Climate Change Parameter Dataset (CCPD): A Benchmark Dataset for Climate Change parameters in Jammu and Kashmir

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Abstract. In this paper, we present a Climate Change Parameter Dataset (CCPD) intending to achieve state-of-the-art results in parameters which effect climate change, including forest cover, water bodies, agriculture and vegetation, population, temperature, construction and air index. The dataset can be used by the research community to validate the claims made in relation to the climate change. Research community has been deeply involved in extending the use case of machine learning algorithms to the effects of climate change. However, the non-availability of sufficient data related to climate change parameters has limited the research in this domain. By presenting this dataset, we want to facilitate the researchers. In this dataset, we provide a large variety of statistical and satellite data acquired by various image processing techniques and on-ground data collection. The data is collected in abundance for a specific region, and then various machine learning techniques are used to extract the useful data related to each parameter separately. We call this amalgam of processed data as CCPD dataset. CCPD dataset contains over 6000 data points for all seven parameters and covers the data from 1960 onwards. We hope this dataset will aid the research community in tackling climate change with the help of AI. . . .

Keywords: Climate change, Machine learning, Reactive strategies.

1 Introduction

Climate change is a long-term process that occurs over decades or longer, and is primarily caused by the emission of greenhouse gases (GHGs) into the atmosphere. These GHGs, such as carbon dioxide, trap heat from the sun and cause the Earth's temperature to rise. The burning of fossil fuels and deforestation contribute significantly to the increase in GHG concentrations in the atmosphere [1].

Since the mid-20th century, climate change has been occurring at an unprecedented rate, and human activities are largely responsible for this acceleration. The Earth's atmosphere and oceans have warmed, and this has caused a range of impacts, including melting glaciers and sea ice, rising sea levels, and more frequent extreme weather events. These changes are irreversible and are having significant impacts on the Earth's systems and ecosystems [2].

There are several environmental factors that contribute significantly to climate change [3], including:

1. **Greenhouse gases:** Greenhouse gases, such as carbon dioxide, methane, and water vapor, trap heat from the sun in the Earth's atmosphere and contribute to the warming of the planet. The burning of fossil fuels, deforestation, and other human activities are the main sources of GHG emissions.
2. **Land use:** Land use practices, such as agriculture and urbanization, can affect the Earth's ability to absorb or reflect heat. For example, urban areas tend to be warmer than rural areas due to the "urban heat island" effect, which is caused by the absorption of heat by buildings and pavement.
3. **Aerosols:** Aerosols are small particles that are suspended in the air, and they can affect the amount of solar radiation that is absorbed or reflected by the Earth. Sulfate aerosols, which are produced by the burning of fossil fuels, tend to reflect solar radiation and can cool the planet, while black carbon aerosols, which are produced by the burning of biomass and fossil fuels, absorb solar radiation and can contribute to warming.

By understanding the impact of these environmental factors on climate change, it is possible to design strategies to mitigate their effects. For example, reducing GHG emissions through the use of renewable energy sources and increasing the efficiency of energy production can help to slow the warming of the planet. Land use practices that increase the amount of vegetation and reduce the amount of impervious surfaces can also help to reduce the urban heat island effect. Additionally, reducing the emission of aerosols through measures such as improved air quality regulations can help to reduce their cooling or warming effects on the climate [4].

Artificial intelligence (AI) can be a useful tool in studying the effects of various environmental factors on climate change [5]. AI techniques, such as machine learning and data analysis, can be used to analyze large and complex datasets related to climate change and identify patterns and trends that may not be immediately apparent. For example, AI can be used to analyze data on greenhouse gas emissions, land use practices, and aerosol concentrations to understand how these factors contribute to climate change and to identify potential strategies for mitigating their effects [6].

In addition to analyzing data, AI can also be used to develop models that simulate the impacts of different environmental factors on the climate. These models can help to predict how changes in these factors may affect the climate in the future, which can inform decision-making and policy development.

Overall, AI has the potential to play a significant role in understanding and addressing the challenges of climate change. By leveraging the power of AI to analyze data and develop models, it is possible to gain a deeper understanding of the environmental factors that contribute to climate change and to design effective strategies for mitigating their impacts.

It is true that the availability of data is an important factor in using AI techniques to study the effects of environmental factors on climate change. In order to use AI to analyze data and develop models, it is necessary to have a dataset that includes relevant information on the variables of interest. For example, if researchers are interested in studying the effects of greenhouse gas emissions on climate change, they will need a dataset that includes data on GHG concentrations, as well as other relevant variables such as temperature, precipitation, and sea level.

The quality and completeness of the dataset can also affect the accuracy and reliability of the results obtained using AI techniques. In order to get meaningful insights from the data, it is important to have a dataset that is comprehensive, accurate, and up-to-date.

Overall, the availability of a dataset that includes relevant information on the environmental factors that contribute to climate change is an important factor in using AI techniques to study these impacts. By leveraging the power of AI to analyze data and develop models, it is possible to gain a deeper understanding of these factors and to design effective strategies for mitigating their effects on the climate.

This work present one such dataset called Climate Change Parameter Dataset (CCPD) that will act as a valuable resource for researchers who are interested in using AI to study the impacts of environmental factors on climate change. By providing a dataset that includes data on seven critical parameters that affect climate change, the CCPD dataset can help researchers to gain a deeper understanding of these factors and to design effective strategies for mitigating their effects.

The fact that the data has been collected from a specific region and processed using machine learning techniques to extract relevant information suggests that the CCPD dataset is likely to be of high quality and reliable for use in AI-based research. The inclusion of data on a variety of environmental factors, such as forest cover, water bodies, agriculture and vegetation, population, temperature, construction, and air quality, means that the CCPD dataset can be used to study a range of issues related to climate change.

Overall, the CCPD dataset will be a useful resource for researchers who are interested in using AI to address the challenges of climate change. By providing a comprehensive and reliable dataset, the CCPD dataset can help researchers to gain a deeper understanding of the environmental factors that contribute to climate change and to design effective strategies for mitigating their impacts.

2 Background and Related Work

In deep learning and computer vision, large datasets are crucial for testing and training new algorithms to address various issues. However, obtaining a comprehensive and robust dataset can be challenging, especially in areas where data collection is sparse or nonexistent. This is the case in the Jammu and Kashmir region, where climate research is scarce due to a lack of consistent data and due to the sparse or nonexistent data collected for many areas over the years. However, having a robust and complete dataset is necessary to perform any experiment in the region. While some prior work has been done, it has either needed areas or covered only some parameters. For instance, small-scale data was collected by Akhlaq et al. while assessing Drivers of Deforestation and Forest Degradation in the PirPanjal region of J&K, but the satellite data collected was only for 2003 and 2013 and cannot be used to train machine learning algorithms [7]. To fill the gaps in the data and provide a comprehensive dataset, a new study proposes a dataset covering the period from 1961 to 2011 to train deep learning models to forecast in the J&K region. The study notes that the area has seen a significant rise in deforestation over the last two decades, resulting in various climatic variations in Kashmir. The lack of consistent data has made it almost impossible to develop counter-strategies to overcome the problems arising at an alarming rate. The geographical location of forests in the region in inaccessible areas has contributed to the need for physical and ecological health, making data collection a challenge.

To address this problem, Majid Farooq et al. used AI-based classification to calculate the percentage of forests over time [8]. Traditional remote sensing techniques have been used to process satellite data. Still, the latest computer vision techniques like edge detection [9], color-based segmentation [10], and threshold have been used to extract relevant features for the data acquired. The study notes that previous surveys have provided limited data and cannot be used to predict any trends or correlations.

In the Reducing Emissions from Deforestation and Forest Degradation (REDD+) strategy framework, Akhlaq et al. evaluated the dynamics of forest cover in the Kashmir Himalayan area [11]. A geospatial modeling technique was used to evaluate historical changes in forest cover that occurred between 1980 and 2009 and estimate similar changes for 2030 based on the previous pattern [12]. Change detection analysis comparing Landsat data from the years 1980, 1990, (2001), and (2009) was carried out using the Multispectral Scanner (MSS), Thematic Mapper (TM), and Enhanced Thematic Mapper (ETM+). The study notes that there are gaps in the data that still need to be filled, which is why the authors suggest a standard dataset that tracks missing data via artificial intelligence interpolation.

Overall, the lack of consistent and comprehensive data has hindered research in the J&K region, particularly in addressing the rise in deforestation and its effects on climate. The proposed study aims to fill the gaps by providing a dataset that can be used to train machine learning algorithms and develop counter-strategies to overcome the problems arising in the region.

3 Methodology

3.1 Overview

When choosing multiple factors in this research, it is important to consider the complexity of climate change and how it is affected by multiple factors.

The method choosen was to analyze the direct and indirect impacts of different factors on climate change. Additionally, we reviewed existing research conducted on climate change to identify the most relevant factors which were taken into consideration. The decisions were taken based on the literature survey and some initial simulations. Based on our thorough literature survey, the following seven parameters were determined as the major contributors to the acceleration in climate change:

1. Forest Cover
2. Water Bodies
3. Agriculture and Vegetation
4. Population
5. Temperature
6. Construction Area
7. Air Index

Some of these parameters are independent variables (influencing factors) and others as dependent variables (factors that are affected by the independent variables).

We have used a combination of computer vision, image processing, and machine learning techniques to collect data for the seven different parameters being studied. We obtained satellite data of Landsat TM from the United States Geological Survey (USGS) for the years 1960 and 2011 [13]. Satellite data can be a useful way to gather information about the earth's surface and can provide a wide range of data on various factors that may affect climate change, such as land use, vegetation, and surface temperature. Satellite data can also be useful for analyzing changes over time, such as comparing data from 1960 to 2011, as in this case.

We have also used satellite data from the Landsat MSS, TM, and ETM+ sensors to study the variables of forest cover, agriculture, and water bodies. We obtained this data from the Earth Explorer gateway for the years 1980, 1992, 2001, and 2009 [14], and selected 12-month data based on availability in the archives. We have used a gap of 4 days between the selected dates due to the non-availability of cloud-free data to measure significant changes.

We used visual interpretation and data analysis tools, such as ESRI ArcMap and the Pandas and NumPy libraries, to process and analyze the satellite data. The satellite data had sub-pixel level accuracy, and as a result, we subset the data using the area of interest (AOI) for the study area (see Figure 1 for AOI). Subsetting the data using the area of interest can help focus the analysis on a specific region or area.

We used a variety of computer vision techniques to process and analyze the satellite data that was collected. These techniques, such as contrast stretching, histogram adjustment, filtering, and variations in band combinations, have been used to improve the clarity and detail of the data and to better define the boundaries between different variables. Note that it's important to carefully select and apply these techniques based on the specific characteristics of the data and the goals of the project.

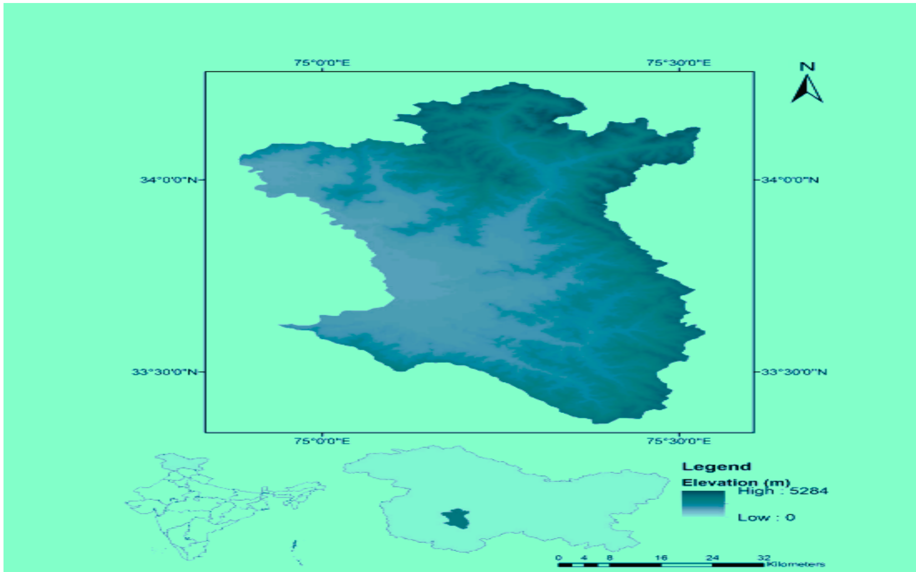

Fig. 1. Data Collection: Region of Interest

Let us now discuss in detail the data collection mechanism related to each parameter separately. In the region of interest, as shown in figure 1, after the data was collected, it was processed to extract the change that happened over the years. This procedure was performed in three steps:

1. Image Processing
2. K Means Clustering
3. Percentage Area Calculation

Image Processing There are two main ways to export or convert raster data to another format: using the Export Raster pane or the Raster geoprocessing tool.

The pane allowed us to export our raster dataset or a part of it in the display using their layers as input. Unlike other raster import or export tools, the Export Raster pane gave us additional capabilities such as clipping via the current map extent, clipping via a selected graphic, changing the spatial reference, using the current renderer, choosing the output cell size, and specifying the *NoData* value. In addition, we choose the output format for the raster dataset as JPEG 2000.

The steps followed are:

1. Establish a geodatabase in a file.
2. Create a geodatabase by default: the default geodatabase that comes with every map document is where your map's spatial data resides. This location is where datasets are added and where the datasets produced by different editing and geoprocessing procedures are stored.

3. Create a new mosaic dataset and insert the Landsat product specification.
4. Include a raster in the dataset for the multispectral mosaic to export.

K Means clustering For the classification of data processed from the satellite images, we used four input variable k-means clustering. K-Means clustering of features can be done either based on location or attribute values. It is an unsupervised classification algorithm that classifies features within a cluster in a way that entities with similar features are grouped in the same cluster. The clustering is done with the intention of reducing the total distance between the two objects or cluster centroid. The frequently used distance measure is quadratic or Euclidean distance.

In our proposed model, K-means is used to solve a classification and optimization problem by minimizing the function, which is the sum of the quadratic distances from each construction group to its cluster centroid. All the objects in a group are represented by a d dimensional vector: $x_1, x_2, x_3 ... x_d$. We assume k groups with the sum of distances of each Construction object to its centroid represented as $S = S_1, S_2, S_3 ... S_k$. The equation to optimize is as follows:

$$\min_s E(\mu_i) = \sum_{x_j \in S_1} d_j^2 + \sum_{x_j \in S_2} d_j^2 + \sum_{x_j \in S_3} d_j^2 \tag{1}$$

Here S represents the entire construction dataset, and μ_i is the centroid of i^{th} group. We want to minimize the expected distance, and we have used the Gradient descent algorithm to achieve the same by doing a partial differentiation with respect to the centroid. After the classification, the data was calculated for forest cover, construction, water bodies, and agriculture. The last step was to calculate the percentage of area contributed by each of the variables.

Percentage Area Calculation In the final step, the google search engine was used to complete this step. We needed to calculate the area covered by each class (variable) after a classification step discussed in Section 3.1. Calculating area for rasters and vectors is a straight forward operation in most software packages, but it is done in a slightly different way in Google Earth Engine. Calculating the area for vector features was done using the built-in *area()* function. We called *geometry*() function on a feature collection which gives the dissolved geometry of all features in the collection. Area calculation for images was done using the *ee.Image.pixelArea*() function. This function creates an image where each pixel's value is the area of the pixel. If the image pixels contain values 0 or 1 – we multiply this pixel area image with our image and calculate the total area using the *reduceRegion*() function.

The result of *reduceRegion*() with a grouped reducer was a dictionary of dictionaries for each variable. The top-level dictionary has a single key named group. To extract the individual dictionaries and get properly formatted results, we did a little post-processing. We took the results of the grouped reducer and mapped a function over it to extract the individual variable areas and converted it to a single dictionary. The dictionary key was of type string. Our keys were variable numbers, so we used the $format()$ method to convert the number to a string. And for all four variables, the area was calculated, and this process was repeated over all the data, visualizing the change in the dynamics of these parameters on each other, and towards the climate change of the region.

Let us now discuss the individual changes in each feature separately.

3.2 Forest Cover

Approximately $126km^2$ of forests were lost to non-forest areas in the choosen ROI. It is mainly because of an increased need of wood, fuel, and feed by population growth. This is likely the cause of some of the study area's substantial deforestation, particularly between 1992 and 2001, when the state's political upheaval made it difficult to adequately maintain the woods. The dataset offers a thorough overview of the regional developments that have taken place during the previous three decades. For the region, the total net change was found to be negative. Table 1 gives the details about the change in forest cover across multiple decades.

Years	Scrub	Open	Closed	Mean(km2)
1981	404.87	382.85	916.49	568.07
1991	424.54	384.03	893.35	567.30
2001	413.23	392.27	839.59	548.36
2011	373.07	380.49	837.53	530.37

Table 1. Forest cover Data with a gap of 10 years

3.3 Water Bodies

In the present study, we used the latest IRS LISS III DATA of 2009 along with the survey of India's Topographical maps to interpret and identify the lakes and water bodies in the study area. We collected information about the lakes and water bodies from these sources and then compiled them using AI techniques into a table for further analysis.

Table 2 contains the area and percentage of the lakes and water bodies that were identified in the study area. The table likely includes information such as the name of the water body, its location, its size, and any other relevant characteristics or features.

By using these sources of data, we were able to create a comprehensive understanding of the lakes and water bodies in the study area. This information could be used for a variety of purposes, such as assessing the health and quality of these water bodies, identifying potential threats or risks to them, and developing strategies for their management and conservation.

Years	Area(km2)	Percentage
1972	3.68	0.77
1982	5.51	1.16
1992	3.22	0.68
2001	5.89	1.24
2012	21.36	4.49

Table 2. Water Bodies Percentage with a gap of 10 years

3.4 Agriculture and Vegetation

The statistical data shows that the agricultural area in 1972 was $7.1km^2$, and in 2012 it was $9.1km^2$. From 1972 to 2012, about 0.42% of the agricultural area has increased, which may be due to the slow and continuous illegal conversion of forest land. This increase can be attributed to the fact that the villagers are degrading the forest for various social and financial reasons. Table 3 gives the details of the agriculture land over multiple decades.

Years	Area(km^2)	Percentage
1972	7.1	1.41
1982	7.32	1.54
1992	7.95	1.67
2001	8.28	1.74
2012	9.1	1.91

Table 3. Variation in the agricultural area over 10 years

3.5 Population

The population of Jammu and Kashmir, as recorded by the 1901 Census, was 2,139,362. With a population of 3.5 million in 1961, the growth rate varies between 5.75 and 10.42. From 1961 to 1971, the growth rate climbed dramatically, rising to 29.69%, a roughly 300% rise, and then stabilized at approximately 30% from 1971 to 1985. Early in the 1990s, a large portion of Kashmir's Hindu population — roughly 100,000 of the 140,000 Kashmiri Pandits — moved away, according to many researchers []. Since 1985, the population began to decline with a growth rate of 23.64%, reaching a population of 12.5 million until the last census in 2011 (see Table 4).

Years	Percentage	Population
1951	21.31	693396
1961	20.73	727508
1971	19.63	906245
1981	19.75	1182510
2001	20.06	2034826
2011	20.33	2549647

Table 4. Population Variation

3.6 Temperature

Based on the observation of prior data, the findings from this study demonstrate that there have been substantial upward trends in seasonal and annual surface air temperatures in the Kashmir valley as a whole from 1980 to 2010. Additionally, all stations experience greater warming throughout the winter and spring seasons (0.01-0.05). The results are consistent with those of prior investigations of climate change in the Himalayas. Further investigation reveals that the winter season had less snowfall, which reduced the amount of snow cover and depth. Due to the rise in temperature, the early spring snowfall takes less heat to melt the pavement. This valley-wide temperature rise with a sharp rise in spring time temperatures might have detrimental effects on drinking water, hydropower, and agriculture (see Table 5 for details).

Years	Temperature(Avg Degree Celsius)
1961	10.9
1971	11.8
1981	11.2
1991	10.4
2001	12.6
2011	12.9

Table 5. Forest cover Data with a gap of 10 years

3.7 Construction

The study observed that the construction of houses and different infrastructures has tremendously increased over the years. Construction in the area has contributed to the loss of forests and wildlands by their conversion to other uses; it has contributed to the loss of forests by the unsustainable use of forests for building timber, bamboo, and other raw materials for construction over the years; by the use of timber to provide energy for building materials production; and indirectly by the atmospheric and water pollution consequences of the construction and building materials production activities. There is an immense requirement to preserve agricultural land. Land reform measures should be strictly implemented, and the construction of residential buildings and other establishments on agricultural land should be banned (See Figure 3.7 for the trend).

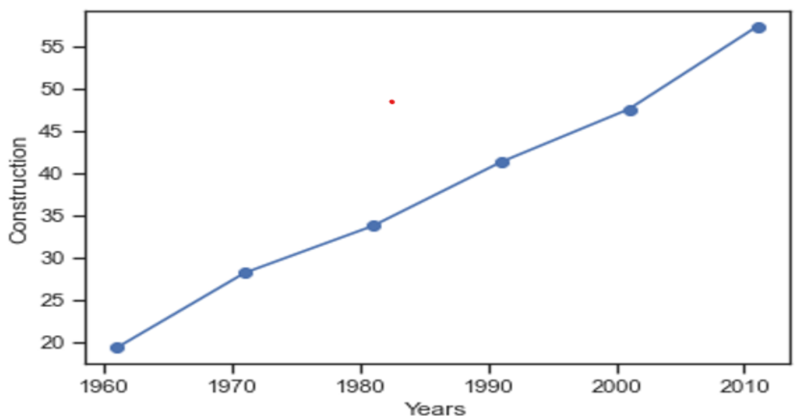

Fig. 2. Construction variation over the years

3.8 Air Index

The study determined that car combustion produces 220.5 tonnes of emissions annually, which is equivalent to 15% of all emissions. The study also found that westerly winds from Afghanistan and the region around it generate a lot of dust, which raises the concentration of PM2.5 throughout the winter. A significant factor in the long-distance transfer of pollutants is the region's geographic position. According to the research, the Kashmir Valley is now undergoing extensive development and is seeing a high rate of population increase, making it the largest urban hub in the whole Himalayan area. The research also said that the valley's rising usage of biofuels and urbanization was causing environmental disruption. In addition, lower mixing heights, limited dispersion, and long-range transport of pollutants lead to higher pollution levels in winter as pollutants are trapped in the lower atmosphere.

4 Dataset Results

The CCPD dataset seeks to remedy these problems. The data set is very diverse and all seven proposed parameters were covered. Data for train/test sections

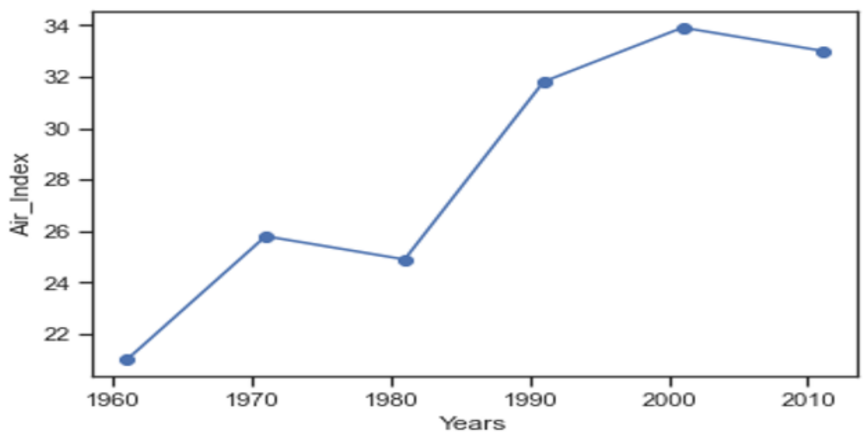

Fig. 3. AirIndex variation over multiple years

are taken from different lines and are different flight. Various data sources were included to avoid overcrowding. Future researchers will have a mechanism to test their algorithms objectively and compare them to other methods thanks to the CCPD dataset.

EXISTING DATASETS and their comparison				
Parameters	Akhlaq et.al	Majid Farooq et.al.	Akhlaq	CCPD
Observations	10	35	30	6002
Start Date	2003(only)	1972	1980	1/1/1961
End Date	2003	2012	2009	14/4/2011
Forest Cover	Included	Included	Included	Included
Water Bodies	_	Included	_	Included
Population	_	_	_	Included
Temperature	_	_	_	Included
Construction	_	_	_	Included
Air Index	_	_	_	Included
Agriculture	_	Included	Included	Included

Table 6. Comparison of datasets used in recent research papers on climate change

After the Data Collection stage, the data correlations were obtained in order to verfiy the data collected and the same is given Table 7. It is clear that almost all the parameters have a positive correlation with each other with forest cover showing a negative correlation as the forest cover has depleted over the years.

variable	**Pop**	**Forest**	**Temp**	**Water**	**Cons**	**Agri**	**Air**
Pop	1.000	-0.960	0.870	0.854	0.922	0.943	0.743
Forest	-0.960	1.000	-0.767	-0.780	-0.986	-0.963	-0.834
Temp	0.870	-0.767	1.000	0.765	0.692	0.698	0.522
Water	0.854	-0.780	0.765	1.000	0.724	0.775	0.369
Const	0.922	-0.986	0.692	0.724	1.000	0.978	0.893
Agri	0.943	-0.963	0.698	0.775	0.978	1.000	0.861
Air	0.743	-0.834	0.522	0.369	0.893	0.861	1.000

Table 7. Correlation Table. In the Table, Pop: Population, Forest: Forest Cover, Temp: Temperture, Water: Water Bodies, Cons: Construction, Agri: Agriculture, Air: Air Index 4

5 Conclusion

Seven climate change variables that either directly or indirectly impact it were the subject of a new data collection that was provided in this work. The aim was to aid in the creation of machine learning models, correlations, and numbering of some parameters in congested contexts with this collection of seven object examples. It sought to emphasize the requirement for a broad and objective data collection that contains a significant number of different parameters of object instances were created this dataset. The cases provide hard circumstances for the most recent state-of-the-art machine learning algorithms, according to dataset statistics and results from the underlying algorithms. The performance of ml algorithms utilizing this dataset can be improved in several potential ways in the future.

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