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AI4WildLIVE: Integrating Biodiversity Monitoring and Earth Observation

Jonas Grieb [1], Claus Weiland [1], Alexander Wolodkin [1], Daniel Bauer [1], Maya Beukes [1], Matthias Biber [1], Martin Jansen [1], Karsten Wesche [123]

[1] Senckenberg Society for Nature Research, Frankfurt, Germany
[2] Senckenberg Museum of Natural History Görlitz, Görlitz, Germany
[3] International Institute Zittau, Technische Universität Dresden, Zittau, Germany

Correspondence: Jonas Grieb (jonas.grieb@senckenberg.de)

Abstract. Growing numbers of biodiversity monitoring data recorded by camera trap devices are becoming increasingly difficult to manage and analyze. The WildLIVE platform is being developed to address these challenges by providing a comprehensive virtual research environment (VRE) that integrates citizen science, machine learning-based annotation, and geo-analysis functionality. Additionally, it serves as a centralized platform for FAIR (Findable, Accessible, Interoperable, and Reusable) data sharing. This paper presents the core concepts of the WildLIVE platform and its underlying data model, highlighting its potential to streamline biodiversity research and enhance data accessibility.

Submission Type. Model, Infrastructure, Project

BoK Concepts. [PS] Platforms, sensors and digital imagery, [IP] Image processing and analysis

Keywords. Biodiversity Monitoring, Biodiversity Loss, Sensor Ontology, Human-in-the-Loop Machine Learning, RO-Crate, Community Curation, Citizen Science, FAIR Digital Object

1 Introduction

Humans impact the biosphere and all its habitats on a vast scale, contributing significantly to adverse effects such as faunal changes, deforestation, and desertification (Newbold et al. 2015). These effects culminate in a substantial loss of biodiversity, having significant negative effects on the benefits, known as ecosystem services (Gudde et al. 2024), that human societies derive from habitats. Long-term environmental monitoring across multiple geographic locations is therefore more important than ever for the quantification of these effects, and for providing a solid data basis for policy-makers, NGOs, and other stakeholders to develop effective and timely mitigation strategies (Haase et al. 2018).

In this respect, camera traps and passive acoustic devices are particularly valuable as non-invasive methods for documenting wildlife diversity, ecology, behavior, and conservation (Buxton et al. 2018; Jansen et al. 2020; Meißner et al. 2023). The application of autonomous devices for in-situ biodiversity monitoring is constantly evolving, generating increasing volumes of biodiversity data that support large-scale analysis and forecasting infrastructures, particularly in the context of the European Green Deal and associated dataspace projects (European Commission: Joint Research Centre 2021).

Accordingly, both the amount of primary data (recorded digital photos, videos, and audio files) and of derived data (automatically assigned annotations such as labels) are expanding at a rapid pace (Delisle et al 2021). Even medium-sized camera trap projects, deploying around 50 to 80 camera traps, can generate up to 100,000 images per year (Palmer et al. 2021). The overwhelming volumes of data often push small teams of scientists to their limits, creating significant bottlenecks for conservation-driven data analyses.

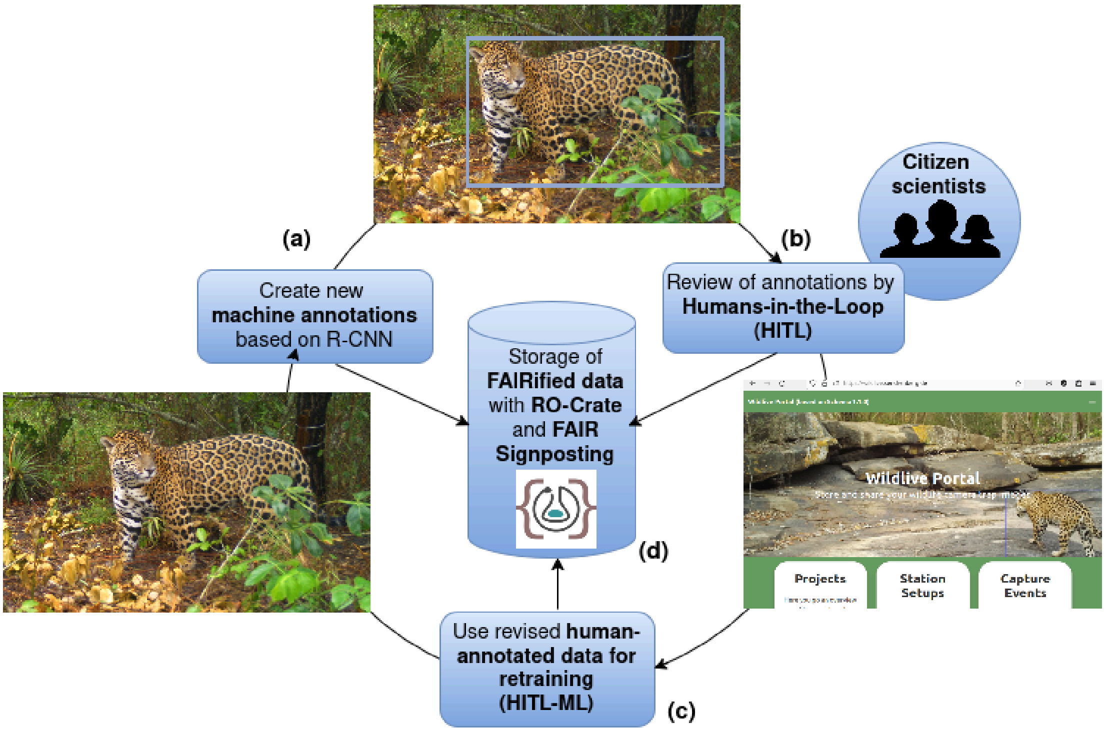

Figure 1: The WildLIVE portal's conceptual model and workflow: High throughput annotations are provided as a baseline by trained machine-learning models (a). Citizen scientists afterwards review and improve the annotations (b). Reviewed data are subsequently used as new training data (c). Central element of the workflow is the capturing of contextual (provenance) information from all human and machine-based operations in RO-Crate packages (d). Figure redrawn from Fig. 1 in Grieb et al. (2024).

Furthermore, the large volumes of sensor data inherently possess a spatio-temporal component, dictated by the location and temporal configuration of the recording stations. This presents both opportunities and challenges.

One key opportunity is the ability to contextualise sensor data with Earth observation data, enabling the assessment of land use changes and their effects on observed biodiversity. However, the challenge lies in publishing the data as openly as possible, while ensuring the protection of sensitive geolocation data for protected species.

2 Solution

To meet the requirements of biodiversity monitoring infrastructures, we developed an integrated data platform with dedicated data pipelines for the rapid analysis of critical ecological data (Grieb et al. 2024). Combined in a "Single Point of Entry", the WildLIVE Portal (https://wildlive.senckenberg.de) provides comprehensive functionalities for the storage, curation, analysis, and publication of biodiversity monitoring data. It integrates pipelines for machine learning-based annotation and community-driven taxon determination, facilitating efficient and scalable data management.

The primary objective of the WildLIVE platform is to facilitate community-based curation of digital images, audio, and video content from camera traps and acoustic recorders based on crowd-sourcing (Jansen et al. 2024). This process is supported by the deployment of machine learning pipelines to run automated species detection based on a trained artificial neural network for newly uploaded media to the platform (Figure 1a). The species detection is currently based on the Faster-RCNN model from the Detectron-2 object detection framework (Ren et al. 2015, Wu et al. 2019). The inferred species detections are stored as annotations to the original media. Citizen scientists can then focus on reviewing and refinement of the annotations (Figure 1b), thus possibly being able to revise more sensor recordings in less time. Currently, under development is a pipeline designed to facilitate the subsequent mobilization of annotated data for the re-training process of the model (Figure 1c); a process known as Human-in-the-loop machine learning (Mosqueira-Rey et al. 2023).

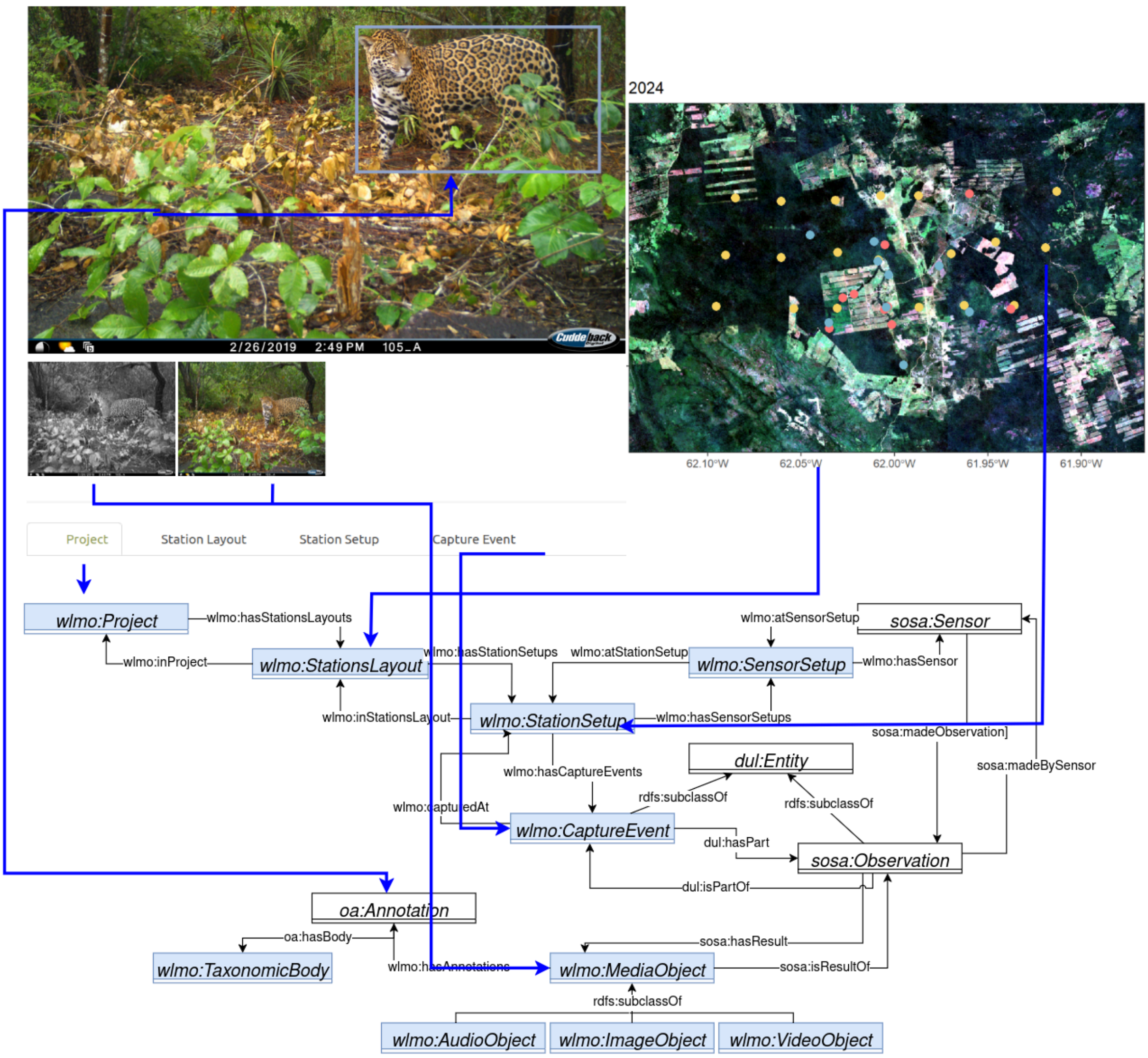

Figure 2: Concepts of the WildLife Monitoring Ontology (WLMO) applied to an annotated observation, including `wlmo:CaptureEvent` for a series of observations that were triggered by the same event, `wlmo:StationSetup` representing the setup of one or several joint monitoring sensors and `wlmo:MediaObject` holding the media metadata and providing a URL to the actual media file.

The WildLIVE platform is still under development. In the first prototype the trained neural network supports the detection of only a limited number of species. This initial species detector was designed to support the biodiversity monitoring project described in Jansen et al. (2024). However, the overall platform is intended to support any audiovisual monitoring project, regardless of the geographic region. While the initial training and refinement of the neural network may take some time for each project, running the inference afterwards is not computationally expensive and thus can also scale effectively for large data volumes. While no user studies have been conducted yet, it can be expected that the project will particularly benefit from the neural network quickly tagging the large amount of empty camera trap images or those depicting for example local cattle herds, thus enabling both citizen scientists and researchers to focus on the more relevant data. A possible issue is the underrepresentation of seldom occurring species in the training data, which in turn could lead to the neural network not detecting such species even if they occur. It is planned to tackle this issue via employment of the general purpose detector Megadetector (Hernandez et al. 2024), to annotate the occurrence of unknown fauna even when the specific species detector fails.

Community projects like Megadetector underline the power of applying trained models provided by the community. In turn, this also highlights the need to share data published via WildLIVE in a way that it can easily found and reused by the community. Notably, the FAIR principles (Findability, Accessibility, Interoperability, and Reusability, Wilkinson et al. 2016) play a key role in guiding the discovery and processing of digital assets with minimal to no human intervention, a capability which is referred to as “machine-actionability” (Jacobsen 2020).

Accordingly, we developed a flexible, FAIR-compliant data model (Figure 1d and Figure 2) comprising all primary data from the biodiversity monitoring process. This model is bundled with rich provenance, metadata, contextual descriptions (such as the setup of sensors), and comprehensive workflow descriptions, leveraging the Research Object Crate (RO-Crate) approach (Soilent-Reyes et al. 2022). To further enable autonomous discovery of the data packages both within and across data space projects, an additional machine-interpretable layer was computed for every RO-Crate using the FAIR Signposting approach (Soiland-Reyes et al. 2024).

Fundamental for the technical implementation of the WildLIVE platform is an ontology based on the Sensor, Observation, Sample, and Actuator (SOSA) ontology (Janowicz 2019). To comprehensively represent all relevant domain-specific concepts (Figure 2), we developed the WildLife Monitoring ontology (WLMO) which serves as the central data schema, with the CaptureEvent as the core entity. The latter is a collection of camera trap media files that include spatio-temporal proximity, such as a set of photos triggered by the same event. The media files are stored as FAIR research objects encapsulating both binary data and metadata. The WLMO provides the semantic framework for this metadata, which is both internally stored and externally provided in the RDF serialization format JSON-LD (Kellog et al. 2019). To further enhance data accessibility in WildLIVE, we employ the web-based or “webby” FAIR digital data approach, building on RO-Crate and FAIR Signposting.

Besides the CaptureEvent, the station where a monitoring device was set up is another principal entity in the platform. CaptureEvents are linked to the stations where they occurred and they share the same geolocation. The location of these stations is the principal entry point into the (still under development) VRE for spatio-temporal patterns, which is based on the software Geo Engine[1]: in a on a map viewer the stations (and the detected species at those) can be visualized together with pre-processed Earth Observation products facilitating for example the analysis of land use change and changes in the patterns of detected species.

The integration of both VRE functionalities for biodiversity monitoring and FAIR sharing of audiovisual data in a single platform also leads to challenges such as preventing accidental exposure of sensitive geolocation data of species that are threatened or at risk of poaching. This issue is currently dealt with by the implementation of a simple obscuring mechanism which removes the precision of the decimal degrees coordinates for unauthenticated users of the WildLIVE platform or its API. Only authenticated users can see the real geolocation coordinates and only for their own submitted data, or after explicitly being granted access by another user. A promising implementation path for the future is to express the fact that more precise geodata can be obtained by users with certain rights in a machine-readable way based on the Open Digital Rights Language (ODRL[2]), for purposes of better accessibility and reusability.

In summary, providing a platform which includes a VRE with machine learning, citizen science and earth observation tools, and where data is shared aligned with the FAIR principles, is expected to further accelerate and facilitate biodiversity monitoring by easier community access to valuable training data.

2.2 Data and Software Availability Section

All data that is uploaded to the WildLIVE platform will be openly available, with the restrictions regarding sensitive location data as mentioned above. An initial excerpt of the overall camera trap data from Bolivia is made available under CC-BY license at doi:10.12761/34zr-fh25.

The WildLife Monitoring Ontology is accessible under: https://wildlive.senckenberg.de/wlmo.

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[1] https://www.geoengine.de/
[2] https://www.w3.org/TR/odrl-model/

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Declaration of Generative AI in writing

The authors declare that they have not used Generative AI tools in the preparation of this manuscript. All intellectual and creative work, including the analysis and interpretation of data, is original and has been conducted by the authors without AI assistance.