Maximum Entropy Modeling and Omniscape for Carnivore Habitat Connectivity in the Adriatic Ionian Region

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Abstract

Habitat fragmentation poses a major threat to large carnivores in Southern Europe so this study applies the Maximum Entropy (MaxEnt) model to map habitat suitability for bears, wolves, and lynx. We combined presence-only occurrence data with multi temporal satellite imagery to identify critical core areas. We then applied the Omniscape algorithm to model connectivity through a moving window approach. These results provide a robust foundation for green infrastructure planning because they identify bottlenecks where wildlife movement is restricted. Our work shows how automated ecological monitoring can support international nature conservation efforts.

1 Introduction

Large carnivores require vast areas to survive but human activities often break these habitats into small patches. This fragmentation leads to isolated populations that struggle to persist over time because they lack genetic exchange (Murphy et al., 2017). This research was conducted as part of the 4PETHABECO project which is an international initiative focused on protecting and restoring terrestrial habitats and large carnivore populations in the Adriatic Ionian region. We specifically target the brown bear (*Ursus arctos*), the grey wolf (*Canis lupus*), and the Eurasian lynx (*Lynx lynx*). We need to understand where these animals live to protect them effectively and we must know how they move between different regions to maintain stable populations. Recent advances in remote sensing provide us with high resolution data about the Earth that we can use for large scale monitoring initiatives.

2 Data and Methods

We collected occurrence points for the three species from various sources including GPS radio collar records and direct field observations. We used environmental layers to describe the landscape such as land cover data from the Corine Land Cover database (European Environment Agency, 2020). We added topographic indices like slope or elevation from the Copernicus Digital Elevation Model (European Space Agency, 2024). Climate data came from MODIS sensors where we tracked variables like the maximum temperature of the warmest month (Wan et al., 2015). We also integrated night time light data from the Visible Infrared Imaging Radiometer Suite (VIIRS) as a proxy for human settlements and anthropogenic pressure (Elvidge et al., 2017). We utilized Google Earth Engine for data preprocessing and feature extraction because its cloud computing capabilities allow for the efficient processing of large planetary scale geospatial datasets (Gorelick et al., 2017).

We used the Maximum Entropy (MaxEnt) model to train our suitability models (Phillips et al., 2006). This method is specifically designed for presence-only data because it handles complex environmental relationships without requiring absence points. We trained separate models for each species at a spatial resolution of 100 meters to capture enough detail for local conservation planning. We evaluated the models using the Boyce Index and the Area Under the Curve (AUC) metric to ensure high predictive accuracy across the study area.

To model connectivity, we used the Omniscape algorithm which treats the landscape as a circuit (Van Moorter et al., 2023). This approach calculates current flow between source and destination points within a moving window. We derived the landscape resistance through which we measure the circuit from the inverse habitat suitability maps. The transformation was performed using a negative exponential function which assumes that resistance decreases rapidly as habitat suitability increases. This is particularly effective for large carnivores because even moderately suitable habitat significantly facilitates movement compared to highly unsuitable areas like urban zones (De Flamingh et al., 2023). The following formula was applied to the Habitat Suitability Index (HSI) to calculate the resulting resistance (R) scaled from 1 to 100:

$$R = 100 - 99 \times \frac{1 - e^{-k \times HSI}}{1 - e^{-k}} \tag{1}$$

In Equation 1, the HSI value is capped at a minimum of 0.0001. We set the shape parameter k to 8 to reflect a steep non linear relationship where high suitability equates to very low resistance.

3 Results

The MaxEnt models show high suitability in mountainous and forested areas where human presence is low. The Dinaric Mountains serve as a primary core habitat for all three species. We found that forest cover and topographic ruggedness are the most important predictors for bear and lynx habitats. Wolves show more flexibility in their land use because they often appear near agricultural areas if there is enough cover available. Further analysis concluded that only about 30 percent of highly suitable large carnivore habitats are protected.

The Omniscape analysis reveals bottlenecks where wildlife movement is restricted by major highways or urban expansion. We identified several transboundary corridors that require international cooperation for effective protection. These areas show high current density which indicates they are critical for maintaining regional connectivity. The resulting suitability and connectivity maps for all three species are provided in Appendix A.

4 Discussion

Our research demonstrates the power of combining MaxEnt with Omniscape for large scale monitoring. Traditional ecological surveys are expensive and often limited in geographic scope so automated models are better for regional planning (Yin et al., 2021). The results show that many carnivore populations are still connected but these connections are fragile due to infrastructure development. There are some limitations to our current approach such as presence data being biased toward accessible areas. We tried to account for this by using spatial thinning techniques during the modeling process.

5 Conclusion

This study provides a comprehensive view of carnivore habitats and connectivity in Southern Europe to help policy makers design green infrastructure. We are now developing these models further through a project funded by the European Space Agency. This new initiative uses high resolution imagery from Sentinel 1 and Sentinel 2 to generate predictors instead of relying on static sources like Corine Land Cover. Our goal is to make these ecological models operate in near real time for better response to environmental changes. Attending the EEML summer school will help us improve this framework with advanced computer vision techniques because we need more robust tools for processing multi temporal satellite data. This training will lead to more accurate and efficient monitoring systems for nature conservation.

Acknowledgments

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A Appendix: Habitat Suitability and Connectivity Maps

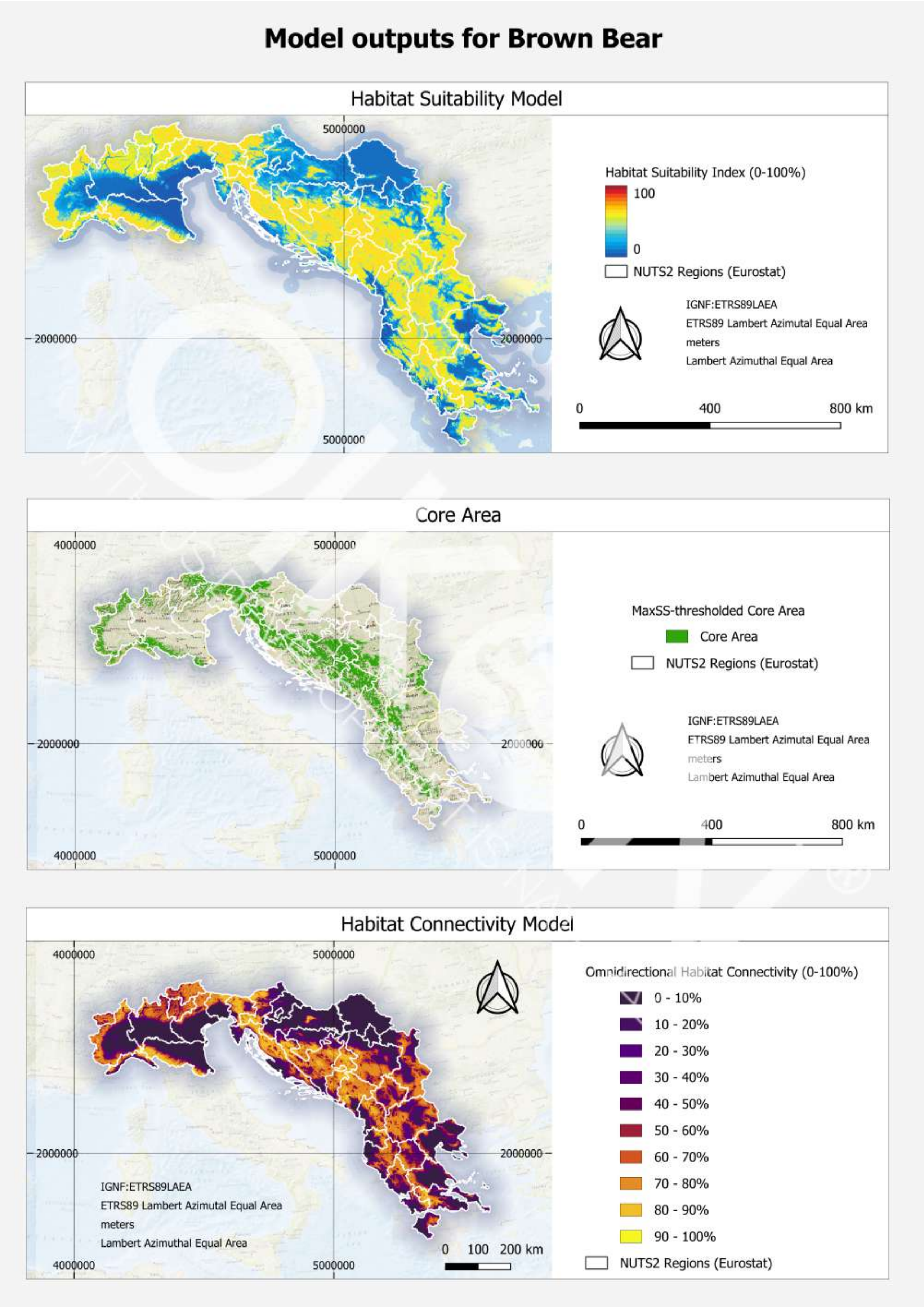

Figure 1: Habitat Suitability and Connectivity Map: Brown Bear (*Ursus arctos*)

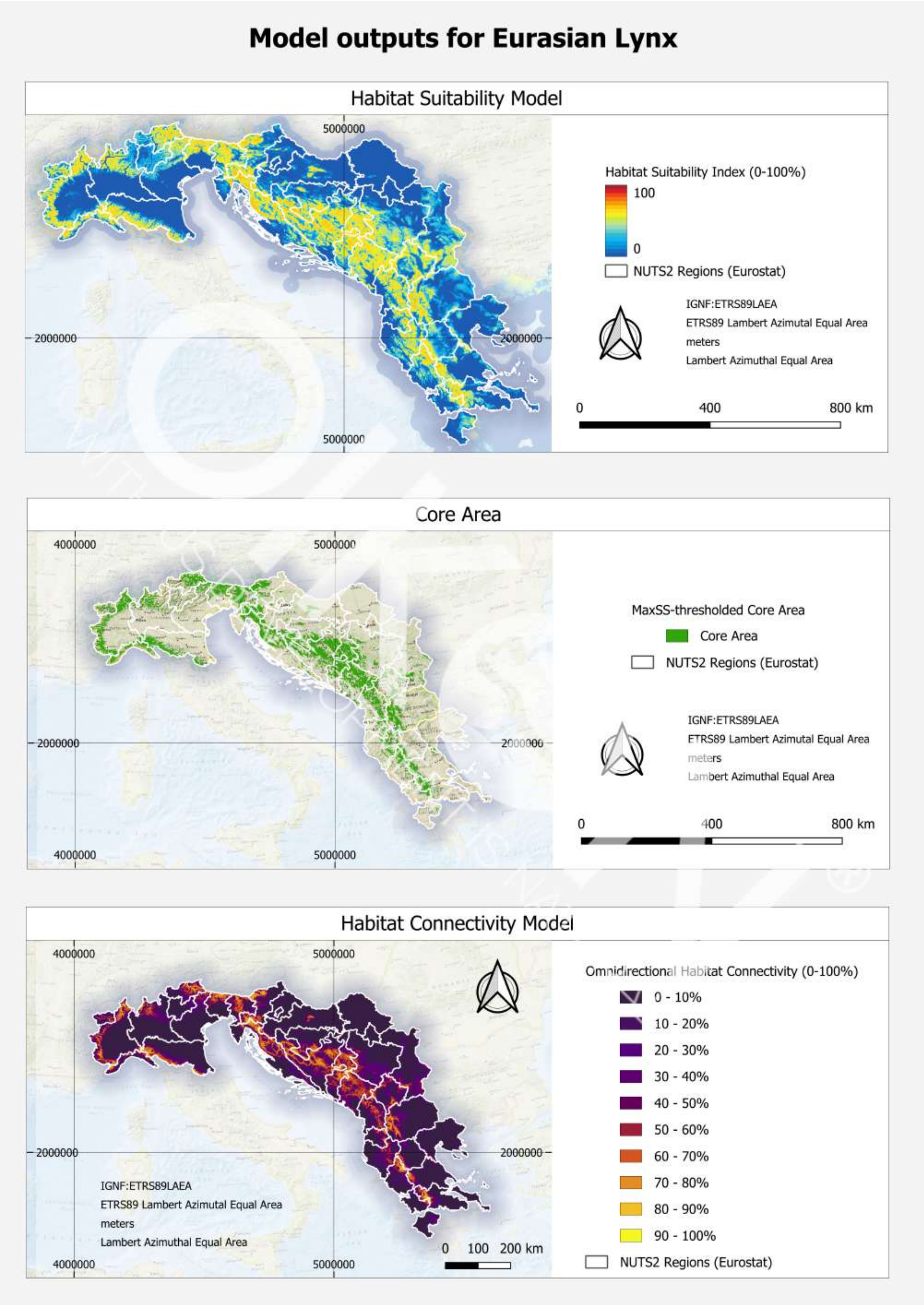

Figure 2: Habitat Suitability and Connectivity Map: Eurasian Lynx (*Lynx lynx*)

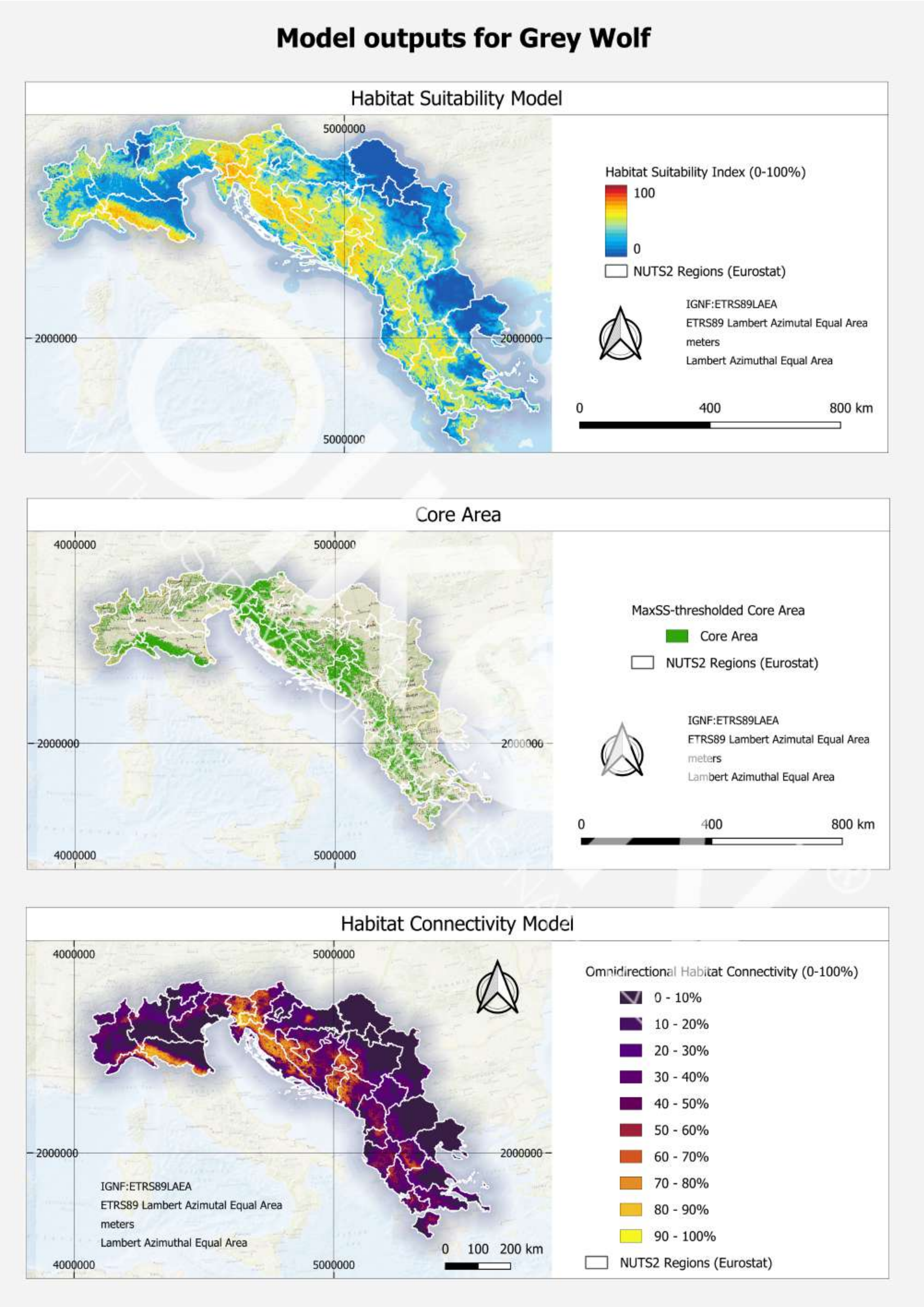

Figure 3: Habitat Suitability and Connectivity Map: Grey Wolf (*Canis lupus*)