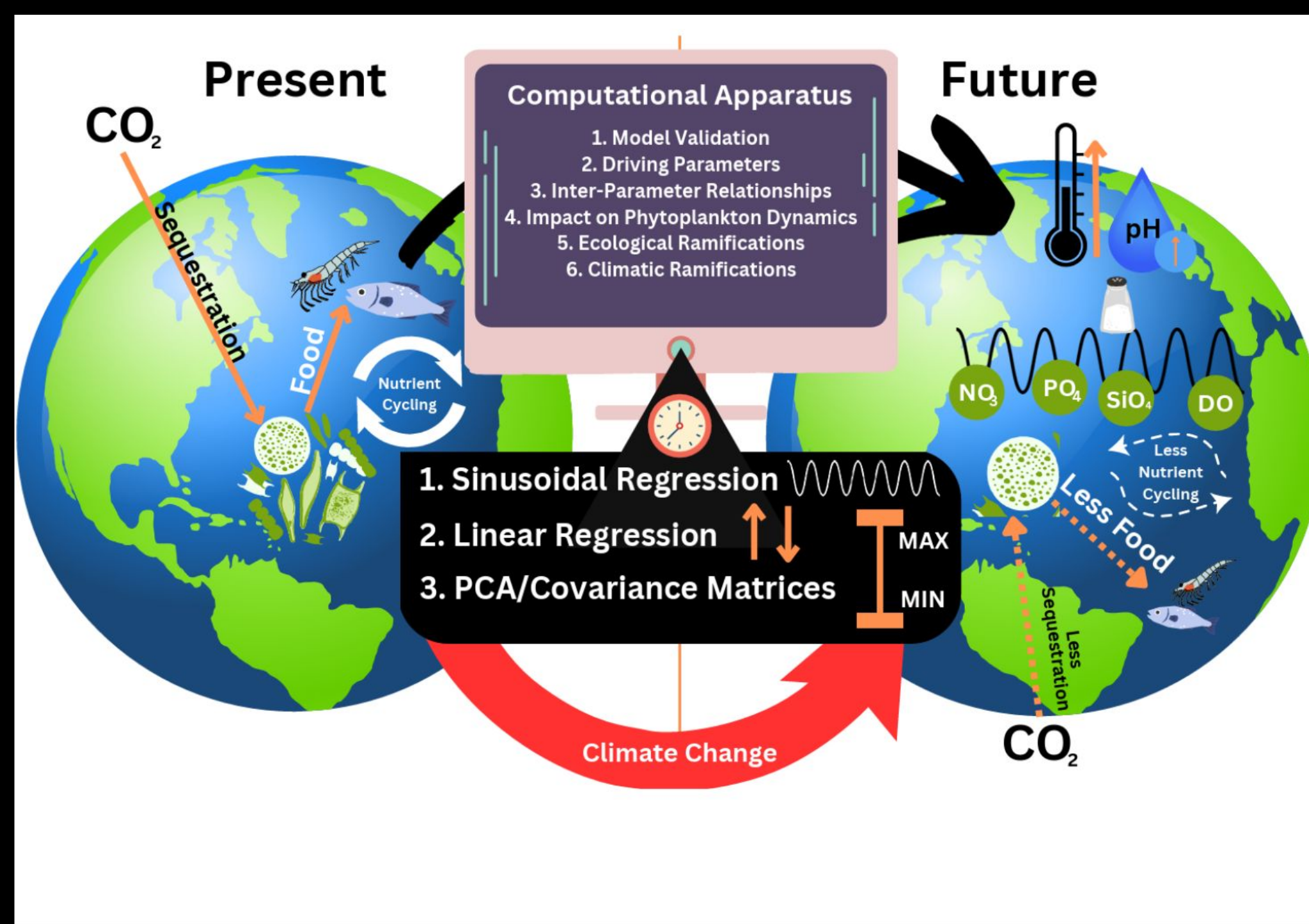


Graphical Abstract



Background

Background

Phytoplankton: An Intro

Phytoplankton are microscopic, aquatic autotrophs from most kingdoms of life. **Crucial for climatic and environmental stability:**

- Sequester 30% of CO2 emissions (Rohr et al., 2023)
- Reflect solar radiation (Deppeler & Davidson, 2017)
- Base of the marine food web (Käse & Geuer, 2018; Loschi et al., 2023)
- Biogeochemical cycling of nutrients (Sarker et al., 2023)

Current Empirical Limitations (Winder & Sommer, 2012)

Factors Limiting Applicability of Phytoplankton Studies:

- Non-uniform changes in oceanic conditions
- Non-uniform biological preferences among different phytoplankton groups
- Complexity from multiple environment parameters
- Limited Data (Ratnarajah et al., 2022)
- Limited Scope of Individual Computational Models

Uni-Dimensional Empirical Analysis + Disconnected Computer Models (Chang et al., 2022)

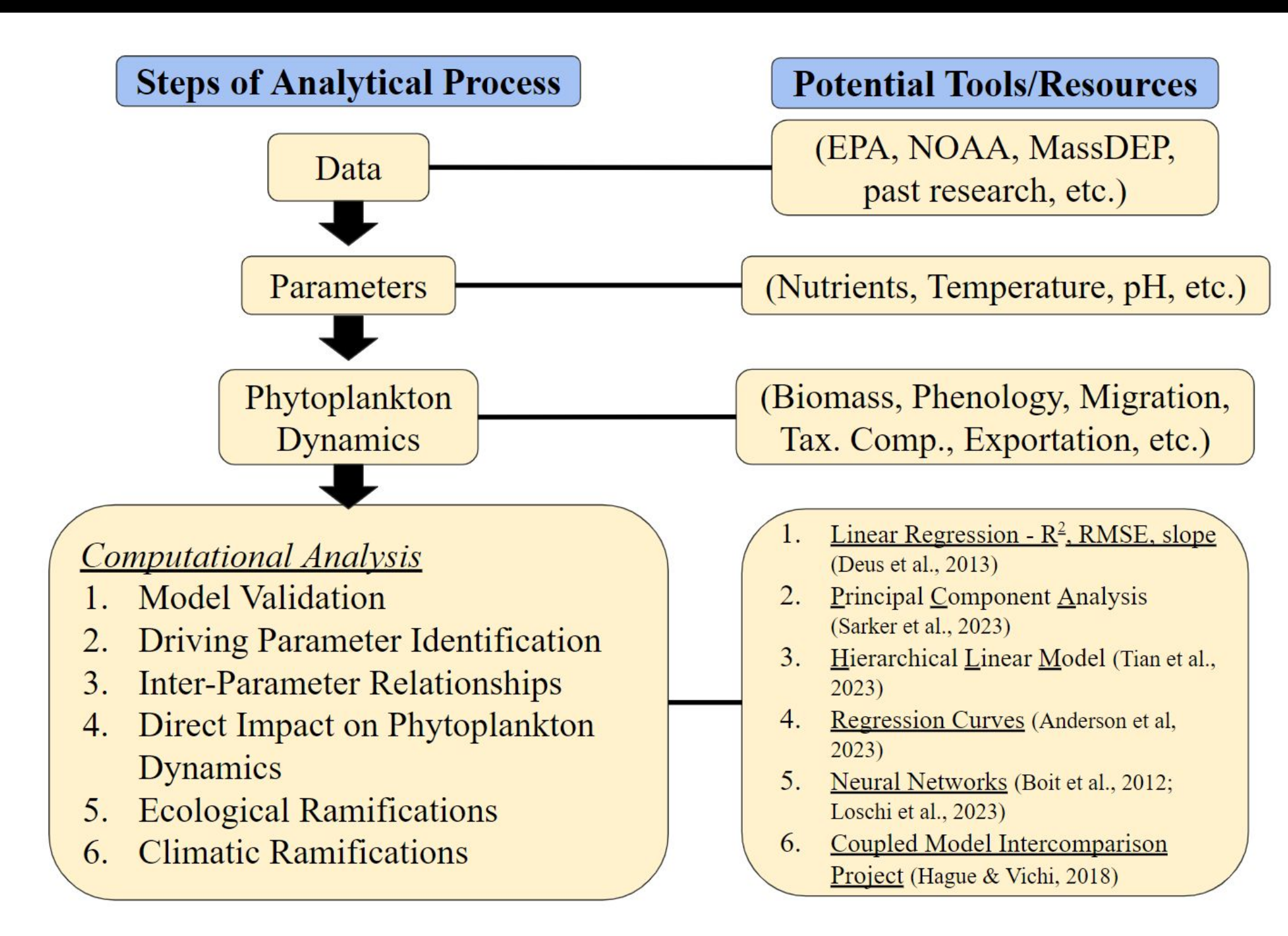
Multi-Dimensional, Unified Computational Apparatus

A Highly Relevant Issue For Scientists and Policymakers

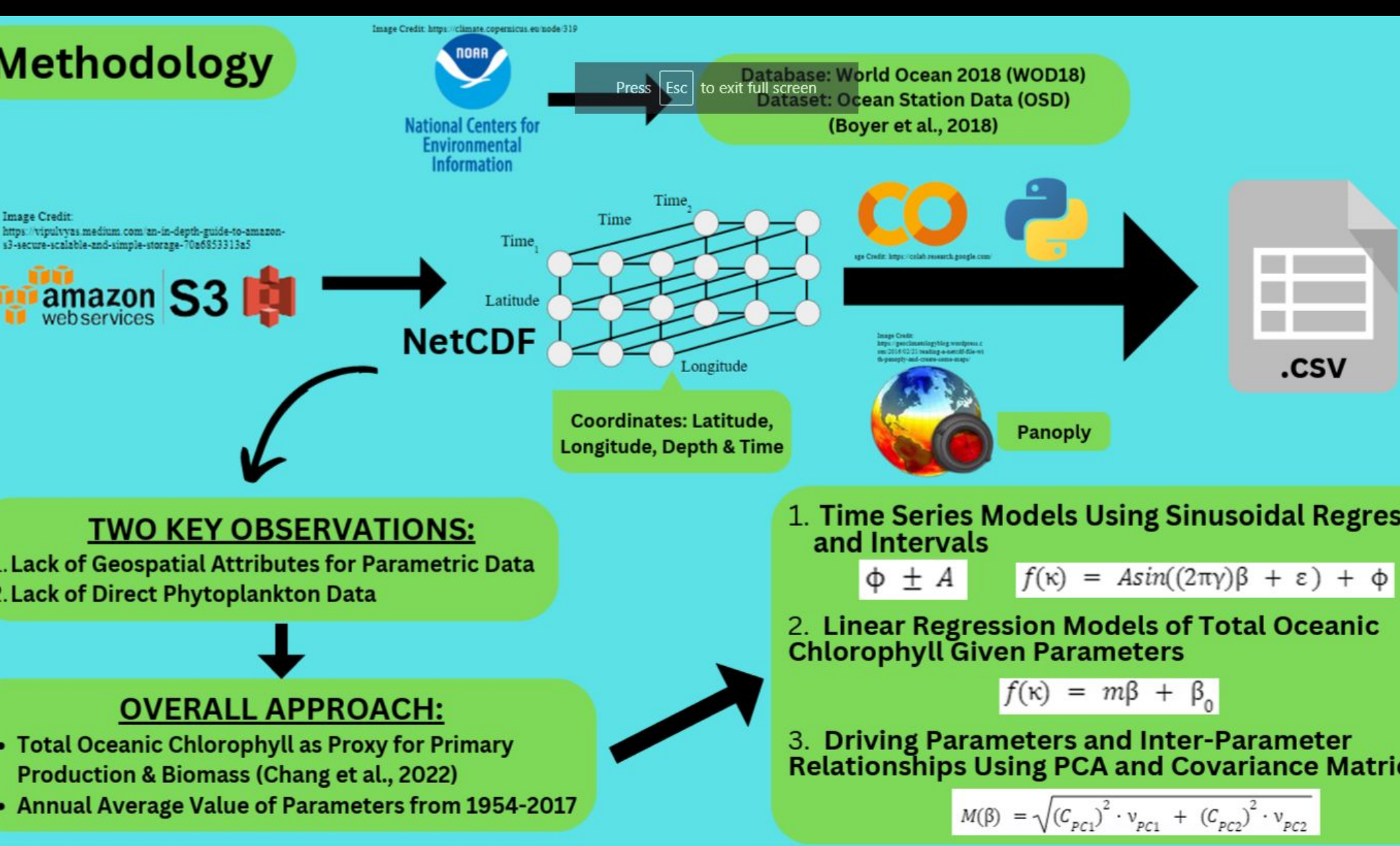
UN Sustainable Development Goals:

- Climate Action, Clean Water, Life Below Water (United Nations, 2015)

Hypothesis (Proposed Apparatus)



Methodology



Computational Modeling of Phytoplankton Dynamics with Climatic and Ecological Ramifications



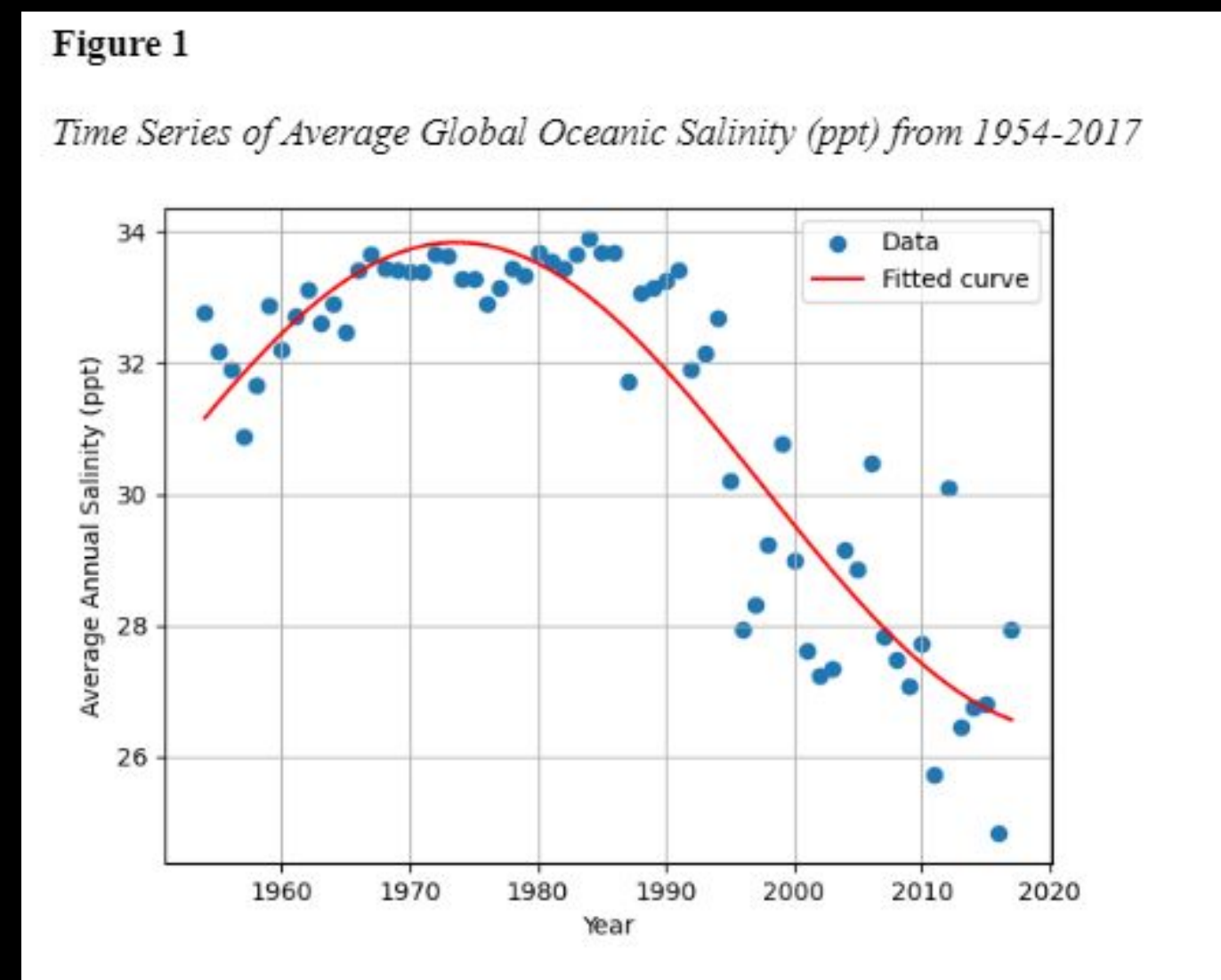
Abhinav K. Sharma
Advisor: Dr. Kevin Crowthers, PhD

Researchable Question:

How can the causes and effects of changing phytoplankton dynamics be computationally modeled?

Key Findings:

- Accuracy of time series models for environmental parameters tested (e.g., oxygen, pH, etc.) varies greatly.
- There exist significant directional relationships between parameters and phytoplankton primary production and biomass, though they are not effective predictors of these metrics.
- At a global scale, pH, followed by salinity and pressure, are the most influential parameters for these aspects of phytoplankton populations.



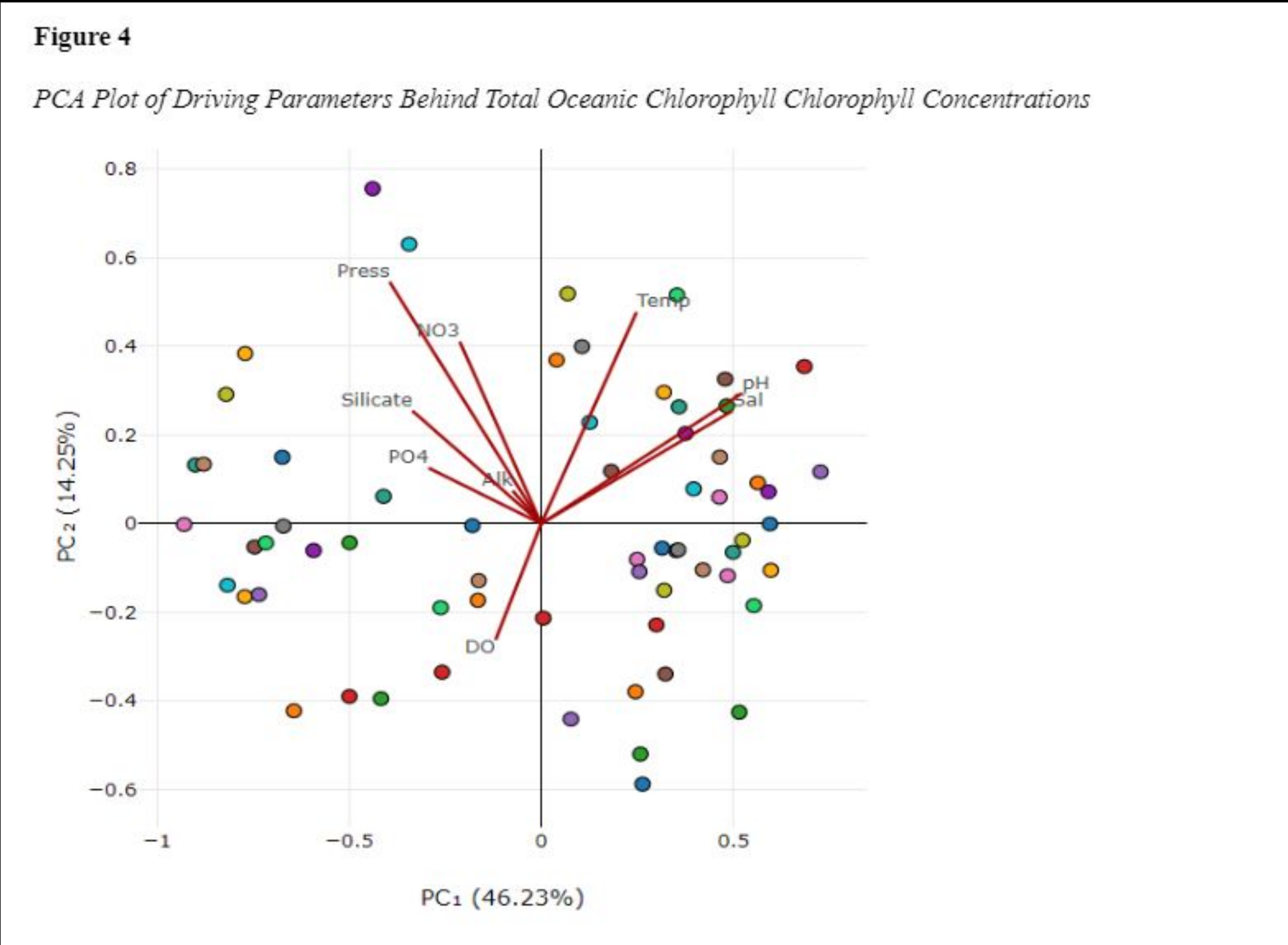
Note. Note. The time series for salinity (s) for year (y) is described by the sinusoidal regression function of $f(s) = 3.724 * \sin(6.220y + 80.552) + 30.112$; $R^2 = 0.847$. Sinusoidal Interval: (26.388, 33.836)

Table 1
Linear Regression Information of Parametric Factors Related to Total Oceanic Chlorophyll

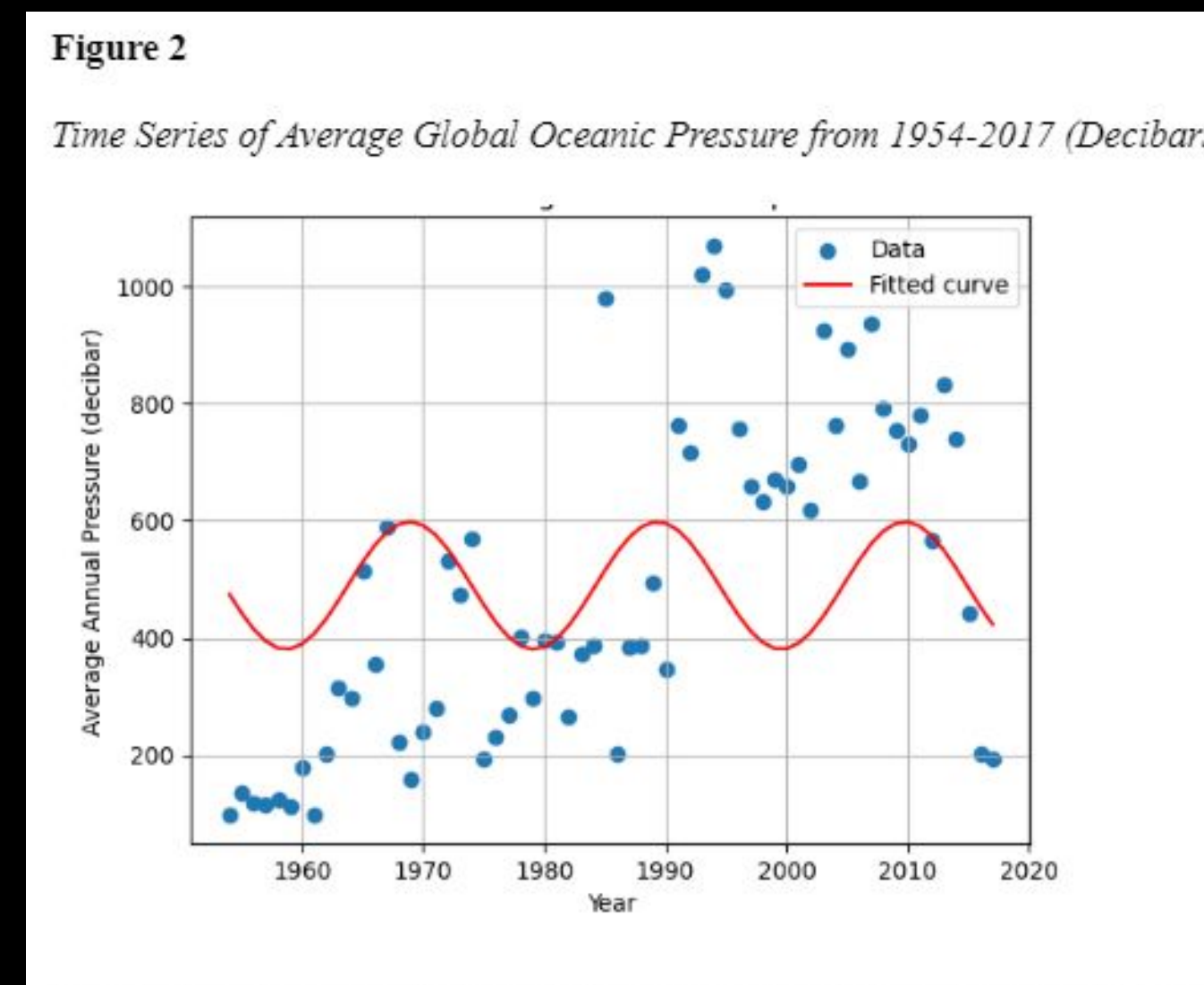
Parameter	Variable	R ² Value (r)	p-value (single-tailed p-value) $\alpha = 0.05$	Equation
Salinity (ppt)	s	0.54 (0.735)	0.0000 (0.0000)***	$f(x) = -0.2248s + 8.6275$
pH	ϕ	0.27 (0.520)	0.0000 (0.0000)***	$f(x) = -3.9346\phi + 33.0813$
Dissolved Oxygen ($\mu\text{mol/kg}$)	d	0.25 (0.500)	0.0000 (0.0000)***	$f(x) = 0.0333d - 5.6467$
Pressure (decibars)	p	0.22 (0.469)	0.0001 (0.00005)***	$f(x) = 0.0014p + 0.9536$
Phosphate ($\mu\text{mol/kg}$)	q	0.10 (0.316)	0.0130 (0.0065)*	$f(x) = 1.8526q - 0.5389$
Nitrate ($\mu\text{mol/kg}$)	η	0.09 (0.300)	0.0171 (0.0086)*	$f(x) = 0.0634\eta + 0.8126$
Silicate ($\mu\text{mol/kg}$)	h	0.08 (0.283)	0.0244 (0.0122)*	$f(x) = 0.0324h + 0.6060$
Temperature ($^{\circ}\text{C}$)	t	0.07 (0.265)	0.0318 (0.0159)*	$f(x) = -0.1641t + 3.2049$
Alkalinity (milli-equivalent/liter CaCO ₃)	c	0.07 (0.265)	0.0368 (0.0184)*	$f(x) = 1.4551c - 1.6810$

Note: From highest to lowest R² value, the parameters are: salinity, pH, dissolved oxygen, pressure, phosphate, nitrate, silicate, temperature, and alkalinity.

Note. A color gradient is used to show the progression of parameters by decreasing R2 values. With a lower p-value, temperature is placed above alkalinity in the table, given their tied R2 values. $\alpha = 0.05$ for all significance levels.

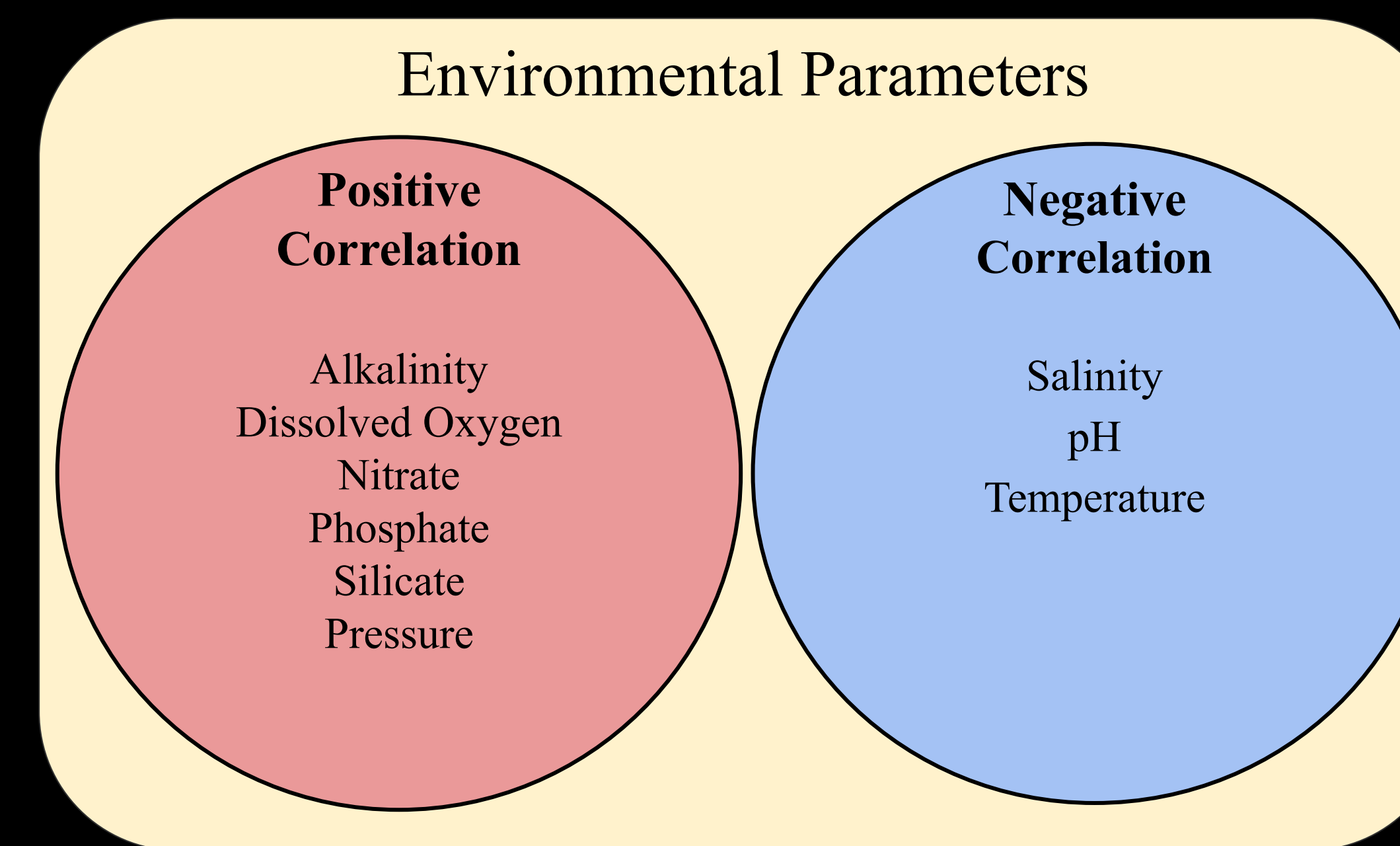


Note. The individual dots of varying color represent various instances of chlorophyll measurements relative to the first two principal components following dimension reduction. The red lines sprouting from the origin represent the vectors of each parameter's contribution to the variance of the first two principal components. Parametric abbreviations are designated as follows: pH (pH), salinity (sal), temperature (temp), nitrate (NO3), pressure (Press), silicate (Silicate), phosphate (PO4), alkalinity (alk), and dissolved oxygen (DO).



Note. Note. The time series for pressure (p) for year y is described by the sinusoidal regression function of $f(p) = 109.099 * \sin(6.951y + 43.661) + 489.463$; $R^2 = 0.077$. Sinusoidal Interval: (380.364, 598.562)

Figure 3



Note. This diagram sorts parameters by their directional relationship with total oceanic chlorophyll. These relationships suggest notable climatic and ecological ramifications.

Table 2
Covariance Among Oceanic Parameters in OSD Dataset of WOD18, 1954-2017

	Temperature ($^{\circ}\text{C}$)	Salinity (ppt)	Dissolved O ₂ ($\mu\text{mol/kg}$)	Pressure (decibars)	pH	Alkalinity (meq/L CaCO ₃)	NO ₃ ($\mu\text{mol/kg}$)	PO ₄ ($\mu\text{mol/kg}$)	Silicate ($\mu\text{mol/kg}$)
Temperature ($^{\circ}\text{C}$)	0.05679								
Salinity (ppt)	0.03166	0.08317							
Dissolved O ₂ ($\mu\text{mol/kg}$)	-0.01647	-0.01959	0.04698						
Pressure (decibars)	-0.005877	-0.03823	0.01677	0.08013					
pH	0.03188	0.06853	-0.01324	-0.03891	0.09541				
Alkalinity (meq/L CaCO ₃)	0.006023	-0.01187	0.001403	0.009997	-0.01088	0.02999			
NO ₃ ($\mu\text{mol/kg}$)	-0.001303	-0.01835	0.003703	0.03955	-0.01663	0.0009591	0.03353		
PO ₄ ($\mu\text{mol/kg}$)	-0.0178	-0.02756	-0.003317	0.02564	-0.03468	0.002638	0.017	0.05649	
Silicate ($\mu\text{mol/kg}$)	-0.02261	-0.03465	-0.007556	0.029	-0.03073	0.004527	0.02327	0.02543	0.06992

Note: Green cells represent the diagonal cells of the covariance matrix. These quantities, rather than inter-parameter covariance, represent the variance seen within water pressure. By contrast, the cell below, -0.0389, represents the covariance between pH and water pressure.

Note. All values are rounded to four decimal places. Green cells represent diagonal cells. These quantities represent the variance observable within the specified parameter. For example, the cell 0.0801 represents the variance seen within water pressure. By contrast, the cell below, -0.0389, represents the covariance between pH and water pressure.

Analysis

- Analysis:
- Highly Variable R² Values: 0.077- 0.847 (Figure 1; Figure 2) → Model Fitness Varies Depends Upon Parameter
 - Impractical Sinusoidal Intervals (Figure 1; Figure 2; Supporting Figures)
 - Alternative Regression Methods Necessary
 - Viable Forecasting Strategy—Crucial For Decision-Making (e.g., Algal blooms)
- Linear Regression Models:
- Low R² Values + Low p-values = poor predictors, but significant directional relationships (Table 1)
 - Negative correlation with temperature (Figure 3) suggests a loss in phytoplankton biomass and reduction in primary production capabilities (Berwyn, 2018)
 - This means less CO₂ sequestration, nutrient cycling, and trophic energy for marine food webs
 - Salinity and nutrient concentrations are predicted to become less spatially homogeneous (Berwyn, 2018), meaning the degree to which biomass and primary production increase/decrease will vary, decreasing ecological stability (Figure 3)

Analysis (Con.)

- PCA:
- pH, followed by salinity and pressure, are driving parameters of phytoplankton biomass and primary production (Figure 4)
 - (With total oceanic chlorophyll as a proxy)
 - Positive Relationships: Among Nutrients; Pressure & Nutrients; pH & Salinity (Figure 4)
 - Negative Relationships: Temperature & DO (Figure 4)
 - Limited applicability: PCs 1 and 2 only account for 60% of variance (Figure 4)
 - Case-by-Case Variability
- Covariance Matrix:
- Strong Independence Among Parameters (Table 2)— low variance values
 - Confounding variables for phytoplankton dynamics, but not one another
 - Strong Homogeneity Within Parameters (Table 2)— low diagonal values
 - Global Scale Homogeneity vs. Specific Ecosystem Variations

Conclusions and Extensions

- Apparatus appears to be viable
 - Critical for addressing climate change, marine ecosystem health, and understanding climatic and ecological patterns
- Limitations:
 - Geography as a confounding variable: lack of geospatial data for parametric data
 - Specific Temporal Scale
 - 1954-2017, using the OSD Dataset
 - Greater Data Integration & Apparatus Modification Required
- Extensions:
 - Integration of Neural Networks for Food Web Modeling (Boit et al., 2012; Loschi et al., 2023)
 - Forming Mechanistic Connections with CMIP and other climate models (Hague & Vichi, 2018)

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