

# Eastern North Pacific Gray Whale Census Estimates

*An Application of State Space Reconstruction*

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# Gray Whale

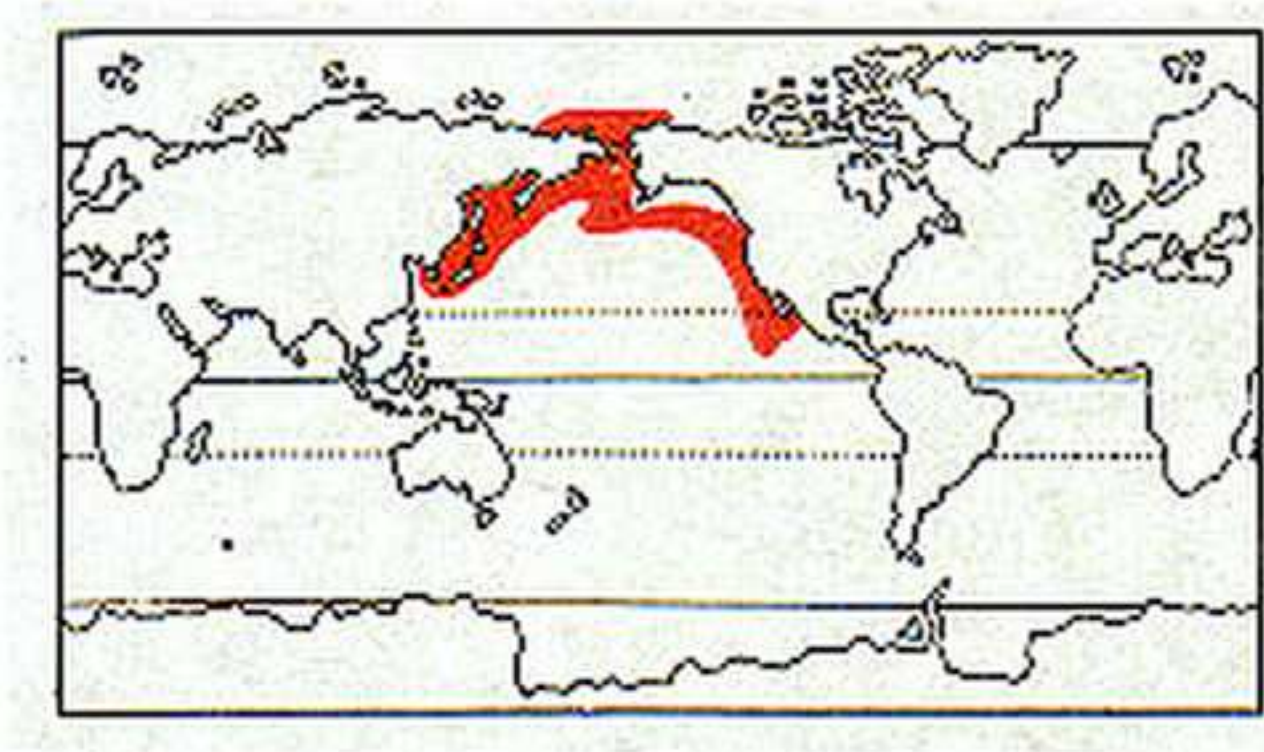
- Latin name *Eschrichtius robustus*, length 40–50 feet (12–15 m), weight 50,000–80,000 lbs (23,000-36,000 kg), lifespan of up to 50 years.



# Brief History

- Hunted by aboriginal peoples as well as 19<sup>th</sup> and 20<sup>th</sup> century commercial whaling industry
- Believed “commercially extinct” in 1900
- Listed and protected as endangered in 1970 by Endangered Species Act.
- Eastern Pacific stock de-listed as “recovered” in 1994.
- Western Pacific stock nearly extinct (approximately 50 individuals)

# Habitat



- Usually found within 2 km of coastline.
- Eastern Pacific females calve in the lagoons of Baja peninsula

# Migration



# Feeding Habits

- Only “bottom feeding” whale
- Prefer to feed with their right sides toward the bottom
- Dredge bottom mud for amphipods and crustaceans
- Have baleen for filtering food from mud



Chip Clark



Howard Braham, NMML

# Recovery?

Q: Has the stock of eastern Pacific gray whales recovered sufficiently that regulatory protection is no longer needed?

- Yearly census results continue to oscillate
- Mathematical models exhibit a decrease in population during 1968–1988 while census numbers showed an *increase*
- Models do not exhibit depletion of stock by 1900

Q: Can the behavior of mathematical models be reconciled with the census data?

# Global Model

From the work of de la Mare (1989) and Punt and Butterworth (1991):

$$P_{t+1} = (P_t - C_t)e^{-M} + (1 - e^{-M})P_{t-t_m+1} \left( 1 + A \left[ 1 - \left( \frac{P_{t-t_m+1}}{P_0} \right)^z \right] \right)$$

$C_t$  catch in year  $t$

$M$  natural mortality rate

$t_m$  age at first parturition

$A$  resilience parameter

$z$  density-dependent exponent

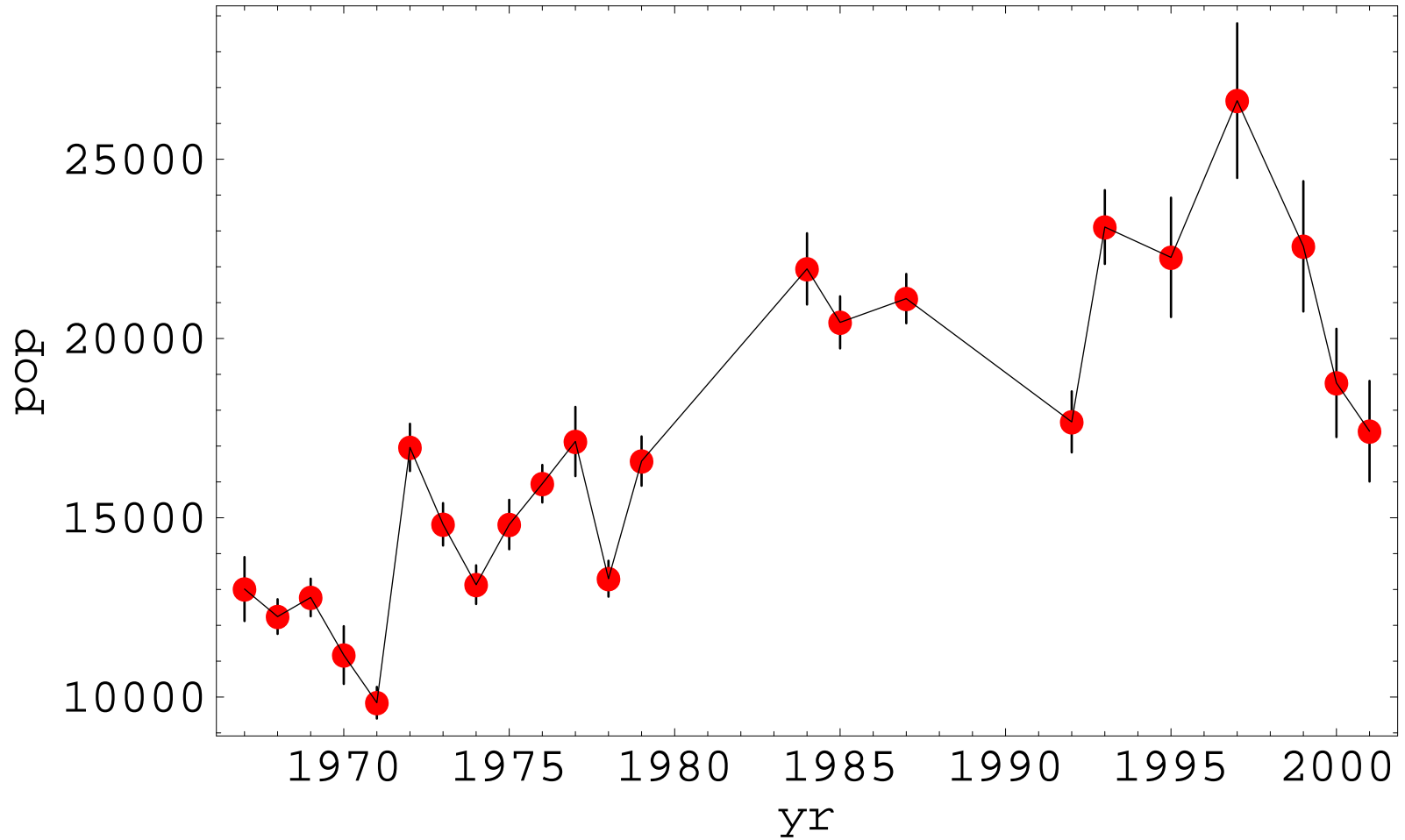


# Local Model

Characteristics of local models:

- Local models received much attention from 1970's through 1990's
- Found application in predicting time series
- Data driven – no ecological fidelity
- Computationally expensive
- Often better at predicting behavior of chaotic dynamical systems (*e.g.* solutions of the Lorenz equation) than global models

# Time Series



# Brief Introduction to Local Modeling

Difference equation model:

$$P_t = F(P_{t-1}, P_{t-2}, \dots, P_{t-j})$$

Sequence of observations over time:

$$\{P_0, P_1, \dots, P_N\}$$

Time delay embedding with dimension  $m$ , Takens (1981):

$$\mathbf{x}_{m-1} = \langle P_0, P_1, \dots, P_{m-1} \rangle$$

$$\mathbf{x}_m = \langle P_1, P_2, \dots, P_m \rangle$$

$$\vdots$$

$$\mathbf{x}_N = \langle P_{N-m+1}, P_{N-m+2}, \dots, P_N \rangle$$

# Takens's Theorem

From Casdagli, *et al.* (1991):

Dynamical system:  $x(t) = f^t(x(0)), \quad x \in \mathbb{R}^n$

Observable:  $y(t) = g(x(t)), \quad y \in \mathbb{R}^d$

Delay construction map:

$$\Phi(x(t)) = \langle g(f^{-\tau m_p}(x(t))), \dots, g(x(t)), \dots, g(f^{\tau m_f}(x(t))) \rangle$$

If  $m = m_f + m_p + 1 \geq 2n + 1$  then  $\Phi$  is a smooth, one-to-one coordinate transformation with a smooth inverse.

# Local Modeling 2

Prediction:

$$\hat{P}_{N+1} = G(\mathbf{x}_N)$$

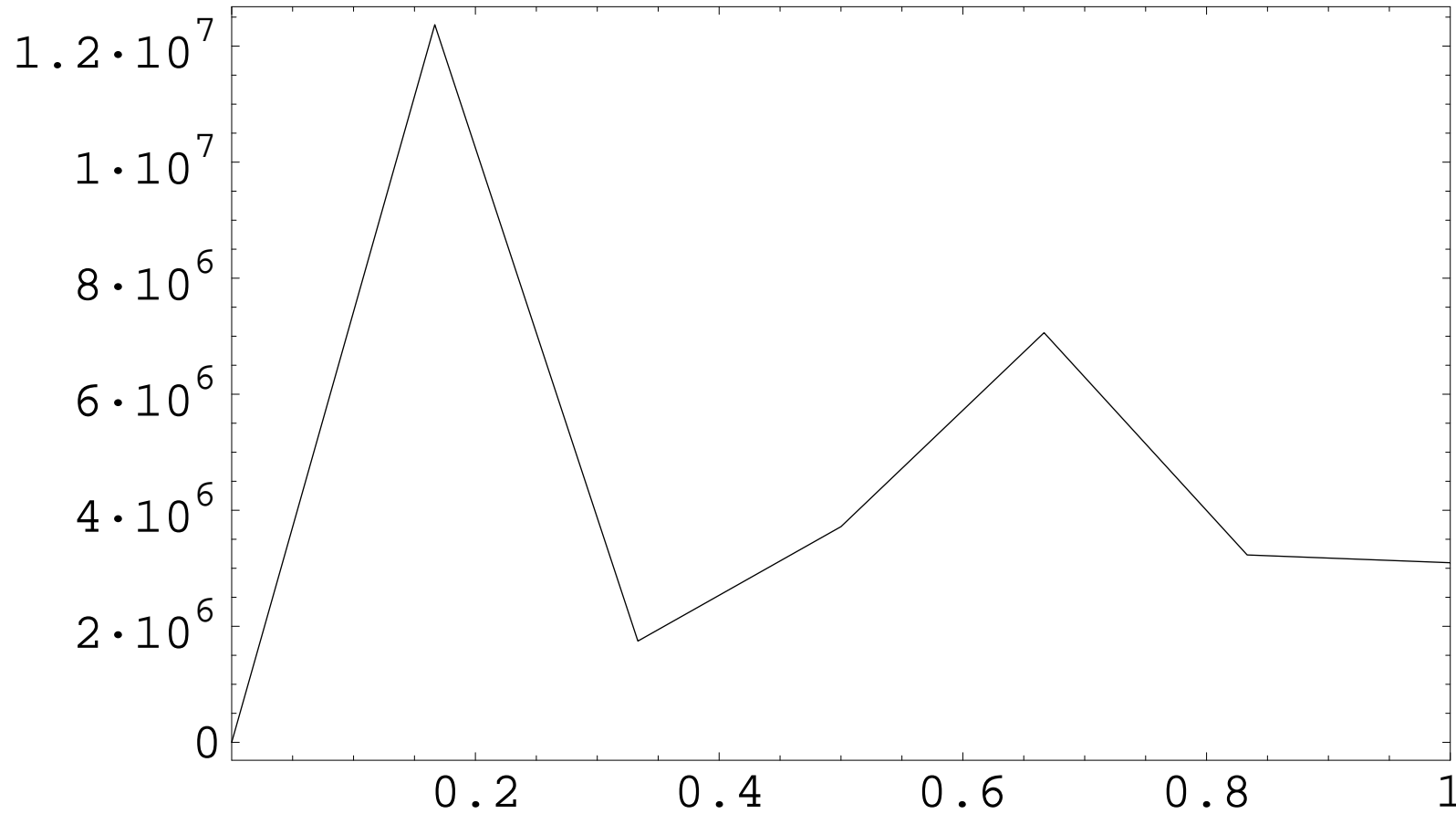
Multi-step prediction:

$$\hat{P}_{N+2} = G(\langle P_{N-m+2}, P_{N-m+3}, \dots, \hat{P}_{N+1} \rangle)$$

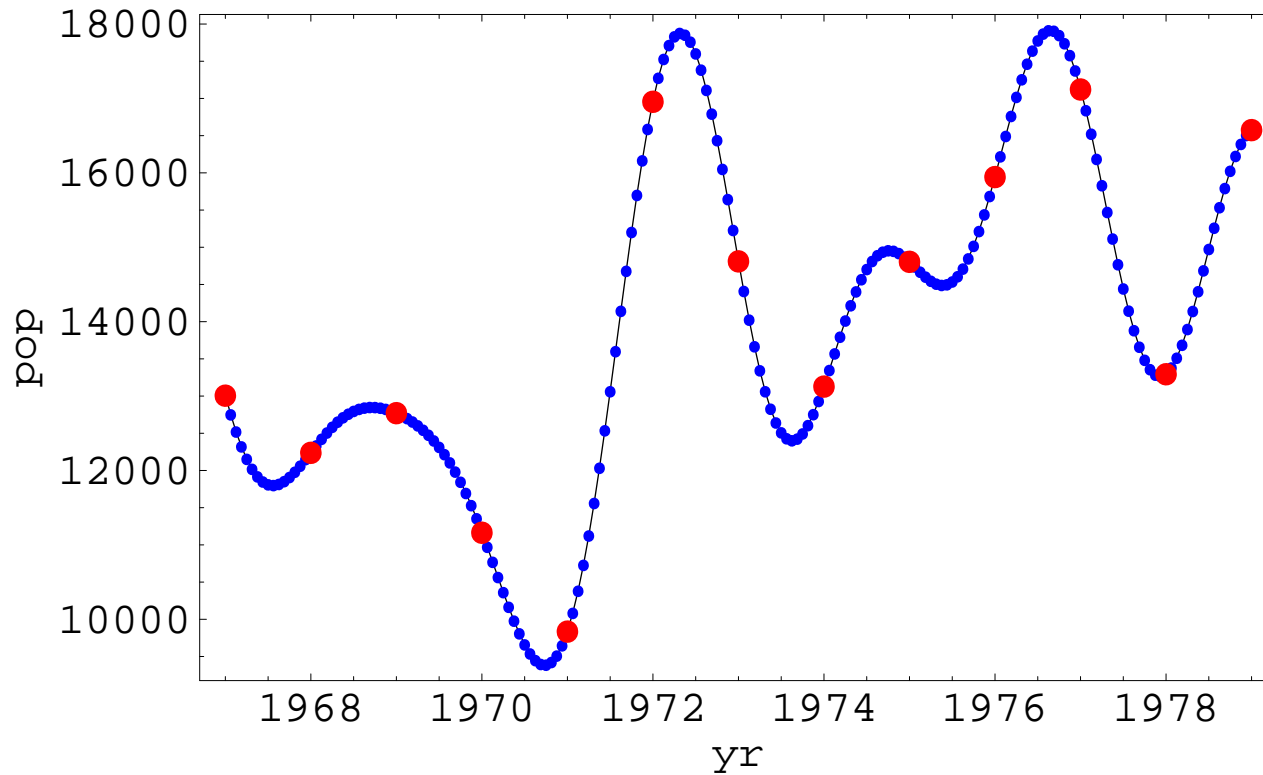
$$\hat{P}_{N+3} = G(\langle P_{N-m+3}, P_{N-m+4}, \dots, \hat{P}_{N+2} \rangle)$$

⋮

# Fourier Spectrum



# Interpolation



Up-sample to fill in the spacing of the sequence of observations.

# Filtering

- Remove high frequency noise
- Reduce data storage requirements
- Perform in parallel with interpolation

$$\mathbf{x}_i = L_3 \circ L_2 \circ L_1(\langle P_{i-w+1}, P_{i-w+2}, \dots, P_i \rangle)$$

$L_1$  Fourier transform

$L_2$  Low pass filter  $m/2$  frequencies

$L_3$  Inverse Fourier transform

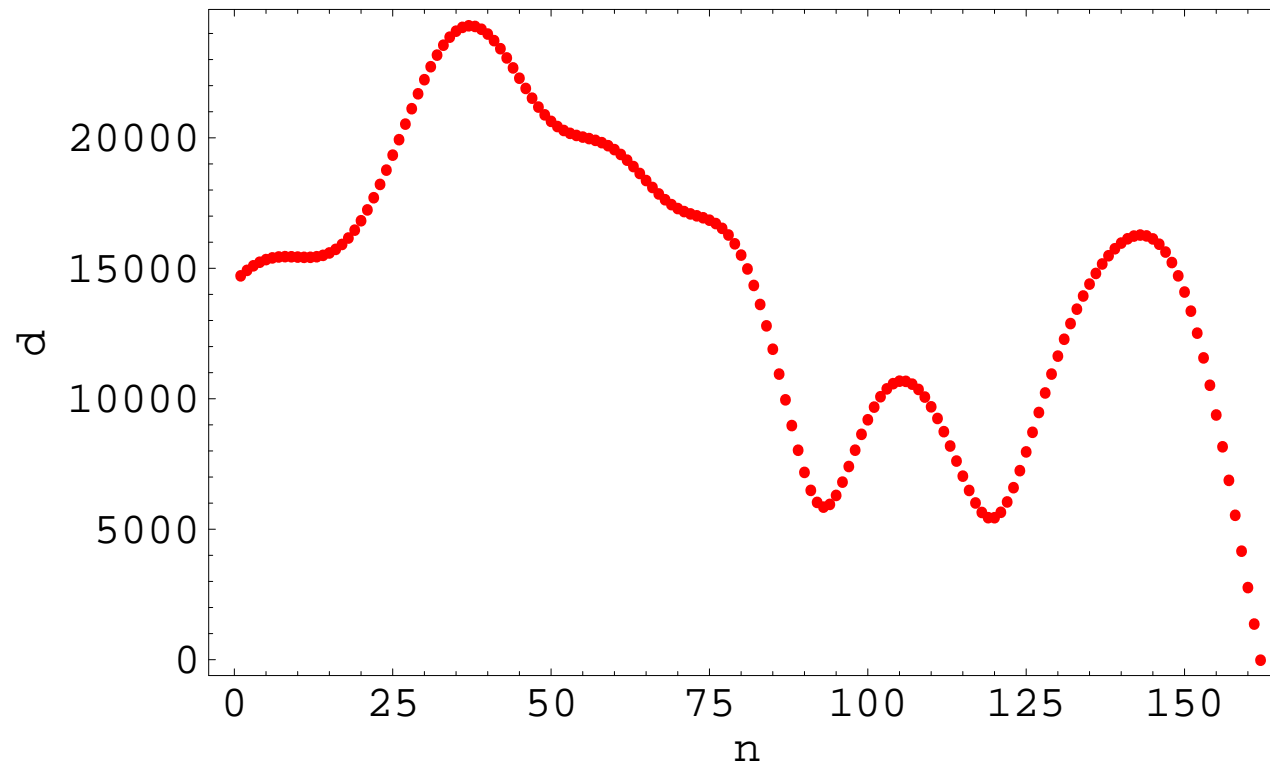


# Nearest Neighbors

Metric:

$$d^2(\mathbf{x}_a, \mathbf{x}_b) = \sum_{i=0}^{m-1} \lambda^i (\mathbf{x}_{a,m-i} - \mathbf{x}_{b,m-i})^2$$

with  $0 < \lambda \leq 1$ .



# Prediction Algorithm

1. Create filtered embedding of sequence of observations
2. Find  $k \geq 1$  nearest neighbors of  $\mathbf{x}_N$
3. For neighbors  $\{\mathbf{x}_{n_1}, \dots, \mathbf{x}_{n_k}\}$  find  $\{P_{n_1+1}, \dots, P_{n_k+1}\}$
4. Approximate the map  $\mathbf{x}_\alpha \xrightarrow{G} P_{\alpha+1}$
5. Evaluate  $G(\mathbf{x}_N) = \hat{P}_{N+1}$

# Types of Maps: Averaging

Direct:

$$\hat{P}_{N+1} = \frac{\sum_{i=1}^k w_i P_{n_i+1}}{\sum_{i=1}^k w_i}$$

Integrated:

$$\hat{P}_{N+1} = P_N + \frac{\sum_{i=1}^k w_i (P_{n_i+1} - P_{n_i})}{\sum_{i=1}^k w_i}$$

Weights depend on the distance between the neighboring vector and the query vector.

$$w_i = \left[ 1 - \left( \frac{d(\mathbf{x}_N, \mathbf{x}_{n_i})}{d(\mathbf{x}_N, \mathbf{x}_{n_k})} \right)^2 \right]^2$$

# Another Type: Linear

From Sauer (1994):

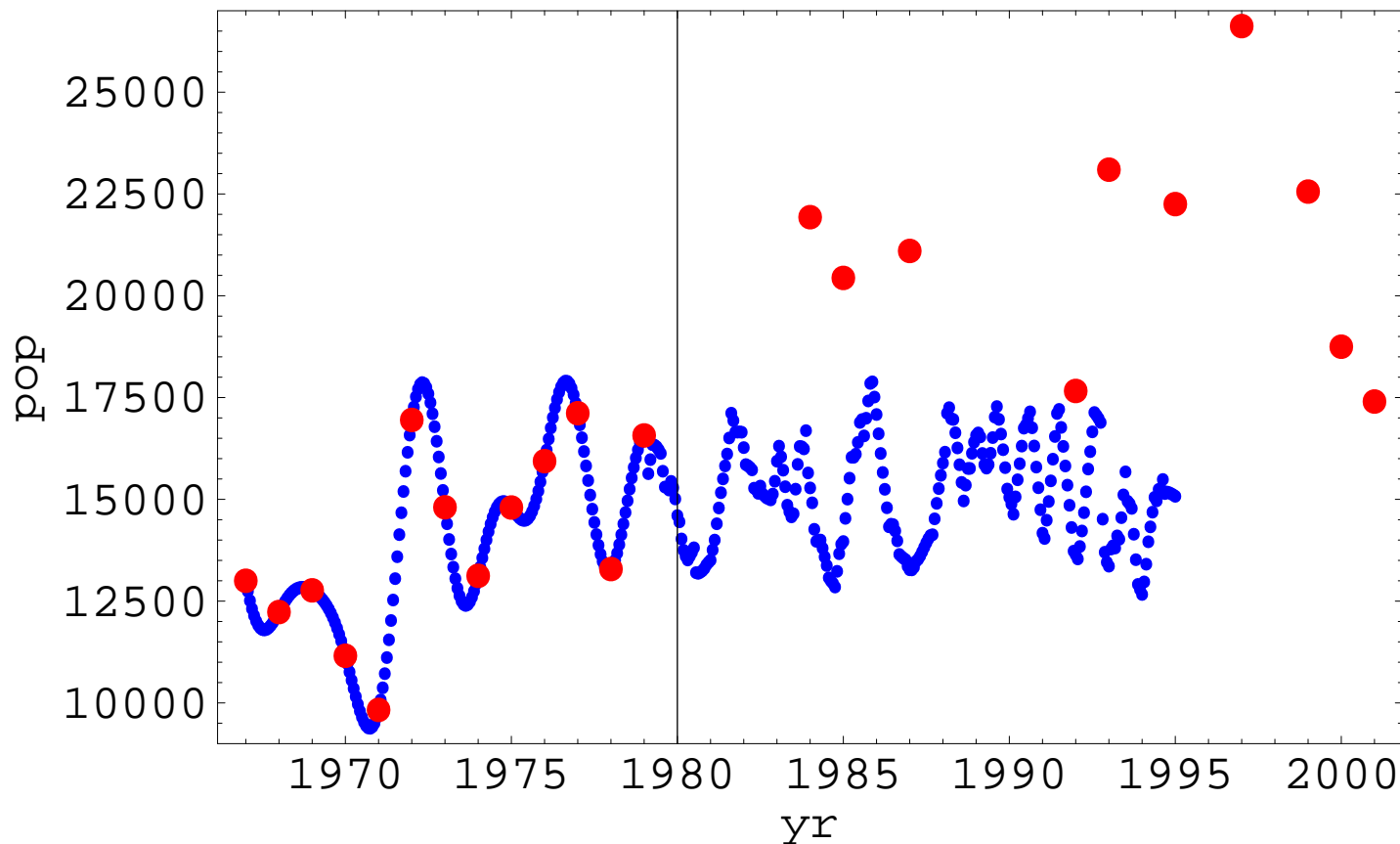
1. Let  $\mathbf{c}$  be the center of mass of  $\{\mathbf{x}_{n_1}, \dots, \mathbf{x}_{n_k}\}$
2. For some  $l \leq m$  find the  $l$ -dimensional subspace of  $\mathbb{R}^m$  containing  $\mathbf{c}$  closest to the span of  $\{\mathbf{x}_{n_1}, \dots, \mathbf{x}_{n_k}\}$

$$A = \begin{bmatrix} \mathbf{x}_{n_1} - \mathbf{c} \\ \vdots \\ \mathbf{x}_{n_k} - \mathbf{c} \end{bmatrix} = U^t D V$$

3. Project  $\{\mathbf{x}_{n_1} - \mathbf{c}, \dots, \mathbf{x}_{n_k} - \mathbf{c}\}$  onto  $\mathbb{R}^l$
4. Find the affine map  $G : \mathbb{R}^l \rightarrow \mathbb{R}$  which best fits the data  $\{(\Pi(\mathbf{x}_{n_1} - \mathbf{c}), P_{n_1+1}), \dots, (\Pi(\mathbf{x}_{n_k} - \mathbf{c}), P_{n_k+1})\}$

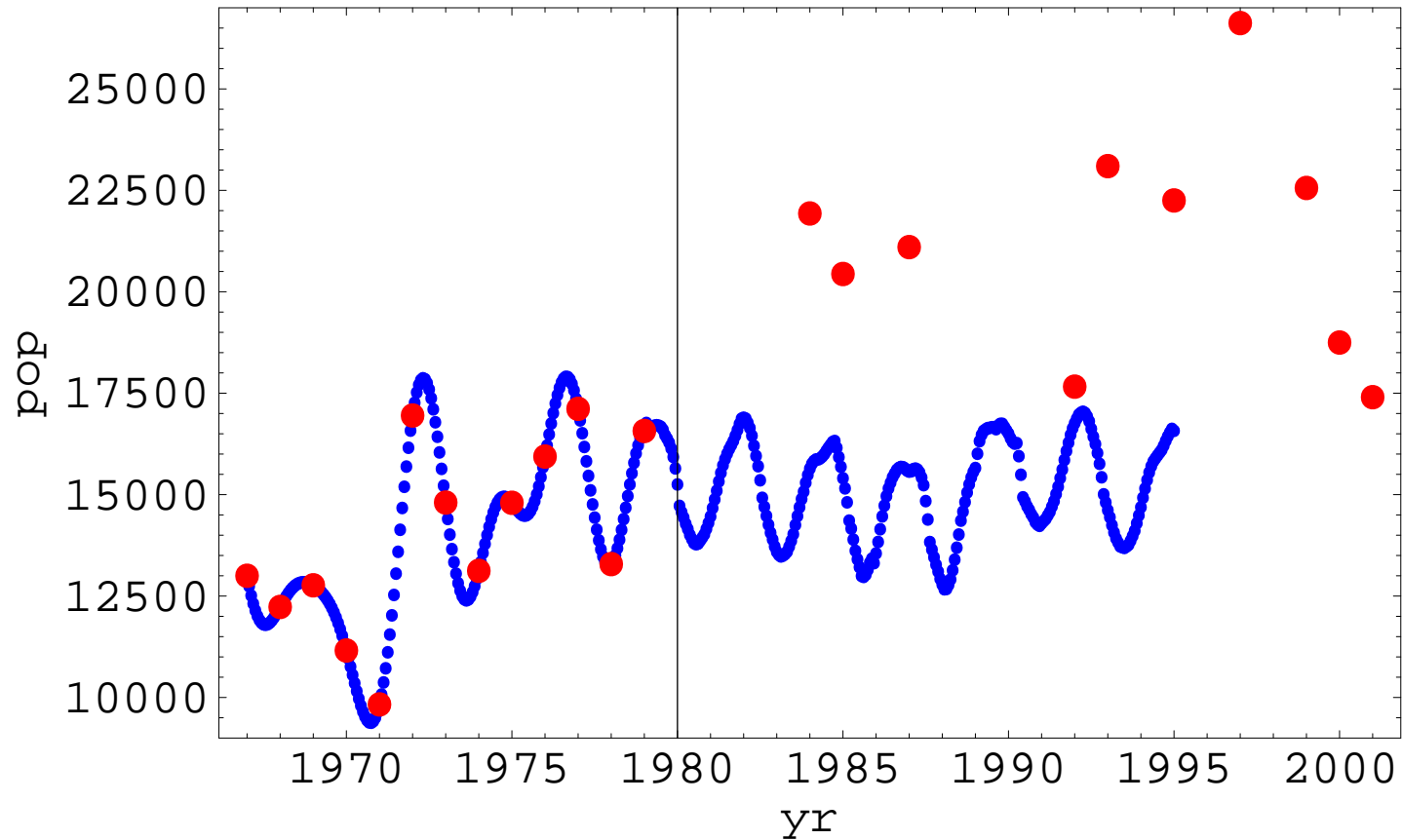
$$\hat{P}_{N+1} \approx G(\Pi(\mathbf{x}_N - \mathbf{c}))$$

# Constant Model, Direct Averaging



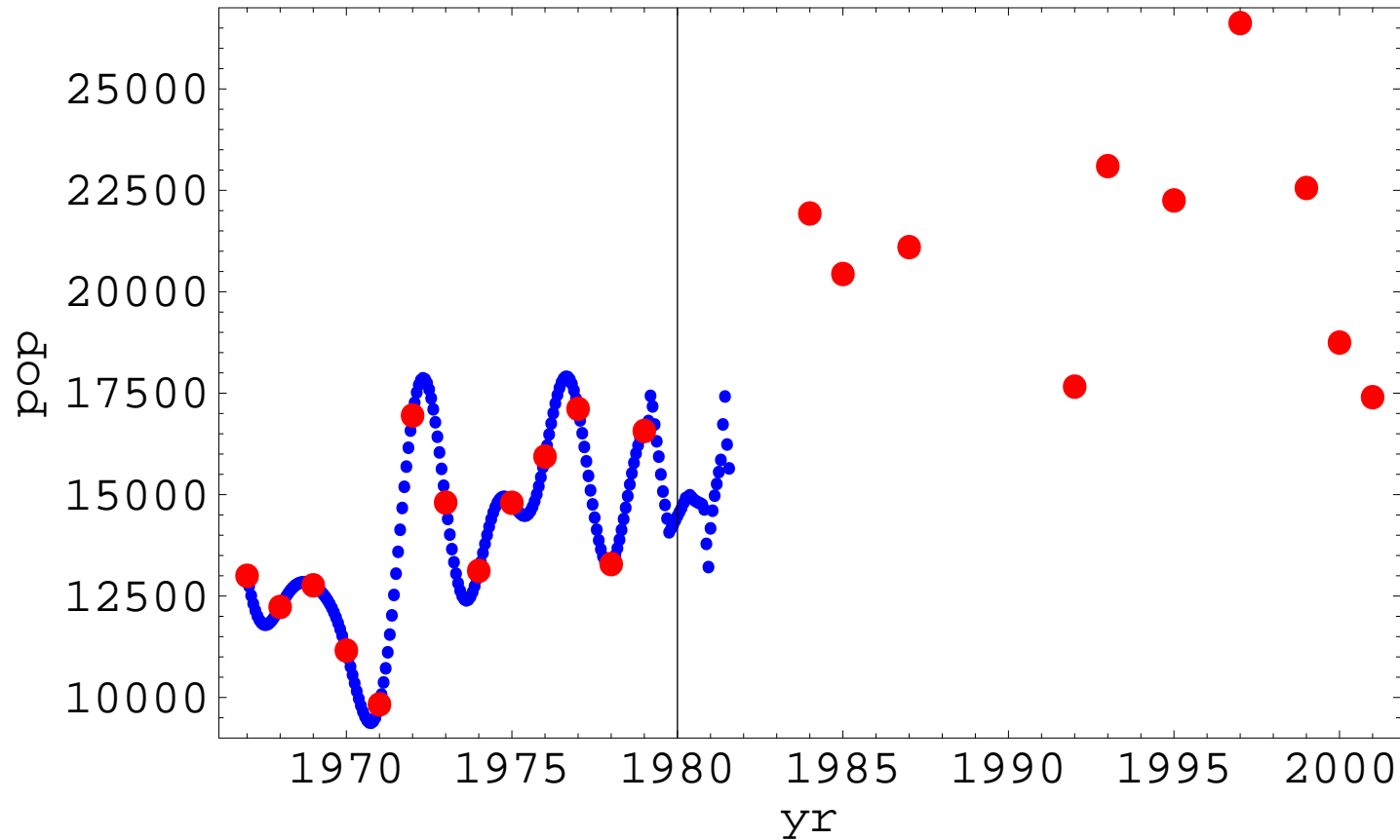
Parameters: Euclidean metric, 2 nearest neighbors, embedding dimension 32

# Constant Model, Integrated Averaging



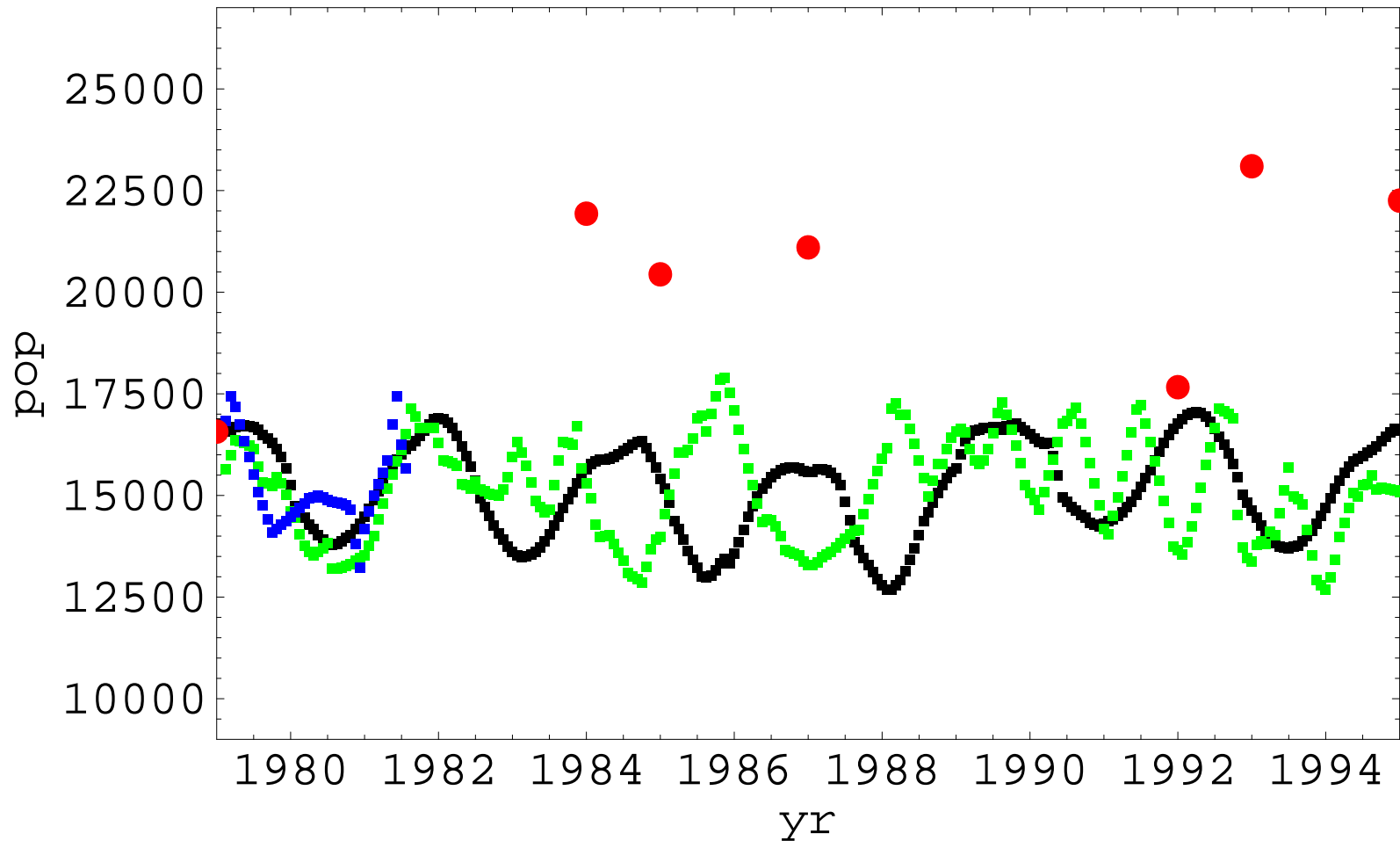
Parameters: Euclidean metric, 2 nearest neighbors, embedding dimension 32

# Linear Model



Parameters: Euclidean metric, 4 nearest neighbors, embedding dimension 32, model dimension 2

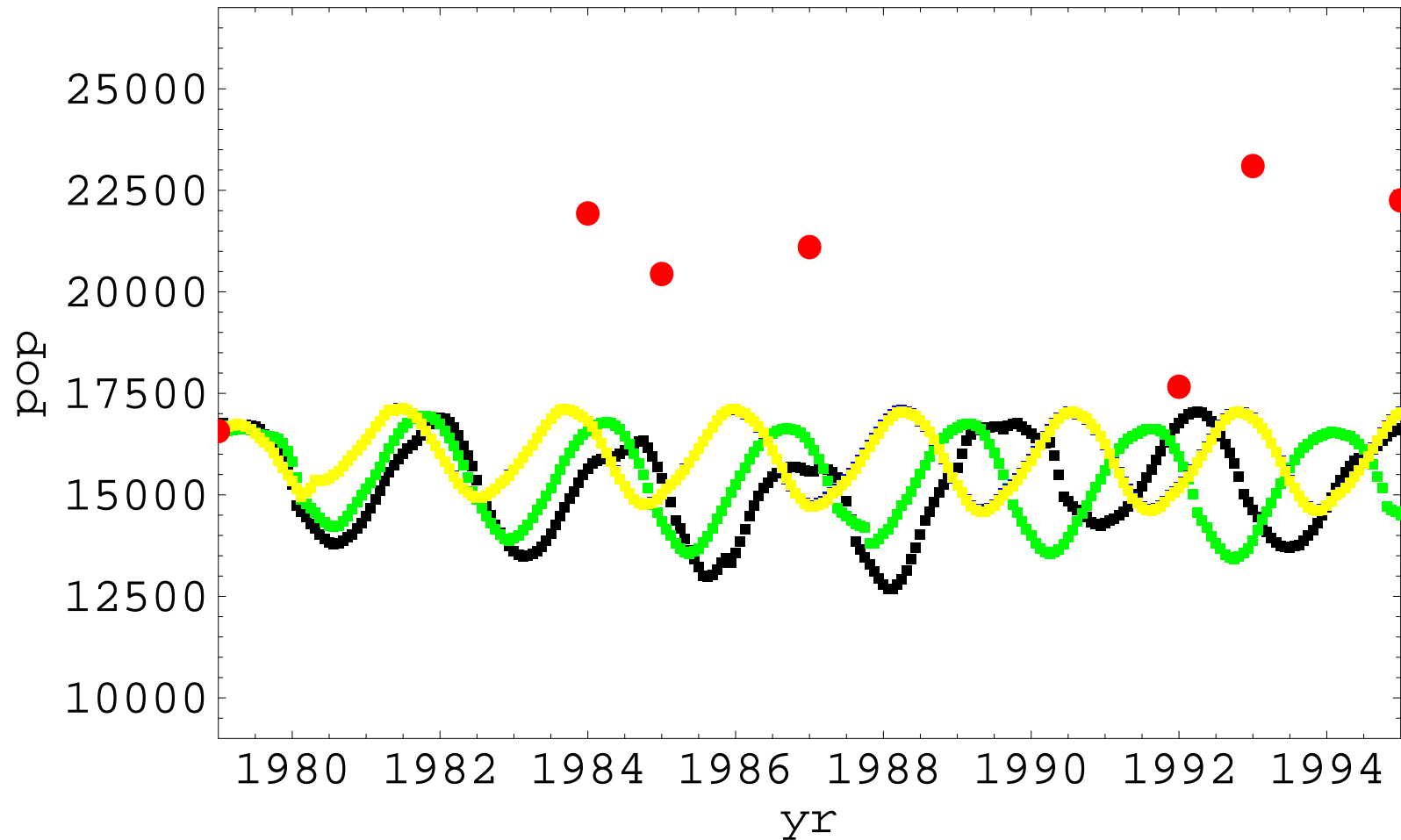
# Overlay of Model Results



Model: integrated, averaged, linear



# Sensitivity to Nearest Neighbors



Number of nearest neighbors: 2, 3, 4, 5

# Comments

- Linear model requires more neighbors than the constant models.
- Linear model requires more data than the constant models.
- Constant models exhibit plausible oscillatory behavior.
- Population levels predicted by the local models exhibit flat average behavior
- Need much more data for model validation.
- Has the gray whale population been above its carrying capacity?

# References

Casdagli, M. *et al.*, “State space reconstruction in the presence of noise,” *Physica D* (51), pp. 52–98 (1991).

de la Mare, W.K., Report of the Scientific Committee, Annex L. The model used in the HITTER and FITTER programs (Program: FITTER.SC40). *Rep. int. Whal. Commn.* (39), pp. 150–151 (1989).

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