STOCHASTIC MODELING OF HYDROLOGICAL AND METEOROLOGICAL DROUGHT IN THE SOUTH-WEST REGION OF BANGLADESH

By

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Stochastic modeling of hydrological and meteorological drought in the south-west region of Bangladesh

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CERTIFICATE OF APPROVAL

The thesis titled "**Stochastic modeling of hydrological and meteorological drought in the south-west region of Bangladesh**" submitted by Noor-E-Ashmaul Husna, Student ID: 1014282007, Session: October 2014 has been accepted as satisfactory in partial fulfillment of the requirement for the degree of Master of Science in Water Resources Development on 16 January 2019.

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Session: October 2014

Dedicated

To

My Parents and My Teachers

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ABSTRACT

Drought is a hindering natural disaster that may affect every aspect of living life. It is believed that the trend of the recent climate change has triggered this disaster more than past. In this study, therefore, meteorological drought and ground water drought (hydrological drought) has been assessed to understand the historical scenario of water deficiency. A more recent and comparatively better performing Reconnaissance Drought Index (RDI) is used to assess meteorological drought. While a threshold level approach is used to derive the groundwater drought scenario. RDI is also used as a climate change indicator in the current study. While the trend in RDI index is calculated using nonparametric Mann-Kendall trend test, fluctuation of the trend is identified using Sequential Mann-Kendall test. Future forecasting drought events are done using ARIMA (Autoregressive Integrated Moving Average) and ANN (Artificial Neural Network) technique.

Seasonal RDI shows that a fluctuation of the wet and dry cycle is common in most of the cases. The study area experienced several moderate but few extreme droughts in three months scale varying spatially and temporally. Six-month RDI reveals that Khulna and Mongla station experienced extreme droughts in 1992-93 hydrologic year in the reference period of April to September. In contrast, in the reference period October to March, only Jessore experienced severe droughts in 1976-77 and 2011-12. On the other hand, annual RDI shows that 1992-93 is an all dry condition for the whole study area varying from mild to extreme condition. However, it is observed that seasonal fluctuation of drought parameters reduces the number of drought events in annual scale. Trends in initial RDI index is used as the climate change indicator and found that most of the negative trends have started from after the ’90s. Results of the trend analysis indicate that there is a change in either precipitation or Potential Evapotranspiration. Future forecasting of RDI index is performed using ARIMA and BPNN (Backpropagation Neural Network). Results show that ANN outperformed ARIMA in future forecasting. BPNN forecast up to 3 times ahead with a reasonable accuracy while ARIMA to 1 ahead.

Groundwater drought in the study area reveals that drought events are mostly confined to the February to June. Spatial distribution of water deficit shows that Satkhira has most water deficit than other areas. Normalized water deficit is found greater than 2m for several wells in the Kalaroa Upozilla of Satkhira district.

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ABBREVIATIONS

ARIMA	Autoregressive Integrated Moving Average
ANN	Artificial Neural Network
ACF	Autocorrelation Function
BPNN	Backpropagation Neural Network
BIC	Bayesian Information Criterion
CMI	Crop Moisture Index
DM	Drought Monitor
EDI	Effective Drought Index
EP	Effective Precipitation
FAO	Food and Agricultural Organization
GDI	Groundwater Drought Index
ICZM	Integrated Coastal Zone Management
IWRM	Integrated Water Resource Management
MK	Mann-Kendall
NDWI	Normalized Difference Water Index
NDVI	Normalized Difference Vegetation Index
NIR	Near Infrared Ray
OFRs	On-Farm Reservoirs
PDSI	Palmer drought severity index
PACF	Partial Autocorrelation Function
RDI	Reconnaissance Drought Index
SDI	Streamflow Drought Index
SRI	Standardized Runoff Index
SWIR	Shortwave Infrared
SPEI	Standardized Precipitation Evapotranspiration Index
SWSI	Surface Water Supply Index
SPI	Standardized Precipitation Index
SARIMA	Seasonal Autoregressive Integrated Moving Average
SQMK	Sequential Mann-Kendal test
VCI	Vegetation condition index
VTCI	Vegetation Temperature Condition Index

Chapter 1. Introduction

1.1 Background of the study

Drought is one of the most creeping natural phenomena. The drought hazard affects more people than any other hazard. However, Characteristics of draught is not well known among the scientist. Research has shown that the lack of precise and clear definition of drought for a specific region is the main obstacle to understand this phenomenon. This creates a problem in decision making for the decision and policy makers (Mishra and Desai, 2005). Like many other countries, the desertification process is now common in Bangladesh. It has an impression that the drought-prone area is mainly confined to the North-West of the country (Habiba et al., 2013; Murshid, 1987). However, the recent study includes the southwestern part to drought vulnerable zone (Shahid and Behrawan, 2008).

The country has suffered from nine severe droughts till 1998 (Paul, 1998). Losses from drought are likely to be more severe than from floods in Bangladesh (Brammer, 1987; Paul, 1998) but it has attracted far less scientific attention than floods. The global climate change in recent years is likely to enhance the frequency of droughts. The phenomenon of global climate changes will also affect Bangladesh. Therefore, drought hazards, vulnerability, and risk assessment are essential for implementing mitigation and adaptation to reduce drought impact in Bangladesh.

In the context of Bangladesh, Brammer (Brammer, 1987) defines drought as a period when soil moisture supply is less than what is required for satisfactory crop growth during a season when crops normally are grown.

Since independence, Bangladesh has experienced droughts of major magnitude in 1973, 1978, 1979, 1981, 1982, 1989, 1992, 1994, and 1995 (Paul, 1998). Although droughts are not always continuous in any area, they do occur sometimes in the low rainfall zones of the country. As listed above, Bangladesh experienced consecutive droughts in 1978 and 1979, 1981 and 1982, and 1994 and 1995. The 1973 drought was labeled 'the worst in recent history,' 1979 drought was dubbed 'the worst in living memory (Murshid, 1987).

Drought severely affects crop output in Bangladesh (Brammer, 1987). Because of the non-availability of relevant data, the figures on the annual drought-related loss of crop production cannot be presented except for the 1982 drought. The total loss of rice production due to drought in 1982 was 52,896 metric tons (Paul, 1998). This accounted for about 41% of the total damage caused by all types of environmental hazards (cyclones, hailstorms, heavy rains, floods, and drought) that occurred in that year. The 1982 flood damaged about 36,000 metric tons of rice, much lower than the damage done by drought. Brammer (Brammer, 1987) claimed that the 1978-79 drought reduced rice production by an estimated two million tons. It directly affected about 42% of the cultivated land and 44% of the population (Ericksen et al., 1994). Ahmed and Bernard (Ahmed and Bernard, 1989) and Hossain (Hossain, 1990) contend that during the 1973-87 period, crop losses to drought were almost as severe as the losses attributed to floods. About 2.18 million tons of rice were damaged due to drought in the above period. The corresponding flood loss was 2.38 million tons. Drought adversely affects all three rice varieties (aman, aus, and boro) grown in three different cropping seasons in Bangladesh. It also causes damage to jute, the country's main cash crop, and other crops such as pulses, potatoes, oilseeds, minor grains, winter vegetables, and sugarcane. Rice alone accounts for more than 80% of the total cultivated land in the country. Droughts in March-April prevent land preparation and plowing activities from being conducted on time. As a result, aman, aus, and jute cannot be sown on schedule. Droughts in May and June destroy aman, aus, and jute plants. Inadequate rains in August delay transplantation of aman in high land areas, while droughts in September and October reduce the yield of both broadcast and transplanted aman and delay the sowing of pulses and potatoes. Boro, wheat, and other crops grown in the dry season are also periodically affected by drought. Fruit trees, such as jackfruit, litchi, and banana, often die during a drought. But the loss of rice production is the most costly damage incurred by droughts in Bangladesh.

The impact of drought spreads disproportionately among regions of Bangladesh. There is a popular impression in Bangladesh that the northwestern districts of Rajshahi, Dinajpur, Rangpur, Bogra, and Pabna are particularly drought-prone (Murshid, 1987). Recently the coastal area also suffers from severe drought events. The coastal region is relatively dry and hot receiving only 60 inches of rainfall annually. The eastern districts, in contrast, receive more than 80 inches of rainfall.

The coastal zone of Bangladesh comparatively more vulnerable to various natural hazards. Bangladesh faces unpredictable drought hazard in the dry monsoon due to inadequate and uneven rainfall. The severity varies from place to place, however, the northwestern region suffers most from the drought.

Combating the drought in coastal Bangladesh requires to utilize its water resources, both surface, and groundwater. However, Bangladesh has increasingly used her groundwater resources to such an extent that the depletion of groundwater resources is accelerating salinity contamination at an alarming rate in the groundwater reservoirs due to over and unplanned withdrawal. Moreover, surface water deficit due to drought is also upsetting. The combined effects are threatening the Integrated Coastal Zone Management (ICZM) approach as well as the Integrated Water Resource Management (IWRM) approaches severely. Considering the above debate, the aim of this study is an assessment of Meteorological and Hydrological drought (ground water drought) occurrence in the southwestern region of Bangladesh (Figure 1.1).

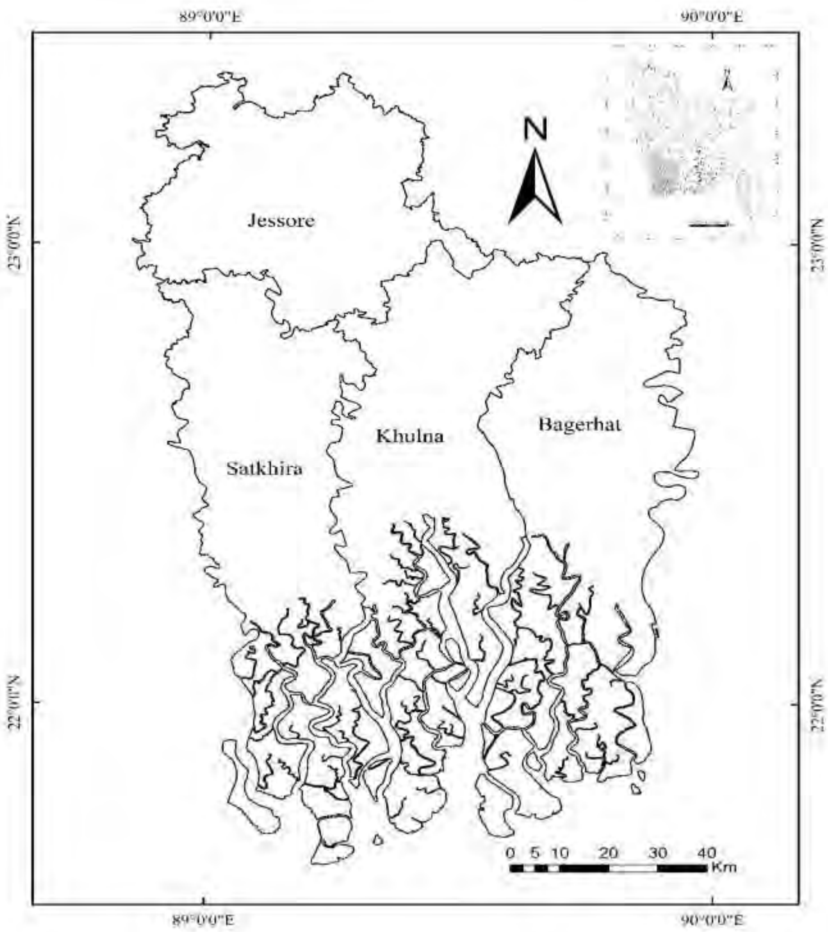


Figure 1.1: Study Area

1.2 Objectives of the study

The main objectives of the study are:

i. To derive and assess hydrological and meteorological drought indices in the South-West region of Bangladesh.
ii. To prepare drought hazard map.
iii. To forecast drought with the help of a stochastic model

1.3 Possible outcome

This study is expected to reveal the characteristics of drought, their trend for coastal Bangladesh and drought forecasting using ARIMA modeling technique. Implementation of both rainfall and temperature based method of drought identification will potentially improve the understanding of drought scenario in the study area and efficiency of future forecasting. Meteorological drought will be calculated on both annual and seasonal basis. Characterization of seasonal drought will significantly help in crop production. Coastal Bangladesh is threatened by salinity intrusion on a massive scale, an increasing drought will fasten the inland salinity movement. Therefore, a clear and accurate understanding of drought might act as a decision-making tool in salinity coping strategy. Frequency analysis of extreme drought will help in understanding how extreme drought events evolve over time. Spatial mapping of change pattern will identify the most vulnerable areas that require extra care. Forecasting of drought will help in advance preparation of drought mitigation strategies. Results obtained from RDI can also be used as a climate change indicator because possible increasing drought events potentially signify the changes in rainfall and temperature.

1.4 Limitations of the study

The considerable limitation of the study could be the several missing values in the ground water level data. However, normalizing the results compensate the effects of missing values index calculation. Furthermore, suitability of other forecasting models except ARIMA is not addressed.

1.5 Outline of the thesis

The first chapter discusses the relevant background and importance of the study. The objectives of the current study are also presented in this chapter.

The Second Chapter elaborately discusses the relevant literature. Several definitions which are relevant to the current study are also discussed in this chapter. Finally, comparative discussion of the available methodologies are also presented.

The third chapter briefly discusses the data collection and various methods used in the current study. Brief description of missing value analysis is also presented here.

The fourth chapter presents the results found in this study. Drought setting obtained from RDI is compared with image based NDVI. The results are followed by some relevant discussion.

The fifth chapter presents a summary of the results. Besides, recommendations for possible future studies are made in this chapter.

Chapter 2. Literature Review

2.1 Introduction

In this chapter, the term drought is defined in brief. Types of droughts and various drought indices are also discussed. History of drought and their possible impact in Bangladesh is reviewed from literature.

2.2 Drought

Droughts are recognized as an environmental disaster that occurs in virtually all climatic zones, such as high as well as low rainfall areas and are mostly related to the reduction in the amount of precipitation received over an extended period of time, such as a season or a year (Mishra and Singh, 2010). In contrast to aridity, which is a permanent feature of climate and is restricted to low rainfall areas, a drought is a temporary aberration (Mishra and Singh, 2010).

2.3 Drought definitions

The World Meteorological Organization glossary define drought as the following (Lloyd-Hughes, 2014):

1. prolonged absence or marked deficiency of precipitation
2. period of abnormally dry weather sufficiently prolonged for the lack of precipitation to cause a serious hydrological imbalance

This definition lacks information like evaporation and transpiration, lateral inflows (stream and ground-water flows) etc.

A better definition of drought is given by Palmer (1965). He defined drought "Is an interval of time, generally of the order of months or years in duration, during which the actual moisture supply at a given place rather consistently falls short of the climatically expected or climatically appropriate moisture supply" (Palmer, 1965).

2.4 Classification of droughts

The droughts are classified into several categories till now. However, for discussion, The droughts are generally classified into four categories (Mishra and Singh, 2010; Wilhite and Glantz, 1985) which are:

2.4.1 Meteorological drought

Meteorological definitions of drought are the most widespread. Precipitation has been used commonly for the analysis of meteorological drought as the definition became solely on the degree of dryness. In terms of precipitation, drought is defined as a lack of precipitation over a region for a period of time (Wilhite and Glantz, 1985). Considering drought as precipitation deficit from long-term average, numerous studies are done already. However, several approaches analyze drought duration and intensity in relation to cumulative precipitation shortages (Chang and Kleopa, 1991; Estrela et al.,2000).

Meteorological drought definitions are also often site-specific. Therefore, they often create problems when intended to apply for another region. This is because “Meteorological drought” more specifically depends on what are the “normal” climatic conditions of a certain region. Therefore, in order to characterize and study the problem of meteorological drought, it is necessary to be familiar with the typical meteorological configurations on the synoptic and sub-synoptic scale responsible for precipitation in the studied region (Rossi et al., 2007).

2.4.2 Hydrological drought

Hydrological drought is related to a period with inadequate surface and subsurface water (Ground water) resources for established water uses of a given water resources management system (Mishra and Singh, 2010).Therefore, hydrological drought can be classified into Surface water drought and Ground water drought.

Definitions of hydrologic drought are concerned with the effects of dry spells on surface or subsurface hydrology, rather than with the meteorological explanation of the event (Wilhite and Glantz, 1985). It is a period during which streamflows are inadequate to supply required water (Dracup et al., 1980). Sometimes hydrological droughts are often out of phase with both meteorological and agricultural drought. It is common that hydrological droughts are defined on the basis its influence on river basin (Wilhite and Glantz, 1985). As the current study focuses on the ground water drought as a hydrological drought, a brief description is given in section 2.5.

2.4.3 Agricultural drought

Agricultural drought refers to a period with declining soil moisture and subsequent crop failure without any reference to surface water resources (Mishra and Singh, 2010). Agricultural drought” links the characteristics of meteorological drought to agricultural needs and is defined as a condition in which the amount of moisture in the soil is insufficient for the needs of a particular crop (Wilhite and Glantz, 1985). Several factors affect the declination of soil moisture which affects meteorological and hydrological droughts (Mishra and Singh, 2010). The deficit derives from the difference between the amount of moisture in the soil and the loss of moisture due to various physical processes (evaporation, runoff, surface infiltration, etc.). To study the agricultural drought several drought indices have been derived based on a combination of precipitation, temperature and soil moisture. It is enumerated that this type of drought depends on the type of crop and of soil (Rossi et al., 2007).

2.4.4 Socio-economic drought

Socio-economic drought is the shortage in supply for an economic good that results from a deficiency in the water supply. However, the water deficiency must be weather related. Sanford (Sandford, 1979) said that drought should not only be linked to precipitation (supply) but also to trends or fluctuations in demand as well as to issues other than weather which influence supply.

2.5 Groundwater drought

Ground water is a type of hydrological drought. The first effect of droughts on groundwater is recharge and later groundwater levels and finally groundwater decrease in discharge (Mishra and Singh, 2010). Groundwater droughts generally occur on a timescale of months to years (Lanen and Peters, 2000). Most often a groundwater drought is defined by the decrease of groundwater level.

2.6 Drought types and characteristics

Droughts are essentially characterized in three dimensions: severity, duration, and spatial distribution. In addition to that, frequency, magnitude (cumulated deficit), predictability, the rate of onset, and timing are also some drought characteristics. However, usage of the terms severity, intensity, and magnitude is not universal, and sometimes their meanings are changed.

2.6.1 Duration

Drought's duration can vary between a week up to a few years depending on the location and weather condition. Besides, a region can experience wet and dry spells simultaneously when considering various timescales. As such, in shorter durations, the region experiences dryness or wetness, while in longer-term, it experiences the opposite (NCDC 2010).

2.6.2 Magnitude and Frequency

Magnitude defines as the accumulated deficit of water (e.g., precipitation, soil moisture, or runoff) below some threshold during a drought period while frequency states the average time between drought events that have a severity that is equal to or greater than a threshold. Frequency is also known as return period.

2.6.3 Intensity and Severity

Intensity is the ratio of drought magnitude to its duration and Severity is the degree of the precipitation deficit (i.e., magnitude), or the degree of impacts resulting from the deficit (Wilhite 2005).

2.6.4 Geographic extent

The areal coverage of the drought which is variable during the event. This area can cover one or several regions.

2.7 Drought indicators

Indicators are variables which can describe the magnitude, duration, severity, and spatial extent of a certain phenomenon. Typical drought indicators are precipitation, streamflows, soil moisture, reservoir storage, and groundwater levels (Wilhite, 2005). These indicators play an important role in defining drought of a region. Several indicators can be synthesized into a single indicator on a quantitative scale, often called a drought index.

Meteorological drought indicators are climatological variables such as precipitation, temperature, and evapotranspiration. However, precipitation is most widely used and a very useful indicator that can directly measure water supplies, influences hydrological indicators, and it can reflect drought impacts over different time periods and sectors. Hydrological drought indicators are water system variables such as groundwater levels, stream flows, reservoir storage, soil moisture, and snowpack.

2.8 Effects of drought

The drought has a substantial impact on the environment and living lives. Drought can cause social, economic and environmental problems. However, the perception of drought hazards varies according to (a) degree of aridity, (b) amount of drought experience, (c) personality differences, (d) age of respondent, (e) education level and (f) type of occupation (Nagarajan, 2009).

2.9 Drought indices

A drought index is a prime variable for assessing the effect of drought and defining different drought parameters (Mishra and Singh, 2010). Therefore, several drought indices have been derived. Different time scales ranging from months to even years are used to quantify droughts. Monthly or seasonal time scales are practically important in many of agricultural and water-related aspects, the annual timescale still helps in understanding the overall drought scenario of a region (Panu and Sharma, 2002).

It should be noted that a drought variable should be able to quantify the drought for different time scales. The most commonly used time scale for drought analysis is a year, followed by a month. The yearly timescale can be used to abstract information on the regional behavior of droughts. The monthly time scale seems to be more appropriate for monitoring the effects of a drought in situations related to agriculture, water supply and groundwater abstractions (Panu and Sharma, 2002). Although drought indices can deliver ease of implementation, the scientific and operational meaning of an index value may raise questions, such as how each indicator is combined and weighted in the index and how an arbitrary index value relates to geophysical and statistical characteristics of drought. Till the date, a number of different indices have been developed to quantify a drought, all with its own strengths and weaknesses.

Based on the studies for drought indices, practically all drought indices use precipitation either singly or in combination with other meteorological elements, depending upon the type of requirements, which were also suggested by WMO (1975) (Mishra and Singh, 2010).The following section discusses commonly used drought indices, their usefulness, limitations, and comparison between different indices.

2.9.1 Standardized precipitation index (SPI)

The standardized precipitation index (SPI) for any location is calculated based on the long-term precipitation record for the desired period (Mishra and Singh, 2010). This long-term record is fitted to a probability distribution, which is then transformed to a normal distribution (McKee et al., 1993). SPI can be calculated for a variety of timescales. The short time SPI index allows monitoring short term water supplies such as soil moisture. Meanwhile, long term SPI allow monitoring long-term water resources, such as groundwater supplies, stream flow, and lake and reservoir levels. Groundwater, streamflow, and reservoir storage reflect the long-term precipitation anomalies. However, the length of precipitation record and nature of probability distribution play an important role in calculating SPI (Mishra and Singh, 2010).

2.9.2 Palmer drought severity index (PDSI)

Using precipitation and temperature for estimating moisture supply and demand within a two-layer soil model, Palmer (Palmer, 1965) formulated what is now referred to as the Palmer drought index (PDI). This was the first comprehensive effort to assess the total moisture status of a region. Since its inception, some modified versions of PDSI have evolved. PDSI is perhaps the most widely used regional drought index for monitoring droughts (Mishra and Singh, 2010). The index has been used to illustrate the areal extent and severity of various drought episodes as well as to explore the periodic behavior of droughts, monitoring hydrologic trends, crop forecasts, and assessing potential fire severity, droughts over large geographic areas, and drought forecasting (Mishra and Singh, 2010).

Limitations of PDSI include: (1) an inherent time scale making PDSI more suitable for agricultural impacts and not so much for hydrologic droughts, (2) assumptions that all precipitation is rain, thus making values during winter months and at high elevations often questionable. PDSI also assumes that runoff only occurs after all soil layers have become saturated, leading to an underestimation of runoff, and (3) PDSI can be slow to respond to developing and diminishing droughts (Mishra and Singh, 2010).

2.9.3 Crop moisture index (CMI)

Palmer (Palmer, 1968) developed crop moisture index (CMI) to evaluate short-term moisture conditions (week to week) across major crop-producing regions. Computation of CMI involves the use of weekly values of temperature and precipitation to compute a simple moisture budget. Variables from the moisture budget computation are compared to long-term average values and are modified by empirical relations to arrive at final CMI values.

Based on a sensitivity analysis an increase in CMI may occur with an increase in potential evapotranspiration. The unnatural response of CMI to changes in temperature is due to the dependence of the abnormal evapotranspiration term on the magnitude of potential evapotranspiration. Secondly, CMI is not a good long-term drought monitoring tool. CMI’s rapid response to changing short-term conditions may provide misleading information about long-term conditions.

2.9.4 Surface water supply index (SWSI)

The surface water supply index (SWSI) was primarily developed as a hydrological drought index and it is calculated based on monthly non-exceedance probability from available historical records of reservoir storage, streamflow, snowpack, and precipitation. The purpose of SWSI is primarily to monitor abnormalities in surface water supply sources.

2.9.5 Vegetation condition index (VCI)

Since the 1970s, several studies have used satellite land observation data to monitor a variety of dynamic land surface processes (Mishra and Singh, 2010). Satellite remote sensing provides a synoptic view of the land and a spatial context for measuring drought impacts which have proved to be a valuable source of timely, spatially continuous data with improved information on monitoring vegetation dynamics over large areas. The VCI allows detection of drought and measurement of the time of its onset and its intensity, duration, and impact on vegetation. However, since the VCI is based on vegetation, it is primarily useful for the summer growing season. It has limited utility for cold seasons when vegetation is largely dormant (Heim, 2002).

2.9.6 Effective precipitation (EP)

Effective precipitation uses daily precipitation data to precisely determine drought duration, onset, and withdrawal of drought periods. EP is followed by three additional indices which are each day's mean of EP (MEP), the deviation of EP (DEP) from MEP and the standardized value of DEP (SEP). Using these three indices, water deficit period are characterized.

2.9.7 Standardized runoff index (SRI)

This index is based on the concept of standardized precipitation index (SPI), discussed earlier. Standardized runoff index (SRI) which incorporates hydrologic processes that determine the seasonal loss in stream flow due to the influence of climate (Mishra and Singh, 2010). As a result, on the month to seasonal time scales, SRI is a useful complement to SPI for depicting hydrological aspects of droughts.

2.9.8 Index based on remote sensing

The normalized difference water index (NDWI) is a more recent satellite-derived index from the near infrared (NIR) and shortwave infrared (SWIR) channels that reflect changes in both the water content and spongy mesophyll in vegetation canopies.

2.9.9 Drought monitor (DM)

Drought monitor (DM) incorporates climatic data and professional input from all levels (Svoboda, 2000). A shortcoming of DM lies in its attempt to show droughts at several temporal scales on one map product (Heim Jr, 2002).

2.9.10 Reconnaissance drought index (RDI)

The Reconnaissance Drought Index (RDI) was developed to address the water deficit in a more accurate way, using both precipitation and potential evapotranspiration as a sort of balance between input and output in a water system (Tigkas et al., 2015). A detail description of RDI as a composite drought indicator is given in section 2.11.

2.10 Drought study in Bangladesh

Drought, a curse for the farmers of Bangladesh had its impact several times in the country. Drought phenomenon is experienced in the country from the past. Drought study in Bangladesh was mainly confined for northwestern Bangladesh due to a popular impression that drought occurs mainly in that part. However, recent studies are expanded to other part of the country considering the recent climate change phenomenon. An empirical literature review of drought studies in Bangladesh is given in here.

Brammer (Brammer, 1987) reported from his long term experience in the country that drought can sometimes cause greater loss than floods and cyclones. He reported that the 1978-1979 drought in Bangladesh affected three crop seasons, reducing rice production by an estimated two million tons. Yet, drought was not considered seriously in the country. However, several innovative initiatives were taken by farmers to compensate for the loss. Karim (Karim, 1995) described that almost every year the entire south-western part of the country covering greater Kushita, Jessore, Faridpur, Barisal and Khulna districts are worst hit by drought following the withdrawal of the Ganges water by India at Farakka Barrage.

A rainfall deficiency and Climatic Indexes based analysis of drought events in the eastern part of Bangladesh by Keka et al. (Keka et al., 2012) shows that November to March all the study area experiences a drought. The study also gives crude information about several drought events in the study area.

A recent study by Hossain et al. (Hossain et al., 2016) suggested that farmers of Barind tract adjusted their cropping pattern and practice to compensate the recurrent drought events. Their study revealed that rainfall pattern has changed, the temperature has increased, and droughts have become more frequent phenomena in the upper Barind region as well as in the study villages. Another study by Kabir et al. (Kabir et al., 2017) in an drought-prone western rural part of Bangladesh reported that limited access to stress-tolerant varieties, extension services, and affordable agricultural credit, combined with high production costs, variability in crop yields and output prices, are the main barriers to adaptation to climate change. They suggested that farmers' adaptation measures can be accelerated proving an aid to them. It is proposed that the government should be prepared for drought long before the occurrence of such an event (Paul, 1998).

Abdullah (Abdullah, 2014) claimed that the northern part of Bangladesh is undergoing a desertification process due to cross-country anthropogenic activities (Barrage/Dams on the upstream) caused a severe negative impact on water resources and eco-systems of Bangladesh in the recent years. Standardized precipitation evapotranspiration index (SPEI) was used to determine drought in 28 meteorological stations in Bangladesh. He also claimed that vulnerability to both extreme and severe drought event is dominant in northeastern part of Bangladesh. Murad and Islam (Murad and Islam, 2011) also reported that central, northern and southwestern districts of the northwestern region of Bangladesh are more prone to agricultural and meteorological drought.

An SPI (Standardized precipitation index) based seasonal drought study was done by Alamgir et al. (Alamgir et al., 2015a). Their study revealed that the spatial characteristics of droughts vary widely according to the season. They also stated that monsoon droughts are dominant in the west and northwest part of the country, Premonsoon droughts in the northwest, winter droughts in the west, and the Rabi and Kharif droughts are more frequent in the north and northwest part. However, as their study included a large number of missing data prediction indices might be over (under) calculated for those timescales. In another study done by Alamgir et al (Alamgir et al., 2015b) monsoon extreme drought events are mainly experienced in north and northwest of Bangladesh. They have found that extreme droughts during monsoon occur once in every 18 years in northwest Bangladesh.

Although, there is a popular impression that drought occurs mainly in the northwestern Bangladesh, moderate and severe drought are reported also in the coastal and central southern region of Bangladesh (Shahid and Behrawan, 2008).

A study on on-farm reservoirs (OFRs) for elevating drought in the Rajabarihat of Godagari Thana of Rajshahi District (Islam et al., 1998) shows that OFRs can be useful but they have various social constraints and sometimes are over-designed.

Till now, as it is realized from the literature, drought study in Bangladesh has been done using precipitation as the main variable particularly using SPI as a drought index. Therefore, in the current thesis, a more advanced index called RDI is intended to use.

2.11 RDI as a composite indicator

This study has been furnished using RDI as a drought indicator. RDI uses both precipitation and Potential Evapotranspiration and therefore expected to outperform Indices based on precipitation only. RDI exhibits significant advantages over the other indices by including potential evapotranspiration together with precipitation (Tsakiris et al., 2007). It is reported that RDI is more sensitive and suitable in cases of a changing environment than SPI (Tsakiris et al., 2007).

A comparative study of SPI and RDI in arid and semiarid regions of Iran recommend RDI for 1 to 6 months scale drought assessment (Shamsnia, 2014). RDI is a simple index that is less data demanding and computationally less intensive (Nalbantis and Tsakiris, 2009). RDI require less data has high sensitivity and resilience (Tigkas et al., 2012; Zarch et al., 2011). In addition to assess meteorological drought, RDI can be used to forecast level of hydrological drought for the entire year in real time when used in conjunction streamflow drought index (SDI) (Tigkas et al., 2012).RDI has been used in Mexico and found that calculated indices agree with the results obtain from agricultural losses due to drought (Bautista-Capetillo et al., 2016).

RDI has been also used to obtain future drought situation based on optimistic scenario in Greece (Tigkas, 2008). While seasonal RDI index is used to develop a drought monitoring system in the same region (Tigkas, 2008). RDI is even used in meteorological monitoring network design (Tsakiris et al., 2008). Besides the use of RDI in assessment, this index can be used as a single climatic index for the detection of possible climate changes (Tigkas et al., 2013). This index can also detect seasonal changes when used for short reference period (Tigkas et al., 2013). Mohammed and Scholz (Mohammed and Scholz, 2017) commented that RDI is better in detecting a trend of climate variability compared to using time series of precipitation and potential evapotranspiration separately.

2.12 Drought forecasting using ARIMA model

ARIMA (Auto Regressive Integrated Moving Average) is a widely used stochastic process in Hydrology (Modarres, 2007). ARIMA is divided in the two general forms namely non-seasonal ARIMA(p, d, q) and multiplicative seasonal ARIMA(p, d, q) x (P, D, Q) in which p and q are non-seasonal autoregressive and moving average, P and Q are seasonal autoregressive and moving average parameters, respectively. The other two parameters, d, and D, are required differencing used to make the series stationary (Modarres, 2007).

ARIMA effectively consider serial linear correlation among observations while SARIMA (Seasonal ARIMA) models are used to describe time series that exhibits nonstationarity both within and across seasons (Mishra and Singh, 2011).

A multiplicative seasonal autoregressive integrated moving average (SARIMA) model is applied to the monthly streamflow forecasting of the Zayandehrud River in western Isfahan province, Iran and found useful (Modarres, 2007).

ARIMA modeling is used in rainfall prediction in Bangladesh (Mahsin et al. 2012; Bari et al. 2015; Mahmud et al. 2016; Rahman et al. 2017). ARIMA has also been used in Boro Rice production in Bangladesh (Rahman, 2010). ARIMA has a vast application on forecasting of rainfall trend, reservoir, and river modeling, economics and production, evapotranspiration (Bari et al., 2015).

ARIMA and SARIMA based approach have been satisfactorily used for drought forecasting up to two months ahead (Durdu, 2010; Mishra and Desai, 2005). Using a multiplicative SARIMA model, Fernández et al. (Fernández et al., 2009) forecasted stream flow with a 12 month lead time and then derived different drought indices based on streamflow mean, monthly stream flow mean and standardized streamflow index. Predicted data were then used to generate future drought events.

It is seen that ARIMA method has been successfully applied for forecasting drought in different areas. Mossad and Alazba (Mossad and Alazba, 2015) commented that ARIMA models can be very useful in forecasting droughts. Mishra and Desai (Mishra and Desai, 2005) applied ARIMA models to forecast SPI series in the Kansabati river basin in India up to the 2-time step. VTCI based drought time series Guanzhong Plain, Shaanxi was forecasted by Han et al. (Han et al., 2010) using the ARIMA model. In addition to univariate drought indices, ARIMA has been used to satellite image-based drought forecasting (Han et al., 2010).

In addition to ARIMA, ANN models has been also applied to forecast drought in several regions. Morid et al. (Morid et al., 2007) applied ANN models to forecast EDI and SPI for several rainfall stations in the Tehran Province of Iran.

Mishra and Desai (Mishra and Desai, 2006) commented that ARIMA and ANN provide satisfactory results for 1 to 4 months ahead.

Chapter 3. Methodology

3.1 Introduction

This chapter discusses the various methods used in this thesis. At first, the Reconnaissance Drought Index (RDI) is narrated in details. After that ARIMA modeling technique and Groundwater Drought Index (GDI) is described. In addition, Mann-Kendall test and Sequential Mann-Kendall tests are also discussed.

3.2 Estimation of reconnaissance drought index (RDI)

The Reconnaissance Drought Index (RDI) is, as a general, meteorological index for drought assessment (Thomas et al., 2016). The RDI is assumed to be more realistic compared to other rainfall based indices as it includes potential evapotranspiration (PET) in addition to precipitation. RDI can be effectively used to compare the drought conditions for areas with varied climatic characteristics (Thomas et al., 2016). This is the distinct advantage of RDI as it enables its universal applicability in contrast to other indices.

The RDI can be expressed in three forms: the initial value (a_k), normalized RDI (RDIn), and standardized RDI (RDIst) (Tigkas, 2008). The initial value (a_k) is presented in an aggregated form using a monthly time step and may be calculated on a monthly, seasonal or annual basis. It is calculated in a time basis of k (months) using the following equation

$$a_k^{(i)} = \frac{\sum_{j=1}^{k} P_{ij}}{\sum_{j=1}^{k} PET_{ij}}, i = 1\ to\ N \text{……….3.1}$$

Where Pij and PETij are precipitation and PET of the j-th month of the i-th year and N is the total number of years of the available data. The normalized RDI (RDIn) is computed using:

$$RDI_{n(k)}^{(i)} = \frac{a_k^{(i)}}{\bar{a}_k} - 1 \text{……….3.2}$$

Where, $\overline{a_k}$ is the arithmetic mean of a_k values.

The initial formulation of the standardized RDI (RDIst) (Tsakiris and Vangelis, 2005) used the assumption that a_k values follow the lognormal distribution, and thus:

$$RDI_{st(k)}^{(i)} = \frac{y_k^{(i)} - \overline{y_k}}{\widehat{\sigma_{yk}}} \text{………..3.3}$$

Where y_k is $\ln(a_k^{(i)})$, $\overline{y_k}$ is the arithmetic mean of y_k and $\widehat{\sigma_{yk}}$ is its standard deviation.

The values of α_k follow satisfactorily both the lognormal and the gamma distributions in a wide range of locations and different time scales, in which they were tested (Tigkas, 2008; Tsakiris et al., 2008). However, gamma shows the best fit in most locations and timescales (Tsakiris et al., 2008).

In case the gamma distribution is applied, the RDIst can be calculated by fitting the gamma probability density function (pdf) to the given frequency distribution of αk (Tigkas, 2008; Tsakiris et al., 2008). For short reference periods (e.g. monthly or 3-months) which may include zero values (in our study) for the cumulative precipitation of the period, the RDIst can be calculated based on a composite cumulative distribution function including:

- the probability of zero precipitation, and
- the gamma cumulative probability

As the Standardized RDI and SPI perform in a similar manner, they have a similar interpretation of results. Therefore, the RDIst values could be compared to the same thresholds as that of the SPI technique (Table 3.1). Positive values of RDIst indicate wet periods (Table 3.1), while negative values indicate dry periods compared to the normal conditions of the study area.

Table 3.1: Classification of drought according to the SPI and RDIst values (Zarch et al., 2011)

RDIst Range	Drought Class
2 or more	Extremely wet
1.5 to 1.99	Very Wet
1 to 1.49	Moderately wet
0.99 to 0.0	Normal
0.0 to -0.99	Near Normal
-1 to -1.49	Moderately dry
-1.5 to 1.99	Severely dry
-2 and less	Extremely dry

In addition to the range in the table, values from -0.50 to -0.99 may be considered as a different category characterized as “mild drought” (Shamsnia, 2014).

It should be emphasized that the RDI is based both on precipitation and on potential evapotranspiration. The mean initial index represents the normal climatic conditions of the area and is equal to the "Aridity Index" (Tigkas et al., 2013). Among others, some of the advantages of the RDI are as follows:

1. It is physically sound since it calculates the aggregated deficit between precipitation and the evaporative demand of the atmosphere.
2. It can be calculated for any period of time (e.g., 1 month, 2 months etc.).
3. The calculation always leads to a meaningful figure.
4. It can be effectively associated with agricultural drought.
5. It is directly linked to the climatic conditions of the region since for the yearly value it can be compared with the FAO (Food and Agricultural Organization) Aridity Index.
6. It can be used under "climate instability" conditions, for examining the significance of various changes in climatic factors related to water scarcity.

It should be noted, that the method of calculation of PET does not have any significant effect on RDIst, meaning that temperature based methods, can be sufficient for producing reliable RDI results (Vangelis et al., 2013).

3.3 Mann-Kendall trend test (MK Test)

Mann-Kendall test (Hamed and Rao, 1998; Kendall, 1970; Mann, 1945) justifies the null hypothesis H_0 of no trend (i.e. the observations xi are randomly ordered in time) against the alternative hypothesis, H_1 of there is trend present (i.e. there is increasing or decreasing trend). The Mann-Kendall test evaluates data as an orderly time series. In the test, each data is compared with all subsequent data values. To perform the test, Kendall's S statistic is computed from the Y, T data pairs. The null hypothesis H_0 is rejected when S (and therefore Kendall's τ of Y versus T) is significantly different from zero. We then conclude that there is a monotonic trend in Y over time.

If x_1, x_2, x_3..... x_i represent n data points where x_j represents the data point at time j, then S is given by,

$$S = \sum_{k=1}^{n-1} \sum_{j=k+1}^{n} sign\ (x_j - x_k) \ \ldots\ldots\ldots 3.4$$

Where

$$Sign\ (x_j - x_k) = \begin{cases} +1\ if\ \ (x_j - x_k) > 0 \\ -1\ if\ \ (x_j - x_k) < 0\ . \\ \ \ 0\ if\ \ (x_j - x_k) = 0 \end{cases}$$

3.4 Sequential Mann-Kendal test (SQMK)

The SQMK (Sneyers, 1990) test is particularly used for determining steep change or fluctuations of the trend over time. This test sets up two series, a progressive one u(t) and a backward one u'(t). If they cross each other and diverge beyond the specific threshold value, then there is a statistically significant trend (Bari et al., 2016). The critical value of u(t) is the same as the z values found in Mann-Kendal trend test (Bari et al., 2016).

This test considers the relative values of all terms in the time series (x_1, x_2,... x_n). Following steps are applied to calculate u(t) and $u'(t)$:

1. The values of x_j annual mean time series, (j=1... n) are compared with x_i, (i =1,...,j−1). At each comparison, the number of cases $x_j > x_i$ is counted and denoted by n_j.

2. The test statistic t is then calculated by equation

$t_j = \sum_1^j n_j$……….3.5

3. The mean and variance of the test statistic are

$E(t) = \frac{n(n-1)}{4}$ and $Var(t_j) = [j(j-1)(2j+5)]/72$……….3.6

4. The sequential values of the statistic u(t) are then calculated as

$u(t) = \frac{t_j - E(t)}{\sqrt{Var(t_j)}}$……….3.7

The values of $u'(t)$are computed similarly backward, starting from the end of the series.

3.5 Kendall's Tau

Tau (Kendall, 1938, Kendal, 1970,1975) measures the strength of the monotonic relationship between x and y. Tau is a rank-based procedure and is therefore resistant to the effect of a small number of unusual values. Tau is easy to compute, resistant to outliers, and measures all linear and nonlinear monotonic correlations.

Kendall’s Tau correlation coefficient is given by

$\tau = \frac{S}{n(n-1)/2}$……….3.8

3.6 Drought monitoring using NDVI

NDVI is widely used to assess the vegetation in any study area. Although NDVI does not gives information about drought in true sense, it is mainly useful in getting information regarding greenness. This idea is however, often used in drought assessment. The methodological steps of NDVI calculation is briefly described in section 4.6.

3.7 ARIMA model

Auto Regressive Integrated Moving Average (ARIMA) is widely used to analyze and forecast equally spaced univariate time series data (SAS Institute, n.d.). The ARIMA modeling process was disseminated widely by Box and Jenkins, and therefore often referred to as Box-Jenkins modeling (Bari et al. 2015; Mahmud et al. 2016). ARIMA is considered to be one of the precise model for predicting time series data (Mahmud et al. 2016).

Developing an ARIMA model require four basic steps: identification, estimation, diagnostic checking, and forecasting (Bari et al., 2015; Mahmud et al., 2016). These steps are presented in Figure 3.1. A detail discussion of ARIMA procedure can be found elsewhere e.g. (Mishra and Desai 2005; Bari et al. 2015; Mahmud et al. 2016).

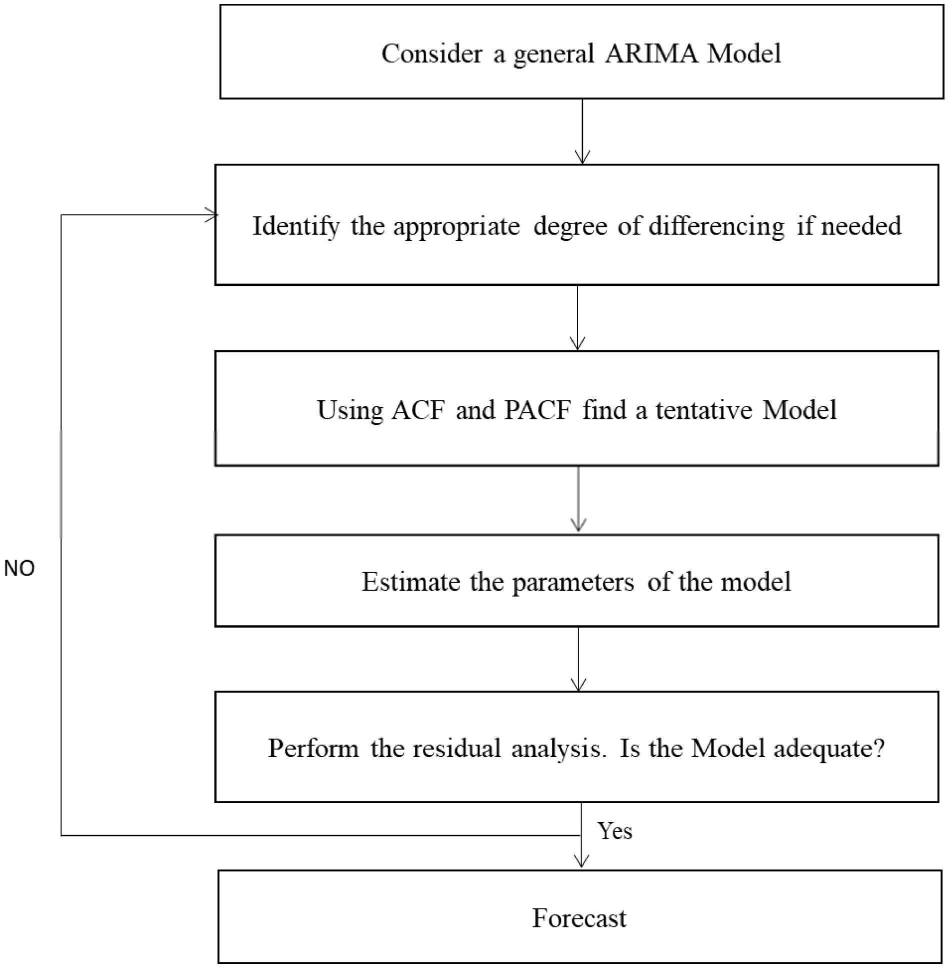


Figure 3.1: ARIMA model development process (Bari et al. 2015)

The seasonal ARIMA model incorporates both non-seasonal and seasonal factors in a multiplicative model. One shorthand notation for the model is ARIMA (p, d, q) × (P, D, Q)S, with p = non-seasonal Auto Regressive (AR) order, d = non-seasonal differencing, q

= non-seasonal Moving Average (MA) order, P = seasonal AR order, D = seasonal differencing, Q = seasonal MA order, and S = time span of repeating seasonal pattern (Box et al. 1994).

3.8 Ground water drought analysis

Among the three available variables of groundwater drought assessment, water level gives a direct and reasonable measurement of groundwater drought assessment (Shahid and Behrawan 2008). This is because the other two variables recharge and discharge measurement cannot be measured directly. In contrast, water level gives an indirect estimation of groundwater recharge and discharge. In this study, the threshold level approach (Hisdal et al., 2000; Lanen and Peters, 2000; Tallaksen et al., 1997) is used to identify groundwater drought. At first, a realistic groundwater level threshold is defined from long-term groundwater level data. Drought scenario is identified based on this threshold level. This method is self-illustrative and presented in the result section.

Chapter 4. Drought Assessment and Forecasting

4.1 Introduction

This chapter describes the details of results and discussion from this thesis. At first, missing values of the data were filled up with suitable techniques. After that RDI were calculated to proceed with the study. A trend analysis of RDI is performed to explore the recent trend drought scenario.

4.2 Data preparation

At the very first of the indices calculation, rainfall and temperature data were checked for inconsistency. As the RDI use monthly average data for PET calculation, monthly maximum and minimum average temperature were obtained from dividing available days. If a month was completely missing, the monthly average for this month was calculated from the average of previous year and next year data of the same station. In the case of rainfall data, a single value was calculated from the average of previous and next value. However, if there were multiple missing values, ARIMA models were used to predict the missing values. After evaluating several ARIMA models based on diagnostic check, ARIMA (0, 0, 0) (0, 1, 1) was found best. It is mentionable that the number of missing values very few, only a yearlong missing values were found for Jessore (1978).

4.3 Drought analysis

The annual drought characterization can provide a general image of the conditions of the area. In contrast, the seasonal variations of drought may play a much more important role in the study of agricultural production (Tigkas and Tsakiris, 2015). Therefore, in the current study annual as well as seasonal drought indices are calculated.

4.3.1 Seasonal drought analysis

Seasonal drought analysis consists of six months and three months duration RDI calculations. While six months RDI represent overall wet and dry period three months RDI is useful in understanding shorter duration scenario. The results of seasonal drought analysis are given in the following sections.

4.3.1.1 Three months drought

April to June

April to June is the time of moderate rainfall in Bangladesh. The RDI calculation for these three months shows a cycle of the periodic dry and wet period in the meteorological stations in the study area. The cycle is 3 to 4 years long in most of the cases. However, the cycle is shorter in recent time. All the stations in this region face several moderate to severe drought in the study period. Jessore faces two extreme droughts in the hydrologic year 1979-1980 and 2005-2006. Satkhira faces an extreme drought event in the year 2009-2010. RDI also reported several wet periods in the study area during the study period. For instance, RDI indicates a flood event in the hydrologic year 2002-2003. The time series plots of April to June RDIst is given in Figure 4.1

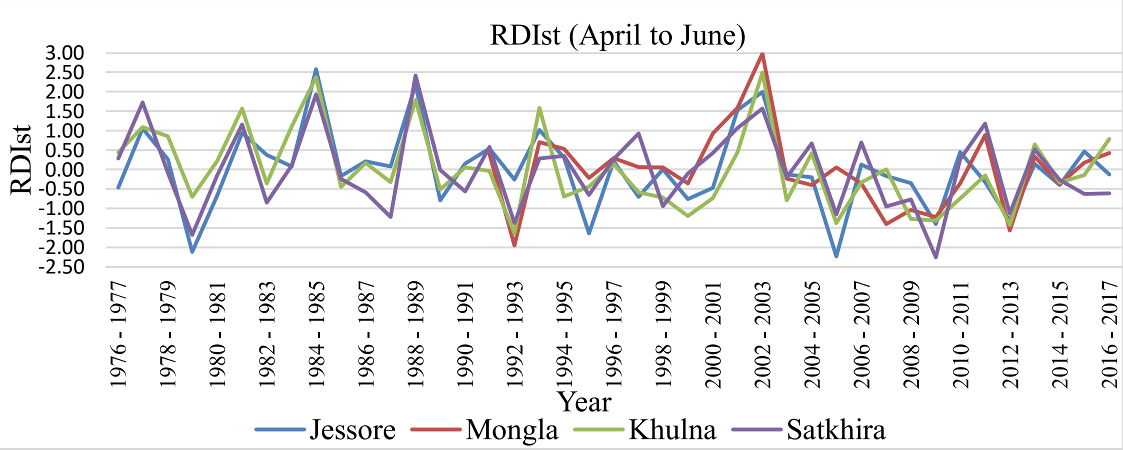


Figure 4.1: 3 Months RDIst (April to June)

July to September

Irregular periodic fluctuation of standardized RDI was found for July to September time scale. Jessore experienced several moderate droughts during the study period and an extreme drought event in the 2001-2002 hydrologic year. However, Khulna station experienced several moderate and severe drought event during the study period. The only extreme drought event found in Khulna was in the 2010-2011 year. All the four severe drought events in this station occurred during the time 1989-1996 with an interval of about 2 years. Two severe drought event occurred at Mongla at 2003-2004 and 2010-2010. In contrast, three severe droughts (1996-1997, 2010-2011, and 2016-2017) occurred at Satkhira during the study period. Both the Mongla and Satkhira experiences few moderate droughts in the study time. It is observed from the RDI that the whole study area experiences Severe to extreme drought in the 2010-2011 year. Time series plots of July to September are shown in Figure 4.2

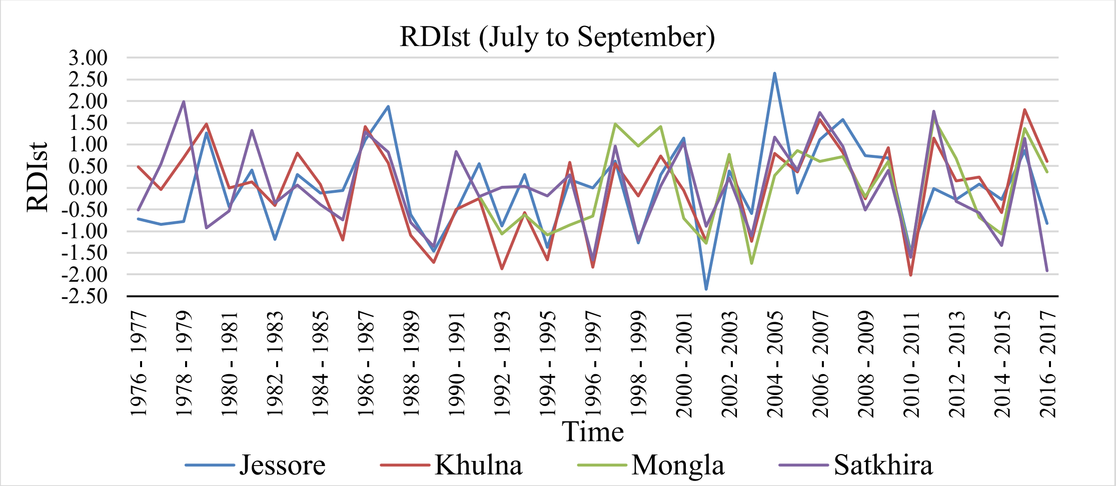


Figure 4.2: 3 Months RDIst (July to September)

October to December

Extreme drought occurred at Jessore (1976-1977), Khulna (2011-2012 and 2014-2015) and Mongla (1997-1998). No extreme drought events are detected for Satkhira station for this time period. However, all stations except Khulna faced two severe drought events during the study period. In addition to that, all stations experienced moderate drought. It is seen that the whole study area experienced moderate to extreme drought during the year 1982-1983, 1997-1998 and 2011-2012. Among these drought years, 2011-2012 is found greater in magnitude. Time series plots of October to December are shown in Figure 4.3

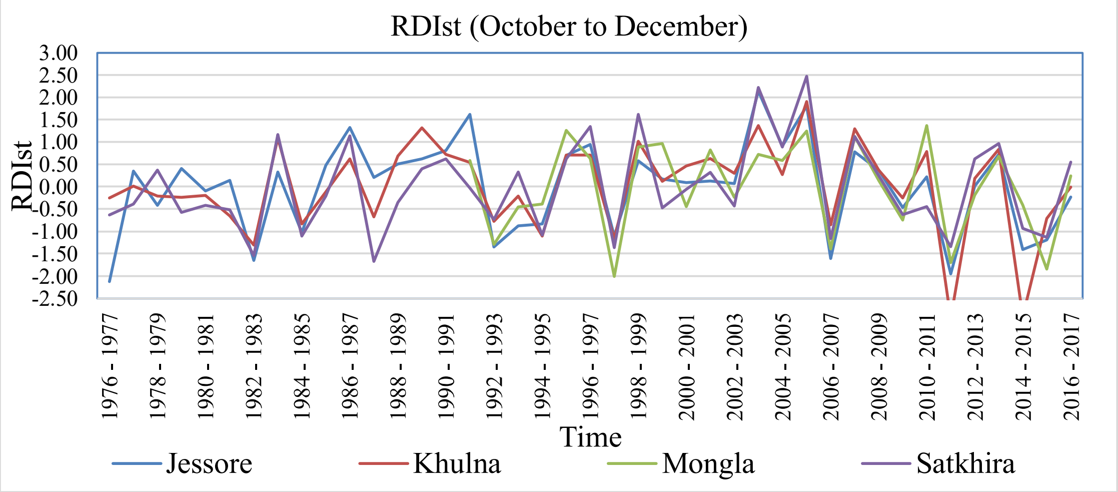


Figure 4.3: 3 months RDIst (October to December)

January to March

It is seen that the whole study area experienced severe drought during the hydrologic year 1998-1999. However, no extreme drought for any of the stations is seen. Standardized RDI shows that the maximum number of severe drought events are found in Satkhira station. While rest of the stations experienced 2-3 severe events. Time series plots of RDIst are shown in Figure 4.4

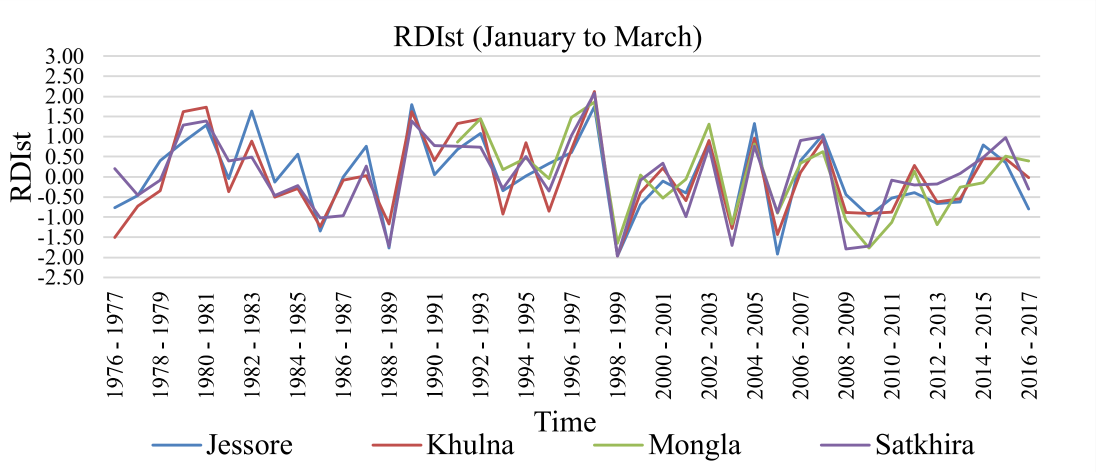


Figure 4.4: 3 months RDIst (January to March)

4.3.1.2 *<u>Six months drought</u>*

In addition to three months short-term drought index, six months index were calculated for the study area. Six months index is calculated for April to September and October to March. The first one represents the wet period while the second period represents a mostly dry period in Bangladesh.

April to September

During the wet period of the year, fluctuations of RDIst as seen in three months index are found (Figure 4.5). It is found that the study area experienced several moderate drought events while some severe drought events are limited (1 to 3). The only extreme drought encountered is at Khulna (1992-1993) and Mongla (1992-1993). Jessore station faced mild to moderate drought. The only severe drought is reported here is in 1989-1990. Meanwhile, Khulna experienced three severe drought events. Mongla station never experienced severe drought events in the study period. However, two severe drought events are found for Satkhira station.

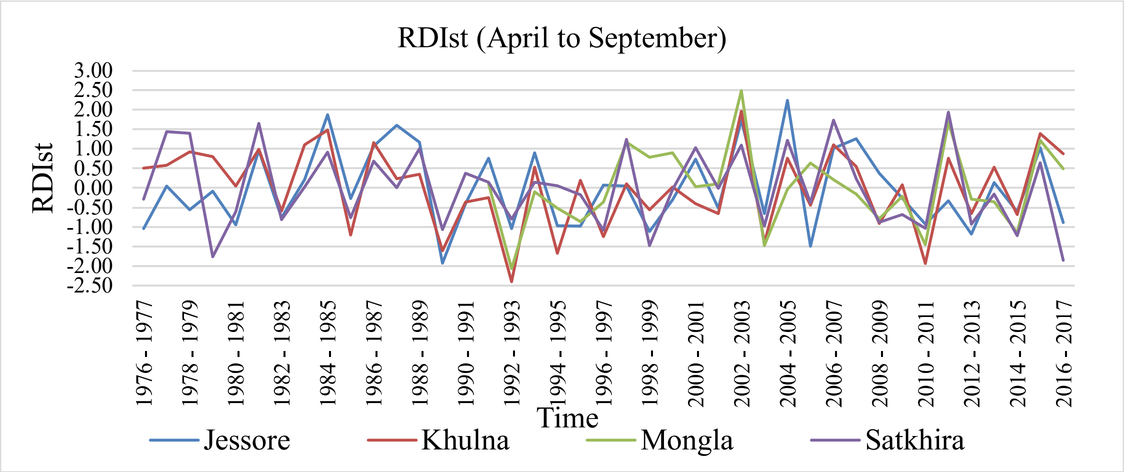


Figure 4.5: 6 Months RDIst (April to September)

October to March

October to march represents the dry months of a year in Bangladesh. Analysis of six-month drought will thus help in understanding the scenario of dry period drought in the study area. Every station experienced moderate to severe drought during the study period except Jessore. Jessore experienced two extreme droughts at 1976-1977 and 2011-2012 but no severe drought events are detected for this station. It is seen that severe drought events occurred during the recent past. In the case of moderate drought, it happened through the study period.

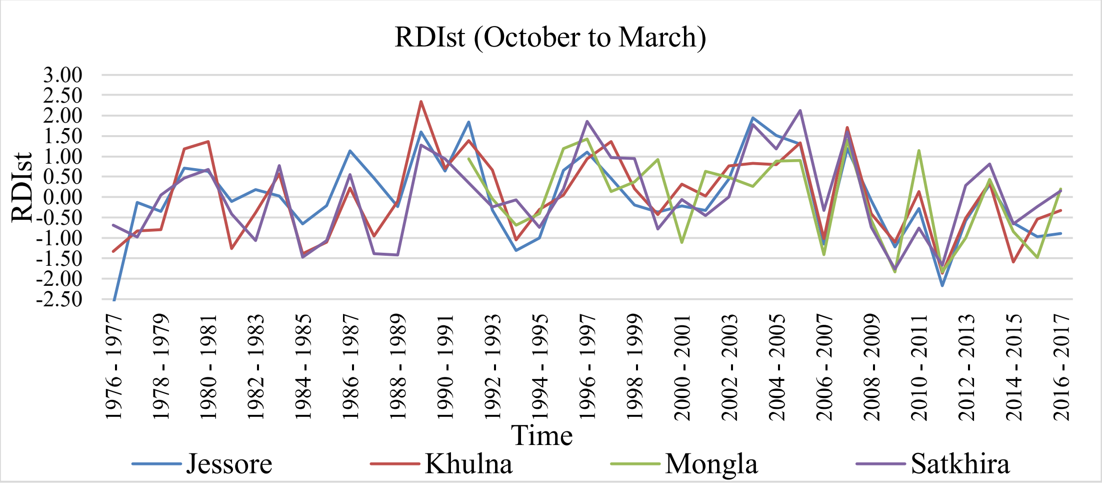


Figure 4.6: 6 Months RDIst (October to March)

4.3.2 *Annual drought*

Annual analysis helps to understand the overall water deficit for s station for a specific year. Although short duration seasonal drought can happen for a specific station, inter-annual positive and negative values can often suppress results of seasonal drought. Therefore, the resulting annual index can significantly vary. The annual RDIst results show that the whole study area experienced mild to extreme drought during the year 1992-1993 (Figure 4.7). During this, Khulna and Mongla experiences extreme event. It is found interesting that just after an all wet period (1991-1992), an all dry period occurred. Drought is found dominating till 2002-2003 when an all wet condition occurred. After a severe drought in 1976-1977 Jessore station does not experience any severe or extreme events. Although there are few moderate drought events. However, the scenario differs for the Khulna station. In addition to an extreme event, Khulna station experienced three severe droughts in the study period and three moderate droughts. No severe drought events are found for Mongla station. In Satkhira, several moderate droughts occurred along with three severe droughts.

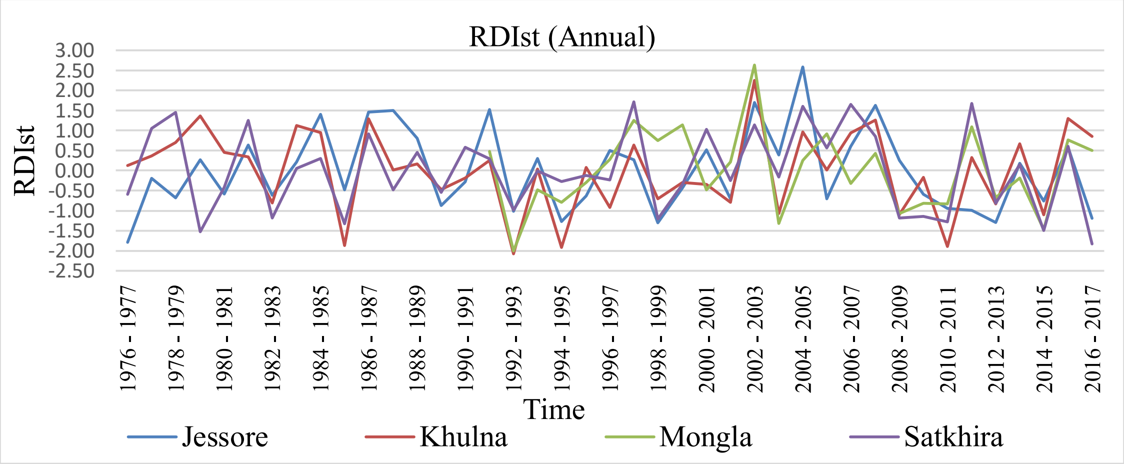


Figure 4.7: Annual RDIst

Although time series plot of seasonal RDI provides information about time and extent of drought events, a categorical representation can ease the process identification important events. Therefore, significant drought and wet events are separated from the time series and presented in Table 4.1

Table 4.1: Vital RDIst index values

Station		Time scale	Extreme Wet	Moderate Drought	Severe Drought	Extreme Drought
Jessore	3 Months	April-June	1984-85, 1988-89	2009-10, 2012-13		1979-80, 2005-06
		July-September		1982-83, 1994-95, 1989-90, 1998-99, 2010-11		2001-02
		October-December	2003-04	1984-85, 1992-93, 1997-98, 2015-16	1982-83, 2006-07, 2011-12, 2014-15	1976-77
		January-March		1985-86, 2003-04	1988-89, 1998-99, 2005-06	
	6 Months	April-September		1976 -77, 1992-93, 1998 -99, 2005-06, 2012-13	1989-90	
		October-March	1976-77	1993-94, 1994-95, 2006-07, 2009-10		2011-12
	12 Months	April-March		1992-93, 1994-95, 1998-99, 2012-13, 2016-17	1976-77	
Khulna	3 Months	April-June	1984-85, 2002-03	1999-00, 2005-06, 2008-09, 2009-10, 2012-13	1992-93	
		July-September		1985-86, 1988 -89, 2001-02, 2003-04	1989-90, 1992-93, 1994-95, 1996-97	2010-11
		October-December		1982-83, 1994-95, 1997-98		2011-12, 2014-15
		January-March		1985-86, 1988-89, 2003-04, 2005-06	1976-77, 1998-99	
	6 Months	April-September		1985-86, 1996-97, 2003-04	1989-90, 1994-95, 2010-11	1992-93
		October-March		1976-77, 1981-82, 1984-85, 1993-94, 2006-07, 2009-10	2011-12, 2014-15	

	12 Months	April-March	2002-03	2003-04, 2008-09, 2014-15	1985-86, 1994-95, 2010-11	1992-93
Mongla	3 Months	April-June	2002-03	2007-08, 2008-09,2009-10	1992-93, 2012-13	
		July-September		1992-93, 1994-95, 2001-02, 2014-15	2003-04, 2010-11,	
		October-December		1992-93, 2006-07	2011-12, 2015-16	1997-98
		January-March		2003-04, 2008-09, 2010-11, 2012-13	1998-99, 2009-10	
	6 Months	April-September	2002-03	2003-04, 2010-11, 2014-15		1992-93
		October-March		2000-01, 2006-07, 2012-13, 2015-16	2009-10, 2011-12	
	12 Months	April-March		2003-04, 2008-09	2014-15	1992-93
Satkhira	3 Months	April-June		1992-93, 2005-06, 2012-13	1979-80	2009-10
		July-September		1989-90, 1998-99, 2003-04, 2014-15	1996-97, 2010-11, 2016-17	
		October-December	2003-04, 2005-06	1984-85, 1994-95, 1997-98, 2006-07, 2011-12, 2015-16	1982-83, 1987-88,	
		January-March	1997-98	1985-86	1988-89, 1998-99, 2003-04, 2008-09, 2009-10	
	6 Months	April-September		1989-90, 1996-97, 1998-99, 2010-11, 2014-15	2016-17	
		October-March		1982-83, 1984-85, 1985-86, 1987-88, 1988-89	2009-10, 2011-12	
	12 Months	April-March		1982-83, 1985-86, 1998-99, 2008-09, 2009-10, 2010-11	1979 - 80, 2014 - 15, 2016 - 17	

4.4 Trend analysis

Trend analysis of annual and seasonal standardized RDI was performed to understand trends in drought time series. Three months RDIst trend results show that there is a negative trend except for three stations from July to September time period and two stations from October to December time period (Table 4.2). July to September has a positive trend except at Satkhira. Meanwhile, Khulna and Satkhira station have positive trends from October to December time period. However, a significant negative trend is found in Khulna (April to June) only. Rest of the stations have a non-significant negative trend in 95% confidence limit.

Table 4.2: Trend analysis results for 3 months RDIst

Time	Station	Kendall's tau	S	Var(S)	p-value (Two-tailed)	alpha
April to June	Jessore	-0.137	-112.000	7926.667	0.212	0.05
	Khulna	-0.239	-196.000	7926.667	0.029	0.05
	Mongla	-0.145	-47.000	2058.333	0.311	0.05
	Satkhira	-0.080	-66.000	7926.667	0.465	0.05
July to September	Jessore	**0.088**	72.000	7926.667	0.425	0.05
	Khulna	**0.080**	66.000	7926.667	0.465	0.05
	Mongla	**0.095**	31.000	2058.333	0.508	0.05
	Satkhira	-0.027	-22.000	7926.667	0.814	0.05
October to December	Jessore	-0.002	-2.000	7926.667	0.991	0.05
	Khulna	**0.066**	54.000	7926.667	0.552	0.05
	Mongla	-0.040	-13.000	2058.333	0.791	0.05
	Satkhira	**0.088**	72.000	7926.667	0.425	0.05
January to March	Jessore	-0.134	-110.000	7926.667	0.221	0.05
	Khulna	-0.022	-18.000	7926.667	0.849	0.05
	Mongla	-0.249	-81.000	2058.333	0.078	0.05
	Satkhira	-0.049	-40.000	7926.667	0.661	0.05

Six months RDIst trends (Table 4.3) exhibits apparently similar results as shown in three months trend results. There is a negative trend in almost all stations with exception at Mongla (April to September) and Satkhira and Khulna (October to march). However, all the positive and negative trends are statistically non-significant at 95% confidence limit.

Table 4.3: Trend analysis results for 6 months RDIst

Time	Station	Kendall's tau	S	Var(S)	p-value (Two-tailed)	alpha
April to September	Jessore	-0.020	-16.000	7926.667	0.866	0.05
	Khulna	-0.095	-78.000	7926.667	0.387	0.05
	Mongla	**0.028**	9.000	2058.333	0.860	0.05
	Satkhira	-0.127	-104.000	7926.667	0.247	0.05
October to March	Jessore	-0.129	-106.000	7926.667	0.238	0.05
	Khulna	**0.005**	4.000	7926.667	0.973	0.05
	Mongla	-0.212	-69.000	2058.333	0.134	0.05
	Satkhira	**0.068**	56.000	7926.667	0.537	0.05

Annual RDIst results (Table 4.4) have a decreasing trend at all stations. All the negative trends are non-significant at 95% confidence limit.

Table 4.4: Trend analysis results for annual RDIst

Time	Station	Kendall's tau	S	Var(S)	p-value (Two-tailed)	alpha
Annual	Jessore	-0.056	-46.000	7926.667	0.613	0.05
	Khulna	-0.098	-80.000	7926.667	0.375	0.05
	Mongla	-0.015	-5.000	2058.333	0.930	0.05
	Satkhira	-0.032	-26.000	7926.667	0.779	0.05

Overall concluding remarks is that most of the stations show negative trends which indicate drought are more frequent. This result might also indicate a possible climate change scenario for the country.

4.5 RDI as a climate change indicator

In addition, to identify possible drought conditions, RDIα can also be used as a climate change index (Mohammed and Scholz, 2017; Tigkas et al., 2013). Tigkas et al. (Tigkas et al., 2013) stated that The Initial RDI (α_k) is an adequate index for assessing the climate condition of a region. The reason is, it is based on both precipitation and temperature (Tigkas et al., 2013). They also stated that any appropriate trend analysis method can be used to identify a possible significant trend that indicates there are strong indications of climate change. The analysis can be done annual basis as well as any desired shorter time period. In the current thesis, Mann-Kendall Trend test and sequential version of Mann-Kendall test are applied to identify possible climate change. The analysis is done for annual and six-month time series. While the first will detect annual climate change the latter will provide a more detail detection of climate change in dry and wet period.

Mann-Kendall trend test results show that all four stations have a negative trend for annual Initial RDI (α_k). This indicates that either rainfall decreasing or PET is increasing. However, none of the negative trends are statistically significant in the 95% confidence limit. Kendall's tau also reveals a weak strength of trend over time. Although there is a negative trend in annual Initial RDI values, investigation in shorter scale indices will give more detail information about possible climate change. Therefore, the trend in six-month initial RDI values is performed. Initial RDI trend of April to September reveals the negative trend in all stations except in Mongla. These trends are non-significant in 95% confidence limit, Kendall's tau indicates comparatively similar trend strength of trend like annual over time. Meanwhile, trend results of October to March shows mix results. There are positive initial RDI trend in Khulna and Satkhira stations. In contrast, Jessore and Mongla show negative trend over time. The only statistically significant trend at 95% confidence limit is found in Mongla station. Kendall's tau also indicates comparatively stronger strength of trend over time for these two stations. Results of the Mann-Kendall trend test with Kendall's tau are presented in Table 4.5

Although there is a negative trend for almost all the cases, the weak strength of trend over time may due to the fluctuation of the trend over time. A detailed analysis for trend fluctuation will, therefore, be able to identify the actual scenario of possible climate change trend over time. It will also detect if there were any shift in climate during the study period. Considering these phenomena, the Sequential Mann-Kendall (SQMK) test was applied to identify possible shift and fluctuation of climate over the study period.

Table 4.5: Trend results of Initial RDI values

Station Name	Time	Kendall's tau	Kendall’s S	p-value (Two-tailed)	alpha
Jessore	April-September	-0.020	-16.000	0.866	0.05
	October-March	-0.129	-106.000	0.238	0.05
	Annual	-0.056	-46.000	0.613	0.05
Khulna	April-September	-0.095	-78.000	0.387	0.05
	October-March	***0.005***	4.000	0.973	0.05
	Annual	-0.098	-80.000	0.375	0.05
Mongla	April-September	**0.028**	9.000	0.860	0.05
	October-March	-0.212	-69.000	**0.042**	0.05
	Annual	-0.015	-5.000	0.930	0.05
Satkhira	April-September	-0.127	-104.000	1.000	0.05
	October-March	***0.068***	56.000	0.537	0.05
	Annual	-0.032	-26.000	0.779	0.05

The results of the annual Initial RDI time series are given in Figure 4.8. The u(t) statistics show that there was fluctuation in Jessore station with several number of change point. Similar results are found for Khulna and Mongla stations also. Satkhira station has also fluctuation but in recent time.

Results of April-September shows sequential fluctuation of Initial RDI trend (Figure 4. 9). Jessore station has a change point after 1980 which change significantly upward till late 85’s. After that, there was negative and positive trend which are non-significant. Khulna station has a steep negative trend followed by a positive trend. After 2000, Mongla station has also fluctuation in trend. Satkhira has considerable negative trend after late 2000.

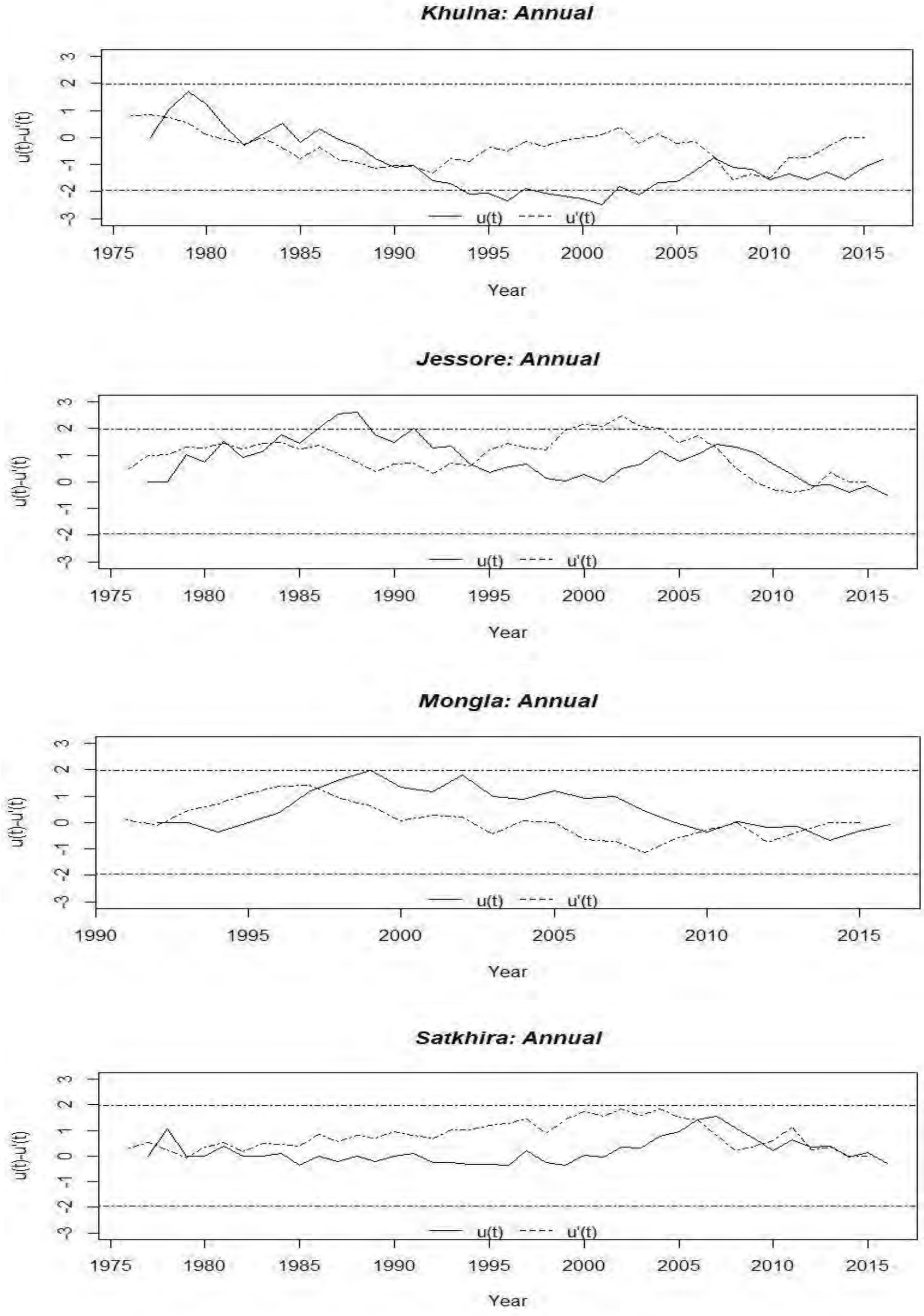


Figure 4.8: SQMK test results of Annual Initial RDI

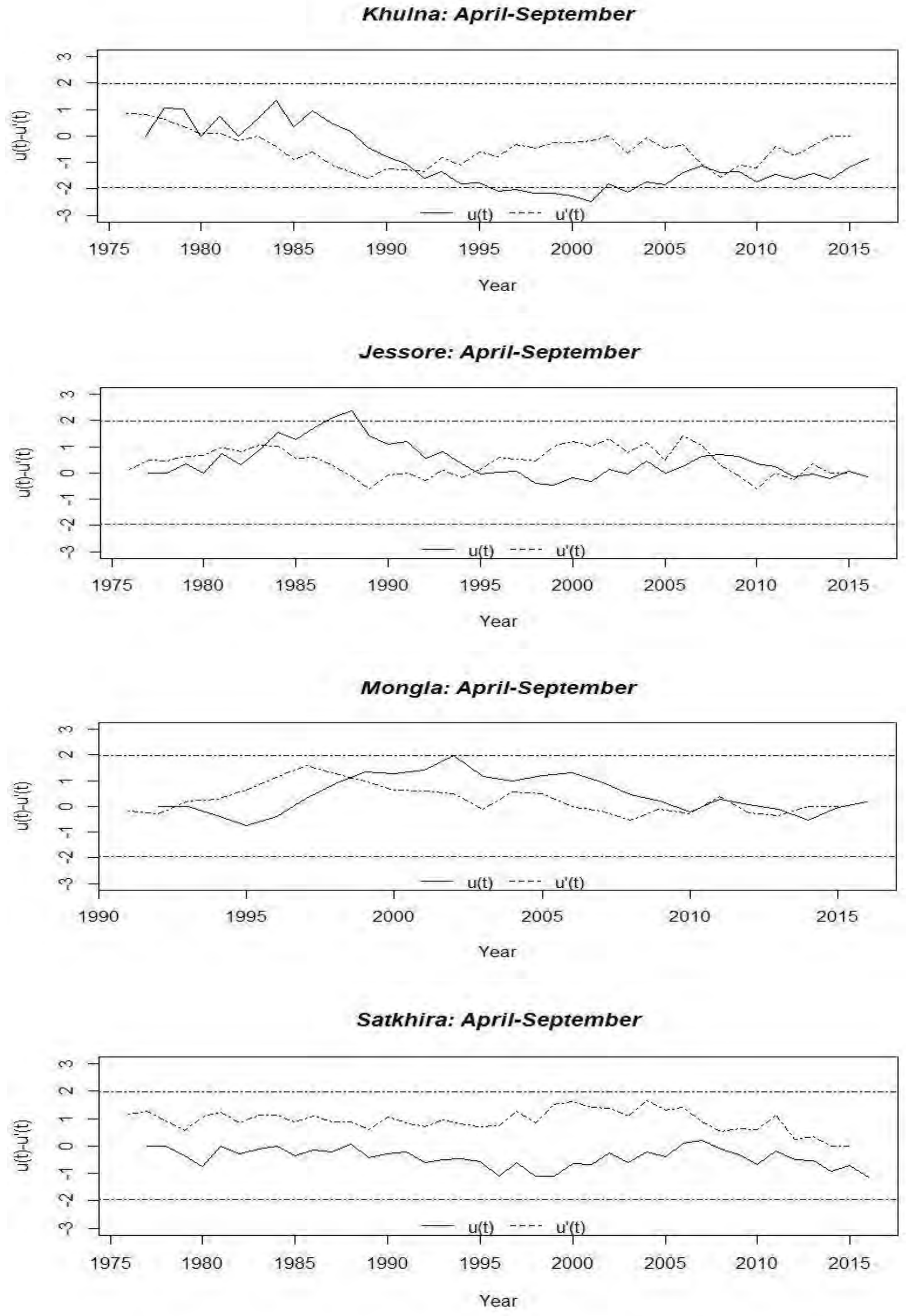


Figure 4.9: SQMK test results of Six months (April-September) Initial RDI

In contrast, SQMK test results of October to March (Figure 4.10) shows frequent fluctuations of the trend for Jessore station. There was a change point after 1990 followed by a declining trend. Khulna station has several change points during the study period. Same results were found for Mongla and Satkhira. It is seen from the graph that fluctuation of trend through the study period weekend the overall trend except for Mongla station. Mongla has a consistent long declining trend after 1995. However, it is evident that all the stations have a negative trend after 2000. If this negative trend persists (optimistic view) there may be a possible long-term potential change in climate for this area.

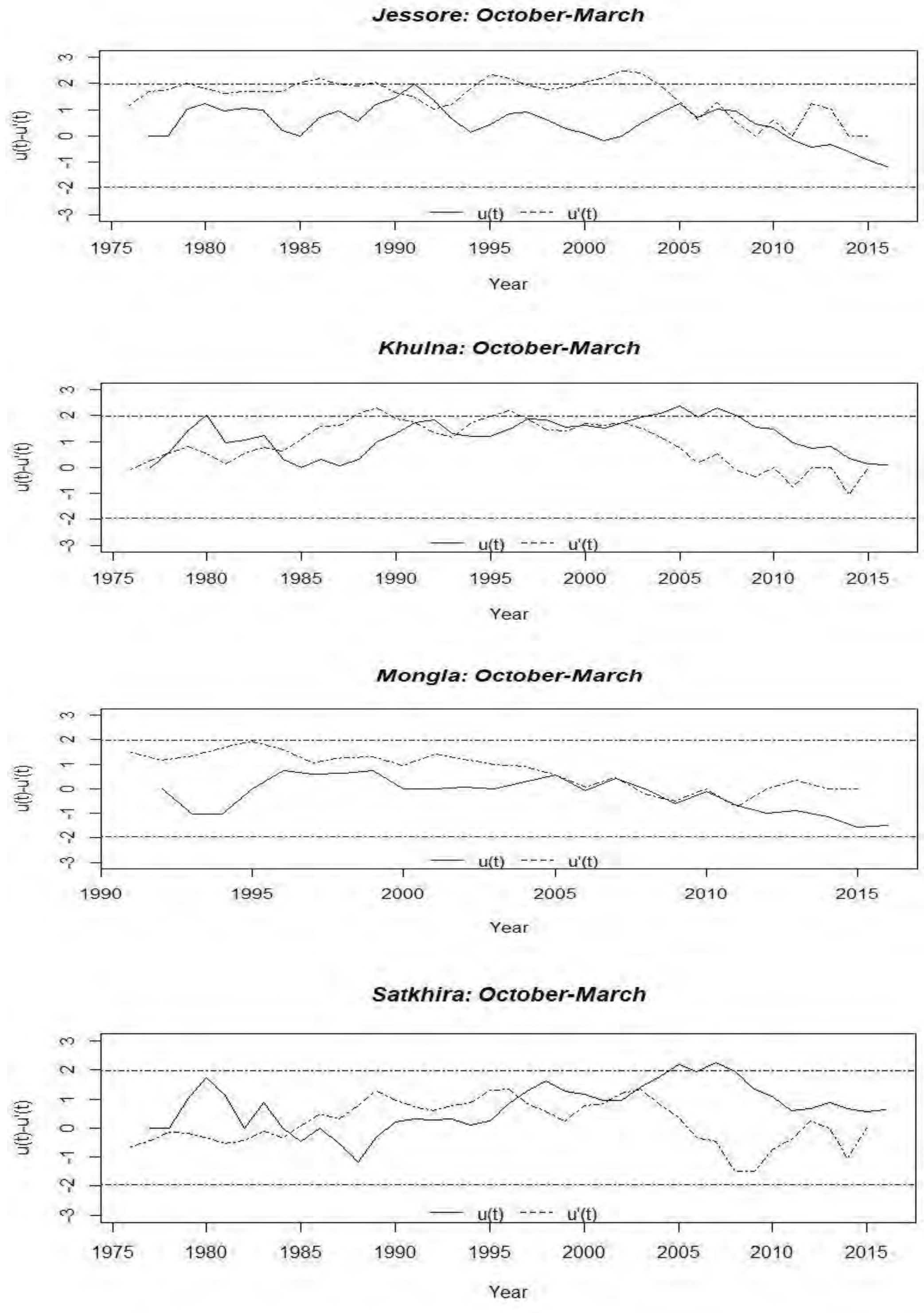


Figure 4.10: SQMK test results of Six months (October-March) Initial RDI

4.6 Drought monitoring using NDVI

In addition to the rainfall and temperature based index, drought in the study area was also assessed using satellite images. NDVI is a widely used vegetation index for drought assessment. Results from the NDVI analysis are compared with the RDI to understand the performance of RDI and the impact of drought in vegetation in the study area.

Firstly Landsat 5 TM and Landsat 7 ETM+ image were collected from USGS. Before calculation the NDVI, Using layer of Bangladesh administrative boundary, subset area for all the required district of Bangladesh has been done for all the images. Inherited cloud problem are then checked as presence of clouds in satellite images is a significant obstacle to land surface studies. Undetected clouds distort the real reflectivity of the land surface and consequently develop into an additional source of error. However, collected Landsat images were almost cloud-free when these images were downloaded. Therefore, no treatment or alteration was made.

After that, the image processing (Radiometric and geometric correction etc.) were done for more accuracy. Then the Raster calculation had been done by using ArcGIS for classifying the NDVI value in 5 classes.

Normalized Difference Vegetation Index has been computed using two bands of surface reflectance images. In Surface reflectance image band 3 represents red and band 4 represents near infrared (wavelength). Mathematically, NDVI can be written as-

NDVI = (NIR - Red)/ (NIR + Red)……….4.1
That is (band4-band3)/ (band4+band3)

After processing above intermediate steps, all the images were stacked.

NDVI index outputs values ranging from -1.0 to 1.0, mostly representing greenness. The higher index values associated with greater green leaf area. Where any negative values are mainly generated from clouds, water, and snow. Values near zero are mainly generated from rock and bare soil. Very low values of NDVI (0.1 and below) correspond to barren areas of rock, sand, or snow.

An illustration of computed NDVI Classifications for Khulna (May 2014) is shown in figure 4.11 according to pixel values. The figure exhibits that most NDVI value lays between -0.52 – 0.011 indicating deficient vegetation in the area. Meanwhile, annual RDI value during the period 2013-14 is -1.89 in Khulna indicating that severe drought occurred within this time.

A comparison between monthly RDIst and Mean NDVI were made to understand how NDVI responses for RDIst values. The results are presented in Table 4.6. Results indicate that RDI and NDVI responses in a similar manner except for Mongla 2015 and Jessore 2017. However, it should be noted that the response of NDVI is rather slow. Because vegetation's response to drought takes considerable time. This could be the cause of exception for Mongla. However, it has been seen that overall annual RDIst was -1.47 for the 2014-15 year. This might have affected the immediate first months of next year NDVI value. Therefore, the relationship between NDVI and RDI at different time lags could be convenient. Ji and Peter (Ji and Peters, 2003) reported that 3 months Standardized Precipitation Index (SPI) has the best correlation with NDVI. NDVI was found highly correlated with different time scales of RDI index at different places in Iran (Shamsnia and Boustani, 2014).

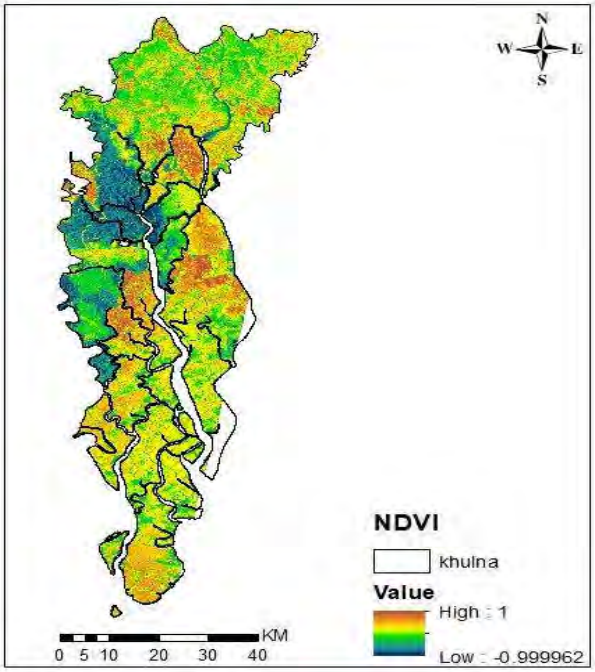


Figure 4.11: NDVI image of Khulna (May 2014)

However, NDVI relation with Precipitation varies across cropping seasons (Ji and Peters, 2003) also. Another important factor in building correlation is land cover type. NDVI appears to respond more quickly to precipitation for croplands, with higher correlation coefficients over shorter durations and shorter time lags, while Forests display the slowest response time to precipitation (Wang et al., 2003).

Table 4.6: RDI and mean NDVI value

Station name and year	Monthly RDI	Annual RDI	Mean NDVI value
Sathkira (2016-17)	-0.62	-1.82	-0.02 (February 17)
Sathkira (2014-15)	-0.36	-1.47	-0.001(June 15)
Mongla (2014-15)	0.91	-1.47	-0.006 (April 15)
Khulna (1994-95)	-0.89	-1.91	-0.09 (March 95)
Khulna (2013-14)	-0.94	-1.89	-0.07 (May 14)
Jessore (2016-17)	0.02	-1.19	0.001 (April 17)

4.7 Drought forecasting using ARIMA

Although ARIMA has been applied successfully to forecast many hydrological parameters, its application in drought forecasting is limited till the date. In the present thesis, ARIMA has been applied to forecast RDIst for the four stations in the study area. As the annual and three/ six-month RDIst time series are non-seasonal, it is assumed that a non-seasonal model would best fit the data. However, a check was performed if there were any cyclic pattern (periodicity) in the data. It has been found that ARIMA does not perform very well for forecasting RDIst data in terms of long-term forecasting. Therefore, appropriate alternative forecasting method needs to be found through dedicated research. The reason for the failure of ARIMA to forecast long-term drought may due to the length of data in the model build up or due to the property of the data set. For illustration, details of 3 months RDIst (April-June) of Mongla station is discussed here. For the rest of the stations and time period, the best models based on BIC (Bayesian Information Criterion), Diagnostic check and R^2 values are given in Table 4.7.

4.7.1 *Model identification*

The identification stage involves checking the stationarity and normality of time series data. Initially, the data series were analyzed to check if the data are stationary. The temporal correlation structure of the monthly time series was identified using Autocorrelation (ACF) and Partial Autocorrelation (PACF) functions. As the original data was not seasonal, only non-seasonal models were used to predict RDIst. Observing properties of data, it seemed that the time series is white noise. Therefore, a first order differencing was done to assign AR/MA component in the model. ACF and PACF plot of differenced series show that the time series is slightly over differentiate for all the station. So the model could be an AR model. However, there is a possibility of a combination of AR and MA exists. Therefore, possible combinations using several P and Q ranging from zero to two were examined to determine the best ARIMA model from the nominee models. The model that gives the best combination of minimum normalized BIC was selected as the best-fitted model.

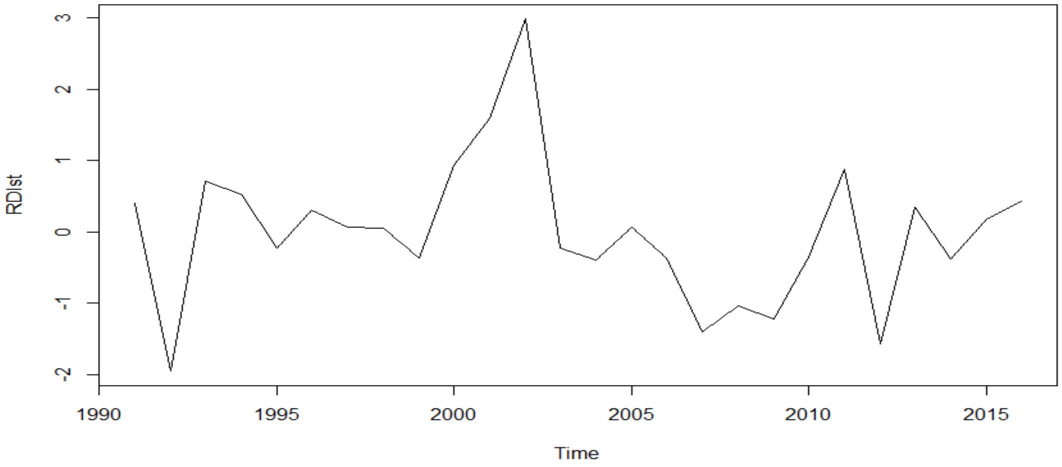


Figure 4.12: Time series plot of 3 months RDIst (April-June) of Mongla station

4.7.2 *Parameter estimation*

Primary estimation of the parameters were done from AR and MA at the identification stage. This preliminary evaluation was then used to compute the final parameter by the procedure described by Box and Jenkins (1976). However, in the current case parameter estimation is automatic in the R environment. It is found that the standard error calculated for the relevant parameter is small compared to the parameter values. Therefore, the parameters are statistically significant.

4.7.3 Diagnostic check

The diagnostic check was done once the model parameters were calculated to verify the adequacy of the prediction. The residuals should be white noise for a useful forecasting model. Several tests carried out on residuals are described below:

ACF and PACF of residuals

The majority of the ACF and PACF values of residuals lie within the confidence limit which indicates no significant correlation among them. It is observed from the figure that the residuals are white noise.

Histogram of residual

Histogram of residuals of the data series is found normally distributed.

Normal probability of residuals

The cumulative distribution of the residuals usually should be a straight line when plotted on normal probability paper. The normal probability plot of residuals was found fairly linear for the 3 months RDI for Mongla Station. The other series also shows an almost similar type of result indicating that residuals are normally distributed. Figure 4.13 shows the normal probability distribution of residuals for 3 months RDI series.

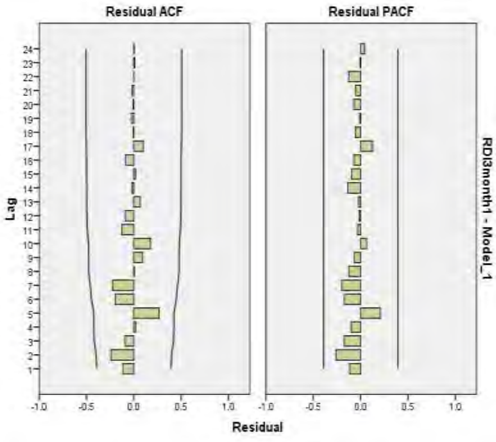
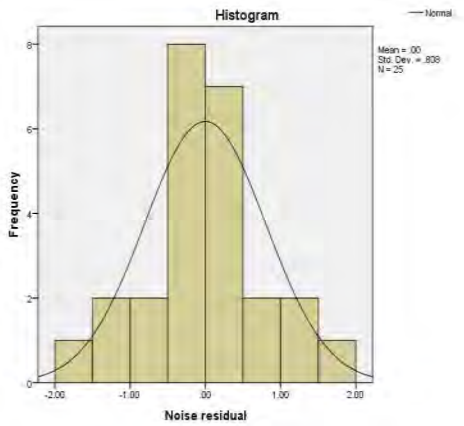
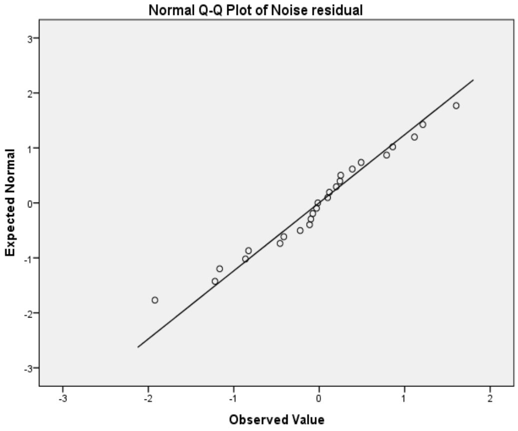
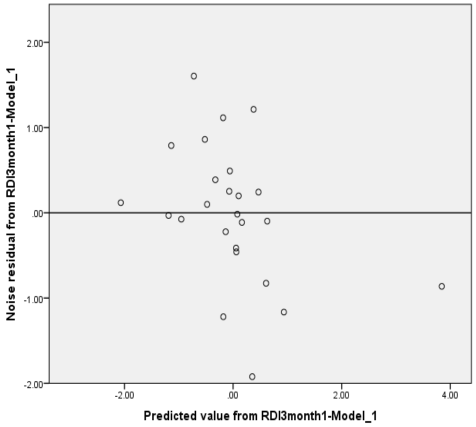
	
Residual ACF and PACF	**Histogram of residual**
	
Normal probability of residuals	**Residuals versus prediction**

Figure 4.13: Diagnostic Check of 3month RDIst Mongla (April-June)

Residuals versus prediction

Residuals were plotted against predicted values. The plot shows that the predicted one follow the observed data pretty well for RDI 3 month of the Mongla station. The prediction versus observed plot for 6 months and 12-month RDI does show a good similar type of result. For the maximum case, the predicted series cannot follow the observed value well. However for 3 months RDI the models worked good enough to predict the series.

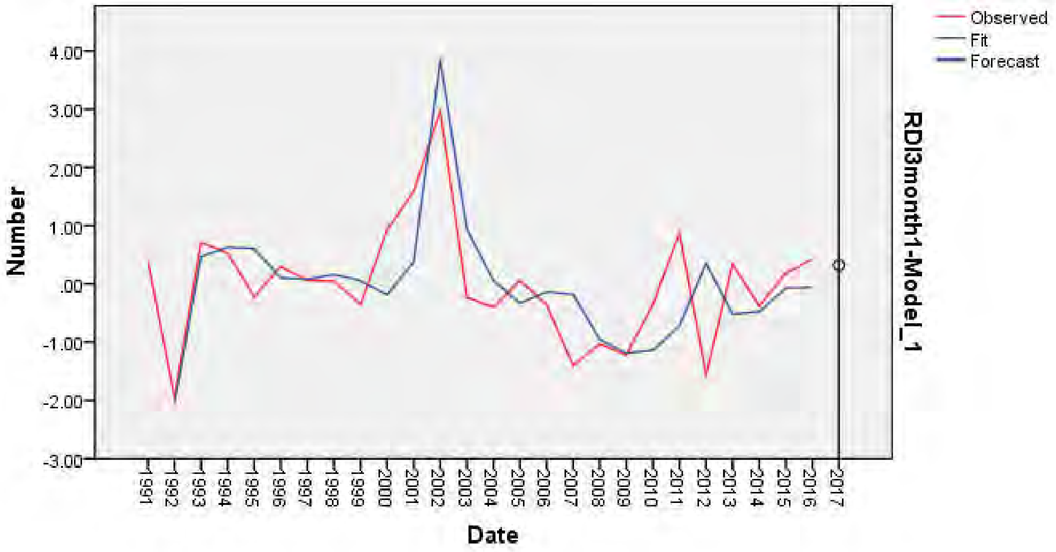


Figure 4.14: Comparison of observed data with predicted of 3month RDIst Mongla (April-June)

It has been seen from the ARIMA results that, forecasting efficiency of ARIMA for RDI is not well enough to forecast longer times span. However, still, these models can be useful in forecasting immediate next year drought events and can be very useful in related planning and management works. As the ARIMA does not perform very well in RDI forecasting, Artificial Neural Network (ANN) further tried in this study to check whether ANN can forecast a longer time period than ARIMA. It can be mentioned that only the annual RDI series is predicted using ANN technique here. Results of ANN is presented in the next section.

Table 4.7: Best ARIMA models for RDIst

Station	Time	ARIMA	Time	
Jessore	Annual	ARIMA(1,1,0)	April-June	ARIMA(3,1,0)
Khulna		ARIMA(1,1,0)		ARIMA(2,1,0)
Mongla		ARIMA(1,1,0)		ARIMA(1,1,0)
Satkhira		ARIMA(1,1,0)		ARIMA(2,1,0)
Jessore	April-September	ARIMA(0,0,0)	July-September	ARIMA(3,1,0)
Khulna		ARIMA(1,1,2)		ARIMA(1,1,0)
Mongla		ARIMA(1,1,0)		ARIMA(1,1,0)
Satkhira		ARIMA(1,1,0)		ARIMA(2,1,0)
Jessore	October-March	ARIMA(0,0,0)	October-December	ARIMA(3,1,0)
Khulna		ARIMA(2,1,0)		ARIMA(1,1,0)
Mongla		ARIMA(1,1,0)		ARIMA(3,1,0)
Satkhira		ARIMA(1,1,0)		ARIMA(3,1,0)
Jessore			January-March	ARIMA(2,1,0)
Khulna				ARIMA(3,1,0)
Mongla				ARIMA(1,1,0)
Satkhira				ARIMA(1,1,0)

4.8 Drought forecasting using ANN

Annual RDIst time series were forecasted using Feedforwrad Back propagation Neural Network (BPNN). The forecasting models have been developed using the software package “Zaitun Time Series”. Zaitun is a free software package that use a trial and error method to find the optimum neurons in each layer of the model.

The neural networks consist of two or more layers or groups of processing elements called neurons. The network processing capability is the consequence of the connections among these units, and it is achieved through the adaptation process or by learning from the set of learning examples. Neurons are connected into a network so that the output of every neuron is the input into one or several other neurons. The neurons are grouped into layers. Three basic types of layers are the input, hidden and output ones. Standard error back-propagation algorithm includes optimization of the error using the deterministic algorithm of the gradient descent. It calculates partial derivations of the quality criterion according to network parameters using a recursive procedure which is performed reversely through the network from the output to the input network layer. The algorithm is based on the assumption that the error derivation propagation through the network is linear.

The efficiency of the neural network models is measured using the most commonly used forecasting errors as following:

Mean Absolute Error (MAE)

$$\text{MAE} = \frac{1}{T}\sum_{t=1}^{T}|y_t - \widehat{y_t}| \ldots\ldots\ldots 4.2$$

Mean Square Error (MSE)

$$\text{MSE} = \frac{1}{T}\sum_{t=1}^{T}(y_t - \widehat{y_t})^2 \ldots\ldots\ldots 4.3$$

Where T is the number of data that is used in the estimate, y_t observed value of the series at moment t, and yt^ forecasted value of the series at moment t. The forecasting models with upto three years ahead forecast results are shown in Table 4.8. The relevant errors are also presented in the table. After three years ahead forecast the accuracy of the ANN model reduced to an undesirable percentage. It is found that a 10-9-1 architecture is the best model for Khulna station. This network architecture indicates that a BPNN neural network with 10 neuron in input layer (IL), 9 Neurons in the hidden layer (HL) and 1 neuron in the output layer (OL) is statistically best model in forecasting annual RDI in Khulna. The graph of actual vs predicted value (Figure 4.15 and Figure 4.16) are also drawn and found satisfactory. Similar taxonomy is applicable to other stations also. A trial and error technique was applied to identify the best BPNN model. In the trial and error process, the **“Hyperbolic Tangent Function”** was found as the best activation function for all the stations. Calculation of the weight was done using as much as 10000 iterations.

Table 4.8: Best models for annual RDI forecasting

					Forecasted			
Station	**Network Architecture Value (IL - HL - OL)**	**Error**	**MSE**	**MAE**	**Year**	**Value**	**Drought**	**Type**
Jessore	10 - 8 - 1	0.115	0.039	0.142	2017	-1.142	Yes	Moderate
					2018	-0.85	Yes	Normal
					2019	-0.25	No	
Khulna	10 - 9 - 1	0.156	0.05	0.16	2017	0.48	No	
					2018	0.46	No	
					2019	-0.032	No	
Mongla	11 - 11 - 1	0.039	0.03	0.134	2017	0.9	No	
					2018	-0.94	Yes	Normal
					2019	-0.76	Yes	Normal
Satkhira	9 - 4 - 1	0.42	0.09	0.176	2017	1.89	No	
					2018	-0.46	No	
					2019	0.89	No	

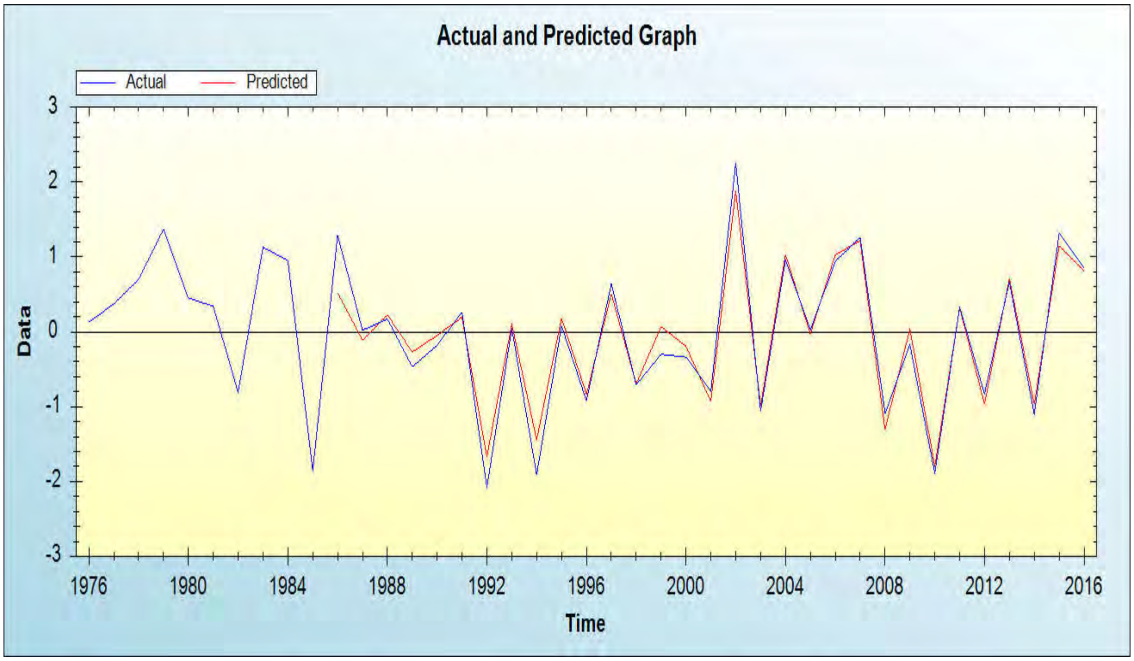


Figure 4.15: Actual and Predicted graph in Khulna

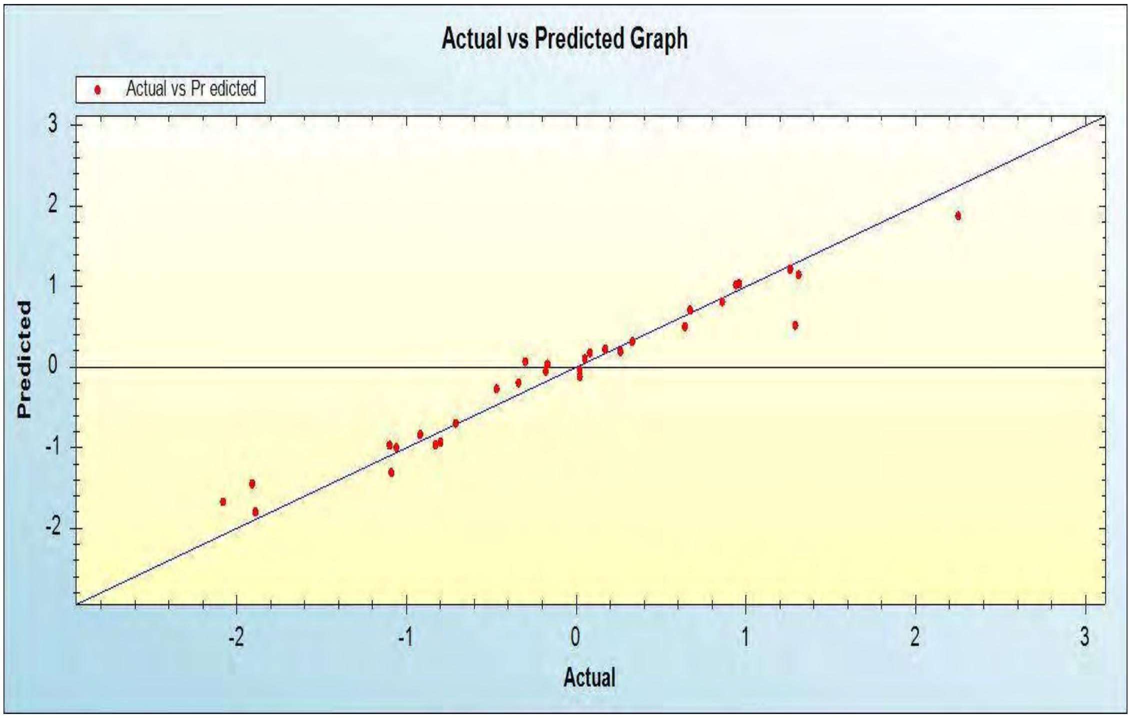


Figure 4.16: Actual vs Predicted graph in Khulna

4.9 Groundwater drought

Groundwater drought was observed using a cumulative threshold approach in this study. The cumulative deficit was calculated using the formula as described in the methodology section. As the time span increases, the cumulative deficit also increases and become a gigantic value. Therefore, the total deficit for a single station was normalized dividing deficit value by a number of months drought occurs. Using a normalized value smooths the fluctuation of yearly drought and cannot be used for detecting the duration of drought events (starting or ending) and magnitude of deficit volume. However, normalized total drought gives information about vulnerable zones in the study area. Which can be used in planning for groundwater management. To understand the onset, severity, and duration, a time series plot would be the best way. Considering these, time series plot for an example well is presented here. Spatial extent of drought is represented by the total normalized deficit and annual total deficit.

Time series plot of well bearing ID GT 8743004 is presented in Figure 4.17. The well is located at Kalaroa upozilla in Satkhira district. This well is chosen for several reasons. There are comparatively less missing values in this well. Results of normalized total and annual deficit shows that drought is far extreme in this area. However, it should be noted that lesser missing values in this well might have impact drought result of this particular tube well.

Time series plot of monthly water level (Figure 4.18) shows that there is an outlier in the series (June 2011). This outlier affects the total deficit calculation for this particular well. However, it does not greatly affect the mean of the time series. Replacement of this outlier with mean value shows that mean value remains same up to one decimal point. Although, outliers can affect total deficit calculation but normalization smooths their effect.

In the threshold level approach of groundwater drought identification, a certain threshold is first selected. Water table fallen below this threshold level is defined as the drought and the magnitude of deviation from threshold is defined as the deficit. Duration of the drought events is calculated from the time span of consecutive drought events. It is, however, can understand that selection of threshold level plays a significant role groundwater drought identification. In the present study Mean, 170% of mean and 190% of the mean was selected as the threshold level.

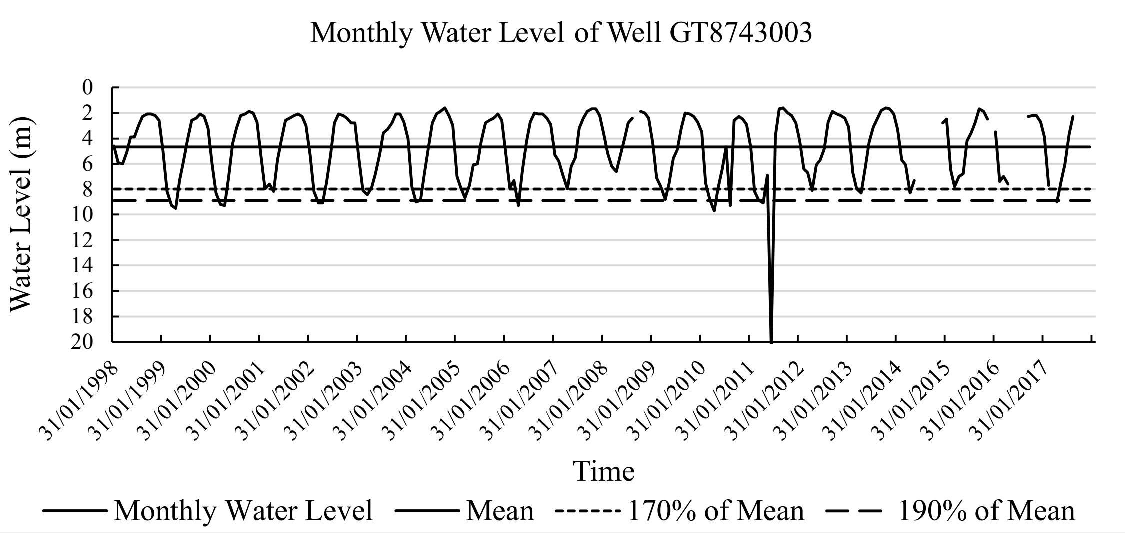


Figure 4.17: Definition sketch of an example well GT8743003

If we assume groundwater drought can only occur in situations when the water table is below the average (4.7m) level, there are droughts in almost every year most ranging 6 months duration. As the threshold level is changed to 8 (170% of mean), drought events and duration is significantly reduced. Whether, previously there was a drought in almost every year, time gaps between consecutive droughts increases here. Results show that the duration of the droughts reduced to 2 to 3 months in most cases. It is also found that drought events are confined to the February to June. A further change of threshold level to a value 9 (190% of mean) shows that drought events are reduced and have a shorter spell. The overall picture from the definition sketch is that groundwater drought was prevailing in the example well during the late ’90s and early 2000s. It is also found that groundwater drought repeatedly coincides with the winter and early summer season when agricultural drought usually prevails.

To understand the spatial extent of drought in the study area annual normalized deficit for the threshold of 170% and 190% of mean groundwater level are presented in the Figure 4.18-4.21 and Figure 4.22-4.25. In addition, the total normalized water deficit for the study period is also presented in Figure 4.26.

Spatial distribution of normalized annual deficit for a threshold of 170% of mean groundwater level for the year 2000, 2005, 2010 and 23017 in Figure 4.18-4.21 shows that northern part of Satkhira district is found mostly vulnerable to drought for a threshold level of 170% of the mean.

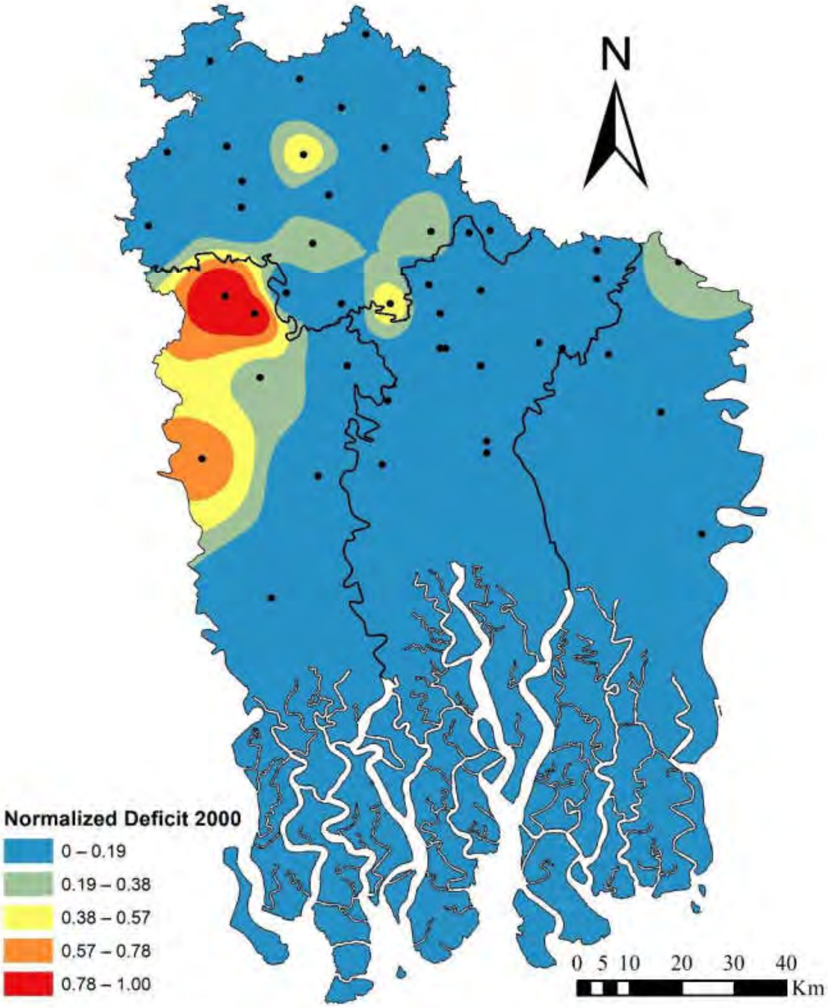


Figure 4.18: Spatial distribution of normalized annual deficit for a threshold of 170% of mean groundwater level for 2000

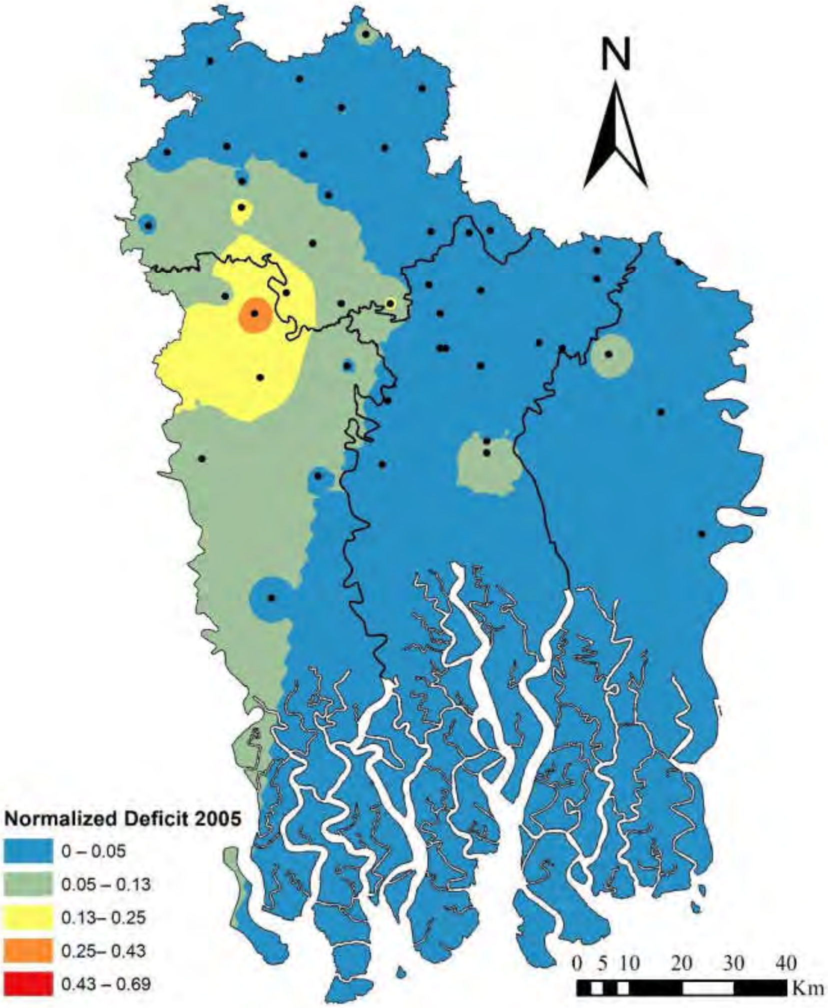


Figure 4.19: Spatial distribution of normalized annual deficit for a threshold of 170% of mean groundwater level for 2005

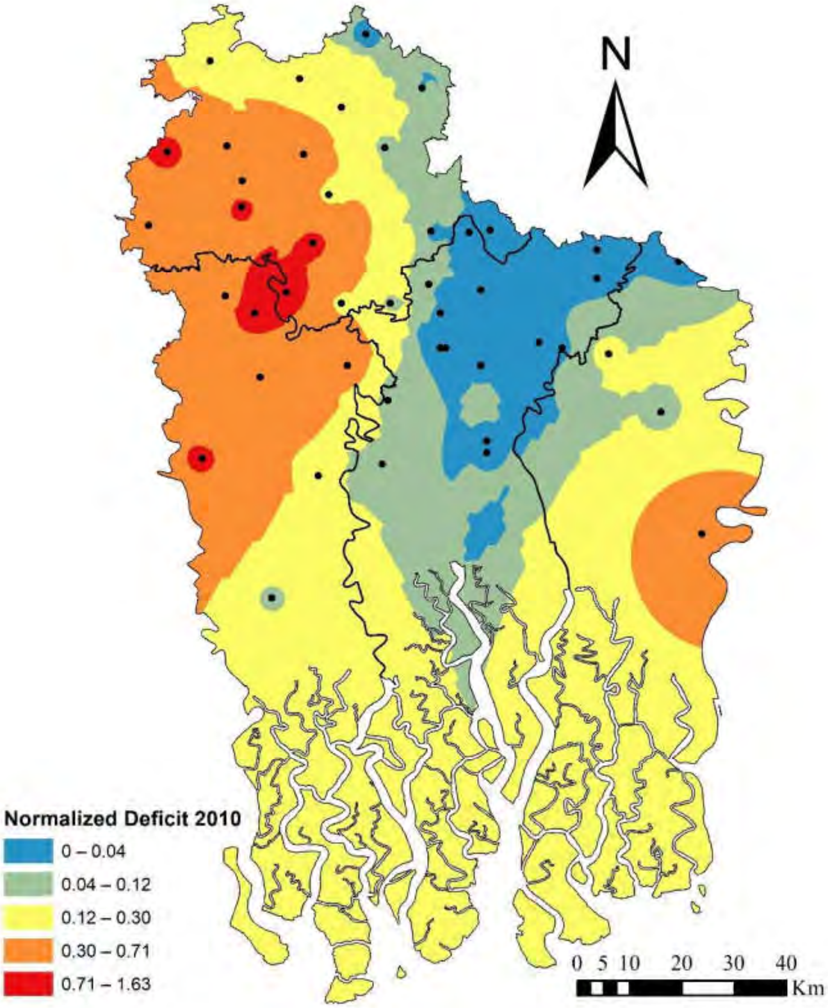


Figure 4.20: Spatial distribution of normalized annual deficit for a threshold of 170% of mean groundwater level for 2010

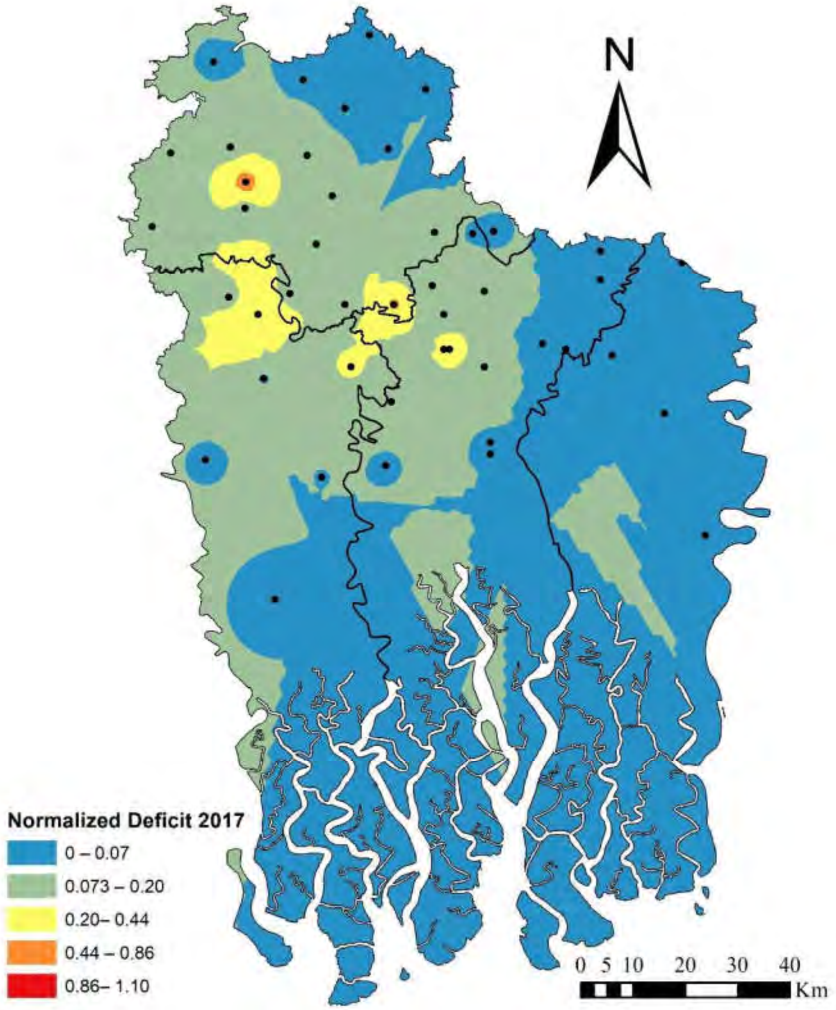


Figure 4.21: Spatial distribution of normalized annual deficit for a threshold of 170% of mean groundwater level for 2017

However, it can be stated that among the study area Kalaroa Upozilla of Satkhira district is most vulnerable drought. In addition, Jessore is also found moderately vulnerable especially in the year 2010. However, the spatial extent of drought varies year to year as seen in the figure. To understand the extreme vulnerability of the study area spatial distribution of normalized annual deficit for a threshold of 190% of mean groundwater level is presented in Figure 4.22-4.25. It is interesting that the spatial extend of extreme vulnerability does not show similar results as in the 170% of a mean level. The map of 2000, 2005, 2010 and 2017 year shows a spatial variation of vulnerability in the study area. However, it can be stated that Satkhira has most water deficit.

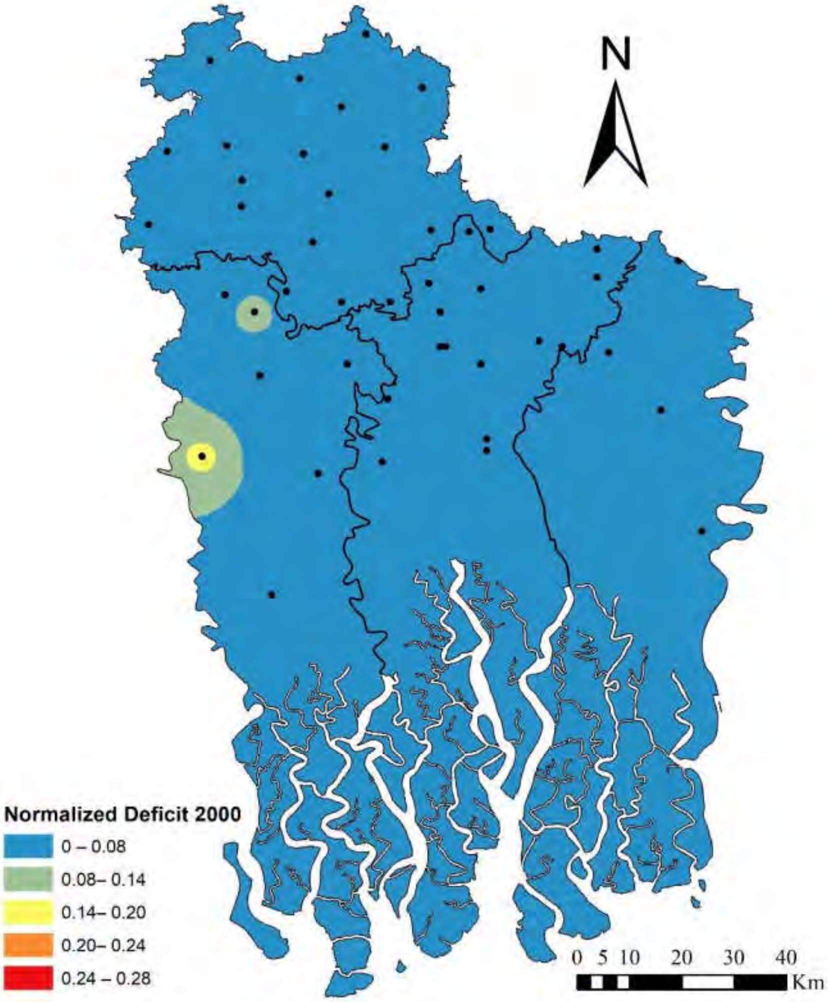


Figure 4.22: Spatial distribution of normalized annual deficit for a threshold of 190% of mean groundwater level for 2000

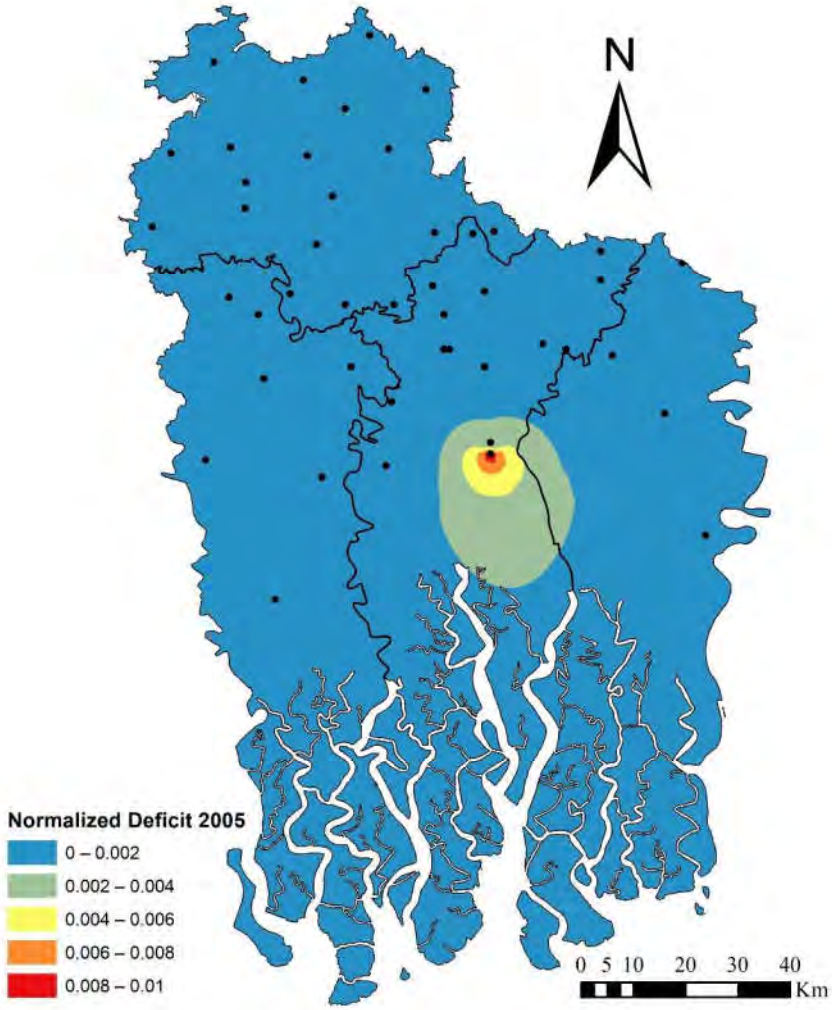


Figure 4.23: Spatial distribution of normalized annual deficit for a threshold of 190% of mean groundwater level for 2005

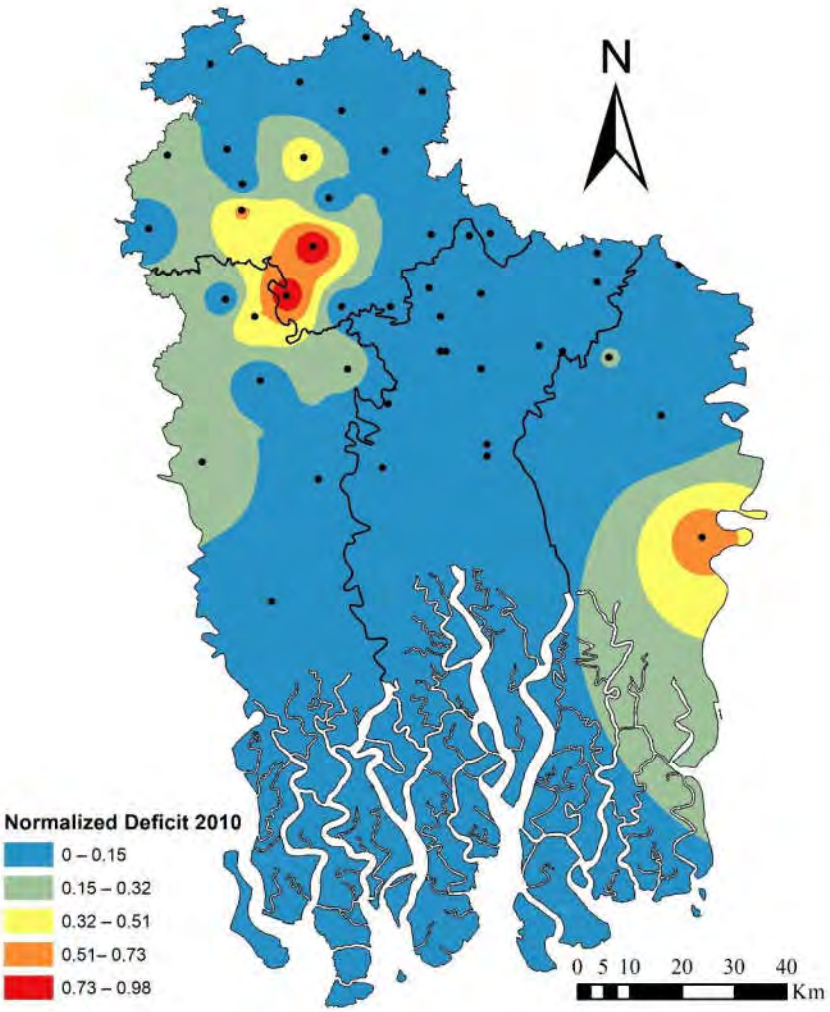


Figure 4.24: Spatial distribution of normalized annual deficit for a threshold of 190% of mean groundwater level for 2010

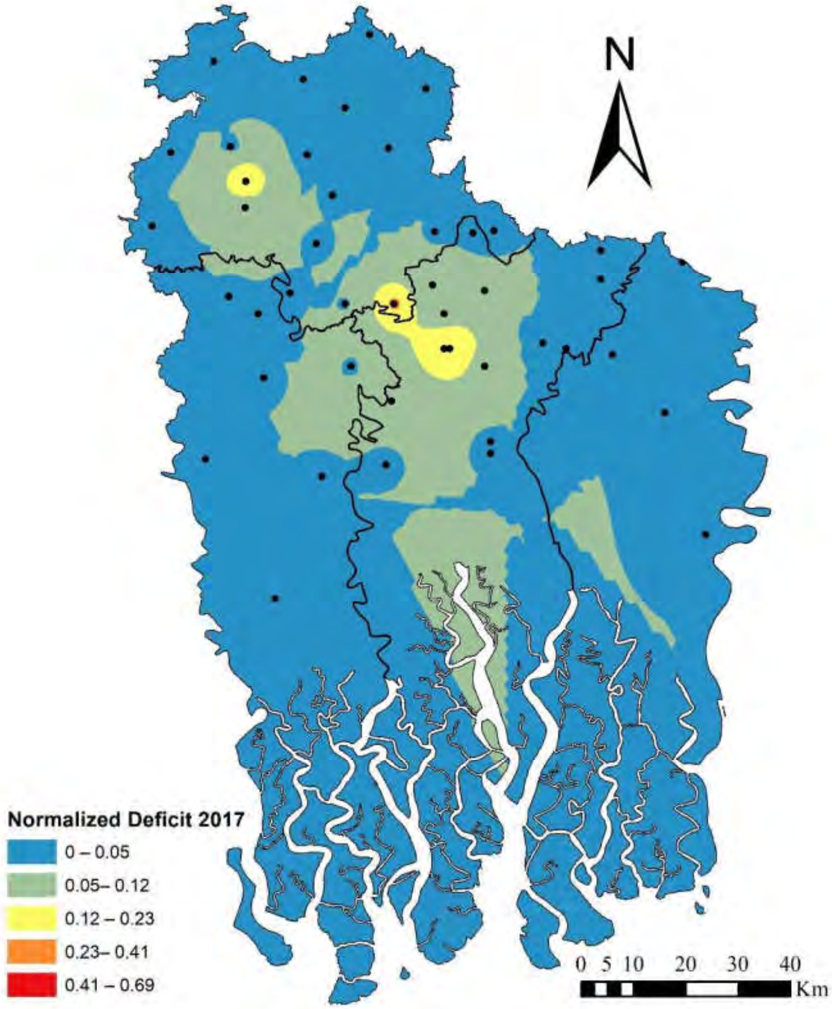


Figure 4.25: Spatial distribution of normalized annual deficit for a threshold of 190% of mean groundwater level for 2017

As the spatial extend of annual water deficit varies year to year, total normalized water deficit is further exhibited in Figure 4.20. The picture illustrated that parts of Satkhira and Jessore district are most vulnerable to groundwater drought. However, it is seen that Satkhira Sadar and Kalaroa is most vulnerable compared to the other part of the district. Normalized water deficit is found greater than 2m for several wells in the Kalaroa Upozilla of Satkhira district. While full Jessore has water ranging normalized total deficit 1m to 1.6m.

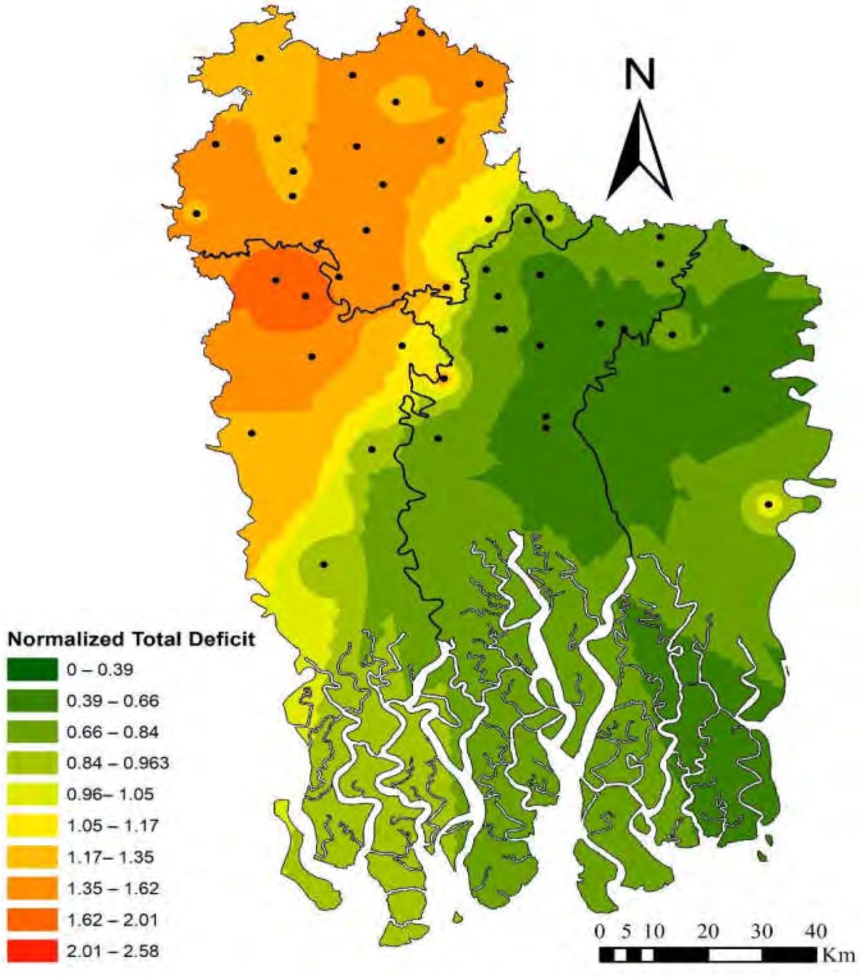


Figure 4.26: Normalized total water deficit for the study area

Chapter 5. Conclusion

This chapter presents the key findings from the present study. Key drought events during the study periods are also narrated in this section. Key findings from the hydrological drought scenario are also presented.

RDI is calculated on an annual and seasonal basis to understand drought scenario of different reference periods. RDI index of three months reference period indicates that there are some periodic cycles of a dry and wet period for April to June. Irregular periodic fluctuation of standardized RDI was found for July to September time scale.

Six months RDI index calculated for April to September and October to March shows that Khulna (1992-93) and Mongla (1992-93) encountered extreme drought in the reference period of April to September. RDI index for dry October to March shows that every station experienced moderate to severe drought during the study period except for Jessore. Jessore experienced two extreme droughts at 1976-77 and 2011-12 only.

Annual RDI shows that the whole study area experienced mild to extreme drought during the year 1992-93. It is found that Khulna and Mongla station experienced extreme drought events during 1992-93 while the other two does not experience any extreme drought events for the annual scale.

It has been seen that seasonal RDI index shows comparatively more drought events than the annual RDI. The reason behind this might be that seasonal fluctuation of rainfall and PET smoothes the results in annual scale.

Trend analysis of annual and seasonal RDI index demonstrates that there is a negative trend in index values indicating a possible increasing drought phenomenon. However, all the negative trend except three months RDI (April to June) in Khulna are statistically non-significant at 95% confidence limit.

To understand the climate condition of the study area RDIα were analyzed using the MK test and sequential version of the MK test. Although found non-significant in 95% confidence limit Mann-Kendall trend test results show that all four stations have a negative trend for annual

Initial RDI (αk) indicating that either rainfall decreasing or PET is increasing. Initial RDI trend of April to September reveals a negative trend in all stations except in Mongla. Trend results of October to March shows that there is positive initial RDI trend in Khulna and Satkhira stations while Jessore and Mongla show negative trend over time. Kendal's tau reveals that trends are comparatively weak over time except for moderate strength at Jessore and Mongla. The only significant negative trend occurs in Mongla for the reference period from October to March.

The sequential Mann-Kendall test reveals that there is sequential fluctuation in trend in initial RDI values in most cases. However, negative trends are more common after the 1990s. Results of the RDI index were intended to validate using NDVI. Comparison of monthly and Annual RDI values with computed NDVI shows similarities between the two.

Forecasting of drought events are performed using ARIMA modeling technique first, however, it has been found that ARIMA performance is poor in forecasting. After one ahead forecast performance of ARIMA reduces drastically. Therefore, further forecasting was performed using ANN. A BPNN network structure performs reasonably well in forecasting RDI values up to 3 years ahead.

Normalized total and an annual deficit of groundwater level shows that GW drought is true for this area. It is found that the northern part of Satkhira district is found mostly vulnerable to drought for a threshold level of 170% of the mean. The results are similar at 190% of mean also. This indicates that Satkhira district is most vulnerable to GW drought. Total normalized water deficit identifies Satkhira as most vulnerable while Jessore tumbles behind Satkhira.

Although this study identifies the meteorological and groundwater drought for the study area, their field significance is yet to be explored. A detail study about the field significance will further helps in preparing a better management plan. In addition to that a hybrid forecasting model comprises of ARIMA and ANN could be an improved option for drought forecasting.

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APPENDIX

RDIst Series

	April to June (3 Months)				January to March (3 Months)			
Year	Jessore	Khulna	Mongla	Satkhira	Jessore	Khulna	Mongla	Satkhira
76-77	-0.46	0.44		0.28	-0.76	-1.50		0.21
1977 - 1978	1.06	1.09		1.73	-0.46	-0.73		-0.45
1978 - 1979	0.25	0.85		-0.09	0.40	-0.34		-0.07
1979 - 1980	-2.12	-0.71		-1.69	0.87	1.62		1.29
1980 - 1981	-0.67	0.22		-0.15	1.29	1.73		1.38
1981 - 1982	0.93	1.57		1.15	-0.04	-0.36		0.39
1982 - 1983	0.38	-0.35		-0.84	1.64	0.89		0.49
1983 - 1984	0.07	1.11		0.11	-0.13	-0.50		-0.47
1984 - 1985	2.58	2.38		1.93	0.57	-0.29		-0.21
1985 - 1986	-0.16	-0.44		-0.25	-1.34	-1.23		-1.02
1986 - 1987	0.20	0.17		-0.58	-0.01	-0.08		-0.96
1987 - 1988	0.07	-0.32		-1.22	0.77	0.03		0.27
1988 - 1989	2.18	1.79		2.41	-1.77	-1.17		-1.73
1989 - 1990	-0.80	-0.51		-0.02	1.79	1.62		1.38
1990 - 1991	0.16	0.06		-0.57	0.06	0.41		0.77
1991 - 1992	0.54	-0.04	0.40	0.58	0.68	1.32	0.87	0.76
1992 - 1993	-0.25	-1.65	-1.95	-1.38	1.08	1.44	1.45	0.74
1993 - 1994	1.02	1.59	0.71	0.29	-0.34	-0.92	0.18	-0.29
1994 - 1995	0.30	-0.69	0.53	0.35	0.02	0.85	0.46	0.51
1995 - 1996	-1.64	-0.43	-0.22	-0.66	0.33	-0.85	-0.04	-0.35
1996 - 1997	0.22	0.15	0.30	0.27	0.60	0.68	1.47	1.03
1997 - 1998	-0.71	-0.59	0.06	0.92	1.75	2.12	1.86	2.09
1998 - 1999	0.00	-0.72	0.05	-0.93	-1.97	-1.97	-1.65	-1.97
1999 - 2000	-0.75	-1.20	-0.36	-0.10	-0.68	-0.39	0.04	-0.08
2000 - 2001	-0.48	-0.73	0.93	0.43	-0.11	0.22	-0.52	0.35
2001 - 2002	1.53	0.44	1.59	1.07	-0.41	-0.58	-0.05	-0.99
2002 - 2003	1.99	2.49	2.98	1.57	0.88	0.90	1.31	0.75
2003 - 2004	-0.13	-0.79	-0.23	-0.20	-1.23	-1.28	-1.17	-1.71
2004 - 2005	-0.21	0.41	-0.40	0.67	1.33	0.96	0.81	0.76
2005 - 2006	-2.24	-1.37	0.06	-1.15	-1.92	-1.44	-0.90	-0.88
2006 - 2007	0.13	-0.34	-0.36	0.70	0.41	0.11	0.34	0.91
2007 - 2008	-0.17	0.00	-1.40	-0.95	1.06	0.93	0.64	1.01
2008 - 2009	-0.35	-1.27	-1.03	-0.77	-0.44	-0.88	-1.09	-1.79
2009 - 2010	-1.39	-1.31	-1.22	-2.26	-0.98	-0.91	-1.77	-1.72
2010 - 2011	0.45	-0.74	-0.35	0.27	-0.53	-0.88	-1.13	-0.08
2011 - 2012	-0.32	-0.15	0.88	1.19	-0.40	0.29	0.14	-0.20
2012 - 2013	-1.33	-1.43	-1.57	-1.13	-0.67	-0.62	-1.19	-0.18
2013 - 2014	0.15	0.64	0.34	0.51	-0.63	-0.54	-0.25	0.08
2014 - 2015	-0.40	-0.34	-0.38	-0.27	0.79	0.46	-0.14	0.48
2015 - 2016	0.46	-0.14	0.18	-0.63	0.35	0.45	0.52	0.97
2016 - 2017	-0.13	0.79	0.43	-0.62	-0.80	-0.02	0.39	-0.30

	July to September (3 Months)				October to December (3 Months)			
Year	Jessore	Khulna	Mongla	Satkhira	Jessore	Khulna	Mongla	Satkhira
1976 - 1977	-0.72	0.48		-0.51	-2.12	-0.26		-0.63
1977 - 1978	-0.85	-0.04		0.55	0.35	0.01		-0.38
1978 - 1979	-0.78	0.70		1.99	-0.42	-0.21		0.37
1979 - 1980	1.27	1.48		-0.92	0.41	-0.24		-0.57
1980 - 1981	-0.44	0.00		-0.53	-0.09	-0.20		-0.42
1981 - 1982	0.41	0.14		1.33	0.14	-0.66		-0.52
1982 - 1983	-1.19	-0.40		-0.35	-1.65	-1.31		-1.54
1983 - 1984	0.31	0.81		0.07	0.33	1.09		1.17
1984 - 1985	-0.12	0.07		-0.39	-1.02	-0.83		-1.10
1985 - 1986	-0.06	-1.20		-0.74	0.47	-0.12		-0.21
1986 - 1987	1.11	1.42		1.29	1.32	0.62		1.14
1987 - 1988	1.88	0.57		0.83	0.21	-0.68		-1.68
1988 - 1989	-0.62	-1.10		-0.80	0.51	0.68		-0.35
1989 - 1990	-1.47	-1.72		-1.36	0.62	1.32		0.40
1990 - 1991	-0.54	-0.50		0.84	0.81	0.72		0.62
1991 - 1992	0.56	-0.24	-0.19	-0.20	1.61	0.54	0.59	-0.03
1992 - 1993	-0.88	-1.87	-1.07	0.01	-1.35	-0.78	-1.30	-0.74
1993 - 1994	0.31	-0.57	-0.63	0.03	-0.88	-0.20	-0.45	0.33
1994 - 1995	-1.38	-1.66	-1.09	-0.18	-0.83	-1.11	-0.38	-1.08
1995 - 1996	0.20	0.59	-0.86	0.29	0.70	0.71	1.26	0.62
1996 - 1997	0.00	-1.84	-0.65	-1.67	0.94	0.71	0.64	1.35
1997 - 1998	0.62	0.56	1.47	0.96	-1.10	-1.17	-2.01	-1.36
1998 - 1999	-1.27	-0.19	0.96	-1.21	0.58	1.01	0.89	1.61
1999 - 2000	0.29	0.74	1.42	0.04	0.17	0.12	0.97	-0.48
2000 - 2001	1.15	-0.06	-0.71	1.03	0.09	0.47	-0.44	-0.06
2001 - 2002	-2.34	-1.24	-1.28	-0.89	0.13	0.63	0.82	0.32
2002 - 2003	0.39	0.71	0.77	0.23	0.08	0.29	-0.24	-0.43
2003 - 2004	-0.59	-1.23	-1.75	-1.10	2.14	1.37	0.72	2.22
2004 - 2005	2.64	0.79	0.29	1.17	0.92	0.27	0.59	0.89
2005 - 2006	-0.12	0.37	0.86	0.40	1.81	1.91	1.24	2.47
2006 - 2007	1.11	1.58	0.61	1.73	-1.61	-0.86	-1.40	-1.16
2007 - 2008	1.58	0.82	0.72	0.95	0.77	1.29	1.12	1.12
2008 - 2009	0.75	-0.26	-0.20	-0.51	0.38	0.37	0.14	0.26
2009 - 2010	0.69	0.93	0.60	0.40	-0.47	-0.25	-0.75	-0.63
2010 - 2011	-1.48	-2.02	-1.57	-1.60	0.21	0.79	1.38	-0.44
2011 - 2012	-0.01	1.15	1.59	1.78	-1.95	-2.95	-1.69	-1.34
2012 - 2013	-0.27	0.16	0.68	-0.31	0.01	0.18	-0.18	0.63
2013 - 2014	0.09	0.25	-0.68	-0.57	0.72	0.84	0.67	0.96
2014 - 2015	-0.27	-0.56	-1.06	-1.33	-1.40	-2.91	-0.41	-0.94
2015 - 2016	0.87	1.81	1.37	1.14	-1.19	-0.71	-1.84	-1.14
2016 - 2017	-0.83	0.60	0.37	-1.92	-0.23	0.00	0.24	0.55

	April to September (6 Months)				October to March (6 Months)			
Year	Jessore	Khulna	Mongla	Satkhira	Jessore	Khulna	Mongla	Satkhira
1976 - 1977	-1.04	0.51		-0.29	-2.64	-1.33		-0.68
1977 - 1978	0.05	0.59		1.44	-0.13	-0.83		-0.98
1978 - 1979	-0.55	0.93		1.39	-0.36	-0.79		0.05
1979 - 1980	-0.09	0.79		-1.76	0.71	1.17		0.46
1980 - 1981	-0.94	0.04		-0.60	0.63	1.37		0.67
1981 - 1982	0.97	0.99		1.66	-0.11	-1.26		-0.41
1982 - 1983	-0.76	-0.60		-0.81	0.18	-0.38		-1.06
1983 - 1984	0.21	1.10		0.02	0.03	0.56		0.77
1984 - 1985	1.87	1.48		0.92	-0.66	-1.38		-1.48
1985 - 1986	-0.28	-1.21		-0.77	-0.21	-1.10		-1.07
1986 - 1987	1.06	1.16		0.68	1.14	0.23		0.55
1987 - 1988	1.60	0.23		0.01	0.46	-0.96		-1.39
1988 - 1989	1.17	0.35		1.00	-0.23	-0.09		-1.43
1989 - 1990	-1.92	-1.61		-1.07	1.60	2.35		1.28
1990 - 1991	-0.40	-0.37		0.38	0.64	0.70		0.94
1991 - 1992	0.77	-0.24	0.10	0.15	1.84	1.39	0.94	0.34
1992 - 1993	-1.04	-2.40	-2.07	-0.80	-0.32	0.66	-0.05	-0.25
1993 - 1994	0.91	0.53	-0.09	0.14	-1.31	-1.06	-0.68	-0.07
1994 - 1995	-0.96	-1.66	-0.52	0.05	-1.00	-0.31	-0.40	-0.74
1995 - 1996	-0.98	0.20	-0.86	-0.17	0.65	0.05	1.19	0.20
1996 - 1997	0.06	-1.25	-0.37	-1.08	1.11	0.94	1.43	1.86
1997 - 1998	0.04	0.11	1.17	1.25	0.46	1.36	0.13	0.97
1998 - 1999	-1.12	-0.56	0.79	-1.48	-0.20	0.21	0.36	0.95
1999 - 2000	-0.30	0.01	0.90	-0.04	-0.36	-0.43	0.92	-0.78
2000 - 2001	0.74	-0.40	0.03	1.03	-0.22	0.32	-1.11	-0.06
2001 - 2002	-0.52	-0.66	0.11	-0.01	-0.33	0.02	0.62	-0.46
2002 - 2003	1.74	1.97	2.49	1.10	0.44	0.76	0.48	0.00
2003 - 2004	-0.66	-1.40	-1.48	-0.99	1.94	0.82	0.26	1.79
2004 - 2005	2.25	0.76	-0.03	1.22	1.51	0.80	0.89	1.18
2005 - 2006	-1.48	-0.44	0.63	-0.38	1.31	1.32	0.90	2.12
2006 - 2007	1.01	1.10	0.21	1.73	-1.15	-1.02	-1.42	-0.33
2007 - 2008	1.26	0.54	-0.16	0.23	1.19	1.71	1.39	1.60
2008 - 2009	0.38	-0.92	-0.79	-0.88	-0.08	-0.40	-0.56	-0.73
2009 - 2010	-0.26	0.08	-0.21	-0.69	-1.23	-1.11	-1.84	-1.76
2010 - 2011	-0.92	-1.94	-1.45	-1.03	-0.28	0.14	1.15	-0.76
2011 - 2012	-0.32	0.76	1.69	1.94	-2.17	-1.87	-1.84	-1.66
2012 - 2013	-1.19	-0.66	-0.29	-0.93	-0.57	-0.51	-1.01	0.28
2013 - 2014	0.13	0.53	-0.35	-0.16	0.31	0.35	0.44	0.81
2014 - 2015	-0.61	-0.68	-1.15	-1.22	-0.64	-1.60	-0.84	-0.67
2015 - 2016	1.03	1.38	1.22	0.65	-0.97	-0.54	-1.49	-0.23
2016 - 2017	-0.89	0.87	0.49	-1.85	-0.89	-0.33	0.20	0.15

	Annual			
Year	Jessore	Khulna	Mongla	Satkhira
1976 - 1977	-1.79	0.13		-0.59
1977 - 1978	-0.19	0.37		1.05
1978 - 1979	-0.68	0.70		1.45
1979 - 1980	0.26	1.37		-1.53
1980 - 1981	-0.59	0.45		-0.43
1981 - 1982	0.64	0.34		1.25
1982 - 1983	-0.61	-0.81		-1.17
1983 - 1984	0.21	1.13		0.06
1984 - 1985	1.40	0.95		0.30
1985 - 1986	-0.48	-1.86		-1.33
1986 - 1987	1.46	1.29		0.92
1987 - 1988	1.50	0.02		-0.48
1988 - 1989	0.81	0.17		0.45
1989 - 1990	-0.86	-0.47		-0.54
1990 - 1991	-0.29	-0.18		0.58
1991 - 1992	1.53	0.26	0.48	0.29
1992 - 1993	-1.02	-2.08	-2.01	-0.97
1993 - 1994	0.30	0.05	-0.48	-0.01
1994 - 1995	-1.27	-1.91	-0.79	-0.27
1995 - 1996	-0.63	0.08	-0.29	-0.11
1996 - 1997	0.51	-0.92	0.28	-0.23
1997 - 1998	0.26	0.64	1.25	1.71
1998 - 1999	-1.30	-0.71	0.75	-1.20
1999 - 2000	-0.43	-0.30	1.14	-0.34
2000 - 2001	0.51	-0.34	-0.49	1.03
2001 - 2002	-0.71	-0.80	0.22	-0.24
2002 - 2003	1.70	2.25	2.63	1.14
2003 - 2004	0.39	-1.06	-1.32	-0.15
2004 - 2005	2.59	0.96	0.25	1.61
2005 - 2006	-0.71	0.02	0.92	0.57
2006 - 2007	0.60	0.94	-0.32	1.65
2007 - 2008	1.62	1.26	0.43	0.86
2008 - 2009	0.25	-1.09	-1.06	-1.17
2009 - 2010	-0.60	-0.17	-0.82	-1.14
2010 - 2011	-0.94	-1.89	-0.83	-1.28
2011 - 2012	-0.99	0.33	1.09	1.68
2012 - 2013	-1.29	-0.83	-0.67	-0.82
2013 - 2014	0.18	0.67	-0.18	0.16
2014 - 2015	-0.75	-1.10	-1.47	-1.50
2015 - 2016	0.57	1.31	0.77	0.61
2016 - 2017	-1.19	0.86	0.51	-1.82