A Digital Ecosystem for Animal Movement Science:
Making animal movement datasets, data-linkage techniques, methods, and environmental layers easier to find, interpret, and analyze

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Abstract

Movement is a fundamental aspect of animal life and plays a crucial role in determining the structure of population dynamics, communities, ecosystems, and diversity. In recent years, the recording of animal movements via GPS collars, camera traps, acoustic sensors, and citizen science, along with the abundance of environmental and other ancillary data used by researchers to contextualize those movements, has reached a level of volume, velocity, and variety that puts movement ecology research in the realm of big data science. That data growth has spawned increasingly complex methods for movement analysis. Consequently, animal ecologists need a greater understanding of technical skills such as statistics, geographic information systems (GIS), remote sensing, and coding. Therefore, collaboration has become increasingly crucial, as research requires both domain knowledge and technical expertise. Datasets of animal movement and environmental data are typically available in repositories run by government agencies, universities, and non-governmental organizations (NGOs) with methods described in scientific journals. However, there is little connectivity between these entities. The construction of a digital ecosystem for animal movement science is critically important right now. The digital ecosystem represents a setting where movement data, environmental layers, and analysis methods are discoverable and available for efficient storage, manipulation, and analysis. We argue that such a system which will help mature the field of movement ecology by engendering collaboration, facilitating replication, expanding the spatiotemporal range of potential analyses, and limiting redundancy in method development. We describe the key components of the digital ecosystem, the critical challenges that would need addressing, as well as potential solutions to those challenges.

Keywords: movement ecology, discoverability, reproducibility, big data, data science
1. Introduction

Movement ecology has become a significant focus of wildlife ecology with an emphasis on analyzing movement data to understand the underlying processes associated with animal behavior and space use. The advent of very-high-frequency (VHF) radio collars, along with its derivations of satellite global positioning systems (GPS), acoustic telemetry, and camera-based tracking, allows researchers to track individual-animal locations at fine spatial and temporal scales. These technologies allow for an almost continuous examination of how individuals move through their environment (Ropert-Coudert and Wilson, 2005). Along with the improved technology in animal collars, camera traps, and applications for citizen science, there has also been an explosion in the availability of animal location data (1,2). Repositories such as Movebank (3), BISON (“BISON-Home,” 2019), Ocean Tracking Network (5), OBIS SEAMAP (6), ATN-IOOS (“Animal Telemetry Network,” 2019), MOTUS (8), eMammal (9), Map of Life (10), and eBird (11) enable researchers to store, share, and access a broad range of animal movement data for a multitude of species. These movement databases accept data formats that include individual-level telemetry movement tracks, animal detections captured via camera traps, movements from acoustic sensors, and presence/absence reports—including those from citizen science (e.g., eBird).

Along with these data repositories, novel data-linkage techniques have enabled the annotation (merging) of movement data with remote sensing data and related derived products (e.g., landcover/land-use, snow albedo, population density), which has made it easier to access information about the environment surrounding animal locations. Examples include the Env-Data System in Movebank (12), environment tools in OBIS SEAMAP (6), Google Earth Engine (13), GIOVANNI (14), EarthCube (15), and Climate Data Online (https://www.ncdc.noaa.gov/cdo-web/), RNCEP (16), and MODIS libraries in R (“Animal Telemetry Network,” 2019). The wide availability of movement datasets, associated environmental data layers and data-linkage techniques has promoted new developments in analysis methods aimed at advancing the understanding of how animals interact with their environment (e.g., Fieberg et al., 2018; Forester et al., 2007; Jordan et al., 2019).

Yet, researchers are often unaware of the availability of movement data, environmental layers, data-linkage techniques, and analysis methods that are accessible to them, as they are not straightforwardly discoverable. This stifles collaboration, curtails scientific advances, weakens replicability, creates redundancies in method development and generally slows the progress of the movement ecology field. This paper highlights the potential gains that could be achieved when animal-location data, data-linkage techniques, environmental layers, and methodological tools are easily discoverable. To promote discoverability, we conceive of a digital ecosystem for animal movement science.

2. Why is discoverability so important?

Data-driven tools have proven essential to conservation, particularly in supporting environmental monitoring, reporting and decision making, and modeling of biodiversity evolution and biogeographic dynamics (20). For example, the analysis of GPS data from tapirs (*Tapirus pinchaqu*) confirmed the species’ significant role as a long-distance seed dispersers (21), which is the primary characteristic that defines it as a keystone species and played a vital role in its conservation status (22). Further, data-driven techniques have helped link environmental drivers and resources that were previously unknown. For instance, the foraging habits of leatherback turtles (*Dermochelys coriacea*) were linked to a relatively narrow temperature range of 13° to 22° Celsius that was previously unknown before advanced modeling via state-space models (6).
With the advent of increasingly sophisticated methods, along with the growth in the amount and types of movement data (23), collaboration between field experts and data analysts has become essential. Along with traditional field expertise in animal ecology, researchers studying animal movements increasingly rely on sophisticated statistical analysis, geographic information systems (GIS), remote sensing, and programming languages such as Python and R (24). While the ideal animal ecologist would have both extensive species-domain knowledge and technical expertise, the reality is that it requires teams of individuals with complementary training and abilities to understand animal ecology in a modern-data-driven framework.

The R programming language serves as an example of the nuanced technical knowledge needed today. Data formats such as the R classes of \textit{ltraj} and \textit{move}, respectively developed in the \textit{adehabitat} and \textit{move} libraries, contain almost identical information about x-y-location, time and animal ID, but are incompatible with tools in the other package. While moving between these types of data structures is relatively inconsequential for experienced coders, the small format mismatches can make analyzing data by a novice R coder or less technical users nearly impossible (25). Furthermore, researchers may be unaware that these basic data structures are paramount to their analysis and may find they are incapable of using the tools a package has to offer.

Incompatibility of data structures can prove to be more consequential for packages with fewer users. Question-and-answer forums such as Stack Overflow, Stack Exchange, or Google Answers may provide easy access to programming help. However, there tends to be less community-driven documentation and discussion specific to animal movement analysis because of the relatively small size of the animal movement user community. A digital space specific to the needs of animal movement scientists could be an ideal platform for sharing nuanced coding and data techniques (see section 4).

Collective engagement is increasing in the animal ecology community, but beyond a handful of workshops and conferences each year, the number of other direct collaborative spaces is still relatively low. Collaborative efforts, such as the AniMove courses (“AniMove,” 2019) provide excellent learning opportunities and allow researchers a face-to-face opportunity to share data, methods, and expertise with students and other scientists. However, the classes are cost-prohibitive for many. The benefits of directly learning through such a course cannot be met simply by sharing data and methods, but the opportunity for greater inclusivity increases when data and methods are available and easily discoverable.

In general, one of the most significant barriers to scientific collaboration is a reluctance to share data (27). Animal movement researchers are often reluctant to share location data (28). In some cases this reluctance is driven by legitimate conservation concerns that the spatial extent or the habitat description in metadata could provide sufficient information to lure poachers or exotic-pet traffickers (29). For example, to study the endangered pink-tailed worm-lizard (\textit{Aprasia parapulchella}) on Australian farmlands, the government required researchers to upload location records to an open-access government website (29). Soon after uploading those records, there were several reports of trespassers searching the area for the lizard. However, in many other cases there is still reluctance for data sharing even when it does not involve conservation concerns.

Data sharing might be engendered by a digital ecosystem for animal-movement science, if the system is secure and safeguards are put in place to anonymize species locations (30). The journals \textit{Science} and \textit{Nature} already work closely with open-data repositories to ensure data about sensitive species are securely published (31,32). A digital ecosystem for animal-movement science would necessarily follow similar procedures and could implement a password structure where only vetted stakeholders have access to the data. Another advantage of the digital ecosystem is the potential to create collective knowledge or pseudo-institutional memory, which is an invaluable commodity that
is critical to conservation, particularly for research of endangered species, which psychologically weighs on scientists and causes higher than average job turnover (28).

While collaboration has become increasingly important to movement ecology, because of the broad skill base that the research requires, the rapid technological advances are also causing issues related to tool duplication. A clear example of this problem again arises in the statistical programming language R. Researchers, probably unaware of the availability of tools, end up "reinventing-the-wheel" for their projects, resulting in redundant and unnecessary development of tools/methods that already exist. A recent study identified 57 R packages focused on processing, visualizing, and analyzing animal tracking data (33). The majority of those packages, which can contain hundreds of functions, were developed in the past decade. While there are often novel approaches, improvements or extensions of existing tools introduced in new packages, there is often a tremendous amount of functional overlap, frequently including the same or similar methodological approaches (e.g., animalTrack and TrackReconstruction for dead-reckoning, or BBMM, Movement Analysis, and mkde for Brownian bridge models) (33). The continued growth in movement ecology (34,35) threatens to exacerbate this duplication issue, as more and more tools become available. A digital ecosystem for animal-movement science could reduce tool duplication, as researchers can visit one place to find which methods are available for specific tasks, how they differ, and how they might be integrated.
3. Idealized digital ecosystem and benefits

Google’s Dataset Search is currently the most comprehensive search engine for science data sets, but is potentially too general for animal-movement sciences, as it cannot spatially and temporally link data and methods. An ideal digital ecosystem would include a robust search engine that can discover data related to search terms, such as location, time range, tracking method, resolution, species and ecosystem, and also identify and link suitable data for the corresponding environmental variables in both space and time (Figure 1). Likewise, techniques could be linked to relevant datasets. For instance, camera trap data can be appropriate for species distribution models (36), but are less useful for inferring behavior through a method like a space-state model (37).
A search engine would require a well-planned metadata structure since discoverability relies heavily on keywords or tags (38). However, devising such a structure would not be simple. Metadata that are too basic would return overly broad results, and metadata that are too specific would overlook data and methods that are potentially of interest. Metadata would also need to be flexible, to account for varying terminologies in movement ecology (39). For example, an “event” is a common camera-trapping term (40), but there is no clear definition or agreement on what the term means (41). For telemetry data, there is no precise equivalent for an “event,” which could conceivably refer to a telemetry point or a movement phase, which also have varying terminologies (e.g., fix or trajectory, respectively) (42). Sensors such as accelerometers or proximity collars are recording information along with capture events (43); these would also need to be included in the metadata. As technologies continue to change over time, metadata will also need to allow for future technologies that have no current analog.

Figure 1: Idealized entity relationship diagram for the digital ecosystem for animal movement science.

4. Challenges in developing a digital ecosystem

A search engine would require a well-planned metadata structure since discoverability relies heavily on keywords or tags (38). However, devising such a structure would not be simple. Metadata that are too basic would return overly broad results, and metadata that are too specific would overlook data and methods that are potentially of interest. Metadata would also need to be flexible, to account for varying terminologies in movement ecology (39). For example, an “event” is a common camera-trapping term (40), but there is no clear definition or agreement on what the term means (41). For telemetry data, there is no precise equivalent for an “event,” which could conceivably refer to a telemetry point or a movement phase, which also have varying terminologies (e.g., fix or trajectory, respectively) (42). Sensors such as accelerometers or proximity collars are recording information along with capture events (43); these would also need to be included in the metadata. As technologies continue to change over time, metadata will also need to allow for future technologies that have no current analog.
Even if technical issues related to a search engine were solved, there would be substantial concerns in the movement ecology community that would have to be addressed. Of particular concern would be the aforementioned issues related to the protection of species. But beyond data protection, there is also a growing sense of unease that the advancement of data-driven techniques is divorcing animal movement researchers from a field-based understanding of animal ecology (44). As animal ecology has become more technical and data-driven, researchers whose interests are more data-centric have entered the field. Scientists are spending less time becoming acquainted with their species of study and are instead relying on “blind” statistical inference to understand animal ecology. It is not unusual to find movement ecologists who have never viewed their study species in the wild or its habitat. There is some concern that this disconnect from the field weakens insights about animal ecology (44). For example, data-driven techniques are good at finding patterns, but patterns do not necessarily equate to behavior. Segmenting slow speeds and high turning angles as foraging behavior makes intuitive sense from a data standpoint, but validating this segmentation and its behavioral underpinning likely requires some amount of ground truth (45). Similarly, machine learning is becoming a more typical way of studying animal movements (46–49), and is increasingly used for data-driven decision making, which makes many uneasy, even among those with advanced science degrees (27).

5. Ideas for implementation of a digital ecosystem

a.) Standardized metadata for animal-movement science

To engender discoverability, a metadata structure for animal-movement science could be relatively simple (Table 1). Key terms could be limited to the spatiotemporal extent, data type (e.g., GPS, VHF, camera trap, acoustic, or environmental layers), and their secondary metadata, additional sensors, other data collected, and the location of the data (i.e., where the data are stored). Basic metadata terms would indicate the species' location and timestamp and in what format of geographic location and time, as well as data about the individual and species tracks and the sensor type, duty cycle and resolution. For environmental layers, data would be labeled as either "observed" or "derived"—also indicating, or providing a link to how the derived data were processed. Keywords could also indicate how the data can be used (e.g., to understand coarse-scale species distributions or individual space-use patterns), and could also link data to method development if the data were used in that manner.

In general, methods would also need a metadata structure, which could be as simple as the method's purpose. For example, tools such as biased random bridge (BRB), kernel density estimators (KDE), minimum convex polygons (MCP), potential path area (PPA), time-geographic density estimation (TGDE), and Time Local Convex Hull (T-LoCoH) could be labeled 'home-range estimators'. However, the structure of method metadata would be challenging as even similar tools might be labeled in various ways. For example, BRB, PPA, TDGE, and T-LoCoH could be labeled as spatiotemporal home range estimators and KDE and MCP as spatial-only home range estimators (Hoover and Miller, 2019). However, these home range methods could be delineated in other ways. For example, MCP and T-LoCoH might be labeled as methods that use convex hulls. TDGE and KDE could be labeled as methods that utilize density estimations. However, TDGE might also be grouped with PPA as a time-geography approach to home range estimation. As the previous example shows, methods can be grouped in various ways. Here too, we propose that ranking based on counts of user-tagged groupings and keywords can generate a meaningful system to classify and identify methods and could emerge organically without a need for a priori effort to agree on keywords and classification terms.

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b.) An animal-movement science wiki

Crowd-sourced solutions offer a different avenue that might be simpler to implement than a search engine. For example, techniques or datasets could have wiki pages (Table 1), which have proven to be a useful format for collaboration and knowledge management (51). In biology, Gene Wiki has more than 10,000 pages and is edited by more than 1,000 people each month and advocates say the pages are indispensable to their work (52). Wikis are relatively simple to set up and maintain because open-source hosting platforms require almost no knowledge of web design. Consequently, maintenance of the site would not fall to one person or team, which should favor the longer-term success of the platform. Method-wiki pages could include use instructions and general guidelines, as well as a brief history of development. Dataset-wiki pages would include the underlying data structure, collection history, what analysis used the data, and links to any papers where the data were used. As the methods and datasets are applied to other research, users can update the wiki to describe the new study. Descriptions in such cases could be brief but would help to create a sort of “pseudo-institutional memory” about the data and tools.

c.) An animal-movement science social media platform

Another crowd-driven digital ecosystem could be a social platform similar to researchgate.net, which is a social network website for scientists and researchers to share papers (Table 1) (53). Similar to a wiki, such a service would be community-driven, so the growth of the system could happen organically. An advantage of a social network site is the likelihood that it would increase community involvement and collaboration, as scientists could directly comment on one another’s work. The social nature of such a site might also give users more comfort in sharing data with others who maintain an active presence on the platform. Collaboration in a social setting might also foster training for researchers, as it could engender a space of discussion among researchers from outside institutions. It should also be a collaborative space to share learning between those with domain knowledge and technical expertise. However, developing a social network site would take considerably more effort than that of a wiki page.

d.) An h-index for animal movement data and methods

Finally, we suggest developing a ranking index of animal movement data and methods, (Table 1) analogous to the scholarly h-index. Such a framework could be developed quickly and might alleviate some of the replicability and redundancy issues addressed in the earlier sections of this paper. An individual entry of use ranking would give some subjective indication of the importance, applicability, quality, and ease of use of datasets and methods that a user has encountered and experienced, hopefully documenting their limitations. Pulling many user rankings will lead to a useful characteristic of datasets and methods. For data, such documentation is of particular importance as there is currently no easy way to assess the limitations of data without testing it oneself.
Table 1: Ideas for implementation of a digital ecosystem

|                  | Description                                                                 | Advantages                                                                 | Disadvantages                                                                 |
|------------------|-----------------------------------------------------------------------------|-----------------------------------------------------------------------------|-------------------------------------------------------------------------------|
| **Metadata**     | Simple keyword structure that would allow for discoverability in a search engine. | Stimulates a search engine of animal movement ecology.                       | Difficult to develop and deploy.                                               |
|                  |                                                                             | Requires considerable effort, time, and money.                               |                                                                               |
| **Wiki pages**   | Wiki pages for collaboration and knowledge management                        | Easy to implement because of open-source templates.                         | Less searchable.                                                              |
|                  |                                                                             | Growth through community-driven development and maintenance.                | Requires the considerable buy-in from the animal movement community.          |
|                  |                                                                             | Creates a sort of “pseudo-institutional memory” about data and tools.       |                                                                               |
| **Social Network Platform** | Social media platform for data and techniques sharing, and collaboration.     | Community-driven growth.                                                    | Difficult to develop and deploy.                                               |
|                  |                                                                             | A space for collaboration through social engagement.                         | Requires considerable effort, time, and money.                                |
| **Ranking index** | Use index of data and methods, similar to the scholarly H-index.             | Indicates how often a data or method is used.                               | Use rate does not equate to suitable data/method.                             |
|                  |                                                                             | Reduces redundancies.                                                       |                                                                               |

6. Conclusions

Discoverability has enabled scientific revolutions in genomic analysis (52). In this paper, we have highlighted the needs and limitations of developing similar strategies for discoverability and interoperability of animal location data and methods to analyze them. We have already seen the impacts that data-driven techniques have had in movement ecology. For instance, meta-analyses of animal movement data has provided novel insights into the origins of animal movement strategies (54), how broad-scale resource dynamics drive movement behavior (55,56), determinants of migratory behavior (57), as well as how animal movements are changing and can be better conserved in the future (58).

Due to the rapid increase in both the volume and types of animal movement and associated data (e.g., environmental, physiological, videos, proximity collars) being collected, as well as specialized tools and packages introduced to analyze them, data discoverability is an urgent need for animal-movement science. Discoverability will increase and enhance the value, interpretation, and relevance of existing data. The field of movement ecology has relied heavily on method development and statistics. Less emphasized is the development and application of hypotheses regarding how and why animals move and the potential consequences for ecosystems and conservation. With a digital ecosystem researchers can reorient their efforts into brainstorming new
ideas, and then testing those ideas with the plethora of easily discoverable data and methods available.

7. List of abbreviations

ATN-IOOS - Animal Telemetry Network Integrated Ocean Observing System
BRB - biased random bridge
GIS - Geographic Information Systems
KDE - kernel density estimators
MCP - minimum convex polygons
MODIS - Moderate Resolution Imaging Spectroradiometer
NGOs - non-governmental organizations
PPA - potential path area
TDGE - time-geographic density estimation
T-LoCoH - Time Local Convex Hull
VHF - very-high-frequency

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Declarations

- Ethics approval and consent to participate
  
  Not Applicable

- Consent for publication
  
  Not Applicable

- Availability of data and material
  
  Not Applicable

- Competing interests
  
  The authors declare that they have no competing interests.

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