# Spatial signatures of an infectious disease on the verge of elimination

Paige B Miller & John M Drake

Odum School of Ecology, University of Georgia

## Introduction

Disease eradication is the ultimate goal of public health. However, sustaining economic and political commitment poses a large challenge to surveillance efforts during the "end-game". Changing statistical trends can predict disease elimination[1] and the goal of our study was to determine if changing spatial patterns can add predictive power when forecasting disease elimination.

## Methods

We simulated disease elimination using a spatial Susceptible, Infected, Recovered (SIR) model of a measles-like infection in a population (N=50,000) of unvaccinated school children over a period of 6 months.

### Spatial Model

- Individuals move within a 50 x 50 cell lattice and become infected depending on the cell-specific infection propensity ($\beta_{i,j}$) and the # of infected individuals in each cell ($I_{i,j}$)
- We simulated transmission in both *Constant* (n=25 replicates) and *Patchy* (n=25 replicates) to see if spatial patchiness "corrupts" EWS reliability

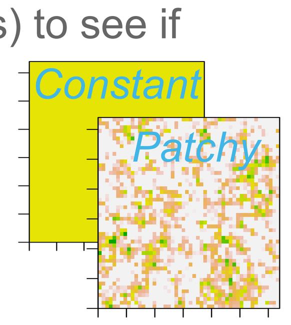



*Table 1. Possible events for individuals in our model.*

| Event | Transition (ΔS, ΔI, ΔR) | Probability |
|---|---|---|
| Birth | (1, 0, 0) | μN |
| Death | (-1, 0, 0), (0, -1, 0), or (0, 0, -1) | μN |
| Infection | (-1, 1, 0) | $1 - e^{-\beta_{i,j} \cdot I_{i,j}}$ |
| Recovery | (0, -1, 1) | $1 - e^{-\gamma}$ |
| Vaccination | (-1, 0 , 1) | $1 - e^{-\alpha(t\text{-vax\_start})}$ |

**Recovery rate scaled to measles-like illness.*

## Data Analysis

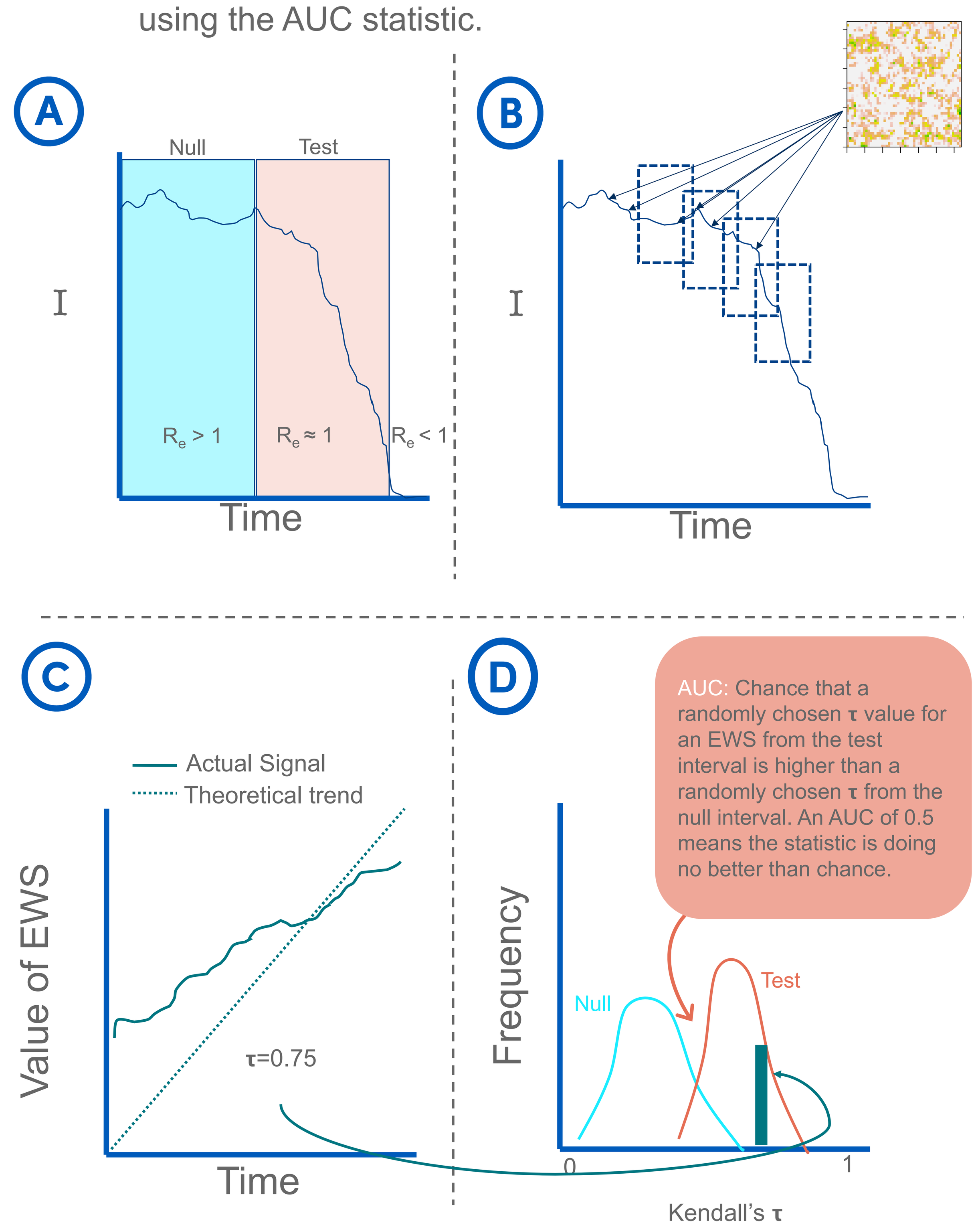
When a system is approaching a critical transition, a handful of statistical trends (i.e., Early warning signals) are expected to change in characteristic ways (due to Critical Slowing Down). Previous work has focused on temporal EWS[1], but slowing down also manifests in space[2]. In this study, we compared the performance of *temporal* and *spatial* EWS:

A. To compare trends in EWS when the system is and is not approaching criticality, we divided the simulation output into *null* and *test* intervals.

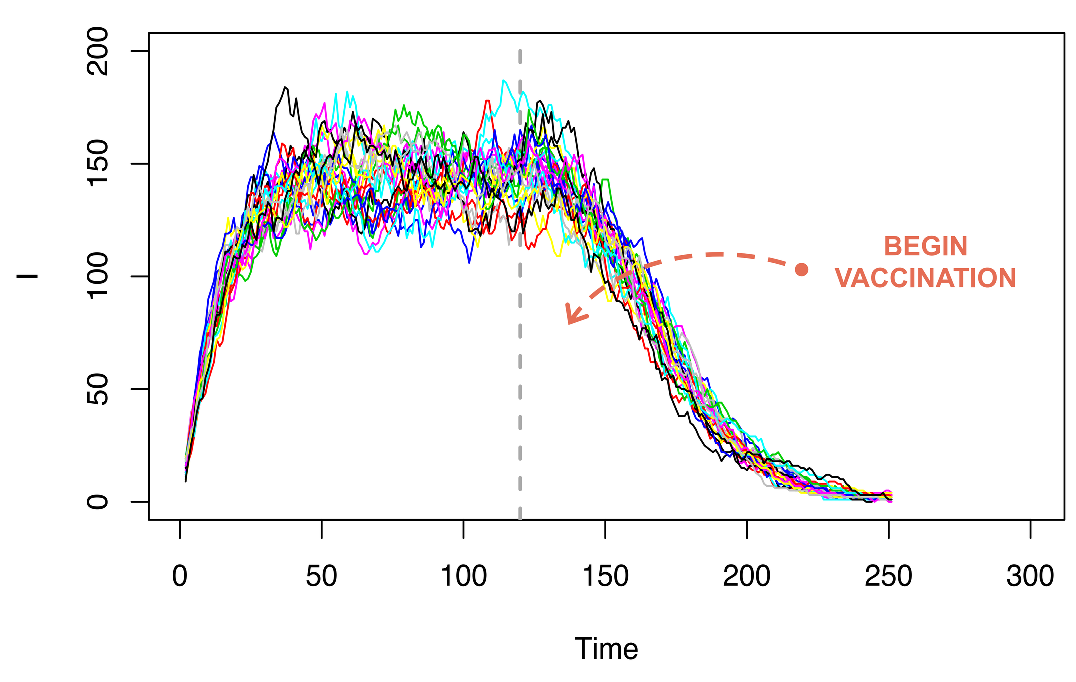
B. We calculated *temporal* and *spatial* autocorrelation, skewness, and coefficient of variation in both intervals.

C. We calculated the correlation of each EWS with that of the expected trend if approaching a critical transition (using Kendall's Tau).

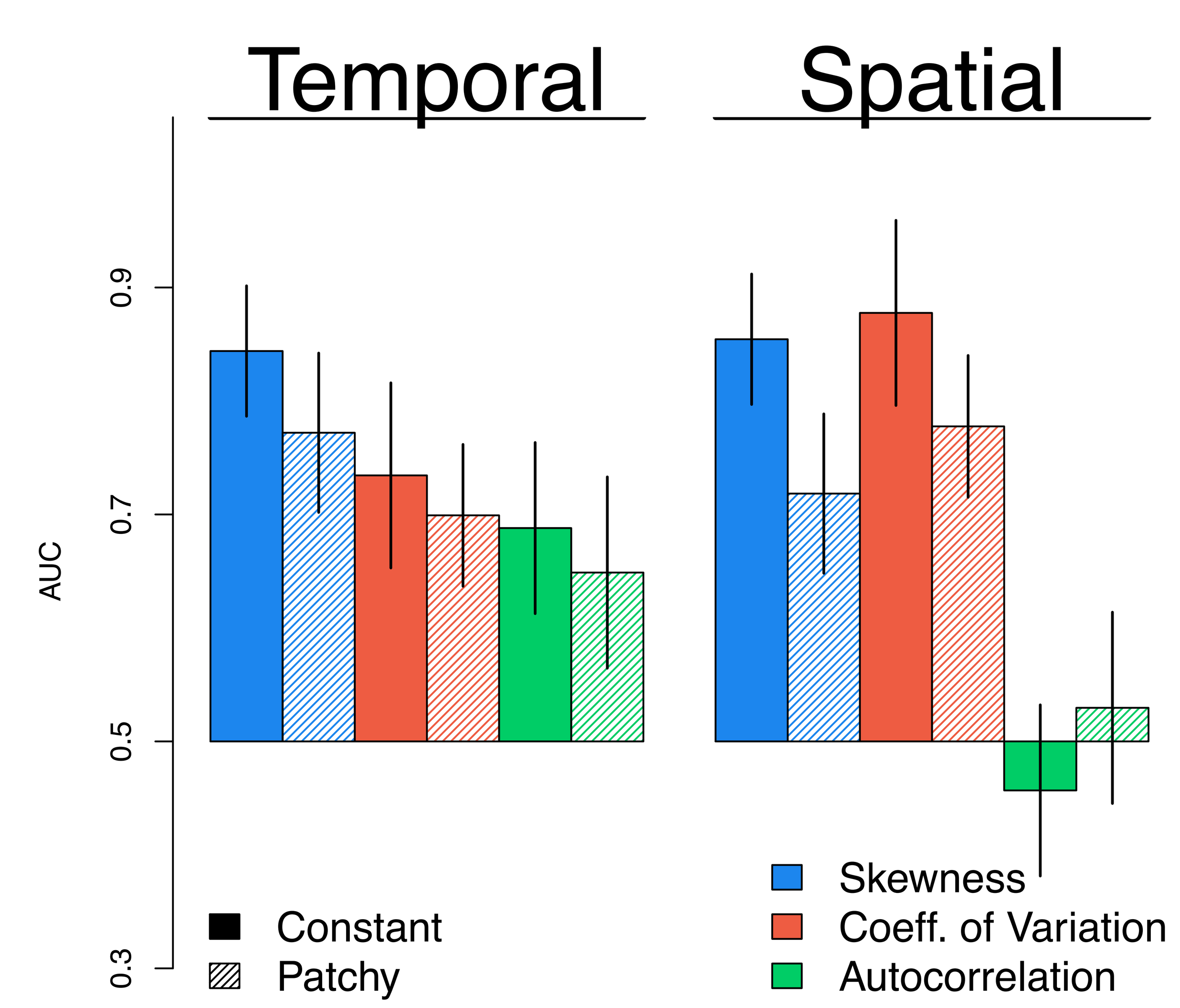
D. Finally, we calculated the performance of each EWS using the AUC statistic.




## Results

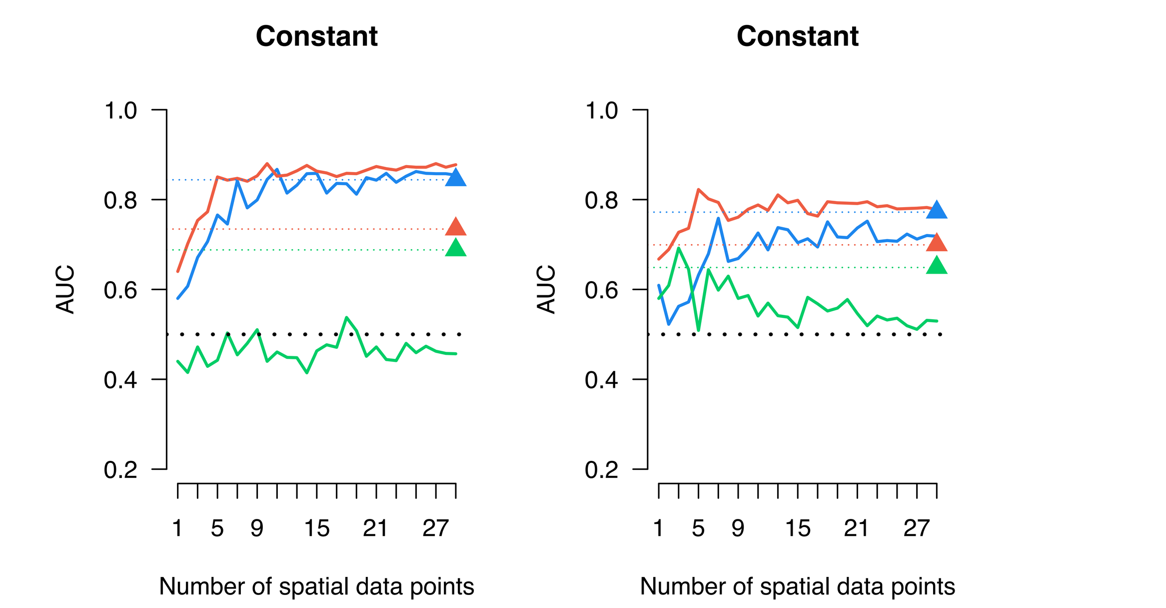



Simulated populations reach an endemic equilibrium around day 50. We start vaccination on day 120 eventually pushing the system to disease elimination around day 250.




**EARLY WARNING SIGNALS PREDICT DISEASE ELIMINATION**

Temporal and spatial early warning signals (skewness, coefficient of variation, and autocorrelation) can predict disease elimination. However, spatial skewness and coefficient of variation are better predictors than their temporal counterparts. Regardless of the type of statistic (temporal or spatial) spatial patchiness reduces predictability.




**FEWER SPATIAL DATA POINTS ARE REQUIRED FOR FORECASTING ELIMINATION THAN TEMPORAL DATA POINTS**

Spatial indicators (solid lines) are more informative indicators of elimination with fewer data points than temporal indicators (triangles)

## Conclusions

Past work has shown that spatial patterns can anticipate the approach to critical transitions in natural systems and are more reliable than temporal patterns alone[2,3]. In agreement with this previous work, we found that specific patterns in spatial incidence reports can anticipate disease elimination, even when the underlying environment is autocorrelated in space. Furthermore, patterns calculated from spatial incidence reports required fewer data points to achieve the same predictive power. All together, our results indicate that spatial surveillance programs may be more efficient ways to measure progress towards disease elimination.

## References

1. O'Regan, S. M., & Drake, J. M. (2013). *Theoretical Ecology*, *6*(3), 333-357.

2. Kéfi, S., Guttal, V., Brock, W. A., Carpenter, S. R., Ellison, A. M., Livina, V. N., ... & Dakos, V. (2014). *PloS one*, *9*(3), e92097.

3. Dakos, V., van Nes, E. H., Donangelo, R., Fort, H., & Scheffer, M. (2010). *Theoretical Ecology*, *3*(3), 163-174.

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