Data Collection, Pre-Processing, and Visualization of IMD Gridded Climate Data for Spatio-Temporal Exploratory Analysis

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Abstract: Climate data is huge and complex data structure witnessing drastic spike in volume and complexity with each passing day. Scientific community is considering this as a challenge and displaying more interest towards climate studies. This is evident with the increasing demand for more user-friendly data access. Climate change is a major concern commonly expressed in almost all the top geopolitical forums these days. Scientists are trying hard to study both natural and anthropogenic climate change. Not only climate scientists, scientists from other domains are also accessing climate data for critical decision-making as part of inter-disciplinary studies. Irrigation, health, travel & tourism, marine studies are some examples of inter-disciplinary studies which incorporates climate datasets for enhancing the decision-making capabilities. Such studies open new avenues for availability of more readily accessible climate data. However, understanding climate datasets and data pre-processing is again a challenge because of its complex data structure. In the current work, attempt has been made to simplify the methodologies adapted for downloading, understanding the data structure, pre-processing, and analysing gridded rainfall data.

1 INTRODUCTION

Climate change is a global scenario. The term is often mentioned in worldwide geopolitical events as a serious concern. Climate data is complex in nature and requires scientific approaches to understand and analyse. Advancements in data collection techniques pose greater challenges to climate scientists. Climate data even though is easily accessible today, understanding and working on the data is still a challenge because of its complex structure. Climate data can be linked with other domains such as agriculture, irrigation, travel and tourism for inter-disciplinary studies. Mature scientific literature on the structure of the climate data is not easily available. If the issue is addressed properly, the use of climate data can enhance opportunities for various multi-disciplinary studies.National Meteorological Service (NMS) is a national agency available in every country. Indian Meteorological meteorology, and marine meteorology. They take care of Department (IMD) is India's NMS provider. The agency is responsible for all the matters relating to various domains in meteorology such as satellite meteorology, hydro

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generating weather and climate data, providing timely forecasts and warnings (Fortin, 2012). Climate data generation requires an evenly distributed network of stations with fine equipment for recording the observation. The stations are equipped with state of art technologies for recording, storing and analysis of climate data. They are instrumental in generating climate models for forecasting. A nation with well managed climate database with better modelling capacity will be the frontrunner in national resource management. Climate data analysis helps in managing variety of

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national resources such as agriculture, water resources, travel and tourism, business, and natural disaster.

Climate data generation process is carried out in three major types – *station data*, *satellite data* and *gridded data*. With the advancement in technology, data generation can be scalable and readily available for analysis. However, understanding the advantages and limitations of each type is significant. Prioritising the information plays a vital role here. Key is to balance between the purpose of use and availability of data. Station data are in situ (positioned at a particular position) measurements of climate variables and are mainly used in recording local climatic conditions. They are not freely accessible and requires frequent quality checks. These datasets are widely used for local adaptation projects.

Since early 1980s, satellite data is being recorded through variety of earth rotating satellites. As a result of it, today there is enough historical climate data available to carry out the analysis. The resolution of satellite data is usually high as a result of its structure which records the data along with its associated spatial and temporal parameter values. Global satellite datasets of temperature and rainfall are available at various online data repositories. However, they are sometimes considered as biased because of its dependency on proxies of temperature and rainfall measurements. Tropical Rainfall Measurement Mission (TRMM) and Land Surface Temperature (LST) are few reliable satellite datasets available online.

Gridded climate data are special data type which includes global datasets with continuous value spatially as well as temporally. Gridded data format is structurally similar to satellite data format. Gridded data format can be formed by combining in situ station data and satellite data. They are later structured in a grid format to reduce the bias in the data. Indian Meteorological Data (IMD) and Global Precipitation Climate Projects (GPCP) are amongst the agencies which produce gridded climate datasets.

2 NATURE OF GRIDDED DATA

Recordings of station data are often considered as the gold standard for meteorological data analysis. However, certain constraints still exist such as measurement accuracy, not able to provide complete coverage of sparsely populated localities, limitations in data quality and so on (Anders, 1977). As an alternative to observed data, to have more spatial coverage and temporal completeness. Gridded datasets are prepared as an integration of several algorithms that combines station data and satellite observation data (Bai, 2018). Consistency across various datasets still remained a concern as these datasets are of various spatial and temporal resolution and constructed using various methods. Several studies have been carried out to assess the differences between the quality of these gridded datasets and station observation data (Khan, 2015). The studies shown significant evidence that the observation patterns are well captured by gridded datasets. The recorded observations in many gridded datasets were displaying poor correlation with station data especially on daily scale (Delcroix, 2011).

3 APPLICATIONS& CHALLENGES

There are mixed opinions among researchers when it comes to Gridded meteorological data, various domains have incorporated the data for variety of studies. Major application areas of gridded meteorological data include the study of extreme events such as draught, floods and hurricanes, ecological processes like hydrological modelling exercises, assess impacts of climate change, record and replace the missing values of the missing station observation data (Delcroix, 2011).

One of the major challenges for understanding and working with gridded data is its structure, which is multi-source, multi-dimensional and its spatio-temporal nature. The data structure comprises of spatial coordinates (referring to latitude, longitude) along with temporal coordinates (referring to date and time). Having multiple dimensions, makes the dataset not so simple for understanding and analysing. Availability of advanced scientific software tools and packages for analysis of climate data helps to conceal the underlying complexity and lets you work on the data. On the other hand, understanding the underlying mechanism of these software or how it works on data is not simple. The focus of the current work is to understand gridded meteorological data structure by utilizing few python packages and how to further proceed with data pre-processing activity.

4 METHODOLOGY:

Considering the complexity of gridded data structure, the current work comprises of an overall objective of reading, understanding and pre-processing of the gridded datasets with the intention of providing a scientific literature to promote multi-disciplinary studies. The work is aimed at the implementation of gridded data analysis using python packages as an effective mechanism to understand the underlying complexity and simplify.

This study uses gridded rainfall data collected from IMD. The dataset consists of daily rainfall data from 01-01-2001 to 31-12-2010. The main focus of the study is to understand the data structure and start working with the multi-dimensional gridded data using some of the Python packages.

5 PACKAGES USED

- Imdlib – The python library imdlib is used to download daily gridded rainfall data from IMD, Pune webpage.
- NumPy – The python library numpy is used for numerical computations.
- Pandas – The python library pandas is used for implementing complex data structures.
- Matplotlib, Seaborn – The python libraries matplotlib and seaborn is used for visualization.
- Xarray – The python library xarray is used to convert multi-dimensional array to two-dimensional array.

5.1 READING GRIDDED METEOROLOGICAL DATA WITH PYTHON

There are many python and R libraries available to read, visualize and analyse gridded data. However, lack of mature research literature in the domain has been a disappointing reason for many enthusiastic researchers to continue their interests. To address the underlying issue and provide a starting point for the budding researchers in climate studies, a small effort has been made through this research article. The following steps are considered to understand the Gridded climate data and proceed with data pre-processing.

STEP 1: READING GRIDDED DATA

Gridded climate data is a three-dimensional data having dimensions - latitude, longitude and date/time. The datasets used in the current work are accessed from IMD, Pune website where rainfall and temperature datasets are available for free download. The gridded data being accessed is a combination of station data and satellite data. Opening gridded data file are not supported by any of the simple data editor or spreadsheet applications. Advanced scientific tools such as GRADS are available to work on these datasets. However, most of these tools require super computing environment. As an alternative, a set of python libraries are also available which supports reading of gridded data and converting the data into relational dataset. This will definitely be the starting point for the beginners in climate studies who can explore gridded datasets on their computer systems for a better understanding of the data structure.

To download the gridded climate data from IMD, Pune website, imdlib library can be used. imdlib library can be downloaded using pip installer for windows. get_data() method of imdlib enables data download. Ipython code for downloading data from imdlib can be seen in Fig(1).

```
# Downloading 10 years of rainfall data for India
start_yr = 2000
end_yr = 2010
variable = 'rain' # other options available in imdlib are ('tmin'/ 'tmax')
#Specifying Path and save the files
imd.get_data(variable, start_yr, end_yr, fn_format='yearwise')
```

Fig(1) : Downloading data using imdlib

STEP 2: UNDERSTANDING DATA STRUCTURE AND CONVERTING INTO MULTI-DIMENSIONAL ARRAY FORMAT

Once the dataset is downloaded, the next challenge is reading data. Xarray library in python facilitates reading multidimensional array. Making use of xarray functionality, the gridded dataset can be read. Xarray supports two types of data structures namely Data Array and Dataset. Data Array can be used to store multi-dimensional array of a single variable along with its coordinates. Whereas, dataset can store data arrays of multiple variables that share the same coordinates. Fig(2) illustrates ipython code to open the dataset using open_data() method of imdlib and access the multi-dimensional array elements into DataArray da.

```
# Opening the downloaded dataset
start_yr = 2000
end_yr = 2010
path='C:/Users/Chandrika M/Documents/RainfallData/'
data = imd.open_data(variable, start_yr, end_yr,'yearwise', path)
# store it in the DataArray da
da = data.get_xarray()
print(da)
```

Fig(2) : reading data and converting into multi-dimensional array

The DataArray da facilitates the understanding of data structure. Fig(3) shows the structure of DataArray da, where the three coordinates lat, lan and time along with its datatype and few values can be clearly noticeable. Rainfall variable, which has been defined while downloading data defines the rainfall value. This value is the recorded rainfall quantity for each latitude, longitude and time in the dataset. Additional information regarding the dataset such as source, title and history are also available here.

```
Dimensions:        (lat: 129, lon: 135, time: 3652)
▼ Coordinates:
  lat              (lat)         float64         6.5 6.75 7.0 ... 38.0 38.25 38.5
    axis :          Y
    standard_name : latitude
    long_name :     latitude
    units :         degrees_north
  lon              (lon)         float64         66.5 66.75 67.0 ... 99.75 100.0
    axis :          X
    long_name :     longitude
    units :         degrees_east
  time             (time)        datetime64[ns]  2001-01-01 ... 2010-12-31
    standard_name : time
    long_name :     time
▼ Data variables:
  rain             (time, lat, lon)  float64     -999.0 -999.0 ... -999.0 -999.0
    units :         mm/day
    long_name :     Rainfall
▼ Attributes:
  Conventions :     CF-1.7
  title :           IMD gridded data
  source :          https://imdpune.gov.in/
  history :         2022-10-28 19:42:32.686320 Python
  references :
  comment :
  crs :             epsg:4326
```

Fig(3) : Structure of xarray dataset

Python commands can be helpful in understanding the data type, shape, coordinates and attributes. Fig(4a) expresses the data type and shape of the DataArray da. Fig(4b) describes the data dimension, coordinates and attributes.

```
# display data type
# print(type(ds))
print(type(da))

<class 'xarray.core.dataset.Dataset'>

# Display the shape of array: data array can contain only single variable
print(da.rain.shape)

(3652, 129, 135)
```

Fig(4a) : Data type and shape of DataArray da

```
#data set dimensions, coordinates and attributes
print('dimensions:',da.dims)
print('coordinates:',da.coords)
print('attributes:',ds.attrs)

dimensions: Frozen(SortedKeysDict({'lat': 129, 'lon': 135, 'time': 40177}))
coordinates: Coordinates:
  * lat      (lat) float64 6.5 6.75 7.0 7.25 7.5 ... 37.5 37.75 38.0 38.25 38.5
  * lon      (lon) float64 66.5 66.75 67.0 67.25 67.5 ... 99.25 99.5 99.75 100.0
  * time     (time) datetime64[ns] 1901-01-01 1901-01-02 ... 2010-12-31
attributes: {'long_name': 'rainfall', 'units': 'mm/day'}
```

Fig(4b) : Data dimension, coordinates and attributes

DataArray can also be converted into Dataset for combining data for multiple variables with common coordinates.

STEP 3: CONVERT THE DATAARRAY INTO PANDAS DATAFRAME, DATA STORAGE & PREPROCESSING

While working on multiple variables such as rainfall, temperature, sea surface temperature (SST), xarray DataArray has to be converted into xarray DataFrame. DataFrame converts the data into relational database format. Each coordinate and variable will become columns and each instance of the data will become rows respectively. Fig(5) illustrates the ipython code to convert DataArray into DataFrame. The output format is also visible here, where the data format can be easily understandable as it is in the tabular structure.

```
df = da.to_dataframe()
df
```

lat	lon	time	rain
6.5	66.5	2010-01-01	NaN
		2010-01-02	NaN
		2010-01-03	NaN
		2010-01-04	NaN
		2010-01-05	NaN
...	...	...	...
38.5	100.0	2010-12-27	NaN
		2010-12-28	NaN
		2010-12-29	NaN
		2010-12-30	NaN
		2010-12-31	NaN

6356475 rows × 1 columns

Fig(5) : Convert the DataArray into Pandas DataFrame

Now, it is easier to perform analysis functions. The DataFrame can also be converted to other file formats such as csv, netCDF and GeoTIFF as shown in Fig(6).

```
# save into csv file

df.to_csv('C:/Users/Chandrika M/Documents/RainfallData/variables/decade.csv')

#Save data in netCDF format:
file_dir='C:/Users/Chandrika M/Documents/RainfallData/variables'
data.to_netcdf('decade.nc', file_dir)

#Save data in GeoTIFF format (if you have rioxarray library):

data.to_geotiff('decade.tif', file_dir)
```

Fig(6) : Convert to csv, netcdf or GeoTIFF formats

Python libraries such as numpy and pandas facilitates data analysis functionalities. Some of the simple analysis code by grouping can be seen in Fig(7). Resampling of dataset can be understood well with fig(8).

```
# Convert DataArray into Dataset
ds=da.to_dataset(promote_attrs=True)

ds.groupby("time.season")

DatasetGroupBy, grouped over 'season'
4 groups with labels 'DJF', 'JJA', 'MAM', 'SON'.

ds.groupby("time.day")

DatasetGroupBy, grouped over 'day'
31 groups with labels 1, 2, 3, 4, 5, 6, ..., 27, 28, 29, 30, 31.

ds.groupby("time.month")

DatasetGroupBy, grouped over 'month'
12 groups with labels 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12.

ds.groupby("time.year")

DatasetGroupBy, grouped over 'year'
10 groups with labels 2001, 2002, 2003, ..., 2009, 2010.
```

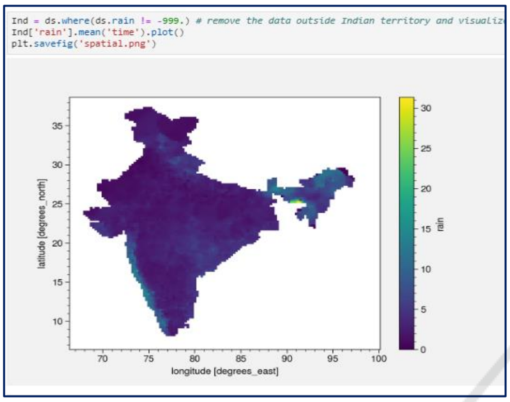
Fig(7): Convert DataArray to Dataset to perform data analysis by grouping

```
# Resample to bimonthly frequency
ds.rain.resample(time="2MS").mean

<bound method ImplementsArrayReduce._reduce_method.<locals>.wrapped_func
60 groups with labels 2001-01-01, ..., 2010-11-01.>

# Resample to 5 days frequency
ds.rain.resample(time="5D").mean

<bound method ImplementsArrayReduce._reduce_method.<locals>.wrapped_func
731 groups with labels 2001-01-01, ..., 2010-12-30.>
```

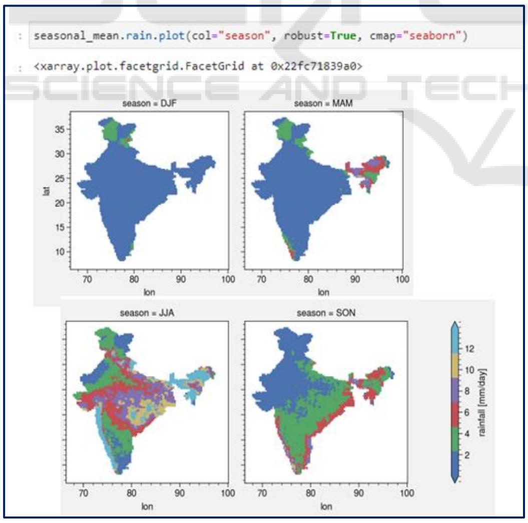
Fig(8): Resampling the xarray dataset with various frequency according to requirements

STEP 4: VISUALIZATION AND ANALYSIS

Xarray supports many of the numpy aggregation methods. A simple map visualization made using a simple Dataset ds is visible in Fig(9a). Seasonal average rainfall visualization can be seen in Fig(9b).

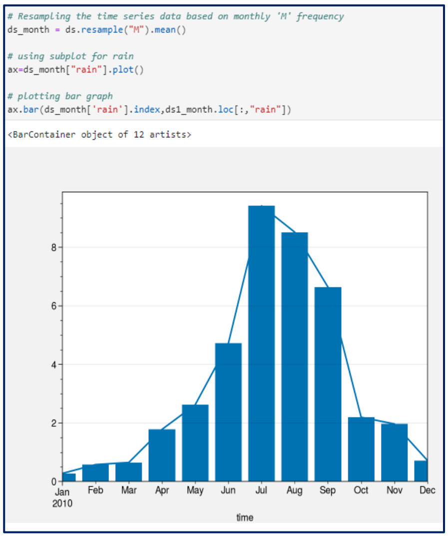


Fig(9a) : Map visualization of average rainfall over the specific time interval



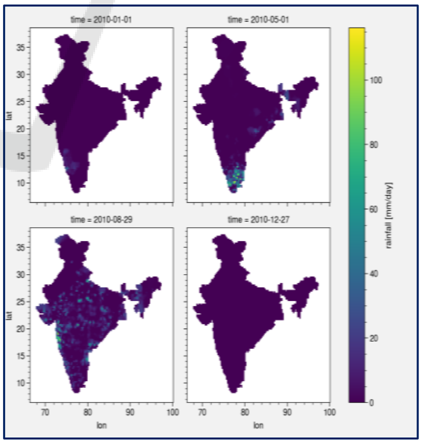
Fig(9b) : Visualization of Seasonal average of rainfall over the specific time interval (Chandrika, 2022)

Fig(10) illustrates the calculation of monthly mean and visualization using bar graph.



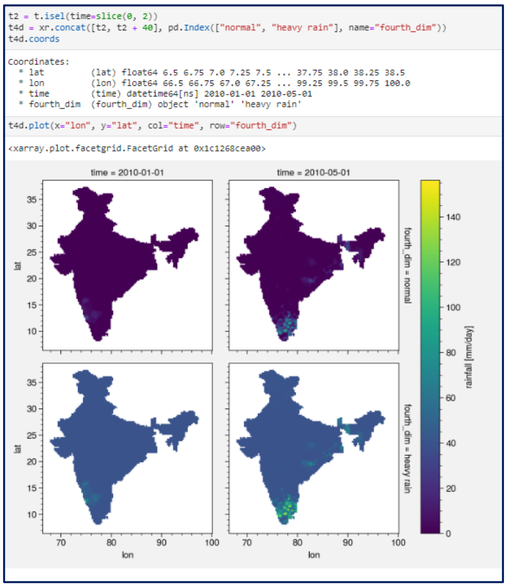
Fig(10) : Visualizing monthly data by resampling (Chandrika, 2022)

Faceting here refers to splitting an array along one or two dimensions and plotting each group. the specific use of small multiples to display the same relationship conditioned on one or more other variables is often called a "trellis plot". Fig(11) displays the multi-facet visualization.



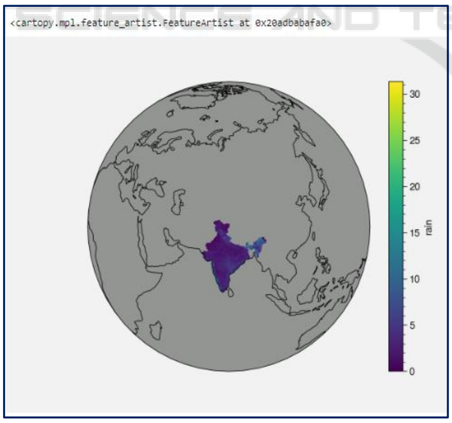
Fig(11) : Multi facet visualization

Fig(12) represents ipython code to add another dimension to the dataset if required for performing analysis.



Fig(12) : Adding a fourth dimension and making it a 4D array

World map templates of various scales can also be downloaded and utilized for visualization. Fig(13) displays one such example where IMD data is visualized on a global scale template.



Fig(13) : Display on a global scale map

6 CONCLUSION

Climatology is one such domain which is having a wide range of applications in many other domains. Researchers often must study climatology as well as computer programming to understand climate behaviour in addition to their domain specific studies. The current paper is designed as an attempt to simplify the data analysis and visualization of gridded data analysis and visualization in Python libraries. Various steps starting from reading the gridded climate data, understanding he data structure, and visualizing is discussed in a simple manner. Hopefully the attempt made here will be helpful for the beginners in the climatology as well as for the inter-disciplinary researchers who want to include climate studies along with python implementation in their field of study.

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