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Presence Only Modeling of Fallowing in Europe with Maximum Entropy

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Abstract

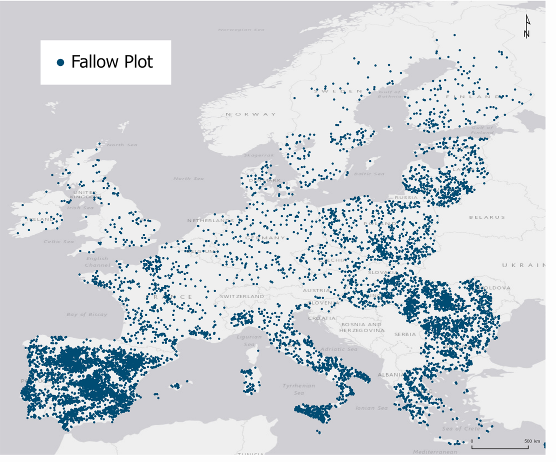
Global food security is a growing concern due to increasing agricultural demands in rapidly changing climatic conditions. As farmers face the pressure to increase yields, it can lead to unsustainable agricultural practices that reduce soil fertility. Land fallowing, or the practice of leaving a plot of land uncultivated for a season or more is a well-known agricultural practice to replenish soils. Modeling and monitoring this practice plays a key role in understanding the connection between food security, soil health, and climate change. We use a species distribution model, MaxEnt, to predict the presence of fallow fields in Europe during 2012. We use soil data from the European Soil Data Center, a remotely-sensed vegetation index from Landsat 5, and ground-truthed fallow field location data from Eurostat's Land Use and Coverage Area Frame Survey. Our results show a high probability of fallow field presence in northern and central Spain, Sicily, and southeast Italy. Our results also show the Normalized Difference Vegetation Index (NDVI), soil texture, and soil cation exchange capacity as the most important variables to predicting fallow field presence.

Introduction

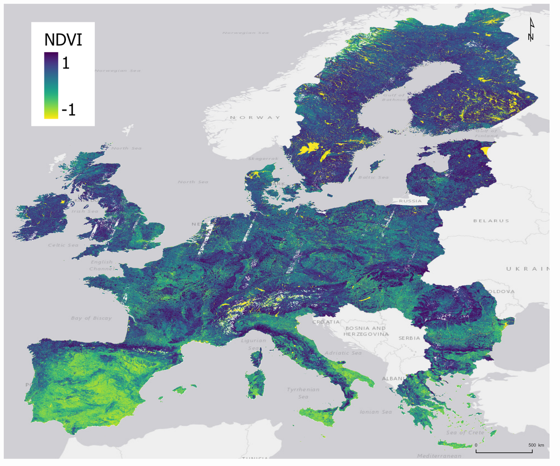
Sustainable agriculture has been identified by the Food and Agriculture Organization of the United Nations (FAO) as one of their strategic objectives of the 21st century. One pillar of achieving this objective is reducing non-renewable agricultural management and employing natural land management methods (FAO, 2021). Land fallowing, or leaving a plot of land uncultivated for a season or more, will play a key role in achieving this goal. The benefits of land fallowing for agricultural sustainability include increased soil organic matter, conservation of soil moisture, pest control, and greater yields in the following season (Nielson & Calderon, 2011; Moret et al., 2007; Tscharntke et al., 2011).

As opposed to certain agricultural land uses, fallowing is a varying use ranging from completely unseeded plots in arid regions to plots seeded with legume cover crops in wetter regions (Boellstorff & Benito, 2005). The heterogeneity of the land cover of fallow fields drives this research to study the soil and vegetative conditions that result in land fallowing. This proposed model of fallowing can contribute to sustainable agriculture efforts and optimize land use.

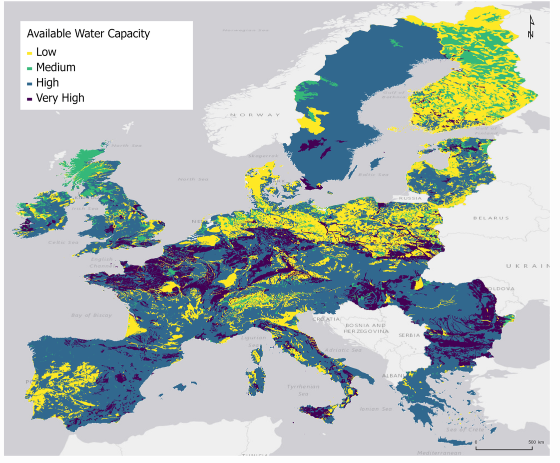
Data



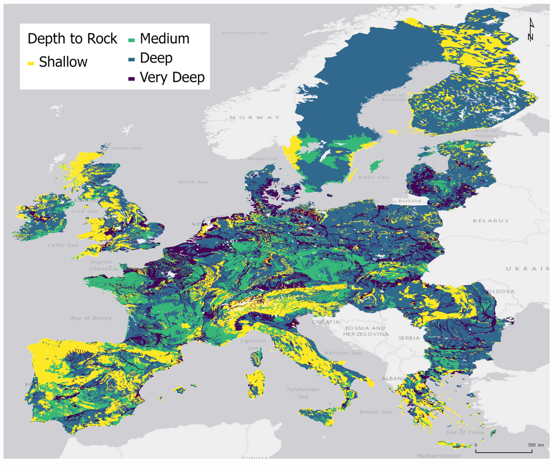
Land Use and Coverage Area Frame Survey (LUCAS). LUCAS is a dataset of 270,273 points over Europe with land use/land cover classification from 2012. The above map shows the extracted points of fallow fields (Eurostat, 2012).



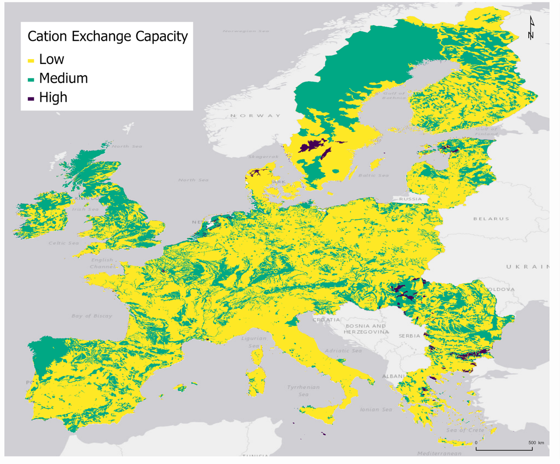
Normalized Difference Vegetation Index (NDVI). NDVI is an arithmetic combination of a sensor's red and infrared bands used to measure vegetation greenness. The above map shows a temporally aggregated NDVI from 2012 summer (Landsat 5, 2012).



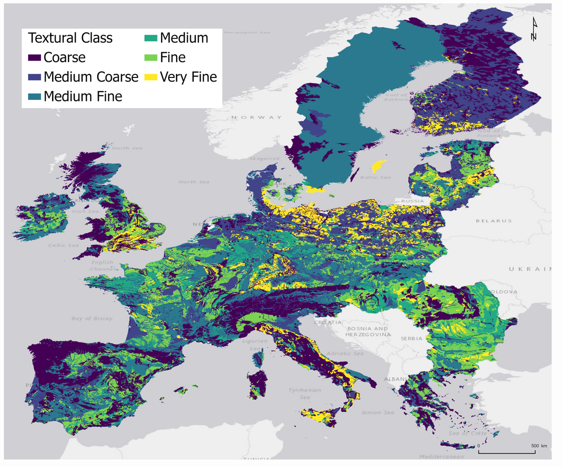
Soil Available Water Capacity. Available water capacity of soil is the amount of water that can be used by plants held in soil (European Soil Data Center, 2013).



Depth to Rock. Depth from surface of the soil to bedrock (European Soil Data Center, 2013).



Soil Cation Exchange Capacity. Cation exchange capacity of soil is a measurement of the soil's ability to hold cations. A high cation exchange capacity indicated healthy soil (European Soil Data Center, 2013).



Soil Textural Class. Soil texture class divides soil into categories based on sand, silt, and clay percentages. Coarse soil is sandy and fine soil is more claylike (European Soil Data Center, 2013).

Workflow

Data preparation

- Extracted ground-truthed points of fallow fields from LUCAS dataset
- Spatially thinned points of fallow fields to reduce sampling bias
- Converted soil data from vector-based "soil mapping units" to a raster
- Gathered Landsat imagery, removed cloud cover, calculated NDVI, mosaicked images, and created a temporal average from all images over the 2012 summer in Google Earth Engine

Maxnet R Package (Phillips, 2017)

- Transformed variables using basis expansion to include linear, quadratic, hinge, threshold, and polynomial transformations.
- Created response plots for each explanatory variable to visualize the logistic probability of a fallow field.

Maxlike R Package (Royle et al., 2012)

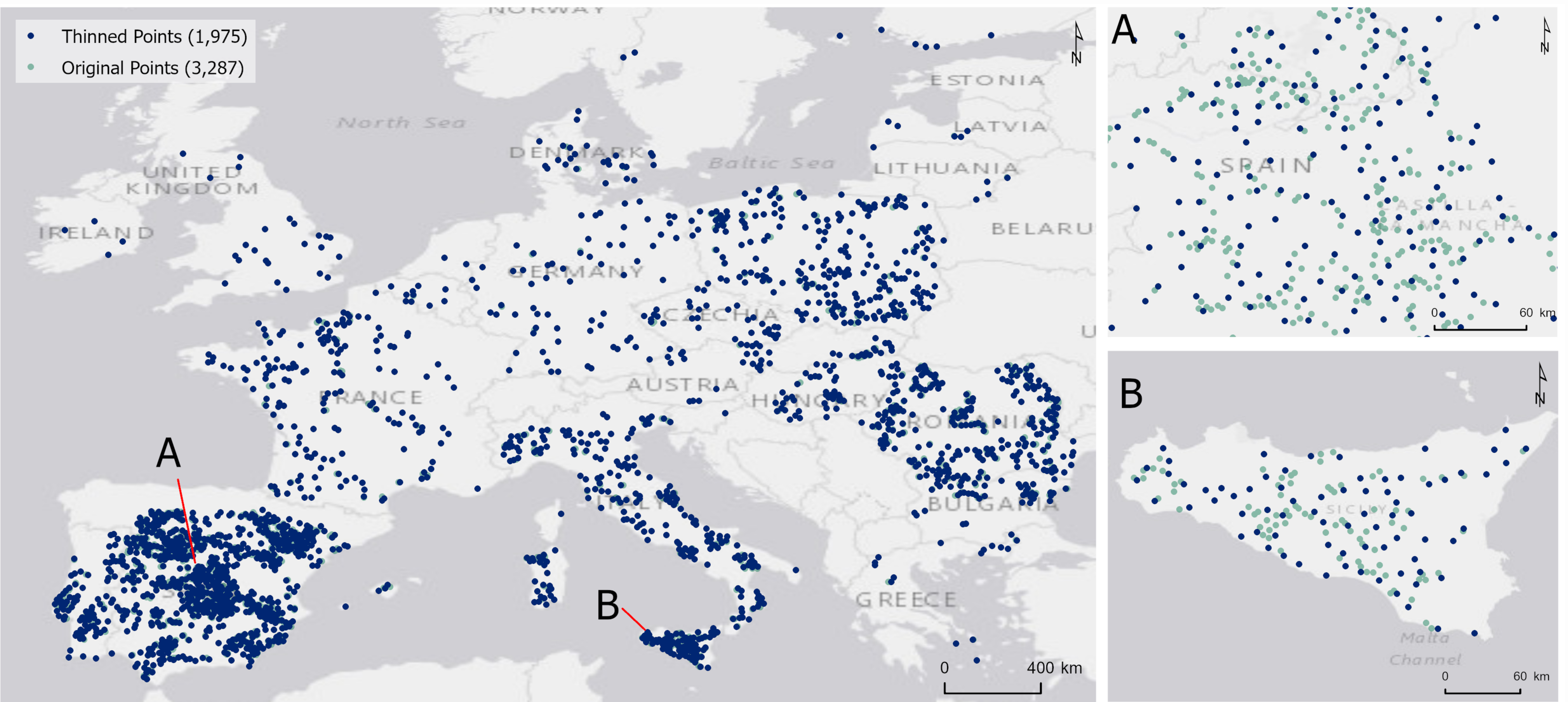
- With the Maxlike package, we created a prediction surface of fallowing using the same maximum entropy model from Maxnet

MaxEnt: The Presence Model

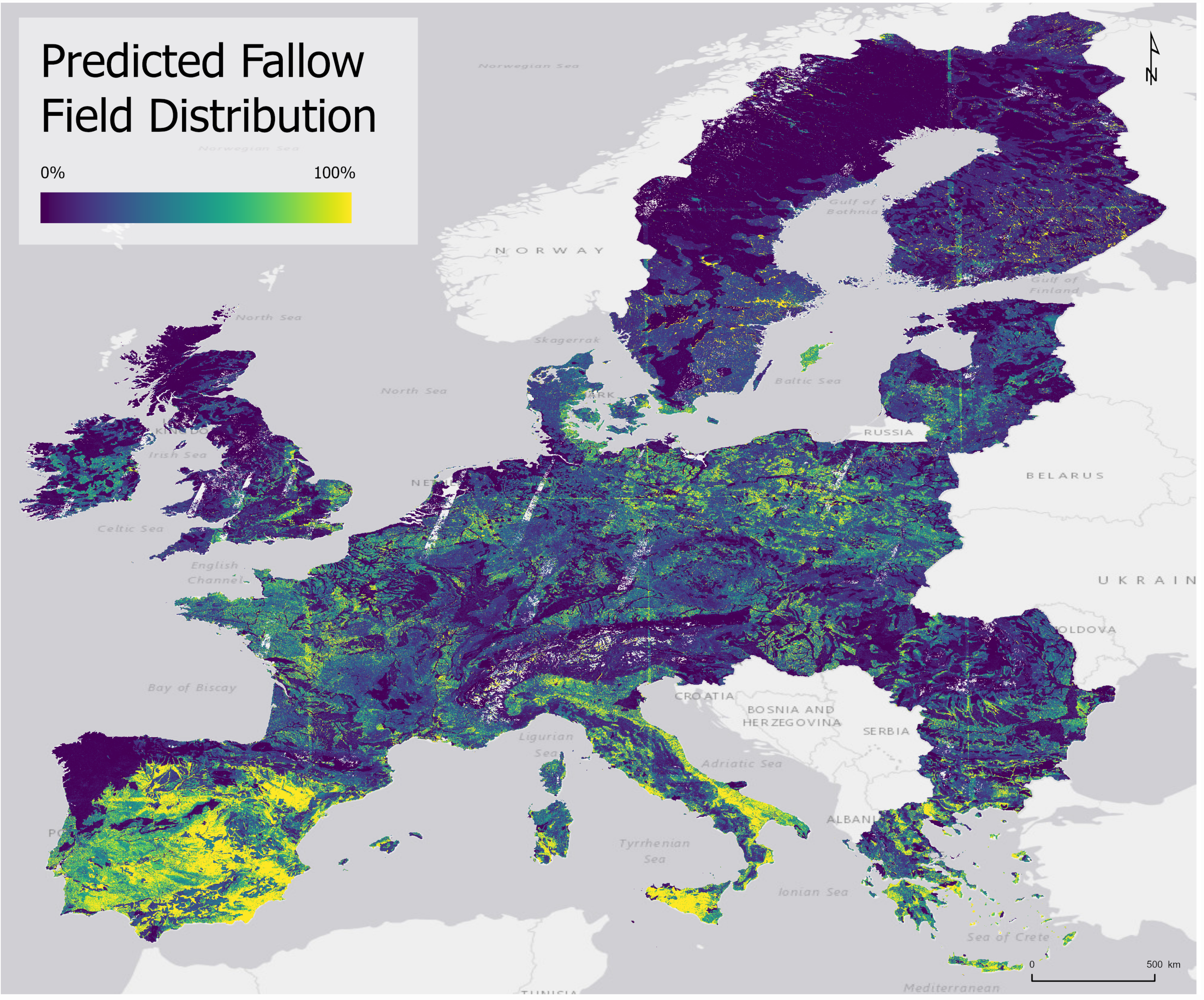
$$H(\pi) = -\sum_{x \in X} \hat{\pi}(x) \ln \hat{\pi}(x)$$

$H(\pi)$ = the entropy of $\hat{\pi}$
X = the set of pixels in the study site
x = the individual pixels of X
$\hat{\pi}$ = the unknown probability distribution over a finite set X
ln = the natural logarithm

Results

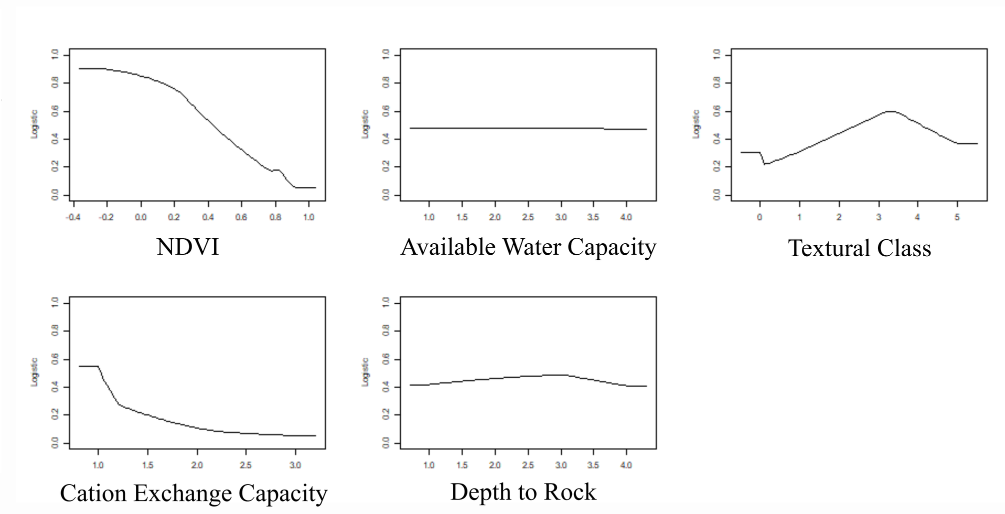


This map shows the result from spatially thinning the original fallow points. The light green points are the points that were removed, and the dark blue points are the thinned points kept for the model.



Explanatory variable	Coefficient
NDVI	-5.601
Cation Exchange Capacity	-3.908
Textural Class	0.314
Available Water Capacity	-0.166
Depth to Rock	-0.007

Response Plots



Conclusions

- Our prediction surface showed the highest probability of fallow fields occurring in northern and central Spain, Sicily, and southeast Italy.
- NDVI, soil texture, and cation exchange capacity had the largest explanatory ability.
- One challenge to predicting fallow field presence that may have resulted in model imperfections is the varying nature of a fallow field's land cover.
- Our next steps will be to explore whether diagnostic metrics like area under the curve and Akaike information criterion have spatial autocorrelation via a spatial jackknifing procedure.

References

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