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# The potential of historical spy-satellite imagery to support research in ecology and conservation

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#### Abstract

Remote sensing data are important for assessing ecological change, but their value is often restricted by their limited temporal coverage. Major historical events that affected the environment, such as those associated with colonial history, World War II, or the Green Revolution are not captured by modern remote sensing. In the present article, we highlight the potential of globally available black-and-white satellite photographs to expand ecological and conservation assessments back to the 1960s and to illuminate ecological concepts such as shifting baselines, time-lag responses, and legacy effects. This historical satellite photography can be used to monitor ecosystem extent and structure, species' populations and habitats, and human pressures on the environment. Even though the data were declassified decades ago, their use in ecology and conservation remains limited. But recent advances in image processing and analysis can now unlock this research resource. We encourage the use of this opportunity to address important ecological and conservation questions.

Keywords: spy-satellite images, Cold War, species habitats and populations, ecosystem extent, ecosystem structure, human pressure

Misunderstanding the past can hinder the design of sustainable solutions for the future (Willis et al. 2007). Ecology and conservation rely on information about how species and ecosystems have changed over time to understand the magnitude and spatial heterogeneity of threats, to set targets for conservation planning, and to identify baselines for restoration (McNellie et al. 2020). However, information on historical ecosystem conditions and species' populations is often inconsistent, inaccessible, or disaggregated (Bonebrake et al. 2010, Grace et al. 2019, Didham et al. 2020). As a result, our understanding of baselines, lagged effects and landscape legacies remains incomplete, biasing ecological assessments and making conservation planning and practice challenging. For example, assessment of recent population dynamics might mask long-term decline in species of conservation concern (Collins et al. 2020). Many communities today may suffer from extinction debt, which can go unnoticed without considering the past (Jackson and Sax 2010). Similarly, planning protected areas based on the current distributions of species heavily affected by human activities can confine them to ecologically marginal habitat and limit future recovery (Singh and Milner-Gulland 2011). Better understanding and considering the past is therefore key in ecology and conservation.

Remote sensing has provided consistent and accessible global information on ecosystem change since the mid-1970s (Kennedy

et al. 2014, Lausch et al. 2016, Radeloff et al. 2019). But high and very high spatial resolution imagery (VHR; less than 5 m), used for assessing species occurrence, distribution, and abundance, as well as other ecological processes, has only become available since the early 2000s (Groom et al. 2011, LaRue et al. 2017, Exton et al. 2019, Fretwell and Trathan 2020). Despite VHR imagery being a central tool for informing conservation decisions (Kennedy et al. 2014, Rose et al. 2015), the lack of historical VHR imagery poses a barrier to ecology and conservation, because many events causing accelerated environmental change predate modern remote sensing data sets that extend back to the 1980s only.

The midtwentieth century was a period of rapid global environmental change induced by transformative geopolitical events including World War II, the Cold War, and decolonization (Brain 2011, Kraemer et al. 2015, Nita et al. 2018). During this time, scientific advances (many driven by military funding) led to a boost in earth observations from space (Day 2015, Oreskes 2021). Much of the environmental data collected using modern earth observation technology today (e.g., Landsat, sonar), is rooted in these historical monitoring efforts. Such historical data sources have advanced climate and land-use science, oceanography, geomorphology, and archaeology (Song et al. 2014, Nita et al. 2018, Casana 2020, Oreskes 2021). In the present article, we argue that historical satellite imagery can also advance ecology and conservation

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**Figure 1.** Temporal and seasonal coverage of spy-satellite images. The data have been classified in three spatial resolution classes as high (0.5–2.5 m), medium (6–12 m), or low (140 m) spatial resolution. Left panel: Satellite missions and their lifetime in relation to modern remote sensing data (grey). Right panel: Image density per day of the year for the three resolution classes. See supplemental figure S1 for a map of seasonal coverage.

by revealing how species and ecosystems respond to long-term global environmental change and how human pressures on the environment have shifted over longer periods of time.

One example of an important remote sensing data set with the potential to transform the fields of ecology and conservation is data collected by the first photo spy satellite, launched by the United States, in the late 1950s. Until 1986, the US military ran more than 100 reconnaissance missions that collected over 600,000 meters of film in 39,000 cans recovered midair as they were returning from space (Day 2015). The program represents the first spy-satellite program to be declassified. Given the continuous technical developments during that time, images were collected by four satellite programs with different technical specifications, primarily differing in their ground resolution and image coverage. The data has near-global coverage at high (0.5 -2.5 meters [m]), medium (6-12 m), and coarse (140 m) resolutions, is available from all seasons and, in many cases, has stereographic properties that allow for 3D terrain reconstructions (Casana and Cothren 2008, Song et al. 2014, Rendenieks et al. 2020). In combination with modern remote sensing data, these images extend modern medium-resolution remote sensing time series (such as Landsat) by approximately two decades into the past and the very high-resolution data records available since the early 2000s by up to four decades (figure 1). Spy-satellite images have been used in geomorphology, glaciology, land-use science, and archaeology (Maurer et al. 2019, Casana 2020, Rendenieks et al. 2020). However, they remain largely unknown and scarcely used in ecology and conservation. However, early applications show they have great potential to reveal historical baselines, ecological legacies, longterm ecological disturbance, and climate change effects, making them a hugely valuable data source for research in ecology and conservation (Bradley and Millington 2008, Rannow 2013, Munteanu et al. 2022).

In the present article, we argue that recent advances in image processing and cloud computing, together with tighter collaboration among remote sensing experts, ecologists, and land-use scientists, can unlock the potential of spy-satellite imagery for longterm ecological and conservation applications. To explore the relevance of spy-satellite imagery to ecology and conservation, we evaluate the temporal, spatial, and seasonal coverage of existing declassified spy satellite imagery; review existing examples of spysatellite imagery use in ecology-related fields; and identify future potential steps to enhance the use of spy-satellite data in ecology and conservation.

## Data coverage, availability, and preprocessing

Spy-satellite images have been progressively declassified for public access since 1996. Scanned panchromatic film strips from low (140 m, Argon) to very high resolution (0.5 m, Hexagon) are available via the USGS Archive (https://earthexplorer.usgs.gov), including approximate image footprints and metadata. Images from four historical satellite programs (Argon, Corona, Gambit, Hexagon) and one experimental program (Lanyard) summing to approximately 1 million declassified images across the different sensors can be accessed online. Metadata are freely accessible, but the scanning of the analogous film currently costs US\$30 per image. Once scanned, the images are freely available, but to date, only about 5% of the archive has been scanned.

To assess the temporal, spatial, and seasonal data coverage of the images, we analyzed the metadata for the four programs by grouping images according to their spatial resolution and generated a global 1-degree raster grid summarizing the number of images in each grid cell for each resolution class (*fasterize* package in R; Ross 2022, R Core Team 2023). We further mapped the seasonal coverage of the grouped images.

More than 1 million images are available worldwide from the four satellite programs, which we group in three spatial resolution classes: high (greater than 2.5 m, at most 834,000 images,



**Figure 2.** Spatial coverage and image density of spy-satellite images. The data have been classified in three spatial resolution classes as high (0.5–2.5 m), medium (6–12 m), or low (140 m) resolution. The left column shows image density for all data in the US Geological Survey archive, the right column only of those scanned and freely accessible data.

29,000 scanned), medium (6–12 m; at most 133,000 images, 6200 scanned), and low (approximately 140 m, 31,000 images, 3500 scanned; figures 1 and 2) Overall, these data have near-global spatial coverage and all seasons have considerable global data availability (supplemental material S1). Given the high proportion of global imagery with medium and high resolution (at most 83% of the scenes available in the US Geological Survey's [USGS] archive), we focus primarily on these data but note that the patterns are similar for the coarse resolution images. We also note that a large proportion of the data has stereographic properties, allowing for 3D landscape reconstructions, but we consider each individual photograph as a separate image.

#### **Recent and current applications**

A search of the scientific literature on spy-satellite images in the scientific databases Web of Science, Google Scholar, and Dimensions.ai covering a variety of disciplines identified only 75 manuscripts published in the English language from 2000 to 2023 (supplemental material S2), covering primarily the disciplines of archaeology, geomorphology, civil engineering, and land-use science (figure 3, supplemental material S3). Only a small proportion of the published studies (17%) have content of direct relevance to ecology and conservation, and only 10 studies were published in ecology or conservation journals. Most of the reviewed studies focused on how to map geological, geomorphological, or land-use features from the data (Fowler and Fowler 2005, Maurer et al. 2019, Zhang et al. 2020), and a few proposed photogrammetric techniques for image rectification and alignment with modern spatial data (Tappan et al. 2000, Altmaier and Kany 2002, Song et al. 2014). Despite the imagery having been declassified and available for several decades now, this suggests that uptake has been very limited, especially in the fields of ecology and conservation.

Historical spy-satellite data has been successfully used for mapping land cover and, therefore, ecosystem extent, especially of forests (Wardell et al. 2003, Rannow 2013, Dao Minh et al. 2017); agriculture (Dao Minh et al. 2009, Munteanu et al. 2020, Rendenieks et al. 2020); shrub encroachment (Frost and Epstein 2013); surface water (Hamandawana 2007, Shugar et al. 2020, Liu et al. 2022); and urban expansion (Cetin 2009). These studies highlight that historical ecosystem changes sometimes outpaced more recent changes mapped with Landsat-era remote sensing data (Nita et al. 2018, Munteanu et al. 2020). For example, the forest harvest rates in Romania in the 1960s were three times higher than those in the 1990s, when forest loss was thought to be at its peak (Nita et al. 2018). Detailed, spy-satellite-based maps of historical forest cover were also essential in identifying areas of forest in Romania that have not experienced disturbance for long periods of time, as well as those that carry legacies of past forest uses (Munteanu et al. 2022). Romania is not unique: Forest area gains in the Latvian-Russian border region due to agricultural



Figure 3. The locations of research studies using spy-satellite images. The studies are coded by the field of research that is best represented in the study question. Each dot represents one scientific paper, and each paper may have one or more case-study locations (not shown; see the supplemental material for a full list of papers and two examples of potential applications).

abandonment were higher prior to 1990 than after the Soviet Union collapsed (Rendenieks et al. 2020), a period when agricultural abandonment has been widely reported. Spy-satellite data has also been used to highlight time lags in upslope forest shifts due to climate change in Scandinavia (Rannow 2013). In West Africa, the extent of savannah woodlands shifted in response to colonial policies (Wardell et al. 2003). Regarding aquatic systems, 90% of the surface water area changes in the Okavango Delta occurred between 1967 and 1990, only a small proportion of which can be captured with modern satellite image time series (Hamandawana 2007). In Albania, river morphology has shifted dramatically over the period 1968–2017, probably in connection with natural (climate) and anthropogenic (deforestation, sediment mining, impact of hydropower) stressors (Spada et al. 2018). Many of these land-cover change processes would have been overlooked in analyses of modern remote sensing data alone.

Shifting the baseline against which changes in ecosystem extent, species populations, or restoration targets are assessed can lead to different interpretations of the observed processes, ultimately affecting conservation and management decisions (Collins et al. 2020, Munteanu et al. 2020). Identifying long-term data is therefore paramount for establishing appropriate recovery targets and assessing species status (Grace et al. 2019). Understanding the related time lags effects and the legacy of historical land uses can only be done with sufficient spatiotemporal resolution, and that may require including several study species generations or rotation cycles in the case of managed forest. Spy-satellite data can also provide information on long-term population dynamics or shifts in habitat use. For example, philopatric steppe marmots (Marmota bobak) responded with a 50-year time lag to historical habitat disturbance (Munteanu et al. 2020), whereas the capercaillie (Tetrao urogallus) recolonized historically disturbed forest patches relatively quickly (Stăncioiu et al. 2021). Similarly, mound-building red wood ants (Formica rufa) responded immediately to changes in canopy openness, relocating mounds since the 1960s along forest edges both in historical and recent time periods (Klimetzek et al. 2021).

Finally, historical spy-satellite imagery can also provide information on past human pressures on ecosystems. For instance, historical logging has been mapped with spy imagery in the United States and Brazil (Song et al. 2014), Romania (Nita et al. 2018), Mali (Ruelland et al. 2010), and China (Leempoel et al. 2013). Spy imagery also showed how historical logging has interacted with industrial pollution to cause forest loss in the 1960s in boreal Russia (Rigina 2003). Similarly, the effects of the century old agricultural practices on landscape structures were reconstructed from Corona imagery in Syria and Iran (Casana 2013). Despite the growing number of case studies using historical spy-satellite images its applications mostly remain limited to mapping exercises related to ecosystem extent (figure 3), but the data presents many other opportunities for ecology and conservation.

#### **Opportunities for ecology and conservation**

The spy-satellite image archive from the Cold War period represents a unique and, so far, largely untapped opportunity to assess ecological phenomena and processes across broad spatial and temporal scales (Nita et al. 2018, Rizayeva et al. 2023). We see several opportunities for interdisciplinary and cross-disciplinary approaches to better integrate historical remote sensing with modern remote sensing (Hansen et al. 2010) and with historical ecological research (Moritz et al. 2008, Tingley and Beissinger 2009). Further integration with other data sets from a range of disciplines (particularly from ecology, conservation science, and social sciences) may provide novel insights into conservationrelevant phenomena, such as shifting baseline syndrome or identifying baselines for restoration planning (Papworth et al. 2009, Jones et al. 2020, Grace et al. 2021). The integration of long-time series of ecological data to inform applied questions is not new, but spy-satellite imagery has several advantages over other historical data sources (table 1).

Compared with historical aerial photographs, individual image footprints of spy-satellite images cover much larger areas, have near-global and year-round availability, and are available in otherwise remote and data-poor regions. However, the original intended use of the data was military intelligence, so strategically important regions for those countries implementing spysatellite missions (e.g., the former USSR, Vietnam, parts of the United States) have higher data densities than others (figure 2). Nonetheless, imagery is available worldwide, including remote Table 1. Opportunities and constraints for the uptake of spy-satellite imagery in ecology and conservation research.

Opportunities	Constraints
Global VHR data from the 1960s until 1980s.	Analogous (nondigital) imagery
Near-global coverage	Requires relatively high amount of reference data collection
Data available from all seasons	Variable data quality among and within missions
Time-and-labor effective methods increasingly available for image	Image distortion
rectification (especially integration of pixel and object-based	Frequently cloud covered
classifications, artificial neural networks for image recognition)	Spatial acquisition bias: image density highest in areas of Cold War
Emerging initiatives for open data sharing (and availability of Geodata	military interest
platforms for data sharing and analyses such as Google Earth Engine) Accurate and exact representation of landscapes and environmental	Most of the imagery has not yet been scanned, which delays analysis, and adds purchasing costs to project budgets
conditions	Lacking standardized, preprocessed, and georectified data
Applicable both in terrestrial and aquatic systems	Limited validation options and possible observer bias

regions (e.g., Antarctica) or recent hotspots of land-use change (e.g., South America and East Africa). Another advantage over other historical aerial images is that comparisons over large geographical areas are in principle possible using the same data sets and approaches, which is rarely the case with aerial photos. Spy-satellite images also have higher spatial accuracy than historical maps, capture the landscape indiscriminately, and allow for 3D terrain reconstructions that may enable analyses of vertical ecosystem structures, such as canopy height. Furthermore, building height, terrain models or archeological sites could be mapped with such 3D information. Compared with modern high-resolution remote sensing data (e.g., GeoEye, Ikonos, Worldview), historical spysatellite imagery lacks multispectral information, but integration with modern multispectral and stereographic imagery can nonetheless provide valuable insight into historical ecosystem conditions.

Conservation or restoration baselines are often defined by data availability, and pushing such baselines as far back in time as possible is beneficial for devising conservation measures or contextualizing species status (Grace et al. 2021). Species' potential habitat is commonly modeled on the basis of the distribution of ecological indicators extracted from remote sensing data across the landscape (Elith and Leathwick 2009, Coops and Wulder 2019, Radeloff et al. 2019). Historical landscape ecological analyses, habitat suitability modeling, spatial distribution of habitat patches, historical landscape connectivity, or range shifts could all greatly benefit from the uptake of spy-satellite data in ecological and conservation practice (figure 4; Wardell et al. 2003, Munteanu et al. 2020).

Historical records such as maps or cadastral surveys have already been successfully used to reconstruct historical habitat and species' distributions (Viana et al. 2022, Clavero et al. 2023). At much broader spatial scales, equivalent species occurrence data or proxies for species occurrences could be extracted from spy-satellite imagery. Such data is commonly sourced from modern VHR data, including direct observations of large-bodied animals, such as whales, polar bears, or large grazers (Laliberte and Ripple 2003, LaRue et al. 2017, Hollings et al. 2018), or proxies for their occurrence, such as burrows or wallowing sites (Löffler and Margules 1980, Tape et al. 2018, Koshkina et al. 2019), or availability of spawning habitat (supplemental material 4). Furthermore, population densities can be estimated via proxies such as marmot burrow densities (Koshkina et al. 2019), penguin guano stains (Lynch et al. 2012, Fretwell and Trathan 2020), or masked boobies' nesting sites (Hughes et al. 2011). Integrating such observations with ecosystem extent, land use, and ecosystem fragmentation data as described above could shed new light onto long-term species responses to land-use and climate change (figure 4).

Finally, spy-satellite imagery could provide novel insights into historical human pressures and their effect on current ecosystem conditions. For instance, historical land use affects the rates of contemporary forest loss (Munteanu et al. 2015) and historical disturbances affect contemporary carbon stocks (Woomer et al. 2004, Thom and Seidl 2016). Historical armed conflict may exert legacies for many decades (supplemental material 5; Kim 1997, Baumann and Kuemmerle 2016, Van den Berghe et al. 2020). Infrastructural development may benefit human well-being while hindering wildlife movement: Diverse cartographic elements extracted from historical spy-satellite imagery may provide surprising insights into the extent and speed of infrastructural changes, as well as on associated human pressure on the ecosystems. For instance, fishing weirs' size, type, and distribution can be an indication of fishing pressure (Exton et al. 2019), the density of roads and tracks can be a proxy for land-use intensity, the effects of water management structures can be monitored via spawning habitat availability (supplemental material S4), or ecological war damage can be quantified from bombing footprints (supplemental material S5).

#### Challenges for remote sensing

The limited uptake of the data for research may be related to the major challenge of operationalizing analyses for large areas (but see Song et al. 2014, Nita et al. 2018, Spada et al. 2018, Gurjar and Tare 2019, Rendenieks et al. 2020, Rizayeva et al. 2023). Recent advances in geoinformation and digitalization suggest that these barriers can be overcome in the coming years. Barriers to the wider use of spy-satellite imagery in ecology and conservation are also related to data access, cost, preprocessing, and a lack of consistent analysis workflows. Because data were collected in analogue format, the scanned images require a large amount of preprocessing (including scanning, georectification, and image enhancement). Data acquisition via the USGS Earth Explorer platform is still relatively cumbersome and covering large areas is time consuming and costly. Furthermore, integrated algorithms for image rectification are still lacking. Despite increasing use of declassified spy-satellite data over the past decades, and ongoing efforts to establish open-source, crowdsourced platforms for data sharing (https://sunspot.cast.uark.edu), the lack of coordinated efforts and integrated methodologies for image preprocessing and sharing makes data hard to transfer between projects and difficult to adapt to research questions other than those investigated by initial users.



Figure 4. Examples of existing and potential (\*) spy-satellite imagery applications for mapping (a) ecosystem extent and structure, (b) species populations, and (c) human pressures on ecosystems. (a1) Forest extent in the Romanian Carpathians (Nita et al. 2018). Left: forest cover in Maramures, Romania. Photograph: C. Munteanu. Right: Maramures, Romania, September 1969. (a2) Lake surface area Tibet.\* Left: Lake in Tibet. Photograph: G. Kirillin. Right: Lake Yinbo surface area, December 1969. (b1) Marmot burrow as proxies for population size in Northern Kazakhstan (Munteanu et al. 2020). Left: Marmota bobak. Photograph: A. Koshkina. Right: Marmot burrows in Kazakhstan, September 1969. (b2) Guano stain on ice shelf, as proxy for emperor penguin colony size.\* Left: Aptenoydes forsteri. Photograph: M. LaRue. Right: Guano stain, Cape Washington, Antarctica, September 1980. (c1) Forest disturbance through bombing during Vietnam War, Vietnam (supplemental material 5). Left: contemporary landscape in Vietnam. Photograph: K. Katzenberger. Right: Bombed Forest in Quang Tri Province, Vietnam, January 1968. (c2) Fishing weirs as proxies for historical fishing pressure in the Persian Gulf.\* Left: Fish Weir, Iranian Coast. Photograph: A. Ghoddousi. Right: Fish Weir in Eastern Persian Gulf, May 1970.

Most of the existing studies employing spy-satellite imagery rely on mathematical modeling and traditional photogrammetric techniques to geolocate the scanned photographs (Tappan et al. 2000, Galiatsatos et al. 2004, Dashora et al. 2007). However, patchy information on camera parameters and complex modeling make this method cumbersome. More recent technological advances in the field of photogrammetry, applied for instance in drone image processing, have made the georectification of historical spysatellite data less work intensive and more accurate (Cassana and Cothren 2008, Nita et al. 2018). Specifically, image processing techniques that rely on overlapping images taken at different angles and structure-from-motion algorithms, have recently allowed for broad scale image rectification (Nita et al. 2018, Rendenieks et al. 2020), and even 3D terrain modeling. An increasingly popular platform to do so is provided by AgiSoft Metashape (www.agisoft.com). However, the collection of reference data is still time consuming and workflows are often hampered by variable image quality, film distortion, camera failures, and changing atmospheric conditions (Zhou and Jezek 2002, Song et al. 2014). We believe that

in the future, AI-based modeling approaches may be trained to recognize persistent features in both historical and contemporary imagery that can be used for image rectification and geolocation (e.g., buildings, lakes, road crossings).

Last but not least, data extraction from the rectified imagery still remains challenging. Many studies to date have relied on manual data digitization (Nita et al. 2018, Munteanu et al. 2020), which is time consuming and prone to observer bias. Methods for automatic data extraction have been rare and relied primarily on object-based classification (Rendenieks et al. 2020, Rizayeva et al. 2023). Pixel-based classifications alone are not very reliable because of the limited spectral information contained in the imagery. Integration of pixel-based and object-based image classification techniques (Rizayeva et al. 2023) and the employment of neural networks and image recognition techniques may boost data extraction, classification, and interpretation and replace traditionally manual image interpretation. Furthermore, data fusion among historical and more recent sensors, and the integration of object-based and pixel-based classification approaches may advance the image extraction processes from this historical data as exemplified successfully by research in the archeology field (Fisher et al. 2016, Albrecht et al. 2019). Finally, the application of artificial neural networks for feature extraction has great potential to speed up the data extraction process.

#### The way forward

We suggest that Cold War spy-satellite images have great potential for advancing both theoretical and applied research in ecology and conservation. We argue that valuable conservation insights can be gained from time series analyses, land-use mapping, species distribution modeling, restoration baseline analyses and mapping of human pressure on ecosystems. In addition, this data has the potential to inform ecological theory—for example, on the role of legacies, lag effects, extinction debt, and colonization credit. To do so, we see six necessary steps to ease the uptake and use of spy-satellite images. These steps will require joint efforts by data holders, remote sensing scientists, and ecologists.

#### Data access

The already-scanned images represent only a small portion of the available film. We recommend that efforts are made to scan the full image archive and make it openly accessible by the data holders (e.g., the US Geological Survey).

#### Image rectification

Consistent and reliable image rectification of the entire archive using harmonized, transparent, and transferrable rectification methods—is urgently needed to make these data a useful resource for more user groups. A first step toward achieving this goal has already been made (Casana and Cothren 2013), but differences in rectification methods, inconsistencies in the reporting of rectification accuracies, and temporary funding for ongoing projects represent large barriers in broadscale uptake of the data. We believe that the image rectification of the entire data archive is at best integrated with the first step above and should be done by data holders to ensure fairness, traceability, and transparency in processing workflows.

#### Data sharing

In the absence of a systematic orthorectification process of the entire spy-satellite image archives, existing platforms for sharing rectified imagery are an interim solution. However, we urge data sharing to happen through dedicated portals of the data holders. Furthermore, the inclusion of the historical spy-satellite imagery in cloud processing platforms such as Google Earth Engine would increase the uptake of the data in many different disciplines, as well as ease and encourage data sharing and the codevelopment of processing techniques.

#### Feature extraction

We call for the development of a dedicated toolbox for the extraction of information from panchromatic, stereographic imagery. Given recent advances in image processing and image recognition research, data fusion and integration of classical pixel-based and object-based classification techniques, as well as the employment of neural networks for image recognition, can advance the automation of feature extraction. Such algorithms could be developed as part of existing open-source remote sensing and geospatial resources (e.g., EnMapBox, QGIS)

#### Enhance uptake in ecological research

Historical data can enhance the understanding of ecological processes and aid conservation decisions. By integrating such data with field-based observations or historical statistics, the research community can gain insights into ecological processes otherwise missed when using singular data sets. We call for the ecological and conservation community to provide examples of applications and test ecological theories using this and other historical data sources in their work. Such studies could focus particularly on underrepresented biomes and anthromes (see figure 3).

#### Opening of other archives

We call for the opening of other historical and recent military mapping archives, including historical military aerial photos for most countries, but also historical maps and other spatial data that can be valuable for research in ecology and conservation.

Compared with other fields, historical spy-satellite images have been underused in ecology and conservation since their declassification more than two decades ago. However, recent advances in image processing and analysis, along with improved practices in data sharing and archiving, have the potential to accelerate the use of this valuable resource in ecological research and conservation. These images offer a unique opportunity to address ecological questions that have so far been limited to small scales or relied on incomplete evidence. We urge ecologists and conservationists to take advantage of this unprecedented opportunity to tackle important ecological and conservation questions. In addition, we encourage the further release and open use of classified military data archives pertaining to the environment for monitoring purposes.

#### **Supplemental Material**

Supplemental data are available at **BIOSCI** online.

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#### Author contributions

Catalina Munteanu (Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Validation, Visualization, Writing – original draft, Writing – review & editing), Benjamin M. Kraemer (Formal analysis, Funding acquisition, Investigation, Methodology, Visualization, Writing – review & editing), Henry H. Hansen (Data curation, Formal analysis, Visualization, Writing – original draft, Writing – review & editing), Sofia Miguel (Data curation, Formal analysis, Investigation, Validation, Visualization, Writing – original draft, Writing – review & editing), E.J. Milner-Gulland (Conceptualization, Investigation, Resources, Supervision, Writing – original draft, Writing – review & editing), Mihai Nita (Data curation, Methodology, Resources, Writing – review & editing), Igor Ogashawara (Data curation, Funding acquisition, Writing – review & editing), Volker C. Radeloff (Investigation, Validation, Writing – review & editing), Simone Roverelli (Data curation, Writing – review & editing), Oleksandra O. Shumilova (Funding acquisition, Writing – review & editing), Ilse Storch (Resources, Supervision, Writing – review & editing), and Tobias Kuemmerle (Conceptualization, Resources, Software, Supervision, Writing – original draft, Writing – review & editing)

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