Understanding the joint effects of plastic and evolutionary change on demography from time series

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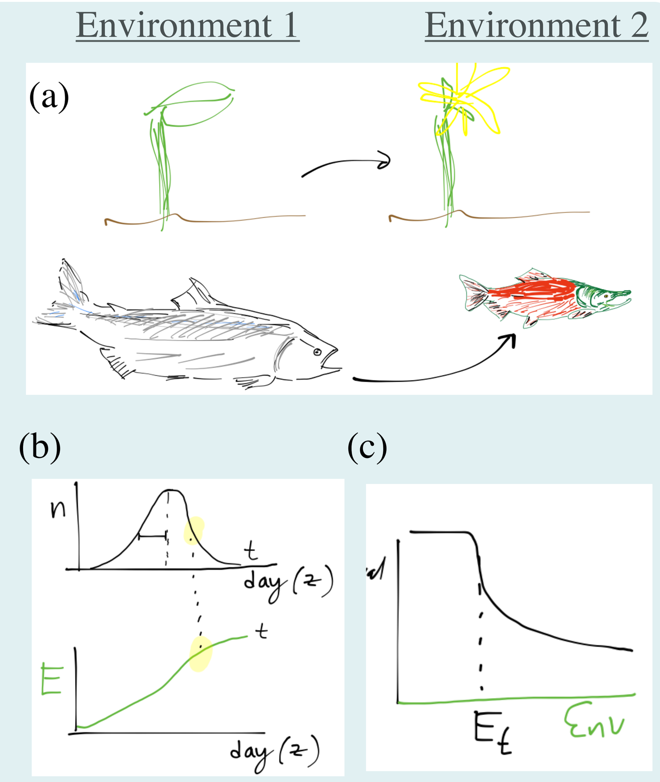
Motivation

Traits that govern life-history timing often respond plastically to aspects of the environment (a). Seasonal trends (b) mean such traits also determine the environment experienced. An environment that imposes differential mortality (c) causes selection on timing, potentially affecting demographic trajectories. To forecast responses to environmental change we wish to **predict population and trait dynamics**, and to do so we must **leverage prior studies** to help us **reduce uncertainty concerning the interaction of plasticity and selection** in our focal system.



A Bayesian approach to eco-evo dynamics

Accommodate prior estimates of heritability, plasticity, and/or demography, while admitting uncertainty about "backcasting" [e.g., 1,4] selection gradients by assuming the true gradient is some smooth function of the environment (see Box II)

Data — *Trait mean* $\bar{z}_t|\bar{\zeta}_t, \theta_z$; *Abundance* $N_t|\eta_t, \theta_N$

Process — *Latent trait mean* $\zeta_t|\zeta_{t-1}, \theta_\zeta, \epsilon_\zeta, X_t, X_{t-1}, S_t$; *Latent abundance* $\eta_t|\eta_{t-1}, S_t, \sigma^2_{z_t}, \theta_\eta, \epsilon_\eta$

Parameters — θ_z ; $\theta_\zeta, \epsilon_\zeta$ *Heritability, plasticity, process noise* ; $S_t|\theta_{GP}, E_t, \tilde{S}_t$ *Selection Differential* ; $\theta_\eta, \epsilon_\eta$ *Productivity, carrying capacity, process noise* ; θ_N

Hyperparameters — θ_{GP} *Gaussian-process priors* ; $\tilde{S}_t|E_t, \bar{z}_t, \sigma^2_{z_t}$

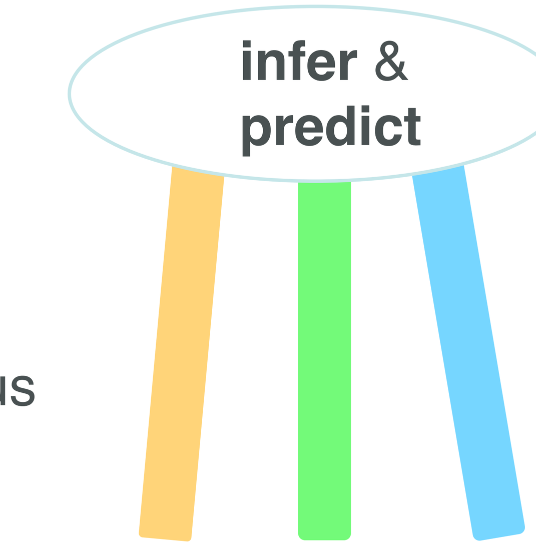
Covariates — X_t *Plasticity-inducing* ; E_t *Selecting* ; $\sigma^2_{z_t}$ *Trait variance*

Methods

- State-space model in Bayesian framework implemented and sampled using MCMC via Hamiltonian Monte Carlo sampler in `Stan` (Gelman *et al.* [2])
- Assumed Gaussian error (i.e., Kalman filter)
- Priors used
  - Heritability of focal trait h^2
  - Population dynamic parameters $\theta_\eta := \lambda, K$
  - Reconstructed selection differentials $S_t|\theta_{GP}, E_t, \tilde{S}_t$

Applying the framework

Population and trait dynamics are influenced by three interdependent processes: selection, response to selection and plastic change ➔ prior information on two of these can help us **infer** the action of the third, and thus **predict** the trajectories of interest.



I: heritability *v* plasticity

1. Strong priors on population dynamics $\theta_\eta := \lambda, K$
2. Assume backcast selection gradients reflect actual selection $S_t = \tilde{S}_t \;\; \forall t$, $\tilde{S}_t = f(E_t, \bar{z}_t, \sigma^2_{z_t})$

Outcomes

- Assess plasticity versus selection h^2 $\mathbf{b}$
- Determine most-explanatory covariates X_t
- Population predictions provide additional data for predictive inference N_t

II: past selection by environment

1. Strong priors on population dynamics $\theta_\eta := \lambda, K$
2. Strong priors on evolutionary processes $\theta_\zeta := h^2, \mathbf{b}$
3. Variation in confidence of backcast selection

$$\tilde{S}_t = f(E_t, \bar{z}_t, \sigma^2_{z_t})$$
$$S_t = \tilde{S}_t \text{ for } t \in \Omega_N$$
$$S_t|\theta_{GP}, E_t, \tilde{S}_t \text{ for } t \notin \Omega_N$$

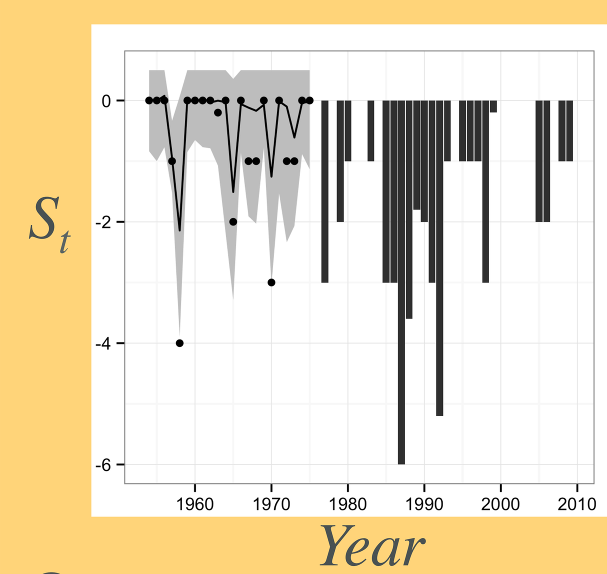
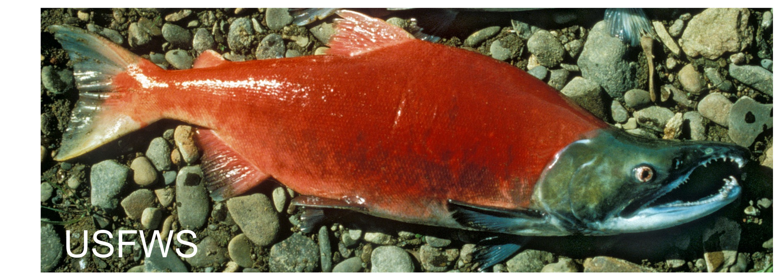


Figure: Prior to 1976 selection differential S_t is modeled as a Gaussian Process based on the relationship between selection and the environment from 1976-2009.

Outcomes

- Understand selection by the environment over time S_t
- Determine most-explanatory covariates X_t



Case study: Sockeye (*O. nerka*) in the Columbia River

1. Strong prior on population dynamic parameter for growth, assuming Ricker form (Myers *et al.* [3])
2. Backcast selection differentials based on temperature-survival relationship (after Crozier et al [1])

Outcomes

- Prediction for population dynamics given out-of-sample environment
- Re-ranking models for best predictors $\mathbf{b}$ X_t

	Model	WAIC [5]	dWAIC	Crozier et al. Rank
1	S+F4+Umay	268.29	0.00	4
2	S+F4+PDO4	284.97	16.68	1
3	S+F4+Umar	294.01	25.72	5
4	S+F4+NPI4	296.67	28.38	6
5	S+F4	303.03	34.73	3
6	S+F4+NPGO4	307.17	38.88	2
7	S+PDO4+NPGO4	316.19	47.89	7

Table: Model scores based on WAIC [5] for a selection of covariates used to predict migration date and abundance. S=selection, F=mean June flow, NPGO/PDO=oceanographic indices, U=upwelling indices. The same covariates were considered in Crozier *et al.* [1], but as shown, including population in the model results in a different ordering of the models.

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