ESW Notes:

## Harris et al. 2020: Early warning signals of malaria resurgence in Kericho, Kenya

* Processed the raw case data by detrending with a Gaussian kernel (gets rid of temporal autocorrelation)
* Used spaero package to investigate critical slowing down in time series
  + Data for reproducing analysis at: <https://github.com/mjharris95/Kericho-EWS.git>
* Determined the trend in each indicator over time by calculating Kendall’s correlation coefficient, τ, between the calculated rolling window statistic at each time and the time index

## Brett et al. 2018: Anticipating epidemic transitions with imperfect data

* Used pomp package to simulate SIR model
* Used spaero package to calculate the EWS
* Used a modified Gillespie algorithm to simulate demographically stochastic data
* Code to reproduce results at: doi:10.5281/zenodo.1185284

## Bury et al. 2021: Deep learning for early warning signals of tipping points

* They developed an algorithm that provides EWS in 268 empirical and model time series with greater sensitivity and specificity than generic EWS
* Sometimes, a system that’s close to equilibrium may experience slowly changing external conditions that move it toward a tipping point where its qualitative behaviour changes
  + Where “tipping point” is understood as a local bifurcation point
* There exist a limited number of typical bifurcations of steady states, each of which may be described by a “normal form”––a canonical example capturing the dynamical features of the bifurcation
  + In a fold bifurcation, the system exhibits an abrupt transition to a very different state
  + A transcritical bifurcation usually causes a smooth transition, although it can cause an abrupt transition
  + A Hopf bifurcation can lead the system into a state of oscillatory behaviour via a smooth (supercritical) or abrupt (subcritical) transition
* Different bifurcation types correspond to distinct types of dynamical behaviour
  + Other behaviours can emerge near the bifurcation that are common to many normal forms
    - Example: all local bifurcations (there where eigenvalues of the respective matrices cross the imaginary axis) are accompanied by a critical slowing down
    - This is where system dynamics become progressively less resilient to perturbations as the transition approaches, causing dynamics to become more variable and autocorrelated
* Math-wise, critical slowing down occurs when the real part of the dominant eigenvalue (a measure of system resilience) diminishes and passes through 0 at the bifurcation point
* Generic EWS are intended to work across a range of different systems by detecting critical slowing down, but these indicators do not tell us which type of bifurcation to expect
* SO, this paper \*allegedly\* developed an algorithm that will make clear the type of transition (ex. Sudden or gradual) the system will undergo/provide information about the new state of the system (ex. Stable or oscillatory)
* They test the DL algorithm on data from systems that showed a critical slowing down before a local bifurcation; EWS of global bifurcations are much more difficult to detect
  + Examples of local bifurcations include: Saddle-node (fold); transcritical; pitchfork; period-doubling (flip); Hopf)
* EWS require high resolution data from a long time series leading up to the tipping point

## Dakos et al. 2008: Slowing down as an early warning signal for abrupt climate change

* Were abrupt climatic changes a result of Earth’s system reaching a critical tipping point?
* They look at 8 abrupt climate shifts and find that they were all preceded by a characteristic slowing down of the fluctuations starting well before the actual shift
  + Such slowing down, measured as increased autocorrelation, can be shown as a hallmark of tipping points

## O’Regan and Drake 2013: Theory of early warning signals of disease emergence and leading indicators of elimination

* This paper considers SIS and SIR models that are slowly forced through a critical transition
* Elimination and emergence of ID involve a transmission system that’s pushed over a critical point
  + Criticality occurs when the basic reproductive number is equal to one
  + Similar critical points occur in other complex systems
* Particularly, in noisy systems, these critical points manifest as transitions between alternative modes of fluctuation
* We call such a stochastic transition a critical transition if there exists a bifurcation in a suitably constructed limit base of the mean field model
* A central problem in the study of critical transition is the identification of phenomena indicating the proximity to a critical transition in the absence of a detailed understanding of the system’s dynamical equations and/or the forcing variables causing the change
  + Recent studies have established that some noise-induced phenomena may signal the approach to a critical transition in a slowly forced dynamical system
  + If true, we could forecast ID emergence in subcritical systems, without models (just looking at data)
  + Many of these characteristic noise-induced phenomena involve critical slowing down, a decline in the resilience of the system to perturbations, which generally gives rise to an increase in the variance and autocorrelation of fluctuations as the system approaches the transition
  + Observing critical slowing down requires that the potential function of the system, if it exists, be smooth
* It’s especially difficult to anticipate critical transitions in ID systems for a number of reasons:
  + ID systems are complicated by amplification of transients and oscillatory dynamics
  + IDs are often seasonally forced
  + … and propagate in demographically open systems subject to imported cases
  + Diseases that are close to elimination/emergence are characterized by low prevalence, and are therefore subject to DS and are difficult to observe
* Leading indicators for SIR systems approaching elimination aren’t always consistent with the standard expectations of increasing variance, increasing autocorrelation, and increasing coefficient of variation (see pgs. 9-16 (or, 341-348)) of this paper for more detail)

## Dibble et al. 2016: Waiting time to infectious disease emergence

# Let’s talk about Gaussian kernels!

* Gaussian kernels (also known as Gaussian filters) are used to de-trend data, and in our case, remove temporal autocorrelation
  + Where temporal autocorrelation refers to the relationship between successive values (i.e. lags) of the same variable
  + Results in observations taken closely together in time being correlated, leading to non-random residuals
* Generally, a kernel is a way of placing a data space into a higher dimensional vector space so that the intersections of the data space with hyperplanes in the higher dimensional space determine more complicated, curved decision boundaries in the data space
* The “kernel”, when used for smoothing, defines the shape of the function that is used to take the average of the neighbouring points; a Gaussian kernel is a kernel with the shape of a Gaussian curve
* The Gaussian smoothing operator is used **to `blur' images and remove detail and noise**.
  + Similar to the mean filter, but uses a different kernel that represents the shape of a Gaussian hump
* <https://shapeofdata.wordpress.com/2013/07/23/gaussian-kernels/>
* <https://towardsdatascience.com/gaussian-process-kernels-96bafb4dd63e>
* <https://matthew-brett.github.io/teaching/smoothing_intro.html>
* <https://pages.stat.wisc.edu/~mchung/teaching/MIA/reading/diffusion.gaussian.kernel.pdf.pdf>
* <https://stats.stackexchange.com/questions/582884/detrending-with-a-gaussian-kernel>
* An R package for this: <https://cran.r-project.org/web/packages/KRLS/KRLS.pdf>
* On the Bury et al. 2021 paper: <https://fabiandablander.com/Deep-Warning.html>