

**MONITORING AMU DARYA RIVER CHANNEL DYNAMICS USING
REMOTE SENSING TECHNIQUES AIDED BY GOOGLE EARTH ENGINE**

Mohammad Asef MOBARİZ

Master's Thesis

Department of Remote Sensing and Geographical Information Systems

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REMOTE SENSING TECHNIQUES AIDED
BY GOOGLE EARTH ENGINE**

Supervisor: Assoc. Prof. Gordana KAPLAN

Eskişehir

Eskişehir Technical University

Institute of Graduate Programs

December 2021

FINAL APPROVAL FOR THESIS

This thesis titled MONITORING AMU DARYA RIVER CHANNEL DYNAMICS USING REMOTE SENSING TECHNIQUES AIDED BY GOOGLE EARTH ENGINE has been prepared and submitted by Mohammad Asef MOBARİZ in partial fulfillment of the requirements in “Eskişehir Technical University Directive on Graduate Education and Examination” for the Degree of Master's in Remote Sensing and Geographical Information Systems Department has been examined and approved on 24/12/2021.

<u>Committee Members</u>	<u>Title, Name and Surname</u>	<u>Signature</u>
Member	: Assoc. Prof. Gordana KAPLAN	
Member	: Assist. Prof. Hakan UYGUÇGİL	
Member	: Prof. Semra Günay AKTAŞ	

Prof. Dr. Murat TANIŞLI

Director of the Institute of Graduate Programs

24/12/2021

SUPERVISOR APPROVAL

Master's student Mohammad Asef MOBARÍZ, whom I supervise, has completed this thesis titled MONITORING AMU DARYA RIVER CHANNEL DYNAMICS USING REMOTE SENSING TECHNIQUES AIDED BY GOOGLE EARTH ENGINE . According to my inspections, the work is scientifically and ethically appropriate for the student to the thesis defense exam.

Supervisor

Assoc. Prof. Gordana KAPLAN

ABSTRACT

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In this study, aims at monitoring Amu Darya River Channel Dynamics using Remote Sensing techniques within Google Earth Engine (GEE). The Amu Darya River covers vast areas within the borders of Turkmenistan, Uzbekistan and Tajikistan. The upper part of the Amu Darya River, the international border between Afghanistan and Tajikistan, have been investigated in terms of river channel dynamics. Thus, for this purpose, satellite imageris from four different periods ten years apart (1990-2000, 2000-2010, 2010-2020), have been used to map and monitor the dynamics of the river over the last three decades. The classification of the images was conducted in GEE using Landsat imagery. In addition to the river mapping and monitoring, a land cover change detection in the study area has been made. The results showed that the increase in irrigated areas, in the four specified periods was significant and played an important role in increasing the vulnerability of the study area to soil erosion which leads to river channel dynamics.

The results also showed that the use of Landsat and GEE can be a significant source of updated data for mapping and monitoring river dynamics, with a classification accuracy of the water areas higher than 90%. For future studies, we recommend using satellite imagery with a higher spatial and spectral resolution, like Sentinel-2, for more detailed investigation.

Keywords: Amu Darya, River Dynamics, Google Earth Engine, Classification, Remote Sensing.

ÖZET

GOOGLE EARTH ENGINE YARDIMIYLA UZAKTAN ALGILAMA TEKNİKLERİ KULLANARAK AMU DARYA NEHİR KANAL DİNAMİKLERİNİN İZLENMESİ

Mohammad Asef MOBARIZ

Uzaktan Algılama ve Coğrafi Bilgi Sistemleri Anabilim Dalı Anabilim Dalı

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Danışman: Doç. Dr. Gordana KAPLAN

Bu çalışmada Afganistan'ın kuzeyinde yer alan Amu Darya Nehri'ne aittir , Google Earth Engine Yardımıyla Uzaktan Algılama Teknikleri Kullanarak Amu Darya Nehir Kanal Dinamiklerinin İzlenmesi amaçlanmaktadır. Amu-Darya Nehri, kuzeybatıda İran'dan başlayarak güneydoğuya doğru uzanır ve Afganistan'ın kuzeyinde bulunur. Bu Nehir Türkmenistan, Özbekistan ve Tajikistan sınırları içerisinde de çok geniş alanları kapsar ve bu bölgelerde de Amu Darya'nın önemli alanlarını bulunmaktadır. Bu çalışmada, Amu Darya nehri kanal dinamiklerinin uzaktan algılama verileri kullanılarak üst kısımları incelenmiştir. Bu amaçla, son otuz yılda nehrin dinamiklerini haritalamak ve izlemek için on yıl arayla (1990-2000, 2000-2010, 2010-2020) dört farklı döneme ait uydu görüntüleri kullanılmıştır. Görüntülerin sınıflandırılması, Landsat görüntüleri kullanılarak Google Earth Engine'de (GEE) yapılmıştır. Nehir haritalama ve izlemeye ek olarak, çalışma alanında arazi örtüsü değişikliği tespiti yapılmıştır. Sonuçlar, belirlenen dört dönemdeki sulanan alanlardaki artışın önemli olduğunu ve nehir kanalı dinamiklerine yol açan toprak erozyonuna karşı çalışma alanının kırılganlığını artırmada önemli bir rol oynadığını göstermiştir.

Sonuç olarak, bu çalışma Landsat ve GEE kullanımının, su alanlarının % 90'ın üzerinde bir sınıflandırma doğruluğu ile nehir dinamiklerinin haritalanması ve izlenmesi için önemli bir güncellenmiş veri kaynağı olabileceğini göstermiştir. Gelecekteki çalışmalar için, Sentinel gibi daha yüksek uzamsal ve spektral çözünürlüğe sahip uydu görüntülerini kullanılmasını öneririz.

Anahtar Sözcükler: Amu Darya, Google Earth Engine, Nehir Dinamikleri, Sınıflandırma, Uzaktan Algılama.

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Mohammad Asef MOBARİZ

STATEMENT OF COMPLIANCE WITH ETHICAL PRINCIPLES AND RULES

I hereby truthfully declare that this thesis is an original work prepared by me; that I have behaved in accordance with the scientific ethical principles and rules throughout the stages of preparation, data collection, analysis and presentation of my work; that I have cited the sources of all the data and information that could be obtained within the scope of this study, and included these sources in the references section; and that this study has been scanned for plagiarism with “scientific plagiarism detection program” used by Eskişehir Technical University, and that “it does not have any plagiarism” whatsoever. I also declare that, if a case contrary to my declaration is detected in my work at any time, I hereby express my consent to all the ethical and legal consequences that are involved.

Mohammad Asef MOBARİZ

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GLOSSARY OF SYMBOLS AND ABBREVIATIONS

ALOS	: Advanced Land Observing Satellite
API	: Application Programming Interface
BAHC	: Biosphere Aspects of the Hydrological Cycle
DN	: Digital Number
EM	: Electromagnetic
EO	: Earth observation
FWHM	: Full Width at Half Maximum
GEE	: Google Earth Engine
GIS	: Geographic Information System
GLOF	: Golden Leaf Orienteering Fest
IGBP	: International Geosphere-Biosphere Program
LULC	: Land Use Land Cover
MNDWI	: Modified Normalized Difference Water Index
MSI	: Multi-Spectral Instrument
NDVI	: Normalized Difference Vegetation Index
NDWI	: Normalized Difference Water Index
OBIA	: Object Based Image Analysis
OLI	: Operational Land Imager
RS	: Remote sensing
S-2	: Sentinel-2
SDG	: Sustainable Development Goals
USGS	: United States Geological Survey

1. INTRODUCTION

1.1. Problem Definition and Objective of the Study

As the essence of life, water is one of the essential substances on Earth. It plays a crucial environmental and societal role in all ecosystem services. People's dependence on water is clear as 82% of the world's population live on previously flooded land, whereas 87% are settled along a river (Tomsett & Leyland, 2019). Also, rivers have been used to divide lands, leading to waterways as political borders. According to Popelka and Smith (Popelka & Smith, 2020), rivers make up 23 percent of international borders, 17 percent of the world's state and provincial borders, and 12 percent of all county-local borders. The number of international borders as river is the highest in South America and lowest in Asia. The division of states, cities, and countries with water bodies often causes political controversies. Also, river dynamics can often cause a considerable hazard to those in the surrounding area (Hirabayashi et al., 2013). River dynamics are often described as natural autogenic occurrences for fluvial rivers generally caused by human modifications such as dam construction, irrigation infrastructure construction, land use changes, and climatic factors (Langat, Kumar, & Koech, 2019). Understanding, monitoring, and mapping the rivers are essential to prevent and lower the hazards caused by the river channel dynamics. If the river is transboundary and natural hazards, it can also cause geo-political problems (fUr Innere Medizin, 1988), (Yousefi, Keesstra, Pourghasemi, Surian, & Mirzaee, 2017). Transboundary waters have been a reason for conflict in many parts of the world (Ovezova, 2015), and it is believed that the struggle for clean and safe water can cause even bigger geopolitical conflicts (Dhaliwal, 2009).

One of the transboundary rivers prone to conflicts is the Amu Darya river. The Amu Darya river is a major river in Central Asia and Afghanistan, and besides being internationally shared water between Tajikistan, Afghanistan, Uzbekistan, and Turkmenistan, it also represents the border between Afghanistan, and Tajikistan and Uzbekistan. Since its watercourse is constantly changing, it is very challenging for the local people who depend primarily on agriculture to claim their rights (fUr Innere Medizin, 1988). Afghanistan, as an impoverished country, is highly dependable on farming. Due to war in the past few decades, economic considerations have been secondary to political and military problems (fUr Innere Medizin, 1988).

Researchers have been searching for solutions for managing transboundary water resources in the Aral Sea Basin (Haleemzai & Sediqi, 2018), as the lack of effective management in the use and development of water caused severe consequences for the natural environment, the human population, and the economies of the sharing countries (Farzaneh & Mohammadi, 2011). Situated in the hearth of the Eurasian continent, the Aral Sea Basin is extending over parts of five Central Asian Republics. One of the two major rivers of the Basin, Amu Darya, originates in the mountains of Afghanistan and Tajikistan, and flows through Uzbekistan and Turkmenistan to the Aral Sea. Amu Darya is one of the major transboundary rivers, also representing an international border between Afghanistan, and Uzbekistan and Tajikistan. Although some attempts have been made for agreements for water resources in the Amu Darya basin, trying to deal with the use and quality of the water resources, no significant progress has been achieved. If no progress is made on this topic, this would result in further economic hardship, environmental damage, and create a potential for conflict (Farzaneh & Mohammadi, 2011). It has been clearly stated that action is required to stop the increase of the crisis in the Aras Sea Basin that affects more than 21 million people, with increased mortality rates, disease and health disorders (Bekchanov, Ringler, & Bhaduri, 2018).

For large areas like the Amu Darya river basin, and developing countries like Afghanistan, efficient and cost-effective scientific tools are important. Geospatial data and tools have become valuable tools for mapping and monitoring land use and river dynamic changes worldwide. However, remote sensing as an efficient tool for modern geospatial mapping has not been widely used in waterways as political borders. Popelka and Smith (Popelka & Smith, 2020) recently released a new geospatial database of the world's river borders for large rivers using Landsat data. Langat et al (Langat et al., 2019) used aerial imagery combined with Landsat for monitoring the river channel dynamics over the river Tana, Kenya and were able to analyze the temporal and spatial channel changes of the river from 1975 – 2017. Similarly, Billah (Billah, 2018) used Landsat imagery from 1975 – 2015 to map and monitor erosion and accretion in the Padma river, Bangladesh. Dabojani et al (Bora, Bhuyin, & Dutta, 2021) made similar investigation over the Manu river in Bangladesh. Remote sensing has been successfully used in many studies for river channel dynamics (Tomsett & Leyland, 2019), (Langat et al., 2019), (Tadese, Kumar, Koech, & Kogo, 2020). With geoformation systems, remote sensing data can provide excellent river channel dynamics, processing, visualization, and analysis tools.

Beside the river channel dynamics, land cover maps can be produced from the remote sensing data. With spatial analysis, the land cover changes caused by the river dynamics can be also determined. Also, few studies can be found in the literature on monitoring shared international waters using remote sensing data, except for few study cases over transboundary lakes (G. J. Kaplan, Avdan, Avdan, & Jovanovska, 2019). This leaves space in the literature to monitor transboundary rivers and river dynamics using remote sensing and geo-information systems. River morphology changes in varying environmental conditions over both spatial and temporal scales due to the erosion and accretion of the river bank and the river's water flow through natural and anthropogenic inputs.

The processes that control river morphology include channel dynamics, discharge, runoff events, sediment supply, and vegetation cover. In addition, channel shifting and its response to changing environmental conditions are highly reliant on local factors (channel type, hydrologic, and vegetation conditions) affected by anthropogenic disturbances.

Understanding the processes attributed to channel shifting and assessing river morphological change has long been of interest to geologists, geomorphologists, and engineers (Akhter et al., 2019). GIS and remote sensing technologies have proven useful for mapping and monitoring River resources (Wu, 2017).

This study aims to find the changes in the displacement and destruction of the Amu Darya River on its aspects. While most studies in the literature focus only on river dynamics (Langat et al., 2019),(Billah, 2018) or land cover changes in the river basin (Cai, Feng, Hou, & Chen, 2016),(Sarif & Gupta, 2021), this study evaluated both land cover changes and river dynamics of Amu Darya river.

The purpose of the presented study is to apply remote sensing data and geo-information techniques to understand the temporal and spatial channel changes and dynamics of the Amu Darya river along Afghanistan's border. The first objective is to map and analyze the land cover changes of four classes over the study area and to determine land conversion from 1990 – 2020 between the investigated classes. The second objective is to map river channel dynamics, quantify lateral river channel erosion and accretion, and detect the most changed areas between 1990 and 2020. To achieve the goals in this study, we use four Landsat images (1990, 2000, 2011, 2020) from the same period (May – July) to avoid seasonal changes. These analyses have been made using object-based classification, further discussed in the methodology section. The results can

be useful in practical applications where regular monitoring of river behavior is needed for decision making. Such information can help both local and international administrations resolve problems due to unresolved water-sharing policies and help make geopolitical decisions beneficial for both parties. Also, the results can be crucial in flood risk management strategies, irrigation plans, monitoring systems, etc.

In the second part of the analyses, the same analyses were made using the GEE platform. Here we used two different types of classification to compare object-based classification methods, which have been proven to be superior over pixel-based classification, and pixel-based classification in the GEE platform using the support vector machine classification method. Although we have used two different methods, the study's main aim was to evaluate the Amu Darya Dynamics. Furthermore, in the GEE platform, we have performed long-term image analysis (1990-2020) and seasonal analyses to evaluate the seasonal shift of the river in the study area.

1.2. Research Questions

The research questions that this thesis is aiming to answer are as given below:

- What is the best method for accurately identifying the Amu Darya Dynamics?
- Temporal analysis to monitor the dynamics of the Amu Darya River Canal.
- What are the results and effectiveness of GEE in this research?
- What is the best season for monitoring Amu Darya River channel dynamics?

2. THEORETICAL BASICS (BACKGROUND)

2.1. Definitions

2.1.1. River

A water body that flows downhill emerged by the gravity forces is called a river. Rivers can be different, in their shapes, areas, and depth. Smaller water bodies than rivers are called stream, creek, or brook. Rivers can be active all the time through the year or seasonally. Seasonally rivers appear after solid rainfall. Some of the largest rivers in the World can be as long as thousands of miles. The erosional power of rivers can form geologic wonders like the Grand Canyon.

The source, the starting point of the river where the water begins its flow, is called headwater. The headwater can come from rainfall or snowmelt in the mountains, but it

can also bubble up from groundwater or form at the edge of a lake or large pond. The other end of a river is called mouth, the place where water empties into a larger body of water, such as a lake or ocean. Along the way, rivers may pass through wetlands where plants slow down the water and filter out pollutants (http-1).

In total, there are around 165 significant rivers in the world. These great rivers are long and wide enough to be categorized as major rivers, and they carry large amounts of water daily. They have tributaries and serve as a source of fresh water for billions of people. There are thousands of smaller rivers, but it is difficult to estimate the total number of small and major rivers in the world. The Amazon, the Nile, and the Yangtze rivers are the world's major rivers. With a length of 6,516 kilometers, the Amazon River is the world's biggest river by volume of water. The Nile is the world's longest river, measuring 6,695 kilometers. The Mississippi-Missouri River System is the largest river system in the United States.

Lakes, springs, marshes, and glaciers are the sources of most rivers. They flow towards the sea, where their waters are emptied. There are, however, a few inland rivers known as virgin rivers with inland source and mouth. Inland rivers include the Amu Darya and the Syr Darya. The cradles of civilization are rivers. The river banks have seen the development of all major civilizations, including Mesopotamia, the Indus Valley, Egypt, and China. Rivers serve as inland rivers for transportation and hydroelectric power generation (http-2).

2.1.2. Worldwide River Dynamics

River channel dynamics are natural autogenic occurrences for fluvial rivers influenced by human alterations and climatic conditions that arise from discharge flow, debris and sediment transfer, channel migration, and floodplain erosion and accretion. Climate change, discharge amount and type of material, and hydrologic regimen fluctuations all influence river bank erosion and accretion, as well as channel course alterations. Anthropogenic development activities such as hydroelectric dam building, irrigation infrastructure construction along the riverbank, and land use changes, on the other hand, accelerate the natural geomorphologic dynamic behavior of rivers across the basin (Langat et al., 2019).

Sediment, drinking water, irrigation, hydroelectric power, transit, food, and recreation are all provided by rivers. Discharge, sediment, and water quality are the factors that influence the shape and function of rivers. These are linked to the watershed's climate, vegetation, and land use. Incision, lateral erosion, and sedimentation can all be caused by changes in discharge. Depending on the discharge regime, sediment load, hydrodynamic pressures, and floodplain characteristics, rivers produce distinct flow patterns such as braided and meandering (Hemmelder, Marra, Markies, & De Jong, 2018).

River shape evolves with changing environmental circumstances on both a geographical and temporal scale owing to river bank erosion and accretion and natural and human inputs to the river's water flow. Channel dynamics, discharge, runoff events, sediment supply, and plant cover are all factors that influence river shape. Furthermore, human disturbances alter local variables that influence channel shifting and its response to changing environmental circumstances. Geologists, geomorphologists, and engineers have long been interested in understanding the mechanisms linked to channel shifting and analyzing river morphological change (Akhter et al., 2019).

The interest in researching river basin and watershed hydrology has increased proportionately among geomorphologists in recent decades. During this period, significant progress has been achieved in understanding channel morphology and explaining channel shifting on a river basin's platform. Investigations of channel morphology are required to assess the natural and human impacts on morphometric parameters and channel dynamics. Because effective variations in these phenomena adapt to changes in the river basin, predicting channel responses is difficult. The deterministic model has been the focus of the majority of channel morphology research to far; nevertheless, the river system is of a dynamic and stochastic nature (Akhter et al., 2019).

2.1.3. River Dynamics in Afghanistan

The most politicized natural resources are freshwater resources such as lakes and rivers. 263 rivers in the world run through two or more nations. International basins cover more than 45 percent of the Earth's land surface. As the globe becomes increasingly water-stressed, pooled water resources can be utilized as a political tool. Furthermore, international rivers support more than 40% of the world's population, with roughly 25%

living in developing nations. Political tensions between neighboring nations are rising as a result of disputes and fights over shared water resources. According to a recent study, almost 300 treaties deal with shared water resources between countries (Yousefi et al., 2017).

On the other hand, Rivers are dynamic natural features, and their changing due to natural erosion and sedimentation processes can result in political disputes over boundary definitions between nations. Furthermore, because natural resources are shared, river borders are subject to water management disputes. The Hirmand River's shape has altered dramatically during the previous 60 years. This is most likely a result of changes in the hinterland. Several studies have shown that land use within a watershed has a major influence on fluvial dynamics. Changes in a catchment's upstream regions impact a river's hydrological, geomorphological, sedimentological, and biological functions (Yousefi et al., 2017).

2.2. Remote Sensing and GIS

Remote sensing is the process of gathering data about an object or phenomena without making direct touch with it. While remote sensing has a wide range of applications, it is most closely associated with Earth Science disciplines, where it is used to detect, monitor, and categorize things on the planet. The use of active or passively transmitted signals in remote sensing is based on electromagnetic radiation. Unlike active remote sensing, where the remote sensing sensor (aircraft or satellite) emits signals and subsequently detects the objects' reflections, passive remote sensing sensors sense the sunlight's reflection.

A Geographic Information System (GIS) is a digital system that allow us to manipulate geographic data. Geographic data is acquired using remote sensing techniques in general, but it is stored, processed, analyzed, and visualized using GIS. Many areas have studied the combination of GIS with remote sensing methods during the last few decades (UN Environment, 2018).

2.2.1. Image classification

Expert and interpreters extract thematic information from satellite pictures using visual interpretation. Tonal variations, texture, size, form, and context are all factors in visual interpretation. Despite its widespread usage for analyzing remote sensing data, visual analysis has the drawback of not giving quantitative information. When there is a large amount of data, visual analysis can only extract a small amount of information. Visual analysis also makes it difficult to make good use of all spectral bands. As a result, computer processing of remotely sensed data is required to fully use the data's ability to detect and quantify characteristics. Typically, land cover classes are mapped from digital remotely sensed data using a supervised digital image classification technique (Wu, 2017).

The objects are distinguished based on the reflectance/emittance fluctuation of their Electromagnetic (EM) radiation (Spectral signature) and other distinguishing characteristics. A pixel is connected with a set of values for each spectral band, i.e. a digital number (DN). The goal of digital classification is to give each pixel in a remote sensing picture a value or label. If the labeling is done for all of the pixels in the image, we obtain a thematic map, similar to visual interpretation.

Spectral response patterns from various surface classes will generally have a mean value and a spread/variability around the mean. A number of factors like atmospheric scattering, topography, class mixture, illumination and view angles etc. cause this spread or variability within a class (Roostaei, Alavi, Nikjoo, & Valizadeh Kamran, 2012).

Using a variety of satellite image processing methods, surveys, and field data to investigate the link between land cover change and water availability, demand, and consumption has proven to be highly successful in determining regional water balances. The categorization employed in this study, in particular, was quite accurate and accurately reflected the various changes in the study region over the previous 30 years. Furthermore, we can analyze the water balances in the Amu Darya river watershed using a mix of satellite and field data. Throughout the literature review, remote sensing has demonstrated superior performance in the investigation of land use/cover changes and the formulation and production of land cover change scenarios for hydrological modeling (Hafyani et al., 2020). Flood and drought disasters can be prevented and mitigated by monitoring river channel dynamics, especially in developing nations. Fluvial river channel dynamics research provides a firm grip on the reasons for and size of erosion and accretion episodes,

which is essential for river behavior management and planning. As modern-day river development planning and project assessment requirements, efficient and cost-effective scientific methods and methodologies for geomorphodynamic mapping and monitoring are critical. Techniques and tools for geospatial analysis because of their capacity to cover spatiotemporal elements utilizing synoptic, RS and GIS have recently become geomorphology tools for change detection in rivers and their floodplain dynamics at the strategic scale. Various RS and GIS approaches are utilized to get insight into the river channel vulnerability as well as a better knowledge of the river reach's temporal and spatial channel alterations and dynamics (Langat et al., 2019).

River morphological dynamics are natural autogenic occurrences caused by discharge flow mechanisms, debris and sediment movement, channel migration, and floodplain erosion and accretion in fluvial rivers. Climate change, discharge amount and type of sediment, and hydrologic regimen fluctuations all play a role in riverbank erosion, accretion, and channel course changes. Anthropogenic development activities such as hydroelectric dam building, irrigation infrastructure construction along the riverbank, and land use changes, on the other hand, accelerate the natural geomorphologic dynamic behavior of rivers across the basin. Human alterations have grown more powerful than natural factors such as floods and droughts, posing a danger to autogenic river channel dynamics, resulting in significant channel deterioration, disruption of sediment supply and water routes, and river provisioning services (Langat et al., 2019).

2.2.2. Object-based classification

One of the most common methods to obtain land-cover information from satellite images is remote sensing image classification. Image classification converts the data into meaningful information. Depending on the supervision, classifications can be supervised and unsupervised, while depending on the data type, two different classification types can be distinguished: pixel and object-based classification. The pixel-based classification has been widely used since the revolution of remote sensing in the 1980s. Pixel-based classification uses multi-spectral classification techniques that assign similar pixel in the same class (Yan, Mas, Maathuis, Xiangmin, & Van Dijk, 2006).

Object-based classification, as opposed to pixel-based classification, classifies images based on objects rather than pixels. Although this approach was first presented in

the 1970s, it was only a decade ago used in remote sensing (Makinde, Salami, Olaleye, & Okewusi, 2016). This approach has been effectively implemented in middle-resolution images, despite being often employed for high and very high-resolution imaging. Object-based image classification is superior than the classic pixel-based classification approach in numerous studies (G. Kaplan & Avdan, 2017),(Esetlili et al., 2018). In order to classify the land cover in the study area, object-based image analysis (OBIA) was used in this paper. The OBIA was performed in eCognition software. The first and most meaningful step of object based classification is the segmentation, in which the pixels are grouped as objects, or segments. The multiresolution segmentation has been successfully used in segmenting middle-resolution satellite images, like Landsat (Benz, Hofmann, Willhauck, Lingenfelder, & Heynen, 2004). The objects are then formed based on the given criteria (Yan et al., 2006). Furthermore, the land cover was classified into four different classes: Water, Cropland, Bare Land, and Wetland. Using the land cover maps, a land conversion analysis of the study area have been made, calculating the changes and shifts from one class to another. In the second part, using only the water class, river channel analysis has been made, thus calculating the erosion and accretion amount and determining the river bank's shift on both left and right side of the river (Figure 4.1). For the accuracy assessment, 400 random points have been used, and the overall accuracy and kappa statistics were calculated.

Landsat satellite images from 1990, 2000, 2011, and 2020 were used to examine land-use change dynamics along the Amu Darya River during the last 30 years. Beginning with the most recent year, these years were chosen to identify probable quick and lengthy changes. The availability of cloud-free pictures for the Amu Darya river was also taken into account. The pictures were obtained from the earth explorer of the United States Geological Survey (USGS, <https://earthexplorer.usgs.gov/>). Four satellite pictures with a path/row of 154 / 034 were collected for the selected years to cover the whole research region. ENVI 5.3 was used to process, classify, and analyze Landsat pictures. Pre-processing of pictures, land-use categorization, accuracy evaluation, and land-use change detection were all part of the digital satellite image analysis from 1990 to 2020 (Tadese et al., 2020).

In this study, land cover was classified into four different classes: Water, Cropland, Bare Land, and Wetland. Using the land cover maps, a land conversion analysis of the study area have been made, calculating the changes and shifts from one class to

anotherand Using the chart below (Figure 2.1), we performed the steps and methods of the study.

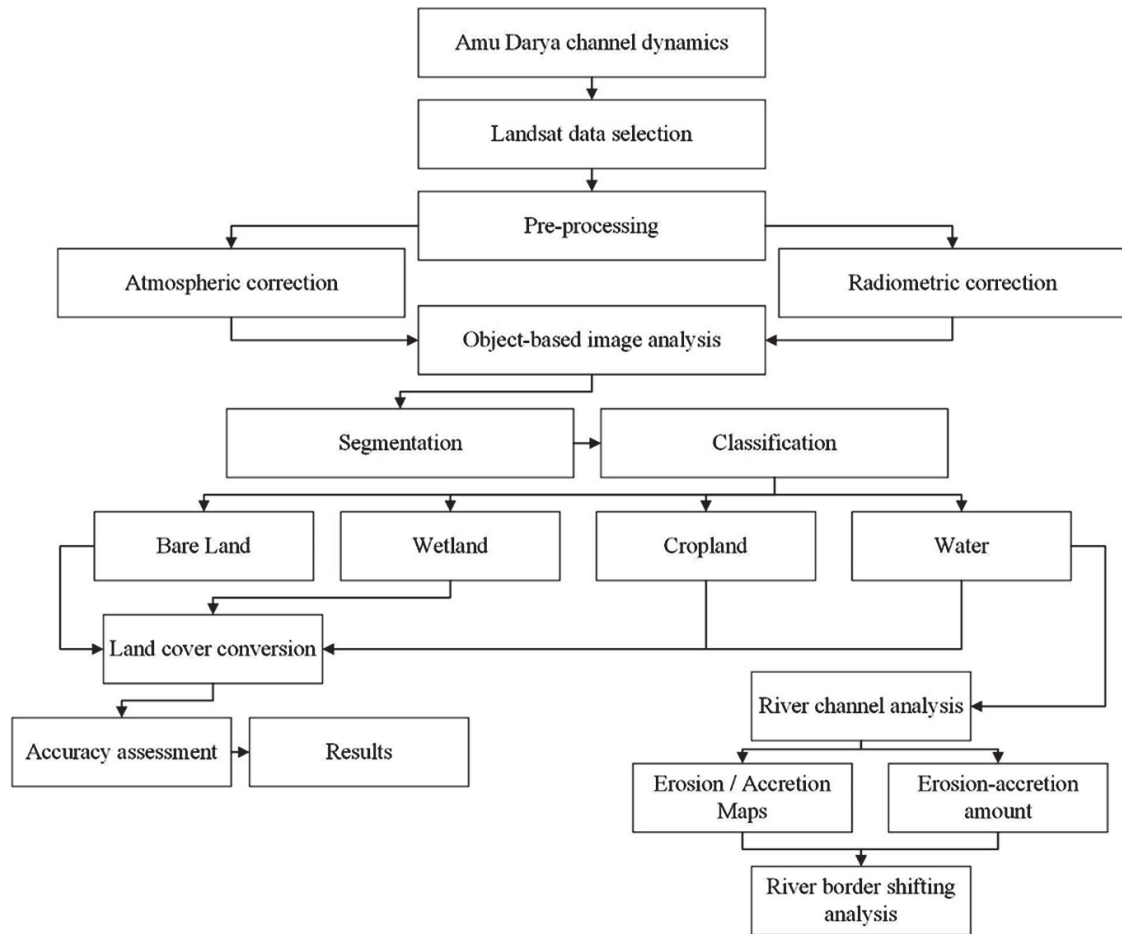


Figure 2.1. Methodology used in this study

2.2.3. Remote Sensing and GIS for River mapping and monitoring

Natural water resources on the earth's surface include river and stream networks with higher geological importance. The rivers exhibit enormous spatiotemporal differences in their shapes and sizes, as well as dynamism. Variability in natural and human activity causes continual changes on the earth's surface. These modifications result in a cut, carry, and deposit of materials from the ground surface as a result of these operations. One of the outcomes of these activities is a change in the base stream and the shape of rivers as a result of river erosion and accretion (Aher, Bairagi, Deshmukh, & Gaikwad, 2012). Climate change has a greater impact on river bank erosion and accretion and channel course alterations.. River bank erosion and accretion, and channel course

changes are more related to climate change, discharge quantity and type of sediment, and variations of hydrologic regimen (Langat et al., 2019).

The assessment of the rate of river erosion known as the change in the form and shape of the river has become crucial. Remote sensing (RS) and Geographic Information System (GIS) which are now-a-days used very commonly for spatiotemporal assessment of the different Topographical, Geomorphical, Geological change. Satellite data can deliver comprehensive, synoptic sight of equitably huge area at regular intervals by using RS. RS and GIS are suitable and idyllic for analyzing and monitoring river bank change or erosion and accretion rate.

Also, by integration of RS and GIS changes of channel configuration and the orientations between the river channel and its embankments can be determined. Using the RS and GIS technology, river profiles at a definite time frame are developed and the rate of erosion and accretion is computed and the use of temporal satellite images to express the dynamics move. The rate of erosion and accretion is computed but also the use of temporal satellite images can express the dynamics move of a definite time frame are developed. The rate of erosion and accretion is computed but also the use of temporal satellite images can express the dynamic movement of the river and its floodplain. Also,, multi-temporal satellite images help predict how the mobility of the river will continue or restore stability which kind of actions will be preferable. The study is undertaken due to the availability of remotely sensed databases and benefit of remotely sensed data like large view, multi-temporal etc (Aher et al., 2012).

Soil is a natural resource that plays an important role in the environment, society, and economy. The absence of precise information on the regions impacted by soil erosion and its size is a constraint of the aforementioned efforts. Most of these efforts, for example, are limited to traditional approaches like the Revised Universal Soil Loss Equation (RUSLE), and conservation initiatives are also regarded a failure because populations in impacted regions lack a feeling of ownership. The ability to measure and monitor soil erosion at local, national, and regional scales has considerably improved because to the use of aerial photos and satellite data.

Traditional erosion modeling approaches use manual identification of erosional levels using air pictures and field work measurements. The main disadvantage of these techniques is that they are time-consuming and expensive and confined to specialist knowledge. In conjunction with GIS, RS offers crucial information on erosional dynamics

and intensity over time and location, which is essential for soil erosion evaluation, management, and prediction. According to the literature, one of the most severe worldwide environmental concerns is soil erosion, including water and wind erosion, chemical degradation, excessive salts, physical and biological deterioration (Sarath, Saran, & Ramana, 2018). Although geomorphologic processes can induce soil erosion, rapid soil erosion is favored mainly by human activities. Rapid population expansion, deforestation, inappropriate land agriculture, unregulated, and overgrazing have all contributed to increased soil erosion globally, particularly in emerging nations (Gelagay & Minale, 2016). Numerous investigations conducted to date using satellite technology have verified this (Sarath et al., 2018).

A coastline is a physical boundary between land and sea. The charting of coasts, which allows observation of how they have evolved across different periods, is one approach to discover changes in wetland habitats. This is because knowing the coastline's location is essential for assessing and describing land and coastal water resources. Shifts in shoreline position are crucial for coastal zone management due to erosion and deposition since extremely dynamic coasts can pose significant dangers to human usage and development. Safe navigation, resource management, environmental protection, and sustainable coastal development and planning all need coastline mapping and measurement of position changes. In addition, the European Union's (EU) Ecosystems Directive has designated several coastal habitats as special protection zones. As a result, it's clear that updating coastal maps and monitoring movement rates would require quick, repeatable procedures (Petrooulos, Kalivas, Griffiths, & Dimou, 2015).

The Earth Observation (EO) technological framework is ideally adapted for habitat mapping and monitoring, and it may offer data for conservation programs such as the European Commission's (EC) Habitats Directive. The potential of EO technology to give cheap, continuous, synoptic views at a range of geographical and temporal scales, even for inaccessible places providing data has been preserved, is one of its main advantages. Indeed, since satellites can offer digital images in infrared spectral regions where the land-water boundary may be well delineated, detecting coastal changes with EO data has been increasingly important in recent decades. Furthermore, EO data may be integrated with GIS to give a robust set of tools for evaluating and extracting spatial data, allowing for more consistent and trustworthy decision-making. This connection with EO datasets provides a fantastic foundation for data collecting, storage, synthesis

measurements, and analysis, all of which are critical in investigating coastal changes (Petroopoulos et al., 2015).

With the advancement of space technology, RS combined with GIS has become an efficient tool for mapping and spatial–temporal monitoring of land use change and providing a thorough knowledge of ecosystem function. As a result, these methods demonstrate a keen interest in obtaining information about the Earth's surface in both space and time. Several studies have been conducted throughout the world to research land use changes using satellite image processing technologies in various climatic situations. The International Geosphere-Biosphere Program (IGBP) and the International Human Dimension Program (IHDP) have made it a priority to understand better the link between biosphere aspects of the hydrological cycle (BAHC) and land use and land cover changes (Hafyani et al., 2020). To build maps and get information and data, researchers utilized RS, and GSI approaches (Chandra Paul, Saha, & Hembram, 2020). Landsat images from the United States Geological Survey are the study's primary data source (USGS). Since 1972, Landsat pictures with a temporal resolution of 16 days have given free up-to-date photographs across the world (Sajjad et al., 2020).

Image processing means the study of any algorithm that takes an image as input and returns an image as output. It is a process of improving the quality of an image for analysis and manipulation. Raw remotely sensed data have found a lot of geometric as well as radiometric errors. The geometric and radiometric corrections are mandatory before using raw remotely sensed data for analysis (Roostaei et al., 2012).

River science and management are becoming more accessible thanks to RS technology. Marcus and Fonstad (Bizzi, Demarchi, Grabowski, Weissteiner, & Van de Bund, 2016) argue that RS methods should be used more broadly in research and management. However, the field's steady advancement has resulted in a surprising diversity of applications to fluvial geomorphology.

Many fluvial features frequently monitored for hydro morphological surveys, like multispectral data, have been assessed in scientific research utilizing RS technology. Due to the high expense of data gathering, however, the use of RS for river characterization has been focused on addressing particular research issues for case studies rather than tackling aspects of operational implementation for large-scale applications, as Marcus and Fonstad argue (Bizzi et al., 2016). However, collecting RS data spanning broad regions (regional or national) has only just begun to attain enough spatial and spectral

resolution for fluvial study. The capacity to survey and define the hydro morphological characteristics of river systems comprehensively at various dimensions, from watershed to reaches, is unparalleled in Europe because to the advent of RS data availability at larger scales and sufficient precision. However, this abundance of data puts existing data analysis abilities to the test, necessitating advanced statistical modeling frameworks to be acceptable for river definition and management (Bizzi et al., 2016).

The impacts of stream bank erosion on channel evolution are important geomorphic research topics in various scientific and technical disciplines. RS satellite data may give a complete, synoptic view of a relatively broad region at regular intervals with a short turnaround time, making it suitable and excellent for researching and monitoring river erosion and bank line movement. Various studies have been conducted in this respect for some of the world's main rivers. Several researchers have used remotely sensed data to determine Brahmaputra River and its tributary channel alterations. The National Research Service Award (NRSA) has completed a river migration study of the Brahmaputra River using an airborne scanner survey, as well as a series of surveys to monitor changes in land use, river channels, and banks in order to provide a foundation for estimating the river's response to flood events (M. & S., 1981).

2.3. Climate and Hydrology of Amu Darya

The Amu Darya basin's rainfall and temperature are determined mainly by terrain. The river basin's major source of precipitation is the mid-latitude westerlies. The precipitation mostly falls as snow during the winter, which helps feed the glaciers in the Amu Darya's source regions, at the highest elevations in the Pamirs and the Hindu Kush, when winter temperatures average below freezing yearly precipitation can surpass 1,015 mm. At lower elevations, mean monthly temperatures rise and precipitation falls. The lowest sections of the Amu Darya get less than 100 millimetres of annual precipitation, with mean July temperatures exceeding 25 °C and mean January temperatures ranging from 0 °C to 10 °C (http-2).

2.4. Climate in Afghanistan

The climate of Afghanistan is typically arid continental, with cold, wet winters (with a rainy peak in April) and hot, sunny summers. However, significant changes depend on location and height: the south is desert, many parts are chilly due to altitude, and the far east, which is partly impacted by the Indian monsoon, is quite wet even in summer.

Precipitation is typically limited, at semi-desert or desert levels, except in the eastern parts, where it surpasses 500 millimeters per year in certain locations, and even reaches 1.000 mm in the extreme east, near the Pakistani border (Kunar and Nurestan provinces). During the winter, disturbances from the Mediterranean reach the country's center-north (and, on rare occasions, the south), bringing rain and even snow to the mountains. Early in the spring, when the southern Asian continent begins to warm up, the battle of air masses intensifies, resulting in more rainfall; in fact, March is frequently the wettest month. The rains lessen as the season progresses, and it rarely rains from June to September. Only in the easternmost region, east of Kabul, is there a little increase in rainfall in July and August due to the final branch of the monsoon that impacts India and Pakistan in (figure 2.2) (<http-3>).

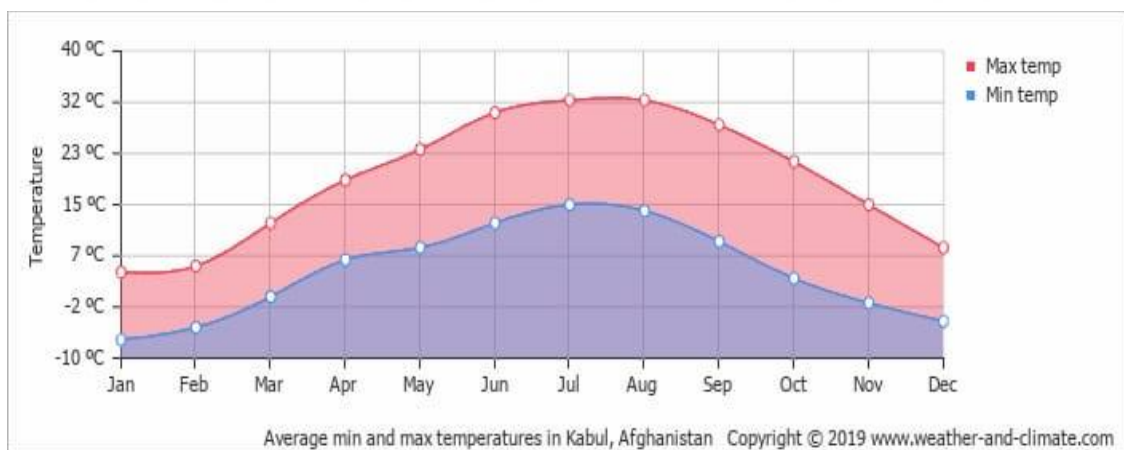


Figure 2.2. Average min and max temperatures in Kabul, Afghanistan, 2019

2.5. Google Earth Engine and Remote Sensing

Google Earth Engine (GEE) is a cloud computing platform for processing Earth observation data that is free and web-based (Stuhler, 2016). For decades, RS systems have been gathering large amounts of data, organizing and analyzing them in ways that are impossible to do with standard software packages and desktop computing resources. In

order to successfully handle the problems of big data analysis, Google has built a cloud computing platform dubbed GEE. This platform, in particular, makes it easier to analyze huge amounts of geodata over broad areas and to monitor the environment over extended periods (Stuhler, 2016). Although the GEE platform was released in 2010 and has demonstrated its tremendous potential for various applications, it has only recently been extensively studied and exploited for RS applications. GEE has also been used in a variety of applications, including LULC (Land Cover/Land Use) categorization. Despite their strength, these categories' somewhat poor spatial resolution might restrict their utility, especially at smaller scales. Surprisingly few algorithms exist to sharpen the spatial resolution of moderate-resolution LULC classifications in light of finer scale imagery, hydrology (Tamiminia et al., 2020), LULC change is a major contributor to global greenhouse gas emissions and can have a wide range of indirect effects, including biodiversity loss and regional hydrologic change, LULC change in the tropics frequently occurs at small scales. Studies on LULC transformation are especially significant in global environmental change and sustainable development because they emphasize the intensity and pattern of human-earth relationships (Hazarika, Das, & Borah, 2015).

This study is included explicitly in this context, to demonstrate GEE's current ability to analyze large amounts of free EO big data (for example, Landsat and Sentinel images) for long-term spatiotemporal monitoring and its relationship to LC changes. GEE is, in fact, Google's freshly launched computing platform "for petabyte-scale scientific (Ravanelli et al., 2018)." Natural disasters (Alam & Ray-Bennett, 2021) have catastrophic consequences for infrastructure, businesses, and individuals in the impacted area. More than 5.7 billion people were impacted by catastrophes between 1998 and 2017, with more than one million people died, and a total loss of 2.9 trillion dollars.

After the initial post-disaster reaction phase, which mostly consists of search and rescue activities, recovery begins. According to the Sendai Framework (Ghaffarian, Farhadabad, & Kerle, 2020), climate variability and change acting at broad scales can lead to divergent changes in plant production at local scales (Ghaffarian et al., 2020). Post-disaster recovery is the process of reconstructing communities in all aspects (for example, physical, economic, social, and environmental) to return life, livelihoods, and the built environment to their pre-impact, or even better, states (Bunting, Munson, & Bradford, 2019).

Quantifying how production responds to climate change at local scales is critical for understanding underlying ecological processes and informing land management decisions. However, it has traditionally been limited in spatiotemporal scale by using discrete ground-based measurements or coarse resolution satellite observations. Production responses to climate may now be assessed across large landscapes overtime at a resolution appropriate for ecological and land management applications, as well as image processing, thanks to the introduction of cloud-based computing through GEE. It is predicted that more consumers from various areas would adopt GEE to tackle their large data processing problems (Amani et al., 2020). GEE takes advantage of Google's computing resources as well as publicly accessible RS datasets (Gorelick et al., 2017). GEE is the most widely used big geodata processing platform, assisting scientists in their research by offering free access to many remotely sensed datasets. GEE is accessible through a web-based Application Programming Interface (API) and an Interactive Development Environment (IDE).

Furthermore, users do not need to be familiar with web programming or the Hyper Text Markup Language to utilize GEE for various applications. GEE offers characteristics such as automated parallel processing and a fast computing platform (Amani et al., 2020). GEE has recently been in the limelight when it comes to large data processing for remote sensing. GEE is a cloud-based technology that makes use of Google's cloud to enable worldwide parallel geospatial data processing. GEE is a free cloud platform that stores petabyte amounts of remotely sensed data from the National Oceanographic and Atmospheric Administration's Advanced Very High Resolution Radiometer Sentinel 1, 2, 3, and 5-P, as well as data from the Advanced Land Observing Satellite (ALOS) (Tamiminia et al., 2020). A more complete study of the GEE platform is required to explore many elements of the platform.

3. MATERIALS AND METHODS

3.1. Study Area

The Amu Darya, also known as the Oxus River in ancient times, is one of Central Asia's longest rivers. From Greek and Roman times, the Amu Darya was known as the Oxus in the Western world, and the Arabs named it the Jayn. Its current name is claimed to be derived from the city of Amul in Turkmenistan, which is said to have formerly been where modern-day Türkmenabat (previously Chärjew) now stands. Although the Amu Darya was well-known in antiquity, until the time of Peter I the Great, Tsar of Russia, the river got little attention in Europe. Although the first reasonably accurate map of the river was created in 1734, organized research in the region did not begin until the late nineteenth century.

The Amu Darya is a west-northwest flowing river created by the confluence of the Vakhsh and Panj (Pyandzh) rivers (at which point it is known as the Amu Darya). The Amu Darya forms part of Afghanistan's northern border with Tajikistan, Uzbekistan, and Turkmenistan along its upper course. It then runs across eastern Turkmenistan's desert, forming part of the border between Uzbekistan to the northeast and Turkmenistan to the southwest in its lower course (Figure 3.1). The Amu Darya is 1,415 kilometers long, but when measured from the headwaters of its headstream, the Panj River in the Pamirs, it is 2,540 kilometers long. The Amu Darya used to flow into the Aral Sea. However, in the twentieth and twenty-first centuries, water diversion for agriculture led to the Aral Sea's shrinkage and assured that the river no longer reaches its original terminal. The Amu Darya is joined by three more tributaries not far below the Panj-Vakhsh junction: the Qonduz River on the left (south) and the Kofarnihon (Kafirnigan) and Surkhan rivers on the right (north). After leaving the highlands, the river turns northwest to pass the dry Turan Plain, where it forms the border between the Karakum and Kyzylkum deserts to the southwest and northeast, respectively. In this location, the Amu Darya loses much water due to irrigation, evaporation, and seepage. The basin of the Amu Darya stretches for 950 kilometers north to south and more than 1,450 kilometers east to west. It is bordered on the north by the Syr Darya basin, east by the Tarim Basin, and south by the Indus and Helmand river basins. Only half of the basin's entire size of 465,000 square kilometers is contained within its source region, the Pamir and Hindu Kush mountain ranges to the east. The water of the Amu Darya is changeable according to the seasons of

the year and also its surface rises in the rainy and wet seasons and its surface returns to normal in the non-rainy and wet seasons, the images of which are shown in (figure 3.1).



Figure 3.1. Location of the study area



Image 3.1. Amu Darya, April 2021 (<http-4>)

Pictures of the current state of the Amu Darya from its various parts, taken in May 2021 by my friend Ali Reza Danesh, are shown in (image 3.2). It is also shown in (image 3.1) of the state of the Amu Desert.

The Syr Darya and Amu Darya river basins have a complex dams and reservoirs that are primarily utilized for winter water storage and summer release for irrigation and electricity generation. According to the World Bank, the Aral Sea Basin has around 80 water reservoirs, 45 hydroelectric facilities, and 57 major dams. Tajikistan (with the third biggest hydroelectric resource in the former Soviet Union) and Kyrgyzstan are the two countries with the most. The Amu Darya and Syr Darya have potential hydropower resources of 306 and 162 billion kilowatt hours. The region's hydroelectric resources have a total commercial potential of 127 billion kilowatt hours, with Tajikistan having 80 billion kilowatt hours, Kyrgyzstan 37 billion kilowatt hours, and Uzbekistan 10 billion kilowatt hours.



Image 3.2. *Flooded parts around Amu Darya (Ali Reza Danish, May, 2021)*



Image 3.3. *Damages around Amu Darya*

Some natural elements such as geography, hydrography, hydrology, climate, ecology, etc.;

- The social and economic requirements of the watercourse states.
- The population that is reliant on water resources; the impacts of water consumption on other states; current and future uses
- Water resource conservation, protection, development, and efficiency and the availability of alternatives to a planned or existing usage.
- Other elements of the 1997 United Nations Convention on International Watercourses that are particularly relevant to the Aral Sea Basin States include the responsibility not to cause serious harm to other watercourse States and the general obligation to cooperate (through joint mechanisms or commissions)
- To regularly share information and offer early notification of planned actions and emergency situations that might substantially negatively impact other watercourse states (Farzaneh & Mohammadi, 2011).

3.2. Materials

3.2.1. Satellite imagery

3.2.2. Landsat

In order to estimate the land cover changes and the river dynamics in the study area, three Landsat TM and one Landsat Operational Land Imager (OLI) satellite images from four different years (1990, 2000, 2011, and 2020), in the period between the end of May till the middle of July, have been used. These periods were cloud-free, enabling us to perform the needed analyses. Also, the date selection was made according to the meteorological data. May to July is the driest period after a wet period in March when the flood is most likely to occur. In 2010, there was no cloud-free imagery, and 2011 was selected instead. Details about the used satellite images can be found in Table 3.1. All of the scenes were level-1 open-access data sets downloaded from the USGS webpage. The satellite images were then pre-processed, applying atmospheric and geometric correction.

Landsat images of 30×30 m spatial resolution were used to assess the Amu Darya river dynamics and monitor the spatial and temporal changes. Three snow and cloud-free scenes of Landsat-5 Thematic Mapper for 1990, 2000 and 2010, and one scene of

Landsat-8 OLI for 2020 from the month of June and July were acquired from the USGS website (<http://5>), Properties of the images used in examining the changes.

Table 3.1. *Landsat satallite features of images used*

No	Sensor	Senor type	Image download date	Spatial Resolution (m)	Date and path/Row	Spectral Resolution (µm)
1	Landsat	TM	22/05/1990	30 m	154/034	7 Bant
2	Landsat	TM	17/05/2000	30 m	154/024	7 Bant
3	Landsat	TM	19/07/2011	30 m	154/04	7 Bant

Table 3.2. *Features of satellite imagery used*

Sensor	Date ve Path/Row	Spectral Resolution (µm)	Spatial Resolution (m)
Landsat 5 Thematic Mapper(TM)	22/05/1990	Band 1 0.45-0.52	30
		Band 2 0.52-0.60	30
		Band 3 0.63-0.69	30
	17/05/2000	Band 4 0.76-0.90	30
		Band 5 1.55-0.75	30
		Band 6 10.4-12.5	120
	19/07/2011	Band 7 2.08-2.35	30
Landsat 8 Operational Land Imager (OLI)	07/06/2020	Band 1 0.435-0.451	30
		Band 2 0.452-0.512	30
		Band 3 0.533-0.590	30
		Band 4 0.636-0.673	30
		Band 5 0.851-0.879	30
		Band 6 1.566-1.651	30
		Band 7 2.107-2.294	30
		Band 10 10.60-11.19	100
		Band 11 11.50-12.51	100

3.2.3. Sentinel – 2

For the seasonal variations in 2020, we obtained image pre-processed and cloud-free optical Sentinel-2 photos from GEE. Sentinel-2 uses 13 spectral bands to detect the electromagnetic spectrum, spanning from visible to short-wave infrared (SWIR). The satellite's visible and near-infrared (NIR) bands have a spatial resolution of 10 meters, while the red-edge and SWIR bands have a spatial resolution of 20 meters. Other bands with a spatial resolution of 60 m are utilized to detect water vapor, cirrus clouds, and coastal aerosols (Brombacher, Reiche, Dijkma, & Teuling, 2020).

Sentinel-2 (S-2) is a polar-orbiting optical mission for land and coastal region surveillance and emergency services, with a wider spectral range and better performance than earlier comparable imaging missions like SPOT and Landsat (Drusch et al., 2012). The Sentinel-2 mission is responsible for monitoring agriculture, forestry, land-use and land-cover change, mapping biophysical variables such as leaf chlorophyll content, leaf water content, leaf area index, and risk and disaster mapping. The Sentinel-2 mission comprises two satellites, Sentinel-2A and Sentinel-2B, each having an optical imaging sensor called MSI (Multi-Spectral Instrument). The MSI is designed to measure reflected radiation in 13 spectral bands ranging from Visible and Near Infrared (VNIR) to Short Wave Infrared (SWIR) (Figure 3.2). On June 23rd, 2015, Sentinel-2A was launched, followed by Sentinel-2B on March 7th, 2017. With the start of the operational phase (June 16th, 2017), the constellation of both satellites allows for picture acquisition over the same area every 5 days or fewer, with a descending node at 10:30 a.m. (Main-Knorn et al., 2017).

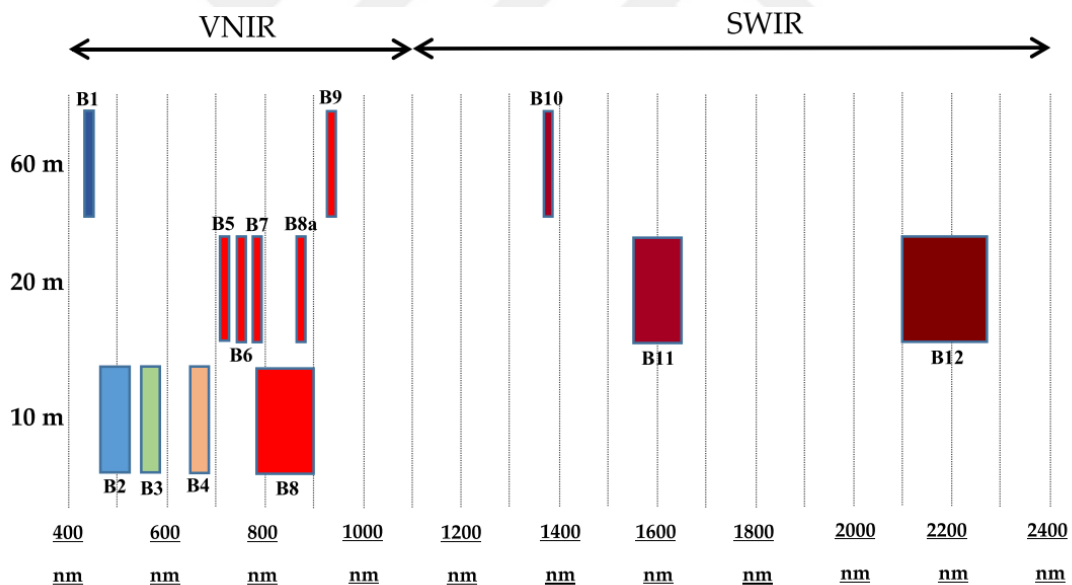


Figure 3.2. *MSI spectral resolution (Main-Knorn et al., 2017)*

The end-to-end Sentinel-2 system are divided into two parts:

The space segment will include the two orbiting satellites and their payload sensor, and the ground section. The ground segment is responsible for data gathering from the space segment, data processing, archiving, distribution, and overall mission control (Drusch et al., 2012).

Frequent five-day revisits around the equator necessitate the use of two identical Sentinel-2 satellites operating simultaneously. The orbit is Sun-synchronous, with a descending node at 10:30 a.m. and a 786 km height (14+3/10 rotations per day). This local time was chosen as the optimum compromise between cloud reduction and adequate solar light. It is near to the Landsat local overpass time and matches SPOT's, allowing long-term time series to be built using Sentinel2 data and historical pictures. (Brombacher et al., 2020), ([http-6](#)), ([http- 7](#)).

3.3. GEE

In the second part of the study, the GEE platform has been used for long-term and seasonal changes classification. For the long term, similar to the OBIA, in GEE we have used Landsat imagery, while for the seasonal changes we have used sentinel-2 imagery taking into consideration its higher spectral and spatial resolution. In the next section, we give overview of the GEE platform and the steps of the classification done in this study.

3.3.1. GEE platform overview

GEE is mainly composed of the following three platforms:

- i. Earth Engine (EE) Explorer;
- ii. EE Code Editor;
- iii. EE Timelapse.

The details of each platform are discussed in the following sections.

EE Explorer is a data viewer tool that allows users to browse the EE Data Catalog's vast datasets. Millions of publicly available datasets are included in the Data Catalog, including the whole Landsat, MODIS, and Sentinel imaging collection and many atmospheric, meteorological, and vector datasets. Every day, the Data Catalog receives over 4000 new datasets. The Workspace and the DataCatalog constitute the EE Explorer. Users may search through huge datasets in the Data Catalog and import them into the workspace. Users may manipulate and visualize datasets in the workspace. The Workspace also allows users to examine, magnify, and pan their data quickly.

It also allows users to control factors relating to visuals, such as contrast, brightness, and opacity levels. Users can add additional levels to the Workspace to better evaluate any changes over time. Users can choose between a three-band RGB

representation or a single-band grayscale/pseudocolor representation for the layers (Amani et al., 2020).

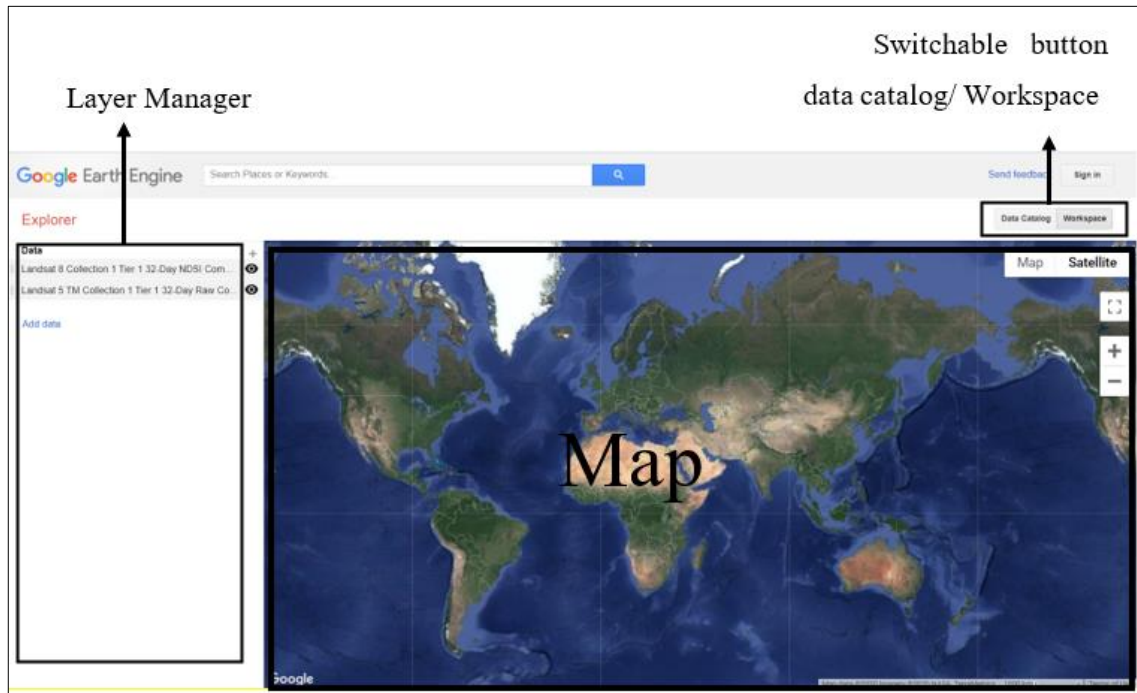


Figure 3.3. *Earth engine explorer; platform*

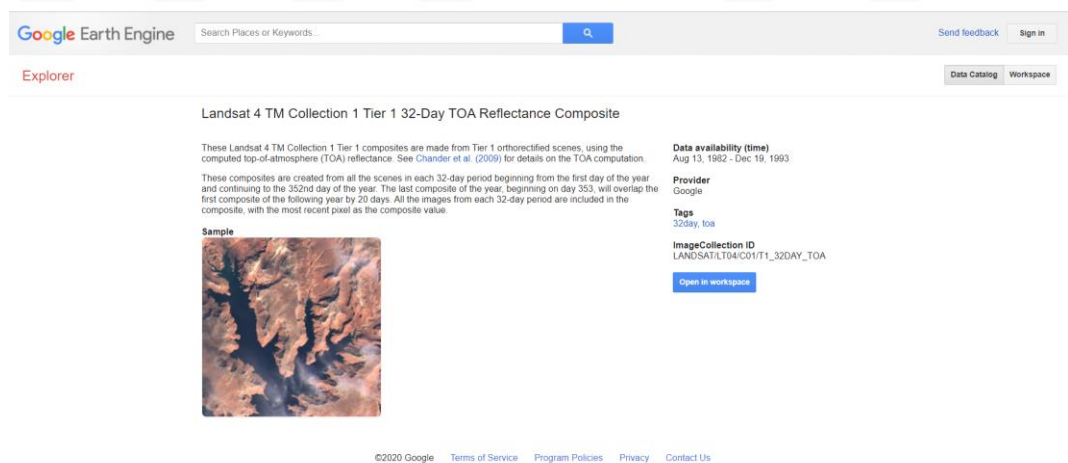


Figure 3.4. *Earth engine explorer; eata catalog*

3.3.2. EE code editor

While the EE Explorer platform is meant to display datasets, the EECODE Editor is designed to analyze large data and create EE applications using the JavaScript programming language. The EE Code Editor is made up of various parts, as shown in

Figure 3.4: a code editor, a map, a layer manager, geometry tools, and several tabs, including Script, Doc, Assets, Inspector, Console, and Tasks.

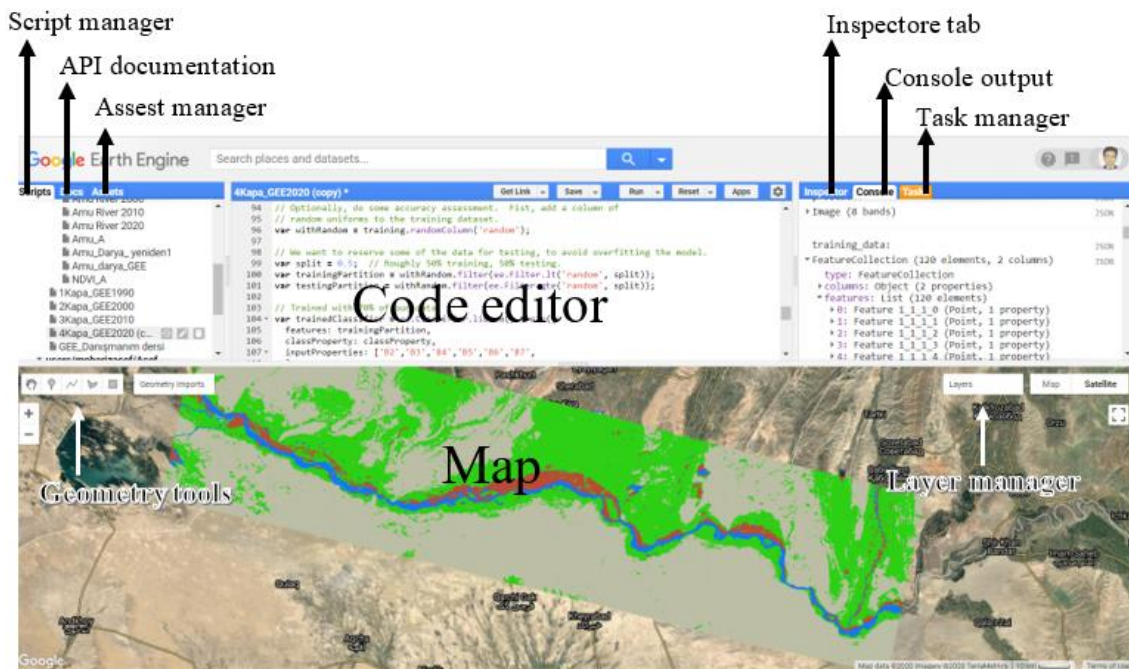


Figure 3.5. Overview of the Earth Engine Code Editor

The central panel allows users to write their JavaScript code. GEE processes the written codes and illustrates the results as images in the Map panel or as messages in the Console Tab. Similar to the EE Explorer, users can set the visualization parameters via the Layer manager in the Code Editor. In the Script tab, numerous examples of scripts facilitate developing applications. There are more than 800 prebuilt functions in the EE library, users can become familiar with them using the Doc tab, providing API reference documentation (Amani et al., 2020).

As previously mentioned, GEE includes big open-access datasets. Users, however, are not restricted to use only these datasets. They can upload and manage their own data using the Asset Asset tab. It is also possible to interactively query the map using the Inspector tab. Finally, the Geometry tools allow users to draw geometric features, such as points, lines, and polygons, which can be used in further analyses (Amani et al., 2020).

3.3.3. EE time-lapse GEE

GEE's Time-laps platform (Amani et al., 2020) integrates petabytes of RS information over four decades to generate a worldwide, zoomable, and cloud-free movie spanning place and time. The GEE platform's enormous computing capability is demonstrated via the Timelapse platform. This platform offers the most comprehensive view of the planet, exposing how its inhabitants treat it. For example, with GEE Time-lapse, one can readily witness the rapid retreat of the Mendenhall Glacier in Alaska, the mining industry's decapitation of the West Virginia Mountains, forest destruction in the Amazon, and the drying of the Urmia Lake in Iran over time.

3.3.4. GEE datasets

Earth Engine comprises a multi-petabyte data catalog that is ready for analysis, as well as a high-performance, inherently parallel compute service. It is managed and accessed via a web-based interactive development environment (IDE) and an Internet-accessible application programming interface (API) that allows for quick prototyping and display of outcomes (Gorelick et al., 2017).

For interactive data and algorithm exploration and processing, GEE provides a somewhat user-friendly front-end solution. The access is granted only after the development team has approved the type of possible usage and the user's background. Academics, researchers, hobbyists, and remote sensing experts will benefit from the GEE (Vasku Marek, 2019).

The EarthEngine with Code Editor can be called via: ([http-12](#)). A detailed guide to the Code Editor can be found here: ([http-8](#)) (Stuhler, 2016).

Landsat datasets are valuable resources to perform temporal analysis. Landsat collection includes seven multispectral satellites: Landsat 1–3 (1972–1983), Landsat-4 (1982–1993), Landsat-5 (1984–2012), Landsat-7 (1999–present), and Landsat-8 (2013 present). Landsat satellites have optical sensors, the images of which may be obscured by clouds. Therefore, temporal cloud detecting, masking, and removing are essential preprocessing steps in different applications, such as image classifications using multitemporal imagery. Additionally, the availability of the multitemporal Landsat datasets has facilitated national and global scale analysis (Mateo-García, Gómez-Chova, Amorós-López, Muñoz-Marí, & Camps-Valls, 2018). Landsat-based datasets within

GEE have been employed in various applications. For instance, Landsat data available in GEE have been widely utilized in generating Land Cover/Land Use (LCLU) maps. Moreover, urban detection and extraction is an important task in the economic investigation due to rapid population growth. Therefore, several studies have utilized Landsat data in river monitoring (Ravanelli et al., 2018).

3.3.5. GEE classification

To classify the study area into four classes: Water, Bare Land, Cropland, and Wetland, image collections from Landsat – 5 (1990, 2000, and 2010), Landsat – 8 (2020), in the cloud computing platform, GEE has been used. The image collections were filtered by date and images from June and July were used in further processing. The obtained images were reduced to a single image to get cloud-free imagery, calculating their median values. Six Landsat bands (Blue, Green, Red, Near Infrared, ShortWave Infrared-1, ShortWave Infrared-2), were used to classify. In addition to the mentioned bands, two spectral indices calculated from Landsat data were added to the investigation; Normalized Difference Vegetation Index (NDVI), Normalized Difference Water Index (NDWI), Modified Normalized Difference Water Index (MNDWI). Details and equations of the indices are given in the table below. NDWI, MNDWI, and NDVI are commonly suggested in the literature for water detection (Kordelas, Manakos, Aragonés, Díaz-Delgado, & Bustamante, 2018). The MNDWI ranges between -1 and 1, with high values corresponding to water and low values to land. The MNDWI is calculated using Sentinel-2's green (Band 3 at 559.8 nm) and short-wave infrared (SWIR) bands (Band 11 at 1613.7 nm) (Brombacher et al., 2020).

Table 3.3. *Spectral indices used in the classification*

	Index	Used Bands	Equation
1	NDVI	Red, NIR	$\text{NIR} - \text{Red} / \text{NIR} + \text{Red}$
2	NDWI	Green, NIR	$\text{Green} - \text{NIR} / \text{Green} + \text{NIR}$
3	MNDWI	Green, SWIR	$\text{Green} - \text{SWIR} / \text{Green} + \text{SWIR}$

The NDWI ranges between -1 and 1, with high values corresponding to water and low values to land. The NDWI is calculated using Sentinel-2's green (Band 4 at

664.6 nm) and NIR bands (Band 8 at 832.8 nm). The NDVI ranges between -1 and 1, with high values corresponding to vegetation and low values to land. The NDVI is calculated using Sentinel-2's green (Band 8 at 832.8 nm) and Red bands (Band 4 at 664.6 nm).

For the four classifications, the same samples have been used. Thus, the samples were carefully selected from the unchanged land covers over the years. The sample training was done over the Landsat data, with validation over high-resolution imagery from Google Earth. The classification was performed using a LIBSVM classifier. 50% of the samples were used in the classification, while 30% were used for the accuracy assessment where overall accuracy and kappa statistics were calculated for every year. The same methodology has been used for the seasonal analysis. Details about the used methodology are given in the flowchart in Figure 3.6.

3.3.6. Support vector machines (SVM)

Support Vector Machine (SVM) has been a prominent supervised machine learning (ML) technique for classification and regression in recent decades (http-10). The perpendicular distance or margin between decision planes (designated as decision border) and data points is crucial to SVM. As a decision boundary, the most significant margin has been chosen. The objects are divided based on this distance or margin, with distinct class memberships (Heenan et al., 2015). The position of the border is determined by a subset of data known as the support vector (Bar, Parida, & Pandey, 2020). The most widely used Mapping and Monitoring Amu Darya River Dynamics of SVM were used to categorize the river mapping in this study.

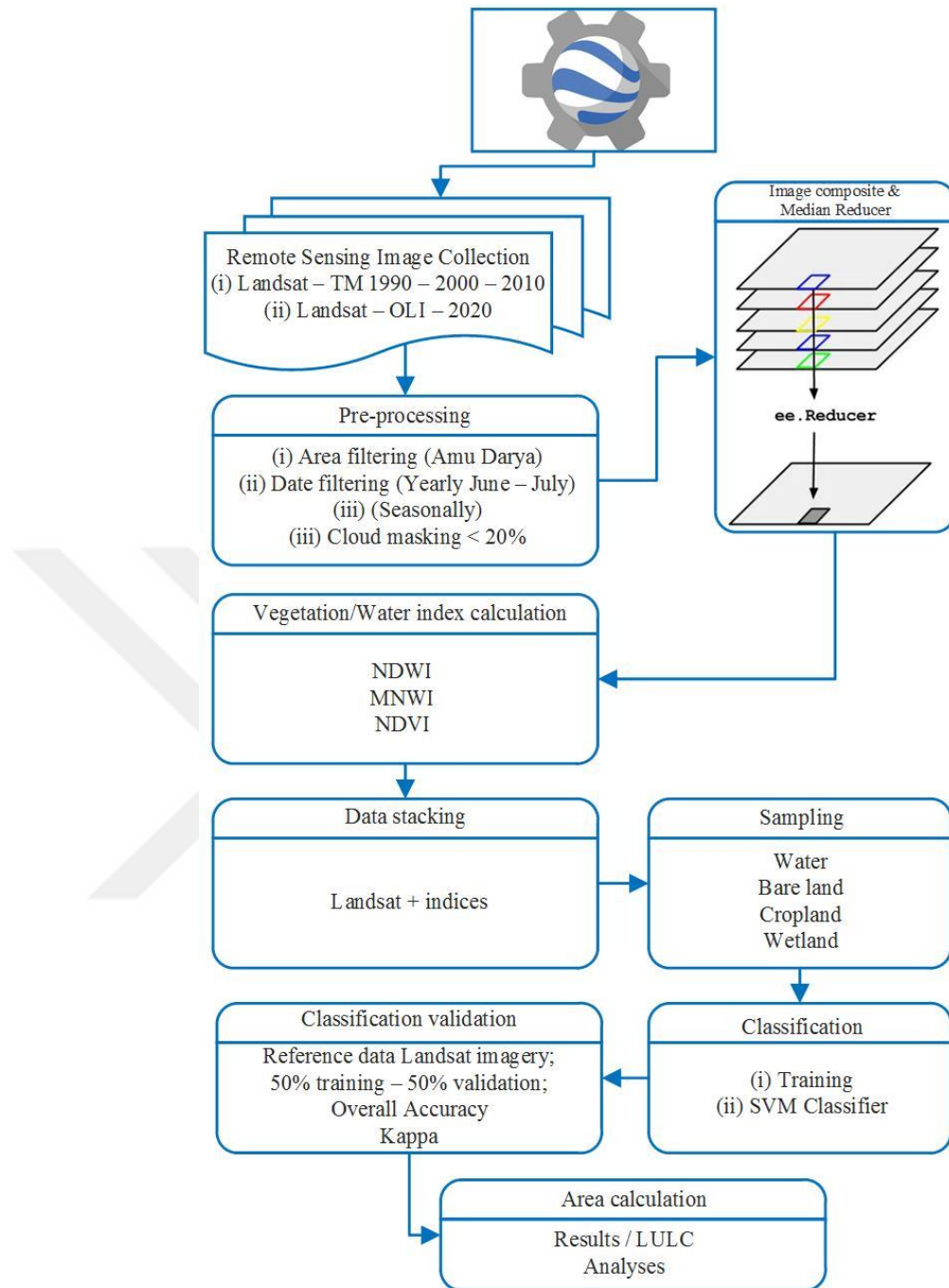


Figure 3.6. Flowchart of the GEE classification

3.3.7. GEE code

After the study area has been selected, it has been added as a Geometry in the GEE platform. Furthermore, the four classes, Water, Cropland, Bare land, and Wetland have been distinguished in the study area. Using Landsat for the yearly, and Sentinel-2 for the seasonal analyses, 30 sample points for each class have been selected. Then, image

collections have been selected and processed. The image collections have been clipped according to the study area, date, cloud cover, and the same bands have been used for Landsat – 5 and Landsat – 8 for the yearly analysis. In Figure 3.7 a sample of the GEE code for image collection has been given.

```

1
2 Map.centerObject(amu);
3 //Map.addLayer(amu);
4
5 // landsat image
6
7 var landsat2020 = ee.ImageCollection('LANDSAT/LC08/C01/T1_SR')
8 .filterBounds(amu)
9 .filterDate('2020-06-01','2020-07-30')
10 .median()
11 .select('B[2-7]')
12 .clip(amu);
13 print('Landsat Image: ',landsat2020);
14 Map.addLayer(landsat2020,{min:200, max:3000,bands:['B4','B3','B2']},'Landsat2020');
15

```

Figure 3.7. GEE code sample for image collection

Three different vegetation indices have been added to the dataset. A code sample for the index calculation using Landsat – 8 is given in Figure 3.8.

```

19 //.....NDVI.....
20 var landsat2020ndvi = ee.ImageCollection('LANDSAT/LC08/C01/T1_SR')
21 .filterBounds(amu)
22 .filterDate('2020-06-01','2020-07-30')
23 var ndvi = landsat2020ndvi.map(function(img){
24   return img.normalizedDifference(['B5','B4']);
25 });
26 var ndvi2020 = ndvi.max().clip(amu).rename('ndvi');
27 print('NDVI2020: ', ndvi2020);
28 Map.addLayer(ndvi2020,{min:0,max:1,palette:['#ffffff','#1bfff0','#000000']},'NDVI2020');
29

```

Figure 3.8. Index calculation in GEE

After stacking the Landsat bands and the calculated indices, the model has been trained using the samplings for each class. Sample of the code for the classifier and the classification has been given in Figure 3.9.

```

73 // .....classifier.....
74
75 var classifier = ee.Classifier.libsvm().train({
76   features: training,
77   classProperty: 'landcover'
78 });
79
80 // .....classification.....
81
82 var classified = prostack.classify(classifier);
83

```

Figure 3.9. Classification in GEE

The accuracy assessment of the classification has been done using 50% of the collected samples. Thus, 50% of the samples were used for classification, while 50% were used for testing the developed model. Sample of the accuracy assessment code is given in Figure 3.10.

```

100 // Accuracy Assessment
101 var split = 0.5; // Roughly 50% training, 50% testing.
102 var trainingPartition = withRandom.filter(ee.Filter.lt('random', split));
103 var testingPartition = withRandom.filter(ee.Filter.gte('random', split));
104
105 // Trained with 50% of our data.
106 var trainedClassifier = ee.Classifier.libsvm().train({
107   features: trainingPartition,
108   classProperty: classProperty,
109   inputProperties: ['B2', 'B3', 'B4', 'B5', 'B6', 'B7',
110 ]
111 });
112
113 // Classify the test FeatureCollection.
114 var test = testingPartition.classify(trainedClassifier);
115
116 // Print the confusion matrix.
117 var confusionMatrix = test.errorMatrix(classProperty, 'classification');
118 print('Confusion Matrix', confusionMatrix);
119
120 //Print the overall accuracy to the console
121 print('Validation overall accuracy: ', confusionMatrix.accuracy());
122 print('Kappa: ', confusionMatrix.kappa());

```

Figure 3.10. Accuracy assessment in GEE

Afterwards, the results have been exported and analyzed in a GIS software (ArcGIS) where spatial analyses for land conversion have been made.

4. RESULTS

The results from the analyses are presented in three different parts;

- i. First, the results of the object-based long-term (1990-2020) classification have been presented. The findings of the research have been published in the *“Moving Borders: Mapping and Monitoring Amu Darya River Dynamics Using Remote Sensing Data and Techniques”* research paper, published in the *Geodetski List* journal. Also, part of the thesis has been compiled as a book chapter in the book “Environmental Degradation in Asia: Land Degradation, Environmental Contamination, and Human Activities” (to be published).
- ii. The long-term (1990-2020) GEE classification results have been presented in the second part of the results section. The findings of the research have been presented at the *“5th International Electronic Conference on Water Sciences”*, titled *“Monitoring Amu Darya river channel dynamics using remote sensing data in Google Earth Engine”*.
- iii. The results of the seasonal analyses have been presented in the third part of the results section.

4.1. Object-Based Classification Results

The land cover classification of the object-based results were mapped and analyzed. The overall accuracy of the classification is 85%. For the accuracy assessment, 400 random points have been used. As a reference data, the Landsat images were used, complied with high-resolution imagery from Google Earth from the same season and year as the classified images. The acceptable critical accuracy value in classification with middle-resolution satellite imagery is 75%, which means that the results of the classification in this paper are acceptable (Barakat, Ouargaf, Khellouk, El Jazouli, & Touhami, 2019). The total area of the study area is approximately 8,720 km². The results revealed that, of the total area, in 1990, 76.8% (6,700 km²) was occupied by bare land, 16.8% (1,470 km²) was occupied by croplands, 2.2% by water, and 4% by wetland areas. In the year of 2000, the land cover has changed as follows, 76% bare land, 17% cropland, 2.6% water, and 4.3% wetland areas. In 2011, there was significant changes in the land cover, where the bare land area dropped to 71.7%, the cropland area increased to 22.6%,

2.4% was covered by water, and 3% by wetlands. The area cover with water was lowest in 2020 with 1.9%. The land conversion between the classes can be seen in Figure 4.1 and Figure 4.2. From Figure 4.2 it can be clearly seen that there is a constant transition between the classes water, wetland, and cropland, where the areas covered with bare land are usually stable. The biggest transition between land cover classes can be noticed between water and wetland classes. Also, it should be noticed that more than 30% of the water areas changed in the investigated periods. In the period between 1990 – 2020, more than 50% of the wetland areas transited to cropland (approximately 30%), and water and bare land (10%).

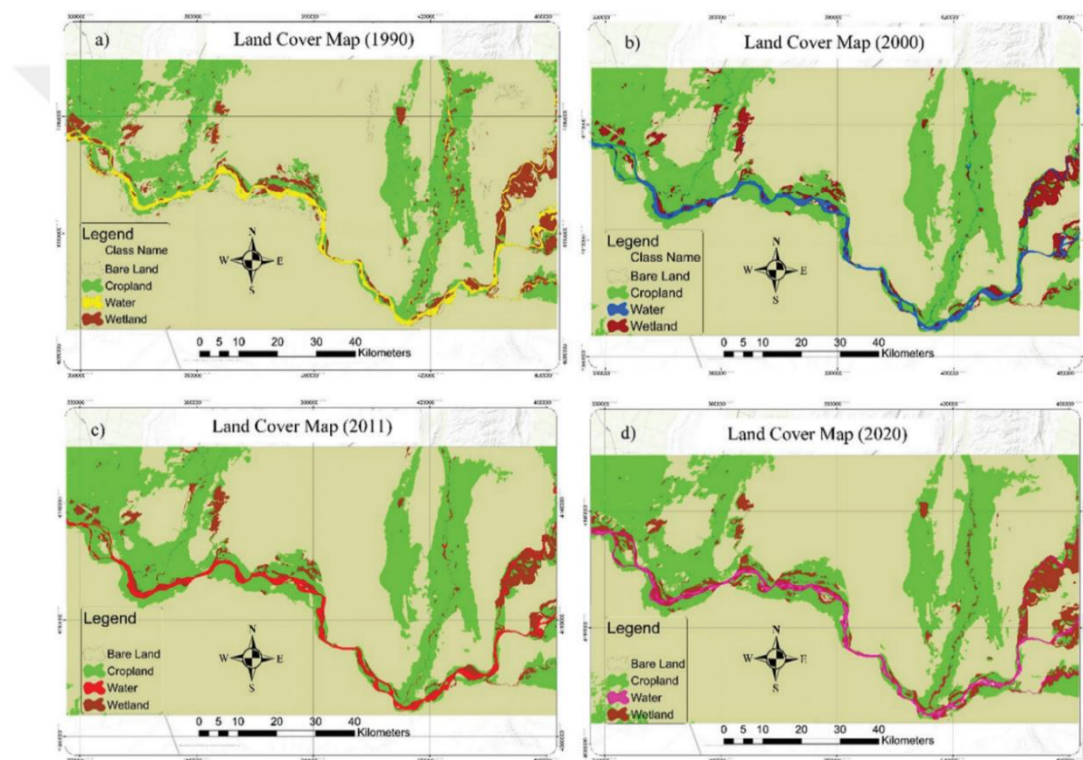


Figure 4.1. Land cover classification results for: a) 1990, b) 2000, c) 2011, d) 2020

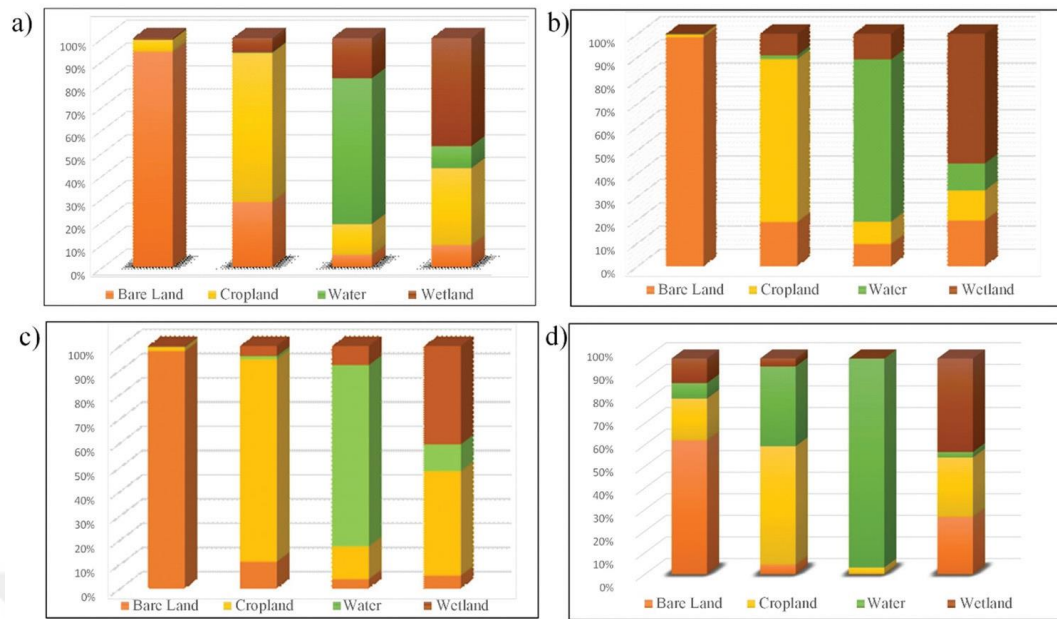


Figure 4.2. Land conversion between: a) 1990 – 2000, b) 2000 – 2011, c) 2011 – 2020, d) 1990 – 2020

Table 4.1. Confusion matrix for the land cover classification

Class	Bare Land	Cropland	Wetland	Water	Total
Bare Land	247	33	2	1	283
Cropland	13	59	4	0	76
Wetland	1	3	19	0	23
Water	1	1	2	14	18
Total	262	96	27	15	400
AA	OA = 85%; kappa = 0.75				

4.2. Spatial and Temporal River Channel Changes and Dynamics

The historical river channel changes are shown in Figure 5.1 (a–c) in three different periods from 1990 – 2020. The blue color represents the active river channel in both years, with yellow color are represented the eroded areas, while with red color are illustrated the accretions. From the results, it can be noticed that very small part of the channel remained unchanged in the last thirty years. Comparing each period individually, and thirty years' changes, during the first period, 1990 – 2000, the overall erosion and accretion areas are 4,878.1 ha and 8,377.4 ha, respectively. The second period, 2000 – 2011, showed different results, where the accretion area was bigger than the eroded area. The overall accretion and erosion areas in this period are 8,257.9 ha and 6,415.8 ha, respectively.

Table 4.2. Erosion-accretion amount from 1990 – 2020 in the study area

Duration	Erosion		Accretion	
	Total (ha)	(%)	Total (ha)	(%)
1990 – 2000 (10 years)	4,878.1	24.9	8,377.4	42.8
2000 – 2011 (11 years)	8,257.9	35.8	6,415.8	27.8
2011 – 2020 (9 years)	7,692.4	36.2	5,069.5	23.9
1990 – 2020 (30 years)	9,775.6	52.5	8,810.0	47.3

Similar were the results from the second period where the overall erosion and accretion were 7,692.4 ha and 5,069.5 ha, respectively. The comparison between the first (1990) and last investigated year (2020), with duration of thirty years, showed overall erosion and accretion of 9,775.6 ha and 8,810.0 ha, respectively. The details are presented in Table 4.2.

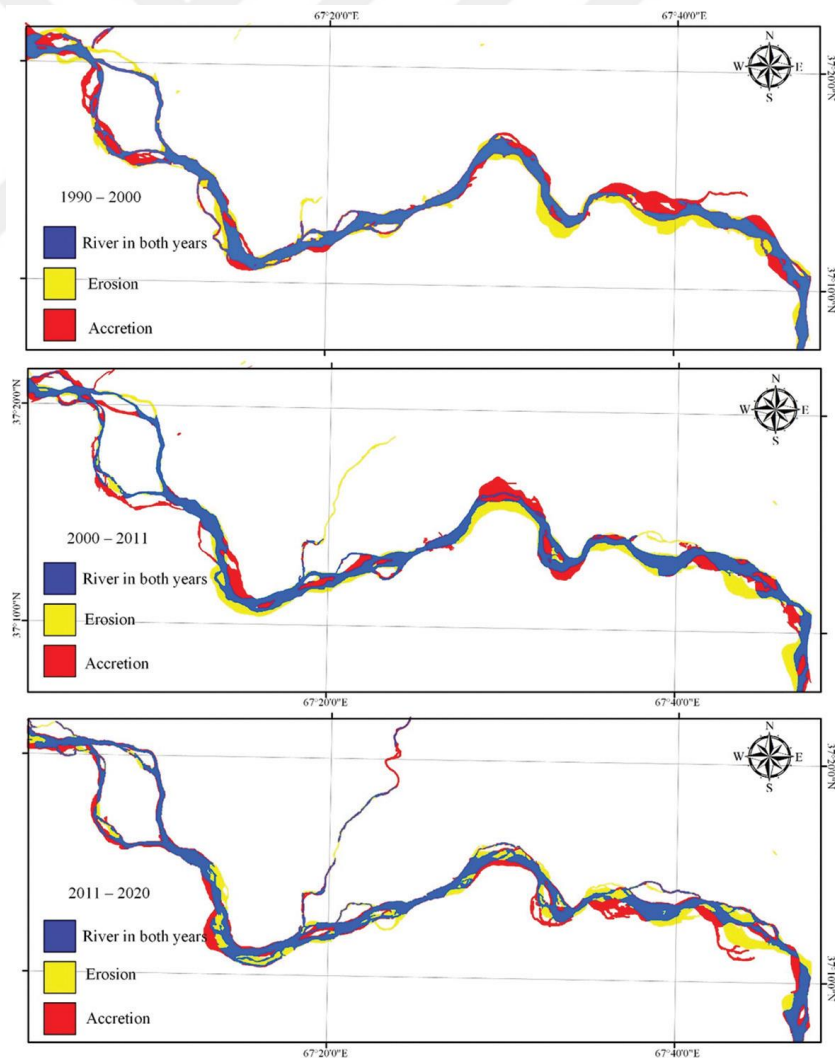


Figure 4.3. Water loss and water gain in Amu Darya river for three periods (1990 – 2020)

The shifting of the channel line from 1990 to 2020 on both sides of the river was measured through 7 cross-sections at an interval of 10 km along the river and the results are presented in. The analysis showed that the highest amount of erosion of land observed on the both sides of the bank occurred in section F (right bank, 1.4 km) in the period of 1990 – 2000. From it can be seen that the maximum amount of accretion of land was noticed in the left bank along section G (1.3 km) in the period of 1990 – 2000.

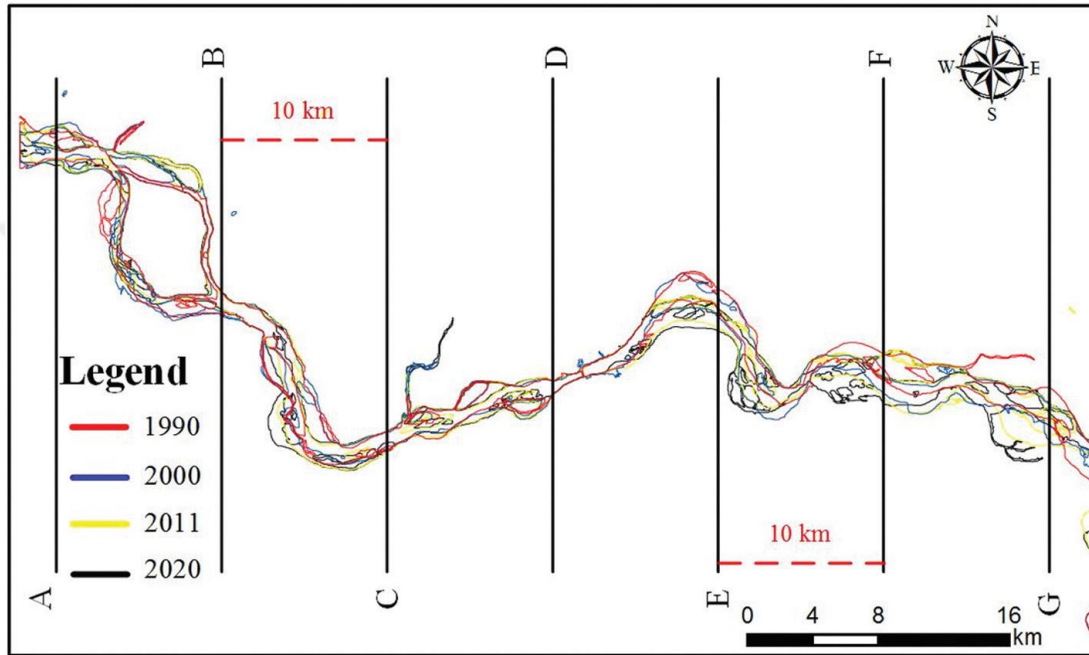


Figure 4.4. River border shifting from 1990 – 2020

Table 4.3. River border shifting 1990 – 2020 in m. Minus sign (–) indicates narrowing (from north to south) and plus sign (+) indicates expanding (from south to north)

Section	1990 - 2000		2000 - 2011		2011 - 2020		1990 - 2020	
	Left bank	Right bank	Left bank	Right bank	Left bank	Right bank	Left bank	Right bank
A	+120	+300	+100	+90	+240	+55	+420	–1023
B	+61	0	– 301	–170	0	+240	+360	0
C	–210	0	180	0	–510	0	520	0
D	+95	0	–63	+60	0	–30	–60	0
E	+420	–450	+730	–660	+150	–390	+1320	–1170
F	+780	–1410	+300	+60	+330	0	+1440	0
G	+1320	–1050	+90	+130	+360	–1140	+420	–930

If the first and the last period of the investigation over the study area is analyzed the maximum amount of erosion of land observed on the both sides of the river occurred in section A and E (over 1 km), and the maximum accretion occurred in sections E and F (over 1.3 km) (Mobariz & Kaplan, 2021).

4.3. GEE Yearly Results

For every inspected year, classification has been performed within the GEE. 50% of the training samples were then used for the accuracy assessment analyses, and the results are presented in. As it can be seen from Table 4.2, the validation overall accuracy is higher than 0.87 in the four classifications, while the kappa statistics vary from 0.83 – 0.97.

Table 4.4. Accuracy assessment results

	Year	Validation Overall Accuracy	kappa
1	1990	0,90	0,86
2	2000	0,96	0,95
3	2010	0,87	0,83
4	2020	0,98	0,97

The results of the classifications are shown in While there are no significant changes in the Bare Land class, a shift of the river bed can be noticed in several points of the study area. For more detailed investigation, land conversion during the three investigated periods (1990 – 2000; 2000 – 2010; 2010 – 2020) has been made. The conversions between the classes are shown in

In all three periods, the class Bare Land did not receive any additional area from the other classes, but small areas of Bare Land were converted to, generally, cropland. The classes Wetland and Water changed the most, with more than 40% conversion of the Water class to Wetland and Cropland. From 1990 to 2000, and 2010 to 2020, this conversion was 20% and 25%, respectively. As expected, the results showed that the river bed mainly shifts towards the Wetland and Cropland, or areas with soft soil. For a more detailed investigation, we recommend considering the geological characteristics of the river bed and its surroundings.

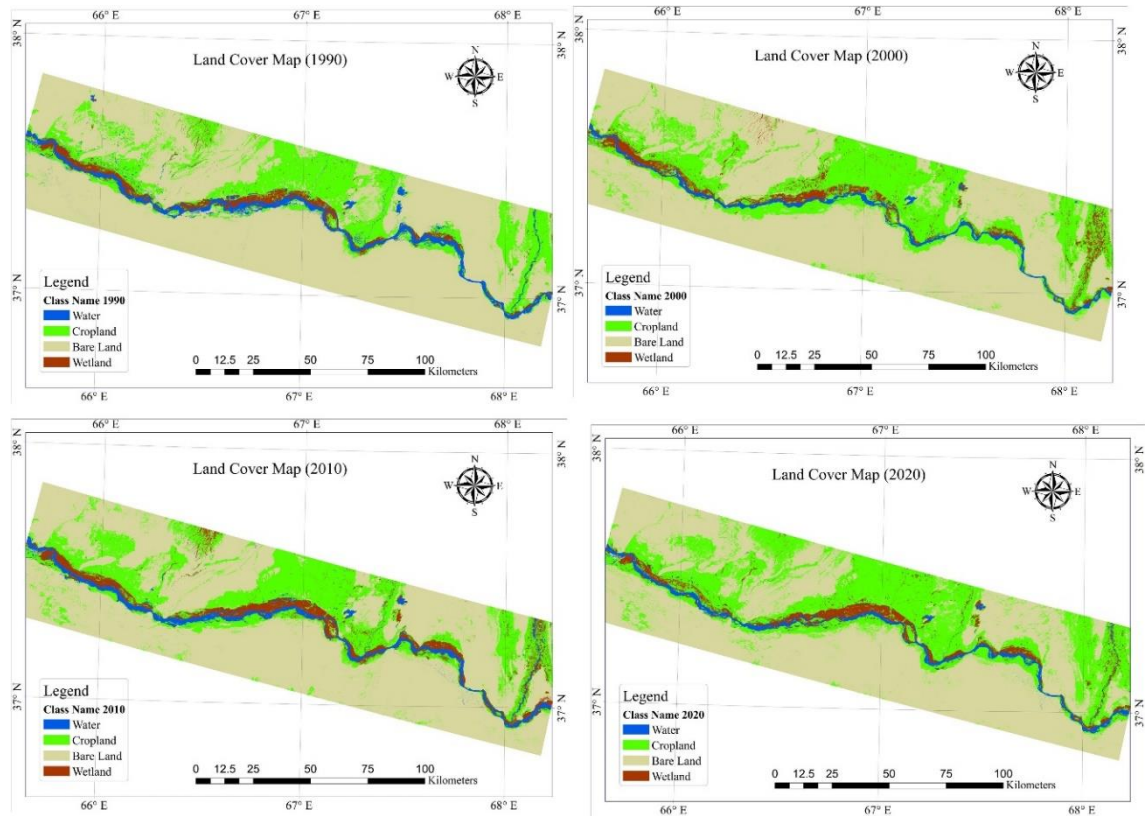


Figure 4.5. GEE Yearly Classification results

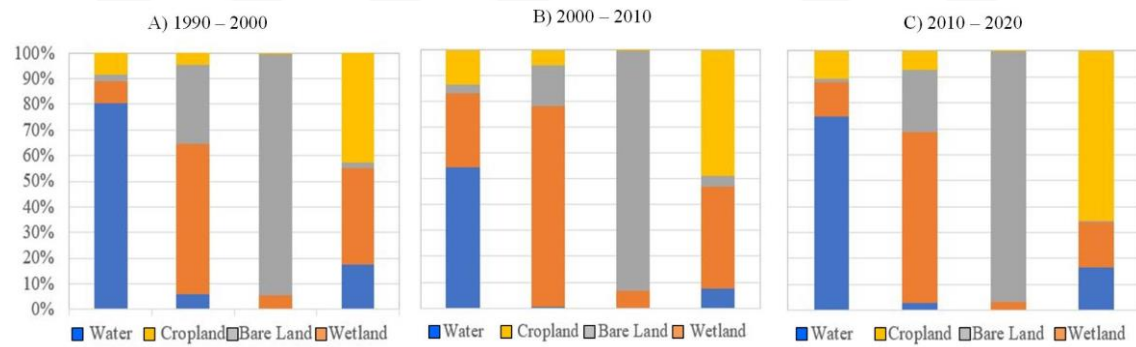


Figure 4.6. Land conversion results; A) 1990 – 2000; B) 2000 – 2010; C) 2010 – 2020

Also, the dynamics of the river in the inspected years can be seen in Figure 4.7. The dynamics of the river are seen in the period between 1990 – 2000, and 2010 – 2020. According to the statistical analyses, the water area in 2000 was approximately 30.000 ha smaller than the area in 1990. The water area then gains approximately 19.000 ha in 2010 in comparison with 2000, and then it got lowered in 2020 for 11.000 ha. The results showed that the river dynamics mainly occupy the wetlands and croplands area, thus causing damages in farmers' land, and also some small villages around the river bed. It

should be also mentioned that the river dynamics are constantly changing the natural border between the sharing countries, which causes even bigger problems for farmers to claim their rights (Sajjad et al., 2020).

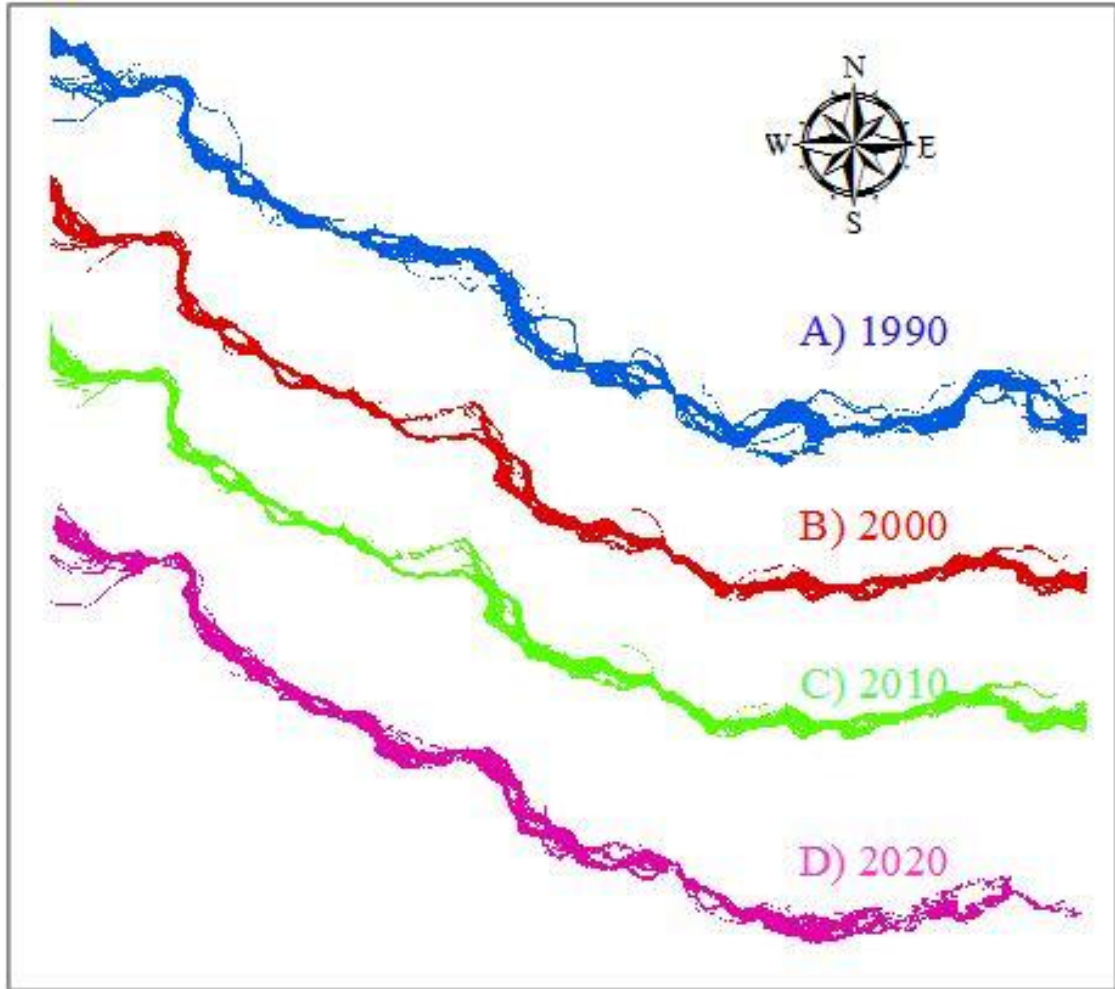


Figure 4.7. *Amu Darya river dynamics; A) 1990; B) 2000; C) 2010; D) 2020*

4.4. GEE Seasonal Results

For every inspected season, classification has been performed within the GEE. 50% of the training samples were then used for the accuracy assessment analyses, and the results are presented in Table 4.5. As it can be seen from Table 4.5, the validation overall accuracy is higher than 0,97 in the four classifications, while the kappa statistics vary from 0.91 – 0.95.

Table 4.5. Accuracy assessment results

Seasons		Validation Overall Accuracy	Kapa
1	Winter	0.94	0.93
2	Fall	0.96	0.95
3	Summer	0.93	0.91
4	Spring	0.96	0.95

While there are no significant changes in the Bare Land class, a shift of the river bed can be noticed in several points of the study area. For more detailed investigation, land conversion during the three investigated periods (fall – summer; summer – spring; spring – winter) has been made. The conversions between the classes are shown in Figure 4.17, Figure 4.18, Figure 4.19.

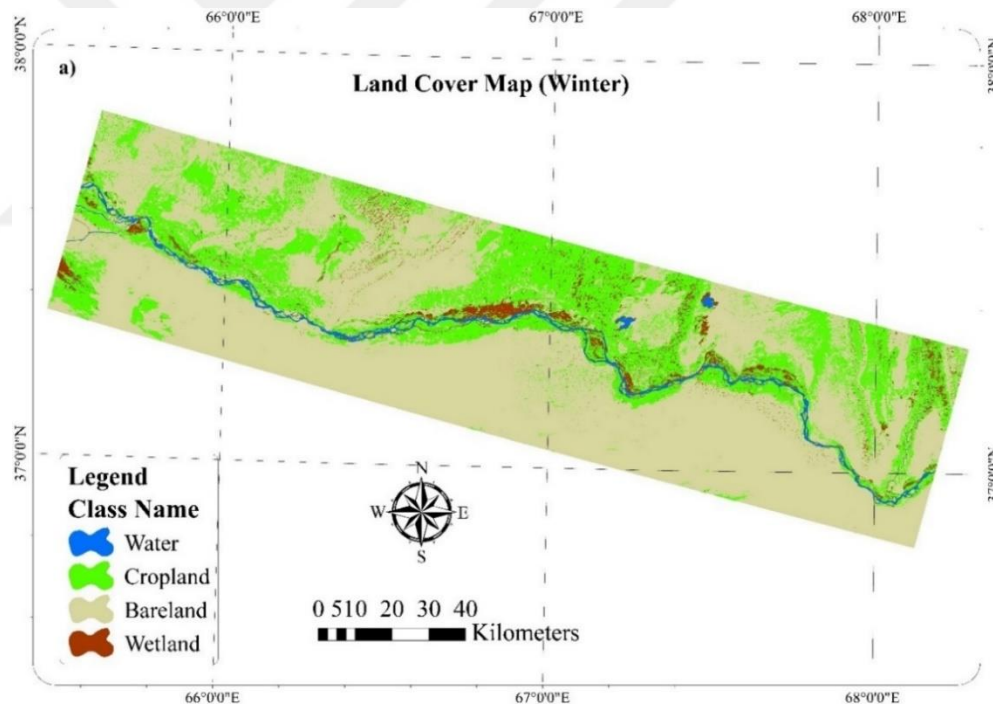


Figure 4.8. Form Winter Season Classification result

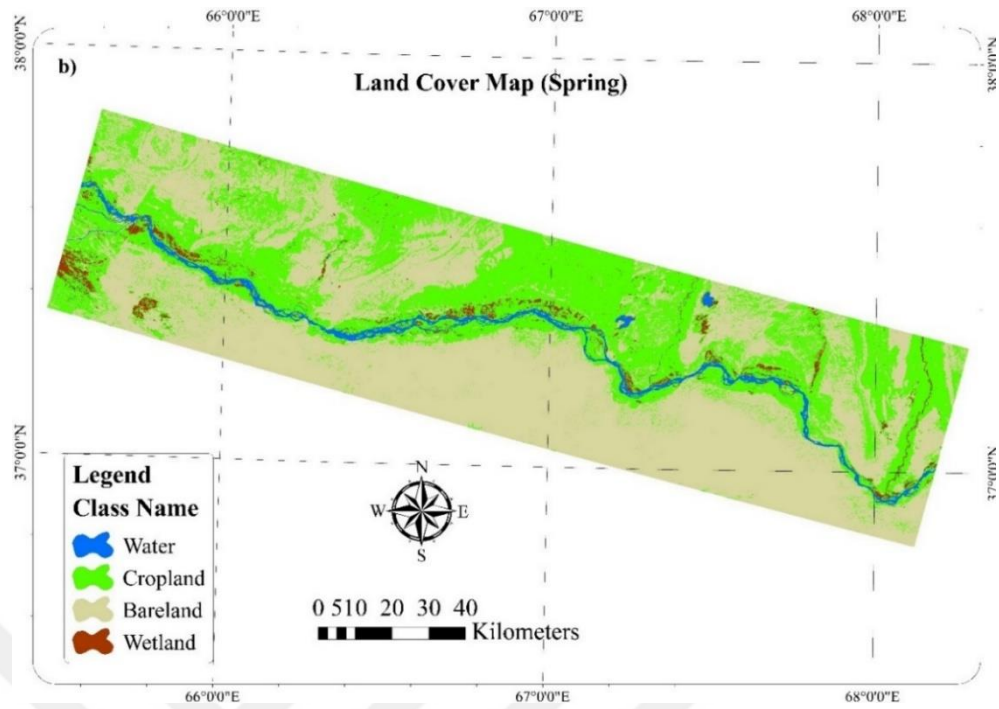


Figure 4.9. Classification result From Spring Season

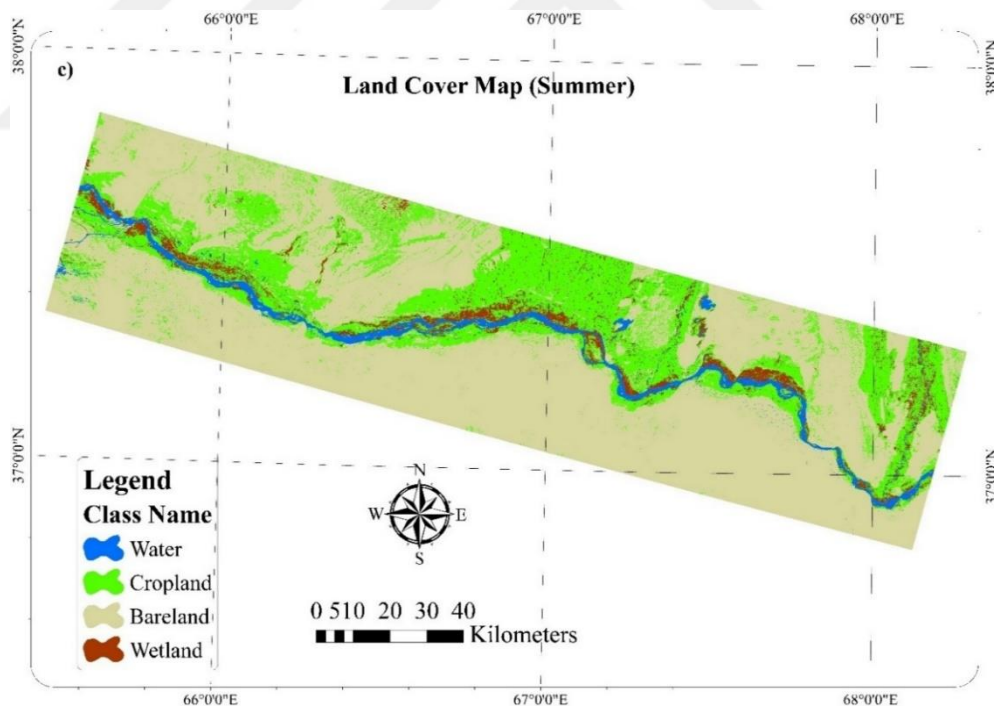


Figure 4.10. Classification result From Summer Season

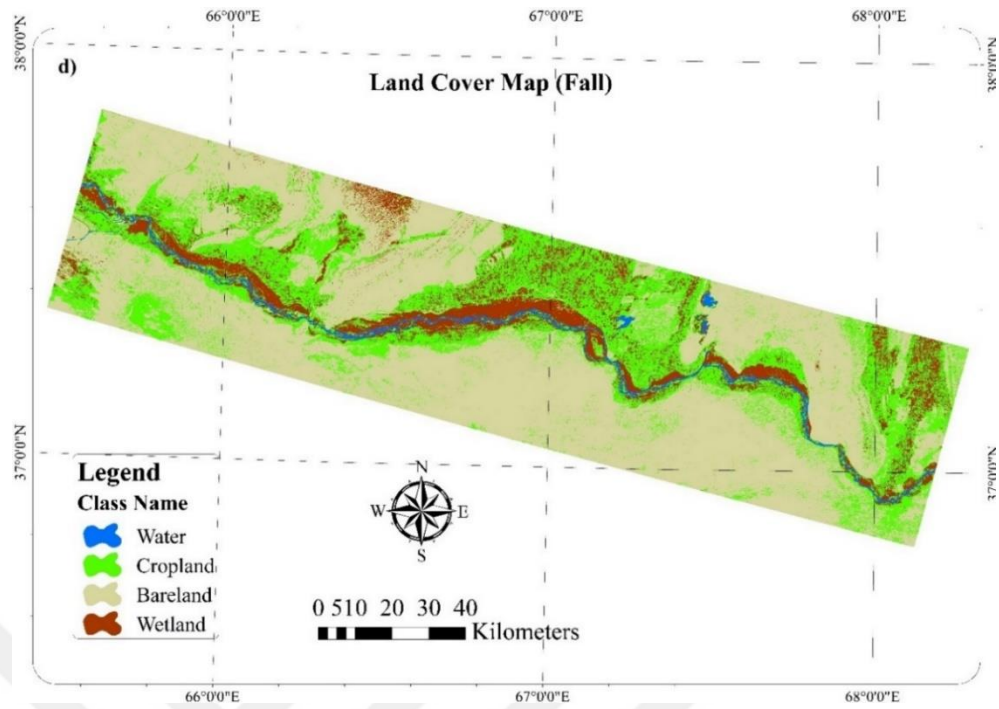


Figure 4.11. Classification result From Fall Season

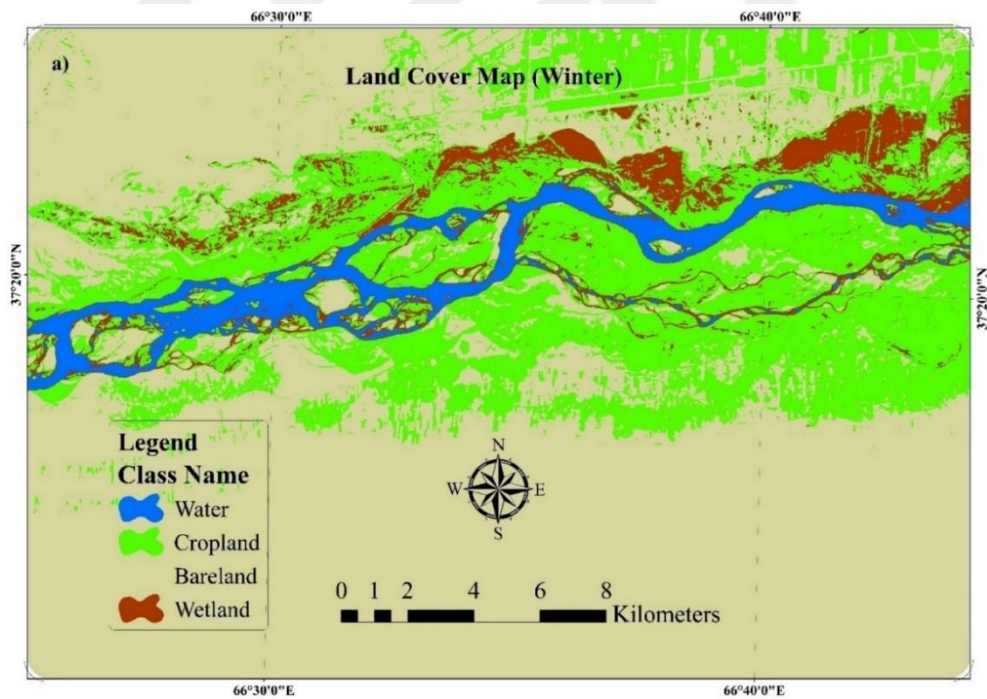


Figure 4.12. Classification result from Winter Season in the zoom mode

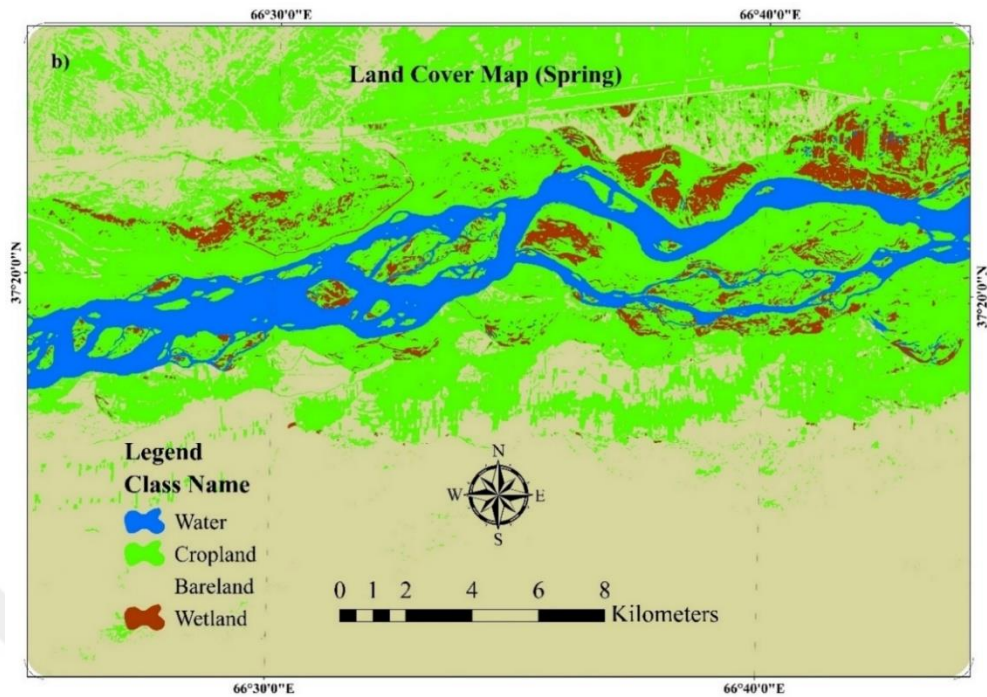


Figure 4.13. Classification result from Spring Season in the zoom mode

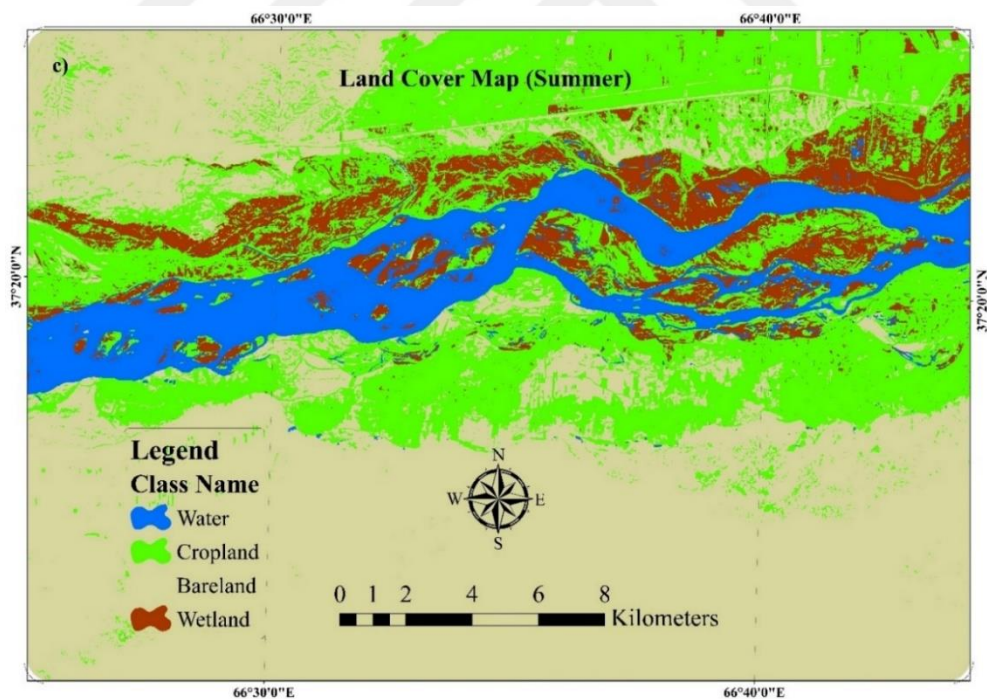


Figure 4.14. Classification result from Summer Season in the zoom mode

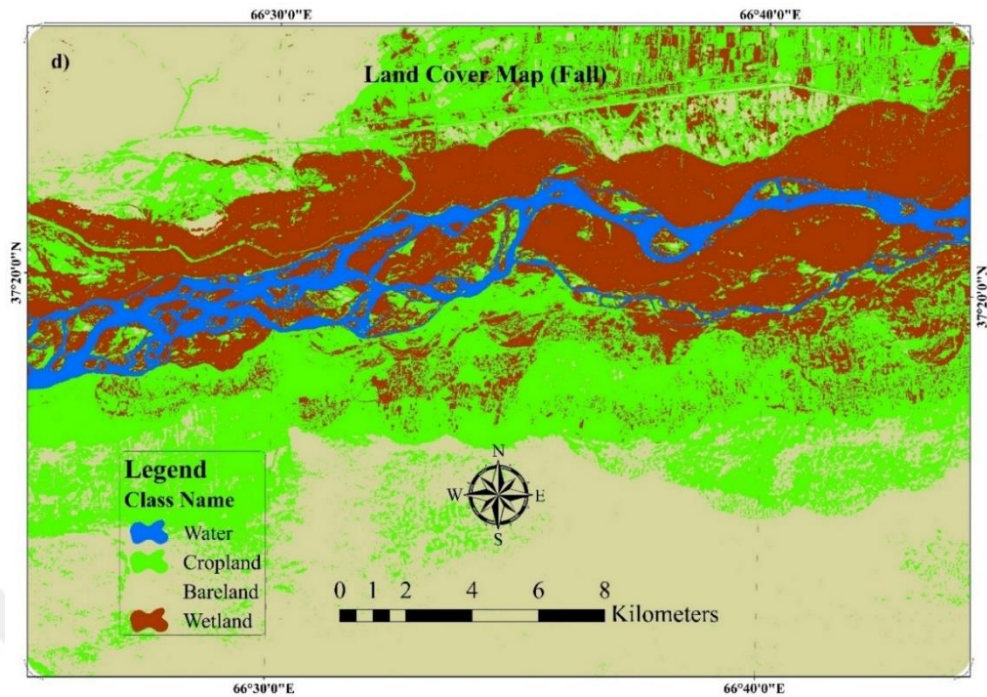


Figure 4.15. Classification result from Fall Season in the zoom mode

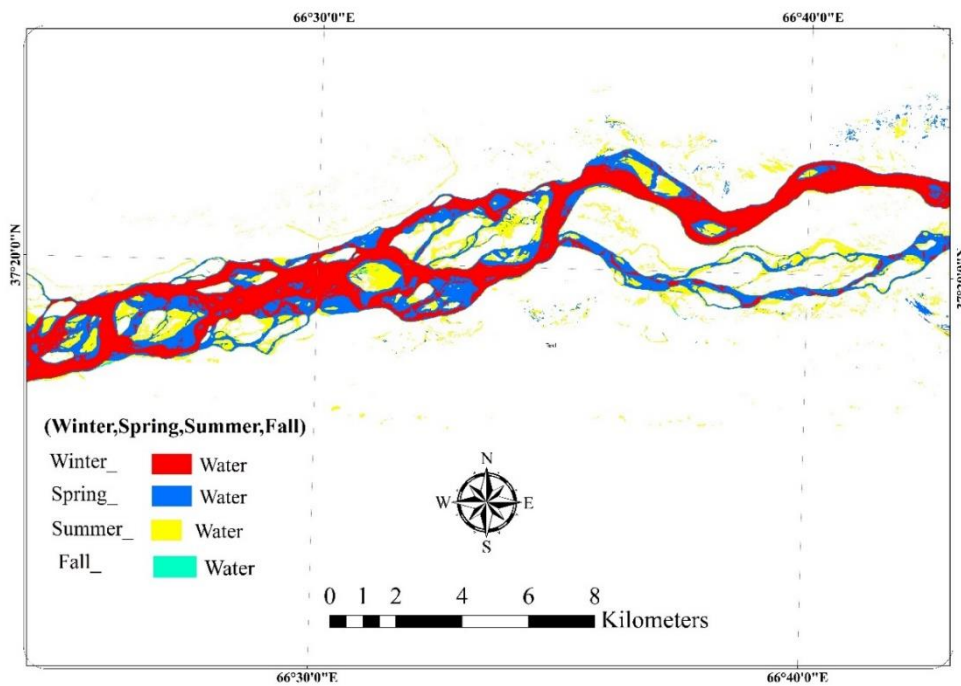


Figure 4.16. Classification result from four season for the water

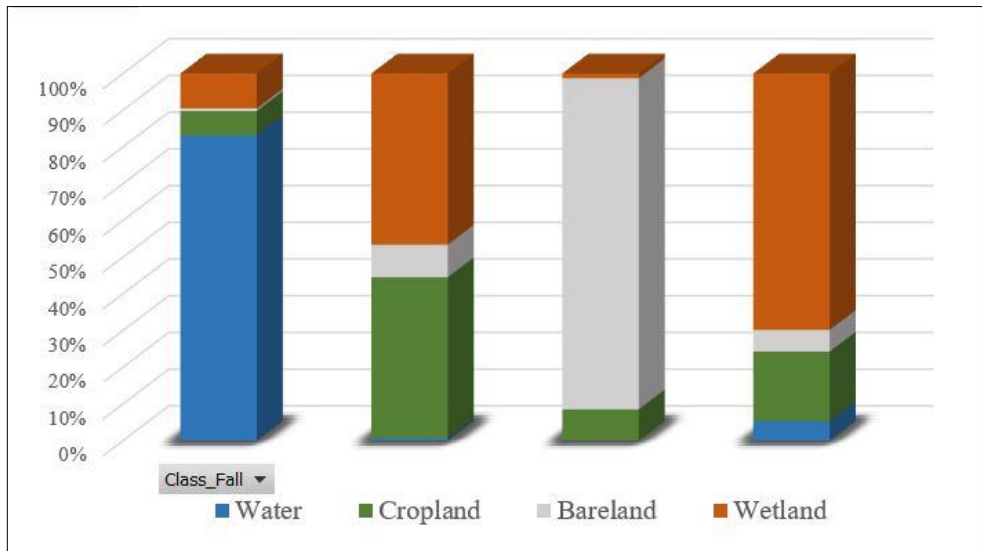


Figure 4.17. Land conversion results (Fall_summer)

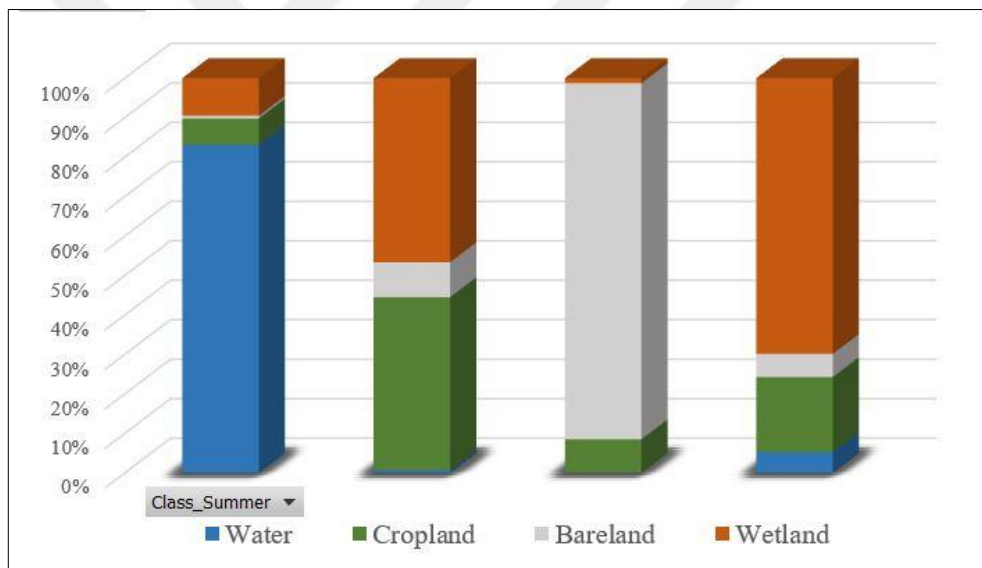


Figure 4.18. Land conversion results (Summer-Spring)

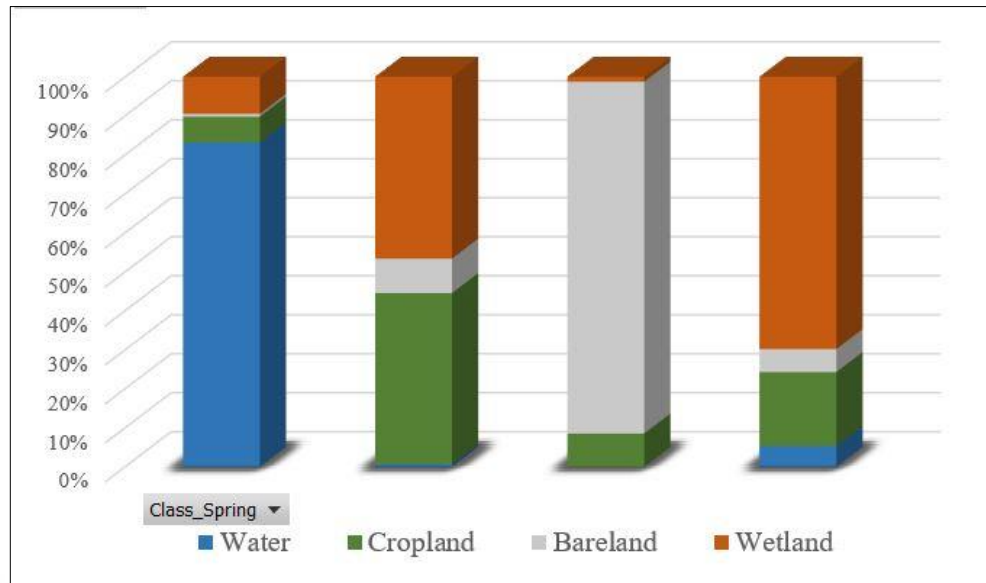


Figure 4.19. Land conversion results (Spring -Winter)

In all three periods, the class Bare Land did not receive any additional area from the other classes, but small areas of Bare Land were converted to, generally, cropland. The classes Wetland and Water changed the most, with more than 40% conversion of the Water class to Wetland and Cropland. From winter to fall, and summer to spring, this conversion was 20% and 25%, respectively. As expected, the results showed that the river bed mainly shifts towards the Wetland and Cropland, or areas with soft soil. For a more detailed investigation, we recommend considering the geological characteristics of the river bed and its surroundings (Mobariz & Kaplan, 2020).

5. DISCUSSION

The main goals of the presented paper were to determine the Amu Darya river channel dynamics and the changes that occurred in its surroundings between Afghanistan, and Uzbekistan and Tajikistan. River dynamics can often cause considerable hazards to those in the surrounding area, it is more complicated for the locals who depend mostly on agriculture to claim their rights as Amu Darya also represents the international border between several countries. In order to help decision-maker and also to lower geo-political tensions between the sharing countries, timely mapping and monitoring of the shared areas as well as its surroundings are crucial.

Landsat as the only satellite that provides historically imagery since 1980, with 30 m spatial resolution offers valuable data that can be used for accurately monitoring of the Amu Darya river dynamics and land cover changes of its surroundings. Thus, in this paper, four Landsat images in the period of 1990 – 2020 were used. However, in future studies, Sentinel-2 that offers better spatial and spectral resolution can be used for more accurate and more detailed results.

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While most studies in the literature focus only on river dynamics (Langat et al. 2019a, Billah 2018) or land cover changes in the river basin (Langat et al. 2019b, Cai et al. 2016), this study evaluated both land cover changes and river dynamics of Amu Darya river. For that purpose, an object-based classification has been made over the study area with four classes (Bare land, Cropland, Water, Wetland) and the land conversion has been estimated for the analyzed thirty-year period. The results showed that large areas of wetland (possible highly watered cropland) and cropland are being flooded by the new course of the river, meaning that the river causes damages to local peoples' lands. Also, it should be noticed that more than 30% of the water areas changed in the investigated periods. In the period between 1990 – 2020, more than 50% of the wetland areas transited to cropland (approximately 30%), and water and bare land (10%). These results are supported with high accuracy of 85% overall accuracy, and accuracy higher than 90% for

the water class. After the first part of the study, analyses of the river dynamic have been made. For that purpose, only water class, or the river line in the same period was analyzed. It should be mentioned that the right part of the river represents Tajikistan, while the left, Afghanistan, and with every shift of the river, left or right, the international border between these two countries is being changed. The erosions and accretions of the river have been addressed thus also presenting the active part of the river in both assessed periods (Fig. 5.1).

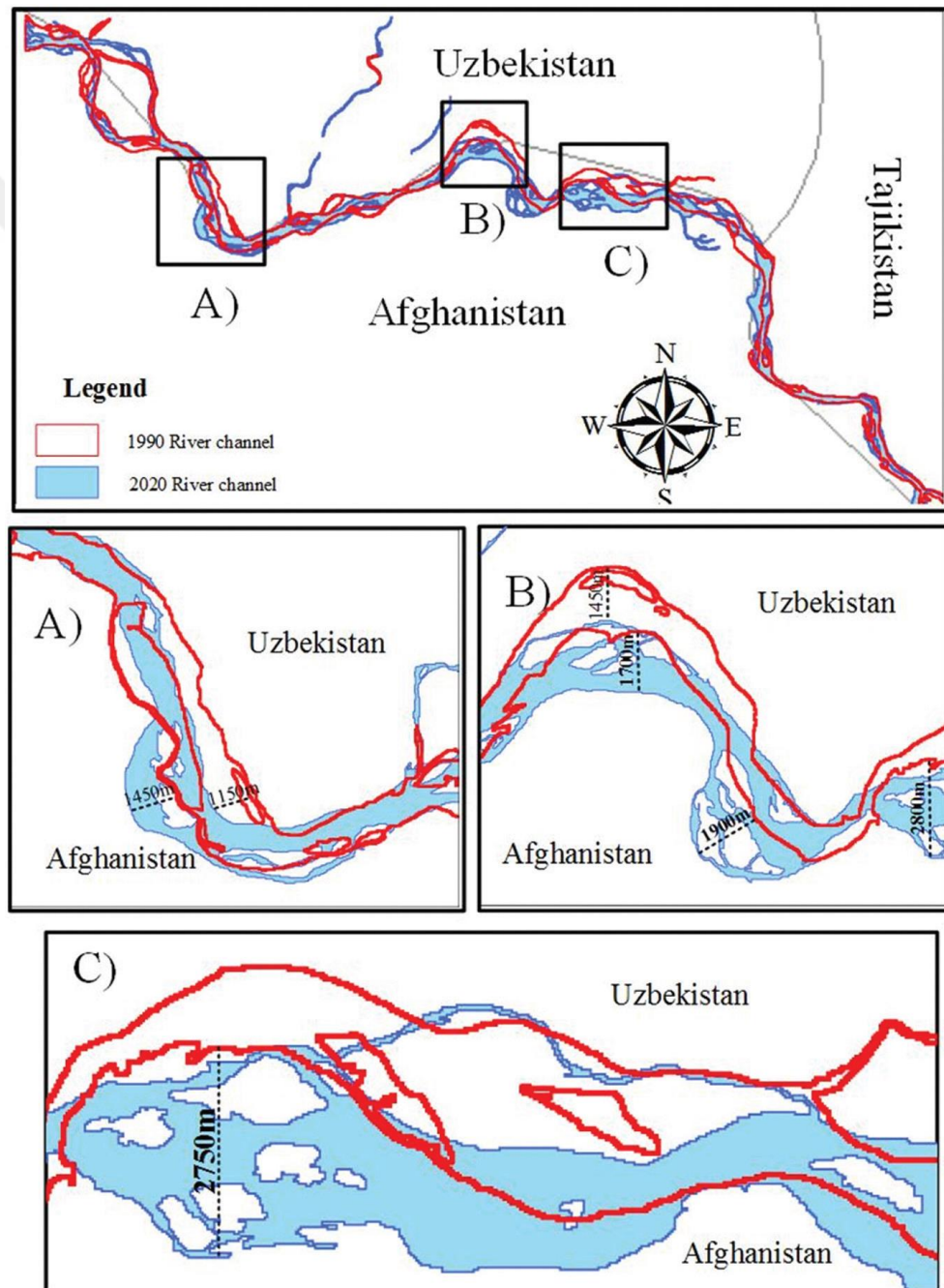


Figure 5.1. River bank shift 1990-2020

Results showed that in the studied part of the river (approximately 70 km length), very small part of the channel remained unchanged. The comparison between the first and last classification showed overall erosion and accretion of 9,775.6 ha and 8,810.0 ha, respectively. However, although the areas differ for approximately 900 ha, the damage is rather higher. From the river shifting results, it can be noticed that most of the time, the river shifts from North to South, causing floods and detriment on the croplands on the local people on the Afghanistan side, and benefits to the local people on the Tajikistan side of the border. The results can be useful in practical applications where regular monitoring of river behavior is needed for decision making. Such information can help both local and international administration in resolving problems due to unresolved water sharing policies, and can help in making geopolitical decisions beneficial for both parties. Also, the results can be crucial in flood risk management strategies, irrigation plans, monitoring systems, etc. The most drastically shifts between 1990 and 2020 are shown on Figure 4.4.

6. CONCLUSION

The Amu Darya is the most water-rich sea in Central Asia, originating in the Pamir Mountains and flowing about 1,126 km along Afghanistan's northern borders with Tajikistan, Uzbekistan and Turkmenistan. The port of Amu Shirkhan is located on the shores of Bandar and Hairatan ports, through which Afghanistan's exports or imports to Central Asian countries are exchanged. Residents of the northern and northeastern provinces of the country have repeatedly complained about the destruction of the Amu Darya River and the government's negligence, but the central and local governments have not yet taken effective action.

As the pressures of increasing destruction by the waters of the Amu Darya on the people and the inhabitants around the sea were greater and a large number of people suffered irreparable damage due to these devastating events and people were forced to leave their homes. It is also noteworthy that climate change is affecting the low-water areas, neighboring countries have increasingly managed and controlled the infrastructure and management of transboundary waters in Afghanistan, and unfortunately have suffered the most from Afghanistan. Similarly, over the past few years, the Government of Afghanistan has raised its awareness of the importance of addressing the issue of cross-border issues with low-water neighbors to ensure the most efficient use of the region's precious water resources. As well as awareness of the damage done to Afghanistan. This research paper is a step towards strengthening Afghanistan's transboundary water dialogue by reviewing the situation and proposing possible solutions to promote cooperation and water management in the Amu Darya Basin.

In the presented study, the land cover changes and river dynamics of international borders and its surroundings were investigated using remote sensing satellite imagery. The most significant contribution of this thesis is that it points out a very important problem many local people are facing, mostly in the developing countries, but in fact, it should also be stated that this is also an international problem. The case study of the Amu Darya river is just an example of what many local people who mainly depend on agriculture are facing with. Having said that, it should not be forgotten, that with the results in the study the international borders are also being monitored through satellite imagery. As not many studies can be found on the topic monitoring river that also represent international borders, we believe that the conducted study can be of great use and open many research opportunities for many interdisciplinary projects. For future

studies, we recommend investigating the same topic on different study area, and for more accurate results, the use of imagery with higher resolution, such as Sentinel-2 (Mobariz & Kaplan, 2021).



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CURRICULUM VITAE

ORCID ID: 0000-0001-8002-1327

Personal Information:

Name : Mohammad Asef
Last Name : Mobariz
Foreign Language : English, Turkish,

Education

- 2019 - 2021 / Master degree / Eskisehir Technical University, Institution of Graduate Schools, Department of Remote Sensing and Geographical Information Systems.
- 2013 - 2017 / B.Sc / Jowzjan University, Faculty of Geology Engineering and Mining, Department of Geodesy Engineering.

Work Experience:

- 2018 / Survey Engineer / Ministry of Urban Development and Land.
- 2017 / Surveyor / Cenderella construction Company, Road project Armaliq – Laman
- 2016 - 2017 / Surveyor assistant / Azizi Global Construction Company, Daresuf Fiber Project.
- 2015 - 2016 / Teacher / Mathematics and Physics at different learning centers.

Piblications:

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