

1 **Jingwei-Nutrients: A global spatiotemporal reconstruction of ocean**
2 **nutrients (1965–2023) using multi-task deep learning**

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13 **Abstract.** Dissolved nitrate, phosphate, and silicate are fundamental drivers of marine primary productivity and the biological
14 carbon pump. However, the development of continuous, long-term global datasets has long been severely hindered by extreme
15 historical data sparsity and complex biogeochemical dynamics. Statistical interpolation methods struggle to simultaneously
16 fill the severely sparse data gaps and capture the non-linear interactions, necessitating advanced artificial intelligence (AI) to
17 explicitly learn and leverage their underlying relationships. Nevertheless, most existing AI methods reconstruct nutrients
18 independently (i.e., Single-Task Learning), failing to exploit the synergistic effects inherent in cross-nutrient stoichiometry.

19 In this study, we present *Jingwei-Nutrients*, a [four-dimensional](#) global monthly [data product](#) at 1°×1° resolution from 0
20 to 2000 m depth spanning 1965 to 2023, reconstructed using a Transformer-based Multi-Task Learning (MTL)
21 framework trained on a comprehensive, quality-controlled multi-source observational database. Evaluation on
22 [chronological K-fold cross-validation yields mean validation R² values across folds](#) of 0.991, 0.969, and 0.990, with
23 RMSEs of [1.295, 0.163, and 4.109 μmol kg⁻¹](#) for nitrate, phosphate, and silicate, respectively. Temporal K-fold cross-
24 validation reveals that the MTL framework consistently achieves higher R² and lower RMSE for all three nutrients
25 compared to single-task models, with larger accuracy gains in data-sparse earlier decades such as 1965-1975. Our [data](#)
26 [product](#) reproduces consistent global climatology patterns and seasonal cycles with World Ocean Atlas (WOA).
27 Furthermore, independent evaluations against long-term monitoring stations (HOT and KERFIX) and GO-SHIP cruise
28 sections (P16N, P16S, and P06E) demonstrate our effectiveness across multi-decadal temporal trends, spatial variability
29 and vertical changes. Additionally, an ensemble-based uncertainty analysis reveals interpretable spatial heterogeneities
30 and a long-term decreasing trend in global uncertainty, which directly mirrors the historical transition from sparse early
31 sampling to modern observing networks. This [product](#) fills a critical gap in historical ocean biogeochemical observations,

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43 providing a reliable, physically consistent foundation for marine biogeochemical modeling and climate change studies.
44 The [product](https://doi.org/10.5281/zenodo.19491198) is openly available at <https://doi.org/10.5281/zenodo.19491198> (Wang et al., 2026).

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45 1 Introduction

46 Nutrients—specifically nitrate, phosphate, and silicate—serve as the fundamental basis for marine ecosystems and function as
47 critical drivers of ocean biogeochemistry (Sigman and Hain, 2012; Moore et al., 2013). Nitrate is often the proximate limiting
48 nutrient in much of the low-latitude surface ocean, directly constraining phytoplankton growth and ecosystem productivity
49 (Moore et al., 2013; Browning and Moore, 2023). Phosphate, while also a limiting factor in specific regions, plays a distinct
50 role in regulating long-term ocean fertility and metabolic processes over geological timescales (Deutsch and Weber, 2012).
51 Silicate is essential for diatoms—a key phytoplankton group responsible for a large fraction of carbon export—thereby
52 controlling the efficiency of the biological pump and the sequestration of atmospheric CO₂ (Benitez-Nelson et al., 2007;
53 Tréguer et al., 2018). Collectively, the availability and concentrations of these dissolved inorganic nutrients determine the
54 magnitude of primary and new production across the global ocean (Fasham, 2003; Moore et al., 2013).

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55 Although these nutrients serve distinct ecological and biogeochemical roles, they do not operate in isolation. Because these
56 nutrients collectively fuel the biological pump, their distributions in the marine environment do not vary independently; rather,
57 they are tightly coupled through biological uptake and regeneration processes (Deutsch and Weber, 2012). Phytoplankton
58 consume nitrate, phosphate, and silicate in fundamentally consistent average stoichiometric proportions during photosynthesis
59 and release them back into the water column during remineralization, establishing a robust biogeochemical linkage among
60 their cycles (Redfield, 1934). However, contemporary syntheses reveal that rather than being rigidly static, this marine
61 ecological stoichiometry is highly dynamic, exhibiting pronounced shifts across large-scale spatial gradients and multi-decadal
62 timescales (Liu et al., 2025). This intrinsic, yet variable, coupling implies that the spatial and temporal distribution of one
63 element is dynamically constrained by the others (Sarmiento and Gruber, 2006). Furthermore, the interplay between these
64 shifting biological drivers and physical transport processes, such as water mass mixing, results in complex, non-linear
65 hydrographic relationships that vary dynamically with depth and latitude (Ascani et al., 2013).

66 Despite their biogeochemical significance and the predictable nature of their elemental coupling, observational data for
67 these nutrients remain limited. While physical variables such as temperature and salinity are now extensively monitored
68 at high spatiotemporal resolution by autonomous platforms like the core Argo array (Roemmich et al., 2019), nutrient
69 concentrations have historically been derived from discrete shipboard sampling and subsequent laboratory analysis
70 (Olsen et al., 2016). Although the advent of the Biogeochemical-Argo (BGC-Argo) program has expanded autonomous
71 nitrate monitoring (Claustre et al., 2020), comparable sensors for phosphate and silicate are not yet available.
72 Consequently, the historical reliance on labor-intensive and costly ship-based operations has resulted in spatiotemporal
73 discontinuities in the global nutrient database. Historical observations are heavily biased toward the Northern

76 Hemisphere and summer months, leaving large regions of the Southern Ocean and the deep sea poorly sampled,
77 particularly during winter seasons (Garcia et al., 2018). Ultimately, this scarcity of continuous, four-dimensional
78 observations hinders our ability to fully resolve the multi-scale variability of global nutrient cycles and their ecosystem
79 responses to climate change.

80 To bridge these observational gaps and generate global nutrient fields, the oceanographic community has developed various
81 mapping strategies over the past decades. Traditional approaches predominantly employ objective analysis or optimal
82 interpolation techniques to map discrete nutrient profiles onto regular spatial grids (e.g., Levitus, 1982; Garcia et al., 2018).
83 However, these statistical interpolation methods require high-density spatial coverage to maintain accuracy. Given the sparsity
84 of historical nutrient observations, these methods are typically limited in capturing the temporal dimension, often aggregating
85 decades of discrete sampling data to construct a single, temporally averaged background field. This spatial-temporal trade-off
86 has led to the development of highly valuable but static climatological products, most notably the World Ocean Atlas (WOA)
87 (Garcia et al., 2018, 2024a). Consequently, while such gridded climatologies provide a crucial baseline for the oceanic mean
88 state, they lose temporal variance and multi-decadal biogeochemical trends, rendering them insufficient for resolving
89 continuous, long-term global nutrient variability.

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90 To address these limitations of statistical interpolation, machine learning (ML) algorithms have emerged as alternative tools
91 capable of resolving complex, non-linear biogeochemical dynamics even within data-sparse regimes (Sauzède et al., 2017;
92 Bittig et al., 2018; Ito et al., 2024; Lu et al., 2024). By leveraging empirical relationships between target biogeochemical
93 variables and widely available physical predictors (e.g., temperature and salinity), these data-driven models can infer missing
94 concentrations and reconstruct continuous fields. Building upon this paradigm, neural networks and ensemble methods have
95 been validated across various oceanographic domains. For instance, they have demonstrated reliability in mapping global
96 ocean carbon parameters and dissolved oxygen inventories (Landschützer et al., 2016; Gregor et al., 2019; Ito et al., 2017),
97 indicating the capability of ML to capture intricate hydrographic couplings. Encouraged by these successes, recent machine
98 learning approaches have been extended to macronutrient reconstruction, yielding valuable specialized products that focus on
99 surface fields, regional domains, or individual nutrient variables, such as satellite-derived global surface macronutrient
100 estimates, pan-European nitrate reconstructions, and historical nutrient reconstructions for the North Pacific (Sundararaman
101 and Shanmugam, 2024; Yu et al., 2025; Du et al., 2026).

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102 Despite these promising ML applications, a limitation persists across nearly all existing nutrient reconstruction frameworks:
103 they rely on Single-Task Learning (STL) paradigms. In these conventional models, nitrate, phosphate, and silicate are treated
104 as independent targets, with a separate neural network trained for each element. This isolated training process does not account
105 for the stoichiometric coupling that governs ocean biogeochemistry (e.g., Redfield, 1934; Deutsch and Weber, 2012).
106 Consequently, single-task models cannot mutually constrain their multi-element predictions, which can lead to physically
107 inconsistent elemental ratios within the reconstructed fields, particularly across vast, data-sparse oceanic domains. Furthermore,
108 STL models impose rigid data requirements, demanding exact target availability for training. For instance, if a historical
109 observation contains valid phosphate measurements but lacks nitrate, the entire profile is discarded during the training of the

115 nitrate model. Consequently, the valuable hydrographic context embedded in that observation cannot be utilized to inform the
116 coupled biogeochemical system. This fragmented approach leads to an underutilization of the already scarce historical data
117 archives, further reducing the available training pool.

118 Recognizing the limitation of single-task models and the scarcity of continuous global time-series products, we design a Multi-
119 Task Learning (MTL) framework (Kendall et al., 2018; Yu et al., 2020) based on the Transformer architecture (Vaswani et al.,
120 2017). The idea of multi-task learning is to train a single model to tackle multiple related tasks at once, enabling progress in
121 one task to implicitly benefit the others. This joint learning approach leverages the intrinsic biogeochemical stoichiometry
122 among nitrate, phosphate, and silicate. By allowing data-rich targets to serve as auxiliary constraints for under-sampled
123 variables, the MTL architecture maximizes the utility of fragmented historical observations, particularly in data-sparse eras.

124 Employing this framework, we present *Jingwei-Nutrients*, a four-dimensional spatiotemporal [data product](#) of global ocean
125 nutrients spanning from 1965 to 2023 (An explanation of the name *Jingwei* [is provided in the section "The Name of Jingwei"](#)).
126 Driven by quality-controlled in situ nutrient archives and hydrographic physical predictors, the product provides continuous,
127 monthly oceanic fields at a $1^{\circ}\times 1^{\circ}$ spatial resolution, covering the global ocean from the surface down to a depth of 2,000
128 meters.

129 To verify the physical and biological representation of the reconstructed fields, we conduct multi-scale validations. These
130 assessments include time-based K-fold cross-validation and comparative evaluations against single-task models to assess the
131 performance of the MTL framework. Additionally, we conduct global climatology comparisons to evaluate large-scale spatial
132 patterns and seasonal cycles, alongside independent verifications against long-term ecological time-series stations (HOT and
133 KERFIX), and cross-section evaluations using GO-SHIP cruise sections (P16N, P16S, and P06E). Furthermore, we incorporate
134 an ensemble-based spatiotemporal uncertainty analysis to quantify model variance and track the historical evolution of
135 reconstruction uncertainties. Ultimately, the *Jingwei-Nutrients* [product](#) offers a [validated and biogeochemically coherent](#)
136 [baseline](#) for investigating multi-decadal ocean biogeochemical dynamics and ecosystem responses to global climate change.

137 To facilitate community access and dynamic data exploration, we develop a dedicated scientific web platform
138 (<https://jingwei.acemap.info/map>). Beyond standard data distribution and visualization, this interactive platform integrates
139 advanced analytical tools, allowing researchers to perform on-the-fly scientific computing, such as generating real-time vertical
140 cross-sections and analyzing long-term time-series trajectories, directly supporting regional or global biogeochemical studies.

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141 **2 Data and Methods**

142 **2.1 Observation Data**

143 To construct the observational targets and training features for the global nutrient reconstruction, we compile a database of
144 historical in situ observations spanning from 1965 to 2023. The target variables—specifically dissolved inorganic nitrate,
145 phosphate, and silicate—are harmonized from quality-controlled public archives, primarily the World Ocean Database 2018

(WOD18; Boyer et al., 2018), the Global Ocean Data Analysis Project version 2 (GLODAPv2.2022; Lauvset et al., 2022), the CLIVAR and Carbon Hydrographic Data Office (CCHDO; Sloyan et al., 2019), and the Biogeochemical-Argo (BGC-Argo) program (Claustre et al., 2020). For BGC-Argo nitrate, we use the officially adjusted profiles with calibration information to reduce sensor-drift and calibration-related biases. The corresponding hydrographic predictors are sourced from the World Ocean Database 2023 (WOD23; Mishonov et al., 2024; Garcia et al., 2026) and collocated with these nutrient samples. Because our reconstruction model relies on the physical identification of water masses, we select only data containing concurrent temperature and salinity (T/S) measurements. To avoid data redundancy across these archives, duplicate profiles are identified and removed based on their spatiotemporal coordinates and cruise identifiers. Following data harmonization, deduplication, collocation, and quality control, the final dataset comprises 5,735,819 collocated T/S profiles. These physical features are paired with target nutrient observations, yielding a total of 4,225,374 nitrate, 3,578,340 phosphate, and 2,931,998 silicate measurements aggregated across the four archives. The detailed distribution of these observations per database is summarized in Table 1. The numbers in Table 1 represent the complete quality-controlled observational archive, while observations reserved for independent station and cruise-section validations are excluded from the training subset as described in Section 2.5.4.

Table 1. Summary of nutrients and hydrographic data compiled from four major databases after quality control.

	WOD	CCHDO	GLODAPV2	BGC-Argo	Total
T/S	5,735,819	0	0	0	5,735,819
Nitrate	1,738,637	69,355	609,016	1,808,366	4,225,374
Phosphate	2,902,300	98,652	577,388	0	3,578,340
Silicate	2,252,702	73,165	606,131	0	2,931,998

2.2 Climatological Features

To provide the machine learning model with a consistent biogeochemical and physical mean state, we incorporate climatological fields from the World Ocean Atlas (WOA). We utilize a combination of the most recent available versions for different variables to ensure the highest data quality. These fields define the spatial reference grid for our study, featuring a 1°×1° horizontal resolution and 67 standard vertical levels (0–2000 m).

We select a total of six variables to characterize the background environment. Specifically, dissolved oxygen, oxygen saturation, and apparent oxygen utilization are obtained from the World Ocean Atlas 2023 (Garcia et al., 2024b). Climatologies for density and conductivity are sourced from the World Ocean Atlas 2018 (Locarnini et al., 2019; Reagan et al., 2019), while the mixed layer depth is derived from the WOA18 temperature and salinity fields (Locarnini et al., 2018; Zweng et al., 2018).

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182 These climatological inputs provide the mean state of the global ocean, serving as static "background" features for the machine
183 learning model.

184 2.3 Time-Varying Hydrographic Predictors

185 For the global inference phase, we require continuous, time-varying, and historically consistent hydrographic inputs. We utilize
186 the EN4.2.2 objective analysis dataset (Good et al., 2013), which provides monthly potential temperature and salinity fields
187 from 1965 to 2023 at a $1^\circ \times 1^\circ$ resolution.

188 We select EN4 as the hydrographic predictors because of its systematic bias correction. EN4 integrates quality-controlled
189 profiles from the World Ocean Database (WOD), the Global Telecommunication System (GTSP), and the Argo array, while
190 applying bias correction schemes (e.g., Gouretski and Reseghetti, 2010) to historical mechanical bathythermograph (MBT)
191 and expendable bathythermograph (XBT) records. This processing reduces time-dependent instrumental biases, ensuring that
192 the decadal trends in the input features represent physical variability rather than measurement artifacts.

193 Furthermore, the objective analysis framework of EN4 effectively bridges observational gaps, providing the spatiotemporally
194 complete fields strictly required to drive global machine learning inferences. Because of its high fidelity in representing
195 historical hydrographic environments, EN4 has been extensively validated as a foundational benchmark for capturing historical
196 ocean heat storage and multi-decadal transport (Cheng et al., 2017; Zanna et al., 2019). Consequently, it is routinely employed
197 as a highly reliable physical forcing dataset to drive large-scale data-driven biogeochemical mappings and carbon cycle
198 reconstructions (Landschützer et al., 2016).

199 2.4 Data Quality Control

200 Because our dataset originates from diverse observational platforms and encompasses highly varied temporal and geographic
201 scales, establishing a strict, multi-tiered quality control (QC) pipeline is critical to eliminate inaccurate records. Guided by the
202 fundamental principles outlined in the World Ocean Database (WOD) documentation (Boyer et al., 2018), we implemented a
203 three-stage hierarchical strategy on the merged global archive. This framework systematically filters hydrographic and nutrient
204 variables at the measurement, station, and cruise levels.

205 The first level of our hierarchical QC protocol targets individual measurements, employing a sequence of seven specific checks
206 to identify and remove potentially erroneous records from the combined datasets. (1) Initially, we apply a depth-specific
207 boundary constraint optimized for our target 0–2000 m water column. By defining physically realistic domains for every
208 variable across designated water strata, any observation exceeding these established boundaries is consequently rejected. This
209 restriction covers temperature, salinity, and the three target nutrient parameters: nitrate (NO_3^-), phosphate (PO_4^{3-}), and silicate
210 ($Si(OH)_4$). (2) We evaluate the biogeochemical consistency of the data by checking empirical relationships between paired
211 variables. We validate observations against accepted theoretical spaces for both physical pairings (T–S) and physical-
212 biogeochemical combinations (e.g., T–N, T–P, T–Si, S–N, S–P, S–Si) to guarantee alignment with recognized water mass

213 signatures. (3) To capture extreme statistical anomalies, we compute the local mean and standard deviation for each standard
 214 depth horizon. Any value shifting beyond six standard deviations from its respective mean is tagged as an outlier. (4) We
 215 assess vertical continuity by calculating the vertical gradient for each parameter. Any measurement showing a vertical rate of
 216 change that exceeds the mean gradient by more than five standard deviations is marked as questionable. (5) A density inversion
 217 assessment targets physically improbable vertical structures. Since parameters such as temperature and nutrients typically
 218 exhibit monotonic relationships with depth or potential density (σ_θ) in stratified waters, measurements violating preset
 219 thresholds for relationships (e.g., Depth–T, Depth–Nutrient, or σ_θ –Nutrient) are flagged. (6) We identify vertical spikes by
 220 comparing each measurement directly against its immediate upper and lower neighbors. If this difference exceeds a preset
 221 limit, the observation is flagged as a spike. (7) Finally, we rely on the original quality flags provided by the source databases.
 222 We only retain measurements explicitly labeled as 'good' and discard any records marked as questionable or bad.
 223 Following the assessment of individual measurements, regarding to the second level, we extend the quality control framework
 224 to the station and cruise levels to address systematic inconsistencies. To ensure vertical profile reliability, any station containing
 225 more than 30% of data points flagged during the initial screening is deemed unreliable and entirely discarded. Similarly, at the
 226 expedition level, cruises exhibiting an aggregate flag rate exceeding 40% are excluded to prevent the propagation of systematic
 227 instrumental errors or calibration drifts. The final selection process integrates flags across this hierarchy, permanently
 228 removing any data identified as erroneous at the individual, station, or cruise stage.
 229 The final level of our quality control protocol is specifically designed to align with the input-output structure of the multi-task
 230 learning framework. Since the reconstruction relies on physical predictors to infer biogeochemical fields, complete availability
 231 of temperature and salinity is mandatory. Therefore, we apply a strict filter to ensure that every retained nutrient observation
 232 is strictly collocated with valid, high-quality physical measurements (T and S). However, unlike single-task models that might
 233 require simultaneous observations of all target variables, our multi-task architecture allows for valid training with partial targets.
 234 To maximize data utilization, we do not require the concurrent presence of all three nutrients. Instead, any data point containing
 235 valid physical predictors and at least one valid nutrient measurement is retained. This flexible inclusion strategy allows the
 236 model to leverage a significantly larger volume of historical data—where specific nutrients might be missing—thereby
 237 enhancing the distinct feature extraction capability for each element. This inclusion strategy maximizes the volume of historical
 238 data available for training. The resulting high-quality dataset exhibits extensive global coverage spanning the period 1965–
 239 2023, with the specific spatiotemporal distribution patterns illustrated in Fig. 1.

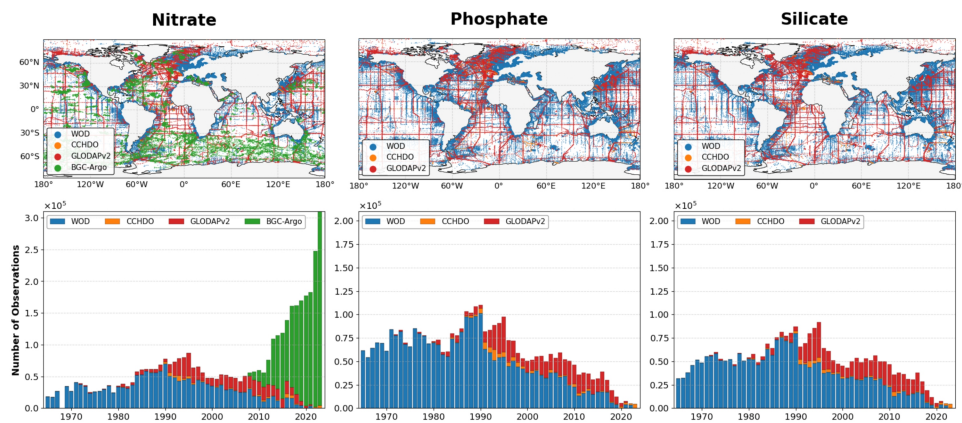


Figure 1. Spatial and temporal distribution of the nutrients data after quality control.

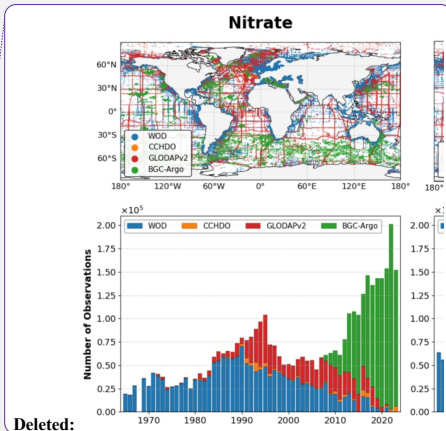
2.5 Model development and Validation

2.5.1 Input Features

The selection of input features is designed to constrain the machine learning model with both physical principles and statistical priors. The input vector consists of three distinct categories: encoded spatiotemporal coordinates, hydrographic predictors, and climatological reference features. To preserve the continuity of the global domain and the cyclical nature of seasonality, we apply specific feature engineering techniques: spatial coordinates are transformed into spherical coordinates, and the month variable is encoded into sine and cosine components to capture the continuous seasonal cycles. A list of all input variables, along with their respective sources and resolutions, is summarized in Table 2.

Potential temperature and salinity are selected as the primary physical drivers based on the fundamental control of water mass dynamics on nutrient distributions. Oceanographic studies have long established that nutrient concentrations exhibit distinct relationships with temperature and salinity along isopycnal surfaces, enabling these hydrographic variables to serve as effective proxies for identifying distinct water masses. Consequently, utilizing collocated temperature and salinity as core predictors has become a standard practice in global biogeochemical reconstruction models (e.g., Sauzède et al., 2017; Bittig et al., 2018; Broullón et al., 2019; Keppler et al., 2020; Carter et al., 2021).

Furthermore, we incorporate six climatological variables from WOA to serve as spatial reference features. By explicitly including these mean environmental states as inputs, the neural network is guided to learn the non-linear relationships between the background hydrographic conditions and nutrient distributions. This "climatology-informed" strategy provides a stable environmental reference baseline, enhancing model stability and convergence.



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261 To align the model inputs with observational reality, we implement a distinct data construction strategy for the training and
 262 inference phases. During the training phase, the model inputs are derived from the quality-controlled observational dataset to
 263 represent in situ conditions. Specifically, we use the in situ measured temperature and salinity, while the corresponding
 264 climatological features are obtained by linearly interpolating the standard WOA grids to the exact spatiotemporal position of
 265 each nutrient observation. In contrast, the global inference phase requires spatially continuous products to generate the full 4D
 266 reconstruction. Drawing on its established role as a robust physical forcing in historical oceanographic reconstructions (Cheng
 267 et al., 2017; Zanna et al., 2019) and large-scale biogeochemical mappings (Landschützer et al., 2016), we directly utilize the
 268 time-varying EN4 gridded fields to represent the historical hydrographic conditions. Concurrently, the WOA climatological
 269 features are drawn directly from their standard grid points. This dual strategy ensures that the model is trained on local
 270 relationships while being capable of projecting these learned patterns onto the global domain driven by spatiotemporal physical
 271 inputs.

272 Table 2. Summary of the input variables used for the global nutrient reconstruction, including their respective data sources, temporal
 273 coverage, and spatial resolutions.

Feature name	Data source	Spatial resolution	Temporal resolution
<i>Geographical features</i>			
Latitude [° N]	Sampling information		
Longitude [° E]	Sampling information		
Depth [m]	Sampling information		
<i>Oceanographic features</i>			
Temperature [°C]	World Ocean Database 2023		
Salinity [unitless]	World Ocean Database 2023		
Dissolved oxygen [$\mu\text{mol kg}^{-1}$]	World Ocean Atlas 2023	$1^\circ \times 1^\circ$	Annual climatology
Percent Oxygen Saturation [%]	World Ocean Atlas 2023	$1^\circ \times 1^\circ$	Annual climatology
Apparent Oxygen Utilization [$\mu\text{mol kg}^{-1}$]	World Ocean Atlas 2023	$1^\circ \times 1^\circ$	Annual climatology
Density [kg/m^3]	World Ocean Atlas 2018	$1^\circ \times 1^\circ$	Seasonal climatology
Conductivity [S/m]	World Ocean Atlas 2018	$1^\circ \times 1^\circ$	Seasonal climatology
Mixed Layer Depth [m]	World Ocean Atlas 2018	$1^\circ \times 1^\circ$	Monthly climatology

274

275 2.5.2 Model Architecture

276 The operational workflow detailing the training and inference phases of the *Jingwei-Nutrients* model is illustrated in Fig. 2. At
 277 the core of this pipeline, to capture the complex, non-linear interactions between physical drivers and biogeochemical tracers,
 278 we employ a Transformer-based deep learning architecture. This framework, originally developed for [sequence representation](#)

learning (Vaswani et al., 2017), has been recently adapted for high-dimensional Earth system modeling (e.g., Bi et al., 2023; Lam et al., 2023) and complex oceanographic field reconstructions (Reichstein et al., 2019; Sonnewald et al., 2021). The cornerstone of this architecture is the self-attention mechanism, which fundamentally distinguishes it from traditional regression models or standard convolutional networks. Unlike static methods that treat input features independently, the self-attention mechanism dynamically calculates "attention weights" to quantify the relevance of different input features relative to one another. In the context of nutrient reconstruction, this capability allows the model to inherently learn and weigh the variable coupling strength between specific physical conditions (e.g., temperature, salinity, depth) and nutrient concentrations. By establishing these adaptive connections, the Transformer can focus on the most critical predictors for identifying distinct water masses, thereby improving prediction accuracy in spatially heterogeneous ocean environments.

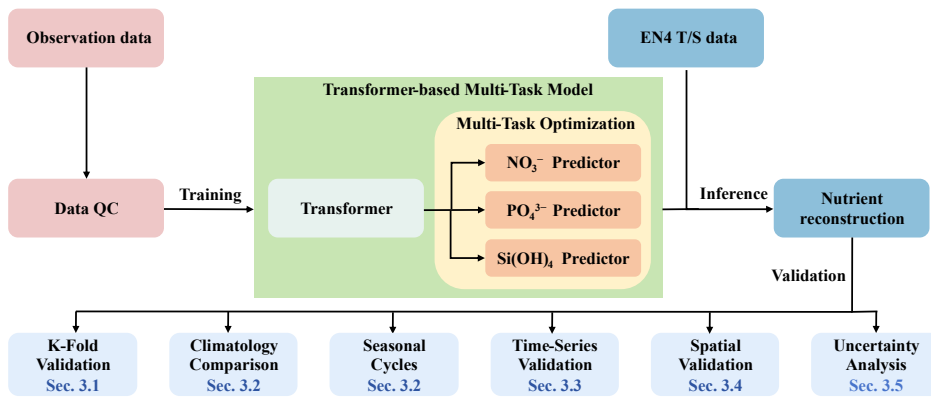


Figure 2. The overall pipeline of the *Jingwei-Nutrients* reconstruction framework, encompassing data preparation, the Transformer-based MTL neural network architecture, global 4D inference, and comprehensive performance validation.

Specifically, the network architecture adopts a Multi-Task Learning (MTL) framework designed to simultaneously reconstruct the three target nutrients (NO_3^- , PO_4^{3-} , and $Si(OH)_4$). The network is composed of a shared feature extraction backbone followed by three element-specific prediction heads. The input feature vector is initially processed by shared Transformer encoder layers, which are designed to capture the coupled physical-biogeochemical linkages driven by the hydrographic environment. Rather than learning isolated generic representations, these shared layers extract the concurrent stoichiometric relationships among the nutrients. Subsequently, the shared feature representations are routed into three parallel, task-specific decoding heads. Each head acts as a specialized regression module dedicated to a single element, optimizing for its unique vertical gradient and spatial distribution. Crucially, during training, the information learned by each nutrient decoding head is continuously propagated back to the shared layers. By jointly shaping the shared representation space, the MTL framework enables the joint learning of coherent biogeochemical patterns. This dynamic mutual calibration not only enhances computational efficiency

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through shared weights but, more importantly, provides a structural mechanism to encourage stoichiometric consistency. By sharing representations across elements, the model is inherently guided to learn their concurrent biogeochemical variations, reducing the likelihood of generating the physically divergent patterns that can arise from training independent single-task models.

2.5.3 Multi-Task Optimization Strategy

The stoichiometric ratios among marine nutrients are not globally static; rather, they exhibit pronounced variability across distinct horizontal domains, depth horizons, and temporal scales (Liu et al., 2025). Consequently, we employ a data-driven multi-task learning approach that enables the neural network to learn and represent these dynamic elemental relationships from observations within a shared latent space.

However, while this multi-task architecture enables flexible information sharing without hard-coded rules, the joint training process introduces two fundamental optimization challenges: loss scale imbalance and gradient conflict. If simply summed with equal weights, tasks with larger loss magnitudes can dominate the optimization process, while conflicting gradient directions between tasks can lead to "negative transfer" (Yu et al., 2020; Vandenhende et al., 2022), where improving the prediction of one nutrient degrades the performance of others. To address these issues and ensure balanced convergence across all biogeochemical variables, we implement a dual-strategy optimization framework.

To strictly address the optimization imbalance caused by differing variances and units among NO_3^- , PO_4^{3-} , and $Si(OH)_4$, we implement an adaptive weighting scheme based on homoscedastic uncertainty (Kendall et al., 2018). Instead of manually assigning fixed hyperparameters, this method treats the task-dependent weight as a learnable parameter derived from the inherent observation noise. The total multi-task objective function L_{total} is formulated as Eq. (1):

$$\mathcal{L}_{total}(W, \sigma_1, \dots, \sigma_T) = \sum_{t \in \{N, P, Si\}} \left(\frac{1}{2\sigma_t^2} \mathcal{L}_t(W) + \log \sigma_t \right), \quad (1)$$

where $\mathcal{L}_t(W)$ denotes the task-specific loss (MSE) for nutrient t , and σ_t represents the learnable noise parameter. In Eq. (1), the term $\frac{1}{2\sigma_t^2}$ automatically down-weights tasks with high uncertainty, while the regularization term $\log \sigma_t$ prevents the variance from increasing indefinitely, allowing the model to dynamically balance the learning focus among the three elements throughout the training process.

Furthermore, to mitigate the geometric conflicts where the gradient update for one task might detrimentally affect another, we integrate the Project Conflicting Gradients (PCGrad) algorithm (Yu et al., 2020). This strategy monitors the cosine similarity between the gradient vectors of any two tasks during backpropagation. When a conflict is detected (i.e., their dot product is negative), the gradient is projected to eliminate the destructive component, as calculated in Eq. (2):

$$g_i^{PC} = g_i - \frac{g_i g_j}{\|g_j\|} g_j, \quad (2)$$

Deleted: imposing rigid empirical constraints, such as the classical Redfield ratio, is insufficient for capturing the complex reality of global biogeochemical cycles. To address this, we employ a data-driven multi-task learning approach, enabling the neural network to autonomously infer and represent these dynamic elemental relationships within its shared latent space.

where g_i and g_j denote the original gradient vectors for task i and task j , respectively, and g_i^{PC} represents the corrected gradient for task i projected onto the normal plane of g_j . By iteratively applying this projection, PCGrad mitigates inter-task gradient conflicts by suppressing destructive gradient components, thereby facilitating more balanced optimization of the shared parameters and reducing negative transfer among nutrient predictions.

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Deleted: effectively eliminating the risk of negative transfer between nutrient species.

2.5.4 Model Evaluation and Experimental Design

The reconstruction performance is quantitatively evaluated using two standard statistical metrics: the Coefficient of Determination (R^2) and Root Mean Square Error (RMSE). Let N denote the total number of matched samples, while $y_{obs,i}$ and $y_{pred,i}$ represent the observed and predicted values for the i -th sample, respectively, and $\bar{y}_{obs}$ is the mean of the observed values. These metrics are calculated as follows:

$$R^2 = 1 - \frac{\sum_{i=1}^N (y_{obs,i} - y_{pred,i})^2}{\sum_{i=1}^N (y_{obs,i} - \bar{y}_{obs})^2}, \quad (3)$$

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (y_{obs,i} - y_{pred,i})^2}, \quad (4)$$

To evaluate the model's performance and the effects of the proposed architecture, we design a rigorous training and comparative framework. We adopt a strict time-based K-fold cross-validation strategy to prevent temporal data leakage. In this study, K = 6, and the 59-year dataset is divided into six chronological folds: 1965–1975, 1976–1985, 1986–1995, 1996–2005, 2006–2015, and 2016–2023. By partitioning the 59-year dataset into chronological blocks rather than random subsets, distinct time periods are rigorously isolated as test sets, providing an objective assessment of the model's generalization. Within this cross-validation framework, we further establish a comparative baseline by training independent Single-Task Learning (STL) models for each nutrient. Comparing the proposed multi-task framework against these single-element counterparts under identical conditions allows us to verify the mutual enhancement effects driven by shared feature learning. Beyond statistical benchmarks, a multi-dimensional verification scheme is implemented to assess the physical and biogeochemical representation of the reconstruction. This comprehensive evaluation includes: (1) Climatological Patterns and Seasonal Cycles, which examines the reproduction of large-scale seasonal variations and long-term trends; (2) Temporal Dynamics through Station Validation, where representative stations are selected to evaluate the time-series dynamics and vertical profiles; (3) Spatial Variability through Cruise Verification, utilizing independent cruise data to assess the spatial representation of nutrient distributions across ocean basins; and (4) Spatiotemporal Uncertainty Analysis, which quantifies the model variance and uncertainties of the reconstructed product across different oceanic regions and historical periods. To ensure independent station and cruise-section validations, all HOT, KERFIX, P16N (2015), P16S (2014), and P06E (2017) observations are excluded from the training data before model development, including duplicate or overlapping records in the source archives. These reserved observations are identified using station information, cruise identifiers, and spatiotemporal

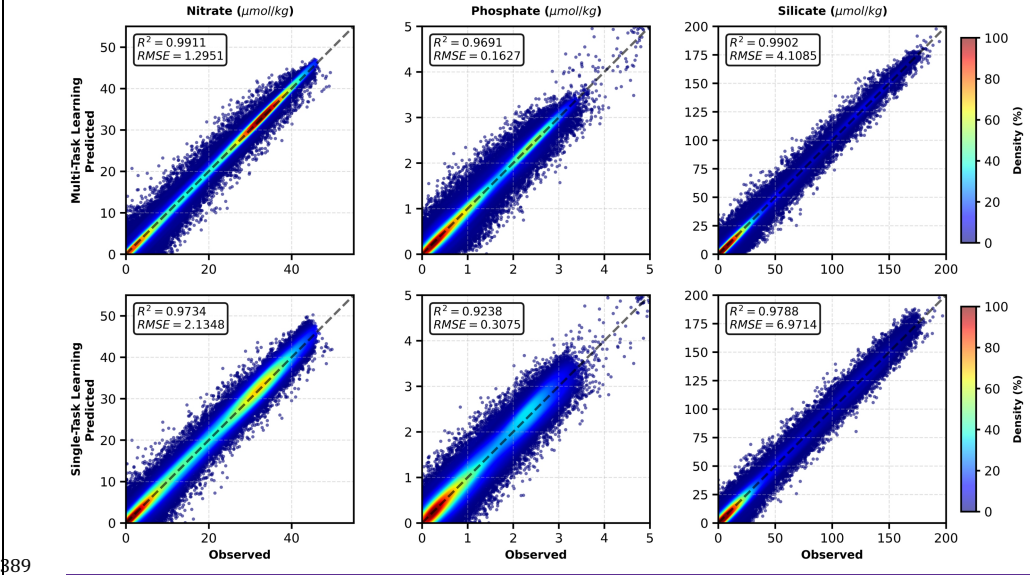
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coordinates, and are used only for the validations described in Sections 3.3 and 3.4. Detailed results and analyses from these validation modules are presented in Section 3.

3 Results

3.1 Model Performance

The reconstruction performance of the proposed Multi-Task Learning (MTL) and Single-Task Learning (STL) models is evaluated using aggregated predictions from the validation sets of the time-based K-fold cross-validation. Figure 3 presents the density scatter plots comparing the reconstructed nutrient concentrations against the in situ observations across the full study period (1965–2023) for both architectures. By utilizing chronological blocking rather than random partitioning, the evaluation mitigates the influence of short-term temporal persistence, providing an objective assessment of the models' generalization capabilities. The scatter distributions for both the MTL and STL models generally align with the 1:1 reference line across the concentration spectrum, indicating that the models can reproduce the concentration limits without systematic bias. Furthermore, a comparison of the scatter distributions reveals that the MTL model shows tighter alignment with the reference line than the STL model, demonstrating improved reconstruction performance for all three nutrients.



390 **Figure 3.** Density scatter plots comparing the *Jingwei-Nutrients* reconstructed concentrations against in situ observations for nitrate,
391 phosphate, and silicate. The plots aggregate all matched test samples from the strict time-based K-fold cross-validation over the entire study
392 period (1965–2023). Colors indicate the density of data points, and the dashed line represents the 1:1 ideal agreement.

393 Table 3 summarizes the quantitative metrics (R^2 and RMSE) to further assess the specific effects of the multi-task architecture
394 compared to the single-task baselines. On average, the MTL framework yields R^2 values of 0.9911, 0.9691, and 0.9902 for
395 nitrate, phosphate, and silicate, respectively, with corresponding mean RMSE values of 1.2951, 0.1627, and 4.1085. As shown
396 in Table 3, the joint learning framework consistently yields lower RMSE and higher R^2 values compared to the single-element
397 models across all chronological folds. Overall, the MTL approach reduces the fold-averaged RMSE by approximately 39.3%,
398 for nitrate, 47.1% for phosphate, and 41.1% for silicate compared with their STL counterparts. This improvement can be
399 attributed to the shared representation mechanism of the MTL architecture. By processing the elements jointly, the model is
400 guided to learn their concurrent biogeochemical variations, which contributes to the observed improvements in numerical
401 accuracy compared to the isolated single-task models.

402 Beyond the performance differences between the two architectures, a common characteristic observed in both the MTL and
403 STL results is a progressive improvement in predictive performance from the 1960s to the 2020s. For instance, the MTL RMSE
404 for nitrate, decreases from 1.8306 in the 1965–1975 fold to 0.9273 in the 2016–2023 fold. This temporal trend corresponds
405 with the historical evolution of global ocean observing systems; the relatively higher errors in earlier decades relate to the
406 spatial sparsity of historical bottle measurements, whereas recent accuracy gains reflect the availability of high-density
407 hydrographic observations that provide additional physical constraints for the models.

408 Table 3. Statistical evaluation metrics (R^2 and RMSE) of the chronological K-fold cross-validation. The results highlight the decadal
409 performance evolution and compare the predictive accuracy of the MTL architecture against independent STL models for nitrate,
410 phosphate, and silicate reconstructions. The unit for all RMSE values is $\mu\text{mol kg}^{-1}$.

Fold	Multi-Task Learning						Single-Task Learning					
	N (R^2 /RMSE)		P (R^2 /RMSE)		Si (R^2 /RMSE)		N (R^2 /RMSE)		P (R^2 /RMSE)		Si (R^2 /RMSE)	
1965-1975	0.9847	1.8306	0.9476	0.1986	0.9794	6.1854	0.9618	3.1264	0.8967	0.4177	0.9605	9.1755
1976-1985	0.9865	1.5452	0.9430	0.2094	0.9834	4.7658	0.9651	2.6278	0.8908	0.4080	0.9672	8.8442
1986-1995	0.9889	1.3298	0.9618	0.1688	0.9881	4.1327	0.9694	2.2483	0.9146	0.3368	0.9753	7.7289
1996-2005	0.9937	1.1494	0.9831	0.1501	0.9958	3.5784	0.9781	1.9364	0.9415	0.2586	0.9883	5.8910
2006-2015	0.9955	0.9883	0.9863	0.1327	0.9968	3.1057	0.9813	1.5911	0.9455	0.2394	0.9900	5.3172
2016-2023	0.9974	0.9273	0.9928	0.1166	0.9977	2.8830	0.9847	1.2788	0.9537	0.1845	0.9915	4.8716
Avg	0.9911	1.2951	0.9691	0.1627	0.9902	4.1085	0.9734	2.1348	0.9238	0.3075	0.9788	6.9714

412 3.2 Climatological Patterns and Seasonal Cycles

413 To evaluate whether the *Jingwei-Nutrients* data product captures the fundamental biogeochemical structure of the global ocean,
414 we compare the model-derived climatologies with the standard World Ocean Atlas 2023 (WOA23). This comparison assesses

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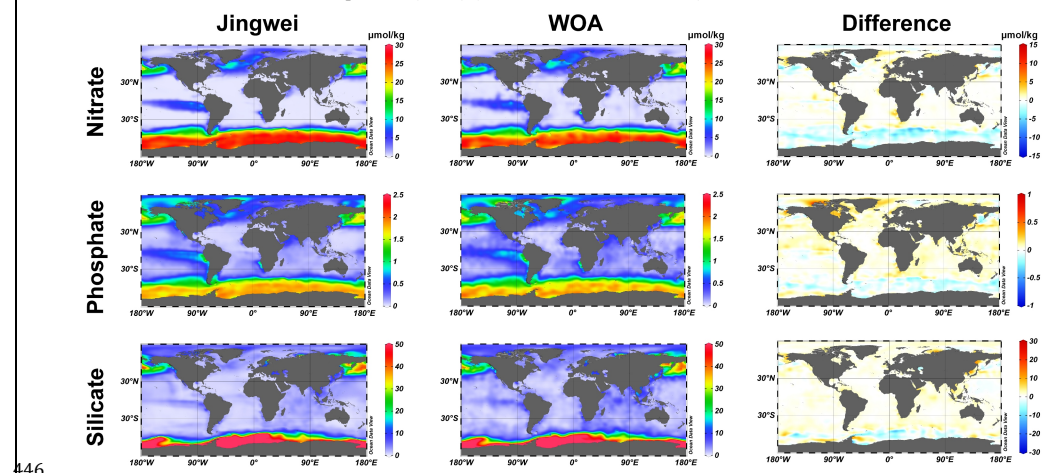
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432 whether the *Jingwei-Nutrients* model captures large-scale spatial patterns rather than overfitting to local observations. Figures
 433 4 to 6 display the comparison of spatial distributions for nitrate, phosphate, and silicate across three representative depth layers:
 434 the surface (0 m), the intermediate layer (500 m), and the deep layer (2000 m). Overall, the reconstructed fields show spatial
 435 agreement with WOA23, reproducing the major global nutrient regimes across these selected depths.
 436 The spatial patterns at each evaluated stratum reflect distinct physical-biogeochemical dynamics. As illustrated in Fig. 4, at
 437 the surface layer (0 m), the model reproduces the global nutrient regimes governed by biological uptake and physical
 438 stratification, identifying the nutrient-depleted oligotrophic subtropical gyres alongside the High-Nutrient Low-Chlorophyll
 439 (HNLC) outcropping in the Southern Ocean (Moore et al., 2013). At the intermediate layer (500 m) in Fig. 5, the spatial
 440 patterns transition to reflect organic matter remineralization and main thermocline ventilation, mapping the accumulation of
 441 regenerated nutrients in the North Pacific and Indian Ocean oxygen minimum zones (OMZs) (Paulmier and Ruiz-Pino, 2009;
 442 Sarmiento and Gruber, 2006). In the deep layer (2000 m), as shown in Fig. 6, the reconstruction captures the large-scale
 443 horizontal gradients associated with the global thermohaline circulation. The spatial distribution aligns with the general nutrient
 444 accumulation pattern (Broecker, 1991), transitioning from the relatively nutrient-poor North Atlantic Deep Water (NADW) to
 445 the older, nutrient-rich Pacific Deep Water (PDW) (Sarmiento and Gruber, 2006).



446 **Figure 4.** Spatial comparison of the climatological mean distributions of nitrate, phosphate, and silicate at the sea surface (0 m). The left
 447 column displays the *Jingwei-Nutrients* reconstruction, the middle column shows the WOA23 standard reference, and the right column
 448 presents the absolute difference (*Jingwei* minus WOA23). The surface fields highlight the model's effective capture of nutrient-depleted
 449 subtropical gyres and nutrient-rich outcropping zones.
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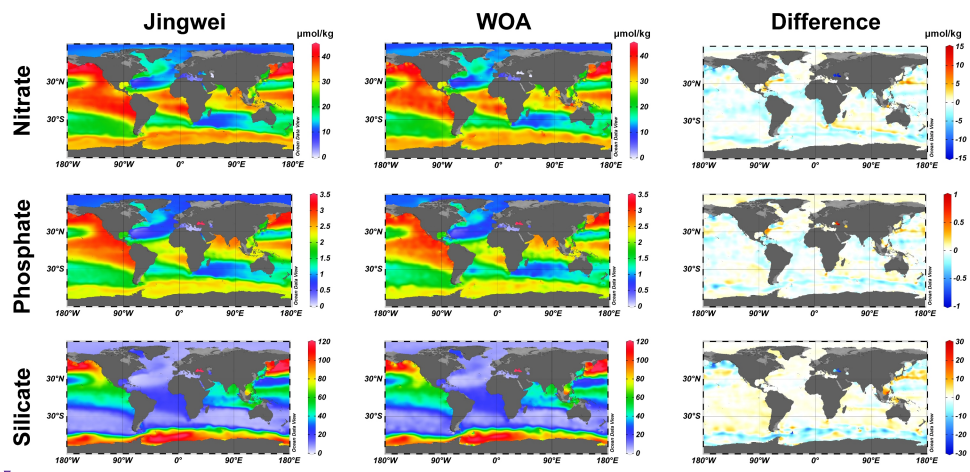


Figure 5. The Global climatological distributions of nitrate, phosphate, and silicate at the intermediate layer (500 m). The column and row layout is identical to Fig. 4.

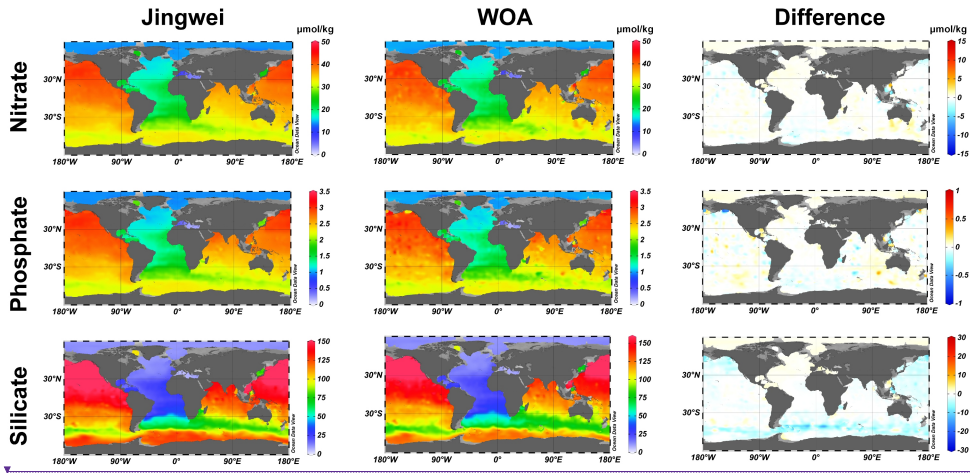


Figure 6. Global climatological distributions of nitrate, phosphate, and silicate at the deep layer (2000 m). The column and row layout is identical to Fig. 4.

461 The difference maps between the reconstructed fields and WOA23 provide further insight into the spatial distribution of
462 residuals. While the anomalies are generally small across open-ocean basins, their spatial and vertical distributions exhibit
463 structured patterns. Spatially, larger deviations are primarily located in high-latitude regions (e.g., the Southern Ocean) and
464 certain coastal margins. Vertically, the differences in the shallow euphotic layers tend to be larger than those in the deep ocean.
465 This spatial-vertical contrast aligns with established oceanographic processes: surface waters and high-latitude regimes are
466 modulated by seasonal biological uptake, atmospheric forcing, and mesoscale dynamics (Benitez-Nelson et al., 2007; Moore
467 et al., 2013), introducing greater natural variability. In contrast, the deep ocean is characterized by relatively stable, slow-
468 moving water masses driven by large-scale circulation. Overall, these regional variations are consistent with known
469 oceanographic processes, and the comparison indicates that the *Jingwei-Nutrients* product provides a consistent representation
470 of global biogeochemical distributions.

471 The vertical representation of the reconstructed fields is examined by comparing meridional sections across distinct ocean
472 basins. Figures 7 and 8 present the vertical distributions of nitrate, phosphate, and silicate along two representative lines: 25°W
473 in the Atlantic Ocean and 90°E in the Indian Ocean. The reconstructed fields capture the basin-scale fractionation patterns
474 associated with the global thermohaline circulation. As illustrated in Fig. 7, the Atlantic sector exhibits relatively lower nutrient
475 concentrations, showing the southward-intruding tongue of the ventilated, nutrient-poor North Atlantic Deep Water (NADW)
476 in the mid-to-deep layers. Conversely, Fig. 8 displays the transition to higher deep-water concentrations in the Indian Ocean
477 interior, reflecting the accumulation of remineralized organic matter along the aging path of the deep circulation (Broecker,
478 1991; Sarmiento and Gruber, 2006). Across both basins, the characteristic vertical gradient—rapid nutrient depletion in the
479 euphotic zone followed by an increase across the thermocline to a deep maximum—is evident, indicating that the
480 reconstruction captures the vertical coupling associated with the biological pump and subsequent subsurface remineralization
481 (Sigman and Hain, 2012).

482 The difference maps in the rightmost columns of Fig. 7 and Fig. 8 provide further details on the distribution of residuals within
483 the ocean interior. Anomalies are generally small across the majority of the water column. However, larger deviations are
484 primarily localized along the boundaries of major water masses and in regions characterized by sharp spatial gradients. For
485 instance, higher differences are observed around the edges of the NADW nutrient tongue and across the stratified main
486 thermocline. This distribution of differences is physically interpretable, as these transition zones feature intense mixing and
487 dynamic frontogenesis, introducing greater natural variability. Furthermore, the observed differences at these complex
488 physical-biogeochemical interfaces may partially arise from distinct methodological approaches. While traditional objective
489 analysis relies on spatial autocorrelation, the data-driven model infers nutrient concentrations through non-linear relationships
490 with varying physical drivers. Overall, these comparisons indicate that the *Jingwei-Nutrients* data product provides a
491 structurally consistent representation of three-dimensional biogeochemical distributions.

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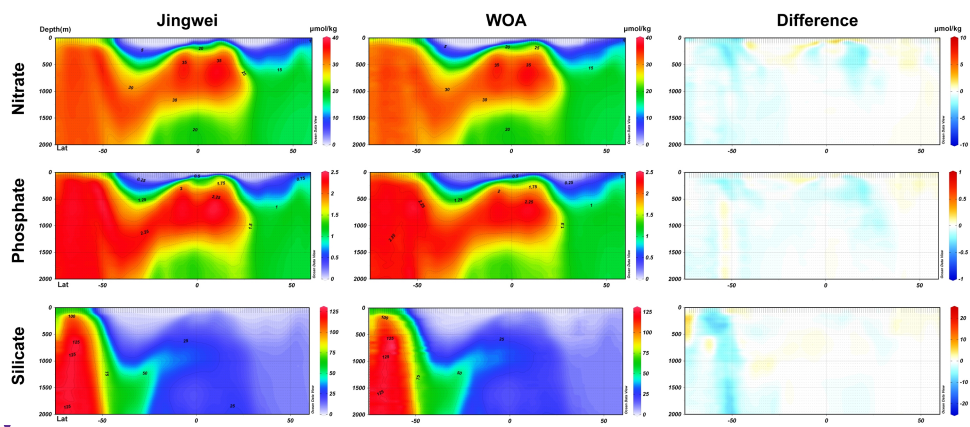


Figure 7. Vertical distribution of climatological mean nutrients along the 25°W meridional section in the Atlantic Ocean. The left column presents the *Jingwei-Nutrients* reconstruction, the middle column displays the WOA23 standard reference, and the right column shows the absolute difference (*Jingwei* minus WOA23). Rows from top to bottom correspond to nitrate, phosphate, and silicate, respectively. Units for all concentrations and differences are $\mu\text{mol kg}^{-1}$.

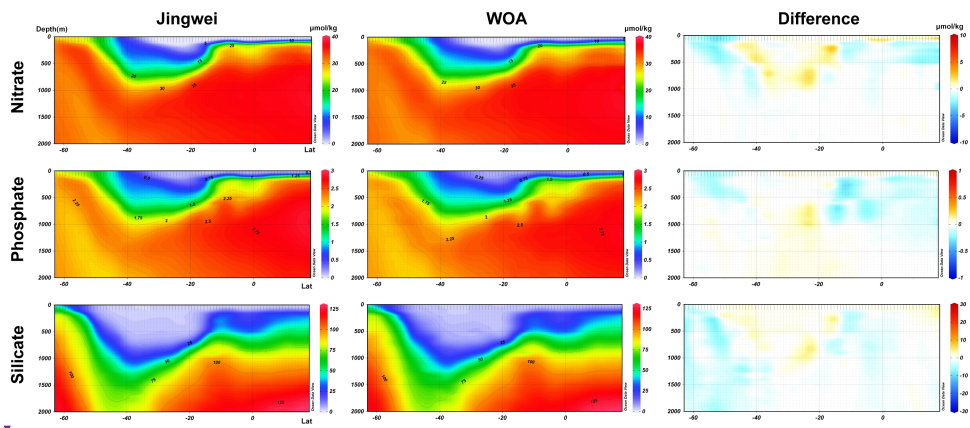
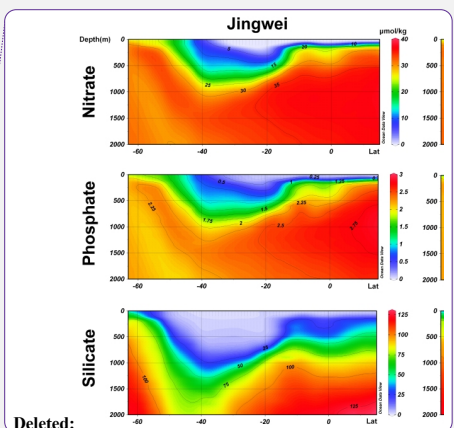
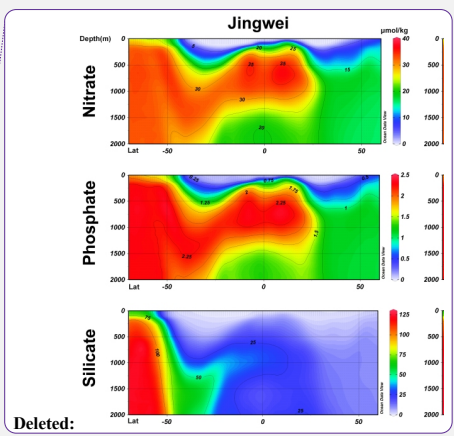
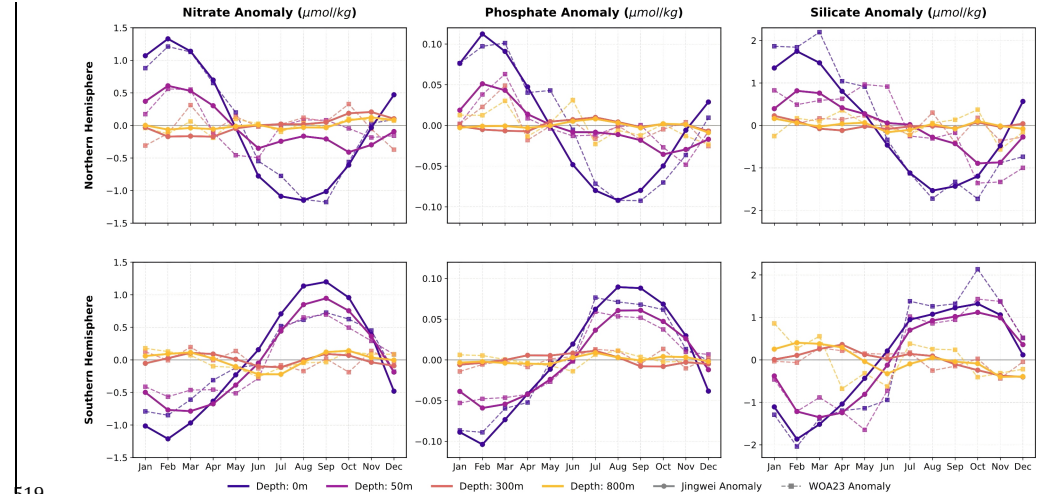


Figure 8. Vertical distribution of climatological mean nutrients along the 90°E meridional section in the Indian Ocean. The panel layout and represented variables are identical to those in Figure 7. Units for all concentrations and differences are $\mu\text{mol kg}^{-1}$.

Beyond static spatial patterns, the temporal evolution of nutrient fields is critical for understanding ecosystem dynamics and phenology (Longhurst, 2007). Figure 9 compares the reconstructed seasonal anomaly cycles with WOA23 data across the



508 Northern and Southern Hemispheres at four representative depths (0, 50, 300, and 800 m). The *Jingwei-Nutrients*
 509 reconstruction (solid lines) aligns with the WOA23 reference (dashed lines), capturing both the phase and amplitude of the
 510 seasonal variations. The model reproduces the out-of-phase seasonal dynamics between the two hemispheres. In the
 511 biologically active shallow layers (0 and 50 m), a pronounced seasonal amplitude is evident: the Northern Hemisphere shows
 512 winter/spring replenishment (Jan–Mar) mediated by convective mixing, followed by a distinct summer/autumn drawdown
 513 (Jul–Oct) driven by phytoplankton blooms (Behrenfeld et al., 2006; Keppler et al., 2020), while the Southern Hemisphere
 514 mirrors this pattern to reflect austral seasonality. Furthermore, the reconstruction captures the vertical attenuation of seasonal
 515 variability. While the euphotic zone experiences significant temporal fluctuations, the seasonal anomalies at deeper layers (300
 516 m and 800 m) are thermodynamically and biologically dampened, maintaining stable, near-zero baseline fluctuations
 517 throughout the year (Talley, 2013). This temporal agreement indicates that the *Jingwei-Nutrients* [data product](#) captures the
 518 phenological timing of global biogeochemical cycles.

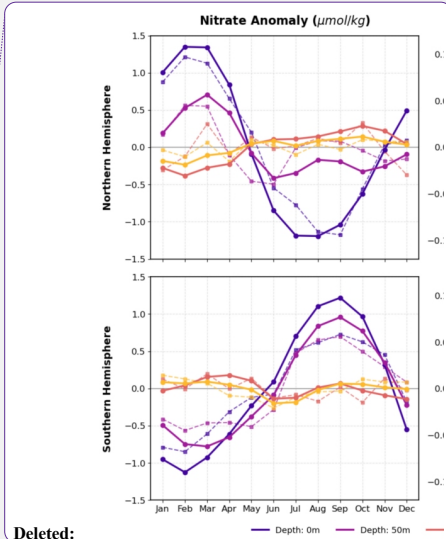


520 **Figure 9.** Seasonal cycles of nutrient anomalies across different hemispheres and depth layers. Solid lines indicate the *Jingwei-Nutrients*
 521 reconstruction, and dashed lines represent the WOA23 reference. The top row shows the Northern Hemisphere, and the bottom row shows
 522 the Southern Hemisphere, encompassing nitrate, phosphate, and silicate (from left to right) at 0, 50, 300, and 800 m depths. Units are
 523 $\mu\text{mol kg}^{-1}$.

524 3.3 Temporal Dynamics through Station Validation

525 To assess the reproduction of localized biogeochemical variability, we perform independent validations using in situ
 526 observations from two globally representative, long-term ecological time-series stations. These observatories encompass

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529 distinct marine biogeochemical regimes: the Hawaii Ocean Time-series (HOT; Karl and Lukas, 1996), which represents the
 530 highly stratified, oligotrophic subtropical gyre of the North Pacific; conversely, the KERFIX station (Jeandel et al., 1998) in
 531 the Southern Ocean represents a dynamic, high-latitude regime dominated by deep convective winter mixing and intense
 532 seasonal blooms. The HOT and KERFIX observations used in this evaluation are excluded from the training data and retained
 533 only for independent station validation.
 534 Figure 10 presents the evaluations for the HOT station. The *Jingwei-Nutrients* data product shows consistent agreement with
 535 observations. As shown in the scatter plots, the predicted concentrations at the HOT station (Fig. 10) tightly cluster around the
 536 1:1 reference line, yielding high localized correlation coefficients ($R^2 \parallel 0.993$) and low RMSE (1.34, 0.11, and 3.32 $\mu\text{mol kg}^{-1}$
 537 for nitrate, phosphate, and silicate, respectively). The vertical profile comparisons reveal that the product delineates the depth-
 538 dependent biogeochemical gradients, capturing the stably depleted surface layers and the depth of the deep nutricline at this
 539 location. Furthermore, for the interannual time-series comparisons, we select depth layers characterized by abundant historical
 540 observations and high biogeochemical representativeness—specifically, the 300 m layer for HOT. The temporal trajectories
 541 at this specific depth demonstrate that the reconstructed fields maintain long-term stable baselines. Notably, while the historical
 542 discrete observations occasionally exhibit localized high-frequency noise or sampling-induced spikes, the continuous
 543 reconstruction smooths these short-term variations while preserving the primary physical and biological signals.
 544 Figure 11 illustrates the validation at the KERFIX station, which represents the complex dynamics of the Southern Ocean. The
 545 time-series trajectory at the surface (0 m) indicates that the product captures pronounced seasonal amplitudes driven by winter
 546 overturning and subsequent summer biological drawdowns. At this station, the model yields high R^2 values for nitrate
 547 ($R^2=0.904$) and silicate ($R^2=0.967$), indicating that it captures the complex regional water mass mixing processes, such as the
 548 upwelling of Circumpolar Deep Water (CDW) (Talley, 2013). However, a relatively lower correlation is observed for
 549 phosphate ($R^2=0.749$). This specific discrepancy can be attributed to two factors. First, the absolute background concentration
 550 of surface phosphate is naturally low, which reduces the signal-to-noise ratio in historical observations and mathematically
 551 amplifies the penalty of analytical errors on the R^2 metric. Second, the intense iron limitation characteristic of the Southern
 552 Ocean (Boyd et al., 2007; Moore et al., 2013) often triggers localized decoupling of the classical N:P uptake ratio (Deutsch
 553 and Weber, 2012), a highly specific regional anomaly that poses a generalization challenge for global-scale reconstructions.
 554 Nevertheless, despite the lower R^2 , the absolute error for phosphate at KERFIX remains low (RMSE = 0.14 $\mu\text{mol kg}^{-1}$). This
 555 suggests that, even in dynamically complex and anomalous oceanic regimes, the *Jingwei-Nutrients* product provides a reliable
 556 basis for large-scale climatological and temporal analyses.

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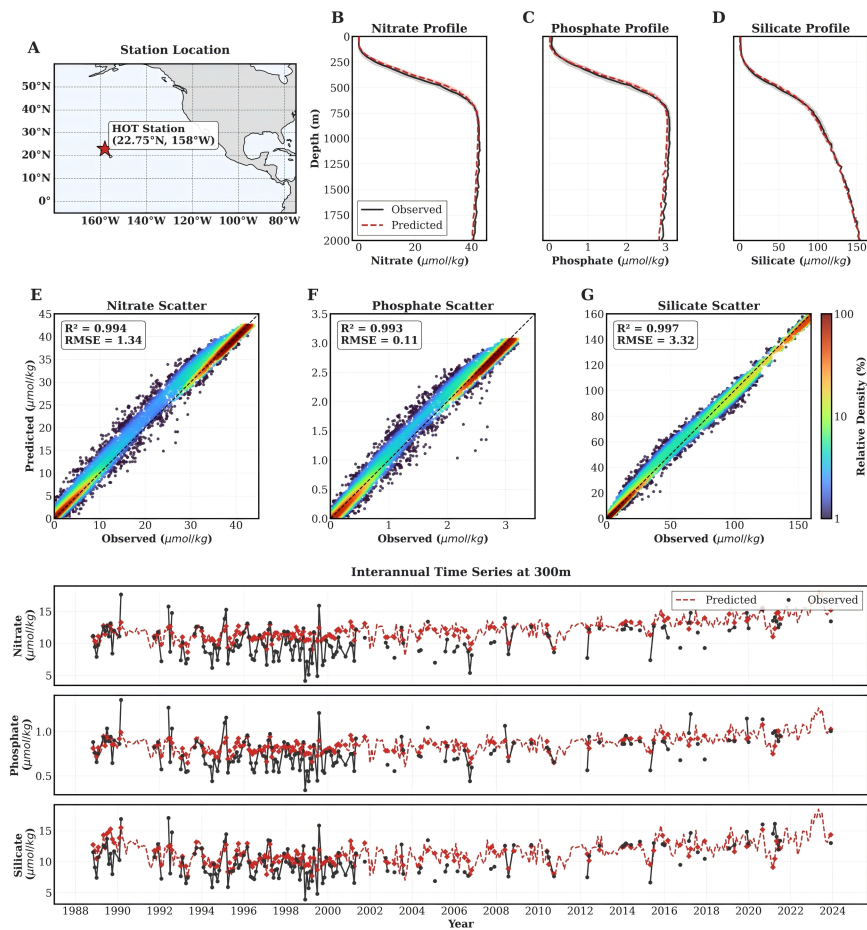
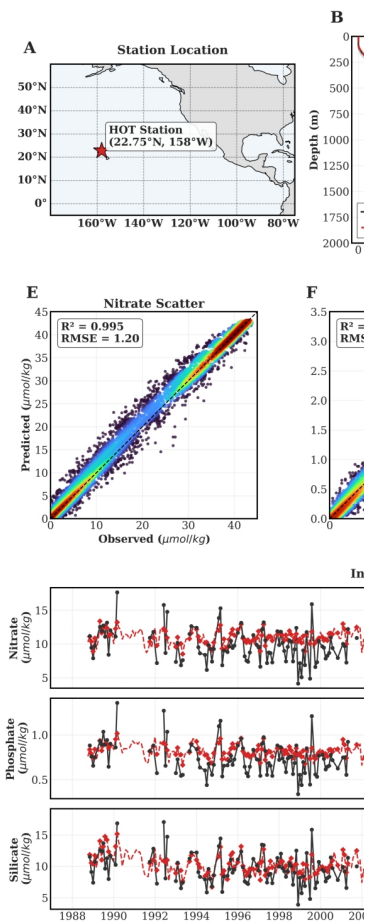
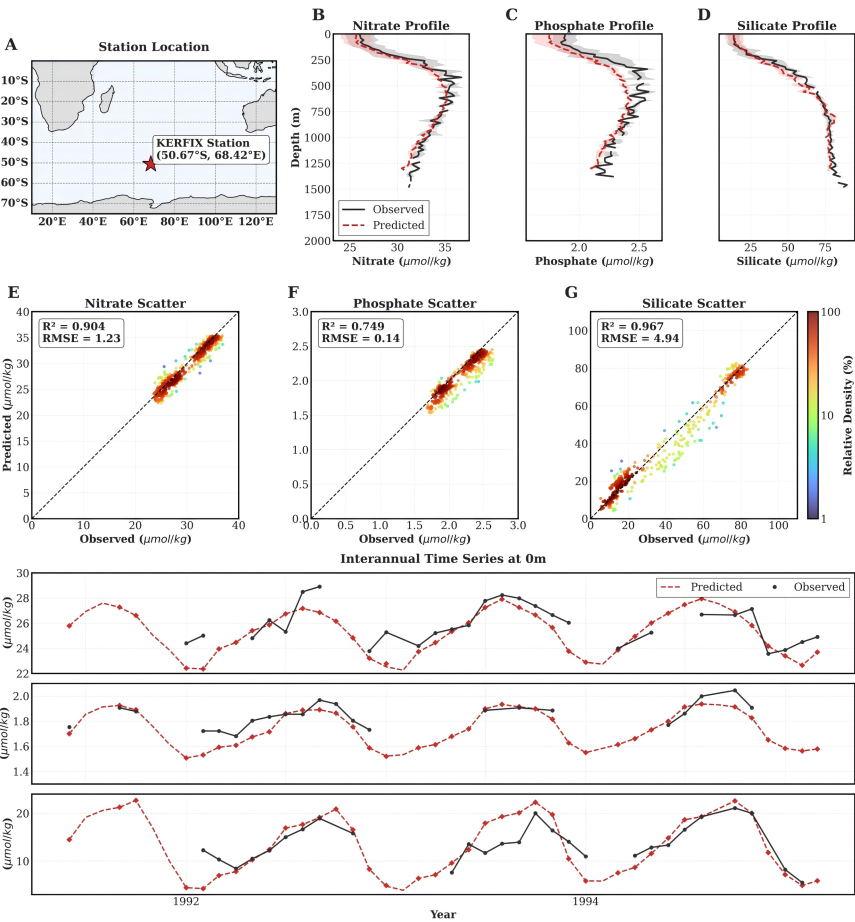


Figure 10. Multi-scale temporal and vertical validation at the Hawaii Ocean Time-series (HOT) station in the North Pacific. (A) Geographical location of the HOT station. (B–D) Climatological vertical profiles comparing in situ observations (black solid lines) and *Jingwei-Nutrients* predictions (red dashed lines) for nitrate, phosphate, and silicate. (E–G) Density scatter plots evaluating the overall predictive accuracy, with R^2 and RMSE metrics embedded. The bottom panels display the interannual time series of nutrient concentrations evaluated at the 300 m depth layer, demonstrating the model's capability to maintain stable, long-term baselines.



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Figure 11. Multi-scale temporal and vertical validation at the KERFIX station in the Southern Ocean. The panel layout is identical to Fig. 10. This figure highlights the model's performance in a highly dynamic, high-latitude regime. The interannual time series (bottom panels) are evaluated at the surface layer (0 m) to explicitly track the massive seasonal amplitudes driven by deep convective winter mixing and summer biological drawdowns.

3.4 Spatial Variability through Cruise Verification

Complementing the temporal validations, capturing the three-dimensional spatial variability of the ocean interior is equally critical. To assess the spatial representation of the *Jingwei-Nutrients* product, we conduct independent validations using high-resolution, synoptic shipboard measurements from the U.S. GO-SHIP program (Sloyan et al., 2019). Unlike gridded climatologies that tend to smooth out transient features, continuous cruise sections provide a "snapshot" of the product's ability to reconstruct sharp frontal zones and mesoscale variabilities. As illustrated in Fig. 12, we select three representative expedition datasets encompassing different spatial domains: the P16S (2014) and P16N (2015) cruises, which together form a nearly complete meridional corridor across the Pacific Ocean, and the P06E (2017) cruise, which provides a zonal cross-section across the South Pacific. The P16N, P16S, and P06E observations used in this evaluation are excluded from the training data and retained only for independent cruise-section validation.

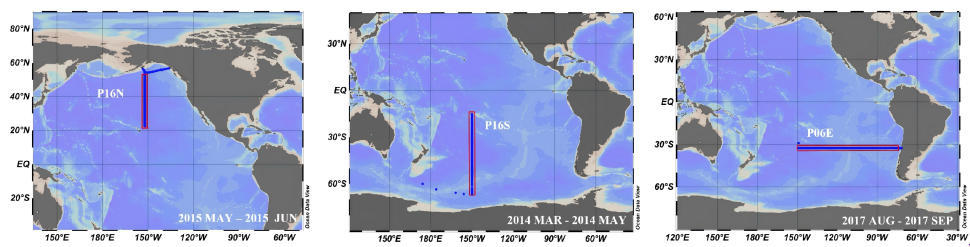
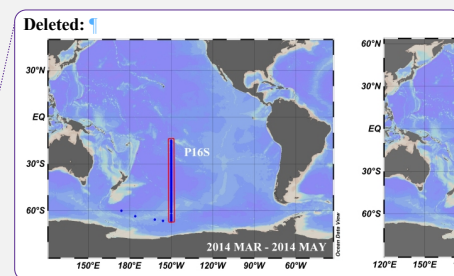


Figure 12. Map of the selected U.S. GO-SHIP cruise trajectories used for independent spatial validation. The solid lines indicate the continuous high-resolution shipboard measurement sections: the P16N (2015) and P16S (2014) meridional cruises in the Pacific Ocean, and the P06E (2017) zonal cruise in the South Pacific.

To facilitate a direct spatial assessment, the dense in situ measurements are objectively interpolated to construct continuous observational sections. These reference fields are then compared against the coincident cross-sections extracted from the *Jingwei-Nutrients* product. Figure 13 presents the comparative contour sections and the corresponding residual error distributions for the P16N cruise in the North Pacific. The reconstructed fields reproduce the large-scale accumulation of nutrients in the deep North Pacific, exhibiting high concentrations in the deep interior. The difference maps in the rightmost column reveal that deviations for nitrate and phosphate are predominantly concentrated in the 200–500 m depth range. This depth directly coincides with the stratified main nutricline, where concentrations change rapidly over short vertical distances. For silicate along this same section, larger residuals emerge deeper in the water column below 1000 m. This specific pattern is biogeochemically consistent with the complex accumulation of dissolved silica in the oldest North Pacific Deep Water, where slow biogenic dissolution processes (Tréguer et al., 2018) contribute to larger absolute variations.

Moving to the Southern Hemisphere, Fig. 14 presents the validation along the P16S section. Here, the reconstruction captures the nutrient outcropping near the Southern Ocean surface. However, the difference maps reveal a distinct error structure compared to the North Pacific. A vertical band of higher anomalies spanning from the surface to the deep ocean is visible



609 around 45°S to 50°S across all three nutrients. This localized feature corresponds to the Subantarctic Front within the Antarctic
610 Circumpolar Current system. This dynamic region is characterized by energetic mesoscale eddies, intense deep vertical mixing,
611 and steeply sloping isopycnals (Marshall and Speer, 2012), creating substantial synoptic variability in the cruise "snapshot"
612 that naturally deviates from the temporally averaged representation of a global [product](#).
613 The zonal P06E section presented in Fig. 15 illustrates the east-west biogeochemical asymmetry across the South Pacific. The
614 reconstructed cross-section captures the nutrient-rich upwelling signals, with concentration contours shoaling towards the
615 South American eastern boundary, which is consistent with the cruise data. Moreover, the difference maps for this zonal section
616 show low anomalies in the deep ocean interior, yielding minimal residuals below 1000 m across the entire basin. Deviations
617 are primarily confined to the upper water column, driven by the coastal upwelling systems (Chavez and Messié, 2009).
618 In summary, the cruise verification supports the three-dimensional spatial representation of the *Jingwei-Nutrients* product. By
619 reproducing the synoptic features of these oceanographic sections across diverse dynamical regimes, the product demonstrates
620 its capacity to reconstruct the continuous, full-depth spatial structure of global marine nutrients. The representation of deep-
621 basin accumulations indicates that *Jingwei-Nutrients* provides a physically consistent global [product](#).

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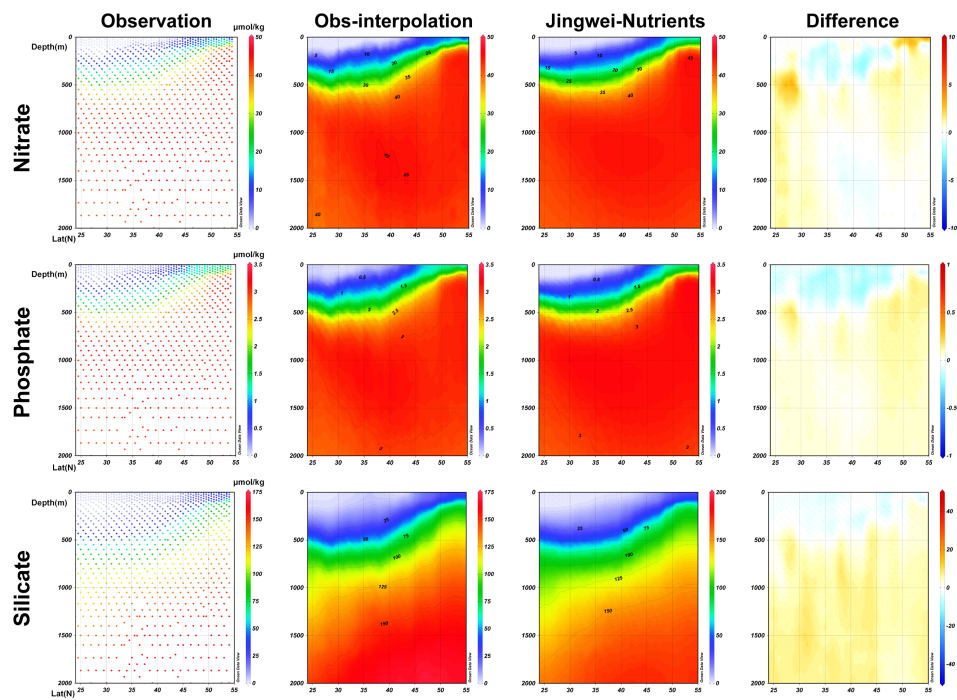
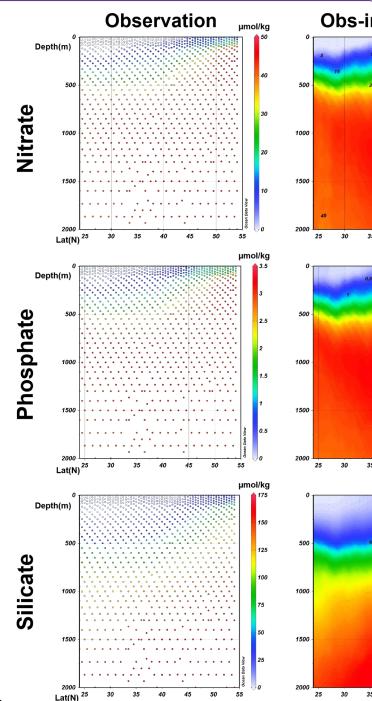


Figure 13. Spatial validation of nutrients along the P16N meridional section in the North Pacific. Columns from left to right display the in situ discrete shipboard measurements, the objectively interpolated observational field, the coincident cross-section extracted from the *Jingwei-Nutrients* product, and the absolute difference (*Jingwei* minus Observation). Rows from top to bottom correspond to nitrate, phosphate, and silicate, respectively.



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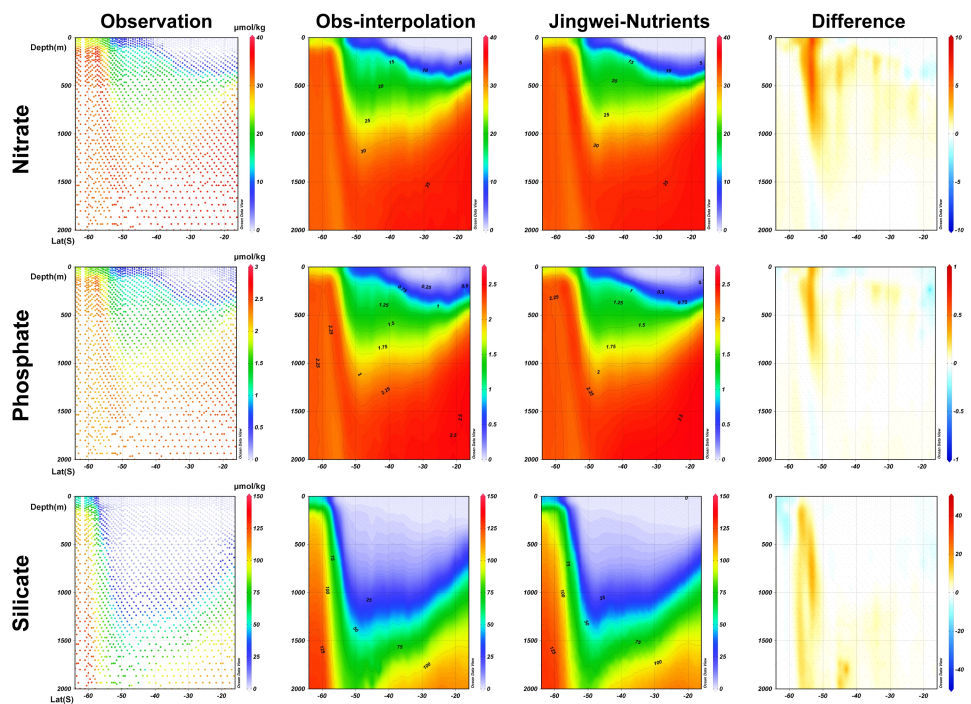
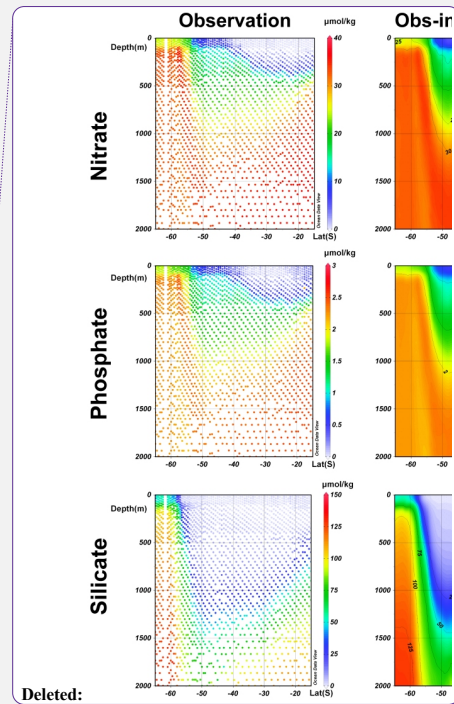


Figure 14. Spatial validation of nutrients along the P16S meridional section in the South Pacific and Southern Ocean. The panel layout and represented variables are identical to those in Fig. 13.



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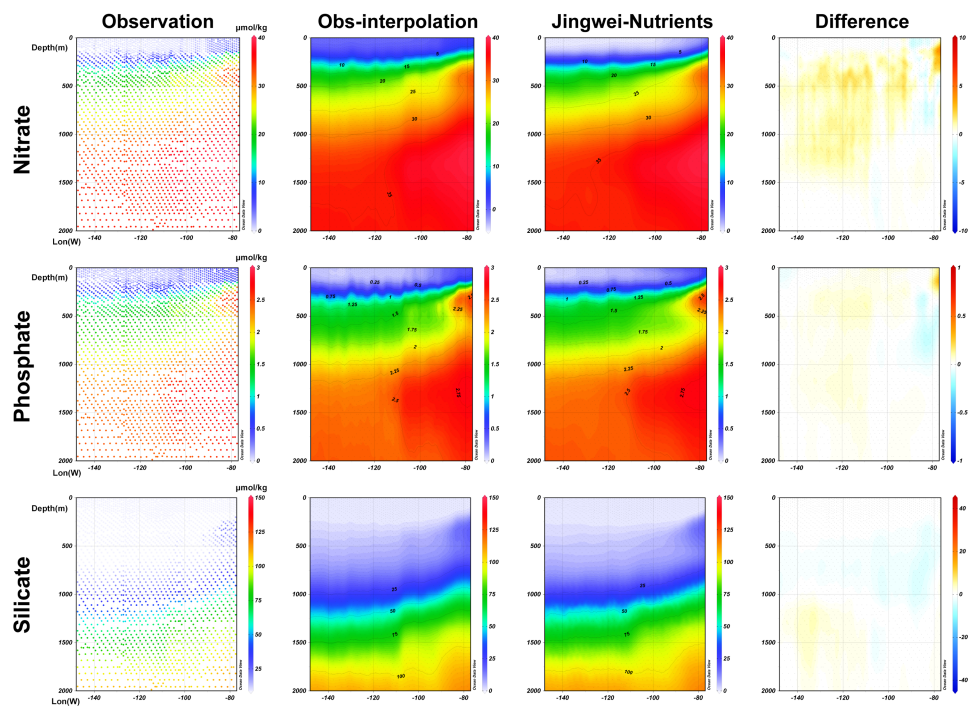
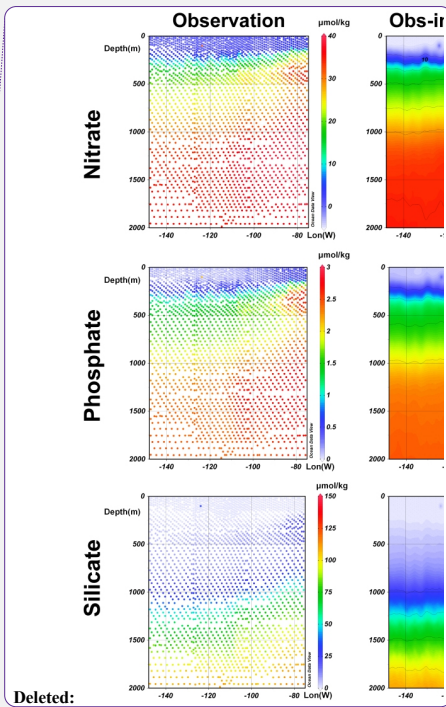


Figure 15. Spatial validation of nutrients along the P06E zonal section in the South Pacific. The panel layout and represented variables are identical to those in Fig. 13.

3.5 Spatiotemporal Uncertainty Analysis

To systematically evaluate the reliability of the *Jingwei-Nutrients* product, it is essential to quantify its spatiotemporal uncertainty. Since mapping sparse data often introduces more uncertainty than inherent measurement errors (Ito et al., 2025), relying solely on analytical errors is inadequate. Instead, we estimate reconstruction uncertainty using the ensemble standard deviation (std) across our six K-fold models (Gregor et al., 2019). As shown in Fig. 16, this ensemble spread remains remarkably low relative to absolute concentrations—particularly across vast open-ocean basins—confirming the high stability and reliability of the product.

The top panels of Fig. 16 illustrate the depth-averaged spatial uncertainty for nitrate, phosphate, and silicate. The global maps reveal that the ensemble standard deviations are generally low across the open-ocean gyres, indicating model consensus in



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these environments. However, the uncertainty distribution exhibits spatial heterogeneities. For all three nutrients, higher uncertainties are localized along coastal margins and high-latitude boundary regions. Higher uncertainty values are observed in the subpolar North Pacific—specifically within the Bering Sea and the Sea of Okhotsk. These marginal seas are characterized by shelf-basin water exchanges, riverine inputs, and seasonal phytoplankton blooms, introducing greater natural variability. Furthermore, for silicate, a band of elevated uncertainty is observed across the Southern Ocean. This is consistent with the upwelling of the Antarctic Circumpolar Current and the presence of diatom blooms, which drive biogenic silica cycling (Tréguer et al., 2018), contributing to larger absolute variations compared to nitrate and phosphate.

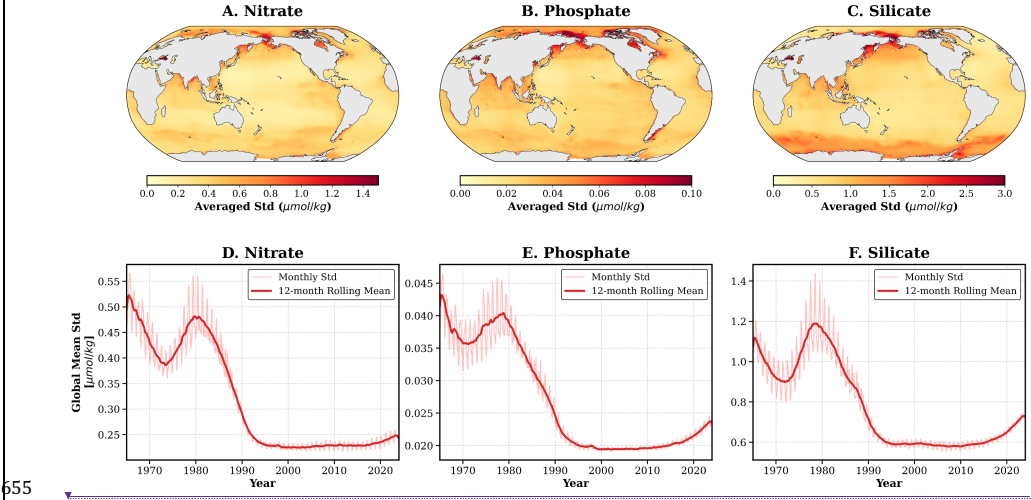
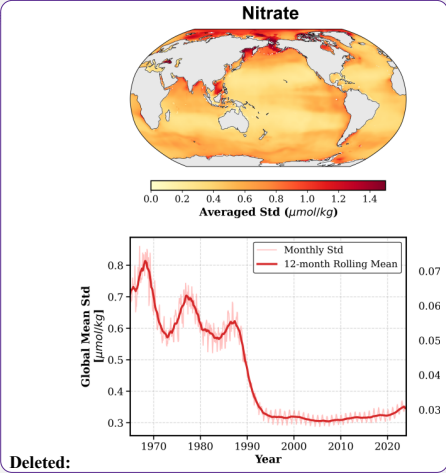


Figure 16. Spatiotemporal uncertainty analysis of the *Jingwei-Nutrients* reconstruction based on the ensemble standard deviation across the 6-fold cross-validation models. The top row displays the spatial distribution of the depth-averaged standard deviation for nitrate, phosphate, and silicate. The bottom row presents the temporal evolution of the global mean standard deviation from 1965 to 2023. Light red lines represent the raw monthly uncertainty, while the thick red lines indicate the 12-month rolling mean.

The bottom panels of Fig. 16 track the temporal evolution of the global mean uncertainty from 1965 to 2023. The time-series demonstrates a long-term declining trend, corresponding to the historical evolution of global ocean observing systems. A notable decrease in the global mean Std occurs around 1990. This reduction in uncertainty aligns with the onset of the World Ocean Circulation Experiment (WOCE) (Siedler et al., 2001) and the Joint Global Ocean Flux Study (JGOFS) (Fasham, 2003), which marked the transition from sparse historical sampling to systematic global hydrographic surveys. Entering the 21st century, the global mean uncertainties for all three nutrients remain generally stable at lower levels compared to earlier decades. For nitrate, the deployment of the Biogeochemical-Argo (BGC-Argo) float array post-2010 (Roemmich et al., 2019; Claustre et al., 2020) provided additional autonomous profiles, contributing to the sustained low uncertainty. For



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669 phosphate and silicate, despite the gradual decline in traditional shipboard measurements in recent decades and the lack of
670 Argo-based sensors for these elements, their mean uncertainties remain relatively low, though a slight upward trend is
671 observable in the most recent years. Ultimately, this analysis indicates that the *Jingwei-Nutrients* product provides stable
672 reconstructions, while also highlighting the regions and periods where data sparsity introduces greater variance.

673 **4 Conclusion**

674 In this study, we develop *Jingwei-Nutrients*, a global continuous [data product](#) of ocean nutrients (nitrate, phosphate, and silicate)
675 at a monthly resolution, spanning from 1965 to 2023. This is achieved by employing a Multi-Task Learning (MTL)
676 Transformer architecture, trained on quality-controlled historical observations from WOD, CCHDO, GLODAP, and the BGC-
677 Argo float array. By extracting complex nonlinear relationships between discrete nutrient samples and continuous
678 spatiotemporal hydrographic predictors, our approach effectively transforms sparse, unevenly distributed historical
679 measurements into a continuous four-dimensional spatiotemporal field. This reconstruction expands the available nutrient data
680 coverage, providing a global perspective on marine biogeochemical dynamics.

681 Validations across multiple scales support the reliability of the *Jingwei-Nutrients* product. The [product](#) accurately reproduces
682 the climatological spatial distributions and phenological seasonal cycles of global nutrients, demonstrating consistency with
683 the WOA23 climatology. The continuous reconstruction also captures the sharp physical-biogeochemical gradients and
684 structural features inherent to the ocean interior. Independent synoptic validations using high-resolution GO-SHIP cruise
685 sections (P16N, P16S, P06E) indicate the model's capacity to resolve complex three-dimensional features, including deep-
686 basin nutrient accumulations, boundary upwelling, and dynamic mesoscale frontal zones. Furthermore, evaluations against
687 long-term ecological time-series stations (HOT and KERFIX) show that the reconstruction captures localized interannual
688 baselines and smooths short-term variations while preserving primary physical and biological signals. Our spatiotemporal
689 uncertainty analysis, derived from a 6-fold ensemble standard deviation, reveals a reduction in global reconstruction
690 uncertainty following the WOCE/JGOFS era in the 1990s. Entering the 21st century, the uncertainty estimates continue to
691 reflect the evolution of the global observing network.

692 Despite these advances, certain limitations remain in global-scale data-driven reconstructions. Regional uncertainties persist
693 in dynamic marginal seas, coastal boundaries, and regions dominated by mesoscale eddies (e.g., the Subantarctic Front).
694 Additionally, biological anomalies, such as the localized decoupling of the classical N:P uptake ratio driven by iron limitation
695 in the Southern Ocean, pose challenges for generalized global models. Future efforts should focus on integrating higher-
696 resolution sub-mesoscale physical forcings, assimilating emerging multi-sensor BGC-Argo data, and developing sub-regional
697 modeling frameworks to better capture localized non-stationary biogeochemical processes.

698 The *Jingwei-Nutrients* [data product](#) provides a physically consistent baseline of global ocean nutrients over the past six decades.
699 It offers an observational benchmark for evaluating Earth System Models (ESMs), supports investigations into long-term

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703 biogeochemical responses to anthropogenic climate change, and serves as high-resolution boundary conditions for future
704 marine carbon cycle and ecosystem studies.

705 **5 Data availability**

706 The *Jingwei-Nutrients* [data product](#), presented in this article is openly available to the public. The reconstructed 4D global
707 monthly fields spanning from 1965 to 2023 for nitrate, phosphate, and silicate can be accessed via Zenodo at
708 <https://doi.org/10.5281/zenodo.19491198> (Wang et al., 2026). The [product](#) is provided in standard NetCDF format.
709 [The file contains monthly global reconstructed fields from January 1965 to December 2023. All nutrient variables are stored](#)
710 [with dimensions \(time, depth, lat, lon\). The time dimension contains 708 monthly time steps, the depth dimension contains 67](#)
711 [standard levels from 0 to 2000 m, the latitude coordinate ranges from 82.5°S to 89.5°N, and the longitude coordinate ranges](#)
712 [from 179.5°W to 179.5°E. The three main variables are nitrate, phosphate, and silicate, with units of \$\mu\text{mol kg}^{-1}\$. Missing or](#)
713 [invalid ocean values are stored as NaN. The corresponding ensemble uncertainty files use the same coordinates, dimensions,](#)
714 [depth levels, and missing-value convention as the main product. These files provide ensemble-based uncertainty estimates for](#)
715 [nitrate, phosphate, and silicate, expressed as the standard deviation among ensemble members, with the same units as the](#)
716 [reconstructed nutrient concentrations.](#)

717 The primary in situ observation data used to train the data-driven non-linear models are harmonized from major public archives,
718 including the World Ocean Database (WOD; <https://www.ncei.noaa.gov/products/world-ocean-database>; Boyer et al., 2018;
719 Mishonov et al., 2024; Garcia et al., 2026), the Global Ocean Data Analysis Project (GLODAP; [https://doi.org/10.25921/1f4w-](https://doi.org/10.25921/1f4w-0t92)
720 [0t92](https://doi.org/10.25921/1f4w-0t92); Lauvset et al., 2022), the CLIVAR and Carbon Hydrographic Data Office (CCHDO; <https://cchdo.ucsd.edu>; Sloyan et
721 al., 2019), and the Argo program (<https://doi.org/10.17882/42182>; Claustre et al., 2020). The physical driver datasets and
722 background reference fields, specifically the EN4 hydrographic objective analyses (<https://www.metoffice.gov.uk/hadobs/en4/>;
723 Good et al., 2013) and the World Ocean Atlas (WOA) climatologies (<https://www.ncei.noaa.gov/products/world-ocean-atlas>;
724 Locarnini et al., 2018, 2019; Zweng et al., 2018; Reagan et al., 2019; Garcia et al., 2024a, b), are publicly available from the
725 Met Office Hadley Centre and the NOAA National Centers for Environmental Information (NCEI), respectively.

726 **The Name of *Jingwei***

727 *Jingwei* is a classic figure in Chinese mythology, featured in the "Shan Hai Jing" (see <https://en.wikipedia.org/wiki/Jingwei>).
728 The story tells of *Jingwei*, the daughter of Emperor Yan, who drowned in the East Sea. She was reborn as a bird and decided
729 to fill the sea with pebbles and twigs, endeavoring to prevent similar tragedies. Today, *Jingwei* symbolizes perseverance and
730 determination, embodying the spirit of never giving up despite difficult challenges.

731 This project is named *Jingwei - Nutrients* to honor the collective determination of generations of oceanographers, researchers,
732 and vessel crews. The historical biogeochemical observations they have painstakingly collected—often scattered across vast

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735 spatial scales and decades of time—might appear as fragmented as the pebbles carried by *Jingwei*. Yet, it is through the
736 persistent accumulation of these "pebbles" of data that we can finally reconstruct the complex patterns of global nutrient
737 cycling. This name serves as a tribute to those who venture into the field to sense the pulse of our oceans, embodying the spirit
738 of persistent exploration that makes global-scale synthesis possible.

739 **Author contributions**

740 BL, MJ, and ZW designed the study and ~~product~~, ZW and YX collected and processed the data, developed the code, and
741 performed the analysis. TI, LZ, LC, YL, and XW provided methodological guidance and advice. ZW wrote the original draft.
742 All authors reviewed and edited the manuscript.

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743 **Competing interests**

744 The contact author has declared that none of the authors has any competing interests.

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751 thanks are owed to all scientists and vessel crews involved in data collection, analysis, and management for these programs.

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