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Review

The Internet of Animals: what it is, what it could be

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One of the biggest trends in ecology over the past decade has been the creation of standardized databases. Recently, this has included live data, formal linkages between disparate databases, and automated analytics, a synergy that we recognize as the Internet of Animals (IoA). Early IoA systems relate animal locations to remote-sensing data to predict species distributions and detect disease outbreaks, and use live data to inform management of endangered species. However, meeting the future potential of the IoA concept will require solving challenges of taxonomy, data security, and data sharing. By linking data sets, integrating live data, and automating workflows, the IoA has the potential to enable discoveries and predictions relevant to human societies and the conservation of animals.

Highlights

The Internet of Animals (IoA) is a new model for understanding and managing life on Earth through digital knowledge and infrastructure.

The internet has revolutionized global communication between humans. The IoA now extends information sharing beyond humans, to include animal life.

The combined data sets on animals around the world enable a novel, emergent understanding of the needs and requirements of animals. At the same time, this IoA knowledge provides important guidance for humans to sustainably coexist with wild animals.

Forecasting ecological living conditions on our planet is an important aim for the future, toward which the IoA contributes a novel source of previously untapped information.

Forecasting systems become better as more and different sources of information are included. Even though the IoA information is far from complete and fully understood, it will provide a framework for life forecasting.

Emergence of an Internet of Animals

Our use of the internet to link data sets and process new information in real time has revolutionized the way humans navigate, do business, and find love. The internet has evolved from a simple network of linked computers to a complex web of data that encompasses all aspects of information. Key innovations in this evolution include a web of linked and machine-readable data sets, constant growth in the flow of new information through **live data** streams (see Glossary), and the development of Artificial Intelligence (AI) to make sense of it all [1]. Most of the internet is built to serve humans, but there is a growing portion of cyberspace focused on the natural world that describes aspects of animal species, populations, and societies that we think also has the potential to make ecological predictions useful for humans and conservation. For example, BirdCast now produces daily bird migration forecasts by combining multiple live and legacy data sets into one automated, AI-driven analysis [2].

There have always been data about animals on the internet, but the past few years have seen four major innovations. First, the amount of data is growing exponentially, as more aspects of ecology transition into Big Data fields [3]. Second, we see a growing variety and velocity of live data streams about animals [4,5]. Third, there are now some formal linkages between these data sets (e.g., [2,6]), although we suggest there is potential for much more. Finally, researchers are applying AI tools for both data collection and automated analysis [7].

Here, we recognize the synergy of these advances by developing the concept of the **IoA** and hope that this will encourage its growth. This term was originally coined to describe live animal-tracking data systems [8], but here we expand its scope to include all types of animal data, linkages between these databases, and automated analyses. We focus this discussion on animals, currently especially vertebrates, and not life in general, because they provide the most well-developed examples. Furthermore, linking data sets requires standards and, when describing aspects of life on Earth, this starts with a standardized taxonomy. While still in flux, only the taxonomy of vertebrates is relatively complete and stable [9]. Here, we first describe the main

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components of the IoA, then present examples of systems that already exist, and finally highlight ideas of what could be possible in the future.

Components of the IoA

Big Data

The amount and diversity of animal data available on the internet is immense and growing rapidly (Figure 1; Table S1 in the supplemental information online). These databases are the core of the IoA because they describe animal life on the planet from several different perspectives. We first highlight the key types of data available within the IoA.

The databases that describe taxonomy are probably the most important to the IoA. Each major taxonomic group of vertebrates (birds, mammals, reptiles and amphibians, and fish; Table S1 in the supplemental information online) has a taxonomic authority. These names are the standards by which data are linked across the IoA.

The next set of IoA databases describes the most important attributes of an animal: genetics, evolutionary history, phenotypes, and conservation status. Repositories for genetic information, such as GenBank or the Earth BioGenome Project, archive genotype data from decades of research. Similarly, phylogeny databases, such as PhylomeDB or the Tree of Life, are becoming increasingly complete. Databases of animal phenotypes (i.e., traits) are proliferating as researchers mine decades of published and unpublished research to systematically describe species in standard ways, such as by body size, reproductive characteristics, and diet [10]. For domestic animals, there are also growing databases of animal health records [11]. Finally, the IUCN Red List provides a rigorous conservation assessment of all vertebrate species, categorizing them into one of eight threat levels [12].

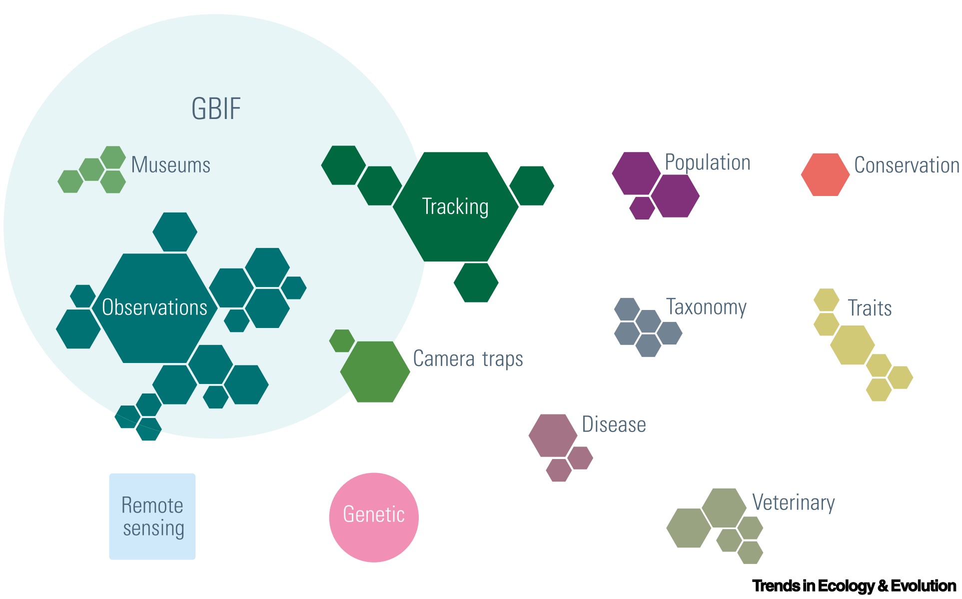

Figure 1. Major components of the Internet of Animals (IoA) that are now online. Hexagons show the 50 largest and most important components of the IoA (see Table S1 in the supplemental information online for details), with shape size showing the relative size of each data set. Much of the spatial data (green shading) is centralized in the Global Biodiversity Information Facility (GBIF). Genetic data are available and relevant for many species and individual animals, if linked properly. Remote-sensing data describe the world animals move through and can be linked by time and location.

Glossary

Application Programming Interface (API): mechanisms that allow two software components to automatically communicate with each other using a set of definitions and protocols. In the IoA, these are used to link separate databases and stream in live data.

Edge computing: a distributed computing paradigm that brings computation to the 'edge' of a network by processing and analyzing data in real-time on the same device that collects the data, rather than sending all data to a centralized location for processing. Examples from the IoA include data processing on-board tracking collars, camera traps, and acoustic recorders.

Internet of Animals (IoA): systems for studying wild or domestic animals with a combination of live data from sensors or citizen scientists, linkages between multiple different kinds of databases, and automated analyses.

Internet of Things (IoT): a network of physical objects or 'things' embedded with sensors, software, and wireless connectivity that enables them to collect and exchange data over the internet. The sensors used to monitor animals can be considered IoT technology.

Live data: information that is updating in real-time, as opposed to static or historical data, providing a real-time view of what is happening in the environment. Live data streams in the IoA typically come from distributed sensors with limited power supplies, and so are often not in fact constantly changing, but update hourly or daily.

Species occurrences: records documenting a particular species in a given geographic location at a specific time. In the IoA, these include observations by citizens, animal tracking locations, or vouchered records that include verifiable evidence, such as a museum specimen, photograph, or a sound recording.

Another growing set of data records is the ecological interactions between species (e.g., Global Biotic Interactions), especially related to disease. There are wildlife disease-monitoring programs at the country and global level (e.g., USGS National Wildlife Health Center or World Animal Health Information System), although the accuracy of reporting and accessibility of the data are sometimes called into question [13]. Additional programs monitor disease or antibiotic resistance in livestock (e.g., Swine Health Information Center or National Antimicrobial Resistance Monitoring System) and pets (Companion Animal Veterinary Surveillance Network). Linking these to other aspects of the IoA will enable a One Health approach to people, animals, and their shared environment (e.g., One Digital Health [14]).

Some of the largest animal databases are dedicated to describing the spatial distribution of animals (i.e., **species occurrences**). Spatial databases of animal records come from a variety of sources, with many collected and redistributed through the Global Biodiversity Information Facility (GBIF). The longest running data series come from museum collections, in which the spatial location represents the location a specimen was collected, including records from Darwin, Wallace, and Linnaeus. These collections link to preserved physical specimens, which are increasingly made digitally accessible as photographs, 3D scans, or as fully measured skeletons[i]. A promising novel development is that the fastest growing databases are collections of citizen science-based observations with no associated specimen collected, especially for birds. For example, eBird registered 179 million observations in 2021 (1.3 billion in total; Table S1 in the supplemental information online). While most of these records are not independently verifiable (because they have no accompanying media), iNaturalist has 16 million vertebrate records accompanied by a photograph that can be used as a voucher to verify species ID. Sensor-based spatial records are also growing rapidly. Tracking tags can collect millions of locations per individual animal, providing rich data on space use and interactions [5,15]. Movebank, the largest repository for tracking data, has over 5 billion location records [16], and other tracking repositories [17,18] hold many millions of records for both terrestrial and marine species. Camera traps are another sensor type that is rapidly growing, with over 14 million records on the Wildlife Insights platform [19]. Monitoring data from acoustic sensors are also accumulating rapidly, but are not yet readily available online due to large file sizes.

Finally, remote-sensing products describe the world that animals are moving through, including weather, vegetation type, and land use. The diversity and density of these data are staggering, with more platforms providing more types of information, at finer spatial and temporal resolution, every year [20]. For example, LIDAR from the GEDI mission now describes vegetation structure at a global scale [21], while weather reanalysis models predict the weather every hour, anywhere on the planet [22]. These spatially and temporally explicit environmental data can be linked to animals based on their location and timestamp, and services, such as Google Earth Engine and Env-DATA, provide streamlined access to these data sets [23,24].

Live data networks

The largest components of the IoA are growing rapidly due to live data streams (Figure 2). These data come from citizen scientists using their phones and specialized sensors that transmit data remotely. However, the quality control needed to make citizen science data 'research grade' can take longer, or never be completed, depending on the taxon [25,26]. Similarly, many disease-reporting networks have standard forms for professionals to upload new information daily [27]. However, the largest live data streams come from automated sensors.

Wireless data transmission (Box 1) is most common in animal-tracking research, where it is often the only way to retrieve data on animals that could move to the other side of the world in a few

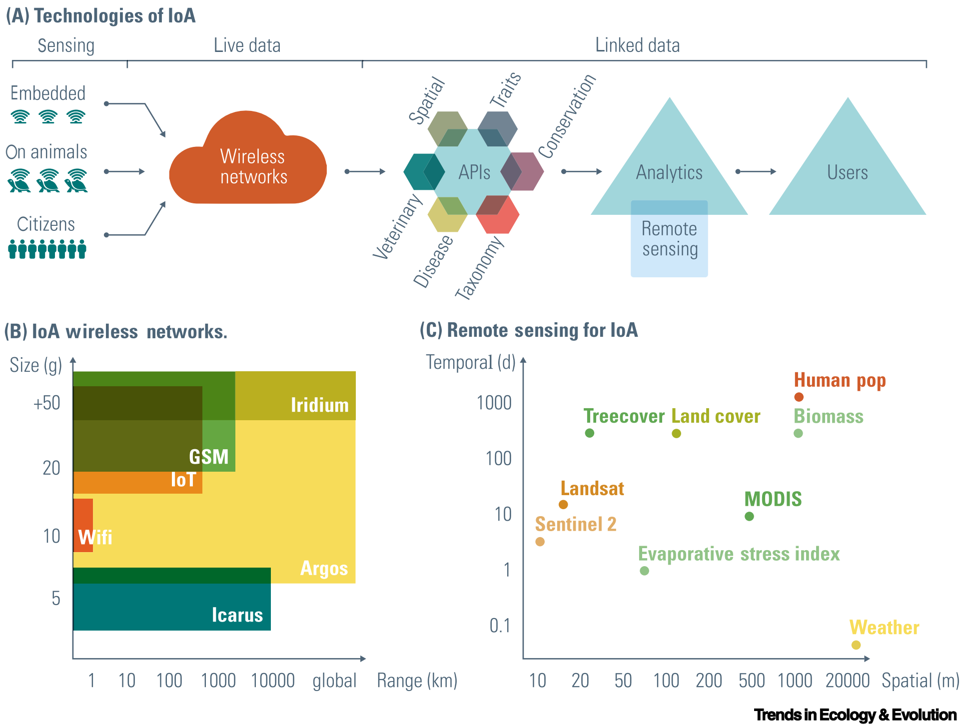

Figure 2. Technologies of the Internet of Animals (IoA) and how they fit together. Live data (A) are generated through networked Internet of Things (IoT) sensors on animals or embedded in the environment and by reports from citizen scientists. These records are added to growing databases, which are linked through Application Programming Interfaces (APIs) using well-defined vocabularies for metadata and taxonomy. Spatiotemporal links to remote-sensing data can quantify the environment through which an animal is moving and be combined with automated analytics to provide users real-time insight and discoveries. Existing wireless networks (B) represent a trade-off between the geographic scale of their coverage and the size (primarily due to battery power required) of their transmitters, which limit the species that can be tracked with them (see also Box 1 in the main text). Remote-sensing data (C) available to intersect with animal data reflect a trade-off between the spatial and temporal resolution of their products (data and references in Table S2 in the supplemental information online).

Box 1. Wireless networks for ecology

The wireless networks available for live data transmission are diverse and represent a trade-off between bandwidth, cost, and spatial scale (see Figure 2B in the main text). There is also a fundamental distinction between connectivity through water and through air, with the water–air boundary providing a significant physical challenge [73]. On land, high wave frequencies are possible, starting with the 150 MHz of VHF radio telemetry and advancing to 400 MHz ARGOS and ICARUS [74]; 900 MHz UHF and IoT; 1600 MHz Iridium satellites; 700, 800, or 1900 MHz cell phones; and 2.4 GHz WIFI [75]. These higher frequencies are more attenuated by vegetation or weather, but allow for faster data transmission. Transmission through the water is more difficult, requiring lower frequencies, usually below 100 dMHz [76]. Early animal tracking data were transmitted through continuous VHF transmitters [77] and later via the ARGOS satellite network [78]. Zoologists have now tapped into the growing global wireless phone network, which has become the mainstay of modern tracking tags, which transmit megabytes of data through global mobile phone connections [79], although they are more power-hungry and expensive.

More recently, scientists have used **Internet of Things** (IoT) networks as a live data solution since they require lower power compared with phone networks, are less expensive, and can cover large areas, although with lower bandwidth. This IoT network infrastructure is still being established, and many protected areas have taken the initiative to establish their own systems to enable larger-scale tracking of wildlife [e.g., solar-powered, <20 g ear tags in black rhinoceros (*Diceros bicornis*) transmit their data up to 186 km in Kruger National Park, South Africa [75]]. There are also now space-based IoT networks (e.g., random access very low power WANs; RA-vLPWAN [74]), which are global in reach but are limited in providing real-time data transmission by small constellation size. We expect that terrestrial and space IoT communication schemes will be merged, such that on-animal tags will choose which communication mode serves best at a given time and place.

weeks [28]. The actual frequency of 'live' data can vary. Real-time, high-resolution, continuous data streams are uncommon in ecology because they are expensive and cannot easily be battery powered, limiting how the sensors are deployed. Their applications have thus far been limited to security applications [29] or using weather radar to detect flying animals [2]. More typically, data are transmitted every few hours or days to save battery power or to synchronize with the orbit schedules of satellites used to send the information. When it comes to data resolution and latency, ecologists often have to find a balance between what is technically possible and what is needed to address the research problem. Now that analyses are being automated as part of the IoA, we expect to see more creative uses of real-time evaluation and science for conservation and discovery.

AI as the lubricant in the Big Data machinery

As the components of the IoA grow, AI and automated analytics are increasingly needed to replace traditional manual processing, both for data input and analysis. Computer vision approaches are now available for classifying animal pictures taken by citizen scientists or camera traps [7] but are thus far only accurate enough to aid, not replace, human image processing [19]. There are several exciting approaches to mine additional animal information from images or video, including individual identification [30], distance from the camera [31], posture and head direction [32], and behaviors associated with sick animals [33]. Automated identification of animal sounds has been challenging [34], but has recently seen great improvement, with approaches classifying sonographic images rather than statistical descriptions of the sounds [35].

AI methods have long been used to analyze animal data [36,37], but the recent innovations of **edge computing** and automated analyses make it a critical technology for the future of the IoA. Efficient algorithms that can run on 'the edge' can improve response time and save bandwidth. For example, GPS tracking tags can adjust their fix rate based on accelerometer data to capture higher resolution data when the animal is moving and save battery when the animal is resting [38]. Similarly, large sensor data (e.g., video or accelerometer data) can be processed at the edge and have the results (e.g., species detected) transmitted on low bandwidth wireless networks [39].

Linking it together: current IoA systems

The potential of the IoA comes not only from having large databases fed by live data, but also in linking these databases together and providing new insight through analytics. **Application Programming Interfaces (APIs)** have made these types of linkage possible (Figure 2), forming the actual linkages between databases [40]. Finally, some analysis is needed to pull insight from this data mixture, ideally in an automated workflow.

Ecology and conservation applications

There are various example IoA systems that automatically pull and analyze data from multiple sources to provide timely results and predictions about the natural world (Figure 3). The best examples of the potential of the IoA come from two systems designed to protect migrating animals. First is the BirdCast project, which creates forecasts of nocturnal bird migration updated every 6 h, combining new and historic radar and weather data, analyzed with machine learning tools [2]. These forecasts are of interest not only to aviation officials guiding aircraft, but also to bird watchers, and are even being used to inform cities of the most important nights to turn off building lights. Collisions with lit-up windows kill ~1 billion birds per year, especially during migration [41]. These forecasts are now being used by cities to create regulations that turn off building lights during the most sensitive periods [42]. Second is the Whale Safe project, which produces near real-time predictions of whale locations along the California coast as advice for when ships should

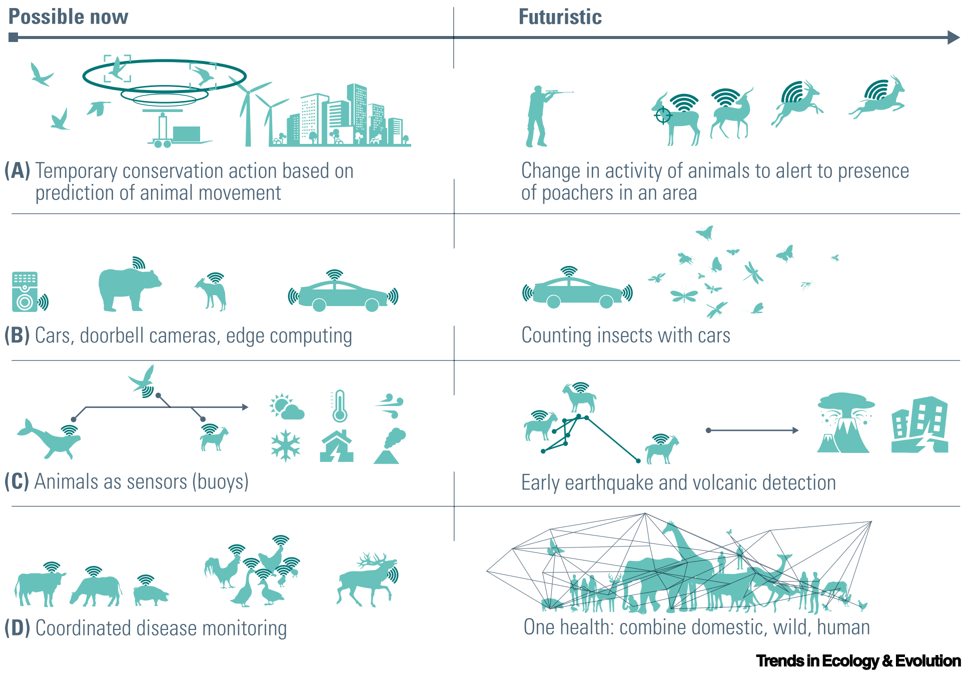

Figure 3. Near horizon and futuristic Internet of Animal (IoA) systems. (A) Real-time conservation: real-time data and predictions of animal movement can avert conservation problems by identifying when certain areas need to be closed for recreation, wind turbines should be shut down, or cities should turn off their lights to reduce bird collisions with buildings. In the future, this concept could include changes in activity of animals to alert authorities to the presence of poachers in an area. (B) Distributed sensors: in addition to the camera traps and microphones being used by scientists, IoA could include data from doorbell cameras, security cameras, and smart cars, using edge computing to share the information, but not the actual videos. In the future, LIDAR and cameras on cars could count insects and provide long-term, broad-scale monitoring that is impossible now. (C) Animals as sensors: weather sensors on animals can record environmental conditions high up in the atmosphere, under sea, or under the forest canopy to improve weather forecasts and environmental monitoring. In the future, the activity of animals themselves could warn of natural disasters. (D) Coordinated disease monitoring: a combination of vet check-ups, artificial intelligence (AI) cameras, and ear-tag monitors can tell when animals in big agricultural settings or protected areas are sick. In the future, these farm systems could be combined and integrated with the same information from wild animals, humans, and remote sensing.

reduce their speed to avoid colliding with whales. The system combines three near real-time data streams (acoustic monitoring from buoys [43], trained observers including tourism operators, and habitat preference maps) into a whale presence rating, shares them with the public and industry, and intersects them with maps of shipping activity to determine which vessels abide by National Oceanic and Atmospheric Administration (NOAA) (still voluntary) speed recommendations. Both of these projects show the potential for linking legacy and live data streams into real-time forecasts to reduce the impact of human infrastructure on migrating animals.

Several other existing examples of IoA systems combine spatial biodiversity with remote-sensing data in an automated way, often including live data. For example, animal trackers can use the Movebank MoveApps platform to automatically combine weather and habitat data with real-time analyses of animal movement [44]. Other applications automate the analysis of biodiversity data and serve up large collections of derived products, such as maps of predicted seasonal abundance (eBird [45]), habitat projections (Map of Life [46]), and animal migration corridors (Migratory Connectivity of the Oceans [47]).

These types of spatial product have long been useful for conservation managers looking to prioritize new areas for conservation, prepare for climate change, or mitigate existing conflict, and these IoA systems have produced better measures, for more species, and made them more easily accessible. More recently, the live data dimension of IoA systems has also opened a new dimension of quick-response conservation implemented through software such as Earth Ranger or SMART conservation tools [48]. Rangers use live tracking data to closely monitor threatened species. Changes in the movement of the observed individuals or groups might indicate that an animal, even a nontagged individual within a group, has been snared, allowing conservation managers to rush to the scene to free the animal. This type of work can also benefit from crowdsourcing. Citizen scientists working in collaboration with professional animal trackers have quickly discovered migrating storks stuck in human infrastructure in time to rescue them [16]. Vice versa, individual 'problem' animals that come into conflict with human communities can be tracked with geo-fenced tags that create alerts if animals come near crops [e.g., Asian elephants (*Elaphus maximus*) in India [49]] or livestock [e.g., African lions (*Panthera leo*) in Namibia [50]].

Agricultural applications

The agriculture industry has developed several IoA applications to enable precision livestock farming to increase efficiency and improve the health of animals [51]. GPS-tracking ear tags can monitor the location of livestock in remote areas [52] and these data have been useful for rescuing individuals that are in danger. Other ear tags fitted with accelerometers made by Sense Hub can detect when an animal is sick and alert the manager to enable early detection of illness. Embedded sensors can also use real-time AI analysis to detect sick animals quickly, for example using video of chicken flocks to detect disabled animals or audio feeds of swine to detect coughs of sick individuals [53,54]. While many companies are using Big Data to manage their animals, linkages between these data sets are rare, in part because of the proprietary nature of the business, but also because many farmers prioritize privacy over data sharing [51].

What it could be: envisioning the next generation of IoA

The IoA is already partially in existence, but we think that the expansion of linked data, live data, and AI will lead to rapid growth of these systems. Here, we focus on some of the advancements that are on the horizon as logical next steps. We then end with two more speculative sections describing how we might monitor wildlife with consumer electronics and how growing our network of monitoring could tap into animal senses to provide a new type of environmental sensing.

Ecological forecasting

Ecologists have long admired meteorological forecasts, and strive to replicate that success for predicting animal populations, distributions, disease emergence, and responses to climate change [55]. The meteorologist's toolkit includes the same components as the IoA we describe here (live data, linked data, and automated analyses), and these are now being connected for ecological forecasting [56]. We see prediction as the ultimate proving ground for the utility of the IoA.

Data integration will be a key component of ecological forecasting, but remains a major challenge in ecology. For example, there is an active research area working to integrate the diverse types of occurrence record that can reflect aspects of the spatial distribution and abundance of a species, including museum specimens, citizen science observations, camera traps, acoustic monitoring, hunter harvest records, and animal tracking [57]. However, understanding the drivers of past population change, and predicting their future, requires an even more diverse set of environmental and demographic information to be combined into more sophisticated models (e.g., integrated population models [58]).

Finally, we also see a role for the IoA to provide unique data from the perspective of the animal that can improve weather predictions. Sensors on animals can record local conditions as the animals move through their environment, which can be useful inputs for environmental models. For example, birds soar through spaces to which meteorologists regularly send weather balloons [59], while seals dive daily to parts of the oceans rarely sampled by oceanographers [60]. Harnessing the natural movement of these species to monitor remote parts of our planet could provide useful information to meteorologists.

Disease

We expect the next generation of disease analytics (e.g., CDC Center for Forecasting and Outbreak Analytics) to establish more linkages between human and animal data sets. Animal distribution, abundance, movement, and interactions are key factors in disease ecology and emergence [61] and are now richly described in components of the IoA. Live tracking data from animals can also be used to map the spread of disease in real time, detecting sick animals through changes in body temperature, movement pattern, or changes in their social networks, or rapidly detecting the death of an animal so that it's corpse can be collected and tested for disease [62]. Finally, new information on virus discovery in wildlife can be linked to existing genetic and evolutionary information to quickly build knowledge graphs to identify reservoir hosts of novel zoonoses [63].

Pets and agriculture

We see potential for IoA advances to not only improve the lives of domestic animals, but also reduce their impact on natural systems, especially related to the improvement of tracking tags. Movements of an outdoor pet cat (*Felis catus*) could be intersected with information about where they crossed roads or were likely to intersect with predators, such as coyotes (*Canis latrans*), to quantify potential risks to the cat. Furthermore, smart collars with **edge computing** could monitor the behavior of cats in real time to detect when they are hunting, and then sound an alarm, such as a bird chip note, to alert potential prey. A similar approach could help map livestock movement relative to risk of predation from large carnivores. Even more, sensors that detect a change in the behavior of prey upon recognizing a predator [64] could trigger a noise (e.g., gunshot or human voices) to deter the predation event. Imagine a system where a smart tag recognizes a potential conflict (a pet cat killing a bird or a wild carnivore killing livestock) and triggers an action to prevent the problem.

Monitoring nature with consumer electronics

Commercial products, from doorbell cameras to smart cars, are now collecting sensor data about the environment at a scale that could not have been imagined a few years ago. We see great potential for linking animal data from those sensors into the IoA framework so that they can be used for science, conservation, and societal applications. Edge computing is the key innovation to make this possible: if AI on the sensor itself can accurately classify the animal being detected, then no original video or other sensor data needs to be shared. This ameliorates privacy concerns and reduces bandwidth and data storage requirements. Scientists do not want a flood of backyard security camera images, but knowing when a deer, coyote, or bear was detected could be useful for monitoring animal populations, and even alerting neighborhoods to the potential risk of a dangerous animal in the general area. Imagine if even a fraction of the 85 million personal security cameras in use in the USA in 2021 were to voluntarily sign up to share data with an IoA-based animal monitoring program; the data would vastly outpace anything collected by scientists [65,66].

Modern smart cars provide a mobile sensor platform constantly scanning the roadsides. Registering the location of animals along the roadside could not only provide standardized animal censuses useful for conservation and wildlife management, but could also alert nearby vehicles to the risk of animal collisions [67]. Furthermore, many modern cars are also fitted with LiDAR and radar systems capable of detecting not only large wildlife but also bats, birds, and insects. A few stationary systems such as this have recently been proven as a promising standard method for monitoring insect populations [68]. Imagine a global network of millions of cars driving billions of km of roads around the world while counting insects as part of a standardized protocol linked into the IoA.

Tapping into animal knowledge

Animals know a lot about the planet that we do not. We think that the IoA can help us translate their knowledge into terms we can understand. New research suggests that the 'sixth sense' of animals is in fact an emergent property of many interacting intelligent sensors (i.e., animals [69]). Animals are in constant contact with other animals of their own and different species, creating an incredibly intelligent, biological sensing network. The sensors and edge computing of the IoA can help us tap into this network to learn not only what the world is like now, but also what the animals are forecasting for the future. For example, climate forecasts might be improved by including information about the nesting behavior of seabirds across the Indo-Pacific because long-lived seabirds are tuned in to predict future food supply and breeding conditions. If seabirds breed when environmental conditions deteriorate, chicks die. Thus, natural selection on forecasting in seabirds is probably very strong [70]. Similarly, the food brought back by seabirds to their growing chicks in Baja California can be used to predict and manage the harvest by human fishing industry 6 months later [71].

The mysterious sixth sense of animals is most famously invoked to explain their ability to predict natural disasters. The erratic and unpredictable nature of these disasters makes this difficult to study, but experimental evidence is accumulating to suggest that the collective sensing and behavior of animals can help detect these events hours before they happen [72]. Imagine a network of sensors monitoring animal behavior to alert local communities of potential pending earthquakes, tsunamis, or volcanic eruptions.

Concluding remarks

As all information moves online, we see the potential for an IoA that links data across domains, streams live data from around the world, and analyzes these in real time to provide insight into the most important problems of our time: animal responses to climate change, the preservation and restoration of biodiversity and ecosystem functions, the preservation of sustainable harvests, the monitoring of disease dynamics in a One-Health alliance between animals and humans, and the forecast of natural disasters. While biodiversity data are accumulating faster than ever, there are still challenges before the full potential of an IoA is realized (see Outstanding questions). All countries, cultures, and socioeconomic communities share space with animals, domestic and wild. The more we can learn about the perspectives of animals on the planet, the more we can benefit from them and create solutions for sustainable coexistence on Earth.

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Declaration of interests

None declared by authors.

Supplemental information

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Resources

[i]https://web.eecs.umich.edu/~fouhey/2021/quantifying/skeletor_cameraready.pdf

Outstanding questions

How can we ensure that legacy biodiversity records are digitized? Most museum collections are not digitized, and many others are only digitized at a superficial level.

How can we extract information from not only past publications, but also the social media networks in a way that renders it semantically described and linked to the rest of the IoA?

How can we make data accessible while still protecting species at risk for poaching? We need to not only guard some data, but also develop ways to anonymize and aggregate information to share beneficial products without disclosing sensitive details.

How can we give credit to those who collect and share ecological data? The accumulation of Big Data from disparate sources creates a disconnect from the original data collectors. Some large analyses could combine data collected by many thousands of researchers, making it difficult to recognize each contribution.

How can we link information about animals across databases when taxonomy is always changing? Species names are the fundamental metadata standard needed to link information across the IoA and the inevitable lumping and splitting will create errors if not accounted for.

Are there benefits to linking genetic data to the morphological, ecological, and behavioral data in the IoA? DNA sequences all come from known species, and can often be linked to particular museum specimens, but secondary use of these linkages is rare.

How can we fund the animal databases and the cyberinfrastructure needed to link and analyze them? Government funding is needed in the short term, but we also see potential IoA predictions to inspire start-up companies creating products useful to human societies or conservation. However, this will also require agreements about how such data and products can be used and commercialized.

Should organizations combine forces toward common goals, cooperating to create centralized IoA infrastructure rather than having multiple competing projects? The pool of resources to drive innovation in the IoA are paltry compared with the venture capital available in Silicon Valley, USA; thus, combining forces makes sense, but formal collaboration also creates bureaucratic and legal headaches.

AI and Big Data come with an environmental cost associated with the energy needed to maintain the computer infrastructure. While the IoA is small compared with the rest of the internet, we should consider whether the conservation benefits of these programs are worth the environmental costs of implementing an IoA solution.

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