Spatial Simulation of Chaparral Vegetation Response to Frequent Wildfire

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Abstract

The recent increase in fire return frequency in the Santa Monica Mountains (SMM) has drastically impacted the surrounding plant life. The majority of this plant life is composed of chaparral shrubs which can be divided into three life history types by their response to wildfires. Nonsprouters are completely killed by fire and reproduce by seeds that germinate in response to fire cues, obligate sprouters resprout after fire but their seeds are destroyed by fire, and facultative sprouters can reproduce by seeds postfire and resprout. We have created a spatial simulation in order to model the behavior of these different plant types in response to wildfires using data collected from a study site adjacent to Pepperdine University over the course of 27 years. Within our model we have incorporated rainfall in order to ensure accurate survivorship and growth patterns in our plants. We projected our site's status 60 years into the future under the current fire frequency and observed a reduction of area coverage from 74.5% to 8.74% which indicates an increased risk of mudslides near our site.

1 Introduction

Adjacent to the Pacific Ocean, the Santa Monica Mountains (SMM) provide a suitable habitat for various species of plants and animals. Chaparral shrubs represent the

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dominant vegetation type in the SMM, whose deep roots are responsible for keeping the hillside in tact. Due to the dry and hot climate of Los Angeles, wildfires are one of the greatest concerns of local residents. In the past, wildfires have not only destroyed plants in the mountains but also houses and other structures. With increasing fire frequency in the SMM, some of the chaparral species are threatened by the potential of localized extinction. A reduction in vegetation cover alters the plant community structure, resulting in the increasing threat of invasion by exotic species and a decrease in slope stability [1, 22]. Often such invasions in California are by exotic grasses that increase flammability and exacerbate fire frequency [14, 16, 25]. From 1925 to 2001, the average time between fires in SMM was about 32 years [25]. Our study site is located in a biological preserve on the Malibu campus at Pepperdine University where the average time between fires is just over 6 years.

Chaparral shrubs can be categorized into three life history types according to their responses to wildfires as described in [11, 21]. Nonsprouters (NS) are completely killed by fire but reproduce by seeds that germinate in response to fire cues and grow in direct sunlight away from existing shrubs [12, 13, 15, 21, 23]. Obligate sprouters (OS) are not completely killed by fire, but instead resprout from the original burned root crown [17]. Obligate sprouters exclusively recruit seedlings in the shade of adult shrubs between wildfire events since their seeds are destroyed by fire [9]. Facultative sprouters (FS) both resprout and reproduce by seeds that germinate in response to fire cues. Facultative sprouter seedlings thrive in the partial shade of resprouts [7, 21, 24]. Within these three life history types, each individual species varies in seedling survival and resprout success. For all three plant types it takes approximately six years for seedlings to reach reproductive maturity [26], but resprouts can start releasing seeds in the first year after fire. Seedlings and resprouts that reach maturity can persist for at least 100 years [10].

Figure 1.1 gives a visual comparison of the three chaparral plant types before and after a wildfire. Figures 1.2, 1.3, and 1.4 from [18] show the life cycles of these three chaparral plant types. These life cycles serve as the basis for our mathematical model of how plants grow, reproduce and interact in a simulated environment.

The first mathematical model of chaparral survivorship in [18] focused on three species: Ceanothus megacarpus (Cm), Ceanothus spinosus (Cs), and Malosma laurina (Ml). Cm is a nonsprouter and the others are facultative sprouters. From this model, we can show that an average fire return interval of greater than 12 years is required for 50% of the initial Ceanothus megacarpus population and 25% of the initial Ceanothus spinosus population to survive. In contrast, the Malosma laurina population has a 90% survivorship for an average fire return interval of at least 6 years. Therefore a



Figure 1.1: Three Plant Types

short fire return interval can result in severe damage to the population of *Ceanothus megacarpus* and *Ceanothus spinosus*. These results are similar to the field data from [4] which is displayed in Figure 1.5.

Our goal is to expand upon the work in [18] to create a spatial model that simulates the plant population in our study site. In this model, individual plants release seeds and seeds are distributed according to seed dispersal assumptions. After wildfires, seeds are promoted to germinate and some species resprout. We model both the height and crown growth, which is restricted by the interaction between individual plants. The growth and survivorship of plants depend both on the amount of rainfall and average time between fires. This model will more accurately reflect the changes in species



Figure 1.2: Nonsprouter (NS) Life Cycle



Figure 1.3: Obligate Sprouter (OS) Life Cycle



Figure 1.4: Facultative Sprouter (FS) Life Cycle

density and localized extinction of some chaparral species.

2 Longitudinal Study of Chaparral

The mathematical spatial model in this paper is inspired by a longitudinal study of several chaparral species at a biological preserve on the Malibu campus of Pepperdine University as described in [4, 5, 24]. The study began after the Piuma Fire of October 14, 1985 near Malibu, CA and has continued through subsequent fires in 1993, 1996 and 2007. After the 1985 fire, 100 burnt stumps were tagged for two different species of facultative sprouters in order to track resprout emergence and resprout establishment. Meanwhile, seedlings of the same species of facultative sprouters and one species of nonsprouter were monitored at 21 permanent quadrats. We also sampled the chaparral population in our study site using the point quarter method [20]. At the site is a 4×8 grid of poles spaced 10 meters apart. From the plants surrounding these poles we have data ranging from 1985 to 2012 on height, crown diameter, two perpendicular basal diameters, and the distance from the base of the plant to the pole. These measurements, which is not consistent from year to year. Using the data from 1985-2012 we will



Figure 1.5: Survivorship of three species of chaparral resprouts and seedlings between wildfires in 1985 and 1993 as seen in [4] and [24]. After 7 years, 99% of *Malosma (Rhus) laurina* resprouts (Mlr) survived and less than 1% of seedlings (Mls) survived. Over that same time period 62% of *Ceanothus spinosus* resprouts (Csr) and 1% of seedlings (Css) survived. In contrast to Mls and Css, 25% of *Ceanothus megacarpus* seedlings (Cms) survived, whereas no adults were observed to resprout after fire and thus survivorship for resprouts of *Ceanothus megacarpus* is 0%.

model annual growth, competition and survivorship for several different species to demonstrate how wildfire changes plant community structure.

In particular we note that in 1985, the relative frequency of Cm, Cs, and Ml were 23.19, 23.19, and 28.99, respectively. However, by 2012 the relative frequency of Cm, Cs, and Ml are 0, 29.79, and 40.63. Due to the extremely short fire return interval between 1993 and 1996, Cm did not have enough time to mature and release seeds, and thus went extinct. With the extremely high *Malosma laurina* resprout survivorship, Ml has dominated our study site.



Figure 3.1: Average height, crown diameter, and basal diameter for *Ceanothus spinosus*, *Malosma laurina* and *Rhus ovata* from 1986-1993.

3 Plant Growth

Since all FS and NS seeds germinate in response to fire cues, we can assume that all seedlings are the same age. Because resprouts sprout directly after fire, we can also assume that all resprouts are the same age. For this reason we used the average measurements for each measurement and year to estimate information about the growth of a given species. As shown in Figure 3.1, the plots of average height and crown for each species against time look similar, implying that they were in some way correlated. However, the graph of basal area does not appear to have the same shape as height and crown. We attribute this to the difficulty in measuring the basal diameter and not to actual growth patterns of the base. Figure 3.2 shows plots of average height



Figure 3.2: Correlation of average height and average crown diameter for *Ceanothus spinosus*, *Malosma laurina* and *Rhus ovata*.

against average crown size for three species of resprouts from 1986-1993. These plots demonstrate that average height and crown growth are linearly correlated.

The longest fire free intervals in our data set are 1985-1993 and 1996-2007. We have data each year for the first period but are missing several years from the second, so we used the data from 1985 to estimate the parameters for the growth curves and tested our hypotheses against the latter interval. By plotting the averages against time, we saw that each curve appeared to depend on another variable in addition to time. As shown in Figure 3.3, there was a significant leveling off of height and crown growth between the years 1989-1991. When we compared growth against annual rainfall we observed that growth was inhibited by drought and increased by an abundance of rain. We used the annual rainfall data from Los Angeles International Airport [3], which was the closest station to our site in Malibu. Because our data was generally taken in October of each year, we calculated the cumulative rainfall from October to September of each year to correspond to the yearly growth of our plants. We calculated the long term average annual rainfall for this site to be 12.02 inches.



Figure 3.3: Annual rainfall at Los Angeles International Airport from 1986-1993 with an average rainfall of 12.02 inches [3]. The corresponding average height and average crown diameter of *Ceanothus spinosus*, *Malosma laurina* and *Rhus ovata* from 1986-1993.



Figure 3.4: Growth models for the height of *Ceanothus spinosus*, *Malosma laurina* and *Rhus ovata* from 1985-1993.

We then checked annual height growth (the difference in growth each year) against rainfall. We hypothesized that annual growth is proportional to rainfall, but either decays exponentially over time or is related inversely to time. Below are the three equations we considered for change in height

$$\Delta h(w,t) = awe^{-bt},$$
$$\Delta h(w,t) = \frac{aw}{t},$$
$$\Delta h(w,t) = \frac{aw}{t^b},$$

where w is the annual rainfall, t is the time since the last wildfire in years, and a, b are constants. We used the curve-fitting toolbox in MATLAB to estimate the parameters for these equations from the 1986-1993 data set. The results in Figure 3.4 demonstrate that the second equation was the best fit for the data.

We then used these parameters to predict height growth for years 1996-2007, our other longest fire free interval. Figure 3.5 shows the actual average heights for three resprout species for the years 1996-2007 and the predicted heights for those years using each of the above equations. Here the annual rainfall at LAX from 1996-2007 was



Figure 3.5: Projected height of *Ceanothus spinosus*, *Malosma laurina* and *Rhus ovata* for 1997-2006

input w. Based on the residual sum of squares for each equation we confirmed that the inverse time relationship best modeled the height differences. Thus, we used

$$\Delta h(w,t) = \frac{aw}{t} \tag{1}$$

to determine the height of a shrub.

We used the curve fitting tool in Matlab to find the parameters that best fit our data. However, when generating plants in our simulation it would not be realistic to give each plant of the same species the same growth parameters. In order to accurately model the randomness in growth patterns we assumed that the growth curves were distributed normally. The growth parameters we found for each species serve as the mean of the normal distribution. In order to find the standard deviation for a given species, we organized the data from 1985-1993 by year and found the standard deviation in height and crown diameter for a given species, counting seedlings and resprouts separately, in a given year. Then we found the standard deviation for a species and plotted the height and crown averages along with the averages with standard deviation added to each point, and with standard deviation subtracted from each point. Then we found the parameters that would best fit the inverse growth curve to the plots of the averages with standard deviation added and subtracted. We compared the original parameter



Figure 3.6: A plot demonstrating the process of finding standard deviation for the growth parameters for Mlr.

with the parameter of the curve fitted to the standard deviation data and used this information to obtain the standard deviation in the parameter. An example of these plots is provided in Figure 3.6.

Since average height and average crown are linearly correlated, we chose to use (1) for both the height and crown diameter of each plant. Generating the parameters for height and crown diameter independently, we used our growth curve models to generate 1000 plants of each species and grew them for 8 years. We took the yearly averages of height and crown diameter and found that the correlation was consistent with the averages of our data. (See Figure 3.7.) For this reason we chose to generate the parameters for height and crown size independently for individual plants.

4 Survivorship

Our data on survivorship consists of the number of seedlings or resprouts of a given species taken approximately a year apart from 1985 to 1993. After a fire, many seedlings and resprouts appear, but some will die due to a combination of crowding, competition,



Figure 3.7: Correlation of average height and average crown in simulated plants.

and drought. Because of the crowding effect, the number of plants in a given year affects the number that die before the next year's data collection. Based on this assumption, Lucas et. al. found that a discrete logistic decay curve best fit the Cms and Csr data, and a discrete Gompertz curve best fit the Css data[18]. We plotted the percentage of seedlings that survived over time starting in the year after the 1985 fire with the annual rainfall corresponding to those years in Figure 4.1, and noticed that dips in rainfall correspond to drops in survivorship.

We experimented with various methods for altering the logistic curve and Gompertz to take annual rainfall into account. We classified a year to be a year of normal rainfall if the annual rainfall fell within 4 inches of the average, which is approximately 12 inches as stated previously. If rainfall was above 16 inches we classified the year as one of abundant rain, and below 8 inches as a drought. We tried varying the carrying capacity and decay rate and used the optimization toolbox in Matlab to test the variations against our data. The result with the lowest residual sum of squares for *Cms* and *Csr* was the modified logistic equation

$$Y_{i} = Y_{i-1} + aY_{i-1} \left(1 - \frac{Y_{i-1}}{Y_{0}(k+b)} \right).$$
⁽²⁾



Figure 4.1: Annual rainfall and seedling survivorship for *Ceanothus megacarpus* and *Ceanothus spinosus* from 1985-1993.

Due to the large drop in seedling population, the modified Gompertz equation

$$Y_{i} = Y_{i-1} \left(\frac{Y_{i-1}}{Y_{0}(k+b)}\right)^{a}.$$
(3)

was the best fit. In both equations Y_i is the number of seedlings in year *i*, *a* is the rate of decay and *k* is the fractional carrying capacity. The parameter *b* alters the carrying capacity based on rainfall such that b < 0 when rainfall is less than 8 inches, b = 0 when rainfall is between 8 and 16 inches inclusive, and b > 0 when rainfall is greater than 16 inches. This model is based on the assumption that there are threshold numbers for which rainfall either adds to or subtracts from the carrying capacity. This model improves upon the original logistic decay and Gompertz models from [18] based on the residual sum of squares. Our parameter estimates for Cms, Csr and Css are

given in Table 4.1 with the corresponding residual sum of squares. A comparison of the survivorship models, (2) and (3), and the survivorship data from 1985-1993 for the same species is displayed in Figure 4.2.

Species	a	K	b	RSS
Cms	0.02	0.0929	0.05	86.25
Csr	0.0313	0.299	0.0887	29.59
Css	0.061	1.5471×10^{-5}	1.3229×10^{-5}	2544.67

Table 4.1: Estimated parameters for the survivorship models of Cms, Csr and Css with the corresponding residual sum of squares .



Figure 4.2: A comparison of the survivorship models (red) and the survivorship data (blue) from 1985-1993 for *Cms*, *Csr* and *Css*.

5 Fire Schedule

In our simulation we wished to create fire return intervals of varying sizes randomly to see how different regiments would affect our system. Initially we simulated the fire return intervals using a Poisson distribution,

$$f(k;\lambda) = \frac{\lambda^k e^{-\lambda}}{k!} \tag{4}$$

While Mandallaz et al. [19] suggests this is a useful predictor of wildfires, their methods are more conducive to predicting when fires will occur in a general area as opposed to a specific site. For the purpose of our simulation, we decided to explore further distributions to increase the flexibility of our interval selection. In [8], Johnson & Gutsell suggest the use of the Weilbull distribution,

$$f(x;\beta,\eta) = \frac{\beta}{\eta} \left(\frac{x}{\eta}\right)^{\beta-1} e^{(-x/\eta)^{\beta}},\tag{5}$$

in order to simulate fire return intervals.

The advantage of this distribution is that it incorporates a shaping parameter β in addition to the scaling parameter η (analogous to the mean λ of the Homogeneous Poisson distribution). The shaping parameter β can drastically change the behavior of our system. While $0 < \beta < 1$ the hazard rate (in our case, the likelihood of a fire occurring) decreases as time goes on which is used to model infant mortality rate. $\beta = 1$ represents a constant hazard rate and is equivalent to the exponential distribution. In the final case, $\beta > 1$, we see an increasing hazard rate which indicates an aging or wearing out of the system. This behavior describes the assumption that fuel build up over time increases the likelihood of fire occurrence. An iterative method for estimating the parameters of the Weibull distribution can be found in [2]. Unfortunately, the data needed to appropriately estimate any parameters for our site is difficult to acquire. Due to the fact that the time between wildfires can range from 6-35 years in the SMM, a sufficient supply of data points could take centuries to gather. Regardless of this hindrance, we can vary the parameters to show how different fire schedules can effect the long term population of the chaparral plants across the SMM.

6 Spatial Simulation

Our simulation models plants as individual agents that grow, reproduce, resprout and interact with the surrounding plants according to the rules described in Figures 1.2, 1.3 and 1.4. The primary class we use is the plant class which stores all relevant information



Figure 6.1: An example of a simulated plant with four distinct radii.

including the height, crown size, location, age, and species of each individual plant. This allows us to generate multiple plants with properties that are independent of the other plants. Each plant's shape is composed of four directional crown radii so that plants can impede the growth of other plants as they push against one another. If there is any overlap with adjacent plants the appropriate directional crown radius is shortened, resulting in deformed ellipses as seen in Figure 6.1. In our display we represent the different species by their color and correlate height with the shade of each plant making them darker as they get taller. In addition, we indicate resprouts by white outlines while seedlings are given black outlines. Figure 6.2 shows a snapshot of our simulated study site.

These plants are stored in a class called the plant grid which is the visible space we use to display our plants. We have distributed poles evenly throughout our plant grid and store the location of nearby plants at each pole. Each plant uniquely belongs to one pole. As plants grow we use a collision function to determine the amount of overlap between nearby plants and the negative effect on each plant's crown growth. Indexing the plants to local poles increases the efficiency of our collision function. Rather than check every plant against every other plant on the grid, we can simply check each plant



Figure 6.2: A 40×20 plant grid with randomly generated plants. The species of each shrub is represented by color (Green corresponds to *M. Laurina*, purple to *R. Ovata*, blue to *C. Spinosus*, red to *C. Megacarpus*) with a white outline for resprouts and a black outline for seedlings. The shade of each shrub is determined by the height so that darker shades correspond to taller shrubs.

against other plants at its own pole and adjacent poles. The plant grid is responsible for creating new plants, calling the grow function for each plant and determining which seedlings and resprouts should be removed from our system due to crowding or other factors.

The final class we use in our simulation is the seed bank. This class has no visual representation but is a cloud of information that holds the location of seeds deposited by the plants in our plant grid and adds these seeds back to the plant grid after germination occurs. The seeds are dropped annually by each plant and then added to the plant grid. The distance of each seed from the plant is distributed exponentially such that 35% of the seeds are contained within the crown's area [6]. The angle of each seed is distributed uniformly over $[0, 2\pi]$. Figure 6.3 shows the distribution of seeds from an individual plant.

At the beginning of each simulation we load a species list with a corresponding relative density array which determines which plants we will use and how many of each we will include in the initial set up. We also generate our intended fire schedule and create a rainfall schedule which then are used to make our survivorship matrix. Given these inputs, we proceed to simulate a year of events. If the fire schedule dictates that



Figure 6.3: Two views of the same plant's crown and where its seeds have been dropped after one dispersal, zoomed out (left) and zoomed in (right). Distances for each seed are drawn from an exponential distribution such that 35% of the seeds are contained within the crown's area. The angle of each seed is distributed uniformly over $[0, 2\pi]$

a fire occurs in a particular year we burn the non-sprouters, reset the resprouters, and germinate seeds from our seed bank. If it is a non-fire year then we remove some of the seeds from the seed bank under the assumption that predators have come through and eaten them. At this point in the simulation we remove burned non-sprouters and check the collision of our plants and remove them if there is any excessive collision due to overcrowding. Finally, we allow the plants to grow while applying impediments due to collision and move on to the next year.

7 Results

We present many different simulations using the spatial model presented above with varying rainfall and fire return intervals. In particular, we varied the scaling parameter η of the Weibull distribution to resemble the mean fire return interval in our study site versus a longer mean more representative of fire return intervals in the Santa Monica Mountains. Also, we wanted to see how different levels of rainfall would affect the plant growth and plant survivorship. Of particular interest was how *Ceanothus megacarpus* (*Cm*), the only nonsprouter species in our site, compared to the facultative sprouters *Malosma laurina* (*Ml*), *Ceanothus Spinosus* (*Cs*) and *Rhus Ovata* (*Ro*).

Figure 7.1 contrasts how Ml and Cm react to frequent wildfires. We generated



Figure 7.1: Simulation of *Malosma laurina* (top) versus *Ceanothus megacarpus* (bottom) with an average fire return interval of 6 years and average rainfall of 12.02 inches.

a fire schedule using the Weibull distribution 6 year mean and shaping parameter $\beta = 5$. This fire schedule gave us fires in years 1, 7, 12, 21 and 25. Using the long term annual rainfall average determined from data collected at the Los Angeles International Airport, we set annual rain to be constant at 12.02[3]. Because Ml is a facultative sprouter, it resprouts after each fire and each of those resprouts has a 99% chance of survival. The seedlings of Ml, however, only have a 1% chance of survival. By the end of the simulation, Ml resprouts survived the frequent fire return intervals and the grid was still dense, as expected. Cm on the other hand is a nonsprouter and does not resprout after fire. The only way Cm reproduces is by dropping seeds that are then germinated by fire cues. However, the plant needs six years to mature before it can drop seeds, and if a fire comes before the plant is able to mature, as it did in year 12, the plant cannot reproduce and thus becomes extinct. In Figure 7.1 it is clear Cm became extinct by year 12, as expected.

Compare Figure 7.1 with Figure 7.2 where we ran a fixed fire schedule with fire occurring at time 0 and time 20. In this simulation Cm survived through the fire at time 20 because each plant had enough time to mature and drop seeds. This simulation demonstrates the importance of longer fire return intervals for the Cm chaparral species.

Using the same fire schedules, one with the 6 year mean and the other with fire occurring every 20 years, we ran the simulation with Cm, Cs, Ml and Ro together in one



Figure 7.2: Simulation of *Malosma laurina* (top) versus *Ceanothus megacarpus* (bottom) with an average fire return interval of 20 years and average rainfall of 12.02 inches.

grid, shown in Figure 7.3. In each simulation we set rain as a constant average value of 12.02 inches. When setting up the initial random plant grid for year 0, the distribution of plants was determined by using the densities for each plant species found at our site in 1985. When fire occurs more frequently Cm is completely eliminated, as expected, but in addition plant survivorship and growth are clearly effected. Because the shrubs from the infrequent fire simulation had more time to grow in between fires, they are taller than the shrubs from the frequent fire simulation. Recall that the height is given by the shade of each shrub. The simulation with frequent fires becomes much more sparse than the simulation with infrequent fires.

Also of concern was how differences in rain would affect the outcome of the simulations. Recall that the growth of both height and crown are proportional to the annual rainfall as given by (1) and survivorship of seedlings and resprouts depends on rainfall by equations (2) and (3). Figure 7.4 shows simulations with varying rainfall and an average fire return interval of 6 years. The first simulation was given a constant annual rainfall of 5 inches to simulate drought, the second was given average rainfall, and the third was given a constant annual rainfall of 19 inches to simulate heavy rainfall. In the simulation with light rain the plants do not grow very tall or very large and the grid is very sparse. In contrast, the simulation with heavy rainfall yielded very tall and large plants and a dense plant grid.



Figure 7.3: Simulation of *Ceanothus megacarpus* (red), *Malosma laurina* (green), *Ceanothus Spinosus* (blue) and *Rhus Ovata* (purple) with a 6 year (left) and 20 year (right) fire return average and an average annual rainfall of 12.02 inches

In order to validate our model, we simulated our study site from 1985-2012 and used the annual rainfall data for each year taken from the Los Angeles International Airport along with a fire schedule that included the fires in 1985, 1993, 1996 and 2007 that burned our study site in Malibu. Figure 7.5 shows the results of the simulation. Because there was a fire in 1993 and 1996 Cm became completely eliminated from our study site, and the same was shown in our simulation. Table 7.1 shows the density of each species found in both 1985 and 2012 at our site and the average density of each species over 1000 simulations.

Finally, we simulated the long term effects of frequent wildfire as shown in Figure 7.6. We generated a 60 year fire schedule with the scaling parameter of the Weibull distribution $\eta = 6$ and the shaping parameter $\beta = 5$. This generated fires in years 1, 5, 9, 16, 20, 25, 32, 38, 44, 47, 50 and 57. Again we distributed our initial plants with the densities found given by our 1985 data, and we kept annual rainfall constant throughout the simulation at 12.02 inches. In the initial plant setup the shrubs covered 75.4% of the total plant grid. However, by the end of the 60 year simulation the plants covered only 8.74% of the total plant grid. This simulation has implications for the long-term effects of frequent wildfire on chaparral shrub communities.



Figure 7.4: Simulation of *Ceanothus megacarpus* (red), *Malosma laurina* (green), *Ceanothus Spinosus* (blue) and *Rhus Ovata* (purple) with an average annual rainfall of 5 (top), 12 (middle) and 19 (bottom) inches/year.



Figure 7.5: A simulation of *Ceanothus megacarpus* (red), *Malosma laurina* (green), *Ceanothus Spinosus* (blue) and *Rhus Ovata* (purple) with actual fire schedule and annual rainfall from our study site from 1985-2012.

	Density	1985	Density	2012
Species	real	simulation	real	simulation
Cm	.179	.170	0	0
Cs	.260	.240	.11	.150
Ml	.374	.380	.624	.550
Ro	.187	.210	.266	.310

Table 7.1: Density of *Ceanothus megacarpus*, *Malosma laurina*, *Ceanothus Spinosus* and *Rhus Ovata* at Malibu study site in 1985 and 2012 and the average density from 1000 simulations.



Figure 7.6: 60 year simulation of *Ceanothus megacarpus* (red), *Malosma laurina* (green), *Ceanothus Spinosus* (blue) and *Rhus Ovata* (purple) with an average fire return interval of 6 years and an average annual rainfall of 12.02 inches.

8 Future Work

In the future we would like to incorporate a few more factors to make our model more realistic. The first is a more realistic rain schedule that approximates the conditions at our site more accurately. Our simulations either incorporate a constant rain schedule or use the LAX rain data from 1985-2012. This will change how our survivorship parameters are generated as well as affect the growth of each of our plants. In addition to the crown growth we would also like to include a basal diameter for each plant. We would like to explore a possible correlation between the basal diameter and the other growth parameters of our plants, but this may be difficult given the inconsistencies in the measurements. Including the basal diameter should yield the ability to leave burnt stumps in our plant grid that would stop seeds from growing in the space they occupy. We were unable to incorporate obligate sprouters in our model due to the lack of data on this type of plant, but we would like to include obligate sprouters in the future in order to bring more plant diversity to our simulations. Additionally, we want to make seed dispersal strategies take into account the different species types, as well as the height and crowns of the individual plants. We also plan on verifying our assumptions on the actual effect of collisions and determining the conditions upon which a plant is removed due to overcrowding. Finally, we would like to consider how to model invasion by exotic species and how it affects the surrounding plant-life and fire frequency.

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