

Continental-scale decline in phytoplankton chlorophyll-a concentrations across Australian coastal waters

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Article

Keywords:

Posted Date: June 17th, 2026

DOI: <https://doi.org/10.21203/rs.3.rs-9913275/v1>

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Additional Declarations: There is **NO** Competing Interest.

Abstract

Coastal water quality is changing under combined climatic and anthropogenic pressures, with consequences for primary production, benthic habitats, and carbon cycling, yet its long-term continental extent remains poorly known. We combine MODIS-Aqua observations with a physics-aware deep learning framework to resolve Australian coastal water quality changes over 2003–2022. Persistent coastal–offshore gradients occur in total chlorophyll-a (TChla), total suspended solids (TSS), dissolved organic carbon (DOC), and diffuse attenuation ($K_d(490)$), with northern coastal waters showing highest TSS and TChla. Across most regions, TSS increased modestly, DOC remained relatively stable, and $K_d(490)$ increased, indicating declining photic depth. TChla declined by $\sim 5\%$ across the Australian coastal ocean, indicating reduced phytoplankton concentrations. Spatiotemporal analyses suggest that TSS variations are the strongest predictor of increasing $K_d(490)$, and elevated attenuation often precedes TChla reductions. These findings reveal widespread darkening and declining TChla in Australian coastal waters, consistent with increasing light limitation and reduced phytoplankton biomass potential.

Main Text:

Introduction

Coastal and continental shelf seas are among the most biogeochemically dynamic regions of the global ocean, mediating exchanges of sediments, nutrients, and carbon between land and open ocean systems while supporting a disproportionate fraction of marine primary production and fisheries. Although they represent only $\sim 7\text{--}10\%$ of the global ocean area, continental shelves account for roughly $15\text{--}30\%$ of marine primary production¹ and a large share of global carbon burial in marine sediments². These environments are strongly influenced by river discharge, storm-driven resuspension, boundary-current variability, and anthropogenic nutrient and sediment inputs, leading to pronounced spatial heterogeneity and rapid temporal variability in suspended particulate matter, coloured dissolved organic matter (CDOM), and phytoplankton biomass. Globally, evidence is emerging of long-term changes in ocean water clarity, chlorophyll concentrations, and photic depth, including a recent synthesis suggesting that $\sim 10\%$ of the global ocean has experienced $> 10\%$ shoaling of the photic depth over the satellite era³ and that low- to mid-latitude regions show statistically robust declines in surface chlorophyll and ocean greenness⁴. Yet these optical marine signals remain unevenly resolved in optically complex coastal shelf waters.

In-situ monitoring networks^{5–7} provide essential process-level understanding required for coastal waters but are spatially sparse, methodologically heterogeneous, and rarely sustained at multi-decadal scales, limiting their capacity to detect continent-scale or basin-scale trends. On the other hand, many biogeochemical (BGC) and ecosystem models provide a larger spatial context, however struggle to represent the subtle long-term trends of optically complex coastal waters, where overlapping absorption and scattering signals from sediments, CDOM, and phytoplankton introduce non-uniqueness, parameter

uncertainty, and weak observational constraints^{8,9}. Multi-decadal ocean-colour missions^{10,11} and merged products such as the ocean colour – climate change initiative (OC-CCI) and GlobColour provide near-global records of chlorophyll and optical variability^{12,13}, but their standard inversion algorithms often transfer poorly across varied oceanic environments and climate zones^{14–17}. Consequently, there remains a critical gap in consistent, long-term, constituent-resolved assessments of coastal biogeochemical change. Bridging this gap requires observational frameworks that combine the synoptic, multi-decadal continuity of satellite ocean-colour remote sensing with physically consistent inversion approaches capable of disentangling particulate, dissolved, and biological contributions to water-column optics.

In Australian coastal waters (Fig. 1A), the in-situ measurements reveal substantial bio-optical complexity: phytoplankton absorption increases with total chlorophyll-a (TChla) concentrations, but the relationship is highly dispersed in lower-salinity and optically complex waters, where pigment packaging, community composition, CDOM, and particulate signals obscure the specific contribution of TChla to reflectance (Fig. 1B). This bio-optical library further shows that coastal reflectance is usually governed by mixed optical signals rather than by phytoplankton alone. Ternary partitioning of absorption components (Fig. 1C) shows that most samples cluster along the CDOM–non-algal particulate (NAP) edge rather than toward the phytoplankton vertex, indicating that dissolved and detrital material often dominate absorption over pigment signals. This optical mixing creates non-uniqueness in satellite inversions and motivates constituent-resolved retrievals of total suspended solids (TSS), dissolved organic carbon (DOC), and TChla. Satellite inversion algorithms use relationships between remote-sensing reflectance, R_{rs} , and these optically active constituents. Empirical (Fig. 1D), quasi-analytical^{18,19}, semi-analytical²⁰, and deep-learning approaches²¹ have all been developed for this purpose, but purely empirical or data-driven models can struggle when different constituent combinations produce similar reflectance signatures in optically complex waters. The DL algorithms, like the empirical algorithms, however, have a limited ability to represent light propagation within the water column because they do not enforce physically consistent relationships between the inherent optical properties (IOP) and in-water BGC constituent concentrations. Recently^{22–24}, there has been increased progress towards retrieving simultaneous in-water concentrations along with IOP behaviours of water packets with improved accuracy. By coupling the computational efficiencies of DL approaches with the underlying physics of light propagation in water, we can achieve improved understanding of in-water constituents without equifinality.

In this work, we study the multi-decadal distributions and changes in BGC parameters across coastal and shelf waters using MODIS Aqua imagery. We applied a physics-based DL-based inversion approach, DL-RS (see Materials and Methods for details), that learns from an ensemble of physics-based forward model simulations referenced to multi-decadal and standardised in-situ measurements across continental Australia. The DL-RS approach overcomes the non-uniqueness in R_{rs} – BGC relationship by attributing changes in R_{rs} not directly to corresponding changes in TSS, DOC, and TChla concentrations, but through their impact on changes in: a) backscatter and absorption of non-algal particulate matter; b)

CDOM absorption; and c) phytoplankton absorption. We carried out a comprehensive validation assessment of the DL approach [coefficient of determination $R^2 = 0.71$, log bias = 1.01 for TChla; Fig. 1E] in capturing the physics of light propagation across diverse aquatic environments (Fig. S1, S2, S3, S4) and demonstrate a strong agreement [coefficient of determination $R^2 = 0.95$, Mean Absolute Error (MAE) = 31%] between modelled and diffuse light attenuation coefficient, $K_d(490)$, which is a measure of photic depth (Fig. 1F). The results reveal a continent-scale decline in TChla in most Australian coastal and shelf waters, indicating reduced phytoplankton chlorophyll-a concentrations over the past two decades. This decline is accompanied by widespread increases in light attenuation, driven primarily by suspended particulate matter. These findings indicate an emerging pattern of particulate-driven coastal darkening and increasing phytoplankton light limitation across Australian coastal ecosystems.

Results

Multi-decadal climatology of BGC constituents and light attenuation

The BGC median climatologies (Fig. 2) reveal that Australia's coastal ocean is structured by strong cross-shelf gradients, with each constituent exhibiting a distinct but partially overlapping spatial footprint. The analysis is presented for major Australian bioregions, namely, the northern (N), Coral Sea (CS), the Great Barrier Reef (GBR), temperate east (TE), south-east (SE), south-west (SW), and north-west regions, each subdivided into a coastal zone (CZ), extending 50 km offshore from the landmass, and an offshore zone (OS) extending from 50 km to the outer boundary of the bioregion. All statistics are computed over pixels not flagged in MODIS data as optically shallow or as bottom contaminated and not flagged as invalid retrievals due to cloud cover/saturation.

The TSS distribution (Fig. 2A) highlights elevated median values along the northern coastline, the Gulf of Carpentaria, and segments of the north-west shelf, where nearshore waters approach ~ 2 mg/l, while adjacent offshore waters experience a rapid drop in TSS concentrations. These elevated TSS distributions persist across wide shelf areas, consistent with extensive shallow and hydrodynamically energetic environments. The Great Barrier Reef lagoon also shows enhanced median TSS in coastal waters relative to offshore Coral Sea waters, reflecting the influence of river plumes, sediment resuspension and shelf mixing. In contrast, the Coral Sea and the offshore portions of the temperate eastern, south-eastern, and south-western bioregions exhibit consistently low median TSS. Across all provinces, the median TSS fields emphasise that suspended sediments remain predominantly a coastal-shelf phenomenon, with the strongest gradients aligned with the near coast boundary.

In the case of DOC concentrations (Fig. 2B), the most prominent feature is its comparatively weak spatial variability relative to TSS, with median values largely confined to a narrower range (approximately 0.5–1.5 mg/l). Elevated DOC is most evident in the northern shelf and Gulf of Carpentaria, where coastal waters exhibit > 1 mg/l. In contrast, offshore waters across the Coral Sea and temperate eastern

bioregions are dominated by low DOC values ($\sim 0.5\text{--}0.7$ mg/l), producing a broad continental-scale separation between river-influenced northern shelves and the oligotrophic open ocean. DOC gradients are generally smoother and less spatially extensive than TSS gradients, suggesting that CDOM contributes to coastal optical structure primarily in specific river-influenced systems rather than broadly across all shelves. This spatial decoupling between TSS and DOC indicates that particulate scattering and dissolved absorption do not uniformly co-vary across Australian waters.

The median distribution of TChla is characterised by a strong separation between oligotrophic offshore waters and elevated nearshore concentrations in selected shelf systems (Fig. 2C). The clearest feature is the extremely low median chlorophyll (< 0.1 $\mu\text{g/l}$) across much of the Coral Sea and offshore temperate east bioregions, reflecting nutrient-limited subtropical and temperate oceanic conditions. In contrast, elevated TChla (~ 0.5 $\mu\text{g/l}$) occurs along the northern coastline, within parts of the north-western shelf, and in the southern GBR lagoonal zone, where seasonal upwelling and frontal systems enhance nutrient availability. The Great Australian Bight in the south-western shelf, and parts of South-Eastern shelf and coastal Tasmania also exhibit enhanced chlorophyll relative to offshore waters, though the spatial footprint is more localised compared to the northern provinces. Notably, regions with high TSS do not consistently correspond to proportionally high TChla, particularly in the northern and north-western bioregions, suggesting that particle-rich waters are mostly not phytoplankton dominated in their optical signal.

The median $K_d(490)$ distribution integrates the effect of all optically active constituents and provides an understanding of light availability (Fig. 2D). Regions of elevated $K_d(490)$ closely mirror high TSS zones with systematic elevation of $K_d(490)$ along the coastal band (~ 0.3 m^{-1}), especially across the northern, north-western and GBR shelves. In contrast, the Coral Sea and offshore temperate east bioregions exhibit low $K_d(490)$ values, consistent with optically stable oligotrophic waters and deeper photic zones. The spatial congruence between elevated $K_d(490)$ and elevated TSS is markedly stronger than that between $K_d(490)$ and either DOC or TChla, indicating that particulate scattering (and associated absorption) exerts the primary control on bulk diffuse attenuation across most Australian coastal waters. Areas of moderate TChla do not necessarily correspond to elevated $K_d(490)$ unless accompanied by increased TSS, highlighting that phytoplankton absorption alone is insufficient to explain regional underwater light climate variability.

When interpreted collectively, the four median climatologies highlight three quantitative and mechanistic contrasts that structure Australia's coastal optical environment. First, all bio-optical constituents exhibit sharp transitions between coastal and offshore waters, that reflect distinguishing nearshore optical regimes. Second, the $K_d(490)$ spatial patterns most closely track TSS distributions, indicating that particulate scattering is the dominant control on underwater light climate in most regions. Third, the elevated TSS patterns do not continentally correspond to elevated TChla patterns, particularly in northern and northwest systems, suggesting that sediment resuspension and river-derived particles sometimes

dominate optical properties. Overall, these median climatologies define the baseline optical and biogeochemical state across Australian coastal and marine waters.

Multi-decadal percentage changes in TSS, DOC, TChla, and K(490)

The percentage-change (PC) analysis (2003–2022) reveals a coherent but asymmetric evolution of BGC properties across Australian marine bioregions (Fig. 3). PC was performed using a Theil-Sen fit and quantifying the percentage difference between the estimated constituent values at the start and end of analysis period. The violin plots denote only statistically significant pixels ($p < 0.05$), as determined using a modified Mann-Kendall trend test (Materials and Methods section in Supplementary materials), and we summarize both the spatial distribution and the relative fraction of statistically significant area within each subregion.

TSS exhibits weak but spatially coherent positive trends across much of the continental shelf (Fig. 3A), particularly in offshore zones of the GBR, parts of Coral Sea, temperate east, and south-west bioregions. Median PC values in many offshore subregions are slightly positive, typically on the order of + 5–15%, with coastal zones (CZ) showing broader distributions and higher variability than offshore (OS) waters. Northern and north-western coastal provinces (N_CZ, NW_CZ) display mixed behaviour, with both positive and negative trends present, but without strong net declines. The violin distributions indicate that significant pixels represent a modest fraction of total area in most regions, yet the directional bias toward positive TSS is consistent across temperate shelves. Overall, the particulate field shows gradual enrichment rather than abrupt regime shifts, suggesting incremental strengthening of sediment resuspension, altered hydrodynamic forcing, or subtle balances in terrestrial sediment delivery.

In contrast to TSS, DOC trends are spatially muted (Fig. 3B). Percentage changes cluster tightly around zero in most offshore provinces, including the Coral Sea, temperate east, and southwest bioregions (CS_OS, TE_OS, SW_OS), indicating long-term stability of background dissolved organic pools. Positive DOC trends are primarily confined to northern coastal zones (N_CZ, NW_CZ), where median increases of ~ 10–20% are observed but over relatively limited spatial extents. The narrower violin spreads relative to TSS confirm lower interannual variability (Fig. S5.A and B) and weaker long-term directional change. This stability suggests that large-scale shifts in coastal optics are unlikely to be driven by continent-wide changes in CDOM abundance, but rather by regionally constrained terrestrial influences.

TChla displays the most spatially consistent directional trend (Fig. 3C): a pervasive decline across nearly all marine bioregions, with a 5% reduction focused around the coastal zones. Median PC values are negative in both coastal and offshore domains, typically ranging from – 10% to – 40%, with some coastal provinces across the northern, southeast, and south-western marine bioregions exhibiting even stronger negative tails. Offshore regions show narrower but uniformly negative distributions, indicating basin-scale oligotrophication. The decline in chlorophyll is evident even in traditionally productive northern and GBR southern coastal waters, where variability remains high (Fig. S5.C), but the long-term trajectory is

downward. This continent-wide reduction in phytoplankton biomass is consistent with enhanced stratification, reduced nutrient entrainment, and climate-driven productivity shifts as reported by (24).

Despite declining chlorophyll and largely stable DOC, $K_d(490)$ exhibits a broadly positive trend across most regions (Fig. 3D). Median percentage increases generally range between + 5% and + 20%, with strongest increases in northern, eastern, and GBR coastal zones, and smaller but coherent increases offshore. The spatial congruence between regions of increasing $K_d(490)$ and modestly rising TSS, coupled with the absence of widespread DOC growth, indicates that enhanced particulate scattering is the primary contributor to the long-term reduction in water clarity. Notably, increases in $K_d(490)$ are observed even where TChla declines sharply, demonstrating a decoupling between biological production and optical attenuation.

The percentage change analysis reveal a systematic shift in Australian coastal optical–biogeochemical structure over the past two decades: a) Particulate concentrations have increased slightly but consistently across many offshore shelves; b) DOC has remained broadly stable, except in northern river-influenced zones; c) Phytoplankton biomass has declined in a majority of coastal and marine bioregions; and d) Light attenuation has increased across most regions. This combination indicates that the observed “darkening” is not phytoplankton driven. Instead, incremental increases in suspended particulate matter are sufficient to elevate $K_d(490)$, compressing the photic zone even as chlorophyll declines. In coastal zones, where variability is largest and significant-area fractions are higher, these changes likely reflect the combined influence of altered hydrology, storm-driven resuspension, and shelf dynamics. Offshore, the coherence of negative TChla and positive $K_d(490)$ suggests a climate-scale reorganization of upper-ocean productivity and optical structure. The simultaneous decline in TChla and increase in $K_d(490)$ implies intensifying light limitation across many coastal and shelf systems. Rather than a nutrient-enrichment regime, the emerging signal is one of particulate-driven optical thickening coupled with biological ungreening, a configuration consistent with increasing stratification and altered sediment dynamics under a warming climate ^{4,25}.

Dominant controls and impact of coastal light availability

The spatial correlation patterns between the three BGC constituents and $K_d(490)$ demonstrate that the Australian coastal underwater light climate is structured by a strong hierarchy of optical controls, with suspended particulate matter exerting the most extensive influence spatially. The TSS– $K_d(490)$ correlation (Fig. 4A) is strongly positive across most tropical and subtropical shelf and offshore waters, with particularly high positive values along the northern and north-west margins and across the GBR shelf, indicating that suspended sediments covary closely with diffuse attenuation in these shallow and resuspension-prone environments. However, this relationship is not uniform continentally: in the offshore southeast and southwest regions, the correlation becomes weak. The strongest spatial coherence of the TSS– $K_d(490)$ relationship occurs in the regions that also exhibit the highest median TSS and highest

median $K_d(490)$, reinforcing the interpretation that particulate-driven turbidity is the primary mechanism defining the baseline optical structure of Australian shelf waters. This positive relationship indicates that increases in suspended sediments are consistently associated with stronger diffuse attenuation and reduced photic depth, confirming that particulate scattering (and associated absorption) dominates the bulk attenuation signal.

In contrast, the DOC– $K_d(490)$ correlation field (Fig. 4B) is more heterogeneous and spatially confined. DOC shows moderate positive correlations with $K_d(490)$ in parts of north-west coastal waters and the Gulf of Carpentaria, consistent with the strong role of CDOM absorption in terrestrial-influenced tropical systems. However, much of the offshore domain exhibits weak or near-zero correlation, and large areas of the Southern Ocean margin show reduced coherence compared to the TSS– $K_d(490)$ field. This indicates that, while DOC is optically important in specific nearshore environments, its influence on $K_d(490)$ is not spatially pervasive at the continental scale. The contrast between the broad TSS– $K_d(490)$ coupling and the more regional DOC– $K_d(490)$ coupling provides a clear optical partitioning: particulate scattering dominates shelf-scale attenuation, while dissolved absorption becomes important primarily in hydro-dynamically shallow and terrestrial input dominated coastal zones.

The TChla– $K_d(490)$ correlation (Fig. 4C) exhibits the most spatially variable pattern of the three constituents, with clear cross-shelf structure. Positive correlations are evident in several coastal zones, particularly within parts of the northern shelf, the northwest coast, the GBR coastal waters, south-west, and sections of the south-eastern shelf, where phytoplankton biomass covaries with diffuse attenuation. However, offshore waters frequently show weak, near-zero, or locally negative correlations. This spatial behaviour suggests that phytoplankton-driven absorption contributes to $K_d(490)$ primarily in nearshore environments where chlorophyll variability is sufficiently large to influence bulk attenuation, whereas offshore waters remain optically dominated by background water and low constituent concentrations. Importantly, this short-term event-based positive co-variation in coastal regions is not inconsistent with the long-term decline in TChla (Fig. 3C) and increase in K_d (Fig. 3D): trends and correlations capture different time scales, where TChla and K_d rise and fall together during events, even as their multi-year trajectories diverge.

Across bioregions, the rank order of explanatory co-variation for K_d is strongest for TSS, followed by intermediate relationship with TChla in coastal regions, and weakest for DOC. While Pearson correlations provide evidence of co-variability, they do not resolve temporal precedence or causal mechanism. The Granger-causality synthesis (Fig. 4D) extends this analysis by testing temporal predictive relationships among BGC constituents and $K_d(490)$ time series, and by identifying the dominant directional pathway at each pixel. The causality map reveals a striking spatial partitioning between offshore and near-coastal waters. Across several offshore regions, the dominant Granger causal pathway is that TSS “granger-causes” $K_d(490)$, represented as $TSS \rightarrow K_d(490)$, indicating that past variability in TSS often improves prediction of subsequent changes in $K_d(490)$. This pattern is especially widespread in offshore waters of the Coral Sea, temperate east, and north-west regions, and is consistent with the large-scale coherence

observed in the Pearson TSS– K_d field. In contrast, within a narrow but continuous near-coastal band (most clearly expressed along the northern, north-western, GBR, south-east, and south-western coastlines), the dominant relationship shifts toward $K_d(490) \rightarrow \text{TChla}$, indicating that changes in light attenuation precede and constrain TChla rather than being driven by it. This result supports interpreting the observed long-term TChla declines (Fig. 4D) in the context of increasing $K_d(490)$, consistent with a progressively reduced photic environment contributing to phytoplankton light limitation over multi-decadal timescales.

The combined correlation and causality results therefore reconcile the long-term trends observed in the satellite record: a) TSS increases are strongly linked to increasing attenuation in several offshore regions; b) DOC remains comparatively stable and only regionally influential; and c) declining TChla is consistent with a shift toward a more light-limited coastal regime. In particular, the causality outcome aligns with the trend synthesis in Fig. 3, where modest increases in TSS and widespread increases in $K_d(490)$ co-occur with a consistent negative chlorophyll percentage change across all bioregions. Collectively, these findings indicate that Australia's coastal waters have experienced a continent-scale shift toward higher optical attenuation, with suspended particles providing the strongest and most spatially extensive explanatory signal, and with phytoplankton declines in many coastal regions consistent with a reduced light availability rather than a direct driver of the optical change.

Discussion

The multi-decadal DL-RS retrievals reveal a coherent picture of how particulate and dissolved constituents jointly control light availability around Australia, and how this has evolved over the past 20 years. The TSS climatology (Fig. 2A) shows the expected strong coastal–offshore gradient, with median concentrations higher within the 50 km coastal zone than offshore in most bioregions, and with the largest absolute values in the turbid northern and north-western shelves. DOC (Fig. 2B) is more spatially homogeneous, with relatively modest coastal–offshore contrasts, while TChla (Fig. 2C) occupies an intermediate position, peaking along coastal margins and frontal zones but remaining low over much of the oligotrophic Coral Sea and temperate east regions.

Despite these differing baselines, the long-term trends are remarkably consistent with emerging global syntheses: TSS shows a weak but widespread tendency to increase, DOC is largely stable, TChla declines across most regions, and yet $K_d(490)$ increases (Fig. 3), implying “darkening” of the upper ocean. At the global scale, ⁴ report a statistically robust decline in ocean “greenness” across low- to mid-latitude basins using a deep-learning reconstruction of multi-sensor chlorophyll-a, interpreting this as a widespread loss of phytoplankton biomass under a warming, increasingly stratified climate. ³ show that darkening also extends into the open ocean. Our coastal ocean results mirror both aspects of this global signal: a continent-scale decline in TChla, especially in temperate and offshore sectors ²⁶, coincident with a broad increase in $K_d(490)$ and hence a reduction in photic-layer depth. In other words, the

Australian shelf and adjacent ocean appear to corroborate the coupled “darkening and ungreening” trajectory detected at planetary scales.

The advantage of the DL-RS framework used in this study is that it allows us to dissect the relative roles of TSS, DOC and TChla, which is difficult to achieve from TChla or $K_d(490)$ -only products used in most global analyses. Satellite climatologies from ESA’s Ocean Colour CCI and other multi-sensor efforts have shown that $K_d(490)$ trends can be regionally linked to both particulate and dissolved drivers²⁷. In our case, the combination of correlation and Granger-causality analysis (Fig. 4) reveals a clear dynamical hierarchy: over most offshore regions, TSS variations exert the dominant influence on $K_d(490)$, whereas DOC plays a secondary, spatially limited role. This is consistent with the modest but positive TSS percentage changes and the near-zero DOC trends and suggests that relatively small increases in particle scattering are sufficient to drive the observed darkening, even without large changes in CDOM.

Across several offshore and shelf sectors, $TSS \rightarrow K_d(490)$ emerges as the dominant Granger causality pathway, supporting the interpretation that particulate backscattering, and not CDOM or phytoplankton absorption, is the principal contributor to long-term changes in light attenuation. In contrast, in a nearly continuous coastal fringe around the continent, $K_d(490) \rightarrow TChla$ dominates, indicating that declining light availability can lead to reductions in TChla rather than resulting from them. This pattern is consistent with evidence that intensification of turbidity and thermal stratification can suppress phytoplankton productivity in warm, coastal seas, even when nutrient inputs remain unchanged^{3,4,25,28}. The combined trends of increasing TSS, stable DOC, decreasing TChla, and increasing $K_d(490)$ therefore point to a coastal optical regime that is increasingly light-limited rather than nutrient-limited, with implications for primary production, ecosystem functioning, and higher trophic levels along the Australian margin.

Our results suggest that around Australia, this decline in coastal TChla is associated with regional changes in particulate distributions, likely associated with altered storminess, river discharge, and shelf resuspension^{29–32}. The slight increase in TSS and corresponding rise in $K_d(490)$ compress the photic zone, thereby exacerbating the impact of warming-driven stratification on phytoplankton, and helping to explain why TChla declines even where DOC remains mostly stable. In coastal and estuarine sectors, this mechanism resonates with the “coastal darkening” component of Davies et al.³, who highlight the role of land-derived material in shrinking photic zones near river mouths and urbanised coasts.

Our bioregion-wise statistics (Table 1) show the dominant Granger-causality pathways are regionally heterogeneous, with $TSS \rightarrow K_d(490)$ most prominent in offshore sectors and $K_d(490) \rightarrow TChla$ prominent in several coastal and shelf regions. These light-limitation hot spots are particularly prevalent in the northern, southeast, GBR, and the southwest coastal zones, regions already recognised as vulnerable to both terrestrial inputs and marine heatwaves^{33,34}. Finally, this coastal southern hemisphere perspective emphasises the value of physics-informed deep learning for regional climate-change assessment. By enforcing optical closure (Fig. S3, S4) and retrieving TSS, DOC, TChla, and $K_d(490)$ consistently from the

same inversion, DL-RS bridges the gap between global climate-driven trend studies and mechanistic process understanding. Extending such regionally resolved, constituent-aware analyses to other continental margins using multi-sensor $K_d(490)$ and chlorophyll products will be crucial for turning the emerging global narratives of declining greenness and shrinking photic zones into actionable, process-based understanding of coastal ecosystem change.

Table 1

Regional areal percentage of dominant Granger-causal pathways. Granger causality evaluated pairwise between BGC constituents and $K_d(490)$ for statistically significant pixels across Australian coastal and marine bioregions.

Bioregions (Area in km ²)	TSS → $K_d(490)$ (% fraction of bioregion area)	DOC → $K_d(490)$ (% fraction of bioregion area)	$K_d(490)$ → TChla (% fraction of bioregion area)
N_OS (395,018)	10.0	11.8	50.7
N_CZ (205,534)	3.3	5.1	16.1
CS_OS (846,432)	88.6	10.5	0.1
GBR_OS (150,308)	49.6	10.6	17.4
GBR_CZ (148,648)	12.3	8.9	26.2
TE_OS (913,379)	66.8	10.0	0.8
TE_CZ (82,385)	17.3	7.5	14.0
SE_OS (1,113,631)	1.9	9.9	4.0
SE_CZ (173,128)	10.8	8.8	28.4
SW_OS (1,120,253)	11.4	9.6	2.1
SW_CZ (227,957)	9.6	7.7	21.3
NW_OS (805,804)	69.6	9.6	7.9
NW_CZ (192,006)	13.6	6.7	18.7

From a management perspective, the results emphasise that light availability in coastal regions is an integrative indicator of multiple pressures and should be considered alongside traditional concentration-based metrics. The DL-RS products provide spatially explicit baselines and trend estimates for TSS, DOC, TChla and $K_d(490)$ across all Australian marine bioregions, resolving systematic differences between near-coastal and offshore domains. These maps and diagnostics can inform regional water-quality targets, help identify hotspots where increasing turbidity and declining TChla coincide (e.g., northern, GBR, and southeast coasts), and support ecosystem models and risk assessments for seagrass, coral reefs and pelagic fisheries.

Because the DL-RS framework is grounded in simultaneous retrieval of IOPs and BGC parameters, it offers a consistent way to integrate future satellite missions and to benchmark scenario simulations of land-use change, restoration actions or climate extremes. Current analysis relies on a single sensor (MODIS-Aqua) at 1-km spatial scale. Vertical structure, nutrient fields and circulation processes are inferred only indirectly through their optical imprint. Extending the DL-RS framework to incorporate multi-sensor ocean-colour records including VIIRS satellite series and Sentinel OLCI sensors, expanding the spectral library to additional regions and seasons, and coupling the optical products with hydrodynamic and biogeochemical models will allow a more explicit attribution of trends to physical and biogeochemical drivers. Nevertheless, the present study demonstrates that physics-informed deep learning can bridge the gap between local bio-optical process studies and continental-scale climate diagnostics. More broadly, our results suggest that coastal darkening should be treated as an emerging ecological pressure, with even incremental increases in suspended particles associated with reduced light availability in regions where phytoplankton greenness is declining.

Materials and Methods

In-situ and satellite datasets

Overlaid on the Fig. 1 map are the in-situ measurement locations that contributed to the continental bio-optical spectral library used in this work. The library spans tropical, temperate, coastal, and reef waters sampled over 20 years (2003–2022) and documents the spectral characterisation of absorption and scattering by in-water constituents, alongside event-scale variability essential for algorithm training and validation.^{35,36} compiled in-situ absorption and scattering measurements in the Queensland inshore and reef waters (including the Keppel Bay, 2003 and Burdekin, 2013 campaigns), emphasizing the variability of phytoplankton, NAP and CDOM absorption across seasons and water masses.

Building on this, Blondeau-Patissier et al.³¹ expanded the library to the tropical northern Australian shelf (Kimberley, Timor Sea campaign in 2010) and demonstrated large variability in inherent optical properties (IOPs) across multiple water masses. Cherukuru et al.³⁷ documented the spatial and temporal variability of specific inherent optical properties (SIOPs) in Moreton Bay (2011 campaign), thereby strengthening the parameterisation of absorption and backscattering for empirical DOC retrieval algorithm development. Event-scale studies further capture the episodic forcing that reshapes coastal spectra: an Eastern-Australia embayment during an extreme flood documented rapid, order-of-magnitude swings in TSS, CDOM and TChla with corresponding spectral changes³⁸. Likewise, the Princess Charlotte Bay campaign in 2013 across coastal northern Queensland showed cyclone-driven pulses where CDOM advected farther offshore than sediments, with detailed IOPs linking constituents to reflectance³². Cherukuru et al.³⁹ report on the mesoscale physical oceanographic drivers that structure bio-optics, supporting the library's use of water-mass context when applying regional priors in the temperate east Tasman Sea, NSW campaign in 2010. More recently, aquatic spectral library datasets (NSW, 2022 campaign) used in Unnithan et al.²² denote the influence of high-flow turbid outflows across

temperate coastal waters in NSW. In Tasmanian and southern coastal waters campaign of 2007, optical properties are shown to co-vary with river discharge and major currents (East Australian, Zeehan currents), with elevated attenuation and constrained light propagation in river-influenced nearshore zones, an explicit coupling of physics and bio-optics that complements the spectral library's geographic breadth ⁴⁰.

Together, these bio-optical measurements define the spectral and inherent optical property parameter space for Australian waters, covering phytoplankton absorption, NAP absorption and detrital scattering, CDOM absorption, and particle backscattering across varying salinity regimes, suspended-sediment loads and phytoplankton assemblages. This rich spectral library allowed us to derive relationships between reflectance and water-constituent concentrations, and thus to train and validate our deep learning reflectance-based retrieval (DL-RS) model with confidence in its applicability across Australia's diverse coastal and shelf domains.

The satellite component of the study uses daily MODIS-Aqua ocean-colour visible 10 band spectrum (between 400 and 700nm) imagery at ~ 1-km resolution that uses standard NASA atmospheric correction algorithm, covering the period 2003–2022 and spanning all the coastal and marine bioregions of Australia ⁴¹. The MODIS time series provides consistent, near-daily global coverage and serves as the primary dataset for retrievals of remotely sensed R_{rs} .

Marine bioregions

The Australian coastal and marine spatial domain of this study (Fig. 1) follows the bioregional framework established by the Department of Climate Change, Energy, the Environment and Water (DCCEEW), encompassing the northern (N), north-western (NW), south-western (SW), southeastern (SE), temperate eastern (TE), Coral Sea (CS), and the Great Barrier Reef (GBR) marine bioregions. To capture near-shore gradients, the analytical boundary used in this study closely follows the official DCCEEW bioregions but includes an additional 50 km coastal buffer adjacent to the shoreline. This subdivision enables a clear distinction between coastal zone (CZ) and offshore zone (OS) waters, allowing BGC patterns in near-coastal regions, where optical complexity and terrestrial influence are greatest, to be identified and contrasted with those of the broader shelf and oceanic domains.

The northwest region, spanning the Timor and Kimberley shelves, is a macro-tidal environment characterised by energetic tidal currents, internal shelf waves, and strong plume dynamics, which together generate high and spatially variable suspended sediment concentrations ⁴². The northern region, including the Gulf of Carpentaria, is a semi-enclosed, shallow tropical basin strongly influenced by the Australian summer monsoon, seasonal stratification, and intense episodic river discharge and cyclone activity ⁴³. These processes drive marked variability in turbidity and water colour through periodic resuspension and CDOM enrichment. The Coral Sea region represents the most oligotrophic and optically stable province ⁴⁴, while the adjacent GBR shelf features complex interactions between

coastal discharge, tidal mixing, and boundary current intrusions that modulate water colour and clarity³⁰. The temperate east region, dominated by the East Australian Current (EAC) and its southward extension and Tasman Front, exhibits high mesoscale variability, with eddy fields and long-term current intensification driving dynamic gradients in temperature, salinity, and biogeochemistry⁴⁵. The southeastern bioregion extends from the southern Australian coast into the Tasman Sea, influenced by winter westerly winds, shelf-edge upwelling, and strong frontal systems that produce marked seasonal variations in phytoplankton biomass and optical conditions⁴⁶. The southwest bioregion encompasses the open, wind-exposed Great Australian Bight and adjacent shelves, where upwelling hotspots and seasonally variable ocean fronts create sharp biogeochemical gradients and episodic productivity pulses⁴⁷.

Bio-optical modelling framework

We collated 264 aquatic spectral library members across different climatological and aquatic regions across coastal and oceanic waters around Australia. Each member consists of co-incident BGC parameters including TSS, DOC, TChla concentrations along with the hyperspectral Inherent Optical Properties (IOPs) given by the absorption due to non-algal particulate matter, a_{nap} , the absorption due to phytoplankton, a_{ph} , the absorption due to colour dissolved organic matter (CDOM), a_y , and the backscattering due to particulate matter, bb_p . We simulate the hyperspectral response R_{rs} based on these in-situ measurements, according to⁴⁸:

$$R_{rs}(\lambda) = f\left(\frac{bb_t(\lambda)}{a_t(\lambda) + bb_t(\lambda)}\right)$$

1

where $bb_t(\lambda)$ (m^{-1}) denotes the sum of total backscattering due to water and particulate matter, given as $bb_t(\lambda) = b_{bw}(\lambda) + b_{bp}(\lambda)$, and $a_t(\lambda)$ (m^{-1}) represents the total absorption, given as $a_t(\lambda) = a_w(\lambda) + a_{nap}(\lambda) + a_{ph}(\lambda) + a_y(\lambda)$, where a_w is absorption due to water. The wavelength-dependent parameter R_{rs} is derived from the polynomial function $f(\bullet)$, which is dependent on the solar and viewing geometries using $g0$ and $g1$ coefficient values of 0.0895 and 0.1247 respectively^{18,49}. In addition, following⁵⁰, we generate the diffuse attenuation coefficient, $K_d(490)$, in the following manner:

$$K_d(490) = (1 + 0.005\theta_a) a_t(490) + 4.18 \left(1 - 0.52 e^{-10.8a_t(490)}\right) bb_t(490)$$

2

where θ_a is the zenith angle in degrees, and the total backscattering and absorption coefficients are calculated at 490 nm respectively. The inversion component of the bio-optical modelling framework

builds directly on the architecture provided in ²², extending its physics-guided learning approach to encompass additional biogeochemical complexity. The deep learning for aquatic remote sensing (DL-RS) framework couples hyperspectral forward simulations with data-driven inversion to infer constituent concentrations from reflectance. Unlike purely empirical regressors, DL-RS learns the internal optical coupling among absorption and backscattering terms, allowing simultaneous retrievals of both constituent BGC concentrations and IOPs from realistic spectral inputs.

The Australian coastal spectral library dataset is augmented, with each R_{rs} -BGC-IOP member contributing ensembles generated with stochastic perturbations in BGC-IOP observations, expanding the training domain without violating the physics of the observational datasets. This augmented spectral library serves as the model training and testing dataset, where the target outputs comprise the BGC parameters (TSS, DOC, and TChla) and their corresponding IOPs (a_{nap} , a_{ph} , a_y , bb_p). The DL-RS network is structured as a dense, fully connected multi-branch model designed to perform simultaneous regression of multiple optical components. A shared backbone encodes common spectral information, followed by constituent-specific output heads to capture differences in spectral sensitivity among suspended sediments, dissolved organics, and phytoplankton absorption. Following grid search hyperparameter tuning, the model architecture uses an input layer corresponding to the input reflectance's spectral bands (for example, in this study we use the 10 R_{rs} bands corresponding to MODIS-Aqua's visible spectrum), five hidden layers of 500 neurons each with tanh activations, batch normalization, and dropout (0.3) for regularization. The model is trained with the Adam optimizer (initial learning rate = 0.001) and a mean-squared-error (MSE) loss.

A key advancement is the explicit integration of TChla retrieval into the inversion workflow, expanding the model's predictive dimensionality beyond the dual-constituent setup (TSS and DOC) used by ²². The TChla head enables the network to learn the spectral imprint of phytoplankton absorption within the joint space of particulate and dissolved constituents, ensuring that retrieved pigment variability remains dynamically coupled with a_{ph} and overall absorption, a_t . This inclusion enhances model realism for bio-optically complex coastal waters where pigment signals overlap with suspended sediments and CDOM. During training, all constituent outputs are optimized jointly, enforcing spectral consistency across the predicted $a_t(\lambda)$ and $bb_t(\lambda)$ terms and maintaining internal consistency between biogeochemical and optical variables. Consistent with the ²² framework, we assess the performance of the DL-RS model with different experimental strategies, namely the inherent error (i.e., model performance when trained on an augmented synthetic dataset and evaluated on independent measured spectra), the 10-fold cross-validation predictive error, a Monte-Carlo based BGC sensitivity analysis to input reflectance spectra, and optical closure evaluations to test model robustness and generalizability (Fig. S1).

From these DL-RS derived outputs, we derive the diffuse attenuation coefficient $K_d(490)$ as a diagnostic optical metric. The predicted IOPs and constituent BGC concentrations along with the viewing geometry are propagated through Eq. (2), ensuring that the attenuation field remains optically closed with the predicted absorption and backscattering components. This formulation allows $K_d(490)$ to be expressed

as a derived state variable rather than a separately trained output, directly linking water-column transparency to the underlying biogeochemical drivers resolved by the DL-RS model. Collectively, this inversion strategy integrates physical parameterisation with neural inference, enabling simultaneous retrieval of TSS, DOC, TChla, and $K_d(490)$ while preserving radiative consistency across Australia's optically diverse coastal and marine environments.

Statistical methods

The statistical comparison between observed (O) and modelled (M) quantities (TSS, DOC, TChla) over n data points employed the coefficient of determination (R^2), in addition to other error metrics following ⁵¹:

$$\text{Bias (B)} = 10 \left\{ \frac{\sum_{i=1}^n \log_{10}(M_i) - \log_{10}(O_i)}{n} \right\} \quad (3)$$

$$\text{Mean absolute Error (MAE)} = 10 \left\{ \frac{\sum_{i=1}^n |\log_{10}(M_i) - \log_{10}(O_i)|}{n} \right\} \quad (4)$$

These error metrics were computed in log-transformed space to accommodate the log-normal distribution of aquatic constituents. Long-term temporal trends in the modelled constituents were evaluated using a non-parametric modified Mann–Kendall (MMK) test coupled with Theil–Sen slope estimation, providing robust statistics against temporal autocorrelation and non-normality in environmental time series. The MMK test ⁵² assesses the significance of monotonic changes in each pixel's 20-year record at a monthly interval, while the Theil–Sen slope gives the median rate of change per year. These slope estimates were then expressed as percentage change (PC) using the monthly time series data point as reference, yielding spatiotemporal maps of relative change across all bioregions. Only statistically significant ($p < 0.05$) MMK trends are retained and summarised in the violin plots to quantify the extent and direction of regional change for both coastal and offshore domains. We then examine the statistically significant pixel-wise covariance and dependence between individual BGC parameters and $K_d(490)$ using the Pearson r correlation analysis. Granger causality analysis ⁵³ was applied to the statistically significant pixel-wise time series to determine the dominant directional influence between BGC constituents and $K_d(490)$, testing whether past variability in one variable provided significant information about subsequent changes in the other, beyond its own temporal autocorrelation structure.

Declarations

Acknowledgments: The authors gratefully acknowledge the able support from the CSIRO Aquatic Remote Sensing Team, CSIRO AquaWatch Australia Group, CSIRO Hobart Bio-optics Laboratory, CSIRO EASI/ADS Team, and the NASA Ocean Biology Processing Group. SLKU gratefully acknowledges Dr. Tim J. Malthus (CSIRO) for his invaluable comments and guidance during the initial preparation of the manuscript.

Funding:

CSIRO Early Research Career (CERC) Postdoctoral Fellowship

CSIRO AquaWatch Australia

CSIRO AI4Missions program

CSIRO Environment Research Unit

Author contributions:

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Investigation: SLKU, DC

Visualization: SLKU, NC, YG, MB, BR

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Competing interests:

Authors declare that they have no competing interests.

Data and materials availability:

All data required to evaluate the conclusions of this paper are provided in the paper and/or the Supplementary Materials. The DL-RS modelling framework²² was developed as part of the AI4Missions and AquaWatch Australia program, funded by CSIRO, Australia's national science agency. The bio-optical datasets are available from Australia's IMOS Australian Ocean Data Network (AODN) portal: <https://portal.aodn.org.au/>, enabled by the National Collaborative Research Infrastructure Strategy (NCRIS), and papers describing the in-situ measurement protocols and datasets are cited in the main text. The MODIS satellite imagery is available at <https://doi.org/https://doi.org/10.5067/AQUA/MODIS/L2/OC/2022.0>, and the water quality maps are available at <https://portal.adias.aquawatchaus.space/>. Spatio-temporal analyses were conducted using

publicly available Python-based tools, including Open Data Cube technology ⁵⁴, scipy (<https://scipy.org/>), and pyMannKendall libraries ⁵⁵.

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Figures

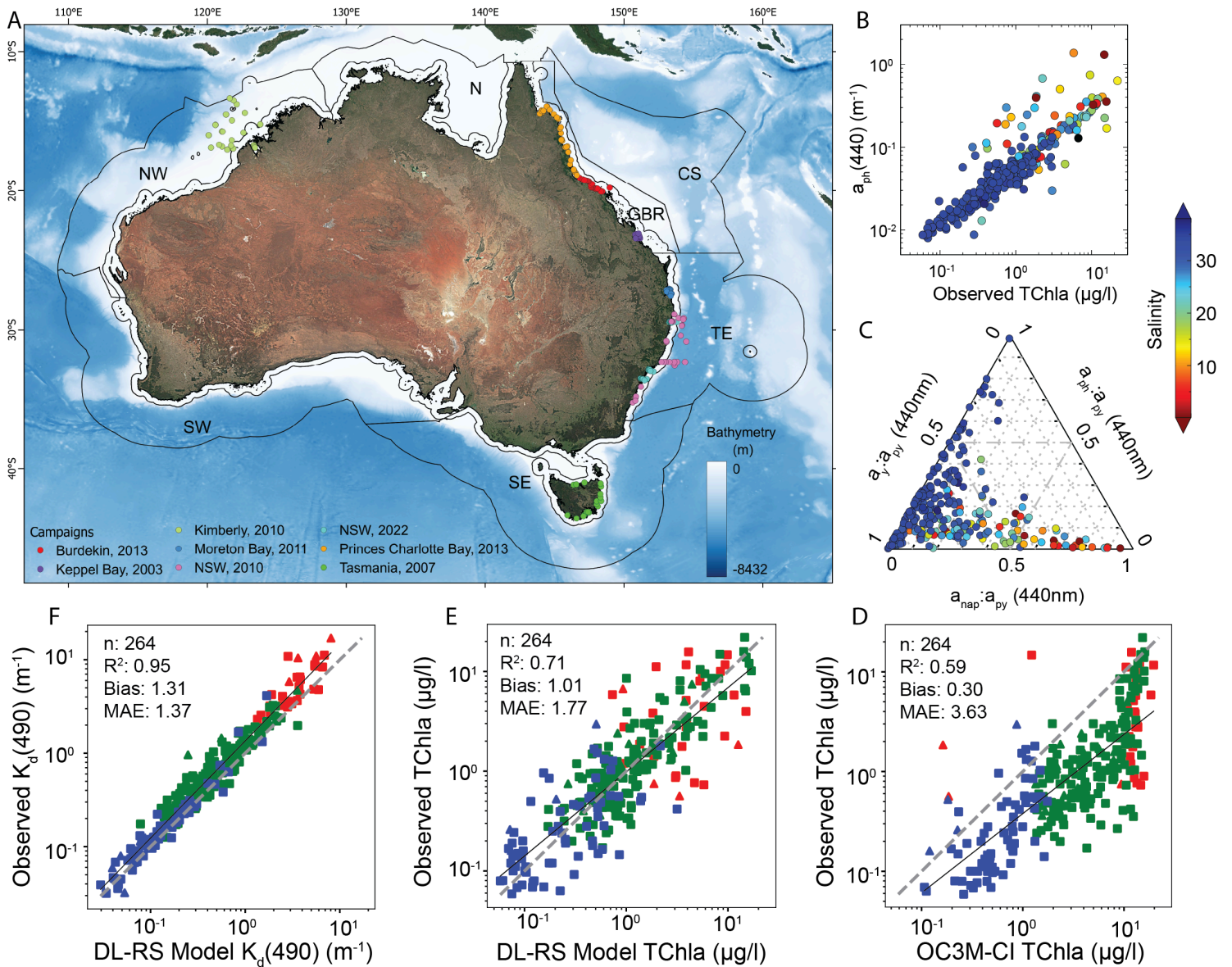


Figure 1

In-situ bio-optical measurement characteristics and inversion algorithm performance A. The map shows the location of in-situ bio-optical observations from 8 surveys of Australian coastal waters and depicts the bioregions used in this study closely following the Australian Department of Climate Change, Energy, the Environment and Water (DCCEEW) classification: north (N), north-west (NW), Coral Sea (CS), Great Barrier Reef (GBR), temperate east (TE), south-east (SE), and south-west (SW); B. Relationship between $a_{ph}(440)$ and TChla, where in-situ measurements are coloured by salinity; C. The ternary plot (middle-right) shows the relative fractional contributions of phytoplankton absorption (a_{ph}), non-algal particulate (NAP) absorption (a_{nap}), and CDOM absorption (a_y) at 440 nm coloured by salinity; D. Benchmark comparison of in-situ observed TChla against MODIS OC3M-CI chlorophyll estimates, where the symbols and colours denote the water-type groupings (freshwater as red, coastal mixing samples as green, open ocean measurements as blue; square symbols indicate CDOM dominant samples, and triangle symbols indicate non-algal particulate dominant sample; dashed line indicates the 1:1 relationship); E. Observed

versus modelled TChla for the DL-RS inversion, for the same water-type groupings; F. Observed versus modelled $K_d(490)$ retrieved within the DL-RS framework, coloured/symbolised by the same water-type groupings.

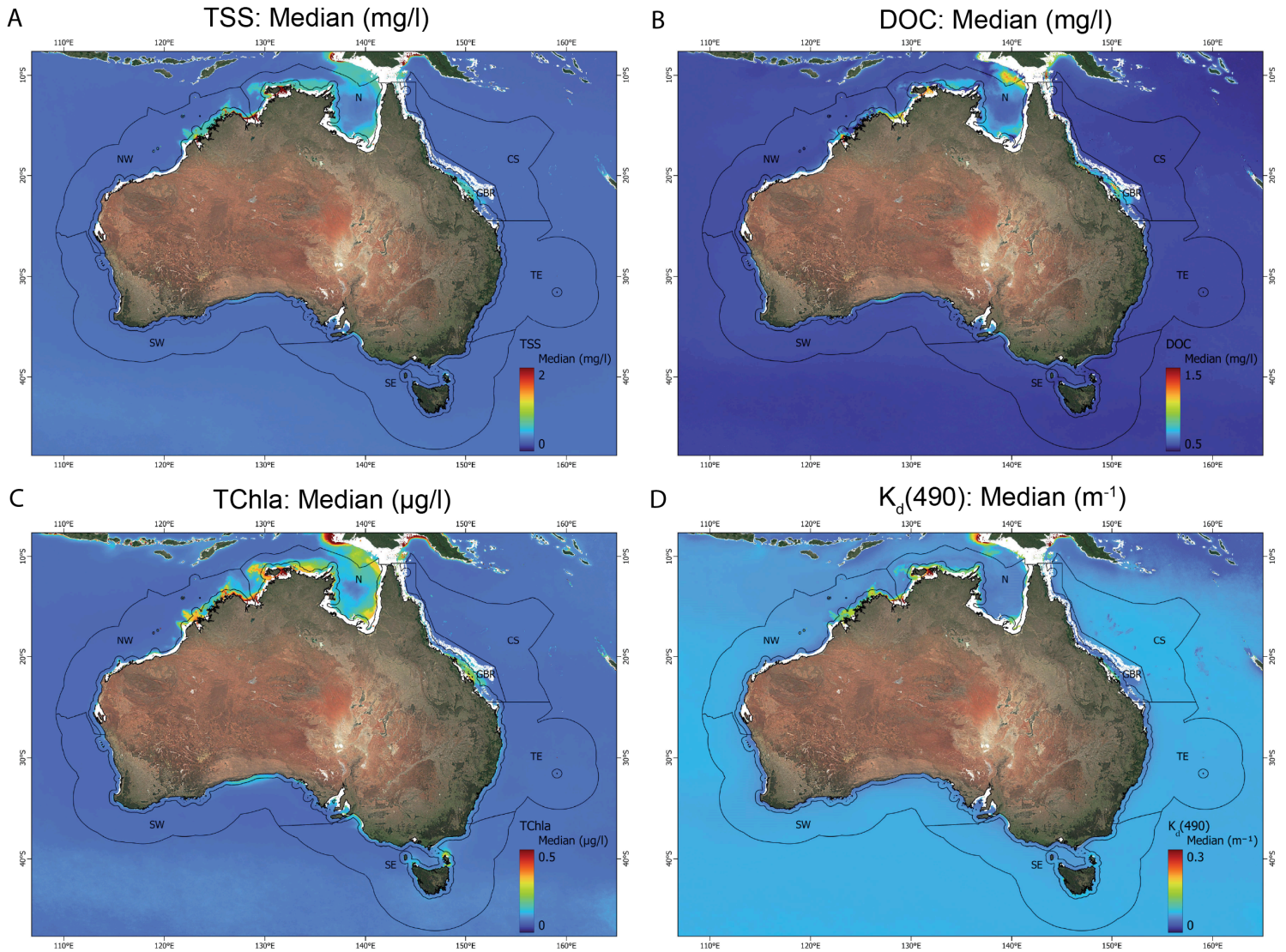


Figure 2

Spatial distribution of the BGC and $K_d(490)$ medians (2003–2022) A. TSS (mg/l), B. DOC (mg/l), C. TChla ($\mu\text{g/l}$), and D. $K_d(490)$ (m^{-1}) retrieved from MODIS-Aqua (1 km) using the DL-RS framework. Black polygons delineate the Australian DCCEEW bioregions used in this study. The mapped fields retain only quality-controlled, non-flagged ocean-colour pixels (excluding shallow-water/bottom-contaminated and otherwise invalid retrievals).

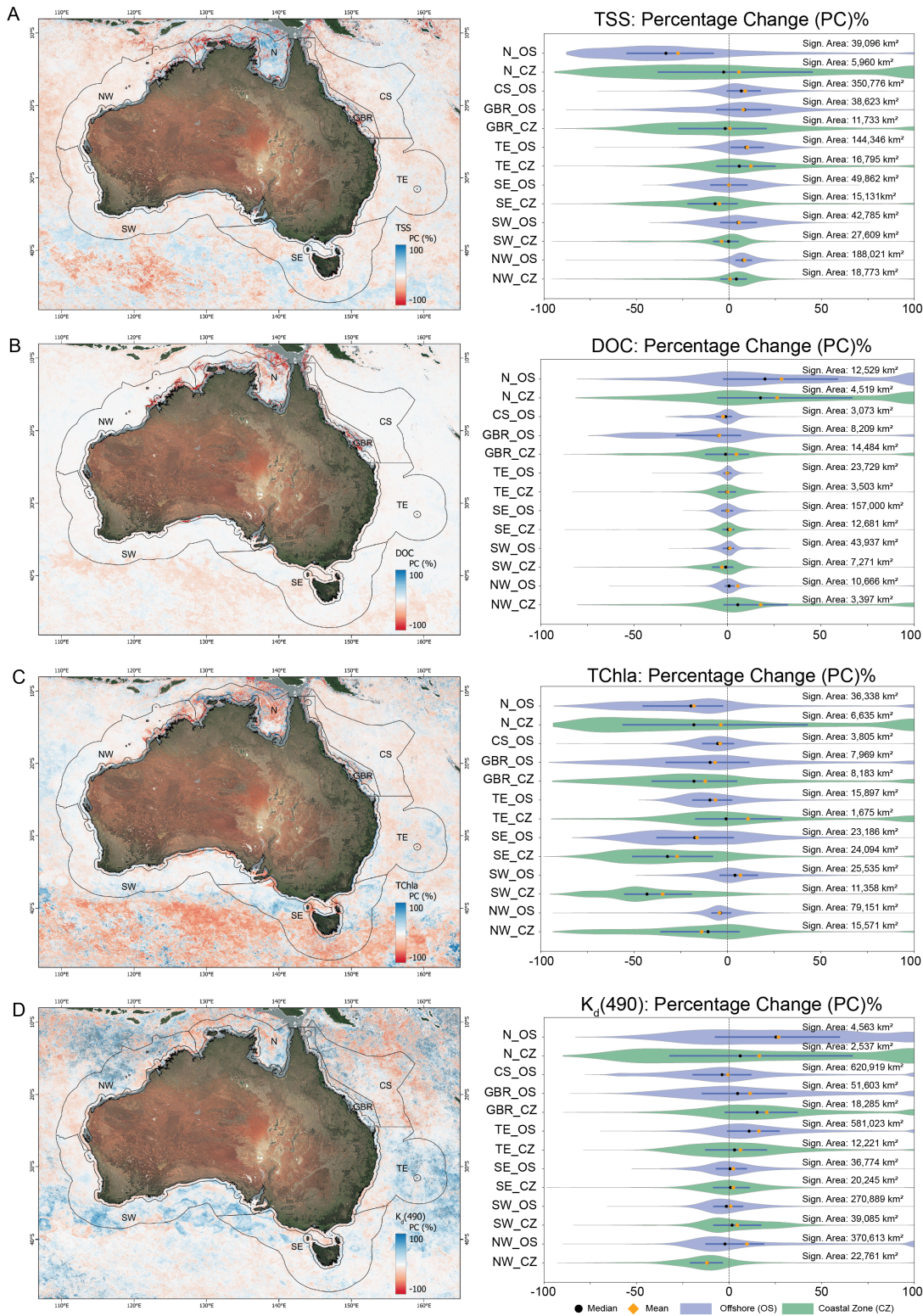


Figure 3

Spatial patterns and regional distributions of multi-decadal percentage change (PC) in water-quality constituents and light attenuation (2003–2022). Left panels show maps of the percentage change (PC, %) derived from MODIS-Aqua (1 km) time series for (a) TSS, (b) DOC, (c) TChla, and (d) $K_d(490)$, calculated for each pixel using a modified Mann–Kendall trend assessment and Theil–Sen slope estimates. Shallow pixels/invalid retrievals masked out in grey. Right panels summarise the distribution

of pixel-wise PC estimates (p -value < 0.05) within each bioregion, partitioned into offshore (OS; blue) and the coastal zone (CZ; green; within 50 km of the coastline) and along with the area of statistically significant pixels within each bioregion (Sign. Area).

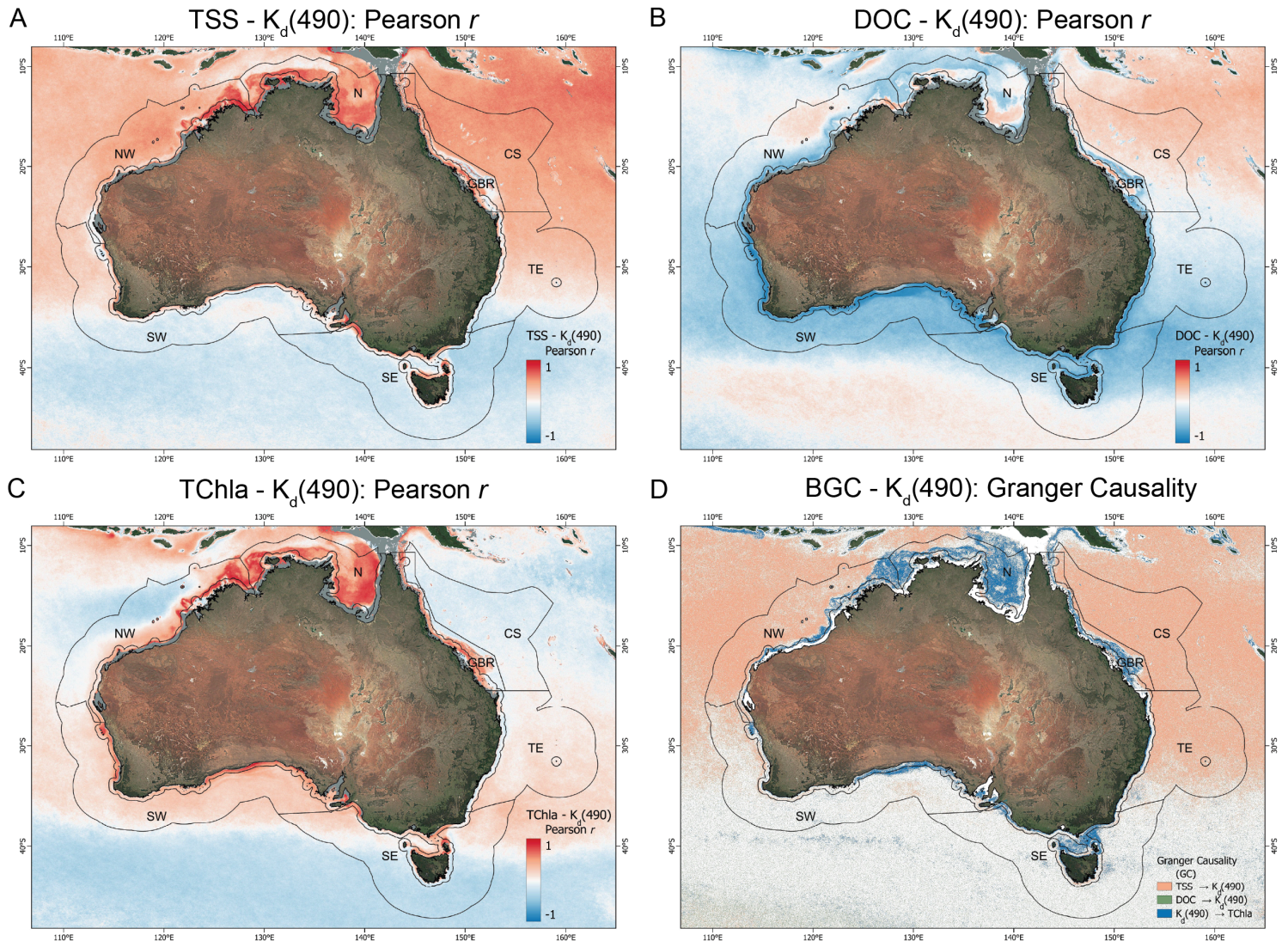


Figure 4

Spatial coupling between biogeochemical constituents and light attenuation, and dominant directional pathways inferred from Granger causality. Panels (a–c) show the pixel-wise Pearson correlation coefficient (r) between the 20-year time series (2003–2022) of $K_d(490)$ and (a) TSS, (b) DOC, and (c) TChla, computed from the DL-RS retrievals applied to MODIS-Aqua (1 km). Shallow pixels/invalid retrievals masked out in grey. Panel (d) synthesises these relationships using a Granger causality (GC) framework, classifying each pixel by the dominant directional link between BGC constituents and light attenuation. Colours indicate where temporal changes are best explained by $TSS \rightarrow K_d(490)$ as pink, $DOC \rightarrow K_d(490)$ as green, $K_d(490) \rightarrow TChla$ as blue, and white denoting non-significant pixels; '→' indicates granger causality direction.

Supplementary Files

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