Identification of Vegetation using Spectral Characteristics and Deep Learning

A PROJECT REPORT

Submitted by

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BONAFIDE CERTIFICATE

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ABSTRACT

Vegetation Classification according to their vegetation composition is one of the valid tasks in the application of remote sensing in clear vegetation. Field identification is a very expensive and time taking task. Hence, few steps should be followed, such as extracting data from the satellite images, which is cheaper and faster. For this study, we first came up with a simple method for identification of the vegetation area in fully cover pixels using their lab-measured spectral reflectance curves Digital **Vegetation** Signature (**DVS**) . After that, based on those pixels, a hybrid method for vegetation area classification, that we call SCDL (Spectral Characteristics and DEEP LEARNING), is proposed. In our proposed method, different vegetation areas divided into three vegetation classes at the three extremes of green, red, and near-infrared along with a recurrent neural network method were used.Here we have taken That Desert for identifying different types of vegetation' . Then use LSTM for finding trends of different kind of vegetation growth in That Desert, Low Vegetation Area and Moderate Vegetation Area are decreasing with time and Desert Area is increasing.

Keywords: Image classification, Deep Learning, NDVI, Vegetation.

Chapter 1
INTRODUCTION

Remote Sensing has been used to monitor inaccessible areas. It is considered as a useful strategy for obtaining important environmental information from remote areas. My goal here will be to identify plant species classification models based on RS and deep learning techniques.

In remote sensing, with the various methods of image classification, the recurrent neural networks method has shown good accuracy. This is because RNN has no preconceptions about data distribution. As a result, the method is a valuable tool for image classification and its development has gained much attention by researchers in recent years.

Determination and detection of species can only be done by the sensors operating in narrow bands. These sensors are imaging in almost continuous spectra and are powerful tools for determination and precise detection of vegetation species.

The vegetation Index (VI) is usually proposed as a data-analysis technique to distinguish between surface vegetation and non-vegetation areas. VIs is a simple and effective algorithm for quantitative and qualitative evaluation of plant Coverage using remote sensing, vegetable strength testing and plant growth dynamics Method. Different VI strategies work for different purposes and require different data for those analyses. Visual atmospheres are among other examples of VI techniques: Resistance Index (VARI), Green Leaf Index (GLI), and Vegetation Index Green (VIgreen). Only red, blue, and green (RGB) channel data are needed to analyze these strategies. Related studies have shown that VI techniques show accurate results, in particular For the information on plantation fields. However, in urban areas that consist of many object divisions, Error judgments exist for non-plant objects of green color, resulting in Wrong object detection. An experiment has proven that the results of VIgreen and VARI may incorrectly classify some non-plant objects as plants because of the values given Within the boundaries of the plant division.

Next challenge with that VI aeria image analysis technique is the need for one Multispectral and modified camera to capture near-infrared (NIR) channels. NIR channel is not visible to the naked eye and is used by a normal camera . Mark C. Dustin (2015) experimented with a low-cost UAV to capture aerial images and post these images using the VI technique, that required both RGB and NIR colors. Band properties for park observation data. The main reason for RGB coordination And the NIR band strategy is to improve the sensitivity to detect green plants.Test results show incorrect detection of non-plant objects due to camera limitations in the ability to set light balance. White balance setting Colors in the image are essential to ensure as accurate as possible.

Pixel-based method. Unlike visual-based methods, the second technique to include all features of phenological is called pixel-based methods. In this case, the normal unit for combining phenological features is a separate pixel, given the idea that the pixel is the most cloud-free of all the scenes available on a research site (Beckschäfer, 2017). Unlike the visual based approach, which has significant cloud coverage in the image that would bail out the whole scene, cloud-free pixels can still be selected in a cloud-contaminated scene to extract meaningful phenological features for invasive species. Consequently, pixel-based methods provide an effective solution to address the two aforementioned barriers related to visual-based methods (Griffiths et al., 2013; Roy et al., 2009; Luck and Van Niekerk, 2016): (1) pixels -Based methods can alleviate the problems of spatial variability because the basic unit for phenology is the individual pixels; (2) Clin-coverage can be better identified regardless of the finology visual level of the invasive species. This is because all cloud-free pixels are used in time series images. Despite the conceptual merits of the visual approach.

Chapter 2

LITERATURE REVIEW

N. Ghasemloo1 , M. R. Mobasheri1, and Y. Rezaei1 first introduced a simple method for determining plant species in full cover pixels (DVS) using their laboratory-measured spectral reflectance curves. Then, based on these pixels, a hybrid method for classifying plant fields, which we call SCANN (Spectral Properties and Artificial Neural Networks)[1]. In this method, spectral reflectance properties of different plants were used on three extremes of green, red and near-infrared, including an artificial neural network method. Comparing the data collected in the field with the DVS results showed almost 100% accuracy. Based on DVS results, SCANN's results showed an overall accuracy of over 94%. And they have suggested this method for unclassified classification using hyperspectral images. And also some other methods have to be created, such as extracting data from satellite images, which is relatively cheap and fast. To improve the applicability of this method, the following data are required: (i) a rich library of spectral reflections for different plant species in their various growing stages, (ii) hyperspectral images, especially airborne, and (iii) a complete set of weather parameters for absolute atmospheric correction[3]. After Lim, J.; Lee, K.S. proposed a new pixel-based phenological feature composite method (PbfCM) based on Google Earth Engine. The PPF-CM method was conceived to combat the aforementioned three obstacles because the basic unit for extracting phonological features is a separate pixel instead of a complete image view. With PPF-CM-derived phenological features as input, we have gone one step further to investigate the effectiveness of the latest deep learning method as opposed to conventional support vector machines (SVMs)[4].

As a result, they found
(1) The developed Ppf-CM method can mitigate phonetic diversity and increase spectral variability between S. alterniflora and background species, regardless of the significant cloud coverage in the study area.
(2) In-depth education, compared to SVM, has presented better possibilities for incorporating new phenological features arising from the PPF-CM method. Jinyan Tian Conventional approaches typically apply the Normalized Difference Vegetation Index (NDVI) for plant identification. Here in-depth education for plant identification and the effectiveness of conventional methods can be investigated. Two in-depth learning methods, DiplabV 3+ and the Convulsive Neural Network (CNN) can be used to evaluate their detection effectiveness when training and test datasets originate from different geographic sites with different image resolutions. An innovative object-based plant detection method, using NDVI and machine learning (ML) techniques, is also proposed. Plant detection methods were applied to high-resolution airborne color images consisting of RGB and Near-Infrared (NIR) bands. Apart from the NIR band, RGB color images alone were also used along with two deep learning methods to test

their detection performance. The identification performance of the deep learning method is discussed with the object-based identification method and is used to display sample images from the dataset.[5]

Chapter 3

PROBLEM STATEMENT AND PRELIMINARIES

3.1 Recurrent Neural Networks

Recurrent neural network (RNN) is a type of neural network where output from the previous step is given as input to the current step. In a traditional neural network, all inputs and outputs are independent of each other, but when the next word in a sentence needs to be predicted, the previous words are needed and so the previous words need to be memorized. Thus RNN came into existence, which solved this problem with the help of a secret layer. The main and most important feature of RNN is the hidden state, which remembers some information about a sequence.

The phrase "recurrent neural network" refers to a type of network that has an infinite impulse response, whereas "convolutional neural network" refers to a type of network that has a finite impulse response. The behavior of both types of networks is temporally dynamic. An infinite impulse recurrent network is a directed cyclic graph that cannot be unrolled and replaced with a strictly feedforward neural network, whereas a finite impulse recurrent network is a directed acyclic graph that can be unrolled and replaced with a strictly feedforward neural network.

A neural network repeats the same principle, albeit in a much simplified version: it repeats through sequence elements and processes the sequence while maintaining a state containing information related to what it has seen so far. In fact, an RNN is a type of neural network that has an internal loop.
The state of the recurrent neural network has been reset in two different, independent sequence processing, so you still consider a sequence a single data point: a single input to the network. What changes is that these data points are no longer processed in a single step; Rather, the network loops on the sequence element internally.

3.2 LSTM

Compared to other recurring networks in 1997, the advantage of long short-term memory (LSTM) networks came back from an improved method of propagating the error. Hochreiter and Schmidhuber called it "constant error back propagation" .

But what does it mean "constant"? We will go through the architecture of LSTM and understand how it propagates front and back to answer questions. We will make some comparisons with the recurrent neural network (RNN) along the way. If you are not familiar with RNN, you may want to read about it here.

However, we must first understand what is the problem with RNN that LSTM claims to solve the presentation. The problem is the explosion and disappearance of the gradient that comes from the step of backward propagation.

Chapter 4

METHOLOGOGY

4.1 CHALLENGES

1. We need to collect the data from last 5 to 10 years of Vegetation Species and identify from there so I will get into some problems that are my challenge.

   First, we need to find a place where we can gather different species of plants from the past 5 to 10 years.

   Since clear satellite images can be good for our model, we need to capture those images that do not have clouds.

2. Selecting appropriate processing techniques for extracting spectral information of plants along with appropriate spatial and spectral resolutions.

3. The remote sensing of land vegetation has some particular challenges that require careful consideration in order to obtain successful results.
   This type of remote sensing is much larger in data volume which leads to storage and runtime problems during experiments.

4.2 Area of Study and Data

Study area

The northeastern part of the Thar Desert is located in the Aravalli Hills. The desert extends to Punjab and Haryana in the north, along the coast to the Great Run of Kutch, and to the silt plains of the Indus River in the west and northwest. Must be the desert area is covered by huge areas, shifting sand dunes that receive silt from sediment plains and coasts. Every year before the onset of monsoon, Bali is very mobile due to strong winds. The Luni River is the only river in the desert. Rainfall is 100 to 500 mm (4 to 20 inches) per year, almost entirely between June and September.

Located in the western part of the kingdom of Baram which forms a part of the Thar Desert. This is the field of special study of this paper. It is all bounded on the north by

Jaisalmer district, on the south by Jalore district, on the east by Pali district and Jodhpur district, and on the west by Pakistan. The district borders Tharpakar district in Sindh, the most populous Hindu district in Pakistan. The total area of the district is 28,387 sq km (10,960 sq mi). The district is located between 24.58 'to 26, 32' north latitude and 70, 05 'to 72, 52' E longitude.

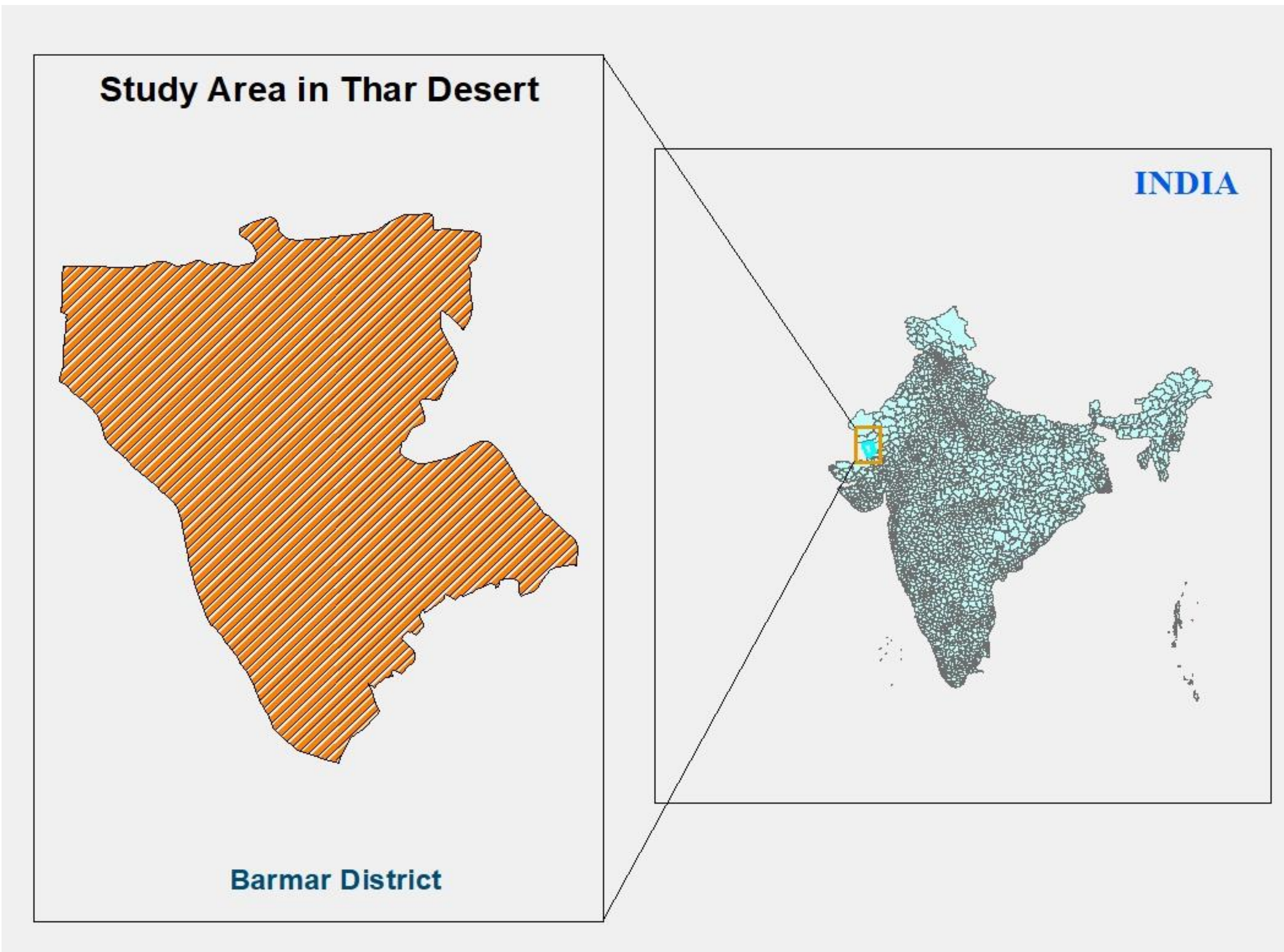

Fig 4.1: Study Area

4.3 Datasets

All USGS Surface Reflections images from Landsat-8 TM and Landsat-9 cover the study site in 30 m spatial resolution for 2014 to 2022 data as OLI input data. Through field observation and careful verification of very high spatial resolution (VHR) images, we found that the expansion of S. alterniflora between frames 3 and 4 was negligible. Therefore, the landsat images referred to in frames 1 and 2 were used to map and monitor the S alterniflora (420 Landsat-5TM and 105 Landsat-8 OLI, 19.96 billion pixels). For each and every Landsat image, six spectral features / bands were applied, including Blue, Green, Red, Near Infrared (NIR), Short-Wave inFrared 1 (SWIR 1), and Short-Wave Infrared 2 (SWIR 2).

Fig 4.2: Barmar-2014

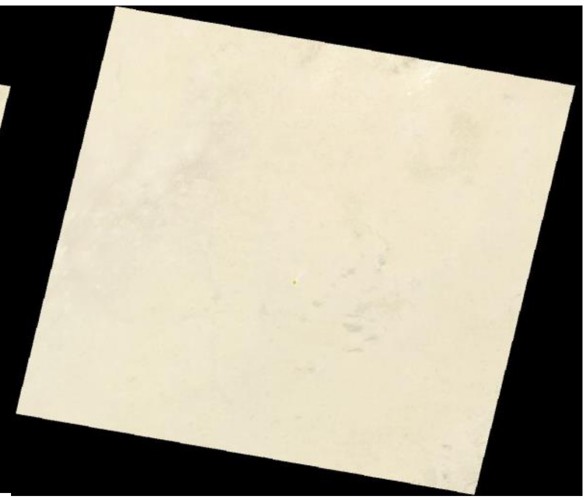

Fig 4.3: Barmar-2015

Fig 4.4: Barmar-2016

Fig 4.5: Barmar-2017

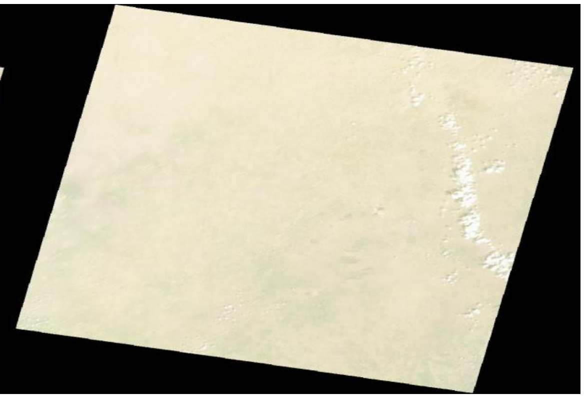

Fig 4.6: Barmar-2018 **Fig 4.7: Barmar-2019**

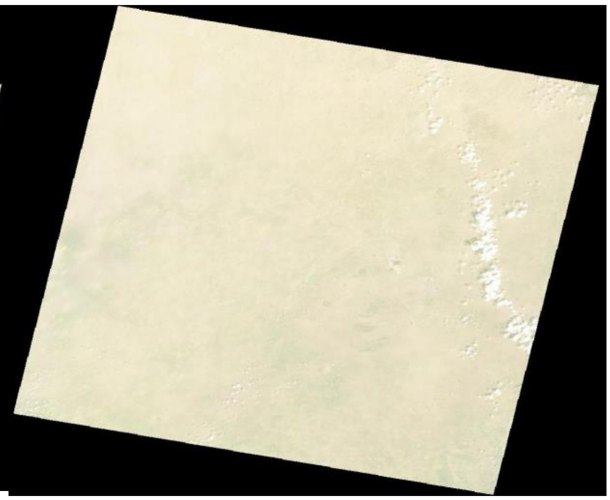

Fig 4.8: Barmar-2020 **Fig 4.9: Barmar-2021**

4.4 NDVI:

This section provides details about the proposed vegetation area identification system. The identified area was divided into two parts. The first part of identification involves converting original RGB images into VI results and removing pixels with VI value below 0 for less than 0.

The Normalized Difference Vegetation Index is the mostly used vegetation index worldwide. Other commonly used plant indicators are Enhanced Plant Index (EVI), Vertical Plant Index (PVI), and Proportion Plant Index.

Generally, healthy plants are a very good absorber of the electromagnetic spectrum. Green chlorophyll absorbs all blue (0.4 - 0.5 µm) and all red (0.6 - 0.7 µm) spectrum and reflects green (0.5 - 0.6 µm) spectrum. Hence, our eyes perceive healthy plants as green. Near infrared (NIR) of healthy plants has a high reflection between 0.7 and 1.3 µm. This is mainly due to the internal structure of the plant leaves. High reflectance in NIR and high absorption in the red spectrum, these two bands are calculated NDVI. The following formula gives a Normalized Difference Vegetation Index.

Band 1=b1, Band 2=b2, Band 3=b3, Band 4=b4, Band 5=b5, Band 6=b6, Band 7=b7

NDVI = (NIR - red) / (NIR + red)
For Landsat-7, NDVI = (b4 - b3) / (b4 + b3)
For Landsat-8 , NDVI = (b5 - b4) / (b5 + b4)
The value of NDVI value from -1 to 1. In general, we can get the following results:

If NDVI is in between -1 to 0 then reservoir
If NDVI is in between -0.1 to 0.1 barren rock, sand
If NDVI is in between If NDVI is in between
If NDVI is in between 0.2 to 0.5 shrubs & grasslands
If NDVI is in between 0.6 to 1.0 vegetation of tropical rainforest

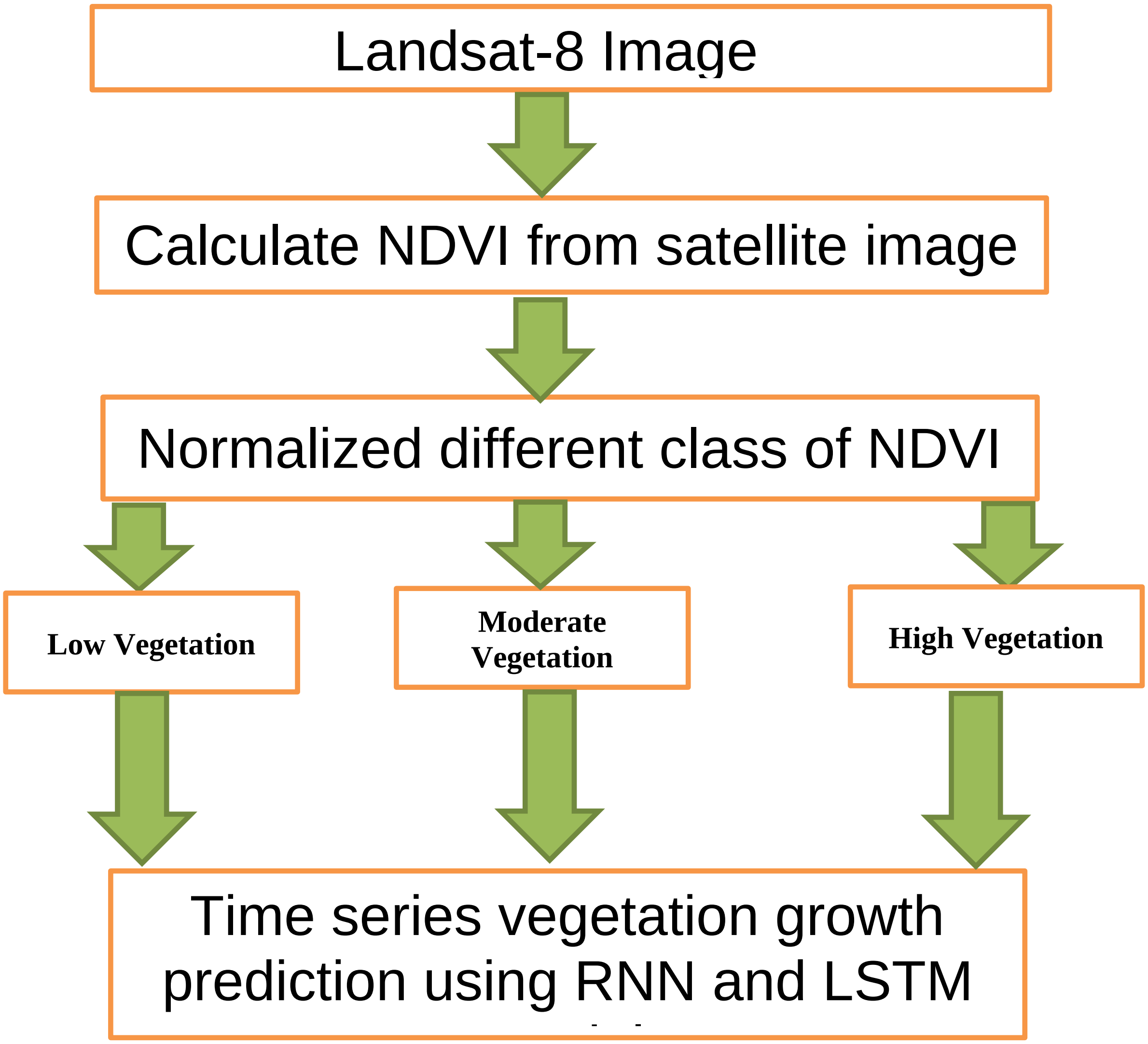

Fig: 4.10: Flow Chart of Work

Chapter 5

Experimental Results

5.1 NDVI Calculation:

The Normalized Difference Vegetation Index (NDVI)
NDVI = (NIR – Red) / (NIR + Red)
For Landsat 8 data, NDVI = (Band 5 – Band 4) / (Band 5 + Band 4)

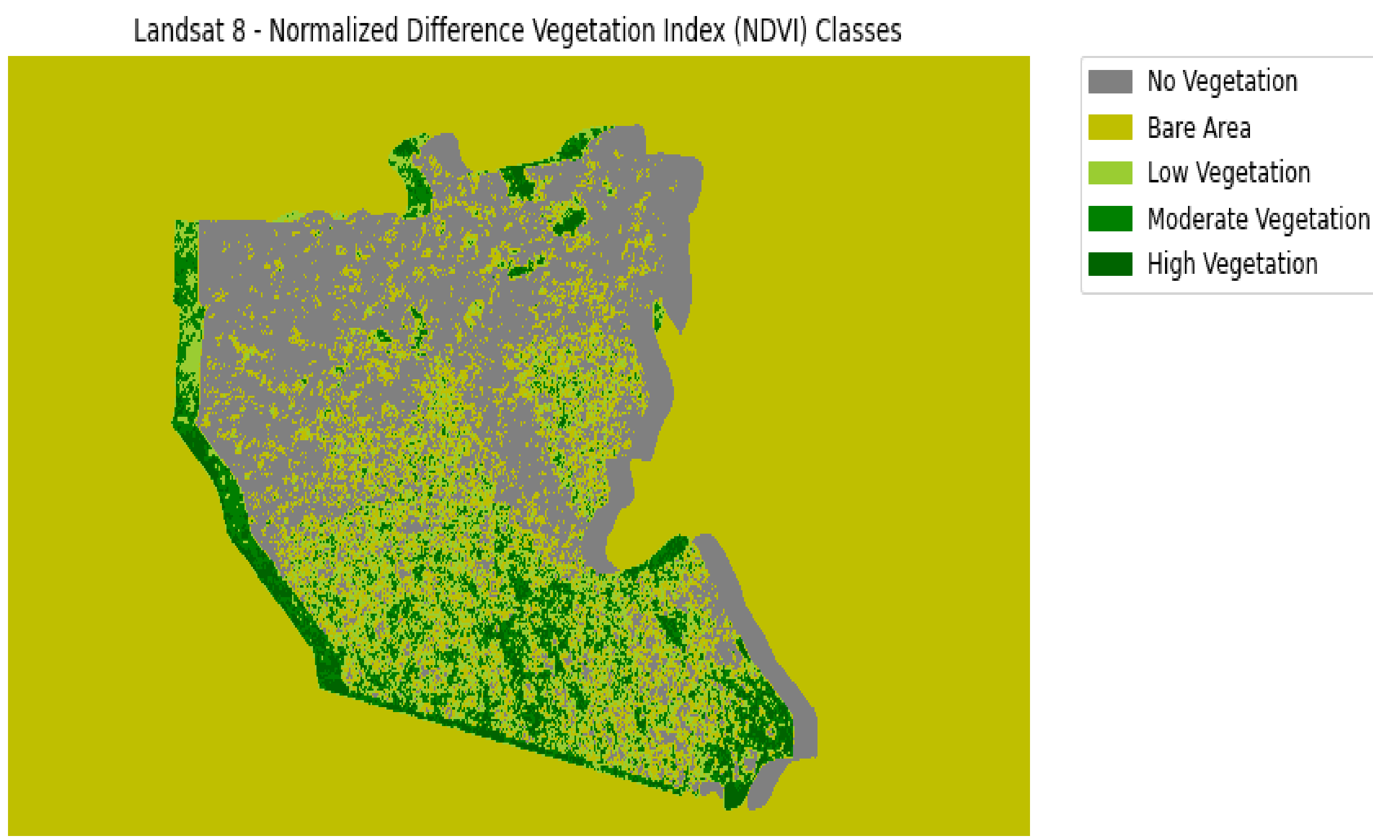

Fig 5.1: NDVI Image of 2014

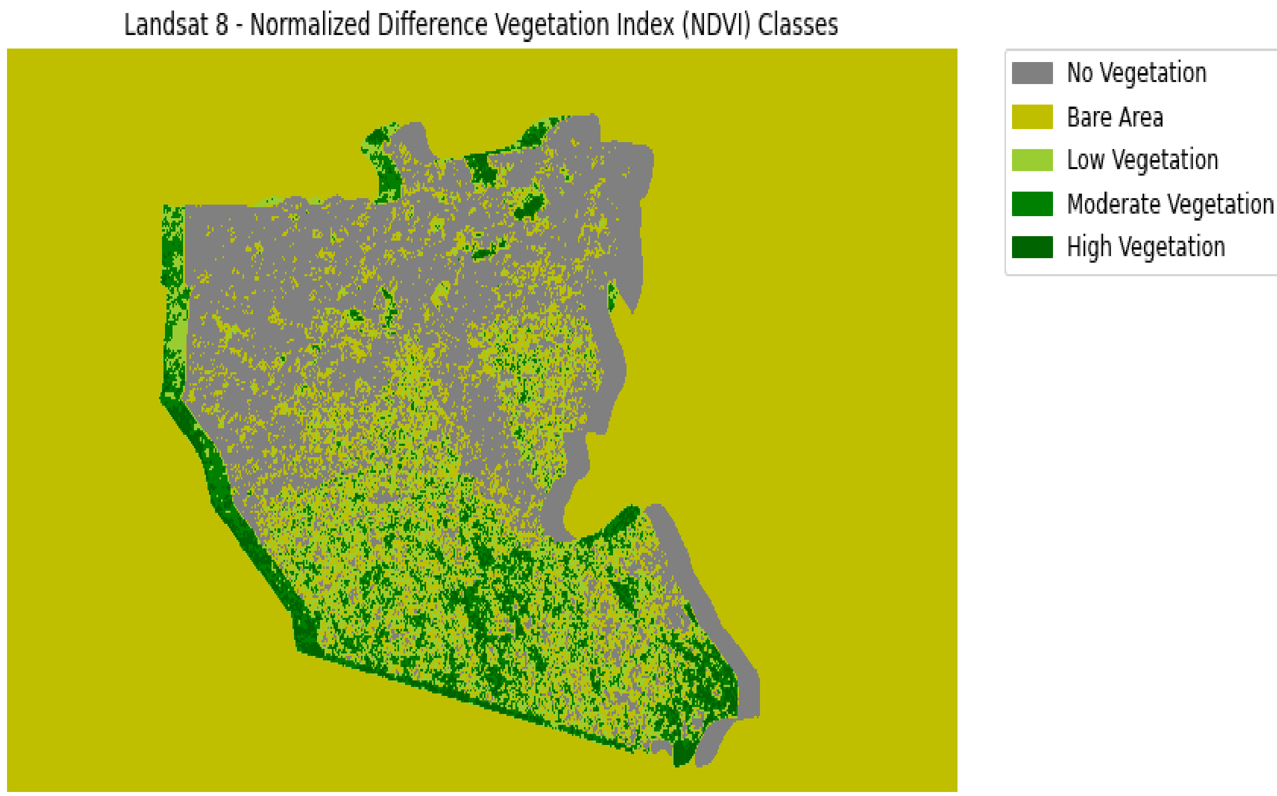

Fig 5.2: NDVI Image of 2017

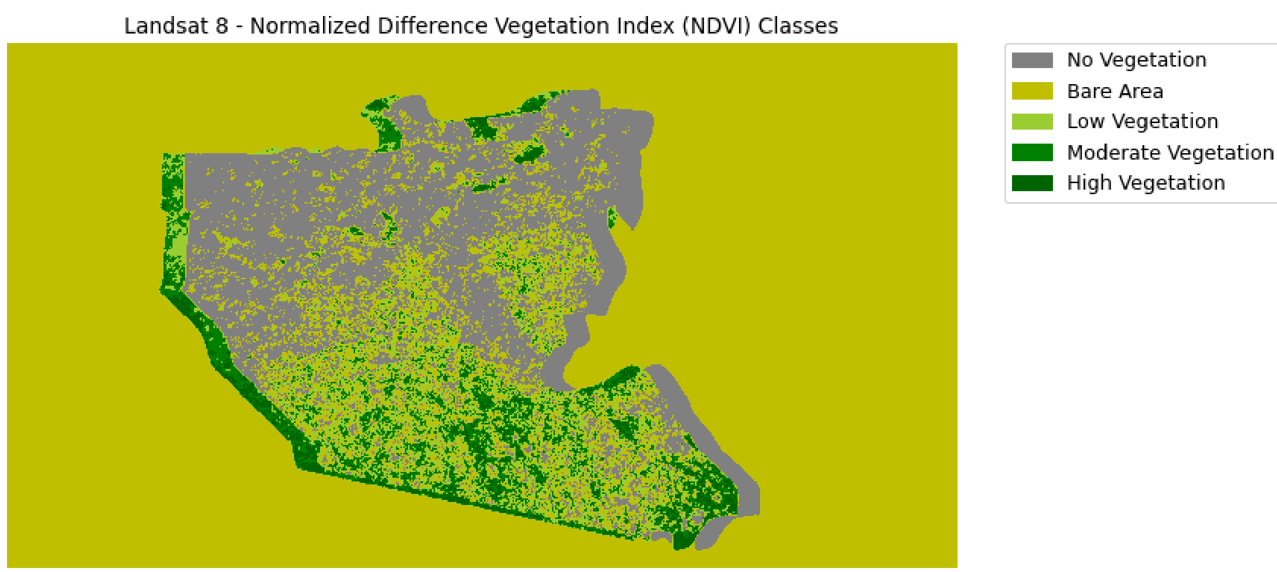

Fig 5.3: NDVI Image of 2019

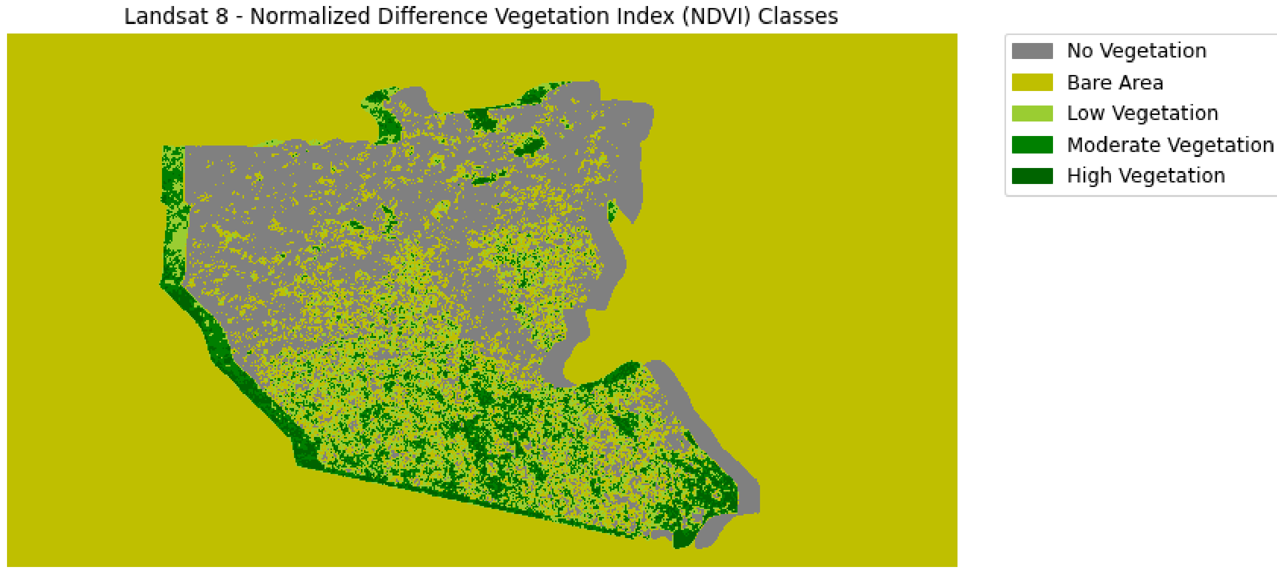

Fig 5.4: NDVI Image of 2020

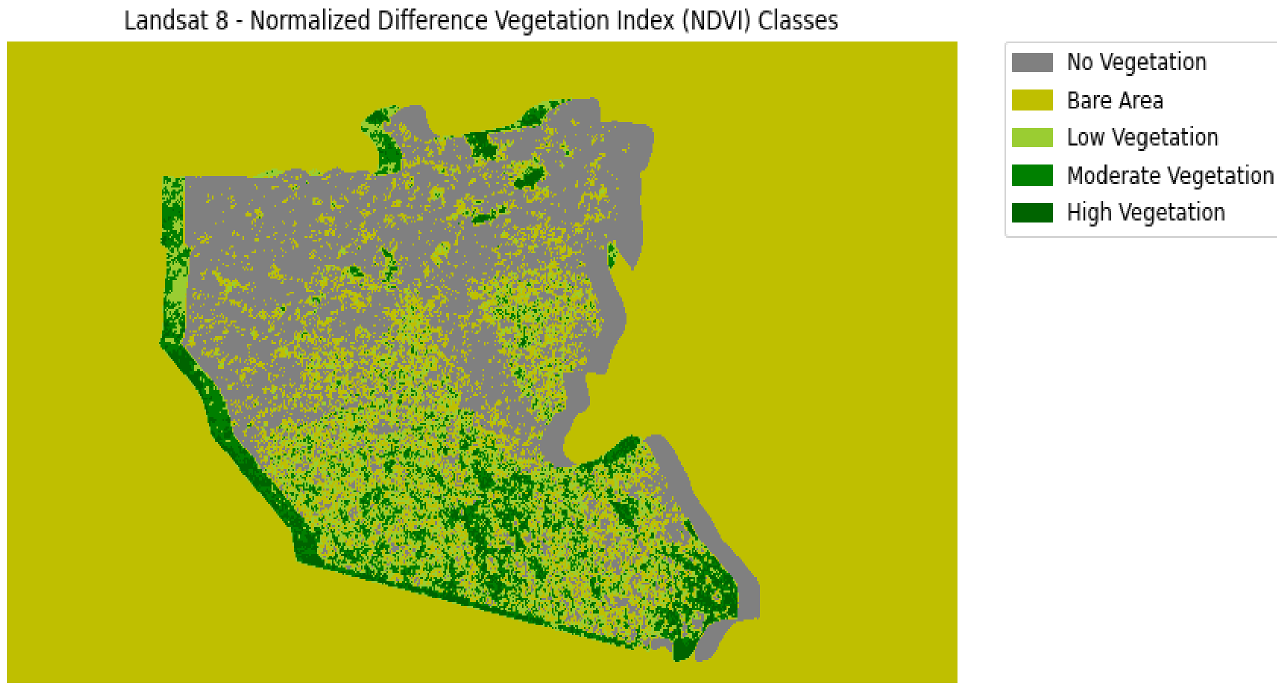

Fig 5.5: NDVI Image of 2022

Here we have classified with NDVI the all satellite image and we see that there is four type of feature.

i. No Vegetation: In this area here we can see there is no vegetation, so this is the desert area in thar desert.
ii. Bare Area: In all the desert there is some population area, here mankind, vegetation and water body.
iii. Low Vegetation: Here we see some shurbs vegetation, that we called low vegetation.
iv. Moderate Vegetation: In thar desert there is Many types of cactus, so we can noted as a moderate vegetation area.
v. High Vegetation: In desert area there is some trees in that area we can call high vegetation.

Year	No_Vgetation %	Low_Vegetation %	Moderate_Vegetation %	High_Vegetation %
2014	18.12	5.21	6.59	6.36
2015	17.95	4.75	6.48	6.19
2016	17.68	4.50	5.44	5.99
2017	17.25	3.85	5.22	5.87
2018	16.12	3.50	4.22	5.65
2019	15.36	3.25	3.92	5.45
2020	15.00	3.00	3.49	5.25
2021	14.95	2.85	3.25	4.92
2022	14.60	2.50	2.95	4.72

Table: 5.1- NDVI Classification value

In this table here we can see the output of all class of NDVI, and we have done a time series prediction using Deep learning.

5.2 Vegetation Spectrum in Thar Desert:

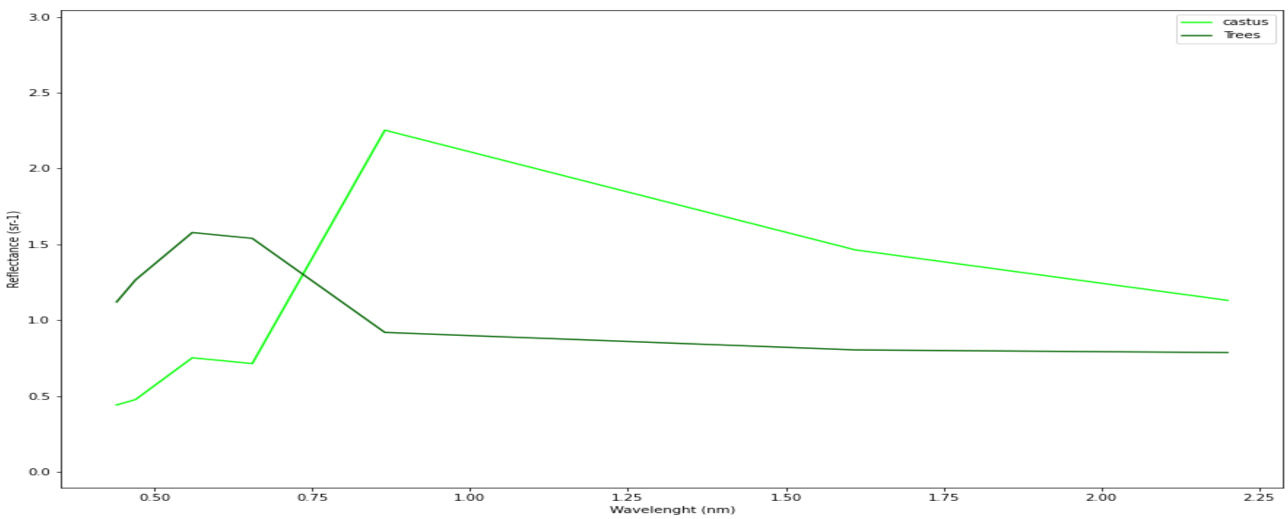

Fig 5.6: **Vegetation Spectrum**

5.3 Time Series Prediction using RNN, LSTM Model

Here we can see high vegetation area are decreasing in thar desert. We used here recurrent neural network, LSTM model to predict the high vegetation value with year.

Here blue line defines real value and orange line define the prediction value.

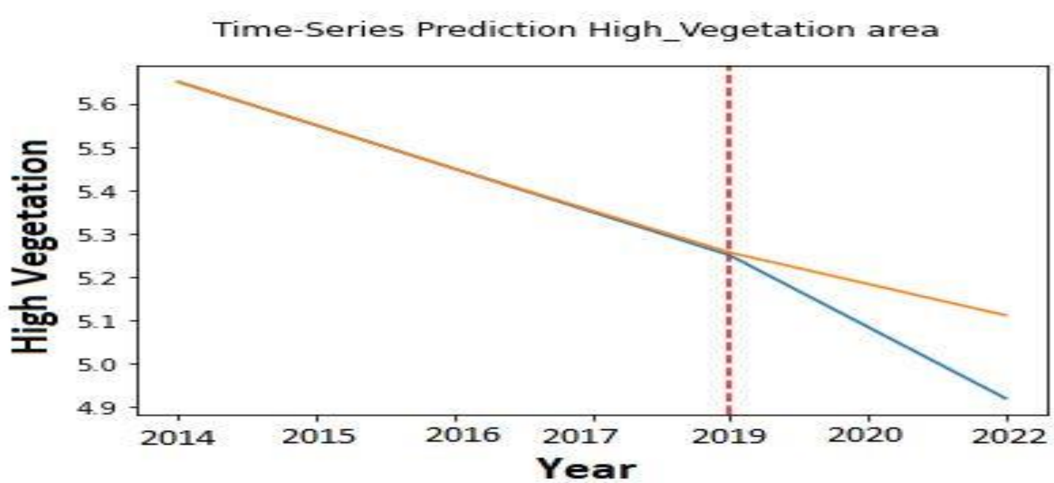

fig:5.7: High Vegetation Image

Here we can see Moderate Vegetation area are decreasing in thar desert. We used here recurrent neural network, LSTM model to predict the high vegetation value with year.

Here blue line defines real value and orange line define the prediction value.

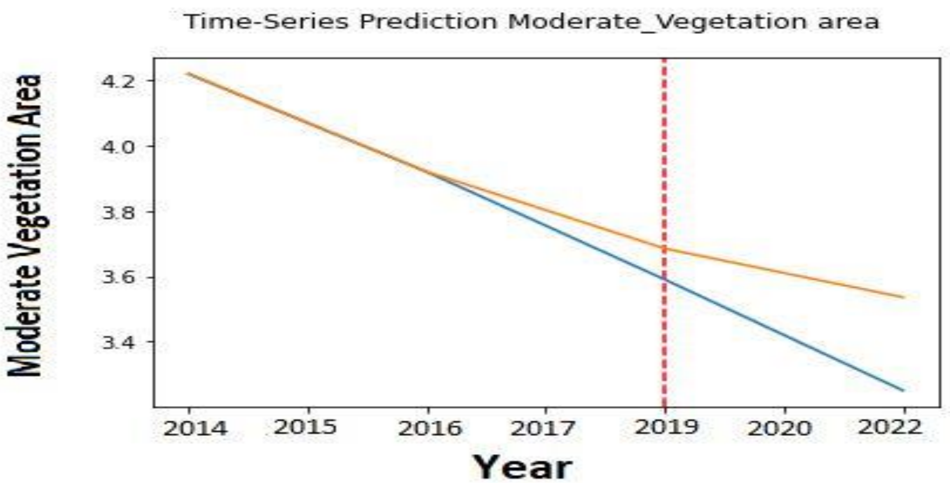

fig:5.8: Moderate Vegetation Image

Here we can see Desert Area are incising over the time in thar desert. We used here recurrent neural network, LSTM model to predict the high vegetation value with year.

Here blue line defines real value and orange line define the prediction value.

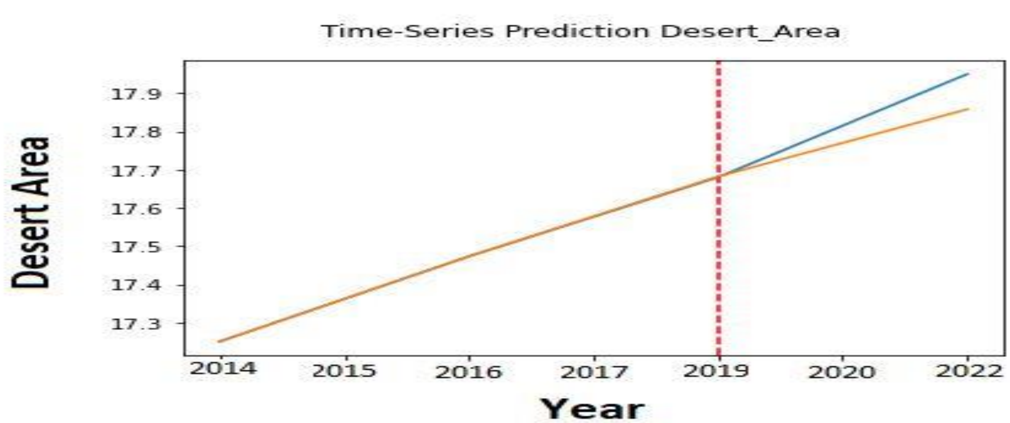

fig:5.9 Desert Area

Chapter 6

CONCLUSION

In this paper, vegetation in the barmer district of Rajasthan has declined over time and the desert area has increased.

Thus if the vegetation in Rajasthan continues to decrease and with it the desert increases, then the desert will gradually increase in the whole of Rajasthan, which is very harmful for the world and mankind. As the desert continues to grow, the amount of heat on the earth will increase and nitrogen gas will be emitted from the soil. This gas is very harmful to plants and people.

Chapter 7

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