[DA-012] GIS&T in Conservation

Abstract

Conservation was one of the first and remains one of the most important domain applications of GIS & technology. As human activities and changing environmental conditions increase and interact to impact the world's natural resources, accurate and precise spatial data are vital to address conservation issues such as deforestation, habitat fragmentation, and biodiversity loss. The unique ability of geographic information science and its associated technologies (GIS&T) to collect, manage, and analyze different types of spatial data (e.g., GPS locations, digital elevation models, administrative boundaries, satellite images) makes it a critical component in our ability to address pressing conservation issues. Here we give an overview of key applications and note recent progress and exciting new developments in GIS and technology applications in conservation.

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Explanation

1. Introduction

The International Union for the Conservation of Nature outlined three objectives in a seminal report in 1980: maintaining essential ecological processes, preserving biological diversity, and sustaining use of species and ecosystems (IUCN 1980). Nature conservation and managing natural resources such as plants, animals, soil, and water have been an important application area of geographic information systems and technology since their introduction. In fact, the earliest geographic information system, Canada GIS (CGIS), was developed to inventory and manage natural resources (Foresman, 1998). Human activities and ecological processes can have a multiplicative effect on natural resources, therefore accurate and precise spatial data are vital to address conservation issues such as deforestation, habitat fragmentation, and biodiversity loss. In addition to the spatial distribution of natural resources, knowledge about the kind, quantity, and quality is important to manage them effectively. GIS and technology can integrate different types of data (e.g., GPS locations, digital elevation models, administrative boundaries, satellite images) and facilitate geovisualization and analysis at multiple scales. GIS data and methods continue to be critical to our ability to measure, monitor, analyze, and manage environmental data at a range of spatial and temporal scales. In this overview, we summarize several key applications of GIS & T in conservation and highlight recent progress and exciting new developments in this field.

2. Key Conservation Applications

Since the introduction of GIS almost 60 years ago, fundamental applications of GIS and technology in conservation have focused on mapping, monitoring, and modeling natural resources ranging from soil types to wildlife habitat. These digital maps can be produced directly from data collected with geospatial technologies, such as classifying remotely sensed imagery into landcover types or can be combined with other layers to generate spatial products. For example, a map of soil loss can be estimated by combining spatial layers of soil factors, rainfall, topography, and vegetation (Fernandez et al., 2003).

2.1 Biodiversity

Biodiversity is a fundamental component of healthy ecosystems, and the ability to measure and monitor biodiversity accurately across large regions has been a conservation priority for decades. Ecosystems with high biodiversity are more stable and are better able to handle environmental changes and disturbances (Oliver et al 2015). Global monitoring is essential for understanding where biodiversity is and how it is changing, as well as for predicting how ecosystems may change in the future. Research has coalesced around the definition of a suite of globally important 'essential biodiversity variables' (EBV) including habitat structure, species abundances/distributions, and taxonomic diversity, and the ability to measure these variables accurately at a global scale continues to foster new advancements in GIS and technology, specifically remote sensing (Pereira et al., 2013).

The term biodiversity hotspot was introduced by Myers (1988) to describe areas characterized by high plant endemism (> 1,500 species of vascular plants) that are vulnerable to habitat loss (contain <30% of its native vegetation) and should be prioritized for conservation. There are currently 36 areas that are considered biodiversity hotspots and while the two criteria remain consistent, the spatial extent of these hotspots continues to be refined as plant diversity and threat status change (Zachos et al., 2011).

At more local scales, ground-based biodiversity monitoring involves using trail cameras for measuring biodiversity at fixed locations. These camera traps are affordable and minimally invasive and have been effective at estimating occurrence and abundance in a variety of terrestrial. As camera traps become more technologically advanced, they can also record interactions, behaviors and ancillary environmental variables. As the volume of data resulting from camera traps expands precipitously, artificial intelligence (AI) is increasingly important for classifying and identifying animals and their behaviors (Vélez et al, 2023).

More recent remote sensing applications involve data collection with unmanned aerial vehicles (UAV). UAV, including drones, have been used to collect data related to biodiversity using both real color and thermal imaging (Beaver et al 2020). Real color imaging of the environment is more established in the ecological literature and has been used for deriving population estimates for target species even as small as gulls (Larus fuscus) (Rush et al 2018). Future directions in this technology include the development of thermal imaging methods. This approach has been applied more successfully to aquatic communities where the environmental temperature provides a starker contrast to the body temperature of a target species (Mota-Rojas 2022). As the thermal resolution on cameras has increased, differentiating between a target individual and bare earth in a terrestrial context is becoming more practical, particularly when the data are collected in the evening to maximize temperature differences (Beaver et al., 2020). In each case, these images present a cost- effective mode of data collection for deriving information on abundance and composition of an ecosystem's population (Corcoran et al 2021).

2.2 Community Science

Data collected from or contributed by the general public (also known as citizen or participatory science) have been an important component of conservation applications and the ubiquity of smartphones and similar devices has drastically increased the volume of data as well as the types of objects. While global biodiversity information facility (GBIF; https://www.gbif.org/) is the largest biodiversity data portal in the world with over 3 billion occurrence records, there are others that focus on monitoring bird nests (https://nestwatch.org/), light pollution (https://globeatnight.org/), invasive species (https://www.natureserve.org/products/imapinvasives) and wildfire smoke (https://www.epa.gov/air-research/smoke-sense-study-citizen-science-project-using-mobile-app).

While still a valuable source of data, it is important to note that community science biodiversity data often contain inherent biases particularly related to geographic region, taxonomy, and even relative accessibility. For example, some regions are more likely to be sampled and studies have shown that birds tend to be oversampled while insects are undersampled (Troudet et al., 2017). There are strategies such as sub-sampling and filtering the observations to help mitigate the bias.

2.3 Species Distribution and Habitat Suitability Models

Species distribution models (SDMs) quantify correlations between some measure of plant or animal species importance (presence/absence, abundance) and environmental factors associated with suitable habitat. These models can be used to extrapolate across space and time, to provide biological inventories and to project future distributions as environmental conditions change, respectively. SDMs are the most commonly used framework to analyze how climate change might affect habitat suitability and the species and environmental data on which they are based continue to improve in quality and volume (Booth 2018).

While this modeling framework was originally developed to quantify species distribution along environmental gradients and was grounded in gradient analysis and niche theory, it is sufficiently broad enough to be used for a variety of biogeographical applications, such as determining locations potentially susceptible to invasion and mapping vector-borne disease spread (Franklin, 2009; Miller 2010).

In addition to environmental gradients such as climate, topography, and soil that can be derived and managed in a GIS, other factors such as distance-to-feature (e.g., roads, fences, water) can be calculated. While less often used, remotely sensed variables that describe vegetation structure and/or productivity may be appropriate for modeling habitats (Zimmermann et al., 2007), including food sources for animals. Once habitat suitability has been mapped, additional factors such as patch shape, size, or connectivity can be calculated. Habitat suitability maps can be extended to identify corridors that facilitate movement of organisms and processes across less suitable landscapes. The idea is that animals will select areas with suitable habitat through which to move, so a map of habitat suitability may be inverted to represent resistance or cost of movement and can be combined with animal movement data and an appropriate connectivity model to identify potential migration corridors (Poor et al., 2012).

2.4 Spatial Planning

Spatial planning for conservation is another application deeply rooted in the manual overlay process on which GIS analysis is based (Daniels, 2019). In the terrestrial and aquatic domains, this involves planning for current and future climate scenarios considering human population growth, changing climatic variables, and patterns of habitat use in both human and non-human environments for sustainable allocation of natural resources. Regarding habitat conservation, methods in GIS are oft leveraged (e.g., species distribution modeling, habitat suitability analysis) to identify priority areas for wildlife conservation considering locations of potentially harmful structures that may negatively alter the behavior, or post a direct risk to, the wildlife species of interest. Mapping spatially explicit variables fundamental to habitat planning, including habitat range, migration routes, and potentially harmful infrastructure such as marine traffic and oil extraction, Sahri et al (2021) use GIS for spatial planning of cetacean habitats in Indonesia. Combining spatial data on suitable habitat, habitat use, current conservation planning, and those potential threats to the target species, GIS facilitated the development of spatial planning recommendations for policymakers and, on a broader scale, represents the role of GIS technologies for informing resource use across sectors.

2.5 Change Detection

In addition to mapping existing resources, GIS & T is uniquely suited for monitoring environmental change. Through the analysis of time-series data, conservationists can track changes in land cover, deforestation rates, or shifts in species distribution in order to assess the effectiveness of conservation interventions and to develop strategies to address emerging threats.

Change detection is largely accomplished via remotely sensed data collection using planes, drones, or satellites that collect values across the electromagnetic spectrum, including RGB, infrared, multispectral, and/ or, more recently, hyperspectral, providing insights into environmental variations that are not detectable using visible light. Color values derived from the bands of these images captured are translated into ecosystem variables indicative of, for example, vegetation cover, and may be compared between images taken across multiple years to identify vegetation cover change patterns.

Satellite systems specifically for earth monitoring such as the Copernicus Sentinel, NOAA's Advanced Very High Resolution Radiometer (AVHRR) and Landsat provide decades of publicly available images and facilitate change detection across large spatial and temporal extents. Hansen et al (2013) used Landsat data to produce a global map of 21st century forest cover change and determined there was a global net loss of 1.5 million square miles globally, particularly in the tropics. A subsequent study on global land change using AVHRR data showed that tree cover increased in the subtropical, temperate, and boreal climate zones and that 60% of all land changes were related to humans (Song et al., 2018).

In addition to being used to classify vegetation cover types, indices have been used as proxies for productivity and other variables, including the Normalized Difference Vegetation Index (NDVI) and Enhanced Vegetation Index (EVI). Beyond changes in productivity and biomass, NDVI time-series can be used to measure phenology, e.g., beginning/end, length, and variability of greening up and senescence (Pettorelli et al 2005). While correlated with

NDVI, the fraction of absorbed photosynthetically active radiation (FPAR) is an essential climate variable that measures photosynthetic activity more directly and has been estimated globally from 1982-2022 at 1/12 degree spatial resolution (Zhao et al, 2024).

3. Recent Progress and New Developments

Many of the most important recent developments in GIS&T involve the ability to measure conservation threats and their impacts at multiple spatial and temporal scales often at real-time. Many of these systems incorporate new sensors and artificial intelligence (AI), described in more detail below, and include the ability to detect invasive species spread and to monitor extreme environmental conditions such as wildfire, drought, flooding, and landslides. In addition to being able to collect data more efficiently, over larger areas, and at increasingly fine spatial and temporal resolutions, new geospatial technology is facilitating the collection and sharing of data that were previously unavailable.

3.1 Real-time Detection and Monitoring

The Internet of Things (IoT) refers to a system of devices that collect and share information and has been fundamental to the development of “smart” cities, cars, homes, healthcare and other applications, as well as environmental monitoring. Wildfire detection, monitoring and prediction are among the most developed applications using these spatial data and technologies and are available at global (e.g., https://firms.modaps.eosdis.nasa.gov/) to regional scales (Oliveira et al., 2023). Other systems that integrate data from ground sensors, drones, and satellites can detect changes in forest cover such as logging or fires in near real-term (Ye et al., 2021).

3.2 Animal Tracking

In 2020, there was a substantial step forward in these initiatives with the launch of the ICARUS satellite system (International Cooperation for Animal Research Using Space; https://www.icarus.mpg.de/28056/about-icarus), which relies on very small solar-powered tags that, in addition to tracking animal locations, can also collect ancillary environmental information. In addition to detailed information on the movement of increasingly small animals including birds and insects, this system will facilitate the ability to monitor zoonotic disease, earthquakes, and climate change (https://www.icarus.mpg.de/4123/basics). The Motus satellite system (https://motus.org/), focusing on migratory animals, is another example of an internationally collaborative research network that has been launched in recent years. Motus targets small flying organisms emphasizing high temporal and spatial resolution in data collection efforts using lightweight tracking devices that can even be fastened to larger-bodied insects (Taylor et al 2017).

Animal biotelemetry or biologging extends this further with increasingly small and light devices that can collect physiological and ancillary information to better understand how animals interact with their environment and other individuals (Börger et al 2020). The ‘Internet of Animals’ initiative has been introduced as a new model that harness the voluminous amount and types of data that are being collected by and about animals (Kays and Wikelski 2023).

3.3 Artificial Intelligence

As the volume of environmental data increases, AI methods have been implemented to process and analyze the data efficiently. Applications include identifying animals from UAV and camera trap photos or acoustic recordings and detecting coral reef bleaching and illegal deforestation and poaching (Nandutu et al., 2019). Generative AI (GenAI) has shown promise for predicting wildfire spread (Shaddy et al., 2024) and for generating intervention scenarios for simulated disturbances such as wildfires or disease spread (Frazier and Song, 2025). To counter the 'black box' connotation of many AI models, explainable AI (xAI) provides tools to discover patterns in voluminous data and to enhance the interpretation of model results (Pichler and Hartig, 2023).

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