Monte Carlo Simulations of Wildfires and Afforestation*

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Wildfires are currently ravaging all across California as I am writing this paper. Climate change will only exacerbate the devastation brought by wildfires. Each year climate change is responsible for roughly doubling the total area burned in Western N. American forests. To combat the fire we present a monte carlo method of simulating wildfire spread, packed into a landscape model. Combining the two we present our Landscape Fire Succession Model (LFSM). We bring in real world physical representations to accurately describe the spread of fire and the evolution of our landscape. In our simulations we observed two equilibrium. A stable oscillation between two plant species and an unstable oscillation between a burned state and a single recovery plant state. We motivate and describe areas of improvement as well as present the code created to run the simulations.

I. INTRODUCTION

A. Motivation

Wildfires throughout the centuries have ravaged wildlife, whether caused by man or nature. The devastation and destruction ripple through the coming decades in the aftermath. Especially in California, where each year we see the fiery blaze cascade through the country side. Unfortunately, wildfires will not go away in the coming decade. Wildfires are only exacerbated by climate change. In the last thirty years Abatzoglou et al found that climate change has nearly doubled the area of wildlife burned in Western N. American forests [1]. In order to preserve the wildlife and prevent the desolation of our structures we must first understand our enemy. Once we can visualize and anticipate the spread of fire in wildfires we can inform our response teams to efficiently mitigate key choke points in wildfires. This motivates our work in this paper, the core belief that modeling the spread of wildfires will provide key insight to the fire response teams and civilians in danger.

B. Background

Wildfire modeling and prevention have been studied for decades. Scott found the key parameters that determined the spread of wildfire was based off of various parameters such as fuel structure, wind, landscape characteristics and weather. params

Scott's parameters drove our search for what models would accurately describe our probability in our simulations. We see from Fig 1. that the dominant metrics

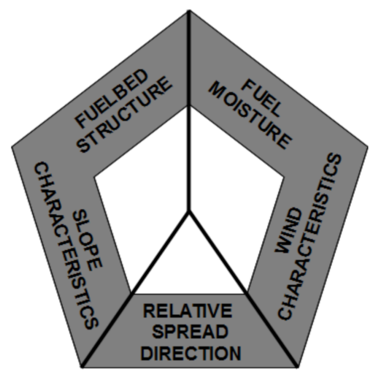

FIG. 1. The five major components to Scott's[2] fire spreading model. We toss these terms into a single component of our Fire spreading term.

for fire spread are Landscape, Fuel type, Moisture, and wind.

C. Landscape, Fire, Response, and Recovery

In order to fully address the complexity of our problem we broke down our system into four key components. Landscape and forest distributions, The outbreak of wildfire in those landscapes, the human response to cull the fires and finally the recovery of the forest as it evolves over time. These key features is what drove each aspect of our model. The Landscape and recovery tackled by Arthofer in her paper, Where I analyzed the spread and outbreak of wildfires with the associated human response. Together we were able to create a model of western N. American forests that ties in all the fundamental principals laid out in the literature. We present a cohesive framework with much needed improvement and fine-tuning to analyze the devastation of wildfires in California and the anticipated recovery of them in the coming decades.

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II. METHODS

Here we lay the framework of our model, describing where each part comes from and how it fits into the bigger picture.

A. MED-Spread

Thanks to the work by the MED-LMD group[3] we have found a tried and true tested method for a stochastic determination of the probability of fire spreading to its surroundings. We present a modified version of their MED-spread model[3]

$$\xi = W_f * F + W_m * M + W_w * W + W_e * E \qquad (1)$$

where,

F = fuel load of species in the area ($tons/km^2$)
M = Moisture content of the area (Moisture Index)
W = Wind speed in the area (km/s)
E = Elevation of the area (km above sea-level)
W_i = weight term of each parameter
where we have defined the probability of ignition (P_i) as

$$P_i = (1 - e^{-\xi})^{Intensity} \qquad (2)$$

Where Intensity is a random float between 0 and 2. The stochasticity of this parameter provides us with an appropriate degree of randomness of fire spreading. The parameter is simply a 50/50 shot at either increasing or decreasing the probability of ignition.

B. Fighting the Fire

We wanted our response to be quick but initially delayed until some critical amount of fire has erupted. Thus we simply needed a delayed switch. To do this we set some maximum number of response teams. In our simulations we use $N_{MAX} = 25$, meaning the teams can cover at total of .25 km^2 and only 1% of the forest. The switch we came up with is a simple polynomial that when N_{MAX} is reached they stay until the fire is over.

$$N_{WRT} = \sum_{i=0}^{D} k_i * (R_L)^i \qquad (3)$$

for our study we have simply set $k_0 = 0$ and $k_i = 10^{-i}$, With D = 3. We have set the response team probability of extinguishing (P_{ex}) a fire. Where,

$$P_{ex} = \frac{1}{3} \qquad (4)$$

To improve our model, we would need a better understanding of the maximum capabilities and response times for fighters in these situations. Once we have a better grasp on these parameters we can implement meaningful knowledge into the response teams. Nonetheless, simple and straight forward approximations yield intriguing results.

C. Discretization

We decided on a 50 x 50 grid due to our computing restraints. Our forest is comprised of 2500 100m x 100m Nodes. To initialize we feed in some initial distribution then randomly place each species into a node. Where they are considered to dominate that area. So any properties of the node will be assumed to be solely dependent on the species that is placed there.

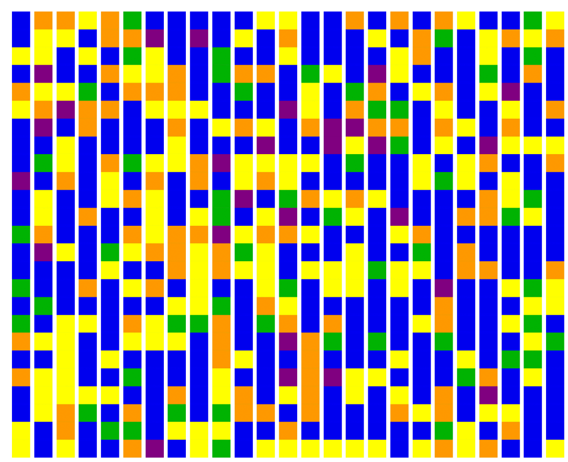

FIG. 2. 25x25 Grid color representation of our forest. Each color represents a different species of plant. The scale of this figure is a quarter of what we use in our simulations.

Figure 2. Gives a colorful visualization of what our forest looks like. Where each color is a different species. Each node as eight neighbors where if set on fire can spread to those eight neighbors. Known as the queen's case, we see a clear representation in Fig. 3 of what is happening as a node is set on fire.

This simplified model for determining neighbors works efficiently and effectively, however ignores a crucial aspect of the physics, wind. In future iterations of this model we hope to implement wind direction as a key parameter to determine the possible spread neighbors.

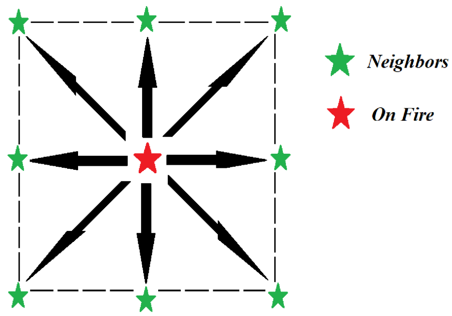

FIG. 3. The queen's case. In order to determine what nodes can be set on fire, we simply use this case. A node can only spread to its 8 neighbors.

III. RESULTS

In this section we present the our model in various forms, a simple analysis of the species of plants when they dominate a entire forest, along with the impact of biodiversity. From there we move on to the pice de rsistance our time series simulations

A. Percentage Burned of Various Wildlife Distributions

We first set out to determine the relative intensity of fires and what they were going to do to forest. We only used the fuel load of each species, given in my collaborator's (Arthofer) paper. In table 1. the order is in descending fuel load, Ranging from 32.1 tons/Node to 8.64 tons/Node. We weighted this parameter with $W_F = .05$. Where dominated means that the forest is comprised of 80% Dominated and 5% for each other species. Mixed is equal distributions of each species (20%). We used 60/40 Deciduous/Pine split due to our findings from our time series analysis.

Table 1. Wildfire Simulations N=100

Percentage Burned		
Dominant Species	MEAN	σ
Shrubland	79.124	2.4897
Pine	19.802	12.548
Transition	25.932	17.681
Deciduous	26.988	17.931
Oak	26.632	17.476
Mixed	21.942	11.064
Pine & Deciduous	26.963	16.853

We see that due to the high fuel load of Shrubland, almost all of the 80% is burned in each simulation. Oak and Deciduous are nearly identical due to their fuel load being identical. Further analysis is left to the discussion section.

B. Time Series Simulation

We first sought out to analyze how a forest is impacted by a wildfire and how it will recover in the coming years. Here we present a few 500 year simulations of various scenarios in hopes of gaining insight to what the future my hold. Our initial distributions remained the same throughout each simulation.

Table 2. Intial Conditions D_0

50 x 50 ; N = 2500		
Species	Count	Percent
Shrubland	500	20
Pine	250	10
Transition	500	20
Deciduous	250	10
Oak	1000	40

We also used $W_F = .05$, $P_{ex} = \frac{1}{3}$, $k_0 = 0$ and $k_i = 10^{-i}$, with D = 3. We did not include any information about the wind, elevation , or moisture. Due to time restraints.

1. No Fire

Our base case, a simple glimpse to how the landscape model provided by (Arthofer , 2017) evolves over the course of 500 years.

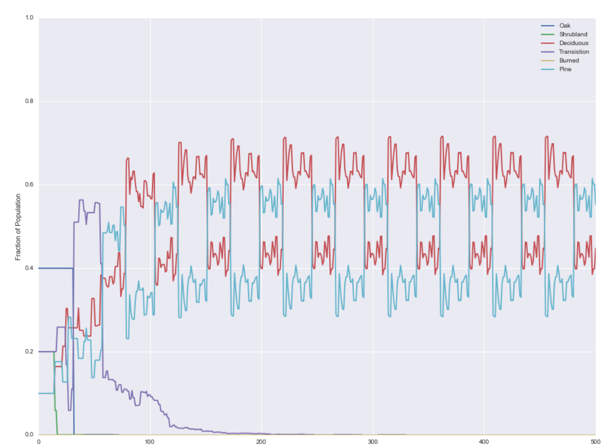

FIG. 4. Time series analysis of Arthofer landscape model. Initial conditions were given by Table 2. and other parameters are unchanged.

Due to the deterministic nature of the model, which forces a transition to a new species, and cannot recover from extinction. We are left with an alternating forest. A forest that switches between dominated by deciduous to being roughly split between deciduous and pine.

2. *Single Outbreak*

A single catastrophic fire rages on (W_F was adjusted to ensure a large area was burned) Yielding Fig. 5

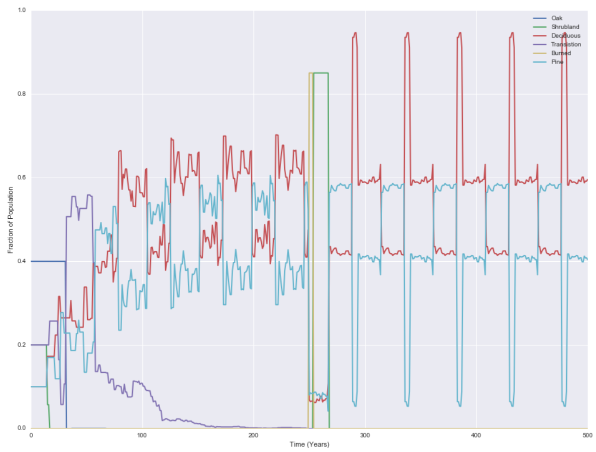

FIG. 5. Time series analysis of over 500 years with initial conditions given by Table 2. We have set a wildfire to occur at 250 years, and to decimate the landscape. We adjusted W_F to accomplish this. We see that roughly 85% of the landscape was burned. After the shrubland has recovered and transitioned to pine or deciduous we see a shift in the oscillating states.

We see that the fire was initiated at 250 years, where roughly 85% of the landscape was burned. Three years later providing the shrubland growth we see. Then due to pines and deciduous being the only species left, the landscape once again oscillates violently between the two species and two distinct states.

3. *Centennial*

The hundred year fires, using the same initial conditions and parameters we simulated our system with wildfires currently every 100 years over the 500 year span we are currently analyzing.

Just as in the single wildfire case we see similar behavior of oscillating between two states of pine and deciduous. Where the wildfire is simply modifying the two states we see.

4. *Quarter-Centennial*

The fire is heating up, using the same initial conditions laid out in Table 2. with the same parameters we set the forest ablaze every 25 years. As seen in Fig 7.

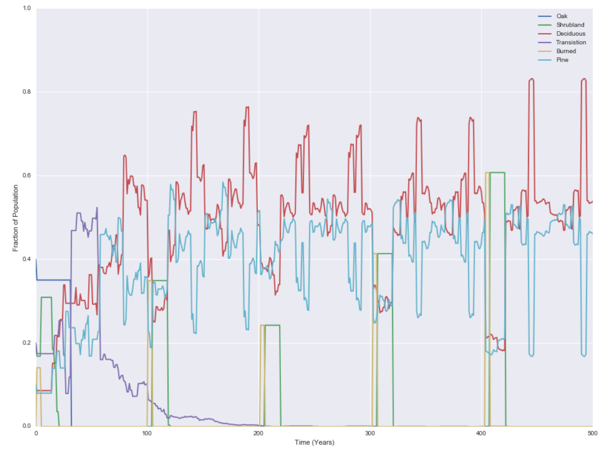

FIG. 6. A Time Series Simulation using the same initial conditions laid out in Table 2. With the same parameters we set the ignite the forest every 100 years. As we have seen before, the system oscillates between two states with two dominant species; Pine and deciduous. Where the wildfire simply shifts the states to a new distribution

FIG. 7. A Time Series Simulation using the same initial conditions laid out in Table 2. With the same parameters we set the ignite the forest every 25 years. As we have seen before, the system oscillates between two states with two dominant species; Pine and deciduous. Where the wildfire simply shifts the states to a new distribution

Because the wildfires occurred at a slower pace than the time it took shrubland to transition into pine or deciduous we observe the same behavior as before.

5. *Decades of Hell*

Here we dive into the dynamical behavior, as the wildfires now occur with some residual shrub land creating an interesting effect.

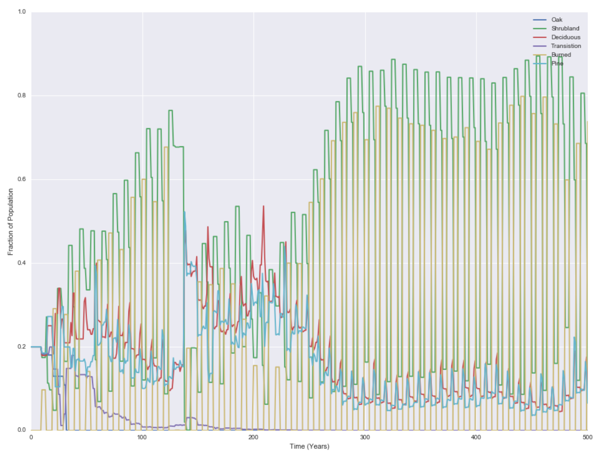

FIG. 8. A Time Series Simulation using the same initial conditions laid out in Table 2. With the same parameters we set the ignite the forest every 10 years. We ran our simulation for only 500 years to converge our system to the shrubland-burned equilbrium

The key feature of Fig 8. is that the area burned after each wildfire is going up. We see that this is strictly tied to shrubland being the only species able to recover in a burned area. While at the same time having the largest fuel load.

IV. DISCUSSION

He we provide a foundation for discussing our results and where our model can take us. We analyze our results, metrics, validity of our parameters and the sensitivity our model has to each parameter.

A. Time Series Analysis

The equilibrium state is highly stochastic but does indeed exist in the landscape model. As we clearly see in Fig. 4, 5 and 6. Nonetheless this is strictly a result of the determination of transitions in the model. We see that pine and deciduous dominate, the landscape and will eventually oscillate between each other. The stochasticity of these states is easily seen in Fig 6. Where the wildfire shifts the distributions, yielding new oscillatory states. The interesting dynamical behavior was encapsulated into Fig 8. where the shrubland did not fully transition before the next fire occurred. We see a snake that eats its own tail. As the fires burn down the forest each year, more shrubs rise from the soil. Shrubland has the highest probability of being ignited. Meaning we would expect over long periods of time for the system to push itself to the extreme state of shrubland - burned oscillation's. This observations provides us with some insight to why wildfires have been growing in size over the past decades when climate change is removed. Our model shows that in particularly at risk forests can be burned more and more each year. Throwing climate change into this effect, the result is disastrous, as we would expect the overall probability of spreading would increase along with the occurrence of wildfires, accelerating the approach to the extreme shrubland-burned state.

B. Metrics

For our data collection we simply used the raw count. However, there are clearly other metrics that have eluded us. For example we could track the transitions of each node, analyze on a micro scale how a single node interacts and evolves in various distributions. This metric would provide insight to why our oaks disappear rapidly, though it is not an error. More of a misstep in the determination of how each node transitions. We could also analyze the path of the wild fires tracking the initial 8 possible spread locations, the beauty of our model is simulating these occurrences to determine the best possible routes for response teams. We could analyze the landscape and provide real time response to the best course of action, to what nodes should be extinguished, efficiently limiting in the spread of the wildfires.

C. Accuracy of Parameters

The level rigour of our parameters is simply not there. We initially sought to fit the parameters to a data set that recorded the total area burned, doing a simple least squares non-linear search for the optimal parameters. If the time allowed for such a search we would have accomplished it. So we leave it to the future work of the model[4].

D. Parameter Sensitivity

Each parameter contains a vast amount of information, in doing so we have inherently put our model at some risk of instability. Consider W_F which scales our fuel term inside an exponential. There is a very small domain for ξ to retain any tractable information for the system. If we were to shift ξ to 0 or simply a larger value than 10 we see the two extremes. Thus W_F we must handle the weighting of our ignition terms very carefully. k_i does not have a similar level of sensitivity, it only acts as a switch to N_{MAX}. Where we might expect N_{MAX} to also be a sensitive parameter. Of course have only hand waved our explanation, in order to describe in rigour we must run the simulations in Table 1. across the vast array of our parameter space.

V. CONCLUSION

Wildfires are only going to get worse in the coming decades due to climate change. We cannot efficiently limit the affect of climate change on such a small scale. Thus we must look to other avenues of persevering wildlife and protecting civilians. We presented a robust framework for modeling the spread of wildfires with insight into the physical system we are analyzing. We also present a simplified model of the fire fighting force with a significant need for improvement. We combine our efforts to analyze a single system over many five centuries. Noting the key equilibrium being an oscillation between two species. Either in a stable case where we oscillate between two plant species. The other being an unstable* configuration where the system oscillates between a single plant and a burned state. This provides some explanation as to why the area of burned forests have been growing even when climate change is accounted for. This also demonstrates the need for quick and swift action to preserve our wild life before we reach the unstable equilibrium. The rigour in the determination of our parameters is missing. However, this provides us with an area that can be improved upon greatly. We can shift our model to real world data, encompassing topographic maps, weather data and a climate change model. Not only will this provide a greater level of detail in our system, it will also limit the sensitivity of some of our key parameters. Bringing Fire, Landscape, Human Response and some math together we can save the planet.

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