Health system demand and the spread of COVID-19

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The University of Queensland

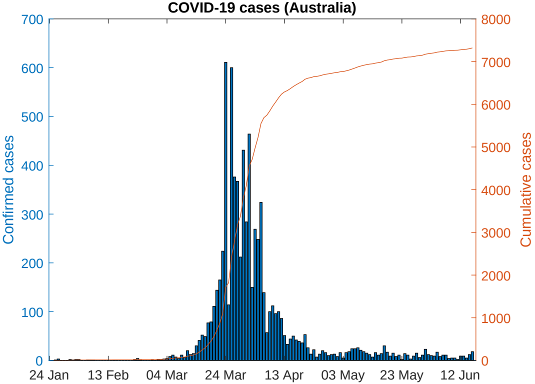
ACEMS COVID-19 Research Workshop

Online, 17 June 2020

AUSTRALIAN RESEARCH COUNCIL CENTRE OF EXCELLENCE FOR MATHEMATICAL AND STATISTICAL FRONTIERS

Aim To predict hospital admissions and ICU bed occupancy in the early stages of the spread of COVID-19 in Australia (prior to social distancing measures taking effect).

Data Daily case numbers taken from `ourworldindata.org` (University of Oxford).



Simulating the progress of COVID-19

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Data Daily case numbers taken from `ourworldindata.org` (University of Oxford).

Methods

- Use Poisson regression to estimate growth rate ($\mu_t := \mathbb{E}(Y|t) = e^{\alpha+\beta t}$, where $Y \sim \mathrm{Poi}(\mu_t)$ is the number of new cases on day t.)
- Use this together with estimates of the *serial interval* ...

  [1] Nishiura, H., Linton, N.M., and Akhmetzhanova, A.R. (April 2020) Serial interval of novel coronavirus (COVID-19) infections. *International Journal of Infectious Diseases* 93, 284–286.

  ... I estimate the *basic reproductive number* R_0.

  [2] Wallinga, J., and Lipsitch, M. (2007) How generation intervals shape the relationship between growth rates and reproductive numbers. *Proceedings of the Royal Society* Series B 274, 599–604.
- Simulate future case numbers using a branching processes, starting at Monday 23rd March.

Simulating the progress of COVID-19

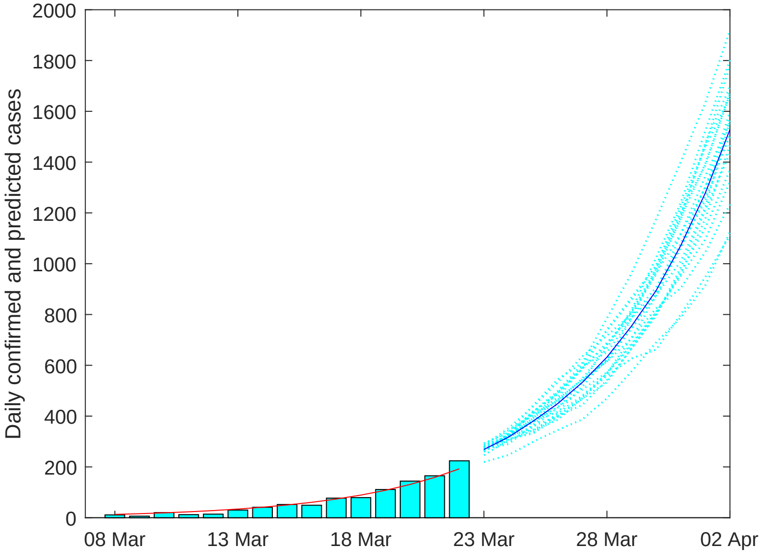
- Simulate hospital admissions, ICU bed occupancy, and deaths using information from the Wuhan (China) experience:

  [3] Ganyani, T., Kremer, D, Chen, Torneri, A., Faes, D., Wallinga, J., and Hens, N. (March 2020) Estimating the generation interval for covid-19 based on symptom onset data. *medRxiv*. doi:10.1101/2020.03.05.20031815.

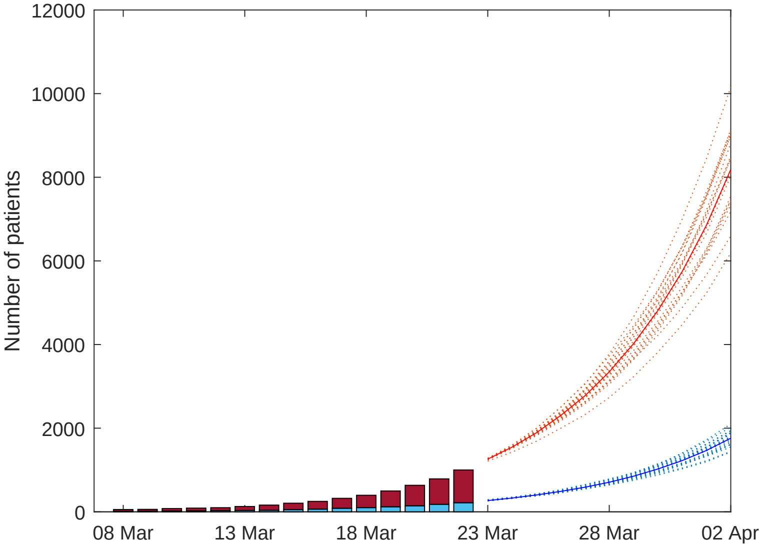
  - **Mild** 81% of patients do not need to be admitted to hospital and recover with 7–14 days $[7 + \mathrm{Bin}(7, 1/2)]$
  - **Severe** 14% of patients are admitted, but recover within 21–42 days $[21 + \mathrm{Bin}(21, 1/2)]$
  - **Critical** 2.7% of patients are admitted, but recover within 21–42 days $[21 + \mathrm{Bin}(21, 1/2)]$
  - **Death** 2.3% of patients are admitted, but die within 21–42 days $[21 + \mathrm{Bin}(21, 1/2)]$

(It would be helpful to have information on the precise distribution of recovery times, et cetera, in the Australian context.)

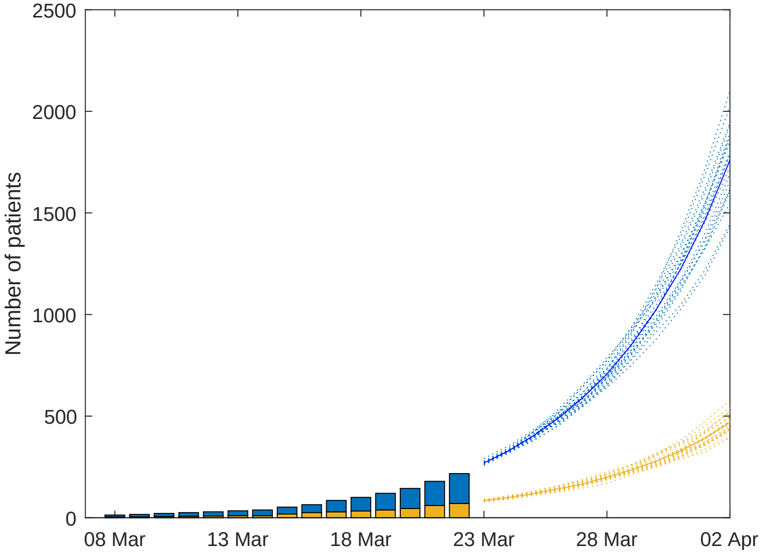
Daily confirmed and predicted cases



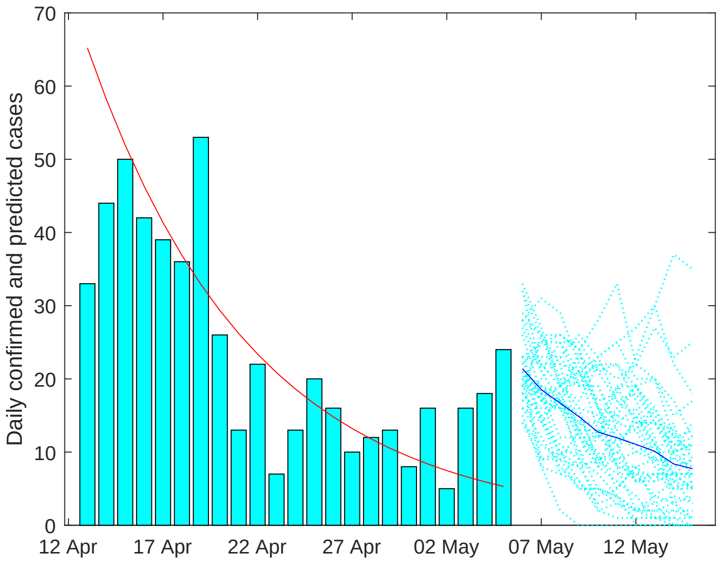
Current and predicted active cases and patients admitted



Current and predicted admissions and occupied ICU beds



Daily confirmed and predicted cases (recent past)



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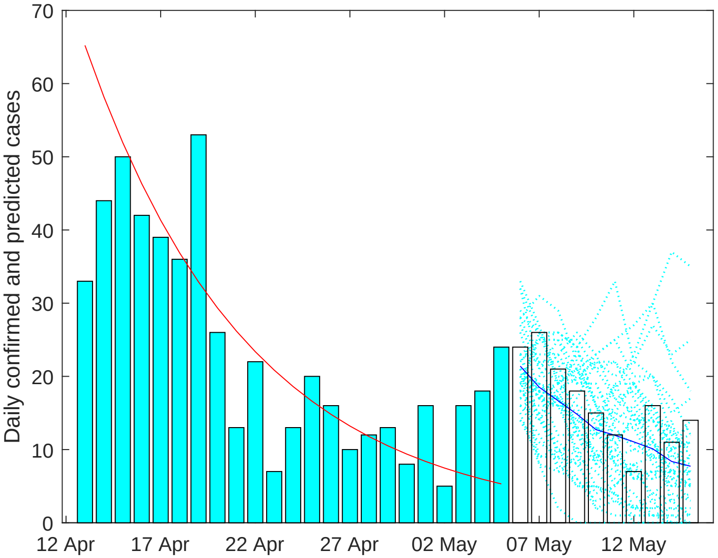

A model for geographical spread

Suppose there are n regions/cities, each containing a largely susceptible population.

Let $\boldsymbol{X}_t^{(n)} = (X_{1,t}^{(n)}, \ldots, X_{n,t}^{(n)})$, where $X_{i,t}^{(n)}$ is a binary variable indicating whether or not the virus is present in Region i at time t.

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Infection: The infection appears in Region i at time t with probability $c(\bar{X}_{i,t}^{(n)})$, where

$$\bar{X}_{i,t}^{(n)} = \frac{1}{n} \sum_{j=1}^{n} X_{j,t}^{(n)} D(z_i, z_j) a_j \quad (\text{"connectivity"}).$$

$D(z, \tilde{z}) \geq 0$ measures ease of movement between regions located at z and at $\tilde{z}$, a_j is a weight related to the size of Region j, and $c : [0, \infty) \to [0, 1]$ is increasing with $c(0) = 0$ and $c'(0) > 0$.

Examples: $D(z, \tilde{z}) = a \exp(-b\|z - \tilde{z}\|)$ (spread through local transport), $D(z, \tilde{z}) = a$ (regions are proximate, or connected directly through air travel), $c(x) = \alpha(1 - \exp(-\beta x)$ (infection potential increases with increased connectivity).

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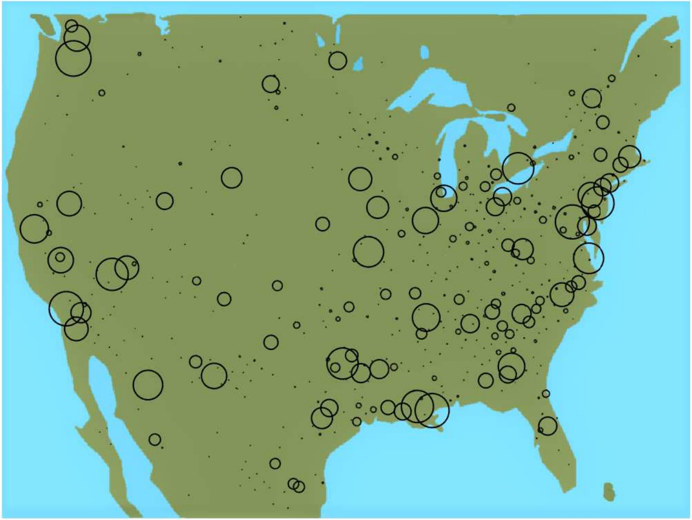
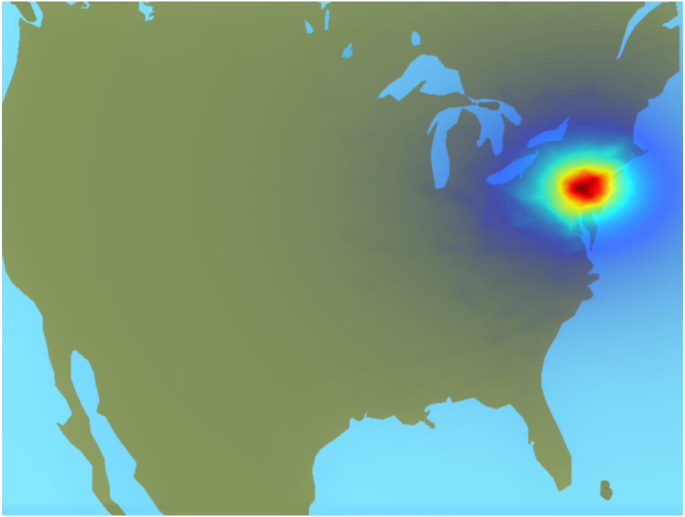
Our technology also allows for the possibility of the virus disappearing from any given region (possibly reappearing at later date), allowing the effectiveness of control measures in the region to vary over time.

USA population centres



Spread of the virus ($t = 1$)

The chance of infection



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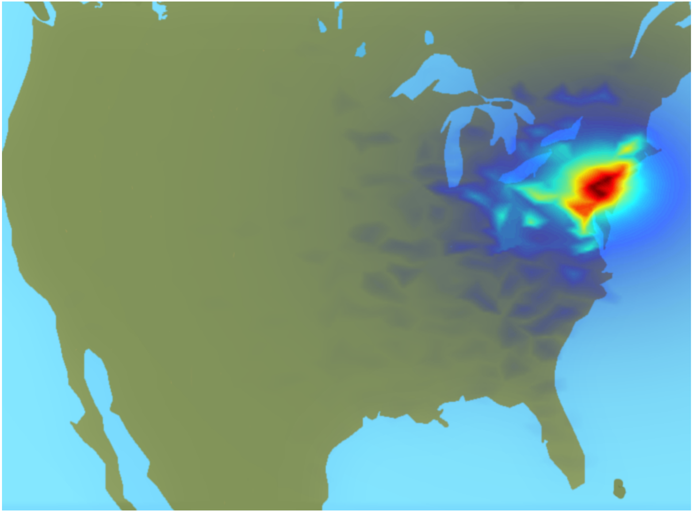
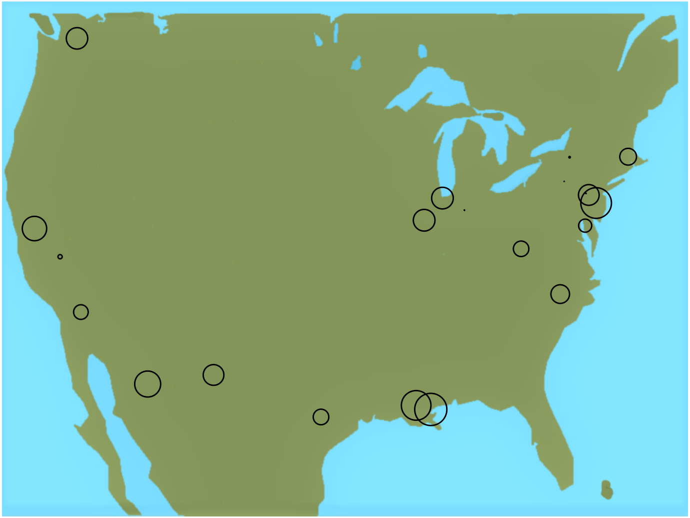
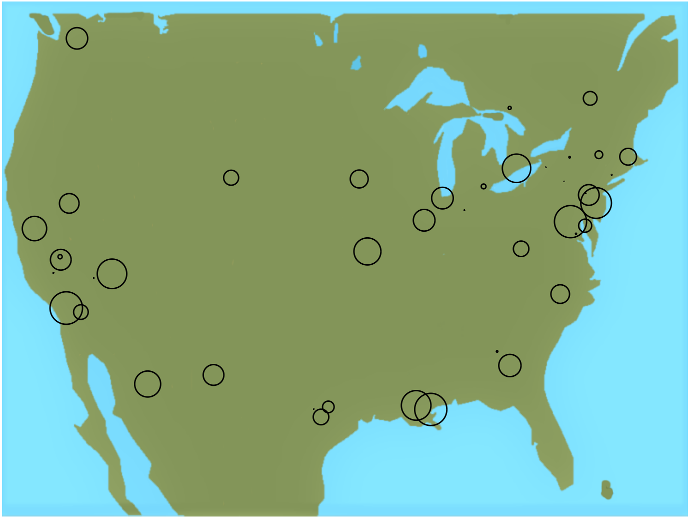


Spread of the virus ($t = 1$)

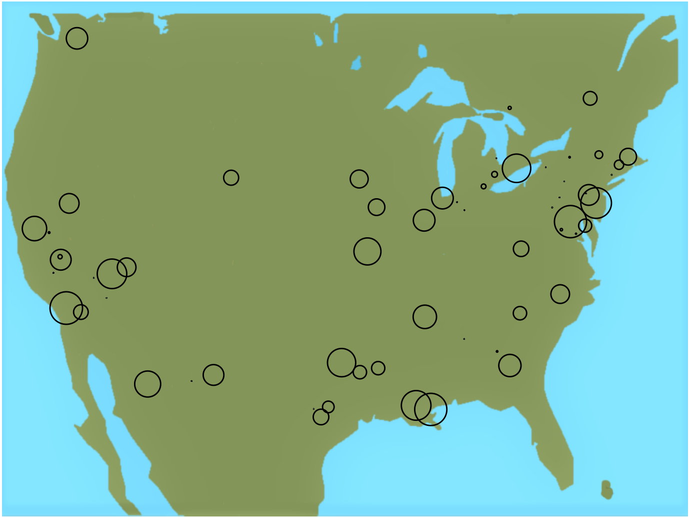
Spread of the virus ($t = 2$)



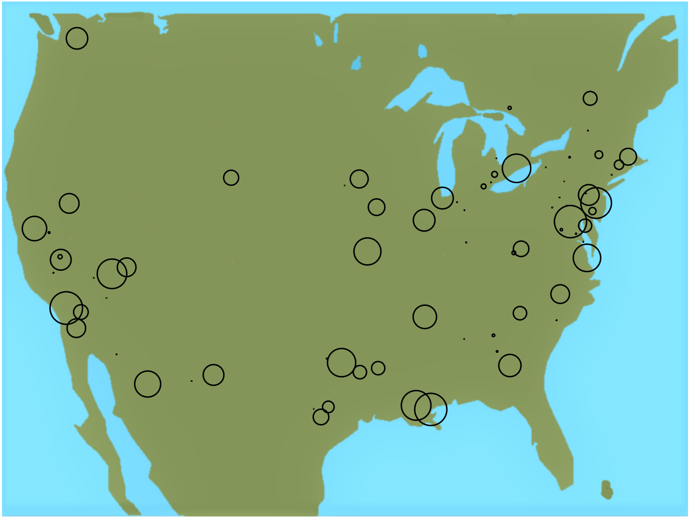
Spread of the virus ($t = 3$)



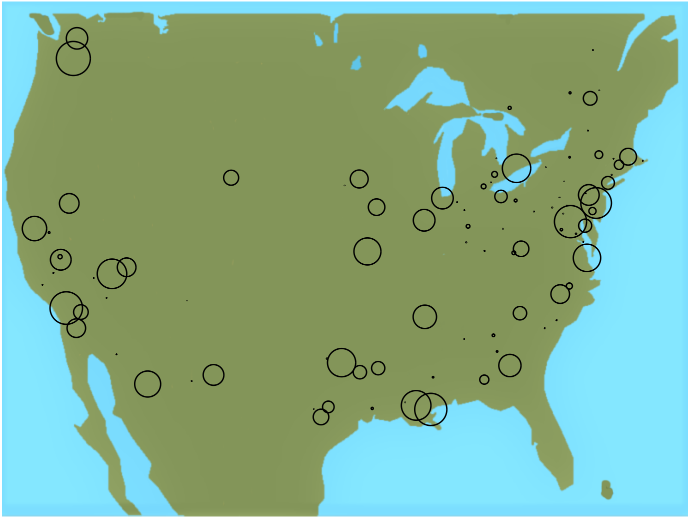
Spread of the virus ($t = 4$)



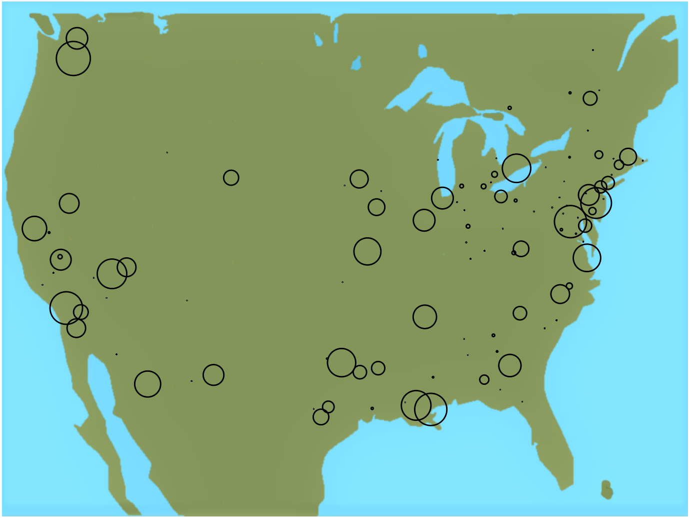
Spread of the virus ($t = 5$)



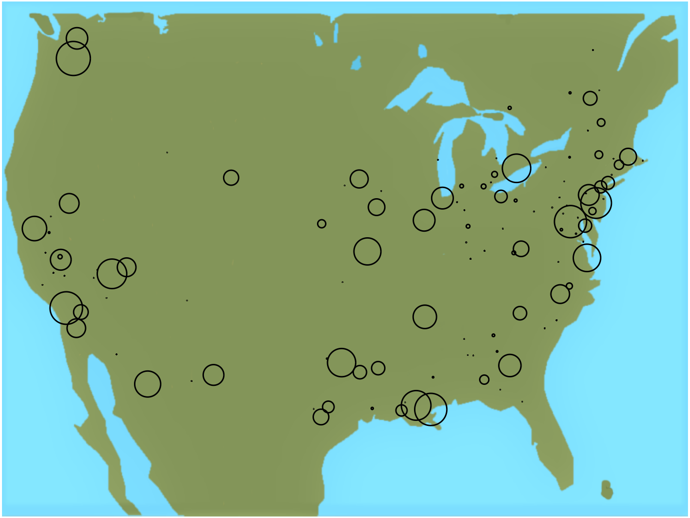
Spread of the virus ($t = 6$)



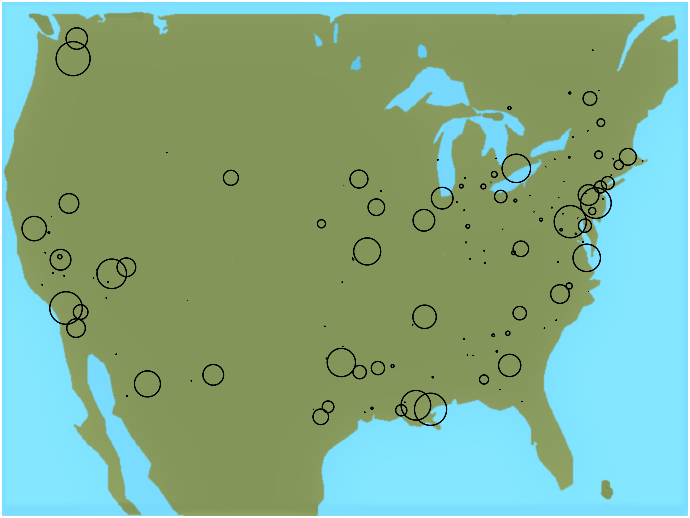
Spread of the virus ($t = 7$)



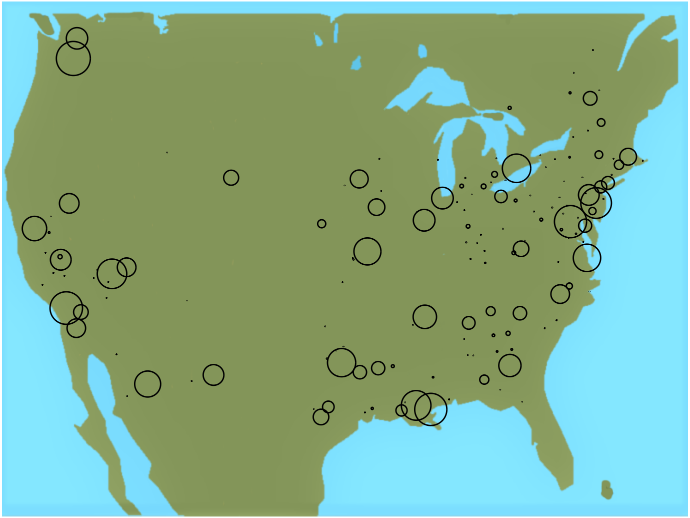
Spread of the virus ($t = 8$)



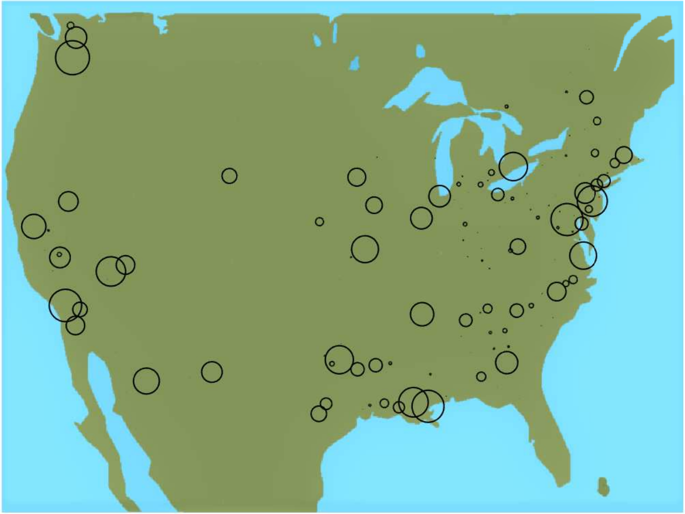
Spread of the virus ($t = 9$)



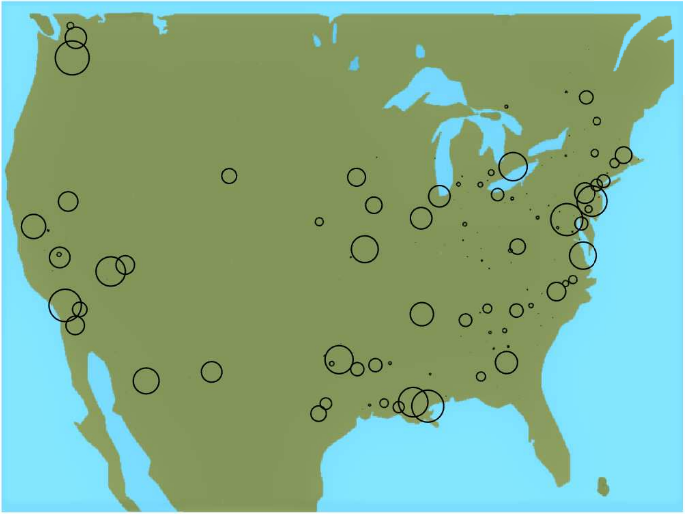
Spread of the virus ($t = 10$)



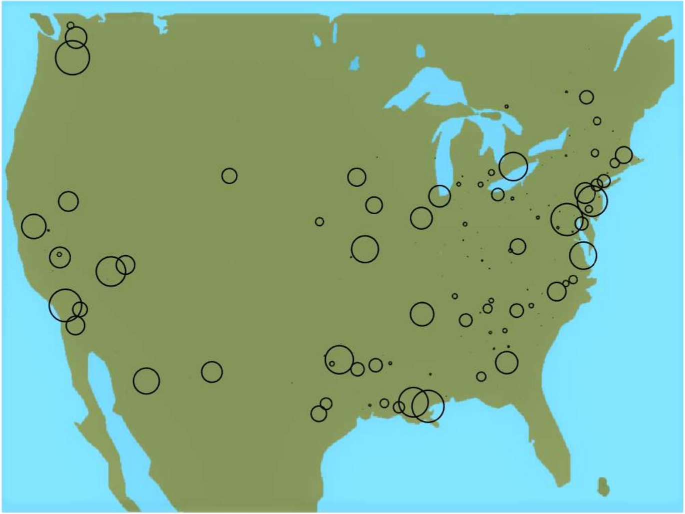
Spread of the virus ($t = 11$)



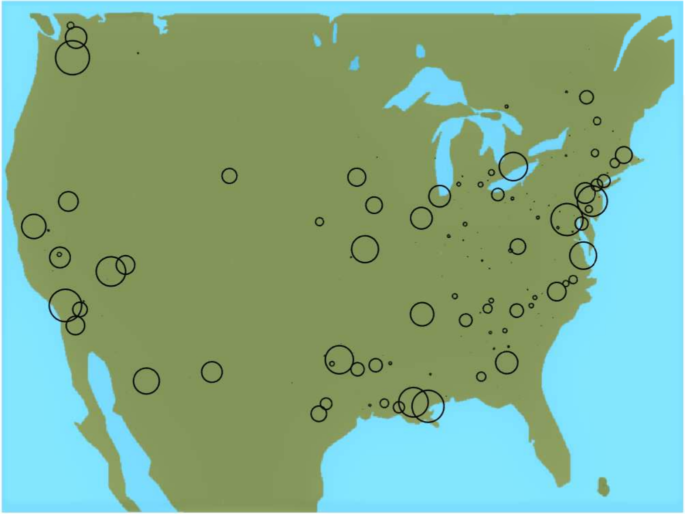
Spread of the virus ($t = 12$)



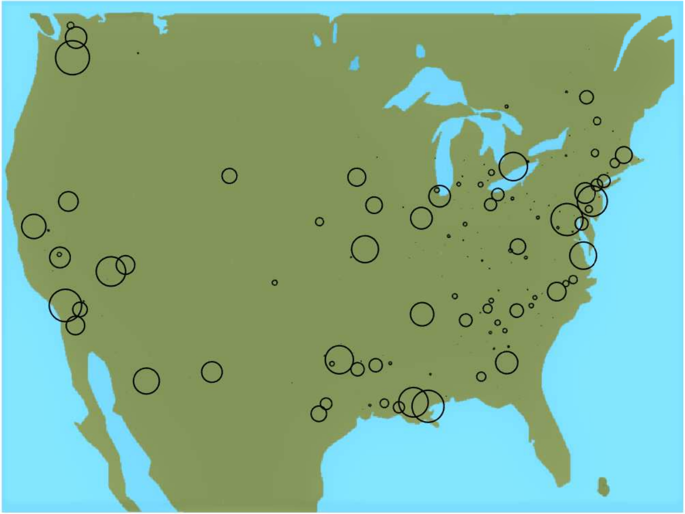
Spread of the virus ($t = 13$)



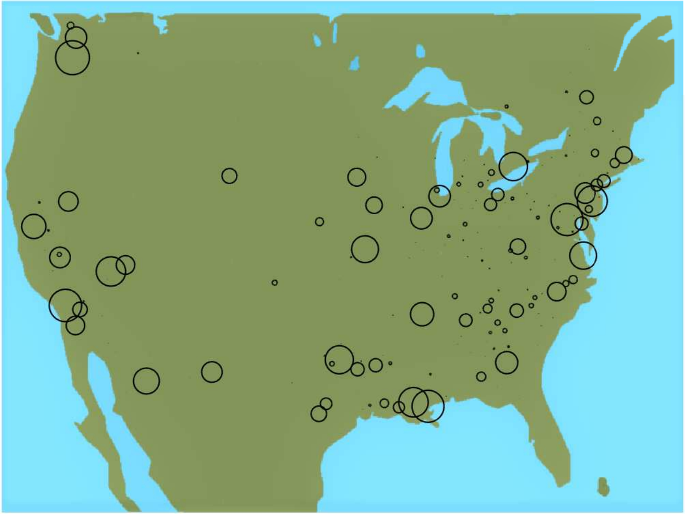
Spread of the virus ($t = 14$)



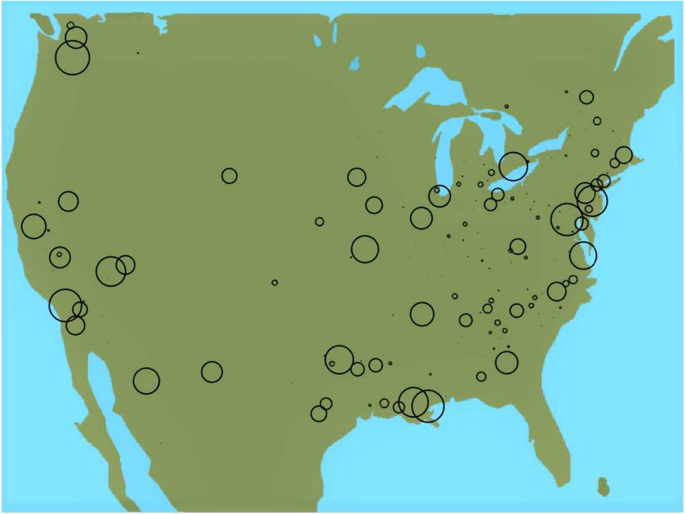
Spread of the virus ($t = 15$)



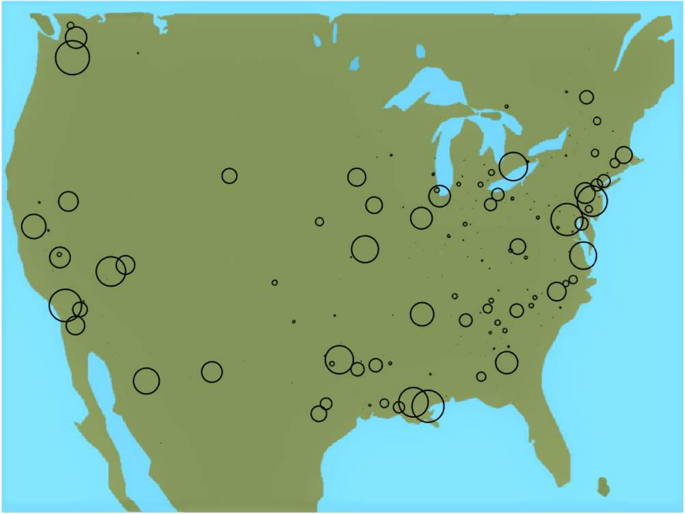
Spread of the virus ($t = 16$)



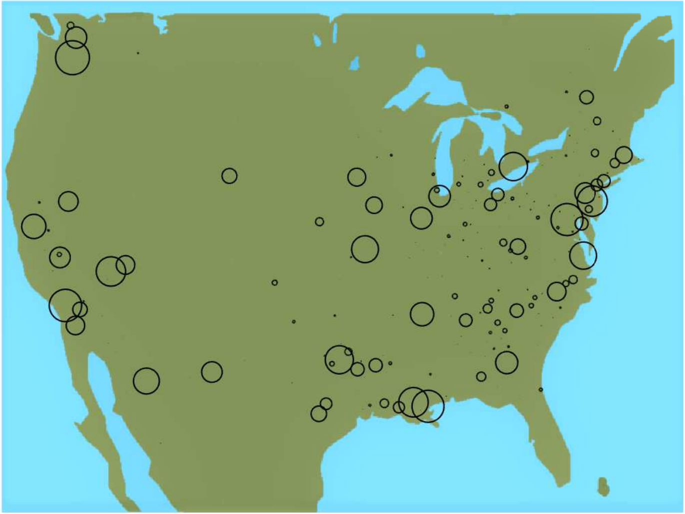
Spread of the virus ($t = 17$)



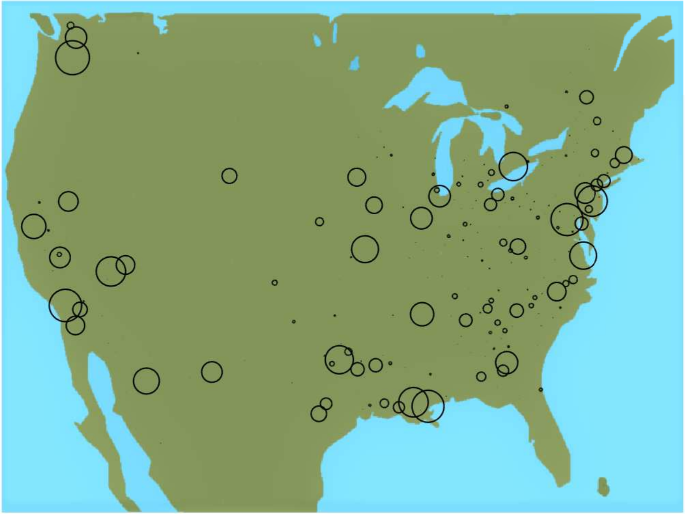
Spread of the virus ($t = 18$)



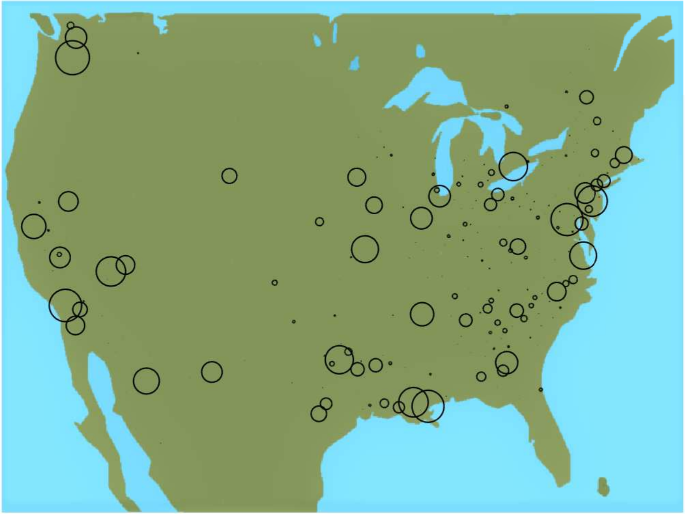
Spread of the virus ($t = 19$)



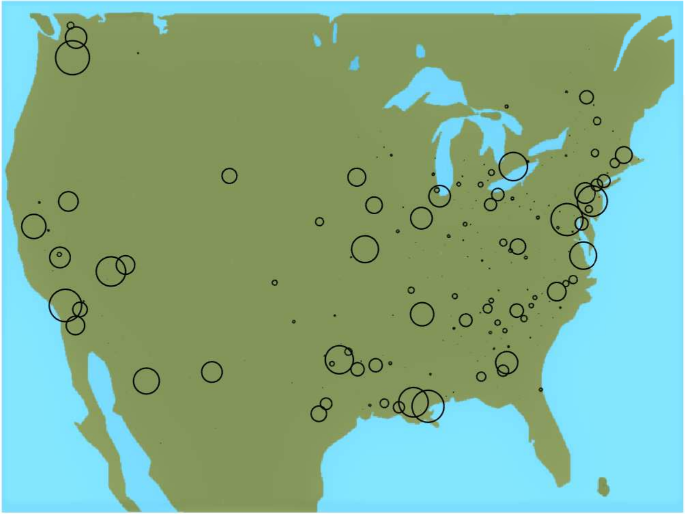
Spread of the virus ($t = 20$)



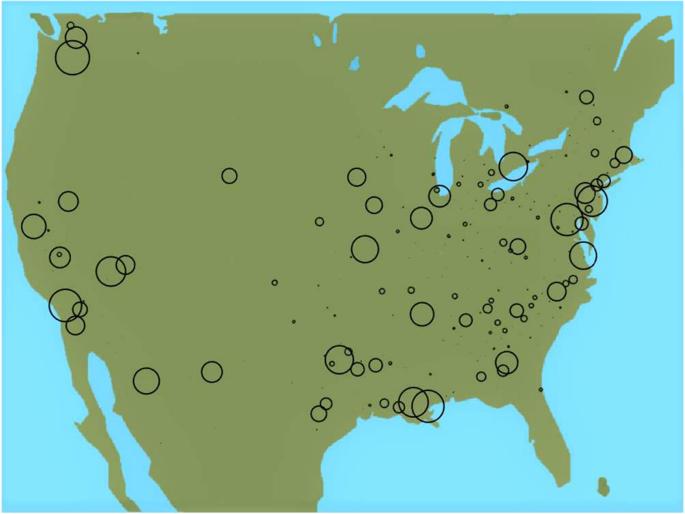
Spread of the virus ($t = 21$)



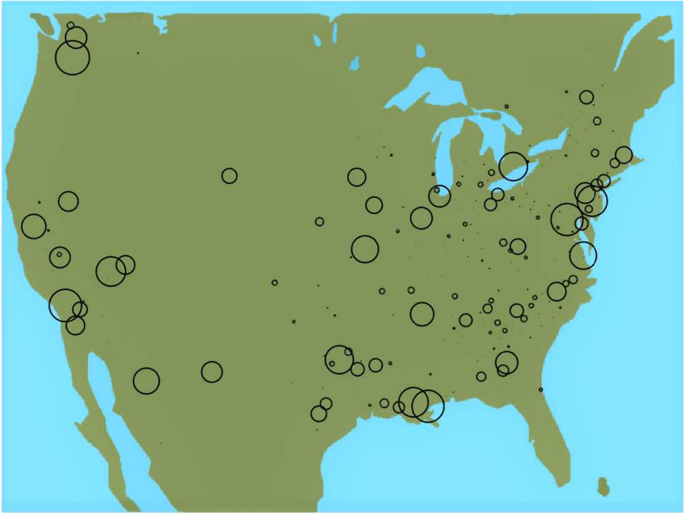
Spread of the virus ($t = 22$)



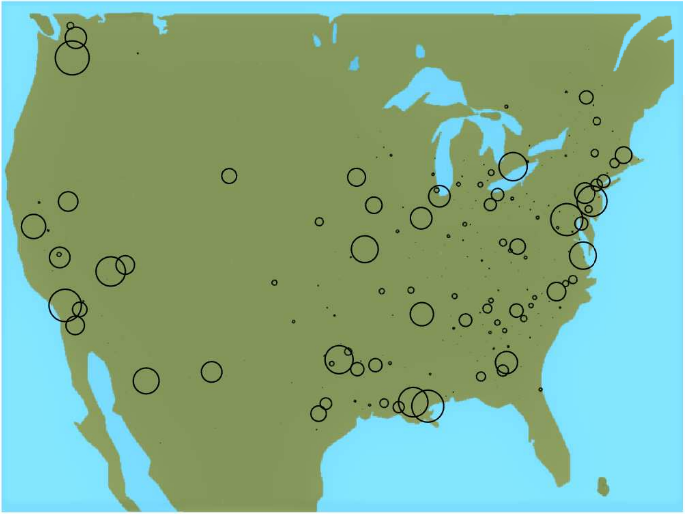
Spread of the virus ($t = 23$)



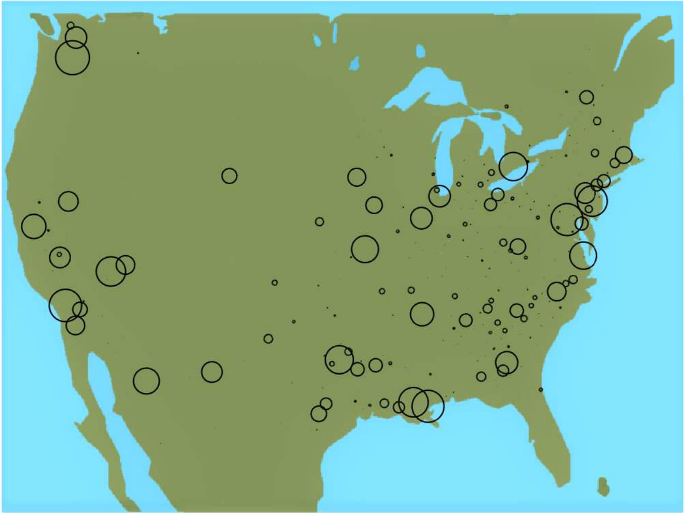
Spread of the virus ($t = 24$)



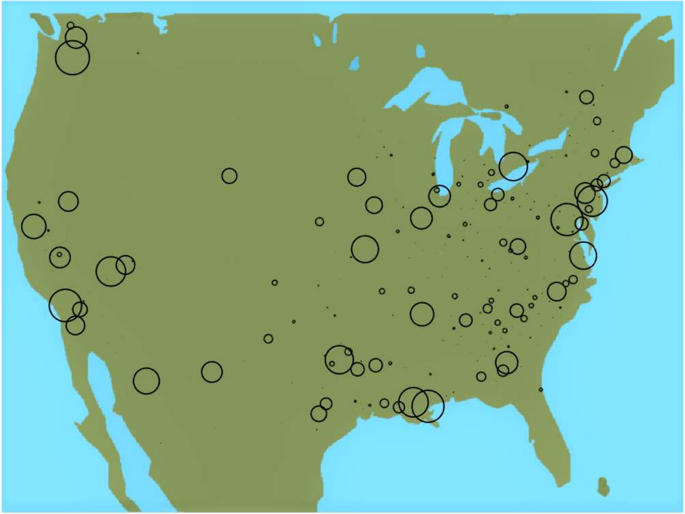
Spread of the virus ($t = 25$)



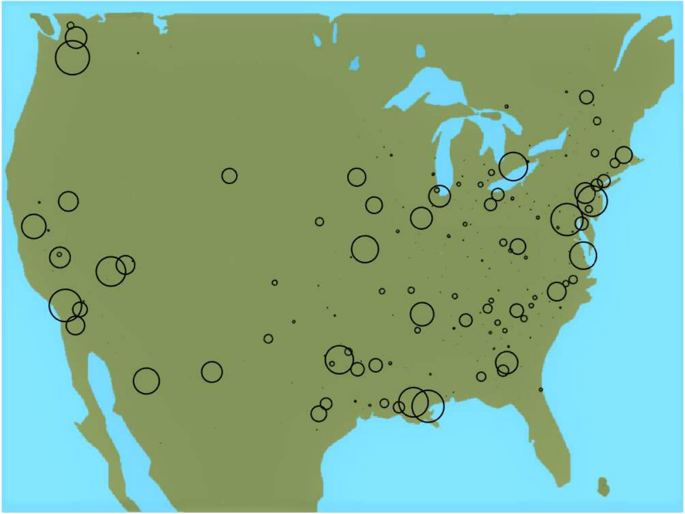
Spread of the virus ($t = 26$)



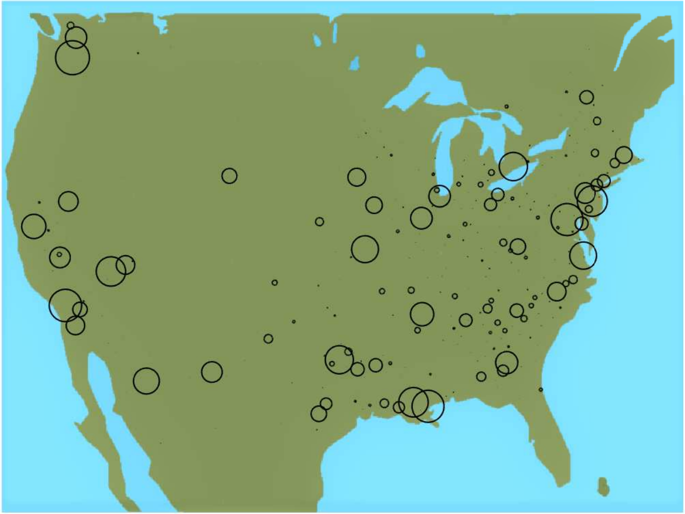
Spread of the virus ($t = 27$)



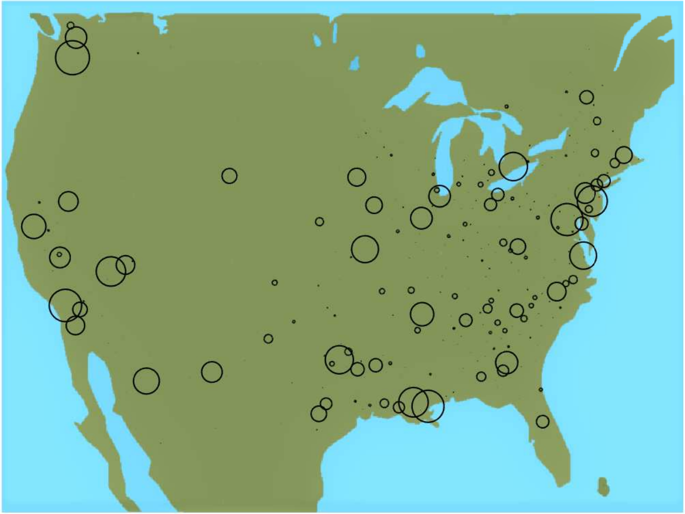
Spread of the virus ($t = 28$)



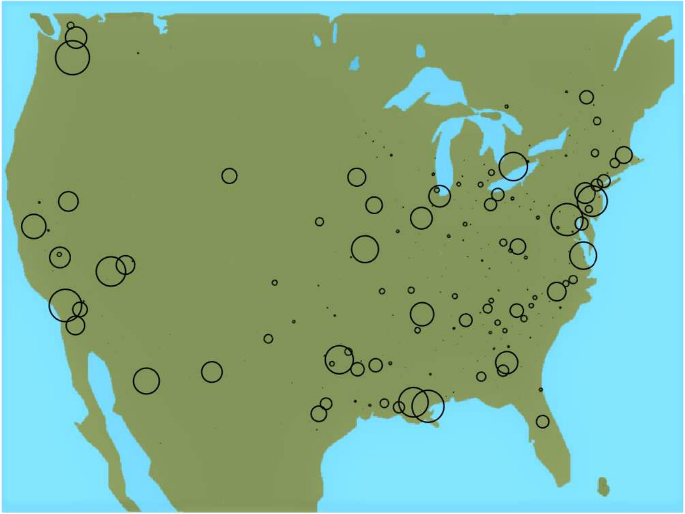
Spread of the virus ($t = 29$)



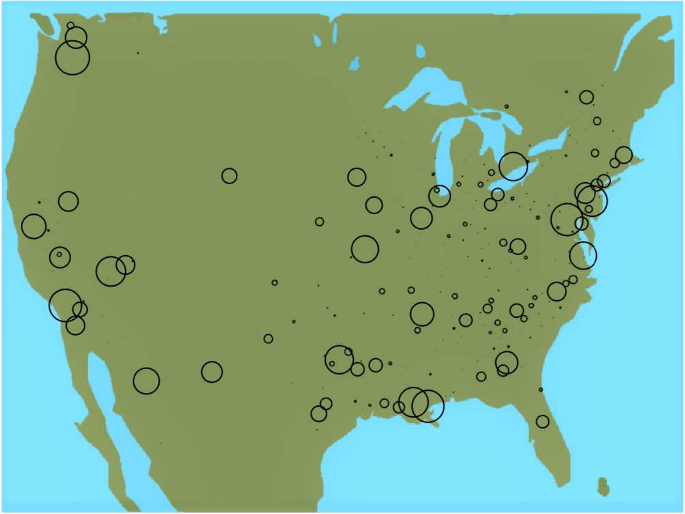
Spread of the virus ($t = 30$)



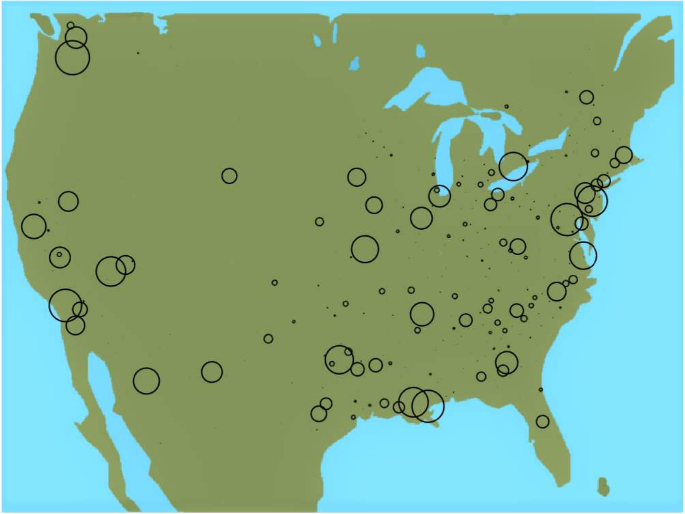
Spread of the virus ($t = 31$)



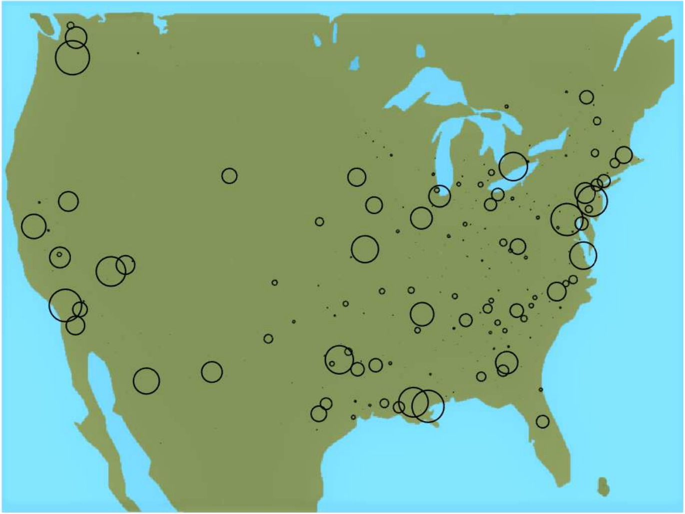
Spread of the virus ($t = 32$)



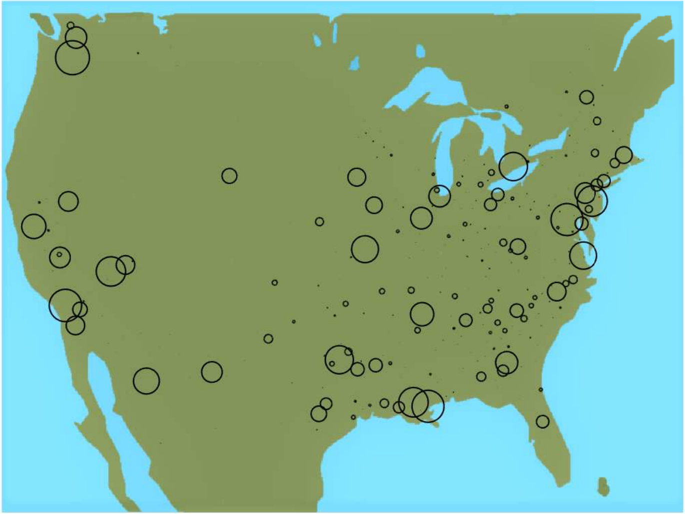
Spread of the virus ($t = 33$)



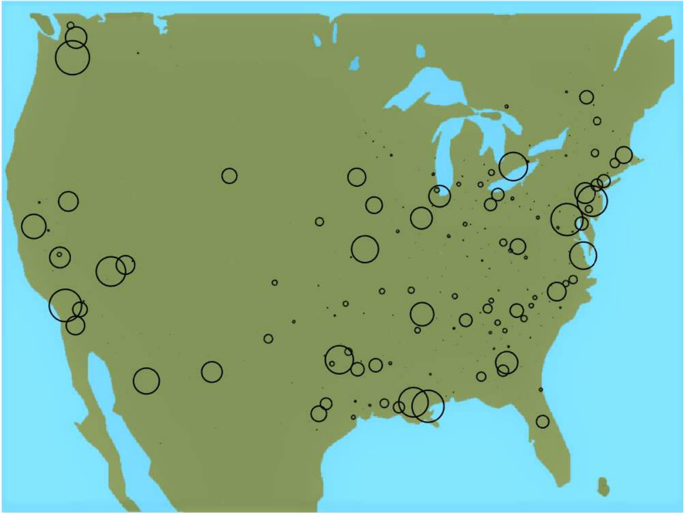
Spread of the virus ($t = 34$)



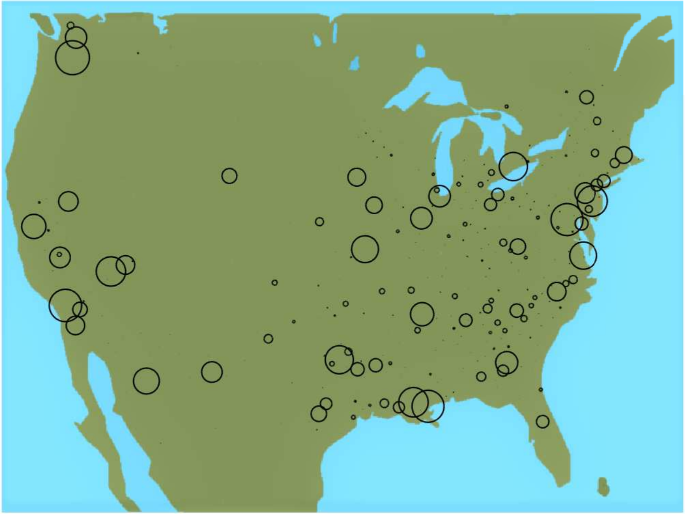
Spread of the virus ($t = 35$)



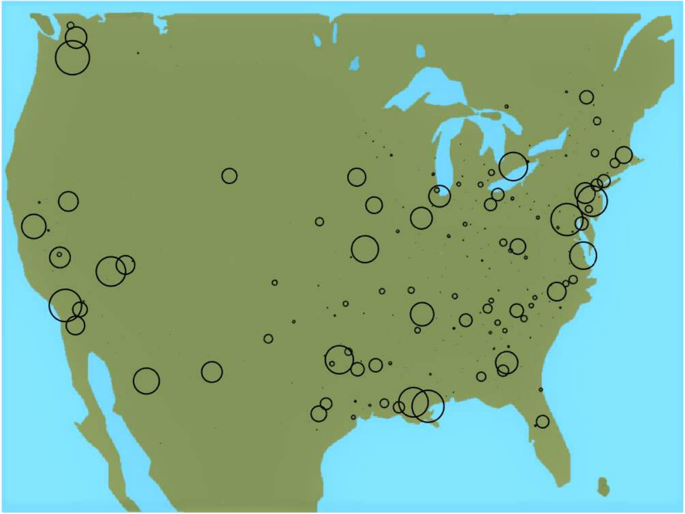
Spread of the virus ($t = 36$)



Spread of the virus ($t = 37$)



Spread of the virus ($t = 38$)



Spread of the virus ($t = 39$)