

Resource book

# Earth observation and climate data analysis for agricultural drought monitoring in South Asia



ICIMOD

CIMMYT<sub>MR</sub>



**Resource book**  
**Earth observation and climate data analysis for**  
**agricultural drought monitoring in South Asia**

**Editors**

Faisal M. Qamer  
Timothy J. Krupnik  
Pradyumna R. Pandey  
Bashir Ahmad



ICIMOD

CIMMYT<sup>MR</sup>

**SAARC Agriculture Centre (SAC), Dhaka, Bangladesh**  
**International Centre for Integrated Mountain Development (ICIMOD),**  
**Kathmandu, Nepal**  
**International Maize and Wheat Improvement Centre (CIMMYT), Dhaka,**  
**Bangladesh**

**July 2019**

**Published by**

SAARC Agriculture Centre (SAC)  
BARC Complex, Farmgate, Dhaka-1215, Bangladesh  
Phone: + 880-2-58153152; Fax: + 880-2-91245996  
Email: director@sac.org.bd, Website: www.sac.org.bd

© 2019 SAARC Agriculture Centre, International Centre for Integrated Mountain Development, and International Maize and Wheat Improvement Centre

This work is licensed under a Creative Commons Attribution Non-Commercial, No Derivatives 4.0 International License (<https://creativecommons.org/licenses/by-nc-nd/4.0/>)

This publication may be reproduced in whole or in part and in any form for educational or non-profit purposes without special permission from the copyright holder, provided acknowledgement and use of the correct citation listed below is made. No use of this publication may be made for resale or for any other commercial purpose.

ISBN 978-984-34-7004-1

**Editors:**

Dr Faisal M. Qamer, ICIMOD, Kathmandu, Nepal  
Dr Timothy J. Krupnik, CIMMYT, Dhaka, Bangladesh  
Dr Pradyumna R. Pandey, SAARC Agriculture Centre (SAC), Dhaka  
Dr Bashir Ahmad, Pakistan Agricultural Research Council (PARC), Islamabad, Pakistan

**Contributors:**

Dr Nawaraj Shrestha, Kathmandu University; Dr Rajesh B. Thapa, ICIMOD; Dr Diego Pedreros, Climate Hazards Centre (CHC) - UC Santa Barbara; Dr Tsegaye Tadesse, University of Nebraska–Lincoln; Dr Poonam Tripathi, ICIMOD; Dr Benjamin Zaitchik, Johns Hopkins University; Dr Lee Ellenburg, SERVIR Science Coordination Office

**Copy editor:** Utsav Madan and Anne-Laure Pilat

**Cover illustration:** Curves and Colors; Sudip Maharjan, ICIMOD

Printed by  
Natundhara Printing Press  
277/3 Elephant Road (1st Floor), Kataban Dhal, Dhaka-1205

**Disclaimer:**

The SAC, ICIMOD, and CIMMYT hereby disclaim any liability to party for any conflicting information or error, considering that all the material included in this compilation comes from invited authors.

The views and interpretations in this publication are those of the authors' and are not necessarily attributable to SAC, ICIMOD, CIMMYT, SERVIR, CSRD, or USAID. This publication shall not be used for advising or product endorsement purposes

**Citation:** Qamer F.M., Krupnik T.J., Pandey P.R., Ahmad B. (Eds) 2019. Resource book: Earth observation and climate data analysis for agricultural drought monitoring in South Asia. South Asian Association for Regional Cooperation (SAARC) Agriculture Centre (SAC). Dhaka, Bangladesh.

## FOREWORD

It gives me immense pleasure to join hands with the International Centre for Integrated Mountain Development (ICIMOD), the Pakistan Agricultural Research Council (PARC), the Pakistan Meteorological Department (PMD), and the International Maize and Wheat Improvement Centre (CIMMYT), in organizing the SAARC regional training workshop on Earth observation and climate data analysis for agricultural drought monitoring in South Asia from 29 July to 1 August 2019 in Islamabad, Pakistan. About 25 participants including local participants comprising scientists and extension officers affiliated to the Ministry of Agriculture, Ministry of Environment and National Agricultural Research System (NARS) of SAARC Member States are expected to participate in this training programme.

The training programme, which aims to build the capacity of agriculture and climate scientists on the techniques of data development and analysis tailored for use in monitoring drought, will also provide a platform for exchanging experiences among participants.

In South Asia, a large majority of people lives in rural areas and depends on agriculture, forestry, fisheries and livestock. These livelihood sources are highly vulnerable to climate-induced hazards such as erratic precipitation, floods and droughts, as well as market price volatility. Considering the adverse impacts of drought on agricultural production and food security, it is critical that we prepare line agencies to understand the drought phenomenon better and monitor them regularly.

This training programme is a timely and important endeavour and the resource book will serve as a ready reference for training participants. I hope that the skills and experiences shared in this training programme will help the participants' in using Earth observation data and climate data analysis to develop a better understanding of droughts, and help them in monitoring them and develop timely and suitable agri-advisories. I thank the ICIMOD team, contributors and Dr. Pradyumna Raj Pandey, Senior Programme Specialist (Crops), for their dedicated efforts in organizing the regional training and for bringing out this resource book.

**Dr. S.M. Bokhtiar**

Director

SAARC Agriculture Centre, Dhaka

## **FOREWORD**

Increasing frequency and severity of climate-induced hazards – droughts –adversely affect agriculture, food security and livelihoods of populations across the Hindu Kush Himalayan region.

To address this issue, ICIMOD has been collaborating with meteorological and agricultural institutions in the Hindu Kush Himalaya (HKH) to establish agricultural drought monitoring and outlook systems. This collaboration aims to improve their capacity in developing data products related to crop monitoring and enhancing the knowledge of national scientists on the interpretation of agro-climatic data in their respective countries.

A considerable amount of research is being undertaken on agro-climatic monitoring and modelling, and large amounts of information on climate variability is being made available. Such information can aid farmers and decision-makers in making informed sustainable crop management decisions. However, use of such information by decision-makers in our region remains low. Provisioning of timely, and actionable scientific information in the form of advisory services can assist adaptation to environmental change, while limiting the economic damage and social disruption caused by environmental disasters.

ICIMOD, through its Mountain Environment Regional Information System programme (MENRIS), contributes to effective evidence-based decision-making processes by governments, communities, and individuals using scientific data, Earth observation information and geospatial technologies in the areas of agriculture, environment, natural resources, and climate change. The SERVIR Hindu Kush Himalaya (SERVIR-HKH) Initiative of MENRIS collaborates with global institutions and government line agencies in ICIMOD's regional member countries to promote the effective use of Earth observation in developing sustainable climate services. This regional training, organized jointly with the SAARC Agriculture Centre (SAC), and the Pakistan Agricultural Research Council (PARC), in collaboration with the Pakistan Meteorological Department (PMD), and the International Maize and Wheat Improvement Centre (CIMMYT), aims to orient participants on using Earth observation information and climate data analysis in monitoring droughts. We hope that through this training workshop, the participants will gain a better understanding of droughts using Earth observation products, and initiate and foster further trainings to promote institutional capacities in drought mitigation and preparedness.

**Dr. David Molden**  
Director General  
ICIMOD

## **List of Acronyms**

ADVI - Absolute Difference Vegetation Index

AMSR-E - Advanced Microwave Scanning Radiometer on the Earth Observing System

APHRODITE - Asian Precipitation Highly Resolved Observational Data Integration Towards Evaluation of Water Resources

ARIMA - Autoregressive Integrated Moving Average

BARC - Bangladesh Agricultural Research Council,

BARI - Bangladesh Agricultural Research Institute

BASIICS – Background Assisted Station Interpolation for Improved Climate Surfaces

BISE - Best Index Slope Extraction

BMD - Bangladesh Meteorological Department

CDF - Cumulative Distribution Function

CHG – Climate Hazard Group

CHIRPS - Climate Hazards Group InfraRed Precipitation with Station

CHPClim - Climate Hazards Precipitation Climatology

CIMMYT - International Maize and Wheat Improvement Centre

CSRD - Climate Services for Resilient Development

DAE - Department of Agricultural Extension

DEWS – Drought Early Warning Systems

EDI - Effective Drought Index

ET - Evapotranspiration

EWS - Early Warning Systems

FEWS NET - Famine Early Warning Systems Network

GDAS - Global Data Assimilation System

GEOSS - Global Earth Observation System of Systems

GIS - Geographical Information Systems

GPP - Gross Primary Productivity

ICIMOD - International Centre for Integrated Mountain Development

ICT - Information and Communication Technologies

IRI - International Institute for Climate and Society

LAI – Leaf Area Index

LIS - Land Information System

LSM - Land Surface Model  
LST - Land Surface Temperature  
MODIS – Moderate Resolution Imaging Spectroradiometer  
MVC - Maximum Value Composite  
NAO – North Atlantic Oscillation  
NASA - National Aeronautics and Space Administration  
NDVI – Normalized Difference Vegetation Index  
NMME - North American Multi-Model Ensemble  
NRI – Near infrared  
PDSI - Palmer Drought Severity Index  
PET - potential evapotranspiration  
PHDI - Palmer Hydrological Drought Index  
PR - Precipitation Radar  
QGIS – Quantum Geographical Information Systems  
R&D - Research and Development  
RADAR - RAdio Detection And Ranging  
SAARC - South Asian Association for Regional Cooperation  
SAC - SAARC Agriculture Centre  
SALDAS - South Asian Land Data Assimilation System  
SARIMA – Seasonal ARIMA  
SDVI - Standardized Difference Vegetation Index  
SLDAS – South American Land Data Assimilation System  
SMMR - Scanning Multichannel Microwave Radiometer  
SMOS - Soil Moisture and Ocean Salinity  
SOI - Southern Oscillation Index  
SPI – Standardized Precipitation Index  
SPIRITS - Software for the Processing and Interpretation of Remotely Sensed Image Time Series  
SSM/I - Special Sensor Microwave/Imager  
SWSI - Surface water supply index  
TCI - Temperature Condition Index  
TIR - Thermal Infrared  
TMI - TRMM Microwave Imager  
TRMM - Tropical Rainfall Measuring Mission  
UPF - University de Passo Fundo



URI - University of Rhode Island

USA - United States of America

USAID - United States Agency for International Development

USGS - United States Geological Survey

VCI - Vegetation Condition Index

VegDRI – Vegetation Drought Response Index

VHI - Vegetation Health Index

VIRS – Visible and Infrared Scanner

## Contents

<b>List of Acronyms</b>	<b>v</b>
<b>1 Drought concept and definitions</b>	<b>1</b>
1.1 Classification of droughts	2
1.1.1 Meteorological drought	3
1.1.2 Hydrological drought	4
1.1.3 Agricultural Drought	5
1.1.4 Socio-economic drought	6
<b>2 Drought detection and assessments</b>	<b>6</b>
2.1 Remote Sensing for drought characterization	7
2.1.1 Vegetation monitoring	10
2.1.2 Surface temperature estimation	10
2.1.3 Soil moisture estimation	14
2.1.4 Rainfall Monitoring	11
2.2 Drought indices	13
2.2.1 Standardized precipitation index	14
2.2.2 Palmer drought severity index (PDSI)	16
2.2.3 Surface water supply index (SWSI)	17
2.2.4 Vegetation condition index	17
2.2.5 Temperature Condition Index (TCI)	18
2.2.6 VegDRI Concept	18
2.3 Criteria for Selecting Drought Indices for monitoring Drought	20
2.4 Data Requirement for Drought Monitoring	21
2.5 Weather forecast and drought prediction	27
2.5.1 Drought forecasting system	28
<b>3 Drought communication and dissemination systems</b>	<b>29</b>
3.1 Drought Preparedness Planning (timing and methods of communication)	30
3.2 Communication of drought information to farmers	30
Exercise 1: NDVI Calculation using MODIS (MOD09A1) Images in QGIS	32
Exercise 2: Visualizing and interpreting time series data; detecting anomalies in NDVI data	38
Exercise 3: Monitoring drought using climate variables - Average, Trend, SPI	54

Exercise 4: Validation of satellite-based rainfall data against rain gauge station data	72
Exercise 5: Background-Assisted Station Interpolation for Improved Climate Surfaces (BASIICS).	83
References	89



[Blank Page]

## **1 Drought concept and definitions**

Droughts are manifestations of climatic fluctuations associated with large-scale anomalies in the planetary circulation of the atmosphere. They imply the absence of, or weak precipitation, for an extended period over large areas. It is very difficult to identify and to clearly determine the onset as well as the termination point of a drought as it is a usually a slow-developing phenomenon. The effects of drought tend to accumulate slowly and persist over long periods of time. Making matters worse, droughts are typically not confined by topography that affects weather conditions, and may extend over large areas.

Droughts are defined as the temporary reduction in quantity of rainfall, runoff, and soil moisture compared to the climatology of a region. Dry climates are prone to drought effects due to the soil moisture deficiency and high variability in occurrence of rainfall events and quantity. Because drought does not have a precise and universally accepted definition, it is difficult to assess its occurrence or measure its degree of severity. This ambiguity is further aggravated as drought implies different meanings and implications for different people. For example, a meteorologist, an agriculturalist, a hydroelectric power plant operator, and a wildlife biologist will have differing definitions of drought.

In addition, drought can be defined conceptually as well as operationally (Wilhite & Glantz, 1985). Conceptual definitions are stated in relative terms (e.g., a drought is a long, dry period), whereas operational definitions attempt to identify the onset, severity, and termination of drought periods. Generally, operationally defined droughts can be used to analyse drought frequency, severity, and duration for a given return period. Among others, the main natural causes of drought are climate effects. Nonetheless, mismanagement of water resources, acid rain pollution, overexploitation, and many other man-made effects also contribute to the extent, appearance, continuity, and severity of droughts.

Severity of droughts is a factor of high temperatures, winds, and low relative humidity. In many parts of the world, drought is also related to the timing of precipitation including principal season of occurrence, delays in the start of the rainy season, the occurrence of rains in relation to crop growth stages and the effectiveness of the precipitation ( i.e. rainfall intensity, its areal extent, and the frequency of occurrence). All these variables indicate that each drought event is unique in its climatic characteristics, spatial extent, and impacts.

In many cases, drought severity is hard to define. Indeed, drought severity is determined by its duration, intensity and geographical extent, coupled with water demand from human activities and vegetation in the given region. Drought characteristics and extensive impacts render it more difficult to identify and quantify the drought effects on the society, economy and environment. To fully appreciate the significance of drought, the societal context in which it is defined also plays an important role. Despite a drought episode occurring during one or several consecutive seasons, its impacts on society can persist for many years thereafter. Additionally, drought impacts depend on the vulnerability of a particular society or population to drought at a particular time. As such, subsequent drought episodes of similar intensity, duration and extent, will likely result in different effects in different areas. The common theme in all drought episodes is the deficiency of precipitation, resulting in moisture stress for socio-ecological processes (e.g. agriculture).

While a number of natural and human factors can have important impacts, impact on water availability, water shortage and stress resulting from drought must however be understood as a relative condition and temporary condition, and not an absolute one (Figure 1.1).

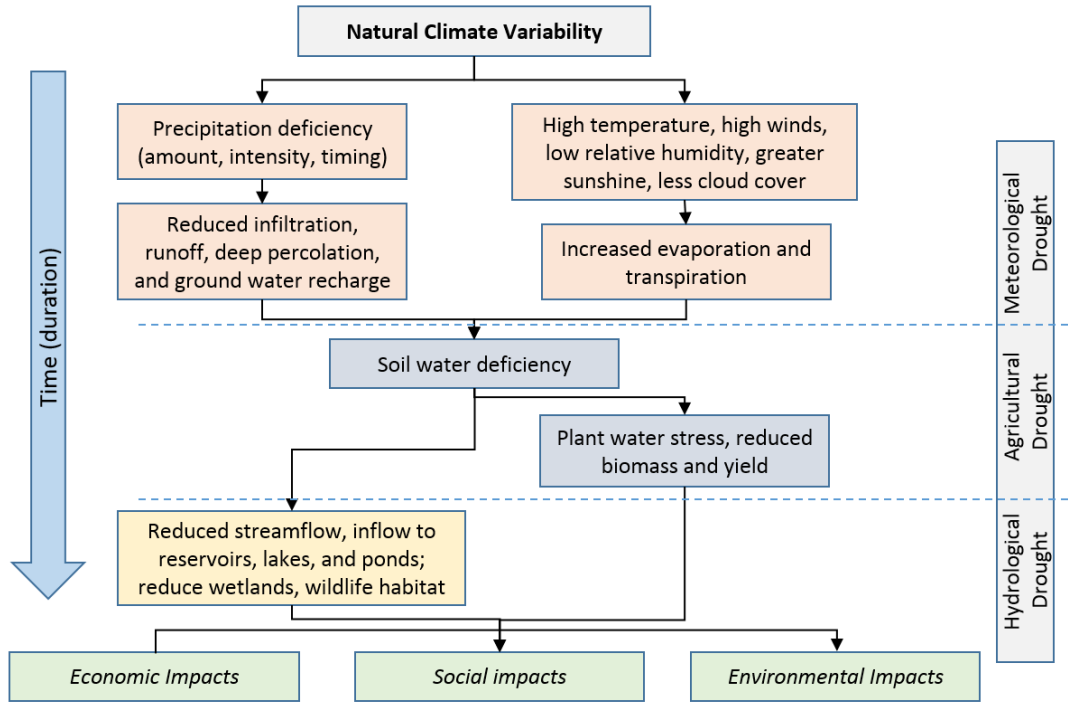


Figure 1.1: Drought types and associated socio-economic and environmental impacts. (Adapted from National Drought Mitigation Centre, University of Nebraska–Lincoln, USA).

## 1.1 Classification of droughts

Available records indicate that there are more than 150 definitions of drought in different disciplines and cultural contexts, and none of them are universal. Rather, the definition depends on the context and region, in addition to the ecological or social process that moisture deficit is related to, thus leading to different conclusions. Despite these differences, every drought events can be characterized by a deficiency in a variable related to the hydrological cycle. Hence, most definitions can be summarized as the lack of adequate water supply relative to demand or need (Quiring & Papakryiakou, 2003). To clarify, droughts can be classified into four categories (Figure 1.2, Wilhite & Glantz, 1985), along with drought components (Figure 1.3), which include:

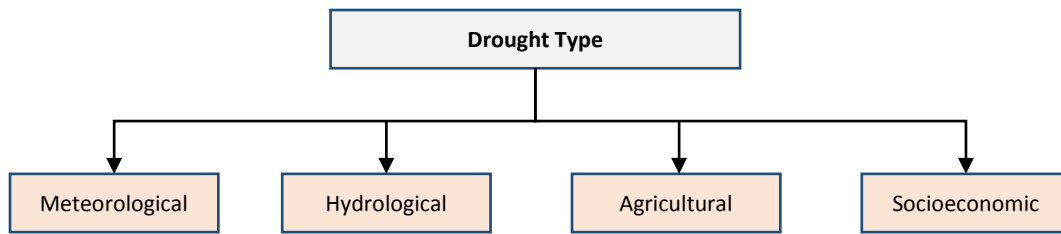


Figure 1.2: Four common categories of drought

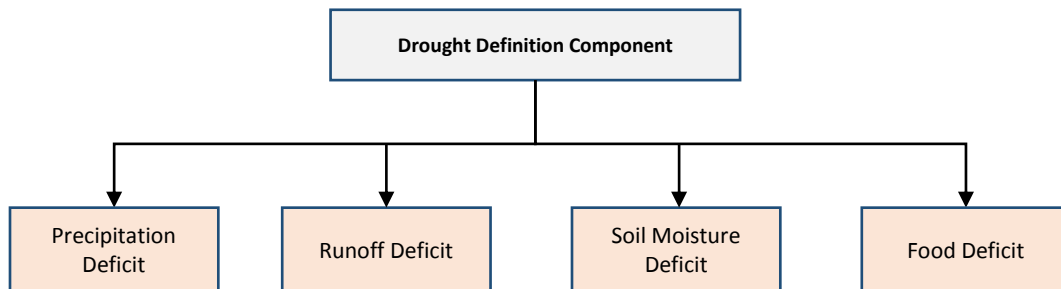


Figure 1.3: Common drought components (Adapted from Sen, 2015)

### 1.1.1 Meteorological drought

The meteorological definition of drought is the most widespread and understood. Using the meteorological definition, drought is described singularly as the degree of dryness and duration of the dry period experienced. Most popular meteorological definitions consider drought as a “...period of more than some particular number of days with precipitation less than some specified small amount...” or as a “...sustained period of time without significant rainfall” (Linsley, Kohler, & Paulhus, 1958).

Meteorological drought is defined as a lack of precipitation over a region for an extended time period (Figure 1.4 a). In order to identify a drought event, meteorologists rely on calculations made from precipitation data. Drought is either identified as a deficit in precipitation in comparison to the average values over the month, or as a cumulative precipitation shortage over a period of several months using historical data.



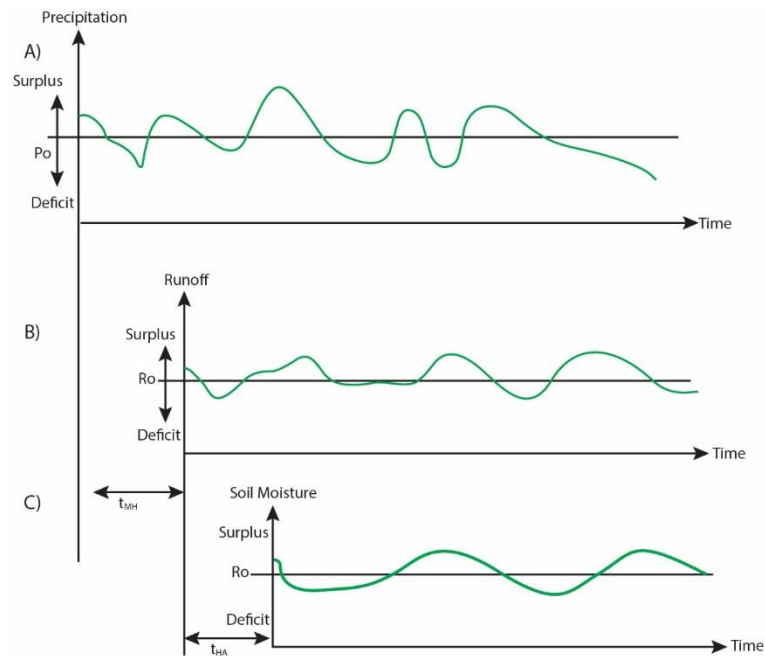


Figure 1.4: Drought types A) Meteorological B) Hydrological C) Agricultural  
(Adapted from Sen, 2015)

In addition, the way and extent to which meteorological drought is defined necessarily depends on location-specific conditions. Thresholds have therefore been developed and can be used to distinguish periods of drought and non-drought, although thresholds themselves may vary from location to location, and are themselves the subject of some controversy. Efforts have been made to identify and apply common elements across definitions that could be used to develop a more ‘universal’ definition of meteorological drought, although only a few examples are prevalent. Some of the common definitions that have nonetheless been developed (Wilhite & Glantz, 1998) include the following:

- 1) Less than 2.5 mm of rainfall in forty-eight hours (United States);
- 2) Fifteen consecutive days that received rainfall as much as 0.25 mm (Britain);
- 3) When annual rainfall is less than 180 mm (Libya);
- 4) A period of six days without rain (Bali)

### 1.1.2 Hydrological drought

Hydrological drought can be defined as a significant lack of water in the hydrological system that impairs hydrological cycling and functioning. To clarify, hydrological drought is a period of inadequate surface and/or subsurface water resources that impair the function and/or provision of water for a specific use. Prolonged lack of precipitation can severely impact the hydrological system, and can result in soil moisture deficiencies (causing soil

moisture drought), reduced level of groundwater (thereby affecting water storage and potential for abstraction), lower water levels in surface storage including lakes and reservoirs, and a low level of stream flow in rivers. When these elements are combined, hydrological drought occurs. The changes in severity from meteorological to hydrological drought can be characterized by the following characteristics defined by Van Loon & Van Lanen (2012) as follows:

- Meteorological droughts are combined into a prolonged hydrological drought (pooling)
- Meteorological droughts are attenuated in hydrological stores, for example in groundwater (attenuation)
- A time differential and delay occurs between meteorological, soil moisture, and hydrological drought (lag)
- Droughts are longer in time, moving from meteorological drought to soil moisture deficit and then to hydrological drought (lengthening)

To define the frequency and severity of a hydrological drought, scientists and experts rely on the influence of water deficits on the river basin water level. If the quantity of the observed runoff is less than the long-term average of water runoff, then the year can be quantified as a drought year. Flow in most of the streams in a watershed affected by drought will be low. If low-flow persists below a threshold level, then drought can be considered to be in progress. Nonetheless, the length (in days) and probability of this length exceeding the threshold to define a hydrological drought period varies from place to place and is often considered to be specific to individual streams or river basins, thereby complicating measurement without an adequate network of monitoring equipment for regular data acquisition. Finally, it is crucial to reinforce the concept that hydrological droughts can be, but are not automatically, synchronized with the occurrence of either meteorological or agricultural drought.

### **1.1.3 Agricultural Drought**

Agricultural drought indicates a condition in which a decline in soil moisture is observed, resulting in crop losses, and in crop failure in extreme cases, but without necessarily having implications for surface water resources. Deficient soil moisture results from some of the effects of meteorological and hydrological drought. The key indicator, however, is the difference between actual evapotranspiration and potential evapotranspiration, which can leave crop plants in a stressed condition. Crop water demand is influenced by weather conditions, the water table, varietal characteristics and crop phenology, as well as the physical and biological properties of soil, in addition to a farmers' management practices.

Many of the variables used to study agricultural droughts are derived from the characteristics of meteorological drought. These include precipitation shortage, departures from normal or other meteorological factors, for example precipitation or evapotranspiration. Well-formed definitions of agricultural drought combine, variables

including but not limited to precipitation, temperature and soil moisture. Fully operational definitions of agricultural drought will consider the varying susceptibility of crops to soil moisture at different stages of phenological development, from seeding to maturity. For example, low topsoil moisture at the sowing period can impede germination, leading to poor plant stands that can ultimately reduce yield. A prolonged deficiency in soil moisture can have additional, significant effects. In rain-fed cropping systems, without sufficient precipitation to meet the crop water demand, further stress and yield loss can result.

#### **1.1.4 Socio-economic drought**

Socio-economic drought may be understood as a situation in which water resources are insufficient to meet the water demands of a given human population. Socio-economic drought is associated with the provision of water as an economic good, and is indicative of an inability to source sufficient water for societal and economic demand. Definitions of socio-economic also incorporate characteristics from meteorological, agricultural, and hydrological drought, though some researchers including Yevjevich (1967), went as far as saying that an objective definition is really only possible if the time and space processes of prevailing supply and demand factors are taken into consideration because of deration. This point is especially relevant because of the capacity of many societies to adapt to drought conditions using technology.

## **2 Drought detection and assessments**

The objective of drought monitoring is to provide data that can be used in early warning systems prior to drought occurrence. Timely and accurate information on potential drought episodes is a crucial component of national drought policy (e.g. for water resources management) and planning, especially in the sectors of agriculture and environmental management, in addition to industry and civil infrastructure. The need for improved drought monitoring methods and approaches is highlighted by the severe droughts experienced in a number of countries that have resulted in serious economic, social, and environmental impacts. Today, most drought monitoring services rely on the use of drought indicators to identify drought risks, which are explained in detail below.

Drought indicators, also called drought indices, include a number of relevant parameters used to describe and monitor the different drought conditions. Indicators are the result of quantitative measures of one or several drought variables (e.g. precipitation, soil moisture, stream flow, groundwater, evapotranspiration, vegetation etc.), which are combined into a single numerical value characterizing a specific level of drought. Drought indices are a particularly important management and decision-making tool for business, policy makers and other public stakeholders. Moreover, they can be a valuable tool in the development of an early warning system prior to the onset of drought.

Various drought indices with different time scales have been developed. For many, a drought index is seen as the “prime variable for assessing the effect of a drought and defining different drought parameters, which include intensity, duration, severity and spatial extent” (Mishra and Singh, 2010). Undeniably, a drought index can be used to quantify: (1) the moisture condition of a region and thereby detect the onset and severity

of drought events, and (2) the spatial extent of a drought event, thereby allowing for comparison of moisture supply. The methods used to monitor drought can be categorized into three main classes i.e., traditional drought monitoring by onsite observation of hydroclimate variables (e.g. standardized precipitation index), and by remote sensing-based methods, including satellite imagery used to construct indices (e.g. the normalized difference vegetation index, vegetation condition index, soil moisture deficit index), and the land surface model (LSM) method.

Drought detection and monitoring is challenging because droughts are a slow-developing phenomena, with an onset and end that are not distinct. In addition, droughts are also a factor of spatial and temporal variabilities. Nevertheless, today there are more than eighty indices used to describe in the most comprehensible way the various possible drought phenomena. Additionally, drought indices are providing the scientific community with data supporting drought detection, monitoring and quantification (e.g. intensity, duration, spatial extent), which are essential information for a diverse number of decision makers.

Yet, we still don't have today a single universally accepted drought index. This may be due to the three physical possible forms of drought (meteorological, hydrological and agricultural), each of which have different definitions. This makes it difficult to agree on a single technique to quantify accurately the severity of each type of drought. Hence, each index presents its own set of advantages and limitations, depending of the kind of drought that is being monitored at a given period of time. Thus, it is important to introduce, explain and discuss the most frequently used meteorological, hydrological, agricultural as well as satellite-based indices.

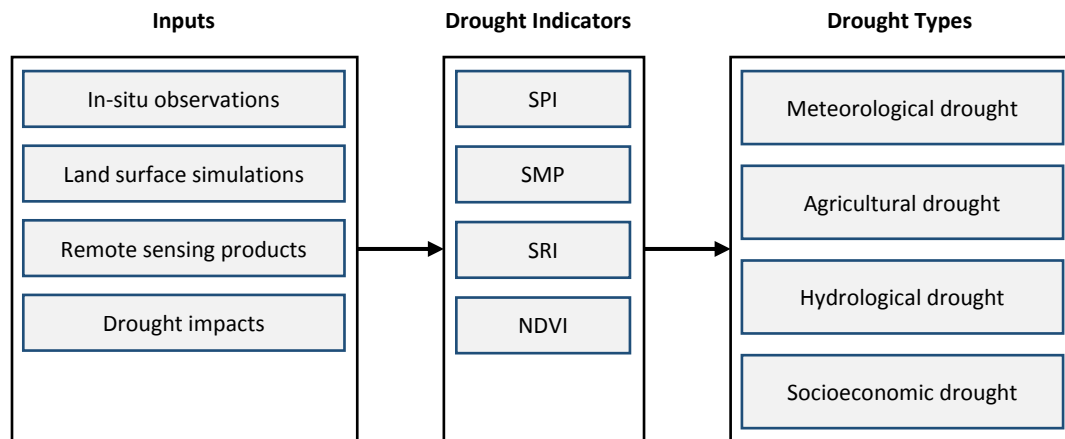


Figure 2.1: Approach in drought monitoring system

## 2.1 Remote Sensing for drought characterization

Remote sensing for drought monitoring and early warning involves data collection and analysis of both meteorological and vegetation conditions.

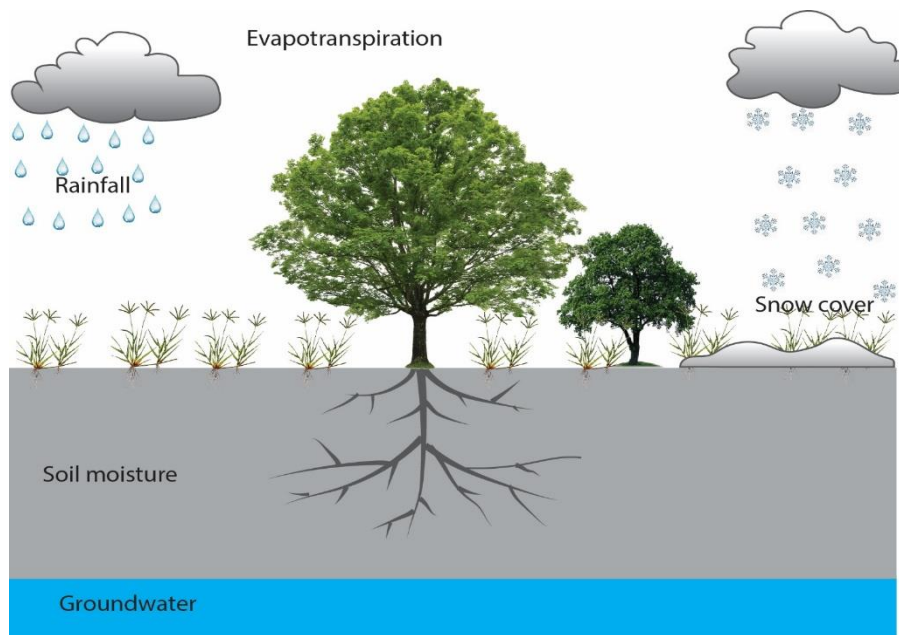


Figure 2.2: Components of hydrologic cycle relevant to drought estimated from satellite remote sensing (Wardlow, et al., 2012)

### 2.1.1 Vegetation monitoring

The previously seen drought definitions –meteorological, hydrological and agricultural –imply that various factors, from precipitation to vegetation condition, need to be monitored to identify drought episodes. Vegetation condition is a good indicator of the effect of climate soil moisture, and agricultural management practices on water deficit. Comparing the state of a current vegetation index to its long-term average can help identify drought and contribute to an early warning system. Therefore, satellite-based images are indispensable in the detection of changes in the canopy.

There are three satellite-based indices used to assess vegetation condition. By extension, each of these indices help in drought identification. Indeed, drought is usually associated with plant vegetation. As such, the following drought indices are most common:

- Indices derived from the optical domain (e.g. NDVI, the vegetation condition index, etc.)
- Indices derived from the thermal channels of the electromagnetic spectrum (e.g. temperature condition index)
- Indices derived from a combination of the previous indices (e.g. vegetation health index)

Today, the Normalized Difference Vegetation Index (NDVI) is the most utilized global-based index. This is due to its near real-time information provision as well as simplicity in utilisation and understanding. The NDVI is presented in the form of a simple

graphical indicator that can be used to analyse remote sensing data (generally obtained by satellite, but not exclusively) to indicate the presence and conditions of green vegetation. NDVI is also correlated with precipitation, which drives plant growth (Figure 2.3). Many studies have explained the link between the red and near-infrared reflected energy and the quantity of vegetation on the ground. Indeed, the reflection of red energy decreases with plant development and growth. On the other hand, the near-red infrared reflected energy increases with the development of healthy vegetation. Still, the quantity of red and near-infrared red energy reflected by the vegetation and received by the satellite can be distorted by various “pollutants” (e.g. solar irradiance or atmospheric conditions) and plant canopy characteristics (e.g. composition, structure etc.). This makes it impossible to simply rely on the reflected energy as an indicator of the overall vegetation condition as linked to moisture deficits. To work around this problem, the currently used NDVI, is based on the ratio difference between the red band and the near-infrared (NRI) and their sum, as follows:

$$NDVI = \frac{(NRI - RED)}{(NRI + RED)}$$

It is important to note that spectral reflectance are themselves ratios of the reflected radiation for each spectral band with value from 0.0 to 1.0. Thus, the value of the NDVI can be found between -1 and +1. The use of “ratio” helps in cancelling out a significant amount of signal variation linked to calibration or change in the irradiance conditions, resulting from various meteorological phenomena such as sun angle or shadow cast by clouds.

Even in the case of densely populated urban areas that would typically lack considerable amounts of vegetation, the NDVI value is positive or closer to zero rather than negative. A negative NDVI value is usually the result of changes in atmospheric conditions.

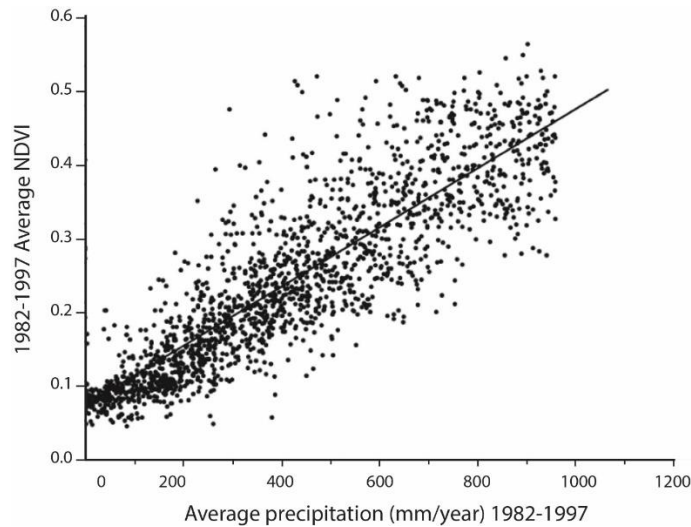


Figure 2.3: Comparison of average precipitation with coincident NDVI  
(Adapted from (Wardlow et al., 2012))

Recent studies have also shown that comparisons of extended time series of NDVI data can help in drought monitoring in a region. The NDVI calculated over several years during the growing season of a plant, can be used as the baseline of the vegetation conditions, whereas the coefficient of variation in NDVI is used to visualize the variation between the growing seasons. Such studies can help in assessing current vegetation conditions in simple formats that can be easily understood, for example including conditions that are “above”, “below”, or “near normal”, with “normal” usually being defined as the historical average.

### **2.1.2 Surface temperature estimation**

Land surface temperature (LST) also derived by satellite data and can be used as a drought index. LST is derived from the range of frequencies in the electromagnetic spectrum, with each range called a ‘band’). The LST is further used to formulate the relationship between emitted energy and the water budget of the Earth’s surface-atmosphere interface (Gutman 1990). Therefore, LST data can help in assessing evapotranspiration, soil moisture and vegetation water stress. LST can also be used as another source of information on the Earth vegetation conditions. This idea led to the development of the temperature condition index (TCI), based on temperature brightness value data. A higher LST is indicative of soil moisture deficiency and thus potentially moisture limiting conditions for vegetation.

### **2.1.3 Soil moisture estimation**

Soil moisture plays an important role in Earth hydrological processes and more precisely in the water and energy budget estimation conducted in the climate studies. Its accurate estimation over time and space is crucial in a wide range of agricultural and environmental studies. The advancement of technology has allowed increased use of various remote sensing techniques to measure soil moisture. Among others, microwave sensing (both passive and active microwave) is the most commonly used approach for remote sensing inference in soil moisture analysis.

All earthly objects emit microwave energy (passive microwaves) in small amounts. These are related to the temperature and moisture properties of the emitting surface or object. A passive microwave sensor, via its antenna, can detect and record naturally emitted energy waves. Recorded energy can be emitted/reflected by the atmosphere, the Earth’s surface or its subsurface (2 to 5 cm). Recording of passive microwaves can be used to quantify (via various algorithms) soil moisture as the amount of moisture that has a direct impact on the emitted quantity of microwaves from an object, including the Earth’s surface. However, since the amount of emitted energy is generally low, the fields of view of the sensor must cover a large enough area of the Earth to be able to record an emission signal. This results in a lower spatial resolution when soil moisture is measured using microwave radiation, which to some extent limits usefulness.

We however now have to our disposition a number of various tools, such as the Scanning Multichannel Microwave Radiometer (SMMR), Special Sensor Microwave/Imager (SSM/I), Tropical Rainfall Measuring Mission (TRMM) Microwave Imager (TMI), Advanced Microwave Scanning Radiometer on the Earth Observing System (AMSR-E), and Soil Moisture and Ocean Salinity (SMOS) sensor. These tools can be used

to measure the natural emission of microwave energy from the land surface (Wang, 1985; Owe et al., 1988; Kerr and Njoku, 1990; Teng et al., 1993; van de Griend and Owe, 1994; Engman, 1995; Jackson, 1997; Kerr et al., 2001; Njoku et al., 2003).

Conversely, an active microwave sensor provides its own source of microwaves used to illuminate a given target (e.g this is the case with RADAR). Sensors emit a microwave directed towards the earth's surface, which are then reflected by Earth and return to the sensor. The physical properties of the Earth's surface or object will in turn influence the amount of microwave energy that is reflected back to the sensor.

Overall, both techniques are based on the changes in soil permittivity, which is in turn linked to the amount of liquid water contained in the soil. Indeed, microwave energy emitted or reflected by the soil to the sensor depends on the soil dielectric constant (permittivity) and consequently soil moisture. Moreover, scientists have developed models to relate water volumetric content of the different soil types to their dielectric constant. It is therefore possible to estimate soil moisture based on the captured microwaves linked to the soil dielectric constant. This approach however must be treated with caution, as different variables including vegetation, rainfall, soil surface roughness, etc. can have an impact on the level of accuracy of soil moisture estimated from detected microwaves.

#### **2.1.4 Rainfall Monitoring**

Rain is one of the determining factors of drought. Compared to conventional method of measuring precipitation through physical capture of rainfall, remote sensing allows for a broader spatial estimation of precipitation. Though still experimental, satellite-based rainfall estimation methods (based on cloud studies) have already shown some promising results and can be grouped into three categories, including (1) visible and infrared techniques, (2) passive microwave techniques, and (3) active microwave techniques, each of which are reviewed below.

##### ***Visible and Infrared sensor (wavelengths between 0.4 and 0.7 $\mu$ m):***

The human eye is unable to detect existing radiation. Satellite sensors can however detect both visible and invisible radiation. Rainfall estimation methods, based on visible and infrared radiation, can be divided into several sub-categories, including cloud-indexing, bi-spectral radiation, and life history and cloud models. Each of these categories relies on specifically physical properties of clouds. The most commonly used approach is the cloud indexing technique. In cloud indexing, an algorithm is used to assign a level of rainfall to each cloud observed in a satellite image.

The thicker a cloud, the less that sunlight will be able to pass through it. Similarly, the thicker a cloud formation is, the more radiation it will reflect back to a given satellite. A thinner cloud will allow more solar radiation to pass through, and therefore will reflect less back to an intercepting satellite. Seen from the ground by the human eye, thicker clouds are darker, whereas on the satellite imagery, they will be brighter (due to a higher amount of reflected radiation) than a thinner cloud formation. Clouds with a higher level of reflection are therefore thicker, and indicate a higher probability of rainfall. In addition, this method allows users to calculate the monthly rainfall (Rr) for a region by using the



past history of recorded images of clouds with greater probability of rain. The number of days ( $N_d$ ) during a month that cloud formations covered a particular region, indicative of regional rainfall potential, can also be calculated. This is accomplished using the equation below:

$$R_r = 62.6 + 37.4N_d$$

Another technique to predict the potential of rainfall a given cloud formation (or more accurately each pixel of satellite image) is related to cloud temperature. This method was developed by Arkin (1979), and is based on the concept that colder clouds are generally more likely to be associated with rainfall potential than warmer ones. This is because cooler clouds tend to have higher elevation tops. Because rain originates from the top of a cloud, clouds with high elevation tops will tend to have a higher rainfall potential. Accordingly, rainfall have a higher probability of originating from clouds that have cooler temperatures, high tops and that have deep convection characteristics (e.g. cumulonimbus clouds). Satellite images retrieved from reflected radiation from clouds can be used to determine cloud temperature depending on the wavelength of the reflected radiation, and thereby if a cloud has a higher potential to rain (or not). This means that rainfall probability as well as its intensity can be predicted, with a certain amount of accuracy, by using satellite based clouds images.

In summary, the first technique helps in the identification of the cloud type, area and growth, while the second technique provides information on clouds top temperature and growth rate. Table 2.1 shows rainfall estimates derived from visible/infrared data based on a cloud Indexing method, where Intensity values are assigned to different cloud types in an area.

Table 2.1 : Rainfall probability estimates by cloud type (Source: Kidd, 2011)

Cloud Type	Relative probability of rainfall	Relative intensity of rainfall
Cumulonimbus	0.90	0.80
Stratiform	0.50	0.50
Cumuliform	0.10	0.20
Stratocumuliform	0.10	0.01
Cirriform	0.10	0.01
Clear Skies	0.00	0.00

$$R_r = \sum_i r_i f_i$$

where  $R_r$  is the rainfall rate,  $r_i$  is the rain rate assigned to cloud type  $i$ ,  $f_i$  is the fraction of time (or fraction of area covered) by cloud type  $i$ .

Finally, the life-history approach is based on the use of visible and infrared radiation images with a higher temporal resolution to track a cloud development and

trajectory, and to relate these to rainfall probability. Based on the temperature of the cloud and its past development, it is now possible to relatively accurately understand its upcoming growth stages and adjust anticipated rainfall and forecasts accordingly.

***Passive microwave technique:***

Precipitation particles are responsible for the change in cloud emitted radiation measurable from the tops of clouds by satellite. Indeed, "...the emission of radiation from atmospheric particles results in an increase of the signal received by the satellite sensor while at the same time the scattering due to hydrometeors reduces the radiation stream" (Levizzani et al., 2001). As such, radiation measured above 60 GHz indicates the presence of ice crystals in the cloud. This is because satellite sensors are currently only be able to detect ice due to its higher radiation scattering effect in comparison to rain droplets. If a measured radiation value is between 19.3 and 85.5 GHz, a higher amount of liquid rain droplets are likely to be in the cloud in question. The most popular instrument used in microwave rainfall monitoring is the SSM/I. This sensor can measure clouds emitted radiation over a span of 1,400 km, indicative of the utility of the SSM/I. However, the disadvantage of SSM/I instrumentation and associated methodologies lays in its low *quality* of spatial and temporal resolution, despite the large distance that can be measured. Diffraction limits the ground resolution of SSM/I measurements, and the interference of other types of radiation from the sea and land under the complicated reliable measurement.

***Active microwave:***

"The most important precipitation measuring instruments from space is the PR, precipitation radar operating at 13.8 GHz on board TRMM, the first of its kind to be flown on board a spacecraft. The instrument aims at providing the vertical distribution of rainfall for the investigation of its three-dimensional structure, obtaining quantitative measurements over land and oceans, and improving the overall retrieval accuracy by the combined use of the radar, and the TMI and VIRS instruments".

## **2.2 Drought indices**

In general, most practical indicators of drought describe the magnitude, duration, severity, or spatial coverage extent water deficit. They are based on meteorological and hydrological variables, including precipitation, temperature, stream flow, soil moisture, reservoir storage, and groundwater level, among others. Some indicators can be combined and synthesized into a single index, most commonly called a drought index. Today, we can classify the existing indicators into two categories, according to their primary concern, which is either environmental or linked to water availability.

Environmental indicators are related to hydro-meteorological and hydrological conditions and measure the direct effect of drought in impairing the functioning of the hydrological cycle. Among the most significant indicators are deficits (dry spells), either in precipitation or stream flow or soil moisture, or in combination. These indicators define the frequency of drought occurrence and characteristics including drought duration and/or severity. Nonetheless, to accurately define these indicators, a threshold level is required. The most common threshold is developed using the arithmetic average or water demand

level, but any other convenient water demand measurement also be adapted and adopted in use.

Water resources indicators quantify drought severity considering overall water deficit impacts on hydrological resources (surface or groundwater) that supply domestic, agricultural, and industrial uses. They also consider the effect of deficits on groundwater recharge, abstraction potential and sustainability, and surface water levels (especially those stocked in reservoirs). Water resource-related drought indicators are dependent not only on natural variation or cessation of rainfall, but also on the human interference in the hydrological cycle, for example a steady increase in water demand in a particular area in comparison to limited supply or recharge capability. Apart from a lack of rainfall or runoff, poor water resource mismanagement or excessive abstraction without adequate attention paid to sustaining recharge exacerbate drought severity.

### **2.2.1 Standardized precipitation index**

The Standardized Precipitation Index (SPI) was developed to assist in drought definition and monitoring. As such, it is not a drought prediction tool. The main goal of the SPI is to allow climatologists to determine the rarity of a drought for a particular time scale, and also to identify periods of abnormal wet events. The SPI is based on a cumulative distribution function (CDF), established using previously observed historical data for precipitation events occurring at a particular observation point or points. In other words, once converted to a CDF, SPI represents the probability of rainfall distribution at a given station. Historical data is crucial in that it allows analysts to tell how likely wise it is for a rainfall event to be less to or equal to a certain amount of precipitation previously observed at different timescales. Therefore, if a particular rainfall event scores low on the probability on the CDF, it is an indication of a possible drought episode (drought here being characterized as a “below-normal” rainfall event). In contrast, a rainfall event with a high probability on the CDF will indicate an abnormally wet situation.

Each probability function, defined for a given station, will have its own standard deviation depending on the rainfall characteristics of the area the station is located in. Thus, each standard deviation will differ from one another, making the comparison of rainfall events for different areas challenging. For example, a rainfall qualify as “normal” for one area can be a surplus or a “below-normal” rainfall event in another area. To solve this issue, the cumulative probability function can be transformed into a standard normal function in a way that each rainfall amount in the old function has a corresponding value in the new function. The conversion process also conserves all the probability rainfall deviations from the old function in the new function. Moreover, this transformation can be done with all the probability functions calculated for the different rainfalls and for the different stations, which will result in a single standard normal distribution function, the SPI (figure 2.4).

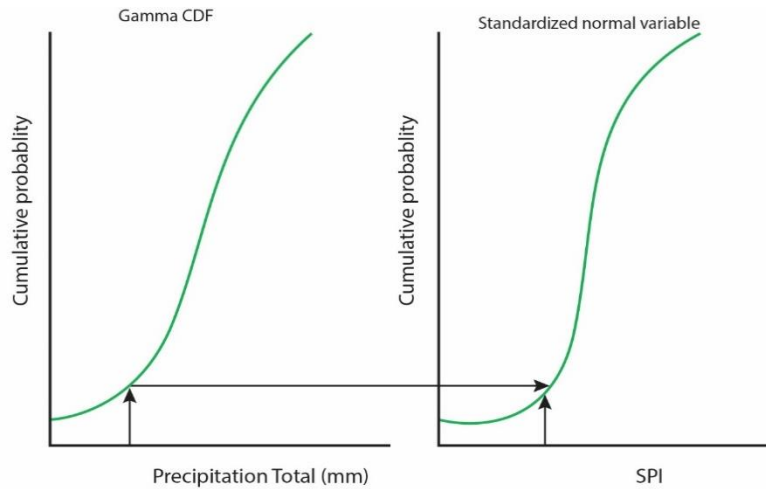


Figure 2.4: Transformation of the observed rainfall via the Gamma cumulative distribution function (CDF) and the CDF of the standardized variable to the standard precipitation index (SPI)

Therefore, the SPI is a “normalized” index representing the probability of occurrence of an observed rainfall amount when compared with the historical climatology at a certain geographical location of interest when measured over a reasonably long-term reference period. When an SPI value is positive relative to the threshold, it indicates a rainfall surplus. Conversely, a negative value indicates a rainfall deficit, which can in turn be used to classify the intensity and severity of a drought event.

Table 2.2: Standard precipitation index classification

SPI Value	Class	Cumulative Probability	Probability [%]
$SPI \geq 2.00$	Extreme wet	0.977 – 1.000	2.3%
$1.50 < SPI \leq 2.00$	Severe wet	0.933 – 0.977	4.4%
<b>1.0</b> $SPI \geq 1.50$	Moderate wet	0.841 – 0.933	9.2%
$-1.00 < SPI \leq 1.00$	Near normal	0.159 – 0.841	68.2%
$-1.50 < SPI \leq -1.00$	Moderate dry	0.067 – 0.159	9.2%
$-2.00 < SPI \leq -1.50$	Severe dry	0.023 – 0.067	4.4%
$SPI < -2.00$	Extreme dry	0.000 – 0.023	2.3%

In summary the strengths and weakness of the SPI are as follows:

#### **Strengths**

- Flexibility: SPI can be computed for multiple timescales
- Shorter timescale SPIs, for those that span 1-, 2- or 3-month SPI periods, can be used to infer early warning of drought and also help to assess drought severity

- SPI is spatially consistent, allowing for comparisons between different locations in different climates
- Because SPI is associated with a probability, it is very suited as a tool for decision-making.

#### **Weaknesses**

- SPI is based only on precipitation, and does not incorporate other variables that may be associated with drought
- SPI lacks a soil water-balance component, thus ratios calculating evapotranspiration to potential evapotranspiration (ET/PET) can't be calculated. This undermines the utility of this measurement method for agricultural decision making in particular.

### **2.2.2 Palmer drought severity index (PDSI)**

The so-called Palmer Drought Severity Index (PDSI) quantifies the degree of aridity of a soil by using information on temperature and precipitation. PDSI can be applied in the comparison on different locations and time-scales, and can be used to assess the length and severity of a drought. In order to achieve this goal, a water balance equation can be applied that uses strings of supply and demand variables, the latter which is comprised by data on temperature, relative humidity, groundwater, soil-available water, etc.). The calculation of PDSI approximates supply and demand variables over a given period of time, which is often around one calendar year, and results in estimates of evapotranspiration, runoff and the soil-water balance from the soil surface at a specific time of interest in relation to cumulative past conditions.

Measurement of PDSI can range from -4.0 (extreme drought) to +4.0 (no moisture deficits) and is universal regardless of location.

Table 2.3s: The PDSI classification ranges

<b>Palmer Drought Severity Index (PDSI) classifications</b>	
4.0 or more	Extremely Wet
3.0 to 3.99	Very Wet
2.0 to 2.9	Moderately Wet
1.0 to 1.99	Slightly Wet
0.5 to 0.99	Incipient Wet Spell
0.49 to -.49	Near Normal
-0.5 to -0.99	Incipient Dry Spell
-0.1 to -1.99	Mild Drought
-2.0 to -2.99	Moderate Drought
-3.0 to -3.99	Severe Drought

-4.0 or less	Extreme Drought
--------------	-----------------

The PDSI has several benefits:

- PDSI is useful in determining long-term drought, especially for locations in the low and middle latitudes.
- PDSI uses models of surface air temperature and a physical water balance and can be used in the consideration of climate change effects through changes in potential evapotranspiration.
- PDSI considers prior conditions (data from the prior month of observed weather and hydrological information are utilized).

Nevertheless, also has several weaknesses:

- PDSI performs poorly in cross regional comparisons. Performance can however be improved through model calibration.
- PDSI is deficient in multi-timescale indices (like SPI). This make it difficult to correlate PDSI results with specific water flow and storage reservoirs, for example runoff, ice or snowpack, lakes and reservoirs, etc.
- Delays in runoff that originate with snowpack or ice are not considered.

### 2.2.3 Surface water supply index (SWSI)

Developed by Shafer and Dezman (1982), the surface water supply index is used to identify and monitor hydrological drought events. SWSI is based on the concept of “monthly non-exceedance” of probability (for example, maximum water supply probability) from historical datasets of reservoir storage, stream flow, snow and ice pack, and precipitation. These data sources constitute the primary inputs used in calculating SWSI.

SWSI is mainly used for monitoring abnormalities in surface water supply and its influence on available water in reference to seasonal hydrological drought. The latter point is important, as the equations that govern the SWSI are written to ‘switch on’ or ‘switch off’ flow from snowpack in the summer and winter, respectively. Similarly, flows will increase or decrease depending on seasonality and intercepted precipitation in watersheds leading to surface water flow. The SWSI is however spatially and temporally variable, and has differing statistical characteristics depending on the region and climate in which it is applied.

### 2.2.4 Vegetation condition index

The most commonly used Normalized Difference Vegetation Index (NDVI), helps in drought monitoring by detecting anomalies in the canopy conditions. Anomalies can be defined as the difference between the NDVI composite value for a specified time period (e.g., weekly, biweekly, or monthly) and the long-term mean value for that period. Thus, the variation in the present-day vegetation conditions can help to identify and established the severity of a current drought event.

Therefore, the vegetation index allows to acquire important information on the time of drought onset and end, intensity, duration and overall impact of vegetation. But, since the vegetation condition index is based on vegetation, it is primarily useful for the summer growing season and has a limited utility for cold seasons when vegetation is largely dormant (Heim, 2002).

In, 1993 Kogan and Sullivan introduced a vegetation index-based drought metric (the VCI), based on the NDVI, that could be used as a global drought monitoring and warning system. The VCI is defined as follows:

$$VCI = \frac{100(NDVI - NDVI_{min})}{NDVI_{max} - NDVI_{min}}$$

Where NDVI,  $NDVI_{max}$ , and  $NDVI_{min}$  are values of the smoothed weekly NDVI and the multiple-year NDVI maximum and minimum, respectively. A low value of VCI would be an indication of a stressed vegetation due to unfavourable weather conditions, while a high value of VCI indicates healthy vegetation conditions.

### 2.2.5 Temperature Condition Index (TCI)

A study conduct in India has put into light the value of combining the VCI with the Temperature Condition Index (calculated from term channels), to improve drought event prediction. The TCI is defined as follows:

$$TCI = \frac{100(BT_{max} - BT)}{BT_{max} - BT_{min}}$$

Where BT,  $BT_{max}$ , and  $BT_{min}$  are the smoothed weekly and multiple-year maximum and minimum thermal brightness temperatures, respectively.

Further studies confirmed that the TCI performed better than NDVI and VCI, especially in cases of excessive soil moisture caused by heavy rainfall or persistent cloudiness. Indeed, these conditions can result in a low value for the VCI and NDVI and be interpreted erroneously as drought. In order to solve the problem of a false positive for drought, Kogan developed in 1995 a third VCI (VHI, Vegetation Health Index), by combining the VCI and TCI. VHI is expressed as follows:

$$VHI = \alpha \times VCI + (1 - \alpha) \times TCI$$

Where  $\alpha$  is a coefficient determining the relative contribution of the TCI and VCI. So, VHI is a proxy characterizing vegetation health by combining estimation of moisture and thermal conditions.

### 2.2.6 VegDRI Concept

VegDRI was developed following an integrated approach to capitalize on the strengths of both satellite and climate-based indices traditionally used for drought monitoring. Therefore, the VegDRI measures the effects of drought on vegetation by blending in its analysis, the general vegetation conditions observed in satellite-derived VI (vegetation index) data and the level of dryness from the climate-based drought indices for a specific location. The VegDRI contains a set of eight identified input variables that can

be divided into three main categories: satellite, climate, and biophysical. The two variables related to general vegetation conditions – the Percent Average Seasonal Greenness (PASG) and Start of Season Anomaly (SOSA) – are calculated from satellite-based observations and incorporated into the VegDRI. Both variables are calculated from NDVI data to monitor and quantify seasonal vegetation dynamics. In addition, other important biophysical and environmental characteristics are incorporated in the index as they can have a direct influence on the climate-vegetation dynamic. These biophysical data are soil available water capacity (STATSGO database), land cover/land use type (USGS National Land Cover Dataset), national irrigated lands map derived from 250-meter MODIS satellite data, ecoregion type, and elevation (USGS National Elevation Dataset). The climate data used for the VegDRI is the 36-week SPI that was found to be highly correlated for the Continental United States (CONUS).

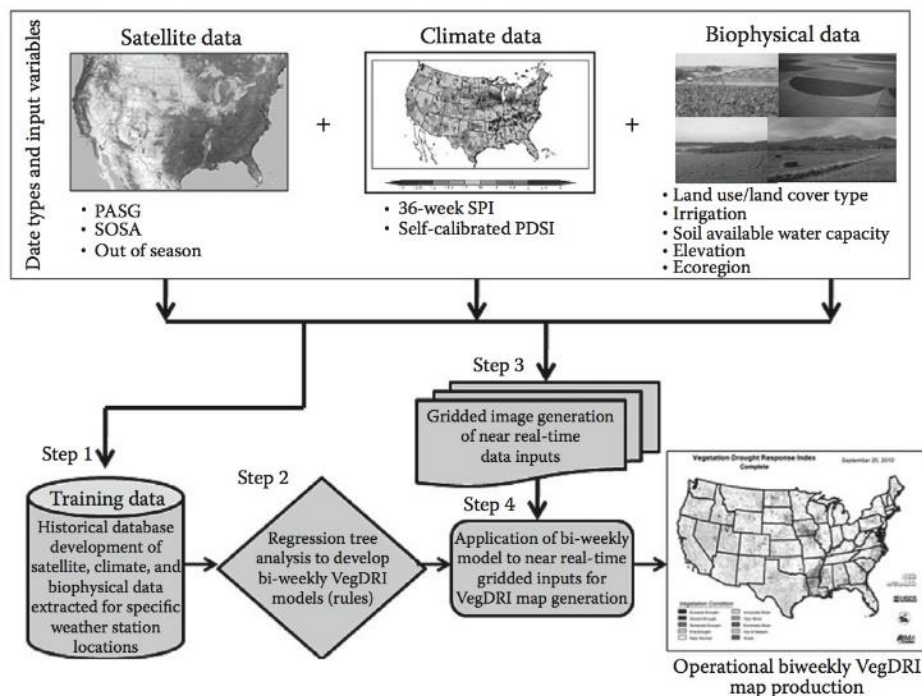


Figure 2.5: Workflow diagram for *VegDRI*

Based on a modified version of the PDSI classification system (Palmer, 1965), the VegDRI values are classified into four dry categories including three classes of drought severity (moderate, severe, and extreme), and a pre-drought class that represents the dry side of the near-normal class value range (see Table 2.4). The pre-drought class was added to identify region that could be nearing a situation of droughtiness. Although, the four non-drought classes (normal, unusually, very, and extremely moist) are characterizing locations with normal to better than normal vegetation conditions, they can also spot areas of



excessively wet condition that could result in poor vegetation health due to flooding or waterlogging. Finally, an “out of season” (OS) class was elaborated with the aim to identify periods of time when the vegetation is dormant (e.g. winter) and for which the VegDRI values are not calculated.

Table 2.4: VegDRI Classification Scheme and Class Value Ranges

<b>VegDRI Class Names</b>	<b>Value Range</b>
Extreme drought	<-4
Severe drought	-4 to -3
Moderate drought	-3 to -2
Predrought	-2 to -1
Near normal	-1 to +2
Unusually moist	+2 to +3
Very moist	+3 to +4
Extremely moist	>+4

### 2.3 Criteria for Selecting Drought Indices for monitoring Drought

Availability of large number of drought monitoring indices, call for the need of the development of objective criterion to easily identify the most suitable drought index for a specific application. The table below, summarized the commonly used criterion to demarcate the drought indexes.

Table 2.5: Criteria for selecting Drought Monitoring Indices

<b>Criteria</b>	<b>Weight</b>
Robustness	0.28
Tractability	0.21
Transparency	0.17
Sophistication	0.17
Extendibility	0.10
Dimensionality	0.07

*Note: Adapted from (Keyantash and Dracup 2002)*

#### **Robustness**

Robustness is related to the usefulness of the index for a wide range of physical conditions. Still, the robustness alone does not weight more than the other criteria in the process of selecting a drought index.

#### **Tractability**

Tractability of an index refers to the practical use of the index by an individual. An

intractable index would require a more complex and higher-level of numerical computing and thus calls for higher level of knowledge from the person using the index.

### **Transparency**

Transparency can be understood as the level of clarity of the objective and rationale behind the drought index. A good drought index is not only understood by the scientific community, but likewise by the end users of the drought information as well. Hence, transparency represent the general utility of an index (Keyantash & Dracup, 2002).

### **Sophistication**

Sophistication is somewhat at odds with transparency, but it has nevertheless been included because of the conceptual merits of an approach. The level of sophistication incorporated in a drought index must be supported by the quality of the available data and the fundamental accuracy of the assessment method.

### **Extendibility**

This criterion represents the degree to which an index can be extend across time to alternate drought scenarios. An index based on simple basic measured data (e.g., temperature or precipitation) can be used for a longer historical periods than a drought index relying on satellite data. Another aspect of extendibility of a drought index relates to the possibility of using the primary index with other indices to refine the drought assessment.

### **Dimensionality**

It refers to the connection of the index with the physical world. An index with fundamental units or a ration of computed physical units (e.g. percentage, probabilistic unit etc.) for indices, instead of only simple dimensionless qualities, can be used more readily to compare features between different location and time periods.

### **Suitability**

This reference to the ability of an index to reproduce specific drought events and impacts (e.g., on vegetation, agriculture, water levels ...). Thus, a highly suitable index captures the important information related to drought for a specific sector of activities (e.g. agriculture and crop water information).

## **2.4 Data Requirement for Drought Monitoring**

Drought data requirements depends on the drought index system that is being designed. Different factors can affect the data requirement for a drought monitoring index such as the type of drought, spatial and temporal resolution etc.

Table 2.6: Factors to be considered for drought monitoring design

<b>Design Type</b>	<b>Observation, data integration</b>
Measurement Type	Meteorological drought index, agricultural drought index, hydrological drought index, integrated drought index

Technology type	Data transformation
Factor Type	Observation period, temporal resolution, spatial resolution
Sample characteristics	Global, regional, local

Due to drought various impacts, different meteorological, hydrological and environmental variables can and are necessary for its accurate monitoring. Moreover, as droughts phenomena vary with time and space, as single variable would not be able to provide enough information on this particular event.

Table 2.7: Data categories used for drought monitoring and prediction

Data Category	Frequency of Data Collection	Variables	Indices
Meteorological Observation	Hourly to annual	Precipitation, Temperature, wind speed, humidity,	Decile, SPI, Rainfall anomaly, PDSI, TCI
Hydrological variables	Hourly to annual	Stream flow, ground water level, reservoir/lakes levels, snow	Surface Water Supply Index (SWSI), PHDI
Environmental Variables	Hourly to annual	land cover, land use, vegetation health/stress, yield, fire	NDVI, VCI
Soil Moisture	Hourly to annual	Moisture	Soil Moisture Anomaly Index

## Precipitation, temperature and vegetation datasets

### APHRODITE

Asian Precipitation Highly Resolved Observational Data Integration Towards Evaluation of Water Resources (APHRODITE), present a 0.25° spatial resolution over the Asian Monsoon region (V1101R1) for the period of 1981–2007. These data were created by using a station-based observation presenting a good spatial variability and representing also other rainfall characteristics (e.g. orographic rainfalls). Additionally, APHRODITE data have undergone a thorough quality control for inconsistencies and errors.

### CHIRPS

The Climate Hazards Group InfraRed Precipitation with Station data (CHIRP/S) provides precipitation data at 0.25° and 0.05° spatial resolutions, in an almost near real-time manner and on a daily- bases for a total of 5 days. These data are the result of a combination between different products, mainly the monthly precipitation climatology (CHPClim, which represents the long-term historical average rainfall accumulation), Thermal Infrared (TIR) satellite observations (or from globally gridded Satellite such as GriSat), and in situ precipitation observations from various national and regional

meteorological departments (C Funk et al., 2015).

The CHIRPS project generates both a preliminary and a final product. The preliminary product comes out two days after the end of the pentad and consists of the combination of CHPClim, TIR satellite and available stations. Station data could be from in-country organizations such as meteorological services or/and from the Global Telecommunication System. The final product is processed two weeks after the end of the month with a greater number of stations from different sources.

### **MOD11A2: MODIS/Terra Land Surface Temperature/Emissivity**

The MODIS LST products provide data for a daily, eight-day and monthly basis time frame. The MOD11A2 product provides a LST information for an average of 8-day per-pixel land and with a resolution of 1200 x 1200 kilometre grid. Each pixel value in the MOD11A2 is a simple average of all the corresponding MOD11A1 LST pixels collected within that 8-day period (for both night and day time).

The table below, summarizes the main characteristic of each products for drought monitoring.

Table 2.8: List of source data products for regional drought monitoring systems

<b>SN</b>	<b>Data / Product</b>	<b>Spatial Resolution</b>	<b>Temporal resolution</b>	<b>Description</b>
1	CHIRP rainfall	5 km	10 days	Gridded rainfall data product
2	MOD13Q1 Vegetation	250 m	16 days	NDVI Maximum Value Composite (MVC) based on 16 days along with Quality tags
3	MOD11A2 Land Surface temperature	1 km	8 days	Land Surface Temperature (LST) MVC based on 8 days
4	Soil moisture	5 km	daily	SALDAS derived data
5	Evapotranspiration	5 km	daily	SALDAS derived data
6	In-situ Rainfall Data	point	daily	Ground station met data

## MOD13Q1

Global MODIS vegetation indices are aiming at providing a consistent spatial and temporal comparisons of vegetation conditions on earth, by using blue, red, and near-infrared reflectance information. This product can help in monitoring the overall Earth photosynthetic vegetation activity, detect changes and interpret the occurring biophysical activities. The MODIS is using a gridded vegetation index maps to visualize spatially and temporally vegetation changes, with a 16-day and monthly intervals.

When producing a single MOD13Q1 dataset, the MODIS algorithm is designed in way to select the best pixels from a choice of sixteen days of images, in order to reduce the amount of pixels that are partially or completely obscured by clouds or other atmospheric contaminants.

### Time series NDVI data cleaning and processing

In theory, the NDVI calculated from a normalized transformation of the red and near-infrared reflected radiations, are an accurate value to estimate the changes in canopy condition. However, the capture of the reflected radiation by the satellite, can be affected by contaminants such as clouds, changes in the atmospheric conditions or by the bidirectional effect. Subsequently, these disturbances can affect the drought monitoring activity. For this reason, in the past few years, several methods were tested and developed to reduce the noises caused by the contaminants and resulted in a higher quality NDVI time-series data set, more suitable for further analysis.

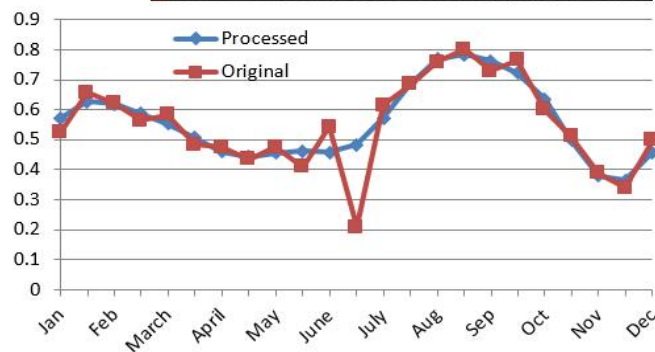
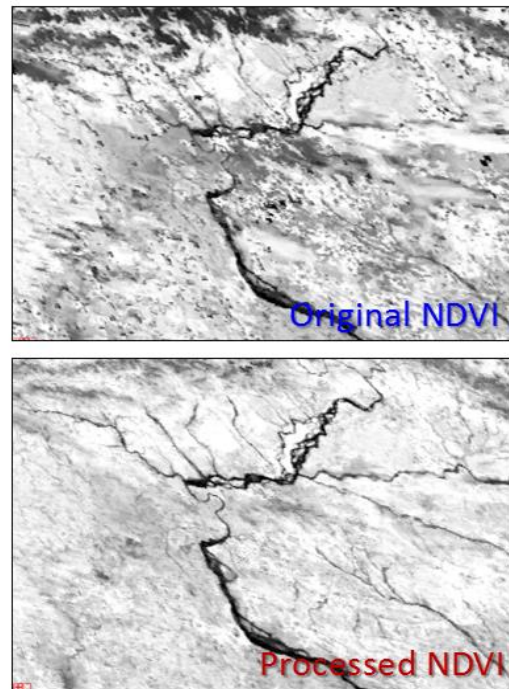


Figure 2.6: Comparison of process and un-processed data

We can distinguish three main group of methods used to reduce the noises in the data:

- The threshold-based methods such as the best index slope extraction algorithm (BISE). The BISE algorithm is used to extract seasonal metrics of vegetation phenology, classify the type of land cover, and estimate the gross primary productivity (GPP).
- The Fourier-based fitting methods. This method is used to derive terrestrial biophysical parameters in order to evaluate the NPP dynamics.
- The asymmetric function fitting methods such as the asymmetric Gaussian function fitting approach and the weighted least-squares linear regression approach, are mainly used to extract seasonality information for phenological studies.

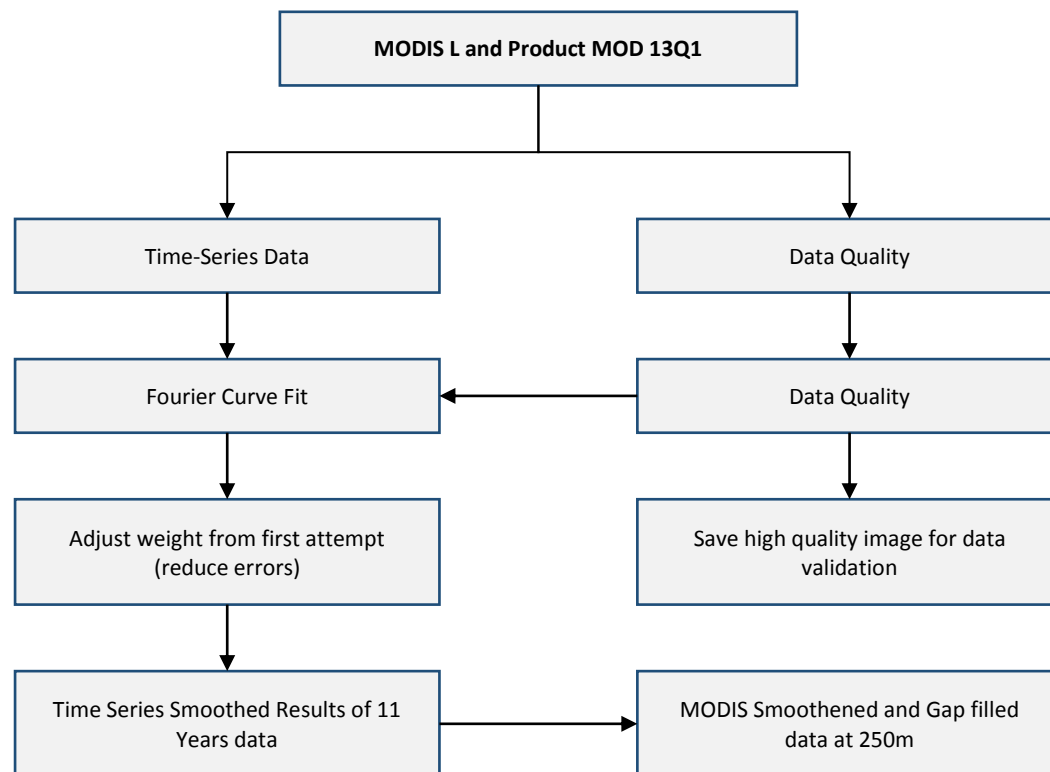


Figure 2.7: Flowchart for NDVI impurities correction

### ***The Fourier-based fitting method***

In a closed interval  $[0; L]$ , each continuous and periodic function  $f(t)$  can be decomposed into a series of harmonic components (sine and cosine waves) with increasing frequency. This method is termed Fourier analysis and has been modified to be applicable to discrete time-series data, like the NDVI of a given pixel (Jakubauskas, Legates, & Kastens, 2001), (Wagenseil & Samimi, 2006). It can mathematically represent by the formula below:

$$f(t) = \overline{f(t)} + \sum_{n=1}^{L/2} \left( A_n \cos \frac{2\pi n t}{L} - \phi_n \right)$$

Where  $f(t)$  is the NDVI of a given pixel location at time  $t$  (1 year = 23 16-days MVCs,  $t = [1..23]$ );  $\overline{f(t)}$  is the mean of  $f(t)$  in  $[0; L]$ , additive term;  $n$  is the harmonic term;  $A_n$  is the amplitude of the  $n^{\text{th}}$  harmonic;  $\Phi_n$  is the phase angle of the  $n^{\text{th}}$  harmonic; and  $L$  is the length of the observation period ( $L=23$ ).

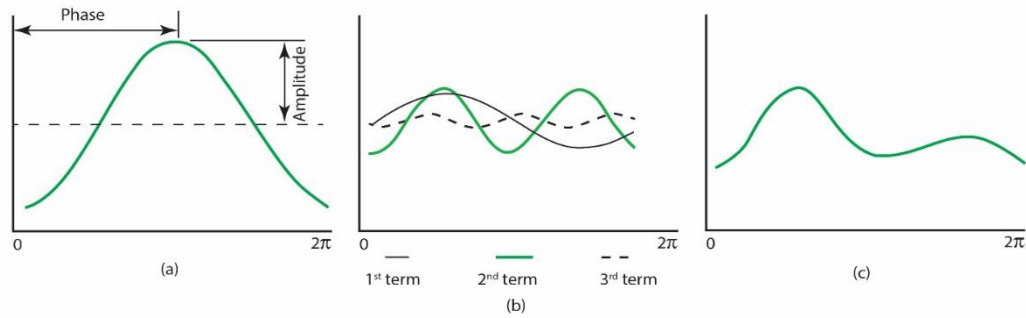


Figure 2.8: (a) Simple cosine curve representative of first harmonic (b) curves for harmonic terms 1, 2 and 3 (c) Curve produced from adding three harmonic curves

The Fourier analysis is a particularly suitable technique for parameterization of NDVI time series for the following reasons:

- The non-periodic and infrequent radiometric noise (e.g. from atmospheric attenuation, pre-processing errors) is restricted to higher terms (the Maximum Value Composites).
- Parameters of lower Fourier terms can be understood as the vegetation growth pattern. This is a suitable measure of the overall greenness for a given pixel location.
- The amplitude values quantify the degree of seasonal biomass production, whereas the number of the corresponding term is related to the number of peaks during the observation period. The phase angle describes the time lag between origin and peak and captures the date of maximum greenness.

But, this method also contains some weakness that are worth mentioning. Admittedly, the Fourier analysis is based on the assumption of a periodical and sinusoidal signal, which is not strictly satisfied by the NDVI of a certain location. Vegetation growth pattern results usually in a complex shape of NDVI, not always sinusoidal and which might require a higher frequency terms for suitable approximation. Even though, this higher terms can be linked to growth patterns of secondary cover types, their meaning is generally not straightforward. Thus, interpretation in this study in relation to vegetation growth is mainly restricted to mean and first term parameters.

## 2.5 Weather forecast and drought prediction

Drought forecasting plays a critical role in understanding drought impacts on water balance and thus for decision making for risk management, drought-preparedness and mitigation. Despite drought forecasting focusing on different aspects of the phenomena, an accurate prediction of the onset and termination point of the event is still remains a major challenge. Method in Drought Forecasting. Drought forecasting methods can be divided into different various approaches. In this part, we are going to have a brief overview of the most commonly used approaches.

### a) Linear regression models:

A linear regression analysis allows to explore the relationship between two or more quantitative variables: a dependent variable whose value we want to predict and a variable for which we do have information available. In other words, a multiple-regression predicts one variable from two or more independent variables and can be mathematically written by using the following formula:

$$Y=a+bX_1+cX_2+dX_3$$

Where Y is the dependent variable, X<sub>1</sub>, X<sub>2</sub> and X<sub>3</sub> are the independent variables, and a, b, c and d are constants.

In case of drought monitoring, the dependent variable is a drought quantifying parameter (i.e., drought index), while the independent variables are explanatory variables for the drought-quantifying parameter (i.e., precipitation, soil moisture, temperature etc.). Scientist have applied the regression model for agricultural drought analysis and forecasting. In that case, the grain yield from the main produced crop was used as a drought quantifying parameter while variables affecting grain yield were used as explanatory variables. The model can successfully predicted the grain yield of the main produced crop before the crop harvesting season and help assess the agricultural drought severity as mild, moderate, or severe.

### b) Time series models

We call a time series models a “ forecasting algorithms that have been used for short-term forecasting by employing the notions of Markov and autoregressive integrated moving average (ARIMA) stochastic models, non-homogeneous Poisson processes coupled with conditional probabilities” (Lohani & Loganathan, 1997). In simple terms, time series models are using serial linear correlation method to describe non-stationary behaviours within and across a given seasons. Furthermore, a time series of a drought quantifying parameter can be used for drought forecasting, depending upon the previous observations. For example, the two linear stochastic models, ARIMA and SARIMA, were developed for drought forecasting (up to two month and with a reasonable accuracy) by using the Standardized Precipitation Index (SPI) (other index could have been used as well) series as drought quantifying parameter.

### c) Probability models

Probability models present a more complex nature and can be used to forecast drought by quantifying it hydro-meteorological variables. Commonly Markov chain models have been used for drought forecasting. A Markov chain is a stochastic process having the



property that the value of the process at time  $t$ ,  $X_t$ , depends only on its value at time  $t-1$ ,  $X_{t-1}$ , and not on the sequence of values  $X_{t-2}$ ,  $X_{t-3}$  ...  $X_0$  that the process passed through in arriving at  $X_{t-1}$ . Cancelliere, et al., (2007) forecasted seasonal SPI by computing transition probabilities from a current drought condition to another in the future based on the statistics of the underlying monthly precipitation.

#### **d) Artificial neural network model**

Neural networks are flexible nonlinear models used to discover patterns in data. In theory, a neural network can learn from past experience and estimate complex functional relationship in data with a high accuracy if an appropriate number of nonlinear processing units is used. However, in general scientist are using three-layer feed-forward models (input layer, a hidden layer and an output layer) for forecasting activities. There are three possibility of inputs nodes as follow: (i) previously suitable observation of drought quantifying time series, ii) explanatory variables for quantifying drought, or (iii) a combination of both (i) and (ii). Then, hidden nodes are used to process the information received from the input's nodes. Finally, the output layer is used to formulate forecast for different time lead. For example, we could use different combination of past rainfall, Effective Drought Index and SPI, climate indices such as SOI and NAO indexes as input layer, to forecast drought.

#### **e) Hybrid models**

Hybrid models are used to predict with higher accuracy and lead time, a drought event by using the strength of individual models. If we take a wavelet transformation method, we can capture information for various resolution levels, but if we used these information with a neural network model, then we can decomposed the sub-signals from wavelets and reconstruct forecasted sub-signals to the original series. For example, in case of drought forecasting, we could use PDSI as a drought index to improve the performance of the neural network to create a more accurate indexed regional drought forecast.

### **2.5.1 Drought forecasting system**

The advances made in the seasonal climate forecast are a promising evolution for the drought prediction improvement and the development of components for a global scale drought forecast system. The South Asian Land Data Assimilation System (SALDAS) was first designed as a drought monitoring tool. In monitoring mode, SALDAS ingests gridded satellite-informed meteorological fields and land surface parameters and uses these data to drive simulations with an advanced land surface model. The system yields near real-time estimates of surface hydrological conditions as well as downscaled meteorological estimates relevant to drought monitoring. SALDAS was recently augmented with a seasonal forecast mode, in which meteorological fields are downscaled from the NASA GEOS global forecast system and are used to drive land surface model simulations as far as nine months into the future. This system is implemented using the NASA Land Information System (LIS), a software framework that allows for flexible integration of diverse datasets and models. As an operational monitoring and forecast system, SALDAS provides an improved detection of soil moisture drought, increase the reliability of hydrological drought forecast products, and finally, a better real-time prediction

information. Nowadays, the main used indices for the global system for drought detection are the SPI or the percentile of soil moisture/runoff.

Nevertheless, drought tendency (e.g., onset and end, persistence etc.) still requires more studies. Essentially, to be able to predict more accurately drought tendency, we need firstly to be able to predict with better accuracy several crucial meteorological variables (i.e., precipitation and temperature). Statistical approaches are based on empirical relationships found in historical data records but they do not take into account the underlying physical mechanisms of drought. However, these approaches are partly useful due to their easy implementation technique. Additionally, drought forecasts from these approaches are only used as baseline or benchmark for dynamical forecasts, as well as to provide complementary forecast information for certain seasons or region.

Figure 2.9 illustrates the essential elements of Land Information System (LIS) based drought forecast system.

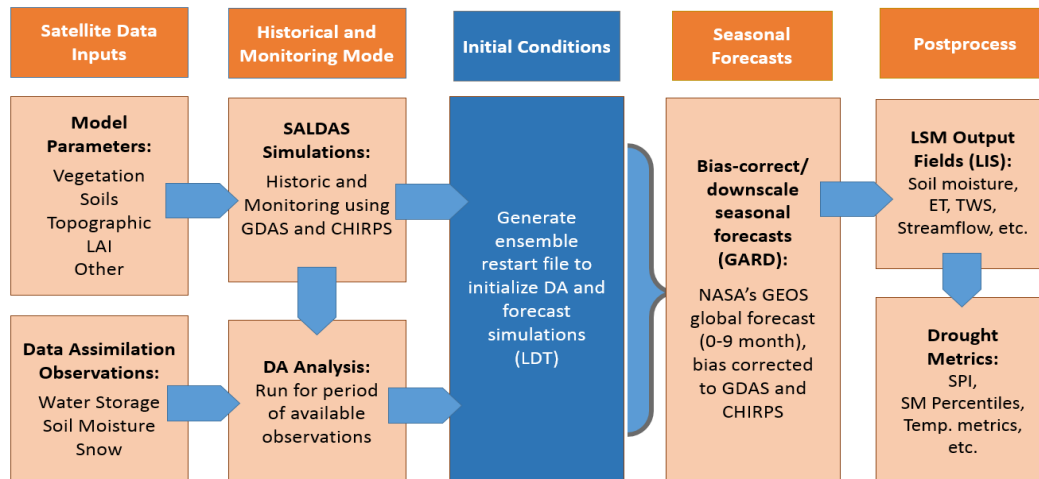


Figure 2.9: Components of SALDAS drought forecasting system

### 3 Drought communication and dissemination systems

Drought Early Warning Systems (EWS) are of crucial importance in drought-prone regions and for communities dependent on reliable water supply (especially those living in semi-arid areas with naturally low rainfall). DEWS can provide a set of drought related information advisories and information required for the selection of the most adequate mitigation and adaptation options to be implemented.

Two key considerations can be identified for drought EWS development. Firstly, they are designed with the goal of institutionalizing the collection of data needed for drought indicators monitoring (i.e., monitoring of weather indicators) and used to detected, predict progression of drought and its impact on water and/or pasture. Secondly, DEWS offer information on the effects of drought, but more importantly provides the drought-prone communities with timely notice on the event which is primordial if we want to have an adequate drought response.

Effectiveness of a drought EWS is based on the quality of the disseminated information and on the use of the most appropriate communication mechanisms/channels. We measure the quality of an information by its level of availability, relevance, timeliness and accessibility. The more commonly identified, as the best, communication channels for information dissemination are electronics (e.g., telephones, phone text message, internet etc.) and printed media (e.g., bulletin), community gatherings or extension services. Still, to select the most suitable channel of communication a context-based approach needs to be adopted. For example, the effectiveness of printed media is directly affected but the low literacy rate of a given community, whereas electronic media effectiveness can suffer from a low access to electricity. Similarly, the content, format, language used in the disseminated information, if not user-friendly, can constitute a setback for the utilization of such information and diminish the effectiveness of the DEWS. Indeed, it is important to ensure that key messages are understood without any difficulties by the targeted communities.

### **3.1 Drought Preparedness Planning (timing and methods of communication)**

Most communities manage drought on a reactive, rather than pro-active basis. DEWS however permit more proactive and adaptive drought management to be implemented. Guidelines and checklists have consequently been developed so that the public or private sector involved in developing a DEWS can be most effective. A 10-step drought planning process has been proposed by Wilhite et al. (2005), including:

#### **10 Steps for Drought Planning**

1. Appoint a Drought Task Force
2. State the Purpose and Objectives of the Drought Plan
3. Seek Stakeholder Participation and Resolve Conflict
4. Inventory Resources and Identify Groups at Risk
5. Develop Organizational Structure and Prepare Drought Plan
6. Integrate Science and Policy, Close Institutional Gaps
7. Publicize the Proposed Plan, Solicit Reaction
8. Implement the Plan
9. Develop Education Programs
10. Post-Drought Evaluation

Each step has an associated goal, with steps 1 to 4 working to ensure that appropriate experts and stakeholders are brought together to assess drought risks and formulate a timely plan. The fifth step underscores the importance of developing an appropriate institutional arrangement to complete the production of an appropriate and cross-sectoral integrated drought management plan. In this step, it is crucial to develop a thorough vulnerability profile for different sectors (agriculture, industry, recreation, forestry, etc.), population groups, regions, and communities. The following steps focus on publicizing the plan, efforts to gain public acceptance and endorsement, and the need for on-going research and coordination between scientists and policy makers. Finally, the 10<sup>th</sup> step emphasizes the importance of adaptation and consistent revision of the drought plan to keep it up to date with the flow of monitoring and research results. Importantly, many of these steps can be implemented simultaneously and can run in parallel following task force formation.

### **3.2 Communication of drought information to farmers**

Increasing connectivity and access to Information and Communication Technologies (ICT) make the dissemination of information from drought prediction systems easy and effective. The dissemination of drought information and warnings, and more broadly of climate information services, has three key components. These include

- 1) Data generation and knowledge production (i.e., climate data collection and analysis),
- 2) ‘Translation’ of this information into a format that can be easily communicated and understood by non-scientists and non-specialists to make more informed decisions, and
- 3) Use of effective strategies to increase information uptake and actual use by end-users.

The previous paradigm of scientific extension was linear, e.g., scientists produce knowledge and deliver it to end-users. Conversely, use of ICTs and the ability to crowd source information has resulted in the multidirectional flow of data between information producers, end users, and others involved in generating, using and validating climate information.

As such, firstly, ICTs can be used to improve weather monitoring and validation. One of the main drought mitigation strategies, by providing remote sensing infrastructure and equipment (e.g., software and hardware, servers, databases, GIS, neural network etc.) for drought data analysis (e.g., statistics, modelling, mapping etc.).

Secondly, ICTs can be an important in information dissemination strategies by offering a range of tools to provide end users of drought monitoring and forecasting information with the most relevant information (e.g., precipitation information for farmers via mobile phone networks, SMSs, interactive voice response systems, etc.). Television, radio and newspapers (including on-line sources) are the most commonly used media for transmitting climate and weather information to the public and decision makers. Smart phones and mobile networks are however skyrocketing in popularity (even in remote rural areas), and are a promising technology for mass dissemination of drought information. Additionally, the use of mobile phone for information distribution has proven in many cases to low-cost, accessible, and consequently efficient.

Finally, ICT can be used to develop client-oriented and people centred drought early warning and information dissemination systems, that help empowering drought affected communities at the local level. Because ICTs are interactive, they can help foster an increased sense of activity and ownership by users, especially when information is crowd sourced. Comprehensive monitoring information and forecasts can then be delivered in tailor-made ways. Evidence indicates that this can increase people’s confidence in drought EWSs, which has positive effects in terms of facilitating informed and adaptive action to mitigate the harmful effects of drought.

## Exercise 1: NDVI Calculation using MODIS (MOD09A1) Images in QGIS

The Normalized Difference Vegetation Index (NDVI) is a versatile index to evaluate the vegetation and dynamic of the vegetation coverage change. This tutorial shows the way to calculate NDVI from multispectral satellite images using QGIS.

The formula for NDVI calculation is:

$$\text{NDVI} = (\text{NIR} - \text{R}) / (\text{NIR} + \text{R})$$

Where, NIR = Near InfraRed band and R = Red band

Principle of NDVI:

Reflectance is the ratio of energy that is reflected from an object to the energy incident on the object. Spectral reflectance of a crop differs considerably in the near infrared region ( $\lambda = 700\text{-}1300\text{ nm}$ ) and in the visible red range ( $\lambda = 550\text{-}700\text{ nm}$ ) of the electromagnetic spectrum. Plants generally have low reflectance in the blue and red portion of the spectrum because of chlorophyll absorption, with a slightly higher reflectance in the green, so plants appear green to our eyes. Near infrared radiant energy is strongly reflected from the plant surface and the amount of this reflectance is determined by the properties of the leaf tissues: their cellular structure and the air cell wall-protoplasm-chloroplast interface.

### Objectives

- To learn NDVI calculation process and visualize spatial patterns of the index over Afghanistan and Pakistan.

### Datasets

- MODIS satellite

### Software

- QGIS

In this tutorial, we will be using the

**MODIS Land Surface Reflectance images** downloaded from <https://earthexplorer.usgs.gov/>. You will need to have username and password for downloading the images.

### Spectral and Spatial MODIS Land Surface Reflectance (MOD09A1):

MOD09A1 consists of seven spectral bands with a spatial resolution of 500 meters. Each product pixel contains the best possible observation during an 8-day period based on high observation coverage, low view angle, absence of clouds and aerosol loading.

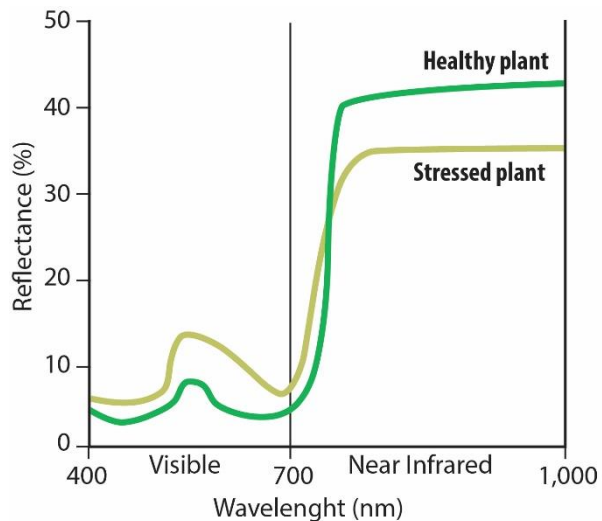



Table: Science data sets for MOD09A1 [1]

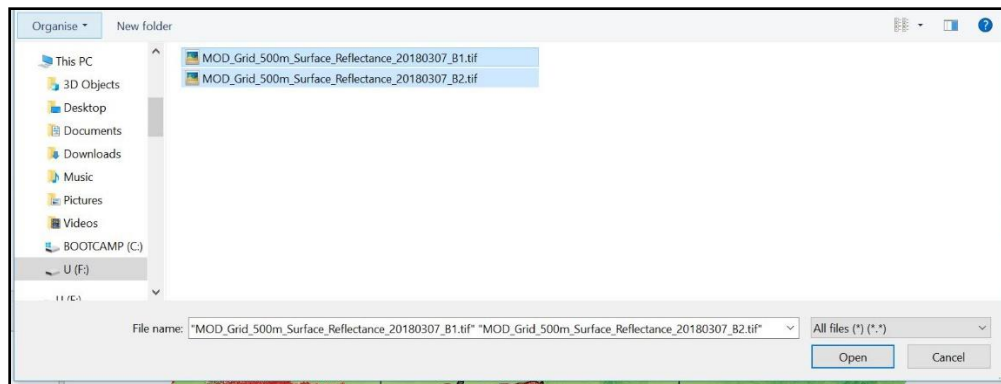
Science Data Sets (HDF Layers (13))	Units	Data Type	Fill Value	Valid Range	Factor Scale
Surface Reflectance for band 1 (620-670 nm)	reflectance	16-bit signed integer	-28672	-100 - 16000	0.0001
Surface Reflectance for band 2 (841-876 nm)	reflectance	16-bit signed integer	-28672	-100 - 16000	0.0001
Surface Reflectance for band 3 (459-479 nm)	reflectance	16-bit signed integer	-28672	-100 - 16000	0.0001
Surface Reflectance for band 4 (545-565 nm)	reflectance	16-bit signed integer	-28672	-100 - 16000	0.0001
Surface Reflectance for band 5 (1230-1250 nm)	reflectance	16-bit signed integer	-28672	-100 - 16000	0.0001
Surface Reflectance for band 6 (1628-1652 nm)	reflectance	16-bit signed integer	-28672	-100 - 16000	0.0001
Surface Reflectance for band 7(2105-2155 nm)	reflectance	16-bit signed integer	-28672	-100 - 16000	0.0001
Surface reflectance 500m quality control flags	Bit field	32-bit unsigned integer	4294967295	NA	NA
Surface reflectance day of year	Julian Day	16-bit unsigned integer	65535	0 - 366	NA

In this exercise, MODIS (MOD09A1) images downloaded on 7 March 2018 will be used. Band 2 and 1 represents the Near Infrared and visible red bands respectively in the images which will be used to calculate the NDVI in Afghanistan and Pakistan. The result will be compared with the NDVI calculated on 15 March 2019.

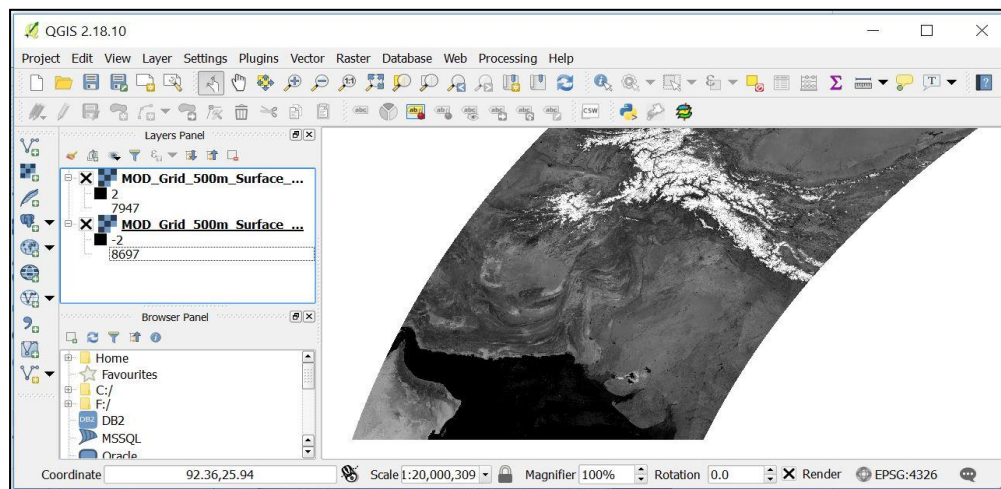
#### Steps:

- Open the *QGIS Desktop* software on your computer.
- In QGIS, on manage layer Toolbars, Click on *Add Raster Layer*  icon to add Raster data
- Now navigate to the folder D:\Drought\NDVI\_calculation or where you have copied your data
- Select both the images with suffix B1 and B2 (.tif) in the file and Click open the Image,

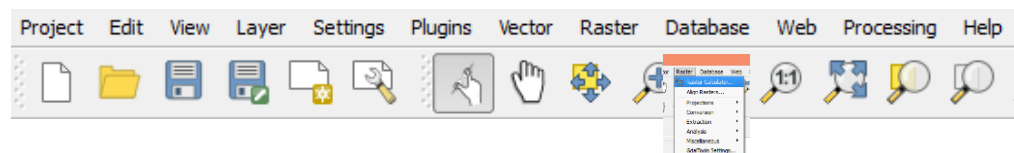




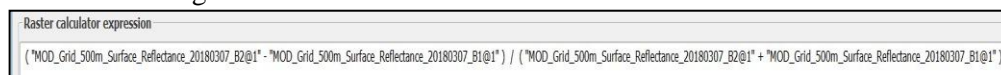
- Browse through and select the satellite image from its location. The image will be displayed in the screen as shown in following figure.

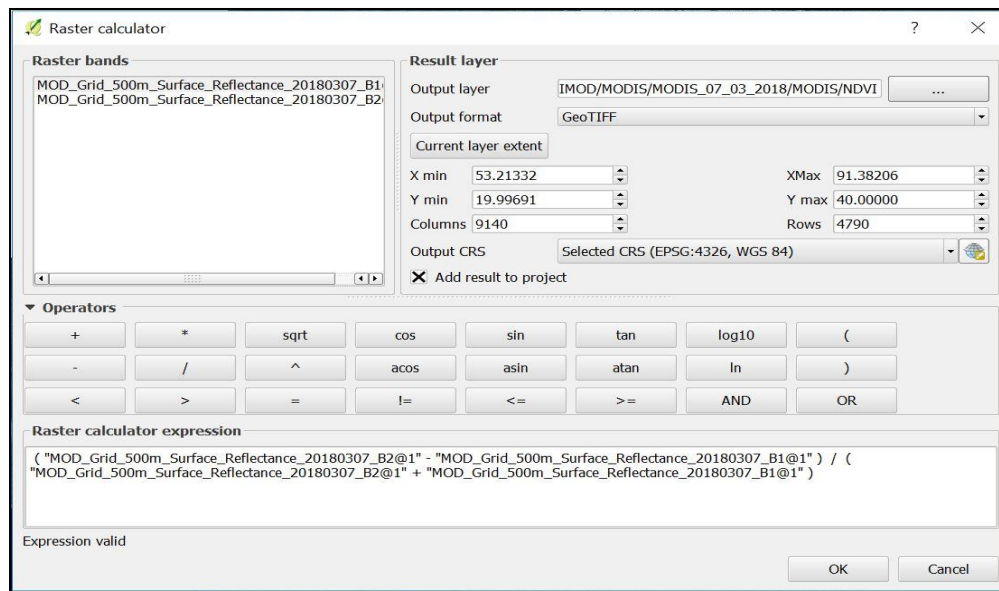


- Click **Raster** on the main tool bar. From the dropdown menu, select **Raster Calculator**.



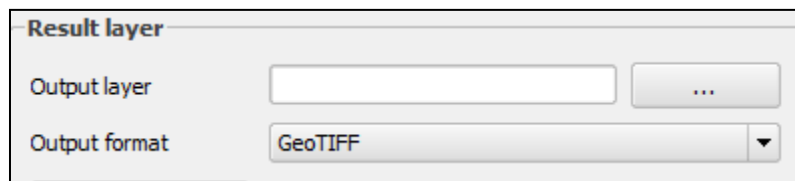
- Then the Raster Calculator window opens up. In the leftmost section, a list of available bands is displayed. From the above table, band 1 and band 2 for the MODIS images are Red and Near Infrared bands respectively.
- Then in the **Raster calculator expression** at the bottom, insert the formula for NDVI calculation using band 2 and band 1. \*Double click raster



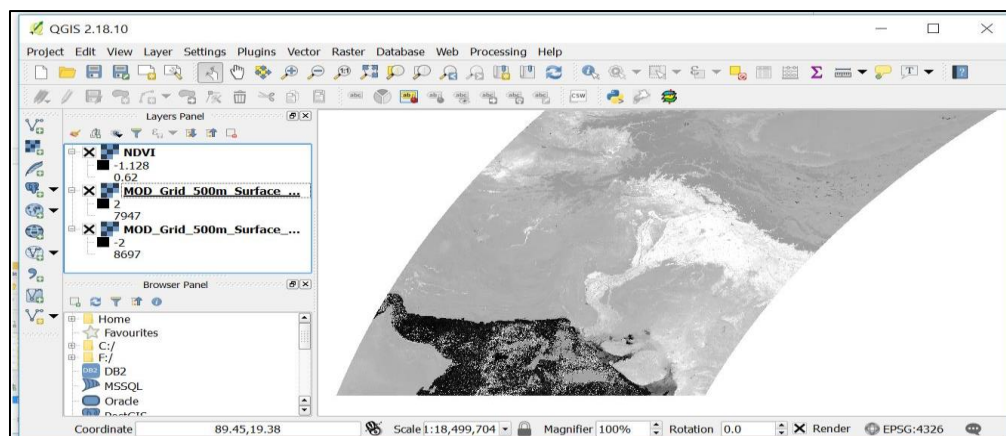


Expression in Raster calculator for NDVI calculation

- Select the output format to the default **GeoTIFF** and provide the location for the output layer. The default Coordinate Reference System will be that of the input satellite data. Click **OK** for calculation of NDVI.



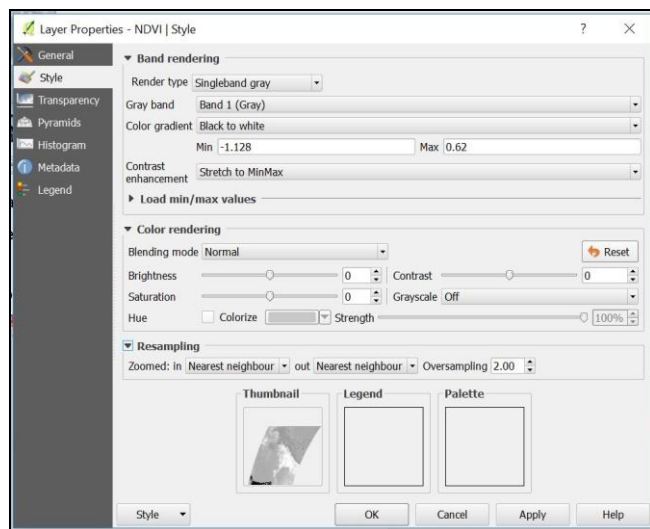
- The resulting raster will be displayed once the process is completed.



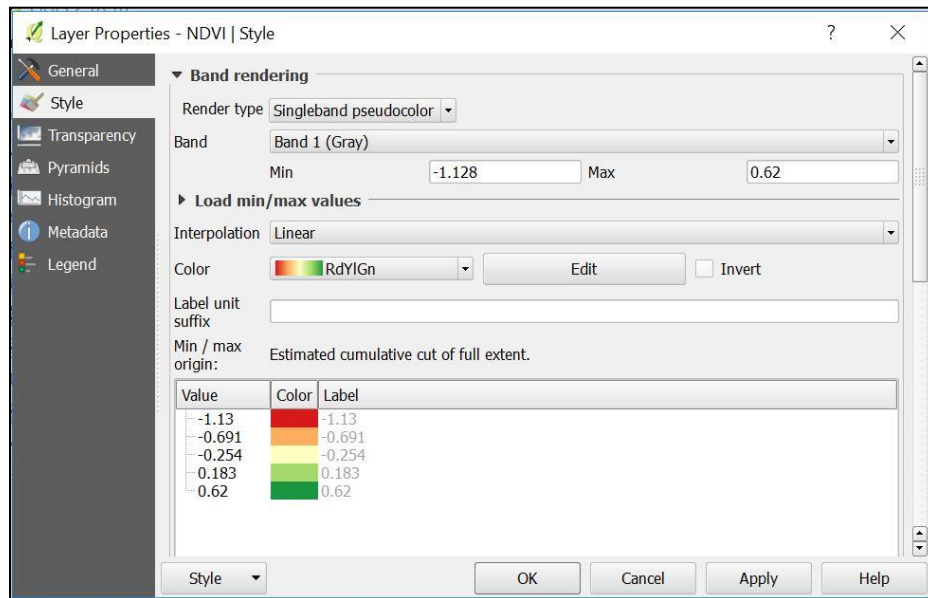
Output NDVI raster



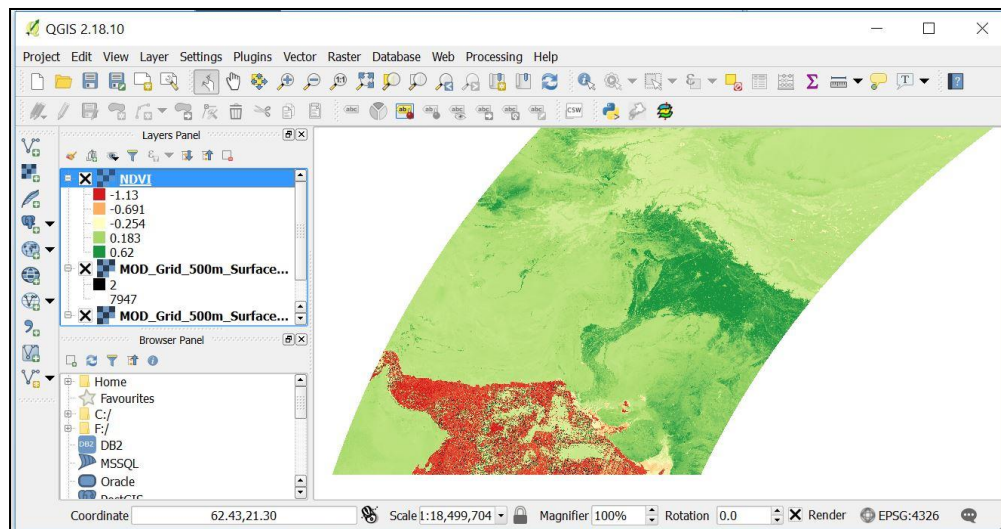
- You can now render this output raster layer to any colour you like from the properties.
- Right click on the NDVI layer and Select Properties



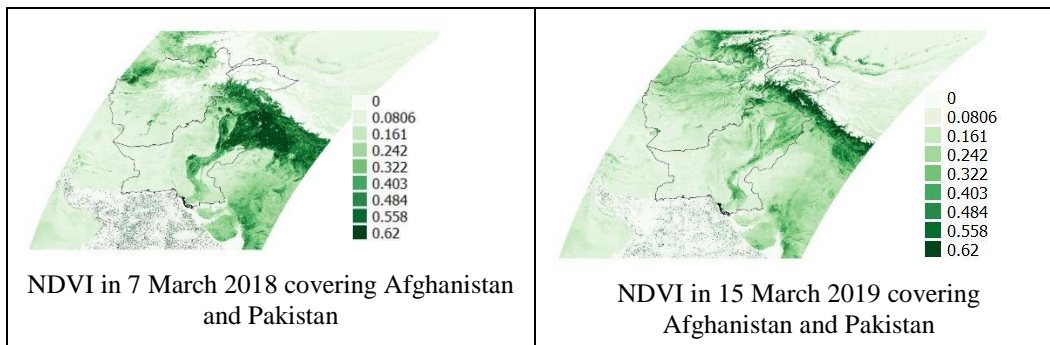
- In style Tab, choose render type as Singleband pseudocolor as seen below,
- In colour, Choose the desired choice of yours and click Apply



Your image should look like this



### Comparing the NDVI between 7 March 2018 and 15 March 2019 in Afghanistan and Pakistan



## **Exercise 2: Visualizing and interpreting time series data; detecting anomalies in NDVI data**

The NDVI is an important parameter to detect vegetation changing conditions. As we already saw, NDVI values changes with the increases (indicates a healthy vegetation) or decreases (indicates a non-healthy vegetation) in greenness. Precipitation are vital for vegetation growth and for the overall plant health condition. Furthermore, this also denotes that NDVI values are linked to precipitation fluctuation and their impacts on vegetation. Thus, NDVI image of a reference year can be used to evaluate the vegetation change in previous and upcoming years. Additionally, anomalies at different spatial and temporal patterns can be analysed and interpreted.

The Software for the Processing and Interpretation of Remotely Sensed Image Time Series software (SPIRITS) aims to provide automated and advanced time series processing for very large series of images with a temporal resolution of one day, 10 days, one month or one year. The following exercise includes some methods for analysing time series data.

### **Objectives**

- To learn how to use the SPIRITS map generator for the display of SPIRITS images.
- To analyse the time series images and learn how to detect anomalies in crop growth.

### **Datasets**

- MODIS satellite based 10-day composite of NDVI data (2007-2017)

### **Software**

- SPIRITS 1.5.0

### **Methodological Steps**

- Importing time series of images
- Masking
- Generate Map Series
- Time series analysis across seasons

### **Outputs**

- Time series map of NDVI for 2015 to 2019
- Anomaly maps based on the comparison with historical year

### **Installation of SPIRITS and getting started**

In this part, we will install the software on our computer and set-up a SPIRITS-project

- Double click on SpiritsExtract\_151 zip file and extract the files to you desired drive for example C:\ drive.

- Create a shortcut for the Spirits.jar file on the desktop.
- To start, double-click on the SPIRITS application icon on your desktop, or double click on Spirits.jar in the installation folder.

Alternatively, you can open the SPIRITS window through cmd.

Note: In order for SPIRITS to work properly, JAVA 1.6 or higher needs to be installed on your computer.


### SPIRITS-Project

When you open SPIRITS for the first time, a default project named SpiritsDefaultProject is created. The project refers to a directory with the same name in the installation folder: ‘\Spirits\SpiritsDefaultProject\’. For this exercise, you will change the project name and project resource folders.

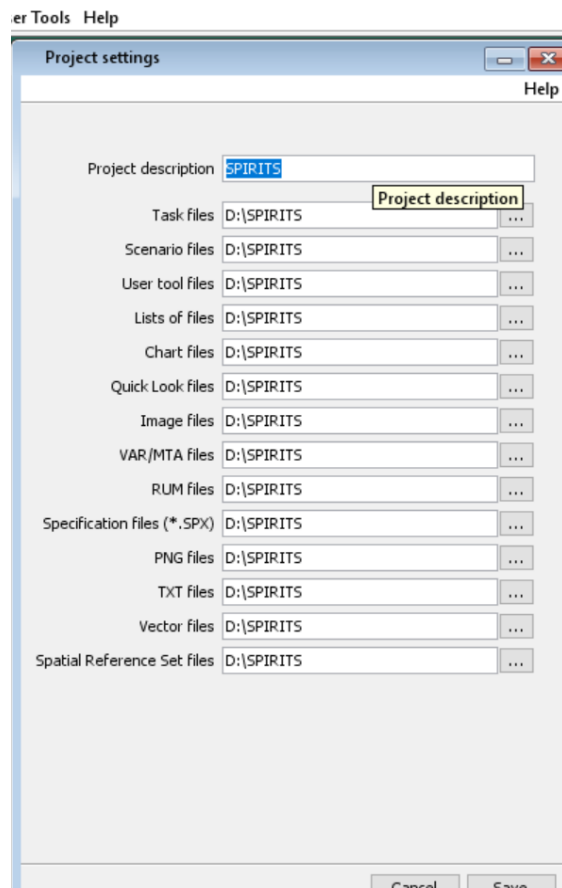
Two important remarks are:

- Be aware that you will generate lots of data in the following exercises, and that there needs to be sufficient (10 GB) free disk storage on the disk where you store the data.
- SPIRITS can show errors when data are stored in a directory with a very long path. Therefore, consider saving the tutorial data directly on your hard disk instead of copying it on your desktop.

Once you have opened the SPIRITS window:

- Go to **File> Projects> Select** and specify the project directory: **D: \SPIRITS\NDVI**. Click  button to browse through your directory and press **Select** when finished.
- To change the links to the different file directories, go to **File> Projects> Define**. Different types of files will be saved in different subdirectories which will make it easier to retrieve these files.


In the project settings you have settings where you have specified a number of default paths per file type : task files (\*.TNT), scenario files (\*.SNS), user tool files (\*.UNT), list of files (\*.LNL), chart files (\*.CNC), Map files (\*.QNT), image files (\*.IMG, \*.HDR), VAR and MTA metafiles (\*.VAR, \*.MTA), Rum files (\*.RUM), Specification files (\*.SPC, \*.SPP, \*.SPS, \*.SPU, \*.SPM), PNG files (\*.PNG), Text files (\*.TXT) and vector files (\*.SHP).



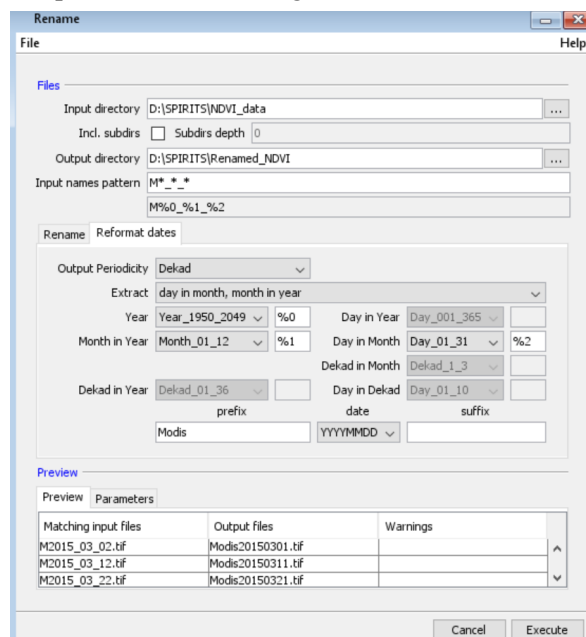
- Change the link to the resource folders as shown in the screenshots above and click **Save**.

### File Naming

The SPIRITS software works on time series of data and the DATE notification is therefore always an essential part of the filename. This software requires the data to be named [prefix][DATE][suffix].[ext.]. The structure of the filenames in the given data is **M\_YYYY\_MM\_DD.tif** (M2015\_01\_01.tif). To rename these files, you have to proceed as follows:

- Click **File> Files> Rename**. Define “D:\SPIRITS \NDVI\_data” or the path where you have stored your data as the input directory by clicking  button and output directory (“D:\SPIRITS\Renamed\_NDVI”).
- Define the input name pattern as “M\*\_\*\_\*.tif” (e.g. M2015\_01\_01.tif) and press **Enter**. Notice that the rename tool gives the variable characters a specific code: “M%0\_%1\_%2.tif”. You will use these codes in the renaming operation.

- Now go to the **Reformat dates** tab. Define **Output Periodicity** as “Dekad” and **Extract** as “day in month, month in year”.
  - Select **Year\_1950\_2049** from the drop-down box as the format to be used in **Year**, **Month\_1\_12** in month and **Day\_01\_31** in day in year.
  - The Year is %0, month is %1 and day in month is %2.
- Define the output date format, by choosing values for prefix (**Modis**), date (“**YYYYMMDD**”), which will result in a filename “**ModisYYYYMMDD**”.
- Check the **Preview** table at the bottom, and make sure there are no warnings (in red).
- Now click Execute and check in the directory if the renaming has worked fine.
- To save these parameters of this rename tool as a task file (**TNT**), click **File>Save As** and provide file name e.g. “**rename.tnt**” Close the rename tool.

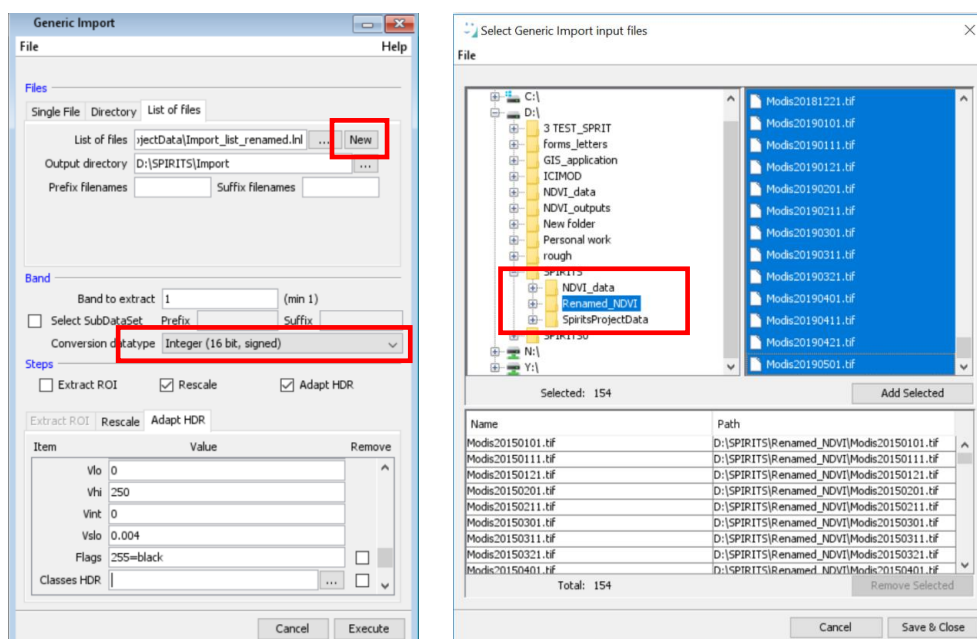


## Importing the time series

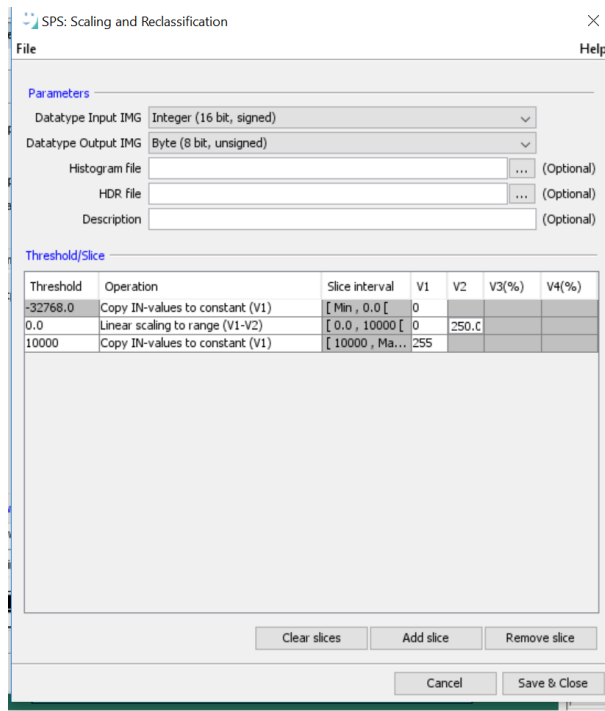
To import time series of files and transform them into SPIRITS, a new scenario has to be configured in the Generic Import tool.

- Go to **Import/Export>Generic importer>Tool**
- Select list of files and create New list, and navigate to the folder **D:\SPIRITS\Renamed\_NDVI**
- Select the .tif files to be imported and add (save) to the list
- Choose “**D:\SPIRITS\Import**” as Output path

- Make sure you select **conversion datatype** as “**Integer 16 bit**”.
- Go to **Adapt HDR** tab.
  - Add description “**MODIS 10 day NDVI**”.
  - Scroll down to **Spectral field** where, **Yname** defines the variable name (“**NDVI**”). **Yunit** defines the variable unit (**unitless**). **Vint** is the intercept to convert DN values to real values in the equation  $V = Vint + Vslo * DN$ . **Vslo** is the slope coefficient in this equation given as  $Vslo = (\text{maximum physical index specified} - \text{minimum physical index specified}) / (Vhi - Vlo)$  i.e.  $(1 - (-0.2)) / (250 - 0) = 0.004$ . **Vint** is the intercept given as  $(\text{minimum physical index specified} - Vslo * Vlo)$  i.e.  $(0 - 0.004 * 0) = 0$ . **Vlo** i.e. **0** is the **minimum digital value** specified and **Vhi** i.e. **250** is the **maximum digital value** specified.
  - Define **Flags** as 255=black.



- Go to **Rescale** tab.
  - Click on **New**
  - Select **Integer (16 bit, signed)** as **input datatype** and **Byte (8bit, unsigned)** as **output data type**.
  - Add the slices as shown in the screenshot of scaling and reclassification tab.
  - Save and close the specification
  - Execute



## Masking

### Rasterize Shapefiles

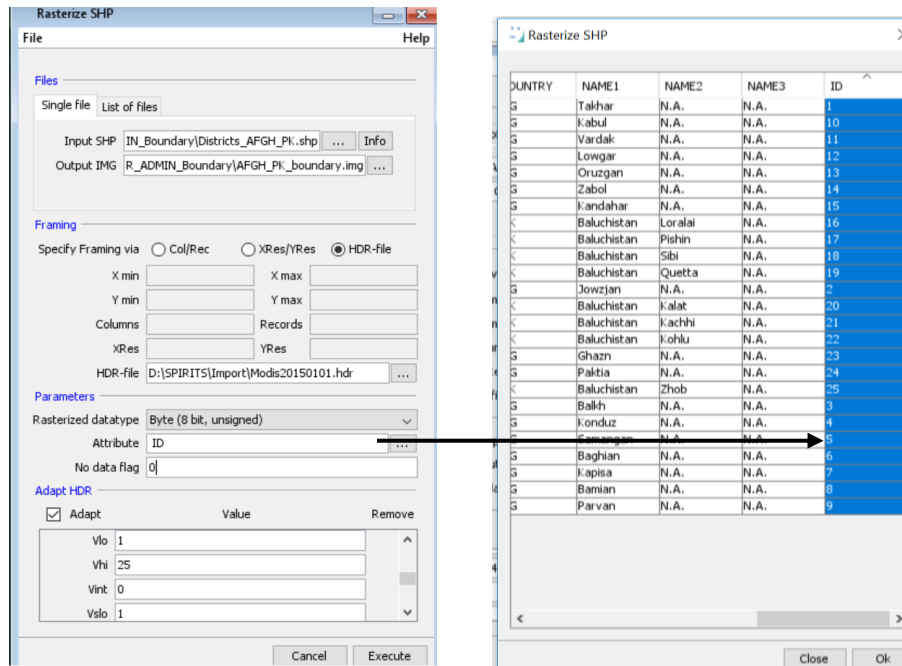
In this part, you will rasterize the ESRI Shapefile (SHP) containing the district of Afghanistan and Pakistan to an ENVI raster image file (IMG).

- Open the <Import / Export> <Vectors><Rasterize SHP> tool.
- As input SHP, choose the “**Districts\_AFGH\_PK.shp**” file from the **D:\SPIRITS\VECTOR\_ADMIN\_Boundary**.
- Check whether the input file is recognized by the gdal\_rasterize utility by clicking on the <Info> button.
- Save the output IMG in the same directory, e.g. choose as output IMG filename: **D:\SPIRITS\VECTOR\_ADMIN\_Boundary\AFGH\_PK\_boundary.img**
- The framing of the output image file can be specified based on corner coordinates and resolution, corner coordinates and number of rows and columns, or by using another HDR file. In this case you will use one of the NDVI header files, so the output IMG from the rasterizing process will have the same framing as the NDVI images. Choose one of the header files in the **“D:\SPIRITS\Import”** as reference.
- Specify the **output parameters**. Use the region ID as attribute in the output raster image. The **Rasterized data type** of the output image can thus be “Byte” (8



bit,unsigned) ”

- Select one column of the SHP attribute table output attribute: <ID>, which contains an ID of the different regions (click on to open the attribute selection panel, select the ID column < ID> and click <Ok>).



The header (HDR) with metadata needs to be adapted. Check the <Adapt> checkbox, and make sure the HDR file will contain the correct spectral information. **Yname = “ID”**

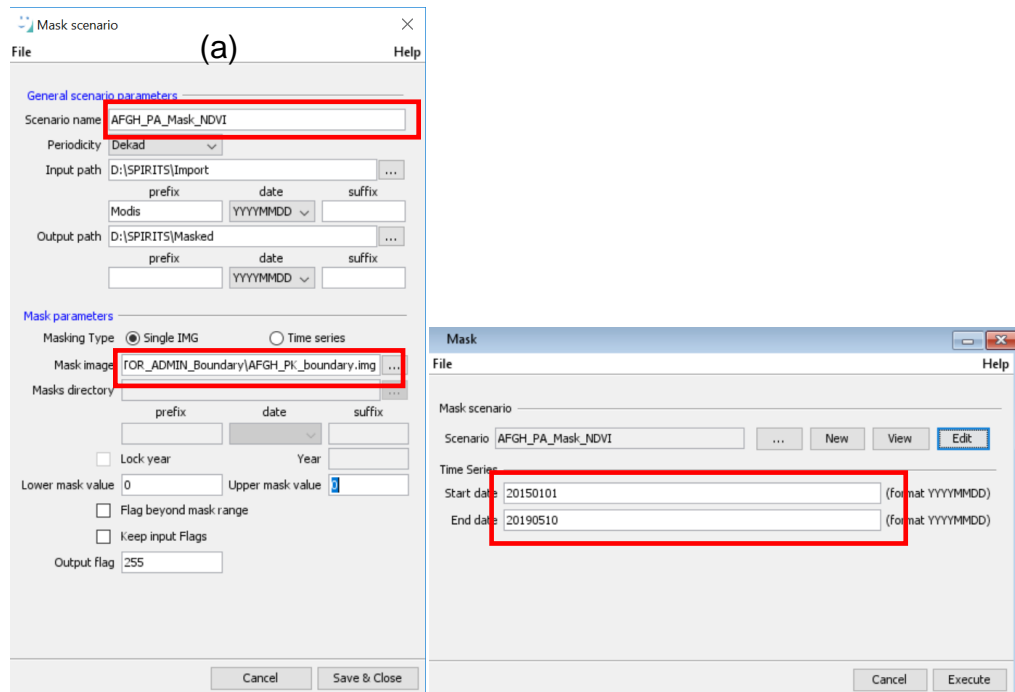
- Yunit = “-“ (none); **Vlo = “1”** (lowest ID number); **Vhi = “25”** (highest ID number) **Vint = “0”** (intercept of scaling); **Vslo = “1”** (slope of scaling); Click <Execute> and follow the process in the Tasks queue.

## Mask

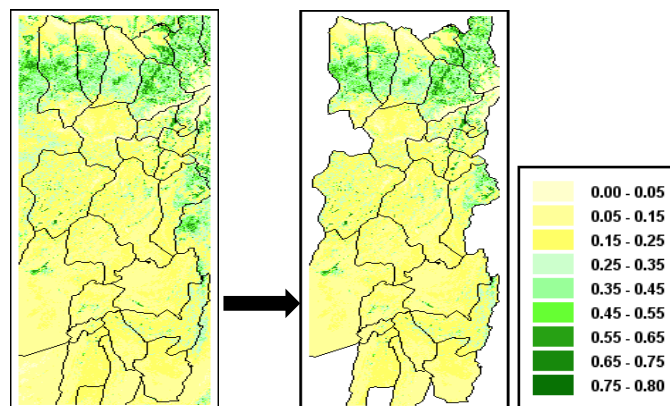
- Open <Processing> <Thematic> <Simple masking> <Time Series >.
- Create a <New> scenario for input images to be masked, and name it “**AFGH\_PA\_Mask\_NDVI**”.
- Select Periodicity as “**Dekad**”
- Select input path directory “D:\SPIRITS\Import” , **Prefix** as “**Modis**” and date as “YYYYMMDD”
- Create a new folder “**Masked**” in D:\SPIRITS and specify the output directory as “**D:\SPIRITS\Masked**” and use “**YYYYMMDD**” as date.
- Under **Mask** Parameters, select **AFGH\_PK\_boundary.img** from “**D:\SPIRITS\VECTOR\_ADMIN\_Boundary**” as Mask image, created in Rasterize

Shapefiles exercise.

- Now specify the Lower and Upper mask value. Pixels with a value in the mask image within this range will be flagged in the out image. Define “0” as both the **lower and upper mask value**, since this is the “no data flag” value in the regions image.
- Specify “255” as **Output flag** (i.e. background). And save the scenario.
- In the mask main window select the Start and End date and Click <execute>.



The masked image is shown in Figure below



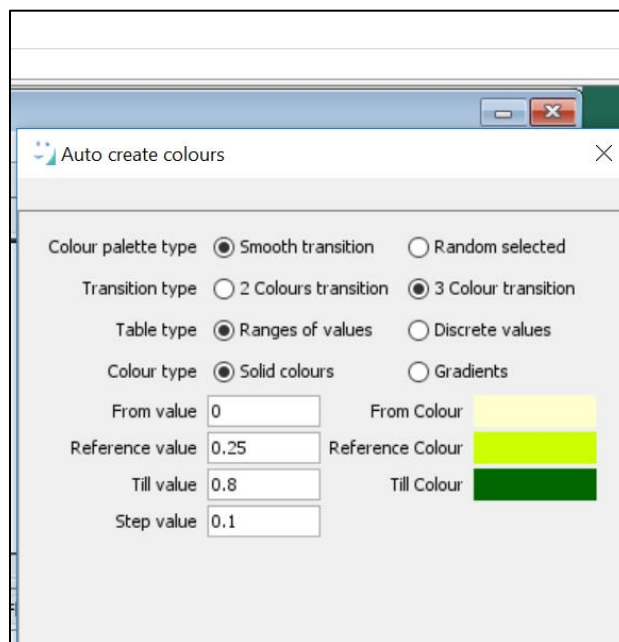
### Creating map template to visualize an image









The map generator enables the visualization of images and vector layers and allows you to add a **legend, title, logo, etc.**

- Open **Analysis>Maps>Create Templates.**
- Go to **Quick Look** tab; load one of the extracted images (for eg. **Modis\_20150101.img**) in the **Image** tab from “**D:\SPIRITS\Masked**”.
- Change the image position and size so it is placed in the upper left corner (eg. **Left=**”10”, **Top=**”10”, **Width=**”150”, **Height=**”450” pixels). The value of the Width field will automatically be adapted to maintain the same ratio between Height and Width
- Change the Border **Width** to “1” and Border **Margin** to “0”.
- Go to **Canvas** tab and adjust the width and height based on the information (legend, title, logo, etc.) to be represented. (for eg. **Canvas Width=**”380” and **Height=**”480”)

To change the colour scaling and legend of the image.


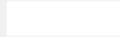



- Go to **Colours** tab, click Auto, select **Transition type “3 colour transition”** and define **From value=** “0”, **Reference value =** “0.25”, **Till value =** “1” and **Step value =** “0.1”.
- Scale the values for the **From Colour, Reference Colour and Till Colour** respectively as shown in the **screenshot.**




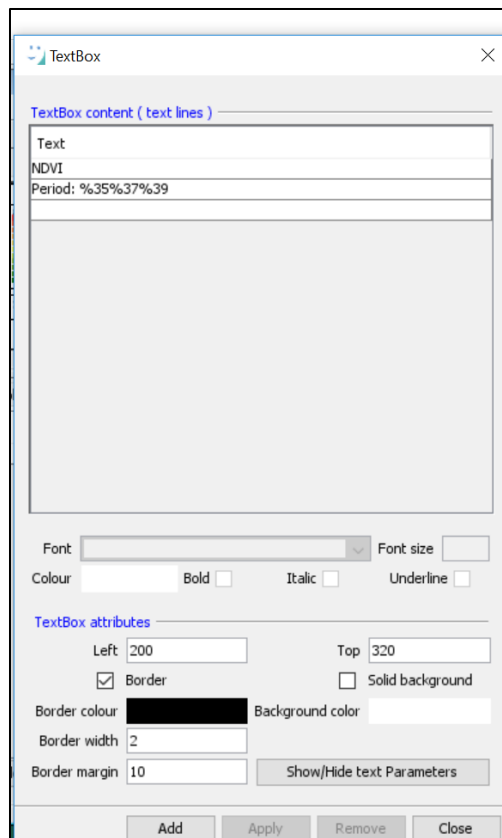
Canvas Image Image Background Flags Colours Legend Vectors Pictures Texts							
From	Till	Digital	Colour	Gradient	Colour 2	Add to legend	Legend Text
0.00	0.10	( 0 - 25 )		<input type="checkbox"/>		<input checked="" type="checkbox"/>	0.00 - 0.10
0.10	0.20	( 25 - 5...		<input type="checkbox"/>		<input checked="" type="checkbox"/>	0.10 - 0.20
0.20	0.30	( 50 - 7...		<input type="checkbox"/>		<input checked="" type="checkbox"/>	0.20 - 0.30
0.30	0.40	( 75 - 1...		<input type="checkbox"/>		<input checked="" type="checkbox"/>	0.30 - 0.40
0.40	0.50	( 100 - ...		<input type="checkbox"/>		<input checked="" type="checkbox"/>	0.40 - 0.50
0.50	0.60	( 125 - ...		<input type="checkbox"/>		<input checked="" type="checkbox"/>	0.50 - 0.60
0.60	0.70	( 150 - ...		<input type="checkbox"/>		<input checked="" type="checkbox"/>	0.60 - 0.70
0.70	0.80	( 175 - ...		<input type="checkbox"/>		<input checked="" type="checkbox"/>	0.70 - 0.80

\*Please note that legend colour can be set manually also.

- Now go to the **Legend** tab and set the parameter as shown in the screenshot below:

Canvas Image Image Background Flags Colours Legend Vectors Pictures Texts									
<input checked="" type="checkbox"/> Show legend		Title		Title Parameters					
		Left 330		Top 60					
<input checked="" type="checkbox"/> Border		Width 2		Margin 10		Colour			
<input type="checkbox"/> Solid background						Background colour			
Title font		SansSerif		Font size 14		Title colour			
<input checked="" type="checkbox"/> Bold		<input type="checkbox"/> Italic		<input checked="" type="checkbox"/> Underline					
Texts font		SansSerif		Font size 12		Texts colour			
<input checked="" type="checkbox"/> Bold		<input type="checkbox"/> Italic		<input type="checkbox"/> Underline					
<input type="checkbox"/> Colours border		Width 1				Colour			

- To add a vector layer, go to **Vectors** tab, click **Add** or  button to add the shapefile of the study area. (from “D:\SPIRITS\VECTOR\_ADMIN\_Boundary\districts\_AFGH\_PK.shp”)
- To add a title, go to **Texts** tab and click **Add** to add a new text box.
- In the Text Box window, again click **Add** to add a first line. Double click on the added line and provide the date of the image displayed (type “Period: %35 %37and Dekad %39). Then apply other changes in this window as shown in the screenshot below:

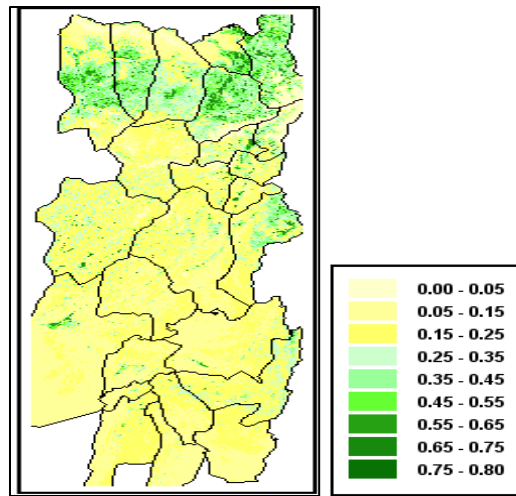


- Click **Apply** and see the result.

**Note:** In order to retrieve this information from the image header, click on **Show/Hide text Parameters**. The advantage of using text parameters for the map title is that this is automatically updated when loading another image.

Parameter	Description
%35	date Year
%36	date Month (1-12)
%37	date Month (Jan-Dec)
%38	date Month (January-December)
%39	date Day in month (1-31)
%40	date Day in year (1-365)
%41	date Dekad in month (1-3)
%42	date Dekad in year (1-36)

- You can now save the map by clicking **File>Save As**. Save the file as e.g. **"D:\SPIRITS\NDVI\Maps.qnq"**.
- You can also export the map to a PNG file (try File>Export PNG). An example of exported map is shown below :



### Generate Map Series

- Go to **Analysis>Maps>Map Series>Time Series**
- Use the button and load the Map template that you created in the previous part of the exercise (Browse to “D:\SPIRITS\NDVI\Maps.qnq”)
- Select “D:\SPIRITS\Masked” as **Input path** and “Month” as **periodicity** in the drop-down menu.
- The file structure is “YYYYMMDD” for the input and “YYYYMMDD” for the **output files**.
- Define “D:\SPIRITS\NDVI\Map Series” as **the output directory**.
- Enter **the start and end date** (“20150101” and “20190510”) and press **Execute**.

**Create Quick Looks**

File Help

---

**Quick Look template**

QnQ template: D:\SPIRITS\SpiritsProjectData\Maps.qnq ... New View Edit

---

**Files**

Input path: D:\SPIRITS\Masked ... Periodicity Dekad

Input files: prefix  date YYYYMMDD suffix

Output path: D:\SPIRITS\Map series ...

Output files: prefix  date YYYYMMDD suffix

---

**Time Series**

Start date: 20150101 (format YYYYMMDD)

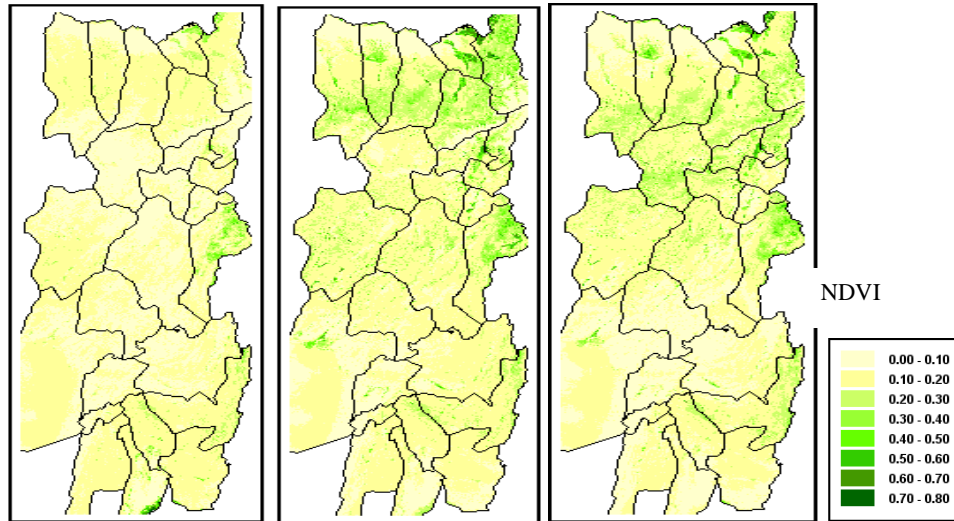
End date: 20190510 (format YYYYMMDD)

Cancel Execute

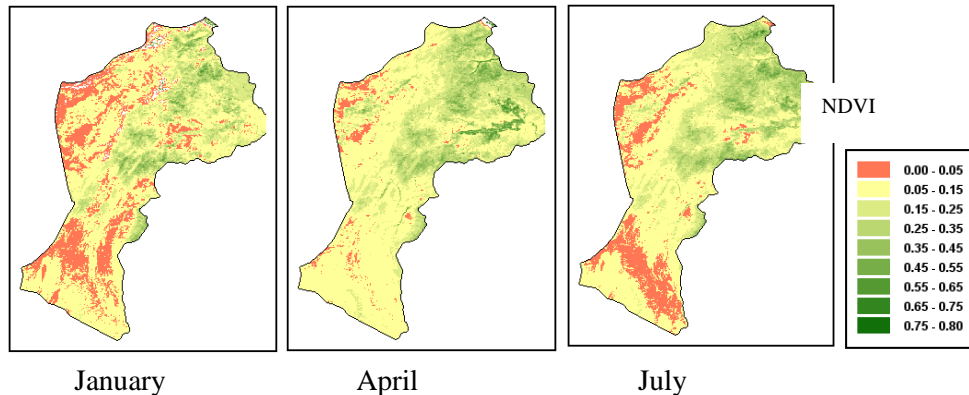
This process takes some time to get completed. You can see the ongoing process at the right side of Spirits' window. Once the execution gets completed, you can go to the path specified and inspect the generated files. The output files are in PNG format.

Some maps for the year 2018 are given below for whole study region and the masked district (Paktia) of Afghanistan.

(a)



(b)



### Anomalies

In this exercise, you will create **anomaly maps** based on the comparison of the NDVI data with the historical year.

In the calculation of anomalies, the current month or dekad or season is compared to a certain reference situation. Many different anomaly algorithms exist, all optimized for particular indicators and environments.

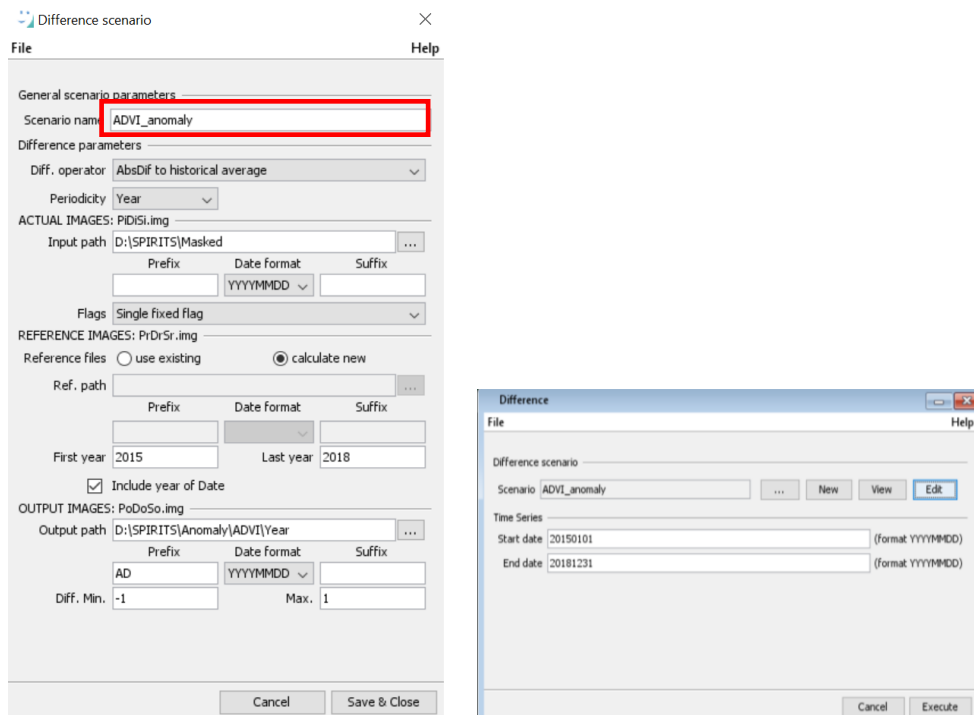
- **Absolute Differences:** The absolute difference is calculated as:  $ADV_{Iy,p} = X_{y,p} - \text{meanp}$ , with  $y$  = the year, and  $p$  = the period in the year (month).
- **Standardized Differences:** The standardized difference is calculated as:  $SDV_{Iy,p} = (X_{y,p} - \text{meanp}) / \text{stdevp}$ , with  $y$  = the year, and  $p$  = the period in the year (month). The Standardized Difference Vegetation Index is thus the difference in terms of standard deviations from the mean situation for that particular month ( April), and for each pixel, or also called the z-score.
- **Relative Differences:** The relative difference is commonly used to estimate the anomalies of rainfall compared to the average situation, and is calculated as:  $RD_{y,p} = (X_{y,p} - \text{meanp}) / \text{meanp}$ , with  $y$ = year, and  $p$ = period in the year). The RD is thus expressed in percentage difference compared to the mean situation in that period of the year, for each pixel of the image.

You will now find the **absolute differences** as follows:

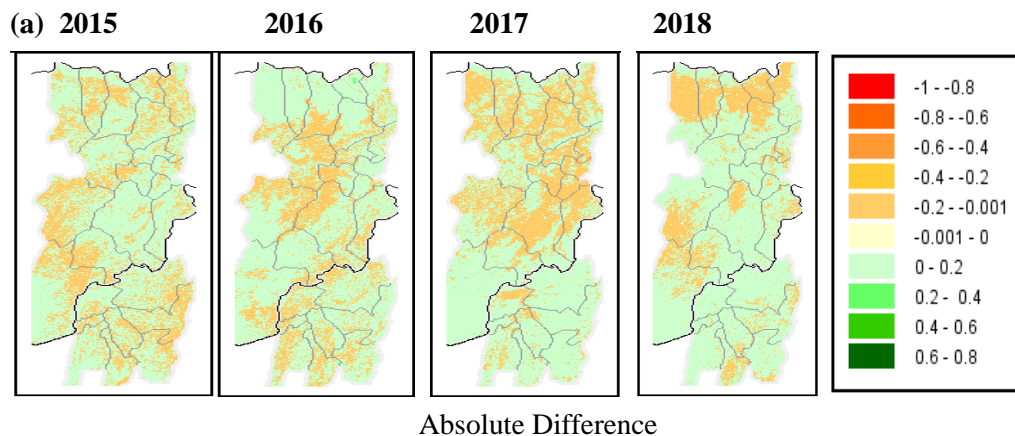
- Go to **Processing>Temporal>Anomalies>Time series**.
- Create a new difference scenario giving a new name (for e.g. **ADVI\_anomaly**)
- As difference operator, choose '**AbsDif to historical average**'. This calculates difference of current period minus historical average for that same period of the year.
- Select the periodicity as "**Dekad/Month/Year**" in this case 'year' from the drop-down menu.
- Define the **input path** as "**D:\SPIRITS\Masked**" and enter the data format as "**YYYYMMDD**".
- Choose "**single fixed flag**" in **Flags**.
- The reference images for the historical year (i.e. long-term average) need to be calculated on the fly and therefore select "**Calculate new**". The historical year can also be computed with a separate module and be stored on the disk. To compute them on the fly you need to select a start and an end date for the historical year. In this case select **2015** as **starting year** and **2018** as **end year**.
- Save the output in the **output path** as "**D:\SPIRITS\Anomaly\ADVI\Year**" with **date format** as "**YYYYMMDD**".
- Set Diff. min as **-1** and Max as **1**.
- **Save** the difference scenario.
- **Execute** the difference scenario from **20150101** till **20181231**.

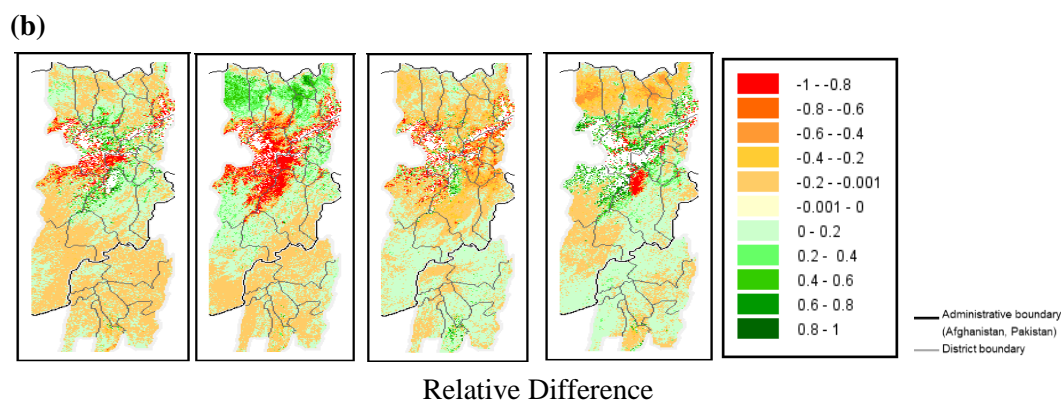
**Note:** You can run the same process for relative difference and other anomaly calculation and for that you have to change the difference operator.



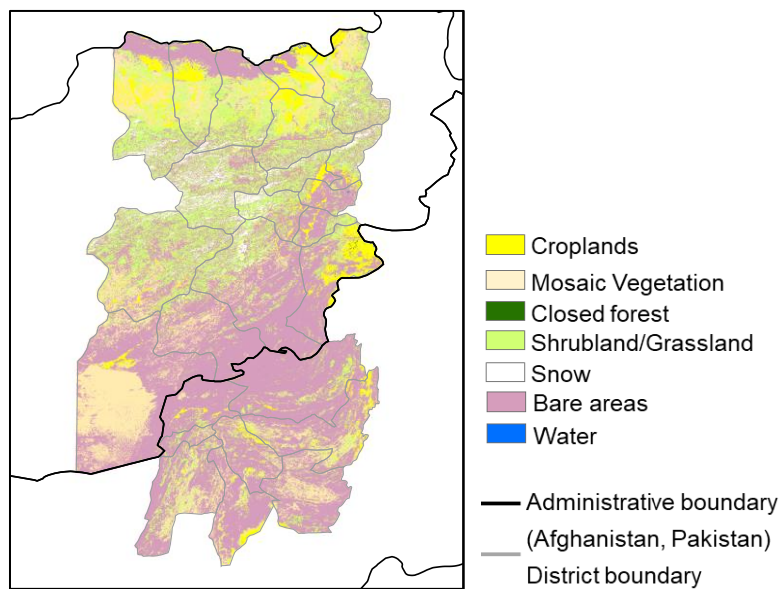


Create a template for a single image and use it to visualize the map series showing anomaly in NDVI pattern. Some maps showing the NDVI anomaly are shown as absolute difference (a) in the figures below, relative difference (b). A comparable land cover map (globcover) of the study region is shown in figure below (c).





**(c) Land cover map (Globcover)**



### Exercise 3: Monitoring drought using climate variables - Average, Trend, SPI

The Standardized Precipitation Index (SPI) developed by Thomas B. McKee is a valuable tool for the estimation of the intensity and duration of drought events (McKee, Doesken, & Kleist, 1993). The SPI is based on the use of historical data by analysts to calculate the probability of a rainfall event to be equal or less than a certain average amount for a given period of time. Indeed, the SPI is based on the use of a cumulative probability function calculated from past rainfall events occurring at a station. To achieve this, the historic rainfall data of the station is fitted to a gamma distribution, as the gamma distribution has been found to fit the precipitation distribution quite well.

Analyst can calculate the probability of a specific rainfall event and compare it to the cumulative probability function to identify either drought event or abnormal wetness event.

The SPI has the following traits (McKee et al., 1993):

- The SPI is uniquely related to probability.
- The precipitation used in SPI can be used to calculate the precipitation deficit for the current period.
- The precipitation used in SPI can be used to calculate the current percent of average precipitation for time period of one months.
- The SPI is normally distributed so it can be used to monitor wet as well as dry periods.
- SPI is normalized so that wetter and drier climates will be represented in a similar way.

By using the SPI as an indicator, we can formulate a functional and quantitative definition of drought for each time scale. A drought event for time scale (i) is defined here as a period in which the SPI is continuously negative and has a value of -1.0 or less. We can say that a drought events starts when we observe for the first time the SPI value falling below zero. Conversely, the end of a drought event can be identify as the first time when the SPI value is positive following a value of -1.0 or less.

Drought intensity is arbitrarily defined for values of the SPI with the following categories:

SPI Values	Drought Category
0 to -0.99	Mild drought
-1.00 to -1.49	Moderate drought
-1.50 to -1.99	Severe drought
<= -2.00	Extreme drought

#### Software:

The GeoCLIM (<https://chc.ucsb.edu/tools/geoclim>) is a specific software designed for climatological analysis of historical rainfall, evapotranspiration and temperature data. With the support from the USAID preparedness and Global Climate Change activities, the

software was developed by Tamuka Magadzire of USGS FEWS NET. Furthermore, the GeoCLIM provides a range of easy to use analysis tools for climate-smart agriculture development. These user-friendly tools can be used to:

- Blend station information with satellite data to create improved datasets,
- Analyze seasonal trends and/or historical climate data,
- Analyze drought for a selected region by calculating the standardized precipitation index (SPI),
- Create visual representations of climate data, create scripts (batch files) to quickly and efficiently analyse large quantities of climate data,
- View and/or edit shapefiles and raster files, and extract statistics from raster datasets to create time series.

### **Hands on Exercise: SPI computation using GeoCLIM**

#### **Objectives**

- To analyse the satellite derived rainfall product
- To calculate SPI for assessing the drought severity

#### **Dataset Used**

- CHIRPS

#### **Software**

- GeoCLIM 1.2.0

### **Step 1: Software Installation and Settings**

#### **System Requirements**

1. Microsoft Windows Operating System (XP or later)

#### **Downloading and Installing the GeoCLIM**

The latest version of the GeoCLIM can be downloaded from:

<https://chc.ucsb.edu/tools/geoclim> or <http://earlywarning.usgs.gov/fews/software-tools/20>

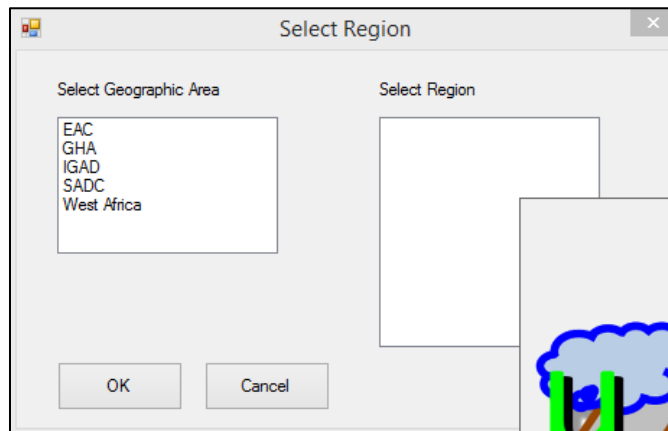
#### **First Time Users:**

- Download the latest GeoCLIM version from above mentioned address.
- Open the file and follow the instructions for default installation.
- Then run the program by going to the **Start Menu**.

## Step 2: Select Geographic Area and Region

The GeoCLIM works on particular geographic regions. The different regions are provided as part of the program and the users also have the option to create their own.

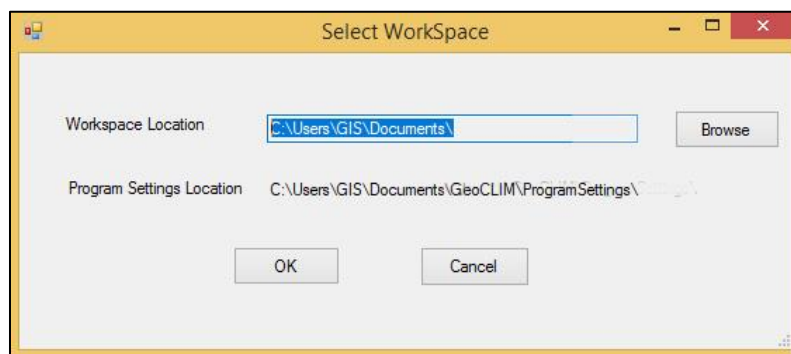
- For selecting the existing regions, open the program.
- Once the program opens, choose a geographic area from the ‘**Select a Geographic Area**’ menu and a region or specific country from the ‘**Select Region**’ menu.



*Select Region of interest. If not available, select one of the available regions and add new one later*

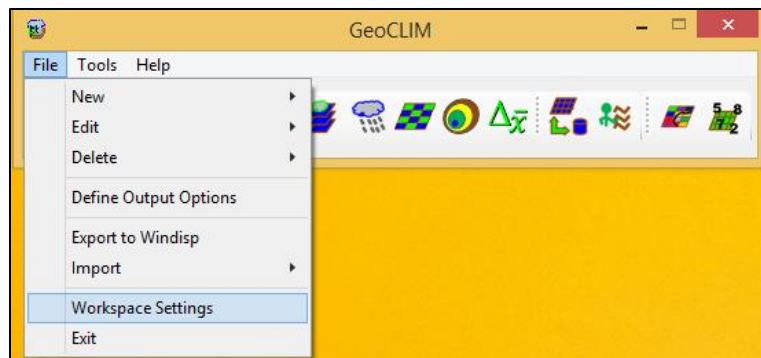
## Step 3: Select the working directory

- Select the directory where you want to locate the default GeoCLIM workspace directory for all the related files, data and outputs. The default workspace will be **C:\Documents**.



Workspace setting

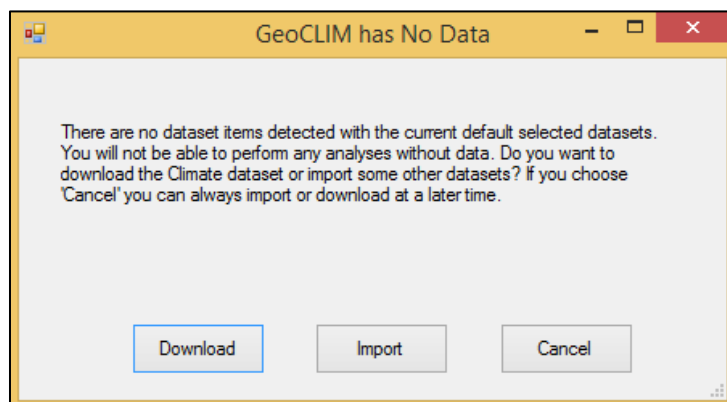
- The workspace directory can also be updated later on from a **workspace setting menu**.



Menu option for workspace setting

#### Step 4: Download or Import Data

- A “**GeoCLIM has no data**” dialogue box will appear. User can either import existing archives by clicking **Import**, download pre-existing GeoCLIM data by clicking **Download** or cancel to load data later on.



Data import of download option

- For our exercise, you will be working on a data provided. So, click cancel to import data later on.

#### About Data

You will be working on a satellite derived rainfall data a raster file called **Climate Hazard InfraRed Precipitation with Station**. The detail information about the data is presented in the following Table:

File Name	CHIRPS_PPT_GLOBAL_monthly.climdata
Spatial Coverage	Global
Temporal Resolution	Monthly, 1981-2018
Spatial Resolution	0.05°

- The raster data is in compressed file format called **climdata** compatible for **GeoCLIM** tools. The **BIL** raster files will be extracted by the GeoCLIM after data import. You can also download the data from Climate Hazard Group website or FEWS NET website:

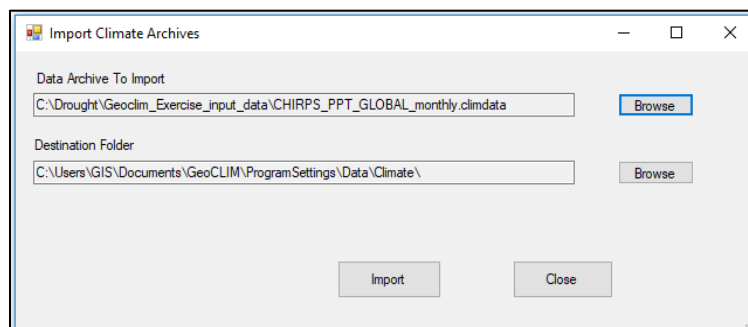
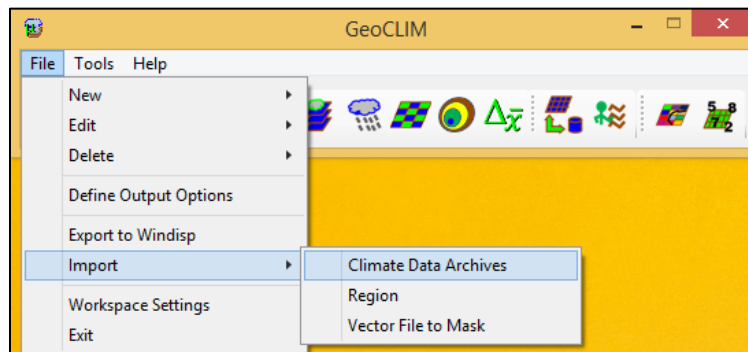
ftp://chg-

ftpout.geog.ucsb.edu/pub/org/chg/products/GeoCLIM/Geoclim\_archives/https://earlywarning.usgs.gov/fews/datadownloads/Global/CHIRPS%202.0

### Import GeoCLIM Climate Archives

A **GeoCLIM archive** is a compressed file containing data for a given climate variable and specific information so that it could be imported into the **GeoCLIM**. The **Import Climate Archives** tool is used to make datasets available in **GeoCLIM** for analysis.

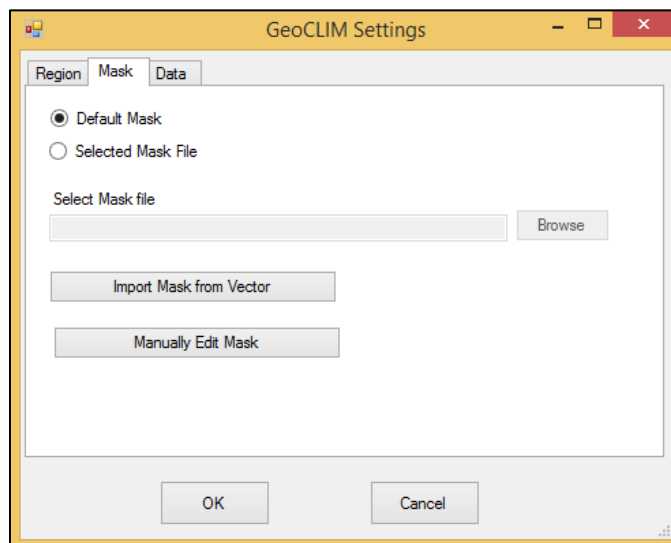
- From the main menu bar click the **Import Climate Archive** menu.
- Then browse through the location where you have placed the data.
- Select the **climdata** archive.
- Then **click import**.
- Then select make it a default dataset after a window pop ups asking.



*Browsing the location of data*

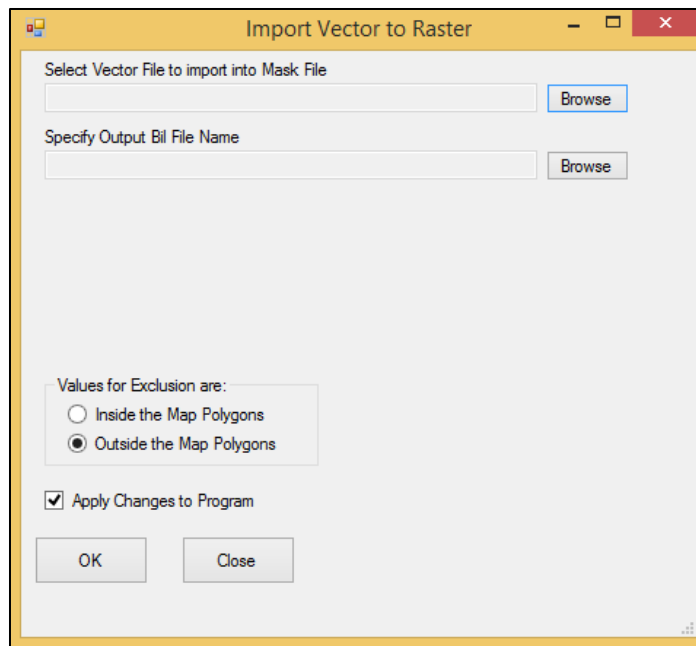
### Creating a mask

- You should define a specific mask for the selected region for computation and display.
- Click the **Setup menu** in the menu bar.
- Select the **mask tab**.
- There you will be presented two options. Select **the Import Mask from Vector** option.
- Then import the **vector shapefile** of the study area you're interested in. In this case let's import shapefile of boundary of Afghanistan and Pakistan.
- Define the output location of the mask file. This mask file will be in **BIL** raster format.
- Select the option **Outside the Map Polygons**. This will assign '0' value for outside the region of interest and a '1' for the area within the region.



*Creating a Mask*

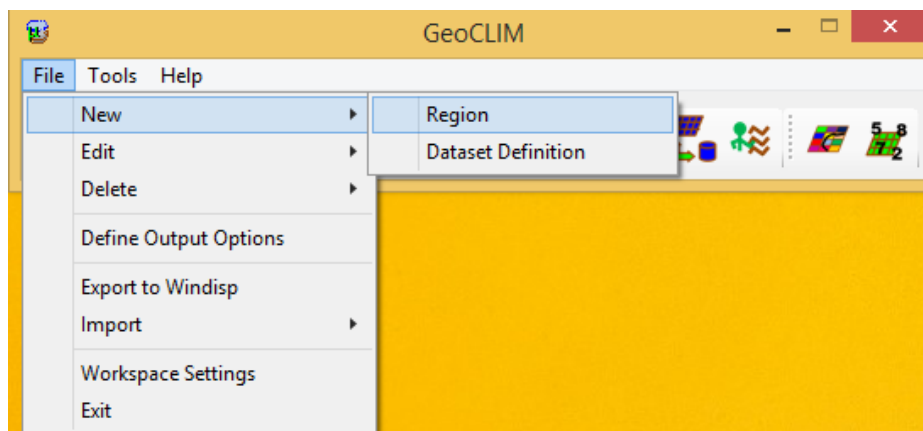




*Importing vector file to create raster mask file*

### Defining a new region

- You have now a mask file for your study area.
- There are two ways to create a user-defined region in the **GeoCLIM** program. The first way is to go to **File>New>Region** and fill out all the fields. The other way is to modify an existing region from **File>Edit>Region**.
- Open a **New** by clicking **File** menu item.




*Creating a new region*

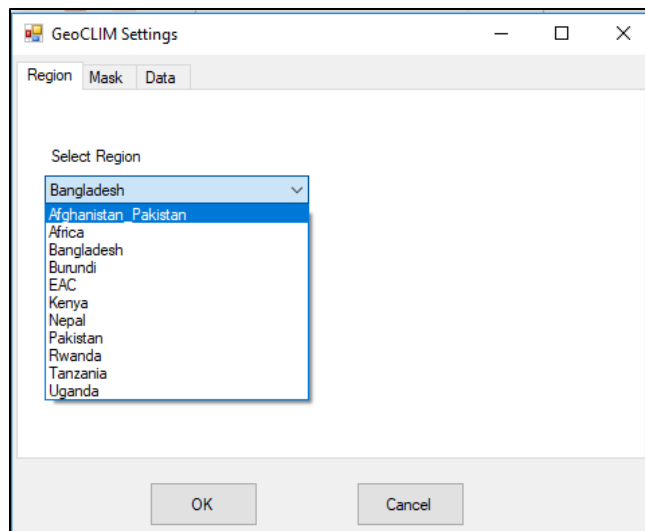
- Then **Edit Region** window opens. You have to fill all the fields in this window to create a new region.

*Edit Region window*

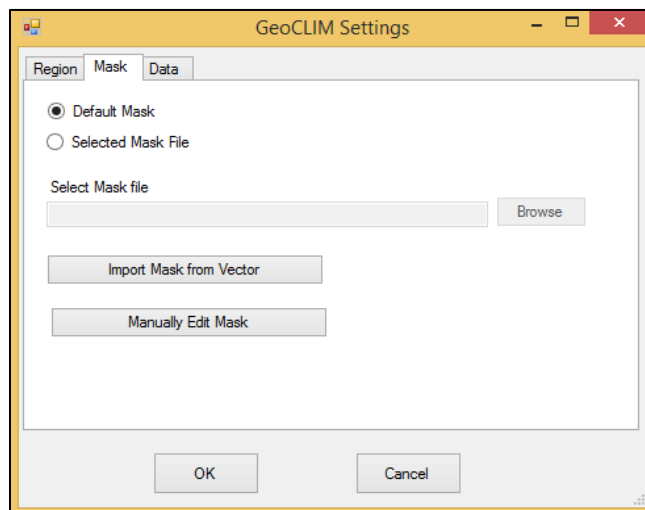
- Import the extent of the region from the shapefile or mask file of the region.
- The fields **Height of pixel** and **Width of pixel** refer to the pixel size that will be used in analysing the data – ideally this should match the pixel size of the source climate data. So, enter **0.05** in both these fields.
- Specify the path of worldmask1deg.bil file as Default Mask File.
- Then specify a shapefile for the new region in the **Default Map File** field. Click the **Define** button shown in the above Figure. This map is used as outline when displaying the results.
- Select the mask file created in **section 3.4** in the mask field.
- Then click **save** and the window will automatically close.

### GeoCLIM setup

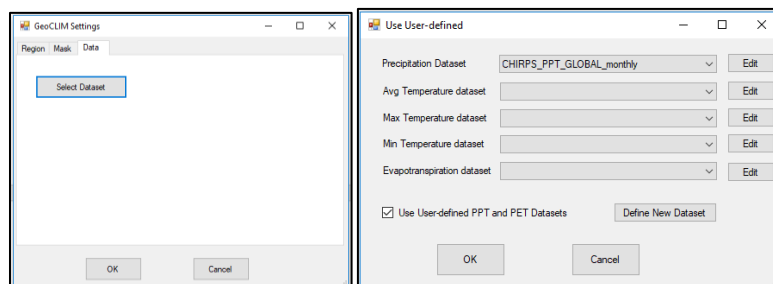
- The user can change settings such as the region of work or the selected climate datasets by clicking  icon from the **GeoCLIM toolbar**.
- Select the **Region** of interest. Select the region created in the above step.
- The **Mask** tab allows the user to select a new mask or edit an existing one. The default mask here will be the one defined in your selected region.
- The **Data tab** facilitates the selection of available datasets (rainfall, temperature and evapotranspiration) for analysis. The **Data tab** also allows the user to add new or edit existing climate datasets.



*Region of interest selection*

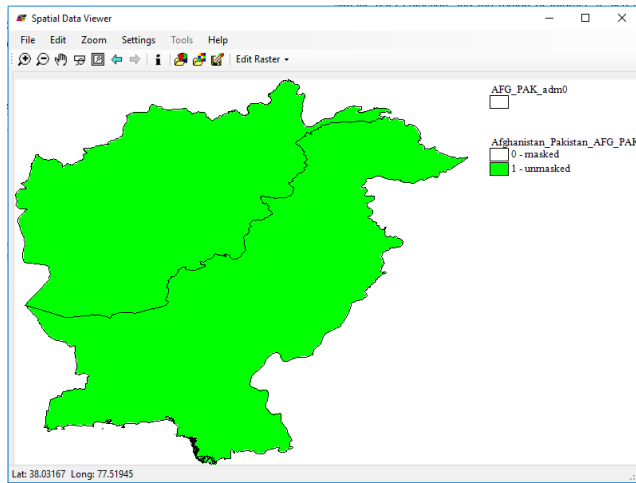


*Selection of Mask in GeoCLIM setup*

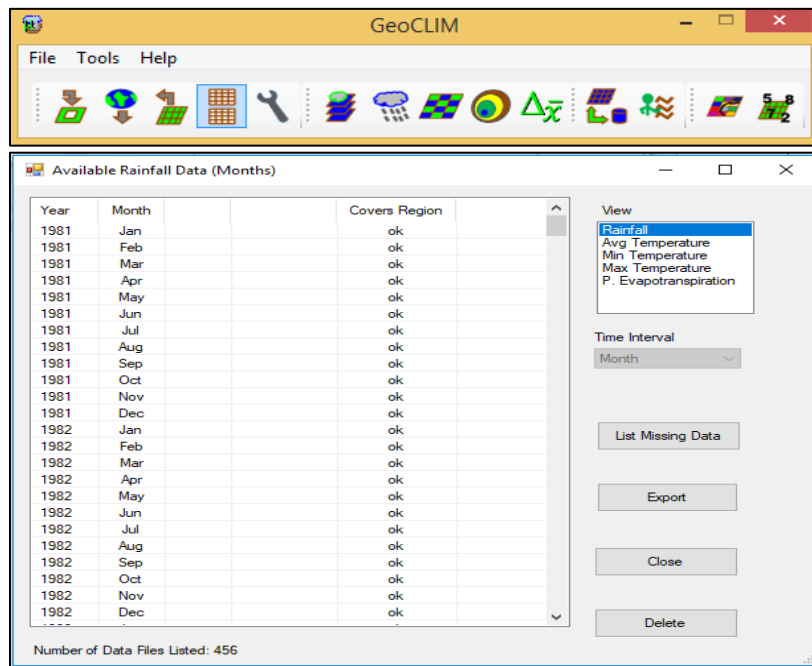


*Data selection*

- Your mask for Afghanistan and Pakistan should look like as shown in the **figure below**.



- The **View Available Data** tool shows a list of the data available for analysis based on the climatic data selection and the region of interest. It also checks whether the selected datasets cover the region of interest or not.
- The **List Missing Data** button provides a list of the missing files in the time series between the first and last date of available data.



*List of Available Data tool for checking the datasets*

## Climatological Analysis

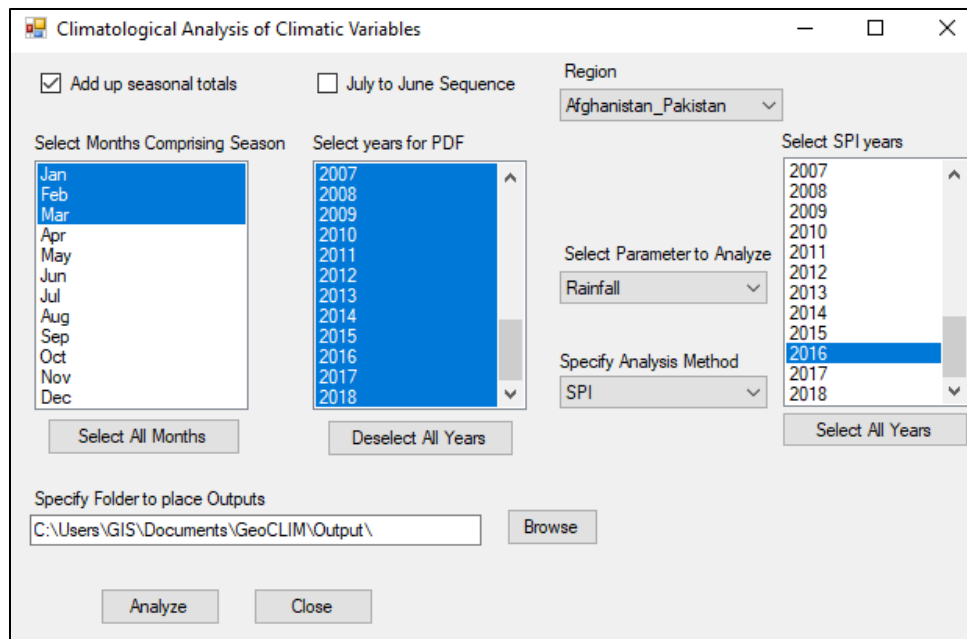
The *Climatological Analysis of Climatic Variables tool* is used for analysing and visualisation of statistical characteristics of rainfall, evapotranspiration, and temperature data based on the time series of the data. The tool displays all the years and periods (months, dekads or pentads) available for a selected climate dataset. Here the user may select a period or a group of periods (i.e. **Dekads/Months/Pentads**) and years to analyse. Furthermore, the user can choose one of the available analysis methods such as Average, Trend, SPI and others.

### SPI Method:

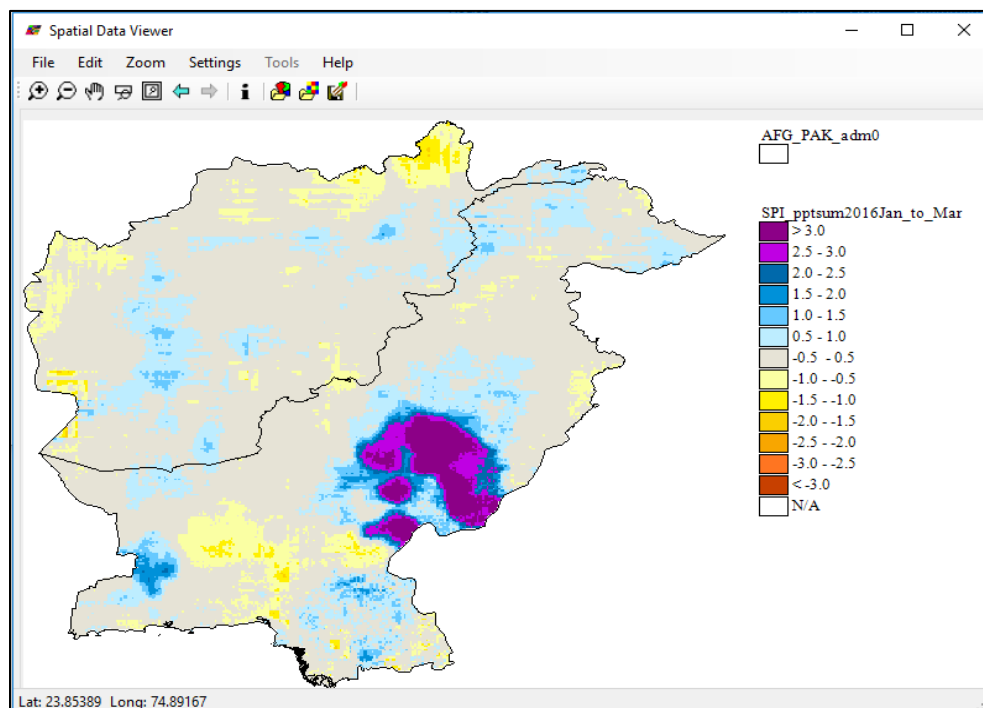
- Open a **Climatological Analysis tool** in the **main toolbar** or from the main **GeoCLIM tool bar**.
- Make sure that the region of interest is selected from the **Region dropdown list** as shown in figure below. The default region selected here will be the region set up during first-time run.
- You'll be calculating SPI from the **CHIRPS rainfall** product. So, select the **rainfall** as parameter to analyse and **SPI** as the analysis method.
- Select the periods comprising a season of interest on the left panel. The data period (pentads, dekads or months) is based on the selected climate dataset, Months in our case. So, select the month January, February and March for the analysis.
- Select **"Select all the years"** on the right panel. These years will be used to calculate the long term mean and express the selected year as anomaly from this mean (i.e. a normalized variable that conveys the probabilistic significance of the observed/estimated rainfall). Select the **year 2016** as the **SPI year**.
- Check the box **Add up seasonal total** to calculate the total of the selected season for each year and **July to June** sequence if the season goes from one year to another.
- Then specify the folder for the output results and click **analyse**.



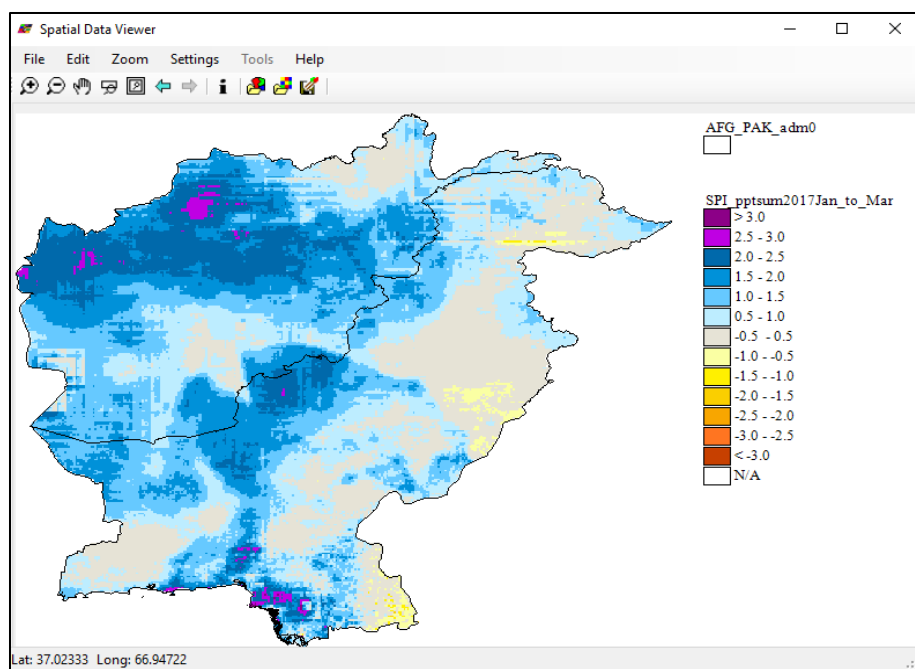
*Climatological Analysis Tool*



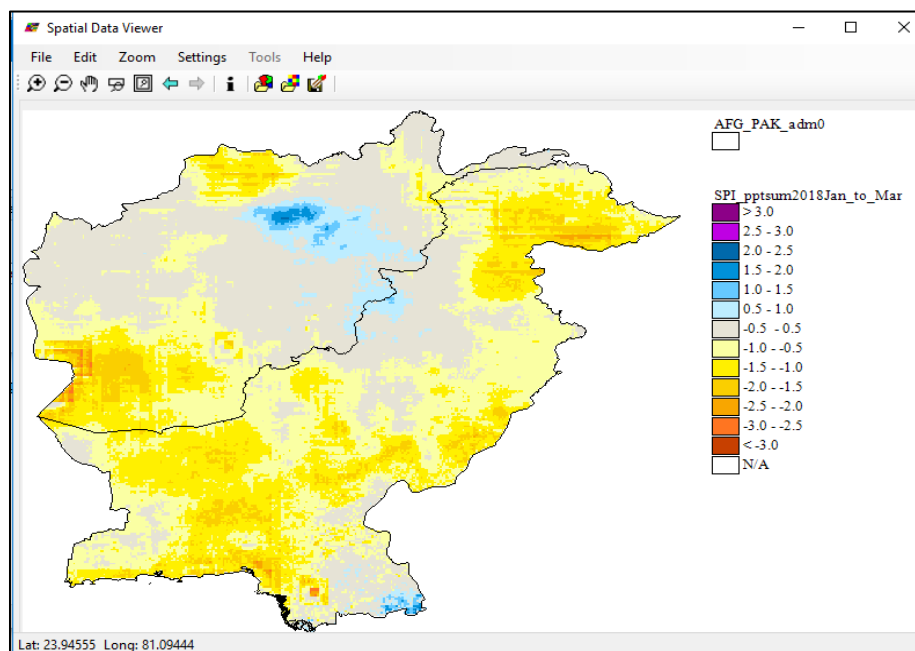
*SPI calculation in Climatological Analysis tool for the January, February and March 2016*



*Output SPI map for the January, February and March 2016 with the color index displayed in the Spatial Viewer*



*Output SPI map for the January, February and March 2017 with the color index displayed in the Spatial Viewer*

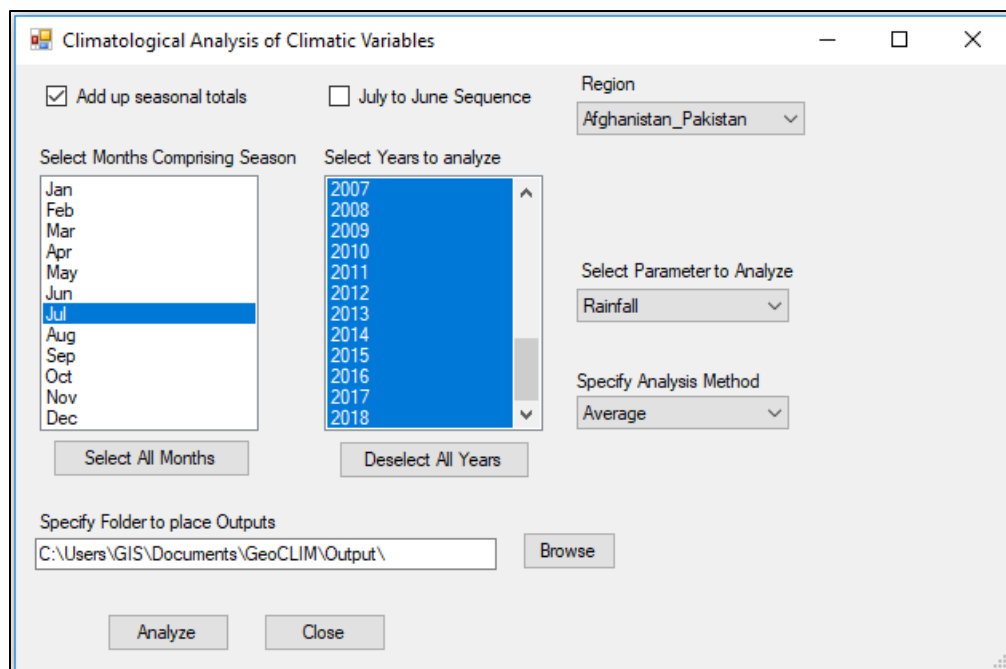


*Output SPI map for the January, February and March 2018 with the color index displayed in the Spatial Viewer*

- For drought analysis, a **SPI** less than **-1.0** indicates that the observation is termed as **“moderate”**. A SPI less than **-1.5** is termed as **“severe”**. Values less than **-2.0** are typically referred to as **“extreme”** drought event. And the **SPI is unitless** as it is only the number of standard deviations from the historical mean precipitation for that particular period.

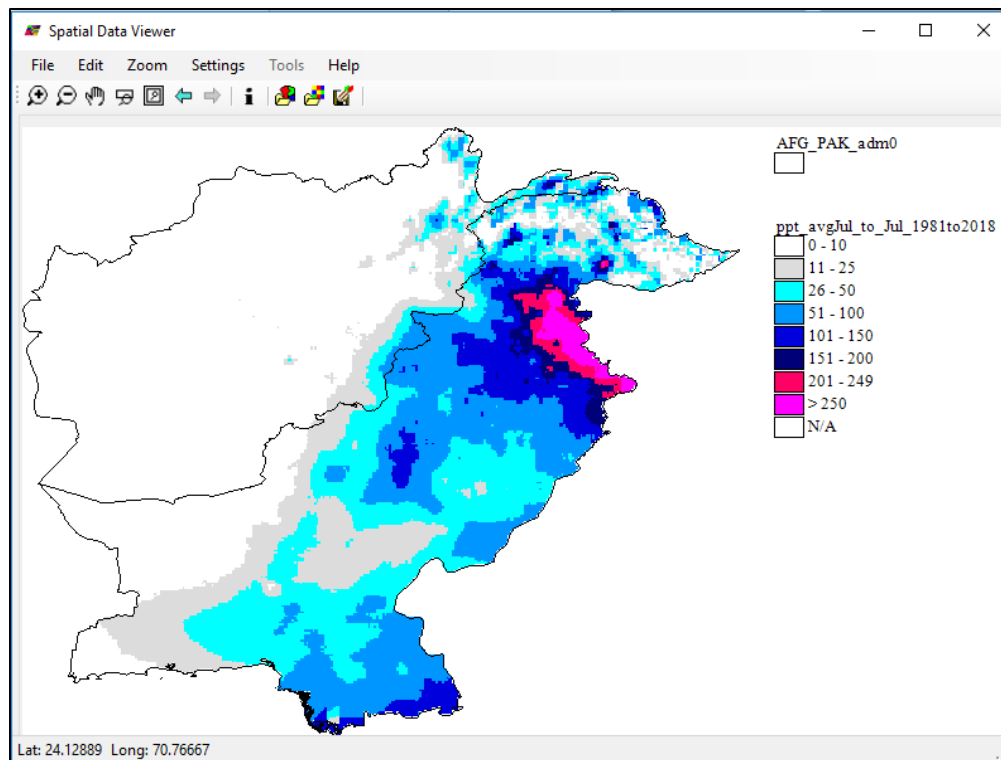
### Average Method

- The **Average** analysis method calculates the statistical average value for each pixel for the season or group of periods using all the years selected.
- Select the **analysis method** as average in the **dropdown** option.
- Select the Month of **July**.
- The seasonal total for all the selected years will be averaged out to produce average output map. **Select all the years** to analyse. Check the box **Add up seasonal totals** here too.



*Average rainfall calculation for the July for the years 1981-2018*

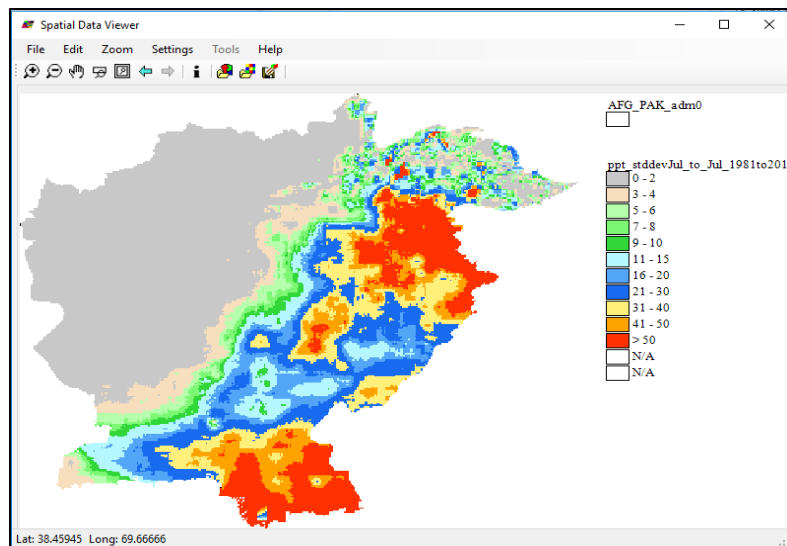




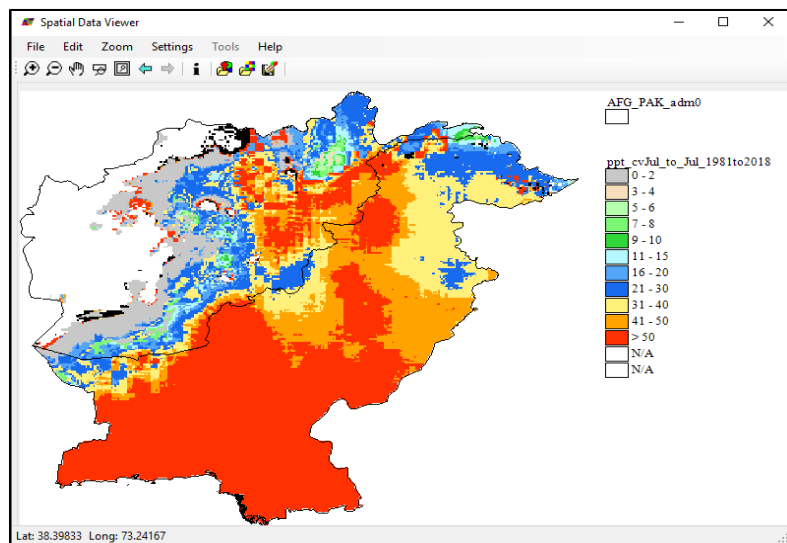
*A output average rainfall map for the July (1981-2018) (unit being mm of precipitation)*

### **Standard Deviation (SD) and Coefficient of Variation (CV) Method**

- These are the methods for estimating variability. The standard deviation shows the variability within the time series while the coefficient of variation shows the SD as percent of average facilitating the comparison of variability among regions.
- SD is a measure of how spread the data are from the mean. In doing analysis based on the average, it is important to include the SD to indicate how much the values could go above or below the mean.
- CV allows for the comparison among different magnitudes of variation or between regions with different means.
- Select **both analysis** methods each at a time and **perform analysis**.



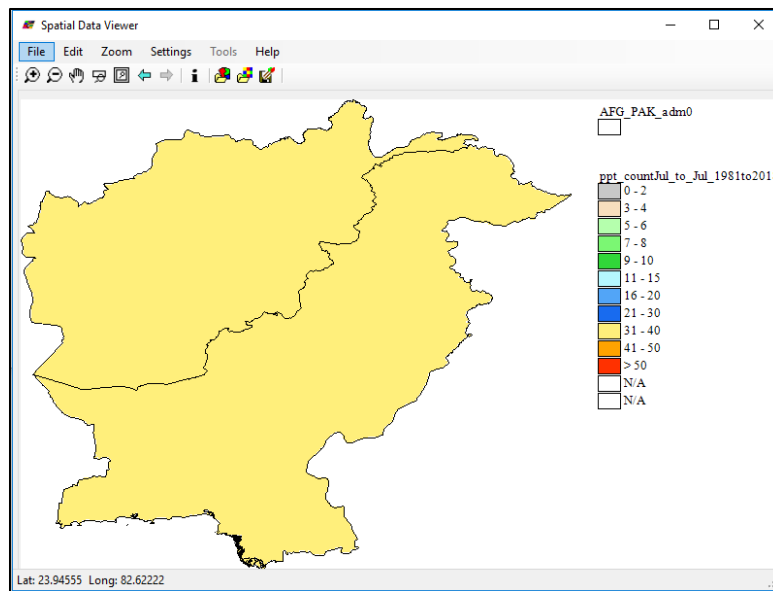
*SD map showing variation in mm*



Coefficient of variation (CV) map showing the standard deviation (SD) as percent of the average

### Count Method

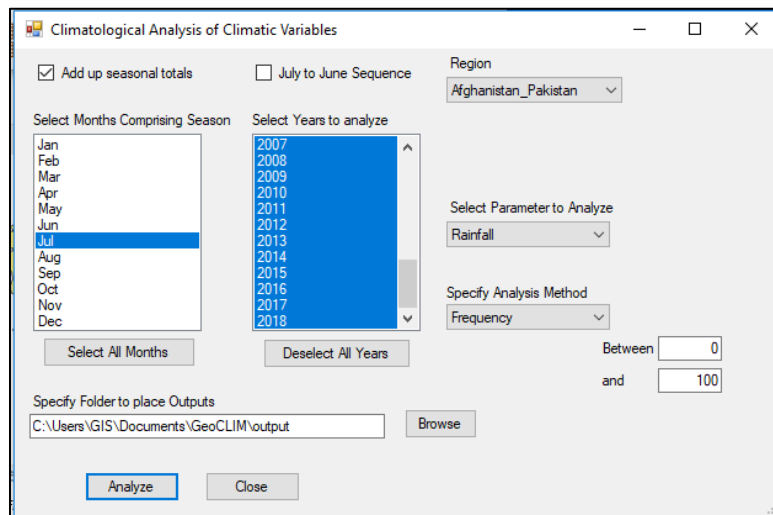
- The **Count** Method in Climatological analysis tool gives the number of times a pixel in the time series with value different than the missing value (-9999) i.e. valid non-missing numbers.
- Select **Count** Method and click **analyse**.



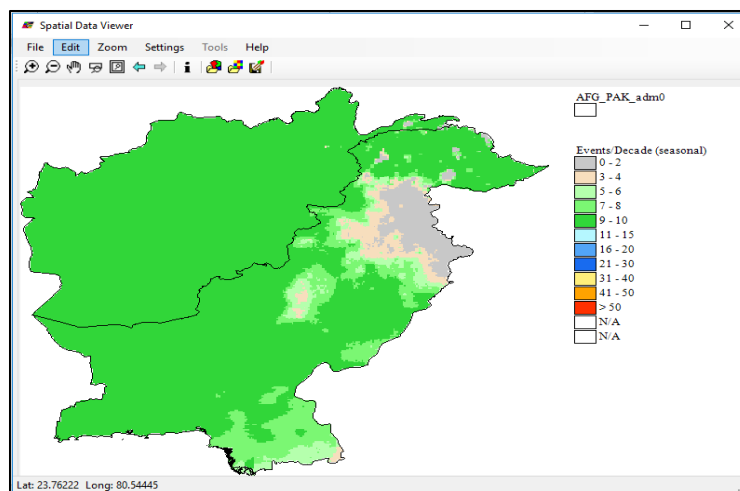
Map showing count for valid non-missing values (no missing data in this case i.e.35)

## Frequency Method

- The **Frequency analysis** method in the Climatological analysis tool calculates the number of times a range of values has occurred in the time series.
- This method helps us to answer to questions such as “How many times has the total seasonal rainfall been less than 100m?” as in figure below.



Frequency method for calculation of number of times seasonal total in the range 0 to 100



Map showing the number of times the range of 0 to 100 mm rainfall took place during the time series.

### Extracting Raster Statistics and Time Series

The **Extract Grid Statistics** tool calculates summary statistics for a polygon or a set of polygons from a **shapefile (SHP)** file over a raster dataset or a group of rasters. These statistics can be used to study the trend over the time period for a particular place.



- **Open Extract Raster Statistics tool** from the menu bar.
- Select a shapefile containing polygon of interest (e.g. districts).
- Select the type of summary '**average**' for the pixels within the polygon in the **Summary** pulldown menu.
- There are two ways to add the data using **T-series** and using **Add button** to select the raster datasets in BIL format. The T-series button allows the generation of a list of raster files to extract based on a time series. The **Add button** allows the adding of individual files.
- Select **T-series** which opens up a new window. Click the "**Use GeoCLIM Data**" at the top right corner. This will load the default climate data in the **GeoCLIM, Monthly CHIRPS** in our case.
- Select the month of start of the season if the computation is on seasonal basis. But now we only want to extract the statistics for the first **July** for **all the years**.
- Click the **Analyze** button and close the window. This create a **list file** of the data which will be loaded as the **raster files** in the **main window of the tool**.
- Specify the **output file** for the statistics and **click ok**. The output file will be exported as a **.CSV file**.

## Exercise 4: Validation of satellite-based rainfall data against rain gauge station data

### Introduction

For the assessment and monitoring of meteorological and agricultural drought, precipitation data is widely used. However, the availability of rainfall data in appropriate temporal and spatial scale is often limited due to data collection being mainly based on ground observation. Furthermore, in developing countries such as Nepal, the number of rain gauge stations is low and in many cases continuous short temporal data for long term period is missing. Fortunately, in the last few decades, advances in remote sensing have made it possible to acquire the rainfall data from space. If the spatial and temporal resolution of such data is adequate, then, this data can be a useful input for drought assessment and monitoring, thanks to a continuous source of data generation. But, prior to the use of this type of data, ones must assess the accuracy of the used satellite to read the rainfall events occurring on the ground. To measure the satellite-based data accuracy, several statistical validation techniques are used. The predominant one relies on the comparisons of satellite-based rainfall data against the data from the ground-based station. In this exercise, we will learn how to measure the accuracy of satellite-based rainfall data. However before doing so, we will first discuss about the data we will use, the measurement techniques and the requirements of software to apply those validation techniques.

### Objective

- To learn how to validate satellite-based rainfall data against rain gauge station data

### Datasets

- Gridded rainfall data products and stations observed rainfall data

### Software

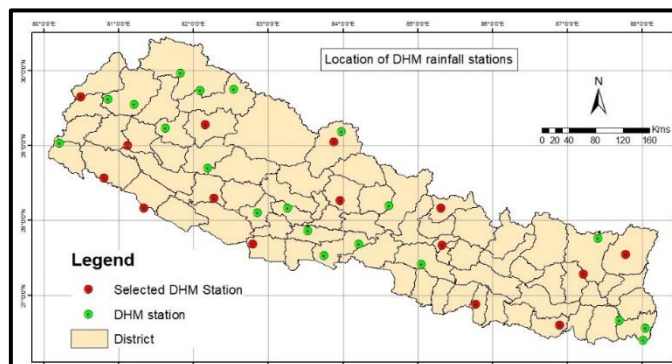
- MS Excel, QGIS

### Datasets

Three rainfall datasets will be used for this exercise: one station-based dataset and two satellite-based datasets. All the rainfall data was collected for the period of 1983 to 2012.

### Station-based data

Station-based rainfall data was collected from Department of Hydrology and Meteorology (DHM). In total, 15 stations have been selected for this exercise (see map above). Station



with no continuous observed data were not considered for the exercise. For this exercise the data has been stored in **D:\Drought\Chirp\_validation\_exercise\DHM** folder.

### Satellite-based data

Nowadays, a number of satellite-based rainfall data products are globally available. During this exercise we are going to focus on two products: a) the Climate Hazards Group InfraRed Precipitation (CHIRP) and (b) the CHIRP blended with ground-based station data (CHIRPS). Both data products have relatively high-resolution (0.05° grid) and both are maintained and distributed by the Climate Hazards Group (CHG) which archives the data products from 1981 to the near-present. Data is available at different temporal scales, e.g., daily, pentad (5 days), dekadal (10 days), monthly and so on. For the purpose of our exercise we are going to use the monthly data. While the CHIRPS product can be considered as more advanced and sophisticated one, the CHIRP product data are more immediately available. Indeed CHIRPS data are usually available with some delay. If you want to learn about these products you can visit the CHG website. (<https://chc.ucsb.edu/data>).

The data for this exercise has been downloaded from CHG website and has been stored in **D:\Drought\Chirp\_validation\_exercise\CHIRP** and **D:\Drought\Chirp\_validation\_exercise\CHIRPS**.

### The validation techniques

We will use three types of validation techniques to compare the satellite data against the rain gauge station data. They are as follow:

- Regression analysis
- Percentage Bias (PBIAS)
- Root Mean Square Error normalized by Standard Deviation (RSR)

By applying the above techniques we will see how two similar data fit well with each other, by describing their *goodness of fit* statistics. The fitness in regression analysis will be evaluated in terms of Coefficient of Determination ( $R^2$ ) value. Although there is no set rule to measure the goodness of fit with any particular value of  $R^2$ , many studies shows that a value of  $R^2 > 0.5$  is good enough to compare climate data. The other two techniques, PBIAS and RSR, can be shown by the following equations:

$$PBIAS = \frac{\sum(R_{gauge} - R_{satellite})}{\sum(R_{gauge})} \times 100$$

$$RSR = \frac{\sum(R_{gauge} - R_{satellite})^2}{\sum(R_{gauge} - \overline{R_{gauge}})^2}$$

Where,  $R_{satellite}$  is the rainfall estimates from the CHG product;  $R_{gauge}$  is the rainfall recorded in a particular rain gauge and  $\overline{R_{gauge}}$  is the average gauge reading over the considered time span.

How good the particular values of PBIAS and RSR can be rated by different qualitative

performance based on several ranges of values (see table-1).

Performance rating	PBIAS (%)	RSR (-)
Very Good	$< \pm 15$	0 - 0.5
Good	$\pm 15 - \pm 30$	0.5 – 0.6
Satisfactory	$\pm 30 - \pm 55$	0.6 – 0.7
Unsatisfactory	$\pm 55$	$> 0.7$

Table 1: Ranges of adopted values of the Percentage of Bias (PBIAS) and Root Mean Squared Error normalized by Standard Deviation (RSR) for a particular qualitative rating (Moriassi et al. (2007) & Shrestha et al. (2017)).

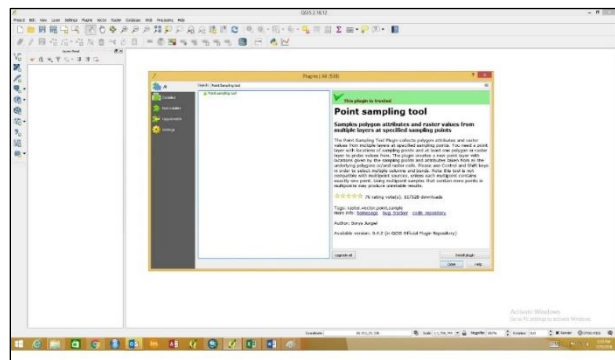
### The files

Datasets	File format	Directory
DHM station	Esri Shapefile	D:\Drought\Chirp_validation_exercise\DHM
DHM Precipitation	Excel	D:\Drought\Chirp_validation_exercise\Validation
CHIRP	TIFF	D:\Drought\Chirp_validation_exercise\CHIRP
CHIRPS	TIFF	D:\Drought\Chirp_validation_exercise\CHIRPS



### Step 1: Extracting satellite data against ground-based station data

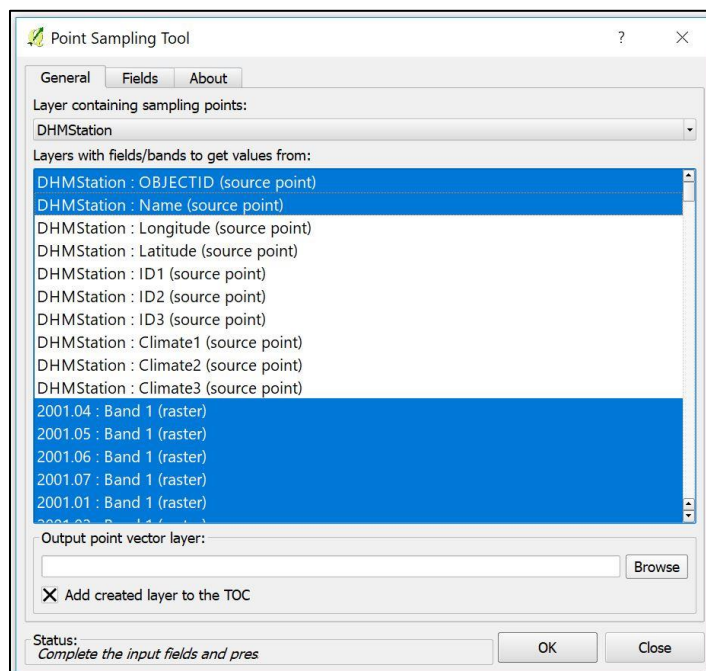
For validation purposes, satellite data need to be extracted against the ground-based station location. To do this work we will extract the rainfall estimates over the pixels of satellite images in which the rain gauge stations are located. Let's follow these –

- Open the QGIS Desktop (it is assumed that you have installed QGIS correctly and the Layer Panel and other visual interface of the software is organized in standard way). To extract the values from satellite images against station points we need “**Point Sampling Tool**”. The tool is not automatically available in the software. We need to plug in it from the Plugins repository. Follow this –
- Click **Plugins** Tab, go Manage and Install Plugins.
- Search **Point sampling tool**
- Click Install **Plugin**.



Now, the Point sampling tool has been installed and available under **Plugins>Analyses**

- Click Add Vector Layer 
- Browse the dataset to **D:\Drought\Chirp\_validation\_exercise\DHM** and select **DHMStation.shp** and open it.
- Click Add Raster Layer 
- Browse **D:\Drought\Chirp\_validation\_exercise\CHIRP**; select all (.tiff) and open. It may take time to open all the data sets considering the configuration of the users' systems.
- Go **Plugins>Analyses>Point sampling tool**.
- Confirm DHMStation under Layer containing sampling points.
- Select DHMStation: OBJECTID, DHMStation: Name and all the Raster bands under "Layers with fields/bands to get values from:". Use CONTROL and SHIFT keys to select quickly.
- Select the output point vector layer as **D:\Drought\Chirp\_validation\_exercise\Shape**
- Name it **CHIRP\_valid** and save.
- Press OK.
- After the processing is complete, close Point sampling tool.



- The **CHIRP\_Valid** shape file is at Layers Panel. Select and right click it. The



program can show “Bad Allocation” signal. This can happen for dealing with big data sets. Don’t worry. In that case close the QGIS and open it again. Add the **CHIRP\_Valid** layer from **D:\Drought\Chirp\_validation\_exercise\Validation\Shape.**

- After right click go to ‘Open Attribute Table’.

This is the time series rainfall estimates of satellite images against the rain gauge station location. Data is extracted in the table under the particular monthly column, where, columns are written as “YYYY.MM”. For example, “1983.01” means the total rainfall of January, 1983.

- Press **CONTROL+A** to select all the attributes.
- Copy all

	OBJECTID	Name	2001.04	2001.05	2001.06	2001.07	2001.01	2001.02	2001.03	2015.12	2015.11
1	84.00000...	Kakerpa...	30.16847	63.31097	265.58316	547.77545	12.57459	51.90885	81.71523	16.04110	52.706
2	85.00000...	Katai	27.58014	96.02219	397.07568	394.67694	18.93454	44.04129	83.17804	11.14487	63.634
3	86.00000...	Sitapur	9.41530	57.41998	502.29956	553.76294	32.95813	32.25795	47.84277	8.77160	44.533
4	87.00000...	Jumla	28.44175	33.39351	81.68275	191.63507	12.93737	41.20874	86.00896	7.31499	64.091
5	88.00000...	Gulariya	11.37832	91.46422	337.07150	646.59680	9.91622	26.23133	28.81066	9.54237	39.710
6	89.00000...	Luwanju...	31.50397	58.17463	300.82901	370.51132	10.46992	35.43637	58.04587	18.83242	53.570
7	90.00000...	Ghami	21.12125	44.41194	92.79113	278.68210	13.68279	22.56013	48.82906	11.44067	53.874
8	91.00000...	Bhaganpur	18.48572	70.14768	367.08865	495.92630	13.17503	14.85780	20.05356	7.81304	57.041
9	92.00000...	Lamachaur	77.39574	235.73708	429.00220	696.15649	16.49524	38.51143	66.63643	13.57025	125.600
10	93.00000...	Tamachit	35.00282	50.95641	129.95534	241.46645	14.47015	28.92182	77.61913	6.10256	42.395
11	94.00000...	Khumaltar	40.75324	113.22907	287.35428	388.99796	10.78880	14.70440	40.32866	11.11619	61.081
12	95.00000...	Gausala	29.89356	146.01056	206.67381	463.44189	11.94080	8.26404	25.16039	6.36236	55.110
13	96.00000...	Barmajhiya	37.01283	144.48235	262.65515	402.78885	12.51307	8.57009	24.25496	4.86163	57.755
14	97.00000...	Tumlingtar	73.24660	157.11913	188.37883	300.14713	13.01120	6.39020	39.84060	6.35512	69.664
15	98.00000...	Lungthung	75.21859	84.71831	196.15904	377.31754	12.93436	18.62710	88.66142	8.96931	83.661

- Now, open an excel file, save as **CHIRP\_Valid** at **D:\Drought\Chirp\_validation\_exercise\Validation** folder location.
- Paste all the copied data from QGIS attribute table to this excel file.
- Select data under ‘Name’ column and all the monthly columns.
- Copy the selected data
- Open a new sheet in the excel file.
- Past special > Transpose (T).
- Rename Name of first cell to Date.
- Organize the first column at Ascending order (A to Z).

Now, time series **CHIRP** data against stations’ locations is ready. Do similar exercise for extracting **CHIRPS** data.

## Step 2: Validating satellite data

Now, we have three excel files in **D:\Drought\Chirp\_validation\_exercise\Validation** folder – a) **DHM Precipitation**; b) **CHIRP\_Valid**; and c) **CHIRPS\_Valid**.

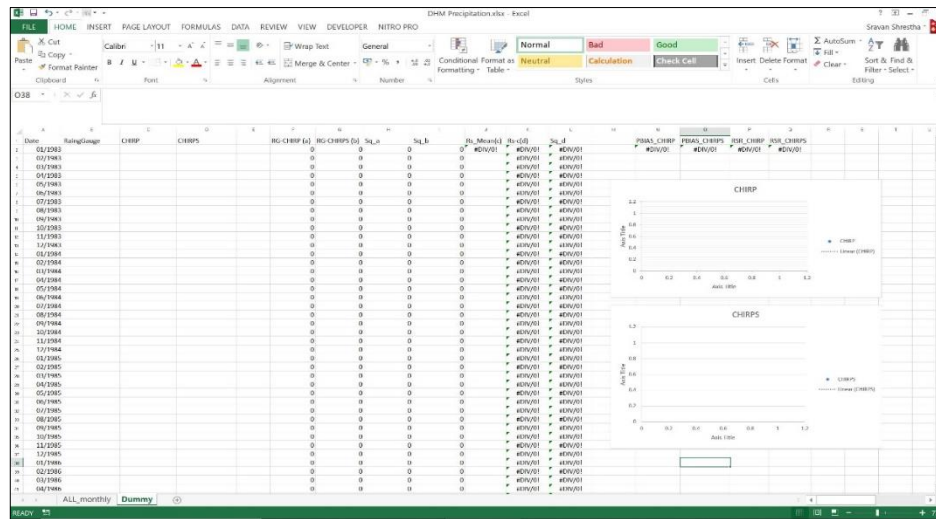
- Open the **DHM Precipitation** file


The excel file has two sheets, named: **All\_Monthly** and **Dummy**.

- The **All\_Monthly** sheet contains the monthly rainfall from January 1983 to December 2012. The format of date is “**MM/YYYY**”. For example, 01/1983 means January 1983.
- The **Dummy** sheet is basically an Excel style sheet to calculate all the validations. Here, the validation equations were designed according to the discussions in the validation techniques section. Using this style sheet we can perform the same validation techniques against all the ground-based stations individually. All we will need to do is to copy the data in the **Dummy** sheet and get the result.

Perform validation

- Right click on the name of **Dummy** at the bottom.
- Select **Move or Copy>Dummy**, check on ‘create a copy’ box, and click **ok**.



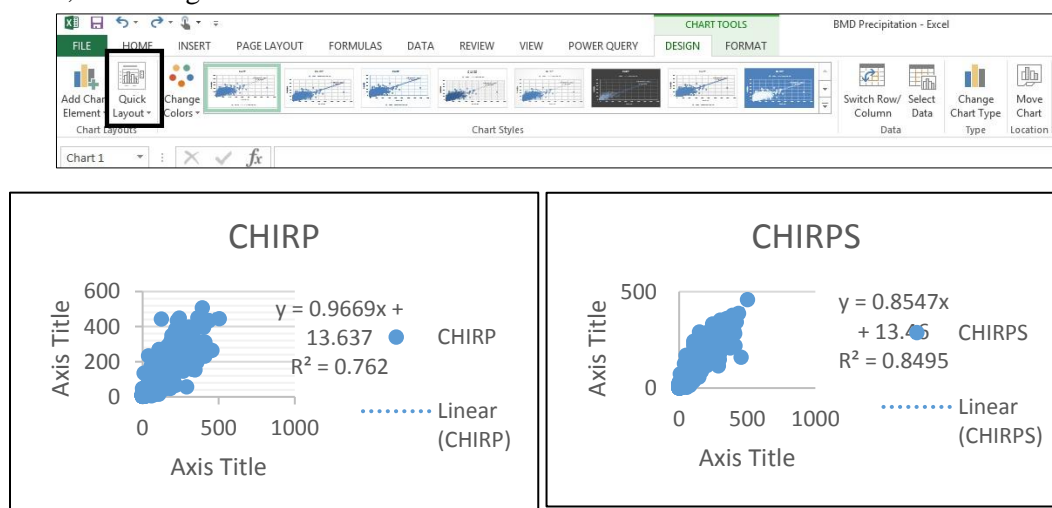
- Rename the new sheet as **Khumaltar**.
- Click or open the **All\_monthly** sheet.
- Click on ‘**Name**’ or top most corner cell.
- Click on **Sort & Filter** tool ; click **filter**.
- Click the filter button on station name and select only **Khumaltar**.
- Copy the data under **RainGauge** column.
- Open the **Khumaltar** sheet and paste the data under **Raingauge** column using **Past**

**Special tool** and paste only values. Before doing this step make sure that date columns in **All\_monthly** sheet and Khumaltar sheet are ascended in same order starting from 01/1983.

- Minimize the **DHM Precipitation** file.
- Open **CHIRP\_Valid** excel file and copy the time series rainfall data till 12/2012 under Khumaltar.
- Go to **DHM Precipitation** file again and click Khumaltar sheet.
- Paste the copied **CHIRP data** using Paste special and paste only values under **CHIRP column**.
- Similarly, follow last three steps to copy and paste **CHIRPS data**.
- Double click one **regression curve**; go to **QuickLayout** and select **Layout 9**.
- Do the same thing for another curve.

## Results

Now, we have gotten all the validation results. The results are as follows:



Here we can see that the result for CHIRPS is 0.85. This means that the CHIRPS fits better for Khumaltar station.

PBIAS_CHIRP	PBIAS_CHIRPS	RSR_CHIRP	RSR_CHIRPS
-10.2020266	1.189243861	0.5477677	0.3874671

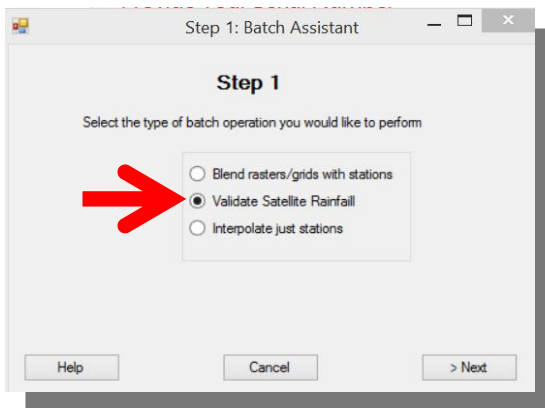
The PBIAS is very good for both CHIRP and CHIRPS; and the RSR is also very good for both cases according to the performance rating that we discussed in table 1.

We can apply similar steps for other stations using the same Excel stylish sheet (dummy sheet) to verify the satellite data has acceptable accuracy against the ground-based data.

## Using the GeoCLIM for Validation of Satellite Rainfall

The **Validate Satellite Rainfall** option allows for the evaluation of grid/raster datasets (e.g., satellite-based rainfall estimates) using discrete points in space (e.g., rain gages). The validation helps to determine if the two datasets are correlated to help in deciding if the blending option can be used with the two datasets. The first step of this process is to extract values from a raster/grid at all locations where the point data have valid values (i.e. non-missing values. Missing values can be specified in the inputs). The result is a dataset of grid values that can be directly compared to the point values. Another result is a diagnostic file with information of the least-squares regression between the observed/in-situ data value at the points being evaluated and the extracted grid values along with a R-squared output value. Once the correlation has been determined, then the raster and station data can be blended into an improved dataset.

To use this option, follow the three steps below:



*There are three Batch Assistant options available; (1) Blend stations and raster data, (2) Validate Satellite Rainfall and (3) Interpolate Just Stations.*

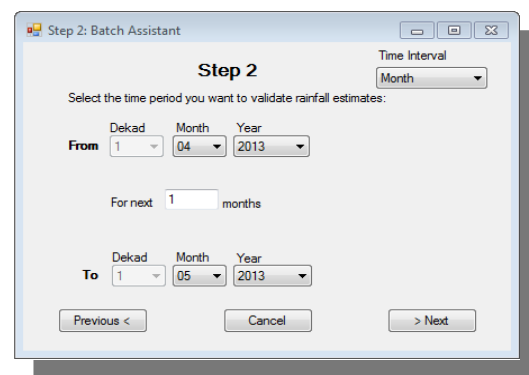
### Step 2: Select the validation time interval and period.

4. Select the time interval (e.g. month, dekad or pentads) and period (e.g. 042013 to 052013) of the rainfall estimate to validate. The time period and time interval are based on the selected climate dataset definition. In this example we are using monthly data.
5. Click on the **> Next** button to proceed to **Step 3**.

### Step 3: This Step has three sections

#### Step 1: Select BASIICS option.

1. Click on the **BASIICS** icon from the GeoCLIM main toolbar to open the Batch Assistant dialog box (**Step 1**).
2. Select the **Validate Satellite Rainfall** option.
3. Click on the **> Next** button to proceed to **Step 2**.



*Step 2 requires specifying of the period and Time Interval of the data to be analyzed.*

Step 3: Validate Rainfall Estimates

Specify the Rainfall Validation parameters **Step 3**

**Grid**

Missing Value: -9999 **Section 1**

Folder containing Grids: C:\GeoCLIM\ProgramSettings\Data\Climate\ethiopia\_ire\_de **GeoCLIM**

Prefix: ire Date Format: 4-digit year; 2-digit dekad (01-36) Suffix: .bil GeoCLIM dataset: ethiopia\_ire\_dekadal\_ppt

**Stations**

☐ The station data is all in one file Missing Value: **Section 2**

Folder containing station data:  Browse

Prefix:  Date Format:  Suffix:

Station Files Look Like:

**Outputs** **Section 3**

Stats file for all outputs: C:\GeoCLIM\ProgramSettings\Data\Climate\ethiopia\_ire\_de Missing Value: -9999 Browse

Previous < Cancel Finish

To validate raster data using station values, it is required to specify the path to the raster data and a table with the station values.

### Section 1: Grid

This section relates to the raster/grid input parameters. GeoCLIM only allows validation of climate datasets that have already been registered in GeoCLIM. To select the climate dataset to be validated, use the **GeoCLIM dataset** pull down menu then click on the **GeoCLIM** button to automatically populate all the fields in this section with the information of the selected dataset.

### Section 2: Stations

This section relates to the station input parameters.

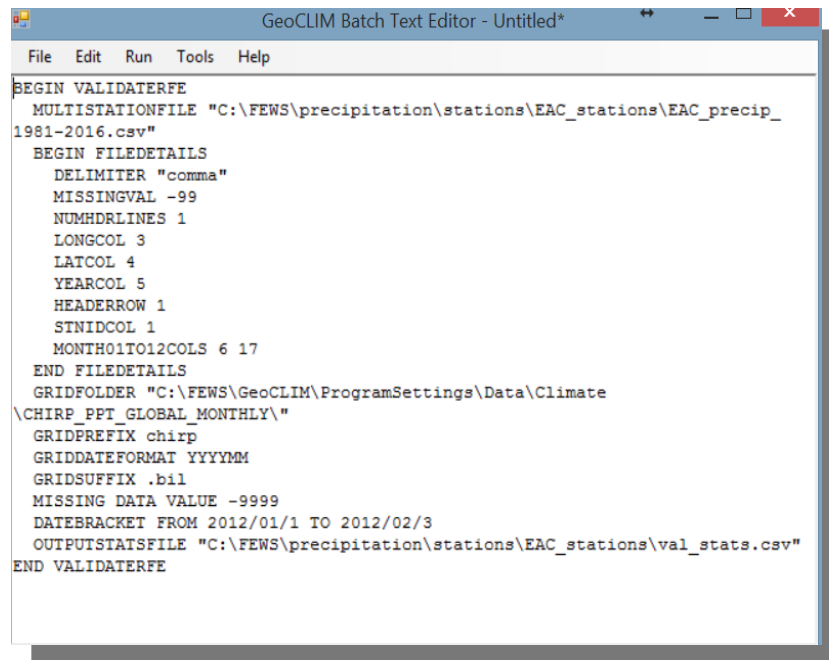
6. Check ☐ The station data is all in one file box, then select the file which contains the station data. The file must be in CSV format, see an example on Figure below. See the Data Types chapter for more information on the format of the table and other file types in GeoCLIM. If the station data are in separate files, leave this box unchecked.
7. After selecting the stations file(s), the **Define Delimited Data Text File** dialog box will open showing the format of the station file: the header row (usually row 1), the first row that contains actual data (usually row 2), and the delimiter (usually comma). Make

any necessary changes for the correct specifications. Click **OK** when all the specifications are defined.

Next, make sure that the columns with **Station ID, Latitude, Longitude, Year Info**, and the first and last period (the period could be pentad, dekad, or month), and the missing value have all been specified.

### Section 3: Outputs

8. Specify the file location where the statistical outputs will be written.
9. Click on **Finish**.
10. A batch file is generated and displayed on the GeoCLIM *Batch Text Editor*. The information displayed comes from the inputs entered on the three previous steps. This batch file can be saved for future reference or edited to run a new process.
11. Go to the **Run** pulldown menu and select **Run Batch File** to start the validation. Alternatively, press the F5 key on the keyboard.



```
GeoCLIM Batch Text Editor - Untitled*
File Edit Run Tools Help
BEGIN VALIDATERFE
MULTISTATIONFILE "C:\FEWS\precipitation\stations\EAC_stations\EAC_precip_
1981-2016.csv"
BEGIN FILEDETAILS
  DELIMITER "comma"
  MISSINGVAL -99
  NUMHDRLINES 1
  LONGCOL 3
  LATCOL 4
  YEARCOL 5
  HEADERROW 1
  STNIDCOL 1
  MONTH01TO12COLS 6 17
END FILEDETAILS
GRIDFOLDER "C:\FEWS\GeoCLIM\ProgramSettings\Data\Climate
\CHIRP_PPT_GLOBAL_MONTHLY\"
GRIDPREFIX chirp
GRIDDATEFORMAT YYYYMM
GRIDSUFFIX .bil
MISSING DATA VALUE -9999
DATEBRACKET FROM 2012/01/1 TO 2012/02/3
OUTPUTSTATSFILE "C:\FEWS\precipitation\stations\EAC_stations\val_stats.csv"
END VALIDATERFE
```

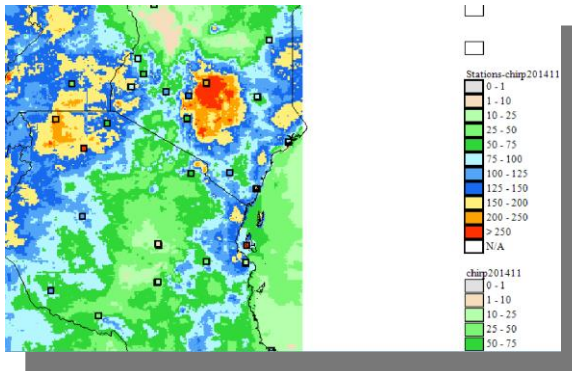
*The batch file is a text file with a list of all the inputs from the three steps of the BASIICS validation form.*

Once the validation process is completed, it creates the following four outputs:

12. A graphic map in PNG format showing the stations used for validation overlaid over the time-corresponding rainfall field.
13. A scatterplot showing the satellite rainfall field values against the station values
14. A CSV file with columns containing the station values, the raster values for the points

where the stations fall, and the at-station interpolated observed data. These at-station interpolated values are produced to improve comparability between the gridded/raster data and the station data. The CSV file includes some statistics showing correlation of the rainfall field and station data.

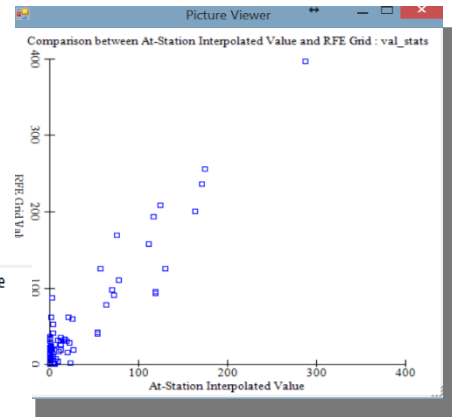
15. A shapefile containing all the stations that were used in the process.
16. These outputs provide the basis to decide if it is appropriate to blend the stations and the raster datasets.



A map of the stations that were used in the process of validating CHIRP.

```
File Edit Format View Help
Name, Filename, Long, Lat, StationValue, InterpAtStationValue, ExtractedValue
id1, v2p0chirps200001, -78.374, 0.295, 115, 116.52, 84
id2, v2p0chirps200001, -78.01, 0.023, 130, 135.93, 98
id3, v2p0chirps200001, -77.88, 0.001, 162, 155.02, 116
id1, v2p0chirps200002, -78.374, 0.295, 113, 115.53, 116
id2, v2p0chirps200002, -78.01, 0.023, 146, 151.7, 129
id3, v2p0chirps200002, -77.88, 0.001, 179, 171.52, 182
id1, v2p0chirps200003, -78.374, 0.295, 122, 125.66, 73
id2, v2p0chirps200003, -78.01, 0.023, 128, 157.94, 95
```

Text file that includes a list of the station value and its corresponding raster value for each date together with statistics describing their relationship.



Scatterplot of station value on X and raster (CHIRP) value on Y.



## Exercise 5: Background-Assisted Station Interpolation for Improved Climate Surfaces (BASIICS).

Satellite data are a valuable source of information on rainfall, evapotranspiration, or temperature patterns. However, they can contain biases and inaccuracies due to incorrect or limited ground data used during calibration processes. Some raster data can also present a low resolution which means the size of the pixel is too large for the area of interest. To improve the satellite data accuracy, we can combine them with ground station information.

### Objectives

- To learn how to use Background-Assisted Station Interpolation for Improved Climate Surfaces (BASIICS) tool in GeoCLIM for improving the results.

### Datasets

- Two different datasets are used: (1) a point dataset with values at discrete points in space (rain gages) and (2) a grid/raster dataset with values varying continuously over space (satellite-based rainfall).

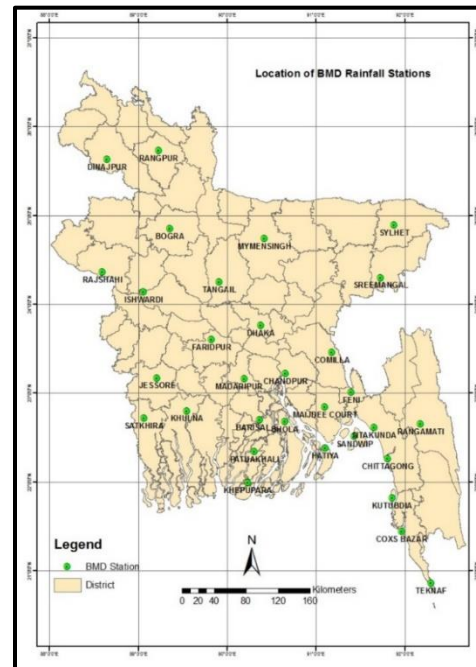
### Software

- BASIICS tool GeoCLIM

The **Background-Assisted Station Interpolation for Improved Climate Surfaces (BASIICS) tool** in **GeoCLIM** blends raster/grids datasets with point datasets like station data. The bleeding of data is achieved by using a modified Inverse Distance Weighting (IDW) approach, which borrows some concepts from simple kriging and ordinary kriging.

### Improve raster with stations using the blending algorithm

- Click on the **BASIICS** button on the **toolbar**.
- This will open up the **Step 1** window. Then select the Blend **raster/grids with stations** batch operation and click on the **Next** button.





**Step 1**

Select the type of batch operation you would like to perform

☒ Blend rasters/grids with stations  
☐ Validate Satellite Rainfall  
☐ Interpolate just stations

Help      Cancel      > Next

- *Select the Blend raster with stations*
- Then select the **Time Interval** and the periods to be improved making sure that there are stations available for the same period to be improved. Click **Next** to continue.

**Step 2**

Select the time period you want to blend Grids+Stations for:

Time Interval: Dekad

From: Dekad 1, Month 01, Year 1981  
 For next 1223 dekads  
 To: Dekad 3, Month 12, Year 2014

Previous <      Cancel      > Next

- Select *the starting and ending dates that would be the part of the process*
- Now a full window of **Background Assisted Station Interpolation** opens up. To use the default climate dataset, simply click on the **GeoCLIM** button to retrieve automatically all the parameters needed for the process. The missing value must be manually typed.
- Then specify the file containing the station data (a **CSV file**), the missing value in the rain gauge data and the column numbers for each of the required input information (Station ID, latitude, longitude, etc.).
- Specify where the outputs should go and what format they should be in. Select the **Output Diagnostic Statistics** for generating the statistics of the blending process for evaluating the operation performed.
- Check the **Advanced Options** checkbox which will open a set of options to the right of the window. The upper section describes parameters for the blending algorithm. The first step in the algorithm is to extract values from the grid at all locations where the point data have valid values. This produces a comparable datasets of grid values that can be directly compared to the point values. As an option, the user can instruct the program to carry out a least squares regression between the collocated point and extracted grid values and output the  $r^2$  value in a statistical diagnostic file. This allows the user to determine whether the relationship between the grid and the point dataset is worth using to interpolate the data.
- In the **Define Map Limits option**, import the spatial extent from a pre-existing **GeoCLIM** region Bangladesh. Define **pixel** size to **0.05 degrees**, set the **Interpolation style** to **Simple**, **Weight power** **2**, **Min stations** **0**, **Search Radius** **500**, **fuzz factor** **1**, **Max Effective** distance **100**, **long range** value **1** and **Max ratio** to **3**.
- Click **finish**, then the **GeoCLIM batch text editor** opens up displaying the batch file of just created **BASIICS settings**. Click **Run** from the menu bar to run the blending operation.

Step 3: Background Assisted Station Interpolation

Specify parameters for the blending process **Step 3**

**Grid**

Missing Value: -9999

Folder containing Grids: C:\Users\GIS\Documents\GeoCLIM\ProgramSettings\Data **GeoCLIM**

Prefix: CHIRP Date Format: 4-digit year; 2-digit dekad (01-36) Suffix: .bil GeoCLIM dataset: CHIRP\_PPT\_HKH\_dekadal

**Stations**

☒ The station data is all in one file Missing Value: -9999

File with all station data: C:\Drought\Geoclim\_Exercise\_input\_data\bangladesh\_stati **Browse**

Delimiter: Comma (,) Number of header lines: 1

Column with Station ID: 1 Column with Year Info: 4

Column with Latitude: 3 Column with Dekad 1 Data: 5

Column with Longitude: 2 Column with Dekad 36 Data: 40

**Outputs**

☒ Output Diagnostic Statistics ☒ Advanced Options

Folder where Outputs will be placed: C:\Users\GIS\Documents\GeoCLIM\Output\Trial Blend **Browse**

Prefix: basics\_C Date Format: 4-digit year; 2-digit dekad (01-36) Suffix: .bil

Stats file for all outputs: C:\Users\GIS\Documents\GeoCLIM\Output\Trial Blend\sta **Browse** **GeoCLIM**

GeoCLIM dataset: **GeoCLIM**

**Weight Power** 2

**Min Stations** 0

**Max Stations** 10

**Search Radius** 500

**Fuzz Factor (pixels)** 1

**Max Effective Dist** 100

**Long Range Value** 1

**Max Ratio** 3

**Interpolation Style** Simple

**Define Map Limits**

UL: X 88.01 UL: Y 26.63 LR: X 92.67 LR: Y 20.74

☒ Define New Pixel Size (degrees) 0.05

☐ Station location data in separate file **Show**

**Previous <** **Cancel** **Finish**

- Step 3 requires information about the raster data to be improved, the stations with station metadata and rainfall values

**New Dataset Details**

Dataset Name (no spaces): StationBlendedCHIRPS

Data Type: Precipitation

Data Extent: GLOBAL

**OK** **Cancel**

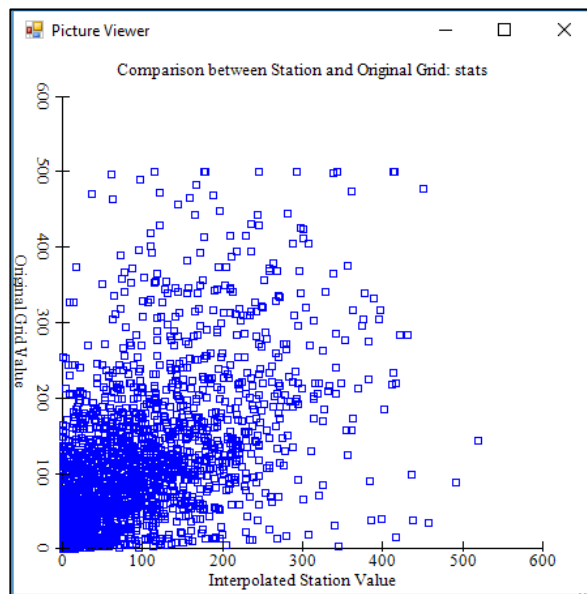
- Setting Dataset name, type and spatial extent (making the dataset default in GeoCLIM)

```

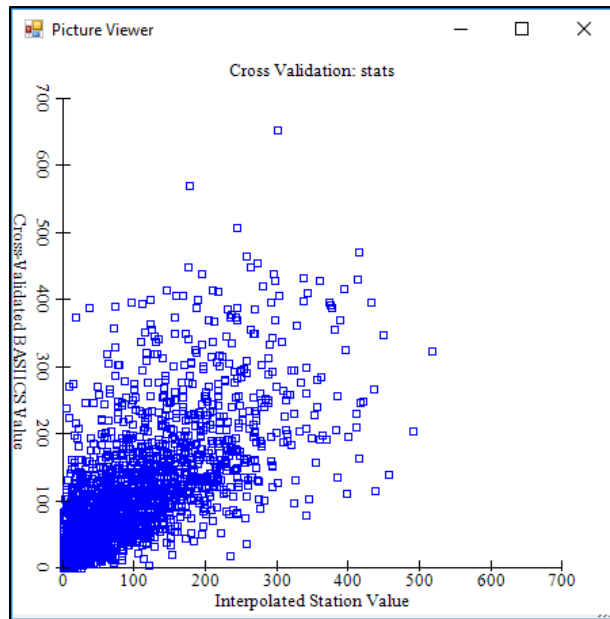
GeoCLIM Batch Text Editor - Untitled*
File Edit Run Tools Help
Run Batch File F5
BEGIN IRE
MULTISTATIONFILE "C:\Drought\Geoclim_Exercise_input_data
\bangladesh_station_dekads.csv"
BEGIN FILEDETAILS
  DELIMITER "comma"
  MISSINGVAL -9999
  NUMHDRLINES 1
  LONGCOL 2
  LATCOL 3
  YEARCOL 4
  HEADERROW 1
  STNIDCOL 1
  DEK01TO36COLS 5 40
END FILEDETAILS
GRIDFOLDER "C:\Users\GIS\Documents\GeoCLIM\ProgramSettings\Data\Climate
\CHIRP_PPT_HKH_dekadal\"
GRIDPREFIX CHIRP
GRIDDATEFORMAT YYYYEK
GRIDSUFFIX .bil
MISSING DATA VALUE -9999
DATEBRACKET FROM 1981/01/1 TO 2014/12/3
OUTPUTSTATSFILE "C:\Users\GIS\Documents\GeoCLIM\Output\Trial Blend
\stats.csv"
DIAGNOSTICOUTPUTS True
OUTPUTFOLDER "C:\Users\GIS\Documents\GeoCLIM\Output\Trial Blend\"
OUTPUTPREFIX basics_CHIRP

```

- *Batch Text Editor for running the batch file.*
- The **output of BASIICS** consists of **blended BIL raster file** for each individual dataset dekadal in our case, a CSV file of statistical diagnostic, image showing comparison between station and grid and cross validation between BASIICS interpolated value and cross validated BASIICS value.



- *Output of Blending process showing comparison between station and grid value*



- Cross validation between BASIICS interpolated value and cross validated BASIICS value.

1	Name	FileName	Long	Lat	StationValue	OriginalGridValue	BASIICSvalue	CrossvalidatedBASIICS	CrossVal-IDW-Interp
2	9390	2/03/1984	89.2	25.7	0	6	0.02	3.52	0
3	9390	3/03/1984	89.2	25.7	20.4	14	20.36	12.77	0
4	9390	2/06/1984	89.2	25.7	153.8	149	153.8	149	NaN
5	9390	2/12/1984	89.2	25.7	0	2	0.04	1.8	1.38
6	9390	3/12/1984	89.2	25.7	0	2	0	0	0
7	9390	2/10/1987	89.2	25.7	7.6	58	7.64	58.16	6.3
8	9390	3/10/1987	89.2	25.7	1.2	8	1.22	8	NaN
9	9390	1/11/1987	89.2	25.7	0	6	0.02	6	NaN
10	9390	1/12/1987	89.2	25.7	0	2	0.01	1.05	0
11	9390	2/12/1987	89.2	25.7	0	2	0.01	0.66	0.05
12	9390	3/12/1987	89.2	25.7	0	2	0.01	0.78	0
13	9390	1/04/1989	89.2	25.7	0	8	0.02	8	NaN
14	9390	2/04/1989	89.2	25.7	0	7	0.02	3.54	0
15	9390	3/04/1989	89.2	25.7	0	8	0.05	2.42	3.74
16	9390	3/10/1989	89.2	25.7	0	8	0.02	8	NaN
17	9390	2/11/1989	89.2	25.7	0	0	0	0	0
18	9390	3/11/1989	89.2	25.7	0	0	0	0	0
19	9390	1/12/1989	89.2	25.7	0	2	0.01	1.17	0
20	9390	2/12/1989	89.2	25.7	0	2	0.01	1.57	0
21	9390	3/12/1989	89.2	25.7	1.2	2	1.2	1.59	0
22	9390	1/01/1990	89.2	25.7	0	2	0.01	0.86	0
23	9390	3/01/1990	89.2	25.7	0	2	0.01	0.96	0

## References

- Alley, W. M. (1984). The Palmer Drought Severity Index: Limitations and Assumptions. *Journal of Climate and Applied Meteorology*, 23(7), 1100–1109. [https://doi.org/10.1175/1520-0450\(1984\)023<1100:TPDSIL>2.0.CO;2](https://doi.org/10.1175/1520-0450(1984)023<1100:TPDSIL>2.0.CO;2)
- Anyamba, A., & Tucker, C. J. (2005). Analysis of Sahelian vegetation dynamics using NOAA-AVHRR NDVI data from 1981–2003. *Journal of Arid Environments*, 63(3), 596–614. <https://doi.org/10.1016/j.jaridenv.2005.03.007>
- Brown, J., Wardlaw, B., Tadesse, T., Hayes, M., & Reed, B. (2008). The Vegetation Drought Response Index (VegDRI): A New Integrated Approach for Monitoring Drought Stress in Vegetation. *GIScience & Remote Sensing*, 45, 16–46. <https://doi.org/10.2747/1548-1603.45.1.16>
- Cancelliere, A., Mauro, G. D., Bonaccorso, B., & Rossi, G. (2007). Drought forecasting using the Standardized Precipitation Index. *Water Resources Management*, 21(5), 801–819. <https://doi.org/10.1007/s11269-006-9062-y>
- Chen, J., Jönsson, P., Tamura, M., Gu, Z., Matsushita, B., & Eklundh, L. (2004). A simple method for reconstructing a high-quality NDVI time-series data set based on the Savitzky–Golay filter. *Remote Sensing of Environment*, 91(3–4), 332–344. <https://doi.org/10.1016/j.rse.2004.03.014>
- Duan, K., & Mei, Y. (2014). Comparison of Meteorological, Hydrological and Agricultural Drought Responses to Climate Change and Uncertainty Assessment. *Water Resources Management*, 28(14), 5039–5054. <https://doi.org/10.1007/s11269-014-0789-6>
- Egeru, A. (2016). Climate risk management information, sources and responses in a pastoral region in East Africa. *Climate Risk Management*, 11, 1–14. <https://doi.org/10.1016/j.crm.2015.12.001>
- Egeru, A., Osaliya, R., MacOpiyo, L., Mburu, J., Wasonga, O., Barasa, B., ... Mwanjalolo, G.-J. M. (2014). Assessing the spatio-temporal climate variability in semi-arid Karamoja sub-region in north-eastern Uganda. *International Journal of Environmental Studies*, 71(4), 490–509. <https://doi.org/10.1080/00207233.2014.919729>
- Estrela, M. j., Peñarrocha, D., & Millán, M. (2000). Multi-annual drought episodes in the Mediterranean (Valencia region) from 1950–1996. A spatio-temporal analysis. *International Journal of Climatology*, 20(13), 1599–1618. [https://doi.org/10.1002/1097-0088\(20001115\)20:13<1599::AID-JOC559>3.0.CO;2-Q](https://doi.org/10.1002/1097-0088(20001115)20:13<1599::AID-JOC559>3.0.CO;2-Q)
- Funk, C., Peterson, P., Landsfeld, M., Pedreros, D., Verdin, J., Shukla, S., ... Hoell, A. (2015). The climate hazards infrared precipitation with stations—a new environmental record for monitoring extremes. *Scientific Data*, 2, 150066.
- Funk, C., Verdin, A., Michaelsen, J., Peterson, P., Pedreros, D., & Husak, G. (2015). A global satellite assisted precipitation climatology. *Earth System Science Data Discussions*, 8(1).
- Grasso, V. F., & Singh, A. (2011). Early warning systems: State-of-art analysis and future directions. *Draft Report, UNEP*, 1.
- Hansen, J. W., Mason, S. J., Sun, L., & Tall, A. (2011). REVIEW OF SEASONAL CLIMATE FORECASTING FOR AGRICULTURE IN SUB-SAHARAN AFRICA. *Experimental Agriculture*, 47(2), 205–240. <https://doi.org/10.1017/S0014479710000876>
- Hao, Z., AghaKouchak, A., Nakhjiri, N., & Farahmand, A. (2014). Global integrated drought monitoring and prediction system. *Scientific Data*, 1, sdata20141. <https://doi.org/10.1038/sdata.2014.1>

- Hao, Z., Hong, Y., Tang, Q., Xia, Y., P. Singh, V., Hao, F., ... Shen, X. (2016). Satellite Remote-Sensing Drought Monitoring and Predictions Over the Globe (pp. 259–297).
- Heim, R. R. (2002). A Review of Twentieth-Century Drought Indices Used in the United States. *Bulletin of the American Meteorological Society*, 83(8), 1149–1165. [https://doi.org/10.1175/1520-0477\(2002\)083<1149:AROTDI>2.3.CO;2](https://doi.org/10.1175/1520-0477(2002)083<1149:AROTDI>2.3.CO;2)
- Heim, R. R., & Brewer, M. J. (2012). The Global Drought Monitor Portal: The Foundation for a Global Drought Information System. *Earth Interactions*, 16(15), 1–28. <https://doi.org/10.1175/2012EI000446.1>
- Hook, S. J., Gabell, A. R., Green, A. A., & Kealy, P. S. (1992). A comparison of techniques for extracting emissivity information from thermal infrared data for geologic studies. *Remote Sensing of Environment*, 42(2), 123–135. [https://doi.org/10.1016/0034-4257\(92\)90096-3](https://doi.org/10.1016/0034-4257(92)90096-3)
- Keyantash, J., & Dracup, J. A. (2002). The Quantification of Drought: An Evaluation of Drought Indices. *Bulletin of the American Meteorological Society*, 83(8), 1167–1180. [https://doi.org/10.1175/1520-0477\(2002\)083<1191:TQODAE>2.3.CO;2](https://doi.org/10.1175/1520-0477(2002)083<1191:TQODAE>2.3.CO;2)
- Kifer, R. S., & Stewart, H. L. (1938). *Farming hazards in the drought area*. Washington: U.S. Govt. Print. Off. Retrieved from <https://catalog.hathitrust.org/Record/001688868>
- Kirchhoff, C. J., Carmen Lemos, M., & Dessai, S. (2013). Actionable Knowledge for Environmental Decision Making: Broadening the Usability of Climate Science. *Annual Review of Environment and Resources*, 38(1), 393–414. <https://doi.org/10.1146/annurev-environ-022112-112828>
- Kogan, F. N. (1995). Application of vegetation index and brightness temperature for drought detection. *Advances in Space Research*, 15(11), 91–100. [https://doi.org/10.1016/0273-1177\(95\)00079-T](https://doi.org/10.1016/0273-1177(95)00079-T)
- Kogan, F., & Sullivan, J. (1993). Development of global drought-watch system using NOAA/AVHRR data. *Advances in Space Research*, 13(5), 219–222. [https://doi.org/10.1016/0273-1177\(93\)90548-P](https://doi.org/10.1016/0273-1177(93)90548-P)
- Kumar, V., & Panu, U. (1997). Predictive assessment of severity of agricultural droughts based on agro- climatic factors. *Jawra Journal of the American Water Resources Association*, 33(6), 1255–1264.
- Levizzani, V., Schmetz, J., Lutz, H. J., Kerkmann, J., Alberoni, P. P., & Cervino, M. (2001). Precipitation estimations from geostationary orbit and prospects for Meteosat Generation. *Meteor. Appl.*, 8, 23–41.
- Li, Z.-L., & Becker, F. (1993). Feasibility of land surface temperature and emissivity determination from AVHRR data. *Remote Sensing of Environment*, 43(1), 67–85. [https://doi.org/10.1016/0034-4257\(93\)90065-6](https://doi.org/10.1016/0034-4257(93)90065-6)
- Linsley, R. K., Kohler, M. A., & Paulhus, J. L. H. (1958). *Hydrology for engineers*. New York : McGraw-Hill. Retrieved from <https://trove.nla.gov.au/version/219866626>
- Liu, W. T., & Juárez, R. I. N. (2001). ENSO drought onset prediction in northeast Brazil using NDVI. *International Journal of Remote Sensing*, 22(17), 3483–3501. <https://doi.org/10.1080/01431160010006430>
- LIU, W. T., & KOGAN, F. N. (1996). Monitoring regional drought using the Vegetation Condition Index. *International Journal of Remote Sensing*, 17(14), 2761–2782. <https://doi.org/10.1080/01431169608949106>
- Lohani, V. K., & Loganathan, G. (1997). An early warning system for drought management using the Palmer drought index. *JAWRA Journal of the American Water Resources Association*, 33(6), 1375–1386.

- Luo, L., & Wood, E. F. (2007). Monitoring and predicting the 2007 U.S. drought. *Geophysical Research Letters*, 34(22), L22702. <https://doi.org/10.1029/2007GL031673>
- M. Quiring, S., & N. Papakryiakou, T. (2003). An Evaluation of Agricultural Drought Indices for the Canadian Prairies. *Agricultural and Forest Meteorology*, 118, 49–62. [https://doi.org/10.1016/S0168-1923\(03\)00072-8](https://doi.org/10.1016/S0168-1923(03)00072-8)
- Makala, J. (2012). Drought preparedness, impact and response: A case of Eastern Cape and Free State provinces of South Africa. *Jamba. Journal of Disaster Risk Studies*, 4(1), 47–57.
- Masinde, M. (2014). An effective drought early warning system for Sub-Saharan Africa: Integrating modern and indigenous approaches (p. 60). Presented at the Proceedings of the Southern African Institute for Computer Scientist and Information Technologists Annual Conference 2014 on SAICSIT 2014 Empowered by Technology, ACM.
- Mckee, T. B., Doesken, N. J., & Kleist, J. (1993). The relationship of drought frequency and duration to time scales. *AMS 8th Conference on Applied Climatology*, (January), 179–184. <https://doi.org/citeulike-article-id:10490403>
- Mishra, A., & Desai, V. (2005). Drought forecasting using stochastic models. *Stochastic Environmental Research and Risk Assessment*, 19(5), 326–339.
- Mishra, A., Desai, V., & Singh, V. (2007). Drought forecasting using a hybrid stochastic and neural network model. *Journal of Hydrologic Engineering*, 12(6), 626–638.
- Mishra, A. K., & Singh, V. P. (2010). A review of drought concepts. *Journal of Hydrology*, 391(1), 202–216. <https://doi.org/10.1016/j.jhydrol.2010.07.012>
- Mishra, A. K., & Singh, V. P. (2011). Drought modeling – A review. *Journal of Hydrology*, 403(1), 157–175. <https://doi.org/10.1016/j.jhydrol.2011.03.049>
- Mittal, S., & Mehar, M. (2012). How mobile phones contribute to growth of small farmers? Evidence from India. *Quarterly Journal of International Agriculture*, 51(3), 227.
- Modarres, R. (2007). Streamflow drought time series forecasting. *Stochastic Environmental Research and Risk Assessment*, 21(3), 223–233.
- Morid, S., Smakhtin, V., & Bagherzadeh, K. (2007). Drought forecasting using artificial neural networks and time series of drought indices. *International Journal of Climatology*, 27(15), 2103–2111.
- Muto, M., & Yamano, T. (2009). The Impact of Mobile Phone Coverage Expansion on Market Participation: Panel Data Evidence from Uganda. *World Development*, 37(12), 1887–1896. <https://doi.org/10.1016/j.worlddev.2009.05.004>
- National Drought Mitigation Centre. (2015). The Standardized Precipitation Index, 16.
- Nijssen, B., Shukla, S., Lin, C., Gao, H., Zhou, T., Ishottama, Lettenmaier, D. P. (2014). A Prototype Global Drought Information System Based on Multiple Land Surface Models. *Journal of Hydrometeorology*, 15(4), 1661–1676. <https://doi.org/10.1175/JHM-D-13-090.1>
- Palmer, W. C. (1965). *Meteorological drought* (Vol. 30). US Department of Commerce, Weather Bureau Washington, DC.
- Rasmussen, L. V., Mertz, O., Rasmussen, K., & Nieto, H. (2015). Improving how meteorological information is used by pastoralists through adequate communication tools. *Journal of Arid Environments*, 121, 52–58. <https://doi.org/10.1016/j.jaridenv.2015.05.001>
- Shafer, B., & Dezman, L. (1982). Development of a Surface Water Supply Index (SWSI) to assess the severity of drought conditions in snowpack runoff areas (Vol. 50, pp. 164–175). Presented at the Proceedings of the western snow conference, Colorado State University Fort Collins CO.



- Sheffield, J., Wood, E. F., Chaney, N., Guan, K., Sadri, S., Yuan, X., ... Ogallo, L. (2013). A Drought Monitoring and Forecasting System for Sub-Sahara African Water Resources and Food Security. *Bulletin of the American Meteorological Society*, 95(6), 861–882. <https://doi.org/10.1175/BAMS-D-12-00124.1>
- Shukla, S., Steinemann, A. C., & Lettenmaier, D. P. (2010). Drought Monitoring for Washington State: Indicators and Applications. *Journal of Hydrometeorology*, 12(1), 66–83. <https://doi.org/10.1175/2010JHM1307.1>
- Singh, R. P., Roy, S., & Kogan, F. (2003). Vegetation and temperature condition indices from NOAA AVHRR data for drought monitoring over India. *International Journal of Remote Sensing*, 24(22), 4393–4402. <https://doi.org/10.1080/0143116031000084323>
- Tucker, C. J., Dregne, H. E., & Newcomb, W. W. (1991). Expansion and Contraction of the Sahara Desert from 1980 to 1990. *Science*, 253(5017), 299–300. <https://doi.org/10.1126/science.253.5017.299>
- Van Loon, A., & Van Lanen, H. (2012). A process-based typology of hydrological drought. *Hydrol. Earth Syst. Sci.*, 16, 1915–1946. <https://doi.org/10.5194/hess-16-1915-2012>
- Vermote, E.F.; Kotchenova, S.Y.; Ray, J.P. MODIS Surface Reflectance User's Guide. *MODIS Basis Doc.* **2011**, 1–40.
- Wardlow, B., Anderson, M., Tadesse, T., Hain, C., Row, W., & Rodell, M. (2015). Remote Sensing of Drought: Emergence of a Satellite-Based Monitoring Toolkit for the United States (pp. 367–398).
- Wardlow, B. D., Anderson, M. C., & Verdin, J. P. (2012). *Remote sensing of drought: Innovative monitoring approaches*. CRC Press.
- Wilhite, D. A. (Ed.). (2000). *Droughts: A Global Assessment* (1 edition). London ; New York: Routledge.
- Wilhite, D. A., & Glantz, M. H. (1985). Understanding: the Drought Phenomenon: The Role of Definitions. *Water International*, 10(3), 111–120. <https://doi.org/10.1080/02508068508686328>
- Wilhite, D. A., Hayes, M. J., & Knutson, C. L. (2005). Drought preparedness planning: Building institutional capacity. *Drought and Water Crises: Science, Technology, and Management Issues*, 93–135.
- Yevjevich, V. M. (1967). *An Objective Approach to Definitions and Investigations of Continental hydrological droughts*. Colorado State University.
- Yuan, X., Roundy, J. K., Wood, E. F., & Sheffield, J. (2015). Seasonal Forecasting of Global Hydrologic Extremes: System Development and Evaluation over GEWEX Basins. *Bulletin of the American Meteorological Society*, 96(11), 1895–1912. <https://doi.org/10.1175/BAMS-D-14-00003.1>
- Yuan, X., & Wood, E. F. (2013). Multimodel seasonal forecasting of global drought onset. *Geophysical Research Letters*, 40(18), 4900–4905. <https://doi.org/10.1002/grl.50949>
- Zargar, A., Sadiq, R., Naser, B., & I. Khan, F. (2011). A review of drought indices. *Environmental Reviews*, 19, 333–349. <https://doi.org/10.1139/a11-013>

## **About ICIMOD**

The International Centre for Integrated Mountain Development (ICIMOD) is a regional knowledge development and learning centre serving the eight regional member countries of the Hindu Kush Himalaya (HKH) – Afghanistan, Bangladesh, Bhutan, China, India, Myanmar, Nepal, and Pakistan– based in Kathmandu, Nepal. Globalization and climate change have an increasing influence on the stability of fragile mountain ecosystems and the livelihoods of mountain people. ICIMOD aims to assist mountain people to understand these changes, adapt to them, and make the most of new opportunities, while addressing upstream and downstream issues. ICIMOD supports regional transboundary programmes through partnerships with regional partner institutions, facilitates the exchange of experiences, and serves as a regional knowledge hub. We strengthen networking among regional and global centres of excellence. Overall, we are working to develop economically and environmentally-sound mountain ecosystems to improve the living standards of mountain populations and to sustain vital ecosystem services for the billions of people living downstream – now and in the future.

## **About SAC**

The Heads of the States or governments established the South Asian Association for Regional Cooperation (SAARC) on the 8th day of December 1985. Seven south Asian Nations, namely Bangladesh, Bhutan, India, The Maldives, Nepal, Pakistan and Sri Lanka were the founder members of the Regional Association. Later Afghanistan became the eighth member country in 2007. SAARC Agriculture Centre (renamed in April 2007 from SAARC Agricultural Information Centre, SAIC) is the first regional Centre established by the SAARC. The Centre started functioning in 1988 with a mandate for information management, primarily in the field of agriculture and allied discipline. With the passage of time, the Centre braced up broader challenges to make regional cooperation more responsive to the needs of the stakeholders and farming communities as South Asia heads for a new order of agricultural transformation. The SAARC Agriculture Centre thus has been given an enhanced mandate for agricultural research and development, policy planning, and knowledge management.

## **About SERVIR**

SERVIR connects space to village by helping developing countries use satellite data to address challenges in food security, water resources, weather and climate, land use, and natural disasters. A partnership of NASA, USAID, and leading technical organizations, SERVIR develops innovative solutions to improve livelihoods and foster self-reliance in Asia, Africa, and the Americas. SERVIR Hindu Kush Himalaya (SERVIR-HKH) is implemented by ICIMOD in its regional member countries, prioritizing activities in Afghanistan, Bangladesh, Myanmar, Nepal, and Pakistan.

## **About CSRD**

Climate Services for Resilient Development (CSRD) is a global partnership that connects climate and environmental science with data streams to generate decision support tools and training for decision-makers in developing countries. Translating complex climate information into easy to understand actionable formats to spread awareness in the form of climate services is core to CSRD's mission. The CSRD consortium in South Asia is supported by USAID and led by the CIMMYT in partnership with the Bangladesh Meteorological Department (BMD), Bangladesh Department of Agricultural Extension (DAE), Bangladesh Agricultural Research Council (BARC), Bangladesh Agricultural Research Institute (BARI), ICIMOD, the University of Reading (UoR) International Institute for Climate and Society (IRI), and the University de Passo Fundo (UPF). This consortium provides strength and technical expertise to develop relevant climate products that can assist farmers and other stakeholders with relevant information to improve decision making, with the ultimate goal of increasing resilience to climate-related risks.

**About CIMMYT**

CIMMYT - the International Maize and Wheat Improvement Center - is the global leader on publicly-funded maize and wheat research and related farming systems. Headquartered near Mexico City, CIMMYT works with hundreds of partners throughout the developing world to sustainably increase the productivity of maize and wheat cropping systems, thus improving global food security and reducing poverty. CIMMYT is a member of the CGIAR Consortium and leads the CGIAR Research Programs on Maize and Wheat. The Center receives support from national governments, foundations, development banks and other public and private agencies.

