Using Earth observation to support the predictive accuracy of species distribution models in ecological restoration: a case study of Poland beavers (Castor fiber)

Harin Aiyanna Cheriyanda Raveendra [1], Lorenzo Picco [1], Francesco Pirotti [1,2]

[1] Department of Land, Environment, Agriculture and Forestry (TESAF), University of Padova. Via dell’Università 16, 35020 Legnaro, Italy – (harinaiyanna.cheriyandaraveendra@phd.unipd.it,lorenzo.picco)@unipd.it

[2] Interdepartmental Research Center of Geomatics (CIRGEO), University of Padova. Via dell’Università 16, 35020 Legnaro, Italy – francesco.pirotti@unipd.it

Keywords: Remote Sensing, Earth Observation, Environmental Monitoring, Species Distribution Modelling, ecosystem restoration.

Abstract

The ability of Earth observation and remote sensing to identify the potential of species to restore ecosystems is a critical element in combating habitat degradation and biodiversity loss. Historical climate data and current species occurrence, coupled with geospatial modelling methods, can significantly aid in decision-making to support ecosystem restoration. We chose Eurasian beavers (spp. Castor fiber) as our case species, which are known ecosystem engineers that create wetland habitats and significantly alter/reinforce the morphology, dynamics, and hydraulics of riverine landscapes. To investigate their ecosystem restoration potential, we applied species distribution modelling (SDM) to determine their current and future distribution scenarios. Our SDMs used current and simulated future environmental data along with different classes of rasters such as elevation, inland swamps, water bodies, natural seasonally or permanently wet grasslands, open mires, riparian mixed forests, riparian swamp broadleaved forests, riparian swamp coniferous forests, watercourses, protected areas, and urban and built-up areas derived from Google Earth Engine to predict areas suitable for beaver habitats. Further, by using the zonation method, we were able to develop a stepping stone model to prioritize habitat conservation efforts. We provide habitat projections according to time periods of "2041-2060", "2061-2080" and "2081-2100", and to different climate change scenarios (SSP126, SSP245, SSP370, and SSP585). Thus, using a potential nature-based solution, we have employed remote sensing data and tools to develop a holistic framework for not only quantifying the ecosystem restoration potential of beavers but will also provide a new direction for understanding species-specific importance in climate change mitigation.

1. Introduction

Rising urbanization and climate change are major global challenges that can be tackled through ecosystem restoration. In the recent past, restoration ecology has received much attention as it helps revamp past and ongoing damages to ecosystems (Laub & Palmer, 2009). Implementing man-made techniques to revive a riverine terrain may aid in mitigating environmental deterioration and contamination, yet they often disregard the intricate interweaving of the biotic stream dynamics (Palmer et al., 2014) as well as the crucial role of riparian vegetation (Rusnák et al., 2022). Ultimately, the ecosystem proves inadequate to accommodate the myriad of life forms that formerly inhabited it.

1.1. Species distribution through Remote Sensing

Driven by five factors: 1) land use change; 2) pollution; 3) climate change; 4) invasive species; and 5) natural resource use and exploitation, species population sizes are subjected to a 68% average decline between just 1970 and 2016 as documented by World Wildlife Fund's Living Planet Report 2020 (Jaureguiberry et al., 2022). In a way to monitor this decline, a novel method called Species Distribution Modelling (herein after SDM) also known as environmental (ecological or niche) modeling, uses computer algorithms to predict the distribution of a species across geographic space and time using environmental data (Anderson, 2013; Fourcade, 2016; Phillips & Dudík, 2008a). Primarily, SDMs fill the gap in understanding the distribution and possible expansion of species populations by providing comprehensive data for effective conservation planning and ecosystem management. Second, the model anticipates potential ecological implications by climate and land use change influence species distribution. Therefore, appropriate satellite derived environmental variables can greatly influence the predictive accuracy of SDM’s to produces real time ecological niche suitable for species.

In the case of Eurasian Beavers, their ecological significance in maintaining a stable hydrological regime (Boyle & Owen, 2007) can be accounted. Beaver dams have been demonstrated to lower channel flow, minimize flashiness, and boost habitat availability, heterogeneity, and connectivity for common frogs and fishes (Wikar & Ciechanowski, 2023). Considering their affinity to wetlands (Nazarov et al., 2023a) and riparian vegetation, it is crucial to have different wetland classes such as river courses, inland marshes, lakes, and ponds coupled with the bioclimatic variables to logically describe their realized niche. Thus, opening horizons for multi-species modelling or Stacked Species Distribution Modelling provides a scientific foundation for informed decision-making, ultimately contributing to the conservation and proactive ecosystem restoration. SDMs can also ensure identifying species at risk of extinction (Rodríguez-Castañeda et al., 2012), prioritizing conservation efforts (Rahman, n.d.), assessing the effectiveness of protected area management (Zurell et al., 2023) as well as capturing biotic interactions by the species. Therefore, coping up with climate change, a holistic approach to maximise accuracy of SDMs prove effective to help in bending the curve of biodiversity decline.

1.2. Climatic change scenarios

The different climate change scenarios that project socioeconomic global changes are called Shared Socioeconomic Pathways (SSPs). The primary SSP scenarios used in this study are SSP126, SSP245, SSP370, and SSP585. SSP126 represents a sustainable development pathway with very low challenges to mitigation and adaptation consistent with the Paris Agreement's goal of keeping global warming well below 2°C. It assumes a world with low population growth, rapid economic growth, and a shift towards renewable energy and sustainable practices in turn reducing greenhouse gas emissions. SSP245 assumes a middle-of-the-road scenario where moderate climate policies are followed. SSP370 represents a world with moderate-to-high challenges to mitigation and adaptation. While SSP585 (worst-case scenario) embodies significant climate change with high greenhouse gas emissions. Based on historical data, such climate models are the primary means for scientists to analyze climate changes. Keystone species such as beavers have their role in improving ecosystem, making it important to have a multidisciplinary approach to delineate essential habitats for their future occurrences.

1.3. Environmental variables for species sustenance

Several critical environmental variables influence beaver survival and dispersal. Hydrology is particularly important for beavers, as they rely on aquatic habitats for survival and require a reliable source of water to build their dams and lodges (Pollock et al., 2007). Given that beavers use both water and terrestrial flora for food, vegetation is a crucial factor to consider (Pollock et al., 2007). The suitability of habitats for colonization as well as the availability of food and water for beavers will be impacted by climate factors like temperature and precipitation (Brazier et al., 2020; Smeraldo et al., 2017), human activities like urbanization, agriculture, forestry, and water management (Pollock et al., 2007). As a result, SDMs can be best used to identify and prioritize beaver dwelling sites where their presence plays an important role in environmental restoration. Further by incorporating stimulated future climate projections (multiple SSPs and time periods) into the models (R. P. Anderson, 2013; Valavi et al., 2022; Zurell et al., 2023), we can assess how changing climate conditions may alter the distribution and activity of beaver populations. Several studies (Smeraldo et al., 2017; Swinnen et al., 2017) have used SDMs to predict and visualize habitat preference as well as range expansions of Eurasian Beavers in different landscapes. However, beavers show a preference for wetlands like swamps, marshes, and rivers, which serve as suitable locations for building lodges and dams (Grudzinski et al., 2022; Spyra et al., 2023). Consequently, the mapping of such habitats holds the utmost significance in predicting the beaver's distribution. Making use of the available satellite data on Land use land cover changes (LULC), species specific SDMs must be carefully built (Araújo & Guisan, 2006; Elith et al., 2006; Fourcade, 2016; Phillips et al., 2006; Rodríguez-Castañeda et al., 2012; Smeraldo et al., 2017) with only relevant environmental variables that contribute to their survival. Since each of the environmental variables have their own influence, this study hypothesizes that water sources such as lakes, river, and ponds along the riparian vegetation specially broadleaves will be critical environmental factors driving the distribution and expansion of beavers in the future. We constructed two Ensemble Species Distribution Model (herein after ESDM) ESDM_1 which encompasses all the 28 environmental variables given in table 1 and ESDM_2 consisting of only the 19 bioclimatic variables. The study thus aims to answer pertinent questions such as "Will Castor fiber broaden or shrink its range in the future?" "What climatic niche would support the persistence and expansion of Castor fiber in Poland?" What is the influence of the environmental variables in habitat prediction excluding the 19 bioclimatic variables?

2. Methods

2.1. Study Area

Poland is a captivating study area because of its diverse landscapes and continental climate (Török, et al., 2017). For survival, beavers are dependent on a wide network of wetlands, rivers, and streams. Poland covers an area of roughly 312,696 km^2, with mountains in the south and forests, lakes, lowland marshes, and rivers in the north. In 1974, the program "Active protection of European beavers in Poland" (Michał, et al., 2020) was launched for re-introduction for Beavers (Nolet, et al., 1997; Kemp, et al., 2012). As of 2014, approximately 100,000 individuals are documented by (Sjöberg et al., 2020) and a study area map is provided in Figure 1.

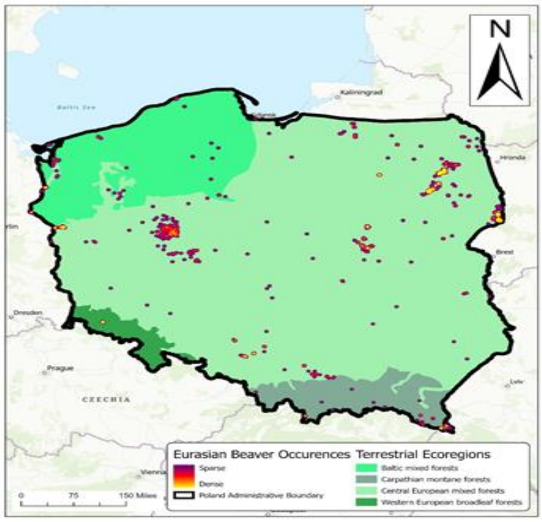

Figure 1: Study Area Map along with beaver occurrences and terrestrial ecoregions of Poland.

The country's forest distribution is diverse, with the Bowiean Forest in the east being one of Europe's last remaining primeval forests, while the Carpathian Mountains in the south include significant mixed forested areas (Angelstam, et al., 2017). These forested habitats supply beavers with a varied range of resources, including a wide range of tree species for food and building materials (Nazarov, et al., 2023). Poland's river network is extensive and diverse, with large rivers such as the Vistula, Oder, and Bug, as well as numerous smaller tributaries and streams. These ecosystems are formed by riparian zones along the continually flowing water, which develop thick vegetation made up of trees, shrubs, broadleaves/coniferous or mixed forests, and herbaceous plants, providing critical resources such as food and predator protection (Cooke & Zack, 2008). Furthermore, the availability of suitable substrates such as clay or silt allows beavers to build dams and establish pond-like habitats (Pollock et al., 2007). These beaver ponds also provide habitat for a range of aquatic and terrestrial species, hence increasing biodiversity and environmental complexity (Orazi et al., 2022).

2.2. Procedure

The study is conducted in two stages. In the first stage, data on the current distribution of beavers in Poland are obtained from the Global Biodiversity Information Facility (GBIF). GBIF is an international network and data infrastructure aimed at providing anyone, anywhere, open access to data about all types of life on Earth (*GBIF*, n.d.). The Species Occurrence library (SPOCC) helped gathering more occurrence data from iNaturalist as well. A combined total of 2045 geo-referenced individuals were used to train our model. We obtained the most detailed bioclimatic data of 30 arcsec (1km*1km resolution) from the WORLDCIM website. Inclusion of multiple future climate change scenarios SSP126, SSP245, SSP370, and SSP585, for the time periods (2021-2040, 2041-2060, 2061-2080, 2081-2100) yielded many future probability habitat distributions. Since beavers rely primarily on wetland ecosystem (Nazarov et al., 2023a), we included the Extended wetland ecosystem layer 2018 (raster 100m) version 1, Jul. 2021 (*Extended Wetland Ecosystem Layer*, n.d.). For the machine learning framework to identify the contribution of each variable, the wetland classes were separated and fed as individual raster to build the ESDM_1. The function ensemble modelling is based on the SSDM package which combine multiple SDMs produced by algorithms Multivariate adaptive regression splines (MARS), Classification tree analysis (CTA), Random Forest (RF), Artificial neural network (ANN), and Support vector machines (SVM) into a single predictive model. To have an unbiased evaluation of the ESDM we used the ‘holdout’ method of cross validation which holds out a portion (25%) of the data as test set while the predictive accuracy on the unseen data is assessed preventing overfitting and assist in compensating for the restricted occurrence data (Yackulic et al., 2013).

Further to increase the model stability and robustness the cross validation was repeated 10 times (Bahn, 2009). SDMs are sensitive, often leading to biases when the dataset is divided into test and train and therefore it is crucial for a fair comparison of multiple SDMs. There are other methods of cross validation as well such as the k-fold and leave-one-out (LOO) (Bahn, 2009) which can strengthen the predictive accuracy and evaluation of SDMs. Results of the ESDM were averaged over 10 replicates (rep=10) and the ensemble threshold was set to ‘0’ as we expect each of the models to contribute equally to the final prediction. The final model ‘ESDM_1’ was projected to the future using the future bioclimatic variables, while the rest of the 9 environmental variables (elev, inland_marshes, lakes_ponds_reservoirs, wet_grasslands, open_mires, rip_mix, rip_broad, rip_coni, rivers) remained the same. We made this assumption as the future changes in environmental is highly uncertain depending on the complex socioeconomic factors.

This might lead to oversimplification of the model but the use of multiple climate change scenarios from GCMs (general climate models), our model explores a range of possible outcomes and associated uncertainties and generalization (Mainali et al., 2015). Isolating these wetland classes, we built ESDM_2 with the 19 bioclimatic variables only (see in appendix). By comparing both the models we intend to isolate the effects of climate change while upholding the influences of wetland classes in ESDM_1.

SDMs using multiple algorithms has shown excellent potential for identifying distributions and habitat selection patterns (Baldwin, 2009; Elith et al., 2006) but are prone to biases as occurrence data are not equivalent to real world data. To evaluate the performance of each model (MARS, CTA, RF, ANN, and SVM) several metrics were analysed (Table 2). Generated continuous suitability predictions were converted to binary presence/absence outputs through the threshold value representing probability cut-off. The area under the receiver operating characteristic curve (AUC-ROC) measure is commonly used to assess the efficacy of SDM (Su, et al., 2019).

Variables	**Explanation**
BIO1	Annual Mean Temperature
BIO2	Mean Diurnal Range (Mean of monthly (max temp - min temp))
BIO3	Isothermality (BIO2/BIO7) (* 100)
BIO4	Temperature Seasonality (standard deviation *100)
BIO5	Max Temperature of Warmest Month
BIO6	Min Temperature of Coldest Month
BIO7	Temperature Annual Range (BIO5-BIO6)
BIO8	Mean Temperature of Wettest Quarter
BIO9	Mean Temperature of Driest Quarter
BIO10	Mean Temperature of Warmest Quarter
BIO11	Mean Temperature of Coldest Quarter
BIO12	Annual Precipitation
BIO13	Precipitation of Wettest Month
BIO14	Precipitation of Driest Month
BIO15	Precipitation Seasonality (Coefficient of Variation)
BIO16	Precipitation of Wettest Quarter
BIO17	Precipitation of Driest Quarter
BIO18	Precipitation of Warmest Quarter
BIO19	Precipitation of Coldest Quarter
elev	Elevation
inland_marshes	Inland Marshes
lakes_ponds_reservoirs	Lakes, Ponds, Reservoirs
wet_grasslands	Natural seasonally or Permanently wet Grasslands
open_mires	Open Mires
rip_mix	Riparian, Fluvial, and Mixed Forests
rip_broad	Riparian Fluvial and Swamp Broadleaved Forests
rip_coni	Riparian, Fluvial and Swamp Coniferous Forests
rivers	Water Courses

Table 1: Environmental variables (both present and future) used in the SDM.

The AUC evaluates the SDM's capacity to differentiate between species presence and absence, demonstrating its overall robustness in evaluating habitat suitability (Raes & Ter Steege, 2007). An AUC of 0.5 implies a random guess, whereas an AUC of 1.0 shows an error-free model. A high AUC value in SDM suggests the model's aptitude to predict the species' presence or absence based on environmental factors. Specificity defines the true negative rates while the sensitivity represents the true positive rate. Cohen’s kappa statistic explains the possibility of chance agreement, subsequently the calibration metric determines how well the model predictions match the observed data, with values nearer to one indicating greater calibration. It is crucial to consider all these metrics to evaluate the accuracy of the SDM predictions (Araújo & Guisan, 2006; Valavi et al., 2022).

To capture the impact of anthropogenic activities we used Dynamic World V1 dataset. It is a near-real-time (NRT) Land use/ Land Cover (LULC) dataset (Brown et al., 2022) that includes class probabilities of different land use feature and leveraging deep learning on 10 m Sentinel-2 imagery. Through Google Earth Engine we retrieved the band depicting Urban and built areas from the LULC image for Poland 2023. The Protected Planet website (*Explore the World’s Protected Areas*) was used to gather information on the available protected areas in Poland. The range expansion of species was predicted by using zonation(Lehtomäki & Moilanen, 2013) to model species-environment relationships in other words a stepping-stone model. Zonation utilized the Urban/built area raster and the protected areas with a specific rank (table 2) to prioritize area that requires conservation.

Raster files used in Zonation	*Priority ranks*
Future Habitat Map (SSP126, 2021-2040)	5
Current Habitat Map	4
Protected Areas	3
Urban Areas	1

Table 2: Rank table for Zonation

The output of zonation gave out the current distribution and then predicted areas near to protected areas while least prioritising urban and built areas.

3. Results

The outputs of the model include habitat distribution appropriateness of habitat for Castor fiber in Poland. Figure 3 is the current habitat suitability map emphasizing places with good ecological niches for the occurrence of the species. This ESDM was projected to the future, for the time periods 2021-2040, 2041-2060, 2061-2080, and 2081-2100 under different climate change scenarios (SSP126, SSP245, SSP370, and SSP585).

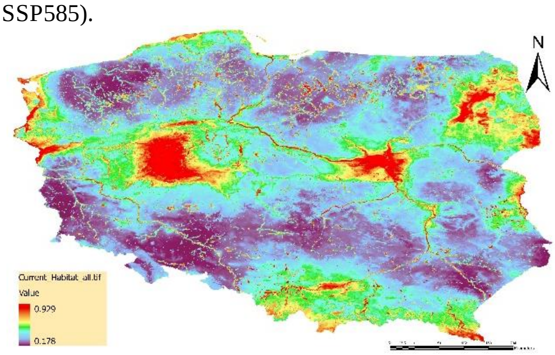

Figure 2: Current Habitat suitability Map (ESDM_1)

Extensive areas across the Poznan region, central Warsaw, northeastern regions of Bialystok as well a portion of the Southern Carpathian areas is presumed suitable by the model.

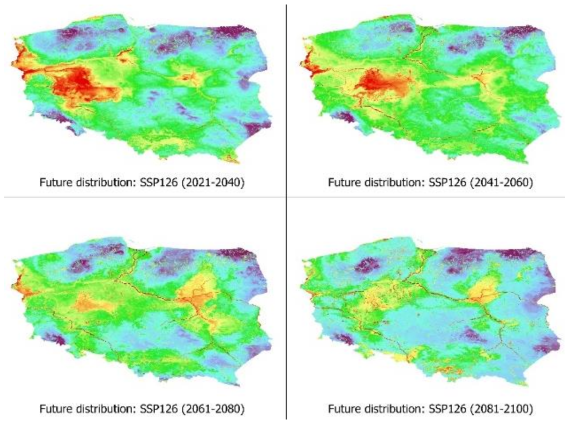

Figure 3: Future Habitat Suitability Maps for SSP126

Under the SSP126 Scenario (also called Taking the Green Road of Sustainability), which represents a low greenhouse gas emission trajectory predicts small losses in habitat suitability, especially at the periphery of currently suitable regions, while core ecosystems remain reasonably constant (figure 3). However, heavy fragmentation is seen further along the timeline. During the period of 2081-2100, the habitat aggregation is seen only close to rivers, lakes and ponds. Under the scenario SSP245 (figure 4) or the intermediate emission scenario we observe an increased fragmentation and much habitat concentration near water courses. Even though there is a significant reduction in suitable habitat over the years, we still observe central Poland is habitable for Eurasian Beavers, especially along the Vistula River near Wloclawek.

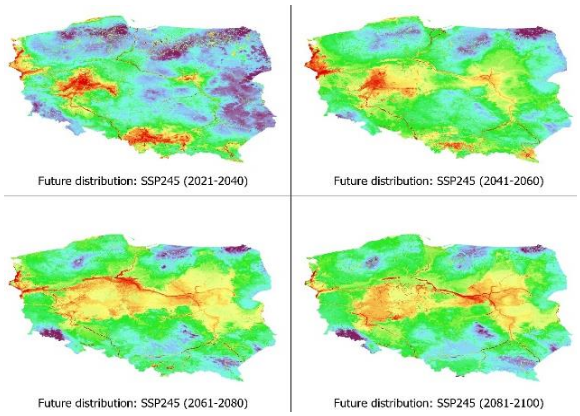

Figure 4: Future Habitat Suitability for SSP245

The scenario SSP370 (figure 5) (a rocky road) writes down a mild or moderate decrease in the future habitat distribution when compared to the rest of the scenarios. Heavy fragmentation is seen along the time period, but a significant suitable habitat yet prevails. The last scenario SSP585, also known as the (taking the highway of fossil fuels) indicates a high emissions pathway, forecasting considerable habitat loss.

Although we can see a significant increase of fragmented habitat for the period 2041-60, but drastically diminishes over the next decades (figure 6). We evaluated the model with several metrics for each of the algorithms. Random Forests gave the highest AUC value (0.932) clearly indicative of a high predictive accuracy. Having the lowest omission rates (0.135) and the best sensitivity (0.865) to accurately identify ecological niches for Eurasian Beavers. Multivariate adaptive regression splines (MARS) showed better performance

(AUC= 0.828) and a moderate sensitivity (0.759) and specificity (0.735).

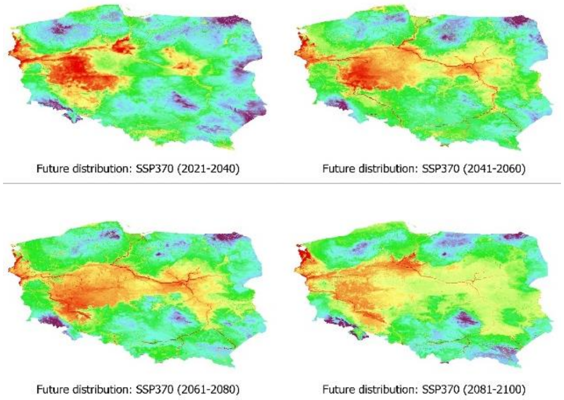

Figure 5: Future Habitat Suitability for SSP370

Compared to the RF, ANN has a less agreement between predicted and observed values (Cohen's Kappa= 0.139) hence has the lowest predictive capacity. However, it earned the highest calibration score (0.902), indicating an excellent match between projected probability and observed frequencies. Figure 8 represents a graph of the variable contribution for the outputs generated by our ESDM_1 that includes all the environmental variables. Lakes, Ponds and Reservoirs, Water Courses and Elevation contributes to the highest while Inland marshes, Open Mires and Natural seasonally or permanently wet grasslands have shown the least importance in habitat prediction.

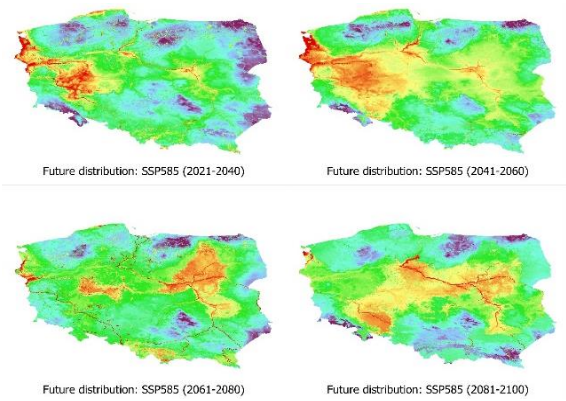

Figure 6: Future Habitat Suitability for SSP585

Figure 7 is an output derived from zonation, which clearly identifies the closeness of prime habitat to protected areas (in red). The map also segregates Urban/built areas inferring that conservation is not required in these zones where humans inhabit.

4. Discussion

Castor fiber distribution in Poland is influenced by a variety of factors (Figure 9). Several contributing variables like 'Lakes, Ponds and Reservoirs and Water Courses, form a prime necessity for the availability of suitable habitats (Geris et al., 2022). To understand species habitat connection, it is suggested to account for the biological necessities for the survival of the species (Fourcade, 2016) and using remote sensing can support the analysis (Dalponte et al., 2023). Primarily dwelling around water sources adequate habitat can beaver build dams which can have a significant impact on the hydrological functioning of rivers and streams (Giżejewska et al., 2015; Nazarov et al., 2023b; Spyra et al., 2023; Stringer & Gaywood, 2016).

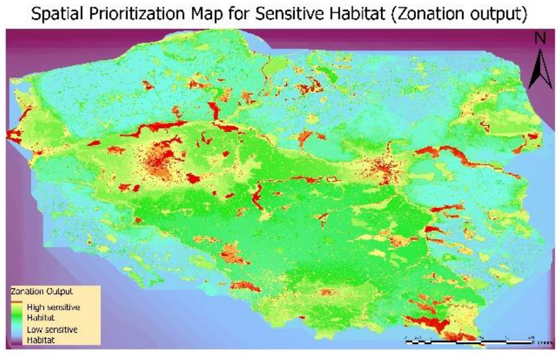

Figure 7: Zonation Output

A study of the effects of beaver dams on zooplankton communities in small lowland streams in NW Poland (Nazarov et al., 2023b) discovered that beaver dams have a major impact on zooplankton assemblages in stream-beaver pond stream systems. The generated suitability map (Figure 2) indicates locations that provide ideal habitats for beavers presenting opportunities for conservation and management activities (J. Anderson & Bonner, 2014).We also observe prime hotspot for beaver occurrences in Warta River Mouth National Park in Poznan, as well as the watery marshes of the Biebrzanski park Narodowy and the Narew valley floodplains near Bialystok. Considering the ideal environmental variables contributing for their occurrences, we clearly observe the spatial aggregation of the wetland classes as in figure 8.

According to the table 3 the individual species distribution model from MARS, CTA, RF, ANN, and SVM have comparatively performed differently giving their contribution to the final prediction. The RF model's outstanding accuracy, as indicated by the high AUC, sensitivity, and specificity, implies that this algorithm was able to successfully interpret the intricate interactions between the species' occurrence and the environmental predictors. The low omission rate of the RF model is additionally notable, as it indicates that there is a small likelihood of failing to identify ideal habitat for the species. Likewise, the high Cohen's kappa value from the CTA model ensures the predictions match closely to the observed data implying a prominent level of agreement between the model and the species' real-world distribution.

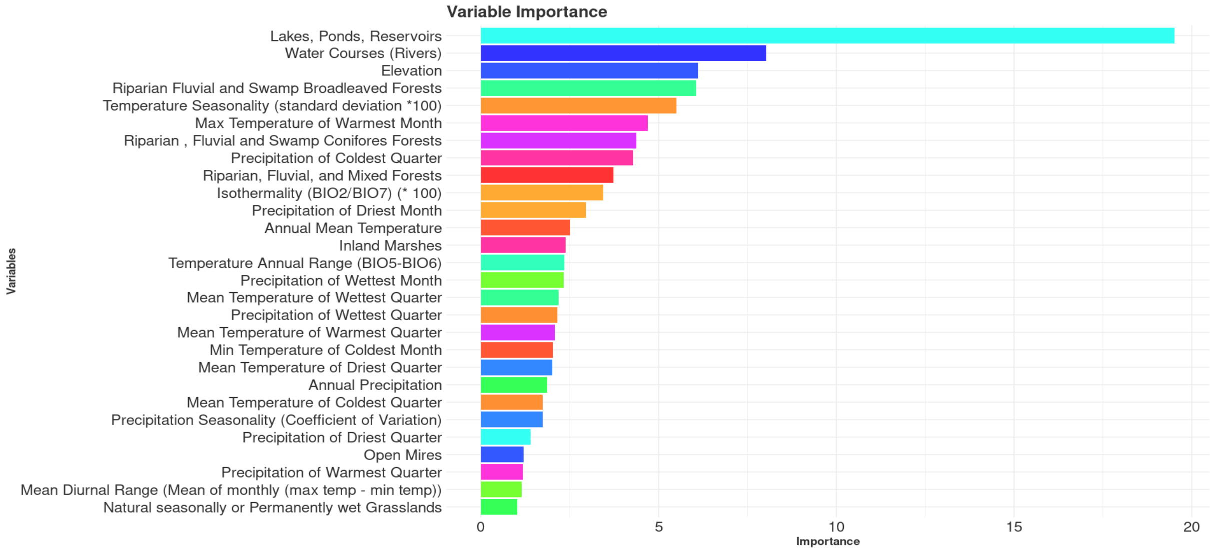

Figure 8: Variable importance graph for ESDM_1 Current Habitat.

Algorithm evaluation	Threshold	AUC	Omission rate	Sensitivity	Specificity	Prop correct	Cohen's Kappa	Calibration	Kept model
MARS	0.675	0.828	0.241	0.759	0.758	0.759	0.453	0.815	10
ANN	0.626	0.581	0.436	0.531	0.612	0.564	0.139	0.902	10
CTA	0.502	0.786	0.263	0.741	0.730	0.737	0.466	0.857	10
RF	0.568	0.932	0.135	0.865	0.865	0.865	0.725	0.860	10
SVM	0.565	0.823	0.254	0.746	0.746	0.746	0.487	0.640	10

Table 3: Evaluation metrics from the model (ESDM_1)

It is important to note that we have used the present-day wetland classes for predicting the future distribution. The model does not account for any LULC changes for the future but multiple scenarios (SSP126, SSP245. SSP370 and SSP585) have ensured a comprehensive understanding and robustness of the framework. SSP scenarios can affect SDMs in unexpected ways in all of the scenarios, we observe an aggregation of suitable habitat close to water bodies (Kanan et al., 2023; Akbar Hossain et al., 2022). Many studies (Elith et al., 2006; Fourcade, 2016; Rodríguez-Castañeda et al., 2012) suggest that the spatial congruence of occurrence points leads to high biases in SDMs. Ensemble SDMs provide accuracy value for each algorithm giving the agreement between range maps and occurrence data. Comparing between scenarios ESDMs, each time period range map shows a unique gradient in habitat prediction.

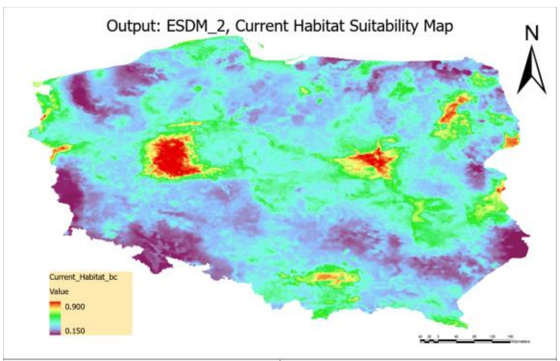

Figure 9: Current Habitat Suitability Map (ESDM_2)

The ESDM_2_Biclimatic model however shows widespread habitat and no influence of wetland classes that were fed to the ESDM_1 (figure 3). Our initial assumption of keeping the same wetland/LULC variables in ESDM_1 suggests changes in river morphology, riparian vegetation, and wetland areas significantly differs between SSP Scenarios. Observing the output maps from the two ESDMs we can say SSP126 can lead to a more stable hydrological regime SSP585 could lead to a dynamic and extreme conditions. Hence, using multiple scenarios for different time periods convinces us that habitat degradation due to climate change prevails.

5. Conclusion

Eurasian beavers (spp. Castor fibers) are a vital species in helping to maintain the natural balance and diversity of rivers. The models ESDM_1 and ESDM_2 highlights the importance of Eurasian beavers (spp. Castor fiber) populations in river restoration initiatives for their ecological and hydrological advantages. Inclusion of wetland and LULC class variables evidently suggests the particular adaptations and preference of Eurasian beavers in Poland. Contradictory trends have been observed between scenarios in ESDM_1 and ESDM_2, which is explained by the interplay between Eurasian Beavers individual habitat preferences and expected environmental scenarios. Predictive accuracy of SDMs can be high based on the way the model is trained or ecological data availability but presence of latent variables such as prey availability, interspecies competition or changes in the hydrological regime can greatly influences future occurrences. Furthermore, use of high resolution, consistent, and timely environmental data enables researchers for a more precises understanding of species-specific habitat dynamics and environmental conditions for species distribution modelling. This study thus promotes a key nature-based method for sustained riverine ecosystem restoration initiatives in Poland and beyond by embracing their presence and leveraging their ecosystem engineering potential.

References

Akbar Hossain, K., Masiero, M., Pirotti, F., 2022. Land cover change across 45 years in the world's largest mangrove forest (Sundarbans): the contribution of remote sensing in forest monitoring. *European Journal of Remote Sensing* 1–17. https://doi.org/10.1080/22797254.2022.2097450

Anderson, J., & Bonner, J. 2014. Modeling Habitat Suitability for Beaver (Castor canadensis) Using Geographic Information Systems.

Anderson, R. P. 2013. A framework for using niche models to estimate impacts of climate change on species distributions. *Annals of the New York Academy of Sciences*, *1297*, 8–28. https://doi.org/10.1111/nyas.12264

Araújo, M. B., & Guisan, A. 2006. Five (or so) challenges for species distribution modelling. *Journal of Biogeography*, *33*(10), 1677–1688. https://doi.org/10.1111/J.1365-2699.2006.01584.X

Bahn, V. (2009, July). A new method for evaluating species distribution models.

Baldwin, R. A. (2009). Use of Maximum Entropy Modeling in Wildlife Research. *Entropy 2009, Vol. 11, Pages 854-866*, *11*(4), 854–866. https://doi.org/10.3390/E11040854

Boyle Steve, & Owen Stephanie. (2007). North American Beaver (Castor Canadensis): a Technical Conservation Assessment - DocsLib. 10.1080/11956860.2017.1395314

Brazier, R. E., Puttock, A., Graham, H. A., Auster, R. E., Davies, K. H., & Brown, C. M. L. 2020. Beaver: Nature's ecosystem engineers. *Wires. Water*, *8*(1). https://doi.org/10.1002/WAT2.1494

Brown, C. F., Brumby, S. P., Guzder-Williams, B., Birch, T., Hyde, S. B., Mazzariello, J., Czerwinski, W., Pasquarella, V. J., Haertel, R., Ilyushchenko, S., Schwehr, K., Weisse, M., Stolle, F., Hanson, C., Guinan, O., Moore, R., & Tait, A. M. 2022. Dynamic World, Near real-time global 10 m land use land cover mapping. *Scientific Data*, *9*(1). https://doi.org/10.1038/S41597-022-01307-4

Cooke, H. A., & Zack, S. (2008). Influence of beaver dam density on riparian areas and riparian birds in shrub steppe of Wyoming. https://api.semanticscholar.org/CorpusID:62833818

Dalponte, M., Cetto, R., Marinelli, D., Andreatta, D., Salvadori, C., Pirotti, F., Frizzera, L., Gianelle, D., 2023. Spectral separability of bark beetle infestation stages: A single-tree time-series analysis using Planet imagery. Ecological Indicators 153. https://doi.org/10.1016/j.ecolind.2023.110349

Elith, J., H. Graham, C., P. Anderson, R., Dudík, M., Ferrier, S., Guisan, A., J. Hijmans, R., Huettmann, F., R. Leathwick, J., Lehmann, A., Li, J., G. Lohmann, L., A. Loiselle, B., Manion, G., Moritz, C., Nakamura, M., Nakazawa, Y., McC. M. Overton, J., Townsend Peterson, A., … E. Zimmermann, N. (2006). Novel methods improve prediction of species' distributions from occurrence data. *Ecography*, *29*(2), 129–151. https://doi.org/10.1111/J.2006.0906-7590.04596.X

Fourcade, Y. 2016. Comparing species distributions modelled from occurrence data and from expert-based range maps. Implication for predicting range shifts with climate change. *Ecological Informatics*, *36*, 8–14. https://doi.org/10.1016/J.ECOINF.2016.09.002

GBIF. (n.d.). Retrieved August 29, 2023, from https://www.gbif.org/

Geris, J., Dimitrova-Petrova, K., & Wilkinson, M. (2022). Establishing the potential influence of beaver activity on the functioning of rivers and streams and water resource management in Scotland.

Giżejewska, A., Spodniewska, A., Barski, D., & Fattebert, J. (2015). Beavers indicate metal pollution away from industrial centers in northeastern Poland. *Environmental Science and Pollution Research International*, *22*(5), 3969. https://doi.org/10.1007/S11356-014-3769-8

Grudzinski, B. P., Fritz, K., Golden, H. E., Newcomer-Johnson, T. A., Rech, J. A., Levy, J., Fain, J., McCarty, J. L., Johnson, B., Vang, T. K., & Maurer, K. (2022). A global review of beaver dam impacts: Stream conservation implications across biomes. *Global Ecology and Conservation*, *37*, e02163. https://doi.org/10.1016/J.GECCO.2022.E02163

Jaureguiberry, P., Titeux, N., Wiemers, M., Bowler, D. E., Coscieme, L., Golden, A. S., Guerra, C. A., Jacob, U., Takahashi, Y., Settele, J., Díaz, S., Molnár, Z., & Purvis, A. (2022). The direct drivers of recent global anthropogenic biodiversity loss. *Science Advances*, *8*(45), 9982.

Kanan, A.H., Pirotti, F., Masiero, M., Rahman, M.M., 2023. Mapping inundation from sea level rise and its interaction with land cover in the Sundarbans mangrove forest. Climatic Change 176, 104. https://doi.org/10.1007/s10584-023-03574-5

Lehtomäki, J., & Moilanen, A. (2013). Methods and workflow for spatial conservation prioritization using Zonation. Environmental Modelling & Software, 47, 128–137. https://doi.org/10.1016/J.ENVSOFT.2013.05.001

Mainali, K., Warren, D., Dhileepan, K., Mcconnachie, A., Strathie, L., Hassan, G., Karki, D., Shrestha, B., & Parmesan, C. (2015). *Mainali et al-2015-Global Change*

Biology-Supporting Information. https://www.researchgate.net/publication/284285002_Mainali_et_al-2015-Global_Change_Biology-Supporting_Information

Nazarov, N., Prokhorov, V., Sharifullin, A., Gusarov, A., & Fedor, L. (2023b). The Influence of Eurasian Beaver (Castor fiber L.) Activity on the Transformation and Functioning of Riparian Phytocoenoses in the Southern Boreal Zone (European Russia). *Earth*, *4*, 384–397. https://doi.org/10.3390/earth4020021

Orazi, V., Hagge, J., Gossner, M. M., Müller, J., & Heurich, M. 2022. A Biodiversity Boost From the Eurasian Beaver (Castor fiber) in Germany’s Oldest National Park. *Frontiers in Ecology and Evolution*, *10*, 873307.
https://doi.org/10.3389/FEVO.2022.873307/BIBTEX

Phillips, S. J., Anderson, R. P., & Schapire, R. E. (2006). Maximum entropy modeling of species geographic distributions. *Ecological Modelling*, *190*, 231–259. https://doi.org/10.1016/j.ecolmodel.2005.03.026

Phillips, S. J., & Dudík, M. (2008). Modeling of species distributions with Maxent: new extensions and a comprehensive evaluation. *Ecography*, *31*(2), 161–175. https://doi.org/10.1111/J.0906-7590.2008.5203.X

Pollock, M. M., Morgan Heim, & Danielle Werner. (2007). *(PDF) Hydrologic and Geomorphic Effects of Beaver Dams and Their Influence on Influence on Fishes*. https://www.researchgate.net/publication/231218389_Hydrologic_and_Geomorphic_Effects_of_Beaver_Dams_and_Their_Influence_on_Influence_on_Fishes

Raes, N., & Ter Steege, H. 2007. A null-model for significance testing of presence-only species distribution models. *Ecography*, *30*(5), 727–736. https://doi.org/10.1111/J.2007.0906-7590.05041.X

Rahman, A. (n.d.). IOP Conference Series: Earth and Environmental Science Species Distribution Modelling to Assist Biodiversity and Conservation Management in Malaysia. https://doi.org/10.1088/1755-1315/269/1/012041

Rodríguez-Castañeda, G., Hof, A. R., Jansson, R., & Harding, L. E. 2012. Predicting the Fate of Biodiversity Using Species’ Distribution Models: Enhancing Model Comparability and Repeatability. *PLOS ONE*, *7*(9), e44402.
https://doi.org/10.1371/JOURNAL.PONE.0044402

Sjöberg, G., Belova, O., Ecke, F., Eklöf, K., Finér, L., Jägrud, L., Kauhala, K., Laanetu, N., Libiete, Z., Lode, E., Ozolins, J., Porokhov, A., Thorell, D., Ulevičius, A., & Wróbel, M. 2020. *Beaver as a renewable resource. A beaver dam handbook for the Baltic Sea Region.*

Smeraldo, S., Di Febbraro, M., Ćirović, D., Bosso, L., Trbojević, I., & Russo, D. 2017. Species distribution models as a tool to predict range expansion after reintroduction: A case study on Eurasian beavers (Castor fiber). *Journal for Nature Conservation*, *37*, 12–20. https://doi.org/10.1016/J.JNC.2017.02.008

Spyra, A., Cieplok, A., & Krodkiewska, M. 2023. Beavers ecosystem altering: Influence of beaver dams on aquatic invertebrates in newly created beavers ponds and small mountain river. *Ecohydrology & Hydrobiology*. https://doi.org/10.1016/J.ECOHYD.2023.06.009

Stringer, A., & Gaywood, M. 2016. The impacts of beavers Castor spp. on biodiversity and the ecological basis for their reintroduction to Scotland, UK. *Mammal Review*, *In Press*. https://doi.org/10.1111/mam.12068

Swinnen, K. R. R., Strubbe, D., Matthysen, E., & Leirs, H. 2017. Reintroduced Eurasian beavers (Castor fiber): colonization and range expansion across human-dominated landscapes. *Biodiversity and Conservation*, *26*(8), 1863–1876. https://doi.org/10.1007/S10531-017-1333-9/METRICS

Valavi, R., Guillera-Arroita, G., Lahoz-Monfort, J. J., & Elith, J. 2022. Predictive performance of presence-only species distribution models: a benchmark study with reproducible code. *Ecological Monographs*, *92*(1), e01486. https://doi.org/10.1002/ECM.1486

Wikar, Z., & Ciechanowski, M. 2023. Beaver Dams and Fallen Trees as Ecological Corridors Allowing Movements of Mammals across Water Barriers—A Case Study with the Application of Novel Substrate for Tracking Tunnels. *Animals*, *13*(8), 1302. https://doi.org/10.3390/ANI13081302/S1

Yackulic, C. B., Chandler, R., Zipkin, E. F., Royle, J. A., Nichols, J. D., Campbell Grant, E. H., & Veran, S. 2013. Presence-only modelling using MAXENT: when can we trust the inferences? *Methods in Ecology and Evolution*, *4*(3), 236–243. https://doi.org/10.1111/2041-210X.12004

Zurell, D., Fritz, S. A., Rönnfeldt, A., & Steinbauer, M. J. 2023. Predicting extinctions with species distribution models. *Cambridge Prisms: Extinction*, *1*, e8. https://doi.org/10.1017/EXT.2023.5