

Notes
9/2/24



Land-based Ice Sheet

Plastic ice, yield stress τ_0

stress balance (Nye, 1952)

$$\text{on } [0, \frac{L}{2}]: \tau_0 = \sigma_i g h \frac{\partial h}{\partial x}$$

$$\rightarrow \frac{\partial h^2}{\partial x} = 2h \frac{\partial h}{\partial x} = \frac{2\tau_0}{\sigma_i g} \equiv \sigma$$

$$\rightarrow h^2(x, t) = \sigma x + c(t)$$
$$h(0, t) = 0 \quad \dots$$

$$\rightarrow h^2(t) = \sigma x$$

$$\text{On } [0, L] : \quad T_0 = -\rho g b \frac{\partial h}{\partial x}$$

$$\rightarrow \begin{cases} h^2(x, t) = D(t) - x \\ h(L, t) = 0 \end{cases}$$

$$\rightarrow h^2(x, t) = \sigma [L(t) - x]$$

use

$$\frac{L}{2} - |x - \frac{L}{2}| = \begin{cases} x & x < \frac{L}{2} \\ L - x & x > \frac{L}{2} \end{cases}$$

On $[0, L]$

$$\rightarrow h^2(x, t) = \sigma \left(\frac{L(t)}{2} - \left| x - \frac{L(t)}{2} \right| \right)$$

$$\rightarrow h^2\left(\frac{L}{2}, t\right) = \sigma \frac{L(t)}{2} = H(t)$$

$$\text{max height: } h_{\max} = H(t)$$

$$= \sqrt{\frac{5L}{2}}$$

Mass balance

$$\Sigma_i \frac{\partial h}{\partial t} = \Sigma_i \beta \left(h - \gamma (x - x_p) \right)$$

$$\int_{Y_2}^L \frac{\partial h}{\partial t} dx = \beta \int_{Y_2}^L \left(\sqrt{G(L-x)} - \gamma(x-x_p) \right) dx$$

$$= \beta \left[\sqrt{G} \left(L-x \right)^{\frac{3}{2}} \left(-\frac{2}{3} \right) \Big|_{Y_2}^L \right. \\ \left. - \gamma \left(\frac{1}{2} x^2 - x_p x \right) \Big|_{Y_2}^L \right]$$

$$= \beta \left[\frac{2}{3} \sqrt{G} \left(\frac{L}{2} \right)^{\frac{3}{2}} - \gamma \left(\frac{1}{2} L^2 - x_p L \right. \right. \\ \left. \left. - \frac{1}{2} \left(\frac{L}{2} \right)^2 + x_p \frac{L}{2} \right) \right]$$

$$= \beta \left[\frac{1}{3} \sqrt{\frac{G}{2}} L \sqrt{L} - \gamma \left[\frac{L^2}{4} - x_p \frac{L}{2} \right] \right]$$

On the other hand :

$$\int_{L_2}^L \frac{\partial h}{\partial t} dx = \frac{\partial}{\partial t} \int_{L_2}^L h dx$$

$$- h(L) \frac{dL}{dt} + h\left(\frac{L}{2}\right) \frac{d(L_2)}{dt}$$

$$= \frac{1}{2} H(t) \frac{dL}{dt} + \frac{\partial}{\partial t} \int_{L_2}^L h dx$$

use $\int_{L_2}^L h dx = \frac{1}{3} \sqrt{\frac{5}{2}} L \sqrt{L}$

$$= \frac{H}{2} \frac{dL}{dt} + \frac{1}{3} \sqrt{\frac{5}{2}} \frac{d(L\sqrt{L})}{dt}$$

$$= \frac{H}{2} \frac{dL}{dt} + \frac{3}{2} \frac{1}{3} \sqrt{\frac{5}{2}} \sqrt{L} \frac{dL}{dt} = H \frac{dL}{dt}$$

Finally

$$+\frac{dL}{dt} = \beta \left(\frac{1}{3} + L - \gamma \left(\frac{L^2}{4} - x_p \frac{L}{2} \right) \right)$$

$$\frac{dL}{dt} = \frac{\beta}{3} L - \frac{\beta\gamma}{4} \frac{L^2}{1+} + \beta\gamma x_p \frac{L}{2+}$$

use $\pm = \sqrt{\frac{\sigma L}{2}}$

$$-\frac{\beta\gamma}{4} \frac{\sqrt{2}}{\sigma} L \sqrt{1} \frac{\beta\gamma x_p}{\sqrt{25}} \sqrt{1}$$

$$\rightarrow F_1 = \frac{\beta\gamma x_p}{\sqrt{2\sigma}}$$

$$F_2 = \beta/3$$

$$F_3 = -\frac{\beta\gamma}{4} \sqrt{\frac{2}{\sigma}}$$

$$\frac{dL}{dt} = F_1 \bar{L} + F_2 L + F_3 L \bar{L}$$

fixed points $\bar{L} = \bar{L}$

$$\rightarrow F_1 \bar{L} + F_2 \bar{L}^2 + F_3 \bar{L}^3 = 0$$

$\bar{L} = 0$: fixed point

$$F_1 + F_2 \bar{L} + F_3 \bar{L}^2 = 0$$

$$\bar{L}_1, \bar{L}_2 = \frac{-F_2 \pm \sqrt{F_2^2 - 4F_1 F_3}}{2F_3}$$

two solutions, when

$$\frac{F_2^2}{F_3} - 4F_1 F_3 > 0$$

Saddle node when: $\frac{F_2^2}{F_3} = 4F_1 F_3$
only for $x_p < 0$

stochastic Diff Eq.

$$dX_t = -rX_t dt + \sigma dW_t$$

Deterministic

$$X(t) = X_0 + \int_0^t -rX(s) ds$$

solution $X(t) = X_0 e^{-rt}$

stochastic

$$X(t) = X_0 + \int_0^t -rX_s ds$$

$$+ \int_0^t \sigma dW_s$$

stochastic integral

Consider smooth function $f(t, x)$

$$f_1 = \frac{\partial f}{\partial t}, \quad f_2 = \frac{\partial f}{\partial x}, \quad f_{11} = \frac{\partial^2 f}{\partial t^2}$$

$$f(t + dt, v_t + dv_t) - f(t, v_t)$$

$$\begin{aligned} &= f_1 dt + f_2 dv_t + \frac{1}{2} \left(f_{11} dt^2 \right. \\ &\quad \left. + 2 f_{12} dt dv_t + f_{22} (dv_t)^2 \right) + \dots \\ &\quad \frac{||}{dt} \end{aligned}$$

$$\sim f_1 dt + f_2 dv_t + \frac{1}{2} f_{22} dt$$

Interval



$$s=0$$

$$s=t$$

$$\begin{aligned}
 & \sum_{j=0}^{N-1} \left\{ f(s_{j+1}, w_{j+1}) - f(s_j, w_j) \right\} \\
 & \approx \int_0^t \left(f_1 + \frac{1}{2} f_{22} \right) ds + \int_0^t f_2 dw_s \\
 & = f(t, w_t) - f(0, w_0)
 \end{aligned}$$

Now $dX_t = A_t dt + B_t dw_t$

see slide

$$f(t, X_t) - f(0, X_0) =$$

$$\begin{aligned}
 & \int_0^t f_1 ds + f_2 \left(A_s ds + \frac{B_s}{2} dw_s \right) + \\
 & \frac{1}{2} f_{22} \left(A_s^2 ds^2 + 2 A_s B_s ds dw_s \right. \\
 & \quad \left. + \frac{B_s^2}{2} (dw_s)^2 \right)
 \end{aligned}$$

Finally

$$f(t, X_t) - f(0, X_0) = \int_0^t \left(f_1 + \frac{1}{2} B_s^2 f_{22} + f_2 A_s \right) ds \\ + \int_0^t f_2 A_s dB_s$$

Example : $A_s = -fX_s$, $B_s = 0$

take $f(t, x) = x e^{ft}$

$$f_1 = f, f_2 = e^{ft}, f_{22} = 0$$

$$\rightarrow X_t e^{ft} - X_0 = \int_0^t \left(f X_s e^{fs} + e^{f(s-t)} f X_s \right) ds \\ + \int_0^t e^{fs} 0 dB_s$$

hence

$$X_t = e^{-\frac{1}{2}t} \left(X_0 + \sigma \int_0^t e^{\frac{1}{2}s} dW_s \right)$$

Ornstein - Uhlenbeck

process

Autocorrelation :

$$\begin{aligned} \text{Cov}[X_t, X_{t+s}] &= E[X_t X_{t+s}] \\ &= E\left[\left(e^{-\frac{\sigma}{2}t} X_0 + \sigma e^{\frac{\sigma}{2}t} \int_0^t e^{\frac{\sigma}{2}q} dW_q\right) * \right. \\ &\quad \left. * \left(-e^{\frac{\sigma}{2}(s+t)} X_0 + \sigma e^{\frac{\sigma}{2}(s+t)} \int_0^{t+s} e^{\frac{\sigma}{2}p} dW_p\right)\right] \\ &= X_0^2 e^{-\frac{\sigma}{2}(2t+s)} + \sigma^2 e^{\frac{\sigma}{2}(2t+s)} * \\ &\quad \left[E\left[\int_0^t dW_q \int_0^{t+s} e^{\frac{\sigma}{2}(q+p)} dW_p \right] \right] \end{aligned}$$

note that $E[dW] = 0$ so
cross products are zero.

Write

$$dW_q = \eta(q) dq$$

$$dW_p = \eta(p) dp$$

η : white noise

then

$$I = E \left[\int_0^t dq \int_0^{t+s} e^{r(p+q)} \eta(p) \eta(q) dp \right]$$

use $E [\eta(t) \eta(t')] = \delta(t-t')$

$$\begin{aligned} I &= \int_0^t dq \int_0^{t+s} e^{r(p+q)} \delta(p-q) dp \\ &= \int_0^t dq e^{2rt} = \frac{1}{2r} \left(e^{2rt} - 1 \right) \end{aligned}$$

Finally

$$\begin{aligned} E[X_t X_{t+s}] &= e^{r(2t+s)} \left[X_s^2 \right. \\ &\quad \left. + \sigma^2 \frac{e^{2rt} - 1}{2r} \right] \end{aligned}$$

s fixed , $t \rightarrow \infty$

$$E[X_t X_{t+s}] = \frac{\sigma^2}{2r} e^{-rs}$$

Variance $E[X_t^2] = \frac{\sigma^2}{2r}$

From time series :

$$X_{t_{n+1}} = e^{-rt_{n+1}} \left(X_0 + \sigma \int_0^{t_{n+1}} e^{rs} dW_s \right)$$

$$\overset{-r\Delta t}{e} X_{t_n} = e^{-rt_n} \left(X_0 + \sigma \int_0^{t_n} e^{rs} dW_s \right)]$$

$$t_{n+1} = t_n + \Delta t$$

subtract :

$$\alpha \in (0, 1)$$

$$X_{t_{n+1}} - \overset{e^{-r\Delta t}}{\cancel{X_{t_n}}} =$$

$$= \sigma \int_0^{t_{n+1}} e^{rs} dW_s - \int_0^{t_n} e^{r(s-\Delta t)} dW_s$$

$$\underline{z_{n+1}}$$

$$\rightarrow X_{n+1} - \cancel{X_n} = z_{n+1}$$

$$\sum \mathcal{N}(0, \sigma^2) \quad \text{Var}[z] = \sigma^2$$

AR(1) process :

$$X_i = \alpha X_{i-1} + \varepsilon_i$$

$$= \alpha (\alpha X_{i-2} + \varepsilon_{i-1}) + \varepsilon_i$$

$$= \varepsilon_i + \alpha \varepsilon_{i-1} + \dots + \alpha^i \varepsilon_0$$

$$E[X_i] = 0 \quad \text{when } E[X_0] = 0$$

Use $\text{Var}[\alpha X + \beta Y] =$

$$\alpha^2 \text{Var}[X] + 2\alpha\beta \text{Cov}[X, Y]$$

$$+ \beta^2 \text{Var}[Y]$$

$$\rightarrow \text{Var}[X_i] = \text{Var}[\varepsilon_i] + \alpha^2 \text{Var}[\varepsilon_{i-1}]$$

$$+ \dots + \alpha^{2i} \text{Var}[\varepsilon_0] = 0$$

$$= \sigma^2 \left(1 + \alpha^2 + \alpha^4 + \dots \right)$$

$$= \frac{\sigma^2}{1 - \alpha^2}$$

$$\begin{aligned}
& E[X_i X_{i+k}] = \\
& E \left[\left(z_i + \alpha z_{i-1} + \dots + \alpha^{i-1} z_1 \right) * \right. \\
& \left. * \left(z_{i+k} + \alpha z_{i+k-1} + \dots + \alpha^{k+i-1} z_1 \right) \right] \\
& = \alpha^k \sigma^2 \left(1 + \alpha^2 + \alpha^4 + \dots \right) \\
& = \alpha^k \sigma^2 / (1 - \alpha^2)
\end{aligned}$$

Hence

$$\begin{aligned}
s_k &= \frac{E[X_i X_{i+k}]}{\text{Var}[X_i]} \\
&= \alpha^k
\end{aligned}$$