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A vision for incorporating human mobility in the study of human–wildlife interactions

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Towards a Dynamic Human Footprint for assessing human-wildlife interactions

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71 Human mobility, Human-wildlife interactions

72
73

74 **Abstract**

75

76 As human activities increasingly shape land- and seascapes, understanding human-wildlife
77 interactions is imperative for preserving biodiversity. Habitats are impacted not only by static
78 modifications, such as roads, buildings and other infrastructure, but also by the dynamic
79 movement of people and their vehicles occurring over shorter time scales. While there is
80 increasing realization that both components of human activity significantly affect wildlife, capturing
81 more dynamic processes in ecological studies has proved challenging. Here, we propose a novel
82 conceptual framework for developing a 'Dynamic Human Footprint', providing a key link between
83 anthropogenic stressors and ecological impacts. Specifically, the Dynamic Human Footprint
84 integrates a range of metrics to fully acknowledge the time-varying nature of human activities and
85 to enable scale-appropriate assessments of their impacts on wildlife behavior, demography, and
86 distributions. We review existing terrestrial and marine human mobility data products and provide
87 a roadmap for how these could be integrated and extended to enable more comprehensive
88 analyses of human impacts on biodiversity in the Anthropocene.

89
90

91 **Introduction**

92

93 More than half of the Earth's surface – 70% on land and 57% at sea – has been substantially
94 altered by human activities¹⁻⁴ driving significant changes in the behavior, distribution and viability
95 of wildlife populations^{5,6}. Despite the negative consequences for biodiversity as a whole, a
96 growing body of evidence suggests that behavioral plasticity and natural selection may enable
97 adaptation to a changing world, even allowing some species to thrive in the Anthropocene^{7,8}. The
98 variable responses of wildlife to anthropogenic stressors indicate that the mechanisms governing
99 human-wildlife interactions and coexistence are complex and context-dependent.

100

101 To study wildlife responses to human activities, ecologists have primarily relied on relatively static
102 proxies, such as measures of land development or human population density⁹⁻¹¹. While useful
103 for many analyses, these datasets fail to capture the more dynamic aspects of human activity

104 ('human mobility'; see ¹²), which may exert additional pressure on wildlife. Dynamic aspects of
105 human activity represent a key link between anthropogenic stressors and ecological impacts, but
106 have yet to be widely adopted in wildlife studies.

107
108 As the COVID-19 pandemic unfolded, researchers started exploring opportunities to leverage
109 human mobility data products to examine how wildlife responded to lockdowns ¹³. Until then, the
110 ecological research community had been largely unaware of advances in measuring human
111 mobility, which were driven by decades of work in other disciplines (e.g., transportation,
112 geography, computer science, physics) and the private sector ¹⁴. The importance of monitoring
113 and managing human movements to stem the spread of COVID-19 (e.g., via social distancing
114 and travel restrictions ¹⁵) spurred some companies to make human mobility data publicly
115 available. This increased data accessibility created exciting opportunities for ecologists to
116 investigate more comprehensively how wildlife is affected by humans – both during and after the
117 COVID-19 anthropause. Human mobility has multiple components ¹². We consider 'human
118 mobility' to encompass the movements of humans and their vehicles (and any associated by-
119 products in the environment), along the full spectrum of spatiotemporal resolutions. This is
120 distinguished from human infrastructure, which encompasses roads, buildings and additional
121 anthropogenic landscape modifications (and their associated by-products). For a schematic
122 overview of key concepts and terminology, please see Figure 1.

123
124 In this contribution we argue that high-resolution human mobility data should be combined with
125 more conventional static measures (e.g., population density and land cover maps) to capture the
126 multidimensional, dynamic nature of human activity, and its complex effects on wildlife. But doing
127 so requires ecologists to understand the accessibility, underpinning, and limitations of human
128 mobility data products. While a handful of recent studies have begun integrating datasets
129 reflecting static and dynamic components of human activity, they have been restricted to local
130 and regional scales ^{16,17}, and their methods are not yet applicable to many other areas across the
131 world, particularly in the Global South.

132
133 Here, we present a new conceptual framework for integrating the static and dynamic components
134 of human activity into a multiscale 'Dynamic Human Footprint'. This extends previous attempts to
135 quantify how humans modify our planet ¹⁸⁻²⁰ by explicitly incorporating the movements of humans
136 and their vehicles. Our framework is 'dynamic' in two senses – first in that it considers time-varying
137 information on human mobility, and second, in terms of allowing flexible data aggregation across
138 a suite of human activities (Fig. 1). We review existing terrestrial and marine human mobility data
139 products that are of relevance to the ecological research community but have not yet been widely
140 adopted (Fig. 2-3, Supplementary Table 1). Using recent empirical examples, we then
141 demonstrate how emerging metrics of human mobility may be integrated into a globally available
142 Dynamic Human Footprint, enabling refined investigations of anthropogenic impacts on wildlife
143 behavior, demography, and distribution. We conclude with a set of recommendations for how the
144 ecological community and other stakeholders can make progress towards integrating a variety of
145 human mobility metrics to achieve a comprehensive analysis of human impacts on biodiversity in
146 the Anthropocene (Fig. 4).

147

148 **Measuring human mobility**

149

150 Here, we outline the major approaches for measuring the dynamic movement of humans and their
151 vehicles. In 2021, mobile phone subscriptions topped 8 billion worldwide, with over 6 billion of
152 those subscriptions registered to smartphones²¹. The proliferation of mobile devices means that
153 we can capture human mobility data across broad spatial and temporal extents in most areas that
154 are inhabited by people. Location data are now commonly collected using mobile phones relying
155 on onboard GPS receivers, or by identifying the network node (WiFi or cellular network tower)
156 they are connected to^{14,22}. Location-based mobile phone services, such as real-time weather,
157 social media, and fitness applications, similarly collect high-resolution location data from their
158 users²³. The spatiotemporal resolution and continuity of these data varies greatly between
159 technologies. While GPS yields precise geographic coordinates, cellular tower networks provide
160 data at spatial resolutions varying from very precise in urban settings to relatively coarse in rural
161 areas, depending on local network coverage. Furthermore, various types of human mobility data
162 vary in their temporal resolution. Data from cellular networks are often more temporally continuous
163 than GPS data collected from smart-phone applications.

164

165 While network and technology companies collect individually identifiable information, they do not
166 typically make raw mobile phone data (publicly) available due to geo-privacy concerns and
167 compliance with national and international regulations (e.g., General Data Protection Regulation
168 of the European Union). Instead, human location data are anonymized, or aggregated to prevent
169 the identification of individuals²⁴. Mobile network data are often aggregated into origin-destination
170 flows, which provide information on how many users moved between two given geographic areas,
171 such as the areas served by two mobile phone towers²⁵. Importantly, the quality of the estimates
172 of human mobility derived from mobile phone data varies based on the number of devices
173 contributing data and therefore becomes less precise in more sparsely populated regions. This is
174 compounded by the fact that access to, and usage of mobile devices varies across the globe²¹
175 and that users of mobile phones, and of different applications, vary geographically and in terms
176 of their socio-demographic characteristics²⁶. Therefore, human location data have inherent
177 spatial, temporal, and socio-demographic biases²⁷.

178 In response to the COVID-19 pandemic, a number of private companies started making large
179 amounts of anonymized human mobility data publicly accessible. Human location data derived
180 from mobile phones have been widely used, for example, to plan and study the impact of
181 government restrictions on human mobility during the pandemic²⁸. Research applications of these
182 data, however, are constrained by fairly rigid data formats (e.g., aggregation or use of fixed
183 reference baseline), which limit the potential for reprocessing²⁹. For example, in the case of
184 Google Mobility products, estimates of human use of 'greenspaces' combine national and local
185 parks into a single index, which may obscure ecological responses. Perhaps most importantly,
186 there is limited clarity on the long-term support of these public products, making research planning
187 difficult and future replication attempts impossible. In some cases, researchers have started
188 working directly with mobile phone network operators to overcome these issues. The European
189 Commission has asked national mobile network providers to release their network data to its Joint
190 Research Centre to build a COVID-19 mobility dashboard³⁰. In general, there is significant scope

191 for strengthening collaboration between the collectors and holders of large human mobility
192 datasets and the wider research community.

193 An alternative to mobile phone-based approaches are data relating to various types of transport.
194 For example, vehicular transportation data have been used during the COVID-19 pandemic to
195 explore changes in flow of vehicular traffic³¹ and cycling behavior, as local authorities provided
196 additional space for recreation³². These types of data are commonly accessible through open
197 data portals housed by local municipalities (e.g.,^{33,34}) or national authorities. The main
198 disadvantage of these datasets is that they are typically collected idiosyncratically at specific
199 locations, most often in urban environments, making them unsuitable for studies in more remote
200 areas or at larger geographic scales (e.g.,³⁵). Other types of human mobility, such as those
201 related to agriculture, forestry and hunting, are either documented through land cover proxies or
202 left uncharacterized.

203 In contrast to the more regional nature of data collection in terrestrial realms, marine traffic is
204 monitored globally by the automatic identification system (AIS) – an anti-collision network that
205 combines transceivers on ships and both *in-situ* and satellite radar receivers to monitor ships'
206 locations. AIS data are available through private companies³⁶ and governmental institutions. For
207 example, European marine data can be requested through the SafeSea net initiative³⁷. These
208 data have been used to study the impacts of vessel traffic, and resultant noise pollution, on wildlife
209³⁸, as patterns of global fishing effort^{39,40}, and the global reduction of marine traffic during the
210 COVID-19 anthropause⁴¹. Marine traffic has also been monitored with nightlight data from VIIRS
211 (Visible Infrared Imaging Radiometer Suite) and VIIRS Boat Detection (VBD) across scales, from
212 individual vessel detections per night to annual summary grids of detection tallies and average
213 radiances⁴². The global scale of marine data that are available at relatively fine spatiotemporal
214 resolution, coupled with its good accessibility, provide ecologists with opportunities for broad-
215 scale analyses that presently are out of reach for terrestrial studies. That said, activities such as
216 recreational fishing cannot currently be assessed at local scales, limiting our understanding of
217 reported increases in recreational marine human activities during the COVID-19 pandemic⁴³.

218 Air traffic can be tracked through data on the total number of flights by FlightRadar24⁴⁴.
219 Additionally, data on passenger flows are available for Europe through the EU Open Data Portal
220⁴⁵, for the US through the International Civil Aviation Organization COVID-19 Air Traffic
221 Dashboard⁴⁶, and for 35,000 city-pairs around the world through the Civil Aviation Data Solutions
222 (iCADS) portal⁴⁷. Air traffic has been severely impacted during the COVID-19 pandemic, with
223 significant reductions in commercial flights^{48,49}.

224 Complementary satellite-sensed data on artificial nightlights and other by-products, such as
225 nitrogen dioxide from fossil fuel combustion, have been used to measure aspects of human
226 activity^{50,51}. For example, artificial nightlights have been used for mapping both vehicles and
227 infrastructure, from maritime traffic to whole cities^{51,52}. However, these products only capture
228 activities that occur at night and produce high-powered lighting, which must be taken into
229 consideration when charting spatiotemporal patterns in human mobility. These data are available
230 directly from⁵³. Daily satellite data on concentrations of various atmospheric gasses have global
231 coverage⁵⁴ and are available from NASA's Earth Data center⁵³ and from the Sentinel 5 Precursor

232 satellite of the European Space Agency (ESA). For example, the TROPOMI sensor on-board of
233 the Sentinel 5P satellite provides measurements of atmospheric gasses, including the most
234 common anthropogenic pollutants, such as NO_x, SO₂, ozone and others⁵⁵. Satellite-recorded
235 nighttime images indicated dimming of light in China⁵¹, and NO₂ data documented decreases in
236 pollution levels across European cities due to COVID-19 related changes in human activity^{42,56}.
237 One obvious limitation of by-product analyses is that it is challenging to estimate the relative
238 contributions of dynamic and static components of human activity, which – as we have argued
239 above – is key for advancing our understanding of ecological impacts.

240 **Towards a Dynamic Human Footprint**

241 In isolation, each of the data types discussed above provide a valuable window into how humans
242 use different spaces over time, but in combination, they reveal the diversity of our impacts on the
243 environment. Current approaches to mapping the global influence of humans, particularly the
244 Human Footprint Index¹⁰ and the Human Modification map¹⁹, aggregate multiple aspects of the
245 built environment – including infrastructure, land use, and transportation networks – along with
246 static estimates of human population density and distribution. These indices have been used
247 extensively, and very productively, for assessing wilderness loss, protected area effectiveness,
248 and wildlife responses to human encroachment (e.g.,^{11,57–60}). But considering the increasing
249 availability of high-quality human mobility datasets, we see an opportunity for extending the
250 concept, by developing a framework for quantifying humans' *dynamic* footprint on Earth.

251 Our proposed 'Dynamic Human Footprint' incorporates the multiple ways in which humans affect
252 environments, by aggregating both static and dynamic metrics spanning the full range of
253 spatiotemporal scales. Importantly, rather than computing a single index (such as the Human
254 Footprint Index), we envision a modular set of products that can be tailored to the specific
255 research question and ecological responses under investigation (Fig 1).

256 The underlying datasets supporting these footprint estimates depend on which drivers and
257 spatiotemporal resolutions are required to link different types of human activity to ecological
258 processes. Questions related to distributional changes for wildlife may require a global-scale,
259 coarse-grained, human footprint estimate³⁹, whereas questions related to behavioral responses
260 would necessitate a fine-grained approach, potentially limited to select locales (e.g.,¹⁶) (Fig. 1).
261 For example, understanding behavioral responses of animals to COVID-19 lockdowns would
262 benefit from quantifying changes in human mobility at high spatiotemporal resolutions^{13,61}. If
263 conducted globally, the footprint estimates for such a study would require all underlying datasets
264 to have global extent or rely on modeling approaches for appropriate interpolation. In contrast, a
265 study with a more limited geographic scope would be able to leverage datasets that are only
266 available locally, such as municipal traffic-flow estimates. In general, our review in the previous
267 section reveals a striking lack of widely available human mobility data products that could be used
268 to address ecological responses at finer spatiotemporal scales (Fig. 1).

269 The development of such products should follow the data processing levels employed by NASA's
270 Earth Observing System Data and Information System (EOSDIS)⁶² and the ESA Earth
271 Observation Data Access Portal⁶³. Under this system, data products are classified along a scale

272 from raw, unprocessed data (Level 0), to corrected data (Level 1), derived variables (Levels 2-3),
273 and, ultimately, modeled outputs (Level 4). In the context of a Dynamic Human Footprint, each
274 dataset would be rated corresponding to its processing level. For example, unstandardized mobile
275 device counts may be considered a Level 0 product, whereas population density estimates may
276 be considered a Level 3 product. Combined datasets, such as daily aggregate products of human
277 mobility, would be given a Level 4 distinction, to indicate their synthetic nature.

278
279 As noted above, aggregating across data types will be at the core of the Dynamic Human Footprint
280 (Fig. 4). When integrating datasets with similar spatiotemporal resolutions and extents, we
281 propose following previous approaches which rely on standardizing values within and among
282 datasets (e.g., ^{10,19}). This step alone is not necessarily straightforward, as it requires handling
283 mismatches in resolutions and a nuanced understanding of the rescaling methods appropriate for
284 different data types. However, we also envision scenarios where the variables of interest are not
285 readily available across the full extent required, necessitating more sophisticated methodologies
286 for interpolation. This would apply, for example, to high-resolution transit or human mobility data
287 which are not currently available at global, or even regional, scales (see above). It may be possible
288 to compute finer-scale human mobility estimates by modeling statistical relationships between
289 coarse mobility data and satellite-sensed auxiliary data, which serve as a proxy for finer-scale
290 movement ^{64,65}. But this would likely involve the use of complex data-fusion methods and modeling
291 techniques ^{64,66}. In general, such approaches need to be employed cautiously, as human mobility
292 is linked, as we had noted above, to a complex set of cultural, socio-demographic, and
293 environmental factors that vary geographically and must be accounted for ^{67,68}.

294
295 In the following sections, we use recent empirical examples to showcase how a Dynamic Human
296 Footprint could be employed to advance our understanding of human-wildlife interactions, and
297 their effects on behavior, demography, and distributions. The datasets used in these case studies
298 remain limited in their applicability and availability – at fine scales, they are often collected
299 idiosyncratically (e.g., AIS; ⁶⁹), while at large scales, they remain relatively coarse proxies of
300 human activity. Therefore, we see these examples as demonstrating the need for a Dynamic
301 Human Footprint that enables research on human-wildlife interactions at appropriate – and as yet
302 largely unachieved – spatiotemporal scales.

303 **Behavioral responses**

304 The 'ecology of fear' hypothesis suggests that the risk of predation alters prey behavior and
305 physiology in the absence of direct mortality ⁷⁰. A 'landscape of fear' is a species' perception of
306 the spatiotemporal patterns of that risk as a result of predator activity ⁷¹. Because many animals
307 are thought to perceive humans as super predators ⁷², the landscape of fear hypothesis predicts
308 that animals will avoid human-occupied areas in a similar fashion as they might avoid areas
309 frequented by predators ^{73,74}. Such human avoidance can manifest in both spatial and temporal
310 shifts in activity. For example, many animals become more nocturnal in the presence of humans
311 ⁷⁵, while some prey species select areas of high human mobility, to 'shield' themselves from
312 predators (i.e., the human shield hypothesis) ^{76,77}. As such, to study behavioral responses of
313 wildlife, human mobility datasets should have high temporal resolution, to capture the dynamic
314

315 nature of humans' movements across habitats (Fig. 1; e.g., sub-daily human mobility or traffic
316 data that can be collected at <1km² resolution).

317
318 Implicitly or explicitly incorporating dynamic human activity data can often help understand
319 animals' behavioral responses. For example, by integrating land-cover and anthropogenic noise
320 data, ⁷⁸ found that the song frequency of White-crowned sparrows (*Zonotrichia leucophrys*)
321 increased in response to early COVID-19 lockdown in the San Francisco Bay Area. In contrast,
322 great white sharks (*Carcharodon carcharias*) showed no change in space use at a seal colony in
323 South Australia when cage-diving tourism operations paused for 51 days during lockdown ⁷⁹. By
324 integrating dynamic human mobility data, such as driving and walking, ⁸⁰ researchers were able
325 to demonstrate that mountain lions (*Puma concolor*) in California ventured deeper into urban
326 areas during the COVID-19 pandemic. These studies demonstrate the impacts of reduced human
327 mobility with little or no corresponding change in infrastructure, indicating that dynamic and static
328 metrics are not redundant measures of human activity.

329

330 **Demographic responses**

331 Human activities can influence wildlife populations by affecting critical life history stages. Vital
332 rates (e.g., survival, fecundity) can be altered over a wide range of temporal scales (i.e., days to
333 years) and therefore require human activity data of moderate spatiotemporal resolution (Fig. 1).
334 Human disturbance can occur even in areas with relatively intact habitat if they attract visitors
335 pursuing recreational activities. Outdoor recreation differs significantly throughout the week (e.g.,
336 weekends vs. weekdays) and is often spatially heterogeneous, with some areas being used more
337 frequently than others ⁸¹. These differences in human mobility may have substantial impacts on
338 demographic responses. For example, ⁸² found that recreational use of beaches impacted piping
339 plover (*Charadrius melodus*) demographics, by lowering chick survival during weekends and in
340 areas of intense use ⁸². Roads, vehicle traffic and collisions are another cause of wildlife mortality
341 ⁸³. Traffic reductions during early COVID-19 lockdowns in central Europe led to strong decreases
342 in road mortality in large mammals, such as roe deer, but increased collisions with badgers
343 indicating heterogeneous effects on demographic responses across species ⁸⁴. But human
344 impacts on demography must not necessarily be negative. For example, Hentati-Sundberg et al.
345 ⁸⁵ discovered that tourism typically shielded a seabird colony in the Baltic from gulls and crows.
346 When tourism declined during COVID-19 lockdowns, visitation rates by White-tailed eagles
347 (*Haliaeetus albicilla*) drastically increased, causing – through disturbance, rather than predation
348 – a 26% decrease in the productivity of common murrelets (*Uria aalge*) ⁸⁵. These nuanced responses
349 of species to human recreation highlight the importance of integrating spatially explicit and
350 temporally dynamic information on human mobility into ecological studies.

351
352 Recent advances in detecting sensory pollutants are offering insights into how humans affect
353 demographic processes of wildlife across larger scales ^{86,87}. For example, datasets on
354 anthropogenic noise and artificial light sources across the United States were combined with
355 citizen science bird observations to show that demographic responses to these pollutants, and
356 adjustments in phenology ⁸⁸, depended on species traits and habitats ⁸⁹. These results emphasize
357 that the impacts of human activities are not uniform across species and that analyses must
358 consider context dependence ^{77,90}. This is key to informing the design of effective conservation

359 interventions ⁸⁷, such as reducing nightlight emission during peak migration periods or limiting
360 recreational activities during critical times of the breeding cycle ⁹¹.

361

362 ***Distributional responses***

363 Metrics that characterize the amount of static human infrastructure in an area are the predominant
364 source of information used to study anthropogenic impacts on species distributions ^{92,93}.

365 Interactions among static and dynamic components of human activity may determine the
366 magnitude and direction of anthropogenic impacts on species abundances and distributions. For
367 example, ¹⁷ coupled static (human population density, human footprint) and dynamic (human
368 noise and artificial nightlight) data with information on bird observations around feeder locations
369 (feederwatch.org), to reveal impacts on the abundance of several bird and mammal species at
370 continental scale ¹⁷. Similarly, by combining the static Human Footprint Index with direct records
371 of the presence of humans captured by camera traps, ⁹⁴ identified thresholds at which species
372 with different traits are able to persist in human-dominated landscapes.

373 While some changes in species distributions can occur abruptly over relatively short time periods,
374 the ranges of individuals, populations and species are typically measured at coarser
375 spatiotemporal resolutions. The integration of static and dynamic variables into a Dynamic Human
376 Footprint will allow us to more accurately predict how the distribution of species may change in
377 response to human by-products (such as anthropogenic noise and artificial nightlights) and
378 human encroachment ^{17,77,95}. Modeling encroachment in a more detailed way may allow us to
379 identify thresholds of anthropogenic development ⁹⁶ or human mobility levels, beyond which
380 animal populations cannot persist. For example, light pollution may lead to nocturnal species
381 abandoning or avoiding areas that would otherwise be suitable ⁷⁷. This may aid our understanding
382 of the 'silent forest' concept which posits that species may be absent in an area because of human
383 activities, despite otherwise suitable environmental conditions.

384

385 The activities of humans are a major driver of species extinction, and exert strong selective
386 pressure on the evolution of species ⁹⁷. The ability to consistently map human modification,
387 showed that mammalian genetic diversity and effective population sizes are lower in urbanized
388 areas when compared to natural areas, but less so for birds ⁹⁸. Further, sociodemographic, such
389 as economic inequality and racial segregation appear to reduce overall genetic diversity in
390 terrestrial mammal, reptiles and amphibians ⁹⁹. A dynamic measure of human activities would
391 allow quantifying the degree to which human activities may affect behavioral plasticity and
392 evolution, and more importantly allow a framework to document behavioral changes of wildlife
393 across a gradient of human activities in both space and time. Such a dynamic measure would
394 allow a much more detailed exploration than the urban-rural gradient, as some rural areas
395 experience very high and consistent seasonal influx of humans

396

397 **A roadmap for driving progress**

398

399 The successful development of a Dynamic Human Footprint critically depends on closer
400 collaboration among research communities, better connecting insights and approaches from the
401 fields of ecology, conservation biology, environmental science, geographic information science,
402 remote sensing, human geography, transportation science, and social science. To bring this

403 vision to life will require engaging with a diverse array of government agencies, local authorities,
404 policy makers, and private industries. In the following sections, we provide a forward-looking
405 vision for facilitating these interactions and for collaboratively tackling specific challenges.

406

407 ***Unify terminology***

408 Productive collaboration will require a consistent, unified terminology for discussing concepts,
409 methods, development goals and implementation strategies. We therefore urge the wider
410 research community to adopt a standardized set of definitions. From an ecological perspective,
411 terminology in this realm is complicated by the wide range of use cases and associated scales of
412 analysis. Our proposed Dynamic Human Footprint uses recently established definitions that
413 clearly distinguish between static and dynamic components of human activity ¹².

414

415 ***Establish data standards***

416 We encourage all parties that create and use human mobility data to adopt a standardized
417 representation and classification system for describing datasets, mirroring approaches employed
418 by NASA's EOSDIS. Doing so, would create transparency across scientific communities and
419 correctly distinguish between raw data and modeled or aggregated products. Adopting an existing
420 schema already in use would promote collaboration with the remote sensing community and other
421 fields (such as the animal tracking community; ¹⁰⁰). Aligning the methods and data standardization
422 used for human and animal tracking will be essential for future efforts to merge these data streams
423 ¹⁰⁰.

424

425 ***Commit to data sharing and long-term support***

426 Commitments from private companies to continue making human mobility data products freely
427 available will be important for future studies on human-wildlife interactions in the Anthropocene.
428 To date, most large data providers explicitly state that mobility reports are publicly available for a
429 limited time to help stem the spread of COVID-19 ¹⁰¹, suggesting that access may become
430 restricted post-pandemic. Committing to data sharing and long-term support does not require
431 releasing raw data and algorithms, which would raise privacy, ethical and commercial concerns.
432 Anonymized, aggregated human mobility data products can afford invaluable insights into human-
433 wildlife interactions, and should be made available to the wider research community.

434

435 ***Increase transparency and flexibility in data aggregation***

436 Considering that data preprocessing can have significant effects on research outcomes, we urge
437 private companies to provide greater clarity about the methods used to generate currently
438 available human mobility data products. Furthermore, we recommend that a higher degree of
439 flexibility be incorporated into aggregate products. Allowing researchers to select the temporal
440 baseline and categorical binning of aggregate mobility products would enable comparisons across
441 different data sources and support a much broader range of research applications. This is of
442 particular relevance for studies of animal species that routinely cross national borders, such as
443 migratory species ¹⁰².

444

445 ***Address social, demographic, economic and cultural factors***

446 Socioeconomic dimensions are increasingly being integrated into ecology and conservation
447 research to demonstrate the myriad impacts of structural ^{103–105}. Clearly, patterns in human
448 mobility are driven by a complex set of social, economic, and cultural factors. For example, the
449 worldwide total activity of fishing vessels records its lowest levels during the Chinese New Year,
450 Christmas and New Year ⁴⁰. In the Middle East, the religious celebration of Ramadan, which
451 typically greatly influences the mobility and behavior of humans across large areas, was
452 significantly disrupted during the COVID-19 pandemic ¹⁰⁶. We therefore urge close collaboration
453 with human geographers and social scientists during the development of the Dynamic Human
454 Footprint.

455

456 ***Develop systems to monitor change***

457 It will be important for policy makers and funding agencies to support research and private-public
458 partnerships that enable a dynamic understanding of humans' footprint on Earth. As the COVID-
459 19 pandemic acutely illustrated, society was overall poorly prepared for changes in human
460 behavior on large scales and is still grappling to understand the implications across sectors. For
461 example, how the COVID-19 pandemic has impacted biodiversity across the world, and thus
462 affected progress towards the United Nations Sustainable Development Goals 14 and 15 (Life on
463 Water and Life on Earth), remains mostly unknown (but see ⁴⁹). We therefore need to develop a
464 higher degree of preparedness, for mapping changes in human mobility, and measuring their
465 environmental impacts¹².

466

467 ***Construct the Dynamic Human Footprint***

468 Being inherently dynamic in nature, the Dynamic Human Footprint will require open-ended
469 development. Therefore, this endeavor should embed flexibility with regards to choosing data
470 sources and modeling approaches, accommodating any future advances. In many regions of the
471 world, high-resolution data on human mobility will be nearly impossible to collect. This is due to a
472 variety of factors including differences in the geographical distributions of human populations,
473 socioeconomic inequalities, technological infrastructure, seasonality, privacy concerns, and
474 geopolitics ¹⁰⁷. Therefore, globally, or even regionally, consistent maps of the Dynamic Human
475 Footprint will require modeling and data-fusion approaches, which are likely to pose significant
476 development challenges.

477

478 **Conclusions**

479

480 As the planet becomes increasingly crowded, we need to understand the complex interactions
481 between humans and wildlife if we are to safeguard biodiversity for generations to come.
482 Achieving this demands a rigorous accounting of the multi-dimensional aspects of human activity.
483 We see an immense, time-sensitive opportunity for the ecological community to engage with other
484 disciplines, to integrate data across spatiotemporal scales and operationalize a Dynamic Human
485 Footprint. Human mobility data providers can make invaluable contributions to these efforts by
486 improving data accessibility, data standardization, and transparency. The insights gained by
487 incorporating a Dynamic Human Footprint into ecological studies could provide decision makers
488 with critical novel information for designing highly effective, targeted conservation interventions.
489 Coordination and collaboration are imperative for understanding and managing human-wildlife

490 interactions in the Anthropocene. We must tackle this challenge with utmost urgency to protect
491 the animals that are forced to share space with us.

492

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494

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501

502 **Author. Contributions**

503

504

505 D.E.S. and R.Y.O. co-conceived and conceptualized the article with significant contributions from
506 C.R. and W.J. and feedback from all co-authors. D.E.S. and R.Y.O. led the writing of the article
507 with significant contributions from C.R., input from V.B.B, J.L. and U.D., and feedback from all co-
508 authors. D.E.S. and R.Y.O. led the development of the figures with input from C.R., W.J., V.B.B.,
509 N.Q., B.J. and R.P. and feedback from all co-authors. Preparation of the article was coordinated
510 by D.E.S, R.Y.O., C.R. and W.J. All co-authors approved submission.

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512

513 Tables and Figures

514

515 Supplementary Table 1: Datasets for static and dynamic components of human activity in
516 the terrestrial and marine realms.

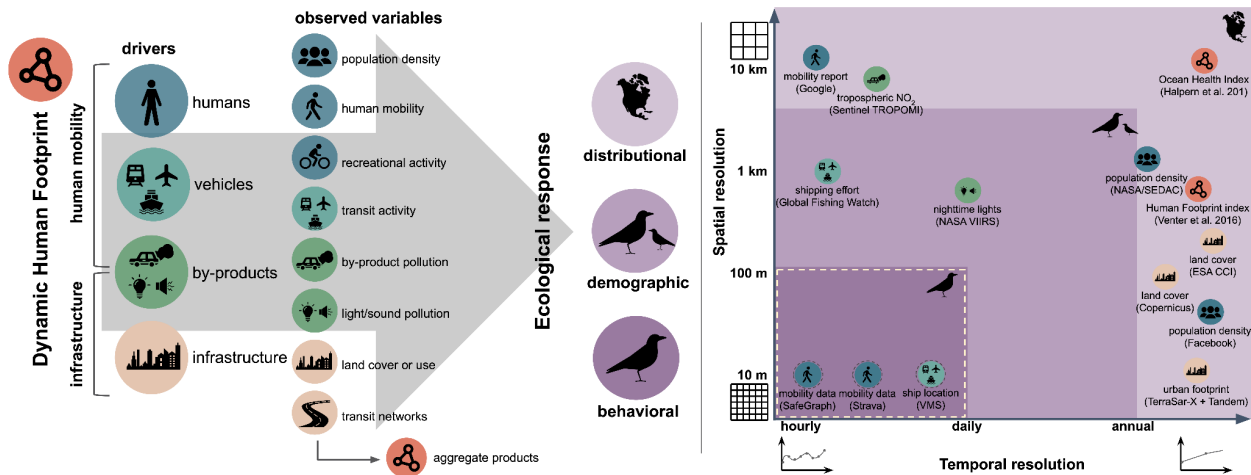
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Realms	Sensing Type	Dataset	Source	Frequency	Spatial Resolution	Geographic Scope	Temporal Scope	Access	URL		
										Resolution	
Terrestrial	Direct	Mobility reports	COVID-19 Community Mobility Reports	Google	Daily	Country and administrative regions	Global	Median value Jan 3 – Feb 6 2020	2020-Present	Currently public	https://www.google.com/covid19/mobility/
			COVID-19 Mobility Trends Reports	Apple	Daily	Countries, regions, sub-regions and cities	Global	13th Jan 2020	13 Jan 2020-Present	Currently public	https://covid19.apple.com/mobility
			Social Mobility Index	Twitter	Daily	City, state or region	100 most populous cities in the USA	13th March 2020	16 March 2020-Present	Currently public	https://dataforpoor.org/analysis.html
			Social Connectedness Index	Facebook	NA	Countries, US counties, Global Administrative Areas (GADM, version 2.8) and the European Nomenclature of Territorial Units for Statistics (NUTS 2016) areas	Global	NA	August 2020-Present	Currently public	Balkey, R, Cao, T, Kuchler, J, Stroebel, and A. Wong. Social connectedness: Measurements, determinants, and effects. <i>Journal of Economic Perspectives</i> , 32(3):259–80, 2018, and the Facebook Data for Good Program, Social Connectedness Index (SCI). https://dataforpoor.org/
			Contact Index	Cuebiq	Daily	County	USA	NA	Jan 2020 - Present	Public	https://www.cuebiq.com/visitation-insights-mobility-index/
			Mobility Index	Cuebiq	Daily	Designated Market Area	USA	NA	Jan 2020 - Present	Public	https://www.cuebiq.com/visitation-insights-mobility-index/
			Traveller Analysis	Cuebiq	Daily	States	USA	NA	Jan 2020 - Present	Public	https://www.cuebiq.com/visitation-insights-mobility-index/
			Foot traffic	Safegraph	Hourly	Point of interest	USA	Custom	Jan 2019-Present		https://www.safegraph.com/weekly-foot-traffic-patterns
			Mobility data	Mapbox	Daily	100 m pixel	Global	NA	NA - Present	Paid	https://www.mapbox.com/
			Strava Metro	Strava	Minute	Street segments	Global	NA	2014-Present	Application required	https://metro.strava.com
	Indirect	Mobility data	Global Heatmap	Strava	Monthly	Street segments	Global	NA	2015- Present	Public	https://www.strava.com/heatmap#7.00,-120.80,0038.36000/hz/all
			Movement Range Maps	Facebook	Daily	Country	14 countries	February 2020	March 2020-Present	Currently public	https://dataforpoor.org/tools/commutingzones/
			Commuting zones	Facebook	3 months	City and sub-city regions	Global	NA	NA	Application required	https://dataforpoor.org/tools/commutingzones/
			Commercial air traffic	Flightradar24	Real time	NA	Global	NA	2009-Present	Public	https://www.flightradar24.com/
			High resolution Population Density	Facebook	Static	30 m pixel	Global	NA	2016 - Present	Currently public	https://dataforpoor.org/tools/population-density-maps/
			GPW Population density	NASA/SEDAC	Annual	1 km pixel	Global	NA	2000 - 2020	Public	https://sedac.ciesin.columbia.edu/data/set/gpw-v4-population-density-ew110a4a-download
			Global Urban Footprint	TerraSar-X + Tandem	Static	12 m	Global	NA	2011	Application required	https://www.dlr.de/eoc/en/desktopdefault.aspx?abid=962816557_read=40454/
			Daily Moonlight-adjusted Nighttime Lights (VNP46A2)	NASA NPP VIIRS	Daily	15 arc seconds	Global	NA	2012-Present	Public	https://landsweb.modaps.eosdis.nasa.gov/products/VNP46A2/
			NASA Black Marble	NASA NPP VIIRS	Daily	<30m	Global	NA	2012-Present	Processing on-demand	https://blackmarble.gsfc.nasa.gov
			Tropospheric NO2	NASA Sentinel 5P TROPOMI	Daily	0.25 degrees pixel	Global	NA	2004-Present	Public	https://landsweb.modaps.eosdis.nasa.gov/missions-and-measurements/
Indirect	Remote sensing	Global land cover	Copernicus	Annual	100m pixel	Global	NA	2015-2019	Public	https://land.copernicus.eu/global/products/lc	
		Global land cover	MODIS	6 months	500m pixel	Global	NA	2001-Present	Public	https://earthdata.nasa.gov	
		Global land cover	ESA CCI	Annual	300m pixel	Global	NA	1992-Present	Public	https://landsweb.modaps.eosdis.nasa.gov/missions-and-measurements/	
		Global land cover	ESRI	Static	10m pixel	Global	NA	2020	Public	https://www.arcgis.com/home/item.html?id=f69c385354400781197946c20e9e2	
		Global footprint index	Venter et al. 2016	Static	1 km pixel	Global	NA	1993-2009	Public	https://sedac.ciesin.columbia.edu/data/set/urban-modification-terrestrial-systems	
		Global human modification	Kennedy et al. 2018	Static	1 km pixel	Global	NA	2016	Public	https://sedac.ciesin.columbia.edu/data/set/urban-modification-terrestrial-systems	
		Automatic identification system (AIS) fishing effort	Global Fishing Watch	Daily	0.01 grees	Global	NA	2012-2020	Public	https://globalfishingwatch.org/datasets-and-co-mms-edu/en/	
		VIIRS Boat Detection (VGD)	NASA/Suomi VIIRS	Daily	15 arc seconds	Global	NA	2014-Present	Public	https://copernicus.eu/en/	
		Mineral extraction	International Seabed Authority	Annual	Regional	Global	NA	2004-Present	Public	https://isa.org/en/insights/data/rock-seabed-page	
		Indirect	Remote sensing	Ocean Cumulative pressures	Halpern et al. 2015	Annual	Country specific EEZ	Global	NA	2008-2013	Public
Ocean health index	Halpern et al. 2021			Annual	Country	Global	NA	2012-Present	Public	https://oceanhealthindex.org	

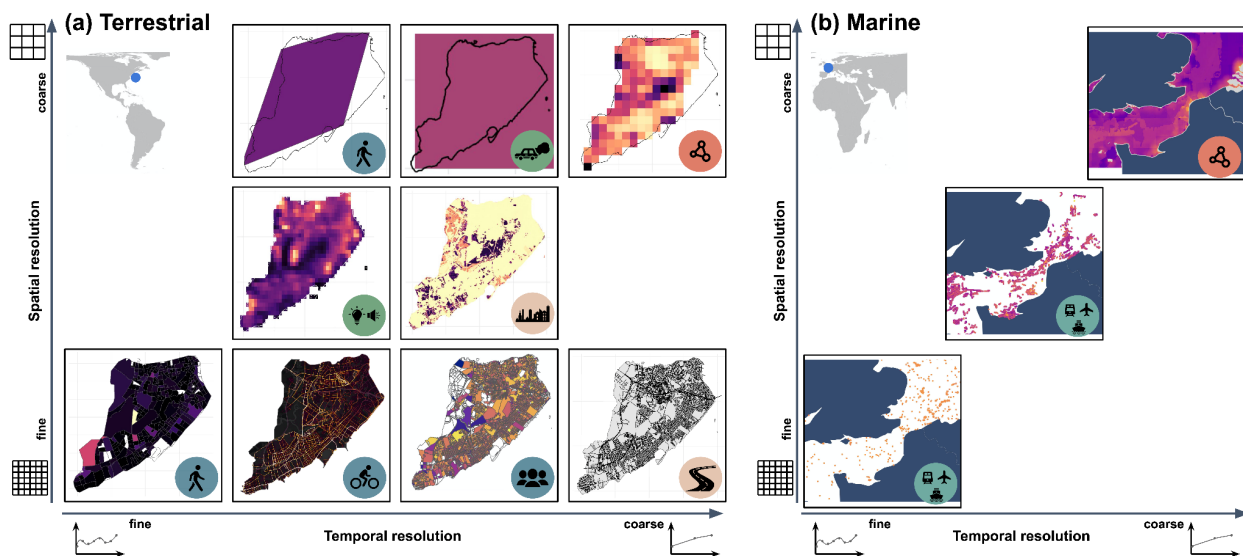
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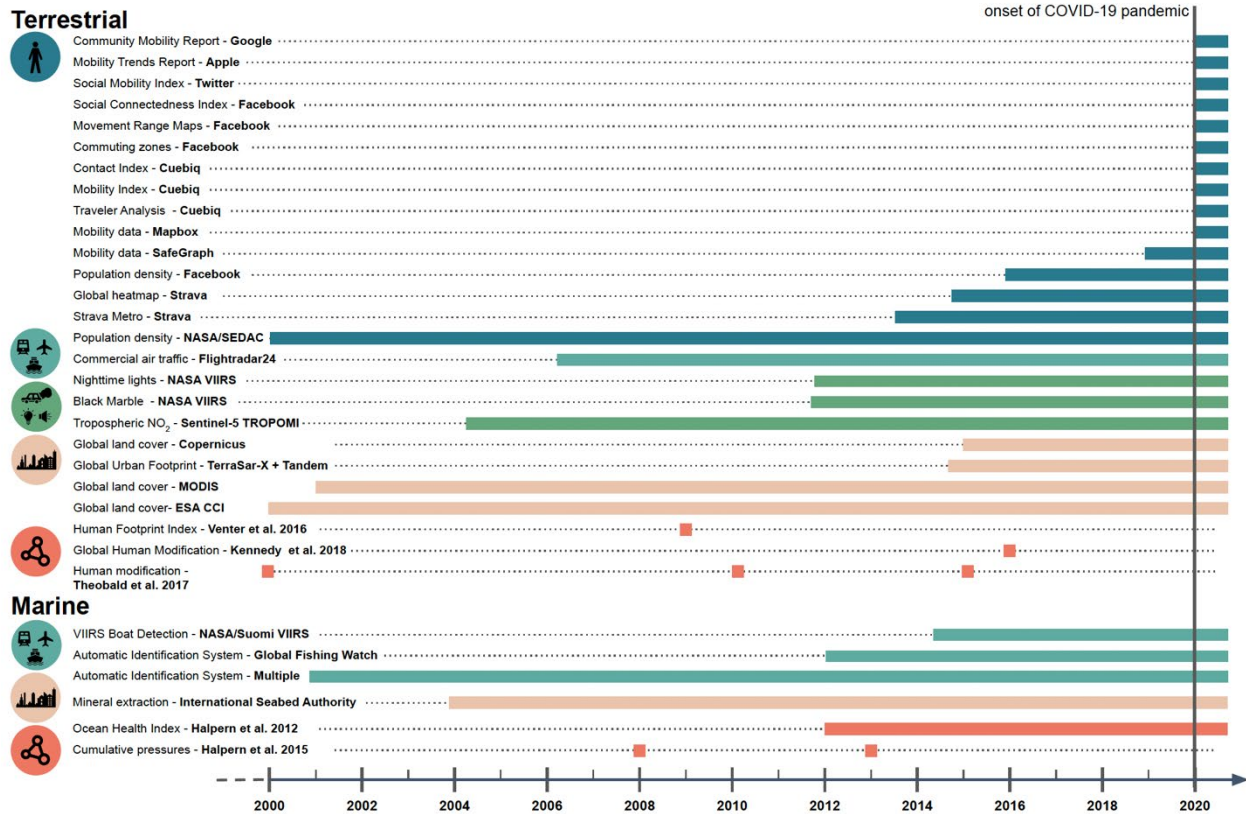


523
524 **Figure 1. Motivation for the development of a Dynamic Human Footprint.** (left) Human activity has
525 both static and dynamic components. In contrast to static landscape modifications (e.g., roads and
526 buildings), human mobility encompasses the dynamic movement of humans and their vehicles. Drivers are
527 quantified as a set of observed variables, ranging from relatively static assessments of infrastructure and
528 population density to highly dynamic approximations of human mobility, and aggregated products. These
529 variables can then be used to examine potential ecological responses along a range of spatiotemporal
530 scales. (right) Each observed variable has an associated spatiotemporal resolution which dictates the
531 ecological scales it may be appropriate for (schematic illustration, left panel). The spatiotemporal resolution
532 of example datasets and their corresponding ecological scale is indicated (right panel). Dashed lines around
533 icons indicate datasets that are not publicly available, and the yellow dashed line highlights the current lack
534 of publicly available datasets with high spatiotemporal resolution.
535

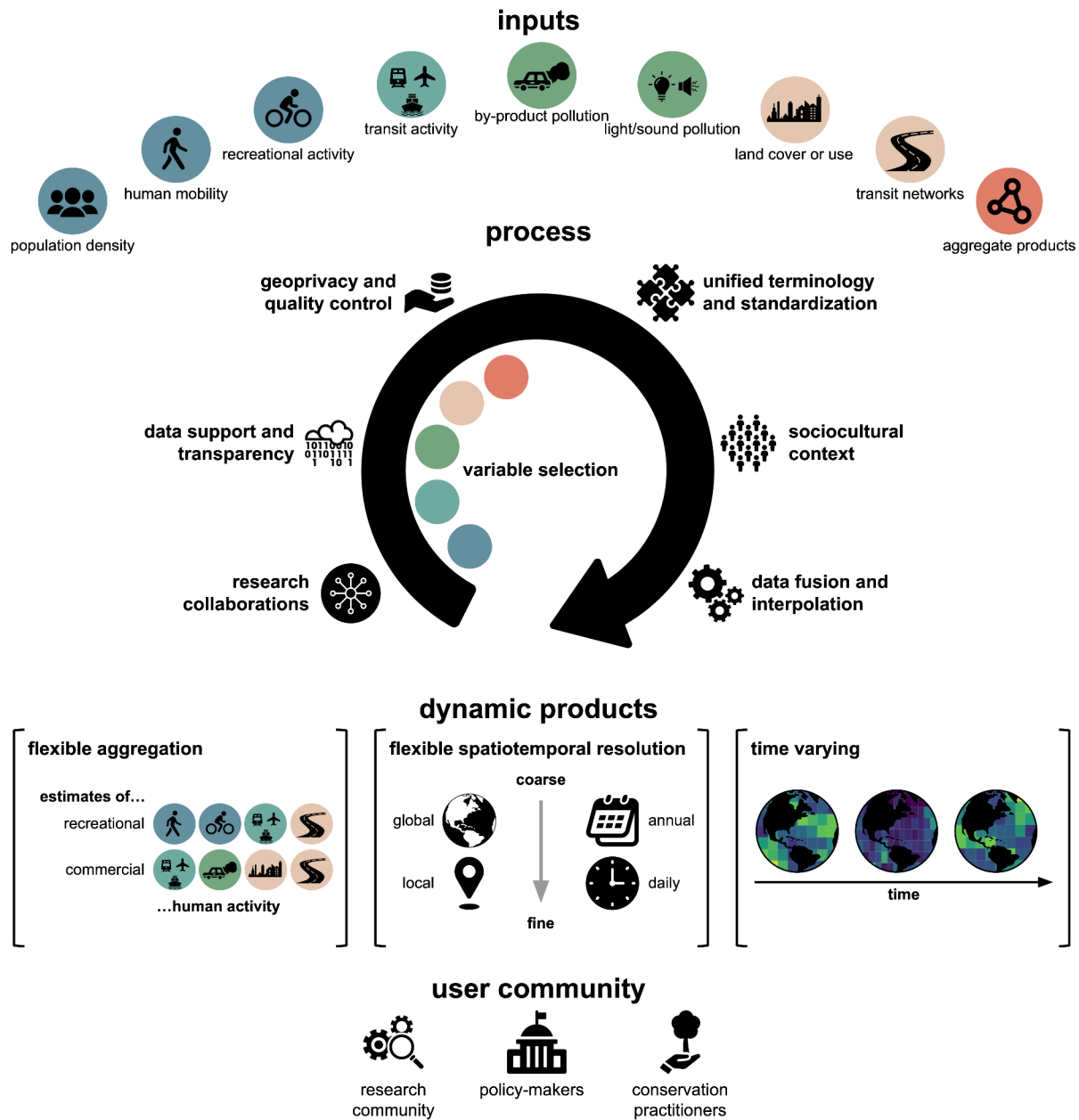


536
537 **Figure 2. Measuring the Dynamic Human Footprint.** Selected examples of datasets quantifying human
538 activities in the terrestrial and marine realms. Spatiotemporal resolutions are presented qualitatively for
539 comparison purposes only. Icons indicate the respective variable type, corresponding to Figure 1. (a) Staten
540 Island, New York (March–May 2020). (top row, left to right) Mobility report at the community level, Google;

541 tropospheric NO₂, Sentinel-5 TROPOMI; Human Footprint index, ¹⁰; **(middle row, left to right)** nightlights,
 542 NASA VIIRS; land cover type, USGS; **(bottom row, left to right)** human mobility, SafeGraph; recreational
 543 activity, Strava Metro; Population Density, US Census Bureau; road network, US Census Bureau. **(b)**
 544 English Channel (December 2019). **(top row)** Cumulative human pressures, ³; **(middle row)** fishing effort,
 545 Global Fishing Watch; **(bottom row)** boat detection, NASA VIIRS.
 546
 547



548
 549 **Figure 3. Timeline of the availability of different human activity data products.** Lifetime of current data
 550 products, demonstrating the recent availability of many human mobility datasets from 2000 to 2022 (some
 551 products have been available for longer). Datasets are grouped and colored by categories of drivers, as
 552 introduced in Figure 1. For details on the spatiotemporal resolution and extent of terrestrial, aerial, and
 553 marine datasets, see Supplementary Table 1.



554
 555 **Figure 4. Constructing the Dynamic Human Footprint.** Framework for a Dynamic Human Footprint,
 556 leveraging a suite of input variables quantifying human mobility and infrastructure. Fundamental to
 557 achieving this vision is an integration process which begins by allowing users to select the human activity
 558 variables relevant to their application target. Dynamic measures of human mobility are primarily held by
 559 private companies; their use depends on continued support to make them available to the research
 560 community (post-pandemic), transparency about data collection and processing, and robust protocols to
 561 ensure geoprivacy and quality control. Cross-disciplinary collaboration will be necessary for developing the
 562 methodologies necessary for integrating disparate datasets across spatiotemporal resolutions. This in turn
 563 will require a unified terminology, to discuss the various components of human activity, and will be greatly
 564 assisted by adopting a standardized schema of data processing levels, to distinguish raw data from
 565 modeled or aggregated data products. In many cases, data fusion or interpolation approaches will be
 566 needed for areas where human mobility data are unavailable, which consider the underlying sociocultural

567 context. This process will generate a suite of products that are inherently dynamic, both in terms of their
568 flexible aggregation and their ability to generate time-varying estimates of human activity.
569
570

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