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How resilient is the United States food system to pandemics and what can be done to increase food system resiliency?

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**How resilient is the United States' food system to
pandemics and what can society do to increase
food system resiliency?**

**Keywords: Food Systems, Pandemics, Resilience, Supply Chains,
Absenteeism, System Dynamics**

Andrew G. Huff, Nicholas. S. Kelley, Walter E. Beyeler, & Joseph A. McNitt

Abstract: Infectious disease threats frequently make the news, be a new respiratory virus like the Middle East Respiratory Syndrome, a new strain of influenza like H7N9, or an outbreak of Ebola. Most of the focus is on minimizing morbidity and mortality once a threat has been identified. Some of these infectious disease threats can cause a pandemic, with influenza being the most likely candidate. Significant work has occurred to prepare for the consequences of a pandemic through medical countermeasures and identifying ways to prevent their emergence. Rarely have studies focused on the second and third order effects of pandemics. Limiting the disruption of critical infrastructures during a pandemic is important for the survival and health of society (i.e., electricity, pharmaceuticals, water, and food) as most medical and public health responses to a pandemic depend on this infrastructure. The studies that have looked at this issue have highlighted alarming gaps in preparedness. This study used a system dynamics model to demonstrate the likely effects of a pandemic on a regional food commodity supply chain on in the United States. The model reveals that a severe pandemic with greater than a 25% reduction in labor availability can create significant and widespread food shortages. The likely effects of the reduction in the amount of available food are difficult to specifically predict; however, it is likely to have severe negative consequences on society. The resilience of the food system must be improved against this hazard and others.

Throughout human history there have been pandemics, and pandemics can be caused by a wide variety of infectious agents. In 165 A.D. the Antonine Plague caused 2,000 deaths per day in Rome and killed one quarter of the people that became infected with smallpox-like illness (Littman & Littman, 1973). In 541 A.D. the Justinian Plague caused 5,000 deaths per day in Constantinople, killing an estimated 25 million people globally (Scott, & Duncan, 2001). The Black Death killed an estimated 100 million people over 7 years (Ziegler, 2013). In 1918, the Spanish flu (H1N1) killed roughly 100 million people and infected 500 million people, while affecting working age people (15 - 54 year olds) the most severely (Glezen, 1996; Johnson & Mueller, 2002). Although the 2009 H1N1 influenza virus did not have the high levels of mortality observed in the previously mentioned pandemics, the pandemic affected working age adults the most severely similarly to the 1918 Spanish flu (20 – 59 year olds; Viboud, Miller, Olson, Osterholm, & Simonsen, 2010). Although the scientific community does not have a crystal ball to predict when the next pandemic will occur, history is likely to repeat itself.

Concerns over climate and environmental change, limited natural resources, and a population expected to reach as much as 13 billion by 2050, highlight several of the challenges forthcoming (Pimentel, Whitecraft, Scott, Zhao, Satkiewicz, Scott, ... & Moe, 2010). Beyond history repeating itself, the world is rapidly changing, making a severe pandemic increasingly likely (Suk & Semenza, 2011). Increasing population (especially in urban areas) and increasing pollution of food, water, air, and soil by chemicals and infectious diseases are causing a rapid increase in the prevalence of disease and human mortality (Pimentel, Whitecraft, Scott, Zhao, Satkiewicz, Scott, ... & Moe 2010; Murray and Lopez, 1996; Pimentel & Pimentel, 2007).

Climate change will cause different ecological interactions; thus, zoonotic diseases will likely emerge in new transitional ecological zones (Harvell, Mitchell, Ward, Altizer, Dobson, Ostfeld, & Samuel, 2002; Patz, Campbell-Lendrum, Holloway, & Foley, 2005). While old diseases will re-emerge in the developed world, their effects will be most detrimental in the third world (Patz, Daszak, Tabor, Aguirre, Pearl, Epstein, J., ... & Working Group on Land Use Change Disease Emergence, 2004). From influenza to HIV, the urbanization of the global population will increase the rate at which zoonotic and anthropogenic diseases are transmitted (Sclar, Garau, & Carolini, 2005). High population density and greater ease of global transportation will increase the frequency and intensity of disease cycles, and increase the demand for limited public health resources (Alirol, Getaz, Stoll, Chappuis, & Loutan, 2011). Complicating matters further, 925 million humans are currently malnourished worldwide, which increases the probability of disease infection (FAO, 2010). An increasing population will cause the competition for water, energy, and food resources to intensify. Furthermore, climate change will increase ecological interactions likely contributing to: growing disease emergence risk; possible reductions in crop productivity due to changing weather patterns, increasing plant pathogens, and pests; and armed conflicts where potable water, natural resources for manufacturing and energy, and nutritious foods are less readily available or extremely scarce. By increasing the variety and transmissibility of infectious agents, and by increasing the stress on food production systems, these challenges will complicate the response to a pandemic in the future.

One of the greatest challenges in pandemic planning is developing systems (e.g., food, water, & energy production) that are resilient enough to continue functioning

during a severe pandemic. Unfortunately, there are no simple solutions to tackle problems of this magnitude and complexity. The combination of multiple interdependent systems and worker absenteeism creates a potentially fragile situation during a pandemic due to the critical interdependencies between multiple systems (Figure 1). Worker absenteeism can place significant stress on product manufacturing, energy production, and transportation systems (Hessel, 2009; Osterholm, 2005). The global food system depends on these systems, as do most other vital systems in modern society. Without a healthy workforce, supply chains operate below optimal capacity or shut down altogether. Sick employees, changes in demand, or inventory shortages can all affect a broad spectrum of supply chains, including supplies needed to combat the pandemic (Kumar & Chandra, 2010). For example, everything created and used in modern medicine is reliant on fossil fuel and electricity systems in some fashion (Osterholm & Kelley, 2009). There is currently an inadequate amount of medical supplies that are vital to pandemic preparedness and response (Adalja, AWollner, Inglesby, & Poste, 2012), and this problem is likely to be exacerbated during pandemic response.

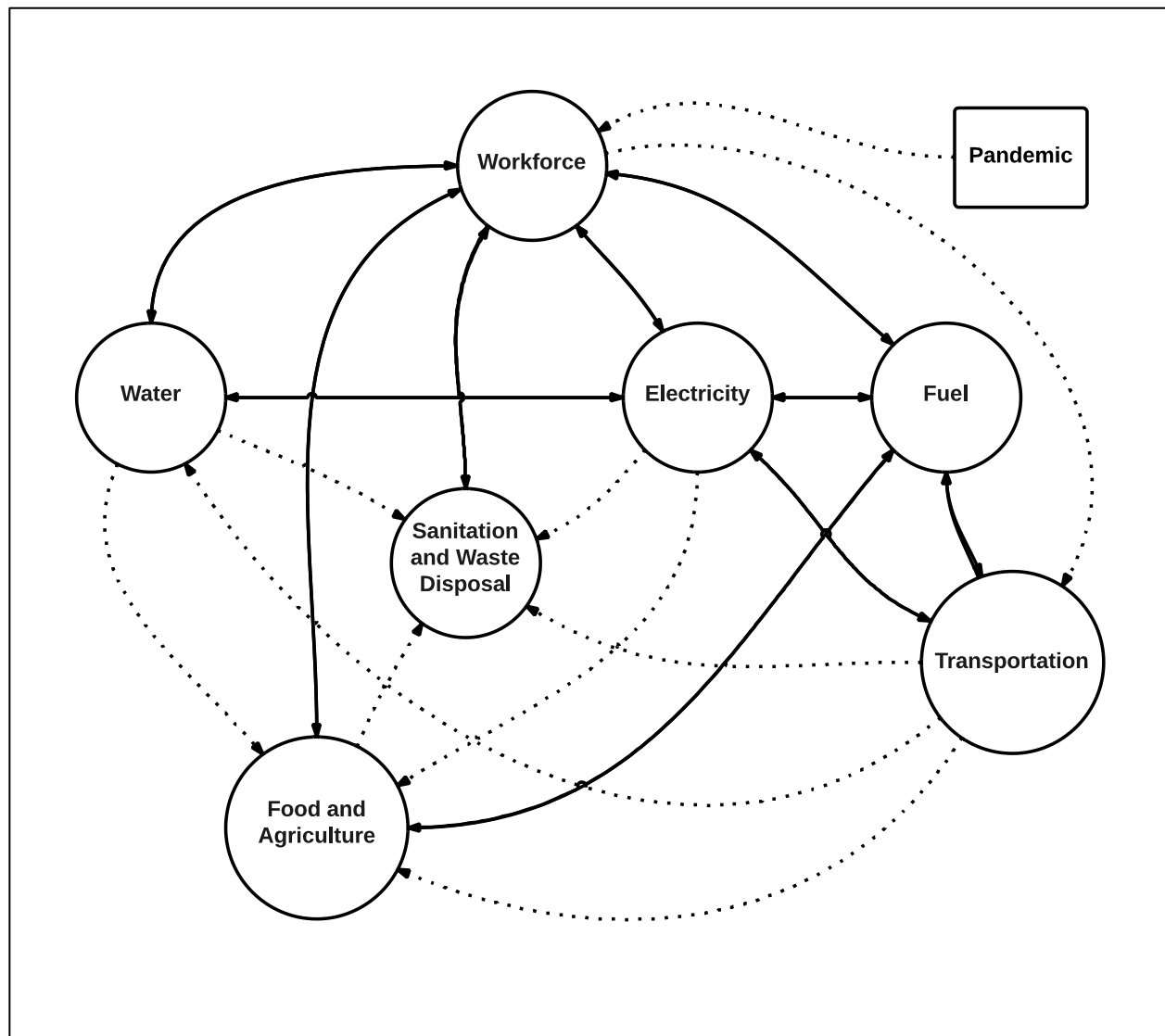


Figure 1. A high-level interdependency diagram of the relationships between a pandemic, the workforce, and the systems that are necessary for the food and agriculture system (communication is implied but not illustrated). The dashed lines represent one-way relationships and the solid lines represent two-way relationships. All components in the diagram (circles) are necessary for the system to function.

A fundamental property of interdependent networks is that failure or degradation in one system may cause the failure of other dependent systems (Buldyrev, Parshani, Paul, Stanley, & Havlin, 2010). There are multiple examples of real world cascading failures, especially in systems that have single points of failure (Carreras, Lynch, & Newman, 2007). The most pervasive cascading system failure is the electric system blackout (Dobson, Carreras, Lynch, & Newman, 2007). On August 14th 2003, a series of failures on the United States and Canadian Northeastern Power grid caused 55 million people to go without electricity causing: sewage systems to overflow, rail service

to retard, gas stations to shut down, communications systems to fail, food to spoil, and food processing and distribution to come to a halt (Lin, Fletcher, Luo, Chinery, & Hwang, 2011; Hines, Balasubramaniam, & Sanchez, 2009). This real world example, and many others, demonstrates the reliance of the food and agriculture system on other interdependent systems. In the case of a pandemic, worker absenteeism may cause multiple points of failure within the food and agriculture system itself, or in the interdependent systems that the food and agriculture system relies upon to function.

For these reasons, private industry is starting to have greater interest in resilience (Meuwissen, Burger, & Lansink, 2010), but private companies in the food system are still unprepared for disruptions to the supply chain (Nikou & Selamat, 2013). Typical food supply chains are large, vertically integrated, and owned by multinational public and private corporations with a high degree of product diversity (Roth, Tsay, Pullman, & Gray, 2008). More than 80% of food is delivered through the global supply chain with a major focus on low cost and high efficiency. Due to the small profit margins across the majority of the food industry, pressure to reduce cost has led to the consolidation of food companies, and now only a few companies control most of the volume of food products in the global food system (e.g., Archer Daniels Midland, Cargill, Kraft, Nestle, PepsiCo, Unilever, and Walmart). The economies of scale created by these companies have created major barriers for new competitors. The dependence on large multinational private food companies for domestic and international food security is a difficult challenge for food system resiliency leaving limited options to government policy makers, especially during a pandemic.

The food system's dependence on the transportation system creates a major vulnerability. The transportation system can shut down during pandemics, causing the movement of vital cargo to halt (Luke & Rodrigue, 2008). The food system has become increasingly dependent on transportation to deliver its products over long distances. On average, food travels 1,300 miles from "farm to fork" (Zsidisin & Ritchie, 2009).

The global food system, with its broad array of perishable products, functions in a just-in-time economy where food inventories are intentionally kept at such low levels that food arrives just in time for consumption. This is the source of much of the increased efficiency in the food system. Since inventories are kept very low, there is vulnerability to unanticipated variations in flow. The reality is that increasing stocks of food costs money and decreases profits; therefore, agricultural businesses are reluctant to build food security resilience via stockpiling (Beck et al., 2006). Modern society heavily depends on the timely delivery of goods (McKinnon, 2006), not only for delivery of food to retail distribution, but for delivery of agricultural inputs to farms (e.g., seeds, animal food, fertilizer), and the delivery of farm products to processors, packagers, spot markets, and exporters.

Two case studies examined the impact of interruption in transportation on food supply. First, in 1979, truck drivers in the United Kingdom went on strike for a few days, and because food inventories were high, the worker absenteeism did not affect local food availability (McKinnon, 2006). In 2000, truck owner operators in the United Kingdom blocked major roads and fuel distribution depots for 3 days. If the blockade had lasted one day more, food retailers in the United Kingdom would have run out of food. The volume of retail traffic dropped to 10-12% below average and the national industrial output decreased by 10%. This experience demonstrates that relatively low

percentage impacts on transportation can cause large problems if they persist. McKinnon (2006) also simulated the effect of a total loss of trucking, and found that bread would be gone within two days from supermarkets. Just recently, worker absenteeism caused by the largest outbreak of Ebola Virus Disease shut down food production and food supply chains in Western Africa (FAO, 2014). As of November 2014, the World Food Program estimated that 460,000 additional individuals became food insecure in Liberia, Sierra Leone, and Guinea as a result of production and trade reductions (FAO, 2014; FAO, 2015). These real world events and simulations highlight the fragile nature of the food system and the important relationship between food and transportation systems.

Unfortunately, the consolidation of retail distribution could increase the consequences of a pandemic (Peck, 2006). Portions of supply chains that are dense, complex, or critical are more vulnerable to disruptions (Lederman, Kurnia, & Lederman, 2009). The United States' food system's critical points are in the middle of the supply chain. This creates a bottleneck effect where there are a large number of farmers and producers, and a large number of consumers, but there are not many processing and packaging plants in the middle of the supply chain (Burger, Warner, Derix, 2010). The reliance on these choke points creates vulnerability where a disruption to the food system's workforce at processing plants, packaging plants, and distribution centers could disrupt the entire food supply chain.

Another potential problem is the United States' reliance on imported food. 10-15% of food consumed in the United States is imported (McDonald, 2013). If a localized outbreak were to affect worker absenteeism abroad, then the food supply chain in other countries would likely be disrupted causing a reduction in the amount of food imported into the United States. Companies are currently unprepared for this possibility, and rely on international borders that remain open to transport, which may not be the case during a pandemic (Meuwissen et al., 2010).

These days consumers do not generally store large amounts of food (Sennebogen, 2011), in part because a large number live in cities without much personal storage space. For example, the average home size is 1,895 square feet in Los Angeles, 1,417 square feet in Chicago, and 1,124 square feet in New York City (Calin, 2012). Currently, 50% of people worldwide live in cities and this percentage is expected to rise to 60% by 2030 (National Intelligence Council, 2013). This will likely exacerbate the problem of small amounts of individual food storage, especially during events that cause disruptions to the food supply chain. Another cause of small individual stores of food is poverty. During the 2002-2004 SARS outbreak in Asia, most people had very little food stored at home (Lederman et al., 2009). The combination of the food supply chain disruption due to the SARS outbreak and the minimal individual stores of food created a situation where many people had difficulty obtaining food. A similar situation could be caused by a wide variety of infectious agents (Brown, 2009).

Though it is not possible to know whether there will be a severe pandemic in any given year, highly pathogenic airborne viruses like pandemic influenza can spread rapidly around the world. A severe pandemic would likely have multiple waves of infection, each lasting 2-3 months, and reaching infection rates of 30% or more (DHS, 2006; FFIEC, 2007; OSHA, 2007). In independent studies, it was determined that a

pandemic could last for up to 18-24 months, with 3 waves each lasting up to 3 months (Hickson et al., 2008; Staples, 2006).

One way that a pandemic would indirectly impact the food supply chain is by altering consumer behavior. Pandemics create uncertainty and volatility in consumer demand, making it particularly difficult to maintain food inventories in a just in time economy (Vo & Thiel, 2008). In a study of the effect of a disaster on behavior, the most frequent response is to stockpile supplies, food, and water (Kohn, Eaton, Feroz, Bainbridge, Hoolachan, & Barnett, 2012). This rush to buy food would quickly raise demand on a weakened food production and transportation system, which would likely lead to more shortages. The most common food items to be stockpiled by consumers are bottled water, milk, and canned food. Even food retailers panic purchase (Peck, 2006).

Another major impact of a severe pandemic is on the workforce, affecting food system output at every step of production. The significance of transportation for the food system is not simply a matter of transporting food from one step of the supply chain to another. Other systems and supply chains, on which the food system depends, like water, electricity, and transportation, are also vulnerable to disruption due to labor shortages (Beck et al., 2006). Absenteeism was found to be a major source of potential vulnerability in the coal supply chain during a severe pandemic in the United States (Kelley et al., 2008). The greatest impact projected by absenteeism along the coal supply chain was in transportation of coal stocks, which over the course of a severe pandemic could lead to power shortages (Kelley et al., 2008).

The National Infrastructure Simulation and Analysis Center (NISAC, 2007) created a model to evaluate the potential impacts of a pandemic on numerous sectors of the United States' economy. NISAC claimed that the food system is vulnerable to disruptions, but could not withstand a labor shortage of over 10% for a few months. NISAC (2007) also found that many aspects of the food system are labor intensive (i.e., transportation, wholesale, processing, and farming), and estimated that a 25% reduction in labor would cause a 49% reduction in food production. Their analysis concluded that with a 10% reduction in labor all elements would remain operational, though there would be major shortages. However, the absenteeism rate of 10% in the NISAC study was highly optimistic. Absenteeism in a severe pandemic could be as much as 20-40% (DHS, 2006; FFIEC, 2007; OSHA, 2007). Furthermore, one of NISAC's analyses examined the effect of worker absenteeism on a regional milk supply chain and found that although milk production facilities did not shut down with a 25% reduction in labor there was a 49% reduction in milk production – a worrisome result.

Despite the direct effects of worker absenteeism on the food production process, worker absenteeism can affect food systems indirectly. A loss of transportation can interrupt waste removal. In a survey (Peck, 2006), one retail distributor stated:

... food production operations would cease within 36 hours if (production) waste could not be disposed of. The food system should be viewed as a pipeline. The supplier at one end, and consumers at the other – there is little capacity to stop the pipeline in mid-flow.

This suggests that a high rate of worker absenteeism in the waste disposal system could bring food production to a halt.

Modeling is one way to explore how the resilience to withstand pandemics can be built into food systems. Hickson et al. (2008) researched several different aspects of Manitoba's resiliency: population, nutritional needs, nutrition of food being consumed, the food system, (i.e., inventories, transportation), and possible mitigation. They simulated a food delivery system with 35% absenteeism due to pandemic and found that some regions of Manitoba could have food shortages due to transportation shortfalls. Hickson et al.'s (2008) research was performed to identify potential solutions to mitigate food shortages during a pandemic, as opposed to identifying root causes of their food system's failure.

Payan (2013) created an agent-based model to examine the effects of worker absenteeism on milk supply. The model incorporates a "bullwhip effect," in which the variation in the purchasing orders is amplified as orders move closer to the source of production. The model assumed no changes to inputs or outputs during a pandemic (an unrealistic assumption). However, the model assumed that every part of the milk production process would be affected by labor shortages except for retail. Lastly, the model assumed about a 10% slack in processing and transportation. The simulation counted the number of days in which demand was not met. The model found that: (1) the greatest amount of disruption to the supply chain was in the middle of milk supply chain; (2) the least amount of disruption was in the retail sector; (3) that the greatest variability in demand was at the farm level; and, (4) that the inventory decreased nearing the consumer. From this analysis, Payan (2013) concluded that the oscillating behavior of the milk inventory reflected the high impact of a pandemic on the milk supply chain.

Method & Model Design

Purpose

To understand the effect of worker absenteeism on the U.S. food system, this model used five stages for the flow of food through the system: farms, processing, distribution, retailing, and consumption. When food is purchased at the retail level, a chain of communication is set in motion: retailers order food from distributors, distributors order from processors, and processors order from farms. Transportation moves the food from each stage to the next.

Entities, state variables, and scales

Food production is divided into five general stages: (1) food production; (2) processing; (3) distribution; (4) retailing; and, (5) food availability. The scale of the model is at the population level for the United States. The model includes all of the minimum necessary components for the food system to operate: communication, electricity, employees, food production (facilities and farms) transportation, water, and waste.

Design Concepts

The model represents the total amount of food available at different stages of the production supply chain. Food is transported through the supply chain as it is produced at the farm, is processed, and distributed. The capacity to produce, process, or transport food at each stage of food production directly depends on the availability of labor. Estimates of the degree of food system functioning, given worker absenteeism, requires detailed information and data along with the food system's contingency plans for emergency operations and training. However, analysis of a range of stylized responses to worker absenteeism identifies where detailed information is most useful and where additional data would be most helpful for designing and implementing mitigation strategies.

Process overview

The model included a range of randomly selected values for food storage capacity at each stage of the food system, selected from a range of 20-150 days of food supply stored at farms, 4-28 days of processing storage, and 2-7 days of distribution, retailer, and consumer storage. Because food can be lost for a variety of reasons at each stage of the system, loss is included in the model as an exponential decay process, using randomly selected values for farm, processing, distribution, and retailing loss rates ranging from 0.02 to 0.20 per day and consumer loss rate ranging from 0.07 to 0.20 per day. Each run of the model covered a period of 800 days. A pandemic lasting 500 days was represented by three waves of illness (and associated absenteeism), each wave lasting 166 days (Figure 2). Each of the three waves reached a peak of 30% absenteeism, declining to 10% absenteeism during troughs of the waves. The simulations continued for 300 days beyond the end of the pandemic to observe what would happen to food system.

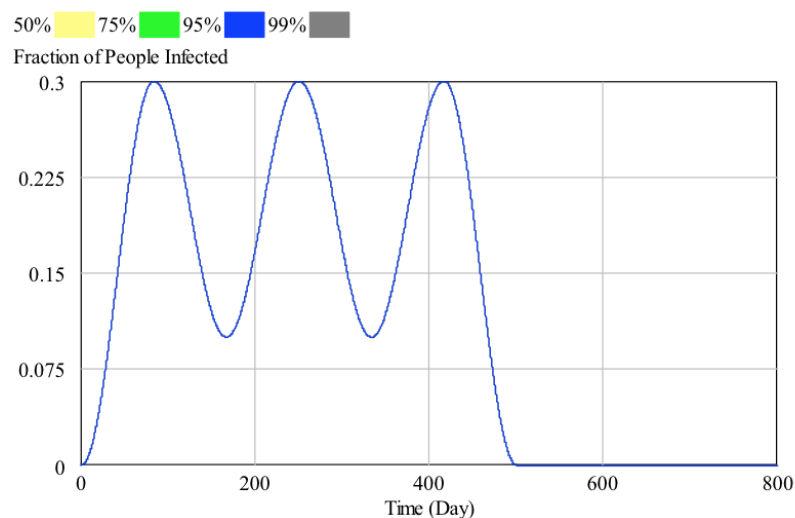


Figure 2. Absenteeism in each simulation run was a randomly selected value between 10% and 50%, with the same peak value for all three waves in the run. The troughs of the waves were always 10% absenteeism.

At each modeled food storage location (e.g., farms, processors, distributors, retail) food is subject to loss from spoilage or other mechanisms that were not specifically represented but were accounted for (this could be any loss imaginable where the loss rate was proportional to the amount of stored food). This food loss is modeled as a first-order decay process. Processes affecting food inventory at distributors, depicted in the model construct for retail establishments, are typical in the food system.

Each production and transportation system in the model has a power-law dependence on the availability of labor (Figure 3). The capacity to move food through the system depends on the availability of labor for each stage of the system, and the availability of labor for transport from one stage to another. Of particular significance is the fact that reduction of function by absenteeism may not be in simple proportion to the reduction in labor. Some parts of the system may have an ability to buffer a partial reduction in labor, maintaining performance closer to normal than the labor reduction would suggest. The opposite could happen in other parts of the system, where a reduction in labor sets in motion a disproportionately greater reduction in function. To incorporate this into the model, we assumed the following relationship between fraction of labor available compared to normal labor supply (L) and fractional performance compared to normal performance (P) (Figure 3). When $r = 1$, reduction in function is in simple proportion to the reduction in labor. When $r < 1$, reduction in function is less than the reduction in labor. When $r > 1$, reduction in function is greater than the reduction in labor.

Because the actual values of r , and r could be different in different parts of the system, the model was run repeatedly with different values of r selected at random from a range of $r = 0.37$ to $r = 2.72$ to see a corresponding range of conceivable simulation outcomes. Randomly selected values of r were used for the transformation of labor supply to functional performance at farms, processing plants, and retail outlets, and transport of farm inputs to farms, transport of food from farms to processing plants, and transport of food from distribution centers to retail outlets.

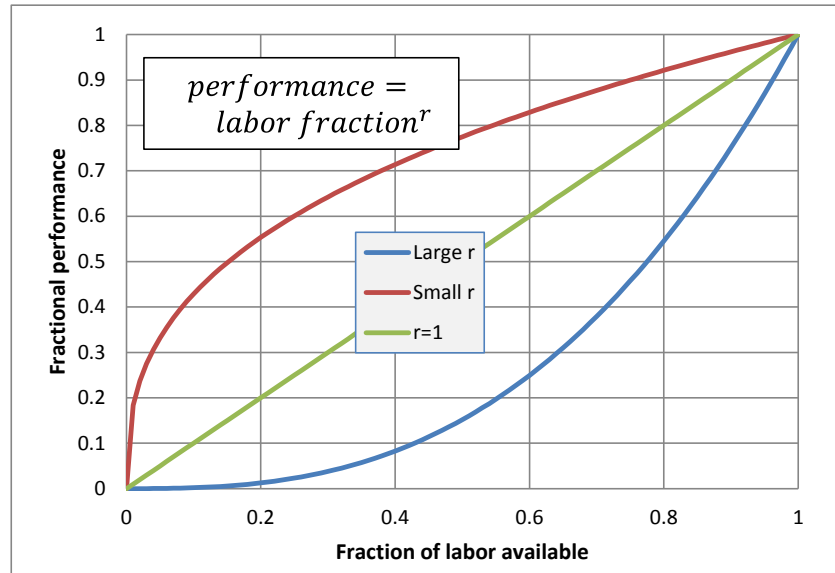


Figure 3. This illustration covers a wide range of qualitative responses. Large exponents model a strong reduction in system performance with small reductions in worker availability; small exponents (<1) allow substantial reduction in worker availability before the system suffers significant performance degradation. The area between the blue and red lines illustrates possible combinations of available labor and food system performance (the ability of the food system to produce food).

Each processing step for each food type is characterized by a few key parameters: (1) the typical amount of food held in inventory expressed as a number of days expressed nominally; (2) the sensitivity of the food production rate to worker absenteeism; (3) a decay rate for stored food (expressed as a time constant); and, (4) the sensitivity of transportation time to worker absenteeism.

The transportation networks that connect major food production steps are subject to disruption by widespread absenteeism, both from the shortage of farm labor, truck drivers, and warehouse operators, and from any disruption in the availability of interdependent systems (i.e., fuel, electricity, water, sanitation and waste disposal) due to worker absenteeism at every step in food production. The effect of worker absenteeism on the shipping rate between food production steps is modeled using the simple power-law dependency described above (Figure 3). The coefficients describing the relative degradation of shipping rate with labor availability between each pair of linked processors are treated as perfectly correlated (no lag time between employee absenteeism and the loss of transportation) since worker absenteeism is likely to have an immediate effect on shipping. The parameter values for the food processing steps are described in Table 1.

Table 1. Ranges of parameter values assigned for each food-processing step.

Processing Step	Typical Inventory (days)	Loss rate (1/day)	Production/Labor coefficient	Shipping/Labor coefficient
Production	10-150	0.02 – 0.20	0.37 - 2.72	0.37 - 2.72
Processing	4-28	0.02 – 0.20	0.37 - 2.72	0.37 - 2.72
Distribution	2-7	0.02 – 0.20	0.37 - 2.72	0.37 - 2.72
Retailing	2-7	0.02 – 0.20	0.37 - 2.72	0.37 - 2.72
Consumption	2-7	0.07 – 0.20	0.37 - 2.72	0.37 - 2.72

The model includes a range of values for food storage capacity at each stage of the food system, selected from a range of 10-150 days of food supply stored at farms, 4-28 days of processing storage, and 2-7 days of distribution, retailer, and consumer storage. Because food can be lost for a variety of reasons at each stage of the system, loss is included in the model as an exponential decay process, using randomly selected values for farm, processing, distribution, and retailing loss rates ranging from 0.02 to 0.20 per day and consumer loss rate ranging from 0.07 to 0.20 per day.

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Each run of the model covered a period of 800 days. A pandemic lasting 500 days was represented by three waves of illness (and associated absenteeism), each wave lasting 166 days (Figure 3). Each of the three waves reached a peak of 30% absenteeism, declining to 10% absenteeism during troughs of the waves. The simulations continued for 300 days beyond the end of the pandemic to observe what would happen to food system.

The simulated food production system can initially supply a nominal 5.5 pounds of food per person per day. However, the value of the initial consumption rate is not important: the model sets food system inventory levels and capacities based on specified time elapsed between consumer demand and production supply. When food is purchased at the retail level, a chain of communication occurs: the retailer orders more food from the distributor, the distributor orders more food from the processors; and the processors order more food from the farms. Three waves of illness pass through the population during a 500-day pandemic simulation (166 days per wave) and the entire simulation runs 800 days (300 illness-free days after the initial 500 illness days), and each wave of the pandemic results in a peak reduction of 30% of the workforce. The deficit in the quantity of food reaching consumers was calculated daily in the course of each simulation run. The daily deficit could range from 0%, when food needs for the day were fully met, to 100% if there was no food delivery to consumers that day. The deficits from each day were summed over the 800 days to calculate the total number of "hunger days" in each run.

The model was run 2000 times, each replicate run based on a different combination of randomly selected values of r , storage capacities, and loss rates listed in Table 1. Each parameter sample was used to simulate food production, transport, and consumption. The daily fractional difference in food demand was multiplied by the current population, and integrated over an 800-day simulation. The resulting count of hunger-days is an aggregated measure of the system's inability to meet the population's food demand. Simply, a hunger-day is a day where some individual eats no food.

Food shortages might be distributed across households in very different ways, leading to different health consequences. For example, a relative consumption rate of 50% might correspond to: (1) all households getting half of their desired intake; (2) half of all households receiving no food while half receive their nominal amount; or, (3) some intermediate condition. Meeting the aggregated demand for food is necessary for meeting individual demands; however, an aggregated model can identify conditions that must be met to prevent shortfalls. This model cannot determine regional or individual levels of food availability during a pandemic.

Results

Model output did not vary significantly between experimental scenarios tested (see supplemental information). The results presented demonstrate the range of all the possible outcomes observed (output from the other scenarios are available in online supplemental material and the model itself is available). The purpose of the model runs presented was to determine if stockpiling of food at various points in the food system (a possible policy solution to food insecurity during a pandemic) could mitigate shortages.

Figure 4 depicts the frequency distribution for the number of hunger days per capita in each of the 2000 simulations. There were significant food deficits in 50% of the runs associated with moderate to high levels of worker absenteeism. In the other 50% of simulations, there were not enough absent employees to cause a significant number of hunger-days. Figure 5 illustrates the distribution of simulated fraction of people infected over time, with three pandemic waves. Figures 6 and 7 depict the resulting distribution of the number of people going hungry. There are few people going hungry during the first wave of a severe pandemic. However, the food supply drops dramatically with successive waves of infection, causing a significant shortage in food supply and a significant increase in cumulative hunger-days (Figures 8) and in the fraction of the population going hungry (Figure 8). In some simulations, food deficits were continuous from one wave of infection to another. To illustrate the factors controlling food shortages, the scatterplots of the effect of absenteeism on transportation (labor transport coefficient) and the effect of absenteeism on production (labor production coefficient) versus hunger-days are illustrated in Figure 9. Large food shortages are associated with high sensitivity of food production to labor. This suggests that knowing (or controlling) the sensitivity of food production on labor is more important for estimating (or alleviating) food shortages.

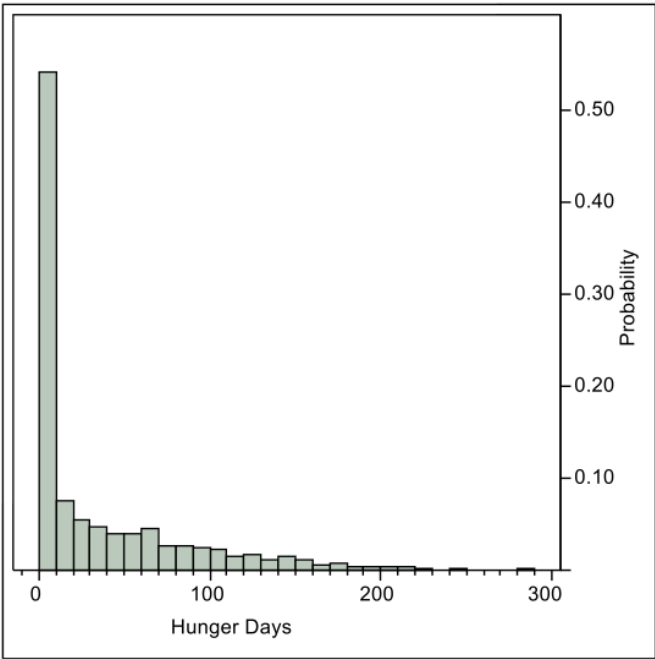


Figure 4. Histogram of cumulative hunger-days per capita (X axis) at the end of 800 days, over 2,000 model runs. The results indicate a significant reduction in the amount of available food during a pandemic due to worker absenteeism. The median of 2,000 simulations is roughly 5 hunger-days per person.

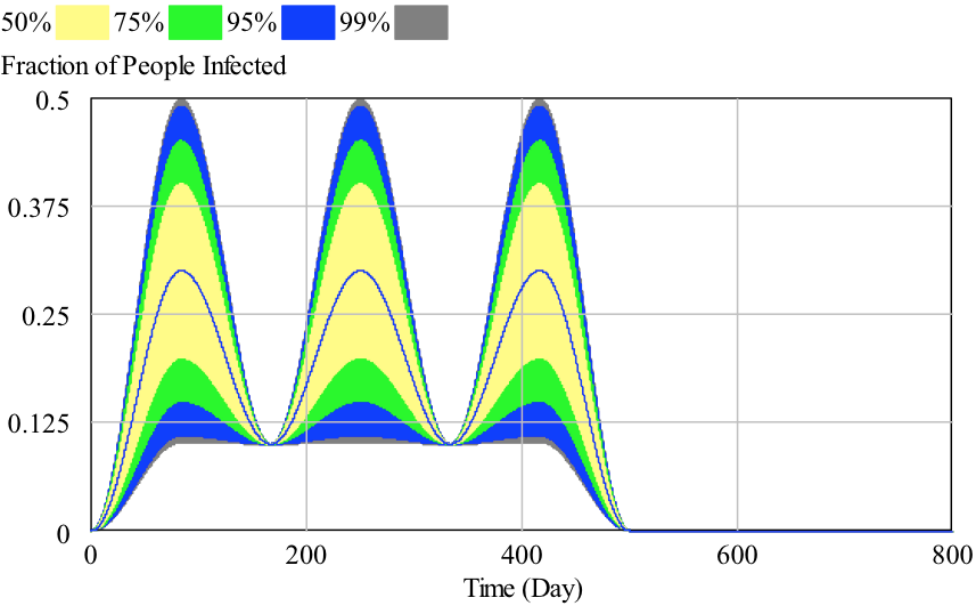


Figure 5. The distribution of the fraction of people infected over time. The blue line in the middle depicts the simulation with the median fraction of people infected

(30% of the population) and the percentages listed at the top of the table represent the range of people infected.

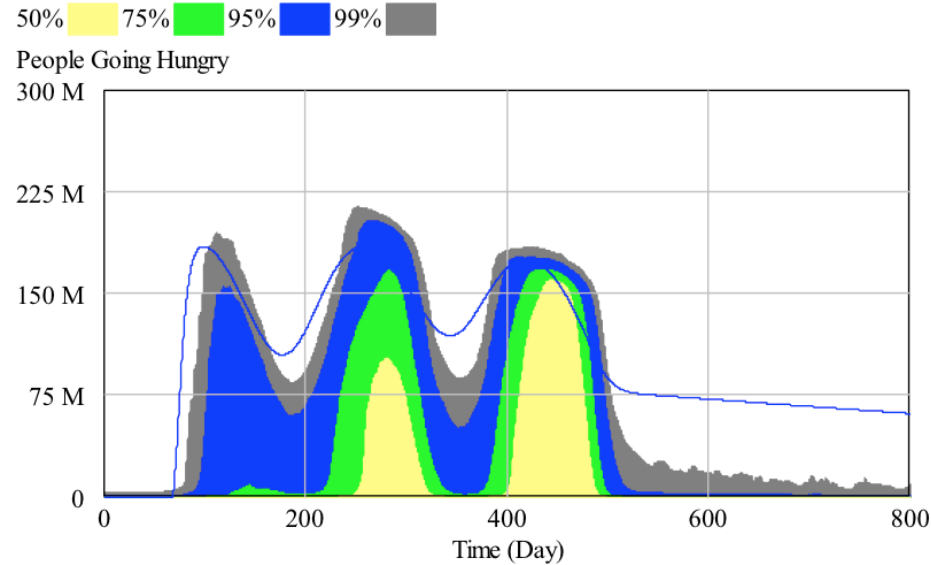


Figure 6. The distribution of the number of individuals going hungry over time. The blue line depicts the median people infected and the percentages listed at the top of the table represent the ranges of people going hungry.

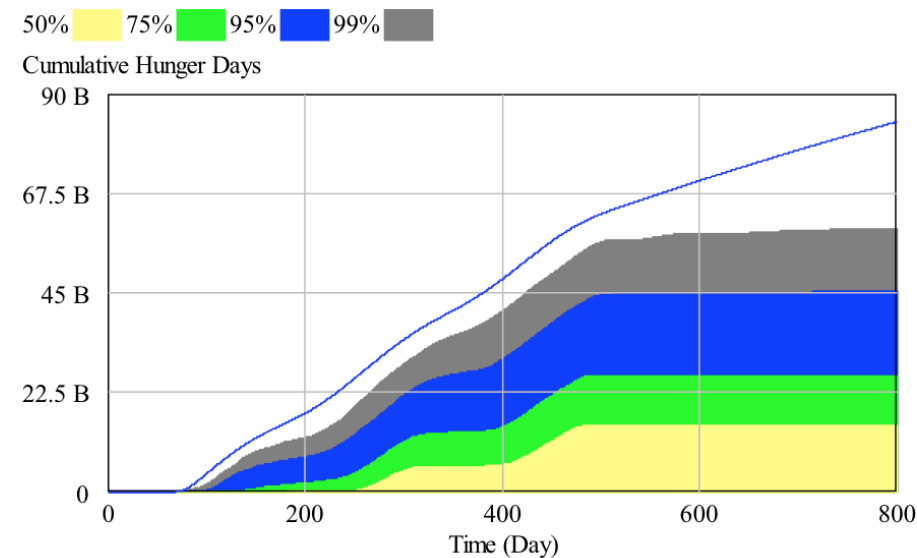


Figure 7. The distribution of the cumulative amount of hunger-days over time. The blue line depicts the median number of cumulative hunger-days. Over time the food system is not able to meet the total demand.

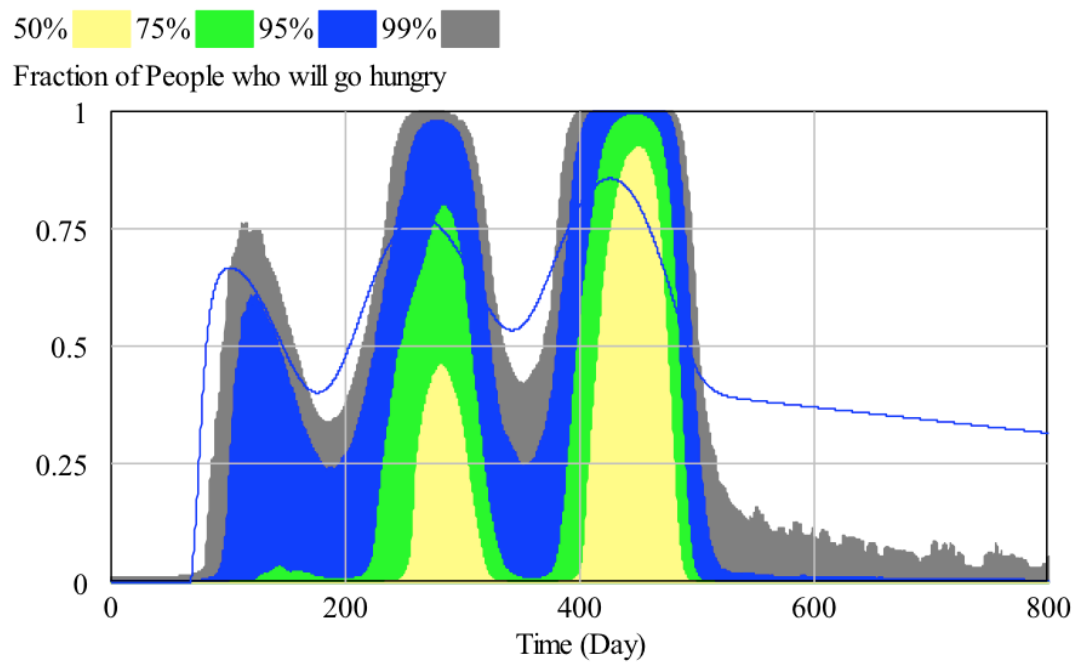


Figure 8. The distribution of the fraction of individuals that do not have an adequate amount of food over time. There are a significant number of individuals that are hungry by the third wave in the pandemic.

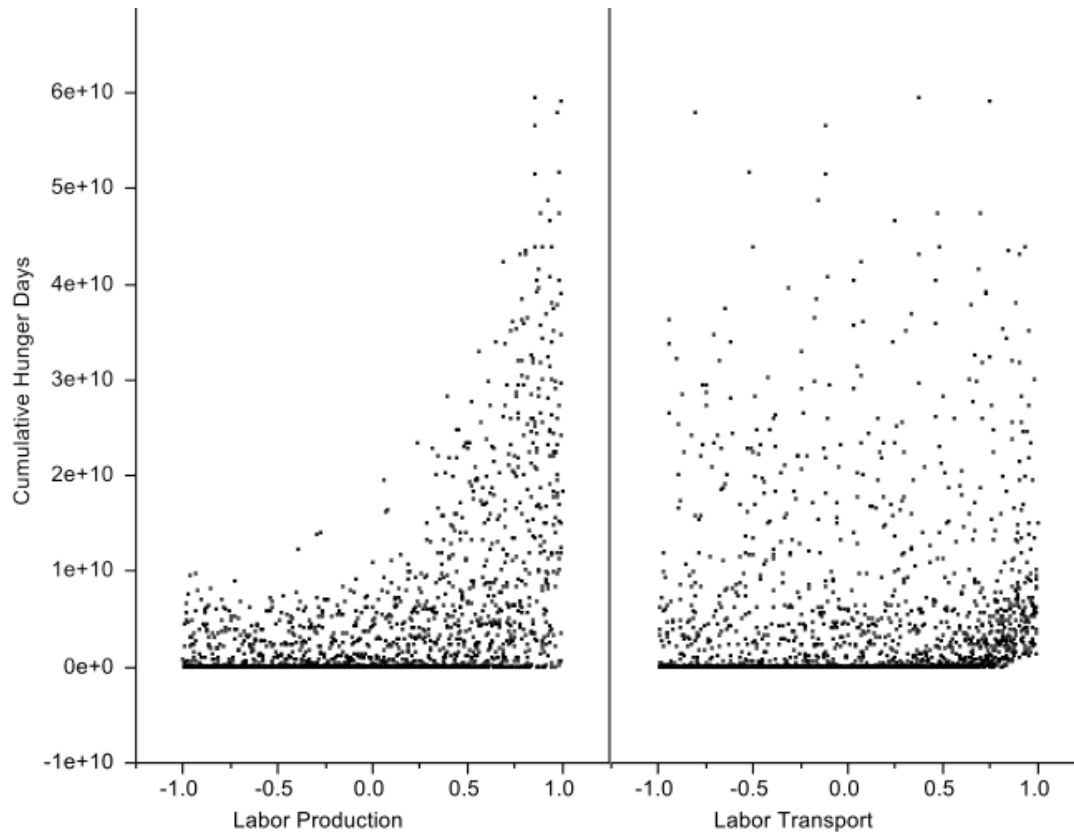


Figure 9. A comparison of the effect of worker absenteeism coefficients (left) on production and the effect of worker absenteeism coefficients (right) on transportation, over 2,000 model runs after an 800 days. Worker absenteeism in transportation generally causes more cumulative hunger-days compared to worker absenteeism in food production.

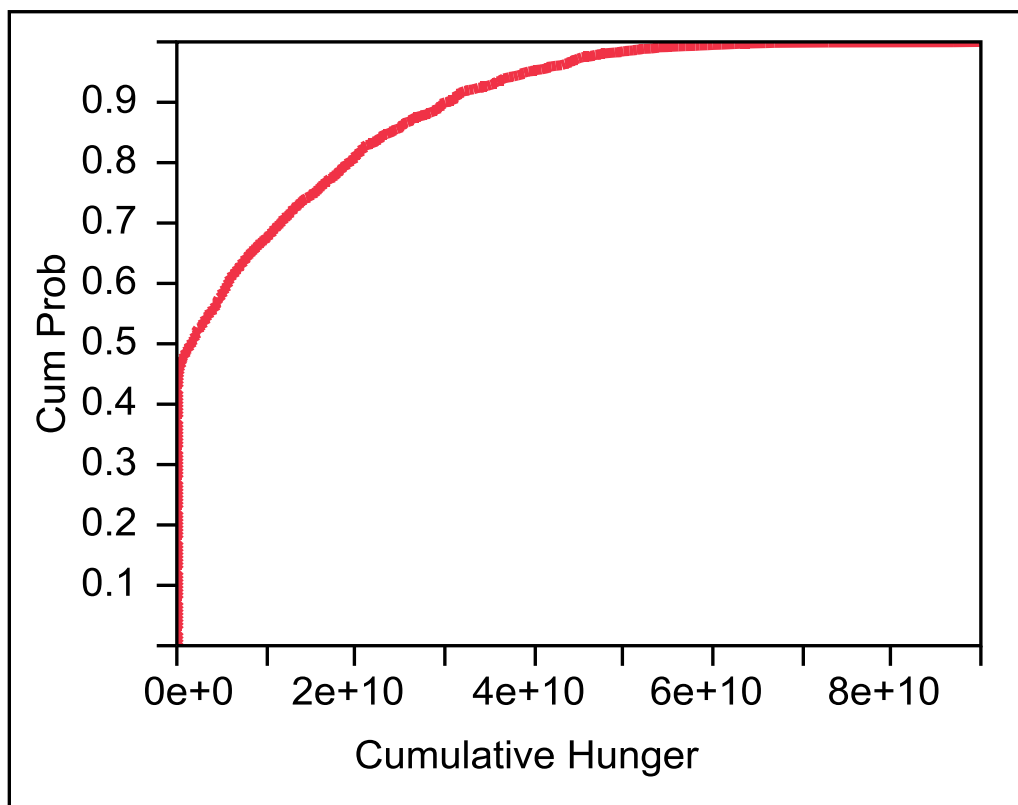


Figure 10. The cumulative distribution function plot illustrating the relationship between cumulative hunger-days and their probability of occurrence. There is greater than a 50% chance that worker absenteeism will result in a significant amount of hunger-days, even when food storage is increased at farms.

Increasing food storage at farms to 200-500 days did not significantly reduce hunger-days (i.e., food deficits). The simulations indicated that there would likely be disruptions to the food system due to labor shortages during a pandemic (Figure 10). There were a significant amount of hunger-days (i.e., food deficits) in half of the simulations. When food deficits occurred, they were almost always significant. The consequences would be devastating to the United States if a disruption to the food system occurred at that scale.

Discussion

This study found that the United States food system is not resilient against the expected level of worker absenteeism (20 - 40%) during a pandemic (DHS, 2006; FFIEC, 2007; OSHA, 2007). Similar to this study, other studies have found that severe pandemics have severe and adverse effects on food supply chains (Kumar et al., 2010; Osterholm, 2005; Osterholm et al., 2009; McKinnon, 2006; NISAC, 2007). One area of uncertainty in this analysis, that directly affects the results, is the epidemiologic characteristics of a future pandemic. Infectious diseases that rapidly burn through the United States population in less than 30 days will likely not have a great impact on supply chains, and diseases that moderately sustain themselves in the population over longer periods are likely to have greater consequences in terms of worker absenteeism. Despite the frightening realization that the United States is not resilient to the tested pandemic scenarios (where there are no intervention strategies that are effective and the illness spreads very rapidly), potential measures to make the food supply chain more resilient to pandemics should be tested to increase the United States resiliency.

Even if the transportation system was somehow able to maintain its functionality during a pandemic, then the results of the sensitivity analysis in scenario 2 indicated that there might still not be enough food available in the system to prevent people from going hungry due to limited production.

The hunger-day statistic in this study implies that the burden of hunger is non-differential across the United States population. However, when food becomes scarce it is likely that the lower social economic status portion of the United States population will bear more of the burden than the portion with higher social economic status. This suggests that lower social economic status individuals will be faced with more hunger-days comparatively speaking, and are at higher risk of starvation. Many of the people that drive trucks and work in the food system are of lower social economic status. This could potentially create an interesting feedback loop and cascading failure in both the transportation system and the food system. For these reasons, future research should measure the likely effect of hunger-days on different levels of social economic status in the United States, quantify the amount of food necessary to remedy the hunger-day disparity, and determine where these vital personnel reside, between low and high social economic status groups. Then, policies should be investigated to determine ways to prevent vital segments of the workforce from starving.

There are many opportunities for future research to improve the resiliency of the food system to pandemics. In theory, transportation and food systems workers could be provided with personal protective equipment to reduce disease transmission risk. Future studies could examine the feasibility of training and disseminating personal protective equipment to vital systems personnel and try to determine what alternate emergency transportation systems exist and their capacity and determine if these types of policies would be acceptable to employees. Another possible solution to make the food and transportation systems' functioning more resilient is to have an emergency reserve workforce to replace critical absent workers. Research should be conducted to identify and quantify the number of critical positions by type through all interdependent systems and rank order their criticality to the functioning of the systems. That way the most critical positions can be replaced first. Based upon this analysis training plans should be crafted to determine how many days are required to train replacement

workers. In a pandemic, many systems will be facing labor shortages and research should be conducted to determine and classify the transferable skills in the workforce. Then, workers will be able to be assigned to positions with minimal training and maximum efficiency. If executed, these studies could increase the resilience of the food system.

Other studies have postulated that hunger during disasters can be mitigated through local food production (e.g., urban agriculture, victory gardens, local commercial production, shared community gardens, etc.). Future research should examine the amount of food that can be generated cumulatively on a national scale, with existing and alternative food production infrastructure, and determine the amount of hunger-days that can be ameliorated. Additionally, the ramp-up time of local and regional production systems needs to be quantified. Depending when the pandemic strikes, the effects on the food system, and the number of hunger-days, could be drastically different due to the seasonality of food production. The effects of pandemic on local, regional, and national level food systems should be quantified based on the seasonality of food production. These future research ideas beg the question: who pays for the lower social economic status population's hunger-days, and what are the likely food prices in a pandemic scenario? Determining the cost of food will be important to know before policies can be put in place to mitigate a surge in food prices during a pandemic and to identify what core foods are needed for survival of the population (assuming that we cannot support them all now).

The United States wastes a tremendous amount of food, and in the current study we did account for food waste. Future research should examine innovative ways to eliminate food waste, or ways to consume the byproducts of food processing in an emergency situation. Furthermore, research should be conducted to determine the feasibility of stockpiling in areas in close proximity to current retail food outlets for 16-43 hunger-days for every person in the United States for non-energy dependent (e.g., frozen or refrigerated) shelf stable foods (e.g., canned, preserved, and/or dried).

This study had several limitations. The input assumptions used in this model were simplified versions of reality (i.e., the consumption of food per person per day was averaged, there was not of empirical data to completely validate the model, the rates of food flowing through the model are averaged between points). The model we used lacked empirical data, for model inputs and for testing model outputs (other than national level based data). The epidemiologic characteristics tested were best guesses. The shortfalls in food supply in Figures 5 and 6 are in some ways conservative because the simulations were based only on direct effects of absenteeism on food production, processing, and distribution. The indirect effects shown in Figure 1 were not included, though their impacts could be equal to or even greater than the direct effects. For example, absenteeism in the transportation sector could lead to a reduction of fuel deliveries to many sectors of the economy – farms, the transportation sector itself, electrical power plants – crippling farm production, food processing, refrigeration, transport, and other essential activities throughout the food system. Future simulation studies should assess the significance of indirect effects, including risks they pose for the possibility of total collapse in the food system. Finally, the model is only generalizable to nations that have food systems with similar interdependences.

The research community needs to identify and quantify the most critical threats to the food system during a pandemic. This study, and others like it, indicates that there will not be enough food when the next pandemic occurs. Every day that passes we are one day closer to the next pandemic. In the case of this body of research, time is our scarcest resource. The tremendous problems and uncertainty the world faces need to be addressed with the combination of empirical research and modeling to get ahead of the next pandemic. There are many things society can live without, but food is not one of them.

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Supplemental

Supplemental 1 – Experiment 1: The effect of worker absenteeism on the transportation system

In the model, the transportation system moves necessary inputs to farms, from farms to processors, from processors to distributors, and from distributors to retail outlets. The only variable manipulated is the rate of worker absenteeism in the transportation system (i.e., a sensitivity analysis). No other variables were manipulated in the model. All other systems and their corresponding variables in the model were set to operate at their maximum capacity (e.g., communication, electricity, fuel, water, and waste). In real life, worker absenteeism could cause degradation to these other necessary systems and their disruption could independently disrupt the food and system. These combinations of disruptions are not tested. The inventory of the food supply upstream of food processors (at farms), which is the largest food storage in the system, is never transported to consumers (Figures S1 & S2 and Table S2). Therefore, there is essentially no food available to consumers at pandemic-level worker absenteeism (30% worker absenteeism peaks in the middle of a 188 day wave).

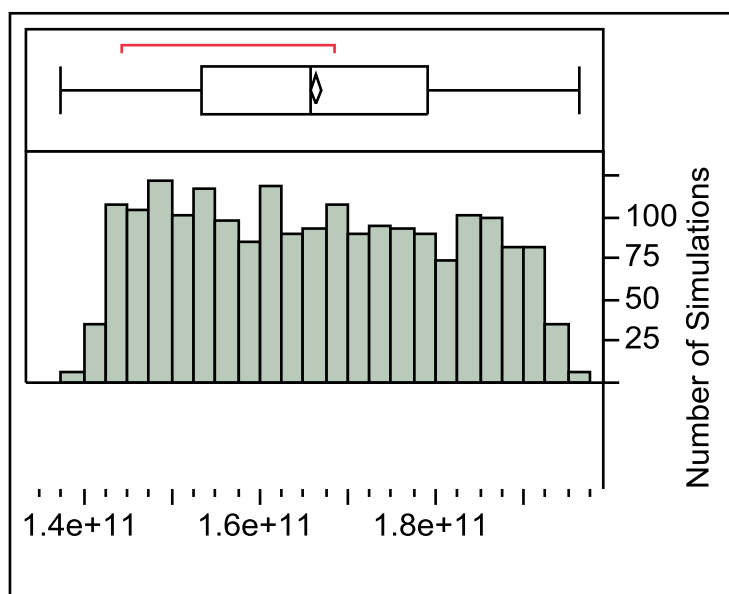


Figure S1. Histogram (below) stacked with box and whisker plot (above) of the distribution of cumulative hunger-days (X axis) over 800 days, over 2,000 model runs. The results indicate a significant reduction in the amount of available food during a pandemic. The median of 2,000 simulations is roughly 566 hunger-days per person, in the United States.

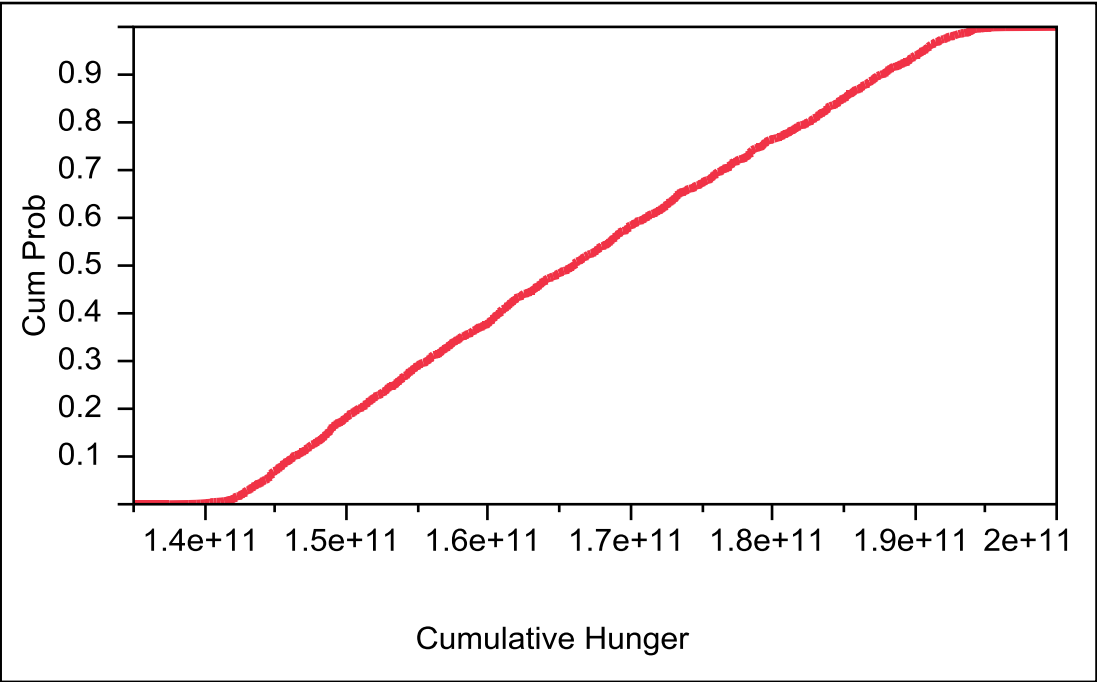


Figure S1. The cumulative distribution function plot illustrating the relationship between cumulative hunger-days and their probability of occurrence.

Table S1. Quantiles and moments; all quantiles result in an amount of hunger-days that are not survivable.

Quantiles			Moments	
100.0%	maximum	2e+11	Mean	1.664e+11
99.5%		1.9e+11	Standard Deviation	1.504e+10
97.5%		1.9e+11	Standard Error Mean	336,362,593
90.0%		1.9e+11	Upper 95% Mean	1.67e+11
75.0%	quartile	1.8e+11	Lower 95% Mean	1.657e+11
50.0%	median	1.7e+11	N	2,000
25.0%	quartile	1.5e+11		
10.0%		1.5e+11		
2.5%		1.4e+11		
0.5%		1.4e+11		
0.0%	minimum	1.4e+11		

Supplemental 2 – Experiment 2: The effect of worker absenteeism on food production

In the model, workers are necessary at farms, and at processing and packaging facilities, to produce food. The only variable manipulated is the rate of worker absenteeism in food production (not transportation). All other systems and their corresponding variables in the model were set to operate at their maximum capacity, including transportation. Thus worker absenteeism variable was only manipulated within the food production elements within the food system (i.e., farms, processors and packagers, and in retail outlets). This scenario analyzes the dependency between worker absenteeism and the production of food in the food system.

Allowing food production to occur with some fraction of the available workforce gives insight into the second research question (described in the methods section). With the workforce coefficients sampled log-uniformly between 0.1 and 1, the median (.5) run has less than 1 hunger-days (.74 hunger-days per person in the United States), implying that existing food stores might satisfy the aggregate demand with a reduced workforce in food production (given adequate functioning of food transportation). However, the peak number of hunger-days observed in 2,000 simulations was 81 billion (270 days of hunger for every person in the United States), and the upper quartile value of 12 billion hunger-days (Table S2) still represents a significant problem of food availability during a pandemic (40 days of hunger for every person in the United States), as illustrated in Figures S3 and S4.

Table S3. Quantiles and moments; only quantiles above 50% result in an amount of hunger-days that are not trivial (greater than 40 hunger-days per person in the United States).

Quantiles			Moments		
100.0%	maximum	8.1e+10	Mean		7.7992e+9
99.5%		5.9e+10	Standard Deviation		1.228e+10
97.5%		4.3e+10	Standard Error Mean		274482247
90.0%		2.5e+10	Upper 95% Mean		8.3375e+9
75.0%	quartile	1.2e+10	Lower 95% Mean		7.2608e+9
50.0%	median	2.23e+8	N		2,000
25.0%	quartile	0			
10.0%		0			
2.5%		0			
0.5%		0			
0.0%	minimum	0			

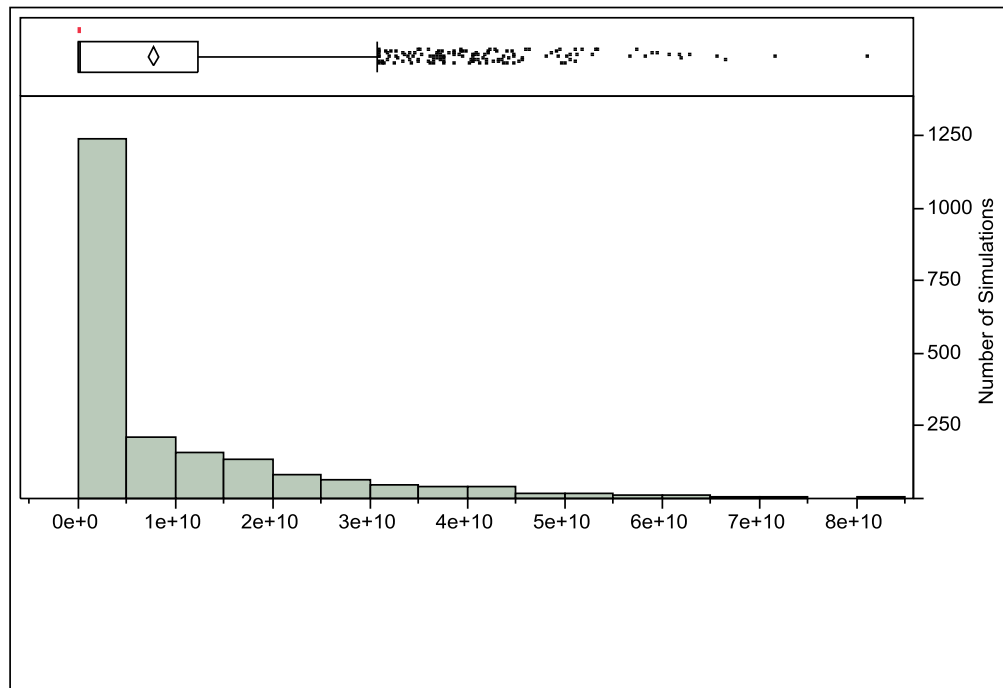


Figure S3. Histogram (below) stacked with box and whisker plot (above) of the distribution of cumulative hunger-days (X axis) over 800 days, over 2,000 model runs. The results indicate a significant reduction in the amount of available food during a pandemic due to worker absenteeism in food production (not transportation). The median of 2,000 simulations is roughly 16 hunger-days per person.

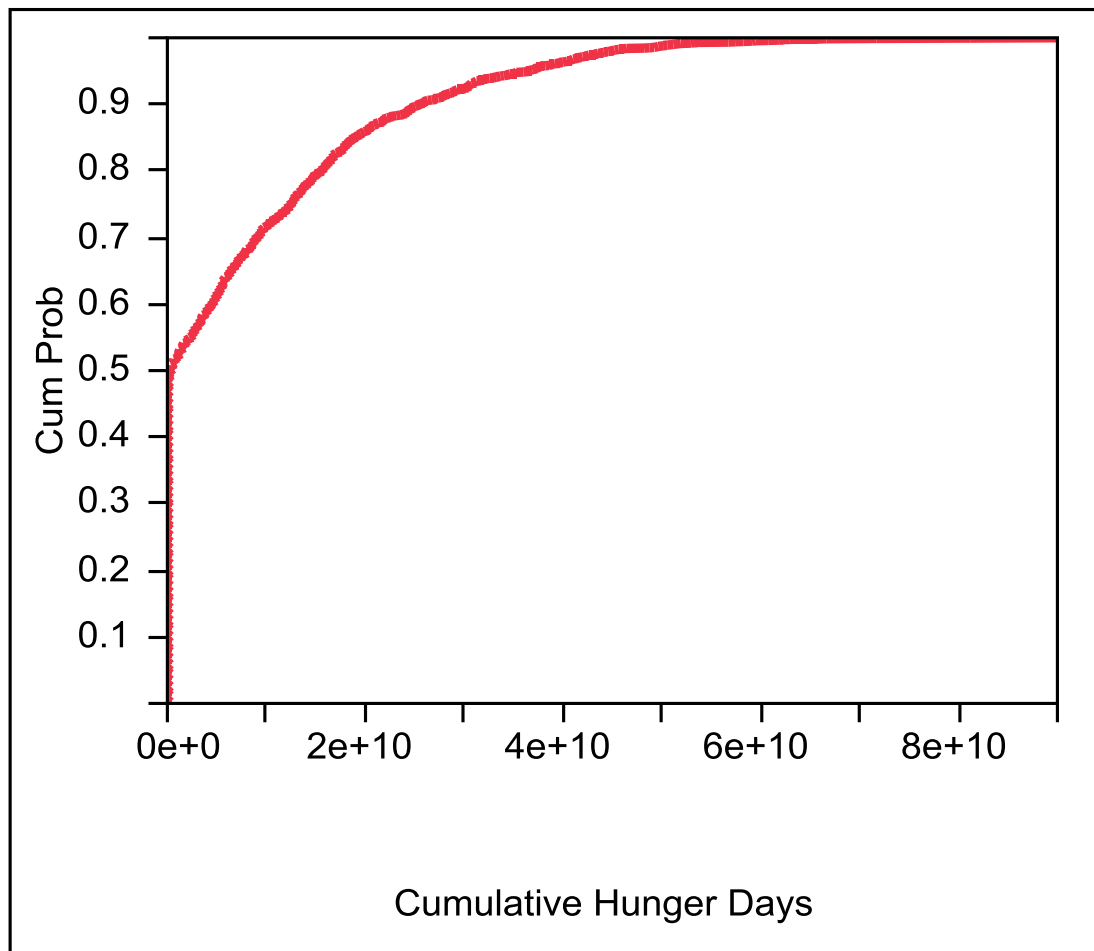


Figure S4. The cumulative distribution function plot illustrating the relationship between cumulative hunger-days and their probability of occurrence. There is greater than a 50% chance that worker absenteeism in food production will result in a non-trivial amount of hunger-days

Supplemental 3 – Experiment 3: Increasing food storage at farms when food production is decreased

In this experiment, the amount of food stored at farms was increased. In the model, and in reality, there is a limited amount of food stored at all points in the food supply chain (i.e., at the farms, at processor and packaging facilities, at distribution centers, and at retail stores). Typically the largest sources of storage in the system are at farms and at retail outlets, with only the minimum amount of food stored in the middle of the supply chain (due to the just-in-time nature of the United States food system). In previous simulations, a value between 50-150 days of food was randomly selected for each simulation. The amount of food available was increased by randomly selecting from a range of 200-500 days of food. While increasing the amount of stored food at farms would be a difficult policy to implement, the purpose was to determine if increasing the amount of stored food would have an effect on food availability when food production was diminished due to worker absenteeism.

The primary factors controlling food system performance are the production/labor coefficient (worker absenteeism) on farms, and the food inventory on hand at farms and at processors. Small values of the production/labor coefficient (labor production sensitivity), which correspond to high sensitivity of the food production rate (due to labor unavailability or worker absenteeism), are associated with the most consequential outcomes (Figure S4). The policy option of storing additional food at the farm is analyzed, and additional food storage at the farm level does not greatly reduce the amount of hunger-days (Figure S5). The most sensitive parameter continues to be worker absenteeism in food production (Figure S6). The probability of the event did not change greatly compared to supplemental 2, and is illustrated in Figure S7.

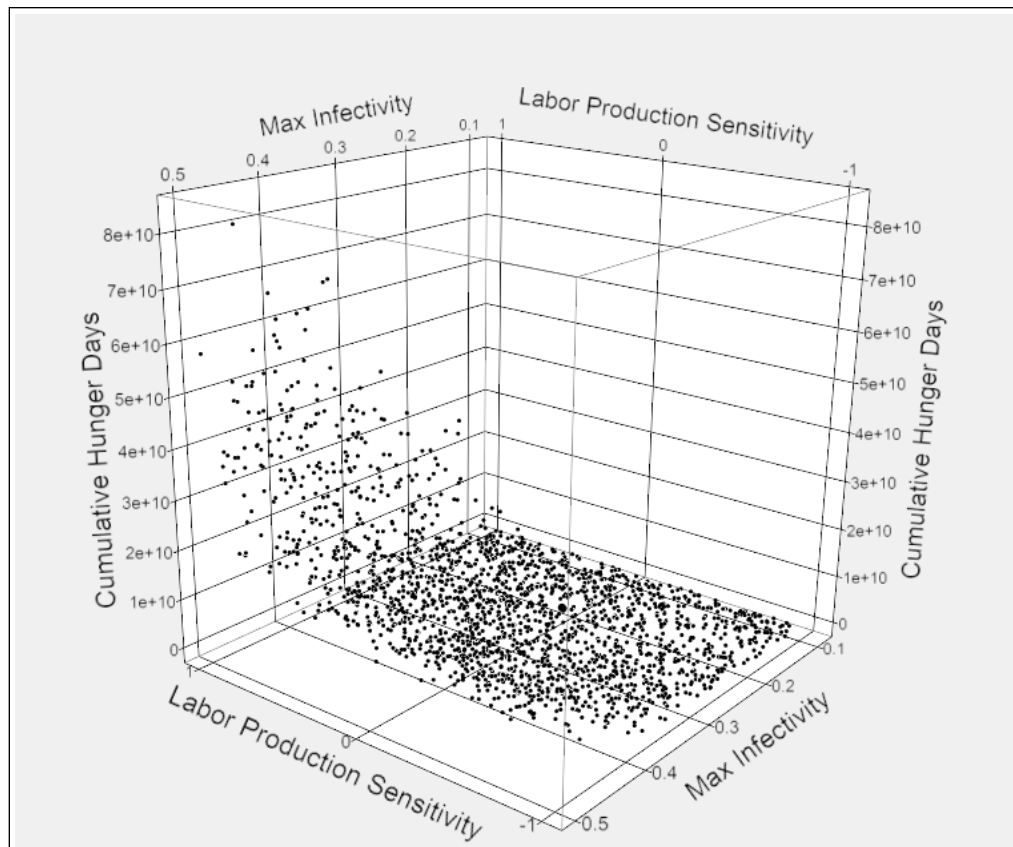


Figure S4. A three-dimensional scatter plot of the results of 2,000 simulations, over 800 days, where less than 50% of the simulations do not result in food shortages of significance. The relationship between excess stockpiles at the farm level is compared with worker absenteeism and the effects are measured in cumulative hunger-days. This portion of the analysis and illustration does not account for the effects of system interdependencies (i.e., transportation, sanitation and waste, water, electricity, fuel). Of most significance, worker absenteeism (infectivity) has a more dominant influence on the amount of hunger-days than food storage, thus food storage was not included on this plot.

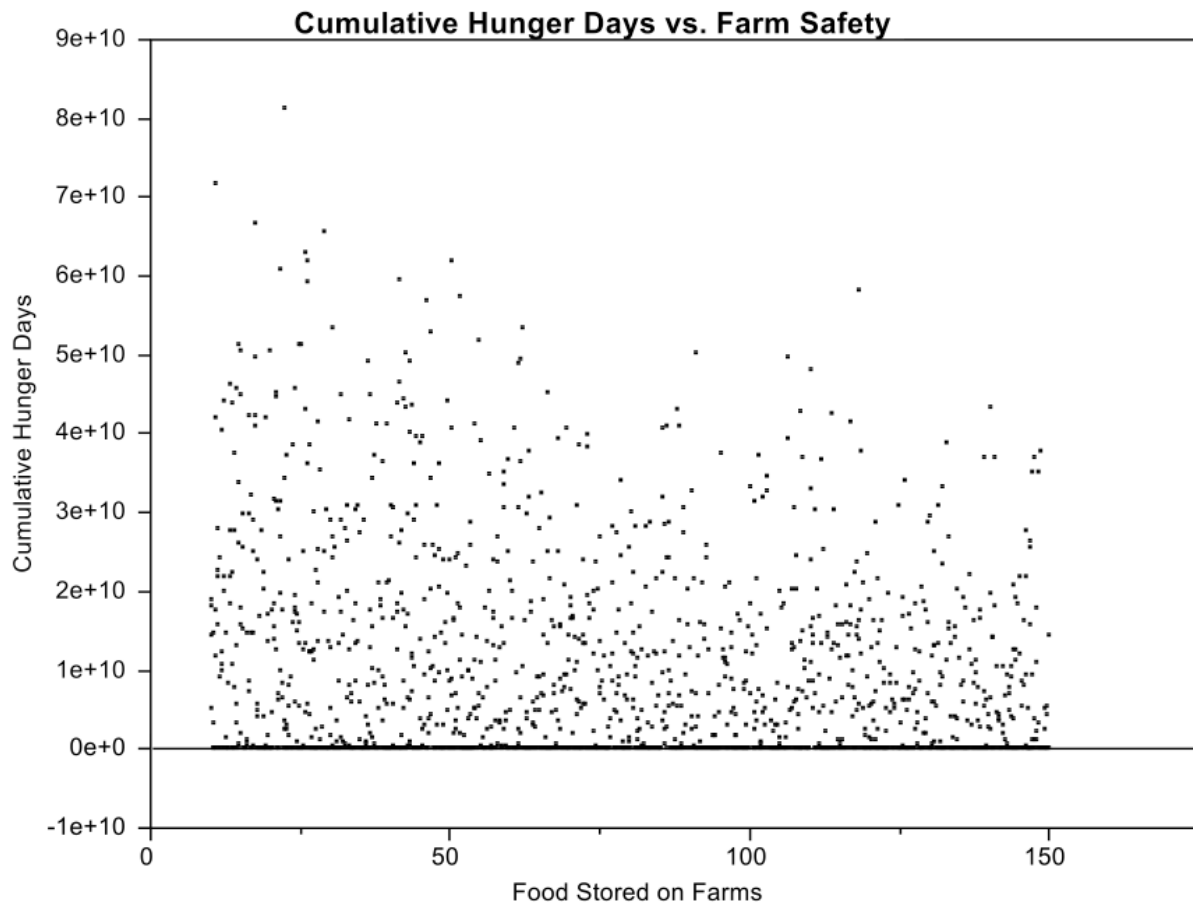


Figure S5. Comparison of food stored on farms and cumulative hunger-days. As the amount of food stored at farms was increased, there was not a significant decrease in the amount of hunger-days in the United States.

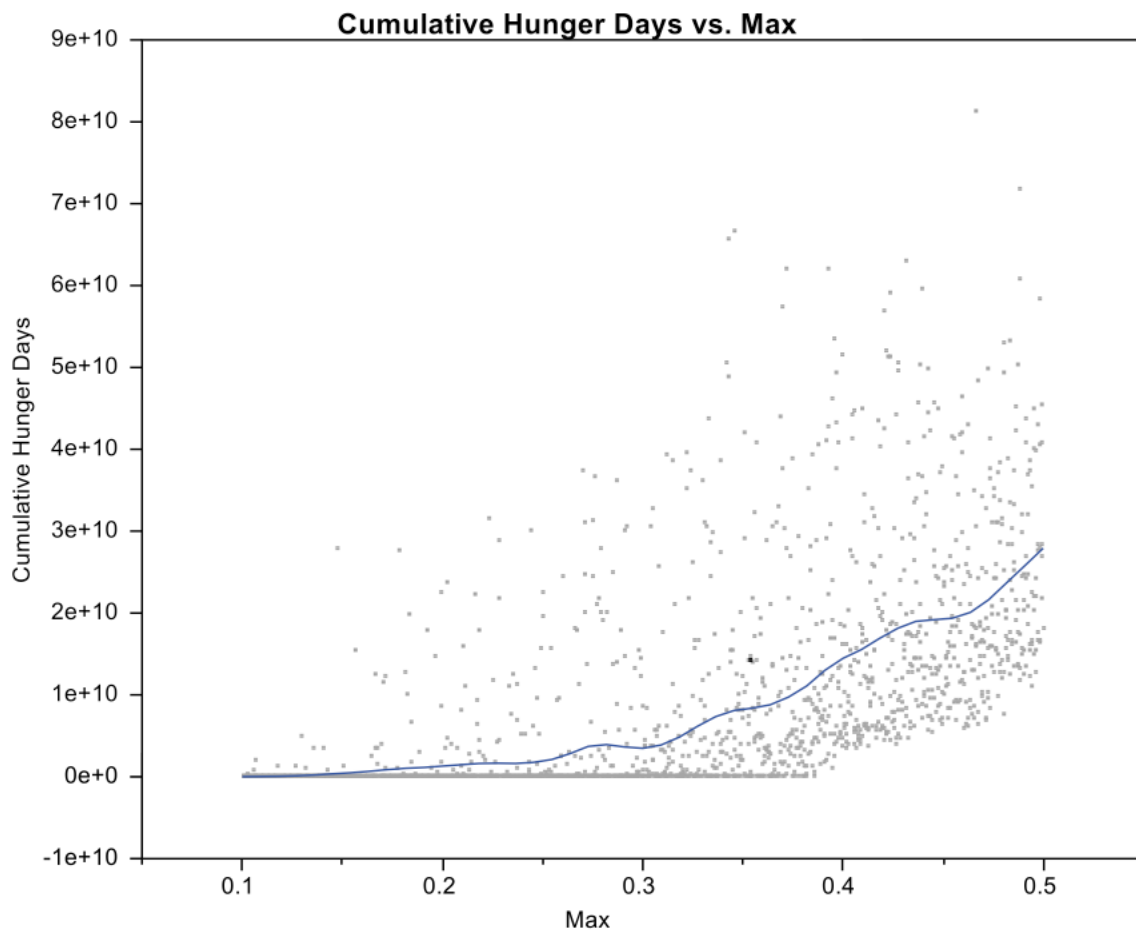


Figure S6. Worker absenteeism (x axis) is the most sensitive parameter, and additional food storage has little effect on the amount of cumulative hunger-days. The blue line is the median of cumulative hunger-days.

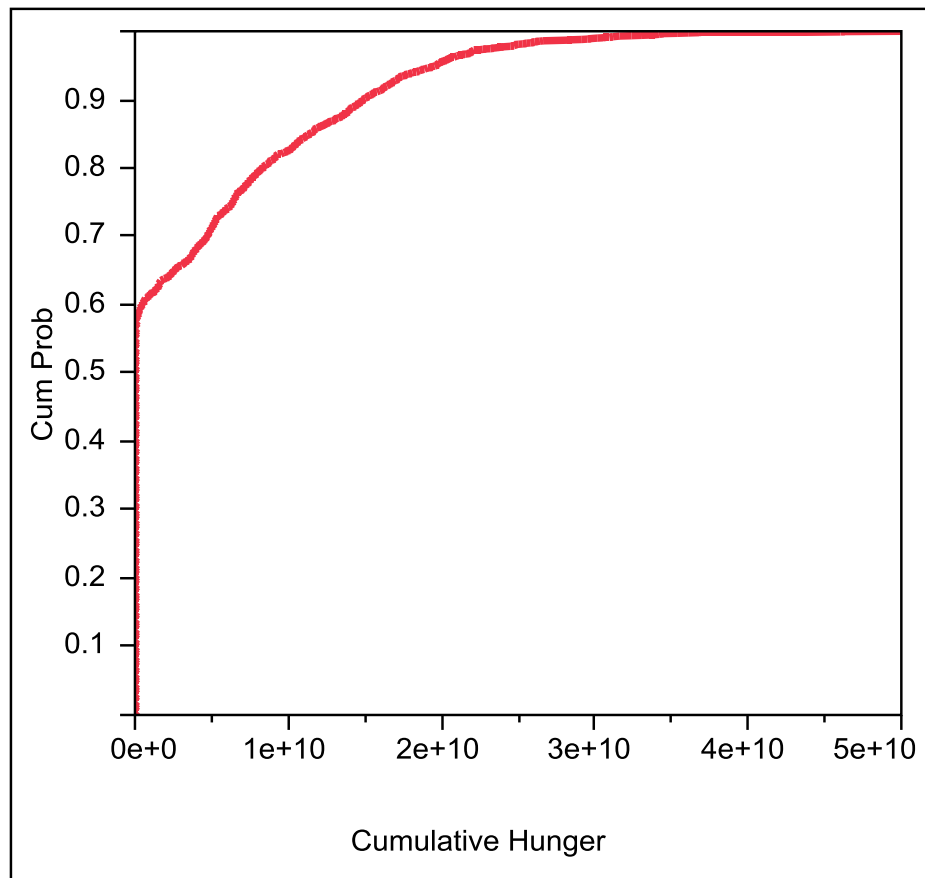


Figure S7. The cumulative distribution function plot illustrating the relationship between cumulative hunger-days and their probability of occurrence. There is greater than a 60% chance that worker absenteeism in food production will result in a non-trivial amount of hunger-days, even when food storage is increased at farms.

Supplemental 4 – Experiment 4: Worker absenteeism effect on food production and transportation

Worker absenteeism was restricted to 30% maximum in transportation. While worker absenteeism was restricted to 30%, the sensitivity of worker absenteeism on transportation and food production were tested. In this case, worker absenteeism gradually rises over the first wave from 10% to 30%. This scenario is meant to test a more realistic situation where a pandemic causes worker absenteeism in food production and in food transportation.

Significant shortages appear when the food production coefficient is greater than 0, (i.e., when the proportional difference in food production is larger than the proportional reduction in the workforce). The food system is more tolerant of reduction in transportation capacity; however, as the transportation coefficient approaches 1 all simulations show widespread shortages of food, and the probability of the event does not change greatly compared to other scenarios, and the severity of hunger-days is reduced (Table S4), as illustrated in Figure S8.

Table S4. Quantiles and moments; only quantiles above 75% result in an amount of hunger-days that are not trivial (greater than 15 hunger-days per person in the United States).

Quantiles			Moments	
100.0%	maximum	5.9e+10	Mean	4.3023e+9
99.5%		4.7e+10	Standard Deviation	8.4632e+9
97.5%		3.2e+10	Standard Error Mean	189242255
90.0%		1.5e+10	Upper 95% Mean	4.6734e+9
75.0%	quartile	4.56e+9	Lower 95% Mean	3.9311e+9
50.0%	median	1.52e+8	N	2,000
25.0%	quartile	0		
10.0%		0		
2.5%		0		
0.5%		0		
0.0%	minimum	0		

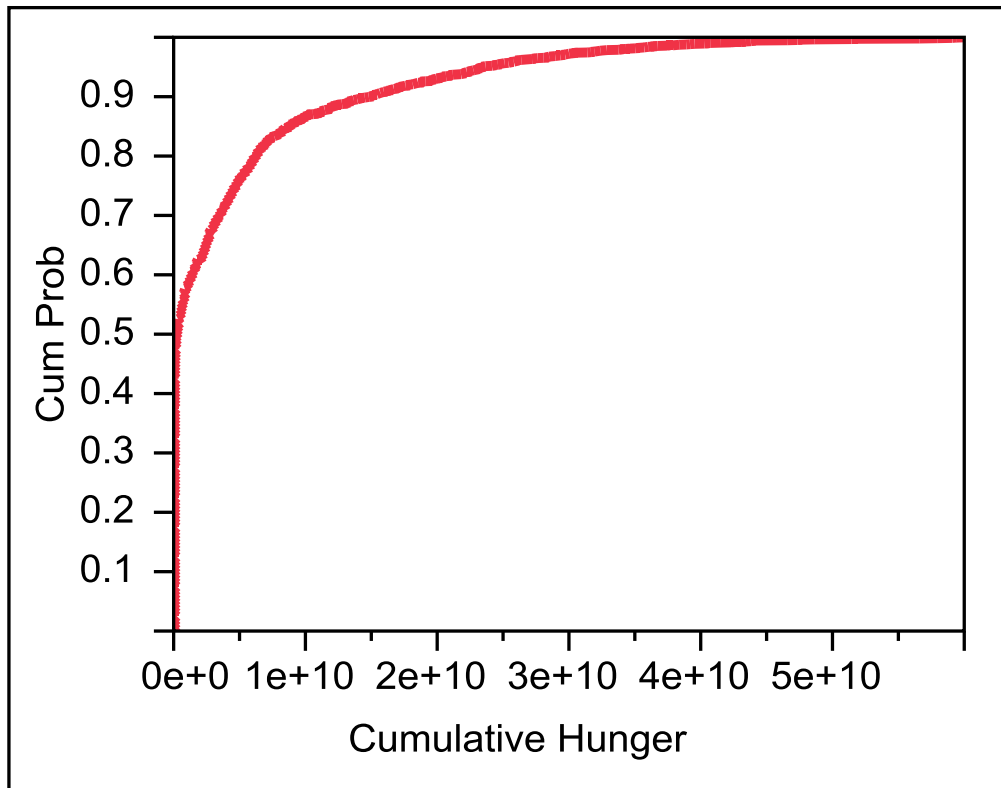


Figure S8. The cumulative distribution function plot illustrating the relationship between cumulative hunger-days and their probability of occurrence. There is a 50% probability that worker absenteeism in food production will result in a hunger-days, although the severity is somewhat reduced.

Supplemental 5 – Experiment 5: 20% fixed worker absenteeism

Worker absenteeism is restricted to a fixed 20% during the pandemic waves. While this is not realistic, the resulting simulation provides information on the effects of lower levels of worker absenteeism on the food system and the overall available amount of food. The resulting simulation provides information on the effects of lower levels of worker absenteeism on the food system and the overall available amount of food. There is a higher probability of no starvation (Table S5), which is reasonable given the non-linear effect of labor loss on production for the high-consequence cases (Figure S9).

Table S5. Quantiles and moments; only quantiles above 75% result in an amount of hunger-days that are not trivial (greater than 15 hunger-days per person in the United States). The population is not severely effected until the 90% quantile.

Quantiles			Moments	
100.0%	maximum	6.2e+10	Mean	2.7021e+9
99.5%		3.7e+10	Standard Deviation	7.1315e+9
97.5%		2.6e+10	Standard Error Mean	159464825
90.0%		1.1e+10	Upper 95% Mean	3.0148e+9
75.0%	quartile	2.67e+8	Lower 95% Mean	2.3894e+9
50.0%	median	0	N	2,000
25.0%	quartile	0		
10.0%		0		
2.5%		0		
0.5%		0		
0.0%	minimum	0		

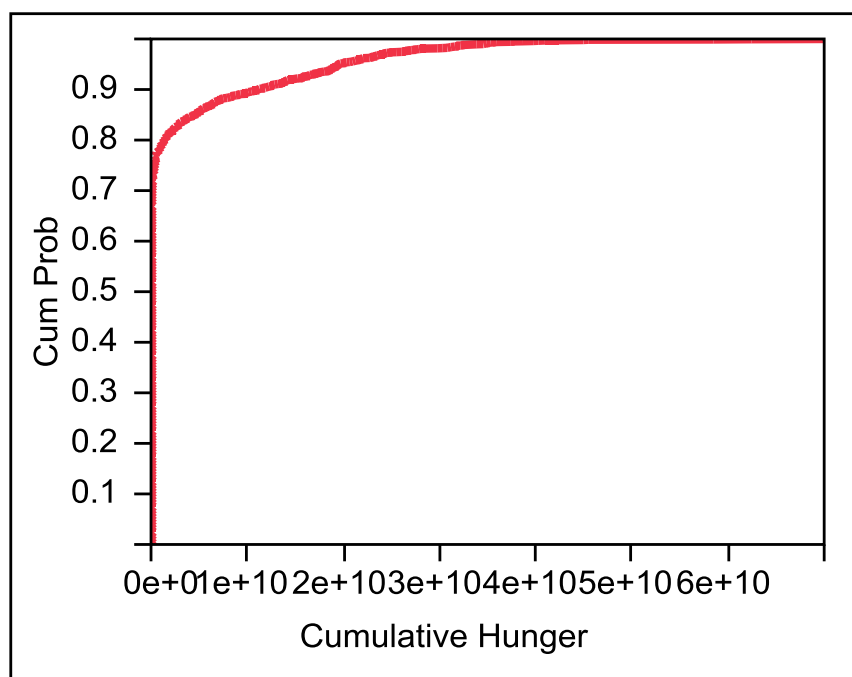


Figure S9. The cumulative distribution function plot illustrating the relationship between cumulative hunger-days and their probability of occurrence. There is greater than an 80% chance that worker absenteeism in food production will not result in hunger-days. However, the severity is not greatly reduced.

Supplemental 6 – Experiment 6: A single wave pandemic with 35% worker absenteeism

A single wave of absenteeism occurs with: 15 days of worker absenteeism at 10%; followed by 20 day period where worker absenteeism increases from 10% to 35%; then 30 days at a peak of 35% worker absenteeism. At the end of the duration of the peak worker absenteeism period, worker absenteeism declines to 10% over 20 days and is followed by 15 days of worker absenteeism at 10% before the simulation is stopped. The population could experience roughly 4 hunger-days (Table S6) during a 120 day time period (Figure S10).

Table S6. Quantiles and moments; only quantiles above 75% result in an amount of hunger-days that are not trivial (greater than 4 hunger-days per person in the United States). The population is not severely effected until the 90% quantile.

Quantiles			Moments	
100.0%	maximum	6.75e+9	Mean	146,083,321
99.5%		4.51e+9	Standard Deviation	609,387,097
97.5%		2.13e+9	Standard Error Mean	13,626,310
90.0%		7.6e+7	Upper 95% Mean	172,806,577
75.0%	quartile	0	Lower 95% Mean	119,360,064
50.0%	median	0	N	2,000
25.0%	quartile	0		
10.0%		0		
2.5%		0		
0.5%		0		
0.0%	minimum	0		

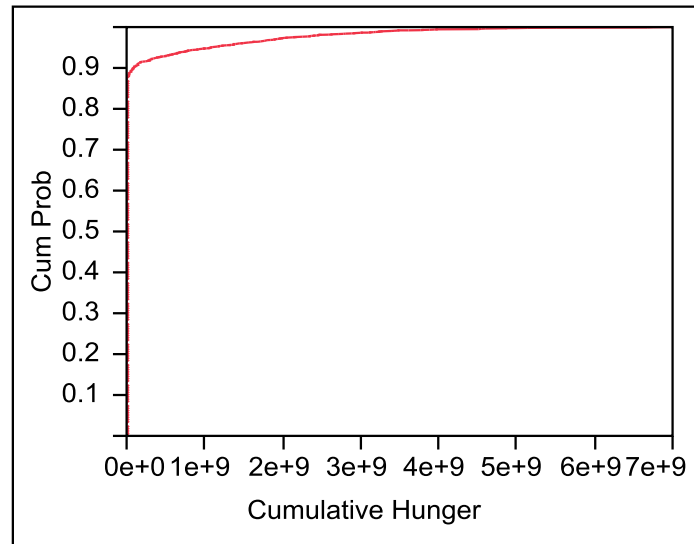


Figure S10. The cumulative distribution function plot illustrating the relationship between cumulative hunger-days and their probability of occurrence. There is greater than an 85% chance that worker absenteeism in food production will not result in hunger-days. However, the severity is not greatly reduced.