Early warning signals for detection of emerging infectious diseases in the presence of seasonality

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Goal

It has recently been shown that infectious disease emergence may be preceded by statistical fluctuations that function as early warning signals (EWS)[1]. However, EWS may perform poorly in the presence of periodic forcing[2], which is common among directly transmitted host-pathogen systems. *The goal of this project was to study how seasonality in disease transmission changes the reliability of EWS, focusing on properties of the wavelet spectrum, which relies on fewer assumptions about stationarity than other, better studied signals[3].*

Background

Epidemics of re-emerging infectious diseases involve a transmission system that is pushed past a critical threshold at R0=1. When these events occur is difficult to predict because the incidence in cases shows little change beforehand and mechanistic models cannot be reliably parameterized from such data[2]. Recent research has focused on model-free methods for constructing early warning signals (EWS) to forecast critical transitions for infectious diseases.

However, a major limitation of existing EWS is that they were developed for non-periodic time-series where the fluctuations due to critical slowing down are small[2]. Since infectious disease data sets are often periodic and critical transitions in periodic systems are not well understood[2], we investigated wavelet-based methods to separate the forcing period of a near-critical system from its stationary fluctuations. Here, we report on simulation studies of seasonally forced SIR transmission systems that vary in parameter space for rate of emergence and amplitude of seasonal forcing.

Methods

Simulations:

- Stochastic Susceptible-Infected-Recovered (SIR) model that is forced to emergence due to an increase in the transmission rate, β
- Spontaneous immigration rate of infected individuals (2/month) in a population of 200,000
- Incidence is calculated by tallying all movements from Susceptible class to the Infected class each day
- R_0=1 at year 20 (day 7300)
- Three levels seasonality (β_1=0, 5e-9, 6e-8; non-seasonal, low, high) obtained using a sinusoidal transmission function, $\beta_1(1 + \sin 2\pi t)$

Moving window statistics:

- Time series of incidence separated into a null (before β begins to increase) and a test interval (β increasing, directly preceding R_0=1) and then aggregated weekly
- Moving window statistics (mean, autocorrelation at lag-1, variance, autocovariance, wavelet, and return rate) calculated for null and test intervals
- Wavelet ratio calculated by dividing the power of a low frequency wavelet by a high frequency wavelet across the time series

Analysis of EWS:

- Kendall's Tau correlation coefficient between moving window statistics and their theoretical predictions
- AUC statistics were calculated for receiver-operator-characteristic curves (ROC) from the distribution of correlation coefficients for null and test intervals

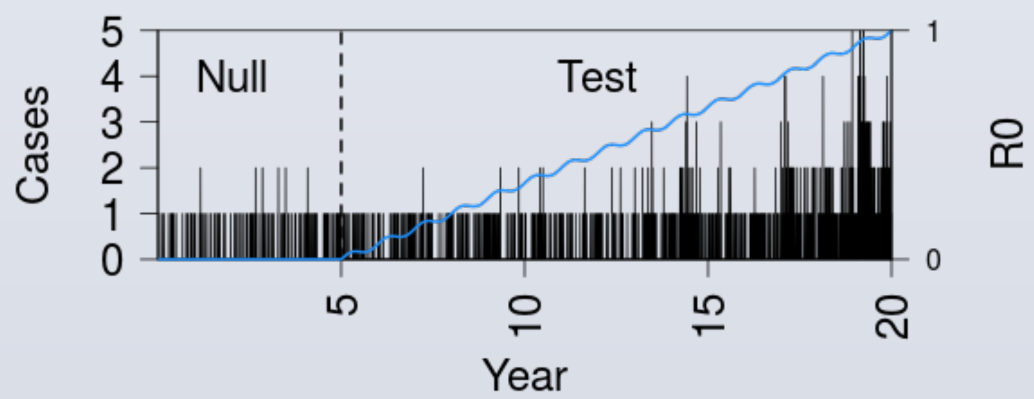

Figure 1. Realization of a stochastic SIR simulation used to quantify EWS. Null and test intervals are used to calculate ROC curves and AUC statistics. We varied the amplitude of transmission seasonality (blue) and R_0 = 1 at year 20, when we cut off the test interval.

Results

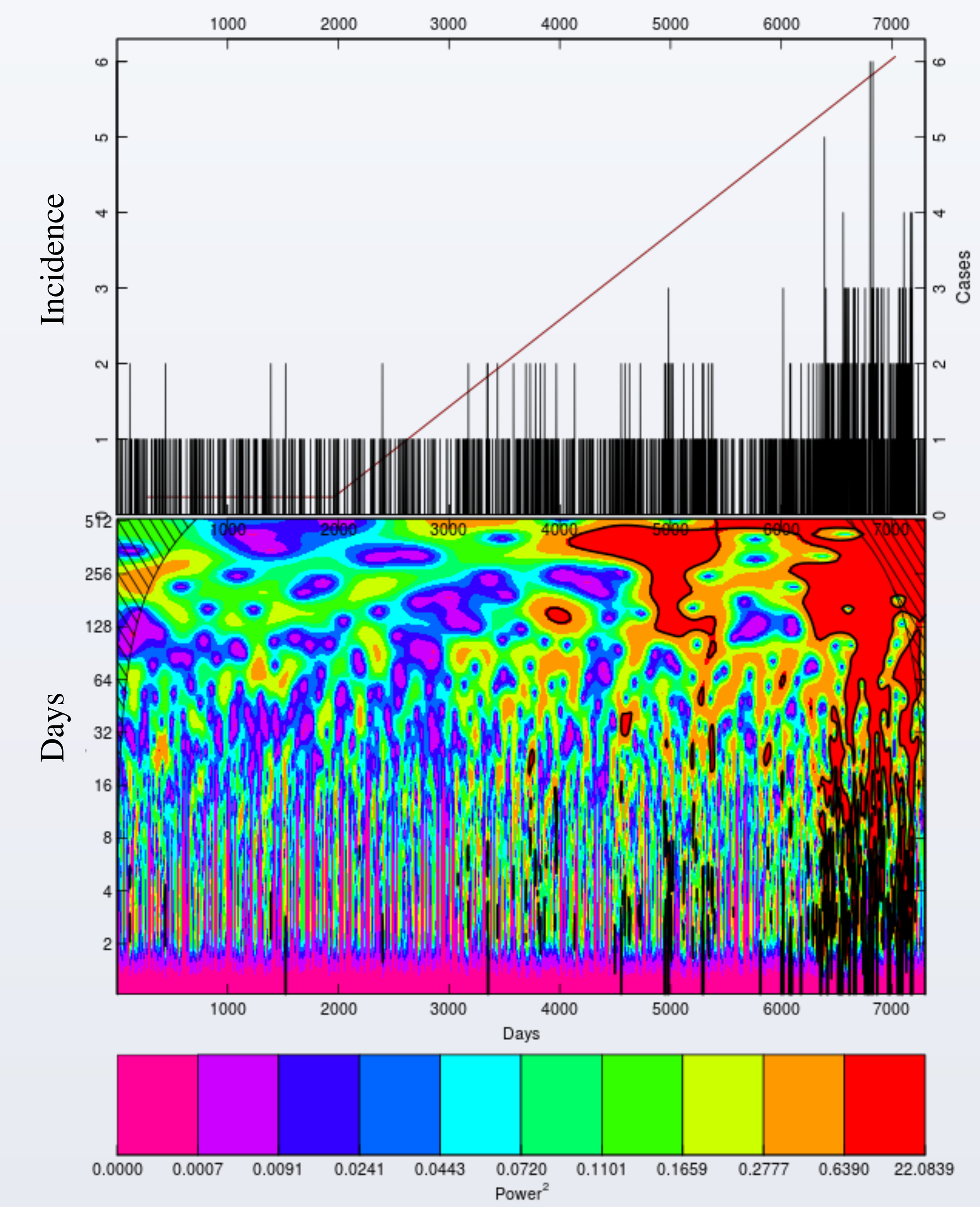

Figure 2. Simulation of SIR model *without seasonality* (a) and wavelet decomposition of time series (b) preceding emergence at day 7300. Transmissibility (red) begins to increase at day 2000. Wavelet spectrum shows how low frequencies begin to dominate prior to the critical threshold at day 7300.

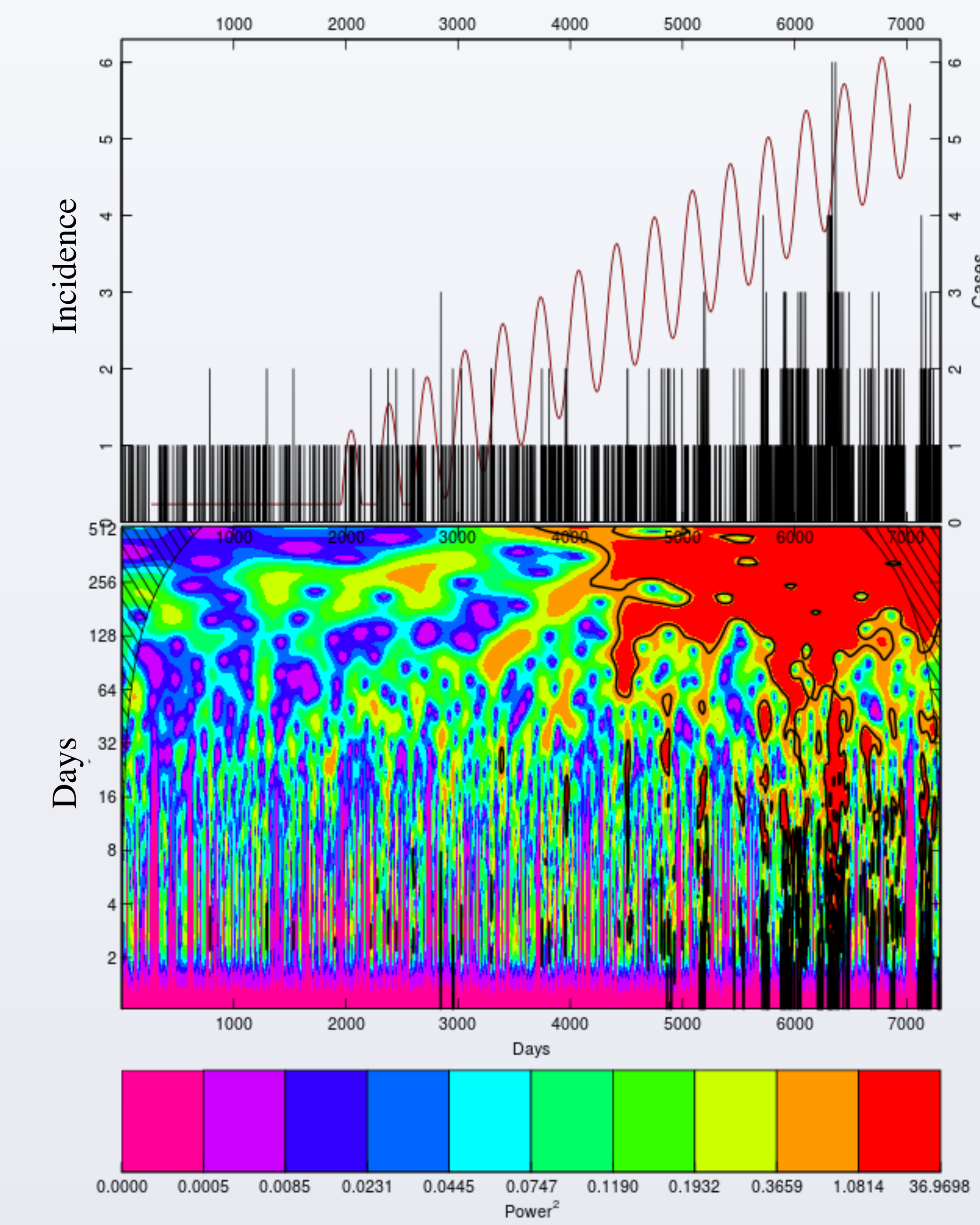

Figure 3. Simulation of SIR model *with seasonality*. Transmissibility (red) fluctuates annually. Wavelet spectrum allows us to separate the changes in disease incidence due to seasonality from the underlying changes in transmission.

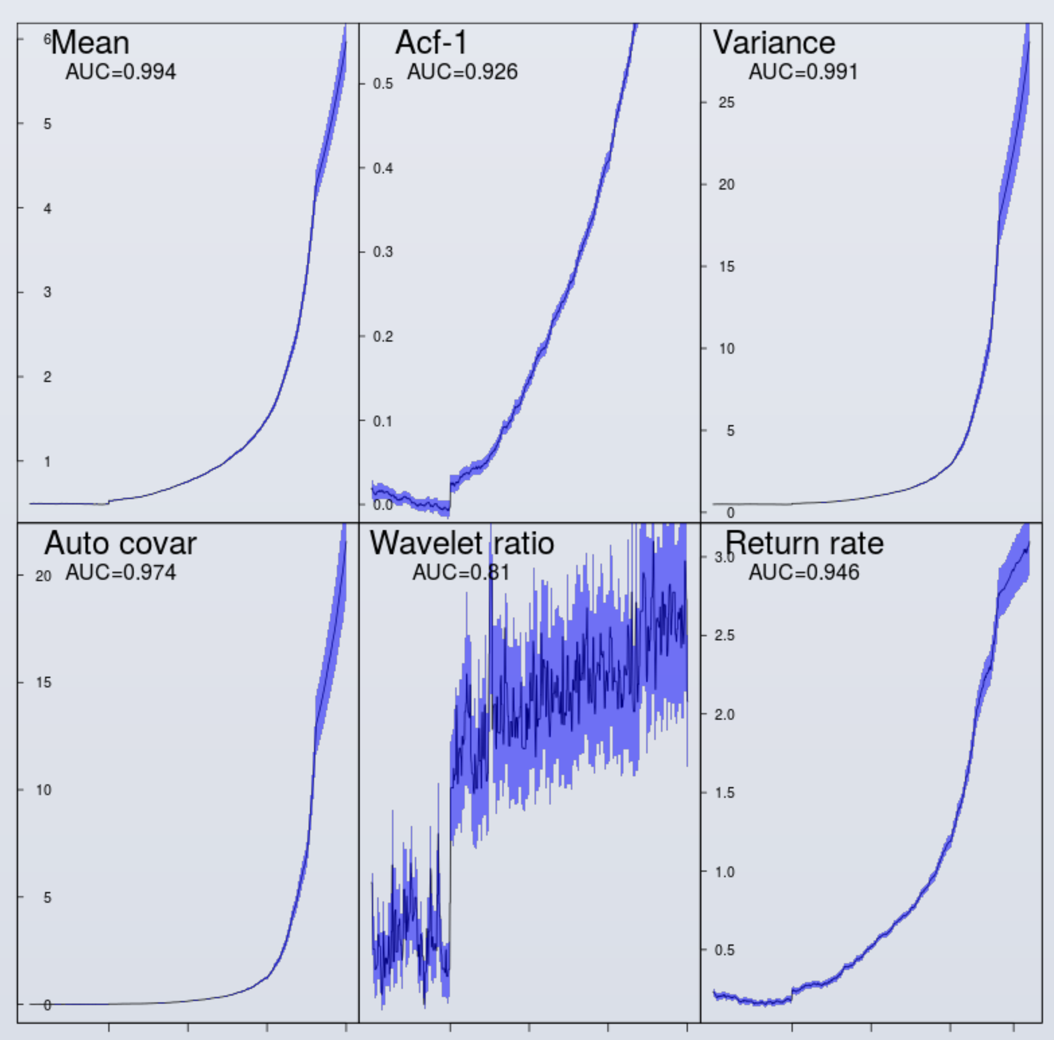

Figure 4. Early warning signals of disease emergence *without seasonality*. Blue line shows average of 100 model simulations. Light blue region shows standard error (SE) of moving window statistics. Each statistic shown here is expected to increase prior to the critical transition (when R_0=1) at year 20. Each EWS shows clear trends of impending critical transition.

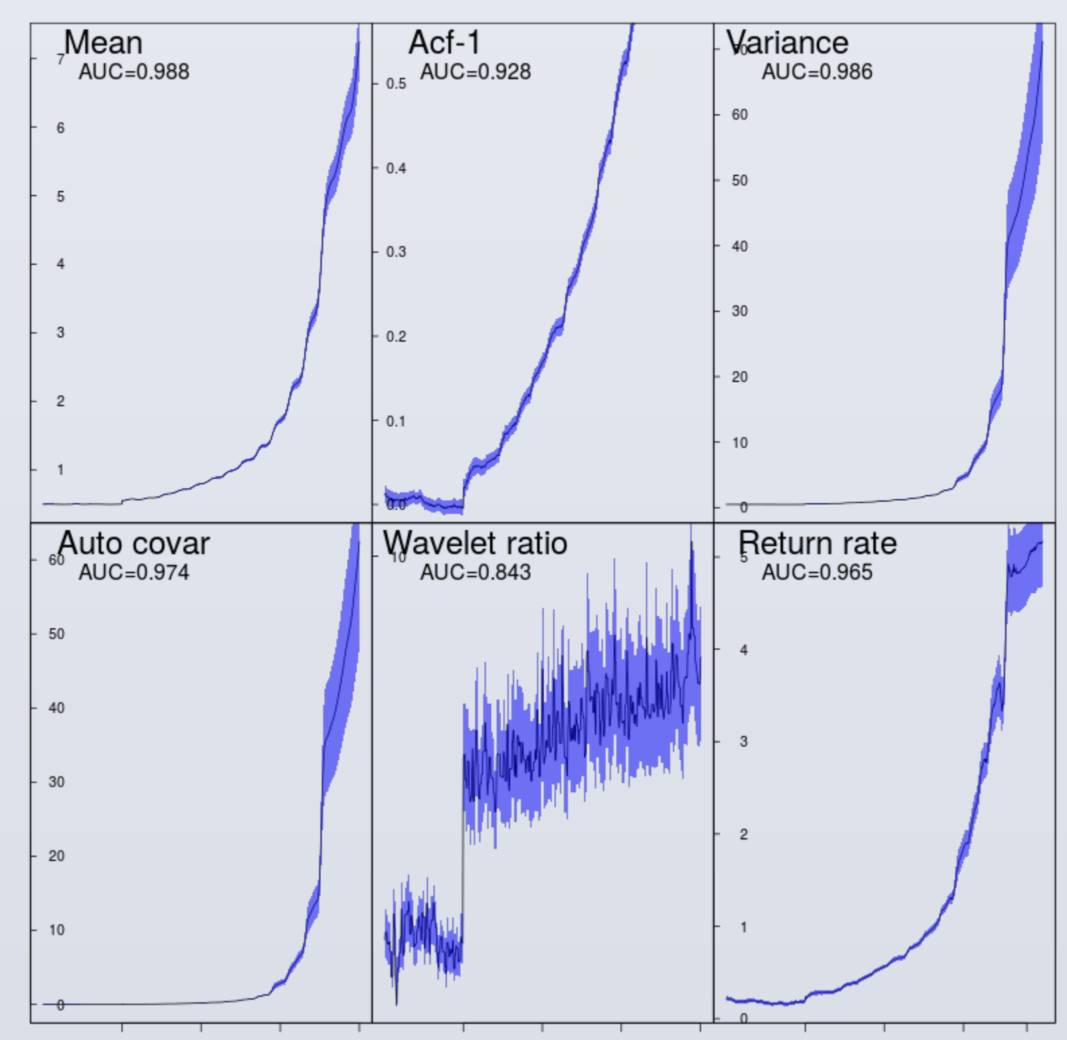

Figure 5. Early warning signals of disease emergence *with seasonality*. The amplitude of seasonality is shown in Fig. 3. Lines and shading are the same as in Fig. 4. The reliability of the wavelet ratio increases in the presence of seasonality. However, even with seasonality all classical EWS were more reliable than the wavelet ratio.

Analysis

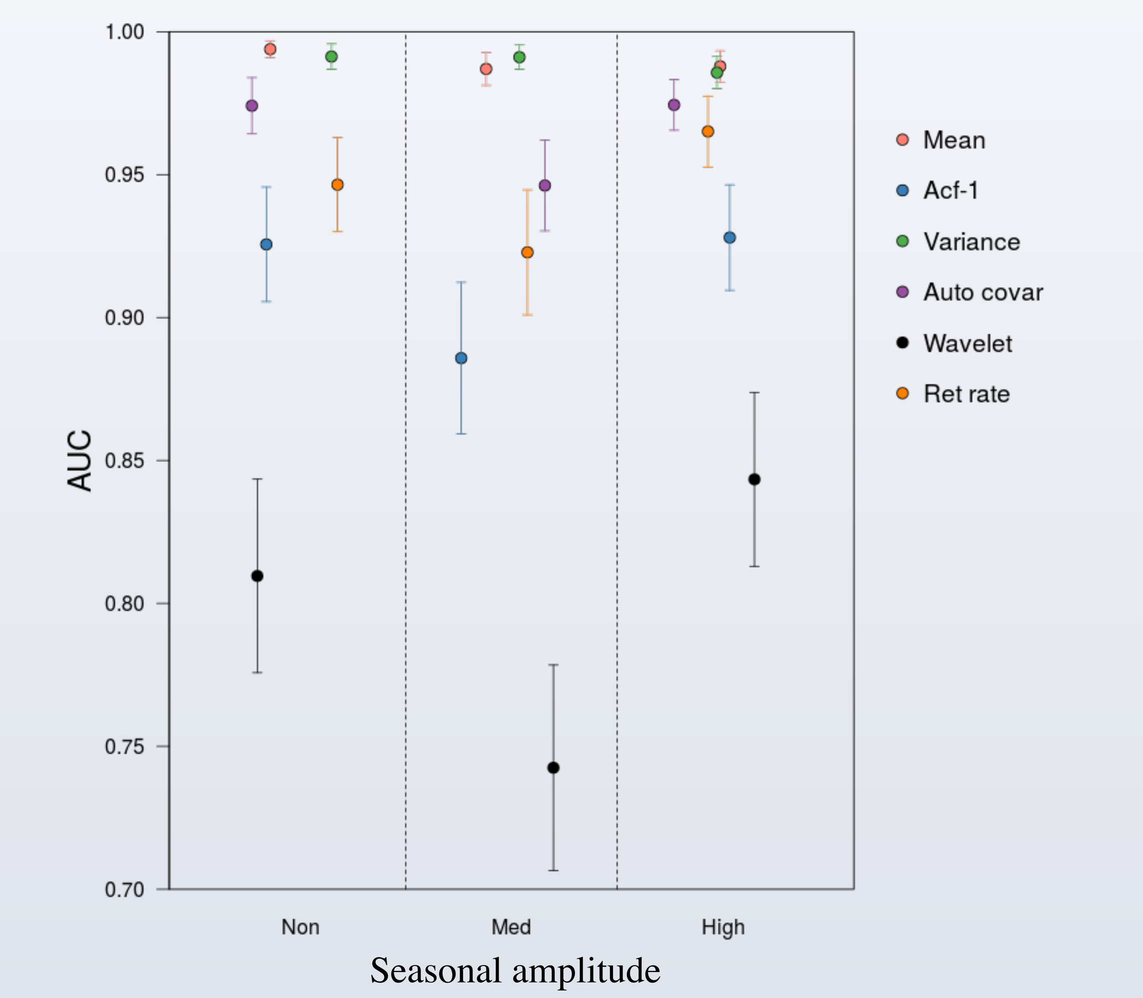

Figure 6. Reliability of EWS for detecting disease emergence. Perfect detection would return an Area Under Curve (AUC) value of 1. No detection ability would return an AUC value of 0.5. AUC statistics are shown for three levels of seasonality (Non-seasonal, medium seasonal, and highly seasonal transmission). Wavelet ratio performs well, but not any better, than classical EWS. Even with seasonality the reliability of EWS remained highly robust. There is no obvious trend in decreasing AUC values with increasing seasonality.

Conclusions

- Seasonality is a limitation to the method of EWS for predicting infectious disease emergence
- Here, we conducted a simulation study of disease emergence with seasonal transmission and studied how the reliability of EWS changes with seasonality
- In addition, we constructed a wavelet-based metric, constructed by examining the power of low frequencies compared with high frequencies across a time series
- We find that classical EWS are reliable, even in the presence of seasonality and that our wavelet metric can also be a reliable indicator of disease emergence
- These findings highlight the robustness of EWS to detecting disease emergence and we hope that these methods will become more widely used

References

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3. Shmueli, Galit. "Wavelet-Based Monitoring for Biosurveillance." *Axioms* 2.3 (2013): 345-370.

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