# 1 Title:

- 2 Connectivity networks and delineation of distinct coastal provinces along the Indian coastline
- 3 using large-scale Lagrangian transport simulations
- 4
- 5 **Running Title:**
- 6 Larval connectivity along the Indian coastline
- 7

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#### 26 Abstract

27

28 Ocean circulation defines the scale of population connectivity in marine ecosystems, and is 29 essential for conservation planning. We performed Lagrangian transport simulations and built 30 connectivity networks to understand the patterns of oceanographic connectivity along the 31 Indian coastline. In these networks, nodes are coastal polygons and the edges connecting 32 them represent the magnitude of larval transfer between them. We assessed the variation in 33 connectivity networks within and between two monsoonal seasons, across El Niño-Southern 34 Oscillation (ENSO) years and for pelagic larval durations (PLD) up to 50 days. We detected 35 well-connected communities, mapped frequent connectivity breaks and ranked coastal areas 36 by their functional role using network centrality measures. Network characteristics did not 37 differ based on the ENSO year, but varied based on season and PLD. Large scale 38 connectance (entire Indian coastline) was small, ranging from 0.5% to 3.4%, and the number 39 of cohesive coastal communities decreased from 60 (PLD <4 days) to 30 (PLD >20 days) 40 with increasing PLD. Despite intra-seasonal variation in connectivity breaks, four 41 disconnected provinces were consistently identified across the entire PLD range, which 42 partially overlapped with observed genetic and biogeographic breaks along the Indian 43 coastline. Our results support the adoption of an adaptive regional management framework 44 guided by fine-scale analysis of connectivity within the four provinces delineated in the 45 present study. A few sites within each province displayed notably higher centrality values 46 than other nodes of the network, but showed variation with season and PLD, and could be 47 targeted for national and transnational conservation and management plans.

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49 Keywords: biophysical model, dispersal, connectivity, Indian Ocean, marine biogeography

#### 50 Introduction

51

52 Marine populations have traditionally been described as 'open', with high exchange of 53 propagules between spatially distant populations owing to oceanic transport of pelagic life 54 stages (Roughgarden et al., 1988). However, it is becoming apparent that local oceanographic 55 features and species-specific traits determine where a population falls in the continuum from 56 'open' to 'closed' (Levin, 2006). Apart from influencing demographic processes at ecological 57 time-scales (Gaines et al., 2007), long distance transport using ocean currents can also have 58 consequences over evolutionary time-scales (Jablonski, 1986; Paulay & Meyer, 2006). This 59 would shape patterns of population genetic connectivity across taxonomic groups and large-60 scale patterns of diversity and community structure.

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62 An understanding of oceanographic processes is therefore important in the study of marine 63 dispersal. However, field studies of pelagic larval transport are prohibitively difficult because 64 of small larval size, challenges in taxonomic identification and navigating the vastness of the open ocean (Pineda et al., 2007). Biophysical modelling combines ocean circulation 65 66 simulations with larval traits and habitat information to provide estimates of larval transport. 67 The latter can be compared to empirical patterns of gene flow between populations to 68 understand the demographic effects of larval transport on marine population connectivity 69 (Liggins et al., 2013).

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71 The accuracy of larval transport estimates depend upon the resolution of ocean circulation 72 simulations (Briton et al. 2018), location of reproductive populations and the degree of 73 species-specificity in larval release timing, pelagic larval duration (PLD) (Di Franco &

74 Guidetti, 2011), and larval behaviour (Guizien et al. 2006). Although larval behaviour can 75 strongly alter dispersal patterns and distribution of suitable habitat can restrict connectivity, 76 ocean flow and PLD are the minimum parameters required to assess seascape connectivity 77 (North et al., 2009). Such general biophysical simulations of larval transport based on global 78 ocean circulation simulations can serve as a foundation for regional ecological studies by 79 delineating disruptions in connectivity (Rossi et al., 2014). Within well connected regions, 80 the frequent exchange of individuals among spatially distinct populations can influence their 81 demography, giving rise to a metapopulation (Hanski & Gagiotti, 2004). Identifying the 82 extent of well-connected populations, within which metapopulation functioning is expected 83 to occur, is a pre-requisite for establishing the scale of biodiversity management (Halpern & 84 Warner, 2003). Since management policies are a national prerogative, it is also important to 85 include all the regions falling within the boundaries of an Exclusive Economic Zone (EEZ) in 86 connectivity studies.

87

88 The EEZ of India includes (1) a coastline of over 5000 km that divides the northern Indian 89 Ocean into two basins – the Arabian Sea in the west and the Bay of Bengal in the east, (2) the 90 Lakshadweep archipelago located in the Arabian Sea, and (3) the Andaman and Nicobar 91 archipelago located in the Bay of Bengal. Sri Lanka is an island located in the Bay of Bengal, 92 which is separated from India by the narrow Palk Strait, where both countries have 93 contiguous EEZs (Figure 1). There is an absence of large-scale connectivity studies from the 94 northern Indian Ocean (see George et al., 2011 and Gaonkar et al., 2012 for local-scale 95 studies) despite a large body of physical oceanography studies from this region (reviewed in 96 Shetye & Gouveia, 1998; Schott & McCreary, 2001; Shankar et al., 2002; Schott et al., 2009; 97 Vinayachandran, 2009; Hood et al., 2017).

98 The upper ocean circulation along the coasts of India is driven by seasonally reversing 99 monsoon winds (Schott & McCreary, 2001). The large-scale monsoon currents flow eastward 100 during summer (June to September, summer monsoon) and westward during winter 101 (November to February, winter monsoon). Coastal currents, namely the East India Coastal 102 Current (EICC) and the West India Coastal Current (WICC) (Shetye & Gouveia, 1998), link 103 coastal circulation with the large-scale monsoon circulation. Saltier Arabian Sea water flows 104 into the Bay of Bengal during the summer monsoon (Vinayachandran et al., 2018) and 105 fresher Bay of Bengal water flows into the Arabian Sea during the winter monsoon.

106

107 During the summer (south-west) monsoon, the West India Coastal Current (WICC) flows 108 towards the equator along the west coast of India (Shetye & Gouveia, 1998, Amol et al., 109 2014), which joins the South-West Monsoon Current (SMC). The latter turns around the 110 southern tip of India and Sri Lanka and flows into the Bay of Bengal, connecting to the 111 northward branch of the Sri Lanka Dome, which reverses direction at 10°N (Vinayachandran 112 & Yamagata, 1998) (Figure 1). The East India Coastal Current (EICC) flows poleward during 113 the summer monsoon (Mukherjee et al., 2014). During this period, coastal upwelling events 114 of varying intensity occur along the west coast of India (Luis & Kawamura, 2004; Hood et 115 al., 2017), with weak upwelling along the eastern coast of India, and the Andaman and 116 Nicobar islands (Varkey et al. 1996; Vinayachandran et al., 2021).

117

118 During the winter (north-east) monsoon, the circulation along the east coast of India reverses
119 direction to flow equatorward (EICC) (Shetye & Gouveia, 1998, Mukherjee et al., 2014),
120 turns around Sri Lanka and the southern tip of India (Winter Monsoon Current) and flows
121 poleward along the west coast (WICC) (Figure 1, Shetye & Gouveia, 1998; Shankar et al.

122 2002; Amol et al., 2014). Together with alongshore flow reversal during the winter monsoon,
123 upwelling reverses into downwelling events within a 40 km wide band along the east coast of
124 India (Varkey et al. 1996) and along the north-west coast of India (Luis & Kawamura, 2004).
125

126 The seasonal wind-driven circulation described above is modulated at several time-scales 127 (Schott et al. 2009). The strong atmospheric-oceanographic coupling in the entire Indian 128 Ocean makes its circulation sensitive to atmospheric intra-seasonal oscillations acting at 129 time-scales ranging from a week (northward propagating precipitation anomalies) to 30-60 130 days (Madden-Julian Oscillation, Madden & Julian 1972). Inter-annual variability in the 131 Indian Ocean circulation arises not only from El Niño Southern Oscillation, which leads to a 132 year-long basin-scale warming after El Niño events, but also from Indian Ocean Dipole 133 events, with cool (warm) and dry (wet) anomalies in the eastern (western) Indian Ocean in 134 some years (Vinayachandran et al. 2009).

135

In such a complex oceanographic context with large to meso-scale structures, various levels of flow connectivity are to be expected along the vast Indian coastline, and it is difficult to a priori anticipate how biological filters such as spawning timing and PLD alter them. Identifying spatial scales at which demographic connectivity and/or gene flow between populations ceases to exist to give rise to biogeographic boundaries, is essential to inform marine resources and biodiversity management (Mertens et al., 2018).

142

143 In the current study, we aim to describe patterns of oceanographic connectivity focusing on 144 the Indian coastline. To do so, we carried out Lagrangian transport simulations of neutrally 145 buoyant larvae released along the study region's coastline during the two major seasons – summer and winter monsoon for three years and across a wide range of PLD. Transport simulations were post-processed to build coastal connectivity networks for different combinations of season, year and PLD. The specific aims of our study were to (1) identify breaks in oceanographic connectivity and analyze their stability across years, seasons and PLD, (2) identify the most central locations within the connectivity network of the larger Indian coastline, and (3) examine the implications of these connectivity networks for biodiversity management.

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154 Methods

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156 *Ocean circulation model* 

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158 The HYbrid Coordinate Ocean Model (HYCOM, Chassignet et al., 2007) is an ocean general 159 circulation model, which uses a combination of vertical coordinate systems (isopycnal, z-160 coordinate and sigma levels) to effectively simulate ocean circulation in three dimensions. 161 The output from this circulation model is available for the global ocean as gridded values of 162 horizontal velocities (eastward and northward), sea surface elevation, salinity and 163 temperature at 1/12° spatial resolution, 3-hour temporal frequency and for 40 z-levels in 164 depth. The model is forced by wind stress and fluxes of heat and freshwater at the surface. 165 This model, however, does not include tidal flows, which would contribute to small-scale 166 coastal processes. Particle transport in the vertical, which is particularly important in coastal 167 areas with upwelling or downwelling, was accounted for after reconstructing vertical velocity 168 values. To do so, the continuity equation of mass conservation was applied to horizontal 169 velocities, and sea surface elevation data for the upper 27 depth levels from surface, i.e. down

170 to 400 m deep. Beyond this depth, the coarse vertical resolution of HYCOM data can lead to 171 anomalies in the derived vertical velocity values. Thus, the horizontal velocities obtained 172 directly from HYCOM and the vertical velocity derived using the continuity equation was 173 used to drive the particle tracking model from the free surface down to 400 m depth.

174

175 We used HYCOM output (GOFS3.0: HYCOM + NCODA Global 1/12° Reanalysis, 176 GLBu0.08: expt 19.1 – https://www.hycom.org/dataserver/gofs-3pt0/reanalysis) for the 177 spatial extent ~30°N-10°S, 50°W-100°E and the 2008-2011 time period for particle tracking 178 simulations spanning the winter (north-east) monsoon (November to February), and the 179 summer (south-west) monsoon (June to September). These years were chosen based on 180 availability of current data, and to capture the variation in ocean circulation presented by 181 various states of the El Niño-Southern Oscillation (ENSO). While 2009-2010 represents an 182 El Niño year, 2011 was a La Niña year (https://psl.noaa.gov/enso/past\_events.html).

183

**184** *Particle tracking model* 

185

186 Connectivity Modeling System (CMS) is an open-source, offline three-dimensionnal
187 Lagrangian particle tracking model written in Fortran, which is compatible with HYCOM
188 output. It works by interpolating velocity values to a given particle position using a fourth
189 order Range-Kutta stepping scheme and advects the particle over a user-defined time-step
190 (Paris et al., 2013).

191

192 In this study, we ran three dimensional particle tracking simulations, where larvae were193 simulated as neutrally buoyant particles, which passively drifted with ocean currents.

194 Particles were released along the coastline of the Indian subcontinent (Indian coastline and 195 parts of neighbouring Pakistan to the west and Bangladesh to the east), Sri Lanka, 196 Lakshadweep islands and the Andaman and Nicobar islands. Particles were released every 5 197 km at 1 m below the surface, yielding a total of 2136 release locations along the length of the 198 study area's coastline. Particle release locations were created using the packages 'raster' 199 (Hijmans, 2020), 'rgeos' (Bivand & Rundel, 2020), 'sp' (Pebesma & Bivand, 2005; Bivand 200 et al., 2013) in R version 3.6.1 (R Core Team, 2019), and further edited in QGIS 3.14.0-Pi 201 (QGIS.org, 2021).

202

203 The release frequency was one particle every three hours from each location between 204 November to February (winter monsoon), and June to September (summer monsoon), 205 summing up to about six million particles tracked during each monsoonal season. Particle 206 positions were calculated using a time-step of 20 minutes, their coordinates were recorded 207 every three hours, and each particle was tracked for a duration of 50 days after release. The 208 tracking duration for particle trajectories was determined based on maximum values of 209 pelagic larval duration reported for marine invertebrate taxa found in this region 210 (Supplementary Information 1). For the purpose of analysis, each season was divided into 12 211 release bouts of ten days each to capture intra-seasonal variation in hydrodynamics that can 212 influence particle trajectories.

213

214 Connectivity networks

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Coastal polygons, each of area ~200 km<sup>2</sup>, including four release locations and numbering 528
in total, were created along the coast of the study area (Supplementary Information 2) using

218 the packages 'raster' (Hijmans, 2020), 'rgeos' (Bivand & Rundel, 2020), 'sp' (Pebesma & 219 Bivand, 2005; Bivand et al., 2013) in R version 3.6.1 (R Core Team, 2019), and further 220 edited in QGIS 3.14.0-Pi (QGIS.org, 2021). Connectivity matrices of larval flux were built by 221 calculating the proportion of particles released in an origin coastal polygon that successfully 222 dispersed to a destination coastal polygon for each PLD ranging from 2 to 50 days, with an 223 interval of 2 days. Considering all polygons as potential origin and destination sites for 224 larvae, the size of a larval flux matrix was 528<sup>2</sup> (i.e. 2,78,784 potential connections). Laval 225 flux per unit surface was obtained by scaling larval flux values with the the area of the 226 destination polygon (Figs 2a, 2b). Given the frequency distribution of PLD for marine 227 invertebrates found in the Indian Ocean, connectivity matrices were averaged into four PLD 228 classes for each spawning period - 2-4 days, 6-12 days, 14-20 days and 22-50 days 229 (Supplementary Information 3).

230

231 In total, 288 connectivity matrices were built corresponding to the different PLD-classes, 232 spawning periods, seasons and years (4 PLD-classes  $\times$  2 seasons  $\times$  12 spawning periods  $\times$  3 233 years). Each connectivity matrix defined a connectivity network, where nodes were coastal 234 polygons and directed weighted edges between each pair of nodes were values of larval flux 235 per unit surface between them (Figs 2a, 2b). Various metrics were used to describe the 236 connectivity network - connectance (proportion of non-zero edges), number of singleton 237 nodes (nodes not connected to any other node within the network) and number of weak 238 subgraphs (group of nodes connected through paths in a single direction) or strong subgraphs 239 (group of nodes connected through paths in both directions) based on the nature of 240 connectivity.

#### 242 Community detection

243

244 Each of the 288 connectivity networks was individually processed to detect communities 245 using the Infomap algorithm (Rosvall & Bergstrom, 2008) (Figs 2a, 2b) by applying the 246 'cluster infomap' function in the 'igraph' package (Csardi & Nepusz, 2006) in R. This 247 algorithm uses information-theoretic principles to define a community based on the ease of 248 flow between network nodes. A community is detected when a random walker visits a set of 249 nodes within the network more often than nodes outside it and is likely to get trapped 250 between them (Rosvall & Bergstrom, 2008). The significance of a detected community was 251 estimated using its coherence ratio - the proportion of particles that originate from nodes 252 within a community and remain within the same community (Rossi et al., 2014). A coherence 253 ratio greater than 0.5 was applied to detect well connected communities, and the location of 254 community boundaries (referred to as community breaks henceforth) was detected. 255 Community breaks were classified based on their frequency of occurrence across spawning 256 periods within a PLD-class. Those occuring with a frequency greater than 50% were termed 257 'frequent' and those with a frequency greater than 90% were termed 'highly consistent'.

258

259 *Centrality measures* 

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For centrality measures using shortest path calculations, larval flux values were transformed
into distance between nodes by applying a log(1/x) transformation (Costa et al., 2017). The
role and importance of each node (coastal polygon) in the connectivity network (PLD-class ×
season × spawning period) was assessed using six different metrics. Node degree (number of
non-zero edges from a node) and strength (sum of weight of edges from a node) were used to

266 rank nodes according to their overall influence on the network (Dubois et al., 2016). 267 Betweenness centrality, which measures the number of shortest paths between node pairs that 268 pass through a given node (Freeman, 1977), was used to identify nodes which control 269 transport within the connectivity network. Clustering coefficient, the proportion of realized 270 directed triangles (three nodes connected in all possible ways) between a focal node and its 271 immediately connected nodes (Fagiolo, 2007), was used to measure the propensity of a node 272 to cluster with its neighbours leading to redundancy within a network. Bridging centrality, a 273 product of betweenness centrality and bridging coefficient (node ranking based on location 274 between dense network sub-graphs) (Hwang, 2008), was used to identify nodes which control 275 connections between network communities. Closeness centrality, the inverse of sum of 276 pairwise shortest distances between a given node and all other nodes in a network, was used 277 to identify nodes that can independently communicate with different regions within strong 278 subgraphs in a network (Freeman, 1978).

279

280 Centrality measures were calculated using the tattoo toolbox (<u>https://github.com/costaandrea/</u>
281 <u>TATTOO</u>, Costa, 2017) in MATLAB R2019b.

282

284

The significance of variation in the distribution of connectance and the number of singleton
nodes, weak and strong subgraphs, and Infomap communities with >1 membership, with
PLD-class, year and season was evaluated using non-parametric Kolmogorov-Smirnov test in
R version 3.6.1 (R Core Team, 2019).

289

<sup>283</sup> *Statistical tests* 

#### 290 Results

291

There was no significant variation in most connectivity network characteristics between
years, while their variation between spawning periods within a year was found to be large
(Supplementary Information 4). Based on these results, variability of all metrics was
estimated by pooling 36 connectivity matrices across years (3 years × 12 spawning periods)
for each PLD-class and season.

297

### 298 Network descriptors

299

300 Connectance was low along the Indian coastline, irrespective of the PLD-class and season, 301 with values ranging from 0.5% to 3.4%. During both the seasons, connectance showed the 302 greatest significant difference between PLD less than 20 days and PLD greater than 20 days 303 (Figure 3). Despite the low connectance, there were less than  $\sim 30\%$  singleton nodes across 304 PLD-classes and seasons, indicating that transport further than 5 km along the coast 305 (minimum distance between release locations in adjacent coastal polygons) was common 306 (Figure 3). The number of singleton nodes increased till a PLD of 20 days, indicating that 307 local connections with neighbouring coastal polygons at shorter PLDs disappeared at 308 intermediate PLDs as particles dispersed away from the coast. Except for the PLD-class 6-12 309 days, the number of singleton nodes was not significantly different between seasons 310 (Supplementary Material 3).

311

312 The number of weak subgraphs largely remained unchanged for PLD less than 20 days313 (ranging from 4 to 36), while the number of strong subgraphs significantly decreased between

the PLD less than 6 days (ranging from 20 to 67) and the PLD greater than 20 days (ranging from 9 to 27) (Supplementary Material 4). This indicates that there was an increase in the number of bi-directional connections within subgraphs with increasing PLD. This densification of subgraphs, for PLD up to 20 days, was more pronounced in the summer monsoon as compared to the winter monsoon (Supplementary Information 4).

319

Put together, a significant increase in the connectance for PLD greater than 20 days indicates that a longer transport duration enabled greater transport distance along the coast and islands, leading to a decrease in the number of isolated singleton nodes and an increase in subgraph size. A concomitant decrease in the number of weak and strong subgraphs for PLD greater than 20 days indicates the formation of more densely connected subgraphs.

325

#### 326 Infomap communities

327

328 Similar to the trend observed with strong subgraphs, the number of Infomap communities 329 (communities hereafter) decreased with an increase in PLD (Figure 4a). Except for the PLD-330 class 6-12 days, the number of communities detected for the same PLD-class was not 331 significantly different between seasons (Supplementary Material 4). The coherence ratio of 332 the detected communities was significantly different between seasons (Supplementary 333 Material 4) and decreased with increasing PLD as seen from the increase in variance within a 334 PLD-class (Figure 4b). The decrease in coherence ratio indicates a decrease in the flux of 335 particles circulating within a community through losses outside it.

336

337 The location of community breaks varied with PLD, season and spawning period (indicated 338 by the variation in the consistency of breaks within a PLD-class). However, a few locations 339 frequently appeared as community breaks across spawning periods (>50% frequency), with 340 some occuring consistently with a frequency greater than 90% (Figure 5). These community 341 breaks were found along the north-west coast of mainland India (south of the Gulf of 342 Khambhat 21°N, and Gulf of Kutch), Palk Strait (a narrow channel separating the Indian 343 landmass from Sri Lanka) and north-east India, across both seasons (Figure 5). In the summer 344 monsoon, a consistent community break appeared at the southern tip of India for all PLDs. 345 Additional breaks also appeared along the west and east coast of India for PLD less than 20 346 days, but were not consistent across season and PLD.

347

348 Node descriptors

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350 As observed with connectance, node degree increased with PLD as a longer transport 351 duration promoted variability in transport from the same release location (Figure 6). 352 However, the increase in node degree was not uniform in the study region, and was observed 353 to be higher in the east coast of India and the Lakshadweep islands during the winter 354 monsoon, southern tip of India during the summer monsoon, and Sri Lanka and the Andaman 355 and Nicobar islands during both the seasons (Figure 6). Another consequence of transport 356 over longer durations was the loss of particles from the coastal zone as observed from a 357 decrease in the node strength across a majority of nodes across seasons (Figure 6). Node 358 strength decreased more gradually with increasing PLD, and nodes with high values were 359 more evenly distributed in space in the winter monsoon as compared to the summer monsoon 360 (Figure 6).

361

The number of nodes with high values of centrality measures reduced drastically for PLD greater than 6 days with spatial disparity based on the season. For the shortest PLD, betweeness centrality and bridging centrality were higher and more uniformly distributed along the west coast of India as compared the east coast, while the opposite pattern was observed for closeness centrality. For this PLD range, limited transport led to high clustering coefficient along large extents of the Indian coastline in both seasons (Figure 7).

368

369 High betweenness and bridging centrality values, depicting nodes controlling larval transfer 370 within a network, were consistently observed in regions along the west coast, south-east coast 371 and western Sri Lanka during the winter monsoon, while in the summer monsoon they 372 occurred in Sri Lanka, north-west coast and the Andaman and Nicobar islands. Both the 373 island groups showed high betweenness and bridging centrality, but did not show consistent 374 patterns across PLD and season. Nodes with high clustering coefficient, indicating node 375 redundancy within a network, were observed in central east and west coasts during the winter 376 monsoon, and the north-west coast and the Bangladesh coastline during the summer 377 monsoon. Nodes with high closeness centrality varied with season and PLD, but the Gujarat 378 and Bangladesh coasts displayed consistently high closeness values, thus facilitating direct 379 larval transfer within the network communities (Figure 7).

380

381 Discussion

382

383 This is one of the first broad-scale studies to use ocean flow data and particle tracking models384 to describe patterns of coastal connectivity along the coastline of the Indian subcontinent and

the adjacent island groups. We found that properties of connectivity networks exhibited intraseason and inter-season variability showing differences with pelagic larval duration (PLD), but were comparable across years. Though values of connectance were generally low within the coastal network, there was an increase in the size and bidirectionality of network subgraphs with increasing PLD, resulting in fewer and larger well connected coastal communities.

391

392 Despite seasonal differences in the location of community breaks, particularly for PLD less 393 20 days, four disconnected provinces along the mainland coast were identified across PLD 394 and seasons put together. From west to east along the coastline of the Indian subcontinent, the 395 first province extended across the Gulf of Khambat and the coast of Gujarat (southern 396 boundary at 21°N), the second province was found along the west coast of India (~21°N to 397 8°N), the third province observed in the summer monsoon extended from the southern tip of 398 India to the Palk strait (Gulf of Mannar, between Sri Lanka and mainland India) and the 399 fourth province was observed along the east coast of India ( $\sim 11^{\circ}$ N up to  $22^{\circ}$ N). Within each 400 of these provinces, a few sites displayed notably higher centrality values than others, but their 401 importance varied based on season and PLD.

402

403 Oceanographic drivers of connectivity

404

A striking feature of the upper ocean circulation along the Indian coastline is the seasonal
reversal of coastal currents, which are anti-clockwise in the summer monsoon and clockwise
in the winter monsoon. Despite the latter, three of the four coastal provinces delineated in our
study remained stable across seasons. Such stability is consistent with two persistent

409 hydrodynamic barriers – one north of 20-21°N in the Arabian Sea (Luis & Kawamura, 2004)
410 and the other associated with a deviation in coastal circulation around Sri Lanka near the
411 southern tip of the Indian coastline (Schott & McCreary, 2001).

412

413 However, some hydrodynamic barriers and connectivity network descriptors exhibited intra-414 seasonal variability due to an interaction of spawning timing within a reproductive season 415 with intra-seasonal flow variability. This flow variability is largely driven by atmospheric 416 oscillations in Indian intra-seasonal the Ocean. resulting in short-lived 417 upwelling/downwelling events along the Indian coastline (Varkey et al., 1996; Luis & 418 Kawamura, 2004; Durand et al., 2009). These oscillations span over a wide range of time-419 scales ranging from a week to 60 days (Madden & Julian, 1972; Fu et al., 2003), which likely 420 explains why intra-seasonal variability was not averaged out across the PLD range of 2 to 50 421 days considered in the present study.

422

423 Inter-annual atmospheric oscillations, such as the El Niño-Southern Oscillation and the 424 Indian Ocean Dipole, are also known to alter Indian Ocean climatology and large scale 425 circulation (reviewed in Schott et al. 2009). Interestingly, though the resolution of a Global 426 Ocean Circulation Model such as HYCOM is more suitable to describe inter-annual variation 427 as compared to short lived atmospheric events, we find that intra-seasonal variability was 428 greater than inter-annual variability for all descriptors of network connectivity. These results 429 advocate for fine-tuning connectivity studies in the future to include a better description of 430 short-lived atmospheric processes and to down-scale flow modelling within each of the 431 provinces delineated in the present study.

432

**433** *Biotic filters of connectivity and biogeographic boundaries* 

434

Biological traits related to spawning season and PLD determine the time-dependent ocean flow scenarios that larvae are exposed to and act as filters over the connectivity patterns that are eventually realized in a given region. By combining empirical information on spawning season and PLD range of the species of interest (Supplementary Information 1) with connectivity descriptors from the present study, it is possible to project taxa-specific predictions of connectivity breaks.

441

442 For instance, in the case of both anthozoans (PLD: <7 days, likely summer spawning) and 443 holothurians (PLD = 12-28 days, likely summer spawning), important connectivity breaks 444 would be predicted to occur around the southern tip of India, Palk Strait, south-west Sri 445 Lanka and  $\sim 20-21^{\circ}$ N on the west coast of India. For several crustaceans (PLD = 8-43 days, 446 likely winter spawning) and gastropods (PLD = 12-46 days, likely winter spawning), 447 connectivity breaks would be predicted to occur around the Gulf of Khambat, Palk Strait and north-east Indian coastline. Finally, for taxonomic groups such as bivalves and non-448 449 holothurian echinoderms, connectivity patterns are not generalizable across species because 450 of a large variability in their spawning period (bivalves) or PLD (non-holothurian 451 echinoderms).

452

453 The occurrence of genetic breaks in connectivity has only been tested in a few studies of 454 marine invertebrates along the Indian coastline, such as in the Indian prawn (the crustacean 455 *Penaeus indicus*, PLD: 12-25 days, spawning: October-April) (Sajeela et al., 2019), intertidal 456 periwinkles (the gastropod *Littoraria* species, PLD: 21-70 days, spawning: throughout year; 457 Echinolittorina species, PLD: 21-28 days, spawning: March-June) (Bharti, 2019) and the 458 Asian green mussel (the bivalve *Perna viridis*, PLD = 17.5 days, spawning period: 459 contrasting between coasts) (Divya et al., 2020). Across these PLD and spawning period 460 combinations, the connectivity break consistently predicted around southern India coincided 461 with patterns of population genetic connectivity (Figure 8a). For Penaeus indicus and 462 Echinolittorina malaccana, genetic breaks also coincided with the predicted connectivity 463 break around 21°N on the west coast of India. However, in many of these studies, the 464 populations are separated by large gaps in sampling, which makes it difficult to identify all 465 the genetic breaks and, more importantly, to differentiate between the role of isolation by 466 distance versus dispersal barriers in shaping the observed patterns (Audzijonyte & 467 Vrijenhoek, 2010).

468

469 The consistent community breaks predicted by our larval transport models in the Palk Strait 470 in both seasons and in the southern tip of India during the summer monsoon, correspond to 471 the separation of southern India and Sri Lanka from the east and west coasts suggested by the 472 Spalding et al's (2007) classification of ecoregions along the world's coastlines (Figure 8A). 473 This scheme uses published studies from multiple taxonomic groups and oceanographic 474 processes to define biogeographic boundaries, where ecoregions represent areas showing 475 similarities in species composition, which may be driven by unique oceanographic and 476 geomorphological features. The distinct biogeography of the east and west coasts of India is 477 also suggested by Ecological Marine Units defined by environmental parameters (Savre et al., 478 2017), and patterns of community composition in marine invertebrates along the Indian 479 coastline (Sivadas & Ingole, 2016; Sarkar et al., 2017). (Figure 8a)

481 The connectivity break south of the Gulf of Khambat, separates the linear coast of western 482 India from the Gujarat, and is seen across at least half of all spawning periods for both 483 seasons and PLD less than 20 days. This corresponds to the classification of an ecological 484 marine unit extending across the Gulf of Oman to the Oman coastline (Savre et al., 2017). 485 This region is characterized by seasonal variation in salinity, with the formation of the 486 Arabian Sea High Salinity Water Mass (Kumar & Prasad, 1999) in the winter monsoon and 487 upwelling during the south-west monsoon, which influences productivity and zooplankton 488 biomass (Madhupratap et al., 1996; Madhupratap et al., 2001). This indicates that ocean flow 489 along with environmental features might drive patterns of biogeography in the northern 490 Arabian Sea.

491

492 However, it is important to highlight the limitations of large-scale transport simulations of 493 neutrally buoyant particles using PLD and spawning season alone, which may lead to an 494 incomplete understanding of taxa-specific connectivity breaks. Firstly, larval transport is 495 influenced by species-specific variation in buoyancy and swimming behaviour, which can 496 deviate from predictions for neutrally buoyant larvae (Guizien et al., 2006; Robins et al., 497 2013), resulting in different connectivity patterns (Le Corre et al. 2018; Blanco et al. 2019). 498 Secondly, large-scale ocean flow simulations, with a spatial resolution of ~10 km, are 499 inadequate to describe meso-scale variability of coastal circulation. Such fine-scale 500 variability has been shown to shape the connectivity of coastal populations in fragmented and 501 spatially complex habitats (Padrón et al. 2018; Frvs et al., 2020). Thirdly, filters acting pre-502 and post-transport (sensu Pineda et al. 2007), which are not accounted for in the current 503 study, are likely to explain additional breaks at the level of demographic or genetic 504 connectivity. Finally, simulations of neutrally buoyant larval transport are not likely to 505 identify connectivity breaks driven by ocean fronts exhibiting sharp differences in 506 temperature and salinity (Sayre et al., 2017) (Figure 8a). This explains why some of the 507 observed biogeographic boundaries, such as those reported in the central east and west coasts 508 for bivalves (Sarkar et al., 2017) and pelagic fishes (Pillai et al., 2007) (Figure 8a), were not 509 predicted as community breaks in our simulations.

510

511 Implications for biodiversity conservation and management

512

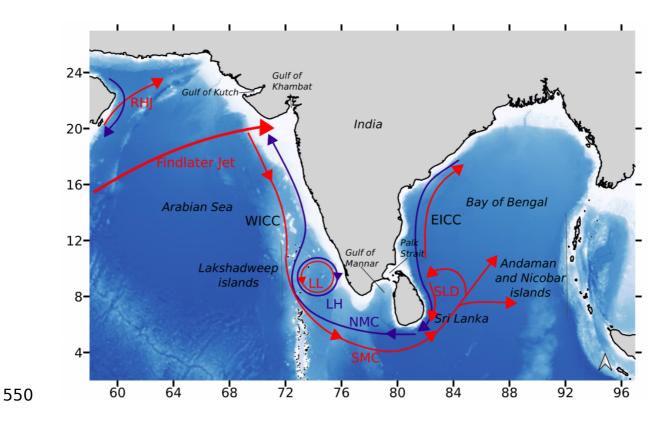
513 The community breaks identified from our study mark the scale and extent of metapopulation 514 connectivity along the Indian coastline, and can be used to guide the management of marine 515 biodiversity. The broad connectivity provinces from our study include the coast of Gujarat, 516 the linear extent of the west coast, southern India and the east coast of India. Currently, 24 517 National Parks and Wildlife Sanctuaries have been identified as Marine Protected Areas 518 (MPA) on the mainland coast of India (Figure 8b), which are located within each of the 519 provinces, with the exception of the linear west coast. Some of these MPAs are located in 520 areas with recurrent connectivity breaks such as the Gulf of Mannar, Palk Strait, Andaman 521 and Nicobar islands and the Gulf of Kutch. In these regions with complex coastal bathymetry, 522 where connectivity breaks were detected at small spatial distances, community detection can 523 be better defined by increasing the spatial resolution of ocean flow and the distribution of 524 release locations (Briton et al. 2018). Spatially and temporally refined transport studies are 525 key in accounting for the effect of small-scale ocean features on flow connectivity at the 526 resolution of coastal populations and local habitat distribution. This defines the relevant 527 spatial scale for assessing vulnerability of coastal populations and designing protection 528 measures (Guizien et al. 2012, 2014).

529

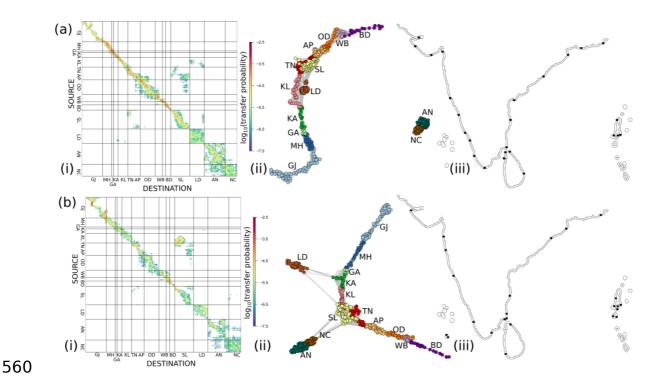
530 The use of centrality measures has been suggested to guide coordinated management at the 531 network level in several studies (Andrello et al. 2013). We find that some areas acting as 532 stepping stones of connectivity (indicated by high betweenness centrality), such as the Gulf 533 of Kutch in the north-west, Gulf of Mannar in the south-east and Sunderbans in the north-east 534 of India, are already under the MPA scheme (Figure 8b). Designation of additional areas for 535 protection, especially along the west coast of India, can improve the existing MPA network. 536 However, within each of the predicted connectivity provinces, the importance of centrality 537 measures differs with season and PLD, indicating that temporally adaptive management 538 measures specific to local biodiversity might be necessary.

539

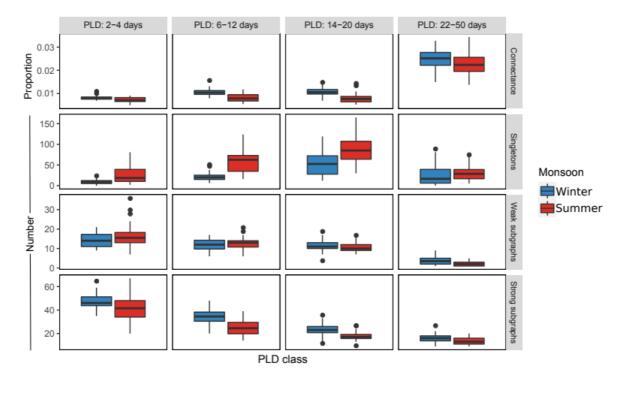
540 To conclude, the present study highlights the importance of intra-season variability in driving 541 patterns of connectivity and provides a coarse prediction of connectivity provinces that fulfill 542 a gap in marine biogeography studies from this region. Our results can guide the spatial 543 scales at which future biophysical models should be set up. Based on the frequency of 544 community breaks, we advocate for refining transport studies based on flow modelling at the 545 appropriate resolution along the Gujarat coastline, around the southern tip of India and Sri 546 Lanka, over two large areas extending along the western and eastern coasts of the Indian 547 subcontinent, and within each of the island groups. Our findings of seasonal and taxa-specific 548 variation in areas exhibiting a large influence on connectivity patterns can inform regional 549 biodiversity management along the Indian coastline.



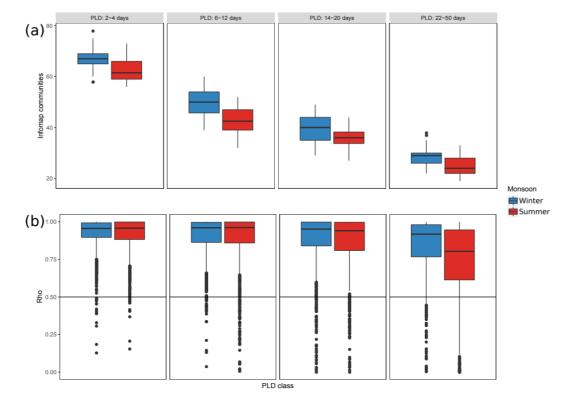
551 Figure 1. Schematic illustration of major currents along the Indian coastline – Ras al Hadd 552 Jet (RHJ), West India Coastal Current (WICC), Lakshadweep Low (LL), Lakshadweep High 553 (LH), South-West Monsoon Current (SMC), North-East Monsoon Current (NMC), SLD (Sri 554 Lanka Dome) and East India Coastal Current (EICC). Findlater Jet is an atmospheric jet 555 observed in the northern Arabian Sea during the summer monsoon. Processes associated with 556 the summer monsoon are in red and those associated with the winter monsoon are in blue. 557 WICC and EICC occur in both monsoons but differ in direction as indicated by the coloured 558 arrows. Schematic adapted from Figure 1 in Luis & Kawamura (2004), Figure 1 in Peng et al. 559 (2015) and Figure 1 in Vinayachandran et al. (2004).



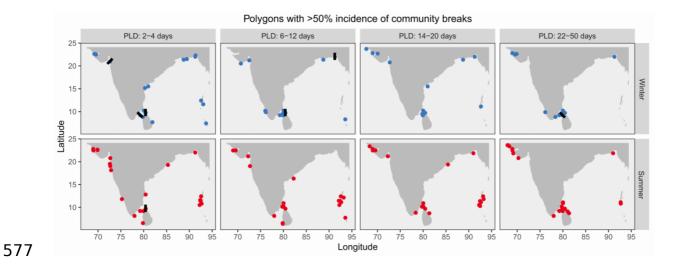
561 Figure 2. Schematic figure depicting the various stages in connectivity analysis. For 562 illustrative purposes, the figures shown here are derived from a mean connectivity matrix 563 across spawning periods and years for the PLD class 14-20 days, for (a) the winter monsoon 564 and (b) the summer monsoon. For each monsoon, subfigures are (i) connectivity matrix 565 represented as log<sub>10</sub>(transfer probability), (ii) connectivity network obtained from the raw 566 transfer probability matrix and (iii) network community boundaries (black squares along the 567 coastline) detected by applying the Infomap algorithm on the connectivity network. The 568 codes presented in (i) and (ii) correspond to GJ – Gujarat, Diu and a section of Pakistan coast, 569 MH – Daman and Maharashtra, GA – Goa, KA – Karnataka, KL – Kerala, TN – Tamil Nadu, 570 AP – Andhra Pradesh, OD – Odisha, WB – West Bengal, BD – section of Bangladesh coast, 571 SL - Sri Lanka, LD - Lakshadweep islands, AN - Andaman islands and NC - Nicobar 572 islands.



574 Figure 3. Summary characteristics of connectivity networks.



576 Figure 4. (a) Number of Infomap communities and (b) their coherence ratio.



578 Figure 5. Distribution of Infomap community breaks. Blue and red circles indicate breaks
579 with frequency >50% across spawning bouts for the winter and summer monsoon
580 respectively. Black bars indicate breaks with frequency >90% across spawning bouts.

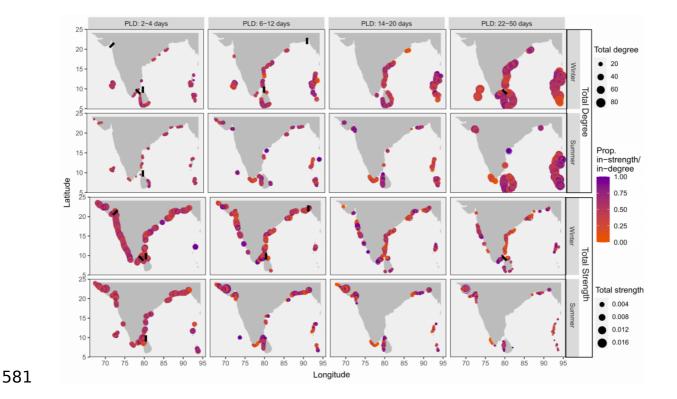
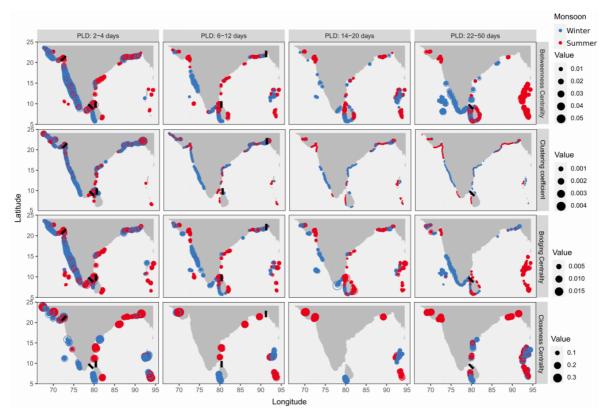


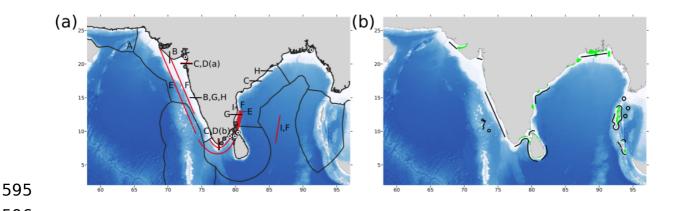
Figure 6. Spatial distribution of total strength (sum of incoming and outgoing edge weights) and degree (sum of number of incoming and outgoing edges) for nodes which have strength/degree values greater than the median atleast 75% times across spawning bouts within a given PLD-class. The colour of a node indicates the magnitude of in-strength/degree, ranging from orange (source) to blue (sink). At each node, filled circles represent the median and the concentric open circles represent the 75<sup>th</sup> quantile of degree/strength. Infomap community breaks with >90% incidence are shown as black bars.



589

Figure 7. Spatial distribution of important nodes based on measures of network centrality.
The nodes displayed on the map have centrality values greater than the median atleast 75%
times across spawning bouts within a given PLD-class. At each node, filled circles represent
the median and the concentric open circles represent the 75<sup>th</sup> quantile of the centrality
measure. Infomap community breaks with >90% incidence are shown as black bars.

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596

597 Figure 8. (a) Biogeographic boundaries (black lines) and genetic breaks (red lines) observed 598 for marine species along the Indian coastline - A. Marine ecoregions along the Indian 599 coastline (Spalding et al., 2007). B. Boundaries of Ecological Marine Units (Savre et al., 600 2017), C. Subdivision of marine ecoregions based on distribution of gastropods, bivalves and 601 polychaetes (Sivadas & Ingole, 2016), D. Genetic breaks observed for the intertidal snails (a) 602 Echinolittorina malaccana and (b) Littoraria strigata (Bharti, 2019), E. Extent across which 603 genetic breaks are observed for the marine fish *Rachycentron canadum* (Divva et al., 2017). 604 F. Extent across which genetic breaks are observed for the shrimp species *Penaeus indicus* 605 (Sajeela et al., 2019); G. Biogeographic divisions based on distribution of bivalve species 606 (Sarkar et al., 2017); H. Boundaries of distribution zones defined for pelagic fisheries (Pillai 607 et al., 2007) and I. Extent across which genetic breaks are observed for the mussel Perna 608 *viridis* (Divya et al., 2020). Community breaks identified from this study are depicted using 609 grey (>50% frequency across spawning periods) and concentric black (>90% frequency 610 across spawning periods) circles. (b) Areas highlighted in green indicate marine protected 611 areas (outlines exaggerated for visibility) and areas highlighted using black lines indicate 612 regions observed to have high betweenness and bridging centrality from this study.

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download from <u>https://www.hycom.org/dataserver/gofs-3pt0/reanalysis</u>. R and MATLAB
scripts used for analyzing simulated particle trajectories will be made available at
<u>https://github.com/bhartidk/larval\_dispersal</u>.