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# 1 Re-wilding collective behaviour: an ecological perspective

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13  
14 **Keywords:** Behavioural ecology, Social behaviour, Bio-logging, Remote monitoring

## 15 16 17 **Summary**

18  
19 **The earliest studies of collective animal behaviour were inspired by and conducted in**  
20 **the wild. Over the past decades much of the research in this field has shifted to the**  
21 **laboratory, combining high-resolution tracking of individuals with mathematical**  
22 **simulations or agent-based models. Today we are beginning to see a ‘re-wilding’ of**  
23 **collective behaviour thanks to technological advances, providing researchers with the**  
24 **opportunity to quantify and model the heterogeneity that exists within the social**  
25 **groupings they study, and within the environments in which these groups live. The**  
26 **perspective we present here aims to inspire and steer this research toward answering**  
27 **fundamental and outstanding behavioural and ecological questions, while also**  
28 **tackling pertinent conservation challenges.**

## 29 30 31 32 33 34 35 **Trends**

36  
37 The field of collective animal behaviour is transforming.  
38 Continuous behavioural tracking in the wild affords an ecological perspective.  
39 Collective behaviour can be studied in the environment in which it has evolved and is  
40 maintained.

41 **Introduction to collective behaviour**

42

43 How and why do animals form groups? The structure and functioning of animal aggregations  
44 have long intrigued scholars. Indeed, pivotal work by Nikolaas Tinbergen, Konrad Lorenz,  
45 and Karl von Frisch conducted during the last century won them a Nobel Prize (1973) for  
46 investigations of the “organization and elicitation of individual and social behaviour patterns”  
47 [1]. Their work, which included von Frisch’s discovery that bees use a type of “dance” to  
48 facilitate collective decisions [2], became the bedrock of studies of animal behaviour and  
49 ethology, and in particular, studies of differences in group structure and patterns of social  
50 relationships within and across species. Moving forward from these early descriptions, the  
51 past several decades have brought us a long way towards understanding the form and  
52 function of social interactions, resulting in the vibrant research field of collective animal  
53 behaviour (see glossary).

54

55 In this article we give a brief history of collective behaviour research and provide an overview  
56 of the state-of-the-art in this fast-developing field, highlighting some of the major gaps in our  
57 current understanding. We then introduce technological advances in bio-logging (see  
58 glossary) and new methods for remote environmental monitoring which enable us to gather  
59 high-resolution behavioural and ecological data in the wild, with a focus on vertebrates. We  
60 suggest that these new tools allow researchers to embrace and model the heterogeneity  
61 (see glossary) in their study systems [3] and to study collective behaviours in the social and  
62 ecological environments in which they have evolved and are maintained [4]. We thus expect  
63 to see a “re-wilding” of collective behaviour research. We end by proposing key behavioural  
64 and ecological questions and pertinent conservation challenges that we can address in the  
65 near future by combining wild and laboratory studies of collective animal behaviour.

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67 **A brief history of collective behaviour research**

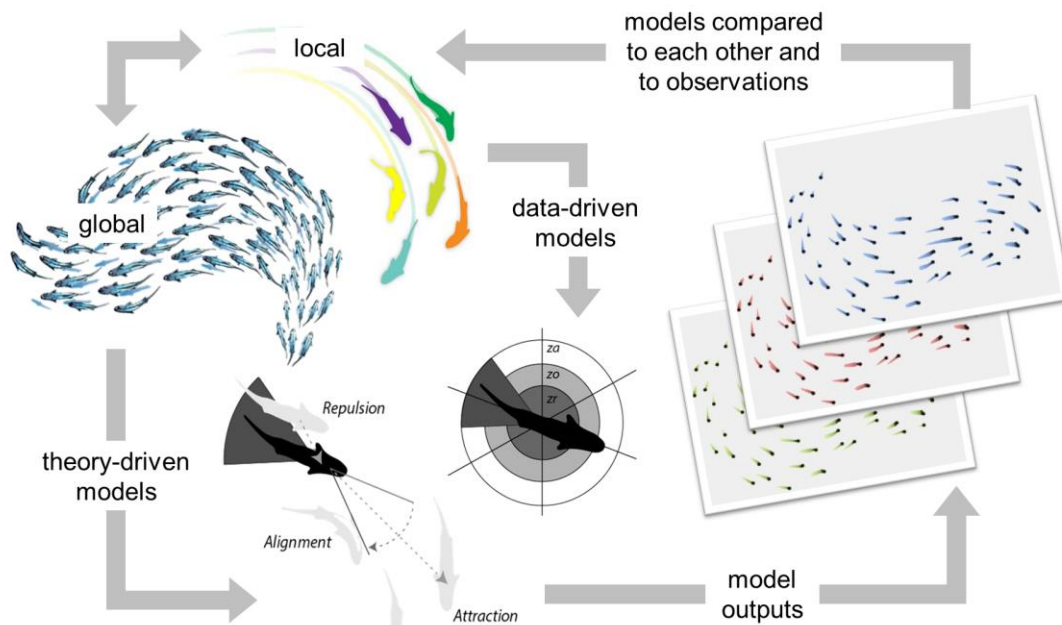
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69 Research in collective animal behaviour tends to adopt a self-organisation (see glossary)  
70 perspective, with investigations of how global-level collective behaviours emerge from local  
71 interactions (see glossary) among individuals [5]. The majority of this work is informed by  
72 laboratory experiments which tend to combine high-resolution tracking of individuals [6],  
73 mathematical simulations or agent-based models of self-organising (see glossary) groups [7]  
74 (Figure 1). These works have provided a mechanistic and predictive understanding of the  
75 behaviour, structure, and performance of animal groups. For example, research on ant  
76 colonies has shown how simple rules (see glossary) of interaction among individuals can  
77 generate spatial structures in their societies which are critical to their organisation and  
78 decision-making [8-11]. Similarly, research with shoaling or schooling fish has uncovered the  
79 behavioural rules fish use to coordinate their motion [12-14] and make collective decisions  
80 about features of their environment [15-17].

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**Glossary Box**

**bio-logger:** an electronic device attached on or in an animal providing data about that animal  
**collective behaviour:** the coordination of individuals' behaviour in space and time  
**flexibility:** capacity for an individual's behaviour or a collective's behaviour to be modified to respond to altered circumstance  
**global properties:** group (or population) level dynamics that result from individual behaviours  
**heterogeneity:** social units or the environment being composed of parts (individuals, habitats, etc.) of different kinds  
**keystone individuals:** individuals that have a large effect on other group members' behaviours and/or the overall group dynamics  
**local interactions:** interactions among individuals within a limited distance and/or range of each other  
**robustness:** ability of an individual's or a collective's behaviour to remain stable following perturbations  
**self-organization:** order at a global level arising from local interactions among individuals



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**Figure 1. Collective animal behaviour research cycle.** Almost all collective behaviour research is related directly or indirectly to mathematical models, and Sumpter et al. [18] explain how regular movement back and forth between mathematical models, experimental data and statistical fitting can provide a comprehensive understanding of how interactions between individuals produce group level patterns. Based on observations of global patterns, researchers use theory-driven approaches to try to replicate group-level dynamics. In contrast, individual-level observations can be used to produce data-driven models to quantify the response of individuals observed in experiments. Both approaches are complementary (and are also not distinct as portrayed here), tending to rely on simple local rules, such as the individual being submitted to a zone of attraction ( $zr$ ), a zone of orientation ( $zo$ ) and a zone of repulsion ( $zr$ ) ([19] as depicted) to produce model outputs. These model outputs can then be compared to each other, and the original or new observations, to quantify how closely each model approximates the real data [20].

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## **Realism and heterogeneity**

Early studies of the mechanisms of coordination in animal groups depicted individuals as essentially identical units: from Reynolds' "boids" [21] to Ballerini and colleagues' starlings [22], neither simulations nor analyses of real data accounted for potential individual heterogeneity (see glossary) among group members. This was due partly to the field showing (as yet) little interest in such heterogeneity, but also to the difficulties in quantifying individual variation in animal collectives that are often composed of thousands of individuals.

Constructing groups of (real or simulated) animals to study collective behaviours can ignore the very inter-individual differences – such as age, sex, reproductive or physiological state, social dominance, kin relations, personality, knowledge, or experience – which can result in differentiated social roles that can function to improve individual and group success [3]. For instance, inter-individual differences in flight speed, knowledge, personality and experience shape the collective dynamics of homing pigeons (*Columba livia*) (Box 1). Similarly, lab experiments with shoaling fish have shown personality differences can influence the structure of and movement dynamics within and between groups [23], but also that the influence of individual personality types can be context-specific [24]. Together, these empirical examples indicate how selection can drive behavioural differentiation between individuals within animal collectives [3].

Quantification and representation of heterogeneity in the environment (as opposed to within-groups as discussed above) has also been lacking. Research undertaken in the laboratory is typically optimised for the requirements of data collection (e.g. short periods of filming and subsequent tracking [6]) and wild studies tend to be restricted to short time periods or specific locations and/or contexts because of methodological constraints [22, 25, 26]. The challenge has therefore been for researchers to incorporate greater realism into their studies (Box 2). Where simple environmental heterogeneity has been introduced in laboratory experiments, their impact has been profound. For instance, studying fish under varying light conditions (dark and light patches varied in space and time) led to the discovery of emergent sensing in fish schools [27].

By bringing greater realism to the social and physical environments of animal collectives, researchers can better understand both the mechanism and function of the behavioural rules and emergent patterns identified. Clever experiments with an evolvable simulation of small prey that were 'preyed upon' by a bluegill sunfish [28] show how this can be achieved. Researchers were able to observe how group formation and specific individual interaction rules can provide collectives with anti-predatory benefits. Embedding animals in such reactive, virtual reality environments provides a fascinating new line of investigation that will afford an "evo-mecho" approach to collective animal behaviour. In the sunfish experiments the researchers were able to observe how group formation and specific individual interaction rules can provide collectives with anti-predatory benefits. In essence, this can reveal which rules "work best". Future VR environments [29] and/or robots [30-32] can help us achieve "closed loop" experiments in which freely moving animals can be precisely perturbed or stimulated, improving our ability to probe the social patterns we observe, as well as their underlying processes. However, we maintain that it will be difficult to test if and how the rules and mechanisms uncovered are adaptive without studying real-life, wild systems over sufficient time and context [33].

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### BOX 1. A birds-eye view



Images: Z. Ákos

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Individual tagging of free-flying birds, and, in particular, the use of study systems in which individual variation can be not only quantified but also manipulated, has provided significant insights into the role of within-group heterogeneity in shaping collective dynamics. Homing pigeons (pictured) provide an experimental model especially amenable to both quantification and manipulation. These birds' long history in studies of individual spatial cognition and navigation [34] allows models to incorporate numerous known sources of individual variation, and, crucially, to do so in collective decision-making scenarios on ecologically valid scales. For example, we know that different birds prefer to fly substantially different routes when navigating home over familiar landscapes [35] and that these differences can give rise to conflict that needs to be resolved when birds with different preferred routes are made to travel together [36]. Rather than choosing the best available route, how "stubbornly" a given bird tries to keep to its own route, even whilst flying with a partner, seems to predict leadership in pairs [37]. In larger flocks transitive leadership hierarchies emerge [38], whose temporal stability and robustness to manipulations of individual navigational knowledge [39] suggest structuring by inherent individual differences among flock members. Perhaps unexpectedly, neither social dominance [40] nor individual navigational competence [41] seem to be significant predictors of leadership. However, solo flight speed [41] and a tendency for greater exploratory behaviour [42] do: faster and "bolder" birds are significantly more likely to assume higher leadership ranks. In combination, variation in these traits provides a simple and elegant link between individual heterogeneity and the organisation of collective movement. Similar mechanisms have now also been identified in fish [23], and confirmed to explain multiple aspects of collective functioning. Interestingly, the observation that there can exist feedback between leadership and the individual traits that structure it (such as knowledge gained through the experience of leading reinforcing leadership [41]) opens up many new and fascinating questions about changes that collective behaviour can undergo over time. Future work will need to further explore such feedback for a longer-term perspective on collective behaviour [4], incorporating the role of learning during collective action as an additional source of individual heterogeneity.

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## BOX 2. A Fish-Eye Lens



Image: A. Ward.

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The challenge for researchers interested in the collective behaviour of shoals and schools is to incorporate greater realism to their laboratory studies and, where possible, to conduct studies in the wild. Wild studies of fish aggregations have a surprisingly long history. Sund applied echo-sounding to the study of cod shoals over 80 years ago [43], while in the 60s, Radakov filmed wild fish schools from aircraft [44]. Recent technological developments offer the tantalising prospect of building on these early advances. Improvements in camera technology now facilitate filming of fish in their natural habitat. One interesting outcome of a recent study of the collective behaviour of wild stickleback shoals [45] was the remarkable concordance between the behaviour of free-swimming shoals and shoals of the same species under the oft-criticised environs of the laboratory. Nonetheless, studies in the wild represent our best opportunity of developing a deep understanding of collective behaviour in its proper ecological context. Until recently, one obstacle has been the difficulty in tracking fish in the wild, due to problems with variable light and contrast, among other issues. The application of artificial intelligence to this problem offers a way forward, for example, the use of trainable algorithms to assist in the detection of target animals. Another challenge for studying fish in the wild is that visibility is often restricted in aquatic systems. Active acoustic techniques provide an alternative to cameras in these cases. Collective manoeuvres and information transfer within pelagic shoals and the interactions of predators and prey have been quantified using sonar and the development of techniques to effectively resolve collective responses in space and time [46-49]. As yet, acoustic techniques lack the resolution to be able to identify individuals consistently over time; however in cases where this is of particular importance, telemetry can offer an alternative solution. Reductions in the size, mass and price of tags now allows for the possibility of tracking individual fish over extended periods of time [50].

230 **Re-wilding collective behaviour**

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232 Whilst there is a long tradition of wild studies in collective behaviour research – von Frisch’s  
233 work on the collective decisions of honey bees was undertaken in the wild [2] – we have not  
234 yet been able to collect the same sorts of data that have become the norm in the lab (Figure  
235 2). For instance, we know from direct observations of primate groups that a type of  
236 “embedded leadership” can emerge from simple and local interactions [51] whereby socially  
237 connected or dominant individuals steer group activities [52, 53]. We assume that this  
238 process might result in faster collective decisions because transmission of information via  
239 central individuals will be quicker than via peripheral individuals (and possibly more accurate  
240 too, since it will pass through fewer individuals) [53]. Similarly, decision accuracy might also  
241 be enhanced since highly connected individuals tend to be dominant and/or elders which  
242 can have superior knowledge of features in their environment [54]. However, whilst  
243 correlational data from elephants (*Loxodonta africana*) [55], and orcas (*Orcinus orca*) [56]  
244 offer some support for these ideas – because individuals in elephant herds and orca pods  
245 gain significant benefits from following older, socially important leaders – we do not yet fully  
246 understand why certain rules evolve. To achieve this, we need more and better data,  
247 adopting similar approaches to those used in the laboratory (Figure 1), but over longer time  
248 periods and in more depth [4]. Only then will researchers be afforded a fully integrated study  
249 of collective behaviour.

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254 **Figure 2. Collective animal behaviour research: traditional observation techniques.** (a)  
255 Observation of chacma baboon troops on foot to study collective movement and decision-  
256 making [52, 57] (image: A. King); (b) Observations of orcas by boat to study leadership and  
257 collective behaviour of pods [56] (image: The Center for Whale Research). (c) Observations  
258 of wild dogs in Botswana to study the collective movement decisions of packs [58] (image:  
259 N. Jordan).

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261 **Tools for re-wilding**

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263 Field researchers tend to gather data on one or a few individuals at a time, or else conduct  
264 repeated scans of all individuals’ behaviour at some interval. Where animals cannot be  
265 followed, observations tend to be restricted to certain resources (e.g. water or food sources,  
266 or at sleeping locations). These are noisy and patchy data. New developments in bio-logging  
267 [59] – which use animal-attached devices to provide data on the individual’s movement,  
268 behaviour, or physiology, without the need to directly observe the animal – can enable  
269 researchers to generate wild data comparable to the “whole-system” information afforded by  
270 laboratory experiments [60] (Figure 3). Three-dimensional accelerometers and  
271 magnetometers, for instance, allow us to reconstruct not only animal movement but also  
272 behavioural states [61, 62], and global positioning systems can provide animal location with  
273 high accuracy [63, 64]. With devices and batteries getting smaller, cheaper, and more  
274 powerful, there is now a real possibility of attaching loggers to the majority or all individuals  
275 in a social group as has recently been done with baboon troops [65-68]. Similarly, high-  
276 resolution sonar imaging can be used to track the motion and interactions among aquatic



277 organisms under water [47], and drones used to track them at the surface [69]. Imaging  
278 techniques can be used to reconstruct the 3D position and velocity of individual birds within  
279 large mobile flocks, too [70]. Note that with all the excitement of new data from these  
280 technologies, researchers must also carefully consider the ethical questions such  
281 technologies raise, related to animal capture and tagging, and disturbance to animals and  
282 habitats via drone use [71].

283

284 New tools are also available for remotely gathering environmental information. For example,  
285 with easy-to-deploy mapping drones we can capture accurate aerial imagery and generate  
286 2D maps and 3D models of research sites on demand [72]. At larger scales, remote sensing  
287 data can not only classify objects and landscapes at high resolution, but also provide  
288 estimates of environmental heterogeneity (and its 'productivity') [73]. In aquatic landscapes  
289 high-resolution mapping data can be generated by Autonomous Underwater Vehicles  
290 (AUVs: [74]), while in aerial landscapes, fine-scale data on variability and predictability in  
291 airflows can be mapped using an Ornithodolite (binoculars with an inbuilt laser-rangefinder,  
292 compass and inclinometer) which can provide a series of coordinates of a target to estimate  
293 groundspeed [75].

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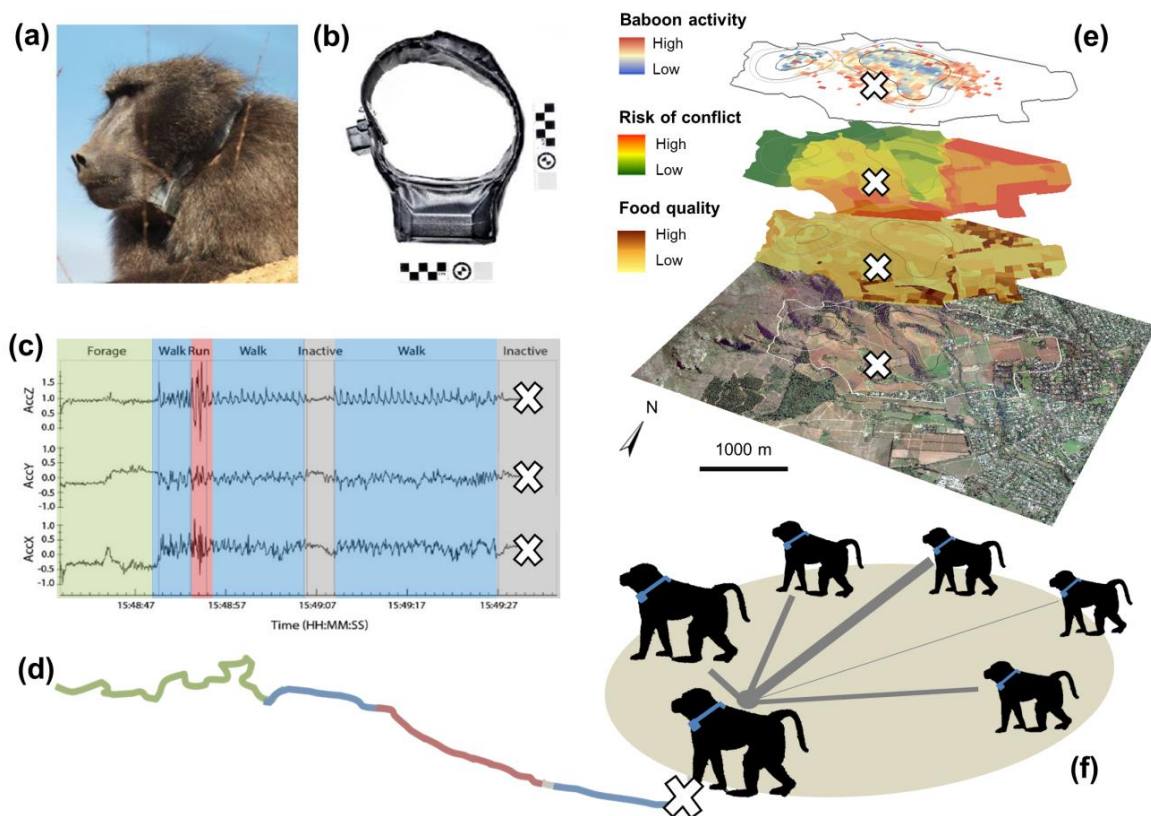
295 Combining bio-logging and remotely sensed data creates "individual-environment" data  
296 streams that can enable researchers not only to model interactions between individuals  
297 according to their relative positions and movements, but to also explicitly measure and  
298 explore the influence exerted by local and global heterogeneity (i.e. how individual traits,  
299 relationships between individuals, and environmental features interact to modify movement  
300 and interaction rules). For example, a recent study of wild baboons in Kenya combine bio-  
301 logging data collected for a majority of individuals in a troop over a number of days together  
302 with environmental mapping [66], providing a benchmark for future wild studies of collective  
303 behaviour.

304

### 305 **A new era?**

306

307 What will all these complex individual-level data paired with environmental information do to  
308 advance the field of collective behaviour? Will it be worth all the effort? We think so. This  
309 new era will provide opportunity to integrate knowledge of the rich, complex, and changing  
310 environments in which social groups live with the behavioural data which are collected. The  
311 approaches we have discussed will allow for a synergy between laboratory and field  
312 experiments, providing insight into why specific rules of interaction evolved and how they are  
313 maintained, enabling better integration of function and mechanism, and therefore a platform  
314 for a more explicit comparative perspective. However, to achieve this requires a degree of  
315 restraint from researchers because it will become all too easy to gather vast datasets on the  
316 movement, behaviour, and environment of wild animal collectives. We therefore urge  
317 researchers to carefully consider (1) what the data are for, and (2) how they will be analysed.  
318 Data should be collected to allow systematic testing of hypotheses and predictions  
319 generated by researchers with good knowledge of the systems being investigated. A  
320 discussion of analytical tools requires a methodological review that is beyond the scope of  
321 this article, but we would point researchers towards new open-access analytical tools and  
322 software for storing, visualising, processing, analysing, and integrating data streams that will  
323 be crucial [e.g. 76, 77]. Below, we provide three inter-linked research themes that represent  
324 the sort of advances that will be possible (see the questions box some for more).



326  
 327 **Figure 3. “Whole-system” information in the wild.** (a) chacma baboon (*Papio ursinus*)  
 328 wearing a F2HK.v2 baboon tracking collar pictured in (b) which can be used to create an  
 329 acceleration ethogram (a catalogue of different acceleration footprints produced by different  
 330 behaviour of an animal) as pictured in (c). For full details on how to build, deploy, and  
 331 interpret data from the F2HK.v2 collar see [62]. (d) Represents a schematic of a baboon  
 332 GPS track coloured by behaviours depicted in the acceleration ethogram and at the end of  
 333 the GPS point “X” marks a location in time and space (Cape Town suburbs) for which  
 334 information has been gathered on habitat types, food quality, risk of conflict with humans [78]  
 335 and which has been combined with information on the average activity type performed by  
 336 baboons from past data to produce a series of landscape layers in (e). The schematic in (f)  
 337 shows that if multiple individuals are collared this allows for individual behaviour and  
 338 positions can be recorded at each time point. In this image, the frequencies of recent  
 339 interactions (e.g. spatial proximity based on GPS data or behavioural interactions based on  
 340 acceleration data) are represented by line thickness. Combining these data one can  
 341 investigate spatial or temporal synchrony in activities and explore variation within these as a  
 342 function of the physical and/or social environment. Supplemental animation 1 provides a  
 343 visualisation of how these data can be combined.

#### 345 Simple rules: fixed or flexible?

346 Over the past decade, one of the major goals for collective behaviour research has been to  
 347 uncover the “rules of interaction” (normally with reference to motion) used by individuals in  
 348 animal groups, but even with sophisticated model selection processes, these are difficult to  
 349 infer [79]. One reason for this could be that the rules might change (i.e. a fixed rule set that  
 350 varies with context or a rule set that changes over time). A ‘flexible phenotype’ [80-82] is  
 351 hypothesised to be a primary causal factor determining individuals’ success when dealing  
 352 with uncertainty in their environment [83]. However, an infinitely flexible phenotype is not  
 353 possible due to the genetic and developmental basis of species-specific traits [84] which limit

354 the range of possible physiological and/or behavioural responses individuals might exhibit  
355 [80]. Ecological constraints too (e.g. predation risk) can limit the types of social interaction  
356 that are possible [84]. As an alternative to flexibility, species can evolve sub-optimal, but  
357 resilient or robust phenotypes that operate well across a broad range of environments [80].  
358 Studying social animals in the wild and collecting “whole-system” information (Figure 3), we  
359 can start to test whether these rules are flexible and/or robust (see glossary). Such  
360 characterisation will be especially important with respect to novel environmental changes  
361 and challenges caused by humans. In doing so, we can also investigate if and how  
362 interaction rules change with greater heterogeneity in systems and the environment (Figure  
363 4a).

364

### 365 Networks and resilience

366 All manner of collective behaviours can be represented and analysed using a network  
367 approach [85, 86], and one of the most exciting avenues for network research and collective  
368 behaviour is to link the rules of interactions (see above) to global network structure and  
369 function. If rules turn out to be flexible, then individuals in animal collectives should  
370 adaptively change their behaviour and/or restructure their social networks to maintain  
371 performance under change. If rules are robust, then individual behaviour or the resulting  
372 social networks should not drastically alter when experiencing change, but instead show  
373 temporary “dips” in performance (Figure 4b). Work on ants in the laboratory has begun to  
374 tackle such questions [87], but, as yet, we have very little idea of how wild animal networks  
375 respond when their physical or social environment is perturbed [88] (Figure 4b). However,  
376 work investigating the effect of short- and long-term differences in predation risk upon fish  
377 collective behaviours offers a useful platform from which to build [89, 90].

378

### 379 Keystone roles

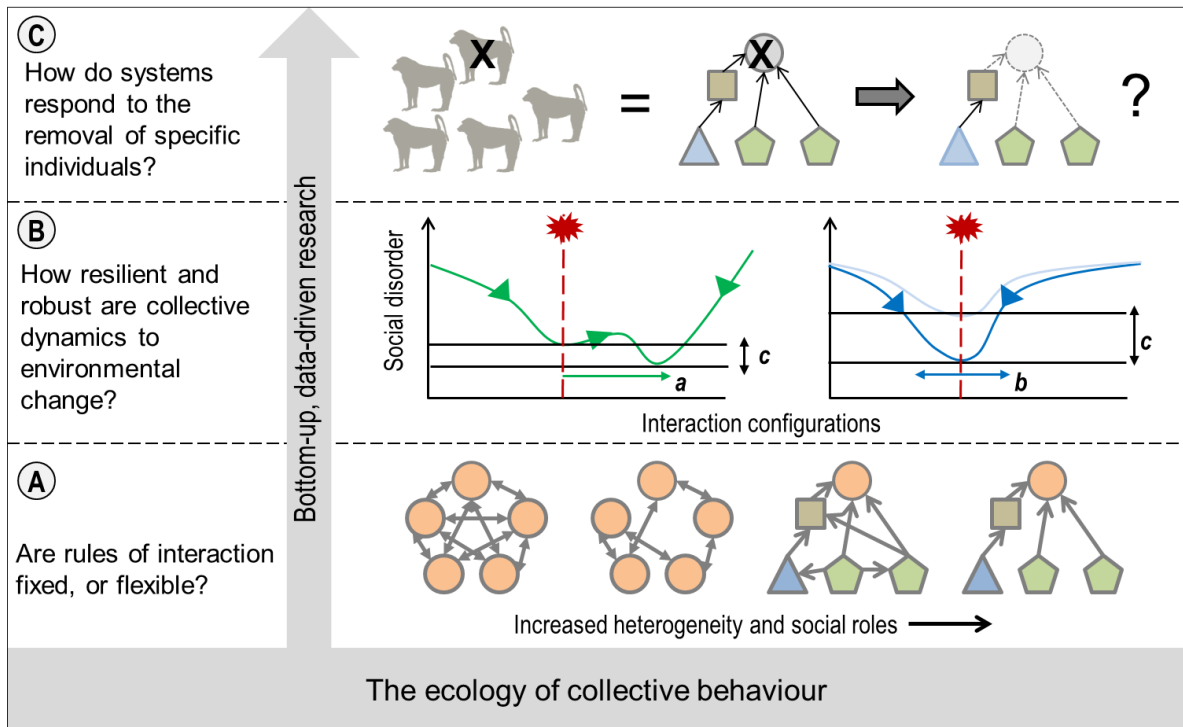
380 Similarly, if specific ‘keystone’ individuals are particularly important for collective animal  
381 behaviour [91, 92] and these same individuals are preferentially hunted, exploited, or  
382 exposed to risks via their own behaviour or via human activity, then this can impact on the  
383 structure and functioning of social units [93] (Figure 4c). Investigations of keystone roles and  
384 complementarity in roles within social units will offer insight for decision-makers tasked with  
385 managing the consequences of harvesting or human-wildlife conflicts. For instance, in the  
386 case of human-wildlife conflicts, if certain individuals play “keystone” roles and steer group  
387 activities, it could be more efficient to attempt to manage these individuals [78]. In the case  
388 of harvesting, research into keystone roles and collective behaviour can be employed to  
389 understand – and crucially, predict – if the removal of specific individuals will result in  
390 temporary or more permanent changes to social dynamics (Figure 4b). In extreme cases,  
391 these data and/or predictions might even help prevent catastrophic change to group stability  
392 and viability [94].

393

### 394 **Concluding remarks**

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396 The frontier of collective behaviour research is riding on a wave of technological  
397 developments, but for the field to progress and answer fundamental behavioural and  
398 ecological questions and solve challenges concerning the consequences of environmental  
399 change (Figure 4) requires technology-enhanced learning and research within a broad multi-  
400 disciplinary research environment. That mouthful of a sentence requires students and  
401 researchers capable of this. Karl Popper, the famous Austrian-British philosopher said in  
402 1963: “We are not students of some subject matter, but students of problems. And problems  
403 may cut right across the borders of any subject matter or discipline.” [95]. We urge  
404 Universities and funding agencies to enable such scientific endeavour [96].



405  
 406 **Figure 4. Environmental change and adjusted phenotypes/networks.** (A) Detailed  
 407 individual level data paired with environmental information will enable researchers to track  
 408 individual interaction rules and resulting collective dynamics, and quantify the level of  
 409 heterogeneity and social roles within their study system. We can then investigate if and how  
 410 interaction rules change with greater heterogeneity in systems and the environment. (B)  
 411 Schematic of social disorder (e.g. a breakdown of social hierarchy or cooperation) as a  
 412 function of possible interaction (network) configurations: Stable states are indicated by the  
 413 horizontal black lines, and a rapid environmental change indicated by the red comic-book  
 414 style crash icon and red dashed vertical lines. Possible routes to maintaining stability: 'a'  
 415 represents flexibility where interaction configurations adaptively change and social networks  
 416 restructure. 'b' represents robustness where there is no significant change to interaction  
 417 configurations and individuals/networks accommodate the change without any impact on  
 418 social order. 'c' represents resilience in the system. (C) Represents a case where individuals  
 419 with specific behaviour (e.g. risk-takers) or morphology (e.g. big horns) die or are removed  
 420 because of human impacts. For example, these individuals can be preferentially hunted or a  
 421 particular exposed phenotype. If these individuals have a disproportionate influence on  
 422 collective behaviours, this can alter the functioning and efficiency of social units. If such  
 423 individuals play keystone roles, then the network might reconfigure (B).

424  
 425 **Acknowledgements**

426  
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 428 from the lab to the wild*” workshop at *The 51st Annual Conference of the Animal Behavior  
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 431 members at Swansea University for sharing of ideas. Finally, thank you to five anonymous  
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433 **References**

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