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Abstract	Deliverable 6.2 details the proof of concept for enhancing modelling applications within protected areas with in-situ and remotely sensed data products. It showcases the manner through which the various partners involved were able to incorporate data provisioned by WP4 and WP5 partners, Remote Sensing and In-Situ respectively, within a modelling framework to enhanced the outputs of their models, or in some cases, the data enabled the models to be run on more than theoretical inputs. The activities detailed within represent an advancement and application of the methodologies proposed and reviewed in Deliverable 6.1 to specific case-study sites representing the Protected Areas of ECOPOTENTIAL as well as Pan-European investigations.
Keywords	Earth Observations, Species Distribution Models, Process-Based Models, Data Assimilation, Ecosystem Monitoring

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Table 1 Abbreviation and acronyms

AUC	Area Under the Curve
Chl-a	Chlorophyll-a
CMLS	Copernicus Land Monitoring Service
DEM	Digital Elevation Model
DTM	Digital Terrain Model
DS	Decision Support
EBV	Essential Biodiversity Variable
EEA	European Environment Agency
EFA	Ecosystem Functional Attribute
EO	Earth Observation
ES	Ecosystem Service
EVB	Essential Biodiversity Variable
EVI -	
GLM	Generalized Linear Model
GPP	Gross Primary Production
HRU	Hydrological Response Unit
LCC	Land Cover Changes
LL	Leaf Longevity
LST	Land Surface Temperature
LSWT	Lake Surface Water Temperature
MERIS	Medium Resolution Imaging Spectrometer
MODIS	Moderate Resolution Imaging Spectroradiometer
MPB	MicroPhytoBenthos
NDVI	Normalized Difference Vegetation Index
NPA	Non-Protected Area
PA	Protected Area
PABs	Protected Area Buffers

PAR	Photosynthetically Active Radiation
RAMMS	RApid Mass Movement Simulation
RS	Remote Sensing
SDM	Species Distribution Model
SDR	Species-DistuRbance
SLA	Specific Leaf Area
SWAT	Soil and Water Assessment Tool
TSM	Total Suspended Matter
VHR	Very-High Resolution
VLab	Virtual Laboratory
VLP	Virtual Laboratory Platform
WP	Work Package

1. Executive Summary

This deliverable illustrates the benefits of adapted and improved models, statistical and process-based, through integration of existing and upcoming Earth Observation (EO) data and in-situ data. The Protected Areas (PAs) involved in ECOPOTENTIAL rely on a combination of monitoring from both direct and remote measurements as well as a series of process based and statistical models in order to determine the past, present, and future states of the ecosystem and its functionalities they are created to protect. Furthermore, such models can help to generate insight into the potential impacts on ecosystems and services in light of management practices and policy measures which can be implemented within the virtual construct in order to determine if certain management and policy pathways would have the expected impacts which they seek and the order of magnitude of such an impact. Such studies and applications can better inform those responsible for the stewardship and preservation of these key biological, cultural, and productive areas. However, such models rely on measured field variables in order to calibrate and validate the parameterization of the model and the quality of generate predictions; such data can even be used as the driving force behind such models, without which, greater assumptions and must be made with synthetic driving forces governing the models themselves. Therefore, it is key to understand the data and monitoring information required to run such ecological models, the benefits their predictions and simulations can provide to policy makers, managers, and other stakeholders while planning the further developments and enhancements to ever increase our understanding of critical ecological functions to guide conservation and management efforts to the benefit of both society and ecology.

ECOPOTENTIAL has created a unique opportunity for protected area managers, ecologists, data scientists, and remote sensing specialists to all work together tackling highlighted problems within Protected Areas. This deliverable shows the benefits that can be reaped when applied modelling focuses to generate key information requested by PA management and policy makers and are paired with Remote Sensing (RS) and Data Science (DS) specialists. Within WP11, the management and stakeholders of the various Pas have expressed their needs for specific information and data sets to be generated either directly from RS or in conjunction with modes. This information has been connected to the WP6 modelling group in order to identify suitable new models or adaptations to currently existing ones in order to enhance the spatial or temporal resolution of the models, include additional proxies and indicators in the outputs which are relevant for PA management and policy decisions, or include additional data sets in order to develop trends on past, present, and future states as well as those resulting from policy pathway adaptations. To achieve this, a large amount of remotely sensed data was generated through Work Package (WP) 4 for affiliated Pas through a data ticket request system; a wide range of proxies and input data, denoted as important and requested by both PA managers and scientists, was produced and made available by ECOPOTENTIAL partners. The partners of WP 6 aim to integrate these data sets into their ecological and ecosystem service modelling efforts by utilizing the data for model inputs and drivers, as calibration and validation measurements, or data assimilation either by automated parameterization or for enhanced state-updating. Deliverable 6.1 has outlined the potential of remotely sensed products as drivers and predictors of ecological models, methods of validation for ecological models through Earth Observation utilization, and integrating ecosystem models and Earth observations via data assimilation. Furthermore, the current status and state-of-the-art applications have been synthesized into scientific publication review piece by the partners of WP6 [1], serving as a foundation for the subsequent application of data within models. These enhancement and improved models will then support the Ecosystem Service (ES) assessments taking place within WP7 by either directly supplying information and metrics on key indicators to the assessment teams or by provisioning additional data and information resources

required to drive additional modelling and assessment systems, such as Bayesian Networks, which comprise the Ecosystem Service Toolbox developed under WP7 and represented within Deliverable 7.3. Furthermore, a subset of the models have been made available within the Virtual Laboratory Platform (VLP) allowing the managers and PA staff to further update and work with the models after the project duration.

The deliverable is divided into subsections, providing details and information on the various models utilized within ECOPOTENTIAL and showcasing how the different in-situ and RS data were incorporated into modelling efforts in order to enhance the predictive and representative capacities of the models. The sections are grouped into terrestrial and marine/coastal Protected areas, provide a brief explanation of the model itself, the present situation within the VLP, and code availability followed by a more detailed application summary with highlights on the RS data products utilized and descriptions of how they were included in the model. This spans the full extent of PA type including marine, mountainous, woodlands, lakes, and range in scale from localized applications to broader Pan-European approaches.

2. Introduction

One of the main goals of ecological and ecosystem modeling is to provide key information to managers and policy makers so that the decisions they are undertaking can be better informed. This can be achieved through developing a better understanding of the system on a fundamental level via developing ever more advance models in the hopes of attaining a better theoretical and numerical construction of the system in question, or through the integration of policy and management pathways within the context of existing models and algorithms, applied for specific case sites. In either case, the end goal is to generate additional information and knowledge on the dynamics of the system and how it may respond to various pressures, management strategies, changing environmental conditions, or a myriad of other factors that can be included in the model deployment. The numerical reproduction of the dynamics of an ecosystem, allowing scientists to better understand past events and generate forecasts of probable future scenarios [2]. This is typically achieved by way of statistical models that correlate the ecosystem variables of interest with its covariates [3], or process-based models that are ground on a mathematical description of the ecological processes governing the system [4]. These mathematical and statistical constructs, as we have conceived them, exist as a series of interactions among various components, parameters, variables, and inputs, which should yield acceptable reproductions of what we observe in reality. However, the ecological systems being reproduced are intricate and complex; high levels of interdependencies exist between the components, thereby requiring simplifications and assumption to be used to construct models [5]. Both statistical and process-based models provide information to stakeholders, managers, and policy makers as to the current trends of ecosystems and their functions as well as the potential impacts of various policy pathways may have on ecosystems and the services they provide [6]. In this way, it is possible to trial several management and policy pathways within a virtual construct in order to determine the acceptability and optimize strategies to yield the best result for both society and the environment. Many models require a wide variety of input data ranging from meteorological drivers, to initial conditions which can vary greatly depending on the time frame and temporal resolution required, and expand to include validated variables which correlate to the model outputs in order to validate the model's capacity and suitability for a study application. This information has been traditionally collected and aggregated through field campaigns, in-situ monitoring, or the construction and maintenance of monitoring networks. These observational strategies can provide a wealth of data on PAs, however encounter issues with the temporal and spatial extent to which they can cover such large regions, as well as the added issue of high labor and time costs associated with the manual collection and maintenance of such systems. Remote Sensing and EO provide a manner by which modelers can gain access to very large spatial extents of data with regular temporal frequencies that can be interpreted to model domains through various scaling strategies and correlated to key indicators and variables that directly correlate to inputs, drivers, or outputs of the ecological models [7]. The generation and upkeep of such RS programs, guided under open-access and freely accessible data policies such as those of ESA and COPERNICUS, in turn, provides a reliable and cost-effective data supply network for modelers to utilize in enhancing models for Protected Areas. This systematic approach of collecting Remote Sensing information, correlating it with in-situ data in order to generate validated Earth Observation data to be used for initial conditions, model drivers, calibration or validation data, and even state-updating and automated assimilation through data assimilation frameworks for a wide range of models is one of the goals of the ECOPOTENTIAL project. Within WP4, a large selection of data products has been requested by the PA stakeholder and modelers involved in the ECOPOTENTIAL project. This data has been obtained from the COPERNICUS platform and others, relying on openly accessible data, and processed utilizing various algorithms which are described in full within deliverables 4.1, 4.2, and 4.3 and are available to other research to utilize via the ECOPOTENTIAL web viewer platform hosted by CREAF. This deliverable focuses on the connection of those validated

Earth observation products that have been prepared as model inputs, initial condition, drivers, and state-updating information for multiple PA specific and Pan-European models, as highlighted by the red arrows in Figure 1, to either support the execution of or further enhance the models in provisioning key data for PA and Pan-European policy and management. These include information on species distribution, population dynamics, water quality, hydrodynamics, habitat quality and distribution, avalanches, and more. All of these model outputs are further utilized in developing a decision support system for the stakeholders of each of the PAs involved. The support systems vary per PA based on the end-user needs, ranging from automated land change detection system incorporated into the Virtual Laboratory in WP4 and WP11, Bayesian Networks utilizing the model outputs to generate probabilistic responses to management in WP7, informing policy pathways and the need for adaptation of PAs in WP9, or direct uptake by the PA stakeholders who can interpret the model outputs to inform management or policy directly.

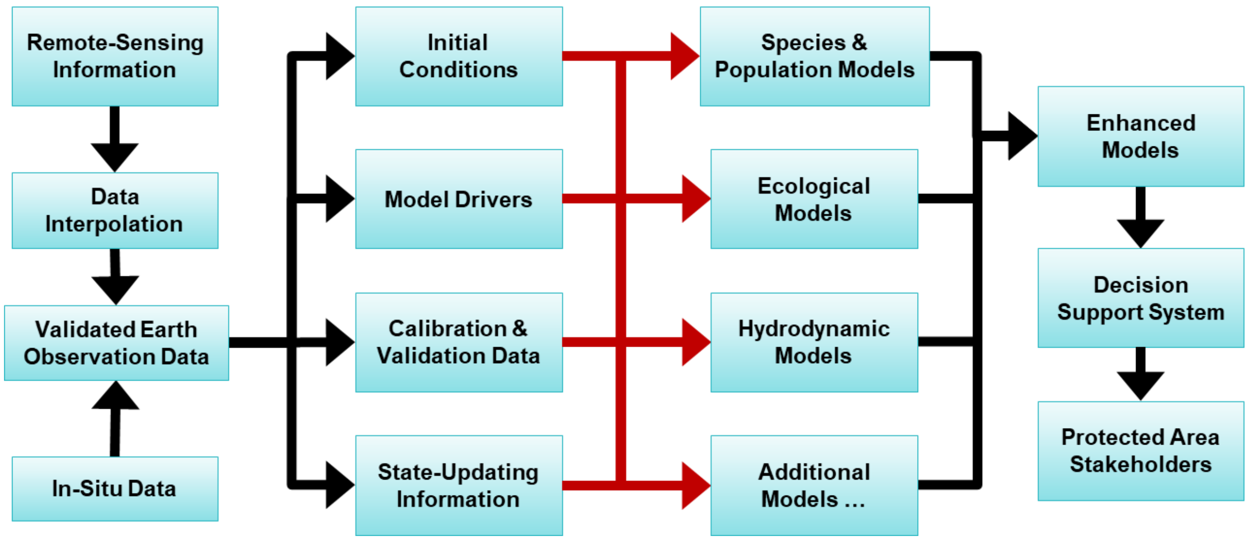

Figure 1: Schematic of the procedural inclusion of Earth Observation data within modelling efforts, highlighted in red are the processes at the core of this deliverable, the integration of Earth Observation into modelling efforts.

The models enhanced through EO data include agent-based, species distribution, habitat quality and distribution, ecological niche, competition, avalanche, and water quality models. One of requirements the development and execution of these, both the process-based and statistical variants, is data points which allow for the calibration, validation, and confirmation of model results. Traditionally, such data are collecting by monitoring networks, including labor intensive surveying campaigns or integrated with autonomous sensor networks which incur a relatively high costs for purchase, operation, and maintenance. Remote Sensing data have been gaining increased use within ecology for the spatial description of the model inputs, for example by the characterization of the land cover and the atmospheric forcing (precipitation, temperature), helping reducing the spatial and temporal uncertainties and inconsistencies associated to the model inputs [1]. Other ECOPOTENTIAL deliverables (4.1, 4.2, 4.2, 6.1) have reviewed the main remote sensing products under consideration and to be utilized in the ECOPOTENTIAL products in conjunction with model improvement and optimization as well as the methodologies in which they can be used, particularly, as inputs, validation, calibration, or updating data points for model hind-casts and forecasts. Through the use of satellite data, particularly the newer satellite series, higher resolution spatial and temporal data sets can be used in the set-up and validation of models representing ecosystem function, structure, or characteristics. Those used within ECOPOTENTIAL have been adapted in order to make use of the large array of Satellite data produced in Work Package 4 to meet the needs of managers and the modelers. The various statistical and process-based models are being utilized within ECOPOTENTIAL are utilized in order to assess the past, present, and future status of ecosystem services via indicators under various management scenarios as well as under climate change conditions. Such models provide insights into the trends and shifts of ecosystem service supply and capacity either through direct correlation of outputs such as the case for population models expressing the number of cork trees to be harvested, or through proxies and indicators such as using water quality variables to track the ability of an ecosystem to mediate wastes and control nutrient cycling.

When the output of process-based or statistical model are compared to Remotely Sense Earth Observation data products, a difficulty of comparing the spatially explicit data in the form of raster maps with the varying spatial and temporal resolution of model outputs can provide difficulties for modelers. Strategies for correcting or accounting for the difference in the spatial and temporal fields of the two data sets must be taken into account. A common strategy for the evaluation of quantitative metrics is to downscale the satellite products to the computational grid of the model, and perform a per-pixel comparison at the temporal resolution of available data. Many of these methods to not account for the resulting inaccuracies or errors in the original measurements, however the data products do still provide critical information which can be used to develop better models as without such source of information, the modeler would find themselves without any form of data outside of the potential spares (both in time and spatial extent) in-situ monitoring points for their particular application. Smoothing model outputs and data by taking monthly or seasonal averages may help to remove local oscillations. It is somehow expected to have some discrepancies in cases where what is modelled (e.g. phytoplankton concentration) is not exactly what is measured (e.g. chlorophyll-a), thus a certain level of model inaccuracy is unavoidable and perfect fits might simply be unrealistic. Deliverable 6.1 goes into great detail on the methods of cross-validation for the range of products utilized in the ECOPOTENTIAL project with specific attention paid to those elements which coincide with the modelling work. Terrestrial, marine, and Pan-European scales are addressed with a wide selection of validation and interpolation methods presented which have been used in the development of validation data sets as well as forcing parameters and function developed to drive the models themselves. This deliverable therefore focuses on the direct application of these methods and data products and showcases the improvements in models and highlights the new capacities in some statistical models which, without these data sets and drivers, would not be possible to execute.

3. Earth Observation Integration into Models

3.1 List of Models and Relevant Storylines

Model	Current status (end of 2018)	Protected areas where the model has been applied
INSTAR Agent Based Model	Complete	Sierra Nevada
MOHID Water Modeling System	Complete	Montado
Species Distribution Model for Plant Species	Complete	Peneda Geres
Habitat Quality and Distribution Model	Complete	Peneda Geres
SWAT Model	Complete	Peneda Geres
Ensemble Ecological Niche Models	Complete	Peneda Geres
Statistical & Empirical Model	Complete	Lake Orhid and Prespa
RApid Mass Movement Simulation (RAMMS)	Complete	Swiss National Park and Davos
Statistical Generalized Additive Model	Complete	Danube River Basin
Delft-3D Water Quality (WAQ)	Complete	Wadden Sea
Statistical Generalized Additive Model	Complete	Pan-European
LPJmL-FIT – Tree Competition Model	Complete	Pan-European

3.2 Terrestrial

3.2.1 Sierra Nevada

3.2.1.1 INSTAR Agent-Based Model (UGR)

INSTAR is an Agent-Based Model aiming to aid environmental decision-making in pine plantations affected by the pine processionary moth (Thaumetopoea pityocampa). Specifically, it aims to generate a deeper understanding of the population dynamics of this pest and to forecast the probability of occurrence and intensity of the pest outbreaks at a landscape scale. INSTAR uses an elevation map and a map of trees distribution as static inputs, and daily maps of minimum and maximum temperatures in order to determine the potential spread and impact of the pine processionary moth on tree populations spread throughout the Sierra Nevada Mountains. This model has utilized Airborne Laser Scanning (ALS) data have been used to generate a map of individual trees for the area to be simulated, which is needed as input, data acquired within the Spanish National Plan for Aerial Orthophotography and processed through WP4 of ECOPOTENTIAL. Suárez-Muñoz et al. describes INSTAR in detail while some calibration experiments and the code can be obtained in order to apply such a model to other regions via the online repository found at the following link: http://sl.ugr.es/github_instar and the model is also located on the Virtual Laboratory Platform that is part of ECOPOTENTIAL.

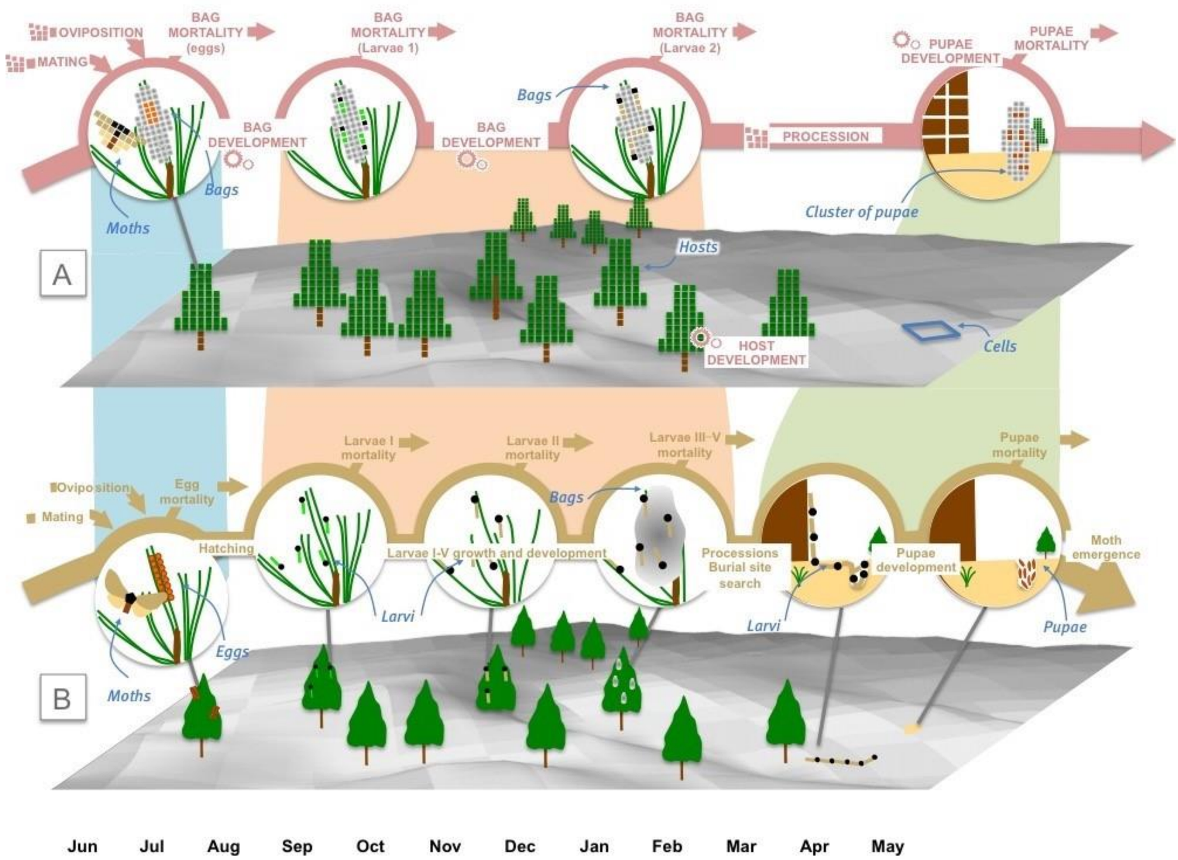

Figure 2: Schematic of INSTAR Agent-Based Model

The pine processionary moth (Thaumetopoea pityocampa) is a typically Mediterranean forest pest feeding on pine needles during its larval stages. The outbreaks of this pest cause important landscape impacts and public health problems (i.e. larvae are very urticant). Larvae feed during winter months and cold temperature is the main limiting factor in their development. Therefore, rising temperatures are thought to benefit this species. Indeed, observations suggest that outbreaks are becoming more frequent and populations are shifting uphill. The objective of this work is to simulate the biological cycle of T. pityocampa to make predictions about where and when outbreaks will occur. Thus, we have created a model called INSTAR that will help to identify hotspots and foresee massive defoliation episodes. This will enhance the information available for the control of this pest.

INSTAR is an Agent-Based Model, schematized in Figure 2: Schematic of INSTAR Agent-Based Model, which allows the inclusion of important characteristics of the system: emergence, feedback (i.e. interaction between agents and their environment), adaptation (i.e. decision based on the mentioned interactions) and path dependence (i.e. possibilities at one time point are determined by past conditions). These characteristics arise from a set of functions simulating pine growth, processionary development, mortality and movement. These functions are easily extrapolable to other similar biological processes and therefore INSTAR aims at serving of example for other forest pest models. INSTAR is the first comprehensive approach to simulate the biological cycle of T pityocampa. It simulates the pest development in a given area, from which elevation and pine trees are considered. Moreover, it is also a good example of integrating environmental information into a population dynamic model: meteorological variables and soil moisture are obtained from a hydrological model (WiMMed, Herrero et al. 2009) executed for the area of interest. These variables are the inputs of the model, which feed the functions that simulate the processionary life cycle.

The Model was applied in two different areas and for relatively long time frames (1993-2014 and 2000-2014) yield relevant information about the biological cycle of the forest pest: the simulated peaks of larvae are followed by minimal values of pine biomass and pine infections are more abundant at the edge of the stands. Moreover, emerging patterns such as denso-dependency can be observed. To sum up, INSTAR is a promising tool for modeling T. pityocampa population dynamics. The obtained model will help to improve the decision making process regarding the control of the forest pest. Moreover, its simple structure of functions will facilitate the design of new models simulating other forest pests.

Publications:

- (Under review) María Suárez-Muñoz; Francisco Javier Bonet-García; José A. Hódar Correa; Javier Herrero Lantarón; Mihai Tanase; Lucía Torres-Muros. INSTAR: an Agent-Based model linking climate and the biological cycle of forest pests in Mediterranean ecosystems. Agricultural and Forest Meteorology.

3.2.2 Montado

3.2.2.1 MOHID Water Modeling System (IST)

MOHID Land is a part of the overall MOHID water modelling system, which can be found on GitHub (https://github.com/Mohid-Water-Modelling-System/Mohid/), is a watershed mathematical model or hydrological transport model designed to simulate drainage basin and aquifer. It is an integrated model with four compartments or mediums (atmosphere, porous media, soil surface, and river network). A limited version of the model has been deployed on the ECOPOTETNTIAL Virtual Laboratory. Water moves through the different mediums provided as inputs to the model based on mass and momentum conservation equations. The atmosphere is not explicitly simulated but provides data necessary for imposing surface boundary conditions to the model (precipitation, solar radiation, wind, etc.) that may be space and time variant. The model is based on finite-volumes organized into a structured grid, rectangular in the horizontal plane, and Cartesian type in the vertical plane. Surface land is described by a 2D horizontal grid and the porous media is a 3D domain which includes the same horizontal grid as the surface complemented with a vertical grid with variable layer thickness. The river network is a 1D domain defined from the Digital Terrain Model (DTM), with reaches linking surface cell centers. Fluxes are computed over the faces of the finite volumes and state variables are computed at the center to assure conservation of transported properties. The model uses an explicit algorithm with a variable time step, that is maximum during dry season when fluxes are reduced and minimum when fluxes increase (e.g. during rain events).

The southern region of the Iberian Peninsula is characterized by a savanna-type agro-silvo-pastoral ecosystem, known as Montado in Portugal (hereafter adopted) and Dehesa in Spain. The Montado system consists of an open formation of cork (Quercus suber L.) and holm oak (Quercus ilex rotundifolia L.) trees, presenting high levels of spatial variability in terms of density, combined with fallow land or pastures, which can be natural, improved, or cultivated. The structural diversity of the system combines with the good overall habitat connectivity over its area of distribution, allowing animals to move around their territories, find mates, hunt, forage, and reproduce, resulting in high levels of biodiversity. As a result, the Montado is considered as a High Natural Value system, providing various ecosystem services (ES) that are perceived by farmers, stakeholders, and society in general as being important for human welfare.

In the last decades, the implementation of the European Common Agricultural Policy has led to an intensification of grazing, which has caused additional stress to the system, promoting the spread of tree diseases and preventing the natural regeneration of the ecosystem. The most significant transformations have been (i) the increase of the stocking (or livestock) pressure (i.e., the replacement of sheep by cattle, the replacement of light indigenous breeds of cattle by heavier breeds, and the increase of livestock units per area); and (ii) the use of heavy machinery for shrub control. These changes have exhausted the natural pastures, decreased tree regeneration, and degraded water and soil quality. Therefore, there is the need for the development of policy instruments that consider the specificities of the Montado silvo-pastoral system; otherwise, its future will be severely threatened in the short term. These policy instruments should be based, for example, on well-established modelling tools capable of accounting for pastures' stocking rates and reducing the adverse impact of grazing in the Montado ecosystem. The MOHID-Land model (Simionesei et al., 2018) was here developed for simulating soil-water dynamics and biomass growth in the Montado ecosystem of the Herdade da Machoqueira do Grou while assimilating LAI derived data from LANDSAT 8 satellite imagery. MOHID-Land is an open-source, physically based, distributed model, which uses a finite-volume approach based on mass and momentum balance equations. The variable-saturated one-dimensional water flow is described using the Richards equation, which includes a sink term for computing root water uptake. For this, a macroscopic approach is used where potential transpiration is linearly distributed over the root zone and may be diminished by the presence of depth-varying root zone stressors, namely water stress. On the other hand, crop development is based on the heat unit theory, which considers that all heat above the base temperature will accelerate crop growth and development, and is modelled by simulating light interception, the conversion of intercepted light into biomass, and LAI development.

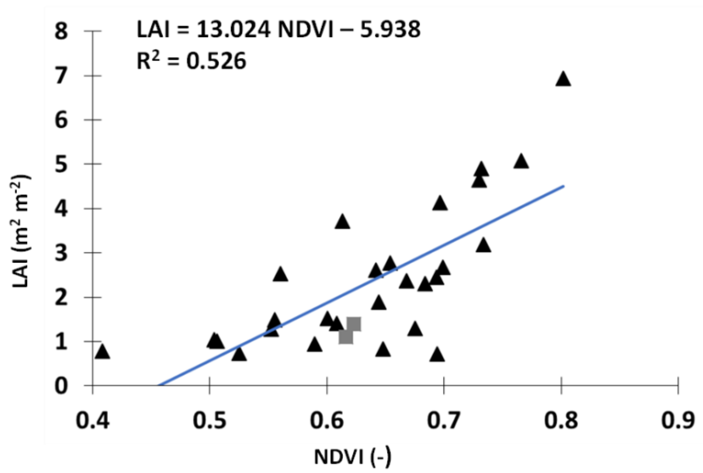

Figure 3: Relationship between pasture's LAI measured in nine sites in southern Portugal and the NDVI. The grey squares correspond to measurements carried out in Herdade da Machoqueira do Grou.

The MOHID-Land model was first calibrated/validated for the 2010–2012 growing seasons by adjusting key input parameters until deviations between model simulations and measured values of soil water contents and dry biomass were minimized. The model was then run again for the same period (2010-2012) to assess how NDVI data assimilation could further improve model performance. Fourteen Landsat 8 images were available for the simulated period. To compute LAI from the NDVI values, in situ measurements of LAI were conducted during March-May in nine different pasture sites located in southern Portugal (total of 29 measurements), using a ceptometer (AccuPAR model LP-80, Decagon Devices, Pullman, USA), allowing an indirect determination of LAI by measuring the fraction of intercepted photosynthetically active radiation (fiPAR) of a canopy. Figure 3 presents the linear relationship between LAI and the respective averaged NDVI values for the March-May period computed from Landsat 8 images. LAI values measured in Herdade da Machoqueira do Grou were within the lowest values found in the monitored sites.

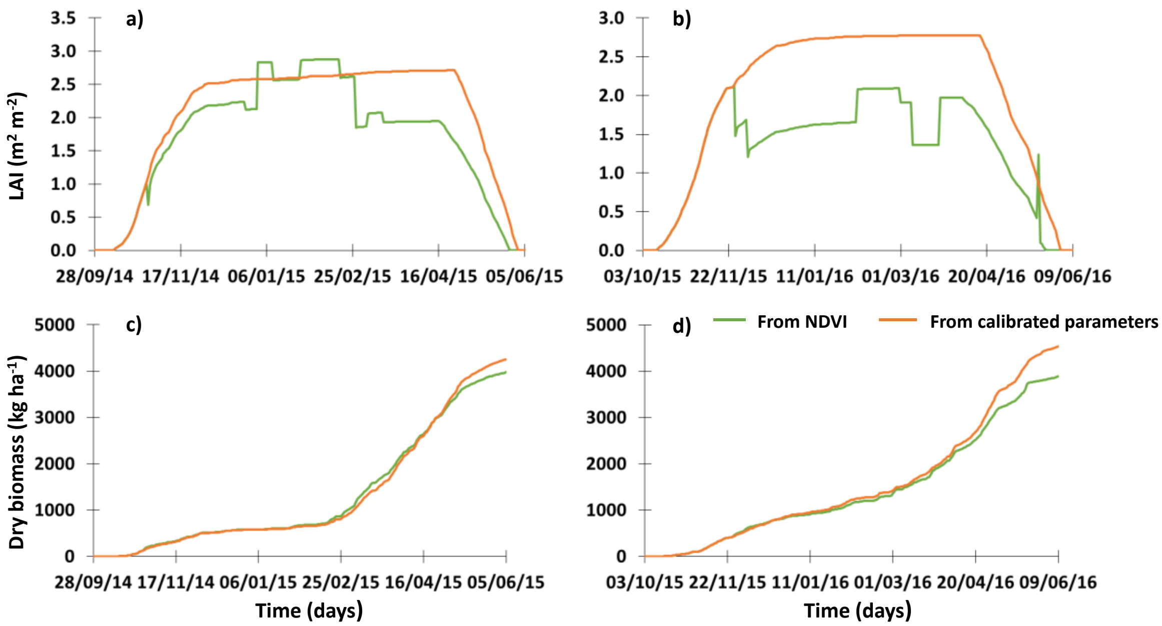

Figure 4: LAI and aboveground dry biomass curves while considering model standard parametrization (calibrated parameters) and the combination of a process-based model with remote sensing data (LAI computed from NDVI values). a) LAI curves during the 2010-2011 season; b) LAI curves during the 2011-2012 season; c) aboveground dry biomass estimates during the 2010-2011 season; and d) aboveground dry biomass estimates during the 2011-2012 season.

Figure 4 shows the LAI evolution and dry biomass estimates provided by MOHID-Land while considering data assimilation. The direct assimilation approach used in MOHID-Land made that LAI simulated results were directly replaced by the LAI values derived from remote sensing data in the dates when satellite images were available. From that date on and until another image was available model simulations followed the default parametrization of the MOHID-Land crop database. As a result, assimilation of remote sensing LAI values using the forcing method available in the MOHID-Land model resulted in several unrealistic discontinuities in simulated LAI (Figure 4), a common feature when using this approach. As LAI assimilated values were much dependent on the relationship found for relating NDVI and LAI values (Figure 3), the uncertainty of the model was assessed using a Monte Carlo approach. For each available date, a population of 10.000 LAI values were derived based on the confidence limits of the regression for each NDVI value provided in the LANDSAT 8 data. Those 10.000 LAI values were then run in the model with their impact on final model estimates of the soil water balance components and dry biomass being then assessed. The model showed that earlier LAI data assimilation had a large impact on final model estimates, bringing large uncertainty to model estimates. The closer the crop growing cycle got to its end, the less impact LAI assimilation had on model results. The MOHID-Land model showed to be a valuable tool for modelling soil water dynamics and dry biomass growth in the Montado ecosystem. The model can thus be considered as a valuable tool for farmers to take the stocking rates into account and reduce the adverse impact of grazing in the Montado ecosystem.

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3.2.3 Peneda Gerês

3.2.3.1 Species Distribution Model for Plant Species (ICETA)

This model application for the Peneda Gerês PA involves a multi-scale modelling assessment of EO data against climate and land-cover to predict habitat suitability derived from Species Distribution Models (SDMs) for two plant species of conservation concern (Iris boissieri and Taxus baccata). Four combinations of predictors (EO, Climate, Land-cover, and Climate + Land-cover) were used to calibrate ten individual modelling algorithms for these two species, and associated derived ensemble models, a schematization of which is provided below in Figure 5: Schematization of Multi-Scale Modelling Approach. These are available in the R package 'Biomod2' (Thuiller et al 2008). Data used to drive and run the models are published in Arenas-Castro et. al. 2018. Furthermore, the model code is published and freely available to download via GitHub and is associated with the official ECOPOTENTIAL GitHub Repository.

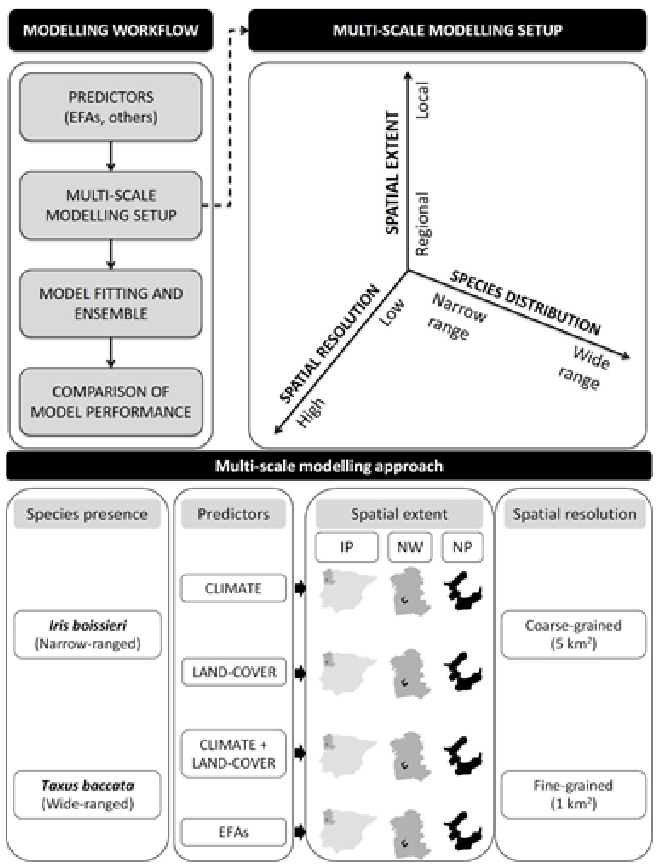

Figure 5: Schematization of Multi-Scale Modelling Approach

Global environmental changes are rapidly affecting species' distributions and habitat suitability worldwide, requiring a continuous update of biodiversity status to support effective decisions on conservation policy and management. In this regard, satellite-derived Ecosystem Functional Attributes (EFAs) offer a more integrative and quicker evaluation of ecosystem responses to environmental drivers and changes than climate and structural or compositional landscape attributes. Thus, EFAs may hold advantages as predictors in Species Distribution Models (SDMs) and for implementing multi-scale species monitoring programs. Here we describe a modelling framework to assess the predictive ability of EFAs as Essential Biodiversity Variables (EBVs) against traditional datasets (climate, land-cover) at several scales. We test the framework with a multi-scale assessment of habitat suitability for two plant species of conservation concern, both protected under the EU Habitats Directive, differing in terms of life history, range and distribution pattern (Iris boissieri and Taxus baccata). Four sets of SDMs were fit for the two test species and calibrated with: interpolated climate variables; landscape variables; EFAs; and a combination of climate and landscape variables. EFA-based models performed very well at several scales (AUCmedian from 0.881±0.072 to 0.983±0.125), and similarly to traditional climate-based models, individually or in combination with land-cover predictors (AUCmedian from 0.882±0.059 to 0.995±0.083). Moreover, EFA-based models identified additional suitable areas and provided valuable information on functional features of habitat suitability for both test species (narrowly vs. widely distributed), for both coarse and fine scales. Our results suggest a relatively small scale-dependence of the predictive ability of satellite-derived EFAs, supporting their use as meaningful EBVs in SDMs from regional and broader scales to more local and finer scales. Since the evaluation of species' conservation status and habitat quality should as far as possible be performed based on scalable indicators linking to meaningful processes, our framework may guide conservation managers in decision-making related to biodiversity monitoring and reporting schemes.

Multiple data sources were utilized in order to generate the input data. Land-cover maps were derived from Landsat TM and ETM+ imagery for the years 2006-2007, this information was used directly in the SDM as predictor variables. Furthermore, the inter-annual means of EFAs for the period 2001-2016 were generated, likewise servicing as predictor variables within the SMD. This information was derived from Enhanced Vegetation Index (EVI-(MOD13Q1.006), Land Surface Temperature (LST-(MOD11A2.005), and Albedo (MCD43B3.005) products based on Moderate Resolution Imaging Spectroradiometer (MODIS) sensor images.

Further Remote Sensing data sets were utilized in the validation and calibration of the SMD as well. Land-cover variables that were derived from optical and thermal multispectral bands of Landsat TM and ETM + images acquired over the same temporal sequence as the target species samplings were carried out. SDMs were fit to these data points and obtained spatial projections under an ensemble-forecasting framework representing the four combinations of predictors. Uncertainties were controlled by generating 30 different sets of pseudo-absences for each target species and executing the entire process 30 times, resulting in 9300 individual models produced for each combination of species, spatial extent and grain size. Model evaluation was based on cross-validation, with the species datasets divided into 80% of the records for model calibration and 20% for model evaluation. The species data sets are of satellite-derived Ecosystem Functional Attributes (EFAs), computed from the EVI, LST and Albedo products for 16-day maximum value composite images captured by MODIS sensor.

Three groups of models representing the effects of the three sets of predictors described above (Climate, Land-cover, and EFAs) on the distribution of the two test species were established. Additionally, a combination of predictors related to climate and landscape composition/configuration was used in a fourth set of models, using the same predictors used for the climate and land-cover models. To analyze and rank model performance, we conducted a modelling workflow testing the effect of the three focal drivers of model performance (predictor set, spatial extent, and spatial resolution), and for the narrow-ranged and the wide-range species. Thus, we compared model performance in three sets of tests:

- 1) Different predictor sets (CLI, LC, CLI+LC, EFAs), at same pixel size and spatial extent
- 2) Different pixel sizes (1 km2 vs. 5 km2), for the same spatial extent and with the same predictor set
- 3) Different spatial extents (IP vs. NW vs. NP), at the same pixel size and for the same predictor set.(**IP**: Iberian Peninsula; **NW**: Northwest Iberian Peninsula; **NP**: Peneda-Gerês National Park.)

All SDMs were calibrated using all 10 modelling algorithms available in the R package ‘Biomod2’, for each set of models and using default parameters. Ensemble models for each combination of EO and traditional predictors as climate and land-cover were computed and projected to derive habitat suitability maps. Overall, models exhibited very good performance regarding AUC and TSS median metrics. EFA-based models performed very well at the several scales (AUC_{median} from 0.881±0.072 to 0.983±0.125), and similarly to traditional climate-based models, individually or in combination with land cover predictors (AUC_{median} from 0.882±0.059 to 0.995±0.083). Comparably, TSS_{median} values were above 0.6 at all cases (ranging from 0.603±0.03 to 0.97±0.17). Moreover, EFA-based models identified additional suitable areas and provided valuable information on functional features of habitat suitability for both test species (narrowly vs. widely distributed), for both coarse and fine scales. In summary, evidence was found of a relatively small scale-dependence of the predictive ability of satellite-derived EFAs, supporting their use as meaningful EBVs in SDMs from regional and broader scales to local and finer scales.

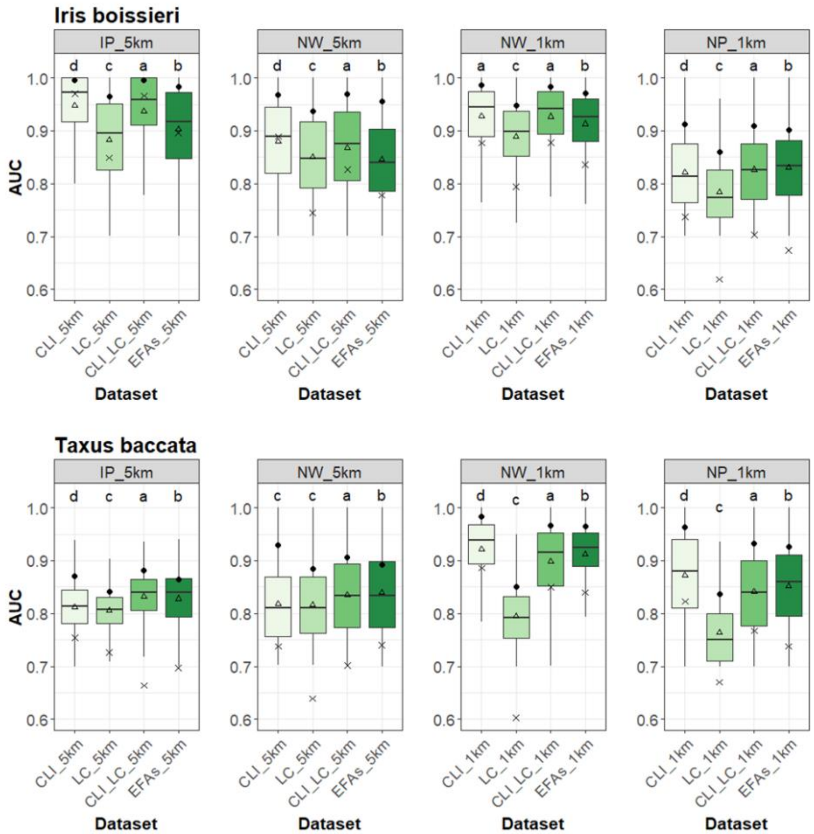

Figure 6: Comparison of relative performance of the Area Under the Curve (AUC) between traditional (climate and land-cover)-based and satellite-derived Ecosystem Functional Attribute (EFA)-based models across all scale combinations and test species. Performance of individual models (boxplots) showing the AUC_{median}, two hinges (first and third quartiles), and two whiskers of each model filtered at AUC≥0.7 (empty-triangle signs represent the AUC_{mean}). Filled-circle dots and crosses represent the AUC_{median} and the TSS_{median}, respectively, of the ensemble models. Different letters indicate significant differences among models (multiple comparisons of means were performed using Tukey's test at the 0.05 significance level.

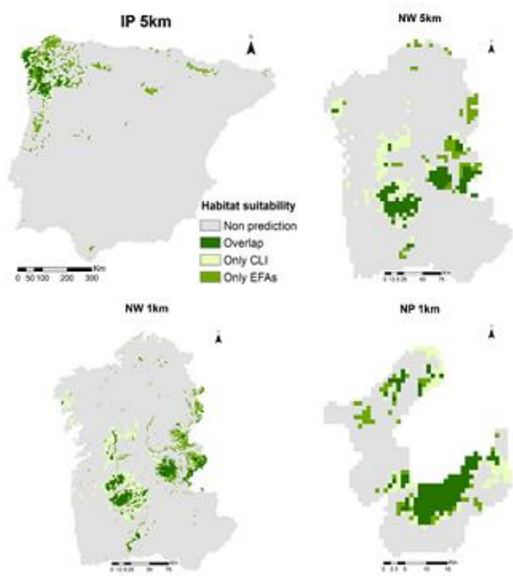

Figure 7: Spatial projections of habitat suitability for Iris boissieri derived from Species Distribution Models (SDMs) based on traditional predictors (climate and land-cover) and on satellite-derived ecosystem functional attributes (EFAs). Overlay maps of current potential presence-absence distributions predicted using an ensemble modelling approach per combination of spatial extent (IP, NW and NP) and resolution (1km and 5km) for Iris boissieri. IP: Iberian Peninsula; NW: Northwest IP; NP: Peneda-Gerês National Park.

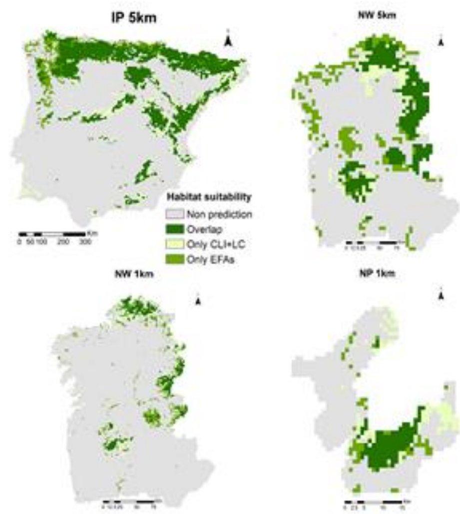

Figure 8: Spatial projections of habitat suitability for Taxus baccata derived from Species Distribution Models (SDMs) based on traditional predictors (climate and land-cover) and on satellite-derived ecosystem functional attributes (EFAs). Overlay maps of current potential presence-absence distributions predicted using an ensemble modelling approach per combination of spatial extent (IP, NW and NP) and resolution (1km and 5km) for Taxus baccata. IP: Iberian Peninsula; NW: Northwest IP; NP: Peneda-Gerês National Park.

Publications:

- Thuiller, W., Lafourcade, B., Engler, R. and Araújo, M. B. BIOMOD - a platform for ensemble forecasting of species distributions. Ecography 2009; 32:369–373.
- Alcaraz-Segura D, Lomba A. Sousa-Silva R, et al. Potential of satellite-derived ecosystem functional attributes to anticipate species range shifts. International Journal of Applied Earth Observation and Geoinformation 2017; 57:86-92. doi: 10.1016/j.jag.2016.12.009.
- Arenas-Castro, S., Gonçalves, J., Alves, P., Alcaraz-Segura, D., & Honrado, J. P. (2018). Assessing the multi-scale predictive ability of ecosystem functional attributes for species distribution modelling. PLOS ONE, 13(6), e0199292. doi: 10.1371/journal.pone.0199292

3.2.3.2 Habitat Quality and Distribution Model (ICETA)

A modeling framework combining predictions from a grassland detection model and from a plant species richness model has been developed to estimate habitat distribution and quality (using plant diversity as a proxy). Grassland detection uses an Ensemble Supervised approach based on three machine learning algorithms implemented in Scikit-learn (Python). The grassland detection model is forced by the Greenness Tasseled Cap Component in spring season (Sentinel-2, Landsat 5-7). The plant species richness model uses correlative generalized linear modelling developed in the CAR and MuMIn R packages and is forced by management (senescence) and canopy variables (chlorophyll/nitrogen) derived from Sentinel-2 and area. Model calibration is based on in-field plant diversity data from 24 grassland patches (collected in Spring-summer 2016). The main output products: grassland habitat distribution (1987-2002-2016); grassland plant species richness (2016); grasslands conservation capacity of the PA; and species-rich grasslands. Between 1987 and 2016, the PA increased the capacity to promote conservation of grassland habitats, although not reaching the levels of 1987. Mean accuracy of the grasslands detection model varied from 0.87 to 0.91. The plant species richness model, forced with three EO-variables, was able to explain 59% of total variation in species richness. Most of the PA's grasslands hold moderate to high plant species richness.

Halting habitat and biodiversity loss in temperate grasslands by 2020 are two Aichi Biodiversity targets. This study assessed the progress of these targets in Southern European grasslands as a measure of conservation action. A framework of analysis using three major societal development windows in Portugal was defined, encompassing Post authoritarian (1989), European Union (2001) and Euro zone (2016) societies. Areal coverage of grasslands and species-rich grasslands in a protected area were the habitat and biodiversity accomplishment metrics. To estimate grassland coverage, supervised mapping with bias-correction based in the stratified area estimator was used in each societal development window.

The grassland cover model for mapping was forced by the greenness tasseled component (TCT greenness) obtained from Landsat and Sentinel-2 data and performed with three classifiers (random forest, nearest neighborhood, decision trees). The model inputs were derived from Sentinel-2 (April, July 2016), Landsat-7 (May 2001) and Landsat-5 (March 1989) and used to drive the model itself to general grassland coverages. The Species-richness model was derived by Generalized Linear Modeling (GLM) with species scaling relationships fed by Sentinel-2 derivatives. These include four continuous derivatives: chlorophyll red-edge (CIred-edge), senescence ratio (Senratio), chlorophyll red-edge change rate (CIchange rate) and senescence change rate (Senchange rate) from Sentinel-2 for the year 2016. 50 training areas recognized as grasslands for supervised mapping of grasslands utilizing Very High-Resolution imagery (VHR) available in Google Earth; the accuracy assessment of grassland coverage was made using a set of 150 validation sites ((10x10m (2016); 30x30m (2001, 1989)).

Results for bias-corrected grassland coverage indicated a significant bi-directional trajectory (p<0.0001) in the Aichi habitat target. A convergence with the target (grassland gain) was observed between in the post authoritarian - European Union window (+554,6ha; cover: 5688,18 ± 1910.1 ha) followed by non-convergence (grassland loss) in the period between Portugal's EU accession and the establishment of the Euro Zone (-1634.0 ha, cover: 4054.15 ha, ±1884.71 ha) (Figure 9: Mapped and bias-corrected grassland areal coverage (±95% confidence interval) for 1989, 361 2002 and 2016 relative to the best mapped estimates (lower standard error of adjusted area estimate 362 (ha)): for 1989 KNN, for 2002 and 2016 RF. Letter A indicates significant differences of areal coverage 363 between 1989 and 2002 as well as 1989 and 2016; letter B indicates a significant difference between 364 2002 and 2016. Differences were significant at p< 0.0001.).

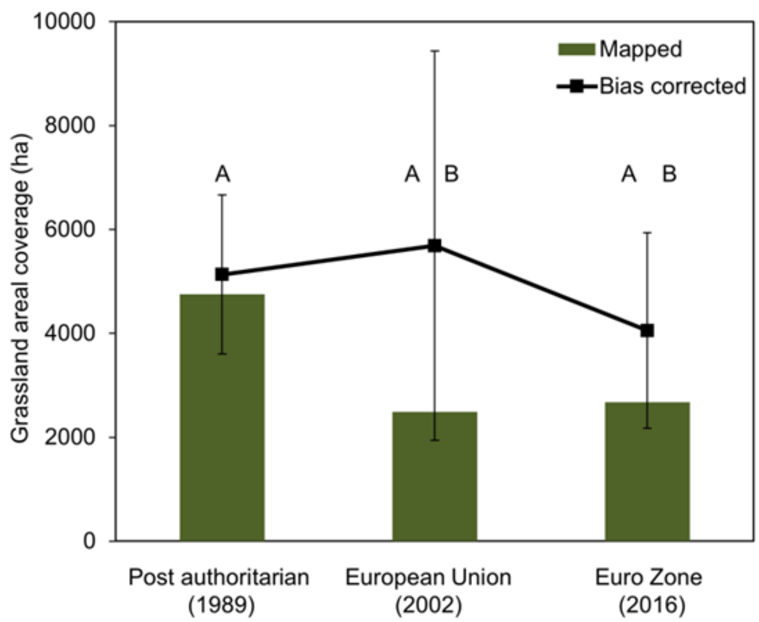

***Figure 9**: Mapped and bias-corrected grassland areal coverage (±95% confidence interval) for 1989, 361 2002 and 2016 relative to the best mapped estimates (lower standard error of adjusted area estimate 362 (ha)): for 1989 KNN, for 2002 and 2016 RF. Letter A indicates significant differences of areal coverage 363 between 1989 and 2002 as well as 1989 and 2016; letter B indicates a significant difference between 364 2002 and 2016. Differences were significant at p< 0.0001.*

For species richness (only Euro Zone window), Species-DistuRbance (SDR) was the most supported species scaling relationship to model and map species richness (AIC=137.6, ΔAIC=0.0, PseudoR2=0.41, p=0.001) with Sentinel-2 derivatives. Species richness was related negatively to spring senescence and the monthly ratio of change in senescence measured between the spring and summer Sentinel-2 scenes. Areal coverage of species-rich grasslands (**Figure 10:**) was significant higher than species-poor grasslands (x2=1043.3, p<0.0001), suggesting a convergence in the Aichi biodiversity target by avoiding the spatial dominance of scarce plant species richness in the remaining grassland habitats of Euro Zone society. Uncertainty in the accomplishment metrics based on Earth observations (omission error's in mapping and unexplained variation in species richness) warrants careful interpretation, but the findings also encourage further research on EO metrics to tackle progress on Aichi conservation targets.

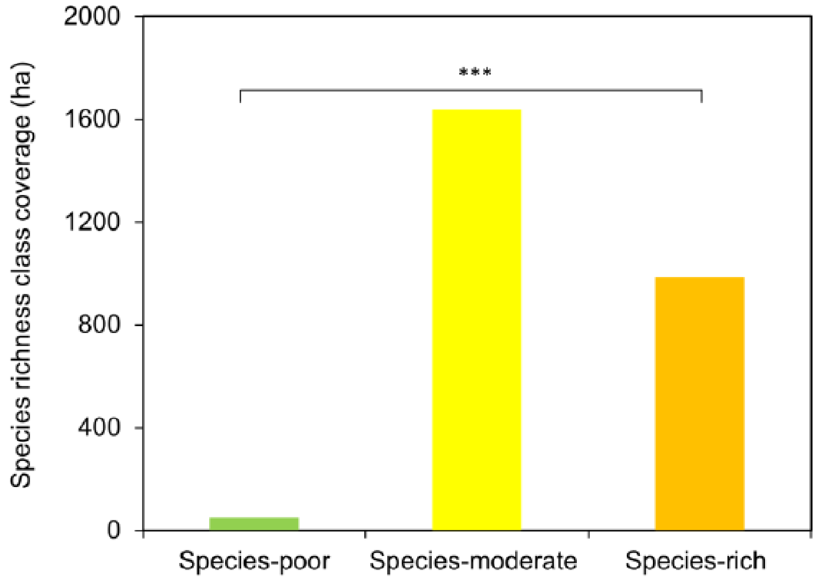

Figure 10: *Areal coverage of grassland plant species richness classes (species-poor, species-moderate, 415 species-rich) in the Euro Zone obtained from analysis of frequency distribution over the spatial 416 distribution species richness in grassland (fig. 6-A and B). The 1/3 (Q1, as species-poor) and 2/3 417 quartiles (Q3, specie-rich) from field data were used as thresholds for each class respectively. Spatial 418 distribution of species richness was obtained from generalized linear modelling with the SDR scaling 419 relationship over the RF grassland mask for Euro zone SDW. Differences between species-poor and 420 species-rich were significant at p< 0.0001.*

The first model is based on EO data (Landsat 1986, 2002 and Sentinel-2 2016) for the classification of grasslands land cover, only possible with EO data and possible to be replicated every year. The second model (plant species richness model) is also based on four variables derived from Sentinel-2 scenes. In-situ measurements for grasslands species richness are important for calibrating the model while a combination of both EO and in-situ measurements proved very important to the implementation of both of the models.

<u>*Publications:*</u>

- Monteiro AT, Alves P, Carvalho-Santos C, Mitchell A, Lucas R, Cunha M, Walz A, Honrado JP. Accomplishment of Aichi grassland biodiversity targets during major societal developments in Southern Europe: insights from earth observations. (under revision in Remote Sensing)

3.2.3.3 SWAT Model (ICETA)

SWAT (Soil and Water Assessment Tool) is a widely used tool for evaluating the effect of management practices and climate change on water resources. It is a physically-based, deterministic and semi-distributed model, operating the HRU (Hydrologic Response Units) level. Digital elevation model, land cover and soil type are needed to define HRU's and daily climate data to force the model. Observed discharge is the main dataset for calibration and validation. Further calibration can be done using water quality parameters (sediments, nutrients), vegetation traits such as LAI (Leaf Area Index) and Evapotranspiration coming from MODIS products. SWAT was applied previously to Vez watershed (part inside Peneda-Gerês) to evaluate the consequences of climate change and alternative land cover scenarios on hydrological services provision (Carvalho-Santos et al., 2016). SWAT is programmed in Fortran language, has open code available at: https://swat.tamu.edu/software/. Here SWAT code was not changed, only the parametrization process was adapted to the local conditions of Vez watershed (Carvalho-Santos et al., 2016).

The provision of hydrological ecosystem services is very important for the human well-being, but fires and climate change are strongly influencing their provision. Among other consequences, fires have a significant impact on surface runoff, soil erosion and water quality, which may be emphasized by climate change. The aim of this study is to simulate fire in a previous application of hydrological model to a medium watershed of Portugal (Carvalho-Santos et al., 2016), and to evaluate the hydrological impacts under scenarios of both fire and climate change. Before running scenarios in SWAT, the model should be calibrated to the local conditions (Vez watershed), including using new EO data products to help interactive calibration, in particular for the vegetation parameters. To improve the vegetation growth performance, LAI from MODIS was used to help to fine tune the related LAI parameters (ALAI_MIN; BLAI; DLAI; LAIMX) and to compare the LAI from satellite and LAI from SWAT. MODIS LAI is improving interactive parameterization of the leaf area index of major vegetation types, therefore accurately simulating evapotranspiration, which is an important component of the water balance. The model is calibrated for vegetation parameters for each land cover class, and LAI from MODIS (MOD15A2 – MODIS/Terra Leaf Area Index - Fraction of Photosynthetically Active Radiation 8-Day_collection6_500m_2003/2008) is being used to approximate modelled LAI to satellite LAI. In addition, Normalized Difference Vegetation Index (NDVI) from MODIS (MOD13Q1 - MODIS/Terra Vegetation Indices 16-Day L3 Global 250 m_collection6_2001_2016) is being used for fire and post-fire regeneration information. So far, MODIS LAI is improving interactive parameterization of leaf area index of major vegetation types and NDVI is informing the management operations for post-fire regeneration (how much time after fire is vegetation starting to growth, how much time after fire is the greenness in the same value as pre-fire levels). Figure 11: shows the improvement of LAI in pine species (monthly values 2003-2008).

To calibrate fires in SWAT, burnt areas from a major fire in 2006 were defined at the HRU level, as well as management operations to settle post-fire regeneration. This was supported by information from NDVI satellite product from MODIS, in which information of how many weeks (MODIS composites of 16 days) after the fire vegetation starts to grow (by land cover class), informing the management operations in SWAT to start growing grass until a level reaching a different greenness, then starting the respective land-cover growing until the level of greenness of pre-fire levels (Figure 12:). The land cover class of evergreen forest (Evg) is the one reaching recovery faster, after 3 years after fire, whereas rocky with low shrub (Roc) class reaches recovery five years after fire, probably related with unfavorable environmental conditions for growth (normally this land cover class is located in the top of the mountains). This way, the hydrological processes will be simulated with a growing vegetation process similar to the one observed in reality by satellite. In terms of SWAT outputs, the hydrological indicators are only sensitive to fire operations at the sub-basin level and not at the watershed level (e.g. total suspended sediments only change in the sub-basins downstream the fire, and not at the outlet of the watershed).

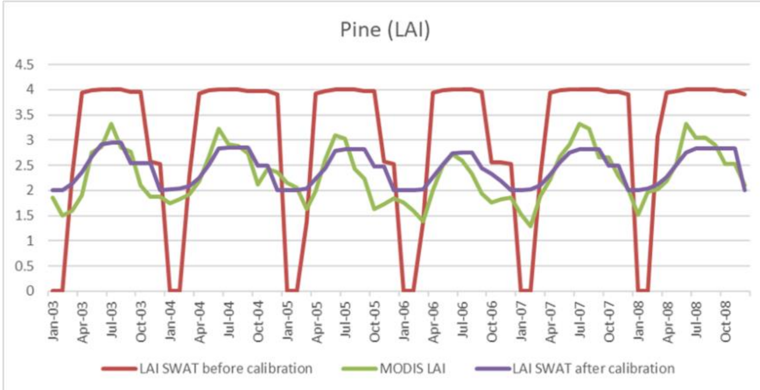

Figure 11: Improvement of pine forest LAI (Leaf Area Index) parameterization based on LAI data from MODIS (MOD15A2), monthly values from 2003 to 2008. For default Pine forest in SWAT, for default enters in dormancy period during winter. However, pines in Vez watershed have photosynthetic activity, so vegetation parameters, in particular the ones related to LAI (ALAI_MIN; BLAI; DLAI; LAIMX) were tuned until reached an acceptable value.

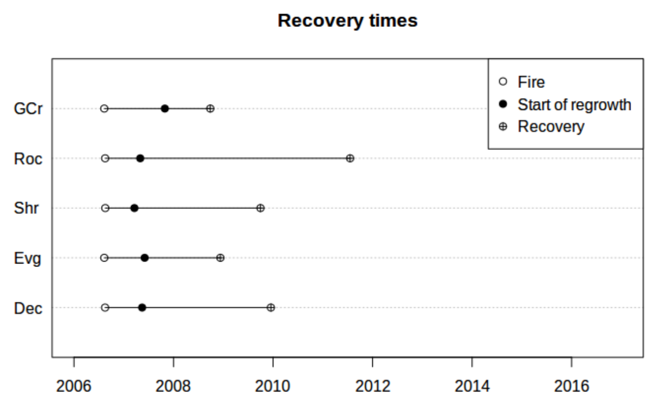

Figure 12: Time for post-fire regeneration (start of regrowth and full recovery) by different land-cover classes based on NDVI in Vez watershed (after the major fire of August 2006).

<u>*References:*</u>

- Carvalho-Santos C., Nunes J. P., Monteiro A. T., Hein L., Honrado J. P., (2016) Assessing the effects of land cover and future climate conditions on the provision of hydrological services in a medium-sized watershed of Portugal. Hydrological Processes, 30, 5: 720-738

3.2.3.4 Ensemble Ecological Niche Models (ICETA)

Ensemble ecological niche models (ENMs) were developed for 27 breeding bird species in the Peneda Gerês PA based on EO data to predict species distributional shifts over the last 10 years caused by land use changes, climate change and their combined effects. All ENMs were calibrated using seven modelling algorithms available in the R package 'Biomod2' (Thuiller et al 2008). A paper describing the models, methods, and results, also presented below in short, is currently under review; data used for models will be published alongside the paper. Figure 13 provides a generalized schematization of the 27 ENMs developed, detailing the methods in which the various drivers are combined in order to determine shifts resulting from changing land-use and climate change effects.

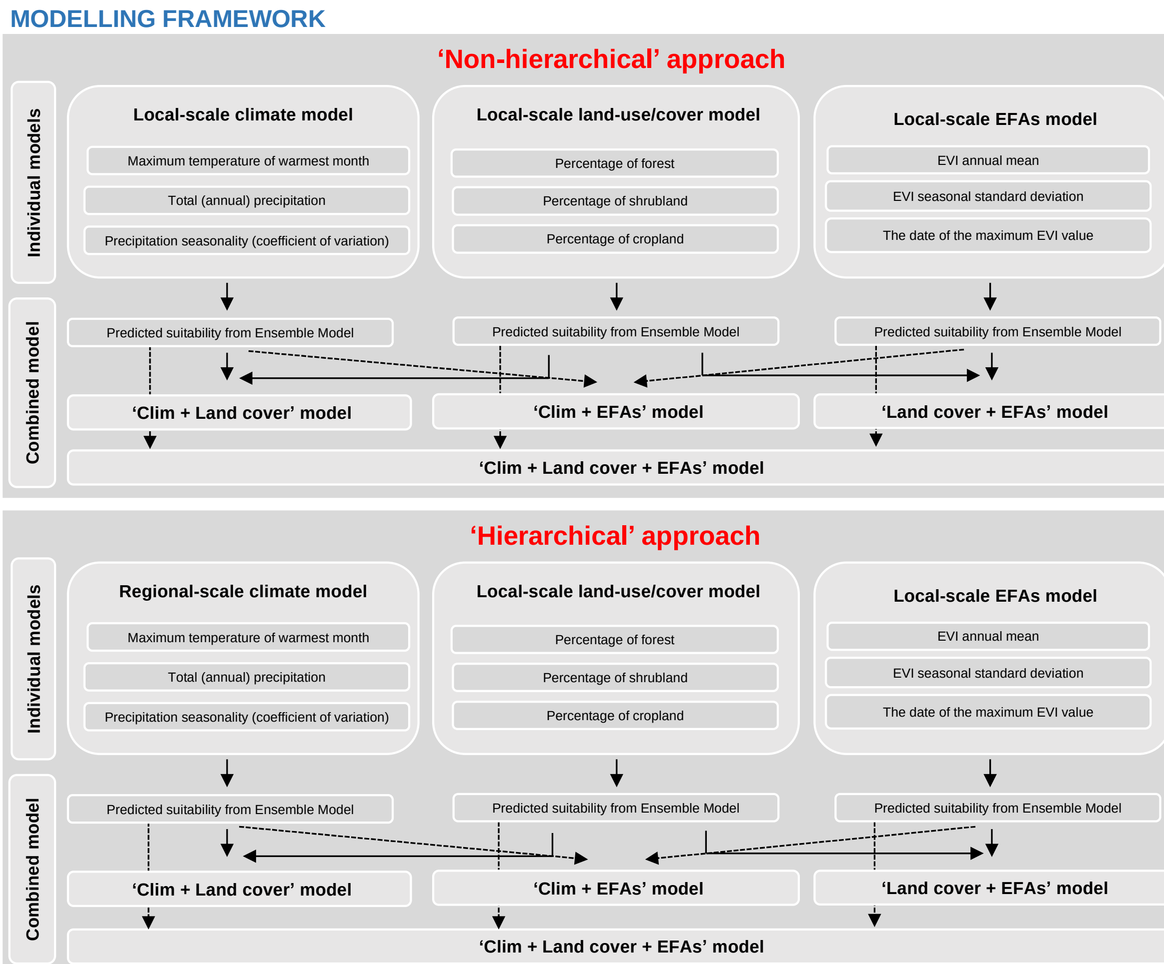

Figure 13:Generalized schematization of the ENMs developed for 27 breeding bird species

The ability of ENMs to produce robust predictions for different time frames (i.e. temporal transferability) may be hindered by a lack of ecologically relevant predictors. Model performance may also be affected by species traits, which may reflect different responses to processes controlling species distribution. In this study, we tested four primary hypotheses involving the role of species traits and environmental predictors in ENM performance and transferability. We compared the predictive accuracy of ENMs based on (1) climate, (2) land-use/cover (LULC) and (3) ecosystem functional attributes (EFAs), and (4) the combination of these factors for 27 bird species within and beyond the time frame of model calibration. The combination of these factors significantly increased both model performance and transferability (Figure 14), highlighting the need to integrate climate, LULC and EFAs to improve biodiversity projections. However, the overall model transferability was low (being only acceptable for less than 25% of modelled species) (Figure 14), which calls for great caution in the use of ENMs to predict bird distributions under global change scenarios. Our findings also indicate that positive effects of species traits (namely Mediterranean, migrant, habitat-specialist species) on predictive accuracy within model calibration are not necessarily translated into higher temporal transferability.

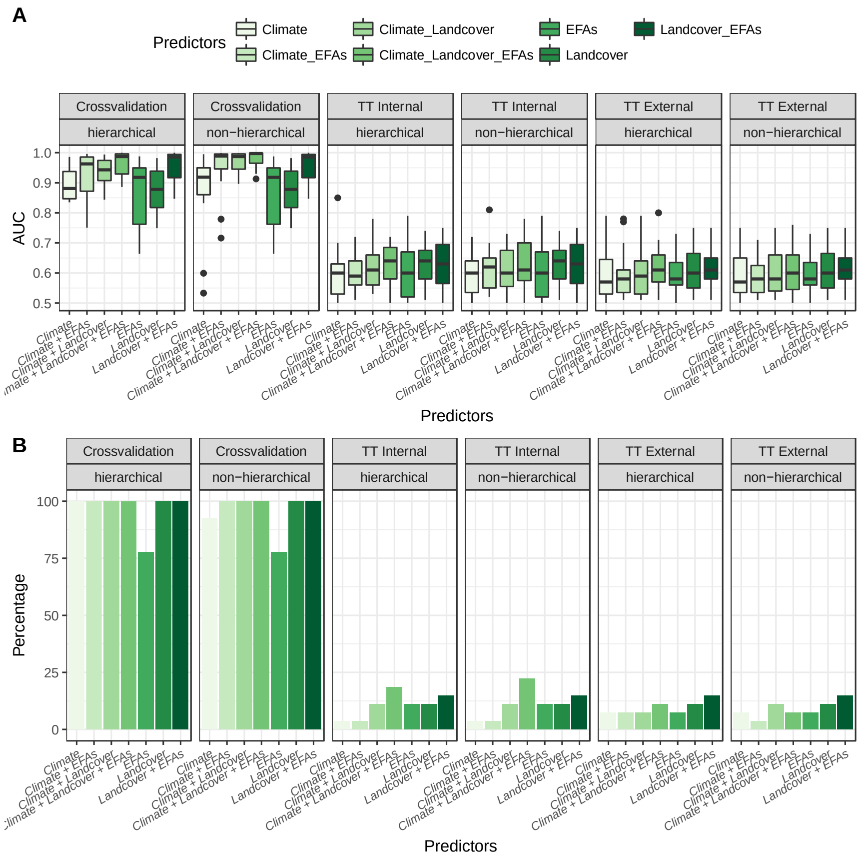

Figure 14: Model performance and transferability measured by AUC values (A) and percentage of species with AUC values higher than 0.7 (B) for each set of predictors, modelling approach, and type of evaluation. For all box plots, lower and upper whiskers encompass the 95% interval, lower and upper hinges indicate the first and third quartiles, and the central black line indicates the median value.

EO data was integrated into the model as input data as well as for validation and calibration. Landsat TM and ETM+ imagery, two images per year for 2000 until 2010, were used to derive land use/cover maps for each year, and subsequently used in the ENMs as predictor variables. EVI indices based on MODIS sensor images for each year from 2000 up to and including 2010 were transformed into EFAs for each year, used in the ENMs as predictor variables. The land-use/cover variables were derived from optical and thermal multispectral bands of Landsat TM and ETM + images acquired over the same temporal sequence as the bird sampling was carried out. The land-cover classification was obtained using a hybrid classification procedure, which combines unsupervised and supervised strategies, a 30-fold split-sample procedure using 70% of the data for calibration and the remaining 30% for model evaluation was utilized for these data sets. The temporal transferability of the ENMs was tested by comparing the environmental suitability predicted for 2010 - derived from ensemble models calibrated for 2000 - against observed occurrence data available for 2010 from two independent sources. Ecosystem functional attributes (EFAs) were derived from the Enhanced Vegetation Index (EVI) obtained from 16-day maximum value composite images captured by the Moderate Resolution Imaging Spectroradiometer (MODIS) sensor. All ENMs were calibrated using seven modelling algorithms available in the R package ‘Biomod2’ to take into account the inherent uncertainty of using different modelling algorithms: generalized linear models (GLM), generalized additive models (GAM), generalized boosted regression models (GBM), random forest (RF), factorized distribution algorithm (FDA), multivariate adaptive regression splines (MARS) and artificial neural networks (ANN). Ensemble models for each species were projected to the land use/cover composition and ecosystem functioning conditions updated from EO data for year 2000 to year 2010. Three sets of tri-variate models based exclusively on each type of environmental predictor (‘individual’ models): 1) Climate, 2) Land cover, and 3) EFAs. We also developed an additional set of models by using the environmental suitability predicted from the ‘individual’ models as predictor variables to integrate in a balanced way all possible combinations of these three environmental drivers within the modelling framework (‘combined’ models): 4) Climate + Land cover, 5) Climate + EFAs; 6) Land cover + EFAs, and 7) Climate + Land cover + EFAs.

The ENMs developed with the three sets of predictors were all useful for describing the distribution of our target species (AUCClimate = 0.919 ± 0.104; AUCEFAs = 0.918 ± 0.117; AUCLCT = 0.878 ± 0.71). However, the integration of the land cover and EFAs information into climate niche models substantially increased model performance within the calibration time frame (AUCmean up to 0.98) (Figure 14). As expected, the enhanced model performance within the calibration time was also translated into an increase in model transferability, providing additional support to the relevance of integrating EFAs and land-use/cover variables to improve biodiversity monitoring and future biodiversity projections. In particular, the integration of predictor variables related to ecosystem functioning - an often-neglected dimension of ecological niche of species - was found to increase model performance and transferability, especially for migrant, forest specialist species.

<u>*References*</u>:

- *Thuiller, W., Lafourcade, B., Engler, R. & Araújo, M. B. BIOMOD - a platform for ensemble forecasting of species distributions. Ecography.* ***32,*** *369–373 (2009).*

3.2.4 Lakes Ohrid and Prespa

3.2.4.1 Statistical Modelling (UP)

Empirical models of Chlorophyll-a (Chl-a) relationships are critical to understanding aquatic ecosystem health and management, yet comparisons of modelling approaches are missing. In the face of climate warming Chl-a – temperature relationships are commonly inferred from elevation data, although Lake Surface Water Temperature (LSWT) may imply differing relationships. Transferability of empirical water quality models to highly vulnerable lakes in mountain regions is sparsely studied in terms of water quality prediction and needs further testing. Numerous studies have investigated Chl-a relationships with linear and non-linear statistical models, but it is unclear a) whether linear or non-linear approaches should be favoured, b) if altitude is an appropriate temperature surrogate, and c) if the identified relationships are transferrable to mountain lakes. We address these issues by 1) comparing Chl-a model performances across linear and non-linear statistical approaches (panel data models, generalized additive models, boosted regression trees), 2) evaluating the effects of altitude as surrogate for LSWT, and 3) investigating the reliability of empirical water quality models across 13 lakes from perialpine and central Balkan mountain regions. Modelling Chl-a was conducted using in situ water quality data from 157 European lakes, as well as elevation data and LSWT in situ data complemented by remote sensing measurements. Our study highlighted non-linear approaches, implying the existence of complex relationships between Chl-a and explanatory variables. Overall, boosted regression trees performed best. Chl-a – nutrient relationships were characterised by sigmoidal curves. In comparison with the often-used temperature surrogate altitude, the utilisation of LSWT led to similar predictive performances but 6 different influence directions. These results recommend utilisations of LSWT when focussing on Chl-a-temperature relationships. For our study region, total phosphorus had the largest explanatory power on Chl-a concentrations. Compared to Chl-a observations, Chl-a predictions of the best performing model for mountain lakes (oligotrophic-eutrophic) led to minor differences in the trophic state categorisations.

References:

- Riffler, M., Lieberherr, G., Wunderle, S. (2015): Lake surface water temperatures of European Alpine lakes (1989–2013) based on the Advanced Very High Resolution Radiometer (AVHRR) 1 km data set. Earth Systems Science Data 7, 1-17, https://doi.org/10.5194/essd-7-1-2015.

3.2.5 Swiss National Park and Davos

3.2.5.1 Rapid Mass Movement Simulation (ETH)

The RApid Mass Movement Simulation (RAMMS) is utilized in the detection of avalanches and determination of avalanche susceptible areas. It is developed at the WSL Institute for Snow and Avalanche Research SLF and the Swiss Federal Institute for Forest, Snow and Landscape Research WSL, is available at the following location (http://ramms.slf.ch/ramms/) and an expanded upon description can be found within Christen et al. 2010. The model simulates avalanche flow, using avalanche dynamics equations to calculate avalanche height and velocity on a Digital Terrain Model (DTM) for specified time steps from avalanche release until the flow stops. The required inputs are the DTM the avalanche release area, and release conditions (height, temperature, snow density). Additionally, a map of forest cover can be used as an input that modifies the friction parameters. The model is primarily utilized in determining avalanche hazards and the associated risks they can pose to the communities susceptible to their effects. A recent development of the model takes into account the detrainment effect of forests on the avalanche flow (where snow is stopped behind trees, thus reducing the avalanche mass). This requires information on stand density, dominant species, and mean stand diameter, key inputs which can be supported via RS information and data sets. The key inputs and drivers which rely on Remotely Sensed data are highlighted in red within Figure 15.

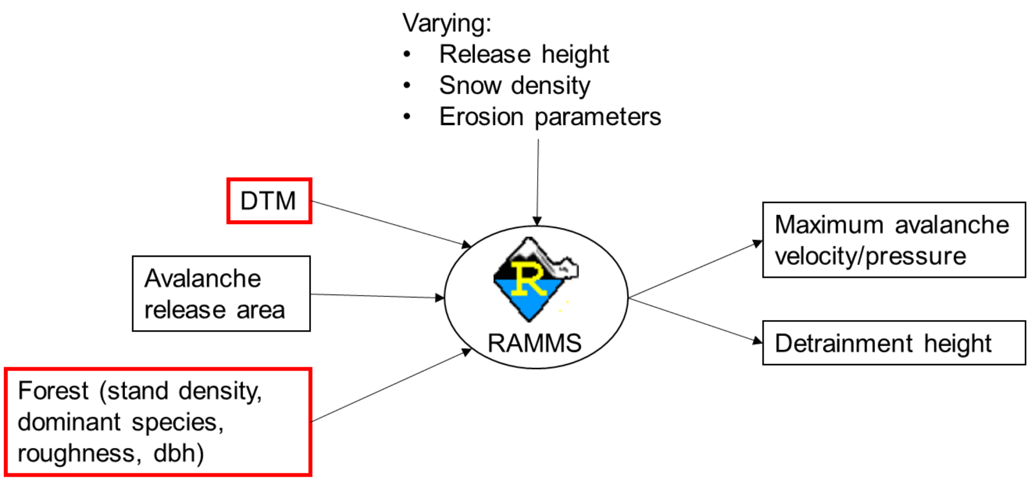

Figure 15: Schematization of the RApid Mass Movement Simulation and inputs

Mountain forests provide an essential ecosystem service for Alpine communities by reducing the risk of snow avalanches. The probability of an avalanche release is significantly lower in forested areas. In addition, when an avalanche flows through a forest, some of the snow is stopped behind trees (this effect is called “detrainment”), reducing the mass of the avalanche flow and thus its velocity and impact pressure. In ECOPOTENTIAL the avalanche protection service provided by forests in the regions of Davos and the Swiss National Park is modeled. In part, the model of the ecosystem service is calibrated using the mass-movement simulation tool RAMMS, which is commonly used in hazard risk assessments in Switzerland. RAMMS is used to predict potential avalanche tracks under different scenarios, and to quantify the relationship between forests’ structure and their detrainment effect.

The quality of RAMMS simulation results strongly depends on the quality of the input DTM, where remote sensing plays an important role. In our case study, we use the aerial LiDAR-based DTM (2m-resolution) produced by the Swiss Federal

Office of Topography (swisstopo). In previous version RAMMS, all types of forest were included simply by modifying the surface friction parameter, which did not take into account differences in forest structure. A new version simulates the forest detrainment effect, which depends on forest density, species composition (evergreen vs. deciduous trees), and terrain roughness (including understory vegetation). We use high-resolution LiDAR data to measure terrain roughness and forest density, and a combination of LiDAR, airborne and Sentinel2 images to differentiate between evergreen and deciduous forests. Furthermore, we include an estimate of mean tree diameter (dbh) for each stand, which is derived from a canopy height model based on the relationship between dbh and height of trees measured on the ground. Based on the dbh and species, RAMMS determines whether trees will be broken during an avalanche.

We applied RAMMS on five observed avalanche events in the Dischma valley, Davos, in order to estimate the relationship between per-pixel avalanche velocity, forest structure, and detrainment. First, the model parameters were calibrated to fit the reported avalanche tracks, and then the parameters of avalanche release height and erodibility were varied in order to estimate the uncertainty in the model. Although the detrainment effect was negligible in large avalanches, including it helped to model the flow of small avalanches more realistically (see Figure 16). Based on information on forest structure, the simulation can predict where tree breakage can occur, and which parts of the forest are providing detrainment, which is important information for forest management.

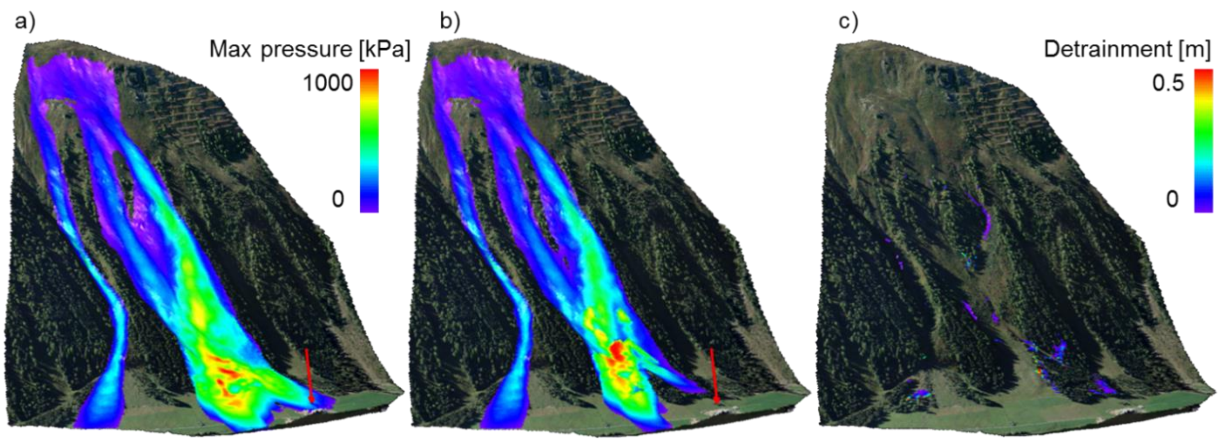

Figure 16: Avalanche in Wildi, Davos, Switzerland, as modelled in RAMMS: a) maximum impact pressure without taking into account the detrainment effect of the forest, with the red arrow marking the location of a building that would be hit by the avalanche with a pressure of 200 kPa, b) avalanche under the same release conditions, taking into account the detrainment effect, where the avalanche no longer reaches the building, c) the amount of snow stopped in the forest (detrainment height) during this avalanche.

The model depends on a high-quality DTM, which was available through aerial LiDAR; previous versions of the model accounted for forest effects on avalanche flow only through the friction parameter, which was assigned for all forests, not taking into account forest structure or species. The new detrainment approach requires information about tree size, species, and stand density, which is derived from remote sensing inputs. Tree species classification can be determined through a combination of aerial multispectral images and Sentinel 2A aiding in the parametrization of per-pixel detrainment coefficient (forest). Parametrization of tree breakage threshold (related to dbh) was derived using a combination of RS products through the efforts of WP4 partners which enhanced the model’s capabilities through increased accuracy in parameterization. Overall, the inclusion of EO data created a better representation of forest effects on avalanches, and also, allows the model to identify areas where tree breakage will occur when there is an avalanche.

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3.3 Marine and Coastal

3.3.1 Danube River Basin

3.3.1.1 Statistical Modelling – Generalized Additive Model (UP)

Niche-based Species Distribution Models (SDMs) have become an essential tool in conservation and restoration planning. Given the current threats to freshwater biodiversity, it is of fundamental importance to address scale effects on the performance of niche-based SDMs of freshwater species' distributions. The scale effects are addressed here in the context of a) hierarchical catchment ordering, considered as counterpart to coarsening grain-size by increasing grid-cell size and b) the influence of the upstream area on the occurrence probability of species. Figure 17 shows the generalized approach to this form of statistical modelling as applied to the Danube Basin. Fish occurrence data from the Danube River Basin is combined; the hierarchical catchment ordering and multiple environmental factors representing local and upstream area effects to model fish occurrence probability across multiple scales. Focus is placed on the reach-scale and 2nd to 5th order catchments.

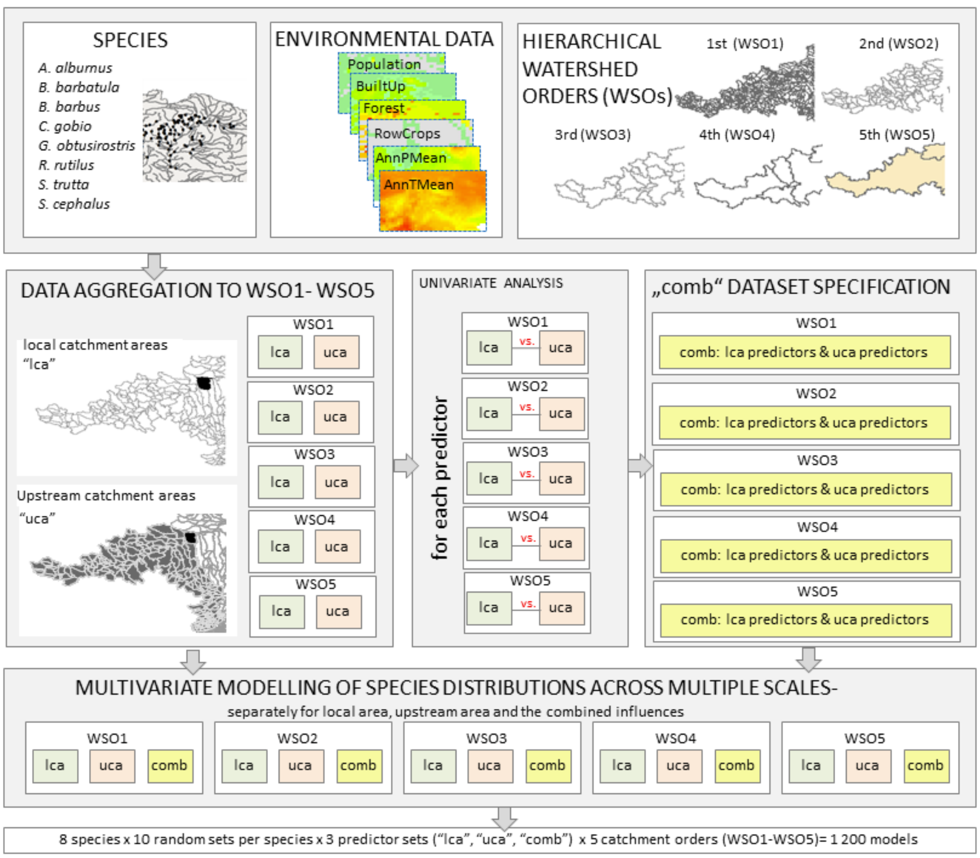


Figure 17: Generalized niche-based SDM applied to the Danube Basin

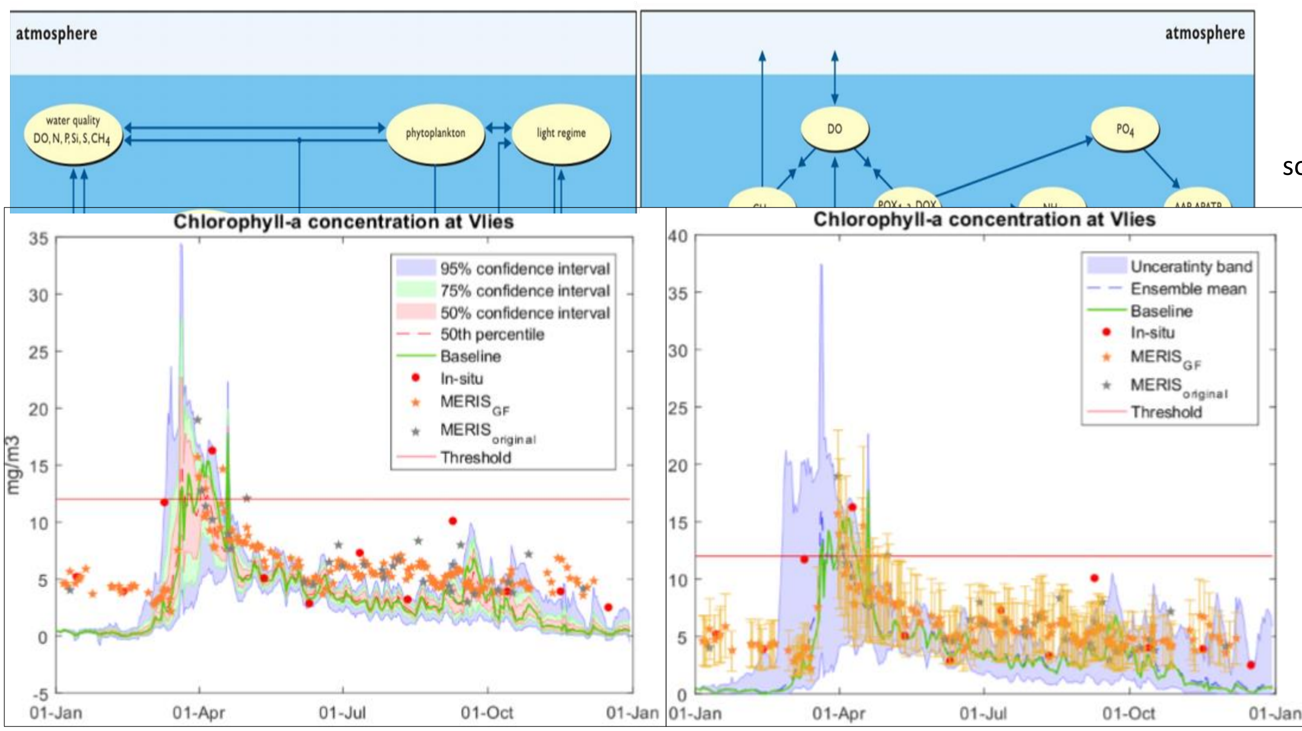
The spatial scale (hierarchical catchment order) and the choice between local and upstream area effects only marginally influence the performance of SDMs. Upstream effects tend to better predict fish distributions than corresponding local effects for anthropogenic and land cover factors, in particular for species sensitive to pollution. Key predictors and their relative importance are scale and species dependent. Our findings have useful implications for choosing proper species dependent spatial scales for river rehabilitation measures, and for conservation planning in areas where fine grain species data are unavailable.

Various data sets are used as critical inputs to drive the SDMs. Critical to this endeavor is a clear delineation of the sub-basins and their borders which were obtained from an open HydroBasin repository (http://www.hydrosheds.org/page/hydrobasins) and is coupled with a EO derived Digital Elevation Model (DEM) from NASA's Shuttle Radar Topography Mission. The CORINE land cover database of the European Environment Agency (EEA) is also utilized in order to discretize the basins into land cover units which are important in determining the niches within the domain of the Danube Basin.

3.3.2 The Wadden Sea

3.3.2.1 Delft-3D Water Quality (Deltares)

The Delft-3D Water Quality model is a component of a large Delft-3D model suite. It is a comprehensive hybrid ecological model combing a three-dimensional hydrodynamic model (Delft3D-FLOW) and the General Ecological Model (GEM) which constitutes the water quality component. The GEM model includes various sub-functions which can be activated including an algal species competition element, benthos element capable of simulating bivalves, and general water quality processes such as denitrification, deposition, advection and diffusion, primary production as well as chemical transport, schematized below in Figure 18. The model most importantly calculates nutrient concentrations, primary production, phytoplankton species composition and Chlorophyll-a concentration while integrating dynamic process modules for dissolved oxygen, nutrient availability and phytoplankton species. Furthermore, the GEM model includes a phytoplankton module (BLOOM) that simulates the growth, respiration and mortality of phytoplankton. Using this module the species competition and their adaptation to limiting nutrients or light can be simulated (Los, et al., 2008). The model offers flexibility in the processes selection and provides general applicability in diverse case studies (Blauw, et al., 2009). The GEM model includes two main components that can be clearly differentiated. Firstly, the transport of state variables in the water column is computed using advection-dispersion equation. Secondly, the concentrations of the state variables are determined by water quality end ecological processes meaning numerous physical, chemical and biological reactions. This model components are open-source and freely available for download from GitHub and from the Deltares website (https://oss.deltares.nl/web/delft3d/download).



This modeling effort sought to utilize

Figure 19: Chlorophyll-a concentrations derived from ensemble modelling for one of the monitoring station within the Wadden Sea. The spread of the results are aggregated into model confidence intervals (L) and compared against in-situ sampling, RS data, and gap-filled RS data, each with confidence interval ascribed (R) to determine the optimal model configurations.

Remote sensing and in-situ data in order to optimize model calibration through the inclusion of RS data within an ensemble modelling approach to select the optimal subset of model parameterizations which falls within a confidence interval for the validation and calibration data utilized. The ensemble techniques use numerous inputs to generate a range of results that are all physically possible and equiprobable. The multiple inputs can be supplied to a single model (single model ensemble), to a single model with different physical parameterization scheme (multi-physics ensemble) or to multiple models (multi-model ensemble). In contrast to the idea of using a single, “best calibrated” parameter set for a deterministic run, the single-model ensemble technique employs multiple set of parameters and/or inputs. The ensemble of inputs is then run through the model as many times as the number of inputs. This is methodology is called the Monte Carlo analysis. The end result is an ensemble of forecasts where the individual model results are called “ensemble members”. By statistically assessing the probability distribution of the model output a quantification of the predictive uncertainty can be achieved and through the association of uncertainty and confidence intervals on the RS data, a subset of model configurations can be selected as the most appropriate or highest likelihood of fit against the available validation data sets as seen in Figure 19.

The variability of the ensemble prediction which is the so-called ensemble spread can be calculated by taking the difference between the maximum and minimum scenarios. The relative percentage of the ensemble spread to the deterministic prediction provides an estimate of the overall uncertainty. Most of the off-shore areas remain unaffected, while significant differences can be found in the near shore, shallow areas of the North Sea such as the Wadden Sea. This might be partly due to the direct effect of perturbations on the river loads in the focus area and this figure indicates the rivers’ zone of reach. However, it could be also explained with the system dynamics in the area since in the near shore shallower zones the water is low-dynamic and the primary production levels are already elevated. Besides the time series analysis at the location of the in-situ stations a spatial analysis is also conducted. This analysis intends to provide spatial information about the differences between the deterministic prediction and the extreme scenarios of the ensemble. With this spatial analysis further information can be obtained about the variability in the prediction of algal bloom peak and timing over the Dutch Wadden Sea, which is essential information for decision making.

Firstly, an attempt is made to consider the previously calculated MERIS measurement errors in the goodness-of-fit. An optimization of the forecast verification values is conducted in order to find out how the ensemble forecast can improve the highest number of verification metrics compared to the deterministic forecast. The accuracy of the deterministic and probabilistic forecast is compared by means of ROC plots and CRPS values. Both single value and probabilistic verification metrics are calculated against the in-situ measurements, the original MERIS and the gap-filled MERIS data. This section demonstrates the verification results as an average of the seven stations. The ensemble forecast implemented in the case study was not able to assess the full predictive uncertainty of the Chlorophyll-a concentration since not all measurements were captured in the ensemble band. This finding indicates that there are more uncertainty sources which should be incorporated in the ensemble generation (e.g. meteorological-, hydrodynamic- or SPM input uncertainty. Ensemble forecasting might require considerably more efforts than the deterministic forecasting, though in return it gives added value to the forecast. Deterministic forecasts only provide point estimate of the predictand, whereas probabilistic forecasts determine the probability distribution function and allow the evaluation of equally viable model constructs in order to best represent the uncertainties in the model construction as well as provide the most holistic set of data points to protect area managers for effective management.

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3.3.2.2 Random Forest Model for MicroPhytoBenthos (Deltares)

This model predicts the concentration of MicroPhytoBenthos (MPB) occurrence in the Dutch Wadden Sea using a combination of EO data, both in-situ and Remotely Sensed, as well as including MPB model predictions from a process-based model. Inventories of available datasets from in-situ measurements, EO data from several satellite missions such as Landsat and MERIS, and Wadden Sea modeling results were gathered to assess viability of data integration for microphytobenthos distribution prediction. Based on previous studies, MPB thrive in areas where the sediments have high mud and nutrient content. These organisms are known to aid in sediment stability due to excreted extracellular polymeric substances. Following this rationale, it was derived that sediment grain size, Total Suspended Matter (TSM), Chlorophyll-a (Chl-a) and Photosynthetically Active Radiation (PAR) can be used as input parameters to determine microphytobenthos occurrence. Three sediment grain size detection algorithms were considered for this study with a decision to utilize the Random Forest model due to its high accuracy and data handling capability. The same algorithm was applied for microphytobenthos training model calibration, and later used for microphytobenthos predictions. This algorithm was processed with the following input parameters: sediment grain size prediction, MERIS Products TSM, Chl-a and PAR as seen in Figure 20. Two main training models were derived from the microphytobenthos prediction algorithm. These models were distinct from each other; in that the first model had a higher and wider microphytobenthos concentration range suitable for spring and summer and the second model had a lower and narrower range suitable for autumn and winter.

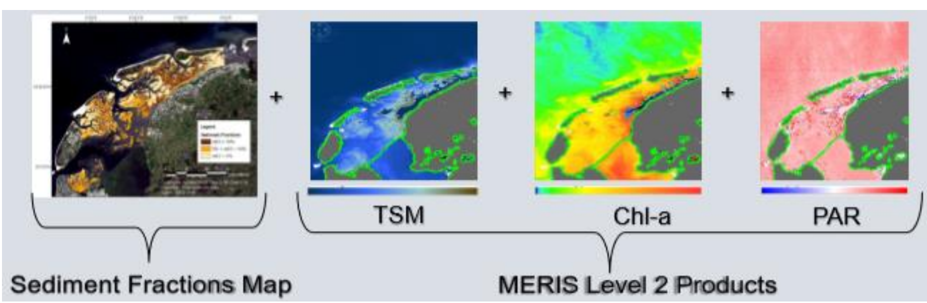

Figure 20: Identification of Remote Sensing Products and Derived Remote Sensing Data to be ingested by the Random Forest model (L) Sediment Fraction map from Landsat 7 ETM+ images and (R) MERIS derived variables

Random Forest (RF) uses a classification and regression tree technique created by Breiman (2001). This method has been used extensively in different fields such as medicine, banking and ecology due to its efficiency and accuracy (Massie, Wilson, Morzillo, & Henderson 2016; E. B.Zhang L. et al., 2014). The algorithmic construct for this application is available in open-source R coding and is therefore easily available to be applied across future sites. A RF randomly and iteratively samples the data and variables to generate a large group or forest of classification and regression trees. A bootstrap aggregated (bagging) technique is applied in RF to create many individual decision trees after which, a final class is defined (Breiman, 2001). The training dataset is comprised of the bootstrapped samples and out-of-bag observations. Homogenous subsets are formed from a random subset of predictor variables obtained from the training dataset wherein the node-splitting variable that leads to highest variance is selected (Mellor et al., 2013) which allows for higher generalization capacity in the overall model before and after the split (Walton, 2008). Accuracy, error rates averaged for all predictions and variable importance are are evaluated using the OOB sample dataset (Breiman, 2001). The classification output from RF represents the statistical mode of many decision trees achieving a more robust model than a single classification tree produced by a single model run (Breiman, 2001). Regression output from RF represents the average of all the regression trees grown in parallel without pruning. The diagram shown in Figure 21 presents the processes undertaken by RF algorithm during training and predictions

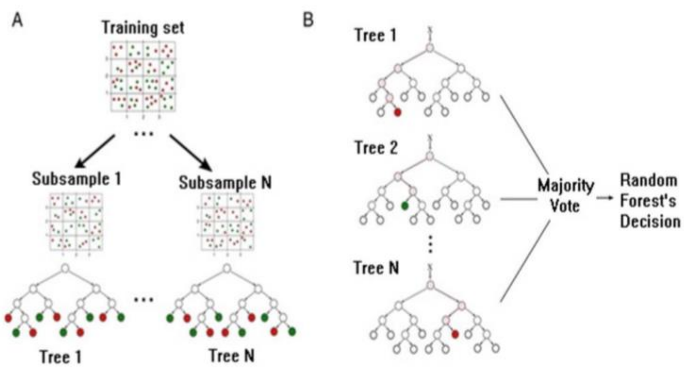

Figure 21: Generalized Schematization of Random Forest Application

The sediment grain size prediction output was coupled or integrated with the MERIS Level 2 products for TSM, Chl-a and PAR in order to map the microphytobenthos in the Dutch Wadden Sea. This mapping was processed by using Random Forest model. The training model achieved acceptable accuracies for the two time periods considered, May 2004 and August 2004, at 65% and 71%, respectively. This is the average accuracy of all classes when validating predicted results versus in-situ data. While there are several steps that can still be done to improve the sediment prediction algorithm, it is interesting to note that the microphytobenthos prediction still produced good results. Another scenario of data integration was tested by using the GEM model output for TSM and Chl-a as substitute input parameters to the MERIS TSM and Chl-a products. This comparison was done for the year 2009 and while a qualitative analysis could be provided, a quantitative assessment was not possible due to a lack of validation dataset.

The temporal changes between seasons can be derived from the significant change between the two microphytobenthos training models, from May 2004 and August 2004, used in this study. The range of microphytobenthos concentration values for May 2004 based on the microphytobenthos map produced ranges from 0 – 7000 mg C / m2 while for August 2004 it was only 0 – 1000 mg C / m2. This is expected due to the peak of phytoplankton bloom occurring during Spring and Summer while there is less during Autumn and Winter. A more robust model for each season would have been ideal to have a more comprehensive analysis of the temporal changes due to seasons but there is a limited selection of Landsat images available and hence became a limiting factor for this study. The multi-model results can be seen below in Figure 22. Without the existence and use of Remote Sensing data, such a model would not be possible to construct outside of utilizing multiple atmospheric and biogeochemical models. The results are promising and provide insights into one of the primary production bases of this ecological system. With the higher resolution data products from the SENTINEL missions, it is envisioned that such an application can be enhanced and better used for predictive capacities.

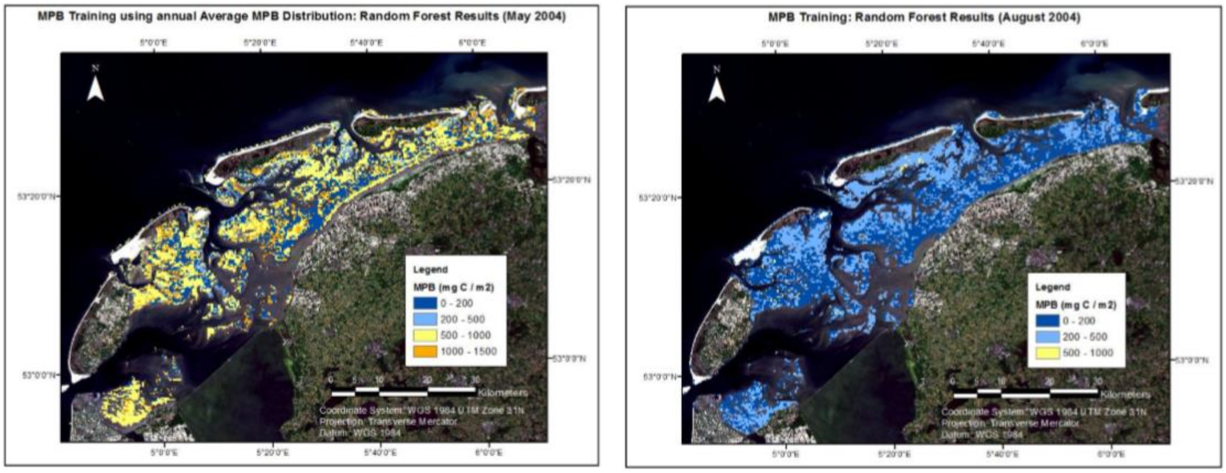

Figure 22: Example of Random Forest Model Results for (L) Summer MPB model in 2004 and (R) Winter Model of 2004

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3.4 Pan-European Scale

3.4.1 Statistical Modelling – Generalized Additive Model (UP)

Climate change and human activities involve land cover changes that threaten ecosystem functioning. Recent studies suggest that also protected areas and especially zones around protected areas undergo land cover changes. The aim of this study is to investigate climatic and socioeconomic effects on land cover changes across Europe from 2000 to 2012 by utilizing boosted regression trees in a data-mining approach. We analyze land cover changes within PAs, 1-km PA-Buffers (PABs), and Non-Protected Areas (NPAs). For this analysis, the CORINE Land Cover Changes (LCC) data products provided by the Copernicus Land Monitoring Service (CMLS) are utilized for the following years : CORINE LCC 2000, 2006, 2012 which are generated using a combination of Remote Sensing data products and missions. These data are utilized in a statistical analysis in order to derive the changes in land cover surrounding protected areas and within certain buffer regions.

Modelling is realized for land cover change categories and flows (i.e. aggregated land cover changes). As categories, we consider artificial surfaces, intensive agriculture, forests, natural grasslands, and pastures; as land cover flows, urbanization, intensification and extensification of agriculture, afforestation and deforestation. Land cover changes and flows are coded as binary response variables at the NUTS3 level of the territorial units for statistics of the European Union (Figure 23). Our results show differing patterns in factor importance across area types (PAs, PABs, NPAs) and for land cover categories/flows. Changes are primarily related to the east/west economic gradient and north/south climatic gradient. Modelling climatic and socioeconomic effects on land cover changes in protected areas and beyond has high potential for monitoring threats to conservation success across Europe.

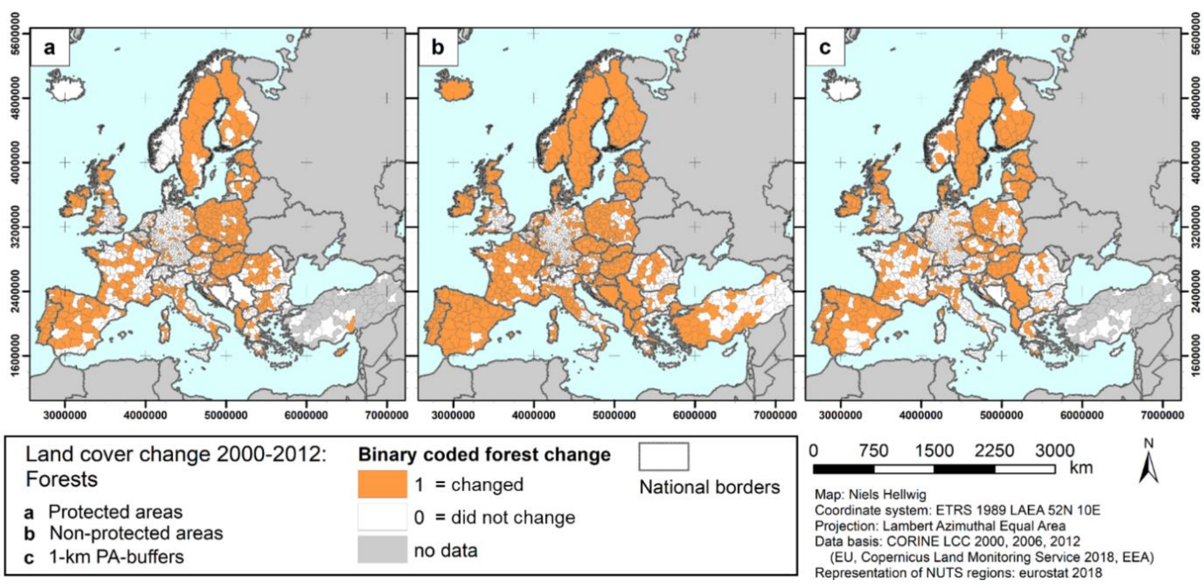

Figure 23: Land cover change for three area types (binary coded, for the example category Forests)

References:

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3.4.2 LPJmL-FIT – Tree Competition Model (UP)

The model LPJmL-FIT simulates patches of competing individual trees with flexible functional traits and empirically derived relations between these traits. Trait composition, productivity and stability of a forest are the results of climatic drivers and ecological sorting, which determines the community composition via competition between trees with flexible individual traits (Sakschewski et al. 2015). The model is driven by the local climate and requires temperature, precipitation and radiation on a daily time step as input. Since the model does not include land use change or land management, it is capable to simulate potential natural vegetation only, however, has been applied in order to determine the functional diversity of natural European forests. The model LPJmL-FIT is a subversion of the global dynamic hydrological vegetation model LPJmL. LPJmL-FIT is currently not open access, however, the original format of the model can be located at the following repository: https://gitlab.pik-potsdam.de/lpjml/LPJmL.

LPJmL-FIT is an individual based gap model that allows simulating individual trees with unique plant functional traits including e.g. Specific Leaf Area (SLA), Leaf Longevity (LL) and wood density. These major plant traits are connected via trade-offs derived from global plant trait observations from the TRY database to ensure a realistic trait space. The individual trees simulated by LPJmL-FIT are the stochastic products of different traits combinations including the associated trade-offs of traits and cannot be assigned to specific species. LPJmL-FIT comprises three hierarchical levels: patch, cell and landscape level. Individual trees are modeled on 10m x 10m patches. These patches are embedded into grid cells representing possible stochastic realizations of the vegetation dynamics in a grid cell. For each grid cell, a number of patches is simulated with the identical climate conditions, which allows an extrapolation from patch to cell level (gap approach). The size of a grid cell can vary with the patch sizes and the spatial resolution of the input climate data. Finally, a mosaic of grid cells represents the landscape level, which is limited mainly by processing capacity and the spatial extend and resolution of input climate data.

A combination of Remote Sensing data products, MODIS, and measured data, FLUXNET, were used to validate the simulated Gross Primary Production (GPP) at sites, which cover a wide range of climate conditions: boreal and alpine (Seitseminen and Kalkalpen), as well as temperate (Bialowieza, Hainich and Lägern) and Mediterranean-type (Dundo) climate conditions (Figure 24 and Table 2). MOD17A2H, monthly Tree canopy cover for 2004-2013 (Hansen et al. 2013) was used for the validation of carbon fluxes (GPP). The MODIS data was retrieved from the online Application for Extracting and Exploring Analysis Ready Samples (AppEEARS), courtesy of the NASA EOSDIS Land Processes Distributed Active Archive Center (LP DAAC), USGS/Earth Resources Observation and Science (EROS) Center, Sioux Falls, South Dakota (Running, 2015). In order to identify the MODIS-pixels, which cover nearly natural vegetation, we used information from websites of the protected areas and literature. If no information was available, we cut the MODIS data by the whole extent of the protected area. In addition, only MODIS-pixel were selected, which contain at least 75% of tree canopy cover in year 2000 according to Hansen et. al 2013.

The Seasonal pattern of simulated GPP compare well against measured data for all sites (Figure 24a). On and off-set of GPP, month of maximum productivity and its intra-annual variability (shown as shaded area in Figure 24a) is well captured in all sites which is also illustrated by a high correlation (Table 2). LPJmL-FIT overestimates productivity in the Kalkalpen (ME of -30.9 gC7m² and NMSE of 0.26, see Table 2). In the temperate forests of the Hainich NP the seasonal pattern of simulated GPP compares well to MODIS data. However, GPP measured by FLUXNET shows a higher productivity in summer months June, July and August (ME of 21.9 and NMSE of 0.2 against FLUXNET, and ME -6.0 and NSME 0.03 against MODIS). In the Nature Reserve Lägern simulated GPP is more productive in spring and autumn months, whereas simulated productivity over the summer months agrees well with both measurements (low ME and NSME, see Table 2).

When comparing monthly distribution of simulated GPP over 10 years (2004-2013; Figure 24b) for all 6 sites, similar pattern of data-model (dis-)agreement emerge. LPJmL-FIT captures the seasonal distribution of GPP over 10 years with small productivity overestimation consistently occurring in Kalkalpen and for some years in Bialowieza (for modelling errors, see Table 2). Summer productivity is lower compared to FLUXNET data in the Hainich, whereas FLUXNET productivity is lower in Lägern in 2004 and 2005, but matches well simulated and remotely sensed values in later years. The GPP amplitude in Dundo is overestimated in some years and shows in general a bi-modal pattern in the summer months in all years which is not as pronounced in the MODIS GPP data. Therefore, the NMSE is higher and the correlation lower compared to the other sites (Table 2). In general, the LPJmL-FIT model is able to simulate inter- and intra-annual variability of vegetation productivity under different climate conditions.

Site	GPP seasonal dynamics (graph a)			GPP (graph b)		
	ME	Corr.	NMSE	ME	Corr.	NMSE
Seitseminen	-5.6	0.99	0.03	-5.6	0.94	0.12
Kalkalpen	-30.2	0.97	0.25	-30.2	0.96	0.27
Bialowieza	-8.9	0.99	0.05	-8.9	0.97	0.11
Hainich	-6.0 (21.9)	0.99 (0.95)	0.03 (0.2)	-6.0 (18.4)	0.96 (0.94)	0.08 (0.19)
Lägern	-23.0 (-22.1)	0.97 (0.95)	0.11 (0.21)	-23.0 (-20.7)	0.96 (0.89)	0.14 (0.29)
Dundo	2.6	0.95	0.15	2.6	0.89	0.29

Table 2: Error measures of GPP validation (Figure 24) for six different sites. Values in brackets correspond to model output compared to FLUXNET. ME = Mean Error, Corr. = Correlation (Pearson's R) and NMSE = Normalized mean square error (Kelley et al. 2013).

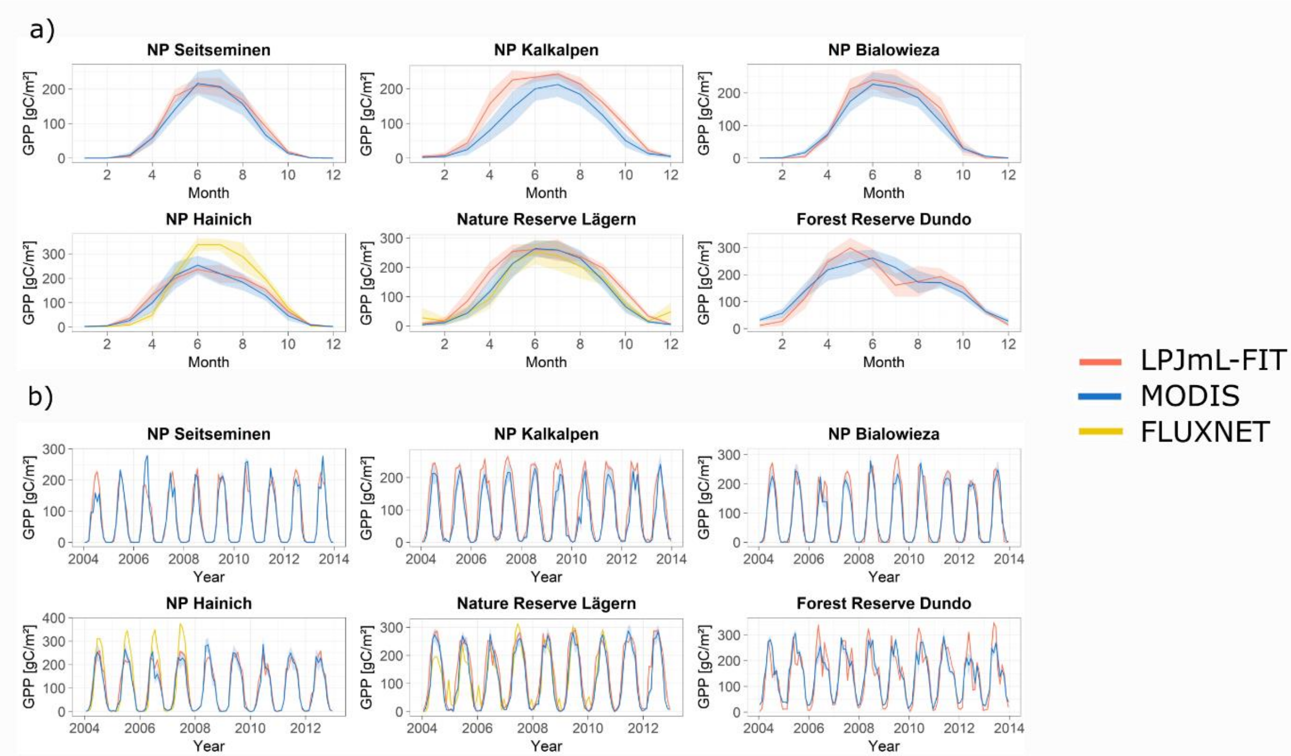

Figure 24: Comparison of simulated (red line) and observed GPP for six different sites representing a wide climatic range. Observed data from MODIS (blue line) and FLUXNET (yellow line). Panel a) shows seasonal distribution averaged over 2004-2013 (range shown in shaded area) and panel b) inter-annual variability from 2004-2013. Information on modelling error, see Table 2: Error measures of GPP validation (Figure 24) for six different sites. Values in brackets correspond to model output compared to FLUXNET. ME = Mean Error, Corr. = Correlation (Pearson's R) and NMSE = Normalized mean square error (Kelley et al. 2013)..

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4. Conclusions

4.1 Impact of EO on Modelling for ECOPOTENTIAL and Beyond

Earth Observation data is a boon to modelling applications, increasing the available information and data sets to be used in model forcing, inputs, calibration, validation or as initialization information for model states. Many of the models explored in this deliverable made use of RS data as drivers and inputs directly driving the processes underlying the model. For larger spatial extent model applications, particularly for Pan-European applications, without the spatial capacity of remote sensing, it would be difficult if not impossible to obtain measurement data points sufficient to drive such models, resulting in a need to create synthetic data points or utilize global models as drivers. Therefore, EO and specifically RS is beneficial to the application of such models. While RS provides enhanced spatial and temporal resolution, features which are improving with newer satellite missions such as the Sentinel series, there are certain limitation to their applications. Monitoring data is still required in order to validate and obtain error metrics on the site specific RS data sets, particularly when using generalized algorithms to derive the proxies and variables extracted from RS raw data. These errors and uncertainties accounted for in the RS data sets allows for understanding and accounting of percolating uncertainties, which carry through the model and can deteriorate the results or create false securities in the accuracy of outputs [8]. Adaptations and methods to account for the mis-match of spatial resolution and alignments between models and RS data products have been well reviewed and published, minimizing the limitations resulting from this obstacle and providing methods to include metrics of uncertainties and resulting errors in for both up-scaling and down-scaling [9] [10] [11]. Therefore, regardless of scaling requirements, highly dynamic and spatially heterogenous models like those of the Wadden Sea and Peneda Gerês can make use of these large spatial domain data sets so as to better quantify and calibrate the models whereas without, they would not be able to fully capture heterogeneity of the entire model domain. Therefore, while the errors in the scaling of data and alignment to model grid space may introduce errors and uncertainties, successfully weighting and considering the introduced error can still provide additional useful information as to the general trend or calibration parameter range over a lack of corroborative data points.

The improved model results and information derived provides added value products to PA managers and policy makers, better informing and enabling optimization of decisions and policy pathways in relation to the well-being and productivity of PAs. These models, integrated with RS data, allow for enhanced hind and nowcasting, deriving the past and present trends of PAs which enable management to determine the effectiveness of prior decisions and to determine what regions, species, or habitats to focus conservation and restoration efforts upon in order to improve the ecological function of these critical zones as well as preserving the biodiversity and well of ESs they provide. The outputs of these models have been confirmed of use to stakeholder and management as seen through the WP11 and WP9 surveys of PA stakeholders, providing information on the critical environmental descriptors. While the RS and EO data products can provide snapshots into instantaneous states of the system, the added value derived from including such information into a functional representation of the PA aids in the confirmation or negation of functional assumptions how the ecosystem works and reacts to pressures and drivers. The combination of models and EO are a pivotal phase in the step-wise approach on Ecosystem Service assessment developed within WP7 of the ECOPOTENTIAL project and described in deliverables 7.1 and 7.2. This iterative approach relies on supporting information from these hybridizes models in order to understand the past, investigate the present, and optimize plans for the future of PAs; indeed as seen through the outputs in this deliverable, the combination of RS and models can support decision makers and management in achieving effective stewardship of PAs. Such decision support systems can exist in the form of

Bayesian Networks, frameworks, and assessment tools, a collection of which have been presented in the decision support toolbox of WP7 deliverable 7.3. These tools rely on data sets to communicate trends and potential impacts on ecosystems; for example the Bayesian Networks developed for the Wadden Sea and Swiss National Parks & Davos require the inputs from the modelling outlined in this deliverable in order to populate the conditional probability tables which generate key information for management decisions. Furthermore, the Pan-European modelling efforts conducted by University of Potsdam address the trends and status shifts of key indicators across Europe and on the border zones of Protected Areas, informing the work and deliverables of WP8 by ingesting the historical RS datasets and generated added value information through models. This European trend information can also support the identification in shifting ecotoptes and ecosystem status, informing efforts of WP9 seeking to evaluate the current status of PAs and potential need to change degree of protection for existing PAs or introduce additional and new regions as protected.

The open source nature and adaptability to many domains of interest for many of the models used here in conjunction with the open-source and freely available nature of the RS data utilized affords transferability of the generic models and approaches to other PAs or potential PAs not already within the project utilizing a similar processing chain and algorithms. The proxies and indicators resulting from the studies within ECOPOTENTIAL have been identified as Essential Biodiversity Variables (EBVs) in the mapping exercises within WP 2 and can be seen per PA within Deliverable 2.1. The models applied within the project therefore have high relevance and transferability potential to other domains in order to investigate the trends and states of ecosystems within PAs and potential PAs, as outlined in the work of WP9. Therefore, demonstrating the applicability, improvements, and methods for including RS data into models serves as a blueprint for further application to support existing and new PAs outside of ECOPOTENTIAL. Furthermore, with the deployment of the core elements of some models within the VLP in WP11, these models can be adapted with minimal entry barriers to new sites and make use of the open source and automated algorithms deployed through WP4. Researchers and management outside of the project may now make use of RS production lines and generalized models, combining them for new site deployment in their areas of interest.

4.2 Relation to Future Work

Showcasing the importance and applicability of EO data as an information source to drive localized and regional models that provide information on key ecosystems and ecological variables will lead to greater uptake and expansion of the methods. As the usage of EO data as forcing and validation data points becomes standardized, and the processing and application methods generally accepted, the expansion beyond to multi-faceted use as input data, initial state calibration, and output calibration and validation to include automated parameterization and potential of state-updating for forecasting and operational ES and ecosystem models. This would entail the introduction of multiple source of EO and RS data in various points throughout the modelling process in order to have higher integration of RS at multiple stages of modelling. The additional inclusion and weighting of RS and in-situ data combined would offer the maximum usage potential of both of these data sources, providing the most information sources to be taken advantage of to optimize and improve models. Further inclusion of data assimilation strategies such as automate parameterization and subsequent state-updating is envisioned. One of the main barriers to the utilization of RS in Data Assimilation (DA) is the requirement for uncertainty and per pixel error statistics as DA framework require the building of covariance matrices to effectively weight the multiple source of information against one another. With the increase communication and knowledge sharing resulting from this work between modelers and RS experts, it is envisioned that it will be possible moving forward to increase the occurrence of DA for PA and ecosystem models.

Many of the RS products utilized within this work and in the ECOPOTENTIAL project are derived from the more historical missions. As the Sentinel Series has only recently been launched, in the past few years, with a selection of sensors still undergoing optimization and calibration (such as the Sentinel-2 and -3 satellites and corresponding sensors) the true advancements in spatial and temporal resolution from these missions is yet to be fully appreciated. The work done in the ECOPOTENTIAL project and within Deliverable 6.2 began to make first use and trials of these new data sources, providing insights and case studies for the adoption and inclusion of these RS inputs to models. Advancing to the new series of remote sensing products from the further sentinel missions and making use of the enhanced spatial and temporal resolution of the data sources to better coincide with the spatial and temporal resolution of the models themselves and help to minimize errors and uncertainties resulting from scaling issues and reprojections.

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