CZECH UNIVERSITY OF LIFE SCIENCES PRAGUE

Faculty of Tropical AgriSciences

Estimating cropland reduction in Nepal with remote sensing data

Bachelor Thesis

Author: Jonathan Teufel

Supervisor: doc. Ing. Miroslava Bavorová, Ph.D.

Department of Economics and Development

Prague 2024

Declaration

I hereby declare that I have written this thesis entitled "Estimating cropland reduction in Nepal with remote sensing data" independently, all texts in this thesis are original, and all the sources have been quoted and acknowledged by means of complete references and according to Citation rules of the FTA.

Prague 16.04.2024

Jonathan Teufel

Acknowledgment

I would like to give thanks to my supervisor Mrs Bavorová for her patience and guidance and most importantly inspiration to delve into this field.

Additionally, I would like to thank my family for their support and my roommate Yorki who always made sure I took enough breaks.

Abstract

This thesis explores the use of remote sensing to estimate cropland reduction in Nepal. Topographic and climatic conditions have always made agriculture challenging in this region. Rapid urbanization shifted economic reliance away from agriculture, increasing the pressure on limited fertile land to feed the nation. Climate change is an emerging threat with significant impacts on food production. To protect fertile croplands for future generations it is crucial to monitor the status of croplands. Traditional agricultural surveys are resource-intensive and impractical for nationwide analysis. Utilizing remote sensing data offers a scalable alternative, capable of capturing data across extensive areas without the logistical burdens of ground-level data gathering. This thesis makes use of already pre-processed satellite data to estimate changes in cropland areas, to offer insights into spatial and temporal patterns of land use. The findings highlight significant cropland reduction concentrated around urban areas and rivers, caused by natural and human factors influencing land use. The study underlines the potential of remote sensing in agricultural monitoring and its usefulness for sustainable development strategies in regions facing similar challenges.

Keywords: Nepal, Remote Sensing, Cropland Reduction,
Land Cover Change, Land Use Change

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1. Introduction

The second United Nation Sustainable Development Goal (SDG) "Zero Hunger", and SDG 16. "promote sustainable use of terrestrial ecosystems" are in conflict with each other in many regions (Sachs 2012). Even though global population growth is leveling off it is still positive and highly concentrated in some regions. Nepal is one such region, with a population growth rate of 2.24 % in 2021 compared to the global rate of 0.82 % (United Nations Department of Economic and Social Affairs 2022).

Rapid urbanization has receded in developed countries and is now happening predominantly in Asia and Africa (Kundu and Pandey 2020). This has effects both on rural and urban environments, as developing countries try to diversify their economy away from agriculture. Meanwhile in 2018, 14 % of the population in South Asia was undernourished (Mughal and Fontan Sers 2020). Policy makers have to support development efforts aimed at economic growth whilst ensuring food security.

Fertile cropland is a limited resource and especially scarce in Nepal with its Himalaya mountain range. Expanding is often not an option because of the considerable negative environmental consequences (Duro *et al.* 2020). Climate change in the form of rising temperatures and erratic rainfall is another threat impacting food production (Ray *et al.* 2019).

The analysis of agricultural production as well as the quantification of changes, their determining factors and the resulting impacts has traditionally been based on data collected by surveys. They provide detailed, on the ground knowledge that is otherwise hard to come by. It is on the other hand limited by time and money, as getting to and around remote areas and access to farmers is no easy task. This means that results are often limited to a specific study area and are not necessarily applicable to a larger region.

Using remote sensing data gathered by satellites eliminates the need for personal data collection and can be used to monitor trends on a national scale. Instead of struggling to gather enough data, the barrier to utilizing remote sensing data is the technical knowledge to handle vast amounts of data (Sajjad and Kumar 2019). This thesis attempts to use remote sensing data with limited technical capabilities to estimate the change of croplands in Nepal.

2. Literature review

2.1. Nepal

2.1.1. Location and population

Nepal is a landlocked country located in South Asia. It borders China to the north and is surrounded by Indian territory to the east, south and west. With a land area of 147,181 km^2 and a population of 29,6 million people it is approximately 22 times smaller than India and has a population size 46 times smaller than India and China.

Topographically, the Himalayan mountain range dominates the landscapes of Nepal. The country can be divided into three main belt regions in a north-west to south-east direction. The high mountains in the north (including Mt Everest), the mid hill region towards the south and the plains in the very south are also referred to as the Terai region. Only 7 % of the population inhabits the high mountain regions while the rest of the population is equally spread between the middle mountain regions and the Terai (Central Bureau of Statistics 2021). The Terai region, which is most suitable for agriculture, makes up around 14 % of the total land area of Nepal (Lillesø *et al.* 2005).

Sources agree that Nepal has one of the lowest but also fastest growing share of urban population. Until 2013 the urbanization rate was only 17 % (Central Bureau of Statistics 2013). According to Nepal's census (Central Bureau of Statistics 2021), this has increased to 56 % in 2019 which conflicts with the 21 % level provided by the UN. This drastic increase is caused in part due to the administrative reforms in 2015 by the government of Nepal, that also reclassified urban centers (Sapkota 2022). Nevertheless, with in-migration being the driving force, there has been an increase in urban population for the last ten years. Of the three regions, the Terai has experienced the largest share of urban growth, while the capital Kathmandu was the fastest growing urban center (Joshi 2023). This trend can be attributed to flat and fertile lands which are beneficial for agriculture but also mobility. Easier access to markets makes it possible to supply an increasing urban population. Socio-economic reasons such as better employment opportunities and direct access to government services are other important pull factors (Rijal *et al.* 2020). The civil war between the government and the communist party lasting from 1996 to 2006 also caused migration from rural to urban areas as they were less affected by the fighting.

2.1.2. Climate

The three different topographical regions divide Nepal into different climatic zones (Karki *et al.* 2016). The Terai region is classified as Tropical Savannah with hot and humid weather. Further north, the hill region has a temperate climate with a dry winter and a hot summer. The mountain region is mostly classified as Polar Tundra Climate.

Summer monsoon is the predominate weather system in Nepal. 80 % of annual rainfall occurs during the rainy season from June to August (Shrestha 2000). During this time the highest level of rainfall was measured in the Pokhara Valley (Karki *et al.* 2017). The concentrated rainfall causes river levels to rise drastically during the monsoon. Figure 1 showcases this effect with the example of the Madi River. The total flow of water during August is almost 10 times higher compared to the level of discharge during winter. Nepal is home to more than 6000 rivers (Simkhada 2022), flowing down the mountain ranges, through the Terai and into India. They form an important landscape feature, providing irrigation and causing flooding.

Nepal's historic and current contributions to global greenhouse gas emissions are minimal, however it is one of the countries with high vulnerability to climate change effects (World Bank 2021). Increasing global temperatures mean higher temperature increases at higher elevation. Rainfall patterns are becoming more erratic (Figure 2), with excessive rain one year and deficient rainfall the next year. Additionally, the reduction of glaciers in the high mountains mean increased waterflow in the short term, but reduced flow in the future (Xu *et al.* 2019).

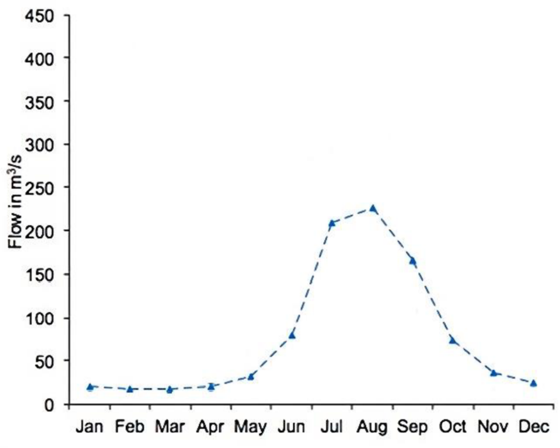

Figure 1 Mean water discharge Madi River per month
Source: Khanal and Watanabe 2017

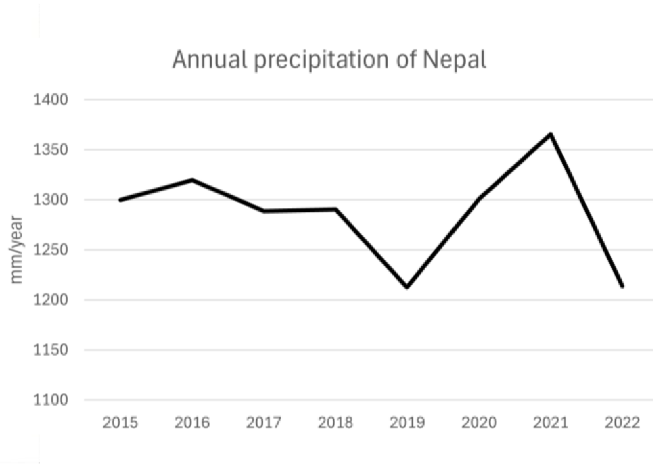

Figure 2 Annual rainfall Nepal 2015 - 2022
Source: Nepal Ministry of Water Resources 2022

2.1.3. Economy

Nepal is dwarfed by its two neighbors, India and China, not just in size and population but also in economic output. Its GDP per capita in 2022 of 1,083 USD was half of India's output and a tenth of China's. The disastrous earthquake in Nepal in 2015 and the Covid 19 pandemic had significant impacts on its economic growth. On the Human Development Index (HDI), Nepal ranks 143 in the world with a value of 0.602 with an annual improvement of 0.94 % per year (Dulal 2021).

In 1995, more than 50 % of the population lived in extreme poverty, by 2010 this was reduced to 8.2%. The multidimensional poverty index (MPI) offers a broader insight into factors affecting poverty apart from income. Surveys in 2011 and 2019 show a decrease from 0,185 to 0,075 with standard of living being the dimension contributing the most to poverty. Another result of the survey was an uneven distribution of poverty. Rural areas had an MPI level of 0,098 compared to 0.044 in urban areas (Bhusal 2013).

In the last 30 years, the economy of Nepal has undergone a transformation. The contribution of the agricultural sector to the economic output declined from 39 % to 21 % of GDP, whereas Industry and Services increased to 22 % and 52 % in 2022. The lack of growth in the manufacturing sector is in part due to lack of resources, a small internal market, and political instability (Mainali 2018). Consequently, Nepal had a growing trade deficit in agricultural commodities making up 21 % of total imports in 2020 (Mahat and Shumsher Kunwar 2021). India is Nepal's most important trading partner, accounting for more than 60 % of both imports and exports.

In addition to in-migration towards urban centers, more than 5 million Nepalis work abroad. Mainly employed in the Gulf region and Malaysia, they send back remittances , amounting to 26 % of annual GDP in 2018 (Shakya and Gonpu 2021).

2.1.4. Agriculture

Even though the role of agriculture in the economy is declining, it still accounts for 61 % of total employment in 2022 (Central Bureau of Statistics 2023). 53 % of farmers own less than 0.5 hectare (ha) of land, collectively making up 18 % of arable land (Roka 2017). A high level of subsistence farming, means that a majority of agricultural households only producing for their own consumption (Central Bureau of Statistics 2013). However, they are not self-sufficient, with a majority purchasing additional food products on the market. Nepal is not able to meet its national demand for food and increasingly depends on food imports from other countries (Adhikari *et al.* 2021). More favorable farming conditions in neighboring India - supported also by substantial government subsidies - meant that in 2022, Nepal imported agricultural products worth 765 million USD from their southern neighbor, which amounts to 5 % of total import value (APEDA 2024). Food imports, from which 80 % are from India, increase annually while food exports remain steadily low as seen in Figure 3.

Through the Agricultural Development Strategy (ADS), running from 2015 until 2023, the government of Nepal attempted to accelerate the growth of the agricultural sector (Paudel *et al.* 2016). With the aim to transform the sector from subsistence farming to specialized, commercial farming, by improving supply chains and agricultural education, the success was somewhat limited (Holmelin 2021).

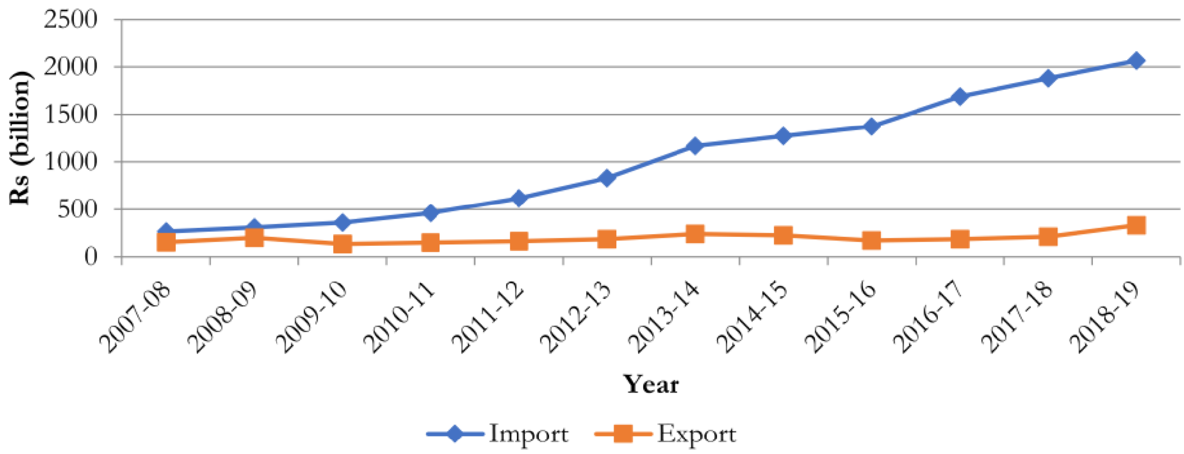

Figure 3 Total annual value of import and export of food products in Nepal
Source: Adhikari et al. 2021

2.1.5. Farming Systems

There are two major crop farming systems being used in Nepal, namely “Khet” and “Bari”, with the former using irrigation while the latter relies on rainwater (Desbiez *et al.* 2004).

According to World Bank data, 29% of all agricultural land in Nepal was irrigated in 2010, which is the 10th highest ratio in the world. Khet fields are mostly located in the low-land, Terai region. They are leveled fields either partially or fully irrigated, depending on the access to water. As many farmers grow paddy rice, Keht fields are often bunded. Even though Khet fields are more suitable for lowlands, farmers also utilize Khet terraces in hill regions (Pradhan and Chidi 2021). These are located on lower slopes, along contour lines. This reduces the risk of erosion and collects all available surface water flowing downhill. Terraces are built as a cohesive system, with water overflowing from the higher paddies then flowing into terraces on lower altitudes. Compared to Khet fields in lowlands this adapted system requires significantly more effort in maintaining the retaining walls.

The most common crop rotation on Khet fields is rice-wheat, being grown on 0.5 million ha out of the total of 1.5 million ha of croplands in Nepal (Naresh 2016). This is typical for the region as many areas in India, Pakistan and Bangladesh also rely heavily on this crop rotation. It involves flooding fields after transplanting rice seedlings during summer and the growing wheat during the winter season on aerobic soil. It is also possible to harvest two rice crops during summer at altitudes of below 900m. Notably, the crop yield of rice and wheat has stagnated in Nepal in the last decades, remaining lower than for its neighbors in South Asia (Lamsal and Khadka 2019).

The Bari farming system is typically used in hill regions, where easy access to water is more limited. Instead, it depends on rainfall for water, with 80 % of annual rainfall occurring during the rainy season between June and September. Due to the terrain, Bari fields are typically very narrow, terraced, and can be located on higher elevations than Khet fields. Crops planted on Bari fields include maize, millet, potatoes and legumes, often in an intercropping system (Marquardt *et al.* 2020) . At higher and dryer locations, Bari fields are mainly used for growing animal fodder. Farmers prefer to maximize their labor inputs in Khet field, due to the higher yield compared to Bari fields.

Another more niche farming system is riverbed farming. The heavy rainfalls during the monsoon season cause the rivers to swell which results in very wide riverbeds. After the rainy season the water level reduces, and land remains underutilized. Around 800 ha of riverbed is being used for vegetable farming (Maharjan 2017), with a focus on watermelons as they are suitable for the soil conditions. This farming system is popular amongst landless farmers allowing them to increase and diversify their income.

2.2. Cropland reduction

2.2.1. Global cropland reduction

The global per-capita cropland area has seen a noticeable decrease over the past two decades, reflecting a trend towards diminished agricultural land availability per individual or a concentration of agriculture on high-potential land areas. Between 2003 and 2019, it fell by 10%, from 0.18 ha per person to just 0.16 ha (Potapov *et al.* 2022). The patterns of cropland change are more closely tied to variables such as agricultural potential, demographic trends, and historical land-use practices. Regional analyses of cropland expansion between 2003 and 2019 show some differences. Africa experienced the most significant increase in agricultural land. In contrast, South America saw minimal expansion, and the rest of the world remained relatively constant in terms of cropland area. Southeast Asia recorded no cropland expansion. Coupled with strong population growth this means that Southeast Asia is the region with the lowest per capita crop-land availability and the strongest negative change.

Recent data highlights the significant impact of urban expansion on agricultural lands, particularly in Asia. Globally from 1992 to 2016, 46 % of expansion of urban areas has been on former croplands (Huang *et al.* 2020). With a rate of 9 %, Asia is the region where the highest percentage of total cropland has been converted to urban land. Studies have also shown that especially in Asia, high-yield croplands have been occupied by urban expansion, as historically people have settled in areas with high levels of fertile soil.

Some would argue that urban expansion is productive land use, erosion on the other hand is a threat to crop production globally (Montgomery 2007). High-income countries in temperate zones typically see smaller increases in soil erosion due to advanced land management and conservation practices, coupled with milder rainfall. Conversely, low- and middle-income countries in tropical and subtropical areas are more prone to significant erosion, driven by intense rainfalls and limited adoption of soil protection measures (Borrelli *et al.* 2020). Farmers in developing countries often utilize fewer soil protection measures, as population growth increases food demand and they are either financially unable or unwilling to bear the cost of reduced productivity in the short run(Pimentel 2006).

It is estimated that in the past, 60 % of soil erosion is attributable to human activity. Global erosion is estimated to increase by 14 % until 2090, with only 9 % being attributed to climate change (Yang *et al.* 2003). Southeast Asia faces the most severe soil erosion challenges globally, with floods being both a driver and consequence of erosion.

1.1.1. Status in Nepal

With only 28 % of total land being suitable for cultivation (Rimal *et al.* 2018), the mountainous topography of Nepal has always presented considerable challenges for agricultural production. The National Census of Agriculture in Nepal 2021/2022 noted that total available cropland increased to 26500 km^2 until 2001 and has decreased since then to 22200 km^2, as shown in Figure 4. This means that currently only 15 % of the total country area is currently used for growing crops. Coupled with strong population growth this means the amount of arable land per person has dropped from 0.12 ha in 1990 to 0.07 ha in 2020 as seen in Figure 5. This is less than half of global average and significantly less than in other South Asian countries.

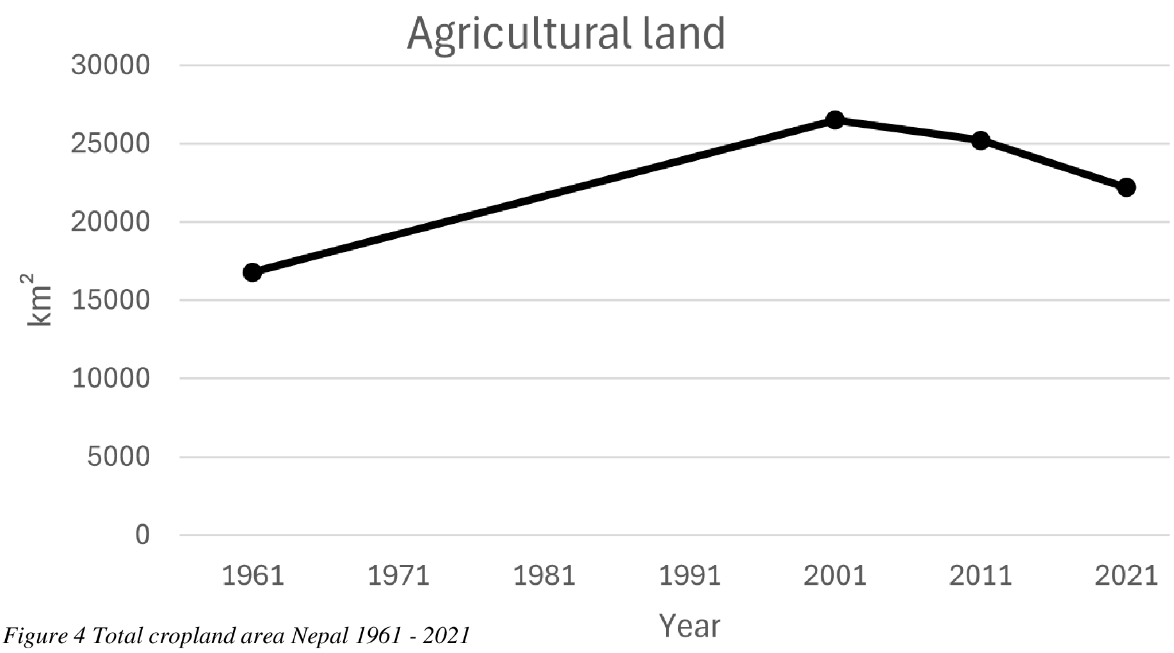

Figure 4 Total cropland area Nepal 1961 - 2021
Source: Central Bureau of Statistics 2023

To understand the reasons for the reduction of cropland in Nepal requires an examination of the social factor of land abandonment by farmers and the physical aspect of land degradation.

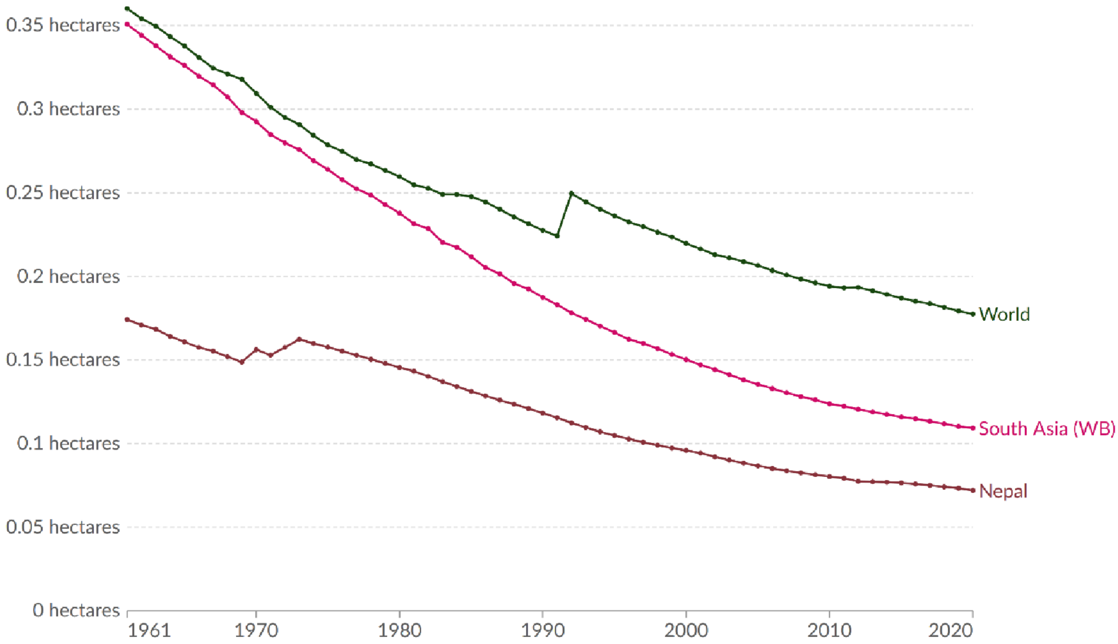

Figure 5 Arable land use per person, comparing World, South Asia, Nepal
Source: Our World in Data 2024

2.2.2. Land abandonment

So far, the scientific community has come to no agreement on a uniform definition of farmland abandonment. In some cases, it can refer to the cessation of agricultural activities on a given surface of land, but it is also used to describe the continuous process of "extensification of practices, which leads to a lower utilization of land and finally to its abandonment" (Pointereau *et al.* 2008). Contrary to intensification, this means less labor and inputs are used on a constant field area.

The debate revolves around the time frames and type of land utilization. Leaving a field fallow for a year is common agricultural practice to allow the soil ecological system to recover. Letting shrubs and eventually trees grow on formerly agricultural cultivated land can make it seem completely unutilized from an outside view. On the other hand, there are the positive environmental effects of afforestation, long term benefits from timber and more short-term earnings from non-timber forest products (Holl *et al.* 2022).

A significant majority of studies on land abandonment in remote hill regions in Nepal have found that out-migration is the key driver for this issue (Ojha *et al.* 2022). The reason for ceasing agricultural activities and migrating is often the high opportunity cost of farming compared to other professions. Regarding commercial farming, the cost of inputs is high due to transport cost and lack of domestic production. On the other hand, access to markets is also limited. For subsistence farming, time and physical labor coupled with the low prestige associated with agricultural work means that young people especially see higher income opportunities by moving to urban centers. This trend is more prevalent the more education people receive (Bista *et al.* 2021).

One result of this migration movement is a reduced rural population. This has the secondary effect of labor shortage (Khanal 2018). Narrow terrace fields and lack of funds limit mechanization opportunities. For the farmers that remain, either yield or profit goes down. Lower profitability in turn makes migration more attractive and the downward spiral continues.

2.2.3. Soil degradation

The use of agrochemicals like fertilizer and pesticides has doubled in the last 20 years while yields have remained stable (Lamsal and Khadka 2019). Soil organic matter content, an indicator for soil fertility, is low in this region as most farmers do not leave any crop residue on the field as they prefer to utilize it as feed for livestock.

The Himalayan mountain range, with its steep terrain and concentrated rainfall patterns, is a region with a high prevalence of erosion (Lal 2001). Natural disasters like floods and landslide are a consequence of that, with detrimental impact on the lives of people and the development of Nepal. While some argue that overall, most erosion is part of a natural process that has been ongoing before civilization began (West *et al.* 2015) there are many studies connecting land use practices to local levels of erosion (Xiong *et al.* 2019) (Borrelli *et al.* 2017).

The lowest level of soil erosion in Nepal can be measured in the Terai lowlands (Uddin *et al.* 2018). Intensive tilling practices exacerbate soil degradation. Most soil loss occurs from May till June, with early monsoon rain washing over the bare and freshly ploughed fields (Bajracharya and Sherchan 2017).

Hossain suggest categorizing declining soil fertility as a negative external cost, as the effects of reduced yields or total infertility will only be felt in the long term. To protect soil quality for future generations, governments could support or enforce soil fertility protection practices (Hossain *et al.* 2020).

Studies agree that the hill region in Nepal is experiencing the highest level of erosion in Nepal. The level of slope is the most important factor while land cover type is also relevant. Barren land shows the highest level of erosion, closely followed by croplands. Ghimire also ranked river basins on their level of erosion, with the Karnali River basin showing the highest mean annual erosion (165 mT) followed by the Gandaki (96 mT), Koshi (78 mT), and Mahakali River basins. This is due to the river swelling dramatically during monsoon seasons. Figure 1 shows this with the example of the Madi river which is a tributary to the Gandaki river. During this time, eroded soil in the form of sediment is transported downstream, changing riverbed structures (Ghimire *et al.* 2013).

The forest area, which constitutes a large part of the hill region's land cover is least affected by erosion as deep tree roots bind soil to its place. Meanwhile, converting forests to cropland massively increases erosion potential (Sharma *et al.* 2011). Terracing on the other hand, a method of creating stepped levels on the slopes of hills and mountains, has been identified as an effective countermeasure against erosion.

Migration from uphill regions to downhill regions is also effecting soil degradation (Jaquet *et al.* 2015). In uphill areas, a decrease in population has led to land abandonment, the spread of invasive species, and neglected terrace management. Low land areas on the other hand have seen an increase in population, leading to more intensive land use, reduced vegetation cover, decline in soil fertility, and encroachment on riverbeds, contributing to riverbank erosion.

2.3. Remote sensing

2.3.1. Application

Remote sensing data has been used for multiple purposes regarding agriculture. The most relevant areas are crop monitoring, yield forecasting, land use monitoring, ecosystem management, and precision farming (Weiss *et al.* 2020). In addition to satellite data, remote sensing data can also be collected via sensors on airplanes and unmanned aerial vehicles (UAV). This allows for higher resolution data if the study area is somewhat limited.

The number of scientific publications working with remote sensing data and agriculture has increased exponentially since the year 2000, (Khanal *et al.* 2020b).

A study published in 2023 analyzed cropland abandonment in subtropical mountainous areas in the south east of China (Hong *et al.* 2023). They analyzed determinants influencing abandonment patterns like slope, water access and proximity to nearest settlement or road. Their result was that slope was the most relevant physiographic factor but that 48 % of land abandonment occurred in areas with good conditions regarding water access and accessibility. This phenomenon was attributed to the rapid urbanization trend, that even with favorable farming conditions the opportunity costs were too high.

2.3.2. Electromagnetic spectrum

Remote sensing is based on measuring electromagnetic radiation (EMR). EMR is emitted by energy sources in the form of waves. These waves can have different wavelengths which is cumulatively referred to as the electromagnetic spectrum (Cracknell and Hayes 1991).

One part of this spectrum is the visible light band. The human eye is capable of sensing EMR from the range of 4e-7 m to 7e-7 m. The brain then associates these different wavelengths with different colors, e.g. the three primary colors blue, green, and red go from shorter to longer wavelengths.

Outside the visible spectrum, moving towards longer wavelengths, is the infrared band, spanning from 7e-7 m to 1e-3 m. Two important subsections are Near-Infrared (NIR), spanning from 0.7 to 1.4e-6 m and Thermal-Infrared (TIR), 3e-6m – 14e-6 m. NIR can be described as a direct reflection of sun radiation, just like visible light. It does, however, have different characteristics that are useful for remote sensing purposes (Martensson 2011). It is sensitive to chlorophyll, reflecting off the mesophyll cells more than off inorganic matter making it suitable for monitoring crops. Thermal radiation (TIR) is the emission of heat by objects, either due to absorption of sun radiation or other sources of energy. As different materials have different characteristics of heat absorption and emission, TIR can be helpful for classification.

These are the most relevant wavelengths of the electromagnetic spectrum as they correlate with the atmospheric window (Joseph and Jeganathan 2018). The earth's atmosphere serves many purposes, one of them is shielding earth from cosmic radiation in conjunction with the magnetic poles. Different gases and water droplets interact with different types of radiation. Ozone for example absorbs UV radiation and oxygen, carbon dioxide and water droplets either reflect or scatter other wavelengths.

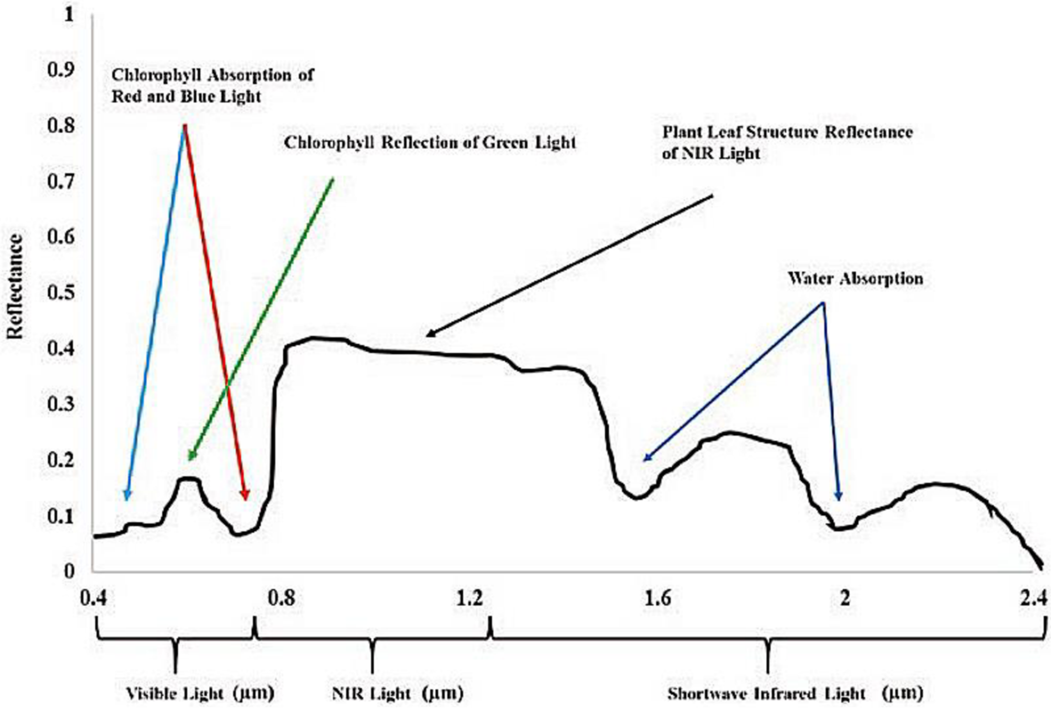

Figure 6 Different levels of green leaf reflectance across the electromagnetic spectrum
Source: Wahbi et al. 2018

2.3.3. Indices

To utilize data from multi-band sensors, scientists have developed different indices, each specialized for a specific purpose. By combining multiple bands, irrelevant data can be filtered out, with the distinct reflectance properties of vegetation remaining (Basso *et al.* 2004). Only with the help of these indices it is possible to accurately estimate the situation on the ground. The following are the formulas for the indices used to create the classification map on which this study is based (Xue and Su 2017).

NDVI Normalized Difference Vegetation Index = (NIR - Red) / (NIR + Red)

Purpose: NDVI is used to assess vegetation health and density. It compares the reflectance in the near-infrared (NIR) spectrum, which healthy vegetation strongly reflects, against the red light, which is absorbed by chlorophyll in healthy plants.

EVI Enhanced Vegetation Index = 2.5 * (NIR - Red) / ((NIR + 6 * Red - 7.5 * Blue) + 1)

Purpose: EVI is designed to optimize the vegetation signal with improved sensitivity in high biomass regions and improved vegetation monitoring through reducing canopy background signal and atmosphere influences. It's particularly useful in areas with dense canopy covers.

SIPI Structure Intensive Pigment Index = (NIR - Blue) / (NIR - Red)

Purpose: SIPI is used to estimate the carotenoid to chlorophyll ratio in leaves, which can be an indicator of stress.

NDMI Normalized Difference Moisture Index = (NIR - SWIR) / (NIR + SWIR)

Purpose: NDMI is focused on the moisture content in vegetation and soil. It uses the near-infrared (NIR) and short-wave infrared (SWIR) bands to monitor moisture.

NIRv Near-Infrared Reflectance of Vegetation () = (NDVI * NIR)

Purpose: NIRv measures the amount of near-infrared light reflected by chlorophyll fluorescence in plants, which is directly related to photosynthetic activity.

2.3.4. Copernicus

The European Space Agency (ESA) and the National Aeronautics and Space Administration (NASA) of the United States are the most important institutions providing public access to remote sensing data. NASA's Landsat satellites series started in 1972 as the first satellite mission studying Earth from above. In 2008 they provided free and open access to all data collected by Landsat, with more than 50 petabytes of data being available via the Google Earth Engine (Wulder *et al.* 2022). This had enormous economic and scientific benefits as people from all over the world were able work with this data collection to advance their research, inform decision makers, as well as integrating it into monitoring services covering a wide range of sectors (Zhu *et al.* 2019).

The ESA Sentinel missions, running under the Global Monitoring for Environment and Security (GMES) programme launched its first Sentinel 1 satellite in 2014. Currently there are 5 Sentinel missions running, each of them equipped with specialized sensors focusing on different objectives (Berger *et al.* 2012). Most relevant for agricultural research is the Sentinel 2 mission, with 13 spectral bands ranging from the visible (VIS) and near-infrared (NIR) to the short-wave infrared (SWIR), with spatial resolutions from 10 to 60 meters (Spoto *et al.* 2012). The two satellites, Sentinel 2 A and B are on a sun-synchronous orbit at 786 km altitude and with 14 earth revolutions per day record every location on earth in a five-day interval. The data collected by the Sentinel missions is also free and openly available.

The advancement of machine learning algorithms in recent years has been extremely valuable for the remote sensing field (Maxwell *et al.* 2018). As opposed to surveys, where the data collection is limited by time and money, the amount of remote sensing raw data available is hard to grasp. It is necessary to sort areas of interest into different classes to be able to understand and analyze the data. These are all things in which machine learning models excel, especially as the older Landsat data can be used for training purposes.

At the open day at the EU Agency for the Space Programme (EUSPA) in Prague, Holešovice the author was introduced to the Copernicus Programme. It is the European Union's Earth observation initiative, aimed at providing information to improve environmental management, address climate change, and enhance civil security (Jutz and Milagro-Perez 2020). After successful years of Research & Development, the intention of Copernicus is to distribute actionable and useful earth observation data to the public. Managed in collaboration with the European Space Agency and other partners, Copernicus provides services in six fields, Atmosphere Monitoring, Climate Change, Emergency Management, Marine Environment Monitoring, Security and Land Monitoring. By providing specialized, already processed datasets for these fields, Copernicus reduces the technical barrier of entry for stakeholders to utilize the data.

The Copernicus Land Monitoring Service (CLMS) provides a wide array of data and services related to land surface monitoring. This service is designed to offer users up-to-date, high-quality information about the land cover, land use, and changes occurring across Europe and globally. CLMS supports a variety of environmental and policy applications, including urban development, agricultural management, forest monitoring, water management, and nature conservation.

At the heart of CLMS are its products, which range from local to global scales. These products include detailed land cover maps, which are the focus of this research. In particular, the global yearly Land Cover dataset, available from 2015 till 2019. It provides ten land use classes, forest, shrubland, herbaceous vegetation, herbaceous wetland, moss & lichen, bare / spare vegetation, cropland, built-up, snow & ice, and permanent water bodies. It is also capable of differentiating between multiple forest types, but as this research focuses on croplands, the single class forest classification was used. This dataset has a resolution of 100 m and an overall independently verified accuracy of 80.2 % (Buchhorn et al. 2020).

The primary earth observation data is gathered from the Sentinel-2 satellites. The raw data was then pre-processed to align tile grids, filter out cloud covers and reduce atmospheric distortion. Indicators derived from the multi spectral satellite data include Normalized Difference Vegetation Index (NDVI), Enhanced Vegetation Index (EVI), Structure Intensive Pigment Index (SIPI), Normalized Difference Moister Index (NDMI), Near-Infrared reflectance of vegetation (NIRv). To then assign a land use class for each 1 ha pixel on earth, the different indices levels running over a year, were used by the Random Forest machine learning algorithm to distinguish between the classes. Forest refers to multiple decisions trees forming a literary forest. 141000 verified locations spread over the globe were identified as training data. The resulting cover map was then validated with 21752 sample locations.

3. Aims

This thesis employs a methodology for utilizing publicly available remote sensing data to monitor and analyze cropland reduction in Nepal, with very limited use of programming capabilities.

Despite the quantity and quality of available remote sensing data, its utilization often appears daunting due to the perceived need for extensive programming skills. However, this study tries to showcase that meaningful insights can be gained through existing platforms and tools that do not require coding expertise.

The methodology makes use of GIS software and online platforms that facilitate the extraction and analysis of satellite data. The primary aim is to detect changes in cropland areas over a specified period (2015-2019) and to connect the spatial and temporal patterns to literature findings.

3.1. Research questions

1) Which districts in Nepal have the highest amount of cropland reduction?
2) Can spatial and temporal patterns of cropland reduction be explained by literature findings?

4. Methodology

4.1. Data collection

Most of the data collection work was outsourced to the European Union. The raw remote sensing data was collected by the Sentinel satellite. The CLMS processed the data on a global scale, providing a complete dataset for 2015, 2016, 2017,2018, and 2019. This data can be viewed on a Land Cover Viewer website and also downloaded on a country level (Buchhorn *et al.* 2020b).

4.2. Processing

After downloading the five datasets for Nepal in TIFF format, the next step was to remove all non-cropland areas. This was achieved with the help of the opensource raster image editor GIMP. For each year, all cropland pixels were selected by color and then the inverted selection deleted.

In the next step, the pixels where the area of croplands had changed from one year to the next were identified. This was done via a python script, which produced TIFF files with blue pixels where cropland was reduced and red pixels where it increased. The script can be found in the appendix.

These files were then further processed with the open-source geographic information system software QGIS. Pixels were first vectorized into polygons but as it is easier to handle and compare points, a centroid of each pixel vector was created. The result was four layers of reduction points and four layers of addition points covering the changes from each year to the following one.

4.3. Analysis

For geo-referencing purposes, additional layers were added. First the country border of Nepal and the borders of its 77 districts. A high-definition satellite image from google earth was also included. The attribute table of the district layer was modified to include three integer fields, number of reduced points, number of added points, and net change. These fields were then filled with the help of the "count points in polygon" tool. Out of areas with high point density, three samples were chosen to understand the topographic context and the specific higher resolution satellite image for these areas were added as well. To provide context for the results, population count on district level was taken from the National census 2001 and 2021 and added to QGIS. This data was used to produce a map showcasing percentage change of population on district level. For both maps, the classes were formed in a quantile equal count mode meaning that each class has the same number of districts.

5. Results

5.1. Base Map

Figure 7 is one of four base maps of Nepal from which this research gathers its data. It illustrates land cover types on a 100 x 100 m or 1 ha pixel resolution from 2019. There are 10 classification types of which croplands (pink), forest (green), herbaceous vegetation (yellow), and bare / sparse vegetation (grey) are the most prevalent. Different shades of green and brown represent different forest types that are not relevant to this research.

The only region where expansive continuous cropland can be found is along the southern border, with larger areas on the eastern side. Going north into the hill region, forests are the dominant land cover type. Few cropland areas are visible in the center of this region. In the eastern part, croplands are concentrated along elongated lines while in the western part they spread over a larger area.

The mountain region along the northern border consists mainly of forest and bare vegetation with significantly more vegetation in the eastern side. Urban, built-up areas are only visible in the Terai and Hill region.

In the lowlands they are scattered in the cropland zones and concentrated on three lines going north to south from the start of the forest zone towards the border. Along the 83rd meridian east the Tilottama Municipality is visible. Further east, along the 85rd meridian east the border city Birgunj is located which is the fifth populated city in Nepal. Biratnagar can be seen along the 88rd meridian east. Further north in the hill region, three major urban concentrations can be identified. Going from west to east these are, Pokhara (second largest city), Bharatpur (third largest city), and Kathmandu (largest city).

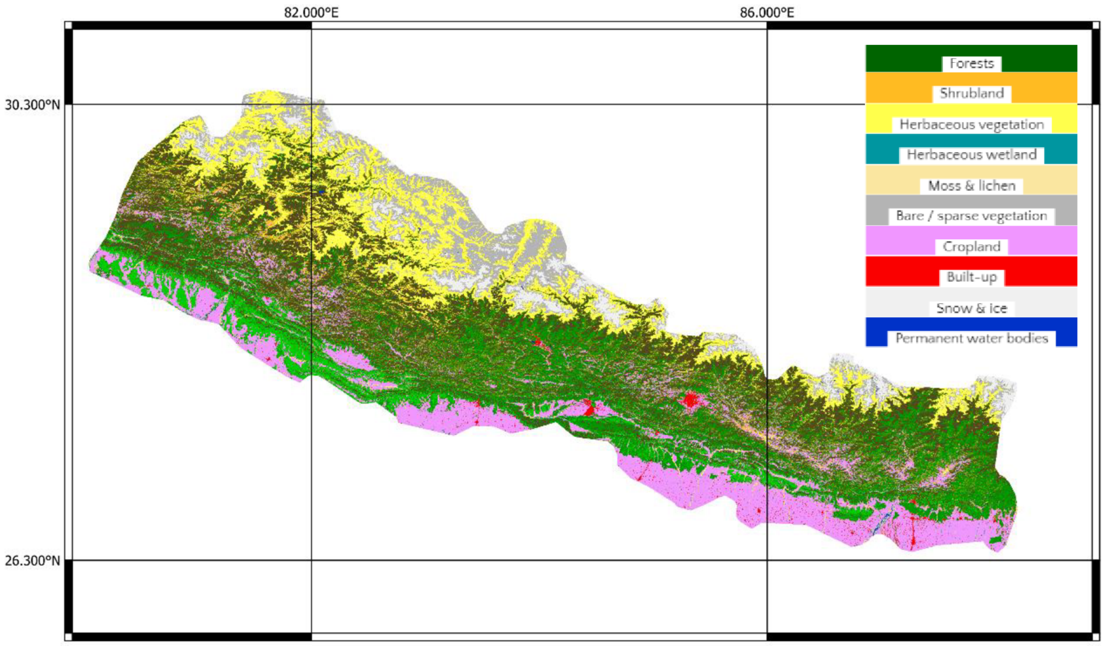

Figure 7 Classified land cover map of Nepal in 2019, 100 m resolution
Source: Buchhorn *et al.* 2020

5.2. Spatial distribution

The points in Figure 8, 9, 10, 11 illustrate the locations where cropland that was identified in one year is no longer visible the next year. Districts are numbered to assist in describing areas of interest. A table with districts names and corresponding numbers can be found in the appendix. Points are scattered in a similar fashion over the years. Lines are visible with some of them following district borders. Most points are in the lowland region along the southern border. In the hill region the highest concentration is in the center with more scattered areas in the west and the east. In the hill region little change is detected. The year with the highest amount of cropland reduction areas was 2016/17 with 1344 locations measured. 2018/19 was the year with the lowest measured change with 505 points (Table 1).

Table 1 Measured occurrences of cropland reduction and addition per year

	Reduction	Addition
2015/2016	912	72
2016/2017	1344	111
2017/2018	867	54
2018/2019	505	20

Looking at the maps in detail and comparing them allows us to identify unique areas of reduction per year that are not visible in other years:

In 2015/16 (Figure 8) there is a half-circle visible in district 33 and a continuous line reaching from the center of district 58 to district 56.

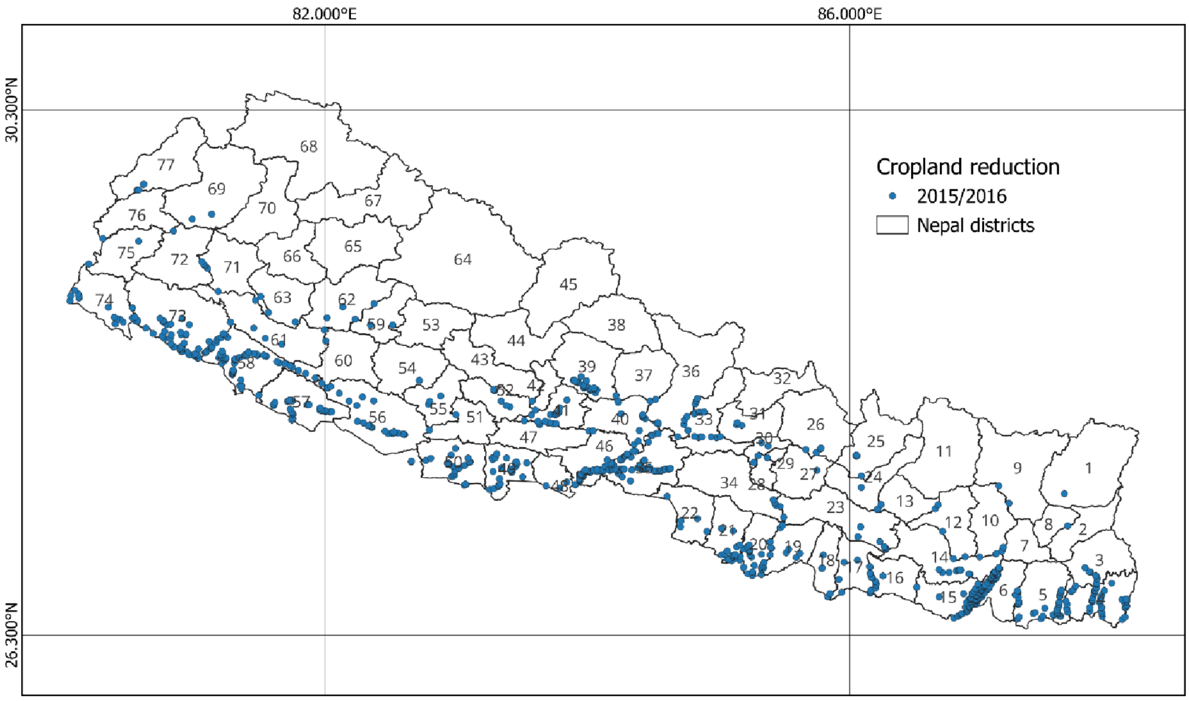

Figure 8 Location of raster cells which ceased to be categorized as cropland from 2015 to 2016

In 2016/17 (Figure 9) there is a large cluster of points covering district 4, 5, and 6. A continuous line from district 46 to 34, which is also present in other years, is significantly expanded towards the east.

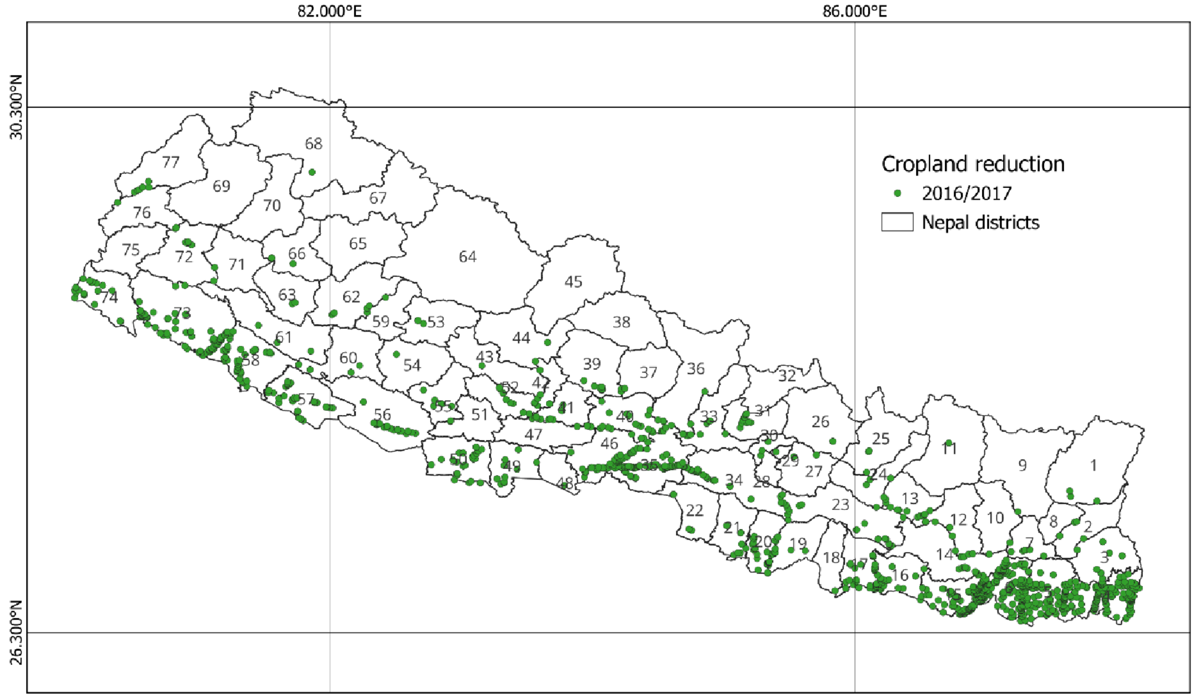

Figure 9 Location of raster cells which ceased to be categorized as cropland from 2016 to 2017

In 2017/18 (Figure 10) the most significant unique cluster is on the border between districts 50 and 49.

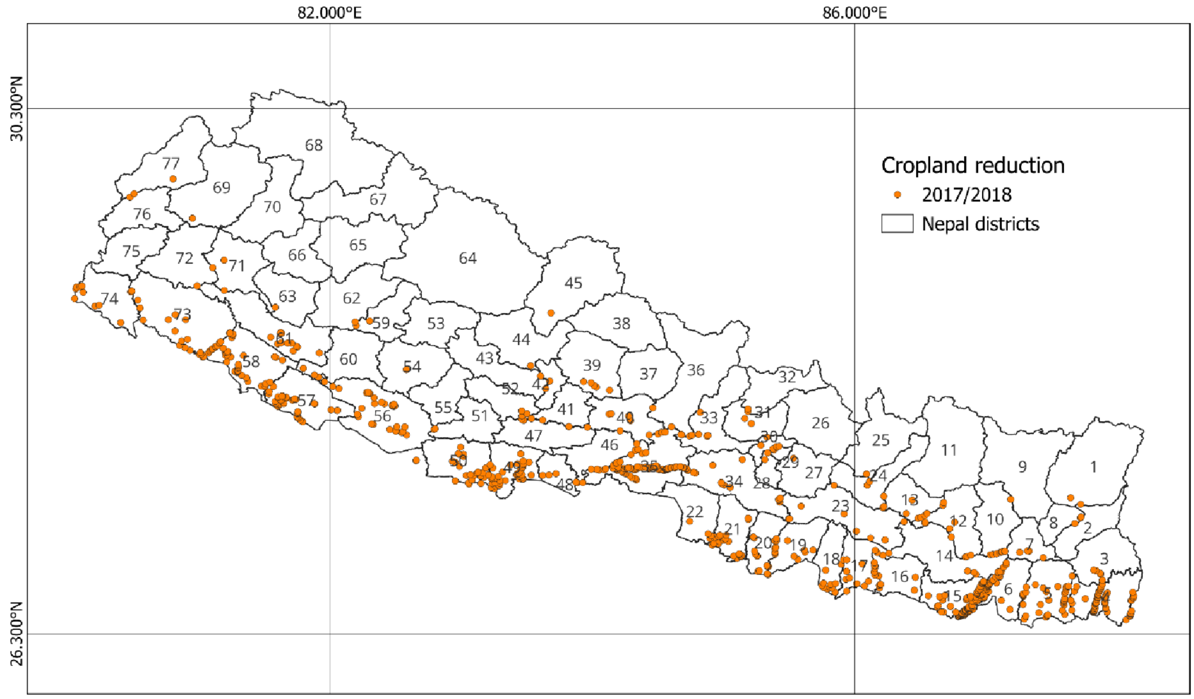

Figure 10 Location of raster cells which ceased to be categorized as cropland from 2017 to 2018

In 2018/19 (Figure 11) no unique areas of cropland reduction could be identified.

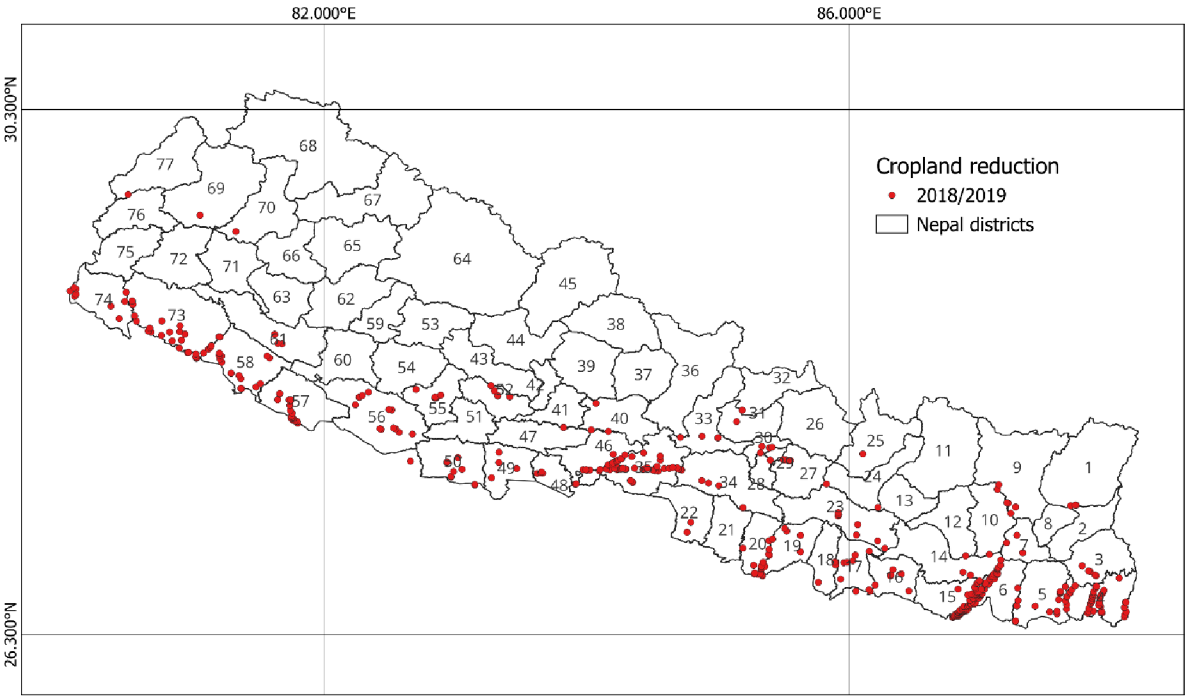

Figure 11 Location of raster cells which ceased to be categorized as cropland from 2018 to 2019

In Figure 12 the location of cropland additions that were measured are all clustered in the same regions over the whole time period. The highest concentrations are along the border between district 73 and 58, in the center of district 57, along a line reaching from district 46 to 34, on the border between district 20 and 19 and on the border between district 15 and 16.

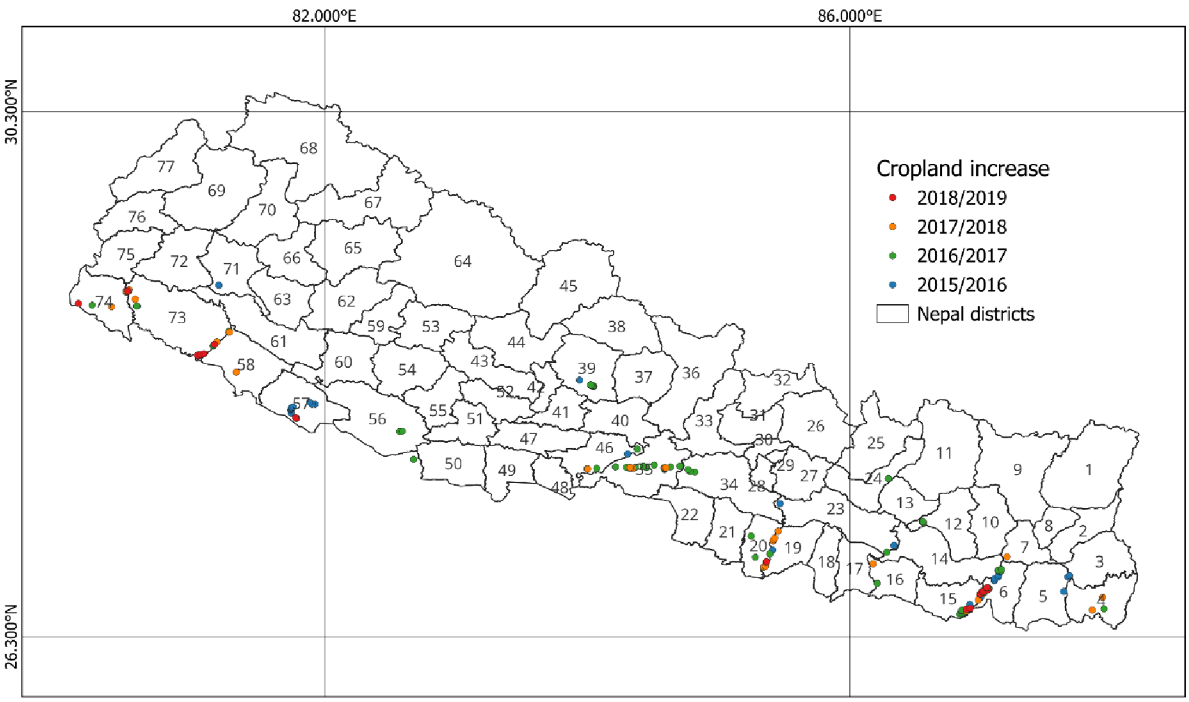

Figure 12 Location of raster cells which were newly categorized as crop land between 2015 and 2019

5.3. District level

In Figure 13 the net change from 2015 till 2019 of croplands is illustrated on district level. With the amount of reduction outweighing all additions, no district has a positive value. The ten districts with the lowest net change 35, 15, 4, 6, 5, 58, 73, 57, are all located at the southern border. There is a second line of districts with net change below -45 but only in the eastern half of the country. The north-west quarter of the country shows the least amount of change together with district 51 and 47 more to the south. The east part of the northern border shows more change, with all but two districts having net change at least below -4.

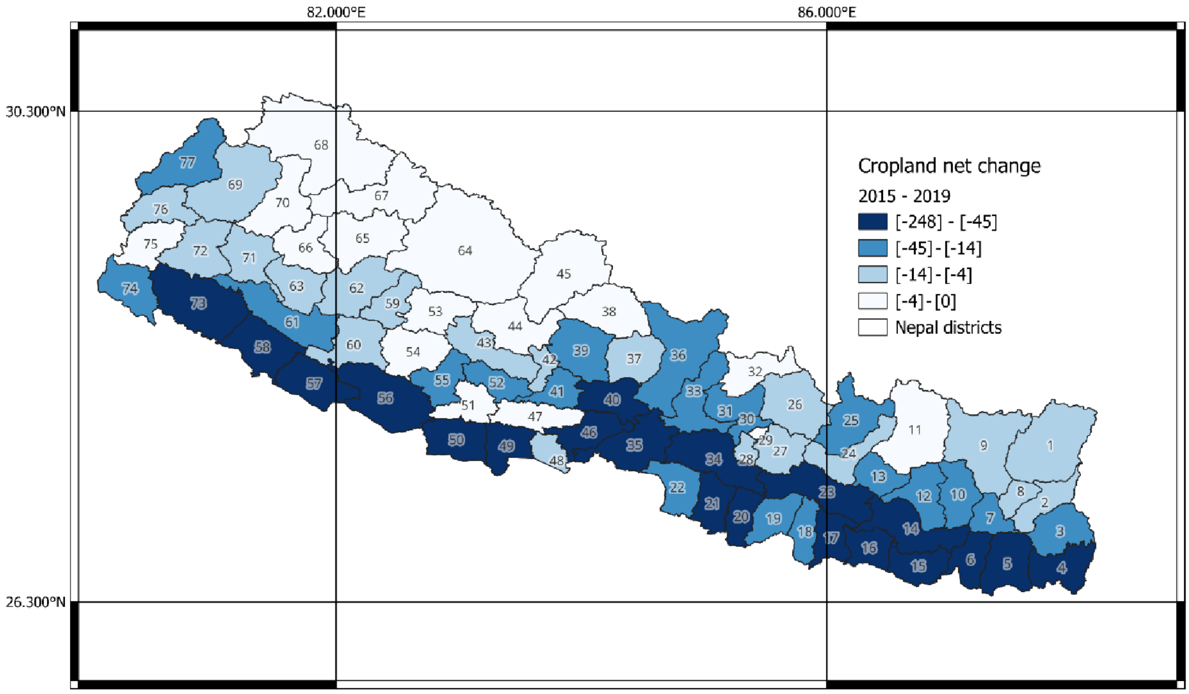

Figure 13
Net change in number of cropland raster cells per district (new cropland cells - dropped cropland cells), 2015 - 2019

Figure 14 illustrates to what extent districts experienced population change in the last 20 years. In the eastern half of the country, the mountain region is clearly experiencing population decline, with 12 of the districts with the highest reduction being in that area. The remaining quarter is located around the center of the country, in the hill region. In the western half, the mountain regions showcase population growth between 26 % and 92 %. Going south, the hill region all over the country is experiencing population growth between -10 % and 26 % while all but two districts in the terai region have grown by over 26 %. Kathmandu, district 30, and two surrounding districts as well as district 39, Kaski are outliers in the hill region as they had population growth above 42 %.

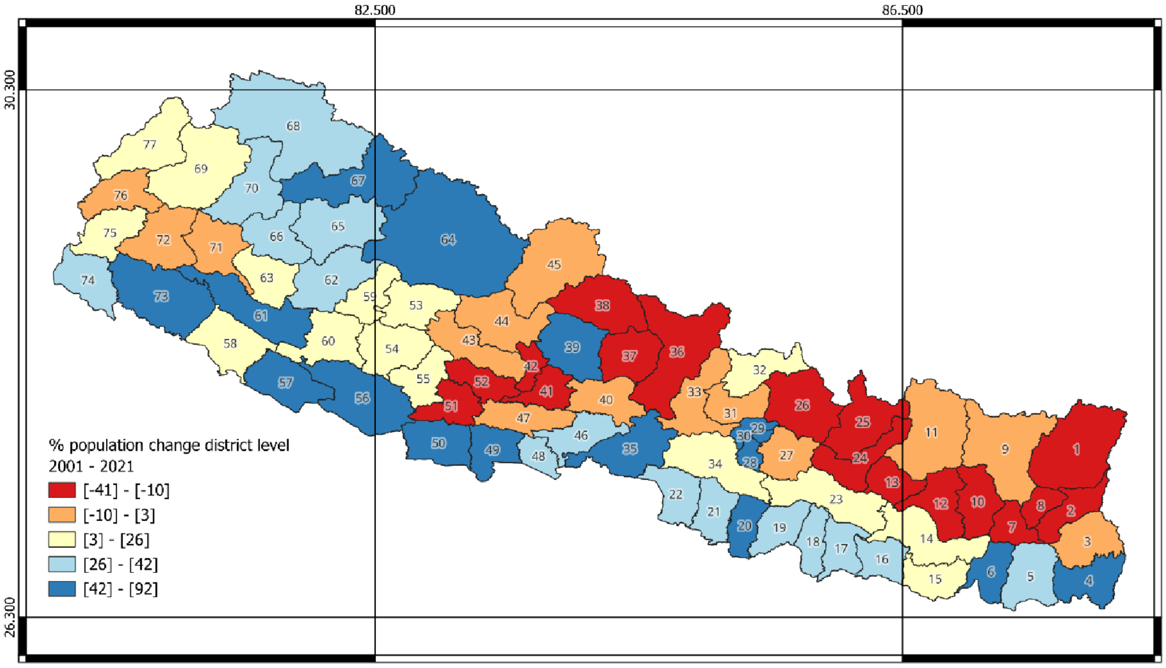

Figure 14 District population change from 2001 to 2021 in percentage
Source: Central Bureau of Statistics 2021

5.4. Samples

After observing the data on a national scale, the next step is to take a closer look at three sample locations to understand the spatial context (Figure 15d). Sample 1 covers the Bardiya district (Nr. 58) which is part of the Lumbini province. Sample 2 ranges from the Bara district (Nr. 21) in the south to the Chitwan district (Nr. 33) in the north. Sample 3 covers the Sunsari district (Nr. 3) which is part of the Koshi province.

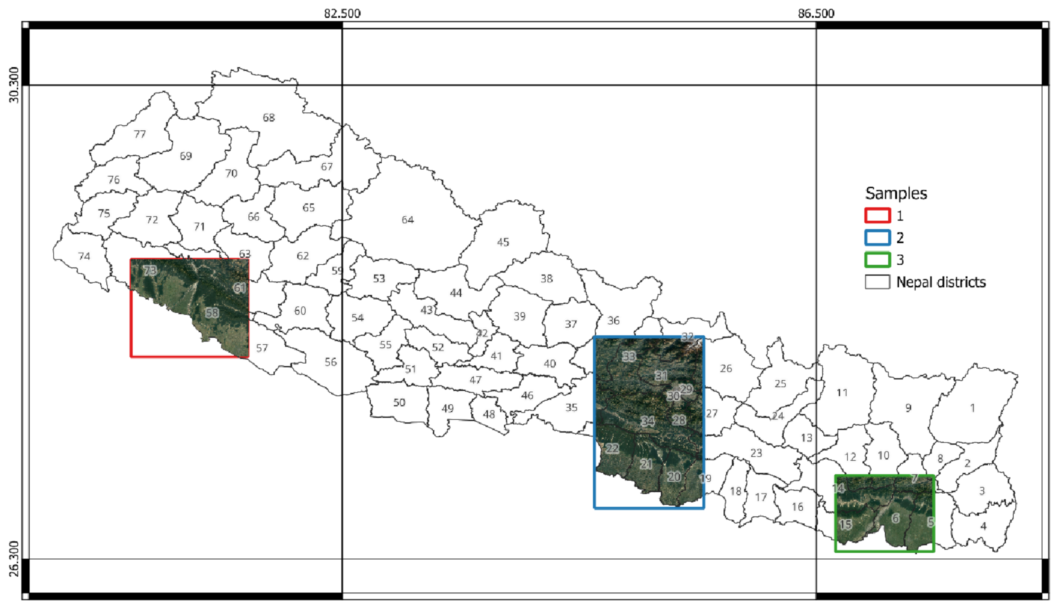

Figure 15 Overview of sample locations 1, 2, 3

5.4.1. Sample 1

Figure 16 shows the location of cropland reduction on a high definition google earth satellite image.

In the western part, reduction points are located loosely around the Khutia Nadi river, as well as along the edge of a forest area further west. There is a high concentration of cropland reduction at the southern border.

In the map center the river Karnali divides into the Kauriala river (west) and the Girwa river (east) and both flow towards the southern border. In each measured year, cropland reduction was detected along the riverbeds of both rivers.

In the east we can identify the Babai River, which flows west from the eastern border of the map until swerving south. Cropland reduction along its riverbed was detected in all measured years. In the southwest reduction can be seen especially in the year 2016/17 around the Kohalpur municipality and in 2017/18 further south around the border city of Nepalgunj. During this period, reduction was also detected further north in the city of Birendranagar.

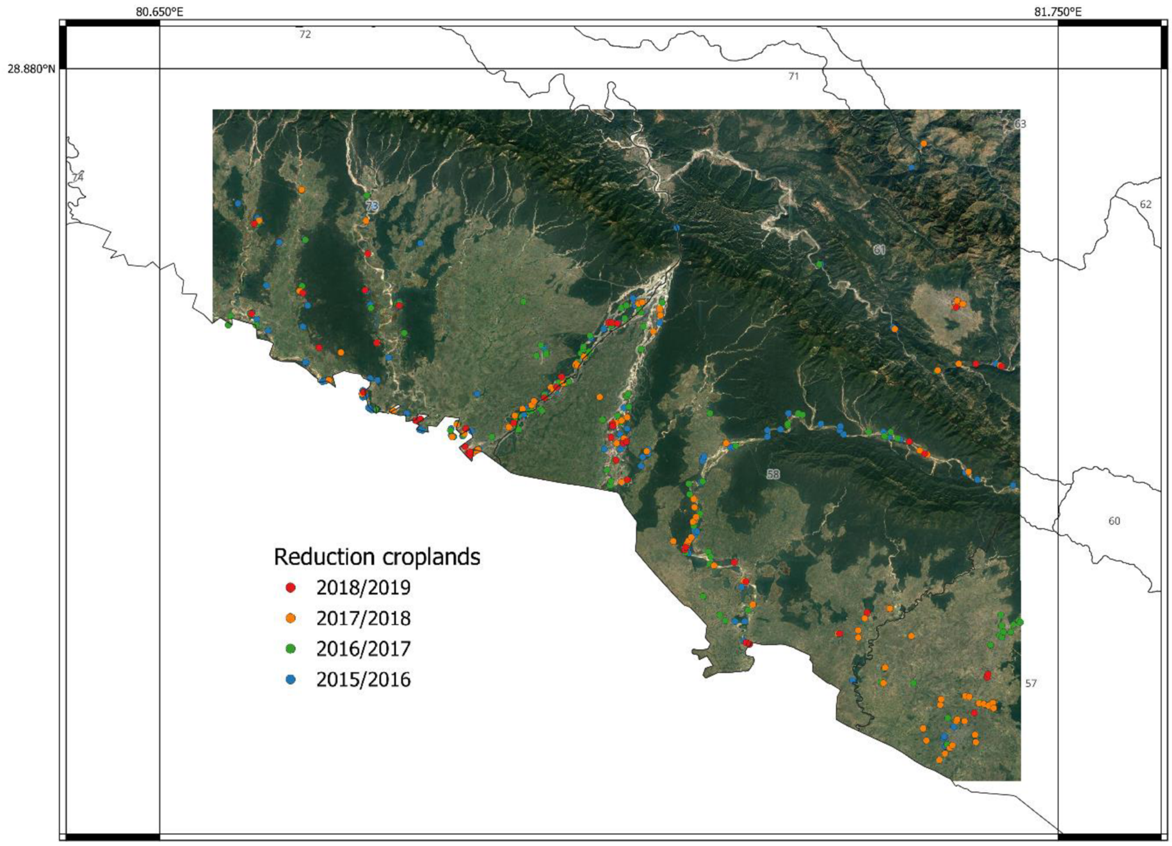

Figure 16 Sample 1, Bardiya district, location of raster cells in which cropland was reduced from 2015 to 2019

5.4.2. Sample 2

Figure 17 shows a cross section of Nepal of all measured cropland reduction areas from north to south. The topographical differences between the three regions are clearly visible.

In the north, at the feet of snow-covered mountains, the only measured points are along river beds. The Budhi Gandaki River in the west and the Trisuli River in the east. It is notable that the changes along the Budhi Gandak River only occurred during 2015/16. At the other rivers, points were recorded over the whole timeframe.

Further south in the east, the satellite image shows the extent of the capital city Kathmandu. In and around the city, cropland has been reduced from 2015 till 2019. Otherwise, the hill region shows only two points that are not along rivers. Separating the hill region from the flatlands is a ridge, with the Narayani River flowing along the norther side and both the

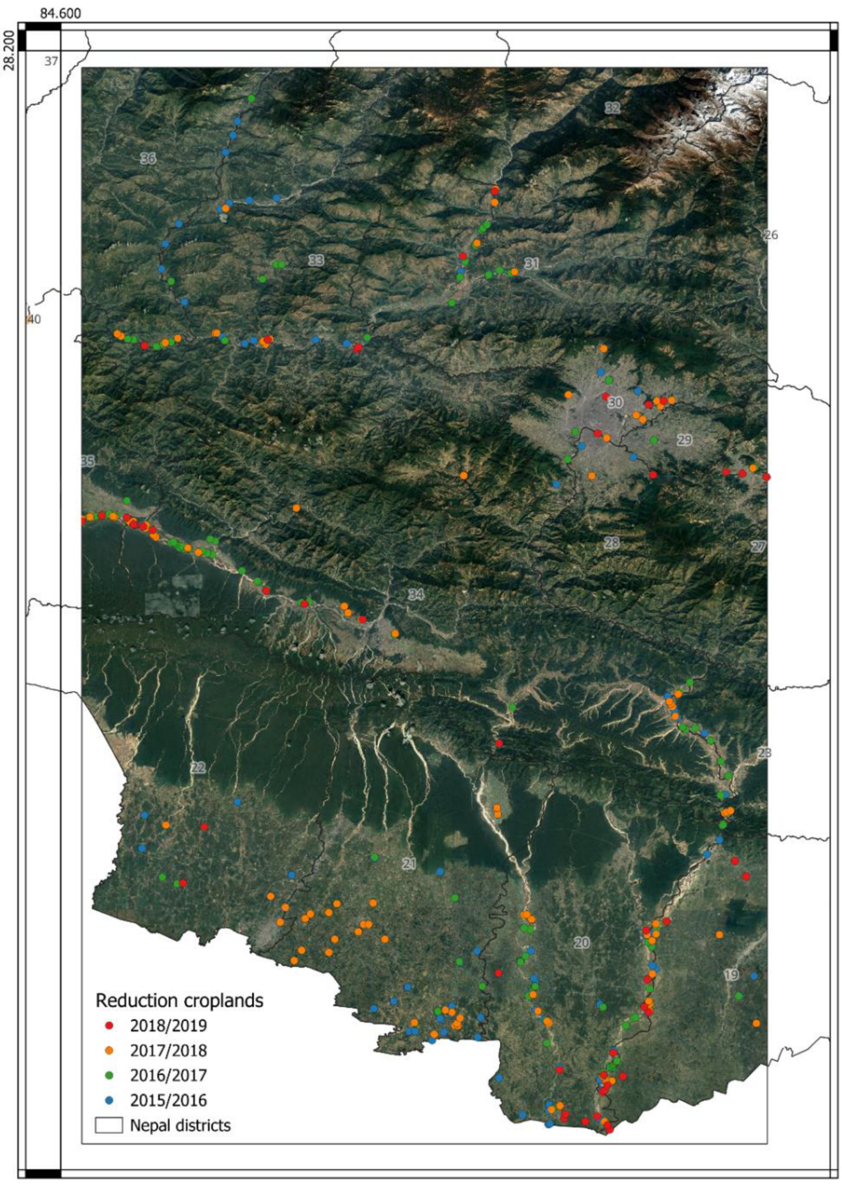

Figure 17 Sample 2, Bara district, location of raster cells in which cropland was reduced from 2015 to 2019

Bakaiya and Bagmati river crossing it flowing south. Reduction points were recorded along these rivers in all years, except for the Narayani River which shows no results for 2015/16.

In the lowlands, points of cropland reduction are scattered over a larger area. Temporal differences are visible, with changes in 2017/18 occurring on the western part of district 21 and around the easter part in 2015/16.

5.4.3. Sample 3

In Figure 18 the predominant feature is the Koshi river flowing north to south in a broad riverbed. In the north, the Sun Koshi River flows from west to east until joining the Koshi River. Further south the Belaka River joins the Koshi River at the southern border.

The most cropland reduction over all years was measured along the Koshi River. Along the Sun Koshi overall numbers are less, but also consistent over the whole time period. From 2015 until 2017, cropland reduction occurred mainly along the upper parts of the Belaka River, while more change was detected from 2017 to 2019 along the lower parts. Cropland reduction measured from 2016 to 2017 occurred in areas that were not affected in other years. First along the Khando River in the very western part and then also scattered over the whole low-land area in the east.

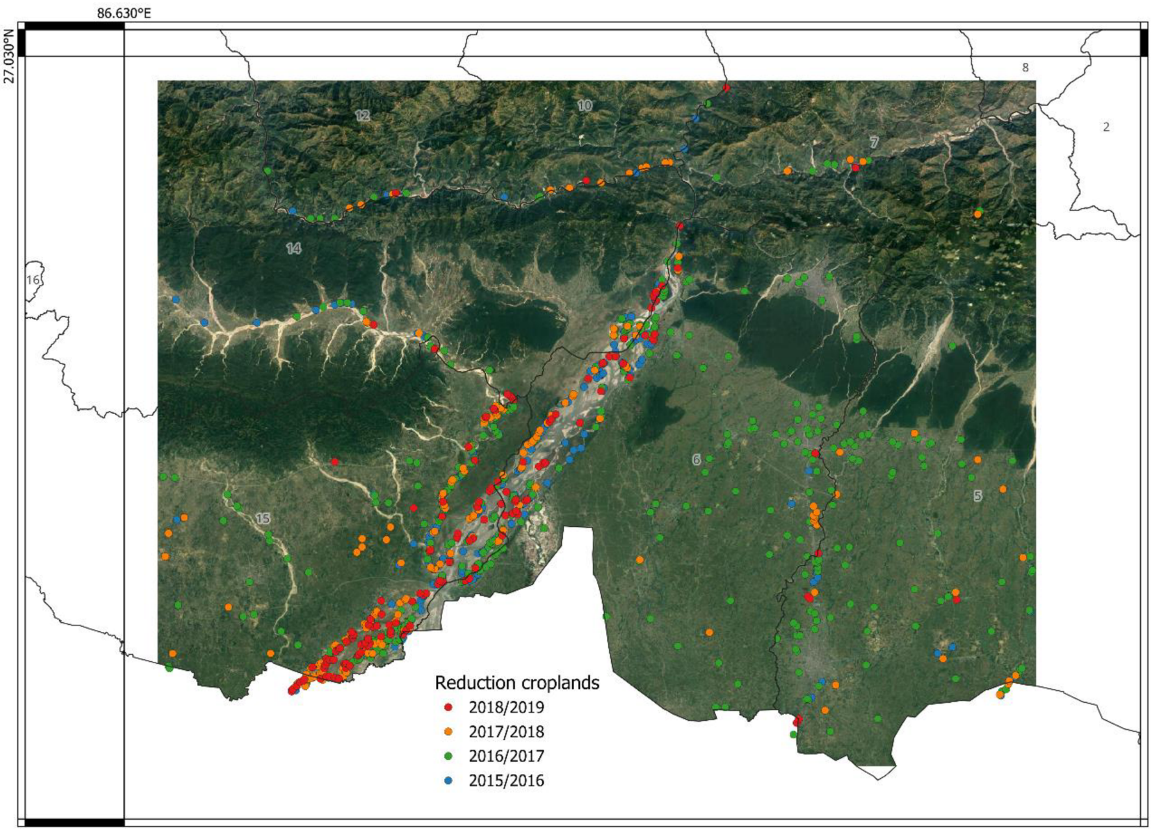

Figure 18 Sample 3, Sunsari district, location of raster cells in which cropland was reduced from 2015 to 2019

6. Discussion

The first research question regarding the districts facing the most crop land reduction has a clear answer. Figure 13 shows that close to all districts with the highest level of reduction are located in the Terai.

Regarding the second research question on explaining spatial and temporal patterns, there are three major spatial patterns observed in the results.

Cropland reduction was measured concentrated in the vicinity of rivers in the hill and Terai region (a); concentrated around cities in the hill and Terai region (b); and spread over larger areas in the Terai region (c).

a) Benefits of farming next to a river are easy access to irrigation and no slope as rivers carve out valleys through the hills. Both factors reduce the workload required for farming as no terracing needs to be constructed and maintained. Most important is the close access to irrigation water. The annual concentrated rainfall during monsoon season from June to August as shown in Figure 1 means that river levels rise significantly over a short time period. The results are the reduced croplands that were found in the results of this research.

This method is not able to recognize land abandonment in rural hill areas (Subedi et al. 2021). No significant reduction points were measured in remote hill areas that were not connected to rivers. This could be either due to the resolution of 1 ha being too large to measure change in narrow, fragmented terrace fields or that unirrigated Bari fields are difficult to distinguish for the classifier.

In Sample 1 (Figure 16) the high concentration of reduction points can be attributed to the sediment erosion of the Karnali River basin. With an estimated 165 mT of mean annual erosion it is the highest level in Nepal with the Koshi River basin (Figure 16) ranking third with 78 mT (Ghimire *et al.* 2013).

There are slight differences between the terai and hill region. Alongside rivers, the abandoned or destroyed croplands are spread wider compared to the hill regions as the riverbeds become wider themselves as they reach the lowlands and flooding covers greater areas. Even though the relevance of no slope next to rivers becomes less important and the flooding risk is high, every year in the measured timeframe cropland increased and reduced alongside riverbeds. This could mean that the benefits of farming close to the river, mainly the access to water, are so high that they outweigh the risk of flooding. This coincides with the positive ongoing trend of riverside vegetable farming (Maharjan 2017) as vegetable production is water intensive.

Comparing the overall measured reduction points with the annual recorded rainfall (Figure 2) shows a certain level of correlation between them. The local maximum rainfall in 2016 explains the peak of reduction points in 2016/17. From 2016 to 2019, annual rainfall has gone down, which results in the minimum of reduction points in 2019. This emphasizes the high level of cropland fluctuations around rivers and its vulnerability to erratic climate conditions. However, 5 years is a very limited timeframe and not enough to form predictions on future trends. To validate the ongoing cropland reduction measured by the census (Figure 4), more data is required.

b) Even though the cropland reduction caused by land abandonment due to migration was not measurable, the effect of urban growth fueled by the same migration pattern was visible. The district of Kathmandu and surrounding districts (28, 29, 30) experienced double digit population growth, as well as the Kaski district (39). The second most populated city of Nepal, Pokhara showed a similar pattern of annual reduced cropland areas. Interestingly, the results show that cropland additions were recorded around Pokhara but not Kathmandu. Farming in the vicinity of metropolitan areas has the advantage of easy access to markets and labor (Qiu *et al.* 2020). However, especially if flat land in the valleys is limited, converting farmland to housing or industrial purposes is more profitable.

c) As the lowland districts are experiencing a population boom (Figure 14), pressure on land both for housing and food production increases. Contrary to the hill region, where cities are concentrated in valleys due to travel and transportation constraints of the topography, settlements can be spread more evenly over a larger area. This is the reason for the cropland reduction points being spread as well.

While this north-south migration trend is threatening the current agricultural system, it also provides opportunities for positive development. With people leaving remote hill areas in search for better income opportunities, and the industrial and other formal sectors still in their take-off stage, enabling the production of high value crops could be an effective strategy to revitalize the agricultural sector and provide economic benefits to the region. This aligns with the goals of the ADS, but insufficient coordination between stakeholders and inadequate legislative provisions are making the implementation of the ADS a difficult and ongoing process (Khanal *et al.* 2020a).

Interestingly there is a noticeable temporal difference. In Sample 1 and 2, the majority of cropland reduction attributable to urban expansion occurred during 2017/18. However, in Sample 3, it was almost exclusively measured during 2016/17. This could potentially be caused by a change in zoning law in these specific regions.

The second research question regarding the explanation for patterns of cropland reduction can therefore be partially answered. Most spatial and general temporal patterns of cropland reduction can be explained with the help of geographic context and literature. To understand localized temporal differences however, detailed local weather data and on the ground information would be required but exceeds the scope of this thesis.

The overall discrepancy between the amount of reduced and added cropland might indicate that farmers are letting go of marginalized, less fertile fields and intensifying their higher yielding fields. The government has made efforts to support this trend (Holmelin 2021) but for many, subsistence farming is deeply culturally ingrained.

This study does not measure land use after it was no longer being cropped. It bases its assumptions on location and context provided by high-definition satellite imagery. Apart from erosion and urban expansion there are other land use types that can improve food security and soil protection. Examples could be agroforestry or pasture for livestock in the hill region, or high-value crops in the Terai (Subedi *et al.* 2022).

7. Conclusion

This study shows significant changes in cropland patterns influenced by physical geography, urban expansion, and climatic variations across different regions of Nepal based on data derived from remote sensing. The inability to detect land abandonment in rural hill areas, most probably due to the resolution of the spatial data, limits the scope of the findings. However, the identified spatial patterns of cropland reduction next to rivers and around cities provides insights into the ongoing shifts in agricultural land use. The multi-dimensional factors influencing land use show the complexity of the issue but also the benefits of land cover monitoring via remote sensing. As Nepal faces challenges by migration and urbanization, accurate knowledge about the situation is vital for decision making in urban and agricultural planning. Promoting high-value crops and agroforestry could enhance the sustainability and productivity of its agricultural sector. This would contribute to national food security and economic stability. To enable widespread utilization of the data collected by the European Space Agency, the Copernicus program should continue their efforts in providing current processed remote sensing data and make efforts to increase its resolution.

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9. Appendix

I. Python code for analyzing pixel change between two pictures

```
import cv2
import numpy as np
import os
def compute_pixel_differences(images):
    # Read the first image to get dimensions
    ref_img = cv2.imread(images[0], cv2.IMREAD_GRAYSCALE)
    height, width = ref_img.shape
    # Initialize arrays to hold differences
    diff_sum = np.zeros((height, width), dtype=np.float32)
    diff_count = 0
    # Compute differences for each image
    for img_path in images[1:]:
        # Read image
        img = cv2.imread(img_path, cv2.IMREAD_GRAYSCALE)
        # Check if dimensions match
        if img.shape != (height, width):
            raise ValueError("Image dimensions do not match.")
        # Compute absolute differences
        diff = ref_img.astype(np.float32) - img.astype(np.float32)
        diff_sum += diff
        diff_count += 1
    # Compute mean differences
    mean_diff = diff_sum / diff_count
    return mean_diff
```

```
def main():
    # Directory containing TIFF files
    directory = (***********)
    # List all TIFF files in the directory
    tiff_files = [os.path.join(directory, file) for file in os.listdir(directory) if file.endswith('.tif')]
    if len(tiff_files) < 2:
        print("There should be at least 2 TIFF files for comparison.")
        return
try:
        # Compute pixel differences
        pixel_diffs = compute_pixel_differences(tiff_files)
        # Save the pixel difference plot as a TIFF file
        output_path = (*************)
        # Normalize pixel differences to range [0, 255]
        normalized_diffs = cv2.normalize(pixel_diffs, None, 0, 255, cv2.NORM_MINMAX,
dtype=cv2.CV_8U)
        # Apply colormap to differentiate between pixels added and removed
        colormap_diffs = cv2.applyColorMap(normalized_diffs, cv2.COLORMAP_COOL)
        cv2.imwrite(output_path, colormap_diffs)
        print(f"Pixel difference plot saved as {output_path}")
    except ValueError as e:
        print("Error:", e)
if __name__ == "__main__":
    main()
```

II. Collected district data

District	Number	% pop. change 01 - 21	Net cropland change
Taplejung	1	-10	-7
Panchthar	2	33	-5
Ilam	3	-1	-25
Jhapa	4	45	-242
Morang	5	36	-164
Sunsari	6	48	-183
Dhankuta	7	-10	-14
Terhathum	8	-22	-5
Sankhuwasabha	9	-1	-8
Bhojpur	10	-22	-17
Solukhumbu	11	-3	-1
Khotang	12	-24	-27
Okhaldhunga	13	-9	-25
Udayapur	14	18	-54
Saptari	15	24	-246
Siraha	16	29	-45
Dhanusa	17	29	-59
Mahottari	18	28	-18
Sarlahi	19	36	-39
Rautahat	20	49	-58
Bara	21	36	-46
Parsa	22	32	-15
Sindhuli	23	7	-50
Ramechhap	24	-20	-5
Dolakha	25	-15	-14
Sindhupalchok	26	-14	-6
Kavrepalanchok	27	-6	-6
Lalitpur	28	63	-4
Bhaktapur	29	92	-2
Kathmandu	30	89	-17
Nuwakot	31	-11	-17
Rasuwa	32	4	-2
Dhading	33	-4	-32
Makwanpur	34	19	-47
Chitawan	35	52	-248
Gorkha	36	-13	-25
Lamjung	37	-12	-5
Manang	38	-41	0
Kaski	39	58	-20
Tanahu	40	2	-52
Syangja	41	-20	-38
Parbat	42	-17	-8
Baglung	43	-7	-6
Myagdi	44	-6	-2
Mustang	45	-4	-1
Nawalparasi East	46	39	-45

District	Number	% pop. change 01 - 21	Net cropland change
Palpa	47	-15	-2
Nawalparasi West	48	-9	-13
Rupandehi	49	58	-80
Kapilbastu	50	42	-67
Arghakhanchi	51	-15	-3
Gulmi	52	-17	-28
Rukum East	53	18	-2
Rolpa	54	12	-3
Pyuthan	55	9	-19
Dang	56	46	-96
Banke	57	56	-100
Bardiya	58	20	-139
Rukum West	59	19	-4
Salyan	60	12	-11
Surkhet	61	44	-23
Jajarkot	62	40	-11
Dailekh	63	12	-4
Dolpa	64	45	0
Jumla	65	32	0
Kalikot	66	38	-2
Mugu	67	47	0
Humla	68	36	-1
Bajhang	69	13	-4
Bajura	70	27	-1
Achham	71	-1	-8
Doti	72	-1	-13
Kailali	73	47	-126
Kanchanpur	74	36	-42
Dadeldhura	75	11	-1
Baitadi	76	3	-4
Darchula	77	9	-14