

The Doñana Digital Twin: integrating heterogeneous data into iterative, mechanistically grounded forecasts of biodiversity change

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Abstract

Natural ecosystems are increasingly impacted by multiple global-change drivers, and these impacts propagate non-linearly from individuals to populations and to communities. To anticipate ecological change under such complexities and mitigate negative impacts, we require integrated, mechanistically-grounded approaches to prediction. For mitigation strategies to be adaptive, predictions must also be updated efficiently as new evidence becomes available. In many protected areas, decades of heterogeneous monitoring data are available, but remain siloed within research groups or projects and are rarely turned into integrated forecasts. Here we present an ecological digital twin of Doñana Natural Area, a Mediterranean biodiversity hotspot under increasing climate and land-use pressures. The digital twin combines long-term biodiversity data with weather, hydrological and remote-sensing products. This data is then used to link demographic, abundance and occurrence models to interspecific interactions, which results in community and ecosystem dynamics. Annual forecasts are generated under global-change scenarios, and uncertainty is explicitly carried through every stage of this chain, from driver to outcome. The digital twin is hosted open-access on the LifeWatch ERIC e-infrastructure, thus ensuring transferability and continuity. Annual evaluation of forecast skill against benchmark models, open forecast submissions by different user groups, and a web interface support continuous updating and decision-making. Importantly, the digital twin is also built on standardized workflows, allowing new models, species, and data streams to be incorporated rapidly and consistently. This design makes the approach directly scalable: the same infrastructure can be extended to other protected areas that already hold numerous ecological datasets but currently lack the integrated products needed to translate that data into actionable ecological knowledge.

Introduction

Many ecosystems across the globe have been shaped by human activity for centuries or even millennia and are now increasingly sensitive to biodiversity loss under the compound effects of climate, land-use change, pollution, resource exploitation, or invasive species (Willcock et al., 2023; Zscheischler et al., 2018). A key objective for ecological research and policy is to anticipate and mitigate the impacts of these global-change drivers on biodiversity (European Political Strategy Centre et al., 2019; Dietze et al., 2024). However, predicting how environmental stressors or management regimes affect biodiversity remains difficult, in part because of the complexity of natural systems. Ecosystems are ultimately built from individuals that respond in non-linear ways to biotic and abiotic drivers (Ickin et al., 2025; Synodinos et al., 2023). For example, differences in genetic or phenotypic traits shape how individuals move, survive, and reproduce under global-change drivers, which determines the relative abundances of different species in natural communities (Tredennick et al., 2016). These abundances, in turn, determine biotic interactions (Twining et al., 2025), which moderate how individuals respond to global-change drivers, creating complex feedback loops (Daugaard et al., 2022; Paniw et al., 2023). Biodiversity patterns then emerge from these ecological dynamics interacting across space and time (Clark et al., 2011; Urban et al., 2016). Models that scale up from individual to biodiversity dynamics can reveal the biological pathways, or mechanisms, through which systems are buffered from, or made more vulnerable to, environmental stressors (Paniw et al., 2022; Pilowsky et al., 2022). Such mechanistic upscaling models are needed to robustly predict outcomes in complex natural systems, but remain rare (Urban et al., 2016, 2021).

The lack of dynamic, mechanistic models to predict biodiversity change may be perplexing given that ecological data are increasingly more available, despite persisting biases (Chapman et al., 2024; Moersberger et al., 2024). International organizations such as the UN Environment Programme World Conservation Monitoring Centre, the Group on Earth Observations Biodiversity Observation Network, and the Global Biodiversity Information Facility, together with research infrastructures such as the Integrated Carbon Observation System and the Integrated European Long-Term Ecosystem, critical zone & socio-ecological Research, have driven remarkable advances in open ecological observation and network science (Affinito et al., 2024). At local and regional scales, these initiatives are fed or supplemented by long-term biodiversity monitoring, especially in protected areas (Pilotto et al., 2020).

Yet, increased data availability has not translated into integrated predictions, for two main reasons. First, global-change effects are typically studied on single species or populations or on aggregated biodiversity metrics, without accounting for dynamic feedbacks (Ickin et al., 2025; Paniw et al., 2026). Second, while scenario-based long-term projections of biodiversity change have become widespread, such as projecting species declines to 2100, the capacity to anticipate ecological change in dynamic, complex systems and to adapt these expectations as new evidence becomes available remains underdeveloped (Boult, 2023; M. Dietze et al., 2024). Thus,

initiatives to couple the decades of ecological data with advanced models to develop integrated and iterative predictions of biodiversity changes are urgently needed (Koerich et al., 2022).

One approach to overcome these challenges is the ecological digital twin (de Koning et al., 2023). Digital twins are modeled representations of real-world (eco)systems, and they distinguish themselves from conventional modelling of biodiversity in two ways. A first strength of digital twins is their capacity to integrate heterogeneous data: they can merge remote sensing, sensor networks, field surveys, citizen-science records, and mechanistic models into a single representation of an ecosystem (Blair, 2021), bridging disciplines that have typically examined ecosystem components separately (Ovaskainen et al., 2026). Second, is that digital twins are living systems. Rather than being calibrated once and then left static, a digital twin is revised regularly: new observations are fed back into its predictions, either through data assimilation or by periodically retraining the underlying models. While their aims and outputs vary, short-term predictions (i.e., ecological forecasts) are usually central, and digital twins are typically designed to inform management decisions, creating a two-way flow of information between model and system (Adade & de Vries, 2023).

The Doñana Digital Twin: Scaling up predictions of biodiversity change

Here, we present the Doñana Digital Twin (DT), which utilizes decades of heterogeneous ecological data collected in Doñana Natural Area together with advanced models to develop integrated predictions of biodiversity and ecosystem change. This digital twin scales up, from individuals to ecosystems, the effects of interacting global-change drivers on population abundances of interacting species across trophic levels in Doñana Natural Area. The data we use are typical of numerous protected areas where long-term monitoring exists (Moersberger et al., 2024). Thus, the Doñana DT can serve not only as an international reference for understanding how complex anthropogenic effects scale up from individuals to ecosystem functioning, but also as an effective data–model integration to derive usable ecological products. The technical backend of the digital twin is being developed by LifeWatch ERIC, a European Research Infrastructure that is part of the European Open Science Cloud and is dedicated to hosting a range of biodiversity applications following FAIR (Findable, Accessible, Interoperable, Reusable) principles. This ensures that outputs are sustained into the future and widely accessible (Islam et al., 2026). In the following, we first describe the study system and then the components of the digital twin, from data and models to scenarios, uncertainty, validation, updating, and user interface.

Why Doñana Natural Area?

The Doñana area is located in southwestern Spain, around the Guadalquivir estuary. Its ecological value has been recognized for centuries and formalized through the creation of Doñana

National Park in 1969 and its designation as a UNESCO Biosphere Reserve in 1980 and a UNESCO World Heritage Site in 1994. The Doñana Natural Area corresponds to the Biosphere Reserve and comprises the National Park, the surrounding Natural Park (peripheral areas of different habitats), and areas with a lower level of protection adjoining agricultural land (Paniw et al., 2026). The region has a subhumid Mediterranean climate, with hot, dry summers and variable rainy seasons that were historically centered in autumn and spring but have shifted toward winter in recent decades (de Felipe et al., 2023; Sánchez-Mejía et al., 2026). Doñana harbors a large variety of terrestrial and aquatic ecosystems, including pine and cork oak forests, shrublands, grasslands, sand dunes, and marshlands of varying salinity. This mosaic of habitats is the main reason why Doñana is considered a biodiversity hotspot (Carmen et al., 2010; Díaz-Delgado et al., 2023; Román et al., 2026).

Municipalities around Doñana live largely from tourism (nature tourism, cultural pilgrimages, coastal resorts), agro-industry, and fisheries (Martín-López et al., 2011). Against this economic backdrop, excessive and unsustainable groundwater extraction, up to 20 m in the deepest aquifer, is currently the biggest threat to Doñana's ecosystems and has created tensions between nature conservation and local economic development (de Felipe et al., 2023; Green et al., 2024; Santamaría & Martín-Ortega, 2023). Climate change is aggravating this water deficit: temperatures have increased over the last three decades, precipitation has decreased over the last decade, and both trends are projected to continue (Paniw et al., 2026). Together, these pressures are lowering aquifer recharge, water inputs to ponds and marshes, and soil moisture, and are reducing water quality through greater salinity and pollutant concentrations (Fernández-Delgado, 2017; Jiménez-Bonilla et al., 2026; Paredes et al., 2021). Impacts on temporary ponds, marshes, and terrestrial vegetation are already evident and are further exacerbated by other global-change drivers, such as invasive species (reviewed in Paniw et al., 2026).

Many single-species conservation interventions in Doñana have not succeeded, highlighting the need for more holistic approaches. The recovery of the Iberian lynx (*Lynx pardinus*) and Spanish imperial eagle (*Aquila adalberti*), for example, has relied on restocking rabbit (*Oryctolagus cuniculus algirus*) populations, which has had limited effect on their predators (Carro et al., 2019), partly due to ongoing global-change pressures keeping rabbit densities low (Ferrer & Negro, 2004). More integrative approaches have been suggested that would restore habitat suitability for rabbits by reinstating the natural hydrology (including the temporary ponds that once provided summer pasture), protecting the shrublands where rabbits breed, and managing the movement of (semi)domestic ungulates more effectively to prevent overgrazing (Cabezas & Moreno, 2007; D'Amico et al., 2014). Because of the complexity of global-change impacts, there are also increasing calls to predict how effectively different measures would alleviate such complex impacts. The Doñana Digital Twin was developed in response to this management and policy need (MITECO, 2022). Informed by participatory work with park managers and other

stakeholders, it supports ecosystem-based conservation centered on ecological processes and functional species interactions.

Components of the Doñana Digital Twin

The conceptual structure of the Doñana Digital Twin closely follows the iterative ecological forecasting cycle (M. C. Dietze et al., 2018). The cycle begins with identifying the questions that matter to researchers, managers, and policy makers, which determine which variables are forecast, at what scale, and over what time horizon (Bodner et al., 2021). These questions guide the assembly of a dynamic database that brings together monitoring, climate, hydrological, and remote-sensing data and keeps them current through automated and periodic workflows (Fig. 1). The data are used to calibrate models of species' demographic rates and abundances, which are then altered by scenarios of future climate and land-use change to produce forecasts. Because a forecast is only useful if its reliability is known, uncertainty is propagated through each of these steps and reported (Fig. 2). As new census data become available, forecasts are validated against observations, and forecast skill is compared with that of benchmark models and that of new forecast submissions. The results inform a decision on whether the underlying models need to be revised, after which the cycle restarts with updated data and models. Exchange with stakeholders runs through the whole cycle: users help shape the initial questions, explore forecasts and scenarios through the user interface, and take part in evaluating outputs and updating models. Below, we describe each step in turn, followed by the technical infrastructure and user interface that make the cycle operational (Fig. 3).

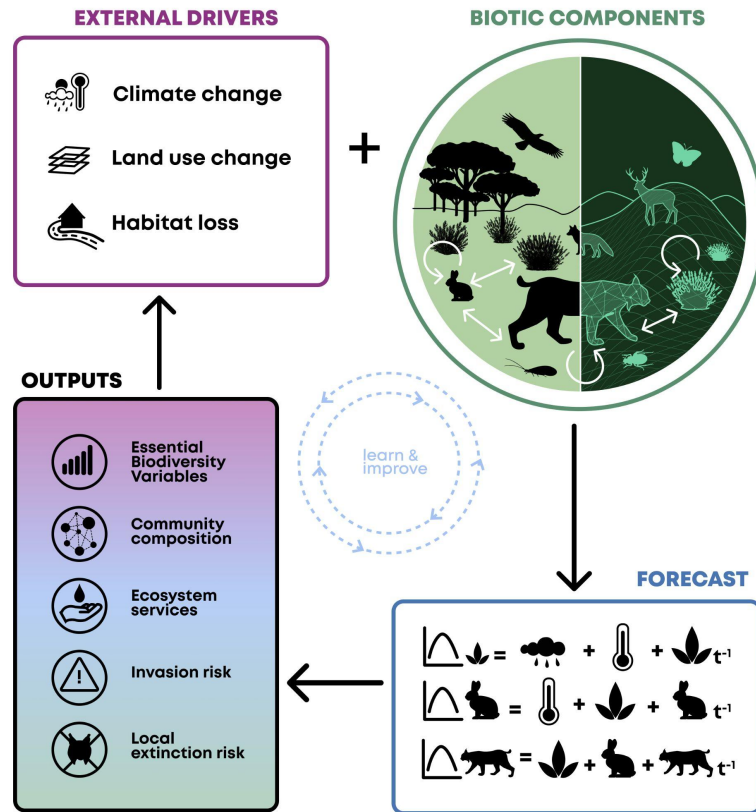


Figure 1. Overview of the iterative modelling and forecasting implemented in the Doñana Digital Twin. External drivers of global change affect the demography of interacting species across trophic levels, which then change species interactions (biotic components of the digital twin). These dynamics are modeled using numerous, heterogeneous data sources. Forecasts are then developed that include how both changes in external drivers and species interactions affect abundances. These forecasted abundances are then used to derive metrics relevant to policy and management. Forecasts are also evaluated against new data and user needs to learn whether outputs are robust and, if not, to change the models, external drivers used or assumptions about species interactions, to then develop new forecasts.

Identifying key questions

To identify management-relevant questions the digital twin should answer, we use a participatory approach with stakeholders involved in managing the Doñana Natural Area. This is possible because the area already has a governing board and a board of trustees on which all institutions and groups directly involved in management are represented; the so-called Doñana Participation Board meets at least twice a year, usually in June and December, and includes administrative authorities at different levels, park managers, NGOs, landowners, scientists, and the private sector (Viti et al., 2024). The digital twin is a living system, and management questions are expected to keep expanding as new stakeholder groups are consulted. In this first implementation presented here, we consulted the National Parks Autonomous Agency (OAPN), park management, researchers at the Estación Biológica de Doñana, and the Regional Government

of Andalusia. The key questions identified in this round, and the prediction targets they translate into, are summarized in Table 1.

Table 1. Management-relevant questions identified through consultation with Doñana stakeholders (OAPN, park management, Estación Biológica de Doñana, and the Regional Government of Andalusia), the biodiversity or ecosystem variables the digital twin forecasts in response, and the policy frameworks each question relates to. This is a first, non-exhaustive set of questions; further stakeholder groups and questions will be added as the digital twin expands.

Management question	Prediction targets	Policy relevance
What tree and shrub species are resilient to climate change?	Relative abundance and cover of main shrub species under climate change	Biodiversity targets under Biodiversity Strategy 2030; climate-change mitigation via carbon sequestration
How is vegetation productivity responding to climate variability?	NDVI (vegetation greenness) under alternative temperature and precipitation scenarios	Ecosystem condition monitoring under Biodiversity Strategy 2030
Which temporary lagoons are most at risk of shrub invasion?	Changes in hydrology and invasion risk by shrubs	Restoration of marshlands under Marco de Actuación
How to increase rabbit numbers in 1–5 years?	Rabbit densities under disease-climate interactions & alternative restocking management	Biodiversity targets under Biodiversity Strategy 2030

Dynamic database

To parameterize predictions that answer stakeholder-identified questions, a key aim of the digital twin is to integrate and continuously update, through dynamic workflows, several types of observational data (Table 2). A core data source is the Singular Scientific and Technical Infrastructure Doñana (ICTS Doñana; <https://icts-donana.csic.es/>), which has continuously monitored environmental states and biodiversity in Doñana for decades and makes all its data openly available (Reserva Biológica de Doñana, 2026). These data include count surveys for various plant and animal species, meteorological and biophysical measurements, and geospatial information derived from open-access international sources such as Copernicus (e.g., monthly and annual marshland flooding duration, downscaled NDVI; Table 2). Additional data on mammal co-occurrence patterns is available from an ongoing camera-trap project (Santoro et al., 2025). In parallel, a large amount of data is available from individual monitoring and experimental efforts (Table 2) and from published literature: Doñana is an intensively studied area, and direct and indirect human pressures on its ecosystems have been described in more than 400 peer-reviewed articles (Paniw et al., 2026). Although these latter data sources are not all continuously updated, together they provide a wealth of information for calibrating mechanistic models. For rabbits, for example, literature-derived parameters (Tablado & Revilla, 2012) are used to build demographic

models that produce indices of rabbit density, which are then validated against continuous count data from ICTS and camera traps. These demographic models are in turn compared with benchmark models built entirely from continuously updated data sources; the same logic is applied to every species we model.

Table 2. Summary of data that is currently being used or will be implemented in the next months in the Doñana Digital Twin.

Dataset	Variables	From	Frequency	How used
Counts of mammals (rabbit, lynx, ungulates) and birds (including aerial surveys)	(Relative) abundance	1980	Monthly-annual, depending on taxon	Validation of demographic models; subset also used to calibrate models (e.g., dynamic N-mixture models)
Counts and biomass of dung beetles, lacewings, and other arthropods	Relative abundance and individual weights or total biomass per trap	2006–2012; 2023	Monthly	Calibration of demographic models via dynamic N-mixture frameworks
Shrub vegetation surveys	Counts of juvenile and adult woody vegetation	2007; 2023	Annual	Validation of demographic models
Individual-based monitoring of shrubs	Individual survival, reproduction, movement	2007	Annual	Calibration of spatially explicit demographic models
Radio-collar tracking of ungulates	Individual movement decisions	2019	Daily	Calibration of ungulate habitat use
Camera trap data of mammals	Species occurrence, relative density, and habitat use	2023	daily	Validation of demographic models
Weather, hydrology, geospatial data	air temperature, precipitation, wind, humidity; water levels and flow; maps of habitat types, flooding extent, NDVI	1980	Daily- monthly	Determines demographic rates and abundances; scenarios

Parameters that are used in the models but not expected to be updated (e.g., body size, movement distances, energetic demands; typically drawn from the literature) are digitized and

stored in open-access repositories (see below). We are working with ICTS technicians to develop APIs that automatically download and process relevant data for modelling; in the meantime, many datasets are still downloaded manually or digitized from ongoing monitoring, following a protocol in which the digital twin's data manager periodically updates all relevant sources. All data and derived products (e.g., monthly NDVI averages) are stored in public and private repositories on LifeWatch ERIC, linked directly to the project's GitLab and virtual-lab environment so that workflow code (mostly R and Python) can read and write to them directly.

Modelling

Using the data sources described above, we estimate demographic rates and abundances for target species, which represent key species (most abundant and/or with the greatest ecological impact) across trophic levels, allowing us to scale from individuals to communities and ecosystems (Paniw et al., 2023). The exact method depends on the species' life history and the data available (can be consulted at <https://gitlab.lifewatch.dev/lfw024-donana-digital-twin/donanadt-shinyapp>). Demographic rates of species are estimated either using individual-based data, or latent-state methods such as autoregressive, Bayesian N-mixture models or Approximate Bayesian Computation (ABC) (Gomez-Peña et al., 2026). Regardless of the method, every model is first calibrated to observational data, then evaluated via a goodness-of-fit test on held-out data (see *Validation*).

Models of abundances of dominant shrub vegetation currently rely on climatic factors and interaction with other shrub species. Outputs of the shrub models are then used to assess the spatiotemporal spread of shrubs into temporary lagoons based on both climate change and changes in groundwater extraction. Shrub abundances, along with climatic variables also inform models of vegetation productivity (NDVI). NDVI is then used as a metric of habitat suitability for a rabbit demographic model. Combined with demographic rates retrieved from the literature and parameterization methods, the demographic model is used to forecast rabbit abundance and spatial distribution. These dynamic species interactions are incorporated through abundance: intra- and interspecific abundances enter as predictors in models (Paniw et al., 2023; Twining et al., 2025), so that a change in one species' forecasted abundance propagates into the forecasts of the species it interacts with. This is what links the separate species-level outputs into predictions of ecosystem-level change, rather than a set of independent, single-species forecasts.

Forecasts

Once calibrated, we forecast each model forward under a given climate or management scenario, at monthly or annual resolution depending on the prediction target, and validate as new observational data become available (see *Validation*). All forecasts are spatiotemporal, forecasting changes in biodiversity from long- term temporal data as well as over habitats where these changes will be most pronounced (spatial). All forecasts also use the same set of climate-

change and land-use change scenarios (see *Scenarios* below). Because species interactions are built into the underlying models, a forecast for one species is not generated in isolation: it responds to, and can shift, the forecasts of the species it interacts with (Fig. 1). Forecasts are therefore dynamic, and every model produces a standardized output following international convention (Lewis et al., 2022): a set of scenario-specific point forecasts with a companion uncertainty layer (Fig. 2), each anchored to the most recent observed value so forecasts connect continuously to the observational record.

Thus far, abundance and ecosystem productivity forecasts have been developed; these are key essential biodiversity variables (EBVs) and thereby provide tangible biodiversity target outputs for managers. As we develop the demographic models further, we are also able to predict changes in key species traits under global change and different management scenarios, e.g., changes in body size or reproduction. From the estimated (relative) abundances and biomass of different taxa, we can derive community-level biomass and composition for insects (with a focus on dung beetles and lacewings), shrubs, mammals, and birds. Predicted changes in vegetation structure will also be used to derive terrestrial productivity, fire risk, phenology, connectivity, and other aspects of ecosystem structure and services, following established methods.

Scenarios

Climate scenarios (changes in temperature and rainfall) are based on the range of short-term regional climate-change projections from AdaptecCa (<https://adaptecCa.es/>), which downscales CMIP-generation global circulation models to the Iberian Peninsula under different emission pathways; we use outputs from at least five global circulation models to parameterize scenarios. For each target month and variable, we currently translate these projections into discrete scenario classes, e.g., temperature as cold, average, or warm relative to that month's historical distribution, and precipitation as dry, average, or wet, so that users and managers can compose custom trajectories (e.g., a warm and dry year followed by an average one) rather than being limited to a single fixed pathway. For processes operating over multiple years, such as shrub demography, we additionally define compound scenarios (wet, dry, average, or fluctuating between wet and dry extremes) that capture sustained versus alternating conditions, which matter for species with lagged or cumulative responses to rainfall.

Scenarios of land-use change are based on socio-ecological information for the study region, primarily agricultural expansion and intensification and the associated groundwater extraction (Jiménez-Bonilla et al., 2026) and urbanization pressure from tourism development. Scenarios will also include restoration, i.e., interventions such as reinstating natural hydrology to temporary ponds and marshes and stricter management of ungulate and wild boar grazing (CITE). For some species (e.g., the rabbit), we also incorporate other relevant scenarios, such as climate-disease feedbacks, based on published literature (Barbero-Moyano et al., 2026; Fordham et al., 2013; Pacios-Palma et al., 2016).

Uncertainty propagation and decomposition

Forecasts carry several sources of uncertainty, which we distinguish explicitly rather than collapsing into a single interval (Fig. 2). **Driver uncertainty** arises because scenarios themselves are uncertain, for example, climate-change projections differ across emission pathways and global circulation models. **Parameter uncertainty** reflects how precisely model coefficients are estimated from data, and includes uncertainty from observation, which is estimated as latent detection parameters or random error. **Initial-condition** uncertainty arises because our models are dynamic: each forecast starts from a population's current abundance, and that starting value is itself an estimate rather than a known quantity. **Stochasticity** captures the role of random demographic and environmental processes that would still generate variation in outcomes even if the drivers, parameters, and initial conditions were known exactly. Finally, **structural** uncertainty encompasses our confidence in having chosen the correct model structure and includes uncertainty around model averaging.

We propagate these sources of uncertainty differently depending on the target species and model. For example, for the machine-learning NDVI and statistical Bayesian shrub forecasts, we run repeated stochastic simulations (currently 100 draws), each combining a resampled parameter set with process stochasticity, so that the spread across draws reflects combined parameter and stochastic uncertainty; individual draws are shown alongside the mean forecast so users can judge how wide this spread is. Not every uncertainty source can currently be propagated to every output; where a source is held fixed for a given forecast because of computational demands or data limitations, we note this alongside the result rather than presenting it as fully accounted for.

For each output (see Fig. 1), we trace and communicate which sources of uncertainty went into the final estimate, and we are developing uncertainty decomposition methods, to be released as scripts and integrated into the Shiny app (<https://donanadt.lifewatch.dev/app/donanadt>), that partition total forecast uncertainty among the main components (drivers, parameters, initial conditions, stochasticity, structural; Fig. 2). This lets users see not only how uncertain a forecast is, but which source dominates it, and therefore where additional monitoring or model development would most reduce that uncertainty. Validation, described next, complements this by testing whether the propagated uncertainty is well calibrated against new observations.

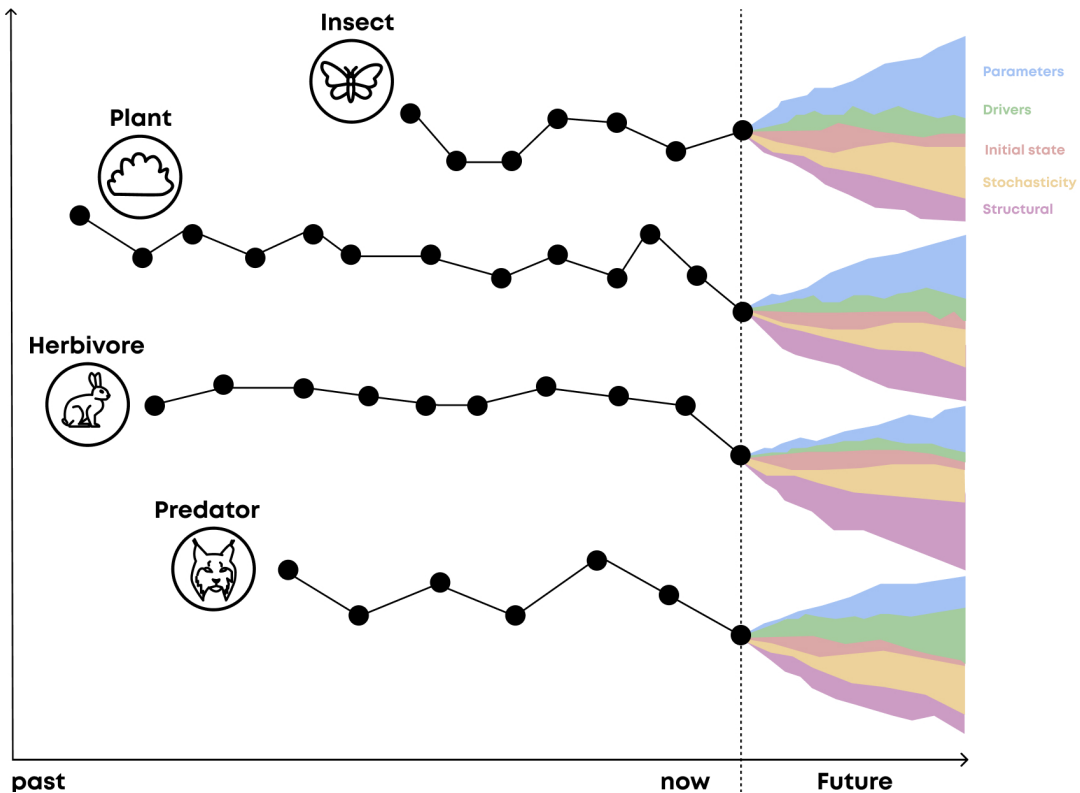


Figure 2. Examples of uncertainty propagation within the Doñana Digital Twin forecasts. Past observations are used to develop forecasts of abundances of several species across trophic levels. The underlying models include several layers of uncertainty, including uncertainty from model parameters, drivers and scenarios (e.g., climate-change projections from different global circulation models), initial abundance estimates of different species; random environmental stochasticity not accounted for by models; and model structure (e.g., model averaging)

Validation

Out-of-sample validation compares forecasts of the digital twin against new census data as they become available. Models are evaluated every fall, and their predictive performance, or forecast skill, is displayed for each output. We report two complementary skill metrics: mean squared error (MSE), computed per draw and then summarized across draws into a mean with a 95% interval, and the continuous ranked probability score (CRPS) (Jordan et al., 2019), which uses the full set of forecast draws as a predictive distribution and so summarizes calibration and sharpness together in a single value per species $\times$ site $\times$ forecast date. Reporting both lets us separate how far off the central forecast is (MSE) from how well the forecast's full uncertainty matches what was observed (CRPS). For the spatial predictions (shrub density, invasion risk), we additionally assess how forecast skill degrades with distance from observation locations: we measure the percentage of species for which observed abundance falls within the 95% prediction interval as a function of distance between prediction and observation points, and identify the distance at which this percentage drops below 50%, which gives a practical forecast horizon for spatial extrapolation (Petchey et al., 2015).

Forecast skill is compared across models for each species and output, including the current best-performing model, a null or benchmark model, and models submitted through the Forecasting Challenge (see below).

Updating

After each annual evaluation round, the digital twin research team receives feedback from stakeholders to decide whether the underlying models need to be revised, for instance if forecast submissions from forecast challenges outperform current models or underlying conditions or scenarios change. This keeps model updates tied to a documented decision. Once the calibrate–evaluate–update cycle has run for three to five years, and enough evaluation rounds exist to define reliable criteria, we envision that routine updating could happen automatically against pre-agreed thresholds. Manual evaluation at this stage can, however, not be eliminated completely when the underlying model structure itself, rather than just its parameters, need to change.

Maximizing engagement: Forecast challenges

Stakeholder engagement in conservation, and particularly in the Doñana Protected Area, has traditionally been complex, and uptake can shift when the political landscape changes, so support for nature-positive interventions, including this one, cannot be taken for granted. The digital twin addresses this in part by using ecological forecasting as a common language across disciplines, which emphasizes standardisation and co-development with end users (Bodner et al., 2021). One particularly promising point of engagement is the forecast challenge embedded within the Doñana Digital Twin. Forecast challenges build on a broader tradition of model comparison and forecasting competitions across disciplines, providing a prospective, large-scale form of model comparison that reveals when and where different modelling strategies succeed or fail (Makridakis et al., 2020; Olsson et al., 2025). Ours is part of the wider Ecological Forecasting Initiative challenge ecosystem (Dietze et al., 2023), and open to researchers, stakeholders and general public alike: participants download the standardized input data, build a model for one of the target outputs, and submit their forecasts through a dedicated dashboard (<https://donanadt.lifewatch.dev/app/donana-forecast>). Submissions can draw on sophisticated modelling approaches that academics want to test on a new system, or on expert-based knowledge from the data collectors and managers themselves. Every submission, temporal or spatial must follow a fixed schema (site and model identifiers, ISO 8601 datetimes, a specified coordinate reference system, and an explicit representation of uncertainty) and is validated automatically on upload; only forecasts that pass are scored, using mean squared error and the continuous ranked probability score, against later observations as they come in, keeping every model comparable regardless of who submitted it or how it was built. The best-performing submissions are then incorporated into the digital twin itself, giving contributors a direct route from a single forecast to a lasting role in an operational system, and embedding the twin in a large,

repeated test of alternative models against the same evolving ecosystem, data streams, and observations.

The technical backend of the digital twin

The infrastructure hosting the digital twin is provided by LifeWatch ERIC, the European e-infrastructure for biodiversity and ecosystem research. LifeWatch ERIC already hosts an operational ecological digital twin effort: the EU-funded BioDT project developed ten prototype digital twins spanning grassland dynamics, forest biodiversity, real-time bird monitoring, and crop wild relative genetics, with its web interfaces likewise hosted on LifeWatch ERIC's cloud infrastructure. LifeWatch ERIC is committed to maintaining these services beyond the project's lifetime (Islam et al., 2026) giving our choice of backend a demonstrated precedent for long-term sustainability of forecast-facing biodiversity infrastructure, beyond Doñana alone.

The digital twin infrastructure is located inside a resilient multi-datacenter Kubernetes cluster at LifeWatch ERIC. Inside the cluster, the digital twin is divided into two main elements: an RShiny-based graphical user interface (GUI) for easy graphical access, and a backend ecosystem for the execution of workflows (Fig. 3).

The GUI is served through ShinyProxy (OpenAnalytics, 2023), which allows the translation of the RShiny application into a production-ready deployment that is served in a resource-effective manner to the users, while still maintaining agile development capabilities for the researchers working on improving the application. A clear lifecycle has been drawn, where a beta version of the digital twin is always available as soon as new changes are developed, and a stable version (with less security guardrails and more resources) is available after a careful revision of each set of changes. The static data required for the GUI (for forecast visualization, dashboard generation, and other functionalities) is mounted from a self-hosted S3 instance at LifeWatch ERIC, where it is updated on-demand by the data maintainers and by automated workflows. The data mount was made using the open-source Mountpoint for Amazon S3 CSI Driver (<https://github.com/aws-labs/mountpoint-s3-csi-driver>). The GUI consists of two levels. The first is an accessible interface presenting the most up-to-date forecasts and letting users explore a limited number of pre-defined scenarios, such as drought timing or specific management options. The second gives stakeholders and researchers access to the digital twin's full workflows, allowing changes across a much larger range of settings and the generation of custom forecasts using the cloud computing resources provided by LifeWatch ERIC.

For the workflows, a set of FAIR (Findable, Accessible, Interoperable, Reusable) workflow components has been developed following the common architecture of LifeWatch ERIC for the provisioning of scientific workflows. Each component is assigned with a separate Gitlab Repository, where researchers can individually decide when to make the repository code public after any possible embargo period. The components are available as Docker images, and each stable component version is also published as an RO-Crate object (Soiland-Reyes et al., 2021)

with a CWL (common workflow language) specification on how to run the component in any agnostic executor (Crusoe et al., 2022). Finally, multiple components can be concatenated and run, either via the official public interface at MyLifeWatch (<https://my.lifewatch.eu>), or via an API interface from the digital twins. The resulting workflows run in the previously mentioned Kubernetes cluster, where they benefit from other specific capabilities such as periodic execution, interaction with S3 storage, usage of local RAM caches to speed up interactions with databases.

The workflow organization is aligned with the principles and the Environmental Research Infrastructures (ENMRI) Community's goals of open science, data-intensive research, and composable services for the European Research Area.

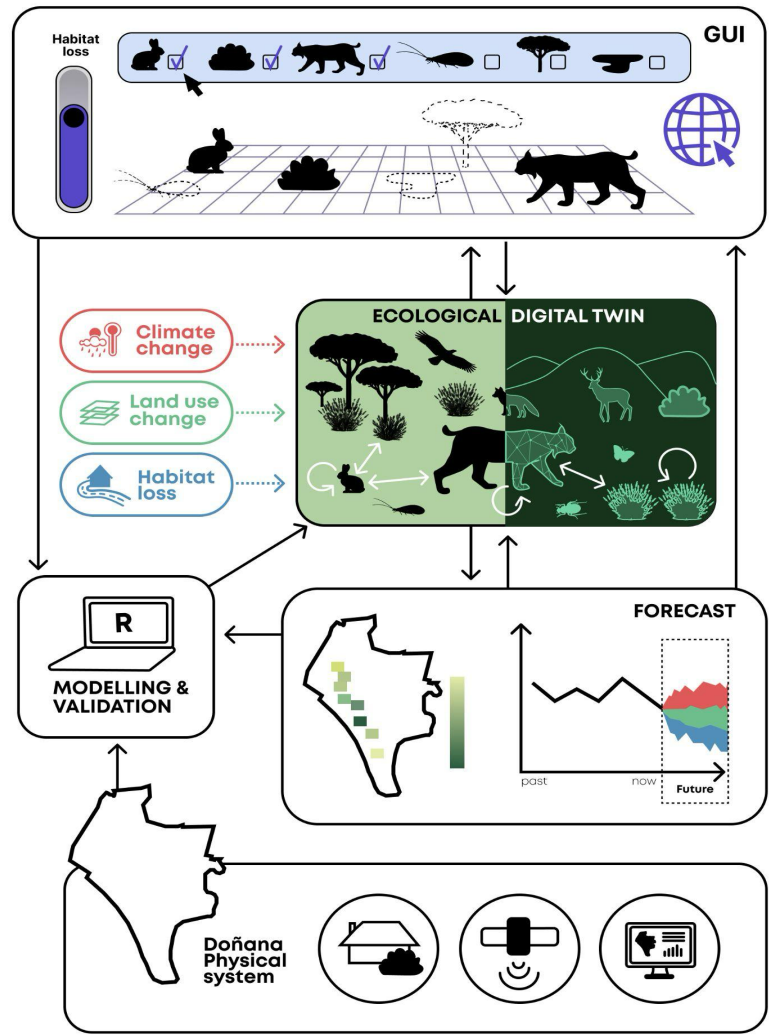


Figure 3. Overview of the Graphical User Interface (GUI) of the Doñana digital twin, and the infrastructure underlying this GUI. Users are able to select different species of interests, and create custom scenarios, such as changing the intensity of expected land-use change. These settings, combined with up-to-date environmental and biological data (Doñana Physical System), inform the models used in the ecological digital twin. These will combine into a forecast for the user specified scenario, which is available to the user from the GUI. Forecasts include essential biodiversity variables as defined in Figure 1. Once per year, all forecasts will be stored permanently with an associated DOI.

Expected scientific and practical impacts/outputs

Doñana Natural Area is an important example of something that plagues many protected areas across Europe: Despite availability of high-quality data and individual lines of research, integrated ecological products resulting from these data do not exist. The Doñana Digital Twin can serve as a promising example for other protected areas in data integration, digital technology, and complex systems modelling. This know-how can then be coupled with the expertise in ecological data collection and analysis to not only synthesize and streamline available abiotic and biodiversity data but also to jointly analyze it under a common framework.

More broadly, understanding biotic mechanisms allowing populations to respond to global-change effects will allow us to develop robust theory and applications of when such mechanisms provide ecosystem resilience (i.e., community structure and functioning resist or recover after perturbations) (Lewis et al., 2023). Most predictions of resilience continue to ignore dynamic feedbacks between individuals in multitrophic systems. Integrating individual interactions and complex-systems biology will improve theory and applications of forecasts of climate-change impacts on biodiversity (Sánchez-Pinillos et al., 2026).

Our open-access policy across the board makes accessible applications that allow a wide variety of users to go through an iterative cycle of continually creating forecasts, evaluating them with new observations, updating the underlying models, and then making new forecasts. This has the potential to accelerate learning about the predictability of different systems across many ecological sub-disciplines, while also supporting user-driven applications with clear societal relevance.

Understanding the Digital Twin as a living system that is constantly updated

As we are writing this text, the digital twin is actively being improved by incorporating more efficient data streams and more species (e.g., dung beetles that interact with rabbits and other ungulates; Iberian lynx that depend on rabbits; ungulates that depend on shrubs). We are also optimizing the GUI, developing new methods to visualize uncertainty partitioning, and providing the first set of forecast skill metrics. We therefore aim for this paper to be a living document as well where we update the developments biannually.

Data and code availability

All modelling and forecasting workflows for all components of the digital twin can be found at: <https://gitlab.lifewatch.dev/lfw024-donana-digital-twin/donanadt-shinyapp>. Users can access and create their own forecasts at: <https://donanadt.lifewatch.dev/app/donanadt>. Forecasting challenges can be accessed at: <https://donanadt.lifewatch.dev/app/donana-forecast>.

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