

1                   **Regime shifts in the Anthropocene: drivers, risks, and resilience**

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15    **Author contributions** RB, GP and JCR conceived the idea for and designed the

16    regime shift database, JCR designed the analysis and conducted simulations with

17    input of GP and RB; JCR, GP and RB conceptualized and wrote the paper.

18    **Author information** The regime shift database is publicly available at

19    [www.regimeshifts.org](http://www.regimeshifts.org) hosted by Stockholm University. Correspondence and request

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## 24 **Abstract**

25 Many ecosystems can experience regime shifts: surprising, large and persistent  
26 changes in the function and structure of ecosystems. Assessing whether continued  
27 global change will lead to further regime shifts, or has the potential to trigger  
28 cascading regime shifts has been a central question in global change policy.  
29 Addressing this issue has, however, been hampered by the focus of regime shift  
30 research on specific cases and types of regime shifts. To systematically assess the  
31 global risk of regime shifts we conducted a comparative analysis of 25 generic types  
32 of regime shifts across marine, terrestrial and polar systems; identifying their drivers,  
33 and impacts on ecosystem services. Our results show that the drivers of regime shifts  
34 are diverse and co-occur strongly, which suggests that continued global change can be  
35 expected to synchronously increase the risk of multiple regime shifts. Furthermore,  
36 many regime shift drivers are related to climate change and food production, whose  
37 links to the continued expansion of human activities makes them difficult to limit.  
38 Because many regime shifts can amplify the drivers of other regime shifts, continued  
39 global change can also be expected to increase the risk of cascading regime shifts.  
40 Nevertheless, the variety of scales at which regime shift drivers operate provides  
41 opportunities for reducing the risk of many types of regime shifts by addressing local  
42 or regional drivers, even in the absence of rapid reduction of global drivers.

## 43 **Introduction**

44 We are living in the Anthropocene, an epoch where human actions intentionally and  
45 accidentally are changing planetary processes<sup>1-5</sup> and ecosystems<sup>6</sup>. While some of  
46 these changes have been gradual, others have led to surprising, large and persistent  
47 ecological regime shifts<sup>7,8</sup>. Such shifts challenge ecological management and

48 governance because they substantially alter the availability of ecosystems services<sup>9</sup>,  
49 while being difficult to predict and reverse<sup>7</sup>. While the importance of ecological  
50 regime shifts is increasingly recognized<sup>3,10-12</sup>, the variety of regime shifts and their  
51 drivers is less well known.

52

53 Following the exponential growth of the world's economy, most drivers of global  
54 change are increasing<sup>4,6,13</sup>, and due to these increases the frequency and intensity of  
55 regime shifts are expected to increase too<sup>14</sup>. However most research on regime shifts  
56 is ill-suited to examine this proposition. Research on regime shifts has typically  
57 focused on theoretical models<sup>8,15,16</sup>, empirical evidence of regime shifts<sup>17</sup>, or potential  
58 early warnings signals<sup>12,18</sup>. These approaches require in-depth knowledge of the  
59 causal structure of the system or high-quality temporal data, leading to a focus on the  
60 analysis of particular cases of regime shifts. Here we complement this work by  
61 synthesizing and comparing different types of regime shifts in terms of global change  
62 impacts and opportunities for management. Our aim is to understand: What are the  
63 main drivers of regime shifts globally? What are their most common impacts on  
64 ecosystem services? And, what can be done to manage or avoid them?

## 65 **Materials and Methods**

66 We addressed these questions using a diverse set of methods in a six phase process.  
67 First we developed a framework for data collection that facilitates comparison among  
68 regime shifts, namely the regime shifts database. Second, we identified and grouped  
69 the different drivers into hierarchical classes, distinguishing direct from indirect  
70 drivers. Third, strategies to manage regime shift drivers were identified and classified  
71 according to the scale at which action needs to be taken to tackle the effect of each

72 driver. Fourth, to better understand what the main drivers of regime shifts are we  
73 studied their patterns of co-occurrence by constructing and simulating networks.  
74 Fifth, to discover what factors explained patterns among regime shifts and their  
75 drivers, exponential random graph models were used to explore what types of local  
76 interactions were consistent with the observed global patterns of the network. Sixth,  
77 to identify the most common impacts on ecosystem services, or the most common  
78 interactions among driver types, we analyzed the drivers and regime shifts datasets  
79 using ordering methods. Each of these steps are described in the following sections.

## 80 **Data**

81 The regime shift database (RSDB) was created to synthesize, compare and share  
82 scientific knowledge about regime shifts in social-ecological systems  
83 [[www.regimeshifts.org](http://www.regimeshifts.org)]. The RSDB currently provides a synthesis of >800 scientific  
84 papers, summarizing over 200 cases and about 25 generic types of regime shifts<sup>19</sup>. It  
85 presents information both in plain text and 92 categorical variables about the i) main  
86 drivers of change, ii) impacts on ecosystem services, ecosystem processes and human  
87 well-being, iii) land use, ecosystem type and spatial-temporal scale at which each  
88 regime shift typically occurs, iv) possible managerial options, and v) assessment of  
89 the reversibility of the regime shift and the level of uncertainty related to the existence  
90 of the regime shift, and its underlying mechanism. The review of each regime shift is  
91 available online and wherever possible each entry has been written or peer-reviewed  
92 by an expert on the topic.

93

94 The database collects the most studied types of regime shifts in social-ecological  
95 systems<sup>10</sup>. Examples of regime shifts include i) well-established cases like

96 eutrophication<sup>17</sup>, where lakes turn from clear water to murky water leading to reduced  
97 fishing productivity and toxic algae blooms; ii) controversial cases like dryland  
98 degradation when dry forest and savanna shift to deserts and bare soils, significantly  
99 reducing ecosystem services such as agricultural production and water cycling<sup>20</sup>; and  
100 iii) proposed shifts like the collapse of the Greenland ice sheet where the frequency  
101 and intensity of warm events will shift the ice sheet from permanent to occasional,  
102 reducing services such as coast line protection and climate regulation<sup>21</sup>. An overview  
103 of the 25 regime shifts analysed in this paper is given in S1 Table.

## 104 **Driver identification**

105 Drivers include natural or human induced changes that have been identified as  
106 directly or indirectly producing a regime shift<sup>6,22</sup>. We first collected a preliminary list  
107 of drivers for each regime shift taking as a starting point that it should be referenced  
108 in the academic literature that the variable has causal influence on the regime shift.  
109 For each regime shift we draw a causal loop diagram, a graphical representation of the  
110 causal structure of the system<sup>23</sup>. References and descriptions of each driver plus  
111 causal diagrams are available in the RSDB. To avoid ambiguities and conflicting  
112 definitions across different scholars, we defined drivers as variables outside the  
113 feedback mechanisms of the system, thus they are variables independent of the  
114 dynamics of the system. Direct drivers are those that influence the internal processes  
115 or feedbacks underlying a regime shift, and indirect drivers those that alter one or  
116 more direct drivers<sup>22</sup>. Based on the minimum distance to a feedback loop, we  
117 assessed the directedness of a driver as the shortest number of steps of separation to  
118 the feedbacks. This classification was done for each regime shift, therefore when  
119 comparing regime shifts a driver in one system can be part of a feedback in another.

120

121 To enable consistent comparison of drivers we systematically ensured that drivers  
122 were defined consistently across the database. After the first identification of drivers  
123 we checked for semantic cohesion, to avoid different words referring to the same  
124 driver. So for example cropping and agriculture were renamed agriculture. When the  
125 variables explicitly referred to different phenomena, different names were kept. For  
126 example rainfall variability and precipitation were kept separately as the first refers to  
127 variability and the second to total quantity. We further classified drivers as belonging  
128 to different types of global change by slightly modifying previous classifications<sup>10,22</sup>.  
129 We identified 15 detailed categories of drivers, which were further grouped into 5  
130 broad categories: *habitat modification*, *food production*, *nutrients and pollutants*,  
131 *resource extraction* and *spill-over effects*. Thus, we distinguish between drivers  
132 stemming directly from human activities (e.g. fertilizer use) and drivers affected by  
133 the knock-on or ‘spill-over’ effects of these activities on natural processes (e.g.  
134 sedimentation or upwelling). A worked example is presented in S1 File.

## 135 **Scale of management**

136 To examine management options for drivers of regime shifts we classified each driver  
137 by the scale it could be managed. Managerial options for each regime shift are  
138 synthesized in the RSDB. We exclusively classified each driver as requiring  
139 management at either local, national, or international scales. We considered a driver  
140 to be local if it could be mitigated substantially by changes made at the landscape or  
141 municipality level. If changes at the watershed or regional level could strongly  
142 counteract a driver we classified it as regional to national, and if actions to influence a  
143 driver require global or continental coordination we coded it as international. For

144 drivers with management options at more than one scale, we chose the broadest scale  
145 at which managerial actions are likely to be strong enough to avoid the shift.

## 146 **Network simulations**

147 To better understand the relative importance of regime shifts and drivers we  
148 constructed a bipartite network where a driver is connected to a regime shift if there is  
149 a reference in the academic literature that suggests causality or influence on its  
150 feedback mechanisms. The bipartite network was analysed by considering two  
151 network projections: a network of drivers connected by the regime shifts they caused,  
152 and a network of regime shifts connected by the drivers they share. Since highly  
153 connected drivers are more likely to cause regime shifts and highly connected regime  
154 shifts are more vulnerable to different sets of drivers, the mean degree, the co-  
155 occurrence index and clustering coefficient<sup>24,25</sup> were measured and compared with  
156 10000 random simulated networks. We assume that the relative importance of a  
157 driver, or the number of times that is reported, depends on our particular sample of  
158 regime shifts. Therefore we randomly reshuffled the associations between drivers and  
159 regime shifts, keeping the number of links per node unchanged. Simulations were  
160 performed in the R statistical software<sup>26</sup>, using a Sequential Importance Sampling  
161 algorithm, in R's networksis<sup>27</sup> and ergm<sup>28</sup> packages. The comparison between  
162 observed interactions and random data is fundamental to understand whether the co-  
163 occurrence patterns are due to sampling noise or corresponds to a real pattern. If the  
164 observed patterns deviate from random, there should be theoretical reasons why they  
165 diverge that are further explored with statistical modeling.

## 166 **Model fitting**

167 Exponential random graph models<sup>29</sup> were used to explore what local processes could  
168 better explain the emergent patterns in the networks. We tested whether certain  
169 minimal configurations are statistically more common (e.g. triangles) or if links are  
170 significantly more likely to occur if nodes share the same attribute (e.g. management  
171 scale). Nestedness<sup>30</sup> was calculated for the bipartite network to test if the generalist or  
172 idiosyncratic character of each driver in the network was related to its scale of  
173 management. We used the number of papers reported per regime shift on the ISI Web  
174 of Science by 2013 as an approximation of how extensively a regime shift has been  
175 studied.

176

177 To explore the processes underlying the network patterns, we modelled scale of  
178 management, nestedness, frequency and directedness as categorical variables or node  
179 covariates for drivers; while ecosystem type, nestedness, number of papers reported,  
180 and frequency were modelled as categorical variables or node covariates for regime  
181 shifts. The presence or absence of categorical variables in the RSDB was used to  
182 construct distance measures of how similar two regime shifts are depending on the  
183 variables shared. These distances were modelled as edge covariates for the regime  
184 shift network projection (see regime shifts clustering below). The bipartite network  
185 was modelled as binary network with geometrically weighted terms<sup>31-33</sup>, while the  
186 one-mode projections were modelled following the specifications for weighted  
187 edges<sup>34</sup> and a Poisson distribution as reference. All models were fitted with `ergm`<sup>28</sup>  
188 and `ergm.count`<sup>34</sup> packages for R<sup>26</sup>.



## 189 **Regime shifts and drivers clustering**

190 We used multi-dimensional scaling to investigate the patterns underlying the  
191 clustering of regime shifts. First we calculated the Sorensen-Dice distance between  
192 regime shifts given the drivers they share. This measure favours the presence of  
193 common drivers in the network rather than their absence, and we use it because we  
194 are analyzing driver co-occurrence or regime shifts rather than straightforward  
195 difference among regime shifts. The hierarchical clustering was performed using the  
196 categorical variables of the RSDB after deleting zero columns, grouped by variables  
197 as follows: ecosystem processes (5 variables), provisioning services (8), regulating  
198 services (8), cultural services (4), drivers (10), land use (11), scales (8), and  
199 reversibility (3).

200

201 We analysed patterns among the drivers and the regime shifts in two ways, first by  
202 using existing classifications from global change research to classify drivers into 5  
203 broad and 15 detailed categories; and second by clustering the drivers based on  
204 patterns produced by their connections to regime shifts. Applying matrix  
205 multiplication of the bipartite data by the drivers categorization, we obtained the  
206 number of drivers per regime shift that fall into each broad and detailed global change  
207 category. Euclidean distances were used to organize the drivers into hierarchical  
208 clusters with an average method using the R package `gplots`<sup>35</sup>. These two approaches  
209 allowed us to compare how global change meta-drivers impact regime shifts, and to  
210 detect emergent patterns from our regime shift data based on the published literature.

## 211 **Results**

212 We identified 57 drivers underlying 25 regime shifts (Fig 1). The mean number of  
213 drivers per regime shift is 11.2, ranging from a low of 3 for *steppe to tundra* to a high  
214 of 22 for *mangrove collapse*. The most frequently reported drivers of regime shifts are  
215 *climate change*, *agriculture* and *fishing*, which are reported as drivers of 19, 17 and  
216 15 regime shifts respectively. There are also 14 idiosyncratic drivers (~24%) that are  
217 unique to specific regime shifts. More than half of the connections between drivers  
218 and regime shifts are accounted for by 13 drivers (~22%). The most frequently co-  
219 occurring drivers, understood as the number of regime shifts they jointly drive, are  
220 *agriculture*, *climate change*, *nutrient inputs*, *deforestation*, *greenhouse gases*, *erosion*  
221 and *sea surface temperature*, where each pair occurs together in 10 or more regime  
222 shifts. The regime shifts with the greatest number of shared drivers are *marine*  
223 *eutrophication*, *sea grass collapse*, *fisheries collapse*, and *kelp transitions*, which  
224 have 8 drivers in common.

225  
226 The regime shift-drivers network had a much higher clustering coefficient, higher co-  
227 occurrence index, and lower mean degree than randomized networks (t-test for all  
228 statistics  $P < 10^{-15}$ , Fig 1). This result suggests that co-occurrence patterns among  
229 drivers are related to underlying processes. Furthermore, the network exhibits a nested  
230 structure: idiosyncratic drivers co-occur only with drivers that also co-occur with  
231 generalist ones (Fig 1 and S1 Fig). Surprisingly, the exponential random graph  
232 models show (S2 Table) that the nested structure of the network is not due to global  
233 drivers being widely shared among regime shifts and local drivers being idiosyncratic.  
234 Rather, drivers that can be managed at local and regional scales are more likely to co-  
235 occur with drivers that can also be managed at the same scale. Drivers are

236 significantly more likely to co-occur if they are indirect and generalist. Aquatic and  
237 subcontinental regime shifts tend to share the same set of drivers; while terrestrial and  
238 subcontinental regime shifts share fewer and more varied sets of drivers. Overall,  
239 regime shifts are more likely to share drivers that affect similar ecosystem processes,  
240 impact similar ecosystem services, occur in similar ecosystems and occur at similar  
241 spatio-temporal scales (S2 Table).

242

243 Ecosystem type has a strong influence on the variety of regime shift drivers as well as  
244 ecosystem services impacted by regime shifts (Fig 2 & Fig 3). Multi-dimensional  
245 scaling reveals that aquatic regime shifts often affect fisheries, water purification,  
246 disease control and aesthetic values, and they occur more often at the local scale (S2  
247 Fig). Terrestrial regime shifts are strongly influenced by food production and habitat  
248 modification, and surprisingly also by oceanic spillovers. They consistently affect  
249 water cycling, the provision of food crops and fresh water, and occur on land uses  
250 related to agriculture. Subcontinental regime shifts are quite different in being almost  
251 completely driven by anthropogenic greenhouse gases, climate, ecological, and  
252 oceanic spillover effects. Interestingly, they consistently affect climate regulation and  
253 occur at time scales of centuries. Based upon our classification of regime shift drivers,  
254 we found that climate related drivers are shared across all regime shifts, while oceanic  
255 and ecological spillovers are shared across the majority of regime shifts. Aquatic  
256 regime shifts are driven by all major types of global change drivers, with no drivers  
257 related to terrestrial resource extraction or fire (Fig 2). Almost two thirds of the  
258 identified regime shift drivers (62%) have the potential to be managed at local or  
259 national scales, while a third (38%) can only be managed internationally (Fig 3).

260

## 261 **Discussion**

262 The variety of drivers revealed by our analysis demonstrates that reducing the risk of  
263 regime shifts requires integrated action on multiple dimensions of global change  
264 across scales (Fig 2 and 3), a non-trivial challenge for governance. Even heroic  
265 actions, such as halting climate change or halting agricultural expansion, if not  
266 combined with other actions, will be insufficient to avoid most regime shifts.  
267  
268 Food production and climate change are key drivers of regime shifts that are  
269 intertwined with one another (Fig 2) and expected to increase in the coming  
270 decades<sup>4,36,37</sup>. These drivers have the potential to synchronize the risk of regime shifts  
271 across many systems as well as to produce cascading regime shifts. Drivers related to  
272 food production consist of a broad set of drivers that tend to occur together. They  
273 combine resource extraction (e.g. fishing, cropping), nutrients and pollution and  
274 strongly co-occur with habitat modification drivers (e.g. urbanization, deforestation),  
275 all of which simplify and homogenize ecosystems. Climate related drivers are a more  
276 narrow set of connected drivers, providing few opportunities for local or regional  
277 management. However in both cases there is strong potential to reduce risk of  
278 synchrony by managing local and national scale drivers<sup>38,39</sup>. Local activities and  
279 global markets connect climate and food drivers, which increases the risk of  
280 synchronized regime shifts, but also provides an opportunity to increase resilience by  
281 diversifying local and national energy, food, and regime shift management.

282

283 The number of regime shifts that share climate and food production related drivers  
284 furthermore increases the potential for cascading effects among multiple regime  
285 shifts. Cascades of regime shifts are possible when some regime shifts enhance the

286 drivers of other types of regime shifts<sup>14,37,40,41</sup>. Regime shifts that contribute to  
287 climate change by releasing greenhouse gases or decreasing albedo, or regime shifts  
288 that increase the demand for food by e.g. decreasing crop production, can increase the  
289 likelihood of other climate or food production driven regime shifts far away.

290

291 It remains unclear whether the differences between aquatic, terrestrial and  
292 subcontinental regime shifts are explained by the extent to which they have been  
293 studied. In the early development of regime shifts theory, aquatic systems were  
294 proposed as ideal candidates to test for the existence and mechanisms underlying  
295 these non-linear dynamics<sup>15</sup>, and consequently have been better studied. Aquatic  
296 environments also have and share more drivers, often accounting for land and ocean  
297 interactions. Subcontinental regime shifts are harder to study since most evidence  
298 relies on observation of long-term processes rather than experimentation. They also  
299 share many drivers but to a lesser extent than aquatic regime shifts, and their drivers  
300 and impacts are typically climate related. This makes them ideal candidates for the  
301 study of cascading effects, when one regime shift acts as a driver of other shifts.  
302 Terrestrial regime shifts tend to have more idiosyncratic drivers. They are also prone  
303 to cross-scale interactions, when the aggregation of many instances of the same  
304 regime shift scales up to affect drivers that further exacerbate the risk of the regime  
305 shift elsewhere. Well studied examples of this effect are percolation thresholds for  
306 fire, erosion and landscape fragmentation<sup>40,42,43</sup>.

307

308 Reducing local drivers can build resilience to continued global change, but unless the  
309 rates of global change are slowed or reversed, these changes will eventually  
310 overwhelm local management<sup>44</sup>. Furthermore, our results (S2 table) suggest that in

311 situations where regime shifts and their drivers are poorly understood, managerial  
312 options that work for well-understood regime shifts could potentially be applied to  
313 uncertain or data scarce regime shifts if they share similar ecosystem processes,  
314 impact similar ecosystem services, occur in similar ecosystems and occur at similar  
315 spatio-temporal scales. Similarly, our results suggest that while  
316 monitoring direct drivers allows change in the risk of a regime shift to be estimated,  
317 management efforts are likely more effective when targeting indirect and generalist  
318 drivers because these drivers influence many types of regime shifts, and therefore  
319 reducing them can reduce the risk of multiple regime shifts.

320

321 This paper has presented a novel comparison of regime shifts and their drivers. The  
322 development of the regime shift database and the framework for comparison offers a  
323 platform for others to extend this work. The regime shifts database framework  
324 facilitated comparison of diverse types of regime shifts, broadening our understanding  
325 of regime shift similarities at the conceptual level while offering the possibility to  
326 translate the observed patterns into useful management insights. Our coding of drivers  
327 was done in a systematic, repeatable way, and although some of the categories could  
328 have been defined differently, we do not believe it would alter the overall pattern of  
329 our results. However, future work needs to take into consideration that the weighting  
330 of drivers is not homogeneous across all regime shifts, as such weights are expected  
331 to be context dependent. Furthermore, our network approach so far does not allow us  
332 to infer the role of dynamics, how changes in the intensity of drivers over time  
333 strengthens or weakens their interaction, or how the ordering of events could  
334 exacerbate or dampen the effect of such interactions.

335

336 Achieving a sustainable future will require meeting needs for ecosystem services<sup>9</sup>,  
337 while avoiding regime shifts that disrupt the resilient production of these services.  
338 Consequently, both theoretical and empirical work is needed to better assess where  
339 regime shifts are most likely to happen, which ecosystems and their services will be  
340 most affected, and which groups of society will be most impacted. Furthermore, better  
341 understanding of the dynamics of regime shifts and their drivers is needed to  
342 understand the i) extent to which increasing drivers of global change can trigger  
343 synchronous regime shifts; and ii) how regime shifts, by altering the drivers of other  
344 regime shifts, can trigger or inhibit cascades of regime shifts.

345

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453 **Figure Legends**

454 **Figure 1. Regime shifts - Drivers Network.** In the centre the bipartite network of 57  
455 drivers (left) and 25 regime shifts (right) organized by their nestedness. Highly nested  
456 nodes are idiosyncratic and are located on the lower part of the graph while nodes  
457 with low nesting are generalist and appear in the upper part. On the right is the one-  
458 mode projection of regime shifts (N=25). The width of the links is scaled by the  
459 number of drivers shared, while node size corresponds to the number of drivers per  
460 regime shift. On the left is the one-mode projection of drivers (N=57), with link width  
461 scaled by the number of regime shifts for which causality is shared, and node size  
462 proportional to the number of regime shifts per driver. Below each projection is the  
463 expected distributions for the co-occurrence index and average degree for the one-  
464 mode projection of the drivers and regime shifts networks. The bottom left panel  
465 shows the clustering coefficient for the bipartite network. For all structural statistics,  
466 the red lines mark the actual values for the observed data.

467 **Figure 2. Driver categories per regime shift.** Shading intensity indicates the number  
468 of drivers per regime shift that falls in each driver category. The dendrogram  
469 represents the similarity of regime shifts given the drivers shared (rows) based on  
470 hierarchical clustering with an average method upon Euclidean distances. The grey  
471 area shows categories with missing drivers. The upper horizontal bar shows the  
472 ecosystem type while the left lateral bar shows the 5 broad categories into which the  
473 15 specific drivers categories shown in the rows (right) are classified.

474 **Figure 3. Managerial opportunities per regime shift.** Each bar shows the  
475 proportion of drivers that can be managed at different scales.

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478 **Supplementary Information**

479 **S1 File. A regime shift worked example and its causal loop diagram.**

480 **S1 Figure. Drivers clustering.** Shading intensity indicates the similarity between  
481 drivers given the regime shifts they cause. The row dendrogram shows a hierarchical  
482 clustering calculated on the Sorencen-Dice distance of the drivers matrix. The column  
483 side bar shows the scale of management per driver.

484 **S2 Figure. Multi-dimensional scaling.** Regime shifts are organized according to  
485 their similarity given shared drivers, with a) names coloured according to ecosystem  
486 type: blue = marine regime shifts, green = terrestrial and orange = subcontinental  
487 regime shifts. Smaller plots show the environmental fitting for subsets of the regime  
488 shift categorical variables: b) ecosystem processes (5 variables), c) provisioning  
489 services (8), d) regulating services (8), e) cultural services (4), f) drivers (10), g) land  
490 use (11), h) scales (8), and i) reversibility (3). Only variables that significantly  
491 ( $p < 0.05$ ) influence the regime shifts ordering given their shared drivers are shown in  
492 purple as vectors, indicating the directionality of their influence.

493 **S1 Table.** Summary of the 25 regime shifts examples from the regime shifts database  
494 used in this analysis. \*Only the main ecosystem service impacts are shown.

495 **S2 Table.** Summary of exponential random graph models fitted to the bipartite and  
496 one mode network data.

497 Extended Data Table 1

Regime Shift	Initial regime	Alternative regime	Ecosystem	Ecosystem Services affected *
Eutrophication	Clear water	Murky water	Aquatic - Coastal	- Fisheries - Water purification - Recreation
Marine food web simplification	Predators dominated	Lower trophic groups dominated	Aquatic - Coastal	- Fisheries - Pest & disease regulation - Recreation
Hypoxia	Normoxia	Hypoxia, anoxia	Aquatic - Coastal	- Fisheries - Pest & disease regulation - Recreation
Fisheries collapse	High abundance of commercial fish	Low abundance of commercial fish	Aquatic - Marine	- Fisheries - Pest & disease regulation - Biodiversity
Floating plants	Submerged plants dominance	Floating plants dominance	Aquatic	- Fisheries - Pest & disease regulation - Recreation
River channel change	Old channel course	New channel regime	Aquatic	- Freshwater - Food production - Regulation soil erosion - Transport
Mangroves transitions	Mangrove forest	-Salt marshes -Rocky tidal - Shrimp farms	Aquatic – coastal	- Fisheries - Timber - Regulation soil erosion - Recreation
Sea grass transitions	Sea grass dominated	-Algae dominated -Bare sediments	Aquatic – coastal	- Fisheries - Water purification - Regulation soil erosion
Marine eutrophication	Clear water	Nutrient rich water	Marine	- Fisheries - Water purification - Recreation
West Antarctica Ice Sheet collapse	Full glacial or modern interglacial	Extreme interglacial	Polar	- Climate regulation - Natural hazards protection
Bivalves collapse	High abundance of bivalves	Low abundance of bivalves	Marine	- Water purification - Fisheries - Biodiversity
Coral transitions	Coral dominated reefs	- Macro-algae - Soft corals - Corallimorpharians - Sponges - Urchin barren	Marine	- Biodiversity - Fisheries - Recreation - Coastal protection

Regime Shift	Initial regime	Alternative regime	Ecosystem	Ecosystem Services affected *
Kelp transitions	Canopy forming algae	- Turf forming algae - Urchin barrens	Marine	- Fishing - Biodiversity - Recreation
Encroachment	Grass dominated savanna	Shrub dominated savanna	Savannas	- Livestock - Climate regulation - Biodiversity
Soil salinization	Low salinity soils	High salinity soils	Dry lands	- Fresh water - Food production - Soil erosion regulation - Biodiversity
Forest to savannas	Forest	Savanna	Forest - Savanna	- Biodiversity - Climate regulation - Water cycling - Food production
Dry land degradation	Dry lands: savannas, dry forest	Deserts	Dry lands	- Freshwater - Food production - Timber and fuel - Climate regulation - Water regulation
Tundra to forest	Tundra	Forest	Tundra	- Livestock - Wildlife food - Climate regulation - Timber
Monsoon	Strong monsoon	Weak monsoon	Marine - Terrestrial	- Water cycling - Food production, timber - Climate regulation
Peatlands	Low productivity & high C accumulation	High productivity & low C accumulation	Peatlands	- Nutrient cycling (C) - Climate regulation
Greenland Ice Sheet melting	Permanent ice sheet	No permanent ice sheet	Polar	- Coastline protection - Climate regulation - Water regulation
Thermohaline Circulation Collapse	Strong thermohaline circulation	Collapse of thermohaline circulation	Polar - Marine	- Climate regulation - Biodiversity - Food production
Salt marshes to tidal flats	Salt marshes	Tidal or subtidal flat	Marine - coastal	- Pollution filtration - Storm protection - Fisheries, food production.

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<b>Regime Shift</b>	<b>Initial regime</b>	<b>Alternative regime</b>	<b>Ecosystem</b>	<b>Ecosystem Services affected *</b>
Arctic Sea Ice collapse	Arctic with summer ice	Arctic without summer ice	Polar	<ul style="list-style-type: none"><li>- Climate regulation</li><li>- Aesthetic values</li><li>- Natural hazards protection</li></ul>
Steppe to tundra	Steppe	Tundra	Steppe	<ul style="list-style-type: none"><li>- Biodiversity</li><li>- Food production</li><li>- Climate regulation</li></ul>

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501 Extended Data Table 2

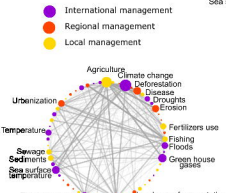
	Mod01	Mod02	Mod03	Mod04	Mod05	Mod41
Density	-1957***	-6.50e+03***	-4.00e+03***	-467.193	-4.88e+02***	-2.80e+03
b1star2		2.64e-01***	5.85e-01***			
b1star3		8.81e-03***	1.31e-02			
b2star2		2.33e-01***	3.94e-01***			
b2star3		-2.77e-03	-5.84e-03			
Three-paths			-5.07e-02			
Cycle-4			1.59e-01*			
GWNSP				-0.230***	6.22e-02	-1.18e-01
gwensp-alpha				0.10629	1.679	1.45***
gwb1deg0.5					-8.22e-01	
gwb2deg0.5					-1.84e+01***	
b1starmix.2						
Driver management:						
global						5.42e-02
local						1.33e-01**
regional						1.01e-01
b2starmix.2						
RegimeShift.Ecotype:						
aquatic						-5.40e-03
subcontinental						2.11e-01***
terrestrial						2.20e-02
Node covariates						
Nestedness.Drivers						-7.43e-01
Nestedness.RegimeShift						-1.32
Frequency.Drivers						3.75***
Frequency.RS						6.61*
<b>AIC</b>	1436	13947	2261	1377	2082	1069
<b>MLE</b>	-717.2127 (df=1)	-6968.571 (df=5)	-1123.731 (df=7)	-685.3822 (df=3)	-1035.953 (df=5)	-521.6868 (df=13)

502

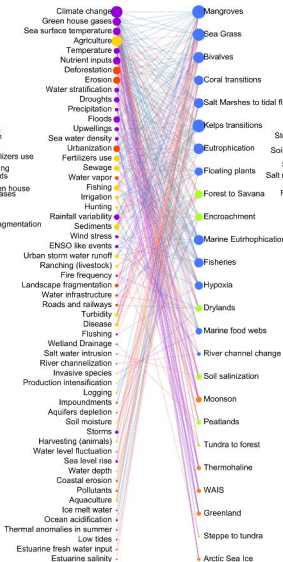
503 Models 01 to 05 are null models following the specifications for bipartite networks of  
504 ref 42. Model 01 is a Markov random model, model 02 explores the effect of 2 and 3  
505 paths on both projections of the bipartite network, model 03 explore the effects of  
506 three-paths and cycles also known as clustering model; model 04 is a curved  
507 exponential model that show the effects of geometrically weighted node shared  
508 partners (gwnsp), complemented in model 05 by adding geometrically weighted terms  
509 for the degree on each one-mode projection. Model 41 is the model that exhibited the  
510 best fit following both Akaike Information Criterion (AIC) and Maximum Likelihood  
511 Estimation (MLE). Model 41 combines a curved exponential model and explores the  
512 effects of homophily –the likelihood of two nodes of being connected on the one-  
513 mode projections given that they share attributes: scale of management for driver  
514 nodes, ecosystem type of regime shifts nodes, and nestedness and frequency as node  
515 covariates respectively. All model are dyadic dependent, only model 41 do not exhibit  
516 degeneracy. Significance levels: \*\*\* $P < 0.001$ , \*\* $P < 0.01$ , \* $P < 0.05$ ,  $P < 0.1$



### Drivers Network



### Bipartite network



### Regime Shifts Network

