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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 activities<sup>1-4</sup> driving significant changes in the behavior, distribution and viability  
95 of wildlife populations<sup>5,6</sup>. 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<sup>7,8</sup>. 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 density<sup>9-11</sup>. While useful  
103 for many analyses, these datasets fail to capture the more dynamic aspects of human activity

104 ('human mobility'; see <sup>12</sup>), 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 <sup>13</sup>. 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 <sup>14</sup>. 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 <sup>15</sup>) 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 <sup>12</sup>. 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 <sup>16,17</sup>, 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 <sup>18-20</sup> 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 smartphones<sup>21</sup>. 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<sup>14,22</sup>. 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 users<sup>23</sup>. 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 individuals<sup>24</sup>. 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 towers<sup>25</sup>. 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 globe<sup>21</sup>  
175 and that users of mobile phones, and of different applications, vary geographically and in terms  
176 of their socio-demographic characteristics<sup>26</sup>. Therefore, human location data have inherent  
177 spatial, temporal, and socio-demographic biases<sup>27</sup>.

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 pandemic<sup>28</sup>. 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 reprocessing<sup>29</sup>. 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 dashboard<sup>30</sup>. 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 traffic<sup>31</sup> and cycling behavior, as local authorities provided  
196 additional space for recreation<sup>32</sup>. These types of data are commonly accessible through open  
197 data portals housed by local municipalities (e.g.,<sup>33,34</sup>) 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.,<sup>35</sup>). 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 companies<sup>36</sup> and governmental institutions. For  
207 example, European marine data can be requested through the SafeSea net initiative<sup>37</sup>. These  
208 data have been used to study the impacts of vessel traffic, and resultant noise pollution, on wildlife  
209<sup>38</sup>, as patterns of global fishing effort<sup>39,40</sup>, and the global reduction of marine traffic during the  
210 COVID-19 anthropause<sup>41</sup>. 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 radiances<sup>42</sup>. 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 pandemic<sup>43</sup>.

218 Air traffic can be tracked through data on the total number of flights by FlightRadar24<sup>44</sup>.  
219 Additionally, data on passenger flows are available for Europe through the EU Open Data Portal  
220<sup>45</sup>, for the US through the International Civil Aviation Organization COVID-19 Air Traffic  
221 Dashboard<sup>46</sup>, and for 35,000 city-pairs around the world through the Civil Aviation Data Solutions  
222 (iCADS) portal<sup>47</sup>. Air traffic has been severely impacted during the COVID-19 pandemic, with  
223 significant reductions in commercial flights<sup>48,49</sup>.

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<sup>50,51</sup>. For example, artificial nightlights have been used for mapping both vehicles and  
227 infrastructure, from maritime traffic to whole cities<sup>51,52</sup>. 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 from<sup>53</sup>. Daily satellite data on concentrations of various atmospheric gasses have global  
231 coverage<sup>54</sup> and are available from NASA's Earth Data center<sup>53</sup> 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<sub>x</sub>, SO<sub>2</sub>, ozone and others<sup>55</sup>. Satellite-recorded  
235 nighttime images indicated dimming of light in China<sup>51</sup>, and NO<sub>2</sub> data documented decreases in  
236 pollution levels across European cities due to COVID-19 related changes in human activity<sup>42,56</sup>.  
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 Index<sup>10</sup> and the Human Modification map<sup>19</sup>, 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.,<sup>11,57–60</sup>). 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 estimate<sup>39</sup>, whereas questions related to behavioral responses  
260 would necessitate a fine-grained approach, potentially limited to select locales (e.g.,<sup>16</sup>) (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<sup>13,61</sup>. 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)<sup>62</sup> and the ESA Earth  
271 Observation Data Access Portal<sup>63</sup>. 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., <sup>10,19</sup>). 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 <sup>64,65</sup>. But this would likely involve the use of complex data-fusion methods and modeling  
291 techniques <sup>64,66</sup>. 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 <sup>67,68</sup>.

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; <sup>69</sup>), 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 <sup>70</sup>. A 'landscape of fear' is a species' perception of  
306 the spatiotemporal patterns of that risk as a result of predator activity <sup>71</sup>. Because many animals  
307 are thought to perceive humans as super predators <sup>72</sup>, 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 <sup>73,74</sup>. 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 <sup>75</sup>, while some prey species select areas of high human mobility, to 'shield' themselves from  
312 predators (i.e., the human shield hypothesis) <sup>76,77</sup>. 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 <1km<sup>2</sup> 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, <sup>78</sup> 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 <sup>79</sup>. By  
324 integrating dynamic human mobility data, such as driving and walking, <sup>80</sup> 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 <sup>81</sup>. These differences in human mobility may have substantial impacts on  
338 demographic responses. For example, <sup>82</sup> 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 <sup>82</sup>. Roads, vehicle traffic and collisions are another cause of wildlife mortality  
341 <sup>83</sup>. 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 <sup>84</sup>. But human  
344 impacts on demography must not necessarily be negative. For example, Hentati-Sundberg et al.  
345 <sup>85</sup> 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*) <sup>85</sup>. 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 <sup>86,87</sup>. 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 <sup>88</sup>, depended on species traits and habitats <sup>89</sup>. These results emphasize  
357 that the impacts of human activities are not uniform across species and that analyses must  
358 consider context dependence <sup>77,90</sup>. This is key to informing the design of effective conservation

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

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 <sup>92,93</sup>.  
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, <sup>17</sup> 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 <sup>17</sup>. Similarly, by combining the static Human Footprint Index with direct records  
371 of the presence of humans captured by camera traps, <sup>94</sup> 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 <sup>17,77,95</sup>. Modeling encroachment in a more detailed way may allow us to  
379 identify thresholds of anthropogenic development <sup>96</sup> 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 <sup>77</sup>. 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 <sup>97</sup>. 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 <sup>98</sup>. Further, sociodemographic, such  
389 as economic inequality and racial segregation appear to reduce overall genetic diversity in  
390 terrestrial mammal, reptiles and amphibians <sup>99</sup>. 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 <sup>12</sup>.

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; <sup>100</sup>). 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 <sup>100</sup>.

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 <sup>101</sup>, 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 <sup>102</sup>.

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 <sup>103–105</sup>. 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 <sup>40</sup>. 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 <sup>106</sup>. 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 <sup>49</sup>). We therefore need to develop a  
464 higher degree of preparedness, for mapping changes in human mobility, and measuring their  
465 environmental impacts<sup>12</sup>.

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 <sup>107</sup>. 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.

511

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.

517

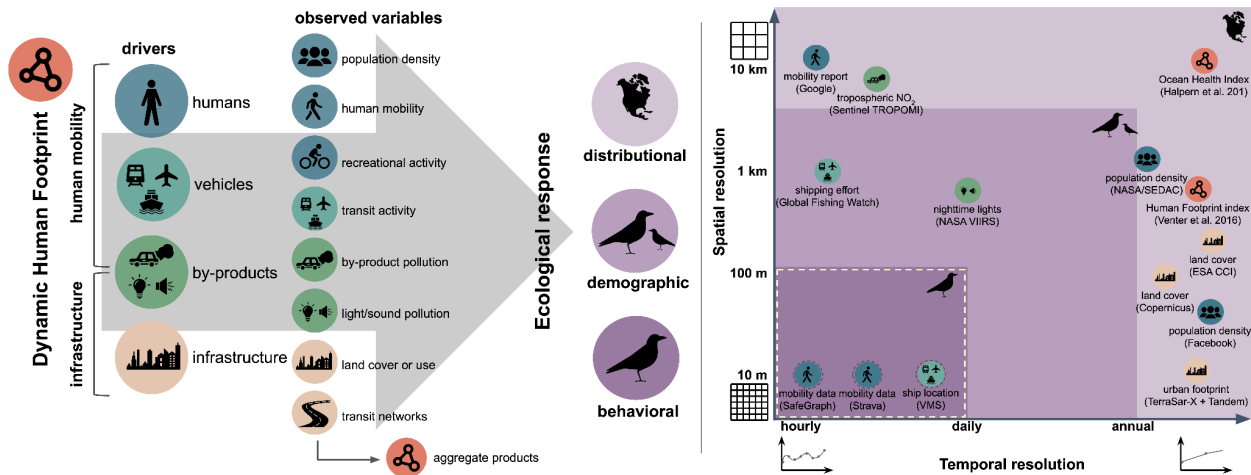
Realms	Category	Dataset	Source	Frequency	Spatial Resolution	Geographic Scope	Temporal Scope	Access	Notes		
										Resolution	
Terrestrial	Direct	Mobility reports	COVID-19 Community Mobility Reports	Google	Daily	Country and administrative regions	Global	Median value Jan 3 – Feb 6 2020	2020-Present	Currently public	<a href="https://www.google.com/covid19/mobility/">https://www.google.com/covid19/mobility/</a>
			COVID-19 Mobility Trends Reports	Apple	Daily	Countries, regions, sub-regions and cities	Global	13th Jan 2020	13 Jan 2020-Present	Currently public	<a href="https://covid19.apple.com/mobility">https://covid19.apple.com/mobility</a>
			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	<a href="https://dataforpeople.com/">https://dataforpeople.com/</a>
			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). <a href="https://dataforpeople.com/">https://dataforpeople.com/</a>
			Contact Index	Cuebiq	Daily	County	USA	NA	Jan 2020 - Present	Public	<a href="https://www.cuebiq.com/visitation-insights-mobility-index/">https://www.cuebiq.com/visitation-insights-mobility-index/</a>
			Mobility Index	Cuebiq	Daily	Designated Market Area	USA	NA	Jan 2020 - Present	Public	<a href="https://www.cuebiq.com/visitation-insights-mobility-index/">https://www.cuebiq.com/visitation-insights-mobility-index/</a>
			Traveller Analysis	Cuebiq	Daily	States	USA	NA	Jan 2020 - Present	Public	<a href="https://www.cuebiq.com/visitation-insights-mobility-index/">https://www.cuebiq.com/visitation-insights-mobility-index/</a>
			Foot traffic	Safegraph	Hourly	Point of interest	USA	Custom	Jan 2019-Present		<a href="https://www.safegraph.com/weekly-foot-traffic-patterns">https://www.safegraph.com/weekly-foot-traffic-patterns</a>
			Mobility data	Mapbox	Daily	100 m pixel	Global	NA	NA - Present	Paid	<a href="https://www.mapbox.com/">https://www.mapbox.com/</a>
			Strava Metro	Strava	Minute	Street segments	Global	NA	2014-Present	Application required	<a href="https://metro.strava.com">https://metro.strava.com</a>
			Global Heatmap	Strava	Monthly	Street segments	Global	NA	2015- Present	Public	<a href="https://www.strava.com/heatmap#7.000-120.800038.36000/hz/all">https://www.strava.com/heatmap#7.000-120.800038.36000/hz/all</a>
			Indirect	Mobility data	Movement Range Maps	Facebook	Daily	Country	14 countries	February 2020	March 2020-Present
	Commuting zones	Facebook			3 months	City and sub-city regions	Global	NA	NA	Application required	<a href="https://dataforpeople.com/tools/commutingzones">https://dataforpeople.com/tools/commutingzones</a>
	Commercial air traffic	Flightradar24			Real time	NA	Global	NA	2009-Present	Public	<a href="https://www.flightradar24.com/">https://www.flightradar24.com/</a>
	High resolution Population Density	Facebook			Static	30 m pixel	Global	NA	2016 - Present	Currently public	<a href="https://dataforpeople.com/tools/population-density-maps/">https://dataforpeople.com/tools/population-density-maps/</a>
	GPW Population density	NASA/SEDAC			Annual	1 km pixel	Global	NA	2000 - 2020	Public	<a href="https://sedac.ciesin.columbia.edu/data/sets/gpw-v4-population-density-ew110a4a-download">https://sedac.ciesin.columbia.edu/data/sets/gpw-v4-population-density-ew110a4a-download</a>
	Global Urban Footprint	TerraSar-X + Tandem			Static	12 m	Global	NA	2011	Application required	<a href="https://www.dlr.de/eoc/en/desktopdefault.aspx?abid=962816557_read-40454/">https://www.dlr.de/eoc/en/desktopdefault.aspx?abid=962816557_read-40454/</a>
	Daily Moonlight-adjusted Nighttime Lights (VNP46A2)	NASA NPP VIIRS			Daily	15 arc seconds	Global	NA	2012-Present	Public	<a href="https://landsweb.modaps.eosdis.nasa.gov/products/VNP46A2/">https://landsweb.modaps.eosdis.nasa.gov/products/VNP46A2/</a>
	NASA Black Marble	NASA NPP VIIRS			Daily	<30m	Global	NA	2012-Present	Processing on-demand	<a href="https://blackmarble.gsfc.nasa.gov">https://blackmarble.gsfc.nasa.gov</a>
	Tropospheric NO2	NASA Sentinel 5P TROPOMI			Daily	0.25 degrees pixel	Global	NA	2004-Present	Public	<a href="https://landsweb.modaps.eosdis.nasa.gov/missions-and-measurements/">https://landsweb.modaps.eosdis.nasa.gov/missions-and-measurements/</a>
	Global land cover	Copernicus			Annual	100m pixel	Global	NA	2015-2019	Public	<a href="https://land.copernicus.eu/global/products/lc">https://land.copernicus.eu/global/products/lc</a>
	Global land cover	MODIS			6 months	500m pixel	Global	NA	2001-Present	Public	<a href="https://earthdata.nasa.gov/">https://earthdata.nasa.gov/</a>
	Global land cover	ESA CCI			Annual	300m pixel	Global	NA	1992-Present	Public	<a href="https://landsweb.modaps.eosdis.nasa.gov/missions-and-measurements/">https://landsweb.modaps.eosdis.nasa.gov/missions-and-measurements/</a>
	Marine	Direct	Remote sensing	Global land cover	ESRI	Static	10m pixel		2020	Public	<a href="https://www.esri.com/home/learn/html?id=69c385354400781176796c20e962">https://www.esri.com/home/learn/html?id=69c385354400781176796c20e962</a>
Global footprint index				Venter et al. 2016	Static	1 km pixel	Global		1993-2009	Public	Venter, O. Sanderson, E., Magrach, A. et al. Global terrestrial Human Footprint maps for 1993 and 2009. <i>Sci Data</i> 3, 160067 (2016). <a href="https://doi.org/10.1038/sdata.2016.167">https://doi.org/10.1038/sdata.2016.167</a>
Global human modification				Kennedy et al. 2018	Static	1 km pixel	Global	NA		2016	Public
Indirect		Remote sensing	Automatic identification system (AIS) fishing effort	Global Fishing Watch	Daily	0.01 grees	Global		2012-2020	Public	<a href="https://globalfishingwatch.org/datasets-and-co-mms-edu/en/">https://globalfishingwatch.org/datasets-and-co-mms-edu/en/</a>
			VIIRS Boat Detection (VGD)	NASA/Suomi VIIRS	Daily	15 arc seconds	Global	NA	2014-Present	Public	<a href="https://scopdata">https://scopdata</a>
			Mineral extraction	International Seabed Authority	Annual	Regional	Global	NA	2004-Present	Public	<a href="https://isa.org/en/insights/data/rock-seabed-page">https://isa.org/en/insights/data/rock-seabed-page</a>
										Halpern, B., Frazier, M., Potapenko, J. et al. Spatial and temporal changes in cumulative human impacts on the world's ocean. <i>Nat Commun</i> 6, 7615 (2015). <a href="https://doi.org/10.1038/ncomms8615">https://doi.org/10.1038/ncomms8615</a>	
										<a href="https://oceanhealthindex.org">https://oceanhealthindex.org</a>	

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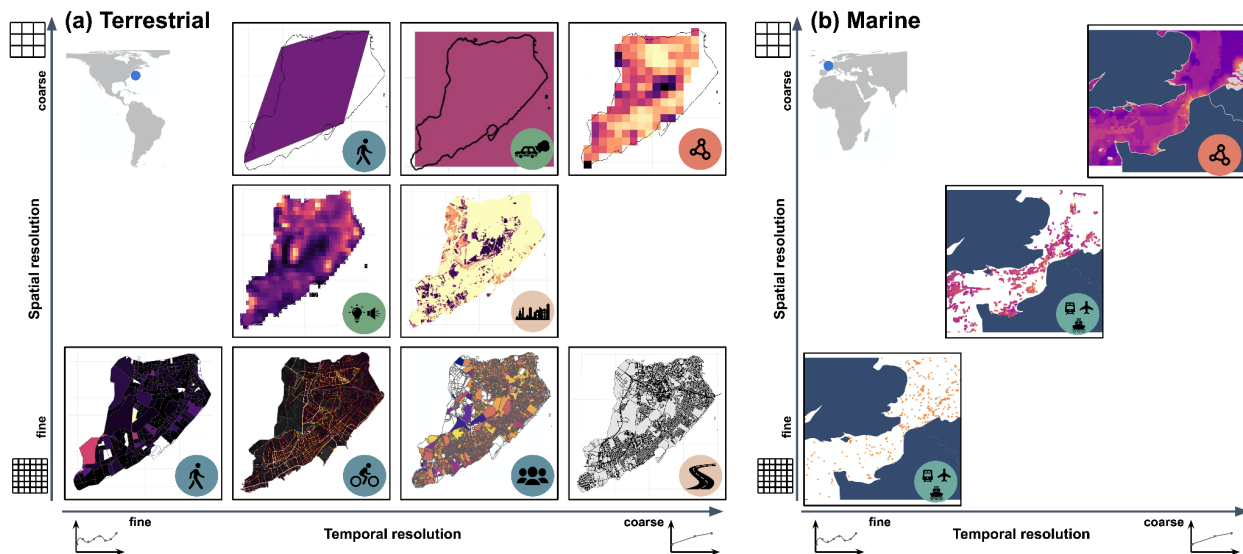
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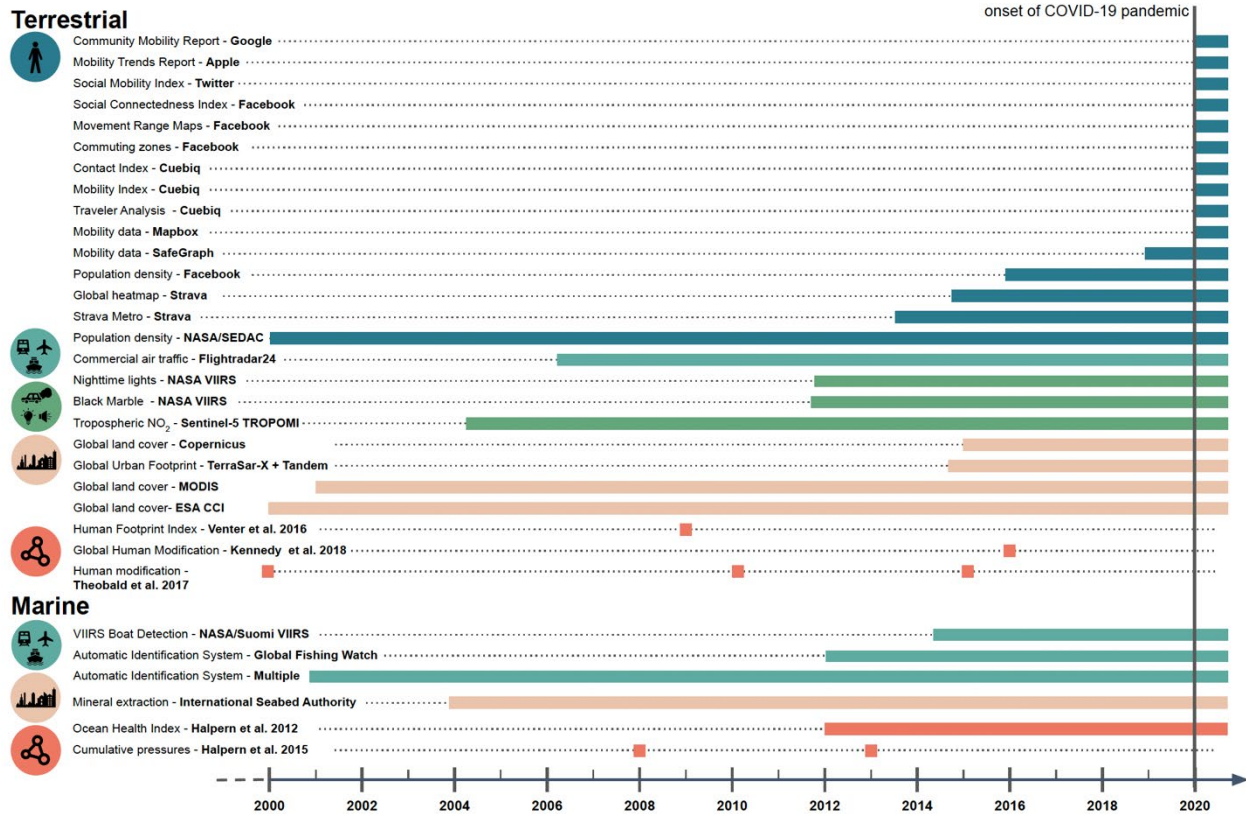


523  
524 **Figure 1. Motivation for the development of a Dynamic Human Footprint.** (left) Human activity has  
525 both static and dynamic components. In contrast to static landscape modifications (e.g., roads and  
526 buildings), human mobility encompasses the dynamic movement of humans and their 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



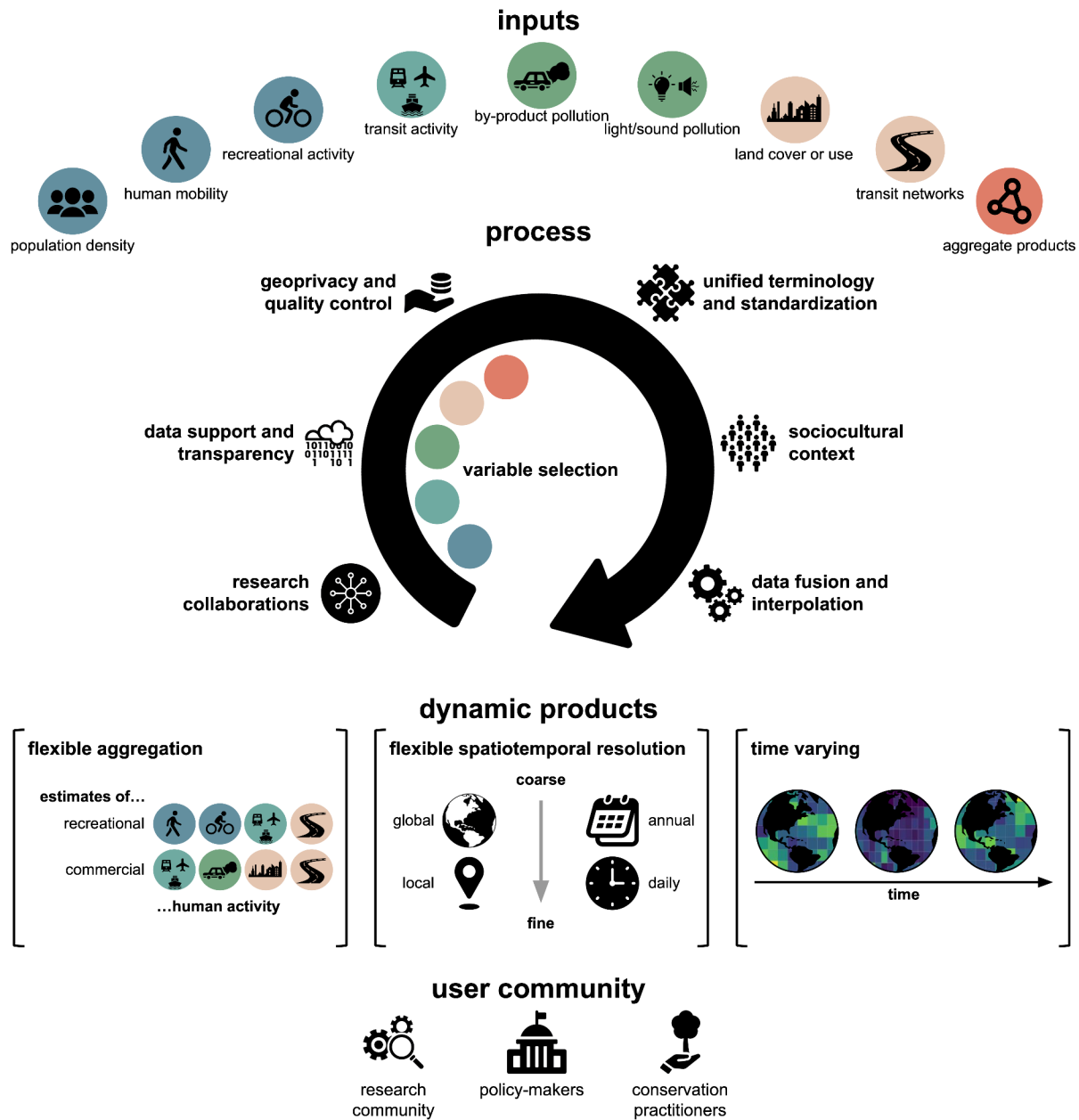
536  
537 **Figure 2. Measuring the Dynamic Human Footprint.** Selected examples of datasets quantifying human  
538 activities in the terrestrial and marine realms. Spatiotemporal resolutions are presented qualitatively for  
539 comparison purposes only. Icons indicate the respective variable type, 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 NO<sub>2</sub>, Sentinel-5 TROPOMI; Human Footprint index, <sup>10</sup>; **(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, <sup>3</sup>; **(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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