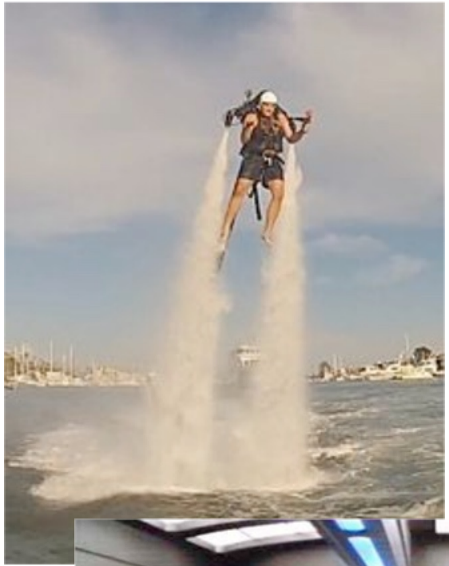
Bigelow | Laboratory for Ocean Sciences

Ocean Forecasting
Methodologies

Nick Record
Tandy Center for Ocean Forecasting

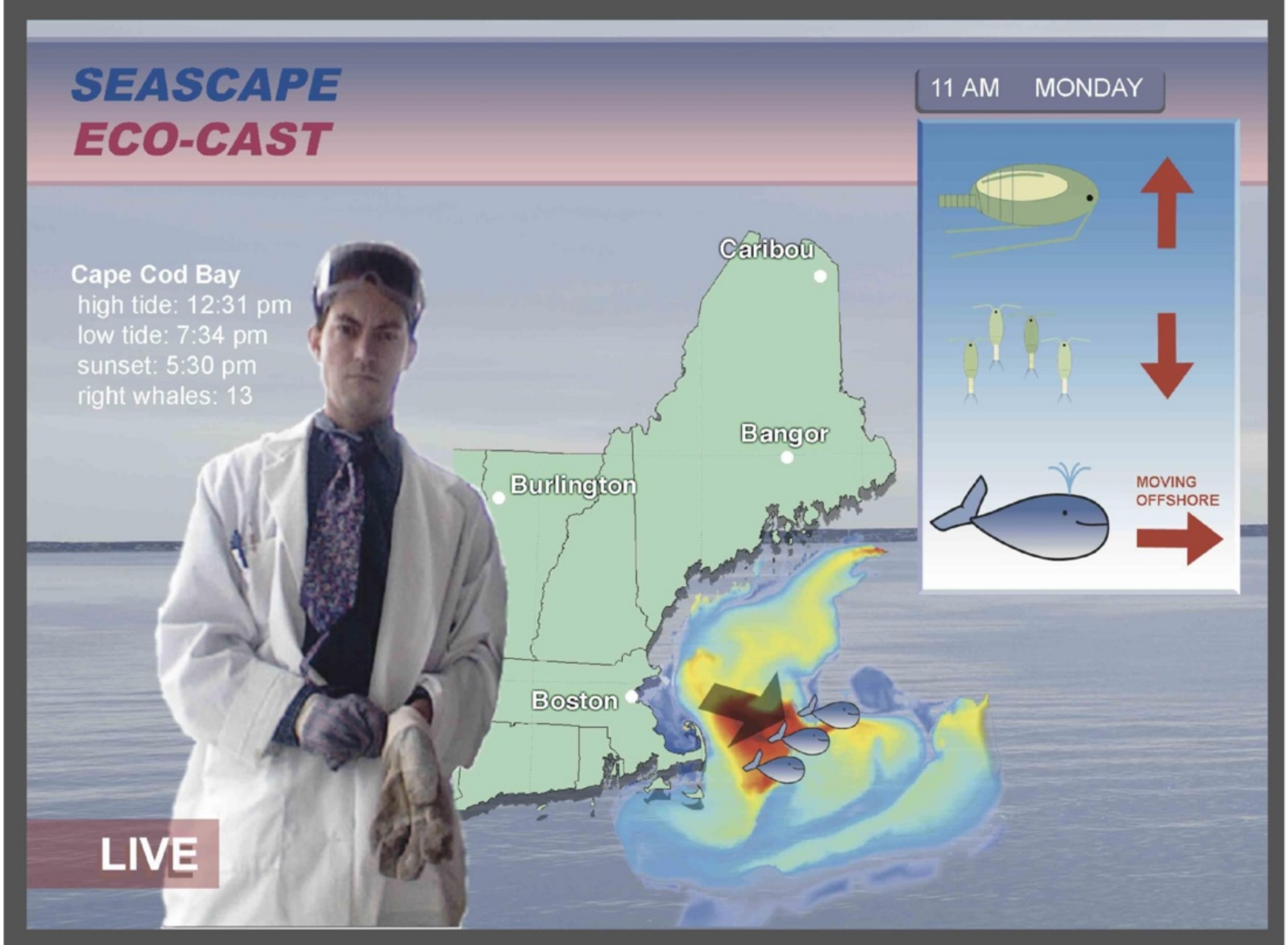
Colby Jan Plan: JP297Dj

The Future …




THE Jetsons


©Dreamworks SKG, Warner Brothers
THE TIME MACHINE


SEASCAPE
ECO-CAST
11 AM MONDAY
Cape Cod Bay
high tide: 12:31 pm
low tide: 7:34 pm
sunset: 5:30 pm
right whales: 13
Caribou
Bangor
Burlington
Boston
MOVING OFFSHORE
LIVE

Today's class

Ocean examples: empirical vs mechanistic

Algorithms and methods: Where do you start?

A History of Weather Forecasting

300 BC

Aristotle: *Meteorologica*

Theophrastus: *The Book of Signs*

"It is a sign of rain when a tame duck gets under the eaves and flaps its wings."

1640s

Barometer

1900s

Numerical (computational) weather forecasting

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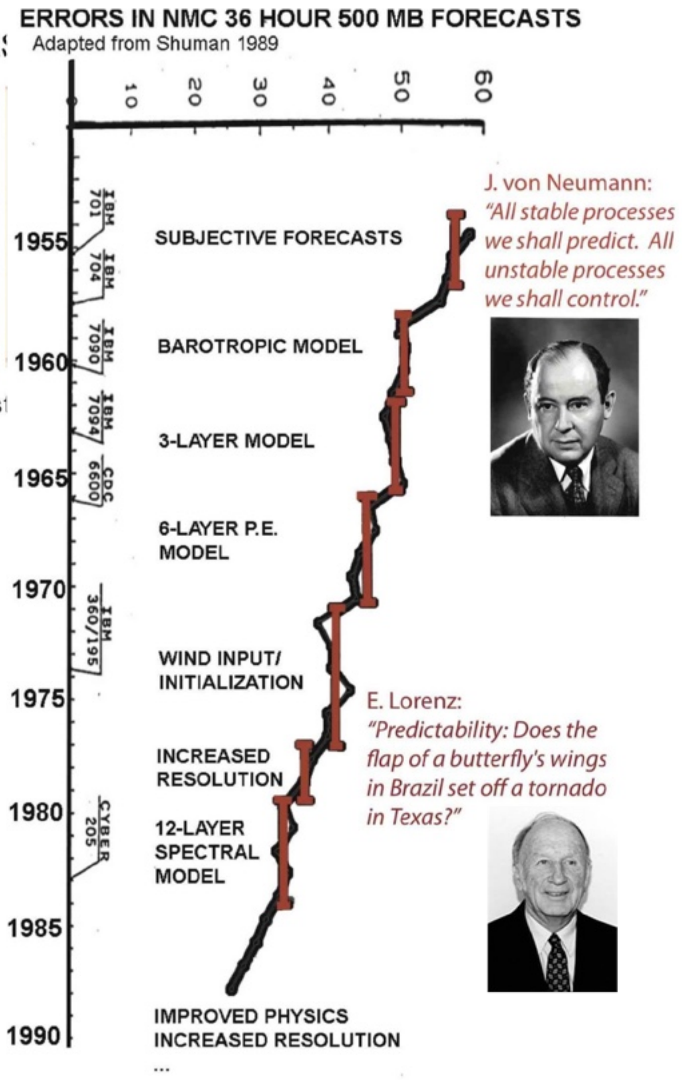
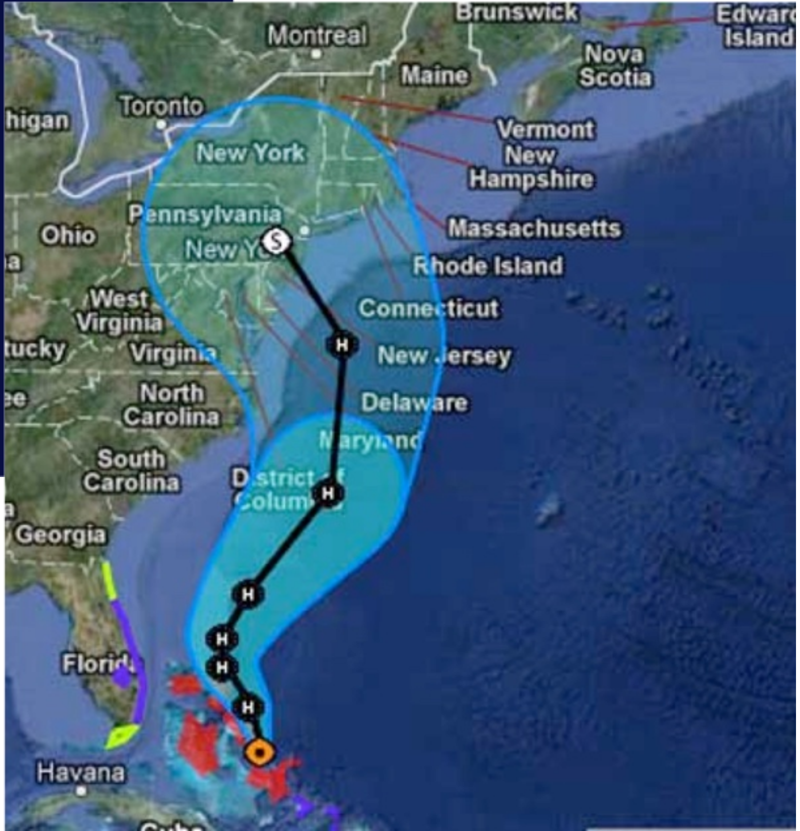


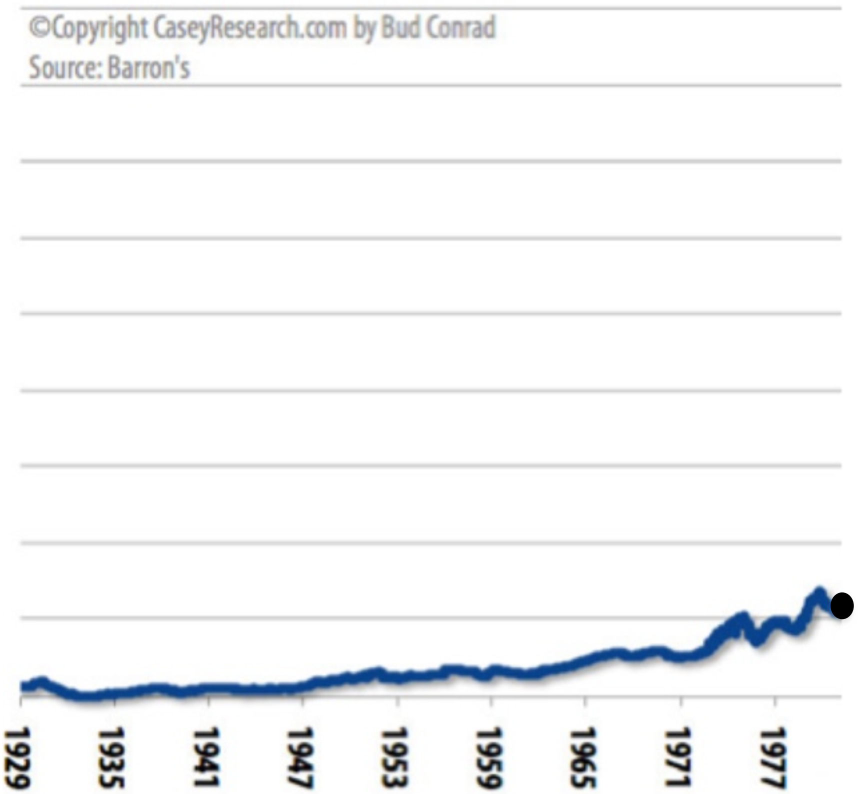
Actual track

Forecasted track

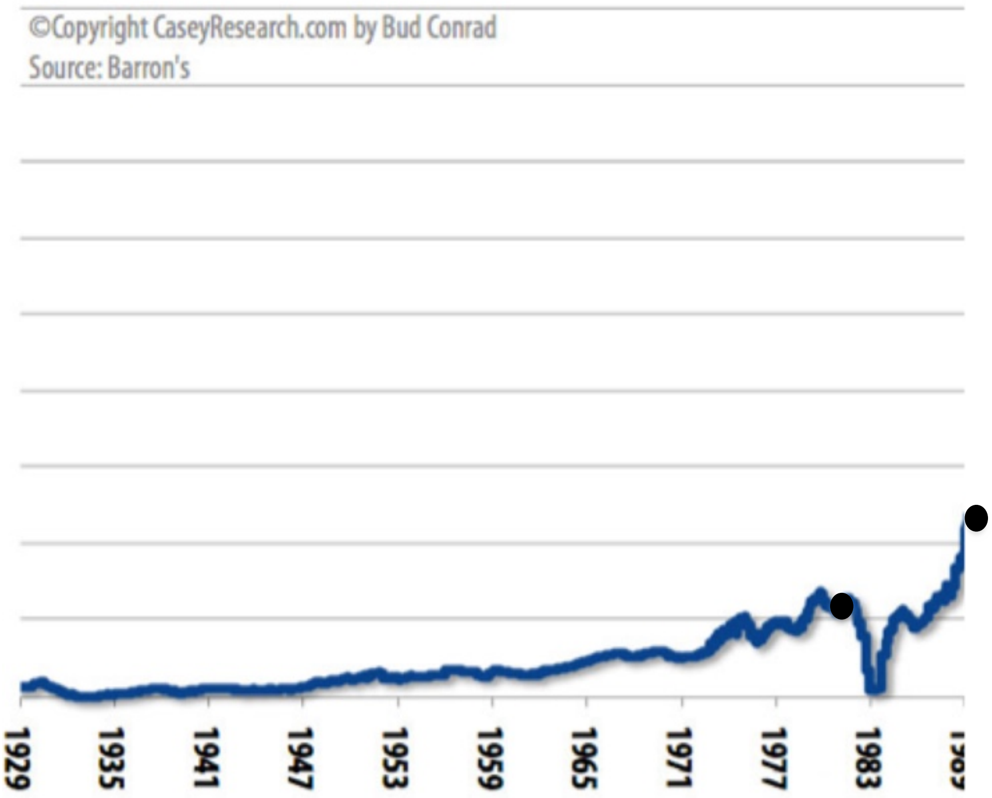


Ocean Examples:
Empirical vs Mechanistic

FORECASTING WARM-UP



FORECASTING WARM-UP



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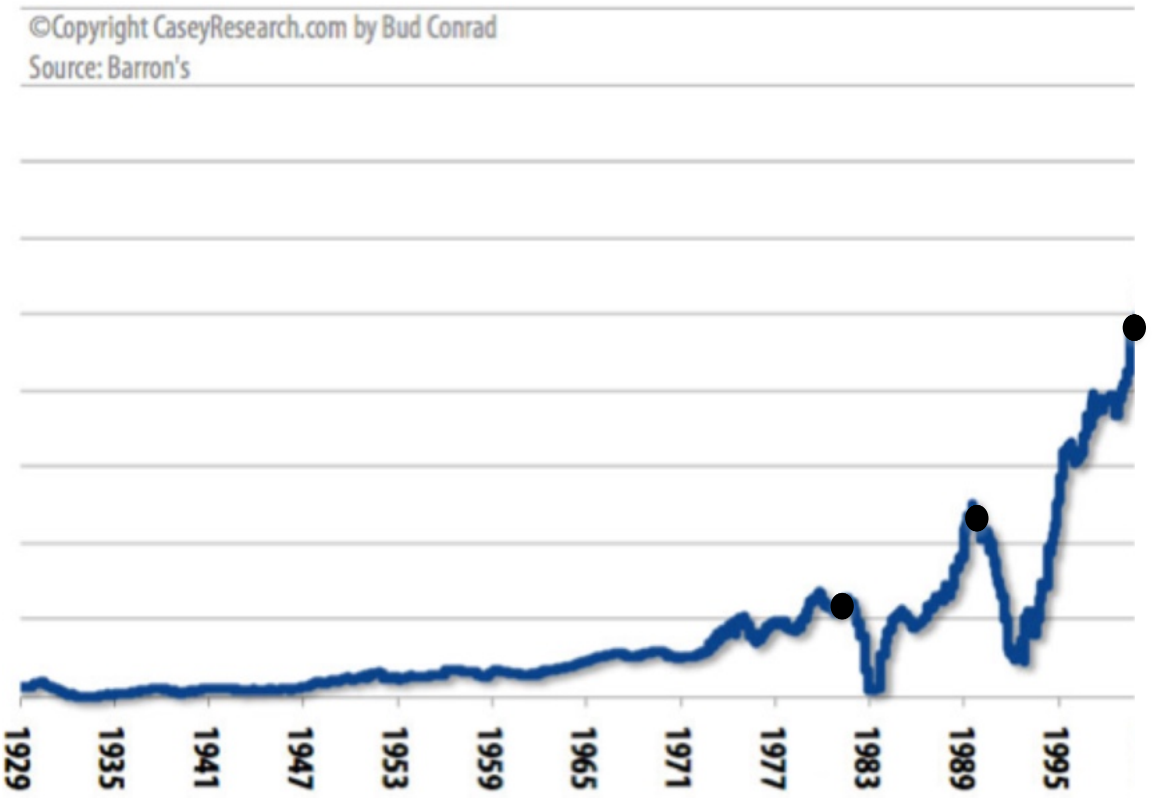
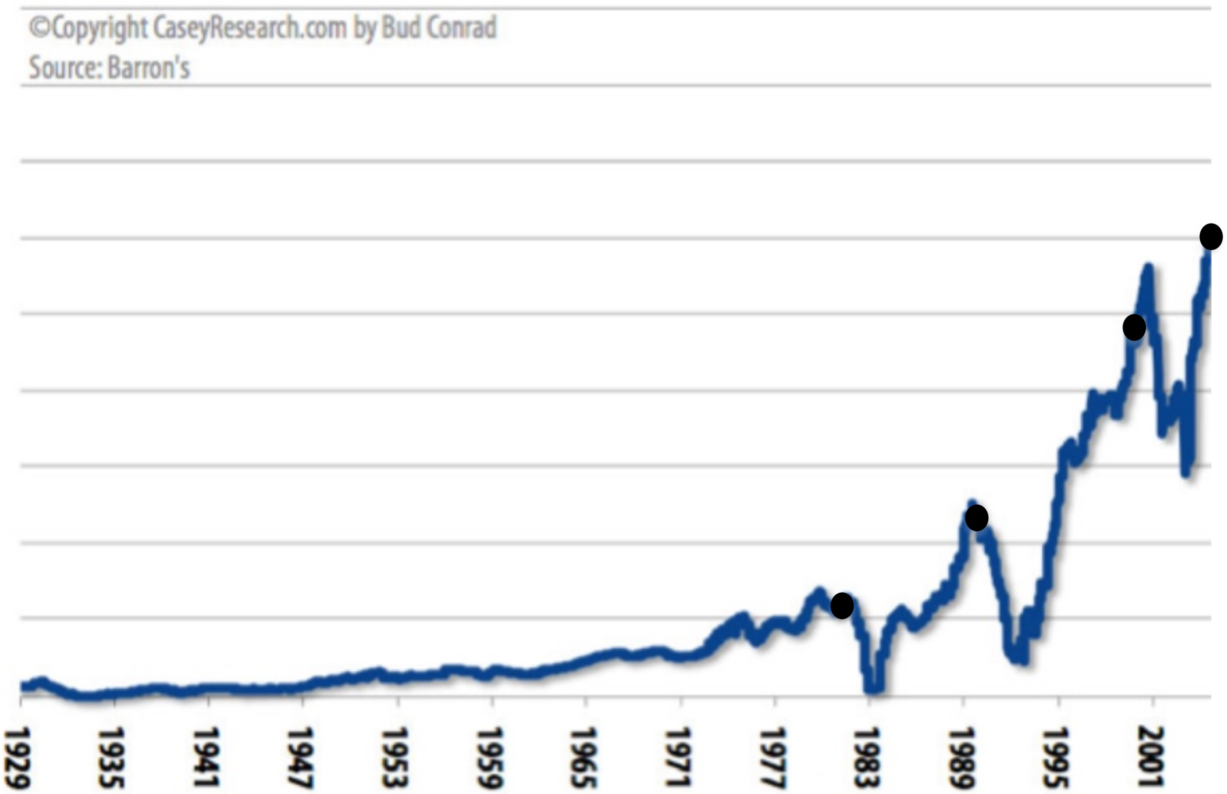
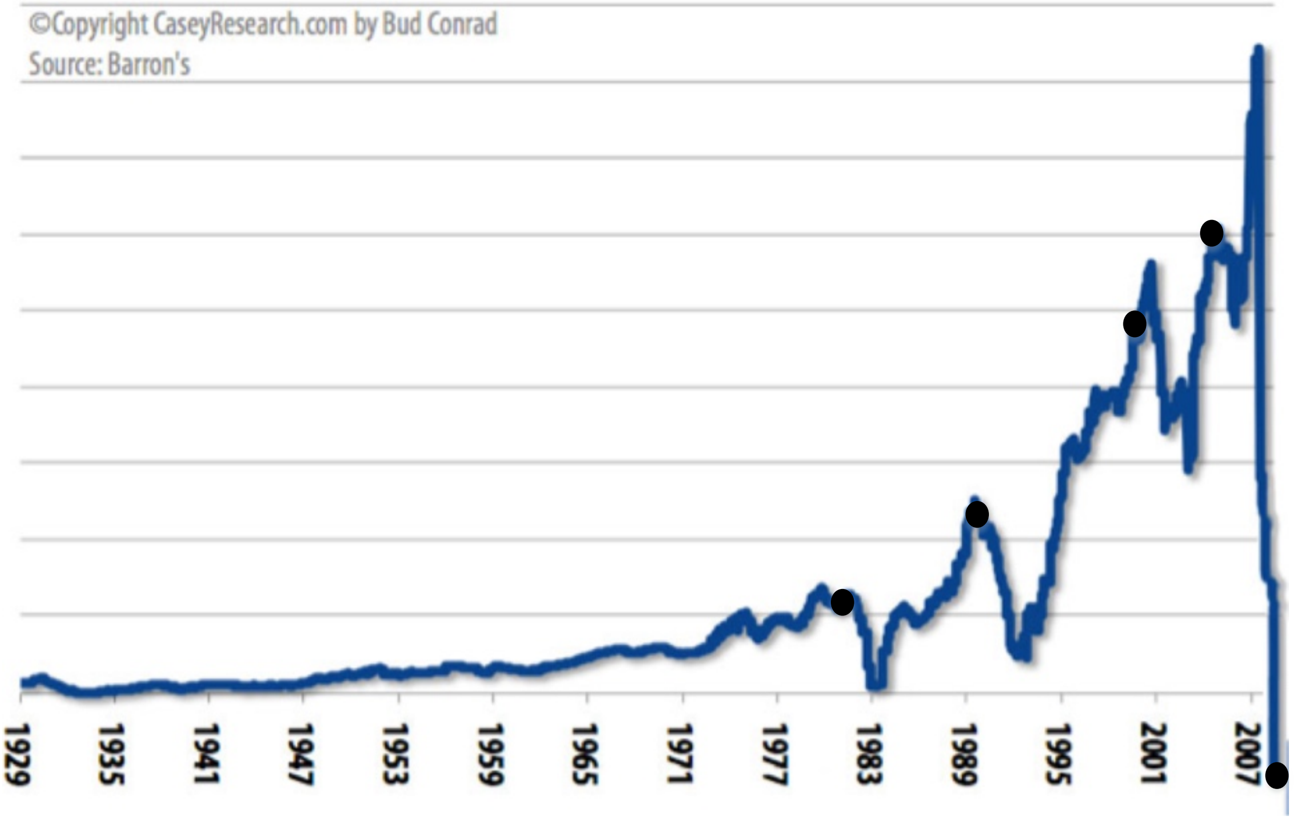
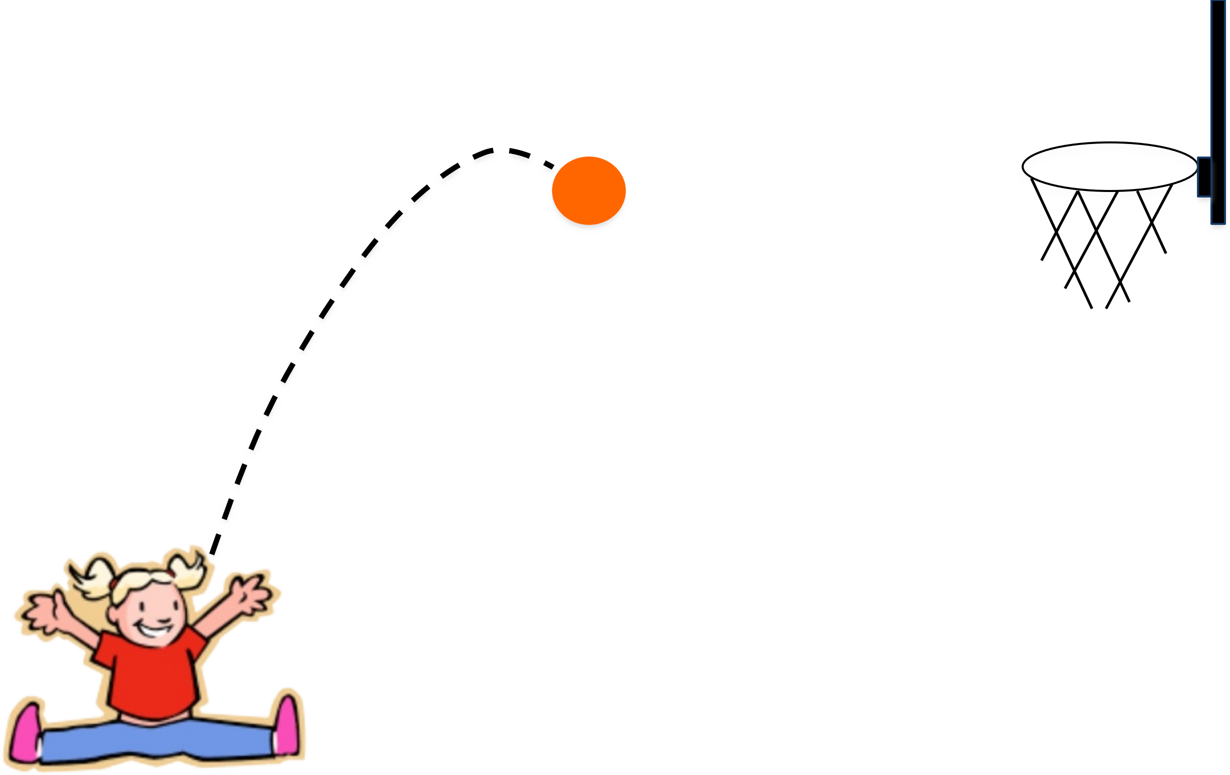


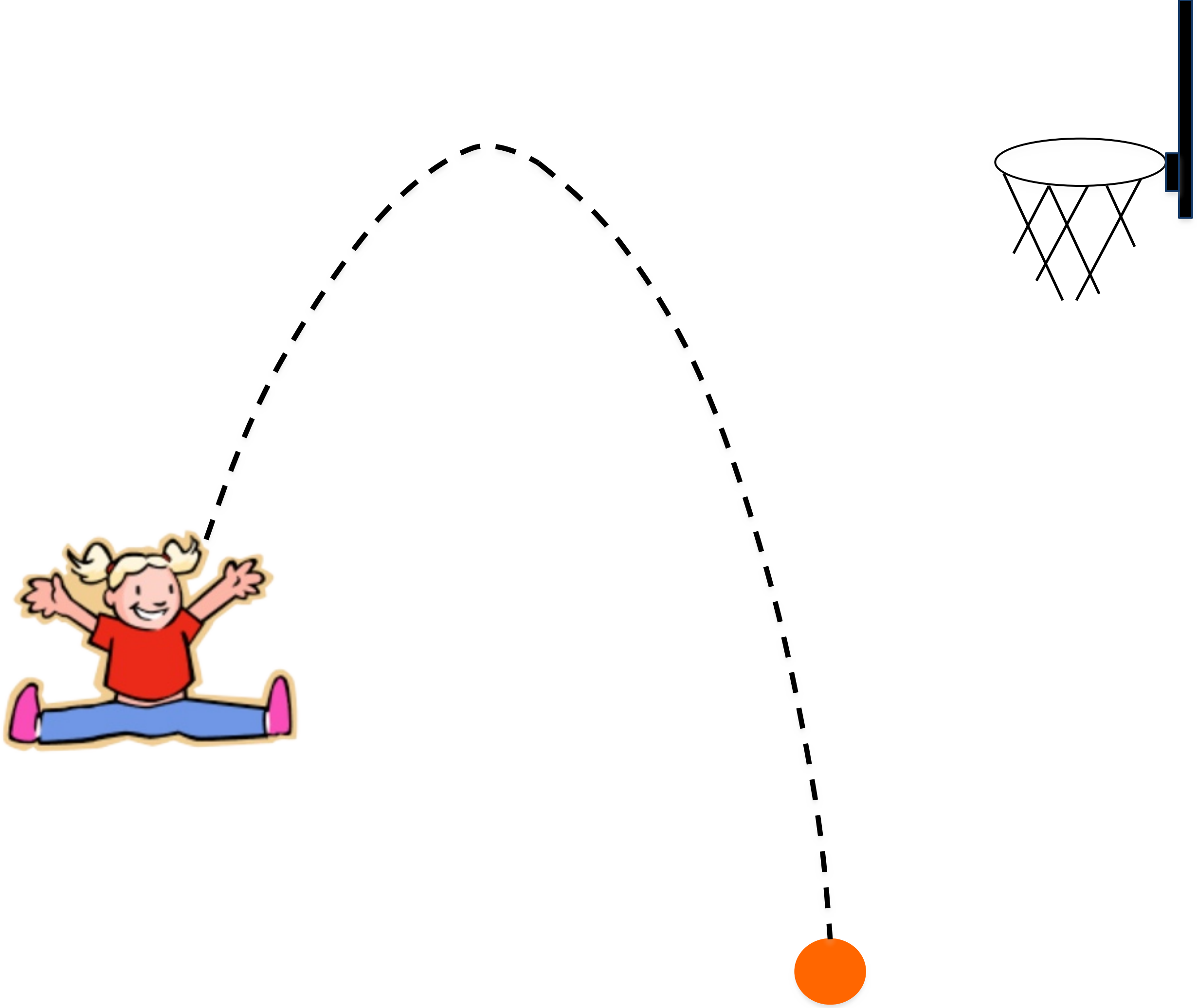
FORECASTING WARM-UP

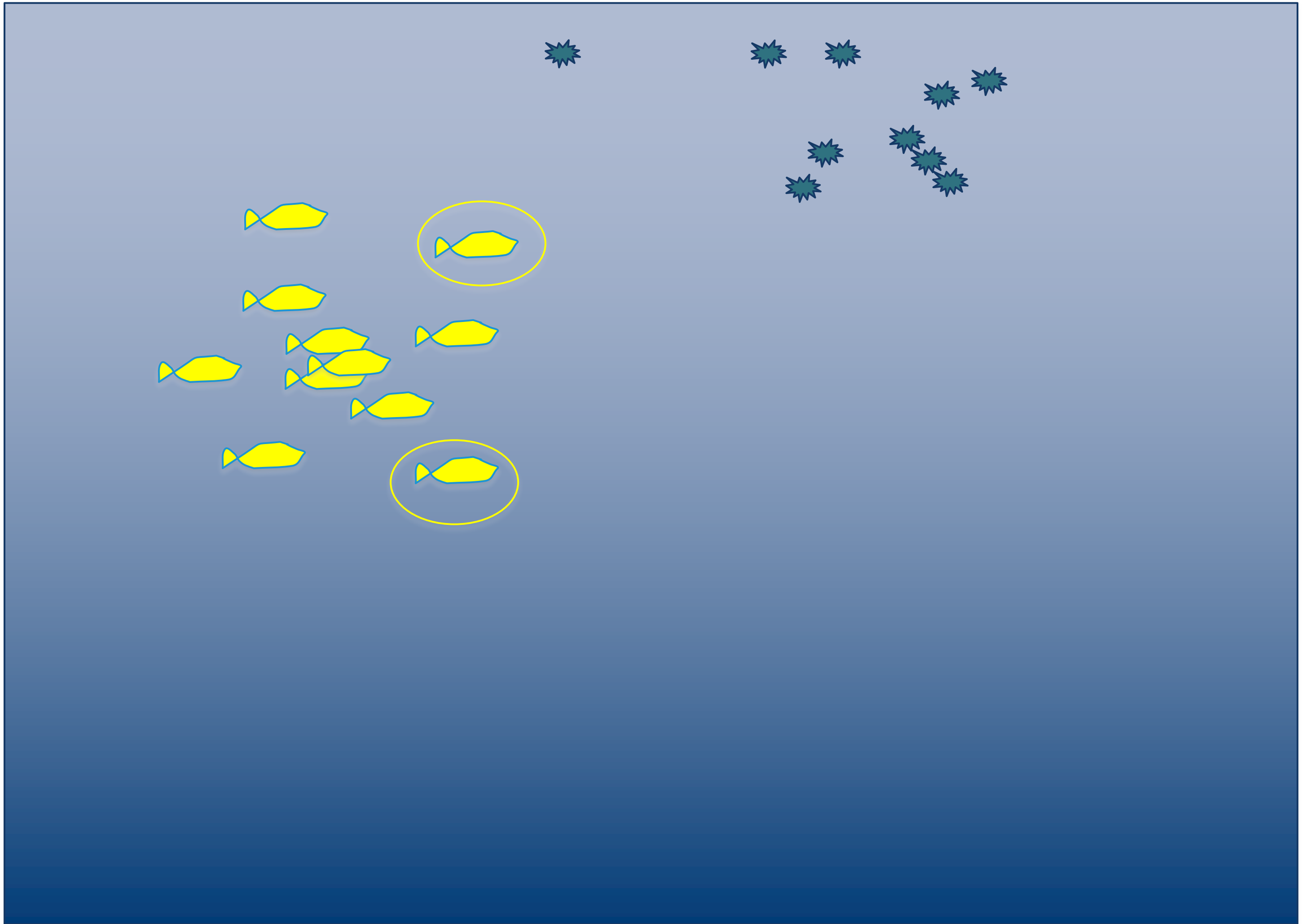


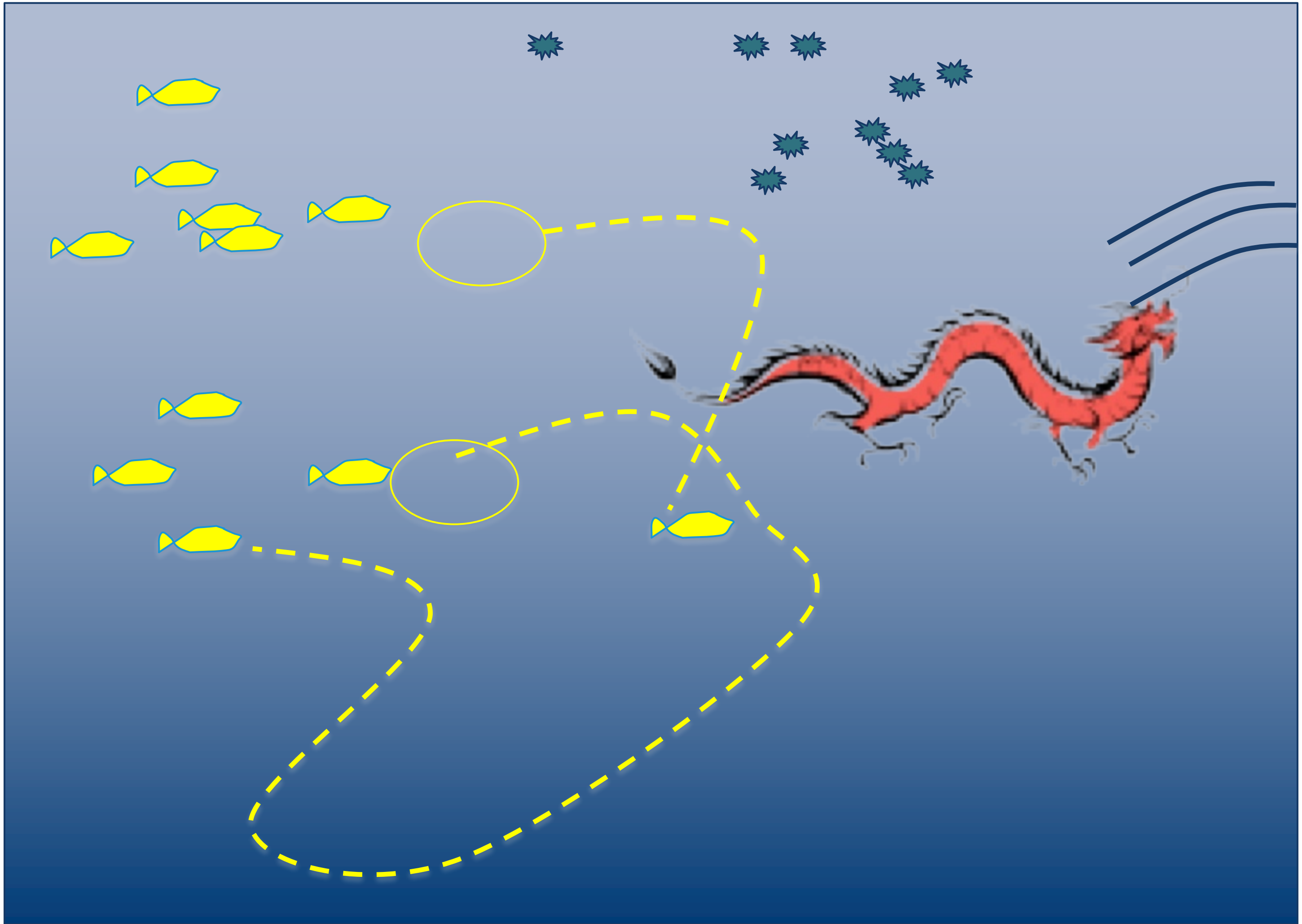
FORECASTING WARM-UP



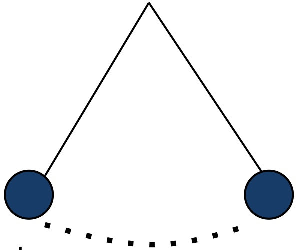








The two sides of forecasting



Mechanistic
Deterministic
Process-based
Causation

Empirical
Probabilistic
Observation-based
Association

<u>1950s</u>

"All stable processes we shall predict. All unstable processes we shall control."
- J. von Neumann

<u>1970s</u>

"Predictability: Does the flap of a butterfly's wings in Brazil set off a tornado in Texas?"
- E. Lorenz 1979

<u>2000s</u>

Bayesian revival

<u>2010s</u>

Machine learning, Neural networks

The two sides of forecasting

Mechanistic
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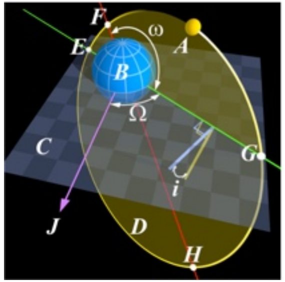
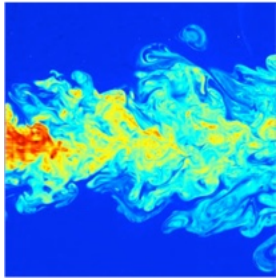
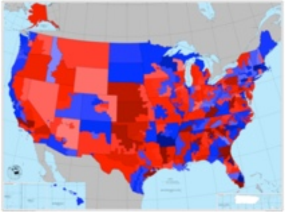
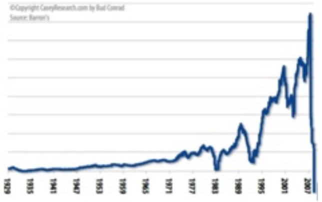
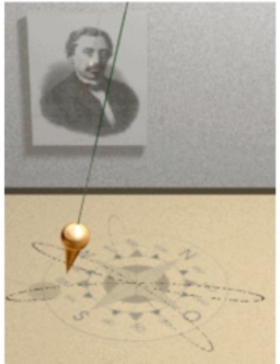
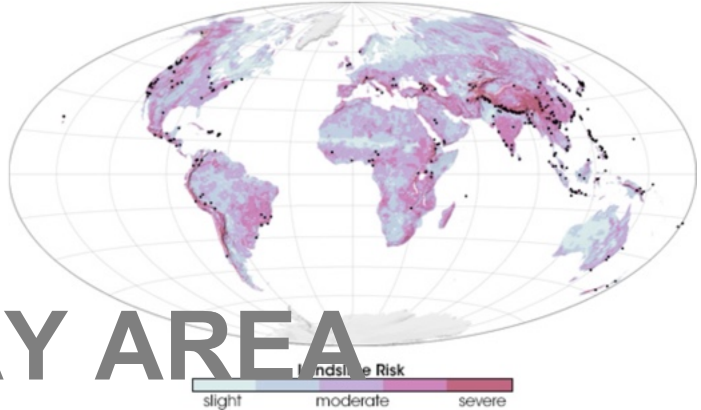












GRAY AREA

Empirical Forecasting example:
Sea Nettles

Chrysaora in Chesapeake Bay

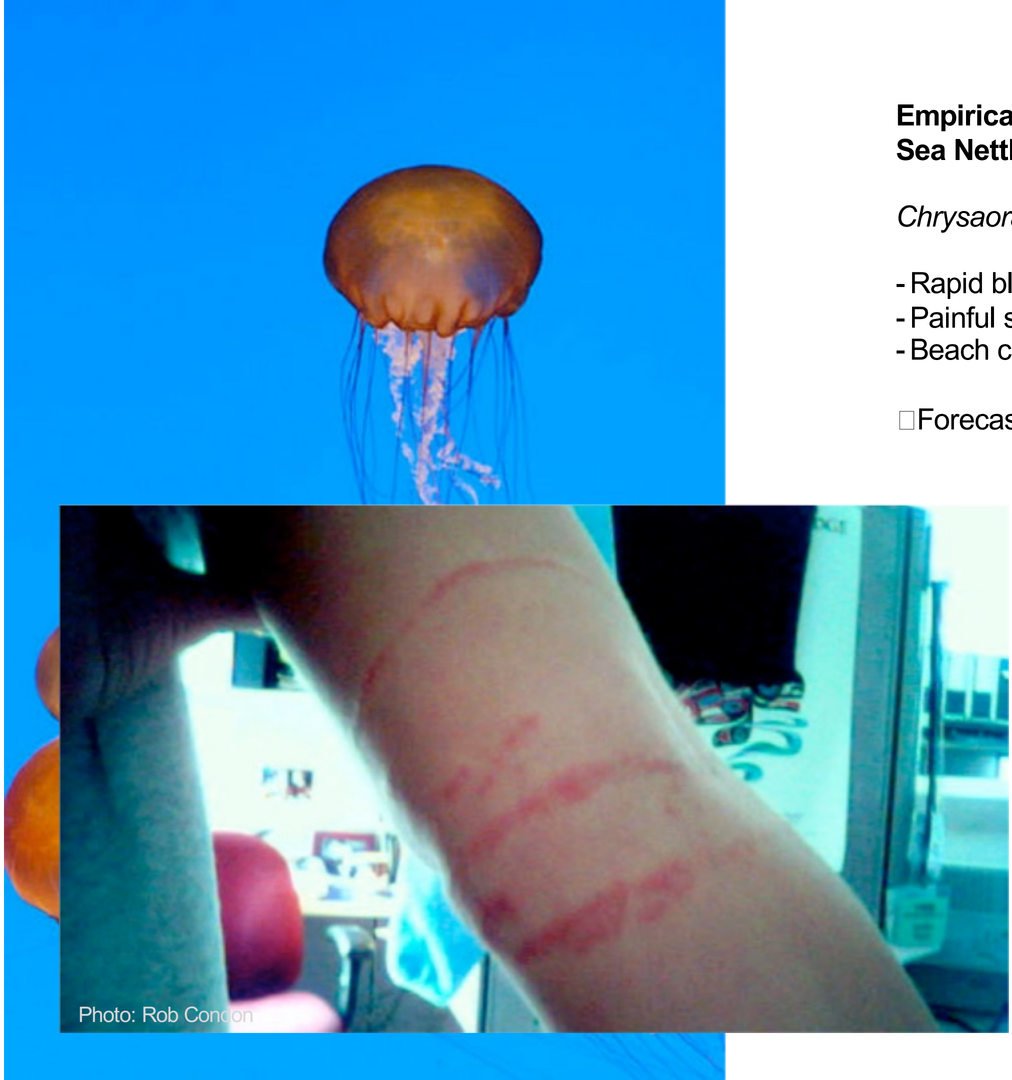


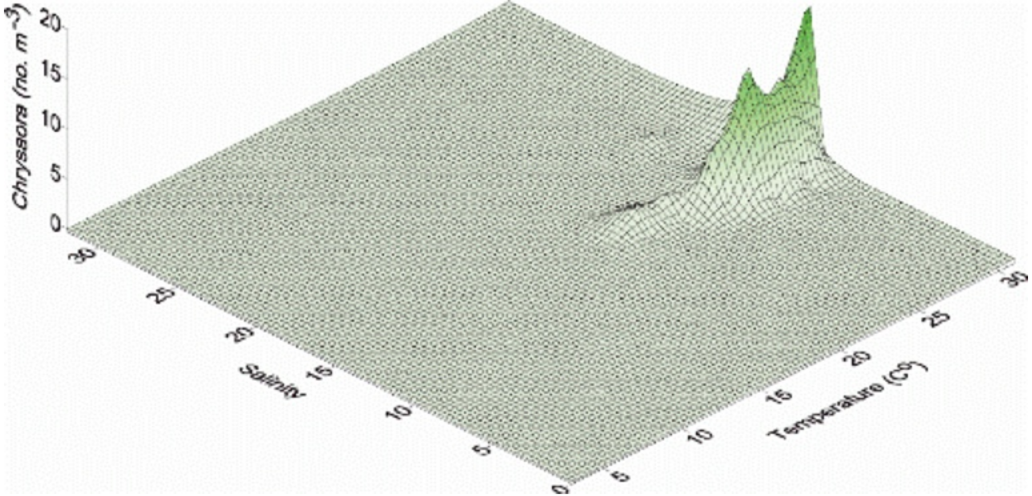
Photo: Rob Condon

Empirical Forecasting example: Sea Nettles

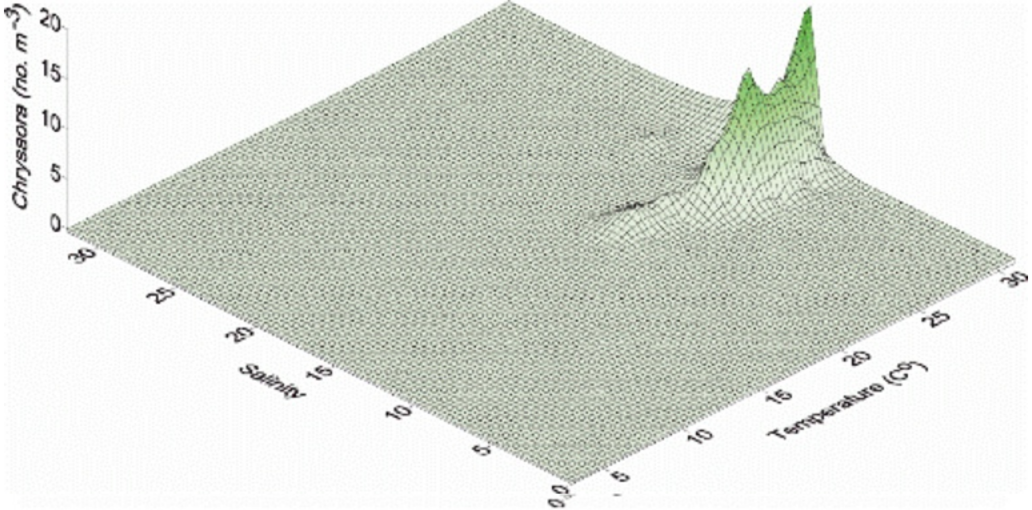
Chrysaora in Chesapeake Bay

- Rapid blooms
- Painful stings
- Beach closures

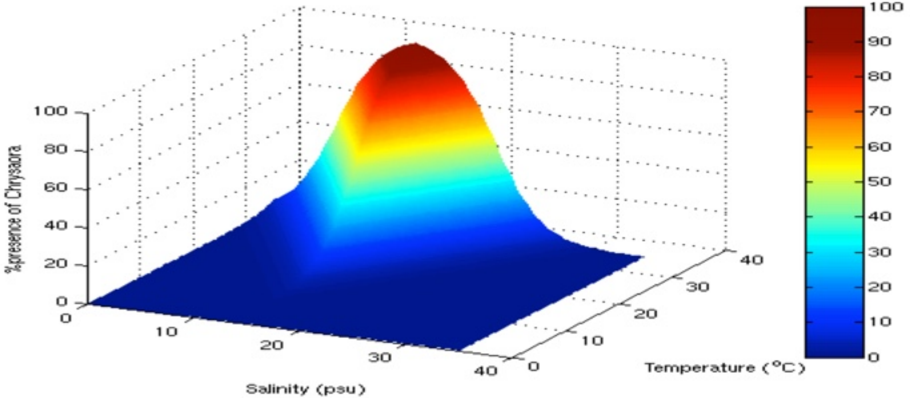
□Forecasting can prevent injury

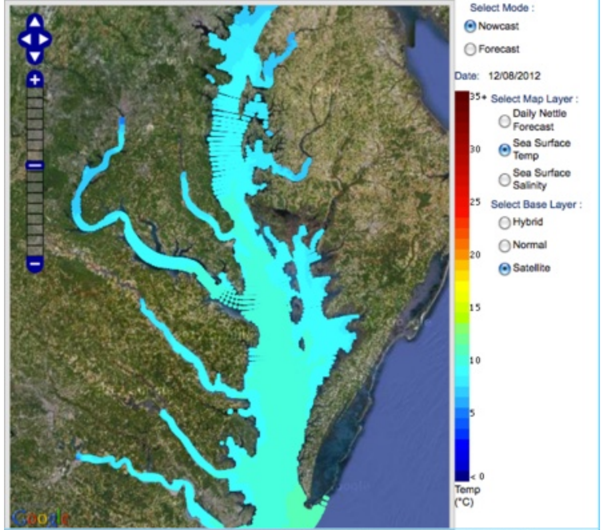


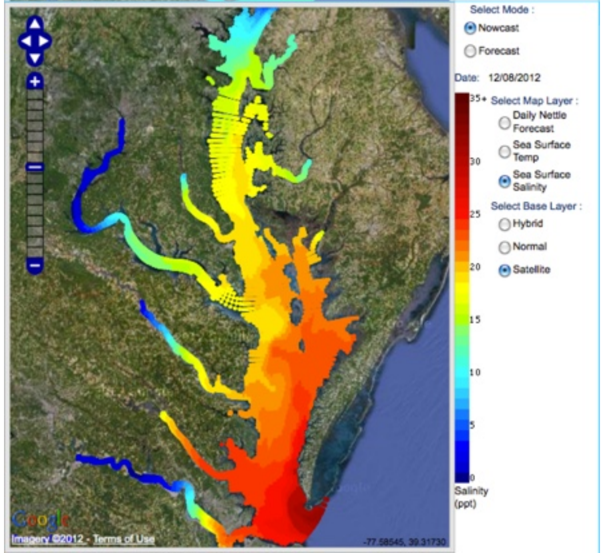
Chrysaora (no. m^{-3})
0
5
10
15
20
Salinity
0
5
10
15
20
25
30
Temperature (C°)
5
10
15
20
25
30

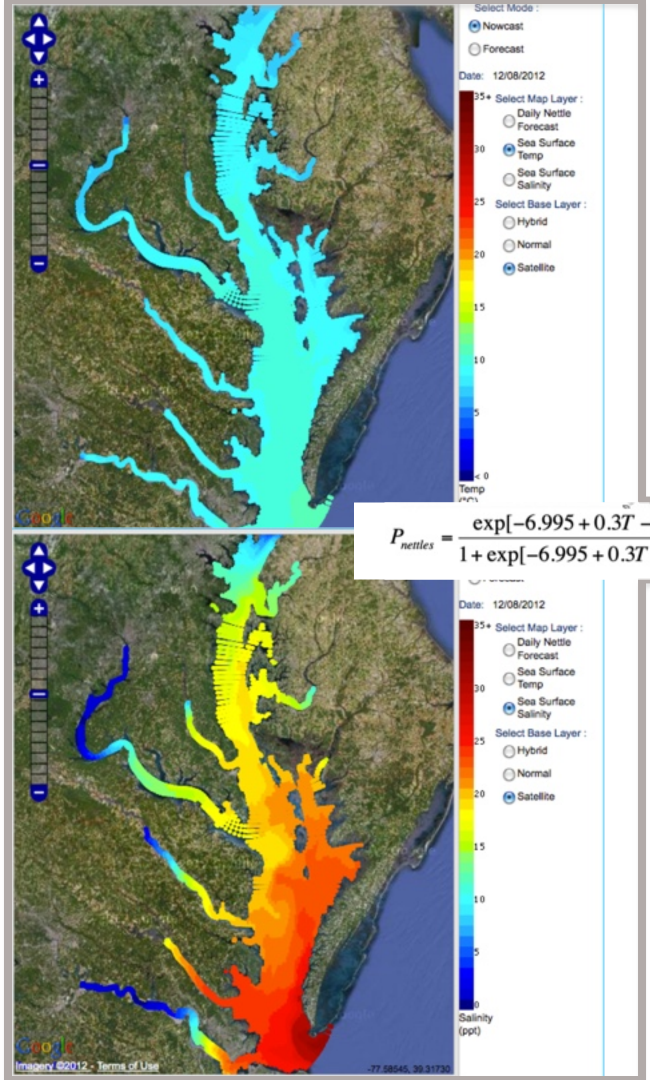


$$P_{nettles} = \frac{\exp[-6.995 + 0.3T - 0.469(S - 13.5)]}{1 + \exp[-6.995 + 0.3T - 0.469(S - 13.5)]}$$




Select Mode :
Nowcast
Forecast
Date: 12/08/2012
Select Map Layer :
Daily Nettle Forecast
Sea Surface Temp
Sea Surface Salinity
Select Base Layer :
Hybrid
Normal
Satellite
35+
30
25
20
15
10
5
< 0
Temp (°C)


Select Mode :
Nowcast
Forecast
Date: 12/08/2012
Select Map Layer :
Daily Nettle Forecast
Sea Surface Temp
Sea Surface Salinity
Select Base Layer :
Hybrid
Normal
Satellite
35+
30
25
20
15
10
5
0
Salinity (ppt)
Imagery ©2012 - Terms of Use
-77.58545, 39.31730



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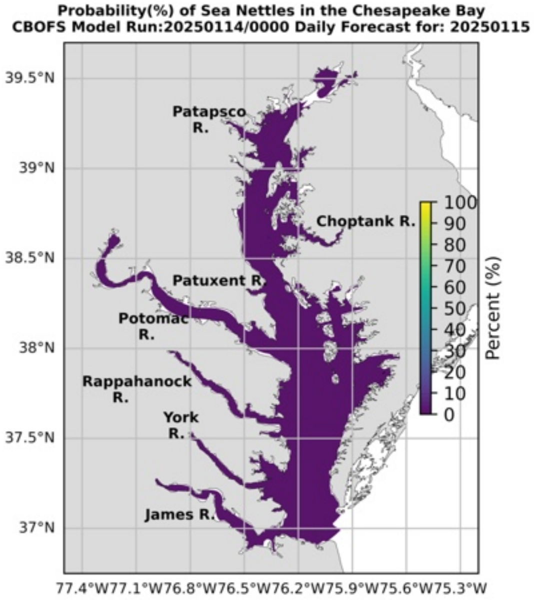
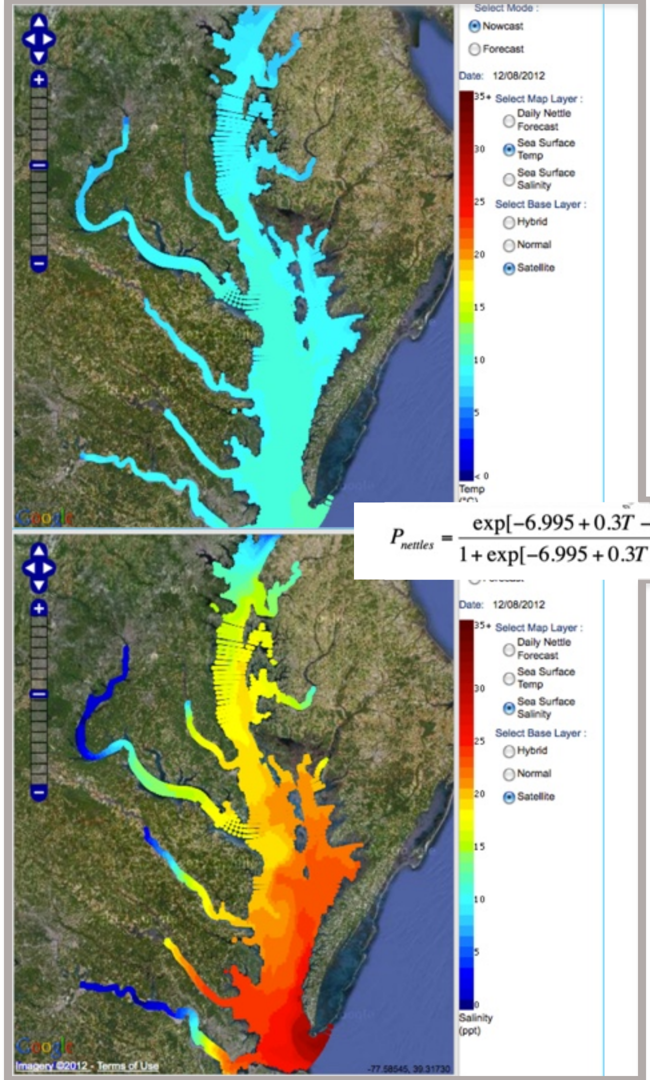


January 14, 2025



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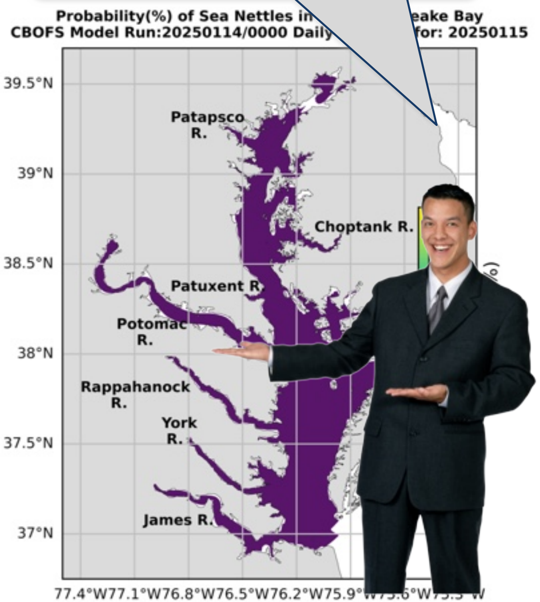
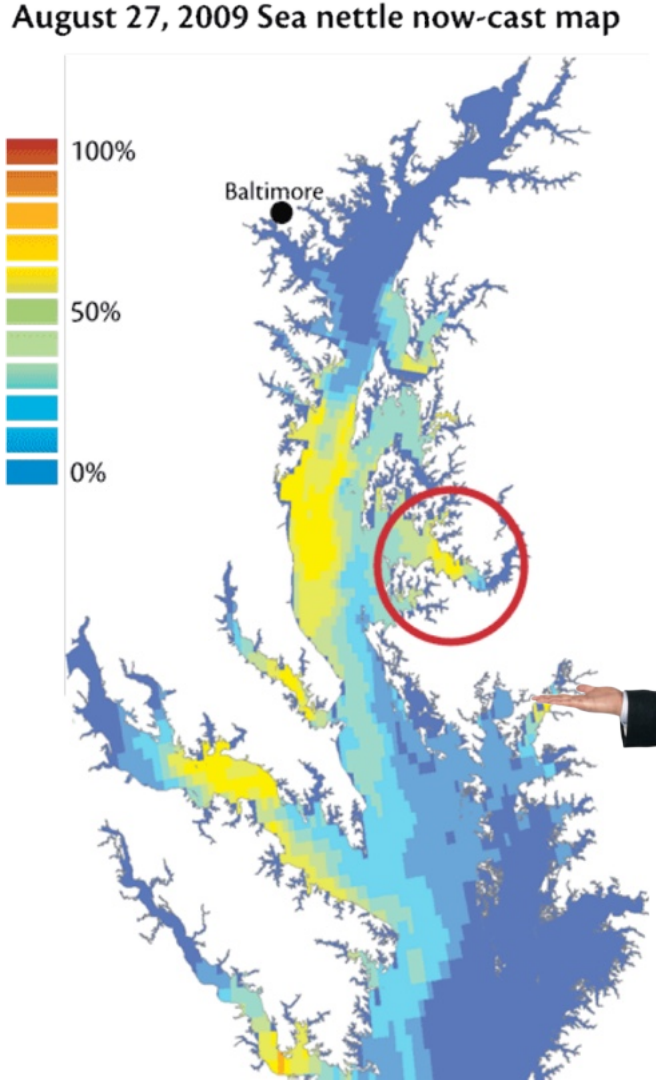
Forecast for this week:
0% chance of nettles



January 14, 2025

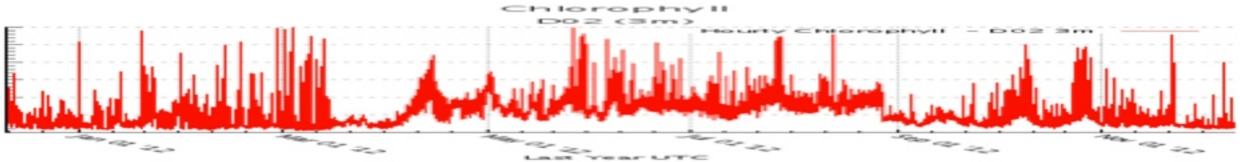
A more typical probability forecast map in summer



Empirical approach

Advantages

- Simple (possibly)
- Doesn’t require theoretical or mechanistic understanding
- New information improves equation / reduces uncertainty (e.g. turbidity, light)
- We live in a data-rich age



Empirical approach

<u>Advantages</u>

- Simple
- Doesn't require theoretical or mechanistic understanding
- New information improves equation / reduces uncertainty
  (e.g. turbidity, light)
- We live in a data-rich age

… but…

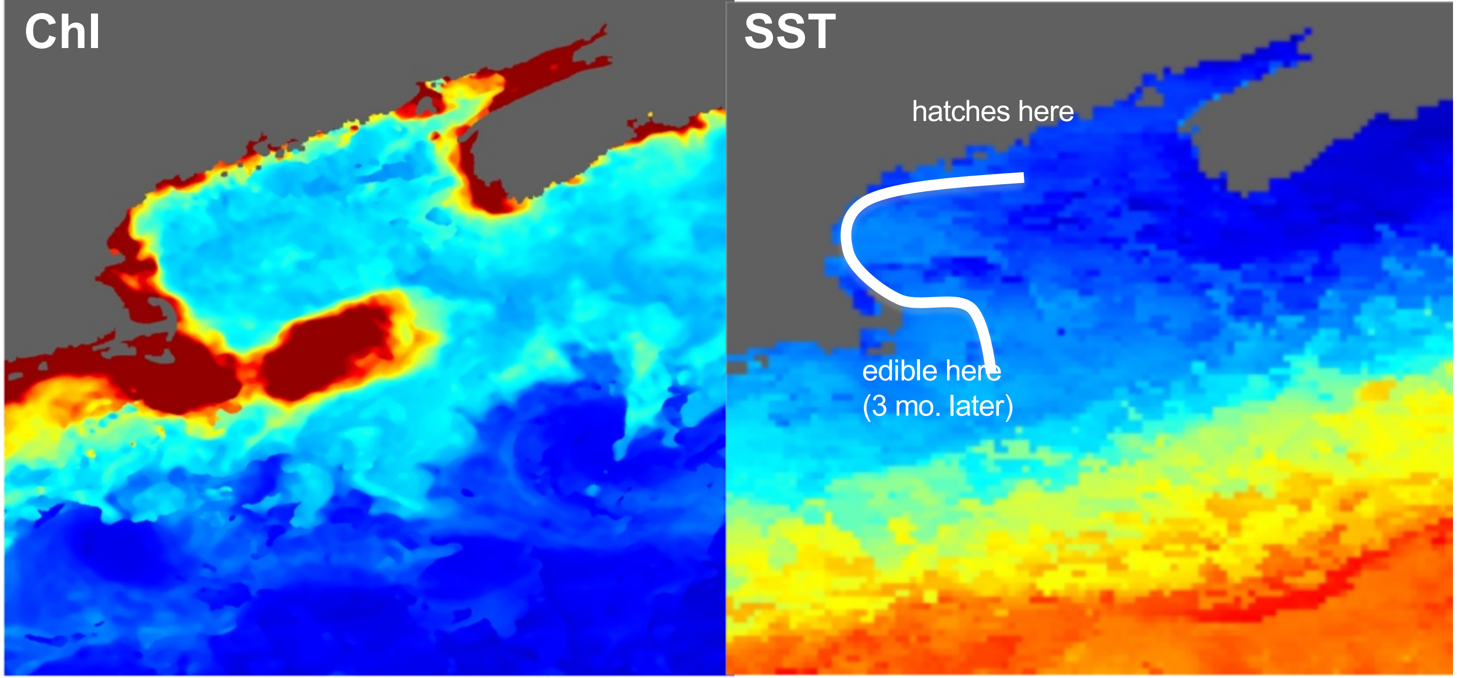
- No causal mechanism
  - Jellyfish don't arise from temperature and salinity

Mechanistic Forecasting example:
“Right whale, wrong time?”

- Northern right whale population: <400
- Mortality: ship strikes, fishing gear entanglements
- Management requires knowing where whales are


Photos Courtesy PCCS

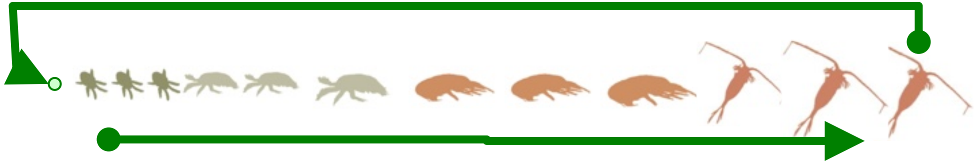
- Whale movements in spring, summer, and fall are tied to copepod abundance
  - Implication: identifying feeding areas should be a good way to locate whales
  - **How can we forecast copepods?**



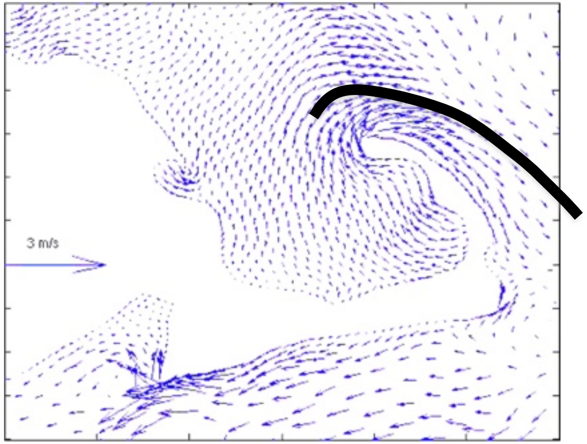
We have data layers
...but copepods can take months to grow to edible size
□ Good conditions don’t necessary imply copepods

Mechanistic model

Reproduction depends on food (i.e. Chl)



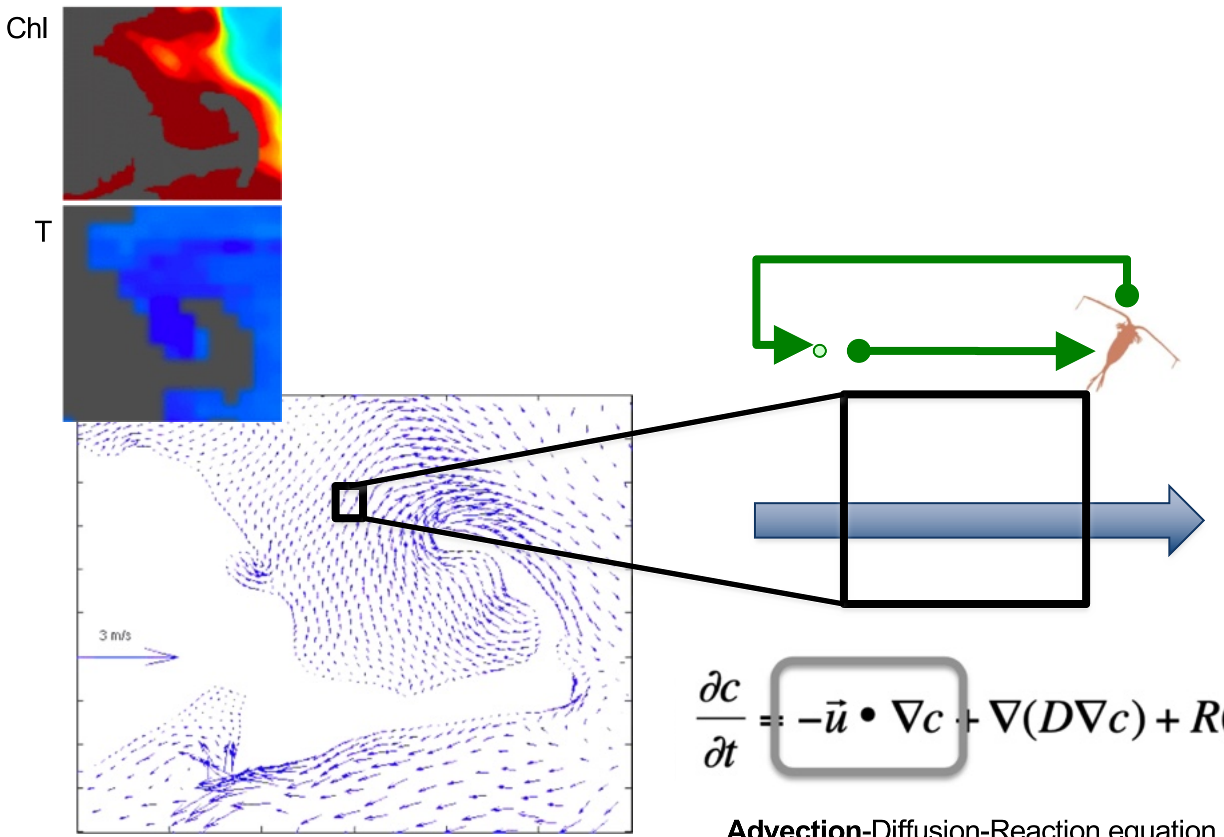
Development depends on temperature



Movement depends on currents

1) We have that information
2) We know what those dependencies (equations) are

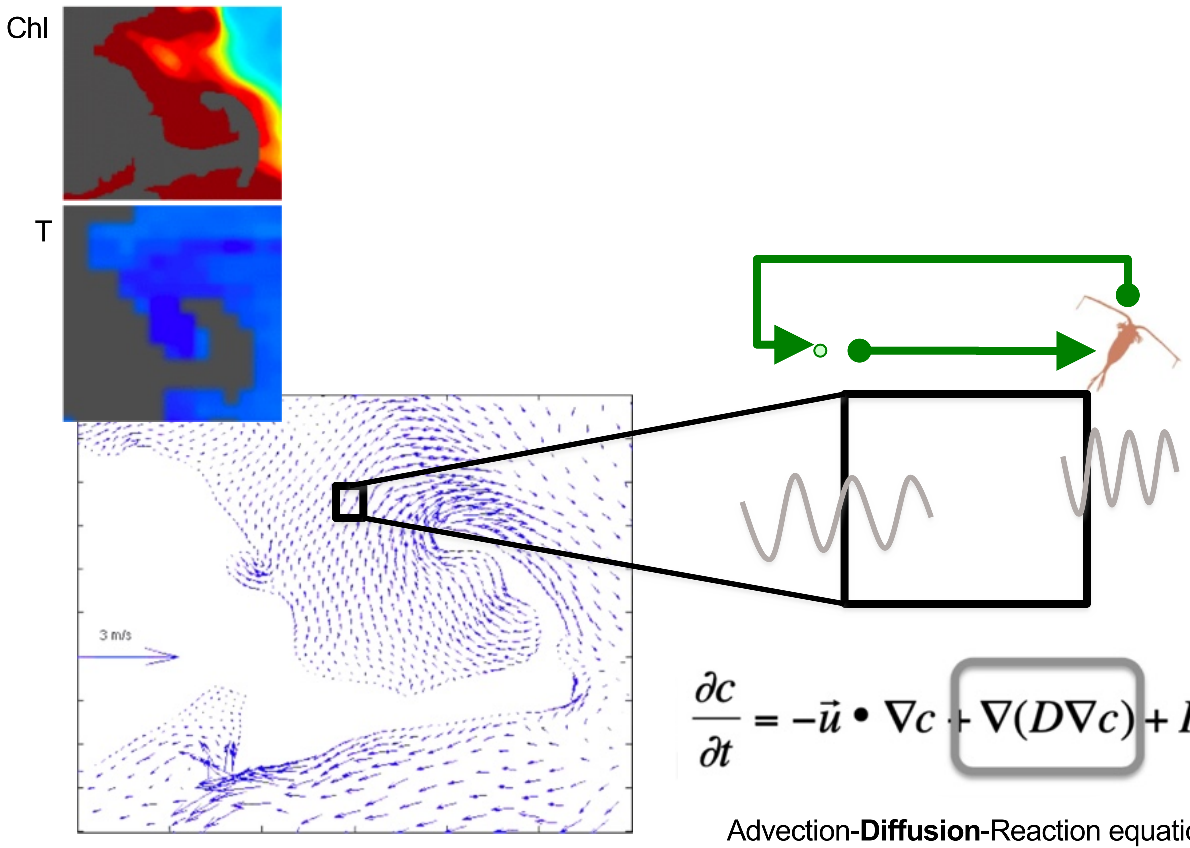
Mechanistic model



$$\frac{\partial c}{\partial t} = \boxed{-\vec{u} \bullet \nabla c} + \nabla(D\nabla c) + R(c,\vec{x},t)$$

Advection-Diffusion-Reaction equation

Mechanistic model

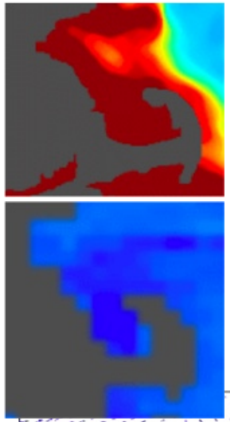


$$\frac{\partial c}{\partial t} = -\vec{u} \bullet \nabla c + \boxed{\nabla(D\nabla c)} + R(c,\vec{x},t)$$

Advection-**Diffusion**-Reaction equation

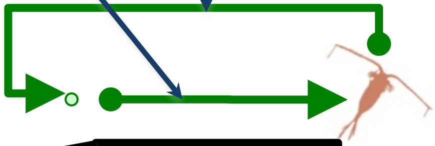
Mechanistic model

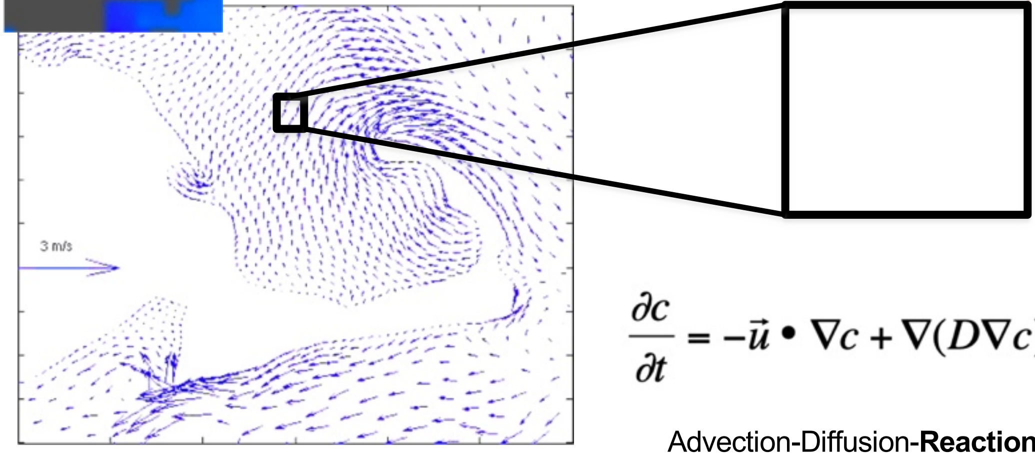
Chl



T

$$R(c,\vec{x},t) = \frac{\partial(\Lambda(T)c)}{\partial s} + c_{12}\Gamma(Chl) - c\mu(T,Chl)$$





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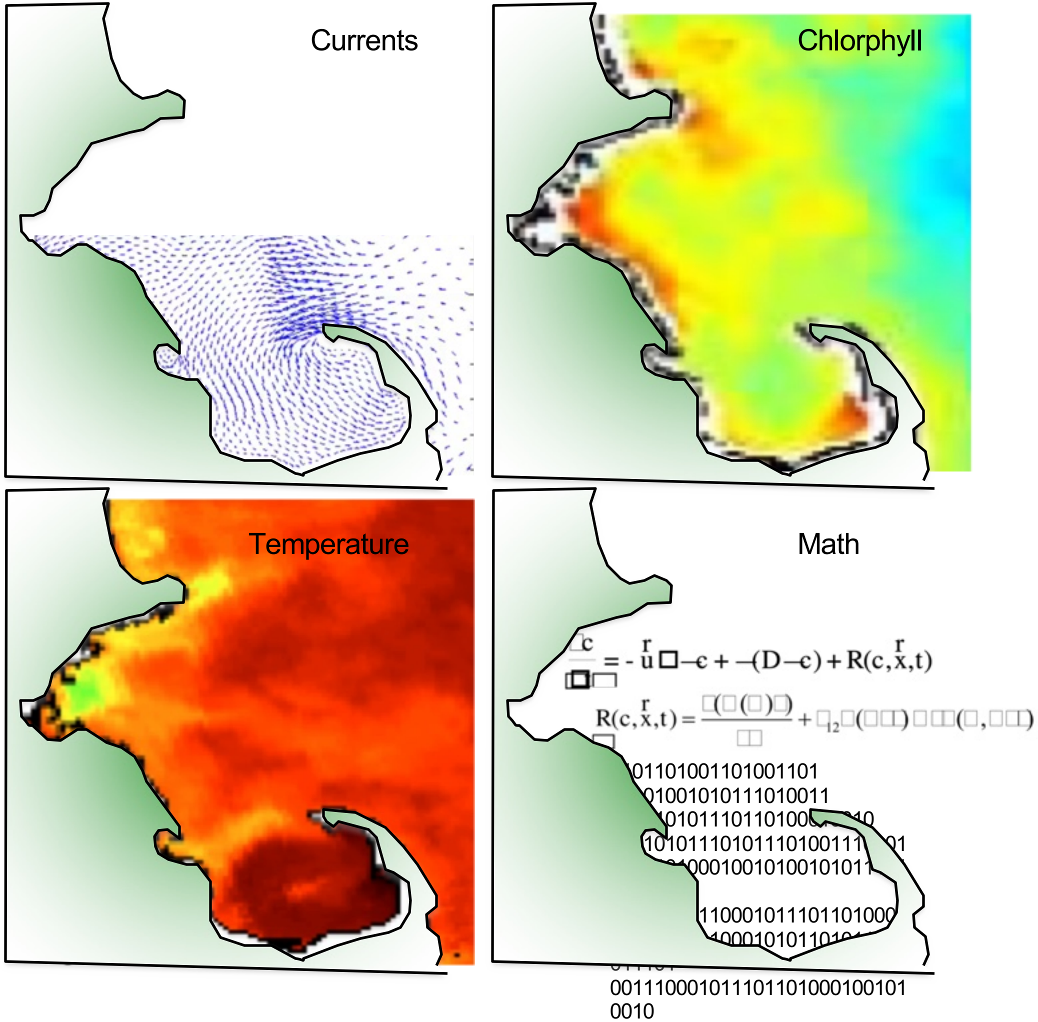
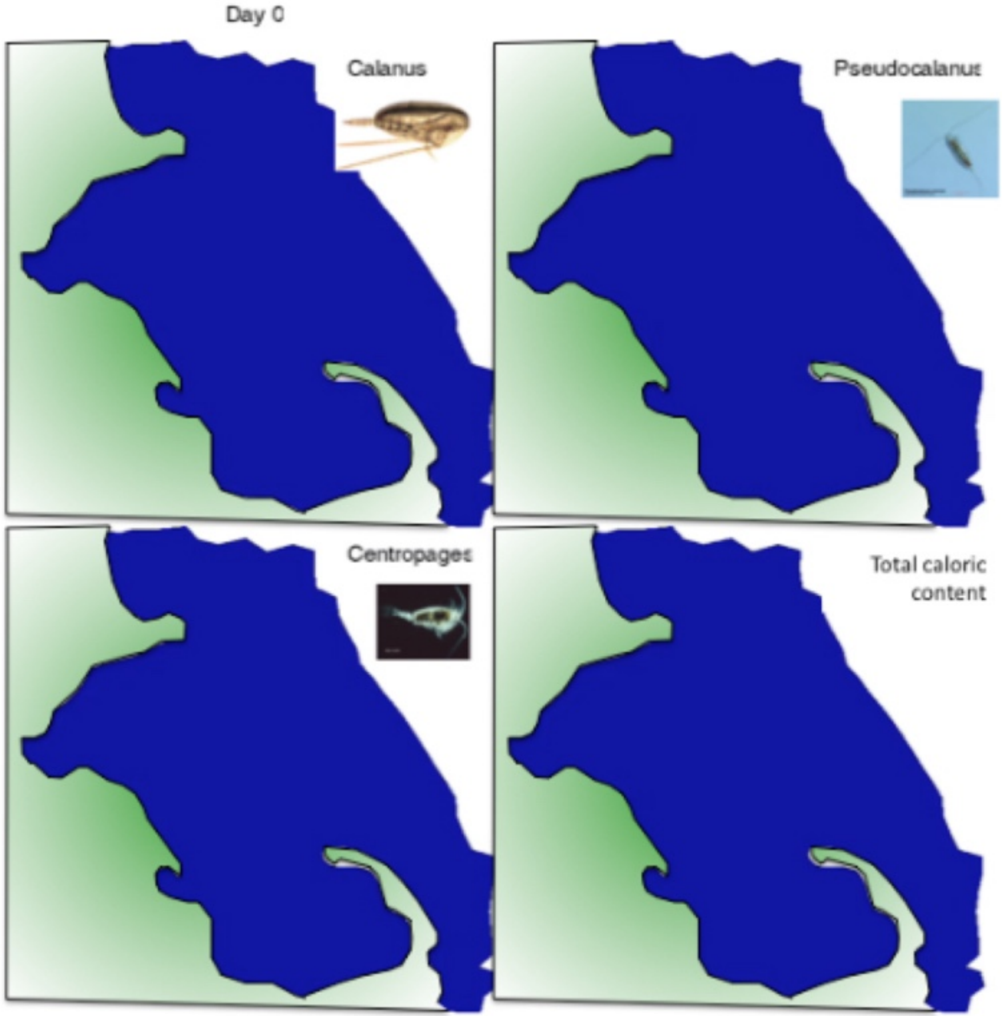
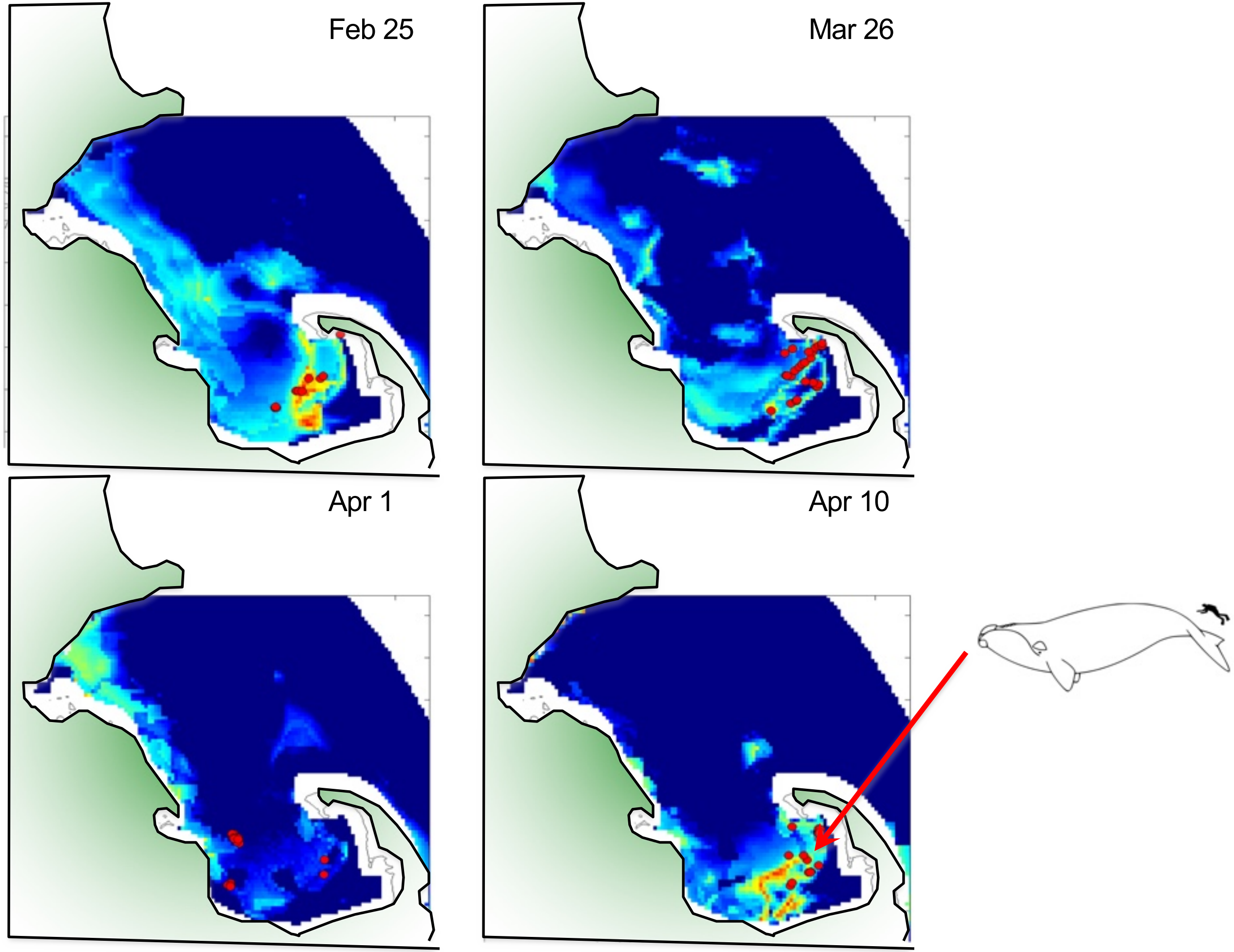
Advection-Diffusion-**Reaction** equation


Currents
Chlorphyll
Temperature
Math


Day 0
Calanus
Pseudocalanus
Centropages
Total caloric content


Feb 25
Mar 26
Apr 1
Apr 10

1) Forecasting is tricky

"*Prediction is very difficult, especially if it's about the future.*"
- Niels Bohr

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2) Forecasting is dangerous

"I found a ... flaw in the model that I perceived is the critical functioning structure that defines how the world works, so to speak."
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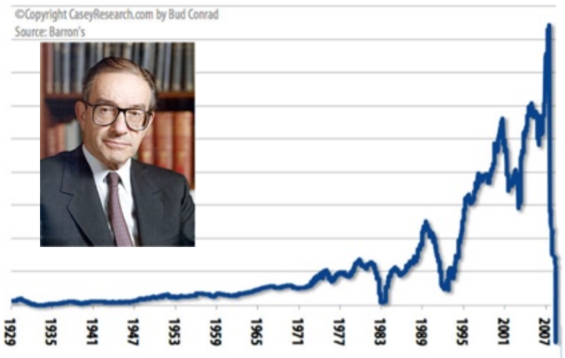


"I found a ... flaw in the model that I perceived is the critical functioning structure that defines how the world works, so to speak."

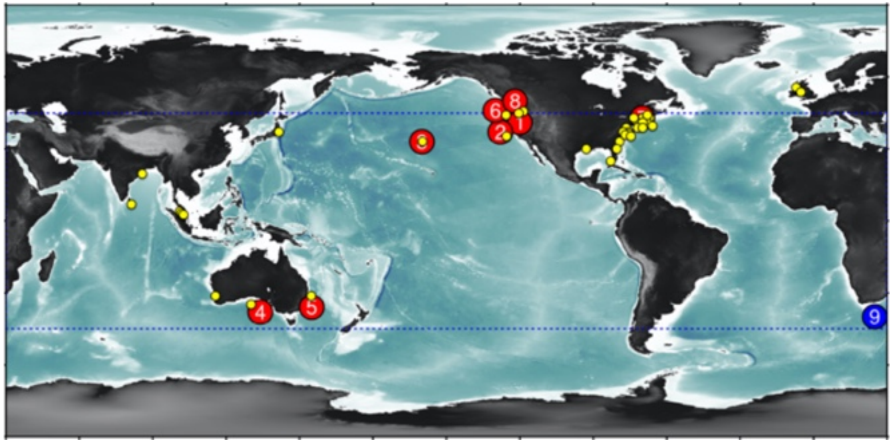
-Alan Greenspan

3) Forecasting is valuable

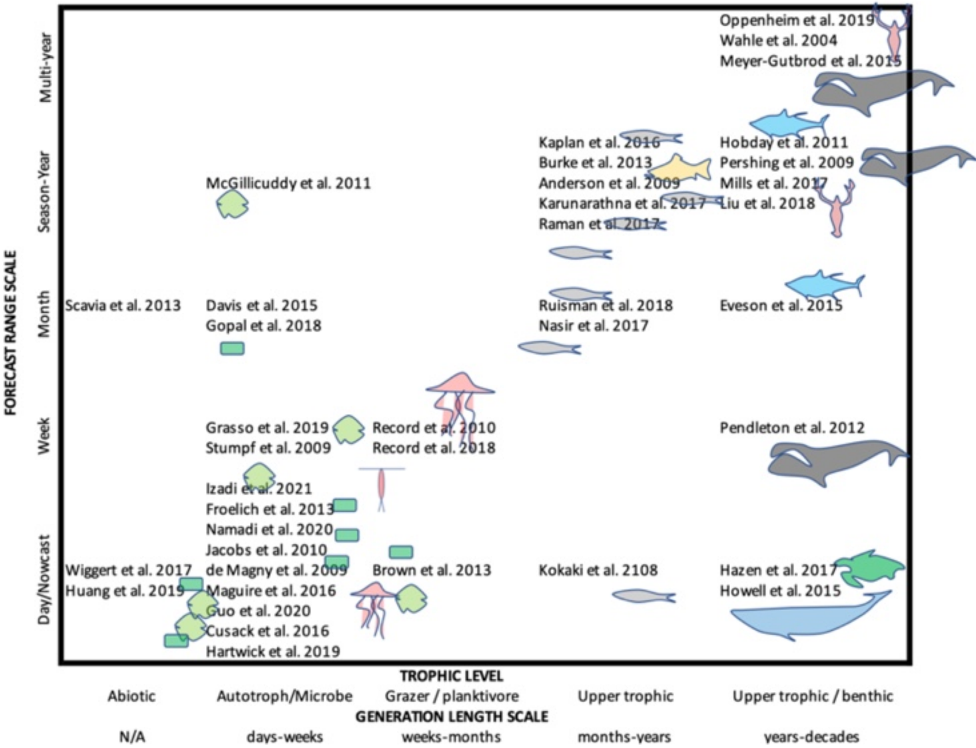
"Get the hell off the beach…It's 4:30, you've maximized your tan. Get off the beach."

- NJ Governor Chris Christie

Ocean Forecasts



Record, Nicholas R., and Andrew J. Pershing. 2021. "Facing the Forecaster's Dilemma: Reflexivity in Ocean System Forecasting" *Oceans* 2, no. 4: 738-751. https://doi.org/10.3390/oceans2040042



Ocean Forecasts

- Anderson JJ, Beer WN. Oceanic, riverine, and genetic influences on spring chinook salmon migration timing. Ecological Applications. 2009 Dec;19(8):1989-2003.
- Brown CW, Hood RR, Long W, Jacobs J, Ramers DL, Wazniak C, Wiggert JD, Wood R, Xu J. Ecological forecasting in Chesapeake Bay: using a mechanistic–empirical modeling approach. Journal of Marine Systems. 2013 Sep 1;125:113-25.
- Burke BJ, Peterson WT, Beckman BR, Morgan C, Daly EA, Litz M. Multivariate models of adult Pacific salmon returns. PloS one. 2013 Jan 11;8(1):e54134.
- Cusack C, Dabrowski T, Lyons K, Berry A, Westbrook G, Salas R, Duffy C, Nolan G, Silke J. Harmful algal bloom forecast system for SW Ireland. Part II: Are operational oceanographic models useful in a HAB warning system. Harmful Algae. 2016 Mar 1;53:86-101.
- Davis BJ, Jacobs JM, Zaitchik B, DePaola A, Curriero FC. Vibrio parahaemolyticus in the Chesapeake Bay: Operational in situ prediction and forecast models can benefit from inclusion of lagged water quality measurements. Applied and environmental microbiology. 2019 Sep 1;85(17):e01007-19.
- de Magny GC, Long W, Brown CW, Hood RR, Huq A, Murtugudde R, Colwell RR. Predicting the distribution of Vibrio spp. in the Chesapeake Bay: a Vibrio cholerae case study. EcoHealth. 2009 Sep 1;6(3):378-89.
- Eveson JP, Hobday AJ, Hartog JR, Spillman CM, Rough KM. Seasonal forecasting of tuna habitat in the Great Australian Bight. Fisheries Research. 2015 Oct 1;170:39-49.
- Froelich B, Bowen J, Gonzalez R, Snedeker A, Noble R. Mechanistic and statistical models of total Vibrio abundance in the Neuse River Estuary. Water research. 2013 Oct 1;47(15):5783-93.
- Grasso I, Archer SD, Burnell C, Tupper B, Rauschenberg C, Kanwit K, Record NR (2019) The hunt for red tides: Deep learning algorithm forecasts fine scale shellfish toxicity in coastal Maine. Ecosphere. 10(12): e02960.
- Gopal K, Shitan M. Development of a Web Portal to Forecast the Monthly Mean Chlorophyll Concentration of the Waters off Peninsular Malaysia’s West Coast. Malaysian Journal of Mathematical Sciences. 2018 Jan 31;12(1):99-119.
- Guo J, Dong Y, Lee JHW. A real time data driven algal bloom risk forecast system for mariculture management. Marine Pollution Bulletin. 2020; 161:111731
- Hartwick MA, Urquhart EA, Whistler CA, Cooper VS, Naumova EN, Jones SH. Forecasting seasonal Vibrio parahaemolyticus concentrations in New England shellfish. International journal of environmental research and public health. 2019 Jan;16(22):4341.
- Hazen EL, Palacios DM, Forney KA, Howell EA, Becker E, Hoover AL, Irvine L, DeAngelis M, Bograd SJ, Mate BR, Bailey H. WhaleWatch: a dynamic management tool for predicting blue whale density in the California Current. Journal of Applied Ecology. 2017 Oct;54(5):1415-28.
- Hobday AJ, Hartog JR, Spillman CM, Alves O. Seasonal forecasting of tuna habitat for dynamic spatial management. Canadian Journal of Fisheries and Aquatic Sciences. 2011 May;68(5):898-911.
- Howell EA, Hoover A, Benson SR, Bailey H, Polovina JJ, Seminoff JA, Dutton PH. Enhancing the TurtleWatch product for leatherback sea turtles, a dynamic habitat model for ecosystem-based management. Fisheries Oceanography. 2015 Jan;24(1):57-68.
- Huang P, Trayler K, Wang B, Saeed A, Oldham CE, Busch B, Hipsey MR. An integrated modelling system for water quality forecasting in an urban eutrophic estuary: The Swan-Canning Estuary virtual observatory. Journal of Marine Systems. 2019 Nov 1;199:103218.
- Izadi
- Jacobs, J.M., Rhodes, M.M.R., Brown, C.W., Hood, R.R., Leight, A., Long, W. and Wood, R., 2010. Predicting the distribution of Vibrio vulnificus in Chesapeake Bay.
- Kaplan IC, Williams GD, Bond NA, Hermann AJ, Siedlecki SA. Cloudy with a chance of sardines: forecasting sardine distributions using regional climate models. Fisheries Oceanography. 2016 Jan;25(1):15-27.
- Karunarathna B, Karunarathna KA. Forecasting fish production in Sri Lanka by using ARIMA model. Scholar J. Agric. Vet. Sci. 2017;4(9):344-9.
- Kokaki Y, Tawara N, Kobayashi T, Hashimoto K, Ogawa T. Sequential fish catch forecasting using Bayesian state space models. In2018 24th International Conference on Pattern Recognition (ICPR) 2018 Aug 20 (pp. 776-781). IEEE.
- Liu G, Eakin CM, Chen M, Kumar A, De La Cour JL, Heron SF, Geiger EF, Skirving WJ, Tirak KV, Strong AE. Predicting heat stress to inform reef management: NOAA Coral Reef Watch's 4-month coral bleaching outlook. Frontiers in Marine Science. 2018 Mar 2;5:57.

Ocean Forecasts

- Maguire J, Cusack C, Ruiz-Villarreal M, Silke J, McElligott D, Davidson K. Applied simulations and integrated modelling for the understanding of toxic and harmful algal blooms (ASIMUTH): Integrated HAB forecast systems for Europe's Atlantic Arc. Harmful algae. 2016 Mar 1;53:160-6.
- McGillicuddy DJ, Townsend DW, He R, Keafer BA, Kleindinst JL, Li Y, Manning JP, Mountain DG, Thomas MA, Anderson DM. Suppression of the 2010 Alexandrium fundyense bloom by changes in physical, biological, and chemical properties of the Gulf of Maine. Limnology and Oceanography. 2011 Nov;56(6):2411-26.
- Meyer-Gutbrod EL, Greene CH, Sullivan PJ, Pershing AJ. Climate-associated changes in prey availability drive reproductive dynamics of the North Atlantic right whale population. Marine Ecology Progress Series. 2015 Sep 15;535:243-58.
- Mills KE, Pershing AJ, Hernández CM. Forecasting the seasonal timing of Maine's lobster fishery. Frontiers in Marine Science. 2017 Nov 2;4:337.
- Namadi P, Deng Z. Modeling and Forecasting Vibrio Parahaemolyticus Concentrations in Oysters. Water Research. 2020 Nov 12;189:116638.
- Nasir N, Samsudin R, Shabri A. Forecasting of Monthly Marine Fish Landings using Artificial Neural Network. Int. J. Advance Soft Compu. Appl. 2017 Jul 1;9(2).
- Oppenheim NG, Wahle RA, Brady DC, Goode AG, Pershing AJ. The cresting wave: larval settlement and ocean temperatures predict change in the American lobster harvest. Ecological Applications. 2019 Dec;29(8):e02006.
- Pendleton DE, Sullivan PJ, Brown MW, Cole TVN, Good CP, Mayo CA, Monger BC, Phillips S, Record NR, Pershing AJ (2012) Weekly predictions of North Atlantic right whale Eubalaena glacialis habitat reveal influence of prey abundance and seasonality of habitat preferences. Endangered Species Research. 18: 147-161.
- Pershing AJ, Record NR, Monger BC, Mayo CA, Brown MW, Cole TV, Kenney RD, Pendleton DE, Woodard LA. Model-based estimates of right whale habitat use in the Gulf of Maine. Marine Ecology Progress Series. 2009 Mar 12;378:245-57.
- Raman RK, Sathianandan TV, Sharma AP, Mohanty BP. Modelling and forecasting marine fish production in Odisha using seasonal ARIMA model. National Academy Science Letters. 2017 Dec 1;40(6):393-7.
- Record NR, Pershing AJ, Runge JA, Mayo CA, Monger BC, Chen C (2010) Improving ecological forecasts of copepod community dynamics using genetic algorithms. Journal of Marine Systems. 82(3): 96-110.
- Record NR, Tupper B, Pershing AJ (2018) The jelly report: Forecasting jellyfish using email and social media. Anthropocene Coasts. 1: 34-43.
- Rusiman MS, Sufahani S, Robi NA, Abdullah AW, Azmi NA. Predictive modelling of marine fish landings in Malaysia. Advances and Applications in Statistics. 2018 Aug 1;53(2):123-35.
- Scavia D, Evans MA, Obenour DR. A scenario and forecast model for Gulf of Mexico hypoxic area and volume. Environmental science & technology. 2013 Sep 17;47(18):10423-8.
- Stumpf RP, Tomlinson MC, Calkins JA, Kirkpatrick B, Fisher K, Nierenberg K, Currier R, Wynne TT. Skill assessment for an operational algal bloom forecast system. Journal of Marine Systems. 2009 Feb 20;76(1-2):151-61.
- Wahle RA, Incze LS, Fogarty MJ. First projections of American lobster fishery recruitment using a settlement index and variable growth. Bulletin of Marine Science. 2004 Jan 1;74(1):101-14.
- Wiggert JD, Hood RR, Brown CW. Modeling hypoxia and its ecological consequences in Chesapeake Bay. InModeling Coastal Hypoxia 2017 (pp. 119-147). Springer, Cham.

Empirical algorithms and methods: Where do you start?

Outline

- Load in and clean up the data
- Build and fit a model
    - Split the data into “training” and “testing”
    - Choose the model/algorithm/engine
    - Fit the model to data (using training data)
- Assessment
    - Make predictions (using testing data)
    - Compare predictions to measurements using skill metrics

Terminology

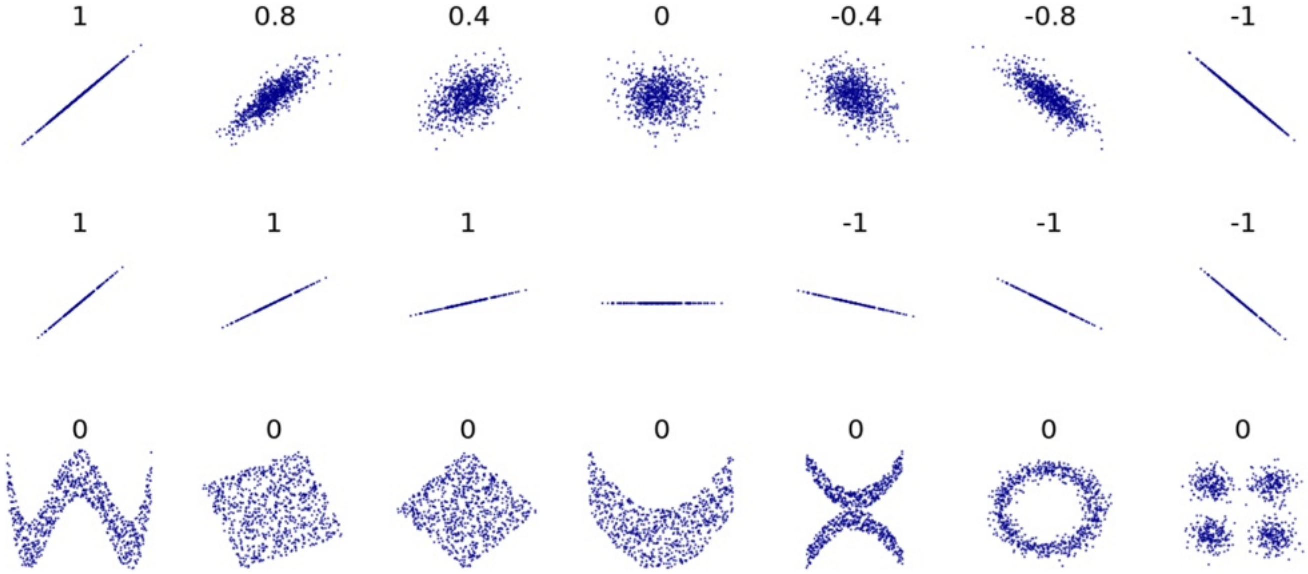
- Fitted value: what you predicted using your model
- Residual: how close your prediction was to the measured value
- Forecast horizon: how far in the future you're predicting

Correlation

- A relation existing between phenomena or things or between mathematical or statistical variables which tend to vary, be associated, or occur together in a way not expected on the basis of chance alone.
- *Correlation is not causation*
- *Correlation may be nonstationary*

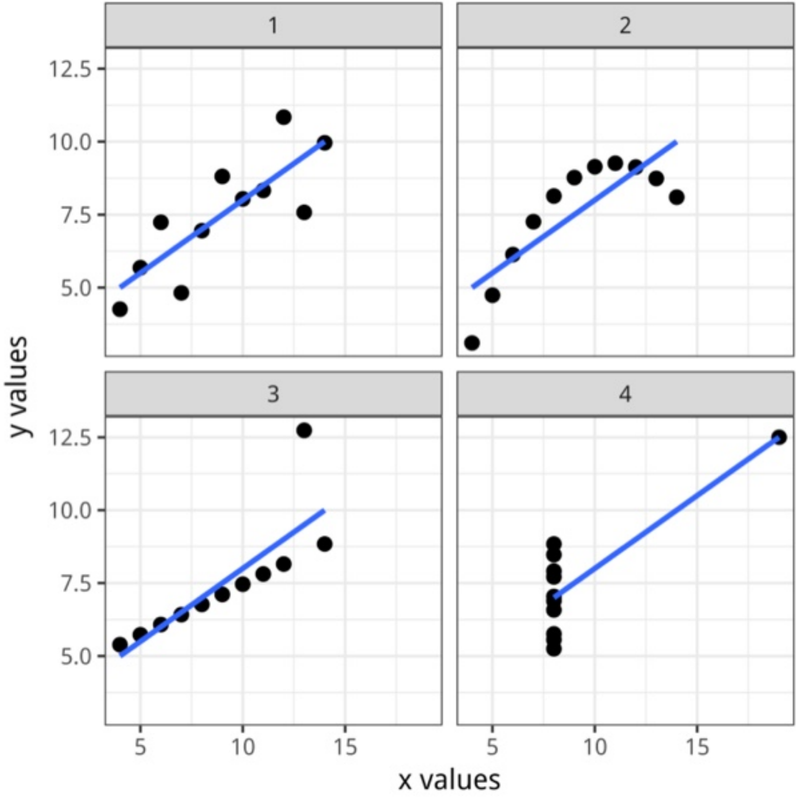
Correlation coefficient

- Evaluate the direction and the intensity of the relationship between two variables
- Range of different correlation coefficients, the most common is the *Pearson correlation coefficient*
- Given the symbol r and describes the linear correlation between two variables
- Takes a value between -1 and 1
- The sign of the correlation coefficient describes the direction of the correlation
- A value of 0 indicates no linear correlation
- Statistical significance measured with a p-value, from 0 - 1, where 0 is stronger significance
- Guess the correlation game: http://guessthecorrelation.com/

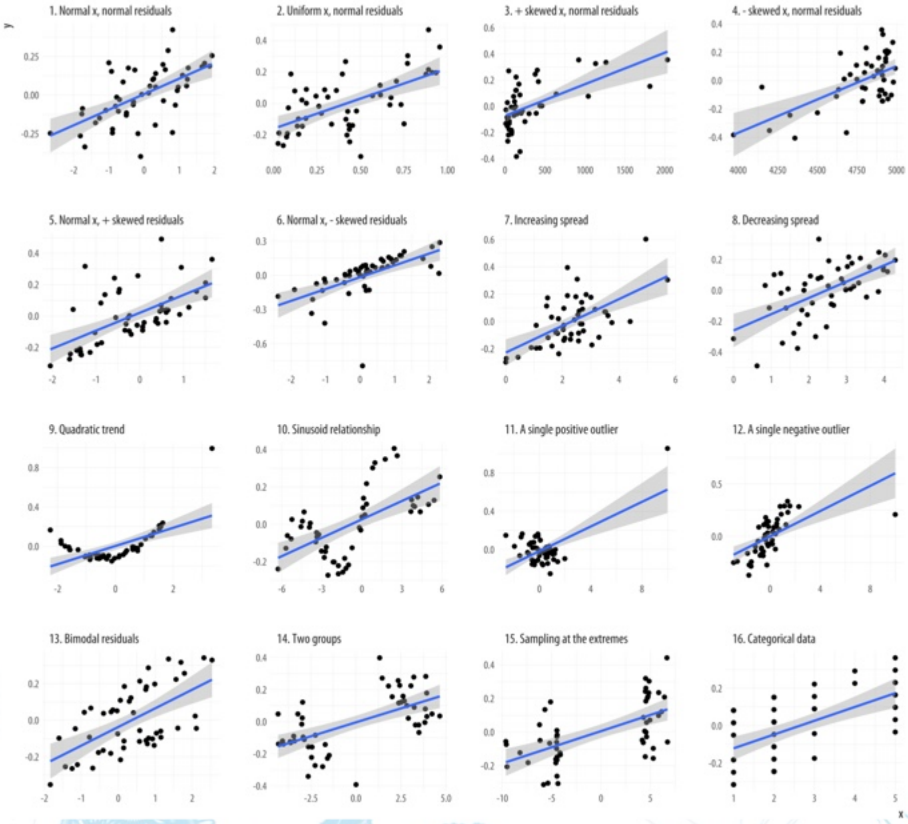


Correlation: Anscombe's quartet

- 11 points
- Nearly identical means
- Same correlation coefficient (0.81)
- (Anscombe, 1973, Source: https://socviz.co/lookatdata.html)

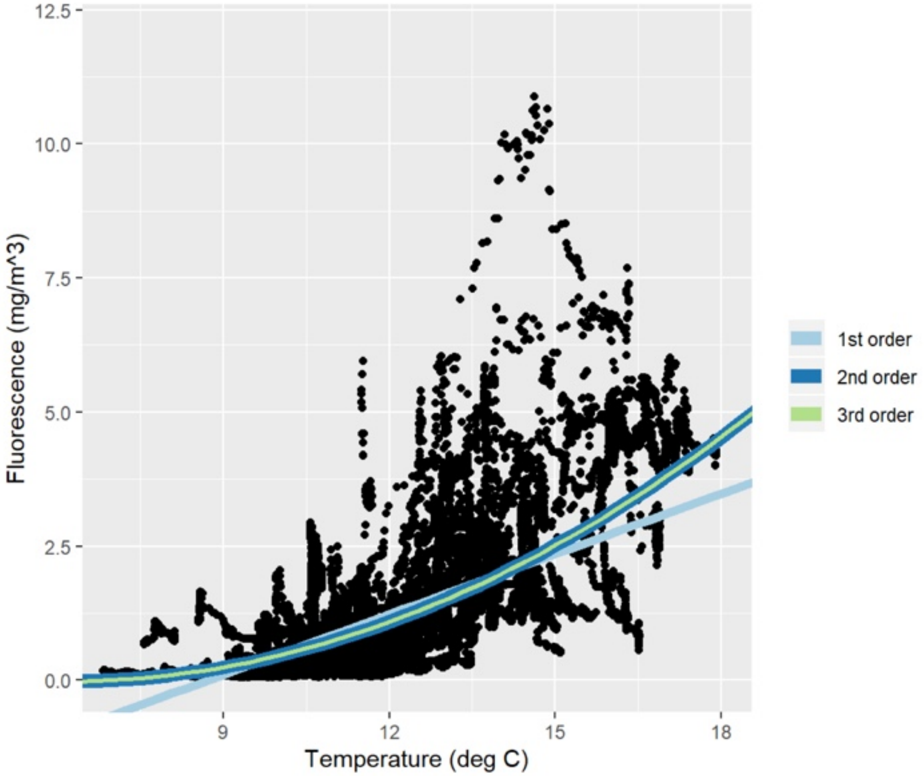


Correlation: Anscombe's quartet

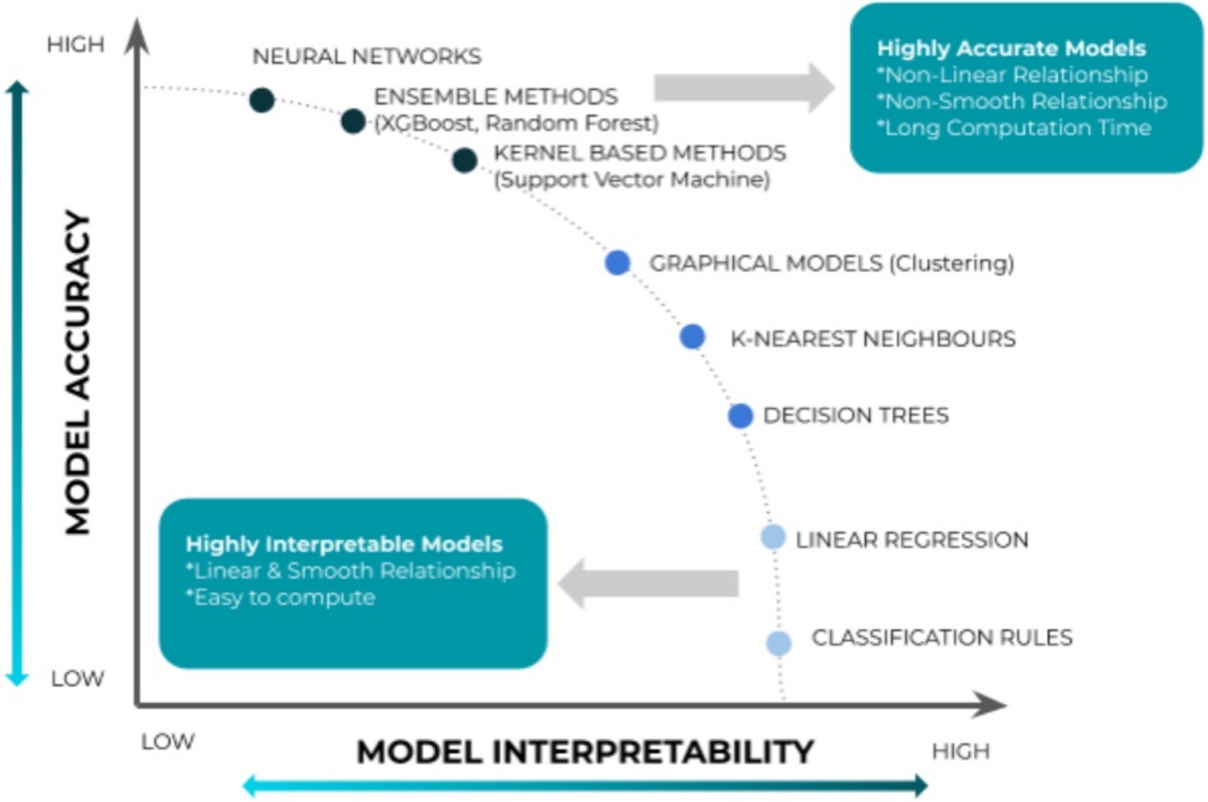


Source: https://socviz.co/lookatdata.html

Correlation: nonlinear



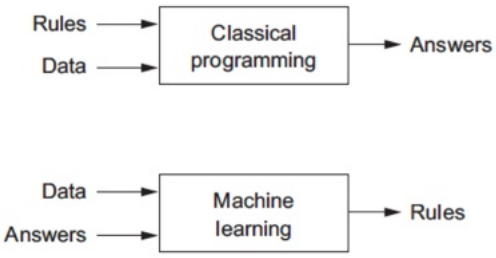
Types of models



Artificial Intelligence and Machine Learning

Artificial General Intelligence: machines solving complex and broad problems flexibly

Artificial Narrow Intelligence: automatic specific tasks e.g with machine learning

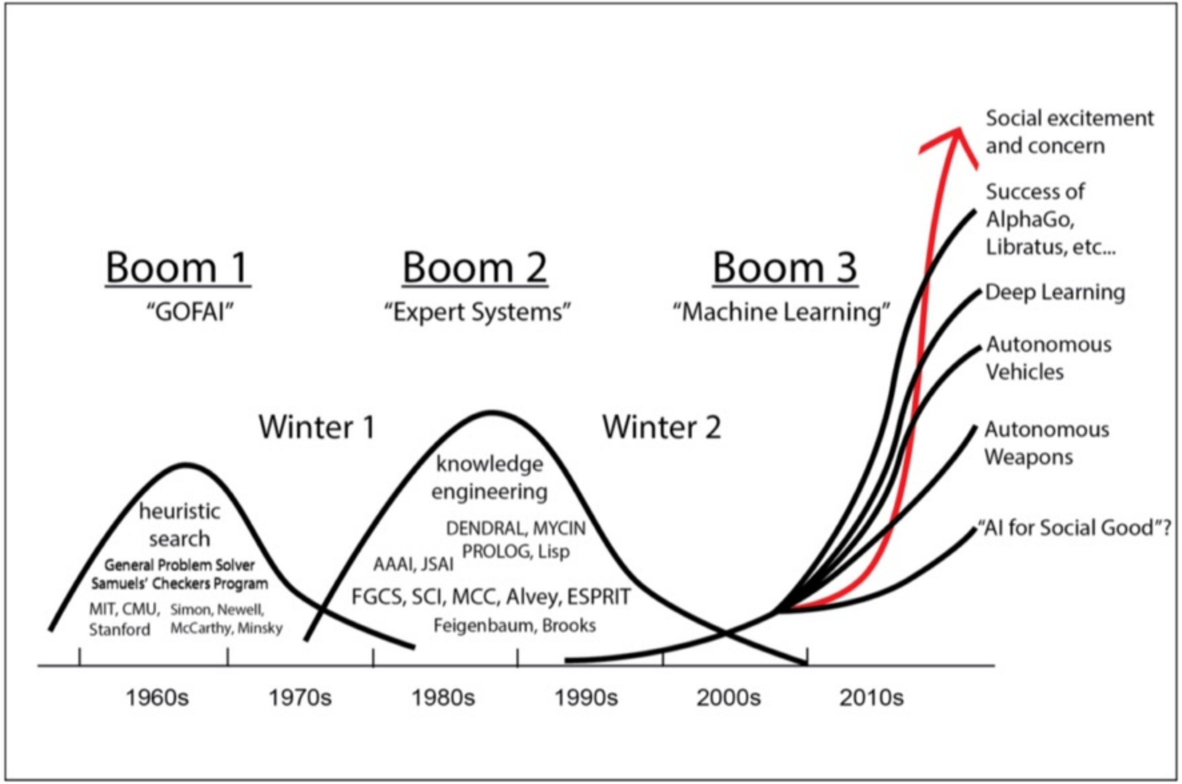


Artificial intelligence: algorithms learn sort of like humans: "the effort to automate tasks normally performed by humans" - Francois Chollet

Machine learning: algorithms learn without being programmed

Deep learning: Advanced neural networks

Artificial Intelligence and Machine Learning



…on to our data and models