CS166 Final Project

Minerva University

CS166: Modeling and Analysis of Complex Systems

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Contents

Feedback

I would like to receive feedback on my simulation implementation.

Introduction

Flooding is a natural disaster that can cause significant damage to both human life and infrastructure. In recent years, the frequency and severity of floods have increased due to climate change, land use changes, and urbanization. In this context, understanding and modeling the dynamics of flooding is crucial to develop effective management strategies and policies to reduce its impact.

In this paper, we present a 2-dimensional cellular automaton model for simulating the flooding and spread of water in a certain area of San Francisco. The model uses an existing topological map of San Francisco to simulate the evolution of the water flow (Figure 1). The cellular automaton approach allows for the simulation of complex systems with simple rules, making it a suitable framework for modeling flooding dynamics.

Figure 1. The topological map of San Francisco.

Blue color indicates the lowest elevation, while red is the highest. The map is taken from https://en-us.topographic-map.com/map-vx51/San-Francisco/?center=37.79397%2C-122.423&zoom=15.

The simulation's primary goal is to predict the flow of water during a flood event accurately. This simulation could enable researchers to understand better how water moves through the region and identify potential areas at higher risk for flooding.

The simulation will measure various quantities related to the flow of water, including the water depth, distribution of water throughout the region, and the proportion of flooded cells over time. The simulation will also measure the impact of different rainfall regimes and flood mitigation strategies, such as drainage systems, on water flow.

The simulation output will be a detailed map (animation) of the water flow through the region during the flood event. This map will show the depth of the water at different points in the area. The simulation will also output data on the impact of the drainage system on the flow of water based on the flood proportion metric, allowing researchers to identify if this strategy effectively reduces the effects of flooding events.

The model is calibrated to include evaporation, absorption into the ground, and flow down the gradient. We demonstrate the model's ability to capture the critical features of the flooding dynamics, such as the inundation area and water depth, and provide insights into the impact of different rainfall scenarios and drainage systems on flooding risk.

Overall, our work contributes to developing more accurate and efficient flood risk management strategies in San Francisco and beyond. The proposed model can be improved and further extended to other urban areas and can aid in designing flood-resilient infrastructure and urban planning.

The Simulation

In this project, we will employ cellular automaton to model flooding, utilizing Python classes called Cell and Grid. The Cell class will initialize cell objects with attributes describing water distribution and associated parameters. The Grid class will initialize the state of all cells as a grid, utilizing a given set of parameters, and will model the movements of water based on specific rules. The model's parameters and variables are as follows:

Class *Cell*

- Elevation (float): the elevation of a cell as defined according to the uploaded topological map, which was converted to grayscale and resized to fifty by fifty pixels. The elevation does not go below 0 and is measured in feet.
- Absorb_rate (float): the rate at which the water would get absorbed (disappear) from the surface of a given cell into the ground underneath at each time step. It is defined as a number between zero and one. The default value is 0.1 for all cells except for the two parks in the terrain, which have an absorption rate of 0.3.
- Evap_rate (float): the rate at which the water would evaporate (disappear) from the surface of a given cell at each time step. It is defined as a number between zero and one. The default is 0.01 for all cells.
- Ground_water_limit (float): the maximum amount of water a cell can contain underground. The default limit is 1 unit of water for all cells but three units of water for the park's areas.
- Water_level (float): the amount of water (in units of water) currently being contained on the surface of a cell.

- Ground_water_level (float): the amount of water (in units of water) currently being contained underground in a cell.

Class *Grid*

- Shape (int): the size (number of cells) of the one dimension of the grid.
- 2D arrays of all the Cell class parameters (except water_level and ground_water_level) to assign to each cell during the initialization.

The updating rules of the simulation are as follows:

- Initialization: The 2D grid of a given shape is initialized with each cell being a class Cell object, which, in turn, is initialized given a certain absorption rate, evaporation rate, elevation, and groundwater level limit associated with that cell.
- Rainfall: Before the simulation begins, a certain amount of water is placed on each cell (rain imitation) governed by a uniform distribution bound from one to three units of water. This decision is motivated by the extremely low precipitation rate in San Francisco, hence one to three units of water seem like a reasonably small amount.
- Water flow: The water flows down the gradient from the higher cells to the lower cells. The 'height' is defined as the elevation plus the amount of water on the surface. Given the current cell, the simulation checks every neighbor in the Moore neighborhood of the current cell and stores all differences between the current cell's elevation plus water level and the lower neighboring cell's elevation plus water level. After all, neighbors are checked, all water flows out of the cell to all lower neighbors. Each lower neighbor gets

the amount of water proportional to its height difference from the current cell. The current cell then retains no water.

- Boundary conditions: The grid implements absorbing boundary conditions, where the cells on the edge of the grid act as barriers, preventing any interaction between the cells outside the grid and those inside the grid. This type of boundary is useful when the simulation is concerned with the system's behavior within a specific area, which is what we are trying to do in this simulation.

These rules are repeated for each time step in the simulation.

While the model effectively simulates water flow based on our rules and parameters, it is important to note that it has certain assumptions and limitations in comparison to the real world:

- The model assumes that the terrain is homogeneous (not considering elevation parameter, which is heterogeneous) and has the same properties everywhere. In reality, different parts of the land can have different properties, such as varying absorption capacity and rate and shielding and flood preventive constructions, affecting flooding patterns. Nevertheless, the simulation accounts for two parks on the chosen terrain, as reflected by higher groundwater capacity and absorption rate.
- The simulation assumes that the surface water depth and groundwater level are the only factors that affect flooding. Other factors, such as soil type, vegetation, and human activities, are not considered.
- The simulation assumes the groundwater does not move or disappear once accumulated to full capacity, which in reality might not be true due to underground water flows.

- The simulation assumes that the rainfall is evenly distributed across the grid, which may not be true in real-world scenarios.
- The simulation assumes that the rate of absorption and evaporation remains constant throughout the simulation, which might not be the case depending on the changing environmental conditions such as wind, sunlight, humidity, temperature, and others.
- The simulation does not consider the impact of man-made structures such as buildings or cars on flooding patterns.
- In this simulation, if a cell with water has a neighbor cell with a lower height, it shares 70% of its water. In reality, the amount of water that flows from a higher point to a lower point is governed by much more complex physical relationships. For example, the water would try to reach equal levels in both cells so that there is no more gradient left.

Overall, the simulation produces valid and correct results as can be seen from the simulation animation and relevant test cases. They show that the water flows off the areas of higher elevation and accumulates in the areas with lower elevation. While our computational model provides a useful starting point for understanding flooding and water flow, its many assumptions that differ from reality mean that the model has limitations and may not accurately reflect real-world flooding patterns. More specifically, the flawed rule for the flow of water from one cell to another will considerably limit the interpretability and reliability of results since these small flaws on the cell level might result in drastic differences in water flow and accumulation patterns on the grid level when compared to reality.

Theoretical Analysis

The Mean Field Approximation (MFA) is a mathematical technique used to analyze the behavior of complex systems consisting of many interacting components. When applied to Cellular Automata (CA), MFA assumes that each cell is influenced by the average behavior of its neighbors rather than individual neighbor states. This means that the behavior of each cell is determined solely by the local average of the states of its neighboring cells, and not by the individual states of each neighbor.

Some common assumptions of MFA as applied to CA include:

- Spatial homogeneity: The system is assumed to be spatially homogeneous, meaning that the behavior of each cell is the same regardless of its location in the grid. This assumption is violated in our simulation since we have a terrain where cells have different elevation levels, which means the water flow behavior will be different for cells with different heights.
- Large population size: MFA assumes that the number of cells in the system is large enough to justify treating the system as a continuous medium rather than a discrete one. Although our CA is not infinite, it is still reasonably large (2500 cells).
- Randomness: MFA assumes that each cell's state is chosen randomly from a distribution of possible states. This assumption is satisfied as we have a certain probability p_rain that governs the rainfall distribution on the grid: each cell gets the random amount of rain from one to three units of water with probability p_rain. Hence, the distribution of empty and flooded cells is random.

- Time homogeneity: The system is assumed to be time-homogeneous, meaning that the probabilities of transition between states do not change with time. This assumption is also satisfied since the terrain (elevation differences between cells) does not change, the water flows according to the same rules throughout the whole simulation, and evaporation and absorption rates stay the same.
- Local interaction: MFA assumes that each cell only interacts with its nearest neighbors and that these interactions are local and do not depend on the states of cells that are further away. This assumption is also satisfied since we only consider a cell's Moore neighborhood when moving the water.

These assumptions can affect the accuracy of the MFA as an approximation of the true behavior of a CA system. In particular, the spatial homogeneity assumption means that MFA cannot precisely model the real-world water flow since, in reality, no terrain is perfectly homogeneous. Also, the violated assumption of spatial homogeneity in our simulation limits comparisons between MFA theoretical results and empirical results. Nevertheless, MFA can be a good starting point for us to approximate the scenario and gain insights into potentially interesting regimes in the parameter space, such as the stable state proportion of flooded cells.

We start MFA by creating a set of probabilities that describe the cell transitions between flooded and non-flooded states, summarized in Table 1 below. A flooded state is defined as having any amount of water in a cell (for this and future analyses).

Current State	**Next State**	**Neighbours**	**Probability**
Not flooded	Flooded	At least 1 neighbor is higher than the current cell and is flooded	$(1 - p_f) \cdot (1 - (1 - p_e p_f)^8)$
Flooded	Flooded	All neighbors are higher	$p_f \cdot p_e^{\ 8}$
Not Flooded	Not Flooded	All neighbors are lower or any higher neighbors have no water	$(1 - p_f) \cdot (1 - p_e p_f)^8$
Flooded	Not flooded	At least one lower neighbor	$p_f \cdot (1 - p_e^{\ 8})$

Table 1. MFA for flooded-not-flooded state transitions with corresponding probabilities.

In the above equations, p_f is the probability of being flooded, and p_e is the probability of a neighbor cell being higher. In our case, we set $p_e = 0.5$ because our terrain is very heterogeneous, meaning for a current cell, every neighbor has an equal probability of being lower or higher than the current cell. Given this heterogeneity, the chance of getting two cells of the same height next to each other is minimal. Hence, the assumption of $p_e = 0.5$ is justified.

Considering the transition from not flooded to flooded state, the first term in the corresponding probability, $(1 - p_f)$, represents the probability of the current cell being not flooded, which is simply a complement of a probability that a cell is flooded, p_f. The second term, $(1 - (1 - p_e p_f)^8)$, can be broken down into several components. $p_e p_f$ is the probability that a neighbor cell is both flooded and higher than the current cell. $(1 - p_e p_f)$ is the probability that a neighbor cell is anything but flooded and higher than the current cell at the same time, which means it can be lower and not flooded, lower and flooded, or higher and not flooded. $(1 - p_e p_f)^8$ is the probability that all eight neighbors of a current cell are anything but higher and flooded at the same time. Finally, $(1 - (1 - p_e p_f)^8)$ is the complement of the previous probability, which means that at least one out of eight neighbors is both higher and flooded. This is the probability we want because only one higher and flooded cell is enough to flood the current cell.

Considering the transition from flooded to flooded state, p_f represents the current cell being flooded, and p_e^8 represents all neighbors being higher. If at least one neighbor was lower than the current cell would not stay flooded in the next step as all the water would flow out to a lower neighbor, hence all higher neighbors are required for a current cell to retain the water.

For the transition from not flooded to not flooded state, the first term, $(1 - p_f)$, again means that the current cell is not flooded now, and the second term $(1 - p_e p_f)^8$, as described above, means all neighbor cells are anything but higher and flooded at the same time because otherwise, the current cell would get water in the next step.

Finally, for the transition from flood to not flooded state, the first term p_f is the probability of the current cell being flooded now, and the second term, $(1 - p_e^{8})$, is the complement of all neighbor cells being higher, which means having at least one lower neighbor. This makes sense because to go from flooded to not flooded, even one lower neighbor is enough to move all the water there.

The next step is to derive the differential equation for the scenario when the next state is flooded since we are interested in p_f, the probability of being flooded. For this, we are only concerned with the first two probabilities since only they describe the transition into the flooded state. To find the probability of the next state, p_{t+1}, being flooded, we combine these two probabilities:

$$p_{t+1} = (1 - p_f) \cdot (1 - (1 - 0.5 \cdot p_f)^{8}) + p_f \cdot p_e^{8}$$

Using this equation, we can create a cobweb plot that shows where the proportion of flooded cells converges in the long run given the initial proportion of flooded cells according to the MFA. Figure 2 shows that the stable state is around $p_f = 0.47$ given the initial $p_f = 0.1$. We also and performed this analysis for different initial proportions from 0.1 to 1, which can be seen in the Empirical Analyses section of the code. For all initial conditions, we obtain the same stable state of $p_f = 0.47$.

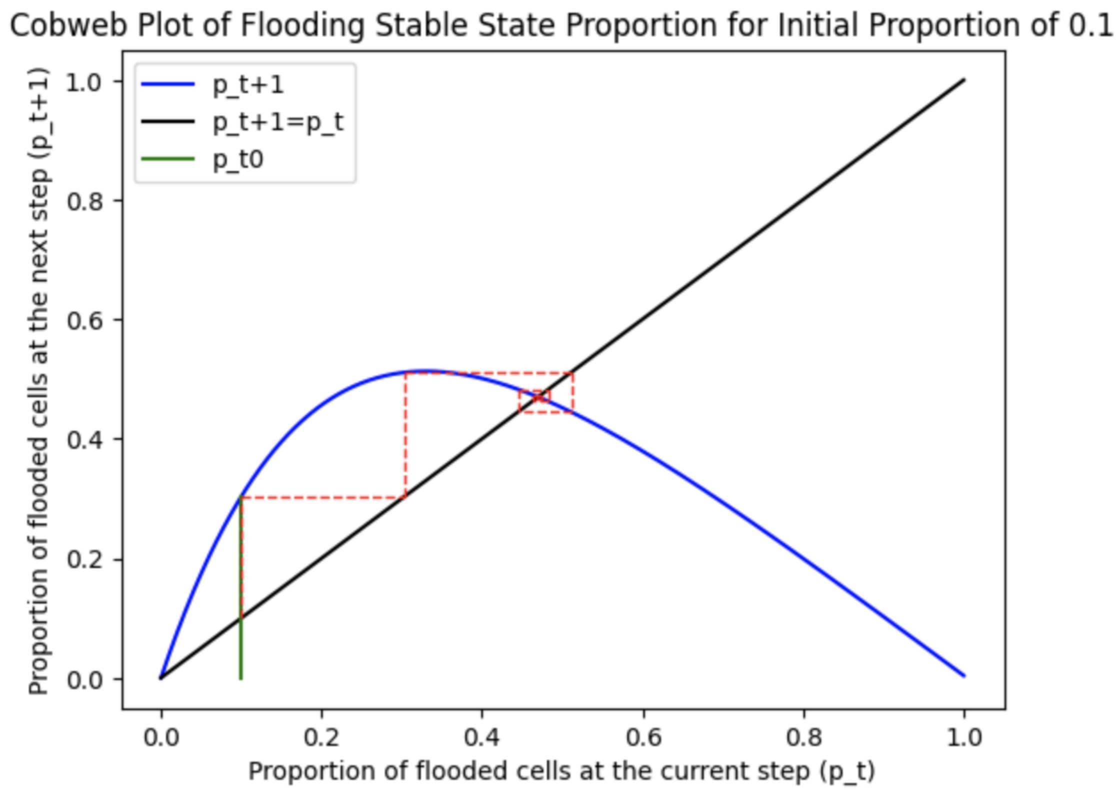

Figure 2. Cobweb plot for the initial proportion of flooded cells of 0.1. The green line shows the initial condition, and the red line shows the convergence of the proportion of flooded cells toward the stable state of 0.47.

Thus, we can see that according to the MFA, one interesting regime in the parameter space is that regardless of the initial condition, the final proportion of flooded cells always converges to 0.47 in the long run.

Comparing Theoretical Results to Empirical

The next step was to confirm the theoretical results using empirical methods. For that, we ran our simulation with a certain set of parameters to match the theoretical assumptions: no absorption, no evaporation, and all cells receive the same amount of rain at the beginning of the simulation. At the end of each simulation, we record the final proportion of flooded cells. We repeat the simulation for the same set of parameters 20 times to find the average final proportion of flooded cells and then repeat this process for each value of the initial flooded cells proportion from 0.1 to 1. The results are presented in Figure 3.

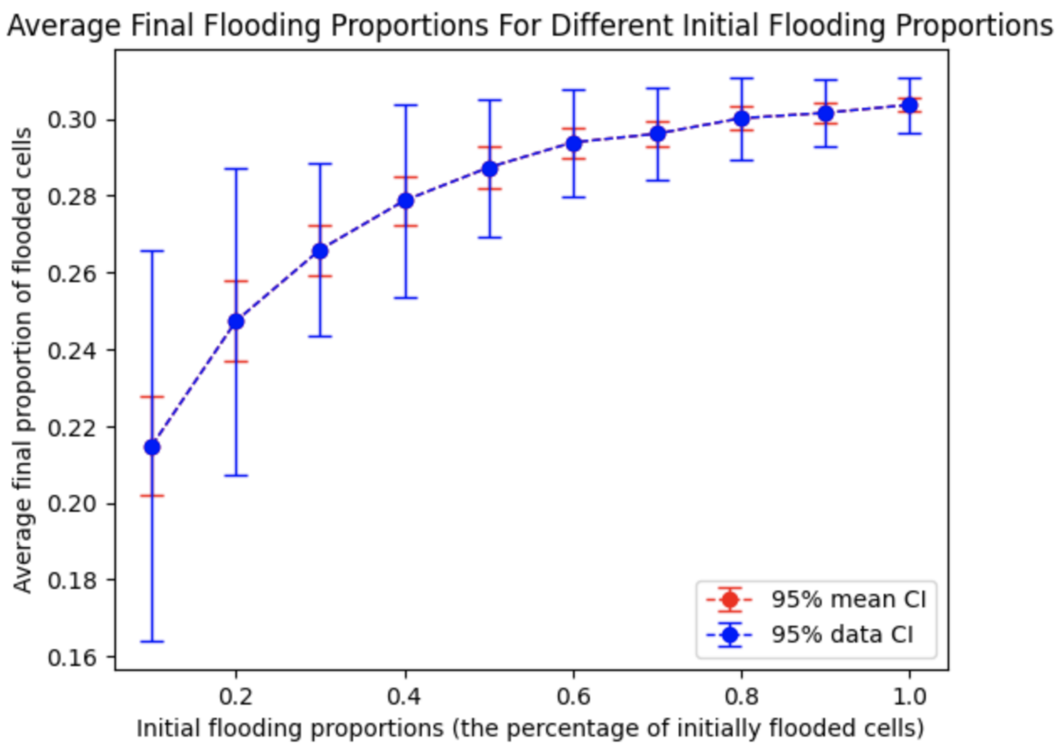

Figure 3. Average final proportion of flooded cells as a function of increasing initial proportion of flooded cells with corresponding CIs. The increasing trend is observed for the smallest initial proportions, with further stabilization of the final flooding proportion at around 0.3.

As we can see, increasing the initial proportion of flooded cells from 0 to 0.2 rapidly increases the average final flooding proportion up to about 0.27. As we increase the initial flooding proportion more, the average final flooding mostly stays the same given its slight increase to and stabilization around 0.3. Generally, the average final flooding is relatively the same for all initial flooding proportions if we pay attention to the 95% confidence intervals (CI). Looking at the CI of the data, we can see that the error bars are really wide, and the upper bounds are very close to each other for all initial flooding values. The 95% CI of the mean is much smaller, although still relatively on the same level for most values of initial flooding. The 95% confidence interval indicates that we can be reasonably certain that the actual average final flooding falls within the range provided by the interval. In this case, the large interval suggests a high degree of variability and uncertainty in our results, making it difficult to draw definitive conclusions from the graph. To improve the accuracy of our estimates and reduce the width of the confidence interval of the mean, we may need to increase the number of simulations performed for each initial flooding proportion. As the standard error of the mean decreases with increasing sample size, running more simulations would help to reduce the variability in our data, unless variability is an essential aspect of our simulation design. By increasing the sample size, we can obtain more information about the distribution of the population, leading to narrower confidence intervals and greater precision in our estimates. However, in case we raise the number of simulations, it's improbable that the actual data's confidence interval will undergo a transformation. The confidence interval serves as a gauge of the accuracy of our estimation of a population parameter, such as the mean or variance, founded on a set of data. The confidence interval does not depict a characteristic of the population, rather it relies on the sample size and data variance.

Comparing this result to the theoretical one, we can see that the average final flooding proportion is 0.47 according to the theoretical method, while the value obtained empirically is around 0.3. Moreover, the theoretical approach produces the exact same value for any initial conditions, while empirically we can see slight variability in the average final proportion value. Although the results do not match perfectly, the values 0.3 and 0.47 are still not too far off, contributing somewhat to our confidence in the correctness of our approach. The discrepancy between empirical and theoretical results can be easily explained by the difference in assumptions. As we described before, MFA assumes spatial homogeneity, which is definitely violated in our simulation due to a specific topology of the area. Moreover, specific update rules for the water flow in the simulation might also contribute to the deviations from expected results.

Empirical Analysis of Different Scenarios

Here, we are exploring the effects of two strategies/scenarios on the average final flooding proportion: different rain patterns (durations from the start in terms of timesteps) and the introduction of a drainage system into the terrain.

Rain patterns

To investigate the effect of the different rain patterns on the average final flood level, we ran the simulation (for San Francisco terrain and corresponding default absorption and evaporation rates and groundwater limit) for every other rain duration ranging from 1 to 20 timesteps given that simulation runs for 20 timesteps total. For each rain duration, we also repeated the simulation 20 times to average the results. The results can be seen in Figure 4. We see that with increasing rainfall duration, the average flooding level also increases, which is expected since the more water falls on the ground, the more cells will get flooded. We can also see an interesting refinement in the parameter space, where after a certain threshold of rain duration, around ten timesteps, the average final flood level stabilizes around 0.8. In other words, we see that when it floods more than half of the time (10 out of 20 timesteps), the increased amount of rain does not make a difference for our topology. Only when it rains less than half of the time we can observe a generally rising trend in the average final flood level. The fact that the average final flood level does not go above 0.8 can be explained by the specificities of the topology, where certain cells are much higher than others and the water always flows down from them regardless of the amount of rain. Lastly, we should comment on the 95% CIs of the mean and the data, both of which are very narrow, indicating we are highly confident of the results. Increasing the number of repeated simulations would only narrow down the CI of the mean. As before, the reliability is questionable due to the simulation's limitations and simplifications as compared to the real world, such as simplified water flow and absorption rules, as well as neglected real-life external factors.

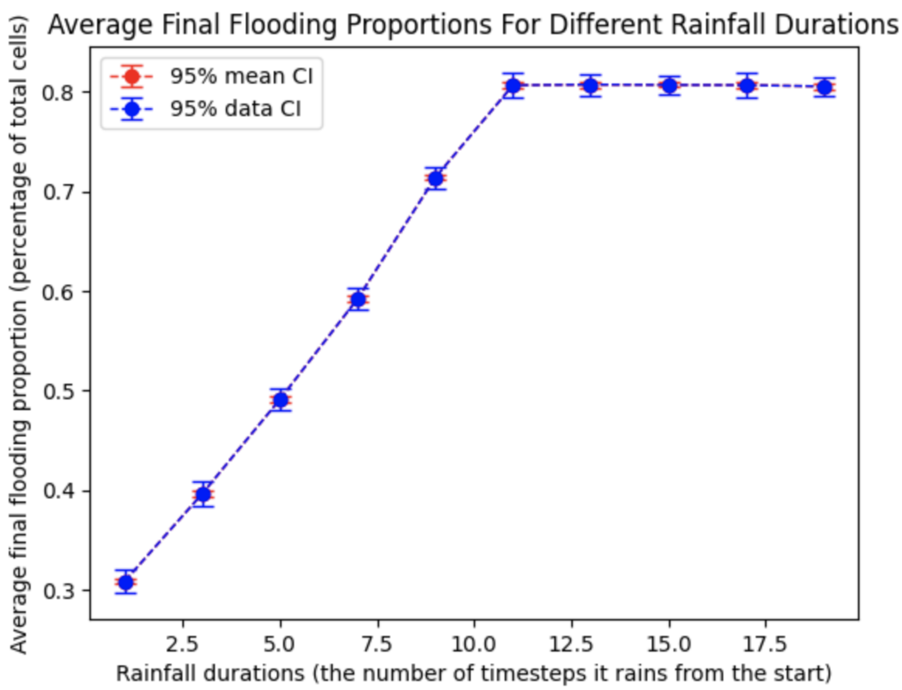

Figure 4. Average final proportion of flooded cells as a function of increasing rain duration with corresponding CIs. The general increasing trend is up until the rain duration is around 10 timesteps, after which the flooding proportion stabilizes at around 0.8.

In addition, we also plotted the histograms of final flood levels for each rain duration to see the distribution of simulation outcomes. The distribution for rainfall duration of 1 timestep is presented in Figure 5 as an example (the rest of the histograms is provided with the code). This histogram supported our observation from very narrow CI intervals in Figure 4 as the range of simulation outcomes is roughly within 0.005 around the mean value (from 0.302 to 0.314 total).

For other histograms, the result is the same, indicating again that we are very confident in the simulation outcomes.

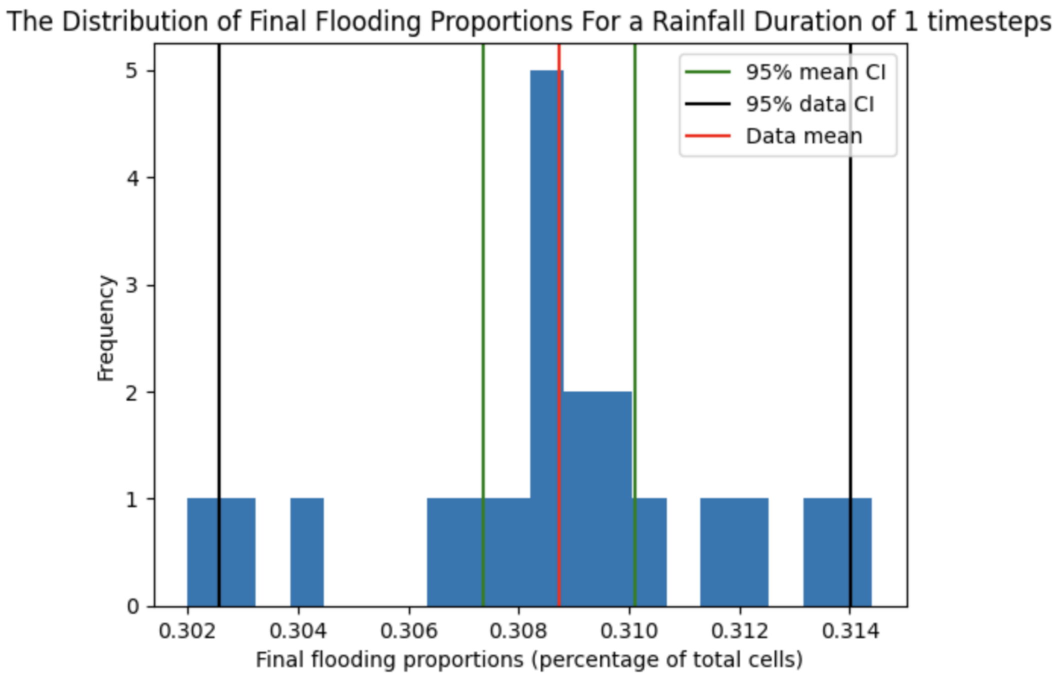

Figure 5. The distribution of flooding simulation outcomes (final proportions of flooded cells) after repeating the simulation 20 times for the rainfall duration of 1 timestep from the beginning. The mean, 95% mean CI, and 95% data CI are provided and labeled.

This analysis can serve as a starting point and guide for further, more sophisticated studies about the effects of precipitation on the flood levels of San Francisco. We showed that for a given terrain, there is a threshold amount of rainfall (corresponding to 10 rainfall timesteps of 1 to 3 units of water per cell), before which the flood level increases at a certain rate and after which almost all area gets flooded, and more rain does not make a difference. This insight can help the relevant stakeholders use precipitation forecast data and estimate how much of a given area will be flooded, how fast it will get flooded, and the maximum stable flood level, after which more water will not make a significant difference. This analysis would be able to help to prepare and organize necessary preventative measures to ensure the safety and comfort of the citizens. For example, from this analysis, we would recommend introducing some measures early on to mitigate the rapidly increasing flood levels we see in Figure 4. One such measure could be a drainage system, whose affects we are exploring in the next section.

Drainage System

To investigate the effects of introducing a drainage system into the terrain, we first ran the simulation for a San Francisco terrain and a default set of parameters and recorded the progression of flooded cells proportion over time for each repetition. Ultimately, we found the 200 most flooded cells and recorded their coordinates, making them the ‘drainage’ cells for the drainage system simulation. These cells differ from normal cells in having an absorption rate of 1 and an extremely large groundwater capacity of 1000000000 units of water, which allows these cells to intake water from the surface as soon as it gets there. After running this simulation multiple times, averaging the recorded flooding progressions, and computing corresponding CIs for both ‘drainage’ and ‘no drainage’ simulations, we plotted the average flood progression for both types of simulations on the same graph, presented in Figure 6.

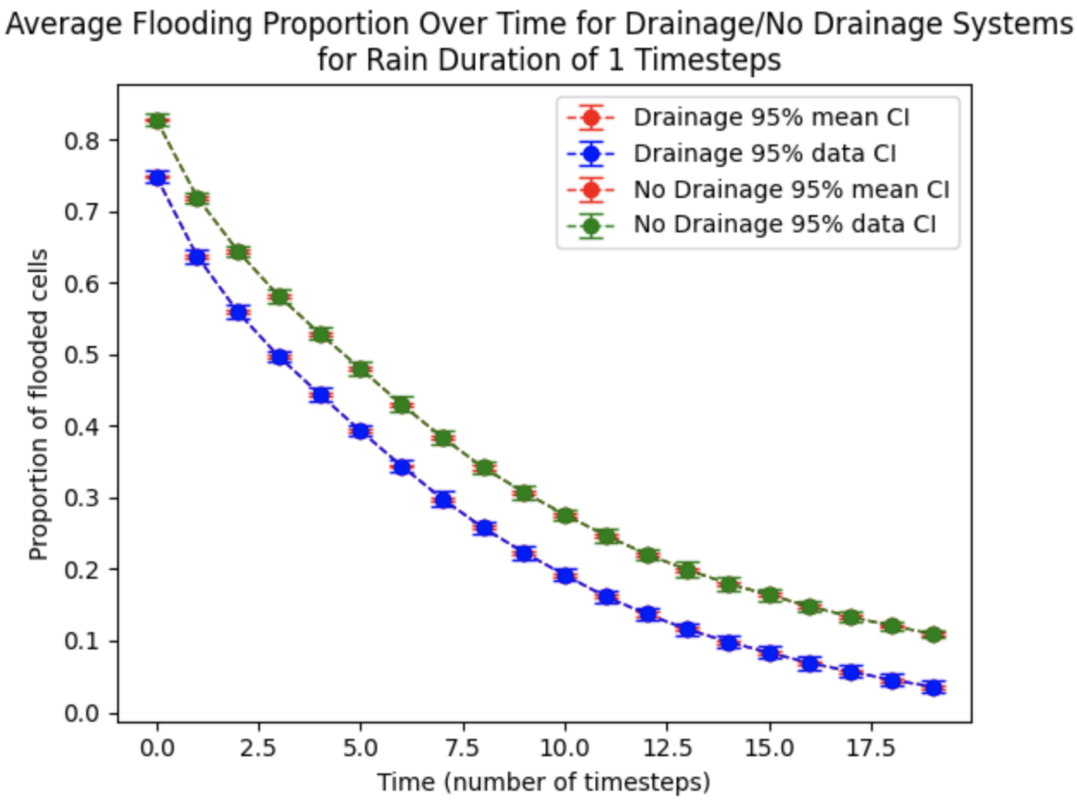

Figure 6. Comparison of the average proportions of flooded cells over time between terrains with drainage system and without with corresponding CIs. Rain duration is one timestep. We can see that the drainage system reduces the amount of flooding by approximately 10%.

We can see that the proportion of flooded cells on the terrain with a drainage system (blue in Figure 6) is lower than that on the terrain without a drainage system (green in Figure 6) for a given timestep by approximately 0.1 (10%). This observation suggests that the drainage system does work and decreases the proportion of flooded cells by 10%, which is 250 more not flooded cells as pared to the terrain with no drainage. We are also very confident in the results since both mean and data CIs are extremely narrow. Increasing the number of repeated simulations would make the mean CI even narrower, which we would not be able to observe.

Figure 6 presents the comparison between the two systems when the rain was only present for one timestep at the beginning of the simulation. We repeated this experiment for different rain duration (1, 6, 11, 16, and 21 timesteps) to see if the difference between introducing a drainage system or not changes with different amounts of rainfall. As a result, the was no effect on the difference between the systems, which remained around 0.1 for any rain duration. For example, Figure 7 presents the comparison between terrains with and without drainage systems when the rain poured for 11 timesteps (a bit more than half of the total simulation time).

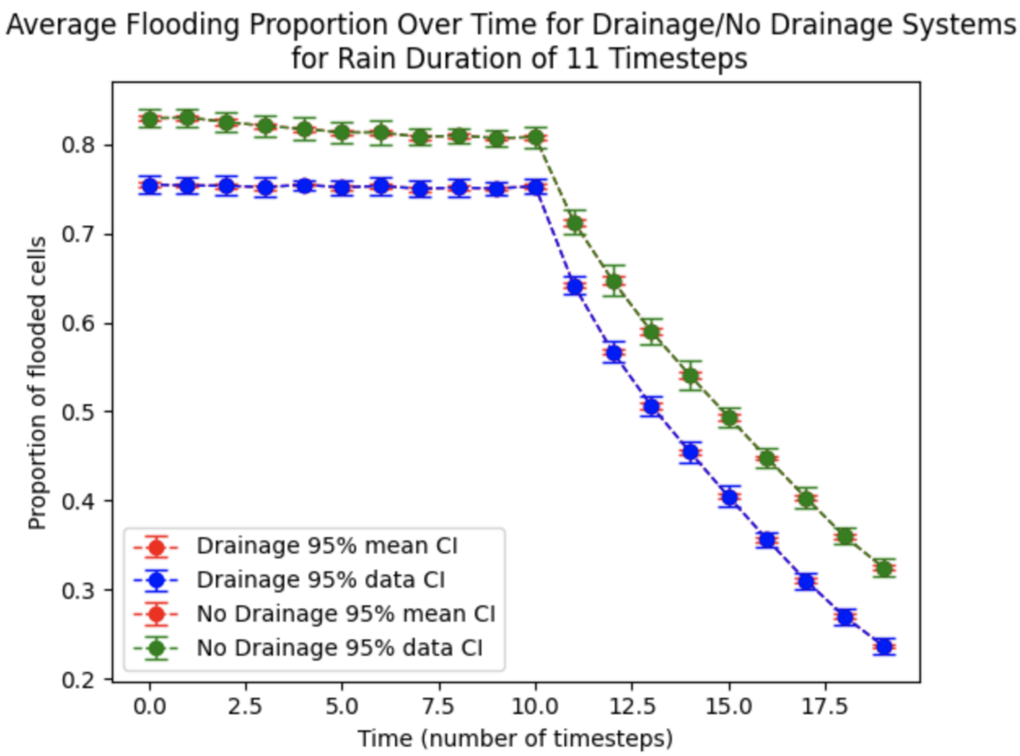

Figure 7. Comparison of the average proportions of flooded cells over time between terrains with drainage system and without with corresponding CIs. Rain duration is 11 timesteps. We can see that the drainage system reduces the amount of flooding by approximately 10%.

Based on these results, we would recommend introducing the drainage system in the areas of the highest flooding for mitigation of flood levels. The next steps could be exploring introducing more drainage cells, as well as at different locations other than the highest flooding cells. To increase the draining effect, we could also consider introducing larger areas of drainage in one place, such as a block of 4 draining cells, for example, rather than one cell, as we did in our analyses. Lastly, we could potentially design such a drainage system that would have more of an effect when the number of rain increases so that a larger amount of water does not cause drastic consequences. Overall, we recommend implementing a drainage system for San Francisco officials to mitigate the effects of precipitation and flooding.

Conclusions

In conclusion, we recommend installing a drainage system in San Francisco as it reduces the amount of flooding overall. However, it should be further optimized and tested. The rain duration analyses showed that the flooding rate and the threshold rainfall amount value could be found computationally, which could be a great tool for forecasting and predicting flooding amount and its effects.

References

San Francisco topographic map, elevation, terrain. (n.d.). Topographic Maps. Retrieved April 16, 2023, from https://en-us.topographic-map.com/map-vx51/San-Francisco/?center=37.79397%2C-122.423&zoom=15

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LO/HC Appendix

#Modeling - In my report, I provided a comprehensive explanation of the rainfall and flooding scenario on a specific area of San Francisco, outlining its relevant features and underlying assumptions. Additionally, I presented both theoretical and computational models, explaining how they accurately represent our specific scenario. I highlighted the assumptions made in these models and compared them with the actual situation. I also discussed how the real-world situation deviates from certain assumptions and how it impacts the accuracy of the models, either improving or reducing their reliability. Furthermore, I identified the variables, parameters, updating rules, and outputs of the model. Throughout the report, I consistently compared and contrasted the characteristics and assumptions of the scenario with the theoretical modeling theory to establish clear connections between them, ensuring a thorough analysis.

#Theoretical Analysis - I carefully selected an appropriate theoretical analysis method (MFA) that matches the specifics of my scenario and derived and utilized relevant formulas to accurately analyze the variables of interest. I considered certain state transition situations and explained and justified all the relevant probabilities, deriving appropriate probabilistic equations. To be able to interpret the results, I utilized derived probabilities to produce a cobweb plot, which helped me find stable states. When interpreting the results, I considered the context of both the model and the scenario, recognizing that theoretical models may not always perfectly reflect reality. Finally, I analyzed the theoretical findings, identifying important parameter regimes, such as stable state final flooding proportion given the initial flooding proportion.

#Python Implementation - I successfully executed the simulation of the model in Python, utilizing relevant Python classes and methods. I efficiently employed lists and arrays to store simulation results and data. I developed code for the flooding simulation and animation, test cases, as well as for theoretical and empirical analyses. I visually represented all the simulations and provided test cases to validate the accuracy of the simulation. Finally, I conducted empirical analysis by running the simulation with various parameter values, tracking relationships between metrics of interest, and appropriately storing and plotting the data for analysis.

#Empirical Analysis - After implementing the flooding system, I conducted experiments to investigate the effects of different initial rain proportions and durations and the introduction of the drainage system on the average final proportion of flooded cells, which was the targeted optimization variable that I wanted to minimize. To support my findings, I utilized appropriate statistical measures, such as 95% confidence intervals, and visual aids such as error plots and histograms. I compared the empirical average final flood level for different initial flood levels with the theoretical estimates to assess their consistency and commented on the validity of both. I interpreted the 95% confidence interval of the mean and compared it to the 95% confidence interval of the data. I also explained the implications of increasing the number of simulations on each confidence interval.

#Code Readability - I made sure to enhance the code's readability and documentation by utilizing consistent docstrings and in-line comments effectively. I optimized the code's implementation by leveraging appropriate and straightforward built-in Python functions, modules, and data structures. I effectively employed object-oriented programming techniques to implement model functionalities and efficiently organize data. Lastly, I used descriptive variable names in the code to facilitate easy identification of each variable's purpose.

#Professionalism - I answered all the questions in the assignment instructions using the knowledge I gained in class. Furthermore, I presented a meticulously organized report and code notebook, effectively conveying our theoretical and empirical analyses through appropriate mathematical equations and well-crafted figures. I ensured accurate labeling and captioning of all tables and figures while avoiding any typographical errors and adhering to formatting guidelines.

#***audience*** - When writing the assignment, I kept in mind the academic audience and wrote my paper is a style suitable for this setting. I included some technical terminology and provided detailed explanations whereever they were needed to construct a clear and comprehensible report. In addition, I recognized the audience of San Francisco officials, to whom I intended to generate certaon recommendations regarding flooding in San Francisco. Hence, I clearly explained and justified the chosen analyses and strategies, and intepreted the results specifically to generate tengible recommendations, such as introduction of the grainage system.

#***modeling -*** I proficiently designed a computational model to simulate flooding and effectively applied a theoretical MFA model to accurately model the water flow in San Francisco. I provided a clear description of the scenario to be modeled, including relevant aspects of both computation and theoretical models, such as variables, updating rules, inputs, and outputs. I justified my choices in a coherent manner. Furthermore, I accurately interpreted and clearly explained the results and implications of the applied models. I also thoroughly evaluated the effectiveness of the models' application and provided a well-supported critique.

AI Note

No AI tools were used for this assignment.

Code Appendix