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Spatial-Temporal analysis of remotely sensed data in the Italian Alpine pastures

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ABSRATCT

Exploring the spatial and temporal dynamic characteristics of regional forest net primary productivity (NPP) in the context of global climate change can not only provide a theoretical basis for terrestrial carbon cycle studies, but also provide data support for medium- and long-term sustainable pastures management planning of mountain regions.

This study focuses on the Alpine Community of Giudicarie, located in the Province of Trento, Italy, through utilizing NASADEM (NASA Digital Elevation Model) 30m data from 2001 to 2020 as the main data sources.

By integrating diverse variables: precipitation, Aspect, and Slopes, a statistical analysis was used in our study to clarify their relationship and interactions to Net Primary Productivity (NPP) in 20 years, then we examined five distinct Machine Learning algorithms: Linear Regression, Lasso Regression, KNN Regressor, Random Forest, and Gradient Boosting to identify the most effective model for estimating NPP in both spatial and temporal dimensions.

The results show that the performance of the KNN model is better than the other models, by its adaptability to our datasets and its superior performance in terms of R^2 and RMSE values.

The developed model is highly relevant for estimating Net Primary Productivity (NPP) in mountain pasture fields in both temporal and spatial dimensions, which serves as a valuable tool for informed decision-making in managing mountainous pastures, ensuring sustainable utilization and preservation of these vital ecosystems.

1. Introduction

(Vitousek ,1992) defined Global Changes as those changes that "*alter the well-mixed, fluid envelope of the Earth's system (the atmosphere and oceans) and hence are experienced globally, and those that occur in discrete sites but are so widespread as to constitute a global change*." The first category of these changes includes the atmospheric changes, while the second category emphasizes the land use/ land cover changes (LULCC) and their impacts on biodiversity. While Barnosky et. al. (2012) defined Global Change as " Any consistent trend in the environment that affects a substantial part of the globe, is not a new phenomenon and has earlier let to species distribution changes and extinctions."

The origins of these concepts date back to consistent observations of CO2 concentration in the atmosphere done at the Mauna Loa Observatory in Hawaii, which demonstrated that human activities have without any doubt a strong direct effect on the global environment (Keeling et. al. 1995; Keeling and Whorf, 2002).

Over the past two centuries, the human interaction and interrelation with technology have changed incredibly, furthermore, the human influence on Earth system have also been modified. As resource consumption, reflected in agriculture expansion, urbanization, food production and industry, has reached a point which they impacts influence the functionality of the Earth system. These human endeavors have changed the Earth surface, altered the ecosystems, and changed the climate (IGBP, 2005). However, global change is occurring at a unprecedented rate than ever, spreading all over the globe, this will affect not only biodiversity and ecosystems, but also all ecosystems services by which each ecosystem contribute to provide society and economies with different services (Hansen and DeFries 2004; Schipper et al. 2008; Barnosky et al. 2012).

1.1 Global Change Drivers

1.1.1 Climate change

Climate change is undeniable fact. We are at the approximately 1.0 °C of global warming above pre-industrial level and likely to reach 1.5 °C between 2030 and 2052 with the current rate. This in turn is increasing temperatures, reducing precipitations, causing sea level rise, and increasing the frequency of natural disasters as floods, droughts, and heatwaves. Apparently, the most vulnerable communities are the small islands states and the poor. Furthermore, climate change worsens the already existing pressures on environment such as increased population, growing urbanization, and unsustainable lifestyles. Disaster impacts are getting worse. (IPCC, 2014; Djalante, 2019).

Between 1900 and 2019 natural disasters occurred 14827 times, resulting in 32.6 million deaths with a total damage of over 3.4 trillion USD (EMDAT Database). Environmental induced risks are dominating the risk landscape and considered as high likelihood and high impact natural disasters. These risks include flooding, droughts and typhoon and the lack of adaptation and mitigation (WEF, 2019).

Climate change has occurred since the industrial revolution, resulting from the emission of greenhouse gases and the rapid development of economy and technology (IPCC, 2007). Climate changes that are related to soil erosion mainly include changes in temperature and precipitation. According to the latest IPCC report (IPCC, 2013), the global mean surface temperature increased by 0.85 [0.65 to 1.06] °C over the period from 1880 to 2012. A new set of scenarios of RCPs, including RCP2.6, RCP4.5, RCP6.0, and RCP8.5, was also published. The radiative forcing level in 2100 of RCP8.5 is the highest while that of RCP2.6 is the lowest. By the end of this century, global temperature is likely to rise > 1.5 °C for all RCPs except for RCP2.6. Specifically, temperature rise is likely to exceed 2 °C for RCP8.5 and RCP6.0, and to exceed no more than 2 °C for RCP4.5. More hot and fewer cold temperature extremes in most places were also projected (IPCC, 2013).

- **Land use change**

The massive increase of human population and associated activities such as herding, hunting, agricultural activities and human settlement has altered land historically (Ellis *et. al.*, 2013). Figure 1 shows that the increase in land transformation induced by human activities has been accelerated since the 18th century (Jones, 2011; Ellis, 2011). (Habrel, 2014) argued that as human population is dramatically increasing, changes of diets and intensive use of biomass for non-food purposes are forcing towards the expansion of crop land more and more.

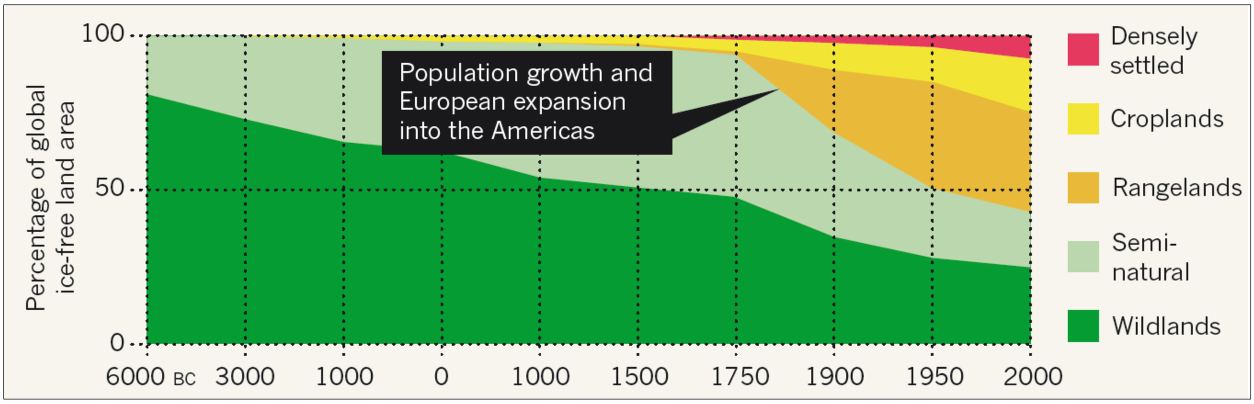

Figure 1: Global transformation of land from 6000 BC to 2000 AD.

Table 1 shows the general trend of global land use in the period between 2000 and 2010 (Lutzenberger et al. 2014). This table indicates that the relevant drivers of net land use changes over the last decade are crop expansion and urbanization, where the major losses are at forest and pasture lands, while the major gains are at the planted forests.

Table 1: General trend of global land use in the period between 2000 and 2010

Land use	2000	2010	Change
Cropland	1514	1541	27
Pasture	3420	3353	-67
Forest	4085	4033	-52
Planted forests	161	274	113
Urban & infrastructure	40	65	25

The agricultural practices used currently are considered unsustainable because they depend on few crop varieties (chemical fertilizers, herbicides, and pesticides). Furthermore, they decrease the biodiversity and agro diversity (Friso et al. 2011); and they require large quantities of water, which in turn lead to serious GHG emissions. (IPCC, 2014) pointed that agriculture is responsible for 30- 35% of GHG emissions globally. However, it is a mutual relation between climate change and agricultural productivity; the more climate change, the less agricultural productivity; and yet this will affect crop production between developing and developed countries (Levinson, 2014).

1.1.1 Influence of global change on mountain pastures

Summer mountain pastures are complex socio-ecological systems. In mountainous regions in Europe, they provide forage for grazing livestock during summer. In most cases, they consist of a mix of open grasslands, tree, or shrub vegetation types (Deléglise et al. 2019; Jäger et al. 2020). Grazing on mountain pastures is affected by the management decisions of herders, farmers, or institutional actors such as forest agencies or regional and national entities specifically devoted to pasture management (Nagy and Grabherr 2009; Herzog and Seidl 2018). Summer mountain pasture management is considered to be decisive for the maintenance of biodiversity, ecosystem services, and landscapes (MEA, 2005; Girard et al. 2008; IPBES, 2017; García-Ruiz et al. 2020). Well-managed mountain pastures are central for the provision of public goods and are a central cornerstone in agro-ecological and low input grazing livestock systems (Borsotto et al. 2014; Furtschegger et al. 2015; Van der Ploeg et al. 2019), whereas most ecosystem impacts are related to inapt stocking densities in alpine meadows. High stocking densities may cause a range of negative impacts on plant and animal communities (Dumont et al. 2009; Jerneck et al. 2011; Negro et al. 2011), pollution, and loss of stored carbon (Abdalla et al. 2018; Mahefarisoa et al. 2021), while grassland abandonment increases the risk for landslides in topsoils (Tasser et al. 2003).

Climate change is an increasing threat to mountain ecosystems (Schmeller et al. 2018; Vicente-Serrano et al. 2021; Lemus-Canovas et al. 2021), and hence also a threat to grazing livestock farmers in mountainous regions (Fuhrer et al. 2014). Farmers need to hedge against these impacts, e.g., through insurance (Vroege et al. 2019), adding cropland feed to ruminant livestock diets (Thornton and Herrero 2014; Mottet et al. 2017), or decreasing stocking densities (Stolze et al. 2019).

All measures are prone to invoke additional or opportunity costs. As an alternative, underexploited mountain grasslands may become necessary for future livestock management strategies to counteract reduced forage availability. Consequently, summer mountain pastures may become more important in years when forage growth is curtailed in the lowlands and can thus increase the flexibility of farmers to cope with these forage shortages (Nettier et al. 2017; Herzog et al. 2018). However, considerate management needs to be implemented to avoid negative trade-offs with biodiversity, biogeochemical cycles, or hydrological processes (Tasser et al. 2005; Garcia-Pausas et al. 2017; Hilpold et al. 2018).

Climate change improves growth condition of woody plants in subalpine areas and leads to a continuous uplift of the tree line. Consequently, shrubs increasingly overgrow mountain pastures. This trend is enforced by land use changes due to a reduction of farming activities. In the European Alps, the most invasive shrub is green alder (Alnus viridis). This nitrogen-fixing pioneer shrub leads to a tremendous decline of biodiversity, pastureland, and appealing landscape. Moreover, the surplus fixed nitrogen is emitted as N2O – a most effective greenhouse gas or it eutrophicates surrounding soils and downstream waters (Caren M et al. 2020).

To predict future patterns of agricultural land and mountain pastures and concomitant ecological impacts, it is crucial to understand the complex interplay between the decisions of farmers and the socio-economic, biophysical, and climatic environment (Schirpke et al. 2017). The diversity and interactions of influencing factors need to be considered when modeling dynamic shifts of livestock between lowland grazing and the exploitation of summer mountain pastures. (Rigolot et al. 2014) found that mountain pastures utilization increases the ability of farmers to cope with climate variability and that decisions about utilization are complex and made collectively. (Herzog et al. 2018) conducted a series of interviews with farmers and extension officers to gain an overview of the main drivers of utilizing mountain pastures in Switzerland. They found that next to forage provision and health benefits for grazing livestock, benefits for labor requirements are important drivers for using mountain pastures in the Swiss Alps.

1.2 Influence of global change on pastures in the Italian Alps

The Alpine chain is about 1200 km long and 200 km wide, stretching across eight European countries (i.e., Austria, France, Germany, Italy, Switzerland, Liechtenstein, Slovenia, and Monaco). The location of the Alps (frontal system crossing Europe in a west-east direction), beside the wide variation in exposure, elevation, and its arc-like shape determine a unique climate which also depends on local differences and position of reliefs (Organisation for Economic Co-Operation and Development, 2007). This in turn determines the presence of a large variety of habitats and species. Within the whole area, grasslands and pastures represent about 25% of the Alpine vegetation, most of them semi-natural after centuries of human activities (Sundseth K et al. 2009).

In mountain areas, pastures and farming systems are paramount important activities for local communities, a source of income for local development, and a key feature of local ecosystems dynamics (Mazzocchi, C et al. 2018). Pasture management has positive effects on land sustainability, maintaining the landscape and cultural value and supporting biodiversity and soil fertility, thereby reducing soil loss and natural risks.

Nowadays, the already high complexity in the understanding of the changes to pastures dynamics in terms of size and composition with the related repercussions on the livestock sector because of aspects such as agricultural land abandonment and land-use policies (Hinojosa.L et al. 2016), is further exacerbated by the current climate change. An average increase of 0.8 _C has been recorded across the European Alps at high elevation stations in the period 1981–2010 (Lamprecht A et al. 2018) and for the future an increase ranging between 1 and 2 _C is expected (Gobiet A et al. 2014). Precipitations show a more uncertain pattern, but all the studies agree to a remarkable reduction in summer (Heinrich G et al. 2014). Natural pastures, i.e., grasslands managed by livestock grazing, located in the Alpine Mountain range are indeed widely acknowledged to be very sensitive and vulnerable to climate conditions (Calanca P et al. 2007; Auer I et al. 2007).
Therefore, the expected increase in temperature associated with changes in precipitation pattern and quantity may lead to changes in the extent and composition of Alpine pastures, resulting in a reduction and/or losses of specific macro-types and plant species with consequences also on forage quality and management practices ((Deléglise. C.et. Al, 2014). As a result of the general predicted warming, an altitudinal shift is expected on the basis of many studies conducted on mountain vegetation.

(Pauli et al. 2013) highlighted in a study that involved 17 ranges all over Europe, the increase of more warm tolerant species with respect to cold tolerant and a generalized upward shift of vegetation species in the future. Other studies, assessing the main climate change foreseen effects on grasslands provided evidence of other ecological consequences, such as a reduction in suitable grassland areas, increasing in xeric species, enhancement of shrubs encroachment (Schwager P et al. 2019).

Providing information on the expected changes in the presence and composition of natural grasslands would be useful for understanding and tackling the future risks to those Alpine regions where the livestock sector still plays a key role for mountain society. To our knowledge, a comprehensive assessment of climate change impacts on the Italian Alpine pasturelands and their evolution on a large-scale basis is still lacking.

The growth of shrubs, grassland biodiversity loss, and increased erosion, wildfire, and avalanche risk, as well as the loss of traditional productive activities and typical landscapes (Faccioni G et al. 2019). During 1990–2010, ca. 17% of the Italian alpine pastures were abandoned (Faccioni G et al. 2019).

In recent decades, climate change has had an impact on Alpine Mountain ranges (Hock R et al. 2019). Already in the last 150 years, the temperature in the Alps increased by ca. +1.5 °C, higher than the global trend (Böhm R et al. 2001; Brunetti M et al. 2009). Warming may result in different evaporation rates, more erratic precipitation, increased frequency of floods, and droughts. Other studies, assessing the main climate change foreseen effects on grasslands provided evidence of other ecological consequences, such as a reduction in suitable grassland areas, increasing in xeric species, enhancement of shrubs encroachment e.g., (Matteodo M et al. 2013; Carlson et al. 2019; Schwager P et al. 2019).

Modified climate and hydrology at high altitudes may influence soil moisture, vegetation growth, and in particular pasture dynamics, which heavily depend upon temperature and precipitation. Snow cover extent and duration also affect pasture growing seasonality, area availability, and biomass (Van Der Wal R et al. 2000; Zeeman M et al. 2017).

1.3 Governance under global changes: the interface between policy and science

"GLOBAL CHALLENGES IN MOUNTAIN AGROPASTORAL SYSTEMS - Scientific evidence on impacts, adaptation and policies" was the stimulating title of the international scientific conference organized in the frame of the LIFE PASTORALP project at Forte di Bard, (Aosta, Italy the 15-17 March 2023). Scientists, policy makers, delegates of local authorities, natural parks' officers, agriculture and extension technicians, farmers' representatives and students participated to the conference.

The science-policy interface presents several challenges to both scientists and policy makers, however, the growing severity of challenges imposed by climate change, and the policies needed to face them, implies that more frequent collaborations between scientists and policy makers are crucial. This session included the presentation of studies and experiences at the interface between policy and science in the context of mountain agropastoral systems, including the definition of adaptation or mitigation strategies or plans. The session aimed also at describing the current gaps, challenges, skills, and strategies facilitating the uptake of scientific knowledge in policy formulation and implementation (Life pastoral, 2023).

Mountain environments are facing growing sustainability challenges as a result of cross-scale and interacting drivers. Climate change is one such driver that alone and in interaction is driving the rapid evolution of mountain social-ecological systems. Addressing these complex challenges and identifying feasible and fair adaptation and mitigation strategies requires a process of knowledge co-production not only between scientists and policy makers, but amongst multiple groups of actors that recognize multiple ways of knowing and doing. However, the existence of diverse perceptions and interests often makes such a process difficult. The co-formulation of governance and management options thus calls for a shared representation of the system in its contextual specificities. Such a common representation is equally necessary in designing the adaptive monitoring programs that are needed to mutually inform science and management. Here, we first present the conceptual model of mountain socio-ecological systems we developed to anchor different stakeholders' perceptions in a common ground of discussion (Life pastoral, 2023).

As climate change continues, and climate extremes such as droughts, heatwaves, and intense precipitation increase, it is important to advance our understanding of their impacts on ecosystem structure and function. Natural and managed ecosystems, such as mountain pastures, have indeed the potential to face future climate change challenges if preserved and sustainably managed. This session focused on observational, experimental and modelling studies related to climate change impacts on mountain grasslands, pastures and other agropastoral systems, as well as studies investigating the role of agropastoral systems for adaptation and mitigation opportunities in mountain areas The science-policy interface presents several challenges to both scientists and policy makers, however, the growing severity of challenges imposed by climate change, and the policies needed to face them, implies that more frequent collaborations between scientists and policy makers are crucial. This session included the presentation of studies and experiences at the interface between policy and science in the context of mountain agropastoral systems, including the definition of adaptation or mitigation strategies or plans. The session aimed also at describing the current gaps, challenges, skills, and strategies facilitating the uptake of scientific knowledge in policy formulation and implementation (Life pastoral, 2023).

1.4 Geospatial Technologies - GIS and Remote sensing

Remote sensing data streams are commonly coupled with machine learning algorithms for land cover and land use classification (Abdi, 2020), crop mapping, and, recently, the detection of mowing and other agricultural practices (Kolecka et al. 2018, Reinermann et al. 2020).

Conventional methods for monitoring pasture biomass and livestock utilisation (i.e., ground-based measurement and proximal sensing) are limited in terms of scope, and both spatial and temporal extent (Hudson et al. 2021). Previous research in Australia (Trotter et al. 2010), the United Kingdom (Punalekar et al. 2018): New Zealand, and the United States has reported limitations of ground sampling approaches (i.e., visual, rising plate meter, and destructive method by clipping) in quantifying the spatial variability of pasture biomass.

By contrast, remote sensing provides timely spatiotemporal information that can predict the availability of feed prior to grazing (Punalekar et al. 2018), allowing for feed budgeting. However, in most cases, remote sensing of pasture biomass is not process-driven (i.e., based on vegetation indices); often the use of such reflectance indices at small field scales (e.g., less than 50 ha) is constrained by the resolution of the satellite imagery and accurate calibration (Punalekar et al. 2018; Morais et al. 2021).

Remote sensing that considers process-based retrieval of pasture biomass and other biophysical variables may invoke site-specific modelling and machine-learning techniques (Ali I et al. 2015). Although some successes have been reported, physical-based techniques such as radiative transfer modelling and light use efficiency modelling can be prohibitive as they may require a set of parametric rules for different study locations (Gitelson AA et al. 2015; Bsaibes A et al. 2009). However, machine learning techniques including artificial neural networks (Chen, Y et al. 2021), random forest (RF) (De Rosa D et al. 2021), and support vector machine (SVM) (Wang J et al. 2019) are not site-specific and can be used to retrieve pasture biomass estimates (Morais TG et al. 2021). The artificial neural networks (Chen Y et al. 2021) was used to estimate pasture biomass leveraging multitemporal Sentinel-2 data collected over dairy farms in Tasmania.

Generally, machine learning methods are applied to multispectral satellite data or derived vegetation indexes to directly model biomass from in situ measurements and vegetation indexes (Reinermann et al. 2020). In this context, it has been suggested that modelling of mountain pasture biomass could be strongly improved by coupling remotely sensed vegetation indexes and vegetation maps (Magiera et al. 2017). The use of supervised classification for the determination of subtle differences of productivity in mountain grasslands, at a scale as fine as the distinction of pastoral categories is still a rather unexplored field of application (Crabbe et al. 2020).

1.4.1 Estimating NPP from APAR

(Net Primary Productivity): NPP is a measure of the amount of carbon fixed by plants through photosynthesis minus the carbon lost through respiration. It indicates the rate at which plants convert solar energy into biomass and is an essential indicator of ecosystem productivity (Running SW et al. 2004).

The notion of a conservative ratio between absorbed photosynthetically active radiation (APAR) and net primary production (NPP), was proposed by Monteith (1972; 1977). Monteith's original logic suggested that the NPP of well-watered and fertilized annual crop plants was linearly related to the amount of solar energy they absorbed.

APAR depends on the geographic and seasonal variability of daylength and potential incident radiation, as modified by cloud cover and aerosols, and on the amount and geometry of displayed leaf material. This logic combined the meteorological constraint of available sunlight reaching a site with the ecological constraint of the amount of leaf-area absorbing that solar energy, avoiding many complexities of carbon balance theory.

- **Daily estimation of NPP**

The essence of the core science in the MOD17 algorithm is an application of the radiation conversion efficiency logic to predictions of daily GPP (figure 2), using satellite derived FPAR (from MOD15) and independent estimates of PAR and other surface meteorological fields (from the DAO), and the subsequent estimation of maintenance and growth respiration terms that are subtracted from GPP to arrive at annual NPP. The maintenance respiration (MR) and growth respiration (GR) components are derived from allometric relationships linking daily biomass and annual growth of plant tissues to satellite-derived estimates of leaf area index (LAI) from MOD15. These allometric relationships have been derived from extensive literature review, and incorporate the same parameters used in the Biome-BGC ecosystem process model (Running and Hunt, 1993).

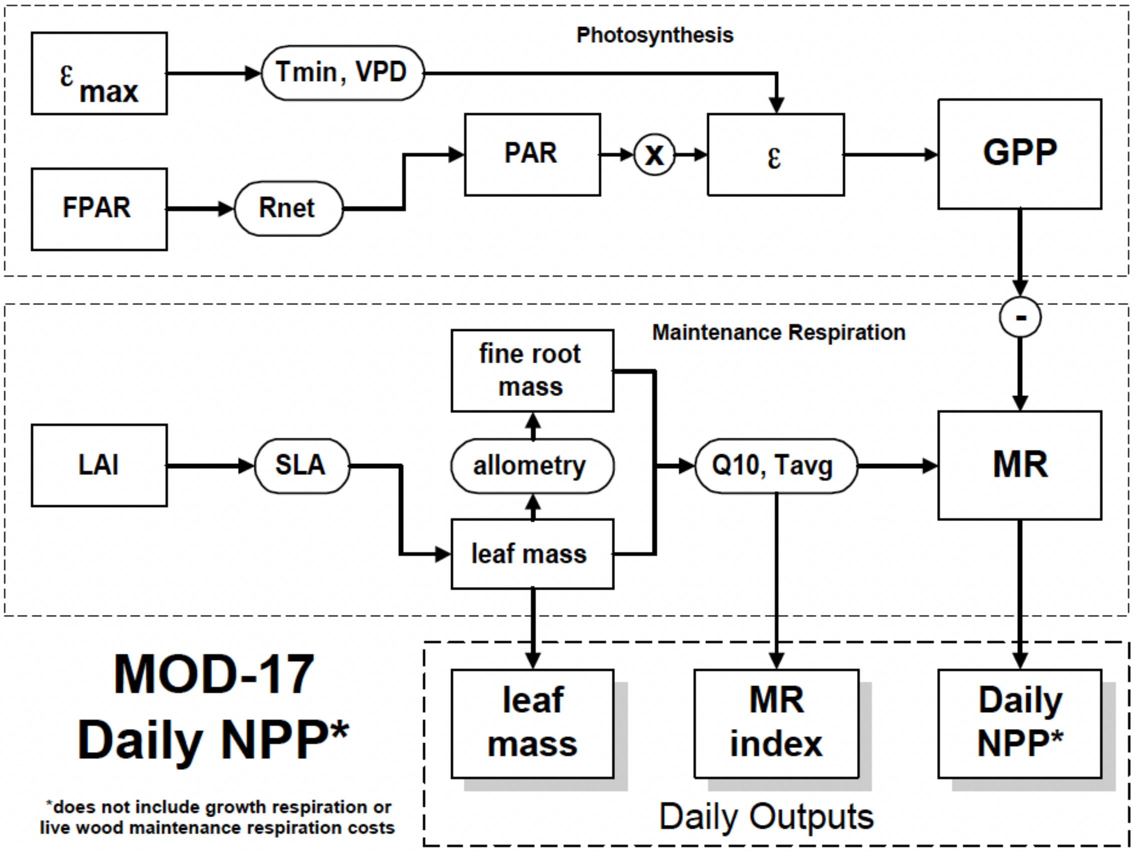

Figure 2: Daily Data Flow in the MOD17 Algorithm

This flowchart illustrates data flow in the daily part of the MOD17 algorithm. Output variables are shown at the bottom, where the notation NPP* indicates that not all of the autotrophic respiration terms have been subtracted. The remaining terms required to produce actual NPP are handled in the annual timestep.

- **Annual estimation of NPP**

The annual algorithm finishes the estimation of annual NPP by first estimating the live woody tissue maintenance respiration, then estimating the growth respiration costs for leaves, fine roots, and woody tissue. Finally, these components are subtracted from the accumulated daily NPP* to produce an estimate of annual NPP (figure 3).

The annual maximum leaf mass, as estimated from the output of daily leaf mass, is the primary input for estimates of both live wood maintenance respiration and whole-plant growth respiration. This approach relies on empirical studies relating annual growth of leaves to annual growth of other plant tissues. The compilation of forest biomass and primary production data by (Cannell, 1982) is one excellent example of the literature surveys required to establish these empirical relationships.

In addition to the annual maximum leaf mass, an estimate of leaf longevity (the inverse of leaf turnover rate) is required to predict the annual leaf growth for evergreen types.

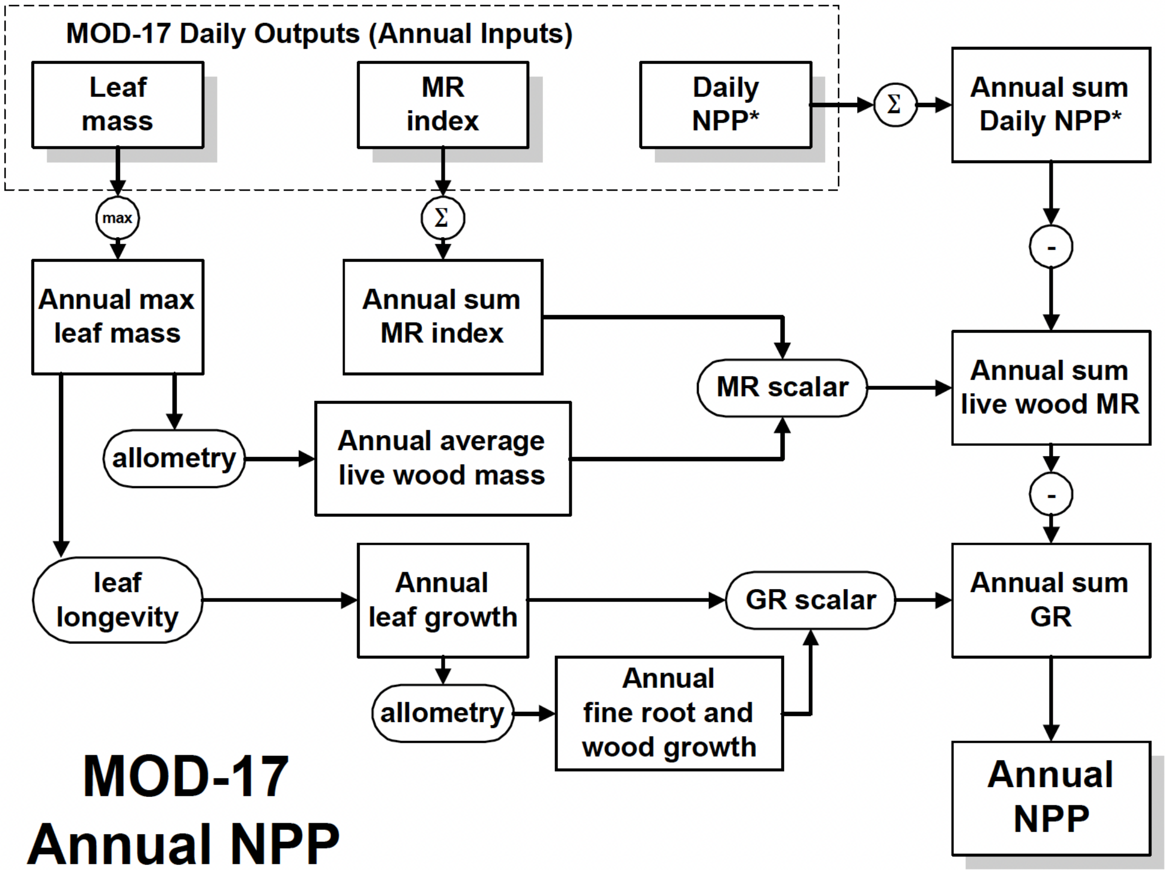

Figure 3: Annual Data Flow in the MOD17 Algorithm

This flow chart illustrates data flow in the annual part of the MOD17 algorithm. Inputs from the daily timestep process are shown at top left. Here the remaining autotrophic respiration terms are taken into account, resulting in an estimate of annual NPP.

1.5 Research questions

In order to address the stated objectives, the following research question was designed:

- How did the pasture biomass productivity, in terms of NPP, evolved in the Giudicarie region of the Italian Alps over the last 20 years? Was there any clear influence by climate change?
- Can we model the pasture productivity of the area, in terms of NPP, relying on independent morphological and meteorological features?

The output of this research assumed to analyse the evolution of biomass productivity on pastures and grasslands in the Giudicarie region of the Italian Alps using remote sensing technology over a 20-year period. By employing remote sensing techniques and machine learning, this study seeks to identify and quantify the impacts of morphological and meteorological variables on the grassland ecosystems. The findings of this research will provide valuable insights into the ecological dynamics of grasslands in the Giudicarie region, contributing to a better understanding of climate change impacts on these ecosystems and facilitating the development of effective conservation and management strategies.

2. Materials and methods

2.1 Study area

2.1.1 The mountain communities

The mountain communities are unions of municipalities, local bodies established between mountain and partially mountain municipalities, also belonging to different provinces, for the enhancement of the mountain areas for the exercise of their own functions, of conferred functions and for the associated exercise of the function's municipal (Gazzetta Ufficiale, 1992).

2.1.2 Community of Giudicarie

The Valle Communities are intermediate entities between the Autonomous Province of Trento and the Municipalities (figure 4). The Community of the Giudicarie extends for about a fifth of the provincial territory, with an altitude that varies from 302 to 3558 m. asl of Presanella, a massif facing the Dolomites, in the heart of the Adamello Brenta Nature Park.The Community borders to the North with the Community of Valle di Sole to the East with the Communities of Val di Non, Paganella, Valle dei Laghi and Alto Garda and Ledro; to the South and West, with the Province of Brescia of the Lombardy Region. The territory of the Community can be geographically divided into Giudicarie Esteriori with the areas of Lomaso, Bleggio and Banale, into Giudicarie Interiori which include the upper course of the Sarca (with the Val Rendena and the "Busa" di Tione) and the basin of the Chiese.

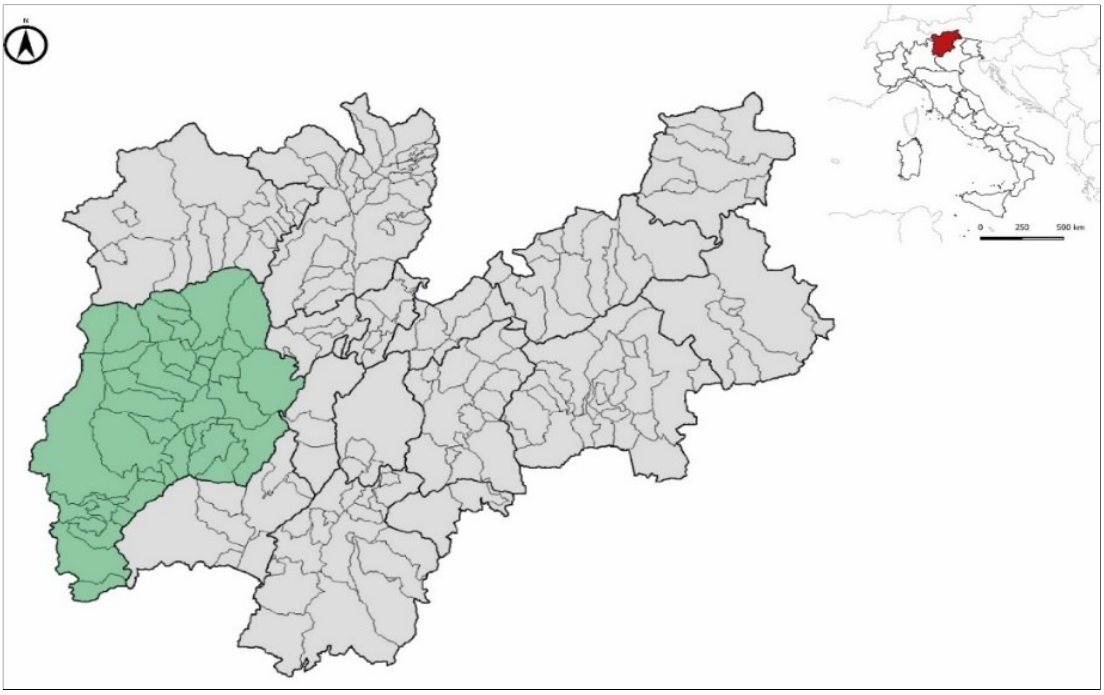

Figure 4: Map of the Localisation of Comunità delle Giudicarie

2.2 Data collection

The data collection process consisted of observing how a grassland in the study area changed over 20 years. We obtained polygon-based data (KML format) from the geocartographic portal of the Giudicarie community (figure 5).

The grassland region encompasses 416,737 total territories, distributed in 23000 hectares. An average elevation of 1676 meters above sea level, varies from 441 to 2823 meters.

This data helped us identify and study particular areas within the grassland, allowing for a thorough analysis of how they changed over time. We used Google Earth to analyse this data, which provided a detailed understanding of how the grassland evolved between 2001 and 2020.

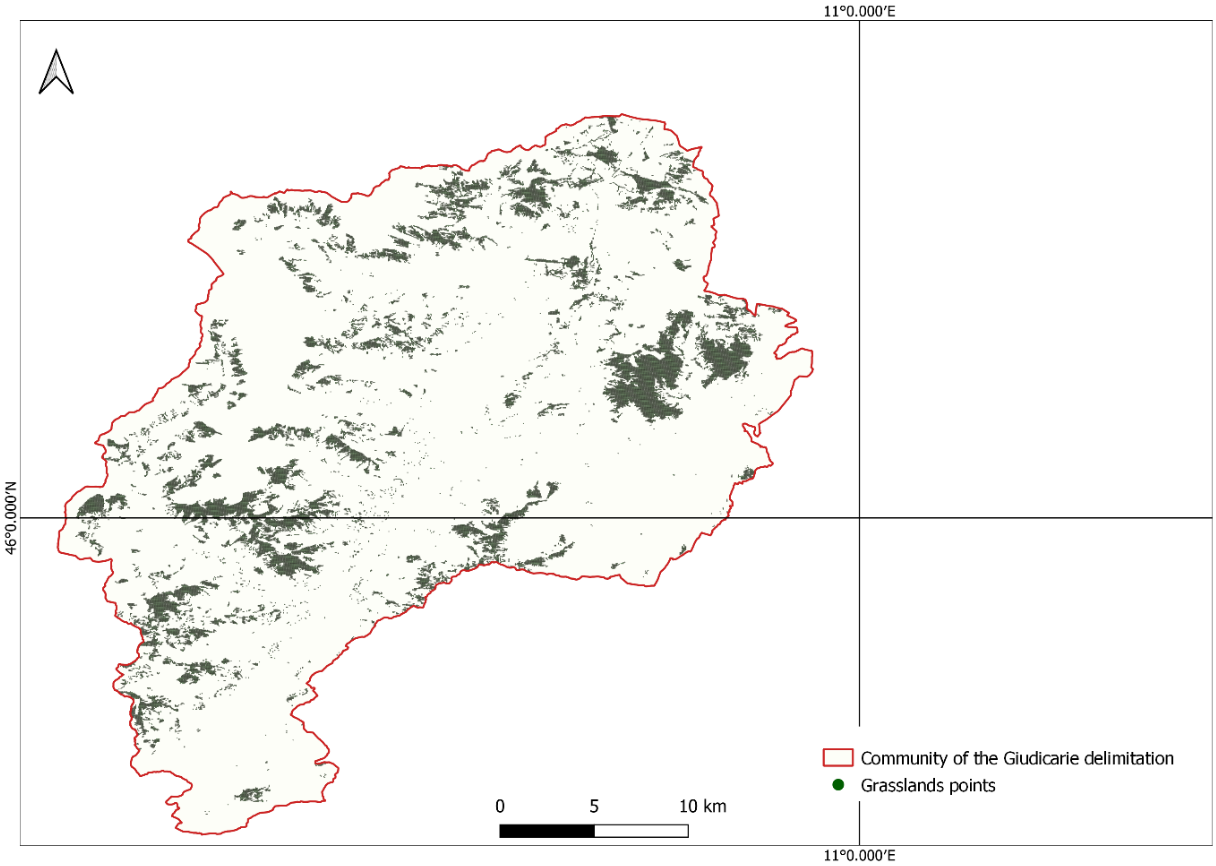

Figure 5: Map of Grasslands polygons in 2020

We partitioned the grassland area into grids of 50-meter segments. From each of these segments, one data point was selected, resulting in a total of 52,938 data points. This grid-based sampling approach allowed for a structured and systematic assessment across the entire grassland territory (figure 6).

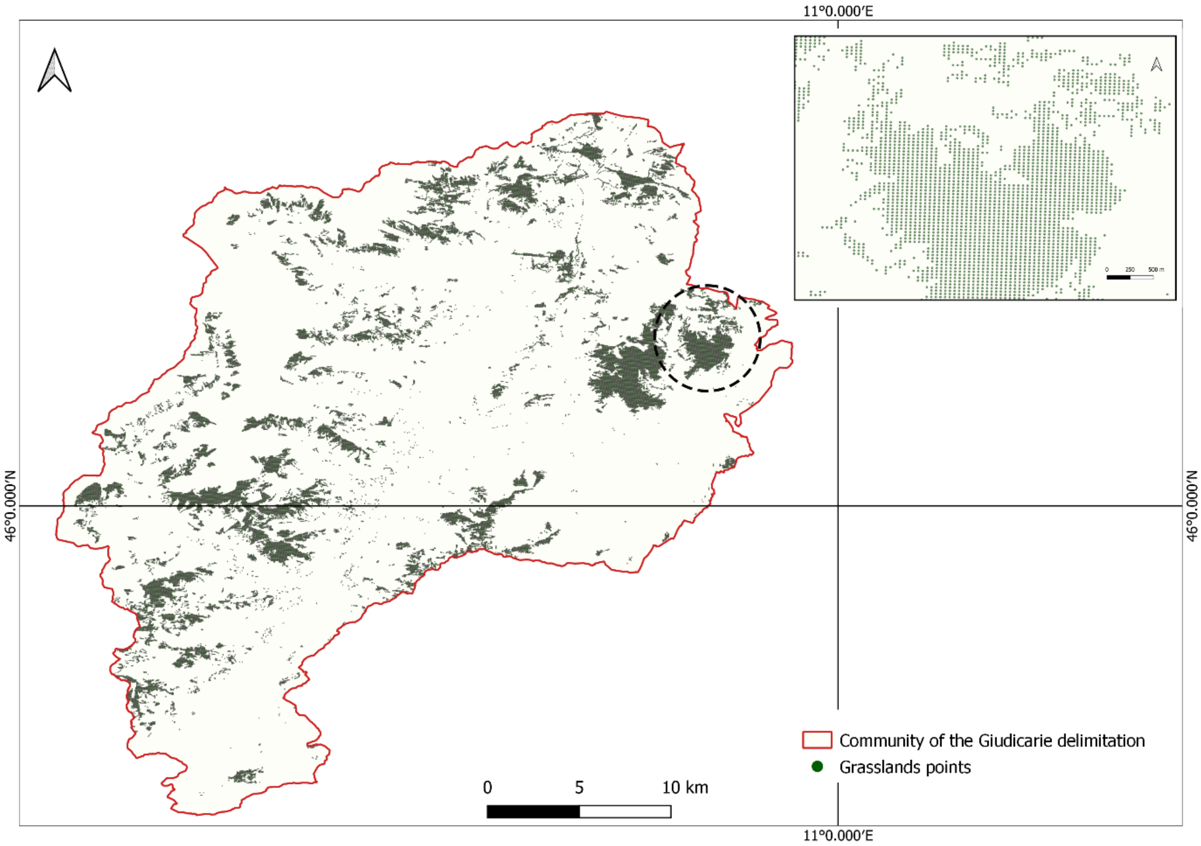

Figure 6: Map of Grasslands points in 2020

We submitted this large dataset to Google Earth Engine so that it could be thoroughly examined. Five variables were assessed for the whole grassland area: Slope, Aspect, Elevation, Net primary productivity (NPP), and mean temperature. across the entirety of the grassland area. This in-depth analysis facilitated the extraction of comprehensive data covering the 20-year period as raster images for each semester of every year (table 2).

Table 2: Environmental Variables Details

Variables	Min	Max	Average	Standard deviation
Slope (%)	0.93	79.11	27.38	12.89
Aspect (degree)	1.03	359.04	170.38	78.12
Elevation (masl)	453	2940	1986.02	456.23
Npp (KgC/m^2/y)	130	11388	4859.37	1830.55
Mean T (K)	262.93	283.84	275.95	2.41
Total Precipitation (m)	0.0027	0.0063	0.0043	0.0011

2.3 NASA dataset

We used NASADEM, or the NASA Shuttle Radar Topography Mission (SRTM) Digital Elevation Model, in our analysis conducted with Google Earth Engine. Digital Elevation 30 meters by NASA NASADEM which characterized by:

- Elevation (m) -512* 8768: Integer heights in the merged void-free DEM files are relative to the EGM96 geoid (whereas the floating-point heights in the SRTM-only DEM files are relative to the WGS84 ellipsoid).
- The NASADEM (NASA Shuttle Radar Topography Mission (SRTM) Digital Elevation Model) is a digital elevation model created by NASA. It provides elevation data for the Earth's land surface, derived from the SRTM mission.
- - The high-quality NASADEM dataset has a spatial resolution of 30 meters, which means that each pixel in the dataset corresponds to a 30-by-30-meter area on the surface of the Earth. The majority of the Earth's landmass is covered by it, and it offers insightful elevation data that is helpful for a variety of applications, such as terrain analysis, land use planning, and environmental modelling.
- A lot of scientific research projects, geographic information system (GIS) applications, and Earth observation studies use NASADEM because of its global coverage and relatively high resolution in comparison to other publicly available elevation datasets. NASADEM is also freely available to the public.

The NASADEM was released by NASA in 2020, which is mainly based on the reprocessing of SRTM data by merging it with additional datasets to improve the accuracy (Buckley et al. 2020). The Copernicus DEM was made available in 2020 through the European Space Agency (ESA), which is based on high spatial resolution commercial radar data acquired during the TanDEM-X Mission (Fahrland et al. 2020). The newly released GDEMs are expected to provide better performances due to improved processing techniques and inclusion of more data and will generate interest among users seeking for high-quality DEMs. While the validation work of these datasets is limited. (Li and Zhao, 2018) evaluated the AW3D30 DEM over five validation sites in China against the ICESat/GLAS (Ice, Cloud and land Elevation Satellite/Geoscience Laser Altimeter System) points. It indicated a RMSE of 4.81 m. (Uuemaa et al. 2020) examined the accuracy of six freely available GDEMs and found that the AW3D30 had the best performance in most of the tests.

(Nikolakopoulos, 2020) found that the RMSE of AW3D30 DEM varied from only 2.69 m in low-relief regions to 14 m in areas with high relief. To date, only few works have examined vertical errors of NASA and Copernicus DEM due to the short period of availability. The assessment conducted by the NASADEM team indicated a RMSE of 5.5 m over the CONUS and southern Canada using ICESat data (Buckley et al. 2020). (Uuemaa et al. 2020) found the accuracy of NASADEM was slightly better than SRTM. (Guth and Geoffroy, 2021) showed that Copernicus DEM was superior to all the other 1-arcsec GDEMs and suggested it should become the first candidate for visual display and quantitative analysis.

2.4 Statistical Analysis and machine learning

Using Python in Jupyter Notebook v.7.0.6 and adding extensions such as NumPy, Matplotlib, scikit-learn, and Pandas these libraries provide a strong Python ecosystem that supports various facets of data management, analysis, and modelling across a range of areas, including scientific computing, data visualization, and machine learning tasks. we processed, worked with, and displayed large datasets obtained from our grassland study. By utilizing Python with these specific extensions, we could carry out complex data processing operations, statistical calculations, and the creation of educational graphics. Furthermore, this setting made investigating trends between other variables we took out of the grassland dataset easier. We specifically sought to determine the relationships between mean temperature, slope, aspect, elevation, and net primary productivity (NPP).

To determine which statistical technique would work best with our dataset we examined five different approaches during the data analysis process:

- Linear Regression
- Lasso Regression
- KNN Regressor
- Random Forest
- Gradient Boosting

Every technique was examined and assessed considering the unique qualities and subtleties present in our data. The goal of this methodical investigation was to determine which statistical technique would best capture the intricacies and patterns found in the dataset, enabling reliable and precise predictions for our analysis and various machine learning algorithms within the Python environment, our objective was to develop a robust estimation model. Such a model has the potential to offer valuable insights into the influential factors governing variations in NPP within the grassland ecosystem, thereby enhancing our comprehension of its dynamic behaviour over the analysed period."

We utilized machine learning techniques to construct a model for estimating Net Primary Productivity (NPP) by iteratively training with diverse sets of variables. This iterative process involved experimenting with different variable combinations to enhance the model's accuracy for temporal and spatial NPP estimation within the grassland ecosystem.

In our machine learning approach, we began by selecting suitable algorithms for NPP modeling. We then conducted rigorous cross-validation to refine the model's performances tuning the hyperparameters described in Table 3. Once validated, the model underwent final testing on an independent dataset, ensuring its accuracy in predicting NPP.

Table 3: Hyperparameter Optimization Across Machine Learning Models

ML Algorithm	Hyperparameters	Tested values
Linear Regression	-	-
Lasso Regression	Alpha value	0.1,0.5, 1.0, 5.0, 10
KNN Regressor	N. of neighbours	3, 5, 7, 10, 12, 20
	Weights	Uniform, Distance
Random Forest	N. of estimators	50, 100, 150
	Max depth	None, 10, 20
Gradient Boosting	N. of estimators	50, 100, 150
	Max depth	3, 4, 5
	Learning rate	0.1, 0.05, 0.01

The presented table 4 illustrates the range of hyperparameters tested for each machine learning algorithm during the model optimization phase. Each algorithm was subjected to process by testing a variety of hyperparameter values to optimize model performance. For instance, Lasso Regression underwent an investigation involving different alpha values ranging from 0.1 to 10, while KNN Regressor was tuned by altering the number of neighbors from 3 to 20 and testing two weight options, 'Uniform' and 'Distance.' Random Forest and Gradient Boosting models were refined by adjusting the number of estimators, maximum depth, and learning rate, probing different combinations within the specified ranges.

3. Result and discussion

3.1 Npp dynamics

The examination of Net Primary Productivity (NPP) demonstrated dynamic oscillations for the period from 2001 to 2020, illustrating both growth and contraction. This temporal variability led to a thorough examination of the patterns that NPP has been exhibiting over time.

Two maps were produced to show the dynamic changes in mean NPP over 14-year period using QGIS's Zonal Statistics function after downloading raster images of Net Primary Productivity (NPP) patterns from Google Earth Engine in 2004 and 2018 (figure 7; figure 8).

These maps offer a visual depiction of how NPP has changed throughout the terrain over this period, illuminating significant ecological trends and alterations.

The NPP maps for 2004 and 2018 serve as valuable tools for assessing changes in ecosystem health, land-use practices, and environmental conditions. By comparing these two time points, we can discern both positive and negative trends in NPP, potentially indicating shifts in vegetation cover, climate influence, or human activities.

By leveraging geospatial technologies and statistical tools, we are better equipped to understand and address the complex interplay of factors affecting NPP and, in turn, the health of our ecosystems.

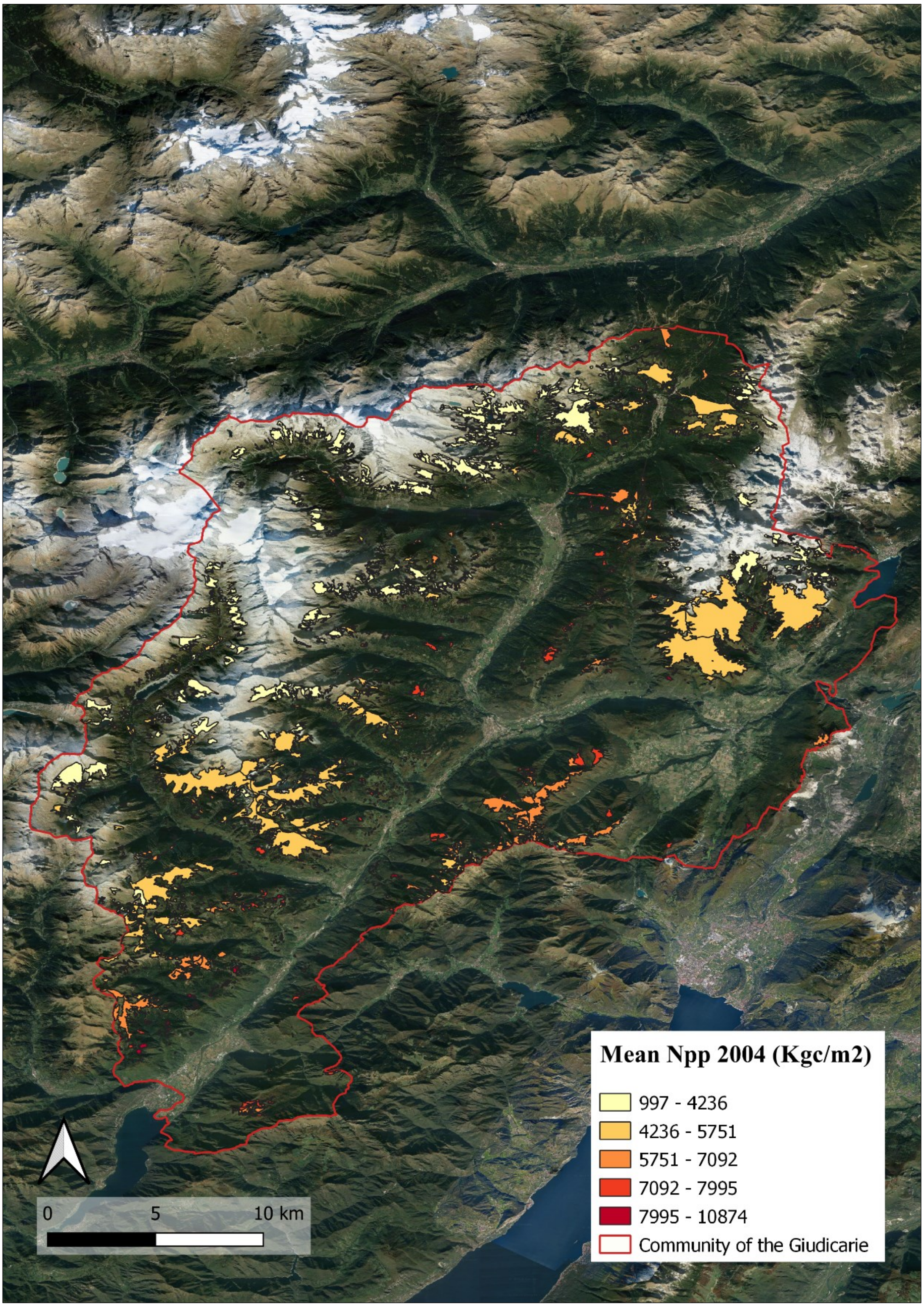

Figure 7: Map of Mean Npp in 2004

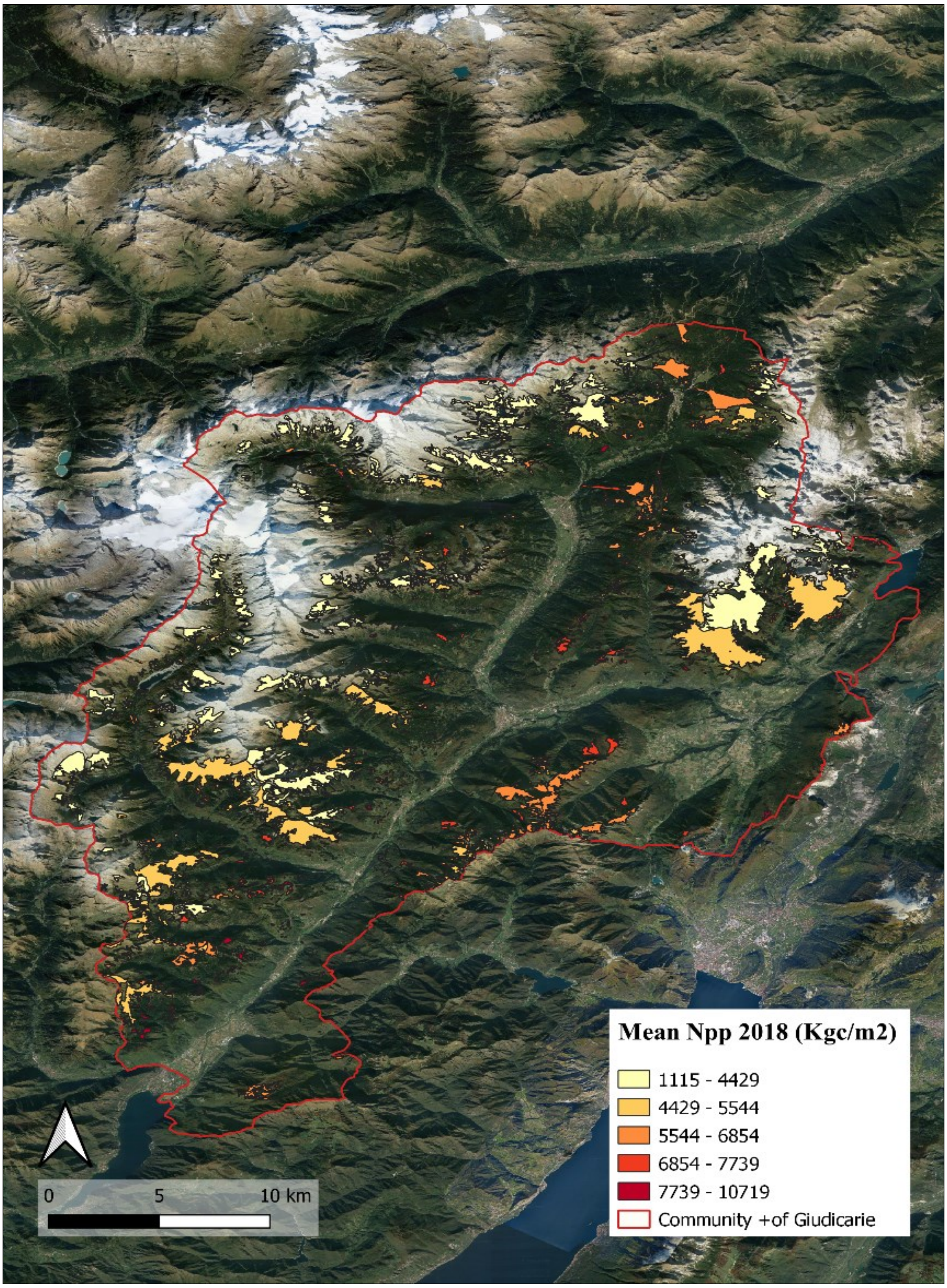

Figure 8: Map of Mean Npp in 2018

The figure 9 depicting Net Primary Productivity (NPP) over a 20-year period from 2001 to 2020 reveals significant fluctuations in NPP levels. Notably, the NPP displays a dynamic pattern, with evident peaks in 2007 and 2011, and a trough in 2013. These fluctuations likely stem from a combination of various environmental and climatic factors. One possible influence on NPP could be climate variability, including temperature and precipitation patterns, as these factors directly impact plant growth and photosynthesis rates. Additionally, land-use changes, such as deforestation or afforestation, could also contribute to the observed fluctuations by altering the composition of ecosystems. Other influences might include variations in nutrient availability, atmospheric CO2 concentrations, and disturbances like wildfires or insect outbreaks. Understanding the complex interplay of these factors is essential for accurately predicting and managing NPP in the face of ongoing environmental changes. Further research and data analysis could help refine these insights and contribute to sustainable land management and conservation strategies.

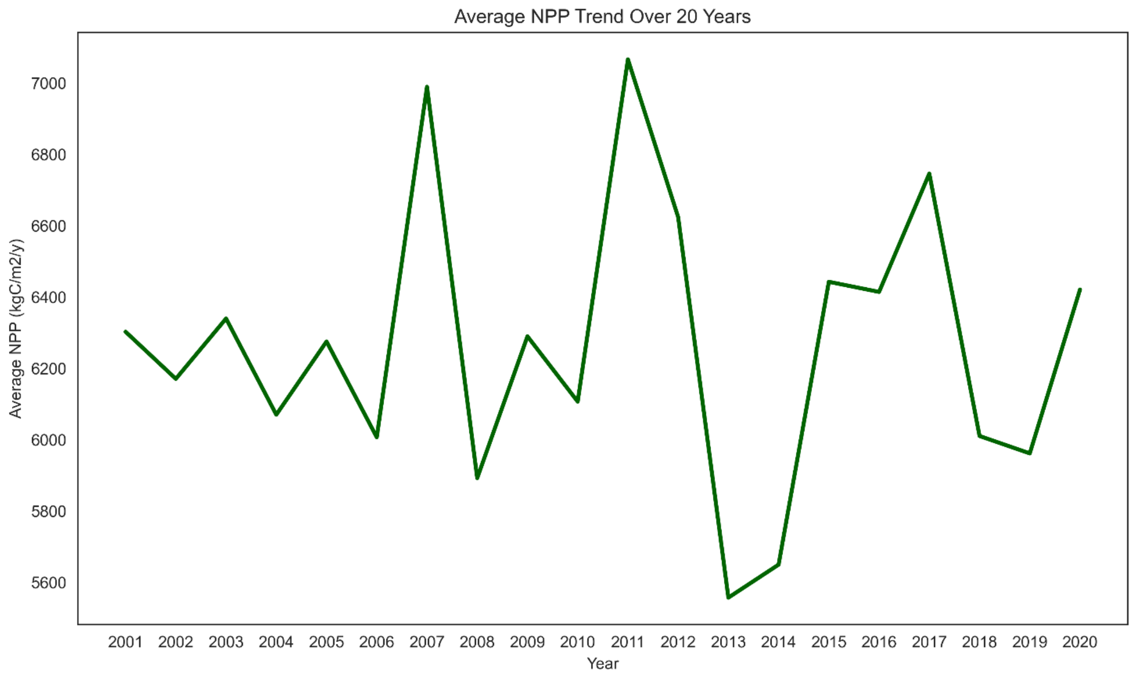

Figure 9: Npp trend over 20 years

3.2 Trends of NPP with environmental variables

Our focus extended beyond mere temporal patterns; we delved into understanding the intricate relationships between NPP and diverse environmental features and factors.

A methodical analysis of NPP's trending with a range of variables was conducted to identify the complex interactions and dependencies between NPP and these variables. The investigation aimed to determine the impact of variables on the observed variations in NPP, including climate factors, land use changes, environmental conditions, and other ecological determinants. By clarifying the complex relationships and contributing factors that underlie the fluctuations in NPP, this multifaceted analysis aims to deepen our understanding of the intricate dynamics within the grassland ecosystem over the studied timeframe."

- **Mean Temperature and mean NPP over 20 years**

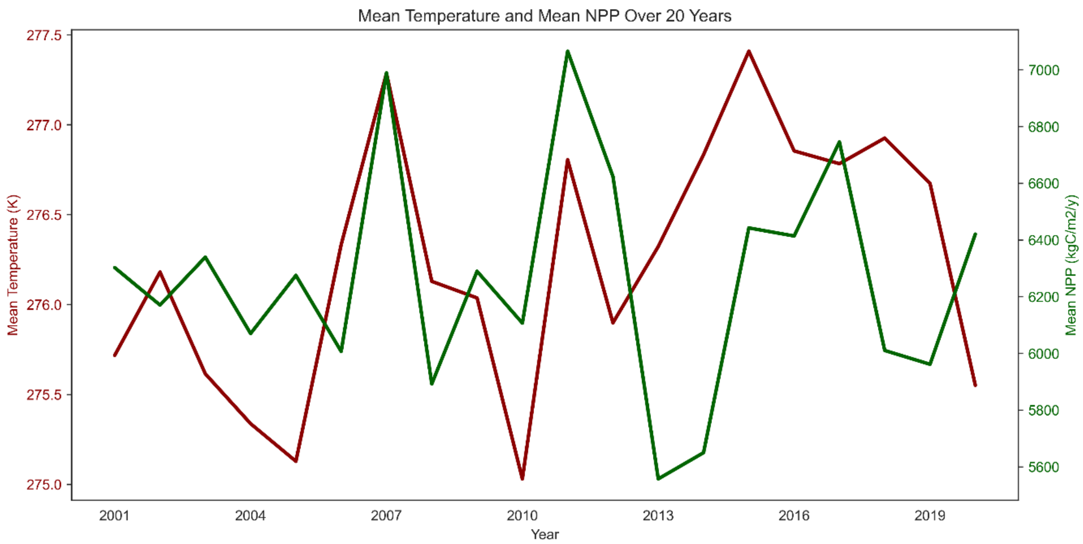

Figure 10: Mean Tc and Npp over 20 years

The figure 10 depicting the relation between Net Primary Productivity (NPP) and mean temperature (fig), with the red line representing temperature and the green line representing NPP, reveals an obvious dynamic.

It's evident from the graph that, for the most part, these two variables exhibit an inverse relationship, where higher temperatures correspond to lower NPP, and vice versa. The only exceptions to this trend are the years 2007 and 2011, during which the mean temperature and NPP align closely.

This discrepancy in the relationship between temperature and NPP can be attributed to a multitude of factors. In the years when temperature and NPP align, it is possible that other crucial environmental drivers, such as precipitation or nutrient availability, are offsetting the typically negative impact of higher temperatures on NPP.

Additionally, interannual climate variability, like extreme weather events or anomalies, can influence NPP independently of the general temperature trend.

- **Mean total precipitation and mean Npp over 20 years.**

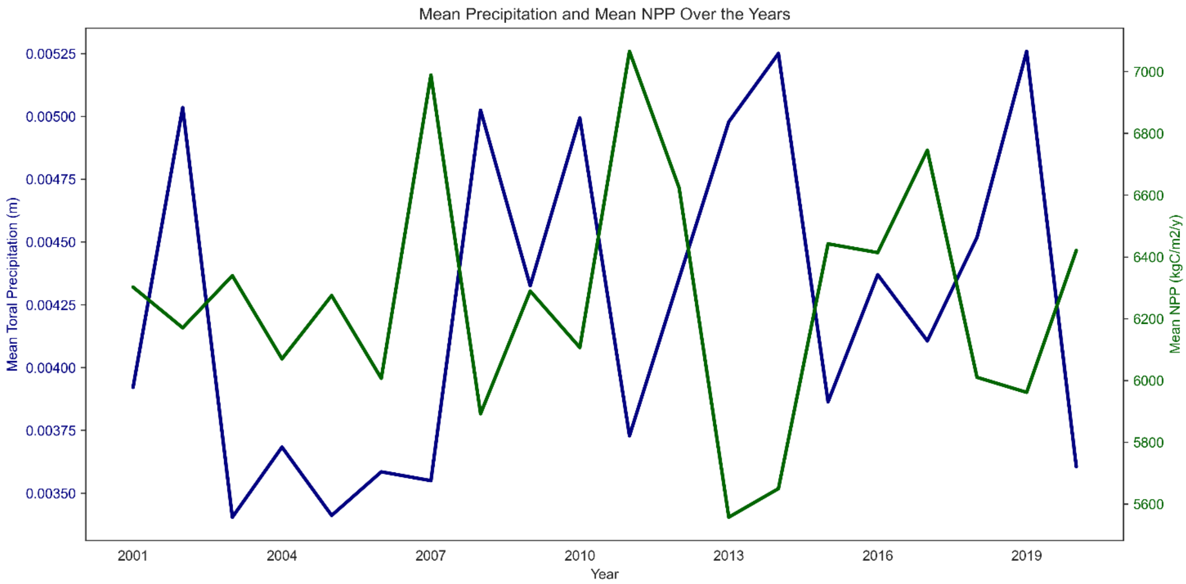

Figure 11: Mean total precipitation and mean Npp over 20 years.

The figure 11 illustrating the relation between mean total precipitation (blue line) and mean Net Primary Productivity (NPP, green line) reveals a striking and consistent inverse relationship between these two variables throughout the years (fig 6). In this dataset, the lines consistently move in opposite directions each year, suggesting that lowest mean total precipitation is associated with highest mean NPP, and vice versa. Interestingly, the years 2007 and 2011 stand out as the periods with the most pronounced divergence between the two patterns.

This intriguing finding raises several possibilities for interpretation. It's essential to consider that while precipitation is a critical factor for plant growth and NPP, excessive or untimely rainfall can lead to waterlogged soils, which hinder nutrient uptake and root respiration, ultimately impacting NPP negatively. Conversely, during drier years, plants may adapt by conserving water and energy, leading to a boost in NPP relative to the water availability. The significant discrepancies in 2007 and 2011 may be attributed to extreme precipitation events, illustrating the sensitivity of ecosystems to climate anomalies. Understanding this intricate relationship between precipitation and NPP is vital for ecosystem management, as it demonstrates that a nuanced approach is required when predicting NPP in the face of changing precipitation patterns.

- **Slope and Npp over 20 years**

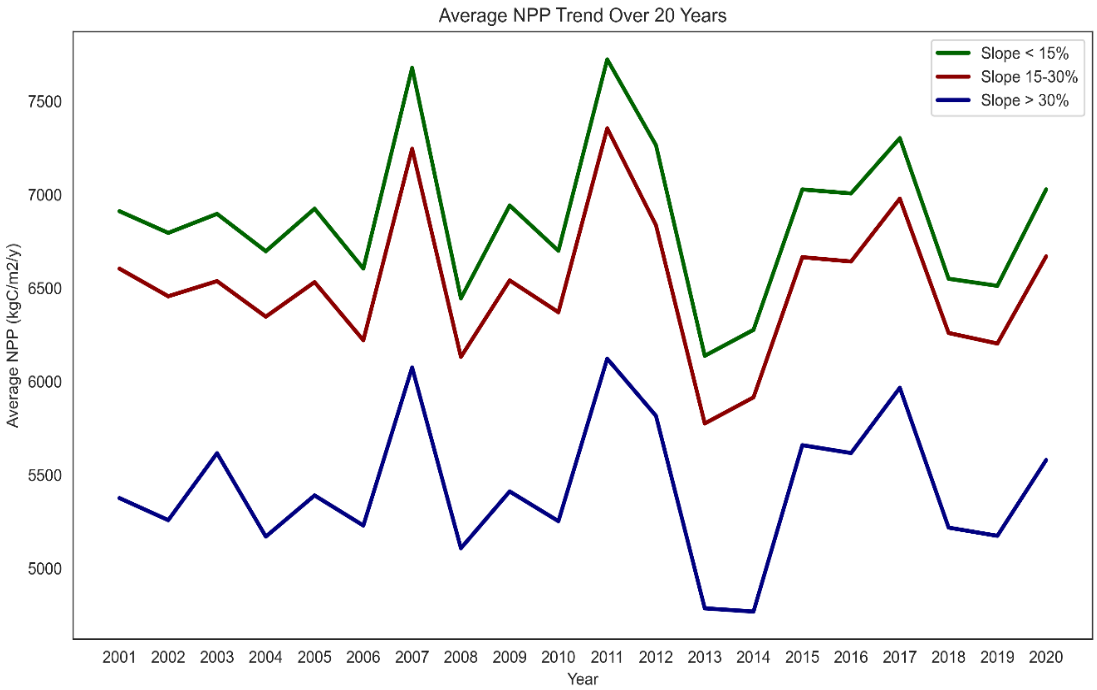

Figure 12: Slope and average Npp over 20 years

The figure 12 showcasing the relation between average slope and mean Net Primary Productivity (NPP) offers an intriguing perspective on how terrain inclination impacts NPP. The three lines, representing different slope categories (slope<15% in green, 15-30% in red, and slope>30% in another color), collectively reveal a positive correlation between slope and NPP. In other words, as NPP increases, so does the average slope, and vice versa. The years 2007, 2011, and 2017 appear as notable peaks in this relationship.

This observed pattern might be attributed to several factors. Ecosystems situated on steeper slopes which is mountainous and potentially less affected by human disturbances, making them conducive to thriving vegetation. Increased slope may also lead to better drainage, helping to avoid waterlogging and enhancing nutrient availability. Furthermore, steeper slopes can sometimes have higher elevation gradients, which could facilitate diverse microclimates and, in turn, boost NPP.

The peak correlation in 2007, 2011, and 2017 could be influenced by a combination of factors. Climate anomalies, shifts in land use, or variations in ecosystem health during these years might have affected the relationship between slope and NPP. Nevertheless, this positive correlation between slope and NPP underscores the significance of terrain characteristics in shaping ecological patterns, providing valuable insights for ecosystem management and conservation strategies, particularly in mountainous regions.

- **Average Npp and aspect over 20 years**

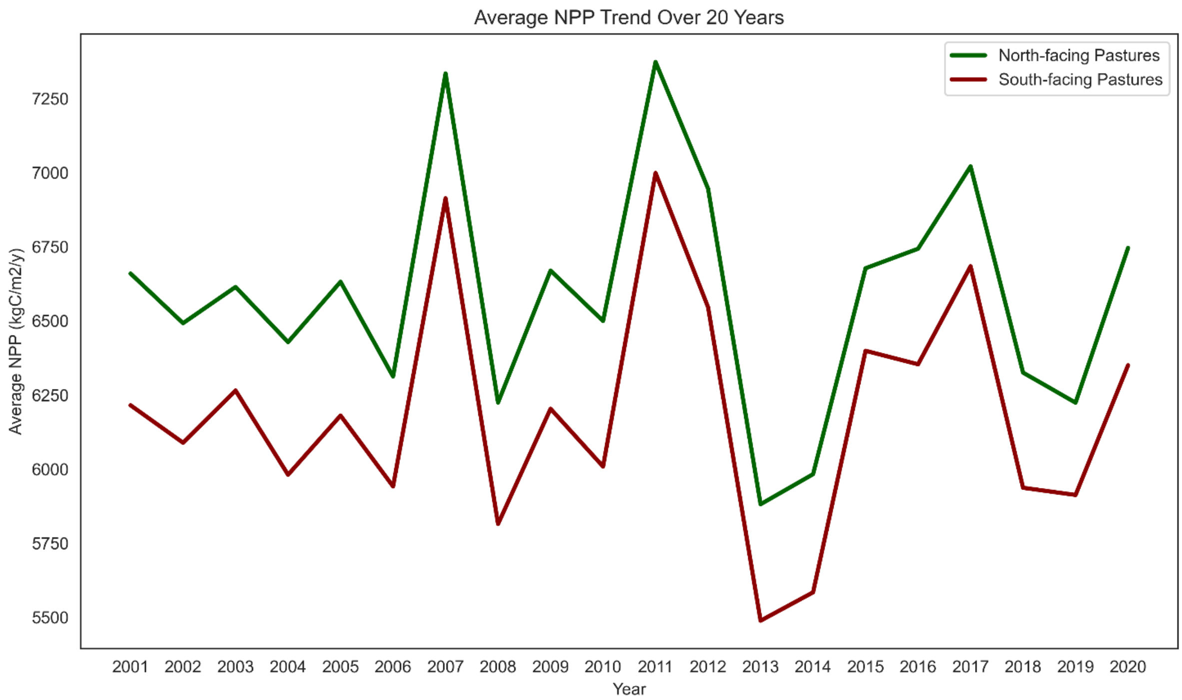

Figure 13: Correlation between average Npp and aspect over 20 years

The figure 13 depicting the relationship between the average Net Primary Productivity (NPP) over a 20-year period and aspect, distinguishing between North-facing pastures (in green) and South-facing pastures (in red), reveals a noteworthy relationship between these variables.

The lines, while moving in tandem, consistently show that NPP in North-facing pastures surpasses that in South-facing pastures. This pattern is evident throughout the 20-year span, with the most prominent peaks occurring in 2007, 2011, and 2017, and a noticeable trough in 2013.

Several factors could contribute to this phenomenon. Aspect, or the direction in which a slope faces, profoundly influences microclimatic conditions. North-facing slopes typically receive more consistent sunlight and warmth, promoting enhanced plant growth and photosynthesis. South-facing slopes, conversely, may experience more variable conditions, including higher temperatures and increased moisture stress, which could limit NPP.

- **Average Npp and altitude over 20 years**

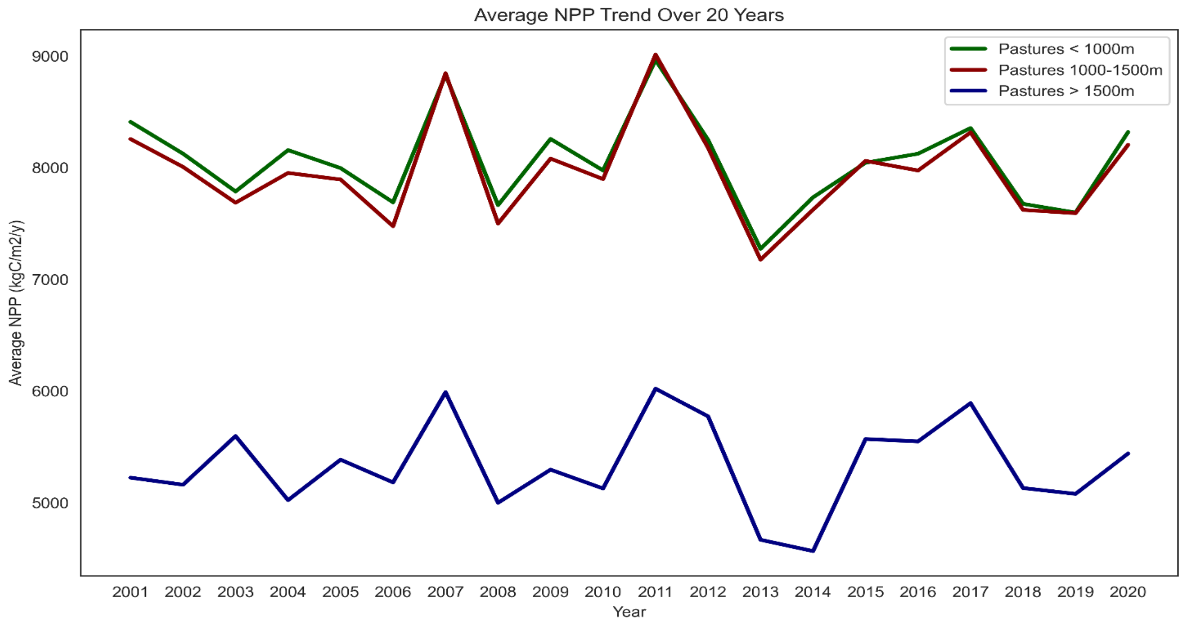

Figure 14: Average Npp and altitude over 20 years

The figure 14 examining the relationship between average Net Primary Productivity (NPP) over a 20-year period and altitude, categorized into three ranges (pastures below 1000m in green, pastures between 1000-1500m in red, and pastures above 1500m in blue) (fig 9), reveals an interesting relationship between these variables. Notably, the red and blue lines, representing pastures at higher altitudes, consistently exhibit higher NPP than the green line, representing lower-altitude pastures. These two lines move in parallel with each other, almost identically, but the blue line consistently maintains a lower NPP compared to the red.

The parallel movement of the blue line with the other two, albeit at a lower NPP level, suggests a correlation between altitude and NPP, with NPP generally increasing with higher altitudes. This pattern may be due to a combination of factors, such as cooler temperatures, increased moisture availability, and different vegetation communities typically found at higher altitudes.

The years 2007, 2011, and 2017 being the peak periods for all lines likely point to favorable climate conditions that benefitted NPP across all altitudes. Conversely, the dip in NPP around 2013-2014 may be attributed to unfavorable climate events or other disturbances that affected NPP negatively.

- **Mean Npp and Soil moinsture over 20 years**

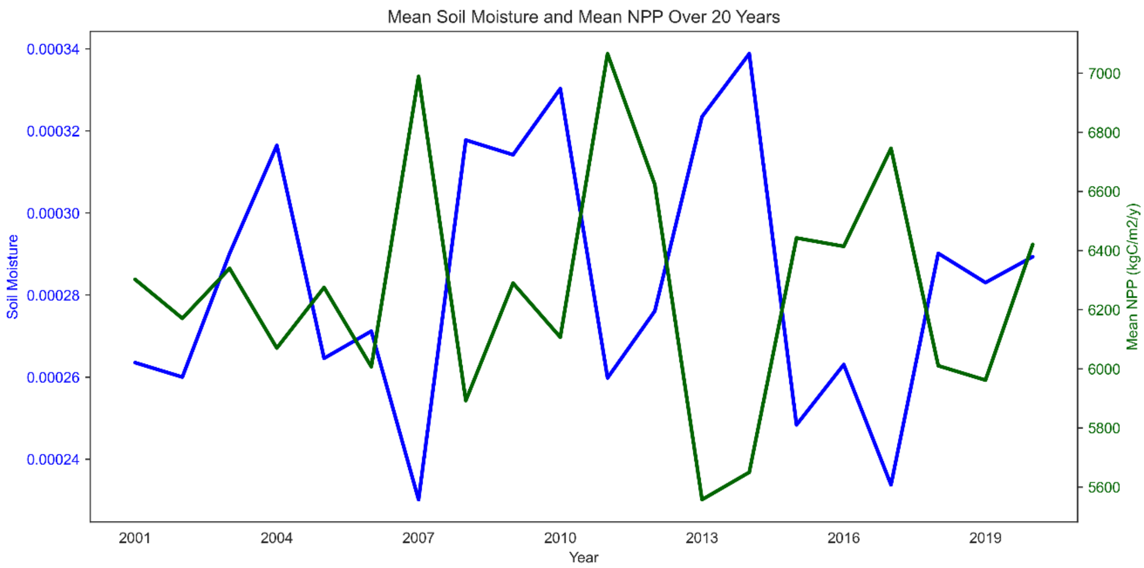

Figure 15: Mean Npp and soil moisture over 20 years

The analysis of the figure 15 depicting the cross-relationship between Mean NPP and soil moisture. the examination of the graph showing how soil moisture and mean NPP are correlated. Between these two variables, a significant inverse correlation appears over the 20 years, with the trends following opposing trajectories. Especially notable are the noticeable differences observed between 2007 and 2013, a pronounced elevation in mean NPP is distinctly observable, coinciding with a sharp decline in soil moisture levels, representing the highest peak in NPP and the contrasting lowest point in soil moisture within the analyzed period.

Conversely, in 2013, a stark reversal occurs, portraying the highest peak in soil moisture while registering the lowest point in mean NPP. The notable and disparate effects that variations in soil moisture levels can have on mean NPP are highlighted by the sharp swings in both variables during these years. The clearly observed inverse relationship highlights the complex interactions between soil moisture availability and NPP, emphasizing their susceptibility to changes in the environment and possibly acting as a vital sign of the resilience and health of the ecosystem over time.

- **Mean Npp and Soil temperature over 20 years**

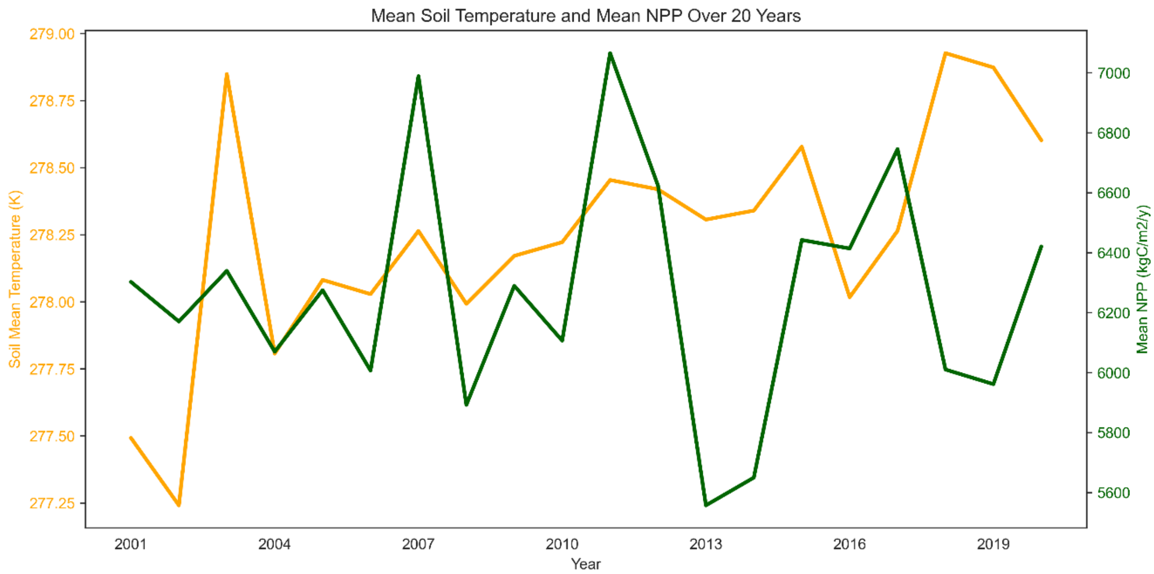

Figure 16: Mean Npp and Mean soil temperature over 20 years

Analyzing the figure 16 that shows the relationship between mean Net Primary Productivity (NPP) (green line) and mean Soil Temperature (yellow line) over time reveals a distinct relationship that is characterized by synchronized fluctuations and divergences. Notably, both variables display a parallel trend of increase and decrease, albeit at varying magnitudes. The year 2002 illustrates a notable disparity, showcasing a substantial peak in soil mean temperature, juxtaposed with a comparatively diminutive peak in NPP. However, 2007 and 2012 present striking contrasts, showcasing prominent peaks in NPP while exhibiting minimal increases in soil mean temperature. Of particular interest is the stark decline in NPP observed in 2013, despite soil mean temperature maintaining a relatively consistent level compared to preceding years. This divergence indicates a potential disruption in the relationship between these variables, signifying the intricate nature of their interdependency. The emergence of an inverse correlation between NPP and soil mean temperature in 2019 further underscores the evolving nature of this association. This evolving relationship accentuates the complexity of their interaction, implying potential shifts in environmental conditions or other underlying factors that influence the ecosystem dynamics. A thorough analysis of these variations reveals important information about how sensitive NPP is to changes in soil temperature, emphasizing its significance as a vital sign of the resilience and health of ecosystems. Subsequent exploration of the fundamental mechanisms underlying these divergent trends may reveal important aspects of ecosystem dynamics and how they react to shifting environmental cues.

- **Mean Npp and snow cover over 20 years**

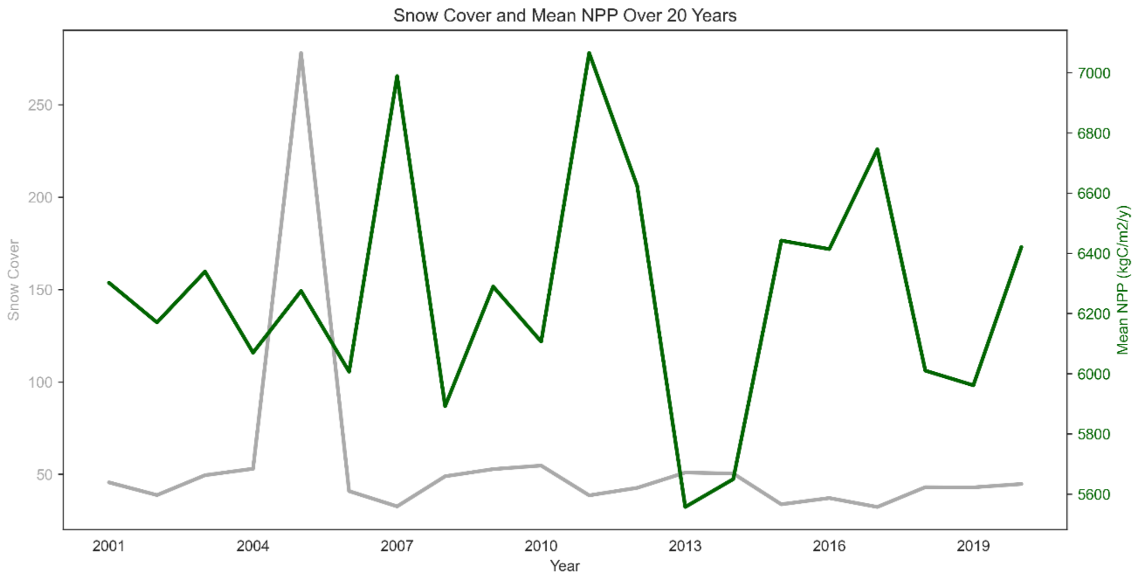

Figure 17: Mean Npp and snow cover over 20 years

An intricate relationship is revealed by analyzing the figure 17 that shows the correlation between mean Net Primary Productivity (NPP) (green line) and snow cover (grey line), indicating that there is no obvious direct correlation between these variables. The trends that have been observed over the course of the study indicate significant differences and equivocal relationships between mean NPP and snow cover.

A noteworthy event in 2005 corresponds to a significant maximum in snow cover, in contrast to a comparatively small rise in mean NPP. Following this, snow cover levels remain low for the remainder of the study, with varying peaks observed in the mean NPP in 2007 and 2012. Interestingly, these NPP peaks do not coincide with significant variations in snow cover, suggesting that there may not be a direct relationship or instantaneous correlation between the two variables. Moreover, the 2013 mean NPP low point does not line up with any notable changes in snow cover, highlighting the intricacy and possible independence of NPP from changes in snow cover during this time.

The lack of a clear correlation between mean NPP and snow cover suggests that there may be more complex ecosystem dynamics or underlying factors that have a major impact on NPP fluctuations. Even though the snow cover may have an impact on ecosystem productivity and health, its direct effect on mean NPP over the studied period looks to be inconclusive, requiring more thorough research and in-depth examination into other environmental factors that may be responsible for the trends in mean NPP that have been observed.

In conclusion, the analysed graphs underscore the importance of considering multiple environmental variables when assessing NPP patterns in ecosystems. These patterns are influenced by a complex interplay of factors, including climate, topography, and human activities.

Upon conducting a thorough analysis, a noteworthy finding was made regarding the relationship between precipitation and Net Primary Productivity (NPP) in the examined grassland ecosystem. Our analysis showed a remarkable and persistent inverse relationship between these variables, as opposed to certain others researches like the research study "Relationships between climate change, phenology, edaphic factors, and net primary productivity across the Tibetan Plateau" that observed a steady rise in NPP in response to increased precipitation levels through their paper:

"Interannual changes in the annual total NPP in the different ecosystems experienced a significant upward trend (slope > 0, $p < 0.05$) in the TP from 2000 to 2020, (Zhang et al., 2014). This phenomenon was inseparable from the impacts of climate change. The results demonstrated that NPP gradually increased with increasing precipitation, temperature, LOS, and soil temperature. A favorable water and heat environment provided important resources for plant growth (Niu et al., 2008, Ye et al., 2020).

Sufficient soil moisture guaranteed that plant photosynthesis operated normally when the light and CO_2 concentrations were sufficient (Gang et al., 2014, Sun et al., 2021a)".

The years 2007 and 2011 emerge as pivotal points in our analyses, displaying notable deviations from typical NPP patterns. These exceptional years likely result from a combination of factors, including climate anomalies or maybe the human influences.

In 2007, the sudden shift in NPP relationships may have been triggered by extreme weather events, such as droughts or heatwaves, which can significantly impact ecosystem productivity. Conversely, increased NPP in this year could be related to changes in land management practices, conservation efforts, or nutrient availability.

Similarly, 2011 showed distinctive patterns that can be attributed to variations in climate, land use, or potentially natural disturbances like wildfires. Additionally, the influence of rising atmospheric CO_2 levels, which can affect plant photosynthesis and NPP, might have played a role.

3.4 Machine learning Models

After comparing the effectiveness of different machine learning algorithms for NPP in our grassland ecosystem, the KNN Regressor proved to be the most efficient (Table3). The KNN Regressor performed better than other models, with a R^2 value of 0.886, the value that was closest to 1, and an exceptionally low Root Mean Square Error (RMSE) of 532.831 KgC/m2/y (table 4).

The machine learning derived model, which uses KNN algorithm and incorporates these environmental variables (slope, aspect, and elevation), is useful and practical for both temporal and spatial estimation of NPP in our study area. The model's adeptness in capturing temporal NPP dynamics is greatly enhanced by the inclusion of these variables, which play pivotal roles in governing ecological processes over time. Moreover, these variables' consideration within the model extends its utility to spatial estimation, offering a comprehensive framework to delineate NPP distributions across the landscape.

Table 4: Performance Evaluation of Machine Learning Algorithms for NPP Prediction

ML Algorithm	R2	RMSE (KgC/m^2/y)
Linear Regression	0.575	1028.348
Lasso Regression	0.438	1181.972
KNN Regressor	0.886	532.831
Random Forest	0.718	837.012
Gradient Boosting	0.706	854.623

Further studies from similar work like the following paper "Estimation and Spatio-Temporal Change Analysis of NPP in Subtropical Forests: A Case Study of Shaoguan,Guangdong, China" where three models applied, including the Random forest (RF), multiple linear regression (MLR), and BP neural network, to estimate forest NPP in the Shaoguan Guangdong, China by using Landsat images and National Forest Continuous Inventory (NFCI) data in the years 1997 to 2007 as the main data sources.

In that study show that the performance of the RF model is better than the MLR and BP neural network models. The selected variables were brought into three models, including the RF, MLR, and BP neural network, to establish forest NPP remote sensing estimation models, which were validated using 10-fold cross-validation.

Comparing the prediction accuracy of the three estimation models, the R2 of the RF (0.492–0.660) was higher than the MLR (0.307–0.532) and BP neural network (0.422–0.471) models in every year. RF sampling was performed twice. Firstly, the algorithm obtained a sampling set of training samples by random sampling with put-back. Then, a variable was randomly selected from all variables. Meanwhile, the best segmentation feature was selected as a node to build a classification and regression tree. The above reasons made the final model of RF have strong generalization and the highest prediction accuracy of NPP."

4. Conclusion

In conclusion, the development of an efficient model utilizing the K-Nearest Neighbors (KNN) algorithm which displaying superior performance, into estimating Net Primary Productivity (NPP) in both spatial and temporal dimensions represents a significant step in pasture management strategies.

However, while the model serves as a powerful predictive tool, the precision and accuracy it offers must be complemented by thorough fieldwork and real-time data collection is essential for refining and validating the model's estimations, ensuring its reliability and applicability in practical on-ground scenarios.

The utilization of our NPP estimation model plays a pivotal role in guiding strategic decisions concerning pasture management. Its predictive prowess aids in optimizing pasture utilization, identifying areas suitable for expansion, and prioritizing conservation efforts, particularly in ecologically sensitive zones. Furthermore, the model's temporal estimations provide indispensable insights into productivity trends, facilitating timely interventions and fostering sustainable land management practices. Empowering stakeholders with precise predictive tools, this model enables informed decision-making, allowing for proactive measures to address environmental changes impacting pasture ecosystems and can ensure the preservation and sustainable utilization of mountainous pastures.

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