Earth/Climate 410

Lab #1: Wildfire/Disease Simulation Model

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Introduction

Wildfires have been rapidly spreading throughout the Canadian region over the course of summer. Modeling the progression of wildfire spread is critical in predicting the areas under the most amount of risk and acting accordingly. When creating a model such as this one, it is important to consider factors that impact the spread of wildfires. For example, the initial amount of forested or vegetated areas (burnable) compared to barren areas (unburnable) is a major factor– areas that cannot sustain wildfire will dictate the areas into which it spreads. Additionally, because wildfires do not automatically and spontaneously spread into all adjacent areas, another component to consider in this model is the probability of wildfire propagation into adjacent areas. This model aims to quantify how wildfire spread is impacted by initial forested areas as well as the rate and probability of wildfire transmission into new areas.

The logic behind most aspects of this wildfire model may be applied into new areas, such as the spreading of infectious diseases. The probability of a disease spreading from one individual to the next would be analogous to the chance of a wildfire spreading into the adjacent region, and a vaccinated individual (or someone who has become infected and recovered) would parallel the barren areas during wildfire propagation. The modeling of infectious disease spreading has become remarkably relevant in recent years; a model such as this one will be aiming to quantify how immune individuals (either due to a vaccine or recovery from infection) impact the transmission of disease.

Methodology

In order to model the progression of wildfire spread, an arbitrary amount of land can be divided into square kilometer grid tiles. Each grid tile can then have a different status (where 1 = barren, 2 = forested, and 3 = burning), and spread may be modeled among the tiles. Therefore, the first step here is to create an initial integer array of zeros and add 2 to each zero value. Doing this creates an array where each “tile” has the value (or status) of 2– a forested tile. This initial array is three dimensional, where two dimensions are left/right (nx) and up/down (ny), and the third dimension is time (nstep).

One scenario is used as a simple proof of concept– an area of 9 square kilometers (3x3 grid) with the center tile on fire, a 100% chance of fire spreading, and a 0% chance of initial bare tiles. The center tile is set on fire initially at nstep = 0 (initial time step) at the width and height dimensions divided by two (the center). An initial color map is created to match with the initial forest array, where each status is equivalent to a different color on the plot.

To model the spread of the fire, several “for” loops are used and nested within each other. The largest loop is the time loop, the next loop is the “nx” loop (horizontal), and the smallest loop is the “ny” loop. Within the smallest loop, there are several “if” statements. The code begins by asking whether there are any tiles in the forest array at the previous iteration that have any burning tiles. Because this is in the smallest loop, the code is checking for burning squares over one column for different “ny” values. If yes, and if the burning tile is not on the very left edge of the plot, the square has a chance of burning to the left and gains a barren status. The same logic follows for the fire to burn to the right, up, and down. After this, the code checks for burning squares for different “ny” values over a new column. Once every tile has been checked and after any spreading events occur, the time loop means that the code moves to the next time step and the loops repeat until either the number of iterations has been reached or there are no more burning squares.

This proof of concept is shown below (Figure M1). The code shows capacity working at edge cases, and the burning tile spreads as expected.

A graph of a forest status

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A green and red rectangle with numbers

Description automatically generated

A graph of a forest status

Description automatically generatedA graph with red squares and a tan cross

Description automatically generated

**Figure M1.** Proof of Concept for Wildfire Model on 3x3 Array. *The wildfire simulation model was run on a 3x3 array with the wildfire starting tile in the middle of the array. The wildfire can be seen spreading as anticipated at each time step.*

Additionally, the code was tested for cases where the initial grid is wider than it is tall (Figure M2). Once again, the code shows competency at working with a grid of these dimensions.

A green and red graph

Description automatically generated A graph with red squares and green squares

Description automatically generatedA graph of a forest status

Description automatically generated

A graph with red and green squares

Description automatically generatedA graph with a red and green bar

Description automatically generatedA graph with a red square

Description automatically generated

A graph of a forest status

Description automatically generated

**Figure M2.** Testing the Proof of Concept on Wide Array. *The proof of concept is successfully tested on an array that is wider than it is tall.*

After the proof of concept was established, other features were added to enable the answering of critical scientific questions. For example, preceding the nested “for” loops is where many of the probability calculations take place. For example, the chance that a tile starts on fire is determined by picking a random value from the “ny” to “nx” range. If this value is less than the “p\_start” probability, the status of that given tile changes to burning. This same logic is applied to setting the probability of any given square having a barren status when the simulation starts. The number of initial bare tiles is counted by asking the computer how many of the tiles at the initial time step have the status of barren and then summing them all up to get a total value. This method is also used to count the initial number of forested tiles to calculate initial forest density.

The number of spread events, or the number of times any tile on fire caught another tile on fire, was calculated by setting a variable “jump” equal to zero. For every time that a new tile gained the status of burning, the counter “jump” was increased by one. The rate of land burning (or rate that fire was spread) was measured by calculating the difference between the number of bare tiles at the start and end of the simulation, and then dividing it by the number of time units. The number of fatalities was calculated by summing up the total number of tiles at the end of the simulation that had the status of deceased. The number of fire or disease jumps, the rate of land burning (or the rate that disease was spreading), and the number of fatalities were the three main ways that spread in this simulation were quantified. Some example simulation outputs are included in the Supplemental Information section.

Results

To determine how the spread of wildfire depends on the probability of fire spreading to a neighboring region and the initial forest density, two separate experiments were performed. In the first experiment, the probability that fire would spread to an adjacent region (p\_burn) was varied over the course of several trials from [0,1] while other parameters were held constant (nstep = 300, ny = 100, nx = 100, p\_bare = 0.2, p\_start = 0.001, p\_fatal = 0.0). Trials were incremented by 0.1 with 3 total trials for each p\_burn value. The value of p\_burn and its impact on the rate of land burning as well as the number of times a fire spread event occurred were graphed respectively in Excel (Figure R1, Figure R2).

**Figure R1.** Rate of Spread vs “p\_burn”. *A plot detailing how changing the probability of the next region burning impacts the rate of land becoming barren.*

From this plot, it is clear that as the probability increases that the next region will be affected from fire spread (“p\_burn”), the rate of spread (defined as the area of land burned in one unit of time) increases. This trendline tracks with intuition—if the probability that fire will spread is higher, it follows that fire will spread more rapidly. Notably, there is a significant outlier when p\_burn is equal to zero. The rate of spread is artificially increased simply due to how rate of spread is defined; it is calculated by taking the difference between the number of initial and ending barren tiles and dividing them by the number of time units (days) it took for the wildfire to stop progressing. When p\_burn is equal to 0, the initial tiles that are on fire immediately become barren in the next time interval, giving the impression that many square kilometers of land became barren due to a high rate of spread. In reality, because there was no spread of fire, the trendline for this graph was given a set intercept of (0,0).

**Figure R2.** Number of Fire Jumps vs “p\_burn”. *A plot detailing how changing the probability of the next region burning impacts the number of times that fire spreads to the next region.*

From Figure R2, it is apparent that as p\_burn increases, the number of “fire jumps” (defined as the number of times a burning tile spread to a forested tile and changed its status to burning) increases with a polynomic trendline. Interestingly, the high R2 value indicates high confidence with this trendline shape. It is possible that the polynomic nature arises rather than linear due to the random nature of the initial tiles that are on fire. Sometimes an individual fire path is blocked by a strip of barren land—as the probability of fire spreading increases, this effect becomes more noticeable as more land becomes barren, causing the slope of the trendline to taper off at higher p\_burn values.

In this next experiment, to quantify how initial forest density impacts the spread of wildfires, several trials were performed where all parameters (nstep = 300, nx = ny = 100, p\_start = 0.001, p\_burn = 0.4, p\_fatal = 0.0) were held constant, and p\_bare was varied from [0,1]. The variable “p\_bare” is inversely proportional to the initial forest density—because “p\_bare” quantifies the probability that any individual tile begins with a barren status, a higher p\_bare value correlates to a lower initial forest density. The value of p\_burn and its impact on wildfire spreading is plotted below (Figure R3, Figure R4).

**Figure R3**. Rate of Spread vs Barren Probability. *A plot detailing how changing the probability of the tiles being initially bare impacts the rate of land becoming barren.*

Generally speaking, as the probability of initial bare regions increases, the rate of fire spread (defined as the area of land burned over the total amount of time) decreases. Some of the scatter in this plot is possibly due to the inherent random nature of how barren spots are generated and randomly block fire paths; however, while this makes the slope of the trendline more difficult to validate, the general trend of the rate decreasing with increasing p\_bare values holds true. The number of fire jumps was also plotted against the initial probability of barren regions (Figure R4).

**Figure R4.** Number of Fire Jumps vs Barren Probability. *A plot detailing how changing the probability of the tiles being initially bare impacts the number of times that fire spreads to the next region.*

This trend is more difficult to quantify. Generally speaking, it would appear that the number of times that fire spreads over the course of the simulation exponentially decreases with respect to the increasing probability of initial bare regions (decreasing forest density).

To model the spread of Buckeyeitis from one person to the next, the same code was used. To determine how disease mortality rate and early vaccination rates affect disease spread, it is important to know how these variables relate to the already established code for the wildfire. Disease mortality rate (p\_fatal)—the probability that any infected individual will perish—was added specifically for this simulation (p\_fatal = 0 for all wildfire simulations). Initial vaccination rates are equivalent to initial bare spots in a forest, so p\_bare is the variable modified for this trial. The effect of disease mortality rate on the spread of Buckeyeitis was modeled by holding all parameters constant (nstep = 300, ny = 100, nx = 100, p\_start = 0.001, p\_burn = 0.4, p\_bare = 0.2) except p\_fatal, which was varied from [0,1]. Similarly, the impact of initial vaccination rates was determined through this model by holding all parameters constant (see above, except p\_fatal = 0.1) while varying p\_bare from [0,1]. The results are plotted below (Figure R5, Figure R6).

**Figure R5.** Rate of Disease Spread vs Fatality Probability. *A plot showing how changing the probability that an individual will die from disease impacts the rate of infection spreading.*

As the probability of an infection-induced fatality increases, the average rate of infection (defined as the total number of tiles that gained the “infected” status divided by the total number of time periods in each trial) decreases relatively linearly. This intuitively makes sense, as a dead individual theoretically cannot pass on the disease. The rate of infection decreasing as fatality rate increases is likely due to the pathway that the disease takes—as individuals die, they become roadblocks for the disease in a similar way that vaccinated individuals do.

**Figure R6.** Rate of Disease Spread vs Initially Vaccinated Individuals. *A plot showing how changing the probability that an individual is initially vaccinated impacts the rate of infection spreading.*

The impact of initially vaccinated individuals on the number of individuals infected per unit of time is shown above (Figure R6). The number of infections per unit of time decreases as the fraction of initially vaccinated individuals increases. Initial vaccinations act as a “roadblock” to disease spreading events—increasing the number of these roadblocks means that there are fewer avenues for disease to spread from one individual to the next.

Discussion

The goal of this code was to model the progression of wildfire spread, and to then apply that logic to the spreading of infectious diseases (Buckeyeitis). The code was successful in modeling those forms of spread under the defined constraints. Importantly, this model is used to demonstrate how different factors impact the rate of wildfire or disease spread. Their effect, as well as the limitations of this model, will be analyzed.

The initial forest density of an arbitrary area undergoing a wildfire simulation understandably has an impact on the spread of wildfire. Having a higher probability of initial barren tiles results in a less destructive wildfire. As forest density increases (meaning that the probability of initial bare spots decreases), the simulated wildfire has a higher chance of having a far-reaching, unobstructed path to burn through. In the disease-spreading simulation, the probability p\_bare is analogous to the fraction of initially vaccinated individuals. The effect of increasing its value, similarly to the wildfire simulation, is that the number of people infected per day decreases with time. It can be concluded, then, that increasing the number of immune individuals (whether through past infection or due to vaccination) greatly drops the transmissibility of the dreaded Buckeyeitis disease. In both simulations, increasing p\_bare (therefore decreasing initial forest density in the wildfire context) should decrease the amount of spreading that is able to happen. This is true for both contexts, which creates confidence in this result.

The probability of wildfire spreading into adjacent regions was tested with this code. As seen in Figures R1 and R2, increasing this probability (p\_burn) causes more area to be burned with time and more fire spreading events occur. Once again, this intuitively makes sense—as a tile is more likely to be burned by a burning tile, more area will be burned. Based on the difference in slope magnitudes of the trendlines in Figures R1 and R3, it appears that the value of p\_burn has a much larger impact on the amount of area burned by a wildfire than the initial forest density (or the inverse of p\_bare) does. It stands to reason that the probability of the next region burning is more critical than initial forest density when evaluating factors that impact wildfire spread.

Though the trends analyzed in this report are generally true, there is a fair amount of scatter on some of the plots (see Figure R3, R4). This is likely largely due to the data collection process. Because each trial was individually run and its data was manually recorded in Excel, there was a reasonable limitation of how many trials could be run for each variable that was being tested. A reasonable next step for this model would be to create a function that ran the simulation several times and plotted key results—having more easily accessible data in this way would likely reduce the amount of scatter on the plots. Another additional step that could be taken in regard to the wildfire progression analysis is tracking not only the total number of fire spreading events that are present, but counting the number of initial wildfires and keeping track of how many times each initial wildfire spreads. This could be useful and potentially elucidate some of the scatter with initial barren areas—the number of spread events for each fire would likely be more consistent rather than taking the total of all the times that any fire spread during the simulation.

A significant limitation of this model is the fact that weather events are not taken into consideration. For example, having rain on the western side of the grid would mean that fire is less likely to spread into that area. Not only that, but even having more lush vegetation may make fire harder to spread in that area—fire spreads more easily in dry areas. Something that could be taken into consideration with future modeling endeavors is altering the p\_burn value for different forested tiles, which would reflect the diversity of vegetation in a more subtle way than being strictly “forested” or “barren”.

Overall, the initial forest density and probability of fire spreading were significant players in the way that wildfire progressed. The increase in both of these factors caused a direct increase in the amount of land that was burned, and an increasing amount of times that fire jumped from one region to an adjacent one. The Buckeyeitis disease model that was created in conjunction with the wildfire simulation model was also tested to see how initial vaccination rates would affect the spread of disease—it was shown that higher vaccination rates hinders the spread of Buckeyeitis. There are a few design limitations (such as lack of diverse vegetation and precipitation) that impact its real-life usage; however, this model was successful in a way that would inform different, more complex modeling simulations.

Supplemental Information (SI)

**Wildfire Simulation Model:**

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**Figure SI 1.** Standard Large Wildfire Simulation. *This is an example output of several iteration of a wildfire with “standard” inputs, i.e., nstep = 300, ny = nx = 100, p\_burn = 0.4, p\_start = 0.001, p\_bare = 0.2, p\_fatal = 0.0.*

**Disease-Spreading Model**

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**Figure SI 2.** Standard Large Disease Simulation. *This is an example output of several iteration of Buckeyeitis with “standard” inputs, i.e., nstep = 300, ny = nx = 100, p\_burn = 0.4, p\_start = 0.001, p\_bare = 0.2, p\_fatal = 0.1.*