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DEPARTMENT OF ENVIRONMENTAL ENGINEERING

LAND COVER CHANGE DETECTION FOR SOMALIA: 2003-2016

(M.Sc. Thesis)

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ABSTRACT

In Somalia, major alterations in land cover occurred in the past decades due to human activities and climate change. Somalia has very sensitive environment and the people of Somalia are directly dependent on nature. In this study, we analyzed the land cover changes in Somalia from 2003 to 2016 using satellite imagery techniques. We also examined the relationships between land cover changes and climatic conditions. Moderate resolution imaging spectroradiometer (MODIS) 16-day composite normalized difference vegetation index (NDVI) data with 250 m spatial resolution were acquired from U.S. Geological Survey for the 2003-2016 period. We also obtained annual precipitation and annual average air temperature data for Somalia from World Bank Climate Change Knowledge Portal. The variations in NDVI, precipitation and air temperature time series were examined. The correlations among these parameters were also calculated. The results showed that vegetation in Somalia showed a dynamic pattern from 2003 to 2016. NDVI responded quickly to changes in climatic conditions. Average NDVI was generally lower under drought conditions. The trends in NDVI and precipitation data were similar. NDVI provided a suitable tool for detecting land cover changes.

Keywords: Land Cover Change, Somalia, Satellite Imagery, MODIS, NDVI

SOMALİ'DE ARAZİ ÖRTÜSÜ DEĞİŞİMLERİ: 2003-2016

Mohamed Omar YAHYE

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ÖZET

İnsan faaliyetleri ve iklim değişikliği son yıllarda Somali'de arazi örtüsü üzerinde önemli değişimlere neden olmuştur. Somali çok hassas çevresel özelliklere sahip olup, Somali halkı doğrudan doğaya bağımlıdır. Bu çalışmada, 2003'ten 2016'ya kadar Somali'deki arazi örtüsü değişiklikleri uzaktan algılama teknikleri kullanarak analiz edilmiştir. Arazi örtüsü değişimleri ve meteorolojik koşullar arasındaki ilişkiler incelenmiştir. 2003-2016 dönemi için 250 m mekansal çözünürlüğe sahip orta çözünürlüklü görüntüleme spektroradiometresi (MODIS) 16 günlük bileşik normalize edilmiş fark bitki örtüsü indeksi (NDVI) verileri ABD'nin USGS kurumu web sayfasından temin edilmiştir. Dünya Bankası İklim Değişikliği Bilgi Portalı'ndan Somali'nin ortalama yıllık yağış ve yıllık ortalama hava sıcaklığı verileri alınmıştır. NDVI, yağış ve hava sıcaklığı zaman serilerindeki değişimler incelenmiştir. Bu parametreler arasındaki korelasyonlar da hesaplanmıştır. Sonuçlar Somali'de bitki örtüsünün 2003'ten 2016'ya değişken olduğunu göstermiştir. NDVI iklim koşullarındaki değişikliklere hızlı bir şekilde cevap vermiştir. Ortalama NDVI, kuraklık koşullarında genellikle daha düşük olduğunu göstermiştir. Yağış ve NDVI verilerindeki eğilimler benzerdir. NDVI, arazi örtüsü değişimlerini tespit etmek için yararlı bir araç sağlamıştır.

Anahtar Kelimeler: Arazi Örtüsü Değişimleri, Somali, Uydu Görüntüleri, MODIS, NDVI

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INTRODUCTION

The forests, water bodies, and manmade features are known as land cover and how humans use these lands are called land use (Fisher et al., 2005). Land use and land cover data give us information related to how human beings are benefiting from natural resources and how their activities are affecting the nature. Land cover is also important for watershed protection, preventing soil erosion, and mitigating climate change.

Human uses nature in different ways. In recent decades, the population of the World has increased rapidly. As population increases, human pressures on nature have also become higher. Many human activities such as logging, agriculture, urbanization, and mining have caused land cover modification (Giri et al., 2008). Natural disasters and climate change are other major causes of land cover changes. Land cover degradation has not only an impact on humans but also on many environmental sectors including climate, biodiversity, atmospheric composition, soil condition, water and sediment flows (Turner et al., 1994; Vargo et al., 2013). The land use/cover change is among the various factors that affects biodiversity on Earth. In 1990, there were 1150 million ha of tropical rain forest; unfortunately 5.8 million ha of land cover clearance were estimated annually (Mayaux et al., 2005). Southeast Asia has the highest rate of land cover change of 0.91% annually and Africa has the second position of World's land cover change rate of 0.43% per year. The third position belongs to Latin-America and it loses 0.38% of its forests annually (Achard et al., 2002).

The land cover in Somalia reflects the interaction of human activities and environmental factors like droughts. The majority of Somalia society derives their livelihood from livestock, which makes nomadism the most dominant land use activity in the country. The ownership of livestock is private, while the rangelands are public, which means there is no grazing management system or protection on the rangelands. This creates large pressure on land cover, and makes the situation worse year after year. Agricultural activities are the second most important land use type, but unfortunately this activity also contributes to land cover change due to shifting cultivations, e.g. a farmer is using plot for growing maize in one season, the next season he moves to another plot for cultivation. In Somalia 11.4% or 7,131,000 hectares are estimated to be forest. The average vegetation lost in ten years from 1990 to 2000 was estimated as 76,700 hectares, which means 0.93% of annual forest lost rate (Omuto et al., 2014). Vegetation decreased from 10.4% to 9.23% in five years from 2000 to 2005. Within 15 years, Somalia lost 13.9% of vegetation cover (Omuto et al., 2014).

The aim of this study is to investigate and understand how land cover changed over time in Somalia from 2003 to 2016 and to discuss the main underlying causes of land cover changes. Due to scarcity of data about Somalia, remote sensing techniques were used to identify spatial and temporal characteristics of land cover changes.

The thesis is composed of four chapters. “Introduction” summarizes the research topic and presents research objectives. Chapter 1, “Background and Literature Review”, provides background information about satellite remote sensing and presents a summary of previous literature. Chapter 2, “Materials and Methods”, first provides information about study area and then explain data sources i.e., satellite imagery and the data processing method. Chapter 3, “Results”, presents the research findings. Chapter 4 provides a discussion of the results and provides recommendations for future studies.

CHAPTER 1

BACKGROUND AND LITERATURE REVIEW

1.1.Background Information on Remote Sensing

Remote sensing has long history. Table 1.1 presents a brief history about remote sensing. In 1859, Gaspard Tournachon took an oblique photo of small village near to Paris from a balloon and this picture was the start of an era of earth observation and remote sensing (Rees and Pellika, 2010). During the World Wars I/II, balloon photography or airborne photography were used to collect ground information for military purposes. Between two World Wars, civilians started to use aerial photography in different fields including geology, forestry, agriculture, and cartography. During the period of the World War II, important developments about aerial photography and image interpretation were achieved. After war, starting from 1950s, remote sensing found new applications and Colour-Infrared (CIR) imagery was used in plant science. In 1956, Robert Colwell conducted an experiment for detection of diseased, damaged, and stressed vegetation from remotely sensed data and worked on classification and recognition of the vegetation type (De Jong et al., 2004).

After World Wars remote Sensing continued to develop from one stage to another. In 1956 Side-Looking Airborne Radar (SLAR) and Synthetic Aperture Radar (SAR) were developed. The aim of these two systems was to acquire the images having the highest possible resolutions. Low image distortion and repetitive multi-spectral coverage, lack of copyright and political restrictions, and availability of the images are the main reasons that made remote sensing a valuable technology (Le Moigne et al., 2011).

. **Tablo 1. 1.** The milestone and history of remote sensing

The year of invention	Invented Materials
1800	Discovery of infrared by Sir William Harschel
1839	The beginning practice of photography
1847	Infrared spectrum shown by A.H.L. Fizeau and J.B.L Foucault to share properties with visible light
1850-1860	Photography from balloons
1873	Theory of electromagnetic spectrum developed by James Clerk Maxwell
1909	Photography from airplane
1914-1918	World war 1 aerial reconnaissance
1920-1930	Development and initial application of aerial photography and photogrammetry
1929-1939	Economic depression generates environmental crises that lead governmental application of aerial photography
1930-1940	Developments in RADAR in Germany, United States Of America, and the United Kingdom
1939-1945	World War 2 application of non-visible portion of electromagnetic spectrum
1950-1960	Military research and development
1956	Colwell's research on plant disease detection using infrared photography
1960-1970	The first use of term Remote Sensing TIROS weather satellite
1972	Launch of Landsat I
1970-1980	Rapid advances in digital image processing
1980-1990	Landsat 4: the new generation of Landsat sensors
1986	Launch of SPOT French earth observation satellite
1980	Development of hyperspectral sensors
1990	Global remote sensing systems LIDAR
1993	Landsat 6 mission fail
1999	Landsat 7 was launched
2002	National Oceanic and Atmospheric Administration (NOAA)
2013	Landsat 8 was launched

The US started placing remote sensors in space for weather observation and later for land observation in the early of 1960s. Landsat 2 and Landsat 3 were launched in 1975 and 1978, respectively, carried the same payload as the first satellite of this series. The payload was changed in 1982 with Landsat 4, Thematic Mapper (TM) sensors that are technically more advanced replaced the (RBV). The progress of remote sensing series continued with Landsat 5, launched in 1984. The development of remote sensing was not only in the U.S. but other countries were also taking a part in this progress. SPOT or French Earth Observation Satellite was launched in 1986 by the French Government. Another important event in remote sensing history was the failing of Landsat 6 mission in 1993. Landsat 7 was launched in 1999. And lastly Landsat 8 was launched in February 2013 (Joseph, 2005).

Television Infrared Observation Satellite (TIROS) was the first meteorological satellite. In 1970, TIROS program was renamed into National Oceanic and Atmospheric Administration (NOAA). Until today, NOAA Advanced Very High Resolution Radiometer (AVHRR) is around the globe and collects information about weather patterns using visible, near infrared and thermal wavelengths. NOAA-17 was launched on June 24, 2002 (Joseph, 2005).

1.1.1. Definition of Remote Sensing

Due to physical and chemical properties, every object on the Earth's surface reflects, radiates, or emits electromagnetic energy in different wavelengths. The measurement of reflected electromagnetic radiation gives us information about the nature of the object. The selected portions of electromagnetic spectrum that can pass through atmosphere are used for remote sensing (Lang, 2008).

Obtaining information from an area or an object without direct contact using electromagnetic radiation is known as remote sensing. After collecting the required data with the sensor, the data are analyzed to convert them to meaningful information. As can be seen in Figure 1.1, remote sensing process involves the interaction between radiation and target of interest. The seven elements that comprise the remote sensing system are provided in Figure 1.1 and explained below (Campbell and Wynne, 2011).

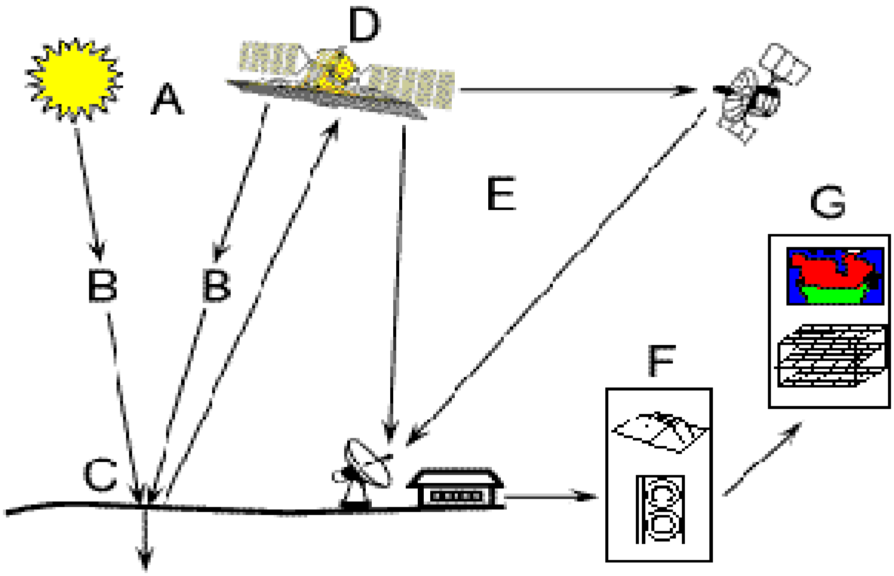

Figure 1.1. The seven elements of imaging system (Campbell and Wynne, 2011).

1-Energy sources or illumination (A), the first required element of remote sensing is to have an energy source to illuminate or provide electromagnetic energy to the target of interest.

2-Radiation and atmosphere (B), while the energy travelling from the sources to the target, it will have contact with and interact with the atmosphere as it passes through. This interaction can take place in the second time as the energy is travelling from the target to the sensors.

3-Interaction with the target (C), once energy passes through the atmosphere, it interacts with the target. The interaction depends on the chemical, biological, and physical properties of both the target and radiation.

4-Recording energy by the sensor (D), the energy is scattered by or emitted from the target. At this stage, a sensor collects and records the electromagnetic radiation without direct contact with the target.

5-Transmission, reception, and processing (E), the energy recorded by the sensor is transmitted usually electronically to receiving and processing station were the data are processed into an image (hardcopy or digital).

6-Interpretation and analysis (F), the processed images are interpreted, electronically, digitally, or visually to extract an information about the illuminated objects on Earth.

7-Application (G), the final element of remote sensing system is application, when we apply the information we extract from the images for getting better understanding about the targeted objects and solve particular problems (Joseph, 2005).

1.1.2. Electromagnetic Radiation

Electromagnetic radiation, the first required element for remote sensing, is emitted by the sun or sensors and used to illuminate the target. The behavior of electromagnetic radiation can be explained according to the wave theory, as seen in Figure 1.2 (Campbell, and Wynne, 2011). Electromagnetic radiation consists of an electric field (E) that varies in magnitude in a direction perpendicular to the direction in which the radiation is travelling, and magnetic field (M) oriented at right angel to the electrical field. Both these fields travelled at the speed of light (C). The characteristics of electromagnetic radiation, wavelength and frequency, are very important for understanding remote sensing (Campbell, and Wynne, 2011).

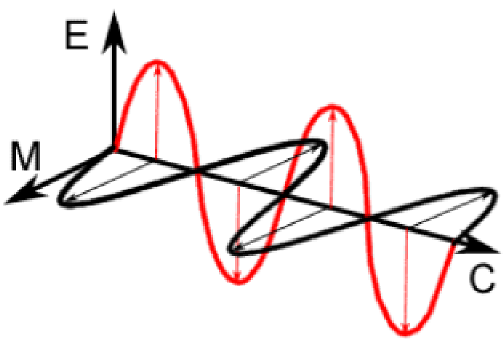

Figure 1.2. Components of electromagnetic radiation

The wavelength is the length of one wave cycle, which can be measured as the distance between the successive wave crests. Wavelength is usually represented by the Greek latter LAMBDA (λ). Frequency refers to the number of cycles of a wave passing a fixed point per unit of time and usually is written as (V) and measured in Hertz (Hz). The formula of wavelength and frequency with light speed is as follows.

$$c = \lambda \nu$$

where:

λ = wavelength (m)
ν= frequency (cycles per second, Hz)
c =speed of light ($3x10^8$ m/s)

As the two are inversely related to each other, seen in Figure 1.3, the shorter the wavelength, the higher the frequency, and the longer the wavelength the lower the frequency.

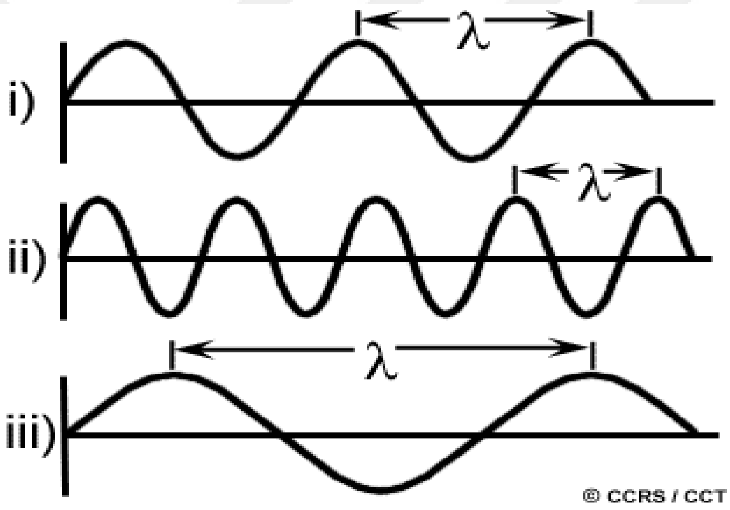

Figure 1.3. The characteristics of wavelength and frequency

Remote sensing uses different sections of the electromagnetic spectrum. Table 1.2 shows the major wavelength regions used for remote sensing.

Tablo 1. 2. The major wavelength regions used for remote sensing

Band	Wavelength (μm)
Visible light (VIS)	0.4-0.7
Blue (B)	0.4-0.5
Green (G)	0.5-0.6
Red (R)	0.6-0.7
Visible-photographic infrared	0.5-0.9
Reflective infrared (IR)	0.7-3.0
Near Infrared (NIR)	0.7-1.3
Infrared (SWIR)	1.3-3.0
Thermal Infrared	3-5
Thermal Infrared	8-14
Microwave	0.1-100

1.1.3. Satellite Imagery

The first images from the space were acquired on orbital flights. On October 1946, the U.S. lunched the V-2 flight, which took images in every 1.5 seconds. On August 14, 1959, the first satellite image was captured by U.S explorer (Ahmed, et al., 2015). The satellite images are mostly available in free of charge in NASA Earth Observatory. In order to take part in the space competition, other countries launched their own satellites and started collecting information for their institutional research. Also private companies play crucial role in producing satellite images for commercial purposes.

There are four types of resolutions in remote sensing: spatial, spectral, temporal, and radiometric. Spatial resolution is defined as the pixel size of the image representing the size of the area measured on the ground and determined by the sensor. Spectral resolution is defined by wavelength interval size (discrete segment of the electromagnetic spectrum) and number of intervals that the sensors measure. Temporal resolution is defined by the amount of time (e.g., days) that passes between imagery collection periods for a given surface location. Radiometric resolution is defined as the ability of an imaging system to record many levels of brightness (contrast) and the effective bit-depth of the sensor (number of grayscale levels) and is typically expressed as 8-bit (0-255), 11-bit (0-2047), 12-bit (0-4095), or 16-bit (0-65,535).

Satellite images have many applications in meteorology, oceanography, fishing, agriculture, biodiversity conservation, forestry, landscape, geology, cartography, regional planning, education, intelligence, and warfare. There are also elevation maps, usually made by radar images interpretation. Analysis of satellite images are conducted using specialized remote sensing software (Ahmed and Al Noman, 2015).

The instruments on Landsat satellites have acquired millions of images. The images archived in the Landsat data receiving stations around the world, these images are unique resources for global changes researches and applications in geology, agriculture, forestry, regional planning, and education, this data can be viewed in U.S Geological Survey (USGS) and Earth Explorer Website (Joseph, 2005).

1.1.3.1. Moderate Resolution Imaging Spectroradiometer (MODIS)

The Moderate Resolution Imaging Spectroradiometer (MODIS) is a sensor operating on the Terra and Aqua satellites, which were launched by NASA in December 1999 and May 2002, respectively. Terra orbits around the Earth from the North to South across the Equator in the morning, and Aqua passes from North to south in the afternoon over the Equator. Terra and Aqua platforms were designed to monitor the Earth’s atmosphere, ocean, and land surface with a set of visible, NIR, MIR, and thermal channels (Zhang et al., 2003).

1.1.3.2. Normalized Difference Vegetation Index (NDVI)

Normalized difference vegetation index (NDVI) is derived from satellite images and used to quantify vegetation by measuring difference between near-infrared which vegetation strongly reflects and red light which vegetation strongly absorbs. NDVI always ranges from -1 to +1. If there are negative values, it is highly likely that there is water. On the other hand, if you have NDVI value close to +1, there is high possibility of green vegetation but when NDVI value close to zero there is no vegetation. As shown in Figure 1.4, NDVI uses NIR and Red channels according to the formula below.

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

Health vegetation (chlorophyll) reflects more Near-Infrared (NIR) and green light compared to other wavelength but it absorbs more red and blue light.

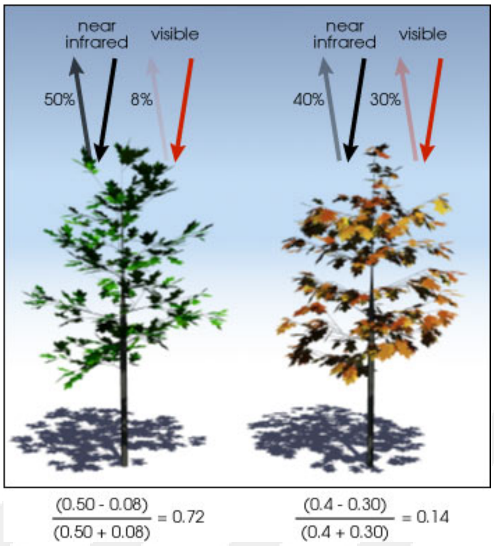

Figure 1.4. Calculation of normalized difference vegetation index

The result of this formula generates a value between -1 to +1, if you have low reflectance in the red channels and high reflectance in the near-infrared (NIR) channel, this will yield a high NDVI value. Overall, NDVI is a standardized way to measure health of vegetation. Generally if we want to see or analyze vegetation change over time, we should consider the values obtained from the NDVI calculations (Gandhi et al., 2015).

1.2. Literature Review

1.2.1. Monitoring Land Use/Cover Changes From Satellite Images

There are many studies in the literature related to land use/cover monitoring using satellite imagery techniques. Below we provide some examples from available literature.

Eckert et al. (2015) examined whether MODIS NDVI satellite data time series can be used for detecting land cover changes and land regeneration in Mongolia for the 2001-2011 period. For their study, they used MODIS NDVI and precipitation data. They found that MODIS NDVI time series data are suitable for detection of land degradation and regeneration in Mongolia. In terms of land cover classes, the major positive and negative trends occurred in barren and sparsely vegetated areas, grassland, and forest areas. The transitional areas were very sensitive, as they found that the major changes occurred around borders between land classes.

Schucknecht et al. (2013) studied regional vegetation trends in north-eastern Brazil. Vegetation variability and trends were analyzed using AVHRR (GIMMS) NDVI data acquired from 1982 to 2006. They compared GIMMS data with MODIS NDVI for the overlapping period of 2001-2006. The results showed that there were huge vegetation losses during the study period. The comparison of GIMMS and MODIS NDVI showed similar spatial patterns and were strongly related to each other.

Fensholt and Proud (2012) examined global long term vegetation trends and compared GIMMS and MODIS global NDVI time series. They evaluated accuracy of this study by comparing the linear regression trend analysis of global terra MODIS NDVI. The trends of GIMMS NDVI data showed acceptable agreement with MODIS NDVI data. Significant trends in NDVI (α=0.05) were found for 11.8% of the MODIS NDVI pixels on global scale; 5.5% were characterized by positive trends and 6.3% with negative trends. GIMMS NDVI analysis produced a total of 10.5% pixels where trends were significant (4.9% positive and 5.6% negative). They found that the correlation between the two datasets was highly significant for areas with distinct phonological cycle.

Jacquin et al. (2010) assessed the vegetation cover degradation between 2000 and 2007 in Madagascar using MODIS NDVI time series. Areas characterized in 2007 by a decrease, an increase or a stability of vegetation activity cover were 20%, 1% and 79% of the savanna extent, respectively. Areas not affected by vegetation degradation in the study period were dominant.

Çakir et al. (2007) used very high resolution satellite images (IKONOS) and aerial photographs together to study 30 years of land cover change in Artvin in Turkey during the 1972-2002 period. The initial forest cover was 88%. In 1985, forest areas decreased to 82% and after 30 years forest decreased to 80%. The main reasons for forest reduction were mentioned to be conversion of 373.9 ha for agricultural activities and settlements. Construction of roads and dams also had a great contribution to the land cover change in the Artvin area.

Lunetta et al. (2006) examined the land cover changes in U.S., using 250 m multi-temporal MODIS NDVI 16 day composite data for the 2002-2005 period. They found that land cover changed by 0.7% annually, varied from 0.4% in 2003 to 0.9% in 2004 for the tidal water zone. For the mountain ecological zones, the land cover change rate was found to be 0.6% to 0.1%, annually.

Eklundh and Olsson (2003) analyzed recent vegetation trends in African Sahel region. They used 8kmx8km NASA/NOAA pathfinder AVRHH Land (PAL) database covering Africa Sahel for the period of 1982-2000. The trends were mapped into four classes, indicating strong or weak positive or negative trends. The results showed that strong positive change in NDVI occurred in 22% of the area excluding no data area. Weak positive trend was detected in 60% of the area and weak negative trend was seen in 17% of the area. Strong negative changes were found in 0.6% of the area.

Yang and Lo (2002) detected land use/cover changes in the period of 25 years in the Atlanta, Georgia metropolitan area in the U.S. using time series analysis of satellite imagery TM and MSS Datasets. The results showed that high-density urban use increased from 4.35% in 1973 to 8.24% in 1998. Low-density urban use increased from 11.63% in 1973 to 25.49% in 1998. Forest and croplands faces continuous decline; forest decreased from 62.60% in 1973 to 49.51% in 1998. Cropland declined from 18.97% in 1973 to 12.66% in 1998. Urbanization was found to be one of the major reasons of forest and cropland destruction in the Atlanta metropolitan area.

1.2.2. Land Use/Cover Changes in Somalia and East Africa

Below we summarize previous studies conducted in Somalia and East Africa to detect land use/cover changes.

Ogallo et al. (2018) analyzed the land cover change in Lower Juba, Somalia using remotely sensed images of Landsat 5, 7, and 8. They covered all the districts of Lower Juba region from 1993 to 1995 and 2000 to 2014. Image classification was done using a supervised classification algorithm through ERDAS. Land cover change analysis was done using

Gebregergis et al. (2016) studied the dynamics of land use/cover change and urbanization in JIGJIGA town, capital city of the Ethiopian Somali region. In this study, they used satellite images for 1985- 2015 period and geographic information system (GIS) working interface. Image analysis was done using (ERDAS) Imagine and ArcGIS software. To classify images, supervised and unsupervised algorithms were used. The images were classified into four classes: built-up, grassland, shrubland, and open area. Finally, the accuracies of the classification results were tested using data for accuracy assessment. Results showed that in 1984, built-up areas covered 2.4%, grassland covered 37.8%, shrubland covered 35.9%, and open area covered 23.9% After 30 years, there were significant changes in every single land cover type. It was described that built-up area increased by 44.2% and grassland decreased by 8.5%. Shrubland also decreased by 5.2%, while there was 42.2% increase in open areas.

Kiruki et al. (2016) examined the land cover changes and woodland degradation in charcoal-producing semi-arid areas in Kenya. They used Landsat imagery in four different years 1986-1999-2005-2014, field plot data, and household interviews to describe land cover changes and the role of charcoal production in woodland degradation. Unsupervised classification was used to determine the land cover change from woodland to open and farmland. Five 16-km transects were used to investigate the extent of charcoal production on targeted woodlands. 117 households were interviewed to understand their perceptions on woodland changes and the role of charcoal production. They found that there were great changes in woodlands. The areas decreased from 31,084 ha in 1986 to 23,930 ha in 2014. The biggest change in woodland cover occurred between 2005 and 2014. Farmland increased from 7.2% in 1986 to 19.7% in 2014.

Mayes et al. (2015) assessed the forest change from 1990 to 2010 in Miombo woodland landscape, Tanzania. Linear spectral mixture analysis (LSMA) approach with Landsat 5-8 data from 1990 to 2010 was used. An unsupervised classification algorithm was used to classify images. Results showed that the study area experienced 15% loss of 1995 forest area, and a 7% overall reduction in the total forest occupied land cover from 1995-2011. Areas of gross forest gain were mentioned to be 13.6% of the forest area in 1995.

Brink et al. (2014) assessed and quantified the land cover change in East Africa by using systematic sampling of medium resolution Landsat and DMC Deimos imagery. 445 samples covering about 3% of the study area taken as a box 20km x 20km around each 1-degree latitude and longitude intersects were processed and analyzed. Statistical estimates of land cover change were produced by means of an automatic object-based classification in seven classes for the years 1990-2000 and 2000-2010. Result highlighted the loss of natural forest and 28% of agricultural expansion over 20-year time frame. Agricultural area expanded at a rate of 1.4% per year for both assessed decades. The deforestation rate was 0.2% per year in the first period and 0.4 per year in the second period.

Rembold et al. (2013) mapped charcoal derived forest degradation during the main period of Al-Shahab (terror group) control in southern Somalia, using very high resolution (VHR) satellite images. All sites were mapped using satellite images acquired in years 2006, 2011, and 2012. Somali experts were interviewed and asked to locate recent charcoal production areas in their regions on a topographic map, in order to better define a woody biomass map for Somalia produced by Wood Fuel Integrated Supply/Demand Overview Mapping (WISDOM) that was used as a background layer. Results showed that there were no charcoal production sites detected in 2006. 533 charcoal production sites were mapped in 2011 to 2012, with an average density of 14 charcoal production sites per km^2. The result also showed that 7.2% of trees lost in five years.

Verbesselt et al. (2012) examined drought related vegetation disturbances in Somalia from 2000 to 2011, using MODIS NDVI time series. The results showed that areas with minimal vegetation cover were severely affected by droughts. In the north-east region and some parts of north-west were found to be having lowest vegetation cover.

Brink et al. (2009) examined the changes in sub-Saharan's natural land cover resources for a 25-year period using remote sensing techniques. Landsat MSS and TM imagery from 1975 and 2000 were used in the analysis. Unsupervised clustering algorithm (ISODATA) was used for image classification. They found that over the 25-year period, significant land use/cover changes occurred in the sub-Saharan Africa due to anthropogenic and natural causes including population growth, floods, landslides, droughts, and climate change.

CHAPTER 2

MATERIALS AND METHODS

2.1. Study Area

Land cover change detection analysis was carried out in Somalia. Somalia locates almost at the eastern portion of Africa, which is known as The Horn of Africa (Figure 2.1). It lies between latitudes 1° 40' 48” S and 12° 6' N and the longitudes 41° 0' E and 51° 22’ 12” E, covering an area of 637,657 km^2. It shares border with Djibouti in the northwest, Ethiopia in the West, and Kenya in the southwest. It also has water border with Indian Ocean in the east and the Red Sea or Gulf of Aden in the north.

The climate of Somalia varies from desert to semi-humid. Movements of northeast monsoon winds blowing from Arabian coast, southwest monsoon winds blowing from Africa, the south winds from Indian Ocean, and inter-continental convergence zone (ITCZ) have great influence on Somalia’s climate. These four different wind systems result in four different seasons in Somalia. Autumn (Gu) season starts in April and continues until June and it is the main rainy season in the country. Summer (Xagaa) season continues from July to September, which is cool, dry, and windy in the interior regions but showers are seen in the northwest highlands and south coastal areas along the Indian Ocean. Spring (Dayr) starts in October and ends in December and it is the second rainy season of the country, but rainfall is less than rainfall in the autumn season. Winter (Jiilaal) continues from January to March, which is the hottest and driest season of the entire country.

Figure 2.1. Physical map of Somalia

Mean annual precipitation over the country is about 300 mm. The precipitation is distributed as follows: about 50 mm along the coast Gulf of Aden, 200 mm in interior regions, 330 to 500 mm in the south, and more than 500 mm in the northwest highlands and southwest parts of the country. Somalia experiences frequent mild droughts in every 3 to 4 years and severe droughts in every 8 to 10 years. Average annual temperature is about 28°C over the country, but it may be as low as 0°C in the mountain areas and as high as 47°C along the coast Gulf of Aden. The climate is hot and dry in the interior regions and coastal areas along the Gulf of Aden, but cool along the Indian Ocean coast and inland areas of floodplains between Juba and Shabelle Rivers. In addition to high temperatures, the country also experiences high relative humidity of between 60% and 80%.

The vegetation cover in Somalia ranges from the forest in Golis Mountains in the north to the Lag Badana ecosystem of the south. Mangrove forests are found in north and north-eastern coastline districts of Zeylac, Berbera, Caluula, and Kismayo in the south coasts. Extensive grasslands are found in Puntland state. Sand dunes sparsely covered large area along the coast. The major land cover classes are described in to seven classes natural woody vegetation closed to open, natural woody vegetation sparse or herbaceous, bare areas, rain-fed crop, irrigated crop, built up areas, and water bodies as you can see in Table 2.1 and Figure 2.2 in detail (Monaci et al., 2007).

Table 2.1. Land cover classes in Somalia (Monaci et al., 2007).

Land Cover Class	Area (ha)
Natural Woody Vegetation Closed to Open	33843064
Natural Woody Vegetation Sparse or Herbaceous	19320323
Bare Areas	7603075
Rainfed Crop	2361997
Irrigated Crop	628050
Built-up Areas	60816
Water Bodies	32318

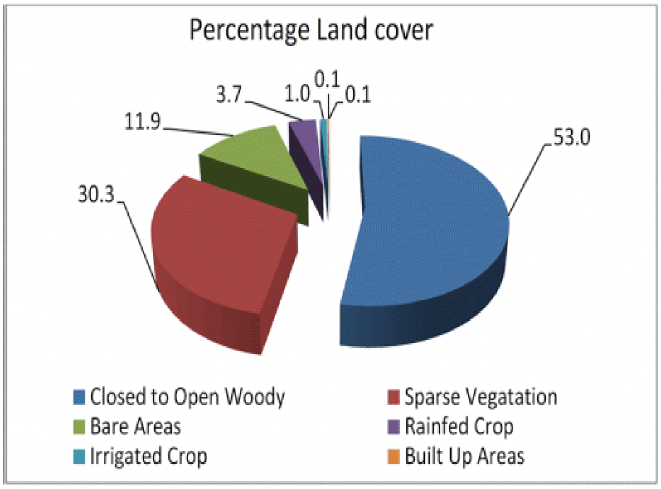

Figure 2.2. Percentage of different land cover classes in Somalia (Monaci et al., 2007).

Livestock is the major economic income of Somalia. Two-thirds of Somali population practice livestock. Livestock-related exports account for more than 70% of Somali's foreign exchange earnings and 91% of Somali’s hard currency inflow come from livestock exports (Samatar et al., 1988). Before the collapse of Somali central government in 1991, there was a system for livestock grazing set by National Range Agency to minimize and mitigate the consequences of overgrazing by dividing the regions into seasonal and drought grazing reserves (Musse, 1987). After the civil war, this system changed. Previously National Range Agency was responsible to manage and decide when and where the Somali pastoralists would move to get water and fodder for their livestock. Now nomads can make a decision about whenever to move and this action encourages land cover destruction. According to FAO statistics (Farah and Fisher, 2004), there were 19 million camel populations in the world, and more than 60% of this camel population were concentrated in northeastern countries of Africa. Somalia has the largest camel population in the world with over 6.2 million (Farah et al., 2007). Camels and other types of livestock are freely grazing with no grazing management systems, which contributes forest degradation. Somali pastoralists even use trees for any type of fencing system and timber for buildings in remote villages.

Charcoal production is the other important economic activity. Charcoal areas were licensed by National Range Agency. Charcoal production is one of the major threats toward Somali’s land cover and all other environmental sectors. Charcoal is locally described as “Black Gold” because of revenue it produces. In the last two decades it become the most exported product from Somalia after the livestock, and also it is the main energy sources for cooking and heating (Samatar et al., 1988).

2.2. Data Used

In this study, Moderate Resolution spectroradiometer (MODIS) NDVI data with 250 m spatial resolutions were acquired from U.S. Geological Survey for the acquisition date of 2003-2016. The moderate resolution spectroradiometer (MODIS) have been geometrically and radiometrically corrected. We also used Somalia’s precipitation and air temperature data from the 2003-2016 from climate change knowledge portal. This meteorological data was the average of data collected from 18 different stations over the country.

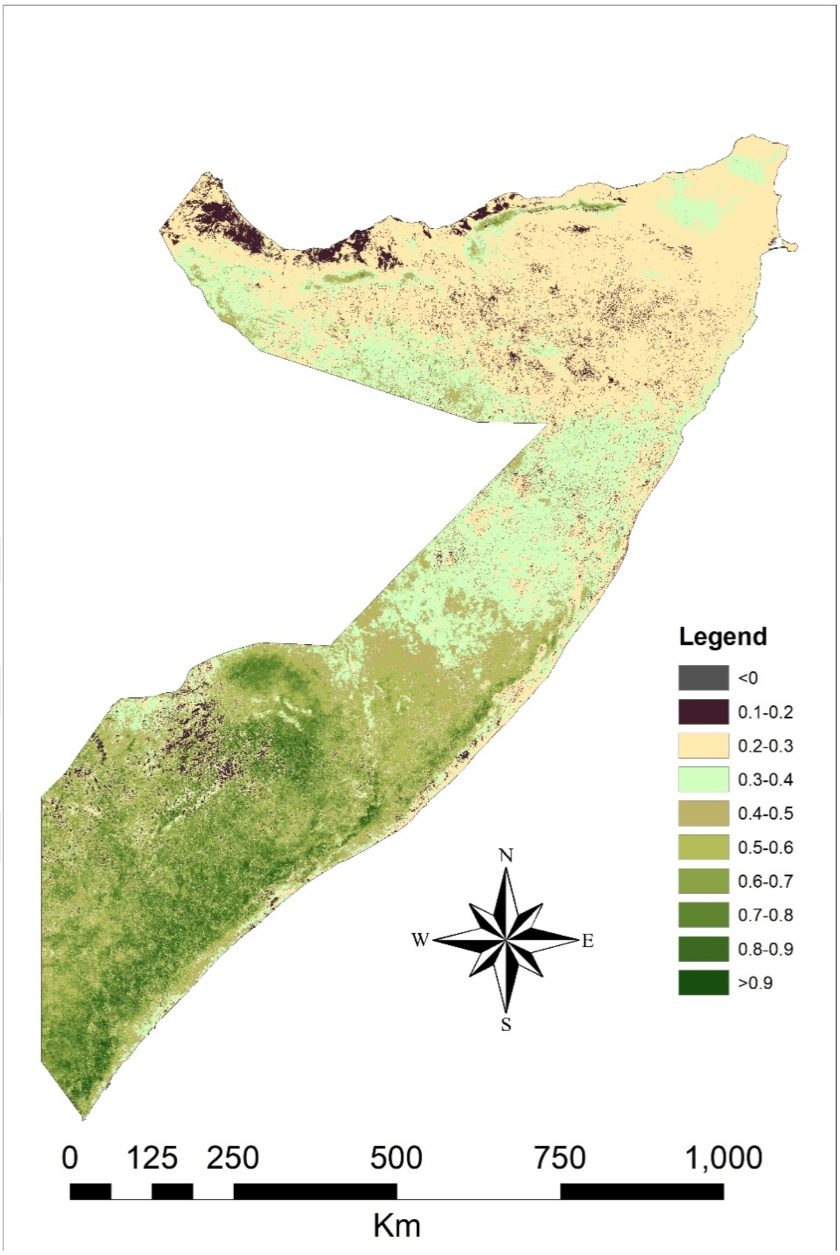

Figure 2.3. MODIS NDVI map for Somalia

2.4. Data Analysis

After the collection of satellite images, we conducted several steps to make our data ready for the analyses. At the first step, we extracted our target area from the main image of MODIS NDVI imagery using Somalia shapefile. Somalia archipelagoes were excluded in our target area.

In this step we processed NDVI anomalies correction before the analysis. The values of NDVI from the extracted data was out of range (highest: 10000 and lowest: -2000) which means not useful for farther NDVI analysis. We rescaled the data into 1 to -1. To get the ideal NDVI values it is been multiplied by 0.0001 using raster calculator in ArcGIS, which is a stander method forNDVI anomalies correction (Hurley et al., 2014). Then, we classified NDVI data into 10 classes and determined the area of each class

We predicted that climatic conditions mainly precipitation and air temperature has significant influence on Somalia’s land cover. Therefore, we obtained annual precipitation and annual average air temperature data of Somalia from World Bank Climate Change Knowledge Portal. We analyzed the characteristics of meteorological data using statistical methods. We also examined seasonal and annual changes. The relationships between NDVI and precipitation and air temperature time series were examined using correlation analysis.

CHAPTER 3

RESULTS AND DISCUSSION

3.1. Meteorological Characteristics of Somalia from 2003 to 2016

We obtained average air temperature and annual precipitation data for Somalia from 2003 to 2016 and analyzed the data using statistical methods.

The air temperature condition of Somalia in 14 years (2003-2016) shows very small changes (Figure 3.1). The average annual air temperature during the 2003-2016 period was 27.5°C, while the minimum and maximum annual air temperature values were found to be 24.8°C and 29.9°C, respectively. The standard deviation for this period was 1.2°C. The hottest year from 2003 to 2016 was 2015 with average annual air temperature of 28.1°C. During the same time period, 2008 was the coldest year with average annual air temperature of 26.8°C.

Average monthly air temperature values from 2003 to 2016 are provided in Figure 3.2. April and May are the hottest months in Somalia and December and January are the coldest months.

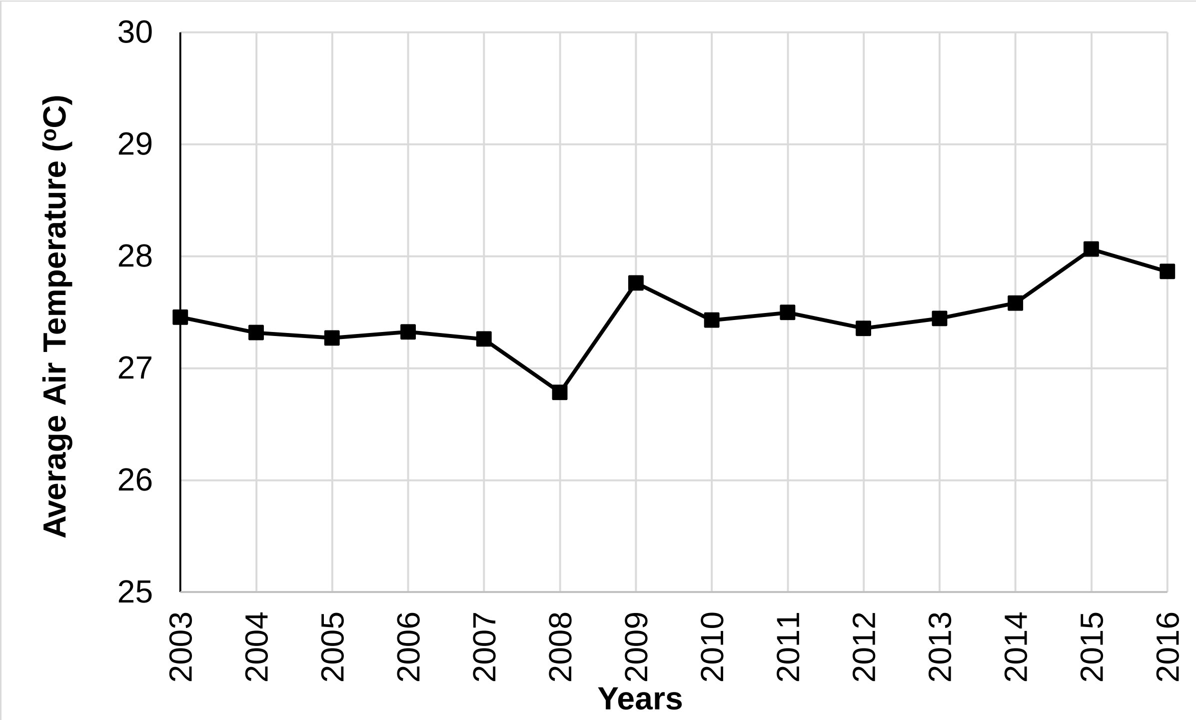

Figure 3.1. Annual average air temperature in Somalia from 2003 to 2016

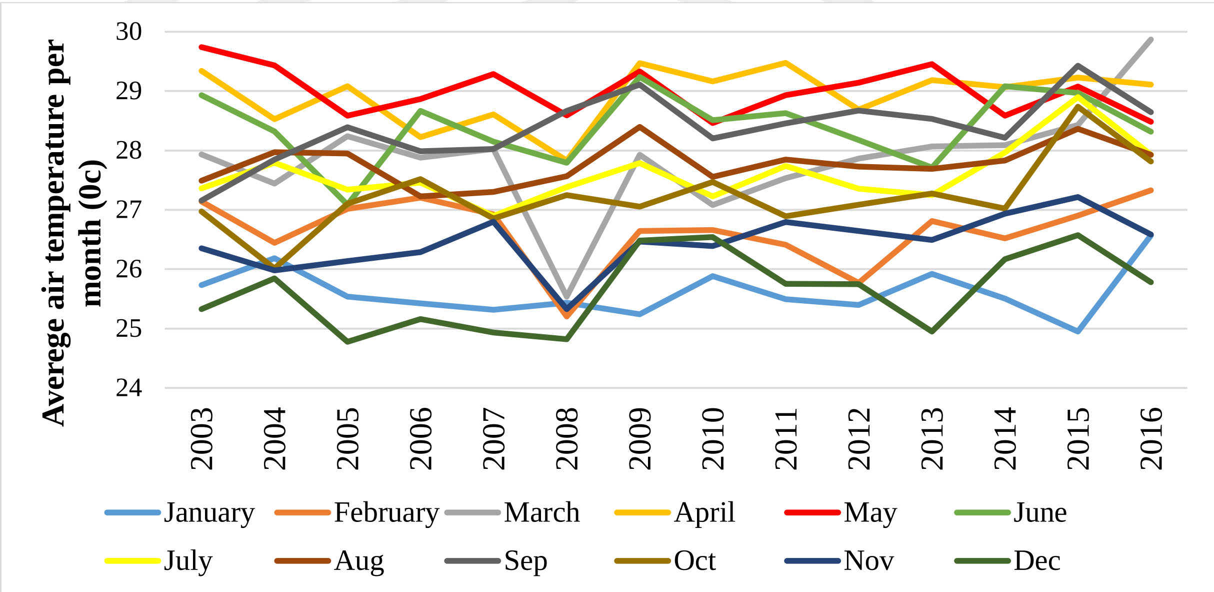

Figure 3.2. Average monthly air temperature in Somalia from 2003 to 2016

Annual and monthly precipitation values in Somalia are plotted in Figure 3.3 and Figure 3.4. As we mentioned in chapter four, Somalia has two rainy seasons in the year which is locally known as Gu the main rainy season and Deyr which is secondary season in terms of amount of rain received by a year. Rainfall is very important for millions of Somali nomads and agricultural societies because the most dominant land use types like rain-fed agriculture and livestock requires enough precipitation to produce pasture for the livestock and irrigation for the farms. Precipitation was very variable in the 14 years of our study period. After the precipitation data analysis, result shows that the annual average precipitation for the 2003-2016 period was 288.2 mm. Maximum precipitation during the 2003-2016 period occurred in the year 2013 with 336.8 mm, while minimum precipitation occurred in 2010 with 242.7 mm. Severe drought broke out in 2010 throughout the country and lasted till the end of 2011. Although 2010 was the year with minimal precipitation, one can notice that 2008 and 2009 was the years when less than average precipitation occurred in the country. Three consecutive years (2008, 2009 and 2010) of dry conditions caused severe drought in 2010. After 2011, where precipitation became higher, absence of expected rainy seasons in 2012 resulted in another drought in most of the country. As we can see in Figure 3.3, in nine years out of fourteen years of our study period, the amount of precipitation was less than 300 mm, which shows that how Somalia is vulnerable to the outbreak of droughts in every year. Droughts cause land cover degradation and even changes in the land use system of the entire country.

From the monthly precipitation data provided in Figure 3.4., we see that April and May are the wettest months, while February and January are the driest months. In the years 2010 and 2012, precipitation during rainy season was considerably lower than other years, which can also explain the droughts in these years.

The discussion about average precipitation values does not accurately reflect the spatial characteristics of precipitation. However, we could not obtain precipitation data from different parts of the country. Although we do not have data, we should mention that coastal area along the Gulf of Aden are exceptional from the other regions of the country when we are discussing the rainfall and air temperature. In this region, precipitation can be as low as 50 mm annually. At the same time, these regions experience the highest temperatures (sometimes higher than 47^{o}C) from August to November.

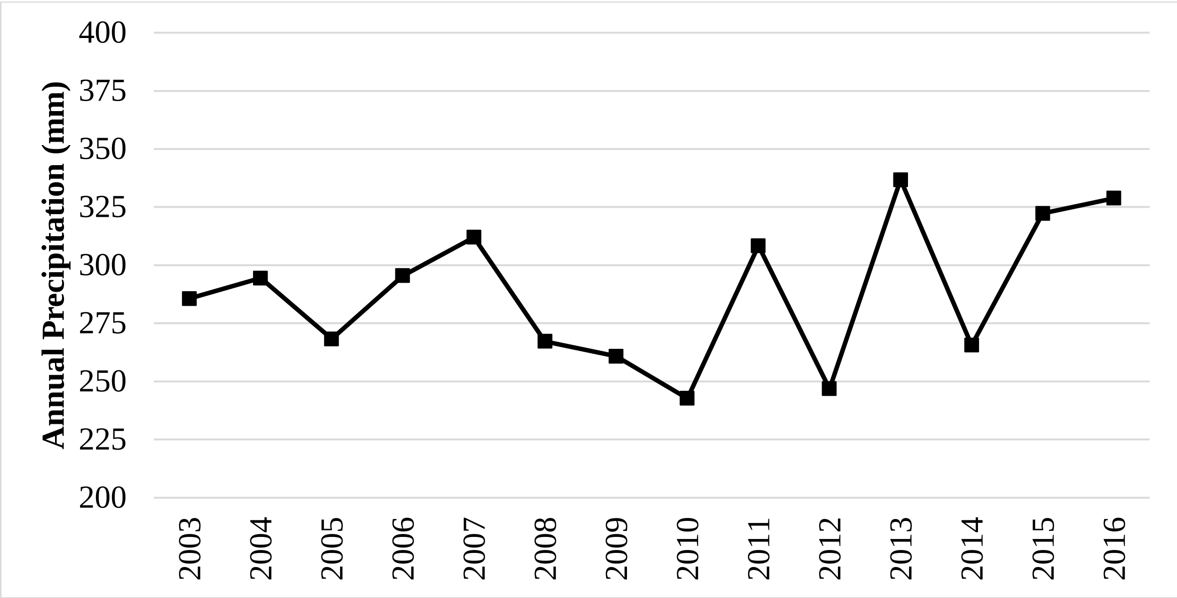

Figure 3.3. Annual precipitation in Somalia from 2003 to 2016

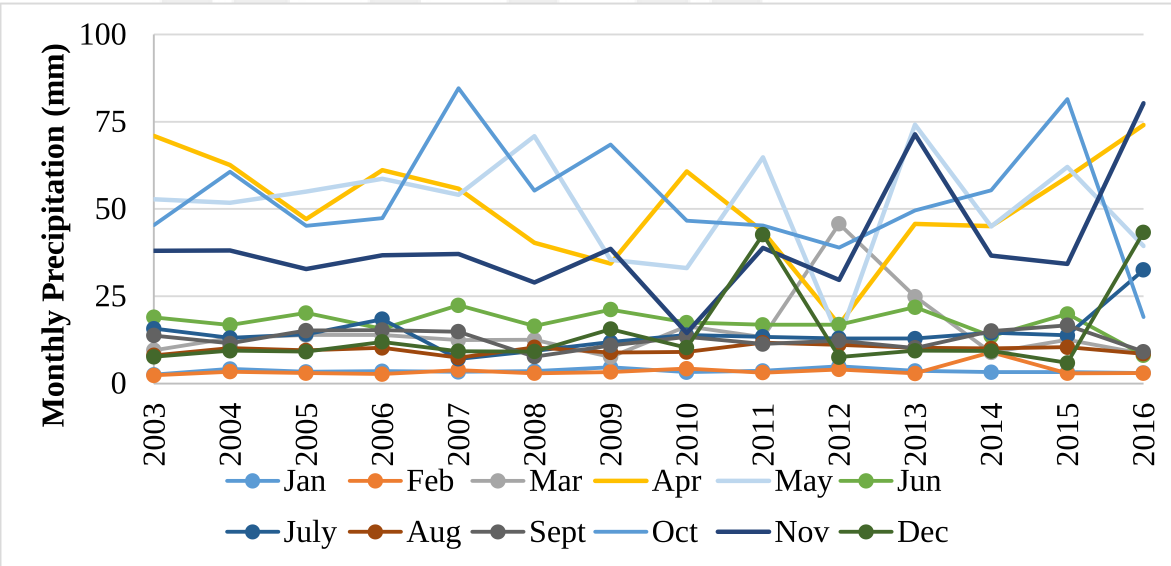

Figure 3.4. Monthly precipitation in Somalia from 2003 to 2016

3.2. Land Cover Changes in Somalia from 2003 to 2016

In this study, MODIS NDVI data were used to detect land cover changes in Somalia from 2003 to 2016. MODIS NDVI is an effective tool for analyzing land cover, particularly for large areas. Here, we examined the land cover changes at the country scale. For each year’s imagery, we classified the NDVI values into 10 classes. When NDVI values are closer to 1, vegetation cover becomes denser. On the other hand, if the NDVI values become closer to zero (0), it indicates that there is very low or no vegetation cover. Negative (-) values of NDVI describe the availability of water and again no vegetation cover.

The average NDVI values from 2003 to 2016 were shown in Figure 3.5. We see that permanently vegetated area in Somalia is very low, at the same time it is dependent on the rainy seasons. Average NDVI in Somalia changed between 0.19 and 0.30. Average NDVI was largest in the year 2013 and lowest in the year 2011. We see that average NDVI was higher than 0.25 in 2010, 2013, and 2015 and it was below 0.2 in years 2009 and 2011. It seems that the years with lowest NDVI values were seen in years where precipitation is below normal, which means that vegetation responds the drought a year after the event.

The classified NDVI data are shown in Figure 4.6 and the areas covered by different classes were depicted in Figure 4.7. Small portions of high altitude areas in the northern regions and southern regions near to the equator have permanent and denser vegetation cover. Other parts of the country have very sparse or no vegetation cover. The land cover classes where NDVI is 0.5-0.6, 0.6-0.7, 0.7-0.8, 0.8-0.9 and >0.9 cover less than 50000 km^2. The largest area in Somalia is covered with the class where NDVI is between 0.2-0.3. This class covers about 300000 km^2. The second and third largest areas belong to the class where NDVI is 0.3-0.4 and 0.4-0.5, respectively. These classes cover about 100000 km^2 and 50000 km^2, respectively. The classes, where NDVI values are negative or 0-0.2, also cover very small areas.

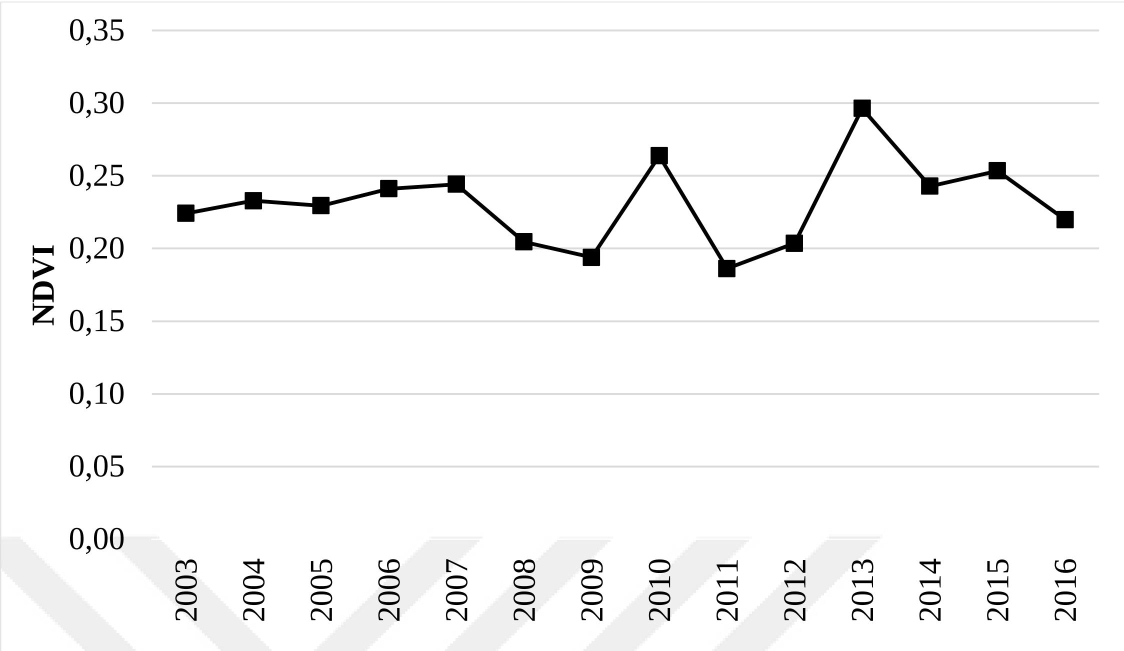

Figure 3.5. Average NDVI values in Somalia from 2003 to 2016

Precipitation has direct influence on agricultural land use in the almost of the country because precipitation is major sources of irrigation in northern, northeastern and central regions of the country. Precipitation does not only have influence in rainfed agricultural land use in Somalia in the same time it has great relation with livestock raring. Therefore, the density of vegetation cover also changes with precipitation.

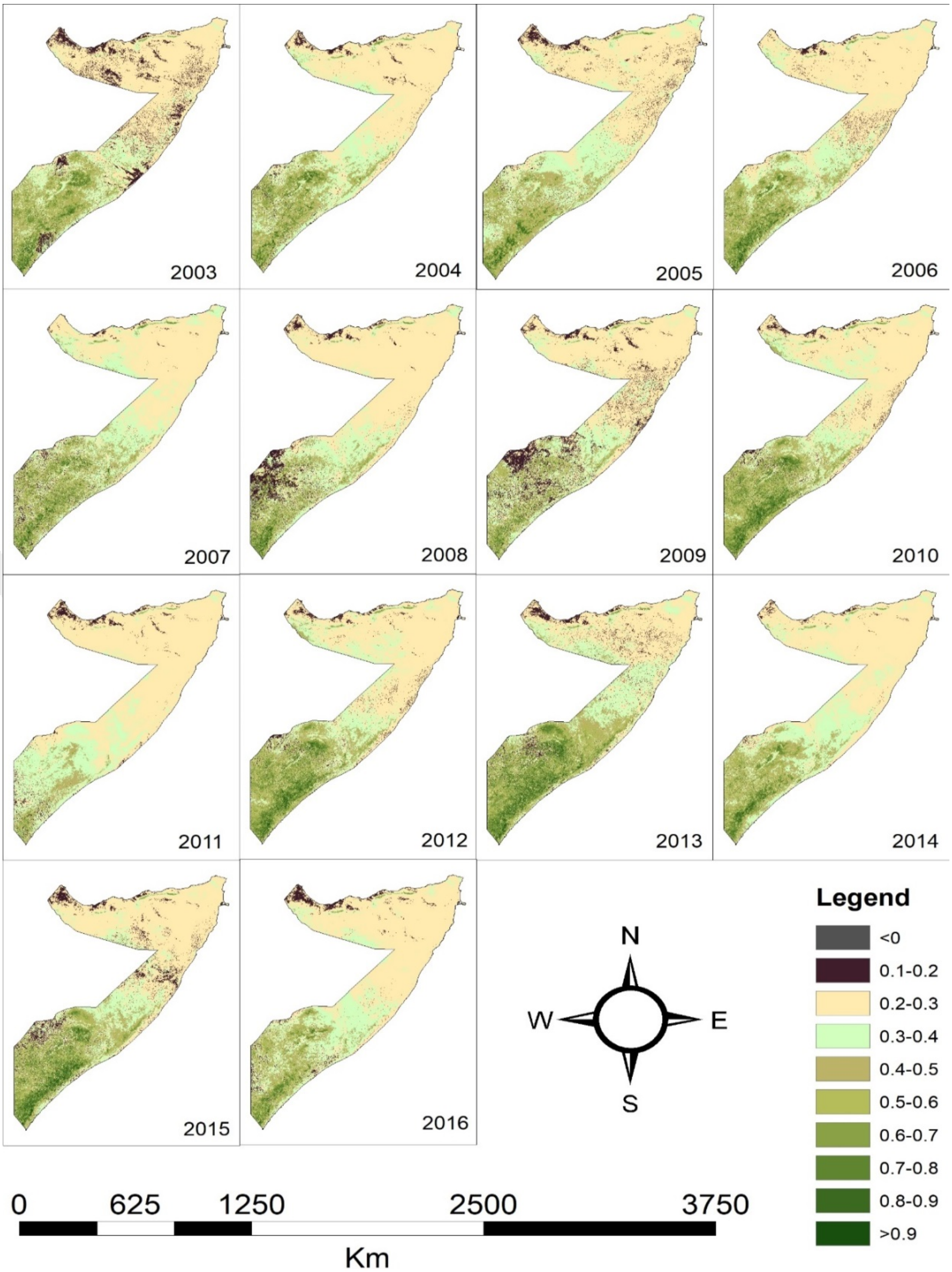

Figure 3.6. MODIS NDVI time series for Somalia

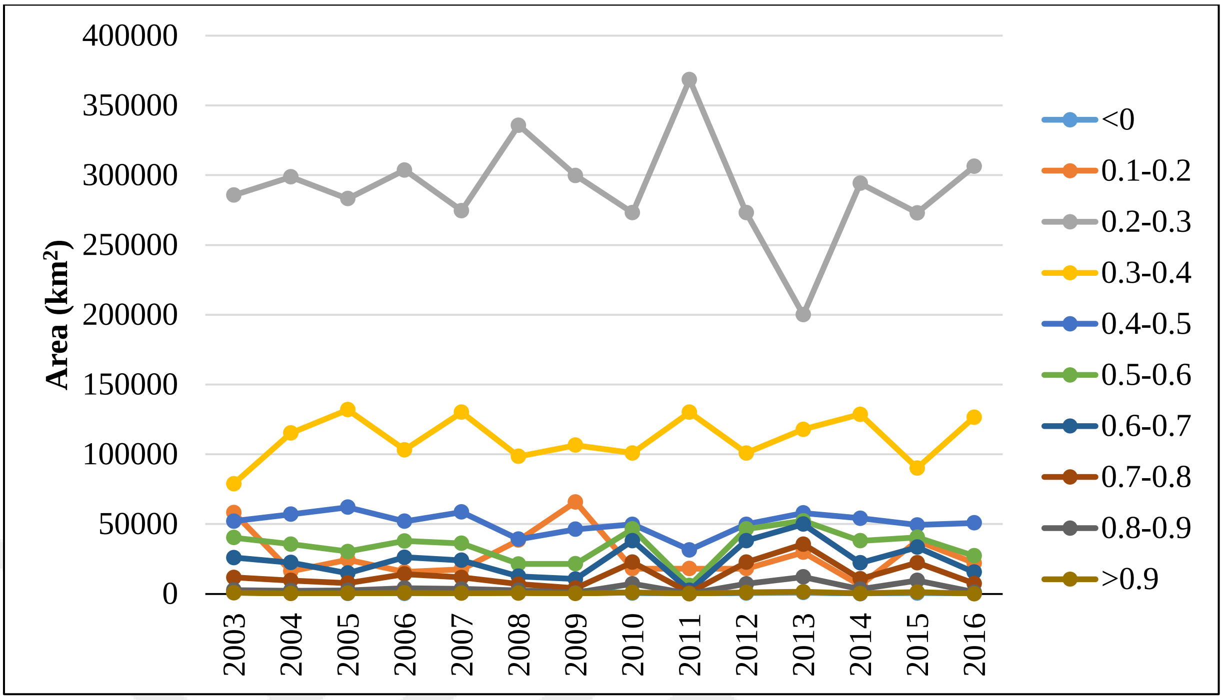

Figure 3.7. Area allocated to different NDVI classes from 2003 to 2016.

3.3. Relationships between Climatic Conditions and Land Cover in Somalia

Dry environment is a common mostly in Somalia. The principle factors which play major role for land cover changes throughout the country are precipitation dynamics and human mismanagement of vegetation cover. According the outcomes of both metrological and NDVI analyses there is relationship between precipitation and land cover. Precipitation also has relationship with land use activities e.g. agriculture and livestock raring. Only areas along the Jubba and Shabelle rivers has permanent irrigation while the other parts of the country people carry out rainfed agricultural activities. Therefore, they are directly dependent on precipitation, which means if there is no or little precipitation in these regions in a particular season there would not be crop cultivation.

In Figure 3.8 and Figure 3.9, annual average air temperature and annual precipitation are plotted together with average NDVI values. The correlation between annual average air temperature and average NDVI was calculated as 0.10. The correlation between annual precipitation and average NDVI was calculated as 0.78.

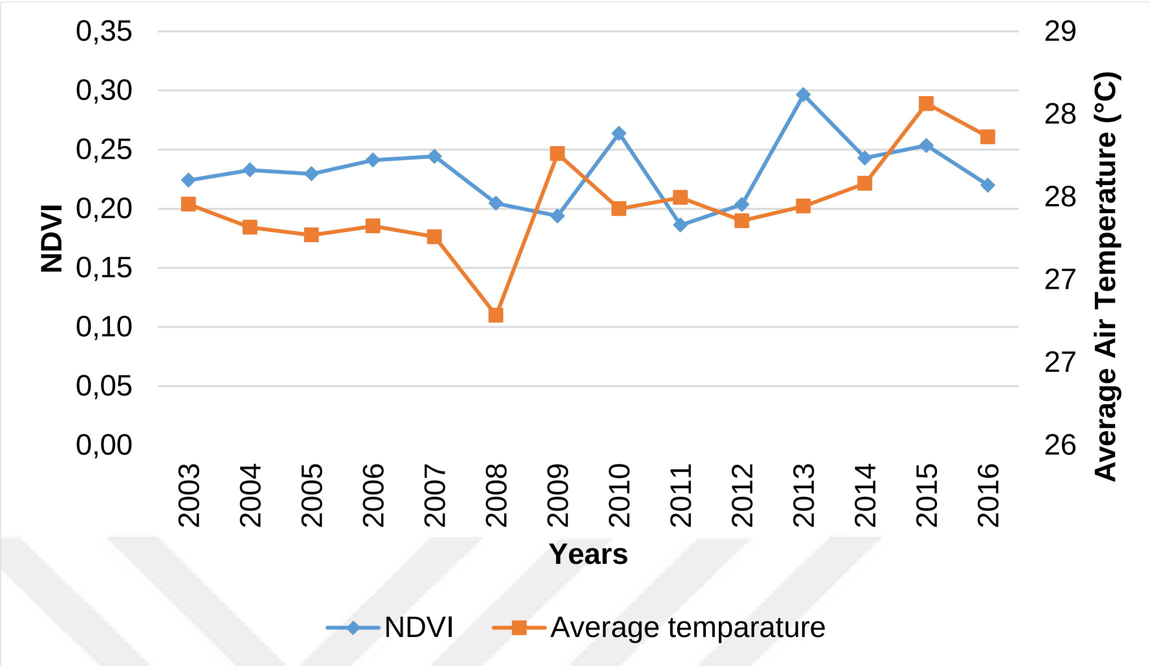

Figure 3.8. NDVI with average air temperature

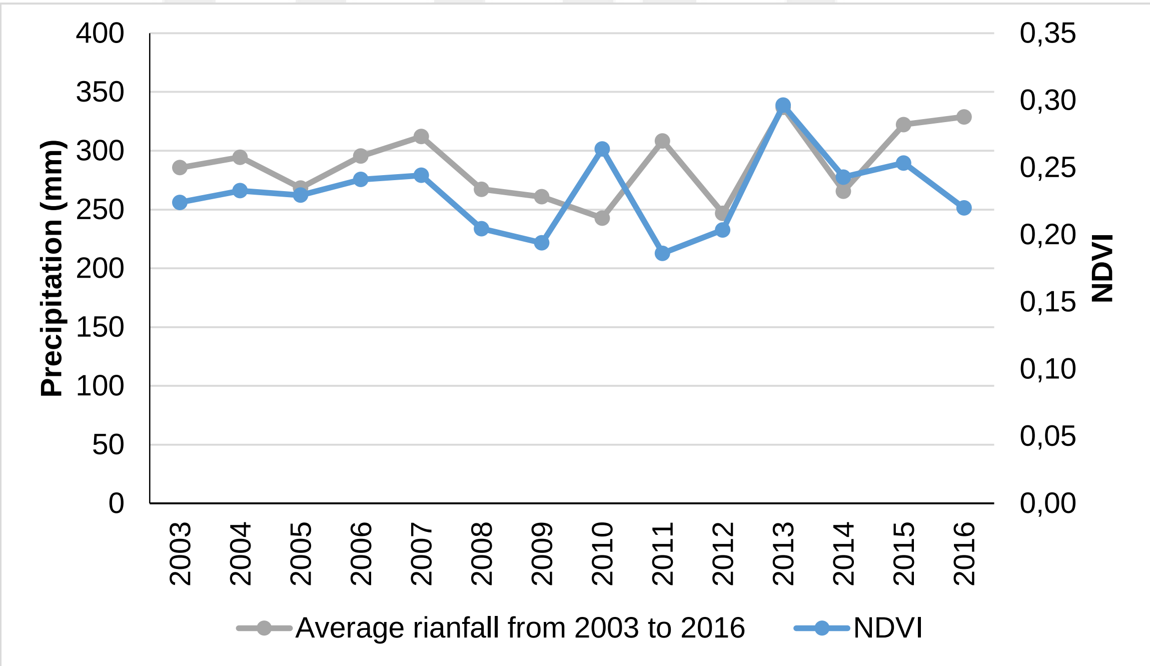

Figure 3.9. NDVI with average precipitation from 2003 to 2016

CHAPTER 4

CONCLUSIONS AND FUTURE WORK

This study aimed to determine land cover change detection using satellite imagery techniques in Somalia. Although Somalia faces many different environmental crises in the last three decades, studies that examine environmental changes are very important. In this study, we investigated land cover change in Somalia from 2003 to 2016 using MODIS NDVI time series and determined the main underlying causes of land cover changes in the country. This datasets have been freely downloaded from Earth Explorer official data store website of US Geologic Survey (USGS). At the same time climatic conditions has great contribution on the land cover and land use systems. Therefore, we also analyzed air temperature and precipitation data downloaded from World Bank Climate Change Portal.

The average annual air temperature during the 2003-2016 period was 27.5°C, while the minimum and maximum annual air temperature values were found to be 24.8°C and 29.9°C, respectively. We found that precipitation was variable in the 14 years of our study period. Average annual precipitation in the period of study was 288.2 mm, this means the country received very low precipitation. In the year of 2013, the country received the highest amount of precipitation of 336.8 mm, whereas in 2010 the amount of precipitation was as low as 242.7 mm. Apart from exceptional areas, generally air temperature of the country is high in May and April also these months are the wettest in the year, while December and February are the driest and the air temperature is low.

We examined the relationships between land cover and climatic conditions. Although we see changes in vegetation cover particularly with changes in precipitation, the analysis were not very conclusive. This means that climatic conditions are not the only causes of land cover variations. Human activities most probably also contributed to land cover changes. The major activities which can contribute land cover changes in Somalia are cutting trees for charcoal production, overgrazing, or agricultural expansion.

It is very important for any institutions concerning about land cover and land use in Somalia to know what kind of change is happening country's forested areas and the magnitude of changes and their causes, management and forest recovery is needed to be investigated the real issue exist in the area.

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