Simulation and Analysis of Disease Outbreaks via Zombie Apocalypse: A MATLAB Approach

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Whilst the zombie apocalypse is one of the most popular themes in entertainment, besides the pop-cultural study surrounding the living dead, another branch of zombie research is more scientific in nature and is concerned with using the attack of the living dead as a metaphor and modeling tool to understand and bring attention to epidemiological processes of infection as well as global disasters including malaria, SARS, STDs, influenza, MRSA, Ebola, rabies, scrapie, and mastitis (e.g. Brooks, 2003; Engler, 2012; Stanley, 2012). This has been applied as a system of 'Susceptible, Infected, Recovered' to model numerous pandemics including the 2020 COVID pandemic (Batista et al., 2021). Conversely, the simulation can be used in drug experimental testing and vaccines through a population-based approach (Computer Simulations, 2018b). Suppose we wish to simulate the effectiveness of a vaccine against a virus, we can tune the potency and population of the antibody and viruses to quantify the success rate of the drug or vaccine. Within the medical scope, a research center utilizes machine learning to predict pregnancy and multiple pregnancy risks following in vitro fertilization-embryo transfer (Wen et al., 2022). However, we believe that with the integration of new parameters and constraints, the zombie simulation can serve as an efficient tool in reproductive medicine to predict the success rate of a vitro fertilization-embryo transfer. Many factors have been known to affect IVF outcomes including age, sperm quality, fertilization rate, embryo quality, frequency of transferred embryos, and endometrial thickness. The humans and zombies would represent the gametes, and the population and fertilization rate of each can be varied as per the gamete recipients' age, sperm quality, fertilization rate, embryo quality, etc. In conclusion, a population-based simulation can be an efficient modeling tool to quantify the outcomes of any engineering problem with Bernoulli distribution, success, and failure parameters.

We model a zombie attack by introducing a basic model of a zombie-to-human ratio in Zombieville, determining the probability of survival/strength of humans against humans(phh) and zombies(phz), then simulating numerous motion steps governed by predetermined laws of motion. Then we examine the impact of phz parameter on the basic, flight, and flight models. The outcomes are illustrated with mathematical interpretation, we derive conditions under which the eradication of humans can occur and what parameters are necessary to preserve the human population. We show that, unlike the expectation, a population of humans with less than 40% the chance of survival against a zombie can go extinct if they follow a fight response. We also show how and why the flight response is overall the smartest strategy in a zombie apocalypse.

Description of ZombieVille:

Zombieville is a square-shaped city divided into evenly distributed squares and represented as an $n \times n$ matrix. Each cell can either be empty, occupied by a zombie, or a living person. Let Xi,j(t) $\in \{-1,0,1\}$ be the state of cell (i,j) at time t, representing the location in row i, column j. Xi,j(t) = 0 means that cell (i,j) is empty, Xi,j(t) = -1 that the cell is occupied by a zombie, and Xi,j(t) = 1 that the cell is occupied by the living. The simulation executes a total of 100,000 steps where only one person can move per step.

The Zombieville we chose to simulate is one with the basic assumption that will be presented in the next section. Both species; humans and zombies move at equivalent rates and are constrained by the same laws of motion. However, 'humans' are either in fight mode, hence fiercer than their counterparts, and hunt the zombies across Zombieville or humans are in flight mode, hence avoid zombies and instead seek refuge in empty cells or other human-containing cells.

Parameters used in the experiments:

T=time steps, $T \geq 0$

M = rows, $M \geq 0$

N = columns, $N \geq 0$

p_living= fraction of humans in the matrix, $0 \leq p\_living \leq 1$

p_zombie=fraction of humans in the matrix, $0 \leq p\_zombie \leq 1$

phh= strength of a human when attacking a human, $0 \leq phh \leq 1$

phz= strength of a human when attacking a zombie, $0 \leq phz \leq 1$

M_h= randomized matrix of cells x_h, $x_h \in 0, 1$

M_z=randomized matrix of cells y_z, $y_z \in 0, -1$

M_i= initial matrix of cells x_i, $x_i \in 0, -1, 1$

Initializing the matrix:

The simulation begins by generating two pseudo-random binomial generated matrices M_h and M_z of size $n \times n$ via the MATLAB function binornd(n,p) that generates random numbers from the binomial distribution shaped by the number of trials n and the probability of success for each trial (*p_living or p_zombie)*. The $M_h$matrix contains cells that can either be empty or occupied by a human, generated by the function binornd(1,pLiving,N,M) where pLiving is the fraction of humans in the matrix defined as 0.2. Whereas the M_z matric contains cells that can either be empty or occupied by a zombie, generated by the function (-1 .* binornd(1,pZombies,M)) where pZombies is the fraction of zombies in the matrix defined as 0.05. The initial state matrix M_i is the sum of the matrices M_z and M_h, hence contains cells that can either be empty, occupied by a zombie, or occupied by a human. Due to the combination of elements' sum of M_h and M_z, there is a cancellation process when $M_h = 1$ and $M_z = -1$ causing a lower probability of zombies and humans in the initial state matrix M_i despite M_h having a pLiving exactly equal to 0.2 and M_z having a pZombie exactly equal to 0.05. The probability of humans and zombies in the initial matrix M_i are called the true probabilities.

Finding the true probabilities mathematically:

By the parameters defined above for M_h, probability of success $p = pLiving = 0.2$ and $q = 0.8$.

$P(x = 1) = 0.2$ and $P(x = 0) = 0.8$.

Likewise, By the parameters defined above for M_z, probability of success $p = pZombie = 0.05$ and $q = 0.95$.

$P(x =- 1) = 0.05$ and $P(x = 0) = 0.95$.

M_h	M_z	$M_i = M_h + M_z$
1	-1	0
1	0	1
0	-1	-1
0	0	0

Table 1: The four scenarios when summing M_h and M_z elements

Mathematically, the true probability can be calculated by computing the following probabilities using the binomial distribution. By the process of generating M_h and M_z individually, we can consider the probabilities of humans and zombies as independent whereby $x_h \in M_h$ and $y_z \in M_z$

$P(human\ in\ M_i) = P(X = 1 + 0) = P(x_h = 1)P(y_z = 0)$
$= (0.2)(1 - 0.05) = 0.19$

$P(zombie\ in\ M_i) = P(X = 0 - 1) = P(x_h = 0)P(y_z = 1)$
$= (1 - 0.2)(0.05) = 0.04$

$P(empty\ \ in\ M_i) = 1 - (P(human\ in\ M_i) + P(zombie\ in\ M_i) = 1 - (-\ 0.19 + 0.04) = 0.77$

By the law of large numbers we can achieve an equivalent value for true probability through simulating a sufficiently large number of matrices, k, then calculating the probability of humans and zombies from the average of k matrices.

Law of large numbers:

Since $M_1^{\ i}, M_2^{\ i}, M_3^{\ i} ... M_k^{\ i}$ are the initial matrices are generated separately, we affirm that the matrices are independent. The law of large numbers states that given the above condition is satisfied then, $P(\left|\frac{M_1 + M_3 + .. + M_k}{k} - \mu\right| > \epsilon) = 0\ as\ k \rightarrow \infty$, for any $\epsilon > 0$.

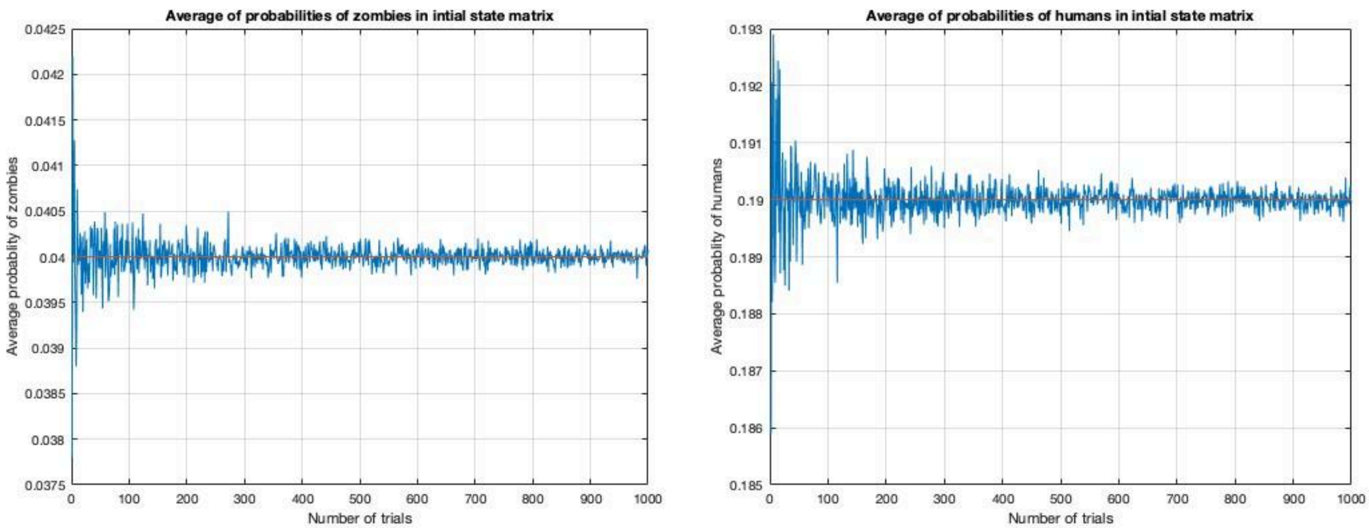


Figure 1: Average of probabilities of species in the initial state matrix

The figures above indicate that for a sufficiently large number k (k>300) the probabilities generated by the binomial command converge to the expected probability calculated above.

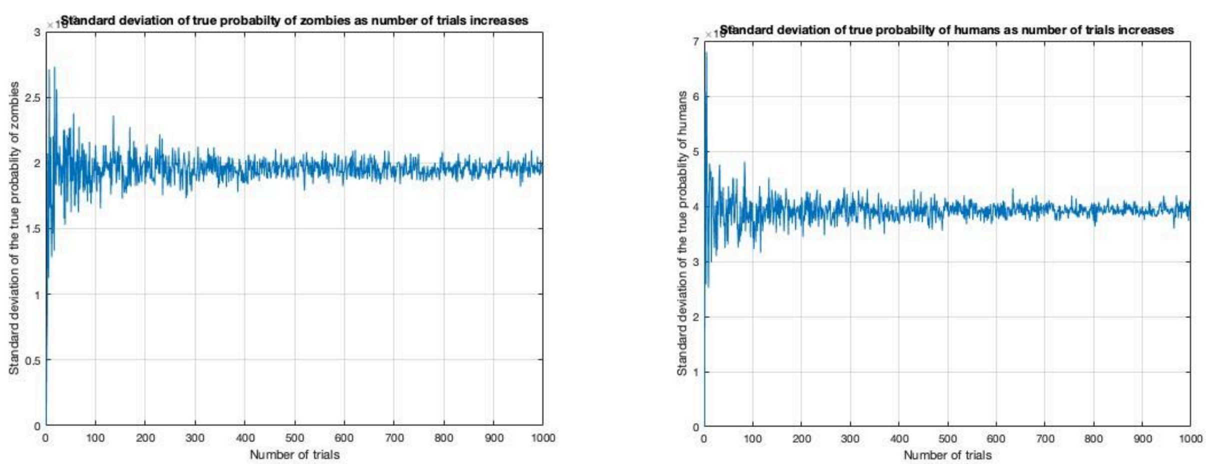
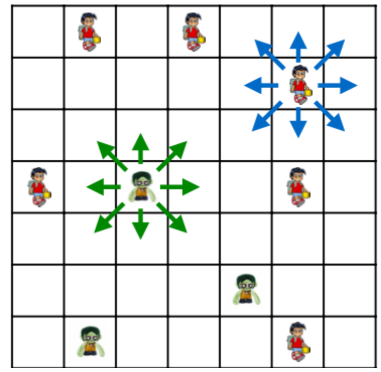


Figure 2: Standard deviation of true probability of species across a large number of trails

Furthermore, the figure above illustrates the variety between the k matrices, from the figure we conclude that as $k \to \infty$, the standard deviation converges. Analyzing the mean and standard deviation by the law of large numbers equation, we conclude that matrices generated for a large k will have a very similar distribution of humans or zombies and therefore we do not have to consider a significant variation between each simulation.

Laws of motion:

If there is a being in cell (i,j), i.e., if either Xi,j(t) = −1 or Xi,j(t) = 1, that person can move to an adjacent cell in the next time step (or remain in (i,j)). With each time step, only one person can make a move.



Choosing a cell to simulate:
A motion begins with a selection of a random cell from the $m \times n$ initial state matrix using the MATLAB rand() function, which generated the cell coordinate (i,j) to refer to as $X_{i,j}(t)$ where t is the time step. Random cell coordinates are continuously generated until the random cell chosen is not an empty cell. The 9 neighborhoods surrounding and including the cell are defined as the cell's neighborhood. The probability for each motion to each cell in $N_{i,j}$ is calculated and a motion is more likely to a cell with a higher score.

Probabilities of cells in the neighborhood:
A score can take the value 0, 1, or 2 to simply illustrate how likely the move is, that is motion is likely to happen to a cell with a higher score. For instance, in this zombie apocalypse simulation, a human in fight mode will target zombies therefore we define the score for a human moving to a cell with a zombie to be maximum, of value 2. On the contrary, a human in flight mode strives to escape a zombie, therefore we define the score for a human to move to a zombie cell to be 0.

$X_{i,j}/X_{k,l}$	0	1	-1
0	0	0	0
1	1	1	2
-1	2	0	1

Table 2: The scores of basic model

Let Ti,j(t) denote the target cell for a being in cell (i,j) in time step t. We may formulate the probability associated with this as follows:

Let the score of move from cell i,j to k,l be denoted by $S_{i,j\rightarrow k,l}(X_{i,j}, X_{k,l})$

$$P_{i,j}(t) = \mathrm{P}(\mathrm{Ti,j}(t) = (\mathrm{k,l}) \mid \mathrm{X}(t) = \mathrm{x}) = \frac{S_{i,j\rightarrow k,l}(X_{i,j}, X_{k,l})}{\sum_{x,y\in N_{i,j}} S_{i,j\rightarrow k,l}(X_{i,j}, X_{x,y})}$$

The probabilities that govern the law of motion respect the axioms of probability:

- **Axiom 1: For any event A, P(A)≥0.**

  $0 \leq S_{i,j \to k,l}(X_{i,j}, X_{k,l}) \leq 2$, by extension the summation of positive integers is a positive integer

  $$\sum_{x,y \in N_{i,j}} S_{i,j \to k,l}(X_{i,j}, X_{x,y}) \geq 0$$

  $$P_{i,j}(t) = \frac{S_{i,j \to k,l}(X_{i,j}, X_{k,l})}{\sum_{x,y \in N_{i,j}} S_{i,j \to k,l}(X_{i,j}, X_{x,y})} \geq 0$$

- **Axiom 2: Probability of the sample space S is P(S)=1**
  Sample space is $N_{i,j}$

  $$\sum_{x,y \in N_{i,j}} P_{x,y}(t) = \sum_{x,y \in N_{i,j}} \left[\frac{S_{i,j \to k,l}(X_{i,j}, X_{x,y})}{\sum_{x,y \in N_{i,j}} S_{i,j \to k,l}(X_{i,j}, X_{x,y})}\right] = \frac{\sum_{x,y \in N_{i,j}} S_{i,j \to k,l}(X_{i,j}, X_{x,y})}{\sum_{x,y \in N_{i,j}} S_{i,j \to k,l}(X_{i,j}, X_{x,y})} = 1$$

- **Axiom3: If A1,A2,A3,⋯ are disjoint events, then P(A1 ∪ A2 ∪ A3⋯)=P(A1)+P(A2)+P(A3)+⋯**

  Let $X_{i,j}(t), X_{(i-1,j)}(t), X_{(i+1,j)}(t)$ be the event of choosing cell $X_{i,j}(t), X_{(i-1,j)}(t), X_{(i+1,j)}(t)$ as target cell at step t respectively then
  because the simulation executes a move to a single target cell, therefore the probability of choosing cell $X_{i,j}(t)$ and $X_{(i-1,j)}(t)$ and $X_{(i+1,j)}(t)$ … is zero. The event of choosing cells $X_{i,j}(t), X_{(i-1,j)}(t), X_{(i+1,j)}(t)$ are naturally disjoint. Since the cells are disjoint then $P(X_{i,j}(t) \cup X_{(i-1,j)}(t) \cup \ldots) = P(X_{i,j}(t)) + P(X_{(i-1,j)}(t)) + \ldots.$

Target cell:

To determine the next step, the interval [0,1] is divided into |Ni,j| smaller intervals. Each interval corresponds to one of the 9 cells (k,l) in the neighborhood of (i,j). A Uniform pseudo-random variate on the interval [0, 1] is generated using MATLAB rand() function. The value returned by rand() function falls between [0,1] and hence falls somewhere between one of the |Ni,j| smaller intervals of range [0,1]. The program checks which of the nine intervals the rand() probability lies in; the corresponding interval determines which cell to move to, referred to as cell $X_{k,l}$. If $X_{i,j}(t) = X_{k,l}(t)$ for $(i, j) \neq (k, l)$, meaning both the cell contains zombies or both living, one advances, the other does not: a flip of Bernoulli, Bsame determines which zombie or human advances. However, If $Xi, j(t) \neq Xk, l(t)$, meaning if a cell has zombie and another has a human flip a different Bernoulli, B_{fight} to decide who wins. In this case, the loser dies leaving their original cell empty.

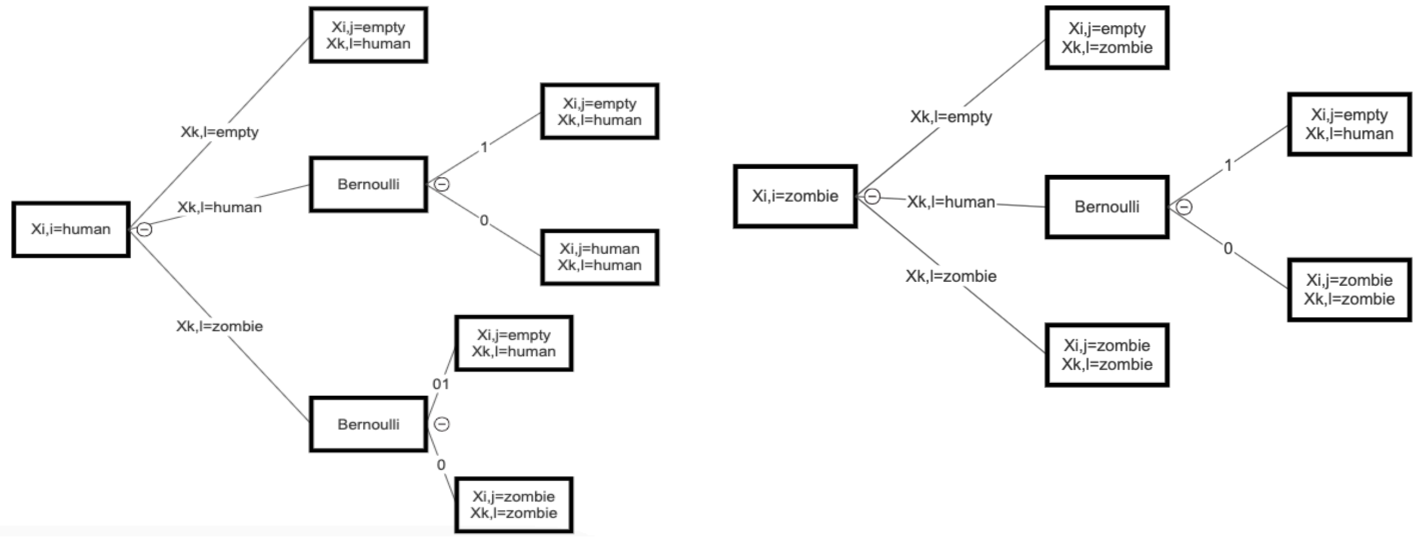


Figure 3: Using Bernoulli to determine the next move

The Simulation:

By the law of large numbers we can assume that the initial matrix will provide a fixed number of human and zombie populations, therefore, running the simulation once will provide a reliable estimate of the zombie apocalypse.

The Basic model:

For all the models, we consider three classes

- ➢ Zombie
- ➢ Human
- ➢ Empty

By the way we defined the laws of motion, the human population can remain constant or decrease. Therefore we can expect to consistently have either a constant or a decaying graph when plotting the fraction of humans against time step irrespective of the phh and phz values.

- A Human can be removed if the human loses against another human, or both can remain alive.

In contrast, a zombie population can remain constant, decrease or increase.

- A Zombie can be removed if the zombie loses the fight against the human, or zombie
- A new Zombie can only come from an infected human that lost an encounter with a zombie.

$X_{i,j}/X_{k,l}$	0	1	-1
0	0	0	0
1	1	1	2
-1	1	2	0

Table 3: The scores of the basic model

The basic model is characterized by the popular culture zombie apocalypse; humans collaborate with their prototype to eradicate their slow-moving counterpart. In this model, the strength of humans against a human (humans killing their prototype or themselves) is as low as 5% whereas the strength of humans against a zombie (humans killing their counterpart) is as high as 90%.

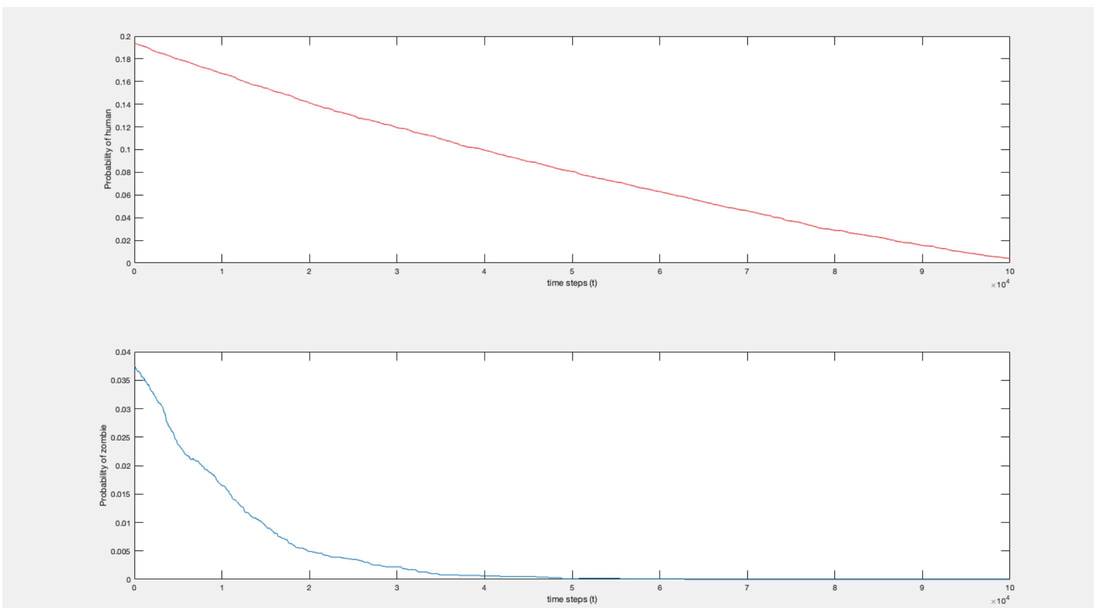


Figure 4: Probability of species over time

The graph shows the rate at which living beings and zombies change over time. Overall, there was a dramatic decrease in the fraction of living beings and zombies that can be represented by two decaying exponential functions. We can note that the zombie population is completely eradicated by $\frac{T}{2}$. Whereas, the human population only decays by 50% by $\frac{T}{2}$. The remaining human population is as low $\approx$ 1% the initial human population.

Whilst this model is ideal because it eradicated the zombie population completely, a real-life zombie apocalypse is far from the popular culture zombie apocalypse displayed in movies and entertainment. The next two models target modeling a zombie apocalypse when governed by human instinct more specifically the fight or flight response. We thus extend the basic model to include the (more 'realistic') possibility that a human experiences a fight or flight response. We model the fight response as an increase in a human's tendency to fight the threatening source, the zombies (higher tendency to kill zombies). Likewise, the flight response is modeled as a decrease in a human's tendency to fight zombies (The Evolution of the Stress Concept 1973).

Whilst maintaining the zombie scores as constant, we vary the human scores to quantify the flight or fight response. A flight and fight response is represented as a change in scores, in flight mode, the human has a lower tendency to confront a zombie therefore the score would be 0, in contrast, a human in flight response wishes to escape to an empty cell and therefore the score is 2. The fight response is characterized by a high human tendency to confront/chase a zombie therefore the score is 2.

Within the two responses, we investigate what parameter settings are necessary to preserve the human population in the zombie apocalypse.

The 'Human fight response' model:

$X_{i,j}/X_{k,l}$	0	1	-1
0	0	0	0
1	1	1	2
-1	0	2	0

Table 4: The scores of the 'human fight response' model

While humans are in fight mode, they are more likely to be threatened by a zombie than a human. We now revise the model to include a human population of high aggression towards their counterpart fueled by the adrenaline released in response to the fight mode. We thus extend the basic model to include the (more 'realistic') possibility that under extremely distressing conditions humans will incline to violence against the zombies. To do so maintained the phh parameter, where phh is a measure of the tendency of humans to kill another human or themselves). Instead, we vary the phz parameter where phz is a measure of the tendency of humans to kill a zombie. After running multiple simulations, we found that the outcomes can be distributed among three cases, $phz < 0.5$, $phz = 0.5$, $phz > 0.5$.
We expect because of the scores set, humans in fight response are twice as likely to attack a zombie, therefore if the $phz > 0.5$ then the zombies' population will be lower compared to the zombie population of humans under a flight response.

Phz < 0.5

The overall trend for any $phz < 0.5$ is that the human fraction plot decays exponentially while the zombie fraction grows dramatically. The human fraction plot for any $phz < 0.5$ can be fitted to an exponential equation of the form ae^{-b}. The higher the phz, the larger the b parameter value, the smaller the a parameter value, and hence the greater the drop in human fraction. On the other hand, the zombie fraction plot can be fitted to a power equation of the form ax^{b}, the smaller the b parameter value and hence the greater the rise in the zombie fraction.

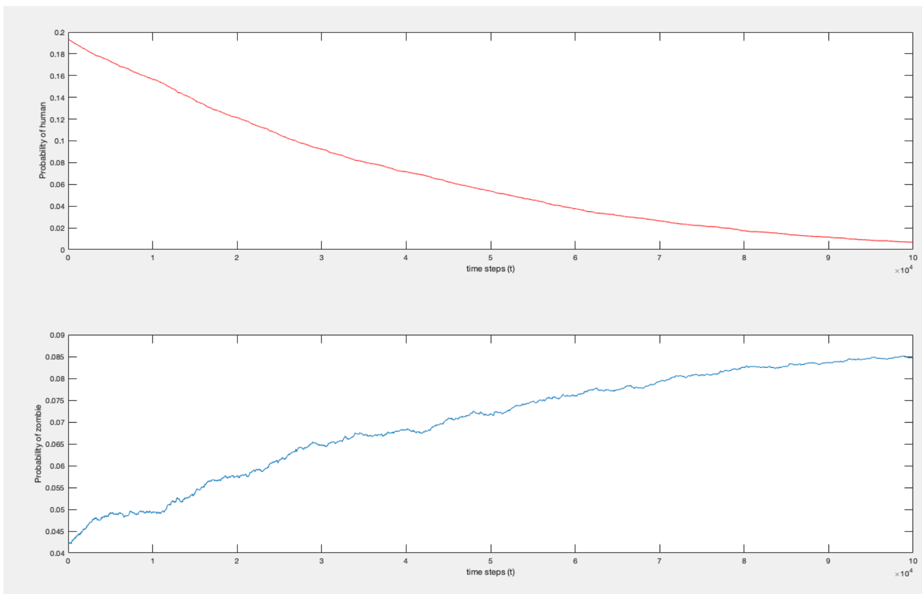


Figure 5: The fraction of species over time for Phz<0.5 in a human fight response

The graph shows the rate at which living beings and zombies change over time. Overall, there is a trend of exponential decay in the human fraction and power growth in the zombie fraction. Nearly 70% the human population died by $\frac{T}{2}$. On the other hand, the zombie population increased 40% by $\frac{T}{2}$. Looking at the trend over time steps T, we can see that the zombie fraction increased dramatically over time and more specifically between the time interval $0 \leq t \leq \frac{T}{2}$. On the contrary, that same time interval is when the human fractions dropped significantly.

phz	% change in humans	% change in zombie
0.2	-100	302
0.3	-99.2	225.9
0.4	-94.7	101.3

Table 5: Percentage change in populations

From table 5 it is obvious that the higher the phz, the lower the percentage drop of humans and the lower the percentage gain of zombies. This could suggest that as the fraction of zombies arise, and because of the 'fight' response, humans hunt zombies and therefore a human vs zombie interaction is more probable. However, due to a low $phz < 0.5$, a zombie is more likely to kill a human, which means that there will be an increase in zombies and a decrease in humans. This initiates a cycle where the higher zombie fraction leads to more interaction which due to low phz yields an overall increase in zombie fraction and the cycle continues until the 'doomsday' scenario: an outbreak of zombies will lead to the collapse of civilization as large number of human are either dead or zombified.

<u>Phz=0.5</u>

At $phz = 0.5$, the fraction of living beings remains a decaying exponential function with the form ae^{-b}. However, the fraction of zombies in Zombieville fluctuates and has no obvious trend.

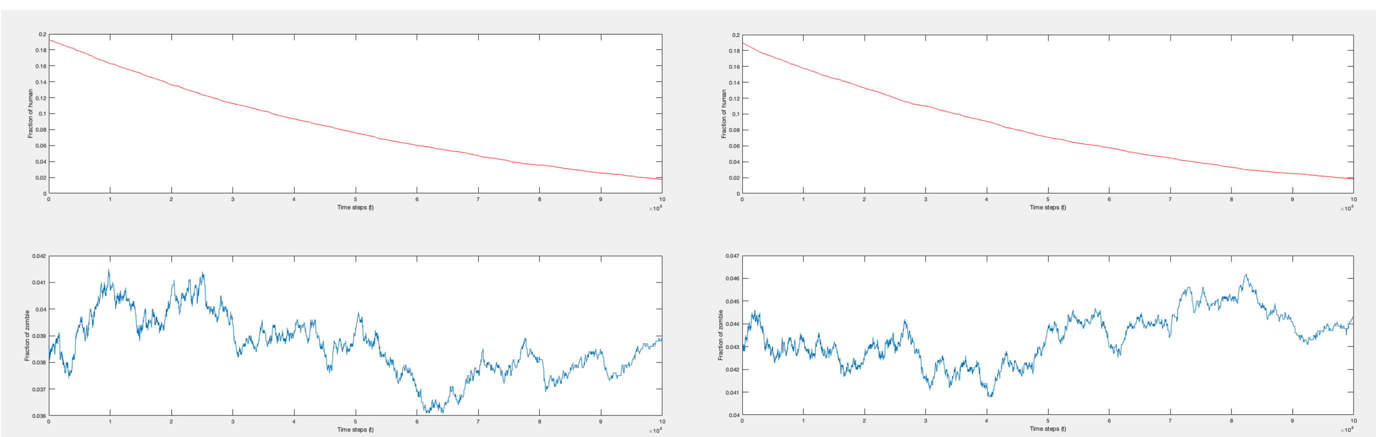


Figure 6: The fraction of species over time for Phz=0.5 in a human fight response

The graph shows the rate at which living beings and zombies change over time. Overall, there is a trend of exponential decay in the human fraction but no obvious trend in the zombie fraction. It is significant to note that would we run the simulation again, the zombie fraction plot would have a different fluctuation pattern. This could suggest that at $phz = 0.5$, the simulation is completely random because the probability of a human killing a human is just as equal as the probability of a zombie killing a human. The number of humans continues to decay because humans can either win a zombie or die therefore the trend is either constant or decaying. In contrast, the fraction of zombies can increase, if a zombie wins or if a human is zombified, or decrease if a zombie dies. Therefore a fraction of the zombie graph can either increase, remain constant or decay between time steps.

Phz>0.5

At $phz > 0.5$, both the fraction of living beings and zombies become a decaying exponential function with the form ae^{-b}.

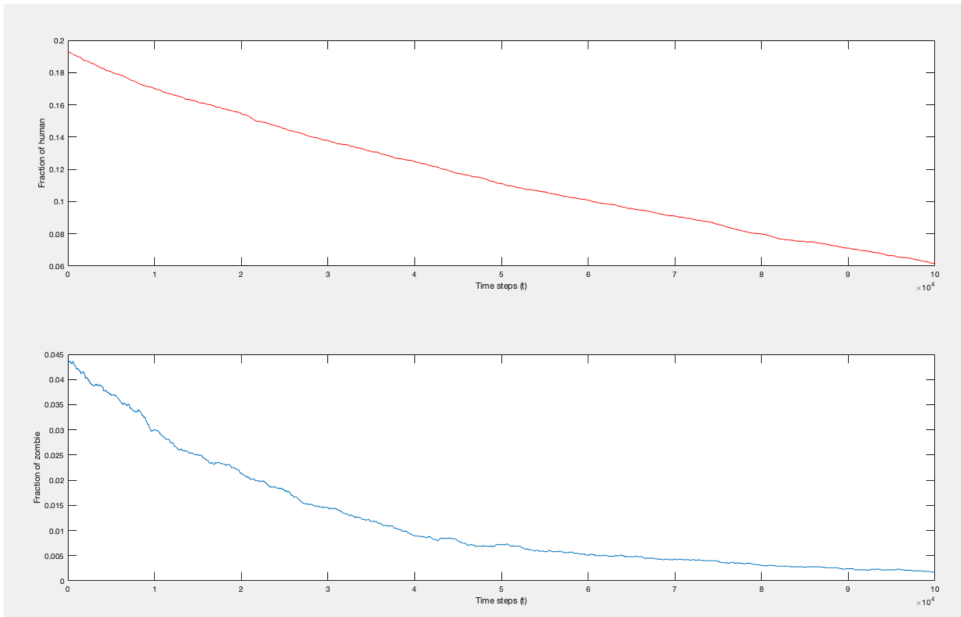


Figure 7: The fraction of species over time for Phz>0.5 in a human fight response

The graph shows the rate at which living beings and zombies change over time. Overall, there was a dramatic decrease in the fraction of living beings and zombies. The 'fraction of human' plot is fitted to an exponential with the form $0.187e^{-1\times10^{-5}}$, likewise the 'fraction of zombie' plot is fitted to an exponential with the form $0.039e^{-4.11\times10^{-5}}$. If we analyze the plot and the equations, we can see that the drop in zombie population occurs at a faster rate than the drop in human population. At $\frac{T}{2}$, nearly 80% of zombies die whereas at that same time step, only 40% of humans dying. This could be attributed to the fact that as humans hunt zombies they are most likely to win against the zombies and hence the fraction of zombies will most likely only remain constant or decrease. We can see that a $phz > 0.5$ is necessary to suppress the spike in zombie population seen in the plot of $phz = 0.5$.

We conclude that with a fight response and a $phh = 0.05$, the following inequality must be satisfied $phz \geq 0.4$ to prevent the dooming outcome of the eradication of human species.

The ‘Human flight response’ model:

$X_{i,j}/X_{k,l}$	0	1	-1
0	0	0	0
1	2	1	0
-1	0	2	0

Table 6: The scores of the ‘human flight response’ model

While humans are in flight mode, they are more likely to seek refuge in empty cells and potentially cells with humans, to escape the vicious zombies. In other words, a human will not hunt a zombie but has a phz chance of killing the zombie. We revise the model to include a human population of low aggression towards zombies. To do so maintained the phh parameter at $phh = 0.05$, where phh measures the tendencies of humans to kill another human or themselves). Instead, we vary the phz parameter where phz is a measure of the tendency of humans to kill a zombie. After running multiple simulations, we found that the outcomes can be distributed among three cases, $phz < 0.5$, $phz = 0.5$, $phz > 0.5$.

<u>Phz<0.5</u>

The overall trend for any $phz < 0.5$ is that the human fraction plot decays exponentially while the zombie fraction grows dramatically. The human fraction plot for any $phz < 0.5$ can be fitted to an exponential equation of the form ae^{-b}. The higher the phz, the larger the b parameter value, the smaller the a parameter value, and hence the greater the drop in human fraction. On the other hand, the zombie fraction plot can be fitted to a power equation of the form ax^{b}, the smaller the b parameter value and hence the greater the rise in the zombie fraction.

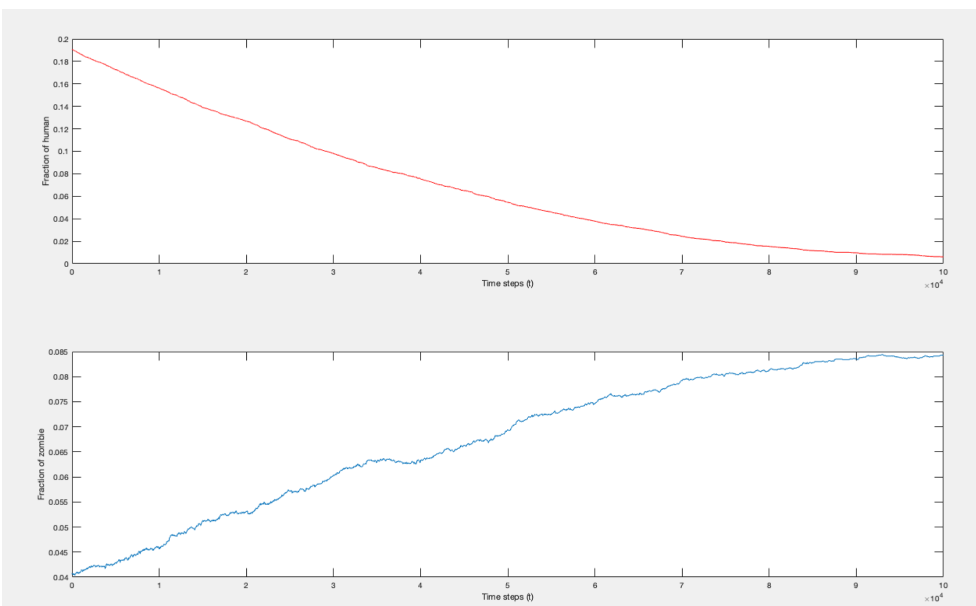


Figure 8: The fraction of species over time for Phz<0.5 in a human flight response

The graph shows the rate at which living beings and zombies change over time. Overall, there is a trend of exponential decay in the human fraction and power growth in the zombie fraction. Nearly 70% the human population died by $\frac{T}{2}$. On the other hand, the zombie population increased 40% by $\frac{T}{2}$. Looking at the trend over time steps T, we can see that the zombie fraction increased dramatically over time and more specifically between the time interval $0 \leq t \leq \frac{T}{2}$. On the contrary, that same time interval is when the human fractions dropped significantly.

phz	% change in humans	% change in zombie
0.2	-100	300
0.3	-99.2	212.5
0.4	-98.9	100

Table 7: Percentage change in populations

From table 7 it is obvious that the higher the phz, the lower the percentage drop of humans and the lower the percentage gain of zombies. When comparing the plot of 'flight response' and 'fight response' at a $phz = 0.4 < 0.5$, the plots appear to be of identical trends; the fraction of zombies oscillates whilst that of humans nearly converges to zero. However, the difference between the two models is that the percentage increase in zombies is lower in the 'human flight response' model.

Although the hypothesis for flight response was that human civilization is more likely to survive with a flight response during an apocalypse, it is interesting that for a low probability of humans killing a zombie ($phz = 0.5$), whether the human hunts the zombie or escapes it results in a dramatic drop in human population and growth of the zombie population. These trends could be attributed to the fact that the zombies have a constant score where they hunt the humans irrespective of the flight or fight response. In addition to the zombie's high tendency to hunt humans, with a low phz such as 0.4, the zombie is 60% likely to kill the human would they fight.

Phz=0.5

At $phz = 0.5$, the fraction of living beings remains a decaying exponential function with the form ae^{-b}. However, much like the 'fight response model' the fraction of zombies in Zombieville fluctuates and has no obvious trend.

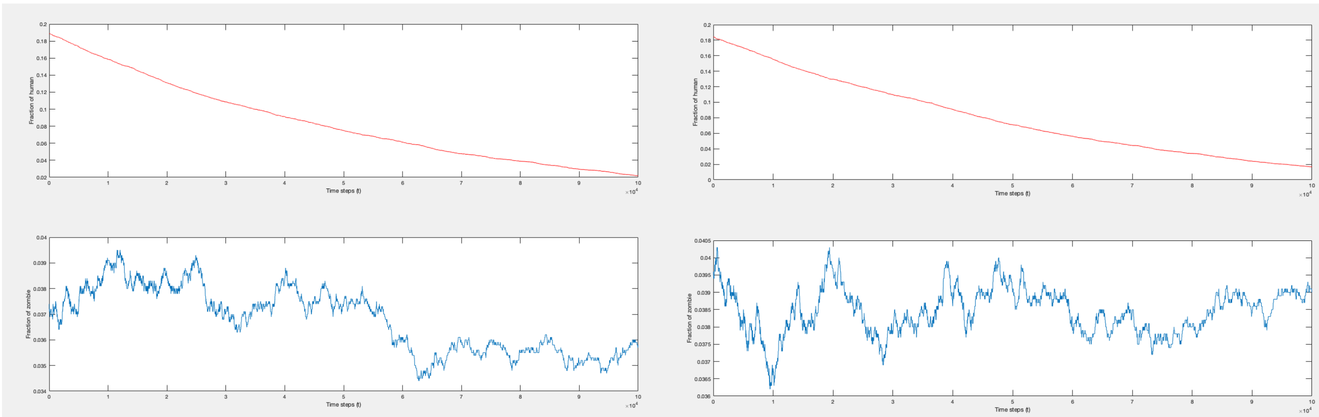


Figure 8: The fraction of species over time for Phz=0.5 in a human flight response

The observations and discussion are similar to that of the 'fight response model'. The graph shows the rate at which living beings and zombies change over time. Overall, there is a trend of exponential decay in the human fraction but no obvious trend in the zombie fraction.

Phz>0.5

At $phz > 0.5$, both the fraction of living beings and zombies become a decaying exponential function with the form ae^{-b}.

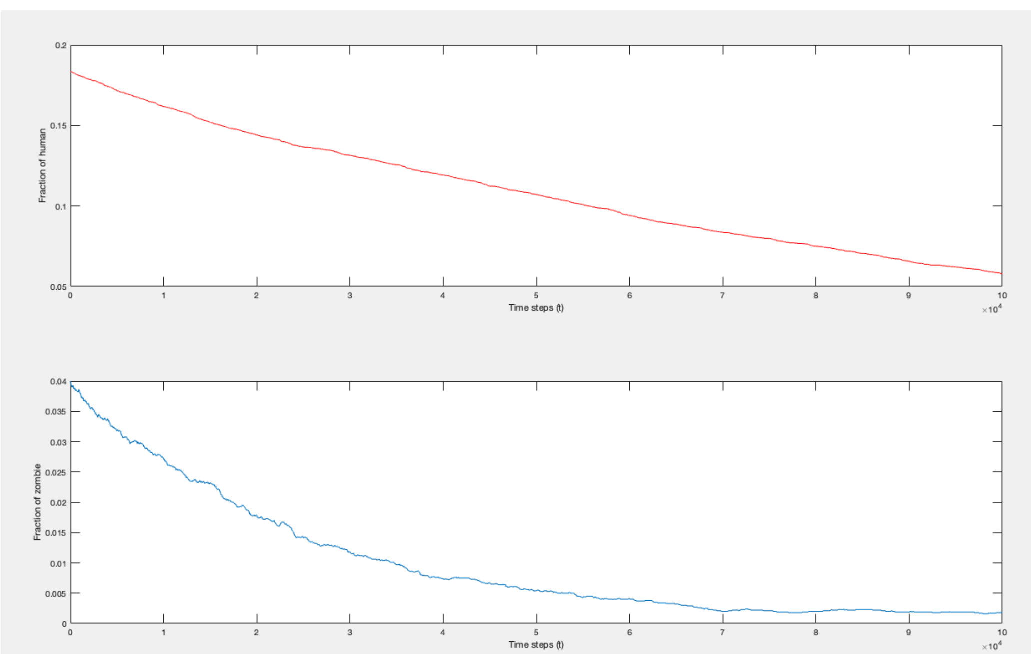


Figure 8: The fraction of species over time for Phz>0.5 in a human flight response

The graph shows the rate at which living beings and zombies change over time. Overall, there was a dramatic decrease in the fraction of living beings and zombies. The 'fraction of human' plot is fitted to an exponential with the form $0.1851e^{-1.09\times10^{-5}}$, likewise, the 'fraction of zombie' plot is fitted to an exponential with the form $0.0395e^{-3.83\times10^{-5}}$. If we analyze the plot and the equations, we can see that the zombie population drops at a faster rate than the drop in the human population. We can see that a $phz > 0.5$ is necessary to suppress the spike in zombie population seen in the plot of $phz = 0.5$.

We conclude that with a flight response and a $phh = 0.05$, the following inequality must be satisfied $phz \geq 0.2$ to prevent the dooming outcome of the eradication of human species.

Conclusions:

An outbreak of zombies infecting humans is likely to be disastrous and would result in the extinction of living beings and the complete eradication of human civilization. While a high phz such as $phz > 0.8$ and a low $phh \leq 0.05$, regardless of whether the human flight or fight response may eradicate the infection, it is very unlikely to happen. The phh parameter in the above experiments was set to a constant 0.05 irrespective of phz and the flight/fight response. The phh in this simulation assumes the best of human nature and eliminates the possibility of human intraspecies aggression or high suicide rate. Likewise, a high phz translate to a scenario where at every encounter of a human and a zombie, the human has an 80% chance of killing the zombie. In real life, we know that the human population ranges in age, size, and physical abilities therefore to rely on a human strength of 80% to save the human population from extinction is naive.

The key difference between the models presented here and other models of infections is that the models depicted here represent the two automatic physiological reactions to an event that is perceived as stressful or frightening; fight and flight. Although the models used are binary, meaning that a human can either be in fight or in flight mode throughout all time steps, they provide a close approximation to the zombie apocalypse.

We anticipated that a fight response would slow down the growth of the zombie population due to the scores setup whereby a human is twice as likely to target a zombie than other cells. We find that when comparing the final zombie population in both models for a $phz < 0.5$ and a $phz > 0.5$ is less than that of the flight mode. The difference is largest at $phz > 0.5$ because humans are twice as likely to attack zombies and if they do, they are more likely to kill it. While some might conclude that the flight response is the safest and smartest option as it guarantees the survival of humans for a significantly low chance of survival and a large range of phz, $0.2 \leq phz \leq 1$. Others suggest that the decrease in zombie population resulting in the fight response is a valuable trade-off to the smaller range, $0.4 \leq phz \leq 1$.

Through assessing multiple ranges of phz we find that $phz = 0.5$ marks a critical point for the fraction of zombies. Below the critical point, zombies grow dramatically, whereas above the critical point the fraction of zombies no longer oscillates and instead much like the fraction of human plot, decays exponentially.

A human population of a range $0.2 \leq phz \leq 1$ is guaranteed to survive a zombie apocalypse when in flight response. Likewise, A human population of a range $0.4 \leq phz \leq 1$ is guaranteed to survive a zombie apocalypse when in fight response, with the added advantage of an overall lowered zombie population in comparison to that of the flight response. In other words, the flight response in a zombie apocalypse is an optimum strategy for populations with groups of highly susceptible individuals such as the elderly, ill, or physically disabled that have a low phz. This is because, by the simulation results for flight response, we find that the human civilization can still survive in a zombie apocalypse despite the survival chance of humans against zombies being as low as 20%. Moreover, populations with more capable groups will have a higher phz and therefore can opt to adopt the fight response. However, for the human species to survive the apocalypse human individuals must have a probability of survival against zombies no less than 40%.

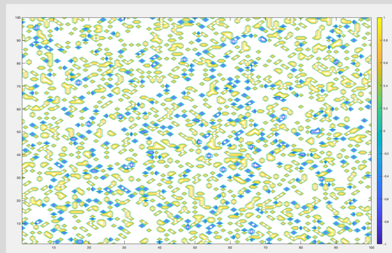
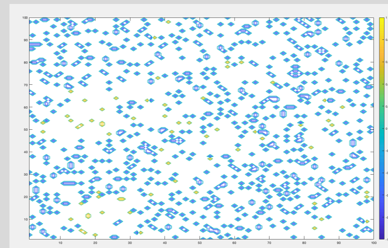
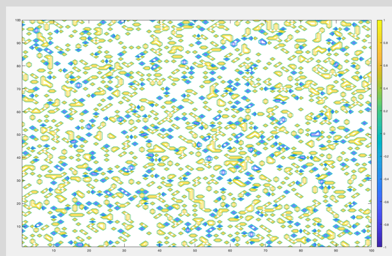
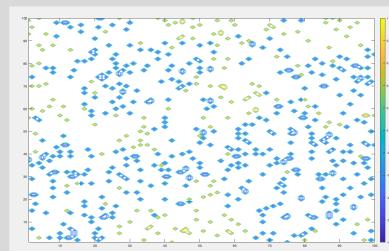
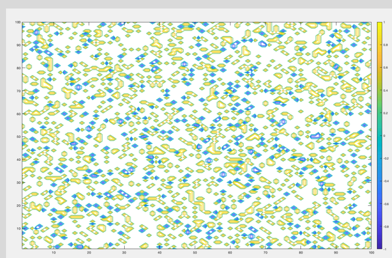
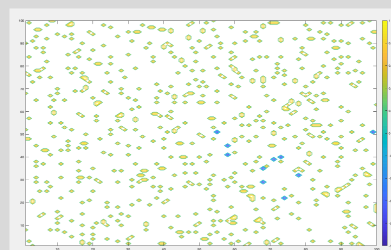
The conclusions drawn from each human response are significant because not only can we recommend the optimum tactic to preserve human populations according to the individuals' strengths but we can also extend these outcomes to draw parallels between this simulation and real-life applications. For instance, we can apply these strategies to the pandemic engineering problem mentioned in the introduction. Let $phz,$ represent the immune system strength whilst factoring in age, family history, and overall fitness of the individuals constituting the population. Then, a population that is composed of highly susceptible groups with a low survival rate against a virus (*low phz*) such as the elderly, unhealthy, or physically unfit, is obliged to stay home and self-isolate. This represents the flight response in our simulation for a low phz. However, if the majority of the population is young, healthy, and strong individuals with a strong immune response (*high phz*), we can allow for more flexibility with everyday activities. This represents the fight response in our simulation for a high phz.

In summary, we derive that the following parameter settings preserve the human civilization:

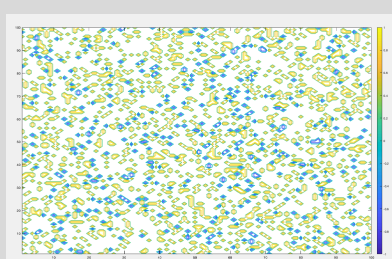
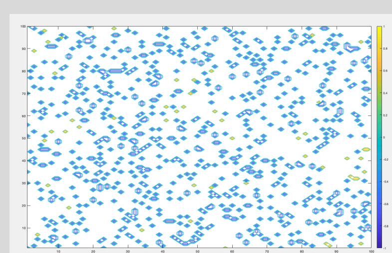
1. A $phz \geq 0.4$ and a fight response
2. A $phz \geq 0.2$ and a flight response

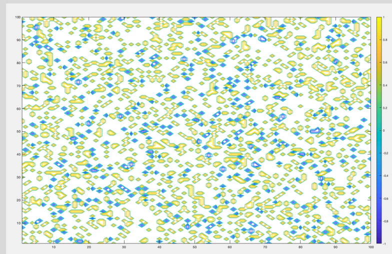
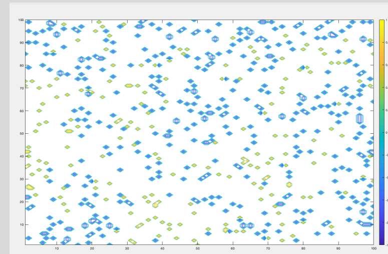
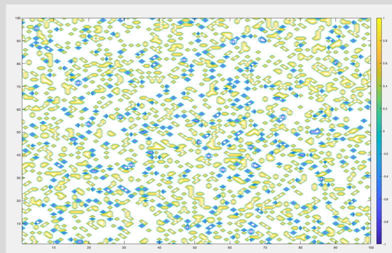
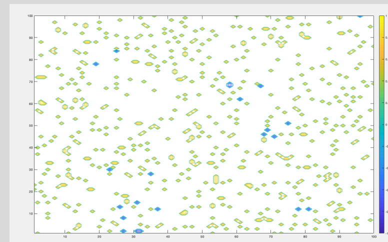
Appendix

The fight response model

phz	Initial matrix	Final matrix
phz<0.5		
phz=0.5		
phz>0.5		

The flight response model

phz	Initial matrix	Final matrix
phz<0.5		

phz=0.5		
phz>0.5		

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