

1 **Coastal phytoplankton blooms expand and intensify in the 21st century**

2 **Authors:** Yanhui Dai^{1,9}, Shangbo Yang^{1,9}, Dan Zhao¹, Chuanmin Hu², Wang Xu³,
3 Donald M. Anderson⁴, Yun Li⁵, Xiao-Peng Song⁶, Daniel G. Boyce⁷, Luke Gibson¹,
4 Chunmiao Zheng^{1,8}, Lian Feng^{1,*}

5 **Affiliations:**

6 ¹ School of Environmental Science and Engineering, Southern University of Science
7 and Technology, Shenzhen, China

8 ² College of Marine Science, University of South Florida, St. Petersburg, FL, USA.

9 ³ Shenzhen Ecological and Environmental Monitoring Center of Guangdong Province,
10 Shenzhen, China

11 ⁴ Woods Hole Oceanographic Institution, Woods Hole, MA, USA

12 ⁵ School of Marine Science and Policy, College of Earth, Ocean, and Environment,
13 University of Delaware, Lewes, DE, USA

14 ⁶ Department of Geographical Sciences, University of Maryland, College Park, MD,
15 USA

16 ⁷ Bedford Institute of Oceanography, Fisheries and Oceans Canada, Dartmouth, Canada

17 ⁸ EIT Institute for Advanced Study, Ningbo, China

18 ⁹ These two authors contributed equally

19 *Correspondence to: fengl@sustech.edu.cn

20 **Abstract:** Excessive phytoplankton growth, or blooms, in coastal oceans, can be
21 beneficial to coastal fisheries production and ecosystem function, but also can cause
22 major environmental problems ^{1,2}, yet detailed characterizations of bloom incidence
23 and distribution are not available worldwide. Here, we map daily marine coastal algal
24 blooms between 2003 and 2020 using global satellite observations at 1-km spatial
25 resolution. We found that algal blooms occurred in 126 of the 153 coastal countries
26 examined. Globally, the spatial extent (+13.2%) and frequency (+59.2%) of blooms
27 increased significantly ($P<0.05$) over the study period, whereas blooms weakened in
28 tropical and subtropical areas of the Northern Hemisphere. We documented the
29 relationship between the bloom trends and ocean circulation, and identified the
30 stimulatory effects of recent increases in sea surface temperature. Our compilation of
31 daily mapped coastal phytoplankton blooms provides the basis for global assessments
32 of bloom risks and benefits, and for the formulation or evaluation of management or
33 policy actions.

34 **Main**

35 Phytoplankton blooms are accumulations of microscopic algae in the surface
36 layer of fresh and marine water bodies. Although many blooms can occur naturally,
37 nutrients linked to anthropogenic eutrophication are expected to intensify their
38 frequency globally ²⁻⁴. Many algal blooms are beneficial, fixing carbon at the base of
39 the food chain and supporting fisheries and ecosystems worldwide. However,
40 proliferations of algae that cause harm (termed harmful algal blooms or HABs) have
41 become a major environmental problem worldwide ⁵⁻⁷. For instance, the toxins
42 produced by some algal species can accumulate in the food web, causing fisheries
43 closures as well as illness or mortality of both marine species and humans ⁸⁻¹⁰. In
44 other cases, the decay of a dense algal bloom can deplete oxygen in bottom waters,
45 forming anoxic “dead zones” that can cause fish and invertebrate die-offs and
46 ecosystem restructuring, with serious consequences for the well-being of coastal
47 communities ^{1,11}. Unfortunately, algal bloom frequency and distribution are projected
48 to increase with future climate change ^{12,13}, with some changes causing adverse effects
49 on aquatic ecosystems, fisheries, and coastal resources.

50 Due to substantial heterogeneity in space and time, algal blooms are challenging
51 to characterize on a large scale ^{5,14}, and hence, present knowledge does not allow us to
52 answer one of the most fundamental questions: whether algal blooms have changed in
53 recent decades on a global basis ^{6,15,16}. For example, although HAB events have been
54 compiled into the UNESCO Intergovernmental Oceanographic Commission Harmful
55 Algae Event Database (HAEDAT) globally since 1985, bloom trends are difficult to

resolve due to inconsistent sampling efforts and the diversity of the environmental/socio-economic impacts⁶. Alternatively, satellite data have been used to monitor the ocean surface continuously since 1997 and have enabled bloom detection in many coastal regions¹⁷⁻¹⁹. However, the technical difficulties in dealing with complex optical features across different types of coastal waters have thus far prohibited their application globally²⁰. To fill this knowledge gap, we developed a novel method to map global coastal algal blooms and used this tool to examine satellite images between 2003 and 2020, addressing three fundamental questions: (i) where and how frequently have global coastal oceans been affected by phytoplankton blooms? (ii) have the blooms expanded or intensified over the past two decades, both globally and regionally? and (iii) what are the potential drivers?

Mapping global coastal phytoplankton bloom

We generated a satellite-based dataset of phytoplankton bloom occurrence to characterize the spatial and temporal patterns of algal blooms in coastal oceans globally. The dataset was derived using global, 1-km resolution daily observations from the Moderate Resolution Imaging Spectroradiometer (MODIS) onboard NASA's Aqua satellite, and all 0.76 million images acquired by this satellite mission between 2003 and 2020 were used. We developed an automated method to detect phytoplankton blooms using MODIS images (Extended Data Fig. 1) (see *Methods*). In this study, we define a phytoplankton bloom as the accumulation of microscopic algae at the ocean surface that exhibits satellite-detectable fluorescence signals²¹. However, whether a bloom produces toxins or is harmful to humans or the marine environment

is not distinguishable from satellites. We delineated bloom-affected areas (i.e., the areas where algal blooms were detected), and enumerated the bloom count at the 1-km pixel level (i.e., the number of detected blooms per pixel) (Fig. 1). We further estimated bloom frequency (dimensionless) by integrating the bloom count and affected areas within $1^\circ \times 1^\circ$ grid cells (see *Methods*), and this metric was used to examine temporal dynamics in bloom intensity. Validation with independent satellite samples selected via several visual inspection techniques showed an overall accuracy level of >95% for our method, and comparisons using discrete events in HAEDAT⁶ indicated that we successfully identified bloom counts at 79.3% of the historical HAB events in that database (Extended Data Figs. 2-6). We examined phytoplankton blooms in the exclusive economic zones of 153 coastal countries and in 54 large marine ecosystems (LMEs) (Extended Data Fig. 7). Our study area encompasses global continental shelves and outer margins of coastal currents, which offer the majority of marine resources available for human use (see *Methods*). Of the 153 coastal countries examined, 126 were observed with phytoplankton blooms (Fig. 1). The total bloom-affected area was 31.47 million km², equivalent to ~24.2% of the global land area and ~8.6% of the global ocean area, with a median bloom count of 4.3 per year during the past two decades (Fig. 1b). Europe (9.52 million km² or 30.3% of the total affected area) and North America (6.78 million km² or 21.5%) contributed the largest bloom areas. In contrast, the most frequent blooms were found around Africa and South America (median bloom counts >6.3 per year). Australia experienced the lowest frequency (2.4 per year) and affected area (2.84 million km² or

9.0%) of blooms.

Phytoplankton blooms frequently occurred in the eastern boundary current systems (i.e., California, Benguela, Humboldt, and Canary), northeastern United States (US), Latin America, the Baltic Sea, Northern Black Sea, and the Arabian Sea (Fig. 1a). Five LMEs were found with the most frequent blooms (annual median bloom count >15), including Patagonian Shelf, Northeast US continental Shelf, the Baltic Sea, Gulf of California, and Benguela Current (Extended Data Fig. 7). These hotspots are often reported with a high incidence of algal blooms, some of which are HABs, driven by either coastal upwelling or pronounced anthropogenic nutrient enrichment^{9,22-26}. European LMEs mostly showed large proportions of bloom-affected areas, and some also with frequent bloom occurrences. By contrast, Asian LMEs mainly exhibited infrequent blooms, given their large affected areas. We identified more bloom events in estuarine regions than along coasts in regions without major river discharge ($P<0.05$, Extended Data Fig. 8), highlighting the critical role of terrestrial nutrient sources on coastal algal blooms³.

Long term trends

The total global bloom-affected area has expanded by 3.97 million km² (or 13.2%) from 2003 to 2020, or 0.14 million km² yr⁻¹ ($P<0.05$, Fig. 2). Furthermore, the number of countries with significant bloom expansion was ~1.6 times those with a decreasing trend. The global median bloom frequency showed an increasing rate of 59.2% (+2.19% yr⁻¹, $P<0.05$) over the observed period. Spatially, areas showing

significant increasing trends ($P<0.05$) in bloom frequency were 77.6% larger than those with the opposite trends (Fig. 2). Globally, our analysis revealed overall consistent fluctuations between the bloom-affected area and bloom frequency between 2003 and 2020 (Fig. 2b). However, there was no significant relationship between bloom extent and frequency in 23 countries and 10 LMEs over the past two decades, underscoring the spatial and temporal variability of algal blooms and the importance of continued satellite monitoring.

The entire Southern Hemisphere was primarily characterized by increased bloom frequency, although weakened blooms were also found on occasion. In the Northern Hemisphere, the low latitude ($<30^{\circ}\text{N}$) coasts were mainly featured with strong bloom weakening (Fig. 2a), primarily in the California Current System and the Arabian Sea. Bloom strengthening was found in the northern Gulf of Mexico and the East and South China Seas, albeit at smaller magnitudes. At higher latitudes, weakening blooms were mainly detected in the northeastern North Atlantic and the Okhotsk Sea in the northwestern North Pacific. Globally, the largest increases in bloom frequency were observed in six major coastal current systems, including Oyashio ($+6.31\% \text{ yr}^{-1}$), Alaska ($+5.22\% \text{ yr}^{-1}$), Canary ($+4.28\% \text{ yr}^{-1}$), Malvinas ($+3.02\% \text{ yr}^{-1}$), Gulf Stream ($+2.42\% \text{ yr}^{-1}$), and Benguela ($+2.30\% \text{ yr}^{-1}$) (Fig. 2a & Fig. 3).

Natural and anthropogenic impacts

Increases in sea surface temperature (SST) can stimulate bloom occurrence. We found significant positive correlations ($P<0.05$) between the annual mean bloom

frequency and the coincident SST (SST data were averaged over the growth window of algal blooms within a year, see *Methods* and Extended Data Fig. 9) in several high latitude regions ($>40^{\circ}\text{N}$), such as the Alaska Current ($r=0.44$), the Oyashio Current ($r=0.48$), and the Baltic Sea ($r=0.41$) (see Fig. 3). These findings agree with previous studies, where the bloom-favorable seasons in these temperate seas have been extended under warmer temperatures²⁷⁻²⁹. However, this temperature-based mechanism did not apply to regions with inconsistent trends between SST and bloom frequency, particularly for the substantial bloom weakening in the tropical and subtropical areas (Fig. 2a and Fig. 3b).

Climate changes can also affect ocean circulation, altering ocean mixing and the transport of nutrients that drive the growth of marine phytoplankton and bloom formation³⁰⁻³². We used the spatial SST gradient (in $^{\circ}\text{C m}^{-1} \text{ decade}^{-1}$) as a proxy for the magnitude of oceanic mesoscale currents (or time-varying velocity of kinetic energy, known as EKE) by following the methods of a previous study³³, and examined its impacts on algal blooms (see *Methods*). The trend in the SST gradient appeared more spatially aligned to bloom frequency than SST. We found significant positive correlations ($P<0.05$) between the SST gradient and bloom frequency for various coastal current systems, including the Canary ($r=0.84$), Malvinas ($r=0.83$), California ($r=0.81$), Benguela ($r=0.73$), Gulf Stream ($r=0.61$), and Oyashio ($r=0.58$) currents.

Trends in bloom frequency in subtropical eastern boundary upwelling regions (i.e., California, Benguela, and Canary Currents) followed the changes in mesoscale

currents (Fig. 3a&c). In the California Current System, the decrease in bloom frequency was likely due to the weakened upwelling (represented by a reduced SST gradient and increased SST) and thus lower nutrient supply ²⁵. Conversely, the Canary and Benguela Currents were characterized by strengthened upwelling and increased bloom frequency. The two western boundary current systems at high latitudes (i.e., Malvinas and Oyashio), albeit characterized by less pronounced upwelling ³⁴, exhibited a similar mechanism to the subtropical eastern boundary regions. For the subtropical western boundary Gulf Stream current, the strengthened current jets (manifested as larger SST gradient) brought more nutrients from the continental shelf ³⁵, triggering more algal blooms. Nevertheless, whether these changes in oceanic mesoscale activities were responses to wind, stratification, the shear of ocean currents, or other factors ³³, requires region-based investigations.

Global climate events, represented as the Multivariate El Niño–Southern Oscillation (ENSO) index (MEI) ³⁶, also showed connections with coastal bloom frequency. The minimum MEI in 2010 (i.e., a strong La Niña year) was followed by a low bloom frequency in the following year, and the largest MEI in 2015 (i.e., a strong El Niño year) was followed by the strongest bloom frequency in 2016 (Extended Data Fig. 10a and Fig. 2b).

Changes in anthropogenic nutrient enrichment may have also contributed to the bloom trends ³⁷. For example, the decline in bloom frequency in the Arabian Sea, without clear linkages to SST or SST gradient changes, could result from decreased fertilizer use in the surrounding countries (such as Iran) (Extended Data Fig. 10). By

contrast, the bloom strengthening in some Asian countries could be attributed to surges in fertilizer use³⁸. We examined trends in fertilizer usage (either nitrogen or phosphorus) and bloom frequency and found high positive correlations in China, Iran, Vietnam, and the Philippines. Paradoxically, decreased fertilizer uses and increased bloom frequency were identified in some countries, suggesting that nutrient control efforts might have been counterbalanced by the stimulatory effects of climate warming or other factors. Furthermore, the intensified aquaculture industry in Finland, China, Algeria, Guinea, Vietnam, Argentina, Russia, and Uruguay may also be linked to their increased bloom incidence, as suggested by the significant positive correlations ($r>0.5$, $P<0.05$) between their aquaculture production and bloom frequency. A similar relationship between aquaculture expansion and positive trends in HAB incidence was reported from an analysis of HAEDAT data⁶. However, analogous positive feedbacks for fertilizer or aquaculture were not found in many other countries. As such, an ecosystem model incorporating terrestrial and oceanic nutrient transport and nutrient-plankton relationships of different species³⁹ is required to quantify the contributions of natural and anthropogenic factors to algal blooms¹⁴.

Future implications

We acknowledge that our criteria for a detectable bloom event is operationally defined by sensor sensitivities and other factors, and that the bloom count metric used here may underestimate algal bloom incidence, particularly compared to harmful events entered in HAEDAT. For example, in a recent global analysis of the HAEDAT events, Hallegraeff et al.⁶ report a dozen or more events per year for each of nine

regions over a 33-year study period, compared to the global median bloom count of 4.3 in this study. There are several possible explanations for this discrepancy, such as the many low cell concentration HABs that are not detectable from space but that can still cause harm, as well as sensor sensitivities and algorithm thresholds. Furthermore, our bloom count was averaged over all 1-km pixels within the EEZs, while HAEDAT entries are based on discrete sampling regions. This underestimation does not, however, alter the trends and other conclusions of this study, as the metrics used here were constant across time and space. Underestimates would have been uniform across regions globally. In this regard, it is of note that the Hallegraeff et al. study ⁶ found a significant linkage between the number of HAEDAT events over time and the global expansion of aquaculture production, as was also found in this study.

The major contribution of our study is to provide the first spatially and temporally consistent characterization of global coastal algal blooms between 2003 and 2020. Globally, increasing trends in algal bloom area and frequency are apparent. Regionally, however, trends were non-uniform due to the compounded effects of climate changes (e.g., changes in SST and SST gradient and climate extremes), anthropogenic eutrophication, and aquaculture development. Our daily mapping of bloom events offers valuable baseline information to understand the mechanisms underlying the formation, maintenance, and dissipation of algal blooms ^{5,40}. This could aid in developing forecasting models (on either global or regional scales) that can help minimize the consequences of harmful blooms, and can also help in policy decisions relating to the control of nutrient discharges and other HAB-stimulatory

factors. Noting again that many blooms are beneficial, particularly in terms of their positive impacts on ecosystems as well as wild and farmed fisheries, the results here can also contribute toward policies and management actions that sustain those beneficial blooms.

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Figure captions

Fig. 1 | Global patterns of coastal phytoplankton blooms between 2003 and 2020.

(a) Spatial distribution of annual mean bloom count based on daily satellite detections.

(b) Continental and global statistics for annual mean bloom count (SA n=3,846,125; AF

n=2,516,225; EU n=17,703,949; NA n=10,034,286; AS n=5,371,158; AU n=2,781,998

pixel observations). Upper and lower bounds of boxes are first and third quartiles, the

bold bar represents the median value, and the whiskers show a maximum of $1.5 \times$ the

interquartile range. (c) Continental statistics for the long-term annual mean bloom-

affected areas (n=18 years), the percentages show the corresponding contributions to

the global total. The bars represent standard deviations associated with the annual mean

values. AF: Africa, SA: South America, EU: Europe, NA: North America, AS: Asia,

AU: Australia. Open circles are sample data points.

Fig. 2 | Trends of global coastal phytoplankton blooms between 2003 and 2020. (a)

Spatial patterns of the trends in bloom frequency at $1^\circ \times 1^\circ$ grid scale. The latitudinal

profiles for positive (pos., red) and negative (neg., blue) trends are presented within the

panels. (b) Interannual variability and trends of annual median bloom frequency (left

axis) and total global bloom-affected areas (right axis), and their linear slopes and

significance (two-sided *t-test*) are annotated. The colors of the curves correspond to the

y-axes. The shading associated with bloom frequency represents an uncertainty level of

5% in bloom detection.

Fig. 3 | Impacts of climate changes on phytoplankton blooms. Global patterns of the

trends for SST gradient **(a)** and SST **(b)** from 2003 to 2020. **(c)** Long-term changes in bloom frequency in different regions and their agreements with SST and the SST gradient. The locations of these regions are labeled in **(a)** and **(b)**. Linear slope (S , in % yr^{-1}) of bloom frequency (black) and the correlation coefficients between bloom frequency and SST (purple) and the SST gradient (red) are presented within each panel, with statistically significant correlations indicated by “*”. The colors of the curves correspond with the y-axes.

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Data and materials availabilities: The satellite-based dataset of global coastal algal bloom at 1-km resolution and the associated code are available at <https://doi.org/10.5281/zenodo.7359262>.

Methods

Data sources

Moderate-resolution Imaging Spectroradiometer (MODIS) on the Aqua satellite provides a global coverage within 1-2 days. All images acquired by this satellite mission from January 2003 to December 2020 were used in our study to detect global coastal phytoplankton blooms, totaling 0.76 million images. MODIS Level-1A images were downloaded from the Ocean Biology Distributed Active Archive Center (OB.DAAC) at NASA Goddard Space Flight Center (GSFC), and were subsequently processed with SeaDAS software (Version 7.5) to obtain Rayleigh-corrected reflectance (R_{rc} , dimensionless, which was converted using the ρ_{rs} (in sr^{-1}) product ($\rho_{rs} \times \pi$) from SeaDAS)⁴¹, remote sensing reflectance (R_{rs} , sr^{-1}) and quality control flags (i.e., $l2_flags$). If a pixel was flagged by any of the following, it was then removed from phytoplankton bloom detection: straylight, cloud, land, high sunglint, high solar zenith angle, and high sensor zenith angle (<https://oceancolor.gsfc.nasa.gov/atbd/ocl2flags/>). MODIS level-3 product for aerosol optical thicknesses (AOT) at 869-nm was also obtained from OB.DAAC NASA GSFC (Version R2018.0), which was used to examine the impacts of aerosols on bloom trends.

We examined the algal blooms in the Exclusive Economic Zones (EEZs) of 153 ocean-bordering countries (excluding the EEZs in the Caspian Sea or around the Antarctic), 126 of which were found with at least one bloom in the past two decades. The EEZs dataset is available at

[https://www.marineregions.org/download_file.php?name=World_EEZ_v11_20191118](https://www.marineregions.org/download_file.php?name=World_EEZ_v11_20191118.zip)
.zip. The EEZs are up to 200 nautical miles (or 370 km) away from coastlines, which
include all continental shelf areas and offer the majority of marine resources available
for human use. Regional statistics of algal blooms were also performed for LMEs.
LMEs encompass global coastal oceans and outer edges of coastal currents areas,
which are defined by various distinct features of the oceans, including hydrology,
productivity, bathymetry, and trophically dependent populations ⁴². Of the 66 LMEs
identified globally, we excluded the Arctic and Antarctic regions and examined 54
LMEs. The boundaries of LMEs were obtained from
<https://www.sciencebase.gov/catalog/item/55c77722e4b08400b1fd8244>.

We used the Harmful Algal Event Database (HAEDAT) to validate our satellite-
detected phytoplankton blooms in terms of presence or absence. The HAEDAT
dataset is a collection of records of harmful algal bloom (HAB) events (dataset link:
<http://haedat.iode.org>), maintained under the UNESCO Intergovernmental
Oceanographic Commission and with data archives since 1985. For each HAB event,
the HAEDAT records its bloom period (ranging from days to months) and
geolocation. We merged duplicate entries when both the recorded locations and times
of the HAEDAT events were very similar to one another, and a total number of 2,609
HAEDAT events were ultimately selected between 2003 and 2020.

We used the 1/4° resolution National Oceanic and Atmospheric Administration
Optimum Interpolated Sea surface temperature (SST) (v. 2.1) data to examine the
potential simulating effects of warming on the global phytoplankton trends. We also

estimated the SST gradients following the method of Martínez-Moreno³³. As detailed in Martínez-Moreno³³, the SST gradient can be used as a proxy for the magnitude of oceanic mesoscale currents (or the time-varying velocity of the kinetic energy, known as EKE). We used the SST gradient to explore the impacts of ocean circulation dynamics on algal blooms.

Fertilizer uses and aquaculture production for different countries was used to examine the potential impacts of nutrient enrichment from humans on global phytoplankton bloom trends. Annual data between 2003 and 2019 on synthetic fertilizer use, including nitrogen and phosphorus, are available from <https://ourworldindata.org/fertilizers>. Annual aquaculture production includes cultivated fish and crustaceans in marine and inland waters, and sea tanks, and the data between 2003 and 2018 are available from <https://ourworldindata.org/grapher/aquaculture-farmed-fish-production>.

The Multivariate El Niño/Southern Oscillation (ENSO) Index (MEI), which combines various oceanic and atmospheric variables⁴³, was used to examine the connections between ENSO activities and marine phytoplankton blooms. The dataset is available from <https://psl.noaa.gov/enso/mei/>.

Development of an automated bloom detection method

A recent study by the UNESCO Intergovernmental Oceanographic Commission revealed that globally reported HAB events have increased⁶. However, such an overall increasing trend was found to be highly correlated with recently intensified

sampling efforts ⁶. Once this potential bias was accounted for by examining the ratio between HAB events to the number of samplings ⁵, there was no significant global trend in HAB incidence, though there were increases in certain regions. With synoptic, frequent, and large-scale observations, satellite remote sensing has been extensively used to monitor algal blooms in oceanic environments ¹⁷⁻¹⁹. For example, chlorophyll a (Chl-a) concentrations, a proxy for phytoplankton biomass, has been provided as a standard product by NASA since the proof-of-concept Coastal Zone Color Scanner (1978–1986) era ^{44,45}. The current default algorithm used to retrieve Chl-a products is based on the high absorption of Chl-a at the blue band ^{46,47}, which often shows high accuracy in the clear open oceans but high uncertainties in coastal waters. This is because, in productive and dynamic coastal oceans, the absorption of Chl-a in the blue band can be obscured by the presence of suspended sediments and/or colored dissolved organic matter (CDOM) ⁴⁸. To address this problem, various regionalized Chl-a algorithms have been developed ⁴⁹. Unfortunately, the concentrations of the water constituents (i.e., CDOM, sediment, and Chl-a) can vary substantially across different coastal oceans. As a result, a universal Chl-a algorithm that can accurately estimate Chl-a concentrations in global coastal oceans is not currently available.

Alternatively, many spectral indices have been developed to identify phytoplankton blooms instead of quantifying their bloom biomass, including the normalized fluorescence line height (nFLH) ²¹, red tide index (RI) ⁵⁰, algal bloom index (ABI) ⁴⁸, red-blue difference (RBD) ⁵¹, *K. Brevis* bloom index (KBBI) ⁵¹ and

red tide detection index (RDI)⁵². In practice, the most important task for these index-based algorithms is to determine their optimal thresholds for bloom classification. However, such optimal thresholds can be regional-or image-specific²⁰, due to the complexity of optical features in coastal waters and/or the contamination of unfavorable observational conditions (i.e., thick aerosols, thin clouds, etc.), making it difficult to apply spectral-index-based algorithms at a global scale.

To circumvent the difficulty in determining unified thresholds for various spectral indices across global coastal oceans, an approach from a recent study to classify algal blooms in freshwater lakes⁵³ was adopted and modified here. In that study, the remotely sensed reflectance data in three visible bands (i.e., red, green, and blue) were converted into two-dimensional color space created by the Commission Internationale de l'éclairage (CIE), in which the position on the CIE chromaticity diagram represented the color perceived by human eyes (Extended Data Fig. 1a). As the algal blooms in freshwater lakes were manifested as greenish colors, the reflectance of bloom-containing pixels was expected to be distributed in the green gamut of the CIE chromaticity diagram; the stronger the bloom, the closer the distance to the upper border of the diagram (i.e., the greener the water).

Here, the color of phytoplankton blooms in the coastal oceans can be greenish, yellowish, brownish, or even reddish⁵⁴, due to the compositions of bloom species (i.e., diatoms or dinoflagellates) and the concentrations of different water constituents. Furthermore, the Chl-a concentrations of the coastal blooms are typically lower than those in inland waters, thus demanding more accurate classification algorithms. As

such, the algorithm proposed by Hou et al.⁵³ was modified when using the CIE chromaticity space for bloom detection in marine environments. Specifically, we used the following coordinate conversion formulas to obtain the xy coordinate values in the CIE color space:

$$x=X/(X+Y+Z)$$

$$y=Y/(X+Y+Z)$$

$$X=2.7689R+1.7517G+1.1302B$$

$$Y=1.0000R+4.5907G+0.0601B$$

$$Z=0.0000R+0.0565G+5.5943B \quad (1)$$

where the R, G, and B channels represent the R_{rc} at 748 nm, 678 nm (fluorescence band), and 667 nm in the MODIS Aqua data, respectively. By contrast, the R, G, and B channels used in Hou et al.⁵³ were the red, green, and blue bands. We used the fluorescence band for the G channel because, for a given region, the 678 nm signal increases monotonically with the Chl-a concentration for blooms of moderate frequency⁵⁵, which is similar to the response of greenness to freshwater algal blooms. As such, the converted y value in the CIE coordinate system represents the strength of the fluorescence. In practice, for pixels with phytoplankton blooms, the converted colors in the chromaticity diagram will be located within the green, yellow, or orange-red gamut (see Extended Data Fig. 1a); the stronger the fluorescence signal is, the closer the distance to the upper border of the CIE diagram (i.e., larger y value). By contrast, for bloom-free pixels without a fluorescence signal, their converted xy coordinates will be located in the blue or purple gamut. Therefore, we can determine a

lower boundary in the CIE two-dimensional coordinate system to separate bloom and non-bloom pixels, similar to the method proposed by Hou et al.⁵³.

We selected 53,820 bloom-containing pixels from the MODIS R_{rc} data as training samples to determine the boundary of the CIE color space. These sample points were selected from nearshore waters worldwide where frequent phytoplankton blooms have been reported (Extended Data Fig. 2); the algal species included various species of dinoflagellates and diatoms²⁰. A total of 80 images were used, which were acquired from different seasons and across various bloom magnitudes, to ensure that the samples used could almost exhaustively represent the different bloom conditions in the coastal oceans.

We combined the MODIS FLH_{Rrc} (i.e., fluorescence line height based on R_{rc}) and enhanced Red-Green-Blue composite (ERGB) to delineate bloom pixels manually. The FLH_{Rrc} image was calculated as:

$$FLH_{Rrc} = R_{rc678} \times F_{678} - [R_{rc667} \times F_{667} + (R_{rc748} \times F_{748} - R_{rc667} \times F_{667}) \times (678 - 667) / (748 - 667)] \quad (2)$$

where R_{rc667} , R_{rc678} , and R_{rc748} are the R_{rc} at 667, 678, and 748 nm, respectively, and F_{667} , F_{678} , and F_{748} are the corresponding extraterrestrial solar irradiance. ERGB composite images were generated using R_{rc} of three bands at 555 (R), 488 (G), and 443 nm (B). Although phytoplankton-rich and sediment-rich waters have high FLH_{Rrc} values, they appear as darkish and bright features in the ERGB images (Extended Data Fig. 3), respectively⁵⁵. In fact, visual examination with fluorescence signals and ERGB has been widely accepted as a practical way to delineate coastal algal blooms

on a limited number of images⁵⁵⁻⁵⁷. Note that the $FLH_{R_{rc}}$ here was slightly different from the NASA standard nFLH product⁵⁸, as the latter is generated using R_{rs} (corrected for both Rayleigh and aerosol scattering) instead of R_{rc} (with residual impacts of aerosols). However, when using the NASA standard algorithm to further perform aerosol scattering correction over R_{rc} , 20.7% of our selected bloom-containing pixels failed to obtain valid R_{rs} (without retrievals or flagged as low quality), especially for those with strong blooms (see examples in Extended Data Fig. 4). Likewise, we also found various nearshore regions with invalid R_{rs} retrievals. By contrast, R_{rc} had valid data for all selected samples and showed more coverage in nearshore coastal waters. The differences between R_{rs} and R_{rc} were because the assumptions for the standard atmospheric correction algorithm do not hold for bloom pixels or nearshore waters with complex optical properties⁵⁹. In fact, R_{rc} has been used as an alternative to R_{rs} in various applications in complex waters^{60,61}.

We converted the R_{rc} data of 53,820 selected sample pixels into the xy-coordinates in the CIE color space (Extended Data Fig. 1a). As expected, these samples of bloom-containing pixels were located in the upper half of the chromaticity diagram (i.e., the green, yellow, and orange-red gamut) (Extended Data Fig. 1a). We determined the lower boundary of these sample points in the chromaticity diagram, which represents the lightest color and thus the weakest phytoplankton blooms; any point that falls above this boundary represents stronger blooms. The method to determine the boundary was similar to Hou et al.⁵³: we first binned the sample points according to the x value in the chromaticity diagram and estimated the 1st percentile ($Q_1\%$) of the

corresponding Y for each bin; then, we fit the $Q_1\%$ using two-order polynomial regression. Sensitivity analysis with $Q_{0.3}\%$ (i.e., three sigma value) resulted in minor changes ($<1\%$) in the resulting bloom areas for single images. Notably, sample points were rarely located near white points ($x=1/3$ and $y=1/3$, represent equal reflection from three RGB bands) in the diagram, and we used two polynomial regressions to determine the boundaries for x values greater and less than $1/3$, which can be expressed as:

$$y_1 = 4.8093 x^2 - 3.0958 x + 0.8357 \quad x < 1/3 \quad (3)$$

$$y_2 = 4.9040 x^2 - 3.5759 x + 0.9862 \quad x > 1/3 \quad (4)$$

Based on the above, if a pixel's xy coordinate (converted from R_{rc} spectrum) satisfies the conditions of " $x < 1/3$ and $y > y_1$ " or " $x > 1/3$ and $y > y_2$ ", it is classified as a "bloom" pixel.

Depending on the local region and application purpose, the meaning of "phytoplankton bloom" may differ. Here, for a global application, the pixelwise bloom classification is based on the relationship (represented using the CIE color space) between R_{rc} in the 667, 678, and 754-nm bands derived from visual interpretation of the 80 pairs of FLH $_{Rrc}$ and ERGB imagery. Instead of a simple threshold, we used a lower boundary of the sample points in the chromaticity diagram to define a bloom. In simple words, a pixel is classified as a bloom if its fluorescence signal is detectable (i.e., the associated xy coordinate in the CIE color space located above the lower boundary). Histogram of the nFLH values from the 53,820 training pixels demonstrated the minimum value of $\sim 0.02 \text{ mW cm}^{-2} \mu\text{m}^{-1}$ (Extended Data Fig.

1a), which is in line with the lower-bound signal of *K. brevis* blooms on the West Florida shelf ^{21,62}. Note that, such a minimum nFLH is determined from the global training pixels, and it does not necessarily represent a unified lower bound for phytoplankton blooms across the entire globe, especially considering that fluorescence efficiency may be a large variable across different regions. Different regions may have different lower bounds of nFLH to define a bloom, and such variability is represented by the predefined boundary in the CIE chromaticity diagram in our study. Correspondingly, although the accuracy of Chl-a retrievals may have large uncertainties in coastal waters, the histogram of the 53,820 training pixels shows a lower bound of $\sim 1 \text{ mg m}^{-3}$ (Extended Data Fig. 1a). Similarly to nFLH, such a lower bound may not be applicable to all coastal regions, as different regions may have different lower bounds of Chl-a for bloom definition.

Although the MODIS cloud (generated by SeaDAS with $R_{rc869} < 0.027$) and associated straylight flags can be used to exclude most clouds, we found that residual errors from thin clouds or cloud shadows could affect the spectral shape and cause misclassification for bloom detections. Thus, we designed two spectral indices to remove such effects:

$$\text{Index1} = nR_{rc488} - nR_{rc443} - (nR_{rc555} - nR_{rc443}) \times 0.5 \quad (5)$$

$$\text{Index2} = nR_{rc555} - nR_{rc469} - (nR_{rc645} - nR_{rc469}) \times 0.5 \quad (6)$$

where Index1 and Index2 were used to remove cloud shadows and clouds, respectively. The nR_{rc443} , nR_{rc488} , and nR_{rc555} in index1 are the normalized R_{rc} , obtained by normalizing R_{rc488} . Similar calculations were performed for index2. The

purpose of normalizations is to eliminate the effect of the absolute magnitude of the reflectance, so that the thresholds of these two indices are influenced by only the relative magnitude (i.e., spectral shape). We determined thresholds for Index1 (>0.12) and Index2 (<0.012) through trial-and-error and ensured that the misclassifications caused by residual errors from clouds and cloud shadows could be effectively removed. After applying the cloud/cloud shadow and various other masks that are associated with `l2_flags`, we obtained an annual mean valid pixel observation (N_{vobs}) of $\sim 2.0 \times 10^5$ for global $1^\circ \times 1^\circ$ grid cells, and the fluctuation patterns and trends of N_{vobs} , either annually or seasonally, are different from that of the global bloom frequency and affected areas (see Supplementary Fig. 1).

Assessments of the algorithm performance

In addition to phytoplankton blooms, macroalgal blooms (i.e., *Sargassum* and *Ulva*) frequently occur in many coastal oceans⁶³⁻⁶⁶. To verify whether our CIE-fluorescence algorithm could eliminate such impacts, we compared the spectra between micro-and macro-algal blooms (see Extended Data Fig. 1b). We found that the spectral shapes of *Sargassum* and *Ulva* are substantially different from those of microalgae, particularly for the three bands used for CIE coordinate conversion. The converted xy-coordinates for macroalgae were located in the purple-red gamut of the CIE diagram, which was far below the predefined boundary (Extended Data Fig. 1). Moreover, our algorithm is not affected by highly turbid waters for the following two reasons: first, extremely high turbidity tends to saturate the MODIS ocean bands⁶⁷, which can be easily excluded; second, without a fluorescence peak, the reflectance of unsaturated turbid

waters, after conversion to CIE coordinates, will be located below the predefined boundary (see example in Extended Data Fig. 1b). We also confirmed that the spectral shapes of coccolithophore blooms are different from dinoflagellates and diatoms (see example in Extended Data Fig. 1b), and thus they are excluded from our algorithm. Three different types of validation methods were adopted to demonstrate the reliability of the proposed CIE-fluorescence algorithm for phytoplankton bloom detection in global coastal oceans, including visual inspections of the RGB, ERGB, and FLH_{Rrc} images, verifications using independent manually delineated algal blooms, and comparisons with the reported HAB events from the HAEDAT dataset.

First, we selected MODIS Aqua images from different locations where coastal phytoplankton blooms have been recorded in the published literature. We visually compared the RGB, ERGB, and FLH_{Rrc} images, and our algorithm detected bloom patterns (see examples in Extended Data Fig. 3). Comparisons from various images worldwide showed that our algorithm could successfully identify regions with high FLH_{Rrc} values and brownish-to-darkish features on the ERGB images, which can be considered phytoplankton blooms.

Second, we delineated additional 15,466 bloom-containing pixels from 35 images covering different coastal areas, using the same visual inspection and manual delineation method as for the training sample pixels. Moreover, we also selected 14,149 bloom-free pixels (bright or turquoise green colors on ERGB images or low FLH_{Rrc} values) within the same images as bloom-containing images. We applied our

algorithm to all these pixels, and compared the algorithm-identified and manually-
delineated results. Our CIE-fluorescence algorithm showed high values in both
producer and user accuracies (92.04% and 98.63%) (Supplementary Table 1), and
appeared effective at identifying bloom pixels and excluding false negatives (blooms
classified as non-blooms) and false positives (non-blooms classified as blooms).

Third, we validated the satellite-detected phytoplankton blooms using *in situ*
reported HAB events from the HAEDAT dataset. For each HAB event in the
HAEDAT dataset, we obtained all MODIS images over the reported bloom period
(from days to months). Within each year, we estimated the ratio between the number
of satellite images with “bloom detected” against the number of valid images (see
definition above) during the bloom periods across the entire globe (Supplementary
Table 1). Moreover, we calculated the number of events with at least one successful
satellite bloom detection (N_s), and then estimated the ratio between N_s and the total
HAB events for each year. Results showed that substantial amounts (averaged at
51.2%) of satellite observations acquired during the HAB event periods were found
with phytoplankton blooms by our algorithm. Overall, 79.3% of the global HAB
events were successfully identified by satellite. The discrepancies between satellite
and *in situ* observations could be explained by the following reasons: first, our study
focused only on the phytoplankton blooms that are resolvable by satellite fluorescence
signals; other types of HAB events in the HAEDAT dataset may not have been
detectable by satellite observations, such as events with lower phytoplankton biomass
but high toxicity, occurrences at the subsurface layers, or fluorescence signals

overwhelmed by suspended sediments⁶⁸⁻⁷⁰. Second, although the HAEDAT recorded HAB events could be sustained for long periods, high biomass of surface algae may not have occurred every day within this period due to the changes in stratification, precipitation, wind, vertical migration of cells, and many other factors⁷¹. Third, the spatial scale of certain HAB events may have been too small to be identified using the 1-km resolution MODIS observations. Fourth, a reduced MODIS satellite observation frequency by the contaminations of clouds and land adjacency effects⁷². Therefore, we believe the underestimations of satellite-detected blooms compared to the *in situ* reported HAB events were mainly due to inconsistencies between the two observations rather than uncertainties in our algorithm.

Because R_{rc} depends not only on water color but also on aerosols (type and concentration) and solar/viewing geometry, a sensitivity analysis was used to determine whether such variables could impact bloom detection. Aerosol reflectance (ρ_a) with different AOTs at 869 nm was simulated using the NASA-recommended maritime aerosol model (i.e., r75f02, with a relative humidity of 75% and a fine-mode fraction of 2%). Then, ρ_a of each MODIS band was added to R_{rc} images, and the resulting bloom areas with and without added ρ_a were compared. Results showed that even with a change of 0.02 in AOT at 869 nm, the bloom areas showed minor changes (<2%) in the tested images; minor changes were also found when we used different aerosol models to conduct ρ_a simulations⁷³. Note that 0.02 represents the high end of the AOT intra-annual variability in coastal oceans (see Extended Data Fig. 5), and the associated inter-annual changes are much smaller. As such, the use of R_{rc} instead of

the fully atmospherically corrected reflectance R_{rs} could have limited impacts on our detected global bloom trend.

We also tried various index-based algorithms developed in previous studies. However, results showed that all these methods require image-specific thresholds to accurately determine algal bloom boundaries for different coastal regions (see Extended Data Fig. 6). In contrast, although our CIE-fluorescence algorithm may lead to different bloom thresholds for different regions, it can identify bloom pixels without adjusting the coefficients and, therefore, is more suitable for global-scale bloom assessment efforts.

We acknowledge that our satellite-detected algal blooms represent only high amounts of phytoplankton biomass on the ocean surfaces without distinguishing whether such blooms produce toxins or are harmful to marine environments. Furthermore, with only limited spectral information from MODIS, it is difficult to discriminate the phytoplankton species of algal blooms; such information could help to improve our understanding of the impacts of these phytoplankton blooms. However, we expect these challenges to be addressed soon with the scheduled launch of the Plankton, Aerosol, Cloud, ocean Ecosystem (PACE) mission by the U.S. NASA in 2022, where the hyperspectral measurements over a broad spectrum (350-885 nm) will make species-level classifications possible ⁷⁴.

Exploring the patterns and trends of global coastal phytoplankton blooms

We applied the CIE-fluorescence algorithm to all MODIS Aqua level-2 R_{rc}

images, and a total number of 0.76 million images between 2003 and 2020 were processed. We mapped all detected blooms into 1-km daily scale level-3 composites. The number of bloom counts within a year for each location can be easily enumerated, and the long-term annual mean values were then estimated (Fig. 1a). We further calculated the total global bloom-affected area (i.e., the areas where algal blooms were detected at least once) for each year and examined their changes over time (Fig. 2b).

We defined bloom frequency (dimensionless) to represent the density of phytoplankton blooms for a year by integrating the bloom count and bloom-affected areas within $1^{\circ} \times 1^{\circ}$ grid cells within that year, which is expressed as:

$$Bloom\ frequency = \left(\sum_{i=1}^n M_i \right) \cdot \frac{n}{N} \quad (7)$$

where M_i is the enumerated bloom count for each 1-km resolution pixel in a year within one $1^{\circ} \times 1^{\circ}$ grid cell, and n represents the associated number of bloom-affected pixels in the same cell (i.e., the number of pixels with $M_i > 0$), and N is the total number of 1-km MODIS pixels in this grid cell. We estimated the bloom frequency for each year between 2003 and 2020, and determined the long-term trend over global EEZs through a linear least-squares regression (see Fig. 2a).

Continental and country-level statistics were performed for bloom count, bloom-affected areas, and bloom frequency (Fig. 1b&c, Supplementary Table 2), using boundaries for the EEZs of different ocean-bordering countries (see above). Similar statistics were also conducted for 54 LMEs (Extended Data Fig. 7, Supplementary

Table 3).

Correlations with SST and SST gradient

To assess the impacts of climate change on long-term trends in coastal phytoplankton blooms, we correlated the annual mean bloom frequency and the associated SST and SST gradient in various coastal current systems for grid cells with significant changes in bloom frequency (Fig. 3c). The SST and SST gradient were averaged over the growth window within a year, assuming that the changes within the growth window, either in water temperatures or ocean circulations, play more important roles in the bloom trends compared to other seasons ³².

We determined the growth window of phytoplankton blooms for each $1^{\circ} \times 1^{\circ}$ grid cell (Extended Data Fig. 9a) using the following method: first, we estimated the proportion of cumulative bloom-affected pixels within the grid cells for a year. Second, a generalized additive model ⁷⁵ was used to determine the shape of the phenological curves (Extended Data Fig. 9b), where a log link function and a cubic cyclic regression spline smoother were applied ^{76,77}. Third, the timing of maximum bloom-affected areas (TMBA) was then determined by identifying the inflection point on the bloom growth curve (Extended Data Fig. 9c). To facilitate comparisons across Northern and Southern Hemispheres, the year in the Southern hemisphere was shifted forward by 183 days (Extended Data Fig. 9c). We characterized the similarity of the bloom growth curve between different grid cells and grouped them into three distinct clusters using a fuzzy c-means cluster analysis method ^{78,79}. We found uniform distributions of the clusters over large geographic areas. Cluster I is mainly

distributed in mid-low latitudes ($<45^{\circ}\text{N}$ and $<30^{\circ}\text{S}$), where the maximum bloom-affected areas were expected in the early period of the year. Cluster II was mostly found in higher latitudes, with bloom developments (quasi-) synchronized with increases in SST. Cluster III was detected along the coastlines, where the bloom-affected areas increase throughout the entire year. In practice, the growth window for Clusters I and III was set as the entire year, and that for Cluster II was set from day 150 to day 270 within the year. We further found that the TMBA for Cluster II showed small changes over the entire period (Extended Data Fig. 9d), indicating relatively stable phenological cycles for those phytoplankton blooms^{32,80}.

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Extended data figure captions

Extended Data Fig. 1. | Development of the CIE-fluorescence algorithm to detect phytoplankton blooms using MODIS satellite imagery. (a). A1: The density plot of manually delineated bloom-containing pixels in the CIE coordinate system ($n=53,820$), and their distribution in the CIE color space (box in A2). A3: Histograms of nFLH and Chla for the delineated pixels, obtained using NASA standard algorithms^{48,59}. (b) MODIS true color composites and selected spectra for phytoplankton blooms, macroalgal blooms (*Ulva* and *Sargassum*), coccolithophore blooms, and sediment-rich turbid waters. The x-y numbers indicate their corresponding positions in the CIE coordinate system. The black rectangular boxes in the three lower panels highlight different spectral shapes between phytoplankton blooms and other features near the fluorescence band.

Extended Data Fig. 2. | MODIS-detected bloom count within certain years for several coastal regions with frequently reported blooms. The MODIS observational year is annotated within each panel, and overlaid points indicate *in situ* recorded harmful algal bloom events from the Harmful Algae Event Database (HAEDAT) within the same year. The lower right panel shows the locations of all the HAEDAT records that were used for algorithm validations in this study (Supplementary Table 1), which also demonstrates the increase in sampling effort in the most recent years.

Extended Data Fig. 3. | Performance of the CIE-fluorescence algorithm for phytoplankton bloom detection in 12 selected coastal oceans. From left to right are the RGB-true color composite, ERGB composite, FLHRrc, and the bloom area (green pixels) detected by the CIE-fluorescence algorithm.

Extended Data Fig. 4 | Examples showing disadvantages of using NASA standard R_{rs} (i.e., with the removal of both Rayleigh and aerosol scattering) in algal bloom detection. From left to right are the RGB composites, ERGB, nFLH, and the bloom areas (green pixels) detected by the CIE-fluorescence algorithm (based on R_{rc} , without the removal of aerosol scattering). Substantial amounts of invalid R_{rs} retrievals can be observed in the red-encircled areas in which severe blooms can be found. Additionally, nFLH shows high values at cloud edges (yellow-encircled areas), making it challenging to use a simple threshold to classify blooms. However, such problems can be circumvented in our CIE-fluorescence algorithm.

Extended Data Fig. 5 | Sensitivity analysis of the impacts of aerosols on bloom detection. (a) Responses of bloom area (BA) to changes in aerosol optical thickness (AOT). Aerosol reflectance (ρ_a) with AOTs of 0.01 and 0.02 at 869-nm is simulated and added to the MODIS images, and the resulting bloom areas (green pixels) with and without added ρ_a are compared. The left columns show the RGB composites, and the right three columns show the bloom areas under different AOTs. The percentages of BA changes are annotated in the panels. **(b)** The standard deviation between the 12

monthly mean values of AOT in global coastal waters (i.e., 66.7% of the intra-annual variability), and the histogram is shown in (c).

Extended Data Fig. 6 | Comparison of different index-based algorithms in algal bloom detection in various coastal regions. Image-specific thresholds (annotated within the panels) are required (labeled within the panels) for RI ⁵¹, ABI (estimated with FLH_{Rrc}) ⁴⁹, RBD ⁵², KBBI ⁵², and RDI ⁵³ to delineate accurate bloom areas (i.e., high nFLH values, which appear as bright and darkish features on the ERGB images). The left panels are the bloom areas (green pixels) extracted using our CIE-fluorescence algorithm. The RGB-true color and ERGB composites are shown in Extended Data Fig. 3.

Extended Data Fig. 7 | Annual median bloom count and the proportion of bloom-affected areas for large marine ecosystems (LMEs). (a) Annual median bloom count, (b) proportion of bloom-affected areas. The data are ordered from the largest to the smallest. The LMEs are grouped by continent, and their names, numbers, and locations are shown in (a) and (b).

Extended Data Fig. 8 | Comparison of bloom counts in the estuarine and non-estuarine regions. Boxplots for long-term mean bloom count in the estuarine (n=13,622 pixel observations) and non-estuarine (n=361,604 pixel observations) regions. Comparison analysis was performed by two sided Welch's t-test ($P<0.001$). Upper and lower bounds are first and third quartiles, the bar in the middle represents the median value, and the whiskers show the minimum and maximum

values. Sixty-two estuarine zones from large rivers were selected, and the boundary of each zone was manually delineated according to high-resolution satellite images.

Extended Data Fig. 9 | Clusters of different bloom growth paths. (a) The spatial distribution of different clusters. The fractions of different clusters across different latitudes are summarized. (b) The development of the maximum bloom-affected areas within a year within $1^{\circ} \times 1^{\circ}$ grid cells, where all global grid cells are grouped into three distinct clusters according to the similarity of the bloom growth curve. The colored bond curves represent the mean values of all the grid cells, and their mean SST and associated standard deviations are shown with dashed lines and gray shading. The proportions of different clusters in the global bloom-affected areas are annotated. (c) and (f) The mean timing of the maximum bloom-affected areas (TMBA) and the associated standard deviations between 2003 and 2019. The whole year in the Southern Hemisphere is shifted forward by 183 days in (c).

Extended Data Fig. 10 | Changes in climate extremes, global fertilizer uses, and fishery production over the past two decades. (a) Changes in the bi-monthly Multivariate El Niño–Southern Oscillation (ENSO) index (MEI) between 2002 and 2020. Positive and negative MEI values represent El Niño and La Niña events, respectively. The dots show annual mean values. (b–c) Trends of nitrogen and phosphorus from 2003 to 2019 for different countries. (d) Trends of fishery production from 2003 to 2018. Gray indicates no data.