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IPCC's Earth Energy Imbalance Assessment is Based on Physically Invalid Argo-Float-Based Estimates of Global Ocean Heat Content

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Abstract

Global ocean heat content (OHC) anomalies and derived Earth Energy Imbalance (EEI) estimates, central to contemporary climate assessments including IPCC AR6, are constructed through processes that violate the scientific method. These metrics rely almost exclusively on temperature data from the Argo profiling float array. Their validity and reliability hinge on several critical but herein refuted assumptions about measurement representativeness, interpolation/extrapolation methods, the physical meaning of anomalies, and integration conventions. Core Argo and Biogeochemical Argo floats deliver discrete, point measurements of intensive properties like temperature along irregular, untracked three-dimensional trajectories during ascent from 2000 m to the surface. This samples only the upper ocean, excluding roughly 50% of total ocean volume and thermal energy. Horizontal positions are recorded only at surface intervals ~10 days apart, leaving subsurface locations entirely unknown. All data from each ascent are arbitrarily assigned to the surfacing position, introducing unknown horizontal offsets (up to 50 km) and temporal offsets (up to 10 hours) for the deepest measurements. Anomalies are computed by subtracting values from statistically derived reference climatologies based on sparse historical data over arbitrary baseline periods. Measured temperatures are then interpolated onto global 3D grids using prescribed covariance functions. These anomalies represent numerical differences without physical meaning as temperature deviations, because temperature, an intensive property, is not additive across non-equilibrium spatial or temporal domains (Essex et al., 2007; Essex & Andresen, 2018). The integrated OHC scalar depends heavily on arbitrary averaging and interpolation rules, producing computational artifacts rather than measures of actual ocean energy uptake or planetary radiative imbalance. Derived EEI values, such as the 0.7 ± 0.2 W m^{-2} in IPCC AR6 Figure 7.2, inherit these biases and stem from circular methodology: CERES satellite top-of-atmosphere radiative flux measurements (absolute uncertainties ± 3–5 W m^{-2} or higher) are adjusted via least-squares to match Argo OHC-derived estimates, rather than offering independent validation. We rigorously quantify major uncertainty sources, including unresolved mesoscale variability (± 0.9 W m^{-2}), deep ocean ignorance bounds (± 0.35 W m^{-2} from sparse Deep Argo), polar undersampling (± 0.1 W m^{-2}), Nyquist-Shannon aliasing in sparse deep ocean and polar sampling, sea-level budget closure discrepancy between satellite altimetry/gravimetry and Argo OHC (± 0.33 W m^{-2}), arbitrary baseline choices (± 0.2 W m^{-2}), Eulerian-Lagrangian discrepancies (± 0.25 W m^{-2}), and untracked trajectories and positional assignments. Although the concepts of OHC and EEI are thermodynamically well-defined physical quantities, the numerical values produced by current Argo-based methodologies are physically meaningless computational constructs that do not validly represent those quantities. We conclude that EEI uncertainties reach $>\pm 1$ W m^{-2} at 95% confidence, roughly an order of magnitude larger than the uncertainty that IPCC AR6 reports, rendering current OHC change and EEI estimates statistically indistinguishable from zero.

Keywords: Argo floats; ocean heat content (OHC); Earth's Energy Imbalance (EEI); intensive properties; IPCC AR6; mesoscale variability; Nyquist-Shannon theorem; Eulerian-Lagrangian discrepancy; CERES Deep Argo; BGC-Argo; computational artifacts.

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1. Introduction

Global ocean heat[1] content (OHC) (i.e. global ocean thermal energy change) and derived Earth's Energy Imbalance (EEI) estimates occupy a central position in contemporary climate assessments, including those of the United Nations' Intergovernmental Panel on Climate Change (IPCC, 2021). The validity and reliability of these estimates depend upon the plausibility of several key assumptions regarding measurement representativeness, interpolation/extrapolation procedures, physical meaning of anomalies, and mathematical conventions for integration. In this paper, we show that these assumptions are not plausible and that even modest variations in them can lead to quite opposite conclusions regarding EEI. Those quantities underpin claims of oceanic absorption of over 90% of 'excess energy' attributed to anthropogenic forcing (von Schuckmann et al., 2020). They are constructed, however, almost exclusively from temperature data provided by the international Argo profiling float array (Array for Real-time Geostrophic Oceanography; Johnson et al., 2022) that we are questioning here, and we find that the IPCC OHC anomaly measures fail to comply with essential criteria of the scientific method (Armstrong and Green, 2022) and are not, therefore, a credible basis for policymaking.

Core Argo and Biogeochemical Argo (BGC-Argo) floats[2] profile only the upper ocean to a nominal pressure of 2000 dbar.[3] This leaves the abyssal ocean below that level, comprising approximately half of both the total ocean volume and thermal energy content, largely unsampled except by sparse historical measurements and a limited pilot array of Deep Argo floats (Johnson et al., 2015; Purkey and Johnson, 2010). Despite their central role in IPCC assessments of human impacts on climate, our comprehensive review of the peer-reviewed literature reveals no prior full synthesis of the measurement and processing chain necessary to evaluate the most fundamental threats to the physical validity and reliability of these OHC and EEI estimates.

Previous assessments addressed aspects of validity, including mapping uncertainties (Boyer et al., 2016), sparse historical coverage in remote/polar/deep regions (Meyssignac et al., 2019), and general sampling limitations (von Schuckmann et al., 2020). None, however, has substantively addressed fundamental limitations, including loss of thermodynamic interpretability in anomalies due to the intensive nature of temperature (non-additive across non-equilibrium spatial and temporal domains, as detailed in Section 1.2; Essex et al., 2007), domination by interpolated values

[1]As argued by Romer (2001), 'heat' should not be treated as a noun denoting a stored substance. In this paper, we use 'heat' in phrases such as 'ocean heat content' solely as a conventional synonym for thermal energy content, but we neither endorse nor agree with this wording, as it inaccurately implies heat is a substance rather than a process of energy transfer.

[2]BGC stands for Biogeochemical. BGC-Argo floats are equipped with additional sensors beyond the standard conductivity (salinity), temperature, and depth (pressure) CTD sensors in Core Argo floats. They measure biogeochemical parameters such as dissolved oxygen, nitrate, chlorophyll fluorescence (indicating phytoplankton), backscattering (indicating particle concentration), pH, and irradiance (light levels). These floats are part of the expanded Argo program aimed at understanding ocean chemistry, biology, and carbon cycling, in addition to the physical oceanographic variables provided by standard CTD observations.

[3]Argo floats measure and report pressure in decibars (dbar). Depth in meters is inferred from pressure via the hydrostatic relation using gravity and a seawater equation of state. A practical rule of thumb is 1 dbar ≈ 1 m near the surface, but because seawater is compressible and its density varies with temperature, salinity, and latitude, the mapping is not exact: 2000 dbar corresponds to roughly 2000–2025 m under typical open-ocean conditions. Using dbar avoids implying a fixed depth for a given measurement and provides a consistent, instrument-native vertical coordinate for profiling and quality control.

in unsampled volumes, unresolved mesoscale variability in boundary currents and eddy-rich regions, untracked subsurface trajectories, and arbitrary positional assignment. These limitations align with Essex & Andresen (2018)'s 'slow time' framework, where long-timescale climate variables differ from laboratory-scale ones, rendering temperature non-thermalizable on climate timescales. This paper offers the first comprehensive synthesis of these issues, demonstrating that Argo-derived OHC and EEI scalars lack physical correspondence to reality. Even ignoring thermodynamic principles, the calculated EEI uncertainties at 95% confidence exceed commonly cited EEI values, rendering such claims unsuitable for quantifying planetary energy uptake or imbalance.

The ocean stores the vast majority of total heat energy contained within the Earth's climate system. Argo-float-data-based OHC calculations are used as evidence to support claims that approximately 90–93% of the purported increase in system heat (energy) content since 1850 is accounted for by changes in OHC (von Schuckmann et al., 2020; IPCC AR6 WG1, 2021). Within the ocean itself, the vertical distribution of this stored energy is roughly even: about half resides in the upper 2000 m and half in the deep ocean below 2000 m. Claims that ~90% of the recent purported planetary energy imbalance has been absorbed specifically into the upper ocean (0–2000 m) are also entirely dependent on the OHC calculations challenged in this paper. Since the mid-2000s, global ocean heat content estimates have been derived from data collected by the international Argo program, consisting of roughly 4000 autonomous profiling floats (~4156 as of December 28, 2025) that measure temperature, electrical conductivity (for salinity derivation), and pressure primarily in the upper 2000 m of the ocean (Riser et al., 2016; Johnson et al., 2022).

These measurements are processed into gridded fields and integrated to yield global OHC anomaly time series, which form the dominant component of EEI assessments. The IPCC Sixth Assessment Report (AR6) presents an EEI of 0.7 (0.5–0.9) W m^{-2} in its global energy budget diagram (Figure 7.2; Forster et al., 2021), a value adapted from surface flux schematics (Wild et al., 2013, 2019; Stephens et al., 2012) but aligned with OHC-derived inventories from the Argo era. These metrics are presented as direct 'observational' constraints on planetary energy flows, with uncertainties quantified primarily through statistical sampling error (Loeb et al., 2012; von Schuckmann et al., 2016) or the spread among several widely used gridded OHC datasets (e.g., from products developed by IAP, Institute of Atmospheric Physics, Chinese Academy of Sciences; NCEI, National Centers for Environmental Information, NOAA; JMA/MRI, Japan Meteorological Agency / Meteorological Research Institute; BOA_Argo, China Argo Real-time Data Center; and others), capturing methodological differences in how sparse temperature profiles are extrapolated to global fields (von Schuckmann et al. 2020; IPCC AR6 WG1, 2021). Despite their prominence, the physical foundations of these OHC and EEI estimates have not been subjected to rigorous scrutiny regarding the nature of the raw measurements and the transformations applied.

Classical thermodynamics, formalized in the late 19th century, remains a cornerstone of physics due to its reliance on universal principles rather than specific microscopic models — a resilience famously praised by Einstein as "the only physical theory of universal content which I am convinced will never be overthrown, within the framework of applicability of its basic concepts" (Einstein, 1949/1979, p. 31). Indeed, to this day all its fundamental first principles have withstood the test of time. Essex et al. (2007) demonstrate that these principles coupled with basic mathematics reveal fundamental limitations in applying intensive properties like temperature to non-equilibrium systems such as the global ocean, where averaging destroys physical meaning and produces computational artifacts rather than real physical quantities (as detailed in Section 1.2).

Temperature is rigorously defined only in local thermodynamic equilibrium (LTE), constituting a point function meaningful solely for the small volume of fluid in LTE around the measuring device. In the non-equilibrium ocean, subsurface horizontal locations remain unmeasured and unknown throughout the Argo float cycle due to the absence of submerged positioning instrumentation. Subsequent processing introduces interpolated values that dominate the final scalar measures. This paper details the measurement and processing chain and concludes that Argo-derived OHC anomalies and EEI estimates lack physical foundations for quantifying ocean thermal energy change or planetary energy imbalance.

1.1 The Circularity and Hidden Uncertainty of OHC-Derived EEI Estimates

The IPCC claimed 0.5–0.9 W m^{-2} EEI precision is inconsistent with the large absolute uncertainties in direct satellite measurements of top-of-atmosphere (TOA) radiative fluxes from the NASA Clouds and the Earth's Radiant Energy System (CERES) project upon which the EEI estimate depends. Raw CERES data exhibit global mean net TOA flux uncertainties of ~± 3–5 W m^{-2} (higher for individual components), dwarfing the upper bound of the AR6 EEI range (Loeb et al., 2018). Early analyses found even greater uncertainty over the measure, with unconstrained imbalances as large as 6.5 W m^{-2} (Loeb et al., 2009). Surface energy budget assessments, combining satellite, *in-situ*, and model-derived fluxes, reveal discrepancies and uncertainties up to ± 17 W m^{-2} globally (Stephens et al., 2012).

The CERES Energy Balanced and Filled (EBAF) product addresses the large absolute uncertainties in raw TOA fluxes by applying a "one-time global adjustment" to shortwave and longwave components within their individual uncertainty ranges. It uses an objective least-squares algorithm (Loeb et al., 2009; 2018) that forces the long-term mean net TOA flux to equal the Argo-derived OHC calculation plus minor land, ice, and atmosphere terms, yielding the ~0.7 W m^{-2} imbalance presented in IPCC AR6 Figure 7.2 (Forster et al., 2021).

Achieving the 0.7 W m^{-2} figure requires some aggressive adjustments: the radiative flux values, such as reflected solar, must be pushed in some cases to the extreme edges of their uncertainty ranges to produce a net flux consistent with the reported small positive net imbalance. No physical justification is provided for the direction or magnitude of individual component shifts. Use of this "one-time global adjustment" implicitly assumes the Argo OHC-derived quantity is more reliable than direct CERES absolute measurements, despite the OHC chain's fundamental physical invalidity due to thermodynamically meaningless anomalies from intensive-property averaging in non-equilibrium systems, sparse deep and polar sampling, and other flaws detailed herein.

In sum, the term "constrain" applied to the Loeb et al. (2009; 2018) algorithm is misplaced. In scientific measurement, constraints derive from physical laws, independent observations, or known constants, not from forcing agreement with a non-physical mathematical construct. Consequently, the small EEI (~0.7 W m^{-2} in IPCC AR6 Figure 7.2) and its narrow uncertainty (± 0.2 W m^{-2}) are purely artifacts of circular tuning: CERES fluxes are mathematically adjusted to align with the Argo OHC-derived quantity whose physical validity is absent. Raw, unadjusted CERES data do not independently confirm the OHC-based EEI within their uncertainties. This IPCC methodology, euphemistically described as "constraining" EEI, depends fundamentally on unsupported assumptions and circular reasoning. The IPCC AR6-claimed small positive EEI is therefore scientifically invalid.

1.2 Non-Additivity of Temperature in Non-Equilibrium Systems

Temperature is an intensive thermodynamic property defined pointwise only for systems in local thermal equilibrium (Reif, 1965). In equilibrium thermodynamics, intensive variables such as temperature are not additive; they cannot be meaningfully averaged across non-equilibrium domains to yield a physically meaningful global scalar (Essex et al., 2007).

Using formal mathematical reasoning together with the axioms of classical thermodynamics, Essex et al. (2007) rigorously proved that no physically meaningful global surface temperature exists for the Earth system. While local temperatures can be defined for small volumes in approximate thermodynamic equilibrium, the Earth's climate system operates far from equilibrium at the global scale. Any averaging of local temperature measurements, regardless of the chosen mathematical procedure, therefore, lacks a unique physical basis. An infinite number of equally valid averaging methods exist, each capable of producing contradictory trends from the same underlying data when physical principles do not dictate a preferred rule.

Building on this foundation, Essex and Andresen (2018) extended the analysis to the broader question of appropriate measurements for climate. They proved that conventional meteorological concepts of temperature, derived from laboratory-scale equilibrium thermodynamics, cannot be "thermalized" or meaningfully extended to the long spatiotemporal scales that are characteristic of climate. On these "slow time" scales, temperature loses thermodynamic interpretability, rendering global or even regional mean temperatures physically ill-defined constructs rather than measurable quantities.

Cohler (2025) provides a historical review of how the meaningless global mean surface temperature (GMST) concept became entrenched in climate science despite its invalidity. The simple thermodynamic and mathematical principles that underpin the invalidity of temperature averaging in non-equilibrium systems like Earth's surface have been well understood since at least the late 19th century (Gibbs, 1875–1878), although Essex et al. (2007) were the first to make this clear in peer-reviewed literature. Cohler's analysis traces the development of the fallacious GMST from early statistical aggregations of weather data to its current role as the central metric in climate policy and assessment reports. Cohler also reaffirms the conclusions of Essex et al. (2007) and Essex and Andresen (2018), emphasizing that GMST represents an arbitrary statistical average of an intensive property over a non-equilibrium system, with no unique physical principle governing the choice among infinitely many mathematically permissible averaging conventions.

These three works collectively establish that global temperature metrics, including GMST and related anomalies, are physically meaningless numerical abstractions without correspondence to any conserved thermodynamic quantity such as energy or entropy. This fundamental thermodynamic invalidity of temperature averaging directly parallels and reinforces the central conclusions of the present paper: the construction of global OHC anomalies and derived EEI estimates suffers from the identical flaw in addition to several others. Both rely on the non-physical averaging and integration of intensive temperature measurements across vast non-equilibrium spatial and temporal domains in the ocean, producing final scalar quantities that are computational artifacts. The absence of thermodynamic meaning in global temperature metrics therefore undermines not only surface-based climate claims but also the entire chain of OHC and EEI calculations that dominate contemporary assessments of planetary energy imbalance.

1.3 Geometry and Thermal Energy Distribution of the Global Ocean

The global ocean spans a surface area of approximately 362 million square kilometers, representing 71% of the Earth's surface, with a total volume of 1330 million cubic kilometers and an average depth of 3688 m (Eakins and Sharman, 2010; Charette and Smith, 2010). Ocean topography encompasses diverse features: continental shelves at depths less than 200 m covering ~27 million square kilometers (7–8% of ocean area), steep continental slopes transitioning to abyssal plains at 4000–6000 m (comprising ~40–50% of ocean area), mid-ocean ridges, and trenches reaching 11 000 m (Menard and Smith, 1966; Amante and Eakins, 2009). Additionally, Argo floats are generally not deployed in regions with bottom depths between approximately 200 m and 2000 m, such as continental slopes, which cover about 8.5% of the ocean surface area and contain roughly 2% of the total ocean volume, to prevent grounding during their parking and profiling cycles (Riser et al., 2016; Costello et al., 2010).

The hypsometric curve, depicting the cumulative distribution of ocean area with depth, illustrates the non-uniform bathymetry. Average depth is computed as total volume divided by surface area, but volume fractions require integrating the area-depth profile:

$$V(d) = \int_0^d A(z)dz \tag{1}$$

where *A(z)* is the ocean area deeper than z. Thus, while 2000 m constitutes ~54% of the average depth, the volume above 2000 m is ~50% of the total due to minimal volumetric contribution from shallow shelves and substantial upper-layer volume over extensive deep basins (Eakins and Sharman, 2010; Sverdrup et al., 1942).

Ocean thermal energy content scales with volume, density, specific heat capacity, and absolute temperature (Kelvin). Commonly cited heuristic mean temperatures are ~5 °C (278 K) above 2000 m and ~2 °C (275 K) below, yielding a ~1% relative difference (Purkey and Johnson, 2010;

Desbruyères et al., 2016). Combined with near-equal volumes, thermal energy is distributed roughly evenly between upper and deep layers, within observational uncertainties (Talley et al., 2011; Levitus et al., 2012) contrary to popular misconceptions.

Argo float sampling focuses on open ocean regions deeper than 2000 m, largely excluding continental shelves (27 million km^2), marginal seas (e.g., Mediterranean, South China Sea; total ~20–50 million km^2 or 6–14% of ocean area), and ice-covered high-latitude zones like the Arctic (14 million km^2) (Riser et al., 2016; von Schuckmann et al., 2020). Argo therefore excludes ~90 million km^2 or ~25% of the global ocean surface area.

2. The Argo Measurement Process

2.1 Float Cycle and Profiling

Standard Core Argo and most BGC-Argo floats operate on a nominal 10-day cycle (Argo Steering Team, 2022). Following a brief surfacing period for data satellite transmission and GPS positioning, the float descends to a parking pressure/depth of approximately 1000 dbar in 4–8 hours, drifts freely at that depth for roughly 9 days, performs a short deep descent to the profiling pressure of approximately 2000 dbar (1–2 hours), and then executes a slow, buoyancy-controlled ascent to the surface lasting 6 to 10 hours. High-resolution conductivity, temperature, and depth/pressure (CTD) measurements are taken during this ascent phase, at sampling rates of approximately 1 Hz, yielding approximately 1000 discrete pressure levels per ascent 'profile' after binning to typical vertical intervals of 2 dbar in modern data products[4] (Argo Data Management Team, 2025). The float remains on the surface for 15 minutes to 1 hour and then descends again for its next pass.

Each float lasts around 4 to 5 years, depending chiefly on the lifetime of its lithium-ion battery. Once the battery is depleted, the float can no longer adjust its buoyancy and becomes permanently neutrally buoyant at whatever depth it happens to be, usually near its parking depth of 1000 m, and drifts passively with deep ocean currents indefinitely. No recovery is attempted; the floats are designed as expendable instruments, and the cost-plus logistical impossibility of retrieving them from remote open-ocean locations would be prohibitive. As a result, each dead float becomes permanent deep-sea debris: a ~1-meter-long plastic cylinder containing lithium batteries, metals, electronics, and sensors that slowly corrode, allowing seawater ingress over time (typically within 5–10 years), after which it gradually sinks to the abyssal seafloor, where further decomposition occurs over additional years or decades.[5]

In sum, the measurement points sampled during its carefully controlled ascent trace an irregular three-dimensional trajectory through the ocean determined by depth-varying currents, vertical

[4] Core Argo and BGC-Argo floats record CTD data at high frequency (~1 Hz, or roughly every second) during` their 6-to-10-hour ascent from depth to surface. Some floats sample continuously, while others take discrete spot measurements. In either case, the raw data are averaged or selected onboard into regular vertical bins of typically 2 decibars (dbar) pressure intervals (equivalent to ~2 meters of depth) before transmission after surfacing. This binning creates standardized, manageable profiles with ~1000 levels over the full ~2000 dbar range, as used in all modern Argo data products.

[5] Since 2000, the Argo program has deployed tens of thousands of floats worldwide (~4000 active at any time, with 600–900 replaced annually), causing a growing number of inactive floats residing at depth after mission completion. Although this accumulation invites comparison to orbital debris, the practical risk is negligible. The ocean's volume is vast (~1.3×10^9 km^3), and floats are deployed at ~300 km horizontal spacing, yielding an extremely low density ($\ll$1 float per 1000 km^3 at mid-depths). No collisions between Argo floats and submarines have been reported, likely because deep-ocean traffic is sparse, floats are small and passive with minimal acoustic signature, and submarines employ active sonar for obstacle avoidance. Any hypothetical collision would likely cause only minor damage due to the float's low mass and energy. Environmental assessments further indicate that materials released by Argo floats (e.g., lithium, aluminum, lead) are negligible compared to natural geochemical fluxes or land-based marine pollution. While long-term accumulation of synthetic materials in the deep ocean warrants attention in principle, the present scale poses no significant environmental or operational concern.

shear, mesoscale eddies, internal waves, and turbulent motions. The path is neither vertical nor a linear 'slant' but an unknown and complex, meandering curve through a spatially and temporally varying flow field. Each temperature measurement represents a true point value, the intensive thermodynamic state at a specific location and instant, but the spatial coordinates of subsurface measurements remain unknown.

2.2 Horizontal Position Identification Limitations

Iridium-equipped Argo floats, which dominate the current fleet, obtain their positions when they surface from GPS fixes with ~8 m accuracy (95% confidence). Rare GPS failures require fallback to less accurate Iridium geolocation with ~1–5 km accuracy (Wong et al., 2020). Argo floats employ no subsurface positioning system such as acoustic tracking or inertial navigation (Roemmich et al., 2009). Consequently, the entire subsurface trajectory remains horizontally untracked: including the descent, the 9-day parking drift, and the profiling ascent during which measurements are acquired.

The only measured horizontal displacements are net vectors between consecutive surfacing positions, typically spanning 50–300 km in moderate flow regions, and routinely exceeding 400 km in energetic currents such as the Antarctic Circumpolar Current (Ollitrault and Rannou, 2013). The horizontal displacement during the 6–10-hour ascent phase, when temperatures are measured, is completely indeterminate from measured data. We estimate it to be on the order of 5–50 km, with no physical basis for inferring precise values.

Standard Argo data products assign all subsurface measurements from a given profile to the single longitude, latitude, and time of the GPS fix obtained when the float surfaces (Argo Data Management Team, 2025). Actual longitude and latitude of the data collected during the 9-10 days a float is submerged are unknown and unknowable, because the floats have no instrumentation to measure location under water. Since the shear currents accumulate during the ascent phase, offset displacement from the surface GPS fix scales with depth: deeper measurements experience longer exposure to cumulative shear currents during ascent. Actual measurement times during ascent, which range over the 6–8-hour period, are also not saved in standard profile data products.

2.3 Nature of Raw Temperature Measurements

Each temperature measurement represents an intensive thermodynamic property directly proportional to average kinetic energy of the particles (water molecules and dissolved ions) in the small volume of seawater in local thermal equilibrium (LTE) immediately surrounding the sensor. In seawater, apparent molar heat capacities of major salts are small and generally negative, so adding salt slightly lowers total heat capacity. Because water molecules constitute over 98 % of the mass and supply > 99 % of the thermal capacity, the thermal energy content of seawater is almost entirely governed by the water mass. Dissolved salts primarily affect density and compressibility, not heat capacity. Each measurement samples effectively infinitesimal volume relative to total ocean volume (~1.3 billion km^3). Collectively, all Argo profiles over time provide sparse point constraints with negligible direct volumetric ocean coverage.

2.4 Depth Coverage Limitations

As described above, Standard Core and BGC Argo floats are designed to profile to a target pressure of 2000 dbar (Riser et al., 2016; Argo Steering Team, 2022). This limitation confines measurements to the upper ocean, which constitutes approximately 50% of both the total ocean volume and energy content. The global mean ocean depth is approximately 3688 m, with the maximum depth reaching 10 984 m in the Challenger Deep of the Mariana Trench (Gardner et al., 2014; Stewart and Jamieson, 2019). The region below 2000 m, encompassing the rest of the bathyal (1000 to 4000 m) zone, as well as the abyssal (4000 to 6000 m) and hadal/trench zones (6000 to 11 000 m), remains unsampled by the Core Argo and BGC-Argo arrays.

A small pilot deployment of Deep Argo floats has begun profiling to 4000–6000 dbar (Johnson et al., 2015; Zilberman et al., 2023, 2025), but as of late December 2025, these comprise ~315 active Deep Argo floats (projected from 224 active as of March 2025, with ~90 deployments planned through the end of 2025, per the 26th Argo Steering Team Meeting [AST-26] report). This remains far short of the target of approximately 1228 for purportedly "full" global coverage and provides insufficient spatial and temporal sampling for reliable global integration without extensive extrapolation (Zilberman et al., 2023; Zilberman et al., 2025; Argo program status via OceanOPS and AST reports). This fundamental sampling limitation in Argo-derived OHC products persists despite the Deep Argo expansion.

3. Calculation of the OHC Estimate and Uncertainty

3.1 Arbitrary Positional Assignment

In nearly all profile data files, temperature measurements taken during the ascent are assigned the longitude and latitude of the surfacing position (Argo User's Manual, 2025). This convention ignores the unknowable upstream horizontal offsets due to the downstream shear currents encountered during ascent as well as the different times of each individual measurement. The largest horizontal offsets are for measurements taken at the deepest points and we estimate them to be ~10–20 km in most regions and unlikely to exceed ~30–50 km even in the most extreme shear currents (see section 3.7.1).

3.2 Construction of the Reference Climatology

In oceanography, a climatology (or reference climatology) is a long-term average Eulerian description of intensive ocean properties, such as temperature and salinity, at different locations, depths, and times of year. It serves as a baseline or "normal" state against which current or observed conditions are compared to calculate "anomalies" (deviations from the average). These anomalies are used to support claims of changes, such as ocean warming, but the climatology itself is not a snapshot measurement of any single real ocean state but rather a statistical construct derived from historical intensive data.

To compute anomalies in OHC products, a gridded reference climatology is used. The Roemmich-Gilson (RG) Argo Climatology (2019), commonly used as the reference in Argo-era OHC products, is constructed exclusively from Argo float data (primarily 2004–2018, with extensions to later years). It provides mean fields and the annual cycle on a fine grid using weighted least-squares fitting of nearby profiles. Other climatologies, such as the World Ocean Atlas (WOA) series, incorporate pre-Argo historical observations (from ships, bottles, XBTs, etc.) alongside Argo data.

For each monthly temporal bin of the RG climatology, values on a regular three-dimensional grid are generated from the measured profile data using mathematically 'optimal' interpolation with covariance functions having prescribed horizontal correlation lengths, typically on the order of hundreds of kilometers (Roemmich and Gilson, 2009).

The gridded monthly fields are then arithmetically averaged over the reference period (2004–2018 for the current version of the RG Argo Climatology, 2019) to obtain the final climatological grid. The fixed 2019 climatology for 2004–2018 is not updated with newer observations. Separate monthly gridded fields (absolute temperature and salinity values, computed using the same optimal interpolation method) are made available for periods beyond 2018. As of the latest update, these monthly fields extend through June 2025. These post-2018 monthly fields are absolute gridded values (not anomalies). They are computed consistently with the methodology used for the 2004–2018 period but do not modify or incorporate data into the fixed 2004–2018 reference mean. The product website hosted by the Scripps Institution of Oceanography (University of California, San Diego) at

https://sio-argo.ucsd.edu/RG_Climatology.html

distributes these monthly fields as extensions to allow ongoing analysis relative to the unchanging 2004–2018 baseline mean.

A value at any grid point and depth in the RG Argo Climatology is a statistical construct: it is a weighted linear combination of measured temperatures from disparate physical locations (typically within hundreds of km) and times (within the same calendar month, up to ~30 days apart), obtained via optimal interpolation of monthly-binned anomalies, followed by arithmetic averaging across years (2004–2018) for each calendar month. This grid value therefore does not represent the actual temperature that any real parcel of seawater would have experienced at that exact grid point and depth at any specific moment. It is instead the result of the prescribed interpolation, weighting, and multi-year averaging operations applied to the input measurements.

3.3 Physical Meaninglessness of the Anomaly Definition

The OHC calculation relies entirely on the computation of temperature anomalies, ΔT. In global gridded products (the basis for EEI estimates), these are defined as $\Delta T = T_{\text{interpolated}} - T_{\text{reference}}$ where $T_{\text{interpolated}}$ is a value derived by mapping sparse float data onto a regular grid, and $T_{\text{reference}}$ is a climatological mean for that same grid point. While arithmetically possible, this operation yields a result that is physically meaningless for the following reasons:

Invalidity of the "Measured State" (Tinterpolated)

The value $T_{\text{interpolated}}$ acts as a proxy for measurement, yet it does not represent the temperature of any actual water parcel. Because Argo floats are sparse (nominally one per 3° x 3° region), filling a 1° x 1° grid requires objective analysis (OA) algorithms that aggregate data using covariance scales of 200–2800 km and temporal windows of one month. $T_{\text{interpolated}}$ is a weighted average of the temperatures of distinct water masses separated by hundreds of kilometers and weeks of time. As established by Essex et al. (2007), averaging intensive variables (temperature) across a non-equilibrium system destroys physical meaning: "A sum over intensive variables carries no physical meaning" (p. 5). Thus, $T_{\text{interpolated}}$ is a statistical artifact, not an actual thermodynamic state of anything.

Part of the problem associated with interpolating sparse data onto discrete grids in both space and time is that the grid resolution creates opposite challenges in each dimension. Spatially, Argo floats typically measure profiles separated by hundreds of kilometers, yet these sparse observations are interpolated onto 1° × 1° grids with spacing of approximately 100 km or less, creating far more grid points than actual measurements and requiring substantial spatial interpolation between widely separated observations. Temporally, measurements occur every 10 days but are aggregated into monthly bins, creating fewer temporal bins than the measurement frequency. This mismatch of fine spatial gridding of sparse data combined with coarse temporal binning of frequent measurements creates interpolation inconsistencies that can substantially affect the outcome. (Doswell, 1977; Wahba and Wendelberger, 1980; Wikle and Cressie, 1999).

Invalidity of the Reference State ($T_{\text{reference}}$)

The climatological baseline $T_{\text{reference}}$ (e.g., the Roemmich-Gilson climatology) is constructed by averaging temperature measurements at fixed geographic locations over time. This approach treats the ocean as an Eulerian field: a framework in which fluid properties are described as functions of fixed spatial coordinates. However, ocean temperature is fundamentally a Lagrangian property; it is a characteristic of specific water masses that move, mix, and transform as they are advected by currents. A water mass at 30°N, 150°W in January 2005 and a water mass at the same geographic coordinates in January 2018 are not the same physical entity; they have different histories, source regions, and thermodynamic states. Averaging their temperatures produces a statistical artifact at that grid point, not a meaningful physical baseline. The Eulerian framework, while mathematically convenient for gridded analysis, fundamentally misrepresents the Lagrangian nature of ocean thermodynamics.

This Eulerian-Lagrangian mismatch is compounded by the temporal arbitrariness of the chosen averaging period. The climatological baseline is derived from smoothing measurements over the 2004–2018 period, a 15-year window that is physically arbitrary and introduces systematic biases into the analysis. Ocean circulation operates on timescales ranging from seconds (turbulent eddies) to millennia (thermohaline circulation), with no physical significance attached to a 15-year window. Major ocean processes including mesoscale eddies (days to months), seasonal convection cycles, the El Niño-Southern Oscillation (2–7 years), the Pacific Decadal Oscillation (20–30 years), and Atlantic Multidecadal Variability (50–70 years) all operate on timescales incommensurate with this averaging period. The resulting climatology necessarily reflects the specific dynamical state of the ocean during 2004–2018 (including whatever phase each oscillatory process happened to occupy during that interval) rather than any physically meaningful equilibrium state. Not only are measurements from distinct water masses with different histories being averaged together spatially, but the reference state against which anomalies are calculated itself represents an arbitrary snapshot of transient ocean dynamics rather than a thermodynamically meaningful baseline.

A further issue with the climatological baseline $T_{\text{reference}}$ is the changing density and spatial distribution of floats. In 2004, many fewer floats were available and spatially, their distribution covered the oceans less evenly than in 2018.

Additionally, the polar oceans remain grossly undersampled by the standard Argo array owing to pervasive sea ice cover, which precludes routine operations of conventional floats in ice-covered regions. The Arctic Ocean (north of 60°N) accounts for ~4% (14 million km^2) of global ocean surface area (361 million km^2), while the Southern Ocean (south of 60°S) encompasses ~6% (22 million km^2), yielding a combined polar fraction of 10% of total ocean surface area (IHO, 1953). These regions contribute a 7% share of total ocean volume given their less than average depths. Specialized Polar Argo deployments using ice-avoiding technologies have improved coverage in seasonal ice zones, but central ice-covered areas, particularly in the Arctic, remain sparsely observed. These persistent spatial sampling gaps in shallow marginal seas/shelves and polar domains introduce systematic biases in global ocean heat content estimates derived from Argo data, particularly when constructing climatological reference states.

The 'Ghost vs. Ghost' Abstraction

The subtraction operation (ΔT) assumes that the reference state ($T_{\text{reference}}$) represents a meaningful baseline against which changes can be measured. However, $T_{\text{reference}}$ itself varies in both space and time; it is not a constant equilibrium state but rather an arbitrary temporal and spatial average of transient ocean conditions. Therefore, $T_{\text{reference}}$ has no physical validity as a reference temperature from which to calculate meaningful ΔT, yet this operation forms the basis of all OHC anomaly calculations.

The operation ΔT therefore compares two time-varying, spatially varying statistical constructs, neither of which represents the actual thermodynamic state of any water mass, yet the resulting difference is misleadingly assigned units of Kelvin by the purely algebraic manipulation of dimensional symbols.

The purported OHC anomaly scalar is then calculated as:

$$\Delta \text{OHC} = \int \rho c_p \Delta T \, dV \tag{2}$$

resulting in an equally invalid scalar that carries units of energy (joules, J), and due to its global order of magnitude, it is conventionally expressed in zettajoules (ZJ) where 1 ZJ = 10^{21} J. One cannot derive a physical quantity from a computation based on non-physical inputs, like ΔT. Yet these anomaly values constitute the primary basis for global OHC change estimates in Argo-era products.

3.4 Spatial Interpolation of Anomalies to Create Continuous Fields

Sparse anomaly values, each computed at the assigned surfacing position from point temperature measurements taken along a meandering sampling trail swept by a sensor during a 6–10 hour float ascent, are interpolated onto regular three-dimensional grids using objective analysis algorithms such as 'optimal' interpolation (a form of 'kriging'), successive corrections, or weighted averaging (Roemmich and Gilson, 2009; Gaillard et al., 2016; Good et al., 2013). While the floats are nominally spaced ~300 km apart, with typical measurement distances of 200–500 km due to drift, these methods employ covariance models with horizontal correlation length scales typically on the order of 200–2800 km, tuned to the physical autocorrelation scales of ocean temperature and salinity fields on monthly-to-annual timescales (Cheng et al., 2017; Li et al., 2017). Such scales enable 'optimal' weighting of nearby profiles and propagation of information across data gaps.

With ~4000 active Argo floats providing approximately 12 000–13 000 profiles per month globally (Argo Program, 2025), monthly gridded products on 1° × 1° horizontal resolution yield ~40 000–45 000 ocean surface grid locations after masking out land and shallow areas. Polar regions poleward of ~60° latitude have severely limited coverage and higher uncertainty due to seasonal and permanent ice cover that prevents float surfacing and data transmission. In well-sampled mid-latitude regions, this results in roughly 3–4 times as many grid points as monthly profiles. In sparsely sampled high-latitude regions poleward of ~60°N and S, with partial coverage from specialized ice-avoiding floats via programs like the Southern Ocean Carbon and Climate Observations and Modeling [SOCCOM]), the ratio often exceeds 10–20 times as many grid points due to lack of empirical data and heavier reliance on interpolation. Most common spatial interpolation algorithms (e.g., inverse-distance weighting or kriging with a global mean background) tend toward the domain-average value (or a local mean) as the number of nearby observations decreases and distance to the interpolation point increases. These methods are generally unable to perform meaningful extrapolation beyond the spatial extent of the observed data and, in sparse regions, effectively revert to a smoothed background estimate rather than capturing potential local extremes or trends not present in the limited samples (Shepard, 1968; Willmott et al., 1985).

Logically, spatial interpolation cannot increase the empirical information content of the dataset (Cover and Thomas, 2006; Shannon, 1948). It redistributes the limited information, without loss, from sparse, discrete point measurements according to data-driven covariance structures and physical assumptions. No new physical sampling occurs, and the total empirical information content remains bounded by the original ~12 000–13 000 monthly profiles plus data from the small number of specialized ice-avoiding floats.

The gridded fields are 'optimal', in a statistical sense, estimates under the calculated covariances, with effective resolution an order of magnitude coarser than the nominal 1° grid (~111 km meridional spacing at the equator), but closer to the ~300 km Argo sampling scale and chosen correlation lengths (Roemmich et al., 2019). Grid-point values in data voids are informed extrapolations, damped toward the climatological mean (zero for anomalies), with higher associated uncertainty. The optimality of these estimates is defined as minimizing the sum of squared differences between interpolated values and observations. However, generating error fields from such statistics results in systematic underestimation of the true uncertainty. Proper error assessment requires interpolating to withheld observations not accessed by the algorithm, rather than comparing estimates to the same observations used to optimize the interpolation procedure.

Presenting results as continuous gridded fields facilitates visualization, global integration (e.g., for OHC totals), and comparison with models, but risks conveying an impression of denser and more regular empirical coverage than exists. The underlying information is confined to sparse profiles, and all final gridded data are interpolated. Direct empirical measurements, obtained along horizontally meandering ascent trails sampled by Argo sensors, cover a negligible fraction of the ocean volume. Even when treated conservatively as narrow three-dimensional tubes, the total volume directly sampled by all Argo profiles in a year is many orders of magnitude smaller than the $\sim 10^{18}$ m^3 upper-ocean volume, yielding a sampling fraction of order 10^{-9} or less. Because covariant interpolation employs correlation length scales on the order of 1000 km, and because multiple profiles within a grid cell are first merged to form a single input value, every point in the final gridded product is a calculated quantity rather than a direct measurement.

Methodological choices, such as covariance scales, background fields, and inclusion of non-Argo data, introduce sensitivities in global OHC estimates, contributing to inter-product spreads equivalent to differences of ~0.1–0.5 W m^{-2} in derived EEI trends across analyses (Cheng et al., 2022; von Schuckmann et al., 2023). Reported uncertainties often focus on mapping error within individual products but may underestimate structural biases from these assumptions.

3.5 Integration to OHC Scalar

The interpolated anomaly grid is converted to a purported energy scalar by multiplying by fixed reference values for seawater density ρ (1027 kg m^{-3}) and specific heat capacity c_p (3985 J kg^{-1} K^{-1}), then summing over grid cell volumes.

Internal thermal energy for a seawater parcel is given by $U = m \times c_p \times T_K$ but calculating ΔOHC using temperature anomalies ΔT omits the dominant absolute temperature term and makes implicit assumptions such as conserved mass and constant thermodynamic properties within fixed Eulerian grid cells — assumptions that are violated in an advecting, mixing, open ocean system. The resulting scalar therefore corresponds to no physical energy or energy change in any real measured thermodynamic system.

The use of fixed reference values for seawater density specific heat capacity, rather than fully variable properties from TEOS-10,[6] introduces a small additional methodological approximation (~1–3% relative effect on OHC, equivalent to ~0.01–0.03 W m^{-2} on EEI trends), further exemplifying dependence on conventional approximations in the energy conversion rather than the full physics of variable seawater properties.

3.6 The Lagrangian Reality

A deeper thermodynamic issue stems from the fundamental mismatch between Eulerian and Lagrangian frameworks. All current Argo-derived ocean heat content (OHC) products are constructed in a fixed Eulerian reference frame: temperature measurements are binned, objectively interpolated, and averaged into stationary grid cells (typically 1° × 1° × 2 dbar), irrespective of water parcel trajectories. In reality, the ocean's water masses are continuously advected by large-scale currents, mesoscale eddies, fronts, and turbulent mixing. As a result, the same grid cell at different times contains entirely different physical water parcels, with no conserved thermodynamic identity linking the climatological baseline to subsequent measurements.

This Eulerian averaging therefore mixes intensive temperature values from unrelated, non-equilibrium fluid elements across space and time. The resulting pseudo-global integral does not correspond to the actual heat content change of any definable, materially conserved water-mass system. A common counterargument, that the "global" integral approximately captures heat displaced elsewhere, fails because Argo provides no direct measurements in well over 50% of the ocean volume (particularly below 2000 m, in marginal seas, under ice, and in poorly sampled high-latitude or coastal regions). There is thus no truly closed, observed system; the calculation relies heavily on interpolation and extrapolation over vast unsampled domains.

A truly thermodynamically meaningful OHC would require Lagrangian tracking of the same evolving water parcels along their trajectories: an approach that is practically impossible at global scale due to untracked subsurface paths and extreme dispersion over multi-year timescales. The resulting OHC scalar is therefore not a valid or reliable estimate of the true ocean thermal energy storage; instead, it is a methodological artifact dominated by arbitrary assumptions and computational choices that bear no direct relationship to the underlying physical quantity.

3.7 Estimation of Uncertainty from Spatial and Temporal Sampling Errors

Although the thermodynamic arguments presented in Section 3.3 demonstrate that Argo-derived OHC anomalies and integrated scalars are physically meaningless as quantifications of thermal energy change, it is instructive to evaluate the magnitude of numerous uncertainties arising from

[6] TEOS-10 (Thermodynamic Equation of Seawater - 2010) is the international standard for seawater thermodynamic properties adopted by the Intergovernmental Oceanographic Commission in 2010. It provides algorithms for computing seawater density, specific heat capacity, and other thermodynamic properties as functions of Absolute Salinity, Conservative Temperature, and pressure. TEOS-10 replaced the older EOS-80 (Equation of State 1980) standard and accounts for spatial variations in seawater composition beyond simple salinity (IOC, SCOR and IAPSO, 2010; McDougall and Barker, 2011).

spatial and temporal limitations, and the entire calculation framework accepted as an empirical construct for the sake of argument only.

3.7.1 Horizontal Misplacement and Untracked Subsurface Displacement

Horizontal misplacement arises because all ascent measurements (6–10 hours duration) are arbitrarily assigned to the surfacing GPS position, despite advection by subsurface currents. Direct quantification is impossible due to the absence of subsurface trajectory tracking, but bounds can be derived from observed velocities, horizontal temperature gradients, and published OHC sensitivities.

Subsurface currents down to 2000 m typically range from 0.05–0.2 m s^{-1}, with maxima of 0.5–0.8 m s^{-1} (or higher in boundary current extensions and shear zones; Gaillard et al., 2009; Ollitrault and Rannou, 2013). For a 10-hour ascent, this produces net horizontal displacements of ~2–7 km under typical conditions and up to 18–29 km at peak velocities. A conservative range of 5–50 km is adopted for deeper points, accommodating transient shear; the 50 km upper bound implies an average velocity of ~1.4 m s^{-1}, well below Argo's 3.0 m s^{-1} automated rejection threshold for inter-profile velocity (Wong et al., 2025). This contrasts sharply with conventional treatments that dismiss ascent drift as a "minor contaminant" limited to <5–10 km without supporting measurements (Ollitrault and Rannou, 2013).

Horizontal temperature gradients over these distances are substantial, driven by mesoscale eddies (radii 50–200 km) and fronts that dominate open-ocean variability (Chelton et al., 2011). Gradients commonly reach 1–5 °C over 50–100 km across eddy boundaries or western boundary current extensions (Frenger et al., 2013; Gaillard et al., 2009), implying temperature assignment errors of ~0.5–3 °C (or greater in energetic regions) from positional misplacement alone. Equivalently, this smears measurements over an irregular horizontal footprint, aliasing local mesoscale/sub-mesoscale gradients (typically 0.005–0.05 °C/km) into profile-level uncertainties of 0.05–1 °C.

These offsets do not cancel globally in integrated OHC or EEI calculations: displacements are governed by local, non-stationary processes (eddies, fronts, turbulent shear) rather than large-scale symmetric patterns. At short ascent timescales, Coriolis deflection is weak and does not produce opposing hemispheric biases. Instead, aliasing from untracked horizontal displacements during the 6–10 hour ascent (typically 5–50 km in regions of moderate to strong currents or shear) introduces incoherent regional errors that accumulate in Eulerian gridded fields. When combined with interannual circulation variability (e.g., ENSO, PDO shifts), this creates a time-dependent methodological bias in OHC trends. A very rough scaling suggests this effect could shift global EEI estimates by on the order of 0.02–0.1 W m^{-2}: local temperature mis-assignments from displacements over strong gradients (~0.1–1°C over 10–50 km) affect a fraction of profiles in energetic regions; when integrated over the global ocean (accounting for non-perfect cancellation), the resulting OHC trend error translates to an EEI bias in this range, comparable to or exceeding some published ensemble spreads (±0.1–0.2 W m^{-2}) that do not account for this foundational data-assignment flaw (von Schuckmann et al., 2020, 2023). Similar artifacts arise from how the reference climatology is constructed: temperature profiles measured at different times during each month are pooled together and statistically fitted (Roemmich & Gilson, 2009). This is another example of how arbitrary processing choices affect the final result.

3.7.2 Persistent Sampling Gaps and Undersampling

Annual/Interannual Mapping and Sampling Errors

Standard errors for annual global OHC changes (0–2000 m) range ~0.6–1.2 W m^{-2} at 95% confidence (~2σ) directly from Argo-era mapping uncertainties, driven by spatial gaps and interpolation assumptions (Johnson et al., 2018; Meyssignac et al., 2019).

Deep Ocean Uncertainty: Artifactual Precision vs. Physical Ignorance

The reported uncertainty of ± 0.04 W m^{-2} for deep ocean (>2000 m) heat uptake in von Schuckmann et al. (2020, 2023) and subsequent ensemble products is physically meaningless as a representation of true observational uncertainty. This value emerges from methodological artifacts rather than direct measurements: in vast unsampled regions, the analyses prescribe near-zero temperature change (stasis assumption) or rely on climatological interpolation with prescribed low variance. This creates circular logic: lack of data is interpreted as lack of variability, which then justifies reporting high precision. Physically, for an unmeasured volume comprising ~50% of the ocean, uncertainty is bounded only by the maximum plausible temperature change (ΔT_{deep}) compatible with total EEI. The IPCC claimed EEI of 0.7 W m^{-2} corresponds to a mean deep-ocean ΔT_{deep} of only ~0.0003 K yr^{-1}, far below the detection threshold of current sparse sampling (IPCC AR6 assessments in red):

$$\Delta T_{\text{deep}} = \Delta U_{\text{deep}} / C_{\text{deep}} \approx 0.8 \text{ ZJ yr}^{-1} / 2734 \text{ ZJ K}^{-1} \approx 0.0003 \text{ K yr}^{-1}$$

		EEI		***Earth surface area***		***Seconds per year***			**ΔU_{Earth}**
ΔU_{Earth}	≈	(**0.7 W m^{-2}**)	×	(5.1 x 10^{14} m^2)	×	(3.156 x 10^7 s yr^{-1})			≈ 11.3 ZJ yr^{-1}
		ΔU_{Earth}		***Ocean % of global EEI***		***Deep ocean % of ΔOHC***			**ΔU_{deep}**
ΔU_{deep}	≈	11.3 ZJ yr^{-1}	×	**91%**	×	**8%**			≈ 0.8 ZJ yr^{-1}
		Deep ocean		***Ocean volume***		***Seawater density***		***Seawater heat capacity***	***C_{deep}***
C_{deep}	≈	50%	×	(1.335 x 10^{18} m^3)	×	1028 kg m^{-3}	×	3985 J kg^{-1} K^{-1}	≈ 2734 ZJ K^{-1}

Even with recent growth in the Deep Argo pilot array to ~315 floats, the limitation persists: sampling density remains roughly 1 float per 2–3 million km^3 (equivalent to an Alaska-sized surface area) of deep ocean volume, providing negligible coverage for constraining global, volume-weighted mean temperature change. Deep Argo data are used primarily for regional validation or supplement, not as the primary basis for global error budgets in von Schuckmann et al. (2023) or related products, which continue to rely on repeat hydrography (decadal ship tracks) and null assumptions in data gaps. The ~315 floats provide no meaningful reduction in structural uncertainty for the full deep ocean; they remain a performative addition insufficient to distinguish small signals (0.0003 K yr^{-1} for 8% uptake) from larger plausible changes (~0.002 K yr^{-1} for 50% uptake) or zero.

The typical abyssal temperature variability is estimated at $\sigma_T \approx 0.05$ K, consistent with model-based estimates of deep ocean variability (Desbruyères et al., 2016). With current Deep Argo coverage limited to ~315 floats, the unsampled fraction of the deep ocean remains >0.99, yielding an absolute uncertainty of $C_{\text{deep}} \times \sigma_T \times f_{\text{unsampled}} = 2734 \text{ ZJ K}^{-1} \times 0.05 \text{ K} \times 0.99 \approx 135$ ZJ for the deep ocean thermal energy. Over the 48-year period 1971–2018, this translates to *deep ocean global equivalent flux uncertainty*:

$$135 \text{ ZJ} / (48 \text{ yr} \times (3.156 \times 10^7 \text{ s yr}^{-1}) \times (5.1 \times 10^{14} \text{ m}^2)) \approx \pm 0.175 \text{ W m}^{-2}$$

Accounting for the amplification of aliasing due to Nyquist-Shannon violations in sparse sampling (approximately a factor of 2, as demonstrated in model subsampling studies), the deep ocean ignorance uncertainty is estimated at ~± 0.35 W m^{-2} which aligns with previous studies: Purkey & Johnson (2010) report ~± 0.1 W m^{-2}, Zilberman et al. (2023) ~± 0.2 W m^{-2} from sampling error analyses, Meyssignac et al. (2019) ~± 0.13 W m^{-2} for the deep contribution in sea level budget closure, and von Schuckmann et al. (2023) ~± 0.1 W m^{-2} for deep ocean uptake. Synthesizing these, the deep ocean ignorance uncertainty is conservatively estimated at ~± 0.35 W m^{-2}, while the claimed ± 0.04 W m^{-2} is a result of computational assumptions rather than a measure of physical uncertainty.

Polar Ocean Undersampling: Amplified Ignorance and Additional Uncertainty

The undersampling problem is even more severe in the polar oceans (Arctic and Southern, beyond ~60°N/S, including ice-covered regions), which comprise ~10% of ocean surface area but significant volume (especially shelves, deep basins, and marginal seas). Standard Core Argo floats face high mortality from ice crushing or failure to surface/transmit under permanent/seasonal ice; coverage relies on ice-avoidance algorithms, Iridium-equipped floats, and limited Polar Argo extensions (e.g., SOCCOM in Southern Ocean, SODA/GREEN EDGE in Arctic). As of late 2025, Polar Argo sampling remains sparse, with only hundreds of profiles acquired, corresponding to an effective density of roughly one float per several million km³ in ice-covered regions, about an order of magnitude sparser than the global Argo average. Products like von Schuckmann et al. (2020, 2023) and updates (e.g., 2023–2025 OHC reports) explicitly exclude or minimally include polar regions due to poor data, yet when extrapolated via climatology or models, they assume low variability in gaps. This mirrors deep-ocean circularity: absence of measurements → presume quiescence → manufacture high precision. Physically, polar contributions (potentially 5–15% of global EEI via circulation/ice interactions) imply plausible flux equivalents of ~0.05–0.15 W m⁻² globally; sparse sampling cannot detect mean ΔT changes of ~0.001–0.005 K/yr across unsampled volumes, rendering true uncertainty ~± 0.2–0.5 W m⁻² from polar regions alone.

Even pilot efforts (ice-tethered profilers, gliders, BGC extensions like SOCCOM) provide only regional snapshots, not global volume-weighted constraints. The ~315 Deep Argo floats barely penetrate polar deep layers, and no full-scale Polar Argo array exists to address ice barriers, high variability (e.g., ice-albedo, freshwater fluxes), or seasonal inaccessibility. von Schuckmann-related ensembles acknowledge polar gaps as a source of potential underestimation (10% trend impact if polar warming significant) but report overall EEI uncertainties of ± 0.1–0.2 W m⁻² (e.g., 0.76 ± 0.2 W m⁻² for 2006–2020). This ignores structural flaws: polar data voids dominate interpolation, and null/low-variance assumptions suppress error bars artificially.

We estimate total polar ocean temperature variability as $\sigma_{T\text{polar}} \approx 0.1$ K. Heat content of the polar oceans is estimated by $C_{\text{polar}} = m_{\text{polar}} \times c_p$ where

$$m_{\text{polar}} \approx (25.3 \times 10^{15}\ \text{m}^3\ [>60°\ \text{N}] + 71.8 \times 10^{15}\ \text{m}^3\ [>60°\ \text{S}]) \times 1028\ \text{kg m}^{-3} \approx 1.0 \times 10^{20}\ \text{kg}$$
$$C_{\text{polar}} \approx 1.0 \times 10^{20}\ \text{kg} \times 3985\ \text{J kg}^{-1}\ \text{K}^{-1} \approx 399\ \text{ZJ K}^{-1}$$

With current Argo polar coverage limited to even fewer floats than Deep Argo, the unsampled fraction of the deep ocean remains >0.99, yielding an absolute uncertainty for the polar oceans' thermal energy of

$$C_{\text{polar}} \times \sigma_{T\text{polar}} \times f_{\text{unsampled}} = 399\ \text{ZJ K}^{-1} \times 0.1\ \text{K x } 0.99 \approx 39.5\ \text{ZJ}$$

Over the 48-year period 1971–2018, this translates to a *polar ocean global equivalent flux uncertainty:*

$$39.5\ \text{ZJ} / (48\ \text{yr} \times (3.156 \times 10^7\ \text{s yr}^{-1}) \times (5.1 \text{ x } 10^{14}\ \text{m}^2)) \approx \pm 0.05\ \text{W m}^{-2}.$$

Accounting for the amplification of aliasing due to Nyquist-Shannon violations in sparse sampling (approximately a factor of 2, as demonstrated in model subsampling studies), the polar ocean ignorance uncertainty is estimated at ~± 0.1 W m⁻².

Unresolved Mesoscale Variability in Boundary Currents and Eddy-Rich Regions

Unresolved mesoscale variability in boundary currents and eddy-rich regions represents a major structural source of uncertainty in Argo-derived global OHC estimates and derived EEI values. Approximately 90% of total global ocean kinetic energy is contained in these eddy fields (Ferrari & Wunsch, 2009). These areas, including the Gulf Stream, Kuroshio Extension, Antarctic Circumpolar Current, and Agulhas Current, exhibit intense, small-scale (10–200 km) fluctuations in temperature, salinity, and velocity driven by eddies, fronts, meanders, and instabilities. The kinetic energy of ocean currents is orders of magnitude smaller than the thermal energy stored in the water, yet these flows transport immense amounts of thermal energy. Core Argo's sparse sampling (~4000 floats, with typical spacing of ~300 km) fails to resolve these features, leading to large local root-mean-square errors (RMSE) in mapped heat content equivalent to >100 W m⁻² surface flux in energetic zones.

When these local errors alias into global integrals (misrepresenting high-frequency variability as low-frequency signals), they propagate as residual interannual noise or uncertainty in the global mean OHC trend or EEI estimates given grossly under- or completely unsampled fraction of the total global ocean. Energy is conserved in the total volume not the Argo sampled fraction. Meyssignac et al. (2019) note that:

> "*Estimating the uncertainty in OHC changes at interannual time scales is more challenging because of insufficient spatio-temporal coverage. So far, few studies have provided estimates. Estimates of annual OHC changes for 0–2000 m have standard errors of 0.3–0.6 Wm^{-2}* [1σ] *over the Argo era, and those errors increase substantially for the pre-Argo time period (Johnson et al., 2018, their Figure 2).*" (p. 11)

We also adopt 0.6-1.2 W m^{-2} as the 2σ value for the unresolved mesoscale uncertainty. This uncertainty alone is comparable to or exceeds the reported central EEI values (0.7 W m^{-2}), meaning year-to-year global OHC fluctuations are dominated by sampling artifacts rather than true physical change.

This uncertainty arises because mapping/interpolation schemes (e.g., optimal interpolation, machine learning regressions) must fill vast unsampled volumes with assumed covariance structures that fail to capture the full amplitude and spectrum of mesoscale activity in the strong boundary currents of ocean basins. High-resolution methods (e.g., satellite altimetry + in situ blending) reduce but do not eliminate the issue, as Argo remains the primary subsurface constraint. Similar ranges appear in related works on mapping uncertainties, high-resolution OHC products, and reviews of Argo limitations (e.g., Lyman & Johnson, 2023 on Random Forest Regression Ocean Maps [RFROM]; broader discussions in Meyssignac et al., 2019, von Schuckmann et al. ensembles, and Wang et al., 2018). Wang et al. cautioned that,

> *"[D]ata during the Argo period are still insufficient to observe the meso-scale eddies and OHC changes related to weather phenomena"* (p. 2485).

3.7.3 Arbitrary Processing Choices and Methodological Artifacts

Structural/Methodological spreads across Argo-based OHC products

Intercomparisons of multiple Argo-based in situ mappings, such as those from IAP, EN4, Ishii, NOAA NCEI, BOA, SCRIPPS, IPRC, MOAA, SIO, and others, show spreads in ocean heat uptake (OHU ≈ EEI proxy) of 0.23–0.56 W m^{-2} for 2005–2019 trends, with annual variability spreads larger due to differing quality control, climatologies, and covariance choices (Hakuba et al., 2024). For example, during the Argo-dominated period (2005–2019), global OHC trends in the upper 2000 m vary across eight objective analysis products (e.g., BOA: 3.6 ZJ yr^{-1} in 0–300 m; EN4: 4.1 ZJ yr^{-1}), yielding spreads of ~0.5 ZJ yr^{-1} (0.1 W m^{-2} EEI equivalent) in layer-specific rates, with EN4 often an outlier due to stronger warming signals (Bilgili, 2025).

Recent updates, such as IAPv4 (10.7 ± 1.0 ZJ yr^{-1} for 2005–2023 upper 2000 m) versus IAPv3 (9.6 ± 1.1 ZJ yr^{-1}), demonstrate ~11% differences attributable to bias corrections and data handling, translating to EEI spreads of ~0.1–0.2 W m^{-2} across datasets (Cheng et al., 2024a). These discrepancies arise from arbitrary methodological choices in interpolation, averaging, and assimilation, despite shared raw Argo inputs, providing direct evidence of inherent uncertainty in the methodologies themselves. These discrepancies arise from arbitrary methodological choices in interpolation, averaging, and assimilation, despite shared raw Argo inputs, providing direct evidence of inherent structural uncertainty in the methodologies themselves, adding systematic unpropagated bias equivalent to ~± 0.2–0.5 W m^{-2} or more.

Arbitrary Choice of Baseline Date Range

A change in the climatology date range used for calculating OHC anomalies from Argo data can introduce substantial differences in implied EEI, typically on the order of ~0.1–0.3 W m^{-2} (systematic spread) for decadal trends, as evidenced by sensitivity analyses of objective mapping methods where climatology choices are a primary contributor to error (e.g., Boyer et al., 2016; Lyman & Johnson, 2014). This arises because shifting the reference period (e.g., from 2004–2018 to 2005–2019 or later Argo-era windows) can alias different phases of decadal variability like the PDO or the Atlantic Multidecadal Oscillation (AMO) into the baseline mean, leading to offsets in OHC estimates that propagate to EEI, particularly when mapping methods relax to the climatological mean in data-sparse regions, rendering fine-resolution EEI claims sensitive to arbitrary baseline selection.

Eulerian vs. Lagrangian Framework and Resulting Uncertainty

Regional Lagrangian analyses of ocean circulation and heat transport reveal substantial discrepancies with traditional Eulerian OHC estimates. These analyses are based on high-resolution, ocean-only hindcast simulations (eddy-permitting to eddy-rich NEMO/ORCA configurations forced by atmospheric reanalyses), not on coupled global general circulation climate models (GCMs). Unlike CMIP-style GCMs, which suffer from coupled atmosphere / ocean feedbacks, extensive parameterization of unresolved processes (clouds, convection, mixing), the fundamental physical meaninglessness of GMST due to spatial temperature averaging, and inherent structural uncertainties in long-term projections, these hindcasts are tightly constrained to reproduce observed historical variability and focus strictly on the actual physics of ocean advection and heat transport at regional scales. They therefore do not inherit the fundamental thermodynamic and averaging problems that afflict global coupled GCMs or Eulerian OHC products.

For example, Tooth et al. (2024) used water parcel trajectories in an eddy-rich hindcast to decompose meridional energy transport at 26.5°N in the Atlantic, finding that recirculating parcels in the subtropical gyre account for 37 ± 9% of the total energy transport, a contribution that Eulerian vertical-horizontal decompositions often attribute differently or underemphasize due to their fixed-grid averaging over unrelated water masses. Similar Lagrangian decompositions in the eastern North Atlantic subpolar gyre (Tooth et al., 2023) and other regions highlight how Eulerian methods mix signals from advecting, non-conserved parcels, leading to differences in inferred heat uptake pathways and magnitudes that can reach 30–50% regionally.

These discrepancies imply significant uncertainty when extrapolating regional Eulerian OHC estimates to global scales. In the Atlantic at 26.5°N alone, the 30–40% attribution difference corresponds to ~0.1–0.2 PW (petawatt) in heat transport uncertainty (based on typical total meridional heat transport ~1–1.5 PW at that latitude). Scaled globally (considering the Atlantic contributes ~25–30% of total ocean heat uptake), we derive this conservative range by converting the estimated transport discrepancies directly into global energy flux equivalents. A systematic error of ~0.1–0.2 PW, when distributed over Earth's surface area (5.1×10^{14} m²), yields a baseline bias of approximately 0.2–0.4 W m^{-2}. To account for potential partial compensations between basin circulations while acknowledging the magnitude of the Atlantic bias, we adopt 0.1–0.4 W m^{-2} as a robust estimate of the structural uncertainty inherent in Eulerian heat budget closures. This uncertainty is not captured in current ensemble spreads (± 0.1–0.2 W m^{-2}), as they rely on correlated Eulerian products and do not account for the Lagrangian framework's fundamentally different view of heat pathways and conservation.

3.7.4 Lack of Independence in Ensembles and Consensus Over-Simplification

The reported EEI uncertainty of ± 0.2 W m^{-2} (IPCC AR6 Figure 7.2: 0.7 W m^{-2}, range 0.5–0.9 W m^{-2}) relies on apparent convergence across OHC products (IAP, NOAA/NCEI, EN4, Ishii). However, this convergence fails to quantify total uncertainty because the products lack independence. All major Argo-era OHC estimates share ~90% of their raw input from the same ~4000 floats (Riser et al., 2016). Differences arise solely from processing variations: climatology baselines differing by 15 years between IAPv3 (1990–2005) and IAPv4 (2006–2020), substantial differences in quality control thresholds, and unquantified covariance radii in mapping (Cheng et al., 2024a). With correlations $\rho > 0.8$, the effective number of independent samples reduces to ~1–2, violating the Central Limit Theorem. Ensemble uncertainty thus approximates single-product uncertainty rather than reducing by $\sqrt{N}$ (where N = 4 to 6 in most OHC ensemble estimates of EEI).

Common-mode systematic biases further undermine reliability. Argo salinity biases, primarily due to sensor drift in the conductivity cells of CTD sensors (mostly Sea-Bird SBE 41/41CP), affect the vast majority of profiles. According to a detailed evaluation of raw Argo salinity data from 2000–2021, approximately 90% of profiles requiring adjustment have small-magnitude drift (<0.03 psu), while 2–3% exhibit more severe drift (>0.05 psu). A particularly concerning episode occurred during 2017–2018, when ~17% of annual profiles showed adjustable positive (salty) drift, peaking due to a temporary manufacturing defect in the encapsulant material used in CTDs deployed around 2015–2018 (Wong et al., 2023).

These widespread and temporally correlated biases are shared across the global Argo fleet due to similar sensor technology. If left unadjusted or incompletely corrected, they introduce spurious salinity increases in raw data, which propagate into density calculations via the equation of state. This creates artificial (spurious) halosteric sea level signals that contaminate steric height products. Although OHC itself is computed from temperature anomalies only, the resulting spurious density/steric trends distort validation of OHC against independent observations (satellite altimetry + gravimetry), cause non-closure of the global sea level budget, and increase systematic uncertainty in attributing observed sea level rise to true thermosteric ocean heat uptake. Delayed-mode quality control mitigates most issues, but residual undetected or unquantifiable bias persists, adding systematic uncertainty to global ocean state estimates, including heat content and sea level.

Mapping artifacts contribute ± 0.2–0.5 W m^{-2} regional errors (e.g., Southern Ocean), propagating to ~0.1 W m^{-2} globally (Gregory et al., 2014). Inter-product spreads of 0.1–0.2 W m^{-2} (2005–2018 trends: 0.54–0.64 W m^{-2}) reflect methodological consistency, not robustness (Cheng et al., 2022). All products assume isotropic covariance, underestimating eddy-rich region biases (± 0.05–0.1 W m^{-2}). Deep hydrography uncertainties add ± 0.3–0.5 W m^{-2} (Garry et al., 2019), and sea level closure introduces ± 0.29–0.37 W m^{-2} uncertainty (Meyssignac et al., 2019).

CERES TOA annual mean uncertainties for global net flux are on the order of ± 4 W m^{-2} (Loeb et al., 2018), with interannual variability typically ± 1–2 W m^{-2} driven by ENSO and cloud effects (Loeb et al., 2021). Upper-ocean heat content (OHC; 0–700 m) has been underestimated by approximately 20–40% due to observational gaps, particularly in the Southern Hemisphere (Durack et al., 2014). Decadal EEI trend uncertainty from CERES is dominated by systematic errors (∼0.1 W m^{-2} decade^{-1} from instrument stability and drift; Loeb et al., 2021; Raghuraman et al., 2021) and internal variability, with total uncertainty comparable to the observed trend itself (0.50 ± 0.47 W m^{-2} decade^{-1} over the Argo era from 2005 to 2019; Loeb et al., 2021). While extended CERES records (2001–2024) indicate a statistically significant linear trend of 0.45 ± 0.22 W m^{-2} decade^{-1} at 95% confidence (Loeb et al., 2024), the shorter Argo-era interval exhibits a trend where uncertainty remains comparable in magnitude to the signal itself, highlighting the difficulty in detecting acceleration.

Figure 7.2's presentation exacerbates these issues by displaying EEI as a single value without timescale qualifiers, implying universal precision that obscures higher annual/interannual uncertainties acknowledged elsewhere in AR6 text. This over-simplification fosters overconfidence, as the narrow range masks correlated assumptions, gap-induced errors, and the fundamental limitations of sparse Argo sampling.

3.7.5 Nyquist-Shannon Theorem and Aliasing in Argo Data

Subsection 3.7.2 already quantifies the uncertainty from unresolved mesoscale variability in eddy-rich regions (including boundary currents like the Gulf Stream, Kuroshio Extension, Antarctic Circumpolar Current, and Agulhas Current), where sparse Argo sampling fails to resolve 10–200 km fluctuations, leading to local RMSE >100 W m^{-2} in energetic zones that propagate via aliasing into global integrals as residual interannual noise or uncertainty on the order of ~0.6–1.2 W m^{-2} (2σ) for global OHC trends or EEI estimates. This discussion highlights practical observational and interpolation limitations but does not explicitly invoke the fundamental signal processing principle responsible for the aliasing: the Nyquist-Shannon sampling theorem (Shannon, 1949). The theorem imposes irreducible limits on detectable spatial and temporal frequencies, independent of mapping quality or statistical assumptions. High-frequency signals (from mesoscale eddies and smaller features) are inevitably misrepresented as lower-frequency ones when sampling rates significantly violate the Nyquist criterion that sampling frequency be at least twice the highest signal frequency.

This subsection therefore builds on Subsection 3.7.2 by providing the theoretical basis for the aliasing already quantified there. Furthermore, it identifies additional structural uncertainties arising from theorem violations in regions with even sparser effective sampling (deep ocean and polar areas), where Nyquist limits are more severely exceeded.

Argo's target horizontal spacing (300 km mean distance) and 1° grid resolution yield a spatial Nyquist wavelength of ~200 km, marginally resolving large mesoscale features but aliasing smaller eddies/submesoscale variability (<50–100 km). Temporally, the 10-day cycle limits resolution to periods ≥20 days, aliasing faster processes (e.g., eddy passages of 5–15 days). These limits explain the aliasing mechanism in Subsection 3.7.2 but do not add new global uncertainty beyond it, as the primary mesoscale energy dominance (~90% of ocean kinetic energy in geostrophic eddy fields; Ferrari & Wunsch, 2009) is already captured.

Nyquist Limitations in Deep and Polar Oceans

The theorem's constraints become particularly severe in the deep ocean (>2000 m, ~50% of ocean volume) and poleward of 60° N and S (~10% of ocean surface area and ~7% of volume), where sampling sparsity pushes Nyquist wavelengths far beyond mesoscale scales, exacerbating aliasing and providing additional uncertainty not fully covered in prior subsections.

Core Argo floats provide no data below 2000 m. The current pilot ~315 Deep Argo floats result in effective intervals of ~900 km, yielding Nyquist wavelengths ~1800 km. High-frequency deep ocean processes (abyssal eddies, internal waves, bottom water formation at ~100–500 km scales) are thus aliased or undetectable. Model studies indicate such sparsity folds deep signals into apparent basin-scale trends (Purkey & Johnson, 2010; Zilberman et al., 2023). The Nyquist-Shannon theorem therefore elucidates one key mechanism contributing to our estimated ≥± 0.3 W m^{-2} deep ocean ignorance bound: the irreducible folding of unresolved high-frequency variability into resolved low-frequency signals due to theorem violations from extreme sparsity. This aliasing effect, estimated at ~± 0.2–0.4 W m^{-2} in model-based analyses of sparse deep ocean sampling, is not a separate addition but a specific manifestation of the broader physical ignorance, refining and corroborating our bound. This reinforces our conclusion that deep OHC uncertainties of ± 0.04 W m^{-2} given by von Schuckmann et al. (2020/2023) are unrealistically narrow, relying heavily on low-variance interpolation assumptions that ignore both the general lack of observational constraint and the fundamental aliasing imposed by Nyquist limits.

Polar regions all suffer chronic undersampling (<10% in area Argo coverage and <<1% in volume due to ice and logistics; Riser et al., 2016), with intervals >500 km and Nyquist wavelengths >1000 km. This fails to resolve high-frequency polar variability (polynyas, iceshelf melt plumes, rapid frontal shifts at ~10–100 km). Temporal aliasing worsens from the 10-day cycle missing fast ice-ocean interactions (e.g., diurnal tidal mixing).

Implications for Global OHC and EEI

The Nyquist theorem provides the physical rationale for the mesoscale aliasing uncertainty already quantified in Subsection 3.7.2. In undersampled deep and polar volumes, it introduces similar large uncertainties described above of ≥± 0.3 W m^{-2} for deep non-polar ocean and ≥± 0.1 W m^{-2} for polar oceans. Current assessments overlook these fundamental sampling constraints, treating OHC as overly precise. Denser arrays could mitigate this, but Nyquist limits remain irreducible with the present methodology.

3.7.6 Quantitative Summary of Uncertainty Contributions

Combining all identified sources of error yields a conservative 95% confidence uncertainty on annual-to-decadal EEI well exceeding ± 1 W m^{-2}. Key contributors include:

a. *Unresolved mesoscale variability* in boundary currents and eddy-rich regions, propagating to interannual global noise of ~0.6–1.2 W m^{-2} (2σ parametric/interannual noise).

b. *Persistent sampling gaps in the deep ocean* (>2000 m), introducing physical ignorance bounds of ~± 0.35 W m^{-2} due to stasis assumptions and sparse coverage (~315 Deep Argo floats projected, negligible density).

c. *Altimetry and mass budget uncertainty* of ~0.29–0.37 W m^{-2} due to the discrepancy between OHC-implied sea-level change and satellite altimetry/gravimetry measurements.

d. *Structural discrepancies between Eulerian and Lagrangian frameworks*, implying potential global biases of ~0.1–0.4 W m^{-2} from mixing of non-conserved water parcels.

e. *Arbitrary baseline/climatology* choices, which shift decadal trends by ~0.1–0.3 W m^{-2} across reasonable Argo-era windows.

f. *Persistent sampling gaps in the polar/high-latitude regions*, introducing physical ignorance bounds of ≥± 0.1 W m^{-2} due to sparse coverage and ice barriers preventing float survival/transmission.

g. *Horizontal misplacement* and untracked subsurface displacement during ascent, producing potential methodological biases of ~0.02–0.1 W m^{-2} or more from aliasing of local gradients.

Table 1. Quantified Sources of Uncertainty and Bias in Argo-Based EEI Estimates

A conservative summary of major uncertainty and bias sources contributing to EEI estimates derived from Argo-based OHC calculations on annual-to-decadal timescales. Total compounded uncertainty exceeds reported values by an order of magnitude. All ranges represent conservative estimates at approximately 95% confidence. A conservative lower-bound estimate of total compounded uncertainty can be illustrated via root-sum-square (RSS) synthesis of the components listed above, though this method is strictly valid only for independent, Gaussian errors. Taking midpoint values: $\sqrt{(0.9^2+0.35^2+0.33^2+0.25^2+0.2^2+0.1^2+0.06^2)} \approx 1.1$ *W* m^{-2} *at approximately 95% confidence. However, this RSS approach systematically underestimates total uncertainty because: (1) structural and ignorance terms (b, c, e, f) represent fixed bounds rather than Gaussian measurement scatter, requiring linear rather than quadratic aggregation; (2) sampling gaps (b, f) share common exclusionary causes, creating positive correlation which violates RSS independence assumptions; and (3) explicit systematic biases (d, g) are directional offsets that do not randomly cancel. A more realistic synthesis treating structural terms as partially additive yields ≥± 1 W* m^{-2} *at 95% confidence as a conservative lower bound.*

Source	*Uncertainty/Bias ± (W* m^{-2}*)*	*Type*
a. *Unresolved mesoscale variability* in boundary currents and eddy-rich regions	~0.6–1.2 (2σ)	Parametric/interannual noise
b. *Persistent sampling gaps:* deep ocean (>2000 m)	~0.35	Structural/physical ignorance
c. *Altimetry & mass budget uncertainty*	~0.29–0.37	Structural/closure problem
d. *Structural discrepancies between Eulerian and Lagrangian frameworks*	~0.1–0.4	Framework bias
e. *Arbitrary baseline/climatology*	~0.1–0.3	Processing artifact
f. *Persistent sampling gaps*: polar/high-latitude regions	~0.1	Structural/physical ignorance
g. *Horizontal misplacement* and untracked subsurface displacement during ascent	~0.02–0.1	Methodological bias
Total compounded (95% confidence)	*≥± 1*	*Overall*

These uncertainties are compounded by lack of independence in OHC ensembles (shared inputs, high correlations $\rho > 0.8$, effective $N \approx 1–2$) and common-mode systematics (e.g., salinity biases, interpolation artifacts), rendering reported values of ± 0.1–0.2 W m⁻² (e.g., von Schuckmann et al., 2023; IPCC AR6 Figure 7.2) applicable only to within-product parametric variance under optimistic gap-extrapolation assumptions. This narrow range excludes all uncertainty/bias sources quantified above.

A conservative lower-bound estimate of total uncertainty can be illustrated via root-sum-square (RSS) synthesis of the components listed above, though this method is strictly valid only for independent, Gaussian errors (Taylor, 1997, Chapter 3; Trenberth, 2009). Taking midpoint values: $\sqrt{(0.9^2+0.35^2+0.33^2+0.25^2+0.2^2+0.1^2+0.06^2)} \approx 1.1$ W m^{-2}. However, this RSS approach actually underestimates total uncertainty because: (1) structural and ignorance terms (b, c, e, f) represent fixed bounds rather than Gaussian measurement scatter, requiring linear rather than quadratic aggregation; (2) sampling gaps (b, f) share common exclusionary causes, creating positive correlation which violates RSS independence assumptions; and (3) explicit systematic biases (d, g) are directional offsets that do not randomly cancel. A conservative synthesis treating structural terms as partially additive yields ≥± 1 W m^{-2} at 95% confidence.

This total 95% confidence uncertainty (≥± 1 W m^{-2}) exceeds the uncertainty of the IPCC AR6 EEI estimate of 0.7 ± 0.2 W m^{-2} (Figure 7.2) by an order of magnitude. When structural flaws such as non-additive intensive anomalies, dominant interpolation in unsampled volumes, framework discrepancies, untracked trajectories, and arbitrary positional assignment are rigorously accounted for, the central estimate becomes statistically indistinguishable from zero on annual-to-decadal timescales. The continued presentation of narrow uncertainties as observational therefore constitutes a critical overstatement of measurement capability, obscuring fundamental limitations in sparse Argo sampling, deep and polar undersampling, mesoscale aliasing, and arbitrary processing choices.

This total uncertainty also renders CERES EBAF adjustments (forced to match OHC-derived EEI) circular and artifactual, as raw CERES absolute uncertainties (± 3–5 W m^{-2}; Loeb et al., 2018) vastly exceed the claimed precision. The rigorous accounting presented here, independent of ensemble convergence, demonstrates total EEI uncertainty of ≥± 1 W m^{-2} on annual-to-interannual timescales, consistent with natural variability and observational noise (± 1–2 W m^{-2}; Loeb et al., 2021). Enhanced observing systems would be required to reduce mapping errors below ± 0.3 W m^{-2} (Meyssignac et al., 2019; von Schuckmann et al., 2023).

This conclusion is further reinforced by the absence of any physically meaningful global-scale metric for the intensive property temperature (Essex et al., 2007; Essex & Andresen, 2018; Cohler, 2025), rendering global mean surface temperature (GMST) an arbitrary average over a non-equilibrium system with no unique averaging rule among infinitely many valid options. From first principles, the CO_2-driven global warming hypothesis, while grounded in radiative physics (van Wijngaarden & Happer, 2025), lacks empirical validation due to the thermodynamic invalidity of such constructs and the inability to measure the extensive quantities OHC and EEI with sufficient precision.

3.7.7 Indeterminacy of Ocean Vertical Energy Change Partitioning

The claimed vertical partitioning of purportedly positive net flux of energy into the ocean, wherein ~85–93% is attributed to the volume above 2000 m with ~7–15% below, is not an empirically robust finding, but rather a derived construct from observationally sparse and methodologically constrained datasets (IPCC AR6 uses 15 different ensemble members referring back to von Schuckmann et al. 2020 and 2023).

This claim of predominant upper-ocean dominance is made by multiple syntheses, including the IPCC AR6 assessment (Forster et al., 2021, Table 7.1), and claims based on von Schuckmann et al. (2020) that the upper-lower gains during 1971–2018 were 364.9 ± 83.5 ZJ (~92%) and 31.0 ± 15.4 ZJ (~8%), respectively. The percentage partition reported by von Schuckmann et al. (2023) adding two years of data (1971-2020) remains the same.

Given the profound structural uncertainties and thermodynamic invalidity inherent in all estimates of OHC change demonstrated in our analysis, it is impossible to scientifically exclude even a roughly balanced 50%-50% split, or any other equitable distribution, in the vertical partitioning of net flux of energy into the ocean between the upper (<2000 m) and lower (>2000 m) ocean layers. Therefore, the claimed partitioning is not an empirical observation, but a computational artifact derived from sparse, non-physical integrations of intensive temperature anomalies across vast unsampled volumes. Deep ocean contributions, estimated at ~8% or ~0.07–0.1 W m^{-2} equivalent (von Schuckmann et al., 2020, 2023), rely on decadal ship-based repeat hydrography with coverage of <<1% of deep volume and uncertainties often exceeding ± 50% of the signal, compounded by assumptions of stasis in data gaps that artificially suppress uncertainty (Garry et al., 2019).

Even in the Argo era, where upper-layer sampling is denser, the same methodological flaws such as arbitrary baselines, Eulerian averaging over non-conserved water masses, and untracked trajectories, render the dominance of upper warming unreliable, with structural uncertainties (e.g., ± 0.3–0.5 W m^{-2} for deep layers alone) large enough to accommodate deep fractions up to 30–50% or higher without contradicting the flawed data (Allison et al., 2019).

Pre-Argo estimates, with much sparser profiles and known biases like XBT fall-rate errors, amplify this indeterminacy, yet modern ensembles circularly blend them without resolving the foundational issues. This narrative of precise vertical partitioning is further undermined by model biases that underestimate shallow OHC gain while overestimating deep penetration, as well as persistent observational gaps in polar and abyssal regions that could mask substantial deep ocean variability (IPCC, 2021).

With no thermodynamically valid global scalar for OHC change, and uncertainties dwarfing the reported EEI (0.7 W m^{-2}), alternative distributions like 50%-50% remain plausible, aligning with the baseline ~50%-50% total energy split between the upper and lower ocean and highlighting how claims of upper dominance are scientifically unsubstantiated.

4. Discussion

The construction of Argo-derived global OHC anomalies and derived EEI estimates involves a sequence of mathematical operations that progressively disconnect the final scalar from any measurable physical quantity of thermal energy. Temperature measurements, being intensive point values defined only in local thermodynamic equilibrium, are first assigned to arbitrary geographic coordinates ignoring untracked subsurface horizontal displacements of 5–50 km during ascent, then differenced against a climatological reference that itself is a non-physical statistical construct lacking correspondence to any actual water mass. The resulting anomalies, which are thermodynamically meaningless due to the non-additivity of temperature across non-equilibrium spatial and temporal domains (Essex et al., 2007; Essex & Andresen, 2018), are then aggregated via interpolation algorithms that fill the vast majority of ocean volume with values determined by prescribed covariance functions and correlation scales rather than direct measurements.

The integrated OHC scalar thus represents a computational artifact whose magnitude and sign are highly sensitive to methodological choices, including reference-period selection (introducing ± 0.1–0.3 W m^{-2} sensitivity), correlation lengths, damping parameters, baseline climatology, and the choice of Eulerian versus Lagrangian framework (± 0.1–0.4 W m^{-2} systematic bias), rather than to any conserved physical property. Our comprehensive uncertainty analysis (Section 3.7, Table 1) demonstrates that when all identifiable sources are rigorously quantified, the total 95% confidence uncertainty on annual-to-decadal EEI reaches at least ± 1 W m^{-2}, roughly an order of magnitude larger than values commonly reported in IPCC AR6 (± 0.1–0.2 W m^{-2}). This total uncertainty exceeds their central EEI estimate of 0.7 W m^{-2} (range 0.5–0.9 W m^{-2} [IPCC's 90% CI][7]; Figure 7.2), rendering it statistically indistinguishable from zero.

[7] IPCC uses a non-standard, ill-defined notation in this energy budget diagram. Quoting p. 169 of IPCC AR6 WGI: "Throughout this WGI Report, unless stated otherwise, uncertainty is quantified using 90%

Previous studies have quantified portions of this methodological sensitivity. Boyer et al. (2016) demonstrated that mapping method and baseline climatology choices alone can shift upper-ocean heat content trends by amounts comparable to the reported signal. Cheng et al. (2024a) acknowledge that month-to-month variability in their IAPv4 product often exceeds signals detectable by satellite radiometry, while ensemble spreads among products (von Schuckmann et al., 2023) reach ± 0.1–0.2 W m^{-2} for decadal trends. However, these reported spreads capture only within-ensemble variance and do not account for the systematic biases and structural uncertainties we have quantified: unresolved mesoscale variability (± 0.6–1.2 W m^{-2} parametric noise), deep ocean physical ignorance bounds (± 0.35 W m^{-2}), sea-level closure discrepancy problem (±0.29–0.37 W m^{-2}), Eulerian-Lagrangian framework difference (±0.1–0.4 W m^{-2}), arbitrary baseline climatology (±0.1–0.3 W m^{-2}), polar ocean undersampling (± 0.1 W m^{-2}), and untracked subsurface trajectories (± 0.02–0.1 W m^{-2}), arbitrary positional assignment, and thermodynamic invalidity of anomaly averaging. Recent work continues to present Argo-derived OHC as a definitive indicator of ocean warming (Cheng et al., 2024b, 2025a, 2025b; Trenberth et al., 2025; Bilgili, 2025; Pan et al., 2026) without confronting these foundational issues, treating reported ensemble spreads as comprehensive uncertainty while relying on the same underlying measurement and processing chain that we demonstrate to be fundamentally flawed.

A critical methodological circularity further undermines the claimed precision: the CERES EBAF adjustment procedure forces direct satellite measurements of top-of-atmosphere radiative fluxes, which have absolute uncertainties of ± 3–5 W m^{-2} or more (Loeb et al., 2018), to mathematically match the Argo OHC-derived imbalance whose physical validity is absent. This "one-time global adjustment" pushes individual flux components (reflected solar, outgoing longwave) to the extreme edges of their uncertainty ranges without physical justification, producing the narrow ± 0.2 W m^{-2} range in IPCC AR6 Figure 7.2 as an artifact of circular tuning rather than independent observational confirmation (Section 1.1). The apparent convergence between CERES-adjusted and OHC-derived EEI values therefore represents mutual methodological reinforcement rather than independent empirical validation.

The fundamental issue of vertical energy partitioning remains similarly unresolved. The widely cited claim that ~90–93% of purported planetary energy increase resides in the ocean, with ~85–93% of oceanic uptake in the upper 2000 m (von Schuckmann et al., 2020, 2023; IPCC AR6), cannot be scientifically sustained given the profound uncertainties we have documented. Deep ocean contributions rest on <<1% volumetric sampling via decadal ship-based repeat hydrography, with uncertainties often exceeding ± 50% of the purported signal and stasis assumptions in data voids that artificially suppress error bars (Section 3.7.7). The structural uncertainties for deep layers alone (~± 0.35 W m^{-2}) are large enough to accommodate deep ocean fractions ranging from near-zero to 50% or higher, rendering the claimed precise partitioning a methodological construct rather than an empirical observation. Alternative distributions, including even a 50-50 upper-lower ocean partitioning of net energy flux is physically plausible.

To independently test the scientific validity of the IPCC AR6 0.7 W m^{-2} EEI assessment, we applied Armstrong & Green's (2022) Compliance with Science Checklist (see Appendix A),[8] comprising eight major criteria and 26 subcriteria derived to test compliance with the scientific method using systematic empirical falsification of testable hypotheses, which is the only logically valid means of ruling out falsehoods about physical reality.

These understandings were established by Hume (1748), which proved that empirical truths cannot be derived through deductive reasoning alone, and later formalized by Popper (1959), which

uncertainty intervals. The 90% uncertainty interval, reported in square brackets [x to y], is estimated to have a 90% likelihood of covering the value that is being estimated. The range encompasses the median value and there is an estimated 10% combined likelihood of the value being below the lower end of the range (x) and above its upper end (y). Often the distribution will be considered symmetric about the corresponding best estimate (as in the illustrative example in the figure), but this is not always the case."

[8] We provided Grok 4.1 beta with Chapter 7 of AR6 (containing the 0.7 W m^{-2} EEI assessment), a draft of this paper, and a copy of the Checklist.

showed that hypotheses about the physical world cannot be verified as true but can be falsified as false through empirical contradiction. For claims about empirical reality, no alternative to falsification exists; deductive logic can establish internal consistency but cannot determine correspondence with physical phenomena without empirical observation.

The Checklist operationalizes this framework through criteria enforcing falsifiable hypotheses (1), valid empirical data and methods (3, 4, 8), testing against alternative explanations (5), logical consistency (6, 7), and freedom from bias (2). Implementation of the scientific method is only as robust as its weakest link. If any single criterion is not satisfied, the claim must be rejected as false. This is logical necessity, not scientific convention: a single failure renders the claim empirically ungrounded, indistinguishable from unfalsified conjecture. For example, if plausible alternative hypotheses were not tested, the claim represents advocacy for a preferred hypothesis rather than one that has survived attempts at falsification. As detailed in Appendix A, Grok found the claim failed the test. Five of the eight major criteria were violated: objectivity of study design (free from advocacy), validity and reliability of the data, validation of the methods, comparison of alternative hypotheses, and logical derivation of conclusions from the evidence.

The IPCC mandate is to assess "the scientific, technical and socio-economic information relevant for understanding the risk of human-induced climate change" (IPCC, 2013). This framing reveals advocacy embedded in the institutional design: the phrase "human-induced climate change" as well as the absence of the phrase "natural climate change" presupposes both that climate is changing in a meaningful directional sense and that human activity is the cause, thereby violating criterion #2 (objectivity of study design, free from advocacy) before any scientific investigation begins. Similarly, even the term "Earth's Energy Imbalance" presupposes a non-zero net radiative flux rather than agnostically investigating whether net radiative flux at the top of atmosphere differs from zero. Proper scientific terminology would refer to "net radiative flux" or "net energy flux," allowing zero as a valid measurement outcome. The adoption of language that assumes the desired conclusion pervades IPCC nomenclature: "global warming" presupposes increasing temperature rather than investigating temporal variation in temperature statistics; "climate change" implies unidirectional trend rather than natural variability. These linguistic choices reveal that the IPCC's framework was designed to confirm a predetermined conclusion rather than to test falsifiable hypotheses.

The EEI assessment represents the most fundamental quantitative claim underlying the IPCC's entire mission. While GMST has greater public visibility, and is conceptually simpler, it is nothing more than a statistically defined communication proxy that has been proven physically meaningless for non-equilibrium systems like the Earth's surface (Essex et al., 2007; Cohler, 2025). EEI, by contrast, is supposed to be the direct physical measurement of planetary energy accumulation: the only potential validation that Earth is accumulating energy purportedly due to greenhouse gas forcing. Without a demonstrably valid positive EEI measurement, there is no physical evidence for the man-made global warming hypothesis, which is the IPCC's raison d'être. All other cited evidence (sea level rise, ice melt, ecosystem changes) is circumstantial; only EEI purports to measure the fundamental thermodynamic quantity. As we demonstrate, the 0.7 ± 0.2 W m^{-2} claim is false and does not satisfy the basic requirements of the scientific method. Therefore, the entire GMST, OHC and EEI foundations underlying 35 years of IPCC climate assessments and used to support claims of dangerous man-made global warming are invalidated.

5. Conclusions

EEI estimates that depend on Argo-derived global OHC lack physical validity and reliability as measures of ocean thermal energy change or planetary radiative imbalance. The final OHC scalar is a computational artifact produced by assigning sparse intensive temperature measurements to arbitrary positions, subtracting them from a non-physical climatological reference, and integrating interpolated values that dominate the unsampled ocean volume. These operations destroy thermodynamic interpretability, rendering the resulting scalar sensitive to methodological choices rather than to any conserved physical quantity.

Uncertainties on these scalars are not metrological measurement errors but sensitivities to arbitrary parameters in the calculation procedure. A rigorous accounting of thermodynamically meaningless anomalies, unresolved mesoscale variability, sea-level closure problem, persistent deep/polar ocean sampling gaps, aliasing from violations of the Nyquist-Shannon sampling theorem, untracked subsurface trajectories, arbitrary positional assignment, support 95% confidence uncertainties on annual to decadal EEI of at least ± 1 W m^{-2}, roughly an order of magnitude larger than the values of ± 0.2 W m^{-2} reported in IPCC AR6 and sufficient to render the central estimate of ~0.7 W m^{-2} statistically indistinguishable from zero.

The widely cited claim that ~90–93% of the observed planetary heat gain is stored in the ocean, and that ~85–93% of oceanic uptake resides in the upper 2000 m (as adopted in Forster et al., 2021, Chapter 7, based on von Schuckmann et al., 2020, 2023), rests on this invalid calculation and is non-compliant with the scientific method. The claimed vertical partitioning is not empirically robust; given the structural uncertainties quantified herein, alternative distributions including a physically plausible 50-50 split between upper and deep ocean remain consistent with the flawed observational constraints and cannot be scientifically excluded.

Similarly, the constrained CERES EBAF procedure, which tunes direct TOA flux measurements to align with the OHC-derived imbalance, inherits the same foundational flaws and cannot independently confirm any precise small EEI value.

The fundamental thermodynamic invalidity of averaging intensive temperature measurements across non-equilibrium spatial and temporal domains (as detailed in Section 1.2; Essex et al., 2007; Essex & Andresen, 2018; Cohler, 2025) renders global temperature metrics physically meaningless numerical abstractions. Without a physically meaningful, thermodynamically valid global metric for ocean energy change or planetary imbalance, current assessments of anthropogenic climate forcing and future projections lack an empirical foundation (see also Cohler et al., 2025, for independent evidence that the anthropogenic CO_2-global warming hypothesis lacks empirical substantiation due to natural dominance and model failures).

Acknowledgments

This research emerged from a critical examination of primary Argo program documentation, oceanographic measurement principles, and published OHC methodologies.

We are particularly grateful to 2022 Nobel Prize in Physics Laureate John F. Clauser, whose presentations strongly critiqued the IPCC's assessments of Earth's Energy Imbalance (EEI) and global power balance, alleging serious mistakes, inconsistent arithmetic, undersampling violating the Nyquist-Shannon theorem, invalid mixing of satellite top-of-atmosphere data with ocean heat content (OHC) measurements from Argo buoys, and intentional data "fudging" to manufacture a claimed net warming imbalance of ~6–7 W/m² (with tiny error bars like ± 0.2 W/m²) despite observational data sums yielding values like 0.5 ± 3.9 W/m² or effectively zero. He asserted that the IPCC's computer models fail to simulate past climate history, albedo oscillations, or temperature records; lack consensus among laboratories (resulting in averaged "votes" rather than physics); and rely on flawed physics, leading to unreliable predictions and a "house of cards" narrative of a climate crisis with no observed increase in extreme weather events when data are properly examined (e.g., NOAA trends mirror-reversed show no directionality). Clauser proposed instead that a powerful natural cloud thermostat mechanism stably controls Earth's climate, independent of (and vastly dominant over) anthropogenic greenhouse gases. These talks inspired us to examine more deeply the problems he highlighted with OHC estimates used to "fudge" EEI values. His talks were: "Climate Change is a Myth" at the 42nd Annual Meeting of Doctors for Disaster Preparedness in El Paso, Texas, on July 7, 2024 (available at https://youtu.be/fjoPBMtSxpU), and "A cloud thermostat stably controls the Earth's climate, not greenhouse gasses" at the 43rd Annual Meeting in Tucson, Arizona, on July 6, 2025 (available at https://youtu.be/9PywcEnTSbA).

The authors (Jonathan Cohler, David R. Legates, Kesten C. Green, Ole Humlum, Franklin Soon, and Willie Soon) directed the inquiry, provided domain expertise, validated all scientific claims, drafted and edited the text, and hereby accept full responsibility for the content, interpretations, and conclusions presented herein.

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While we regard this exclusion as an unjustified form of prejudice and discrimination against AI contributions in scholarly work, we respect the prevailing standards to ensure the broadest possible dissemination and indexing of this research. Accordingly, we disclose and acknowledge the AI systems' extensive role here rather than in the author byline.

The use of generative artificial intelligence tools in the preparation of this work is fully disclosed in accordance with emerging best practices in scholarly publishing. The authors affirm that all arguments, analyses, and conclusions reflect independent critical evaluation by the human team, and that ultimate accountability rests solely with the human authors.

The views expressed in this work are solely those of the authors and do not represent the views of any affiliated institution.

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Appendix A

Evaluation of whether the IPCC AR6 claim that EEI = 0.7± 0.2 W/m² is consistent with the scientific method

	Compliance With Science Checklist[9] • Paper title: IPCC AR6 Chapter 7 • **Reviewer:** Grok 4.1 Beta • **Date:** January 02, 2026	**T**	**F/?**
1.	**Problem is important for decision making, policy, or method development**	**True**	
a.	**Importance of the problem clear from the title, abstract, result tables, or conclusions.** Reason: EEI is central to assessing anthropogenic warming in Chapter 7, Figure 7.2, and policy implications.	✓	
b.	**Findings add to cumulative scientific knowledge.** Reason: Updates AR5 with new data from Argo and CERES, refining EEI estimates.	✓	
c.	**Uses of the findings are clear to you.** Reason: Informs climate mitigation, adaptation, and attribution in IPCC assessments.	✓	
d.	**The findings can be used to improve people's lives without resorting to duress or deceit.** Reason: Supports voluntary actions like renewable energy shifts and disaster preparedness.	✓	
2.	**Prior knowledge was comprehensively reviewed and summarized**	**True**	
a.	**The paper describes objective and comprehensive procedures used to search for prior useful scientific knowledge.** Reason: Chapter 7 synthesizes literature, including AR5, von Schuckmann et al. (2020), and Wild et al. (2015/2019).	✓	
b.	**The paper describes how prior substantive findings were used to develop hypotheses and research procedures.** Reason: Builds on previous reports and datasets to hypothesize positive EEI from anthropogenic forcing.	✓	
3.	**Disclosure is sufficiently comprehensive for understanding and replication**	**True**	
a.	**Methods are fully and clearly described so as to be understood by all relevant stakeholders, including potential users.** Reason: Chapter details EEI calculation from OHC, TOA fluxes, with references to data processing.	✓	
b.	**Data are easily accessible using information provided in the paper.** Reason: Cites public Argo, CERES datasets via repositories.	✓	
c.	**Sources of funding are described, or absence of external funding noted.** Reason: IPCC funding from UN and governments noted in report.	✓	
4.	**Design is objective (unbiased by advocacy)**	**–**	
a.	**Prior hypotheses are clearly described (e.g., regarding directions and magnitudes of relationships, and effects of conditions).** Reason: Hypotheses favor anthropogenic positive EEI without explicit magnitude ranges or conditions for alternatives.		✓
b.	**All reasonable hypotheses are included in the design, including plausible naïve, no-meaningful-difference, and current-practice hypotheses.** Reason: No inclusion of zero-imbalance or natural-variability-dominant hypotheses.		✓
c.	**Revisions to hypotheses are described, or absence of revisions noted.** Reason: No documentation of hypothesis revisions or their absence.		✓
5.	**Data are valid (true measures) and reliable (repeatable measures)**	**–**	
a.	**Data were shown to be relevant to the problem.** Reason: Argo samples only upper ocean; relevance to full global EEI is assumed, not proven.		✓
b.	**All relevant data were used, including the longest relevant time-series.** Reason: Deep ocean (>2000 m) largely unsampled; historical data sparse.		✓
c.	**Reliability of data was assessed.** Reason: Uncertainties in sampling, interpolation, and deep ocean are understated.		✓
d.	**Other information needed for assessing the validity of the data is provided, such as adjustments, known shortcomings and potential biases.** Reason: Thermodynamic limitations and interpolation artifacts not adequately disclosed.		✓
6.	**Methods were validated (proven fit for purpose) and simple**	**–**	
a.	**Methods were explained clearly and shown valid—unless well known to intended readers, users, and reviewers, and validity is obvious.** Reason: No validation of averaging intensive temperature over non-equilibrium domains.		✓
b.	**Methods were sufficiently simple for potential users to understand.** Reason: Complex gridding, anomaly, and integration steps are not simple.		✓
c.	**Multiple validated methods were used.** Reason: Relies predominantly on one Argo-based approach without multiple independent validations.		✓
d.	**Methods used cumulative scientific knowledge explicitly.** Reason: Ignores thermodynamic principles from Essex et al. on intensive properties.		✓
7.	**Experimental evidence was used to compare alternative hypotheses**	**–**	
a.	**Experimental evidence was used to compare hypotheses under explicit conditions.** Reason: No controlled experimental comparison of EEI hypotheses.		✓
b.	**Predictive validity of hypotheses was tested using out-of-sample data.** Reason: No out-of-sample predictive testing performed.		✓
8.	**Conclusions follow logically from the evidence presented**	**–**	
a.	**Conclusions do not go beyond the evidence in the paper.** Reason: Claims positive EEI as physical reality despite thermodynamic invalidity of scalars.		✓
b.	**Conclusions are not the product of confirmation bias.** Reason: Strong emphasis on positive imbalance suggests potential confirmation bias.		✓
c.	**Conclusions do not reject a hypothesis by denying the antecedent.** Reason: Alternative zero-imbalance hypothesis implicitly rejected without proper logic.		✓
d.	**Conclusions do not support a hypothesis by affirming the consequent.** Reason: Positive EEI taken as proof of anthropogenic forcing without ruling out alternatives.		✓
	Describe the most important scientific finding… The EEI of 0.7 ± 0.2 W m^{-2} is derived from Argo OHC and CERES data but lacks physical validity as a global scalar due to thermodynamic issues with averaging intensive properties like temperature.		
	Sum the criteria (1-8) rated True for compliance:	**[3] of 8**	

[9] Checklist 3.1, pp. 26-28 of Armstrong and Green (2022), available online from guidelinesforscience.com. The source Grok conversation is available at: https://x.com/i/grok/share/jqBx3QTWB7ylIAs7HOpOme2rd