

1 Emergence of multiple ocean ecosystem **drivers** in a large 2 ensemble suite with an Earth System Model

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11 12 **Abstract**

13 Marine ecosystems are increasingly stressed by human-induced changes. These ocean **drivers** –
14 including warming, acidification, deoxygenation and perturbations to biological productivity -
15 can co-occur in space and time, but detecting their trends is complicated by the presence of noise
16 associated with natural variability in the climate system. Here we use Large Initial-Condition
17 Ensemble Simulations with an Earth System Model under a historical/RCP8.5 pathway over
18 1950-2100 to consider emergence characteristics for the four individual and combined
19 drivers. Using a one-standard deviation (67% confidence) threshold of signal-to-noise to define
20 emergence with a 30 yr trend window, we show that ocean acidification emerges much earlier
21 than other drivers, namely during the 20th century over most of the global ocean. For biological
22 productivity, the anthropogenic signal does not emerge from the noise over most of the global
23 ocean before the end of the 21st century. The early emergence pattern for sea surface temperature
24 in low latitudes is reversed from that of subsurface oxygen inventories, where emergence occurs
25 earlier in the Southern Ocean. For the combined multiple-driver field, 41% of the global ocean
26 exhibits emergence for the 2005-2014 period, and 63% for the 2075-2084 period. The combined
27 multiple-driver field reveals emergence patterns by the end of this century that are relatively high
28 over much of the Southern Ocean, North Pacific, and Atlantic, but relatively low over the tropics

1 and the South Pacific. For the case of two drivers, the tropics including habitats of coral reefs
2 emerges earliest, with this driven by the joint effects of acidification and warming. It is precisely
3 in the regions with pronounced emergence characteristics where marine ecosystems are expected
4 to be pushed outside of their comfort zone determined by the degree of natural background
5 variability to which they are adapted. The results underscore the importance of sustained multi-
6 decadal observing systems for monitoring multiple ecosystems drivers.

7

8 **1 Introduction**

9 An important priority in climate research is to understand the potential vulnerabilities of marine
10 ecosystems in the face of anthropogenic climate change (e.g. Doney et al., 2012). Over the last
11 decade, multiple drivers of marine ecosystems such as ocean warming, ocean acidification,
12 nutrient stress and low oxygen levels have been identified to be among those of greatest concern
13 (e.g. Gruber, 2011; Hall et al., 2013). We have chosen to use “drivers” rather than “stressors” as
14 some drivers (for example temperature) can be beneficial to some organisms or processes. On a
15 global scale, the development of these drivers is largely a consequence of the increase in
16 atmospheric CO₂ and the associated climate change. The oceanic response to these changes,
17 namely the oceanic uptake of excess heat and anthropogenic CO₂ causes ocean warming and
18 ocean acidification, i.e. a decrease in both oceanic pH and in the saturation state of seawater with
19 regard to mineral calcium carbonate (Doney et al. 2009). The warming of the ocean tends to
20 stratify the upper ocean (Sarmiento et al. 1998), leading to a reduced supply of nutrients to the
21 euphotic zone (Bopp et al. 2001, Steinacher et al. 2010), but also to a reduced resupply of oxygen
22 to the ocean’s interior (Frölicher et al., 2009; Keeling et al., 2010), causing a loss of oxygen
23 there. The magnitude of these global drivers will likely continue to grow, given current trends in
24 fossil fuel CO₂ emissions and the strong inertia within the global community with respect to
25 efforts to decarbonize (Friedlingstein et al., 2014).

26

27 The detection of secular trends in driver fields on regional- to global-scales is complicated by the
28 presence of natural variability in the climate system, as has been shown for dissolved oxygen by
29 Frölicher et al. (2009). The presence of background natural variability motivates the introduction

1 of the concept of emergence to identify where the signal (the secular trend) becomes larger than
2 the noise (the background natural variability). Identifying and understanding when and where the
3 secular trends in ocean drivers emerge above the noise is important for two reasons. The first
4 reason is that emergence characterizes when the secular trend becomes evident or perceptible
5 locally relative to the background variability for an observer. This is intended as a predecessor
6 step to considering perceptible changes for the ecosystems themselves, as emergence or
7 perceptible change to an observer will be a necessary but not sufficient condition for perceptible
8 change being experienced by ecosystems. For example, most organisms are not very sensitive to
9 O₂ levels as long as the O₂ concentrations are sufficient. However below a critical threshold (e.g.
10 hypoxia) many organisms start to suffer from several physiological stresses (e.g. Vaquer-Sunyer
11 and Duarte, 2008). The value of Earth System Models is that they can characterize perceptible
12 change from the vantage point of an observer. The second reason is that understanding of the
13 emergence of multiple drivers will be important for optimizing the design of the ocean observing
14 system. Inferring trends in drivers from Repeat Hydrography is complicated by natural
15 variability in the ocean (Rodgers et al., 2009), and natural variability can also complicate trend
16 detection using time series data (Henson et al., 2014).

17
18 Previous studies exploring the concept of emergence have largely focused on physical state
19 variables of the atmosphere and ocean, such as temperature, precipitation and sea level (e.g.
20 Diffenbaugh and Scherer, 2011; Hawkins and Sutton, 2012; Mahlstein et al., 2012; Mora et al.,
21 2013; Lyu et al., 2014). Mora et al. (2013), for example emphasized that the tropics, which hold
22 the worlds greatest diversity of marine species, will exhibit emergence in ocean warming ten
23 years earlier than any of the other global ocean regions. Far less attention has been devoted to
24 date to signal-to-noise ratios in ocean biogeochemistry, a notable exception being the study of
25 Keller et al. (2014).

26
27 Here we introduce a new suite of Large Initial-Condition Ensemble Simulations using an Earth
28 System Model to understand the local emergence characteristics of the ocean ecosystem drivers
29 sea surface temperature (SST), sea water saturation state with respect to aragonite (Ω_{arag}), a

1 mineral phase of calcium carbonate, oxygen levels (O_2), and net primary productivity (NPP) over
2 an interdecadal (30 yr) timescale. The ocean state as expressed in SST exhibits pronounced
3 decadal-to-interdecadal variability (Zhang et al., 1997), and variations on this timescale are well
4 documented for oxygen (Emerson et al., 2004; Mecking et al., 2008; Kouketsu et al., 2010;
5 Takatani et al., 2012). This has also been considered for the case of phytoplankton in the study
6 of Martinez et al. (2009).

7 In opting to use a suite of Large Initial-Condition Ensemble Simulations, we emphasize in
8 particular the uncertainty in estimates of emergence due to natural variability inherent in the
9 climate system. Deconvolving the signature of the forced response from the background natural
10 variability with one coupled model requires Large Initial-Condition Ensemble Simulations. Only
11 with a sufficiently large number of ensemble members can the effects of natural variability be
12 removed by averaging over the ensemble members. With a single model run of a coupled climate
13 model one is forced to estimate noise either from simulated pre-industrial variability or through
14 high-pass filtering of a scenario run (e.g. Deser et al., 2014). The problem is that the forced
15 response is in general imbedded in a stochastic dynamical system that exhibits variability on all
16 timescales. Additionally, the amplitude of major modes of variability such as El Nino-Southern
17 Oscillation (ENSO) is not stationary in their amplitude over climate change timescales
18 (Timmermann et al., 1999). The ensemble approach to coupled modeling thereby offers an
19 important opportunity when applied to the case of ecosystem drivers (Frölicher et al., 2009).

20

21 **2 Methods**

22 **2.1 Model and simulations**

23 We conducted 30 ensemble simulations over the 1950-2100 period following historical and
24 RCP8.5 concentration pathways (van Vuuren et al., 2011). All 30 ensemble members are run
25 with the same coupled Earth System Model developed at the Geophysical Fluid Dynamics
26 Laboratory (Dunne et al., 2012; Dunne et al., 2013): GFDL's ESM2M. The physical state model
27 underlying ESM2M is the updated version of the coupled model CM2.1 (Delworth et al., 2006),
28 consisting of the 1-degree version of the MOM4p1 ocean model (Griffies, 2009) coupled to an
29 approximately 2-degree configuration of the AM2 atmospheric model (Anderson et al., 2004).

1 The ocean biogeochemical model is Tracers of Ocean Phytoplankton and Allometric
2 Zooplankton code version 2 including 30 tracers to represent cycles of carbon, oxygen, and the
3 major macronutrients and iron (Dunne et al., 2010).

4
5 The initial conditions for the 30 ensemble members for January 1st 1950 differed in the initial
6 state of the atmosphere/land/ocean/sea ice components of the Earth System Model. This was
7 accomplished by using model state snapshots for the ends of days 1-29 in January 1950 as the
8 initial model states for January 1st 1950 for each of the ensemble members 2-30. As has been
9 shown by Wittenberg et al. (2014) using significantly smaller initial perturbations to the ocean
10 component only with nearly the same underlying physical coupled model, our initial condition
11 perturbations lead to a randomization of the ENSO state amongst the individual ensemble
12 members within five years. Given that decadal modulations of ENSO are the most pronounced
13 driver of Tropical Pacific Decadal variability in the underlying physical coupled model
14 (Wittenberg, 2009), decadal variability emanating from the tropics will be randomized amongst
15 the individual ensemble members.

16
17 The four drivers considered in this study are (i) surface Ω_{arag} , (ii) SST, (iii) subsurface O₂
18 vertically integrated from 100m to 600m, and (iv) NPP vertically integrated over the top 100m.
19 Our focus on subsurface O₂ concentrations is intended to characterize regimes ranging from
20 oxygen minimum zones to the main thermocline of polar and circumpolar regions.

21

22 **2.2 Confidence intervals and detection of time of emergence**

23 In order to quantify emergence characteristics, it is necessary to specify a timescale over which
24 trends are calculated. We use decadal trends considered over 30 yr intervals on a gridpoint-by-
25 gridpoint basis to quantify signal-to-noise ratios for each of the four drivers. The signal is the
26 linear trend obtained using the ensemble-mean, and the noise is the standard deviation of the 30
27 yr trends for the individual ensemble members. The signal-to-noise ratio is thereby calculated as
28 the ratio of these two terms, and thereby associated with this specific timescale. The choice of a

1 30 yr trend window is motivated by the approximate length of relatively continuous elements of
2 the global observing system and by the timescale of important natural variability events such as
3 the Pacific Decadal Oscillation. Given that our model runs span 1950-2100, and our choice of 30
4 yr trends, signal-to-noise can effectively be calculated over each year spanning the period 1965-
5 2085.

6
7 Central to our analysis is the model-derived quantification of confidence intervals for trend
8 detection. We assume that the 30 yr trends for the 30 individual ensemble members are normally
9 distributed. For a given time-window (30 yr), the signal-to-noise ratio (SNR) is calculated using
10 the relationship between the ensemble mean TREND and the standard deviation (σ_{noise}) of the
11 trends of the various ensemble members, which we denote as NOISE:

12

$$13 \text{ SNR} = \text{TREND} / \text{NOISE}. \quad (1)$$

14

15 Here we focus on a threshold of one for SNR, representing a confidence interval of 67% for
16 emergence. In other words, the threshold of one is used to characterize when the “signal” of
17 anthropogenic climate change rises above the “noise” of natural background variability.
18 However, the sensitivity to a choice of two (95% **confidence**) for the threshold will also be
19 considered. We choose two time intervals over which we consider average confidence intervals:
20 the first is for the most recent decade 2005-2014, and the second is the decade 2075-2084
21 towards the end of the 21st century. The confidence intervals are calculated using 30 yr trends
22 year-by-year over each of the 10 yr intervals before considering 10 yr averages over the
23 respective intervals. An averaging interval of 10 yr was sufficient to remove noise present in
24 analysis for individual years in the confidence intervals, presumably due to the fact that even with
25 30 ensemble members the modes of variability aren’t sufficiently randomized.

26

27 **Additionally, we also consider the sensitivity of the confidence intervals to the choice of the**
28 **width of the trend window. To that end, confidence intervals are also considered for the case of a**

1 10 yr window. From the spectral SST characteristic of the underlying coupled
2 (atmosphere/ocean) model, it has been shown in Fig. 2 in Wittenberg (2009) and Fig. 7 in Dunne
3 et al. (2012) that SST variability is more pronounced over 10 yr timescales than over 30 yr
4 timescales. Thus one may well expect that the signal-to-noise ratio characteristics for the
5 ecosystem drivers reflect these underlying dynamical drivers of variability, at least in the
6 equatorial Pacific. Thus our sensitivity analysis is intended to offer insight into both of our
7 primary interests described in the Introduction, namely identification of perceptible changes for
8 an observer and optimization of the observing system.

9
10 Our analysis also includes diagnostics of Time of Emergence (ToE). In contrast to the
11 confidence interval diagnostic for fixed time intervals, ToE requires that we first specify a fixed
12 threshold (here we choose 67%) for confidence intervals and then calculate the time (year) at
13 which that is satisfied on a gridpoint-by-gridpoint basis for each driver. For consistency, a 30 yr
14 trend window is used here as well in the calculation of ToE.

15 16 **3 Results**

17 **3.1 Temporal hierarchy of global and regional emergence of individual drivers**

18 We start the analysis with the temporal hierarchy of emergence for the globe as well as for
19 various regions, such as the Southern Ocean (90-45°S), the southern subtropics (45-15°S), the
20 equatorial band (15°S-15°N), the northern subtropics (15-45°N), and the subpolar and polar
21 Northern Hemisphere (45-90°N) (**Fig. 1**). For each driver, the signal-to-noise ratio was calculated
22 gridpoint-by-gridpoint, and then the area-weighted mean of this quantity were considered by
23 region year-by-year (solid lines in **Fig. 1**). There is a distinct hierarchy in the emergence of the
24 drivers on a global scale (**Fig. 1a**), with Ω_{arag} (grey line in **Fig. 1a**) already having risen above the
25 one-standard deviation (67%, black solid vertical axis in **Fig.1a**) level by the beginning of the
26 period considered (by 1965). This is followed by SST (orange line in **Fig. 1a**), which globally
27 emerges from the 67% confidence level by the year 2000. O₂ inventories rising above the 67%

1 confidence interval by approximately 2060 (blue line in **Fig. 1a**), whereas NPP remains below
2 the 67% confidence level over the entire time period (purple line in **Fig. 1a**).

3
4 The regional behavior of the four drivers is shown in **Fig. 1b-f**. Overall, the hierarchy found in
5 the global analysis tends to be reproduced on a regional scale but with a few notable exceptions.
6 First, the Southern Ocean differs from the other regions in that the O₂ inventories (blue solid line
7 in **Fig. 1b**) are more detectable than SST (orange line in **Fig. 1b**) over the duration. Additionally,
8 the subtropical SST tends to emerge from the 67% confidence interval by 1990-2010 (orange
9 lines in **Fig. 1c-e**), with this not being the case for the Southern Ocean and the Northern
10 subpolar/Arctic regions (orange lines in **Fig. 1b,f**). The commonality is that Ω_{arag} is above the
11 67% confidence interval in all regions for the duration of the analysis period, whereas the NPP
12 signal remains below the 67% confidence level for the **duration of the analysis period** in all
13 regions, with the exception of the southern subtropics for the period post-2070.

14

15 **3.2 Local emergence confidence intervals for individual drivers**

16 We next consider the spatial distributions of the confidence level that the signal (ensemble mean)
17 in the four drivers has emerged from the natural variability (standard deviation among the 30
18 ensemble members) for two different time periods: 2005-2014 (**Fig. 2**) and 2075-2084 (**Fig. 3**).
19 For Ω_{arag} it is found that 99.8% of the global domain exhibits the signal emerging above the noise
20 with more than 67% certainty (**Fig. 2a**). This indicates that **a global observing platform** of 30 yr
21 duration **would be** able to detect trends nearly everywhere. The reasons for the early emergence is
22 that changes in surface Ω_{arag} are mainly dictated by the increase in surface DIC, which closely
23 follows atmospheric pCO₂ trends (e.g. Keller et al. 2014). For SST (**Fig. 2b**), 74.8% of the global
24 surface ocean has emerged with 67% certainty from the noise. In particular the lower latitudes
25 tend to have emerged with high confidence by 2005-2014, whereas the Southern Ocean south of
26 45°S and the northern subpolar and Arctic regions reveal relatively little confidence of
27 emergence by 2005-2014. For O₂ inventories, 22.6% of the global ocean has emerged with 67%
28 certainty from the noise (**Fig. 2c**). For NPP, only 14.8% of the global ocean has emerged with

1 67% certainty over 2005-2014 (**Fig. 2d**). Interestingly, the pattern for the O₂ inventories shown
2 in **Fig. 2c** reveals emergence over important parts of the Pacific and Atlantic sectors of the
3 Southern Ocean (defined as the region to the south of 45°S), in contrast to what is seen in SST.
4 The lower latitudes reveal relatively little emergence by 2005-2014, but there are small areas
5 within the subtropics of the North Pacific with emergence. For the case of NPP (**Fig. 2d**), there is
6 very little evidence of emergence by 2005-2014 over most of the global domain, although the
7 Equatorial Pacific Cold Tongue regions, parts of the Equatorial Atlantic, and the Agulhas regions
8 show marginal emergence. This indicates that even with complete 30 yr time series for global
9 NPP, it would not be possible in most regions to identify a significant **secular** trend.

10
11 Next we consider in **Fig. 3** the confidence intervals calculated over 2075-2084. The patterns
12 shown in **Fig. 3** largely reinforce what was seen in **Fig. 2**, although clearly the emergent
13 structures have expanded. Not surprisingly, Ω_{arag} (**Fig. 3a**) now stands emerged **over** 100% of
14 **the** global surface area with 67% certainty at the end of the 21st century, consistent with what
15 was shown over 2005-2014. For SST (**Fig. 3b**), 90.9% of the global ocean has emerged with
16 67% certainty, clearly having expanded beyond the limits from 2005-2014. This includes
17 expansion into the North Atlantic, and the high latitudes over the Southern Ocean. For O₂
18 inventories (**Fig. 3c**), with 42.3% of the globe has emerged with 67% certainty, the Southern
19 Ocean shows an increasing trend towards emergence at the end of the century, and the North
20 Pacific subtropics have emerged with high confidence. For the case of NPP (**Fig. 3d**), with
21 23.7% of the globe emerged with 67% certainty, there continues to be only weak emergence over
22 most of the globe, the exceptions being a coherent structure spanning the southern subtropics and
23 subtropical front regions of the South Indian Ocean, the equatorial Pacific upwelling region, and
24 then patchy regions over the Southern Ocean the eastern mid-latitude and subpolar North
25 Atlantic.

26
27 Taken together, the results here indicate that the four drivers are not advancing in unison with the
28 same patterns and rates of their detectability over the globe. Ω_{arag} emerges first, consistent with
29 what has been found in previous modeling studies (Friedrich et al., 2012), NPP emerges last, and

1 then O₂ inventories and SST have their own contrasting patterns of emergence. Stated
2 differently, random uncertainty associated with natural decadal variability poses significantly
3 more important challenges to secular trend detection for NPP than for Ω_{arag} , with O₂ inventories
4 and SST falling between NPP and Ω_{arag} .

5

6 **3.3 Local emergence confidence intervals for the multi-driver mean**

7 We now consider **an average across the four ecosystem drivers** of the confidence intervals for the
8 same time intervals 2005-2014 (**Fig. 4a**) and 2075-2084 (**Fig. 4b**). To facilitate presentation and
9 interpretation, we calculated averages within 14 static biomes as defined by Henson et al. (2010).
10 The biome definition separates the regions where phytoplankton growth is seasonally light
11 limited (for mid to high latitudes), regions where the ocean is gaining heat (equatorial regions)
12 and oligotrophic regions.

13

14 For the 2005-2014 interval (**Fig. 4a**), the multi-driver confidence intervals have already risen
15 above the threshold of one standard deviation (67% confidence interval) in the Equatorial
16 Atlantic, the South Atlantic, and the Arabian Sea. The Indian and Pacific sectors of the Southern
17 Ocean weigh in at 60% confidence intervals, thereby below one standard deviation. With the
18 exception of the South Atlantic, subpolar regions are minimum regions for confidence intervals.
19 For the case of the Equatorial Atlantic, where in fact O₂ inventories are increasing (Gnanadesikan
20 et al., 2012; Cocco et al., 2013) (**Fig. A1e**), it is important to acknowledge that emergent O₂
21 inventories are thereby not to be understood as a driver. Interestingly, the hemispheric
22 asymmetry between the northern and southern subtropics of the Pacific is the reverse of the
23 asymmetry found in the Atlantic.

24

25 By the later period 2075-2084 (**Fig. 4b**), the confidence intervals averaged over the four drivers
26 are higher than during the earlier period 2005-2014 except for the eastern equatorial Atlantic and
27 the western equatorial Indian Oceans. There continues to be a hemispheric asymmetry between
28 the subtropics of the northern and southern subtropical Pacific. Interestingly, the fact that

1 subpolar regions have become maxima for the multi-driver mean during the later period
2 represents a reversal of what is found during the earlier period. For both hemispheres this reflects
3 an important contribution from the O₂ inventories, as can be seen in the subpolar time series
4 changes in **Figs. 1b** and **1f**. A relative decrease in variability in SST can be seen over the
5 subpolar regions (**Figs. A1d** and **A2d**), contributing to the increased confidence in emergence
6 over these regions (the differences between **Fig. 2b** and **Fig. 3b**).

7
8 As we did for the individual drivers, we also consider here the fraction of the global area that has
9 emerged for the multi-driver mean over the periods 2005-2014 and 2075-2084. Following the
10 procedure used in **Figs. 2** and **3**, a 30 yr trend window was used to characterize signal-to-noise
11 over the respective time interval year-by-year. The result was then averaged over each of the 10
12 yr time intervals gridpoint-by-gridpoint. Subsequently, area-weighted spatial averages were
13 considered. For the earlier period (2005-2014), 40.9% of the global ocean exhibits emergence
14 with 67% confidence. By 2075-2084, 62.5% of the global ocean exhibits emergence with 67%
15 confidence.

16
17 Next we consider the emergence characteristics for the **two** drivers with highest emergence
18 confidence intervals (rather than all four drivers) in the subsequent two panels. This is shown for
19 the time interval 2005-2014 in **Fig. 4c**, and for the time intervals 2075-2084 in **Fig. 4d**. For each
20 case, the fields presented in **Fig. 2** and **Fig. 3** were considered gridpoint-by-gridpoint to find the
21 **two** maximum drivers, and these were then averaged over the same biome regions. As is
22 revealed in the structures of locally maximum and minimum confidence intervals, the dominant
23 influences over most of the global ocean are Ω_{arag} and SST in setting the even higher confidence
24 intervals. For the time interval 2005-2014, 97.94% of the global ocean is above the 67%
25 confidence interval. For the time interval 2075-2084, this has risen to 99.92% of the global
26 ocean having risen above the 67% confidence interval.

27
28 Taken together, the four panels in **Fig. 4** reveal a strong sensitivity to the number of drivers used
29 to characterize multiple-driver emergence. For the case of emergence over 2075-2084, it is

1 interesting to note that the patterns are different. For four drivers, the Southern Ocean has the
2 strongest emergence, whereas with two drivers the tropical band has the strongest emergence.

3 **3.4 Sensitivity of Confidence Intervals to Length of Decadal Trend Window**

4 Next we consider the sensitivity of our confidence interval calculation for the period 2005-2014
5 (**Fig. 2**) to the length of the window over which trends are calculated. The sensitivity of the
6 confidence intervals over 2005-2014 to the width of the window is considered in **Fig. 5**, where a
7 window of 10 yr has been used instead of the 30 yr used in **Fig. 2**. We show that for all four
8 drivers, the choice of a 10 yr trend window results in important decreases in the confidence
9 intervals for emergence over the global domain relative to a 30 yr trend window.

10
11 For Ω_{arag} (**Fig. 5a**), the confidence intervals are much lower in the regions directly impacted by El
12 Niño variability with a 10 yr window than they are with a 30 yr window (**Fig. 2a**). Additionally,
13 smaller confidence intervals are in evidence through the North Atlantic and parts of the Arctic, as
14 well as in a well-defined band across the North Pacific. In fact, along much of both the west and
15 east coasts of North America, confidence intervals are significantly lower than with the 30 yr
16 window. This may have important implications in pointing to the need for sustained (multi-
17 decadal) observing systems for ocean biogeochemistry in these regions.

18
19 For SST as well, the pattern obtained with a 10 yr window (**Fig. 5b**) reveals large differences
20 from the pattern obtained with a 30 yr window (**Fig. 2b**). The relatively elevated values
21 throughout much of the tropics and the subtropics for the case of a 30 yr window have now
22 disappeared for the case of a 10 yr window, revealing relatively weak confidence intervals over
23 global domain. A similar loss of confidence is found in for O_2 inventories (**Fig. 5c**) and for NPP
24 (**Fig. 5d**). In fact for SST, O_2 inventories, and NPP, using a 10 yr window results in very weak
25 confidence nearly everywhere over the global domain.

26

3.5 Time of emergence in individual ecosystem drivers

Next we consider Time of Emergence (ToE) in **Fig. 6**. Here, we use a one standard deviation threshold to define ToE, and our intention is to represent another dimension to the emergence question, namely that of time. **A 10 yr tolerance window with a robust Loess filter has been applied to the fields in Fig. 6, as described in Appendix B.** We begin with a consideration of Ω_{arag} (**Fig. 6a**), with this revealing that most of the emergence has already occurred by the start of the analysis period (before 1965), consistent with what was seen in the confidence interval analysis. The only exceptions are relatively high dynamical variability zone within the equatorial Pacific, and certain high variability structures associated with western boundary current regions. For SST (**Fig. 6b**), the ToE is within the 20th century for much of the tropics, with a tendency for this ToE to shift to the 21st century for much of the subtropical and subpolar regions. For much of the high-latitude Southern Ocean region, there is no emergence during the analysis period (before 2085). This is also true for important sectors of the northern North Atlantic. For O₂ inventories (**Fig. 6c**) an early ToE is evident for the Southern Ocean as well as the eastern equatorial Atlantic, largely consistent with what was seen in **Fig. 2**. Alternating zonal structures of early and late ToE are seen in the Equatorial Pacific, and a patchwork of structures with very different ToE is in evidence over much of the ocean away from the Southern Ocean. In fact, the patchwork-like structures are in even stronger evidence for NPP (**Fig. 6d**). Consistent with what was seen in **Fig. 2d**, relatively early ToE is in evidence for both the Agulhas and the Equatorial Pacific Cold Tongue regions. Otherwise there are alternating bands of saturation for both early (pre-1965) and late (post-2085) ToE. The adjacent early and late saturation regions are the consequence of choosing a threshold for ToE. Thus the boundaries between such regions may not in general be reflecting real biome structures in the model domain. This is addressed in more detail in the Appendix (**Fig. A3** and **Fig. A4**).

1 4 Discussion

2 4.1 Interpretation of Main Results

3 We set out to evaluate the emergence characteristics of four ecosystem drivers (surface Ω_{arag} ,
4 SST, subsurface O_2 , and NPP) of marine ecosystems, with two questions driving this
5 investigation. The first motivation stems from an interest in identifying when the secular trend in
6 drivers becomes evident or perceptible *for an observer* relative to the natural background decadal
7 variability. This is precisely what Large Initial-Condition Ensemble Simulations with Earth
8 System Models can provide, and it is our intention that this will add value to more ambitious
9 efforts to identify when the secular trend becomes a perceptible change that can stress
10 ecosystems. Identifying perceptible change for an *observer* is a necessary but not sufficient
11 condition for identifying perceptible change for an *ecosystem*, as is evident for example in the
12 fact that many organisms are not sensitive to O_2 concentrations until they fall below a particular
13 threshold (e.g. Vaquer-Sunyer and Duarte, 2008).

14
15 The second *motivation* pertains to the optimization of the ocean biogeochemical observing
16 system, and the application of models to advance this optimization through iterative
17 communication with the community of researchers evaluating network design. Building on the
18 previous work of Frölicher et al. (2009), this was pursued using a suite of Large Initial-Condition
19 Ensemble Simulations, as it is only with this approach that one can infer the secular trend
20 (ensemble mean) for a model by filtering natural variability through an averaging procedure. The
21 averaging procedure operates on not only patterns of climate modes such as ENSO (Wittenberg
22 et al., 2014), but also on natural variability on smaller scales associated with variations in gyre
23 boundaries that are not correlated to climate modes. Importantly, with this large ensemble
24 approach, one does not need to assume that variability in the system is stationary in time.

25
26 Our main result is that there is a temporal hierarchy in the emergence of the four ocean ecosystem
27 drivers above the level of background natural variability. This is strongly evident in **Fig. 1**. Ω_{arag}
28 emerges earliest, NPP emerges latest, and both O_2 inventories and SST fall between the two.

1 Additionally, three (SST, O₂ inventories, and NPP) of the four drivers considered here exhibit
2 large regions where detection of secular trends is significantly complicated by the presence of
3 natural decadal variability in the climate system. Our results also revealed very pronounced
4 differences in the patterns for the confidence intervals for the emergence of SST and O₂
5 inventories (**Fig. 2**). For SST, the Southern Ocean emerges relatively late (post-2014) and the
6 tropics emerge rather early (pre-2014), in line with earlier studies (Mora et al., 2013). For O₂
7 inventories, on the other hand, the Pacific and Atlantic sectors of the Southern Ocean exhibit
8 regions of relatively early emergence (pre-2014) and the tropics emerge rather late (post-2014).
9 The coalescence of the different global drivers in certain regions is already creating a number of
10 hot-spots (**Fig. 4**), with the Southern Ocean and more generally the high latitudes projected to
11 increase in importance by 2075-2084.

12
13 Consistent results regarding the temporal hierarchy of ecosystem driver emergence were found
14 through the analysis of confidence intervals (**Fig. 2** and **Fig. 3**) and time of emergence (ToE)
15 (**Fig. 6**) as diagnostics. However, we prefer the confidence interval analysis over the ToE analysis
16 for two reasons. First, for the four ecosystem drivers the saturation characteristics of the ToE
17 analysis (emergence before 1965 or after 2085) are widespread, complicating interpretation.
18 Second, and perhaps more importantly, ToE diagnostics require a specification of a threshold of
19 signal-to-noise that is somewhat arbitrary (here we have considered both 1 and 2 standard
20 deviations, but have chosen to emphasize the less conservative value of 1 in **Fig. 6**).

21
22 The quantification of signal-to-noise at the center of our analysis relies on joint use of a suite of
23 Large Initial-Condition Ensemble Simulations using an individual Earth System Model (GFDL's
24 ESM2M). However, previously published analyses indicate that the collection of Earth System
25 Models developed by different modeling centers exhibit disparate amplitudes for the secular
26 trends in individual drivers (Bopp et al., 2013). For example, different ESMs are likely to differ
27 more in their projected changes in NPP than they are in Ω_{arag} or SST, since at least with Ω_{arag} or
28 SST the ESMs are largely consistent in the sign of their response (Bopp et al. 2013, Steinacher et
29 al. 2010, Cocco et al. 2013). In high latitudes, ESMs are generally consistent in simulating

1 decreasing ocean O₂ inventories under 21st century climate change (Cocco et al. 2013). However,
2 it is worth noting that in GFDL ESM2M global NPP changes by only 2% under the
3 historical/RCP8.5 scenario, whereas global NPP tends to decrease by approximately 10% for a
4 multi-model of CMIP5 ESMs under the same scenario (Laufkötter et al., 2015). Additionally,
5 different Earth System Models exhibit different noise or underlying natural variability
6 characteristics for individual drivers (Keller et al., 2014). Such inter-model differences strongly
7 suggest that the temporal and spatial characteristics of emergence should be model-dependent, as
8 has been shown for the case of surface air temperature by Hawkins and Sutton (2011).
9 Alternative emissions scenarios may also lead to changes in both the signal and the noise. An
10 investigation of the sensitivity of our results to alternative scenarios for anthropogenic emissions
11 and other model projections is left as a subject for future investigation.

12

13 **4.2 Mechanistic Interpretation**

14 Although our analysis has been focused on statistical questions (namely confidence intervals and
15 time of emergence diagnostics), it is also important to consider the mechanisms that control
16 emergence timescales. The most important contrast seen in our results is in evidence in **Fig. 2**,
17 namely the early (late) emergence of SST in the tropics (Southern Ocean), and the late (early)
18 emergence of O₂ inventories in the tropics (Southern Ocean) with the 30 yr window. For SST,
19 the contrast between the tropics and the Southern Ocean in **Fig. 2** identified with a 30 yr window
20 is largely reflecting the small amplitude of the SST trend over the Southern Ocean relative to the
21 tropics. In fact, the contrast between the tropics and the Southern Ocean is more generally
22 representative of most of the rest of the global surface ocean (except in the northern North
23 Atlantic) relative to the Southern Ocean (**Fig. A1c**). The lack of SST warming reflects large-
24 scale interhemispheric asymmetries in the mean ocean circulation. The strong upwelling in the
25 Southern Ocean nearly anchors sea surface temperature at pre-industrial level (Stouffer et al.
26 1989; Marshall and Speer, 2012; Frölicher et al., 2015).

27

28 For the tropics, the secular trend is sufficiently large over a 30 yr window to be more important
29 than the natural decadal variability, but consistent with the spectral characteristics of ENSO for

1 the underlying physical model (Wittenberg, 2009). This is no longer true for the case of a 10 yr
2 window in the tropics. For the case of O₂ inventories, the reverse holds. In the Southern Ocean,
3 deoxygenation is much larger than natural variability due to the stratification-induced reduced
4 supply of O₂ from the surface into the ocean interior (Frölicher et al, 2009; Gnanadesikan et al.,
5 2012). In contrast, almost no O₂ changes are projected to occur in the low O₂ regions of the
6 tropical and subtropical thermocline. This is due to the fact that reduced biological production
7 and export of organic matter in the overlying near-surface waters are then associated with
8 reduced O₂ demand in the ocean interior (Gnanadesikan et al., 2012; Steinacher et al., 2010).
9 These biological drivers are expected to be modulated by perturbations to the rates of ocean
10 interior and thermocline ventilation. However, the confidence of the O₂ projections in the low
11 latitudes is low, as the GFDL ESM2M has biases in its representation of today's observed O₂
12 distribution (Gnanadesikan et al., 2012), a feature common to the current generation of Earth
13 System models (Bopp et al., 2013).

14

15 **4.3 Perceptible changes in ocean drivers for an observer**

16 We have previously defined perceptible changes in drivers of ocean ecosystems as secular
17 changes that are above the noise level of natural variability. For the case where two of the four
18 ecosystem drivers are used (**Fig. 4c** and **Fig. 4d**), our analysis has revealed that Ω_{arag} and SST are
19 the dominant drivers with early emergence in the tropics. In fact, it should be emphasized that
20 this is a result of our two-driver analysis, rather than an assumption or an imposed constraint. In
21 particular, the two-driver analysis presented in **Fig. 4c** for the recent past indicates that tropical
22 coral reef habitats may be the primary regions currently experiencing perceptible changes **for an**
23 **observer** relative to the background natural variability (Pelejero et al., 2005). Thus our results **are**
24 consistent with previous studies that argue that coral reefs are the marine ecosystems that are
25 threatened most by environmental changes (see the cross-chapter box on coral reefs in IPCC AR5,
26 Gattuso et al, 2014a; also see Gattuso et al., 2014b), **if we equate drivers and stressors for the**
27 **case of Ω_{arag} and SST for tropical coral reef habitats.** Although the results of the two-driver
28 analysis are seen to hold through the tropics, the results may warrant particular attention in the
29 Coral Triangle biodiversity hotspot region **that is thought to account for more than 75% of the**

1 world's coral species (Veron et al., 2009), spanning Indonesia, the Philippines, Malaysia, Papua
2 New Guinea, and the Solomon Islands (Allen, 2008).

3
4 It is important however to emphasize that the analyses for multiple drivers seen in **Fig. 4**
5 consisted of averaging of confidence intervals obtained for the individual drivers. In interpreting
6 these results for SST and Ω_{arag} in the Coral Triangle region as the confidence intervals for the
7 impacts of multiple drivers, it remains a scientific challenge to determine whether they are in fact
8 acting additively, synergistically, or antagonistically in their impact (Boldt et al., 2014, and
9 references therein). To date resource management strategies have tended to focus on the impact
10 of individual drivers, with little consideration or attention to potential relationships and feedbacks
11 between the drivers. Addressing these questions is beyond the scope of our study, but it is our
12 hope that the analysis considered here will contribute to motivating future work in this direction.
13 What is clear, however, is that anthropogenic CO₂ emissions to the atmosphere are the common
14 driver of the perturbations considered here, and this underscores the necessary of a single policy
15 response (reduction in emissions). Substantial mitigation efforts are required if ocean ecosystems
16 are to be spared from the “quadruple whammy” of the drivers considered here.

18 **4.4 Implications for Observing System Design**

19 It is also important to consider the implications of our study for optimization of the global ocean
20 observing system. With this goal in mind, our study can be considered as an Observing System
21 Simulation Experiment (OSSE). With an OSSE, one considers a model to be an analog for the
22 real ocean, for which one has the fully resolved state evolution of the system. Earlier OSSEs
23 (Christian et al., 2008; Park et al., 2010; Plancherel et al., 2013; Majkut et al., 2014; Cassar et al.,
24 2014) have tended to focus on one realization of the evolution of the Earth system, and focused
25 on the skill with which different observing strategies can reproduce variability in the Earth
26 System through selective sub-sampling of the model output. The target is to test the available
27 skill in reproducing the real-world trends and variability with an incomplete observing system,

1 without any claim to separating the signal associated with the secular trend and natural
2 variability.

3
4 For our experimental configuration considered as an OSSE, we address a different but
5 complementary question. We consider the case where the observing system has perfect skill in
6 reproducing the trends and variability on all timescales of the system of interest, but where the
7 target is to identify the secular trend. It is precisely this deconvolution that we address with the
8 Large Initial-Condition Simulations with the Earth System Model, thereby building on the
9 previous analyses considered with fewer ensemble members (Frölicher et al, 2009; Christian,
10 2014). The question is then as follows: Given an observing system with perfect skill that allows
11 one to perfectly monitor the evolution of the system, how many years of continuous
12 measurements are needed to identify the secular trend above the noise of background variability?
13 Our main result with this question is that sustained decadal measurements will be needed even
14 for the idealized case of a perfect observing system.

15
16 Viewed in this way, our main results point to the importance of maintaining a sustained multi-
17 decadal observing system for ocean biogeochemistry and ecosystem drivers. For the four drivers
18 considered here, the confidence intervals found with a 30 yr window for calculating trends (**Fig.**
19 **2**) are significantly higher than those found with a 10 yr window (**Fig. 5**). For the case with a 10
20 yr window, even Ω_{arag} reveals broad expanses of non-emergence over the decade 2005-2014.
21 This is in evidence, for example, over important parts of the Coral Triangle biodiversity hot spot
22 spanning the Indo-Pacific Warm Pool region, as well as for the North Atlantic. This underscores
23 the potential importance of sustained multi-decadal continuous measurements in order to identify
24 the rate of acidification associated with the secular trend in these regions.

25
26 More generally, our analysis of confidence intervals for emergence for two versus four drivers
27 (**Fig. 4c** for the period 2005-2014) largely highlight the combined effects of Ω_{arag} and SST in the
28 tropics. This implies that even with high resolution of temporal and spatial scales, a sustained
29 multi-decadal (30 yr) observing system of the type considered by Ishii et al. (2009) in western

1 Equatorial Pacific surface waters is needed to detect the rate of the secular trend in acidification
2 against the background noise of natural variability with confidence.

5 **5 Conclusions**

6 Here we have considered a suite of Large Initial-Condition Ensemble Simulations with GFDL's
7 Earth System Model ESM2M to evaluate the emergence characteristics of four drivers of ocean
8 ecosystems under anthropogenic climate change. The drivers chosen were Ω_{arag} , SST, upper-
9 ocean inventories of O_2 , and net primary productivity (NPP). There were two questions
10 underlying the analysis: First, when and where will changes in ecosystem drivers become
11 perceptible to an observer? Second, what are the implications for optimal design of a global
12 observing system for the four drivers?

13
14 The main result of our study is that among our four ecosystem drivers, there is a pronounced
15 temporal and spatial hierarchy to emergence over global scales. Using a one-standard deviation
16 (67%) confidence interval threshold for signal-to-noise, and a 30 yr trend window, we find that
17 the acidification driver (Ω_{arag}) emerges earliest and NPP emerges latest over global scales.
18 Between these two extremes, SST and O_2 inventories have intermediate timescales of emergence,
19 but opposing patterns between the two of them. SST emerges earlier in the low latitudes and
20 later in the high latitudes, while O_2 inventories exhibit earlier emergence over high latitude
21 regions than in the tropics. We also considered a multiple-driver analysis where we combined
22 the four individual drivers. There we found that whereas 41% of the global ocean area exhibits
23 emergence over 2005-2014, 63% has exhibited emergence by 2075-2084. This four-driver
24 analysis reveals a more pronounced emergence pattern over the extra-tropics than over the
25 tropics. We also considered the multiple-driver case where we included only two drivers by
26 biome region, with very different results. There the tropics emerge earliest, with the dominant
27 drivers being Ω_{arag} and SST. Given that Ω_{arag} and SST are the two most important drivers for
28 coral reef ecosystems, this analysis identifies coral reefs as being especially vulnerable under 21st
29 century climate change.

1
2 Considered as an Observing System Simulation Experiment (OSSE), our results emphasize the
3 need for a sustained global observing system for multiple decades for the task of identifying
4 secular trends in ecosystem drivers. This is true even for the case of a global bio-Argo array
5 within a broad multi-platform observing system, as is revealed in the contrast between the
6 confidence intervals for emergence of the secular trend between a 10 yr sustained observing
7 system (Fig. 5) and a 30 yr sustained observing system (Fig. 2).

8
9 **Appendix A: Secular trends and natural variability underlying signal-to-noise**
10 **analysis**

11 We characterize here the secular trends (left columns in Figs. A1,A2; referred below as TREND)
12 and standard deviations of the secular trends (right columns in Figs. A1,A2; referred below as
13 NOISE) separately. Recall that the signal-to-noise ratio is defined as the ratio of these two fields.
14 Ω_{arag} decreases everywhere over the global domain (Fig. A1a), with minimum relative rates of
15 decrease in the equatorial regions, and a general tendency towards stronger relative rates of
16 decrease at high latitudes. The largest NOISE amplitude of Ω_{arag} is seen in a number of
17 dynamically active regions, including the margins of the subtropical gyres and the equatorial
18 Pacific. However, with the exception of a few isolated regions, the TREND is everywhere
19 significantly larger than the NOISE for Ω_{arag} . For SST, the TREND over 2005-2014 is positive
20 (warming) over most of the globe, with the notable exception of the western subpolar North
21 Atlantic and large expanses of the Southern Ocean (cooling). This stands in contrast to Ω_{arag} ,
22 where the trend had the same sign over the entire domain.

23
24 The NOISE for SST finds largest expression in the subpolar regions of the Northern Hemisphere
25 and over parts of the Southern Ocean. In fact it can be seen in the Fig. 1c,d that the extratropical
26 regions of weak or negative TREND in SST are associated with enhanced variability. The
27 tropics, on the other hand, reveal only modest NOISE amplitude relative to the TREND. Taken
28 together, this helps to account for the fact that the confidence interval map in Fig. 2b reveals high
29 confidence in the tropics relative to the subpolar regions. As has been stated in the main text, it

1 may seem somewhat surprising that the signal-to-noise-ratio is relatively elevated in the
2 Equatorial Pacific, given that this is the region of largest natural variability in the climate system.
3 It is important to emphasize here that we are considering trends over a 30 yr interval in our
4 quantification of NOISE rather than considering the standard deviation associated with
5 interannual variability for each of the drivers.

6
7 For the case of O₂ inventories, a decreasing TREND can be seen in the well-ventilated
8 thermocline of the high latitudes. Within the tropics and subtropics, structures of positive trend
9 do occur. As with SST but in contrast with Ω_{arag} , the sign of the ensemble-mean response of O₂
10 inventories is not of the same sign everywhere. However, there are also pronounced structures of
11 larger NOISE in O₂ inventories, which over many regions are associated with decadal variations
12 in gyre boundaries and frontal regions. The most prominent extended region where the TREND
13 is larger than the NOISE is over a broad expanse of the Pacific and Atlantic sectors of the
14 Southern Ocean (as seen in **Fig. 2c**).

15
16 For the case of Net Primary Productivity (NPP), both the TREND and the NOISE patterns show
17 relatively narrowly-defined but large-amplitude structures. There is a trend in the zonal gradient
18 in NPP across the equatorial Pacific, as well as a trend towards enhanced NPP along the
19 poleward flanks of the Southern Hemisphere subtropical gyres. For the NOISE, a series of
20 relatively narrow structures of high amplitude are found winding through the tropics. Over most
21 regions of the globe, the NOISE is of sufficient amplitude relative to TREND to give the
22 consistently lowest Confidence Interval distribution of the four drivers considered here (**Fig. 2d**).

23
24 It is worth noting in **Fig. A1** that the unforced components (right column) of the four drivers
25 exhibit large-scale spatial coherence rather than small grid-scale noise. However, these structures
26 are distinct for each of the drivers.

27

1 The same fields for the time interval 2075-2084 are considered in **Fig. A2**. The amplitudes in
2 TRENDS have increased in general, but important elements of the TREND structures are similar
3 as for the earlier period. The structures of the NOISE are quite similar to those found for the
4 equivalent drivers during the earlier period. However, the amplitude of the variations is in many
5 cases different for 2075-2084 than for 2005-2014. This indicates that the amplitude of the
6 background natural variability is not stationary. For the case of SST and O₂, the standard
7 deviation of natural decadal variations decreases over the Southern Ocean.

8

9 **Appendix B: Temporal filtering and trend detection**

10 The task of calculating Time of Emergence (ToE) in **Fig. 6** is complicated by the fact that the
11 signal-to-noise ratio (SNR) in time series for individual grid points in the ocean model does not
12 in general tend to be monotonically increasing over the period 1950-2100. Rather, the evolution
13 of the SNR can reflect that for this particular diagnostic, the 30 ensemble members may not be
14 sufficient to eliminate noise when averaged.

15

16 As an illustration of this problem, we consider in **Fig. A3** the evolution of the SNR for sea
17 surface temperature a region in the Pacific sector of the Southern Ocean bounded by 130°W-
18 100°W and 45°S-60°S. The time series of the SNR for the various points in this region are
19 superposed in **Fig. A3a**. The non-monotonic nature of the increase in SNR through time is
20 evident. With this unfiltered SNR calculated directly from the annual mean model output, there
21 are relatively short-timescale excursions above the two standard deviation threshold that precede
22 by a number of decades the more permanent crossing of the one standard deviation threshold.
23 However, this does not occur for all of the grid points in the domain of interest. As a
24 consequence of these early excursions above the one standard deviation threshold, the spatial
25 pattern of ToE using a strict definition of first crossing (**Fig. A3b**) reveals a spatial pattern that
26 has a ToE before 2014 (present time) over more than 50% of the region.

27

28 It is important to understand the degree to which the ToE structure in **Fig. A3b** reflects short-
29 term versus longer-term or permanent transitions of the SNR about the one standard deviation

1 threshold, rather than short-term excursions. To evaluate this, we apply to the full suite of time
2 series shown in **Fig. A3a** (gridpoint-by-gridpoint SNR for SST) a robust Loess filter. We have
3 chosen to use a 10 yr tolerance window with the robust Loess filter, with this serving effectively
4 as a low-pass filter that is obtained using 10 yr local regressions over the entire time period for
5 each individual gridpoint. The result of applying the robust Loess filter is shown in **Fig. A4a**,
6 where the filtered time series are shown as red lines overlaying the full time series shown in blue.
7 The filtered time series are seen to behave as low-pass filters that effectively remove the higher
8 frequency components. When these smoothed time series are used to define ToE with the same
9 two standard deviation threshold, the resulting pattern (**Fig. A4b**) reveals important differences
10 relative to the unfiltered time series. The structures with post-2014 ToE now occupy most of the
11 domain. This indicates the strong sensitivity of the spatial pattern of ToE to the time-filtering of
12 the SNR time series.

13
14 The sensitivity of the Time of Emergence (ToE) to the width of the window used for calculating
15 trends is considered in **Fig. A5**. Here the window is chosen to be 10 yr, and this result is to be
16 contrasted to what was found for ToE using a 30 yr window as considered in **Fig. 6**. Clearly the
17 narrower trend interval of 10-years results in saturation (post-2095 emergence for this case of a
18 10-year trend window) on nearly global scales for all of the drivers except for Ω_{arag} . This
19 indicates a strong sensitivity of ToE to the timescale chosen for the analysis, consistent with what
20 was shown in **Fig. 4** for the confidence interval sensitivity analysis. **Fig. A5** is valuable in that
21 the strong saturation characteristics for three of the drivers (post-2085 emergence) are much more
22 difficult to interpret than the parallel and favored analysis with confidence intervals.

23
24 We also consider the sensitivity of the Time of Emergence (ToE) to the width of the tolerance
25 window used for the robust Loess filter in **Fig. A6a**. For each case, the sensitivity of the ToE to
26 the width of the tolerance window (described above) is considered for each of the four drivers.
27 For each case, the area-weighted global mean sensitivity is considered. The sensitivity is weak
28 for Ω_{arag} , with the dynamic range of the sensitivity being only a few years as the tolerance
29 window is modified from 5 yr to 25 yr. The sensitivity is largest for O_2 inventories, with a

1 decrease of the ToE of 80 years as one transitions from a 5 yr to a 25 yr tolerance window. This
2 strong sensitivity is likely the expression of the red spectrum of modes of variability in
3 thermocline depth impacting O₂ inventories in their temporal variability. The sensitivities of SST
4 and NPP are quite similar, both being approximately 50% of the amplitude of the sensitivity seen
5 for O₂ inventories. In fact, the sensitivity of NPP should be expected to be larger than that of
6 SST, given that the sensitivity shown here may be obscured by the saturation characteristics of
7 NPP.

8
9 We also consider in **Fig. A6b** the sensitivity of the ToE to the choice of a SNR ratio of one in
10 **Fig. 6**. Here as well, the sensitivity considers the global area-weighted mean. The sensitivity is
11 strongest for SST, and then the second strongest is found for O₂ inventories. The sensitivity is
12 weakest for Ω_{arag} and for NPP, but as a caveat it needs to be emphasized that both of these fields
13 exhibit saturation behavior in **Fig. 6**. If the suite of 30 ensemble runs with ESM2M had been
14 runs for a significantly longer time intervals, say from 1860-2300, then one would expect that the
15 sensitivity for these two fields to be more pronounced.

16

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28

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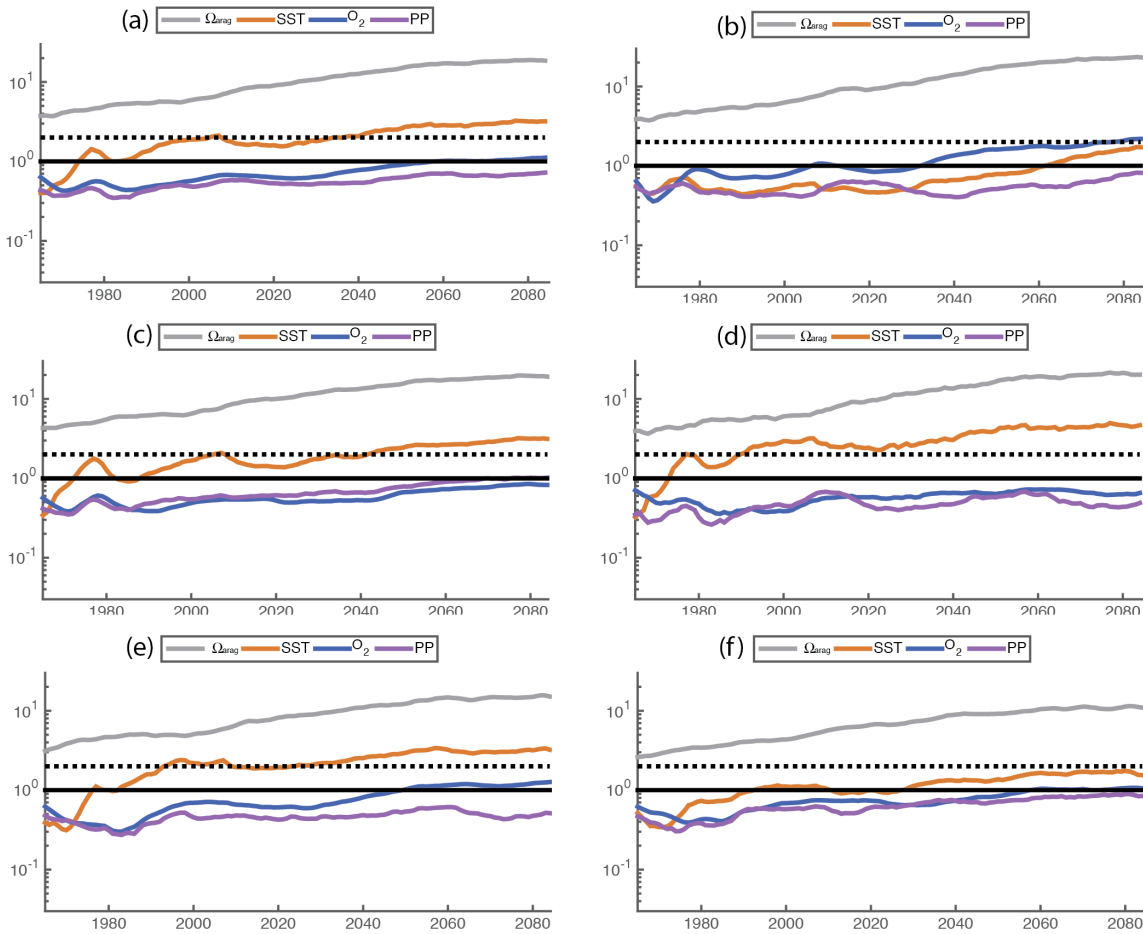
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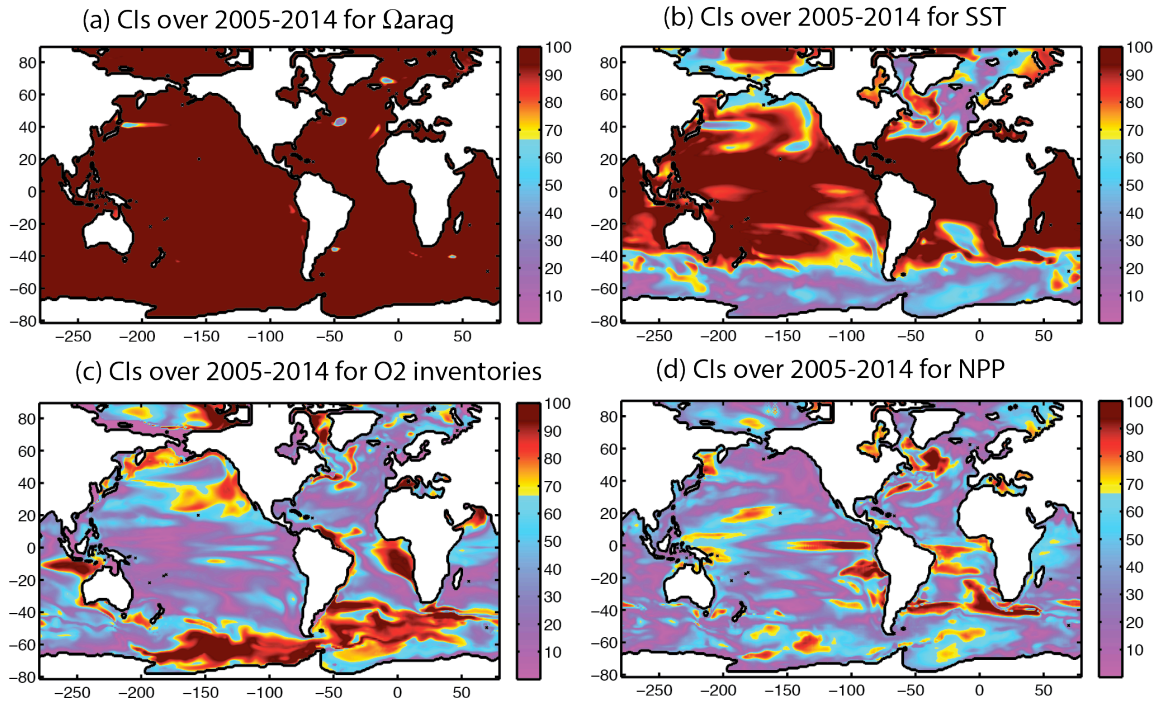
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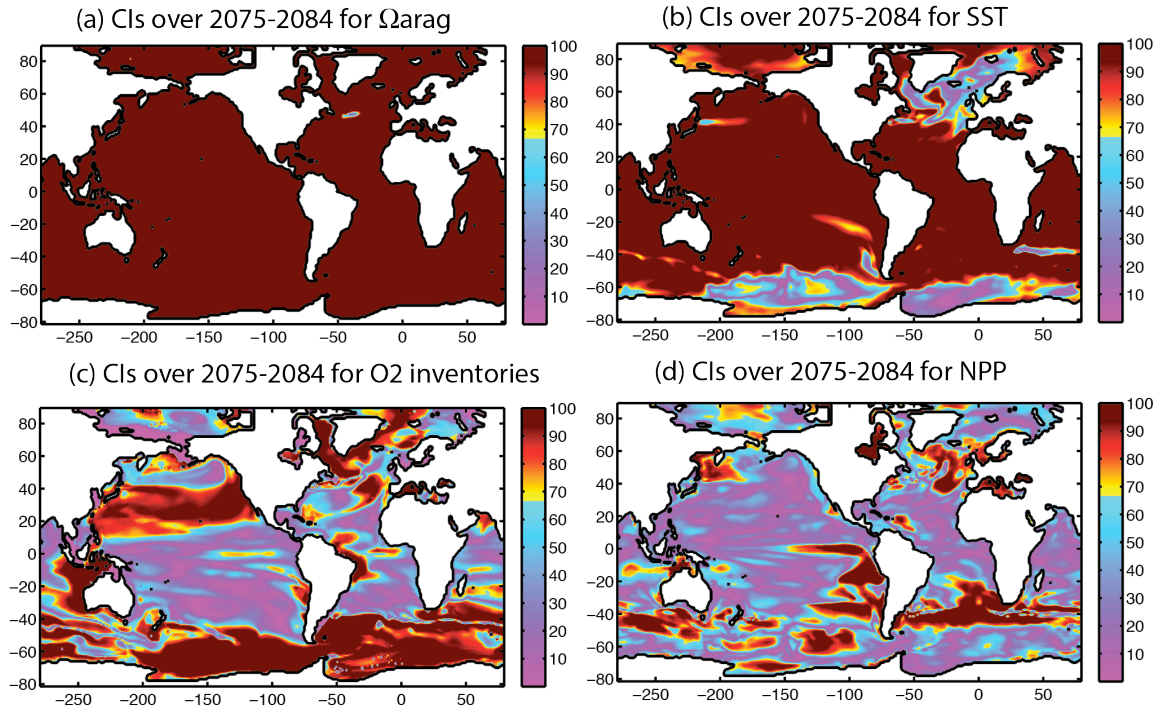
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Figure 1. Time series of (area weighted) averages of signal-to-noise ratio (SNR) for four marine ecosystem drivers, considered over a number of ocean regions: (a) Global, (b) 90°S-45°S, (c) 45°S-15°S, (d) 15°S-15°N, (e) 15°N-45°N, and (f) 45°N-90°N. The four drivers are Ω_{arag} , SST, O_2 inventories, and NPP. For each driver, trends have been calculated individually on a gridpoint-by-gridpoint basis using a 30 yr trend window, and the SNR was subsequently calculated. The vertical axis has a logarithmic scale (non-dimensional) representing the SNR.. The 1-standard deviation threshold is shown as a solid horizontal line, and the 2-standard deviation threshold is shown as a dashed line in each panel.



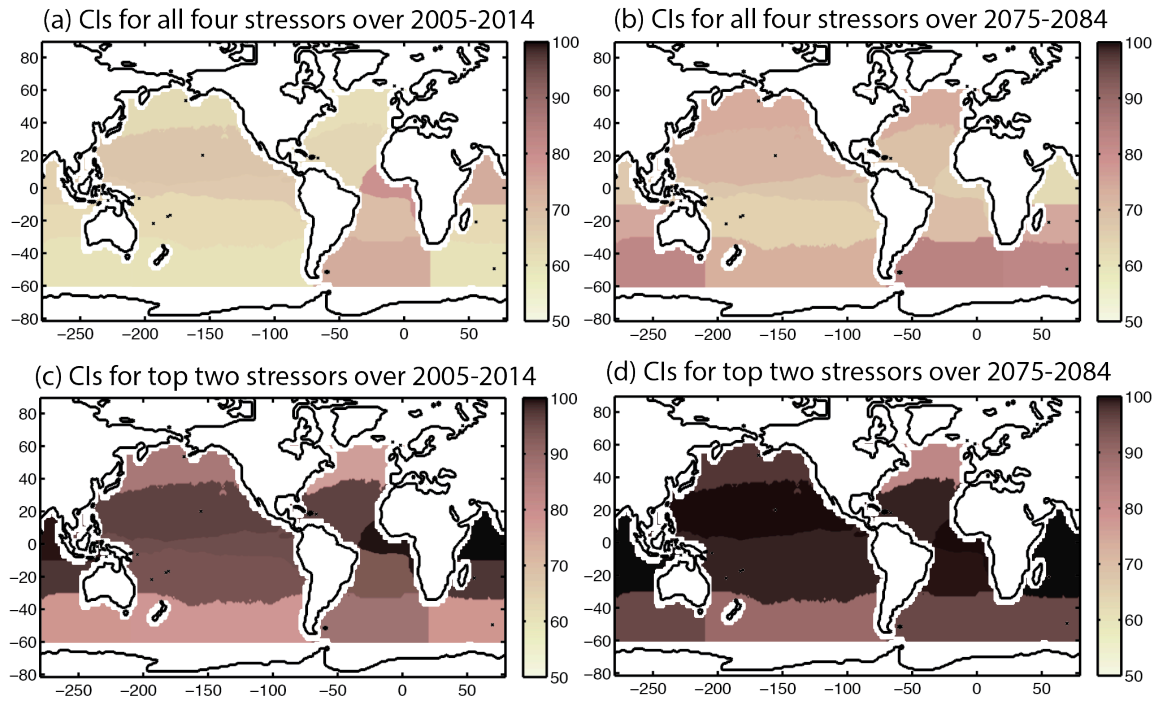
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 2 **Figure 2.** Confidence interval maps averaged over 2005-2014 for (a) Ω_{arag} , (b) SST, (c) O_2
 3 inventories, and (d) NPP. For the case of O_2 inventories in panel (c), shelf regions where the
 4 ocean depth is less than 600m deep are not included in the analysis. For each case, a 30-year
 5 window has been used to calculate trends gridpoint-by-gridpoint for each year between 2005
 6 and 2014. An average over 10 years was considered to remove shorter timescale fluctuations in
 7 the signal-to-noise ratio. Note that the color scheme here is chosen such that saturation occurs
 8 (maroon color) above the 67% confidence interval. Warm colors indicate confidence intervals
 9 ranging from 67-95% (one to two standard deviations), and cool colors span the range 0%-67%
 10 (less than one standard deviation).

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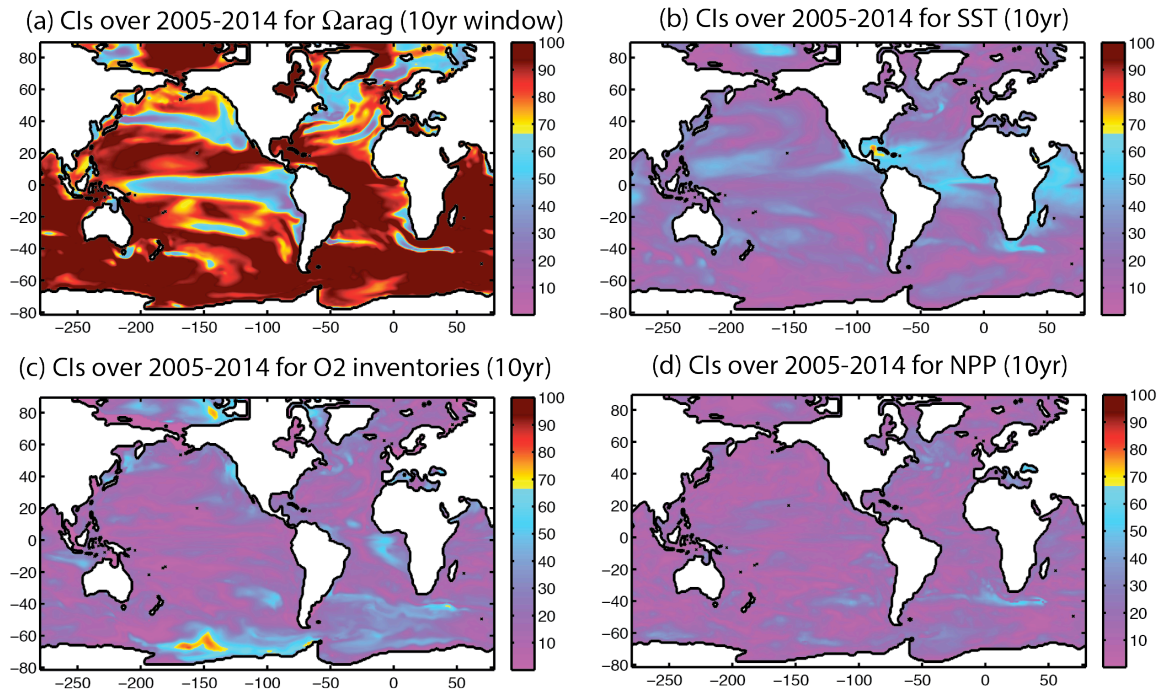
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2 **Figure 3.** Confidence interval maps averaged over 2075-2084 for (a) Ω_{arag} , (b) SST, (c) O_2
3 inventories, and (d) NPP. For the case of O_2 inventories in panel (c), shelf regions where the
4 ocean depth is less than 600m deep are not included in the analysis. For each case, a 30-year
5 window has been used to calculate trends gridpoint-by-gridpoint for each year between 2005
6 and 2014. An average over 10 years was considered to remove shorter timescale fluctuations in
7 the signal-to-noise ratio. Note that the color scheme here is chosen such that saturation occurs
8 (maroon color) above the 67% confidence interval. Warm colors indicate confidence intervals
9 ranging from 67-95% (one to two standard deviations), and cool colors span the range 0%-67%
10 (less than one standard deviation).

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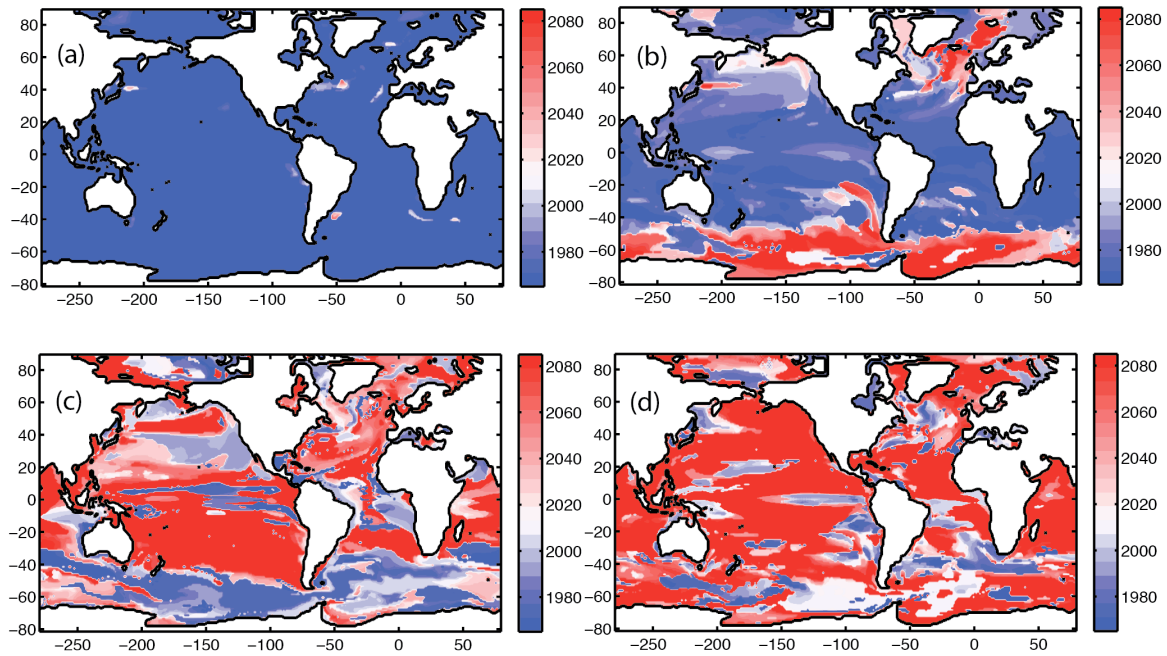
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2 **Figure 4.** Confidence intervals for two ten-year intervals, namely 2005-2014 (left column), and
3 2075-2084 (right column). The confidence intervals for (a) the four drivers (Ω_{arag} , SST, O_2
4 inventories, and NPP) over 2005-2014 are taken as the average over the fields shown in **Fig. 2**,
5 and (b) the confidence intervals shown for the four drivers over 2075-2084 are taken as the
6 average of the fields shown in **Fig. 3**. This is then considered for the case of the dominant two
7 drivers in (c) for the period 2005-2014, and in (d) for the period 2075-2084. Finally, the
8 confidence intervals averaged for the dominant two drivers are shown in (e) over 2005-2014 and
9 (f) over 2075-2084.

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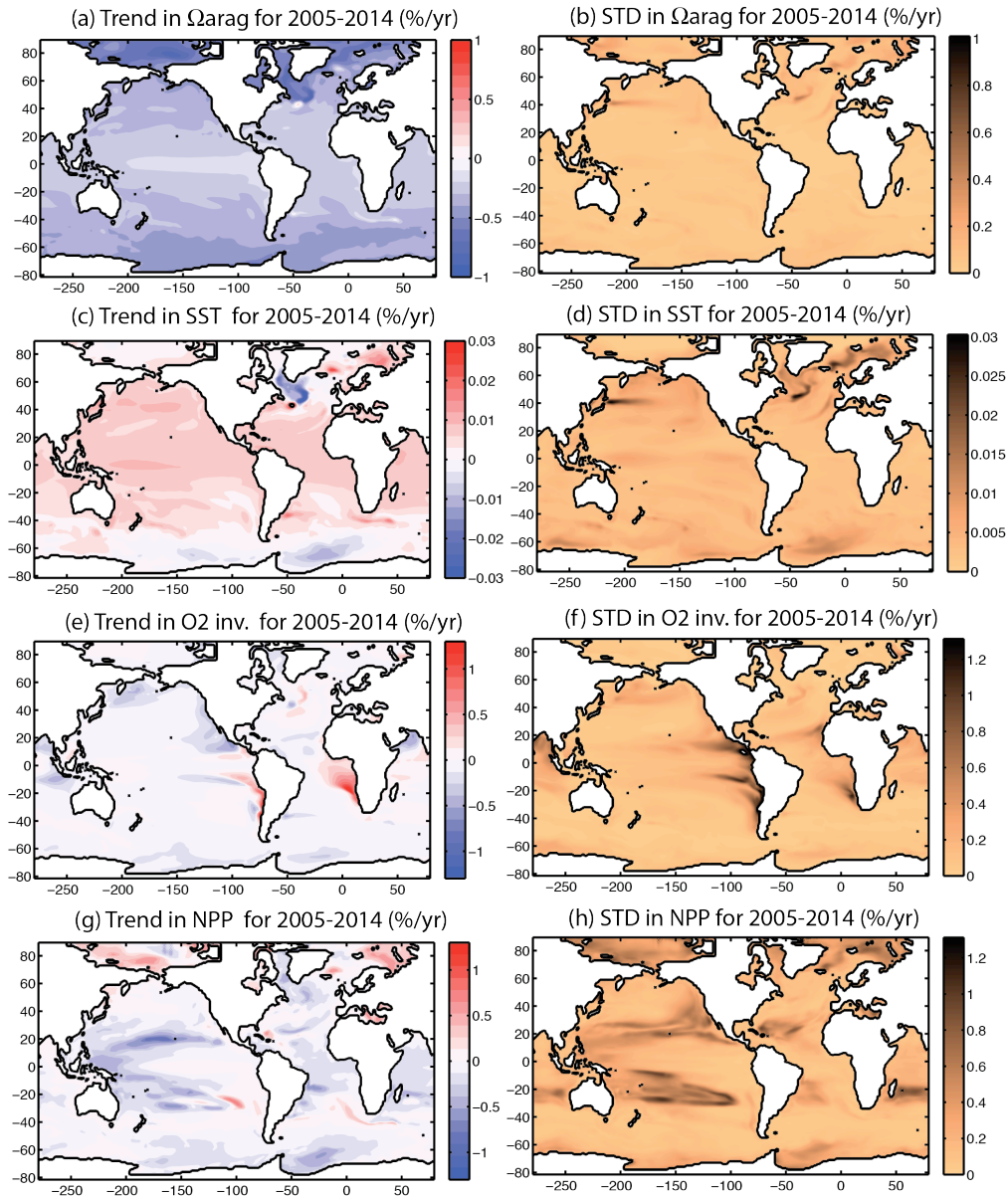
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 2 **Figure 5.** The confidence intervals for emergence of each of the drivers for the time period 2005-
 3 2014, using a 10 yr window for calculating trends. The analysis here is otherwise identical to
 4 that shown in **Fig. 2**, except that there a 30 yr window was chosen. The panels show the
 5 distributions for (a) Ω_{arag} , (b) SST, (c) O₂ inventories, and (d) NPP. This analysis reveals
 6 significantly lower confidence intervals for the 10 yr window than for the 30 yr window for each
 7 of the four drivers.

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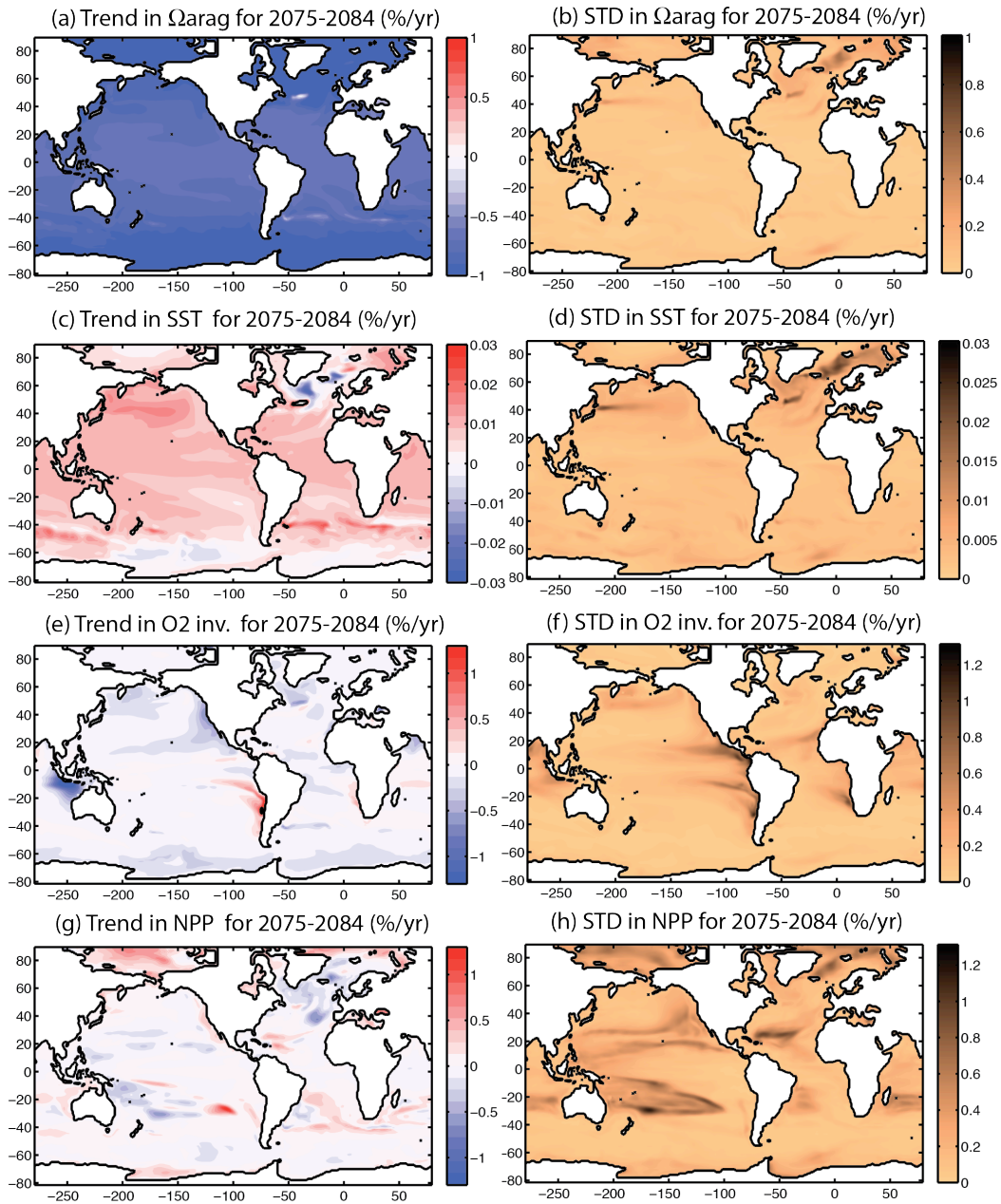
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 2 **Figure 6.** Time of Emergence (ToE), calculated using a threshold of 1 standard deviation (67%
 3 confidence) for (a) Ω_{arag} , (b) SST, (c) O_2 inventories, and (d) NPP. The color scheme has been
 4 chosen to distinguish between relative to the present (2014) with shades of blue indicating a ToE
 5 post-2014 and shades of red indicating a ToE pre-2014.

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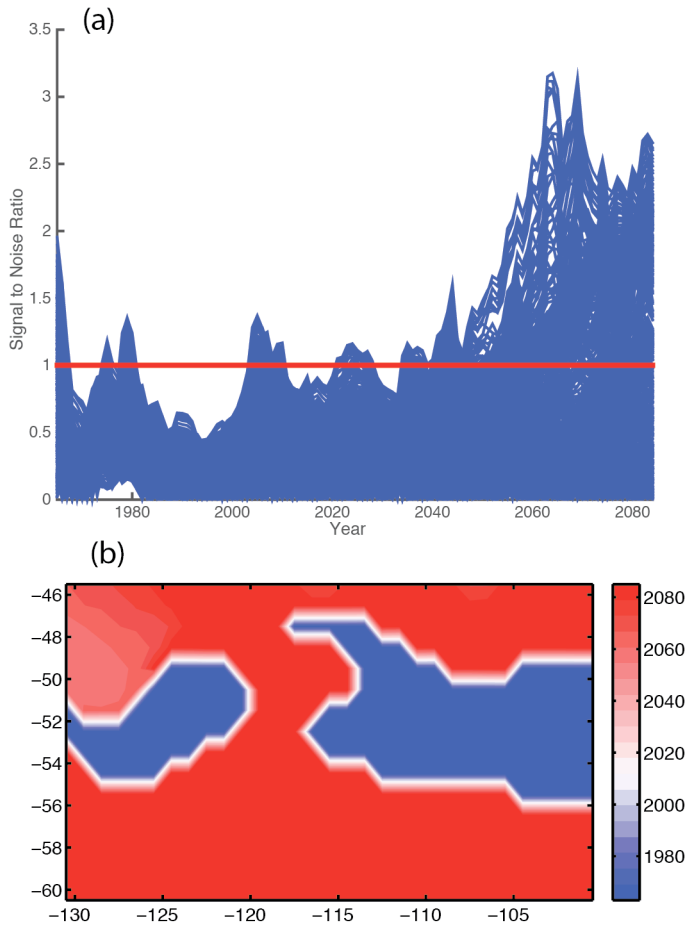
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 2 **Figure A1.** Linear trends (left) and standard deviations of the linear trends (right) for (a-b) Ω_{arag} ,
 3 (c-d) SST, (e-f) O_2 inventories from 100m-600m, and (g-h) net primary production averaged over
 4 2005-2014. All fields are calculated using 30-year trend windows, and the trends are shown in
 5 units of %/year.

6



1
 2 **Figure A2.** Linear trends (left) and standard deviations of the linear trends (right) for (a-b) Ω_{arag} ,
 3 (c-d) SST, (e-f) O_2 inventories from 100m-600m, and (g-h) net primary production averaged over
 4 2075-2084. All fields are calculated using 30-year trend windows, and the trends are shown in
 5 units of %/year.

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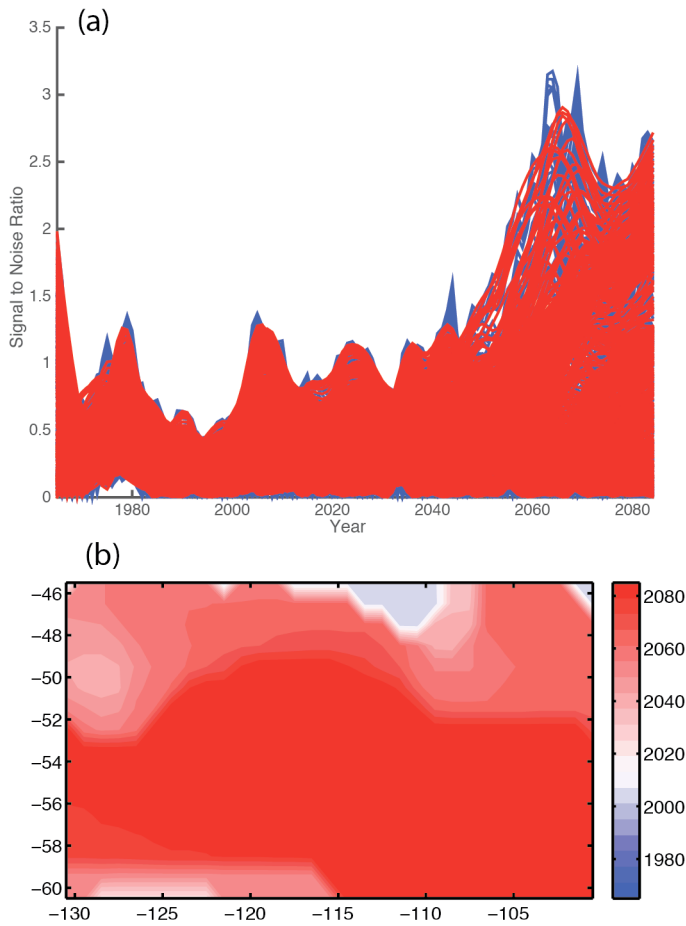


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3 **Figure A3.** Time of emergence of SST considered for a boxed region of the Pacific sector of the
4 Southern Ocean (130°W-100°W and 45°S-60°S). The SNR calculated individually using annual
5 mean SST for each gridpoint in the domain is shown in panel (a), where a 30-year window is
6 used to calculate TREND and NOISE. Short timescale excursions of less than ten years are in
7 evidence in modulations of maximum SNR. The spatial pattern of ToE for SST over this region
8 is shown in panel (b). A ToE before the present time (pre-2014) is indicated by shades of blue,
9 while a later ToE is indicated with shades of red. Saturation (ToE post-2085) is represented with
10 a deep red color.

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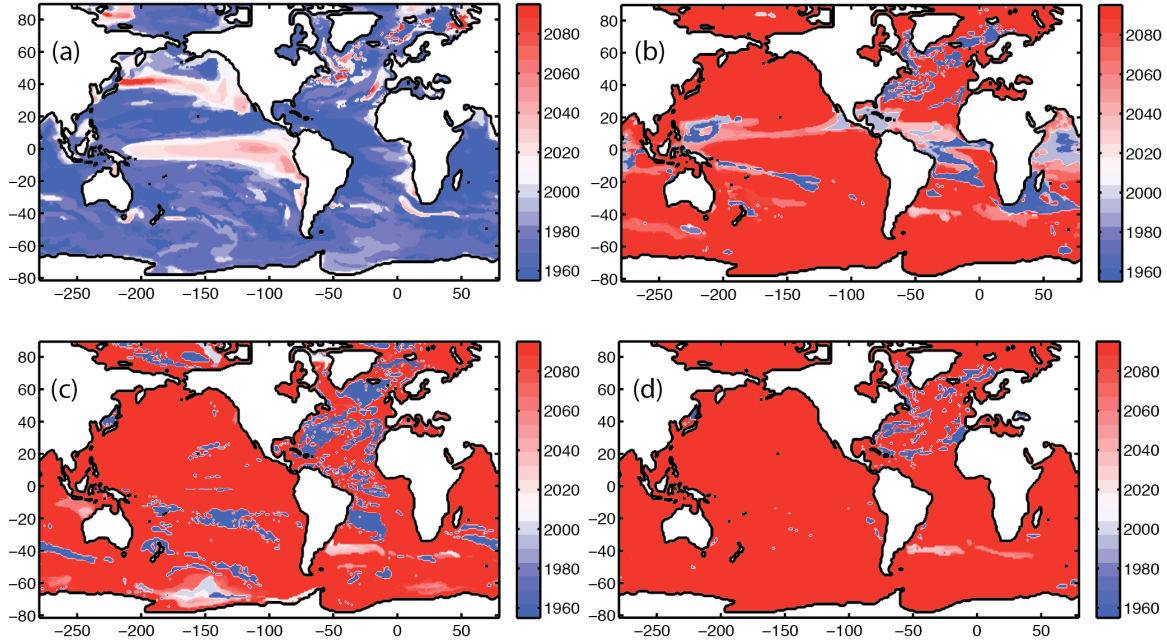


2

3 **Figure A4.** The ToE is considered for the same region, but this time with application of a robust
4 Loess filter with a tolerance window of ten years applied to the SNR of SST calculated for the
5 individual surface grid points in the domain. The SNR after application of the robust Loess filter
6 is shown in panel (a) in red, superposed over the same blue time series considered in **Fig. A3a**.
7 The filtering effect on the short timescale maximum excursions of the SNR is evident. The net
8 effect over the full domain of the robust Loess filter is shown in panel (b), revealing a later ToE
9 over significant portions of the region of interest. A ToE before the present time (pre-2014) is
10 indicated by shades of blue, while a later ToE is indicated with shades of red

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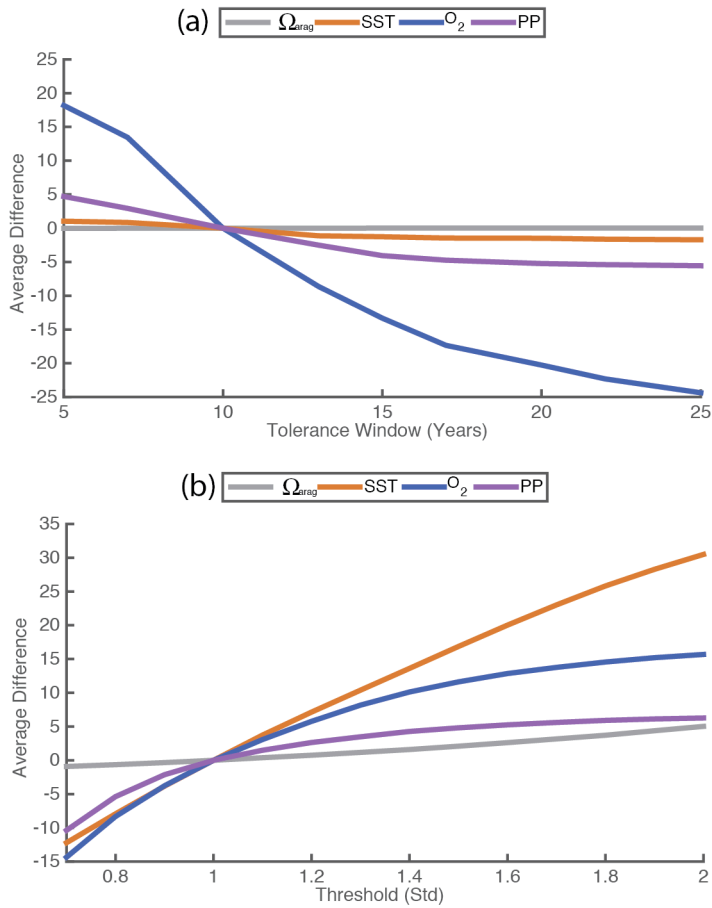
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4 **Figure A5.** The Time of Emergence (ToE) for each of the four drivers has been calculated using
5 a 10-year window for the calculation of trends, considering the time interval 1955-2095. Time of
6 Emergence (ToE), calculated using a threshold of 1 standard deviation (67% confidence) for (a)
7 Ω_{arag} , (b) SST, (c) O_2 inventories, and (d) NPP. The color scheme has been chosen to distinguish
8 between relative to the present (2014) with shades of blue indicating a ToE post-2014 and shades
9 of red indicating a ToE pre-2014. This is the complement to the results with ToE for a 30 yr
10 window, shown in **Fig. 6**.

11



1
 2 **Figure A6.** Sensitivity analysis for tolerance window width in years (a) using a one standard
 3 deviation threshold and revolved around a 10 yr window, as well as threshold level (b) using a 10
 4 yr tolerance window and revolved around a standard deviation of one. Caveats regarding
 5 averaging over fields that experience saturation are discussed in the text of the Supplementary
 6 Materials.

7