Modélisation de la dynamique d'une population de poisson exploitée par un modèle de production de Biomasse

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Etienne RIVOT

Institut Agro, Rennes

Département Ecologie, UP Ecologie Halieutique

UMR DECOD Ecosystem Dynamic and Sustainability

etienne.rivot@institut-agro.fr

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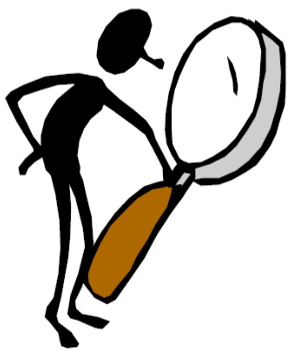
La modélisation intégrée en écologie statistique

Methodological challenges of statistical ecology

Methodological challenges of Statistical Ecology

- **Model issues**
  - **Multiple form of dependencies (time, space, clustering …)**
  - **Variability and stochasticity (demographic, environmental)**



- **Data issues**
  - **Highly correlated**
  - **Hierarchical structure**
  - **Incomplete (missing data)**
  - **Noisy**
  - **Not directly related to the process of interest**

The Ecological Detective - Hilborn et Mangel, 1997

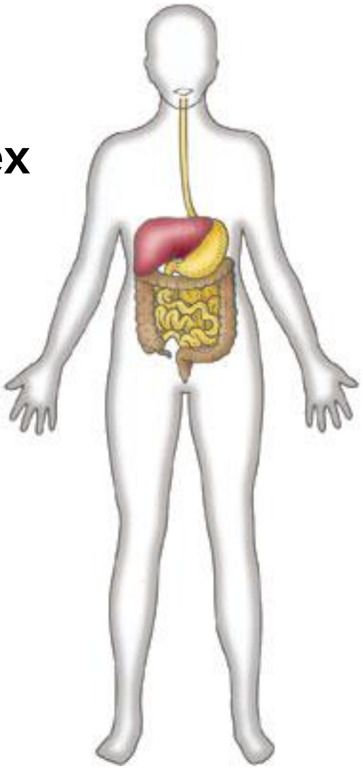
« Counting fish is like counting trees, except they are invisible and they move »

R. Sheperd

« On ne peut pas vider la baignoire »

Integrating multiple sources of information in complex models

Complex system (hidden state)



Multiple observation process with errors

Requires a flexible approach to fusing models with data, an approach that can accomodate uncertainties in the way ecological processes operate and the way we observe them

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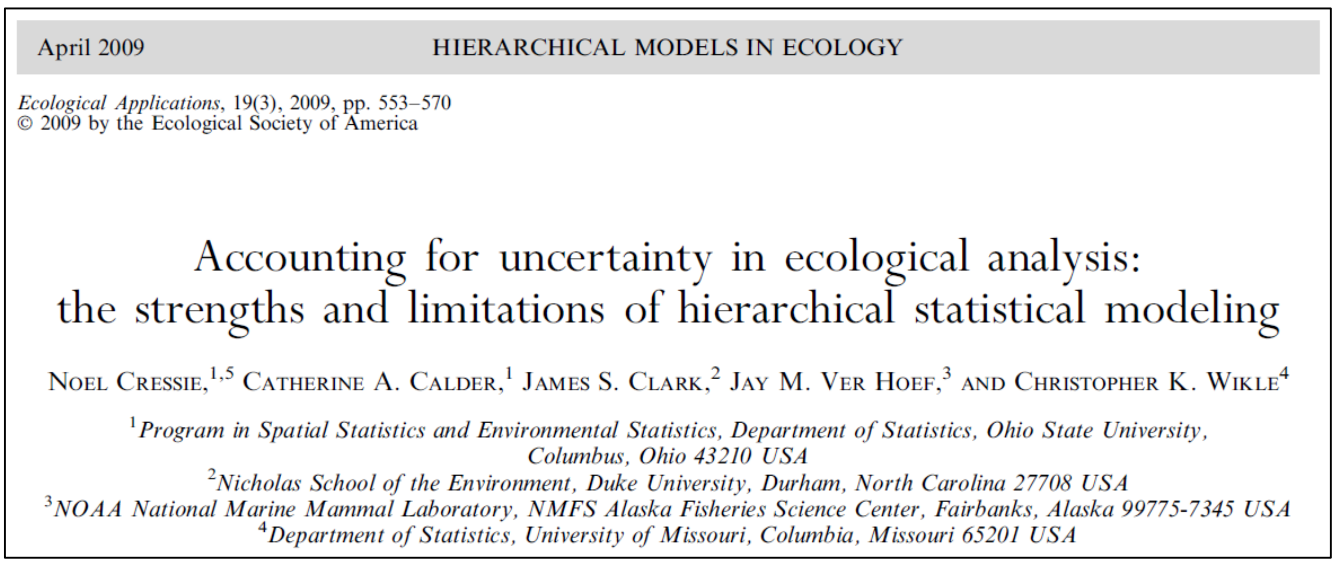
Hierarchical models
State-space models

Hierarchical models (random effects models)

- **A wide class of models**
  Key tools in modern statistical ecology with multiple applications
- **Bayesian <u>or</u> “Classical” framework**



April 2009 HIERARCHICAL MODELS IN ECOLOGY

Ecological Applications, 19(3), 2009, pp. 553–570
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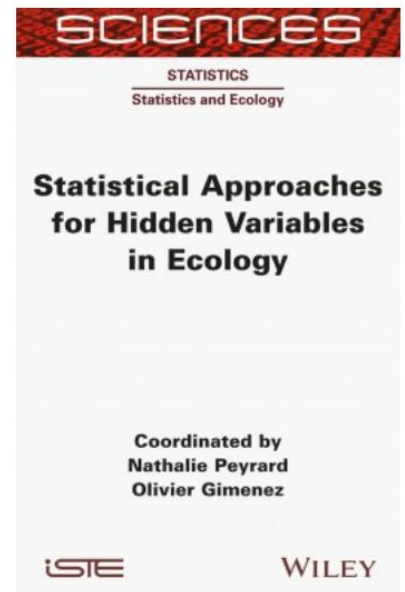
Accounting for uncertainty in ecological analysis: the strengths and limitations of hierarchical statistical modeling

Noel Cressie,[1,5] Catherine A. Calder,[1] James S. Clark,[2] Jay M. Ver Hoef,[3] and Christopher K. Wikle[4]

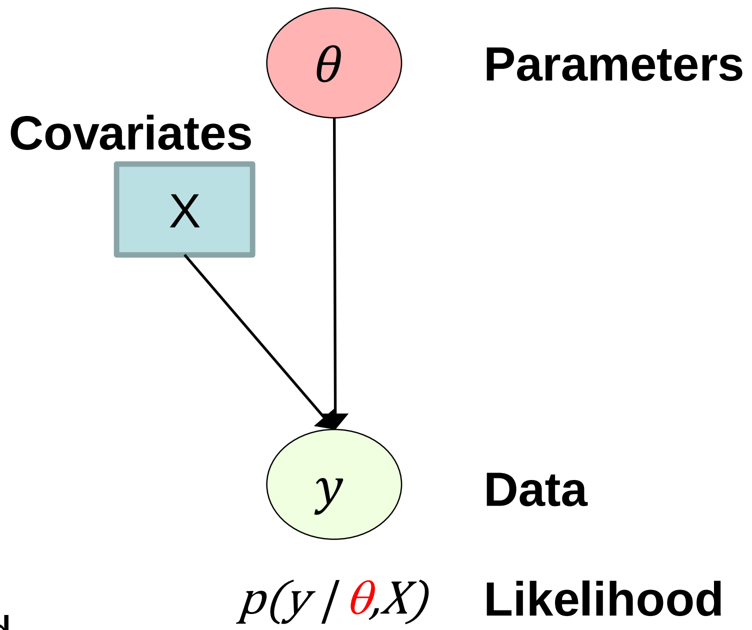
[1] *Program in Spatial Statistics and Environmental Statistics, Department of Statistics, Ohio State University, Columbus, Ohio 43210 USA*
[2] *Nicholas School of the Environment, Duke University, Durham, North Carolina 27708 USA*
[3] *NOAA National Marine Mammal Laboratory, NMFS Alaska Fisheries Science Center, Fairbanks, Alaska 99775-7345 USA*
[4] *Department of Statistics, University of Missouri, Columbia, Missouri 65201 USA*



Simple (non hierarchical) models

- "Simple" (non hierarchical) statistical models directly express the sampling distribution of the data y conditionnaly upon parameters θ and fixed covariates X *(the likelihood function)*

$$L(\theta, y, X) = p(y \mid \theta, X)$$



- Generally limited to correlative approaches, seeking to
  - Estimates "effects" of covariates X
  - Quantify the amount of variance explained by covariates / residual noise

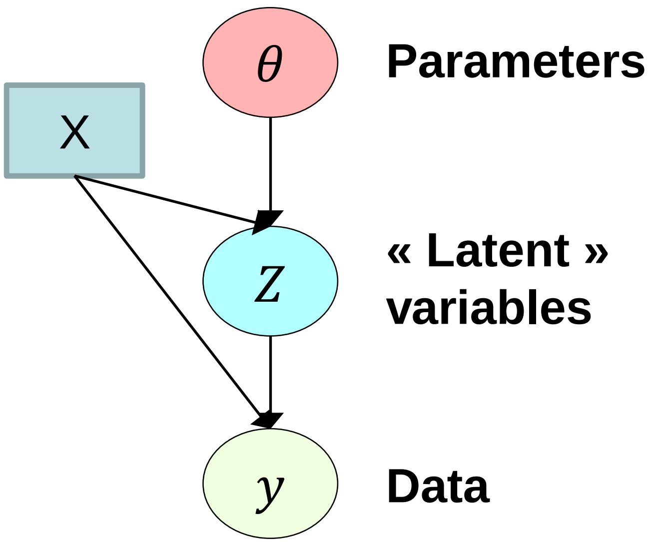
Hierarchical (multi-level) models

- **Hierarchical models** (or multi-level models) **make use of intermediate non observed (latent, hidden) variables**

  Observed data, which are random variables at one level, depend upon another set of random variables, generally not observed directly (= the latent variables), at a higher level

  The latent variables *Z* can be structured in multiple layers

  Conditional probability distributions are used to structure the dependencies

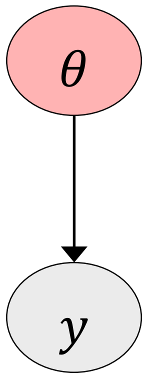


Likelihood

$$p(y,Z|\theta,X) = p(Z|\theta,X) \times p(y|Z,\theta,X)$$

Non hierarchical models

Unknowns



Parameters *(hyperparameters)*

Data

p(y / θ) *Likelihood*

Maximum likelihood

Latent states must be integrated out

$$\hat{\theta} = argmax\ \{P(y|\theta)\}$$

Bayes

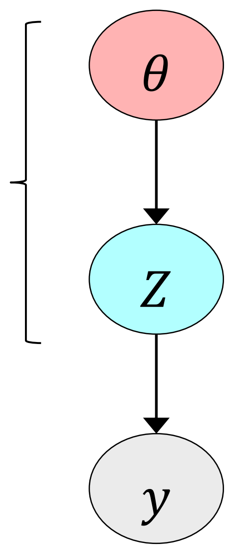
Joint posterior distribution

$$P(\theta|y) \propto \underbrace{P(\theta)}_{Param.} \times \underbrace{P(y|\theta)}_{Lik.}$$

Inferences on Hierarchical Models

Clark, 2005 ; Buckland et al., 2007 ; Cressie et al., 2009 ; Parent and Rivot, 2013

Unknowns



Parameters

$p(Z\,/\,\theta)$

All intermediate “process” of interest

Z = « latent » or « hidden » variables

$p(y\,/\,Z,\theta)$

Maximum likelihood

Latent states must be integrated out

$$\hat{\theta} = argmax\ \{L(\theta, y)\} = argmax \left\{ \int_{States=z} L(\theta, Z, y)\ dz \right\}$$

Bayes

Joint posterior distribution

$$P(\theta, Z|y) \propto \underbrace{P(\theta)}_{Param.} \times \underbrace{P(z|\theta)}_{Latent\ var} \times \underbrace{P(y|Z,\theta)}_{Lik.}$$

State-space models

- **State-space models are a special class of hierarchical models where the latent layer has a dynamic dimension (and by extension, spatial or spatio-temporal dimensions)**

- **In SSMs, inferences on the latent process $Z|\theta$ may have as much interest (or even more) than the top level parameters**

  Exp : $Z|\theta$ is the population dynamics model with transition rates θ

REVIEW

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A guide to state–space modeling of ecological time series

Marie Auger-Méthé,[1,2,13] Ken Newman,[3,4] Diana Cole,[5] Fanny Empacher,[6] Rowenna Gryba,[1,2] Aaron A. King,[7] Vianey Leos-Barajas,[8,9] Joanna Mills Flemming,[10] Anders Nielsen,[11] Giovanni Petris,[12] and Len Thomas[6]

https://doi.org/10.1002/ecm.1470

State-space models

Process equation

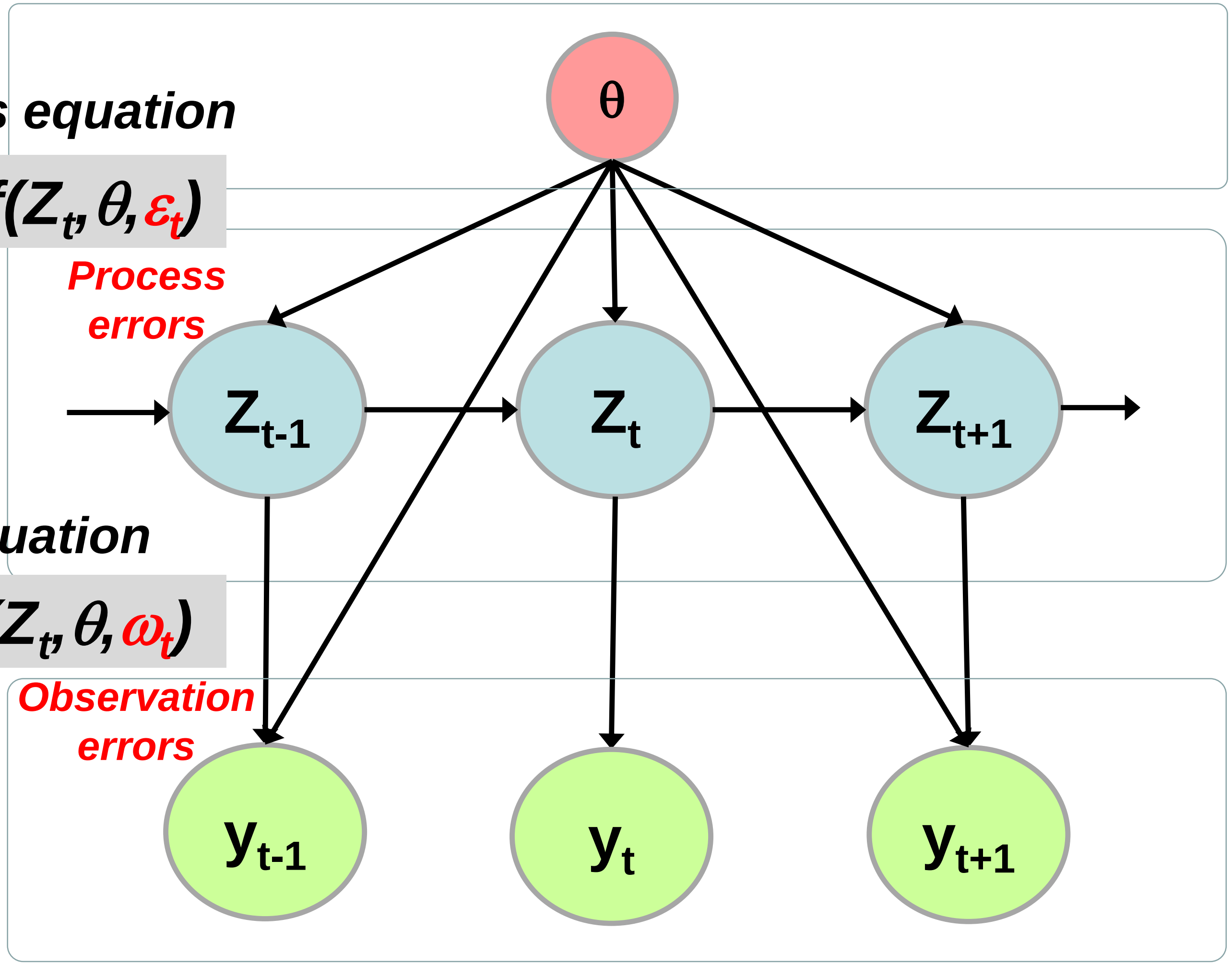
$$Z_{t+1} = f(Z_t, \theta, \varepsilon_t)$$

Process errors

Obs. equation

$$y_t = g(Z_t, \theta, \omega_t)$$

Observation errors



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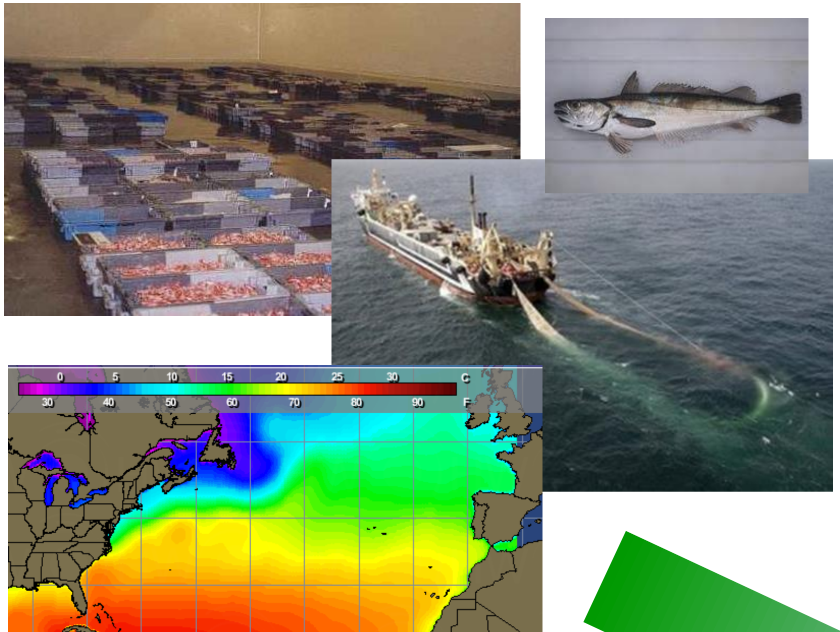
Hierarchical models
State-space models
&
Fisheries sciences

La modélisation : une charnière essentielle



Observations

Modelling
- Demography
- Anthropic pressure
- Envir. pressure
- Inter-specific interactions

Advice
Decision

Integrated state-space population models are key tools in fisheries ecology

in particular in modern stock-assessment

"Integrating more data and more biological and ecological knowledge in stock assessments"

Aeberhard, W. H., Mills Flemming, J., & Nielsen, A. (2018). Review of State-Space Models for Fisheries Science. *Annual Review of Statistics and Its Application*, *5*(1), 215-235. https://doi.org/10.1146/annurev-statistics-031017-100427

Punt, A. E., Dunn, A., Elvarsson, B. Þ., Hampton, J., Hoyle, S. D., Maunder, M. N., Methot, R. D., & Nielsen, A. (2020). Essential features of the next-generation integrated fisheries stock assessment package : A perspective. *Fisheries Research*, *229*, 105617. https://doi.org/10.1016/j.fishres.2020.105617

Auger-Méthé, M., Newman, K., Cole, D., Empacher, F., Gryba, R., King, A. A., Leos-Barajas, V., Mills Flemming, J., Nielsen, A., Petris, G., & Thomas, L. (2021). A guide to state–space modeling of ecological time series. *Ecological Monographs*, *91*(4), e01470. https://doi.org/10.1002/ecm.1470

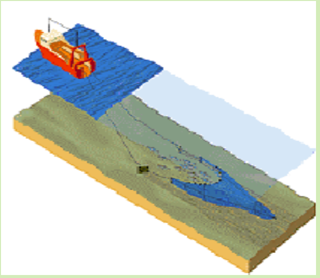
State-space models

What I want to represent

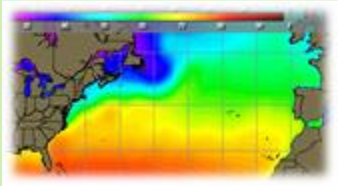
What I see

Commercial data

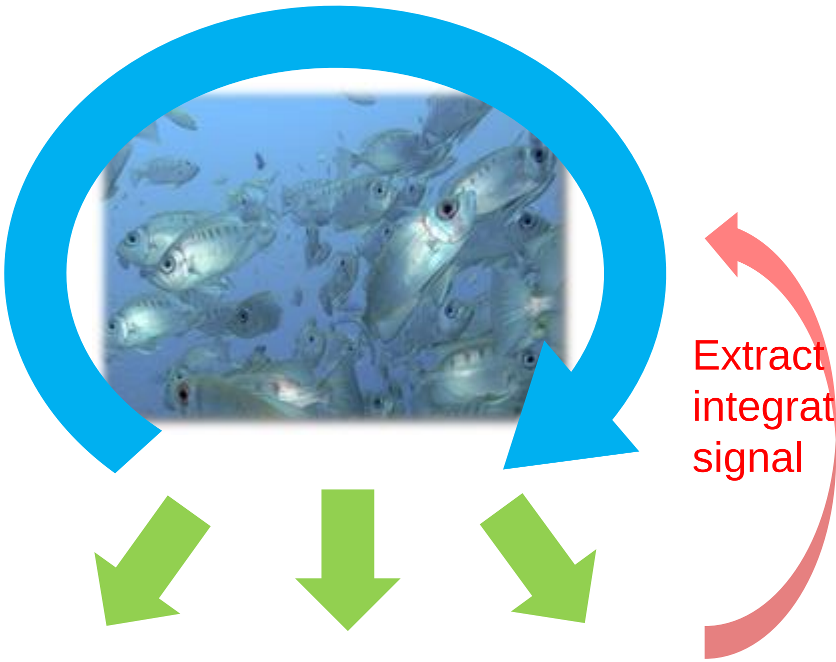
Scientific data



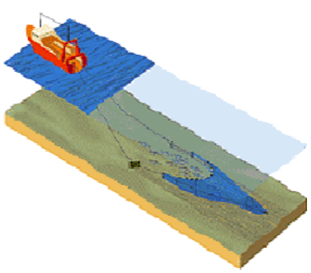
Environmental data

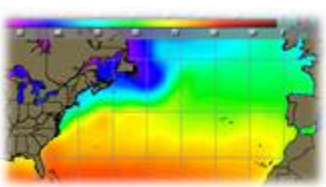


Develop integrated approaches to fusing multiple sources of observations in complex models



Commercial data | Scientific data | Environmental data





Complex ecological systems

- Hidden
- Demography
- Influence of multiple factors
- Multiple sources of variability and uncertainty
- A hierarchy of scales

Multiple observations with errors

- Heterogeneous surveys
- Sampling & measurement errors
- Missing data

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The Namibian hake fishery

Namibian Hake

The most important fish resource in Namibia

2 species

Merluccius capensis ("white hake")

"white hake"

the dominant species

Merlucius paradoxus

"black hake"

Treated as a single stock

Look very similar

Difficult to record data separately

Merluccius capensis

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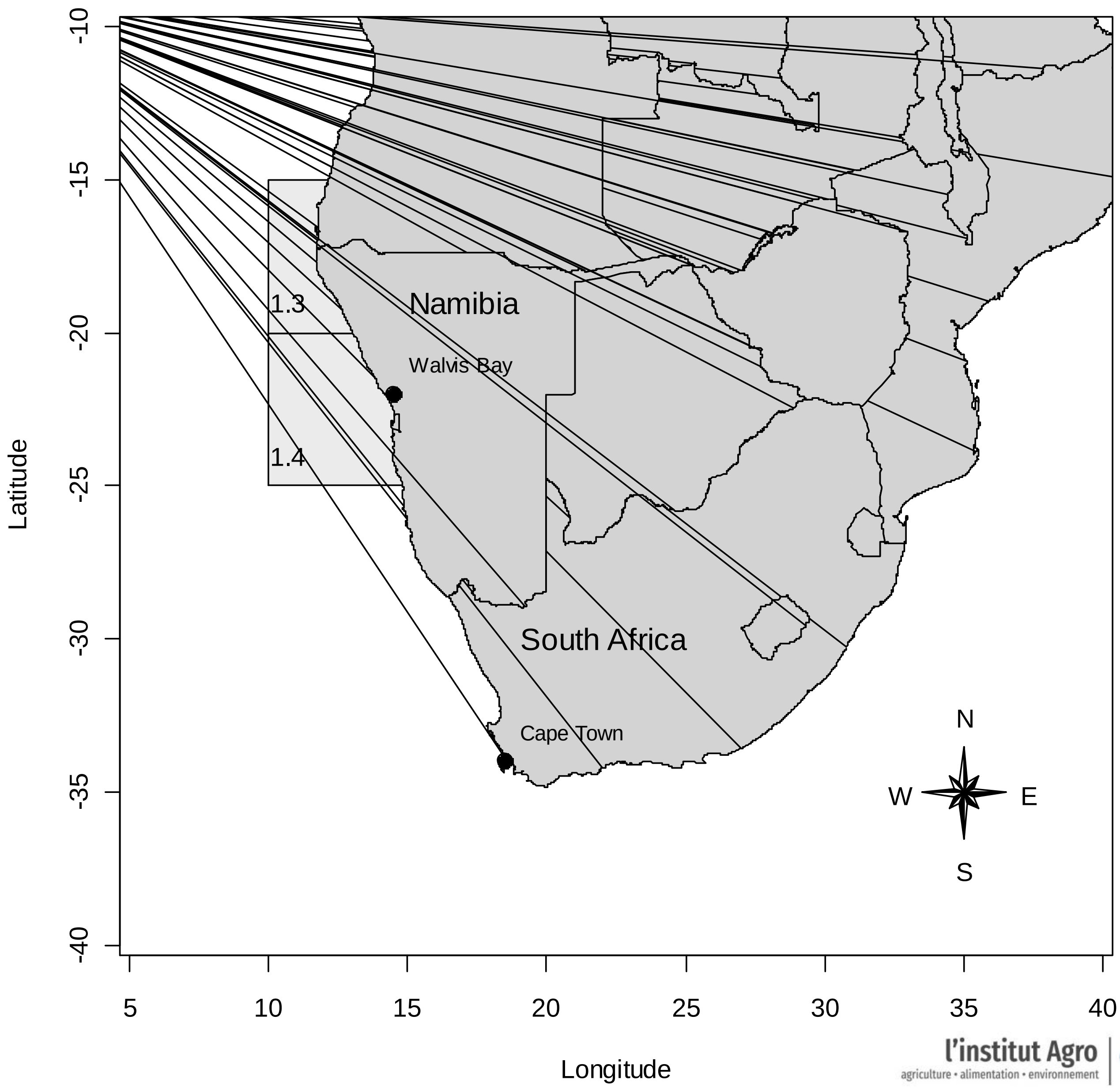
The Benguela upwelling system

One of the world‟s major eastern boundary upwelling systems



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Namibian Hake fishery - 1964-1988

A textbook case

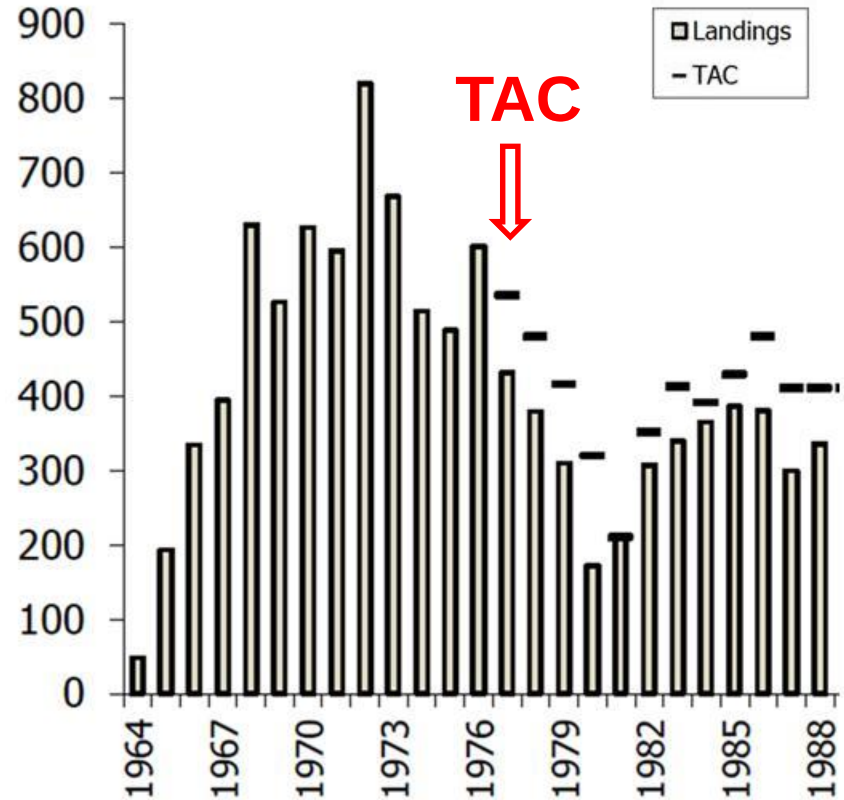
Exploitation of the Namibian hake resource commenced in 1964.

The fishery was unregulated over the period 1964-1976. During this period, an average of about 500 000 tonnes of hake was reported landed per year.

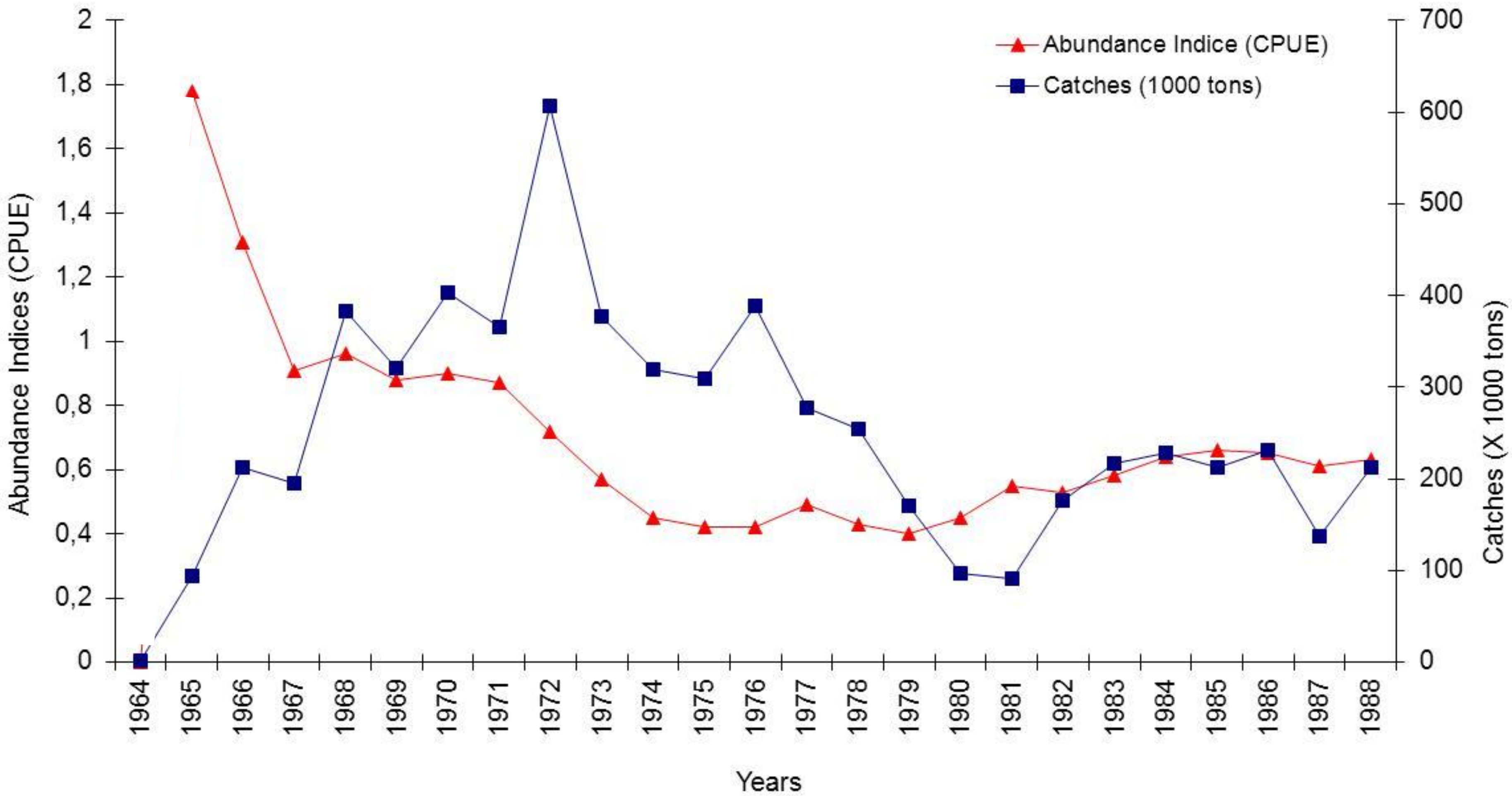
The International Commission for South East Atlantic Fisheries (ICSEAF) was formed in 1969.

A minimum mesh size of 110 cm was introduced in 1975.

From 1977 through 1989, the fishery is managed through annual TACs.
Between 1980 and 1990, the average annual catch was reduced to about 325 000 tons.



Namibian Hake fishery - 1964-1988



Objectives

- **Assess fishery / stock status with regards to management reference points**

  - Maximum Sustainable Yield (MSY)

  - Biomass at MSY …

  (based on historical data)

- **Evaluate alternative management options (scenarios)**

- **All within a probabilistic rationale accounting for all sources of uncertainty**

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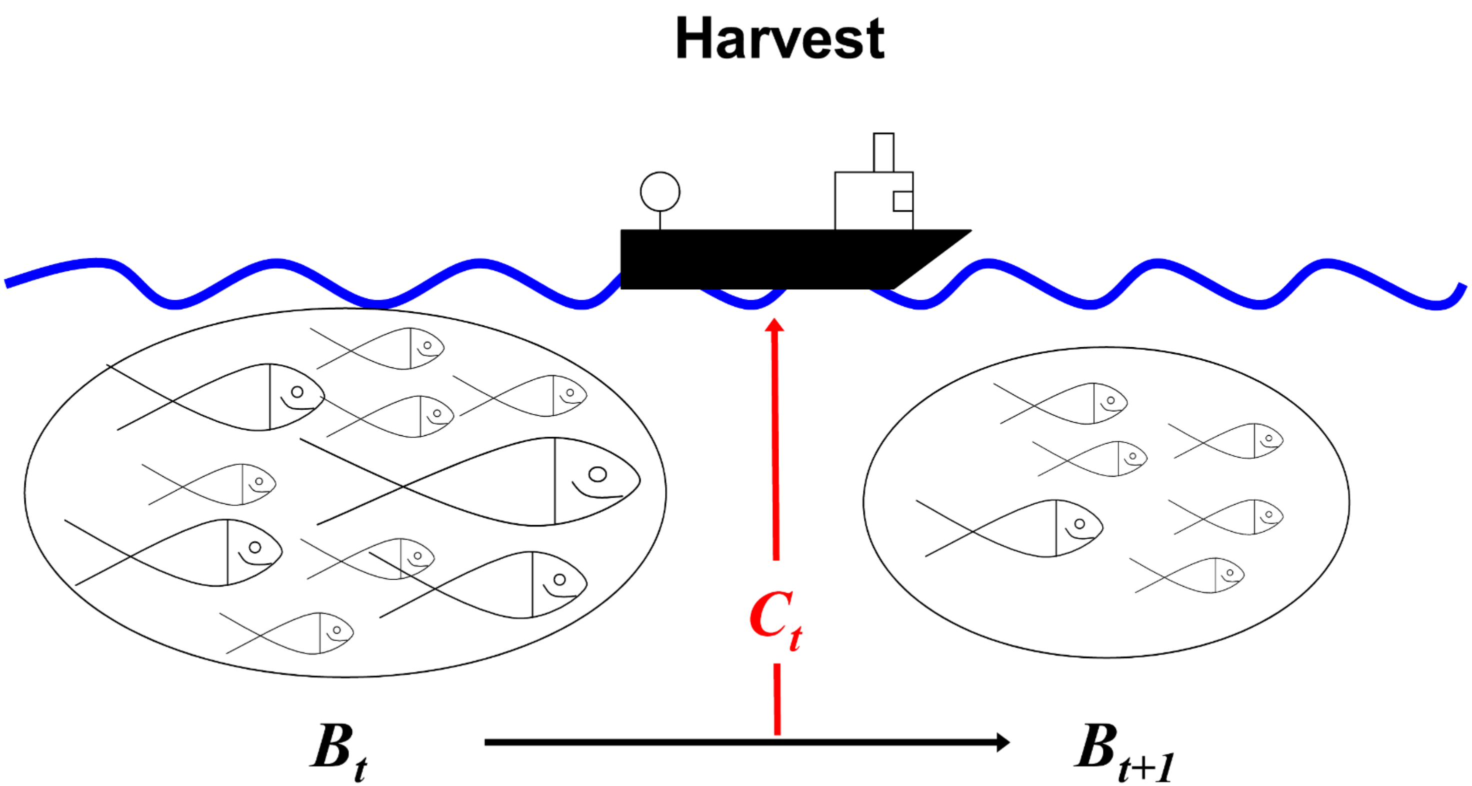
The Biomass production model

The Biomass production model



$$B_{t+1} = B_t + g(B_t) - C_t$$

The Biomass production model

A model to mimic the dynamic of the Biomass

A non-age-structured model (global model) used in practical stock assessments and fisheries management

Pro's of the surplus production model :

- Simple, parcimonious

- No need of detailed data (*e.g.* age –structured data)

- Quantity of interest for management are easily derived :
  - C_{MSY}, : Captures at Maximum Sustainable Yield
  - B_{MSY} : Biomass level at MSY
  - F_{MSY} : Harvest rate at MSY

- Link with bio-economic modelling

The Biomass production model

$$\frac{dB(t)}{dt} = g(B(t),\theta) - C(B(t))$$

g = production function with parameters θ

C = captures (control). Generally C = F.B

Difference model (discrete time)

Next biomass =

old biomass + recruitment - nat. mortality - captures

$$B(t+1) = B(t) + g(B(t),\theta) - C(t) \qquad (with\, C(t) = F(t) \cdot B(t))$$

The Biomass production model

Production function *g*

Schaefer

$$\frac{dB(t)}{dt} = r \cdot B(t) \cdot (1 - \frac{B(t)}{K}) - C(t)$$

Fox

$$\frac{dB(t)}{dt} = r \cdot B(t) \cdot (1 - \frac{\log_e(B(t))}{\log_e(K)}) - C(t)$$

Pella-Tomlison
(general prod. model)

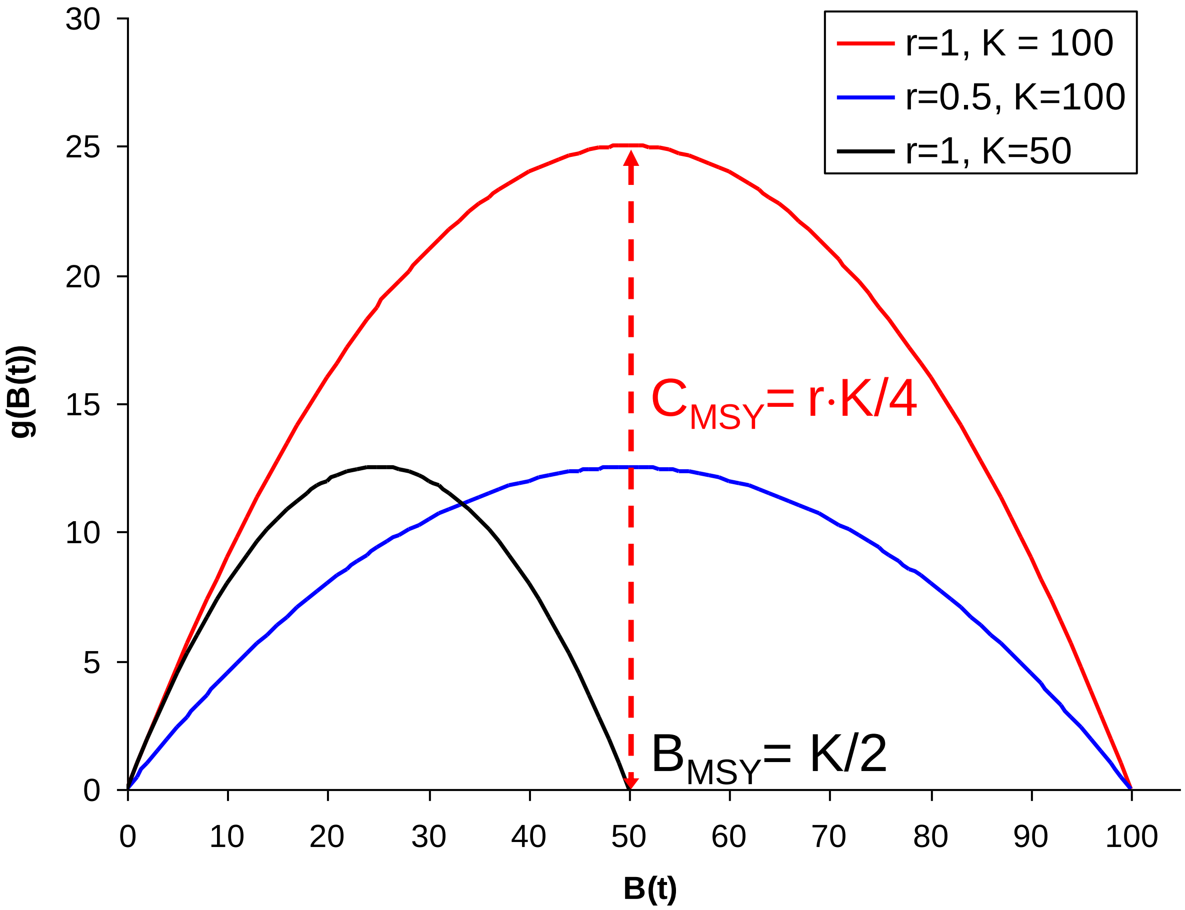
$$\frac{dB(t)}{dt} = r \cdot B(t) \cdot (1 - \left(\frac{B(t)}{K}\right)^{m-1}) - C(t)$$

Rk :

C(t) = q·E · B(t)

Reference points (for management)

Example : Schaefer



Deriving management reference points

Shaefer production model

$$B(t+1)=B(t)+g(B(t))-C(t)$$

$$g(B(t))=\rho\cdot B(t)\cdot(1-\frac{1}{\kappa}\cdot B(t))$$

Equilibrium state

$$B=B+g(B)-C \quad \Rightarrow \quad C=g(B)$$

MSY (maximum captures)

$$\left.\frac{\partial g(B)}{\partial B}\right|_{B_{MSY}}=0$$

$$\frac{\partial g(B)}{\partial B}=\rho\cdot(1-\frac{1}{\kappa}\cdot B)-\frac{\rho\cdot B}{\kappa}=\rho-2\cdot\frac{\rho\cdot B}{\kappa}$$

$$\left.\frac{\partial g(B)}{\partial B}\right|_{B_{MSY}}=0 \quad \Rightarrow \quad B_{MSY}=\frac{\kappa}{2}$$

$$\boxed{B_{MSY}=\frac{\kappa}{2} \qquad C_{MSY}=\frac{\rho\cdot\kappa}{4} \qquad F_{MSY}=\frac{C_{MSY}}{B_{MSY}}=\frac{\rho}{2}}$$

Deriving management reference points

	Modèle généralisé (m quelconque)	m=2 : Modèle de SCHAEFER	m→1 : Modèle exponentiel
Be(E)	$K.\left(1-\frac{q}{r}.E\right)^{\frac{1}{m-1}}$	$K-\frac{q.K}{r}.E$	$K.e^{\left(-\frac{q.Ln(K)}{r}.E\right)}$
Ue(E)	$q.K.\left(1-\frac{q}{r}.E\right)^{\frac{1}{m-1}}$	$q.K-\frac{q^2.K}{r}.E$	$q.K.e^{\left(-\frac{q.Ln(K)}{r}.E\right)}$
Ye(E)	$q.E.K.\left(1-\frac{q}{r}.E\right)^{\frac{1}{m-1}}$	$q.K.E-\frac{q^2.K}{r}.E^2$	$q.E.K.e^{\left(-\frac{q.Ln(K)}{r}.E\right)}$
E_r	$\frac{r}{q}$	$\frac{r}{q}$	∞
E_M	$\frac{r}{q}.\frac{m-1}{m}$	$\frac{r}{2.q}$	$\frac{r}{q.Ln(K)}$
MSY : Y_M	$r.K.\frac{m-1}{m^{\frac{m}{m-1}}}$	$\frac{r.K}{4}$	$\frac{r.K}{e.Ln(K)}$

Key assumptions

All parameters are constant over time

- Biological/ecological processes *r,K*
- *Fisheries dependent process q*
  - *Explore the sensitivity of the results to change in q ?*
  - *See Cook et al. 2021 for an example of modelling change in fishing power*

Cook, R., Acheampong, E., Aggrey-Fynn, J., & Heath, M. (2021). A fleet based surplus production model that accounts for increases in fishing power with application to two West African pelagic stocks. *Fisheries Research*, *243*, 106048. https://doi.org/10.1016/j.fishres.2021.106048