A thesis submitted to the Department of Environmental Sciences and Policy of Central European University in part fulfilment of the Degree of Master of Science

Analyzing Land Degradation in Kyrgyzstan:

Climate Factors, Proportion of Degraded Land, and Relationship with Environmental Factors using Publicly Available Geospatial and Satellite Data

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Author's declaration

No portion of the work referred to in this thesis has been submitted in support of an application for another degree or qualification of this or any other university or other institutes of learning.

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ABSTRACT OF THESIS submitted by:
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for the degree of Master of Science and entitled: *Analyzing Land Degradation in Kyrgyzstan: Climate Factors, Proportion of Degraded Land, and Relationship with Environmental Factors using Publicly Available Geospatial and Satellite Data*

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Land degradation is one of the environmental factors which has a huge impact on human civilization, especially agriculture. Kyrgyzstan, a country with agriculture as main activities, land degradation issue is very crucial to study. Spatial analysis is one of the robust techniques to study land degradation because the amount of publicly available geospatial data source is abundant. The publicly available spatial and statistical analysis tools, especially Google Earth Engine, Trends.Earth extension in QGIS software and RStudio were used. The proportion of degraded land over the total land resulted that 37,32% of the total area is degraded. This result is like one land productivity which one among three sub-indicators. Thus, the analysis of the climate factor will be focused on the land productivity presented in NDVI. The climate factor includes temperature, precipitation, and PDSI. The highest correlation presented by NDVI-Precipitation with significant negative correlation found in 23.93% of the total area. The environmental factors and land degradation relationship analysis is limited by publicly available geospatial satellite and data. The environmental variable use specifically population, climate factors (temperature, precipitation, PET, aridity), biophysical factors (landform, land cover, landform, slope, biomass density, carbon storage, and ecoregion), and agriculture including crops and livestock. The relationship analysis applied to determine the indication of land degradation driving factors. Bivariate analysis namely Chi-squared test, Kruskal Wallis test, and Spearman Rank rho test is used. Most environmental factors showed there is a significant relationship or has influence with land degradation. The distribution of total variable usually found in the stable lands, except population, bare lands, poultry density, and sheep density.

Keywords: Agriculture, Land degradation, Land productivity, LDN, Population, Climate, Environmental, Biophysical

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List of Abbreviations

1OAO	One Out All Out
AVHRR	Advanced Very-High-Resolution Radiometer
CHIRPS	Climate Hazards Group InfraRed Precipitation with Station Data
CRU	Climate Research Unit
DEM	DEM Digital Elevation Model
ESA CCI	European Space Agency Climate Change Initiative
EVI	Enhanced Vegetation Index
FAO	Food and Agriculture Organization
GAUL	Global Administrative Unit Layers
GDP	Gross Domestic Product
GEE	Google Earth Engine
GIMMS	Global Inventory Modelling and Mapping Studies
GLADA	GEF-funded Land Degradation Assessment in Drylands project
GLADIS	Global Land Degradation System
GLASOD	Global Assessment of Human-induced Soil Degradation
GlobCover	GlobCover land Cover Map from European Space Agency initiative
GPG	Good Practice Guidance
GRIDMET	University of Idaho Gridded Surface Meteorological Dataset
IPBES	Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services
IPCC	Intergovernmental Panel on Climate Change
IUCN	International Union for Conservation of Nature
LADA	Land Degradation Assessment in Dryland
LCCS	Land Cover Classification System (LCCS)
LDN	Land Degradation Neutrality
MODIS	Moderate Resolution Imaging Spectroradiometer
NDVI	Normalized Difference Vegetation Index
PDSI	Palmer Drought Severity Index
PET	Potential Evapotranspiration, and Transpiration
QGIS	Quantum Goegraphic Information System
RESTREND	Residual Trend Analysis
RUE	Rain-Use Efficiency
SDGs	Sustainable Development Goals
SOC	Soil Organic Carbon
UNCCD	United Nation Convention on Combat Desertification
UNCOD	UN Conference on Desertification
UNDP	United Nations Development Programme
UNEP	United Nations Environment Programme
USD	US Dollar
WOCAT	World Overview of Conservation Approaches and Technologies
ZNLD	Zero Net rates of Land Degradation
File extension	
.png	Portable Network Graphics, an image file extension
.tif	Tagged Image Format, an image file extension with georeferencing
.csv	Comma-Separated Values: a delimited text file that uses a comma to separate values

1. Introduction

1.1. Background

Land degradation is a worldwide and widespread phenomenon that affecting climate change, food security, ecosystem service, and human wellbeing (Montfort et al., 2021a). Land degradation estimated to affect globally varied between 15% to 63% of total land depending on the ecosystem but normally average between 25-30% of the total land (IUCN, 2015). To address this issue, United Nation launched Land degradation neutrality (LDN) in 2012. LDN is a new concept for the target of the UN 2030 agenda of zero degraded lands according to number 15.3 of the Sustainable Development Goals (SDG).

Land degradation is a global problem that threatens the livelihoods of billions of people around the world. The most affected people have predicted the rural population where 80% of them are in extremely poor condition and 65% of them are dependent on agriculture. Agriculture is one of the most important sectors in Kyrgyzstan with about 37,3% of the country is agricultural land (Orozumbekov et al., 2009) and about 30% of the population rely on agriculture activities (World Bank, 2018). Thus, the extent and effect of land degradation are very important to study.

Economically, land degradation costing a lot of money. In Central Asia, land degradation costs about 6 billion dollars annually due to land use and land cover change from 2001 to 2009 (Mirzabaev et al., 2016). In Kyrgyzstan, as the poorest country in the region, land degradation costs 11% of their GDP for about 0,55 billion USD per 5 billion USD in 2009 which also the largest amount of the other countries in the region. This land degradation problem will cost much more money if there are no actions to measure this problem. Mirzabaev et al., (2016) estimated that 6 billion USD is needed for action to reduce land degradation in 30 years and 30 billion USD for inaction for land degradation.

There are many analyses of land degradation status in the region of Central Asia (Mirzabaev et al., 2016; Robinson, 2016; Simonett & Novikov, 2010; Strikeleva et al., 2018), but very few that only focus on Kyrgyzstan. Whereas, Kyrgyzstan, different from Kazakhstan and Uzbekistan, is the most mountainous country in the Central Asia region (Klein et al., 2012). Moreover, the rate of the land degradation study located in Kyrgyzstan is only 1-9 paper per year compared to the neighbouring country of Kazakhstan and Uzbekistan which has 10-29 paper per year (Xie et al., 2020). Thus, this study will give an additional study case of Land Degradation in Kyrgyzstan. Even though there are many studies related to land degradation is taken place in the Central Asia region but the different driving factors of desertification is lack attention (Jiang et al., 2020). Thus, this study will address the relationship of land degradation to the climate factors, agriculture, biophysical, and population aspect as a provisional study of land degradation drivers in Kyrgyzstan.

1.2. Problem Statement and Research Question

Land degradation is one of the major problems in countries where agriculture is the main activities is such as Kyrgyzstan. Thus, the understanding of the proportion of land degradation, climate factors effect on land productivity, and the relationship of affected sectors is very crucial. Thus, the study will focus on the following questions:

1. What is the proportion of degraded land over the total land area in Kyrgyzstan?
2. What is the correlation between climate factor and land productivity in Kyrgyzstan?
3. How is the relationship and distribution of degradation status with selected environmental factors (population, agriculture, and biophysical aspects) in Kyrgyzstan?

1.3. Research Aim and Objective

This research aims to understand the land degradation phenomena from its state, climate factors, and relationship with other environmental aspects in Kyrgyzstan. More specifically, the research objectives are:

1. To analyze the state of land degradation in Kyrgyzstan using the SDGs 15.3.1 Indicator tools of Trends.Earth
2. To analyze the correlation of climate factor in land productivity
3. To understand the land degradation relationship with population, agriculture system and biophysical aspect in Kyrgyzstan
4. To calculate the quantity of the selected environmental factor in every land degradation status

2. Literature Review and Theoretical Background

This chapter will address different key concepts that will be used in this research to set the stage for a further chapter. This chapter also will describe the theoretical background for this study through the definition of the keywords, underlying theories, and through the lens of the ecogeographical hierarchical theory of the existing literature. Five main frameworks will be discussed in this chapter including:

First, Land Degradation as a foundation of the study land degradation neutrality application will be explained. How this definition evolves how the different concept in the existing studies, and what is the assumption and underlying theories will be addressed to understand the focus of this research.

Second, the drivers of land degradation will be identified as well as the relation of the climate aspect, anthropogenic aspect, topography aspect, and agriculture activity aspects.

Third, the different approach and methodology of the land degradation that has been used including the assumption, source of data, tools, and the result will be discussed.

Fourth, the Land Degradation Neutrality framework as the United Nation Convention on Combat Desertification (UNCCD) concept for addressing land degradation and Trends. Earth as land degradation global standard assessment for land degradation is the main tools that will be used in this study will be explained.

2.1.Land degradation: definition, types, and driving factors

2.1.1. Land degradation definition

Land degradation has no single definition and more of a construction term that does not have any readily identified feature but in general, worse changing over time of land resource including soil, water, vegetation, rocks, air, climate, and relief (Stocking &

Murnaghan, 2001). A land defined as a delineable area of the earth's terrestrial surface encompasses feature attributes of biosphere immediately below and above this surface, the soil and terrains forms, the hydrology in the surface, sedimentary layers and groundwater association, plant and animal population, and the human settlement pattern including past to recent activity (FAO & UNEP, 1999). Degradation comes from the Latin word of "derivation" means the reduction to a lower rank in which the rank is related to the actual or possible uses and reduction implies the problem for those who use land (Blaikie & Brookfield, 2015).

UNCCD in 1994 defined land degradation as a reduction of productivity and complexity of the different type of land use such as rainfed cropland, irrigated cropland, range pasture, forest, and woodlands as a result of a process or a combination process including human activities and habitation patterns by soil erosion from wind and or water, deterioration of physical, chemical, biological, or chemical properties of soil, and long-term loss of natural vegetation, in arid-semi-arid, and sub-humid areas (McDonagh & Lu, 2007). In a broader perspective, land degradation defined as the natural or human-induced process that negatively enforce the land to function effectively (Bobrowsky, 2013). From the perspective of ecosystem services, land degradation defined as the decline or loss in biodiversity, ecosystem function, or ecosystem services in any terrestrial and associated aquatic ecosystem within the landmass (IPBES, 2018). On the other hand, land degradation can be caused by a direct or indirect human-induced process including anthropogenic climate change resulting in the negative trend in the land condition in the form of long-term reduction or loss of biological productivity of land, ecological integrity or value of land for human (IPCC, 2019).

Land degradation notions originally from the soil degradation term which usually used as a synonym of soil degradation even though the land and soil term do not have the same meaning (Stocking & Murnaghan, 2000). The term of the land refers to a more complex ecosystem than soil, land terms compromising land, landscape, terrain, vegetation, water, and climate (Eswaran et al., 2001). While there is a clear difference in soil and land terms, there is no clear distinction between the term degradation and desertification (Eswaran et al., 2001). To standardize the term, UNCCD defined desertification as land degradation in arid, semi-arid, and dry sub-humid area which can be caused by both human activities and climatic variations (IPCC, 2019). Thus, the definition of land degradation used in this study will be using the UNCCD Good Practice Guidance (GPG), land degradation is caused by a plethora of pressures such as usage and management of land which results in decline or loss of economic or biological productivity of various croplands including those which exclusively rely on rain for its water, irrigated cropland, forest, woodlands and pasture (UNCCD 2017). Land considered as degraded land usually when there is a significant negative trend in land productivity, soil organic carbon (SOC), and land cover as well as other negative change of relevant indicator at the national level (UNCCD, 2016a).

2.1.2. Land Degradation Types

There are several points of view when it comes to the types of land degradation due to the different assumption of land degradation definition. Eswaran et.al (2001), indicate types of land degradation include water erosion, wind erosion, chemical degradation, and physical degradation. The World Overview of Conservation Approaches and Technologies (WOCAT) determined six types of land degradation:

1) Soil erosion by water (W), including surface erosion or loss of topsoil, gully erosion, mass movement or landslides, riverbank erosion, coastal erosion, and other offsite degradation effect such as deposition of sediments, downstream flooding, siltation of reservoirs and waterways as well as water bodies pollution from eroded lands. This degradation usually caused by scarce vegetation cover altogether with the poor management of soil and crop and amplified by topography and heavy/extreme rainfall (UNCCD, 2016a).

2) Soil erosion by wind (E), including loss of topsoil because of the uniform displacement, deposition, and deflation as a result of uneven removal of soil material, and other offsite degradation effects such as covering of the terrain with windborne sand particle from distant source or known as overblowing.

3) Chemical soil deterioration (C), including the decline of soil fertility and loss of soil organic matter content caused by leaching, soil fertility mining, volatilization, and nutrient oxidation, acidification, soil pollution from toxic materials, and salinization or alkalinization in the topsoil later which related to the reduction of productivity of the soil. These degradation types usually caused by overwatering, insufficient drainage and poor crop management which is typically found in large-scale irrigation plantation (UNCCD, 2016a).

4) Physical soil deterioration (P), including compaction of soil (reduction of soil structure from trampling or weight or high-frequency use of machinery); slacking and crusting which means clogging of pores with fine material and resulting in the formation of an impervious layer at the soil surface and resulting on destruction to the infiltration of rainwater; soil sealing caused by covering the ground with an impermeable material such as construction, mining, road and buildings; waterlogging as a result of human-induced water saturation; subsidence of organic soils or settling of soil; and loss of bio-productive function due to other activities.

5) Water degradation, including aridification or decrease of average soil moisture content, change in the quantity of surface water from the fluctuation of flowing water volume such as flood, peak flow, low flow, or drying up of rivers and lakes; changing aquifer or groundwater level such as the over-exploitation or reduce recharge of groundwater affecting the decreasing height of groundwater table; the decline of surface water quality due to enlarged sediment and pollutant into freshwater bodies; the decline of groundwater quality

as a result from infiltration of pollutant to aquifers; and reduction of buffering capacity of wetland areas to cope with flooding and pollution.

6) Biological degradation including the decreasing number of vegetation cover resulting in the bare or unprotected soil; loss of habitats due to the decreasing vegetation diversity such as fallow land and mixed systems or the rising number of fragmentation habitats; reduction of quantity or biomass from the reduction of vegetative production for different land use; detrimental effect of fires on the forest, grazing land, bushland, and cropland; the decline of quantity and composition or diversity of species such as reduction of natural species, palatable perennial grasses, spreading of invasive, salt-tolerant, unpalatable species or weeds; loss of soil life because of decreasing of soil macro and microorganism in quality and quantity; and increase of pests or diseases or loss of predators and reduction of biological control.

Land desertification is often used as interchangeable terms with land degradation, but actually, this term refers to the narrower definition of land degradation where land desertification is land degradation that happened in the arid, semi-arid, arid, and subhumid area (FAO & UNDP, 1994) as a result from human-induced activities.

2.2. Land Degradation: Driving Factors

Land degradation caused by different types of drivers which is usually because of a complex interaction between natural phenomena and human activities. There are two different types of drivers, specifically direct or proximate drivers which linked to the land-use system practice, and indirect or underlying drivers which related to the demographic, economic, and socio-political circumstances on a local, national, or global scale (UNCCD, 2016a). Direct and indirect drivers of land degradation adapted from WOCAT in UNCCD (2016) technical guidance document are given in Table 2. 1.

Table 2. 1 : Direct and indirect drivers of land degradation.

Direct drivers	Indirect drivers
• Natural cause such as topography and natural disaster • Poor management of soil such as non-adoption of soil-conservation management practices and unbalance fertilizer use • Overgrazing • Poor management of annual, perennial, scrub and tree crops such as shifting cultivation without break fallow period and improper crop rotations • Deforestation and removal of natural vegetation especially in unsuitable land • Over-exploitation or overcutting of vegetation for domestic or industrial use. • Urbanization and infrastructure development • Industrial activities, waste deposition, and mining, • Discharge such as problem in canal irrigation planning and management • Release airborne pollutants. • Disturbance of the water cycle • Over-abstraction of water and over-pumping of groundwater • Extension of cultivation inland with high potential of natural hazard	• Land tenure • Poverty or wealth • Labor availability • Population pressure and increase • War and conflict • Education access to knowledge and support services • Governance, institutional settings, and policies (including taxes, subsidies, incentives) • Inputs (including access to credit/financing) and infrastructure. • Land shortage • Economic pressure and attitude

Source: FAO&UNEP, 1994 and WOCAT modified by UNCCD 2016

The driver of land degradation is way harder to define than the definition. The main drivers of land degradation are various from over-cultivated cropland, overgrazing of rangeland, deforestation, irrigated land affect to waterlogging and salinization until pollution and others industrial origin discharge (Stocking & Murnaghan, 2000). Aside from human activities, land degradation also can be caused by natural degradation hazard. The natural hazard factor that drives land degradation is dependent on the types of land degradation as given below (FAO & UNDP, 1994):

1. Water erosion can be caused by the high intensity of monsoonal rains, physical properties of soil with a low resistance to water erosion i.e silty soils and vertisols, and steep slopes of the hills or mountains lands.
2. Wind erosion related to the high rainfall variability as well as drought condition, the climate region in semi-arid to arid climates, soils properties with a low resistance to wind such as sandy soils, and land with an open cover of natural vegetation.
3. Soil fertility declined usually happened in the soil with a high level of acidity or low natural fertility and the effect of strong leaching in humid climates.
4. Waterlogging usually associated with the morphology of land in alluvial plains or inside part of basins which has limited outward drainage of groundwater.
5. Salination mostly found in the interior basins or plain in which restrict outward drainage of groundwater, land in semi-arid to arid climates with low leaching intensity, and natural slightly saline soil condition.
6. Lowering of water table usually happened in the land within semi-arid to arid climates with low rates of groundwater recharge.

Apart from those natural hazard factor of land, climate change including drought and flooding will accelerate land degradation in this fragile system (Olsson et al., 2019).

The driving factor of land degradation is complex which entangles proximate or direct cause and underlying cause. The proximate or direct cause of land degradation drivers are:

1) natural factors: biophysical factors including topography (steep-slope), soil erodibility, pest and diseases, climatic factors related to rainfall, temperature, and climate extreme.
2) anthropogenic factors such as land cover change, deforestation, and unsustainable land management practice (monocropping, land clearing, unsustainable land practices, and excessive fertilizer application) (Dubovyk, 2017; Li et al., 2015; Mirzabaev et al., 2016)

The underlying cause of the degradation including land tenure, economic development, population density, infrastructure development, and access to agricultural extension, market access, poverty, decentralization, non-farm employment, institutions, policies, and international policies (Dubovyk, 2017; Li et al., 2015; Mirzabaev et al., 2016).

In a more practical approach, the driving factor of land degradation has three component: urbanization factor related to distance to urban, rural, road, and mining, water condition factors including distance to a water body, temperature, and precipitation and human disturbances factor including population and livestock (Batunacun et al., 2019). The other approach of addressing the driver of land degradation is an assessment of greening and browning of the NDVI trends which related to the factors of natural and anthropogenic factors (Gichenje et al., 2019). The natural factors affecting greening and browning of NDVI trends are related to moisture zones (sub-humid, humid, moist, dry, and desert), vulnerability to climate change impact, slope, soil type, soil depth, and different Landform (water bodies, badland, valley, foot slope, plain, alluvial plain, delta or coastal plain, depressions, escarpment, volcanic crater or shields, hills and mountains footbridges, mountains, plateau, and complex landform (Olsson et al., 2019). While the anthropogenic factor related to yield of the crop, potential agriculture land per land area, fertilizer used per unit area, cattle density, distance to a river, road, and town, protected area, nightlight and nightlight change, population density and population density growth, annual income per capita, gender disparity index, underweight children, child mortality, population with primary education proportion and growth of primary education, electricity, piped water, and sewer.

To address the drivers of land degradation trends, require several steps using causal chains as follows (UNCCD, 2016a):

1. Identify the types of land degradation in each specific area affected,
2. Identify proximate drivers causing the identified types of land degradation, and
3. Identify the underlying drivers of land degradations.

The drivers of land degradation in this study will be limited only to biophysical factors such as climate-related (temperature and precipitation) and topography using DEM and slope. The effect of temperature and precipitation to address land degradation can use the relation to NDVI trends, NDVI climate data correlation, and residual trend analysis in Mozambique (Montfort et al., 2021a).

2.3. Methods of studying land degradation using remote sensing approach

Remote sensing application in land degradation study can be as a leading role or supporting role as which require preliminary datasets and methods (Dubovyk, 2017). The study of land degradation assessment relies on remote sensing generally using vegetation cover dynamic or vegetation cover and productivity decline as an approach. While the study with remote sensing as a supporting role in land degradation analysis specifically are driving factors of land degradation, spatial decision support of land degradation, and spatial assessment of the impact of land degradation or land rehabilitation.

Vegetation covers represent the integrated indicator of vegetation response to an environmental factor, which usually derived from land use land cover change from long term satellite imagery data (Li et al., 2015). On the other hand, gradual loss of vegetation productivity act as an intermediary of land degradation assessment. Vegetation productivity usually presented as Net Primary Productivity (NPP) which derived from normalized difference vegetation index (NDVI). Thus, the most common proxy for land degradation assessment is NDVI which can be derived from long-term satellite imagery product (Bai et al., 2008a; Easdale et al., 2019; Gichenje & Godinho, 2018; Higginbottom & Symeonakis, 2014; Le et al., 2016; Mirzabaev et al., 2016; Montfort et al., 2021a; Vicente-Serrano et al., 2015; Vu et al., 2014). The formulation of NDVI formulated as below:

$$NDVI = \frac{(NIR - RED)}{NIR + RED}$$

where NIR is a near-infrared band and RED is a visible red waveband. The result of NDVI range between -1 to 1 where pixel value <0 indicate cloud or water and dense canopy surface has a pixel value of >0,7 (Higginbottom & Symeonakis, 2014).

Higginbottom and Symeonakis (2014) analyzed the NDVI from a different source of data to analyze the difference of NDVI concerning temporal and spatial resolution. NDVI trends analysis using linear regression model: a non-parametric trend of Theil-Sen and Mann Kendall Test as well to understand the trend of NDVI (dependent variable) over time (independent variable). On the other hand, Bai et.al. (2008) calculated the proxy of global land degradation using NDVI data derived from GIMMS radiometer AVHRR. The annual sum of the NDVI showed the greenness of the vegetation. But, in this study, the NDVI negative trend will not be translated directly as land degradation, while it needs to be calibrated with the rainfall and temperature data.

Study of land degradation analysis in Semiarid region by Vicente-Serrano, et. al. (2015), also incorporate the drought variability using SPEI database, precipitation, and evapotranspiration from Climate Research Unit (CRU) TS3.2 database and land cover type map (GlobCover). This study analyzes the trend, correlation, and regression between NDVI and SPEI data. While Le et. al. (2016) analyzes land degradation using the biomass approach where the annual NDVI correlated with rainfall and corrected with atmospheric and fertilization effect. The study done by Easdale et. al. (2019) argues that the study of land degradation using NDVI needs trend-cycle analysis which combines trend in the long-term change and cycle from smoother fluctuation around long-term trend such as seasonal data. Land degradation assessment by Montfront et. al. (2021) analyzing vegetation underlying factors using NDVI trends analysis methods correlated with climatic data and land cover data in Mozambique.

The supporting role of remote sensing of land degradation means that several data cannot be derived from remote sensing but required additional information from in situ and another geospatial source. Even though there are some other topics in this discussion in this study will be limited in the driver of land degradation. Mirzabaev et.al. (2016) discussed the drivers of land degradation in Central Asia which incorporate NDVI as a proxy of land degradation, as the result of NDVI response to other additional information such as biophysical, social, agriculture data to understand the proximate cause of land degradation. The biophysical variable such precipitation, length of the growing period, and land use/land cover. Population density, infant mortality rate, GDP per capita, distance to market, nighttime light, land tenure security, and rule of law are the other variable.

While Vu et. al. (2014), which analyze the land degradation drivers in Vietnam at the national level had slightly different variable such as 1) environmental variable consists of slope variable, soil quality, distance to the main road, distance to town, forest abundance, and agriculture abundance; 2) demographic variable include population density and change in population density, urban population growth, rural population growth; 3) economic variable namely poverty index, mean growth of GDP, mean and growth of annual agriculture gross product, the annual growth rate of the area of main crops, and annual growth rate of cereal crop yields. Li, et.al. (2014) analyze land degradation in North China Plain used several parameters such as rainfall, temperature, DEM, Slope, soil organic matters, percentage of land conversion from cultivated land to built-up and forest, fertilizer use per unit area, population density, rural farmers' per capita income, gross domestic production per capita, the share of production value of agriculture animal husbandry and fishery in GDP, and distance to the highway.

On the other hand, land degradation drivers analysis in Xilingol China as province scale, based on three-parameter 1) Urbanization/industrialization including distance to urban distance to rural, distance to road, and distance to mining; 2) water conditions related to distance to water bodies, precipitation, and temperature; and 3) human disturbance including population density and livestock unit density (Batunacun et al., 2019). Land degradation (using GIMMS-NDVI data as a proxy) drivers analysis in Kenya as the national scale is analyzed by incorporating natural and anthropogenic variable (Gichenje et al., 2019). The natural variables including moisture zone, vulnerability to climate change impact, slope, landform, soil type, and soil depth. While anthropogenic variable consists of the proportion of low potential agriculture per land area, the proportion of land use fertilizer, maize yields, cattle density, protected area, nighttime light and difference, distance to a river, distance to road, distance to town, and travel time to an urban area, population density, growth in population density, gender, child mortality, child underweight, children participate in primary school, growth in primary school enrollment, electricity, access to piped water, access to water disposal to sewer, and income.

2.4. Land Degradation Neutrality (LDN) framework

2.4.1. History of Land Degradation Assessment

Land degradation firstly got world attention in the 1970s when there were alarming phenomena of the acute drought-hit African large-scale dryland in the Sahelian region from 1968 to 1973 (Caspari, 2015). This triggered the first assessment of state and change of drylands in the transboundary region related to the desertification and human survival in dryland in the 1977 UN Conference on Desertification (UNCOD). The annual rate of land degradation estimated as 5,825 Mha/year in 1977 (Caspari, 2015). The assessment of land degradation then continued in 1984 with collaboration with UNEP, used the questionnaire approach which sent to all countries affected by desertification but there was a general failure of countries to conduct such an assessment hence there is absent simple methodology present to assessed land degradation (Caspari, 2015). During 1987-1990, the UNEP project of Global Assessment of Human-induced Soil Degradation (GLASOD) marked as the first global assessment of land degradation. This project mapped the extent, type, degree, rate, and the main cause of degradation based on expert knowledge. This resulted that 15% or 1.964 Mha of the terrestrial surface are degraded with one-third of it is an agricultural area (Caspari, 2015).

The assessment of land degradation then evolved using anecdotal evidence, research report, expert opinion, and local experience to estimate the degradation in dryland by Dregne and Chou in 1992 but the accuracy is considered low even though there is a field experiment involved (Dregne, 2002). Since the 1990s considered a silent period of land degradation era as there was no available global land-based assessment after GLASOD (Caspari, 2015).

Even though UNCCD established in 1994, while under force in early 1997 global scale of land degradation and desertification have not been addressed yet (Safriel, 2017). Then in 2006-2009, GEF-funded Land Degradation Assessment in Drylands project (GLADA) hosted by FAO (ISRIC-World Soil Information) found that 24% or 3.510 Mha of world land area was undergoing degradation during 1981-2003 (Caspari, 2015). GLADA or LADA project defined land degradation as long-term net primary productivity and ecosystem function decline. The remote sensing approached used to generate Normalized Vegetation Index (NDVI) as a proxy. This assessment then improved using climate adjusted NDVI using Global Inventory Modelling and Mapping Studies (GIMMS) data. Then the rain-use efficiency (RUE) estimated to identify the drought effect which calculated from the ratio of annual sum NDVI to annual rainfall (Bai et al., 2008a).

During 2009-2011 as a follow up of GLADA/LADA, FAO and partners established Global Land Degradation System (GLADIS). Land degradation focused on the ecosystem approach and defined as the reduction of the capacity of the land to provide ecosystem services and goods throughout times (Caspari, 2015). The goods and services of the ecosystem were divided into six measurable units if Biomass, Biodiversity, Soil health, Water quantity, Social Services, and Economic services. The assessment is broken down into several categories namely biophysical status and trends, biophysical land degradation process, land degradation classes, and land degradation impact index. The result related to biophysical classes showed that the fracture of terrestrial land status 23% is strongly degraded, 13.5% is a weak process of degradation, 3,6% is improving, 32,2 is medium to strong improving, and 5,6% is stable to improving (Caspari, 2015).

UNCCD in 2008 initiated horizon scanning of tools to invigorate and improve visibility of soil and land which would enable UNCCD to address land degradation globally not only in dryland (Safriel, 2017). This action then developed to the offsetting principle for addressing land degradation globally or Zero Net rate of Land Degradation (ZNLD). Then, there was an initial scientific assessment which resulted in a document entitled "*So much depend on so little - soil, a global common under threat*" in the Caux Forum for Human Security in Switzerland in July 2011 by Gnacadja (Safriel, 2017). The document entitled Zero Net Land Degradation, A Sustainable Development Goal to Rio +20… is a basic scientific document of ZNLD advocacy. But then, the term of ZNLD replaced by Land Degradation Neutrality (LDN) in the 3rd UNCCD Scientific conference in Cancun, Mexico in March 2015 (Safriel, 2017).

Land degradation and land degradation neutral world is explicitly mentioned in the UN general assembly document no 66/288 The future we want paragraph 206. "*… the need for urgent action to reserve land degradation. In view of this, we will strive to achieve a land-degradation-neutral world in the context of sustainable development."* (United Nations, 2012). Then, Sustainable Development Goals (SDGs) No 15.3. specifically stated that "*15.3 By 2030, combat desertification, restore degraded land and soil, including land affected by desertification, drought and floods, and strive to achieve a land degradation-neutral world"* (United Nations, 2015). Afterwards, the UN in 2017 specifies the goals with: "*15.3.1 Proportion of land that is degraded over total land area"*(United Nations, 2017). SDGs as a global target and subject to a member state to follow, this concept then translated as a world where nations individually endeavour to achieve land degradation neutrality (UNCCD, 2016b).

2.4.2. Land Degradation Neutrality Concept and Assessment

Land degradation neutrality defined as "*a state whereby the amount and quality of land resources necessary to support ecosystem functions and services and enhance food security remain stable or increase within specified temporal and spatial scales and ecosystems"* (UNCCD, 2016a). This LDN concept has two main targets which different from other land degradation assessment that the target is to reduce or halt the degradation process of healthy land and strive to reserved degraded land. This concept objective is to balance the losses (degradation/negative change) with gain (improvement of degraded land).

The logical description of the connection between theory (key factors and variables) and action described in a scientific conceptual framework. A scientific conceptual framework provides the underlying scientific process and principles of land degradation neutrality. The interrelationship among the key element of LDN is presented in the scientific conceptual framework illustrated in *Figure 2. 1* (UNCCD, 2017b). The vision of LDN presented in the top part emphasizing the link between food security, human wellbeing, and a healthy ecosystem. This vision can be achieved through the land-based natural and capital and ecosystem service for each land which depends on the balance between losses from new degradation and gains from reserved past degradation. This balance illustrated as a neutrality mechanism in the balance scale in the middle of the figure. The base of the scale shows the priority of the response in land degradation in a hierarchy with the highest priority is avoiding degradation, then reduce the degradation process and the least is reserve degradation. The arrow in the bottom part reflected that the neutrality is accessed by monitoring of land degradation indicator compared to fixed baseline which also needs to be maintained over time through anticipate and plan of losses and applied interpretation and adjust of the land degradation (UNCCD, 2016a). The most important part of this study is in the bottom part of the diagram where the monitoring of indictor of land degradation will be addressed.

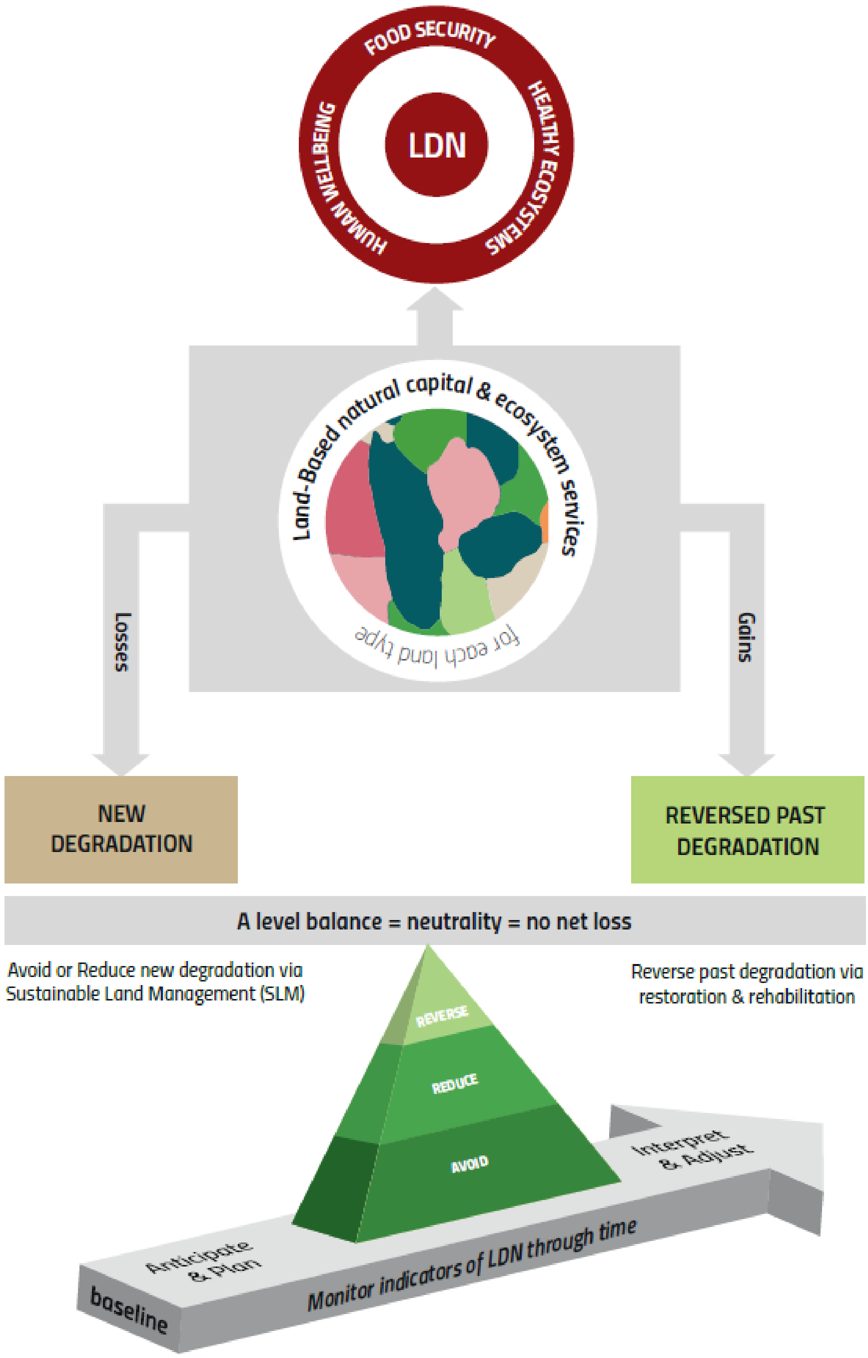


Figure 2. 1. Land Degradation Neutrality Conceptual Framework (UNCCD, 2017)

The indicator of LDN specifies what to measure to reflect the proxies that LDN seeks to maintain and present the key process that connected land-based natural capital. This indicator is chosen as a reasonable proxy of the change to deliver land-based ecosystem service capacity (UNCCD, 2017b). Some of the global indicators of LDN monitoring is the same as the SDG target indicator 15.3 (UNCCD, 2016a). The three-sub indicator of LDN which aligned with SDG 15.3 are:

- Land cover change is seen as the change in class to classify as negative change or positive change. The class FAO LCCS classes.
- Land productivity assessed through estimates of NPP (tDM/ha/yr) which can be quantified using NDVI or EVI (Enhanced Vegetation Index)
- Carbon stock assessed using estimation of SOC (tC/ha, to 30 cm), change in the absolute numerical value of positive of negative.

In addition to this tree global indicator, the national indicator may be added according to the national needs. The time dimension of these indicators should be considered where the value of NPP and SOC should be averaged over 10 to 15 years and a land cover minimum of 5 years. The monitor of LDN should be implemented in 2030 as the target year (t1) and should be compared with baseline year (t0) with at least two intermediate monitoring points. To determine the land significant negative change or degradation should result from a comparison between t1 and t0 (UNCCD, 2017b).

Apart from the above indicator, LDN monitoring also requires a trade-off mechanism to achieve neutrality, but that is not addressed in SDG 15.3.1: "*Proportion of land that is degraded over total area"*(UNCCD, 2017a). Thus, degraded land must be defined. Land degradation defined as "*the reduction or loss of the biological or economic productivity and complexity of rain fed cropland, irrigated cropland, or range, pasture, forest and woodlands resulting from a combination of pressures, including land use and management practices"* based on Good Practice Guidance document which provides details on how to calculate the extent of land degradation for reporting on SDG Indicator 15.3. Trends.Earth an open-source QGIS plugin is designed to calculate the indicator of SDG Indicator. This study will use Trends. Earth to analyze the proportion of degraded land over total land as well as to analyze the relationship with the proximate driver of land degradation in the study area.

Summary of literature review and state the art of study

There are several studies of land degradation which apply the land degradation framework especially the sub-indicator such as land degradation in Botswana by Akinyemi et. al. (2020) using remote sensing data but without using Trends.Earth platform and applying national dataset or National Metric. The other study of land degradation and climate factor relationship in Kenya by Gichenje and Godhino (2018) using the source of the data of land productivity with GIMSS NDVI Time-series and MODIS NPP data as well as did not integrate the result from Trends.Earth. The other study by Gichenje et.al. (2019) in Kenya also address the drivers of land degradation but did not use the product of land degradation from Trends.Earth platform as a dependent variable.

The study of land degradation in Mozambique by Montfort et. al. (2020) apply the LDN framework but did not use the Trends.Earth platform and the effect of agriculture and other environmental problem using stakeholder definition from interview result without any geospatial data. The study of land condition in the Republic of Srpska (Solomun, et. al. 2018) use the LDN framework sub-indicator and discuss drivers of land degradation, but only using literature study without any geospatial data incorporated in this study. The study of the driver of land degradation in Vietnam by Vu et. al. (2014) did not use the land degradation assessment with the LDN framework.

There is one study about land degradation in Kyrgyzstan using the LDN framework and Trends.Earth as tools by Sultanaliev and Bobushev (2020) with the result of land degradation for each specific land cover class from UNCCD indicator compared to national indicator. The result of this study is numerical of land degradation over land cover class in area unit presented in table form without any spatial distribution map. This study also did not study the drivers or relationship of land degradation with other environmental data.

This study will combine the result of land degradation calculation using Trends. Earth platform which provided to calculate SDGs 15.3.1 indicator and calculation of land degradation over several geospatial data related to population, agriculture, livestock, and other environmental factors to understand the preliminary study of the proximate driver of land degradation in Kyrgyzstan. Besides many studies related to the driver of land degradation mentioned in the previous part, this study will be focusing more on the relationship of land degradation and its possible drivers which also will be limited to the publicly available geospatial data. This thesis will combine the spatial analysis with statistical analysis of relationship using coefficient correlation with Kruskal Wallis test and Chi-square test with regards to the data type in the variable used in this study. This relationship is one of the provisional studies addressing the drivers of land degradation.

3. Method and Approach

3.1. Study area and list of data

Central Asia is one of the regions that has hardest hit by land degradation. Among the other country, Kyrgyzstan has the most different from other country situation where most of the land is a mountainous area. Thus, this study will focus on Kyrgyzstan. The detailed information about the study area presented in part 4 of this study. The study area defined for the whole country area which the boundaries adopted from Natural Earth administrative boundaries to match the boundaries of land degradation calculation using QGIS. This dataset needs to be extracted from the global countries' boundaries using export data by a selected feature which the step illustrates in Figure 3. 1. The other boundaries of Kyrgyzstan that used in this study are from FAO GAUL (FAO Global Administrative Unit Layers 2015) dataset where it is used in Google Earth Engine and Kyrgyzstan Spatial.

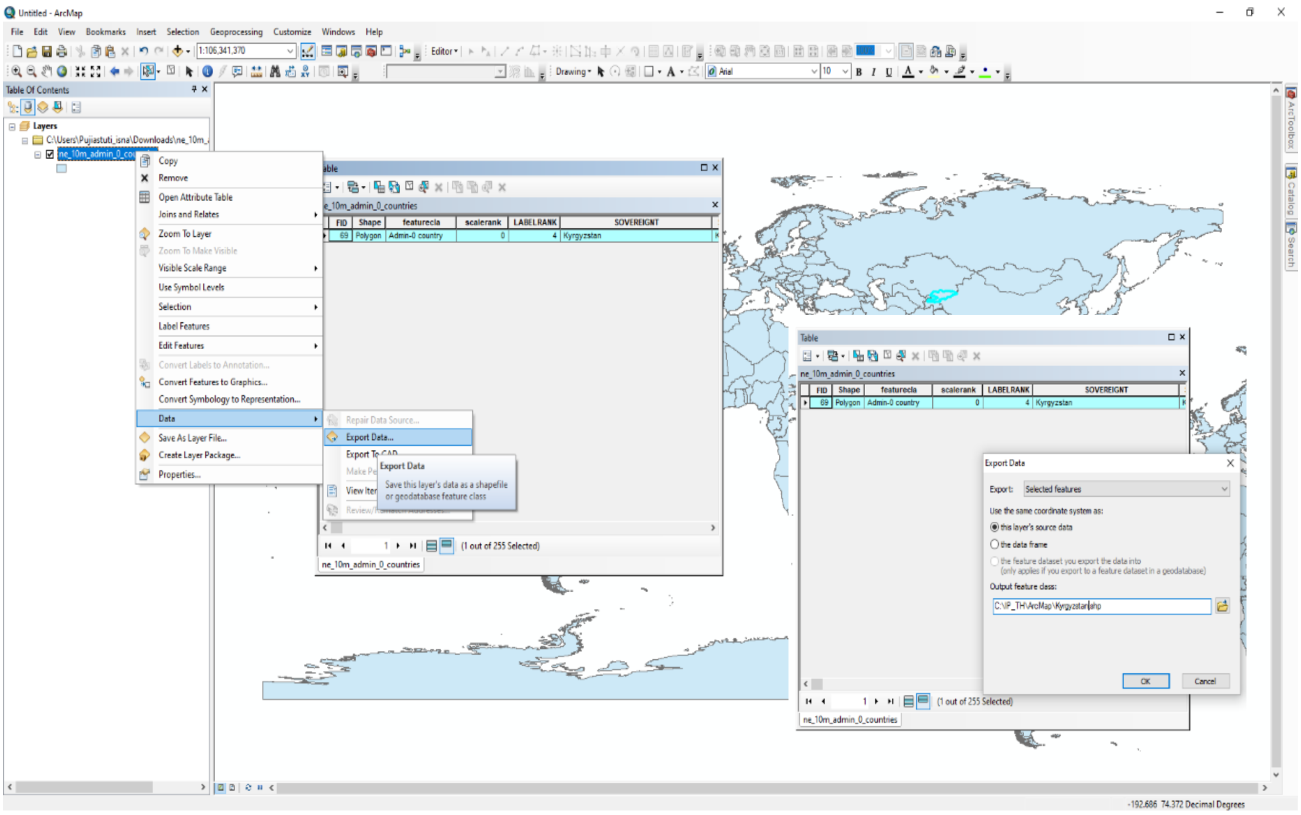


Figure 3. 1. Kyrgyzstan boundaries extracted from Natural Earth dataset

3.2. Flow Chart Methodology

The summaries of the variable and methodology in this research is presented in flowchart methodology in Figure 3. 2.

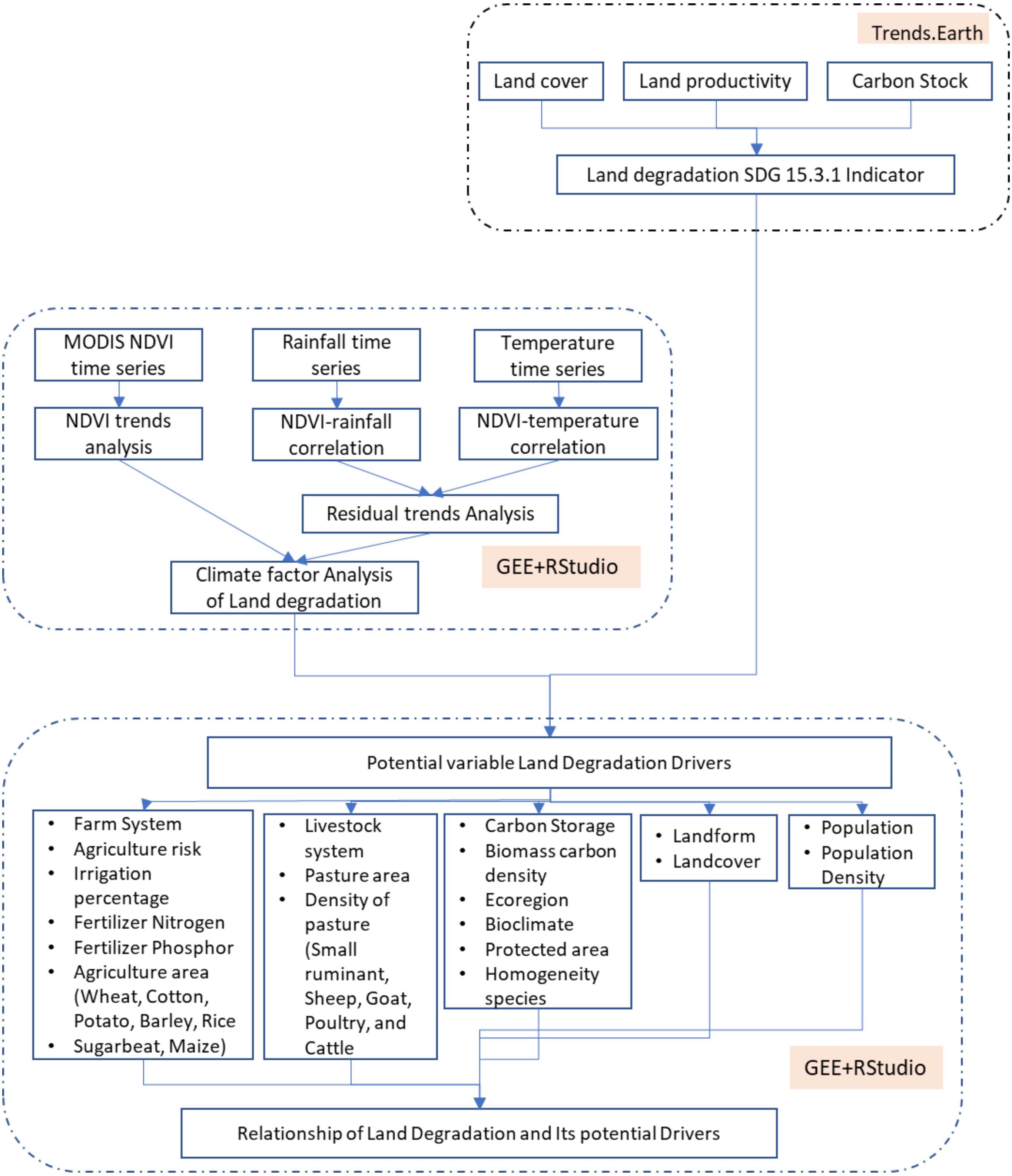


Figure 3. 2. Flowchart of Methodology

3.3. Data acquisition methods

There are three data mining methods for this study that specifically acquired from Google Earth Engine using certain programming language JavaScript API, download from open-source datasets, and automatically available default dataset from Trends. Earth.

3.3.1. Google Earth Engine

Google earth engine (GEE) is one of the most fast-growing powerful platforms in the remote sensing world to acquire data as well as process it based on the cloud programming language of JavaScript API. This platform is a powerful tool where make the research project with a large study area with a huge amount of dataset possible to do by a single researcher within a few months (Pruckner, 2018). This global platform possible to collect time-series satellite imagery from various source, download it, and perform the complex calculation (Sidhu et al., 2018). Figure 3. 3 illustrate the user interface of the GEE platform where there are four main windows where 1) on the left are tabs for *Scripts* for script collections, *Docs* for default algorithm provided by google developer, and *Assets* where we can upload and store our dataset, 2) the right side is *Inspector* act like information cursor in ArcGIS and QGIS to give

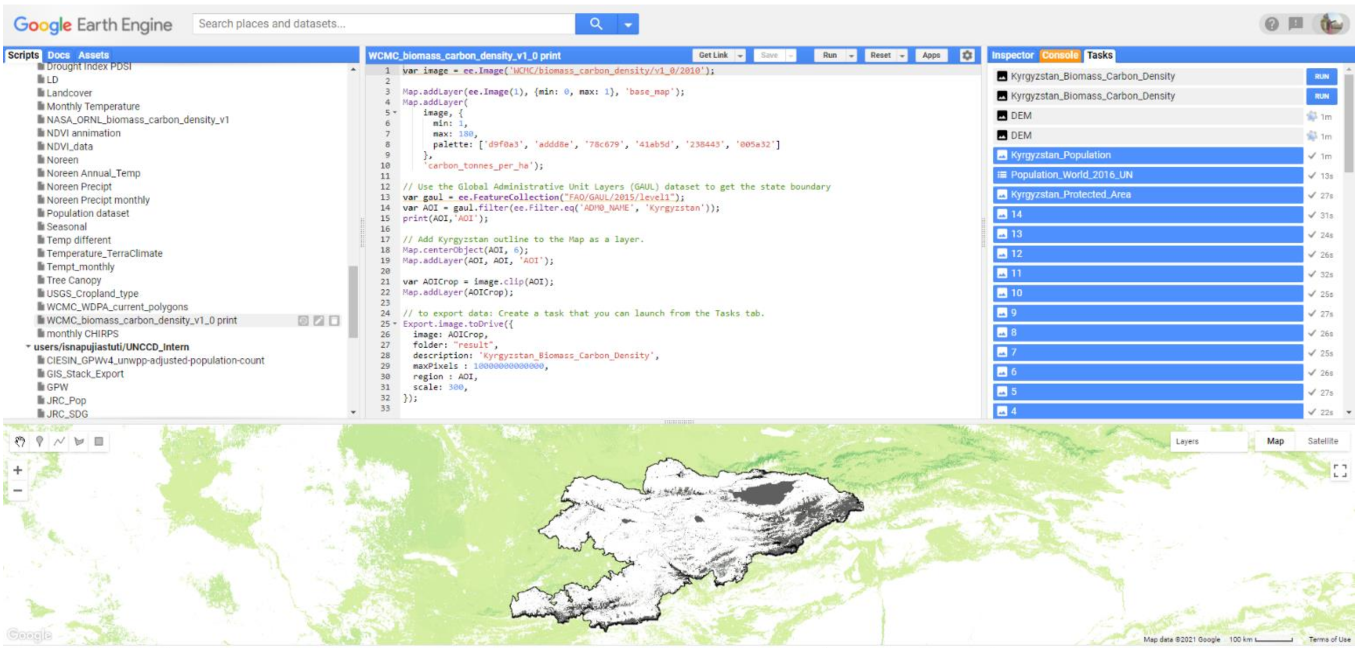


Figure 3. 3. Example of User Interface of Google Earth Engine

information for bands any point in designated satellite imagery, *Console:* provide information about the calculation process and result as well as visualize the graph from the calculation, and *Task* tabs provide a list of download task to export on an asset or drive which can be run on demand, 3) in the middle contain the main script where we can put command for data collection, calculation, and download command, and 4) the bottom part of the interface provides the visualization of result *Maps* and allow us to add any point, line or polygon to define study area.

This study will only perform a very small part of the computation available to do in GEE. Three types of computation will be performed in this study such as download data for a single dataset, a time-series dataset, and generate a chart. The computed time series dataset including the annual NDVI, annual temperature, annual precipitation, and annual drought index. The acquisitions of a single dataset are Digital Elevation Model (DEM), Slope, gridded population dataset, protected area dataset, biomass carbon density, and crop dominance. The list of datasets, source of a dataset and the GEE script to obtain is provided in Table 3. 1.

In general, there are three steps required to obtain the desired dataset used in this study. The first step is to define image collections and this step can be simple or complicated depending on their characteristics such as specific bands, a specific year, or specific iteration time series (Figure 3. 4). The simple step performs in the single band dataset including biomass carbon density, crop dominance, and protected area. Another simple computation is multiple bands dataset without time limitation such as DEM and Slope. More complicated computation is the data that has multiple bands with multiple years such as population dataset. The most complicated computation is to obtain a time series dataset from multiple bands and different time frames available such as annual precipitation from daily precipitation, annual NDVI from bimonthly NDVI and annual temperature from monthly temperature.

WCMC_biomass_carbon_density_v1_0 print *

```
// load the dataset
var image = ee.Image('WCMC/biomass_carbon_density/v1_0/2010');
```

DEM-SRTM_90

```
// Load the SRTM image.
var srtm = ee.Image('CGIAR/SRTM90_V4');

// Calculate slope.
var slope = ee.Terrain.slope(srtm);
var elevation = srtm.select('elevation');
```

Population dataset *

```
Imports (1 entry)
// load population data

worldPop = ee.ImageCollection("WorldPop/POP")

var WP_2010  = worldPop
//  .filter(ee.Filter.inList('country', ['KGZ']))
  .filter(ee.Filter.equals('UNadj', 'yes'))
  .filter(ee.Filter.equals('year', 2015))
  .select('population');
```

Annual Precipitation Print *

```
// load precip data (mm, daily total): 365 images per year
var precipCollection = ee.ImageCollection('IDAHO_EPSCOR/GRIDMET')
                    .select('pr')   // select  precip band only
                    .filterDate('2001-01-01', '2015-12-31');
print(precipCollection);

// reduce the image collection to one image by summing the 365 daily rasters
var annualPrecip = precipCollection.reduce(ee.Reducer.sum());
print(annualPrecip);

// equivalent shortcut syntax
var annualPrecip2 = precipCollection.sum();
```

Annual NDVI

```
var month_mean = ee.List.sequence(0, 14*1).map(function(n) { // .sequence: number of years from starting year
  var start = ee.Date('2001-01-01').advance(n, 'month'); // Starting date
  var end = start.advance(1, 'year')
var finish = ee.Date('2001-12-31') ; // Step by each iteration
  return ee.ImageCollection("MODIS/006/MOD13Q1")
        .filterDate(start, end)
        .select ('NDVI')
        .median ()
        .multiply(0.0001)
        .set('system:time_start', start.millis());
});
print(month_mean);

var collection = ee.ImageCollection(month_mean);

print(collection);
```

Figure 3. 4. Define Image collection and its characteristic

The second steps are to define the study area using the clip function. There are three types to define study area such as draw polygon, upload shapefile of the study area or other is select the dataset available online such as country boundaries from FAO GAUL dataset. Figure 3. 5 illustrate to define study area using dataset available online (FAO GAUL) and study area from shapefile assets with additional calculation such as the conversion of a unit from Kelvin to Celsius (subtract 273.15) and if there is need to adjust the value inside the pixel value with scale (multiply (0,1).

Table 3. 1. List of Dataset obtained from Google Earth Engine

Data	Source of datasets	Link to the GEE script
Normalized Vegetation Index (NDVI)	ee.ImageCollection('MODIS/006/MOD13Q1')	https://code.earthengine.google.com/c41b2160c4b3c8bfa6ac4ee833555338
DEM and slope	ee.Image('USGS/SRTMGL1_003')	https://code.earthengine.google.com/bd1ff0ba253bd701b71c1d7763930055
Annual temperature	ee.ImageCollection('IDAHO_EPSCOR/TERRACLIMATE')	https://code.earthengine.google.com/6778f9177d3ebd26c98eb935f48c52ff
Annual precipitation	ee.ImageCollection('UCSB-CHG/CHIRPS/DAILY')	https://code.earthengine.google.com/94a79af5cb258380cf2471b18f6e7aa5
Gridded Population	ee.ImageCollection('WorldPop/POP')	https://code.earthengine.google.com/bdbc72cb116637504933e1d0985a656e
Protected area	ee.FeatureCollection('WCMC/WDPA/current/polygons')	https://code.earthengine.google.com/e98cc4061dc670fa68d3314e36f4270e
Biomass Carbon Density	ee.Image('WCMC/biomass_carbon_density/v1_0/2010')	https://code.earthengine.google.com/06aea0611b104be1ff20c00591ee46ec
Crop dominance	ee.Image('USGS/GFSAD1000_V1')	https://code.earthengine.google.com/4f278790e3e592d95ae046976230bb62

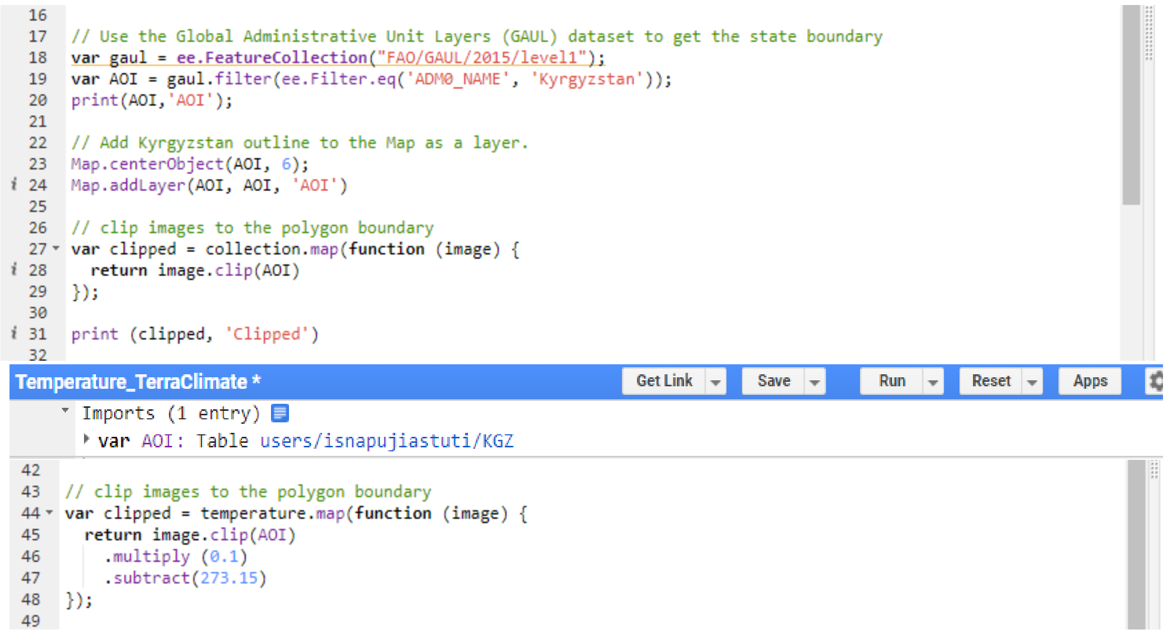


Figure 3. 5. Define study area in GEE

The third and last steps are to download the dataset in a designated location whether cloud storage, EE assets, or drive. Two types of download used in this study including a single raster image and a set of time-series image. For single raster image, the command will be straightforward and the list of available the dataset for download will appear in the *Tasks* tab and press run to download the dataset (Figure 3. 7.) The downloading process shown in the moving sign, the failed process shown in the red mark in the *Tasks* tab, and the tick symbol represent download finished and successful. On the other hand, the time-series image requires a batch function of fitoprincipe (Figure 3. 6) which will automatically command the engine to download all the dataset at once within an order (0-14) to a designated folder.

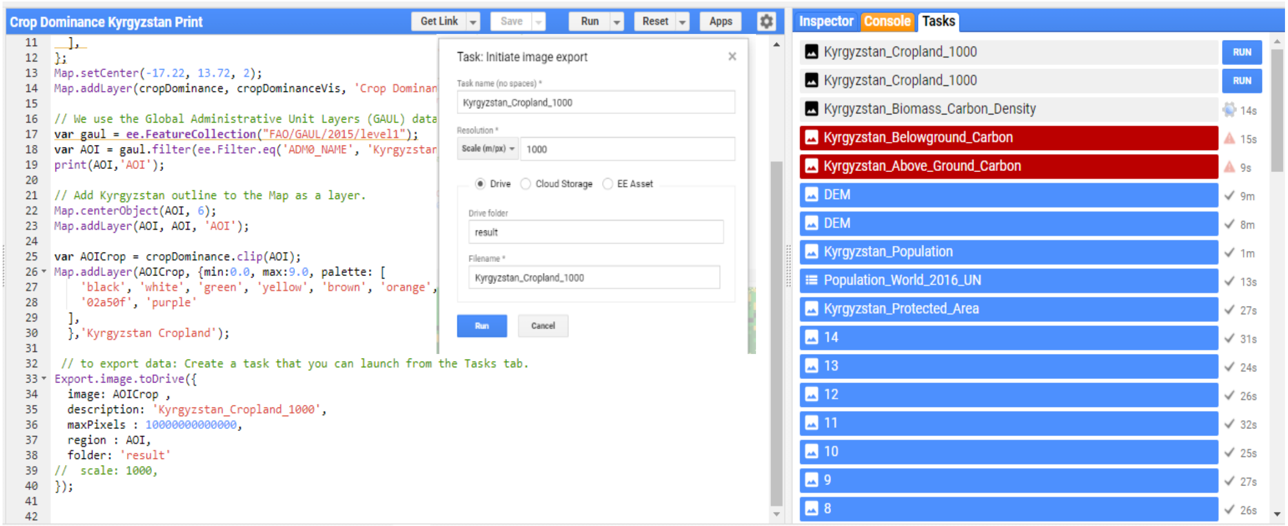


Figure 3. 7. Download single dataset

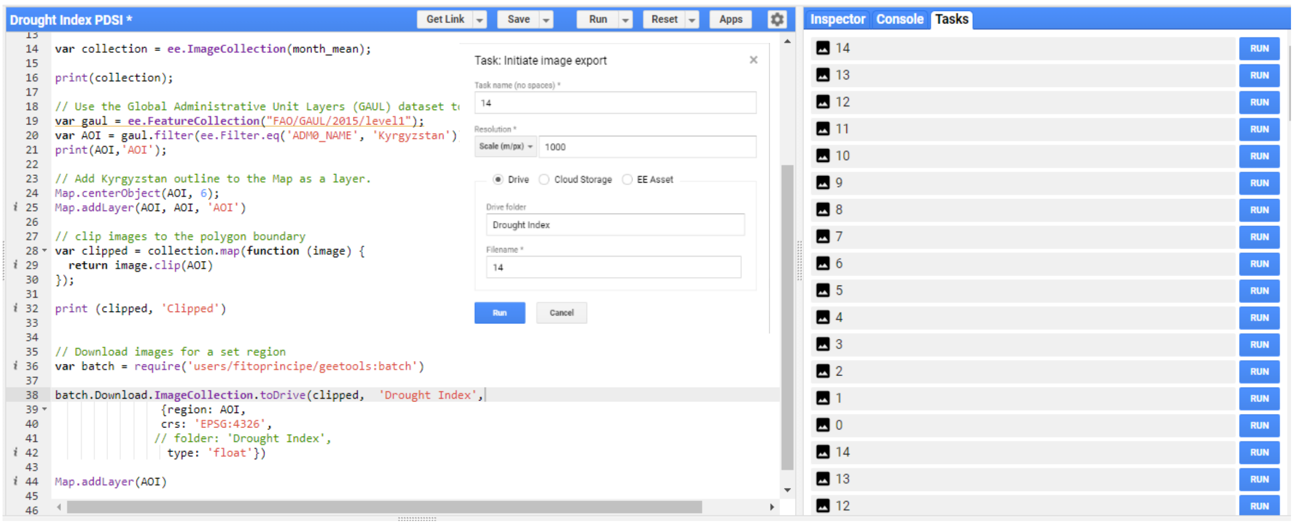


Figure 3. 6. Download timeseries dataset

GEE enable the user to generate chart automatically from the selected collection raster dataset. The chart result shown in the Console tabs. To download the chart, the red rectangle in Figure 3. 8 need to be clicked. The new window will pop up and there are choices where this chart can be downloaded directly in picture extension as a .png file or raw data as a .csv file with the small button in the right corner of the chart (Figure 3. 9). The result from this analysis presented in study area chapter 4.

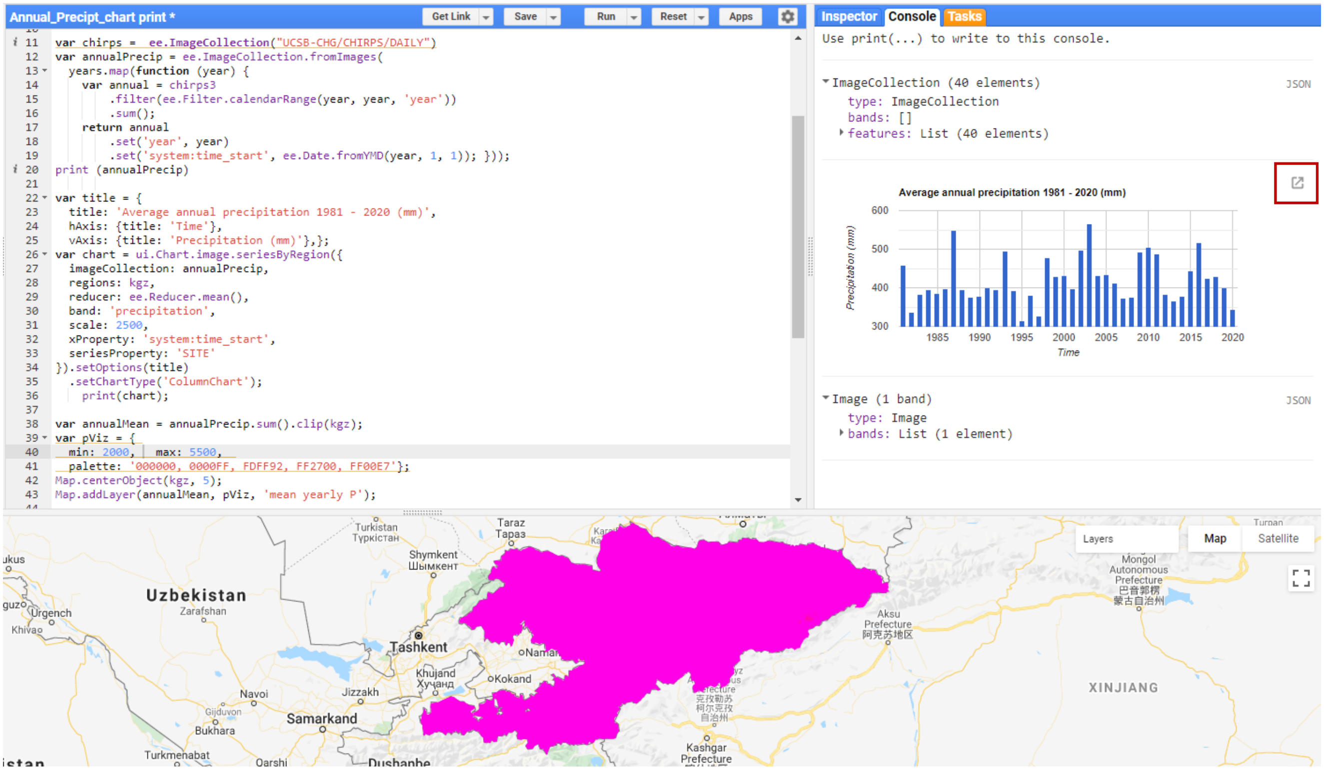


Figure 3. 8. Generating chart from Google Earth Engine

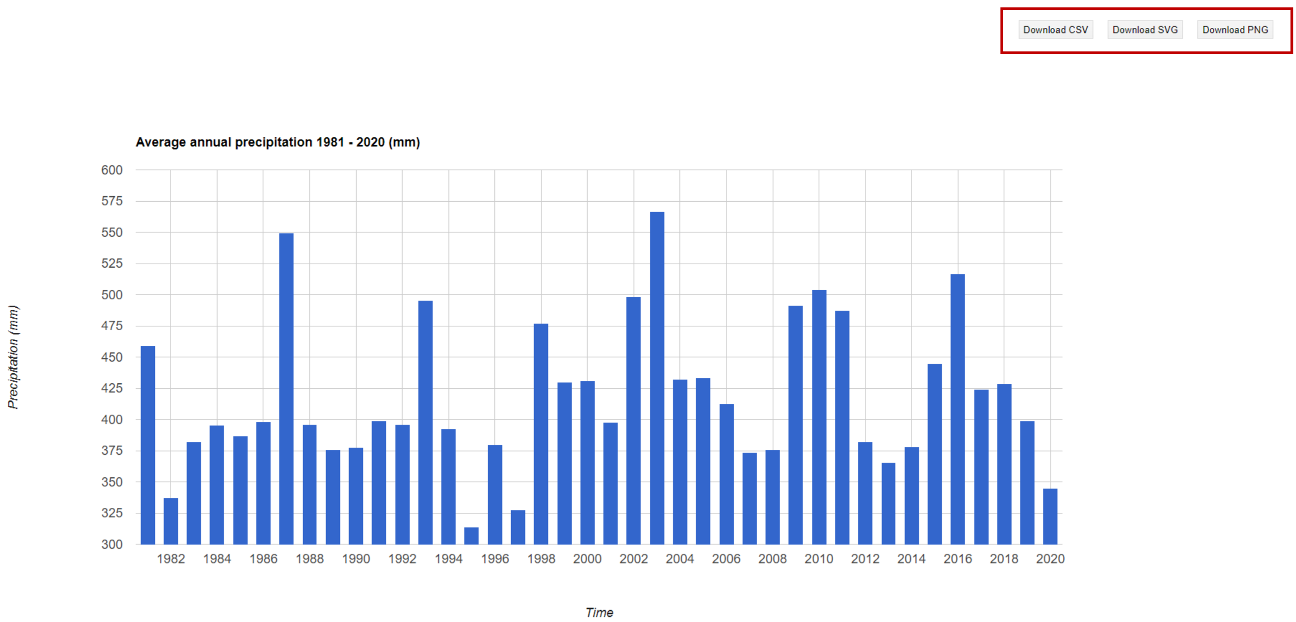


Figure 3. 9. Download chart from computation in Google Earth Engine

3.3.2. Open-source datasets

The publicly open-source geospatial data are usually available in medium and coarse spatial resolution (250-500m and 1-8 km) are very still useful for country scale analysis. Some data also did not provide spatial data but only statistical data. The following Table 3. 1 provide the information of open data sources for this study.

Table 3. 1. Open Source Geospatial Dataset

No	Data	Source
1	Land degradation sub-indicator: land cover, land productivity, and soil organic carbon	Trends.Earth plugin in QGIS
2	EarthStat: Agriculture and production and yields	http://www.earthstat.org/
3	Open Street Map (OSM) – humanitarian data	https://data.humdata.org/dataset
4	FAOSAT – Agriculture data	http://www.fao.org/faostat/en/#data
6	Kyrgyzstan Spatial	http://www.kyrgyzstanspatial.org/map
7	Central Asia Water Info portal map	http://www.cawater-info.net/map_e.htm
9	United Nation Environmental Program	http://geodata.grid.unep.ch/results.php
10	Free GIS Data	https://freegisdata.rtwilson.com/
11	Climate data	https://www.worldclim.org/data/worldclim21.html
12	FAO Geonetwork	http://www.fao.org/geonetwork/srv/en/main.home
13	Kyrgyzstan Statistic	http://www.stat.kg/en/opendata/category/4/
14	World Research Institute	https://datasets.wri.org/
15	Habitat Heterogeneity	http://www.earthenv.org/texture
15	Natural Earth Administration Boundaries	https://www.naturalearthdata.com/?s=country+boundaries

Source: Various source, 2021

The data used in this study which collected from an open-source dataset are listed in Table 3. 2. The data collected from the open-source usually have global coverage or slightly different coverage. This type of data needs to be adjusted to the border of Kyrgyzstan using a function in ArcGIS. There are two functions to perform adjusted boundaries dataset to Kyrgyzstan boundaries including:

1. Extract by mask function for raster dataset (Figure 3. 11)
2. Clip from geoprocessing function for shapefile or vector dataset (Figure 3. 10)

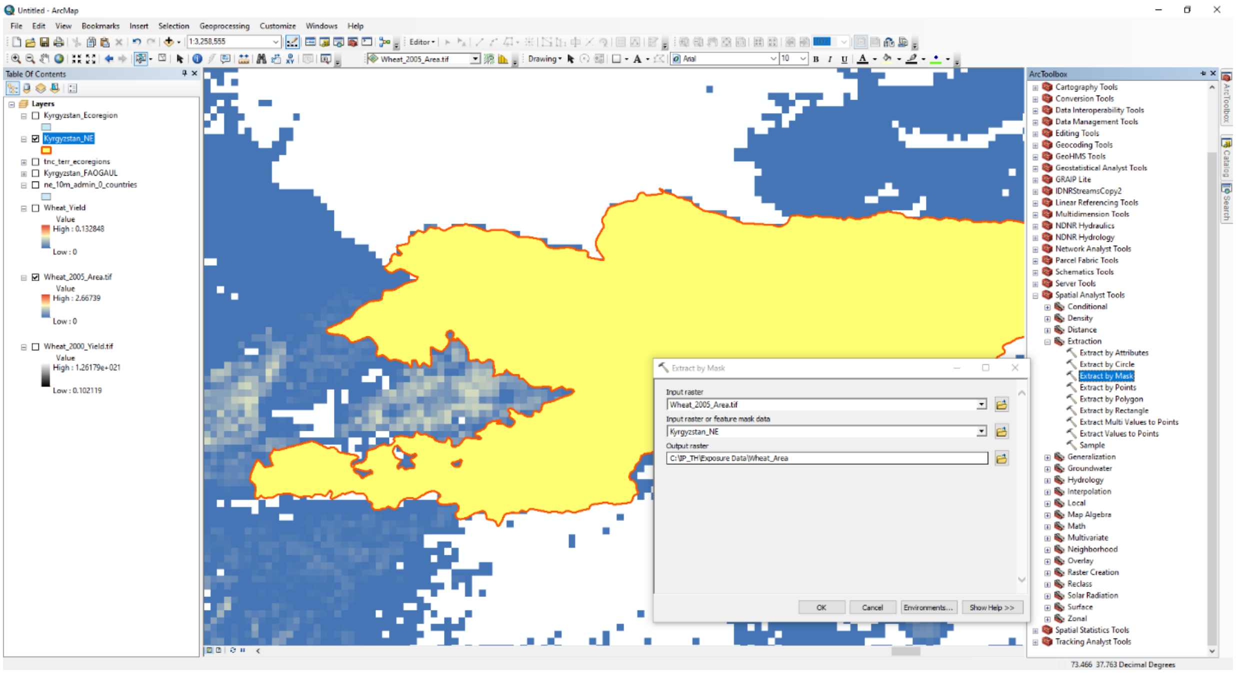


Figure 3. 11. Extract by mask raster

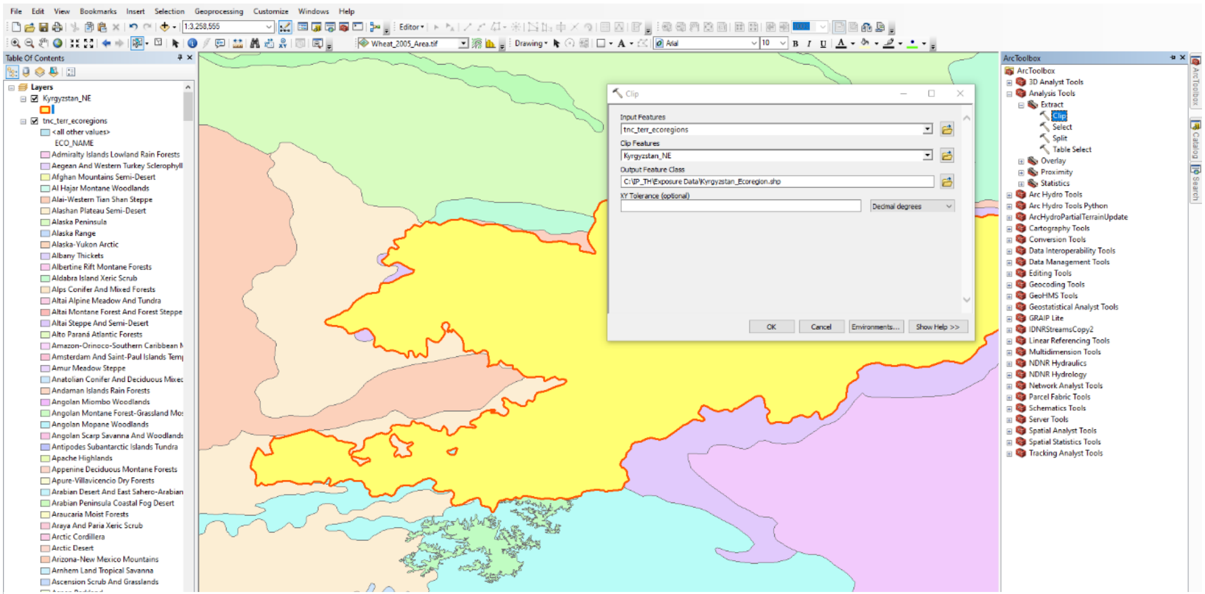


Figure 3. 10. Clip Geoprocessing

Table 3. 2. List of the data collected from an open-source dataset

No	Data Available	Source	Unit
1	Landform	Kyrgyzstan Spatial	
2	Land cover	Kyrgyzstan Spatial	
3	Bioclimate	Kyrgyzstan Spatial	
4	Annual PET	Kyrgyzstan Spatial	mm/year
5	Aridity Index	Kyrgyzstan Spatial	0,1-5.8
6	Ecoregion	The Nature Conservancy	
7	Homogeneity Species	EarthEnv	number of species
8	Carbon storage	EarthStat	ton C per hectare
9	Population Density	Kyrgyzstan spatial	Person
10	Farm System	GeoNetwork	
11	Agriculture risk	WRI	
12	Irrigation percentage	WRI	percentage area of land (0-95)
13	Livestock System	Kyrgyzstan Spatial	
14	Pasture	Kyrgyzstan Spatial	percentage area of land (0-95)
15	Fertilizer: Phosphorus	EarthStat	kilogram per Ha
16	Fertilizer: Nitrogen	EarthStat	kilogram per Ha
17	Small ruminants	Kyrgyzstan Spatial	number per pixel
18	Sheep	Kyrgyzstan Spatial	number per pixel
19	Goat	Kyrgyzstan Spatial	number per pixel
20	Poultry	Kyrgyzstan Spatial	number per pixel
21	Cattle	Kyrgyzstan Spatial	number per pixel
22	Wheat	Kyrgyzstan Spatial	Ha
23	Cotton	Kyrgyzstan Spatial	Ha
24	Potato	Kyrgyzstan Spatial	Ha
25	Barley	Kyrgyzstan Spatial	Ha
26	Rice	Kyrgyzstan Spatial	Ha
27	Sugarbeat	Kyrgyzstan Spatial	Ha
28	Maize	Kyrgyzstan Spatial	Ha
22	Wheat	Kyrgyzstan Spatial	kg/ha
23	Cotton	Kyrgyzstan Spatial	kg/ha
24	Potato	Kyrgyzstan Spatial	kg/ha
25	Barley	Kyrgyzstan Spatial	kg/ha
26	Rice	Kyrgyzstan Spatial	kg/ha
27	Sugarbeet	Kyrgyzstan Spatial	kg/ha
28	Maize	Kyrgyzstan Spatial	kg/ha
29	Province boundaries	Kyrgyzstan Spatial	
30	District boundaries	Kyrgyzstan Spatial	

There are some data from the Kyrgyzstan Spatial data source which does not have any legend, then the legend needs to assign manually using the add field data function and editor to label the file. Figure 3. 12 below illustrates the example of the addition of the legend process in bioclimate.

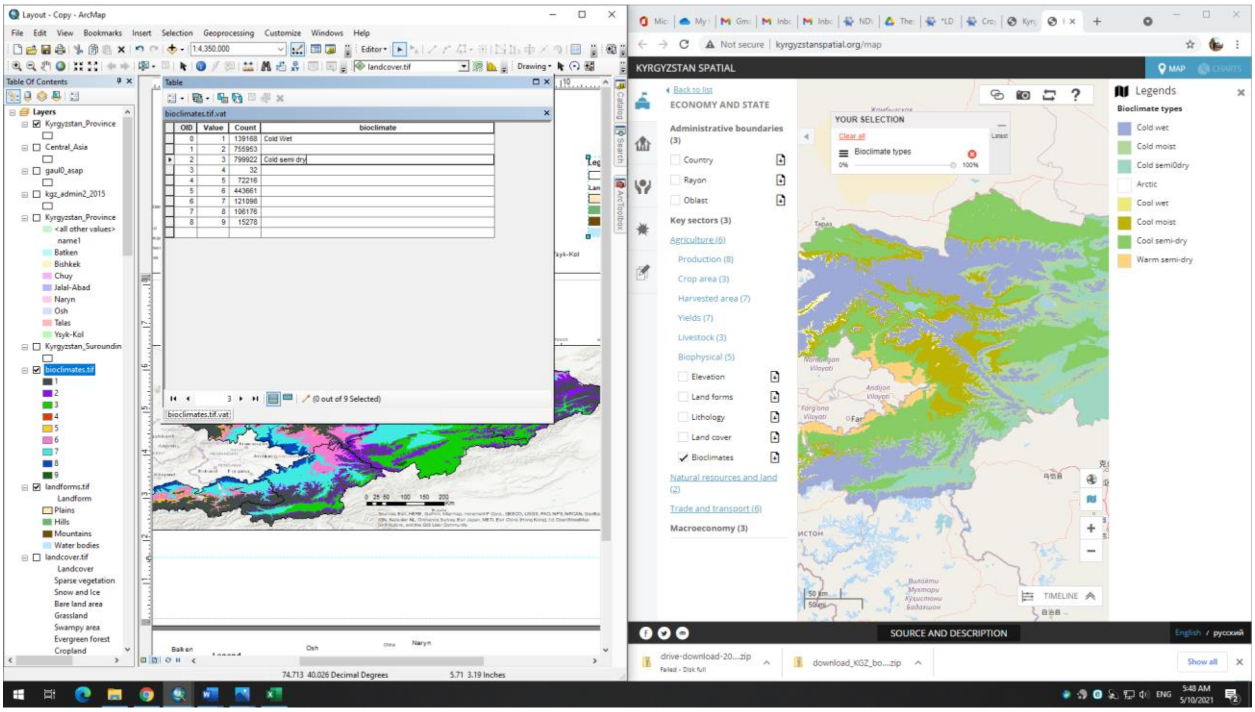


Figure 3. 12. Add legend in ArcGIS

3.3.3. Trends.Earth data

Trends.Earth as one of the platform analyses in this study is a QGIS plugin product from Conservation International institution which allow the calculation of land degradation. This plugin enables to call the data automatically from various sources based on cloud computing because it is connected to the Google Earth Engine (GEE). The data used in Trends.Earth is obtained from various sources listed in Table 3. 3.

Table 3. 3. Data source of land degradation assessment using Trends.Earth

No	Parameter	Dataset	Temporal	Spatial Resolution	Coverage
1	NDVI	AVHRR/GIMMS	1982-2015	8 km	Global
		MOD13Q1-coll6	2001-2016	250 m	Global
2	Land cover	ESA CCI Land Cover	1992-2018	300 m	Global
3	Soil carbon	Soil Grids (ISRIC)	Present	300 m	Global
4	Administrative boundaries	Natural Earth Administrative boundaries	Present	10/50m	Global
5	Agroecological zones	FAO - IIASA Global Agroecological Zones (GAEZ)	2000	8 km	Global
6	Soil Moisture	MERRA 2	1980-2016	0.5° x 0.625°	Global
		ERA I	1979-2016	0.75° x 0.75°	Global
7	Precipitation	GPCP v2.3 1 month	1979-2019	2.5° x 2.5°	Global
		GPCC V6	1891-2019	1° x 1°	Global
		PERSIANN-CDR	1983-2015	25 km	Global
		CHIRPS	1981-2016	5 km	Global
8	Evapotranspiration	MOD16A2	200-2014	1 km	Global

Source: Trends.Earth, 2018

3.4. Data Analysis

3.4.1. Land Degradation Analysis using Trends.Earth

Land degradation assessment in this study applies the land degradation definition and assessment method from SDGs 15.3. This study will use Trends. Earth, a QGIS plugin product from Conservation International institution which allows the calculation of land degradation especially the proportion of land degraded over a total land area (Trends.Earth, 2018). This platform is designed for monitoring land degradation to supports countries in data analysis for reporting of land degradation commitment to the United Nations Convention to Combat Desertification (UNCCD).

Land degradation assessment based on SDGs Indicator 15.3.1. defined as binary quantification of land as degraded and not degraded land based on the analysis of the three sub-indicators namely land cover trends, land productivity trends, and carbon stocks trends (UNCCD, 2017a). The quantification of land degradation achieved from the summarize of the negative change between these indicators including:

1. Land cover and land cover change assessment
2. Status and trends of land productivity analysis
3. Soil organic carbon as a proxy for assessing carbon stock value and change.

The statistical significance test is used to determine the evaluation of change with the method of computation applying the statistical principle of one out all out (1OAO). The 1OAO assumptions mean that if one of three sub-indicators have negative or stable status compared to the previous year of assessment for a particular unit of land, then the land considers as degraded land. This 1OAO principle for three indicators resulted in three categories of change: 1) positive or improving, 2) negative or declining, and 3) unchanging or stable (UNCCD, 2017a). This negative trend is defined as the land degraded area. The illustration of the assessment is presented in Figure 3. 13.

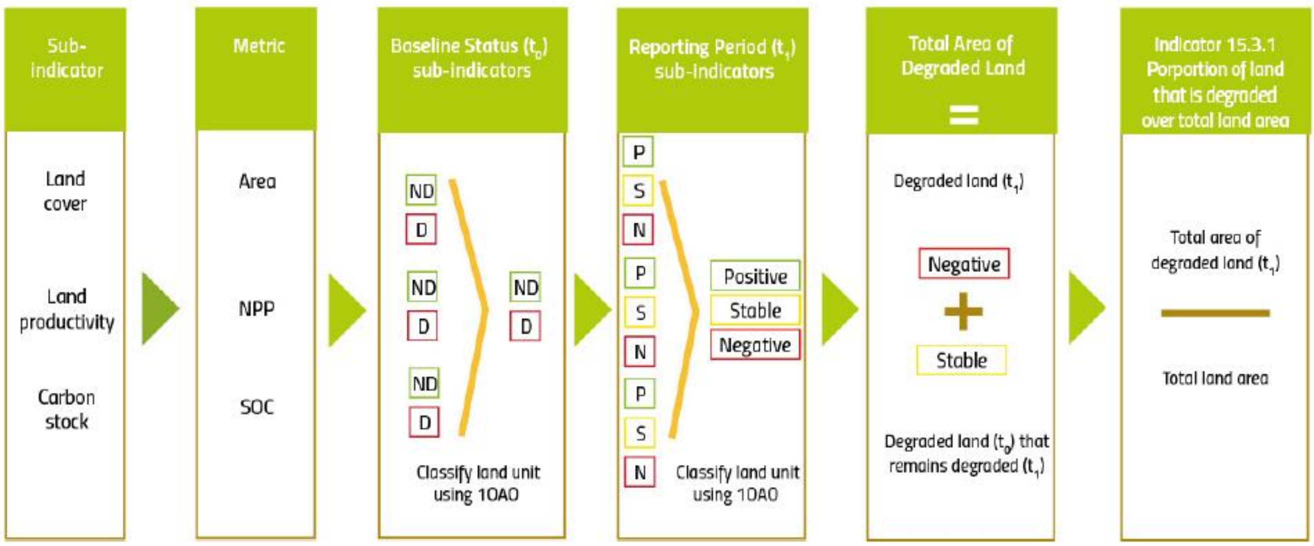


Figure 3. 13. Land degradation neutrality framework assessment (Source: UNCCD, 2017a)

Three sub-indicators (land cover, land productivity, and carbon stock) with each metric will be calculated to be determined as positive change or non-degraded (ND) or degraded (D). The next step is this classification will be classified as positive, stable, and negative trends of each three-parameter and combine using the 1OAO principal to determine the status of land as positive, stable, and negative. Total degraded land is consisting of the degraded land and stable land which then compared to total land area to obtain SDGs 15.3.1. indicator total degraded land over total land (UNCCD, 2017a). This study will be focusing on calculating the baseline period of the SDGs indicator is 2015 (UNCCD, 2021)which mean that the calculation of time series data for three sub-indicators during the period of 2000 to 2015.

The platform for the computation method of land degradation in this study is Trends.Earth. This QGIS plugin allows the calculation of sub-indicators in the spatial dimension where the raster map will be produced to generate the table and final SGDs 15.3.1 indicator map.

3.4.1.1. Computation methods of Trends.Earth

The general overview of the calculation method illustrated in Figure 3. 14 where land degradation calculated from three sub-indicators namely land productivity, land cover and soil carbon but, the land productivity also has sub-indicators: state, performance, and trajectory.

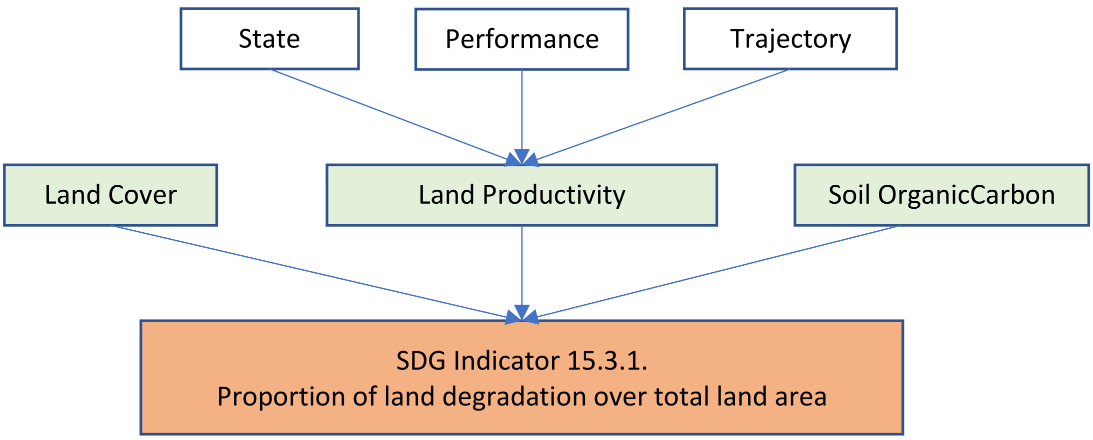


Figure 3. 14. General overview of SDG Indicator 15.3.1 (UNCCD, 2017a)

Land productivity assessment consists of trajectory, performance, and state indicator. The trajectory represents the rate of primary productivity trends over time. This indicator uses Mann-Kendall non-parametric significant test to calculate regression of changes in primary productivity during the period of analysis for each pixel value. Annual NDVI trends with p-value <0,05 identified as significant trends in primary productivity. There are corrections for the effect of climate using Rain Use Efficiency (RUE) and Water Use efficiency (WUE). The Residual trend analysis (RESTREND) also performed to predict NDVI for a given rainfall amount (Sims et al., 2019).

The productivity states indicator provides the change of primary productivity between the target year and baseline year. The state of improvement, stability and degradation will be generated. The performance productivity measures the local productivity relative to other similar vegetation types in similar bioclimatic region and land cover types within the study area. The productivity performance resulted in the stable and degradation category. The result of a category of three indicators of productivity then combined to produce the productivity component for calculating SDGs 15.3.1 indicator. The combination of this category summarized in Figure 3. 15. The principle of 1OAO is applied to determine the improvement, stable, and degradation but also there is an additional of 5 class of land productivity specifically stable, stable but stressed, early signs of decline, declining, and improving.

Trajectory	State	Performance
Improvement	Improvement	Stable
Improvement	Improvement	Degradation
Improvement	Stable	Stable
Improvement	Stable	Degradation
Improvement	Degradation	Stable
Improvement	Degradation	Degradation
Stable	Improvement	Stable
Stable	Improvement	Degradation
Stable	Stable	Stable
Stable	Stable	Degradation
Stable	Degradation	Stable
Stable	Degradation	Degradation
Degradation	Improvement	Stable
Degradation	Improvement	Degradation
Degradation	Stable	Stable
Degradation	Stable	Degradation
Degradation	Degradation	Stable
Degradation	Degradation	Degradation

3 Classes	5 Classes
Improvement	Improving
Improvement	Improving
Improvement	Improving
Improvement	Improving
Improvement	Improving
Degradation	Stable
Stable	Stable
Stable	Stable
Stable	Stable
Degradation	Stable but stressed
Degradation	Early signs of decline
Degradation	Declining
Degradation	Declining
Degradation	Declining
Degradation	Declining
Degradation	Declining
Degradation	Declining
Degradation	Declining

Figure 3. 15. Aggregating the productivity of Land Productivity sub indicator (UNCCD, 2017a)

Land cover assessment requires overlay analysis between the land cover maps in baseline year and target year using the acceptable accuracy map for valid comparison (Figure 3. 16). The default land cover map generated using Trends.Earth is from ESA CCI land cover maps. This land cover map will be reclassified into 7 land cover namely forest, grassland, cropland, wetland, artificial area, bare land, and water. Then for each pixel of raster maps need to determine whether the land cover change or remain unchanged using land cover transition analysis. This analysis will be possible to be adjusted based on the local knowledge of land conditions in each study area. The transition analysis determined in this study is presented in Figure 3. 17 where the degradation corresponds to the minus (-) sign, improvement in plus (+) sign and unchanged as zero (0).

Soil organic carbon (SOC) quantify using the SoilGrids 250m dataset containing carbon stocks for the first 30cm of the soil profile as a proxy. This carbon stock will be assigned to land cover maps to generate the SOC based on the land cover. The carbon conversion factor then needs to be defined to obtain the change in carbon stocks. The degradation of soil organic carbon defines when the reduction of SOC is more than 10% (Figure 3. 18).

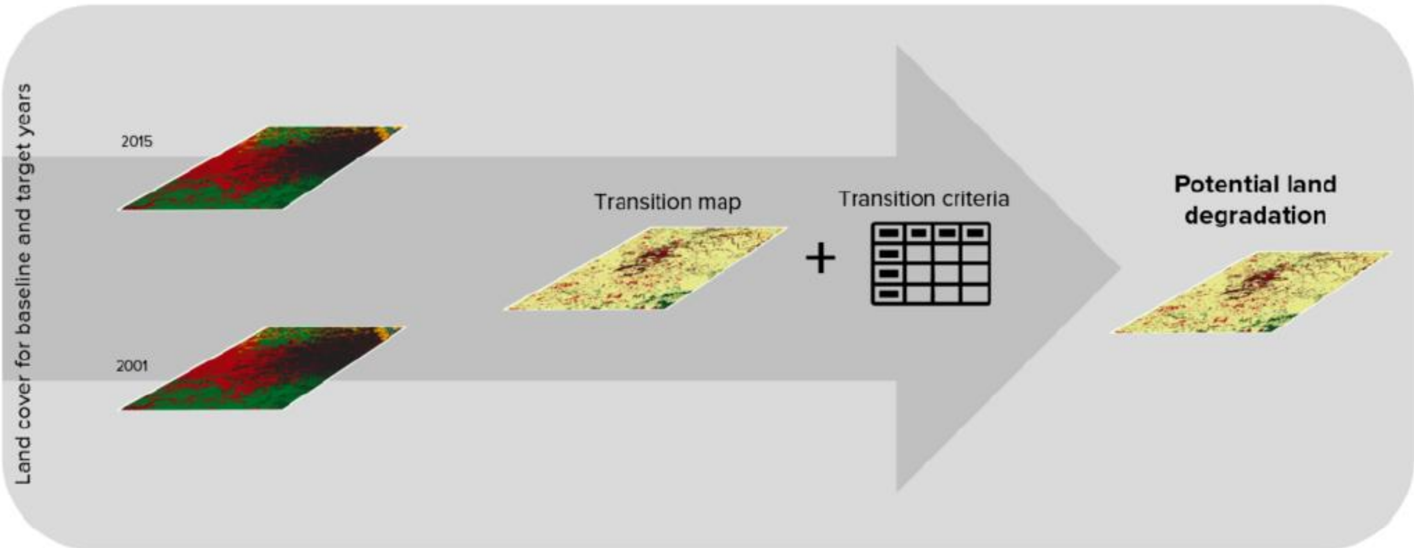
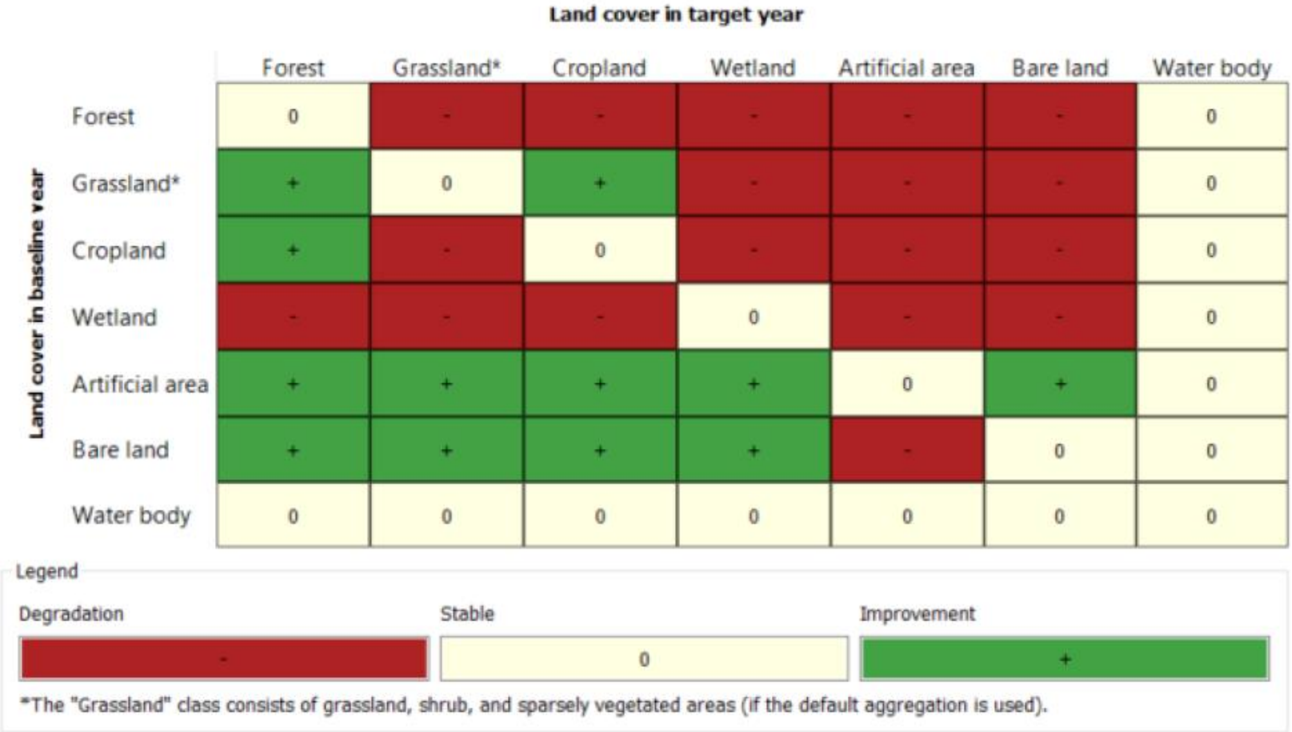


Figure 3. 16. Overlay land cover and transition map (UNCCD, 2017a)



Land cover in target year

Land cover in baseline year	Forest	Grassland*	Cropland	Wetland	Artificial area	Bare land	Water body
Forest	0	-	-	-	-	-	0
Grassland*	+	0	+	-	-	-	0
Cropland	+	-	0	-	-	-	0
Wetland	-	-	-	0	-	-	0
Artificial area	+	+	+	+	0	+	0
Bare land	+	+	+	+	-	0	0
Water body	0	0	0	0	0	0	0

Legend

Degradation	Stable	Improvement
-	0	+

*The "Grassland" class consists of grassland, shrub, and sparsely vegetated areas (if the default aggregation is used).

Figure 3. 17. Land cover transition criteria (source: UNCCD, 2017a)

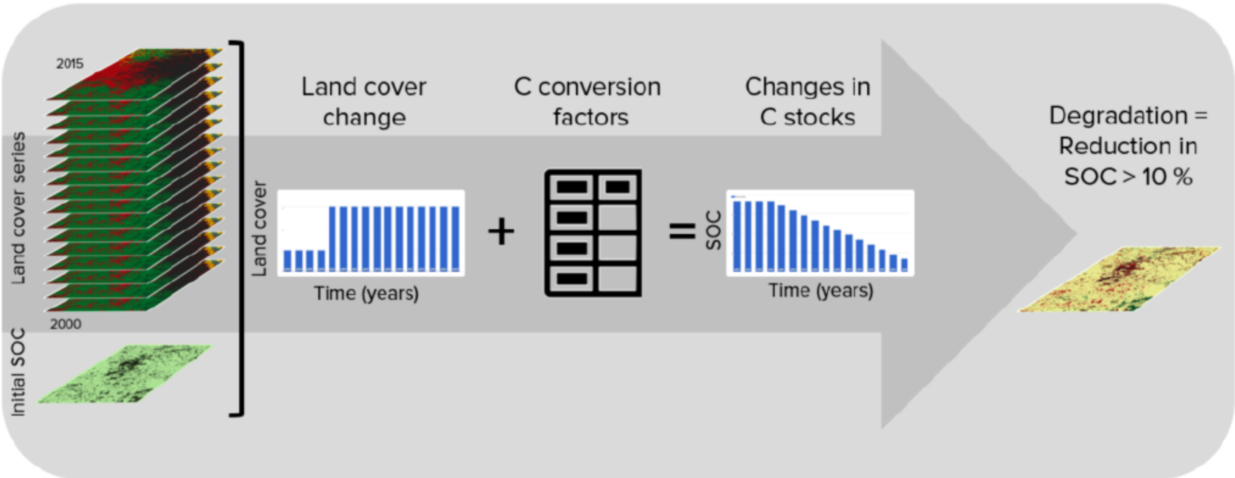


Figure 3. 18. Soil Organic Carbon computation (source: UNCCD, 2017a)

The result from the three sub-indicators then will be combined to produce land degradation status as required in SDG 15.3.1. The principle of one out all out (1OAO) is applied. It is mean that for a particular pixel in the raster map combination when there is one sub-indicator categorize as degradation status, then this certain pixel will be classified as degradation status (Figure 3. 19)

Productivity	Land Cover	SOC	SDG 15.3.1
Improvement	Improvement	Improvement	Improvement
Improvement	Improvement	Stable	Improvement
Improvement	Improvement	Degradation	Degradation
Improvement	Stable	Improvement	Improvement
Improvement	Stable	Stable	Improvement
Improvement	Stable	Degradation	Degradation
Improvement	Degradation	Improvement	Degradation
Improvement	Degradation	Stable	Degradation
Improvement	Degradation	Degradation	Degradation
Stable	Improvement	Improvement	Improvement
Stable	Improvement	Stable	Improvement
Stable	Improvement	Degradation	Degradation
Stable	Stable	Improvement	Improvement
Stable	Stable	Stable	Stable
Stable	Stable	Degradation	Degradation
Stable	Degradation	Improvement	Degradation
Stable	Degradation	Stable	Degradation
Stable	Degradation	Degradation	Degradation
Degradation	Improvement	Improvement	Degradation
Degradation	Improvement	Stable	Degradation
Degradation	Improvement	Degradation	Degradation
Degradation	Stable	Improvement	Degradation
Degradation	Stable	Stable	Degradation
Degradation	Stable	Degradation	Degradation
Degradation	Degradation	Improvement	Degradation
Degradation	Degradation	Stable	Degradation
Degradation	Degradation	Degradation	Degradation

Figure 3. 19. Land degradation definition matrix from its sub indicator (source: UNCCD, 2017a)

3.4.1.2. Step by steps of the calculation in Trends.Earth

The calculation method of this study employs Trends.Earth plugin in QGIS platform. The indication that the QGIS has the Trends.Earth plug-in is the presence of the toolbar in Figure 3. 20. To begin the calculation, the calculator icon showed in the red rectangle must be selected. This plugin created for calculating SDGs 15.3.1 and SGDs 11.3.1. Figure 3. 21 but, this study will only use the land degradation indicator calculation.

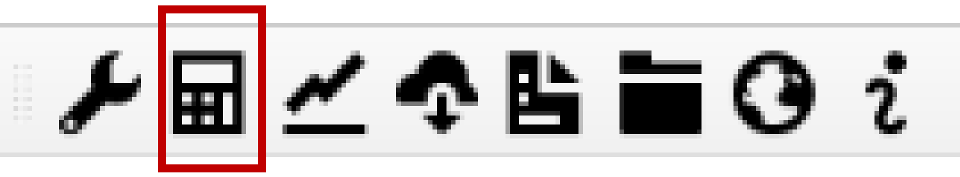


Figure 3. 20 Trends.Earth toolbar (source: Trends.Earth, 2018)

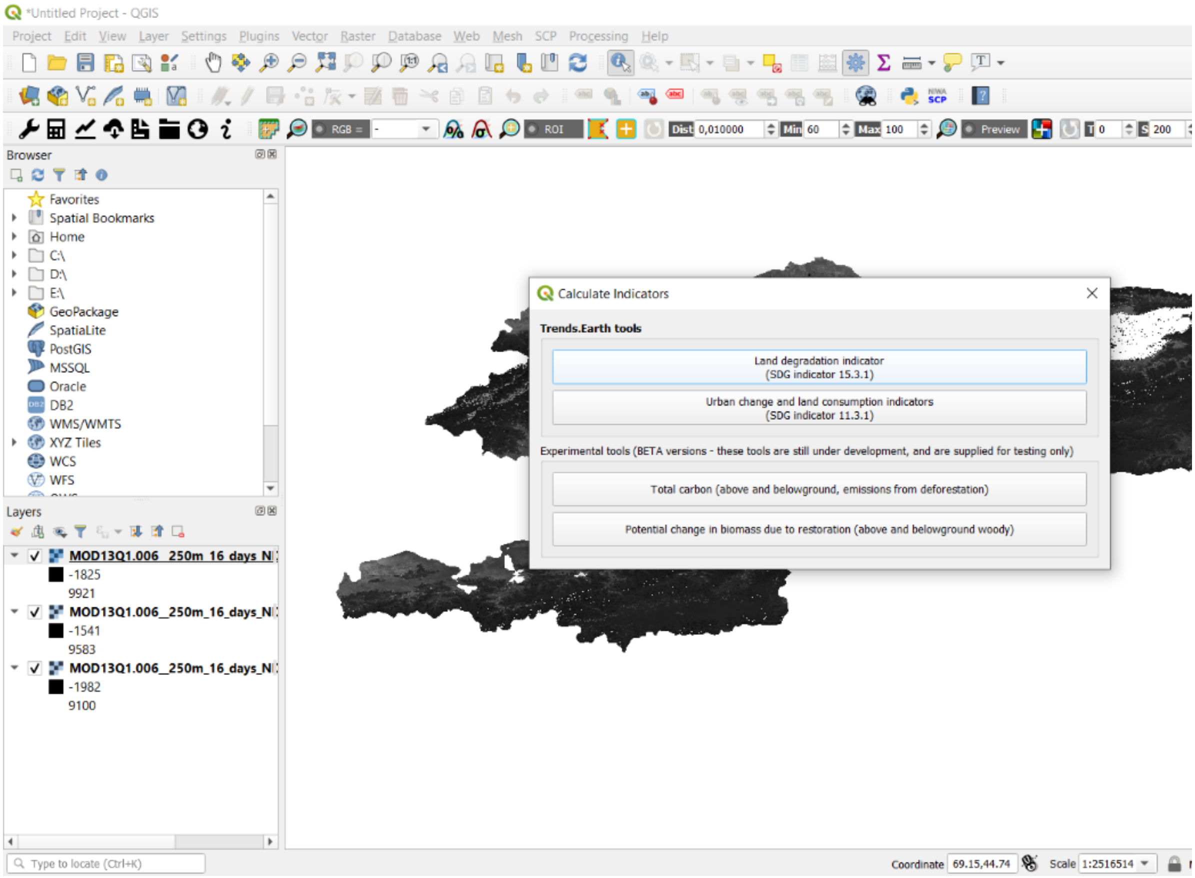


Figure 3. 21. Trends.Earth calculation of SDG Indicator (source: Trends.Earth, 2018)

There are two main steps to obtain a land degradation map using Trends.Earth. The first step is calculating the sub-indicator and the second step is calculating the land degradation over the total area of SDGs indicator 15.3 (Figure 3. 22). The main idea of this study is to incorporate publicly open satellite data therefore the default of UNCCD is the option that will be selected.

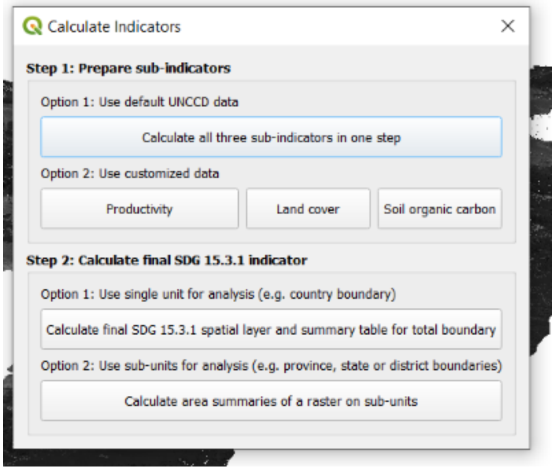


Figure 3. 22. Calculation steps (source: Trends.Earth, 2018)

Some part sections need to be defined for calculating the sub-indicator including the setup of the initial year and final year, land cover setup, define the effect of land cover change, and study area. The period of land degradation analysis in this study is the baseline year of land degradation status, the initial year is 2001 and 2015 is the final year Figure 3. 23. The next section is land cover setup. The land cover dataset by default is acquired from Land cover CCI from the European Space Agency which has many classes of land cover but to fit the LDN framework, land cover needs to be defined into 7 classes. There are possibilities to change the land cover definition, but this study will apply the default definition Figure 3. 23. The effect of land cover change requires transition criteria to obtain the status of land cover as degraded, stable, or improvement Figure 3. 25. There are possibilities to adjust the definition, but the default definition is used. Then, finally, the study area is defined in Kyrgyzstan for the whole country (Figure 3. 25). The last step is to rename the task (Figure 3. 24).

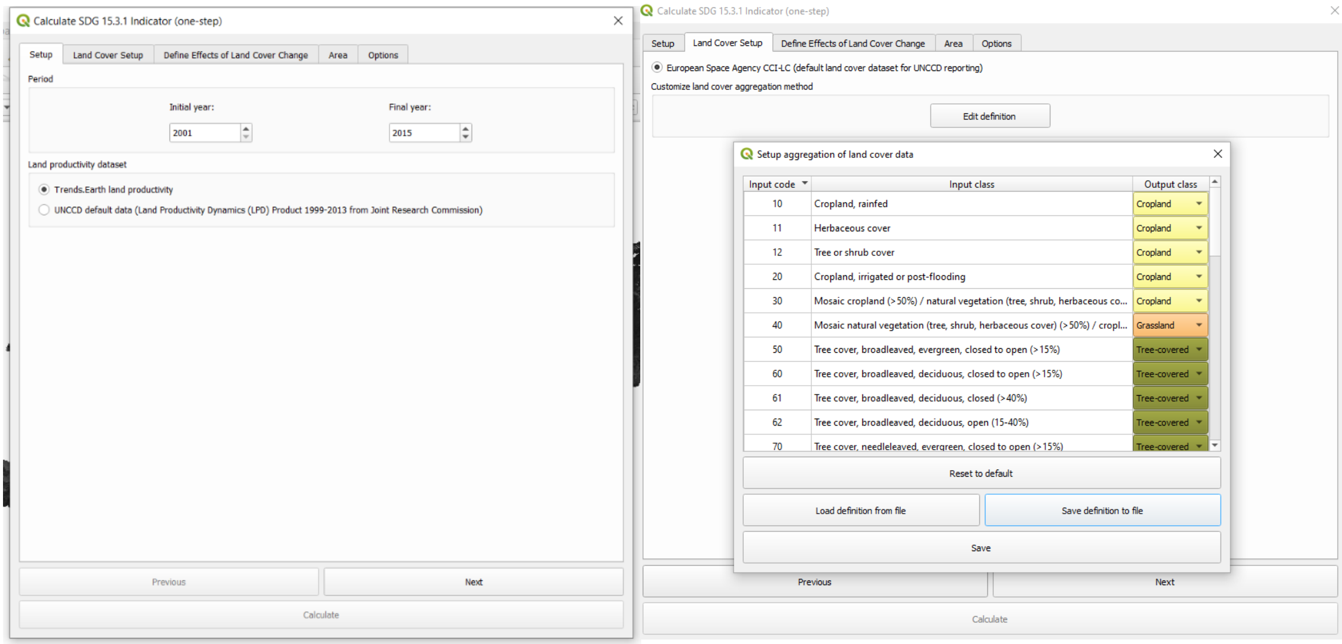


Figure 3. 23. Baseline study definition and 7 classes land cover re-classification

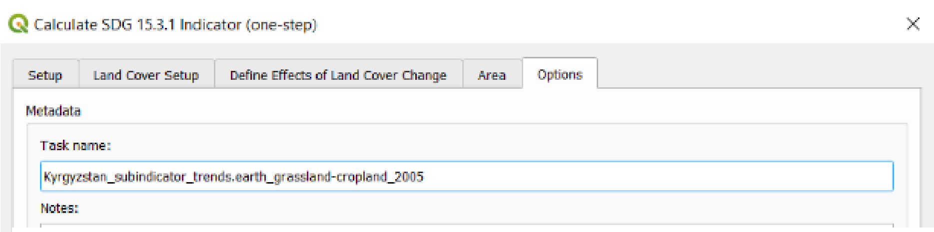


Figure 3. 24. Task renames (source: Trends.Earth, 2018)

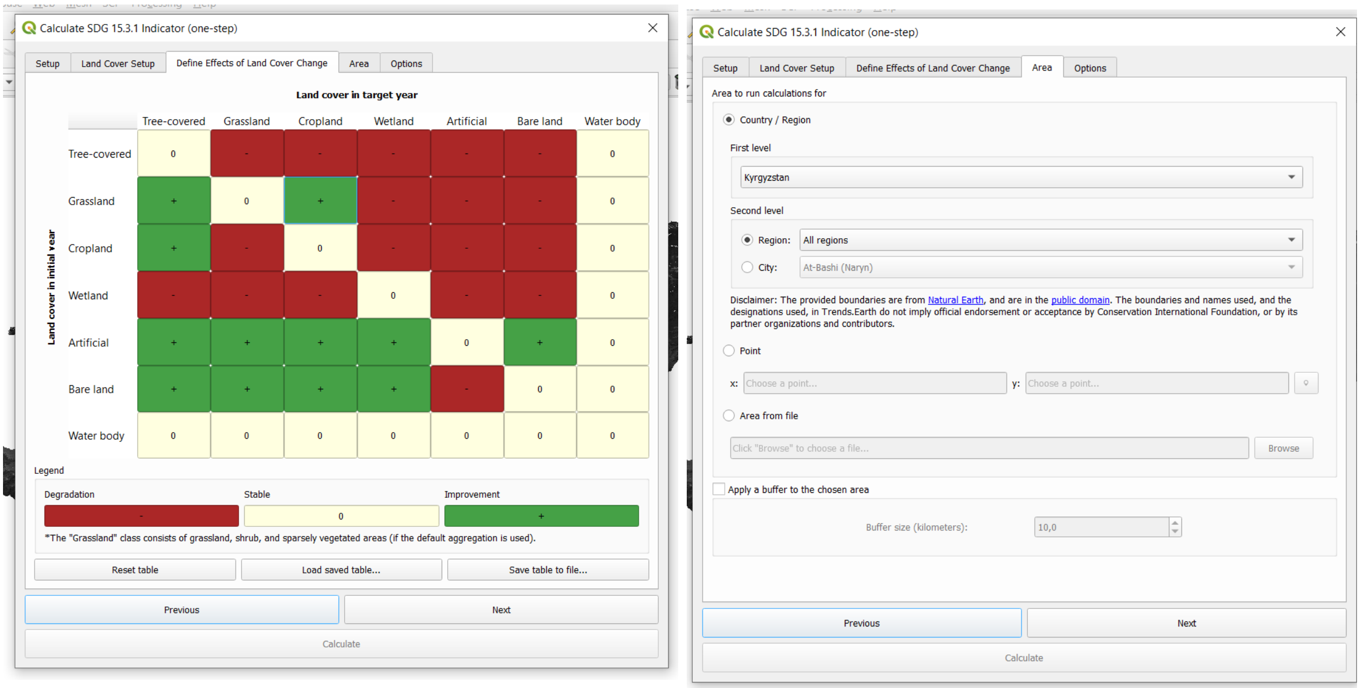


Figure 3. 25. Land cover degradation definition and area of study definition (source: Trends.Earth, 2018)

The computation of land degradation in Trends.Earth employ the cloud computing calculation of GEE. The status of the calculation can be monitored using the download button in the toolbar and after it is finished the calculation result will be ready to save and can be opened in QGIS as a .json file contains all the layer of sub-indicator (Figure 3. 26).

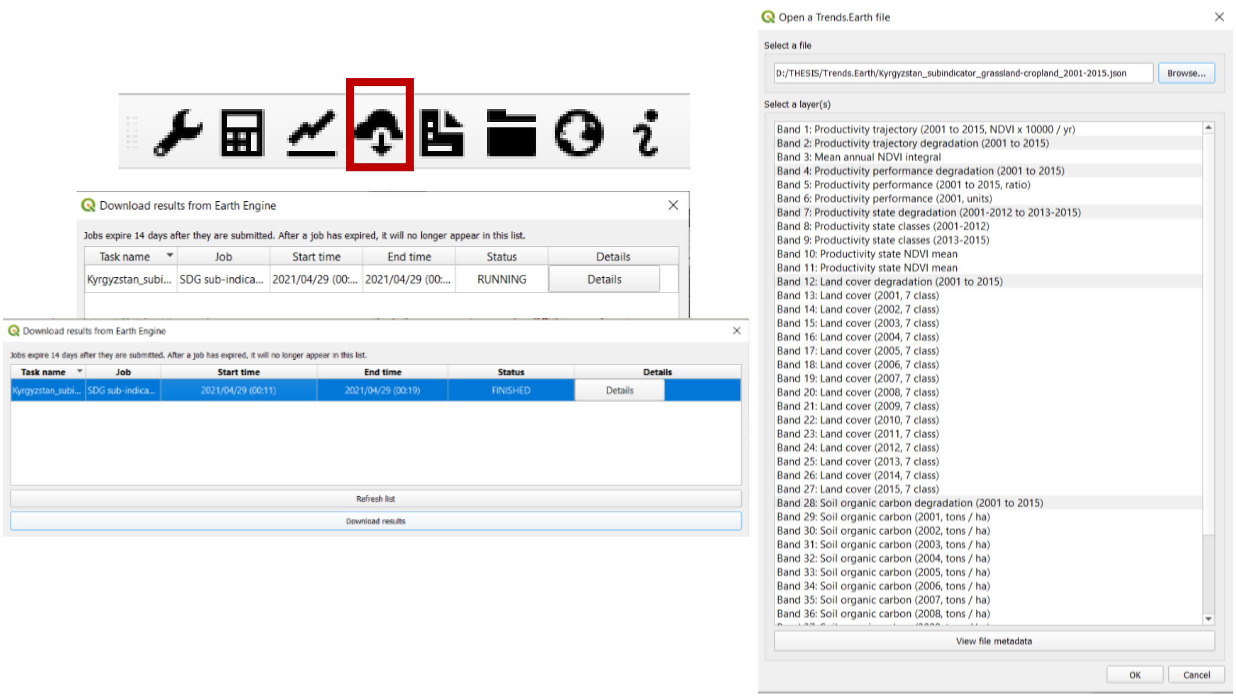


Figure 3. 26. The download of calculation process and sub-indicator calculation result (source: Trends.Earth, 2018)

The second step for this computation is the calculation of the final SDGs 15.3.1 indicator in spatial layer format and summary table (Figure 3. 27). The input of the calculation is the result of the first step calculation. The input will be automatically selected and ready for the calculation Figure 3. 27. The last step is to define the output directory, define the study area, and define the task name

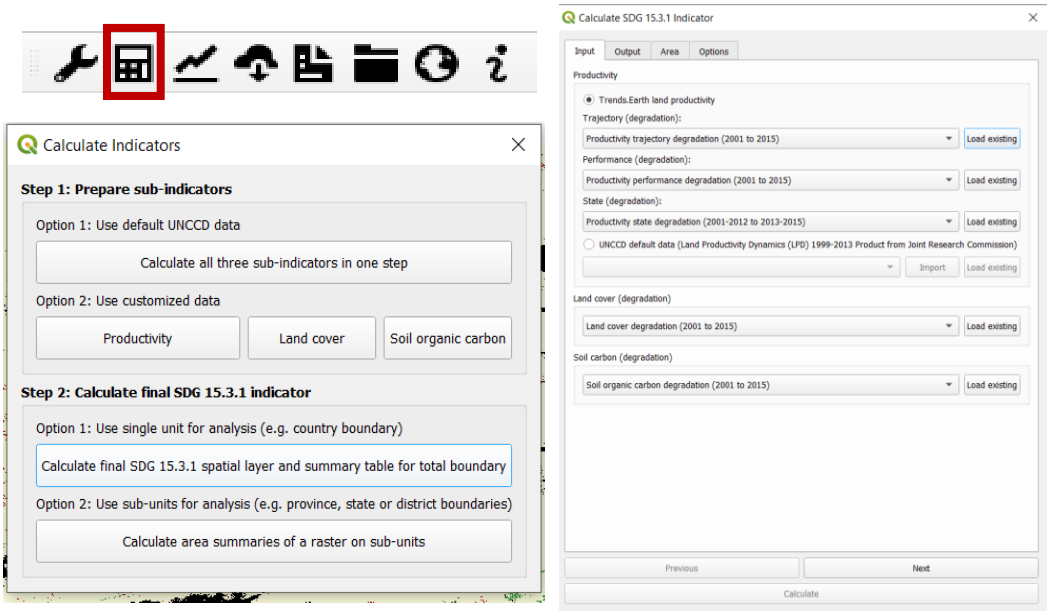


Figure 3. 27. Calculation of Land Degradation (source: Trends.Earth, 2018)

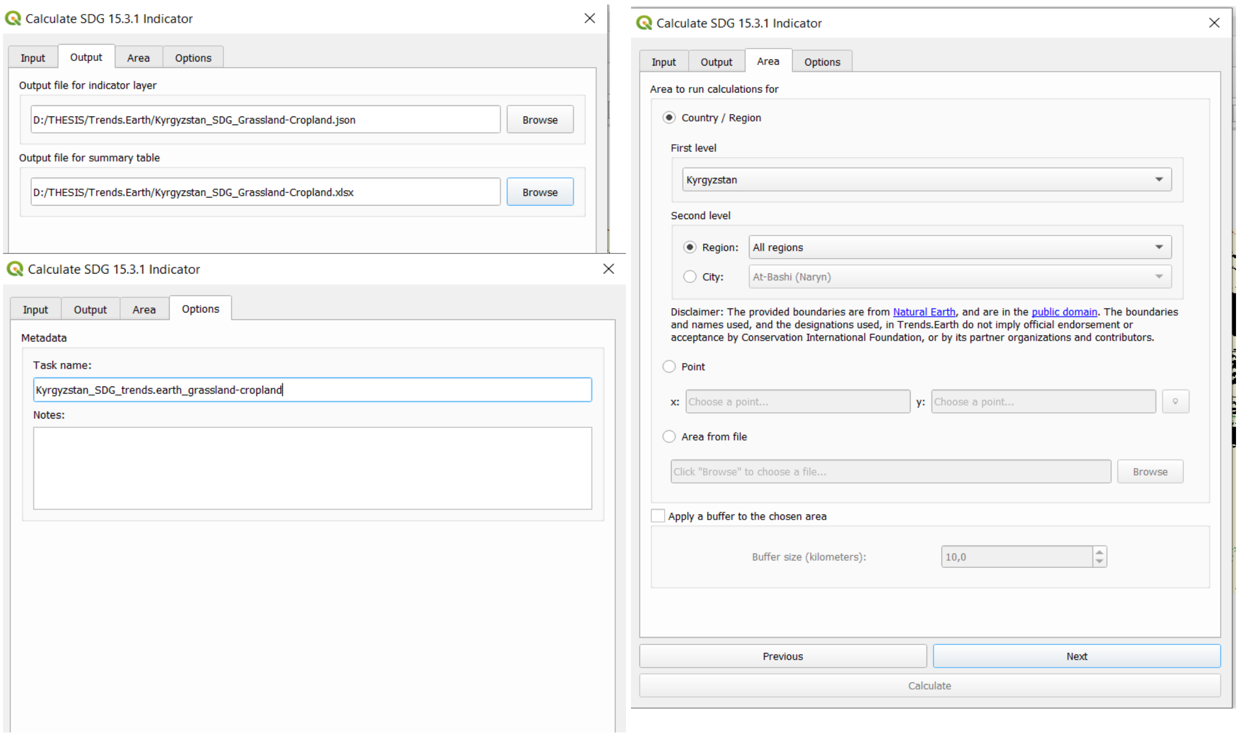


Figure 3. 28. Define the directory, area, and task name (source: Trends.Earth, 2018)

The results of this study are the excel file of land degradation status summary and a file with the extension of .json which will be possible to open in QGIS. This file contains two layers namely SDG 15.3.1. Indicator and land productivity with 5 classes This data will be possible to extract to raster image with .tif file extension for further calculation.

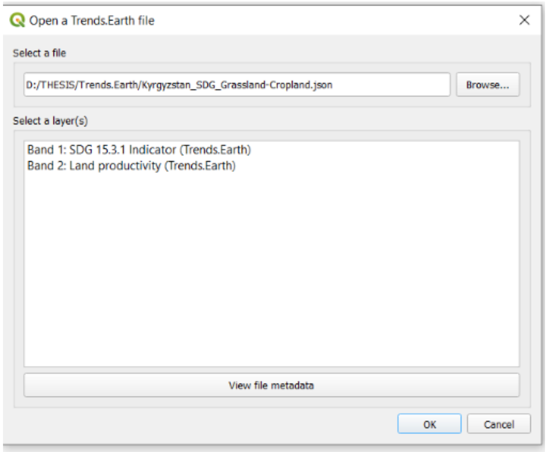


Figure 3. 29. Open the result of Land Degradation Calculation (source: Trends.Earth, 2018)

3.4.2. Climate factor analysis

Two types of climate data will be used in this study specifically rainfall data and temperature data. These climate data are chosen as the most essential climatic condition related to vegetation and land productivity as a proxy of land degradation. Land productivity change analysis will be performed using NDVI trend analysis as a proxy (Gichenje et al., 2019).

3.4.2.1.NDVI trend analysis

The statistical trends analysis is applied to each pixel of Annual MODIS NDVI. The statistical analysis of trend is used linear model regression where NDVI value change as dependent variable against time as an independent variable. The period of study used in this study is 2001 to 2015. The result of trends expressed as slope value where the positive slope coefficient indicates the increase of productivity and the negative slope indicates the decrease of productivity. The significant value determined as significant using a confidence level of 95% where the p-value <0,5 indicate that the trend is significant. The result's category of this calculation are significant increase, significant decrease, and non-significant change (p-value

>0,5). The calculation of annual time-series NDVI will require sorting the data using a stack raster (Figure 3. 30). In general, the calculation of NDVI trends using RStudio software illustrates in Figure 3. 31, the steps including:

1. stack raster of annual NDVI time series
2. calculate the slope of annual NDVI time-series
3. masking the significant raster with p-value < 0,5, and
4. export the raster calculation to .tif extension.

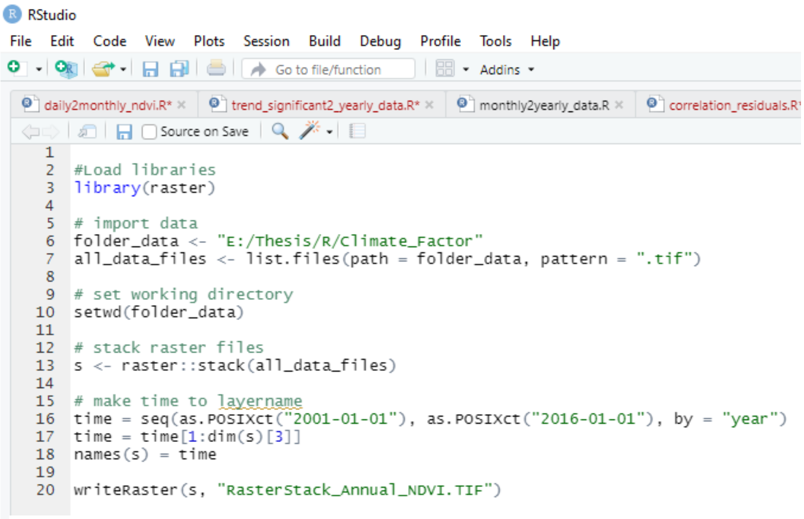


Figure 3. 30. Stack raster of annual NDVI

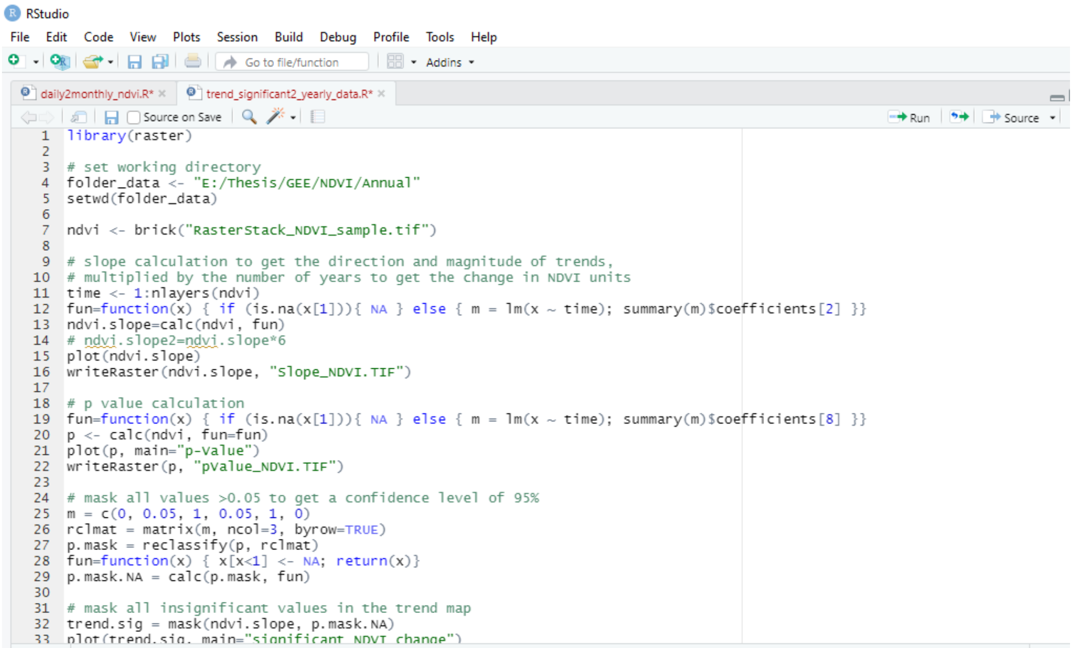


Figure 3. 31. NDVI trends calculation

3.4.2.2. NDVI-Climate correlation

The Pearson correlation coefficient is used to analyze the correlation between annual NDVI value and annual rainfall value and annual average maximum temperature value from 2001 to 2015. The correlations are considered as statistically significant at the confidence level of 95% where the p-value <0,5. The correlation result interpreted as a part of productivity which is explained by precipitation or temperature or climate in general (Gichenje et al., 2019). The illustration example of correlation analysis using RStudio illustrate in Figure 3. 32.

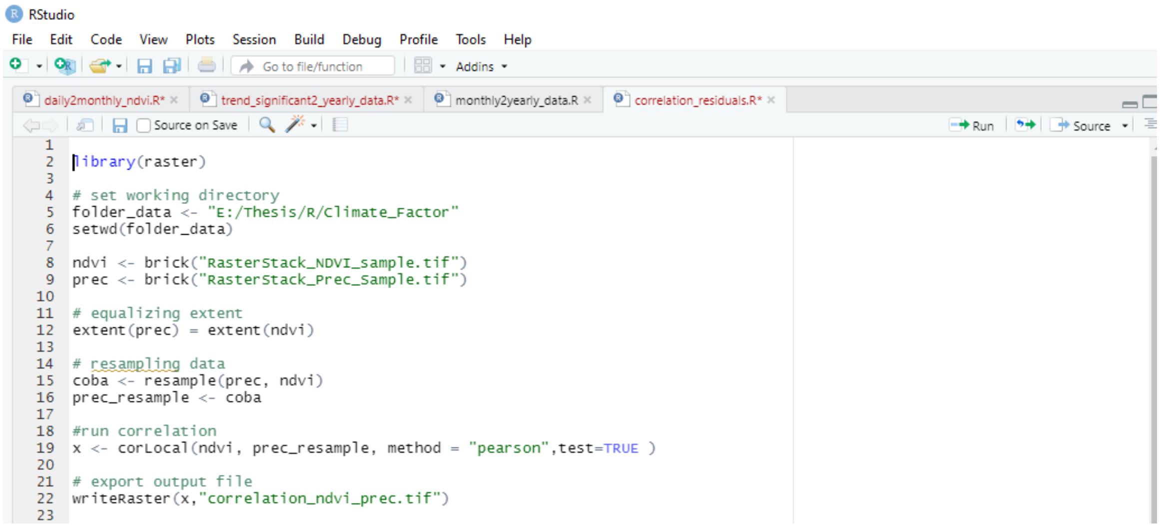


Figure 3. 32. NDVI-Climate correlation calculation example

3.4.3. Land degradation and environmental factor relationship

The result of land degradation from Trends.Earth analysis will be used as the source of further analysis. The land degradation raster data is the main variable to identify the distribution and relationship of land degradation with population, agriculture, and other environmental factors. The other environmental factors are obtained from the selected open and publicly available spatial dataset. This data selected based on the availability and possibility to run in the RStudio software. The list of the data used in this study is listed in

Table 3. 4. list of the data used in this study

Factor	No	Data Available	Source	Data type	Unit
Population	1	Population Density	Kyrgyzstan spatial	continue	person
	2	Population	GEE	continue	person per km
Climate	3	Bioclimate	Kyrgyzstan Spatial	nominal	
	4	Annual PET	Kyrgyzstan Spatial	continue	mm/year
	5	Aridity Index	Kyrgyzstan Spatial	continue	0,1-5.8
	6	Temperature change	GEE	continue	Celcius per year
	7	Precipitation change	GEE	continue	mm per year
Biophysical factor	8	Landform	Kyrgyzstan Spatial	nominal	
	9	Land cover	Kyrgyzstan Spatial	nominal	
	10	Ecoregion	The Nature Conservancy	nominal	
	11	Lithology	Kyrgyzstan Spatial	nominal	
	12	Homogeneity Species	EarthEnv	continue	number of species per Ha
	13	Carbon storage	EarthStat	continue	ton C per hectare
	14	Slope	GEE	continue	% of slope
	15	Biomass Density	GEE	continue	tons per ha
Agriculture Crop	16	Farm System	GeoNetwork	nominal	
	17	Agriculture risk	WRI	nominal	
	18	Irrigation percentage	WRI	continue	percentage per area of land
	19	Fertilizer: Phosphorus	EarthStat	continue	kilogram per Ha
	20	Fertilizer: Nitrogen	EarthStat	continue	kilogram per Ha
	21	Barley	Kyrgyzstan Spatial	continue	kg/ha
	22	Cotton	Kyrgyzstan Spatial	continue	kg/ha
	23	Maize	Kyrgyzstan Spatial	continue	kg/ha
	24	Potato	Kyrgyzstan Spatial	continue	kg/ha
	25	Rice	Kyrgyzstan Spatial	continue	kg/ha
	26	Sugarbeet	Kyrgyzstan Spatial	continue	kg/ha
	27	Wheat	Kyrgyzstan Spatial	continue	kg/ha
	28	Barley	Kyrgyzstan Spatial	continue	ha
	29	Cotton	Kyrgyzstan Spatial	continue	ha
	30	Maize	Kyrgyzstan Spatial	continue	ha
	31	Potato	Kyrgyzstan Spatial	continue	ha
	32	Rice	Kyrgyzstan Spatial	continue	ha
	33	Sugarbeet	Kyrgyzstan Spatial	continue	ha
	34	Wheat	Kyrgyzstan Spatial	continue	ha
Agriculture Livestock	35	Livestock System	Kyrgyzstan Spatial	nominal	
	36	Pasture	Kyrgyzstan Spatial	continue	percentage per area of land
	37	Small ruminants	Kyrgyzstan Spatial	continue	number per pixel
	38	Sheep	Kyrgyzstan Spatial	continue	number per pixel
	39	Goat	Kyrgyzstan Spatial	continue	number per pixel
	40	Poultry	Kyrgyzstan Spatial	continue	number per pixel
	41	Cattle	Kyrgyzstan Spatial	continue	number per pixel
Potential solution	42	Restoration	UNCCD	nominal	
Admin	43	District	Diva-GIS	nominal	
	44	Province	Diva-GIS	nominal	

Correlation analysis will be applied to understand the relationship between land degradation and other factors. The general overview of the correlation analysis steps in this study will include the following steps:

1. Data exploration
2. Data visualization (box plot and bar chart)
3. Bivariate analysis (Kruskal Wallis test, Chi-Square test, and Spearman Rank Test)
4. Calculated distribution of environmental factors in each land degradation types

The initial stage in data analysis is data exploration. At this stage, the data will be identified according to its type. it is very important to know what types of data are contained in the attributes of the data used in the study. The information of this data type is a very crucial concept in statistics. To determine the correct application of statistical measurement, assumption, and the correct conclusion about the analysis, data types need to identify correctly. In general, based on measurement scale data classified to categorical data and numerical data. More specifically, the categorical data include nominal and ordinal data, and numerical data consist of interval and ratio data. This data divided based on the measurement scale with the detailed explanation provided below (de Smith et al., 2018).

1. The data classified as nominal data when the data distinguished between each object without any implication of ranking or potential of arithmetic. As an example, the data about the land cover class is nominal where there is a distinction between one and other types of data but there is no order of the class.
2. The data is categorized as ordinal when the data have order meaning or implies ranking such as class 2 is better than class one, but no arithmetic operations make sense. For example, land degradation status can be classified as ordinal data when we classified the improved land as the best, followed by the middle class of stable land, and the worst class is degraded land.

3. The numerical data or continuous data consist of interval and ratio data. Data categorized as interval if the differences among number make sense as an example is elevation data where the elevation value is potential for arithmetic but there is no absolute zero. Data categorized as ratio if the data make sense to divide one measurement by other measurements and has absolute zero. For example, the population density is one of the ratio data where there is absolute zero the zero is meaningful.

Based on the explanation above, the dataset of the environmental factor used in this study can be divided into two dataset namely nominal data and continuous data, while land degradation data is ordinal data. This division of dataset will be useful for determining the visualization data where the nominal dataset will be presented in a bar chart and continuous data presented in a box plot diagram. The illustration of box plot generation using RStudio presented in Figure 3. 33 while the example of bar chart generation presented in Figure 3. 34.

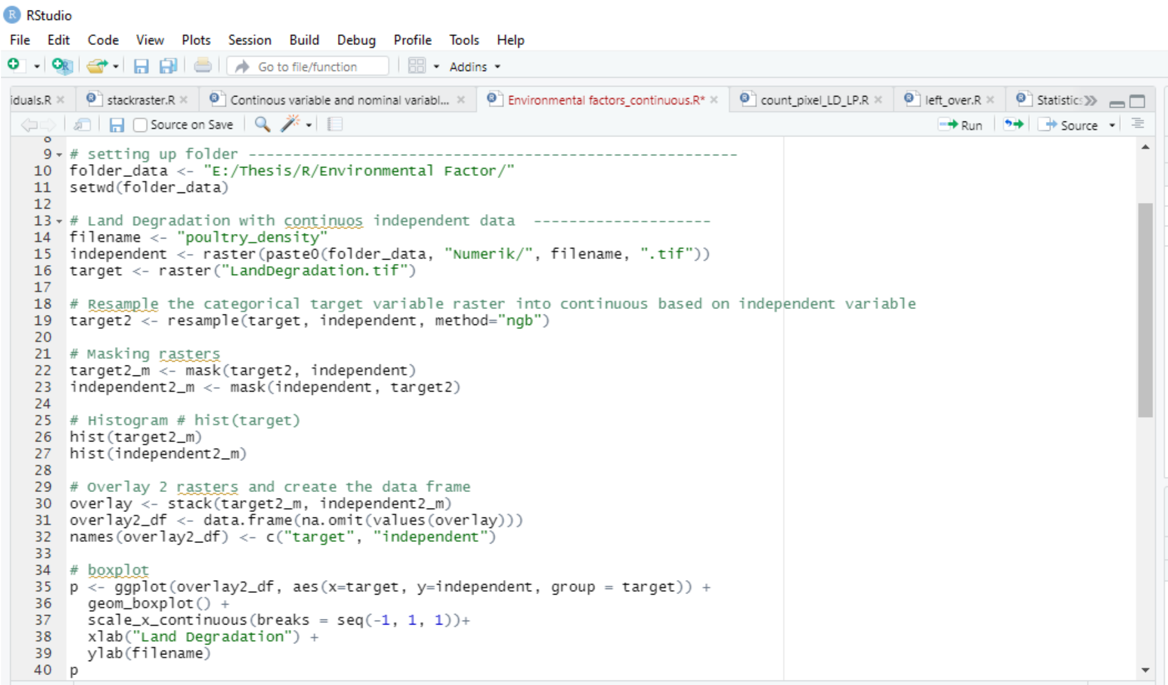


Figure 3. 33. Boxplot generation of environmental factors data for each land degradation status class

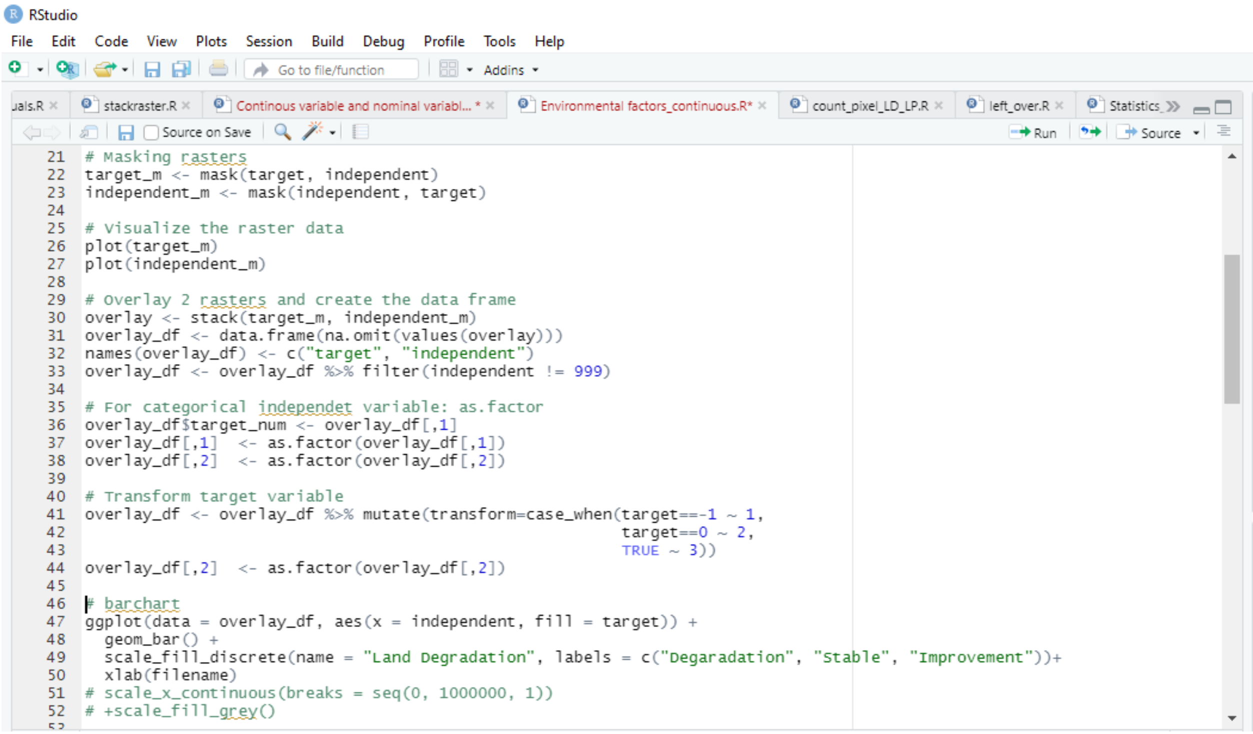


Figure 3. 34. Bar chart generation of environmental factors data for each land degradation status class

The are many variables of environmental factor data that will be determined whether they have an association with land degradation This study applied the approach of bivariate analysis to determine whether there was an association or correlation with land degradation for each existing factor. The bivariate analysis allows the calculation of the concurrent relationship between two variables to explore the dependency between variable (Bertani et al., 2018).

The accuracy of selecting the bivariate analysis method is very influenced by the data type of the two variables being analyzed. Identifying the data type of each variable is the first step in carrying out a bivariate analysis correctly. The classification of the data used in this study presented in Table 3. 4. In this study, the dependent variable is a categorical data type of land degradation status, while the variable data or independent variables consist of categorical and numeric or continuous. Thus, bivariate analysis was carried out in three ways:

1) independence test of the categorical dependent variable and the numerical or continuous independent variable using Kruskal Wallis Test,

2) the independent test of the categorical dependent variable and the categorical independent variable using Chi-Square test, and
3) the correlation test of Spearman Rank Test for a continuous independent variable with the assumption of land degradation is categorical data types with an ordinal scale so that it is possible to carry out a correlation test.

Bivariate Analysis Types

1. The chi-squared test is the independence test method approach to analyze independence and dependence variable with both categorical data whether nominal or ordinal scale (Schumacker, 2015). This method was chosen because this is a nonparametric test so the normal distribution assumption does not need to be fulfilled. This test is very suitable for a spatial dataset. The null hypothesis (H0) defined as there is no relationship between independent variable. The confidence level in this study defined as 95%. Thus, H0 will be rejected when the p-value <0,05, or where H1 will be accepted means that there is a relationship between variables. The calculation of Chi-Square in RStudio presented in Figure 3. 35.

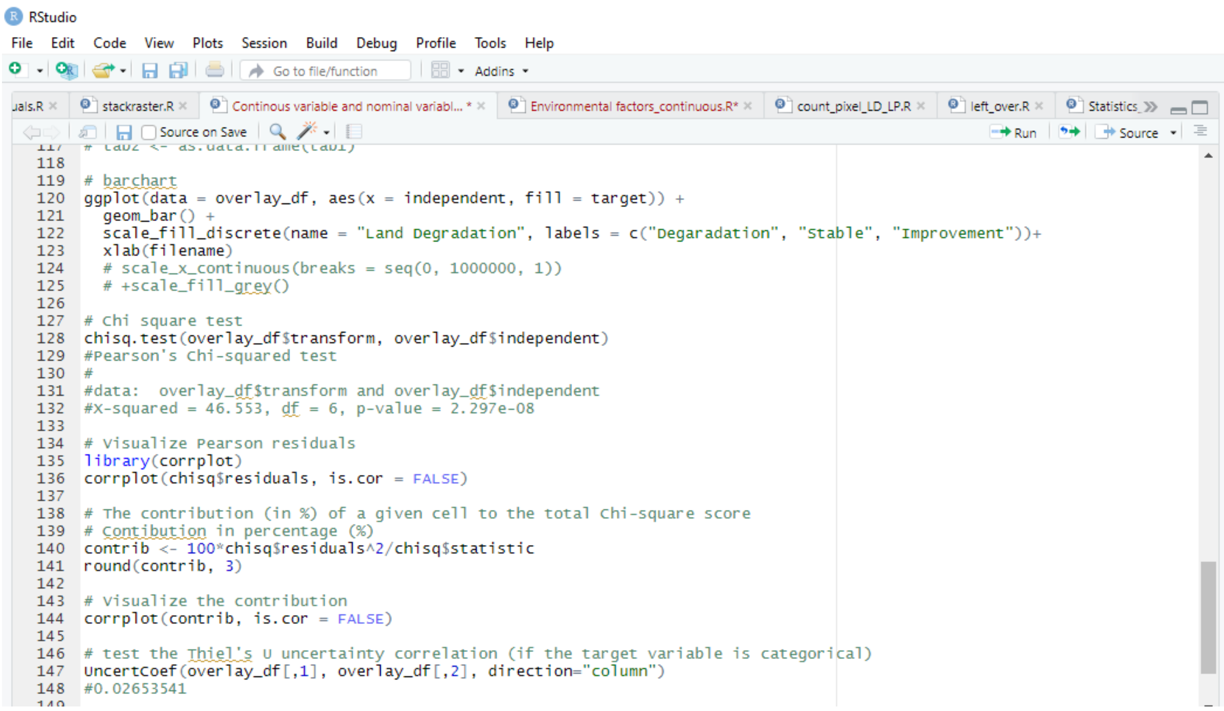


Figure 3. 35. Part of script for Chi square calculation in RStudio

2. Kruskal Wallis test is analogous to the one-way ANOVA test but in this approach, the test is a non-parametric test where there is no assumption of normal distribution in the data, so this known as ANOVA on ranks (Xia, 2020). The independence test of the categorical dependent variable and the numerical independent variable were performed in RStudio (Figure 3. 36). The null hypothesis (H0) defined as there is no relationship between independent variable. The confidence level in this study defined as 95%. Thus, H0 will be rejected when the p-value <0,05, or where H1 will be accepted means that there is a relationship between variables.

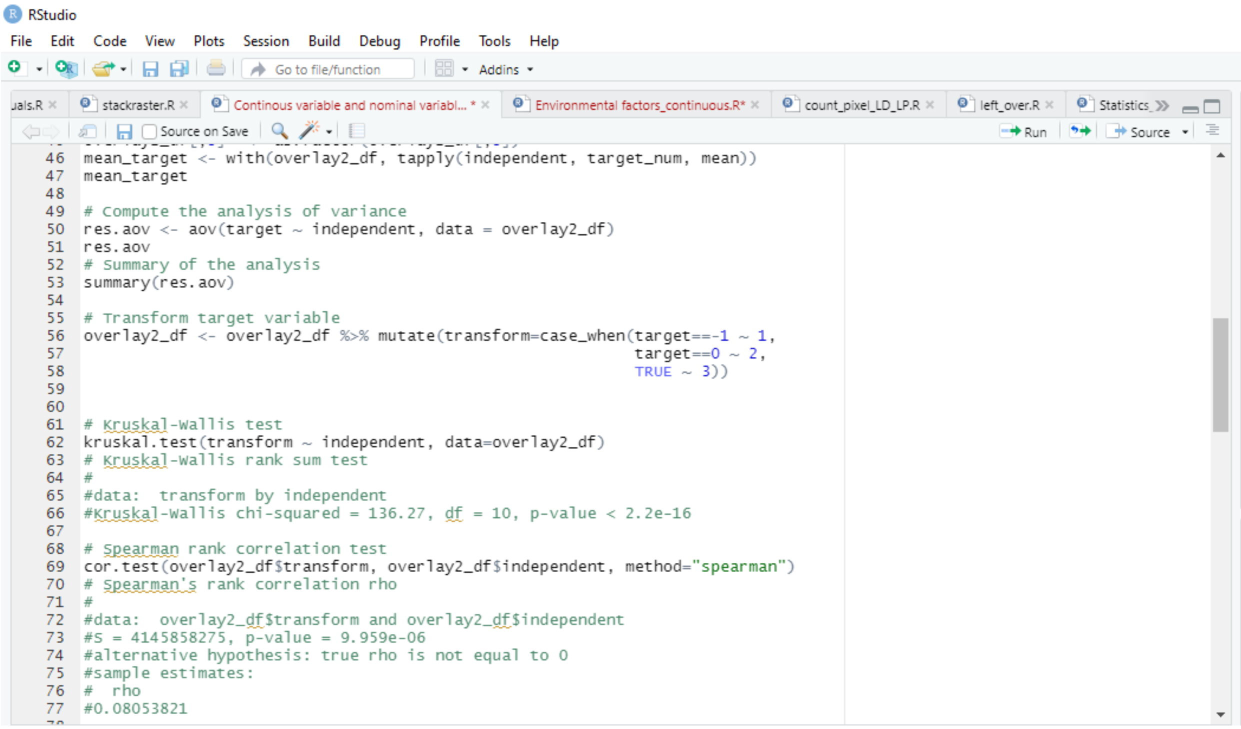


Figure 3. 36 Part of script for Kruskal-Wallis test and Spearman Rank test calculation in RStudio

3. Spearman Rank test is the correlation is a nonparametric correlation approach to measure the degree of relationship between two variables (Frey, 2018). The result is presented in Spearman rho. This value represents the strength between two variables when the variables are measured on a scale that is minimum ordinal. The calculation of the Spearman Rank test is illustrated in Figure 3. 36.

The calculation of the distribution of environmental factors in each land degradation types (degradation, stable, and improvement) are obtained from the matrix table for categorical environmental factors variable and overlay aggregate for the numerical variable. Calculation RStudio illustrated in Figure 3. 37 for categorical variable and Figure 3. 38 for the numerical variable.

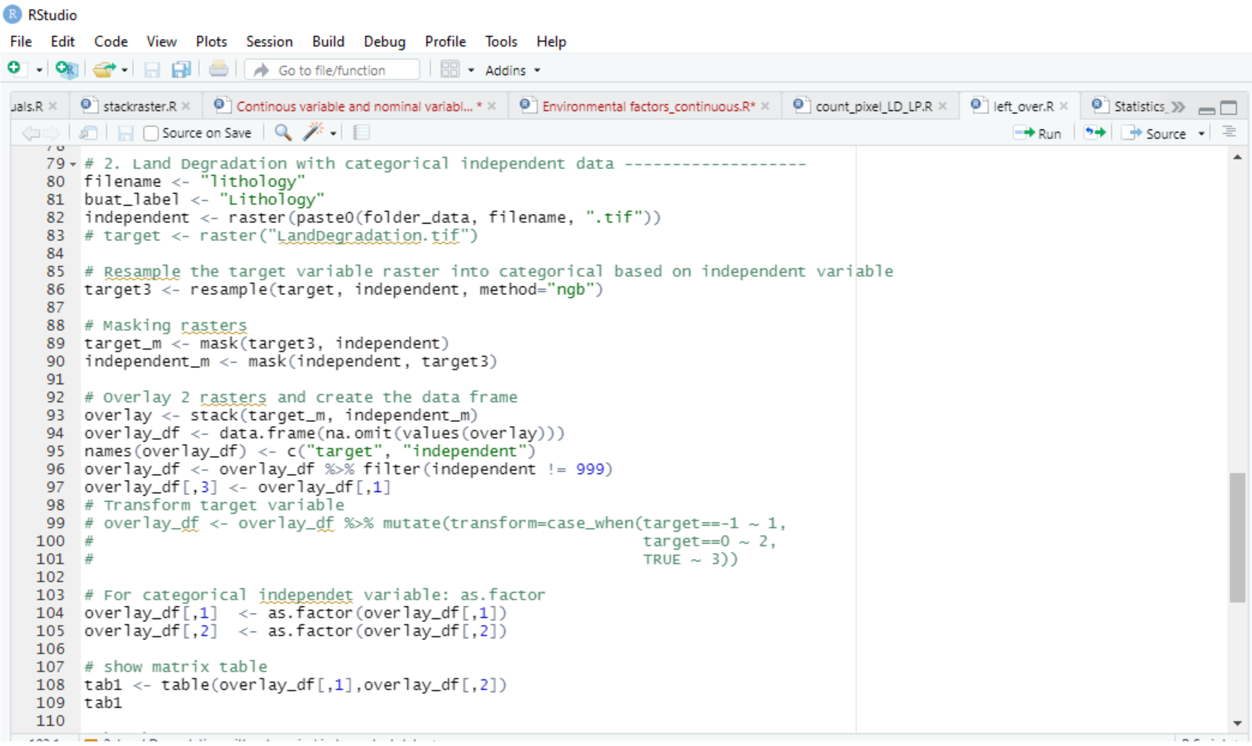


Figure 3. 37. Matrix table for calculating total variable in land degradation status types

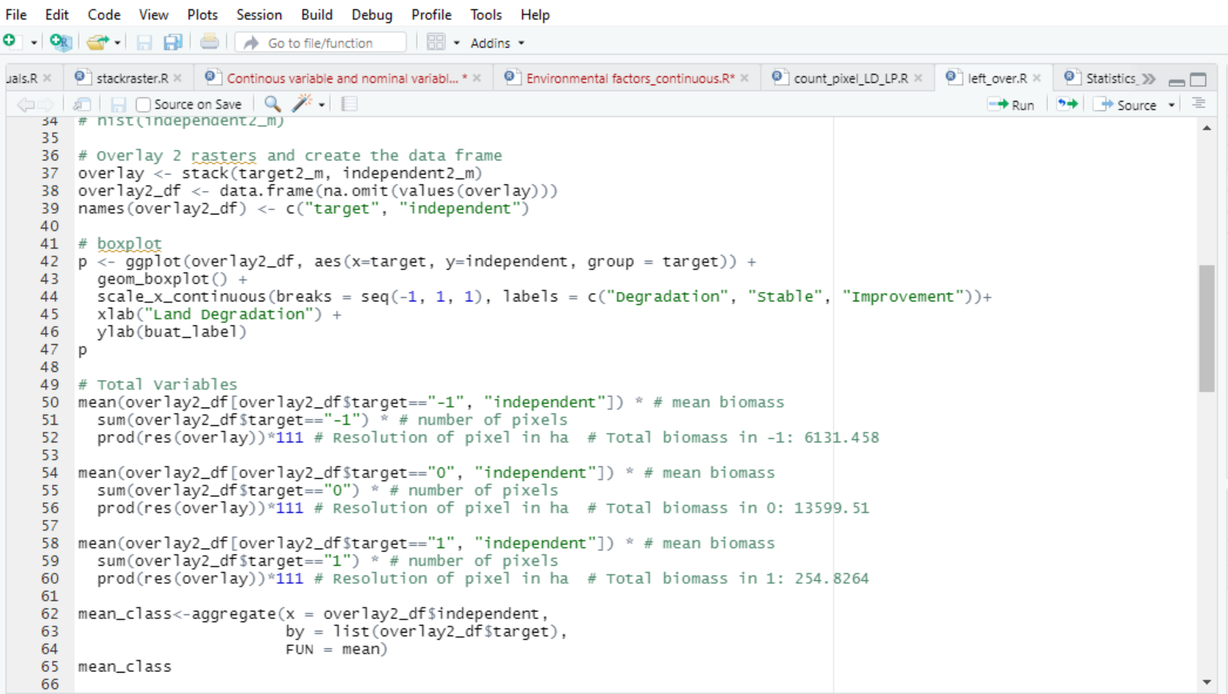


Figure 3. 38. Overlay aggregate for calculating total variable in land degradation status types

4. Study Area profile of Kyrgyzstan

4.1. Location, Topography, and Administration

Kyrgyzstan is a part of the Central Asia region alongside Kazakhstan, Uzbekistan, Turkmenistan, Tajikistan. The countries surrounding the border are China in the east, Kazakhstan in the north, Uzbekistan in the west, and Tajikistan in the south Figure 4. 1. Kyrgyzstan as a small part of Central Asia has unique characteristic compare to the other countries (except Tajikistan) which is the topography of the country is dominated by a mountainous area. The topography of the country illustrated in the elevation model from the Digital Elevation Model (DEM) is presented in Figure 4. 2. The country elevation range from 132 m to 7440m with 90% of the country is located above 1500 meters above sea level (National Statistical Committee, 2020). The average elevation is 2750 meters with the highest point is Pik Pobedy Mount 7439 meters (Kustareva & Naseka, 2015). The highest elevation is in the Tien Shan mountains on the southern and east border of Kyrgyzstan with Tajikistan and China.

Figure 4. 1. Central Asia region and surrounding (shapefile acquired from FAO administrative boundaries)

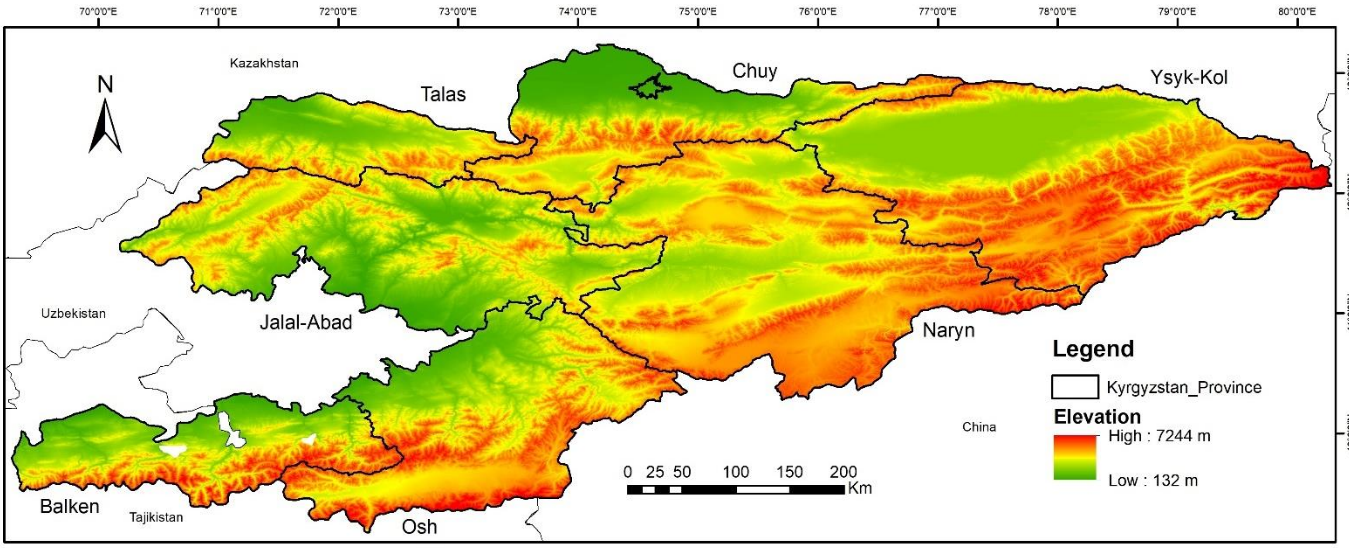


Figure 4. 2. Digital elevation model (DEM) of Kyrgyzstan (source of raster data acquired from GEE)

The topography of the country classified in the landform class of mountains, hills, and plains are presented in Figure 4. 4 shows that the mountains and hills are dominated the region. The plains landform only occupies 15% of the total landform while hills are 38% and mountains are 47%. The Pamir and Tian Shan mountain range lie in about 65% of total the country territory (Kustareva & Naseka, 2015). The abundant water bodies illustrated in Figure 4. 3 which is found in more than 3.500 thousand meters of rivers and rivulets with a combined length of approximately are 150.000km as well as 1923 lakes (National Statistical Committee, 2020). There are four big water bodies visible in Figure 4. 4 which occupy 3,57% of the country area with the biggest lake is Issyk Kul, followed by Son-Kul Lake in the middle part of the country, Chatyr-Kul lake in the southern-middle of the country, and Toktogul Reservoir in the western part of the country.

Kyrgyzstan, a landlocked developing country with a total country area of199.950 km^2, divided into 7 provinces or oblast and two cities of republican level namely Bishkek City and Osh City. Figure 4. 3 illustrate the region division and distribution of selected cities. In total, there are 40 administrative districts and 31 cities (National Statistical Committee, 2020).

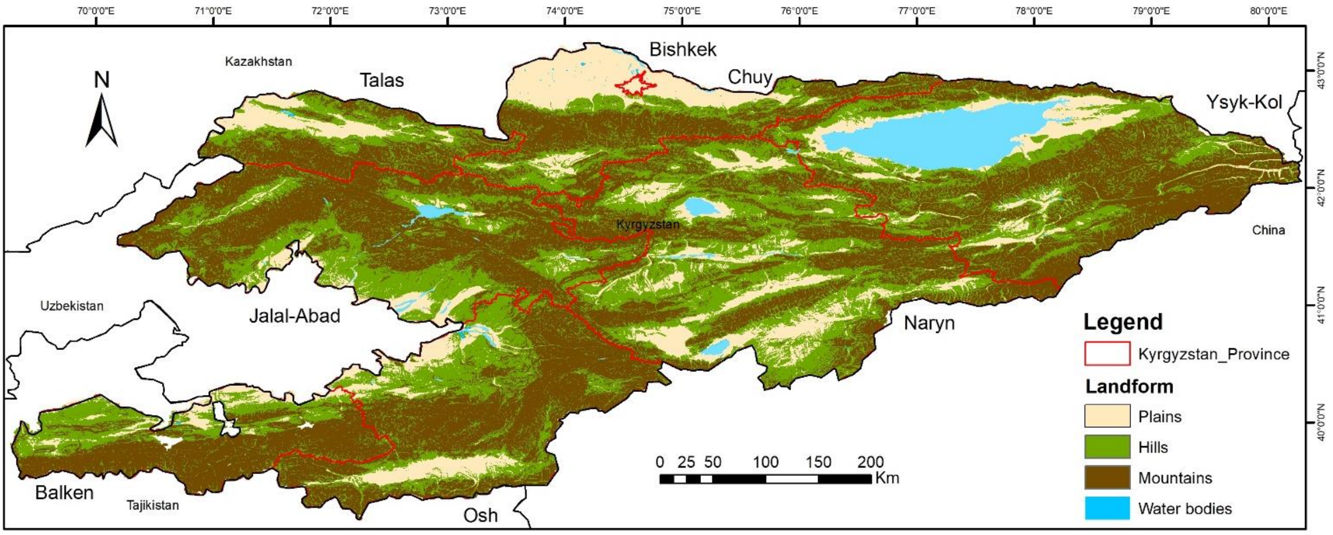


Figure 4. 4. Landform of Kyrgyzstan (shapefile source: kyrgyzstanspatial.org)

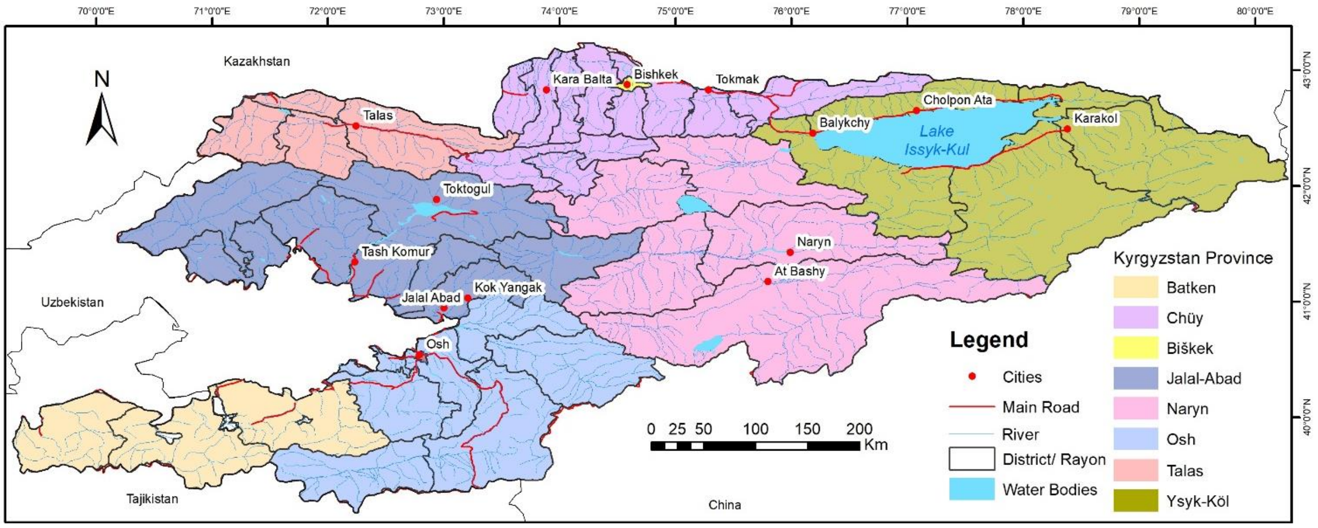


Figure 4. 3. Kyrgyzstan administration province and district

4.2. Climate

As a landlocked country, Kyrgyzstan has a continental climate with hot summer and cold winter. The average temperature in summer is $+27^0$C, with an average maximum is $+33^0$C and the average minimum is $+16^0$C. During winter the average is $+1^0$C with a minimum average of -12^0C and a maximum of 10^0C (National Statistical Committee, 2020). The monthly mean temperature is presented in Figure 4. 5 shows that the peak of the mean monthly temperature found in July and August. The monthly precipitation varies from 60 to 12 mm/month with the highest precipitation in May and the lowest in September (World Bank, 2020).

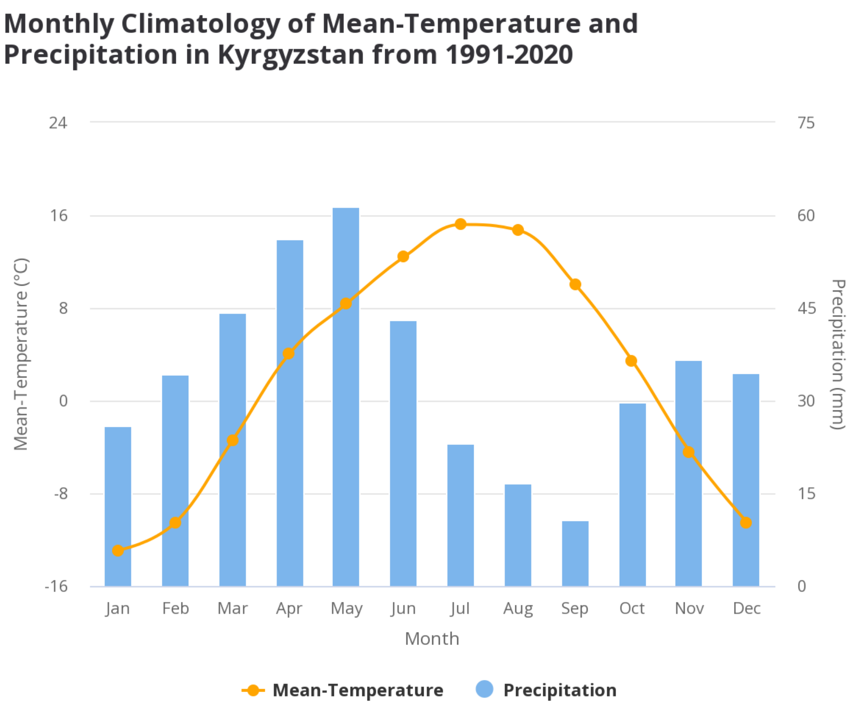


Figure 4. 5. Monthly mean precipitation and temperature (source: World Bank, 2020)

The average annual temperature data obtained from GEE (TerraClimate dataset) indicate that there is a positive trend during 1981 as presented in Figure 4. 6 with a positive R square value. The average annual temperature during the 1981-2020 period is 7,3^{0} C, but from 2001 to 2015 is 7,6^{0} C. The annual precipitation in Kyrgyzstan from 1981-2020 is 418 mm/year

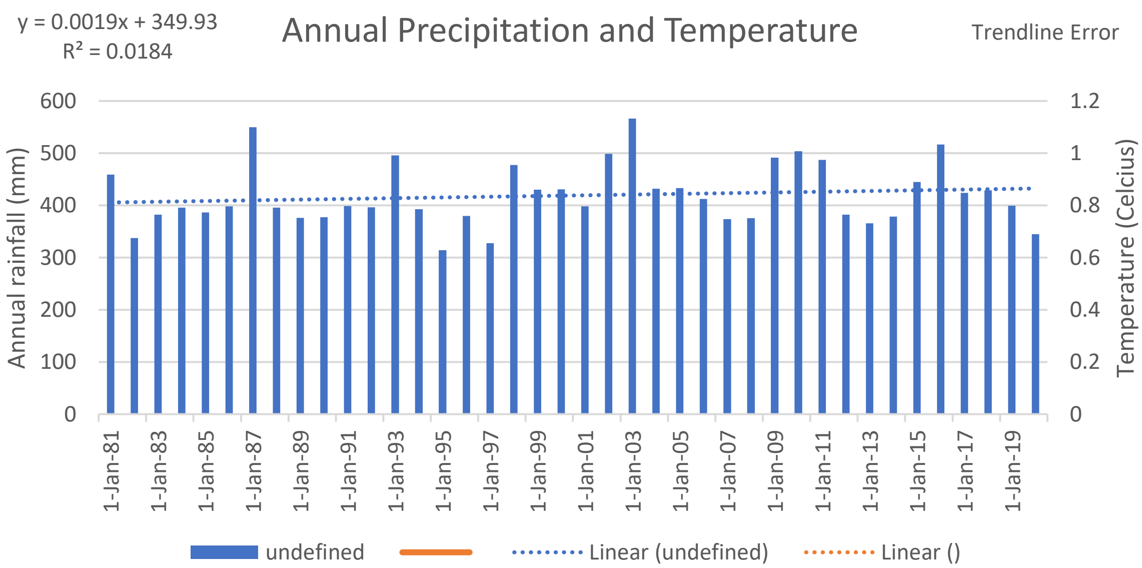


Figure 4. 6. Annual Temperature and precipitation of Kyrgyzstan during 1981-2020, source: GEE

but during the study period is calculated as 436 mm/ year. In general, there is an increasing trend in annual precipitation as presented in Figure 4. 6.

Frosts are commonly found in the entire country especially in the valley area. Naryn valley as an example has a free frost period of only 120-140 (FAO, 2012). Thus, the cities are mostly located in cool and warm climate as illustrated in Figure 4. 7. In general, there are nine types of bioclimate region in Kyrgyzstan with cold wet and cool semi-dry dominance which cover almost 29% and 25% of the country area.

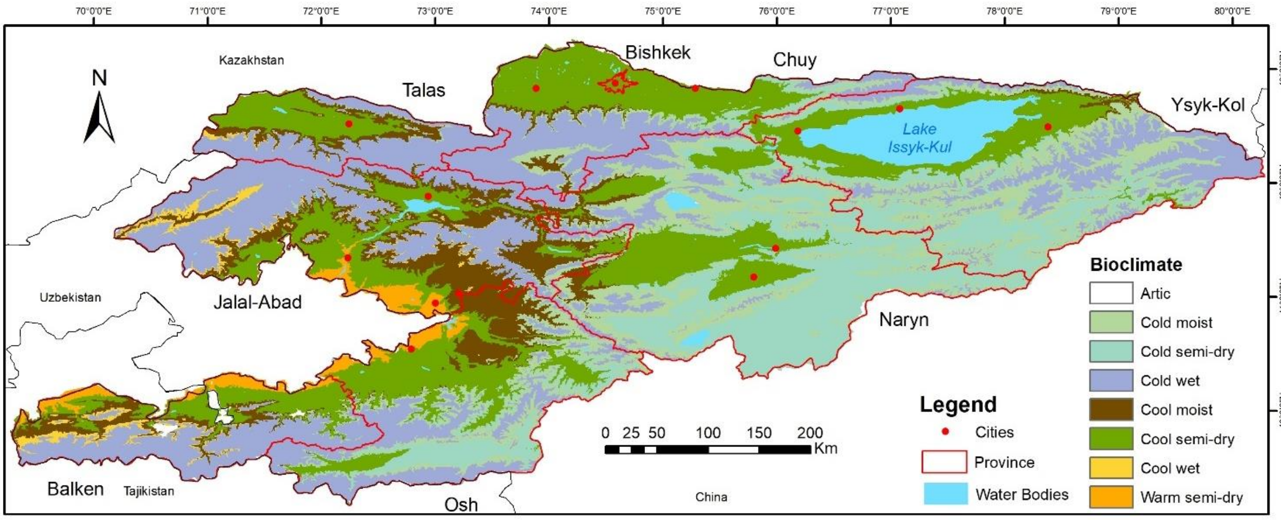


Figure 4. 7. Bioclimate types in Kyrgyzstan (source of shapefile: kyrgyzstanspatial.org)

4.3. Social and Economic Data

The total population in 2015 recorded as 5.895.100 and 6.389.500 in 2018 (National Statistical Committee, 2020). The distribution of population based on age and sex are presented in the population pyramid in Figure 4. 9. The ratio between female and male population is almost identical and the majority of the age group is the productive group (15 to 64 years old). Natural population growth is high with 21.9 per 1000 population or 2.19%.

The average population density in Kyrgyzstan is 33 people per square kilometres with the most populous city in Bishkek as the capital city estimated to have more than 1 million people (National Statistical Committee, 2020). The spatial distribution of population density presented in Figure 4. 8 showed that the distribution of the population mostly associated with the plains to hills landform, nearby water bodies, and located in a cool and warm climate. People living in the rural area is more than 64% over total population (World Bank, 2018).

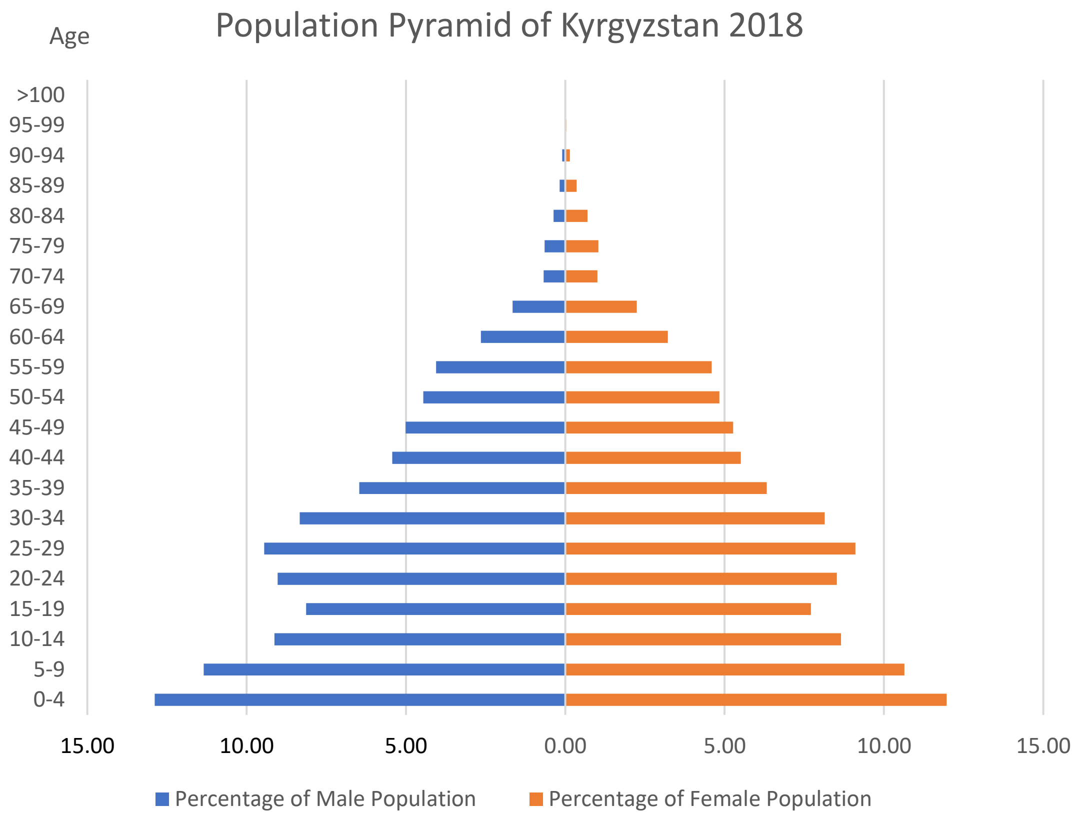


Figure 4. 9. Population Pyramid of Kyrgyzstan

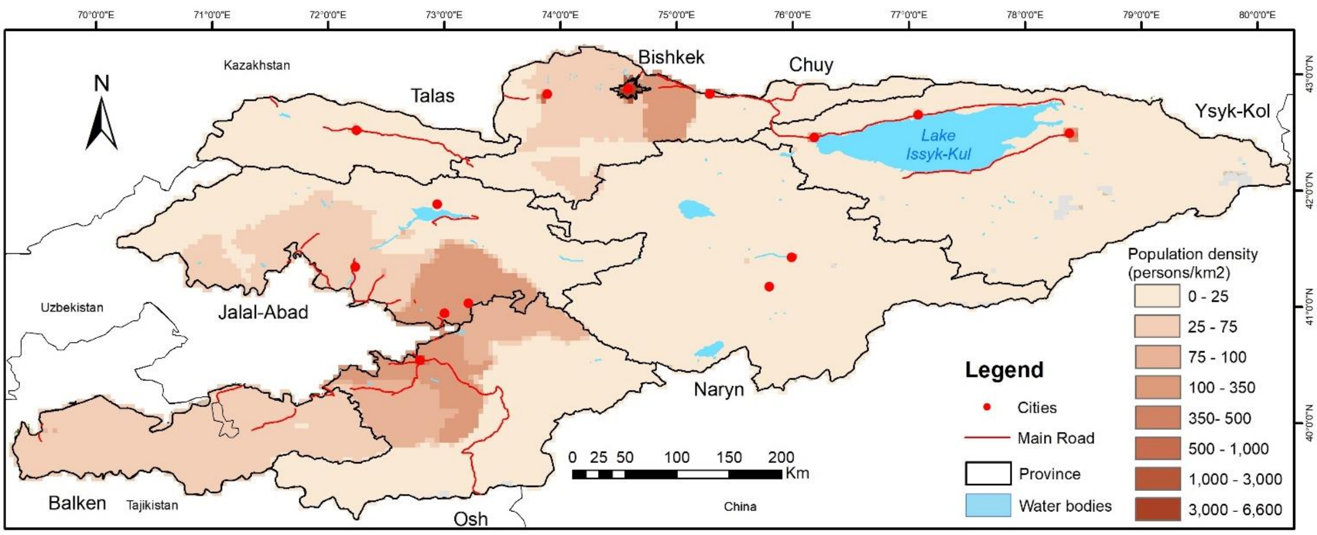


Figure 4. 8. Population density in Kyrgyzstan (source of shapefile: kyrgyzstanspatial.org)

Gross domestic product (GDP) in 2018 recorded as 530,5 billion soms Kyrgyz or 6.34 billion USD with GDP per capita is 1067,97 USD. Employment in the agriculture, forestry, and fishing sector dominance the labour structure with 20,3% over the total population. The number of poverty in Kyrgyzstan is quite high with 1.000.429 people live under the poverty line where 68% of them are rural population (National Statistical Committee, 2020). While the poverty percentage over the total population in the general poverty level category recorded as 28,4% in the rural area and 20,4% in the urban area. Kyrgyzstan classified as a lower-middle-income country by World Bank and ranked as 120th out of 180 countries by the 2016 Human Development Index (World Bank, 2018).

4.4. Agriculture

Agriculture is one of the main economic activities in Kyrgyzstan where the agricultural land occupied 33,5% of the total land area and contributed 21% of the total GDP (FAO, 2012). There are about 391.935 farms registered in the country with most of the farm about 94% are small-scale with an average of 3 hectares of farm size (World Bank, 2018). Despite the size of the farm, the type of farm is quite varied as shown in Figure 4. 10. Dry rangeland and highland agriculture occupied 42% of the total country area with each type of farm system occupied 21%. The next domination of the agriculture system is irrigated land with 8,5% of the total area and temperate rangeland with 6,4% of total country area.

The export product from Kyrgyzstan 9.9% are related to agriculture where the common commodity is vegetables, fruits, cotton, tobacco, meat, and dairy product. The main agricultural

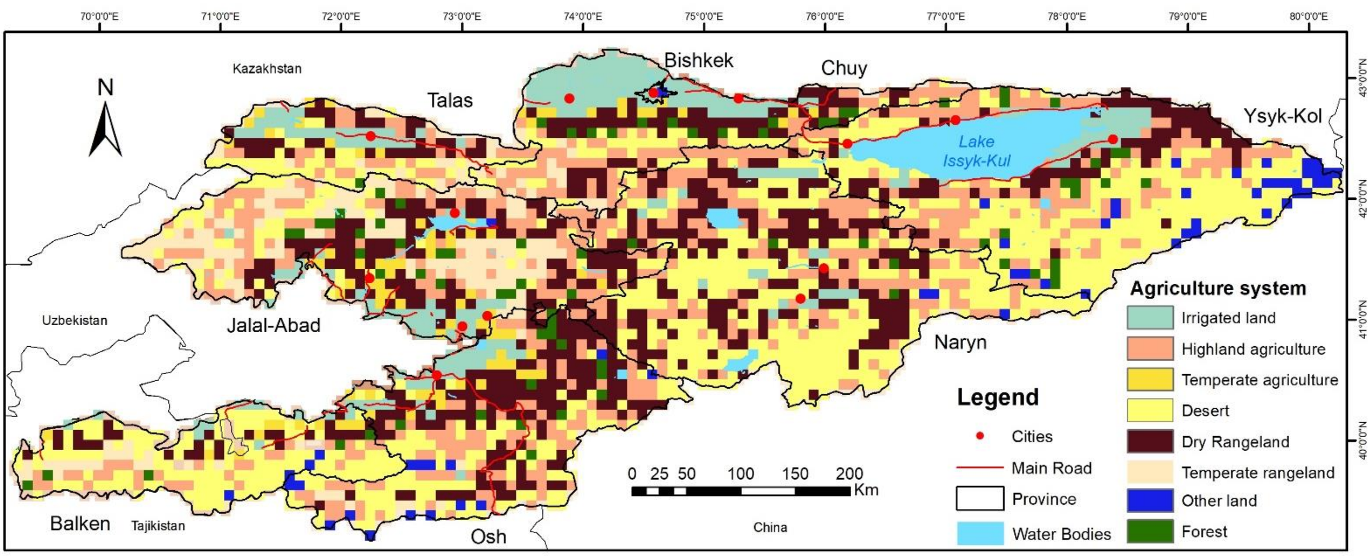


Figure 4. 10. Farm System in Kyrgyzstan

products are cereals, leguminous crop, cotton, tobacco, potatoes, sugar beet, vegetables, raw milk, and meat. The main livestock types are cattle, sheep and goats, horses, pigs, and domestics birds (National Statistical Committee, 2020). The various livestock system presented in shows that the dominant type is the temperate highland grassland-based system.

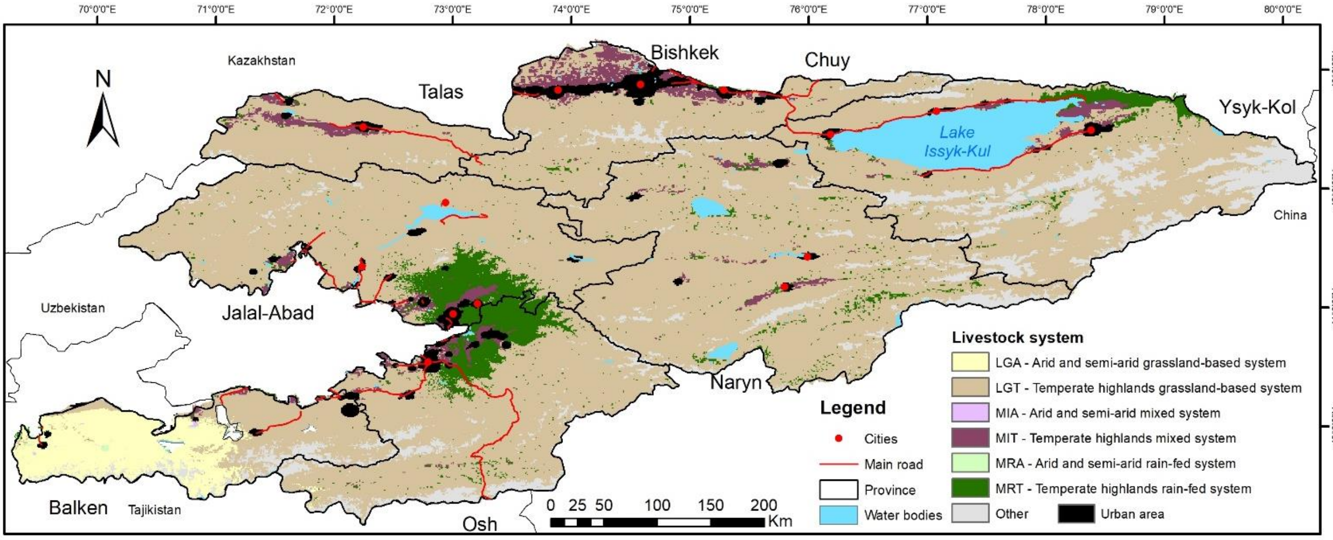


Figure 4. 11. Livestock system in Kyrgyzstan

4.5. Land Degradation National Target

Kyrgyzstan as a mountainous region where two-third of their population live in the rural area which highly depends on land-based livelihood are supporting the UNCCD and Global Mechanism initiative to achieve land degradation neutrality by 2030. It is stated on the UNCCD website national voluntary LDN target as followed:

National voluntary LDN target of Kyrgyzstan:

- *"Improve the environmental condition of pastures through the introduction of a pasture rotation system in at least 40 village districts (ayil aimaks);*
- *Improve access to 10,000 ha of pastures via improved pasture infrastructure (bridges/roads, water points);*
- *Sustainable land management practices are adopted in 100,000 ha of land (including both pastures and forests)*
- *Land improvement works are conducted on 10,000 ha."*

5. Land Degradation in Kyrgyzstan

This part will discuss land degradation status in Kyrgyzstan resulted from Trends.Earth analysis as well as the sub-indicator of land degradation such as land productivity, land cover change, and soil organic carbon.

5. 1. Land Use Land Cover Change

Land cover in Kyrgyzstan aggregated in 9 class from 22 class of land cover from GlobCover 2009 dataset is presented in Figure 5. 1 (kyrgyzstanspatial.org). The land cover is dominated by the grassland and bare land with the percentage 30.56% and 29.36% of the total country area or 61.012 km^2 and 58.580 km^2. The third-largest areas are cropland with 18.35% of the area of the country or 37.879 km^2 and the fourth is Sparse vegetation with 13.13% or 26.219 km^2. The small area of the land cover are permanent snow and ice with 2.66% or 5.318 km^2 and 3,57% or 7.121 km^2 is water bodies. The rest of the area is urban with 0.1% or 190 km^2 and 0.02% of a swampy area and 1km^2 is deciduous forest.

The spatial distribution of bare land and grassland is quite even in many parts of the country, but the most interesting distribution is the cropland area where there are some concentrations. In general, croplands are concentrated in the northern part of the country around Bishkek and northern west of Talas province, in the middle of the country around the border with Uzbekistan especially between Jalal-Abad province and Osh province. The cropland also concentrated near the biggest lake of Issyk Kul and around Song Kul Lake as well as in the middle of Naryn province. This cropland distribution is very well connected with the landform where the majority of the cropland is located in the plains region.

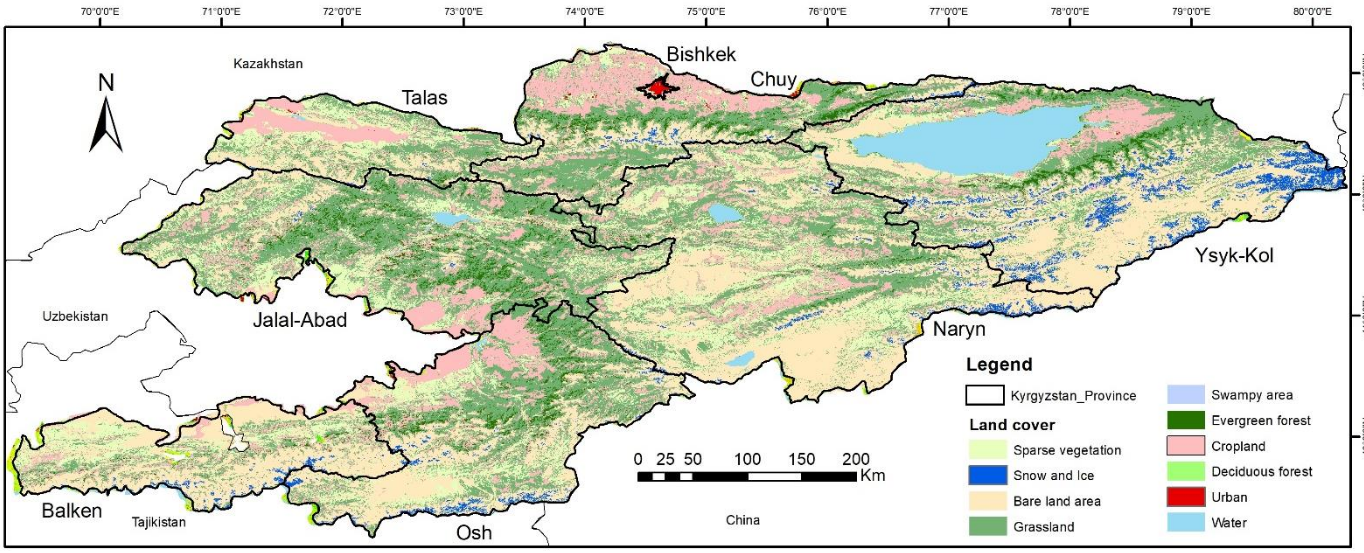


Figure 5. 1. Land cover and land use in Kyrgyzstan (source: Kyrgyzstan spatial)

The land cover classification in Trends.Earth classified as a tree-covered area, grassland, croplands, wetlands, water bodies, artificial areas, and other lands. The land cover classifications are aggregated from the Landcover ESA CCI (European Space Agency Climate Change Initiative) Land Cover dataset. The reclassification of land cover from the original 37 land cover class to 7 class land covers are presented in Figure 5. 2.

Input code	Input class	Output class
10	Cropland, rainfed	Cropland
11	Herbaceous cover	Cropland
12	Tree or shrub cover	Cropland
20	Cropland, irrigated or post-flooding	Cropland
30	Mosaic cropland (>50%) / natural vegetation (tree, shrub, herbaceous cover) (<50%)	Cropland
40	Mosaic natural vegetation (tree, shrub, herbaceous cover) (>50%) / cropland (<50%)	Grassland
50	Tree cover, broadleaved, evergreen, closed to open (>15%)	Tree-covered
60	Tree cover, broadleaved, deciduous, closed to open (>15%)	Tree-covered
61	Tree cover, broadleaved, deciduous, closed (>40%)	Tree-covered
62	Tree cover, broadleaved, deciduous, open (15-40%)	Tree-covered
70	Tree cover, needleleaved, evergreen, closed to open (>15%)	Tree-covered
71	Tree cover, needleleaved, evergreen, closed (>40%)	Tree-covered
72	Tree cover, needleleaved, evergreen, open (15-40%)	Tree-covered
80	Tree cover, needleleaved, deciduous, closed to open (>15%)	Tree-covered
81	Tree cover, needleleaved, deciduous, closed (>40%)	Tree-covered
82	Tree cover, needleleaved, deciduous, open (15-40%)	Tree-covered
90	Tree cover, mixed leaf type (broadleaved and needleleaved)	Tree-covered
100	Mosaic tree and shrub (>50%) / herbaceous cover (<50%)	Tree-covered
110	Mosaic herbaceous cover (>50%) / tree and shrub (<50%)	Grassland

Input code	Input class	Output class
110	Mosaic herbaceous cover (>50%) / tree and shrub (<50%)	Grassland
120	Shrubland	Grassland
121	Shrubland evergreen	Grassland
122	Shrubland deciduous	Grassland
130	Grassland	Grassland
140	Lichens and mosses	Grassland
150	Sparse vegetation (tree, shrub, herbaceous cover) (<15%)	Grassland
151	Sparse trees (<15%)	Grassland
152	Sparse shrub (<15%)	Grassland
153	Sparse herbaceous cover (<15%)	Grassland
160	Tree cover, flooded, fresh or brakish water	Wetland
170	Tree cover, flooded, saline water	Wetland
180	Shrub or herbaceous cover, flooded, fresh/saline/brakish water	Wetland
190	Urban areas	Artificial
200	Bare areas	Other land
201	Consolidated bare areas	Other land
202	Unconsolidated bare areas	Other land
210	Water bodies	Water body
220	Permanent snow and ice	Other land

Figure 5. 2. Reclassification of land cover to 7 class

There are different numbers of land cover because of the difference between classification from Globcover and Trends.Earth definition (Figure 5. 3). Based on Trends.Earth definition, Kyrgyzstan has 58% of grassland which acquired from grassland, shrubland, and sparse vegetation. The cropland landcover data are relatively similar with 20% based on Trends.Earth and 18% based on the Globcover map. The artificial areas are very different in Trends.Earth because the urban area is more defined well in the ESA CCI land cover dataset. The forest is similar amount in Globcover (3% of evergreen forest and deciduous forest) and 4% Trends.Earth. The area and the most different in number are other lands where the definition should be bare lands and snow and ice which should be 31% but only detected as 12% in Trends.Earth.

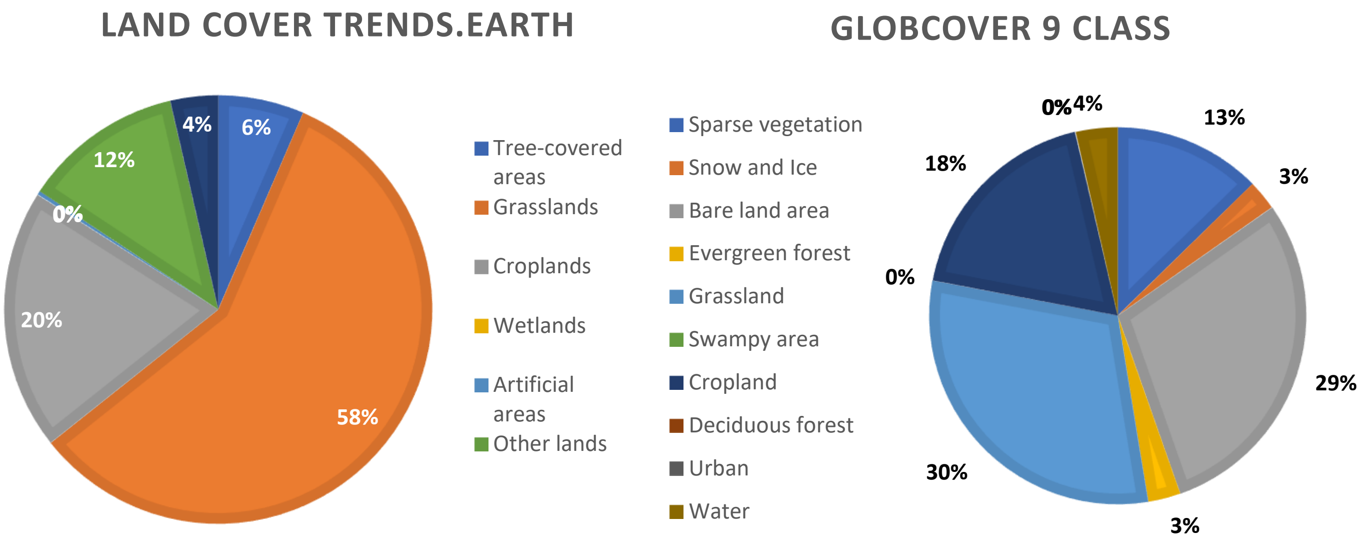


Figure 5. 3. The difference of land cover classification

Despite the difference, analysis result from Trends.Earth shows that there is no significant amount of land cover change happening during the period of analysis from 2001 to 2015, presented in Table 5. 1. The significant changes have happened in the artificial area with 806,2% or increase and in contrast, decrease happened in other lands with 2,6%, grassland with -0,74%, and water bodies with -0,21%.

Table 5. 1. Summary of change in land cover during 2001 to 2015 period

Land Cover	Change in the area (%)
Tree-covered areas	1,02
Grasslands	-0,74
Croplands	2,14
Wetlands	0,00
Other lands	-2,60
Water bodies	-0,21
Artificial areas	806,20

In general, most of the land cover remains the same or stable is 186, 675km^2 or 97,32 area of the country (Table 5. 2). The degradation of land cover changes also only happened in 1,58% of the country area or 3.034 km^2 and distributed in the urban area of Bishkek and surrounding cropland area (Figure 5. 4). The improvement of the land cover only present in 1,09% area of the country total area and it is distributed in the forest area.

Table 5. 2. Summary of land cover degradation status during 2001 to 2015 period

Land Cover Change	Percentage (%)	Km^2
Land area with improved land cover:	1.09	2,097
Land area with stable land cover:	97.32	186,675
Land area with degraded land cover:	1.58	3,034

The changing land cover trends presented in Figure 5. 5 shows that the tree-covered area has a declining trend from 2004 to 2015 while there is an increasing trend from 2001 to 2004 from 12.800km^2 to 13.200km^2. The artificial surface has a rapid increase from 70 km^2 to over 600 km^2. Tree covered area mostly changes to grassland and croplands, with small amount to artificial land, and other lands Table 5. 3.

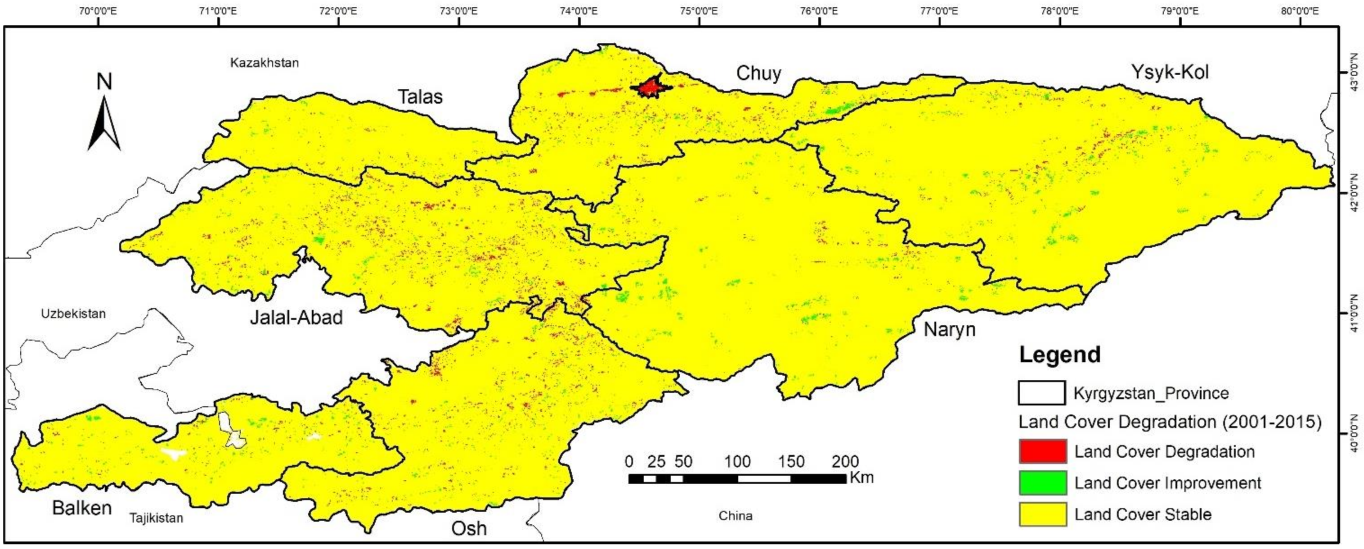


Figure 5. 4. Land cover degradation in Kyrgyzstan (2001-2015)

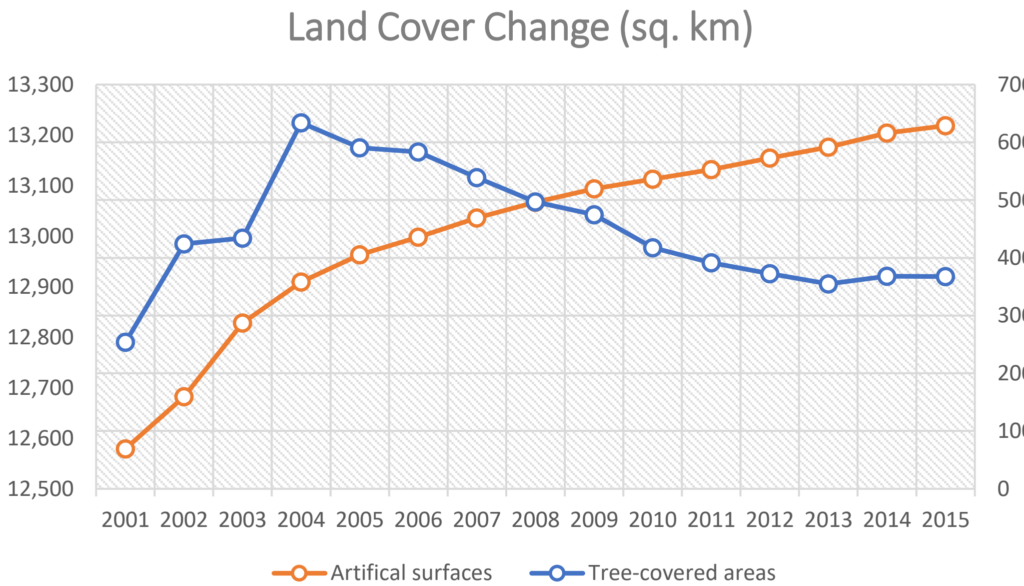


Figure 5. 5. Artificial surfaces and tree-covered area changes

The trend of grassland change presented in Figure 5. 6. shows a declining trend from 115.900 km^2 during 2001-2007 and remain stable after that in 115.000 km^2. Grassland changed mostly to cropland then small amount to artificial area, and other lands Table 5. 3. On the other hands in Figure 5. 6 shows that the trend in cropland shows the increasing trend from 115.100km^2 to 115.800 km^2 from 2001 to 2010 and the remaining stable after that. Even though it is stable, there are land area changes from croplands to artificial lands and grassland. Table 5. 3 also shown that other land area changes to grassland, cropland, and artificial area.

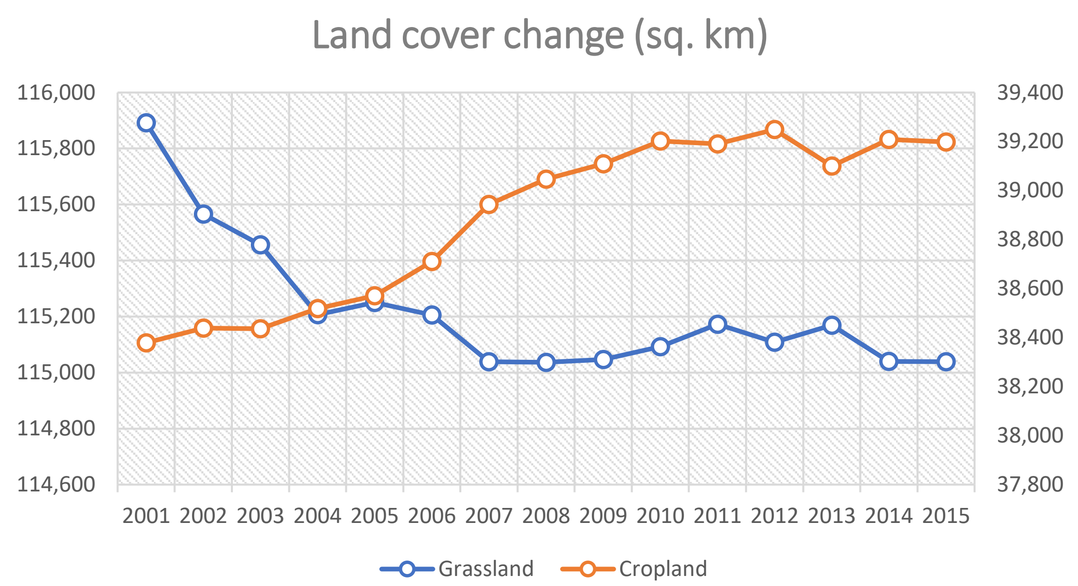


Figure 5. 6. Grasslands and croplands area changes

Table 5. 3. Matrix land cover change during baseline to target year (2001 to 2015)

Land cover type in the baseline year	Land cover type in the target year						
	Tree-covered areas	**Grasslands**	**Croplands**	**Wetlands**	**Artificial areas**	**Other lands**	**Water bodies**
Tree-covered areas	12.254,35	449,61	83,79	0,00	0,87	0,98	0,23
Grasslands	636,00	113.167,37	1.625,02	0,00	151,86	310,52	1,54
Croplands	28,31	478,86	37.461,47	0,00	403,46	6,11	0,42
Wetlands	0,00	0,00	0,00	0,00	0,00	0,00	0,00
Artificial areas	0,00	0,00	0,00	0,00	69,38	0,00	0,00
Other lands	1,09	928,19	25,31	0,00	2,36	23.701,43	4,46
Water bodies	0,14	14,82	2,63	0,00	0,82	3,61	7.175,99

Source: Calculation, 2021

5. 2. Land Productivity

Land productivity change between 2001 to 2015 analyze from Trends.Earth presented in Figure 5. 7. shows land with improved, degraded, and stable productivity. Land area with stable productivity dominance the proportion of land with almost half of the total area with 48% of the total area of 91.458 km^2 area stable in productivity within the period of study. In contrast, the land area with improved land productivity is the smallest area with only 7% of the area or 14.023 km^2. The land with degraded productivity occupied 36% of the area or 69.867 km^2 and the land area with no data for productivity is 9% of the total area.

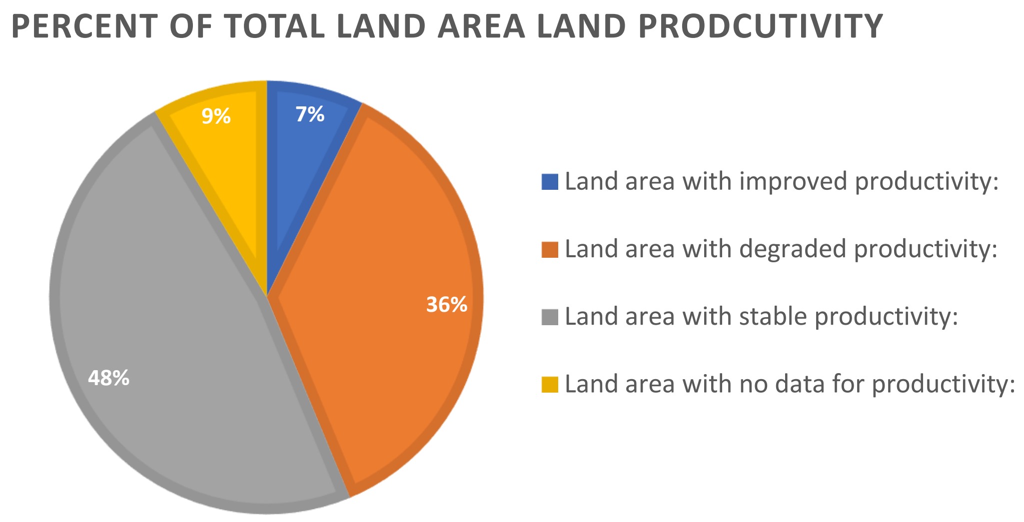


Figure 5. 7. Land Productivity change during 2001 to 2015 from Trends.Earth

Land productivity change based on five classes of change including declining, an early sign of declining, stable but stressed, stable, and increasing is presented in Figure 5. 8. The majority of land productivity with 48% of the total area of 91.111,8 km^2 area is in the stable state, followed by the moderate decline of 19% or 37,493,35 km^2 and declining 9%. The increasing change presented in the smallest area with 7% or13.989 km^2 of the total area of Kyrgyzstan.

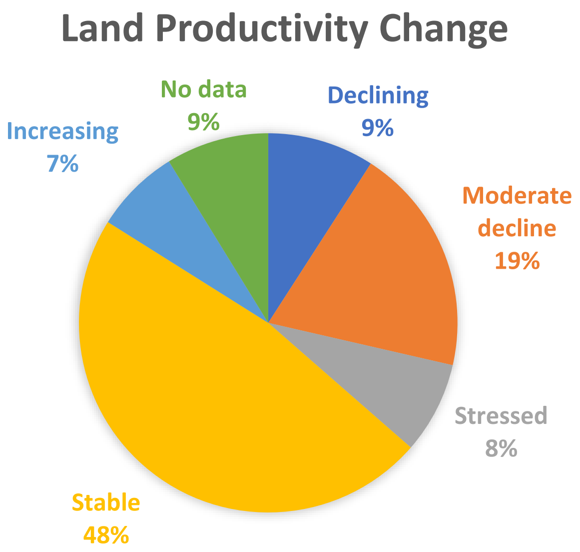


Figure 5. 8. Land productivity change in 5 class

The spatial distribution of land productivity in five class is presented in (Figure 5. 9). The declining change concentrated in Naryn province where the bare land is concentrated, in Chuy province near Bishkek where the agriculture most located, and northern part of Talas province. While increasing change in land productivity concentrated in the cropland land cover in the middle of the country as well as in the southern part of Osh province.

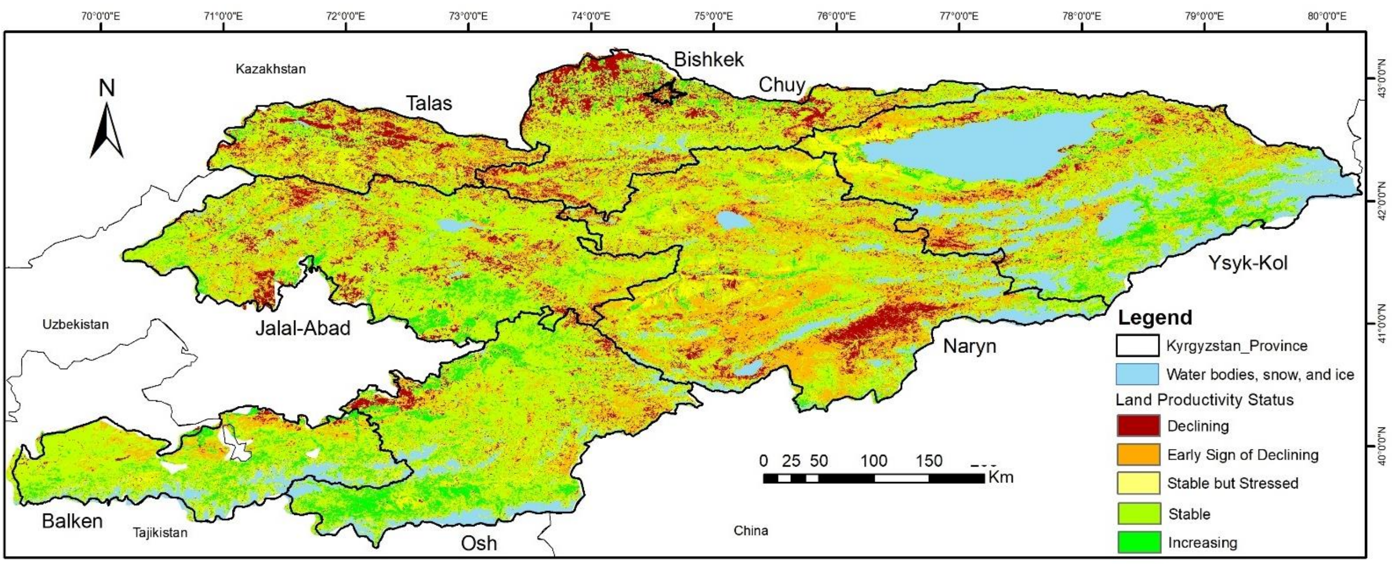


Figure 5. 9. Spatial distribution of land degradation status in Kyrgyzstan (2001 to 2015)

The distribution of land productivity in five class based on the land cover presented in Table 5. 4. Overall, most land productivity categorized as stable followed by a moderate decline and declining. The most declining land productivity found in grassland followed by croplands.

Interestingly, the change in grassland and croplands is the most in the area. This is due to the proportion of the land cover also mostly composed of grassland and croplands.

Table 5. 4. Matrix land productivity change based on land cover change during baseline to target year (2001 to 2015)

Land cover class	Declining	Moderate decline	Stressed	Stable	Increasing	No data
Tree-covered areas	0.49	1.27	0.06	4.34	0.39	0.02
Grasslands	5.68	13.53	6.50	28.70	3.74	2.47
Croplands	2.71	4.05	0.32	10.72	2.24	0.03
Wetlands	0.00	0.00	0.00	0.00	0.00	0.00
Artificial areas	0.01	0.00	0.00	0.02	0.00	0.00
Other land	0.22	0.61	0.95	3.72	0.93	6.27
Total	9.12	19.47	7.83	47.50	7.29	8.79

Source: Calculation, 2021

5. 3. Soil Organic Carbon

The proportion of soil organic carbon (SOC) in topsoil based on land cover type are presented in Figure 5. 10. Tree cover area has the largest percentage of the soil organic carbon with 26% over overall carbon although the percentage of tree-covered area is only 4% of the total area. The second-largest SOC percentage found in the grassland with 24% of total SOC whilst the land grassland cover 58% of the total area of the country. The SOC percentage found in croplands are 21% where croplands cover 18% of the total country areas. The other land holds 16% of the total SOC and artificial surface holds 13% of the total SOC. Figure 5. 11 shows the amount of the SOC compares to the land cover area. The tree-covered area with a small amount of land cover has the biggest SOC content even compared to the grassland area as the biggest land cover area.

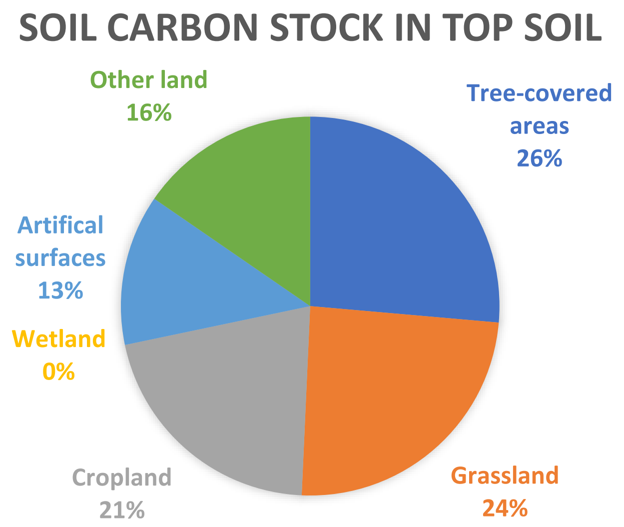


Figure 5. 10. Grasslands and croplands area changes

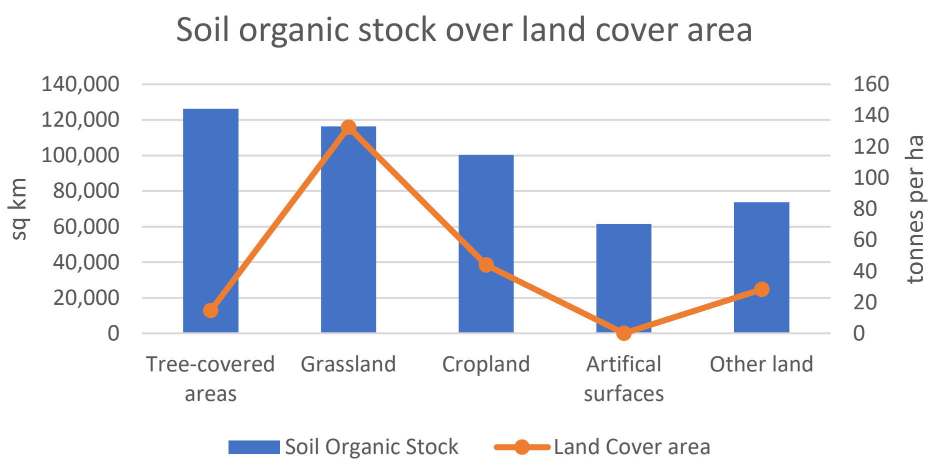


Figure 5. 11. Grasslands and croplands area changes

The total change in SOC presented in Table 5. 5 shows that the SOC carbon in Kyrgyzstan remains the same where 99,43% of the land area has stable SOC only 0,34% land area with degraded SOC and 0,23% land area with improved SOC. This fact is very logical where only 4% of the land cover holding most of SOC and does not have any significant change but the most change in land cover only hold a small portion of SOC in Kyrgyzstan. The spatial distribution of SOC change presented in Figure 5. 12 shows that the degraded SOC distributed in the urban area of Bishkek and croplands area as well as area nearby Toktogul reservoir. The improved SOC distributed around the forest land cover area.

Table 5. 5. Summary of change in land cover during 2001 to 2015 period

Land area category	Percentage of total land area
Land area with improved soil organic carbon	0,23%
Land area with stable soil organic carbon	99,43%
Land area with degraded soil organic carbon	0,34%

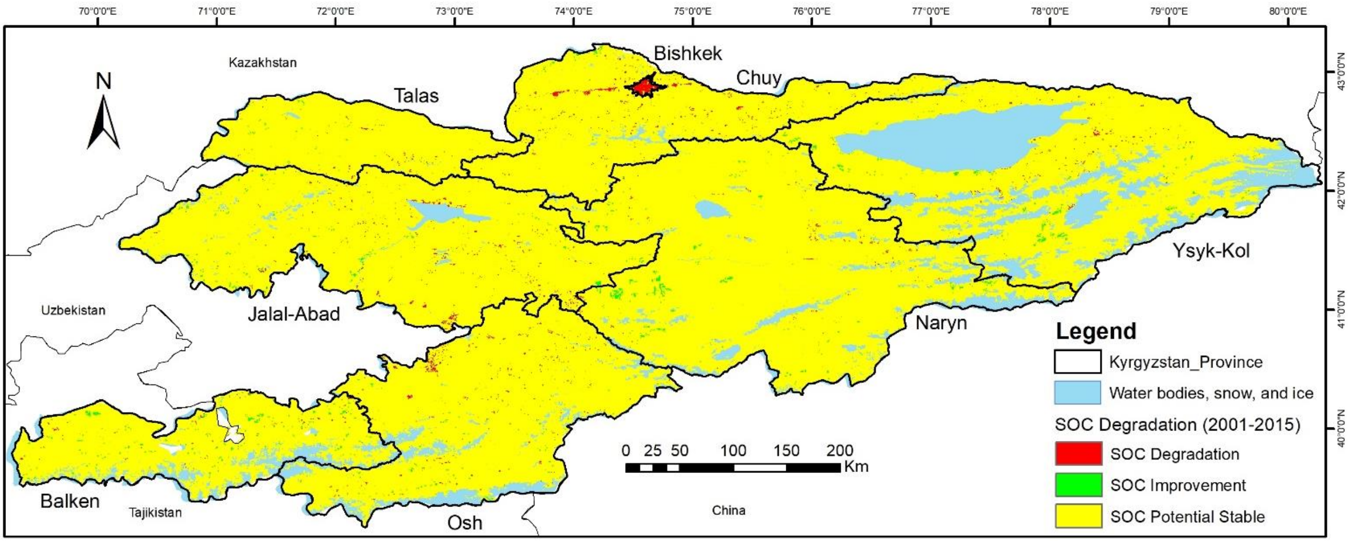


Figure 5. 12. SOC Degradation (2001-2015)

SOC changes based on the land cover from 2001 to 2015 presented in Table 5. 6 shows that the decreasing SOC found in the grassland and other lands with -15.165.773 tons carbon and -1.097.575 tons carbon, respectively. This decreasing amount of SOC in grassland might be related to the decreasing of grassland land cover. The improvement of SOC found in the artificial land area where 805% SOC improved in SOC. This is because the changes in land cover of artificial area are also very high.

Table 5. 6. Summary of change in land cover during 2001 to 2015 period

Land cover	Change in soil organic carbon (tonnes)	Change in soil organic carbon (percent)
Tree-covered areas	1.788.524,65	0,97%
Grasslands	-15.165.773,63	-0,98%
Croplands	8.548.400,16	1,94%
Wetlands	0,00	0,00%
Artificial areas	3.933.033,14	805,01%
Other lands	-1.097.575,16	-0,53%

5. 4. Land Degradation Status

The analysis of Trends.Earth for land degradation status resulted in raster data and numerical data. The numerical data presented in Figure 5. 13 showed the overall land degradation status as well as the sub-indicators in Kyrgyzstan. The overall land degradation status shows a similar pattern with land productivity while SOC and land cover pattern are similar. Land area with stable land dominate the land area with 46,14% of land or 88.501 km^2, the land area with degraded status cover 37,32% or 71,583km^2 and the smallest land area with improved status is 7,79 over the total area or 14.942 km^2. It can be concluded that land productivity most influential factor of land degradation status followed by land cover and SOC.

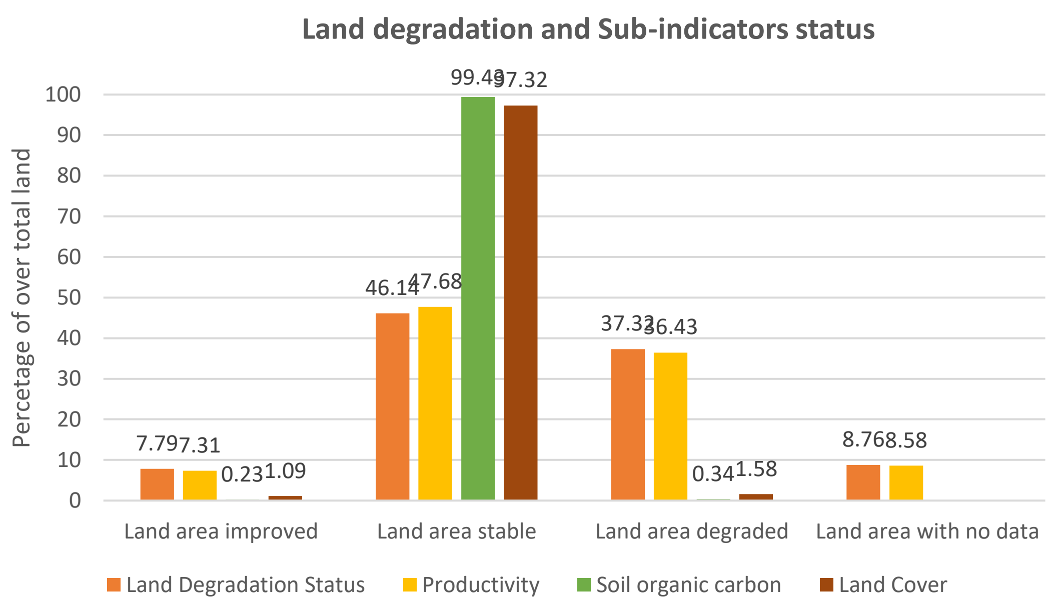


Figure 5. 13. Land degradation status and sub-indicator in Kyrgyzstan

The spatial distribution of land degradation shows that land degradation happened all over the country area without any specific area of concentration (Figure 5. 14). However, the stable land and improved land mostly concentrated in the middle of the country in the Jalal-Abad and Osh province as well as in some area in the Balken province. The concentration of stable land degradation and improvement is related to the land cover of cropland. While land degradation mostly located in the area where the bare lands are located. Further analysis of land degradation related to the land cover, landform, slope, population, agriculture system, livestock system, pasture, and other environmental factors are presented in chapter 7.

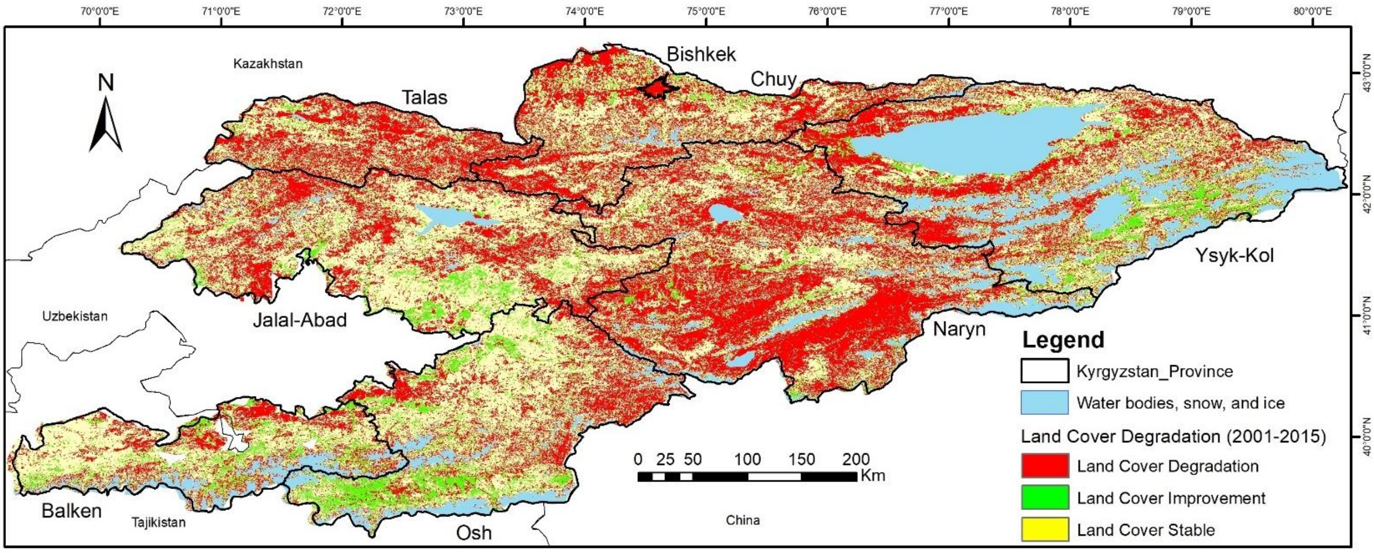


Figure 5. 14. Land degradation status in Kyrgyzstan based on 2001-2015

6. Climate factor in Land Productivity

Land degradation status in Kyrgyzstan based on the previous chapter shows that land productivity is the most influence in land degradation calculation. Thus, in this chapter, NDVI will be used as a proxy of land productivity and land degradation as well as to understand the effect of climate factor on NDVI. The climate factors used in this study are precipitation, temperature drought index, and potential evapotranspiration. This part of the study has resulted from the analysis of time-series data for every variable.

6.1. NDVI trends as a proxy of Land Degradation

Around 45.85% of the country (91.554 km^2) shows significant positive land productivity change throughout the study period from 2001 to 2015 (Figure 6. 1). While 24.69% (49.301 km^2) of the total the country shows decrease land productivity. By contrast, 29% of the country (58.113 km^2) shows no significant trend of land productivity. The spatial distribution of non-significant land productivity change is spread all over the country except there is one big concentration in the Southern part of Ysyk-Kol province in the mountainous area of barren lands.

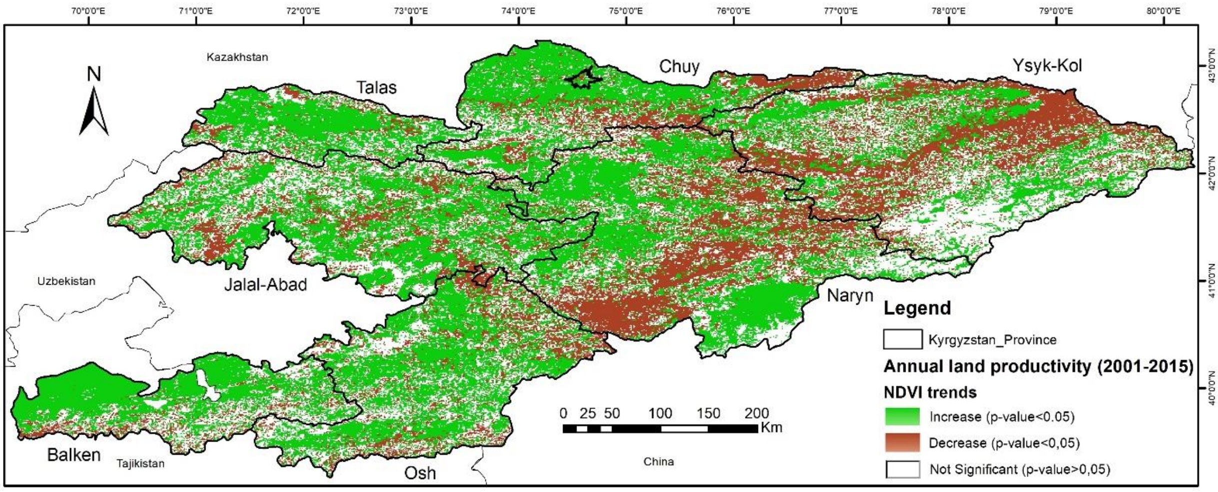


Figure 6. 1. Annual land productivity in Kyrgyzstan (2001-2015)

In general, the decrease in land productivity is founded in the land cover of bare land. While the increasing NDVI mostly located in the grassland area. Aside from the proxy of land degradation, NDVI also a proxy of NPP (Bao Le et. al. 2014) but, it is very interesting that the other study related to NPP in Kyrgyzstan from Wang et al (2020) shows that the decrease of grassland land productivity is found in the northern part of the country while in this study the decreasing land productivity is in the southern part of the country and more scattered.

6.2. Selected climate factors

In this study, there are only two climate factors selected which has a major influence on vegetation growth. The major influence of climate factor in vegetation growth in Kyrgyzstan is temperature and precipitation (Wang et al., 2020). Thus, this study will address temperature and precipitation as climate factors in land productivity trend. Additionally, the other variable also will be added such as Palmer Drought Severity Index (PDSI), Annual PET (Potential Evapotranspiration, and Transpiration), and aridity index in further analysis.

Annual precipitation aggregated from daily precipitation data from Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) over the study period. To obtain precipitation trends, linear regression for each pixel based on linear trends analysis applied from 2001 to 2015. The spatial distribution of precipitation trends presented in Figure 6. 2 where the increasing trends of precipitation are concentrated middle part of Kyrgyzstan. The trends of presentation show that the trends range from negative 23 mm /year and positive 30 mm/year.

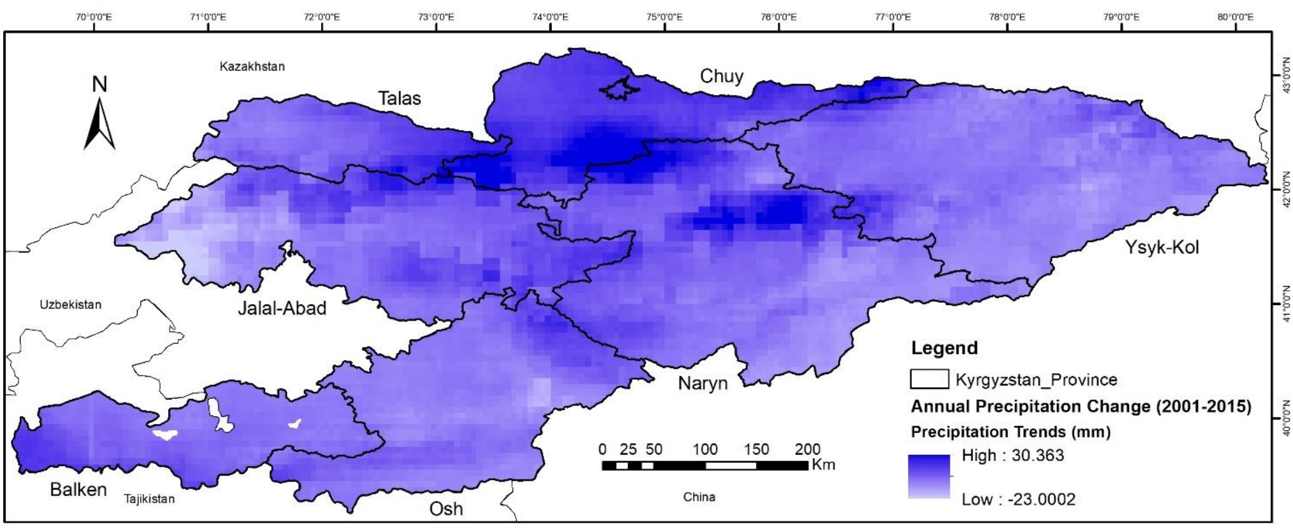


Figure 6. 2. Annual Precipitation Change in 2001-2015

While the study from Wang et al. (2020) resulted that the significant decreasing trend is 4.94 mm/year. The negative represents the decreasing trends and the positive represents increasing trends. The significant trends of precipitation show that the dominance if decreases trends were an only small amount of significant increase found in the west part of the country (Figure 6. 3). in Jalal-Abad province.

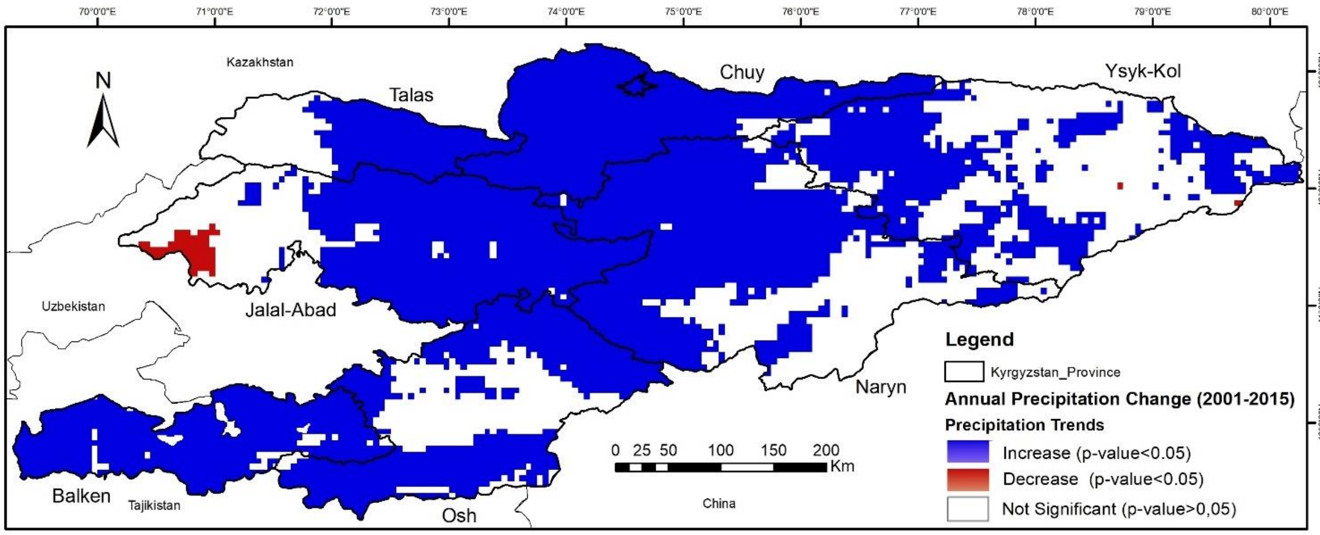


Figure 6. 3. Annual precipitation changes in Kyrgyzstan 2001-2015

Annual temperature data are aggregated from the monthly temperature dataset from GRIDMET: University of Idaho Gridded Surface Meteorological Dataset with 2,5 minutes degree or 4,6 km spatial resolution. Other than precipitation and temperature this dataset has 16 bands of the dataset in total including the Palmer Drought Index (PDSI). The annual maximum temperature has slight decrease trends from -0.000^{0}C to -0.04^{0}C with the only limited

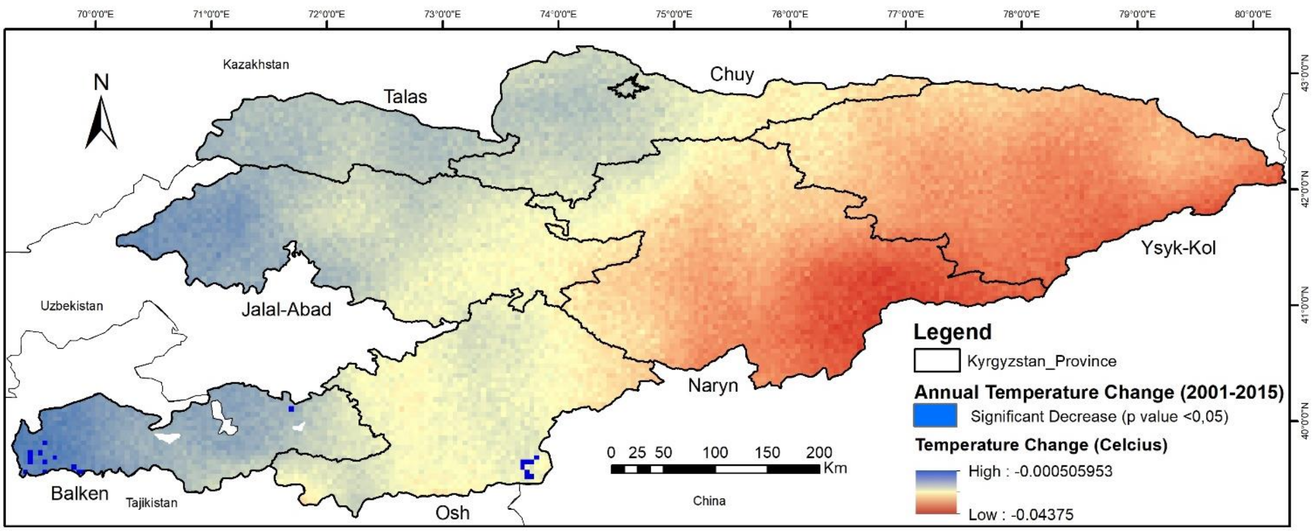


Figure 6. 4. Annual Temperature Change in Kyrgyzstan 2001-2015

area has a significant decrease in the western part of Balken province and small areas in the south-east of Osh (Figure 6. 4). While the other study found that the annual mean decreasing trend is 0.01^{0}C (Wang et al., 2020).

The PDSI trends from 2001 to 2015 shows that the increasing trends of the drought index are concentrated in the southern part of the country particularly in Naryn and Osh province as well as the western part of the country especially in Talas and Jalal-Abad province (Figure 6. 5). The increasing trend of drought majority located in the bare land. The decreasing trends found in the eastern part of Ysyk-Kol province near the Issyk-Kul lake. This area is a mountainous area with some permanent snow cover.

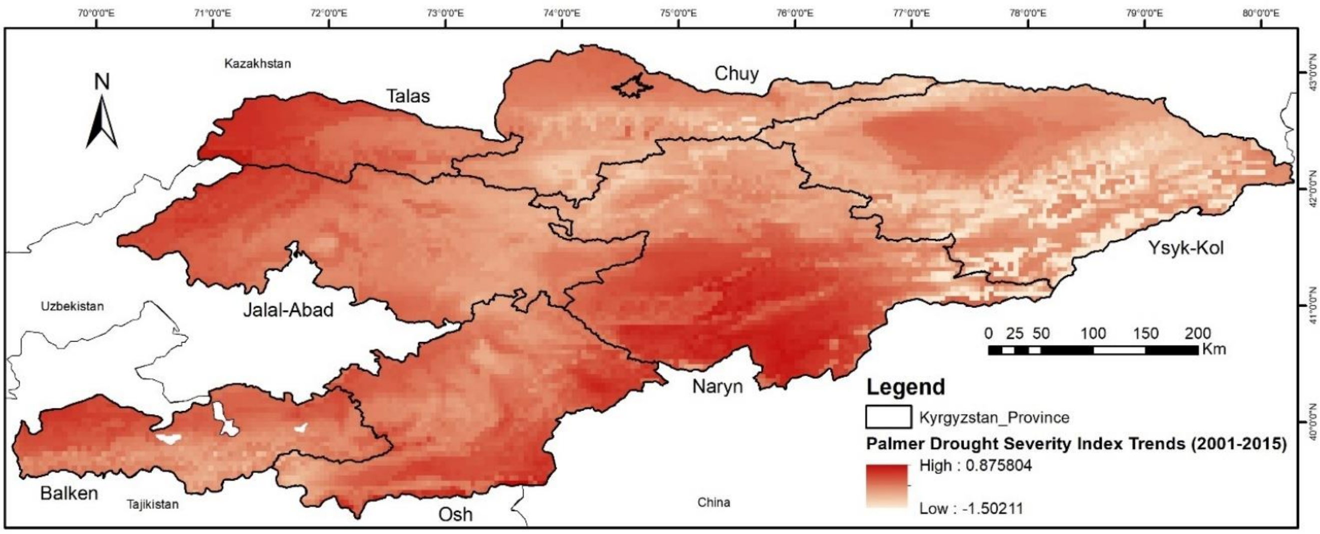


Figure 6. 5. Palmer Drought Severity Index Trends in Kyrgyzstan 2001-2015

6.3. NDVI- Climate correlation

The correlation between NDVI and climate factor will be presented with the correlation value and residual value between NDVI-Precipitation, NDVI-Temperature, and NDVI-Drought Index. The correlation between NDVI-Precipitation presented in Figure 6. 6 shows that the area covered by negative correlation is 48.76% of the total area of 97,365km^2 but only 23.93% or 47.787 km^2 of the negative NDVI-Precipitation correlation is significant as shown in Figure 6. 7. The positive NDVI-Precipitation correlation covers 51.24% of the total area or

102.305 km ^{2} but the significant positive correlation only 19.01% over the total area or 37.952 km^2 (Table 6. 1).

Spatial distribution of significant positive correlation between NDVI and precipitation found in improved land productivity and mostly in cropland land cover. Significant negative correlation between NDVI and precipitation found in the area with decrease NDVI and decrease precipitation as well as non-significant trends in precipitation. Thus, the NDVI has a stronger influence than the precipitation in this correlation.

Table 6. 1. NDVI-Climate correlation and significant

Category	% of the total area	area in km2
Negative_NDVI_Prec	48.76	97364.8189
SigNeg_NDVI_Prec	23.93	47787.30321
Positive_NDVI_Prec	51.24	102305.1811
SigPos_NDVI_Prec	19.01	37951.91004
Positive_NDVI_Temp	44.49	88823.22395
SigPos_NDVI_Temp	21.17	42265.80935
Negative_NDVI_Temp	55.51	110843.8035
SigNeg_NDVI_Temp	9.06	18083.44975

The correlation between NDVI-Temperature presented in Figure 6. 8 shows that the area covered by negative correlation is 55.51% over the total area but only 9.06% of this correlation

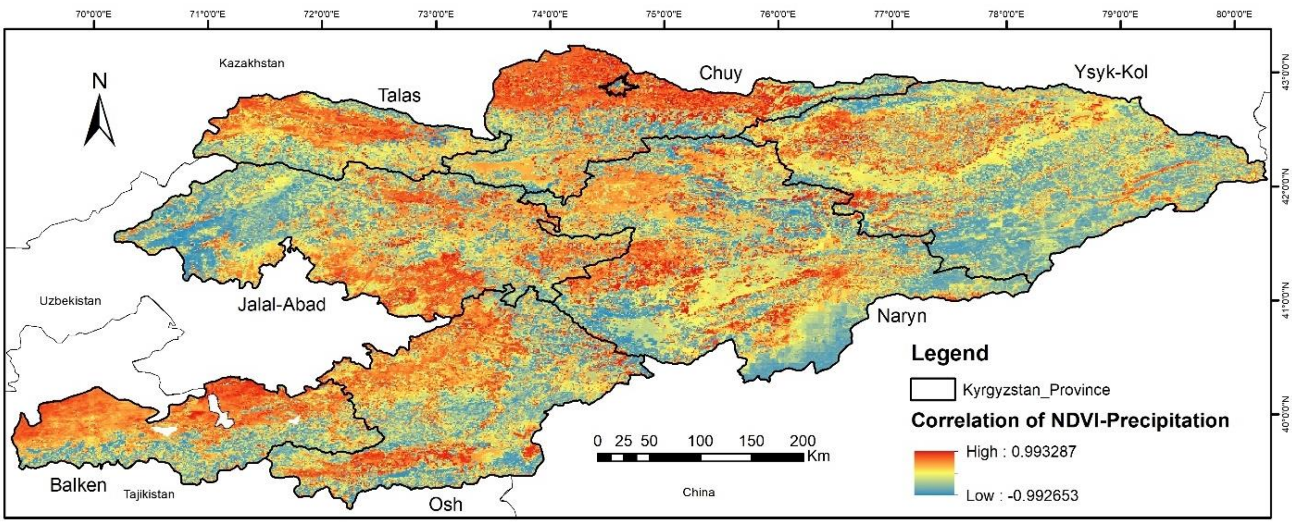


Figure 6. 6. Correlation of NDVI-Precipitation

is significant and positive correlation cover 44.49% of the total area but the significant positive correlation only 21.17% over the total area Table 6. 1.The interesting part is that there are no significant positive temperature trends in this region while very limited areas have significant negative temperature trends but there some region has NDVI-Temperature significant as presented in Figure 6. 9.

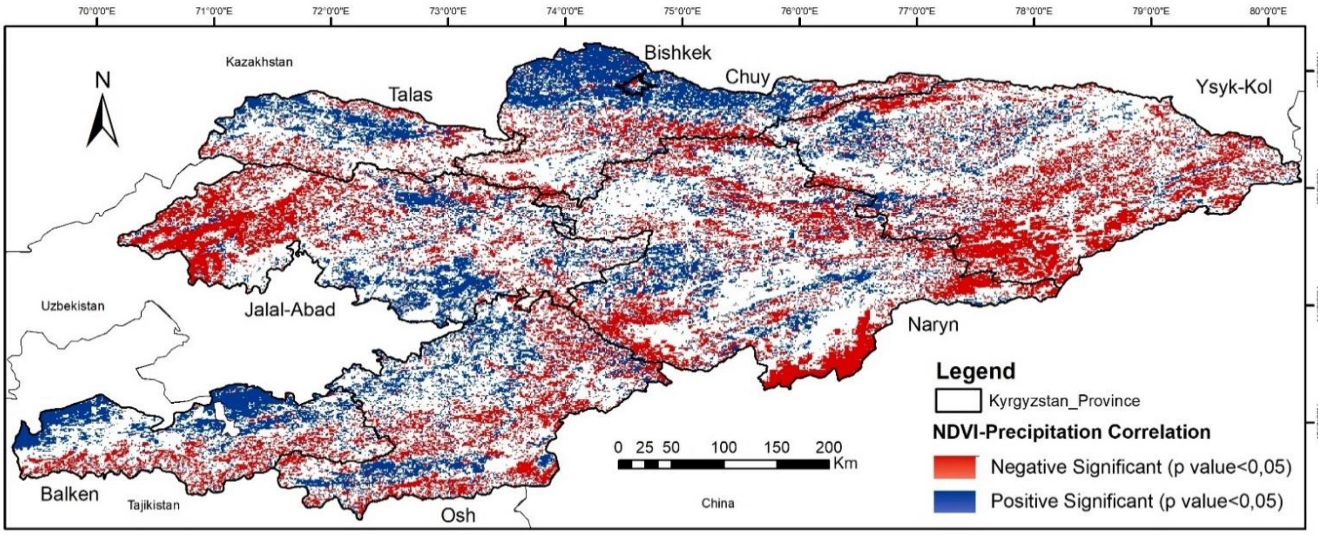


Figure 6. 7. NDVI-Precipitation correlation significant

In general, precipitation and temperature have an opposite influence on NDVI. Area with a significant negative correlation between NDVI and precipitation located in the same area with a positive correlation of NDVI-temperature and vice versa. However, the total significant negative NDVI-temperature correlation almost half of the significant positive NDVI-

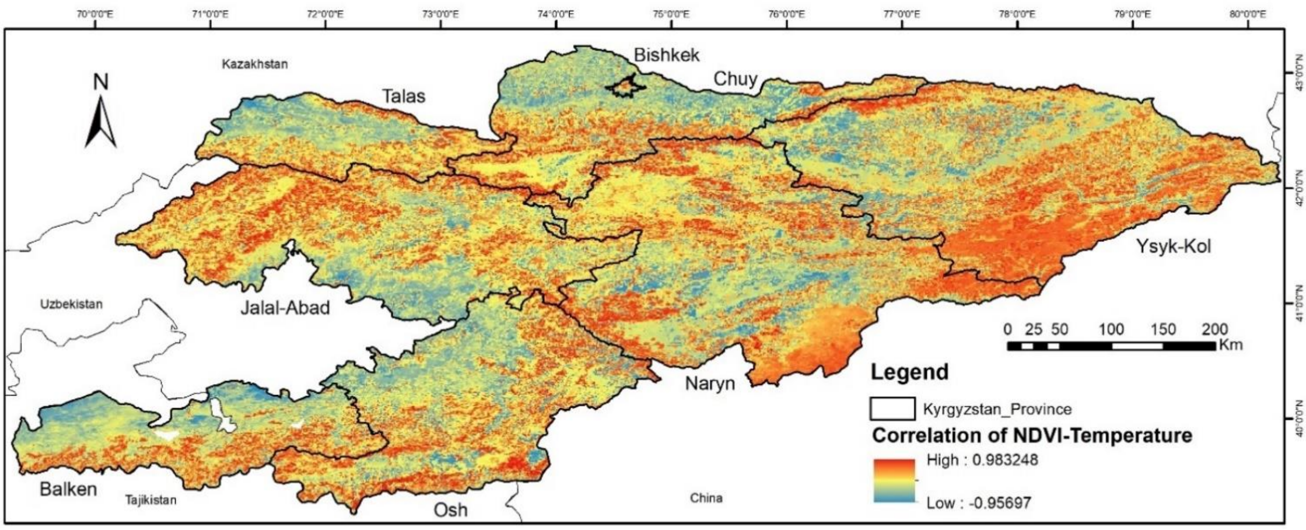


Figure 6. 8. NDVI-Temperature correlation

precipitation. Thus, the total area of significant correlation between NDVI-Precipitation and NDVI-Temperature is 73.16% of the total area.

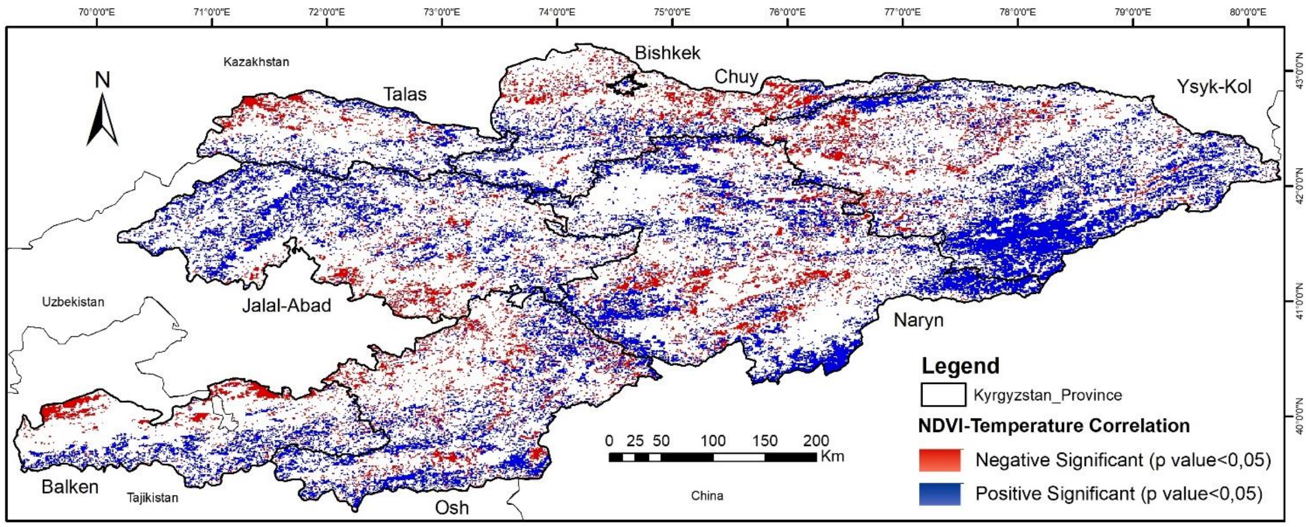


Figure 6. 9. NDVI-temperature correlation significant

The correlation of NDVI-climate shows that the area covered in the same area has a significant negative in NDVI-Precipitation correlation, but significant positive temperature. This means that the increasing precipitation resulting in a decreasing NDVI, but the temperature does not have a significant role in this correlation because the significant trends in temperature also located in a very small area.

The correlation between NDVI and Palmer Drought Index (PDI) presented in Table 6. 2 shows that the positive NDVI-PDI correlation cover 53.51% of the total area but only 0.98%

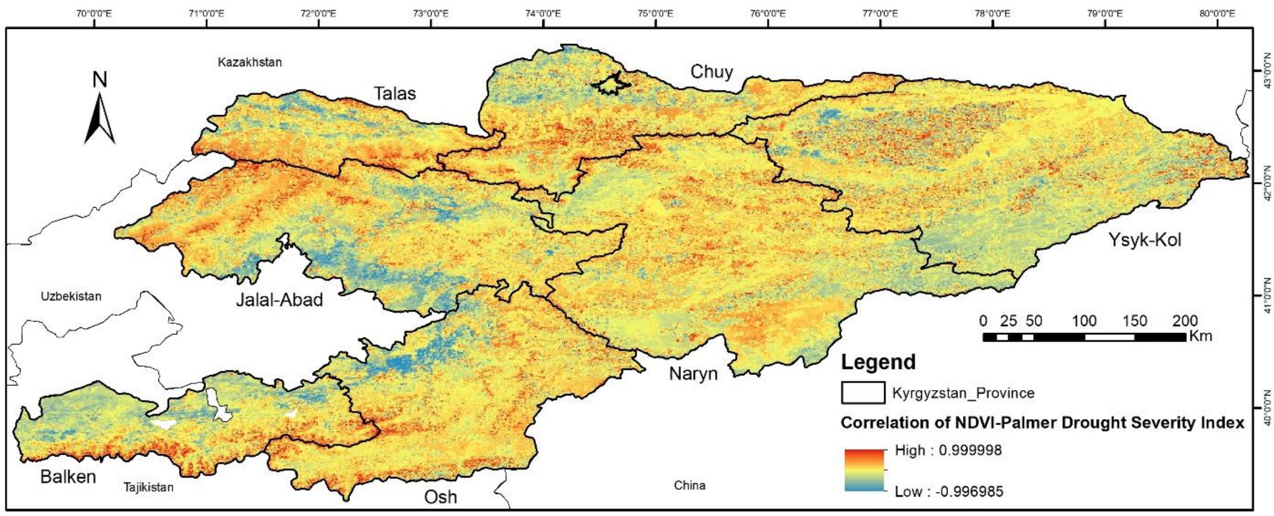


Figure 6. 10. NDVI-Palmer Drought Severity Index Correlation

of this correlation is significant. A similar pattern found in the negative NDVI-PDI correlation where only 46.49% of the area but only 1.57% of this area is significantly correlated. The total area of significant correlation between NDVI and PDI only 2.54% or 5.080 km^2 over the total area of 199.670 km^2. Thus, the correlation between the drought index with the NDVI is very small. The spatial distribution of NDVI-PDI correlation presented in Figure 6. 10 shows that the very sparse correlation is visible and Figure 6. 11 shows that negative correlation found in the cropland area while positive correlation is very small and distributed heterogeneously across the country.

Table 6. 2. NDVI- PDI Correlation summary

Category	% of the total area	area in km2
Positive_NDVI_PDI	53.51	106,837
SigPos_NDVI_PDI	0.98	1,951
Negative_NDVI_PDI	46.49	92,833
SigNeg_NDVI_PDI	1.57	3,129

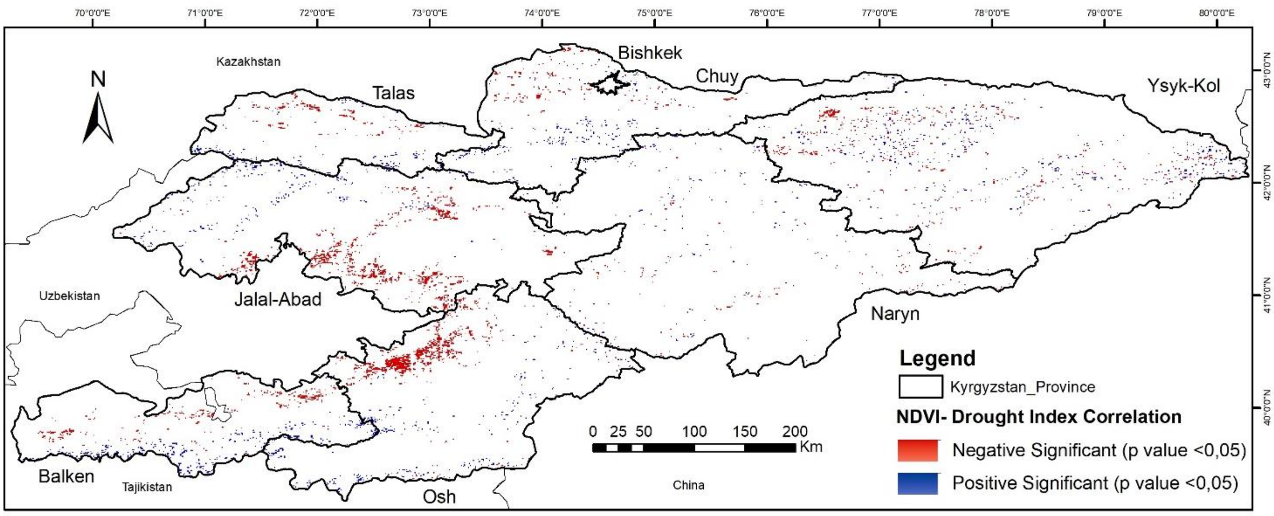


Figure 6. 11. NDVI-Palmer Drought Severity Index Correlation Significant

7. Land degradation and environmental factors

Analysis of land degradation status including degraded land, improved land, and stable land related to the environmental factor will be addressed in this chapter. There will be some part of the analysis namely the population aspect, biophysical aspect, and agriculture aspect. Climate factor includes annual potential evapotranspiration (PET), aridity index, temperature change, and precipitation change. Biophysical factor includes slope, landform, land cover, ecoregion, lithology, homogeneity species, carbon storage, and biomass density. Agriculture factor includes the crop-related agriculture such as agriculture risk, farm system, irrigation percentage, and fertilizer of nitrogen and phosphorus. Additionally, the administration boundaries also will be used to analyze the distribution of land degradation status in the province and district. The summary of the relationship between land degradation status and environmental factor presented in Table 7. 1.

7.1. Land degradation and population aspect

The population aspect of land degradation in this study consists of population and population density. The population data acquired from Google Earth Engine (GEE) platform especially from WorldPop dataset: *WorldPop Project Population Data: Estimated Residential Population per 100x100m Grid Square (*`ee.ImageCollection('WorldPop/POP').` This dataset provides the estimated number of people for the year 2010 and 2015 in each grid cell of 100m x 100m. For study purpose, this data also adjusted with the UN dataset.

Analysis of the distribution of population related to land degradation status presented in Figure 7. 1. The distribution of population data value showed that many outliers of the data found in degraded land compared to stable and improved land. This means that the population of more than 35 people in one grid is more likely to live inland degradation rather than in the improvement of land. Furthermore, the average of people living in degraded land is 0.21, while in stable land is 0.15 and in improvement land is 0.45 (people per 100x100m). The independence test analysis performed with the Kruskal Wallis test resulted in a p-value of the population dataset related to land degradation is 2,2 x 10^{-16} which is significant according to 95% of confidence level. Then, it can be inferred that the population influences land degradation status variations.

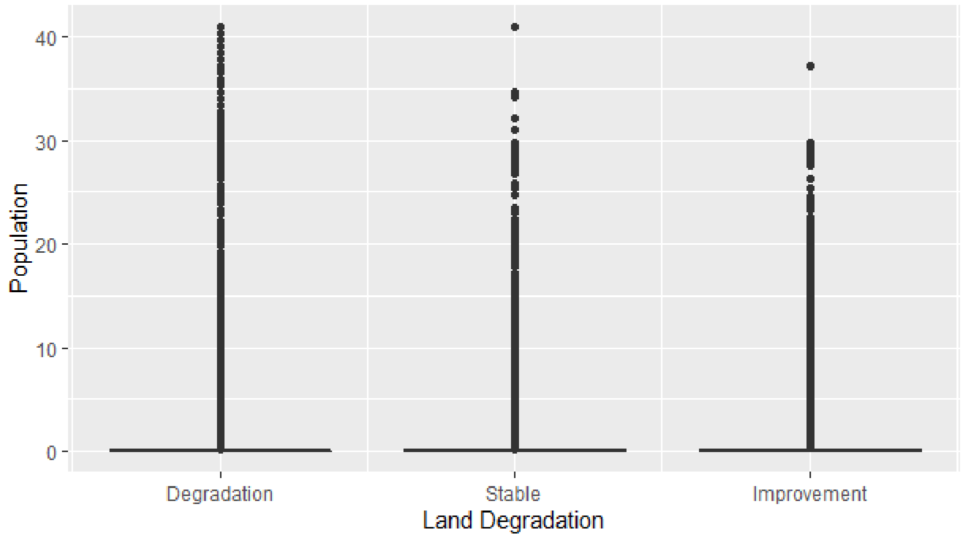


Figure 7. 1. Distribution of population in land degradation category based on WorldPop

The population density dataset acquired from the Kyrgyzstan Spatial website which originally from Gridded Population of the World version 3 (GPWv3) for the population density grid. This dataset presented the number of people per km^2 for each grid value. The analysis of land degradation status related to population density illustrated in Figure 7. 2. This result shows that the pattern of people living in the land degradation is similar to the previous population dataset. The outlier data in degraded land is more presented and exceed until more than 6000 people living in one square kilometre. Population density for more than 3000 persons per km^2 is likely to be found in degraded land and absence in stable and improved land.

However, based on calculation, the average number of people in improvement land is 31 people per km^2 while in stable land is 30 people per km^2 and 34 people per km^2 in degraded land. Based on Table 7. 1, the p-value from population density is 2,2 x 10^{-16} which is significant according to the confidence level of p-value <0,05. Then, it can be inferred that the population density influences land degradation status variations. However, the degree of influence is very small at 0.209.

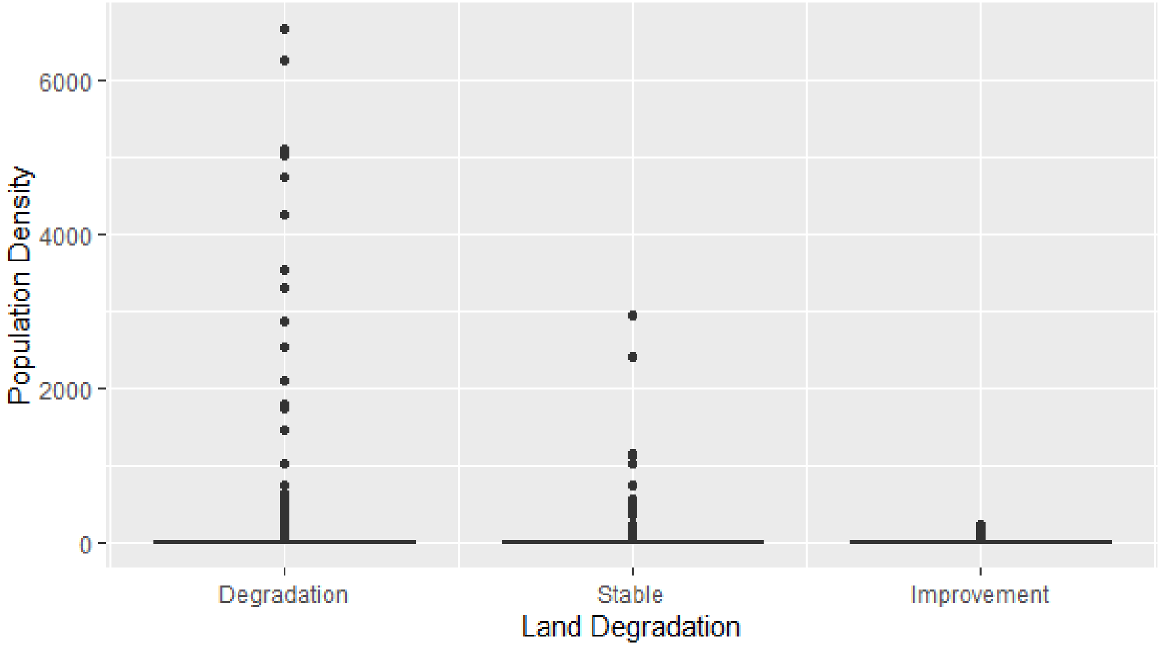


Figure 7. 2. Distribution of population density in land degradation category

Additionally, based on the calculation of population lives in land degradation shows that 1.304.969 people living in degraded land which based on the area located in 37% over the total country area. On the other hand, people living in stable land are 1.779.780 people which represent 46% of the total area. Furthermore, people living in improved which occupy 8% of the country resulted as 206.287 people. Thus, the population majority live in land degradation.

7.2. Land degradation and biophysical factors relationship

Some biophysical factors will be described in this section such as topography, land cover, climate, and ecosystem. The topography factors include slope and landform. While climate factors include bioclimate, annual PET, aridity index, temperature change, and precipitation change. Then, ecosystem factors include ecoregion, homogeneity of species, carbon storage, and biomass density.

Table 7. 1. Summary between environmental factors and land degradation type class

Environmental Factor	No	Data Available	Data type	Kruskal Walis/ Chi-Square	Spearman rank rho
Climate	1	Annual PET	continue	2.20E-16	0.132
	2	Aridity Index	continue	2.20E-16	-0.007
	3	Temperature change	continue	2.20E-16	-0.087
	4	Precipitation change	continue	2.20E-16	-0.080
Climate	5	Bioclimate	nominal	2.20E-16	
Biophysical factor	6	Homogeneity Species	continue	1.615E-13	-0.007
	7	Carbon storage	continue	2.2E-16	0.081
	8	Slope	continue	3.75E-01	
	9	Biomass Density	continue	2.2E-16	0.053
Biophysical factor	10	Landform	nominal	2.20E-16	
	11	Land cover	nominal	2.20E-16	
	12	Ecoregion	nominal	2.20E-16	
Population	13	Population Density	continue	2.20E-16	0.209
	14	Population	continue	2.2E-16	-0.027
Agriculture Crop	15	Farm System	nominal	4.60E-08	
	16	Agriculture risk	nominal	1.89E-08	
Agriculture Crop	17	Irrigation percentage	continue	5.11E-01	
	18	Fertilizer: Phosphorus	continue	0.484	
	19	Fertilizer: Nitrogen	continue	0.484	
	20	Barley	continue	2.2E-16	0.016
	21	Cotton	continue	2.2E-16	0.002
	22	Maize	continue	2.2E-16	-0.066
	23	Potato	continue	2.2E-16	0.003
	24	Rice	continue	2.2E-16	0.002
	25	Sugar beet	continue	2.2E-16	0.025
	26	Wheat	continue	2.2E-16	0.009
	27	Barley	continue	2.2E-16	0.048
	28	Cotton	continue	0.22	
	29	Maize	continue	2.2E-16	-0.023
	30	Potato	continue	2.2E-16	-0.005
	31	Rice	continue	2.2E-16	-0.014
	32	Sugar beet	continue	2.2E-16	0.008
	33	Wheat	continue	2.2E-16	-0.027
Agriculture Livestock	34	Livestock System	nominal	2.2E-16	
Livestock Agriculture	35	Pasture	continue	0.5163	
	36	Small ruminants	continue	2.16E-01	
	37	Sheep	continue	4.53E-06	0.000
	38	Goat	continue	2.07E-07	0.048
	39	Poultry	continue	2.026E-12	0.105
	40	Cattle	continue	2.20E-16	0.099

7.2.1. Land degradation and topography

Topography is one of the aspects which control one of the specific types of land degradation such as erosion. Soil erosion is key factors in the driving process of land degradation (Smetanová et al., 2019). One of the controls in erosion is the slope, then it can be inferred that slope is one of the key aspects in land degradation, but from the calculation in this study slope does not have a relationship with land degradation. The Kruskal Wallis test result showed that the p-value for slope is 0.375 which is not significant. Therefore, Figure 7. 3. Distribution of slope in land degradation category illustrated the average slope for each land degradation category shows that the average slope for land degradation in Kyrgyzstan is 8.3%. In contrast, stable land degradation has an average slope of 9.4% and land improvement has an average slope of 8.5%.

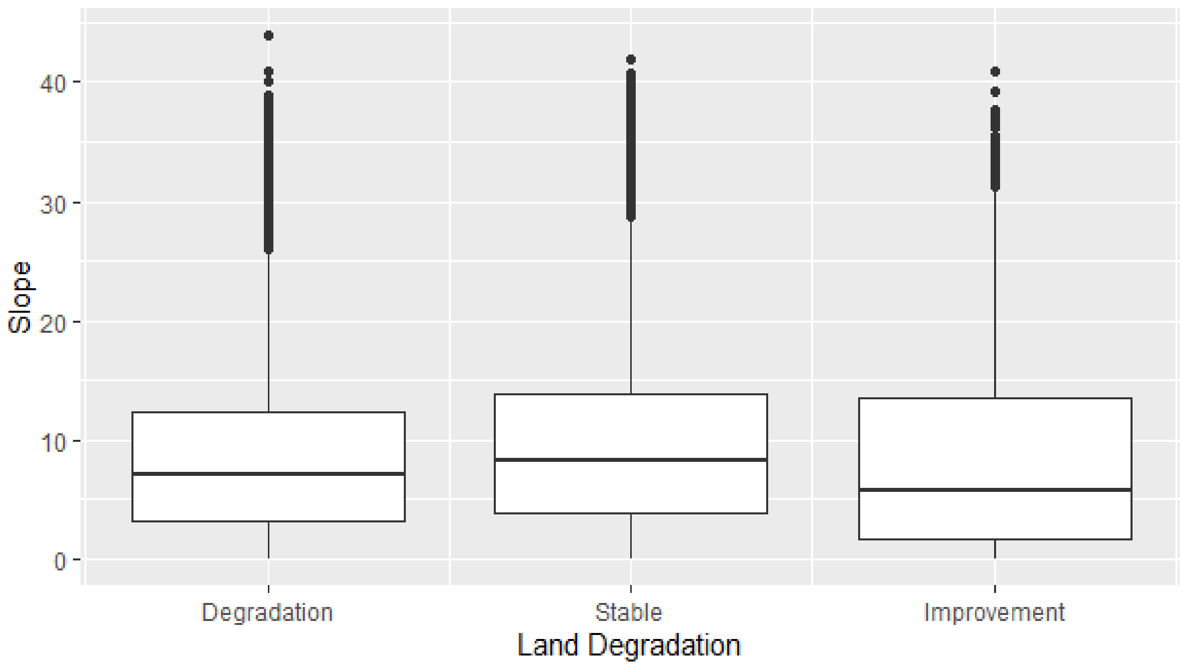


Figure 7. 3. Distribution of slope in land degradation category

Landform distribution in each type of land degradation presented in Figure 7. 3 shows that the stable land has the biggest proportion among the other landform. Landform 1 represent plains, 2 represent hills, 3 represent mountains and 4 represent water bodies. In the mountains area have the biggest proportion is stable land (23,7%), followed by degradation land (16%)

and a small portion of improvement land (3,8%). While in hills area the biggest proportion is stable land with 19.8%, followed by degradation land (17,4%) and improvement land for 2.2%. The plains area shows the same pattern with 6.9% is stable land, 6.7% is degradation land, and 2.4% is improvement land. The p-value from the Chi-squared test is 2,2 x 10^{-16} means that the landform has a relationship with land degradation class, but the relationship only visible in stable land not in degraded land.

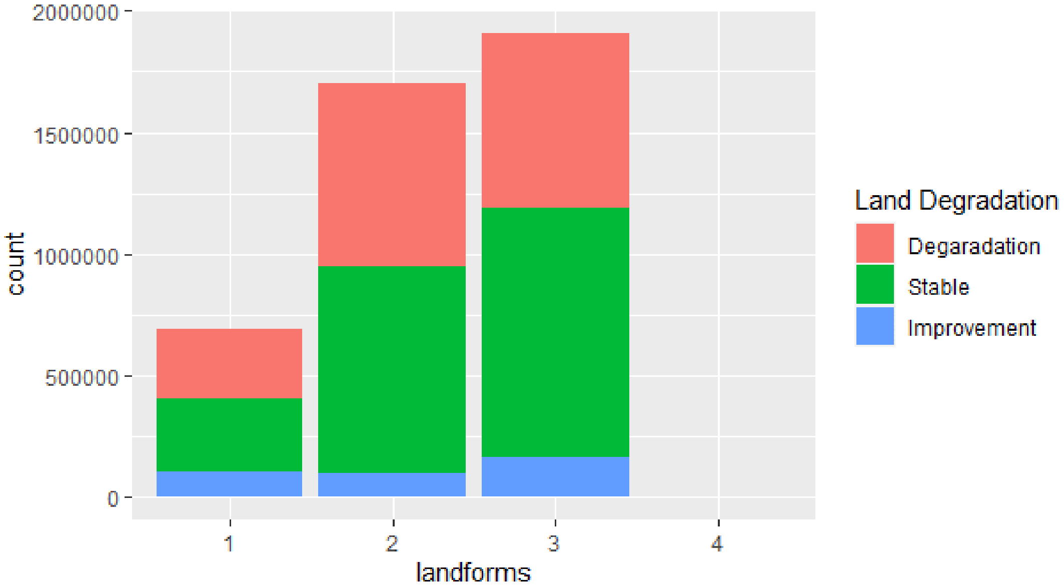


Figure 7. 4. Landform in each type of land degradation category

7.2.2. Land degradation and land cover

The relationship of land degradation status with land cover presented in Table 7. 1 shows that the independence test of Chi-square resulting p-value of 2,2 x 10^{-16} which means that the land cover is one of the variables that influence land degradation. This is can be explained as one of the sub-indicators of land degradation computation is land degradation. In contrast, there is only some of land cover type which has significant land degradation. The proportion of land degradation category for each land cover type presented in Figure 7. 5 shows the only significant amount of land degradation only found in sparse vegetation (1), bare land area (3), grassland (4), cropland (7), and evergreen forest (6). Based on Table 7. 2, the highest degradation found in the grassland land cover followed by bare land, cropland, and sparse vegetation. Even though the number of land cover in each type of land degradation has a similar pattern, the improvement land found the most in bare land area.

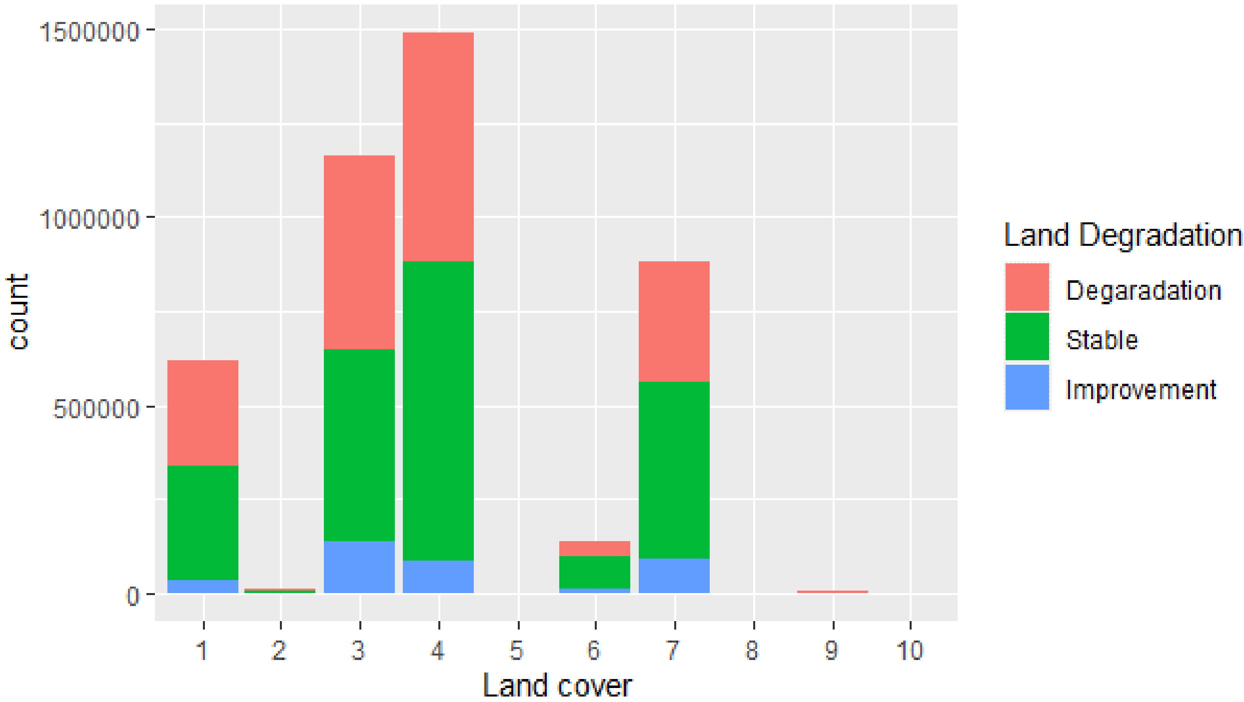


Figure 7. 5. Proportion of each land cover type in each land status

Table 7. 2. Land cover type in Kyrgyzstan

LC code	Land cover type	Degradation (%)	Stable (%)	Improvement (%)
1	Sparse vegetation	6.54	7.03	0.85
2	Snow and Ice	0.12	0.15	0.02
3	Bare land area	11.92	11.88	3.15
4	Grassland	14.08	18.54	1.99
5	Swampy area	0.00	0.01	0.00
6	Evergreen forest	0.80	2.05	0.28
7	Cropland	7.45	10.83	2.15
8	Deciduous forest	0.00	0.00	0.00
9	Urban	0.08	0.02	0.00
10	Water	0.02	0.03	0.01

7.2.3. Land degradation and climate variable

Climate variable including bioclimate, annual PET, aridity index, temperature change, and precipitation change, relationship with land degradation will be discussed in this part. The distribution of the bioclimate types already discussed in chapter 4 showed that the cool wet and cool semi-dry dominate the region. In general, as presented in Figure 7. 6 the distribution of the number of area coverage by certain bioclimate types are proportional with the number of the land degradation types. However, Table 7. 3 shows that there is one outlier found in the bioclimate of cold semi-dry where land degradation has a bigger proportion than the stable land. This area is dominance by bare land and high mountainous area. This outlier distribution explained the Chi-square result with a p-value of 2,2 x 10^{-16} which means that the bioclimate variable influences land degradation. In the other world, it can be interpreted that there is influence from bioclimates in land degradation. On the other hand, cold wet bioclimate has the highest number of land degradation followed by cool semi-dry. The cool semi-dry region has one of biggest is the area with the dominance of urban area and agriculture area.

Table 7. 3. Bioclimate types for each land degradation class in percentage

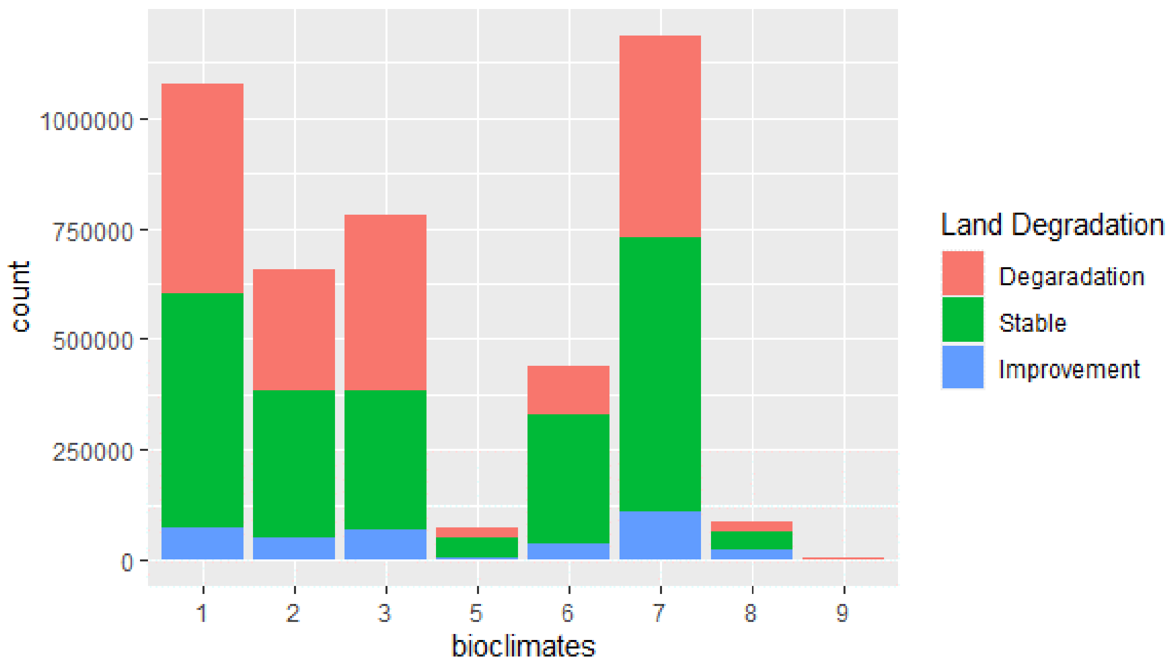


Figure 7. 6. Bioclimates types in each land degradation category

Bioclimates Code	Bioclimates	Degradation (%)	Stable (%)	Improvement (%)
1	Cold wet	11.12	12.25	1.69
2	Cold moist	6.43	7.74	1.12
3	Cold semi-dry	9.23	7.26	1.60
5	Cool wet	0.47	1.08	0.11
6	Cool moist	2.61	6.76	0.85
7	Cool semi-dry	10.61	14.39	2.58
8	Warm semi-dry	0.52	1.03	0.49
9	Water	0.02	0.03	0.01

The temperature change between 2001 to 2015 presented in Figure 7. 7 as temperature slope shows that land degradation has a slightly higher temperature than stable land and improved land. This is can be inferred that there is a relationship between land degradation and temperature. The calculation of Kruskal Wallis also resulted in a p-value of 2,2 x 10^{-16} which means that the temperature variable has influence in land degradation, but the degree of influence is very small with only -0.087 based on Spearman Rank rho coefficient in Table 7. 1.

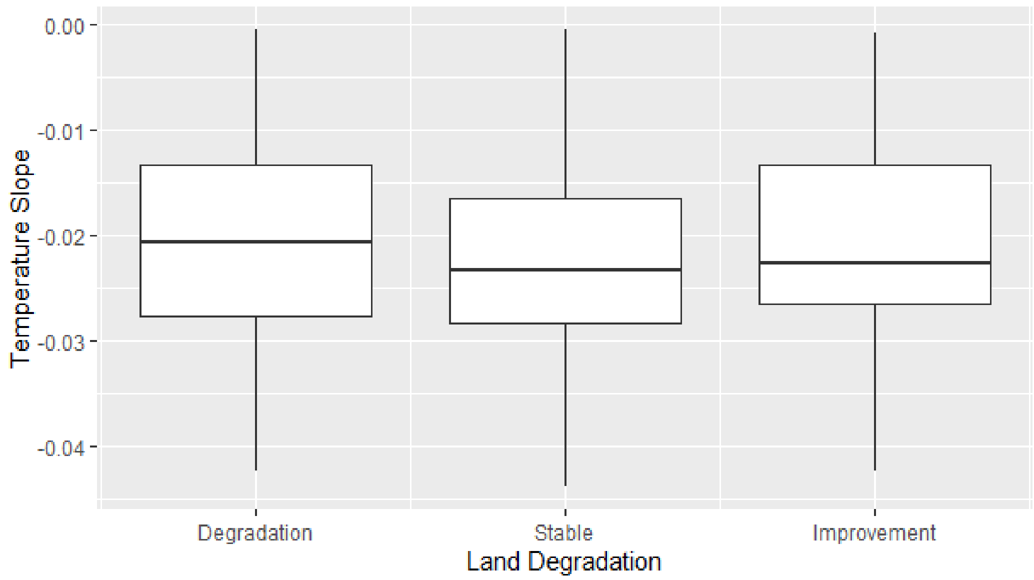


Figure 7. 7. Temperature change between 2001 to 2015 (slope) in each land class

Precipitation change presented in Figure 7. 8. Precipitation change in each type of land degradation status shows that the mean of precipitation in degraded land is higher than stable land and improved land. The Kruskal Wallis independence test also resulted in a significant p-value, but the influence is very low as presented in Spearman rank rho is a very small value. Thus, there is an influence of rainfall on land degradation. The average change of precipitation in land degradation recorded as 7,8 mm/year where the average precipitation change in stable land is 7,1 mm/year and improved land have 5.4 mm/year of precipitation change.

The opposite of precipitation is evapotranspiration, thus the analysis of annual potential evapotranspiration (PET) is conducted next. Based on Table 7. 1, the independence test of annual PET fulfils the significant p-value rule, and the value of Spearman rank rho is positive. In contrast, PET has higher than temperature and precipitation variable. This can be inferred that the annual precipitation has a bigger influence on land degradation status with positive influence. Figure 7. 9. Annual PET in each type of land degradation status shows that the PET in degradation land has a smaller average with about 736 mm per year where the stable land has a higher mean with 786 mm/year and improvement land shows an 810 mm/year average.

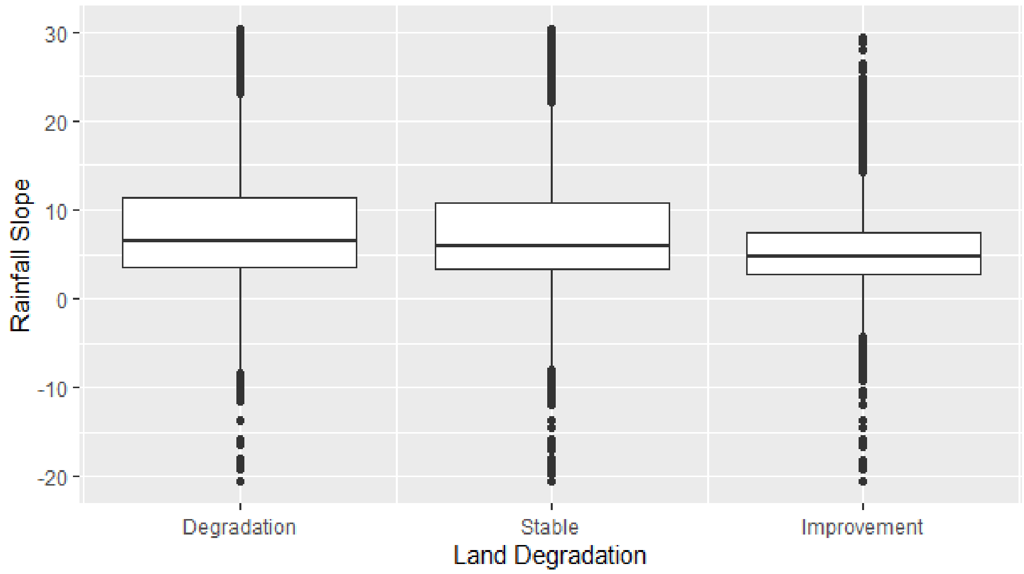


Figure 7. 8. Precipitation change in each type of land degradation status

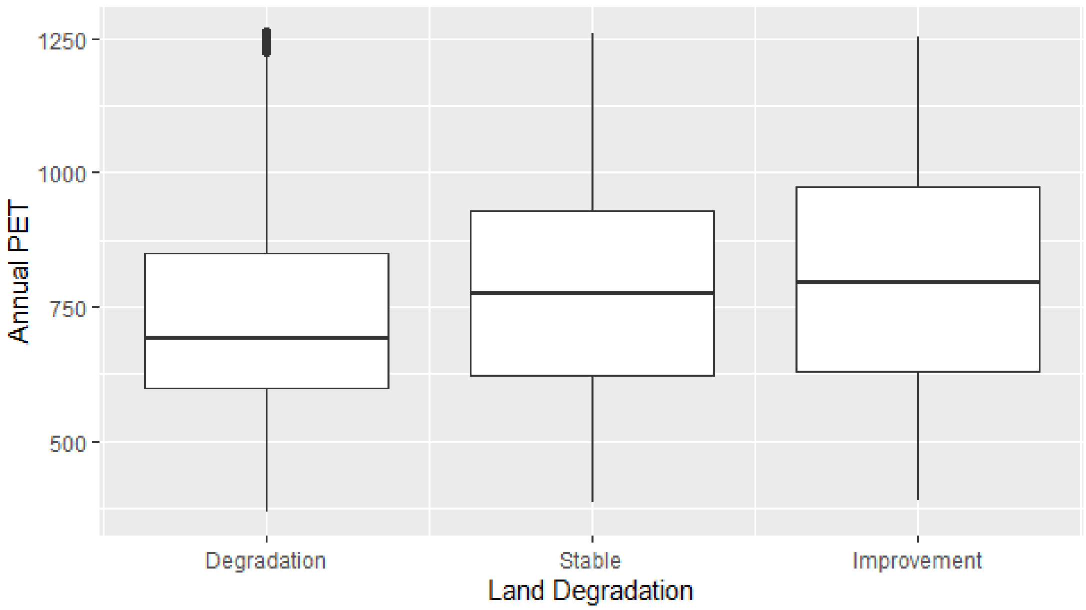


Figure 7. 9. Annual PET in each type of land degradation status

The other selected climate variable in land degradation is the aridity index. The result from Kruskal Wallis calculation in Table 7. 1 for aridity index shows that the p-value is less than 0.05 which means that there is an influence of aridity index in land degradation class. However, the degree of influence is very low with a very small value in Spearman rank rho with -0.007. The distribution of aridity index value in each type of land degradation status presented in Figure 7. 10 shows that the average aridity index in degradation land is almost the same with stable land with an average of 0.588 and 0.586 respectively.

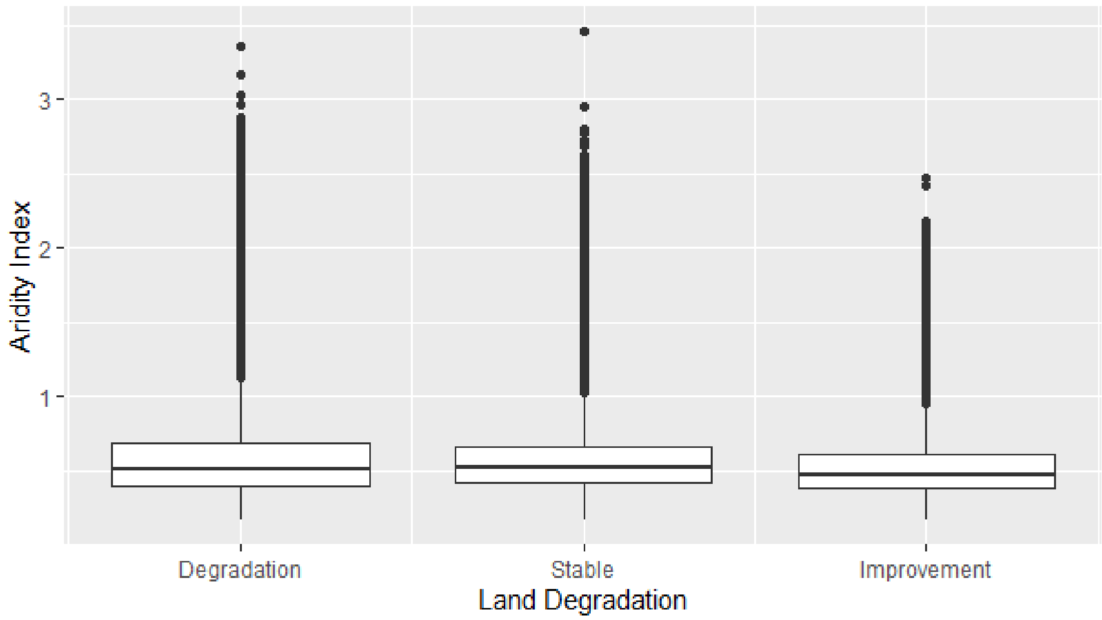


Figure 7. 10. Aridity Index in each type of land degradation status

7.2.4. Land degradation and other biophysical factors

The distribution of ecoregion in Kyrgyzstan is presented in Figure 7. 11 shows that Tian Shan mountains and Pamir Alpine dominate the region followed by Gissaro-Alai and a small part of Central Northern Desert. The distribution of land degradation in each land degradation status has a similar pattern as presented in Figure 7. 12. The stable land has higher coverage than degradation land and the least is a land improvement for every single ecoregion. However, there is an outlier where degradation land is slightly higher than stable land in the Tian Shan Montane Conifer Forest. Furthermore, resulted from the chi-squared test for ecoregion shows that ecoregion influences land degradation. Thus, it can be inferred that there is an influence of ecoregion in land degradation.

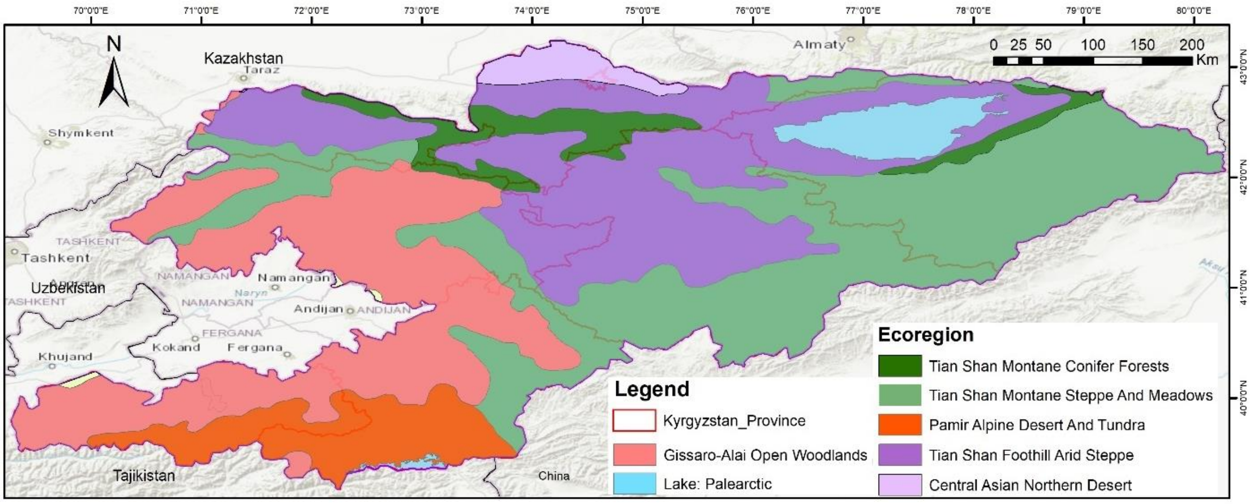


Figure 7. 11. Ecoregion in Kyrgyzstan (source shapefile: kyrgyzstanspatial.org)

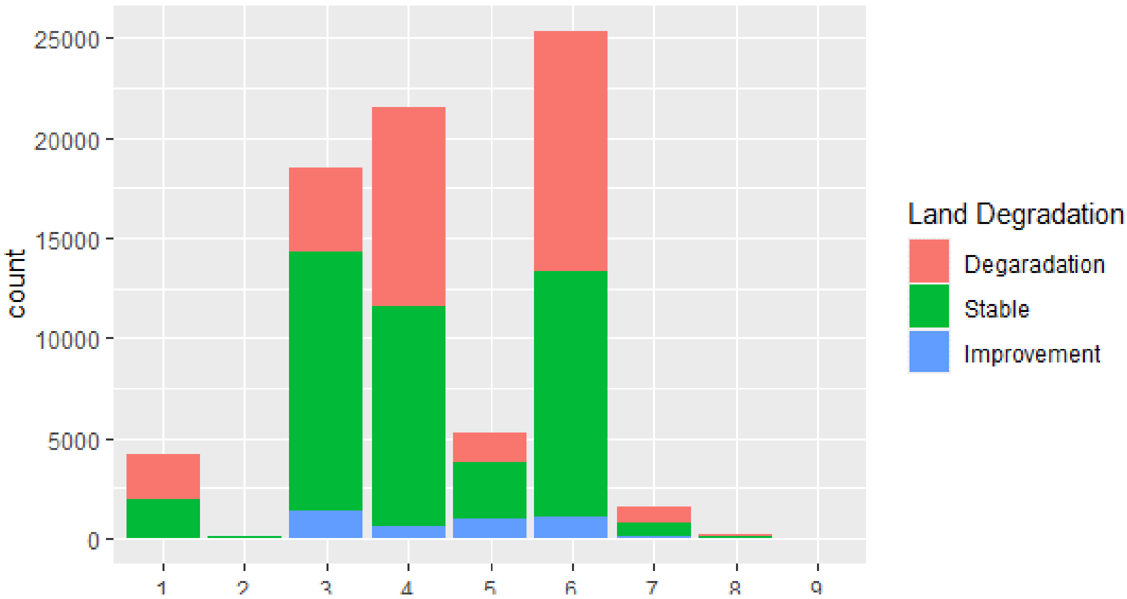


Figure 7. 12. Ecoregion distribution in each type of land category

Table 7. 4. Ecoregion in each type of land degradation

Code	Ecoregion	Degradation (%)	Stable (%)	Improvement (%)
1	Tian Shan Montane Conifer Forests	2.83	2.53	0.04
2	Alai-Western Tian Shan Steppe	0.02	0.09	0.02
3	Gissaro-Alai Open Woodlands	5.51	16.99	1.71
4	Tian Shan Foothill Arid Steppe	12.94	14.44	0.73
5	Pamir Alpine Desert and Tundra	1.87	3.67	1.27
6	Tian Shan Montane Steppe and Meadows	15.66	16.03	1.39
7	Central Asian Northern Desert	0.97	0.94	0.09
8	Lake: Palearctic	0.07	0.12	0.04
9	Rock and Ice: Palearctic	0.01	0.01	0.00

Species distribution in Kyrgyzstan has no influence on land degradation based on the chi-squared p-value presented in Table 7. 1. There is no relationship between the degradation status of land and homogeneity species per square kilometre. However, Figure 7. 13 illustrates the average number of species living in degraded land is 3.149 species per kilometer, in improvement land is 3289 species per kilometer and in stable land is 2975 species per km. Based on the total calculation, the total species living in degraded land are 2.709.918 species, while in stable land are 3.198.119 species and improvement land are 534.265 species.

Biomass density has a relationship with land degradation according to the p-value

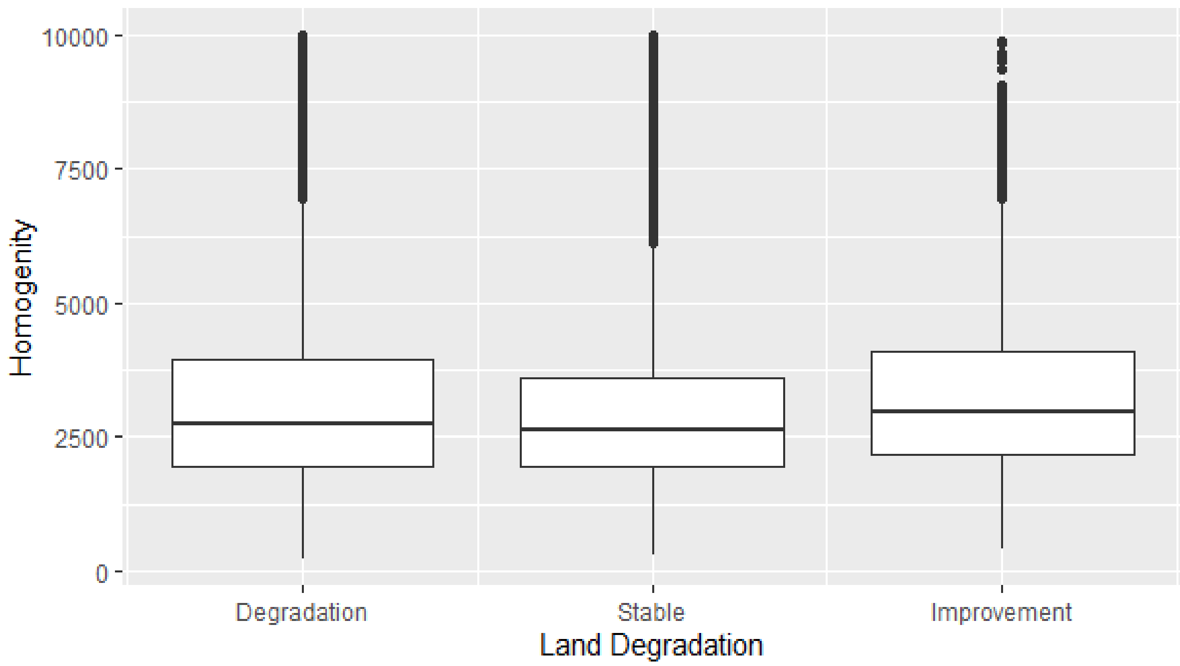


Figure 7. 13. Distribution of homogeneity species number of species in square kilometer per land degradation status

from the Kruskal Wallis test result in Table 7. 1. However, the degree of relationship is very low with only 0.053. The distribution of biomass carbon density per each land status are presented in Figure 7. 14. The data distributed quite scatter where many data did not fit the mean but the mean class for degradation land is 6.4, for stable land is 8.4, and for improvement land is 7.7 tons. The number of biomass carbon located in degraded land is 5.111 tons, in stable land is 8.083 and in improvement land is 1.170.

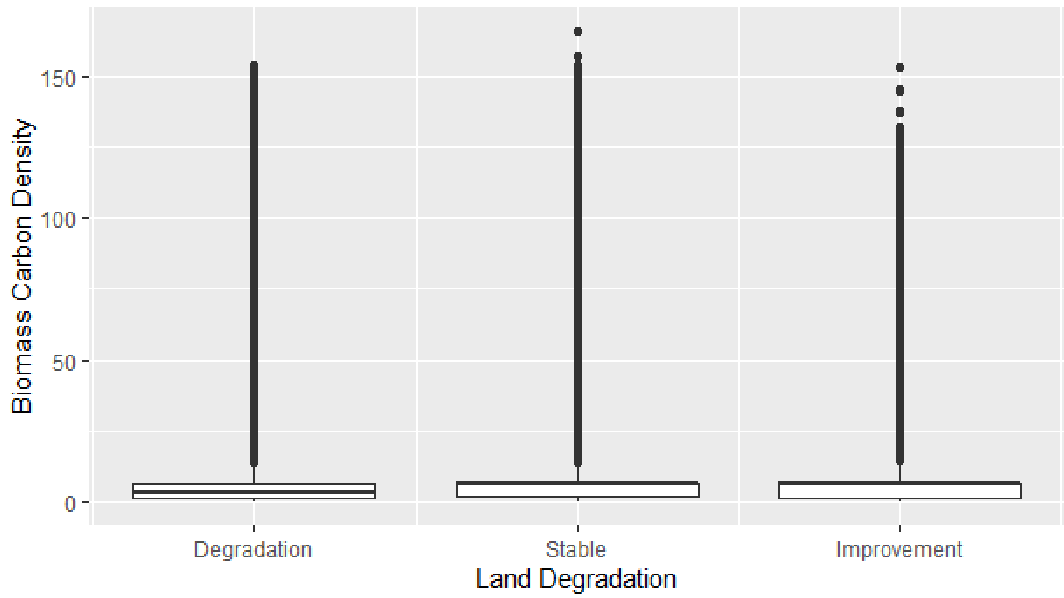


Figure 7. 14. Biomass Carbon Density per each land status

The distribution of carbon storage per ha in each type of land status is presented in Figure 7. 15. The distribution of carbon storage data per pixel value is very scattered where there are some data in degradation and stable land which very far away from the average value of carbon storage per hectare with more than 60 tons per ha. While the average pixel value is 8.2 for degraded land, 10.6 in stable land, and 4.5 in improved land. The total carbon storage in degraded land recorded as 6.805 tons, in stable land is 15.095 tons and 282 in improvement land. However, based on the Kruskal Wallis test the p-value is significant which means that there is a relationship of carbon storage in land degradation, but the relationship is small at about 0.081. even though this is a small value for the degree of relationship, this variable has the largest degree of relationship among other variables in the ecosystem. Thus, it is mean that the land degradation with selected ecosystem variable does not have a significant relationship with land degradation.

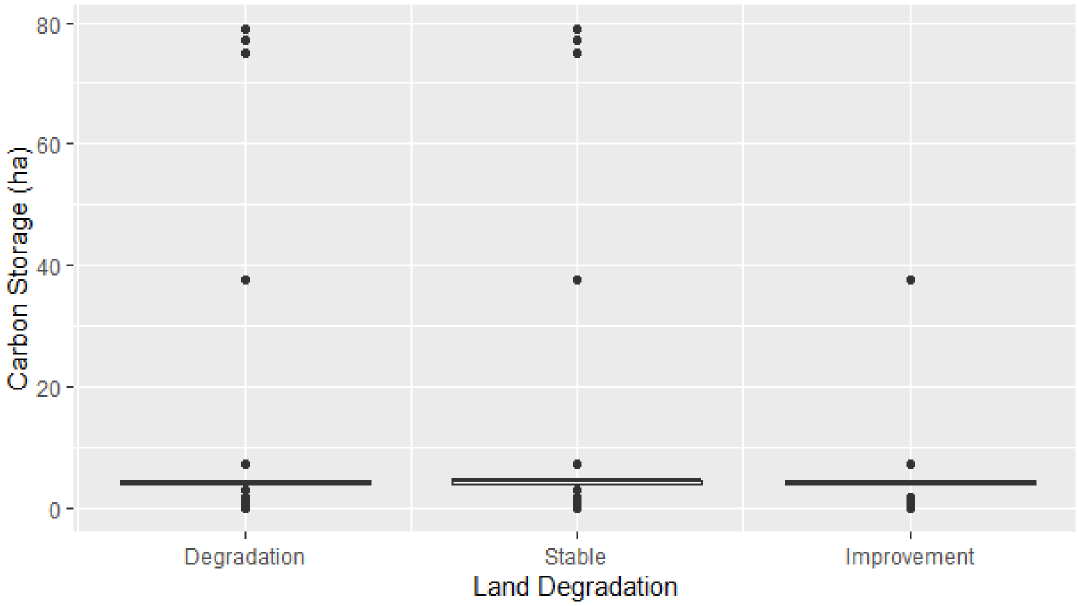


Figure 7. 15. Carbon Storage per hectare in each type of land degradation status

7.3. Land degradation and agriculture aspect relationship

Agriculture factors selected in this study are farm system, agriculture risk, irrigation percentage, fertilizer balance, area of crops and yields of crops, livestock system, pasture, and each type of animals.

7.3.1. Farm and Crop

The distribution of the farm system for each land degradation status presented in Figure 7. 16. Farm System for each land degradation status shows that the stable land dominates the other land degradation status for every farm system. The improvement land almost absent in every type of farm system but the biggest improvement land found in the Desert for about 1,27% Table 7. 5. Desert also cover most of the farm system. Even though based on Table 7. 1 the farm system has a significant p-value, but the interference of this statistic result is quite hard to understand as the distribution of the data is not supporting the relationship.

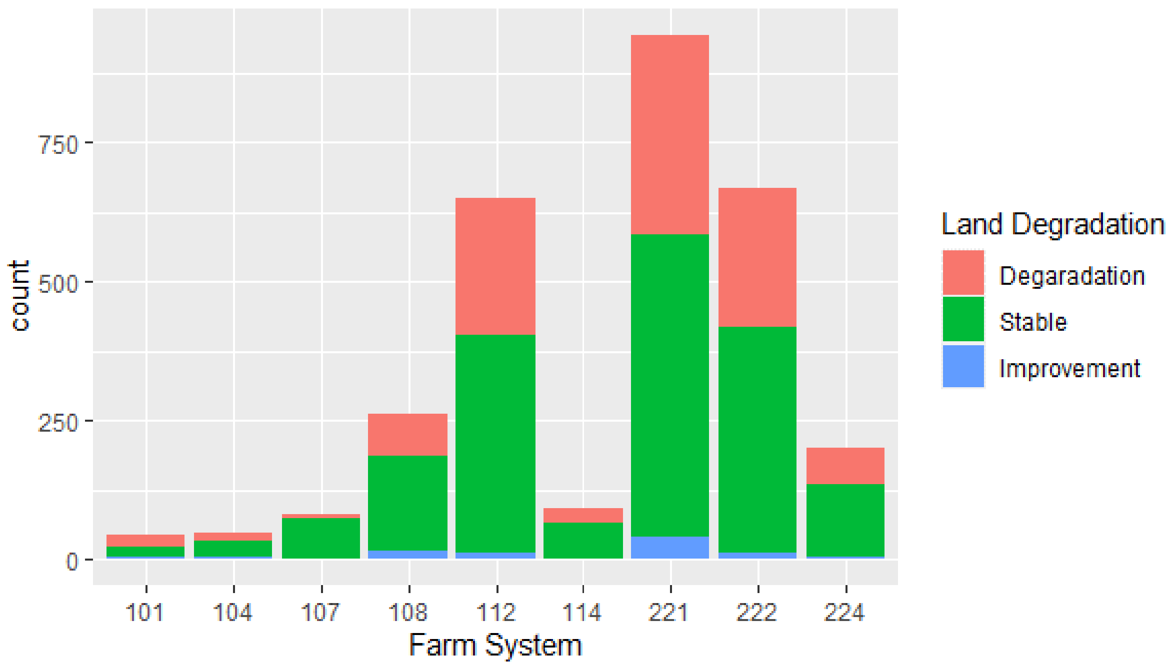


Figure 7. 16. Farm System for each land degradation status

Table 7. 5. *Farm type in each type of land degradation*

Code	Farm type	Degradation (%)	Stable (%)	Improvement (%)
101	Water	0.64	0.70	0.07
104	Other land	0.47	1.01	0.10
107	Forest	0.30	2.38	0.00
108	Irrigated land	2.61	5.73	0.44
112	Highland agriculture	8.27	13.13	0.37
114	Temperate agriculture	0.87	2.14	0.00
221	Desert	12.13	18.26	1.27
222	Dry Rangeland	8.48	13.67	0.30
224	Temperate rangeland	2.11	4.46	0.10

The distribution of land degradation status in agriculture risk shows that stable land found as most of the area coverage. The distribution of land degradation status in every agriculture risk shows the same pattern (Figure 7. 17). The majority categories of agriculture risk in Kyrgyzstan is low land and water risk which almost cover 63% of the total area as illustrated in Table 7. 6. While the second-largest agriculture risk is water scarcity where the biggest improvement land can be found. This water scarcity area has the largest proportion of improved land.

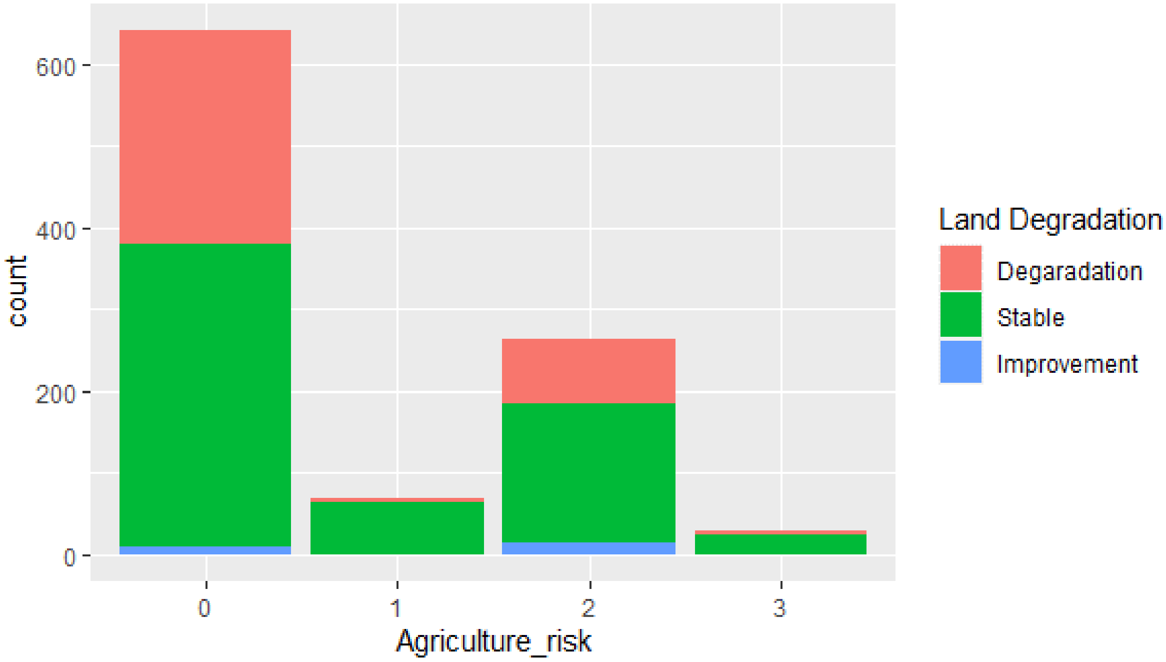


Figure 7. 17. Agriculture risk per land degradation status

Table 7. 6. Agriculture risk per land degradation

Agriculture Risk	Degradation (%)	Stable (%)	Improvement (%)
Low L&W scarcity	25.92	36.94	0.89
Land scarcity	0.70	6.16	0.10
Water scarcity	7.75	17.18	1.39
Land and Water scarcity	0.50	2.38	0.10

The distribution of irrigation percentage pixel value related to land degradation status are presented in Figure 7. 18. The improvement land has the highest average with 11.2% of irrigation per pixel area, but the most scatter data is stable land. Based on the calculation as presented in Table 7. 1, there is no relationship between land degradation and irrigation percentage.

The p-value of the chi-squared calculation of fertilizer (both phosphorus and nitrogen) and land degradation did not fulfil the criteria of confidence level (p-value <0.05). Thus, both of this variable does not have any relationship in land degradation status. However, presented in Figure 7. 19 and Figure 7. 20 the average value of fertilizer balance per land degradation which is negative for both variables.

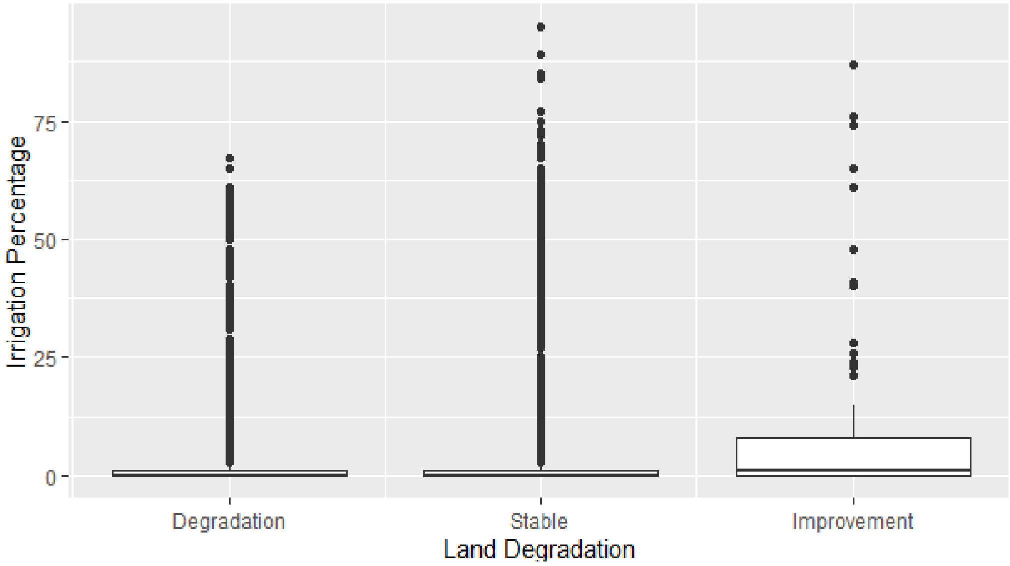


Figure 7. 18. Irrigation percentage per land degradation status

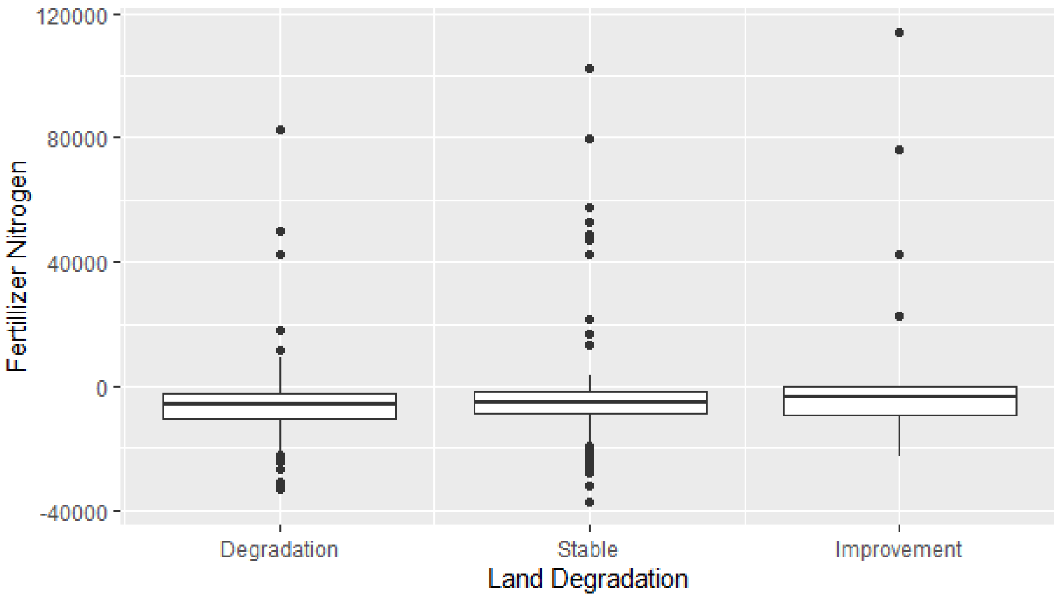


Figure 7. 19. Nitrogen balance per land degradation status

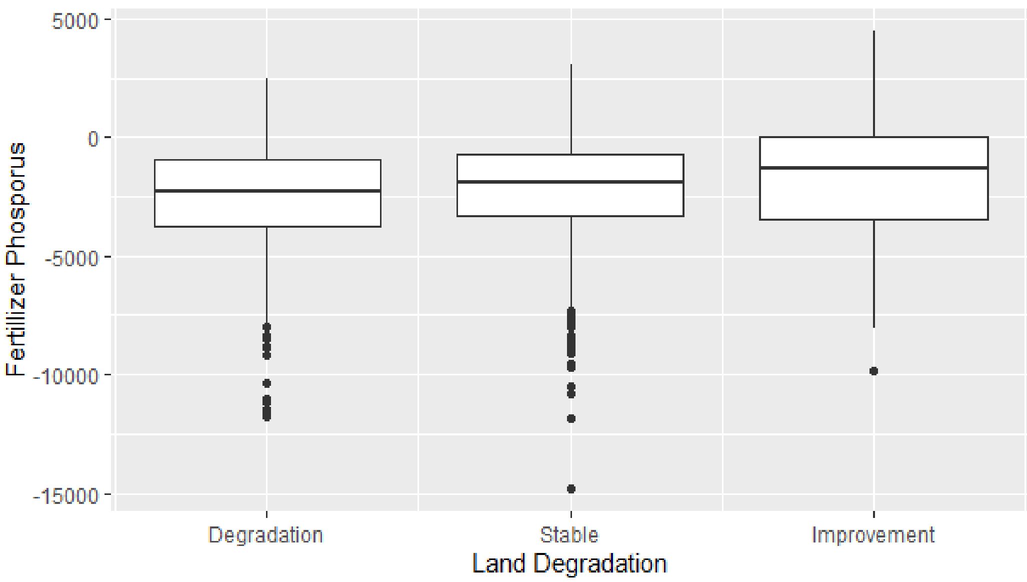


Figure 7. 20. Phosphorus balance per land degradation status

The crop production in Kyrgyzstan are grains, wheat, barley, corn or maize, rice, sugar beet, cotton, tobacco, vegetables, melons, grapes, fruits and berries (National Statistical Committee of Kyrgyz Republic, 2020). However, in this study, only seven crops will be analyzed namely barley, cotton, maize, potatoes, sugar-beet, rice, and wheat, due to the availability of the spatial data from kyrgyzstanspatial.org. There are two types of crop data specifically the total area and yield. Based on Table 7. 1, the result of p-value classification for the area of crops is significant (p-value <0.05) means that there is a relationship between land degradation status and crop types. However, the degree of relationship is very small as presented in Spearman rank rho value. This pattern also similar to the yield of crops.

The distribution of area with crops per hectare per pixel in each type of land degradation presented in Figure 7. 21 to Figure 7. 27. In general, the average area of crops is small as presented in Table 7. 7 and the box plot for every crop in figure 7.22 to 7.28, compared to the outlier data presented in the black circle found on the outside of the box. The exceptions are for wheat Figure 7. 26. Wheat crops area distribution in land degradation type and sugar beet (Figure 7. 27. Sugar beet crops area distribution in land degradation type where the distribution of the data is less number in outlier data. The average areas per crops in each land degradation and the total amount of area per crops in each type of land degradation presented in Table 7. 7. The total area in stable land is the largest total area for every type of crops, but the number of total areas in degradation land is higher than improvement land.

Table 7. 7. Average of crops area and crops total area in each land degradation type

Crops	Average (Ha)			Total Area (Ha)		
	Degradation	Stable	Improvement	Degradation	Stable	Improvement
Barley	25.10	25.99	39.29	21,822.97	31,125.91	4,578.97
Cotton	13.29	14.49	25.32	11,524.82	17,400.42	2,935.59
Maize	14.30	19.77	53.67	12,452.47	23,727.16	6,187.76
Potato	22.49	23.44	31.40	19,616.08	28,048.73	3,629.15
Rice	2.12	2.17	3.28	1,843.17	2,610.08	379.52
Sugar beet	7.24	7.54	10.16	6,311.09	9,012.40	1,187.57
Wheat	157.13	158.73	196.10	136,680.60	190,130.80	22,817.78

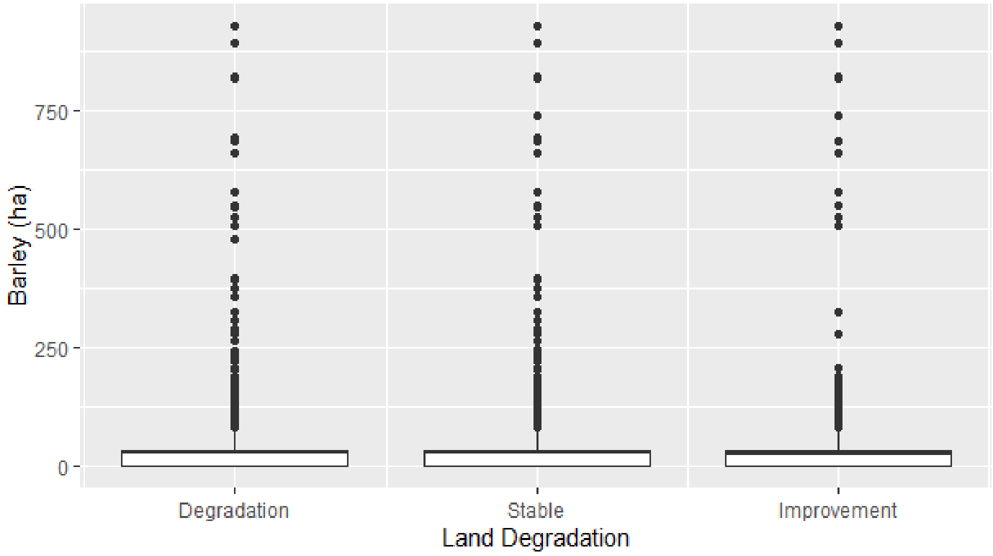


Figure 7. 21. Barley crops area distribution in land degradation type

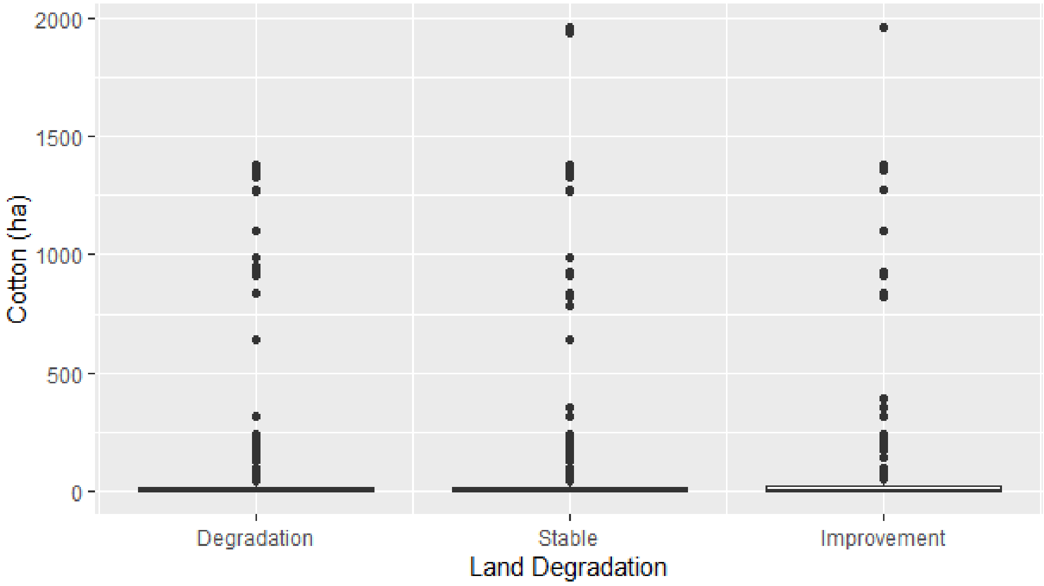


Figure 7. 22. Cotton crops area distribution in land degradation type

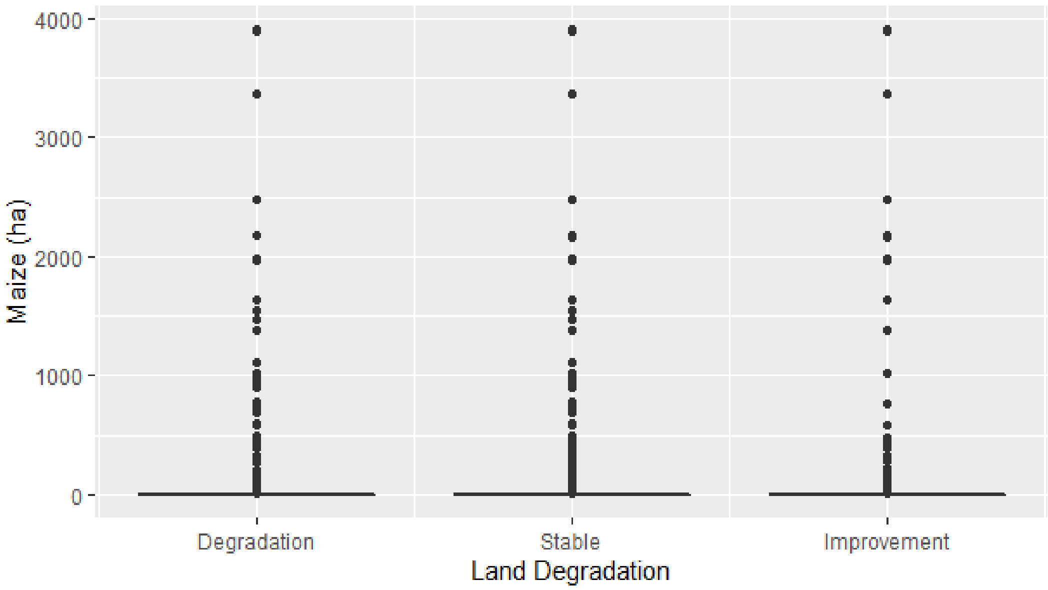


Figure 7. 23. Maize crops area distribution in land degradation type

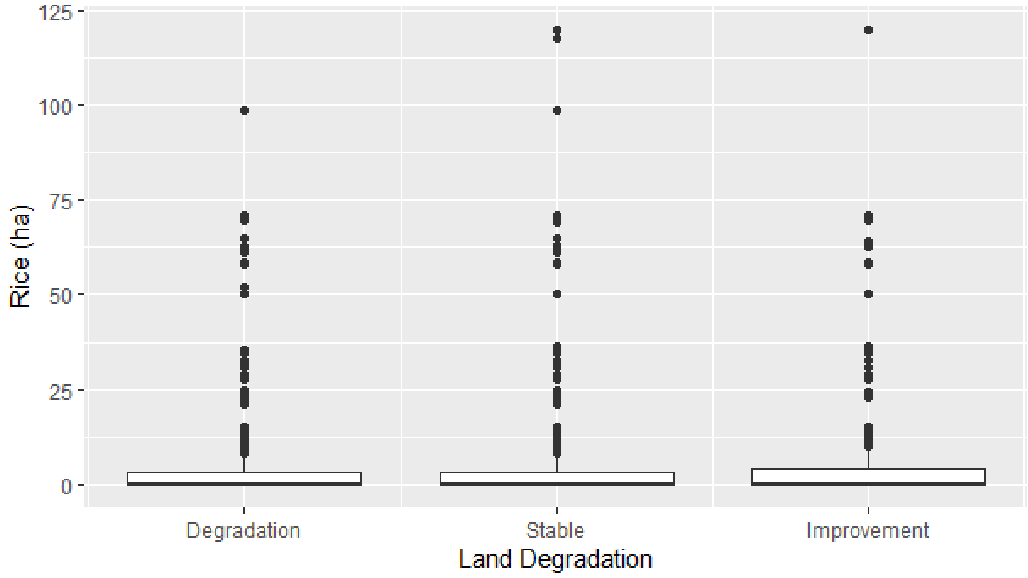


Figure 7. 24. Rice crops area distribution in land degradation type

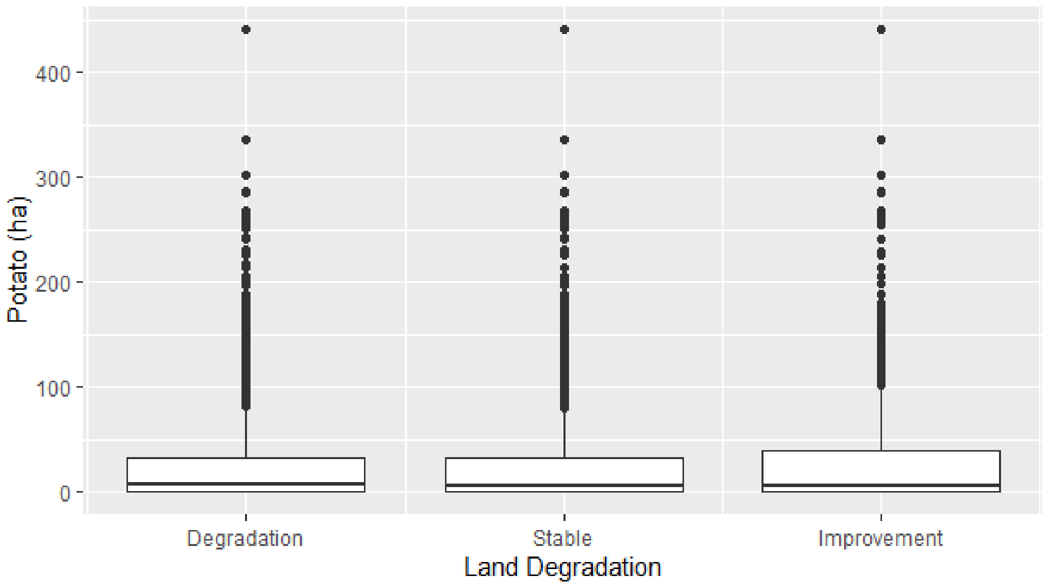


Figure 7. 25. Potatoes crops area distribution in land degradation type

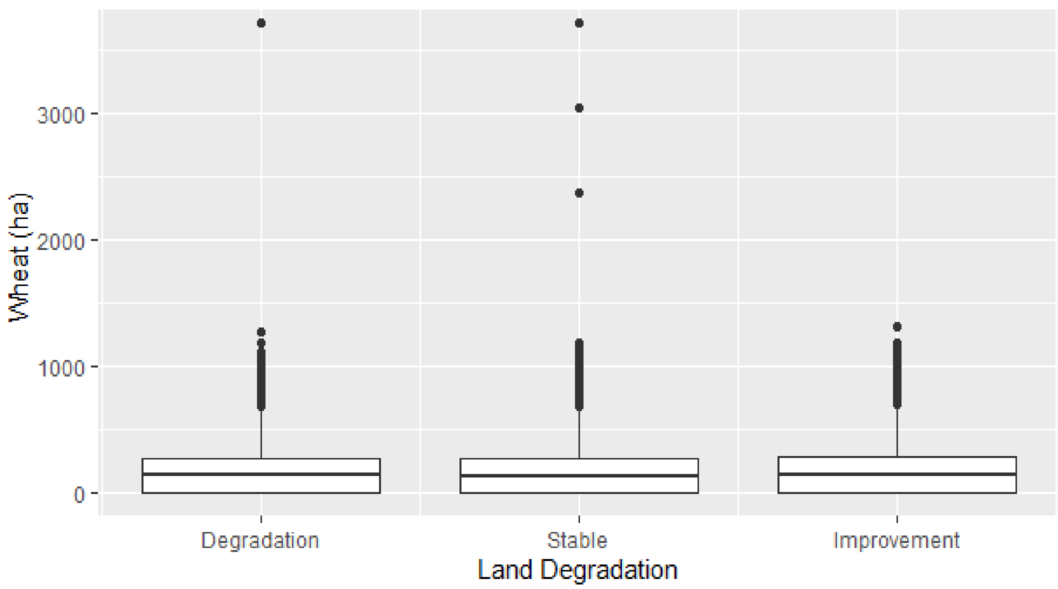


Figure 7. 26. Wheat crops area distribution in land degradation type

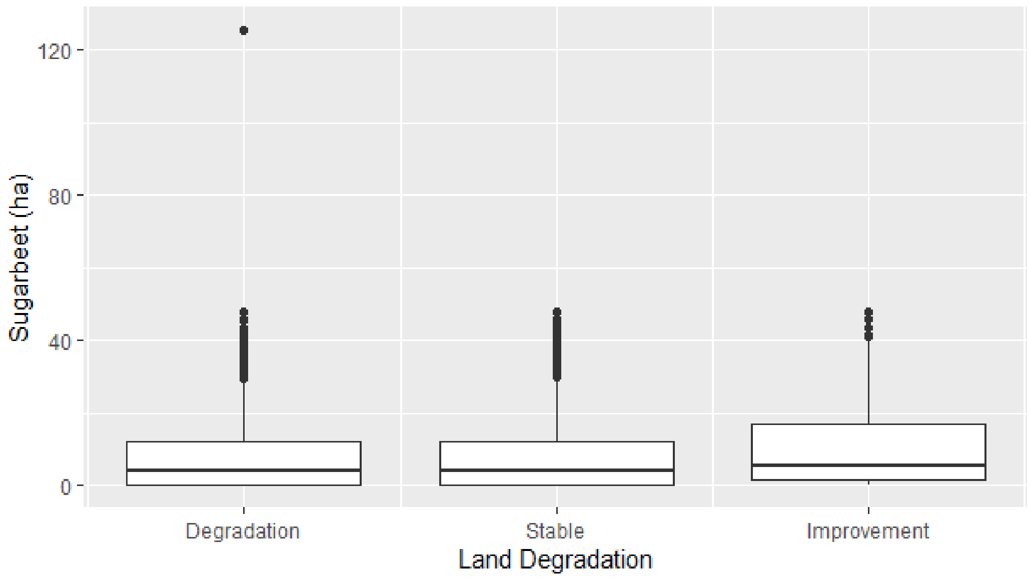


Figure 7. 27. Sugar beet crops area distribution in land degradation type

The distribution of total crops area compared to each land status type presented in Figure 7. 2 shows that wheat is the largest area of crops followed by barley and potatoes. The distribution of areas found in degradation and stable land. The interesting fact is that even though wheat has the largest area of crops the yields are quite small as presented in Figure 7. 28. The largest yield is sugar beet and followed by potatoes.

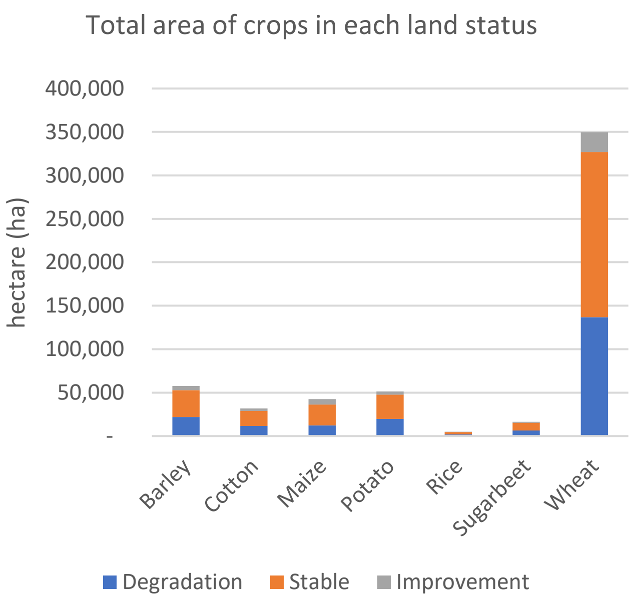


Figure 7. 29. Total areas of crops in each land status

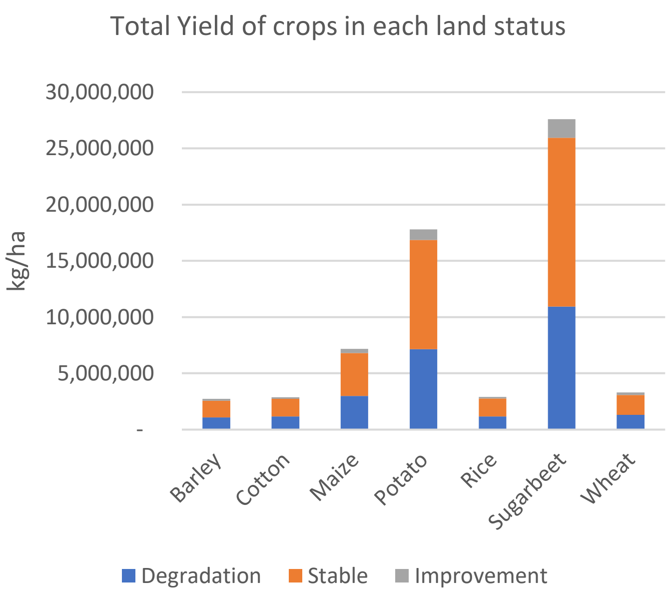


Figure 7. 28. Total yields of crops in each land status.

7.3.2. Pasture and Livestock

Apart from crops, Kyrgyzstan has livestock product including meat and dairy product. The main grazing management for livestock product in Kyrgyzstan is pasture. Pasture has characteristic of enclosed area and separated from other areas by a barrier such as a fence (Allen et al., 2011). The distribution of pasture area in Kyrgyzstan in percentage per pixel area is presented in Figure 7. 31. The concentration of the pasture is found in the middle of the country especially in the surrounding border area of Talas, Jalal-Abad, Osh, Naryn, and Chuy province. The distribution of pasture area percentage in each land status presented in Figure 7. 31 shows that the average of pasture in degradation land is higher with 52% than stable land with 48.6%

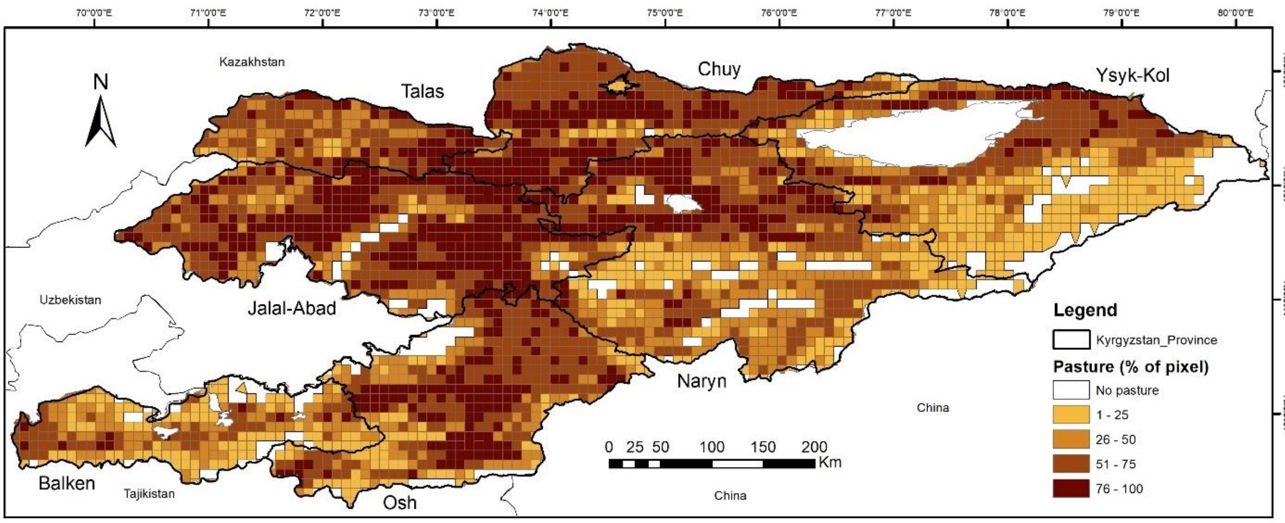


Figure 7. 31. Pasture area percentage of pixel in Kyrgyzstan

and

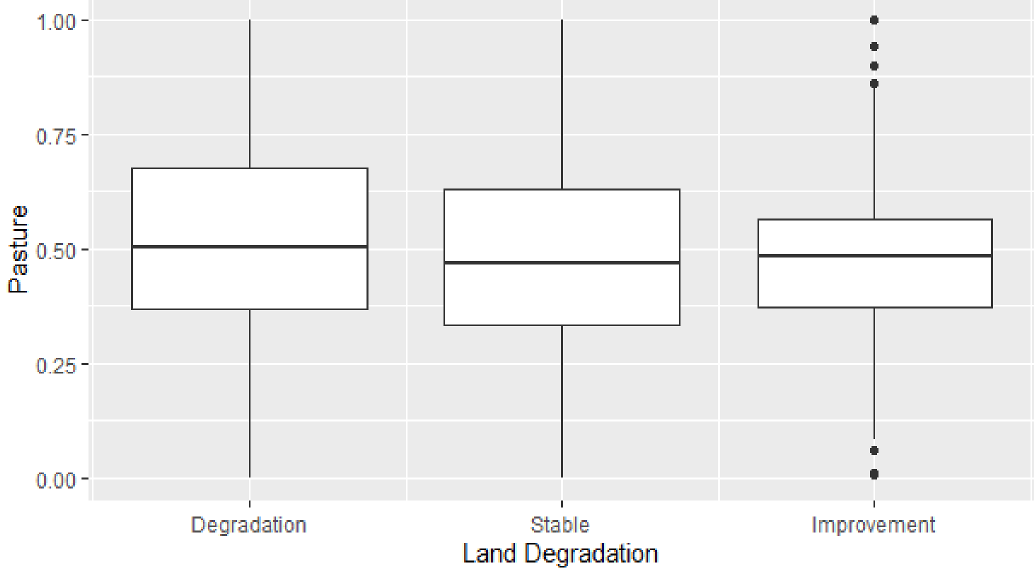


Figure 7. 30. Distribution of pasture percentage per pixel in each type of land status

improvement land with 48.1%. However, based on Table 7. 1 p-value of pasture percentage, shows that there is no relationship between this variable with land degradation status.

The livestock system in Kyrgyzstan as a percentage in chapter 4 before has the highest number in Temperate highlands grassland-based system. Thus, the distribution of degraded land is also in this livestock system, but overall the stable land still dominates the other land type for each livestock system Figure 7. 32. The livestock system is shown in the p-value of the chi-squared test in Table 7. 1 influences land status. However, the relationship is that stable land has the highest area compare to the other land as presented in Table 7. 8.

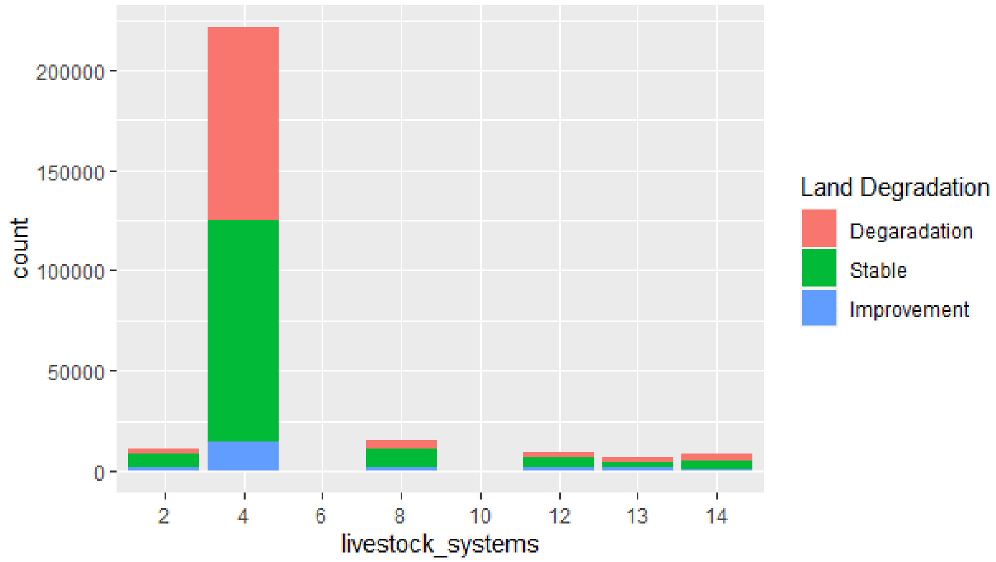


Figure 7. 32. Livestock system in each land status

Table 7. 8. Livestock system in each land status

Code	Livestock System	Degradation (%)	Stable (%)	Improvement (%)
2	LGA - Arid and semi-arid grassland-based system	1.02	2.63	0.47
4	LGT - Temperate highlands grassland-based system	35.37	40.63	5.37
6	MRA - Arid and semi-arid rain-fed system	0.01	0.06	0.00
8	MRT - Temperate highlands rain-fed system	1.38	3.60	0.53
10	MIA - Arid and semi-arid mixed system	0.00	0.01	0.01
12	MIT - Temperate highlands mixed system	0.98	1.70	0.63
13	Urban area	0.98	1.16	0.46
14	Other	1.20	1.51	0.26

Apart from the crop, Kyrgyzstan also has high production in livestock. There are some common breeds in the livestock system in Kyrgyzstan including cattle, sheep, goats, horses, poultry, and pigs recently (Mogilevskii et al., 2017). The selected livestock analysis in this study is limited due to the availability of the spatial dataset from kyrgyzstan.org. The selected livestock are poultry, small ruminants, sheep, goat, and cattle. Based on the Kruskal Wallis test p-value result in Table 7. 1, the livestock has influence in land degradation except for the small ruminant where the p-value is >0.05. However, the degree of influence is very small with the largest degree is poultry 0.1, followed by cattle with 0.09, the goat with 0.04, and sheep with -0.0001.

The distribution of livestock density (heads per hectare) in every land status of degradation, stable, and improvement land presented in Figure 7. 34 to Figure 7. 38. Distribution of cattle density (heads per square km) in each land status. The average livestock density per livestock is quite small as presented in Table 7. 9 with a range from 3.61 heads per square kilometers to 20.94 heads per square kilometer. Nevertheless, the distribution of data has many outliers with almost 1500 heads per square kilometer such as in Poultry (Figure 7. 34). and small ruminants (Figure 7. 35. Distribution of small ruminant density (heads per square km) in each land status). Total livestock in each land status presented in Figure 7. 33 shows that the largest number of livestock is small ruminants while the smallest is the goat. The highest total livestock is found in stable land, followed by degraded land, and the least in improved land.

Table 7. 9. Average of the distribution of livestock per heads/sq km

Livestock	Degradation (head/km^2)	Stable (head/km^2)	Improvement (head/km^2)
Poultry	17.07	15.58	16.46
Small ruminants	20.10	20.94	17.40
Sheep	17.79	15.63	8.64
Goat	3.89	4.31	5.74
Cattle	4.19	5.83	3.61

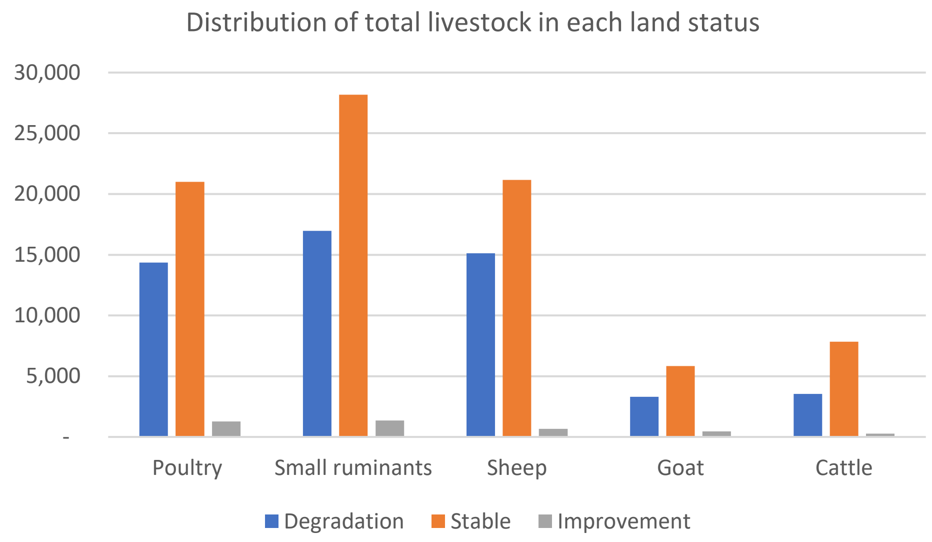


Figure 7. 33. Distribution of total livestock is each land status

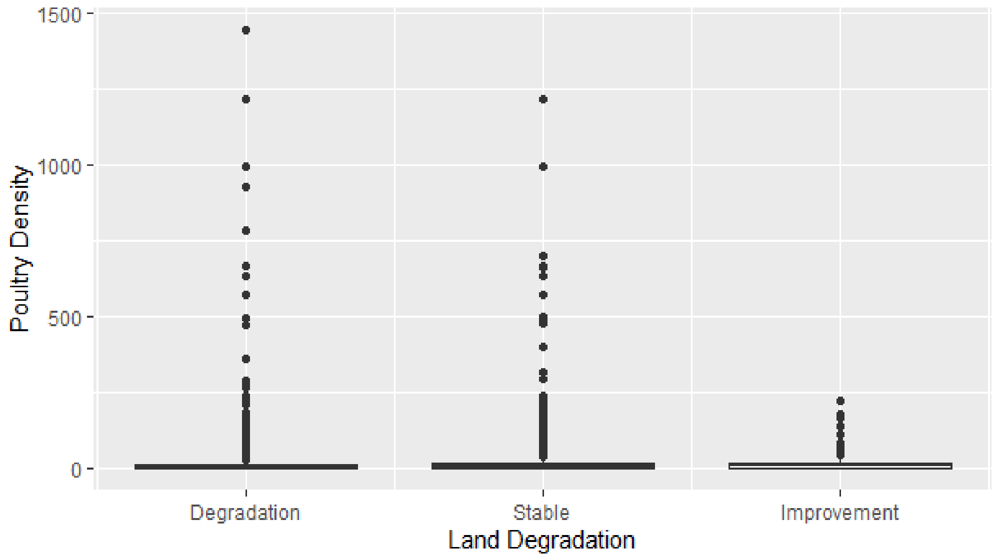


Figure 7. 34. Distribution of poultry density (heads per square km) in each land status

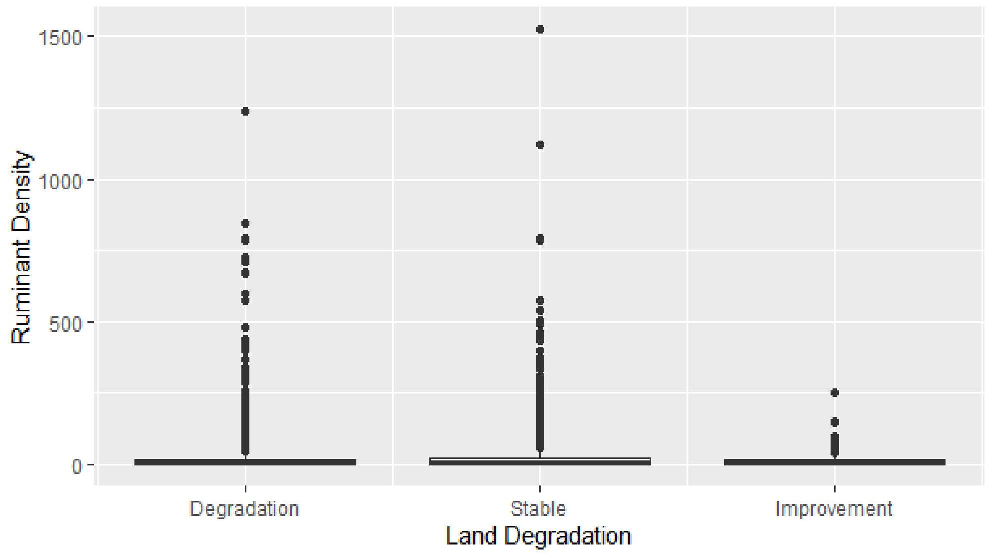


Figure 7. 35. Distribution of small ruminant density (heads per square km) in each land status

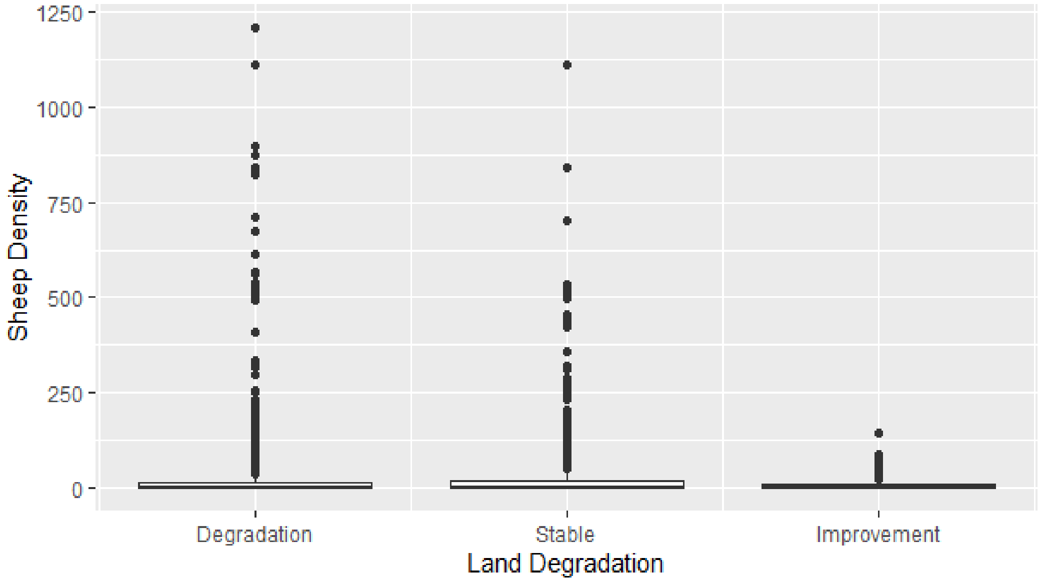


Figure 7. 36. Distribution of sheep density (heads per square km) in each land status

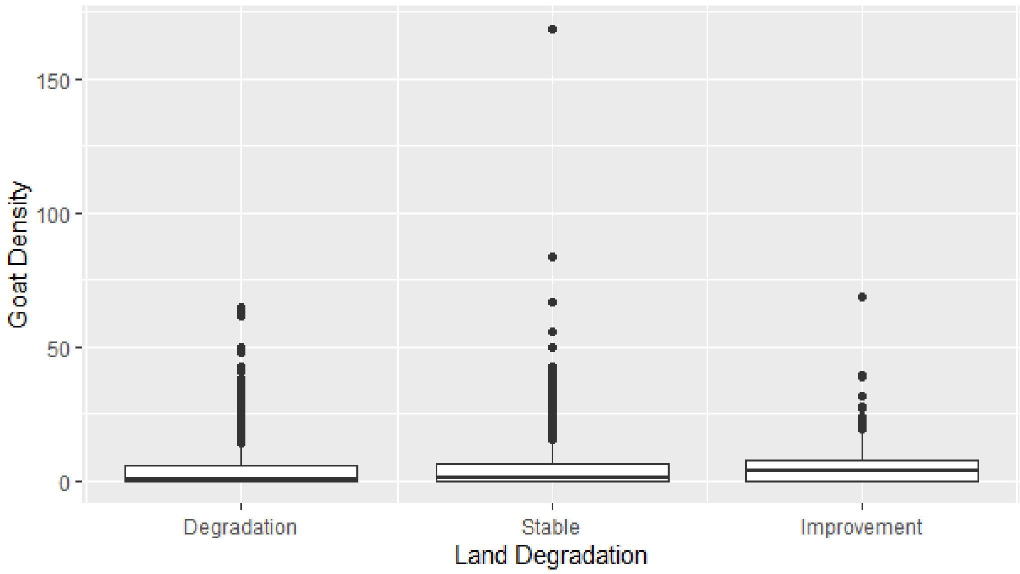


Figure 7. 37. Distribution of goat density (heads per square km) in each land status

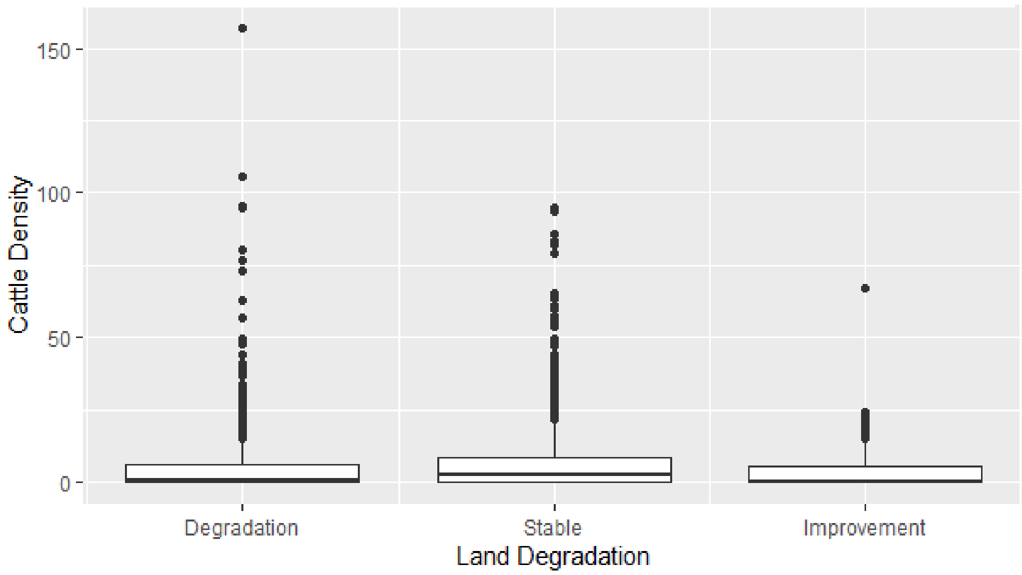


Figure 7. 38. Distribution of cattle density (heads per square km) in each land status

8. Discussion

Land degradation in Kyrgyzstan affected 37.32% of the total country area or 71.574 square km for the 2001-2015 study period compared to the degraded land of 23.189 square km or 11.68% of the total country area for the 1981-2003 study period (Bai et al., 2008). This huge difference cannot be directly inferred that a large amount is increasing of land degradation but also need to consider the different approach to calculate land degradation. This study uses three sub-indicator and the other study only used the NDVI. The other consideration is the input data quality where this study using NDVI with 250 meters resolution and the other study used a global scale of AVHRR GIMMS data with 1km resolution. Thus, the calculation of the previous study will have many errors.

Land Degradation National target setting

Based on this study result, the number of poultry and sheep has a higher average in degraded land and one of the LDN target settings in Kyrgyzstan to improve pasture using rotation pasture system. The rotation system is one of the best strategies to tackle degradation in the pasture area. The other degradation national target in Kyrgyzstan has conducted land improvement in 10.000 ha. This can be achieved through sustainable land management (SLM) or sustainable use system which require promotion and serious engagement with the concerned farmer, the right institutional framework, proper communication, and extensive work (Ruppert et al., 2020). This is since the SLM is a strange concept in agriculture practice in Kyrgyzstan, so then the knowledge of different groups is much more disconnected (Wolfgramm et al., 2013). Raising awareness among farmers, planners, stakeholder, and policymakers is the key to reduce land degradation.

Climate factors in land productivity

NDVI trends analysis methods enable the mapping of land productivity change using non-parametric analysis (Montfort et al., 2021). Furthermore, the NDVI time series can be paired with the climate factor to analyze the factor of climate effect in land productivity. Such as the negative NDVI-PDSI correlation presented in increasing land productivity is one of the results of this study. This result is in line with Vicente-Sergio et al. (2015) studies where there is a negative gradient between NDVI trends and drought severity index shows that the increasing NDVI related to the less drought severity index. However, the vegetation activity process is very complex where solely climate factors will not be enough to understand land productivity factors. The other alternative approach is to incorporate climate oscillation and analyze seasonal weather conditions (Tomaszewska & Henebry, 2020) instead of using a general summary like in this study using annual climate data variable.

Relationship between land degradation and environmental factors

The study by Mirzabaev et al. (2016) stated that the drivers of land degradation in rangeland area mainly driven by overgrazing of pasture is relevant with this study where the high percentage of pasture areas are found in degraded land. However, the drivers of land degradation in mountainous area are related to slope has in the form of sloping cultivation has different result with this study. This study resulted as there is no influence from slope to land degradation.

Agriculture practice is one of the prominent cause of land degradation especially soil degradation in Central Asia including Kyrgyzstan and overgrazing of pasture especially is the cause of land degradation in Kyrgyzstan (Qushimov, n.d.). This result is also supporting the result of this study where the crops and livestock influence land degradations. However, Conversational Agriculture (CA) concept is suggested to reverse land degradation trends through increasing carbon storage, soil fertility, infiltration, and water retention (Pereira & Bogunovic, n.d.). The major factors of the soil degradation process in the Kyrgyzstan area include wind erosion, deflation, waterlogging of lands, overwetting of lands salinization, and progressive development of solonization (Shpedt & Aksenova, 2021).

The distribution of the total variable in land degradation status

The total population affected by land degradation is 12.71% or 682.072 people during the 1981 to 2003 study period (Bai et al., 2008). While the calculation result from this study shows that 1.779.780 people or 46% population is living in degraded land according to 2015 population data. This difference possibly because of the urbanization process and the proportion of people living in the village which is in degraded land. On the other study, the total population living in degrading agricultural land in 2010 is 1.170.989 people or 33.2% of the total population compared to 1.009.656 or 31.9% in 2000 (Global Mechanism of the UNCCD, 2018). This calculation using the same approach as the LDN framework.

Potential solution of Land Degradation

Apart from degraded land, the degradation process also needs to be considered to achieve land degradation neutrality. Based on the science conceptual framework, the avoid of land degradation has the highest priority, followed by reducing the degradation process and even the reversion of land degradation has the least priority (Sims et al., 2019). Thus, reduction of the land degradation process is much more encouraged than reverse degraded land. In Kyrgyzstan, at least 88% of the lands are undergoing a land degradation process (Shpedt & Aksenova, 2021). On the other hand, land degradation also reducing crop yields by 20-60% (Shpedt & Aksenova, 2021). Moreover, The cost of land degradation in Kyrgyzstan calculated as 601 million USD which equal 16% of the GDP of the country (Global Mechanism of the UNCCD, 2018).

As resulted in this study that the majority of the SOC is held by tree-covered area which is only 4% of the total area, the possible solution is through restoration. The restoration distribution over land degradation status presented in Figure 8. 2 where 0 represent no restoration, 3 represent mosaic restoration, and 4 is agriculture lands. The restoration is most likely to present in stale land than in degraded land. The distribution of restoration presented in Figure 8. 1 shows that the area without restoration is still dominated in the entire region.

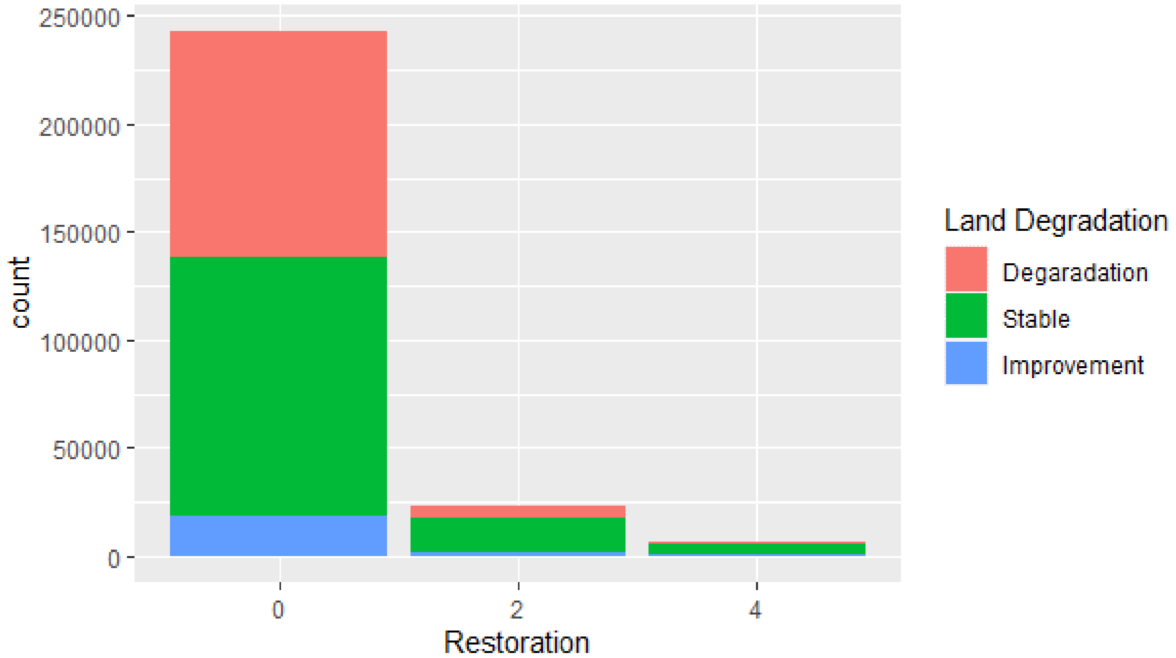


Figure 8. 2. The distribution of restoration land in every land degradation types

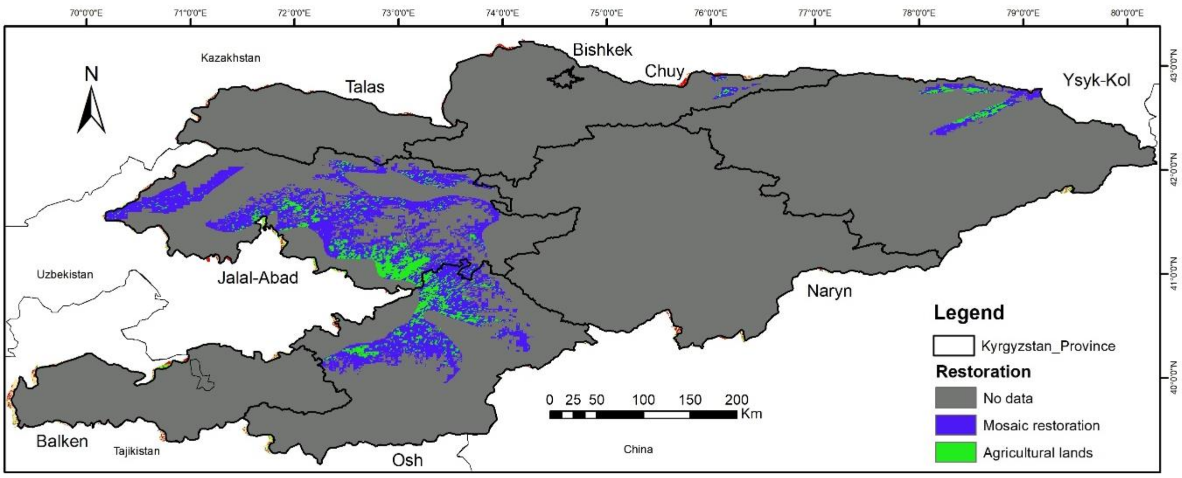


Figure 8. 1. Spatial distribution of restoration land in Kyrgyzstan

9. Conclusion

The main objective of this study is to do a deep analysis regarding land degradation in Kyrgyzstan from its status, climate factor, and relationship land degradation with environmental factors in Kyrgyzstan. The research question elaborated from main objective including the extent of land degradation in Kyrgyzstan, climate factor in land productivity, and the relationship between land degradation with population aspect, topography aspect, land cover, climate factors, biophysical aspect, and agriculture aspect.

The extent of land degradation explained and calculated following the land degradation neutrality framework which incorporating sub-indicator namely land cover change, land productivity change, and soil organic carbon. Land cover change in Kyrgyzstan shows that the majority of the area is categorized as stable land cover with a small amount of degradation found on 1.09% of the total area. Similarly, soil organic carbon has the stable status for 99.43% of the total area with the majority of SOC found in the tree-covered area which only 4% of the total country. Even though the land productivity shows the same pattern with the most area categorized as stable in land productivity, but there are also stressed, moderate decline, and declining status which resulted as 36% of the area has degraded land productivity. In general, the calculation of land degradation was done by utilizing the publicly available plug-in in QGIS designed especially for calculating the SDGs indicator 15.3.1: Proportion degraded land over the total area. The degraded land in Kyrgyzstan occupies 37.32% of the total area of Kyrgyzstan.

The result of the first analysis shows that land productivity is the most factor that influences land degradation. The analysis of climate factors in land degradation will be only applied for the land reproductivity (presented in NDVI) which the data are collected from the publicly available platform of Google Earth Engine. The dataset is a time-series dataset from NDVI, Temperature, Precipitation, and Palmer Severity Drought Index. The result shows that the significant decrease in NDVI trends occupied 24.69% of the total country area. The correlation of NDVI-climate shows that precipitation has a stronger influence on NDVI change. The correlation between NDVI and PDSI is very small with a 1,57% significant negative which means that the increasing drought will decrease the NDVI value.

The relationship between land degradation status with environmental factors illustrated from the bivariate analysis shows that there is influence from several environmental factors. These environmental factors are selected based on the publicly available geospatial and satellite data. The nominal variable which has influence inferred by the result of chi-squared p-value fulfilling the confidence level of 95% namely bioclimate, landform, land cover, ecoregion, farms system, agriculture system, and livestock system. However, the significant p-value from the Kruskal Wallis test represents the nominal variable that influences land degradation. This nominal variable includes climate factors (annual PET, Aridity Index, Temperature change, Precipitation change), population aspect, crops areas and yield (barley, maize, potatoes, rice, sugar beet, and wheat), and livestock type (sheep, goat, poultry, and cattle). These nominal variables are possible to apply for further analysis of the Spearman Rank Rho test. This test shows that the result of overall value is very small which means that the degree of influence is very small. Furthermore, the irrigation percentage, fertilizer (nitrogen and phosphorus), percentage pasture area, small ruminants, cotton areas and slope does not have a significant p-value which means that this variable is not independent of land degradation.

The distribution of total area for each variable categorised show that the stable lands, most of the time have the largest proportion in each type of environmental variables followed by degraded land, and improved land. However, there are some variables where land degradation has a bigger portion than stable land such as the population where the largest number of the population residing in land degradation; the bare land area where based on the land cover shows that in bare land, degradation is more occurred than the stable land; Poultry and Sheep where the average of livestock density (heads per ha) has a bigger value than in stable land.

This study will provide additional study case in the Central Asia region, especially in the mountainous region. This will be one of the provisions in the future study to have more analysis of land degradation analysis concerning topography and the relationship with agriculture factor. Furthermore, this study will add more literature in the study of driving factor in land degradation which is still quite limited. Additionally, this study will add to existing geospatial data in statistical analysis which need to be done more especially for land degradation using the land degradation neutrality framework.

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Appendices

A. Trends.Earth original result data

Area of land with improving productivity by type of land cover transition (sq. km)

Land cover type in the target year (columns); Land cover type in baseline (rows)

	Tree-covered areas	Grasslands	Croplands	Wetlands	Artificial areas	Other lands	Water bodies	*Total:*
Tree-covered areas	725.35	23.15	3.32	0.00	0.28	0.05	0.00	*752.15*
Grasslands	35.46	6,976.62	112.25	0.00	14.44	25.06	0.05	*7,163.87*
Croplands	2.26	14.17	4,172.23	0.00	43.82	0.33	0.00	*4,232.81*
Wetlands	0.00	0.00	0.00	0.00	0.00	0.00	0.00	*0.00*
Artificial areas	0.00	0.00	0.00	0.00	5.11	0.00	0.00	*5.11*
Other lands	0.14	116.87	16.24	0.00	0.18	1,734.65	0.05	*1,868.13*
Water bodies	0.00	0.32	0.75	0.00	0.00	0.05	30.79	*31.92*
Total:	*763.21*	*7,131.13*	*4,304.79*	*0.00*	*63.83*	*1,760.13*	*30.89*	***14,053.98***

Area of land with stressed productivity by type of land cover transition (sq. km)

Land cover type in the target year (columns); Land cover type in baseline year (rows)

	Tree-covered areas	Grasslands	Croplands	Wetlands	Artificial areas	Other lands	Water bodies	*Total:*
Tree-covered areas	109.81	19.99	0.61	0.00	0.00	0.38	0.00	*130.79*
Grasslands	1.51	12,132.29	17.94	0.00	6.84	132.84	0.33	*12,291.76*
Croplands	0.00	20.71	598.01	0.00	0.23	2.18	0.14	*621.28*
Wetlands	0.00	0.00	0.00	0.00	0.00	0.00	0.00	*0.00*
Artificial areas	0.00	0.00	0.00	0.00	0.14	0.00	0.00	*0.14*
Other lands	0.14	8.30	0.05	0.00	0.00	1,773.09	1.12	*1,782.70*
Water bodies	0.00	1.34	0.52	0.00	0.00	0.55	27.64	*30.06*
Total:	*111.47*	*12,182.65*	*617.13*	*0.00*	*7.21*	*1,909.05*	*29.23*	***14,856.74***

Area of land with stable productivity by type of land cover transition (sq. km)

Land cover type in the target year (columns); Land cover type in baseline year (rows)

	Tree-covered areas	Grasslands	Croplands	Wetlands	Artificial areas	Other lands	Water bodies	*Total:*
Tree-covered areas	8,109.31	290.69	59.90	0.00	0.28	0.28	0.00	*8,460.45*
Grasslands	409.17	53,578.91	919.86	0.00	56.57	110.16	0.28	*55,074.94*
Croplands	16.53	179.93	20,004.67	0.00	179.86	1.63	0.28	*20,382.91*
Wetlands	0.00	0.00	0.00	0.00	0.00	0.00	0.00	*0.00*
Artificial areas	0.00	0.00	0.00	0.00	30.12	0.00	0.00	*30.12*
Other lands	0.57	559.36	5.76	0.00	1.02	6,940.27	1.49	*7,508.48*
Water bodies	0.00	0.97	1.04	0.00	0.14	0.79	72.62	*75.55*
Total:	*8,535.58*	*54,609.86*	*20,991.23*	*0.00*	*267.97*	*7,053.13*	*74.67*	***91,532.44***

Area of land with a moderate decline for productivity by type of land cover transition (sq. km)

Land cover type in the target year (columns); Land cover type in baseline year (rows)

	Tree-covered areas	Grasslands	Croplands	Wetlands	Artificial areas	Other lands	Water bodies	*Total:*
Tree-covered areas	2,361.40	76.88	14.65	0.00	0.14	0.05	0.00	*2,453.12*
Grasslands	132.40	25,261.37	354.76	0.00	14.65	9.43	0.00	*25,772.61*
Croplands	7.74	138.55	7,563.11	0.00	45.29	0.37	0.00	*7,755.07*
Wetlands	0.00	0.00	0.00	0.00	0.00	0.00	0.00	*0.00*
Artificial areas	0.00	0.00	0.00	0.00	9.07	0.00	0.00	*9.07*
Other lands	0.09	191.73	2.38	0.00	0.42	1,144.19	0.00	*1,338.81*
Water bodies	0.00	0.00	0.09	0.00	0.05	0.00	13.25	*13.38*
Total:	*2,501.63*	*25,668.52*	*7,934.99*	*0.00*	*69.62*	*1,154.04*	*13.25*	***37,342.06***

Area of land with declining productivity by type of land cover transition (sq. km)

Land cover type in the target year (columns); Land cover type in baseline year (rows)

	Tree-covered areas	Grasslands	Croplands	Wetlands	Artificial areas	Other lands	Water bodies	*Total:*
Tree-covered areas	919.24	37.93	5.22	0.00	0.18	0.23	0.00	*962.80*
Grasslands	57.33	10,606.86	219.41	0.00	59.00	14.59	0.00	*10,957.19*
Croplands	1.77	123.53	5,065.86	0.00	134.25	1.50	0.00	*5,326.91*
Wetlands	0.00	0.00	0.00	0.00	0.00	0.00	0.00	*0.00*
Artificial areas	0.00	0.00	0.00	0.00	24.22	0.00	0.00	*24.22*
Other lands	0.00	30.84	0.66	0.00	0.74	407.06	0.00	*439.28*
Water bodies	0.00	0.14	0.05	0.00	0.05	0.09	16.01	*16.33*
Total:	*978.34*	*10,799.29*	*5,291.19*	*0.00*	*218.43*	*423.47*	*16.01*	***17,726.73***

Area of land with no data for productivity by type of land cover transition (sq. km)

Land cover type in the target year (columns); Land cover type in baseline year (rows)

	Tree-covered areas	Grasslands	Croplands	Wetlands	Artificial areas	Other lands	Water bodies	*Total:*
Tree-covered areas	29.24	0.97	0.09	0.00	0.00	0.00	0.23	*30.53*
Grasslands	0.14	4,611.32	0.80	0.00	0.37	18.43	0.88	*4,631.94*
Croplands	0.00	1.96	57.59	0.00	0.00	0.09	0.00	*59.64*
Wetlands	0.00	0.00	0.00	0.00	0.00	0.00	0.00	*0.00*
Artificial areas	0.00	0.00	0.00	0.00	0.73	0.00	0.00	*0.73*
Other lands	0.14	21.09	0.23	0.00	0.00	11,702.17	1.81	*11,725.44*
Water bodies	0.14	12.05	0.18	0.00	0.59	2.13	7,015.68	*7,030.77*
Total:	*29.66*	*4,647.38*	*58.89*	*0.00*	*1.69*	*11,722.82*	*7,018.60*	***23,479.04***

Matrix land productivity change based on land cover change during baseline to target year (2001 to 2015)

Land cover class	Declining	Moderate decline	Stressed	Stable	Increasing	No data
Tree-covered areas	919.24	2,361.40	109.81	8,109.31	725.35	29.24
Grasslands	10,606.86	25,261.37	12,132.29	53,578.91	6,976.62	4,611.32
Croplands	5,065.86	7,563.11	598.01	20,004.67	4,172.23	57.59
Wetlands	0.00	0.00	0.00	0.00	0.00	0.00
Artificial areas	24.22	9.07	0.14	30.12	5.11	0.73
Other land	407.06	1,144.19	1,773.09	6,940.27	1,734.65	11,702.17
Total	17,023.24	36,339.13	14,613.36	88,663.27	13,613.96	16,401.04

Soil organic carbon change from baseline to target by type of land cover transition (as a percentage of initial stock)*

Land cover type in the target year

Land cover type in baseline year	**Tree-covered areas**	**Grasslands**	**Croplands**	**Wetlands**	**Artificial areas**	**Other lands**
Tree-covered areas	0.00%	0.00%	-7.36%		-44.36%	-50.02%
Grasslands	0.00%	0.00%	-8.49%		-50.87%	-22.00%
Croplands	8.86%	6.15%	0.00%		-43.91%	-32.70%
Wetlands						
Artificial areas					0.00%	
Other lands	29.38%	41.92%	40.09%		-0.46%	0.00%

Page 8 of 34 - SO1-3 Trends in carbon stock above and below ground

Soil organic carbon stock in topsoil, tonnes per ha						
	Tree-covered areas	**Grassland**	**Cropland**	**Wetland**	**Artificial surfaces**	**Other lands**
2001	144.24	133.06	114.84	0.00	70.41	83.58
2002	144.24	133.06	114.83	0.00	70.41	83.59
2003	144.24	133.05	114.82	0.00	70.41	83.60
2004	144.23	133.04	114.81	0.00	70.41	83.64
2005	144.23	133.03	114.79	0.00	70.41	83.71
2006	144.23	133.02	114.78	0.00	70.41	83.80
2007	144.23	133.00	114.76	0.00	70.41	83.91
2008	144.22	132.98	114.74	0.00	70.41	84.05
2009	144.21	132.96	114.72	0.00	70.41	84.20
2010	144.21	132.93	114.70	0.00	70.41	84.36
2011	144.20	132.91	114.68	0.00	70.41	84.55
2012	144.19	132.87	114.66	0.00	70.41	84.74
2013	144.19	132.83	114.65	0.00	70.41	84.93
2014	144.18	132.79	114.63	0.00	70.41	85.14
2015	144.17	132.75	114.62	0.00	70.41	85.35
	Tree-covered areas	Grassland	Cropland	Wetland	Artificial surfaces	Other lands

Land area by type of land cover transition (sq. km)

Land cover type in baseline year

Land cover type in the baseline year	**Land cover type in the target year**							
	Tree-covered areas	**Grasslands**	**Croplands**	**Wetlands**	**Artificial areas**	**Other lands**	**Water bodies**	*Total:*
Tree-covered areas	12,254.35	449.61	83.79	0.00	0.87	0.98	0.23	*12,789.83*
Grasslands	636.00	113,167.37	1,625.02	0.00	151.86	310.52	1.54	*115,892.32*
Croplands	28.31	478.86	37,461.47	0.00	403.46	6.11	0.42	*38,378.62*
Wetlands	0.00	0.00	0.00	0.00	0.00	0.00	0.00	*0.00*
Artificial areas	0.00	0.00	0.00	0.00	69.38	0.00	0.00	*69.38*
Other lands	1.09	928.19	25.31	0.00	2.36	23,701.43	4.46	*24,662.84*
Water bodies	0.14	14.82	2.63	0.00	0.82	3.61	7,175.99	*7,198.01*
Total:	*12,919.89*	*115,038.84*	*39,198.23*	*0.00*	*628.76*	*24,022.65*	*7,182.64*	***198,991.00***

Land cover change by cover class

	Baseline area (sq. km)	Target area (sq. km)	Change in the area (sq. km)	Change in the area (percent)
Tree-covered areas	12,790	12,919.89	130.06	1.02%
Grasslands	115,892	115,038.84	-853.47	-0.74%
Croplands	38,379	39,198.23	819.61	2.14%
Wetlands	0	0.00	0.00	0.00%
Artificial areas	69	628.76	559.38	806.20%
Other lands	24,663	24,022.65	-640.19	-2.60%
Water bodies	7,198	7,182.64	-15.37	-0.21%

Trends in land cover

	Tree-covered areas	Grassland	Cropland	Wetland	Artificial surfaces	Other lands
2001	12,789.83	115,892.37	38,378.65	0.00	69.38	24,662.84
2002	12,985.04	115,565.54	38,438.87	0.00	159.83	24,641.75
2003	12,996.35	115,456.62	38,435.99	0.00	287.32	24,611.32
2004	13,224.54	115,206.91	38,518.35	0.00	358.32	24,486.73
2005	13,174.83	115,250.30	38,571.09	0.00	405.21	24,393.48
2006	13,166.84	115,205.76	38,710.73	0.00	435.86	24,278.43
2007	13,115.92	115,038.96	38,942.91	0.00	469.35	24,231.69
2008	13,068.10	115,036.78	39,046.78	0.00	496.40	24,161.10
2009	13,042.15	115,046.67	39,109.18	0.00	519.58	24,091.57
2010	12,977.06	115,092.44	39,202.32	0.00	536.06	24,001.41
2011	12,947.66	115,172.24	39,190.08	0.00	552.85	23,946.64
2012	12,925.56	115,108.55	39,248.70	0.00	572.67	23,954.04
2013	12,905.36	115,169.46	39,100.19	0.00	591.48	24,043.02
2014	12,920.72	115,040.44	39,208.21	0.00	616.10	24,022.98
2015	12,919.89	115,038.90	39,198.25	0.00	628.76	24,022.65

Indicator	Area (sq km)	Land Degradation Status	Productivity	Soil organic carbon	Land Cover
Total land area:	191,808.70	100.00%	100.00%	100.00%	100.00%
Land area improved:	14,936.90	7.79%	7.31%	0.23%	1.09%
Land area stable:	88,501.10	46.14%	47.68%	99.43%	97.32%
Land area degraded:	71,574.10	37.32%	36.43%	0.34%	1.58%
Land area with no data:	16,796.60	8.76%	8.58%	0.00%	0.00%

B. Climate change factor in Land Degradation

```r
library(raster)
# set working directory
folder_data <- "E:/Climate/data/sample/"
setwd(folder_data)

ndvi <- brick("RasterStack_NDVI_sample.tif")
# slope calculation to get the direction and magnitude of trends,
# multiplied by the number of years to get the change in NDVI units
time <- 1:nlayers(ndvi)
fun=function(x) { if (is.na(x[1])){ NA } else { m = lm(x ~ time); summary(m)$coefficients[2] }}
ndvi.slope=calc(ndvi, fun)
# ndvi.slope2=ndvi.slope*6
plot(ndvi.slope)
writeRaster(ndvi.slope, "Slope_NDVI.TIF")

# p value calculation
fun=function(x) { if (is.na(x[1])){ NA } else { m = lm(x ~ time); summary(m)$coefficients[8] }}
p <- calc(ndvi, fun=fun)
plot(p, main="p-Value")
writeRaster(p, "pValue_NDVI.TIF")

# mask all values >0.05 to get a confidence level of 95%
m = c(0, 0.05, 1, 0.05, 1, 0)
rclmat = matrix(m, ncol=3, byrow=TRUE)
p.mask = reclassify(p, rclmat)
fun=function(x) { x[x<1] <- NA; return(x)}
p.mask.NA = calc(p.mask, fun)

# mask all insignificant values in the trend map
trend.sig = mask(ndvi.slope, p.mask.NA)
plot(trend.sig, main="significant NDVI change")

# masking + calculaitn class significant ndvi
Significant_negative <- (ndvi.slope<0)*(p<=0.05)*1
nonSignificant_negative <- (ndvi.slope<0)*(p>0.05)*(p<= 0.1)*1
noTrend_negative <- (ndvi.slope<0)*(p>0.1)*1

Significant_positive <- (ndvi.slope>0)*(p<=0.05)*1
nonSignificant_positive <- (ndvi.slope>0)*(p>0.05)*(p<= 0.1)*1
noTrend_positive <- (ndvi.slope>0)*(p>0.1)*1

# export output files
writeRaster(Significant_negative, "Significant_Negative_NDVI.TIF")
writeRaster(nonSignificant_negative, "Non_Significant_Negative_NDVI.TIF")
writeRaster(noTrend_negative, "No_Trend_Negative_NDVI.TIF")
writeRaster(Significant_positive, "Significant_Positive_NDVI.TIF.TIF")
writeRaster(nonSignificant_positive, "Non_Significant_Positive_NDVI.TIF")
writeRaster(noTrend_positive, "No_Trend_Positive_NDVI.TIF")

# count pixel
Significant_negative_pixel_count <- freq(Significant_negative, value = 1)
Significant_negative_pixel_area <- Significant_negative_pixel_count/ncell(Significant_negative)
nonSignificant_negative_pixel_count <- freq(nonSignificant_negative, value = 1)
nonSignificant_negative_pixel_area <- nonSignificant_negative_pixel_count/ncell(nonSignificant_negative)
noTrend_negative_pixel_count <- freq(noTrend_negative, value = 1)
noTrend_negative_pixel_area <- noTrend_negative_pixel_count/ncell(noTrend_negative)

Significant_positive_pixel_count <- freq(Significant_positive, value = 1)
Significant_positive_pixel_area <- Significant_positive_pixel_count/ncell(Significant_positive)
nonSignificant_positive_pixel_count <- freq(nonSignificant_positive, value = 1)
nonSignificant_positive_pixel_area <- nonSignificant_positive_pixel_count/ncell(nonSignificant_positive)
noTrend_positive_pixel_count <- freq(noTrend_positive, value = 1)
noTrend_positive_pixel_area <- noTrend_positive_pixel_count/ncell(noTrend_positive)
```

The R script for Climate Factors Correlation

```r
library(raster)

# set working directory
folder_data <- "E:/Climate/Annual Data/input_stack_raster/"
setwd(folder_data)

ndvi <- brick("RasterStack_Annual_NDVI.tif")
prec <- brick("RasterStack_Annual_Prec.tif")
temp <- brick("RasterStack_Annual_Temp.tif")

# equalizing extent
extent(prec) <- extent(ndvi)
extent(temp) <- extent(ndvi)

# resampling data
prec_resample <- resample(prec, ndvi)
temp_resample <- resample(temp, ndvi)

#run correlation
a <- corLocal(ndvi, prec_resample, method = "pearson",test=TRUE )
b <- corLocal(ndvi, temp_resample, method = "pearson",test=TRUE )

# export output file
writeRaster(a,"correlation_ndvi_prec.tif")
writeRaster(b,"correlation_ndvi_temp.tif")

# get residuals
m_ndvi_prec <- lm(getValues(ndvi) ~ getValues(prec_resample), na.action=na.exclude)
summary(m_ndvi_prec)

m_ndvi_temp <- lm(getValues(ndvi) ~ getValues(temp_resample), na.action=na.exclude)
summary(m_ndvi_temp)


# Create a grid object for the residuals
r_ndvi_prec <- ndvi
r_ndvi_temp <- ndvi

r_ndvi_prec[] <- residuals.lm(m_ndvi_prec)
r_ndvi_temp[] <- residuals.lm(m_ndvi_temp)
# to see the graph
#plot(r)

# create mean of residuals
r_mean_ndvi_prec <- mean(r_ndvi_prec)
r_mean_ndvi_temp <- mean(r_ndvi_temp)


# export residuals file
writeRaster(r_ndvi_prec,"residuals_ndvi_prec.tif")
writeRaster(r_ndvi_temp,"residuals_ndvi_temp.tif")

writeRaster(r_mean_ndvi_prec,"residuals_mean_ndvi_prec.tif")
writeRaster(r_mean_ndvi_temp,"residuals_mean_ndvi_temp.tif")
```

Annual temp print * Get Link Save Run Reset Apps

```
// .sequence: number of years from starting year to present
var month_mean = ee.List.sequence(0, 14*1).map(function(n) {
  var start = ee.Date('2001-01-01').advance(n, 'month'); // Starting date
  var end = start.advance(1, 'year')
var finish = ee.Date('2001-12-31') ; // Step by each iteration
  return ee.ImageCollection("IDAHO_EPSCOR/TERRACLIMATE")
        .filterDate(start, end)
        .select ('tmmx')
        .mean()
        .multiply(0.1)
        .set('system:time_start', start.millis());
});
print(month_mean);

var collection = ee.ImageCollection(month_mean);

print(collection);

// Use the Global Administrative Unit Layers (GAUL) dataset to get the state boundary
var gaul = ee.FeatureCollection("FAO/GAUL/2015/level1");
var AOI = gaul.filter(ee.Filter.eq('ADM0_NAME', 'Kyrgyzstan'));
print(AOI,'AOI');

// Add Kyrgyzstan outline to the Map as a layer.
Map.centerObject(AOI, 6);
Map.addLayer(AOI, AOI, 'AOI')

// clip images to the polygon boundary
var clipped = collection.map(function (image) {
  return image.clip(AOI)
});

print (clipped, 'Clipped')


// Download images for a set region
var batch = require('users/fitoprincipe/geetools:batch')

batch.Download.ImageCollection.toDrive(clipped, 'Temperature Year',
                {region: AOI,
                crs: 'EPSG:4326',
                 type: 'float'})

Map.addLayer(AOI)
```

WCMC_biomass_carbon_density_v1_0 ... Get Link Save Run Reset Apps

```
// load data
var image = ee.Image('WCMC/biomass_carbon_density/v1_0/2010');

Map.addLayer(ee.Image(1), {min: 0, max: 1}, 'base_map');
Map.addLayer(
    image, {
      min: 1,
      max: 180,
      palette: ['d9f0a3', 'addd8e', '78c679', '41ab5d', '238443', '005a32']
    },
    'carbon_tonnes_per_ha');

// Use the Global Administrative Unit Layers (GAUL) dataset to get the state boundary
var gaul = ee.FeatureCollection("FAO/GAUL/2015/level1");
var AOI = gaul.filter(ee.Filter.eq('ADM0_NAME', 'Kyrgyzstan'));
print(AOI,'AOI');

// Add Kyrgyzstan outline to the Map as a layer.
Map.centerObject(AOI, 6);
Map.addLayer(AOI, AOI, 'AOI');

var AOICrop = image.clip(AOI);
Map.addLayer(AOICrop);

// to export data: Create a task that you can launch from the Tasks tab.
Export.image.toDrive({
  image: AOICrop,
  folder: "result",
  description: 'Kyrgyzstan_Biomass_Carbon_Density',
  maxPixels : 10000000000000,
  region : AOI,
  scale: 300,
});

```

Population dataset * Get Link Save Run Reset Apps

```
Imports (1 entry)
// load data
worldPop = ee.ImageCollection("WorldPop/POP")

var WP_2010  = worldPop
//  .filter(ee.Filter.inList('country', ['KGZ']))
  .filter(ee.Filter.equals('UNadj', 'yes'))
  .filter(ee.Filter.equals('year', 2015))
  .select('population');

var pop2010 = WP_2010.mosaic()
                    .select('population')
                    .rename('pop2010')
                    .set('system:time_start',ee.Date.fromYMD(2015,1,1));

var viz = {min:0.0, max:20, palette:"F3FEEE,00ff04,075e09,0000FF,FDFF92,FF2700,FF00E7

Map.addLayer(pop2010,viz)

Export.image.toDrive({
  image: pop2010,
  description: 'Kyrgyzstan_Population',
  maxPixels : 10000000000000,
//  region : AOI,
//  scale: 1000,
});

Export.table.toDrive ({
  collection: WP_2010,
 folder: "Thesis_ok",
  description:'Population_World_2016_UN',
//  selectors:(["wld_rgn","country_co","country_na","sum","area"]),
  fileFormat: 'csv'
  });
```

DEM-SRTM *

```
// Load the SRTM image.
var srtm = ee.Image('USGS/SRTMGL1_003');

// Calculate slope.
var slope = ee.Terrain.slope(srtm);
var elevation = srtm.select('elevation');

// Load a country border as a region of interest (roi).
var countries = ee.FeatureCollection('USDOS/LSIB_SIMPLE/2017');
var roi = countries.filterMetadata('country_na', 'equals', 'Kyrgyzstan');

// Clip the image to the region of interest.
slope = slope.clip(roi);
var DEM = elevation.clip(roi)

// Displaying slope for the region of interest.
var visualization_slope = {min: 0, max: 45, palette:'white,red'};
Map.centerObject(roi);
Map.addLayer(slope, visualization_slope, "slope");

var visualization_DEM = {min: 0, max: 45, palette:'white,black'};
Map.addLayer(DEM, visualization_DEM, "DEM");

// Export the image
Export.image.toDrive({
  image: slope,
  region: roi,
  description: 'Slope',
  scale: 30,
  maxPixels: 1e12,
});

Export.image.toDrive({
image: DEM,
region: roi,
description: 'DEM',
scale: 30,
  maxPixels: 1e12,

});
```

Crop Dominance Kyrgyzstan (copy) *

```
//Selecting Data for Dominant Crop
var dataset = ee.Image('USGS/GFSAD1000_V0');
var cropDominance = dataset.select('landcover');
var cropDominanceVis = {
  min: 0.0,
  max: 9.0,
  palette: [
    'black', 'white', 'green', 'yellow', 'brown', 'orange', '02be11', '015e08',
    '02a50f', 'purple'
  ],
};
Map.setCenter(-17.22, 13.72, 2);
Map.addLayer(cropDominance, cropDominanceVis, 'Crop Dominance');

// We use the Global Administrative Unit Layers (GAUL) dataset to get the state boundar
var gaul = ee.FeatureCollection("FAO/GAUL/2015/level1");
var AOI = gaul.filter(ee.Filter.eq('ADM0_NAME', 'Kyrgyzstan'));
print(AOI,'AOI');

// Add Kyrgyzstan outline to the Map as a layer.
Map.centerObject(AOI, 6);
Map.addLayer(AOI, AOI, 'AOI');

var AOICrop = cropDominance.clip(AOI);
Map.addLayer(AOICrop, {min:0.0, max:9.0, palette: [
    'black', 'white', 'green', 'yellow', 'brown', 'orange', '02be11', '015e08',
    '02a50f', 'purple'
  ],
  },'Kyrgyzstan Cropland');

 // to export data: Create a task that you can launch from the Tasks tab.
Export.image.toDrive({
  image: AOICrop ,
  description: 'Kyrgyzstan_Cropland_1000',
  maxPixels : 10000000000000,
  region : AOI,
//  scale: 1000,
});
```

C. Land Degradation and Environmental Factors

RStudio

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trend_significant2_yearly_data.R | monthly2yearly_data.R | correlation_residuals.R | stackraster.R | Continous variable and nominal variabl... * | count_p

```r
# import libraries ---------------------------------------------------------
library(raster)
library(ggplot2)
library(ggpubr)
library(plyr)
library(dplyr)
library(rgdal)

# setting up folder ---------------------------------------------------------
folder_data <- "E:/Thesis/Envi Factor/trend_correlation/new_data2/"
setwd(folder_data)

# 1. Land Degradation with continuos independent data  --------------------
filename <- "poultry_density"
independent <- raster(paste0(folder_data, "Numerik/", filename, ".tif"))
target <- raster("LandDegradation.tif")

# Resample the categorical target variable raster into continuous based on independent variable
target2 <- resample(target, independent, method="ngb")

# Masking rasters
target2_m <- mask(target2, independent)
independent2_m <- mask(independent, target2)

# Histogram
# hist(target)
hist(target2_m)
hist(independent2_m)

# Overlay 2 rasters and create the data frame
overlay <- stack(target2_m, independent2_m)
overlay2_df <- data.frame(na.omit(values(overlay)))
names(overlay2_df) <- c("target", "independent")

# boxplot
p <- ggplot(overlay2_df, aes(x=target, y=independent, group = target)) +
  geom_boxplot() +
  scale_x_continuous(breaks = seq(-1, 1, 1))+
  xlab("Land Degradation") +
  ylab(filename)
p

# mean calculation from factor each class target variables
overlay2_df$target_num <- overlay2_df[,1]
overlay2_df[,3]  <- as.factor(overlay2_df[,3])
mean_target <- with(overlay2_df, tapply(independent, target_num, mean))
mean_target

# Compute the analysis of variance
res.aov <- aov(target ~ independent, data = overlay2_df)
res.aov
# Summary of the analysis
summary(res.aov)

# Transform target variable
overlay2_df <- overlay2_df %>% mutate(transform=case_when(target==-1 ~ 1,
                                                          target==0 ~ 2,
                                                          TRUE ~ 3))


# Kruskal-Wallis test
kruskal.test(transform ~ independent, data=overlay2_df)
# Kruskal-Wallis rank sum test
#
#data:  transform by independent
#Kruskal-Wallis chi-squared = 136.27, df = 10, p-value < 2.2e-16

# Spearman rank correlation test
cor.test(overlay2_df$transform, overlay2_df$independent, method="spearman")
# Spearman's rank correlation rho
#
#data:  overlay2_df$transform and overlay2_df$independent
#S = 4145858275, p-value = 9.959e-06
#alternative hypothesis: true rho is not equal to 0
#sample estimates:
#  rho
#0.08053821
```

20:1 | 1. Land Degradation with continuos independent data | R Script

```r
# import libraries ---------------------------------------------------------
library(raster)
library(ggplot2)
library(ggpubr)
library(plyr)
library(dplyr)
library(rgdal)

# setting up folder -------------------------------------------------------
folder_data <- "E:/Thesis/Envi Factor/trend_correlation/new_data2/"
setwd(folder_data)

# Land Degradation with nominal independent data ------------------
filename <- "bioclimates"
independent <- raster(paste0(folder_data, "Nominal/download_bioclimates_lang1/", filename, ".tif"))
target <- raster("LandDegradation.tif")

# Resample the target variable raster into categorical based on independent variable
target <- resample(target, independent, method="ngb")

# Masking rasters
target_m <- mask(target, independent)
independent_m <- mask(independent, target)

# Visualize the raster data
plot(target_m)
plot(independent_m)

# Overlay 2 rasters and create the data frame
overlay <- stack(target_m, independent_m)
overlay_df <- data.frame(na.omit(values(overlay)))
names(overlay_df) <- c("target", "independent")
overlay_df <- overlay_df %>% filter(independent != 999)

# For categorical independet variable: as.factor
overlay_df$target_num <- overlay_df[,1]
overlay_df[,1]  <- as.factor(overlay_df[,1])
overlay_df[,2]  <- as.factor(overlay_df[,2])

# Transform target variable
overlay_df <- overlay_df %>% mutate(transform=case_when(target==-1 ~ 1,
                                                        target==0 ~ 2,
                                                        TRUE ~ 3))
overlay_df[,2]  <- as.factor(overlay_df[,2])

# show matrix table
tab1 <- table(overlay_df[,1],overlay_df[,2])
tab1
# tab2 <- as.data.frame(tab1)

# barchart
ggplot(data = overlay_df, aes(x = independent, fill = target)) +
  geom_bar() +
  scale_fill_discrete(name = "Land Degradation", labels = c("Degaradation", "Stable", "Improvement"))+
  xlab(filename)
# scale_x_continuous(breaks = seq(0, 1000000, 1))
# +scale_fill_grey()


# Chi square test
chisq.test(overlay_df$transform, overlay_df$independent)
#Pearson's Chi-squared test
#
#data:  overlay_df$transform and overlay_df$independent
#X-squared = 46.553, df = 6, p-value = 2.297e-08

# Visualize Pearson residuals
library(corrplot)
corrplot(chisq$residuals, is.cor = FALSE)

# The contribution (in %) of a given cell to the total Chi-square score
# Contibution in percentage (%)
contrib <- 100*chisq$residuals^2/chisq$statistic
round(contrib, 3)

# Visualize the contribution
corrplot(contrib, is.cor = FALSE)

# test the Thiel's U uncertainty correlation (if the target variable is categorical)
UncertCoef(overlay_df[,1], overlay_df[,2], direction="column")
#0.02653541

# linear regression (alternative)
linear <- lm(overlay_df[,3] ~ overlay_df[,2])
summary(linear)
#Residual standard error: 0.5102 on 1003 degrees of freedom
#Multiple R-squared:  0.0359, Adjusted R-squared:  0.03301
#F-statistic: 12.45 on 3 and 1003 DF,  p-value: 5.367e-08
#R = 0.189473


```