

1                   **Computational Oceanography is Coming of Age**

2           Thomas W. N. Haine\*, Renske Gelderloos, Miguel A. Jimenez-Urias, Ali H. Siddiqui,

3                   *Earth & Planetary Sciences, Johns Hopkins University, Baltimore, MD*

4                   Gerard Lemson, Dimitri Medvedev, Alex Szalay,

5                   *Physics & Astronomy, Johns Hopkins University, Baltimore, MD*

6                   Ryan P. Abernathey,

7                   *Earth & Environmental Sciences, Columbia University, New York, NY*

8                   Mattia Almansi,

9                   *National Oceanography Centre, Southampton, UK*

10                  Christopher N. Hill

11                  *Earth, Atmospheric, & Planetary Sciences, MIT, Cambridge, MA*

12 \*Corresponding author: Thomas Haine, Thomas.Haine@jhu.edu

## ABSTRACT

13 Computational Oceanography is the study of ocean phenomena by numerical simulation, especially  
14 dynamical and physical phenomena. Progress in information technology has driven exponential  
15 growth in the number of global ocean observations and the fidelity of numerical simulations of the  
16 ocean in the past few decades. The growth has been exponentially faster for ocean simulations,  
17 however. We argue that this faster growth is shifting the importance of field measurements and  
18 numerical simulations for oceanographic research. It is leading to the emergence of Computational  
19 Oceanography as a branch of marine science on par with observational oceanography. Although  
20 some specific limits and challenges exist, many opportunities are identified for the future of Compu-  
21 tational Oceanography. Most important is the prospect of hybrid computational and observational  
22 approaches to advance understanding of the ocean.

23 *Capsule summary.* Computational oceanography is an emerging discipline that asserts that high-  
24 resolution numerical ocean circulation models have the potential to be equally valuable as data  
25 from the natural ocean.

## 26 **1. Introduction**

27 The number of observations of the global ocean has grown tremendously over the last several  
28 decades. Oceanography has been transformed by this growth, particularly, knowledge of ocean  
29 circulation and dynamics, and the ocean's role in Earth's climate. Meanwhile, the fidelity of ocean  
30 general circulation models (OGCMs) has also grown tremendously. We are reaching the point that  
31 some OGCM solutions are essentially indistinguishable from observations (see Fig. 1). In the words  
32 of Ed Lorenz, we should anticipate that numerical "experiments will...duplicate the circulation to  
33 any desired degree of accuracy" (Lorenz 1967).<sup>1</sup> This essay explores the history of this growth  
34 and its prospects. We show that ocean observations and OGCMs have grown at different rates. We  
35 argue therefore that OGCMs are becoming equally important as ocean observations in advancing  
36 oceanography. We call this the coming of age of Computational Oceanography.

## 37 **2. Unequal Exponential Growth**

38 Two examples illustrate the growth of ocean observations. First, consider temperature observa-  
39 tions in the global deep ocean over the last half century. Fig. 2a shows the cumulative number  
40 of temperature observations deeper than 1000m. They have grown exponentially (notice the y  
41 axis is logarithmic). Averaged over the last century, the exponential growth has a doubling period  
42 of 10.5 years, giving an approximately 50-fold expansion in the deep temperature database since  
43 1960. Technology transitions have maintained this exponential growth, specifically, advances

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<sup>1</sup>The prescient Lorenz was writing about atmospheric models in the late 1960s, but the message applies to OGCMs today.

44 in micro-electronics and information technology. In the 1990s conductivity-temperature-depth  
45 (CTD) sensors on autonomous profiling floats took over from ship CTD sampling, for example,  
46 leading in the 2000s to the transformative Argo global float network (Argo 2020).

47 Second, consider the history of sea level observations from satellite altimeters. Sea level data  
48 have revolutionized physical oceanography by providing information on the surface circulation,  
49 mesoscale eddies, tides, and sea level change. Fig. 2b shows the sequence of altimeter missions  
50 (coloured bars) and the cumulative number of observing days (black line). The number of observing  
51 days reveals the growth in sea level observations (although there is great variety between missions).  
52 The number of sea level observations has grown nearly exponentially since the mid 1980s with a  
53 doubling time of about 8.2 years and a  $\approx 20$ -fold expansion in the sea level database since 1985.  
54 Again, micro-electronic and information technology advances have maintained this growth.

55 Technology advances have also fueled growth in the fidelity of OGCMs. For example, Fig. 2c  
56 shows the history of global OGCM resolution. We use the global ocean models from the Inter-  
57 governmental Panel on Climate Change (IPCC) reports and measure the model resolution with the  
58 total number of grid points. The peak resolution of the ocean OGCMs in the first IPCC report  
59 was  $2.7^\circ$  with 9 vertical levels. The peak resolution in the latest (sixth) IPCC report is  $0.067^\circ$   
60 with 75 vertical levels. The growth in OGCMs is exponential with a doubling time of 2.8 years  
61 and a 1700-fold increase since 1990. For the most highly-resolved models in each assessment, the  
62 doubling time is even faster at 2.1 years.

63 Now compare the horizontal resolution of ocean measurements with OGCM resolution. The  
64 Argo profiling float network operates about 4000 floats at any one time. Each float makes a vertical  
65 profile from 2000m depth to the surface every ten days. The global average spacing of profiles

66 is therefore 300km.<sup>2</sup> The spacing between altimeter tracks for the TOPEX/Poseidon and Jason  
67 satellite altimeters is also about 315km (at the equator), with a repeat period of ten days. The  
68 present day peak OGCM resolution of  $0.067^{\circ} \approx 7\text{km}$  is therefore 40 times higher.

### 69 **3. Prospects for Future Growth**

70 Looking ahead, the future is bright for the Argo network. The reason is that Argo is part of  
71 the Global Ocean and Global Climate Observing System, which implements the Paris Agreement  
72 on climate change and United Nations sustainable development goals. New capacities, like deep  
73 profiling floats, and new technologies, like biogeochemical sensors, are planned over the next few  
74 years (GCOS 2016). It is unclear how the network can double in size in the next decade and  
75 maintain long term exponential growth, but it is plausible.

76 The future is also bright for sea level measurements. The Surface Water and Ocean Topography  
77 (SWOT) mission, scheduled for launch in 2022, will start a new era of sea level observation. SWOT  
78 will observe sea level over a swath, rather than over a single patch. It will have 15km resolution,  
79 or better, covering most of the global ocean every 21 days (Morrow et al. 2019). It will improve  
80 the spatial resolution of sea level data by a factor of about ten. Therefore, the prospects for the  
81 altimetry record to continue growing exponentially in the 2020s are good.

82 For OGCMs, resolution improves as supercomputer technology advances. Historically, that  
83 follows Moore's "law," which says that transistor density in microprocessors doubles every two  
84 years (Moore 1975). For instance, machines first achieved petaflop speeds ( $10^{15}$  floating point  
85 operations per second) in 2008 and exaflop speeds ( $10^{18}$ ) in March 2020, a doubling every 1.1  
86 years (see Fig. 2d). On this basis, the OGCM resolution will probably continue to double every 2.8

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<sup>2</sup>The vertical resolution of Argo profile data is about 5m, which is about 7 times higher than the best AR6 OGCMs and about 3 times higher than the Poseidon Project run mentioned below.

87 years, at least for another few years. It is reasonable to expect exascale IPCC OGCMs by the mid  
88 2020s with horizontal resolutions of a few kilometers. After that, with widespread anticipation  
89 that Moore's law will end (Waldrop 2016), future growth is uncertain. Exploiting new application-  
90 specific hardware accelerators and new OGCM software architectures, like lower precision (Palem  
91 2014), will be crucial.

#### 92 **4. Regime Shift**

93 This evidence shows that information technology advances are driving exponential growth in  
94 ocean observations and exponential growth in OGCM resolution. But the OGCM growth rate  
95 is faster. Therefore, OGCM resolution is also growing exponentially faster than the growth in  
96 ocean field data. This faster growth points to a regime shift in the scientific importance of  
97 OGCMs. In 1990, OGCMs were obviously biased compared to measurements, for example, of  
98 deep temperatures or sea level. In 2020, OGCMs are achieving resolutions that are substantially  
99 greater than the gaps between measurements, at least for some regimes, like deep and abyssal ocean  
100 currents.

101 We should expect this trend to continue for the foreseeable future. Therefore, physical oceanog-  
102 raphy is leaving the era in which most knowledge came from observations of the real ocean.  
103 It is entering an era in which numerical circulation models are as important as observations  
104 for advancing knowledge. The ascending methodology in this new era we call **Computational**  
105 **Oceanography**. We argue that it is emerging as a new branch of marine science.

## 5. Emergence of Computational Oceanography

What are the criteria to claim that OGCM solutions should be treated, in some cases, as seriously as real measurements? Realizing them would mark the emergence of Computational Oceanography.

These criteria are on our checklist:

### 1. Confidence in the fidelity of the basic tools and methods. Consider two types of tool:

First, consider the theoretical definition of the ocean circulation problem. Computational Oceanography relies on software to compute approximations to the incompressible rotating-stratified Navier Stokes equations, with equations for the conservation of dissolved salts and heat (McWilliams 1996; Fox-Kemper et al. 2019). There is little doubt that these are the right equations for ocean circulation. The software is mature, stable, and diverse. The issue of unresolved processes, and parametrizing their effects remains an important area of research. For example, it is still unclear how to represent unresolved submesoscale processes on the larger scale flow. Although much progress has been made on this problem in the last 30 years (Gent 2011; Fox-Kemper et al. 2019), we believe that resolution improvements have been more important (Fig. 2d). In other words, we believe that the problem of parametrizing unresolved scales is not so pathological that it contaminates all of the resolved scales. A corollary is that OGCMs are less complicated than the real ocean, meaning that OGCM variability is a lower bound on the variability in the real system. These are *de facto* working hypotheses of all theoretical and numerical approaches to understanding the ocean circulation.

Second, we need tools to adjust OGCM solutions to agree with observations; that is, to solve the data assimilation and state estimation problem (Bennett 1992; Wunsch 1996, 2006; Kalnay 2002). For example, state estimation is used to produce retrospective reanalyses of the time-evolving ocean state and data assimilation is used to initialize prospective forecasts

129 of the future. Although many questions remain open, these methods are also now mature,  
130 stable, and diverse.

## 131 2. **The number of OGCM degrees of freedom exceeds the number of observational con-**

132 **straints.** This criterion concerns the state estimation and data assimilation problems. In  
133 essence, it is about whether it is possible (in principle) to adjust an OGCM solution to fit the  
134 observations exactly or not. If the OGCM can be adjusted to fit the data exactly, the state esti-  
135 mation problem is under-determined. Otherwise, it is over-determined.<sup>3</sup> For example, fitting  
136 a straight line through three distinct data points is over-determined because no line exists that  
137 passes through all three points (in general). But fitting a quadratic curve through two data  
138 points is under-determined because an infinite number of quadratic curves will pass through  
139 the points. The number of OGCM degrees of freedom scales as the number of grid points.  
140 The number of observational constraints scales as the number of distinct measurements. Fig. 2  
141 shows evidence that the number of OGCM grid points per observational constraint exceeds  
142 one because, loosely, the peak OGCM resolution is now 40 times higher than the Argo and  
143 Jason data spacing. This gap is growing exponentially because OGCM resolution is growing  
144 exponentially faster than data density. Therefore, the state estimation problem is moving from  
145 (in principle) being over-determined to under-determined.

146 Crossing this threshold has interesting implications: First, OGCMs pass Turing or Feigen-  
147 baum tests (Turing 1950; Feigenbaum 2003; Harel 2005). That is, OGCM solutions become  
148 indistinguishable from observations of the real ocean and a subject-matter expert cannot tell  
149 them apart. In our regional OGCM simulations of the Denmark Strait Overflow (DSO) at  
150 resolutions of 0.5–2km, we are approaching this point (Fig. 1, Magaldi and Haine 2015;

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<sup>3</sup>Ignoring the atypical case of the problem being exactly determined.

151 Almansi et al. 2020). Similarly, our high-resolution, regional state estimates are nearly  
152 under-determined (Lea et al. 2006; Dwivedi et al. 2011).

153 Second, the OGCM solutions make accurate, testable predictions about the real ocean. His-  
154 torically, advances from theoretical and numerical research in dynamical oceanography have  
155 lagged advances from observational research. Once OGCMs become under-determined by  
156 data, it will be common for them to make predictions that can be tested by field programs.  
157 For example, our DSO simulations show exchange of dense water out of the overflow onto  
158 the east Greenland continental shelf, and vice versa (Magaldi et al. 2011). They also show  
159 entrainment of near-surface waters south of Iceland into the DSO within a few months, at  
160 least during hard winters (Saber et al. 2020). It remains to be seen if these predictions occur  
161 in the real ocean.

## 162 **6. Limits to Computational Oceanography**

163 Although these opportunities are exciting, there are clear limits to Computational Oceanography.  
164 Specifically, direct numerical simulation (DNS) of the global ocean circulation is inconceivable  
165 today. DNS in this context means running OGCMs that resolve all scales of motion; from the  
166 planetary scale to the dissipation scale (around 1mm), and from centuries to seconds. DNS would  
167 avoid the challenge of parametrizing the effects of the unresolved scales, but at vast computational  
168 cost. Fig. 3 shows why. It shows the full range of space and time scales relevant to the ocean  
169 general circulation, about ten orders of magnitude in both. It also shows the space time volumes  
170 accessible to present-day supercomputers, including the best AR6 OGCMs shown in Fig. 2, the  
171 Poseidon Project run, and turbulence simulations (DNS and large eddy simulations, LES). To span  
172 the entire space time plane, super computers would need to resolve about  $10^{25}$  grid points and  
173  $10^{10}$  time steps. That is about 16 orders of magnitude more grid points than is possible today.

174 Extrapolating the doubling time of 2.8 years in Fig. 2c, it would take 150 years to achieve this  
175 increase, which is impossible to envision. Clearly, OGCM simulations cannot replace observations  
176 of the natural ocean.

## 177 **7. Opportunities for Computational Oceanography**

178 The opportunities for Computational Oceanography to advance marine science include:

- 179 • Migration from the study of specific instances of phenomena to the study of statistics of these  
180 phenomena. The DSO is one of many currents that is affected by rotation, stratification,  
181 and bathymetry. It is inconceivable to observe all of them, but they can all be simulated  
182 in an exascale OGCM. Empirical characterization of these numerical overflows would be an  
183 important step forward.
- 184 • Discovery and characterization of intermittent, time-dependent, three-dimensional phenom-  
185 ena, which are hard to observe. Submesoscale currents are in this class, which occur at  
186 horizontal scales shorter than several kilometers (Thomas et al. 2008). Diapycnal mixing is  
187 another example, which occurs at scales shorter than meters (MacKinnon et al. 2017).
- 188 • Comprehensive and illuminating analyses of ocean mass, heat, salt, momentum, energy, and  
189 vorticity budgets, in a way that is nearly impossible with direct observations.
- 190 • Discovery and characterization of ocean circulation regimes that cannot be observed. Ex-  
191 amples include the circulation during the last glacial maximum (paleo-oceanography) or in  
192 extra-terrestrial oceans (exo-oceanography). For these ocean circulation problems, the data-  
193 sparseness challenge is much worse than for the modern ocean (LeGrand and Wunsch 1995;  
194 Amrhein et al. 2018; Way et al. 2017). Criterion 2 was achieved with smaller computational

resources for these fields, and therefore they have already entered the era of Computational Oceanography by the rationale in section 5.

- Robust observing system design using OGCM solutions as synthetic data. These Observing System Simulation Experiments (Errico et al. 2012) should become the best-practice standard for fieldwork design. There are implications for making the OGCM output accessible and easy to work with (see below), but the payoff from engaging observational oceanographers is great.
- Insight from OGCM state estimation to support fieldwork, ideally in real time. The community should embrace the fact that the under-determined state estimates imply an infinite number of OGCM solutions that match the data exactly. This means that techniques are needed to characterize and handle the OGCM null space (indeterminacy). For example, observational oceanographers at sea could make decisions about where, when, and how to observe using OGCM information that captures the range of possible circulation states consistent with data. This practice is common in atmospheric science already.
- More efficient identification of interesting phenomena using automatic methods, like artificial intelligence and data mining (Kutz 2017; Lguensat et al. 2019). In fact, such automatic methods will become essential as the size of OGCM output grows exponentially and overwhelms manual feature identification (see below).
- Increasing transition of dynamical oceanography to an experimental (computational) science. It has long been recognized that idealized models isolate physical mechanisms relevant to the general circulation and thereby build dynamical understanding. We still require idealized models; in particular, we need a hierarchy of models that span the gap between geophysical fluid dynamics problems and realistic simulations of the circulation. This hierarchy will

218 ensure that the increasing OGCM realism does not outpace understanding of the basic physics  
219 (Held 2005; Vallis 2016; Emanuel 2020).

## 220 **8. Prospects for Computational Oceanography**

221 How can these priorities be achieved and what are the prospects for Computational Oceanogra-  
222 phy? We should focus on these issues in the next several years:

- 223 • OGCM simulation output must be “democratized” to lower barriers to dissemination. The  
224 output should be freely available, including to non-professional users. Traditionally, effort  
225 has focused on the challenges of calculating OGCM solutions with supercomputers. The  
226 OGCM output has become increasingly harder to use, because of the massive data volume,  
227 and the technical complexities that attend the high-performance computation. Access to  
228 high-resolution OGCM output is restricted to a few experts in practice.

229 The remedy is to build high-performance data science infrastructure to match the high-  
230 performance compute infrastructure. These data portals must be open and have low thresholds  
231 to getting started. We must be able to sample the simulations the way that we sample the real  
232 ocean. For example, it should be easy for an observational oceanographer to plot a synthetic  
233 hydrographic section or mooring timeseries. The data portals must include open software  
234 and significant compute resources to process and analyze the simulation data. We must avoid  
235 the inefficient practice in which users are forced to download voluminous data to their local  
236 machines and then write their own code to analyze them. Technologies and infrastructure  
237 to achieve these goals are under development, such as the OceanSpy OGCM data analysis  
238 package (Almansi et al. 2019), the Pangeo community in geoscience big data ([pangeo.io](http://pangeo.io)),  
239 the SciServer big data science platform (Medvedev et al. 2016), and other cloud analysis  
240 clusters.

241 • “Benchmark” OGCM reference solutions should be computed using the best available compute  
242 resources and served to the public. For example, we are computing global OGCM solutions  
243 at (nominally) 1km horizontal resolution as part of the Poseidon Project ([poseidon.idies.  
244 jhu.edu](http://poseidon.idies.jhu.edu)).<sup>4</sup> Such benchmark solutions are of intrinsic value to all oceanographers, not  
245 just ocean modellers, for the reasons stated above. Benchmark solutions for regional ocean  
246 circulation problems are valuable for the same reasons, as are idealized simulations of specific  
247 ocean dynamical processes. The track record of other fields using this approach is impressive.  
248 For instance, the Johns Hopkins Turbulence Database exposes large-scale turbulent data to  
249 researchers and provides easy-to-use interfaces to retrieve and interact with the data using novel  
250 metaphors like immersing virtual sensors into the 4-D data ([turbulence.pha.jhu.edu](http://turbulence.pha.jhu.edu);  
251 Perlman et al. 2007; Li et al. 2008).

252 • OGCMs will migrate to exascale compute resources in the next few years. This migration will  
253 involve new paradigms to access the data. For example, with today’s petaflop supercomputers  
254 only about 0.1% of the OGCM solution can be permanently stored for analysis. The problem  
255 arises because of the prohibitive time needed to transfer the massive output volume to long-  
256 term storage media, and the prohibitive expense of the media. This loss of OGCM data will  
257 be much worse on exaflop machines.

258 To mitigate this problem consider the strategy adopted by the Large Hadron Collider (LHC),  
259 the world’s most sophisticated experimental facility. The LHC provides a single source of data  
260 on subatomic particle collisions. Several experiments tap the data stream in so-called “beam-  
261 lines.” Within each experiment, customized hardware monitors the stream. Only about one  
262 event in ten million is retained for storage and detailed analysis. In exascale oceanography the  
263 analogous idea (see section 3.3.5 in Asch et al. 2018) is to enable automatic identification of

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<sup>4</sup>The Poseidon Project is unrelated to the TOPEX/Poseidon altimeter.

264 selected circulation events and trigger storage while the OGCM runs. For example, we could  
265 target intermittent intense mixing events, plus their antecedents and fates. An implication is  
266 that we must build a software interface for community-supplied software plugins to implement  
267 the custom triggers. Also, we need to enable posterior re-computation of small space-time  
268 chunks of the full solution, with customized diagnostics, and possibly at higher resolutions.

269 Computational Oceanography promises powerful new tools to address previously intractable  
270 problems. It does not aim to supplant observational oceanography. Indeed, observing the natural  
271 ocean must never cease. Instead, the greatest opportunity lies in merging these hitherto disparate  
272 branches of our field. Lasting progress will require that we trust computational insights, verify  
273 them with real world observations, and understand them with fundamental theory.

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277 *Data availability statement.* Codes to make the figures are available at  
278 [github.com/hainegroup/Computational-Oceanography-Commentary](https://github.com/hainegroup/Computational-Oceanography-Commentary). Fig. 1 is  
279 based on model and field data in Haine (2010). For Fig. 2, the temperature data  
280 are from the National Centers for Environmental Information World Ocean Database,  
281 the altimeter mission data are from [www.altimetry.info](http://www.altimetry.info), the IPCC data are from  
282 the IPCC reports and [pcmdi.llnl.gov/CMIP6](http://pcmdi.llnl.gov/CMIP6), and the supercomputer data are from  
283 [en.wikipedia.org/wiki/List\\_of\\_fastest\\_computers](http://en.wikipedia.org/wiki/List_of_fastest_computers). The data for AR6 are from the  
284 HighResMIP project in July 2020, which was incomplete then. Fig. 3 is based on Klinger and  
285 Haine (2019).

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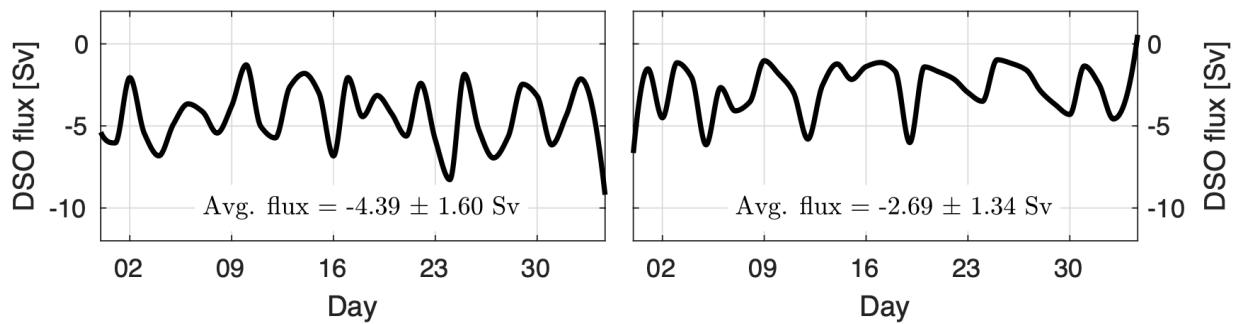
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392 371 pp.

393 **LIST OF FIGURES**

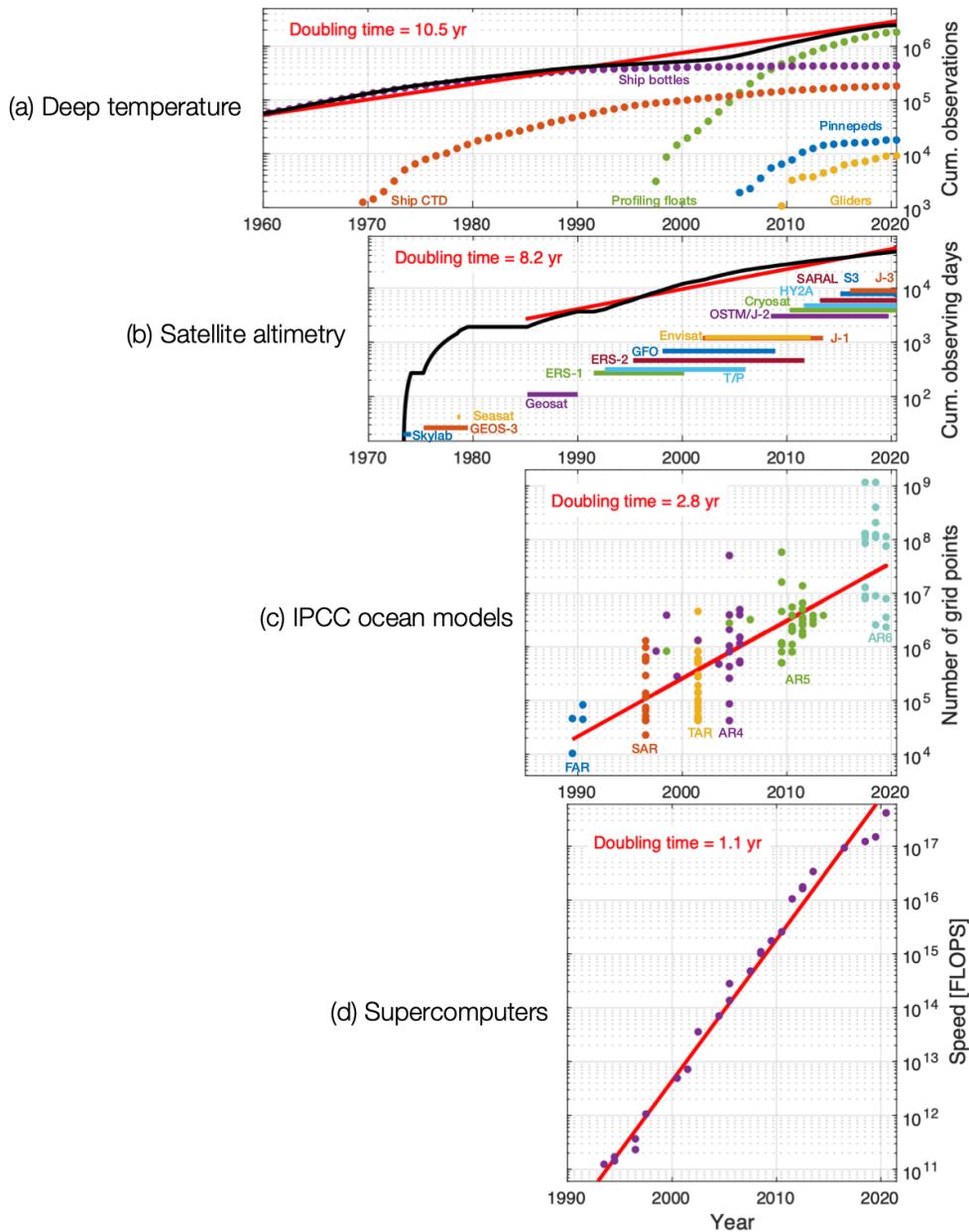
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406 of model grid points. Each coloured dot represents one ocean model: the colour indicates  
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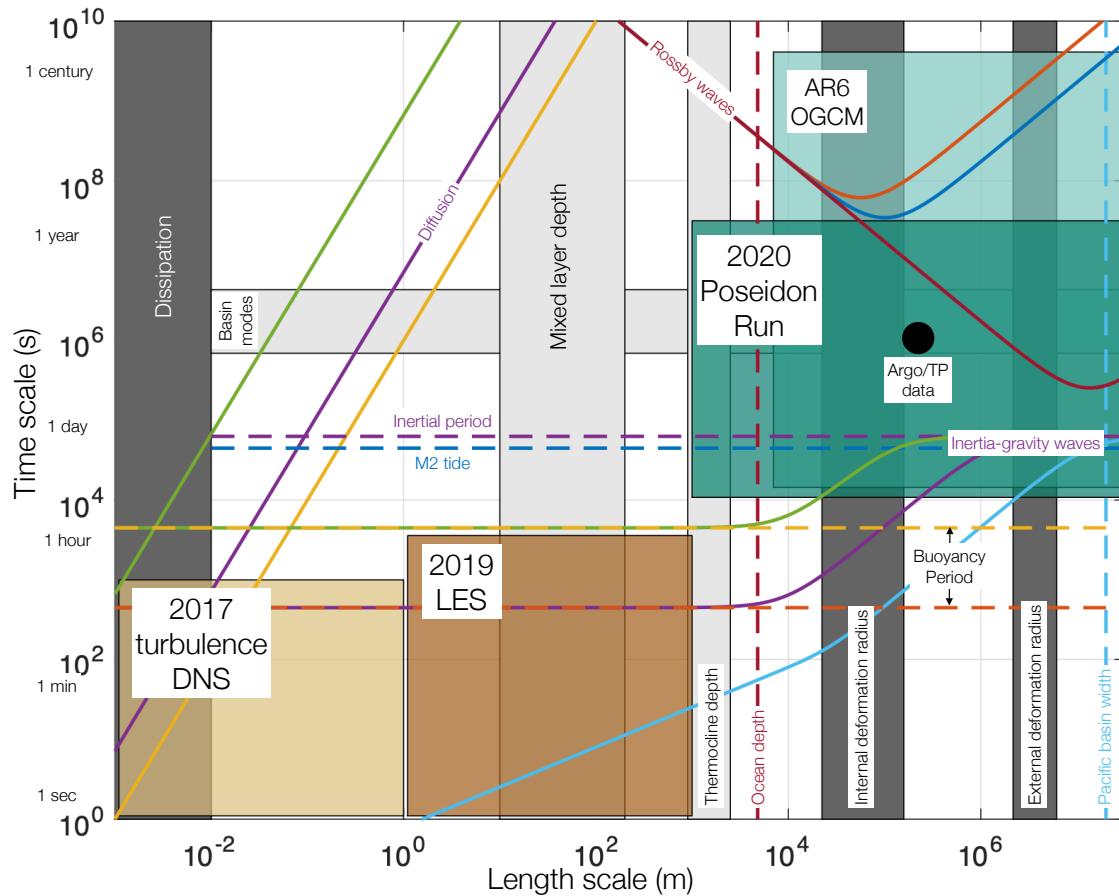
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