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Global Biogeochemical Cycles

RESEARCH ARTICLE

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Potential Predictability of Net Primary Production in the Ocean

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Key Points:
- Marine net primary production is potentially predictable for at least 1 year in advance for many oceanic regions
- Regions where nutrients are the primary driver of net primary production are more predictable than light- or temperature-driven regions
- The dynamic prediction system improves predictability of net primary production in some Large Marine Ecosystems over a persistence forecast

Supporting Information:
- Supporting Information S1

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Abstract

Interannual variations in marine net primary production (NPP) contribute to the variability of available living marine resources, as well as influence critical carbon cycle processes. Here we provide a global overview of near-term (1 to 10 years) potential predictability of marine NPP using a novel set of initialized retrospective decadal forecasts from an Earth System Model. Interannual variations in marine NPP are potentially predictable in many areas of the ocean 1 to 3 years in advance, from temperate waters to the tropics, showing a substantial improvement over a simple persistence forecast. However, some regions, such as the subpolar Southern Ocean, show low potential predictability. We analyze how bottom-up drivers of marine NPP (nutrients, light, and temperature) contribute to its predictability. Regions where NPP is primarily driven by the physical supply of nutrients (e.g., subtropics) retain higher potential predictability than high-latitude regions where NPP is controlled by light and/or temperature (e.g., the Southern Ocean). We further examine NPP predictability in the world's Large Marine Ecosystems. With a few exceptions, we show that initialized forecasts improve potential predictability of NPP in Large Marine Ecosystems over a persistence forecast and may aid to manage living marine resources.

Plain Language Summary

Marine net primary production (NPP) is the base of the marine food web, as well as an important component of the ocean carbon cycle. Year-to-year variations in NPP can influence the availability of living marine resources, such as fish. In this study, we show that an Earth System Model can be used to generate near-term (1 to 10 years) forecasts of marine NPP. Earth System Model-based forecasts of NPP show an improvement over a persistence forecast, where NPP the following year is assumed to be the same as the current year's NPP. Annual NPP variations can be predicted for 1 to 3 years in advance in many oceanic regions, from temperate waters to the tropics. NPP in colder regions, however, is harder to predict. The main drivers of NPP influence its predictability. Places where nutrient availability primarily drives variations in NPP are more predictable than regions of the ocean where light and temperature are the main drivers (primarily high latitude regions). We further demonstrate NPP predictability in coastal regions, the world's Large Marine Ecosystems. We show that NPP predictions could be potentially useful in many Large Marine Ecosystems, and this may help to sustainably manage coastal marine ecosystems.

1. Introduction

Net primary production (NPP) by ocean phytoplankton provides energy to marine ecosystems. Fluctuations in oceanic NPP can therefore lead to variations in living marine resources (Pauly & Christensen, 1995). Not only is marine NPP ecologically important, but it is also a major component of the global carbon cycle, as marine phytoplankton are responsible for roughly half of carbon fixed through photosynthesis each year on a global scale (Falkowski, 2012). A portion of the carbon fixed through NPP in the surface ocean sinks to depth, concentrating carbon in the deep ocean. NPP can vary significantly from year to year, as bottom-up environmental factors controlling phytoplankton NPP (e.g., nutrients, light, and temperature) are subject to long-term trends, as well as substantial interannual variability (Krumhardt et al., 2017; Séférian et al., 2014). While NPP is the ultimate control on net ecosystem production, upper trophic level biomass is not always related to NPP in a straightforward way (see, e.g., Friedland et al., 2012;

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Sherman et al., 2009; Stock et al., 2017). Nevertheless, making near-term (1 to 10 years) forecasts of marine NPP could contribute to more effective management of living marine resources (e.g., Lotze et al., 2019; Payne et al., 2017; Tommasi et al., 2017), improve conservation efforts in marine protected areas (Edgar et al., 2014), and inform climate change adaptation strategies.

Recent progress has been made in generating near-term ("decadal") predictions of physical and biogeochemical quantities using Earth system models (ESMs; see, e.g., Meehl et al., 2014). Initialized ESM forecasts have proven useful for predictions of ocean heat content (Yeager et al., 2012, 2018), sea surface temperature (SST) and air surface temperature (Smith et al., 2007; Stock et al., 2015; Yeager et al., 2018), ocean carbon uptake (Li et al., 2019; Lovenduski et al., 2019), precipitation (Yeager et al., 2018), and sea ice (Yeager et al., 2015) on timescales ranging from 1 to 10 years in advance. Most recently, Park et al. (2019) described seasonal to 2-year predictability of ocean chlorophyll concentration and demonstrate connections with annual fish catch data, illustrating the feasibility and utility of ESM predictions for marine ecosystem quantities. While chlorophyll concentration is subject to substantial variability from phytoplankton physiological changes that may not be indicative of phytoplankton biomass (Behrenfeld et al., 2015), NPP quantifies the net rate of carbon fixation by phytoplankton, an important quantity for marine ecosystem modeling (Lotze et al., 2019). Yet the predictability of NPP on decadal timescales has been explored in relatively few studies. Séférian et al. (2014) demonstrated 3-year predictability of NPP in the tropical Pacific Ocean, surpassing predictability of SST and showing that nutrient advection plays an important role for multiyear prediction of NPP. Further, Yeager et al. (2018) also showed that ESM-based decadal prediction system holds promise in predicting marine NPP in numerous ocean regions, including the tropical and subtropical Atlantic and Pacific, and some eastern boundary upwelling systems, leading to questions about what enables predictability in NPP.

An important requirement for forecasting interannual variations in marine NPP is adequate prediction of its drivers. Bottom-up drivers of NPP include temperature, nutrient availability, and light, while grazing constrains NPP in a top-down sense (Laufkötter et al., 2015). Each of these NPP drivers is influenced by internal climate variability (Krumhardt et al., 2017); the extent to which NPP is predictable may depend on the predictability of its primary drivers. SST, which influences phytoplankton metabolic rates, has been shown to be potentially predictable on wide spatial scales for up to 9 years, with the exception of the Southern Ocean (Yeager et al., 2018). Though the persistence of nutrient anomalies in the tropical Pacific was shown by Séférian et al. (2014) to be an important driver of NPP, the predictability of nutrient advection, a potentially large driver of NPP in much of the ocean, has not been demonstrated using a dynamic ESM-based prediction system.

While predictions of NPP in open ocean regions are ecologically and biogeochemically important, fluctuations of NPP in coastal regions may be of higher interest for society. The world's Large Marine Ecosystems (LMEs) comprise oceanic areas on which humans are most dependent; roughly 90% of living marine resources are harvested within the LMEs (Pauly et al., 2008; Sherman, 2005). LMEs are characterized by distinct bathymetry, hydrography, productivity, and trophically dependent populations. As such, these regions are seen as effective units for marine ecosystem management (Sherman, 2014). Additionally, LMEs contain a majority of marine protected areas which are seen as primary management regions for mitigating the threats of climate change and other human influences on marine biodiversity (Bruno et al., 2018). Predictions of NPP in these regions may aid to effectively manage LMEs with the goals of sustainability and conservation (Edgar et al., 2014).

Forecasts of physical and ecological variables using dynamical prediction systems are commonly compared to a null "persistence" forecast, which assumes that the following year will be same as the current year (lagged autocorrelation; e.g., see Stock et al., 2015; Yeager et al., 2018). A persistence forecast therefore provides a baseline with which to describe the benefit of using a more complex prediction system. While a persistence forecast may be adequate for certain variables or regions that show longer timescales of variability, those that have strong interannual fluctuations (like marine NPP in most regions) would potentially benefit most from a dynamical prediction system.

In addition to comparing to persistence, there are also two different types of forecast predictability measures. "Skillful prediction" refers to the ability of a forecast to match observations. For instance, Park et al. (2019) assess skillful prediction of chlorophyll by comparing to satellite-derived estimates of ocean chlorophyll content. In contrast, "potential predictability" assesses forecasts of ocean variables using a historical reconstruction of the ocean state, generated by an ESM simulation forced by atmospheric observations.

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This allows full field initialization of the ESM for each forecast and evaluation of forecasts over the entirety of the historical reconstruction, rather than being limited to the satellite era. Given the uncertainty and variation across satellite-derived NPP estimates (e.g., see Saba et al., 2011), we focus our analysis on potential predictability of NPP in the global oceans in this study, comparing NPP forecasts to a ESM-based historical reconstruction of marine NPP.

We use a large ensemble of initialized forecasts from the Community Earth System Model (CESM) to demonstrate that interannual variations in NPP are potentially predictable for 1 to 3 years in many regions of the ocean, showing an improvement over a simple persistence forecast. By using a large ensemble of forecasts (each ensemble member differs by round-off level differences in initialization; see section 2), we are able to derive the most statistically probable forecast, the ensemble mean. We examine the main drivers of marine NPP in the global ocean in order to understand why NPP is more predictable in some regions than in others. We further focus on NPP predictability within the world's LMEs in order to assess potential predictability in societally relevant regions. We show that NPP forecasts in some coastal LMEs still offer a substantial improvement over persistence. This study highlights the potential for dynamic ESM-based prediction systems to forecast critical ecosystem metrics like marine NPP.

2. Materials and Methods

2.1. CESM Decadal Prediction System

We use the CESM Decadal Prediction Large Ensemble (CESM-DPLE Yeager et al., 2018) to explore potential predictability of marine NPP. This prediction system is described in detail elsewhere (Lovenduski et al., 2019; Yeager et al., 2018); we thus provide only a brief overview here. The CESM-DPLE consists of 40 forecasts starting each year from 1955 to 2016. Forecasts are initialized in November of the preceding year and then run for 10 full calendar years; therefore, a lead Year 1 forecast refers to the January through December year following initialization. The ensemble of forecasts produced for each year only differ by round-off level (10^{-14}°C) differences in the initial air temperature field, which is sufficient to rapidly generate spread across the ensemble.

The code base for the CESM-DPLE is CESM version 1.1 with ocean biogeochemistry (Long et al., 2013; Moore et al., 2004, 2013) run fully coupled at a nominal 1° resolution. Initial conditions for the land and atmosphere were initialized using a single member of the CESM large ensemble (Kay et al., 2015) and, thus, were not constrained by observations. The ocean and sea ice, however, were initialized using a CESM forced ocean-sea ice (CESM-FOSI) simulation (including marine biogeochemistry) that was forced by historical atmospheric state and flux fields based on the Coordinated Ocean-Ice Reference Experiment reanalysis data set (Yeager et al., 2018); this setup allows full field initialization of physical and biogeochemistry ocean variables. In the section below, we evaluate this CESM-FOSI NPP reconstruction with respect to observationally based, satellite-derived NPP estimates. The forecast ensembles drift from their initialized state; thus, the variables from the CESM-DPLE presented here are all drift corrected by removing a forecast lead year-dependent model climatology from each variable, resulting in forecasted anomalies (see Yeager et al., 2018).

2.2. Data Processing and Statistics

We focus on the predictability of interannual anomalies in marine NPP integrated over the upper 150 m. We removed a linear trend from the forecasts and CESM-FOSI reconstruction in order to focus on the interannual variability apart from long-term trends over the study period. In this study, as in previous decadal prediction studies (e.g., Lovenduski et al., 2019; Yeager et al., 2018), we use anomaly correlation coefficients (ACC) between our observation-based initialization data set (here, the CESM-FOSI reconstruction) and the corresponding "forecasted" year from the CESM-DPLE to evaluate the "potential predictability" of variables in the Earth system. This comparison does not depend on model skill but rather evaluates the potential for initialized forecasts to predict the evolution of the system. We also note that ACC does not provide information on the magnitude of NPP anomalies but provides a measure of how variations in NPP match between forecasts and the CESM-FOSI reconstruction. Here, we use ACC as a measure of the relative association of the average forecast with the CESM-FOSI simulation. We compare NPP forecasts from the CESM-DPLE to a simple persistence forecast, which assumes that the following forecast period will be same as the current forecast period (i.e., autocorrelation). We use a z-test to evaluate the statistical difference in ACC at the 95% level between the persistence forecast and the CESM-DPLE forecast.

We assess the influence of bottom-up drivers on NPP using variables from the CESM-FOSI reconstruction. These include the limitation terms for temperature, light, and nutrients, which modify the maximum growth rates of the phytoplankton functional types (PFTs) in the model. Each of these limitation terms ranges from 0 to 1, with 0 being the most limiting and 1 indicating plentiful supply. We determined the most limiting nutrient for each PFT for each grid cell in the top 150 m; therefore, the nutrient limitation term in this analysis corresponds to the nutrient most limiting phytoplankton growth. We created biomass-weighted limitation terms, weighting each limitation term by the biomass of the PFT experiencing the limitation over the top 150 m of the water column. The limitation terms for temperature, light, and nutrients were then detrended and correlated with depth-integrated NPP anomalies. We interpret the correlation coefficient as a measure of the influence of each limitation term on NPP, noting that this does not directly take the magnitude of the influence into account.

We also analyzed the CESM-DPLE potential predictability of various bottom-up drivers of NPP, including SST, photosynthetically active radiation (PAR) at the surface, mixed layer depth, and the total physically mediated tendency (i.e., rate of change) of PO_4 in the upper 100 m, not including biological uptake/remineralization. Though PO_4 is not always the nutrient that limits phytoplankton growth in the model, we chose PO_4 rather than NO_3 to represent macronutrient flux because (1) unlike NO_3 it is not complicated by NOx fluxes from the surface, (2) its influence on phytoplankton NPP is more straightforward than NO_3 (nitrogen fixation/ammonia supply influence N availability), and (3) NO_3 and PO_4 are highly correlated (Figure S1 in the supporting information) so their physical fluxes are likely very similar in most regions.

2.3. Evaluating the CESM-FOSI NPP Reconstruction

To assess the skill of CESM to simulate observed NPP, we compare the CESM-FOSI NPP reconstruction to NPP derived from the Moderate Resolution Imaging Spectroradiometer (MODIS) over the time period 2003 (first full year of MODIS) to 2015 (last year of the FOSI reconstruction). There exist numerous algorithms for calculating NPP from ocean color data, which offer substantially different solutions for estimating ocean NPP (Saba et al., 2011). Rather than selecting one of these algorithms, we opted to use the mean of three prominent models: the Vertically Generalized Production Model (VGPM; Behrenfeld & Falkowski, 1997), the Eppley-VGPM (Eppley; Behrenfeld & Falkowski, 1997; Eppley, 1972; Morel, 1991), and the Carbon-based Productivity Model (CbPM; Behrenfeld et al., 2005; Westberry et al., 2008). To evaluate the CESM-FOSI reconstruction in simulating marine NPP, we compare the mean annual NPP. We also interpolated CESM NPP and satellite-derived NPP to a common 2° grid in order perform correlations of NPP variability and compare standard deviation over the satellite period between the satellite-derived NPP and depth-integrated NPP from the CESM-FOSI reconstruction.

3. Results and Discussion

In this section we first provide an evaluation of the the CESM-FOSI NPP reconstruction with respect to satellite-derived NPP. We then present a global overview of NPP predictability and evaluate how NPP drivers may influence its predictability. Lastly, we examine NPP predictability in the world's LMEs.

3.1. Evaluation of the CESM-FOSI Reconstruction of NPP

Here, we evaluate the CESM-FOSI reconstruction of NPP as a surrogate for NPP observations. We focus on the evaluation of NPP because other ocean variables in the CESM-FOSI reconstruction have been previously evaluated in the literature (e.g., Lovenduski et al., 2019; Yeager et al., 2018). Marine NPP in the CESM-FOSI reconstruction shows good correspondence to satellite-derived marine NPP, as both show similar geographic patterns in marine NPP (Figures 1a and 1b). Many areas of the ocean show a significant positive correlation between modeled NPP and the satellite-derived NPP over the satellite period (Figure 1c; red areas). The CESM-FOSI reconstruction, however, tends to underestimate the overall magnitude of the coastal NPP according to the satellite-derived observations, especially in Eastern Boundary Upwelling systems and in the western Indian Ocean (Figures 1a and 1b). The relatively coarse resolution of the model likely contributes to this bias. The model underestimates NPP variability in these same regions (pink regions on Figure 1d), while overestimating NPP variability in the subpolar Southern Ocean and central equatorial Pacific (green regions on Figure 1d). These are also the regions where we observe the highest mean absolute error in the CESM-FOSI reconstruction referenced to satellite-derived NPP (Figure S2).

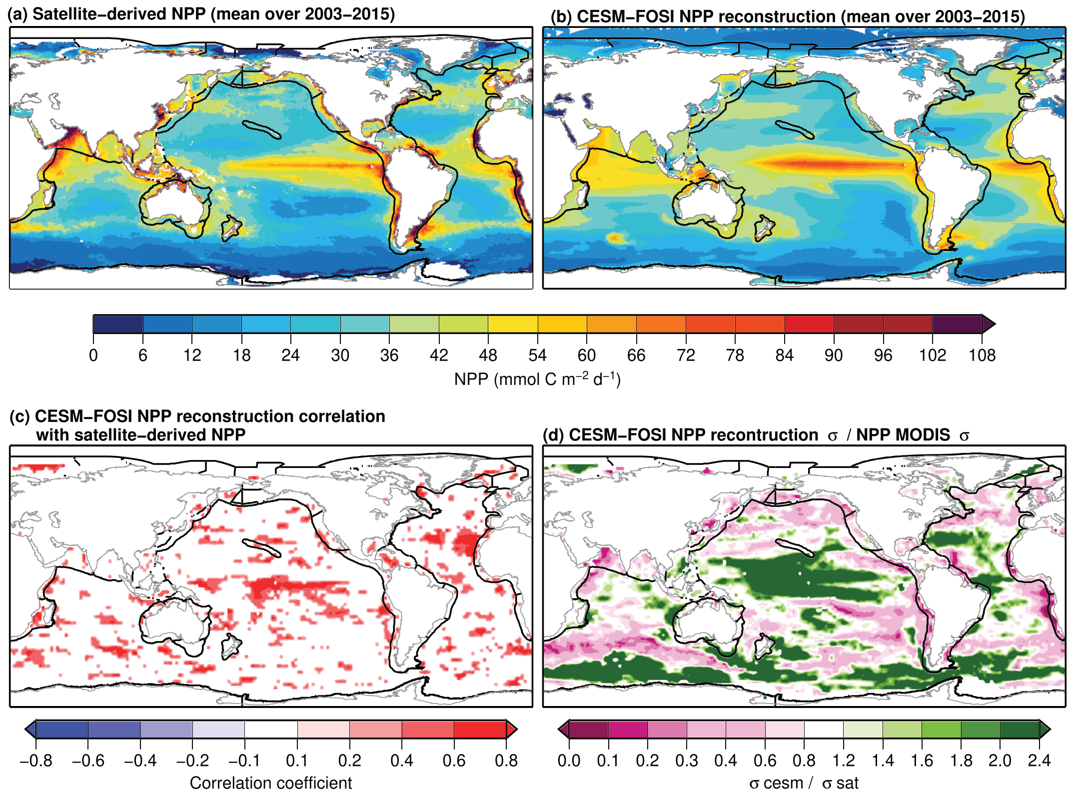

Figure 1. A comparison of the CESM-FOSI NPP reconstruction and satellite-derived NPP (mean of VGPM, Eppley, and CbPM; see section 2) over the period 2003 to 2015. Panels (a) and (b) show annual average satellite-derived NPP and NPP from the FOSI reconstruction, respectively. Panel (c) shows the correlation coefficients between annual mean FOSI NPP reconstruction and satellite-derived annual mean NPP (mean of VGPM, Eppley, and CbPM; see section 2); only correlations at 90% significance are shown. The ratio in standard deviation (σ) of annual means between the FOSI NPP reconstruction and satellite-derived NPP is plotted in panel (d). Large Marine Ecosystem (LME) boundaries are shown by black lines.

3.2. Potential Predictability of Marine NPP: A Global Overview

For each year of the CESM-DPLE, 40 retrospective forecasts of annual marine NPP anomalies each provide a plausible trajectory for marine NPP, with the ensemble mean being the most probable forecast. In Figure 2a, drift-corrected forecasts are shown for four example years to illustrate this concept (ensemble members shown in light green with the ensemble mean in dark green). Globally integrated NPP anomalies are predictable 1 year in advance, as a lead Year 1 forecast time series corresponds well to the CESM-FOSI NPP reconstruction (Figure 2b). Indeed, the correlation between the two lines in Figure 2b is ~0.8, but this rapidly decreases for subsequent lead years (Figure 2c, dark green line). Though the CESM-DPLE global NPP anomaly forecast shows higher potential predictability than a persistence forecast for lead Years 1 and 2, it is not significantly higher than a persistence forecast at the 95% level (Figure 2c, yellow line). A geographical view of potential predictability offers more insight into regions where NPP anomalies may show a significant improvement over a persistence forecast.

In Figures 3a–3c, we present maps of the potential predictability (measured by ACC) of marine NPP for forecast Years 1, 3, and 5 (see Figure S3 for maps of all forecast lead years). The improvement in potential predictability over a simple persistence forecast is presented Figures 3d–3f, with stippling highlighting areas where the CESM-DPLE NPP prediction shows a significant improvement over persistence. Potential predictability in marine NPP is high for most areas of the ocean 1 year in advance (Figure 3a). NPP is especially predictable from temperate waters to the tropics. The subpolar and polar regions of the Southern Ocean show low potential predictability in NPP, as do some equatorial regions (e.g., northern Indian Ocean, far west equatorial Pacific). Areas where there is a significant improvement over persistence for a lead Year 1 NPP forecast are mainly in the Southern Hemisphere, as well as some regions in the subtropical and temperate regions of the North Atlantic and North Pacific (Figure 3d). However, there are areas where a persistence

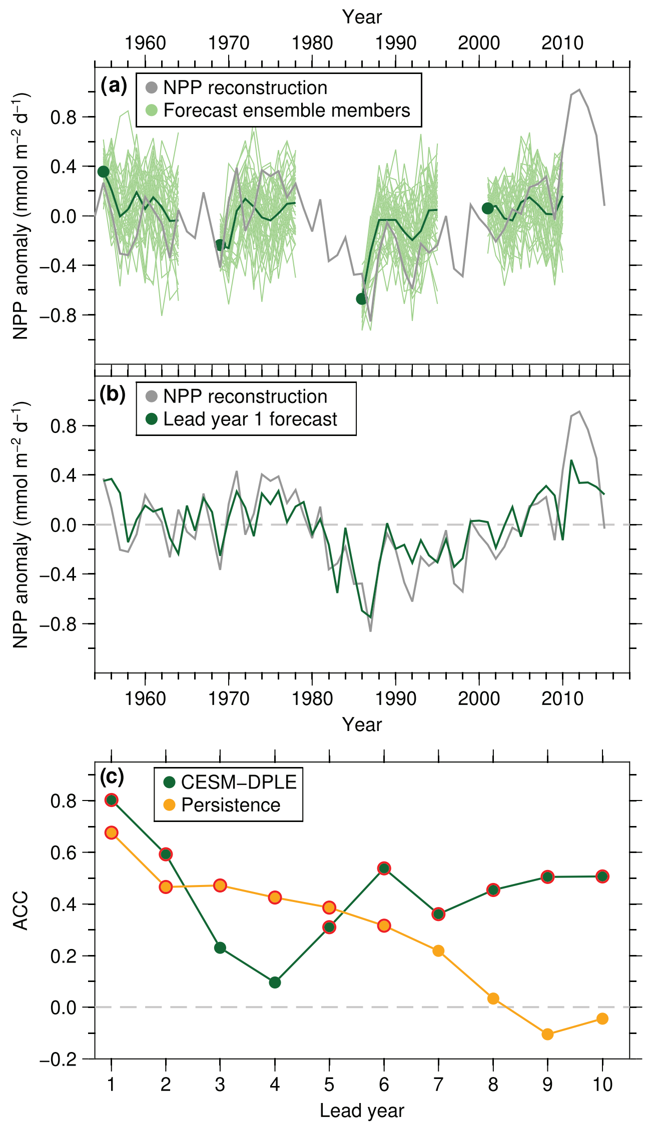

Figure 2. Predictability of globally integrated marine NPP anomalies in the CESM-DPLE: Panel (a) shows initialization of 40 ensemble members (in light green) from the CESM-FOSI NPP reconstruction (in gray) for initialization years 1955, 1969, 1986, and 2001 (ensemble means are shown in dark green); panel (b) shows correspondence between NPP anomalies over time for the FOSI NPP reconstruction and the lead Year 1 forecast; panel (c) shows anomaly correlation coefficients (ACC) as a function of lead year for a persistence forecast and the CESM-DPLE forecast for global NPP anomalies. Red circles indicate that the ACC is significant at 95%.

forecast performs better than the CESM-DPLE (brown areas in Figures 3d–3f), such as the upwelling regions along the eastern boundary of the South Atlantic. As forecast lead time increases, potential predictability of marine NPP tapers off quickly for many areas of the ocean (Figures 3b and 3c). Some regions, however, show NPP potential predictability for lead times >1 year; those include the South Pacific, western Atlantic, and southern Indian Ocean.

In order for predictions of marine NPP to be applied in a management sense, NPP must be accurately simulated in the ESM and predictable. Yeager et al. (2018) showed a global view of "skillfull predictability" for a lead Year 1 NPP forecast using the CESM-DPLE (see their Figure 10d). Here, we evaluated the ability of CESM to simulate NPP when forced by an observational atmospheric forcing product (CESM-FOSI reconstruction; see section 3.1), examining "potential predictability" separately. Some oceanic regions do indeed show higher correspondence when compared to satellite-derived NPP than others. For example, CESM-FOSI-reconstructed marine NPP in subtropical regions correlates well with satellite-derived NPP (red

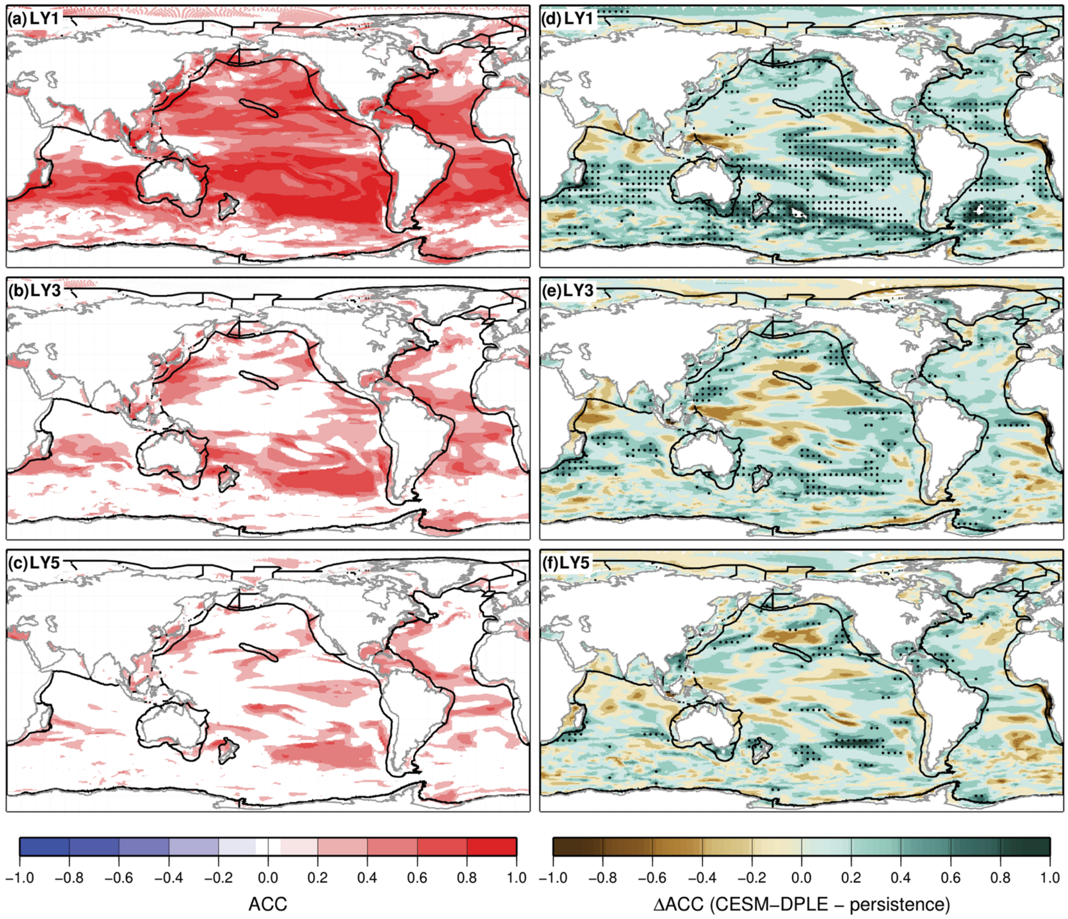

Figure 3. Potential predictability of marine NPP in the CESM-DPLE: Anomaly correlation coefficients (ACC) between the CESM-FOSI NPP reconstruction and NPP predicted by the CESM-DPLE for lead Years 1 (a), 3 (b), and 5 (c). Only significant correlations (95%) are shown; white areas denote nonsignificant correlations. Panels (d), (e), and (f) show the CESM-DPLE potential predictability improvement over a persistence forecast (ΔACC), with stippled areas showing where there is a significant improvement over persistence at the 95% level . Large Marine Ecosystem (LME) boundaries are shown by black lines.

areas in Figure 1c) and shows similar levels of variability (Figure 1d). These subtropical regions also have high potential predictability 1 year in advance (Figure 3a), demonstrating the potential applicability of subtropical NPP predictions. Likewise, parts of the North Atlantic, Western Pacific, and Eastern Indian Ocean show adequate model skill (as evaluated using the the CESM-FOSI simulation; section 3.1) and potential predictability. However, some high-latitude regions, such as the subpolar and polar Southern Ocean, show adequate correspondence to satellite-derived NPP but low potential predictability (Figures 1 and 3), suggesting low ability to predict the evolution of NPP drivers. In the following section we explore why some regions may have better potential predictability using the CESM-DPLE forecasting system than others.

3.3. Drivers of NPP Affect Its Predictability

We expect that interannual variations in NPP will be potentially predictable if the bottom-up drivers exhibit high potential predictability. To understand which bottom-up drivers (temperature, nutrients, or light) have the greatest influence on variations in marine NPP, we correlate biomass-weighted phytoplankton limitation terms with depth-integrated marine NPP anomalies from the CESM-FOSI reconstruction (see section 2.2 for more details). From this analysis, we interpret that marine NPP is most controlled by the limitation terms that show the highest correlation with NPP in the CESM-FOSI reconstruction. We further classify regions as being primarily controlled by a single bottom-up driver based on highest correlation to NPP anomalies. Nutrient limitation appears to drive NPP variations in the low- to middle-latitude ocean regions (Figure 4a). Light and temperature limitations show similar geographic patterns for driving marine NPP (see Figures 4b

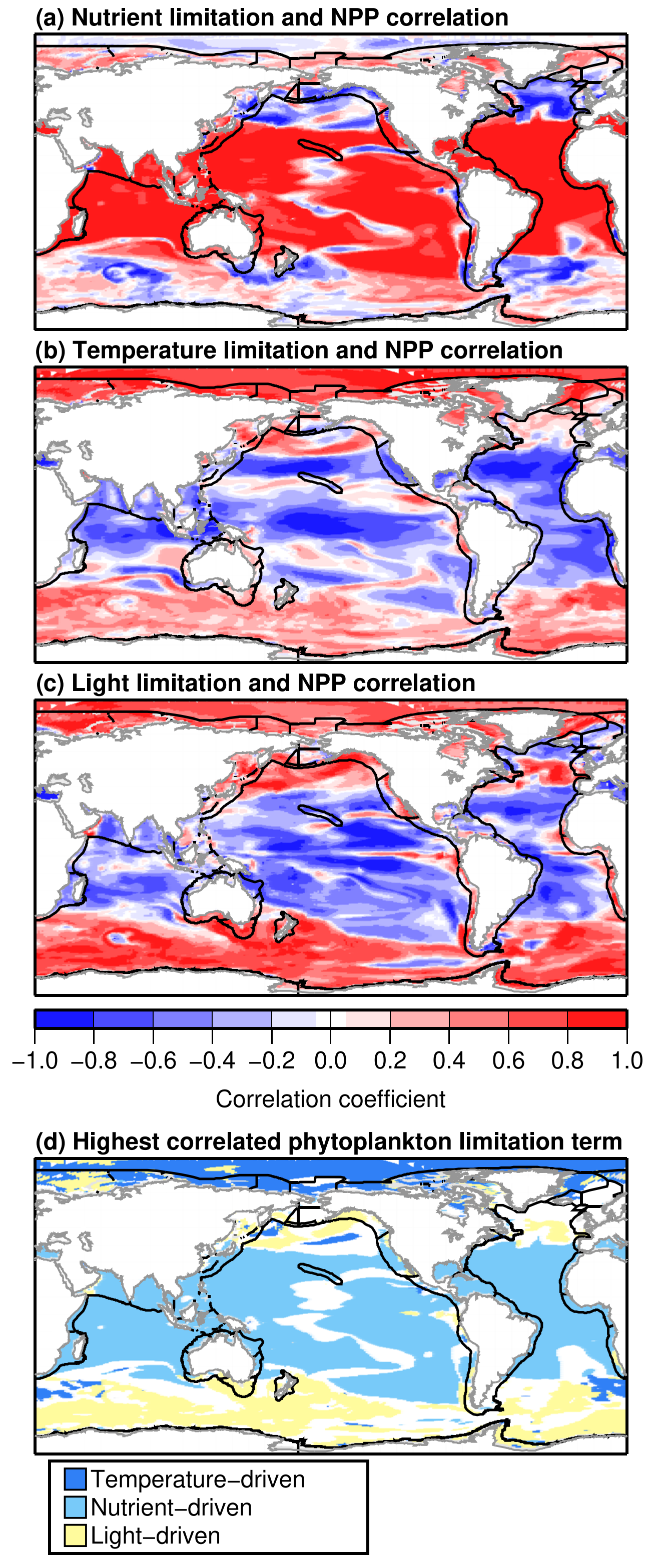

Figure 4. Correlations between annual mean NPP anomalies and biomass weighted limitation terms from the CESM-FOSI reconstruction: (a) nutrient limitation (most limiting nutrient; see section 2), (b) temperature limitation, and (c) light limitation (nonsignificant correlations are masked with white). All variables were annually averaged and detrended prior to doing correlations. Panel (d) shows the limitation term with the highest correlation coefficient with NPP ("main driver"), with white areas denoting places were none of the correlations were significant at 95%. Large Marine Ecosystem (LME) boundaries are shown by black lines.

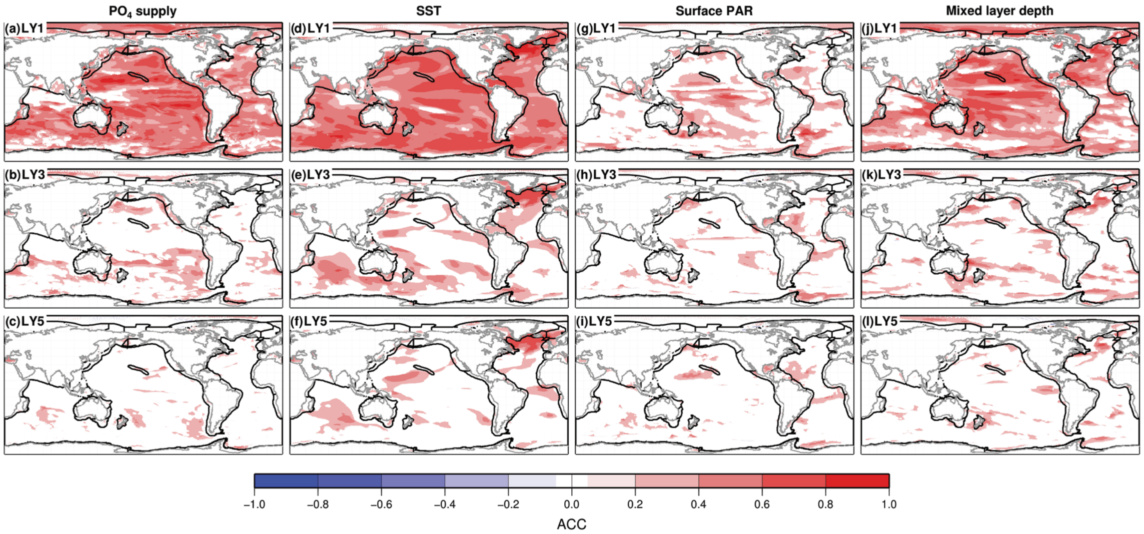

Figure 5. Potential predictability (anomaly correlation coefficients, ACC, between CESM-DPLE ensemble mean and the CESM-FOSI reconstruction) for lead Years 1, 3, and 5 for four NPP drivers: PO_4 physical supply (panels (a), (b), and (c)), sea surface temperature (SST; panels (d), (e), and(f)), surface photosynthetically active radiation (PAR; panels (g), (h) and (i)), and mixed layer depth (panels (j), (k), and (l)). See supporting information for all lead years. Only significant correlations (95%) are shown; white areas denote nonsignificant correlations. Large Marine Ecosystem (LME) boundaries are shown by black lines.

and 4c): Variability in temperature and light explains most NPP variance in the high-latitude oceanic regions. Interannual variability in NPP in the North Atlantic and most of the Southern Ocean appears to be primarily driven by variations in light, while NPP in the Arctic, and some small regions in the subpolar Southern Ocean south of Africa and parts of the North Pacific are primarily influenced by variations in temperature (Figure 4d). Though increases in temperature, light, and nutrients all have a positive effect on NPP in CESM, negative correlations also result from this analysis (blue areas on Figures 4a–4c). This is due to anticorrelations between the drivers. For instance, deeper mixed layer depths in the subtropics will result in more available nutrients to fuel phytoplankton production, but this also leads to lower light levels and cooler sea water temperatures. Likewise, the negative correlation between the nutrient limitation term and NPP in the North Atlantic (Figure 4a) is explained by a strong positive correlation with the light limitation term; nutrients are more limiting during high light conditions associated with increased stratification.

These correlations between the phytoplankton limitation terms and NPP anomalies help to explain why NPP is potentially predictable in some oceanic regions and not in others. Regions where NPP is driven by nutrient availability, in general, have especially high potential predictability (Figures 3 and 4d). This is in agreement with Séférian et al. (2014), who found that nutrient advection plays an important role in predicting NPP in the tropical Pacific. One obvious exception is the northern Indian Ocean, where NPP is controlled by nutrient input, but predictability is low. Interestingly, chlorophyll is predictable in the northern Indian Ocean (Figure S4), highlighting the differences between chlorophyll and NPP potential predictability in the CESM-DPLE. Areas of the ocean in which variability in NPP is driven predominantly by temperature are more limited in spatial extent; these have moderate to low potential predictability 1 year in advance (CESM-DPLE NPP predictions in primarily temperature-driven regions do not show a significant improvement over a persistence forecast; Figures 3 and 4). While we do observe a few light-driven regions with high potential predictability (e.g., western subpolar North Atlantic), most areas where variability in NPP is driven by light (e.g., subpolar Southern Ocean) are not predictable even 1 year in advance. Indeed, interannual variations in PAR at the surface are not predictable in most regions (Figures 5g, 5h, and S5) and mixed layer depth is predictable for one lead year in many oceanic regions but not in the Southern Ocean (Figures 5j–5l and S6). This explains why we observe low potential predictability in the light-controlled Southern Ocean; we hypothesize that variations in cloud cover or sea ice may be contributing to the unpredictability in surface PAR. In contrast, the potential predictability of the physical flux of PO_4 (as a representative nutrient; see section 2) is high 1 year in advance for many areas of the ocean (Figures 5a–5c and S7). SST also shows high potential predictability for lead times of several years (Figures 5d–5f), especially in the North Atlantic, where SST ACC is high for forecast lead times >9 years (Figure S8; Yeager et al., 2018). The parts of the

North Atlantic where temperature is the primary driver are therefore quite predictable (e.g., the region north of Iceland). In contrast, the areas of the North Atlantic where there was no dominant driver show lower predictability (white areas on Figure 4d). There are, however, some patches of predictable NPP in the light-driven regions of the North Atlantic subpolar gyre (yellow areas on Figure 4d), indicating that mixed layer depth (which does show high ACC in this region; Figures 5j–5l and S7) may be the primary driver of light variations in this region.

Interestingly, there are some regions where NPP is potentially predictable even though the potential predictability of bottom-up drivers is quite low. This includes parts of the western Atlantic and southeast Pacific for lead times >1 year (Figures 3 and 5). This points to another potential driver of NPP: the persistence of phytoplankton biomass from 1 year to the next within a region. In low productivity regions where nutrients are efficiently recycled in the upper ocean, initialization of biomass anomalies in the CESM-DPLE forecasts may be contributing to predictability by initializing how much biomass (and the nutrients contained therein) is in a region. Places and forecast lead times where NPP is potentially predictable despite low predictability of bottom-up drivers are typically oligotrophic systems, and we speculate that biomass initialization is enabling this predictability. To assess how much biomass persistence could contribute to predicting NPP, we calculated a persistence forecast for phytoplankton biomass using the CESM-FOSI reconstruction; phytoplankton biomass indeed has high persistence in the above-mentioned regions (Figure S9). Though we did not assess the potential predictability of phytoplankton biomass using the CESM-DPLE, chlorophyll predictability in these regions is high for several lead years (Figure S4), suggesting that biomass could also gain additional predictability over persistence using the CESM-DPLE forecasting system. This helps to explain why NPP may maintain predictability even though its physical drivers do not. Another specific example of this phenomenon can be seen in the Gulf of Mexico LME, where marine NPP is primarily controlled by nutrient availability (Figure 4). However, neither physical supply of nutrients nor SST is predictable here, while light has low to moderate predictability (Figure 5), and yet NPP has fairly consistent potential predictability out to forecast lead Year 10 (Figures 3 and S3). Here persistence of phytoplankton biomass and efficient nutrient recycling may be helping maintain long-term predictability. In the following section we further explore the predictability of marine NPP in the world's LMEs.

3.4. NPP Predictability in LMEs

Assessing potential predictability of marine NPP in LMEs could be useful to societies dependent on living marine resources. LMEs are primarily coastal regions, and thus, the physical dynamics that influence the drivers of marine NPP could be difficult to adequately simulate given the coarse (nominal 1°) resolution of CESM. However, we do observe predominately positive correlations between modeled NPP from the CESM-FOSI reconstruction and satellite-derived NPP over the MODIS satellite record, yet variability in these regions is generally underestimated (Figure S10). Therefore, despite the model's coarse resolution and an underestimation of NPP variability, NPP prediction using the CESM-DPLE may help to inform the direction of interannual anomalies of marine NPP in LMEs. Potential predictability for all LMEs is presented in Table S1 for forecast lead Years 1 through 5. In this section, we invoke NPP correspondence with satellite-derived NPP (which admittedly contains its own uncertainties) in combination with potential predictability to assess how useful NPP forecasts may be for various LMEs.

In general, as with open ocean regions, LMEs in oceanic regions where NPP is driven by variations in nutrient availability have higher potential predictability than those driven by light/temperature (Figure 6, top half of LMEs in panel (m)). One of these is the California Current LME (Figures 6a and 6g), an economically important region for fisheries. Here, wind-driven upwelling brings nutrients to the surface, stimulating production by phytoplankton (Rykaczewski & Checkley, 2008); NPP is simulated well by the CESM in the California Current (Figure S10), and potential predictability of NPP is significantly higher than a persistence forecast for a lead Year 1 forecast (Figures 6a, 6g, and S11), indicating that CESM-DPLE NPP predictions may be useful here. Likewise, NPP in two other nutrient-driven LMEs, the Insular Pacific-Hawaiian LME and the Agulhas Current, has good correspondence to satellite-derived NPP (Figure S10), and forecasts show particularly good improvement over a persistence forecast (Figures 6b, 6h, 6m, and S11). Also noteworthy, NPP in the northeast and east central Australian Shelf regions has high potential predictability (Figure 6m) and moderate correspondence to satellite-derived NPP. These two Australian LMEs contain the Great Barrier Reef, and therefore, high NPP predictability could be relevant to conservation efforts. Other nutrient-driven

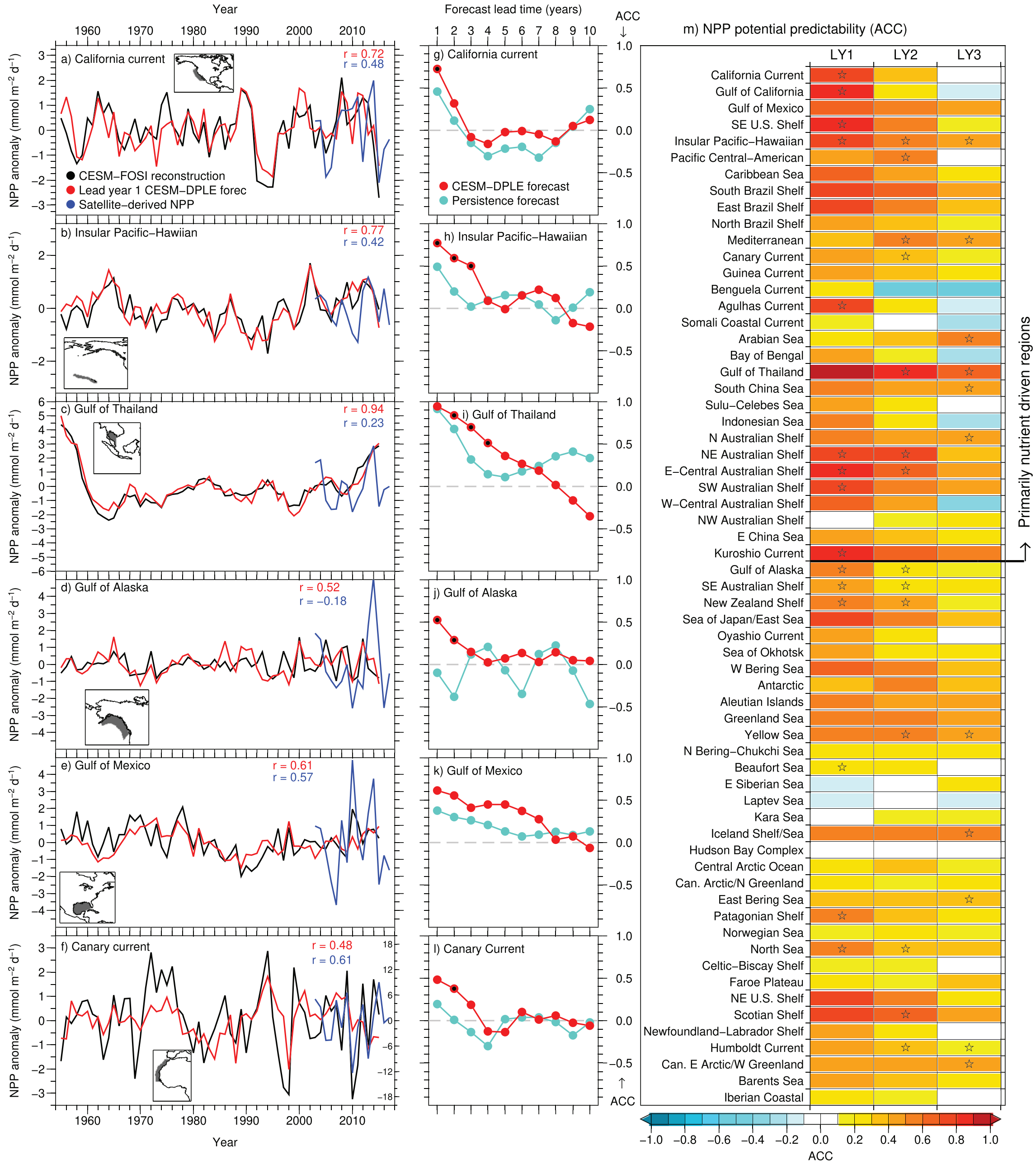

Figure 6. Potential predictability of marine NPP in Large Marine Ecosystems (LMEs). Panels (a)–(f) show time series of NPP anomalies from the CESM-FOSI NPP reconstruction (black), the lead Year 1 forecast (red), and the satellite-derived NPP (blue) for six example LMEs; red and blue *r* values in the upper right of each plot refer to the correlation between the CESM-FOSI reconstruction and a LY1 forecast and the CESM-FOSI reconstruction and the satellite-derived NPP, respectively. Note that the right *y* axis in panel (f) is on a different scale and used to plot the satellite-derived NPP. Panels (g)–(l) show potential predictability (ACC) as a function of forecast lead year for the CESM-DPLE initialized forecast (red) and a persistence forecast (turquoise) for the same example LMEs as in the first column. Panel (m) shows the potential predictability (ACC) for all LMEs for forecast lead Years (LY) 1, LY2, and LY3, ordered with nutrient-driven regions on the top and temperature/light-driven regions on the bottom half. Black dots in the second column of plots and stars in panel (m) indicate a significant improvement in ACC over persistence.

LMEs (e.g, Gulf of California, southeast U.S. Shelf, and the Kuroshio current) have high potential predictability for at least 1 year in advance, but NPP in these regions from the CESM-FOSI reconstruction does not correlate highly with satellite-derived NPP (Figures S10 and S11).

Some temperature and light-driven LMEs have significantly higher potential predictability than persistence for at least one lead year, though these generally have lower ACC than nutrient-driven regions (Figures 6 and S11). One of these is the Gulf of Alaska, where an ACC of ~0.5 denotes a large improvement over a

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persistence (Figures 6d, 6j, and S11); a persistence forecast for NPP appears to be particularly inadequate in this variable region. Potential predictability of mixed layer depth in the Gulf of Alaska (Figures 5j–5l) may be enabling this improvement over persistence. Other similar LMEs include the southeast Australian Shelf, New Zealand shelf, Yellow Sea, Beaufort Sea, Patagonian Shelf, and the North Sea (Figure 6m, bottom half of LMEs). NPP anomalies from the CESM-FOSI reconstruction show positive correlations with both light and temperature in these regions (Figure 4), but since surface PAR is not particularly predictable in these regions, we attribute most the potential predictability in these LMEs to temperature-driven variations in NPP and mixed layer depth anomalies. However, NPP variations from the CESM-FOSI reconstruction in most of these high-latitude LMEs do not correlate highly with satellite-derived NPP observations, limiting their applicability.

Many LMEs show modestly improved potential predictability over a persistence forecast during the first several forecast lead years (Figure 6m, regions without stars). The Gulf of Thailand LME shows the highest ACC of all the LMEs (ACC = 0.94), but surprisingly, the CESM-DPLE forecast is not significantly better than persistence for a lead Year 1 forecast (see Figures 6c and 6i). In this region the interannual variability in marine NPP is quite low compared to decadal variability (Figure 6c) and therefore initialized forecasts only show only a slight advantage over persistence for a lead Year 1 forecast, although this advantage widens for subsequent forecast lead years (Figure 6i). As mentioned above, the Gulf of Mexico shows persistence in phytoplankton biomass which, along with efficient nutrient recycling, may help drive NPP potential predictability. Though we see only a small improvement using a CESM-DPLE NPP forecast over persistence in this region, we do note that CESM-FOSI-simulated NPP in the Gulf of Mexico (as well as the Caribbean LME) corresponds well to satellite-derived NPP (Figure S10) suggesting that forecasts here may still be somewhat useful. Lastly, though overall NPP variability in the Canary Current LME is underestimated (Figures 6f and S10b), interannual variations correlate quite well with satellite-derived NPP (Figures 6 and S10a) meaning that predictions could help inform the direction of NPP anomalies in this region. Potential predictability of NPP in the Canary Current is higher than a persistence forecast, but the improvement is only significant for forecast lead Year 2 (Figures 6f and 6l).

Finally, while the CESM-DPLE offers improved forecasts (over persistence) in many LMEs, there are regions where potential predictability using the CESM-DPLE is always low. These include the Benguela Current LME, the northwest Indian Ocean LMEs, and Antarctic and Arctic LMEs. In a few regions a persistence forecast is simply superior. In fact, the Benguela Current is the only LME where a persistence forecast has significantly better ACC than the CESM-DPLE forecast (Figure 3). There are also places where NPP is difficult to predict whether using an initialized forecast system, such as the CESM-DPLE, or a persistence forecast. Predicting NPP in high-latitude LMEs (e.g., Arctic LMEs), where temperature and light are controlling factors on NPP, is difficult; ACC is usually somewhat higher using the CESM-DPLE than persistence but still too low to be useful. These regions highlight the limitations of ESM-based prediction systems for forecasting interannual anomalies of NPP in the oceans.

4. Conclusions

Here we have demonstrated that initialized Earth system prediction is capable of forecasting interannual variations in marine NPP for many regions of the ocean. We show that the principle drivers of marine NPP variability influence its potential predictability and that nutrient-driven regions are, in general, more predictable than light- and temperature-driven regions. As marine NPP quantifies converted energy that is available to the rest of marine ecosystems, including living marine resources, we demonstrate NPP potential predictability in society-relevant regions, the world's LMEs. We find that initialized prediction using the CESM-DPLE offers an improvement over persistence in some LMEs and many open ocean regions for predicting NPP anomalies at least 1 year in advance.

Making decadal forecasts of NPP using a ESM prediction system, such as the CESM-DPLE, carries several caveats. The coarse resolution of the model lacks the simulation of mesoscale currents which can be important for variations of NPP in some regions (Harrison et al., 2018), as well as coastal upwelling processes (Brady et al., 2019; Siedlecki et al., 2016; Small et al., 2015). Additionally, marine ecosystems in CESM are represented in a simplified way, simulating only three PFTs and one zooplankton, while lacking upper trophic levels (Moore et al., 2013). This simplification could make translating NPP predictions to predictions of living marine resource availability more challenging.

One future direction of this research would be to link NPP with fishery yields as Park et al. (2019) have done with chlorophyll and SST prediction. While we showed NPP predictability in LMEs, the link between NPP and productivity of living marine resources is not always straightforward (see, e.g., Friedland et al., 2012), complicated by uncertainties around fish catch estimates, variable fishing technology and effort, and diverse marine food web dynamics. For instance, Stock et al. (2017) developed an energy-based model that combined NPP with other ecosystem and management characteristics (e.g., benthic versus pelagic energy pathways and fishing effort) to explain fish catch in LMEs better than a model that uses NPP alone. In any case, NPP, as the base of the marine food web, remains an important metric for fishery management and the basis for most fish biomass models (Lotze et al., 2019). Therefore, improving the simulation of marine NPP in ESMs would add utility to NPP forecasts. Such efforts could entail the incorporation of river nutrient inputs into coastal regions or refinement of atmospheric forcing.

This study contributes to a growing body of research using marine ecological forecast products. While ocean physics forecasts are more widespread (e.g., Stock et al., 2015; Yeager et al., 2012), marine ecological forecasting is still in the early stages (Park et al., 2019; Payne et al., 2017; Tommasi et al., 2017). NPP is a complex variable to predict, requiring the adequate simulation and parameterization of physical drivers, as well as ecological processes. We build on regional predictability studies (e.g., Séférian et al., 2014) by evaluating NPP prediction across the open oceans, as well as in coastal LMEs. This study provides a benchmark of using an initialized Earth system prediction system in forecasting interannual fluctuations of NPP in the world's oceans.

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