Prediction of poverty as a consequence of climate change impacts using deep learning: A review

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Abstract: With the advancement of Machine Learning and Deep Learning technologies, the field of Computer Science is dealing with the real-world challenges. Climate change is one of the serious problems that the world is facing currently, and climate of India has been negatively affected too. There has been an increase in precipitation, and a rise in the water levels in the rivers and the seas which led to an increase in incidents like floods, hurricanes, and storms. Its effects are not just restricted to one but on many spheres, for instance healthcare, infrastructural change due to varying terrain, natural calamities etc. One of the major challenges, that is poverty, has also been affected due to Climate Change. Since independence the Government of India has been working continuously to reduce poverty as a challenge and threat to the economy. But nowadays it has been observed that the climate change is also impacting poverty in certain ways. These socioeconomic problems are a big challenge, especially for the developing countries. In this paper, we will talk about the impacts of climate change on poverty in the context of India with the help of different emerging technologies that is artificial intelligence and computer vision. We will look for the ways to reduce the cause of poverty so that growth and development does not get hampered due to the environmental issues. Our goal in this review paper is to investigate a relationship between the Poverty and Climate Change impacts. Climate Change impacts here refers to the irregular pattern of rainfall or change in the frequency of floods and increase in carbon dioxide emissions. To find a relationship, we have reviewed several poverty and climate change research papers and analyzed their content. In the end we have gathered the required dataset for both Poverty and Rainfall and tried to study the trend between the two using a Big Data visualization tool that is Tableau. This will provide us a base for our further research study in prediction of Poverty with Climate Change Impact as a developmental parameter.

Index Terms: Poverty Prediction, Climate Change Impacts, Machine Learning, Deep Learning, Big Data Analysis.

I. INTRODUCTION

Climate change and Poverty issues are one of the biggest challenges globally. All countries in the world are coming together to act and take collective initiatives for the same. Joint efforts are being made to combat climate change and eradicate poverty. Efforts and Policies are being made in building a sustainable environment for our future generation. In 2015, United Nations has set up 17 goals, which are interlinked to each other to make a sustainable development. It aims to fulfill all the goals till 2030. Out of those 17 goals, Goal 1 aims to end poverty and goal 13 talks about climate action [1]. India has also been consistently making efforts to eradicate poverty and combat climate change to reach its target of sustainability. Various schemes have been introduced at the national level and international levels in the form of global, regional and community initiatives and India has been an active participant in the same. [2]

In the past few years, With the scope of machine learning and data science, the data for poverty was extracted through the help of satellite imagery and geospatial data, although initially the nighttime light images were being used to make estimation of poverty as there is a correlation between the economic activity and nightlight intensity but now with the advancement of image processing techniques, the use of High Resolution Imagery (HRI) and deep learning has been used in studies to evaluate socioeconomic development and each type of satellite data is different and has its own pitfalls for instance some have less level of information required for a particular study [3,4]. If more structured form of geospatial data is available, an affective Econometric model can be made, and estimation can be performed which can help the policymakers to make action initiatives accordingly. Some Other traditional methods for the prediction of poverty includes various socioeconomic surveys that are done based upon different parameters such as income criteria and household expenditure and so the measure based on expenditure is taken into consideration because a certain household is considered poor if it spends less than a certain amount monthly on food and non-food items and also the United Nations development program tells about different challenges which comes with poverty such as public budget financing, increase in inflation and scarcity of resources. [5,6]. The criteria of deciding the poverty line depends upon choosing the income/expenditure and the gap is measured based on different estimates collected from National Service Scheme Surveys and National Accounts Statistics [6,7]. Other recent approaches include using mobile phone data to estimate poverty show promise but could be difficult to scale across countries given their reliance on disparate proprietary data sets [8]. But the method of collecting data through surveys are extensive and requires more of manual effort and monetary resources which may further lead to ineffective implementation and even wasteful expenditure and so Satellite imagery is one of the cost-effective data sources and provides a wealth of information. [9-13] While this technique has shown promise in enhancing the existing country-level economic production statistics, it appears less capable of distinguishing differences in economic activity in areas with populations living near and below the international poverty line. In these impoverished areas, luminosity levels are generally also very low and show little variation making nightlights potentially less useful for studying and tracking the livelihoods of the very poor.

For the climate change analysis, it has been observed that the Supervised Learning is one of interesting techniques for the atmospheric scientists and the methods such as the Decision Tree, Artificial Neural Network, Deep Learning and Support Vector

Machine is used which has solved complex issues in the weather forecasting. [14]. Various parameters have been considered which affects the climate change in a major way in India so that action initiatives can be taken in that direction and to name a few of them parameters are Forest area, Agricultural irrigated land, Access to electricity, Carbon dioxide Emissions from gaseous Fuel Consumption etc. [15]. Earth System related measurements such has the Earth System Model [ESM] is used for creating linkages between the locations, time and quantities in the datasets and ESM's uses the concentration of atmospheric greenhouse gases (GHS's) and model their interaction thus predicting the climate change [16-18].

In this paper we will try to relate both the issues and will consider the work done on that previously. By taking all the aspects and techniques used in the research papers, our aim would be to find out how poverty is affected due to the climate change impacts as one of the developmental parameters. We will visualize the datasets of poverty and climate change and try making a relationship in between the two and find out how the changing environment affects the socioeconomic problems of the Country so that it helps the policymakers in defining the poverty and issues which comes along the poverty such as human displacement, unemployment, and hunger due change in climate.

II. Related Reviews

Geospatial data can play a crucial role in poverty prediction in India by providing valuable information about the spatial distribution of poverty. Some ways to use geospatial data for poverty prediction in India include:

Satellite imagery: Analyzing high-resolution satellite images to identify features such as housing quality, infrastructure, and access to resources, which can be indicative of poverty levels.

Geospatial mapping: Mapping poverty levels in different regions using GIS (Geographic Information System) tools, combining socio-economic indicators with geospatial data to provide a more comprehensive view of poverty.

Nighttime light data: Using nighttime light intensity data to infer economic activity and poverty levels, as areas with higher levels of nighttime light are typically associated with higher levels of economic activity and lower levels of poverty.

Mobile phone data: Analyzing mobile phone usage patterns and call detail records to infer poverty levels, as phone usage patterns can be strongly correlated with socio-economic status.

It's important to validate and interpret the results of these analyses carefully, considering factors such as data quality and representation, and taking onto account local context and the specific needs and challenges of different regions.

III. Literature Review for poverty Prediction

The research methodology of this study is divided into three phases. The first phase is dataset phase that starts by identifying data examined in this study and analyzing its source, details, and quantity. This is followed by the second phase which is Pre-processing phase which aims to prepare the data for processing. Pre-processed data was then used in the third phase to establish a comparative analysis among the different techniques to identify the best machine learning and deep learning techniques.

Village-level poverty identification using machine learning, high resolution images and geospatial data [3] -

In this research study related to the prediction of poverty, the data source which has been used is the census data and the remote sensing images and geospatial data including the HRI, POI (Point of Interest), OSM (Open Street Maps) AND DSM (Digital Surface Model) data. The census data incudes the total and poor population of each village and it is provided by the local government. So, the approach which follows is by first identifying the explanatory variables and then generating the explanatory variables from the remote sensing images and geospatial data. The explanatory variables which have been used to predict poverty in a village is access to facilities and services, Agricultural production conditions and Socioeconomic conditions.

Data processing is the first step to generate the explanatory variables from the remote sensing images and geospatial data and so an image-based classification in E-cognition developer is used with 50 image scenes with a grid size of 10 Kilometers by 10 kilometers. The classification has been done using support vector machine (SVM) classifier. In addition to HRI which include red, green, and blue, the NDVI (Normalized Difference Vegetation Index) was calculated using the red (RED, color) and near-infrared (NIR) as shown in the formula –

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

Combining the land use map, the point of interest (POIs) of the schools, hospitals and markets and the Open Street maps (OSM) road type data the distance cost to the nearest Schools and Hospitals was calculated using cost-distance tool ArcMap software.

For measuring the village disparity, Thiessen polygons were used, and the CV (Coefficient of variation) of the Thiessen polygon is defined by the formula where, μ (mu) is the mean area of a village and σ (sigma) is the standard deviation-

$$CV = {}^{\sigma}/_{\mu}$$

The measurement of the spatial distribution of village settlements using Thiessen polygons also provided valuable information for identifying poverty. In the end, a relationship was modelled between the poverty incidence and explanatory variables using a machine learning Algorithm called the Random Forest Algorithm. This algorithm uses the technique of "bagging" to integrate multiple decision trees and the final prediction is the average value or majority vote of the prediction of all the individual trees. Random Forest also provides the importance of the explanatory variables. The results demonstrate that the explanatory variables generated from the remote sensing images and geospatial data yielded an accuracy of 54% and for the identification of poor category the prediction accuracy of 72%. Thus, the approach can help us identify the poorest of poor regions restricted by backward public services.

Predicting Poverty Using Geospatial Data in Thailand [4]

In the next research study, we examined that satellite imagery and geospatial data can provide wide range of case studies showcasing various applications. Many studies till date have found a profound relationship between the intensity of night light and data like GDP, electricity consumption, inequality, and infant mortality rate. The NTL (Nighttime light) data is compiled through Defense Meteorological Satellite program (DMSP) in Thailand. The NVDI on the other hand represents the spatiotemporal pattern of forest and cultivated areas and is considered conventional indices used in remote sensing analysis of vegetation. A correlation between the urban expansion and decreasing NVDI has been documented and statistical relationship between the NDVI and spatial distribution of income inequality has been verified. Land surface temperature (LST), NDWI (Normalized difference water index), NDSI (Normalized Difference Soil Index) and NDBI (Normalized Difference Built Index) are several geospatial indicators used by various researchers. The OpenStreetMap database also features the presence of roads, rivers, built up areas and point of interests (POI's) enabling the relationship between the geographical indices and socioeconomic conditions. Some studies have also found that OpenStreetMap can provide distribution of population and economic activities. Some studies have additionally also found significant relation between the rainfall on income, human capital, and economic activity in the developing countries. Data on land surface temperature is another type of geospatial information used by researchers to predict poverty. In this study the data of NTL, LST, and NVDI along this OSM, GUF (Global Urban footprint), GHSL (Global Human Settlement Layer), the US Geological Survey and European Space Agency Land Cover has been used as the dependent variables for the further study. Satellite data from the Google Earth Engine and poverty data from the Multidimensional poverty Index (MPI) compiled by National Economic and Social Development Council and National Electronic and Computer Technology Centre is used.

For the data pre-processing task, which includes the transformation of spatial resolution, variable normalization, and data integration, four computational methods have been applied that is the Generalized Mean Square (GLS), and three other machine learning algorithms that is the neural network (NN), Random Forest (RF) estimation and support vector regression (SVR). The results show that Random Forest is the best prediction method, yielding an accuracy of more than 80%. The study also shows the integration of data, composed of the national surveys, geospatial information and satellite imagery can be of great help to predict the poverty of a region for the developing countries.

Poverty Classification Using Machine Learning: The Case of Jordan [5]

Further research study begins with the approach which consists of three main phases that is the Data pre-processing, Classification using 16 machine learning models and Handling of the Imbalanced Data (Random under sampling, Random oversampling Synthetic Minority Over-sampling Technique and class weights). The data is collected by the DoS (Department of Statistics) in different national household expenditure and income surveys are combined altogether and only common features are extracted. The dataset consists of 63,211 household with 47 features. For the data representability, the DoS followed stratified cluster sampling. Data collections are sampled using a systematic random sampling approach. But the major challenge in the dataset was that the data collected was highly imbalanced. Data pre-processing is an important stage, which improves the performance of the predictive model and thus can improve its accuracy. Here, the 17 categorical features need to be transformed into numerical format and hot encoding method has been used for the same. After encoding of categorical features, the dataset now consists of 96 features. Small portion of dataset is saved for testing purposes. Now, that all the features are not on comparable scale, it is important to put it on comparable stage.

The technique of spot-checking algorithm has been used here which corresponds to checking of machine learning algorithms that leads to useful results and determine which machine learning algorithm can be explored further. Here, 16 different classification algorithms were applied, and different algorithms are evaluated using stratified 10-fold cross validation. The performance of each algorithm is accessed using The F1 score is a commonly used metric in binary classification tasks that considers both precision and recall. It is the harmonic mean of precision and recall, and is calculated using the following formula:

F1 score = 2 * (precision * recall) / (precision + recall)

where:

Precision = true positives / (true positives + false positives)

Recall = true positives / (true positives + false negatives)

True positives (TP) represent the number of correct positive predictions, false positives (FP) represent the number of incorrect positive predictions, and false negatives (FN) represent the number of incorrect negative predictions.The F1 score ranges from 0 to 1, with a higher score indicating better performance. It is a useful metric for assessing the overall performance of a binary classification model. As a result, the top performing algorithms has been showed, out of which Light GBM and Bagged Decision Trees are the top two performing algorithms with f1-score around 80% and so these two algorithms were considered for considering the standardization technique.

Satellite data and machine learning tools for predicting poverty in rural India [6]

The satellite data for the next study has been extracted from an open source by the University of Michigan. The dataset is named as 'India Lights API (Application Programming Interface)' and it provided the data for a period of 20 years and for about 6,00,000 villages of India. India lights API provides data in JavaScript Object Notation format which is converted into an excel file format. For prediction of poverty, machine learning based supervised learning that is regression is used. For use of satellite data in machine learning for econometric analysis is of recent origin. It maximizes the prediction performance as it accounts the bias-variance trade-offs. The machine learning algorithms can handle non-linear relationships and the most frequent algorithm in empirical research is the Artificial Neural Network (ANN) and the ANN can be further classified based upon its architecture and learning algorithm. Night light data and income data are two different types of data, and a comparison has been made between both to compare data predicted from the different techniques. The approaches used to check are external checks and internal checks. Another method which uses the statistical tests like Kolmogorov-Smirnov test also compares the observed and predicted data. Apart from these methods, Root Mean Square Error (RSME) is also considered to be a useful to compare the prediction performance of the model. Both RSME and R-square methods has been used to compare the prediction performance of satellite night light data and per capita GDP (Gross Domestic Product) data. The results show a complex relationship between the night-light and poverty.

Multi-Task Deep Learning for Predicting Poverty from Satellite Images [7]

In another research study of poverty, the 2011 Census of India is utilized which includes the statistics about the number of households, type of roof, source of lighting and drinking water in the rural regions of India in the most populous state of India that is Uttar Pradesh. Google Geocoding API to obtain the coordinates of the center of the village is used and Google Static maps API to extract the images of the villages. For the prediction developmental Statistics, the prediction task is divided into 2 parts and 2 different models are made. The first task consists of training the model to predict the material of the roof, Source of lighting and source of drinking water as the inputs. For the second task, a model is made to predict the household income level using the outputs of the first model as the inputs. For the comparison purposes, a separate model is trained on the 2011 Census of India data. Hence, using the satellite imagery we can estimate income and poverty close to the ground values with less manual effort and monetary expenses.

Combining satellite imagery and machine learning to predict poverty [8]

In some of the research study, there has been demonstration of a novel machine learning approach for extracting socioeconomic data from high-resolution daytime satellite imagery. A multi- step "transfer learning" approach whereby a noisy but easily obtained proxy for poverty is used to train a deep learning model. To estimate these outcomes, the transfer learning pipeline involves three main steps. First, they have started with a convolutional neural network (CNN) model that has been pretrained on ImageNet, a large image classification data set that consists of labeled images. Despite being trained partially on nightlights, the model is on average substantially more predictive of variation in consumption and assets than nightlights alone. For expenditures, the model outperforms nightlights at nearly all points in the consumption distribution.

Machine Learning Approach for Bottom 40 Percent Households (B40) Poverty Classification [9]

The dataset for the next study comes from the National Poverty Data Bank called as 'eKasih' Which is centralized data bank in Malaysia. For this study, a total of 99,546 households records were used from three different states. The 'Waikato Environment for Knowledge Analysis (Weka)' version 3.8 software was used as a tool to perform the pre-processing task. Weka is a java-based machine learning software, developed by the University of Waikato, New Zealand. Weka contains various types of machine learning algorithms and operates on an open-source license. It also provides various visualization tools for data analysis and predictive modelling. Three classification algorithms are compared in this study, which are Naive Bayes, Decision Tree (J48) and k-Nearest Neighbors. Each classifier is tuned using different tuning parameters to produce high accuracy results. A series of experiments are conducted to get the optimal values of each classifier. The performance between the three classifiers is then evaluated and compared.

Estimation of Poverty Using Random Forest Regression (RFR) with Multi-Source Data: A Case Study in Bangladesh [10]

It has been said that NTL data can record artificial lights from human settlements at night and have been proved to have good ability to estimate various socioeconomic parameters such as GDP, population, electric power consumption, carbon dioxide (CO_2) emissions. In this study, implementation of RFR by using a Python package named scikit-learn is done. Firstly, they have standardized the input variables, that is, features extracted from multiple data sources, by removing the mean and scaling to unit variance. Secondly, backward elimination method was used to select variables that would offer the best predictive ability of the RFR model. Then they started the RFR model with all the variables and removed the least important variable at each iteration. If the OOB error of the model increased, they added this variable back to the model. And repeated this until no further improvement was observed on removal of variables. After that, they used the remaining variables to train the RFR model. When training the model, several parameters need to be determined. The values of parameters were determined by the grid search method using all the samples as the training data [10].

Predicting energy poverty with combinations of remote-sensing and socio-economic survey in India: Evidence from machine learning [11]

In developing countries Energy poverty describes the insufficient access to modern energy services such as lighting and powering appliances. It has been shown that the remote sensing data can help us understand and predict both energy and poverty. Predicting energy poverty from the multidimensional perspective using environmental remote sensing data and machine learning techniques has not yet been undertaken.

Impact of Climate Change on Rural Poverty Vulnerability from an Income Source Perspective: A Study Based on CHIPS2013 and Country-Level Temperature Data in China [12]

Energy poverty is somewhat different from poverty vulnerability. Energy poverty is in the low living energy use level, poor energy structure, weak energy use capacity and the resulting health and economic and social consequences. Energy poverty is usually found in the developing countries and regions. Here the study examines the impact of climate on the vulnerability of individual poverty using climate data and micro-research data (CHIPS 2013). The benchmark result has found that extreme temperatures help reduce poverty vulnerability. The same conclusion was found using the temperature median and mean.

IV. LITERATURE REVIEW FOR CLIMATE CHANGE

Climate Change Analysis using Machine learning [13]

Coming to the climate change research papers, there are so many ideas and projects about rainfall prediction, weather forecasting, temperature prediction. Some of those ideas are taken for the reference purpose. In this project we are mainly visualizing rainfall. For that the weather prediction-based ideas and projects are focused mainly. This concept is focusing only on rainfall. It doesn't provide any information about temperature or greenhouse gases.

Machine Learning in Weather Prediction and Climate Analyses-Applications and Perspectives [14]

Also, in the recent years there has been a growing interest in machine learning methods from post processing and bias correction of model forecasts. One of the most challenging problems with very high-resolution NWP model is related to the land-cover classification. Apparently used databases are available with coarse resolution and with numerous errors. CNN can be used to improve them with the help of Sentinel-2 satellite data, the CORINE land-cover and the Big Earth Net database.

Analysis of various climate change parameters in India using Machine learning [15]

Climate Change is one of the alarming problems faced by our Country and many studies have done the analysis of the various climate change parameters with machine learning. One of the recent studies shows prediction of some of these parameters for the year 2025,2030,2035. The paper shows in total of 65 climate change parameters out of which 17 were selected for the final prediction. To name a few parameters, they were Forest area, Agriculture irrigated land, Cereal yield, access to electricity, carbon dioxide emissions, methane emissions etc. For the task of data pre-processing, Panda's library is used. And normalization is done for the selected 17 parameters. It is also called Min-Max scaling.

After preprocessing, the data was passed through various regression algorithms that is the linear, polynomial, and exponential and the results were evaluated. The linear and polynomial regression is done using the sklearn library in python.

Deep Learning Based Forecasting of Indian Summer Monsoon Rainfall [16]

Forecasting of Indian Summer Monsoon Rainfall is also done using Deep Learning by various researchers. Short range forecasting of 1-3 days in advance is important as the high impact of weather conditions are prevailing with global warming. Here ConvLSTM network is used to develop a deep learning model for precipitation forecasting. ConvLSTM model uses the spatiotemporal information to generate the forecast. In this study two types of Geoscience data are used for the forecasting of precipitation. One of them is the ground based in-situ precipitation data of Indian Meteorological Department (IMD) and the other is the remotely sensed Tropical Rainfall Measuring Mission (TRMM) data which includes lighting Imaging Sensor, TRMM microwave Imager and Visible Infrared Scanner. The resolution of the data was 0.25 into 0.25.

For the task of data preprocessing, different techniques are used for both the datasets. For the IMD Dataset there are several undefined values which are assigned as 'NaN (Not a Number)'. So, identifying all the non-NaN points and normalizing them with the maximum value in the dataset was the first step. After that transformation was applied. The third step which followed was to apply zero to NaN in the rearranged dataset. In this way zero rainfall value was transformed to one. Network maps input to output in the exponential space and spatial structure of the data is preserved. Hence, spatial correlations can be learned. The LSTM networks has a forget gate, an input gate, an output gate with its weights in which it can control what information to retain and what to forget, thus learning long term associations. In the fully connected LSTM, the inputs and outputs are 1-D vectors transformed by weights through standard matrix multiplication. Thus, the model produced shows forecast reliable skill with observations up to 2 days only.

Machine learning and artificial intelligence to aid climate change research and preparedness [17]

Deep learning approaches uses a directed graph. Data are input at the base, transformed by hidden layers, and output at the top of the graph. Some recent applications of Deep Learning neural networks to climate sciences includes the dryland disturbance, inverse problems for remote sensing and replacing costly components of climate models. Another emerging concept is coming where neural networks utilize data to characterize short-term rainfall-runoff relationships constrained by prior knowledge of physical catchment attributes. Static but location specific modelled processes can include, parameterization of topography, soil properties and the land cover. Recent studies have done some emphasis on the drought warning as Droughts are high impact weather events, estimated to have a cost $1.5 billion globally between year 1998-2017 and representing 33% of the cost of weather hazards over that period.

Disaster and Pandemic Management Using Machine Learning: A Survey [18]

Some of the researchers have tried to define the economic impacts of the earthquakes. The idea behind the training of a model is to estimate the economic losses by looking at the business and structure loss, lifeline network disruption and spatial impacts that occurred due to the disasters. The key technology which was used for the estimation of damage was GIS and drives the state-of-art EPEDAT (Early Post-Earthquake Damage Assessment Tool) model. Although these models tell us the impact and cost of the climatic disasters, they do not tell us about the long-term impacts on the economy and its growth and development.

V. RESULTS AND DISCUSSION

It has been observed that the recent studies do not provide a direct link between poverty and climate change. Most of the recent studies have used Night light satellite images and day light High-Resolution Satellite images of specific regions/states for poverty estimation and prediction. High-Resolution images have an advantage over night light satellite images as night light images make it difficult to study the development of a region/state. High-resolution satellite images help for more accurate study of the land cover and development of a region/area and help in tracking the physical environment like land, water, air, vegetation, and the human footprint across the region. Climate change is one of the major factors that has impacted Human footprint and the physical environment. Climate change in an acute treat to the poor population of the world.

We aim to make experimental based claims to support that climate change is a factor of poverty. Also, to introduce climate change factors High resolution dataset in the already present poverty estimation methods. In this paper, we have used big data analytics tool that is tableau to support our goal. We have made a link between poverty, rainfall, average surface temperature and carbon dioxide emissions of different states in India to study the behavior and analyze the pattern of impact of Irregular pattern of rainfall, Temperature, and carbon dioxide emissions on poverty since last 30 years. We have segregated the data using tableau and have chosen two states for our analysis, Bihar; The poorest State of India and U.P.; the populous state of India. [19-21] We have observed irregular trends in different states for Head Count Ratio, Rainfall but average temperature was not much fluctuated. With temperature, rainfall is perhaps the most important factor in defining Climate Change. Excess rainfall can cause flooding and enormous property and crop damage. Still, a deficiency of rainfall can cause drought and crop failure. Rainfall is also the major source of energy that drives the circulation of the atmosphere. Rainfall trend is irregular in many states, we have shown two states for better analysis. The tabular representation can be seen in Table 1 and Table 2.

Table 1 Shows Head Count Ratio, Average Temperature in Kelvin (K), Rainfall (in Millimeter), Co_2 Emissions (in $MtCO_2e$; stands for megatons of carbon dioxide equivalent) Per Capita for Bihar [19-23]

State	Bihar			
year	Head Count ratio	Average Temperature in K	Rainfall (In Millimeter)	CO_2 Emission ($MtCO_2e$) per Capita
1993	60.5	298.4	12084	0.20
2004	54.4	298.94	13538	0.21

2009	53.5	299.56	8895	0.27
2011	33.7	298.78	10973	0.32
2015	51.91	298.45	8727	0.31

Table 2 Shows Head Count Ratio, Average Temperature in Kelvin (K), Rainfall (in Millimeter), Co_2 Emissions (in $MtCO_2e$; stands for megatons of carbon dioxide equivalent) Per Capita for U.P. [19-23]

State	Uttar Pradesh			
year	Head Count ratio	Average Temperature in K	Rainfall (In Millimeter)	CO_2 Emission ($MtCO_2e$) per Capita
1993	48.4	298.7	8029.5	0.31
2004	40.9	299.36	10718.5	0.46
2009	17.1	299.74	5796	0.54
2011	14	299	7792.5	0.78
2015	37.79	299	5930.5	0.77

From Table 1 and Table 2, we can see temperature does not have much fluctuation, so it is very difficult to see poverty change only based on temperature. To see change in poverty, we can compare headcount ratio with rainfall and Carbon dioxide Emissions. The headcount ratio is a useful indicator for poverty analysis. The headcount ratio, also known as poverty headcount, measures the proportion of the population living below a certain poverty line. It provides a simple and easily understandable way to determine the extent of poverty in each area. Irregular patterns of rainfall, that is a consequence of climate change, can impact poverty levels as it affects agriculture, which is often a major source of income for the poor in rural areas. Drought and poor rainfall can lead to crop failure and reduced income, increasing the risk of poverty. On the other hand, good rainfall can result in higher crop yields and improved income, reducing poverty levels. An increase in carbon dioxide (CO_2) emissions can sometimes be associated with an increase in economic activities. This is because many economic activities, such as industrial production, transportation, and energy generation, are major sources of CO_2 emissions. An increase in economic activities can result in increased economic growth and increased prosperity, which can contribute to reduced poverty and improved living standards for people in the region. Thus, by analyzing headcount ratio, rainfall patterns and Co_2 Emissions, a more comprehensive understanding of poverty can be gained, which can inform targeted interventions and policies aimed at reducing poverty and dealing with change in the environment.

Taking the Case of Bihar. We can divide it into 4 cases. The first case from 1993 to 2004 and 3rd case from 2009 to 2011, we can see an increase in rainfall and a decrease in headcount ratio would generally indicate a positive impact on poverty. When rainfall increases, it can lead to higher crop yields and improved agricultural productivity, providing a source of income for the rural poor. And its vice versa can be seen in the case 4th i.e., from 2011 to 2016 we can see a decrease in rainfall and an increase in headcount ratio. In the 2nd case from 2004 to 2009 we can see a decrease in rainfall and a decrease in headcount ratio, which can have a mixed impact on poverty. On one hand, a decrease in rainfall can lead to reduced agricultural productivity and income, increasing the risk of poverty, especially in rural areas where agriculture is a major source of livelihood. This can result in an increase in the headcount ratio, as more people fall below the poverty line. On the other hand, a decrease in the headcount ratio could indicate that poverty reduction efforts are having a positive impact. This could be due to increased access to education, health services, and job opportunities, among other factors. Therefore, while a decrease in rainfall can have a mixed impact on poverty.

The CO_2 Emissions has also increased since 2011 which can be observed from the table 1 as a result, we can see a decline in the headcount ratio till 2011. This has led to an increase in the income of people which can lead to a decrease in the headcount ratio, as fewer people fall below the poverty line.

Taking the case of U.P. we have divided it into same 4 Cases. The first case from 1993 to 2004 and 3rd case 2009 to 2011, we can see an increase in rainfall and a decrease in headcount ratio would generally indicate a positive impact on poverty. And its vice versa can be seen in the case 4th i.e., from 2011 to 2016 we can see a decrease in rainfall and an increase in headcount ratio. In the 2nd case from 2004 to 2009 we can see a decrease in rainfall and a decrease in headcount ratio, which can have a mixed impact on poverty. Similar trend with CO_2 can be observed in the case of Uttar Pradesh too.

It is important to look beyond just these indicators and analyze other factors such as infrastructure, and economic growth to gain a more comprehensive understanding of poverty and its underlying causes. We further aim to study the factors with the help of image classification. Image classification can be a useful tool in understanding poverty and rainfall patterns in each area. By using satellite imagery and applying image classification algorithms, it is possible to gather information about the physical environment of a region. This information can then be used to analyze various indicators of poverty and rainfall patterns, including land use patterns, agricultural productivity, and access to resources such as water and electricity. For example, satellite imagery can be used to identify areas of land degradation due to drought or excessive rainfall, which can have a negative impact on agricultural productivity and increase the risk of poverty. It can also be used to identify areas with limited access to resources such as water, which can have a negative impact on agricultural production and increase poverty levels. Additionally, image classification can be used to identify areas with limited infrastructure such as roads, schools, and hospitals, which can impact access to education, health services, and job opportunities, factors that are important in reducing poverty. Therefore, image classification can provide valuable information for understanding the physical environment and its impact on poverty and rainfall patterns in a given area, helping inform targeted interventions and policies aimed at reducing poverty.

VI. CONCLUSION

After reviewing the research articles of poverty and climate change separately, we have observed that although the work on poverty has started in the recent times by the Computer Science and Artificial Intelligence tools but there has been a substantial growth in this field. We also observed that there is no such article which has worked upon the poverty using climate change impact as one of the developmental parameters. Hence, in this paper we have tried to find an answer to the question that whether change in rainfall patterns and carbon dioxide emissions affect the poverty. To have a broader understanding of the topic, our first step has been to study the trends of poverty and rainfall in different states of India. We have further tried to study these irregular trends. The data for the poverty is taken from the official website of the Government of India (GOI) and rainfall from Indian Metrological Department (IMD). Our future work would include the climate change impacts as one of the dependent variables other than predicting poverty based on land area, road built, access to electricity and others. By altering the parameters, we will check and compare the accuracy of the model with the previous models.

VII. References

1. "United Nations, department of Economic and Social Affairs, Sustainable Development, The 17 goals", https://sdgs.un.org/goals.
2. "SDG India", SDG India Index and Dashboard, https://sdgindiaindex.niti.gov.in/#/.
3. Shan Hu, Yong Ge*, Mengxiao Liu, Zhoupeng Ren, Xining Zhang, Village-level poverty identification using machine learning, high-resolution images, and geospatial data, International Journal of Applied Earth Observations and Geoinformation 107 (2022) 102694
4. Puttanapong, N.; Martinez, A., Jr.; Bulan, J.A.N.; Addawe, M.; Durante, R.L.; Martillan, M. Predicting Poverty Using Geospatial Data in Thailand.
5. Alsharkawi, A.; Al-Fetyani, M.; Dawas, M.; Saadeh, H.; Alyaman, M. Poverty Classification Using Machine Learning: The Case of Jordan. Sustainability 2021, 13, 1412.
6. S P Subash *, Rajeev Ranjan Kumarb and K S Adityac, Satellite data and machine learning tools for predicting poverty in rural India, Agricultural Economics Research Review 2018, 31 (2), 231-240
7. Shailesh M. Pandey, Tushar Agarwal, Narayanan C Krishnan, Multi-Task Deep Learning for Predicting Poverty from Satellite Images, The Thirtieth AAAI Conference on Innovative Applications of Artificial Intelligence (IAAI-18)
8. Neal Jean, * Marshall Burke, *, Michael Xie, W. Matthew Davis, David B. Lobell,Stefano Ermon, Combining satellite imagery and machine learning to predict poverty , science.sciencemag.org , August 18, 2016.
9. Nor Samsiah Sani, Mariah Abdul Rahman, Azuraliza Abu Bakar, Shahnorbanun Sahran, Hafiz Mohd Sarim , Machine Learning Approach for Bottom 40 Percent Households (B40) Poverty Classification, International Journal on Advanced Science Engineering Information Technology , Vol.8 (2018) No. 4-2, ISSN: 2088-5334
10. Xizhi Zhao, Bailang Yu, *, Yan Liu 3, * , Zuoqi Chen, Qiaoxuan Li, Congxiao Wang and Jianping Wu, Estimation of Poverty Using Random Forest Regression with Multi-Source Data: A Case Study in Bangladesh , Remote Sensing , MDPI , February 13 ,2019.
11. Hanjie Wang, Lucie Maruejols, Xiaohua Yu, Predicting energy poverty with combinations of remote-sensing and socioeconomic survey data in India: Evidence from machine learning, Energy Economics 102 (2021) 105510
12. Qihang Li, Peng Sun, Bo Li, * and Muhammad Mohiuddin, Impact of Climate Change on Rural Poverty Vulnerability from an Income Source Perspective: A Study Based on CHIPS2013 and County-Level Temperature Data in China, International Journal of Environmental Research and Public Health, MDPI , March 11,2022.
13. Himanshu Vishwakarma, Climate Change Analysis Using Machine Learning, International Journal of Science and Research (IJSR), ISSN: 2319-7064, Volume 9 Issue 8, August 2020
14. Bochenek, B.; Ustrnul, Z. Machine Learning in Weather Prediction and Climate Analyses -Applications and Perspectives, Atmosphere 2022, 13,180, January 13,2022.
15. Rutvij Wamanse, Tushuli Patil, Analysis of various climate change parameters in India using machine learning, SciPy India Conference 2021, IIT Bombay.
16. Chris Huntingford, Elizabeth S Jeffers, Michael B Bonsall, Hannah M Christensen, Thomas Lees and Hui Yang, Machine learning and artificial intelligence to aid climate change research and preparedness, Chris Huntingford et al 2019 Environ. Res. Lett. 14 124007, November 22,2019.
17. Bipin Kumar, Namit Abhishek, Rajib Chattopadhyay, Sandeep George, Bhupendra Bahadur Singh, Arya Samanta, B.S.V. Patnaik, Sukhpal Singh Gill, Ravi S. Nanjundiah and Manmeet Singh, Deep learning-based forecasting of indian summer monsoon rainfall, arXiv:2107.04270v1 [physics.ao-ph] 9 Jul 2021
18. Vinay Chamola, Vikas Hassija, Sakshi Gupta, Adit Goyal, Mohsen Guizani, and Biplab Sikdar, Disaster and Pandemic Management Using Machine Learning: A Survey, IEEE Internet of Things Journal, May 14,2021.
19. Ministry of Earth Sciences Government of India, India District Rainfall Statistics, https://mausam.imd.gov.in/imd_latest/contents/rainfallinformation.php.
20. "Head Count Ratio", Wikipedia, Wikipedia Foundation, January 16, 2023, https://en.wikipedia.org/wiki/Head_count_ratio
21. "List of Indian states by population", https://statisticstimes.com/demographics/india/indian-states-population.php, May 13,2020.
22. Tapas Ghoshal, Ranajoy Bhattacharyya, Carbon Dioxide Emissions of Indian States: An Update, SSRN, October 26, 2012.
23. GHG Platform India, Methodology National & State Level, Greenhouse Gas Estimates , 2005 to 2015 , September 2019.