

Stochastic Modeling and Chaotic Epidemic Outbreaks

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Outline

- # SEIR model - a model for epidemics in childhood diseases (Yorke and London (1973); May and Anderson (1979); Schwartz (1983); Grenfell et al. (2000); Hethcote (2000))
- # Add stochastic perturbations to represent noise in population size
- # Generic setting for bifurcation to stochastic chaos
- # Possible vaccination strategies to control and prevent future outbreaks

Modeling Epidemics: Assumptions

The population:

Assume the population is large and well mixed.

Variables and parameters:

S: Susceptibles

α^{-1} : mean latent exposed period

E: Exposed

γ^{-1} : mean infectious period

I: Infectives

μ : birth and death rate

R: Recovered

β : contact rate (for **S** & **I**)

Normalize the population: **S** + **E** + **I** + **R** = 1

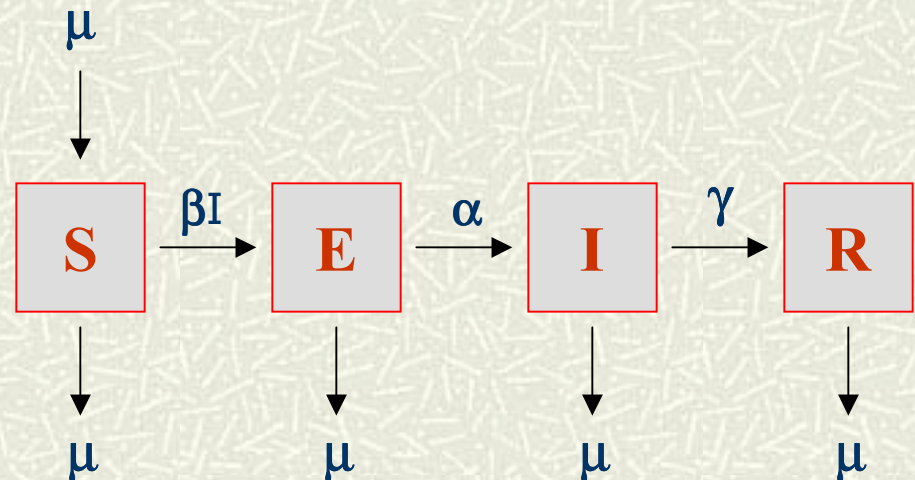
The SEIR model

$$\frac{dS}{dt} = \mu - \beta(t)IS - \mu S$$

$$\frac{dE}{dt} = \beta(t)IS - \alpha E - \mu E$$

$$\frac{dI}{dt} = \alpha E - \gamma I - \mu I$$

$$\frac{dR}{dt} = \gamma I - \mu R$$

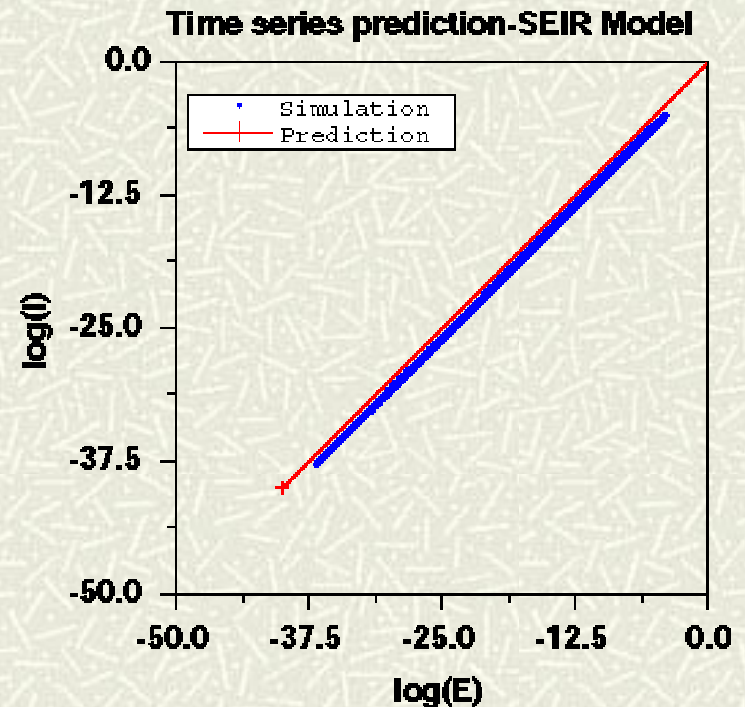


The SEIR model

■ The contact rate: $\beta(t) = \beta(t+1) = \beta_0(1 + \delta \cos 2\pi t)$

■ The infectives are roughly proportional to the exposed
[Schwartz, J. Math. Biol. 1985]

$$I(t) \approx \left(\frac{\alpha}{\mu + \gamma} \right) E(t)$$



The SEIR model

The final model (MSI)

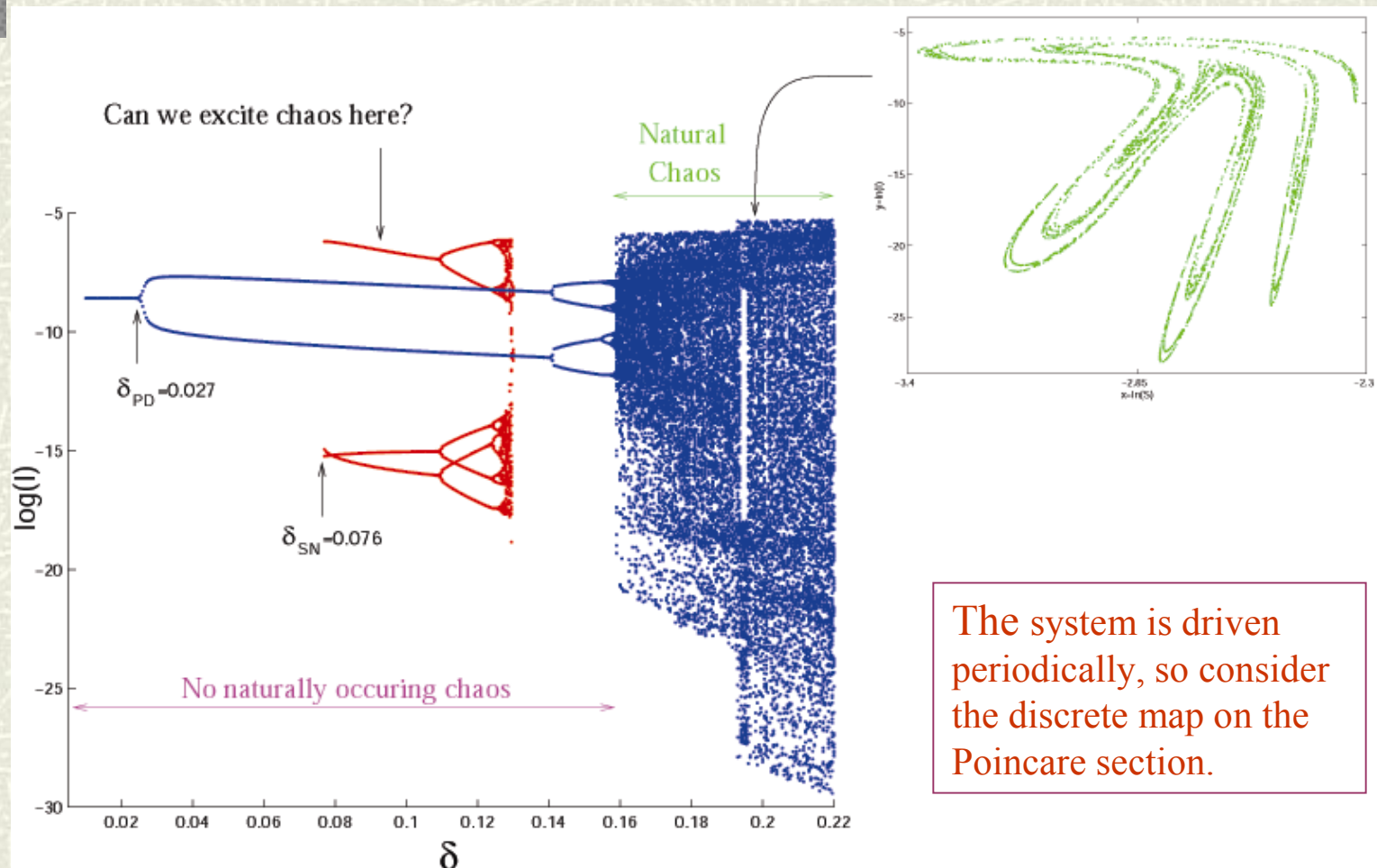
$$\frac{dS}{dt} = \mu - \beta(t)IS - \mu S$$

$$\frac{dI}{dt} = \left(\frac{\alpha}{\mu + \gamma} \right) \beta(t)IS - (\mu + \alpha)I$$

$$\beta(t) = \beta_0(1 + \delta \cos(2\pi t))$$

↖ The parameter we vary

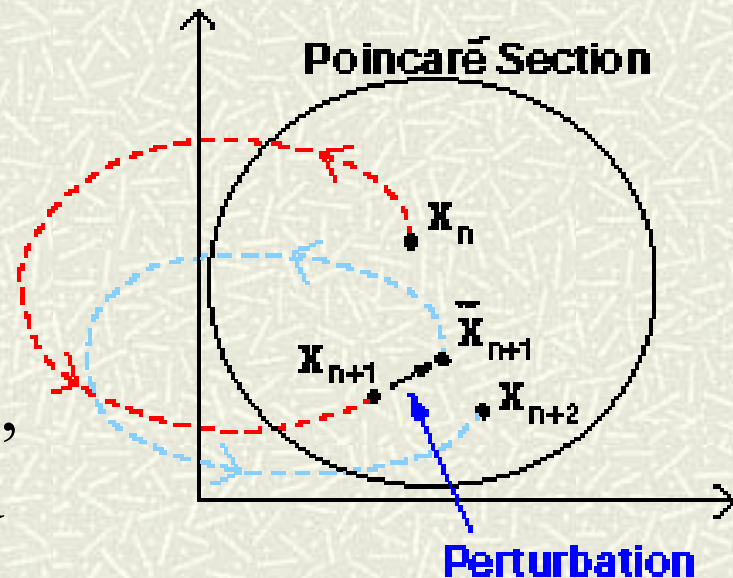
Bifurcation diagram



The system is driven periodically, so consider the discrete map on the Poincaré section.

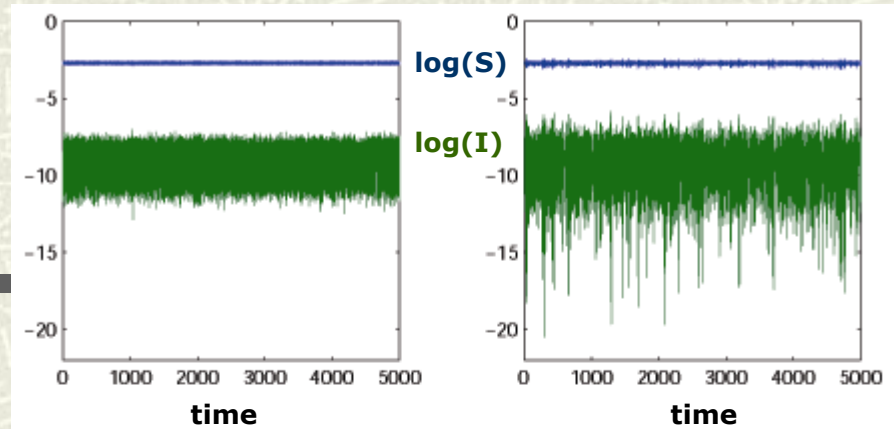
Adding noise

- # The system is driven periodically, so add noise as if it is a map.
(Additive noise)
- # Noise: normal distribution, mean=0, vary the standard deviation (σ)

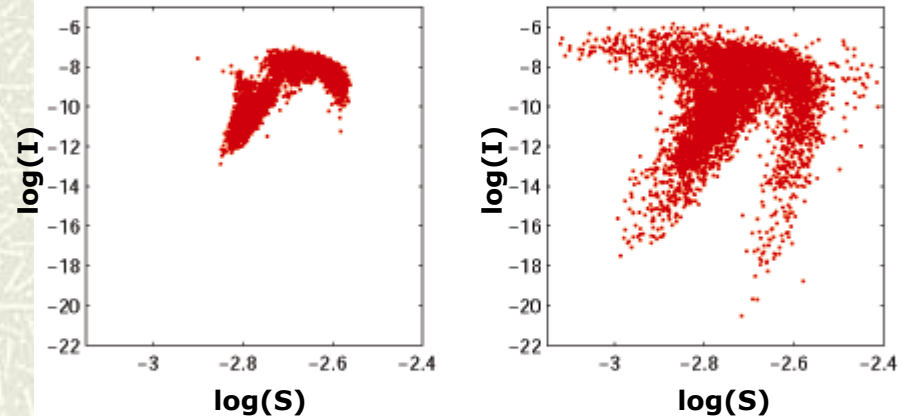


Noisy dynamics

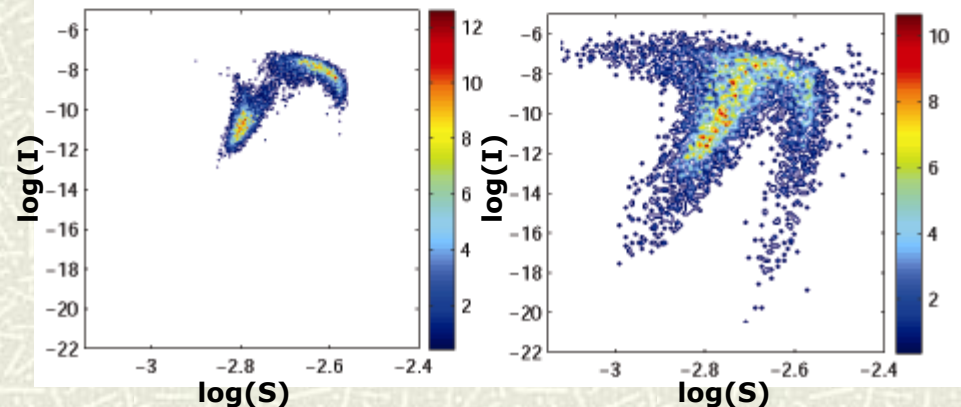
Time series



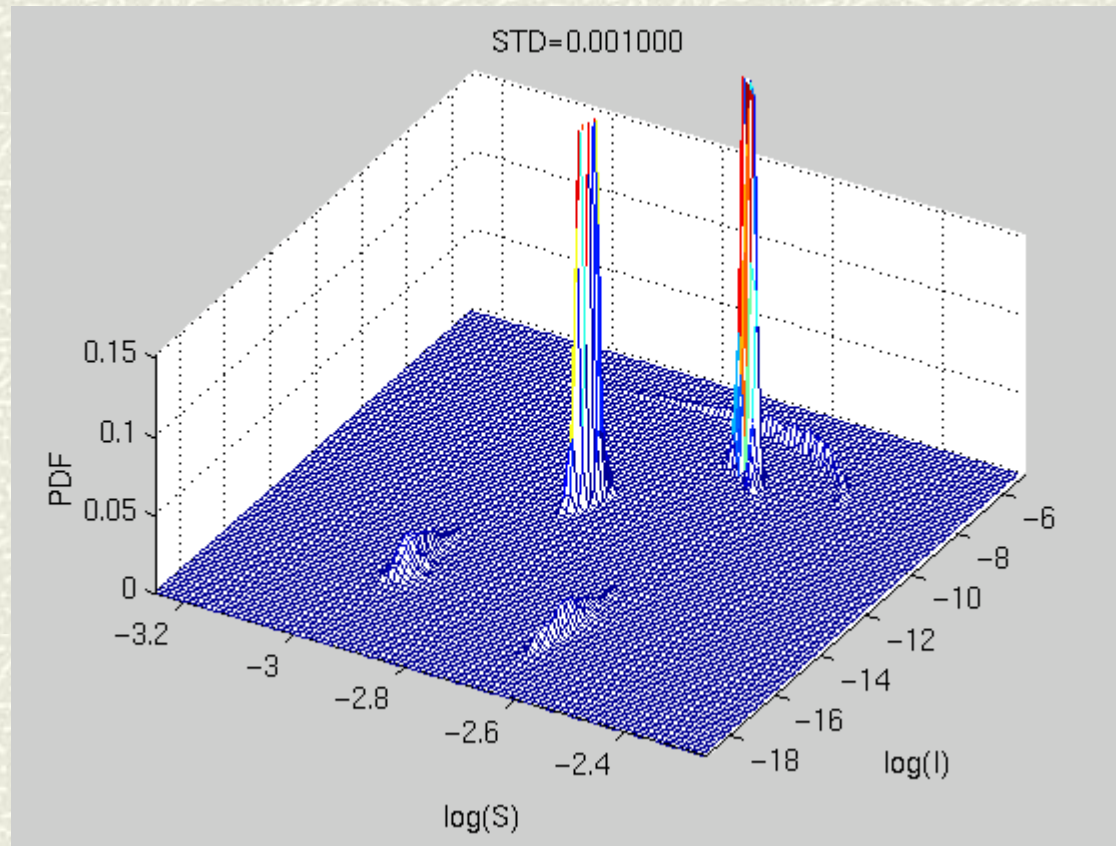
Phase space diagram



Probability density function



Probability Density Function



Stochastic Chaos?

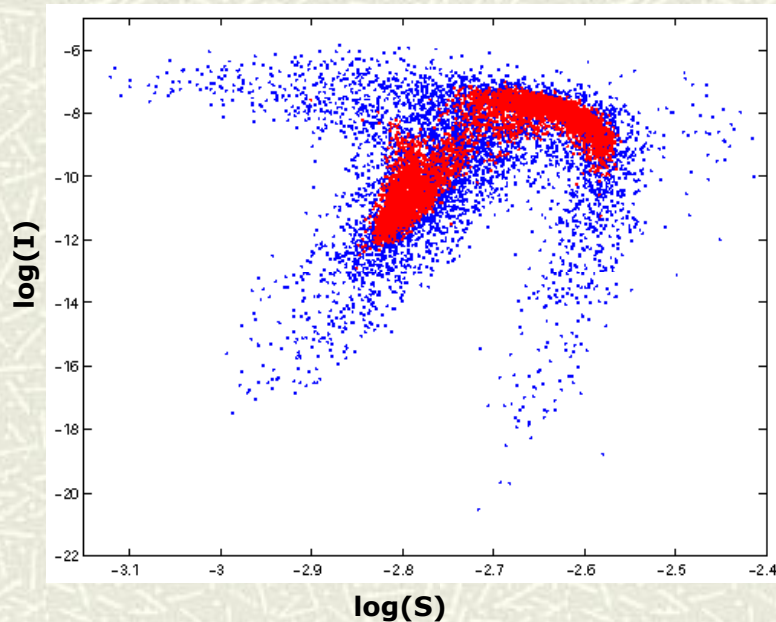
Deterministic definition (numerical)

- Compact set
- Positive Lyapunov exponent
- Not asymptotically periodic

Stochastic version?

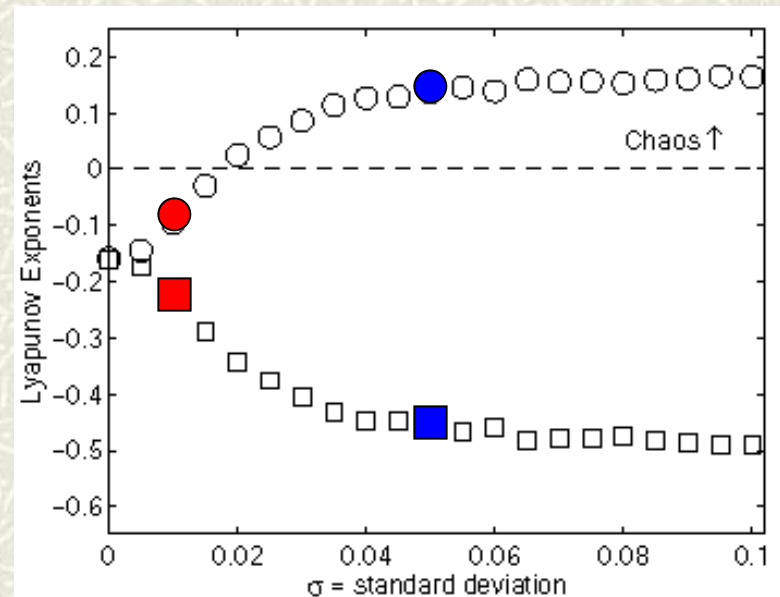
- Compact set
- Positive Lyapunov exponent
- Homoclinic/heteroclinic topology
(makes chaotic orbits possible)

Lyapunov exponents



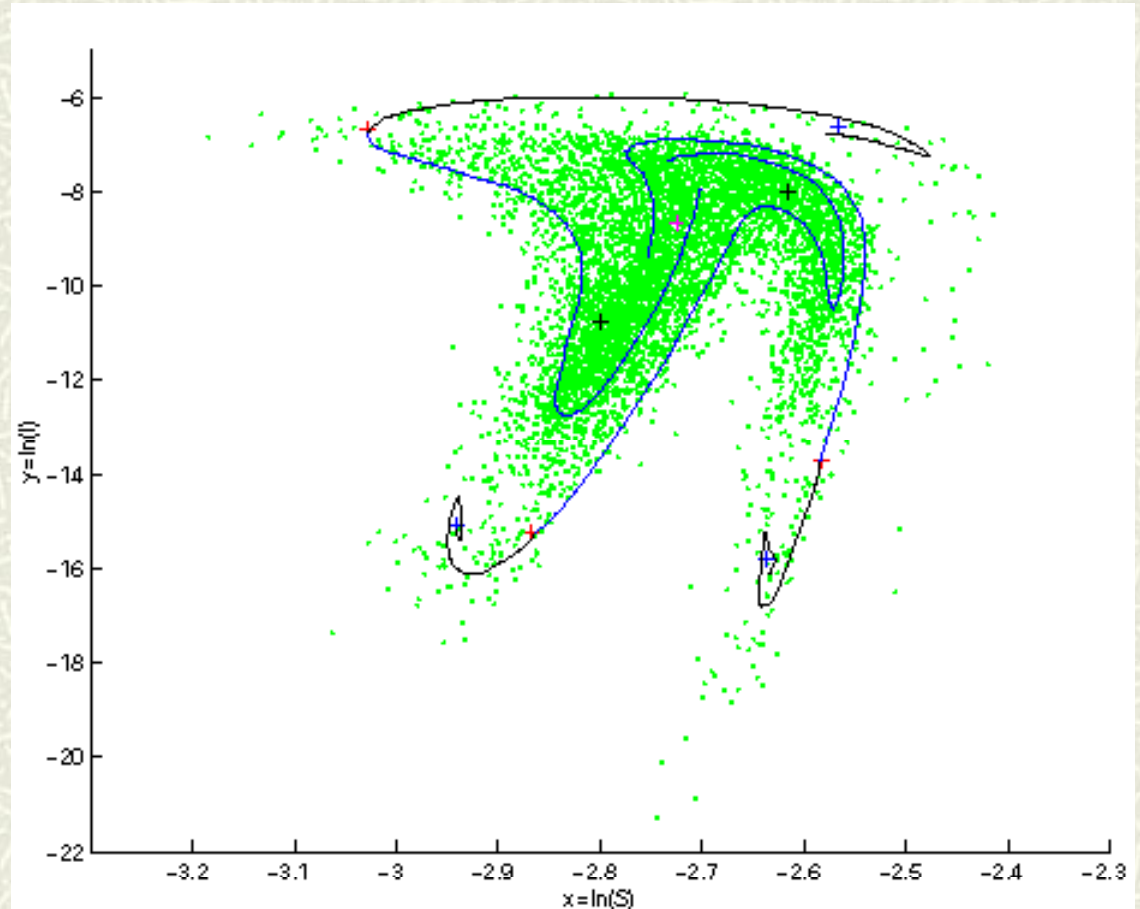
But Lyapunov exponents
can yield false results

- # Red: $\sigma = 0.01$ (noisy)
- # Blue: $\sigma = 0.05$ (chaotic)

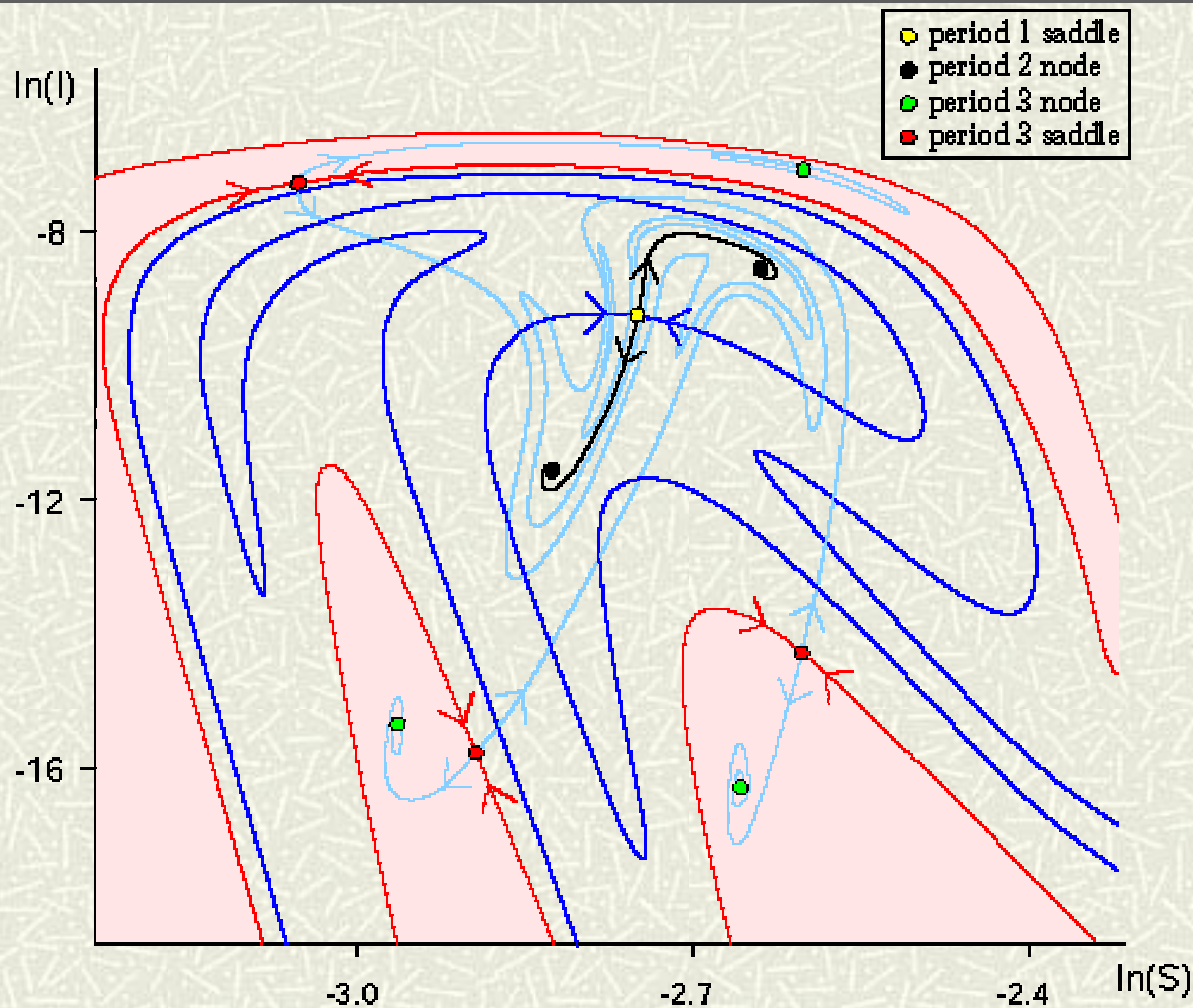


Unstable manifolds

- Random trajectories follow the unstable manifolds of the period three saddle
- What is the role of the manifolds?

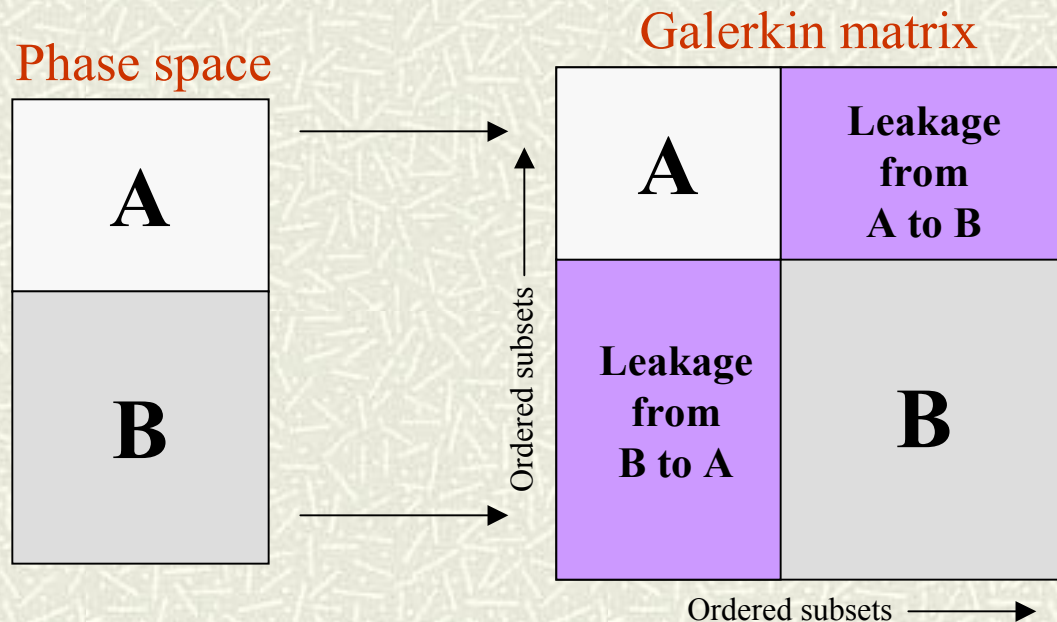


Stochastic Chaotic Saddle



New tool to detect transport

- # Use the Galerkin approximation **Stochastic Frobenius-Perron Operator** to detect the flux across a basin boundaries and predict the most probable regions of transport created by noise.



Theory for Galerkin Matrix

- Add noise using a random variable η , standard deviation σ

$$F: M \rightarrow M, x \rightarrow F(x) + \eta$$

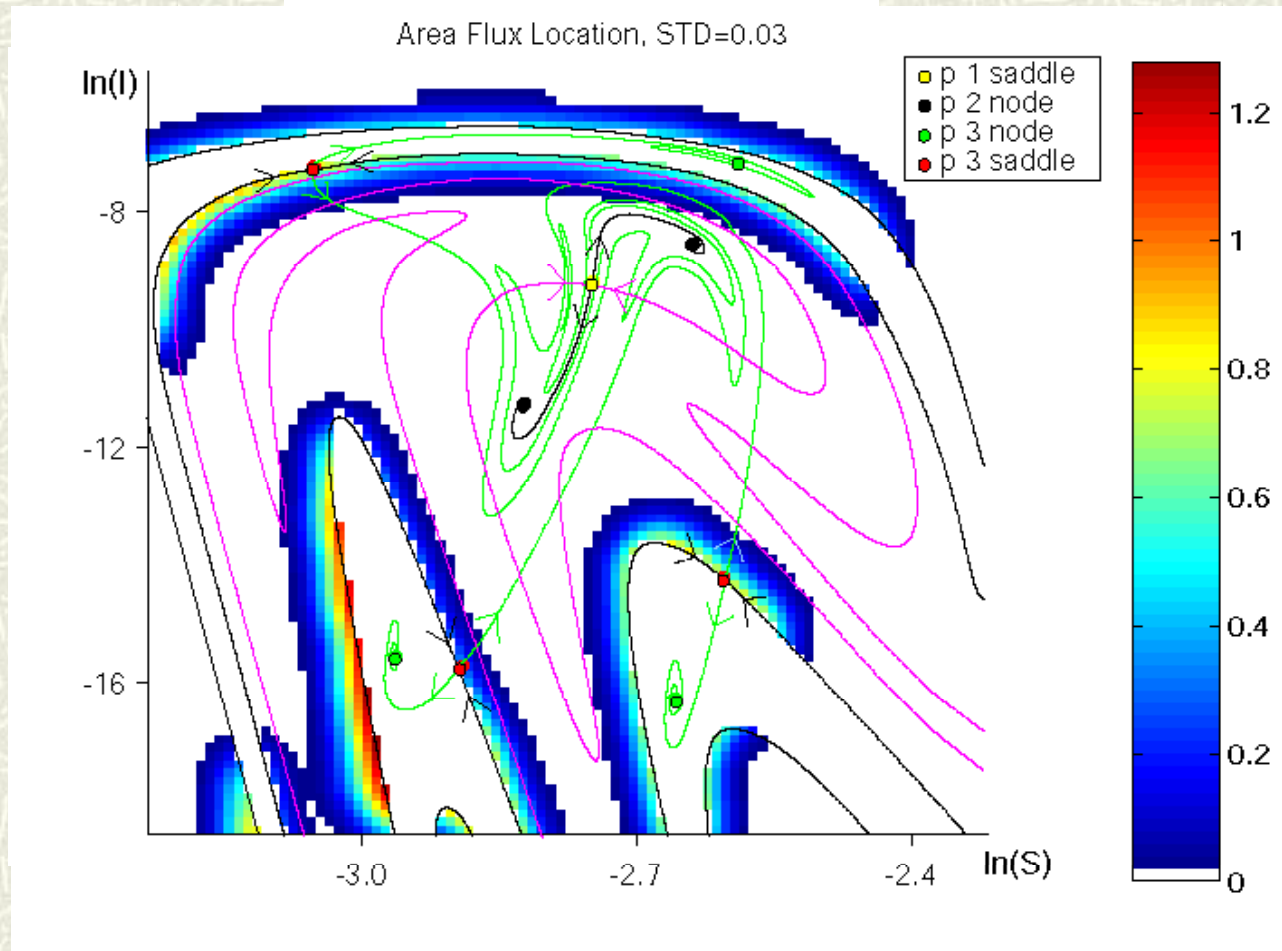
- Stochastic Frobenius-Peron operator

$$P_{F\sigma}[\rho(x)] = \frac{1}{\sqrt{2\pi\sigma^2}} \int_M e^{-\frac{\|x-F(y)\|^2}{2\sigma^2}} \rho(y) dy$$

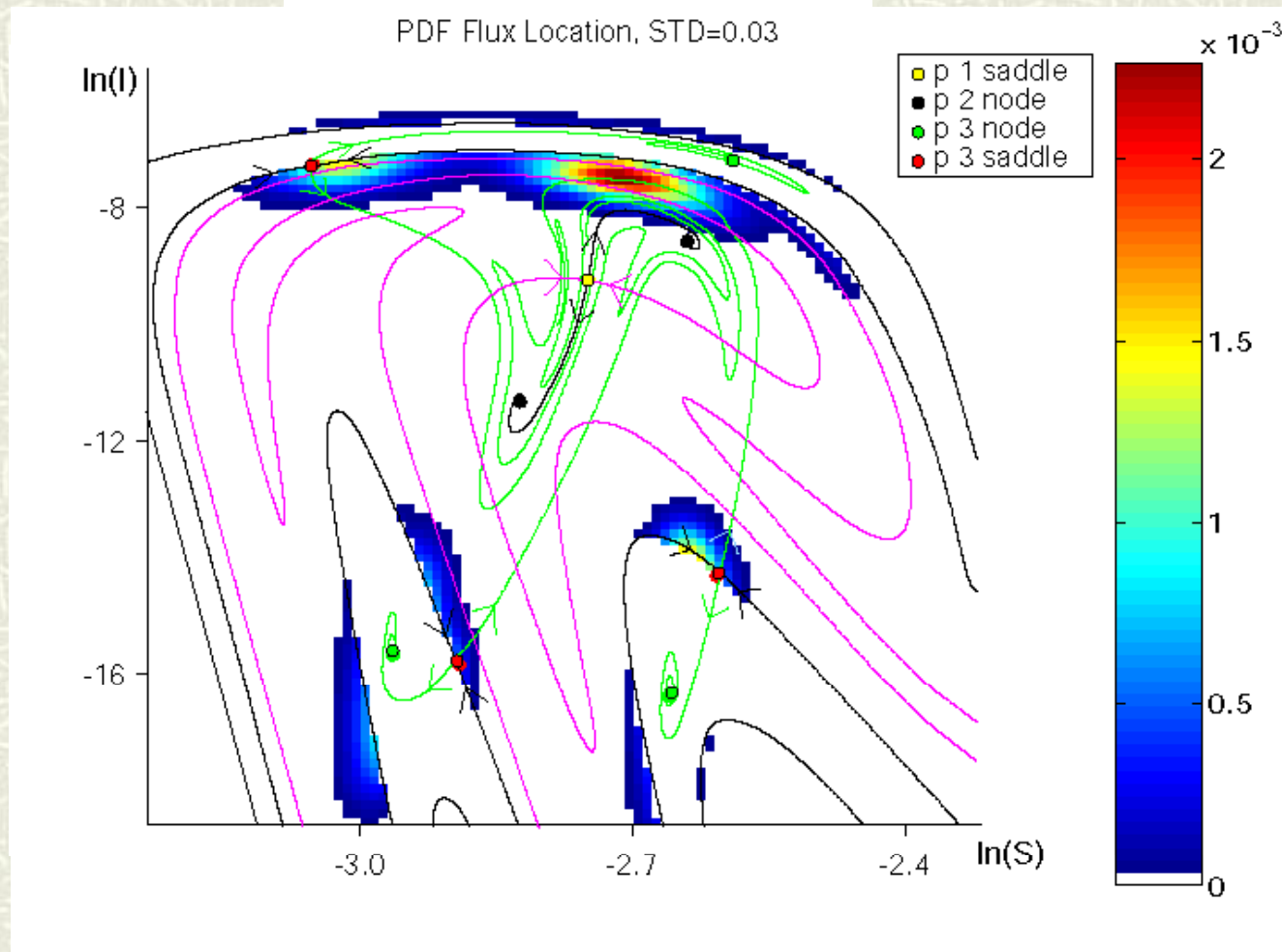
- Galerkin approximation

$$A_{i,j} = (P_{F\sigma}[\varphi_j], \varphi_i) = \int_M P_{F\sigma}[\varphi_j(x)], \varphi_i(x) dx$$

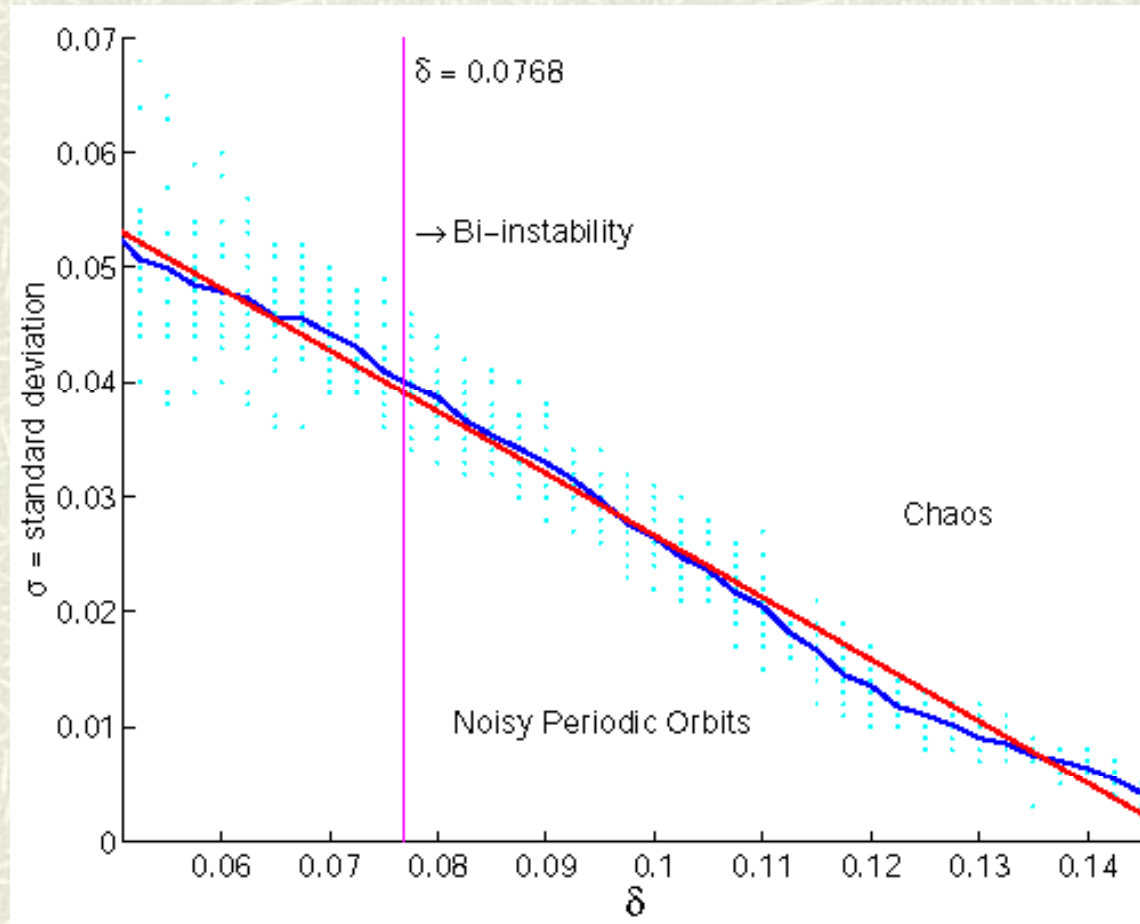
Area Flux



PDF Flux



Predicting chaos



Conclusions

- # Stochastic perturbations can induce new, emergent dynamics in models
- # Chaos-like behavior is induced in both models by additive noise
- # We have shown a new stochastic bifurcation to chaos (completion of heteroclinic orbit)
- # We have presented a tool that detects transport (Galerkin matrix)