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Study on drought characteristics in Nalaikh and Terelj area using GIS with SPI and NDVI for 1990-2018

Bachelor Thesis

Submitted by

Dulaanjargal Mendbayar

Supervisor 1/ Examiner 1	M.Sc. Enkhjargal Sodnomdarjaa
Supervisor 2/ Examiner 2	Prof. Dr. Gantuya Ganbat

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Statutory Declaration

Mendbayar, Dulaanjargal	15348179261872
Last Name, First Name	Student ID number

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Abstract

As the effects of climate change is continuing to pose large problems that affect ecosystems and communities around the world, arid and semi-arid places where there is a big imbalance between annual precipitation and evapotranspiration are exposed to more frequent and intense droughts due to temperature increases. Therefore, understanding different drought types concerning their severity, duration, and spatial extent is crucial to mitigate drought risks which can prevent huge environmental and economic losses. In this study, an analysis of long-term drought conditions in Nalaikh, Terelj region was done using the Standardized Precipitation Index (SPI) and Normalized Difference Vegetation Index (NDVI) between the years 1990 to 2018. Precipitation records of the study period were analyzed to define drought characteristics using the SPI and to identify drought events at 1-, 3-, 6-, 9- and 12-month timescales. The results showed that there were several moderate to extreme drought events from 1990 to 2018 with ranging durations. Significant drought events with SPI values higher than −2.0 were recognized at all time scales, although the frequency of each episode was decreasing as time scales increased. Moderate and severe drought events were observed the most at SPI 1- and 3-month timescales respectively with 54 and 21 events. Vegetation data from the Landsat 4,5 and 7 were collected and utilized to generate maps at a two-year interval from 1990 to 2018 using NDVI. Even though dry periods led to less vegetation, an indication of severe drought events could not be seen from the NDVI values as the value did not fall below −0.7 at SPI values with different intensities. The NDVI values were able to show variability and spatial distribution of drought events, excluding several years with weak correlation.

Keywords: drought, precipitation, SPI, NDVI, drought severity, remote sensing, Nalaikh, Mongolia

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1 Introduction

Over the last several years, attention towards the major environmental problems such as climate change and the growing scarcity of water resources has been gaining attention among the researchers following the rise in water demand and increasing level of greenhouse gases in the atmosphere. According to the 2018 study by the UNCCD, globally approximately 40% percent of the population has difficulty accessing potable water resources, and livestock losses due to drought conditions were estimated to be a staggering 85.5% percent (1). Among many other environmental problems that we are facing, drought is acknowledged as one of the most damaging and urgent natural hazards considering its impacts on significant economic and ecologic losses (2). Because of their long-term persistent nature, it is often extremely hard to determine the drought characteristics as it increases in size and expands slowly for years (3). As the global temperature is rising at an unprecedented level compared to the pre-industrial level, its effects are resulting in extreme climate events such as severe thunderstorms, droughts, and heatwaves across the world (4,5). As a result of climate change, in countries around the middle latitudes, more severe and frequent droughts are expected to occur in the 21st century (6–8). Therefore, it is crucial to identify and define the characteristics of drought before it brings a significant negative impact both on the environment and on the livelihood of people living in those impoverished places. Depending on the severity and frequency, drought can affect people's lives immensely in the long term, particularly in arid and semi-arid areas of the world (9). Because of its unusual complexity compared to other natural hazards and far-reaching effects, defining drought has been one of the challenging parts of earlier studies. Without a clear definition, it is difficult to identify and monitor the major characteristics of drought: intensity, duration, severity, and spatial magnitude (10). However, by considering its various aspects, drought classification can be divided mainly into four different types depending on the disciplinary views: meteorological drought, socioeconomic drought, agricultural drought, and hydrological drought (10,11). Meteorological drought is a phenomenon in which there is a very little rainfall or rainfall deficit causing a long period of dryness further increasing the probability of causing origins of other types of droughts. Agricultural drought combines the effect of reduced crop yields, water deficit in soil, and other various characteristics of meteorological and hydrological drought (12). If the period without precipitation persists over a long period, the water supply cannot be satisfied with the insufficient amount of groundwater and the lack of streamflow. Such a condition is called hydrological drought which usually follows meteorological drought after it ends. When the impacts of drought influence the economic chain and livelihoods of people by disrupting the supply and demand of socioeconomic goods, it is associated with socioeconomic drought (10). Generally, drought can be understood that it concerns water shortage and is a normal, recurrent feature of climate (13). Globally, drought is the second biggest (7.5%) natural hazard in terms of land area after floods which is 11% percent of the earth's land area where severe droughts have doubled the percentage of area affected in several decades from the 1970s (14).

As drought occurs mostly in the grass- and bare lands especially in semi-arid and arid regions around the world, it is one of the most widespread natural hazards in Mongolia where over 25% percent of the total land area of the country is affected by drought (15). Therefore, the understanding of the precipitation patterns and drought characteristics including its key factors such as frequency and spatial extent is extremely crucial to combat its biggest negative effects: pasture desertification and imminent threat to the lives of nomadic people (2). For that reason, the study of drought occurrence and its development is important for effectively evaluating the situation, increasing awareness, and avoiding conceivable losses (16,17).

With the help of technological developments such as advanced remote sensing and geographic information system (GIS), monitoring of drought has become more accessible and larger areas can be analyzed (13). Drought monitoring methodologies are being developed by researchers for several decades and they differ in their use of available data, monitoring area, and other relevant influencing factors. Commonly, there are site-based and remote sensing-based indices (18). For Mongolian Plateau, applying indices that use available precipitation data is more practical than utilizing complex drought indices that often use the data from potential evapotranspiration (ET) in their calculation. Considering the lack of sufficient ET data in arid and drylands of the developing world, McKee et al. (19) introduced the Standard Precipitation Index (SPI) which is suitable for such conditions and has been attracting significant attention for its performance and relatively simple measurement of drought (2). Drought characteristics are unique to the regional environment, and it is crucial to understand the leading factors with specific indices suitable to analyze certain aspects of the drought. Therefore, setting specific study objectives will be significant for the outcome of this study.

1.1 Objectives of the study

The thesis aims to assess meteorological SPI-based drought and agricultural NDVI-based drought conditions in territories around Nalaikh district in Ulaanbaatar city by characterizing based on satellite datasets during the period from 1990 to 2018. The main objectives are the followings:

- To define long-term drought conditions based on satellite-based meteorological data using the Standardized Precipitation Index (SPI) with different time scales for 12 months from 1990 to 2018.

- To characterize drought spatial distribution regarding agriculture period (vegetation peak growing season) in one of the months of June, July, and August regarding the data availability using satellite-based Normalized Vegetation Difference Index (NDVI) during the period from 1990 to 2018.

- To identify drought conditions with their frequency, intensity, and duration at different timescales based on SPI.

- To analyze the correlation between NDVI and SPI indices regarding its point results.

1.2 Study Area

Nalaikh is one of the nine districts of the capital city which is located around 40 kilometers away from the downtown area of Ulaanbaatar, Mongolia. Since the official closure of coal mining activity in 1992, illegal mining activities have been continued for several years causing several environmental issues in the area (20). At 1459 meters above sea level, Nalaikh has a cold and semi-arid climate with an average precipitation of up to 250 mm. During the summer months from June to August, the mean air temperature fluctuates between 10℃ and 26.7℃. In the wintertime, the air temperature reaches −15℃ to −30℃. Nalaikh, Terelj area is surrounded partially by Khentii Mountain Range and Bogd Khan Mountain where the entire area is used as pastures covered by taiga forest-steppe and steppe. Because of the surrounding mountains, Nalaikh valley’s geological features are comprised of alluvial sediments which mostly contain clay, sand, and sparse gravel. Around the massif, mostly rock soil and loamy sand are present with soil types of Kastanozems and Chernozems (21).

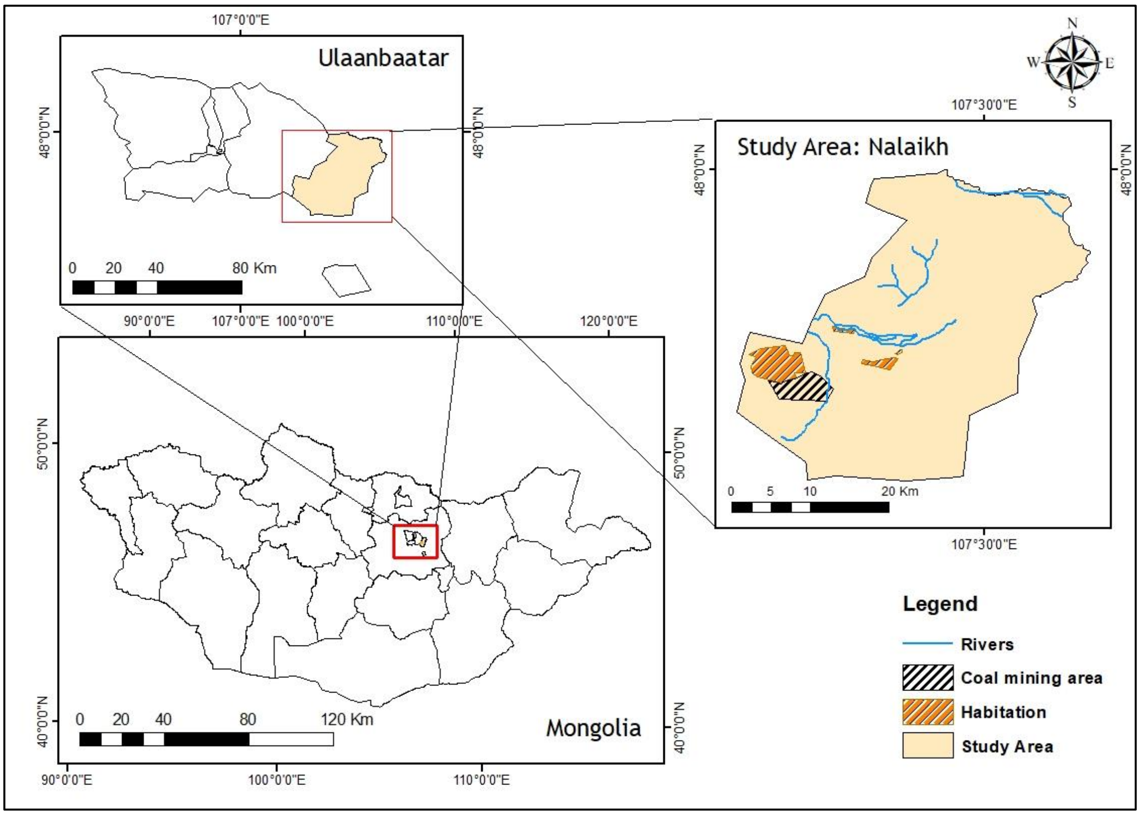


Figure 1. Study area map of Nalaikh, Ulaanbaatar

2 State of the art

As a result of climate change, precipitation patterns are changing and an increase in the magnitude of drought and flood events are observed around the world (22). Amongst many other natural disasters, the economic damage caused by drought accounted for 22% percent of the total, while it increased to 33% percent of the damage when the number of people who were impacted was accounted. To that extent, it is considered the most catastrophic and damaging natural hazard in terms of economic damage (23). Therefore, drought mitigation and prevention against the risks and their impacts are important. If the duration of the drought continues for a longer period and covers a larger area, permanent damage can be done to the environment (24). Consequently, researchers have developed definitions to describe drought characteristics such as frequency, duration, and intensity. Drought frequency is defined as the number of droughts occurring in a given period. Duration of the drought refers to the total amount of time until the end of the drought from the beginning. Intensity can be defined as the severity of drought while in its occurrence (17,25). As the definition of drought characteristics and its classification is the first step toward the assessment of drought, understanding drought as a part of the hydrologic cycle is also important. Rossi et al. (24) estimated that the relationship between precipitation and evapotranspiration is a critical component depending on the time of the season and other factors including precipitation duration and rainfall events.

Over the years, to evaluate the drought condition and its impacts, many indexes have been developed and used by researchers (2,11,17,18,26). Because of the complexity of drought events, it is often required to utilize different indices and variables to characterize them. Many drought indices have been developed over the past few decades where they became more comprehensive in terms of approaches, complexity, and the use of remote sensing data as its input as well as experts' inputs. Among many indexes that are used, the most common are the Standardized Precipitation Index (SPI), Palmer Moisture Anomaly Index (z-index), and the Palmer Drought Severity Index. As a standardized index, since its introduction by McKee et al. (19), it has received much attention due to its simplicity (27). The SPI is based on only precipitation, and it was developed for different time scales to quantify the precipitation deficit. Sternberg et al. (2) suggested that SPI can be a useful tool to predict both future and immediate drought events by selecting a timescale to identify precipitation patterns. However, drought prediction remains a difficult task as the variable precipitation field characteristics are random. A study conducted by Bayarjargal et al. (28) concluded that the use of satellite-driven drought indices was more effective at identifying broader areas than PDSI. With the help of the capacity of remote sensing data, acquiring necessary information has been no longer inconvenient (22). The effectiveness of the drought assessment can be increased by combining different indicators such as precipitation and soil moisture and Hao et al. (10) suggested that drought monitoring and warnings can be done with different aspects of drought characteristics.

The assessment of drought depends on the quality of the primary data. As it was advised by Rossi et al. (24) that it is highly preferable to have easy to access data that covers the study area equally at all points with a sufficiently long duration to process statistically. When comparing drought conditions, the SPI is suitable because of its standardization (29). Since SPI uses a univariable: precipitation as its input, the addition of other influential climate parameters affecting drought is needed to be discussed. Therefore, the advancement in remote sensing technology enables researchers to track drought conditions and variables over significantly larger areas and higher temporal scales with the help of modern approaches by using different variables as inputs (27). This has been discussed by Sternberg et al. (2) that the use of remote sensing data as an input for drought assessment using SPI improved the number and extent of droughts to be measured in a significantly short amount of time while allowing researchers to identify trends at a larger scale. The author emphasized that with the help of the tool, researchers would be able to distinguish the implications of a drought event whether the drought is a part of a dry period or solely an isolated episode.

When assessing drought, attributed factors are important to be considered. Several of those factors include precipitation, temperature, evapotranspiration, atmospheric circulation, and the hemispheric nature of the area (14). The primary cause of the drought is undeniably a decreased rate of precipitation. And a large number of existing studies in the broader literature have examined that during the months when the precipitation is substantially low, signals of drought events were recognized significantly compared to the months with lower rainfall (29–34). This has been reported by Karl et al. (35) that difference between the precipitation amount during the normal period and a precipitation deficient period depends commonly on the amount of precipitation from a small number of storms. The authors concluded that the occurrence of drought in a season is possible when the number of large storms is significantly low. However, it was noted that when the amount of rainfall is not substantially lower than the normal period, the drought condition is not necessarily expected to be the result. It was reported in the literature that multi-year droughts were generally in correlation with significantly higher surface-air temperatures.

As the lack of rainfall for a longer period can result in drought conditions, another factor is as influential as the amount of precipitation. One of the most significant elements of hydrology is evapotranspiration and it plays a crucial role in both meteorological and hydrological drought assessment. It refers to the water exchange between the land surface and it depletes the amount of water that is remaining in lakes, rivers, and soil (14,36). It was estimated that about 67% of water is transmitted by ET. In the past, there has been a question of whether the pattern of drought is repetitive. A study on the association between the drought event and atmospheric circulation patterns (ACP) showed that frequent and persistent ACP is closely connected with drought conditions (14).

There have been numerous studies investigating drought conditions in Mongolia (2,32,37–39). According to Nagarajan (14), the view on droughts should not only be limited to their physical effects but also their impacts on many other fields. In the research work by Tumenjargal as cited by (36), because of the precipitation decline in arid regions and decrease in relative humidity, the duration of rainfall lasted shorter combined with the increasing number of dust events and low infiltration of water into the soil. Consequently, there is evidence of pasture production being reduced to a significantly low level due to the stress caused by long-term exposure to drought which proves the severe negative impacts of drought on herders' livelihoods. Therefore, as suggested by Natsagdarj & Renchin (40) that weather forecasting during a period with significantly higher dryness is essential for all-natural zones from high mountains to steppe and desert. According to the study done by Engman as cited by Vova (36), as a result of carbon emissions only under the scenario of low-moderate level, it was found that until the end of the 21st century the increase in the frequency of droughts in arid and dry regions is highly likely. However, this phenomenon of dry regions becoming drier is hypothesized, but it was only confirmed under the scenarios where drought occurrences were driven by precipitation deficiency (30). Previous studies have shown that for the last couple of decades, in countries located in the Northern Hemisphere, extreme drying trends have been reported including Mongolia which led to a substantial decrease in vegetation activities over drought-affected areas as shown by NDVI (38,41). Nandintsetseg and Shinoda (39) studied drought characteristics from 1965 to 2010 using various data from the growing season from April to August including soil moisture and meteorological data. They concluded that even though the frequency of drought in different zones did not differ significantly, the occurrence of short-term meteorological droughts was more frequent than agricultural drought where persistency was noticeably higher than that of agricultural or pasture drought. Another earlier finding from Sternberg et al. (2) discovered that drought events varied with the location of the meteorological stations and measured time scales. The author concluded that as a result of global warming and the amount of precipitation with its temporal variations, Mongolia has been affected by drought events.

As a significant factor affecting drought occurrences, climate change has received attention for the last few decades (14). Studies on the various aspects of climate change are well documented, and it is also well acknowledged that its impacts are significant for the livelihood of humanity and the ecosystem that surrounds us (42). Following the increase in water consumption because of population growth, it was studied that the vulnerability of arid and semi-arid areas around the world is relatively higher to drought events with less precipitation (27). Hence, it was recognized by the Intergovernmental Panel on Climate Change (IPCC) as the most vulnerable region being affected by climate change. According to Köppen's climate classification system, there are five climatic types including tropical moist climate, dry climate, moist mid-latitude climate with mild winters, moist mid-latitude climate with severe winters, and lastly, polar climates (14). Mongolia has an extreme continental climate with long, harsh winters and short summers where most of the precipitation falls. It can be classified generally as Dwc climate type: a snow climate with dry winters (43).

In cases of extreme droughts and other natural events, considering vegetation in affected areas is crucial for both agricultural and economic purposes (26). For the assessment of vegetation, Normalized Difference Vegetation Index (NDVI) is used. It indicates the difference between the near-infrared (NIR) and red reflectance which is used for plant stress as a result of drought. One of the biggest advantages is that NDVI can be used in many different areas including pasture fields, agricultural areas, and drought monitoring (27,44). There exists a considerable body of literature on monitoring drought using NDVI commonly in agriculture-related studies (26,41,45). As studied by Myneni and Hall and cited by Vova (36) it has been shown that NDVI is closely in connection with the plants' photosynthetic capacity. It was reported by Rotjanakusol et al. (41) that the relationship between the vegetation index and precipitation is important to identify the areas affected by drought. Calculation of the NDVI is done by digital image processing coupled with mathematical computation of the remote sensing data gathered by satellites. The result of the NDVI illustrates the condition of vegetation in a specific period and its change concerning weather and climate variations. Because of the characteristics of NDVI value, it is commonly used with meteorological indicators such as SPI, PDSI, and Moisture Anomaly index. This has been explored by Rimkus et al. (44) that there was a positive correlation between SPI and NDVI when used in agricultural areas which depend on rainfall for their irrigation. On the other hand, a negative correlation was established in irrigated areas. As reported by Gebrewahid et al. (45) the application of SPI and NDVI together was able to demonstrate the drought variability with 3-months and 6-moths SPI and NDVI analysis performed by using Landsat 5 imagery. Previous research showed that drought indices that use satellite-based data can identify broader areas that are affected by drought than the meteorological-based indices and ground-observed drought-affected areas (DAA) maps (28). The authors concluded that the selection of the most suitable drought index depends on the researchers' objective and is difficult to choose the most reliable considering each of the indices provides individual outcomes. They also noted that the information from ground observations was insufficient to validate the results of the drought indices that used satellite data.

Several studies previously reported that the impacts of climate change and the changing precipitation patterns are already influencing the water supply around the world which in turn leads to water scarcity (46). One of the biggest negative effects of drought is to both disturb the water supply and create long-term economic challenges for the livelihoods that are affected. Therefore, a comprehensive study on drought events is essential in terms of mitigating the adverse consequences and preventing future risks. As a result of meteorological drought, moisture deficit in the soil occurs. From regular moisture deficit in the soil to surface water shortages to disturbance in the water supply system, the whole process can have environmental, economic, and intangible impacts.

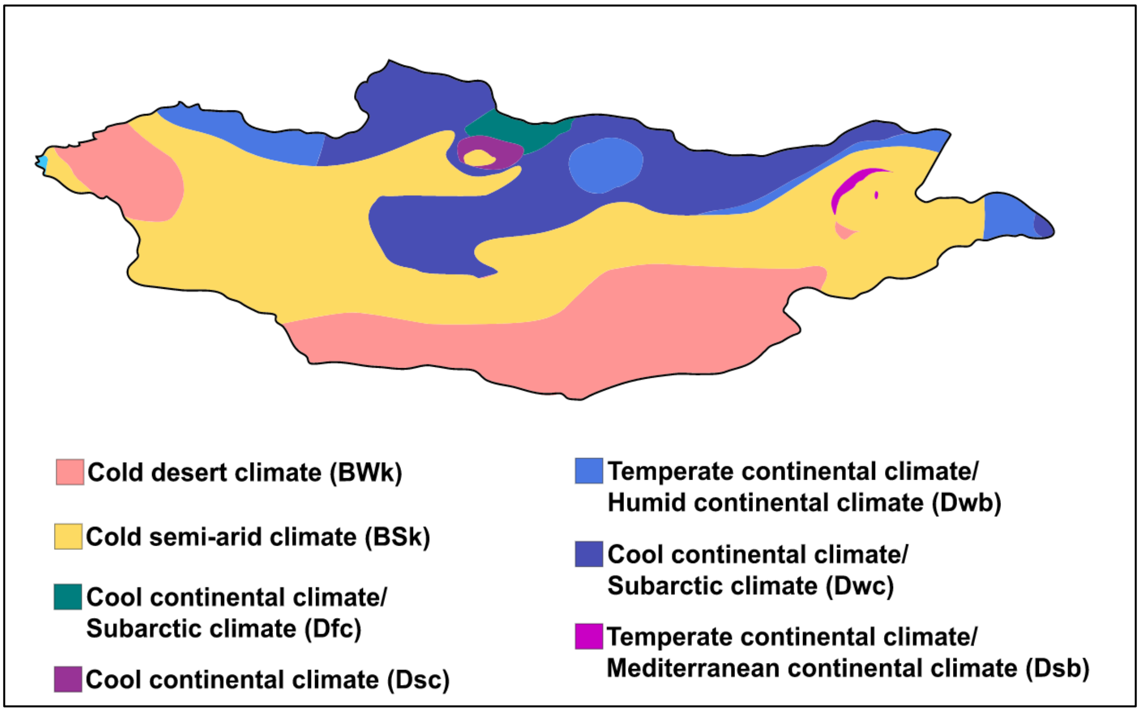


Figure 2. Köppen climate classification for the Mongolian territory (14)

Consequently, even though precise classifications of drought impact are complicated, there are three main categories: economical, environmental, and social.

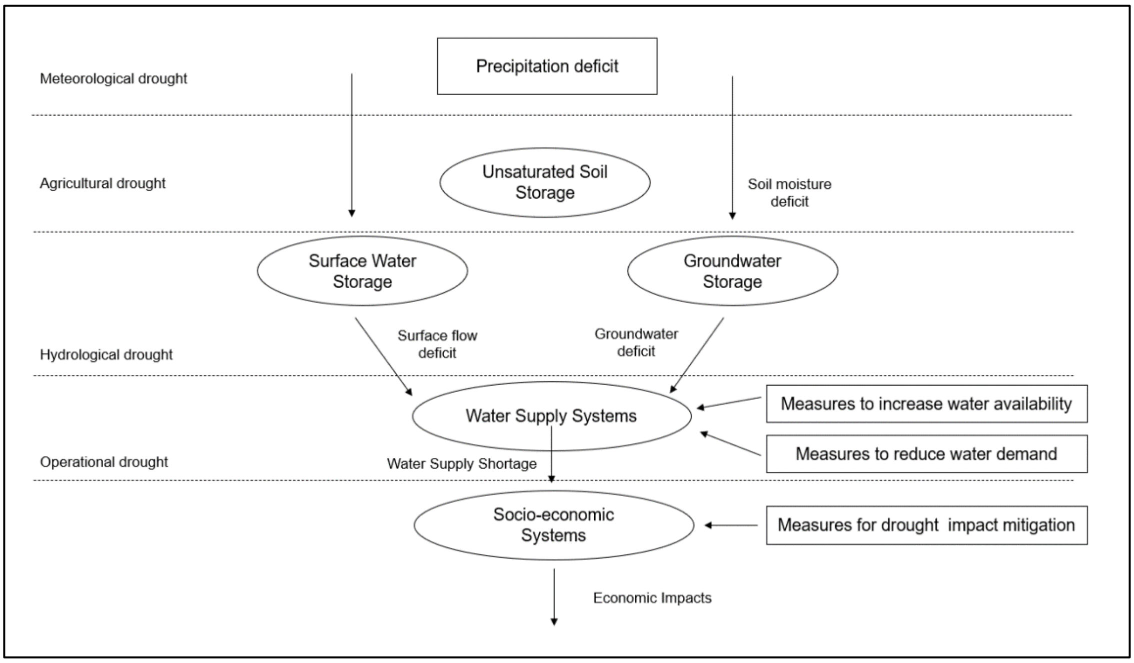


Figure 3. Drought phenomenon and the role of mitigation measures (24)

In figure 3, common types of droughts and their impacts are listed with mitigation measures (24). Because of drought, a chain of both environmental and economic damages can occur. Examples: economic losses in agriculture-related and dependent industries, unemployment in those fields, and financial pressure on the water supply system including transportation of water and development of sources. On the environment, a major impact takes place on land and soil. Research conducted on the topic has emphasized that the main effect is erosion as a result of the loss of plants and wind. The process is amplified by wildfires and anthropogenic activities which cause erosion. Because of the wildfires, the permeability of soil decreases heavily which further becomes the cause of soil moisture deficit. The concentration of dust and contaminants in the air rises due to a lack of precipitation and humidity. In contrast to other natural hazards, drought does not cause severe impacts in a short amount of time. However, in the long term, the spatial extent of drought-affected areas increases considerably (14). On this account, substantial and effective drought mitigation can be done with the help of an effective plan along with a constant and reliable drought monitoring system (24). It was suggested that the most important aspect of implementing effective drought management is to prevent the environment and water supply system to be affected by drought events.

3 Methodology

3.1 Chapter objective

The objectives of this chapter are to provide systematic structure to the process of this study and to develop further insight into the topic. In this chapter, methods of the data collection and processing as well as the processes of the drought assessment will be discussed.

3.2 Data and method

3.2.1 Drought Indices

There are more than 100 known drought indicators and indices that have been used to assess various types of droughts (47). Generally, the use and the application of the drought index depend on the type of drought under assessment. According to the National Drought Mitigation Centre (NDMC), the type and the impact of drought play an important role in the determination of a specific drought index. In figure 4, the drought impact classification with its associated types can be seen. As shown in figure 4, researchers apply various types of indices based on the type of drought with its impact and the objective of the specific study. Commonly used indices include Standardized Precipitation Index (SPI), Normalized Difference Vegetation Index (NDVI), Palmer Drought Severity Index (PDSI), Standardized Precipitation Evapotranspiration Index (SPEI), Drought Area Index (DAI), Palmer Hydrological Drought Severity Index (PHDI), Surface Water Supply Index (SWSI), Crop Moisture Index (CMI) and Palmer Moisture Anomaly Index (Z index) (48).

PDSI was developed in 1965 and is ideally a standardized measure of moisture supply developed originally for U.S agricultural regions.

The range of the PDSI is usually between −4 and +4 where negative values indicate a water shortage. For studies related to climate change in which the role of temperature is crucial, SPEI was developed as a multi-scale drought index by including temperature as one of its inputs. It is based on the difference between potential ET and monthly precipitation. In its nature, SPEI is closely related to SPI where both can be calculated at various timescales. Its main application includes the study of future climate change (10). The DAI is an index used to calculate drought persistency. However, because it was specifically developed for India, calibration is required to be used for other regions around the world. The following two indices are developed for the assessment of hydrological drought. The PHDI is similar to PDSI, but the difference is that the PHDI has a stricter criterion for drought eradication. An ending of a drought event happens according to the PHDI when the water deficit disappears (11). It is suitable for the PHDI since the development of hydrological drought is slower than meteorological drought. For the assessment of mountainous areas, Shafer and Dezman developed the SWSI which specifically describes snowpack and its runoff (48). Compared to meteorological and hydrological drought, agricultural drought explicitly deals with cultivated plants. Agricultural droughts can occur quickly due to plants' constant demand for sufficient water, likewise, they can also end abruptly. Significant and short-term variations in volumetric soil moisture characterize the nature of agricultural drought (49). In agricultural drought, CMI was developed to monitor short-term variations in moisture conditions affecting the growth of crops. It is derived from the summation of ET deficit and soil water recharge. Despite the advantages of the CMI, its biggest weakness is as

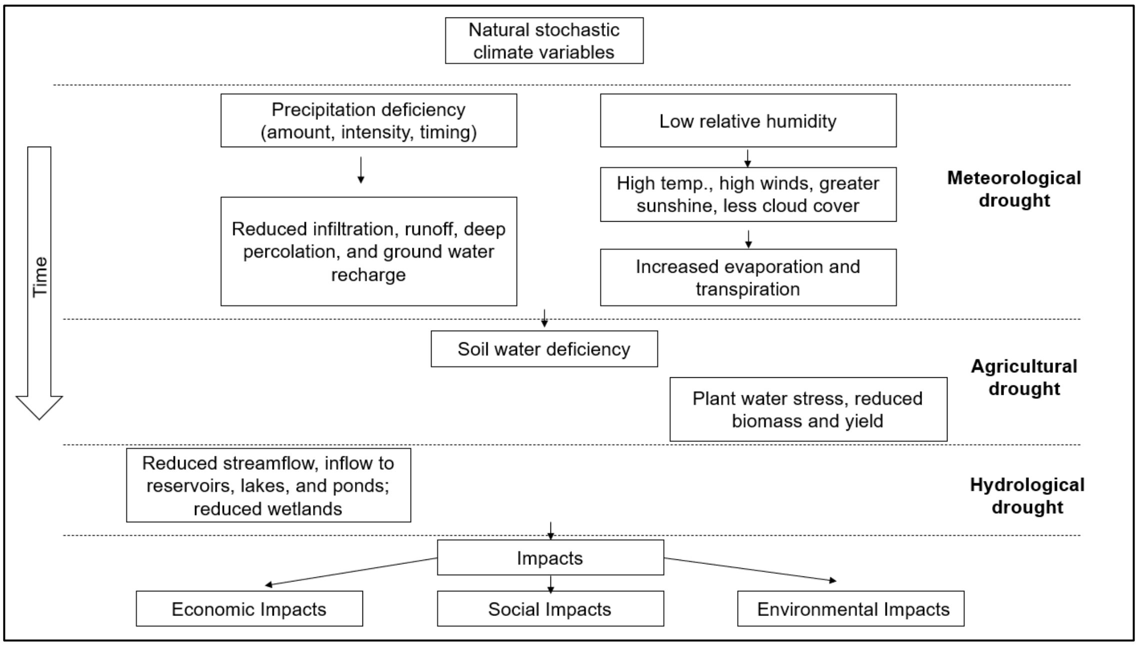


Figure 4. Drought impacts associated with meteorological, agricultural, and hydrological drought (48)

studied by Hayes as cited by Keyantash et al. (48) its lack of ability to assess long-term drought. In this study, because of its simplicity and ability to take multiple timescales, SPI was used with the NDVI for assessing the vegetation cover during the growing seasons. The advantages and disadvantages of those two indices were discussed accordingly in the following chapters, as well as the details of the application in this study.

3.2.1.1 Standardized Precipitation Index (SPI)

As a recommended drought forecasting index by World Meteorological Organization (WMO), SPI is one of the most popular drought indices and it has been commonly used by researchers since its introduction by McKee et al. (19). Ondrasek (22) defined it as 'The number of standard deviations that the observed cumulative rainfall at a given time scale would deviate from the long-term mean for that same time scale over the entire length of the record' (p.11). The calculation of the SPI can be achieved by constructing a frequency distribution using precipitation data (preferably at least 30 years) at a certain location for precipitation accumulated over a specific period. For example, if it is one month (SPI 1), three months (SPI 3), 12 months (SPI 12), etc. Depending on the objective of the study, the choice of different timescales can differ such as indices from SPI 1 to SPI 6 are mainly used for seasonal variations in soil moisture meaning for the short-term, while the long-term indices are useful for determining groundwater and reservoir shortage are SPI 12 and above. As categorized by McKee et al. (19), drought can be divided into several categories based on the value of SPI and it is used to define drought intensities from the SPI. (Table 1)

Table 1. SPI value classification (19)

SPI value	Drought Characteristics
2.0+	Extremely wet
1.5 to 1.99	Very wet
1.0 to 1.49	Moderately Wet
−0.99 to 0.99	Near normal
−1.0 to −1.49	Moderately dry
−1.5 to −1.99	Severely dry
−2 and less	Extremely dry

In Table 1, positive SPI values are the indication of the greater than average precipitation and negative values indicate the opposite. As shown, due to its normalization, SPI values can also be used for wet periods in the same way as the dry period.

The occurrence of drought events happens when the value of the SPI reaches the value of −1.0 or less. When the intensity quantity becomes positive, the drought event ends. Therefore, it can be realized that the intensity of each drought event can be determined, including the duration which can be defined by its beginning and end.

In addition, the positive-sum of the SPI for all the months during the drought event can be considered as the drought's magnitude.

Because of its versatility, SPI has been used by many researchers and drought planners around the world. As mentioned before, SPI uses only one parameter as its input and is considered a simple yet extremely effective index compared to other drought indices. However, its several weaknesses include its ability to quantify only the precipitation deficit, values of the index may change based on the initial data following the change in the period of record increases (19). One of the major advantages of the SPI is the ability to determine the rarity of the present drought event because of its standardization. Also, it enables the possibility to assess the amount of precipitation that is necessary to end the current drought event. Additionally, the user can be able to properly compare previous and present droughts across different climatic and geographic regions when determining how rare or common (Table 2) a particular drought occurrence is (50).

Table 2. Probability of drought recurrence (50)

SPI	Category	Number of times in 100 years	Severity of event
0 to −0.99	Mild dryness	33	1 in 3 years
−1.00 to −1.49	Moderate dryness	10	1 in 10 years
−1.5 to −1.99	Severe dryness	5	1 in 20 years
<−2.0	Extreme dryness	2.5	1 in 50 years

As evaluated by the World Meteorological Organization (51) strengths and weaknesses of the SPI are summarized.

Strengths include:

- It is simple and flexible for computation in multiple timescales
- Short timescales of SPIs from 1- to 2-month SPIs have the potential to warn against drought and mitigate before the severity level increases

- Its spatial pattern is consistent: it enables researchers to compare the results from different locations and climates around the world
- Because of its probabilistic character, it has historical significance for decision-making purposes.

Weaknesses include:

- It is based only on precipitation
- For the determination, soil water balance is not included: thus, calculations including evapotranspiration (ET) cannot be calculated.

In this study, 1-, 3-, 6-, 9-, and 12-month SPI timescales were chosen.

The 3-month SPI can compare the precipitation over a specific 3-month period with the precipitation totals from the same 3-month period for all the previous years in the record. It is the reflection of moisture conditions in the short and medium-term, and it estimates the seasonal precipitation. Compared to other indices, short-term SPI is extremely useful in providing information about moisture because of the time delay. The comparison between the 3-month SPI and longer timescales is crucial due to the fact that a normal or wet period occurrence is possible during a long-term drought. The process is the same as 3-month in a 6-month scenario. However, the result of a 6-month SPI is the indication of medium-term precipitation trends. It has been considered that compared to Palmer Drought Index, the sensitivity of the 6-month SPI is higher (18,52). In the case of a 9-month SPI, inter-seasonal rainfall patterns can be demonstrated. Developments of drought happen at least over a season or more. For 12-month SPI, long-term precipitation patterns can be shown. Considering the nature of the 12-month timescale which is the cumulative result of a period in the SPI values in negative and positive, as the timescale of the SPI gets longer, it develops an inclination to reach zero if any distinguishable period of wetness or dryness does not occur (52).

3.2.1.2 Normalized Difference Vegetation Index (NDVI)

As a result of the increasing impact of drought on the earth's ecosystem, acknowledgment of vegetation response to drought severity has been gaining much attention among researchers. (34) For this reason, to measure vegetation land cover which is one of the eleven indicators of impact recommended by the UNCCD, NDVI is used to monitor land degradation and vegetation from satellite-based tools by gathering remote sensing data measurements. It is an unsophisticated indicator that quantifies the vegetation by simply measuring the difference between near-infrared and red light. The reflectance of near-infrared (NIR) lights is strong among vegetation, but on the other hand, they absorb red light. The basic principle behind the application of vegetation indices is that crucial data such as land and vegetation cover or water content of the vegetation can be obtained depending on the band of the remote sensing spectrum. (53) Interaction of the vegetation occurs differently with the sunlight where two main processes including absorption and reflection of the sunlight occur within the vegetation. Absorption of the sunlight is the strongest in green leaves, especially in the spectral ranges where the colors are blue and red. However, as the wavelength of the light increases, absorption no longer occurs, and reflectivity increases. The reflectance of the vegetation in a different wavelength of the sunlight can be seen in figure 5. (53)

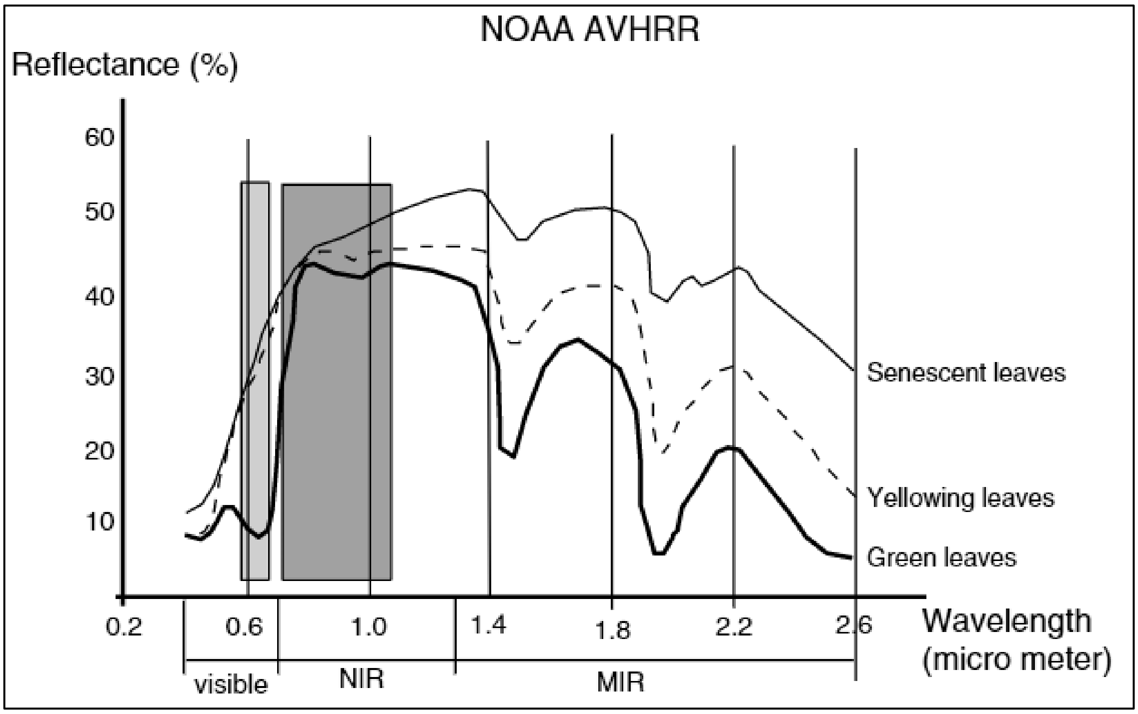


Figure 5. Vegetation response to different spectral wavelengths (53)

It was studied by numerous researchers that for vegetation index to be more effective, sensitivity to affecting factors that influences reflectance of the vegetation such as solar illumination and atmospheric conditions should be significantly low. (54,55) NOAA AVHRR is one of the most used sensors for studying NDVI and figure 5 illustrates the spectral band of the sensor to its reflectance.

The calculation of the NDVI is shown below in Equation 1. as developed by (Rouse Jr et al. 1974) and cited by Yengoh et al. (53).

$$\mathrm{NDVI} = \frac{\mathrm{NIR}-\mathrm{RED}}{\mathrm{NIR}+\mathrm{RED}} \tag{1}$$

Here, NIR is the reflectance in near-infrared and RED is the reflectance in the visible red band. NDVI is connected to photosynthetic capacity and combines these reflectance characteristics in a ratio. The value of the NDVI ranges from -1 to +1. Positive values of NDVI represent vegetation and as the amount increases, so does the chlorophyll content of the specific zones. In figure 6, the illustration of the NDVI calculation is demonstrated based on the amount of visible and near-infrared it reflects and absorbs.

On the left-hand side, healthy green vegetation can be seen where it absorbs more visible light than the one on the right. On the right, it can be seen that sparse vegetation reflects less NIR light. (56)

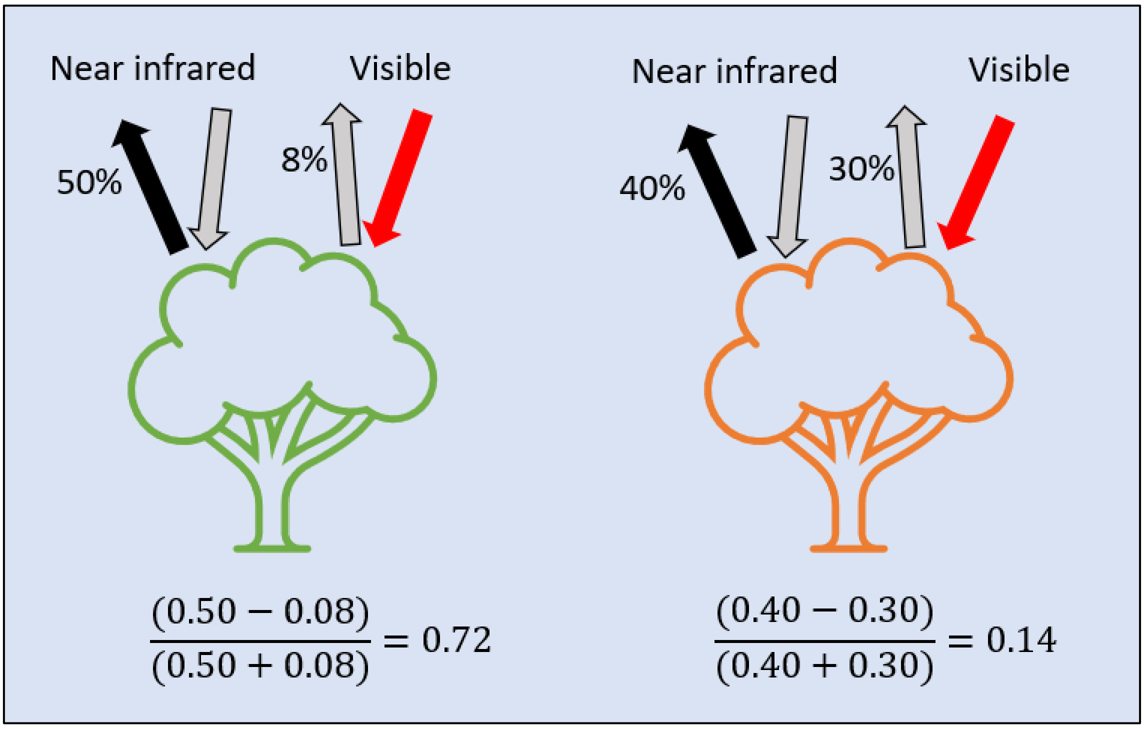


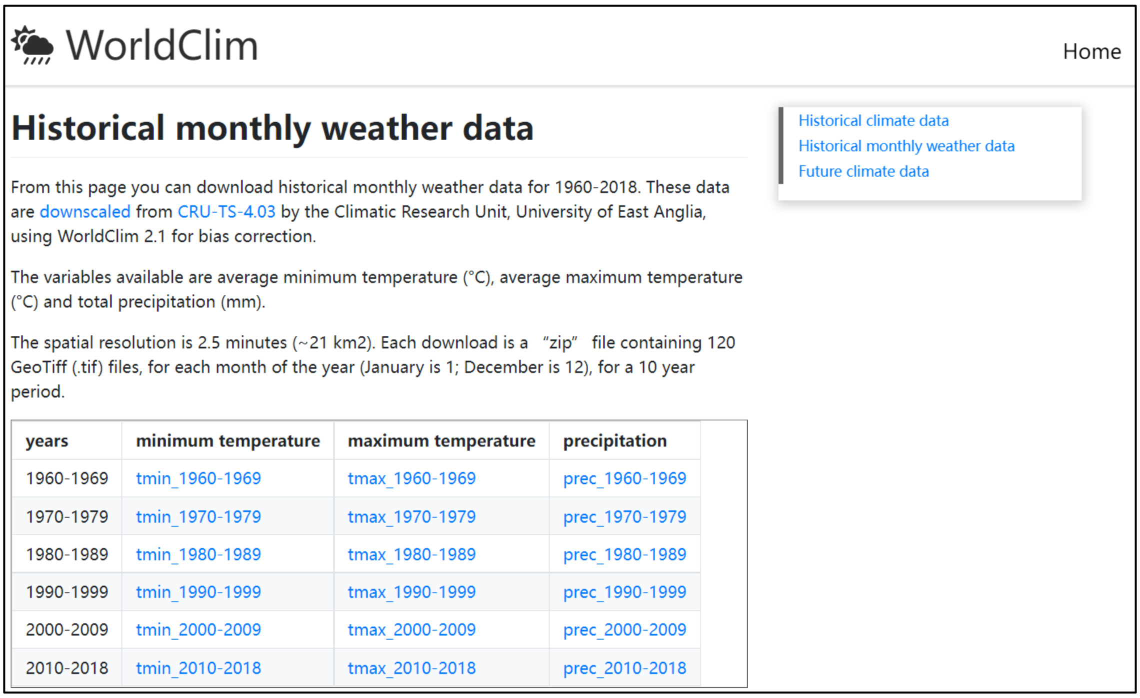
Figure 6. Illustration of the NDVI calculation (56)

With the help of the index, the growing season duration and the time when the maximum amount of photosynthesis occurs can be determined. In drought applications, the impact of climate variations on the vegetation cover allows scientists to discover the drought events and assess the severity in terms of their effect on plants and lands. (26)

3.2.2 Data collection and processing

3.2.2.1 SPI data collection and processing

The data of the monthly precipitation were collected from the website of WorldClim which is a database of high spatial resolution global weather and climate dataset. For the assessment of SPI, in this study, historical monthly total precipitation data from 1990 to 2018 were originally downscaled from CRU-TS-4.03 by the Climatic Research Unit, University of East Anglia, using Worldclim 2.1 for bias correction. The unit of the total precipitation data is in millimeters (mm). The spatial resolution was 2.5 minutes which is approximately 21km^2. As shown in figure 7, each available data was compressed into a “zip” file that contains 120 GeoTiff (.tiff) files, for each month of the year (January is 1; December is 12), for ten years. As a result of the unavailability of the precipitation data from 2019, and 2020 on the data source, the last 28 years of data from 1990 to 2018 were taken.



Historical monthly weather data

From this page you can download historical monthly weather data for 1960-2018. These data are downscaled from CRU-TS-4.03 by the Climatic Research Unit, University of East Anglia, using WorldClim 2.1 for bias correction.

The variables available are average minimum temperature (°C), average maximum temperature (°C) and total precipitation (mm).

The spatial resolution is 2.5 minutes (~21 km2). Each download is a “zip” file containing 120 GeoTiff (.tif) files, for each month of the year (January is 1; December is 12), for a 10 year period.

years	minimum temperature	maximum temperature	precipitation
1960-1969	tmin_1960-1969	tmax_1960-1969	prec_1960-1969
1970-1979	tmin_1970-1979	tmax_1970-1979	prec_1970-1979
1980-1989	tmin_1980-1989	tmax_1980-1989	prec_1980-1989
1990-1999	tmin_1990-1999	tmax_1990-1999	prec_1990-1999
2000-2009	tmin_2000-2009	tmax_2000-2009	prec_2000-2009
2010-2018	tmin_2010-2018	tmax_2010-2018	prec_2010-2018

Figure 7. Interface of the WorldClim website

After the successful download of the precipitation data, downloaded files were extracted into a specifically designated folder to be used in the program ArcGIS. In this study, for our data analysis and mapping, ArcMap 10.8 software was utilized to obtain the desired results.

As the amount of data contained within the single .tiff file is immense and therefore, the processing time of those data would take a significant amount of time unnecessarily, it is reasonable to only select the data associated with our study area and separate it from the rest. As a step-by-step process, the data collection and analysis process were included in this chapter. In Figure 7, our study area was separated individually from the shapefile which initially contained Mongolian administrative boundaries. As can be seen in the white outline, the Nalaikh area was taken to process the precipitation data from the source data file. It should be noted that the geographic coordinate system was set to WGS 1984 earlier and the projected coordinate system was set to UTM, WGS 1984, Northern Hemisphere, and WGS 1984 UTM Zone 48N.

As our primary data was raster data, first it was converted into point data thus providing the data only connected with the study area. In figure 9, the basic nature of the raster data where each pixel is associated with a specific geographical location can be shown. (14)

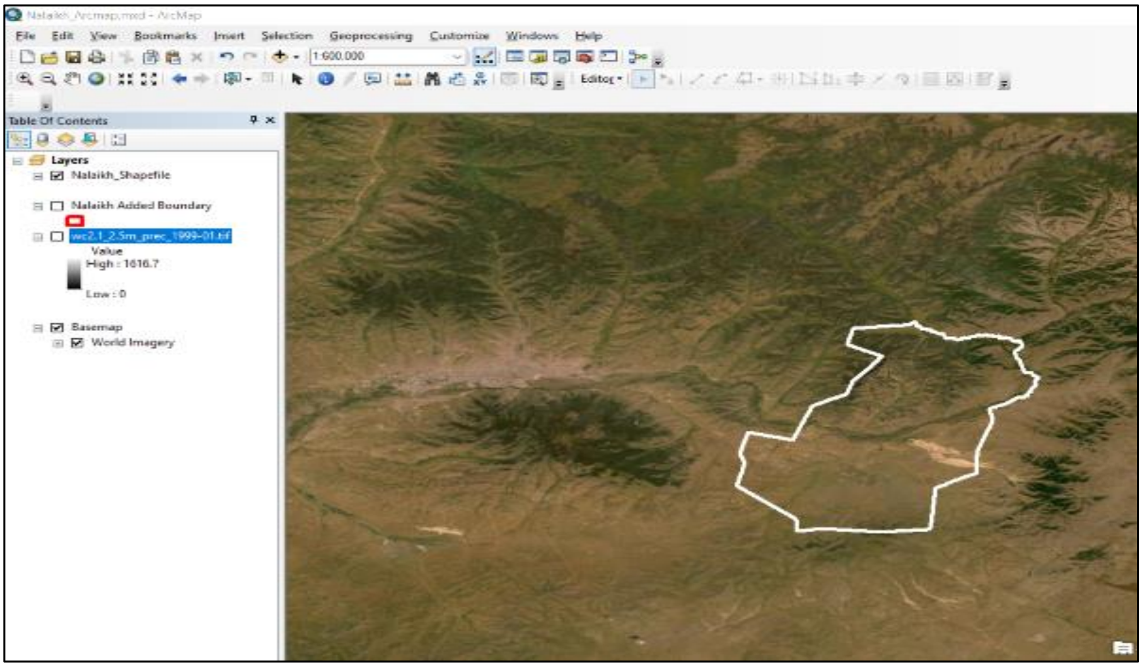


Figure 8. Study area separated from the original shapefile

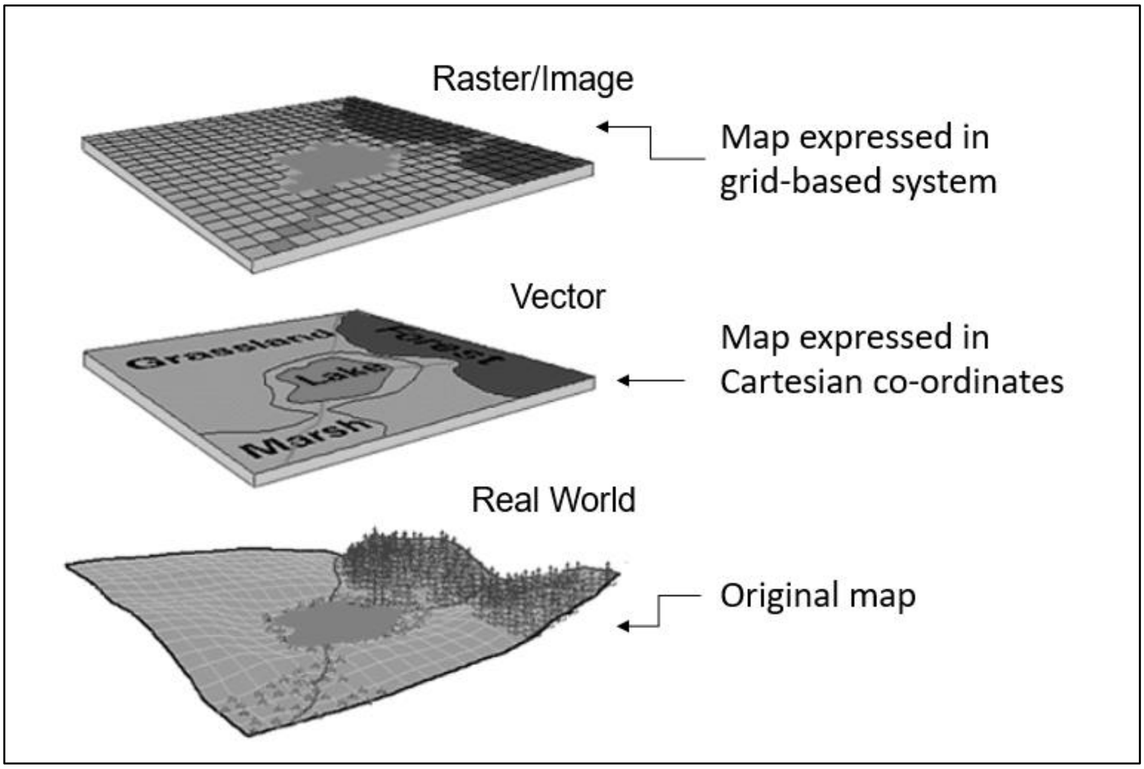
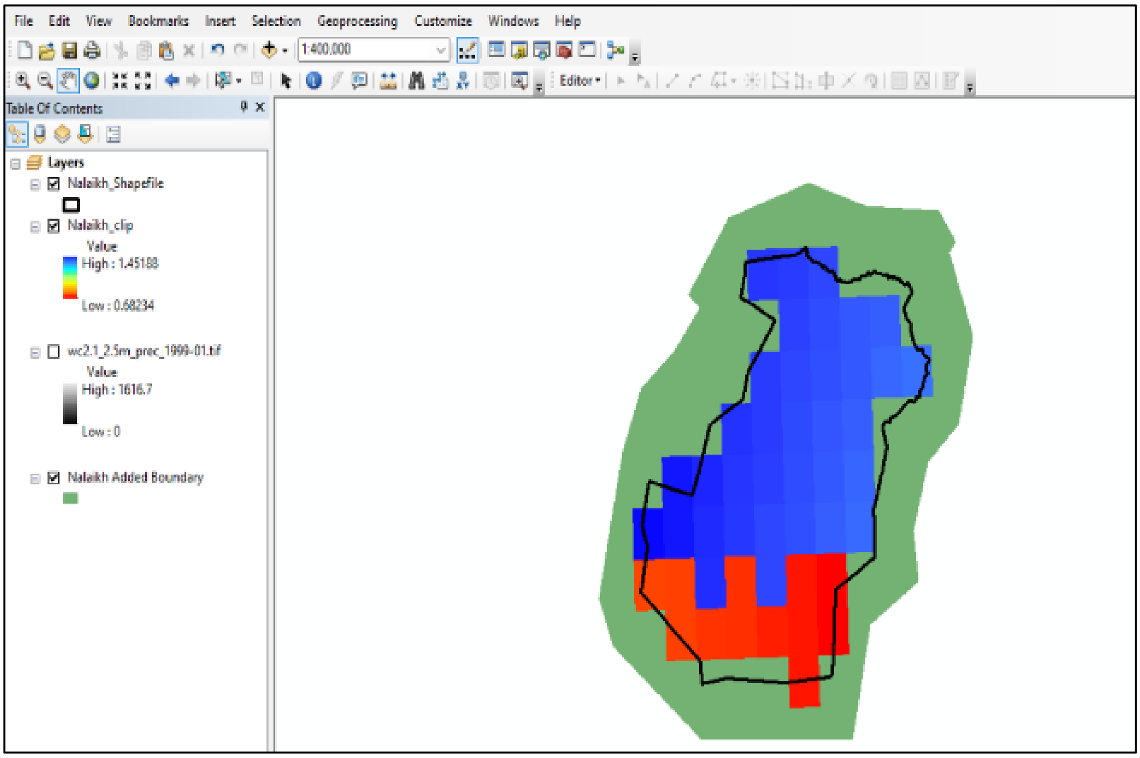


Figure 9. Raster, vector, point data illustration



1:400,000

Layers
- ☑ Nalaikh_Shapefile
- ☑ Nalaikh_clip
  - Value
  - High : 1.45188
  - Low : 0.68234
- ☐ wc2.1_2.5m_prec_1999-01.tif
  - Value
  - High : 1616.7
  - Low : 0
- ☑ Nalaikh Added Boundary

Figure 10. Clipping of the Nalaikh data from the WorldClim dataset

Therefore, for the conversion of raster to point data, clipping of the whole raster dataset was done in the study area which is a hollow area with a black outline as illustrated in figure 11. By doing so, in essence, only the necessary data remained, and it accelerated the data processing of the software by a large margin since our initial dataset contained the precipitation data of the world.

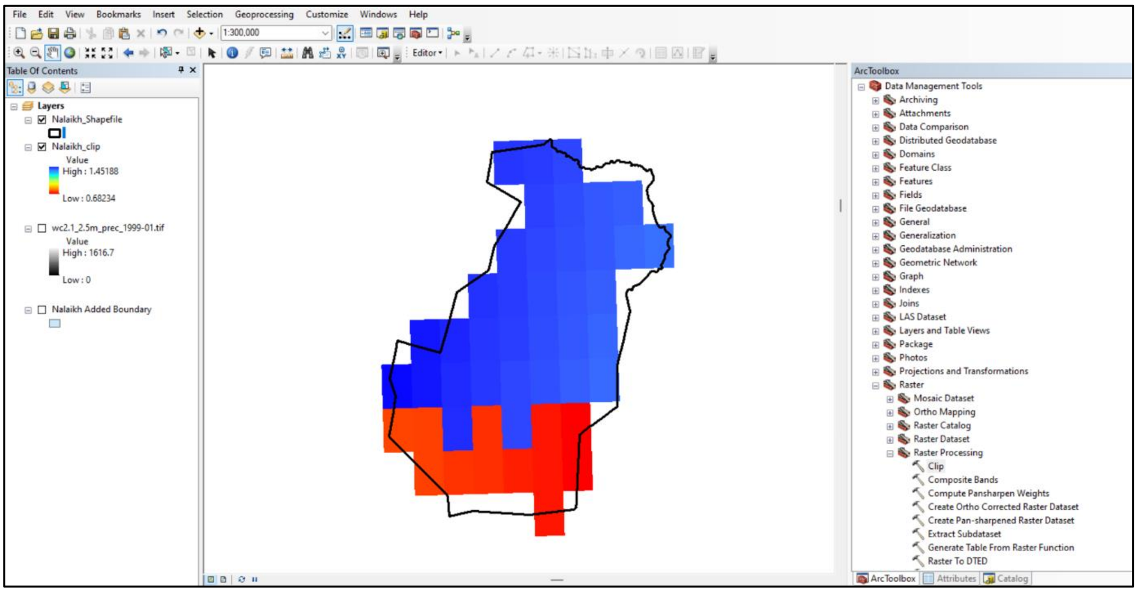


Figure 11. Study area of Nalaikh with Added Boundary

Since the boundary condition is the Nalaikh area, the data clipping process of the whole study area could not be entirely obtained as shown in figure 11 where blue and red clipping data is not sufficiently covering the Nalaikh study area.

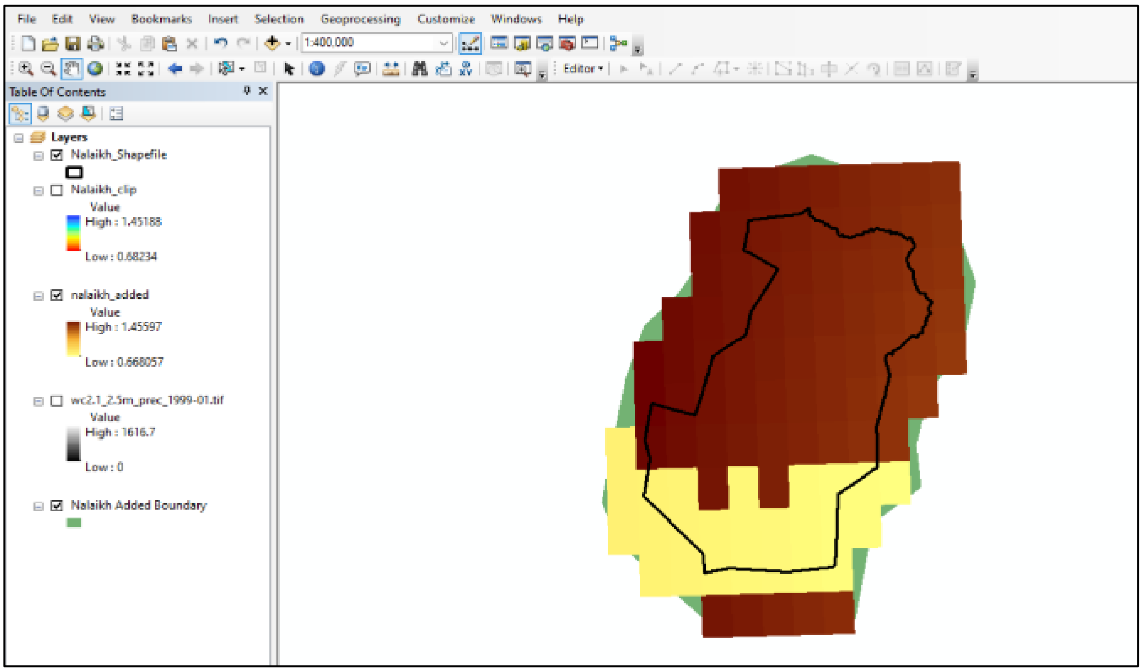


Figure 12. Clipped data of study area

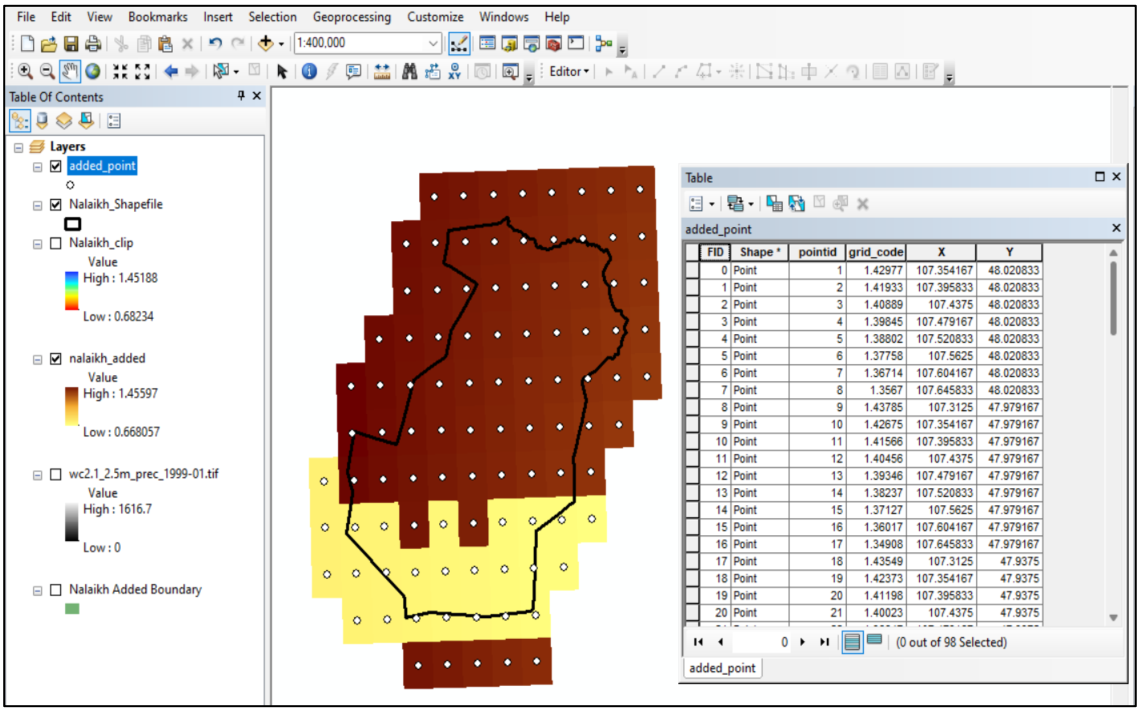
For this reason, an additional boundary was added to the Nalaikh study area which successfully obtained the remaining data for the study area as shown in figure 12.

The next step in our data analysis was to convert raster data into point data and the coordinate system was added to the attribute table in figure 13.

The annotation X represents the longitude values, while Y represents the coordinate of the latitude values. On the attribute table, the grid code is the value of monthly precipitation at a specific point in millimeters (mm).

Lastly, obtained point data was copied into the Microsoft Excel program to be processed and the average monthly precipitation of each selected year was calculated. Furthermore, the calculated average precipitation values were uploaded into the SPI analysis tool developed by the WMO.

Before analyzing the data on the SPI tool, average precipitation values of the data were placed in a special order for the SPI tool, which was then copied and converted into a (txt.) file on notepad. After the conversion, the data was uploaded to the SPI tool during the calculation process. In figure 14, above-mentioned processes and the data processing of the SPI analysis tool was illustrated. Likewise, the remaining datasets of the SPI were obtained in the same way.

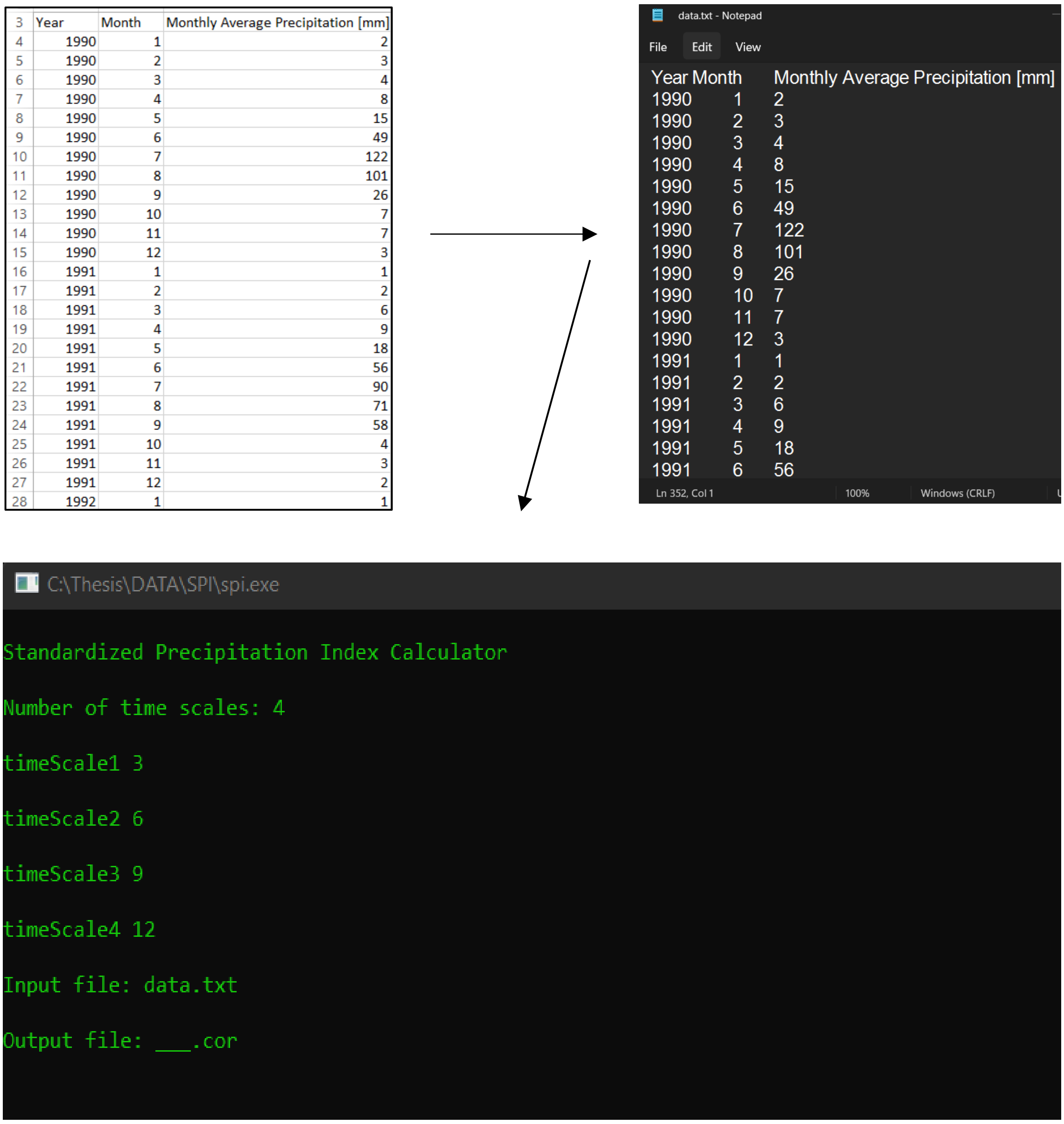


FID	Shape *	pointid	grid_code	X	Y
0	Point	1	1.42977	107.354167	48.020833
1	Point	2	1.41933	107.395833	48.020833
2	Point	3	1.40889	107.4375	48.020833
3	Point	4	1.39845	107.479167	48.020833
4	Point	5	1.38802	107.520833	48.020833
5	Point	6	1.37758	107.5625	48.020833
6	Point	7	1.36714	107.604167	48.020833
7	Point	8	1.3567	107.645833	48.020833
8	Point	9	1.43785	107.3125	47.979167
9	Point	10	1.42675	107.354167	47.979167
10	Point	11	1.41566	107.395833	47.979167
11	Point	12	1.40456	107.4375	47.979167
12	Point	13	1.39346	107.479167	47.979167
13	Point	14	1.38237	107.520833	47.979167
14	Point	15	1.37127	107.5625	47.979167
15	Point	16	1.36017	107.604167	47.979167
16	Point	17	1.34908	107.645833	47.979167
17	Point	18	1.43549	107.3125	47.9375
18	Point	19	1.42373	107.354167	47.9375
19	Point	20	1.41198	107.395833	47.9375
20	Point	21	1.40023	107.4375	47.9375

0 (0 out of 98 Selected)

added_point

Figure 13. Raster to point data conversion of the study area



3	Year	Month	Monthly Average Precipitation [mm]
4	1990	1	2
5	1990	2	3
6	1990	3	4
7	1990	4	8
8	1990	5	15
9	1990	6	49
10	1990	7	122
11	1990	8	101
12	1990	9	26
13	1990	10	7
14	1990	11	7
15	1990	12	3
16	1991	1	1
17	1991	2	2
18	1991	3	6
19	1991	4	9
20	1991	5	18
21	1991	6	56
22	1991	7	90
23	1991	8	71
24	1991	9	58
25	1991	10	4
26	1991	11	3
27	1991	12	2
28	1992	1	1

```
Year Month    Monthly Average Precipitation [mm]
1990    1     2
1990    2     3
1990    3     4
1990    4     8
1990    5     15
1990    6     49
1990    7     122
1990    8     101
1990    9     26
1990    10    7
1990    11    7
1990    12    3
1991    1     1
1991    2     2
1991    3     6
1991    4     9
1991    5     18
1991    6     56
```

```
Standardized Precipitation Index Calculator

Number of time scales: 4

timeScale1 3

timeScale2 6

timeScale3 9

timeScale4 12

Input file: data.txt

Output file: ___.cor
```

Figure 14. Data processing of the SPI calculation tool

The SPI calculation tool uses certain theoretical equations for its calculation of the SPI and the theoretical background of the tool is:

Firstly, monthly precipitation data is prepared for the desired period of “x” months (Preferable to select at least 30 years of continuous data). To determine a series of timescales of period "j" months, a set of average periods is chosen, with j ranging from 3, 6, 9 to 24, 48 months. The numbers representing the average periods are arbitrary. The Gamma function is used to describe the relationship of probability to precipitation. The specific calculation of the SPI is as follows:

If we assume that the precipitation in a specific period was x, Γ distribution of probability density function was given by:

$$ƒ(x) = \frac{1}{B^{\gamma}\Gamma(\gamma_0)} x^{\gamma-1} e^{-x/\beta}, x > 0 \quad (1)$$

where β and γ are the scale and shape parameters of the Γ distribution function.

The probability of the random variable x is less than x_0 can be obtained for precipitation x_0 in a certain year.

$$F(x < x_0) = \int_0^{\infty} ƒ(x)dx, \quad (2)$$

$$F(x = 0) = \frac{m}{n}, \quad (3)$$

Where m is the number of samples with precipitation of 0 and n is the total number of samples.

For normal standardized processing of Γ probability distribution, the substitution of the result of probability value into the normalized normal distribution function was used:

$$F(x < x_0) = \frac{1}{\sqrt{2\pi}} \int_0^{\infty} e^{-x^2/2} dx, \quad (4)$$

The following formula is the solution to the above equation:

$$SPI = S \frac{t-(c_2 t + c_1) + c_0}{[(d_3 t + d_2)t + d_1]t + 1}, \quad (5)$$

Where:

$$t = \sqrt{ln \frac{1}{F^2}}, \quad (6)$$

$C_0 = 2.515517 \quad C_1 = 0.802853 \quad C_2 = 0.010328$

$d_1 = 1.432788 \quad d_2 = 0.189269 \quad d_3 = 0.001308$

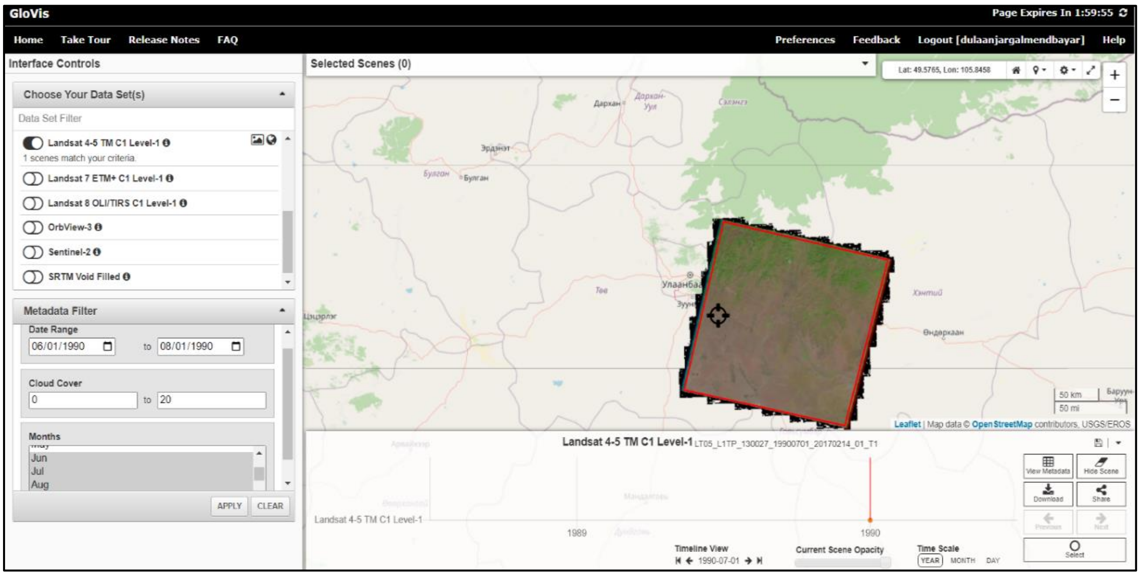
S is the probability density plus or minus coefficient. If F>0.5, then S=1; if F <0.5, then S= −1

3.2.2.2 NDVI data collection and processing

The original data which was used for this study was obtained from the official website of the United States Geological Survey (USGS): the USGS Global Visualization Viewer (GloVis). It provided the dataset for vegetation cover during the growing season. In this study, the long-term NDVI data from the satellite dataset was taken at a two-year interval from 1990 to 2018.

The NDVI dataset was composed of vegetation index product of the Landsat 4-5 TM C1 Level-1 for the dataset earlier than 2000.

Landsat 7 ETM+ C1 level-1 was used for the collection of datasets created later than 2000. Thematic Mapper (TM) Level-1 is a 30-meter multispectral data from Landsat 4 and 5. The image data files consist of seven spectral bands. For Landsat 7, enhance thematic mapper plus (ETM+) which is a 15 to 30-meter multispectral data was used.



● Landsat 4-5 TM C1 Level-1
1 scenes match your criteria.
○ Landsat 7 ETM+ C1 Level-1
○ Landsat 8 OLI/TIRS C1 Level-1
○ OrbView-3
○ Sentinel-2
○ SRTM Void Filled

Date Range 06/01/1990 to 08/01/1990

Cloud Cover 0 to 20

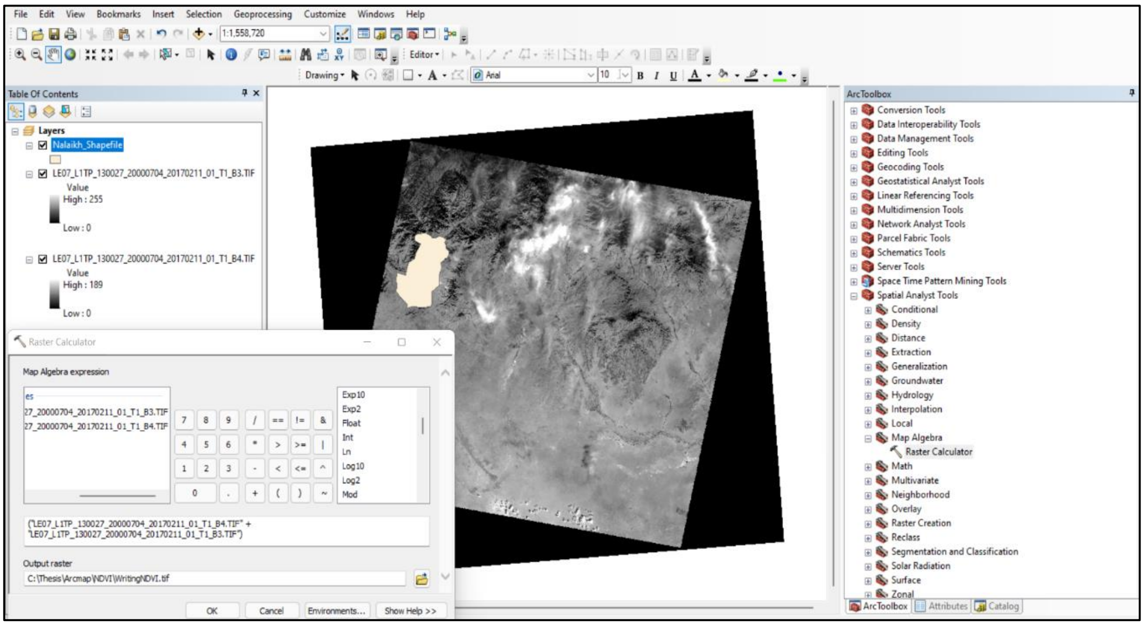
Months Jun Jul Aug

Lat: 49.5765, Lon: 105.8458

Landsat 4-5 TM C1 Level-1 LT05_L1TP_130027_19900701_20170214_01_T1

Figure 15. NDVI data collection from the GloVis

The data collection process began with obtaining the data from the year 1990. Firstly, in the interface controls section of the website, Landsat 4-5 TM C1 Level-1 option was chosen under the year 1990, since the desired data belongs to the period earlier than 2000. Then, on the metadata filter field, desired date range of the data was provided with the specific months and cloud cover from 0 to 20% percent. The specific months were chosen to be the primary growing season months from June to August. Depending on the presented available data, there could be several data components to choose from. After the desired data was selected, it was downloaded with the file format GeoTIFF (.tif), to be later processed in the ArcGIS program. The remaining data from the years 1992, 1994, 1996, 1998, 2000, 2002, 2004, 2006, 2008, 2010, 2012, 2014, 2016, and 2018 were gathered using the same method.



Map Algebra expression

```
("LE07_L1TP_130027_20000704_20170211_01_T1_B4.TIF" +
"LE07_L1TP_130027_20000704_20170211_01_T1_B3.TIF")
```

Output raster: C:\Thesis\Arcmap\NDVI\WritingNDVI.tif

Figure 16. NDVI data processing on ArcGIS program

In figure 15, NDVI data taken from the USGS website GloVis was processed to analyze the NDVI data in Nalaikh and Terelj areas.

Firstly, geographic, and projected coordinate systems were set to WGS 1984 and UTM, WGS 1984, Northern Hemisphere 48N. As shown in figure 16, for the analysis, the raster calculator tool from the spatial analyst tools was used to calculate the NDVI data based on float function and equation 1 (57).

Here in equation 7, NIR represents the spectral reflectance of the near-infrared and RED represents the reflection of the light in the red band. The values of NDVI vary between −1 and +1. For the calculation on the ArcGIS program, the float function was used to formulate equation 1.

Since the main objective of the NDVI data analysis was to create NDVI maps of the study area in different years to illustrate vegetation response, the clipping function of the data management tool was utilized to separate NDVI data of the study area from the original data. After the clipping of the data, the datasets were classified by their range into five different colors and grouped by seven and eight different years for NDVI maps shown in figures 20 and 21.

4 Results and Discussion

In this study, a comprehensive monthly drought record in the period from 1990 to 2018 was analyzed across Nalaikh, Terelj area using the NDVI and SPI. Drought conditions during the study period were studied using monthly precipitation data. The results demonstrated that the study area was facing moderate to extreme drought events for 28 years. Periodic fluctuations with both wetter and drier conditions were observed wherein SPI 1-month and 3-month timescales the frequencies of the variations were the highest. On the other hand, durations of moderate and severe droughts were increasing as the timescale increased. Development of large-scale drought events presented from the beginning of the year 2002 in multiple timescales including SPI 6-, 9-, and 12-month. Several similarities between the drought events from duration to intensity in SPI 9- and 12-month timescales were observed.

The SPI data from 1990 to 2018 was analyzed according to Table 3 in different timescales.

Table 3. Number of drought events at different timescales

	1-month SPI	3-month SPI	6-month SPI	9-month SPI	12-month SPI
Extreme dry	13	8	7	5	3
Severe dry	9	21	21	15	16
Moderate dry	54	26	30	41	45
Near normal	202	237	235	226	224
Moderate wet	49	34	28	33	27
Very wet	17	17	25	27	31
Extreme wet	4	5	2	1	2

The intensity of each drought event during the study period was identified and the duration of the drought was evaluated accordingly. For SPI 1-month, it is often difficult to assess drought events because of the short-term measurement. The following tables from Tables 4 to 8 show the number of only extreme drought events with the duration. In contrast with the 9-month timescale, wet periods were significantly lower in the 12-month timescale where the SPI values were positive only from 1990 to 1996, and from 1997 to 1999 for a long duration. The number of extreme drought events were decreasing as the timescale increased.

Table 4. Extreme drought events at SPI 1-month

Extreme drought events, SPI 1-month					
	onset		end		
Intensity peak	year	month	year	month	Duration months
−2.79	1996	4	1997	5	14
−2.35	1998	3	1998	6	4
−2.06	1998	12	1999	8	9
−2.07	2003	10	-	-	-
−2.07	2005	10	2006	4	7
−2.01	2007	9	2008	4	8
−2.13	2008	11	2009	2	4
−2.19	2014	7	2015	2	8
−2.66	2015	6	2015	10	5
−2.21	2015	8	-	-	-
−2.06	2017	12	2018	6	7
−2.13	2018	11	-	-	-
−2.06	2018	12	-	-	-

From Table 4, it can be observed that the magnitude, duration, and frequency of drought events differ distinctly in different years. For several drought events in 2003, 2015, and 2018, the duration of the events was not written because of a lack of data and to avoid double reference in the same year where a drought event has more than one intensity peak.

Table 5. Extreme drought events at SPI 3-month

Extreme drought events, SPI 3-month					
	onset		end		
Intensity peak	year	month	year	month	Duration months
−2.17	1996	4	1997	6	15
−2.38	1996	5	-	-	-
−2.38	1999	2	1999	9	8
−2.16	2005	12	2007	1	14
−2.02	2014	9	2015	10	14
−2.21	2017	6	2017	8	3
−2.23	2017	7	-	-	-
−2.16	2018	12	-	-	-

Table 6. Extreme drought events at SPI 3-month

Extreme drought events, SPI 6-month					
	onset		end		
Intensity peak	year	month	year	month	Duration months
−2.25	1992	3	1992	7	5
−2.19	1996	4	1997	6	15
−2.08	1996	5	1997	6	14
−2.56	1998	3	1998	6	4
−2.1	2014	12	2016	1	14
−2.34	2017	6	2017	10	5
−2.51	2017	7	-	-	-

For timescales longer than 1-month, SPI values were graphed from the duration 1990 to 2018. Both from the graph and the table, the intensity and the duration of the drought events can be identified clearly. Compared to the table of SPI 1-month, drought events at a 3-month timescale are less frequent and the number of extreme events was significantly lower.

However, in terms of the duration, occurred drought events were much longer. In figure 17, the red lines represent the SPI values lower than 0 where the value of the SPI is less than −1, it can be recognized as a drought event. For the blue lines, SPI values higher than 0 are represented.

Table 6 illustrates the drought events occurring at SPI 6-month timescale. In comparison with the SPI 3-month, the number of drought events has not decreased significantly. The frequency of the extreme drought occurrence was decreased. Intensities of extreme drought events were slightly higher in a certain number of years. Despite the addition of extreme drought events that occurred in 1992 and 1998, overall durations of extreme drought events remain unchanged.

Table 7. Extreme drought events at SPI 9-month

Extreme drought events, SPI 9-month					
	onset		end		
Intensity peak	year	month	year	month	Duration months
−2.31	1997	5	-	-	-
−2.14	2008	5	-	-	-
−2.08	2015	3	2016	4	14
−2.03	2015	8	-	-	-
−2.41	2017	7	2018	1	7

A noticeable trend was observed between the relationship of the SPI time scale and the number of extreme drought events. As the time scale increases, a decrease in the number of extreme drought events were observed.

Table 8. Extreme drought events at SPI-12month

Extreme drought events, SPI 12-month					
	onset		end		
Intensity peak	year	month	year	month	Duration months
−2.15	2007	7	2008	6	12
−2.62	2015	6	2016	7	14
−2.19	2015	8	-	-	-

During the study period, a particularly dry period took place between the beginning of 2005 and the year 2008 where measured drought intensity was greater as well. This result ties well with previous studies which investigated drought conditions in Mongolia. (2,38,39) Overall, at different timescales, at the beginning of the study period, significant drought events did not occur. At the same time, the amount of precipitation was substantially greater during the years from 1990 to 1996. When comparing the results from Sternberg et al. (2), it was identified that in both studies, severe droughts were more frequent than moderate and extreme drought events. In comparison with dry and wet periods, periods with near-normal SPI values subsisted the most over the study period, only demonstrating slight fluctuations between timescales as shown in Table 3. The most intense in magnitude −2.79 (SPI 1-month) occurred in 1996 when the drought continued for approximately 2 years. At each time scale, the occurrence of extreme events was present. However, the duration and intensities of drought events differ significantly depending on the time scale where 1-month and 3-month droughts were significantly shorter in duration, not exceeding a few months and a year respectively. At timescales 6-, 9- and 12-month, drought events between the end of 2014 to 2017 indicated both severe and extremely dry periods and the duration of the event was the second-highest within the study period. The severity and frequency of drought occurrences fluctuated between SPI periods highlighting the drought variation at different time scales. For SPI 12-month time scale, the occurrence of extreme drought events was lower. However, the duration of the drought events increased in several events in 2002, 2004, and 2015. Comparison between the extreme drought events in different time scales showed varied results as the period increased.

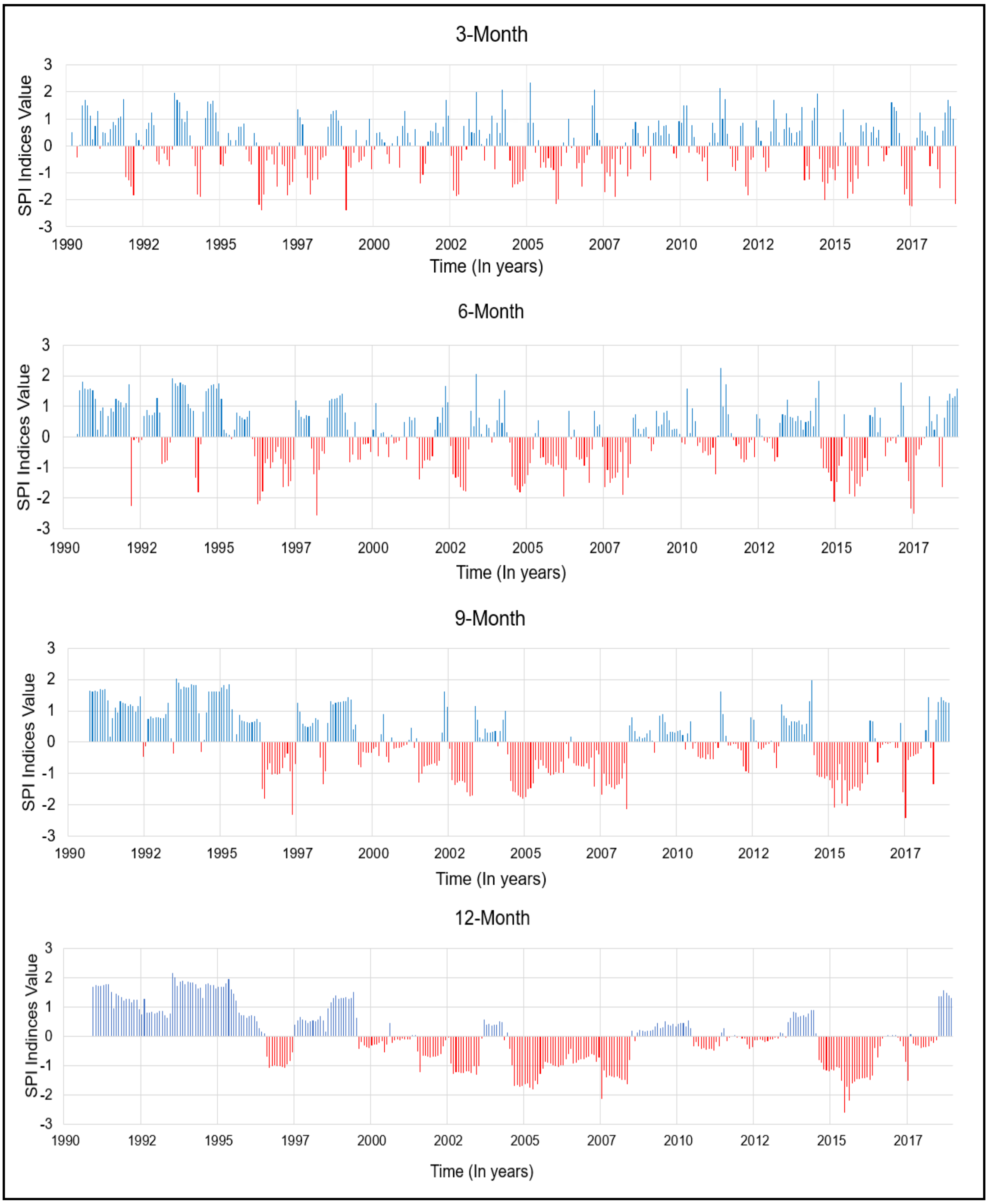


Figure 17. SPI values at different timescales from 1990 to 2018

At different time scales, from the beginning of 2005 to 2008, persistent drought events can be observed where intensity reaches severe levels at all time scales. However, extreme drought episodes were recognized only at SPI 1- and 3-month time scales. These findings correspond to the finding of Nandintsetseg et al. (39) in which, it was found that prolonged and severe meteorological droughts during the 2000s were attributed to lower precipitation and increased evapotranspiration due to warmer temperatures.

From figure 18, the number of extreme dry events was at the lowest on SPI 12-month time scale and the number of near-normal drought events did not differ significantly between the time scales. For moderate dry events, a decreasing trend from the 12-month SPI time scale to the 3-month SPI timescale, but at the 1-month SPI timescale, the number was substantially higher than the rest.

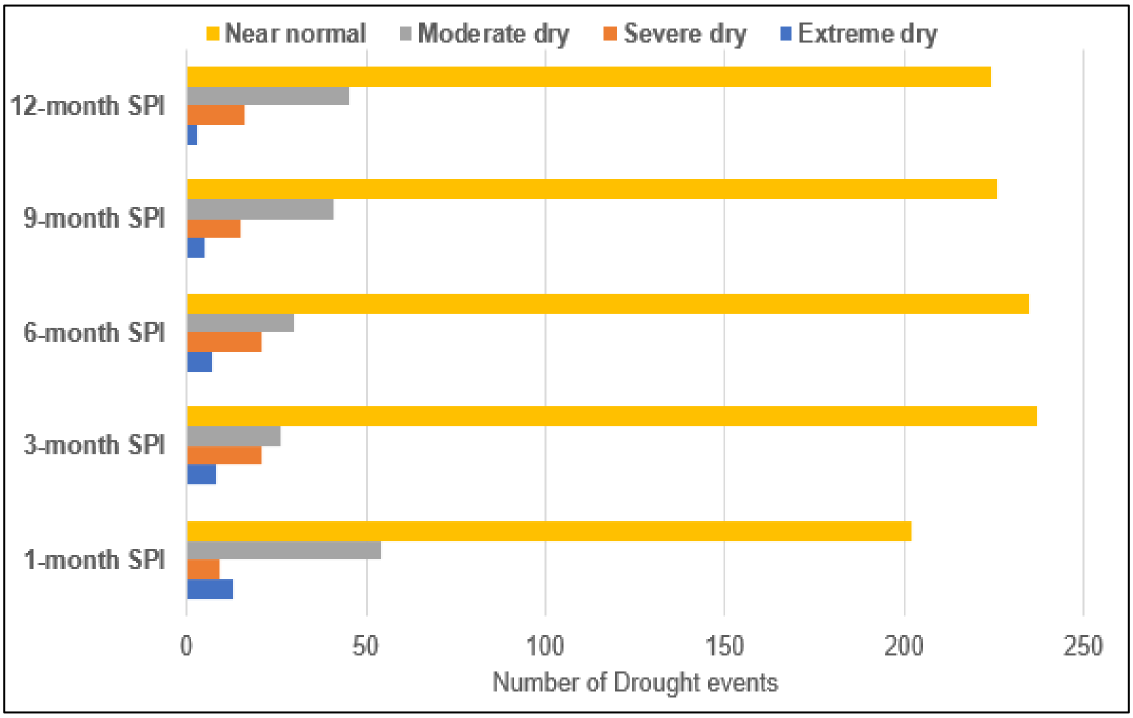


Figure 18. Number of drought events at different SPI time scales

Precipitation data which was taken from the WorldClim website was plotted in 12 months from 1990 to 2018. In figure 19, it can be observed that most of the annual precipitation falls during the months between June and September. Compared to the northern part of Mongolian regions where rainfall is abundant (over 300mm per year), it can be observed that the Nalaikh area receives much less rainfall annually. Considering the result of figure 19, for the NDVI mapping, available data from vegetation growing seasons, especially June and July were mapped in the two-year interval from 1990 to 2018. The maps were created in ArcGIS 10.8 program. In figure 20, NDVI maps from 1990 to 2004 were illustrated. NDVI index values range from -1 to +1. However, during the study period, NDVI values did not reach lower than -0.7. It can be observed that because of the months with the most rainfall, mostly more than half of the study area consisted of vegetation with NDVI values higher than 0.1 which is a good indicator of vegetation. From 1990 to 1994, there was no sign of loss of vegetation. On the other hand, starting from the year

1996, the number of NDVI values decreased gradually to the year 2004 when the vegetation index reached less than -0.3 in some areas.

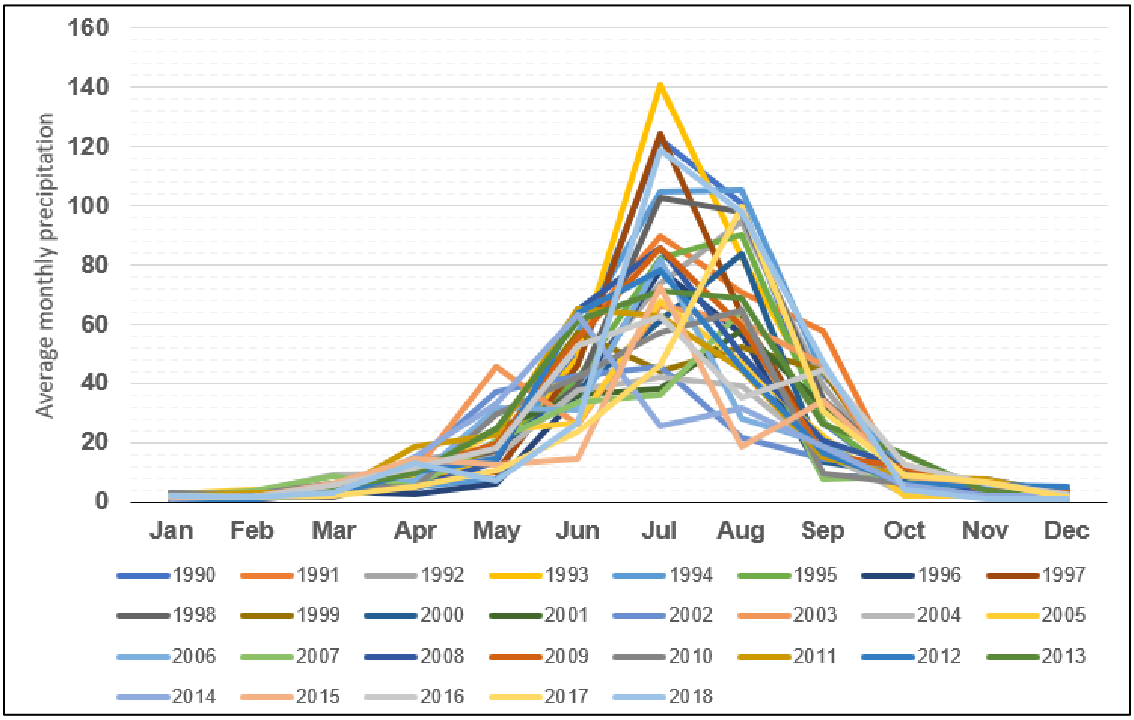


Figure 19. Average monthly precipitation of Nalaikh from 1990 to 2018

The NDVI was calculated during the growing season from June to July based on the available data with a two-year interval between the years 1990 to 2018 to highlight the difference in vegetation spectral reflectance. Due to the lack of sufficient data with the desired amount of cloud coverage, datasets with satisfactory results were obtained and utilized during this study. Overall, the NDVI values coincide with the SPI values where a lack of precipitation was followed by a period with sparse vegetation. Correspondingly, negative NDVI values were mainly associated with negative SPI values. A similar pattern of results was obtained in Khosravi et al. (33). During the months with precipitation deficit, moderate to extreme drought events have major impacts on the vegetation cover over the study area. Notably, vegetation cover over the old Nalaikh mine was relatively sparse throughout the study period despite seasonal changes, presumably due to soil erosion and land degradation as a result of mining activities. With the help of simple and effective drought evaluation indices, sufficient results were obtained in this study. However, it presents some limitations due to the applicability of the study results. Since our study was based on a simple and effective measure of drought (SPI) which uses precipitation data as its input, several other important factors such as temperature, soil moisture, deforestation, etc. Therefore, further studies that include these factors can provide more insight into drought characteristics and can help to find solutions for mitigation for specific types of drought conditions.

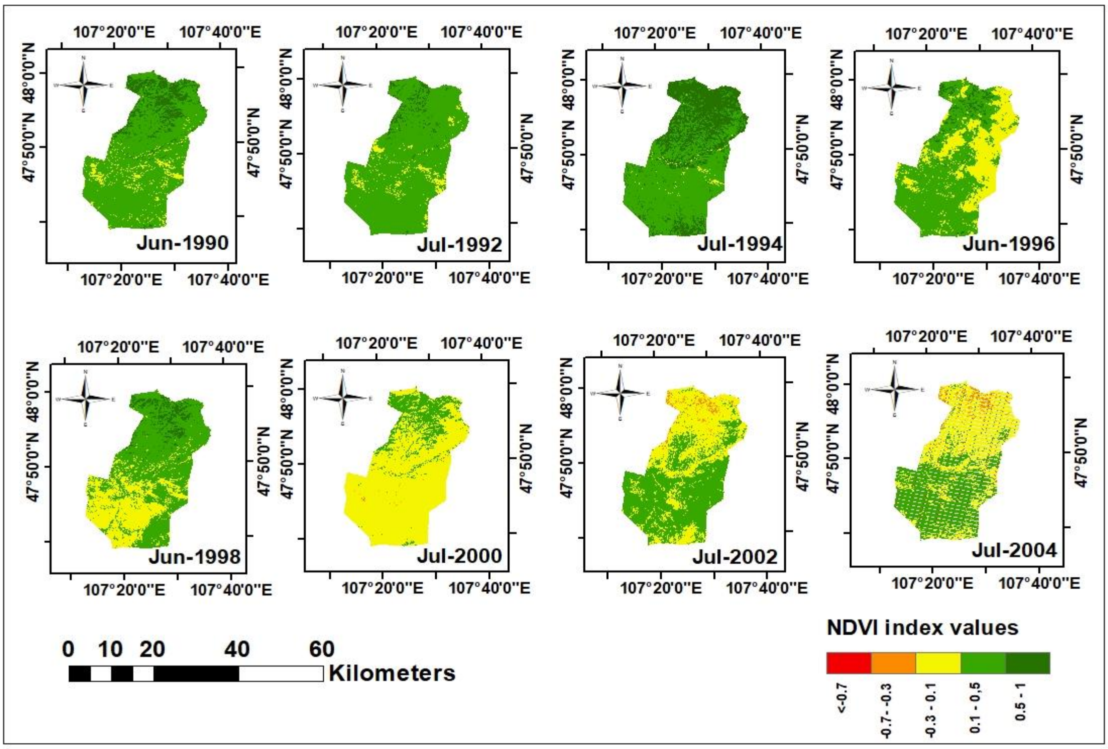


Figure 20. NDVI map of Nalaikh area from 1990-2004

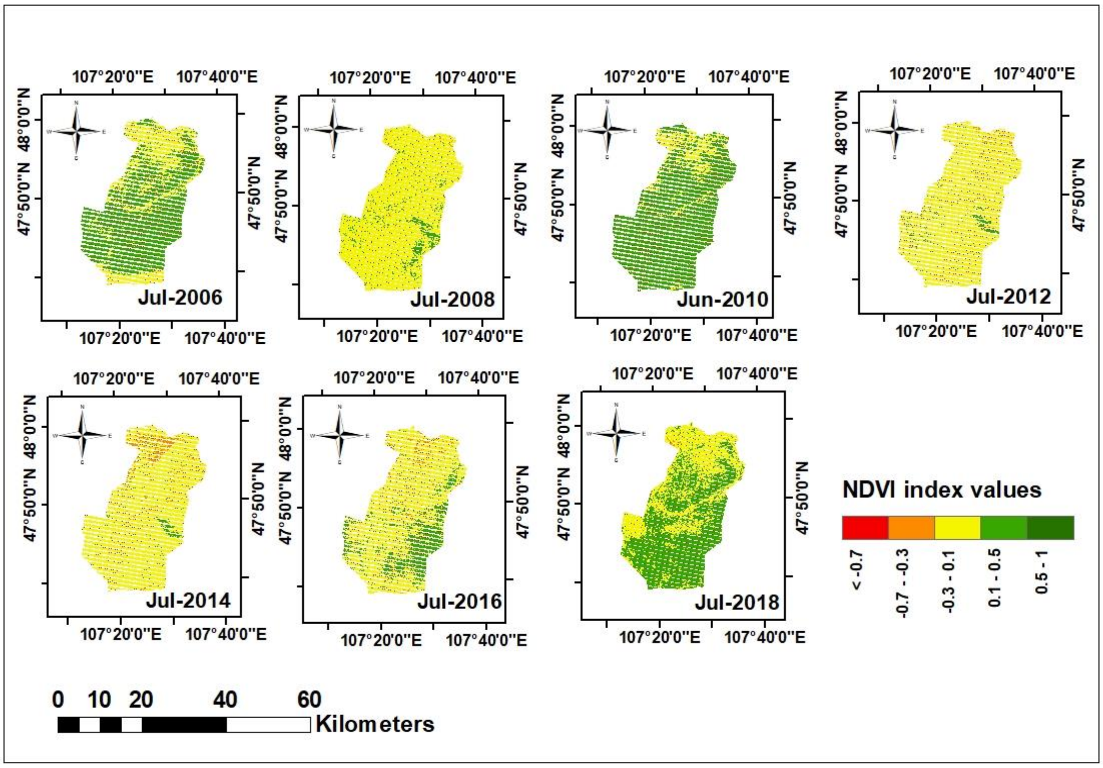


Figure 21. NDVI map of Nalaikh area from 2006-2018

Conclusion

Increased dynamics precipitation and other meteorological variables are expected to occur in the future as a result of climate change, resulting in more frequent droughts whose effects will be exacerbated by rising water demands (13). Despite the significant progress made in drought analysis and modeling by researchers over the past few decades, there is much work that needs to be carried out in the future. This contribution provides an analysis of drought characteristics in the Nalaikh, Terelj area using SPI and attempts to define drought during the years from 1990 to 2018. The study aimed to develop vegetation cover maps of the Nalaikh area with a focus on examining the correlation between the SPI and NDVI while taking the interrelationship between precipitation and vegetation growth into account. During the study period, several drought events have occurred of different intensities and duration. Notably, several drought events occurred in 1996-1997, 2002-2003, 2005-2008, and 2015-2017. Each drought event had different characteristics where the occurrence of severe to extreme cases fluctuated between the time scales. During each drought event, the loss of vegetation cover could be observed from the NDVI maps in Figures 20 and 21. The main conclusion that can be drawn from this aspect of the research is that correlation between the NDVI and the SPI is positive at a 3-month, 6-month, and 9-month timescale, excluding several outlier years of 2004, 2008, and 2012. This study is one of the key components in future attempts to overcome possible severe and extreme drought events. Future studies could explore this issue further by investigating the causal link between climate change, desertification, and drought patterns to create solutions for mitigating imminent environmental challenges.

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Appendices

Appendix 1. Annual monthly precipitation data from 1990 to 2018

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
1990	1.939023	3.078696	3.83022	8.265397	14.60376	49.38863	122.4823	100.951	26.32277	6.561761	7.365985	2.659564
1991	1.466296	1.882372	5.525328	9.058544	17.59536	56.42169	89.72926	70.78992	57.63078	3.772301	3.214027	1.759977
1992	1.432547	1.416358	2.218343	13.84562	17.79854	40.10574	73.8062	94.82901	39.16991	5.049248	4.195539	2.436767
1993	1.130709	2.805287	3.21625	7.296877	14.47329	48.45845	141.0045	82.69879	32.6731	12.69321	4.212776	2.836892
1994	1.895222	1.03751	3.036196	5.189545	7.325672	57.0978	104.9969	105.1028	42.89592	9.995849	2.952996	3.234592
1995	1.063656	1.082997	4.56217	10.75034	17.73396	41.5136	82.31677	90.4011	26.84676	6.407891	1.802718	2.702308
1996	1.612212	1.970715	3.63264	2.428647	5.90936	35.67325	78.12934	56.71245	8.644548	7.976673	3.406553	2.572796
1997	1.34098	1.102233	2.40514	7.095787	10.04652	46.13789	124.2863	63.01607	17.79995	3.291489	1.672838	1.823193
1998	1.992517	1.993481	1.311295	9.74771	16.48567	39.04723	102.5962	97.62507	34.81359	9.715416	6.304996	1.181726
1999	1.216989	1.479181	3.920173	6.925992	18.35288	57.17379	44.2341	52.3788	43.94294	4.531496	2.77826	2.205401
2000	2.802561	1.717804	3.884639	10.10256	18.75788	36.92037	61.28361	83.74429	13.30463	9.029911	5.448376	3.362936
2001	2.52612	1.112071	3.69122	9.931781	24.73056	35.85286	38.22861	57.93226	32.05239	8.930806	4.464751	3.497912
2002	2.86721	1.190212	3.654709	12.97755	37.00687	42.86362	45.39325	21.54436	14.64234	11.48164	4.464473	1.619364
2003	1.526806	3.562135	2.732134	9.885005	45.57239	25.95046	65.95499	60.70653	46.23931	1.996926	5.709348	2.339127
2004	1.648111	3.137264	8.916995	9.498706	15.19304	37.56889	41.98436	39.28888	16.44867	2.561617	2.766918	3.568926
2005	2.688986	3.772778	3.406125	7.352096	23.88999	26.62258	67.73722	46.93701	22.25581	1.819099	1.906351	1.561605
2006	1.280871	2.368639	4.595867	7.271632	31.57002	30.98375	81.95855	28.25539	19.62906	5.549022	2.579822	2.663869
2007	2.185009	3.630716	8.351949	4.942322	20.7776	33.6615	36.04913	64.83068	7.442745	8.395852	1.774094	2.915362
2008	1.535693	1.049988	4.723647	4.644848	13.3186	64.84711	85.74807	49.83323	20.36147	11.68229	1.354257	3.558469
2009	1.143003	2.253613	5.996923	11.01814	19.30721	55.03807	85.7797	58.94588	16.2551	11.38003	4.031481	3.493485
2010	3.018025	2.687483	6.209492	4.741678	29.78052	42.21261	56.9339	64.78426	9.53609	6.165559	6.059547	1.991067
2011	1.553028	3.144315	2.942547	18.74053	22.47287	65.11422	62.55509	44.62569	14.91527	8.451192	7.49234	2.252951
2012	1.167091	1.131558	2.322845	10.20904	14.76062	63.62831	78.12983	44.89101	16.34668	6.264127	5.311791	4.792935
2013	1.78005	1.425784	4.562468	9.466827	24.80059	60.92933	71.05989	68.81014	26.25301	15.97707	3.412804	2.204109
2014	1.030432	1.918613	2.383503	15.10987	32.90092	63.32447	25.75211	31.69151	18.52	5.766032	1.788307	2.230859
2015	1.728408	1.474581	6.248313	14.38798	12.59236	14.62444	72.46788	18.73037	34.30396	8.319717	6.331305	1.893694
2016	1.94492	1.27569	5.505064	11.44749	17.89046	52.52452	62.771	34.92077	44.82225	12.43318	6.229012	2.719403
2017	1.97386	1.5863	1.791284	5.156549	10.30049	23.73849	46.05297	99.8085	30.44233	9.18605	6.452917	1.422452
2018	1.792475	1.668937	3.085797	12.83386	6.985043	26.71461	118.5697	97.58996	47.16118	3.973887	1.095617	1.177813

Appendix 2. Monthly annual SPI values at different timescales

	Month	SPI-1 Month	3-Month	6-Month	9-Month	12-Month
1990	1	0.36	0	0	0	0
1990	2	1.08	0	0	0	0
1990	3	0.08	0.51	0	0	0
1990	4	-0.2	0	0	0	0
1990	5	-0.38	-0.43	0	0	0
1990	6	0.44	0.04	0.09	0	0
1990	7	1.51	1.51	1.52	0	0
1990	8	1.33	1.71	1.81	0	0
1990	9	0.1	1.5	1.58	1.64	0
1990	10	0.01	1.11	1.57	1.61	0
1990	11	1.5	0.24	1.58	1.64	0
1990	12	0.61	0.73	1.54	1.62	1.68
1991	1	-1.26	1.3	1.26	1.69	1.74
1991	2	0.2	-0.1	0.23	1.67	1.72
1991	3	1.01	0.51	0.85	1.7	1.73
1991	4	0.08	0.49	0.96	1.33	1.74
1991	5	-0.01	0.13	0.07	0.18	1.77
1991	6	0.87	0.63	0.69	0.76	1.77
1991	7	0.62	0.88	0.93	1.11	1.5
1991	8	0.42	0.77	0.84	0.95	0.94
1991	9	1.9	1.04	1.26	1.31	1.45
1991	10	-1.02	1.09	1.19	1.25	1.4
1991	11	-0.36	1.73	1.13	1.23	1.33
1991	12	-0.48	-1.15	0.96	1.17	1.21
1992	1	-1.26	-1.29	1.11	1.22	1.28
1992	2	-1.05	-1.5	1.72	1.17	1.26
1992	3	-1.26	-1.84	-2.25	0.99	1.17
1992	4	1.21	0.49	-0.11	1.17	1.25
1992	5	-0.01	0.22	-0.02	1.47	1.24
1992	6	-0.17	0.04	-0.19	-0.46	0.91
1992	7	0.1	-0.14	-0.09	-0.13	0.74
1992	8	1.16	0.62	0.69	0.74	1.27
1992	9	0.95	0.86	0.88	0.82	0.79
1992	10	-0.63	1.24	0.73	0.78	0.81
1992	11	0.22	0.77	0.72	0.79	0.84
1992	12	-0.48	-0.59	0.81	0.81	0.76
1993	1	-1.26	-0.68	1.29	0.76	0.81
1993	2	1.08	-0.1	0.79	0.78	0.85
1993	3	-0.51	-0.28	-0.88	0.89	0.86
1993	4	-0.5	-0.53	-0.82	1.25	0.72
1993	5	-0.51	-0.75	-0.77	0.12	0.64
1993	6	0.38	-0.13	-0.19	-0.35	0.76
1993	7	1.96	1.96	1.93	2.03	2.16
1993	8	0.81	1.71	1.75	1.91	2.01
1993	9	0.58	1.61	1.67	1.69	1.73
1993	10	1.39	0.99	1.77	1.78	1.87
1993	11	0.22	0.89	1.73	1.75	1.89
1993	12	0.61	1.28	1.7	1.75	1.78
1994	1	0.36	0.38	1.08	1.86	1.87
1994	2	-1.05	-0.1	0.93	1.82	1.84
1994	3	-0.51	-0.74	0.85	1.82	1.82
1994	4	-1.2	-1.8	-1.34	0.92	1.77
1994	5	-1.72	-1.89	-1.81	-0.31	1.63
1994	6	0.93	-0.13	-0.25	0.08	1.67
1994	7	1.06	1.03	0.84	0.95	1.31
1994	8	1.44	1.63	1.49	1.63	1.78
1994	9	1.17	1.55	1.6	1.61	1.8
1994	10	0.77	1.68	1.69	1.63	1.75
1994	11	-0.36	1.24	1.74	1.62	1.75
1994	12	0.61	0.53	1.59	1.62	1.63
1995	1	-1.26	-0.68	1.76	1.74	1.68
1995	2	-1.05	-0.75	1.24	1.82	1.69
1995	3	0.58	-0.28	0.25	1.71	1.7
1995	4	0.57	0.49	0.12	1.85	1.79
1995	5	-0.01	0.22	0.07	1.06	1.94
1995	6	-0.03	-0.01	-0.08	0.02	1.6
1995	7	0.37	0.2	0.24	0.26	1.46
1995	8	1.02	0.71	0.8	0.88	1.21
1995	9	0.17	0.71	0.69	0.69	0.79
1995	10	-0.29	0.83	0.62	0.67	0.72
1995	11	-1.08	-0.13	0.59	0.64	0.71
1995	12	0.61	-0.59	0.66	0.63	0.62

1996	1	0.36	-0.68	0.86	0.65	0.7
1996	2	0.2	0.48	-0.07	0.66	0.72
1996	3	0.08	0.13	-0.64	0.75	0.69
1996	4	-2.79	-2.17	-2.19	0.65	0.51
1996	5	-1.96	-2.38	-2.08	-1.49	0.28
1996	6	-0.48	-1.8	-1.78	-1.81	0.17
1996	7	0.24	-0.56	-0.84	-0.88	0.1
1996	8	-0.1	-0.14	-0.71	-0.67	-0.7
1996	9	-1.66	-0.31	-1.01	-1.04	-1.07
1996	10	0.28	-0.69	-0.82	-1.01	-1.02
1996	11	-0.36	-1.52	-0.49	-1.03	-1
1996	12	0.61	0.12	-0.32	-1	-1.02
1997	1	-1.26	-0.68	-0.71	-0.82	-1.02
1997	2	-1.05	-0.75	-1.65	-0.48	-1.04
1997	3	-1.26	-1.84	-0.88	-0.36	-1.07
1997	4	-0.5	-1.45	-1.61	-0.94	-0.95
1997	5	-1.13	-1.34	-1.43	-2.31	-0.84
1997	6	0.25	-0.48	-0.74	-0.69	-0.54
1997	7	1.56	1.34	1.2	1.27	0.38
1997	8	0.13	1.06	0.88	0.97	0.53
1997	9	-0.58	0.81	0.66	0.59	0.66
1997	10	-1.48	-0.34	0.61	0.51	0.56
1997	11	-1.08	-1.19	0.71	0.49	0.55
1997	12	-0.48	-1.79	0.69	0.52	0.45
1998	1	0.36	-1.29	-0.38	0.61	0.52
1998	2	0.2	-0.1	-1.23	0.77	0.54
1998	3	-2.35	-1.25	-2.56	0.73	0.52
1998	4	0.33	-0.53	-1.07	-0.49	0.57
1998	5	-0.25	-0.43	-0.47	-1.34	0.68
1998	6	-0.25	-0.36	-0.55	-0.92	0.53
1998	7	1	0.7	0.63	0.63	0.16
1998	8	1.25	1.18	1.19	1.32	0.94
1998	9	0.71	1.3	1.25	1.22	1.17
1998	10	0.77	1.33	1.26	1.25	1.3
1998	11	1.12	0.95	1.27	1.28	1.39
1998	12	-2.06	0.73	1.35	1.29	1.27
1999	1	-1.26	-0.13	1.42	1.32	1.31
1999	2	-1.05	-2.38	0.79	1.3	1.3
1999	3	0.08	-0.74	0.25	1.44	1.34
1999	4	-0.5	-0.82	-0.82	1.36	1.27
1999	5	-0.01	-0.24	-0.57	0.41	1.29
1999	6	0.93	0.58	0.48	0.57	1.51
1999	7	-1.13	-0.6	-0.73	-0.72	0.62
1999	8	-0.3	-0.55	-0.74	-0.8	-0.42
1999	9	1.22	-0.4	-0.25	-0.31	-0.19
1999	10	-0.63	0.21	-0.25	-0.34	-0.3
1999	11	-0.36	1.01	-0.21	-0.33	-0.37
1999	12	-0.48	-0.86	-0.49	-0.34	-0.39
2000	1	1.5	-0.13	0.25	-0.22	-0.31
2000	2	0.2	0.48	1.12	-0.16	-0.28
2000	3	0.08	0.51	-0.64	-0.43	-0.28
2000	4	0.33	0.25	0.12	0.25	-0.22
2000	5	0.1	0.13	0.15	0.9	-0.18
2000	6	-0.4	-0.3	-0.25	-0.46	-0.54
2000	7	-0.38	-0.67	-0.66	-0.65	-0.27
2000	8	0.84	0.09	0.07	0.15	0.46
2000	9	-1.11	-0.03	-0.21	-0.2	-0.24
2000	10	0.53	0.36	-0.19	-0.19	-0.15

2000	11	0.7	-0.8	-0.13	-0.17	-0.1
2000	12	0.61	0.73	0.02	-0.15	-0.14
2001	1	1.5	1.3	0.49	-0.1	-0.09
2001	2	-1.05	0.48	-0.75	-0.08	-0.11
2001	3	0.08	0.13	0.66	0.08	-0.11
2001	4	0.33	0	0.55	0.47	-0.11
2001	5	0.72	0.63	0.64	-0.19	0.02
2001	6	-0.48	-0.01	-0.02	0.13	0.03
2001	7	-1.44	-1.38	-1.4	-1.29	-0.53
2001	8	-0.06	-1.06	-1.03	-1	-1.22
2001	9	0.52	-0.66	-0.76	-0.78	-0.67
2001	10	0.53	0.15	-0.73	-0.76	-0.66
2001	11	0.22	0.57	-0.78	-0.73	-0.69
2001	12	0.61	0.53	-0.62	-0.7	-0.72
2002	1	1.5	0.85	0.25	-0.66	-0.69
2002	2	-1.05	0.48	0.66	-0.74	-0.69
2002	3	0.08	0.13	0.46	-0.59	-0.68
2002	4	1.01	0.72	0.96	0.32	-0.61
2002	5	1.7	1.69	1.68	1.62	-0.33
2002	6	0.04	1.12	1.14	1.13	-0.14
2002	7	-1.08	-0.38	-0.3	-0.2	-0.04
2002	8	-1.97	-1.66	-1.22	-1.2	-0.93
2002	9	-0.88	-1.87	-1.32	-1.36	-1.27
2002	10	0.99	-1.81	-1.31	-1.28	-1.22
2002	11	0.22	-0.54	-1.64	-1.24	-1.22
2002	12	-0.48	0.73	-1.74	-1.23	-1.26
2003	1	0.36	-0.13	-1.79	-1.29	-1.26
2003	2	1.78	1	-0.4	-1.59	-1.19
2003	3	-0.51	0.51	0.85	-1.72	-1.19
2003	4	0.33	0.49	0.34	-1.7	-1.26
2003	5	2.31	2	2.06	1.17	-1.02
2003	6	-1.36	0.58	0.63	0.72	-1.3
2003	7	-0.19	0.07	0.11	0.16	-1.02
2003	8	0.06	-0.55	0	0.11	-0.09
2003	9	1.33	0.26	0.41	0.44	0.56
2003	10	-2.07	0.44	0.29	0.32	0.38
2003	11	1.12	1.13	-0.17	0.32	0.42
2003	12	-0.48	-0.86	0.17	0.33	0.35
2004	1	0.36	0.85	0.55	0.37	0.4
2004	2	1.08	0.48	1.24	-0.12	0.38
2004	3	2.09	2.09	0.46	0.35	0.5
2004	4	0.08	1.36	1.54	0.71	0.47
2004	5	-0.38	0.13	0.15	1.01	-0.14
2004	6	-0.32	-0.55	-0.19	-0.4	0.12
2004	7	-1.23	-1.55	-1.31	-1.25	-0.43
2004	8	-0.91	-1.41	-1.57	-1.56	-1
2004	9	-0.78	-1.43	-1.73	-1.61	-1.69
2004	10	-1.48	-1.34	-1.82	-1.71	-1.66
2004	11	-0.36	-1.3	-1.61	-1.75	-1.74
2004	12	1.49	-0.86	-1.52	-1.81	-1.69
2005	1	1.5	0.85	-1.24	-1.76	-1.64
2005	2	1.78	2.36	-0.84	-1.49	-1.62
2005	3	-0.51	0.87	-0.4	-1.47	-1.75
2005	4	-0.5	-0.26	0.12	-1.31	-1.8
2005	5	0.62	0.22	0.56	-0.57	-1.53
2005	6	-1.26	-0.8	-0.68	-0.86	-1.65
2005	7	-0.11	-0.6	-0.66	-0.57	-1.28
2005	8	-0.52	-0.81	-0.9	-0.75	-1.11
2005	9	-0.22	-0.46	-0.85	-0.82	-0.88
2005	10	-2.07	-0.81	-0.91	-0.97	-0.9
2005	11	-1.08	-0.9	-0.98	-1.05	-0.92
2005	12	-0.48	-2.16	-0.64	-1.02	-1

2006	1	-1.26	-1.98	-0.91	-0.96	-1.02
2006	2	0.2	-0.75	-1.03	-0.99	-1.06
2006	3	0.58	0.13	-1.95	-0.61	-1
2006	4	-0.5	-0.26	-1.07	-0.98	-1
2006	5	1.32	1.01	0.86	-0.06	-0.79
2006	6	-0.89	-0.07	-0.08	-0.52	-0.62
2006	7	0.37	0.29	0.24	0.19	-0.43
2006	8	-1.54	-0.83	-0.66	-0.67	-0.93
2006	9	-0.39	-0.62	-0.73	-0.75	-0.9
2006	10	-0.29	-1.52	-0.71	-0.76	-0.8
2006	11	-0.36	-0.62	-0.93	-0.77	-0.78
2006	12	0.61	-0.34	-0.66	-0.77	-0.79
2007	1	0.36	-0.13	-1.51	-0.68	-0.73
2007	2	1.78	1.49	-0.4	-0.85	-0.69
2007	3	1.76	2.09	0.85	-0.5	-0.61
2007	4	-1.2	0.49	0.34	-1.43	-0.65
2007	5	0.32	0.22	0.4	-0.25	-0.88
2007	6	-0.64	-0.67	-0.31	-0.4	-0.73
2007	7	-1.56	-1.72	-1.65	-1.67	-2.15
2007	8	0.2	-0.98	-1.09	-1	-1.16
2007	9	-2.01	-1.14	-1.5	-1.38	-1.4
2007	10	0.28	-0.48	-1.36	-1.35	-1.34
2007	11	-1.08	-1.88	-1.34	-1.44	-1.37
2007	12	0.61	-0.11	-1.15	-1.5	-1.39
2008	1	0.36	-0.68	-0.49	-1.37	-1.36
2008	2	-1.05	-0.1	-1.88	-1.34	-1.44
2008	3	0.58	0.13	-0.18	-1.15	-1.49
2008	4	-1.2	-1.12	-1.34	-0.67	-1.49
2008	5	-0.66	-0.86	-0.87	-2.14	-1.65
2008	6	1.37	0.63	0.63	0.53	-0.81
2008	7	0.5	0.88	0.75	0.79	0.19
2008	8	-0.39	0.47	0.27	0.35	-0.16
2008	9	-0.39	-0.07	0.1	0.09	0.13
2008	10	1.19	-0.41	0.27	0.18	0.21
2008	11	-2.13	-0.29	0.33	0.14	0.2
2008	12	1.49	0.73	-0.02	0.15	0.15
2009	1	-1.26	-1.29	-0.46	0.27	0.18
2009	2	0.2	0.48	-0.23	0.39	0.2
2009	3	1.01	0.51	0.85	0.06	0.22
2009	4	0.57	0.94	0.34	-0.34	0.34
2009	5	0.1	0.39	0.4	0	0.45
2009	6	0.81	0.73	0.79	0.86	0.27
2009	7	0.5	0.76	0.87	0.89	0.3
2009	8	-0.02	0.45	0.54	0.65	0.51
2009	9	-0.78	0.03	0.23	0.26	0.38
2009	10	0.99	-0.27	0.27	0.34	0.36
2009	11	0.22	-0.45	0.27	0.34	0.42
2009	12	0.61	0.92	0.1	0.31	0.33
2010	1	1.5	0.85	-0.18	0.35	0.42
2010	2	1.08	1.49	-0.23	0.38	0.44
2010	3	1.01	1.51	1.59	0.24	0.44
2010	4	-1.2	-0.26	0.12	-0.24	0.32
2010	5	1.16	0.78	0.94	0.29	0.53
2010	6	-0.03	0.32	0.53	0.67	0.28
2010	7	-0.54	-0.24	-0.3	-0.2	-0.34
2010	8	0.2	-0.3	-0.17	-0.04	-0.2
2010	9	-1.51	-0.57	-0.53	-0.46	-0.33
2010	10	-0.29	-0.44	-0.47	-0.51	-0.44
2010	11	1.12	-1.3	-0.59	-0.49	-0.39
2010	12	-0.48	0.12	-0.57	-0.53	-0.46

2011	1	0.36	0.85	-0.35	-0.39	-0.44
2011	2	1.08	0.48	-1.23	-0.55	-0.44
2011	3	-0.51	0.13	0.04	-0.54	-0.5
2011	4	2.1	2.13	2.25	-0.04	-0.19
2011	5	0.42	1.01	1.01	-0.19	-0.35
2011	6	1.37	1.72	1.74	1.61	0.14
2011	7	-0.3	0.45	0.75	0.89	0.27
2011	8	-0.62	-0.1	0.12	0.2	-0.18
2011	9	-0.88	-0.78	-0.11	-0.11	-0.06
2011	10	0.28	-0.92	-0.3	-0.11	-0.02
2011	11	1.5	-0.54	-0.25	-0.06	0.01
2011	12	-0.48	0.73	-0.71	-0.05	-0.05
2012	1	-1.26	0.85	-0.83	-0.22	-0.03
2012	2	-1.05	-1.5	-0.75	-0.26	-0.07
2012	3	-1.26	-1.84	-0.18	-0.78	-0.09
2012	4	0.33	-0.53	-0.11	-0.94	-0.28
2012	5	-0.38	-0.43	-0.67	-0.98	-0.42
2012	6	1.32	0.93	0.74	0.81	-0.38
2012	7	0.24	0.67	0.6	0.73	-0.13
2012	8	-0.62	0.19	0.05	0.06	-0.13
2012	9	-0.78	-0.42	-0.13	-0.22	-0.11
2012	10	-0.29	-0.96	-0.17	-0.23	-0.15
2012	11	0.7	-0.8	-0.04	-0.19	-0.19
2012	12	2.23	0.53	-0.38	-0.09	-0.18
2013	1	0.36	1.71	-0.79	-0.06	-0.11
2013	2	-1.05	1	-0.66	0.04	-0.11
2013	3	0.58	0.13	0.46	-0.34	-0.05
2013	4	0.08	0	0.75	-0.82	-0.07
2013	5	0.72	0.63	0.71	-0.13	0.14
2013	6	1.16	1.22	1.23	1.22	0.1
2013	7	0	0.67	0.66	0.86	-0.06
2013	8	0.35	0.47	0.63	0.77	0.48
2013	9	0.1	0.12	0.52	0.53	0.64
2013	10	1.92	0.5	0.68	0.68	0.83
2013	11	-0.36	0.57	0.54	0.68	0.8
2013	12	-0.48	1.45	0.25	0.65	0.66
2014	1	-1.26	-1.29	0.49	0.69	0.7
2014	2	0.2	-0.75	0.52	0.57	0.72
2014	3	-1.26	-1.25	0.85	0.26	0.65
2014	4	1.4	0.94	0.34	0.59	0.76
2014	5	1.4	1.42	1.29	1.32	0.9
2014	6	1.27	1.93	1.83	1.99	0.89
2014	7	-2.19	-0.49	-0.37	-0.42	0.1
2014	8	-1.3	-1.35	-1.03	-1.06	-0.8
2014	9	-0.48	-2.02	-1.01	-1.11	-0.9
2014	10	-0.29	-1.38	-1.17	-1.11	-1.14
2014	11	-1.08	-0.8	-1.44	-1.15	-1.17
2014	12	-0.48	-0.86	-2.1	-1.09	-1.19
2015	1	0.36	-1.29	-1.46	-1.2	-1.14
2015	2	-1.05	-0.75	-0.93	-1.46	-1.16
2015	3	1.01	0.51	-0.64	-2.08	-1.05
2015	4	1.21	1.36	0.75	-1.22	-1.07
2015	5	-0.66	0.13	-0.02	-0.7	-1.53
2015	6	-2.66	-1.96	-1.86	-1.95	-2.62
2015	7	0.03	-1.34	-1.11	-1.2	-1.74
2015	8	-2.21	-1.78	-1.96	-2.03	-2.19
2015	9	0.65	-0.73	-1.53	-1.54	-1.61
2015	10	0.28	-1.21	-1.61	-1.5	-1.55
2015	11	1.12	0.77	-1.29	-1.42	-1.45
2015	12	-0.48	0.53	-0.68	-1.45	-1.46
2016	1	0.36	0.85	-1.11	-1.55	-1.44
2016	2	-1.05	-0.75	0.73	-1.31	-1.44
2016	3	1.01	0.51	0.66	-0.64	-1.41
2016	4	0.57	0.72	0.96	-1.02	-1.49
2016	5	-0.01	0.3	0.15	0.69	-1.33
2016	6	0.69	0.58	0.63	0.67	-0.4
2016	7	-0.3	-0.07	0.01	0.12	-0.72
2016	8	-1.12	-0.59	-0.64	-0.64	-0.35
2016	9	1.28	-0.33	-0.19	-0.18	-0.09
2016	10	1.19	-0.07	-0.13	-0.09	0
2016	11	1.12	1.62	-0.04	-0.02	0.01
2016	12	0.61	1.45	-0.2	-0.05	-0.03

2017	1	0.36	1.3	0.06	-0.04	0.01
2017	2	0.2	0.48	1.77	0.02	0.04
2017	3	-1.26	-0.74	1.04	-0.19	-0.05
2017	4	-1.2	-1.8	-0.82	-0.17	-0.17
2017	5	-1.13	-1.6	-1.43	0.63	-0.33
2017	6	-1.56	-2.21	-2.34	-1.61	-0.88
2017	7	-1.03	-2.23	-2.51	-2.41	-1.52
2017	8	1.3	-0.17	-0.61	-0.56	0.08
2017	9	0.39	0.31	-0.4	-0.46	-0.26
2017	10	0.53	1.24	-0.27	-0.43	-0.32
2017	11	1.12	0.57	-0.02	-0.38	-0.32
2017	12	-2.06	0.53	0.34	-0.36	-0.41
2018	1	0.36	0.38	1.34	-0.22	-0.37
2018	2	0.2	-0.75	0.52	0	-0.37
2018	3	-0.51	-0.28	0.25	0.39	-0.34
2018	4	1.01	0.72	0.75	1.44	-0.17
2018	5	-1.72	-0.86	-0.98	-0.19	-0.23
2018	6	-1.26	-1.57	-1.63	-1.35	-0.13
2018	7	1.43	0.55	0.63	0.73	1.36
2018	8	1.25	1.25	1.19	1.29	1.37
2018	9	1.38	1.71	1.42	1.43	1.56
2018	10	-1.02	1.48	1.28	1.35	1.47
2018	11	-2.13	1.01	1.34	1.29	1.39
2018	12	-2.06	-2.16	1.6	1.27	1.29