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Exploring the Influencing Factors of Net Ecosystem Productivity (NEP) Based on Random Forest and SHAP

Zhen He [1, 2], Weibo Yuan [3, *]

[1] College of Computer, Qinghai Normal University, Xining 810016, China
[2] The State Key Laboratory of Tibetan Intelligent Information Processing and Application, Xining 810008, China
[3] Qinghai Provincial Key Laboratory of Medicinal Plant and Animal Resources of Qinghai-Tibet Plateau, School of Life Sciences, Qinghai Normal University, Xining, Qinghai, 810008, China

*** Corresponding author:** Weibo Yuan

Abstract: As global climate change intensifies, Net Ecosystem Productivity (NEP) serves as a crucial indicator for measuring the carbon absorption and release of ecosystems, playing a vital role in understanding the carbon cycle and shaping climate policy. The Northwestern region of China, characterized as a typical inland arid and semi-arid area, is particularly sensitive to global changes. Understanding the environmental drivers of NEP in this region is critical for both regional ecological protection and global environmental management. This study utilized environmental data from five provinces in Northwestern China, applying the Random Forest (RF) model and SHapley Additive exPlanation (SHAP) method to analyze the primary environmental factors influencing NEP. The research integrated climatic data (including temperature, precipitation, wind speed, and solar radiation), soil characteristics such as pH, organic carbon content, and soil texture, topographic attributes elevation and slope, and a Human Footprint. The RF model identified significant environmental factors impacting NEP, and SHAP values were used to explain the specific contributions of these factors. Furthermore, multiple linear regression analysis revealed interactions among environmental factors. The results indicate that solar radiation (Srad), precipitation, topsoil reference bulk density (T_REF_BULK), temperature, and the topsoil clay fraction (T_CLAY) significantly influence NEP. Notably, interactions between aspect and T_CLAY, aspect and T_REF_BULK, as well as the human footprint (HFP) and Srad, also show significant impacts on NEP. This study confirms that solar radiation, precipitation, soil characteristics, and human activities are the primary environmental drivers of NEP in the Northwest region of China, with solar radiation playing the most critical promotional role. The findings not only provide a scientific basis for the management of ecosystems in Northwestern China but also offer references for formulating global climate change mitigation strategies and estimating the global carbon budget. Future research should further explore the specific mechanisms and interactions of these drivers across different ecosystems to more comprehensively understand and predict the trends in NEP changes.

Keywords: Net Ecosystem Productivity; Random Forest; SHAP Values; Environmental Drivers.

1. Introduction

Northwestern China, encompassing Shaanxi Province, Ningxia Hui Autonomous Region, Gansu Province, Qinghai Province, and Xinjiang, is a region with diverse ecological types including cropland, grassland, desert steppe, desert, and plateau. As typical inland arid and semi-arid areas, Northwestern China is not only crucial for ecological construction in the country but also one of the area's most sensitive to global changes [1]. This region serves as an important national security barrier, an ecological shield, and a strategic rear area for China. Covering about 30% of the country's area, it suffers from severe soil erosion and urgently needs ecological management [2].

The RF is an ensemble learning method that uses bootstrap resampling techniques to construct training sample sets for tree predictors by resampling the original training set with replacement. It then combines these tree predictors using an ensemble learning algorithm [3,4]. RF demonstrates excellent performance in dataset handling, with its key feature being the introduction of randomness, evident in the random selection of training samples for each tree and the random selection of attribute sets for node splitting in each tree. These randomness features help avoid the occurrence of overfitting [5], RF combines bagging and decision trees in a boosting method; while a single decision tree may have certain predictive accuracy, increasing the number of trees enhances overall predictive accuracy. This is because each tree in the random forest participates in making the final decision, which is the core idea of the algorithm [6]. Some scholars have used the RF regression algorithm to predict plant transpiration based on environmental parameters and leaf area index, finding that light intensity is the most critical factor influencing transpiration, followed by the relative humidity of the air [7]. Although many machine learning algorithms have built-in methods to assess the relative importance of predictive variables, such as feature importance plots, these methods generally evaluate global importance and do not provide insights into the predictive drivers for given observational points, presenting many limitations [8-10]. Interpretative methods in machine learning are developed to identify the predictive drivers of various predictive variables within a model. The SHAP algorithm posits that a model's prediction is the result of the cooperation of input features, and thus, the SHAP value of each feature for each sample indicates the contribution of each feature to the prediction [11,12]. SHAP provide a more intuitively appealing interpretation of variable importance [13]. SHAP has been widely applied in understanding machine learning models. JI Peng [14] used SHAP to explain four types of machine learning algorithms: RF, XGBoost, SVM, and ANN. DENG Menghua [12] used SHAP to elucidate the factors influencing residents' willingness to pay for ecological compensation.

In recent years, frequent human activities have led to substantial carbon dioxide emissions, accelerating global warming and ultimately impacting the global carbon cycle process [15]. The global carbon cycle plays a key role in regulating the Earth's climate system. Within this cycle, NEP serves as a critical measure of the net effect of carbon absorption and release by terrestrial ecosystems [16], and is an important tool for assessing ecosystem responses to climate change. NEP not only reflects the biogeochemical cycles within ecosystems but also forms the basis for understanding the global carbon balance. The definition of NEP is the difference between vegetation Net Primary Productivity (NPP) and carbon emissions from soil microbial respiration (R_H) within an ecological area.

Formula: $NEP = NPP - R_H$

NEP > 0 indicates that the carbon fixed by photosynthesis in the ecosystem exceeds the carbon released by total ecosystem respiration, meaning the ecosystem is a "carbon sink." This implies that the ecosystem net absorbs CO2 from the atmosphere, helping to reduce greenhouse gas levels and combat global warming. NEP < 0 indicates that the carbon released by total ecosystem respiration exceeds the carbon fixed by photosynthesis, meaning the ecosystem is a "carbon source." This implies that the ecosystem net releases CO2 into the atmosphere, increasing atmospheric greenhouse gas levels and exacerbating global warming. NEP = 0 indicates that the carbon fixed by photosynthesis is equal to the carbon released by total ecosystem respiration, achieving a balance in the ecosystem's CO2 emissions and absorption. In this state, the ecosystem has a neutral impact on atmospheric CO2 concentrations. Scholars believe that climatic factors and anthropogenic influences are the two main drivers of changes in grassland primary productivity [17]. Previous studies have found a highly significant correlation between forest NEP and precipitation [18], and Xiaowei Yin et al.'s research highlights that understanding the impact of high-altitude flash droughts on vegetation net primary productivity (NPP) is crucial for ecosystem management [19]. The comprehensive effects of soil's physical, chemical, and biological characteristics influence plant growth, development, distribution, and productivity [20]. However, under rapidly changing climate conditions, the dynamics of NEP and its primary drivers are not fully understood, especially when considering the diversity of environmental factors.

Therefore, this study delves into the specific contributions of various environmental variables to NEP using the Random Forest model and SHAP analysis method, with further analysis of the interactions between environmental factors through multiple linear regression. This aims to provide theoretical and empirical support for ecosystem management, climate change mitigation strategies, and global carbon budget estimation.

2. Materials and Methods

2.1. Data Collection

In this study, NEP data were obtained from the National Earth System Science Data Center (https://www.geodata.cn/). The scope data for the five provinces in Northwestern China were sourced from the Resource and Environmental Science Data Platform (https://www.resdc.cn/). Climatic data including wind speed, solar radiation, average temperature, and precipitation were acquired from WorldClim (https://worldclim.org). Elevation data were imported into ArcGIS 10.8 to extract slope and aspect data. Soil attributes were derived from the World Soil Database (HWSD) (https://www.fao.org/soils-portal/). Human footprint data were taken from "A global record of annual terrestrial Human Footprint dataset from 2000 to 2018," which consists of human activities such as built environments, population density, night lights, farmland, pasture, roads, railways, and navigable waterways. Refer to TABLE 1.

2.2. Data Processing

Using R, random points were generated within the study area. Using ArcGIS, NEP values and various environmental factors were extracted for these locations. The extracted data were organized into an XLSX file, and outliers were removed using R. Descriptive statistical analysis and correlation analysis were performed to initially explore the relationships between factors and NEP, and to assess the data's validity.

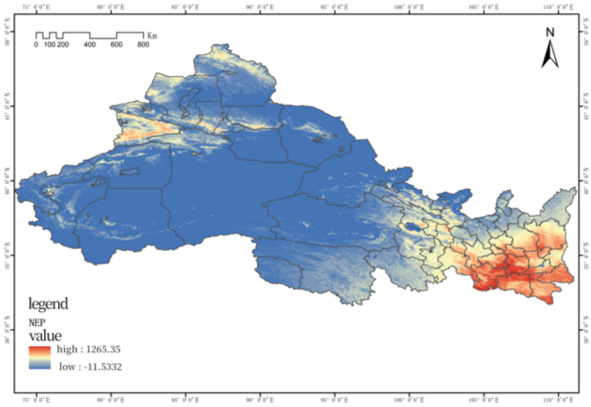

Figure 1. Overview of NEP in the Study Area

2.3. Statistical Analysis

Table 1. The meaning of environment variable data

Name	Mean	Unit
NEP	Net Ecosystem Productivity	$gC \cdot m^{-2} \cdot a^{-1}$
aspect	aspect	degree
Elev	Elevation	m
slope	slope	degree
T_CEC_SOIL	Topsoil CEC (soil)	Cmol/Kg
T_CLAY	Topsoil clay fraction	%wt
T_GRAVEL	Topsoil gravel content	%vol
T_OC	Topsoil organic carbon	%weight
T_PH_H2O	Topsoil pH (H_2O)	-log(H+)
T_REF_BULK	Topsoil Reference Bulk Density	Kg/dm3
T_SAND	Topsoil sand fraction	%wt
T_SILT	Topsoil silt fraction	%wt
HFP	Human Footprint	Level (1-50)
Temperature	average temperature	°C
Precipitation	precipitation	mm
Wind	wind speed	m/s
Srad	solar radiation	$kJ \cdot m^{-2} \cdot day^{-1}$

The “randomForest” package in R was used to train a Random Forest model with NEP as the target variable and all environmental factors as feature variables. The data were randomly split into a training set and a test set at a 70% ratio. A grid of parameters for the Random Forest was set up, and the trained model was used to predict the test set using the predict function. The coefficient of determination (R^2) was calculated to evaluate the model's performance. To further understand the contributions of each predictor variable to the estimation of NEP, the iml package in R was utilized to compute SHAP values. SHAP values are a quantitative measure of the impact of features on the model output, providing a detailed and interpretable method for assessing feature importance. Variables with high importance in SHAP were selected for multiple linear regression analysis to further analyze the interactions between environmental factors.

3. Results

3.1. Descriptive Statistical Analysis

Through the means, standard deviations, maximum values, and minimum values, we can understand the dispersion and range of the data. From TABLE 2 and FIGURE 2, it is evident that the data used in this study are reasonably distributed and cover a wide area, reflecting good capture of environmental diversity.

Table 2. Basic Information of the Data

Name	average	Standard Deviation	minimum	maximum
NEP	347.74	189.39	69.04	745.14
aspect	154.39	104.22	12.65	358.62
Elev	2018.97	1093.69	377	4760
slope	3.48	3.17	0.06	13.64
T_CEC_SOIL	14.66	5.66	6	38
T_CLAY	19.4	7.38	5	47
T_GRAVEL	7.9	4.31	2	24
T_OC	1.06	0.64	0.36	3.02
T_PH_H2O	7.1	0.95	5.1	8.3
T_REF_BULK	1.43	0.09	1.22	1.7
T_SAND	42.85	14.66	10	89
T_SILT	37.75	9.97	6	54
HFP	14.45	9.29	0.44	39.32
Temperature	6.25	4.71	-6.88	14.72
Precipitation	38.11	17.96	3.33	92.17
Wind	2.39	0.49	1.52	3.7
Srad	15092.97	964.99	13104.25	17012.25

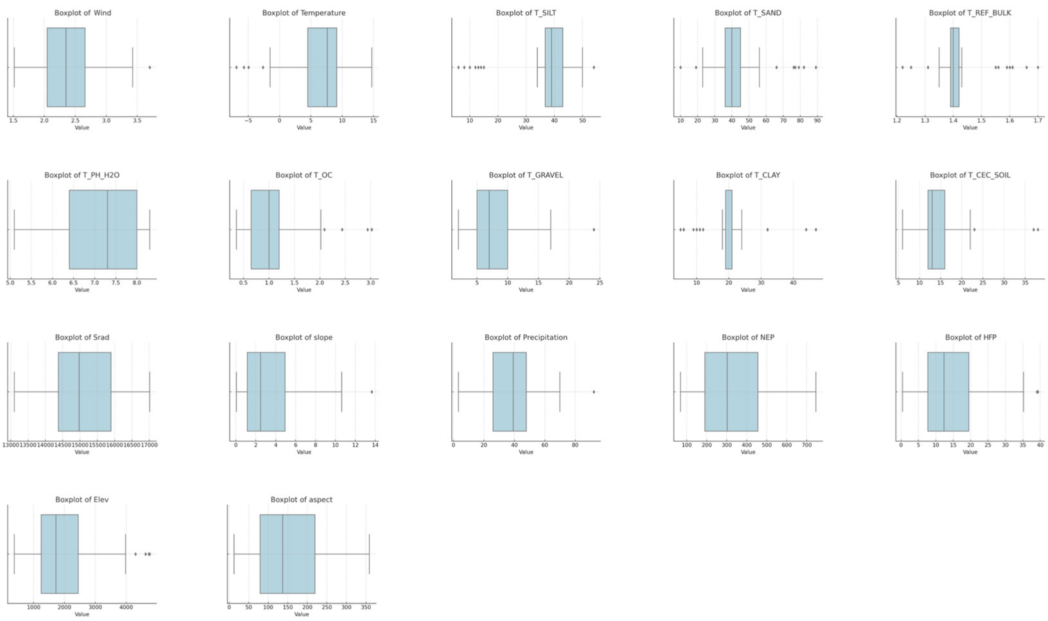

Figure 2. Boxplot of Basic Data Information

Correlation analysis was conducted using SPSS software, and the results were visualized using R. The analysis showed that the correlation coefficient between Temperature and Elevation is -0.96, indicating a very strong negative correlation; as Elevation increases, temperature generally decreases. This finding is consistent with the fundamental principles of geography and climatic science, indirectly verifying the reliability and rationality of the data.

3.2. Random Forest Simulation

Coupling the Random Forest model with the SHAP method, we analyzed the direction of influence and the relative importance of driving factors for NEP in the study area (as shown in FIGURE 4). The importance of NEP drivers in descending order is srad, Precipitation, T_REF_BULK, T_CLAY, Temperature, HFP, aspect, T_CEC_SOIL, T_GRABEL, Elev, wind, T_SAND, T_OC, T_SILT, T_PH_H2O, slope. Among surface climatic conditions, srad is the most important driver affecting NEP, followed by Precipitation, with slope being the least important. Regarding the direction of influence of the drivers, srad, T_REF_BULK, T_CLAY, and aspect.

3.3. Multiple Linear Regression Analysis

From SHAP analysis, factors strongly driving NEP (chosen with SHAP values greater than 3) included seven variables: Srad, T_REF_BULK, T_CLAY, aspect, HFP, Temperature, and Precipitation. A multiple linear regression analysis was constructed using R to explore the interrelationships among these seven factors and their impact on NEP. Our results indicated that the interaction term between aspect and T_CLAY is statistically significant in the model, suggesting that the combined effects of land slope and clay content significantly influence the ecosystem's NEP. The significance of the interaction term aspect:T_REF_BULK suggests that considering the slope or soil bulk density alone may not sufficiently reveal their impacts on NEP. Furthermore, the significant interaction between HFP and srad indicates that human activities might also interact with other environmental factors as a whole, collectively influencing NEP.

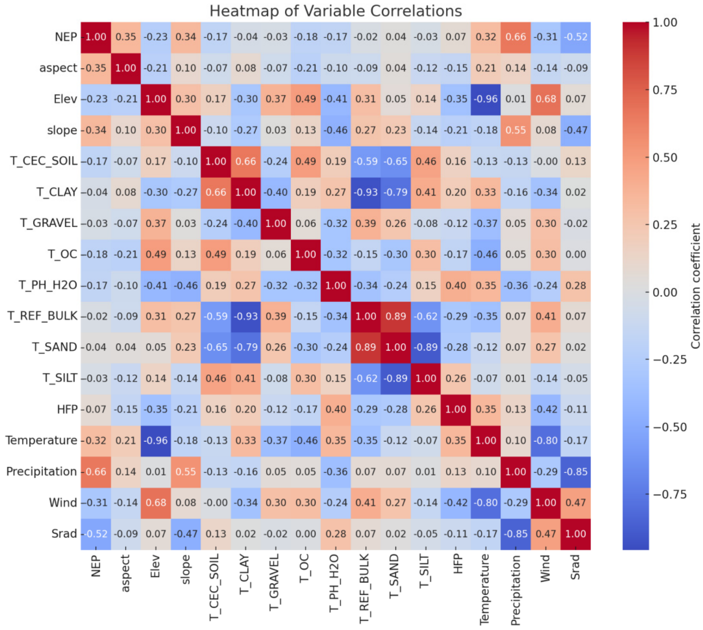

Figure 3. Heatmap of Correlations Among Factors

Table 3. SHAP Values of Each Factor

Name	SHAP_values
Srad	5.762153583
T_REF_BULK	4.482324216
T_CLAY	4.455572117
aspect	3.342999929
T_CEC_SOIL	2.995941909
Elev	2.483418756
T_OC	1.224301556
T_PH_H2O	0.170039409
slope	-0.060874055
T_SILT	-0.231707001
T_SAND	-1.82764097
Wind	-2.01705201
T_GRAVEL	-2.708125475
HFP	-3.920637791
Temperature	-4.373084215
Precipitation	-4.555035252

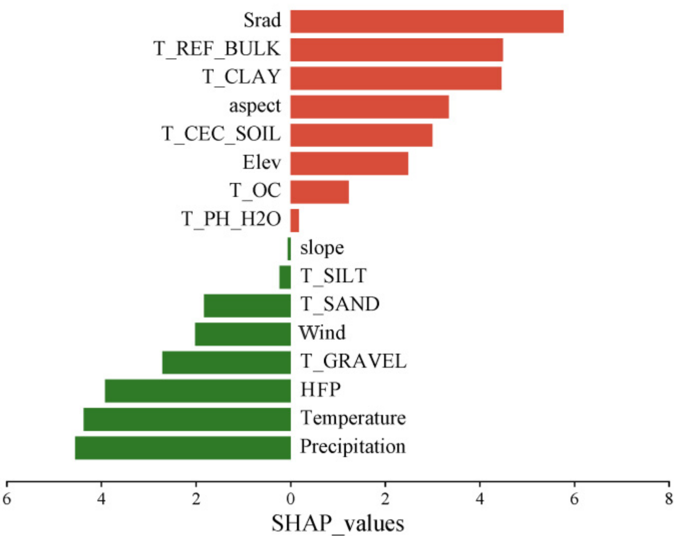

Figure 4. SHAP Values of Each Factor

T_CEC_SOIL, Elev, T_OC, and T_PH_H2O positively influence NEP in the study area, whereas Precipitation, Temperature, HFP, T_GRAVEL, wind, T_SAND, T_SILT, and slope negatively impact NEP.

Table 4. Results of Multiple Linear Regression Analysis for Each Factor

Name	Estimate	t value	Pr(>|t|)
aspect:T_CLAY	-0.709248833	-2.864361097	0.007990246
aspect:T_REF_BULK	-54.06936287	-2.913398967	0.007096829
aspect:HFP	-0.023210499	-0.865196939	0.394553322
aspect:Temperature	-0.053385018	-0.915406973	0.368081757
aspect:Precipitation	0.042854289	1.638998156	0.11281572
aspect:Srad	0.000282929	0.642027445	0.526269366
T_CLAY:T_REF_BULK	201.2313493	1.743746325	0.092580889
T_CLAY:HFP	0.915171334	0.373240616	0.711883829
T_CLAY:Temperature	0.651757448	0.125393055	0.9011414
T_CLAY:Precipitation	0.948703075	0.477054314	0.637162238
T_CLAY:Srad	-0.023621445	-0.579005987	0.567384684
T_REF_BULK:HFP	-68.6928441	-0.503207728	0.618898863
T_REF_BULK:Temperature	73.1063777	0.208717775	0.83623519
T_REF_BULK:Precipitation	113.1619569	0.747191548	0.461405919
T_REF_BULK:Srad	-0.244148379	-0.081775638	0.935428337
HFP:Temperature	1.474377564	1.510932876	0.142421856
HFP:Precipitation	0.361640752	0.882117978	0.385499159
HFP:Srad	0.012883504	2.43813225	0.021624542
Temperature:Precipitation	-0.141047656	-0.173665057	0.863424194
Temperature:Srad	-0.003088549	-0.214678229	0.831631409
Precipitation:Srad	0.001564595	0.989170883	0.331361857

Estimate: Indicates the size and direction (positive or negative) of the variable's impact.
t value: A statistic used to test if the estimate is significantly different from zero.
Pr(>|t|): Reflects the probability of statistical significance, where a value less than 0.05 typically means significant.

4. Discussion

NEP is influenced by various factors including climatic elements, soil conditions, and land use [21,22]. This study examines the impacts of climate, soil, topography, and human activities on NEP. We found that temperature has a negative contribution to NEP, similar to the findings of HUA Langqin [23]. This may be due to Northwestern China's inland and arid location, where increased temperatures and insufficient precipitation lead to higher evapotranspiration, causing vegetation degradation and reduced plant net primary productivity [24,25], consistent with situations observed by Pang Zhaoyue et al. in central counties of Xinjiang [26]. Generally, studies suggest that more precipitation favors plant growth and enhances carbon fixation capabilities, but for arid and desert grassland areas in Northwestern China, some scholars have proposed different views that align with our findings, suggesting that only precipitation above 5mm is effective, and rainfall events under 7mm should be considered ineffective for the desert grasslands, as these minor precipitations likely evaporate after being intercepted by shrub layers or sand surfaces, and their retention in the soil surface layer has limited impact on vegetation growth. In plateau areas like the Tibetan Plateau, precipitation is often accompanied by temperature drops, and the water retained in the soil surface may exist in solid form, posing a freeze threat to plants. More importantly, small rainfall events may cause leaching or result in nutrient loss due to water restrictions, leading to inadequate nitrogen supply in nutrient-poor areas, which is detrimental to vegetation growth and productivity [27-29]. Scholars have also found that aspect influences the net primary productivity of *Quercus mongolica* Forests [30]. Solar radiation, being the sole energy source for photosynthesis, can enhance plant photosynthetic efficiency under constant variables; however, once the light intensity exceeds a threshold, the efficiency no longer increases. This phenomenon indicates that excessive light intensity may damage the protoplasts of plant cells, leading to chlorophyll degradation and excessive cell dehydration, which causes stomatal closure and ultimately reduces or stops photosynthesis. On the Tibetan Plateau, intense solar radiation significantly affects the content of chlorophyll, carotenoids, and flavonoids within plants; moreover, light quality is a key factor determining the development of plant roots, root growth, chlorophyll synthesis and accumulation, and protein synthesis [31]. Studies have shown that forest GPP is significantly positively correlated with photosynthetically active radiation, and grassland annual mean NPP is also affected by solar radiation [32,33], findings by SUN Qiang [34] that vegetation NPP in the Gannan Tibetan Autonomous Prefecture region correlates positively with solar radiation are consistent with our results.

WANG Ziwen [35] using biomod2 simulations found that clay content and aspect significantly affect the growth and distribution of Datura stramonium. Additionally, researchers pointed out that effective soil water content and clay content are major factors affecting grassland NEE [36]. Soil, as a natural resource, is the growth mechanism for terrestrial vegetation. Soil particles, being specific geometric bodies, determine the fundamental physical properties of soil, such as bulk density, porosity, and water content, which are crucial indicators of soil structure, hydrological conditions, and soil quality assessment. These properties can directly or indirectly affect soil aeration, water retention, and nutrient preservation capacities, thereby significantly influencing the vegetation growing above [37]. In the inland areas of Northwestern China, the soil is relatively infertile and compact, excessive soil compaction might lead to poor aeration, and in some parts of Northwestern China, particularly in the Tibetan Plateau area, the high altitude and harsh environment cause plants to be stunted, overly compact soil may hinder plant rooting and growth. Soil texture, which is the percentage composition of different soil particle sizes, also known as mechanical composition, affects soil water, air, heat, and nutrient conditions, thereby influencing the growth and development of plant roots and aerial parts [38]. Besides natural factors, as human activities intensify, anthropogenic factors are also gradually considered in environmental issues, with researchers using process-based terrestrial ecosystem models and remote sensing-based (CAS) methods to simulate the combined effects of climate change and human activities on grassland productivity in the Tibetan Plateau area from 1982 to 2011, finding that the factors driving regional productivity in the first 20 years shifted from climate change to human activities in the last 10 years, with over 20% of the area shifting from climate change dominance to human activity dominance, indicating that human activities are becoming a major factor affecting the terrestrial vegetation productivity on the Tibetan Plateau [39]. LU Xiaoquan[40] found that as urbanization intensity increases, ecosystem total primary productivity GPP shows a declining trend. This suggests that soil factors might influence NEP by affecting plant growth and development, while human factors also have a certain impact on NEP, and the impact brought by human factors may become more apparent with the development of the socio-economy in the future.

This study also has certain limitations; although it considered human, topographic, soil, and climatic factors, some aspects like water body proportion and socio-economic factors were not covered. This paper primarily used Random Forest for analysis, and alternative approaches could be explored in the future to evaluate environmental effects on NEP.

5. Conclusion

This study, through Random Forest and multiple linear regression, analyzed the impact of environmental and anthropogenic factors on NEP, with SHAP providing explanations for feature importance values in the Random Forest model. It was found that srad, T_REF_BULK, T_CLAY, Aspect, T_CEC_SOIL, Elev, T_OC, and T_PH_H2O promote NEP in the study area, with the highest for srad at 5.762153583. Precipitation, Temperature, HFP, T_GRAVEL, wind, T_SAND, T_SILT, and slope suppress NEP, with the highest for Precipitation at -4.555035252. Multiple linear regression analysis showed that the interaction between Aspect and T_CLAY and T_REF_BULK significantly affected the ecosystem's net primary productivity, while the significant interaction between HFP and srad indicates that human activities might also interact with other environmental factors as a whole, jointly affecting NEP.

ORCID

Weibo Yuan https://orcid.org/0000-0002-7233-9594.

Competing Interests:

All authors declare that they have no conflicts of interest.

Author Agreement:

All authors agree with the responses of Detailed Response to Reviewers and Revised Manuscrip.

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