Modeling the California Mosquito Fires using Cellular Automata

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Background

- Wildfires are uncontrolled fires burning across any type of combustible vegetation such as brushland, forests, and agricultural fields
- Due to its chaotic nature, it has been the interest of various mathematical modelling efforts
    - Most common modeling technique is Cellular Automata (Freire, 2019)
    - Less common modeling techniques include physics based 2D and 3D models
        - Computationally very complex
- Mosquito Fires in California lasted 09-06-2022 ➔ 10-22-2022 burned over 300 kilometers (Alves, 2023)
    - Largest fire in 2022 result of extreme drought and heatwave
    - Displayed extreme behaviors making it difficult to combat the fire
    - High wind speeds contributed to its progress towards Lake Tahoe

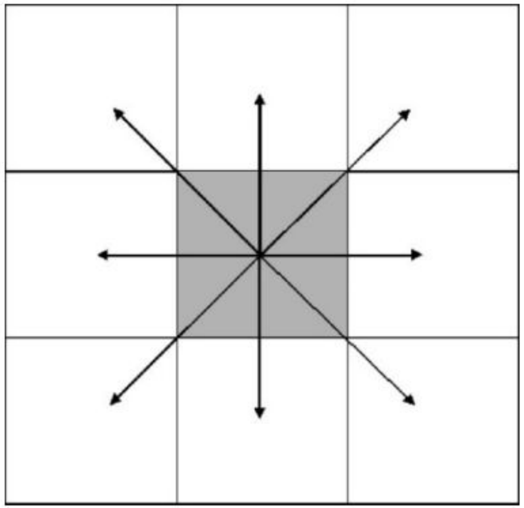
Location of the Mosquito Fire in Northern California

Scope

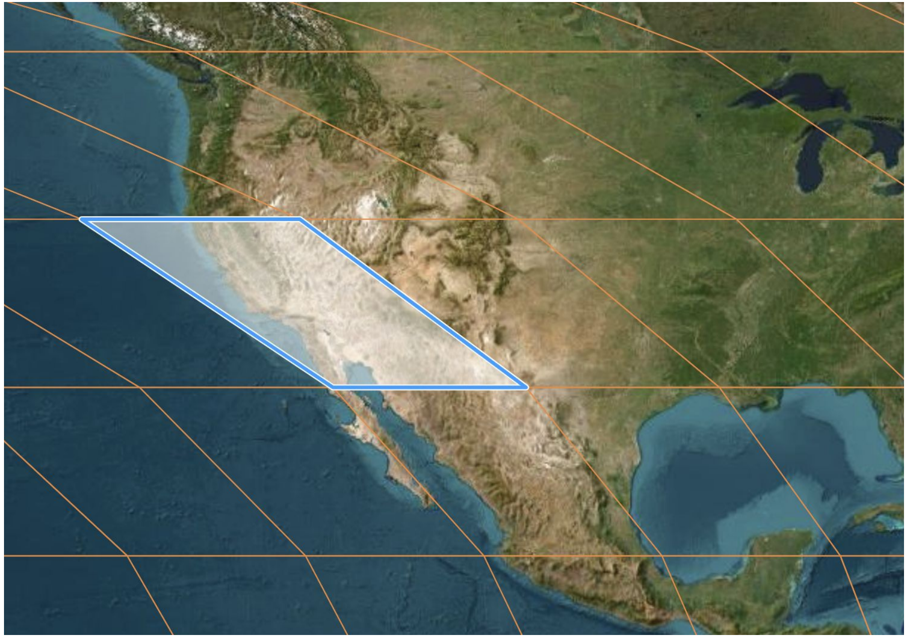
- Mosquito Fires analyzed from 09-07 → 09-14 because of the chaotic conditions
  - After the 16th majority of the fire was under containment.
- Data used collected daily from Terra and Aqua Satellites at 1 km resolution
  - Vegetation data, burn data before and after fire, wind data, and fire detection data
- CA Model 1: Stochastic CA Model where probability determined by fire confidence levels
- CA Model 2: Stochastic CA Model tracking fire propagation
  - Probability determined by fire confidence levels and fire propagation angles
- CA Model 3: Fuzzy Stochastic CA Model where probability determined by "burnable" levels, fire confidence levels, fire propagation angles, and general wind direction/speed

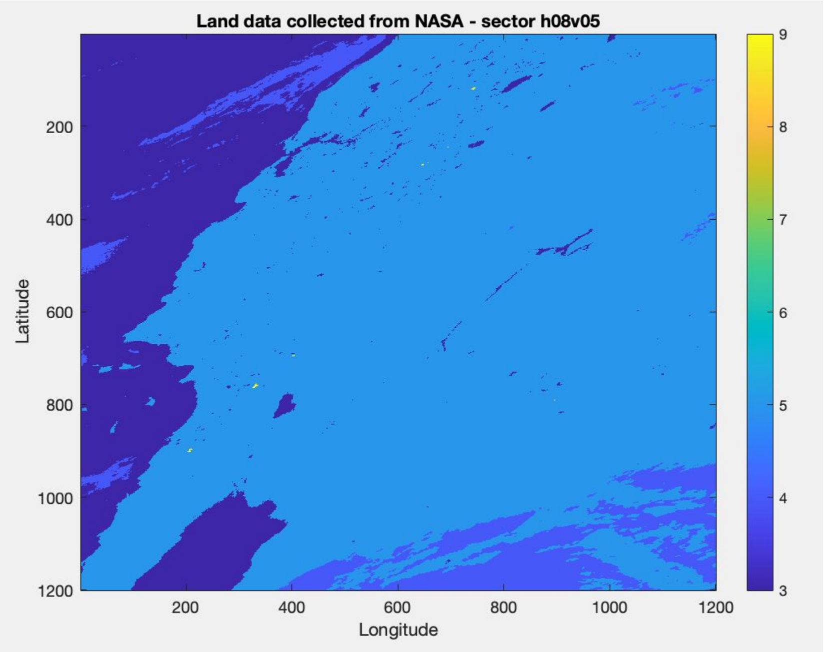
Cellular Automata

- Basic Concept is that an **automata or cell is a function of all its neighbors**
- The function is updated at time step t+1 based on all its neighbors and its own last state
- Can increase complexity by adding probabilities dependent on values at time t



Stochastic Cellular Automata Model - Data



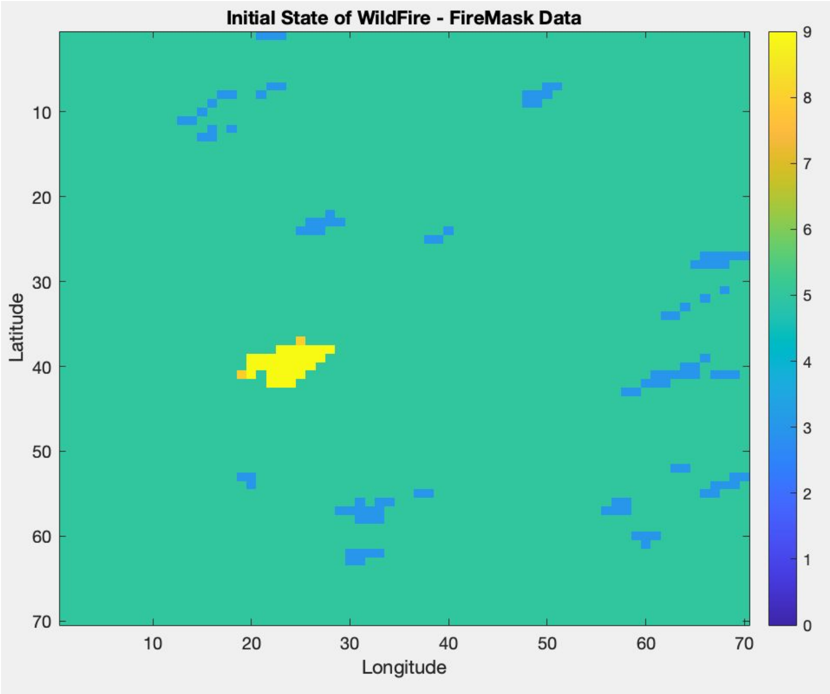


Bits: 0-2, 6 (bad data), 3 - water, 4 - cloud, 5 - land, 7 - fire (low conf), 8 - (mid conf), 9 - (high conf)

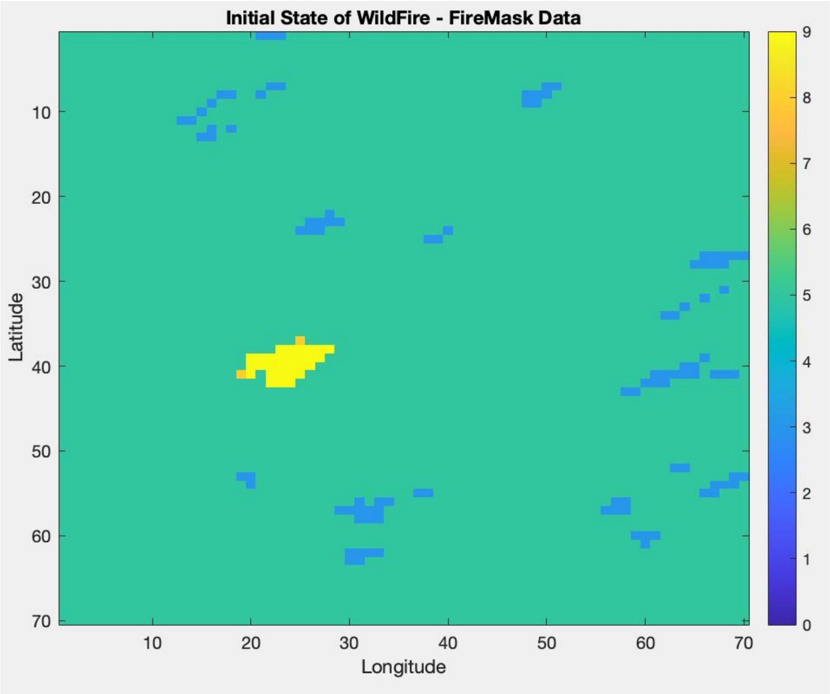
Source: NASA LP DAAC

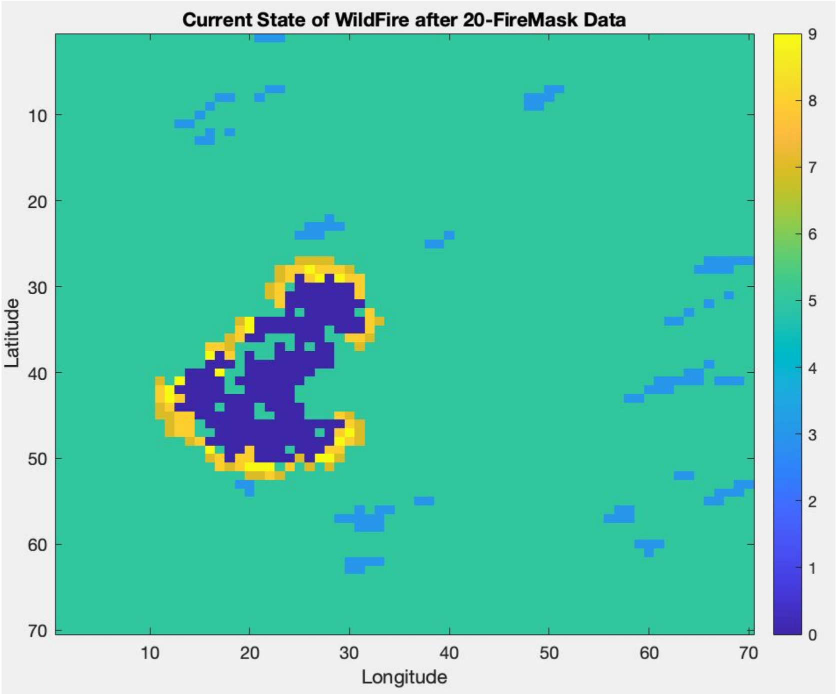
Stochastic CA Model - Rules

- Rule 1: Water can never transition (3)
- Rule 2: Land can transition to fire with a random confidence
- Rule 3: Low confidence fire can transition to either mid or high confidence
- Rule 4: Mid confidence fire can transition to high confidence
- Rule 5: High confidence fire can transition to charred land (not burnable).
- Rule 6: Charred land cannot be burned again.



Stochastic CA Model - Results

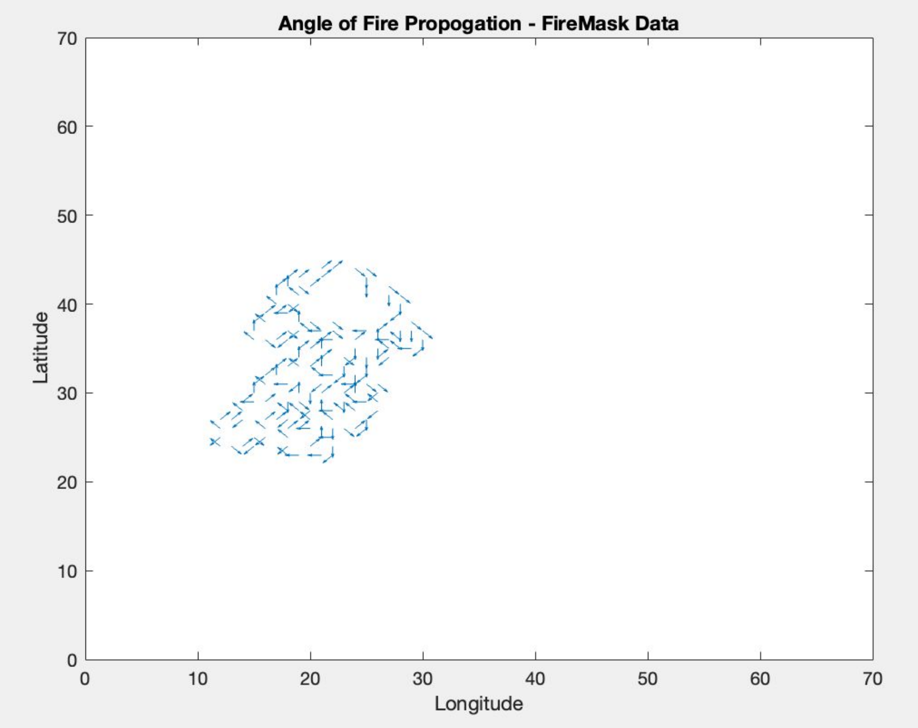




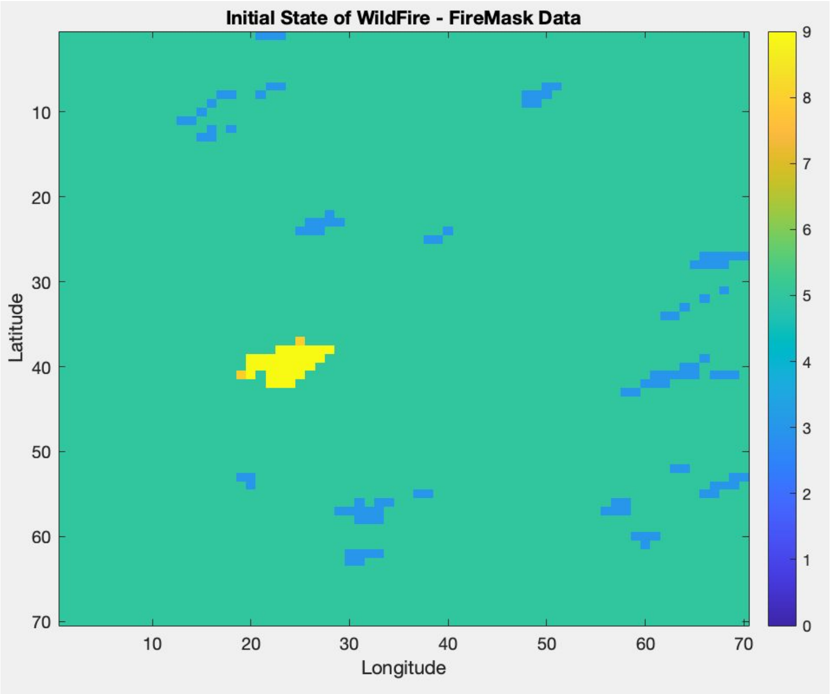
Stochastic CA Model Fire Tracking- Rules

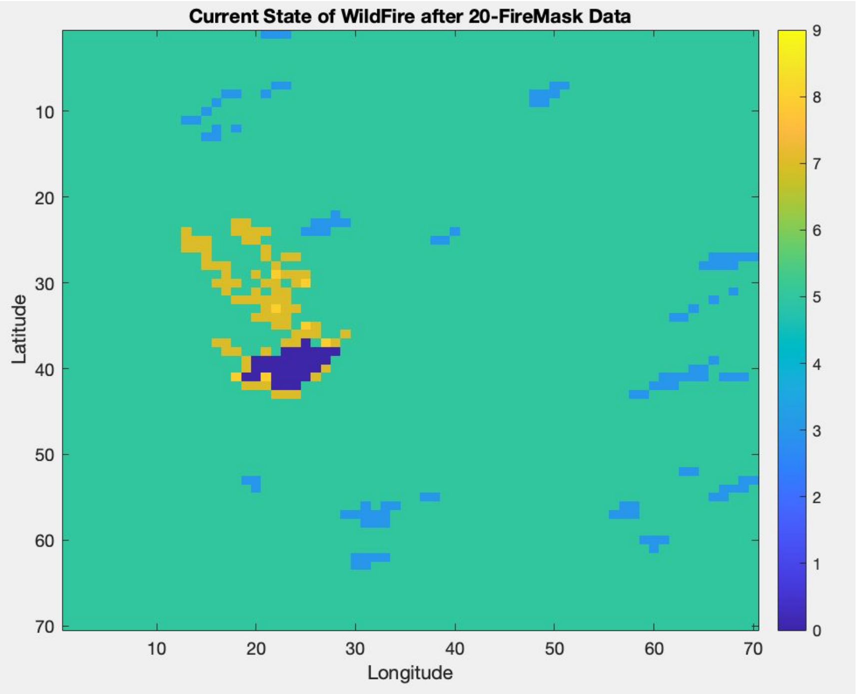
- Add fire propagation rule!
- Track angle of fire propagation
- Compare last angle and current measured angle
  - Angle diff gives probability if fire should transition to a given cell
- **Equation to calculate propagation probability:**

$$p_{propagation} = e^{c1 + c2 * cos(\theta) - 1}$$



Stochastic Fire Tracking CA Model - Results



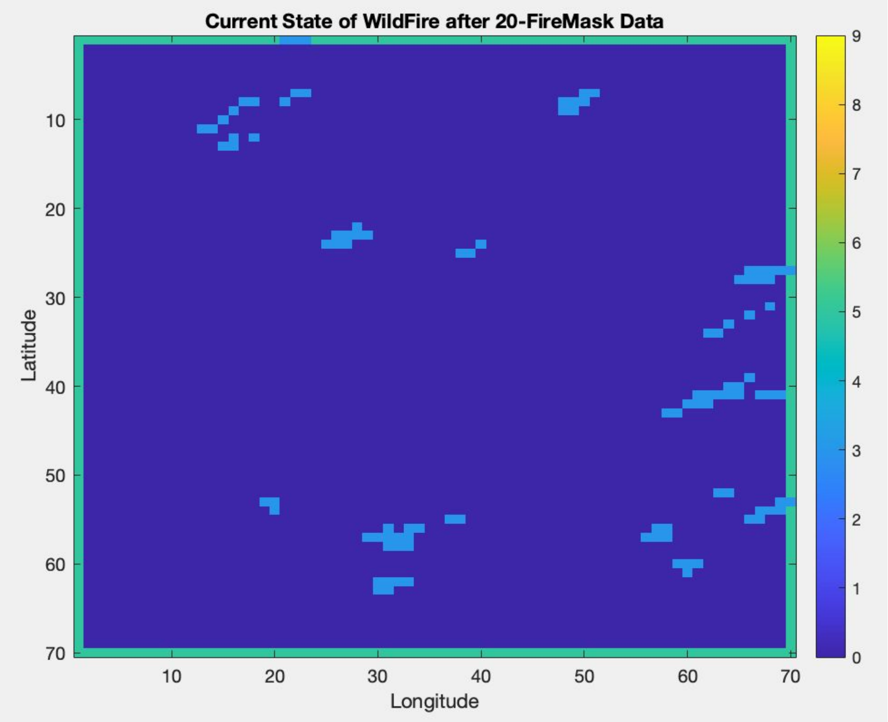


Values: c1 = 0.05, c2 = 0.5

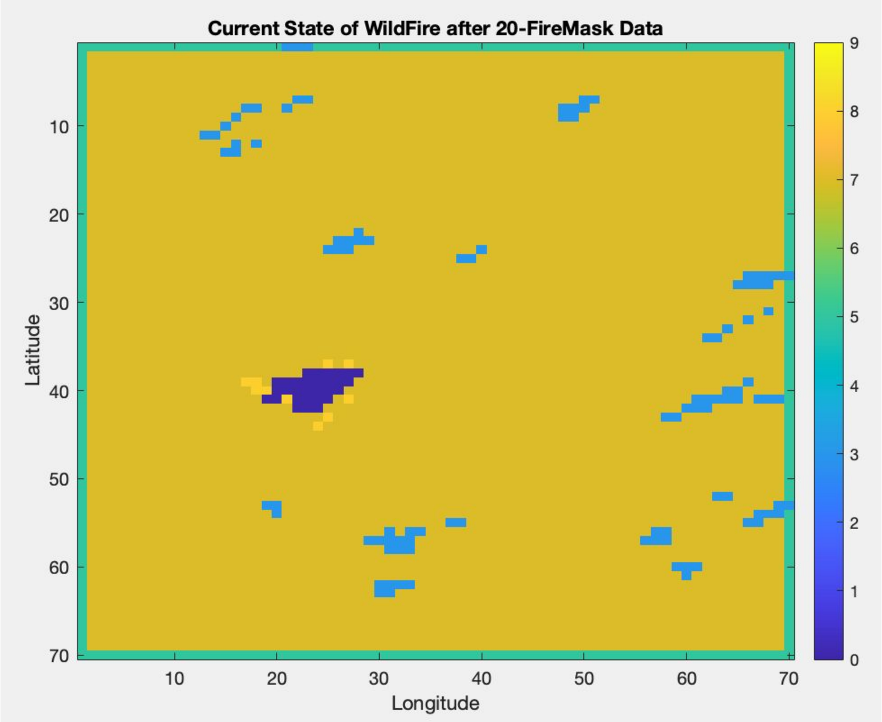
Stochastic CA Model fire tracking- parameters

- **Values for c1, c2 were chosen through experimentation**
- Bifurcation was exposed where model became unstable based on parameter values
- **Transition rules analyzed propagation probability and current probability of each cell**
  - If the propagation probability is larger than max in current conf level - transition higher
  - If propagation probability * current probability is between the range transition higher
    - Else if greater than max transition 2 states higher
  - Else stay in same state

Stochastic Fire Tracking CA Model - Bifurcation



Values: V = 1, c1 = 0.09, c2 = 0.5



Values: V = 1, c1 = 0.05, c2 = 0.6

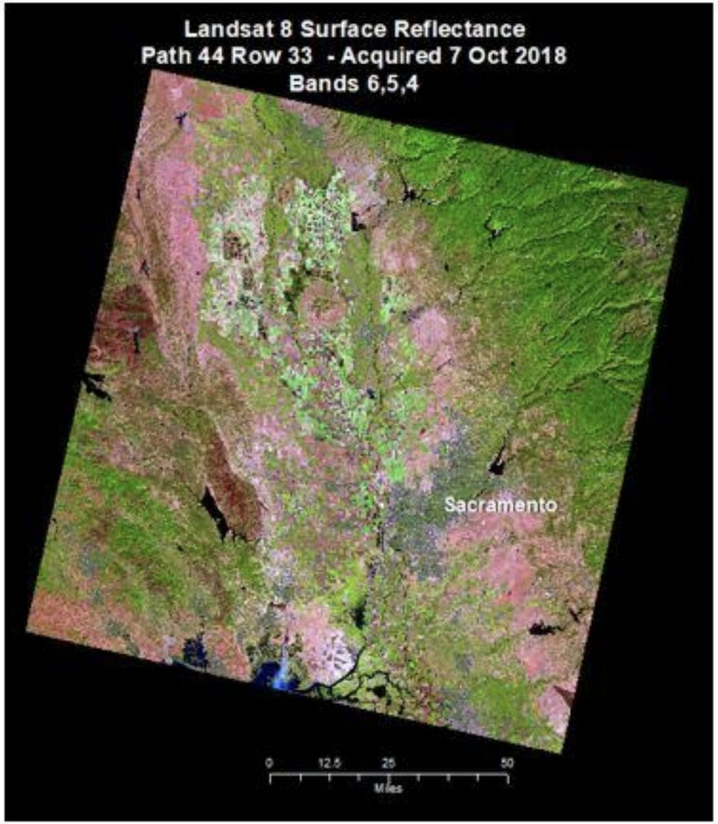
Fuzzy Logic

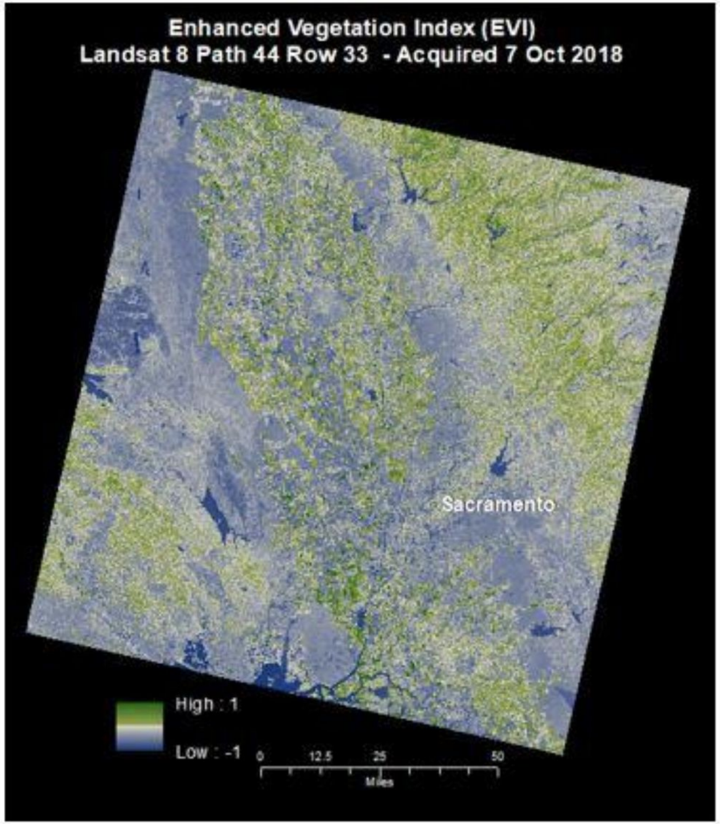
- Basic Concept is to derive membership functions for linguistic variables
- Degree of membership indicates strength of that linguistic variable
- Ex: What is “tall” or HOW “tall”?
- **What does it mean if land is burnable?**
    - High vegetation index likes trees or brush
    - High density like forestland
- **What does it mean if land is NOT burnable?**
    - Low vegetation index like agricultural land
    - Low density like rough terrain with uncovered rock
- Image: Freire, 2019

Categories	p_{veg}
No vegetation	−1
Agriculture	−0.4
Forests	0.4
Shrubland	0.4

Categories	p_{dens}
No vegetation	−1
Sparse	−0.3
Normal	0
Dense	0.3

NDVI vs EVI Images





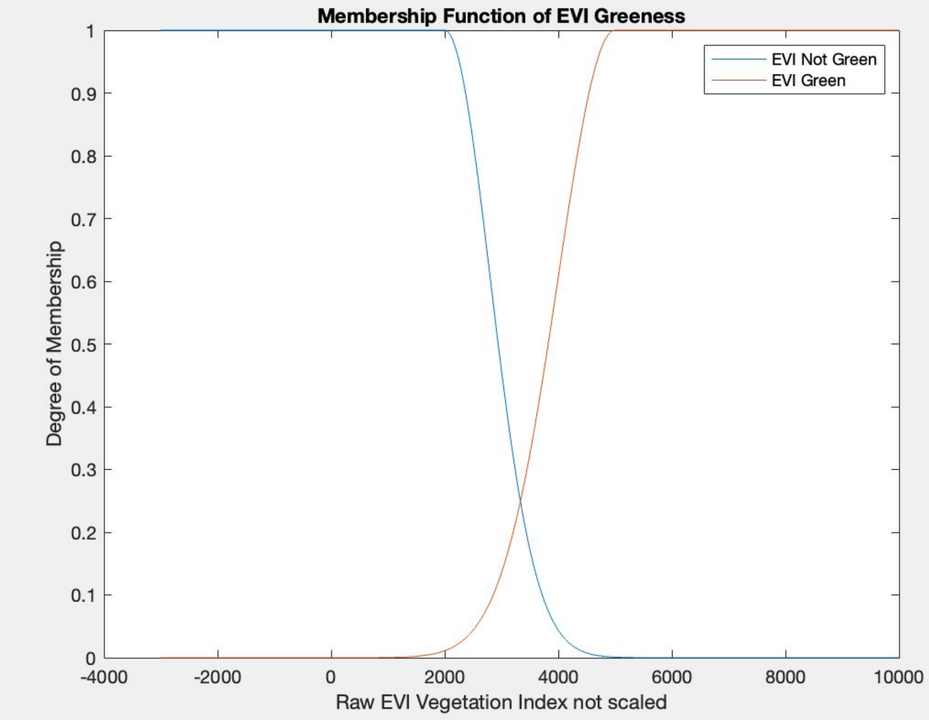
Fuzzy Logic - Derived Membership Functions

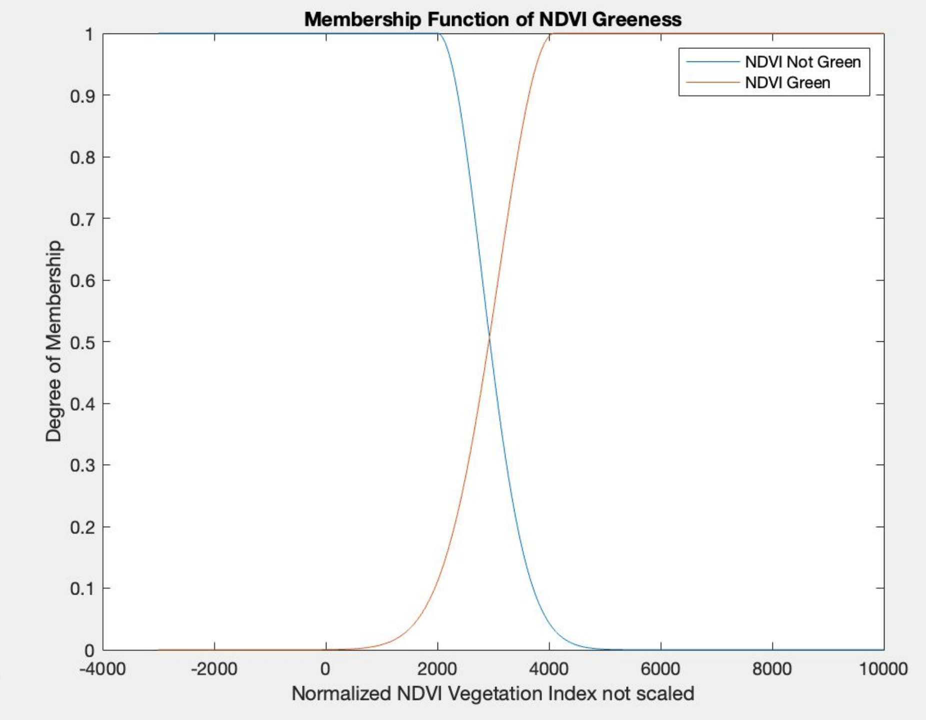
- "Burn State" of a cell - [not burnable, burnable]
- "EVI_Green_State" of a cell = [not_green, green]
  - Raw - increased sensitive to denser areas, corrects for atmospheric conditions, and less noisy background data
- "NDVI_Green_State" of a cell = [not_green, green]
  - Normalized vegetation index

```
y = x;
index = length(x);
for i = 1:index
    if (x(i) <= c1)
        y(i) = exp(double(-0.5.*((x(i) - c1)./sig1).^2));
    elseif ((x(i) < c2) && (x(i) > c1))
        y(i) = 1;
    else
        y(i) = exp(double(-0.5.*((x(i) - c2)./sig2).^2));
    end
end
```

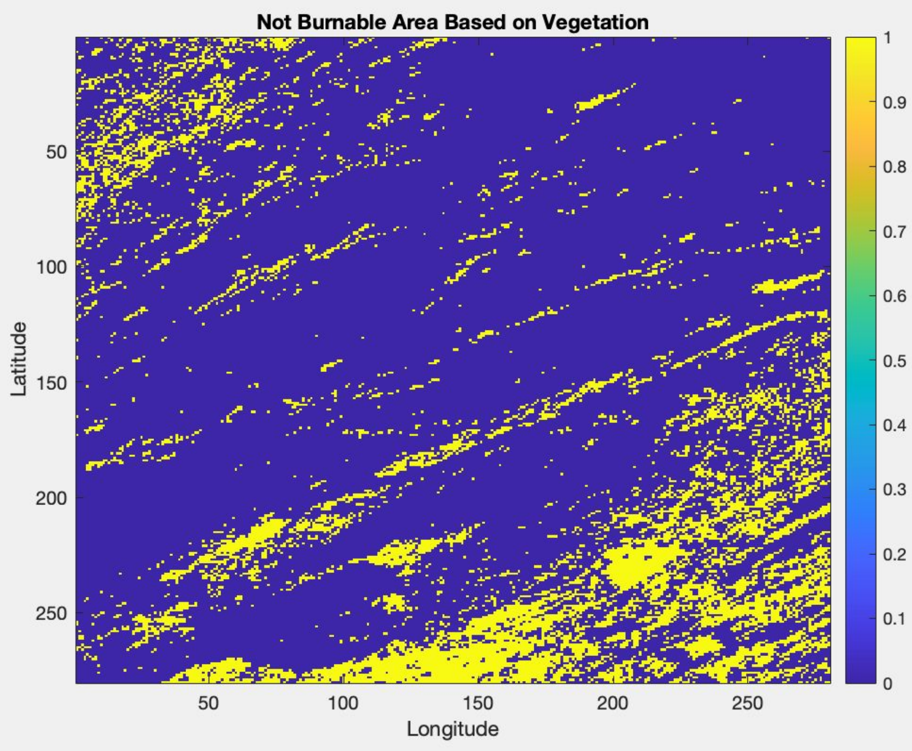
$$t_{conorm} = max(set_{inputs}\{ \prod_{i=1} input(i)\})$$

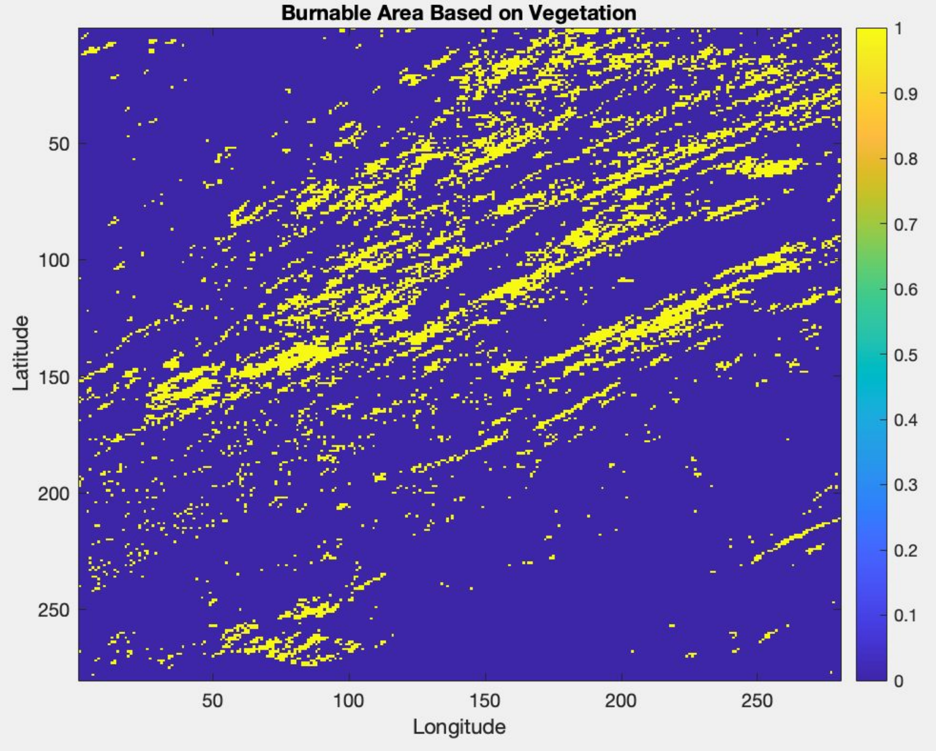
Fuzzy Logic - Derived Membership Functions





Burnable, Not Burnable Land at Wildfire Location





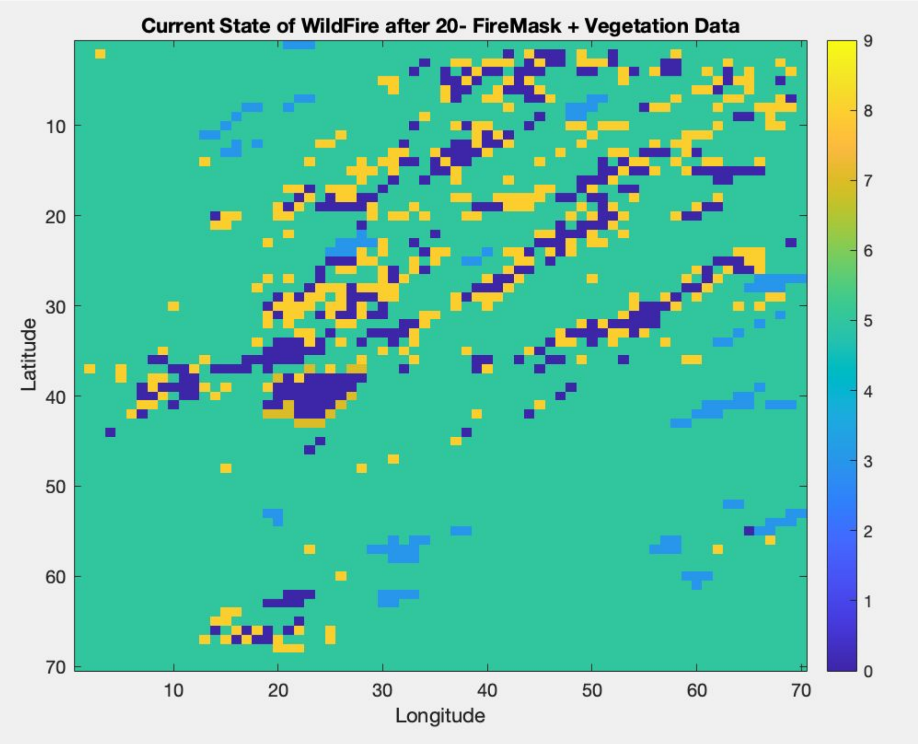
Fuzzy Fire Tracking CA Model

$$p_{wind} = V * e^{c1 + c2*cos(\theta) - 1}$$

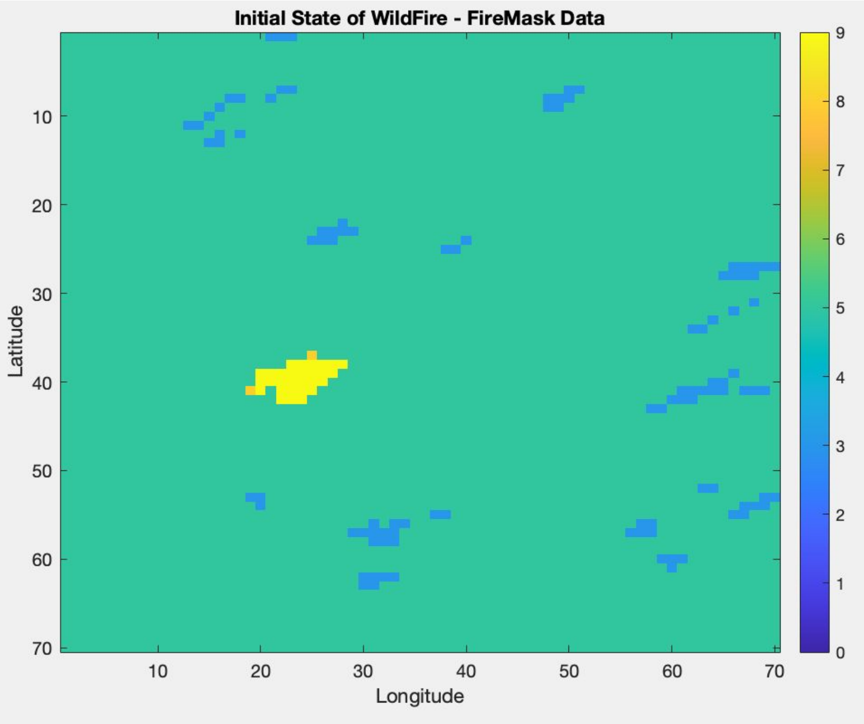
$$p_{propagation} = e^{c1 + c2*cos(\theta) - 1}$$

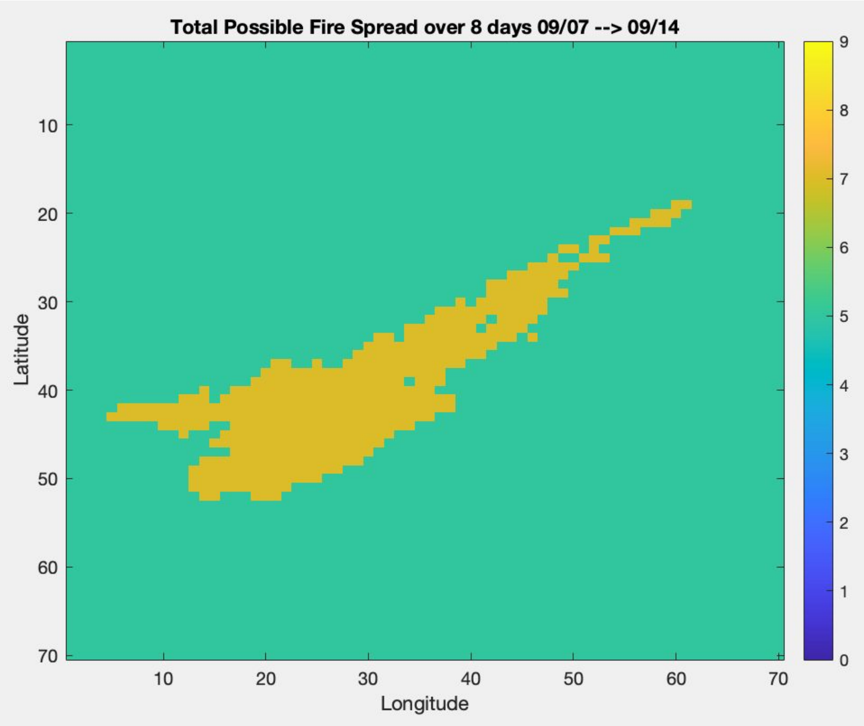
$$p_{directional} = p_{wind} * p_{propagation}$$

$$p_{burncell} = p_{burnable} * p_{directional}$$

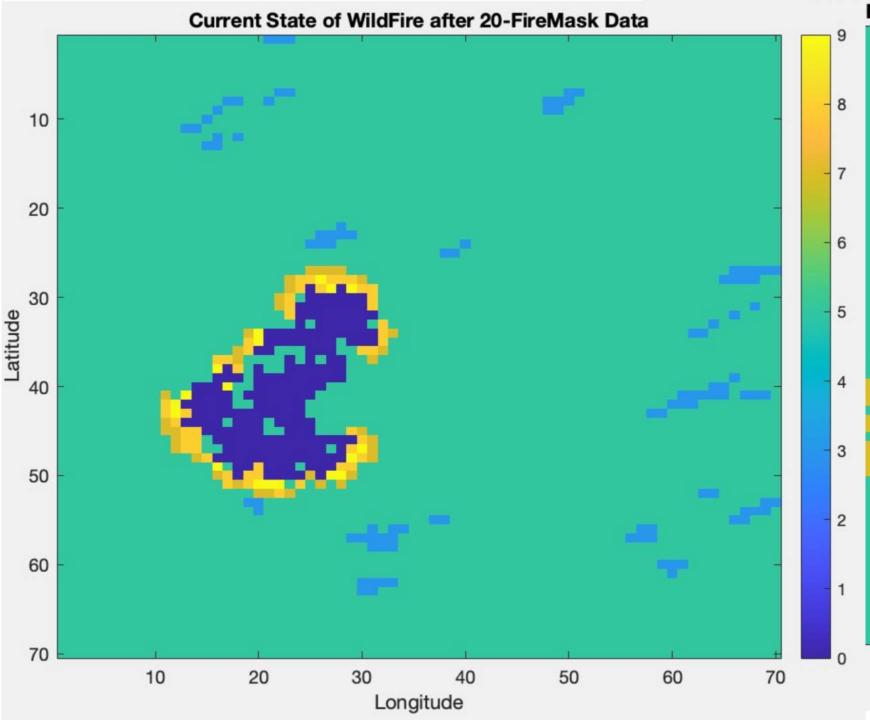


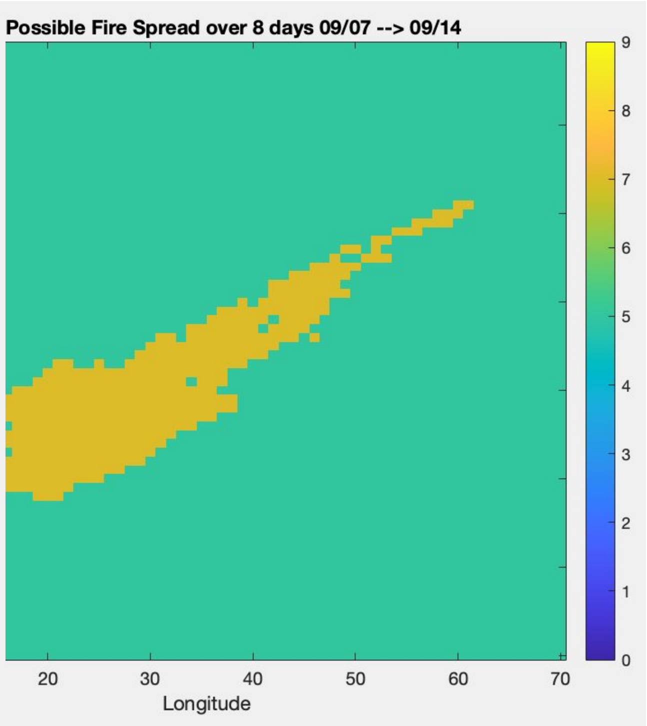
Comparison to Final Macroscopic Spread



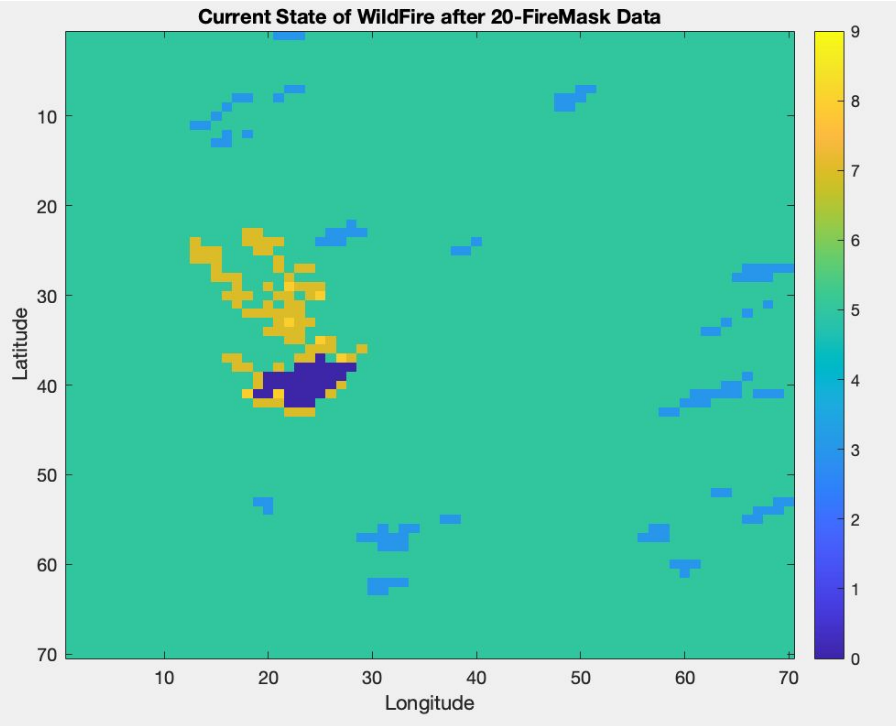


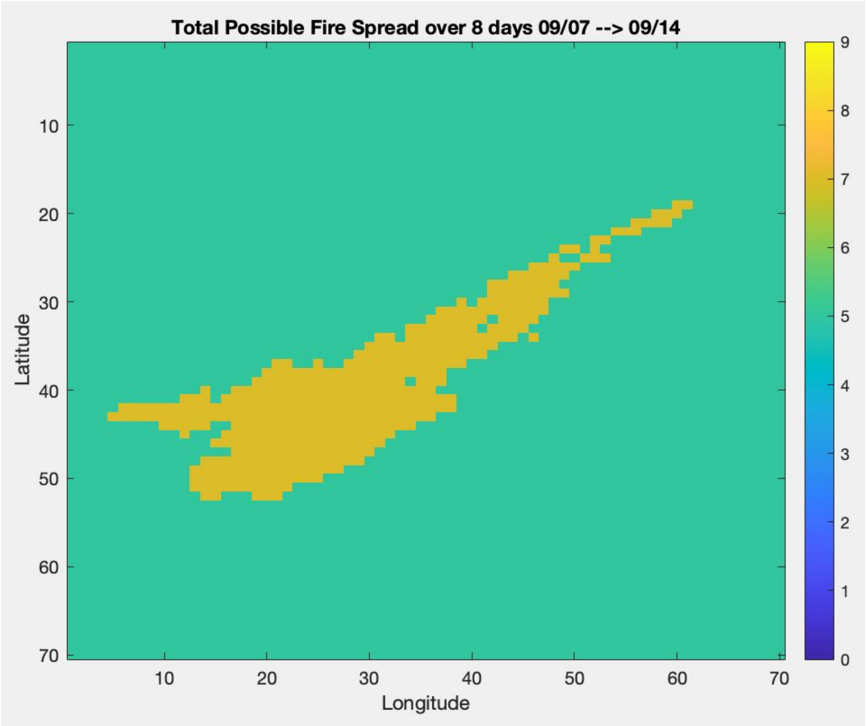
Stochastic CA Model vs Final



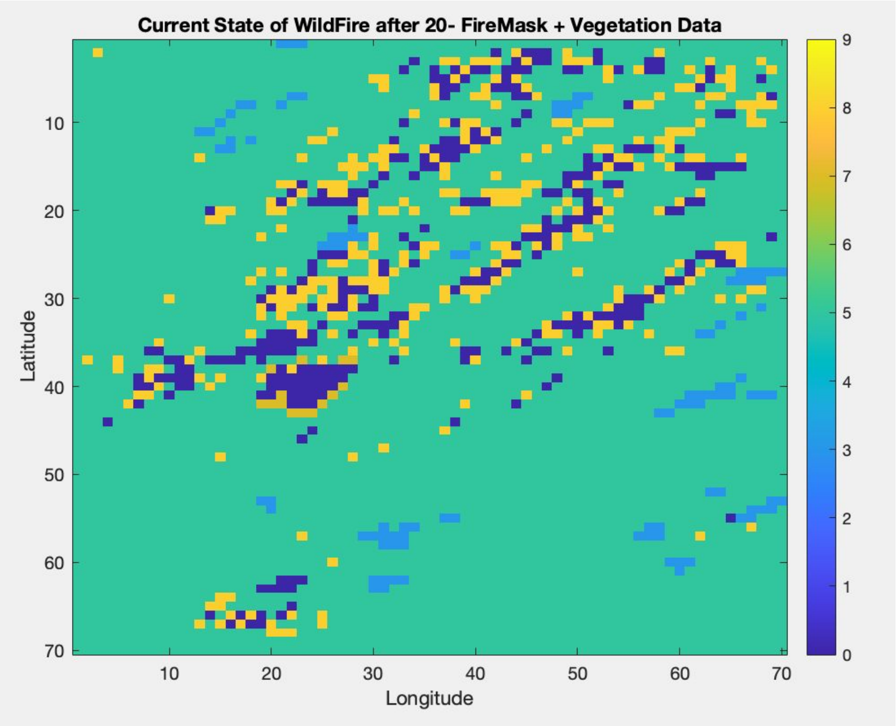


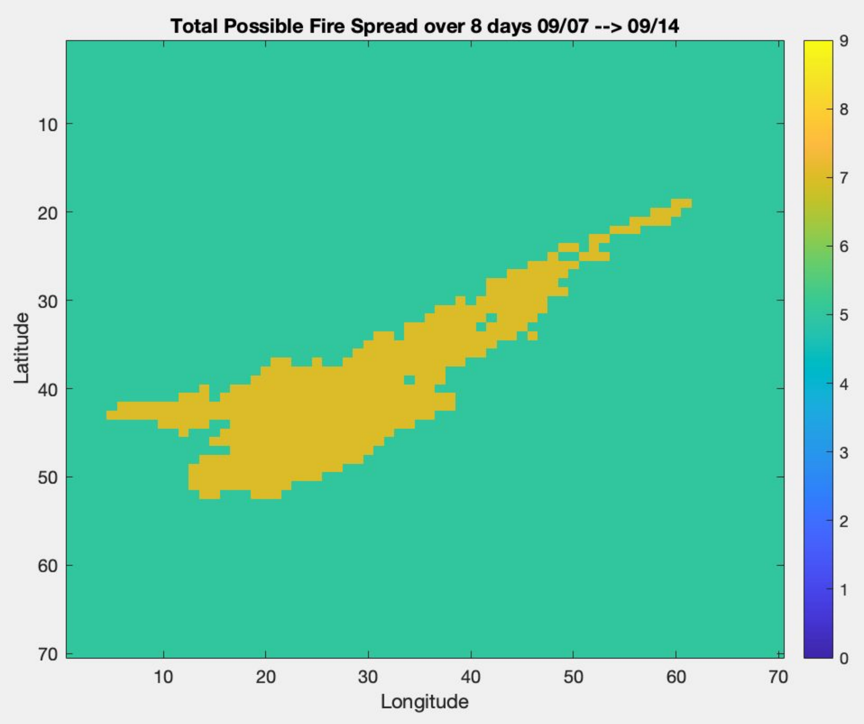
Stochastic Fire Tracking CA Model vs Final





Fuzzy Fire Tracking CA Model vs Final





How can we better model this wildfire?

- Accurate wind speed modelling would support generating a better model of this wildfire
    - Wind speed can be predicted
    - Wind direction is more difficult to predict due to rotations
- Taking into account the terrain of the wildfire
- Fire mitigation techniques present in the area
- More data into wildfires in this area to have more accurate parameters

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