

The importance of sample size in marine megafauna tagging studies

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Abstract

Telemetry is a key, widely-used tool to understand marine megafauna distribution, habitat use, behaviour, and physiology, however, a critical question remains: “how many animals should be tracked to acquire meaningful datasets?” This question has wide-ranging implications including considerations of statistical power, animal ethics, logistics and cost. While power analyses can inform sample sizes needed for statistical significance, they require some initial data inputs that are often unavailable. To inform the planning of telemetry and biologging studies of marine megafauna where few or no data are available or where resources are limited, we reviewed the types of information that have been obtained in previously published studies using different sample sizes. We considered sample sizes from one to more than 100 individuals and synthesized empirical findings, detailing the information that can be gathered with increasing sample sizes. We complement this review with simulations, using real data, to show the impact of sample size when trying to address various research questions in movement ecology of marine megafauna. We also highlight the value of collaborative, synthetic studies to enhance sample sizes and broaden the range, scale, and scope of questions that can be answered.

Keywords

Movement behaviour, tracking data, telemetry studies, key questions, number of tags, animal welfare

Introduction

Tracking studies of marine animals have proliferated in recent years as a new generation of miniaturized, cost-effective and reliable telemetry tags are deployed on an ever increasing array of species (Figure 1) (Evans et al. 2013). These technological advances have led to a dramatic increase in the use of the Argos and GPS satellite systems to track highly migratory marine vertebrates (including the large-bodied marine megafauna) that surface to breathe or spend time on land (enabling transmitters to communicate with satellites). Simultaneously, an expansion of acoustic telemetry networks to track gill-breathing animals that remain submerged, like tunas or sharks, has occurred. These advances also have been coupled with an increasing diversity in the sensors available on tags and other bio-logging devices (Hebblewhite and Haydon 2010, Hussey et al. 2015, Kays et al. 2015). Combined with advanced analytical techniques, these technological innovations have transformed our knowledge of movement patterns, behaviour, habitat use and ecophysiology of animals with movement data driving a series of positive conservation outcomes across multiple taxa such as the creation of marine protected areas and other conservation zones (Hays, 2019). However, the deployment of tags can involve procedures that stress the target animals (Wilson and McMahon 2006), including capture and restraint, anaesthesia, chemical immobilization, and surgery (Harcourt et al. 2010). Further, costs and logistics associated with purchase and deployment of tags are considerable. For example, satellite-linked Argos tags cost several thousand \$US per unit with on-going operational costs for satellite time. Consideration of these various elements leads to a fundamental but complex question: what is the minimum number of animals that should be tagged and tracked for a given study to deliver sufficient data to address the research aims (Wilson and McMahon 2006, Hays et al. 2016), while ensuring the number of animals tagged complies with ethical pillars of the three R's of Reduce, Replace and Refine (Russell and Burch 1959)?

There are well-established metrics to determine sample size and provide the statistical power necessary to draw probability-based conclusions from datasets (e.g., Green 1989,

Johnson et al. 2015). Hence, answering the question of how many tags to deploy in any given study would seem straightforward. However, power analyses require some initial data or knowledge of the expected movements of animals, such as on the variance of the behaviour being studied, or on the movement range. This information is often not available because researchers are studying new species or working in new areas. Furthermore, an important caveat to the application of power analyses is that many of these studies are still in the ‘discovery’ phase and the most interesting or relevant questions or observations are still unknown. Although it is always prudent to undertake power analyses when possible, here, we take a complementary approach to assist the planning of telemetry and biologging studies of marine megafauna where little or no prior data are available. We focus on marine megafauna and satellite tracking, given the growth of this area, but some of our conclusions are relevant to other biologging approaches. For example, data-storage tags that measure parameters such as diving and body acceleration, are widely deployed on marine megafauna and the increasing use of acoustic arrays, often in networks spanning 1,000s of km (Lennox et al. 2017), means that acoustic tags are also widely used within this group including smaller life stages of some taxa, such as hatchling sea turtles (Thums et al. 2013). We do not focus on smaller bodied, commercial species because there are complexities associated with sample size for this size range that need separate consideration, for example their common fine scale stock structure (Righton et al. 2007). Here, we review the types of information that have been obtained by studies with different sample sizes of marine megafauna (Figure 2). In doing so, we provide guidance for researchers embarking on tracking studies of marine megafauna by summarizing what has been achieved with sample sizes from one to well over 100 individuals. We provide examples of simulation exercises that can be used to estimate the sample size needed to address specific questions. We show evidence that significant advances can be made with small sample sizes while highlighting the benefits obtained from employing greater sample sizes, and supplement this review with simulations from real data to illustrate how the ability to answer specific research questions changes with the sample size of tracked individuals. We illustrate this, showing how different sample sizes are needed when addressing different questions of interest for the same taxa (using turtles as example), and also when addressing the same question (using home range or utilisation area as example) for multiple taxa (sharks, seabirds, seals). We also highlight the value of data-sharing and showcase some of the seminal discoveries made by combining data across studies to reach very large sample sizes.

The value of different sample sizes is best exemplified in work from individuals who pioneered tagging on the same system or species, necessarily starting with the use small numbers of tags before attaining larger sample sizes that altered the scope of their work allowing new questions to be addressed. For example, a thread of work tracking leatherback turtles in the Atlantic began with $n=3$ (Hays et al. 2004a), progressed to $n=21$ (Fossette et al. 2010), then $n = 106$ (Fossette et al. 2014) to recently become part of a study involving >2500 tracked marine animals across multiple species (Sequeira et al. 2018). At each iteration, the questions that were addressed changed, and this increasing capability is reflected in the synthesis presented here.

Dare to dream (sample size of one)

136 Many researchers assert that tracking studies with sample sizes of one are of no value, but the
137 history of animal tracking includes many startling discoveries made from tracking one
138 individual. While, statistically, a sample size of one is expected to capture a ‘normal’ or
139 common trajectory, the value of such studies actually lies in their ability to show that certain
140 feats are possible. Examples of extraordinary feats detected in single animal studies include

141 the journey of >1000 km by a leatherback turtle (*Dermochelys coriacea*) tagged off South
142 Africa (Hughes et al. 1998), and the discovery that white sharks (*Carcharodon carcharias*)
143 can last more than a month on a single large meal (Carey et al. 1982, but see Semmens et al.
144 2013). Additionally, despite multiple tags having been used in another white shark study, it
145 was the track from a single white shark traversing an entire ocean basin while performing
146 deep dives to nearly 1000 m (combined with photo ID data) that was central to the discovery
147 that these sharks are not coastal obligates (Bonfil et al. 2005). A single tagged sea turtle was
148 also found to routinely conduct sequences of dives each 6-8 h followed by short inter-dive
149 surface intervals suggesting operation within its aerobic dive limit and fundamentally altering
150 the expectations of the eco-physiological capacity for this species (Hochscheid et al. 2005).
151 Individual tracks can also provide significant information with conservation implications. For
152 example, the track of a single grey whale (*Eschrichtius robustus*) tagged within the feeding
153 grounds of the critically endangered western stock off Sakhalin Island, Russia, and migrating
154 to the breeding lagoons of the eastern stock in Baja California, Mexico, questioned whether
155 these two stocks were indeed distinct (Mate et al. 2015). This individual whale also broke the
156 world record (previously held by a humpback whale) for the longest known mammalian
157 migration at 22,511 km.
158 Data from one individual can also reveal aspects of behaviour linked to physical abilities,
159 and if sampled at very high frequency, they can provide high resolution movement
160 information. For example, flipper sensors attached to a turtle revealed how swimming effort
161 was linked to depth-dependent, air-mediated buoyancy and swim angle (Hays et al. 2004c).
162 Finally, and importantly, a sample size of one may provide critical proof of concept for novel
163 equipment or attachment procedures, providing a starting point for follow up studies. For
164 example, one of the first animals tracked by Argos satellite-linked tags was a plankton-
165 feeding basking shark (*Cetorhinus maximus*) that oriented along thermal fronts for 17 days
166 (Priede 1984). The species was studied further with increasing numbers of tags providing
167 insight into other ecologically-relevant questions (Sims et al. 2003, Sims et al. 2005, Southall
168 et al. 2006).
169 As animal-borne tags are increasingly used to obtain data on the environment, single tags
170 can also provide highly valuable data that would be difficult to obtain with any other
171 observing system. For example, the use of a CTD (conductivity, temperature and depth) tag
172 on a single southern elephant seal (*Mirounga leonina*) provided an 8-month hydrographic
173 profile that allowed an assessment of the seasonal evolution of the upper ocean (Meredith et
174 al. 2011). Similarly, a CTD tagged Weddell seal (*Leptonychotes weddellii*) provided some of
175 the first data on the wintertime conditions over the Weddell Sea continental shelf (Nicholls et
176 al. 2008). Indeed, marine mammals and particularly seals, now provide the bulk of the
177 physical oceanographic observations in the polar regions and are a central component of the
178 global ocean observing system (Treasure et al. 2017). Despite the common perception of the
179 limited value of a sample size of one, the examples above show evidence that even a single
180 tag can provide ground-breaking information allowing insights into population- and species-
181 level ecology and guiding future studies.

182

183 **Understanding variability (sample sizes up to 10)**

184 As sample sizes increase, so too does the probability that tags will reveal individual
185 variability in the behaviour being observed. Statements based on such data can move from
186 possible limits of animal performance to plausible and ecologically valuable metrics for the
187 species, such as diving behaviour, home ranges and foraging areas. Variations in individual
188 foraging patterns have been observed with surprisingly small sample sizes. For example,
189 three distinct foraging patterns were detected in data derived from nine Galapagos sea lions
190 (*Zalophus wollebaeki*) (Villegas-Amtmann et al. 2008), which were, in subsequent studies,

191 correlated with differences in the physiological capability of these animals (Villegas-
192 Amtmann and Costa 2010). Sample sizes of only a few individuals may also be immensely
193 valuable when high resolution temporal data are available. This is the case for diving data of
194 marine vertebrates downloaded from the archive of recovered tags that are equipped with
195 pressure sensors (e.g. SPLASH tags; pop-off satellite-linked archival transmitters, PSAT; and
196 dive loggers), which allow for greater insight into the environmental and physiological
197 drivers of movement patterns (e.g., Deutsch et al. 2003, Meekan et al. 2015). This type of
198 high resolution temporal data is more easily collected for animals that return to areas that are
199 predictable in space and time (e.g. breeding areas) and thus facilitate tag recovery. This is
200 because the data that are transmitted to satellite are binned summaries only and the detailed
201 patterns of vertical movements are only available in the tag archives. So, for animals that do
202 not return to breeding or over-wintering sites, such as whale sharks (*Rhincodon typus*), the
203 detailed patterns of vertical movements can only be obtained when detached tags are
204 recovered by chance (e.g., when these sharks wash up on beaches). Such limitations to data
205 acquisition, in addition to problems with tag failure and loss, need to be factored into the
206 initial sample size of tags. Therefore, information on the expected return of data from all
207 animals tagged is important when writing ethics approvals, to estimate the cost of the project
208 and to define the research scope.

209 Although larger sample sizes typically are recommended for many ecological questions, a
210 sample size of up to 10 individuals may be immensely valuable for some applications. For
211 example, when testing and developing new methods or technologies, deploying more than 10
212 tags may lead to potentially unforeseen negative impacts on animals and waste financial
213 resources. A sample size ≤ 10 may also be appropriate when studying critically endangered
214 species. Indeed, in such cases, the limit of ≤ 10 might be enforced by permitting agencies.
215 When generating hypotheses about unknown phenomena, a sample size of up to 10 tags
216 could also be a good starting point, allowing this exploration phase to dictate if the
217 phenomenon is worth exploring further. Also a sample size of ≤ 10 may be appropriate for
218 species or questions that are difficult to study, such as following social groups on long
219 migrations, or where high logistics costs for deployment may limit funds available for tags, as
220 is the case, for instance, for killer whales (*Orcinus orca*) (Durban and Pitman 2012).
221 An early example of the value of relatively small sample sizes is a satellite tagging study of
222 six wandering albatrosses (*Diomedea exulans*), which revealed individuals travelling
223 thousands of km in a single foraging trip during an incubation shift in the southwestern
224 Indian Ocean (Jouventin and Weimerskirch 1990). Although such a small dataset might not
225 provide sufficient precision to determine preferred foraging areas, the consistency of the
226 distances covered provoked a fundamental shift in how researchers thought about habitat use
227 by these birds. Similarly, for 50 years, basking sharks were thought to hibernate in deep
228 waters of the North Atlantic Ocean during winter until satellite tracking of five individuals
229 showed that they exhibit extensive horizontal and vertical movements at this time (Sims et al.
230 2003).

231 As sample size increases, variability in space use can be defined in more detail. For
232 example, while a study of nine leatherback turtles in the Atlantic Ocean revealed individuals
233 all moving in disparate directions (Hays et al. 2004b), the majority of nine grey reef sharks
234 (*Carcharhinus amblyrhynchos*) in the Great Barrier Reef, Australia, showed fidelity to a
235 single reef, while one individual undertook a 134 km movement across the deep open ocean
236 (Heupel et al. 2010). Inclusion of nine individuals in the latter study indicated that although
237 large movements were present, they were not representative. In contrast, the former study
238 indicated that a larger sample size is required to fully understand patterns in movement for
239 leatherback turtles.

240 When a study species is rare or endangered, small sample sizes are unavoidable, but their

241 value is amplified because they may represent a larger proportion of the population
242 (McMahon and Hays 2006). However, the scope of questions that can be addressed for such
243 species through tracking and biologging are likely to be constrained by low sample sizes.
244 Sample sizes of approximately ten tagged individuals have been useful in identifying
245 responses to environmental variation, and possible drivers of movement of some species. For
246 example, the diving behaviour of 10 satellite tracked female Antarctic fur seals
247 (*Arctocephalus gazella*) highlighted their differential use of oceanographic features (Lea and
248 Dubroca 2003). Insights into size or sex-based differences in behaviour can also become
249 evident. For example, active acoustic tracking of only two male and two female benthic
250 catsharks during a 14-day period (Sims et al. 2001) suggested sexual segregation by habitat.
251 This result stimulated further studies that revealed the mechanisms underlying these sex
252 differences in behavioural patterns (e.g., Wearmouth et al. 2012).

253 To further exemplify how small sample sizes can lead to insightful sex-based differences in
254 marine megafauna, we used a simulation exercise to explore how differences in breeding
255 periodicity between male and female turtles can be detected with even small increments in
256 sample size. Understanding these differences in breeding periodicity is important because
257 turtles have temperature-dependent sex determination, and the rising incubation temperatures
258 due to climate change will likely produce increasingly sex ratios skewed towards females.
259 For our simulation, we used information published in a recent study for loggerhead turtles
260 (*Caretta caretta*) in the Mediterranean, where males tend to return to breed after one year
261 with probability of 0.76 ($p_{male}=0.76$) whereas females returned after longer intervals (i.e., the
262 probability of returning to breed after one year $p_{female}=0.00$) (Hays et al. 2014a). These
263 probabilities were originally based on tracks from 25 individuals (17 males and 8 females)
264 but we use them here to show the likelihood of the same biological conclusion being reached
265 with smaller sample sizes. Using these probabilities, and assuming equal numbers of tracked
266 males and females, we ran 1000 simulations for sample sizes ranging from 1 to 8 female and
267 male individuals, randomly selecting the number of males and females that would be
268 recorded to return after one year. When only three males and three females were tracked, the

269 probability of recording a significant difference in numbers returning was only 0.331, but this
270 rose to 0.983 when eight females and eight males were tracked (Figure 3A). This simulation
271 exercise illustrates how researchers can use available data to optimise the number of
272 deployments they need to address their question of interest.

273

274 **Defining the norm (sample sizes of 10s up to 100)**

275 A better assessment of overall patterns of movement or behaviour at the population scale may
276 be possible after tens of individuals of the same species have been tagged. While specifying
277 the sample size needed for these types of studies is challenging, simulation exercises can be
278 useful as exploratory tools to understand how much data are needed. Using another
279 simulation exercise, we illustrate how confidence in observed results can be improved by
280 sample sizes increasing from < 10 to a few tens of tags (Figure 3B). As an example of a study
281 question, we focused here on what is the clutch frequency of turtles, i.e., the frequency with
282 which eggs are laid within and among seasons, which is a critical life-history trait for
283 quantifying population trends of turtles. The number of nesting females in a population is
284 typically determined by counting tracks on beaches associated with nesting and then dividing
285 by a nominal mean frequency of clutches. A recent study that tracked 10 green turtles
286 (*Chelonia mydas*) in Diego Garcia, Indian Ocean, showed that their mean clutch frequency
287 was six (Esteban et al. 2017), and led to the understanding that the population at this locality
288 was about half the size of that estimated from previous studies that patrolled beaches on foot
289 to intercept females when they nested. Using the probabilities obtained in Esteban *et al.*

290 (2017), we can simulate how the confidence limits on estimates of mean clutch frequency
291 change with sample size. For each sample size (3 – 40), we ran 1000 simulations and then
292 determined the standard deviation (SD) of the estimate for mean clutch frequency, which
293 reflects the variation in the estimate of mean clutch frequency that might be recorded with
294 that sample size (Figure 3B). When the sample size was three, the SD was ~ 1.20 (i.e., the
295 95% confidence limit on the estimate of mean clutch frequency that might have been derived
296 was +/- 3 clutches), but when the sample size was increased to 30, the SD reduced to 0.38,
297 and to 0.34 when the sample size was 40 individuals (i.e., 95% confidence limit = +/- 0.11
298 clutches). Examples of improvement on previous results through increased sample sizes are
299 also found in published literature. For example, assessment of the diving behaviour of 13
300 female northern elephant seals showed maximum dive durations of 106 minutes (Le Boeuf et
301 al. 2000) and was confirmed as a good approximation in a later study with a sample of 211
302 females aimed at identifying drivers of their large-scale distribution and inter-annual
303 variability in foraging and breeding success (Robinson et al. 2012). Despite the different
304 focus of these two studies, the later data confirmed that the earlier study had a large enough
305 sample size to provide a general understanding of the dive behaviour of the species.
306 Commonly, tagging studies aim to quantify space use and identify important utilisation
307 areas (e.g., 50 % kernel densities). Such estimates are highly sensitive to sample size due to
308 variability in movement among individuals, as shown by Gutowsky *et al* (2015) with
309 albatrosses. That study demonstrated that the sensitivity of group-level space-use estimates
310 stabilizes with increasing sample size of albatrosses, in that the areas covered by space use
311 estimates generated from datasets comprising different individuals roughly approached an
312 asymptote in median area estimates around a mean sample size of 17 – 21 individuals.
313 However, the range of estimates remained large with the 95% and 50% contour area
314 estimates varying by 7.2 and 1 million km², respectively. For other seabirds, like European
315 shags (*Phalacrocorax aristotelis*) and Black-legged kittiwakes (*Rissa tridactyla*), sample
316 sizes of 39 and 83 have been used, respectively, to estimate space use (Soanes et al. 2013).
317 Estimates of area utilisation are also highly dependent on the animal's range and the context
318 of habitat utilisation. For example, a sample size of 30 was sufficient for calculating the area
319 used by flatback turtles (*Natator depressus*) during the nesting season but not for calculating
320 the typically larger area used post breeding (Thums et al. 2018b).

321 To demonstrate the effect of sample size on utilization area and kernel estimates for a
322 range of species, we used a resampling approach to test whether an asymptotic relationship
323 between sample size and monthly utilisation area estimates was attained. We did this for
324 probability contours of 50% and 25% (typically considered of relevance to marine spatial
325 planning) using tracking data from six different species in the Pacific Ocean (results detailed
326 in Figure 4). Together, these studies demonstrate the power and limitations of a moderate
327 number of tags to improve our understanding of animal movements. Another example
328 showing how an increasing number of tracks can assist our understanding of animal
329 movement was a study tracking 75 loggerhead turtles across the Mediterranean finding that
330 they exhibit disparate dispersal patterns. The study highlighted that extending protected areas
331 to include 10 of the core sites used by loggerhead turtles would result in better protection for
332 64 % of the population (Schofield et al. 2013).

333 To depict the effect of sample size on our understanding of dispersal of individuals from a
334 population, we used a simulation of a hypothetical population of 100 individuals in location
335 'X' where tagging took place, and then assumed equal probabilities of 0.65, 0.30 and 0.05 for
336 individuals to go to location '1', '2' and '3', respectively (Figure 3C). Increasing the number
337 of randomly tagged individuals from 5 to 50, and repeating this procedure 10,000 times,
338 showed that accurate detection of movements to location '3' was only possible at the higher
339 number of tags (n ~ 40). Moreover, precision around the percentage of the population

340 travelling to each location increased with increasing numbers of tag deployments. In our
341 example, 95% confidence intervals for the percentage of the population travelling to '1'
342 narrowed from between 61.0 – 69.1 % to between 64.1 – 66.0 % as sample size increased
343 from 1 to 40 tags, with similar reductions obtained for the other locations. As we have
344 demonstrated, power-analysis needs some understanding of the system to allow the model to
345 be parameterised, and can be used to assess if there is further information likely to be
346 obtained by tagging more individuals. However, it is important to highlight that simulation
347 results only provide an idea of how many representative tracks are needed and do not account
348 for the excess tags needed to account for potential problems with data acquisition, such as
349 early tag failure or loss prior to exhaustion of battery, as mentioned earlier. So, interpretation
350 of the results presented above are that little further detail would be gained after obtaining
351 more than 40 representative tracks to answer a specific question about dispersal patterns.
352 However, new and different questions may emerge to justify further tag deployments.
353 Examples would include the need to assess inter-annual variability in movements or to
354 address tagging sampling design to adjust not only for sample size but also sex ratio of
355 animals tagged, size range, or range of capture and release sites.

356 As sample size increases, improved evaluation of the use of marine protected areas (MPAs)
357 also becomes possible. Although the following studies provide only examples of detected
358 patterns for the sample size used, what is crucial here is that having a large enough sample
359 size across different seasons, sites or stages (e.g., breeding *versus* non-breeding) allows
360 detection of gradients across other variables of interest including environmental variables for
361 habitat use detection. For example, acoustic tagging of 57 sharks showed that only half of the
362 available protected space was used while sharks made excursions in and out of MPAs at
363 consistent locations along the boundaries (Knip et al. 2012). Deployment of multiple tens of
364 tags (simultaneous or staggered in time) can therefore, provide insight into the scale of
365 spatio-temporal movements to assist tailoring MPA design for improved effectiveness.
366 Similarly, tens of tags can assist the assessment of movement variability driven by changes in
367 environmental conditions. For example, behavioural changes by 32 fur seals were associated
368 with strong El Niño conditions (Lea et al. 2006), movement of 40 bonnethead sharks
369 (*Sphyrna tiburo*) changed in association with decreased salinity due to freshwater discharge
370 (Ubeda et al. 2009), and foraging success of 50 little penguins (*Eudyptula minor*) was shown
371 to relate to boundary current anomalies in different years (Carroll et al. 2016). Detection of
372 philopatry in highly migratory species has also been possible when using a sample size of
373 tens of tags. Jorgensen *et al.* (2010) showed high philopatry in the migratory behaviour of
374 white sharks based on the results from 68 satellite-linked tags and revealed a predictive
375 migratory cycle within the same network of coastal hotspots for a genetically distinct
376 population. The larger sample sizes used in these examples enabled researchers to claim that
377 their results were representative of the wider population of these species.

378 Although an individual study might include only a few tags, sample sizes in the 10's (and
379 greater) can be obtained by pooling data across studies, allowing researchers to pose new
380 questions and search for general patterns. For example, the compilation of eight studies with
381 low individual sample sizes (1 – 13 summing to 50 tags) across the Mediterranean Sea and
382 the Pacific, Atlantic and Indian oceans confirmed previous concerns of high sea turtle
383 mortalities by fisheries (Hays et al. 2003). The same applies for multispecies studies, where
384 even low sample sizes for individuals of different species pooled together allow some level of
385 inter-species comparisons. For example, informed comparison of vertical movement patterns
386 and their statistical properties across taxa were obtained with data from 31 individuals from
387 seven species (Sims et al. 2008). While the sample size of the later study was relatively small,
388 the high resolution of the diving data contained in the tracks, which included over one million
389 data points, allow for a comparative multispecies analysis.

390

391 Defining population parameters (sample sizes approximately 100)

392 With the implicit assumption that each tag results in an appropriate amount of data (e.g.,
393 number of locations and enough resolution), improved accuracy in our understanding of
394 patterns (e.g., space use) can be obtained using a larger number of tagged animals (see
395 examples of northern elephant seals and salmon sharks, *Lamna ditropis*, in Figure 4A). As
396 sample sizes approach 100, it becomes possible to assess movement behaviour between
397 populations of the same species and across large areas. For example, 101 tracks of
398 leatherback turtles were used to define areas of high susceptibility to by-catch across the
399 Atlantic Ocean (Fossette et al. 2014). In this example, a large sample size was necessary to
400 encompass a range of different nesting populations, all of which foraged within the Atlantic.
401 Likewise, Breed *et al.* (2006) investigated segregation of seasonal foraging habitats of grey
402 seals from 95 tagged individuals. In cases where sex or age leads to segregated behaviour, the
403 number of tags needed to detect specific patterns of movement will necessarily be inflated to
404 identify potential behavioural mechanisms, and more so if a comparison across populations is
405 to be completed. As the spatial scale under consideration increases, so too does the minimum
406 number of tags, until even sample sizes of 100 may be insufficient. For example, when
407 Sequeira *et al.* (2013) compiled all publicly available tracking data for whale sharks, they
408 found that the existing ~100 tracks (average 90 d deployment with a range from hours to > 3
409 years) were insufficient to reveal global migration patterns.

410 Assessment of animal health and increasing anthropogenic impacts on movement is also
411 highly relevant and urgently sought for many species. For example, data from 136 West
412 Indian manatees was used to assess rehabilitation success following release (Adimey et al.
413 2016). However, the large sample sizes needed for assessing effects at the species-level are
414 not commonly available (but see Fossette et al. 2014), and pooling data across species of the
415 same guild might provide the means to obtain relevant information. This was the case for a
416 dataset of 113 oceanic sharks examined to detect spatial overlap with commercial fisheries.
417 This dataset comprised tracks from 6 species (average of 17 tags per species) and led to the
418 revelation that shark hotspots in the North Atlantic Ocean may be at risk from overfishing
419 (Queiroz et al. 2016). Similarly, passive acoustic tracking of 116 reef sharks of five species
420 (average of 17 tags per species) together with 25 hawksbill turtles (*Eretmochelys imbricata*)
421 determined the long-term, fine-scale space use inside and outside a marine protected area
422 (MPA) for each species. This study also revealed that a modest increase in MPA size could
423 lead to a 34% increase in spatial coverage of these predator's movements (Lea et al. 2016).
424

425 Moving toward big data analysis (very large sample sizes; >> 100)

426 Common areas of space use at large spatial scales can be revealed using a large number of
427 tagged individuals (>> 100). For example, Wakefield *et al.* (2013) used tracking data of 184
428 northern gannets from different breeding areas to assess the levels of foraging area overlap
429 around the British Isles. A much larger tracking dataset of 287 individual elephant seals led to
430 an improved understanding of how these seals utilise the circumpolar habitat in the Southern
431 Ocean (Hindell et al. 2016). Large datasets also allow application of *big data* approaches,
432 which are scalable to very large numbers of tracks (e.g., as used in human mobility studies).
433 A recent example of the application of such approaches to tracking data of 272 southern
434 elephant seals showed that, despite idiosyncrasies in movement, a clear signature of directed
435 movement emerged, highlighting the presence of intrinsic drivers of movement such as
436 memory (Rodriguez et al. 2017). In addition, samples size in the hundreds can reveal
437 correlated or coordinated movement patterns among individuals. An example is the coherent
438 movement patterns suggested by the *sonification* of movement (i.e., the generation of sound
439 based on the movement patterns in the tracking data) of over 300 northern elephant seals

440 tagged over ~ 10 years in the Northeast Pacific Ocean (Duarte et al. 2018). These studies
441 show that the use of techniques that can deal with big data (Leek et al. 2017) might bring new
442 insights to movement ecology.

443 Very large sample sizes of single species can also be useful to increase the probability of
444 defining events not commonly detected using tags, such as colonization of a new site or
445 mortality (Hays et al. 2003). To illustrate this point, we extended the simulation exercise
446 presented above to consider how many tags would be needed to detect a rare event with a
447 probability of 0.001 and showed that hundreds of tags would be required (Figure 3E).

448 For multiple species, the quantity of information returned climbs dramatically as sample
449 size increases to many hundreds, particularly for assessing movement patterns in response to
450 resource fields within the same geographical extent. For example, in east Antarctica, a
451 compilation of 268 satellite tracks for six top predators including penguins, albatrosses and
452 seals revealed areas of particular ecological significance for these multiple species (Raymond
453 et al. 2015). Maxwell *et al.* (2013) used tracks from 685 individuals of eight species in the
454 North Pacific, to show high variability in the distribution of cumulative impacts across
455 species and highlight that effective spatial management will need to account for trade-offs
456 among stressors. These individuals had been tagged as part of the Tagging of Pacific
457 Predators (TOPP) project, a much larger collaborative effort under the Census of Marine Life
458 field programme, which led to the deployment of an unprecedented number of tags (4,300).
459 Of these, 1791 tracks were used in a single study to assess space use by multiple predatory
460 species in the Pacific Ocean highlighting hotspots, migration pathways, and niche
461 partitioning among species (Block et al. 2011), and was used to predict how climate change
462 will affect the available habitat for different species (Hazen et al. 2013). Another subset of
463 1,648 tracks representing 14 species was also used to show annual patterns of movements
464 through the high seas and across geopolitical boundaries in the Pacific Ocean (Harrison et al.
465 2018). Most recently, the coastal movements of 2181 individuals from 92 species including
466 fish, sharks, turtles and marine mammals were used to identify four distinct functional
467 movement classes in the coastal waters of Australia, with these classes emerging only
468 through aggregating data across the entire dataset (Brodie et al. 2018). Finally, the Marine
469 Megafauna Movement Analytical Program (MMMAP, mmap.wordpress.com) used > 2,500
470 individual tracks across 50 species of marine vertebrates including whales, sharks, seals,
471 seabirds, polar bears, sirenians, and turtles, to show that, unlike terrestrial animals, movement
472 patterns in marine animals are strongly conserved across species regardless of evolutionary
473 history, with movements being more complex in the coastal than in the open ocean (Sequeira
474 et al. 2018). As these large aggregated datasets increase further in size, their temporal and
475 spatial coverage may become sufficient to retrospectively detect signals of climate change or
476 other perturbations in the movement patterns of component species (Weimerskirch et al.
477 2012).

478 In the last decade, many tens of thousands of tags have been deployed on animals, and if
479 shared, the resulting datasets will allow for powerful analysis at large spatio-temporal scales
480 (Thums et al. 2018a). Such datasets can assist in answering topical questions (Hays et al.
481 2016), refine conservation benefits (Allen and Singh 2016), and facilitate the use of big data
482 approaches to enhance our understanding of animal movements (Meekan et al. 2017,
483 Rodriguez et al. 2017). The advantages of data sharing for researchers are clear (Nguyen et
484 al. 2017), and well-recognised in some fields of scientific inquiry such as molecular ecology
485 and physical oceanography (ncbi.nlm.nih.gov/genbank; aoml.noaa.gov/envids/gld).
486 Encouragingly, some tracking programs already have some type of open data policy, and a
487 large range of online repositories are now available (Campbell et al. 2016), including:
488 Zoatrack (Dwyer et al. 2015), Movebank (movebank.org), the Integrated Marine Observing
489 System (IMOS; imos.org.au), and the Ocean Tracking Network (OTN;

490 oceantrackingnetwork.org). The increasing use of telemetry technology also supports
491 unprecedented opportunities for collaboration among researchers studying different species.
492 By combining satellite tracking with acoustic detection and making relatively minor
493 compromises on equipment sampling parameters (i.e., scanning range of tag frequencies and
494 using collaborative acoustic monitoring arrays), there is potential for researchers to expand
495 the spatial and temporal range of tracking efforts and collect data for multiple species
496 simultaneously (Lidgard et al. 2014, Aven et al. 2015). The big, but heterogeneous data
497 acquired by pooling datasets from a variety of sources will present a challenge for analysis,
498 data visualization and storage. Ways to overcome such challenges have already been
499 addressed in other disciplines. For example, studies of human mobility interrogate massive
500 and rapidly-growing databases of geolocations available from smart phones and internet
501 records, which describe the movements of humans (Gonzalez et al. 2008). Although such
502 studies focus on a single species (humans; *Homo sapiens*), they have shown the power of data
503 encompassing tens of thousands of individuals to address questions associated with collective
504 responses and with processes occurring at the population level. Great examples include the
505 study of epidemics (see gleamviz.org), transmission of culture or mood (Mocanu et al. 2013),
506 or the development of models describing mobility patterns (e.g., radiation model; Simini et
507 al. 2012).

508

509 **Conclusion**

510 The answer to “how many animals should be tracked?” is intrinsically dependent on the
511 species of interest, on the tagging methods used, and – primarily – on the question that needs
512 to be addressed, including spatial and temporal coverage (see examples in Table 1). We
513 suggest that tracking studies usually develop in stages, including (i) an initial phase of
514 ‘innovation and discovery’ that commonly involves small sample sizes ($N \leq 10$), through to
515 (ii) a stage of ‘confirmation and consolidation’ of results with intermediate sample sizes (10
516 $< N \leq 100$), and lastly to (iii) more synthetic, overarching, and inter-disciplinary studies for
517 larger sample sizes ($N \gg 100$). At each stage, the impact of the sample size on the key
518 conclusions can be assessed (e.g. the proportion of individuals travelling to different sites)
519 and the outcomes of this assessment can be used to objectively plan how the sample size
520 needs to be increased to answer different questions with the required level of confidence. As
521 sample size increases, both in relation to the number of individuals tracked and the length of
522 individual tracks, there is improved ability to resolve a range of questions associated with
523 movement, such as home-range estimates, migration patterns including identification of high-
524 use corridors, migration distance and variability in destinations, and foraging search patterns.
525 How large a sample size is needed to resolve these various movement components to a
526 certain level of confidence will depend on the extent of individual variability and on the
527 behaviour of the species being tracked.

528 We caution that the same given number of tags can also lead to very different data
529 depending on when the tags are deployed and the duration of the tag deployment. For
530 example, for pinnipeds, tagging the individuals close to molting may result in a track of very
531 short duration with the tag coming off before its battery is exhausted, while post-molt
532 deployments will likely result in eight to nine months of tracking data (Treasure et al. 2017).
533 For species that display different seasonal movement patterns, such as sirenians, differences
534 in the data obtained with the same sample sizes can vary as much as detection of little
535 movement in the peaks of summer or winter, to hundreds of kms of movement being captured
536 in spring and fall (Aven et al. 2016). In the latter example, if a tag continues to function for 9-
537 10 months, both high resolution local data and wider regional habitat use can be obtained. In
538 such cases, the timing and duration of a small number of tags may yield more or better
539 information than larger sample sizes deployed at the wrong time. Moreover, as variability

540 increases, so too will the sample size needed to resolve research questions. Similarly,
541 variability has implications in studies pooling datasets across species and aiming to make
542 inferences on comparisons across groups. In such cases, the number of individuals
543 representing each specific group will affect the high-level inferences that can be made based
544 on the pooled datasets. Comparing changes in space use over time is only as powerful as the
545 smallest within-year group size, however, pooled datasets are generally useful to draw
546 conclusions across groups.

547 We suggest that the planning of a tracking study should include a thorough search of the
548 published literature where similar questions have been addressed (even if for other species).
549 For example, studies provided in Table 1 show the types of questions that have been asked
550 for species of different guilds with increasing sample size, and can be used as guide for
551 minimum numbers required by future studies. If prior information is available for the specific
552 study species, then the use of simulation exercises similar to those presented in Figure 3 and
553 Figure 4 (refer to code made available in SI) can be informative. Also, when estimating
554 utilisation areas and kernel densities, a full evaluation of sensitivity to sample size should be
555 carried out and results should be reported with the confidence estimates (Figure 4).

556 It is often not possible to do *a priori* assessments of the importance of sample size as the
557 various tracking outcomes are not known. In such cases, we suggest that the question to be
558 addressed is explicitly defined so it becomes clear in which phase of research the question
559 falls, i.e., ‘innovation and discovery’, ‘confirmation or consolidation’, or ‘synthetic,
560 overarching, inter-disciplinary approach’. Depending on the phase, the relative sample size
561 (small, intermediate or large) becomes easier to estimate. Once this target sample size has
562 been identified, then it becomes useful to consult Table 1 to have an idea of the types of
563 questions that have been addressed with specific sample sizes for different taxa. Generally,
564 within each phase, the largest logistically feasible sample size should be employed, within
565 ethical and logistical constraints. This is because larger sample sizes will provide greater
566 confidence in species or population level inferences. However, sample sizes will necessarily
567 be lower for rare or cryptic species, small or critically endangered populations, and when
568 tagging may be too disruptive. The number of individuals tagged within populations, the
569 amount and resolution of data, as well as, their accuracy also impact the types of questions
570 that can be addressed. Therefore, in addition to the practical limitations in sample size in such
571 situations, there will also be financial and research scope limitations.

572 Recent advances made in the field of telemetry and bio-logging have led to an exponential
573 increase in satellite telemetry studies (Thums et al. 2018a), with very large sample size (>>
574 1000 tracks) recently starting to appear in the literature (e.g., Block et al. 2011, Brodie et al.
575 2018, Sequeira et al. 2018). In spite of that, a sample size of one with sufficient track length
576 can still lead to scientific insights. This is particularly relevant for species that have never
577 been tracked before, when previous deployments have not been successful, or when testing
578 new sensors (Lennox et al. 2017). In such situations, and where the current knowledge of a
579 species’ movement is still in its infancy, any new insights from small sample sizes have the
580 potential to significantly advance knowledge. In contrast, for species where tracking is well
581 established (e.g., some seals or turtles and seabirds), the questions relating to population
582 densities, biologically important areas, population structure or social networking will require
583 tracks of many individuals, or can be addressed by retrospective analysis after combining
584 existing data across studies and including multiple researchers. Clearly, there are many
585 challenges to statistically estimate an appropriate sample size for telemetry studies across the
586 many and varied contexts. Our review highlights these challenges and provides
587 recommendations based on examples and data simulations to assist in decision making.

588

589 **Acknowledgements**

590 GCH conceived the study and a first draft was compiled by AMMS, GCH, MH, M-AL, VME
591 at a workshop organized by MT, AMMS, CMD, MGM, and VME. AMMS and GCH led the
592 writing of the manuscript. AMMS, GCH, A-LH and HJC prepared the figures. All authors
593 contributed to the manuscript and commented on drafts. AMMS was supported by an ARC
594 Grant (DE170100841), and HJC by an Australian Government RTP scholarship at UWA.
595 Workshop funding was granted to MT, AMMS, and CMD by the UWA Oceans Institute, the
596 Australian Institute of Marine Science, and the Office of Sponsored Research at King
597 Abdullah University of Science and Technology (KAUST). We thank F Bailleul, S
598 Goldsworthy, M Hindell and all other workshop attendees for initial discussions.
599

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Table 1: Summary of examples of information that has been captured using different sample sizes of tags (N) for seabirds, sharks, turtles, 943 and pinnipeds, highlighting the types of questions that have been answered with different sample sizes.

Table 1: Summary of examples of information that has been captured using different sample sizes of tags (N) for seabirds, sharks, turtles, and pinnipeds, highlighting the types of questions that can be answered with different sample sizes.

Question	Birds	Sharks	Turtles	Pinnipeds
N = 1				
<ul style="list-style-type: none"> • Provide proof-of-concept of methodology • Discovery of new behaviours 		<ul style="list-style-type: none"> • Demonstrated feasibility of satellite-based monitoring of movements of basking sharks (Priede 1984) 	<ul style="list-style-type: none"> • Detected >1000 km trip for leatherback turtles (Hughes et al. 1998) • Demonstrated the potential eco-physiological capacity (aerobic limits) for loggerhead turtles (Hochscheid et al. 2005) • Revealed link between swimming effort to depth-dependent, air-mediated buoyancy and swim angle (Hays et al. 2004c) 	<ul style="list-style-type: none"> • Proved that elephant seals could act as samplers of the environment providing an 8-month CTD hydrographic profile that allowed an assessment of the seasonal evolution of the upper ocean (Meredith et al. 2011) • First free ranging heart rate recorded for an adult female southern elephant seal during the post-breeding migration (Hindell and Lea 1998)
N <= 10				
<p>Initial insights into:</p> <ul style="list-style-type: none"> - Individual variability 	<ul style="list-style-type: none"> • Revealed wandering albatrosses travel thousands of km in 	<ul style="list-style-type: none"> • Revealed that basking sharks exhibited extensive horizontal and 	<ul style="list-style-type: none"> • Recorded the first dive profiles outside the nesting season based on 	<ul style="list-style-type: none"> • Revealed the vertical distribution of southern elephant seal's prey is

<ul style="list-style-type: none"> - scale of movements - drivers of movement 	<p>foraging trips during an incubation shift (Jouventin and Weimerskirch 1990)</p>	<p>vertical movements during winter rather than hibernating (Sims et al. 2003)</p> <ul style="list-style-type: none"> • Provided evidence for reverse diel vertical migration in basking sharks (Sims et al. 2005) • Revealed diel vertical migration for 10 individuals (Sims et al. 2006) 	<p>3 individuals (Hays et al. 2004a)</p> <ul style="list-style-type: none"> • Revealed that 9 individuals all moved in disparate directions in the Atlantic Ocean (Hays et al. 2004b) 	<p>tightly related to light-level (Jaud et al. 2012)</p> <ul style="list-style-type: none"> • Identified three distinct foraging patterns for Galapagos sea lions (Villegas-Amtmann et al. 2008)
<p>Generate hypotheses</p>				
<p><i>10 < N < 100</i></p>				
<ul style="list-style-type: none"> • Estimate space-use • Characterise spatio-temporal patterns • Identify specific behaviours (e.g., sex and age differences) 	<ul style="list-style-type: none"> • Defined space use for albatrosses (Gutowsky et al. 2015), shags and kittiwakes (Soanes et al. 2013) • Showed that foraging success of penguins relates to boundary current anomalies in different years (Carroll et al. 2016) 	<ul style="list-style-type: none"> • Used to quantify the annual space-use patterns of basking sharks within political-economic zones in the north-east Atlantic • Demonstrated that basking sharks seasonally migrate to mesopelagic tropical waters • Confirmed that the species does not travel long distance (based on 12 individuals) 	<ul style="list-style-type: none"> • Used to assess spatio-temporal foraging patterns in the Northern Atlantic based on 21 turtles (Fossette et al. 2010) • Calculated the area used by flatback turtles while nesting (Thums et al. 2018b) • Identified the probability of individual turtles using disparate foraging areas across the Mediterranean (Schofield et al. 2013) 	<ul style="list-style-type: none"> • Used to estimate the extent of movements and spatio-temporal habitat use for weaner southern elephant seals (McConnell et al. 2002) • Revealed diving behaviour showing maximum dive durations of 109 minutes (22.3 min ± 4.6 SD and 312 m ± 117 (SD) with a maximum depth of 1380 m) for northern elephant seals (Le Boeuf et al. 2000)

	(Rodriguez-Cabello et al. 1998)	• Revealed pronounced philopatry of female basking sharks (Sims 2003) and of white sharks Jorgensen <i>et al.</i> (2010)	• Confirmed high mortalities of sea turtles by fisheries (Hays et al. 2003)	• Identified the water bodies in the Southern Ocean where elephant seals improved their body condition (Biuw et al. 2007)
<i>N ~ 100 or >> 100</i>				
<ul style="list-style-type: none"> • Quantify habitat use over large spatial scales • Assess shifts in space use with time, among sub-populations or with gender, age class and period (e.g., breeding cycles) • Estimate susceptibility to interactions with human activities 	<ul style="list-style-type: none"> • Assessed the levels of foraging area overlap for northern gannets from different breeding areas Wakefield <i>et al.</i>, (2013) • 	<ul style="list-style-type: none"> • Revealed that oceanic shark hotspots may be at risk from overfishing (Queiroz et al. 2016) 	<ul style="list-style-type: none"> • Used to define areas of high susceptibility for fisheries by-catch at the scale of the Atlantic Ocean based on 106 tracks (Fossette et al. 2014) 	<ul style="list-style-type: none"> • Led to a better understanding of how seals use the circumpolar habitat in the Southern Ocean based on 287 seals (Hindell et al. 2016). • Allowed application of big data approaches to show memory as an intrinsic driver of movement for southern elephant seals (Rodríguez et al. 2017) • Reveal correlated or coordinated movements from a 10-year movement dataset of northern elephant seals suggested through

**• Allow multispecies
assessments at large
spatial scales**

sonification (Duarte et al.
2018)

- Revealed areas of particular ecological significance for these multiple species (Raymond et al. 2015)
 - Showed high variability in the distribution of cumulative impacts across multiple species Maxwell *et al.* (2013)
 - Highlighted hotspots, migration pathways, and niche partitioning among multiple species in the Pacific Ocean (Block et al. 2011)
 - Showed that movement patterns in marine animals are strongly conserved across species regardless of evolutionary history (Sequeira et al. 2018)
-

945 **Figure legends**

946 Figure 1: Across a broad range of species and habitats, electronic tags are used to assess
947 patterns of animal movement. Across studies a prevailing question is “how many animals
948 need to be tagged?” To illustrate the breadth of tracking studies (a) shows an ocean sunfish
949 (*Mola mola*) fitted with a satellite tag, (b) a jellyfish (*Rhizostoma octopus*) equipped with a
950 time-depth recorder, (c) a hatchling green turtle (*Chelonia mydas*) equipped with a miniature
951 acoustic tag, (d) a juvenile loggerhead sea turtle (*Caretta caretta*) equipped with an Argos
952 satellite tag, (e) a ruddy turnstone (*Arenaria interpres*) equipped with a light-based
953 geolocator tag on its leg, (f) a harbor seal (*Phoca vitulina*) with a “mobile phone tag” that
954 relays Fastloc-GPS locations via the mobile phone network. In each panel the scale bar is 10
955 cm. Photographs courtesy of Graeme Hays, Gower Coast Adventures, Joan Costa, George
956 Balazs, Erik Kleyheeg and Paul Thompson.

957

958 Figure 2: Examples of tracking studies using various sample sizes to understand different
959 animal movement and behaviours. A) Track of a great white shark showing a transoceanic
960 migration from South Africa to north-western Australia (adapted from Bonfil et al. 2005); B)
961 Track from a leatherback turtle revealing that the species was able to travel > 1000s of km
962 (adapted from Hughes et al. 1998); C) Tracked movement of eight green turtles equipped off
963 Diego Garcia, Chagos, used to evaluate effectiveness of marine protected areas in the region
964 (adapted from Hays et al. 2014b); D) Movements of grey reef sharks in the Great Barrier
965 Reef, Australia, showing site fidelity to single reefs (adapted from Heupel et al. 2010); E)
966 Comparison of vertical movement patterns across taxa showing levy-like scaling laws
967 (adapted from Sims et al. 2008); F) Satellite tag location estimates from great white sharks
968 tagged along the central California coast, showing patterns of site fidelity and seasonal
969 variations in movements (adapted from Jorgensen et al. 2010); G) Habitat use patterns of
970 pelagic sharks in the North Atlantic Ocean, used to examine key areas of spatial overlap with
971 longline fisheries (adapted from Queiroz et al. 2016); H) Networks of species-specific
972 detections obtained from passive acoustic tracking of blacktip reef sharks, used to evaluate
973 and subsequently update a marine protected area in the Seychelles (adapted from Lea et al.
974 2016); I) Trajectories obtained for 272 southern elephant seals (left) and resulting occupancy
975 map (right), used to identify movement patterns that indicated memory may play a role in the
976 movement patterns of this species (adapted from Rodriguez et al. 2017); J) Global map of
977 tracking dataset used to quantify the movement patterns of > 50 marine vertebrate species,
978 showing movement patterns are strongly conserved across species and vary based on the
979 habitats the animals move through (adapted from Sequeira et al. 2018).

980

981 Figure 3: Simulation examples to understand the effects of sample of size when addressing
982 different key questions for the same guild (i.e., turtles). A) Probability of finding differences
983 in breeding periodicity of loggerhead turtles by simulating the number of males and females
984 that would be recorded to return after 1 year and then testing if there is a significant
985 difference ($p < 0.05$) in the numbers of returning males and females for increasing sample
986 sizes up to 10 individuals. B) Standard deviation of the estimate for mean clutch frequency
987 for green turtles reflecting the variation that might be recorded for the mean estimate with
988 different samples sizes. C) Percentage of individuals perceived to travel to locations ‘1’, ‘2’
989 and ‘3’ shown in the schematic representation displayed in the centre of the figure as the
990 number of tags deployed increases from 5 to 40. The central scheme depicts movement
991 dispersion and probabilities of detection of dispersion to different locations and detection of a
992 rare event, with arrow width proportional to probability of dispersion from the tagging
993 location X to each of the locations ‘1’, ‘2’ and ‘3’ (0.65, 0.30, and 0.05) for a population of

994 100 individuals. D) Percentage of the population expected to travel to each of the locations A,
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995 B and C depicted in the central scheme showing a decrease in the confidence intervals as the
996 number of tags increases. E) Representation of the confidence intervals for detection of
997 possible rare events such as colonization of a new site.

998

999 Figure 4: Effects of sample size on estimates of utilisation area at core probability contours
1000 (50%, and 25%) as function of sample size for six marine predator species. Bootstrapped
1001 estimates of area (100,000 km²) as a function of sample size (number of individuals tracked)
1002 of the 50% (light blue) and 25% (dark blue) contours of population utilization distributions
1003 calculated for electronically tracked marine animals. A) Estimates for five migratory marine
1004 predators for the month of September pooled across years (2002-2009; available sample sizes
1005 varied across species). B) Monthly estimates for white shark (pooled across years, 2000-
1006 2007, available sample sizes varied across months). Circles represent mean values and lines
1007 represent standard deviations. Adapted from Harrison (2012) using data from the Tagging of
1008 Pacific Predators project (Block et al. 2011). The evaluated dataset consisted of 604
1009 individual tracks and sample sizes varied across species (12 to 231 individuals) and across
1010 months (1 to 114 individuals). Plots show means and standard deviation of home range area,
1011 with mean estimates initially increasing as a function of the number of individuals tracked
1012 (the home range area of one individual is likely much smaller than the utilization distribution
1013 of 10 individuals). Once most of the variability in the population is captured, the estimate of
1014 space use of the population stabilizes resulting in an asymptote in the plot. Estimates of home
1015 range size approached an asymptote for Northern elephant seals and salmon sharks (species
1016 with datasets 57 to 108 individuals) at sample sizes of 20-40 individuals in most months at all
1017 contour levels. In contrast, for estimates calculated from samples sizes between 10-30
1018 individuals for (A) black-footed albatross, Laysan albatross, sooty shearwater, and Pacific
1019 bluefin tuna that were recorded to undertake their trans-Pacific migration, and (B) white
1020 sharks from June through September), the sample size was insufficient to observe an
1021 asymptote in estimates of utilisation area (especially at the largest probability contours that
1022 would capture rare events). There were also large confidence intervals around the area
1023 estimates for these species' datasets, implying that larger datasets were needed to increase the
1024 precision and accuracy of the estimates.

1025 **Figure 1: Across a broad range of species and habitats, electronic tags are used to assess**
1026 **patterns of animal movement.**

1027 Across studies a prevailing question is “how many animals need to be tagged?”. To illustrate
1028 the breadth of tracking studies (a) shows an ocean sunfish (*Mola mola*) fitted with a satellite
1029 tag, (b) a jellyfish (*Rhizostoma octopus*) equipped with a time-depth recorder, (c) a hatchling
1030 green turtle (*Chelonia mydas*) equipped with a miniature acoustic tag, (d) a juvenile
1031 loggerhead sea turtle (*Caretta caretta*) equipped with an Argos satellite tag, (e) a ruddy
1032 turnstone (*Arenaria interpres*) equipped with a light-based geolocator tag on its leg, (f) a
1033 harbor seal (*Phoca vitulina*) with a “mobile phone tag” that relays Fastloc-GPS locations via
1034 the mobile phone network. In each panel the scale bar is 10 cm. Photographs courtesy of
1035 Graeme Hays, Gower Coast Adventures, Joan Costa, George Balazs, Erik Kleyheeg and Paul
1036 Thompson.

1038 **Figure 2: Examples of tracking studies using various sample sizes to understand different**
1039 **animal movement and behaviours**

1040 A) Track of a great white shark showing a transoceanic migration from South Africa to north-
1041 western Australia (adapted from Bonfil et al. 2005); B) Track from a leatherback turtle

1042 revealing that the species was able to travel > 1000s of km (adapted from Hughes et al.
1043 1998); C) Tracked movement of eight green turtles equipped off Diego Garcia, Chagos, used
1044 to evaluate effectiveness of marine protected areas in the region (adapted from Hays et al.
1045 2014b); D) Movements of grey reef sharks in the Great Barrier Reef, Australia, showing site
1046 fidelity to single reefs (adapted from Heupel et al. 2010); E) Comparison of vertical
1047 movement patterns across taxa showing levy-like scaling laws (adapted from Sims et al.
1048 2008); F) Satellite tag location estimates from great white sharks tagged along the central
1049 California coast, showing patterns of site fidelity and seasonal variations in movements
1050 (adapted from Jorgensen et al. 2010); G) Habitat use patterns of pelagic sharks in the North
1051 Atlantic ocean, used to examine key areas of spatial overlap with longline fisheries (adapted
1052 from Queiroz et al. 2016); H) Networks of species-specific detections obtained from passive
1053 acoustic tracking of blacktip reef sharks, used to evaluate and subsequently update a marine
1054 protected area in the Seychelles (adapted from Lea et al. 2016); I) Trajectories obtained for
1055 272 southern elephant seals (left) and resulting occupancy map (right), used to identify
1056 movement patterns that indicated memory may play a role in the movement patterns of this
1057 species (adapted from Rodriguez et al. 2017); J) Global map of tracking dataset used to
1058 quantify the movement patterns of > 50 marine vertebrate species, showing movement
1059 patterns are strongly conserved across species and vary based on the habitats the animals
1060 move through (adapted from Sequeira et al. 2018).

1062 **Figure 3: Simulation examples to understand the effects of sample of size when addressing**
1063 **different key questions for the same guild (i.e., turtles).**

1064 A) Probability of finding differences in breeding periodicity of loggerhead turtles by
1065 simulating the number of males and females that would be recorded to return after 1 year and
1066 then testing if there is a significant difference ($p < 0.05$) in the numbers of returning males
1067 and females for increasing sample sizes up to 10 individuals. B) Standard deviation of the
1068 estimate for mean clutch frequency for green turtles reflecting the variation that might be
1069 recorded for the mean estimate with different samples sizes. C) Percentage of individuals
1070 perceived to travel to locations '1', '2' and '3' shown in the schematic representation
1071 displayed in the centre of the figure as the number of tags deployed increases from 5 to 40.
1072 The central scheme depicts movement dispersion and probabilities of detection of dispersion
1073 to different locations and detection of a rare event, with arrow width a proportional to
1074 probability of dispersion from the tagging location X to each of the locations '1', '2' and '3'
1075 (0.65, 0.30, and 0.05) for a population of 100 individuals. D) Percentage of the population
1076 expected to travel to each of the locations '1', '2' and '3' depicted in the central scheme
1077 showing a decrease in the confidence intervals as the number of tags increases. E)
1078 Representation of the confidence intervals for detection of possible rare events such as
1079 colonization of a new site.

1081 **Figure 4: Effects of sample size on estimates of utilisation area at core probability contours**
1082 **(50%, and 25%) as function of sample size for six marine predator species.**

1083 Bootstrapped estimates of area (100,000 km²) as a function of sample size (number of
1084 individuals tracked) of the 50% (light blue) and 25% (dark blue) contours of population
1085 utilization distributions calculated for electronically tracked marine animals. A) Estimates for
1086 five migratory marine predators for the month of September pooled across years (2002-2009;
1087 available sample sizes varied across species). B) Monthly estimates for white shark (pooled
1088 across years, 2000-2007, available sample sizes varied across months). Circles represent
1089 mean values and lines represent standard deviations. Adapted from Harrison (2012) using
1090 data from the Tagging of Pacific Predators project (Block et al. 2011). The evaluated dataset

1091 consisted of 604 individual tracks and sample sizes varied across species (12 to 231
1092 individuals) and across months (1 to 114 individuals). Plots show means and standard
1093 deviation of home range area, with mean estimates initially increasing as a function of the
1094 number of individuals tracked (the home range area of one individual is likely much smaller
1095 than the utilization distribution of 10 individuals). Once most of the variability in the
1096 population is captured, the estimate of space use of the population stabilizes resulting in an
1097 asymptote in the plot. Estimates of home range size approached an asymptote for Northern
1098 elephant seals and salmon sharks (species with datasets 57 to 108 individuals) at sample sizes
1099 of 20-40 individuals in most months at all contour levels. In contrast, for estimates calculated
1100 from samples sizes between 10-30 individuals for (A) black-footed albatross, Laysan
1101 albatross, sooty shearwater, and Pacific bluefin tuna that were recorded to undertake their
1102 trans-Pacific migration, and (B) white sharks from June through September), the sample size
1103 was insufficient to observe an asymptote in estimates of utilisation area (especially at the
1104 largest probability contours that would capture rare events). There were also large confidence
1105 intervals around the area estimates for these species' datasets, implying that larger datasets
1106 were needed to increase the precision and accuracy of the estimates.
1107

Fig. 1

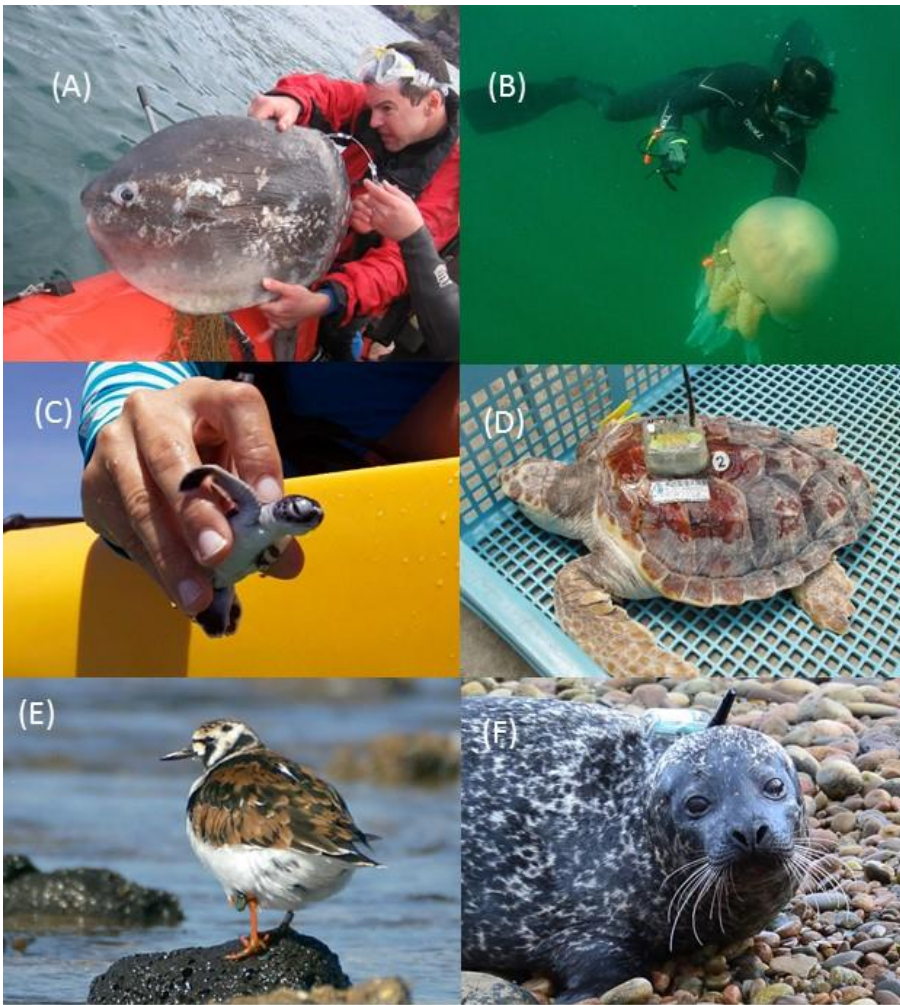


Fig. 2

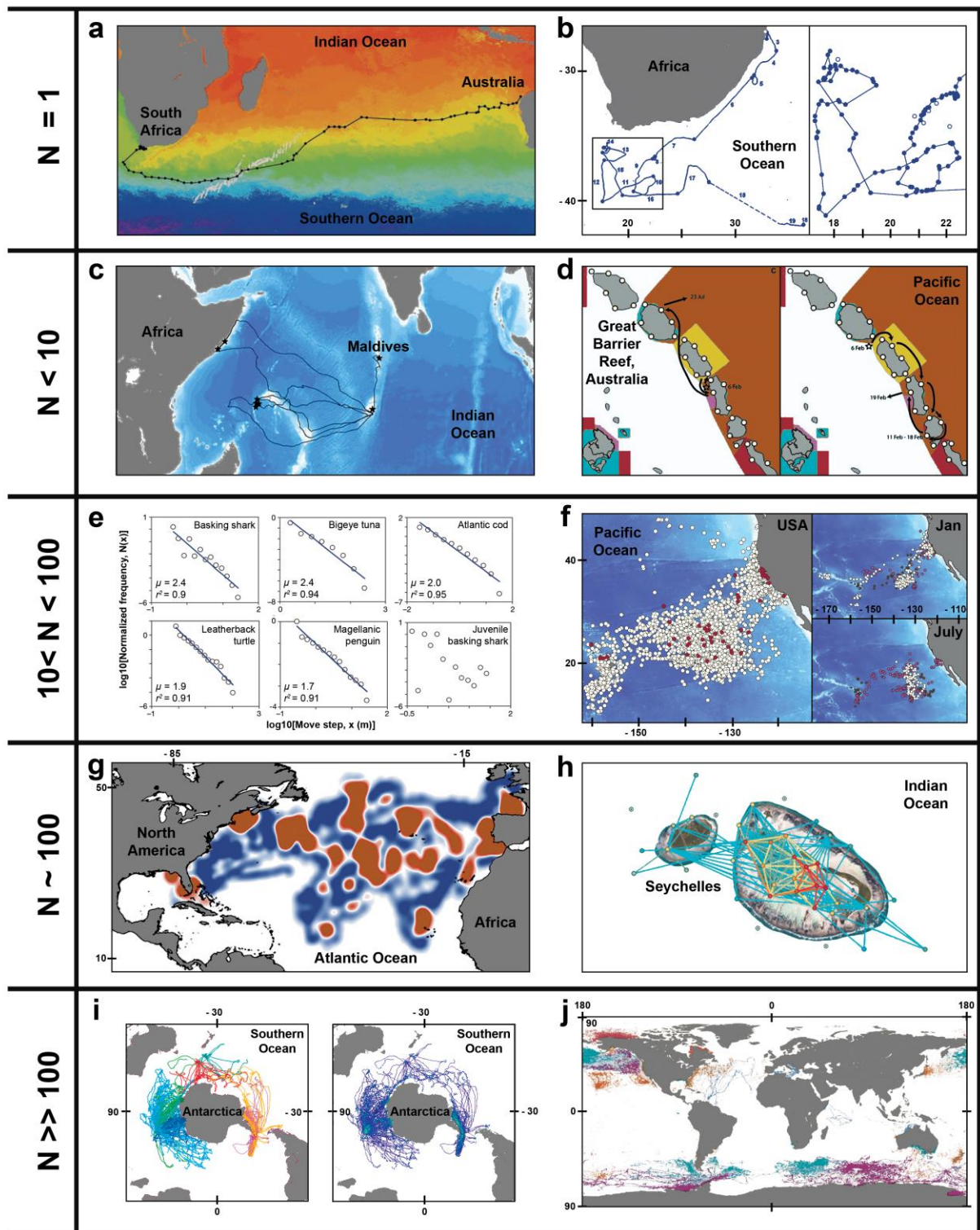


Fig. 3

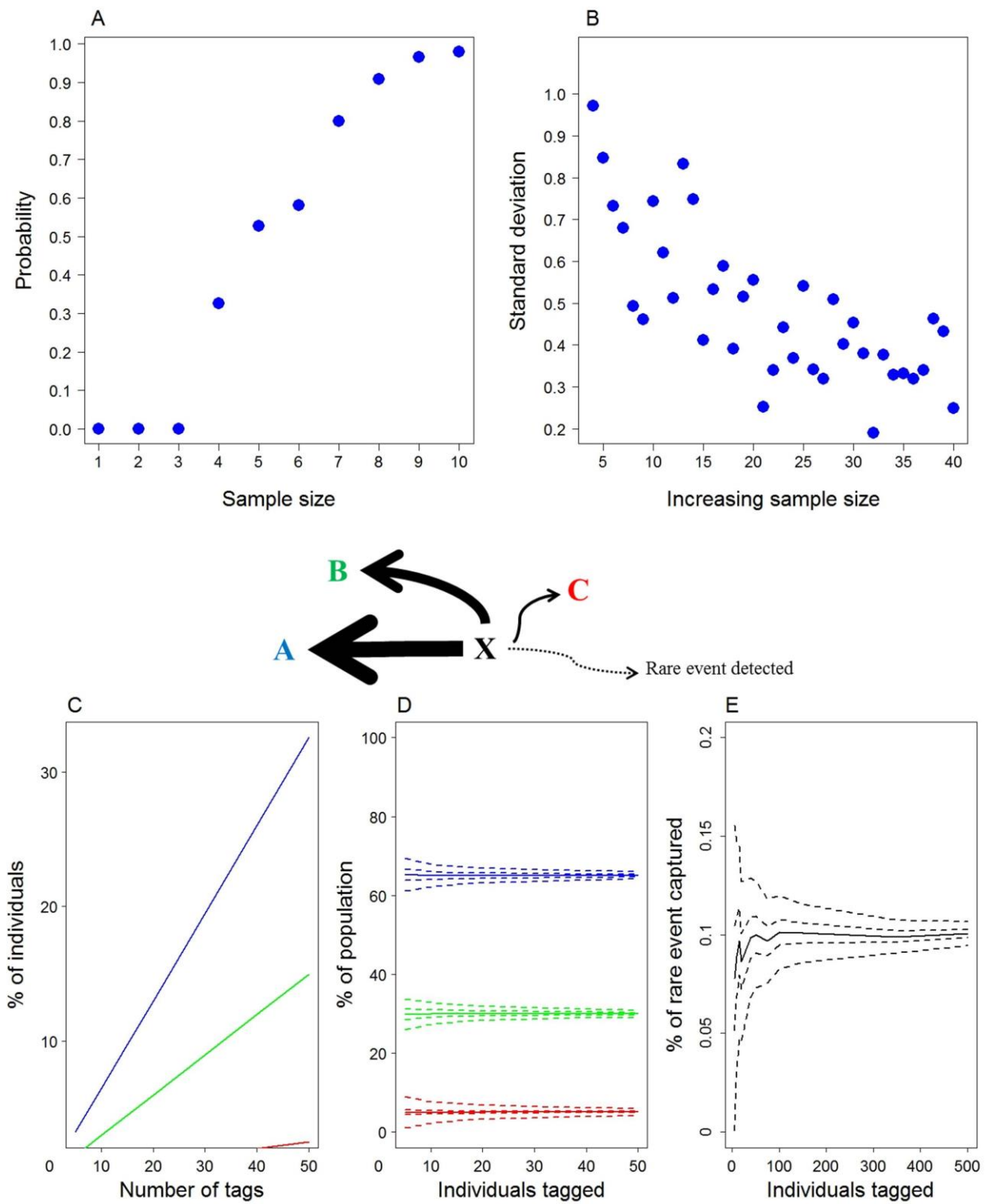


Fig. 4

