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Predicting GPP in Carpathian Beech Forests: Uncovering spatial and temporal patterns using a regression model with climatic, topographic and additional features

KEYWORDS: Gross primary product, remote sensing, regression model, temperature, precipitation, digital elevation model

Introduction

Climate change impact ecosystems globally, including the mixed forests of the Carpathian Mountains (Kruhlov et al. 2017). The primary manifestations of climate change are shifts in temperature and precipitation regimes, which undoubtedly affect biomass growth in complex ways. Since direct observations of the future are impossible, we rely on various modeling methods. Machine learning is the most popular contemporary approach for addressing such tasks.

The aim of our study is to develop a regression model that predicts the behavior of Gross Primary Product (GPP) based on a range of climatic, topographic, and other variables. We use this model to forecast the growth of beech forests over the next 20 years under different climate scenarios.

Methods

GPP values were derived from the NASA Moderate Resolution Imaging Spectoradiometer (MODIS) Aqua satellite imagery database(Justice et al. 2002). GPP data aggregated annually from biweekly intervals over 500m resolution. The study period spans from 2003 to 2020.

We utilized NASA Shuttle Radar Topography Mission (SRTM) Digital Elevation Model (DEM) (van Zyl. 2001) data with a 30 meter-level resolution, focusing on topographic variables such as elevation, slope, and aspect. Statistical measures (median, mean, and standard deviation) are computed at scales of 500m and 5km.

Climatic variables were sourced from the E-OBS gridded dataset, limited to temperature and precipitation data collected daily with a spatial resolution of 0.25 degree (Cornes et al. 2018). Monthly averages and variations for both temperature and precipitation were calculated.

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Latitude and longitude wee included as separate variables, as they can indirectly influence GPP growth through variations in day length.

We also introduced categorical variables derived from visual analysis of GPP data patterns. These include:

1) Size Class: GPP values range from 8000 g C/m²/year to 18000 g C/m²/year. Annual GPP distribution across the Carpathian basin can be unimodal or bimodal. Considering the maximum GPP values from 2003-2020, we distinguished two size classes based on which peak of the distribution the maximum GPP values belong to.(see Fig. 1)

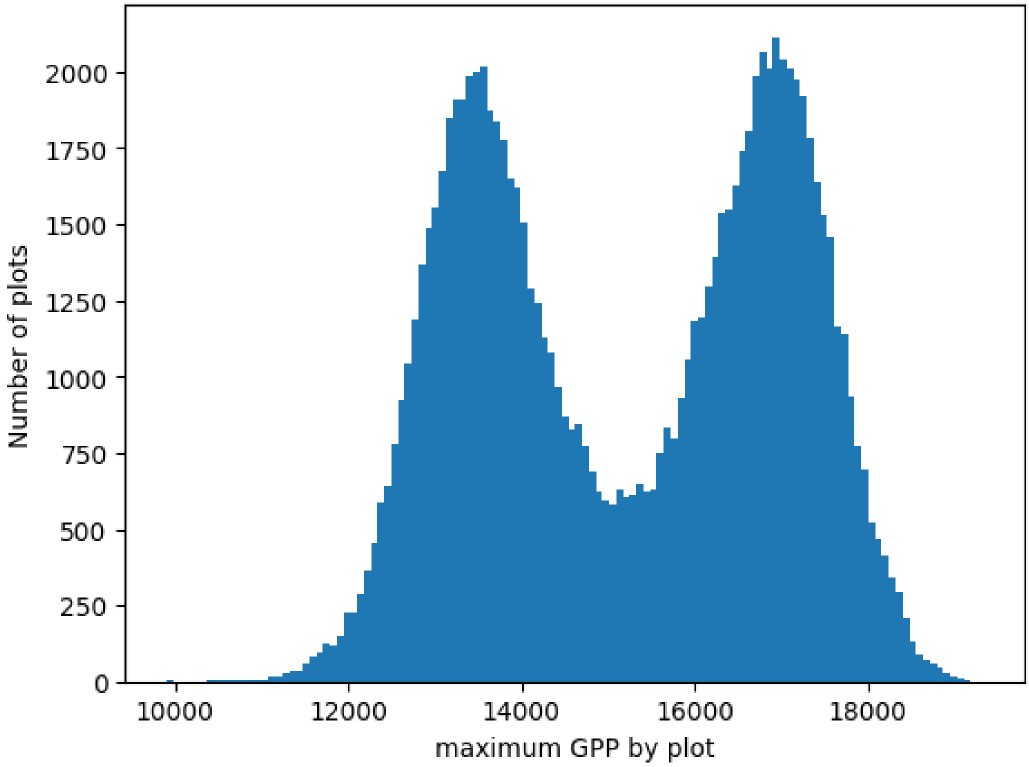

Fig. 1. Maximum GPP distribution

2) Masting Index: Temporal analysis shows GPP fluctuations, with low GPP years followed by high GPP years, suggesting a masting cycle. The Masting Index (whether a site is in a masting year) is used to assess its importance, but cannot be used directly in regression due to future uncertainty. We used 7-year cycle proxy for the Masting Index. (see Fig.2)

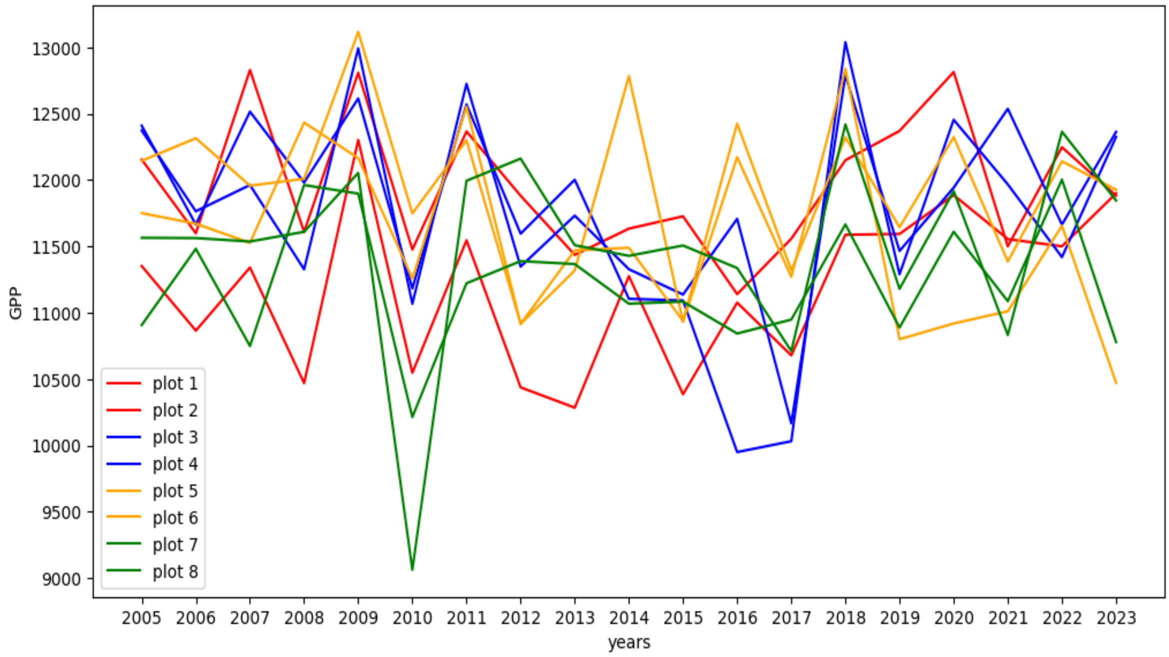

Fig. 2. Temporal GPP distribution

We tested a wide range of models: Light Gradient Boosting Machine (LGBM), Extreme Gradient Boosting (XGBOOST, xgb_limitdepth), CatBoost, Random Forest (RF), and ExtraTrees, each with an extensive set of internal parameters (He et al. 2021) .

Results

The LGBM model showed the best results. Model accuracy, evaluated using the R^2 score, was tested yearly through cross-validation and with various training and test year sets. Cross-validation accuracy ranges from 0.78 to 0.85, while regression accuracy on training sets from one year and test sets from another ranges from 0.63 to 0.77.

The accuracy of models trained solely on numerical features (climatic, topographic, coordinates) varies from 0.45 to 0.52.

We assess the contribution of different features, with the size class contributing the most significantly (see Fig. 3). We also analyze the spatial and temporal variability in feature importance.

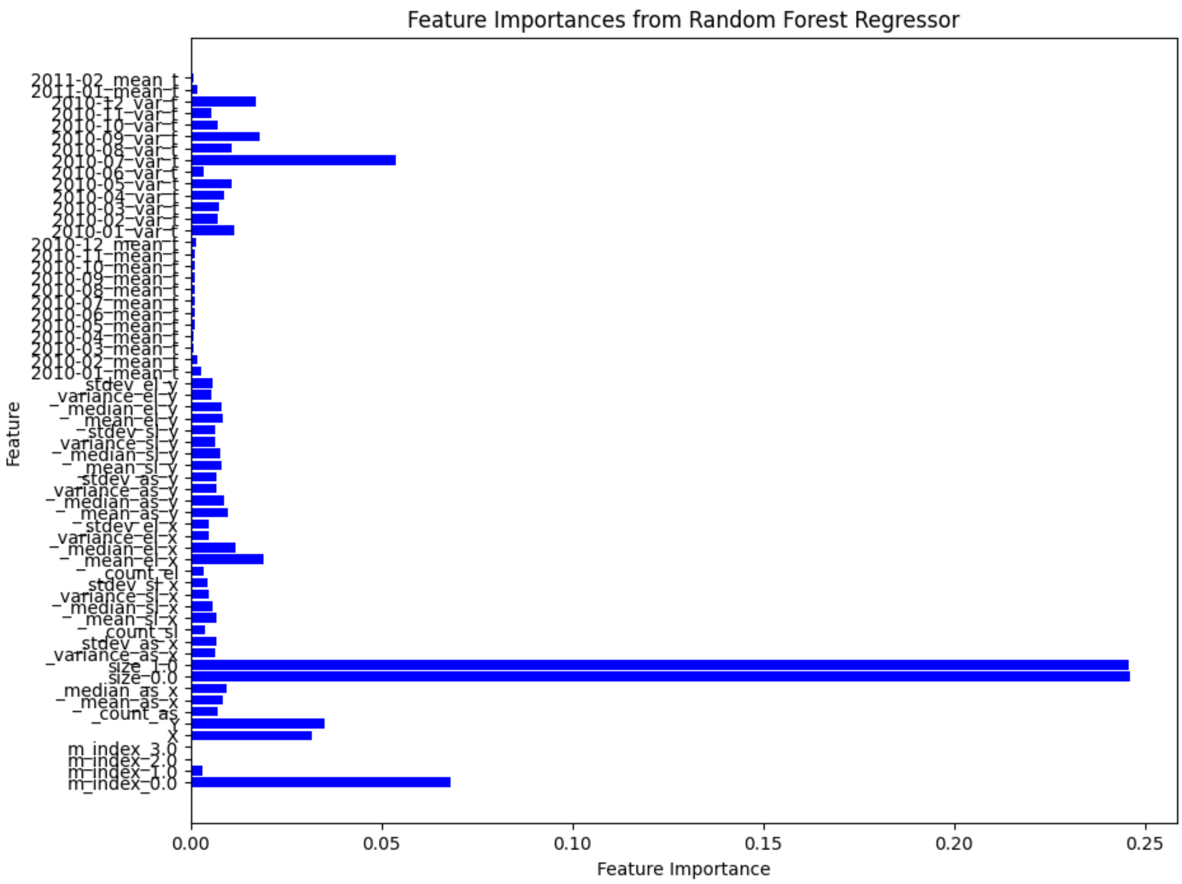

Fig.3. Feature importance of different variables

Conclusions

Our model can be used both for direct predictions of GPP values and for analyzing the factors influencing its formation. We have observed significant spatial and temporal variability. This variability is largely consistent with the tree ring observations conducted by J. Kaspar. Specifically, a relatively greater dependence on precipitation is characteristic of the northern and southeastern slopes of the Carpathians. In contrast, the role of temperature is significant for the southeastern slopes but not for the northern ones.

We also analyze the physical nature of the two size classes. The higher GPP tends to be in the foothills facing the open plains (Pannonian and Wallachian) (see Fig.4).

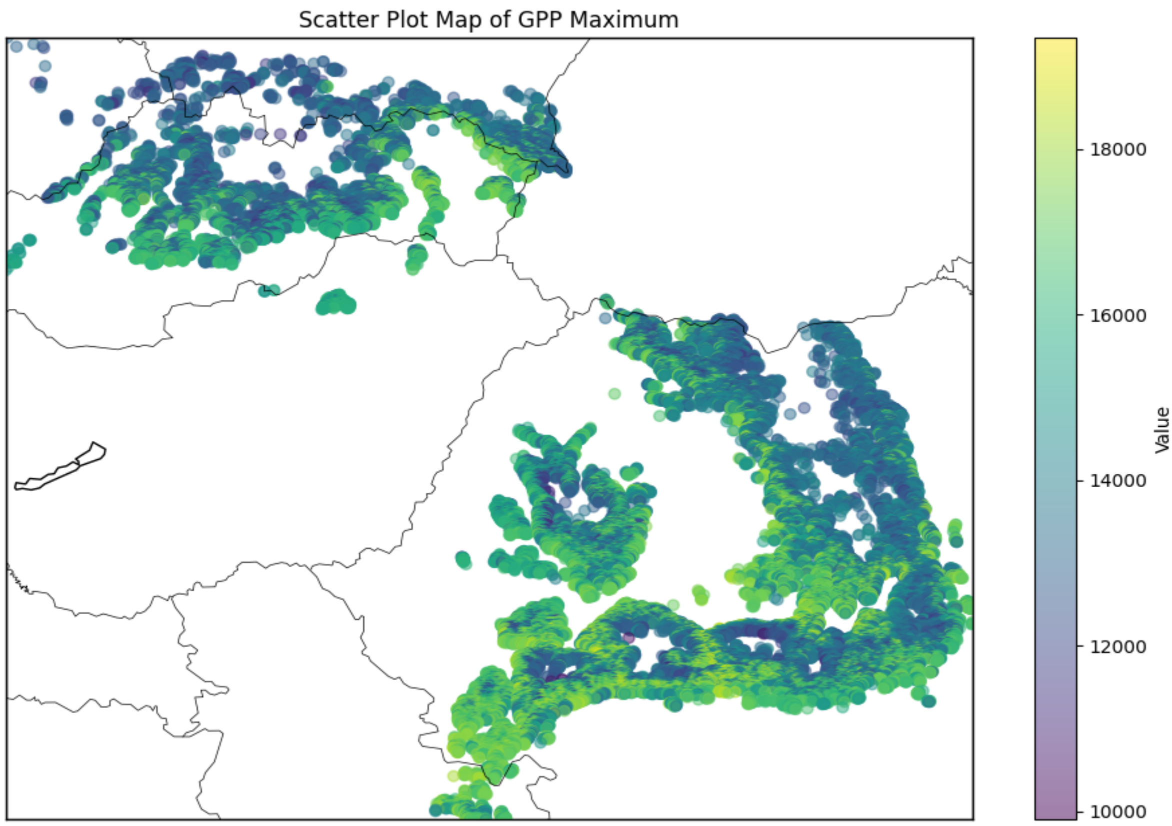

Fig.4. Maximum GPP distribution

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