Linkages between Atmospheric Circulation, Weather, Climate, Land Cover and Social Dynamics of the Tibetan Plateau

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Linkages between Atmospheric Circulation, Weather, Climate, Land Cover and Social Dynamics of the Tibetan Plateau

Shobha Kumari Yadav

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Linkages between Atmospheric Circulation, Weather, Climate, Land Cover and Social Dynamics of the Tibetan Plateau

Shobha K Yadav

Dissertation submitted
to the Eberly College of Arts and Science at West Virginia University
in partial fulfillment of the requirements for the degree of
Doctor of Philosophy in Department of Geology and Geography

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Department of Geology and Geography
Morgantown, West Virginia 2023

Keywords: Land use and land cover change, land-atmosphere interactions, land degradation, critical physical geography, geomorphon, remote sensing, Tibetan Plateau

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ABSTRACT

Linkages between Atmospheric Circulation, Weather, Climate, Land Cover and Social Dynamics of the Tibetan Plateau

Shobha Kumari Yadav

The Tibetan Plateau (TP) is an important landmass that plays a significant role in both regional and global climates. In recent decades, the TP has undergone significant changes due to climate and human activities. Since the 1980s anthropogenic activities, such as the stocking of livestock, land cover change, permafrost degradation, urbanization, highway construction, deforestation and desertification, and unsustainable land management practices, have greatly increased over the TP. As a result, grasslands have undergone rapid degradation and have altered the land surface which in turn has altered the exchange of heat and moisture properties between land and the atmosphere. But gaps still exist in our knowledge of land-atmosphere interactions in the TP and their impacts on weather and climate around the TP, making it difficult to understand the complete energy and water cycles over the region. Moreover, human, and ecological systems are interlinked, and the drivers of change include biophysical, economic, political, social, and cultural elements that operate at different temporal and spatial scales. Current studies do not holistically reflect the complex social-ecological dynamics of the Tibetan Plateau. To increase our understanding of this coupled human-natural system, there is a need for an integrated approach to rendering visible the deep interconnections between the biophysical and social systems of the TP. There is a need for an integrative framework to study the impacts of sedentary and individualized production systems on the health and livelihoods of local communities in the context of land degradation and climate change. To do so, there is a need to understand better the spatial variability and landscape patterns in grassland degradation across the TP. Therefore, the main goal of this dissertation is to contribute to our understanding of the changes over the land surface and how these changes impact the plateau's weather, climate, and social dynamics. This dissertation is structured as three interrelated manuscripts, which each explore specific research questions relating to this larger goal. These manuscripts constitute the three primary papers of this dissertation. The first paper documents the significant association of surface energy flux with vegetation cover, as measured by satellite based AVHRR GIMMS3g normalized difference vegetation index (NDVI) data, during the early growing season of May in the western region of the Tibetan Plateau. In addition, a 1°K increase in the temperature at the 500 hPa level was observed. Based on the identified positive effects of vegetation on the temperature associated with decreased NDVI in the western region of the Tibetan Plateau, I propose a positive energy process for land-atmosphere associations. In the second paper, an increase in Landsat-derived NDVI, i.e., a greening, is identified within the TP, especially during 1990 to 2018 and 2000 to 2018 time periods. Larger median growing season NDVI change values were observed for the Southeast Tibet shrublands and meadows and Tibetan Plateau Alpine Shrublands and Meadows grassland regions, in comparison to the other three regions studied. Land degradation is prominent in the lower and intermediate hillslope positions in comparison to the higher relative topographic positions, and change is more pronounced in the eastern Southeast Tibet shrublands and meadows and Tibetan Plateau Alpine Shrublands and Meadows grasslands. Geomorphons
were found to be an effective spatial unit for analysis of hillslope change patterns. Through the extensive literature review presented in third paper, this dissertation recommends using critical physical geography (CPG) to study environmental and social issues in the TP. The conceptual model proposed provides a framework for analysis of the dominant controls, feedback, and interactions between natural, human, socioeconomic, and governance activities, allowing researchers to untangle climate change, land degradation, and vulnerability in the Tibetan Plateau. CPG will further help improve our understanding of the exposure of local people to climate and socio-economic and political change and help policy makers devise appropriate strategies to combat future grassland degradation and to improve the lives and strengthen livelihoods of the inhabitants of the TP.
Dedication

For my parents and family.

For my husband and son.

Thank you for your love and support.
Acknowledgments

The journey has been long with so many ups and downs, twists, and turns; however, I met many nice people along this journey whom I am indebted to acknowledge here for their encouragement, support, and guidance in reaching the Ph.D. defense. I would never have been able to finish my dissertation without the guidance of my committee members, help from very kind and lovely friends, and support from my family. Just saying thank you is not enough to express how grateful I am.

I thank my committee chair, Dr. Aaron Maxwell, for his insightful comments and suggestions that enabled the completion of this dissertation. I would like to express my deepest gratitude to my advisor. I am grateful for his financial support for the summer of 2020 and 2021 and for the spring of 2023. Next, I would like to thank my dissertation committee members: Dr. Eungul Lee, Dr. Timothy Warner, Dr. Nicolas Zegre, and Dr. Jamie Shinn, who generously provided knowledge and expertise, and for being a part of my advisory committee and sharing their wealth of knowledge. They generously gave their time to offer me valuable comments toward improving my work. I would like to express my deepest gratitude to Dr. Eungul Lee, who provided me with constructive criticism, which helped me develop a broader perspective on my dissertation. His invaluable advice will benefit me throughout my life. I am also extremely grateful to Dr. Shinn for her valuable suggestion and guidance in improving my dissertation. Your discussion, ideas, and feedback have been invaluable. I would also like to thank Dr. Warner for his generously provided knowledge and expertise. I am very grateful to hi valuable and timely guidance during Fall of 2019 and Spring of 2020 while teaching 107: Physical geography class as an instructor. I cannot forget his incredible advice that helped me to navigate through the difficult time. My gratitude also goes to Dr. Nicolas Zégre. I learned so much from his class and I am thankful for his creative suggestions for my term project.

I would express my sincere gratitude to West Virginia University and the Department of Geology and Geography for giving me the opportunity to write this dissertation. To all the wonderful people of the Department of Geology and Geography. The entire Department of Geology and Geography at West Virginia University was a second home for more than seven years. All of the faculty, staff, and fellow graduate students provided a safe and dynamic place to study, argue, and research.

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The successful completion of this dissertation would not have been possible without these people's tremendous contributions. Just saying thank you is not enough to express how grateful I am. Thank you very much, everyone!

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<th>Description</th>
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<tbody>
<tr>
<td>ASTER</td>
<td>Advanced Spaceborne Thermal Emission and Reflection Radiometer</td>
</tr>
<tr>
<td>AVHRR</td>
<td>Advanced Very High-Resolution Radiometer</td>
</tr>
<tr>
<td>BFAST</td>
<td>Breaks for Additive Seasonal and Trend</td>
</tr>
<tr>
<td>CAPE</td>
<td>Convective available potential energy</td>
</tr>
<tr>
<td>CESM</td>
<td>Community Earth System Model</td>
</tr>
<tr>
<td>CMIP</td>
<td>Coupled Model Intercomparison Project</td>
</tr>
<tr>
<td>CPG</td>
<td>Critical Physical Geography</td>
</tr>
<tr>
<td>CRU</td>
<td>Climate Research Unit</td>
</tr>
<tr>
<td>CTPAS</td>
<td>Central Tibetan Plateau Alpine Steppe</td>
</tr>
<tr>
<td>DEMs</td>
<td>Digital Elevation Model</td>
</tr>
<tr>
<td>DHSVM</td>
<td>Distributed hydrology soil vegetation model</td>
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<tr>
<td>DTM</td>
<td>Digital terrain model</td>
</tr>
<tr>
<td>EAM</td>
<td>East Asian Monsoon</td>
</tr>
<tr>
<td>EASM</td>
<td>East Asian summer monsoon</td>
</tr>
<tr>
<td>ECMWF</td>
<td>European Center for Medium-Range Weather Forecasts</td>
</tr>
<tr>
<td>ECMWF</td>
<td>European Centre for Medium-Range Weather Forecasts</td>
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<tr>
<td>ENSO</td>
<td>El Niño and the Southern Oscillation</td>
</tr>
<tr>
<td>ESA</td>
<td>European Space Agency</td>
</tr>
<tr>
<td>ESRI</td>
<td>Environmental Systems Research Institute</td>
</tr>
<tr>
<td>ESTARFM</td>
<td>Enhanced spatial and temporal adaptive reflectance fusion model</td>
</tr>
<tr>
<td>ETM+</td>
<td>Enhanced Thematic Mapper Plus</td>
</tr>
<tr>
<td>GCM</td>
<td>General Circulation Model</td>
</tr>
<tr>
<td>GDEM</td>
<td>Global Digital Elevation Model</td>
</tr>
<tr>
<td>GEE</td>
<td>Google Earth Engine</td>
</tr>
<tr>
<td>GIMMS</td>
<td>Global Inventory Modeling and Mapping Studies</td>
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<tr>
<td>GIS</td>
<td>Geographical Information Systems</td>
</tr>
<tr>
<td>GUI</td>
<td>Graphical User Interface</td>
</tr>
<tr>
<td>HCRS</td>
<td>Household Contract Responsibility System</td>
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<tr>
<td>IQR</td>
<td>Interquartile range</td>
</tr>
<tr>
<td>IRI</td>
<td>International Research Institute for Climate and Society</td>
</tr>
<tr>
<td>IVC</td>
<td>Vegetation Classification</td>
</tr>
<tr>
<td>JJAS</td>
<td>June, July, August, and September</td>
</tr>
<tr>
<td>JRA</td>
<td>Japanese Reanalysis</td>
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<tr>
<td>LaSRC</td>
<td>Land Surface Reflectance Code</td>
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<tr>
<td>LBP</td>
<td>Local binary patterns</td>
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<tr>
<td>LD</td>
<td>Land Degradation</td>
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<tr>
<td>LOS</td>
<td>Line-of-sight</td>
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<tr>
<td>LTPs</td>
<td>Local ternary patterns</td>
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<tr>
<td>LULCC</td>
<td>Land Use and Land Cover Change</td>
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<tr>
<td>MODIS</td>
<td>Moderate Resolution Imaging Spectroradiometer</td>
</tr>
<tr>
<td>MSI</td>
<td>Multispectral Instrument</td>
</tr>
<tr>
<td>NASA</td>
<td>National Aeronautics and Space Administration</td>
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<tr>
<td>NCAR</td>
<td>National Center for Atmospheric Research</td>
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<tr>
<td>NCEP</td>
<td>National Centers for Environmental Prediction</td>
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<tr>
<td>Abbreviation</td>
<td>Description</td>
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<tr>
<td>NDVI</td>
<td>Normalized difference vegetation index</td>
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<tr>
<td>NetCDF</td>
<td>Network Common Data Form</td>
</tr>
<tr>
<td>NOAA</td>
<td>National Oceanic and Atmospheric Administration</td>
</tr>
<tr>
<td>NPP</td>
<td>Net primary production</td>
</tr>
<tr>
<td>NTPKMAD</td>
<td>North Tibetan Plateau-Kunlun Mountains Alpine Desert</td>
</tr>
<tr>
<td>OBIA</td>
<td>Object-based image analysis</td>
</tr>
<tr>
<td>OLI</td>
<td>Landsat 8 Operational Land Imager</td>
</tr>
<tr>
<td>PBLH</td>
<td>Planetary boundary layer height</td>
</tr>
<tr>
<td>QBSD</td>
<td>Qaidam Basin Semi-Desert</td>
</tr>
<tr>
<td>RCMs</td>
<td>Regional climate models</td>
</tr>
<tr>
<td>RLRG</td>
<td>Retire livestock and restore grassland</td>
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<tr>
<td>SETSM</td>
<td>Southeast Tibet shrublands and meadow</td>
</tr>
<tr>
<td>SPOT</td>
<td>Satellite Pour l’Observation de la Terre</td>
</tr>
<tr>
<td>SRTM</td>
<td>Shuttle Radar Topography Mission</td>
</tr>
<tr>
<td>TEOW</td>
<td>Terrestrial Ecoregions of the World</td>
</tr>
<tr>
<td>TM</td>
<td>Thematic Mapper</td>
</tr>
<tr>
<td>TP</td>
<td>Tibetan Plateau</td>
</tr>
<tr>
<td>TPASM</td>
<td>Tibetan Plateau Alpine Shrublands and Meadows.</td>
</tr>
<tr>
<td>TPE</td>
<td>Third Pole Environment</td>
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<tr>
<td>TPEORP</td>
<td>Observation and Research Platform</td>
</tr>
<tr>
<td>TPI</td>
<td>Topographic position index</td>
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<tr>
<td>WaTEM</td>
<td>Topography-based model</td>
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1. Introduction

The global environment and land surface have experienced an unprecedented rate of modification over the last few decades. Within the last millennia, humans have modified around 75 percent of the Earth's terrestrial surface (Luyssaert et al., 2014; Arneth et al., 2019), which has resulted in changes to surface energy budgets and has the potential to profoundly influence Earth's climate. As one of the most significant terrestrial ecosystems, grasslands impact and regulate temperature and the carbon cycle at the global scale (Zhang et al., 2018). Further, grasslands provide several ecological services and functions at both the regional and local scale including regulation of climate, carbon storage, tourism, aesthetical recreation, water resources control, pastoral production, and more (Dong et al. 2020). They are a vital part of terrestrial ecosystems and affect global climate change, food security, and ecological processes (Tian et al., 2021). Grassland conservation and management are crucial for sustainable local and regional socioeconomic growth and ecological security (Bi et al., 2020). However, as adverse anthropogenic activities and extreme weather events have escalated over the past several decades, ecological issues including the degradation of grasslands have sharply increased in many parts of the world (Liu et al., 2019; Zhang et al., 2016). Increased temperatures and altered precipitation patterns (Ravi et al., 2010) together with unsustainable land use practices, including overgrazing, urbanization, hydropower and transportation facilities development, and tourism (Tian et al., 2021) have resulted in degradation of around 49.3% of global grasslands (Gang et al., 2014), affecting millions of people worldwide (Wessels et al. 2012). Around 39.1% of global grassland degradation occurred between 2000 and 2019 (Liu et al., 2016). Studies have demonstrated that grassland degradation has developed into a significant environmental and socioeconomic issue that may eventually endanger the sustainable use of grassland resources and regional biogeochemical cycles (Wang et al., 2016).

Because of its geographical significance, which is comparable to Antarctica and the Arctic, the Tibetan Plateau (TP) is called the “Third Pole” and “water tower of Asia” (Qiu, 2008; Chen et al., 2020). It plays a significant role in the regulation and variations of regional weather and climate in east and south Asia, as well as the atmospheric circulation of the Northern Hemisphere (Flohn 1968; Wu et al. 2012). Due to its fragile ecosystem and complex geographic environment, the region is sensitive to global climate change and is regarded as the “sensor” of global climate change (Deng et al., 2022; Liang et al., 2022). The extensive grasslands of the TP cover an area of 1.5 million km², accounting for 60% of the TP and 30% of total Chinese grasslands (Cao et al. 2019; Dong et al. 2015). The vast grassland ecosystem of the TP has been used by Tibetans for grazing and sustaining their pastoral livelihood and culture for thousands of years (Li and Huntsinger, 2011). However, in recent decades the environmental and social systems that have evolved on the TP have undergone extreme interruptions due to climate change resulting from anthropogenic activities (Yang et al. 2014). The TP has warmed significantly; the surface temperature has increased by 1.8°C since the 1980s (Li et al. 2010; Yang et al. 2014) with a warming rate 1.5 times higher than the global average (Zhang et al. 2013).

Since the 1980s anthropogenic activities such as the stocking of livestock, land cover change, permafrost degradation, urbanization, highway construction, deforestation and desertification, and unsustainable land management practices have greatly increased over the TP (Cui and Graf 2009; Harris, 2010). As a result, grasslands have undergone rapid degradation due
to the dual effect of climate change and human land use practices (Harris, 2010; Liu et al. 2012; Wang et al. 2013). Xue et al. (2017) documented those anthropogenic activities, such as changing land-use practices, were the primary force driving grassland degradation in the TP. Currently, about 1.5 million km$^2$ of alpine grasslands in the TP are degraded, which has reduced the productivity of alpine grasslands by an estimated 30% over the last 20 years (Cui and Garf 2009, Dong et al., 2012).

Land degradation is a leading global issue that has an immediate impact on the well-being of millions of people around the world (Wessels et al., 2012). Many factors aggravate land degradation including unsustainable intervention by humans and extended periods of warming, torrential precipitation, and flooding associated with climate change. For the TP specifically, land degradation due to overgrazing and inappropriate land management practices (Yongnian, 2003) is a widespread phenomenon. The TP is ecologically fragile, making it vulnerable to different types of degradation (Li et al., 2010; Yang et al., 2014). At the same time, the Chinese government has initiated policies and plans in an attempt to control this degradation and implement measures to protect grasslands in the TP using sedentary and individualized production systems that differ from the traditional, Tibetan practices that developed over thousands of years (Foggin 2008). These conflicting practices have resulted in the further degradation of rangeland, further fueling the cycle of land degradation. However, the impacts of land degradation on climate and social vulnerability have not been well-researched using an integrated approach. For example, only a few studies have explored the impact of climate change on social vulnerability in the TP (Wang et al. 2014; Wu and Yan 2002; Yeh et al. 2014).

The climate exerts a significant impact on the terrestrial ecosystem. Similarly, the terrestrial biosphere influences climate through vegetative cover and soils and mediate energy and water balances at the land surface (Foley et al., 2003). Therefore, any alteration of the land surface can alter the exchange of heat and moisture properties between land and the atmosphere (Mahmood et al., 2014; Niyogi et al., 2010; Snyder, 2010). Hence, change in land surface properties can significantly impact the exchange of energy and the water budget in the TP. But gaps still exist in our knowledge of land-atmosphere interactions in the TP and their impacts on weather and climate around the TP, making it difficult to understand the complete energy and water cycles over the TP. Previous studies have focused on the variability of either atmospheric conditions (Jin et al. 2011; Yan et al. 2020; Zhao et al. 2020) or land surface conditions (Ma et al. 2020; Sun et al. 2017; Zhong et al. 2019). However, relatively few studies have examined the integrated associations between the land surface and atmosphere over the highland plateau (Babel et al. 2014; Liu et al. 2020; Shen et al. 2015). Additionally, there are only a few studies on the associations between climatic and land surface conditions over the alpine steppe grasslands in the western TP, compared to the eastern TP (Gong et al. 2017; Zhang et al. 2011).

The Normalized Difference Vegetation Index (NDVI) has been widely used as an indicator of vegetation occurrence and health and associated changes due to its correlation with energy absorption and photosynthesis activity (Tucker and Sellers, 1986; Xu et al. 2012; Zhu et al. 2013). Changes in NDVI generally correspond with increases and decreases in vegetation cover (Morawitz et al. 2006). The Global Inventory Modeling and Mapping Studies (GIMMS) NDVI product and time series derived from the Advanced Very High-Resolution Radiometer (AVHRR) sensor developed by the National Oceanic and Atmospheric Administration (NOAA) has been
extensively used in regional climate studies (Ibrahim et al. 2015; Zhu et al. 2013; Lee and He, 2018; Shull and Lee, 2019; He et al. 2018). Compared to its previous version (i.e., NDVIg), the AVHRR/2 to AVHRR/3 NDVI bias has been attenuated in the third generation NDVI3g, which greatly enhances the possibility to detect climate-related non-stationary seasonal and inter-annual variabilities (Pinzon and Tucker, 2014).

Human and ecological systems are interlinked, and the drivers of change include biophysical, economic, political, social, and cultural elements that operate at different temporal and spatial scales. Current studies do not holistically reflect the complex social-ecological dynamics of the Tibetan Plateau. To increase our understanding of this coupled human-natural system, there is a need for an integrated approach to rendering visible the deep interconnections between the biophysical and social systems of the TP. There is a need for an integrative framework to study the impacts of sedentary and individualized production systems on the health and livelihoods of local communities in the context of land degradation and climate change. To do so, there is a need to understand better the spatial variability and landscape patterns in grassland degradation across the TP. Therefore, the main goal of this dissertation is to contribute to our understanding of the changes over the land surface and how these changes impact the plateau’s weather, climate, and social dynamics. This dissertation is structured as three interrelated manuscripts, which each explore specific research questions relating to this larger goal. These manuscripts constitute the three primary chapters of this dissertation (Chapters 2-4). The titles and abstracts of each manuscript have been provided in this introduction section. Collectively, the goal of this dissertation is met by the work presented in these three manuscripts and by exploring the following objectives:

i. Examine the spatiotemporal distribution of vegetation from 1982 to 2015 in the Tibetan Plateau using the satellite-based vegetation index NDVI from AVHRR GIMMS3g (Chapter 2).

ii. Examine changes in the near-surface and upper-level climatic conditions associated with the vegetation change and identify plausible physical processes that could cause the observed vegetation effects on climate (Chapter 2).

iii. Explore patterns of grassland degradation at the Landsat scale (i.e., 30 m spatial resolution) using NDVI time series data from a prior study, digital terrain data, and geomorphons (Chapter 3).

iv. Critique the methodological approaches traditionally used in climate change and land degradation studies and offer insights from critical physical geography (CPG) for a more comprehensive approach to the study of complex human-natural dynamics within the Tibetan Plateau (Chapter 4).
2. Positive Associations of Vegetation with Temperature over the Alpine Grasslands in the Western Tibetan Plateau during May


Abstract

The Tibetan Plateau (TP) has undergone extreme changes in climatic and land surface conditions due to a warming climate and land cover changes. We examined the change in vegetation dynamic from 1982 to 2015 and explored the associations of vegetation with atmospheric variables over the alpine grasslands in the western TP during May as an early growing season. The linear regression analysis of area-averaged Normalized Difference Vegetation Index (NDVI) over the western TP in May demonstrated a 7.5% decrease of NDVI during the period from 1982 to 2015, an increase of NDVI by 11.3% from 1982 to 1998 and a decrease of NDVI by 14.5% from 1999 to 2015. The significantly changed NDVI in the western TP could result in the substantial changes in surface energy balances as shown in the surface climatic variables of albedo, net solar radiation, sensible heat flux, latent heat fluxes, and 2m temperature. The land and atmosphere associations were not confined to the surface but also extended to the upper-level atmosphere as indicated by the significant positive correlations between NDVI and temperatures up to 300 hPa level and resulting in a 1K increase in the temperature at the 500 hPa level. Therefore, we concluded that the increasing (decreasing) vegetation cover in the western TP during May can increase (decrease) the temperatures near the surface and upper atmosphere through a positive physical linkage among the vegetation cover, surface energy fluxes, and temperatures. The positive energy processes of vegetation with temperature could further amplify the variations of temperature, and thus water availability.

**Keywords:** Vegetation Changes, Land Cover/Land Use Changes, Land-Atmosphere Interactions, Positive Energy Process, Alpine Grasslands, Tibetan Plateau

Significance Statement

The Tibetan Plateau (TP) is an important landmass that plays a significant role in both regional and global climates. This study aims to examine the vegetation change in the TP during May as an early growing season, to examine the changes in the near-surface and upper-level climatic conditions associated with vegetation change, and to identify the plausible physical processes of the vegetation effects on atmosphere. The satellite-derived vegetation index showed 7.5% decrease from 1982 to 2015 in the western TP during May. This study identified the positive associations of vegetation activity with temperature and proposed a positive energy process for land-atmosphere interactions over the alpine grasslands in the western region of TP during the transition period from winter to spring.
2.1. Introduction

The long-term atmospheric conditions exert a significant impact on the terrestrial ecosystem. Similarly, the terrestrial ecosystem influences climate through vegetative cover and soils and mediates energy and water balances at the land surface (Foley et al. 2003). Vegetation plays a vital role in carbon exchange between the land and atmosphere, making it a key component of the terrestrial ecosystem (Cleland et al. 2007; Liu et al. 2015). Changes in vegetation can impact not only the carbon cycle but energy and water cycles and have significant and broad implications on hydrology and climatology (Nemani, 2003; Zhang et al. 2016). Any alteration of the vegetation dynamic, therefore, can alter the exchange of heat and moisture properties between the land and atmosphere (Lee et al. 2009; Mahmood et al. 2014; Niyogi et al. 2010; Snyder, 2010).

The impact of land cover change on climate have been extensively studied using observed as well as modelled data (Pielke et al. 2011; Mahmood et al. 2014). Numerous studies have shown that even a small change in land surface conditions can affect local as well as regional climates (e.g., Cao et al. 2015; Chase et al. 1996; Foley et al. 2005; Pielke, 2005). Understanding and modeling land and atmosphere coupling relating to land cover change and regional climate continues to be a major research need in land-atmosphere interaction studies and studying these processes is inherently challenging and complex (e.g., Santanello et al. 2018). In an early study, Charney (1975) first presented a theory of how a reduction in vegetation might feedback to produce a decrease in rainfall through land-atmosphere interactions. Changes in land cover can modify surface roughness and impact heat and moisture exchange between the land surface and atmosphere and eventually can modulate temperature and precipitation (Boyaj et al. 2020; Chen et al. 2020; Pielke et al. 2016; Pielke and Niyogi 2010; Ahmad et al. 2020). For instance, Boyaj et al. (2020) examined the impact of urbanization on rainfall in peninsular India and observed that increased surface temperatures, sensible heat flux, planetary boundary layer height (PBLH), water vapor mixing ratio, and convective available potential energy (CAPE), resulting in the increased rainfall. Chen et al. (2020) studied land use cover change impact on hydroclimate using the Weather Research and Forecasting (WRF) model simulations and identified the intensified precipitation over the downwind areas of urban and built-up lands in central Taiwan. Further Pielke et al. (2016) revealed that changes in land cover impact climate at local and regional scales and can produce significant spatial variation in climate-system fluxes which can influence weather pattern of distant through teleconnections. Over the past several centuries, the globe has witnessed the unprecedented changes in the pace, magnitude, and spatial extent of changes in the land surface, which could result in changes in surface energy and water budgets and thus regional as well as global climates. As a result, changes in land variables and their impacts on land-atmosphere interactions, and ultimately on climate, have been investigated throughout the world at various spatial and temporal scales (Bonan, 2008).

Land-atmosphere interactions encompass two key biogeophysical processes that have significant implications on the thermal, hydrological, and aerodynamical characteristics of the planetary boundary layer (Mahmood et al. 2014). The first process constitutes energy feedback through albedo and the partitioning of radiation into sensible and latent heat fluxes (Pielke et al. 1998). Land surface characteristics, such as soil and vegetation properties, can alter the exchange of heat and moisture between the land and atmosphere through energy, momentum, and moisture exchanges (Foley et al. 2005; Niyogi et al. 2010). Therefore, any perturbation in land surface
characteristics due to urbanization, agriculture intensification, grassland degradation, deforestation, or afforestation can result in shifting the albedo and turbulent heat flux regimes. For instance, the removal of vegetation may increase albedo, resulting in less energy available for transferring to the lower atmosphere and a disturbance of the balance between sensible heat flux and latent heat flux. This further induces atmospheric subsidence thereby reducing rainfall (Charney, 1975). This results in a positive feedback loop, as the drier conditions cannot sustain the vegetation. These perturbations can further reduce vegetation cover and increase albedo, resulting in a decrease in precipitation, drier conditions, and further reduction through the positive feedback (Charney, 1975; Lee et al. 2015).

The second feedback mechanism, moisture feedback, occurs through a change in moisture content driven by evapotranspiration. Such processes have been described and quantified in several prior studies (Douglas et al. 2006, 2009; Koster, 2004; Lee et al. 2009). Soil moisture plays a crucial role in land-atmosphere interactions and modulation of the water cycle (Bao et al. 2010; Betts et al. 1996) through the modification of latent heat flux and atmospheric moisture flux convergence (Foley et al. 2005; Sud et al. 1996). The water availability in the soil regulates evapotranspiration which in turn modulates air temperature and humidity in the lower atmosphere (Erdenebat and Sato, 2018). For instance, the elevated soil moisture inducing greater evaporation provides an increased moisture source for enhanced precipitation which further increase soil moisture (Dirmeyer et al. 2006; Meehl, 2004). At the same time, soil moisture can also enhance cooling effects through the partitioning of radiative heat flux into latent heat, inducing negative effect on temperature. However, the preexisting environmental conditions, which vary over spatial scales, determine the feedback mechanism. For instance, Yang et al. (2018) observed a predominant positive soil-precipitation feedback over land surfaces and a contrasting negative feedback across dry and wet regions. The interaction between soil moisture and precipitation is often complex and involves confounding factors (Tuttle and Salvucci, 2016).

Inter-relations of energy and moisture feedbacks, govern the land-atmosphere interactions, vary among different land cover types. For example, conversion of natural vegetation to croplands can increase or decrease temperature depending on whether conversion occurs in tropical, temperate, or boreal areas and can increase or decrease humidity depending on the type of natural vegetation replaced and the type of crops established (Bounoua et al. 2002). These changes can impact the thermodynamic conditions and the general circulation of air masses far from the original surface forcing (Snyder et al. 2004). A review of dominant forcing in three different vegetation type, tropical forests, boreal forests, and temperate forests, was proposed by Bonan (2008). According to the Bonan’s study, tropical forests are dominated by moisture (cooling) feedback whereas boreal forests are dominated by energy (warming) feedback due to low surface albedo that leads to the absorption of incoming solar radiation. However, the land and atmosphere feedback in the temperate region, especially over the highland plateau, is still complex and currently undecided.

The Tibetan Plateau (TP), with its unique topographical and physiographical characteristics, is an important landmass that plays a significant role in both regional and global climate (Wu et al. 2012). The mechanical and thermodynamic forcing of the TP is crucial in influencing the regional climate and the Asian monsoon systems (Duan et al. 2012). Due to its location and elevation, the TP has a significant and globally unique impact on the atmosphere.
The complex interactions of land-surface processes and conditions, linked to vegetation, surface energy balance, snow cover, soil moisture, and frozen soil, with the atmosphere play an important role in modulating the local, regional, and global climates (Gao et al. 2016). Therefore, the land-atmosphere interactions over the TP can influence the large-scale atmospheric circulations not only in Asia but the entire globe by absorbing a large amount of incoming solar radiation with marked seasonal variations (Duan et al. 2011; 2012). The complicated boundary-layer processes resulting from differences in land surface variables over the TP could lead to frequent rainfall and flooding in eastern China during summer (Tao and Ding, 1981). The strong surface heating over the TP is also a fundamental factor in producing inter-annual variability of the East Asian summer monsoon (EASM) and numerous studies have observed a strong correlation between winter TP snow cover and the EASM (Wu et al. 2016; Zhang et al. 2004).

In recent decades, the environmental systems of the TP have undergone extreme changes due to climatic change and variability (Yang et al. 2014). The plateau has warmed significantly, and the surface temperature has increased by 1.8 °C since the 1980s, which has had a significant impact on the transfer of heat, moisture, and momentum from the ground to the atmosphere (Yang et al. 2014), which could further exaggerate the changing climates over the TP region through the land-atmosphere feedback mechanisms. Additionally, anthropogenic activities such as stocking of livestock, land cover change, over grazing, urbanization, highway construction, deforestation and desertification, and unsustainable land management practices have greatly increased over the TP (Cui and Graf, 2009; Harris, 2010). As a result, grasslands have undergone rapid degradation since the 1980s due to the dual effect of climate change and human activities (Harris, 2010; Cao et al. 2019). Babel et al. (2014) indicated that there is reduction in transpiration and increase in evaporation due to pasture degradation over the TP. The study conducted by Wu et al. (2015) revealed that there was increase in near-surface temperature because of grassland degradation in the Inner Mongolia. Cao et al. (2015) suggested increase in winter temperature and subsequent decrease in summer temperature through the modification of surface energy budget due to land cover changes from croplands to grasslands and grasslands to barren land in the agro-pastoral transitional zone of North China. On the other hand, Shen et al. (2015) showed an evapotranspiration induced cooling effect due to increase in vegetation activity in the growing season from May to September over the TP, resulting in negative feedback between climate and vegetation. The TP soil temperature and number of thawing days have also significantly increased from 1980 to 2005, resulting in drying of soil and a reduction in precipitation (Xue et al. 2009). These changes can further modify the ecosystem and consequently affect the regional, and potentially Asian, climates (Cao et al. 2018; Wu et al. 2016), which could threaten billions of people’s lives downstream (Hua and Wang, 2018; Wang, 2016).

But gaps still exist in our knowledge of land-atmosphere interactions in the TP and their impacts on the weather and climate around the TP, making it difficult to understand the complete energy and water cycles over the TP. The previous studies have focused on the variabilities of either atmospheric conditions (e.g., Jin et al. 2011; Yan et al. 2020; Zhao et al. 2020) or land surface conditions (e.g., Ma et al. 2020; Sun et al. 2017; Zhong et al. 2019). However, relatively few studies examined the integrated associations between land surface and atmosphere over the highland plateau (e.g., Babel et al. 2014; Liu et al. 2020; Shen et al. 2015). Additionally, there
are only a few studies on the associations between climatic and land surface conditions over the alpine steppe grasslands in the western TP, compared to the eastern TP (Gong et al. 2017; Zhang et al. 2011). Therefore, this study aimed to examine the changes in vegetation dynamic from 1982 to 2015 and to explore its effect on vegetation and climate interactions over the alpine grasslands in the western TP during May as an early growing season. The growing season of grasslands in the TP starts in early May and ends in late September (Wang et al. 2016).

The Normalized Difference Vegetation Index (NDVI) has been widely used as a vegetative index due to its correlation with energy absorption and photosynthesis activity, and its success as an indicator of vegetation change information (Tucker and Sellers, 1986; Xu et al. 2012; Zhu et al. 2013). The NDVI products derived from the Global Inventory Modeling and Mapping Studies (GIMMS) of the Advanced Very High-Resolution Radiometer (AVHRR) developed by the National Oceanic and Atmospheric Administration (NOAA) has been extensively used in climate study (e.g., Ibrahim et al. 2015; Zhu et al. 2013; Lee and He, 2018; Shull and Lee, 2019; He et al. 2018). Compared to its previous version (i.e., NDVIs), the AVHRR/2 to AVHRR/3 NDVI bias has been attenuated in the third generation NDVI3g, which greatly enhances the possibility to detect climate-related non-stationary seasonal and inter-annual variabilities (Pinzon and Tucker, 2014). Thus, the objectives of this study are, to examine the spatiotemporal distribution of vegetation in the TP during an early growing season using the satellite-based vegetation index NDVI from GIMMS3g, to examine the changes in the near-surface and upper-level climatic conditions associated with the vegetation change in May, and to identify the plausible physical processes of the vegetation effects on climate in the western TP to depict the land and atmosphere interactions over the alpine grasslands.

2.2. Data and methods

2.2.1. STUDY AREA

The Tibetan Plateau is the largest continental plateau on the earth and is therefore known as the “roof of the world”. The TP is situated in central and eastern Asia (Figure 1) with an average elevation of 4,000 m (Huang et al. 2016; Kuang and Jiao, 2016). It is a sensitive and ecologically fragile area that plays a vital role in global climate conditions and change (Gao et al. 2016; Liu and Chen, 2000). Because of its complex topography and sensitive climate, it is regarded as one of the hot spots in climate change study and served as indicator area for climate change (Peng et al. 2014; Yao et al. 2012). The mean annual temperature of the plateau varies from -5 to 10 °C (Huang et al. 2016) with mean annual precipitation of about 100 to 1,000 mm with high spatial variability from high in the southeast to low in the northwest (Wang et al. 2015). The climate is warm and humid in the southeast and cold and arid in the northwest, with marked wet and dry seasons (Li et al. 2014). The TP monsoon climate is mainly controlled and influenced by a complex interaction of the Indian monsoon, the westerlies, and to a lesser extent by the East Asian monsoon (Yao et al. 2012). The summer monsoon accounts for 60-70% of the total annual precipitation in the TP whereas winter accounts for only 10% (Bookhagen and Burbank, 2010; Tong et al. 2014) and the snow accounts for a large portion of precipitation on the TP (Maussion et al. 2014).
Grassland types
- Central Tibetan Plateau alpine steppe
- Eastern Himalayan alpine shrub and meadows
- Karakoram-West Tibetan Plateau alpine steppe
- North Tibetan Plateau-Kunlun Mountains alpine desert
- Northwestern Himalayan alpine shrub and meadows
- Qaidam Basin semi-desert
- Qilian Mountains subalpine meadows
- Southeast Tibet shrublands and meadows
- Terai-Duar savanna and grasslands
- Tibetan Plateau alpine shrublands and meadows
- Western Himalayan alpine shrub and Meadows
- Yarlung Tsango arid steppe

Figure 1: Grassland types over the Tibetan Plateau (TP), derived using International Vegetation Classification (IVC) grassland types and the map of Terrestrial Ecoregions of the World (TEOW), as suggested by Dixon et al. (2014). The study area of this study was indicated with the dotted box. The map was generated in ArcGIS Pro.

There is spatial difference in vegetation types both horizontally and vertically due to difference in hydrothermal environment in the TP (Huang et al. 2019). The high altitudes are cold whereas low altitudes are hot and humid in the TP. Therefore, land cover on the TP varies greatly and includes forests, grasslands, permanent snow and ice, croplands and bare land (e.g., Cheng et al. 2018; Wang et al. 2020; Zhou et al. 2020), with grasslands as a prevailing type. The deciduous, evergreen, and mixed forests were mainly in the eastern and southeastern region of the TP (Huang et al. 2019). Around 70% of the TP was covered by permafrost with moisture content, and thus supported more vegetation growth in comparison to seasonally frozen soil regions (Wang et al. 2017). The alpine steppe and meadow were the dominant grassland type covering around 50% to 60% of the area, making alpine grasslands principal vegetation of the TP (e.g., Liu et al. 2017; Wang et al. 2015; Wei et al. 2019). The growing season of grasslands in the...
TP starts in early May and ends in late September (Gao and Liu, 2013). The vast grassland ecosystems of the TP have been used by Tibetans for grazing and sustaining their pastoral livelihood and culture for thousands of years (Wei et al. 2019). The western TP mainly consists of alpine steppe along with alpine meadows and deserts as shown in Figure 1, based on International Vegetation Classification (IVC) grassland types and the map of Terrestrial Ecoregions of the World (TEOW), as suggested by Dixon et al. (2014).

The study area is a region of mainly alpine steppe in the western TP, as indicated by the dotted box in Figure 1 (i.e., 30-35 °N and 80-90 °E), in which a few studies have focused on the associations between vegetation and climate. According to vegetation map of the TP thus supporting more vegetation growth compared one of the alpine meadows to alpine steppe. We examined the vegetation dynamics during the month of May as our study period, because May is the start of the growing season as well as the pre-monsoon season. The climatic condition over the TP in the pre-monsoon season has tremendous implications on the Asian monsoon (Zhang et al. 2011). Therefore, the vegetation dynamics in May is of great significance not only for local climate but also for the regional climate. Also, the linear regression trend of May NDVI over the TP revealed overall a significant decreasing trend of NDVI from 1982 to 2015 with a decrease in the NDVI by 7.5% for the thirty-four years (see Figure 5). Thus, the change of vegetation dynamic in May from 1982-2015 was selected to study the association of vegetation variability with the surface fluxes and upper atmosphere over the alpine grasslands in the western TP.

2.2.2. DATA SOURCES

a. Vegetation Data

The remotely sensed NDVI has been extensively used to quantitatively assess vegetation dynamics and health (Eckert et al. 2015; Huang et al. 2019). NDVI is a key indicator of vegetation cover and structure, photosynthetic activity, and other vegetation traits (Tucker and Sellers, 1986). The index is a good indicator of net primary productivity, vegetation coverage, leaf area index, and biomass. Therefore, changes in NDVI generally reflect changes in vegetation coverage (Morawitz et al. 2006). NDVI has been extensively used in climate and atmosphere interaction studies in Asia (e.g., Lee and He, 2018; He et al. 2018). The NDVI computed from the red (RED) and near-infrared (NIR) ratio of vegetation reflectance in the electromagnetic spectrum (i.e., \( \text{NDVI} = \frac{(NIR - RED)}{(NIR + RED)} \)) (Prince et al. 2009) and its values range from -1.0 to +1.0, with positive values representing some greenness or photosynthetic activity and negative values representing snow or other surfaces with no vegetation (Gillespie et al. 2019; Tucker et al. 2005).

In this study, we used the GIMMS third generation NDVI (NDVI3g) from 1982 to 2015, with a pixel scale of 1/12° (Tucker, 2005; Pinzon and Tucker, 2014). Temporally, the NDVI3g comprised bimonthly (15 days) composites generated using the maximum value composite (Holben, 1986). It is a source of the longest time-series of global imagery available for land cover change, vegetation phenology, and dynamic studies (Peng et al. 2012; Wu et al. 2015). The GIMMS NDVI3g has been shown to effectively remove artifacts caused by changes in factors such as orbital drift, cloud cover, volcanic aerosols, and solar zenith angle (Pinzon and Tucker, 2014). The dataset used for this study was obtained from the Global Land Cover Facility at the University of Maryland which comprises bimonthly values for the time span of July 1981
to December 2015 at a grid increment of 0.08° with WGS84 datum. Figure 2 shows annual and May climatology of the NDVI distribution in the TP based on GIMMS NDVI3g dataset from 1982 to 2015. The NDVI values in the study area of western TP during May ranges between 0 and 0.2, generally increasing from northwest to southeast (Figure 2b).

\( T_E = T + T_M \) \hspace{1cm} (1)

where \( T \) is the air temperature and \( T_M \) is the moisture content of the air temperature which is given by Eq. (2).

**Figure 2:** Average (a) Annual and (b) May NDVI climatology over the TP using the GIMMS NDVI3g datasets from 1982-2015. The study area is indicated by the dotted box.

b. Atmospheric data

We used reanalysis data from the European Centre for Medium-Range Weather Forecasts (ECMWF), hereafter ERA5 (Hersbach et al. 2020). ERA5 is the fifth generation of ECMWF atmospheric reanalysis of the global climate. It is the latest data from ECMWF with a horizontal grid increment of 0.25° x 0.25° on a regular latitude-longitude grid stratified by 37 pressure levels for atmospheric variables and 0.1° x 0.1° for land variables (i.e., ERA5-Land). The data were available from 1979 for atmospheric reanalysis and from 1981 for ERA5-Land. To be consistent with the GIMMS NDVI3g, data from 1982 to 2015 were used. The land variables from ERA5-Land were used to investigate the effects of vegetation dynamics on near surface climate using albedo, net solar radiation, sensible heat flux, latent heat flux, 2 m air-temperature (K), temperature at pressure levels (K), specific humidity (kg/kg), and mean sea level pressure. The effects of vegetation dynamics on the upper atmosphere were examined using temperatures (K) from 500 to 100 hPa levels. The surface net solar radiation, sensible heat flux and latent heat flux, which are in units of J/m², and mean sea level pressure in Pa, were converted to W/m² and hPa, respectively. We calculated the annual means of equivalent temperature (\( T_E \)) by using the equations using the ERA5 variables of air temperature (K) and specific humidity (kg/kg) at the different levels of 700 and 500 hPa, respectively (Younger et al., 2018). The \( T_E \) includes both dry and moist heat content and thus provides a more complete measure of changes in the near-surface energy budget (Zhang et al., 2019). Also, \( T_E \) corresponds to moist enthalpy (Davey et al., 2006; Fall et al., 2010). In this study, we have used monthly averaged data of temperature at different pressure levels and specific humidity. The \( T_E \) was calculated using the following equations of Eq. (1) and Eq. (2) (Zhang et al., 2019).
\[ T_M = \frac{L_v q}{C_p} \]  \hspace{1cm} (2)

where \( L_v \) is the latent heat of vaporization \((2.5 \times 10^6 \text{ J Kg}^{-1})\), \( q \) is the specific humidity \((\text{kg/kg})\), and \( C_p \) is the specific heat of air \((1005 \text{ J Kg}^{-1} \text{K}^{-1})\). Therefore, we can calculate the \( T_E \) by using the following expression:

\[ T_E = T + \frac{L_v q}{C_p} \]  \hspace{1cm} (3)

Further, to evaluate the performance of ERA5, we selected observed data from 110 meteorological stations from China Meteorological Data Service Center from 1982 to 2013 (Meng et al. 2014). We also chose additional reanalysis data, including National Centers for Environmental Prediction (NCEP) Reanalysis 2 (Mesinger et al. 2006), Japanese Reanalysis (JRA55) (Kobayashi et al. 2015), and Climate Research Unit (CRU) (Harris et al. 2020) global gridded atmospheric data to assess their performance against the weather station data.

### 2.2.3. STATISTICAL METHODS

#### a. Comparisons of global gridded data with weather station data

While the meteorological station data could provide the most accurate climatic information in the TP, they have limited spatial coverage and their coverage varies over time. In addition, because of the complex terrain and extreme environmental conditions, most surface observational stations were situated in the lower parts of the eastern and central TP, often in valley locations. Global gridded atmospheric data, including reanalysis data, provide a promising alternative that are homogeneous in both time and space. The reanalysis data sets are produced using coupled numerical models in which the past and present state of our climate system is represented by incorporating a large amount of observation data (Martens et al. 2020). Additionally, reanalysis datasets are temporally and spatially homogeneous data (Colston et al. 2018). Previous studies have suggested that reanalysis data is more appropriate to use in the TP due to lack of sufficient observational data which hinder our understanding of the interactions between land surface conditions with the atmosphere (Mazhar et al. 2021; Ma et al. 2020). In the TP, the reanalysis dataset has been widely used to study the climate variability due to its spatial and temporal homogeneity (Shi and Liang, 2014). In this study, we compared three reanalysis data (ERA5, NCEP2, and JRA55) and CRU with Chinese weather station data to select the best gridded dataset among the four datasets to be used in the TP climate study. We selected daily temperature from 110 Chinese meteorological ground stations in the TP. The data was then converted to monthly data. The temporal correlations analysis of the global gridded data with the Chinese meteorological data at the 110 weather stations were performed for annual and May mean temperatures using Pearson correlation. Non-parametric correlation analysis was also assessed by using Kendall rank and Spearman’s rank correlations. Kendall and Spearman’s rank correlations were used to measure the degree of association between two variables without any assumptions about the distribution of the data (Lehmann, 1975).

#### b. Linear regression analysis

Linear regression analysis is a statistical method used to analyze the functional relationship between two or more variables (Freund et al. 2006). Specifically, the relationship
between the two variables is determined by evaluating the degree to which one variable can be predicted or explained by the others. We performed linear regression trend analysis to determine the spatial characteristic of vegetation (i.e., NDVI in this study) over the plateau. We showed the linear regression trends of May, as an early growing season, over the three periods of 1982-1998, 1999-2015, and 1982-2015, respectively. We also estimated the NDVI change in percent over the three different periods, respectively. The slope of the regression line utilized to determine how NDVI changed over time. Its significance was tested by a Student’s $t$ test at the 10% level.

c. Detrended Correlation Analysis

The correlation analysis was performed to examine the associations between the climate variables and the time series of May NDVI, area-averaged only over the region with significantly changed NDVI in the western TP. Pearson’s correlation coefficient ($r$ value) was calculated at each grid point for all climatic variables to quantify the strength and direction of relationship with the alpine vegetation. The climatic variables include albedo, net solar radiation, sensible heat flux, latent heat flux, 2 m air temperature, and mean sea level pressure in the early growing season of May. To reduce the impacts from global warming, we removed the trend of NDVI and the climatic variables by subtracting $n*\text{slope}$ from the original NDVI, and climatic variables ($n$ is 1, 2, 3, . . . , 34 years), where the slopes were estimated by the ordinary least squares method (Hurley and Boos, 2013). The vertical cross section of the detrended correlation of temperature was calculated using zonally averaged temperatures over the western TP (80°-90°E) to explore the effects of vegetation on the upper-level temperatures. Further, the significance of the correlation coefficient was tested by using Student's $t$ test at the 10% level. The detrended correlations for the periods of 1982-1998 and 1999-2015, respectively, were analyzed and shown in Supplementary materials.

d. Detrended Composite Difference Analysis

We used a detrended composite analysis to evaluate the potential physical processes observed in the correlation analysis by examining climatic variables of albedo, net solar radiation, sensible heat flux, latent heat flux, 2 m temperature, and mean sea level pressure. Composite analysis is a sampling technique based on the conditional probability of a certain event occurring (i.e., change in vegetation in the study area) (NOAA, 2021). The same process for detrending in the correlation analysis was performed for composite difference analysis. The detrended May NDVI time series of 1982-2015, area-averaged only over the region with significantly changed NDVI in the western TP, were then used to identify the eight years of the highest May NDVI (approximately top 25\textsuperscript{th} percentile) and the corresponding eight of the lowest May NDVI (approximately bottom 25\textsuperscript{th} percentile). The composite differences of the surface and atmospheric variables between the eight years of the highest May NDVI and the eight years of the lowest May NDVI were calculated. The composite analysis was applied to each grid cell. The vertical cross section of the detrended composite of temperature was also calculated over the western TP of 80°-90°E. A $t$-test for a two-sample difference of means (Walpole et al. 1993) was applied to examine the statistical significance of the composite differences with the rejection of the null hypothesis with zero difference between the means of two variables at the 10% level. The detrended composite differences for the periods of 1982-1998 and 1999-2015, respectively, were analyzed with the four years of the highest May NDVI and the corresponding four years of the lowest May NDVI. The results are shown in the Supplementary materials.
2.3. Results

2.3.1. EVALUATION OF GLOBAL GRIDDED DATASETS OVER THE TP

The scatter plot with the correlation between the weather station and global gridded datasets is presented in Figure 3. The Pearson coefficients (r values) for CRU, ERA5, JRA55, and NCEP2 were found to be 0.805, 0.808, 0.748, and 0.629, respectively, with weather station data at the annual scale and, for May, they were 0.814, 0.867, 0.753, and 0.605 for CRU, ERA5, JRA55, and NCEP2, respectively. The results obtained from non-parametric correlation were similar to those from parametric correlation (Table 1). The non-parametric correlation indicated that Kendall tau and Spearman’s rho correlations of 0.618 and 0.801 were for CRU on annual basis and 0.616 and 0.792 for May. For ERA5, the Kendall and Spearman correlations of 0.622 and 0.810 were found on an annual basis and 0.685 and 0.862 for May. For JRA55, the Kendall and Spearman correlations were 0.546 and 0.732 on annual basis and 0.555 and 0.730 for May. For NCEP2, the Kendall and Spearman correlations of 0.430 and 0.591 were on the annual scale and 0.414 and 0.60 for May. Additionally, all the correlation values were significant at the 1% level, considering the degree of freedom of 108 (=110-2). In summary, among CRU, ERA5, NCEP2, and JRA55 dataset, annual mean and May temperatures from ERA5 showed the highest correlations with those from the Chinese weather station data in the TP. The correlation values of the CRU were similar to those of the ERA5. CRU provided data for temperature and precipitation but lacked information for other atmospheric variables, which restricted its use for the analysis of the land and atmosphere interactions. Therefore, ERA5 was used to examine the associations of vegetation changes with the climate in subsequent analyses.

Table 1: Correlation coefficients between the station data with CRU, ERA5, JRA55, and NCEP2 in annual and May using parametric and non-parametric (Kendall tau and Spearman’s rho) correlations.

<table>
<thead>
<tr>
<th></th>
<th>Annual</th>
<th>May</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Pearson</td>
<td>Kendall</td>
</tr>
<tr>
<td>CRU &amp; OBS</td>
<td>0.805</td>
<td>0.618</td>
</tr>
<tr>
<td>ERA5 &amp; OBS</td>
<td>0.808</td>
<td>0.622</td>
</tr>
<tr>
<td>JRA55 &amp; OBS</td>
<td>0.748</td>
<td>0.546</td>
</tr>
<tr>
<td>NCEP2 &amp; OBS</td>
<td>0.629</td>
<td>0.430</td>
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</tbody>
</table>
Figure 3: The linear association and correlation between the weather station (x-axis) and global gridded (y-axis) temperatures at the locations of 110 weather stations for (a and b) CRU; (c and d) ERA5; (e and f) JRA-55; and (g and h) NCEP2. The left panel of the figure shows the annual mean, and the right panel is the May temperature.
2.3.2. CHANGES IN EQUIVALENT TEMPERATURE (TE)

Time series of annual $T_E$ at the 700 and 500 hPa levels, which are approximately near the surface and the lower atmosphere over the study region of western TP, are shown in Figure 1. Over the thirty-four years of 1982-2015, $T_E$ has increased by 1.3 K at the 700 hPa and 1.16 K at the 500 hPa, with a decreasing trend after around the year 2000. The results suggest that the plateau has warmed significantly based on not only the dry bulb temperature (Yang et al. 2014) but on the equivalent temperature.

2.3.3. NDVI CHANGES DURING THE EARLY GROWING SEASON

In the study area of western TP, the trends of May NDVI were distinct between the first half and the second half over the thirty-four years of 1982-2015 (Figure 4b). To completely understand the vegetation variation in the TP, the study duration was divided into three periods: the complete thirty-four years from 1982 to 2015, the first seventeen years from 1982 to 1998, and the last seventeen years from 1999 to 2015. We conducted the linear regression trend analyses of May NDVI over the periods of 1982-2015, 1982-1998, and 1999-2015, respectively. The spatial patterns of linear regression trends over the plateau with the three study periods are shown in Figure 4a. The time-series of NDVI (Figure 4b) were area-averaged in the western region of the plateau only over the region with significantly changed NDVI during the specific study periods. The percentage changes of May NDVI, which were estimated by the slope over the mean of linear regression lines, were 7.5% decrease, 11.3% increase, and 14.5% decrease during 1982-2015, 1982-1998, and 1999-2015, respectively. Also, the percentage change of NDVI at each grid point over the plateau with significantly increased and decreased NDVI during the three specific periods are shown in Figure 4c. The analyses revealed a significant decreasing trend of NDVI in the southwestern TP during the month of May over the period from 1982 to 2015 for the thirty-four years. A significantly increasing trend of May NDVI during 1982 to 1998 was observed in the western and eastern TP and, during 1999 to 2015, a significantly decreasing trend was found in the western and central plateau, as shown in Figure 4c.
2.3.4. ASSOCIATIONS OF VEGETATION ACTIVITY WITH NEAR-SURFACE ATMOSPHERIC CONDITIONS

To examine the impact of vegetation activity in the western plateau on the surface energy balance and thereby near-surface conditions during May, we used the climate variables, including albedo, net solar radiation, sensible heat flux, latent heat flux, and 2 m temperature, and also mean sea level pressure as a dynamic variable. Figure 5 shows the detrended correlation between time-series of NDVI, area-averaged only over the region with significantly changed NDVI in the study area, and each gridded atmospheric variable in May from 1982 to 2015. The detrended correlation results showed strong positive associations of NDVI with net solar radiation, sensible heat flux, and 2 m temperature, with an r-value exceeding 0.5 in each case in parts of the western plateau (Figures 5b, 5c, and 5e). In contrast, statistically significant negative correlations were observed between NDVI and albedo, latent heat flux, and mean sea level pressure for most of the area (Figures 5a, 5d, and 5f). As for the spatial patterns of the western TP, the positive correlation of 2 m temperature with NDVI (Figure 5e) was associated with the negative correlation of albedo (Figure 5a) and the positive correlation of net solar radiation (Figure 5b). Assuming NDVI increased, it could result in decreased surface albedo and increased net solar radiation at the surface and thus also increased air temperature at 2 meters. The increased net solar radiation would induce more sensible heat transfer from the surface to the atmosphere (Figure 5c). The corresponding decrease in the latent heat flux would be a response to increasing sensible heat flux (Figure 5d). Additionally, the negative association of mean sea level pressure with NDVI (i.e., lower pressure with higher NDVI) was observed in response to
the thermodynamic process over warmer surfaces with increased vegetative cover (Figure 5f). The results of detrended correlation analyses for the periods of 1982-1998 and 1999-2015, respectively, were consistent with those from 1982 to 2015 (Figure S1 and Figure S2 in Appendix I at the end of this dissertation).

![Figure 5: Correlation patterns of detrended time-series of May NDVI, area-averaged only over the region with significantly changed NDVI in the western plateau, with detrended (a) albedo, (b) net solar radiation, (c) sensible heat flux, (d) latent heat flux, (e) 2 m temperature, and (f) mean sea level pressure at each grid cell in May from 1982 to 2015. The green contour is the 10% significance level. The study area is indicated with the dotted box.]

The composite analyses further confirmed the associations between vegetation and near surface climatic variables (Figure 6). The detrended composite patterns of the land surface variables were generally consistent with the detrended correlation results. Figure 6 showed the composite differences of climate variables between the eight years of highest and of lowest May NDVI in the western TP. Albedo was generally significantly decreased during the years of high NDVI values and the spatial extent (Figure 6a) was consistent with that in the correlation pattern (see Figure 5a). The detrended composite analysis results showed a statistically significant increasing net solar radiation of more than 0.8 W/m² over the significantly different regions of the western plateau during the years of high NDVI values (Figure 6b). A significantly positive difference in sensible heat flux (Figure 6c) was found in the northwestern region of TP when
subtracting the sensible heat flux of the eight lowest years of May NDVI from the eight highest years. Correspondingly, the composite differences indicated statistically significant positive temperature anomaly in the western region during the eight highest years of May NDVI, compared to the eight lowest years of NDVI (Figure 6e). The negative composite differences of mean seal level pressure (i.e., weakened mslp) during the high May NDVI years (Figure 6f) was consistent with significantly positive differences of 2 m temperature. Further, a negative composite difference of latent heat flux was observed which was consistent with significantly positive differences of sensible heat flux (Figure 6c). The composite patterns of the climate variables with the high and low NDVI years during the period of 1982-1998 were similarly consistent (Figure S3), as were the 1982-2015 and 1999-2015 periods (Figure S4).

Figure 6: Composite difference patterns of detrended (a) albedo (0-1 scale), (b) net solar radiation (W/m²), (c) sensible heat flux (W/m²), (d) latent heat flux (W/m²), (e) 2 m temperature (K), and (f) mean sea level pressure (hPa) at each grid cell in May between the years of high May NDVI values and low
May NDVI values in the western TP from 1982 to 2015. The green contour is the 10% significance level. The study area is indicated with the dotted box.

2.3.5. POSITIVE ASSOCIATIONS OF VEGETATION WITH UPPER-LEVEL TEMPERATURES

A modified energy balance due to vegetation variability was not just observed close to the surface but was also observed from the lower to upper atmosphere. For the lower atmosphere, which is 500 hPa over the plateau, there were positive relationships of NDVI with temperature at the 10% significance level in the western plateau in May during 1982-2015 (Figure 7a). The positive relationships over the western TP, spreading both horizontally and vertically and reaching to the upper troposphere at 300 hPa level in the western TP as shown in the vertical cross sections of detrended correlation, zonally averaged temperatures over 80°-90°E (Figure 7b). There was a greater than 1 K increase in the temperature for parts of the 500 hPa level (Figure 7c) and extending to 400 hPa level with a significant composite pattern over the latitudinal domain of study area (i.e., 30°-35°N) during the eight years with highest NDVI in the western TP (Figure 7d). The analyses of the depth-layered temperatures in troposphere supported the positive associations of NDVI with temperatures, not only near the surface but also in the troposphere over the western plateau.

Figure 7: (a) Correlation patterns of detrended time-series of May NDVI, area-averaged only over the region with significantly changed NDVI in the western plateau, with detrended temperature at 500 hPa at each grid cell in May from 1982 to 2015, (b) vertical cross section of detrended correlation of the area-averaged time-series of NDVI with temperatures, zonally averaged over the western TP (80°-90°E), (c) composite difference pattern of detrended 500 hPa temperature (K) at each grid cell in May between the
years of high May NDVI values and low May NDVI values in the western TP from 1982 to 2015, and (d) vertical cross section of detrended composite differences of May temperature (K), zonally averaged over the western TP (80°-90°E), between the high and low May NDVI years. The green lines delineated areas that were statistically significant at the 10% level. The study area is indicated with the dotted box.

2.4. Discussion and Conclusions

The positive energy process identified in this study is comparable to the studies in the alpine grasslands of the TP (e.g., Babel et al., 2014; Wu et al., 2015; Shen et al., 2015). Our result suggested that positive process of vegetation cover with temperature is dominant during the early growing season of May. However, Shen et al. (2015) used WRF mesoscale modeling simulations to demonstrate the cooling effect of the enhanced vegetation growth on the weather in the TP. The study indicated the negative feedback between vegetation and temperature leading to the cooling effect during the entire growing season from May to September, as compared with the Arctic region where a warming effect was found. This could result from competing effects in the energy and moisture processes that produce complex mechanisms of climatic responses to vegetative change. For example, Babel et al. (2014) used eddy covariance and observations data along with modified land surface and atmospheric models and revealed that pasture degradation induced a shift in evapotranspiration timing and a decrease in incoming solar radiation that could have a significant influence on the larger-scale climate of the high-land area of the TP. In contrast, Cao et al. (2015) used a WRF Model to study the impact of land-cover and land-use change (LCLUC) on the regional climate in the agropastoral transitional zone of North China and found that change in LCLUC led to decline of summer temperature with local cooling of 18°C, along with increase in winter temperature of 0.88°C with local warming effect. Similarly, He et al. (2020) identified near-surface cooling effect due to cropland expansion during the late growing season from August to September in north-eastern China by using several statistical approaches and observation and remote sensing data. Moreover, the resulting cooling effect due to cropland expansion extended atmospheric column reaching up to upper troposphere influencing its circulation.

Depending on land heterogeneity, the response of vegetation change has impact on the regional circulation pattern resulting in various response of temperature and precipitation (Pielke 1974). For example, Ahmad et al. (2020) depicted positive relationship between NDVI and precipitation and negative relationship between NDVI and maximum and minimum temperature in the hilly areas of Pakistan using observation and remote sensing datasets. Several studies have illustrated a difference in surface energy partition into sensible heat flux and latent heat flux affecting the total surface energy distribution over the TP due to difference in vegetation types (e.g., Xie et al., 2017; Zuo and Zhang 2016). As a result, pronounced differences in the energy exchange processes throughout the TP was found (Hu et al., 2018). Further, Wen et al. (2020) used a high-resolution assimilation dataset of the water–energy cycle in China and found that the sensible heat flux was mostly higher in barren land region over the western TP, resulting in a higher net radiation in this region. Similarly, Ma et al. (2020) used hourly land–atmosphere interaction in situ observation data from high-elevation and cold-region observation network and illustrated that sensible heat flux dominates surface energy balance in the TP during pre-monsoon season, followed by the latent heat fluxes in the monsoon sea-son. In another study, Han et al. (2019) evaluated surface heat fluxes data from ERA-Interim reanalysis and concluded that from March to May, sensible heat flux dominates most of the TP, which is high in the west.
Further, Xie et al., (2019) implemented empirical orthogonal function analysis to study sensible heat flux from 1981 to 2013 by using ERA-Interim, JRA-55, and the MERRA reanalysis and demonstrated that there is a marked spatiotemporal differences of sensible heat flux in the TP. In recent study by Ma et al. (2021), the sensible heat flux was found to be decreasing from 2001 to 2018 in the western TP based on a number of satellite images such as SPOT/VGT (i.e., vegetation), Terra/MODIS, geostationary satellite (FY-2C) data and observational data from the Third Pole Environment (TPE) Observation and Research Platform (TPEORP).

As a major component of the surface energy balance, latent heat flux plays an important role transferring moisture from the surface to atmosphere (e.g., Ma et al., 2017). In the TP, latent heat flux shows heterogeneous spatial variation and largely depends on the local soil moisture condition, which is in turn affected by precipitation, glacier, and permafrost distribution (Li et al. 2020). The study conducted by Ge et al. (2017) confirmed that precipitation and air temperature are the major factors, affecting the latent heat in the alpine grasslands of the TP including meadow and steppe using dynamic composites and statistical analyses. Further, Wu et al. (2016) also noted difference in feedback processes for the sensible heat flux and latent heat flux over the TP. Song et al. (2017) observed a decreasing trend of actual evaporation from 2001 to 2010 from meteorological observation and satellite remote sensing data. Similarly, Li et al. (2020) calculated latent heat flux employing the maximum entropy production model from three reanalysis datasets (ERA5, JRA-55, and MERRA-2) forced by the net radiation, surface temperature, and soil moisture and noticed decreasing trend of latent heat flux from 1980 to 1991. However, there is lack of consensus about the trend and distribution of latent heat flux over the TP. Various studies indicated that the pre-monsoon period, sensible heat flux is greater than the latent heat flux making sensible heat flux as a major source for delivering heat to the atmosphere, whereas in the monsoon season latent heat flux is greater than sensible heat flux (Ma et al., 2020; Shi and Liang 2014). In addition, topography, location, and land-cover type also affect the land and atmosphere interactions with seasonal variation. Besides the energy and moisture processes, permafrost degradation, glacier melting due to climate warming, thawing–freezing process, and their combined effects have significant impact on the vegetation dynamic and spring phenology (Chen et al., 2011; Yao et al., 2012), producing complex pattern of land interactions. Additionally, human activities and socio-economic factors interact with the environment, complicating the energy exchange process (Wang et al., 2017). Overall, climatic and environmental factors affecting the long-term change of latent heat flux in the western TP are unclear and uncertainties exists.

Based on the findings of this study, positive associations of vegetation with temperature over the alpine grasslands were observed in the western TP that can extend to the upper atmosphere, resulting in 1-K increase in the temperature at the 500-hPa level. Although energy and moisture feedbacks and processes compete in the temperate region as identified by Bonan (2008), our findings implied a dominant energy process in the western TP during May. According to Bonan (2008), the moisture feedback is predominant in the summer while the albedo feedback is prevalent in the winter in the temperate region, resulting in positive radiative forcing because of radiation absorption with a lower albedo (Snyder et al., 2004). Based on the findings of this study, we suggest that the positive energy processes of vegetation with temperature could be dominant in the May, which is the transition period from winter to spring in the high-altitude grasslands on the TP. Since May is the transition season from dormancy to
growing season in the study region of western TP, which is the temporally and spatially marginalized region, the identified energy processes help to better understand the energy process and association of vegetation with atmospheric variables and explore land–atmosphere interactions in the region. Also, many studies have recognized the importance of the western TP surface condition in global climate system (e.g., Wu et al., 2016; Xiao and Duan 2016). The identified positive effects of vegetation on temperature associated with increased/decreased NDVI in the western region of the TP, we proposed a positive energy process for land–atmosphere associations as shown in Figure 8.

![Diagram](image)

**Figure 8:** The proposed positive associations of vegetation with temperatures with plausible positive energy processes in the western TP during the early growing season.

The identified positive association between vegetation and temperature in the western TP is based on the remotely sensed vegetation data and the near-surface atmospheric variables from the ERA5 reanalysis data by undertaking various statistical methods. However, to study detailed feedback mechanism an idealized simulation using a coupled land–atmosphere climate model is required to identify more robust relationship between vegetation activity and climate in the TP.
(Eastman et al. 2001). Additionally, future explorations using observational data rather than reanalysis data are also needed to exclusively identify the land–atmosphere interactions in the TP. As the TP with its rugged topography and high altitude plays a key role in the modulation of climate at the local, regional, and global scales, any changes in the land surface can have serious implications on climate characteristics, impacting millions of people not only downstream but also remote regions through atmospheric teleconnection. Besides, a warming climate is expected to have a profound impact by melting glaciers, thawing the permafrost, and modifying hydrological and carbon cycles, and complicating feedback mechanisms. Therefore, it is important to acknowledge heterogeneous land surface characteristics in the TP associated with permafrost degradation and glacial loss because of surface warming while studying effect of land-cover change on the atmosphere in the TP, which can help to improve our understanding of land-cover change and its impact on local as well regional atmospheric conditions.

The linear regression trend analysis indicated a changing trend of NDVI in the western region of the plateau from increasing of 1982–98 to decreasing of 1999–2015. Both increased and decreased NDVIs showed the consistent biogeophysical associations with near-surface and atmospheric variables. As a result, increased or decreased NDVI was respectively linked to decreasing or increasing albedo and subsequently increasing or decreasing, respectively, net solar radiation at the surface, the result of which was a statistically significant respective increase or decrease in sensible heat flux and thereby 2-m temperature. The changes in the near-surface climatic conditions further induced changes in the lower- and upper-atmospheric conditions. The biogeophysical processes during the early growing season, which is “positive associations of vegetation with temperature,” were consistent between the two periods with distinct trends of vegetation over the alpine grasslands of western TP (i.e., 1982–98 vs 1999–2015). The increasing or decreasing vegetation cover in the western plateau can modify the surface energy balance, hydrological balance, and the carbon cycles, thus complicating the responses and feedbacks of the alpine steppe to global climate change. The positive energy processes of vegetation with temperature in the highland plateau proposed by this study could further impact soil moisture and water availability, affecting millions of people downstream.

Acknowledgments

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Data Availability Statement

The GIMMS NDVI3g are available from the Global Land Cover Facility at the University of Maryland at https://www.nasa.gov/nex as cited in Pinzon et al. (2014). The climate data are available for the ERA5 at https://cds.climate.copernicus.eu, the JRA55 at https://rda.ucar.edu/datasets/ds628.0/, the NCEP2 at https://psl.noaa.gov/data/gridded/data.ncep.reanalysis2.html, and the CRU at https://lr1.uea.ac.uk/cru/data.
3. Exploring NDVI Change Patterns Across the Tibetan Plateau at the Hillslope Scale using Geomorphons

Abstract

The Tibetan Plateau (TP), dominated by grasslands, is an important landscape that plays a significant role in regional and global climate and is extremely sensitive to climate change. Grassland degradation is of great concern across this landscape and is attributed explicitly to climate change, overgrazing, and land management practices and policy. Therefore, there is a need to understand better the spatial variability and landscape patterns in grassland degradation across the TP at a high spatial resolution, equivalent to a hillslope scale, which is not possible using coarse spatial resolution satellite data, such as that provided by the Moderate Resolution Imaging Spectroradiometer (MODIS) or Advanced Very High-Resolution Radiometer (AVHRR) sensors. This study explores potential patterns in land degradation, using Landsat-derived normalized difference vegetation index (NDVI) growing season change estimates generated for a prior study by comparison to grassland types, Shuttle Radar Topography Mission (SRTM) digital terrain model (DTM)-derived geomorphons, a geomorphic landform classification system described below, topographic slope, and the topographic position index (TPI). The goal is to assess whether changes in growing season NDVI are more prominent in or associated with specific grasslands or landforms and whether there is a correlation with topographic characteristics. The study was conducted for three time periods: 1990 to 2018, 2000 to 2018, and 1990 to 2002. An increase in NDVI or greening within the TP was observed especially during the 1990 to 2018 and 2000 to 2018 time periods. Higher growing season median NDVI change values were found for the more eastern and southeastern Southeast Tibet Shrublands and Meadows (SESTM) and Tibetan Plateau Alpine Shrublands and Meadows (TPASM) grassland regions in comparison to the other three regions included in the study. Small differences in NDVI change were observed for different geomorphon-based landforms, while topographic slope and TPI showed only modest correlations with the NDVI change data for all time periods and grassland types. More localized patterns of land degradation were masked by the widespread greening trends. Further analysis of only random samples from the larger set that experienced an NDVI decrease of less than or equal to -1.0 also generally suggested more change in the SETSM and TPASM. The percentage of samples with a negative change was not evenly distributed by geomorphon type. Although no landform units in any grassland type over any time period had more than 10% of their randomly selected pixels with a NDVI change less than -0.1, depression, valley, slope, and hollow landforms generally had a larger percentage of samples with a negative NDVI change, whereas flat, summit, ridge, and shoulder landforms tended to have a lower percentage of negative NDVI change. While this study generally supports the use of geomorphon as an analysis and aggregating unit for studying change patterns at the hillslope scale, more research is required to fully grasp the dynamics of landscape change at the hillslope scale in the TP and to distinguish between the effects of climate change and anthropogenic impacts.

Keywords: Tibetan Plateau, Grassland Degradation, Geomorphon, Spatial-Temporal Analysis, DTM, NDVI
3.1. Introduction

Over the past several centuries, particularly over the last half-century, the land cover and land use characteristics of large areas of Earth’s surface have rapidly changed due to anthropogenic impacts resulting from urbanization, agriculture forest and rangeland use, and climate change. More specifically, land degradation, defined here as the reduction of the ecological and economic productivity of a location (Bai et al., 2008), currently impacts an estimated 1.9 billion hectares of land and two billion people globally (Naseer & Pandey, 2018). This degradation is especially pronounced in grassland and rangeland ecosystems, which occupy approximately 13% of the Earth’s land surface (Gong et al., 2013). Nearly half of the global grasslands have been degraded due to climate change and other anthropogenic impacts, such as overgrazing and grassland clearing for cultivation and urbanization (Gang et al., 2014). Thus, grassland degradation is a widespread phenomenon impacting the well-being of millions of people around the globe (Wessels et al., 2012) and is further exacerbated by ineffective or inappropriate intervention by humans, unsustainable land use policies and practices, and natural or climate change-induced perturbations, such as extended periods of warming, torrential precipitation, and flooding (Naseer & Pandey, 2018; Lanfredi et al., 2015; Bai et al., 2006, 2008).

The Tibetan Plateau (TP), dominated by grasslands, is an important landscape that plays a significant role in regional and global climate (Flohn 1957; Wu et al., 2012). Unfortunately, the grasslands of the TP are extremely sensitive to climate change (Bibi et al., 2018), and grassland degradation is of great concern across this landscape. This degradation is attributed explicitly to climate change and overgrazing; however, some studies also suggest that degradation may be dominantly caused by changes in land management practices and policy (Cao et al., 2019). The grassland resources of the TP are under pressure to sustain and increase livestock production and meet growing economic demands for milk and meat (Wu et al., 2012). In the Tibet Autonomous Region of the TP specifically, human populations have increased from 1.1 to 3.2 million people over the past 60 years.

Further, livestock numbers increased by 0.3 million per year from 1951 to 2003 but are now decreasing due to grassland protection policies introduced in 2004 by the Chinese government. While protecting some grasslands, these policies have resulted in high livestock concentrations in some areas and are associated with excessive grazing and grassland degradation (Arthur et al., 2008, Cai et al., 2015). Currently, about 1.5 million km² of alpine grasslands in the TP are degraded, which has reduced the productivity of alpine grasslands by an estimated 30% over the last 20 years (Cui and Garf 2009, Dong et al., 2012). In summary, many interconnected factors have resulted in land degradation in the TP, a globally significant landscape sensitive to climate change. These changes have had impacts not just on land cover and land use but also on the livelihoods of the traditional pastoralist inhabitants of the plateau.

I argue for the need to understand better the spatial variability and landscape patterns in grassland degradation across the TP. Towards this goal, this study explores potential patterns in land degradation, as estimated using Landsat-derived normalized difference vegetation index (NDVI) change estimates generated by Fassnacht et al. (2018), by comparison to grassland types, digital terrain model (DTM)-derived geomorphons (Jasiewicz and Stepinski, 2013), a geomorphic landform classification system described below, topographic slope, and the topographic position index (TPI). My goal is to assess whether changes in NDVI are more
prominent in or associated with specific grasslands or landforms and whether there is a correlation with topographic characteristics.

3.2. Background

Land degradation is a globally significant ecological and environmental issue, especially in arid and semiarid regions (Fensholt et al., 2012; Wessels et al., 2008). As a result of land degradation, grassland resources are lost, biological productivity declines and ecological conditions worsen (Li, 2018). It is critical to understand the spatial-temporal patterns of land degradation at appropriate spatial and temporal scales (Wang et al., 2020) in order to devise strategies to prevent degradation (Fensholt et al., 2012). Land degradation has been studied using several methods, including fieldwork and remote sensing. Since a vast ground area of hundreds of square kilometers may be analyzed from a single image or series of images, remote sensing is far more time and cost-efficient than field techniques. Remotely sensed multispectral images, which provide spectral data representing vegetation characteristics, are frequently employed in monitoring land degradation because of their spatially explicit and temporally dynamic properties (Zha, 2004; Prince et al., 1998; Wu, 2012). Remote sensing makes available an efficient source of information, particularly vegetation index data from which vegetation change information can be collected quickly and affordably over broad regions (Zhou et al., 2015). Particularly, widely accessible and freely available earth observation data from the Moderate Resolution Imaging Spectroradiometer (MODIS) and the Advanced Very High-Resolution Radiometer (AVHRR) have been shown to be applicable for the evaluation, detection, and mapping of land degradation (Liu et al., 2014; Sun et al., 2017). One of the most useful indicators, the Normalized Difference Vegetation Index (NDVI), is frequently derived from these data and used to describe the properties of vegetation cover and its dynamic changes at the global, national, and regional scales (Sun et al., 2016; Pan et al., 2018; Wang et al., 2022).

Remote Sensing is widely used in large-scale grassland degradation studies due to its efficiency and the ability to generate spatial explicit estimates (Xu et al., 2012). For example, Murthy and Bagchi (2018) studied the spatial patterns of long-term vegetation greening and browning to monitor land degradation in the cold-arid Trans-Himalayan ecosystem of northern India. Specifically, this study used long-term satellite-derived vegetation indices, such as NDVI, generated from three datasets: MODIS at 250 m, 500 m, 1 km, and 5.5 km spatial resolutions; SPOT (Satellite Pour l’Observation de la Terre) at 1 km spatial resolution; and Global Inventory Modeling and Mapping Studies (GIMMS) from AVHRR at 8 km spatial resolution. By analyzing the temporal trends at each pixel location over time, the study characterized intra-annual and inter-annual patterns of NDVI using the Theil-Sen regression slope estimate (Murthy and Bagchi, 2018). The result was broadly consistent across spatial scales; however, the dynamic nature of greening/browning across space and time was not captured by composite annual metrics such as sum-NDVI, max-NDVI, and mean-NDVI, highlighting the importance of intra-annual and inter-annual assessments. The study stressed the significance of evaluating greening/browning trends across various geographic and temporal scales for monitoring and assessing vegetation degradation. Similarly, Wang et al. (2022), using 30 m spatial resolution land cover data for Mongolia derived from the Landsat 5 Thematic Mapper (TM) and Landsat 8 Operational Land Imager (OLI), examined the trends in land degradation and restoration between 1990 and 2010 and 2010 and 2015 and identified factors that contributed to the changes such as natural factors, including precipitation and temperature changes, and socioeconomic
factors, such as overgrazing, mining, rapid urbanization, and increasing infrastructure. The findings demonstrated a strong transitional character in the geographic distribution of newly increasing land degradation and regeneration.

Zhang et al. (2007) analyzed the regional and temporal dynamics of land use change and land degradation in China as revealed by land use survey information from 1991 to 2001 conducted by the Ministry of Land and Resources (MLR) of China. Desertification, secondary salinization, loss of agricultural use, deforestation, grassland degradation, and loss of wetlands were the six main land degradation processes identified. Using spatial analysis methods, conversion rates were estimated, and distribution patterns were mapped. The study indicated that these land use changes impacted the larger ecosystem and accelerated land degradation.

Similarly, van Wesemae et al. (2006) examined how tillage in a small catchment in southeast Spain's Murcia Region was converted to almond plantations in the late 1970s, causing systematic changes in soil attributes. In addition, the effects on the water balance from the almond cropping practices were related to spatial variation in soil parameters. A topographic assessment of the buildup and removal of soil along field borders was used to verify the findings from the spatially distributed topography-based model (WaTEM). Likewise, Deng et al. (2022) used the enhanced spatial and temporal adaptive reflectance fusion model (ESTARFM) to improve the spatial resolution of the GIMMS NDVI3g (8 km) data for the TP in 1990 and 1995 based on MODIS NDVI (500 m) data to study long-term spatiotemporal patterns of vegetation change and associated driving factors. The study demonstrated a significant correlation between the MODIS NDVI data and the fused GIMMS NDVI3g products, which highlighted the accuracy and reliability of the fused GIMMS NDVI3g products and their ability to provide fundamental information for the assessment of spatial and temporal patterns of vegetation and vegetation change on the TP.

Landsat data from 1987 and 2008 were analyzed by Dawelbait et al. (2012) to assess the processes of desertification in the Central North Kurdufan State of Sudan. To assess the dynamic change and associated transfer matrix of land desertification in the Silk Road Economic Zone, Liu et al. (2017) analyzed the 250 m spatial resolution MOD13Q1 data from 2000 to 2014 using a decision tree classification approach. Thiam et al. (2003) evaluated the risk of land degradation in southern Mauritania using rainfall, soil type, field survey data, and multitemporal 1 km spatial resolution NOAA/AVHRR NDVI maximum composite images. To identify temporal and geographic change trends over the research region, image deviation was applied to maximum NDVI composites generated for the growing season dates (June to October) from 1990 to 1999. When areas under threat were defined as cells with values lower than 0.5 standard deviations from their temporal mean, all soil types in southern Mauritania were suggested to be susceptible to degradation.

A survey of published studies suggests that few have employed high to moderate spatial resolution data, such as those made available by the Landsat time series, which offers a 30 m spatial resolution, and that most studies on land degradation have used coarse spatial resolution data (e.g., 250 m to 8 km). As a result, most studies only characterize macro-distributions and broad trends of change resulting from land degradation (Lu et al., 2004). To analyze NDVI variability across different vegetation types, landscapes, and time periods to evaluate land degradation, I argue that it is important to assess the correlation of vegetation index changes with
landscape characteristics at the hillslope scale. Thus, this study explores geomorphons (Jasiewicz & Stepinski, 2013) as landscape aggregating units by which to explore NDVI changes at the hillslope scale and assess change relative to relevant landform delineations.

### 3.3. Geomorphons and Applications

The geomorphon methodology (Jasiewicz and Stepinski 2013) offers an innovative means to classify the terrain surface, as represented using raster-based digital terrain models (DTMs), into meaningful landforms at the hillslope scale. This method is based on the concept of pattern recognition as opposed to the more commonly used differential geometry. It also self-adapts to determine the best spatial scale of analysis for each cell based on a line-of-sight method (Jasiewicz and Stepinski 2013). The process results in 498 distinct geomorphons, or 6,561 if the orientation is taken into consideration. These patterns are then aggregated into a set of geomorphically meaningful units: flat, peak, ridge, shoulder, spur, slope, hollow, foot slope, valley, and pit (Jasiewicz and Stepinski 2013).

More specifically, geomorphons categorize or differentiate terrain features or landform types that are size-, orientation-, and local relief-invariant. The method is based on the image analysis concept of local binary patterns (LBP) and the terrain analysis concept of local terrain pattern (LTP) (Ojala et al., 2002). The texture operator assigns an 8-tuple pattern of 0s and 1s to a focus cell by thresholding pixels in a 3-by-3 neighborhood with the value of the focus, or center, cell (Yokoyama et al., 2002). A cell is compared to its neighbors in eight directions to characterize the patterns on the landscape and determine in which directions elevation is higher, lower, or at the same altitude as the reference cell location. So as not to limit the analysis to a 3-by-3 cell window and to allow for mapping similar landforms with variable sizes or scales, a line-of-sight method is used as opposed to the direct cell neighbors (Liao et al. 2010). Each line of sight is attributed as ‘−’, ‘+’ or ‘0’, depending on whether it ends downwards, upwards, or horizontally, respectively. A different landform type is assigned based on the observed ternary pattern of higher, lower, or equal elevations surrounding the focal pixel. As noted above, a total of 498 patterns are categorized, which can then be subsequently grouped into common terrain features or landforms (Jasiewicz and Stepinski, 2013). The line-of-sight analysis is constrained by a user-specified search distance that determines the maximum extent at which features can be identified. With a larger search distance, features can be identified across broader extents. However, landform classifications quickly converge over increasing search distances as the line-of-sight approach adapts to the local terrain.

The classification of landforms has been performed and implemented at different geographic scales and extents, spatial resolutions, and for various purposes (Evans, 2012). Stepinski and Jasiewicz (2011) were the first to deploy the geomorphon approach to study and classify the Earth’s terrain surface based on ten dominant shapes using a digital terrain model (DTM) and LBP and LTP algorithms. The geomorphon classification approach has been successfully used in a variety of recent problems, ranging from the characterization of submarine bedforms (Mayer, 2018), topographic modeling for landscape architecture (Harmon et al., 2018), wildfire detection (Heyns et al., 2021), landform mapping (Gioia et al., 2021), hydrological modeling (Melo et al., 2021), and landslide susceptibility mapping (Luo and Liu, 2018). For example, Libohova et al. (2016) demonstrated the value of the classification method for predicting soil properties on a glacial moraine to offer a new perspective for the quantitative
analysis of landforms while Sărășan et al. (2019) used the geomorphon approach for drumlin extraction. Luo and Liu (2018) used the geomorphon method to delineate ridge and valley lines to form slope units for landslide susceptibility mapping (LSM) in I-Lan, Taiwan. The weights of the relevant components for LSM were objectively assigned using the geographical detector method and a spatial variance analysis technique. As a result, the study provided a general framework for LSM mapping.

Gioia et al. (2021) used geomorphons to perform automatic landform categorization across a substantial portion of the Ionian coast in southern Italy. Notably, this study suggested that geomorphon-based categorization may be a foundational and reliable method for consistently identifying the primary geomorphological components of landscapes over broad spatial extents. This method may also be useful for more sophisticated geomorphological mapping procedures, such as the genetic interpretation of landforms and the precise delineation of complex and composite geomorphic elements. Sărășan et al. (2019) examined the applicability of geomorphons for the automated extraction of drumlins and outlined a novel automated method for determining the precise threshold of the maximum scale of mapping based on topographic grain. Its ability to produce reliable and accurate results in drumlin extraction was evaluated based on an object-based image analysis (OBIA) approach. Melo et al. (2021) investigated the performance of a fully distributed hydrology soil vegetation model (DHSVM) that incorporated geomorphons in the Lavrinha Creek Watershed of the Mantiqueira Range, southeast-eastern Brazil. Additionally, a sensitivity analysis of soil parameter values in relation to the geomorphon-derived landforms was carried out to examine the parametrization implications of landform characteristics on the modeling results. This study suggests that a map with a geomorphological foundation is appropriate and suitable for spatially differentiating hydrological parameters in the DHSVM.

Further, Gruber et al. (2015) proposed a methodology that examines the applicability of an area-wide elementary landform map generated for the entire country of Austria to designate significant natural geomorphological zones by examining spatial variability and distribution of elementary landforms. Flynn et al. (2020) sought to stratify the soil landscape through aggregated geomorphons at the farm scale (i.e., 1:25,000 scale) in the Western Cape, South Africa. The associations of geomorphon units with distinct soil classifications were compared after producing them at various spatial resolutions. The best-fitting geomorphon result was combined into a 5-unit system that corresponded to the national resource inventory for South Africa. A decision tree was used to aggregate the data depending on the soil type. The results of this study demonstrated that aggregating geomorphons may meaningfully stratify the soil landscape even at the farm scale and can be used as a first indicator of the spatial variability of soil characteristics. Pinto et al. (2016) mapped soil water transmissivity through fuzzy logic, environmental covariates, and geomorphons. The study demonstrated a superior accuracy compared to the Iwahashi and Pike (2007) approach. Iwahashi and Pike (2007) used binarized greyscale pictures of the slope gradient, local convexity, and surface texture using an unsupervised nested-means algorithm that is created using methods modified for DEMs from digital image processing to classify the global topography.

In summary, geomorphons have been documented to be geomorphically meaningful and valuable for categorizing the landscape at the hillslope scale. Thus, I argue that these features are
an appropriate unit by which to explore patterns in NDVI change at a finer spatial resolution than undertaken in prior studies. Geomorphons are particularly useful as an aggregating unit as they align with hillslope conditions, landforms, soil characteristics, and land use units.

3.4. Data and Methods

3.4.1. TIBETAN PLATEAU

The TP is the highest plateau in the world, with an average elevation of more than 4,000 m (Figure 9). Extending from 25° to 45°N latitude and 75° to 105°E longitude (Liu et al. 2015), it stretches approximately 1,000 km north-to-south and 2,500 km east-to-west (Duan et al. 2012). Elevation generally decreases from the higher mountains in the northwest to the lower ones in the southeast. The TP includes all of Tibet and Qinghai and portions of China's Sichuan, Xinjiang, Gansu, and Yunnan provinces (Jin et al., 2022). Due to its complex topography and sensitive climate, the TP is known as the 'Third Pole' (Kang et al., 2010). As the world's largest and highest plateau, it is regarded as a sensitive area to global climate change, as the ecosystems it hosts are extremely fragile (Yao et al., 2012; Wang et al., 2015). The climate of the TP is generally characterized by low air temperature, high daily temperature differences, low annual temperature differences, and intense solar radiation (Pan et al., 2017). Due to its high elevation, the TP has harsh winters, moderate summers, and significant diurnal temperature fluctuations. Its annual average air temperature ranges around from -5° to 8°C (Xiong et al., 2019).

The TP is home to various mountain ranges, including the Tanggula Mountains, Kunlun Mountains, and the Himalayas. It differs greatly from other mid-latitude mild temperate zones and subtropical areas in terms of its high elevations, which provide unique environmental conditions (Yue et al., 2014). The hydrothermal environment in the TP produces a strong regional gradient of vegetation horizontally and vertically (Huang et al., 2019). According to Li et al. (2017), vegetation characteristics substantially influence the hydrological properties, carbon cycle, and surface stability of this region as well as the climate and ecology of China specifically and the entire planet more generally. Therefore, it is crucial to investigate the TP’s spatial and temporal vegetation distribution characteristics and to determine the main causes of regional vegetation changes.
3.4.2. NDVI DATA

As a sensitive indicator of vegetation change, NDVI is widely applied in vegetation monitoring research (e.g., Li et al., 2017; Piao et al., 2011; Zheng et al., 2019; Zhang et al., 2015). It has been extensively used to assess vegetation dynamics and health (Eckert et al., 2015; Huang et al., 2019). The NDVI is a key indicator of vegetation cover and structure, photosynthetic activity, vegetation health, and other vegetation traits (Tucker and Sellers, 1986). In order to examine vegetation change, the NDVI has been successfully used in a variety of regions, including the Sahel (Anyamba et al., 2005; Jamali et al., 2014; He and Lee 2016; Lee et
I used NDVI change data derived from the Landsat time series and produced by Fassnacht et al. (2018). Fassnacht et al. generated annual mosaics of Landsat data by determining the median NDVI value of all available scenes within a seasonal subset (scenes collected between June 1st and the last day of September each year) and in which a non-cloud-contaminated observation was available at the cell location. Three NDVI change products were generated representing the periods of 1990 to 2018, 1990 to 2002, and 2000 to 2018. These study periods were selected for a number of reasons. First, the period from 2000 to 2018 coincides with the availability of MODIS data. Secondly, the approximate time span from 2000 to 2018 has been examined in a number of prior studies. It is therefore possible to compare the latter with previously documented patterns at lower spatial resolution. Furthermore, the time period is intriguing since it coincides with the introduction of a few significant government initiatives to slow the loss of grasslands, such as the "Grain for Green" program in 1999 and the "Grazing Withdrawal Program" in 2003.

The study used the surface reflectance data available for the TM, Enhanced Thematic Mapper Plus (ETM+), and OLI instruments onboard the Landsat 5, 7, and 8 satellite platforms, respectively, within Google Earth Engine (Gorelick et al., 2017). The satellite-measured radiances were converted to estimated surface reflectance (USGS Landsat Surface Reflectance Tier 1) using the Land Surface Reflectance Code (LaSRC) algorithms for Landsat 8 OLI and the Landsat Ecosystem Disturbance Adaptive Processing System (LEDAPS) algorithms for Landsat 5 TM and 7 ETM+ data. The CFMASK algorithm (Zhu et al., 2015) was used to mask clouds, cloud shadows, and snow. The study then estimated the NDVI using the red and near-infrared bands. Additionally, the study applied an adjustment, as an intercept and offset, to the Landsat 8 OLI data to account for the differences in band spectral ranges in comparison to Landsat 5 TM and Landsat 7 ETM+ (Roy et al., 2016). To eliminate any lingering artifacts, such as those caused by the Landsat 7 scan-line corrector (SLC) failure, NDVI values larger than 0.9 or less than -0.9 were masked out. Then, by aggregating the remaining data to obtain the median NDVI of all scenes for the specified seasonal period within a year (Fassnacht et al., 2019), yearly NDVI mosaics were created. The median was used, as opposed to the mean, since it is less impacted by outliers (Fassnacht et al., 2018).

Typically, low spatial resolution satellite images, such as AVHRR and MODIS, are used for investigating land use and land cover change (LULCC) in the TP. For instance, Wang et al. (2019) used MODIS to statistically examine the patterns in land change and the variables that influenced change in the TP between 2001 and 2015. One reason for the use of coarser spatial resolution data is that cloud contamination and data gaps impact data availability, which is generally less of an issue for coarser spatial resolution data due to a more frequent return interval (Liu et al., 2020). Using single images to detect LULCC on the TP is difficult (Coulter et al.,
Further, long-term monitoring of land surface attributes requires a consistent NDVI time series. AVHRR observations provide the longest records of continuous global satellite measurements while MODIS offers a more recent alternative (Du et al., 2014). However, using low spatial resolution satellite data may result in an erroneous interpretation of trends in grassland alteration, particularly in mountainous locations like the TP (Tian et al., 2015; Zhang et al., 2017). Despite using similar MODIS datasets with a spatial resolution of 250–1,000 m for comparable time periods, previous research has observed varying trends in certain regions (Li et al., 2017). Further, grassland degradation is usually initiated over limited geographical extents, which may not be observable in coarse spatial resolution data (Fassnacht et al., 2019). Therefore, the 30 m spatial resolution, Landsat-derived NDVI change product produced by Fassnacht et al. provides an opportunity to study vegetation change at a potentially more appropriate hillslope scale.

3.4.3. GRASSLAND DATA

Land cover (Figure 9) on the TP varies greatly and includes forest, grassland, shrubland, glaciers, and bare land (Xue et al., 2017). The growing season of grasslands starts in early May and ends in late September (Wang et al., 2016), and their season lengths vary geographically. Alpine grasslands dominate 60% of the TP’s grassland areas and experience one growing seasonal cycle (Wang, 2016). We used a vegetation distribution of grasslands developed by Dixon et al. (2014). The grassland type map was developed using the International Vegetation Classification (IVC) of grassland types and the map of Terrestrial Ecoregions of the World (TEOW). According to Faber-Langendoen et al. (2014), the IVC is a non-spatial vegetation-based categorization system that describes a hierarchy of terrestrial ecosystems using the EcoVeg methodology. This method, which organizes vegetation patterns into an eight-level hierarchy using a combination of physiognomic, floristic, ecological, and biogeographical patterns, serves as the foundation for a vegetation classification standard across several continents (Baldwin & Meades, 2008; Faber-Langendoen et al., 2009; Sayre et al., 2013).

The TEOW spatial system comprises 867 eco-regions nested within a collection of 14 global biomes. A broad group of ecosystems with comparable biophysical properties and species compositions make up an ecoregion. Specifically, ecoregions are defined at the regional level, with borders created by combining information from earlier ecosystem delineation efforts with biophysical and remotely sensed data (Olson et al., 2001). The TEOW framework incorporates precise ecological characterizations based on the composition of grasslands (Olson et al., 2001). In this study, we investigated five different grasslands as defined by the TEOW and occurring within the TP. These grasslands were selected because they had the largest land areas within the TP of all available grasslands. The used grassland types include the Central Tibetan Plateau Alpine Steppe (CTPAS), North Tibetan Plateau-Kunlun Mountains Alpine Desert (NTPKMAD), Qaidam Basin Semi-Desert (QBSD), Southeast Tibet Shrublands and Meadows (SETSM), and Tibetan Plateau Alpine Shrublands and Meadows (TPASM).

3.4.4. DTM DATA

The DTM data used in this study were extracted from the Shuttle Radar Topography Mission (SRTM) Version 4.1 product (http://www.cgiar-csi.org). SRTM DTM offers new possibilities for landform classifications at regional and global scales, which were previously hindered by the uneven quality and availability of data. The SRTM product has a spatial
resolution of about 30 m and is derived from X- and C-band interferometric synthetic aperture radar (InSAR) data collected from a space shuttle platform during an 11-day mission in February 2000, which resulted in publicly available elevation data for approximately 80% of the Earth’s surface from 60° N to 56° S (Reuter et al., 2007).

The topographic slope was calculated from the DTM data in degree units in ArcGIS Pro using the Slope Tool within the Spatial Analyst Extension (ESRI, no date). The Topographic Position Index (TPI) was calculated as the difference between the elevation at a cell location and the average elevation in a neighborhood surrounding that cell (Chendes et al., 2008). Specifically, the elevation at the center cell was subtracted from the local mean elevation within the window. Positive TPI values indicate local high points, such as ridges, whereas lower values indicate topographic low points, such as valleys. TPI values close to 0 indicate flatter terrain. The topographic position is a scale-dependent phenomenon that is impacted by the size of the defined moving window. For our purpose, TPI was calculated using a circular moving window with a 7-cell (e.g., 210 m) radius to characterize patterns at the hillslope scale. The parameters were empirically chosen based on a visual comparison of a range of scales.

![Figure 10: Elevation map of the TP. Elevation data are derived from the SRTM Version 4.1 DTM.](image-url)
Geomorphons were calculated from the 30 m SRTM DEM in QGIS (QGIS, no date) using the r.geomorphons "add-on" (Jasiewicz and Stepinski, 2012). Notably, the geomorphon approach depends on three core parameters: input DTM, inner and outer search radius, and a flatness threshold. A key consideration is the search radius (L-cells), representing the maximum distance for each pixel's line-of-sight (LOS) calculations. In particular, the outer or maximum search radius (lookup distance) sets the maximum distance for LOS calculations for each pixel, which is strictly related to scale recognition of the basic landform class. An outer radius of 21 cells and an inner radius of 3 cells were used to produce this geomorphon product (Figure 10). A flatness threshold of 5 and a flatness distance of 11 were applied. The number of landform elements in the geomorphic map was then reduced to suit a typical terrestrial landscape where the ten most frequent and commonly recognizable geomorphons are flat, peak, ridge, shoulder, spur, slope, hollow, footslope, valley, and pit (Jasiewicz and Stepinski, 2012; Neteler and Mitasova, 2007). The ten most universally accepted landform units were obtained by applying a pattern recognition algorithm based on a 3-by-3 cell local neighborhood search radii from a central focal point (Jasiewicz and Stepinski, 2013). As described above, the advantage of the geomorphon method is that it classifies the landform elements by analyzing the extent and shape of a cell’s neighborhood by automatically adapting to the geometry of the local terrain derived from the DTM surface.

3.4.5. ESRI LAND COVER

The Environmental Systems Research Institute (ESRI) 2020 10 m spatial resolution land cover dataset was created using imagery from the Multispectral Instrument (MSI) sensors onboard the Sentinel-2A and 2B satellites operated by the European Space Agency (ESA) and a deep learning semantic segmentation model developed by ESRI and the Impact Observatory and deployed on Microsoft computer clusters (Karra et al., 2021). The deep learning model was trained using more than 5 billion manually annotated Sentinel-2 pixels collected from over 20,000 locations spread across the world's main biomes. Sentinel-2 surface reflectance data in six bands (blue, green, red, near-infrared, and two shortwave infrared bands) were used as predictor variables. The trained model was applied to images representing variable phenology throughout the year, and the results were aggregated to produce a final map representing 2020 conditions (Karra et al., 2021).

3.4.6. DATA SUMMARIZATION

Once the geomorphons were created, I generated a large set of random points from which I then extracted a subset occurring within the extent of the TP, which resulted in a total of 1,087,050 points. Any points with missing data in any of the used datasets were excluded. Missing data generally resulted from gaps in the three Fassnacht et al. NDVI change products due to cloud cover or an inadequate number of available scenes. Also, I only considered points classified as grass, shrub, or barren in the ESRI 2020 land cover product since I was specifically interested in transitions in grassland or rangeland classes. Once only points occurring within the five grasslands of interest were selected, a total of 137,869 points remained for use in the analysis. I used grouped box plots to compare the distribution of NDVI change by geomorphon unit and the distribution of NDVI change by geomorphon unit and grassland type. Further, I used Spearman’s correlation coefficient to compare the correlation of NDVI change with topographic slope and TPI within each grassland type. I also explored the percentage of samples with a predicted NDVI change of less than or equal to -0.10 within the combined geomorphon units and
grassland types. These analyses were performed using the R data science environment (R Core Team, 2022).

3.5. Results

The geomorphon classification produced from the 30 m spatial resolution SRTM DTM is shown in Figure 11, which includes insets to highlight the spatial detail and differentiation of landforms at the hillslope scale. Variability in landform conditions is notable across the TP. For example, the more mountainous regions in the south and southeast are distinct from the northwestern extent where large expanses of flat terrain are present. Generally, these visualizations suggest that this landform classification method adequately characterizes landforms at the hillslope scale and also offers a consistent product across a broad spatial extent.

Figure 11: Geomorphometric map of TP generated using the geomorphons method.

The analysis of NDVI change by geomorphon unit and time period is presented in Figure 12 in which boxplots are used to visualize the relationship between NDVI change according to geomorphon types and different time periods. The median of NDVI change for all time periods and across all geomorphon classes is positive, suggesting that the landscape is experiencing greening over time. This trend is specific to growing season conditions since the NDVI change
products produced by Fassnacht et al. used growing season imagery only. Generally, the lowest amount of change is observed over the 1990 to 2002 time period while the largest amount of difference occurred over the 1990 to 2018 time period. This could potentially be attributed to the differences in timespan. Further, comparing the 1990 to 2002 and 2000 to 2018 time periods suggests more change over the second decade. Given that the median change across time periods was positive, landscape degradation patterns may be difficult to detect using only NDVI, especially when the data are aggregated using a large cell size or geographic boundaries of interest (i.e., watersheds, ecological zones, or political boundaries). For example, a global mean or median for an entire province or grassland type may not be informative or useful for assessing local-scale change or implementing policy or management. Major differences in change patterns are not observed between the landform types for all time periods, other than some slight difference in the median NDVI change value and/or the variability in change as represented by the interquartile range (IQR).

![Figure 12: NDVI change by geomorphon type in the TP based on analysis of Landsat time series by Fassnacht et al. over three different time periods.](image)

In Figure 13, I compare NDVI change by landform units within each grassland type, as defined by Dixon et al. (2014), and time period, as opposed to collectively for all of the randomly sampled locations (i.e., Figure 12). The analysis suggests more variability in the change in NDVI in flat regions in all grassland types in comparison to all other landforms. Again, the median change values, especially for the 1990 to 2018 time period, are positive. Further larger medians are observed for the SETSM and TPASM regions in comparison to the other three regions. These two regions make up the eastern and southeastern extents of the TP, suggesting differing change patterns between the eastern and western extents of the plateau.
Table 2 provides the Spearman correlation coefficients for NDVI change for each time period and grassland type combination with topographic slope and TPI. The low or near-zero correlation values suggest weak monotonic correlation with these two topographic parameters. In other words, changes in NDVI do not appear to be heavily correlated with the steepness of the slope or the local topographic position within any of the grassland types.

<table>
<thead>
<tr>
<th>Grassland type</th>
<th>Time period</th>
<th>Slope Correlation</th>
<th>TPI Correlation</th>
</tr>
</thead>
<tbody>
<tr>
<td>CTPAS</td>
<td>1990-208</td>
<td>-0.0876</td>
<td>-0.0647</td>
</tr>
<tr>
<td>CTPAS</td>
<td>1990-2002</td>
<td>-0.0437</td>
<td>-0.0358</td>
</tr>
<tr>
<td>CTPAS</td>
<td>2000-2018</td>
<td>-0.0824</td>
<td>-0.0548</td>
</tr>
<tr>
<td>NTPKMAD</td>
<td>1990-2018</td>
<td>0.0565</td>
<td>-0.0193</td>
</tr>
<tr>
<td>NTPKMAD</td>
<td>1990-2002</td>
<td>-0.0162</td>
<td>-0.0104</td>
</tr>
<tr>
<td>NTPKMAD</td>
<td>2000-2018</td>
<td>0.0795</td>
<td>-0.0145</td>
</tr>
<tr>
<td>QBSD</td>
<td>1990-2018</td>
<td>0.0743</td>
<td>-0.0614</td>
</tr>
</tbody>
</table>

Figure 13: NDVI change by geomorphon type and grassland in the TP. The red dotted line indicates zero change in NDVI. CTPAS = Central Tibetan Plateau Alpine Steppe; NTPKMAD = North Tibetan Plateau-Kunlun Mountains Alpine Desert; QBSD = Qaidam Basin Semi-Desert SETSM = Southeast Tibet shrublands and meadows; TPASM = Tibetan Plateau Alpine Shrublands and Meadows.

Table 2: Correlation between the NDVI change by time period with topographic slope and topographic position index (TPI).
<table>
<thead>
<tr>
<th>Region</th>
<th>Time Period</th>
<th>NDVI Change</th>
<th>NDVI Change</th>
</tr>
</thead>
<tbody>
<tr>
<td>QBSD</td>
<td>1990-2002</td>
<td>-0.0175</td>
<td>-0.0012</td>
</tr>
<tr>
<td>QBSD</td>
<td>2000-2018</td>
<td>0.0921</td>
<td>-0.0697</td>
</tr>
<tr>
<td>SETSM</td>
<td>1990-2018</td>
<td>-0.0338</td>
<td>0.0086</td>
</tr>
<tr>
<td>SETSM</td>
<td>1990-2002</td>
<td>0.0224</td>
<td>-0.00318</td>
</tr>
<tr>
<td>SETSM</td>
<td>2000-2018</td>
<td>-0.073</td>
<td>0.0136</td>
</tr>
<tr>
<td>TPASM</td>
<td>1990-2018</td>
<td>0.0362</td>
<td>-0.0172</td>
</tr>
<tr>
<td>TPASM</td>
<td>1990-2002</td>
<td>-0.0234</td>
<td>-0.029</td>
</tr>
<tr>
<td>TPASM</td>
<td>2000-2018</td>
<td>0.0389</td>
<td>0.00175</td>
</tr>
</tbody>
</table>

I argue that detecting local patterns in land degradation may be difficult in the TP as these more localized patterns may be masked by the stronger greening signal. This could result in difficulty in detecting potential patterns in land degradation or NDVI change by landform unit. As a result, as a second phase of the analysis I extracted only samples that had an NDVI change less than or equal to -0.1 and investigated patterns for these samples by landform type and by grassland type. The results are presented in Figure 14 and 15 in which the percent of the samples from the larger random sample that had an NDVI change of less than or equal to -0.1 are visualized. Figure 14 shows the results without differentiating by grassland type. These results suggest that the percentage of samples with a negative change is not evenly distributed by geomorphon type. Specifically, a larger percentage of cells in the depression, valley, slope, and hollow landforms were shown to have a negative NDVI change from 1990 to 2018 and 2000 to 2018 time periods. In contrast, flat, summit, ridge, and shoulder landforms tended to have a lower percentage of negative NDVI change. This suggests that land degradation may be more prominent in the lower and intermediate relative topographic positions in comparison to the higher relative topographic positions. However, no landforms had more than 10% of their randomly selected pixels with a NDVI change less than or equal to -0.1. Differentiating the results by grassland type (Figure 15), suggest more change in the SETSM and TPASM regions in comparison to the other three regions. These two regions make up the eastern and southeastern extents of the TP. The percent of samples with an NDVI change less than -0.1 in the CTPAS, NTPKMAD, and QBSD regions are never above 1.0%, except for depression landforms in the NTPKMAD. Similar to the results presented in Figure 14, in the SETSM and TPASM regions, negative NDVI change is more pronounced during the 1990 to 2018 and 2000 to 2018 time periods and occurs more often in depression, valley, slope, and hollow geomorphon units.
Figure 14: Percent of samples with an NDVI change of less than or equal to -0.1 by landform and time period in the TP.
### Figure 15: Percent of samples with an NDVI change of less than or equal to -0.1 by landform, time period, and grassland type.

CTPAS = Central Tibetan Plateau Alpine Steppe; NTPKMAD = North Tibetan Plateau-Kunlun Mountains Alpine Desert; QBSD = Qaidam Basin Semi-Desert; SETSM = Southeast Tibet shrublands and meadows; TPASM = Tibetan Plateau Alpine Shrublands and Meadows.

### 3.6. Discussion

This hillslope scale analysis of growing season NDVI change, as estimated by Fassnacht et al. using Landsat time series data at a 30 m spatial resolution and Google Earth Engine, generally suggests that increases in NDVI, or greening, especially during the 1990 to 2018 and 2000 to 2018 time periods, is the dominant vegetation change pattern or trend within the TP. Less change was noted for the 1990 to 2002 time period, suggesting more greening during the more recent decade studied. Based on grassland types or regions delineated by Dixon et al. (2014), larger median NDVI change values were observed for the SETSM and TPASM.
grassland regions in comparison to the other three regions studied: CTPAS, NTPKMAD, and QBSD. The SETSM and TPASM regions comprise the eastern and southeastern portions of the TP (see Figure 9), suggesting variable change patterns between the eastern and western extents of the plateau. Minimal differences in NDVI change were observed for different geomorhon-based landforms, calculated from an SRTM-derived 30 m spatial resolution DTM in the TP. Further, topographic slope and TPI were weakly correlated with the NDVI change data across all time periods and grassland types. Given that the median change across time periods was positive, landscape degradation patterns may be difficult to detect using only NDVI, especially when the data are aggregated using a large cell size or geographic boundaries of interest (i.e., watersheds, ecological zones, or political boundaries). For example, a global mean or median for an entire province or grassland type may not be informative or useful for assessing local-scale change or implementing policy or management. Major differences in change patterns are not observed between the landform types for all time periods, other than some slight difference in the median NDVI change value and/or the variability in change as represented by the interquartile range (IQR).

Climatic factors may explain some of the variability in NDVI change observed between the studied grasslands. The interannual variability of the NDVI pattern throughout the TP is largely regulated by the preceding May-August precipitation and concurrent June - September sunlight duration (Mao et al., 2022). The NDVI variability in the southeastern plateau can be attributed to significant summer rainfall of up to 500 mm from the East Asian Monsoon (EAM) (Du et al., 2016). He et al. (2020) also suggested that precipitation, cloud cover, and solar radiation are responsible for the variability in the NDVI over the eastern TP. Also, there is a sharp contrast between the western and eastern plateaus in terms of NDVI (Lehnert et al., 2016; Wang et al., 2019). Lehnert et al. (2016) reported that the degradation of grasslands in the western arid region of the plateau was due to a strong increase in air temperature over the past decades and that the climatic conditions have become less favorable for vegetation growth in the western plateau. Further, warming has also accelerated evaporation, decreased humidity, and led to the browning of vegetation, a trend that is most evident in the central and southwest plateau (Bao et al., 2015; Zhang et al., 2013). As a result, the link between the NDVI and climatic parameters is clearly heterogeneous in time and space across the TP (Gao et al., 2016; Huang et al., 2016; Pang et al., 2017). Again, it should be noted that the NDVI change data generated by Fassnacht et al. and used in this study represent growing season conditions; as a result, intraannual variability was not assessed or explored in this study.

I argue that these findings indicate that widespread greening trends can overwhelm more local-scale land degradation patterns that, though potentially important, are less abundant on the landscape. Further analysis of samples from the larger set that experienced an NDVI decrease of less than or equal to -1.0 generally suggested more change in the SETSM and TPASM, similar to the results using the entire set of random sample locations. Also, the percentage of samples with a negative change was not evenly distributed by geomorphon type. Although no landform units in any grassland type over any time period had more than 10% of their randomly selected pixels with a NDVI change less than -0.1, depression, valley, slope, and hollow landforms generally had a larger percentage of samples with a negative NDVI change for 1990 to 2018 and 2000 to 2018 time periods whereas flat, summit, ridge, and shoulder landforms tended to have a lower percentage of negative NDVI change. More generally, this suggests that land degradation may be
more prominent in the lower and intermediate hillslope positions in comparison to the higher relative topographic positions. This analysis of random samples experiencing NDVI loss, similar to the results using the entire dataset, suggested more change in the SETSM and TPASM regions. Further, the percent of samples with an NDVI change less than -0.1 in the CTPAS, NTPKMAD, and QBSD regions were never above 1.0%, except for depression landforms in the NTPKMAD.

The pronounced increase in temperature due to global climate change has impacted vegetation cover over the TP as estimated by changes in the NDVI (Mao et al., 2012; Sun et al., 2013; Shen et al., 2015; Peng et al., 2012). The TP's climate from 2000 to 2020 was primarily warmer and more humid (Wang et al., 2022). An increase in temperature might provide the heat necessary for plant development in alpine regions. Additionally, it could accelerate the thawing of frozen soil, increasing the amount of water available to plants. The impacts of an increase in temperature would be noticeably different in regions with varying topographies and vegetation types. The change also shows spatial heterogeneity owing to large spatial heterogeneity in temporal and spatial trends of temperature and precipitation throughout the plateau (Zhang et al., 2015; Wang et al., 2012; Lehnert et al., 2015; Gao et al., 2013).

For meadows and grasslands with a moderate abundance of plant cover, precipitation has been suggested as a possible driver of annual maximum NDVI variability (Ding et al., 2013). Temperature and precipitation affect the steppe’s NDVI throughout the growing season (Zhang et al., 2013). Furthermore, in dry and semi-arid locations, it has been documented that the effects of temperature and precipitation on plant development demonstrate substantial geographical variation (Huang et al., 2014; Sun et al., 2016). Numerous studies indicated that there is a strong relationship between the magnitude of vegetation response to precipitation and the aridity gradient in many dry climates around the world, such as Inner Mongolia (Gao et al., 2021) and the TP (Ding et al., 2007). For example, a study conducted by Wang et al. (2021) indicated a positive correlation between temperature and NDVI in the central and western portions of the TP. Higher temperatures boost photosynthesis, which encourages plant growth as long as rainfall is comparatively consistent and does not become a limiting factor (Diao and Xia, 2016). The CTPAS has some of the least disturbed ecosystems in temperate Eurasia. The environment is too arid and cold to sustain people and their livestock. Because of the cold and dry alpine climate, a range of vegetation with various growth patterns is found across the TP, and therefore, the amplitude and the impact of climatic factors are different over different regions of the TP (Li et al., 2018; Mao et al., 2022). The lack of change in the NTPKMAD and QBSD grassland regions specifically may be attributed to climate change (Luo et al., 2018, Wang et al., 2016; Wang et al., 2018). As a result, land degradation may be less pronounced in this region. The impacts of land degradation on NDVI change may be offset by the impacts of climate change. This suggests that NDVI change, and specifically median or mean growing season NDVI change, may be an incomplete metric or surrogate for land degradation when other factors may be impacting vegetation dynamics.

In addition to multiple environmental factors, anthropogenic activities also affect vegetation; these activities include grazing, afforestation, policy-driven land use conversions, agriculture development, tourism development, animal husbandry, urbanization, infrastructure development, and mining (Yu et al., 2012). The human population, the number of livestock, and
grazing intensity are believed to be important driving factors in vegetation degradation at local scales (Gao et al., 2013; Li et al., 2016), and the role of human activities has shown an increasing role in causing vegetation change over time (Li et al., 2018). Several studies even argue that anthropogenic activities were the primary contributors to changes in one-third of alpine vegetation on the TP since 2000 (Chen et al., 2014; Wang et al., 2016). The escalating human population; livestock abundance; and expanding agriculture, mining, and urbanization all significantly negatively impact grassland ecosystems (Shang and Long, 2007; Wu et al., 2018).

As noted by Fassnacht et al. (2018), coarse spatial resolution data may be inadequate for characterizing land degradation based on changes in NDVI. Furthering Fassnacht et al.’s argument, I argue that additional factors that can cause changes in NDVI, such as climate change, further complicate the use of NDVI as a means to quantify and detect land degradation, as in this study more local decreases in NDVI were difficult to detect when the larger trend is increasing NDVI. In short, this study and the work of Fassnacht et al. highlight issues in using coarse spatial resolution products, such as those derived from AVHRR and MODIS, for characterizing local scale land degradation and that interpreting NDVI in the context of land degradation requires considering other factors that can cause change. An et al. (2018) highlighted the influence of terrain effects on the elevational shifts of greenness isolines by noting that variations in terrain slope angle explained large spatial variations in the elevational gradient of greenness and, consequently, the velocity of elevational shifts of greenness isolines and the sensitivity of elevational shifts of greenness isolines to temperature. The discrepancies and terrain impact observed in this study imply that there may be significant micro-topographical variation in plant response and adaptation to temperature fluctuations. To relate the discrepancy to particular environmental causes and biological processes, such as vertical changes in community structure, plant physiology, and species distribution, more extensive in situ measurements, fine-resolution remote sensing observations, and fine-gridded temperature data are needed.

One limitation of this study and the growing season median NDVI change data created by Fassnacht et al. is the inability to model or describe seasonal patterns in NDVI. Given the return interval of the Landsat satellites (i.e., every 8 to 16 days depending on the number of sensors active at a specific time) and the impacts of cloud cover, these data do not allow for the characterization of seasonal and/or phenology patterns. In other words, there is a tradeoff between return interval and spatial resolution. A large body of studies reports longer growing seasons in the east and shorter growing seasons in the northwest within the TP as a result of climate change (e.g., Zhang et al., 2013; Wang et al., 2015; Piao et al., 2012; Lehnert et al., 2016). Further, increases in grassland vegetation cover on the TP have been documented by many studies (e.g., Shen et al., 2015; Xu et al., 2018; Zhong et al., 2010; Zhang et al., 2013; Wang et al., 2013; Zhang et al., 2013) whereas other studies note a decline in vegetative cover in alpine grasslands within the TP (Hu et al., 2008; Chen et al., 2011; Yadav et al., 2022). Peng et al. (2017) reported an increasing NDVI trend from 2000 to 2016. Zhao et al. (2015) documented mainly positive changes in the NDVI derived from MODIS satellite data at a spatial resolution of 1 km and for the time period between 2000 and 2012. They observed that 25% of the research region had drastically decreasing or increasing NDVI patterns while around 75% of it had rather steady trends. In contrast, a study by Lehnert et al. (2016) based on MODIS data at a 500 m spatial resolution from 2000 to 2013 noted increasing trends for the northern TP’s vegetation
cover but declining trends for the TP’s center and western regions. In their research, they also suggested that climatic variability had a larger role in determining these patterns than livestock density, which is often associated with land degradation. A recent study by Zhou et al. (2020) using GIMMS NDVI3g data documented that the vegetation in the TP had an overall greening pattern from 1982 to 2012. In summary, studies have reported varying and even contradictory results regarding vegetation and NDVI change. Some of these differences may be a result of the time period or region studied, the spatial resolution at which the study was performed, and the time period investigated. Our research further suggests that local or hillslope scale changes may be difficult to map or document or attribute to a specific cause.

There were certain areas where this study might be strengthened. Land degradation can occur across a wide range of topographic, geomorphologic, and land cover conditions. NDVI is widely used to estimate land degradation status as a proxy indicator of greenness, vegetation density, vegetation growth, and biomass productivity (Nachtergaele et al., 2009). However, the alpine environment, which is often cold and dry, supports a diverse range of vegetation across the TP with varying growth patterns (Mao et al., 2022). Thus, NDVI may be an imperfect signal of land degradation, especially over broad spatial extents with variable topography, temperature and precipitation patterns, and vegetation communities.

Information on human activities and their associated impacts are lacking within the TP, making it difficult to attribute changes in NDVI to specific causes with sufficient evidence. One of the most important factors of degradation is overgrazing. I argue that better assessing land degradation patterns at the hillslope scale will require a combination of both social and ecological data, which can be challenging to obtain remotely. Another limitation lies in unpacking the often-complex biophysical interactions that lead to systems becoming more prone to land degradation in general, including the adaptive capacity of ecosystems. Future studies should concentrate on exploring different factors, such as human interventions (e.g., overgrazing, construction, and urbanization) and climate information sources to potentially enhance the precision of land degradation studies. I argue that geomorphons should be considered as an analysis or aggregating unit in future studies.

3.7. Conclusions
This study observed increases in NDVI or greening within the TP, especially during the 1990 to 2018 and 2000 to 2018 time periods. Larger median growing season NDVI change values were observed for the SETSM and TPASM grassland regions in comparison to the other three regions studied. The regions comprise the eastern and southeastern portions of the TP. Minimal differences in NDVI change were observed for different geomorphon-based landforms, and topographic slope and TPI were weakly correlated with the NDVI change data across all time periods and grassland types. The widespread greening trends overwhelmed more local-scale land degradation patterns. A more focused analysis of only locations experiencing NDVI decreases suggests that negative NDVI change was not evenly distributed by geomorphon type. Although no landform units in any grassland type or during any time period had more than 10% of their randomly selected pixel experiencing decreased NDVI, depression, valley, slope, and hollow landforms generally had a larger percentage of samples with a negative NDVI change between 1990 to 2018 and 2000 to 2018 whereas flat, summit, ridge, and shoulder landforms tended to have a lower percentage of negative NDVI change. More generally, this suggests that
land degradation is more prominent in the lower and intermediate hillslope positions in
comparison to the higher relative topographic positions, and that change was more pronounced in
the more eastern SETSM and TPASM grassland regions. Generally, this study supports the use
of geomorphons as an analysis and aggregating unit for studying hillslope scale change patterns.
More work is needed to understand landscape change dynamics in the TP at the hillslope scale
and to differentiate the impacts of climate change and anthropogenic impacts.
4. Critical Physical Geography of the Tibetan Plateau

Abstract

Over the past several centuries, the world has witnessed unprecedented increases in the pace, magnitude, and spatial extent of changes in land use; these patterns are especially pronounced in grassland ecosystems, which occupy approximately 25% of the global land area. The Tibetan Plateau (TP) is one of the last remaining agro-pastoral regions in the world that play an important role in the regional global climate. The extensive grasslands of the TP cover an area of 1.5 million km², accounting for 60% of the TP and 30% of the total Chinese grasslands. Currently, critical components of the TP’s ecosystem are undergoing major transformations due to climate change and adverse human activities. The grasslands have declined in overall productivity in the last decade, and traditional livestock and grazing management systems have been altered due to political, social, economic, and ecological transformations. The Chinese government has initiated a policy to control grassland resource extraction and degradation using sedentary and individualized production systems that differ from the traditional nomadic practices developed over thousands of years. Additionally, the TP has warmed significantly, with surface temperatures increasing by 1.8 °C since the 1980s. The human and ecological systems are interlinked, and the drivers of change include biophysical, economic, political, social, and cultural elements that operate at different temporal and spatial scales. Current studies do not holistically reflect the complex social-ecological dynamics of TP. To increase our understanding of this coupled human-natural system, there is a need for an integrated approach. Critical physical geography (CPG) is one such integrative approach that assumes that human and environmental problems can only be well understood through a mixture of social and physical science research methods and seeks to provide an interdisciplinary synthesis of causation related to land-use change, political change, social processes, and climate change, among many other underlying issues. Therefore, the main goal of this study is to critique the methodological approaches traditionally used in climate change and land degradation studies and offer insights from CPG for a more comprehensive approach to the study of complex human-natural dynamics of the TP. It will aid researchers, development organizations, and governmental organizations in better understanding the complexities of ecological and human systems and the roles that biophysical, economic, political, social, and cultural factors play as drivers of change at various temporal and spatial scales.

Keywords: Tibetan Plateau, critical physical geography, land degradation, climate change, Land Cover/Land Use Changes, social-ecological dynamics, interdisciplinary
4.1. Introduction

The pace, magnitude, and spatial extent of changes in land use have increased significantly over the past several centuries; these patterns are most prominent in grassland ecosystems, which comprise around 25% of the world's land area (Zhou et al., 2019). Grasslands provide several ecological services and functions at regional to local scales, including climate regulation, carbon storage, tourism, aesthetic recreation, water resources control, pastoral production, and more (Dong et al., 2020). Climate change, coupled with unsustainable land-use practices, has resulted in the degradation of nearly half of global grasslands (Gang et al., 2014), impacting millions of people around the globe (Wessels et al., 2012). As a result, grassland degradation poses a significant environmental challenge threatening biodiversity and ecosystem services worldwide and jeopardizing millions of livelihoods.

The Tibetan Plateau (TP) is one such grassland and is an important physiographic and cultural region that plays a significant role in regional and global climate (Flohn, 1968; Wu et al., 2012b). The extensive grasslands of the TP cover an area of 1.5 million km², accounting for 60% of the TP and 30% of total Chinese grasslands (Cao et al., 2019; Fayiah et al., 2020). Tibetan grasslands are dominated by alpine meadow, alpine steppe, and temperate mountain meadow vegetation. Unfortunately, grasslands have declined in overall productivity in the last decade, and traditional livestock and grazing management systems have been altered due to political, social, economic, and ecological transformations (Shang et al., 2014). The Chinese government has initiated a policy to control grassland resource extraction and degradation using sedentary and individualized production systems that differ from the traditional nomadic practices developed over thousands of years (Foggin, 2008).

Additionally, the TP has undergone extreme alterations due to climate change (Yang et al., 2014). The TP has warmed significantly, with surface temperatures increasing by 1.8 °C since the 1980s (Li et al., 2010; Yang et al., 2014), and a warming rate 1.5 times higher than the average global rate (Zhang et al., 2013). At the same time, anthropogenic activities, such as livestock stocking, land cover change, urbanization, deforestation and desertification, and unsustainable land management practices, have significantly intensified over the TP (Cui and Graf, 2009; Harris, 2010). Moreover, infrastructure development, such as highways and railroad construction, tourism, and mining, exert increasing pressure on the TP grassland ecosystems (Li et al., 2017b). As a result, grasslands have undergone rapid degradation since the 1980s due to the dual effect of climate change and adverse human activities (Harris, 2010; Liu et al., 2012).

The human and ecological systems are interlinked, and the drivers of change include biophysical, economic, political, social, and cultural elements that operate at different temporal and spatial scales. Current studies do not holistically reflect the complex social-ecological dynamics of the TP. To increase our understanding of this coupled human-natural system, there is a need for an integrated approach to rendering visible the deep interconnections between the biophysical and social systems of the TP. Critical physical geography (CPG) is one such integrative approach that assumes that human and environmental problems can only be well understood through a mixture of social and physical science research methods and seeks to provide an interdisciplinary synthesis of causation related to land-use change, political change, social processes, and climate change, among many other underlying issues (Engel-Di Mauro, 2014).
The TP is an excellent area in which to explore the potential of CPG and further develop associated research methods and practices to better understand the interconnected issues of land degradation, climate change, land use policy and practice, and social vulnerability. This article uses the case study of the TP to argue that physical scientists (e.g., physical geographers, climate modelers, ecologists, and geospatial scientists) and social scientists (e.g., human geographers, sociologists, and political scientists) should prioritize interdisciplinary research and the implementation and further development of CPG and associated methods in order to more holistically explore problems and solutions related to land degradation and climate change and to support research that is applicable to vulnerable individuals and communities. Based on an extensive survey of the literature on previous research on climate and land degradation in the TP, in addition to findings from chapters 2 and 3 of this dissertation, the main goal of this study is to critique the methodological approaches traditionally used in climate change and land degradation studies and offer insights from CPG for a more comprehensive approach to the study of complex human-natural dynamics of the TP.

4.2. Background

4.2.1. THEORETICAL FRAMEWORK: CRITICAL PHYSICAL GEOGRAPHY

CPG investigates physical geographic processes through the integrative analysis of biophysical processes and critical theory, including power relations and social processes (Lave et al., 2013). Lave et al. (2014) contend that the complicated relationship between people and their environment can only be meaningfully addressed through an integrated analysis of social processes and environmental change. It cannot rely on explanations grounded in physical or critical human geography alone. Also, socio-biophysical landscapes are not only the result of unequal power relations, histories of colonialism, and racial and gender disparities but also of climate, hydrology, geology, ecology, and other abiotic and biotic factors. For instance, the grassland degradation in the TP is not only from climate change but also from the implementation of grassland policies. CPG is thus based on integrative work that applies critical inquiry within physical and human geography to support the production of fair and ecologically sustainable environmental futures (Tadaki et al., 2014) and promote social and environmental transformation (Lave et al., 2013). It is a distinctive combination of the physical and social sciences that examines the role of people, power, politics, and place in shaping physical landscapes (Blue and Brierley, 2016).

CPG consists of various environmental topics, research methods, and epistemological commitments. However, it is centered on three fundamental scholarly ideologies (Lave et al., 2018). The first ideology is that human actions and considerations of race, gender, and class have shaped natural landscapes. Second, social, cultural, and political-economic linkages impact how research is effectively conducted because natural and social sciences are intrinsically linked. Thirdly, the people and natural environment studied can be impacted by the knowledge created. According to Lave et al. (2018), there isn’t a set of universal research techniques to conduct CPG. Instead, CPG researchers must be able to select the approaches that are most appropriate for the particular situation at hand because they address contingent problems across a wide range of environmental themes. There isn't a set of universal research techniques to conduct CPG. However, CPG researchers must be able to select the approaches that are most appropriate for
the particular situation at hand and can address problems across a wide range of environmental themes, as shown in Table 3.

**Table 3: Range of epistemological positions for CPG study (adapted from Lave et al., 2018)**

<table>
<thead>
<tr>
<th>Natural Science</th>
<th>Qualitative Methods</th>
</tr>
</thead>
<tbody>
<tr>
<td>quantitative methods</td>
<td>qualitative methods</td>
</tr>
<tr>
<td>frequency/magnitude curves, geospatial analysis</td>
<td>descriptions of species and ecosystems, soil classification, aerial photograph analysis, description of vegetation structure/composition</td>
</tr>
<tr>
<td>hydraulic modeling, soil chemistry, climate modeling</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Social Science</th>
<th>Qualitative Methods</th>
</tr>
</thead>
<tbody>
<tr>
<td>surveys, social network analysis, Q-method econometrics</td>
<td>ethnography/participant observation, interviews, document analysis archival, oral history, linguistic analysis, focus group discussion.</td>
</tr>
</tbody>
</table>

Several studies highlight the importance of using a CPG approach, or are closely aligned to such an approach, even if they do not use the terminology of CPG (Richter, 2001, 2007; Swidler, 2009; Colven and Thomson, 2018; McClintock, 2015). While conducted before CPG was put forth as a framework, Lane et al. (2011) used a radical participatory framework to research flood risk management where local community members participated in identifying research questions and aims and contributed to developing conceptual models. The study was conducted in Pickering, a small market town in Ryedale, North Yorkshire, United Kingdom from 2007 to 2008. The study used a unique approach involving local people and hydrological modeling scientists to study flood risk and its management. Local members had the knowledge required to not only inform what the modeling should accomplish but also contribute to its conceptual development. Also, by repositioning scientists in the process, the project constitutes a dramatic shift from the standard approaches to flood risk science. As a result, the study harnessed, developed, and negotiated a new and common sense of knowledge about social-ecological flooding dynamics.

Brazel (2017) more directly explored the possibilities of CPG in studying urban climate. The study claimed that physical geographers should include socio-natural relationships while studying urban climatology through the inquiry of ecology, vulnerability analysis, climate and environmental change, environmental justice, city design, health risks, and many others. Lahsen (2010) examines the possibilities for approaches from geography to inform more interdisciplinary approaches to climate modeling, engage in more democratic practices of knowledge, enrich understandings of climate change, and more effectively serve goals of social and environmental justice. The study found that the complex interactions between political, professional, and psychological involvement in the models, as well as changes in time and environment, appear insufficiently represented by a single, visual diagram. Therefore, it is necessary to identify any restrictions or errors that may result from a convergence of
psychological, social, and political elements. A more dynamic model with the ability to display numerous dimensions and fluctuations over time would be necessary for an accurate representation of the complexity of climate models. Further, the various social environments that impact how various climate modelers relate to the technology would also need to be taken into consideration. Similarly, Adamson (2022) investigated the impact of regional, institutional, and personal context on scientists' motivations and research practices on El Niño and the Southern Oscillation (ENSO) by the National Oceanic and Atmospheric Administration (NOAA), National Center for Atmospheric Research (NCAR), and International Research Institute for Climate and Society (IRI). The study showed that ENSO has many facets and that experts' conceptualizations of it vary and can even be conflicting. Some had never worked with scientists outside of the Global North or even traveled to regions thought to be impacted by ENSO variability outside of the United States. Therefore, more interaction between modeling centers and ENSO-affected regions will be beneficial to produce ENSO information. Future research on the key geographies of ENSO should thus concentrate on how institutions restrict and shape policy and practice, how the research is practiced, and more importantly, how it is translated and presented outside of the realm of science.

McClintock (2015) demonstrated how the understanding of social and natural factors that contributes to soil contamination complement each other to support environmental justice. By measuring soil lead (Pb) pollution in the flatlands of Oakland, California as an example, McClintock observed that the co-production of social relations and soil processes across time and space is important to understand soil contamination. Carey et al. (2014) used a combination of social science methods and modeling to show how water availability is changing due to glacier shrinkage caused by climate change and the importance of this for local communities. Using the Santa River watershed, the study provided a holistic hydro-social framework to study hydrological modeling and devise climate adaptation plans. These authors suggest that to comprehend watershed dynamics and predict future water scenarios, the hydrosphere and social sphere must be studied concurrently and across places and time. Human modification of the watershed dynamic shapes the legal, economic, political, cultural, and social dynamics that eventually affect water consumption patterns. Therefore, to predict water consumption scenarios, historical social science factors are essential.

These studies demonstrate the contribution of CPG, and related approaches, to deepening integrated understandings of natural and social processes and how it opens the door to incorporating relations of power and social context into studies of climate change (Lave, 2013; Engel Di-Mauro, 2014; McClintock, 2015). Together, these research commitments show the value of the CPG viewpoint in studying socio-biophysical landscape entities and support the applicability of CPG as a methodological framework for improving socio-biophysical studies. Hence, we propose that a CPG study is imperative in the TP to understand biophysical, socio-economic, and political changes in a complex of nonhuman and human processes on varying spatiotemporal scales (Richter, 2007). These studies demonstrate that humans shape the physical world by impacting legal, economic, political, cultural, and social processes. Whether it is climate modeling, glaciology, soil contamination, ENSO modeling, or hydrological modeling, it is imperative to consider human actors and social dynamics. CPG helps uncover the historical, social, political, and economic forces and power relations that impact and are impacted by land use, water use, urban climatology, and flood management, in a particular place and time. It also
denotes that each specific event is linked to a specific spatial and temporal context and therefore must be explored (Livingstone, 2003). The interaction of physical and social processes serves as a driving force that is closely connected to and governs ecosystem function and social development; thus, CPG provides potential avenues to better understand coupled human-natural systems (Lave, 2014).

4.2.2. THE TIBETAN PLATEAU

a. The Physical Landscape

The TP is the highest terrain globally, with an average elevation of more than 4,000 m (Figure 16). Extending from 25° to 40°N and 74° to 104°E (Liu et al., 2015), it stretches approximately 1,000 km north-to-south and 2,500 km east-to-west (Duan et al., 2012). The elevation ranges from 3,000 m to 5,000 m with an average elevation of 4,000 m. (Wang et al., 2020). It is characterized as an expansive continental plateau with rugged topography (Xu et al., 2013). The mean annual temperature ranges from -15 to 10°C (You et al., 2013). The mean annual precipitation is more than 600 mm in the southeast, dropping to less than 200 mm in the northwest (Zhong et al., 2010). The winter is characteristically dry and cold, whereas the summer is cool and wet. Temperature varies with elevation, and the northern plateau is generally colder than the southern extents. The TP differs greatly from other mid-latitude warm temperate zones and subtropical regions in terms of its high elevations, which provide unique environmental characteristics (Yue et al., 2014). There are spatial differences in vegetation and ecosystem types across longitudinal, latitudinal, and elevational gradients due to differences in the hydrothermal environment (Huang et al., 2019). The alpine steppe and meadow are the dominant grassland types and cover around 50% to 60% of the plateau (Liu et al., 2017; Wei et al., 2019), as shown in Figure 1 (Dixon et al., 2014). The predominant land types in TP are cold and dry with low agricultural productivity; deserts and other hostile land types make up more than 30% of the total area (Zhang et al., 2019).

b. Land use, pastoral practices, and livelihoods

Traditionally, Tibetan people were the main inhabitants of the TP and have been dependent on pastoral systems for thousands of years (Wei et al., 2019). Their mobile and flexible livestock grazing practices have enabled Tibetan herders to be self-reliant, adapt to harsh environmental conditions, and sustain their livelihoods (Wang et al., 2014). Tibetan nomads graze several animals, including yak, sheep, goats, and horses, to maximize grassland resources (Wang et al., 2014). Historically, to avoid natural disasters such as droughts and snowstorms, the herders migrated between shady and sunny mountain slopes (Wang et al., 2015). Similarly, herders have successfully maintained a sustainable and mobile lifestyle, traveling from winter to summer pasture lands and from autumn to spring pasture lands. The population is sparsely distributed throughout the TP (Liao et al., 2003), and a delicate balance has developed over thousands of years between local herders, their livestock, and the alpine grassland ecosystem; as a result, adaptative pastoral practices have become an integral part of the TP’s socio-environmental system (Banks et al., 2003; Yan et al., 2005). However, beginning in 1950 government systems have undergone fundamental changes in the TP after the region came under the control of the government of China, resulting in a shift from traditional nomadic pastoralism into sedentary pastoral systems. The major reforms which affected pastoralism on the TP include collectivization in the 1960s and 1970s, reform and opening in the 1980s, Household Contract
the Responsibility System (HCRS) or the “Grassland Law” in 1985, privatization in the late 1990s, and "retire livestock and restore grassland" (RLRG) in 2003.

Socio-economic activities and urbanization have increased ever since. The population has increased rapidly over the past few decades (Fan et al., 2010). Human activity, such as changes in land cover and grazing activities, has accelerated influencing the ecological environment (Harris, 2010). Further, the confinement of herd sizes, the fencing of pastures, and the displacement of nomads into permanent settlements due to a change in policy by the Chinese government have forced herders to seek alternate sources of income. Millions of Tibetan nomads have been compelled to give up their traditional way of life and relocate to resettlement camps where there are limited chances for employment to support a respectable lifestyle. These large-scale settlements characteristically lack healthcare and education services and employment opportunities that would allow former herders to support their families and maintain their cultural identity (Du 2012). As a result, youth unemployment and alcoholism are rampant (Ptackova, 2011) resulting in culture shock and social disruption (Li 2008).

As a result of the Chinese government's intervention in grassland management policy, the Tibetan ecosystem has been severely damaged, and its people are suffering. The uncontrolled and poorly planned urbanization since 2016, and especially the “development of western regions”, “new-type urbanization planning” and the “Belt and Road Initiative”, resulted in rapid socioeconomic development (Chen et al., 2018; Wang et al., 2020). Also, industrialization and the expansion of transportation have increased urbanization and spawned many urban clusters (Qi, 2019). Urbanization has resulted in several ecological and environmental issues, including the loss of natural habitats, a decline in biodiversity, air pollution, and deteriorating water quality, posing a threat to the TP's sustainability (Piao et al., 2019; Sun et al., 2019).

Additionally, increased mining and drilling activities associated with oil and natural gas, as well as other mineral resource extraction practices, have gained momentum, resulting in severe social, cultural, and environmental suffering (Bauer and Nyima, 2010).
c. Land degradation and climate change issues

The TP is one of the most fragile and sensitive regions to global climate change (Jiang et al., 2019; Shang et al., 2014). Studies suggest that since 1980 the TP has warmed due to climatic and anthropogenic activities (Kang et al., 2010; Yang et al., 2014). Surface temperatures of the TP have increased by 1.8°C on average over the past 50 years (Wang et al. 2008), with a warming rate of 0.36°C per decade. The warming rate in the TP generally increases from the southeast to the northwest (Xu et al., 2017). The highest warming rate occurs in winter, and the lowest occurs in spring (Zheng et al., 2015). The warming of the TP has caused significant glacial retreat, snowmelt, and permafrost degradation (Guo and Wang, 2013; Yang et al., 2010).
Precipitation, on the other hand, shows heterogeneous spatial variability but generally decreases from the southeast to the northwest (You et al., 2012). The spatial pattern of changes in precipitation is complex, and the total annual precipitation does not show a uniform increasing or decreasing trend across latitudinal, longitudinal, or elevational gradients. Further, precipitation totals have increased in some sub-regions and decreased in others (Kuang and Jiao, 2016). Some regions are becoming warmer and wetter, while some subregions are becoming warmer and drier.

Land degradation is also occurring at unprecedented rates across the TP due to the dual effect of climate change and adverse human activities (Harris, 2010; Wang et al., 2013). Approximately 5.0 x 10^5 km^2 of the TP’s land area is experiencing various degrees of degradation, of which 16% is considered severely degraded (Cui and Graf, 2009). Several studies claim that about two million km^2 of grasslands within the TP have been degraded, resulting in a 30% reduction in net primary productivity (NPP) over the past two decades (Liu et al., 2018; Dong et al., 2012), with other studies suggesting figures of 50% (Dong et al., 2013, Wu et al., 2014), 40% (Cai et al., 2015, Wang et al., 2016a), and 33% (Li et al., 2013b).

Xue et al. (2017) documented those anthropogenic activities—changing land-use practices, curtailing of mobile pastoral systems, urbanization, industrialization, mineral exploration, tourism, the construction of ecological projects, and the production of Chinese traditional medicines— that are the primary forces driving grassland degradation in the TP (Liu et al., 2018; Sun et al., 2013). This has resulted in reduced plant species richness and declining grazing land productivity (Wang, 2009) and food production (Harris, 2010). Various studies suggest that overgrazing is the primary factor contributing to changes in alpine vegetation on the TP since 2000 (Gao & Li, 2016; Xue et al., 2017). In addition, the initiation of major highway and railway construction and other infrastructural development projects, such as the “West-East Gas Pipeline Project” and “Qinghai-Tibet Railway” by the Chinese government since 2000, has resulted in ecosystem fragmentation and grassland degradation (Fayiah et al., 2020; Han et al., 2018). The extensive use of heavy machinery during road and railway construction can damage biodiversity and lead to soil nutrient loss and compaction (Li et al., 2017). With improvements in transportation systems, including railways, highways, and aviation, people worldwide traveled with greater ease to the TP, leading to ecological and environmental issues including air and water pollution and biodiversity loss (Chen et al., 2019). These factors, combined with a changing climate, have led to extensive land degradation in the TP.

d. Impact of the Chinese government policy on pastoral societies and land use practices

The TP has undergone significant change because of the implementation of the Grassland Law in 1980 (Figure 17) by the Chinese government, which intensified pasture management and resulted in a shift from traditional nomadic pastoralism into sedentary pastoral systems. It resulted in the division of pasture use rights and regulations to limit household livestock holdings to government-established livestock carrying capacities on grassland (Yeh et al., 2017). As depicted in Figure 2, the introduction of the household responsibility system in 1980 resulted in the demarcation of grazing areas for households on winter pastures while summer grasslands were grazed collectively by several households. Under the promulgation of the 1985 Grassland Law, state or collective land can be leased to households on a long-term basis of 30 to 50 years, changing the historic pasture use rights for the TP. As a result, herders started to settle and fence
their contracted pastures to reduce quarrels concerning property matters (Yeh 2003). Li et al. (2017) suggested that the privatization of pasture from 1984 to 1992 created a land-use regime shift that reduced the flexibility and mobility of pastoral communities and threatened the sustainability of the delicate grasslands. It resulted in the privatization of grassland, which weakened the power of the community to manage grassland and contributed to overgrazing. The privatization of grassland was again reiterated in the Grassland Law of 2002 (Figure 17). In 2003, China's state and local authorities initiated a program called "retire livestock and restore grassland" (RLRG). RLRG aimed to move livestock into fenced areas and nomadic herders into villages, which resulted in the fencing of grazing land, exacerbation of pasture degradation and associated loss of ecosystem services, and significant impacts on the livelihood of herders (Fan et al., 2015). However, the Rural Land Contract Law of 2002 and the Property Law of 2007 mandated that land, including grazing land, be contracted to specific families (Nyima 2012). As a result, laws and policies have been contradictory when it comes to the fundamental unit of allocating grassland use rights and whether pasture should be utilized individually or collectively following the introduction of land-use rights contracts (Cao et al., 2013). The "Suggestions on Improvement of Ownership Rights, Contractual Rights, and Use Rights on Rural Land" initiative was launched in 2016 to convert the two current rights—ownership and contractual use rights—into three rights—ownership, nontradable contractual rights, and tradable contractual use rights (State Council 2016).

While some of these interventions were partially successful in managing degradation in some grasslands, the long-term ecological implications of privatizing rangeland and reducing the mobility of herders between seasonal pastures and restructuring the herd composition along commercial lines have generally resulted in the further deterioration of grasslands and loss of production and household sustainability (Sheehy et al. 2006). Studies have found that privatization and grazing sedentarization have reduced the flexibility of grassland resource use by herders (Wu and Yan, 2002; Bauer 2005; Yan et al., 2005; Foggin 2008; Klein et al., 2011; Du 2012). Studies that quantified human influences on grassland dynamics (Chen et al., 2014; Lehnert et al., 2016; Li et al., 2018b) and mapped human-influence intensity on the TP (Li et al., 2017b) revealed that the reduction in flexibility and mobility of grazing are important drivers of grassland degradation and result in negative social and environmental impacts (Gongbuzeren et al. 2015; Harris 2010; Yan et al., 2011; Yan and Wu 2005; Yeh 2009; Yeh 2013; Yeh et al., 2014). While the socioeconomic, political, ecological, and institutional changes did impact local people's use of rangeland resources, there is a general lack of ecological and socioeconomic baseline data to support an integrated understanding of social and ecological driver interactions and feedback processes (Fassnacht et al., 2015).
4.3. Literature Review

4.3.1. CLIMATE CHANGE AND MODELING STUDIES METHODS

Climate change and climate modeling studies on the TP have received considerable attention due to the plateau’s role in the regional and global climate (Zhang et al., 2015; Wang et al., 2017) (Table 4). In the TP, meteorological station data have limited spatial coverage, and the availability and abundance of these data vary over time. Because of the complex terrain and extreme environmental conditions, most surface observational stations are situated in the lower elevations of the eastern and central TP. Reanalysis data provide an alternative representation and have been employed because they can better reflect the long-term and large-scale thermodynamical condition of the atmosphere (Gao et al., 2019). Reanalysis data are produced by combining actual observations with outputs from numerical weather prediction models representing past and present conditions and are designed to estimate the state of the atmosphere and land surface (Simmons et al., 2010). Various reanalysis datasets, such as the Climate Research Unit (CRU) (Harris et al., 2020), National Centers for Environmental Prediction (NCEP) (Mesinger et al., 2006), Japanese Reanalysis (JRA-55) (Kobayashi et al. 2015), and European Center for Medium-Range Weather Forecasts (ECMWF) reanalysis (ERA-5) (Hersbach et al., 2020) datasets, have been developed for and used in climate change and climate modeling studies.

Figure 17: Grassland policy trajectory over time (adapted from Bauer and Nyima, 2010; Du et al., 2012; Goldstein, 2012; Ptackova, 2011; Sheehy et al., 2006; Yeh, 2003, 2005; Yeh and Garang, 2011; Yeh et al., 2013; Gongbuzeren et al., 2018).
With the development of Global Climate Models (GCMs) in the 1950s, climate modeling over the TP began. Since then, GCMs have been created to model atmospheric dynamics and processes, the global climate system, and climate change (Gao and Chen, 2017). Regional climate models (RCMs) were developed in the 1970s because of an increasing understanding of GCMs' limitations regarding representing regional or local spatial scale atmospheric processes over varied terrain and the need for this information to support local decision-making (Bao et al., 2015; Gao et al., 2018). Since then, several modeling studies have explored the dynamic and thermodynamic effects of the TP on the summer monsoon across East and South Asia. In addition to topographic heterogeneity, the effects of changing and heterogeneous land cover on regional climate have been extensively predicted through sensitivity studies. Both GCMs and RCMs have been used to study climate change and climate modeling using the Coupled Model Intercomparison Project (CMIP). Most climate forecasts are based on ensemble means, or averages of many CMIP models, where each ensemble member is given equal weight toward the mean. However, the equal model weighting strategy may lower projection reliability due to varying levels of model independence and competency (Zhao et al., 2022).

Climate modeling studies have improved our knowledge of how regional and global climate varies; for the TP specifically, temperature, precipitation, and extreme events have been related to mechanical and thermal forcing processes. Based on CMIP3 and CMIP5 (Phase 3 and 5 of the CMIP) GCMs, general warming and a rise in precipitation have been documented across the TP (Su et al., 2013; Jia et al., 2019). Applications of RCMs include case studies (Zhang et al., 2019), simulations of the current climate and model calibration (Guo et al., 2018; Gu et al., 2020), studies of aerosol transportation and effects (Yang et al., 2020), and, more generally, climate change projections using various RCMs, mostly the Weather Research & Forecasting Model (WRF) and RegCM regional climate model (Bao et al., 2015; Gao et al., 2018; Hui et al., 2018; Lu et al., 2019; Yu 2019). Zhu et al. (2013) used a statistical regional climate model to project the TP climate from 2015 to 2050. Ma et al. (2017) monitored and modeled interrelated water-cryosphere-atmosphere-biology processes to study climate change over the TP. Similarly, Fu et al. (2021) studied climate change projections over the TP based on a set of RCMs simulations. Findings from the above-mentioned studies suggest that the warming of the TP since the 1960s cannot be completely explained by current climate models.

According to Zhou et al. (2021), the Plateau is warming faster than projected by many climate models. Through a quantitative comparison of observations and modeled responses, the attribution study conducted by Zhou and Zhang (2021) revealed that the CMIP5 ensemble and current global climate models underestimate the anthropogenically-induced warming trend on the TP. The TP is a vast area with a harsh environment characterized by high altitude, thin air, and dry, frigid temperatures. Due to difficulties in field data collection, there have been disparities between studies in regard to land cover change patterns, their geographic distribution, and suggested causes of change (Harris, 2010; Wu et al., 2014; Li et al., 2020). More than two-thirds of the TP comprises alpine grasslands, crucial for the region's energy balance, temperature, and carbon storage. These alpine grasslands primarily consist of alpine meadows and alpine steppe flora (Wang et al., 2002) and are the main form of subsistence for Tibetan pastoralists. However, grassland processes is not incorporated into climate modeling studies.
Human activities, particularly greenhouse gas emissions, can be connected to the warming that has been seen in the TP since the 1960s (Zhou and Zhang, 2021). It can be easier to forecast and evaluate future changes if we have a clear understanding of the TP's historical warming, particularly the underlying human influence. Because of global warming, the TP's climate and ecological characteristics are changing significantly. Due to complex topography, different parts of the TP have had very different vegetation responses to climatic abnormalities (Jiang et al., 2019). Additionally, human activities are significant contributors to land cover change (Liu et al., 2018c). Therefore, to study how global climate change may impact regional vegetation variability and patterns (Pang et al., 2017) and to predict future climate change impact, it is essential to understand the spatiotemporal dynamics in vegetation conditions and the impact of human activities on this vegetation (Li et al., 2020).

Additionally, implementing grazing rules that prevent grazing in certain areas has led to significant concentrations of grazing outside of enclosures and the deterioration of grasslands (Li et al., 2018). This, in turn, has altered the surface energy balance, which is a critical component of climate modeling. Therefore, the importance of social, economic, and human factors must be highlighted and fully integrated with climate change and climate modeling studies. A CPG approach would result in greater attention to socio-biophysical processes by analyzing quantitatively and qualitatively the complex, direct, and indirect connections between the components of human and environmental factors at various spatial and temporal scales. CPG can facilitate climate modeling studies conducted within a framework of coupled social and natural systems (Wu et al., 2015b; Su et al., 2015) by recognizing the integrated and coupled nature of human and ecological systems (Dong et al., 2011).

Further, it is also important to explore the practicality and reliability of climate model output at the local spatial scale. Issues of spatial and temporal scales of models must be taken into consideration. Large-scale patterns of temperature and rainfall frequently differ from observed and simulated climate trends (Shin and Sardesh-mukh, 2011), which inevitably result in biases in the modeling of the direction and amplitude of local-scale changes (Gonzalez et al., 2014). At the local spatial scale, the seasonal cycle cannot be captured by models (Yang et al., 2014), and models provide a poor representation of daily rainfall features, especially at small temporal scales and for extremes (Stephens et al., 2010; Kharin, et al., 2013), which are the most critical for risk assessments. GCM output is too coarse (more than 100 km) to be used in local or regional impact assessment studies, adaptation planning, or decision-making processes (Gutmann et al., 2012). In addition to having a coarse spatial resolution, GCMs' biases and uncertainties grow from global to regional to local spatial scales, which restricts their usefulness and application in local-scale impact assessment studies (Lutz et al., 2016).
Table 4: Methods employed in climate modeling studies.

<table>
<thead>
<tr>
<th>Reference</th>
<th>Approach/Variables</th>
<th>Spatial Extent</th>
<th>Spatial Scale</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sun et al., 2021; Zhao et al., 2022; Gao et al., 2020; Huang et al., 2021; Li et al., 2021; Liang 2004; Maussion et al., 2011; Gudongze et al., 2022; Zhang et al., 2019; Zhang et al., 2022</td>
<td>Precipitation</td>
<td>TP</td>
<td>9 km, 100 km, 4500 km, 1500 km, 300 km, 60 km, 10 km, 25 km</td>
</tr>
<tr>
<td>Li et al., 2013</td>
<td>Change on the runoff of TP rivers</td>
<td>The Yarlung Tsangpo River</td>
<td>50 km</td>
</tr>
<tr>
<td>Gao et al., 2022; Ma et al., 2022; Gao et al., 2018; Gao et al., 2015b; Gu et al., 2020; Wang et al., 2021; Ma et al., 2017; Fu et al., 2021</td>
<td>Climate (Temperature and Precipitation)</td>
<td>TP</td>
<td>25 km, 30 km, 300 km</td>
</tr>
<tr>
<td>Chen et al., 2017; Wang et al., 2018; Qin et al., 2022; Zhou et al., 2022</td>
<td>Temperature</td>
<td>TP</td>
<td>300 km</td>
</tr>
<tr>
<td>Gao et al., 2015a</td>
<td>Moisture</td>
<td>TP</td>
<td>30 km</td>
</tr>
<tr>
<td>Gao et al., 2017b</td>
<td>Land surface processes; Land surface and hydrological modeling</td>
<td>TP</td>
<td>30 km</td>
</tr>
<tr>
<td>Li et al., 2018</td>
<td>Wind</td>
<td>TP</td>
<td>30 km</td>
</tr>
<tr>
<td>Zhao et al., 2006; Deng et al., 2022</td>
<td>Climate-vegetation modeling</td>
<td>TP</td>
<td>500 m – 50 km</td>
</tr>
<tr>
<td>Ban et al., 2020</td>
<td>Temperature, precipitation, snow cover</td>
<td>The Yarlung Zangbo River Basin</td>
<td>25 km</td>
</tr>
<tr>
<td>Zhu et al., 2013</td>
<td>Future climate</td>
<td>TP</td>
<td>200 km</td>
</tr>
<tr>
<td>Iqbal et al., 2022</td>
<td>Climate and Land-Use Changes on Hydrological Processes</td>
<td>The Source Region of Yellow River</td>
<td>90 m</td>
</tr>
<tr>
<td>Tong et al., 2014; Sun et al., 2021</td>
<td>Hydrology and climate modeling</td>
<td>TP, River basins</td>
<td>25 km; 9 - 30 km</td>
</tr>
<tr>
<td>Wang et al., 2018; Ji et al., 2018; Zhao et al., 2022; Xue et al., 2013</td>
<td>Hydrological modeling</td>
<td>High mountain Mabengnong catchment; the Sanjiangyuan Region</td>
<td>100 km, 300 km, 90 m-100km</td>
</tr>
</tbody>
</table>
4.3.2. LAND DEGRADATION/REMOTE SENSING STUDIES METHODS

Numerous land degradation (Table 5) and land cover change (Table 6) studies have been performed on the TP. In most of these studies, remotely sensed data has been used to monitor grassland changes, and several techniques, data, and indicators have been developed and applied. Examples include the comparison of multi-period grassland status data using visual interpretation and human-computer interaction to obtain information on grassland change (Liu et al., 2008); an example of such a method is applying the Breaks for Additive Season and Trend (BFAST) algorithm for trend analysis of normalized difference vegetation index (NDVI) time series data (Shen et al., 2018). Other methods, including breakpoints detection and breakpoints trend analysis (Ni et al., 2020), the NDVI-based residual trend (RESTREND), Linear Regression Analysis, Mann–Kendall Trend Test, Change-Point Test, and Correlation Analysis (Zhnag et al., 2019), have been used to attribute driving factors of land degradation (Evan and Geerken 2004). The primary data sources for remote sensing are the National Oceanic and Atmospheric Administration (NOAA) Advanced Very High-Resolution Radiometer (AVHRR)-NDVI, Moderate Resolution Imaging Spectroradiometer (MODIS)-NDVI, and Landsat series images. The NDVI, net primary production (NPP), vegetation coverage, and geographical heterogeneity are the most commonly used monitoring indicators for studying grassland degradation (An et al., 2021).

Table 5: Land use and Land cover (LULC) studies in the TP.

<table>
<thead>
<tr>
<th>Ref</th>
<th>Data &amp; Period Used</th>
<th>Spatial Resolution</th>
<th>Class Differentiated</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gong et al., 2017</td>
<td>1990, 2000, and 2010 from Landsat TM 5 and 7 satellite images</td>
<td>30 m</td>
<td>cropland, woodland, grassland, wetland, waterbody, construction land, and unused</td>
</tr>
<tr>
<td>Cao et al., 2022</td>
<td>Landsat-5 TM (January 2000–December 2011), Landsat-7 ETM+ (January 2000-December 2020), and Landsat-8 OLI (February 2013–December 2020) MOD09Q1 (2000-2020)</td>
<td>30 m, 250 m</td>
<td>Alpine vegetation, grass, steppes, deserts, broadleaf forest, swamp, cultivated vegetation, meadows, scrubs, and needleleaf forest</td>
</tr>
<tr>
<td>Zhang et al., 2019</td>
<td>MODIS (2000–2015)</td>
<td>500 m</td>
<td>Seven class of vegetation change statistics</td>
</tr>
<tr>
<td>Liu et al., 2020</td>
<td>Landsat TM and OLI Collection 1 Tier 1 top-of-atmosphere (TOA) reflectance (2000, 2009, 2018)</td>
<td>30 m</td>
<td>Seven classes</td>
</tr>
<tr>
<td>Guo et al., 2022</td>
<td>Sentinel-2 multi-spectral dataset</td>
<td>13 spectral bands which include four bands at 10 m, six</td>
<td>Forest mapping</td>
</tr>
</tbody>
</table>
bands at 20 m, and three bands at 60 m spatial resolution.

<table>
<thead>
<tr>
<th>Study</th>
<th>Data Source</th>
<th>Resolution</th>
<th>Land Cover Types</th>
</tr>
</thead>
<tbody>
<tr>
<td>Feng et al., 2022</td>
<td>Sentinel-2 imagery - 1 June to 30 August in 2018 and 2020</td>
<td>Spatial resolution of 10 m (Upper Yellow River Basin)</td>
<td>Forest, shrubland, grassland, wetland and water body, agriculture land, construction land, barren, snow and ice</td>
</tr>
<tr>
<td>Hao et al., 2021</td>
<td>Landsat OLI</td>
<td>30 m</td>
<td>Coniferous forest, broad-leaf forest, shrubbery, non-forestry land, and water</td>
</tr>
<tr>
<td>Mazhar et al., 2021</td>
<td>MOD11C3 (2001 to 2019)</td>
<td>500 m</td>
<td>Grasslands, forests, shrubs and savannas, snow, water, permanent wetlands, croplands, urban and build up, and barren lands</td>
</tr>
<tr>
<td>Wang et al., 2015</td>
<td>MOD09A1 (2011)</td>
<td>500 m</td>
<td>Alpine desert, alpine steppe, alpine meadow, barren/desert, lake, permanent snow/glacier, cultivated land, scrub, forest</td>
</tr>
<tr>
<td>Zhao et al., 2022</td>
<td>Landsat Collection 1 Tier 1 surface reflectance satellite imagery for Landsat 5 Thematic Mapper I, Landsat 7 ETM +, and Landsat 8 Operational Land Imager (OLI)/TIRS (1991-2018)</td>
<td>30 m</td>
<td>Lake mapping</td>
</tr>
</tbody>
</table>

Generally, the mapped or estimated extent and area of land cover change and land degradation in the TP differs between studies because of varying methodologies and remotely sensed data used (Cai et al., 2015; Ren et al., 2013a; Wang et al., 2016a); obtaining an accurate quantitative measure of vegetative cover remains a challenge (Lehnert et al., 2015). Additionally, various time periods and sensor shifts might affect the quality of remote sensing data obtained from the same satellite. The remote sensing data currently used to measure grassland degradation cannot adequately represent the availability of nutrients and water, making it impossible to determine whether poor plant cover is due to heavy grazing pressure or a result of specific site conditions (Lehnert et al., 2015). Also, it is challenging to use remote sensing in the TP considering the complex topography, heterogeneous landscape, and insufficient satellite.
observations, which is exacerbated by frequent clouds in the summer formed by warm and humid airflow raised by topography (Lu et al., 2016; Ma et al., 2021). Therefore, identifying and segregating underlying causes of grassland degradation and identifying appropriate measures to address them are critical concerns in the TP. It is a fundamental challenge to untangle the relative contributions and interrelationships of climate change and human activities to grassland degradation.

Table 6: Land degradation studies in the TP.

<table>
<thead>
<tr>
<th>Reference</th>
<th>Approach/Variables</th>
<th>Spatial Extent Scale</th>
<th>Spatial Scale</th>
</tr>
</thead>
<tbody>
<tr>
<td>Li et al. (2020); Zhou et al., 2014; Lehnert et al. 2015</td>
<td>Vegetative cover (NDVI)</td>
<td>Regional (Three Rivers Headwater Regions); TP</td>
<td>500 m</td>
</tr>
<tr>
<td>Huang et al., 2016; Pan et al., 2017b; Zhou et al., 2022</td>
<td>Climatic factors such as precipitation and temperature</td>
<td>Regional</td>
<td>500m to 8 km</td>
</tr>
<tr>
<td>Xiong et al. 2016</td>
<td>NDVI, Temperature, precipitation, population, agricultural gross domestic product</td>
<td>Three-River Headwater conservation area (TRH zone) in the south and the non-conservation area (NTRH zone) in the north</td>
<td>1 km, 500 m, 8 km</td>
</tr>
<tr>
<td>Wu et al., 2018</td>
<td>Human population, livestock, agricultural expansion, mining, and urbanization</td>
<td>Local (Muli Town in the northwestern part of the Haixi Mogolian and Tibetan Autonomous Prefecture)</td>
<td>500 m</td>
</tr>
<tr>
<td>Zhong et al., 2019</td>
<td>Climate</td>
<td>TP</td>
<td>1 Km and 8 Km</td>
</tr>
<tr>
<td>Liu et al., 2018; Chen et al., 2020; Miehe et al., 2019</td>
<td>Soil organic carbon (SOC), N stocks, aboveground and belowground plant biomass; Kobresia pygmaea</td>
<td>TP</td>
<td>Literature survey and experimental studies</td>
</tr>
<tr>
<td>Dong et al. 2010b</td>
<td>Human and environment factor</td>
<td>Hindu Kush-Himalaya (HKH)</td>
<td>Theoretical</td>
</tr>
<tr>
<td>Harris, 2010; Zhong et al., 2019; Liu et al., 2018a; Piao et al., 2006</td>
<td>Overgrazing</td>
<td>TP</td>
<td>500m, 1 km, 8 km, Literature survey</td>
</tr>
<tr>
<td>Cui and Graf, 2009</td>
<td>Land cover change</td>
<td>TP</td>
<td>Literature Survey</td>
</tr>
<tr>
<td>Chen et al., 2014; Zhou et al., 2014;</td>
<td>Climate change and anthropogenic activities</td>
<td>Local to entire TP</td>
<td>30m, 8 km</td>
</tr>
<tr>
<td>Study(s)</td>
<td>Focus Area</td>
<td>Data Source(s)</td>
<td></td>
</tr>
<tr>
<td>------------------------------------------------</td>
<td>--------------------------------------------------------</td>
<td>----------------------------------------------------</td>
<td></td>
</tr>
<tr>
<td>Fassnacht et al., 2015</td>
<td>Human activities</td>
<td>NDVI, Climate data, livestock number</td>
<td></td>
</tr>
<tr>
<td>Lehnert et al., 2016</td>
<td>TP</td>
<td>The Tibetan Autonomous Region 500 m</td>
<td></td>
</tr>
<tr>
<td>Li et al. 2010</td>
<td>NDVI, Climate data, livestock number</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Goldstein et al., 1990, Miller et al., 1992, Miller, 1999, Miller, 2002, Miller, 2005; Foggin, 2000; Banks et al. 2003; Holzner and Kreichbaum, 2001</td>
<td>Socio-economic systems and alteration of land tenure arrangements</td>
<td>Local to regional region Socioeconomic data</td>
<td></td>
</tr>
<tr>
<td>Gongbuzeren et al., 2018</td>
<td>Socioeconomic</td>
<td>Village level Socioeconomic data</td>
<td></td>
</tr>
<tr>
<td>Xu and Grumbine, 2014</td>
<td>Climate change</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Li et al. 2013</td>
<td>Overgrazing</td>
<td>Dawu, Maqin County, Guoluo Tibetan Autonomous Prefecture of Qinghai Province 500 m, 1 km</td>
<td></td>
</tr>
<tr>
<td>Yang et al. 2018</td>
<td>Soil condition under different grazing intensity</td>
<td>Eastern Tibetan Plateau Soil data</td>
<td></td>
</tr>
<tr>
<td>Sun et al. 2018</td>
<td>Soil ecological processes</td>
<td>Naqu Ecological and Environmental Observation and Research Station Soil data and experiment</td>
<td></td>
</tr>
<tr>
<td>Chen et al. 2014; Wang et al. 2016; Li et al. 2016; Xu et al. 2016</td>
<td>Climate, Human activities, NPP, remote sensing data</td>
<td>TP 8 km</td>
<td></td>
</tr>
<tr>
<td>Ni et al., 2020; Wang et al. 2020</td>
<td>Climate, NPP</td>
<td>TP 8 km</td>
<td></td>
</tr>
<tr>
<td>Zhang, et al., (2016)</td>
<td>Climate and Human activities</td>
<td>Three Rivers Headwaters Region (TRHR) SRTM3 DEM</td>
<td></td>
</tr>
<tr>
<td>Cai et al. (2015)</td>
<td>Human activities</td>
<td>Three Rivers Headwaters Region (TRHR) 1 km</td>
<td></td>
</tr>
</tbody>
</table>

The studies presented in Table 6 use vegetation data such as the NDVI as a proxy for vegetative degradation. With the growing use of remotely sensed products and imagery (Li et al., 2020b), increased focus has been placed on assessing the changes in grassland productivity.
through trend analysis of the NDVI as a proxy for NPP or above-ground biomass (Bai et al., 2008, Fensholt et al., 2012, Shen et al., 2018). For example, Li et al. (2020) used NDVI data and argued that grassland degradation can be explained by changes in grassland cover area and that its spatial heterogeneity serves as an early indicator of desertification. However, local and temporal variability in the environment may mask the effects of land degradation since they do not consider the impacts of climate variations on grassland productivity over time and at the local spatial scale. In addition to human activities, the climate, which is influenced by water availability and heat conditions, also affects vegetation status and growth rates, which need to be reflected in the interpreting the causes of the degradation (An et al., 2021).

Moreover, empirical evidence suggests that biophysical factors, including soil properties, climatic characteristics, topography, and vegetation, can sometimes interact to yield grassland degradation that is independent of, or not associated with, anthropogenic impacts (Lehnert et al., 2016; Li et al., 2021). Understanding and assessing land degradation under climate change and anthropogenic influences are critical, as it helps planners and decision-makers in conservation planning and environmental management. CPG encourages the integration of various methodologies to deepen our understanding of coupled human-natural systems (Simon 2014). A CPG approach in the TP would integrate findings on land degradation and climate models with those on power relations, policy outcomes, land-use decisions, and resource access to illuminate the intersections of grassland degradation and the impact of climate change.

4.4. Discussion and Recommendations for methodological integration

Climate modeling plays a key role in assessing and understanding risks and identifying potential hazards and opportunities for society. The introduction of interconnections between human and natural systems represents a significant difficulty in creating climate model predictions and projections. The TP is an area with very complex terrain, land surface characteristics, and climate in space and time. Similarly, natural ecosystems and human/social systems are interrelated, and changes in the physical systems are anticipated to affect socioeconomic circumstances, livelihoods, infrastructure, and living situations. The common landform types in the TP include mountain, grassland, plateau, plateau desert, glacier, snow, lake, farmland, and wetland. To study the socioeconomic, ecological, and environmental impacts of climate change, large amounts of hydrometeorological, soil, vegetation, snow, glacial, and social and economic data are needed to integrate with results from climate modeling studies.

It is essential to understand how climate risks are perceived by people and what major initiatives are being undertaken to mitigate these risks. Understanding the connection between science and politics is crucial when doing this (Mahony and Hulme, 2018). Despite this, studies that generally emphasize the social dimensions of climate research and the CPG framework remain underutilized. As a result, there is a need to explore how interdisciplinary approaches might enrich our understanding of climate change on the TP and contribute to our knowledge of global climate change. This will expand and potentially improve how scientific knowledge derived from climate modeling and climate change studies are translated into practical applications for sustainable grassland management. More broadly, it will inform how effective government policies associated with grassland management can be developed and implemented within a framework of coupled human-natural systems.
Because of the unique geographical characteristics of the region, TP climate modeling faces many challenges (Bao and Li, 2020). Alpine grassland degradation on the TP is the result of a combination of natural factors and human activities (Huang et al., 2016; Wang et al., 2017). Increased anthropogenic activities and climate change have led to numerous environmental challenges on the TP (Piao et al., 2012, Tian et al., 2018). Other than climate change, overgrazing, the privatization of livestock ownership and grassland, and the re-settlement of herdsmen (Liu et al., 2003, Yan and Wu 2005) are common occurrences. Coupled with location-dependent changes to population and economic infrastructure (e.g., road networks, railroads, etc.), local ecosystems have undergone significant changes (Tian et al., 2018). Similarly, climatic extremes can also alter these coupled relationships and dynamics. Hence, the CPG approach enables the study of climate modeling in a way that promotes an open discussion on land use, political and economic change, and the scope of science, among many other unspoken, yet underlying issues. Also, it can reduce critical limitations in current climate modeling methods and research, as it can foster a better understanding of the role of institutions in limiting and influencing how research is conducted and, more importantly, how it is translated and presented outside of the realm of science (Adamson 2022; Tadaki 2017). To achieve this goal, methods commonly used in the social sciences, such as household surveys, focus group discussions, and key interviews, can be used to facilitate the integration of insights provided by human geography (Mark et al., 2014; McClintock 2015; Simon 2014; Tadaki et al., 2014) as proposed in Figure 3.

Remotely sensed data and their derivatives inform land degradation research. Remote sensing is a valuable tool for tracking land degradation at regional to global spatial scales. However, products created from remotely sensed datasets may have systematic or structural flaws due to using multiple or inconsistent data sources and/or preprocessing, analysis, and aggregating methods; variable temporal and spatial resolution and extent inconsistencies; and differing levels of detail and/or accuracy. The applicability of remotely sensed data depends heavily on the link between the spatial and/or temporal resolution of the data and the spatial/temporal resolution of the event or phenomenon of interest. Many studies demonstrate that terrain impacts can be masked or not adequately detected when using data with a low spatial resolution (Dong et al., 2013). Detecting grassland degradation from coarser resolution remotely sensed data is difficult due to the interaction of spatial variability, topography impacts, and seasonality of grassland usage (Tomaszewska et al., 2021). Prior research has shown that land degradation in the TP is significantly impacted by climate change (Song et al., 2018; Zhang et al., 2016). The two most often used remote sensing techniques for land degradation studies are examining vegetation cover dynamics and estimating vegetation decline using NDVI as a proxy for vegetation dynamics (Dubovyk 2017). NDVI datasets are available for a variety of time periods and at varying spatial and temporal resolutions (e.g., 30 m–8 km). Analyses aiming to combine or compare datasets face significant difficulties owing to these issues of differing timelines and resolutions. This has posed a severe challenge to analyses attempting to use such datasets for estimating land degradation (Anderson and Johnson, 2016). A mismatch between the spatial and temporal resolution of the currently available satellite images and the ecological and socioeconomic scales of land degradation processes and their causes is another factor contributing to the difficulties of using remote sensing to study land degradation. Micro-scale measurements are required to account for significant environmental variability and to discriminate between the effects of climatic fluctuation and human activity on land degradation.
processes (Landmann & Dubovyk, 2013). Also, analysis of the drivers of land degradation at different spatial and temporal scales is essential (Bai et al., 2008).

Similarly, it is necessary to consider both natural and altered environments (such as land use management practices and land cover change) and evaluate the benefits and losses that land transformation processes bring (Aw-Hassan et al., 2016). The influence of underlying issues, including land policy, land tenure, poverty, economic pressures, and migration, need to be considered while assessing land degradation using remote sensing. To overcome the spatial and temporal mismatch of environmental drivers and ecological processes in land degradation and climate change studies, there is a need for widespread in situ measurements, finer spatial resolution remote sensing observations, and fine-gridded climate data (An et al., 2018). Apart from these, there is a need for the collection of ground data associated with land degradation and vegetation change to train classification algorithms and predict changes in land cover, land use, and NDVI. Besides, validation of remote sensing products against in situ data is vital (Dubovyk 2017). The issues of spatial and temporal resolution need to be fully considered, and it is important to separate spectral land use classes to characterize land cover change and land degradation. The reconstruction of multi-source spatiotemporal data is needed to produce long-term remotely sensed data by fusion methods (Feng et al., 2006; Zhang et al., 2017).

In the TP, where grasslands are the dominant type of vegetation and animal husbandry is one of the key sectors, the status of the livestock industry has a direct bearing on individual and community vulnerability (Wang et al., 2014). A significant portion of herders depend on producing livestock for a living, and the regional environmental regime will immediately impact livestock production (Pan et al., 2014). Therefore, it is important to include indicators representing local climate and socioeconomic conditions in grassland degradation studies. For example, policy changes regarding grassland use, socio-economic hardships herder face after giving up their nomadic life, and the local socioeconomic and ecological realities are not reflected in the assessment process. Exploring governance actions and processes during grassland planning, management, and monitoring using CPG aids in promoting understanding and appreciation of how various institutions, actors, and stakeholders’ roles and perspectives are recognized and considered. Apart from these, it is also imperative to explore how alpine grassland management interacts with climate change to affect the grassland ecosystem (Wu et al., 2017). It is hard to fully comprehend the regional variation of human activity intensity because data on human activities are often only collected at a certain administrative level. To better comprehend the regional variations in human activities and their effects on alpine grassland, there is a need for customization of human activity intensity data using novel methodologies, such as simulating the grazing pressure based on household studies (Moritz et al., 2010), as highlighted in Figure 3. We argue that to adequately balance the needs of the local inhabitants with those of national or regional grassland management plans and strategies, socioeconomic and human components must be emphasized and effectively integrated with scientific objectives and policy priorities. CPG offers unique insights to identify the causation of grassland degradation by exploring the links between social and biophysical characteristics as shown in Figure 3. Understanding human-environmental issues more fully requires a combination of social and environmental change.
Hence, an integrated analysis of the effects of the natural environment, social vulnerability, socioeconomic activities, and humans is required due to the complexity of the social, economic, and ecological aspects connected with grasslands in terms of geography and time in the TP. Critical human geographers concentrate on social and environmental injustices because they are material, and we cannot comprehend their co-constitutive links without examining biophysical and social processes. Most natural scientists acknowledge the limitations caused by social and political constraints imposed on their research. These constraints include institutional politics, intellectual property issues, funding priorities, and many other factors influencing scientists’ day-to-day research practices. While increasing physical geographers’ exposure to and understanding of the power relations and human practices that shape physical systems and their research practices, the integrative methodology of CPG necessitates critical human geographers’ substantial engagement with the physical sciences and the significance of the material environment in shaping social relations.

Figure 18: Coupled Human-Natural conceptual framework to study grassland degradation in the TP (Adapted from Chen et al., 2015).

This calls for interdisciplinary research among the TP’s climatologists, social scientists, and atmospheric scientists on climate change vulnerability, land degradation, and climate modeling. The integrative, holistic approach of CPG requires critical human geographers to engage substantively with the physical sciences and material environments in their study of social relations while providing opportunities for physical geographers to expand their understanding of the power relations and human practices that impact and shape physical
systems (Lave et al., 2013). This framework encourages synthesizing research approaches to foster innovative studies that advance our understanding of complex socio-biophysical phenomenon and develop socially and environmentally resilient policy outcomes for a sustainable future. Therefore, we recommend an integrative approach to study the complex relationship between climatic variability and the socio-economic system using CPG as it provides physical geographers with the tools, they need to analyze the relationships between their study and the social, economic, and political environment of that research, enhancing their comprehension of how their knowledge is located in time and space (Livingstone, 2003; Tadaki et al., 2012). We suggest that there are substantial benefits for both physical and critical human geography from the active integration of both disciplines, as demonstrated by the work of geographers who combine critical attention to social power relations with a detailed understanding of a particular field of biophysical science in the service of social and environmental transformation (Lave et al., 2013). It also fosters a broader understanding of institutional economic and cultural foundations (Clifford 2009; Lane et al. 2011). Thus, biophysical assessments must substantively engage with social processes to understand environmental change. It further helps physical geographers to understand the ‘criticality’ which is a critical aspect of the physical world (Tadaki et al., 2015).

4.5. Conclusion

We recommend using CPG to study environmental and social issues in the TP, as presented in Figure 3 and suggest that such a model could also apply to the study of complex social-ecological political frameworks and systems in other settings. We advocate this new research method because natural and social systems cannot be studied separately. According to scientists from various biophysical fields, human activity currently significantly influences Earth’s most fundamental processes. The proposed conceptual model will help develop an understanding of the dominant controls, feedback, and interactions between natural, human, socioeconomic, and governance activities to untangle climate change, land degradation, and vulnerability in the TP. It will further help improve our understanding of various exposures of local people to climate and socio-economic and political change and devise appropriate strategies to combat future grassland degradation and improvement of lives and livelihood of the people. Similarly, it will facilitate researchers, development organizations, and governmental organizations to understand the complexities of ecological and human systems and the role that biophysical, economic, political, social, and cultural factors play as drivers of change at various temporal and spatial scales. The proposed framework offers a possible course of action as an example. It blends methodologies from the biophysical sciences, social science, political ecology, science and technology studies, and environmental history to examine the interplay of physical processes and uneven social power relations. CPG integrates patterns and processes that link human and natural systems, as well as interactions and feedback between human and natural system components at both the within-scale and cross-scale levels. It can be modified to best suit the needs of a specific study. While acknowledging these socio-natural circulations, CPG centers the analysis on the physical characteristics of the issue under consideration and the manner in which the interaction of sociopolitical and biophysical processes and histories shapes the issues.
5. Conclusions and future study

5.1. Conclusion

The grassland ecosystem is the dominant terrestrial ecosystem of the Tibetan Plateau and plays a crucial role in linking the pedosphere, atmosphere, and hydrosphere in the region and the whole of Asia (Tan et al., 2010; Yao et al., 2015). Further, the Tibetan Plateau is significant in terms of CO₂ fluxes from regional to global scales (Zhang et al., 2007) and accounts for around 2.5% of global carbon storage on land (Hafner et al., 2012). The Tibetan Plateau acts as an important reservoir of water, regulating climate change and water resources in east Asia and even for the whole world (Yao et al., 2012), as the Tibetan Plateau is the headwater region of the ten largest Rivers in Asia which are collectively the source of water resources and hydropower for more than 1.5 billion people (Cai et al., 2015). Because of its complex geographical settings and fragile ecosystems, it is highly susceptible to changes in global climate (Piao et al., 2006). Therefore, the Tibetan Plateau is an ideal location to investigate the response of vegetation growth to climate change and human activities (Piao et al., 2016). At present, the mapped or documented the extent of land degradation in the Tibetan Plateau differs between studies as a result of the underlying methodology and types of datasets used (Cai et al., 2015; Ren et al., 2013; Wang et al., 2016), and obtaining an accurate quantitative measure of vegetative cover remains a challenge (Lehnert et al. 2015). As grassland degradation threatens environmental and socio-cultural values not only for the local people but also for millions of people living downstream, identifying and segregating underlying causes of degradation and identifying appropriate measures to address them are critical concerns in the Tibetan Plateau. Therefore, the first major paper of this dissertation (Chapter 2) contributed to an assessment of changes over land and how these changes impact the weather and climate, and social dynamics.

The results presented in Chapter 2 document the significant associations of surface energy fluxes with vegetation changes that occur during the early growing season of May in the western region of the Tibetan Plateau based on the NDVI, as represented with AVHRR GIMMS3g data. Lower albedo with increased NDVI was observed, which further influenced the surface energy balance, resulting in increased net solar radiation at the surface and, subsequently, increased sensible heat flux. Further, the results document a statistically significant positive correlation between NDVI and 2 m above-ground temperature. The 2 m above-ground temperature significantly increased with more thermal energy transfer from the surface, which resulted from reduced albedo. The land and atmosphere associations were not confined to the surface, but also extended to the upper-level atmosphere as indicated by significant positive correlations between NDVI and temperatures up to the 300 hPa level. Also, a 1K increase in the temperature at the 500 hPa level was observed. Based on the identified positive effects of vegetation on the temperature associated with increased/decreased NDVI in the western region of the Tibetan Plateau, I proposed a positive energy process for land-atmosphere associations.

In Chapter 3 and based on a Landsat-derived NDVI time series, an increase in NDVI, or greening, within the TP was observed, especially during the 1990 to 2018 and 2000 to 2018 time periods. Larger median growing season NDVI change values were observed for the Southeast Tibet shrublands and meadows and Tibetan Plateau Alpine Shrublands and Meadows grassland regions in comparison to the other three regions studied. The regions comprise the eastern and
southeastern portions of the TP. Minimal differences in NDVI change were observed for different geomorphon-based landforms, and topographic slope and TPI were weakly correlated with the NDVI change data across all time periods and grassland types. The widespread greening trends tended to obscure more local-scale land degradation patterns, when the landscape is studied in the aggregate. However, by focusing on areas where vegetation loss is greatest, land degradation was found to be more prominent in the lower and intermediate hillslope positions in comparison to the higher relative topographic positions, and that change was more pronounced in the more eastern Southeast Tibet shrublands and meadows and Tibetan Plateau Alpine Shrublands and Meadows grassland regions. Generally, this study supports the use of geomorphons as an analysis and aggregating unit for studying hillslope scale change patterns. More work is needed to understand landscape change dynamics in the Tibetan Plateau at the hillslope scale and to differentiate the impacts of climate change and anthropogenic impacts.

Through the extensive literature review presented in Chapter 4, this dissertation recommends using critical physical geography (CPG) to study environmental and social issues in the TP. The conceptual model proposed in this chapter will aid in understanding the dominant controls, feedback, and interactions between natural, human, socioeconomic, and governance activities to untangle climate change, land degradation, and vulnerability in the Tibetan Plateau. It will further help improve our understanding of various exposure of local people to climate and socio-economic and political change and devise appropriate strategies to combat future grassland degradation and improvement of lives and livelihood of the people. The critical physical geography approach can be transformative in understanding how climate variability, unequal power, and institutional barriers to access grassland resources induce land degradation which could further impact the local climate and result in social vulnerability in the Tibetan Plateau. Within the geographic discipline, the work presented in Chapter 4 contributes to the emerging literature on critical physical geography and offers specific insights for applying critical physical geography in the context of “critical” climatology, on which the literature and guidance are extremely limited.

5.2. Future study

Given the results of this dissertation, several opportunities for future research can be identified. The followings recommendations are made for future research:

i. I would like to further explore how the increase in temperature affects human beings in the dryland areas of the Tibetan Plateau. Comparing the results from climate models could improve our understanding of physical mechanisms related to how land use and land cover change affect climate. A detailed feedback mechanism and an idealized simulation using a coupled land-atmosphere climate model are required to identify the more robust relationships between vegetation activity and climate in the Tibetan Plateau. Future explorations using observational data rather than reanalysis data are also needed to exclusively identify the land-atmosphere interactions in the Tibetan Plateau.

ii. More accurate assessment of land degradation patterns at the hillslope scale will require a combination of both social and ecological data, which can be challenging to collect remotely. Another limitation lies in unpacking the often-complex biophysical interactions that lead to systems becoming more prone to land degradation in general, including the adaptive capacity of ecosystems. Future studies should concentrate on exploring different
factors, such as human interventions (e.g., overgrazing, construction, and urbanization) and climate information sources to potentially enhance the precision of land degradation studies.

iii. This dissertation critiques the methodological approaches traditionally used in climate change and land degradation studies and offers insights from critical physical geography (CPG) for a more comprehensive approach to the study of complex human-natural dynamics of the TP. However, applying critical physical geography requires in-depth study through fieldwork. Further research is needed to establish a rigorous and practical methodological approach to studying the complex social-human systems in the TP.
Appendix I: Supporting Information for Chapter 2

Figures S1, S2, S3, and S4

Introduction

The supporting information of Figures S1, S2, S3 and S4 provides the information about detrended correlation analysis (S1 and S2) and detrended composite difference analysis (S3 and S4) during the periods of 1982 to 1998 (S1 and S3) and 1999 to 2015 (S2 and S4).

**Figure S1.** Correlation patterns of detrended time-series of NDVI, area-averaged over the study area, with detrended (a) albedo, (b) net solar radiation, (c) sensible heat flux, (d) latent heat flux, (e) 2 m temperature, and (f) mean sea level pressure at each grid cell in May from 1982 to 1998. The green contour is the 10% significant level. The study area was indicated with the dotted box.
Figure S2. Same as in Figure S1, but from 1999 to 2015.
**Figure S3.** Composite difference patterns of detrended (a) albedo (0-1 scale), (b) net solar radiation (W/m$^2$), (c) sensible heat flux (W/m$^2$), (d) latent heat flux (W/m$^2$), (e) 2m temperature (°K), and (f) mean sea level pressure (hPa) at each grid cell in May during the years of high May NDVI values and low May NDVI values in the western TP from 1982 to 1998. The green contour is the 10% significant level. The study area was indicated with the dotted box.
Figure S4. Same as in Figure S3, but from 1999 to 2015.
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