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# Dynamic partitioning of tropical Indian Ocean surface waters using ocean colour data - management and modelling applications

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# Abstract

Over the past few decades, partitioning of the surface ocean into ecologicallymeaningful spatial domains has been approached using a range of data types, with the aim of improving our understanding of open ocean processes, supporting marine management decisions and constraining coupled ocean-biogeochemical models. The simplest partitioning method, which could provide low-latency information for managers at low cost, remains a purely optical classification based on ocean colour remote sensing. The question is whether such a simple approach has value. Here, the efficacy of optical classifications in constraining physical variables that modulate the epipelagic environment is tested for the tropical Indian Ocean, with a focus on the Chagos marine protected area (MPA). Using remote sensing data, it was found that optical classes corresponded to distinctive ranges of wind speed, wind stress curl, sea surface temperature, sea surface slope, sea surface height anomaly and geostrophic currents (Kruskal-Wallis and post-hoc Tukey honestly significantly different

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tests,  $\alpha = 0.01$ ). Between-class differences were significant for a set of subdomains that resolved zonal and meridional gradients across the MPA and Seychelles-Chagos Thermocline Ridge, whereas between-domain differences were only significant for the north-south gradient (PERMANOVA,  $\alpha = 0.01$ ). A preliminary test of between-class differences in surface CO<sub>2</sub> concentrations from the Orbiting Carbon Observatory-2 demonstrated a small decrease in mean  $pCO_2$  with increasing chl, from 418 to 398 ppm. Simple optical class maps therefore provide an overview of growth conditions, the spatial distribution of resources – from which habitat fragmentation metrics can be calculated, and carbon sequestration potential. Within the 18 year study period, biotic variables were found to have decreased at up to  $0.025\% a^{-1}$  for all optical classes, which is slower than reported elsewhere (Mann-Kendall-Sen regression,  $\alpha = 0.01$ ). Within the MPA, positive Indian Ocean Dipole conditions and negative Southern Oscillation Indices were weakly associated with decreasing chl, fluorescence line height (FLH), eddy kinetic energy, easterly wind stress and wind stress curl, and with increasing FLH/chl, sea surface temperature, SSH gradients and northerly wind stress, consistent with reduced surface mixing and increased stratification. The optical partitioning scheme described here can be applied in Google Earth Engine to support management decisions at daily or monthly scales, and potential applications are discussed.

*Keywords:* Remote sensing, biogeography, habitat fragmentation, Orbiting Carbon Observatory-2 (OCO-2), Marine Protected Area, epipelagic

## 1 1. Introduction

Physical drivers such as light, temperature and dynamical mixing shape 2 the epipelagic ecosystem, and the biota of deeper water layers is determined, 3 at least in part, by the productivity of upper layers (Jerlov, 1976; Longhurst, 4 2007; Spalding et al., 2012; Kavanaugh et al., 2016; Proud et al., 2017). Di-5 viding the oceans into geographical areas with common physical conditions 6 has been approached using a range of methods and suites of data (reviewed by 7 Krug et al., 2017; Kavanaugh et al., 2016), and referred to variously as eco-8 logical geography, partitioning, biogeography, biohydrography, biogeographi-9 cal provinces and seascapes. Most schemes include nested spatial scales with 10 slightly different nomenclature for different elements of heirarchical structure. 11 Partitioning the oceans is similar to habitat mapping and species distribu-12 tion modelling in the sense that a geographical representation of resources is 13 produced. However, it does not relate to specific organisms, and no model 14 of the relationships between predictor and response variables is produced 15 (c.f. Blanco et al., 2015; Coelho et al., 2013; Scales et al., 2014; Zydelis et 16 al., 2011). Partitioning schemes have found application to two key challenges. 17 Firstly, they provide static and dynamical geographical boundaries to guide 18 management planning (over the long term) and intervention (in the short 19 term). Management tasks include monitoring ecosystem health, assessing 20 risk and implementing control measures such as fishery closure, and informa-21 tion is required at multiple spatial scales and depth ranges to support these 22 actions (Rice et al, 2011; Spalding et al., 2012; Caldow et al., 2015; Roberson 23 et al. 2017). Short-term responses can only be supported when the frequency 24 at which new data is available exceeds the rate of critical fluctuations occur-25

ring within the ecosystem. The second use is to provide spatial context for 26 the evaluation of climate model reliability (Vichi et al., 2011; Kavanaugh 27 et al., 2014; Fay & McKinley, 2014). The focus here is on the exchange of 28 climate-relevant gases across the air-sea interface and there is no require-29 ment for low-latency information. Partitions serve as a proxy for ecosystem 30 function with the inference that they constrain rates of  $CO_2$  diffusion, bi-31 otic carbon uptake and the efficiency with which carbon is removed from the 32 surface layer. Earth system models (ESM), in which the representation of 33 biogeochemical cycles remains quite simplistic (Hense et al., 2017; Jung et 34 al., 2019; Sreeush et al., 2018) and which are sensitive to feedback between 35 biotic and abiotic components (Lim & Kug, 2017; Park & Kug, 2014; Ro-36 manou et al., 2014) can then be evaluated in the context of static or dynamic 37 seascapes (Landschützer et al., 2019; Lovenduski et al., 2019). 38

Satellite remote sensing data, which currently provides the best compro-30 mise between area coverage and temporal resolution for surface ocean studies, 40 has increasingly been used for partitioning, as the disparate worlds of marine 41 management and oceanography converge on how this rich data source can 42 best be used (Kachelriess et al., 2014; Maxwell et al., 2015; Miloslavich et 43 al., 2018). Figure 1 illustrates some of the pelagic abiotic and biotic factors 44 that can be derived from remote sensing data, and characteristics relevant 45 for modelling and management decisions. 46

47

## [FIGURE 1 HERE: SINGLE-COLUMN; COLOUR ONLY ONLINE]

<sup>48</sup> Of the variables amenable to remote sensing, only ocean colour is di-<sup>49</sup> rectly affected by the pelagic ecosystem at short time-scales. Partitioning <sup>50</sup> schemes mostly use an ocean-colour-derived variable, chlorophyll-a concentration (hereafter chl), as a measure of biomass and combine it with other key physical drivers such as temperature. However, being a function of the concentrations of dissolved and particulate substances in the surface ocean, ocean colour itself represents a response to the physical drivers. Using ocean colour to derive chl incurs spatially-varying errors (Jackson et al., 2017) and ignores other coloured variables of interest that may, or may not, covary with chl (O'Reilly et al., 1998; Werdell et al., 2018).

Classifications based on water colour alone have shown that, whilst chl is 58 generally constrained by these classifications, information about other water 59 mass tracers is also present (Alvain et al., 2005, 2008; Vantrepotte et al., 2012; 60 Trochta et al., 2015; Krug et al., 2018; Monolisha et al., 2018; Dierssen, 2010). 61 Taken together with the knowledge that physical dynamics at all scales com-62 bine to control the growth environment, this suggests an opportunity to use 63 pure optical classes as the smallest scale in a seascape heirarchy, with the 64 advantage that it is a low-latency product which could feed into decision-65 making flows on a daily basis (e.g. using GoogleEarthEngine; Gorelick et al., 66 2017) where coverage allows. This possibility is explored here, with a focus 67 on the Chagos marine protected area (MPA). If optical classes are found to 68 constrain abiotic drivers as well as biotic response, then a further question 69 arises of whether they can also be used to estimate carbon flows (extending 70 Kavanaugh et al., 2014) without the need to identify individual elements, 71 such as phytoplankton function type, as an intermediate step. 72

73 1.1. The study area

The Chagos marine protected area occupies 640,000 km<sup>2</sup> in the tropical Indian Ocean, with the Chagos Archipelago system of islands and atolls at it

centre (Figure 2; UNEP-WCMC, 2016). The coastline of the Indian Ocean 76 is shared amongst over twenty countries, representing a substantial fraction 77 of the human population with variable socio-economic status and strong re-78 liance on coastal and open-ocean fisheries (Hermes et al., 2019). The MPA 79 is of particular value because of its coral health, resilience and diversity, 80 extensive seagrass beds, potential support for the wider Indian Ocean fish-81 eries and related benefits (Koldeway et al., 2010; Ateweberhan et al., 2018; 82 Gravestock & Sheppard, 2015; Esteban et al., 2018). In common with shallow 83 tropical corals around the world, reefs in the Chagos MPA are vulnerable to 84 temperature increases associated with climate change as well as to increases 85 in extreme high energy dynamics. Their relative resilience compared with 86 other reef systems is associated with protection from human disturbance as 87 well as to geographical location. Although extensive coral bleaching has oc-88 curred (Sheppard et al., 2008), interactions between dynamical processes at 89 a range of scales and topographic diversity may alleviate temperature stress 90 (Sheppard, 2012; Hosegood et al., 2019). Understanding whether this nat-91 ural protection will continue under ongoing climate change is important in 92 terms of economic as well as natural resource value. 93

The Chagos Archipelago lies at the edge of the South Indian tropical gyre within the influence of the Indian Ocean monsoon. In austral summer, northerly winds drive an anticyclonic cell and the gyre contracts, so that the archipelago is at the northern edge. For the rest of the year, the MPA lies at or near the southern edge of the gyre. The location and large-scale circulation features are summarised in Figure 2. In the west, divergent winds and negative wind stress curl lift the thermocline along 5-12°S creating the Seychelles-Chagos Thermocline Ridge (SCTR), with a thermocline depth
around of 50 m and no surface signature, which extends around the MPA
throughout the year (Hermes & Reason, 2008, 2009; Aguiar-Gonzalez et al.,
2016; Xie et al., 2002).

[FIGURE 2 HERE: SINGLE or 1.5 COLUMN; COLOUR ONLY ON LINE]

The South Equatorial Current (SEC), flowing to the south of the MPA, 107 denotes the boundary between relatively nutrient replete but O<sub>2</sub>-poor surface 108 waters to the north and southern sub-tropical gyre waters to the south which 109 are nutrient-depleted throughout the water column but represent a  $CO_2$  sink 110 (Garcia et al., 2018; Landschützer et al., 2016). In situ biogeochemical data 111 are sparse across the tropical Indian Ocean and considerable deviations from 112 the mean conditions in the World Ocean Atlas have been reported (Subha 113 Anand et al., 2017; Chinni et al., 2019). Whilst the tropics are generally 114 considered to be oligotrophic, year-round elevated phytoplankton biomass 115 is observed close to the archipelago as well as over the Mascarene Plateau 116 to the west and broadly over the SCTR (Wilson & Qiu, 2008; Levy et al., 117 2007). In situ measurements of net primary production in this region range 118 from close to zero up to  $20 \text{ mgCm}^{-2}\text{d}^{-1}$  and can be exceeded by bacterial 119 production (Subha Anand et al., 2017; Fernandes et al., 2008; Veldhuis et al., 120 1997). A few high temporal resolution datasets from moored fluorometers 121 have shown high frequency, high magnitude fluctuations in phytoplankton 122 biomass (Hosegood et al., 2019; Strutton et al., 2015). Phytoplankton as-123 semblages have been found to be dominated by Prochlorococcus and Syneco-124 coccus as expected in the oligotrophic gyres, but substantial fractions of di-125

atoms, dinoflagellates and prymnesiophytes have also been reported in the 126 TIO (Thorrington-Smith, 1971; Veldhuis et al., 1997; Soares et al., 2015). 127 To my knowledge, there are no long-term biogeochemical monitoring efforts 128 in the pelagic SCTR, despite detailed repeat monitoring in the shallow reef 129 waters of the MPA (e.g. Sheppard, 2012). Many studies have used cou-130 pled ocean-biogeochemical models, together with available in situ or remote 131 sensing data, to elucidate biophysical coupling in the tropical Indian Ocean 132 (TIO) (e.g. Wiggert et al., 2006; Jin et al., 2012; Liu et al., 2013; Resplandy 133 et al., 2009; George et al., 2018). Of particular interest here are the results 134 of George et al. (2018), Dilmahamod et al. (2016) and Wiggert et al. (2006), 135 who explore meridional and zonal gradients in the SCTR. 136

The epipelagic growth environment is directly modulated by entrainment 137 and advection of nutrients and plankton, fluctuations in mixed layer tem-138 perature and depth, the relative euphotic to mixed layer depths, turbulence 139 and varying illumination conditions. Conversely, feedback effects have been 140 demonstrated between chl and shortwave heating, SST, surface convergence 141 and basin-scale dynamical features (Back & Bretherton, 2009; Park & Kug, 142 2014). At the seasonal scale, the eastward extent of the SCTR and westward 143 extent of Indonesian Throughflow (ITF) respond to monsoon wind weakening 144 and reversal (Aguiar-Gonzalez et al., 2016). Two of the eight Madden-Julian 145 Oscillation (MJO) phases are centred in the TIO (Hendon & Salby, 2994), 146 with a westward-progagating Rossby wave (Seiki et al., 2013) impacting SST, 147 evaporation, precipitation, cloud cover, rainfall, salinity gradients (Guan et 148 al., 2014; Jin et al., 2013; McPhaden & Foltz, 2013) and wind-driven en-149 trainment of nutrients into the mixed layer (Jin et al., 2012b). At the in-150

terannual scale, El Nino and the Southern Oscillation (ENSO) and Indian 151 Ocean Dipole (IOD) events have been reported to affect surface conditions 152 and surface chlorophyll concentrations. Nino conditions affect mixed layer 153 temperatures through precipitation, downwelling (anticyclonic) winds and 154 westward propagating Rossby waves (Santoso et al., 2010; Dilmahamod et 155 al., 2016; Ma et al., 2014; Racault et al., 2017). Positive IOD phases coincide 156 with cooler surface temperatures in the eastern TIO and warmer conditions 157 to the west (SST anomalies of 0.1 to 0.3 °C or more; Currie et al., 2013; 158 Vialard et al., 2009). The impact of ENSO and IOD events is amplified when 159 they coincide, and both are expected to increase in frequency (IPCC, 2013; 160 Sheppard et al., 2008; Currie et al., 2013; Cai et al., 2014). 161

Despite the scarcity of data in the epipelagic in and around the Cha-162 gos MPA, the importance of conditions in these waters has recently been 163 highlighted by electronic tagging of seabirds and high trophic level pelagic 164 feeders, which has been used to document foraging at considerable distances 165 (Pecoraro et al., 2017; Danckwerts et al., 2014; Le Corre et al., 2012), with 166 measurable positive impacts on reef health through nutrient redistribution 167 (Graham et al., 2018). The near-shore pelagic biome is also a critical food re-168 source for corals (Houlbréque & Ferrier-Pagés, 2009) and the strength of this 169 relationship has now been demonstrated using remotely sensed ocean colour 170 data (Fox et al., 2019). Elevated chl related to the wind-driven circulation 171 around the Chagos MPA is therefore a potential resource both for the reef 172 and for pelagic organisms. 173

The underlying hypothesis for this study is that water colour represents the evolving trophic status of the upper ocean and is characteristic of the suite of physical drivers of ecosystem function as illustrated in Figure 1 (e.g. Jerlov,
1976), making it a candidate as a low-latency, fine-scale level in a seascape
heirarchy. This paper addresses how methodological choices affect optical
classifications, whether pure optical classes provide useful information about
the physical environment and potential applications of optical class maps.

# 181 2. Methods

# 182 2.1. Remote sensing data

This study spans August 2002 to October 2018. Remote sensing re-183 flectance (Rrs), chlorophyll-a concentration (chl), normalised fluorescence 184 line height (nFLH) and sea surface temperature (SST) data from the NASA 185 Moderate Resolution Imaging Spectrometer aboard the Aqua satellite (MODIS-186 Aqua), at Level 2 and Level 3, were acquired from the Ocean Biology Pro-187 cessing Group (oceancolor.gsfc.nasa.gov). Rrs is the ocean colour product 188 with the least degree of processing and therefore the lowest uncertainty, with 189 errors on the order of  $0.001 \text{ sr}^{-1}$  but varying with waveband and water type 190 (Franz et al., 2007; IOCCG, 2019). Reflectances from the seven 1 km reso-191 lution, 10 nm wavebands in the visible domain were augmented by band 1, 192 with 250 m resolution (50 nm waveband) and bands 3 and 4, with 500 m res-193 olution (20 nm wavebands), and these three bands were spatially averaged to 194 match the 1 km wavebands. Globally, chl is the best-validated ocean colour 195 product, with mean errors of ca.  $\pm 33 \text{ mgm}^{-3}$  (Hu, et al., 2012; O'Reilly et 196 al., 1998). Little product validation data is available for nFLH in the tropi-197 cal Indian Ocean, but the MODIS-Aqua and MODIS-Terra products perform 198 well against *in situ* data in the Southern and Atlantic Oceans (Erickson et 199

<sup>200</sup> al., 2019; Hoge et al., 2003).

Daily sea surface height (SSH), height anomalies (SSHA) and geostrophic 201 current velocities (denoted eastwards u and northwards v), from merged al-202 timeter datasets, were acquired at ca. 30 km resolution from the Coper-203 nicus Marine Environment Monitoring Service (CMEMS). Reported errors 204 on these products range from < 1 cm to 30 cm, with higher uncertainties 205 under more dynamic conditions (CMEMS, 2020). Eddy kinetic energy was 206 calculated as  $EKE = 1/2(u^2 + v^2)$ . Sea surface slope was calculated pixel-207 wise as  $\nabla SSH = \partial SSH / \partial x + \partial SSH / \partial y$ , with no smoothing. Each product 208 was subsampled to 4 km resolution before applying the optical class masks 209 (section 2.7). 210

Daily surface wind fields from the SeaWinds and ASCAT scatterometer 211 sensors were acquired at 25 km resolution from the Jet Propulsion Labo-212 ratory Physical Oceanography Distributed Archive Center (SeaPAC, 2006; 213 EUMETSAT/OSI SAF, 2018). Errors in these products are of order 0.1 214  $ms^{-1}$  (Verhoef et al., 2017). Wind stress curl was calculated pixelwise as 215  $\nabla \times \tau = -\partial \tau_N / \partial x - \partial \tau_E / \partial y$ , where  $\tau_N$  and  $\tau_E$  are the north-south and east-216 west components of the wind stress and  $\partial x$  and  $\partial y$  are the pixel dimensions. 217 Monthly averages were calculated before subsampling to 4 km resolution and 218 applying the optical class masks (section 2.7) 219

Profiles of the partial pressure of CO<sub>2</sub> derived from Orbiting Carbon Observatory 2 (OCO-2) data using the full physics model version 7.3 (O'Dell et al., 2018) were acquired at native resolution (ca. 3 km<sup>2</sup>) from the Goddard Earth Sciences Data and Information Services Center (OCO-2 Science Team, 2016, GES DISC). Only estimates of pCO<sub>2</sub> from the lowest model altitude were used and the ramifications of this are discussed in section 3.4. No spatial
or temporal compositing was applied.

Bathymetry data were acquired at 1 arc-second resolution from the National Centers for Environmental Information (ETOPO1, 2019) and regridded using nearest-neighbour gridding to match the Level 3 Rrs data.

Data products, sources and abbreviations are summarised in table 1.

231 [TABLE 1 HERE]

#### 232 2.2. Dynamic partitioning based on ocean colour

Fuzzy classification was applied to the Indian Ocean domain surrounding 233 the BIOT MPA (after Moore et al., 2001; Jackson et al., 2017). This method 234 was chosen for its potential to allow a single pixel to have multiple class 235 memberships, which is likely in natural phytoplankton populations, particu-236 larly at the relatively coarse spatial scales of remote sensing data (1 to >30237 km) in waters where mesoscale and submesoscale processes may be at play. 238 The study bounds were  $40^{\circ}$  to  $100^{\circ}$  E,  $-20^{\circ}$  to  $15^{\circ}$  N, spanning the central 239 tropical Indian Ocean with the BIOT MPA roughly central to the domain 240 (Figure 3: UNEP-WCMC, 2016). In the absence of *in situ* data with which 241 to verify class memberships or interpret class composition, only the dominant 242 class assigned to each pixel at any given time was retained (multiple class 243 memberships were removed, to be considered in future work when validation 244 data are available). Biovolumes calculated from miscroscopy analysis on five 245 stations within the MPA were used as a preliminary test of whether differ-246 ent classes represented different phytoplankton biomass (Kruskal-Wallis test; 247 Schwarz, 2020). 248

Variable	Abbreviation	Source
Remote sensing reflectance, Level 2	L2 Rrs	Ocean Biology Processing Group Level 2 data ocean-
		color.gsfc.nasa.gov
Remote sensing reflectance, Level 3	L3 Rrs	
Surface chlorophyll-a concentration	chl	
Surface normalised fluorescence line height	nflh	MODIS Asus Land 2 monthly data Ciamani data
Ratio of fluorescence line height to	flh:chl	moblis-Aqua Level 3 monthly data, Giovanni data
chlorophyll-a		portal giovanni.gsic.nasa.gov
Sea surface temperature	SST	
Metric for within-class spectral variability	R555:443	
(chlorophyll-like pigments): ratio of residual		
reflectances (Rrs - class mean) at 555 nm to		
443 nm		
Metric for within-class spectral variability	R555:488	
(accessory pigments): ratio of residual re-		
flectances (Rrs - class mean) at 555 nm to		
488 nm		
Sea surface height (absolute dynamic topog-	SSH	AVISO Level 4 reprocessed gridded sea surface
raphy)		heights and derived variables (product suite
Sea surface slope	$\nabla$ SSH	SEALEVEL GLO_PHY_L4
Sea surface height anomaly	SLA	REP_OBSERVATIONS_008_047),
Eastward component of the geostrophic cur-	u	marine.copernicus.eu, $0.25^o \ge 0.25^o$ regridded to 4 $\ge$
rent		4 km
Northward component of the geostrophic	v	
current		
Eddy kinetic energy	EKE	
Eastward component of the surface wind	$\tau_E$	Quikscat and ASCAT Level 3 gridded wind fields,
field		podaac.jpl.nasa.gov, 25 x 25 km regridded to 4 x 4
Northward compoent of the surface wind	$ au_N$	km
field		
Wind stress curl	$\nabla \times \tau$	
Water depth	z	ETOPO 1 arc-minute bathymetry regridded to 4 x 4 $$
		km (Amante & Eakins, 2009)
Indian Ocean Dipole index	IOD	Dipole mode index (Saji & Yamagata, 2003)
		esrl.noaa.gov/psd/gcos_wgsp/Timeseries/DMI
Madden Julian Oscillation index	MJO	Kilidas et al. (2014) esrl.noaa.gov/pas/mjo/mjoindex
Southern Oscillation Index	SOI	Ropelewski & Jones (1987)
		esrl.noaa.gov/psd/data/20thC_Rean/ time-
		series/monthly/SOI
Surface partial pressure of $CO_2$	$pCO_2$	Level 2 OCO-2 physical model surface $pCO_2$ , release
		9, GES DISC (Boesch et al., 2019)

Table 1: Optical, biological and physical remote sensing products used to explore optical classes

# [FIGURE 3 HERE: SINGLE-COLUMN or 1.5 COLUMN; PLEASE QUOTE FOR COLOUR PRINTING COSTS]

## 251 2.3. Impact of spatial and temporal compositing on optical classification

As noted by Jackson et al. (2017, hereafter JSM), averaging of the re-252 motely sensed reflectance spectra from instantaneous, Level 2 (ca. 1 x 1 253 km resolution) to Level 3 (ca. 4 x 4 km resolution, weekly or monthly) 254 data incurs a risk of smoothing out phytoplankton dynamics associated with 255 growth/decay/advection events that are short-lived, and it increases the dif-256 ference between any available *in situ* reflectance data used in characterising or 257 evaluating optical classes from the already spatially-averaged remote sensing 258 pixel values. Daily data may also be most appropriate for some management 259 applications. However, cloud-cover and the reduced overpass rates at low 260 latitudes make the use of daily data for capturing spatial patterns challeng-261 ing in this region. The impact of spectral aliasing (from averaging) on the 262 classification was tested by creating classes firstly from all the Level 2 (L2) 263 data for 2003, with no averaging or regridding. The resulting classes were 264 compared against the same suite of classification procedures applied to the 265 Level 3 (L3) monthly, 4 km gridded data for 2003 and against the hybrid 266 classification scheme produced by JSM and Moore et al. (2001) who used in 267 situ data. 268

Both the L2 and L3 data were classified in three forms: Remote sensing reflectance (Rrs), Rrs with the mean 2003 Rrs subtracted (Rrs- $\overline{Rrs2003}$ ) and Rrs normalized to 488 nm (Rrs/Rrs488). Training data were selected randomly in space and time from the study domain. For comparability with previous studies, three sizes of training dataset were used. The smallest

dataset contained 42,000 pixels, corresponding approximately to the volume 274 of data used by JSM for two of their study sites - they used two central 275 Indian Ocean sites referenced to Longhurst (2007) provinces. Additional 276 datasets of double and fifty times the original size were added to test for 277 sensitivity of the classification scheme to dataset size. Each dataset was 278 classified using the Matlab fcm function (Bezdek, 1981) with between 2 and 9 279 classes and the weighting exponent m was varied between 1.05 and 2.0. Class 280 separability and compactness were assessed using the partition coefficient 281 (F) and compactness and separation index (S) as in Moore et al. (2001); 282 Windham (1982); Xie & Beni (1991). In contrast to previous studies, all 283 ten available MODIS visible wavebands were used in the fuzzy classification 284 procedure. 285

### 286 2.4. Interpretation of within-class spectral variability

The use of ten wavebands for an optical classification allows limited explo-287 ration of within-class spectral variability, which may be related to pigmen-288 tation and size differences caused by change in phytoplankton community 289 composition or physiology, differences in backscatter related to the viral, 290 bacterial and phytoplankton communities, variability in the relative quanti-291 tites of coloured, dissolved organic matter or inorganic particulate matter, 292 variability in the depth distributions of coloured materials and noise in the 293 satellite signal (Kirk, 1994; Brown et al., 2008; Defoin-Platel & Chami, 2007; 294 Alvain et al., 2005; Lain & Bernard, 2018; Brewin et al., 2011b). Having 295 excluded water depths shallower than 200 m and in the absence of in situ 296 validation data, the main focus here is on testing whether Rrs spectra varied 297 uniformly with optical class. Residual reflectance ratios Rrs(555)/Rrs(443)298

and Rrs(555)/Rrs(488) were calculated after subtracting the dominant class mean reflectance spectrum (Table 4) at each pixel, as indicators of spectral variability. In a full application of the fuzzy classification scheme (Moore et al., 2001), this step could be pre-empted by allowing multiple class memberships at each pixel.

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# <sup>305</sup> 2.5. Comparison against other classifications

Class spectra produced in this study and by JSM were mapped to other 306 interpretations for comparison. Firstly, the standard NASA OC3M-CI algo-307 rithms were applied to each central class spectrum to produce chl concentra-308 tion (O'Reilly et al., 1998; Hu, et al., 2012). This was passed to abundance-309 based algorithms for phytoplankton size class published by Brewin et al. 310 (2010, Atlantic Ocean), Brewin et al. (2011a, global *in situ* data), Brewin et 311 al. (2012, eastern Indian Ocean) and Devred et al. (2011) (North Atlantic 312 and global in situ data; IOCCG, 2014). Chl was also used to select the 313 closest stratified water trophic class from Uitz et al. (2006). For comparison 314 against Alvain et al. (2005, 2008), every 10th Level 2 MODIS Rrs file from 315 2003 was used to generate local PHYSAT-equivalent mean-chl spectra (39 chl 316 divisions from 0.01 to 4.00 mgm<sup>-3</sup> in intervals of ln(0.15); between 67016 and 317 5488110 pixels per chl interval with a total of 64733448 pixels). These were 318 subtracted from each mean optical class spectrum and the residual compared 319 against the criteria provided by Alvain et al. (2008). 320

Name	Weighting coefficient m	Partition coefficient F	Separation index S	Source	
N5	1.05	10	0.986	0.211	This study
N8	1.05	10	0.982	0.342	This study
JSM	Unknown	6	Unknown	Unknown	Jackson et al.
					(2017)

Table 2: Classification schemes used for further analysis. See supplementary online material, Table S1, for full classification evaluation metrics.

### <sup>321</sup> 2.6. Classification of the 17 year Level 3 dataset

Following evaluation of the L2 and L3 classifications, a suite of three classification schemes was chosen and applied to 17 full years of MODIS-Aqua Level 3 Rrs version 2018.0 (Table 2). Water depths shallower than 200 m were excluded from analysis. This provided the framework for testing whether other remotely sensed parameters were well constrained by the optical classes. [TABLE 2 HERE]

### <sup>328</sup> 2.7. Relationship between colour class and biophysical parameters

Summary statistics of remotely sensed biological and physical variables were produced to characterize each class in each of seven geographical domains (Figure 3): SCTR-W (10° to 5° S, 50° to 62° E), SCTR-E (10° to 5° S, 63° to 75° E), SCTR-C (10° to 5° S, 76° to 88° E), Wiggert-N (7° to 2° S, 60° to 85° E), Wiggert-S (12° to 7° S, 60° to 85° E), the MPA, z200 (the whole study domain at depths greater than 200 m) and z1000 (the whole study domain at depths greater than 1000 m).

The potential of purely optical classifications as indicators of the pelagic growth environment was explored using within- and between-class statistics. Non-parametric analysis of variance was used to test whether the optical classifications reflected differences in each of the the biological and physical

variables (Kruskal-Wallis, applied to one variable at a time, assuming that 340 underlying distributions of each variable within each class subset of each geo-341 graphical domain are the same, followed by post-hoc Tukey's honestly signifi-342 cantly difference, HSD, tests between pairs of classes; Ruxton & Beauchamp, 343 2008) for each of the geographical domains. The distinctiveness of smaller 344 domains for which contrasting processes across zonal or meridional gradients 345 have been discussed in the literature (SCTR-W,E,C; Wiggert-N, S Wiggert 346 et al., 2006; George et al., 2018; Dilmahamod et al., 2016) was tested using 347 permuted multivariate analysis of variance (PERMANOVA; Anderson, 2001, 348 2017) on standardised variables (z-scores), with all fifteen biological and phys-349 ical variables. Anomaly time-series were used in addition to simple z-scores 350 where clear seasonal cycles were present. Because of the large dataset sizes, 351 100 subsets of 1000 pixels were selected randomly through time within each 352 geographical domain for bootstrapped testing; pixels with missing data were 353 excluded at each iteration. Domain was taken as the first, fixed, factor and 354 class as the second, nested factor. Euclidean distance, correlation distance 355 and squared correlation distance gave similar PERMANOVA hypothesis test 356 results, whilst  $\chi$  and  $\chi^2$  results varied; euclidean distance and 1000 permuta-357 tions were used for all reported results (McCune & Grace, 2002; Anderson, 358 2017; Pillar, 2013). The fathom Matlab toolbox was used for PERMANOVA 359 tests (Jones, 2012). Mann-Kendall-Sen correlation coefficients (Sen, 1968; 360 Hamed & Rao, 1998) were used to identify which biological and physical 361 variables covaried within each class. Correlations were tested firstly using all 362 data and secondly using bootstrapping to insure against spatial and temporal 363 autocorrelation effects (100 random subsamples of 1000 pixels). 364

A full comparison of optical classes with OCO-2  $pCO_2$  data was beyond 365 the scope of this study - OCO-2 was launched in July, 2014, and the data 366 therefore do not span the study period considered here. OCO-2 data are also 367 lower in spatial and temporal coverage, although the recent launch of OCO-3 368 will mitigate this. As a proof of concept, a single month of OCO-2 surface 369  $pCO_2$  data were matched to MODIS Level 2 optical classes for January 2015 370 (same-day match-ups only), and between-class differences evaluated using 371 Kruskal-Wallis and post-hoc HSD tests, for the z1000 study domain. 372

Assuming that optical classifications do partition pixels dynamically in 373 space and time according to the physical and biological variables that can 374 be derived from remote sensing data, two additional tests were applied to 375 establish whether conditions within pixels assigned to each class changed 376 during the study period, and whether they are correlated with basin- and 377 global-scale circulation patterns. Mann-Kendall-Sen trend tests were ap-378 plied in regressions of the class-averaged time-series of each remote sensing 379 variable against climate indices that characterize the Indian Ocean Dipole 380 (Dipole Mode Index, referred to hereafter as IOD; Saji & Yamagata, 2003), 381 Madden-Julian Oscillation (MJO; Kilidas et al., 2014) and El Nino-Southern 382 Oscillation, Southern Oscillation index (SOI; Ropelewski & Jones, 1987). 383 The SOI was chosen because it represents variability in the Walker circula-384 tion, rather than directly in SST or combinations of variables. Habitat frag-385 mentation metrics were used to characterise the distribution of lower trophic 386 level resources in the MPA, Wiggert-S and Wiggert-N domains to investigate 387 whether changes related to climate patterns can be detected in the pelagic 388 growth environment using available remote sensing data between 2002 and 380

2018. Patches of the same optical class were created using each month's 390 class map as a binary image, grouping adjacent pixels of like-class (Matlab 391 bwconncomp) and finding the perimeter, patch centre and number of pix-392 els contained within each class patch (Matlab regionprops). Average patch 393 area, distance between patches and patch density were calculated (Wang 394 et al., 2014) for each month for temporal regression and regression against 395 climate indices (Mann-Kendall-Sen test). Finally, correlations between the 396 total area occupied by each optical class within each subdomain and climate 397 indices were tested (Mann-Kendall-Sen trend test). 398

To test whether optical classifications could form a useful basis for fish-399 eries management and enforcement, fishing catch and effort data from the 400 Indian Ocean Tuna Commission were acquired at monthly temporal resolu-401 tion, in  $1^{\circ}$  and  $5^{\circ}$  grids (IOTC, 2020, 2014). The most common optical class 402 was assigned to each of these coarse fisheries grid cells, matched by year and 403 month, and between-class differences in catch, effort and catch per unit effort 404 (CPUE) were evaluated (Kruskal-Wallis and post-hoc HSD). This compari-405 son was applied across the z1000 domain and within the IOTC data gridcells 406 that contain the MPA as well as  $15^{\circ} \ge 15^{\circ}$  and  $25^{\circ} \ge 25^{\circ}$  domains centred 407 on the MPA and the full z1000 area. Long-line fishing effort was reported in 408 hooks, whereas surface fishery effort was reported in hours; the two datasets 409 were analysed separately. 410

All data analysis and visualisation was carried out using Matlab 2018a
 running under MacOS10.12.6.

# 413 3. Results & Discussion

3.1. Comparison of classification results with Level 2 and Level 3 input data 414 Classification results were similar for L2 and L3 data for the two smaller 415 datasets, but classes were less compact when the largest dataset was used. 416 Partition coefficients (F) remained above 0.9 for all three Rrs treatments 417 with weighting coefficients 1.05, 1.1 and 1.2, but separation coefficient S 418 increased from O0.15 to O0.3 as the number of classes, N, was increased 419 from two to nine, and the best separability was obtained for 2 classes with 420 all data treatments. Beyond N=8 classes, processing time increased signifi-421 cantly and F and S values were unstable between repeat runs, therefore no 422 classification with 9 or more classes was pursued. Classification performance 423 metrics (F and S) for all L2 and L3 classifications are provided in full in the 424 Supplementary Online Material, Table S1, sheet 'L2 L3 Classification F S'. 425 Rrs treatment made little difference to F and S for Rrs and Rrs-(Rrs(2003))426 (<1% variability in performance metrics for m < 1.3), but separation index 427 increased by a factor of 20 for  $\operatorname{Rrs}/\operatorname{Rrs}(488)$ . 428

Figure 4 shows the JSM classes and the L2 and L3 class spectra produced 429 using Rrs with m = 1.05 and two to eight classes, and Table 3 shows the pro-430 portions of pixels mapped to each class, with N=5 and N=8 class schemes 431 mapped to JSM classes using Euclidean distance between Rrs values at the 432 six common wavebands. Fewer of the JSM classes were reproduced in L3 433 classifications than in L2 classifications, with the extreme blue-water spectra 434 (highest and lowest Rrs(412) values) lost in an N=8-class scheme (Table 3). 435 Class spectra fell within or at the edges of the JSM classes, with most devi-436 ation in spectral shape (relative to the closest JSM class) in the blue: green 437

wavebands. Only one of the three JSM coastal water classes was found in
the N=8 classifications produced here, and none with N=5.

#### 440

# [FIGURE 4 HERE, SINGLE-COLUMN; COLOUR ONLINE ONLY]

441 [TABLE 3 HERE]

As a compromise between F and S metrics and representation of the JSM classes, and to enable direct comparison of results against similar studies, the 5- and 8-class schemes (henceforth N5 and N8) produced using m=1.05, 42,000 training pixels and absolute Rrs spectra were used for further analysis, together with the 6-waveband JSM classification. These Level 2 and 3 classifications for 2003 are summarized in Table 3 and the class spectra are given in Table 4.

# 449 [TABLE 4 HERE]

Mapping of the N5 and N8 classifications from Level 2 and Level 3 data 450 to abundance-based and reflectance-based PFT algorithms is shown in Fig-451 ure 5. PFT algorithms consistently interpreted the lower-OC3-CI chl classes 452 as being dominated by picoplankton, with the contribution of nano- and 453 microplankton fractions increasing with increasing chl. Eutrophic-type dis-454 tributions, dominated by microplankton, were only produced in the N8 clas-455 sification, but this was the only difference between 5- and 8-class schemes. 456 Since the proportion of pixels assigned to the 8th class was 0.3% (Table 3), 457 the abundance-based PFT algorithms generally classify these optical classes 458 as dominated by small cells. In contrast, switching from Level 2 to Level 3 459 data produced more PHYSAT-type spectra that fell into the pseudo-diatom 460 class (similar spectral shape to PHYSAT-diatom, but higher Rrs values). 461 The N5 and N8 schemes correspond to JSM classes between 1 and 9, and 462

Class	Level 2 $\%$ pixels assigned to each class				Level 3 $\%$ pixels assigned to each class				
	N5	N8	$_{ m JSM}$	N5	N8	JSM			
1		5.7	1.9			0.5			
2	10.7		6.7	11.9	8.1	5.6			
3		14.8	14.6		14.0	13.2			
4	24.7	19.7	18.0	20.9	16.3	17.2			
5	28.0	20.9	16.6	24.7	17.7	17.2			
6		18.5	13.4		14.8	12.9			
7	23.9		9.7	19.7	10.9	8.3			
8		14.0	7.7			6.0			
9	12.8		4.6	12.0	6.0	3.5			
10		6.3	3.6			2.3			
11			2.6			0.8			
12			0.3			0.3			
13		0.3	0.2		0.3	0.2			
14			0.1			0.1			

Table 3: Total number of Level 2 and Level 3 dominant classes mapped to each fuzzy cluster in the 10-waveband classifications (5 classes and 8 classes, N5, N8) and in the Jackson-Moore 6-waveband classification. The 10-waveband classes are mapped to the JSM classification by Euclidean distance (Figure 4).

Classification	$\operatorname{Rrs}(412)$	$\operatorname{Rrs}(443)$	$\operatorname{Rrs}(469)$	$\operatorname{Rrs}(488)$	$\operatorname{Rrs}(531)$	$\operatorname{Rrs}(547)$	$\operatorname{Rrs}(555)$	$\operatorname{Rrs}(645)$	$\operatorname{Rrs}(667)$	$\operatorname{Rrs}(678)$
/ class no.	x1000									
N5: 1	15.032	11.065	9.366	7.298	2.621	1.929	1.535	0.009	0.204	0.256
N5:2	12.186	9.035	7.988	6.455	2.523	1.857	1.489	0.076	0.197	0.248
N5:3	9.620	7.332	6.782	5.672	2.447	1.814	1.458	0.059	0.191	0.247
N5:4	6.974	5.602	5.482	4.787	2.388	1.807	1.468	0.058	0.196	0.262
N5:5	3.961	3.476	3.748	3.480	2.215	1.768	1.474	0.085	0.224	0.324
N8:1	15.530	11.400	9.556	7.381	2.558	1.861	1.467	0.077	0.183	0.236
N8:2	13.131	9.683	8.426	6.718	2.519	1.842	1.469	0.070	0.189	0.241
N8:3	11.193	8.355	7.507	6.138	2.462	1.808	1.445	0.057	0.184	0.236
N8:4	9.375	7.166	6.656	5.583	2.418	1.787	1.433	0.048	0.183	0.241
N8:5	7.500	5.948	5.743	4.965	2.375	1.778	1.435	0.045	0.186	0.250
N8:6	5.514	4.593	4.680	4.196	2.313	1.779	1.457	0.054	0.195	0.271
N8:7	3.184	2.913	3.268	3.103	2.146	1.746	1.467	0.096	0.236	0.348
N8:8	7.662	9.253	11.578	12.541	14.101	14.027	13.220	4.781	3.947	3.880

Table 4: Class Rrs spectra for the N5 and N8 classifications produced in this study using Level 3 data.

with a finer gradation of Rrs spectra corresponding to 0.03 to 0.5 mgm<sup>-3</sup>, the 463 JSM classes include more scope for identifying mixed size-class waters with 464 the PFT algorithms included here. The PHYSAT classification was designed 465 to identify cases in which a single PFT dominates water colour and, corre-466 spondingly, not all classes could be mapped to a PHYSAT class (Figure 5). 467 Of those that did, Synechococcus-like cyanobacteria was the most common 468 designation (3 classes at Level 2, N5; 4 classes at Level 2, N8; 1 class at Level 469 3, N5 and JSM and 2 classes at Level 3, N8). 470

# 471 [FIGURE 5 HERE: SINGLE-COLUMN; ONLINE COLOUR ONLY]

Class maps for every second month of 2003 (Figure 6) show more fragmented spatial distribution of classes in the L2 data, corresponding to the higher spatial resolution of the data and higher spectral separability. Broader spatial patterns (O1000 km) are consistent between all classifications and include a limited seasonal north to south shift in class, distinction of coastal, Somali Current and Arabian Sea waters from the central domain and coherent and elongated patches of higher class (4-5 in the N5 classification) waters in the central Indian Ocean, often enveloping the Chagos MPA. These zonal bands are more evident in Figure 7, which summarises class diversity at each pixel, as corresponding to the seasonally-varying SCTR, SEC and SECC domains. Figure 8 shows a subset of the remote sensing climatologies, for comparison.

# <sup>484</sup> [FIGURE 6, 7, 8 CLOSE TO HERE: SINGLE-COLUMN or 1.5 COL-<sup>485</sup> UMN; PLEASE QUOTE FOR COLOUR PRINTING]

Whether or not the smaller features correspond to ecologically meaning-486 ful variations in the microbial biome or carbon cycling can only be answered 487 definitively with in situ data. The microscopy stations lay within classes 3 488 and 4, and a significant difference in phytoplankton biovolume was confirmed 489 (class 3 mean biovolume =  $8.1 \times 10^5 \pm 2.6 \times 10^5 \ \mu m^3 l^{-1}$ , N=3; class 4 mean 490 biovolume =  $2.3 \times 10^6 \pm 8.4 \times 10^5 \ \mu m^3 l^{-1}$ , N=9; Kruskal Wallis p = 0.0126). 491 There was also an order of magnitude difference in the ratio between phyto-492 plankton and zooplankton biovolume (Schwarz, 2020). In the absence of a 493 larger *in situ* dataset with which to evaluate the full classification, comparison 494 between these classifications and previous studies is helpful. In spatial and 495 temporal variability, these optical classifications are most similar to previous 496 studies that use Rrs or radiance, as expected, and to some of the mesopelagic 497 biogeographies. The degree of patchiness is consistent with examples given 498 by JSM, and the classes assigned to the SCTR in their example of July 2004 499 are in direct agreement with the N5 classification produced here (JSM classes 500 7/8, based on 6 wavebands, correspond to N5 class 4, based on 10 wavebands; 501 Table 3). A similar degree of patchiness is reported by Oliver & Irwin (2008) 502

using nLw412, nLw551 and SST, and their approach, allowing the number 503 of classes to emerge from the data, assigned up to ten classes over the TIO, 504 which supports the richer N8 or JSM (N=14) classifications tested here in 505 terms of spectral separability. George et al. (2013) reported multiple patches 506 of elevated chl extending some 200 km along  $67^{\circ}$  E in the SCTR, as well as 507 suppression of surface chl by eddies further south. In contrast, classifications 508 that used chl as the only ocean colour variable, together with other physical 509 drivers, have been less spatially diverse (e.g. Longhurst, 2007; Spalding et 510 al., 2012; Reygondeau et al., 2013; Fay & McKinley, 2014; Sayre et al., 2017, 511 surface zone) and do not distinguish the SEC or SCTR domains clearly. 512

Mesopelagic classifications using a range of approaches including derived 513 ocean colour variables, acoustic data, World Ocean Atlas data and species 514 abundance mostly do distinguish the SCTR and SEC zones (Proud et al., 515 2017; Sutton et al., 2017; Sutton & Beckley, 2017; Sayre et al., 2017, 200 to 516 800 m zones) although in some cases the distinction between coastal influ-517 ences and SEC/SCTR features is unclear (Costello et al., 2017; Revgondeau 518 et al., 2018). Differences in the spatial richness of mixed-input epipelagic 519 classifications relate partly to the scales and methods used, but may also 520 reflect subtle changes in the growth environment that are related to phyto-521 plankton community composition that are not detected in the chl algorithms, 522 or to chl variability being outweighed in a classification by the contribution 523 of SST, producing spatially coarser structures because of dynamics that have 524 no surface signature in SST (e.g. Santoso et al., 2010; Drushka et al., 2012; 525 Strutton et al., 2015), or both. Previous analysis of phytoplankton bloom 526 dynamics in the TIO, based on satellite-derived chl and biogeochemical mod-527

elling, suggested a summer bloom spanning the full breadth of the basin at 528 SEC latitudes, but no winter bloom (Levy et al., 2007), and the modelled 529 emergent biogeography of Follows & Dutkiewicz (2011) predicted a band 530 of Prochlorococcus analogs and low species richness in this region which is 531 consistent with the PFT algorithm interpretation of classes 1 to 3 with N5. 532 However, Wiggert et al. (2006) predict larger phytoplankton cells between 533 January and May in the deep chlorophyll maximum in the SCTR and Jeffries 534 et al. (2015) found eukaryotes contributed >10% to relative cell abundance 535 at a deep water site within the Chagos MPA. Similarly, Thorrington-Smith 536 (1971) found diatom and dinoflagellite communities in water samples from 537 100 m depth across the western TIO - a signal that is consistent with the 538 higher-chl PFT interpretations of classes 5 (N5) and 6-8 (N8) which could be 539 expected to be detected in satellite data in zones of strong vertical mixing, 540 such as the tropical gyre boundaries. 541

The loss, at L3, of classes representing high and very low chl values, 542 may be important for monitoring carbon export and ecosystem resources and 543 Duarte et al. (2013) suggested that a chlorophyll concentration of  $0.44 \text{ mgm}^{-3}$ 544 represents a transition between heterotrophic and autotrophic communities. 545 Application of the Duarte et al. (2013) threshold to L3 chl values in this area 546 is consistent with Fernandes et al. (2008), who reported net heterotrophic 547 production between  $1^{\circ}$  N and  $5^{\circ}$  S at  $83^{\circ}$  E, but the appearance of higher 548 ranges in L2 data, the prevalence of higher classes for most of the year and 549 the paucity of *in situ* data for the pelagic MPA domain area renders this 550 use of the classification results uncertain. Level 2 data classifications are 551 therefore potentially valuable for modelling and monitoring tasks (Tweddle 552

et al., 2018), despite the low daily spatial coverage. For the purposes of exploring spatiotemporal variability over the MPA and wider TIO domain, Level 3 classifications are explored further.

# 556 3.2. Are biological and physical variables distinct for each optical class ?

The class-specific ranges of remote sensing variables are summarised for 557 the MPA and z1000 domains in Figure 9 and Appendix 1. The N5 optical 558 classification constrained all variables most effectively. For the MPA, only sea 559 surface height (classes 4 and 5), eddy kinetic energy (classes 3 and 5) and the 560 R443:R555 reflectance ratio (classes 1 and 5) were ambiguous (Kruskal-Wallis 561 with post-hoc HSD tests, p < 0.01, N > 10000). Increasing class number in the 562 MPA was associated with increasing chl, FLH,  $\nabla$ SSH, u,  $\tau_N$  and depth, and 563 with decreasing FLH:chl ratio, SST, SSH, v and  $\tau_E$ . Westerly and northerly 564 currents, and westerly wind stress, associated with SWM wind reversals, were 565 associated with class 1 only (lowest chl). 566

#### 567

# [FIGURE 9 HERE; SINGLE-COLUMN; COLOUR ONLINE ONLY]

Greater between-class ambiguity in optical and physical variables was 568 found with N8 and JSM, both of which included sparse classes (N < 10000). 569 For N8, class 8, representing OC3M-CI chl =  $2.39 \text{ mgm}^{-3}$ , was always sparse 570 and class 7 (chl =  $0.46 \text{ mgm}^{-3}$ ) was sparse in the SCTR-E and -C domains. 571 Similarly, JSM classes 10 to 14, representing  $chl > 0.62 \text{ mgm}^{-3}$ , were al-572 ways sparse or empty, and class 9 (chl =  $0.47 \text{ mgm}^{-3}$ ) was sparse in all the 573 sub-domains except z1000 and SCTR-W. Between-class variability was not 574 significant in the MPA for the majority of physical variables in N8 and JSM 575 (SSH, EKE, u, v,  $\tau$ ,  $\nabla \times \tau$ ) or for FLH, but chl and the residual reflectance 576 ratios were significantly different in all 8 classes. This could be interpreted as 577

a smaller number of physically-distinct conditions hosting a larger number 578 of optically distinct conditions, consistent with growth, decay and succes-579 sion occuring within each physical 'province' over the averaging period of 1 580 month. In JSM, only 8 classes were well-populated (No. pixels > 10000) and 581 all variables except  $\nabla \times \tau$  were ambiguous for two or more classes. In the 582 wider z1000 domain, between-class variability was significant for most vari-583 ables in each of the classifications (exceptions were N5: SST for classes 2 and 584 3; N8:  $\nabla$ SSH for classes 4 and 7, u for classes 6 and 7; JSM: SST for classes 585 1 and 8, v for classes 7 and 8 and  $\tau_E$  for classes 1 and 2), reflecting the much 586 greater size of this dataset. In this wider domain, the tendency of windstress 587 variables with increasing class number was reversed so that increasing class 588 and chl were associated with increasing  $\tau_E$  and decreasing  $\tau_N$ . 589

All between-class test results are given in Supplementary Online Mate-590 rial Table S1, sheet 'Variable Ranges by Class'. The optical classifications do 591 correspond to distinct ranges of biotic and abiotic variables, suggesting their 592 potential value in providing a useful diagnostic for management and mod-593 elling applications. Five optical classes produces least ambiguity in physical 594 variables, although significant residual ocean colour differences are detected 595 in up to 7 classes. However, the biophysical relationships vary within the 596 wider domain, as may be expected from the known oceanographic processes 597 in the region, suggesting that the use of optical classes may be most appro-598 priate within a heirarchical scheme (c.f. Kavanaugh et al., 2014; Oliver et al., 599 2004; Oliver & Irwin, 2008). Exploration of between-class variability within 600 different sub-domains is addressed in the next section. 601

602

To test whether seasonal variability in winds and associated mixing and

entrainment (Halkides & Lee, 2011; Wiggert et al., 2006) produces between-603 class ambiguity, Kruskal-Wallis tests were applied to the MPA data for each 604 month (Online Supplementary Figures S2, S3; Tables S2, S3). Seasonal wind 605 stress reversals were detected with the annual average conditions (negative 606  $\tau_E$  decreasing with increasing class number) found during austral winter and 607 the opposite trend (positive  $\tau_E$  increasing with increasing class number) dur-608 ing austral summer (Figure S2). The winter months were significantly differ-609 ent at  $\alpha = 0.01$  for classes 3, 4 and 5 (higher chl), whereas austral summer 610 months were distinct in classes 2 and 4, and  $\tau_N$  trends generally mirrored  $\tau_E$ 611 trends. Less pronounced seasonal reversals were found for u, v and  $\nabla$ SSH. 612 One heirarchical partitioning approach could therefore be to use the optical 613 classifications with a monthly or seasonal interpretation to constrain vari-614 ability in the epipelagic growth environment, but a more objective approach 615 using the physical variables at higher levels of the heirarchy avoids the need 616 to assume a regular seasonal cycle. In either case, the correspondence be-617 tween optical class and biotic environmental conditions needs to be explored 618 using *in situ* biogeochemical data if the optical classification is to be used to 619 deduce ecological function. 620

# 3.3. Do optical classifications capture zonal or meridional differences around the Chagos MPA?

Between-class variability in remotely sensed variables for each of the subdomains is shown in Figure 10. Most remotely sensed variables tended to increase or decrease monotonically with increasing optical class number, and spatially segmenting the dataset had little effect on these tendencies. Of the three SCTR domains, the westernmost area had the lowest SST values in

all classes, as well as lower SST and higher  $\tau_N$  in the highest-chl class 5. 628 The central TIO domain, SCTR-C, which is the easternmost of the three, 629 had the highest SST and EKE values and much lower nFLH:chl values in 630 all classes. Stronger contrasts were evident between the Wiggert-N and -S 631 domains. nFLH, v,  $\tau_N$  and nFLH:chl were lower in the northern than the 632 southern domain in some or all classes, whilst SST,  $\nabla$ SSH, EKE, u and 633  $\tau_E$  were higher. Whereas the depth-resolved modelling studies of George et 634 al. (2018) and Dilmahamod et al. (2016) suggested east-west gradients in 635 biophysical mechanisms operating across the SCTR, sub-domains SCTR-E,-636 W and -C could not be distinguished in the surface remote sensing variables 637 studied here (PERMANOVA, p > 0.1, N > 691x100; Table ??), although the 638 optical classes were significantly different in all domains and classifications 639 (p < 0.005, N > 692x100). In contrast, differences were detected between 640 classes and domains for the north-south division discussed by Wiggert et al. 641 (2006) (p < 0.037, N > 692; Table 5). Excluding the shelf slope depths 642 between 200 and 1000 m had no impact on class ambiguities in any variable 643 (Figure 10). 644

# <sup>645</sup> [FIGURE 10 HERE; SINGLE-COLUMN; ONLINE COLOUR ONLY] <sup>646</sup> [TABLE 5 HERE]

<sup>647</sup> Correlations between physical and biological variables within each class <sup>648</sup> and domain are shown in Figure 8. Chl was negatively correlated with SST in <sup>649</sup> all but the z200/z1000 domains. In the MPA, increasing SST was associated <sup>650</sup> with lower EKE and  $\tau_N$  and with higher v,  $\tau_E$  and  $\nabla \times \tau$  in the lowest-chl <sup>651</sup> class (class 1) only, with the reverse relationships found in classes 2 to 5. The <sup>652</sup> lower chl class 1 is therefore associated with conditions in which  $\tau_E$  and  $\nabla \times \tau$ 

Table 5: Results of PERMANOVA tests for differences between regions. a) Fixed factor 1 is location in the western or eastern SCTR or adjacent central Indian Ocean domain; nested factor 2 is optical class. All 15 remotely sensed variables were included in the test as z-scores. Average values are from 100 random draws of 1000 data points from each domain, time-matched. Pixels with any missing data were excluded, yielding residual degrees of freedom between 600 and 800 (denoted 'Resid'). p-values were calculated using 999 permutations. b) Fixed factor 1 is location in the northern or southern central Indian

Ocean sectors; other details as for a).

a) Seychelles-Chagos Thermocline Ridge W / E / C (George et al., 2018)							
	Factor	df	$\overline{F}$	$\overline{p}$	p range		
N5	F1: Domain	2	1.096	0.406	0.104 to $0.847$		
	F2: Class	10.9 (10-12)	15.066	0.0012	0.001 to $0.006$		
	Resid:	[691-766]					
N8	F1: Domain	2	1.256	0.271	0.048 to $0.700$		
	F2: Class	15.8 (14-18)	13.785	0.001	0.001 to $0.003$		
	Resid:	[703-765]					
$_{\rm JSM}$	F1: Domain	2	1.515	0.142	0.015 to $0.424$		
	F2: Class	18.3 (16-22)	12.825	0.001	0.001 to $0.001$		
	Resid:	[688-771]					
b) Cei	ntral tropical In	dian Ocean N $/$	S (Wigger	rt et al., 2	006)		
	Factor	df	$\overline{F}$	$\overline{p}$	p range		
N5	F1: Domain	1	3.420	0.0093	0.001 to $0.037$		
	F2: Class	74(6.8)					
		7.4 (0-8)	20.871	0.0011	0.001 to $0.005$		
	Resid:	[692-755]	20.871	0.0011	0.001 to $0.005$		
N8	Resid: F1: Domain	[692-755] 1	20.871 4.030	0.0011	0.001 to 0.005 0.001 to 0.014		
N8	Resid: F1: Domain F2: Class	[692-755] 1 10.2 (9-11)	20.871 4.030 18.127	0.0011 0.003 0.001	0.001 to 0.005 0.001 to 0.014 0.001 to 0.001		
N8	Resid: F1: Domain F2: Class Resid:	[692-755] $1$ $10.2 (9-11)$ $[708-775]$	20.871 4.030 18.127	0.0011 0.003 0.001	0.001 to 0.005 0.001 to 0.014 0.001 to 0.001		
N8 JSM	Resid: F1: Domain F2: Class Resid: F1: Domain	[692-755] 1 10.2 (9-11) [708-775] 1	20.871 4.030 18.127 4.415	0.0011 0.003 0.001 0.0023	0.001 to 0.005 0.001 to 0.014 0.001 to 0.001 0.001 to 0.013		
N8 JSM	Resid: F1: Domain F2: Class Resid: F1: Domain F2: Class	[692-755] 1 10.2 (9-11) [708-775] 1 12.1 (10-15)	20.871 4.030 18.127 4.415 16.044	0.0011 0.003 0.001 0.0023 0.001	0.001 to 0.005 0.001 to 0.014 0.001 to 0.001 0.001 to 0.013 0.001 to 0.001		

do not correspond to surface cooling and the northward geostrophic current 653 component is positive. Chl and nFLH were positively correlated everywhere 654 except in class 1 (lowest chl) in the MPA, SCTR-C and Wiggert-N,S areas. 655 Higher nFLH:chl ratios were associated with lower  $\tau_E$ ,  $\nabla \times \tau$ , u, EKE,  $\nabla$ SSH, 656 SSH and SST in the MPA class 5, and to a lesser extent for classes 3 and 4, 657 suggesting the importance of the tropical gyre strength for surface chl. These 658 relationships are similar, but less pronounced, in the SCTR-W, Wiggert-N 659 and Wiggert-S domains, and in z1000 classes 3 and 4. Assuming relative 660 homogeneity of the phytoplankton community within a given optical class, 661 nFLH:chl can be interpreted as a proxy for relatively high iron limitation 662 (as opposed to other limiting factors, Behrenfeld et al., 2009). Although 663 Chinni et al. (2019) and Wiggert et al. (2006) suggest Fe-limitation in some 664 seasons within and north of the SCTR, George et al. (2013) reported that 665 the deep chlorophyll maximum (DCM) followed the nitricline and did not 666 measure iron concentrations, so the interpretation of nFLH:chl requires more 667 in situ data in this region. SLA, which is related to westward-propagating, 668 downwelling Rossby waves in the SCTR (George et al., 2018), decreased 669 with increasing optical class and was negatively correlated with chl in at 670 least 4 classes in all domains, including z1000 (Figure 11). The use of class-671 specific correlations across different sub-domains captured other contrasts in 672 physical relationships, such as a switch from positive to negative coupling 673 between u and EKE in MPA class 1, SCTR-W classes 1,2,3 and 5; SCTR-C 674 classes 1 and 2; Wiggert-N class 1, whilst the relationship was negative for 675 all classes in Wiggert-S, suggesting dominance of the westward SEC in the 676 southern domain and more varied interactions in the northern SCTR (e.g. 677

mesoscale and fine-scale processes, George et al., 2013; Hosegood et al., 2019). For all domains, the greatest between-class differences were found between classes [1,2] and classes [3,4,5], suggesting that the different physical processes driving the growth environment can be distinguished by the chl 0.08 mgm<sup>3</sup> isoline (Figure 5). Biophysical coupling in the Chagos MPA was most similar to that in the Wiggert-S domain (Figure 10; Supplementary Material Table 1, sheet 'Variable Ranges by Class').

# [FIGURE 11 HERE; SINGLE-COLUMN; COLOUR ONLINE ONLY]

# 686 3.4. Modelling applications of optical partitioning

Assessment of the global carbon cycle and sequestration of anthropogenic 687  $CO_2$  emissions underpins the Paris Agreement (UN, 2015). The oceanic bio-688 geochemical models used for global carbon cycle assessment remain fairly 689 simplistic and uncertainties are high (Lim & Kug, 2017; Le Quéré et al., 2013, 690 2018; Gruber et al., 2019); increasing the complexity of ecosystem dynamics 691 in models without rendering them unstable is challenging (Anderson, 2005) 692 and different approaches are still being developed (e.g. Hense et al., 2017; 693 Wanninkhof et al., 2013). Optical classes offer an empirical contstraint on 694 ecosystem models and provide a dynamic framework for aggregating model 695 outputs and assessing model skill, for example in the prediction of  $CO_2$  up-696 take or sequestration rates. The preliminary comparison of  $pCO_2$  between 697 optical classes supports both of these applications (Figure 12). Between-698 class differences in surface partial pressure of  $CO_2$  were significant (p < 0.01, 699 N > 13,000 for all N5 classes. pCO<sub>2</sub> distributions were mostly bi-modal, 700 reflecting a background latitudinal gradient in class (increasing class num-701 ber, reflecting increasing chl, to the north) with patches of higher classes to 702

the south. The average  $pCO_2$  value decreased slightly with increasing class 703 number  $(416\pm49, 418\pm48, 404\pm44, 406\pm48, 398\pm48 \text{ ppm})$ , in contrast with 704 Nagelkerken et al. (2015) who reported no simple relationship between pri-705 mary production and  $CO_2$  uptake in this area. Between-class differences in 706 this study were within the version 8 OCO-2 model error for  $X_{CO_2}$ , but uncer-707 tainties in the profile retrieval are not specified (O'Dell et al., 2018). Because 708 of these uncertainties, the scope of this comparison and because too few data 709 were available to test between-area differences, a more complete comparison 710 is reserved for a future study. 711

712

# [FIGURE 12 HERE; TWO-COLUMN; COLOUR ONLINE ONLY]

In a fully-realised fuzzy optical classification, multiple colour class mem-713 berships enable mixed phytoplankton communities (or mixed water types) 714 to be represented and this has been shown to be useful in enhancing the in-715 terpretation of ocean colour data as well as constraining chl algorithm errors 716 (e.g. Moore et al., 2001, 2009). Better remote sensing information about the 717 ocean surface microbial community feeds into the Conservation on Biodi-718 versity as well as monitoring and understanding the ecosystem services they 719 provide (CBD, 2010; Tweddle et al., 2018; Roberts et al., 2017). In this study, 720 the Rrs class residuals did not show promise for identifying details of phyto-721 plankton community composition, but ensemble class biophysical agreement 722 suggests that ecosystem function may be constrained by optical class. 723

# 724 3.5. Management and conservation applications of optical partitioning

Information is lost when Rrs spectra are partitioned into discrete classes,
rather than applying an algorithm to produce a continuous biological variable
such as chl, but a distinct advantage of this is the possibility of using habitat
fragmentation metrics on the class maps. Fragmentation metrics applied to 728 the N5 class maps are shown in Figure 13 for the MPA and the Wiggert-729 N and -S domains. The lower-chl classes 1 and 2 behaved differently in 730 the three domains: Class 1 patches were of order 5000  $\mathrm{km}^2$  and generally 731 largest to the south, where they were separated by ca. 200 km. In the 732 MPA, between-patch distances were shorter and stable through time, whereas 733 they fluctuated between 20 and 100 km to the south. The 2011 La Nina 734 period coincided with particularly high separation distances in Wiggert-N 735 (separation ca. 500 km) and with high patch sizes in Wiggert-S (areas up to 736 ca. 15 000 km<sup>2</sup>; Figure 13). In contrast, class 2 patches were larger overall 737  $(O20\ 000\ \mathrm{km}^2)$  with higher values to the north, and a maximum coinciding 738 with the 2015 El Nino (mean patch size ca. 50 000 km<sup>2</sup>). Class 2 patch 739 separation distances fluctuated in Wiggert-N as for class 1 but with a lower 740 range (20 to 70 km). The 2015 El Nino coincided with the highest class 2 741 patch sizes in Wiggert-N (up to ca. 50 000  $\rm km^2$ ). Classes 1 and 2 represent 742 clear, warm water, which is a foraging habitat used by seabirds preving on 743 flying fish and squid, often in association with subsurface predators (e.g. 744 Weimerskirch et al., 2005; Catry et al., 2009b; Le Corre et al., 2012). The 745 absence of seasonal cycles in the fragmentation metrics for these classes is 746 marked: Prey occurence, driven by cetaceans and tuna, is stochastic, but 747 patches of similar foraging conditions are predictable at the monthly scales 748 used here, with patch separations that are within the known range of some 749 seabirds (Weimerskirch et al., 2007; Nel et al., 2001; Pinaud & Weimerskirch, 750 2007). 751

# <sup>752</sup> [FIGURE 13 HERE: SIGNLE-COLUMN; BLACK AND WHITE]

Patch sizes were smaller in the higher-chl classes 3 and 4 (mostly within 753  $5000 \text{ km}^2$ ), with separation distances between 20 and 200 km and marked 754 seasonality. For classes 1 to 4 the MPA clearly straddles the Wiggert-N 755 and Wiggert-S conditions, potentially providing stability of resource within 756 foraging range in the event of extreme (Nino/Nina/IOD) conditions. The 757 highest-chl class 5 was not always present (Figure 13e, j, o) and represents the 758 smallest but most intense resource patches (10 to  $300 \text{ km}^2$  in size), separated 759 by 20 to 100 km in the MPA, 40 to 300 km in Wiggert-S and 20 to 1000 760 km in Wiggert-N. Scott et al. (2010) and Trevail et al. (2019) highlight the 761 importance of fine spatial and temporal scales in prey resource; Level 2 (ca. 762 daily, 1 km) or higher spatial resolution data are therefore also of interest. 763

Class 5 patches were largest within the MPA domain up to 2014, after 764 which increasingly large class 5 patches appear in Wiggert-N (Figure 13). 765 However, the time-series is too short to confirm whether this is a robust 766 trend. Significant temporal trends in fragmentation metrics were only found 767 for fragmentation distance in the MPA, where the average distance between 768 class 2 patches increased over the study period, whilst the distance between 769 class 3 patches decreased (p < 0.05, N = 204). There is evidence of a shift in 770 the spatial distribution of resources over the study period, but without loss 771 of any of the colour classes, suggesting that the range of niches that seabirds 772 exploit has been maintained across the Wiggert-N and -S domains (Waugh & 773 Weimerskirch, 2003; Catry et al., 2009a; Le Corre et al., 2012). In this study, 774 water depths shallower than 200 m were excluded to avoid land adjacency 775 and bottom reflectance effects, so the MPA domain metrics do not include 776 the near-shore and lagoon waters which may augment class 5. 777

Although mesopelagic biomes have been shown to reflect the spatial dis-778 tribution of primary production (Proud et al., 2017), the only direct link 779 between optical classes and large, commercially-fished species that could be 780 expected is through water clarity for foraging. To test whether optical classes 781 could provide useful fisheries management information, class maps were com-782 pared against fisheries records. The Chagos MPA has been a no-take zone 783 since it was established in 2010, and IOTC fishing records amalgamated over 784 the study period (2002 to 2018) are correspondingly lower in waters imme-785 diately adjacent to the MPA and increase further away (Table 6). However, 786 284 surface fishery records and 43 longline records were reported after 2010 787 in the IOTC gridcells that contain the MPA (-2.3 to  $-10.8^{\circ}$ S, 67.9 to 79.4°E). 788 Figure 14 shows the distribution of average effort, catch and CPUE at in-789 creasing distances from the MPA for the surface and longline fisheries. In 790 the wider domain (z1000), surface fishery catch and CPUE mostly increased 791 with increasing N5 class, as expected (e.g. Solanki et al., 2015, 2017; Mo-792 hamed et al., 2018), with significant between-class differences between low-793 and high-chl waters (Kruskal-Wallis, p < 0.01), and effort focussed in class 5 794 waters. Longline fishery effort and catch were highest in class 3, and although 795 a trend for increasing CPUE with increasing class was apparent, it was not 796 statistically significant. Few significant between-class differences were found 797 in the MPA, but CPUE was highest in class 4, whereas effort was decreased 798 from class 2 to 4 (Figure 14d, f). These patterns reflect reported catches, but 799 may be used to infer behaviours of illegal fisheries and so target monitoring 800 resources. This management application of the optical classification is easy 801 to apply using L2 data, but is limited by cloud cover and ca. 1 day data 802

Table 6: Number of fishing records submitted to the IOTC within the 1° and 5° IOTC gridcells that contain the MPA, then incrementally as boxes of  $3 \ge 3$  and  $5 \ge 5$  of the 5° IOTC gridcells are added around the MPA area, and finally for entire z1000 domain. LL=long-line fisheries; Surf=surface fisheries; + denotes an increment from the MPA number and Total is the number of records reported within the full z1000 domain.

N5 class	MPA		$3x3 x5^{o}$		$5x5 x5^{\circ}$		z1000		Total	
	LL	$\mathbf{Surf}$	LL	Surf	LL	Surf	LL	Surf	LL	Surf
1	0	73	+15	+131	+84	+254	+792	+948	891	1406
2	14	588	+527	+1375	+650	+2821	+1691	+12078	3152	16862
3	23	668	+648	+1381	+1681	+4674	+3264	+20870	5616	27593
4	6	82	+63	+178	+701	+1665	+2614	+20746	3384	22671
5	0	0	0	0	+25	+100	+1266	+11457	1291	11557

<sup>803</sup> latency.

# 804 [TABLE 6 ROUGHLY HERE]

Knowledge of fishing behaviours is also relevant to MPA design and, po-805 tentially, to the use of dynamic MPA designations. Dynamic protection 806 boundaries serve as a compromise between static MPA boundaries, which 807 protect relatively small areas of rare or valuable habitat (e.g. Oppel et al., 808 2018; Heerah et al., 2019; Handley et al., 2020; Williamson et al., 2019), and 809 the very large foraging domains that are intractable to static protection but 810 where seabirds, cetaceans and large predatory fishes such as tuna are known 811 to colocate in the tropical Indian Ocean (Anderson, 2014; Letessier et al., 812 2017, 2019; Pinheiro et al., 2019; Hobday et al., 2010). 813

# [FIGURE 14 ROUGHLY HERE: 1-COLUMN or 1.5-COLUMN; COLOUR ONLINE ONLY]

3.6. Are there class-specific temporal trends in biological/physical variables?
All conservation and management efforts must consider temporal variability and the possible impacts of climate change (IPCC, 2013). The 17-year

study period used here is sufficient to characterise temporal variability but not to detect long-term change in this region (Henson et al., 2016). However, where biophysical conditions are coupled to large-scale climate indices for which robust, long-term time-series are available, the patterns observed can be extrapolated backwards and, with modelling, forward in time.

Time-series of selected variables are shown in Figure 15 for the MPA and 824 Figure S4 for the Wiggert-S domain. A weak tendency for increased chl 825 values in the austral winter was observed, but with no clear seasonal cycle 826 either for the MPA as a whole or within a given class. This is consistent with 827 removal of seasonality by class-switching (c.f. Figure 6). The class 4 and 828 5 chl values overlapped (Figure 15a), with class 4 representing an elevated 829 background level of chl compared with classes 1 to 3, superimposed with 830 stochastic, higher chl events in class 5, which often coincided with increases 831 in nFLH. The strongest chl peak, in 2011, coincided with higher  $\nabla$ SSH and a 832 protracted period of positive SOI index (Nina conditions). Higher nFLH:Chl 833 ratios and SSH values were evident for class 1 in both the MPA and Wiggert-S 834 domains, as were lower SST values for class 5. Class 5 chl peaks in the MPA 835 were not synchronised (or time-lagged, judging by visual inspection) with 836 those in the Wiggert-S domain, suggesting small-scale, rather than basin-837 wide processes are being captured, despite the use of composited Level 3 838 data. Significant trends are not shown on Figures 15 and S4, for clarity, but 839 are summarised in Figure 16a. Chl, nFLH and nFLH:Chl decreased over the 840 study period in most classes and most sub-domains (when appraised using 841 both absolute values and with anomaly time-series). For chl, the rate of 842 change was between -7.5  $\rm x10^{-6}$  and -1.2  $\rm x10^{-4}~mgm^{-3}a^{-1}$  (up to 0.025%a^{-1}

in the MPA and  $0.055\%a^{-1}$  in z1000, compared with decreases of  $0.7\%a^{-1}$ reported by Gregg et al., 2017, for the Indian Ocean).

Of the abiotic variables, significant trends in all five N5 classes were only found for the MPA, z1000 and Wiggert-N domains, with weaker positive trends in some areas (domain-integrated) and classes for SST,  $\nabla$ SSH, u and v, and a positive trend in  $\nabla \times \tau$  in Wiggert-S only. Full temporal trend results, including 95% confidence intervals on the rates of change, are given in Table S1, sheet 'Trends Correlations'.

<sup>852</sup> [FIGURE 15 ROUGHLY HERE: SINGLE-COLUMN; PLEASE QUOTE
 <sup>853</sup> FOR COLOUR PRINTING]

[FIGURE 16 ROUGHLY HERE: 1.5 OR SINGLE-COLUMN; PLEASE
 QUOTE FOR COLOUR PRINTING]

No significant correlations were found between the MJO and remotely 856 sensed variables, consistent with the brief residence of MJO events over the 857 TIO as well as the short time-scales of response of chl to MJO events which 858 precludes detection of MJO effects in this Level 3 data analysis (order of 850 days to weeks; Vialard et al., 2009; Jin et al., 2012; Wheeler & Hendon, 860 2004). Surface cooling and enhanced surface primary production have been 861 documented in response to the MJO (Vialard et al., 2009; Resplandy et al., 862 2009, Supplementary material Figure S5), making the use of higher temporal 863 resolution data desirable where coverage allows. The monthly-averaged MJO 864 index was not correlated with the IOD or SOI indices over the study period. 865 However, a weak, negative correlation was found between the IOD and SOI 866 (SOI = -0.39 IOD + 0.27; n = 202, p = 0.084), in contrast to the decoupling of 867 these cycles found using EOF analysis by Saji et al. (1999). Fragmentation 868

metrics for N5 class 3 were related to the SOI (negative relationship for patch 869 density: positive relationship for patch area) and IOD (positive relationship) 870 for patch density only). No relationships between fragmentation metrics 871 and any climate index were found for the Wiggert-S domain, whereas for 872 Wiggert-N, patch density increased with increasing IOD for classes 1 and 873 3, and decreased with increasing IOD for classes 4 and 5. Similarly, patch 874 area increased with increasing IOD for classes 1 and 2 and decreased for 875 classes 3 and 4. Fewer significant relationships were found with the SOI, but 876 they mirrored the IOD relationships, consistent with a negative relationship 877 between the two climate indices. These results suggest that within the MPA, 878 if the frequency of Nino events increases as predicted, incurring more negative 879 SOI conditions, the higher chl N5 classes 3 and 4 will yield to larger and more 880 closely spaced patches of lower N5 class 1. If positive IOD events increase 881 in frequency, fewer, smaller N5 class 4 and 5 patches separated by greater 882 distances are predicted. The observed North-South diversity in epipelagic 883 conditions and temporal trends may contribute to resilience of reefs and 884 mobile species in the MPA. However, only surface effects are characterised 885 and, in this study, processes lasting days to weeks, such as MJO events and 886 cyclones that have an impact on vertical mixing (Jin et al., 2012; Webster et 887 al., 2005), may be averaged out. 888

Positive IOD events are associated with elevated SST in the western TIO as the easterly wind driving the SEC converges further west (Saji et al., 1999). Domain-specific correlations between IOD and SST (Table 16) were in agreement, with positive correlations in all but the SCTR-C (eastern-most) domain. Positive relationships were also found for SSH,  $\tau_N$  and nFLH:chl,

whilst negative relationships were found with Chl, FLH, R555:488, EKE and 894  $\tau_E$ . Mostly positive, class-specific relationships only were found for  $\nabla SST$ , 895 suggesting stronger gradients at the sub-domain spatial scale which can not 896 be explained by the regressions undertaken here as the spatially coarse altime-897 try products used to calculate  $\nabla$ SSH and EKE, which might indicate small-898 scale processes, tended to decrease with increasing IOD. The SST product (4 899 x 4 km resolution) is more sensitive to mesoscale and perhaps submesoscale 900 processes. 901

Negative impacts of Nino and (positive) IOD conditions on biotic re-902 motely sensed variables is consistent with surface warming and deepening of 903 the mixed layer in the western TIO, corresponding to down-mixing of phyto-904 plankton within a strong, westward SEC current extending several hundreds 905 of metres below the surface (Vialard et al., 2009). The response of elevated 906 nFLH:chl ratios (Figure 15) under such a deeply-mixed layer could indicate 907 nutrient stress (e.g. Fe,  $NO_3$ ) or possibly a thin, surface freshening related to 908 precipitation that is isolating a surface, light-stressed population (Behrenfeld 900 et al., 2009; Chinni et al., 2019; George et al., 2013). The satellite data used 910 for this study can not distinguish between these possibilities and are further 911 limited by their short time-span (Dilmahamod et al., 2016; Landschützer 912 et al., 2019), coarse spatial and temporal resolution (Hosegood et al., 2019; 913 Vialard et al., 2009) and lack of information about depth variability. In situ 914 data are needed to interpret many of the possible biophysical interactions in 915 the MPA domain in terms of management application. For example, deep-916 ening of the mixed layer in the SCTR has been found to be associated with 917 deepening of the DCM with an increase in chlowing to nutrient entrainment 918

(George et al., 2013); or with no net impact on water-column productivity 919 owing to redistribution of light (Resplandy et al., 2009) or with a decrease in 920 chlowing to reduced nutrient entrainment (Ma et al., 2014). Mesopelagic bio-921 geographies suggest a strong positive relationship between satellite-derived 922 primary production and zooplankton scattering layers (Proud et al., 2017), 923 which is consistent with two of those scenarios. Depending on the response 924 of grazers, a deepened DCM may have a protective effect on pelagic fish 925 that are forced to forage further from the surface (Vialard et al., 2009) but 926 a negative effect for surface-foraging seabirds, so that any future increase in 927 the frequency of these events may have unexpected ramifications at higher 928 trophic levels and for the Chagos MPA reefs (Graham et al., 2018; Fox et al., 920 2019). 930

#### 931 4. Conclusions

Pure, optical classifications of unnormalised satellite remotely sensed re-932 flectance data have been shown here to constrain physical variables that 933 shape the epipelagic growth environment, making them a potentially useful 934 source of management-relevant information at low- to medium latency. Con-935 straint of most remotely sensed variables was best when used within spatial 936 sub-domains such as the MPA area, suggesting their use within a seascape 937 heirarchy. Potential applications discussed here include monitoring ecosys-938 tem services, including CO<sub>2</sub> uptake, and resource distribution, but in all cases 939 in situ validation data are needed to elucidate optical biome composition and 940 function. 941

942 Optical classification provides a snapshot at monthly (or better) time-

scales of spatial variability of epipelagic resources that are amenable to habi-943 tat fragmentation analysis, which suggested a change in the spacing and size 944 of richer surface food resources in response to Nino and IOD events in this 945 study. However, ecological interpretation of the trends and interactions be-946 tween remotely sensed variables requires knowledge of higher trophic level 947 responses. Inclusion of fragmentation metrics in species distribution models 948 might help to address this, where target species observations are sparse. Al-940 though ocean colour remote sensing is among the most finely resolved satellite 950 products in space and time, it is limited by cloud cover and does not capture 951 the full range of dynamical interactions that are relevant to habitat structure 952 and use. Increased spatiotemporal coverage is needed and may be provided 953 by combining information from all available sensors (though this is prob-954 lematic) and by increased in situ monitoring using moorings and perhaps 955 unmanned devices. The improved spectral resolution of NASAs forthcoming 956 PACES mission may provide better discrimination of microbial community 957 composition. 958

The suggested applications of optical classifications are globally applica-950 ble, but the need for more *in situ* data is not restricted to the tropical Indian 960 Ocean. Data requirements include repeat vertical profiles (reflectance, tem-961 perature, salinity, vertical mixing, nutrient concentrations and carbon cycle 962 parameters) and spatial fields of surface bio-optical and oceanographic condi-963 tions that resolve sub-pixel variability, so that appropriate spatial scales can 964 be identified for a given question. This scope of fieldwork has been attempted 965 in a few international, inter-disciplinary projects and it is to be hoped that 966 more will take shape under the biogeoscapes programme (?). 967

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## <sup>1632</sup> 5. Figure captions

Figure 1: Schematic representation of key biophysical linkages (not ex-1633 haustive). The flow of information begins with sunlight to the left. Physical 1634 variables that can be detected using remote sensing, followed by the oceano-1635 graphic variables derived from them, are shown between the sun and the 1636 ocean surface processes. Oceanographic variables of interest that can be de-1637 rived from remote sensing data are outlined in blue and abbreviations are 1638 explained in Table 1. The other variables shown are of interest to conser-1639 vation, management or climate change applications but are not amenable to 1640 remote sensing. 1641

Figure 2: Location of the study domain, adapted from Talley et al. (2011); Aguiar-Gonzalez et al. (2016). SCTR = Seychelles Chagos Thermocline Ridge; MPA = Chagos Marine Protected Area; SECC = South Equatorial Countercurrent

Figure 3: Bathymetry of the study domain. Shaded regions denote the sub-areas related to other published studies. Black line: coast; grey line: 200 m contour; black dashed line: 1000 m contour; thick black line: MPA boundary.

Figure 4: Central spectra for the 10-band classifications from Level 2 (upper) and Level 3 (lower) datasets with two to nine classes, compared with the 6-band JSM classification (shaded).

<sup>1653</sup> Figure 5: Mapping of the N5, N8 and JSM classes onto published PFT al-<sup>1654</sup> gorithms. SLC=Synechococcus-like cyanobacteria; xDiat was assigned where the residual PHYSAT-like spectrum resembled the diatom criteria in Alvain et al. (2008) but with higher values; SynPro=spectrum matches SLC or Prochlorococcus except for one waveband, which fell in the other small-cell category. Algorithm acronyms are explained in section 3.1.

Figure 6: Comparison of class maps produced with the Level 2 and Level 3 Rrs data, classifications N5, N8 and JSM, in 2003. The Chagos MPA outline, 0 m and 1000 m isobaths are shown in black and the 2000 m isobath in grey.

Figure 7: Number of classes held at each pixel over the 17 year study period, by month, for Level 3 data, N=5. The Chagos MPA outline is shown in black.

Figure 8: Monthly 17-year climatologies of key remote sensing variables. The Chagos MPA outline and 0 m contour are shown in black, and the 3000 m isobath in grey.

Figure 9: Variability of remotely sensed parameters in the MPA and z1000 domains: Top row = N5; Middle row = N8; Lower row = JSM; black=MPA; cyan=whole domain with depth > 1000 m (z1000).

Figure 10: Variability of remotely sensed parameters for each sub-domain
using the N5 classification.

<sup>1674</sup> Figure 11: Averaged Mann-Kendall-Sen correlation coefficients between <sup>1675</sup> variables within each class for each domain: a) MPA, b) SCTR-W, c) SCTR- <sup>1676</sup> C, d) Wiggert-N, e) Wiggert-S, f) z1000. Only results with a p-value < 0.01,</li>
<sup>1677</sup> confirmed using bootstrapping to remove autocorrelation and subsampling
<sup>1678</sup> effects, are shown.

Figure 12: OCO-2 lowest altitude  $pCO_2$  distributions within the z1000 domain for the N5 classes applied to MODIS Level 2 data, January 2015.

Figure 13: a) to e) Density of patches of each N5 class (a=class 1, e=class 5); f) to j) Average patch area (f=class 1, j=class 5); k) to o) Average distance between patches (k=class 1, o=class 5) for the MPA, Wiggert-N and Wiggert-S domains. Note different y-axis limits are used to show detail.

<sup>1686</sup> Figure 14: IOTC fishing catch and catch per unit effort for the Indian <sup>1687</sup> Ocean surface (top row; a, b,c) and longline (lower row; d, e, f) fisheries.

Figure 15: Time-series for each N5 class within the MPA for a) Chl, b) FLH, c) FLH:Chl, d) SST, e) SSH and f)  $\nabla$ SSH.

Figure 16: a) Summary of the temporal trends found within each do-1690 main (p < 0.05), including ranges of the Sen regression coefficient and rates 1691 of change. Trends for specific classes are denoted by class number; trends 1692 for the entire domain are indicated by block colour (red=positive trend; 1693 blue=negative trend). b) Summary of significant (p < 0.05) correlations be-1694 tween remotely sensed variables and the Indian Dipole Mode Index, including 1695 ranges of the Sen regression coefficient. Correlations for specific classes are 1696 denoted by class number; correlations for the entire domain are indicated 1697

<sup>1698</sup> by block colour (red=positive trend; blue=negative trend). Full correlation
<sup>1699</sup> results, including 95% confidence intervals on the regression slopes, are given
<sup>1700</sup> in Table S1.

1701 Appendix A. Appendix 1

						Me	an $\pm 1\sigma$						
Variable			N5							N8			
Class	1	2	3	4	5	1	6	e	4	ъ	9	7	×
N (%)	13	25	30	22	10	10	15	21	21	17	11	5	< 1
$_{\rm chl}$	0.053	0.086	0.122	0.181	0.456	0.049	0.074	0.097	0.126	0.166	0.242	0.612	1.914
	$\pm.011$	$\pm.013$	$\pm.022$	$\pm.065$	$\pm.994$	$\pm .009$	$\pm.010$	$\pm.012$	$\pm.021$	$\pm .044$	$\pm.127$	$\pm 1.336$	$\pm 1.508$
Чŀ	0.040	0.045	0.050	0.064	0.107	0.040	0.044	0.046	0.051	0.061	0.076	0.128	0.248
	$\pm .021$	$\pm.022$	$\pm .027$	$\pm .040$	$\pm .077$	$\pm.021$	$\pm.021$	$\pm.022$	$\pm.028$	$\pm.037$	$\pm.050$	土.087	$\pm.163$
flh/chl	0.778	0.528	0.409	0.346	0.277	0.822	0.595	0.473	0.399	0.360	0.306	0.264	0.142
	$\pm.433$	$\pm.258$	$\pm.208$	$\pm .197$	$\pm.142$	$\pm.457$	$\pm.294$	$\pm.228$	$\pm.205$	$\pm.203$	$\pm.170$	$\pm.127$	$\pm .094$
$\mathbf{TSS}$	27.62	28.58	28.65	28.02	27.30	27.55	28.22	28.77	28.61	28.10	27.76	27.01	28.67
	$\pm 1.67$	$\pm 1.99$	$\pm 1.73$	$\pm 1.56$	$\pm 1.3$	$\pm 1.57$	$\pm 2.03$	$\pm 1.88$	$\pm 1.71$	$\pm 1.62$	$\pm 1.35$	$\pm 1.36$	$\pm 1.43$
$\mathbf{SLA}$	0.083	0.060	0.048	0.038	0.026	0.087	0.067	0.055	0.047	0.039	0.035	0.023	0.074
	$\pm.080$	$\pm .076$	$\pm .072$	$\pm.075$	$\pm .090$	$\pm.078$	$\pm.080$	$\pm.073$	$\pm .073$	$\pm .074$	$\pm.079$	$\pm.094$	$\pm .085$
$\Delta SSH$	-23.1	-5.8	-0.3	-1.7	-1.3	-23.8	-13.3	-1.0	-0.4	-3.1	2.8	-1.3	-22.4
	$\pm 62.0$	$\pm 52.9$	$\pm 49.1$	$\pm 55.7$	$\pm 72.5$	$\pm 62.9$	$\pm 56.5$	$\pm 49.9$	$\pm 49.0$	$\pm 54.8$	$\pm 59.2$	$\pm 80.7$	$\pm 67.5$
n	-0.059	0.002	0.018	-0.010	0.020	-0.058	-0.031	0.023	0.016	-0.012	0.003	0.029	-0.000
	$\pm.146$	$\pm.188$	$\pm.196$	$\pm.211$	$\pm.244$	$\pm.141$	$\pm.177$	$\pm.193$	$\pm.196$	$\pm.207$	$\pm.223$	$\pm.257$	$\pm.171$
^	0.012	-0.006	-0.003	0.012	0.021	0.013	-0.000	-0.008	-0.002	0.010	0.016	0.027	-0.028
	$\pm .089$	$\pm.111$	$\pm.120$	$\pm.147$	$\pm .222$	$\pm .087$	$\pm.104$	$\pm.115$	$\pm.121$	$\pm.138$	$\pm.178$	$\pm.245$	$\pm.201$
EKE	0.017	0.024	0.027	0.034	0.056	0.016	0.022	0.026	0.027	0.032	0.042	0.066	0.037
	$\pm.024$	$\pm.036$	$\pm.041$	$\pm.057$	$\pm.107$	$\pm.022$	$\pm.032$	$\pm.038$	$\pm.041$	$\pm.052$	$\pm.075$	$\pm.124$	$\pm .059$
$\tau_E$	-0.064	-0.033	-0.023	-0.021	-0.004	-0.066	-0.044	-0.026	-0.023	-0.024	-0.013	0.002	-0.012
	$\pm.044$	$\pm .057$	$\pm.057$	$\pm.055$	$\pm .054$	$\pm.041$	$\pm.055$	$\pm .056$	$\pm .057$	$\pm .057$	$\pm.048$	$\pm.058$	$\pm .053$
$\tau_N$	0.031	0.024	0.023	0.022	0.008	0.031	0.028	0.023	0.024	0.025	0.011	0.013	0.003
	$\pm .027$	$\pm.034$	$\pm.038$	$\pm.048$	$\pm.064$	$\pm.025$	$\pm.033$	$\pm.035$	$\pm.039$	$\pm.046$	$\pm.054$	$\pm.069$	$\pm .046$
$\nabla\times\tau$	-1.43	-3.66	-3.80	-2.20	-2.14	-0.86	-3.38	-3.86	-3.76	-2.57	-1.77	-2.12	-0.76
	$\pm 31.8$	$\pm 23.2$	$\pm 20.8$	$\pm 22.9$	$\pm 27.0$	$\pm 32.9$	$\pm 25.7$	$\pm 21.7$	$\pm 20.7$	$\pm 22.8$	$\pm 21.8$	$\pm 31.7$	$\pm 43.4$
$\mathrm{Depth}$	4350	4275	3988	3599	3309	4320	4365	4184	3953	3666	3453	3192	677
	$\pm 1005$	$\pm 980$	$\pm 1047$	$\pm 1222$	$\pm 1347$	$\pm 1002$	$\pm 992$	$\pm 978$	$\pm 1057$	$\pm 1197$	$\pm 1276$	$\pm 1378$	$\pm 674$
3555:443	0.006	0.022	0.101	-0.90	0.070	0.136	0.156	0.179	0.207	0.272	0.350	0.485	-0.893
	$\pm 8.05$	$\pm 9.75$	$\pm 23.38$	$\pm 32.55$	$\pm 30.69$	$\pm.028$	$\pm.058$	$\pm.082$	$\pm.093$	$\pm.103$	$\pm.126$	$\pm.152$	$\pm 31.044$
3555:488	-0.352	0.356	0.437	0.262	2.896	0.201	0.218	0.236	0.258	0.309	0.367	0.451	-0.003
	$\pm 88.63$	$\pm 15.80$	$\pm 50.55$	$\pm 22.06$	$\pm 482.27$	$\pm.095$	$\pm.054$	$\pm .077$	$\pm.089$	$\pm .098$	$\pm.115$	$\pm.127$	$\pm 16.181$
hline													

Table A.7: Characterisation of variables within each class for the N5, N8 and JSM classification schemes in the whole study

(total no.	pixels ;	5,343,300	9).										
Variable						Me	an $\pm 1\sigma$						
			N5						~	18			
Class	1	2	ŝ	4	ы	1	2	e	4	2	9	7	×
N (%)	×	37	39	16	1	4	20	32	26	15	e	11	11
chl	0.063	0.088	0.123	0.180	0.253	0.058	0.077	0.099	0.128	0.171	0.227	0.244	0.404
	$\pm.008$	$\pm.012$	$\pm.021$	$\pm .046$	$\pm .087$	$\pm .007$	$\pm .009$	$\pm.012$	$\pm.019$	$\pm .036$	$\pm .073$	$\pm .099$	$\pm.108$
Ĥћ	0.049	0.049	0.060	0.094	0.117	0.050	0.048	0.050	0.062	0.089	0.114	0.081	0.092
	$\pm .022$	$\pm.021$	$\pm .027$	$\pm .037$	$\pm .053$	$\pm .024$	$\pm .020$	$\pm.021$	$\pm.028$	$\pm.035$	土.044	$\pm .049$	$\pm.002$
flh/chl	0.791	0.560	0.482	0.521	0.460	0.868	0.632	0.510	0.479	0.521	0.503	0.357	0.209
	$\pm.376$	$\pm.240$	$\pm .197$	$\pm.190$	$\pm.198$	$\pm.427$	$\pm.269$	$\pm.214$	$\pm.195$	$\pm.191$	$\pm.187$	$\pm.205$	土.070
SST	29.59	29.41	28.71	27.62	27.43	29.55	29.56	29.22	28.60	27.70	27.35	28.05	28.41
	士.77	$\pm.89$	$\pm.99$	$\pm 1.06$	$\pm 1.04$	$\pm.72$	$\pm.87$	$\pm.89$	$\pm.99$	$\pm 1.08$	$\pm.94$	$\pm 1.20$	$\pm.41$
SLA	0.147	0.072	0.027	0.008	0.015	0.163	0.100	0.051	0.023	0.009	0.008	0.025	0.110
	$\pm.084$	$\pm.074$	$\pm.066$	$\pm.063$	$\pm .042$	$\pm.084$	$\pm.078$	$\pm.070$	$\pm.065$	$\pm.063$	$\pm .057$	$\pm .039$	$\pm.049$
$\Delta SSH$	24.3	0.83	8.52	2.66	8.35	-29.4	-8.19	6.74	8.55	2.55	5.38	14.04	9.05
	$\pm 39.4$	$\pm 34.3$	$\pm 33.1$	$\pm 34.6$	$\pm 32.6$	$\pm 38.7$	$\pm 37.1$	$\pm 32.2$	$\pm 33.5$	$\pm 34.9$	$\pm 33.2$	$\pm 29.3$	$\pm 15.5$
n	-0.118	0.018	0.071	0.040	0.048	-0.138	-0.038	0.058	0.071	0.041	0.046	0.048	0.110
	$\pm.162$	$\pm.190$	$\pm.193$	$\pm.175$	$\pm.175$	$\pm.150$	$\pm.184$	$\pm.192$	$\pm.192$	$\pm.177$	$\pm.169$	$\pm.178$	$\pm.160$
>	0.002	-0.014	-0.020	-0.010	-0.038	0.003	-0.007	-0.019	-0.020	-0.009	-0.019	-0.074	0.038
	$\pm .089$	$\pm .090$	$\pm.088$	$\pm.093$	$\pm.111$	$\pm.086$	$\pm .090$	$\pm.090$	$\pm.088$	$\pm.092$	$\pm.102$	$\pm.110$	$\pm.051$
EKE	0.024	0.023	0.026	0.021	0.024	0.025	0.022	0.025	0.025	0.021	0.021	0.026	0.020
	$\pm .026$	$\pm .028$	$\pm.033$	$\pm.029$	$\pm .029$	$\pm .026$	$\pm .026$	$\pm.031$	$\pm.033$	$\pm .030$	$\pm .030$	$\pm .027$	$\pm.036$
$\tau_E$	0.003	-0.007	-0.027	-0.056	-0.047	0.002	-0.001	-0.014	-0.030	-0.055	-0.057	-0.016	-0.069
	$\pm.034$	$\pm .040$	$\pm .047$	$\pm .050$	$\pm .059$	$\pm.034$	$\pm .037$	$\pm.042$	$\pm.048$	$\pm .049$	$\pm.051$	$\pm.068$	$\pm.0008$
$\tau_N$	0.000	0.011	0.027	0.047	0.040	-0.001	0.005	0.016	0.029	0.046	0.047	0.020	0.057
	$\pm .017$	$\pm.025$	$\pm.032$	$\pm.034$	$\pm .039$	$\pm.017$	$\pm .022$	$\pm .027$	$\pm.032$	$\pm.034$	$\pm.034$	$\pm.046$	$\pm.003$
$\nabla\times\tau$	-7.48	-7.04	-7.92	-7.85	-7.16	-7.86	-6.70	-7.52	-7.99	-7.77	-8.12	-3.01	0.00
	$\pm 17.7$	$\pm 16.4$	$\pm 16.5$	$\pm 17.3$	$\pm 26.6$	$\pm 18.5$	$\pm 16.5$	$\pm 16.4$	$\pm 16.4$	$\pm 16.6$	$\pm 22.0$	$\pm 25.4$	$\pm 8.2$
$\operatorname{Depth}$	3891	3730	3598	3396	3011	3938	3785	3688	3574	3441	3129	3113	368
	$\pm 1143$	$\pm 1083$	$\pm 1173$	$\pm 1368$	$\pm 1433$	$\pm 1149$	$\pm 1102$	$\pm 1087$	$\pm 1193$	$\pm 1343$	$\pm 1446$	$\pm 1471$	$\pm 140$
R555:443	-0.113	0.048	0.216	0.250	0.139	0.117	0.147	0.173	0.203	0.260	0.300	0.620	6.934
	$\pm 8.70$	$\pm 9.88$	$\pm 21.98$	$\pm 28.20$	$\pm 22.04$	$\pm.028$	$\pm.048$	$\pm .080$	$\pm.099$	$\pm.110$	$\pm.084$	$\pm.123$	$\pm 17.700$
R555:488	-5.161	0.477	0.825	0.179	15.117	0.179	0.207	0.229	0.252	0.295	0.325	0.559	-12.526
	$\pm 136.2$	$\pm 16.07$	$\pm 51.55$	$\pm 21.12$	$\pm 617.4$	$\pm .538$	$\pm .046$	$\pm .076$	$\pm.094$	$\pm.105$	$\pm .075$	$\pm .084$	$\pm 40.68$

Table A.8: Characterisation of variables within each class for the N5, N8 and JSM classification schemes within the MPA



Figure 1: Schematic representation of key biophysical linkages (not exhaustive). The flow of information begins with sunlight to the left. Physical variables that can be detected using remote sensing, followed by the oceanographic variables derived from them, are shown between the sun and the ocean surface processes. Oceanographic variables of interest that can be derived from remote sensing data are outlined in blue and abbreviations are explained in Table 1. The other variables shown are of interest to conservation, management or climate change applications but are not amenable to remote sensing.



Figure 2: Location of the study domain, adapted from Talley et al. (2011); Aguiar-Gonzalez et al. (2016). SCTR = Seychelles Chagos Thermocline Ridge; MPA = Chagos Marine Protected Area; SECC = South Equatorial Countercurrent



Figure 3: Bathymetry of the study domain. Shaded regions denote the sub-areas related to other published studies. Black line: coast; grey line: 200 m contour; black dashed line: 1000 m contour; thick black line: MPA boundary.



Figure 4: Central spectra for the 10-band classifications from Level 2 (upper) and Level 3 (lower) datasets with two to nine classes, compared with the 6-band JSM classification (shaded).



Figure 5: Mapping of the N5, N8 and JSM classes onto published PFT algorithms. SLC=Synechococcus-like cyanobacteria; xDiat was assigned where the residual PHYSATlike spectrum resembled the diatom criteria in Alvain et al. (2008) but with higher values; SynPro=spectrum matches SLC or Prochlorococcus except for one waveband, which fell in the other small-cell category. Algorithm acronyms are explained in section 3.1.



Figure 6: Comparison of class maps produced with the Level 2 and Level 3 Rrs data, classifications N5, N8 and JSM, in 2003. The Chagos MPA outline, 0 m and 1000 m isobaths are shown in black and the 2000 m isobath in grey.



Figure 7: Number of classes held at each pixel over the 17 year study period, by month, for Level 3 data, N=5. The Chagos MPA outline is shown in black.



Figure 8: Monthly 17-year climatologies of key remote sensing variables. The Chagos MPA outline and 0 m contour are shown in black, and the 3000 m isobath in grey.



Figure 9: Variability of remotely sensed parameters in the MPA and z1000 domains: Top row = N5; Middle row = N8; Lower row = JSM; black=MPA; cyan=whole domain with depth > 1000 m (z1000).



Figure 10: Variability of remotely sensed parameters for each sub-domain using the N5 classification.



Figure 11: Averaged Mann-Kendall-Sen correlation coefficients between variables within each class for each domain: a) MPA, b) SCTR-W, c) SCTR-C, d) Wiggert-N, e) Wiggert-S, f) z1000. Only results with a p-value < 0.01, confirmed using bootstrapping to remove autocorrelation and subsampling effects, are shown.



Figure 12: OCO-2 lowest altitude  $pCO_2$  distributions within the z1000 domain for the N5 classes applied to MODIS Level 2 data, January 2015.



Figure 13: a) to e) Density of patches of each N5 class (a=class 1, e=class 5); f) to j) Average patch area (f=class 1, j=class 5); k) to o) Average distance between patches (k=class 1, o=class 5) for the MPA, Wiggert-N and Wiggert-S domains. Note different y-axis limits are used to show detail.



Figure 14: IOTC fishing catch and catch per unit effort for the Indian Ocean surface (top row; a, b,c) and longline (lower row; d, e, f) fisheries.



Figure 15: Time-series for each N5 class within the MPA for a) Chl, b) FLH, c) FLH:Chl,d) SST, e) SSH and f) ∇SSH.



Figure 16: a) Summary of the temporal trends found within each domain (p < 0.05), including ranges of the Sen regression coefficient and rates of change. Trends for specific classes are denoted by class number; trends for the entire domain are indicated by block colour (red=positive trend; blue=negative trend). b) Summary of significant (p < 0.05) correlations between remotely sensed variables and the Indian Dipole Mode Index, including ranges of the Sen regression coefficient. Correlations for specific classes are denoted by class number; correlations for the entire domain are indicated by block colour (red=positive trend; blue=negative trend). Full correlation results, including 95% confidence intervals on the regression slopes, are given in Table S1.