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Automatic Detection of Natural Disaster Effect on Paddy Field from Satellite Images using Deep Learning Techniques

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Automatic Detection of Natural Disaster Effect on Paddy Field from Satellite Images using Deep Learning Techniques

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***Abstract*—Rice is the main food in Bangladesh and for more than the world's half population. As Bangladesh is prone to natural disasters, it's important to detect where rice production is compromised so that government can reach with aid and can take preventive measures. This paper used high-resolution satellite imagery (Sentinal-2) to detect damaged rice penology from natural disaster. The authors developed ground truth data for rice field damage from the field level. At first, NDVI differences before and after the disaster are calculated to identify possible crop loss. The areas equal to and above the 0.33 threshold are marked as crop loss areas as significant changes are observed. The authors also verified crop loss areas by collecting data from local farmers. Later, different bands of satellite data (Red, Green, Blue) and (False Color Infrared) are useful to detect crop loss area. We used the NDVI different images as ground truth to train the DeepLabV3plus model. With RGB, we got IoU 0.41 and with FCI, we got IoU 0.51. As FCI uses NIR, Red, Blue bands and NDVI is normalized difference between NIR and Red bands, so greater FCI's IoU score than RGB is expected. But RGB does not perform very badly here. So, where other bands are not available, RGB can use to understand crop loss areas to some extent. The ground truth developed in this paper can be used for segmentation models with very high resolution RGB only images such as Bing, Google etc.**

***Index Terms*—Semantic segmentation, DeepLabV3+, Sentinal-2, Google Earth Engine, Paddy field**

I. Introduction

Rice is the staple food of about 135 million people in Bangladesh. It provides nearly 48% of rural employment, about two-third of the total calorie supply in the country. Rice sector contributes one-half of the agricultural GDP and one-sixth of the national income in Bangladesh [1]. There are mainly four types of rice grow here aush, amon, boro & irri. Compare to the total production of rice boro is almost 50%. Boro is dry season rice crop. It is planted between December to early February and harvested between April and June [2]. But nature plays a vital role on rice production. Bangladesh is extremely sensitive to natural disasters due to its geographical location, terrain characteristics, river diversity, and monsoon climate. Many natural disasters like floods, heatwaves, cyclones, storm surges, riverbank erosion, drought, and salinity intrusion occur, impacting rice production [1]. For example, from the news article [20], we find out at 2021 for heatwave boro production was compromised. According to the Department of Local Agriculture Extension office, 47000 hectares have been affected in Kishoreganj, Netrakona, Mymensingh, Sunamgnaj, Moulvibazar, Barishal and Patuakhali [20].

It is essential to know where the crop is destroyed to take preventive measures or to provide governmental aids to affected people. However, collecting these data requires a lot of human and economic resources. Additionally, the data can be prone to human error. A great alternative is to use high-resolution satellite images (sentinel 2 images from Google Earth Engine (GEE)) to automatically detect crop loss and segment the affected area.

To develop a automatic framework to segment paddy crop loss, we need to collect ground-truth data. We use Normalized Vegetation Index (NDVI) to identify the crop loss area in the first step. NDVI is a vegetation measuring technique introduced in 2000 [21]. Chlorophyll in plant leaves absorbs visible light (between 0.4 and 0.7 m) and converts it to energy for photosynthesis. Therefore, unhealthy vegetation reflects more visible light but not as much near-infrared light. On the other hand, Sentinal- 2A images with NDVI algorithm has used to monitor the paddy rice phenology [15]. Paddy greenness values are recorded from Sentinel 2-A images with NDVI algorithm. Greenness values are also observed with CCTV recording on paddy rice fields. The results showed that Sentinel 2-A imagery can monitor the paddy rice phenology by measuring the value of NDVI vegetation index. NDVI can also detect the slow growth and development of the paddy caused by heat stress using the relationship with cumulative growing degree days[18]. In the second step, we identify crop loss area according to the NDVI and ask the farmers for further validation.

In order to calculate NDVI, we need image with NIR and Red bands. In contrast, if we have a normal RGB aerial/satellite images, calculating NDVI is impossible. To solve this problem, we can train a segmentation model with the above ground truth data to detect paddy loss area from RGB images, that will be very helpful where special type of band is not available. Therefore, in this paper, we have used DeepLab V3 plus for semantic Segmentation with RGB. We also trained and tested for False Color Infrared (FCI) to compare our RGB image test result. FCI composite maps near-infrared spectral band B8 with red and green bands. Plants reflect near-infrared and green light while absorbing red. Since they reflect more near-infrared than green, plant-covered land appears deep red, and denser plant growth is darker red. It is expected that FCI will do better than RGB during the test with the segmented model.

The contributions of this research are summarized below:

- We use NDVI differences to identify possible paddy loss area due to natural disasters.
- We validate the ground truth data from the real fields and the farmers.
- We use ground-truth for performing semantic segmentation using RGB images and GCI images at input to the models.
- We perform comparative analysis between the performances using RGB and GCI images.

The rest of the paper is organized as follows. In the next section, we discuss the related literature for automatic crop loss detection and deep learning-based semantic segmentation models. Then we describe the process for data set ground truth process. In this section, we also describe the validation part. In the fourth section, we talk about our experiment setup, train and test set etc. In the sixth section, we provide comparative result analysis where we describe results for RGB and FCI difference images. Finally we conclude the paper and describe some limitations of our proposed approach with future work.

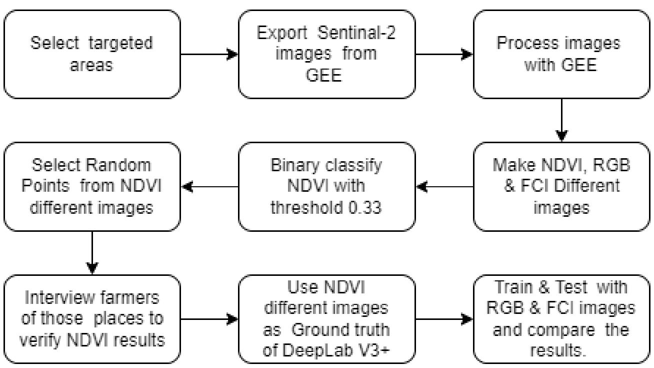

Fig. 1. Work flow

II. Background & Context

Some work has been done on yield estimation on rice. They are estimated by NDVI value. Initially, we wanted to focus on boro paddy loss due to the heatwave, which occurred on 4th April 2021. But we cannot find any related work which shows estimating paddy loss due to heatwave from remote-sensing data. This mainly leads us to do this research. On the other hand, we annotated crop loss area using RGB image difference and FCI image difference as input in DeepLab V3 plus model. We also wanted to see how different band compositions performed at semantic segmentation to measure crop loss region.

From sentinal-2, combination images are used, which consists of multiple bands. Combination imagery like False Color Infrared (FCI) is used for vegetation detection [11]. RGB satellite image was also combined to experiment and compare with FCI. For Ground truth, we have used the Normalized difference vegetation index (NDVI).

John Weier and David Herring (2000) first introduce NDVI as one of the measuring vegetation techniques [21]. NDVI is calculated by how much visible and near-infrared light is reflected from vegetation. The majority of visible light that strikes healthy plants is absorbed, whereas a considerable part of near-infrared light is reflected. Vegetation that is unhealthy or sparse reflects more visible light but not as much near-infrared light. Because Chlorophyll, a pigment found in plant leaves, absorbs visible light (between 0.4 and 0.7 m) and converts it to energy for photosynthesis.

On the other hand, the leaf cell structure reflects near-infrared light well (between 0.7 and 1.1 m). These wavelengths of light are affected more by the number of leaves a plant has. The NDVI value for a given pixel always ranges from minus one (-1) to plus one (+1); however, if there are no green leaves, the value is near zero. A zero value implies no vegetation, whereas a value near +1 (0.8-0.9) represents the highest density of green leaves conceivable [21].

In 2020's paper "Model of paddy rice phenology using Sentinel 2-A imagery with NDVI algorithm in Subang Regency" they showed paddy rice phenology using Sentinel 2-A imaginary from NDVI band composition [15]. They verify greenness value with CCTV footage of the paddy field. There they find that Sentinel Image 2-A can be used to estimate the paddy rice phenology, and the start and end of the paddy rice planting season can be determined using the NDVI greenness value. They find out that at ndvi value 0.326946, the first Phase of paddy Vegetative started. This NDVI value is very significant for us. Because later, we will use this NDVI value as our threshold.

In another paper, "Performances of Vegetation Indices on Paddy Rice at Elevated Air Temperature, Heat Stress, and Herbicide Damage," published at 2020, authors wanted to see which vegetation index is most suitable for understanding paddy response on-air temperature, heat stress and herbicide damage [18]. They collected their data from a controlled environment which is temperature gradient field chamber (TGFC). Their studied vegetation indexes were Normalized difference vegetation index (NDVI), MERIS terrestrial chlorophyll index (MTCI) & Photochemical reflectance index (PRI). Their experiment found out that NDVI can detect slow growth in paddy for stress. They sowed the relationship with cumulative growing degree days (GDD). As we initially want to see heatwave effect on paddy from sentinal-2 image by using NDVI, this might be possible.

Later we used deeplabv3+ for annotation crop loss area from RGB and FCI. DeepLabV3+ has already been used on many LULC datasets. One of them is the Potsdam and the Vaihingen dataset, which covers the areas in Germany [10]. The classes included in this dataset are Imprecious Surface, Building, Low-vegetation, Tree, Car and Background. In this paper [10], the mean IoU with DeepLab v3+ was 66.82%. The deep learning architecture used was DeepLabV3+, developed by Google[14]. One of the main features in DeepLabV3 and DeepLabV3+ is the Atrous convolution [13].

III. Data set preparation

A. Study Area in Bangladesh

According to the daily star's 9th April 2021 news, a massive nor'wester heat wave swept over the country on 4th April 2021 [20]. According to the Department of Agricultural Extension (DAE), in this article, 47,000 hectares of boro paddy(BRRI-29) have been affected in Kishoreganj, Netrakona, Mymensingh Sunamgnaj, Moulvibazar, Barishal and Patuakhali.

We select our study area among seven districts in Sunamganj, Kisorganj & Netrokona. These districts are side by side. All of these three districts are haor districts. According to the Department of Agricultural Extension 2020, Sunamganj has 219,300 hectares, Kishoreganj has 166,710 hectares and Netrakona has 184,530 hectares area where boro is cultivated, which is 73%, 62%, and 22% respectively among haor districts [12].

Sunamganj is a district in Bangladesh's Sylhet Division, located in north-eastern Bangladesh. Between 24°34' and 25°12' north latitudes and 90°56' to 91°49' east longitudes are the geolocational coordinates [7]. Kishoreganj and Netrokona are Dhaka Division's two districts. Kishoreganj is located between the latitudes of 24°02' and 24°39' north and the longitudes of 90°35' to 91°15' east. Netrokona is between the latitudes of 24°34' and 25°12' north and the longitudes of 90°00' and 91°07' east [5][6].

Fig. 2. Administrative map of Netrokona Sunamganj & Kishorganj collected from Wikimedia

B. Source of satellite data

Google Earth Engine (GEE) is a large publicly available geospatial dataset. Anyone can access this dataset via python API or google earth engine's own web-based IDE, which is accessible via the internet. Users can also export data as GeoTiff or TFRecord for offline use. GEE is free to use for research, education and non-profit use. All of the images captured by a single sensor are grouped together and this group is called "collection".

Users can easily search through this collection. As an example, suppose a user wants to export a sentinal-2 image. Then the user needs to select ImageCollection as 'COPERNICUS/S2_SR'. Then give their targeted area at filterBounds and range of date at filterDate. Even they can also filter by cloud coverage pixel.

GEE has its own lots of functions for operations on data, which saves time. GEE has a bulk catalog of datasets, including the entire Lanset archive, Sentinal-1, Sentinal-2, entire MODIS and so on [17]. We exported our sentinal-2 images from GEE for our studied areas.

Sentinal 2 is a European mission which provide high-resolution and multi-spectral imaging. This mission consists of two satellites which are flying in the same orbit but phased at 180°. One is Sentinal-2A and another is Sentinal-2B. Sentinal 2A launched on 23 June 2015 and Sentinal 2B on 7 March 2017. Though two m [8].

Sentinal 2 carries an optical instrument payload which gives 13 spectral bands: four bands at 10 m, six bands at 20 m and three bands at 60 m spatial resolution [8]. We can combine these bands in various way for our task. In Table I we can see Sentinal-2 band's details.

TABLE I
SENTINAL-2 BAND INFORMATION

Band Number	Band Name	Original Resolution (m)
Band 1	Coastal aerosol	60
Band 2	Blue	10
Band 3	Green	10
Band 4	Red	10
Band 5	Vegetation red edge	20
Band 6	Vegetation red edge	20
Band 7	Vegetation red edge	20
Band 8	NIR	10
Band 8A	Narrow NIR	20
Band 9	Water Vapour	60
Band 10	SWIR Cirrus	60
Band 11	SWIR	20
Band 12	SWIR	20

As different channels capture different land textures, we use different combinations from Sentinel-2 data. These combinations are formulated in a certain way to accomplish specific tasks. In this research, RGB and FCI are the combinations of three bands. NDVI is a single band image that we calculate from other bands using a formula.

Each index image has a specific characteristic that can detect specific classes. For example, NDVI is used to detect greenery. Vegetation in an area can be measured using this index [21].

NDVI : Because near-infrared (which vegetation strongly reflects) and red light (which vegetation absorbs), the vegetation index is good for quantifying the amount of vegetation. The formula for normalized difference vegetation index is (B8-B4)/(B8+B4). While high values suggest dense canopy [21].

$$NDVI = \frac{B8(NRI) - B4(R)}{B8(NRI) + B4(R)}$$

C. Ground Truth making

1) Making NDVI Different images: To make ground truth, we subtract 2nd imageś NDVI band composition from 1st imageś NDVI band composition. We can see 1st and 2nd image dates at Table III. As we are conducting our study on three districts, each district has three years of data. So, we will get nine NDVI different images.

NDVI is a single band image for better visualization; we colored them using QGIS render type single-band pseudocolor. We colored NDVI values above 0.33 or equals red and others as yellow. Later we exported our Rendered GeoTIFF images from Qgis.

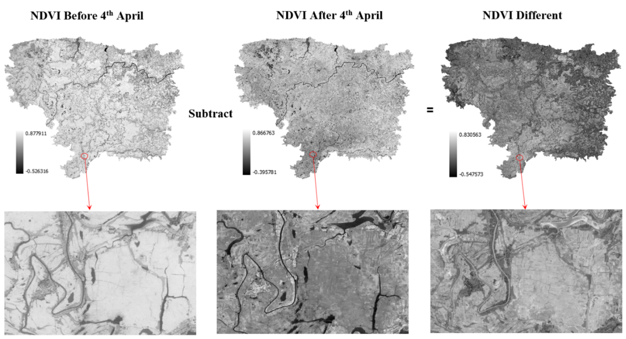

Fig. 3. Illustration of NDVI Different. As an example, we took 2021's NDVI Before 4th April and NDVI After 4th April of Sunamganj. We can see that NDVI Before image is whitish than NDVI After which indicates there is some loss of vegetation at NDVI After

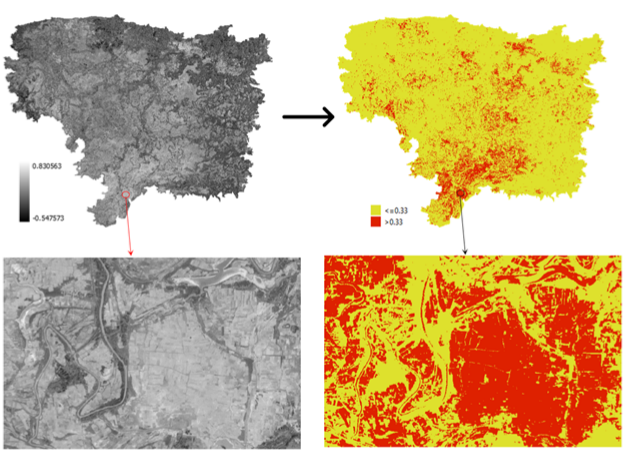

Fig. 4. Coloring grayscale NDVI Different as the binary class where red means crop loss area & yellow indicates the okay region

At figure 6,7 and 8 we will see NDVI Different for Sunamganj, Kisorgang & Netrokona.

As expected, we can see that in 2021 there is more NDVI difference than in 2020. However, here we can also see that in 2019 there is also a vast NDVI difference. It is because a 30-minute-long hailstorm struck south Sunamganj on 15-04-2019 morning [3]. Kisorhganj and Netrokona both are neighbour districts of Sunamganj; for that, we can see hailstorms impact on Kisorganj and Netrokona too. In the next

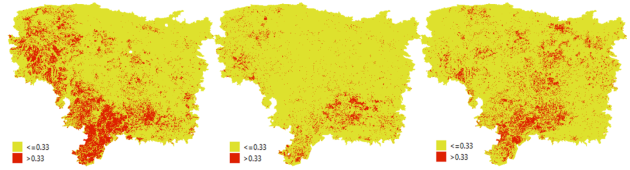

Fig. 5. Sunamganj NDVI different from left to right 2019,2020 & 2021

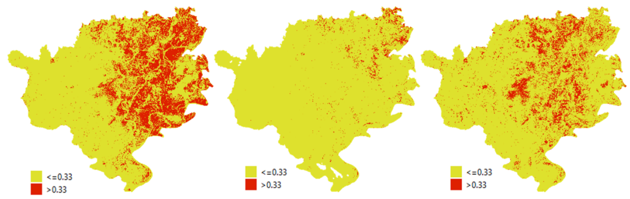

Fig. 6. Kisorganj NDVI different from left to right 2019,2020 & 2021

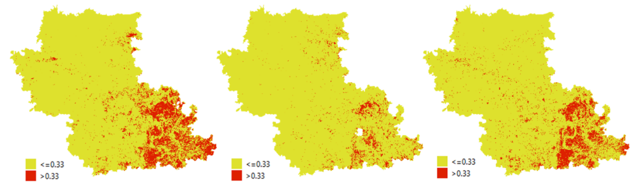

Fig. 7. Netrokona NDVI different from left to right 2019,2020 & 2021

subsection, we verify these outcomes with field-level interview with corresponding farmers.

2) Verify NDVI different as Ground Truth: As we have seen from [15], NDVI can monitor rice phenology. But we need to be sure about our NDVI difference to use it as the ground truth of the deep lab v3+ model. For that, we need to go to each pinpoint location.

To do this, we selected two districts, Sunamganj and Kisorganj. Because from section 3.4.1, we can see a similar pattern of NDVI different images of all districts. Suppose we can confirm Sunamganj and Kisorganj NDVI's different areas are rice field and affected due to hailstorms in 2019 and heatwave in 2021. In that case, we can also take Netrokona's NDVI different as correct and use all these NDVI different images as ground truth.

We randomly picked 30 points on Sunamganj and Kisorganj. Then by using their latitude and longitude, we found their address by reverse geocoding API. Here we use google map reverse geocode api & barikoi reverse geocode api.

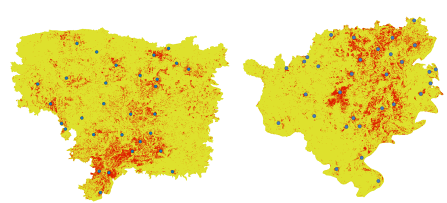

Fig. 8. 2021 before and after NDVI different of Sunamganj and Kisorganj with 30 sparsely selected points

From these 30 places, we chose ten places to visit at

Sunamganj and Kisorganj. Table II presents selected 10 places for Sunamganj & Kisorganj

TABLE II
SELECTED PLACES

Latitude	Longitude	Address
25.03127366	91.40633625	Godhar, Molla Para, Sunamganj Sadar Thana, Sunamganj
25.06882737	91.31783475	Dharerpar, Palash, Bishwambarpur Thana, Sunamganj
25.11783779	91.24608894	Amuria, Dakshin Badaghat, Bishwambarpur Thana, Sunamganj
25.07634649	91.54067507	Balijuri, Paikurati, Dharmapasha Thana, Sunamganj
25.02162867	91.1344541	Boala, Beheli, Jamalganj, Sunamganj
25.00367912	91.27979931	Damodarpur, Sachna Bazar, Jamalganj, Sunamganj
24.8140884	91.23486263	Rafinagar, Rafinagar, Derai Thana, Sunamganj
24.81346006	91.33952291	Kadmatoli, Rajnagar, Derai Thana, Sunamganj
24.67946683	91.25543025	Sultanpur, Bahara, Sulla, Sunamganj
24.67431445	91.29120366	Perarpar, Bahara, Sulla, Sunamganj
24.29882252	90.94981902	Gurai, Gunday, Nikoli, Kishoreganj
24.49659909	90.9734382	Chandrapur, Chowganga, Itna, Kishoreganj
24.57129475	91.08279046	Etna, Kishoreganj
24.54631292	91.15907587	Mriga, Itna, Kishoreganj
24.33220732	91.04755473	Kargaon, Castile, Ashtagram, Kishoreganj
24.30586285	90.81647285	Dhanki Para, Mumurdia, Katiadi, Kishoreganj
24.50567203	90.79288206	Maiz Khapan, Maiz Khapan, Kishoreganj Sadar Thana, Kishoreganj
24.47453559	90.83024692	Bhati Manoharpur, Kadir Jangal, Karimganj Thana, Kishoreganj
24.37941162	90.78739173	Jashiyil, Chaudsate, Kishoreganj Sadar Thana, Kishoreganj
24.44701016	91.06274823	Mussoorie, Gopadighi, Mithamain, Kishoreganj

We mainly focus on these questions at each point:

- Was there a paddy field? (This question is to verify if we can successfully recognize paddy field pattern from Sentinal-2A image)
- If yes, then is that boro/any paddy?
- Was the field of the circle affected by the heatwave in 2021 April and if yes, then how much?
- Was the field of the circle affected by any natural disaster in 2020 and if yes, then how much?
- Was the field of the circle affected by a hailstorm in 2019 and if yes, then how much?

In most of these areas, we went by motorcycle, battery autorickshaw & speed boat. At Sunamganj, we faced lots of trouble because of rain & poor transportation system. Sunamganj has no communication with its thanas. For this, going to anywhere cost us lots of money, time, and physical and mental pressure. But at Kisorgonj, there is a very good transportation system which helped us a lot. Nevertheless, people were very helpful in both areas. They provided us with pieces of information which we needed.

At all places, we talked with farmers, and they gave us similar kind of information. We found that-

- All selected ten places were rice fields. They always cultivate rice on them. At that time of the year, they grow Boro.
- For 2021 they all said they faced boro crop loss due to heatwave. They told their crop was burnt by hot air.
- In 2020 they did not face any vast kind of natural disaster and got very good Boro production.
- For 2019 Few of them can't recall 2019, but most of them said about hailstorms. Even they told the hailstorm had a much more devastating effect on the crop than 2021's heatwave. Even some of them freed their livestock on their paddy field because all crops were destroyed; they had nothing to do with them without feeding them to their animals.

Fig. 9. Interviewing people

From this ground level evaluation, we understand that our NDVI Different is indicating crop loss region correctly. So, it can be used as the ground truth for the segmentation model.

IV. EXPERIMENTAL SETUP

A. Export Sentinel 2 images from Google Earth Engine (GEE)

Heatwave swept over Bangladesh on April 4, 2021. That means if we want to get an idea about crop loss, we need to collect sentinel-2 images before April 4 and after April 4. But we faced a big obstacle because most of the time Bangladesh's sky is covered with clouds. Though we used sentinel-2 cloud mask but it is not very much effective for heavily covered with cloud. So, we need to set our date range strategically.

For better understanding, we need to collect all years of images that are available at the google earth engine at that period. (Before April 4 and after April 4) of Sunamganj, Kisorganj and Netrokona. We are able to find only three years' images of sentinel-2 at google earth engine. Those are 2019,2020 and 2021. All images were in GeoTIFF format. We exported them at a scale 10 meters per pixel. At Table III presents the before and after image dates of Sunamganj, Kisorganj and Netrakona.

B. Input image

We want to see if the RGB difference and FCI difference can be used to recognize the crop loss region by Deeplab V3+. So, for the input image, we exported the RGB difference between before and after and the FCI difference between before and after from the Google earth engine. After exporting the images from the google earth engine, we opened them with Qgis. We then exported the rendered images. We got a total of nine RGB

TABLE III
COLLECTED IMAGE DATES

Area	1st image date	2nd image date
Sunamganj	13 March,2019	27 April,2019
Sunamganj	12 March,2020	26 April,2020
Sunamganj	12 March,2021	26 April,2021
Kishorganj	08 March,2019	27 April,2019
Kishorganj	12 March,2020	26 April,2020
Kishorganj	12 March,2021	26 April,2021
Netrakona	13 March,2019	27 April,2019
Netrakona	12 March,2020	26 April,2020
Netrakona	12 March,2021	26 April,2021

Different images and nine FCI Different images. That means three RGB Different images and three FCI Different images for each district.

RGB : True color composite uses visible light bands red (B04), green (B03) and blue (B02) in the corresponding red, green and blue color channels, resulting in a natural-colored result [19]. This is a good representation of the earth surface as humans would see it naturally.

FCI : The false color infrared band combination is meant to emphasize healthy and unhealthy vegetation. By using the near-infrared (B8) band, it's especially good at reflecting chlorophyll content found in green plants. This is why in a false color infrared image, denser vegetation is red.

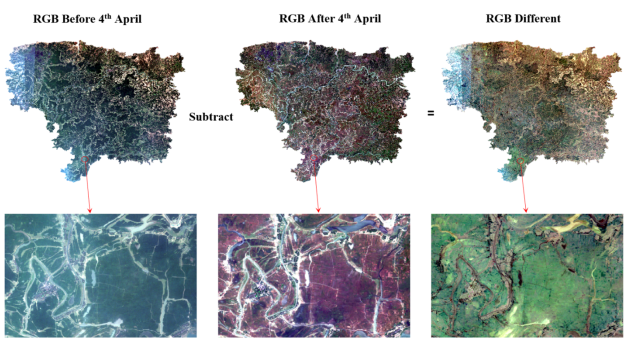

Fig. 10. Illustration of RGB Different. As an example, we took 2021's RGB Before 4th April and RGB After 4th April of Sunamganj. We can see that RGB Before image is greener than RGB After which indicates there is some loss of vegetation at RGB After

At figure 13,14,15,16,17 and 18 we will see RGB and FCI Different for Sunamganj, Netrokona & Kisorganj.

C. Pre-Processing

1) 4-channels to 3-channels: Rendered Images of qgis were four-channel rasters. The first three were red, green & blue respectively. The last one was the alpha channel. We removed the alpha channel and concatenate red, green and blue channels by using python gdal library. We set projection and set geo transform as the original image. For that, our latitude and longitude information were reserved at our new three-channel rasters.

2) Split raster to feed model: The original image is split into 256x256 to feed into the network. For this, we first zero-padded our images by using gdal. Then split them into

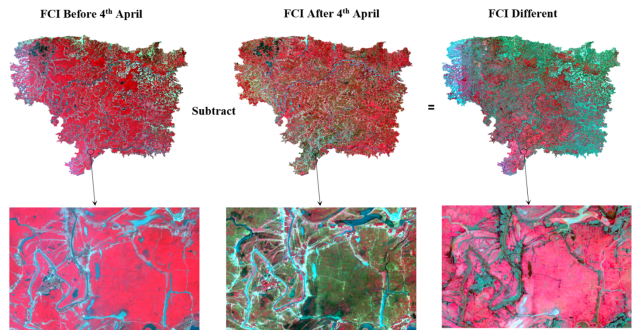

Fig. 11. Illustration of FCI Different. As an example, we took 2021's FCI Before 4th April and FCI After 4th April of Sunamganj. We can see that FCI Before image is redder than FCI After which indicates there is some loss of vegetation at FCI After

Fig. 12. Sunamganj RGB different 2019,2020,2021

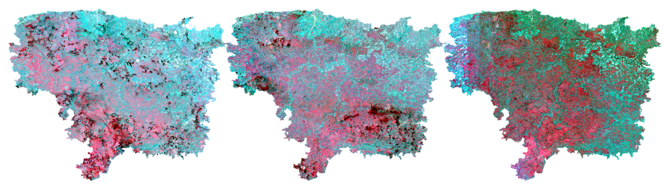

Fig. 13. Sunamganj FCI different 2019,2020,2021

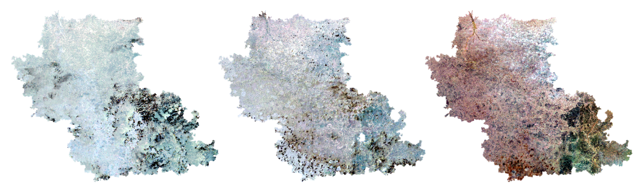

Fig. 14. Netrokona RGB different 2019,2020,2021

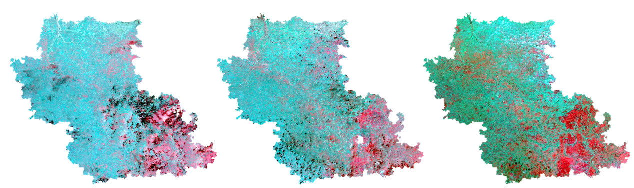

Fig. 15. Netrokona FCI different 2019,2020,2021

256X256. As an example, Sunamganj's 2021 RGB different image's original dimension was 8987X7108. We zero-padded that for 256X256, which was 9216X7168. Then we split that image.

All split images were in GeoTIFF format. As we split our images, so from a single image, we have 1008 GeoTIFF for

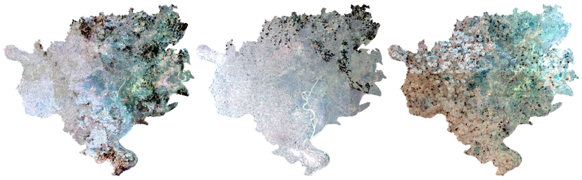

Fig. 16. Kisorganj RGB different 2019,2020,2021

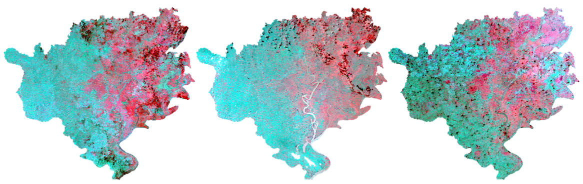

Fig. 17. Kisorganj FCI different 2019,2020,2021

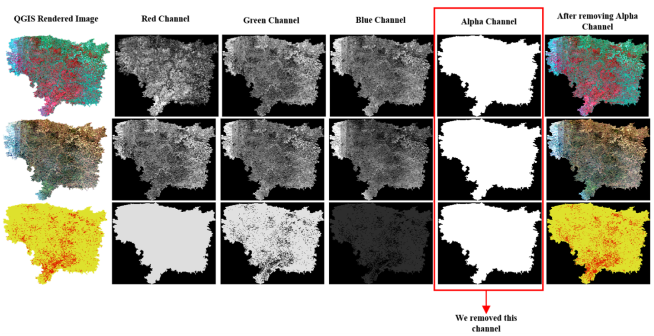

Fig. 18. Illustration of removing the Alpha channel from Qgis rendered image

Sunamganj, 924 GeoTIFF for Netrokona and 810 GeoTIFF for Kisorganj. We have three years of data for each district. So in total, we got 3024 split images for Sunamganj, 2772 for Netrokona and 2430 for Kisorganj. We also mapped each split image with corresponding ground truth, in this case, which corresponds to split NDVI different GeoTIFF. For mapping, we keep naming in such a way that we can get the ground truth for the corresponding image after sorting them.

D. Class Label

We can see that our NDVI difference has mainly three colors. Black is in the background, red for the crop loss area and yellow for rest. So, for our segmentation, we have three classes. We declared our classes in the CSV file. In our model, we read these classes from that file.

TABLE IV
CLASSES AND THEIR COLORS

Class Name	r	g	b	Color Name
background of the image	0	0	0	Black
crop compromised area	222	33	0	Red
rest of the areas	222	225	45	Yellow

E. Train, Validation and Test Splits

We have three districts' data as each district has three years of data. So, we have a total of nine images. But we have split our images into 246X246. So now, we have a total of 8226 GeoTIFF images. We will use Sunamganj's data which is 36.76% of our total dataset, as our train dataset, Netrokona's data which is 33.70% of our total dataset, as our validation dataset & Kisorganj data, which is 29.54% of our total dataset as our test dataset.

F. Evaluation Metrics

IoU : We have calculated Intersect over Union (IoU) and from the model's prediction and ground truths over test image pixels. IoU is calculated by dividing the area of overlap by the area of union. We compute the area of overlap in numerator and the area of union in denominator.

$$IoU = \frac{Target \cap Prediction}{Target \cup Prediction} = \frac{TP}{TP + FP + FN}$$

Mean IoU : It means IoU average all over the classes. First, we calculated IoU by using the above formula for each class. In this case, for three classes. Then we divided by the number of classes. We used this at our testing result evaluation.

Micro IoU : Unlike mean Iou we calculate overall IoU for our model. We used micro IoU at training and validation phase. As an example in this experiment, we calculated micro iou by using below formula.

$$MicroIoU = \frac{BackgroundTP + LossTP + OkTP +}{BackgroundTP + LossTP + OkTP + BackgroundFP + LossFP + OkFP + BackgroundFN + LossFN + OkFN}$$

BackgroundTP means Background True positive. The background pixels which our model correctly predicted.

BackgroundFP means Background False positive. The other pixels which our model wrongly predicted as background pixels.

BackgroundFN means Background False negative. The background pixels which our model wrongly predicted as other classes' pixels.

LossTP means Crop compromised area True positive. The crop compromised area pixels which our model correctly predicted. Here red colored pixels.

LossFP means Crop compromised area False positive. The other pixels which our model wrongly predicted as crop compromised area pixels.

LossFN means Crop compromised area False negative. The crop compromised area pixels which our model wrongly predicted as other classes' pixels.

OkTP means Rest of the area True positive. The area other than background and crop compromised area which our model correctly predicted. Here yellow colored pixels.

OkFP means Rest of the area False positive. The background and crop compromised area which our model wrongly predicted as rest of the area.

OkFN means Rest of the area False negative. The rest of the area pixels which our model wrongly predicted as other classes' pixels.

G. Augmentation

Though after splitting, we have lots of data for training. But from augmentation, we can achieve stronger generalization ability. We usually augmented our data by flipping, rotating, panning etc [16]. We augmented our train data as Horizontal Flip, Vertical Flip and Random Rotate 90 degrees with a probability of applying one of these transforms 0.75. Here we use albumentations which is a fast and flexible image augmentation library.

H. Post-Processing

After getting output from Deeplab V3+, we set the same geotransform & projection to output images as our input image. We do that by using python's Geospatial Data Abstraction Library (GDAL) and saving those split rasters. After all split image prediction, we merged all splitted images to one raster. Now we have one whole geo tiff predicted mask for one RGB or FCI different image.

V. Experiment & Result

We used RGB and FCI difference images as input in our experiments. We applied augmentation to our train input data and corresponding ground truth mask. We used dice Loss as our loss function. We have used resnet101 as an encoder & softmax2d as our activation function. As an optimizer, we used the Adam algorithm. Our learning rate was 0.0001. For the training dataset, our batch size was 16 and for the validation dataset, our batch size was 1. In both cases, the number of worker was 2. We ran our model for 110 epochs. We saved our model when we got a better micro IoU score for validation dataset. Our training took almost 4.30 hours. After training, we predicted our split test images and stored them. Later we merged them to get year-wise result. For all experiments, we used Colab pro.

We perform following experiments:

1) Train, Validate, and Test with RGB difference images.
2) Train, Validate, Test with FCI difference images.

For RGB difference images, our best micro IoU score for the validation dataset was 0.9581 on epoch 87. At that time, the dice loss was 0.02386 for the validation dataset and for the training dataset IoU score was 0.9432 and the dice loss was 0.02964. This was our saved model for RGB.

Fig. 19. Training vs Validation dice loss for RGB images

TABLE V
For RGB Training and Validation mean IoU and dice loss for ten multiple epochs

Epoch	Training Micro IoU	Training Dice Loss	Validation Micro IoU	Validation Dice Loss
10	0.912923	0.048496	0.561067	0.353111
20	0.924010	0.040592	0.953634	0.027001
30	0.928520	0.037766	0.954002	0.026720
40	0.929587	0.037100	0.954985	0.025995
50	0.932619	0.035400	0.956717	0.024712
60	0.937782	0.032634	0.956113	0.025273
70	0.939451	0.031691	0.956238	0.025132
80	0.942313	0.030144	0.956710	0.024872
90	0.943163	0.029645	0.956932	0.024635
100	0.943615	0.029385	0.957089	0.024571

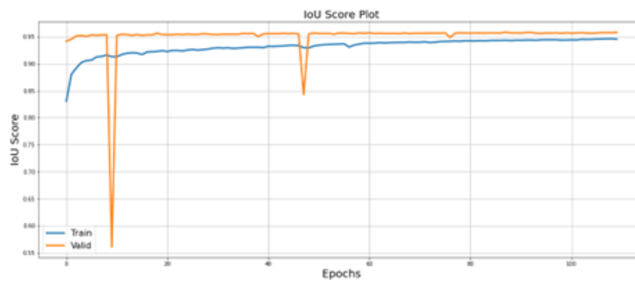

Fig. 20. Training vs Validation micro IoU score for RGB images

At figure 19 & 20, we can see some spikes for the validation dataset in RGB. As our batch size is 1 for validation, so spikes are expected. Because in each epoch, start gradient descent with a random data point and pick the following data points randomly. We see these spikes particularly for RGB because RGB images were noisier than FCI images.

For FCI different images, our best IoU score for the validation dataset was 0.9697 on epoch 80. At that time loss was 0.01659 for the validation dataset and for the training dataset IoU score was 0.9474 and loss was - 0.02741. This was our saved model for FCI.

TABLE VI
For FCI Training and Validation mean IoU and dice loss for ten multiple epochs

Epoch	Training Micro IoU	Training Dice Loss	Validation Micro IoU	Validation Dice Loss
10	0.927010	0.039986	0.964434	0.020339
20	0.925422	0.039961	0.964333	0.020074
30	0.932096	0.035829	0.966152	0.018836
40	0.937801	0.032764	0.967820	0.017840
50	0.941919	0.030517	0.967423	0.018096
60	0.943727	0.029581	0.967450	0.018018
70	0.944548	0.028968	0.963782	0.020257
80	0.947101	0.027582	0.969351	0.016861
90	0.947312	0.027444	0.968636	0.017281
100	0.949916	0.026066	0.967956	0.017673
110	0.950806	0.025548	0.968944	0.017055

The micro IoU score was a little better for FCI at the training phase. However, the difference is minimal.

At the testing phase, we have three years of data. First, we describe the overall performance for RGB and FCI difference

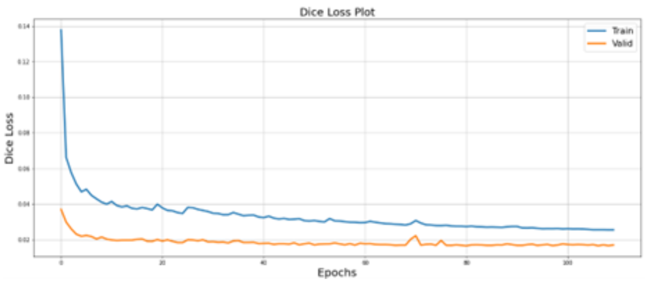

Fig. 21. Training vs Validation dice loss for FCI images

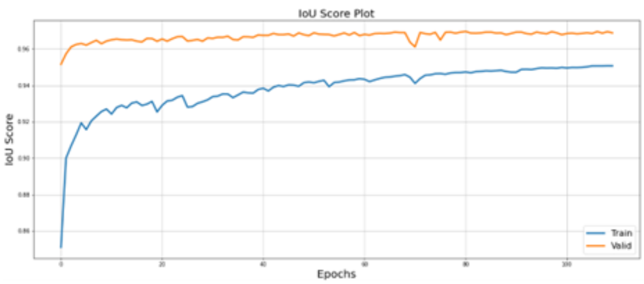

Fig. 22. Training vs Validation micro IoU score for FCI images

images in test data; later, we analyze separate performance for each year's image for test data. We provide the mean IoU and F1 here to compare the performance.

TABLE VII
OVERALL EVALUATION OF RGB AND FCI DIFFERENCE IMAGES IN TEST SET

Type	**Matric**	**Background of the image**	**Crop compromised area**	**Rest of the areas**	**Mean**
RGB	Mean IoU	0.9991	0.4085	0.9045	0.7707
	F1	0.9995	0.5801	0.9498	0.8431
FCI	Mean IoU	0.9994	0.5154	0.9162	0.8103
	F1	0.9997	0.6802	0.9563	0.8787

TABLE VIII
EVALUATION OF RGB AND FCI DIFFERENCE IMAGES OF TEST DATA FROM 2019

Type	**Matric**	**Background of the image**	**Crop compromised area**	**Rest of the areas**	**Mean**
RGB	Mean IoU	0.9990	0.4936	0.8452	0.7792
	F1	0.9995	0.6609	0.9161	0.8588
FCI	Mean IoU	0.9993	0.6140	0.8770	0.8301
	F1	0.9996	0.7608	0.9344	0.8983

At Table VII we can see mean IoU is 0.77 for RGB and 0.81 for FCI images. If we look particularly at crop compromised

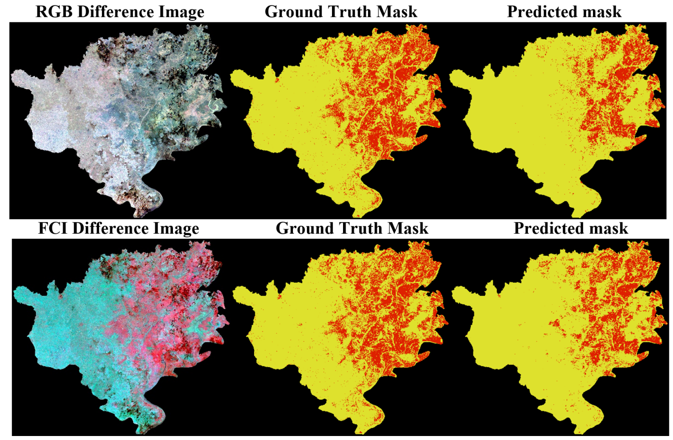

Fig. 23. 2019's RGB and FCI difference images with ground truth mask and predicted mask

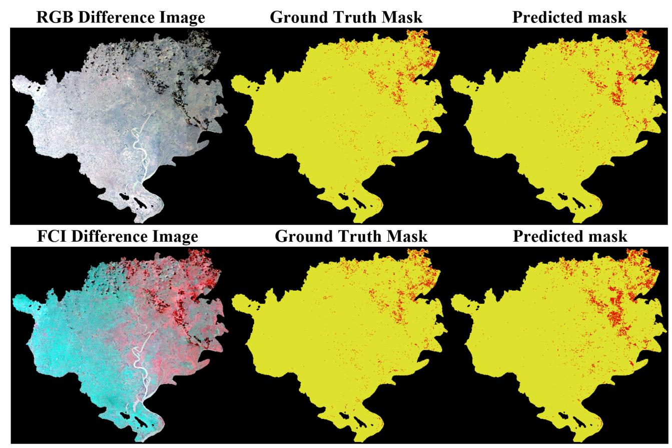

Fig. 24. 2020's RGB and FCI difference images with ground truth mask and predicted mask

TABLE IX
EVALUATION OF RGB AND FCI DIFFERENCE IMAGES OF TEST DATA FROM 2020

Type	**Matric**	**Background of the image**	**Crop compromised area**	**Rest of the areas**	**Mean**
RGB	Mean IoU	0.9989	0.4459	0.9757	0.8068
	F1	0.9994	0.6168	0.9877	0.8680
FCI	Mean IoU	0.9993	0.3998	0.9654	0.7881
	F1	0.9996	0.5712	0.9824	0.8511

area's IoU score, we can see for RGB 0.41 and for FCI, it's about 0.52.

By analyzing data from Table VIII,IX X for the heatwave in 2021, there is a very low IoU score at compromised areas both for FCI and RGB. On the other hand, in 2020, there is a lot of false-positive for loss area's pixel at FCI. Here, RGB did a much better job. In the hailstorm affected year 2019 affected area's IoU score is greater than other years. For RGB

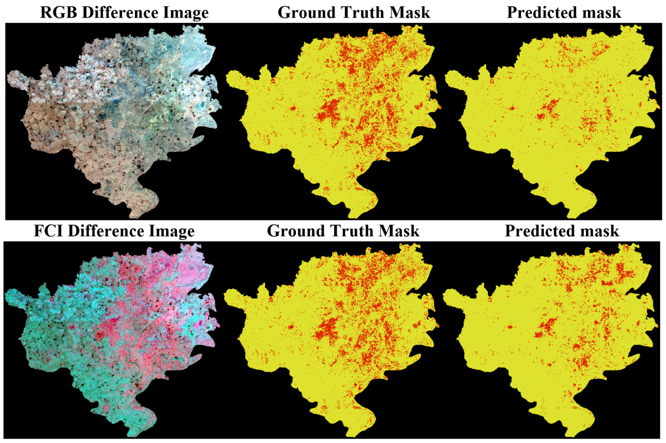

Fig. 25. 2021's RGB and FCI difference images with ground truth mask and predicted mask

TABLE X
EVALUATION OF RGB AND FCI DIFFERENCE IMAGES OF TEST DATA FROM 2021

Type	**Matric**	**Background of the image**	**Crop compromised area**	**Rest of the areas**	**Mean**
RGB	Mean IoU	0.9995	0.2414	0.8859	0.7090
	F1	0.9997	0.3890	0.9395	0.7761
FCI	Mean IoU	0.9995	0.3850	0.9003	0.7616
	F1	0.9997	0.5559	0.9475	0.8344

it is 0.49 and for FCI it is 0.61.

VI. CONCLUSION

This paper proposes an approach to develop ground truth data for paddy loss detection. It shows that performing Sentinal-2's NDVI subtraction before and after a disaster can be a way to develop ground truth of paddy loss. The ground truth can use to train various segmentation models. After the training, RGB and FCI images seem effective for automatic segmentation of paddy loss area. Though our IoU score was not very good. For the loss area's IoU, we got a better result for FCI than RGB. Another observation is, from the year-wise segmentation result, we found that result was not the same for paddy loss for the heatwave in 2021 and paddy loss for hailstorm in 2019. As we know, hailstorms and heatwaves affect paddy field in different ways, the different outcomes are expected. However, RGB & FCI both do better for hailstorms. We can tell for very destructive disasters for paddy filed like hailstorms, tornado, cyclone, flood; we can use RGB in these cases. Our research is prone to heavy cloud-covered areas. In future, we will do further study to develop the segmentation model with Synthetic Aperture Radar (SAR) data that are not affected by clouds.

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