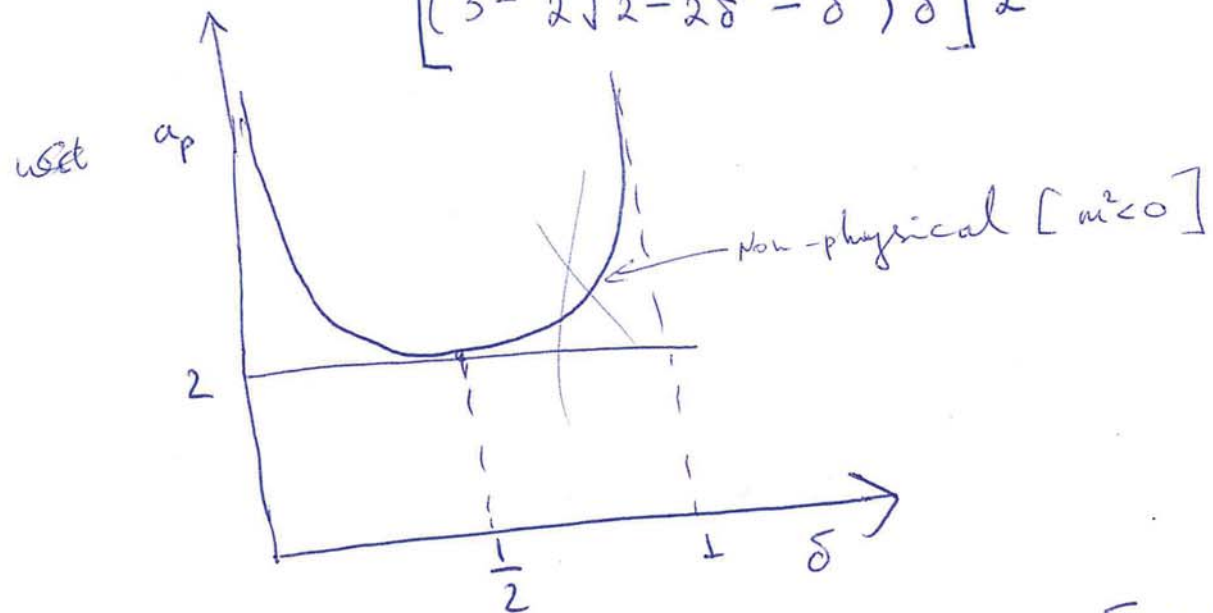


In general, the Turing instability first appears as a is decreased below $a = a_p$; the value of a_p is determined using a double-root condition: $\begin{cases} \lambda = 0 \\ \frac{\partial \lambda}{\partial m} = 0 \end{cases}$ (5)

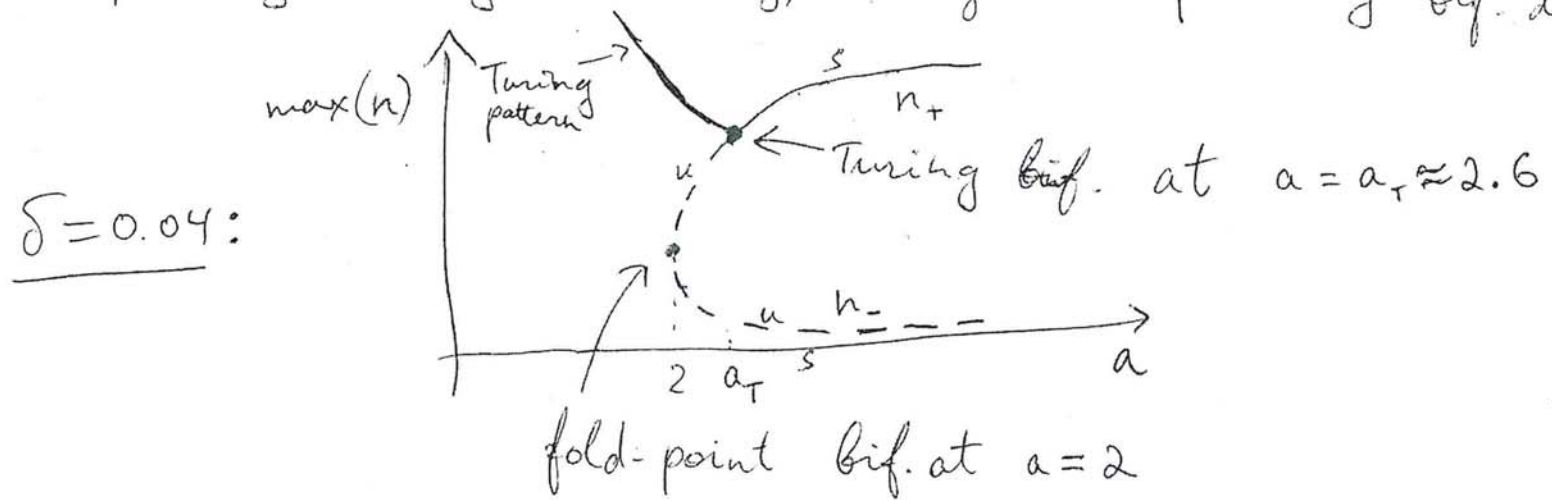
which yields, after some algebra,

$$a_p = \frac{3 - 2\sqrt{2 - 2\delta}}{[(3 - 2\sqrt{2 - 2\delta} - \delta)\delta]^{\frac{1}{2}}}, \quad 0 < \delta < \frac{1}{2}$$



\Rightarrow Turing instability exists as long as $0 < \delta < \frac{1}{2}$
 [no Turing instability if $\delta > \frac{1}{2}$].

- Incorporating Turing instability, we get the following bif. diagram



- Turing bif. leads to spatially inhomogeneous patterns
- These patterns extend well beyond the fold-point and allow vegetation to survive in "patches" with limited precipitation
- See FlexPDE script for numerical simulations of this.

Turing instability, slow drift and noise [1]:

⑦

-Imagine there is a gradual decrease in precipitation
so that

$$a = a_0 - \epsilon t + \text{"noise"} \quad \left[\text{or } a = a_0 + \frac{a_1 - a_0}{2} (1 - \cos(\epsilon t)) + \text{noise} \right]$$

where $a_0 > a_c$ is above Turing bifurcation point

- If i.c. are homogeneous and there is no noise, then the Turing bifurcation never gets activated!
- Even when the noise is present, it takes some time for the Turing patterns to grow; there is a delay in the bifurcation.
- Depending on the size of the delay, if the delay is too large, you may fall off the fold point $a_c = 2$ before the system has a chance to transition to patterned state! [causing extinction]
- Mathematical analysis (see below) shows that extinction is more likely if precipitation decreases more rapidly [i.e. bigger ϵ , or ...]

Analysis:

$$\begin{cases} \frac{dn}{dt} = \delta n_{xx} - n + n^2 \omega \\ 0 = \omega_{xx} - \omega + n^2 \omega + a(\varepsilon t) + \sigma_0 \frac{dW}{dt} \end{cases} \quad (8)$$

Where $a(s) =$ is a decreasing function with
 $a(0) > a_p$ and $a(\varepsilon t_{\text{end}}) < a_p$

eg. $a(s) = a_0 - s$, with $a_0 > a_p$

and $dW = \sum_m \sqrt{dt} \xi_m(t) \exp(imx)$, $\xi_{-m} = \overline{\xi_m}$

$\xi_m(t) \equiv$ Gaussian random variable with mean 0, std. 1

• This is a spatio-temporal Wiener process

• See [1] for details and matlab code.

Recall that the quasi-steady state is given by

$$n'_{\pm} = \frac{a}{2} \pm \sqrt{\frac{a^2}{4} - 1}, \quad \omega_{\pm} = \frac{1}{n_{\pm}}; \quad \begin{aligned} a &= a(\varepsilon t) \\ n_{\pm} &= n_{\pm}(\varepsilon t) \\ \omega_{\pm} &= \omega_{\pm}(\varepsilon t) \end{aligned}$$

We linearize around n_+, ω_+ :

$$n(x,t) = n_+(\varepsilon t) + \varphi(x,t), \quad \omega(x,t) = \omega_+(\varepsilon t) + \psi(x,t), \quad \text{with } \varphi, \psi \ll 1$$

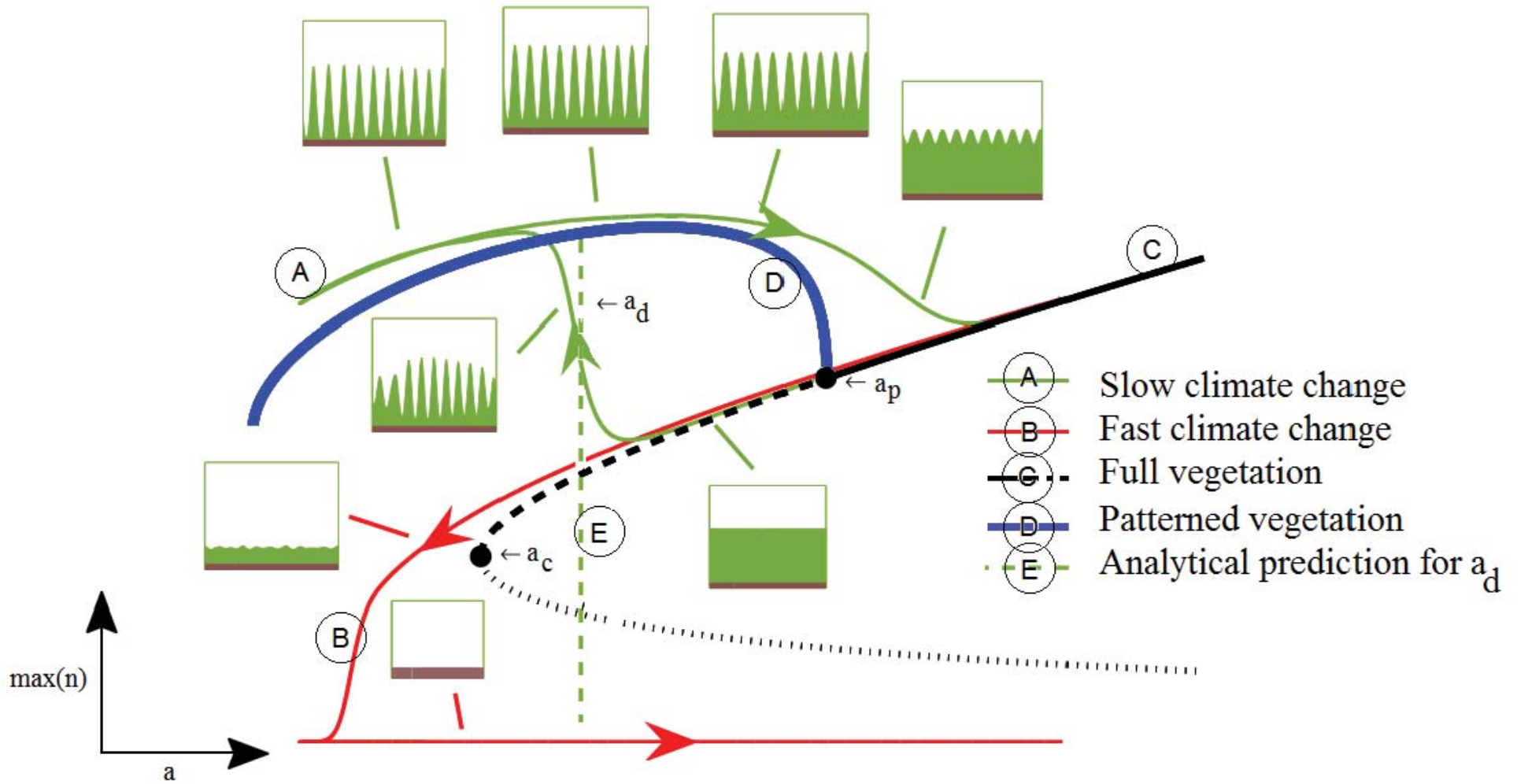


FIG. 1. (colour online) Evolution of vegetation patterns in the presence of slow precipitation drift. The green curve A avoids the tipping point by going into a reversible patterned state. The red curve B falls off the fold point leading to irreversible extinction. Model (1) is used with a given by (5). The Green curve A corresponds to slow decrease ($\varepsilon = 0.006$, corresponding to a change of 2 mm/year) while the red curve B corresponds to a faster decrease ($\varepsilon = 0.03$, corresponding to a change of 40 mm/year). Other parameters are $a_0 = 2.85$, $a_1 = 1.75$, $\sigma_0 = 0.0001$, $\delta = 0.05$, $d = 1$, $c = 0$ on a domain of size $L = 22.839$ with periodic boundary conditions. The full vegetation state (black curve C) bifurcates into a patterned state (blue curve D, computed by the software package AUTO [12]) at $a = a_p = 2.4743$, and has a fold point at $a_c = 2$. For values of a below a_p and above a_c , the full vegetation state still exists (dashed black curve C) but is unstable to spatial perturbations. The vertical green dashed line E at $a = a_d = 2.18$ is the asymptotic prediction for the delayed “take-off” value of the green curve. Excellent agreement between the asymptotics and numerics is observed.

$$\begin{cases} \varepsilon n'_+(et) + \varphi_t = \delta \varphi_{xx} - \varphi + 2\varphi n_+ \omega_+ + n_+^2 \psi \\ 0 = \psi_{xx} - \psi - 2\varphi n_+ \omega_+ - n_+^2 \psi + \sigma_0 \frac{d\omega}{dt} \end{cases}$$

Decompose $\begin{cases} \psi = \sum \psi_m e^{imx} \\ \varphi = \sum \varphi_m e^{imx} \end{cases}, \quad d\omega = \sum \sqrt{dt} \xi_m e^{imx}$

Dropping the "m" we get, with $m \neq 0$:

$$\begin{cases} \varphi_{et} = -\delta m^2 \varphi - \varphi + 2\varphi n_+ + n_+^2 \psi \\ 0 = -m^2 \psi - \psi - 2\varphi n_+ \omega - n_+^2 \psi + \frac{\sigma_0 \sqrt{dt} \xi}{dt} \end{cases}$$

$$\rightarrow \psi = \frac{2\varphi n_+ \omega - \sigma_0 \frac{\sqrt{dt} \xi}{dt}}{m^2 + 1 + n_+^2}$$

$$\hookrightarrow \boxed{\frac{d\varphi}{dt} = \alpha \varphi + \beta \frac{\sqrt{dt} \xi}{dt}}$$

Where $\begin{cases} \alpha(et) = \frac{-\delta m^2 - 1 + 2n_+}{m^2 + 1 + n_+^2} + \frac{2n_+ \omega_+ + n_+^2}{m^2 + 1 + n_+^2} \\ \beta(et) = \frac{\sigma_0 n_+^2}{m^2 + 1 + n_+^2} \end{cases}$

$$[\dots + \beta(et) \sqrt{dt} \xi]$$

Simplest SDE: Introduction to SDE

10

• $dx = \sqrt{dt} \xi$, here $\xi \equiv \text{Gaussian}$;

• Matlab implementation:

```
dt = 0.01;
X = 0;
for t = 0:dt:5
    X = X + sqrt(dt) * randn;
end
```

• Sol'n is interpreted in terms of

probability density:

- Let $u(x, t) \equiv \text{prob. density}$; that is:

$$\int_{x_1}^{x_2} u(x, t) dx \equiv \text{probability that } x_1 \leq x(t) \leq x_2.$$

• Key property of $u(x, t)$:

$$u(x, t + \Delta t) = \int_{-\infty}^{\infty} \underbrace{G(x, y)}_{\frac{1}{\sqrt{2\pi\Delta t}} e^{-\frac{(x-y)^2}{2\Delta t}}} u(x + \sqrt{\Delta t} y, t) dy$$

- Expand in Taylor series; $\frac{1}{\sqrt{2\pi}} e^{-\frac{(x-y)^2}{2}}$

$$u(x, t) + \Delta t u_t + O(\Delta t^2) = \int G(x, y) \left(u + u_x \sqrt{\Delta t} y + \frac{u_{xx} \Delta t y^2}{2} + O(\Delta t^{3/2}) \right) dy$$

add

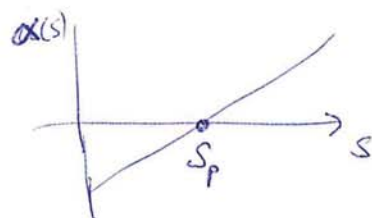
\Rightarrow Let $\Delta t \rightarrow 0$:

$$\boxed{U_t = \frac{U_{xx}}{2}}$$

"Fokker-Planck eq'n"

Now consider the SDE $\begin{cases} \frac{dx}{dt} = \alpha(\epsilon t) x + \frac{\sqrt{\Delta t}}{\Delta t} \xi \beta(\epsilon t) \\ x(0) = 0 \end{cases}$, $\boxed{\epsilon, \sigma_0 \ll 1}$

Suppose $\alpha(s)$ is something like



i.e. $\begin{cases} \alpha(0) < 0 \\ \alpha(s) \text{ is increasing} \\ \alpha(s_p) = 0 \\ \alpha'(s_p) < 0 \end{cases}$ eg. $\alpha(s) = -1 + s$, $s_p = 1$

- In the absence of noise ($\beta=0$), the ODE $x' = \alpha(s) x$ has a s.s. $x=0$ which is "stable" if $\alpha < 0$, "unstable" if $\alpha > 0$.
- If $\beta \ll 1$ and α is increased slowly

some time before instability is fully realized, it takes
i.e. $x(t)$ may remain small (even for) $\epsilon t > s_p$

Back to $\frac{d\phi}{dt} = \alpha \phi + \beta \sqrt{t} \xi$, $\phi(0) = 0$

(10)

• The Turing bifurcation corresponds to $\alpha = 0 = \frac{\partial \alpha}{\partial m}$;

• with $\alpha < 0$ when s.s. is stable.

Ex: Suppose $\alpha(\varepsilon t) = -1 + \varepsilon t$; take $\beta(\varepsilon t) = 10^{-5}$, $\varepsilon = 0.02$

Then $\phi = 0$ is "stable" when $\alpha < 0$, "unstable" if $\alpha > 0$

However the instability is only "observed" when $\alpha \approx 0.65$,
much later, than $\alpha = 0$ - see Matlab example.

- We define "observed" by the time at which $|\phi| > 1$
[for numerical purposes].

Q:
- Better definition: the "take-off" or "blowup" time is
when the variance of the density
becomes "very big".

The associated Fokker-Planck Eq'n is given by:

$$u_t + (\alpha(\varepsilon t) x u)_x = \frac{\beta(\varepsilon t)}{2} u_{xx}; \quad u(x, 0) = \delta(x)$$

or, w.r.t. slow variable $s = \varepsilon t$,

$$\varepsilon u_s + \alpha(s) x u_x + \alpha(s) u = \frac{\beta(s)}{2} u_{xx}.$$

i.e. are interested in $\sigma^2(s) = \int x^2 u(x, s) dx$ [one can show that]

Solving
$$\begin{cases} \varepsilon u_s + a(s) x u_x + a(s) u = \frac{\varepsilon^2}{2} u_{xx} \\ u(x, 0) = \delta(x) \end{cases} \quad (F-P) \quad (11)$$

Change var ①: $y = x e^{-\frac{A(s)}{\varepsilon}}$, where $A(s) = \int_0^s a(s') ds'$
 $u(x, s) = U(y, s)$,

$\rightarrow u_x = e^{-\frac{A}{\varepsilon}} U_y, u_{xx} = e^{-\frac{2A}{\varepsilon}} U_{yy}$ $\rightarrow \varepsilon u_s + a x u_x = \varepsilon U_s$
 $u_s = -x \frac{a e^{-\frac{A}{\varepsilon}}}{\varepsilon} U_y + U_s$

$\Rightarrow \varepsilon U_s + a(s) U = \frac{\varepsilon^2}{2} e^{-\frac{2A(s)}{\varepsilon}} U_{yy}$

Change var ②: $\begin{cases} U(y, s) = e^{-\frac{A(s)}{\varepsilon}} V(y, s) \Rightarrow \varepsilon U_s + a U = e^{-\frac{A}{\varepsilon}} V_s \\ \Rightarrow \varepsilon V_s = \frac{\varepsilon^2}{2} e^{-\frac{2A(s)}{\varepsilon}} V_{yy} \end{cases}$

Change var ③: $V(y, s) = W(y, \tau(s))$; $\varepsilon \tau'(s) = \frac{\varepsilon^2}{2} e^{-\frac{2A(s)}{\varepsilon}}$
 $\Rightarrow \boxed{W_\tau = W_{yy}}$; where $\tau(s) = \frac{1}{2\varepsilon} \int_0^s e^{-\frac{2A(s')}{\varepsilon}} ds'$
 $\hookrightarrow \boxed{W(y, \tau) = \frac{1}{\sqrt{4\pi\tau}} e^{-\frac{y^2}{4\tau}}}$

$$\Rightarrow u(x, s) = \frac{e^{-x^2/(2\sigma^2)}}{\sqrt{\pi 2\sigma^2}}, \text{ where}$$

$$\sigma^2(s) = e^{\frac{2}{\varepsilon} A(s)} \int_0^s \beta^2(s') e^{-\frac{2}{\varepsilon} A(s')} ds'$$

where $A(s) = \int_0^s \alpha(s) ds$

• Note that $A'(s_p) = 0$

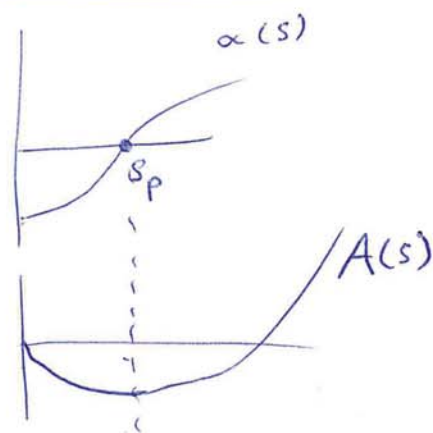
and s_p is a min of $A(s)$

So apply Laplace's method :

If $s > s_p$ then

$$\sigma^2(s) \sim e^{\frac{2}{\varepsilon} A(s)} \beta^2(s_p) e^{-\frac{2}{\varepsilon} A(s_p)} \left(\frac{\pi}{\varepsilon A''(s_p)} \right)^{\frac{1}{2}}$$

$$\Rightarrow \sigma(s) \sim \exp\left(\frac{1}{\varepsilon} \int_{s_p}^s \alpha(\tau) d\tau\right) \beta(s_p) \left(\frac{\pi}{\varepsilon \alpha'(s_p)} \right)^{\frac{1}{4}}$$



Thus $u(s, x)$ is a Gaussian!

- Has mean zero;

• Compute variance: $\sigma^2 = \int_{-\infty}^{\infty} u(x, s) x^2 dx = e^{\frac{2A(s)}{\varepsilon}} \underbrace{\int V(y, s) y^2 dy}_{\int W(y, \tau) y^2 dy}$

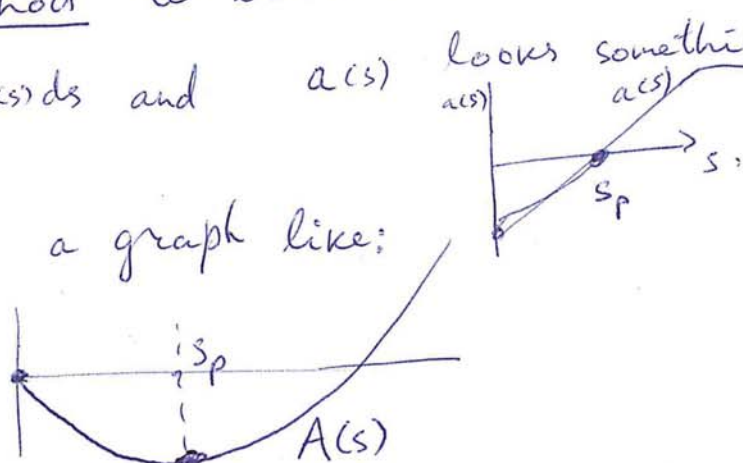
\downarrow
 $e^{-\frac{1}{\varepsilon} V}$ \downarrow
 $x = e^{\frac{A}{\varepsilon}} y$ $2\tau(s)$

$$\Rightarrow \sigma^2 = e^{\frac{2A(s)}{\varepsilon}} 2\tau(s) = e^{\frac{2A(s)}{\varepsilon}} \frac{\sigma_0^2}{\varepsilon} \int_0^s e^{-\frac{2A(s')}{\varepsilon}} ds'$$

Next, apply Laplace's method to evaluate the resulting integral:

- Recall that $A(s) = \int_0^s a(s') ds'$ and $a(s)$ looks something like:

so that $A(s)$ has a graph like:



- It has a min at $s = s_p$. Thus, for $s > s_p$, we have:

$$\int_0^s e^{-\frac{2A(s')}{\varepsilon}} ds' \sim e^{-\frac{2A(s_p)}{\varepsilon}} \int_{-\infty}^{\infty} e^{-\frac{A''(s_p)(s-s_p)^2}{\varepsilon}} ds$$

$$\sim e^{-\frac{2A(s_p)}{\varepsilon}} \sqrt{\frac{\varepsilon \pi}{A''(s_p)}}$$

- Define s_d to be such that $\sigma(s_d) \sim 1$; let $a_d = a(s_d)$.
 - Then $\begin{cases} \sigma(s) \ll 1 & \text{if } s \leq s_d \\ \sigma(s) \gg 1 & \text{if } s > s_d \end{cases}$ and

So s_d satisfies:

$$* \quad \begin{cases} \alpha(s_p) = 0 \\ \int_{s_p}^{s_d} \alpha(s) ds + \varepsilon \ln \left\{ \beta(s_p) \left(\frac{\pi}{\varepsilon \alpha'(s_p)} \right)^{\frac{1}{4}} \right\} = 0 \end{cases}$$

with $\alpha_d = \alpha(s_d)$.

... Back to $\alpha(s) = -1 + s$, $\beta(s) = \beta$, then $s_p = 1$,

and

$$a_d = \sqrt{-2\varepsilon \ln \left(\beta \left(\frac{\pi}{\varepsilon} \right)^{\frac{1}{4}} \right)}$$

ex. $\varepsilon = 0.02$, $\beta = 10^{-5} \Rightarrow$

$$a_d = 0.64$$

Excellent agreement with theory!

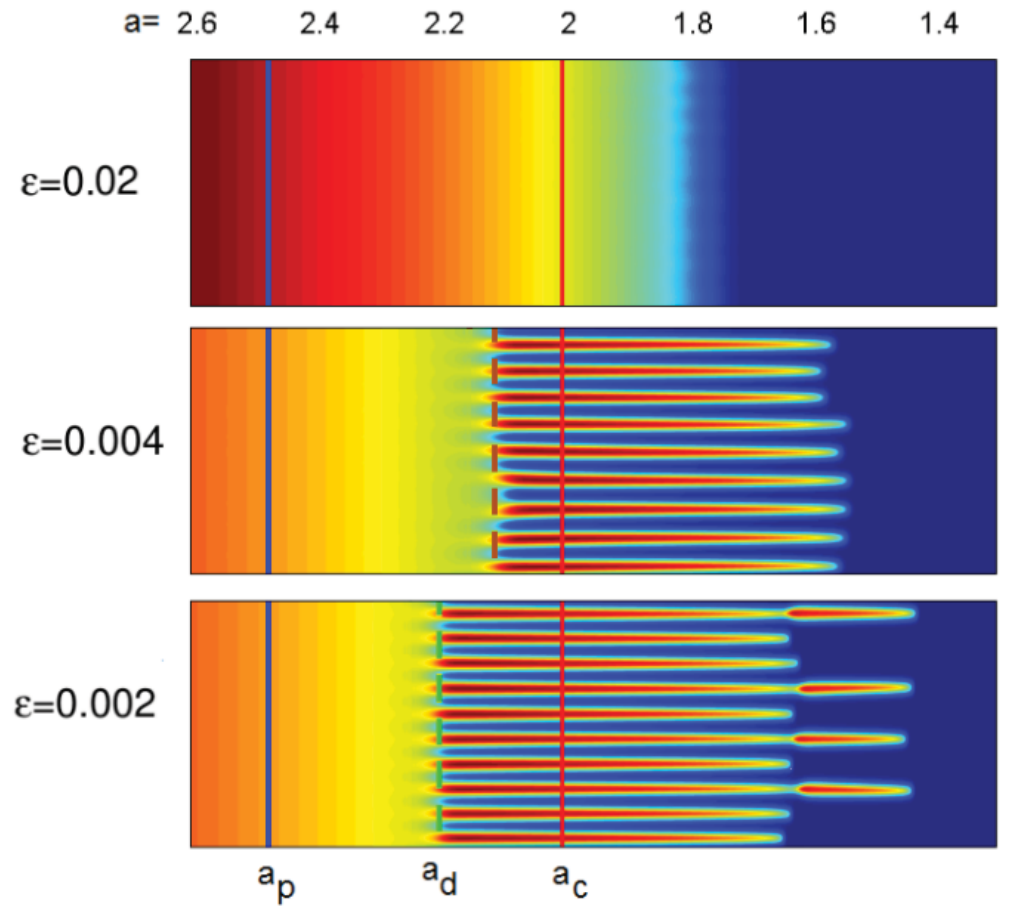
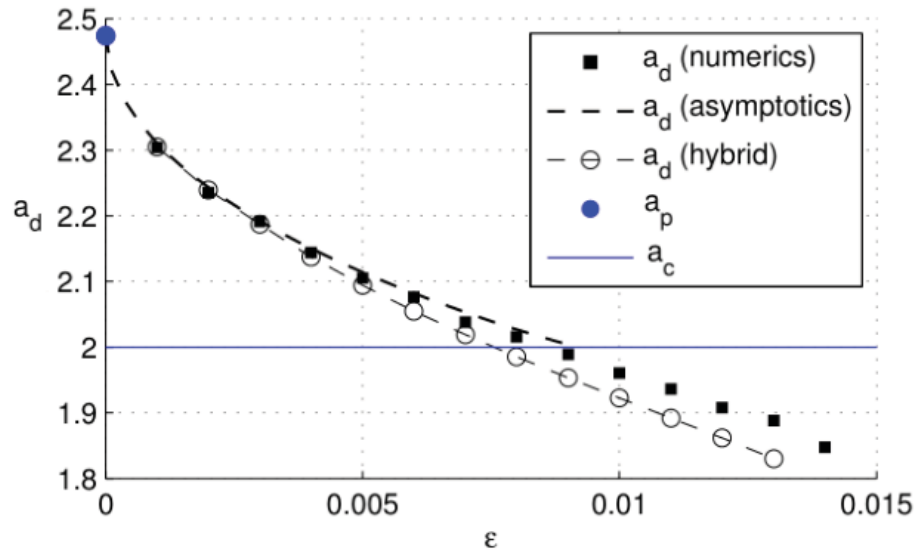
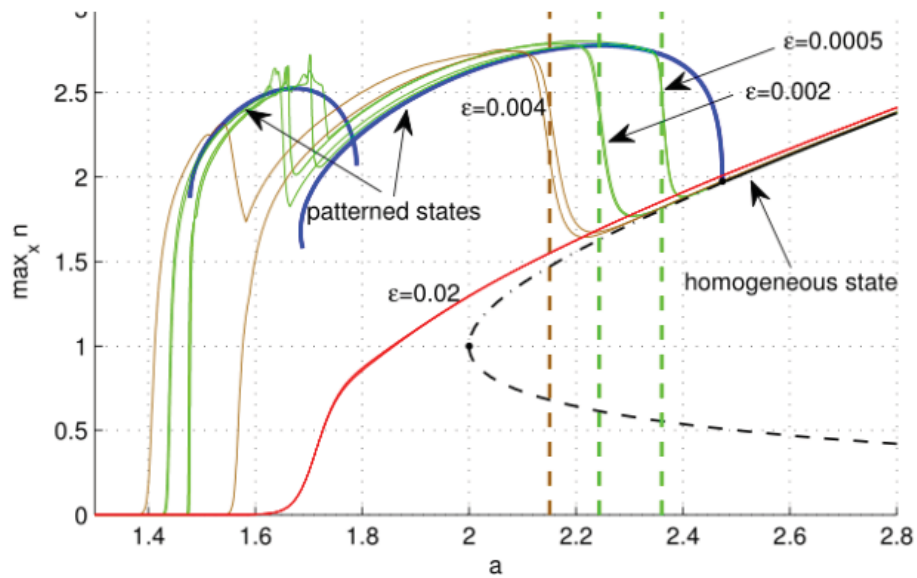


FIG. 2. Numerical verification of a_d as given in (16) for (6). The slow drift is taken to be $a = a_0 - \varepsilon t$ with $a_0 = 3$, $\sigma_0 = 0.0001$, $L = 22.839$ and $\delta = 0.05$. Top left: the evolution of $\max_x n$ as a function of a with ε as indicated. The dashed lines show a_d as given by (16). The patterned state (blue on-line) to the left corresponds to a single-bump solution, whereas the patterned state on the right corresponds to the wave-number 10 born from a Turing bifurcation at $a = a_p = 2.47439$. Top right: color plot of $n(x, t)$ as it evolves in time. The Turing bifurcation point a_p , the delayed bifurcation a_d and the fold point $a_c = 2$ are indicated. Bottom left: Comparison of asymptotic and full numerical results for a_d . The hybrid curve is obtained by using the full homogeneous state (17) instead of (7) when computing (16). The value of a_d is estimated numerically as discussed in the text, and an average over 50 simulations is used. We used $N = 100$, $dt = 0.1$ (see Appendix A for numerical implementation details).