Management of coupled nonstationary dynamic bioeconomic systems

Keith R. Criddle

School of Fisheries and Ocean Science, University of Alaska Fairbanks, 17101 Point Lena Loop Road, Juneau, Alaska, 99801, USA.

keith.criddle@uaf.edu

The dynamics of a collection of fish stocks can be represented as:

$$(1) \qquad \mathbf{x}_t = f\begin{pmatrix} \mathbf{x}_{t+\infty},\ldots,\mathbf{x}_t,\ldots,\mathbf{x}_{t-l},\ldots,\mathbf{x}_{t-\infty}, \\ \mathbf{y}_{t+\infty},\ldots,\mathbf{y}_t,\ldots,\mathbf{y}_{t-k},\ldots,\mathbf{y}_{t-\infty}, \\ \mathbf{h}_{t+\infty},\ldots,\mathbf{h}_t,\ldots,\mathbf{h}_{t-j},\ldots,\mathbf{h}_{t-\infty}, \\ \mathbf{w}_{t+\infty},\ldots,\mathbf{w}_t,\ldots,\mathbf{w}_{t-i},\ldots,\mathbf{w}_{t-\infty}, \end{pmatrix} + \boldsymbol{\varepsilon}_t$$

where

$\mathbf{x}_t$ is a vector of the biomass (or numbers),

$\mathbf{y}_t$ is a vector of the of environmental factors,

$\mathbf{h}_t$ is a vector of fishing mortalities,

$\mathbf{w}_t$ is a vector of additional control variables, and

ε_t is a vector of process errors.

Equation (1) can be written more compactly as:

$$(1') \qquad \mathbf{x}_t = f\left(\mathbf{X}_{t-l}, \mathbf{Y}_{t-k}, \mathbf{H}_{t-j}, \mathbf{W}_{t-i}\right) + \boldsymbol{\varepsilon}_t$$

It is usually assumed that $f(\bullet)$ is observable, that $\mathbf{x}_t$ and $\mathbf{y}_t$ are observable and stationary, and that $\mathbf{h}_t$ and $\mathbf{w}_t$ are controllable.

The error will be characterized by contemporaneous and serial correlations; in practice, it may also include observation, specification, and estimation error.

Equation (1) offers a description of changes in $\mathbf{x}_t$ conditional on $\mathbf{y}_t$, $\mathbf{h}_t$, and $\mathbf{w}_t$.

While this may be useful for describing the past, the utility of any predictions about future or conditional future values of $\mathbf{x}_{t+h}$ will be contingent on:

- **the quality of predictions about $\mathbf{y}_{t+h}$, $\mathbf{h}_{t+h}$, and $\mathbf{w}_{t+h}$,**
- **the validity of the assumption that the variables are observable and controllable,**

and

- **the validity of the stationarity assumption or the validity of characterizations of the nature of nonstationarities**

While equation (1) describes the suite of feasible states of nature ($\mathbf{x}_t$), it does not identify preferred states of nature.

That is, equation (1) does not provide or represent management objectives.

Management objectives can be described in terms of maximum utility or minimum regret functions.

The utility maximization objective can be represented by:

(2) $$max(\mathbf{U}) = \left(\frac{1}{1+r}\right)^{t} \sum_{t=0}^{\infty} \mathbf{u}_t = g(\mathbf{x}_t, \mathbf{y}_t, \mathbf{h}_t, \mathbf{w}_t, \varepsilon_t)$$

where $\mathbf{u}_t$ is the total net utility that society derives from given combinations of $\mathbf{x}_t$, $\mathbf{y}_t$, $\mathbf{h}_t$, and $\mathbf{w}_t$, and r is the rate at which society discounts future utility.

Equation (2) offers a description social preferences about alternative states of nature ($\mathbf{x}_t$, $\mathbf{y}_t$), but does not ensure that preferred solutions are feasible.

Implicit in the specification of equation (2) are assumptions that:

- **The utility associated with stocks and flows of use and nonuse benefits can be reified**
- **That mechanisms exist for reconciling gains and losses across individuals**
- **That the controls ($\mathbf{h}_t$,$\mathbf{w}_t$) are legally permissible, efficacious, and enforceable**

Equations (1) and (2), together with admissibility restrictions, represent the constrained optimization problem of fisheries management from the scale of single species surplus yield models through to multiple criterion ecosystem models.

$$max\left(\mathbf{U}\right) = \left(\frac{1}{1+r}\right)^{t} \sum_{t=0}^{\infty} \mathbf{u}_t = g\left(\mathbf{x}_t, \mathbf{y}_t, \mathbf{h}_t, \mathbf{w}_t, \boldsymbol{\varepsilon}_t\right)$$

(3)

$$\mathbf{x}_t = f\left(\mathbf{X}_{t-l}, \mathbf{Y}_{t-k}, \mathbf{H}_{t-j}, \mathbf{W}_{t-i}\right) + \boldsymbol{\varepsilon}_t$$

$$\mathbf{x}_t \geq 0 \quad \mathbf{x}_t \geq \mathbf{h}_t \geq 0$$

The challenges are that:

- **$f(\bullet)$ and $g(\bullet)$ are unknown with respect to**
  - **the form of functional relationships,**
  - **the nature of lagged relationships,**
  - **the complexity of contemporaneous and intertemporal interactions in modeled relationships and associated errors,**

and

- **the variables are, for the most part, unobservable.**

In theory, there is no difference between theory and practice. In practice there is.

Yogi Berra

Fisheries models are merely imperfect metaphors; to be used to emphasize tangible attributes that are asserted to be similar to the intangible attributes of the real world.

One advantage of formal models is that their assumptions are exposed to criticism.

Equation (3) can be used as a basis for contrasting the assumptions of competing models.

For example, single species surplus yield models coupled with MSY objectives can be represented as

(4)

$$max(SY_{\lambda}) \quad x_{\lambda t} = f(x_{\lambda t-1}, h_{\lambda t-i}) + \varepsilon_{\lambda t} \quad \forall \lambda$$
$$x_{\lambda t} \geq 0 \quad h_{\lambda t} \geq 0$$

A model that omits species interactions, ignores environmental variation, assumes that bycatch is trivial, identifies catches as the sole control variable and suggests that social benefits can be characterized in terms of the magnitude of catches.

If the true system is characterized by interactions among species, simultaneous maximization of MSY across species is unlikely to be feasible.

For estimation, it is necessary to further simplify equation (4) by specifying particular functional forms and lag relationships, e.g., simple logistic surplus yield models with and without Ricker recruitment:

$$max\left(SY_{\lambda}\right) \quad x_{\lambda t} = \beta_1 x_{\lambda t-1} + \beta_2 x_{\lambda t-1}^2 + \beta_3 h_{\lambda t-1} + e_{\lambda t} \quad \forall \lambda$$

$$x_{\lambda t} \geq 0 \quad h_{\lambda t} \geq 0$$

(4')

$$max\left(SY_{\lambda}\right) \quad \begin{aligned} x_{\lambda t} &= \beta_1 x_{\lambda t-1} + \beta_2 x_{\lambda t-1}^2 + \beta_3 h_{\lambda t-1} \\ &+ \beta_4 x_{\lambda t-4} \mathrm{e}^{\left(\beta_5 x_{\lambda t-4}\right)} + e_{\lambda t} \end{aligned} \quad \forall \lambda$$

$$x_{\lambda t} \geq 0 \quad h_{\lambda t} \geq 0$$

If the true system is characterized by equation (3) and it is modeled by equation (4'), the estimated parameter values (growth, recruitment, and the effect of fishing) will be biased by the omission of nontrivial trophic, environmental, lag, and nonlinear effects.

That is, while we can be confident that that the estimated parameter values are wrong, we can't know if they are biased high or low or whether the bias depends on the absolute magnitude of biomass or catch.

Moreover, there is no basis for supposing that the MSY harvest level maximizes overall economic or social benefits from harvests of the target stock, let alone harvests of composite stocks.

Furthermore, the solution will be infeasible under varying environmental conditions.

It is usually the case that the values of $\mathbf{x}_t$ and $\mathbf{h}_t$ are themselves estimates and unfortunately, while there are mechanisms for adjusting the estimates to be self-consistent, the true values are unobservable.

Consequently, we have no ability to assess whether the estimates are biased or to characterize the shape or spread of the distribution of the estimation errors.

$$
\begin{aligned}
& x_{\lambda t} + \upsilon_{1\lambda t} = \beta_1 \left(x_{\lambda t-1} + \upsilon_{2\lambda t-1} \right) \\
max\left(SY_{\lambda}\right) \quad & + \beta_2 \left(x_{\lambda t-1} + \upsilon_{2\lambda t-1} \right)^2 \qquad \forall \lambda \\
& + \beta_3 \left(h_{\lambda t-1} + \upsilon_{3\lambda t-1} \right) + e_{\lambda t}
\end{aligned}
$$

$$x_{\lambda t} \geq 0 \quad h_{\lambda t} \geq 0$$

Another, perhaps less well recognized, problem with estimation of parameters for equation (4) has to do with stationarity.

A data series is said to be stationary if the data generating process is time invariant.

Time varying processes could be thought of as random coefficients, e.g.,

$$max(SY_{\lambda}) \quad \begin{aligned} &x_{\lambda t} = \beta_{1t}(x_{\lambda t-1}) + \beta_{2t}(x_{\lambda t-1})^2 \\ &+\beta_{3t}(h_{\lambda t-1}) + e_{\lambda t} \end{aligned} \quad \forall \lambda$$

$$x_{\lambda t} \geq 0 \quad h_{\lambda t} \geq 0$$

If one time series is used to describe changes in a second time series, and both are affected by a changing exogenous variable, such as a random walk process, it will not be clear if the estimated relationship among the two time series reflects a true relationship between them or merely a spurious correlation induced by the third time series.

For example

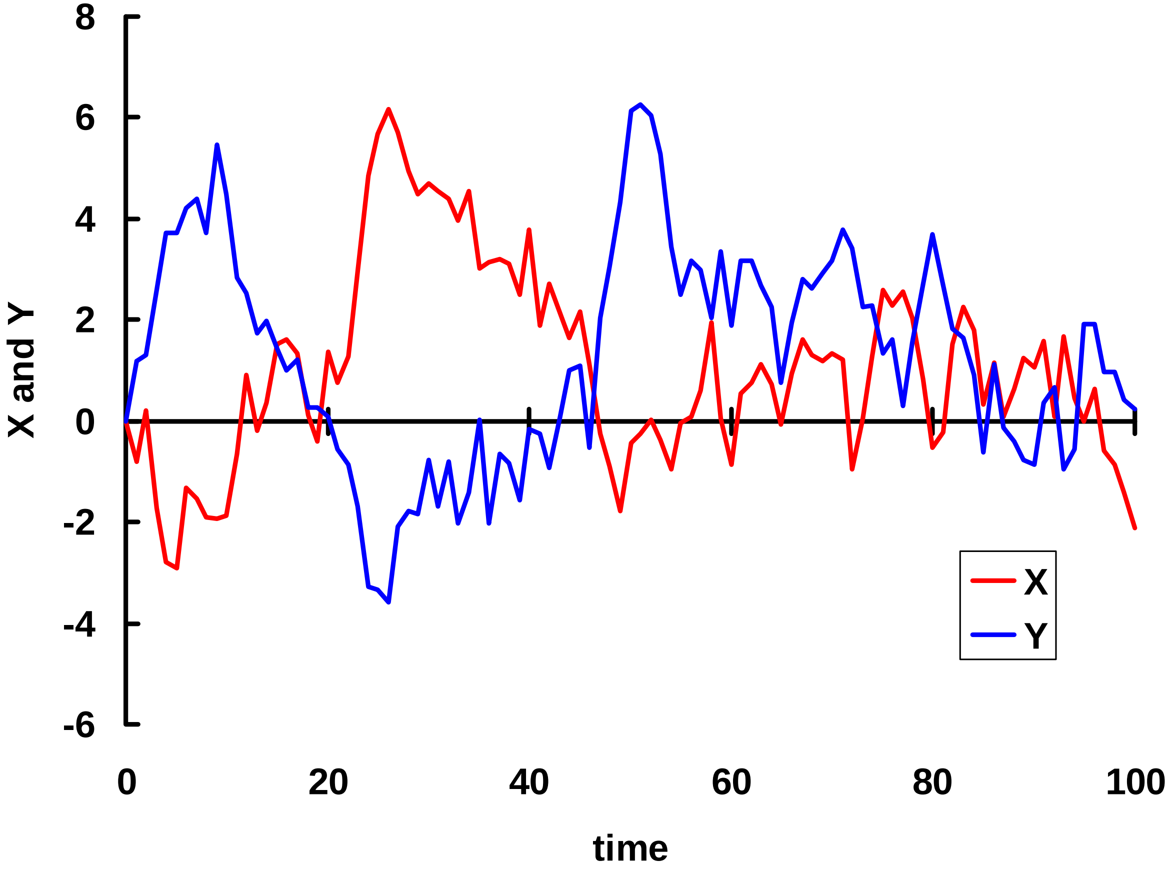
$$y_t = y_{t-1} + z_t \quad z_t \sim \mathcal{N}\left(\mu_z, \sigma_z^2\right)$$

$$x_t = x_{t-1} + \eta_t \quad \eta_t \sim \mathcal{N}\left(\mu_\eta, \sigma_\eta^2\right)$$

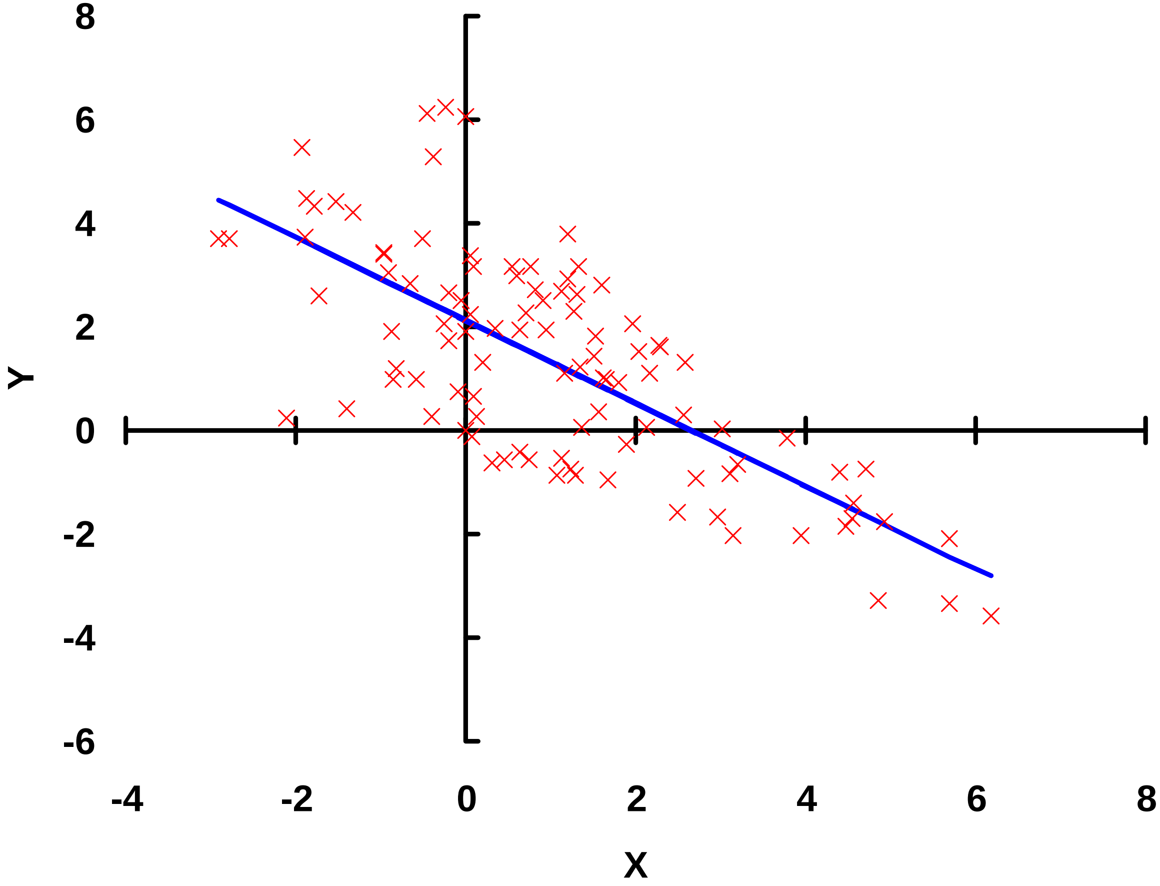
$$E\left(y_t\right) = t\mu_z \quad Var\left(y_t\right) = t\sigma_z^2$$

$$E\left(x_t\right) = t\mu_\eta \quad Var\left(x_t\right) = t\sigma_\eta^2$$

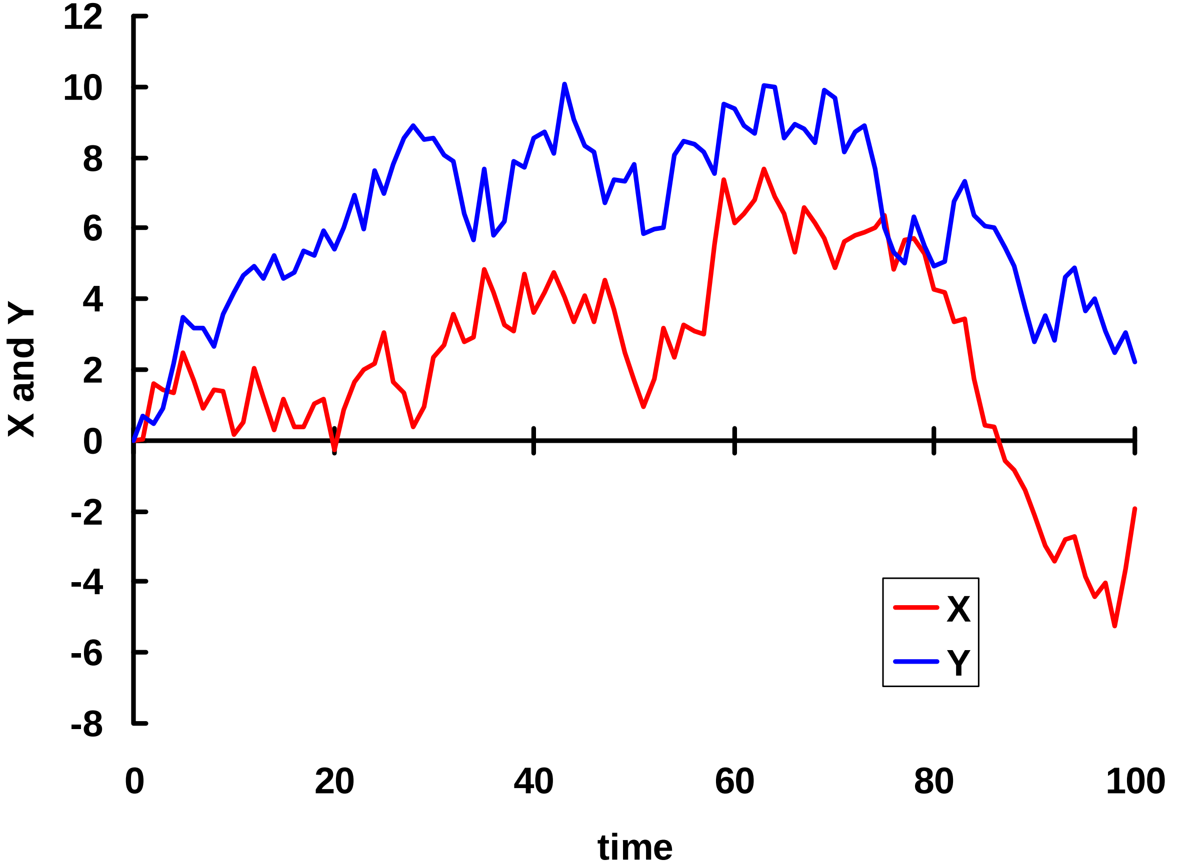
1st Draw from 2 Random Walk Processes



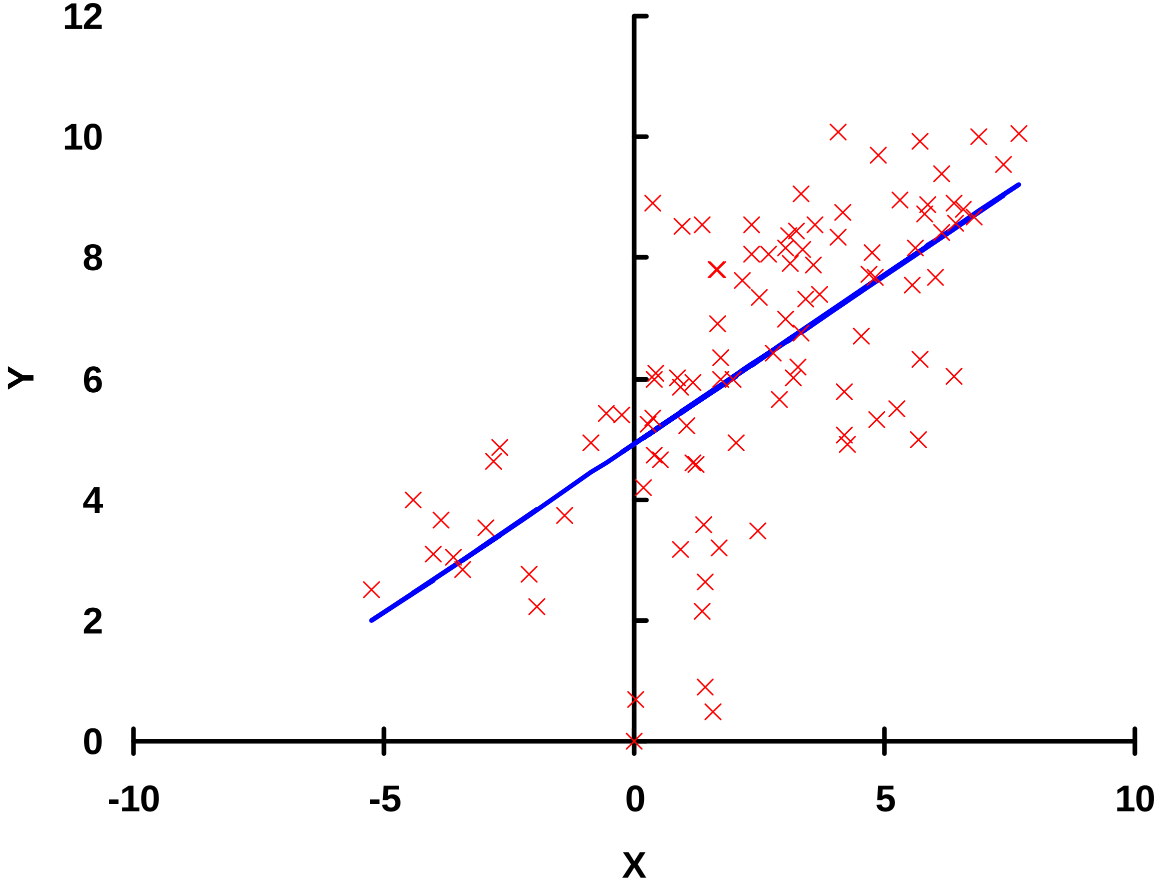
1st Draw from 2 Random Walk Processes



2^{nd} Draw from 2 Random Walk Processes



2nd Draw from 2 Random Walk Processes



Spurious relationships can arise from fitting a stochastic trend model to a time series generated by a deterministic trend or from fitting a deterministic trend model to time series generated by a stochastic trend.

Two common tests for the presence of stochastic trends are the Dickey-Fuller (DF) and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests. The DF test begins with a null hypothesis that the time series are generated by a random walk process. The KPSS test begins with a null hypothesis that the time series were not generated by a random walk process.

It should come as no surprise that many so-called recruitment functions cannot be differentiated from random walk processes.

Unmodelled environmental factors that influence the realization of biomass are examples of deterministic or stochastic trends that could lead to spurious estimates of the coefficients of equation (3).

However, including environmental variables into our model does not eliminate the problem of spurious relationships if the variables that we include (e.g., SST, PDO, SOI, regime shift) are themselves imperfect proxies for the functional relationships (e.g., the quality and availability of food) that affect the realization of biomass or other series of interest.

Consider a simple extension to equation (4)

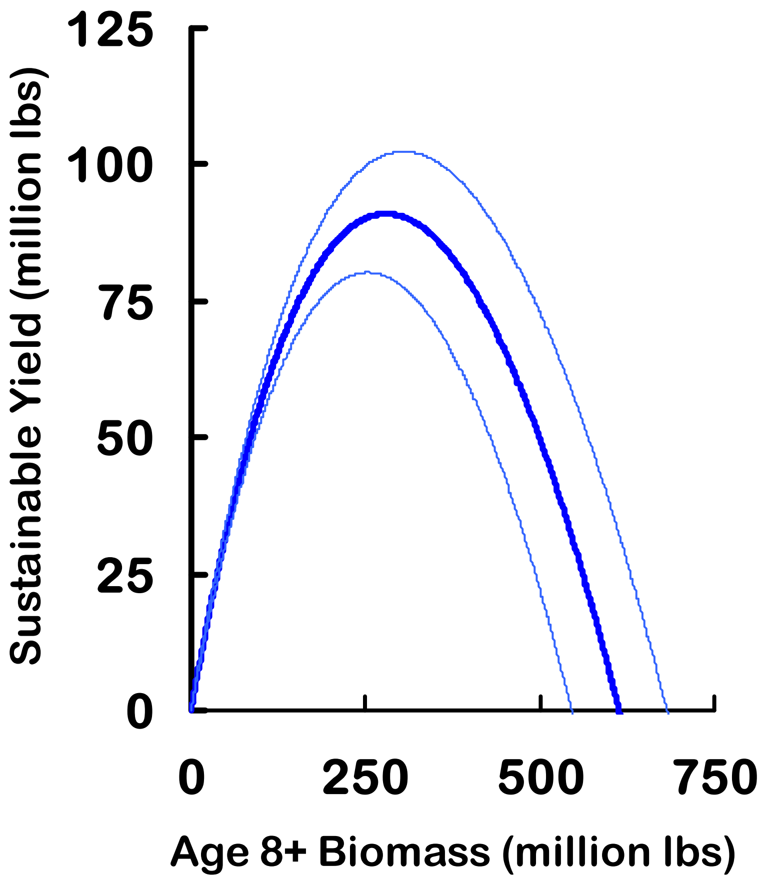
$$x_t = \beta_1 x_{t-1} + \beta_2 x_{t-1}^2 + \beta_3 x_{t-8}\, e^{(\beta_4 x_{t-8})} - h_{t-1} + \varepsilon_t$$

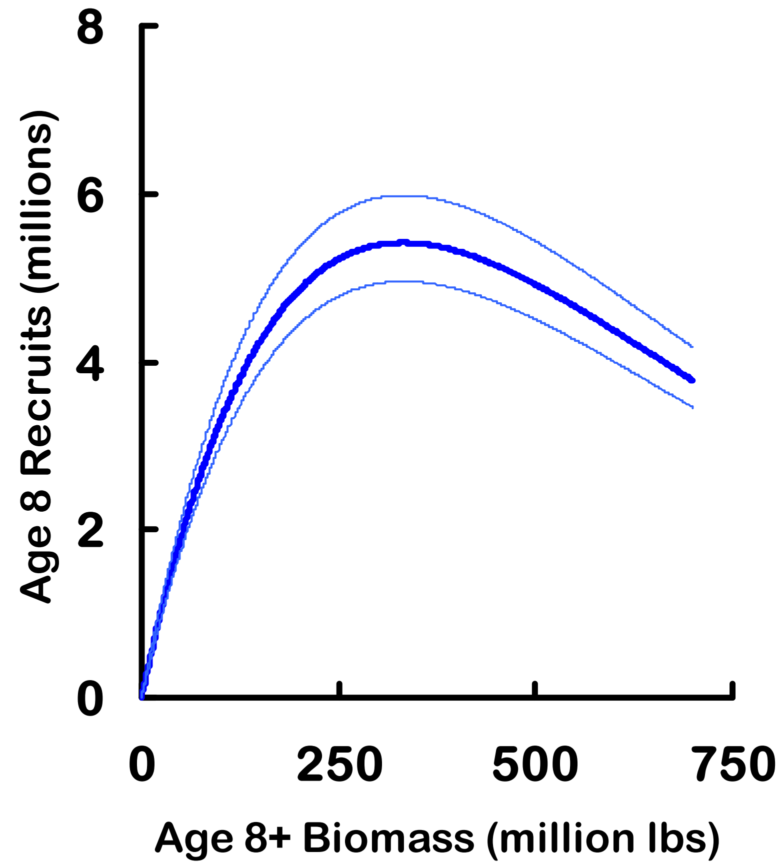
(5) $$\begin{pmatrix} \varepsilon_t \\ \mathbf{y}_t \end{pmatrix} = \begin{pmatrix} \mathbf{c} & \mathbf{C} \end{pmatrix} \begin{pmatrix} \boldsymbol{\tau} \\ \mathbf{z}_t \end{pmatrix} + e_t$$

$$\begin{pmatrix} \boldsymbol{\tau}_{t+1} \\ \mathbf{z}_{t+1} \end{pmatrix} = \begin{pmatrix} \mathbf{a} & \mathbf{bC} \\ \mathbf{0} & \mathbf{A} \end{pmatrix} \begin{pmatrix} \boldsymbol{\tau}_t \\ \mathbf{z}_t \end{pmatrix} + \begin{pmatrix} \mathbf{b} \\ \mathbf{B} \end{pmatrix} e_t$$

The first equation represents a deterministic trend. The second equation maps the residuals from the first equation and a vector of environmental variables into short- and long-period dynamic states. The third equation models deterministic and stochastic trends in the state variables.

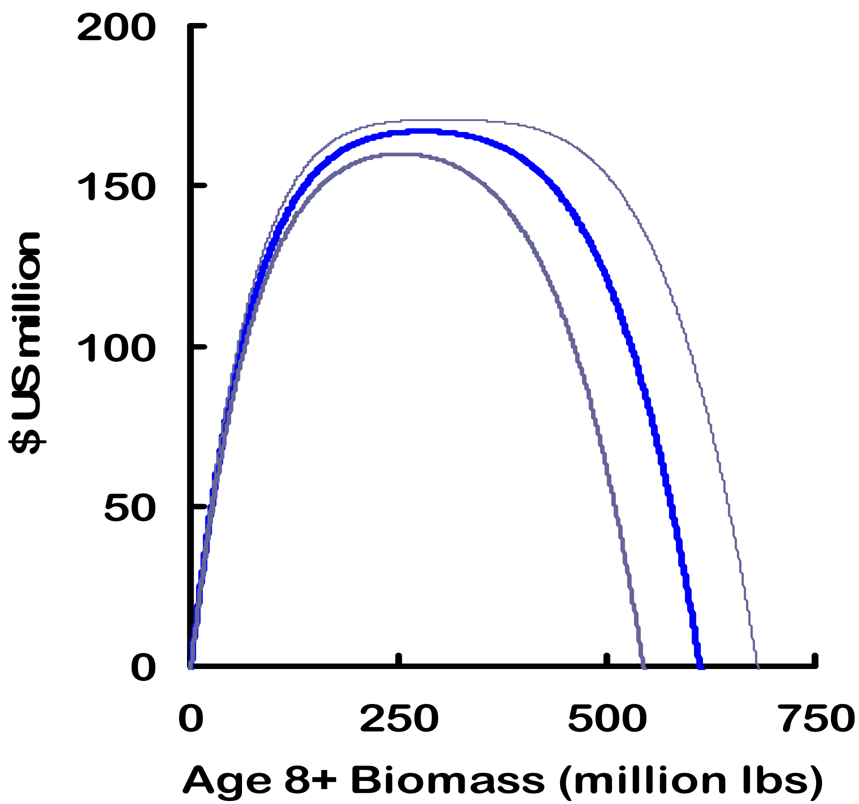
How do sustainable yields and recruitment vary in response to environmental change?

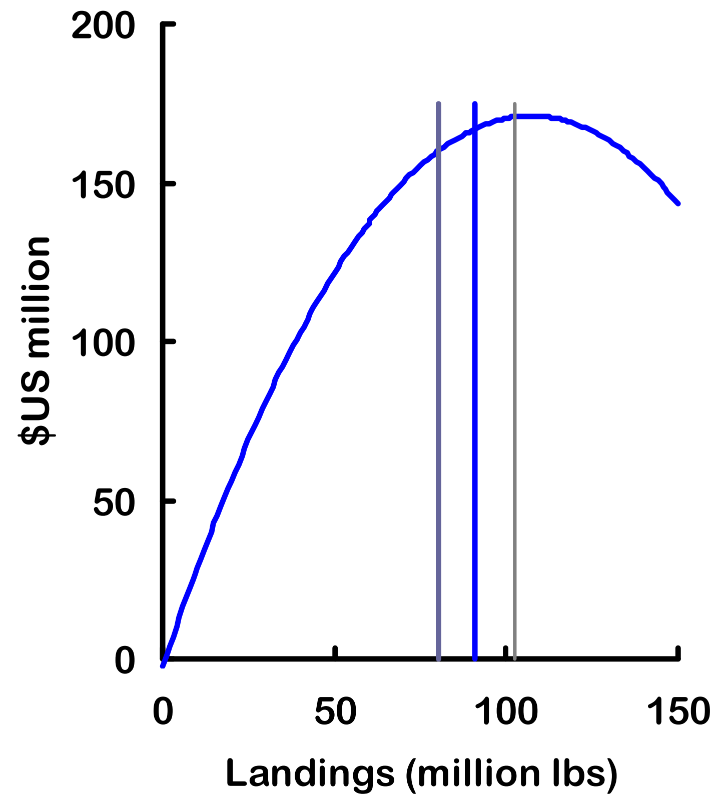




± 10% Change in Productivity

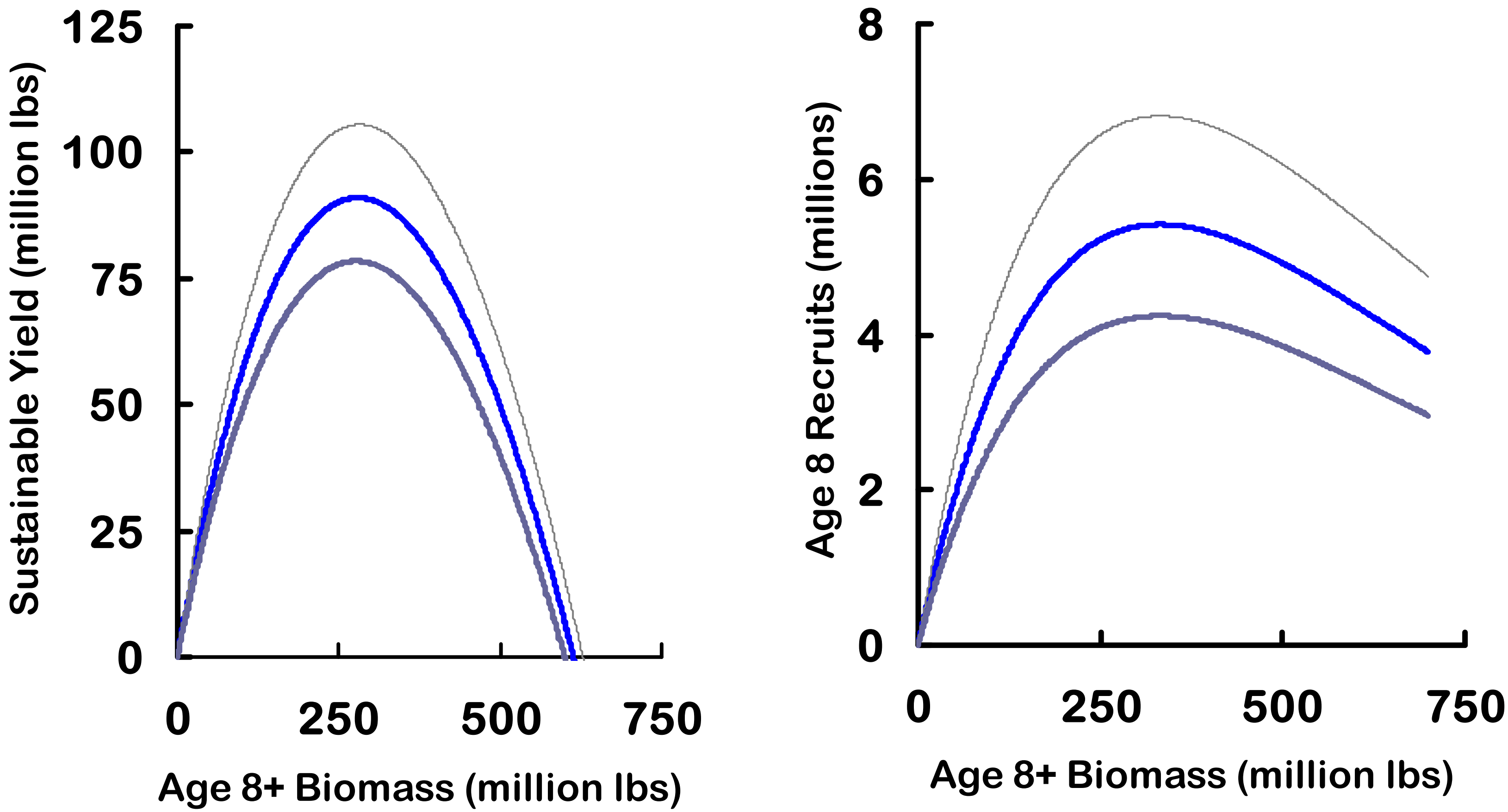
How do sustainable revenues vary in response to environmental change?





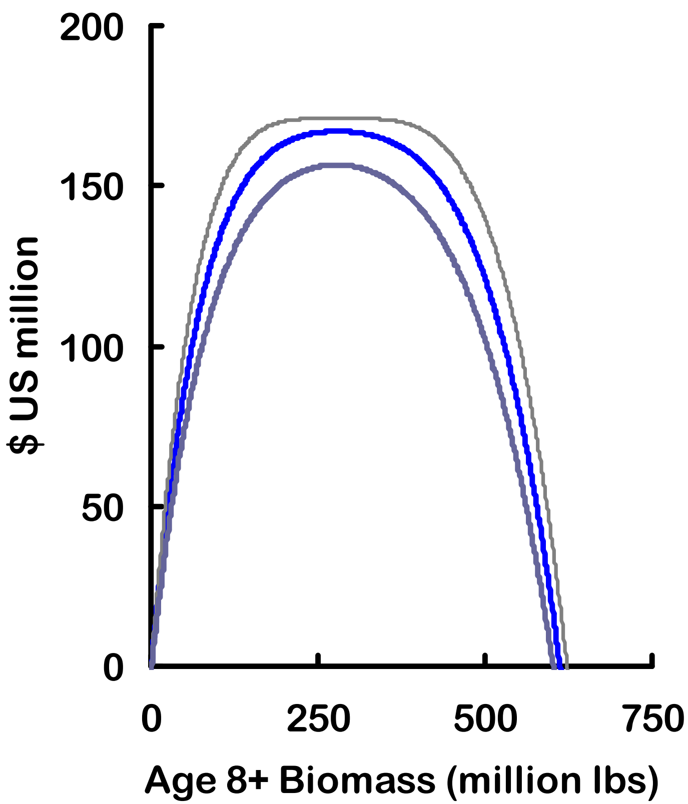
± 10% Change in Productivity

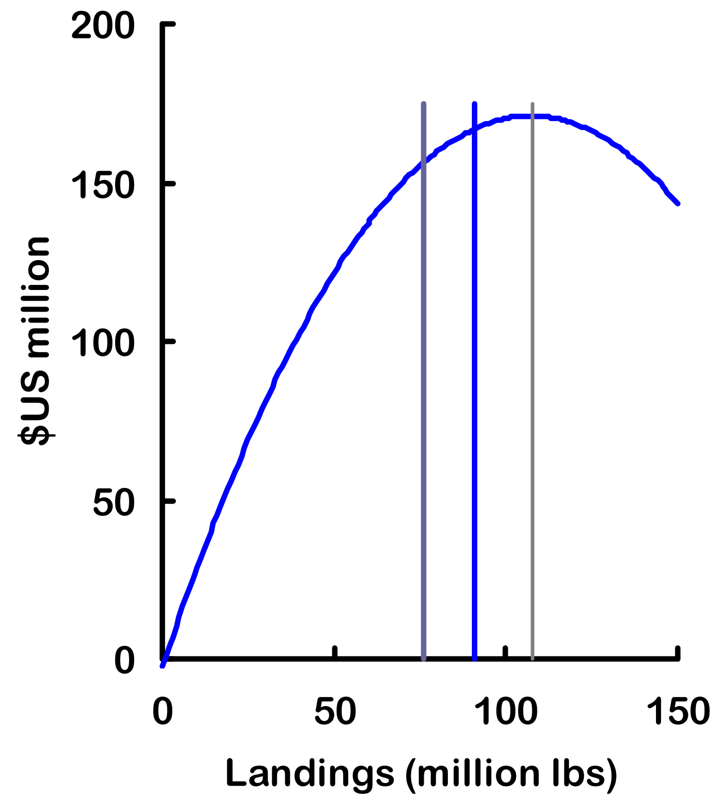
How do sustainable yields and recruitment vary in response to environmental change?



± 5% Change in Growth Rate

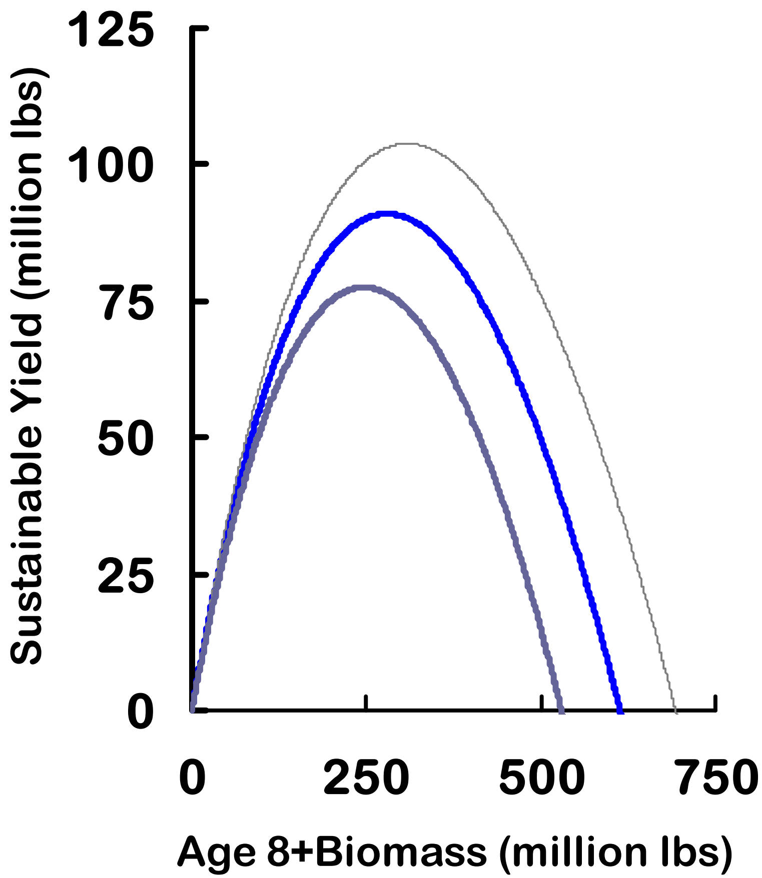
How do sustainable revenues vary in response to environmental change?

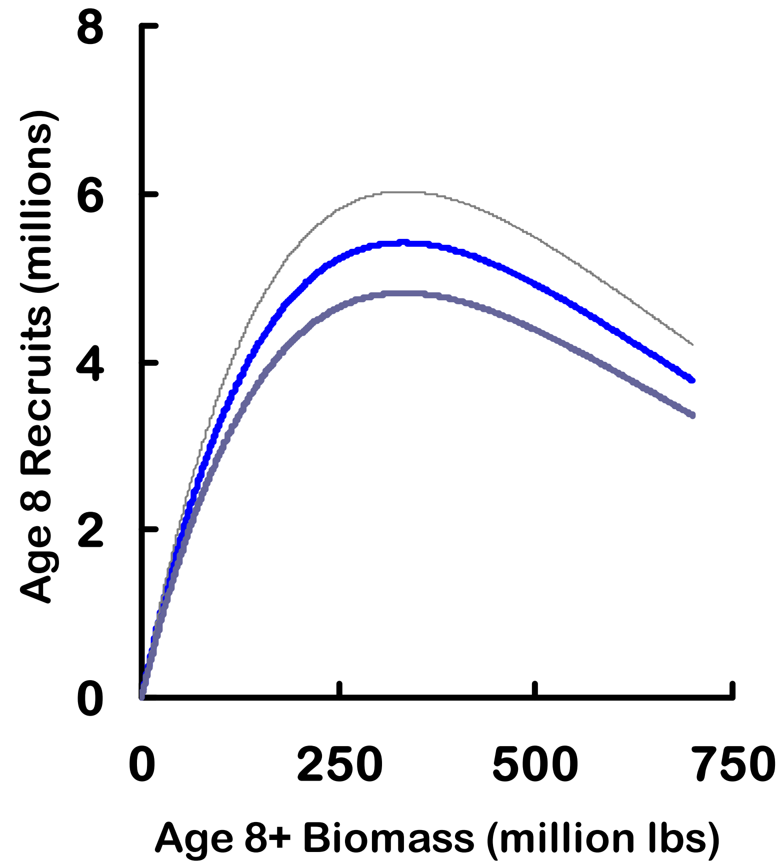




± 5% Change in Growth Rate

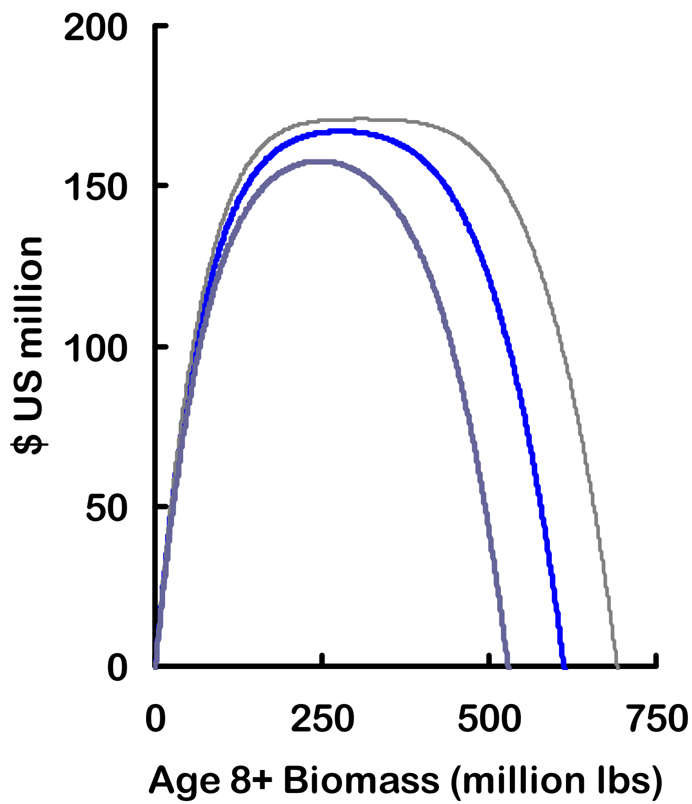
How do sustainable yields and recruitment vary in response to environmental change?

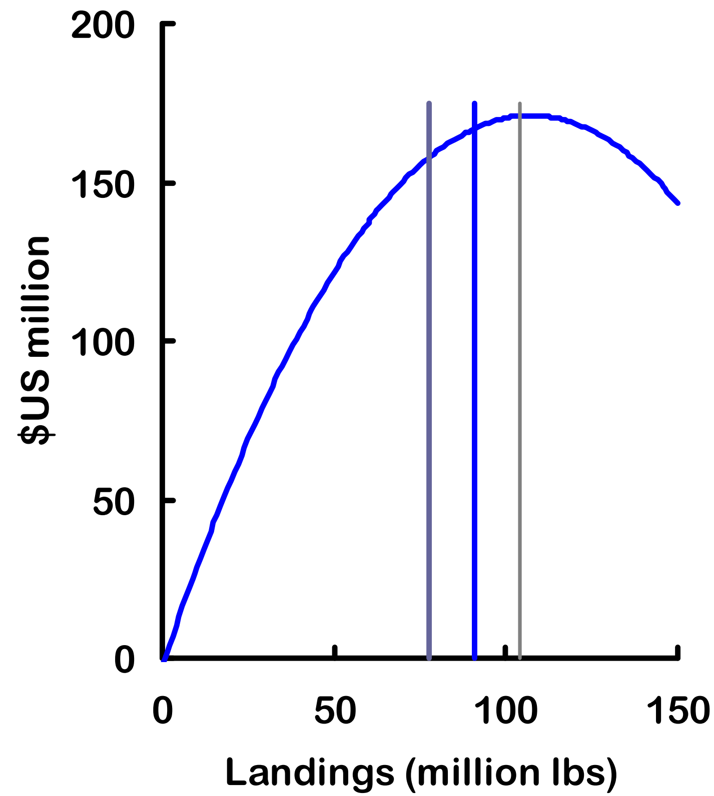




± 10% Change in Recruitment Success

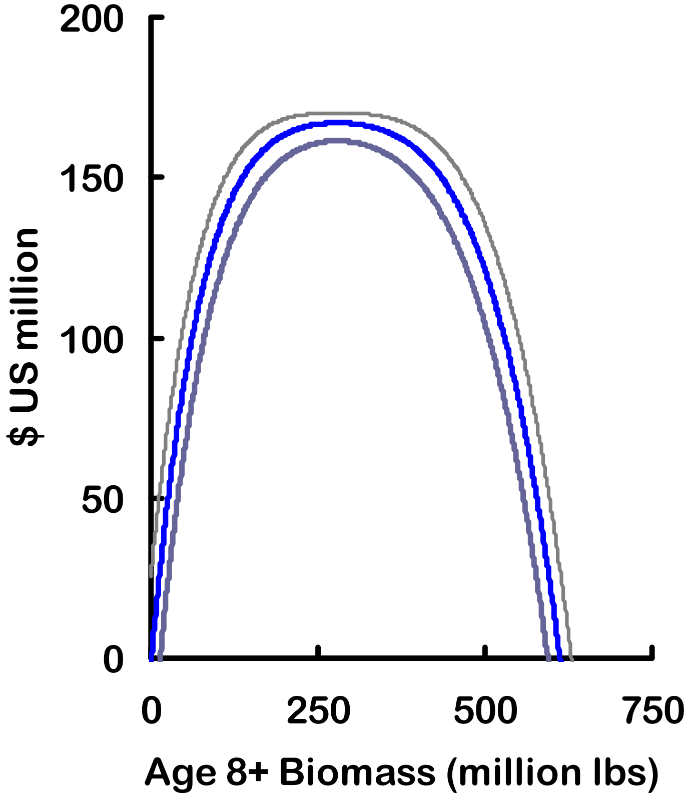
How do sustainable revenues vary in response to environmental change?

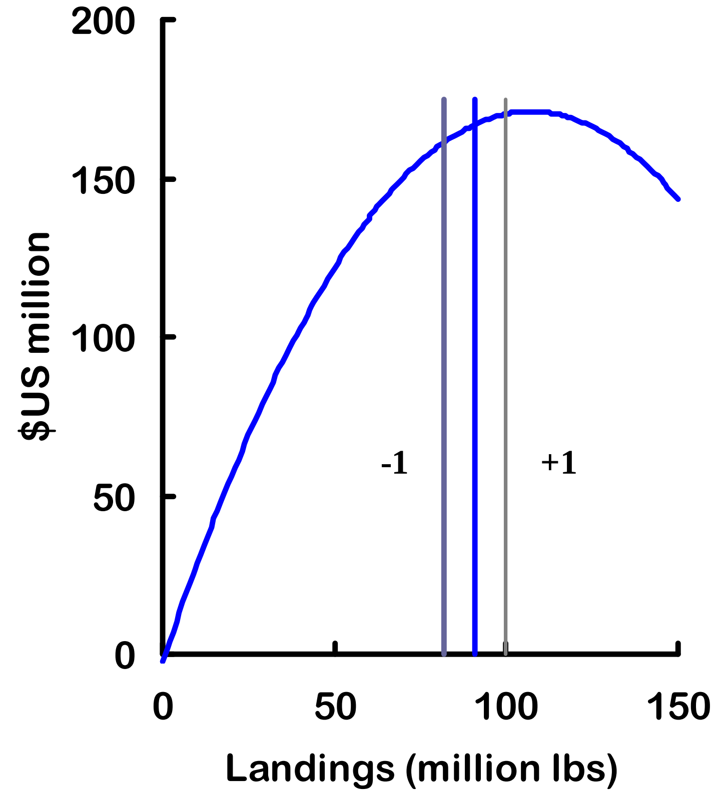




± 10% Change in Recruitment Success

How do sustainable yields and recruitment vary in response to environmental change?





± 1° Change in PDO Anomaly

Management objectives for living marine resources are often couched in terms of reference values that are based on observations of past levels of abundance and geographic extent, and historic patterns of use.

Satisfying static reference points may not be feasible or desirable when rapidly evolving environmental conditions affect growth, recruitment, or carrying capacity.

Moreover, governance systems and management strategies designed to enshrine an Elysian status quo may not only fail in their objective, but they may add to instability.

The problem is that the current management paradigm is predicated on a false assumption that linked biological, environmental and social systems are stationary, where in fact it is well known that they are not.

Nonstationary systems are inherently different from stationary systems and management of living marine resources governed by nonstationary dynamics is inherently different from management of living marine resources governed by stationary dynamics.