would show the vulnerability that Marin County has toward wildfire events, with this said the “Community Resilience” component of the NRI shows the adaptive capacity that the population in the county have for recovery against wildfire disasters, seen in *figure 3* located in the *appendix*.

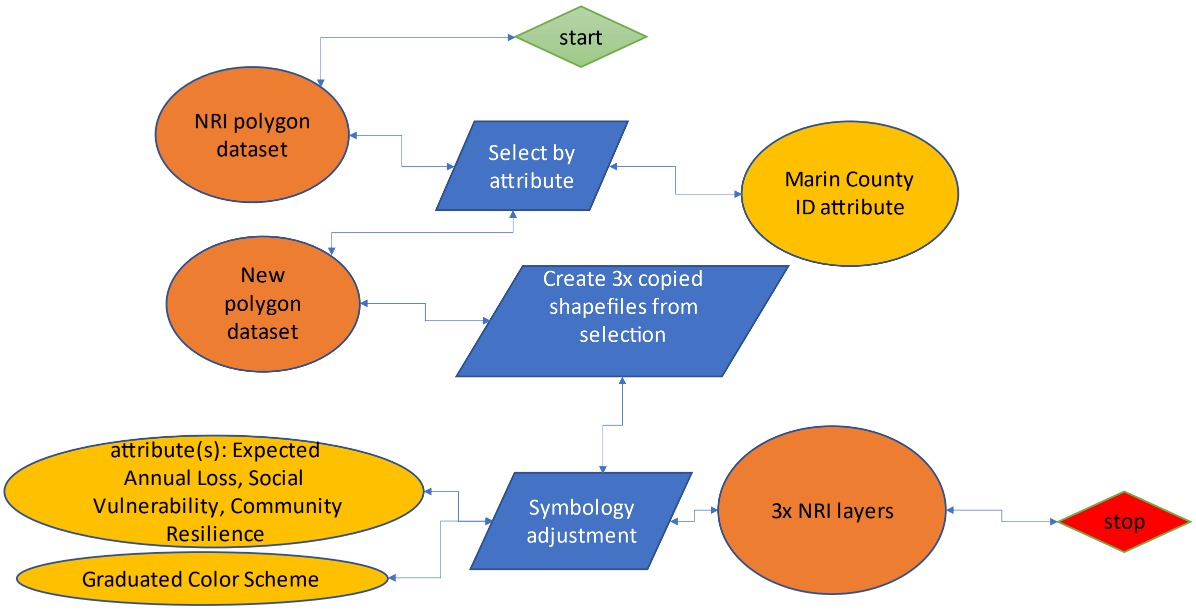


Figure 13.

Kernel Density

From the thermal point dataset(s) that I had previously separated, I can produce a "Kernel Density" (KD) layer from the recorded thermal anomalies captured by the MODIS satellite, for each year of the time range of 2018-2021. This KD layer will be overlayed with the NRI 'overall risk' layer , in efforts to assess the precision of the NRI predictions for this particular county. If the predictions of the NRI match the ignition patterns seen in the kernel density outputs for 2018-2021, then this analysis would prove that the NRI holds credit in its predictions. However, if the predictions do not match the ignition patterns of the following years, 2018-2021, then it would mean that further analysis of geographic and environmental variables would need to be examined closer to determine improved predictions of wildfires.

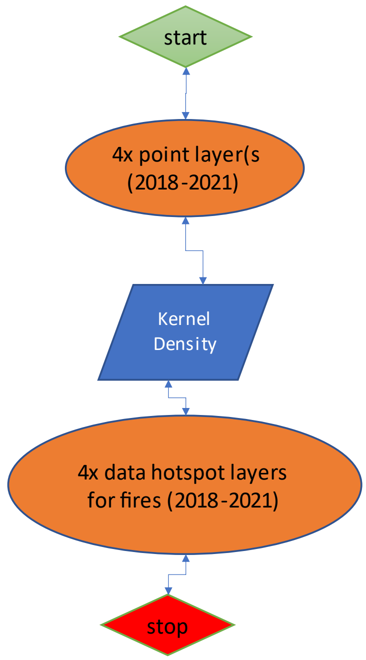


Figure 14.

DEM

Using the DEM raster dataset(s), sourced from USGS: The National Map, I need to perform a “Mosaic to new raster” operation to combine the numerous DEM raster files that construct the Marin County. This in turn would allow me to manipulate the DEM layer accurately and efficiently emphasizing the elevation levels of high-low, to show the portions of topography that would be susceptible to either high-severity fires or low-severity fires, see *figure 8* located in *appendix*. The next step after the DEM has been processed and merged together, is to utilize the “Boolean” operation on the new DEM that was created to separate the different categories of low-elevation to high-elevation landscapes that are within the Marin County. This would leave me with general areas for the two categories of elevations, allowing me to further cross examine the two areas:

1. Areas that hold variables that *are* amendable to human intervention to the occurrence of wildfires. (Low elevation)

   VS.

2. Areas that hold variables that *are not* amendable by human intervention to the wildfire occurrences. (High elevation)

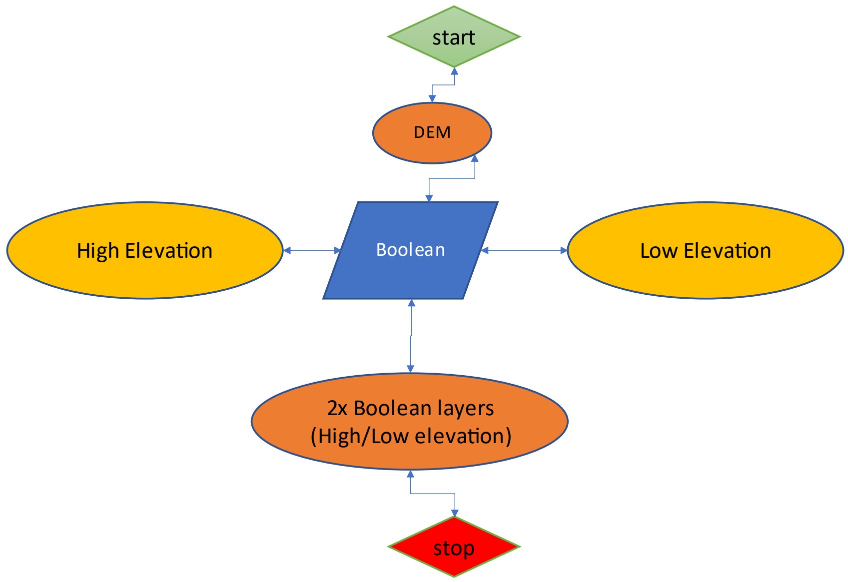


Figure 15.

Land Cover

Using land cover datasets, sourced from the Golden Gate National Parks Conservancy and ArcGIS Online, I will be able to display the various types of land types of the region (fragmented forests, cropland, developed land). The vector layer will be narrowed down by using a "Clip" tool function to only display the land cover data within Marin County, refer to *figure 7* located in *appendix*. Once this layer is finished with processing, I will then be able to use the land cover data to identify wildfire-prone land types then utilize them for further analysis in this report.

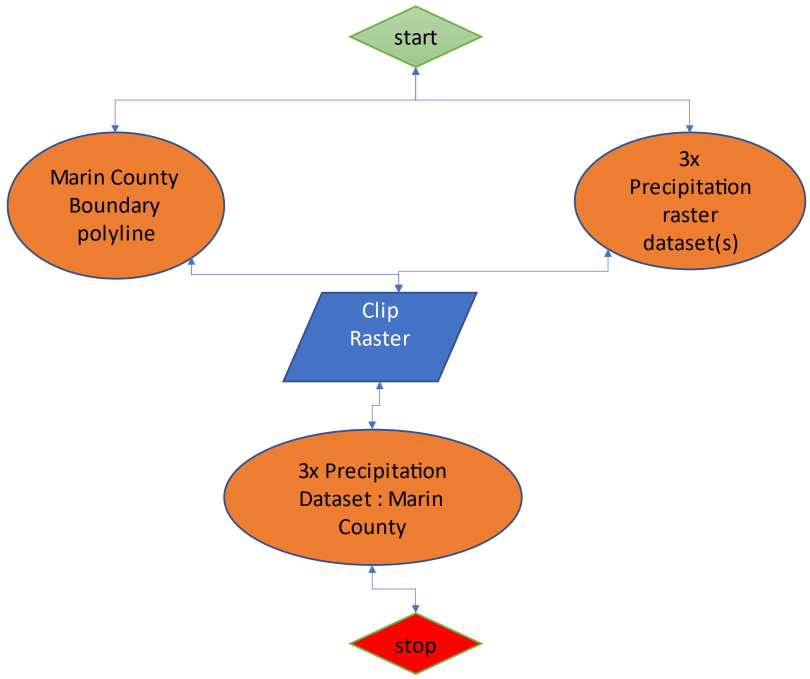


Figure 16.

Boolean Layer analysis & Raster Calculator Math

From the listed environmental layers, I will conduct Boolean operations that pull the following criteria from the environmental datasets that lead to wildfire occurrences:

Environmental variables

- *Previous burned areas* from the Kernel Density layer
- *High-Low elevation* from the DEM layer
- *Low soil moisture* from the Soil moisture layer
- *Low precipitation* from the Precipitation raster
- *High drought* from the Drought indices for years 2018-2021
- *Land cover* (forest, shrubland, cropland)

The various output(s) of the Boolean layers will essentially show the high-risk areas in each environment layer within the Marin County. After which the "Raster Calculator" will be used to multiply the various layers together, essentially merging all the environmental Boolean variables. This combined Boolean layer will then be overlayed with the Kernel Density to exhibit the correlation of fire events and environmentally known high-risk areas. This will also represent a current model of 'overall risk' from wildfire incidents based on local environmental and geographical perspective, compared to the NRI that shows predictions of wildfire susceptibility on a socioeconomic perspective.

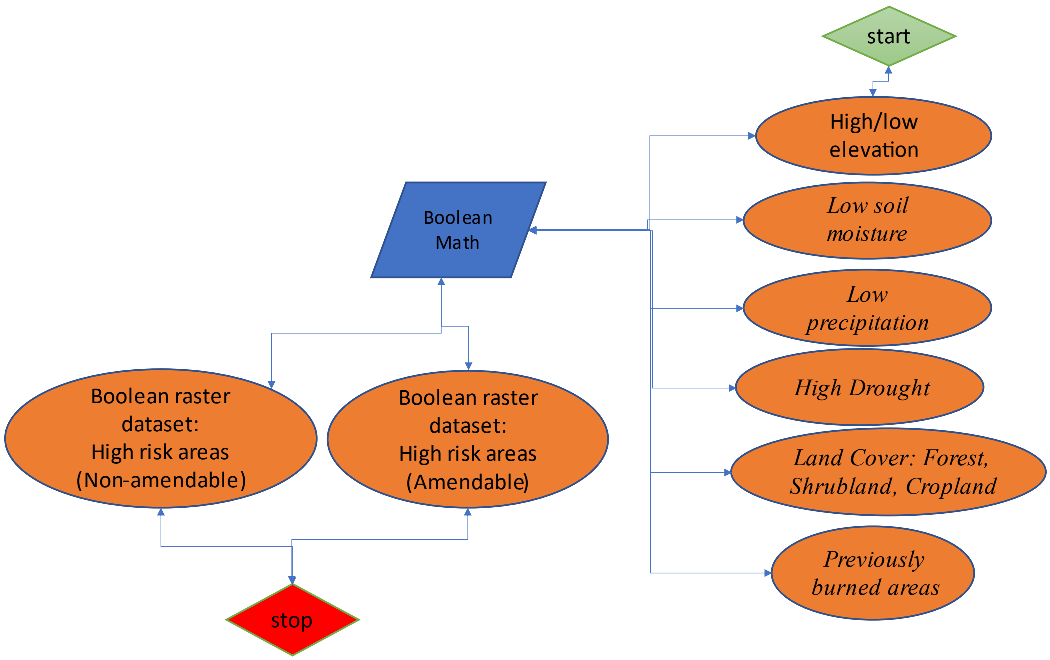


Figure 17.

Overview of Analysis:

- Linear regression graph (correlating environmental variables vs thermal anomalies)
- Separation of point dataset (forest fire) based on year.
- Kernel density analysis of forest fire point dataset (2018-2021)
- Intersect operation for : Drought data, NRI data, soil moisture datasets
- Clip Raster operation for the precipitation dataset
- Overlay of NRI and Kernel Density layers
- Mosaic to new raster operation for the numerous DEM files that construct the Marin County
- Boolean operation and Raster calculator analysis on:
    - DEM (Low - High elevation)
    - Environmental data (precipitation, drought, soil moisture)
    - Land cover
- Export of merged layers to CSV file

Results

The expected results of this analysis will produce five maps of the Marin County, reviewing the compounding effects of environmental factors impacted by the increase in climate change of our world. The first map will display an overly of FEMA's census tract NRI for the county and a kernel density of the collected thermal anomalies of 2018-2021. The second, third and fourth maps will display the various drought patterns over the time span of 2018-2021, the precipitation patterns and soil moisture. The fifth is going to be a Boolean analysis of all fire-encouraging environmental factors that forecast areas to have a high likelihood of wildfire occurrences. Using regression models, I will output a linear regression graph that would corelate water stress (drought, soil moisture and precipitation) and thermal anomalies, supporting the premise of this project. I anticipate that the maps I output will show the gradual change over the time span of 2018-2021 from water stress and indicate hot spot locations for forest fires that need improved fire management mitigation by the local government.

Discussion

***Research Question 3**: How can the risk-response coordination be enhanced based on Q1 & Q2 in the Marin County?*

Fire Management improvements

As mentioned before, climate controllers over fire regimes (for example, frequency of droughts or high-wind events, or length of fire season) will dominate some ecosystems, while others are controlled by local factors (for example, topology, fuel-loads, ignitions[human/natural], and vegetation structure) (Batllori, E, 2014). Thus, fire resilience is context-dependent, fluctuation based upon the biophysical environment and desired future conditions (Batllori, E, 2014). The Bay Area's surrounding environment consists of multiple microclimates that vary based on location, from the North Bay (Sonoma, Napa, Solano, Marin Counties), East Bay (Contra Costa, Richmond, Alameda Counties) to South Bay (Santa Clara County) and the Peninsula (San Mateo County). Environments, such as the Peninsula and parts of the North Bay, experience high-winds and related high-wind events, chilling surface temperatures and high rates of soil moisture from precipitation. While the environments of the East, South and parts of the North Bay experience high incidences for surface temperatures, drought, and moderate-low ratings for soil moisture.

A governing factor over the type of fire management strategies is the economic viability of the method used. The current methods of forest management of mechanical fuel reductions, which is the removal of trees in rows or strips at fixed spacing intervals throughout the harvest region, is inefficient for the goal of economic and environmental stability management. The method of mechanical fuel-reduction typically generates more surface-fuel residues (unmerchantable treetops and chopped limbs) but is utilized regardless as it offsets the operational costs (Batllori, E, 2014). As an environmental domino effect, this opens up overstory canopy and increases sunlight penetration to the ground below, increasing the growth of highly flammable understory vegetation (Batllori, E, 2014). If mechanical fuel reductions would adapt a staggered method of spacing intervals, it would reduce the amount of sunlight penetration through the canopy and reduce growth rates of understory vegetation. With the addition of supplemental fire management, such as prescribed burning, as a way of controlling fuel-loads, fire behavior and stimulating vegetation growth regeneration for native plant species over non-native and fire-intolerant plant species, will result in an environmental stability. In many areas, ecological restoration and fuel-load management reduction may be best balanced and accomplished through fire, creating natural heterogeneity and provides for fire-dependent species (Batllori, E, 2014), (Abatzoglou, J. T., et al, 2021), (Arianoutsou, M., et al, 2011). As mentioned by the Journal of Environmental Management, “fire spread rate can be facilitated or retarded by landscape heterogeneity”, thus the spatial pattern of fire ignition and spread rate across landscapes is affected by fire proneness factors (Arianoutsou, M., et al, 2011).

Thus, the practice of prescribed burns could be utilized in fire management methods on the areas outlined in the Boolean analysis, which would show the highest risk areas that are prone to fire based on environmental and geographic factors. The existing land and fire management have not sufficiently considered the role of the future fire management opportunities, wildfire suppression without supplementary programs to address the fuel accumulation due to the aggressive suppression policies is a major federal error of fire management (Calkin, D. E., et al, 2015). Recent research from the Springer open journal on fire ecosystems, explains that managers of fire management are susceptible to status quo bias, which makes them reluctant to select beneficial use strategies over the established fire suppression methods (Calkin, D. E., et al, 2015). Societal factors such as funding, conflicts of objectives and priority of resource values has limited implementation of beneficial fire management programs to restore forest resilience to wildfires (Calkin, D. E., et al, 2015). The current scale of fuel treatment, in comparison to the advancement of climate changes, is far less than required to achieve a resilient landscape to fire (Calkin, D. E., et al, 2015). Societal factors aside, barriers from environmental regulation from the ‘Clean air’ Act or the ‘Endangered species’ Act, also limit the ability to achieve substantial reduction of wildfire hazards in the western US (Calkin, D. E., et al, 2015).

Technology Innovation

As mentioned previously the county of Marin has an established plan for wildfires, evacuation and alert-response arrangements. Arrangements such as emergency water transport, websites deliberating urgent info (blocked routes & evacuation locations) and camera networks set for fire detection. The camera network utilized by the Marin county’s fire department can be further supplemented with the usage of autonomous drone technology and Machine Learning methods. Machine learning or AI advancement of technology could be used to facilitating and expediting critical intelligence for the fire departments and other related agencies. In 2006-2010 the NASA and the US Forest Service have deployed high altitude fixed wing drones with multispectral scanners to autonomously collect imagery data, imagery data that consists of 16 bands (Shao, G., et al, 2015). Normally data acquisition of the wildfire target areas would take hours or days to procure, but drone technology as a remote sensing platform has the potential to increase the efficiency of data acquisition (Shao, G., et al, 2015). Drones can carry a variety of remote sensing instruments such as (Shao, G., et al, 2015):

Visible light cameras	Near Infrared (NIR)
Shortwave Infrared (SWIR)	Thermal Infrared (TIR)
Radar	LiDAR Sensors

As mentioned by the Department of Forestry and Natural Resources of Purdue University, drone operations provide near real-time (5-10 min) intelligence to support forest fire management (Shao, G., et al, 2015). Simultaneous use of multiple autonomous drones will allow larger areas to be measured and obtained complementary views to wildfires with minimize human risk to the wildfire hazards (Shao, G., et al, 2015). Drone LiDAR can also be a pivotal tool in locating areas of overgrowth for understory vegetation and deliver timely imagery that indicates concentrated areas of vegetation for prescribed burns. If drone technology is coupled with AI or Machine Learning algorithms, imagery data and other environmental data could be processed and dispersed to the related agencies at a faster rate than previous methods. This would increase alert and response times for fire management to the public and improve fire management by ensuring regular oversight of fuel-load accumulations via drone surveillance. Also, note that resources to acquire the same imagery from drone operations versus flying helicopters or other maned aerial vehicles inefficiently incur costs of gas, labor and have higher risk of loss-of-life factor to the employees conducting the aerial imagery operations. Satellite imagery from overhead would take a certain amount of time, hours to days, before an available satellite is in the correct position to capture high-resolution imagery. Moreover, the act of processing the raw data and analyzing the imagery would take additional time for the intelligence to be utilized by fire management, time that is costly in respects to accurately and efficiently mitigating fire spread and damage extent.

Appendix

SoVI Variables Table 1

Median gross rent for renter-occupied housing units	% Population speaking English as second language (with limited English proficiency)
Median age	% Asian population
Median dollar value of owner-occupied housing units	% African American (Black) population
Per capita income	% Hispanic population
Average number of people per household	% Population living in mobile homes
% Population under 5 years or age 65 and over	% Native American population
% Civilian labor force unemployed	% Housing units with no car available
% Population over 25 with < 12 years of education	% Population living in nursing facilities
% Children living in married couple families	% Persons living in poverty
% Female	% Renter-occupied housing units
% Female participation in the labor force	% Families earning more than $200,000 income per year
% Households receiving Social Security benefits	% Employment in service occupations
% Unoccupied housing units	% Employment in extractive industries (e.g., farming)
% Families with female-headed households with	% Population without health insurance (County

no spouse present	SoVI only)
	Community hospitals per capita (County SoVI only)

Table 1: This table displays the 29 socioeconomical variables used in the SoVI analysis, sourced from the FEMA NRI technical documents published on the open-source database and supported by the University of South Carolina. (FEMA, 2016).

Community Resilience (BRIC) Variable Table 2

Negative absolute difference between % population with college education and % populations with less than high school education	% Population below 65 years of age
% Households with at least one vehicle	% Households with telephone service available
% Population proficient English speakers	% Populations without sensory, physical, or mental disability
% Population under age 65 with health insurance	Psychosocial support facilities per 10,000 persons
Food security rate	Physicians per 10,000 persons
% Owner-occupied housing units	% Labor force employed
Negative Gini coefficient	% Employees not in farming, fishing, forestry extractive industry, or tourism
Negative absolute difference between male and female median income	Ratio of large to small businesses
Large retail stores per 10,000 persons	% Labor force employed by federal government
% Population not foreign-born person who came to US within pervious five years	% Population born in state of current residence
% Voting age population participating in presidential election	Persons affiliated with a religious organization per 10,000
Civic organizations per 10,000 persons	Red cross volunteers per 10,000 persons
Red Cross training workshop participants per 10,000 persons	Ten-year average per capita spending for mitigation projects
% Housing units covered by National Flood Insurance Program	Governments and special districts per 10,000 persons
Presidential disaster declarations divided by number of loss-causing hazard events from 2000 to 2009	% Population in communities with Citizen Corps program
Proximity of county seat to capital	Proximity of county seat to nearest county seat within a Metropolitan Statistical Area
Population changes over previous five-year period	% Population within 10 miles of nuclear power plant
Crop insurance policies per square mile	% Housing units not manufactured homes
% Vacant units that are for rent	Hospital beds per 10,000 persons
% Housing units built prior to 1970 or after 2000	Hotels/motels per 10,000 persons
Public schools per 10,000 persons	Rail miles per square mile
Farms marketing products through Community Supported Agriculture per 10,000 persons	% Population with access to broadband internet service
Megawatt hours per energy consumer	% Land in wetlands
Inverted water supply stress index	Average percent perviousness

Table 2: This table displays the 50 variables that are considered in the community resilience calculation for the NRI map in *figure 3b*, pulled from the National Risk Index documentation (FEMA, 2021).

Figure 2: This map displays the Marin County Fire Department (MCFD) network and metrics across the region sourced from the County of Marin Fire Department Strategic Plan 2017-2020. (County of Marin, 2017)

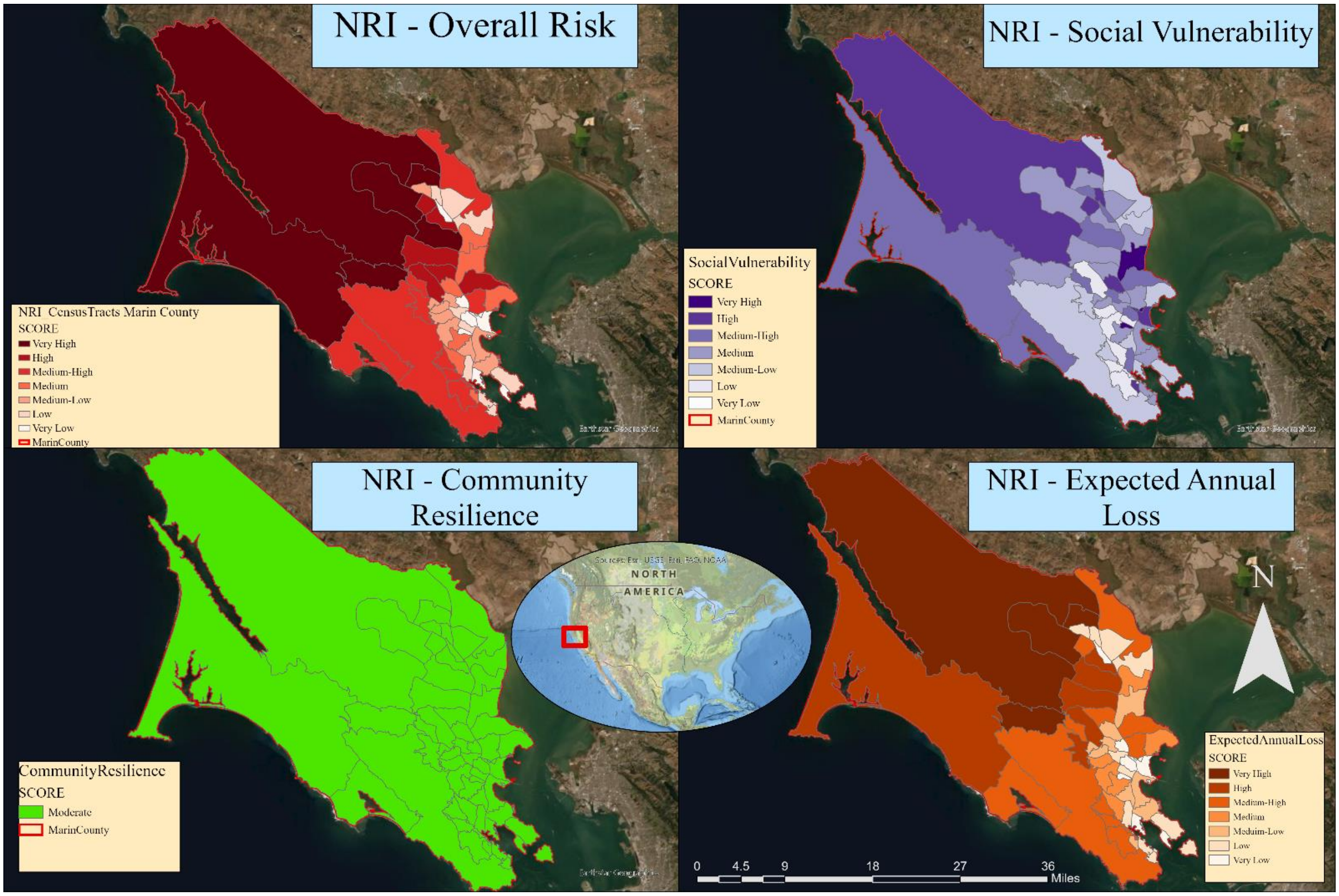


Figure 3: This map displays the Marin County National Risk Index (NRI) census tract, outlining the various levels of scoring across the region for each of the three components that construct the 'Overall Risk', sourced from FEMA database. See *figure 1* for FEMA's equation for 'Overall Risk'.

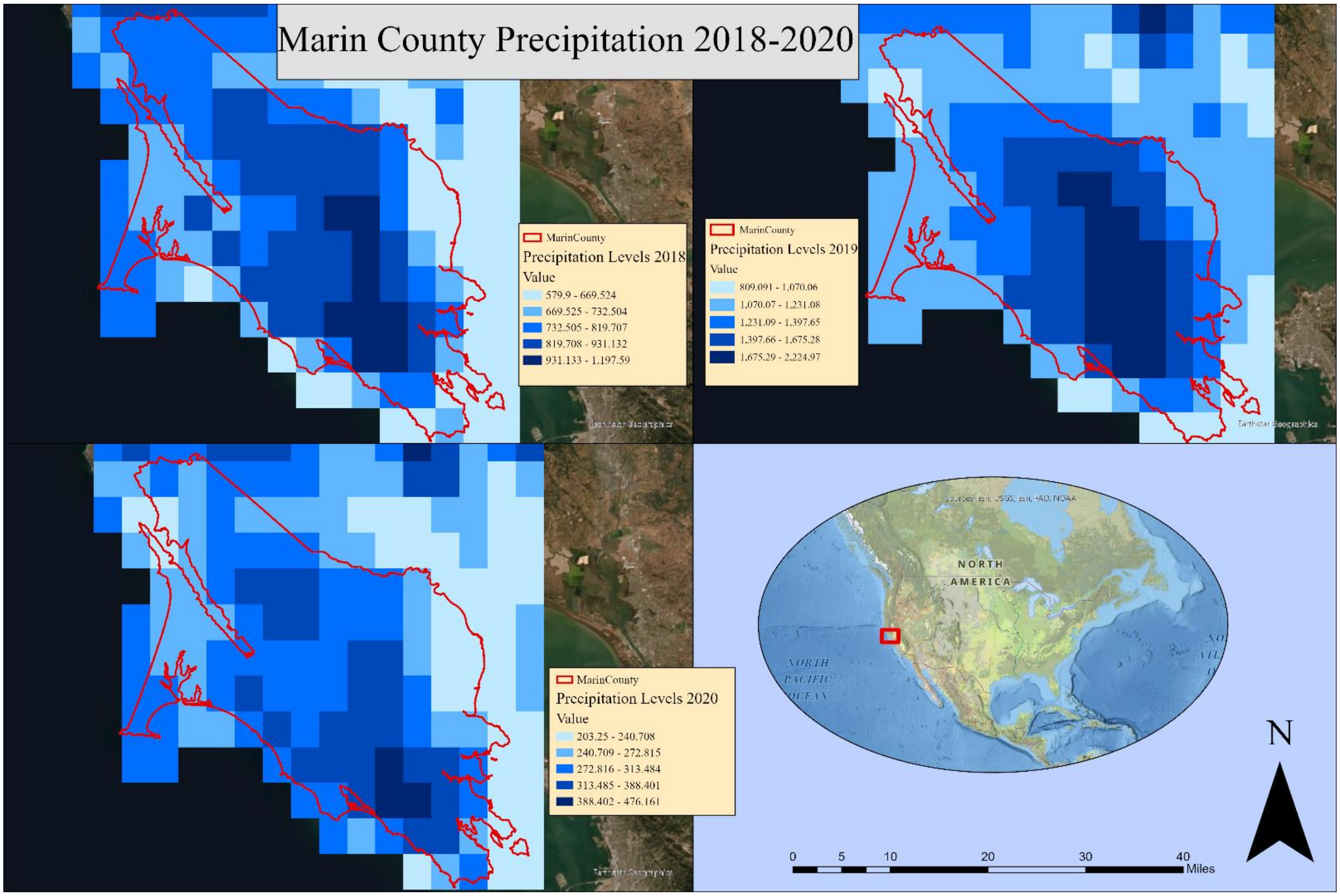


Figure 4: This map displays the three years' worth, 2018-2020, of archived 4km resolution precipitation data sourced from PRISM Climate Group.

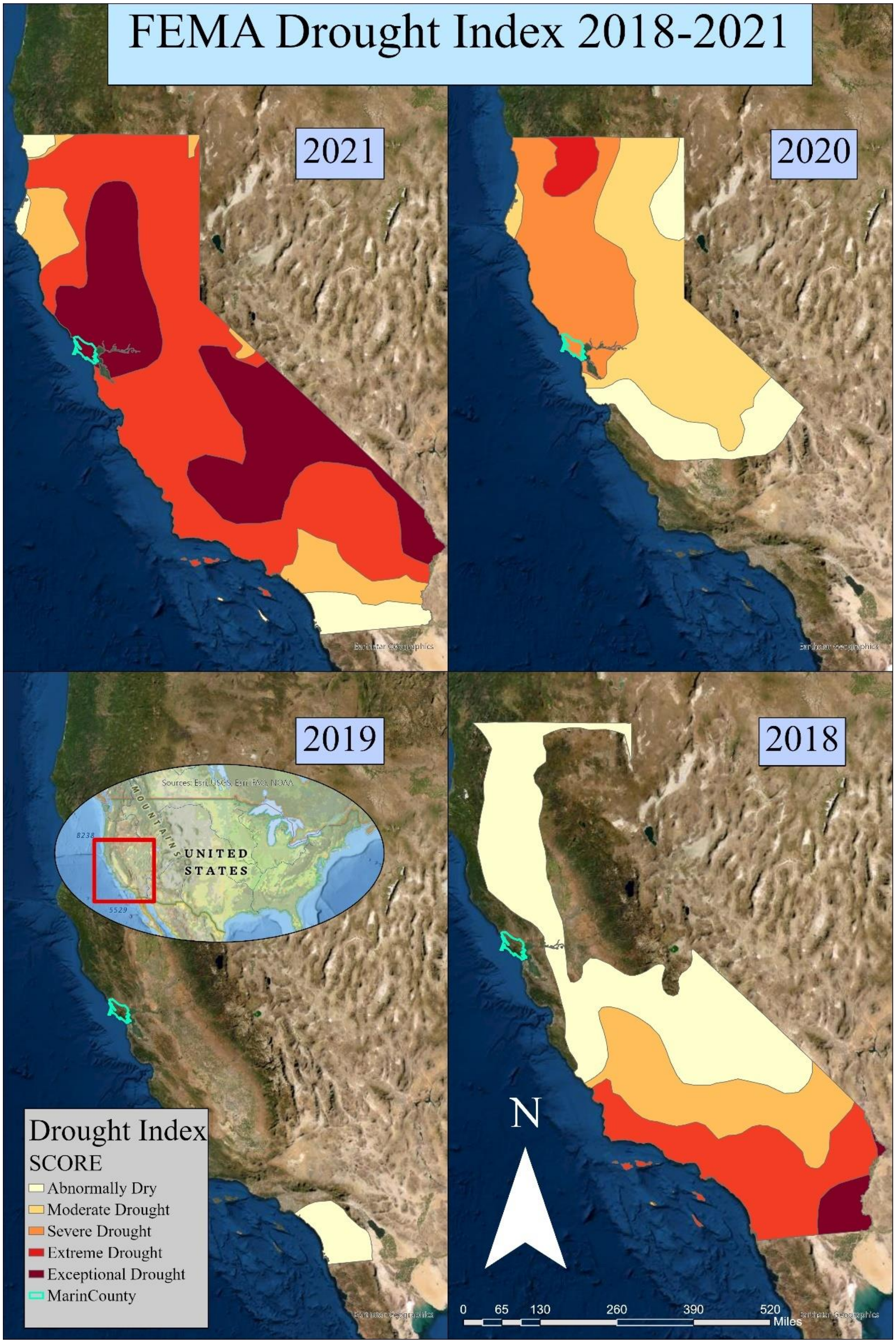


Figure 5: This map displays the time period of four years, 2018-2021, for drought levels within the California State, this data was sourced from the FEMA & FIRMS database.

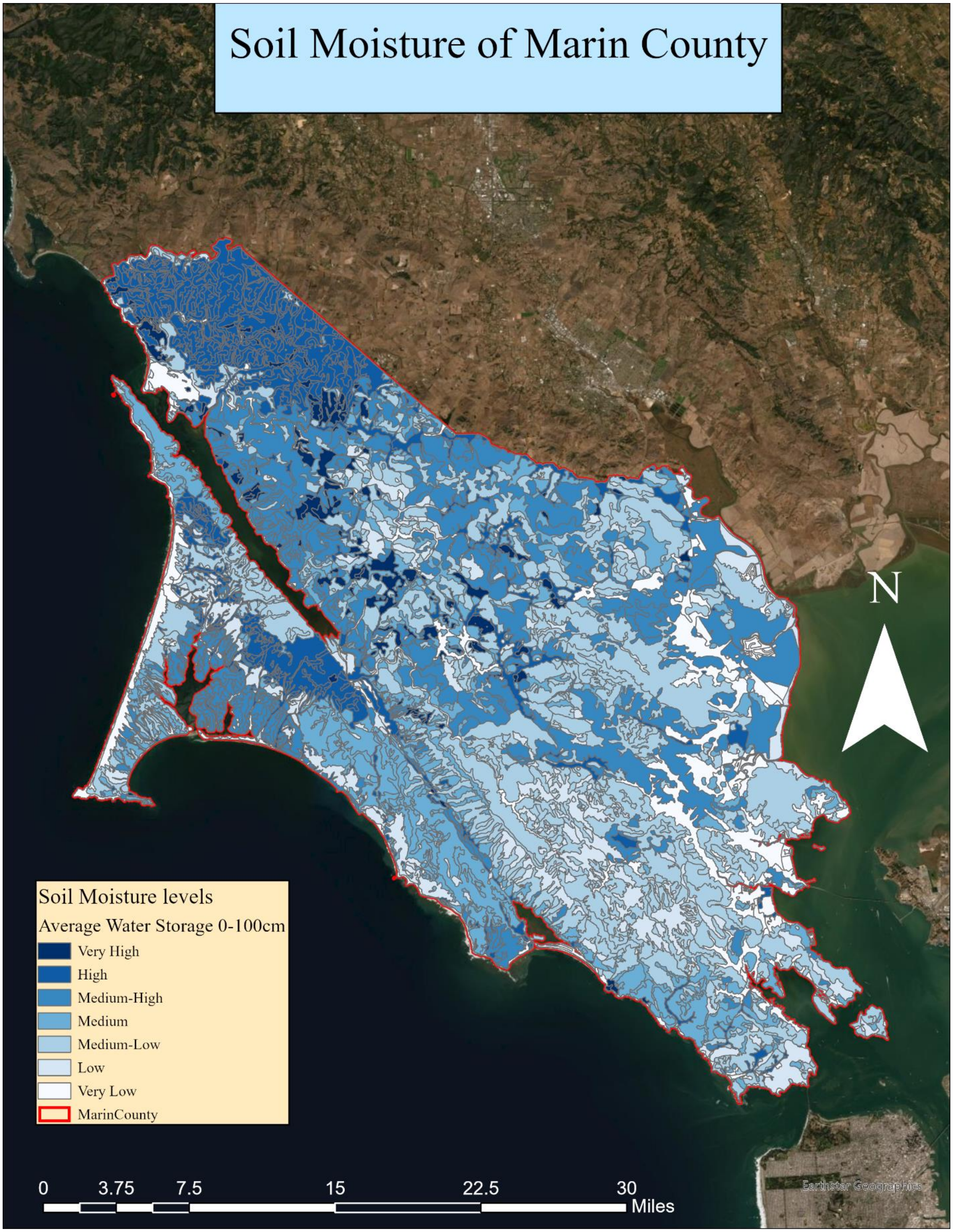


Figure 6: This map displays the Marin Counties soil moisture levels sourced from the Department of Conservation and ArcGIS Online databases.

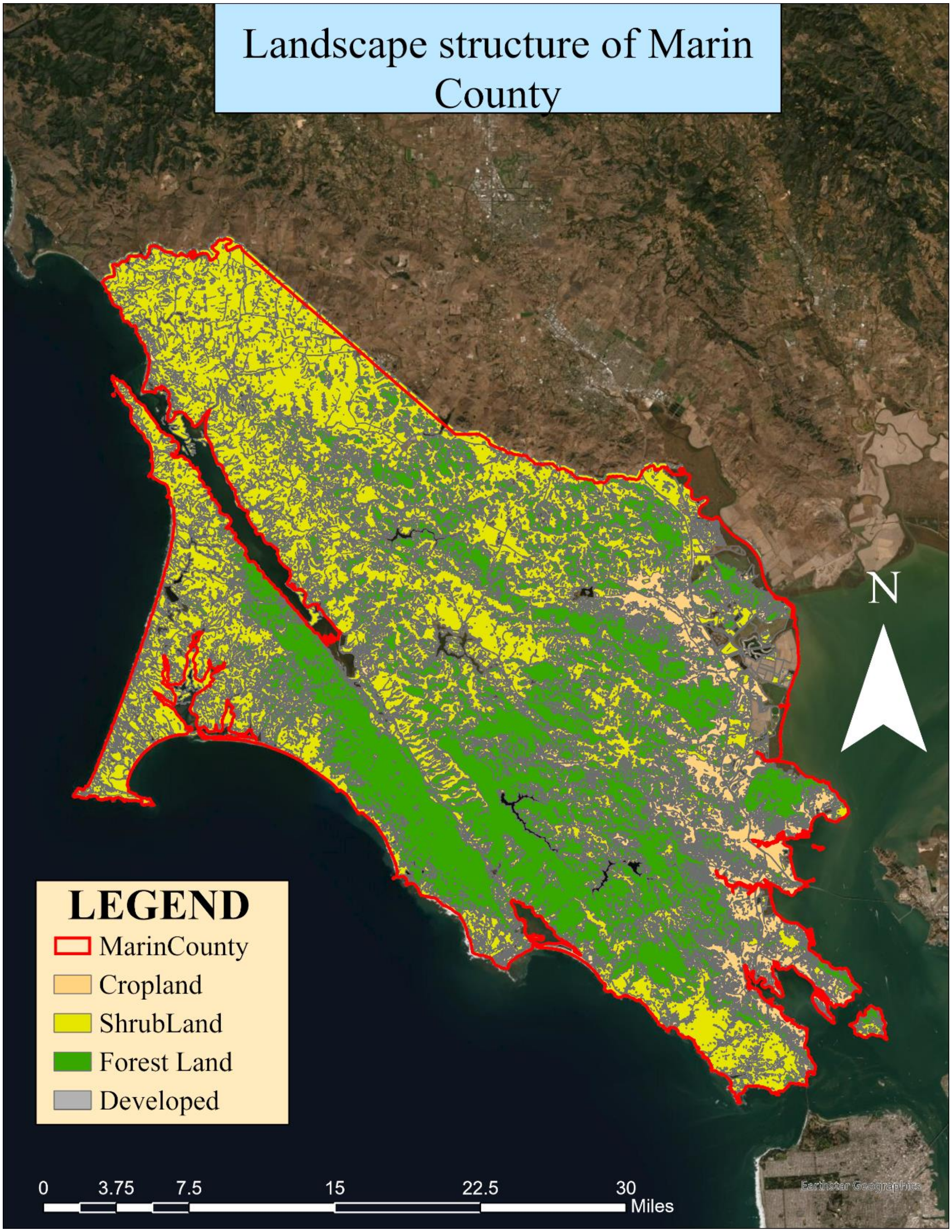


Figure 7: This map displays the land cover of the Marin County, separated into 4 general categories that describe the landscape structure: Cropland, Developed, Shrubland, Forest. Sourced from the Golden Gate Conservancy.

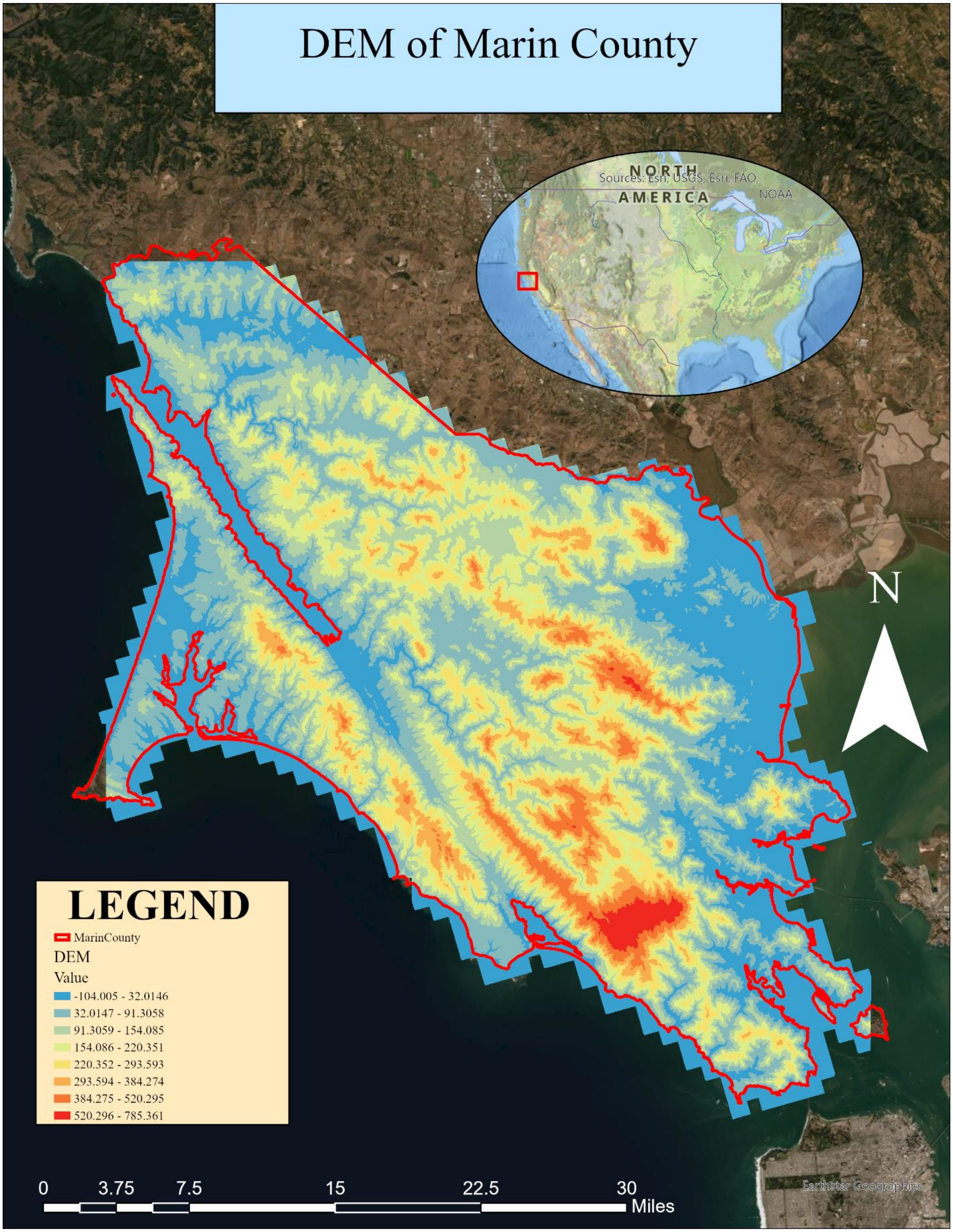


Figure 8: This map displays the Digital Elevation Model (DEM) of the Marin County region, denoting the high vs low elevations that exist throughout the landscape.

Acknowledgements

All Maps within report *:*

Data provided by: FEMA, USGS, NOAA, US Forest Service, FIRMS, NASA, ArcGIS Online, CA.gov, Data.gov

Penn State University

ESRI & ArcMap

Capstone 596A

Map Generated by: Matthew Price

Datum: WGS 1984 Mercator (auxiliary sphere)

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