An Exploration of the Influence of Health Related Risk Factors Using Cellular Automata

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Abstract:

An exploration is made of the application of a cellular automata model to population health improvement. The model is presented in the context of the current epidemic of obesity and type 2 diabetes. The focus is on end state health improvement strategy not disease spread. Boundary conditions identified by the model suggest target areas for cost-benefits improvements. The model also helps set general expectations for outcomes given initial conditions.

Objective:

To investigate potential health trends in a population and then to identify the boundary conditions for changes in population health.

Introduction:

There is an increasing incidence of type 2 diabetes with its associated co-morbidities (i.e. cardiovascular, renal and ophthalmologic complications). The prevalence of obesity has almost doubled in the United States in the last 25 years (CDC). Obesity, hypertension, and type 2 diabetes are recognized as the metabolic syndrome.

Obesity is multifactorial. Obesity emerges from the interaction of a pre-disposing genome with an environment of excessive caloric intake and insufficient physical activity. Obesity is a global phenomena with nearly a half billion of the world's population overweight or obese.

This unhealthy population trend along with an approach that addresses the problem in all affected dramatically increases the cost of healthcare. A model is needed to better understand this decreasing population health, to devise a strategy for health improvement, focus resources for cost benefits, and set expectations the for outcomes.

Methods:

A model of the problem was constructed using a cellular automata approach. Each agent was characterized by an initial state of health (0, 1), and severity of composite risk factors (1 to 8) for becoming unhealthy. These composite risk factors conceptually include diet, physical inactivity, stress, and obesity.

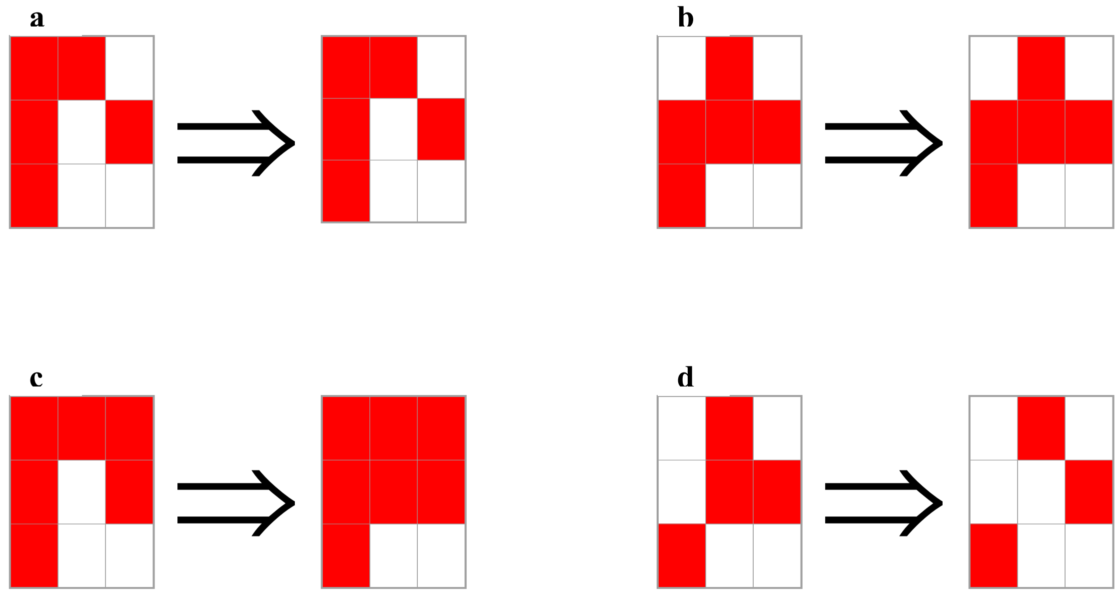


Figure 1 – Transition rules between healthy and unhealthy individuals in the population allow for the 8 nearest neighbors in the population to influence the health of each individual. **a.** For Risk Factor (RF=5), the center, "unhealthy" individual is affected by 5 "healthy" individuals, which is insufficient to cause a state transition. **b.** For RF=5, the center, "healthy" individual is affected by 4 unhealthy individuals, which is insufficient to cause a state transition. **c.** For RF=5, the center, "unhealthy" individual is affected by 6 "healthy" individuals, which is sufficient to cause a state transition to "healthy". **d.** For RF=5, the center, "healthy" individual is affected by 5 "unhealthy" individuals, which is sufficient to cause a state transition to "unhealthy".

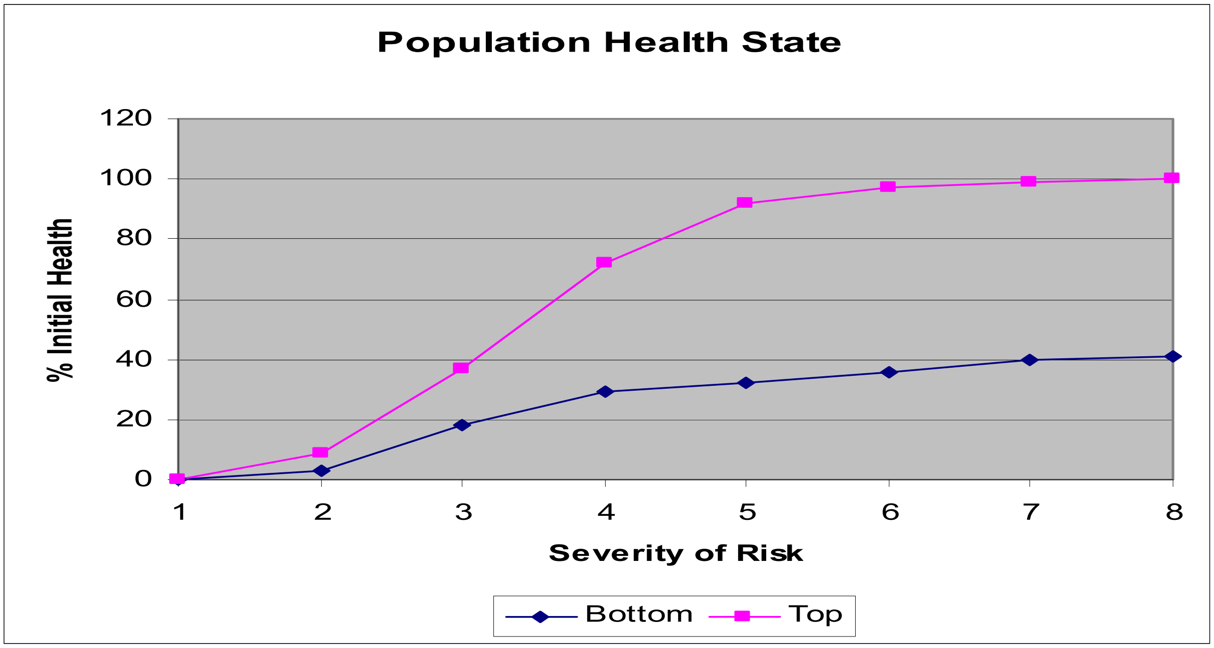
The initial conditions were then set to interact with a complex social influence - peers and environment. This interaction was described by a set of transition rules for each agent (see figure 1).

Agent Initial State	Transition Rule	
0	$n_1 > RF$	(switch state)
1	$n_0 > n_1$	(switch state)

where
0 = unhealthy state
1 = healthy state
n_1 = the number of healthy neighbors
n_0 = the number of unhealthy neighbors
RF = composite risk factors

The final state of population health was defined after 100 iterations of the model. Three regions of population health were identified in the final state - all healthy, a heterogeneous population with varying distributions of health and all unhealthy. The boundary conditions for defining these regions were determined by investigating all possible combinations of initial conditions(800) and then further analyzing areas of interest with multiple runs of the model at selected points. The boundary points were designated by 100% healthy (upper bound) or 0% to 1% healthy (lower bound) (see figure 2).

Figure 2



Results:

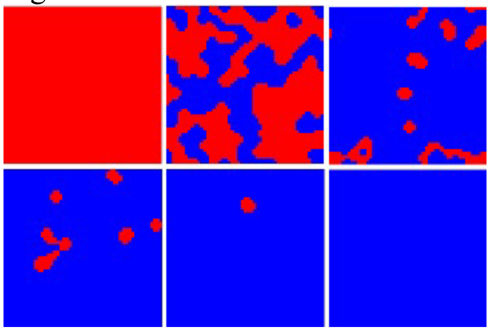
1) Boundary plot

There are three distinct regions in the boundary plot. Above the upper boundary, the final state of the population is a hundred percent healthy, whereas underneath the lower boundary the population is a hundred percent unhealthy. A heterogeneous population in the final state characterizes the region between the two curves.

2) Horizontal scan of a final state

Figure 3 below displays sections of the final state of the model across risk factors at 51% initial health. Sections show varying patterns of population health. This display should be examined from left to right and top to bottom. Starting from a totally healthy population with a risk of 3 (all red) and ending with a totally unhealthy population wit the complete risk of 8 (all blue).

Figure 3



3) Figure 4 below is a 3-D plot of initial conditions and final states for the total universe of possibilities within the specifications of the model.

a **b**

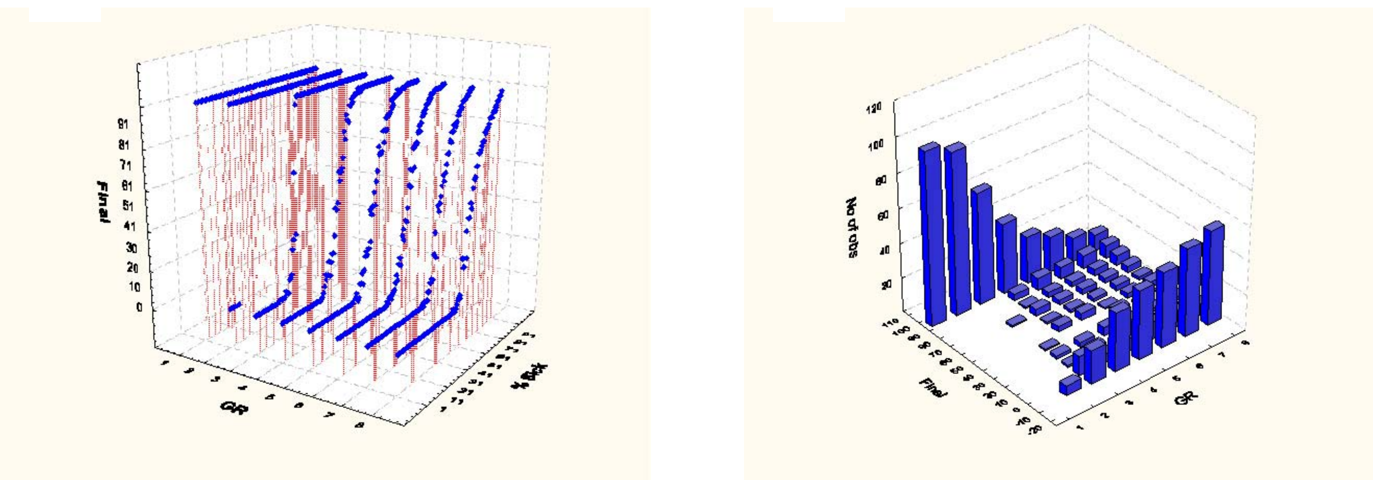


Figure 4 – The graphical representation for the outcomes of the 800 possible runs of the model. **a.** Outcomes of complete health and complete unhealth occupy approximately 70% of the graph; the ~30% remaining outcomes appear as nearly exponentially determined for each level of RF (risk factor) modeled. **b.** The outcomes were aggregated to consider the frequency of outcomes for a given level of RF across all of the 100 levels of initial percent healthy.

The three-dimensional graphs suggest that the model produces large areas of either all-healthy population or all-unhealthy population. In areas where the model output is neither all-healthy nor all-unhealthy, the relationship between the percentage of the initial population that is healthy and the final outcome becomes variable (multiple runs of the model at each of these levels provide levels of variability based on the distance from the boundary – where the outcome is more variable as the distance from the "phase" boundary increases).

Discussion:

In this model health is a property of a population of agents, rather than a property of the individual agents. The goal was to see if the model could give some actionable insights into describing ways to improve population health. From the model it is apparent that a small decrease in risk factor close to the upper phase transition boundary should result in significant improvement in population health. The same degree of risk factor reduction farther from the upper boundary results in less health improvement. This prediction is consistent with the observed benefit of increased physical activity without weight loss in decreasing myocardial infarction.

Identifying the boundary allows the targeting of areas for greatest cost-benefit improvements and sets expectations for potential degree of improvement.

Other health-related applications of cellular automata modeling describe epidemics or aspects of immunology. Typically epidemic models look for spatio-temporal phenomena. This model is directed towards the final state for intervention strategies.

Conclusions:

Cellular automata modeling can provide valuable insights into managing risk in population health. However, further studies should be conducted to incorporate differing distributions of risk factors across the population. Also further changes might be made to the underlying transition rules.

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