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Research Article

TEMPORAL NDVI CHANGE DETECTION OF NEPAL USING MODIS IMAGERY

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ABSTRACT

This article presents an extraction of valuable information with the help of trend analysis from a long time series of spatial data demands precision and the enormous amount of scientific computation. The trends themselves are exciting estimators of studying spatial and temporal changes in climate and its effects at global and regional scales. The present study was done to investigate the impact of the modifiable temporal unit problem (MTUP) which arises due to temporal aggregation. In this study, an attempt has been made in analysing vegetation change detection that took place between 2001 and 2016 using Terra MODIS13A3 monthly 1 km resolution time series data on a monthly basis. With the launch of National Aeronautics and Space Administration (NASA) on-board aqua and terra platform, a new generation of satellite sensor data is now available. Normalized Difference Vegetation Index method has been employed for accurate classification of images and has proved to be successful. The results of this research work were the significant trend maps which were helpful in analysing spatial patterns in varying trends access different aggregation level to show the effect of MUTP on NDVI and climate forcing data over Nepal. The analysis showed that the average NDVI was higher during May to October in Nepal and lower during the rest of the months. While analysing the data from 2001 to 2016, the NDVI was least in 2001 and highest in 2015. Finally, the different type of session categorises and determines the NDVI of Nepali sessions and months.
Keywords: NDVI, remote sensing, vegetation, MODIS, MTUP.

1. INTRODUCTION

Vegetation index is a simple and effective measurement parameter, which is used to indicate the earth surface vegetation covers and crops growth status in remote sensing field [1]. There are several indices for highlighting vegetation bearing areas on a remote sensing scene out of the Normalized Difference Vegetation Index (NDVI) is a common and an vital vegetation index, widely applied in research on global environmental and climatic change [2]. The NDVI is the calculated as a ratio difference between measured canopy reflectance in the red and near-infrared bands respectively [3].

Normalized Difference Vegetation Index values vary with the absorption of red light by plant chlorophyll and the reflection of infrared radiation by water-filled leaf cells [2]. The NDVI has also been used to estimate a large number of vegetation properties from the value of this index;

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the Leaf Area Index, biomass, chlorophyll concentration in leaves, plant productivity, fractional vegetation cover, accumulated rainfall, etc. Such relations are often derived by correlating space-derived NDVI values with the ground-measured value of these variables. Normalized Difference Vegetation Index employs the Multi-Spectral Remote Sensing data technique to find Vegetation Index, land cover classif ication, vegetation, water bodies, open area, scrub area, hilly areas, agricultural area, thick forest, thin forest with few band combinations of the remote sensed data. The multispectral remote sensing images are very compelling for obtaining a better understanding of the earth environment [2,4].

The multispectral remote sensing is the science and art of acquiring information and extracting the features in form of spectral, spatial and temporal about some objects, area or phenomenon, such as vegetation, land cover classification, urban area, agriculture land and water resources without coming into physical contact of these objects [5]. The remote sensing data has many application areas including land cover classification, soil moisture measurement, forest type classification, measurement of liquid water content of vegetation, snow mapping, sea ice type classification, oceanography [2]. The multispectral remote sensing images carry essential integrating spectral and spatial features of the objects [2,6]. From wavelength, remote sensing is classified into three types as visible and reflective infrared remote sensing, thermal infrared remote sensing, and microwave remote sensing [7]. Digital image processing of satellite data provides tools for analysing the image through different algorithms and mathematical indices. Features are based on reflectance characteristics, and indices have been devised to highlight the features of interest on the image [8].

Many researchers have reported the use of NDVI for vegetation monitoring [9], assessing the crop cover [10], drought monitoring [11,12], and agricultural drought assessment at national [13,14], and estimating the vegetation status of growing crops by determining the appropriate wavelength or combination of wavelengths to characterize crop deficiency at global level [1,9].

Recently, the researchers have employed, and new space-borne remote sensing missions provide the opportunity to monitor agricultural applications and produce up-to-date information in space and time domain. Optical remote sensing is one of the most common used data source for obtaining biophysical variables [15], crop variables such as yield estimation [16], biomass estimation [17], and crop type mapping [18] due to sensitivity of crop leaves to visible and infrared bands [12,19]. Contrary to optical sensors, Synthetic Aperture Radar (SAR) sensors are capable of acquiring images under all weather conditions which makes suitable for long-term and multi-seasonal monitoring [20]. Current SAR systems have become a useful source increasingly to help agriculture monitoring [19,21,22]. Discriminate crops and produce reliable and accurate crop map for cultivated areas using multi-temporal analysis is conducted. Finally, object-based image analysis is applied to achieve multi-temporal crop mapping [19]. Accurate extraction of the agricultural crop pattern and its spatial-temporal monitoring has vital importance for long-term agricultural management. It is needed to maintain sufficient production of crops, and it is crucial to forecasting crop production for decision makers where food security is vulnerable [19,23].

Several different techniques have been reported in the literature for analysis of satellite images such as NDVI, Artificial Neural Network (ANN) and Satellite Image Contrast Enhancement using Discrete Wavelet Transform (DWT) and Singular Value Decomposition (SVD). The NDVI has been proposed by Kim H., Kwak HS and Yoo JS (2008). In an artificial neural network technique, the performance parameters of a feed-forward neural network are the weights which are varied so that the predicted output is close to true output value corresponding to the input values. This technique is based on two types of learning algorithm: supervised and unsupervised learning which has proposed by [12]. Another technique has been proposed by H. Demirel et al. 2010, named DWT and SVD. In all such method, the objective function is the same feature extraction from the multiband data.

The NDVI is highly useful in detect ing the surface features of the visible area which are incredibly beneficial for policy makers in decision making. The vegetation analysis is very important for predicting the unfortunate natural disasters to provide humanitarian aid, damage assessment and furthermore to device new protection strategies [24].

The NDVI is highly useful in detecting the surface features of the visible area which are extremely beneficial for policy makers in decision making. The Vegetation analysis can be helpful in predicting the unfortunate natural disasters to provide humanitarian aid, damage assessment and furthermore to device new protection strategies [24].

In this study, the results of this research work were the significant trend maps which were helpful in analysing spatial patterns in varying trends access different aggregation level to show the effect of MUTP on NDVI and climate forcing data over Nepal. The analysis showed that the average NDVI was higher from May to October in Nepal and lower during the rest of the months. While analysing the data from 2001 to 2016, the NDVI was least in 2001 and highest in 2015. At the end of this study, the different type of session categorises and determines the NDVI of Nepali sessions and months.

2. MATERIALS AND METHODOLOGY

2.1. Study Area

Nepal is a South Asian country with Kathmandu as the capital city, and 0.03% areas occupy in the world. The area of Nepal is 1, 47,181 square kilometers. For administrative purposes, Nepal is divided into seven states, 14 zones, and 75 districts. Nepal is located on Southern Asia between China and India. It has geographically located from 26022'N and 30027'N latitude and 80004'N and 88° 12' E longitude. The Himalayas lie along the country’s northern border, East-western average length 885 km and North-southern length 193 km. The altitude of Nepal ranges between 59 m to 8,848 m above the sea level. The study area is shown in figure 1.

Figure 1. The study area of this research work

2.2. Moderate Resolution Imaging Spectroradiometer (MODIS)

Moderate Resolution Imaging Spectroradiometer instrument operates on both the Terra and Aqua spacecraft, Terra (originally called EOS AM-1) and Aqua (originally called EOS PM-1) satellites. The orbit of Terra is designed such that it passes from north to south across the equator in the morning, while Aqua passes south to north over the equator in the afternoon. The temporal resolution of Terra MODIS and Aqua MODIS is every 1 to 2 days and acquires data in 36 spectral bands between 0.405 and 14.385 μm at three spatial resolutions 250m, 500m, and 1,000m. MODIS has the four major products; Land, Atmosphere, Ocean, and Cryosphere. Land Products are available through the Land Processes DAAC at the U. S. Geological Survey EROS Data Center (EDC). The specification and product information of MODIS data are as follows:

Table 1. Specification and product information of MODIS image

Characteristic	**Description**
Short name	MOD13A3
Platform	Terra
Instrument	MODIS
Processing Level	Level-3
Temporal esolution	Monthly
Spatial Resolution	1 km
File NamingConvention	MOD13A3.AYYYYDDD.hHHvVV.CCC.YYYYDDDHHMMSS.hdf • YYYYDDD = YearandDay of Year of acquisition • hHH = Horizontaltilenumber (0-35) • vVV = Verticaltilenumber (0-17) • CCC = Collection number YYYYDDDHHMMSS = ProductionDateand Time
Keywords	ClimateChange, CanopyCharacteristics, Biomass, Vegetation Index, PlantPhenology, Length of GrowingSeason
Orbit	705 km, 10:30 a.m. descending node (Terra) or 1:30 p.m. ascending node (Aqua) sun-synchronous, near-polar, circular
Scan Rate	20.3 rpm, cross track
Swath Dimensions	2330 km (cross track) by 10 km (along the track at nadir)
Telescope	17.78 cm diameter off-axis, a focal (collimated), with the intermediate field stop
Size	1.0 x 1.6 x 1.0 m
Weight	228.7 kg
Power	162.5 W (single orbit average)
Data Rate	10.6 Mbps (peak daytime); 6.1 Mbps (orbital average)
Quantization	12 bits
Spatial Resolution	250 m (bands 1-2), 500 m (bands 3-7), 1000 m (bands 8-36)
Temporal Resolution	1-2 days
Design life	Life 6 years

2.3. The Methodology based on NDVI

Normalized Difference Vegetation Index (NDVI) is a simple graphical indicator that can be used to analyse and monitor greenery in the vegetation. NDVI uses multispectral remote sensing data to identify vegetated areas and their condition quickly. It is the most well-known and used index to detect live green plant canopies. It seems feasible to detect vegetation and also quantify the photosynthetic capacity of plant canopies. Live green plants absorb solar radiation in the Photo-synthetically Active Radiation (PAR) spectral region, which they use as a source of energy in the process of photosynthesis. Live green plants appear relatively dark in the PAR and relatively bright in the near-infrared. The pigment in plant leaves, chlorophyll, strongly absorbs visible light (from 0.4 to 0.7 μm) for use in photosynthesis. The cell structure of the leaves, on the other hand, strongly reflects near-infrared light (from 0.7 to 1.1 μm). NDVI is a simple numerical display that can be used to analyze remote sensing measurements from a remote measurement and evaluate whether the observed target or object contains live green vegetation [14]. The NDVI is calculated from these individual measurements as follows:

$$NDVI = (NIR - RED) / (NIR + RED)$$

Where red and NIR stand for the spectral reflectance measurements acquired in the red (visible) and near-infrared regions, respectively. They take on values between 0 and 1. By design, the NDVI itself thus varies between -1.0 and +1.0. The simple ratio (unlike NDVI) is always favourable, which may have practical advantages, but it also has a mathematically infinite range (0 to infinity), which can be a practical disadvantage as compared to NDVI. NDVI is functionally and linearly equivalent to the ratio NIR / (NIR+VIS), which ranges from 0 to 1 and is thus never contrary, nor limitless in range. The meager value of NDVI (0.1 and below) correspond to barren areas of rock, sand, or snow. Moderate values represent shrub and grassland (0.2 to 0.3), while high value indicates temperate and tropical rainforests (0.6 to 0.8). Bare soil is represented with NDVI values, which are closest to 0 and water bodies, are represented with negative NDVI values. The degree of greenness is equal to the chlorophyll concentration [5].

2.4. Measurement

The MODIS13A3 data were downloaded from LP DAAC the official page of USGS. It required the registration before data download. The LP DAAC2 Disk download manager will allow users to simplify the search HTTP download process of the LPDAAC2 data pool holdings. The data was downloaded using a web-based interface. The desired destination of required time frame was added in ordered to download the data. The downloaded data contains a variety of data sets and four tiles covering whole Nepal in Sinusoidal projection. The MODIS re-projection Tool was required to select the NDVI sub-dataset, mosaic the four tiles into a single image and then project the Sinusoidal to WGS 84 system. The NDVI sub-dataset that is both mosaic and re-projected was used as input data in a GIS environment. The analysis required the area within the boundary of Nepal. So, the Mosaic image was then clipped using the boundary layer of Nepal. Since there are hundreds of images requiring the same process of analysis, The Model Builder was used as the best tools. The Model Builder has the iteration functionality, which allows the rigorousness and simple and quick processing.

2.5. Analysis and Interpretation

The NDVI is directly related to the photosynthetic capacity and hence energy absorption of plant canopies. The NDVI value was found in the extracted image month wise which was then multiplied by the factor of 0.0001. Calculating average NDVI was plotted in Excel file. The NDVI amount of the vegetation of the area over the period 2001-2016 years in every month was representing in Microsoft Excel to analysis and interpretation of NDVI.

2.6. Workflow Diagram

In this way, the workflow diagram of this research study was as follows:

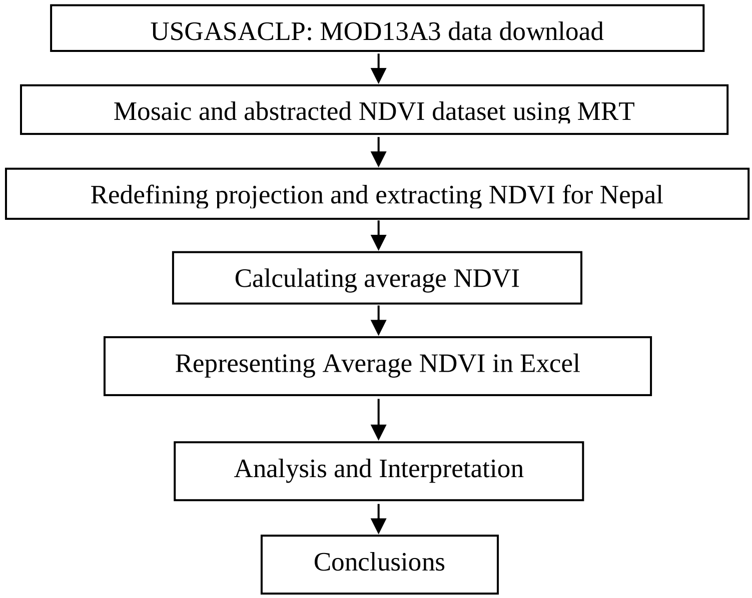

Figure 2. Work flow diagram of this research work

3. RESULTS AND OUTPUTS

From this research study, the variation in significant trends for NDVI at different temporal granularities of Nepal that has taken place between the periods from 2001 to 2016 using MODISA13A3 of every monthly composite time series. The average NDVI of each month in the year 2001 to 2016 were found in Table 2.

Table 1. The average monthly NDVI from year (2001 to 2016)

The Monthly Average NDVI From Year 2001-2016													
Year	Jan.	Feb.	Mar.	Apr.	May	Jun.	Jul.	Aug.	Sept.	Oct.	Nov.	Dec.	Average
2001	0.351	0.344	0.355	0.350	0.382	0.396	0.416	0.422	0.415	0.399	0.371	0.359	0.380
2002	0.354	0.365	0.364	0.358	0.375	0.406	0.420	0.425	0.414	0.403	0.382	0.368	0.386
2003	0.367	0.367	0.363	0.374	0.373	0.406	0.419	0.420	0.420	0.404	0.380	0.367	0.388
2004	0.365	0.356	0.340	0.362	0.381	0.405	0.412	0.415	0.415	0.406	0.381	0.367	0.384
2005	0.365	0.364	0.366	0.360	0.393	0.408	0.423	0.429	0.421	0.405	0.381	0.372	0.391
2006	0.353	0.343	0.353	0.358	0.388	0.408	0.420	0.418	0.419	0.404	0.389	0.372	0.385
2007	0.351	0.365	0.357	0.360	0.393	0.417	0.421	0.420	0.419	0.406	0.384	0.375	0.389
2008	0.360	0.357	0.354	0.357	0.392	0.415	0.419	0.421	0.418	0.406	0.378	0.362	0.387
2009	0.350	0.343	0.344	0.358	0.382	0.404	0.423	0.422	0.415	0.404	0.383	0.372	0.383
2010	0.363	0.360	0.353	0.351	0.381	0.409	0.419	0.422	0.419	0.403	0.383	0.374	0.386
2011	0.361	0.358	0.357	0.363	0.402	0.417	0.420	0.425	0.425	0.409	0.378	0.363	0.390
2012	0.361	0.355	0.341	0.363	0.383	0.401	0.427	0.429	0.423	0.407	0.384	0.370	0.387
2013	0.366	0.377	0.371	0.363	0.393	0.410	0.422	0.428	0.425	0.413	0.388	0.381	0.395
2014	0.380	0.372	0.365	0.365	0.392	0.408	0.424	0.427	0.427	0.417	0.387	0.380	0.395
2015	0.379	0.379	0.375	0.377	0.398	0.421	0.432	0.436	0.424	0.414	0.396	0.372	0.400
2016	0.359	0.366	0.367	0.366	0.403	0.421	0.426	0.426	0.431	0.413	0.384	0.372	0.395
Average	0.362	0.361	0.358	0.362	0.388	0.409	0.421	0.424	0.421	0.407	0.383	0.371	-

The NDVI represents the amount of the vegetation of the area; therefore, NDVI change over the period also represents the change in vegetation. The amount of vegetation was found minimum during January to April and maximum during July to October in Nepal. Similarly, the amount of vegetation in Nepal from 2001 to 2016 fluctuates time and again. These fluctuate average NDVI data were illustrated with different line and radar diagram given in Figure 3.

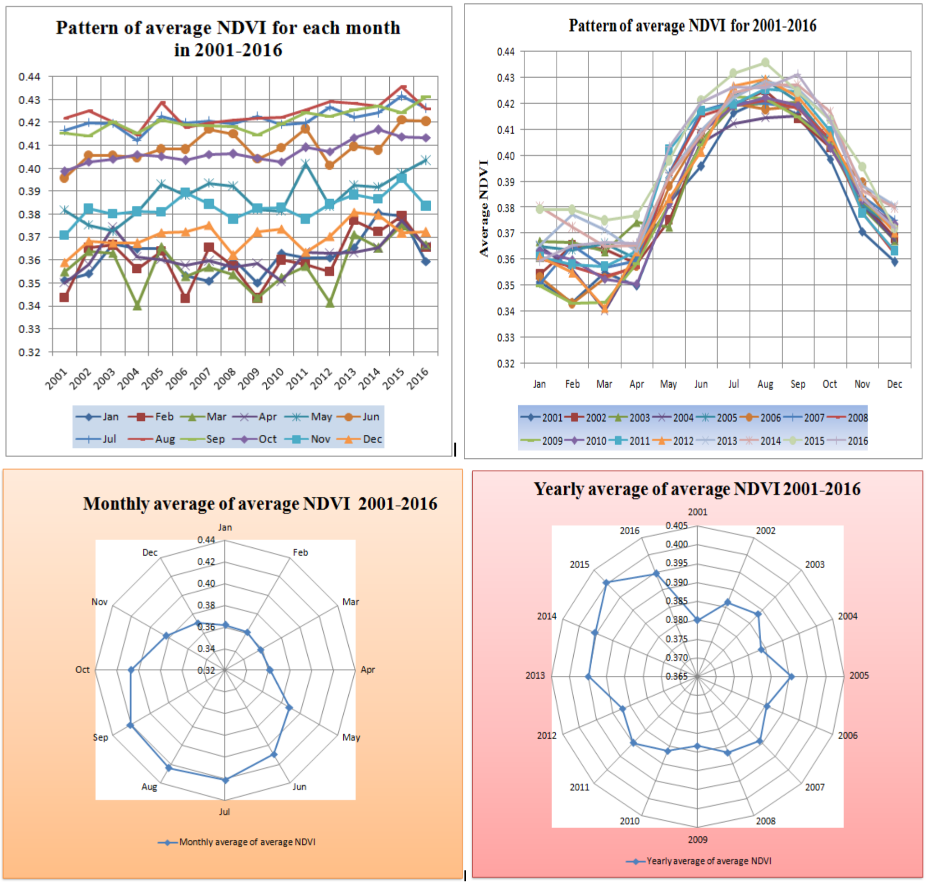

Figure 3. Pattern of average NDVI in Radar and line diagram

From above Figure 3: line and radar diagram showed that in the year 2001 to 2003 NDVI increased, 2003 to 2004 decreased, 2004 to 2005 increased, 2005 to 2006 decreased, 2006 to 2007 increased, 2007 to 2009 decreased, 2009 to 2011 increased, 2011 to 2012 decreased, 2012 to 2015 increased and 2015 to 2016 decreased. The temporal NDVI changes of Nepal from 2001 to 2016 shows that monthly average of average NDVI was found lower during January to April and November to December, as it was the dry seasons in Nepal. In the rest of the months, from May to September the NDVI was found relatively high due to the rainy seasons. While analysing the yearly average of average NDVI, the lowest value was detected at 0.380 in 2001 and the highest of 0.395 in 2016 (Table 2). The average NDVI map of Nepal was prepared as follows:

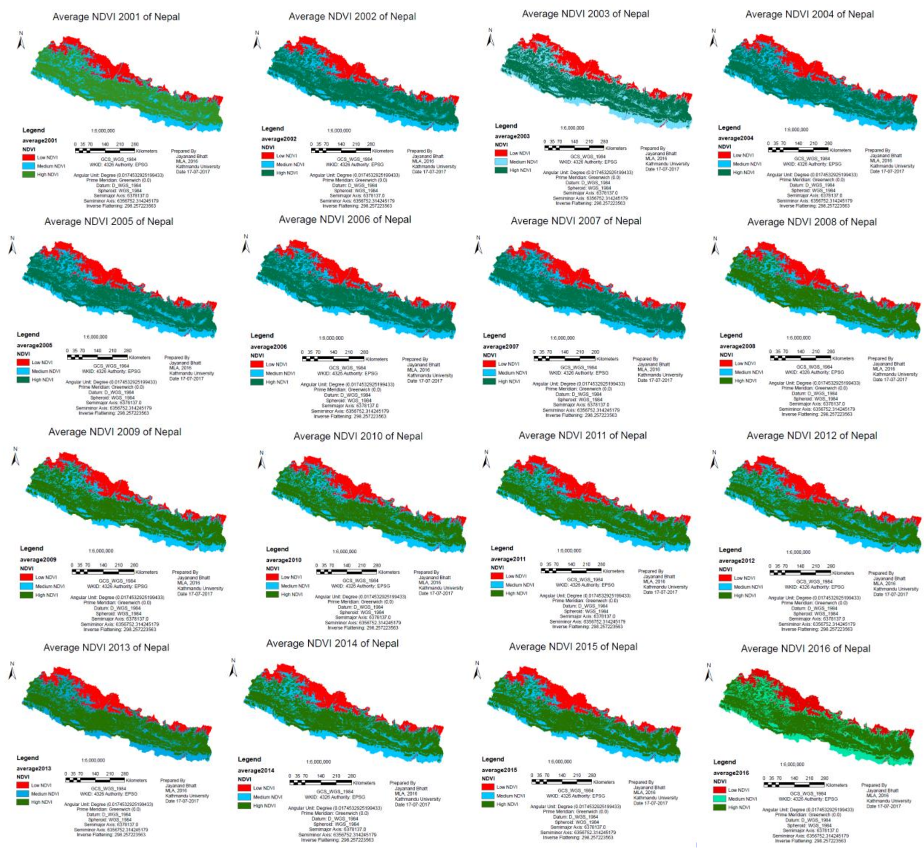

Figure 4. Map of the yearly average of NDVI in the period 2001-2016 of Nepal

The above Figure 4: showed that the yearly average NDVI map of Nepal. There was no significant change in the NDVI values and neither there is any specific trend in increase or decrease of NDVI value (Figure 3). The NDVI value was found fluctuating from 2001 to 2016 (Figure 3). The average NDVI of the year were found in line diagram given in Figure 5.

The above figure showed that Average NDVI of each year and every month NDVI pattern which comfortable for well known about the pattern of each month in every year 2001 to 2015 (Figure 4).

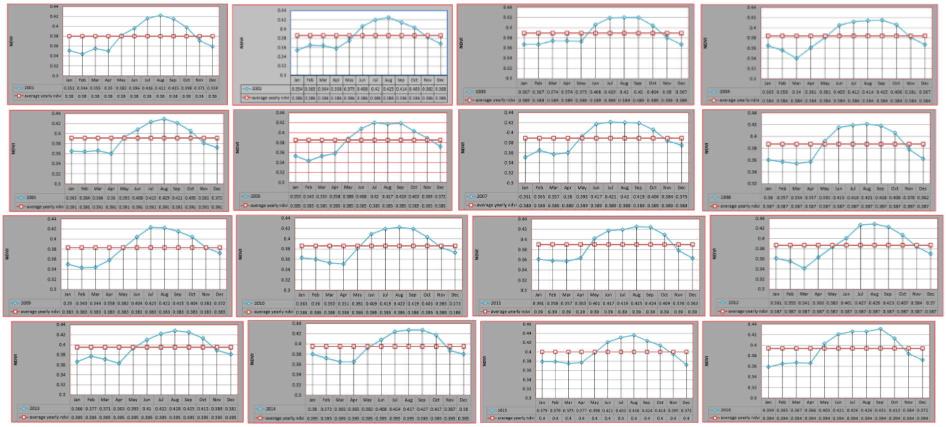

Figure 5. Line diagram of the yearly average of NDVI in the period 2001-2016

4. DISCUSSIONS

With the imaging data the MODIS and AVHRR instruments provide, scientists should be able to use these indices to get daily measurements of vegetation density over most of the Earth's surface. In this study, all of the proactive maps are very helpful in monitoring and understanding environmental and climate changes such as deforestation, desertification, and drought. Also, the maps can play a significant role in other types of satellite measurements. For instance, they are crucial in helping scientists classify different types of vegetation over the world's landscapes as well as detecting changes in land surface cover over time. For some examples: vegetation change detections can use the following applications.

4.1. Classification of Image

The analysis would be more specific if we could have used data of higher spatial resolution of 250m or 500m. Since the spatial resolution of data used is 1km, there are specific factors affecting water bodies, soil moisture affecting the NDVI values. It can be seen from the negative values during the analysis. Normalized Difference Vegetation Index method has been employed for accurate classification of images and has proved to be successful. The results of this research work were the significant trend maps which were helpful in analysing spatial patterns in varying trends access different aggregation level to show the effect of MUTP on NDVI and climate forcing data over Nepal.

4.2. Identifying change in climate change

It is susceptible to many damaging factors, including the calculation of the NDVI value which is following.

➢ Atmospheric effects: The actual composition of the atmosphere (in particular concerning water vapor and aerosols) can significantly affect the measurements made in space,

➢ Clouds: The effect of the thick cloud is considerable and can be identified, but the effect of thin cloud and cloud shadow contaminates the observed NDVI,

➢ Soil effects: The presence of soil moisture can affect the NDVI values considerably,

- Spectral effects: Because each sensor has its characteristics and performances, a single formula like NDVI gives different results when applied to the measurements obtained by different instruments, especially regarding the position, width, and shape of spectral bands.

For these reasons, NDVI should be used with great caution. In any quantitative application requiring a certain level of accuracy, all harmful factors that may lead to errors or uncertainties in this magnitude must be explicitly considered; this can be aided and requires extensive action based on other sources of information.

4.3. Land use planning

For this, study work has employed MODIS satellite images during the period 2000 to 2016. The results obtained in this research will help to prevent loss of forest cover and agriculture vegetation from being disappeared and also help take necessary decisions for better sustainable land use and land cover management in the future. It can be helpful for suitable and effective Land use/land cover planning policy and implement it.

"The Russian mathematician Andrei Andreyevich Markov (1856–1922) developed the theory of Markov chains in his paper Extension of the Limit Theorems of Probability Theory to a Sum of Variables Connected in a Chain" [25]. This phenomenon would indict that the elements would change into different elemental states over a period. Also, it helps us to predict the status of the element in the future with the results from the past, enabling us to define the time for which the element would be active in that period. The results obtained from the Markov Model would help us choose how the land could be used effectively in the future [26].

The method employs the multi-spectral remote sensing data technique to find the spectral signature of different objects such as vegetation index, land cover classification, concrete structure, road structure, urban areas, rocky areas and remaining areas presented in the image. For land cover classification, some band combinations of the remotely sensed data are exploited, and the spatial distribution such as road, urban area, agriculture land and water resources are easily interpreted by computing their normalized difference vegetation index. The different values of the NDVI threshold are used to create a false colour composite of the classified objects. Simulation results show that NDVI is quite useful in determining the surface properties of the visible area, which is extremely useful for municipal planning and management. Vegetation analysis can be used for the situation of unfortunate natural disasters to provide humanitarian aid, damage assessment and also new protection strategies. These assessments are supported to applicable in land use planning.

4.4. Monitoring and detecting of seasonal changes

From this research study, the variation in significant trends for NDVI at different temporal granularities of Nepal that has taken place between the periods from 2001 to 2016 using MODISA13A3 of every monthly composite time series. This work plays a vital role in the development of approved, global, interactive world system models that can accurately predict the global change to help policymakers make the right decisions about the protection of the globalization.

a) Climate varies from semi-arid in the west to humid in the east dominated by Asian summer monsoon. The year is broadly divided into four seasons: [27].

- Winter- Jan to Feb
- Summer- Mar to May
- Summer Monsoon- Jun to Sep
- Post-monsoon or north-east monsoon- Oct to Dec

While the comparison to high season and NDVI value and obtained the result which is as the following table 3.

Table 3. Relationship bet NDVI and Sing and Sontakke's seasons

Seasons	Month	NDVI	Pattern	Range difference
Winter	Jan to Feb	0.362- 0.361	Decreasing	0.001
Summer	Mar to May	0.358-0.362-0.388	Increasing	0.03
Summer-monsoon	Jun to Sep	0.409- 0.421-0.424- 0.421	Increasing-Decreasing	0.015
Post-monsoon	Oct to Dec	0.407- 0.383-0.371	Decreasing	0.036

b) Climate plays an important role and varies from place to place depending upon elevation and geographical location. At the base, it has the tropical climate and permanent ice and snow at the high altitudes. It has four seasons namely: [28].

-Cold winter season- Dec to Feb
-Hot summer season- Mar to May
-Monsoon season- Jun to Sep
-Post-monsoon season- Oct and Nov

While the comparison to high season and NDVI value and obtained the result which is as the following table 4.

Table 4. Relationship bet NDVI and Basistha's seasons

Seasons	Month	NDVI	Pattern	Range difference
Cold winter	Dec to Feb	0.371- 0.362-0.361	Decreasing	0.01
Hot summer	Mar to May	0.358- 0.362-0.388	Increasing	0.03
Monsoon	Jun to Sep	0.409- 0.421-0.424- 0.421	Increasing-Decreasing	0.015
Post-monsoon	Oct to Nov	0.407- 0.383	Decreasing	0.024

c) Generally, the season of the year is divided into four seasons: (Metrological Survey of Nepal)

- Winter- Jan-Feb-Mar
- Summer- Apr-May-Jun
- Summer Monsoon- Jul-Aug- Sep
- Post-monsoon -Oct-Nov-Dec

While the comparison to high season and NDVI value and obtained the result which is as the following table 5.

Table 5. Relationship bet NDVI and MSON's seasons

Seasons	Month	NDVI	Pattern	Range difference
Winter	Jan to Mar	0.362- 0.361- 0.358	Decreasing	0.004 (Less)
Summer	Apr to Jun	0.362- 0.388- 0.409	Increasing	0.047 (High)
Monsoon	Jul to Sep	0.421- 0.424- 0.421	Increasing-Decreasing	0.003 (Less)
Post-monsoon	Oct to Dec	0.407- 0.383- 0.371	Decreasing	0.036 (High)

d) Suitable season for Nepal:

- Winter- Jan-Feb-Mar-Apr
- Summer- May-Jun
- Summer Monsoon- Jul-Aug- Sep-Oct
- Post-monsoon Nov-Dec

While the comparison to above season and NDVI value and obtained the result which is as following table 6.

Table 6. Relationship between NDVI and suitable seasons of Nepal

Seasons	Month	NDVI	Pattern	Range difference
Winter	Jan to Apr	0.362- 0.361- 0.358- 0.362	Decreasing-Increasing	0.004 (Less)
Summer	May to Jun	0.388- 0.409	Increasing	0.021 (Less)
Monsoon	Jul to Oct	0.421- 0.424- 0.421-0.407	Increasing-Decreasing	0.017 (Less)
Post-monsoon	Nov to Dec	0.383- 0.371	Decreasing	0.012 (Less)

In this way, the above table seasons should be matching for Nepal because,

✓ Winter should be tentatively bell-shaped rather than post-summer and summer, and it has less range difference of NDVI due to first gradually decreasing then increasing change environment season. In this season, the range difference of NDVI value is 0.004. In this season has the lowest NDVI value 0.358 in Mar due to the dry season. Therefore, winter season should be Jan to Apr in case of Nepal,

✓ Summer should be tentatively straight line-shaped rather than monsoon and winter seasons, and it has less range difference of NDVI due to increasing change environment medium season from winter to monsoon. In this season, the range difference of NDVI value is 0.021. Therefore, the summer season should be May to Jun in the case of Nepal,

✓ Monsoon should be tentatively bell-shaped rather than post-summer and summer and it has less range difference of NDVI due to gradually increasing then decreasing change environment season. In this season, the range difference of NDVI value is 0.017. In this season has the high NDVI value 0.424 in Aug due to the rainiest season. Therefore, monsoon season should be Jul to Oct in the case of Nepal,

✓ Post-monsoon should be tentatively straight line-shaped and greater range difference of NDVI rather than monsoon and winter due to decreasing change environment medium season from monsoon to winter. In this season, the range difference of NDVI value is 0.012. Therefore, the post-monsoon season should be Oct to Dec in case of Nepal.

In the Western world, there are 4 seasons. However, in Nepal, there are six seasons. Two additional seasons in Nepal are Rainy Season and Pre-winter Season. Nepali seasons are 2-months long. According to the Nepal calendar the season class is classified as follows:

- Spring (Basant Ritu): Mid-Mar to Mid-Apr and Mid-Apr to Mid-May
- Summer (Grisma Ritu): Mid-May to Mid-Jun and Mid-Jun to Mid-Jul
- Rainy (Barsha Ritu): Mid-Jul to Mid-Aug and Mid-Aug to Mid-Sep
- Autumn (Sharad Ritu): Mid-Sep to Mid-Oct and Mid-Oct to Mid-Nov
- Pre-winter (Hemant Ritu): Mid-Nov to Mid-Dec and Mid-Dec to Mid-Jan
- Winter (Shishir Ritu): Mid-May to Mid-Jun and Mid-Jun to Mid-Jul

While the comparison to high season and NDVI value and obtained the result which is as the following table 7.

The table 6 and below table 7 are relatively close to each other according to change the pattern and corresponding change NDVI values. Therefore the last two are the proper season for Nepali environment.

Table 7. Relationship between Nepali sessions and Nepali months with NDVI

Seasons	Month	Nepali Months	NDVI	Pattern	Fluctuate NDVI
Spring (Basant Ritu)	Mid-Mar to Mid-Apr Mid-Apr to Mid-May	Chaitra Baishakh	0.3600- 0.3750 0.3750- 0.3985	Increasing	0.0385
Summer (Grisma Ritu)	Mid-May to Mid-Jun Mid-Jun to Mid-Jul	Jetha Ashadh	0.3985- 0.4150 0.4150- 0.4225	Increasing	0.0240
Rainy (Barsha Ritu)	Mid-Jul to Mid-Aug Mid-Aug to Mid-Sep	Saun Bhadra	0.4225- 0.4240 0.4240- 0.4140	Increasing Decreasing	0.0015
Autumn (Sharad Ritu)	Mid-Sep to Mid-Oct Mid-Oct to Mid-Nov	Ashwin Kartik	0.4140- 0.3950 0.3950- 0.3770	Decreasing	0.0370
Pre-winter (Hemant Ritu)	Mid-Nov to Mid-Dec Mid-Dec to Mid-Jan	Mansir Paush	0.3770- 0.3665 0.3665- 0.3615	Decreasing	0.0155
Winter (Shishir Ritu)	Mid-Jan to Mid-Feb Mid-Feb to Mid-Mar	Magh Falgun	0.3615- 0.3595 0.3595- 0.3600	Decreasing Increasing	0.0020

The fluctuate NDVI with Nepali sessions were found as following figure 6.

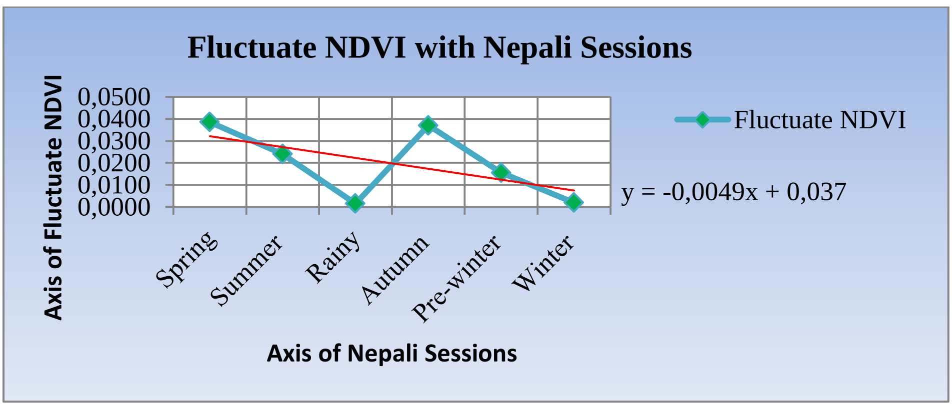

Figure 6. Fluctuate NDVI with Nepali Sessions

The average NDVI with Nepali months were found as following figure 7.

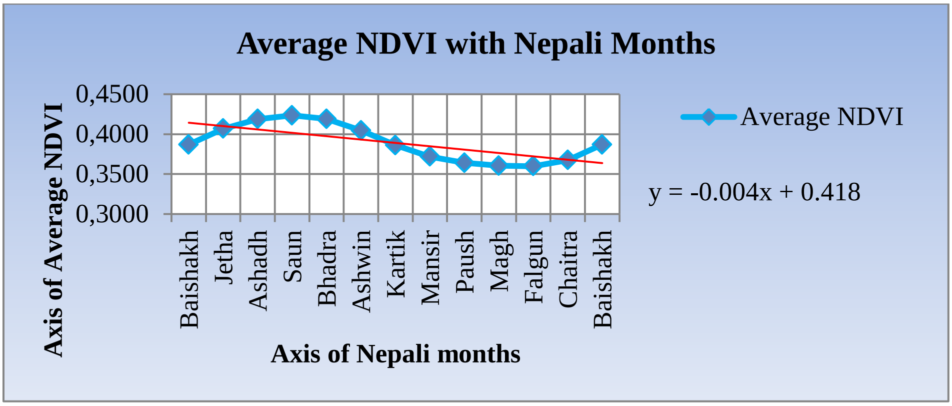

Figure 7. Average NDVI with Nepali Months

The temporal NDVI changes of Nepal from 2001 to 2016 shows that average monthly NDVI is lower from January to April and November to December, as it is the dry seasons in Nepal. In the rest of the months, from May to September the NDVI is relatively high due to the rainy seasons. While analysing the yearly NDVI, the lowest value is 0.380 in 2001 and the highest at 0.40 in 2016. There is no significant change in the NDVI values and neither there is any specific trend in increase or decrease of NDVI value. The NDVI value is fluctuating from 2001 to 2016. Finally, fluctuate NDVI with Nepali sessions and average NDVI with Nepali months are determined as above figure 6 and figure 7.

5. CONCLUSIONS AND RECOMMENDATIONS

In this study, assess the MODIS every month composite time series images in detecting the vegetation change. Finally, a different type of session categorizes and determines the NDVI of Nepali sessions and months. Remote Sensing is the only useful tool for monitoring, mapping and analysing the earth's surface on large scales at low cost. Remote Sensing techniques are superior to conventional ground-based methods of vegetation mapping and have proved to be successful in many research studies. A developing country like Nepal needs necessary measures to attain sustainable land use and land cover planning. Predicting the future change in vegetation is essential for future land use planning and overall management. The potential of MODIS Satellite images has proved successful in determining the vegetation change detection for the given period 2000-2016 in this study area. Each image of MODIS in this study area was taken at a time interval of 32 days. This research used the Normalized Difference Vegetation Index (NDVI) method for accurate classification of images which is used widely for estimation of changes in vegetation condition or state. It has been observed that a significant change has occurred all over in Nepal during the study period. The changes are due to deformation, human interventions, forest regeneration, cattle grazing, deforestation and agricultural expansion.

For further investigation of a vital role in the development of validated, global, interactive Earth system models able to predict global change accurately enough to assist policy-makers in making sound decisions concerning the protection of our environment. Furthermore, the results obtained in this research will help to prevent loss of forest cover and agriculture vegetation from being disappeared and also help take necessary decisions for a better sustainable land use/land cover management and environment management in the future.

REFERENCES

[1] Pereira, L.S. Allen, R.G. Smith, M. & Raes D. (2015). Crop evapotranspiration estimation with FAO56: past and future.*Agricultural Water Management,147 (1),* 4-20. https://doi.org/10.1016/j.agwat.2014.07.031

[2] Bhandari, A.K., Kumar, A. & Singh G.K. (2012). Feature extraction using normalized difference vegetation index (NDVI): a case study of Jabalpur city. *Procedia Technology,6,* 612–621. doi:org/10.1016/j.protcy.2012.10.074.

[3] Nageswara, R.P.P. Shobha, S.V. Ramesh, K.S. & Somashekhar R.K. (2005). Satellite - based assessment of agricultural drought in Karnataka State. *Journal of the Indian society of remote sensing, 33,* 429-434. https://doi.org/10.1007/BF02990014

[4] Ahmadi, H. & Nusrath, A. (2012). Vegetation change detection of Neka river in Iran by using remote sensing and GIS. *Journal of Geography and Geology,2(1),* 58-67.

[5] Karaburun, A. & Bhandari, A.K. (2010). Estimation of C factor for soil erosion modelling using NDVI in Buyukcekmece watershed. *Ozean Journal of applied sciences,3(1),* 77-85.

[6] Chouhan, R. & Rao, N. (2010). Vegetation detection in multi spectral remote sensing images: protective role-analysis of coastal vegetation in 2004 Indian Ocean Tsunami. *Geo-Information for Disaster Management Procedia Technology,* 612-621.

[7] Merwan, A. Stefan, B. Antoine, D. & Damien, O. (2014). A Model of road network and buildings extension co-evolution agent-based modeling. *Simulation of Cities Procedia Computer Science, 32,* 828 – 833. doi: 10.1016/j.procs.2014.05.498

[8] Shikhar, D. & Akansha, S. (2014). Urban sprawl modeling using cellular automata. *The Egyptian Journal of Remote Sensing and Space Sciences, 17(2),* 179-187. https://doi.org/10.1016/j.ejrs.2014.07.001

[9] Yang, Y. Zhu, J. Zhao, C. Liu, S. & Tong, X. (2010). The spatial continuity study of NDVI based on kriging and BPNN algorithm. *Journal of Mathematical and computer modelling, 54(3-4),* 1138-1144. https://doi.org/10.1016/j.mcm.2010.11.046

[10] Bechtel, A. Puttmann, W. Carlson, T.N. & Ripley, D.A. (1997). On the relation between NDVI fractional vegetation cover, and leaf area index. *Remote Sensing Environment, 62(3),* 241- 252. https://doi.org/10.1016/S0034-4257(97)00104-1

[11] Kim, H. Kwak, H.S. & Yoo, J.S. (2008). Improved clustering algorithm for change detection in remote sensing and its appications. *International Journal of Digital Content Technology,2(2),*55-59. doi:10.1.1.151.5757

[12] Yamaguchi, T. Kishida, K. Nunohiro, E. Park, J.G. Mackin, K.J. Matsushita, K.H.K. & Harada, I. (2010). Artificial neural network paddy field classifier using spatiotemporal remote sensing data. *Artificial life and robotics, 15(2),* 221-224. https://doi.org/10.1007/s10015-010-0797-4

[13] Zhang, X. Hu, Y. Zhuang, D. Oi, Y. & Ma, X. (2009). NDVI spatial pattern and its differentiation on the mongolian plateau. *Journal of geographical Sciences, 19(4),* 403-415. https://doi.org/10.1007/s11442-009-0403-7

[14] Demirel, H. Ozcinar C. & Anbarjafari G. (2010). Satellite image contrast enhancement using discrete wavelet transform and singular value decomposition. *IEEE Geosciences and remote sensing letters,7(2),* 333-337. doi**:**10.1109/LGRS.2009.2034873

[15] Frampton, W.J. Dash, J. Watmough, G. & Milton, E.J. (2013). Evaluating the capabilities of Sentinel-2 for quantitative estimation of biophysical variables in vegetation. *ISPRS Journal of Photogrammetry and Remote Sensing, 82,* 83-92. https://doi.org/10.1016/j.isprsjprs.2013.04.007

[16] Alganci, U. Ozdogan, M. Sertel, E. & Ormeci, E. (2014). Estimating maize and cotton yield in southeastern Turkey with integrated use of satellite images, meteorological data and digital photographs. *Field Crops Research, 157(15),* 8-19. https://doi.org/10.1016/j.fcr.2013.12.006

[17] López-Serrano, P.M. López-Sánchez, C.A. Álvarez-González, J.G. & García-Gutiérrez, J. (2016). A comparison of machine learning techniques applied to Landsat-5 TM spectral data for biomass estimation. *Canadian Journal of Remote Sensing, 42(6),* 690-705. https://doi.org/10.1080/07038992.2016.1217485

[18] Ustuner, M. Esetlili M.T. Sanli F.B. Abdikan S. & Kurucu Y. (2016).Comparison of crop classification methods for the sustainable agriculture management. *Journal of Environmental Protection and Ecology, 17(2),* 648-655.

[19] Abdikan, S., Sekertekin, A., Ustuner, M., Sanli, F.B., & Nasirzadehdizaji, F. (2018). Backscatter analysis using multi-temporal sentinel-1 sar sata for srop growth of maize in Konya basin, Turkey. *ISPRS TC III Mid-term Symposium Developments, Technologies and Applications in Remote Sensing,* 9-13. doi:org/10.5194/isprs-archives-XLII-3-9-2018

[20] Liao, C. Wang, J. Shang, J. Huang, X. Liu, J. & Huffman T. (2018). Sensitivity study of Radarsat-2 polarimetric SAR to crop height and fractional vegetation cover of corn and wheat. *International Journal of Remote Sensing,39(5),* 1475–1490. https://doi.org/10.1080/01431161.2017.1407046

[21] Soria-Ruiz, J. Fernandez-Ordonez, Y. McNairn, H. (2009). Corn monitoring and crop yield using optical and microwave remote sensing. *Geoscience and Remote Sensing, InTech,* 407-419. ISBN 978-953-307-003-2. www.intechopen.com

[22] Canisus, F. Shang, J. Liu, J. Huang, X. Jiao, X. Geng, X. Kovacs J.M. & Walters, D. (2017). Tracking crop phenological development using multi-temporal polarimetric Radarsat-2 data. *Remote Sensing of Environment, 210,* 508-518. https://doi.org/10.1016/j.rse.2017.07.031

[23] FAO (2017). Review of the available remote sensing tools, products, methodologies and data to improve crop production forecasts. *ISBN 978-92-5-109840-0 Rome.* http://www.fao.org/3/a-i7569e.pdf

[24] Meera, G.G. Parthiban, S. & Nagaraj, T.C.A. (2015). NDVI: Vegetation change detection using remote sensing and GIS – A case study of vellore district. *3rd International Conference on Recent Trends in Computing (ICRTC), Vellore: ELSEVIER,57,* 1199-1210. https://doi.org/10.1016/j.procs.2015.07.415

[25] Balzter, H. (2000). Markov chain models for vegetation dynamics. *Ecological Modelling, Volume 126(2),* 139-154. https://doi.org/10.1016/S0304-3800(00)00262-3

[26] Maranganti Sashikiran. (2009). Vegetation Change detection in India Using MODIS Satellite Images. *Master's Thesis in Geo-Informatics in Department of Computer and Information Science, Linköping Universitet SE-581 83 Linköping, Sweden,*76-87. ISRN: LIU-IDA/FFK-UP-A--09/005—SE.

[27] Singh, N. & Sontakke, N.A. (2002). On climatic fluctuations and environmental changes of the indo-gangetic plains, India. *Climatic Change, 52(3),* 287- 313. https://doi.org/10.1023/A:1013772505484

[28] Basistha, A. Arya, D.S. & Goel, N. K. (2008), Analysis of historical changes in rainfall in the Indian Himalayas. *International Journal of Climatology, 29(4),* 555-572. https://doi.org/10.1002/joc.1706