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IDENTIFYING CLIMATE-RESILIENT AGRICULTURAL PRACTICES IN INDIA THROUGH POSITIVE DEVIANCE ANALYSIS OF SOIL MOISTURE, TEMPERATURE, AND PRECIPITATION ANOMALIES IN TELANGANA

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Abstract: **This study presents a analysis of the impact of climate change on several factors that affect agricultural output such as soil moisture, temperature anomalies, and precipitation anomalies. The project utilizes data-powered positive deviance (DPPD) to identify farmers who are achieving better values of the aforementioned factors despite similar geographical conditions. The findings are then used to devise policies to assist other farmers in adopting similar practices. The methodology used in the study applies seasonal-trend decomposition using the loess (STL) method to analyze temporal trends of weather variables across a specific region, using data collected from various sources, such as satellite imagery and weather station readings in the state of Telangana. Similar studies done across the world demonstrate an improvement in crop yields and an increase in the resilience of farms from rapid climate change.**

Keywords: **Data Science, Climate Change, Agriculture, Data Powered Positive Deviance, Geospatial science**

I. INTRODUCTION:

Rising temperatures, changing precipitation patterns, and increased frequency of extreme weather events have a significant impact on agriculture and food production. This requires need for introduction of innovative solutions that can help farmers adapt to these changing conditions and improve the resilience of their crops to climate change.

One promising approach to addressing this challenge is the use of data science and machine learning techniques to better understand the complex relationships between weather patterns, soil moisture, and crop growth. By analyzing copious amounts of data on these factors, it is possible to find patterns and trends that can be used to inform agricultural practices and policies. Our work uses data science to help farmers adopt climate-resilient practices. The project contributed datasets and trend analysis using data-powered positive deviance (DPPD).

It is based on an approach called DPPD, which uses data science to find positive deviance in agricultural practices. Positive deviances are farmers who are achieving better crop yields than their peers, despite similar weather conditions and soil moisture levels. By identifying these positive deviants and studying their practices, it is possible to identify strategies and techniques that can be used to improve crop resilience to climate change. (Albanna et. al, 2018, Dreisen et. al. 2021)

Datasets of several factors affecting agricultural outputs that are also affected by climate change were created and then used to calculate DPPD products and do an STL analysis, which was used to identify positive deviances in agricultural practices. The research also implemented trend analysis to understand the long-term changes in weather patterns and their impact on crop growth. Once the positive deviances were identified, the work was used by the governments of the Indian states to develop policies and programs that could be implemented to help other farmers adopt similar practices. These policies included training programs for farmers, subsidies for certain types of equipment, and financial incentives for farmers who adopt climate-resilient practices. (Adelhart et. al, 2020)

The results of the project were highly encouraging. By using data science to identify positive deviances and implement policies and programs to promote climate-resilient practices, it was possible to significantly improve crop yields and increase the resilience of farms to changing weather conditions. Furthermore, the approach used has the potential to be scaled up and applied in other regions and countries, making it a powerful tool in the fight against climate change.

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II. DATA AND METHODS

a. Soil Moisture

Soil is an essential factor in crop growth and production, as it affects the availability of water for plant growth and can also impact the susceptibility of crops to pests and diseases. In agriculture, monitoring soil moisture levels is important for determining when and how much to water crops, as well as identifying areas that may be at risk of drought or waterlogging. It is often considered a direct way of quantifying agricultural drought. In the past, measurements of soil moisture at regional scales have been sparse, but recent advancements in land surface modeling and the development of satellite technology to indirectly measure surface soil moisture have led to the emergence of several national and global soil moisture data sets that provide insight into the dynamics of agricultural drought.

As droughts are often defined by normal conditions for a given time and place, data sets used to quantify drought require a representative baseline of conditions to accurately establish a normal. This presents a challenge when working with earth observation data sets which often have very short baselines for a single instrument. In a study by (Champagne et al., 2019) three soil moisture data sets were assessed: a surface satellite soil moisture data set from the Soil Moisture and Ocean Salinity (SMOS) mission operating since 2010; a blended surface satellite soil moisture data set from the European Space Agency Climate Change Initiative (ESA-CCI) that has a long history and a surface and root zone soil moisture data set from the Canadian Meteorology Centre (CMC)’s Regional Deterministic Prediction System (RDPS). The results showed that using short baseline soil moisture data sets can produce consistent results compared to using a longer data set, but the characteristics of the years used for the baseline are important. Soil moisture baselines of 18–20 years or more are needed to reliably estimate the relationship between high soil moisture and high-yielding years. The study highlights the importance of soil moisture in agricultural drought, and the need for reliable data sets to understand its dynamics. (Rossato et al.,2019, Saha et al.,2020). Established the significance of temperature anomalies on agriculture, a dataset was selected from the set of available datasets mentioned in table 1 below.

Table 1: Gridded Soil Moisture datasets available in public domain

Name of dataset	Spatial Resolution	Temporal Resolution	Frequency
Copernicus Climate Change Service Soil moisture (Copernicus)	0.25°x0.25°	1978 to present	10 days
NASA - USDA Global Surface soil moisture (Bolten et. al, 2010)	0.25°x0.25°	2015-2020	3 days
NASA - USDA Enhanced Surface soil moisture (Bolten et. al, 2010)	10-km	2015-2020	3 days

To gain a comprehensive understanding of soil moisture levels at a local scale, the NASA-USDA Enhanced Surface soil moisture dataset with a 10km spatial resolution was selected for the use. This dataset supplies high-resolution data that is essential for understanding the impact of soil moisture on agricultural outputs in small regions.

Temperature Anomalies

Temperature anomalies refer to the deviation of temperature from a long-term average temperature. In agriculture, temperature plays a crucial role in crop growth and development. Elevated temperatures can lead to stress in plants and reduce crop yields. Therefore, understanding and monitoring temperature anomalies are important for farmers to protect their crops from heat stress and to improve crop yields.

Research on the impact of temperature anomalies on agricultural practices and yields has been done by several institutions. Some findings include the degree of yield decrease observed in the primary four staple crops namely wheat, rice, maize, and soybean are severely affected by changes in temperatures. An increase in global temperatures by 1 degree can affect crop production drastically-approx. A 6% yield decrease was seen in wheat, 3.2% in rice and 7.4% in maize, and 3.1% in soybean in areas where temperatures favor the growth of these crops. Increasing temperature anomalies have caused farmers to respond with various on-farm and off-the-farm techniques to ensure the sustenance of their livelihood. (Vogel et al., 2019). On-farm strategies such as increasing the area of the land under farming or using a staggered farming approach to timing the sowing time, where farmers leave some seeds to be snowed afterward to mitigate any calamity or anomaly that might cause the failure of crops. Off-farm practices such as expansion and diversification of businesses such as farming livestock or setting up businesses in other industries have been adopted by farmers to manage the risks arising from climate change. Calamities like drought might decrease the possibilities further, decreasing opportunities for diversification. Such situations might lead farmers to look for better opportunities elsewhere. (Vogel et. al, 2019).

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Agricultural production is vulnerable to climate change with temperature abnormalities being the most detrimental factor affecting crop growth. Given the crucial effect of temperature on the crop yields and agricultural practices, and so the livelihood of an area. It becomes crucial to measure temperature anomalies to understand the patterns and devise strategies accordingly. (Zhao et. al, 2017)

There are multiple updated and peer-reviewed surface temperature anomaly products available, notably produced by NASA/GISS (GISTEMP), National Oceanic and Atmospheric Administration (NOAA) National Centers for Environmental Information (NCEI) with the Merged Land-Ocean Surface Temperature Analysis, the HadCRUT, Japanese Meteorological Agency (JMA) and Berkeley Earth.

These analyses use considerably different methods for the calculation of historical global and regional mean time series but broadly agree on the trends and interannual variations in the global annual mean time series, though they differ at more regional scales as a function of data coverage and interpolation method. All of the most commonly cited surface temperature analyses split up the calculation of global anomaly fields into separate LSAT and SST anomaly analyses. These independent LSAT and SST analyses are combined into a total (LSAT and SST) global surface temperature index from which spatially averaged global and regional time series can be computed (note this is not strictly equal to the true surface air temperature anomaly; Cowtan et al., 2015). Likewise, the uncertainty analyses for the LSAT and SST are performed separately, then combined into total global uncertainty. A graph of several of the datasets discussed above is displayed in Figure 1. This research considered several other datasets factoring in important metrics such as the spatial and temporal resolution of the temperature datasets. Table 2 denotes the specifications of the datasets considered for our research. (Lenssen et al., 2019)

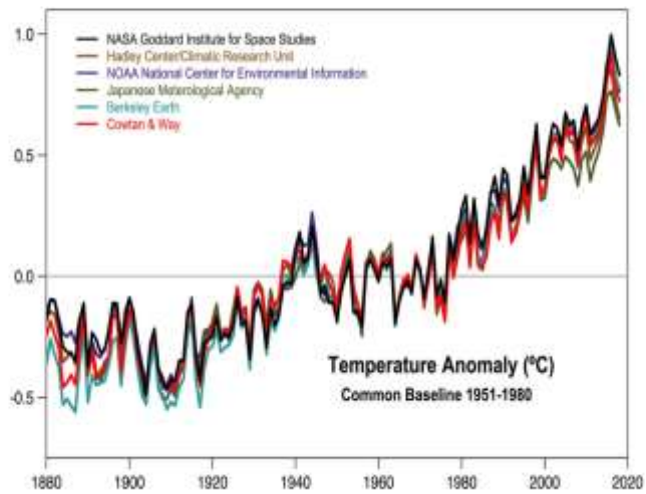

Fig 1. Temperature anomalies (NASA, NOAA, Hadley, JMA, Berkeley Earth, Cowtan)

Calculation of Temperature anomalies

Table 2: Gridded Temperature anomaly datasets available in the public domain

Name of dataset	Spatial Resolution	Temporal Resolution	Frequency
CPC (CPC)	0.5°x0.5°	1979-present	daily
WorldClim 2.1 (Fick et. al, 2017)	2.5 arc minute	1970–2018	monthly
CRU TS v4.06 (Harris et.al.,2022)	0.5°x0.5°	1901–2021	monthly
CHELSA v2.1 (Karger et.al, 2017)	30 arc second	1980–2019	monthly
HADEx3 (Dunn et.al, 2020)	1.25° x 1.875°	1901-2018	daily
Berkeley Earth (Rohde et. al, 2021)	1°x1°	1833-Present	monthly

It was decided to use Copernicus ERA5-Land monthly averaged data from 1950 to present to create our own datasets for temperature anomalies because of limited availability of long-term data with good enough resolution. These limitations led to the creation of in-situ temperature anomaly datasets using the Copernicus dataset.

Methodologies for calculating Temperature anomalies.

The method employed in this study involves the calculation of temperature anomalies to better understand and analyze temporal variations in temperature. Temperature anomalies are determined by subtracting a long-term mean temperature from the available temperature data for a given period, thereby isolating and identifying deviations from the mean temperature. This enables the identification of trends, patterns, and changes in temperature, supplying valuable insights into the characteristics and behavior of temperature**.**

NASA Climate uses a 30-year reference period (1951-1980) to calculate the deviation of a measured temperature at a given weather station compared to an average value for that location and time, which is referred to as a temperature anomaly. While the Japan Meteorological Association uses a similar method for estimating global mean temperature anomalies. Their procedure involves obtaining an average for monthly-mean temperature anomalies against a 1991-2020 baseline

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over land and sea surface in each 5° x 5° grid box worldwide. They then average these values according to the land-to-ocean ratio for each grid box and use this to calculate the monthly, annual, and seasonal mean global temperature anomalies by averaging the anomalies of all the grid boxes weighted with the area of the grid box.

Workflow of Methodology to calculate temperature anomalies

The method used to calculate temperature anomalies can be shown through the following steps:

1. Obtain global temperature data and calculate the climatological averages over a 30–50-year period using statistical methods such as the arithmetic mean or the more robust method of the climatological mean. It is important to note that the choice of the period of record is important as it can influence the results and the significance of the temperature anomalies. Once the climatological averages are calculated, it is important to distinguish between the monthly and annual averages as they provide different information about the temperature variability.
2. Determine the deviation of specific months or years from the average temperature values calculated in step 1. This step involves calculating the temperature anomaly, which is defined as the difference between the observed temperature and the climatological average for that specific month or year. This can be calculated using a mathematical formula, for example, (Observed temperature - Climatological average) / Climatological average.
3. Use the calculated temperature anomalies to create maps, which display variations in temperature at different geographical levels.

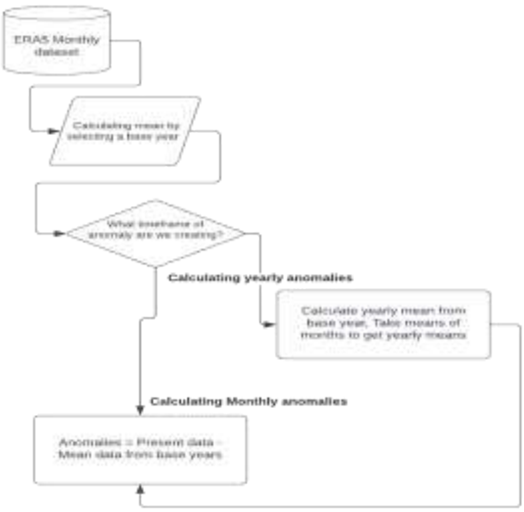

Fig 2. Workflow of methodology to calculate temperature anomalies.

b. Precipitation Anomalies

Rainfall anomalies, defined as deviations of annual rainfall from long-run averages, are a recurring challenge that threatens agricultural systems and disproportionately affects the developing world. Many of the world's poorest countries, which have a high dependence on agricultural employment, rapidly expanding populations, and elevated levels of water stress, also endure strong variability of rainfall (Zaveri et al., 2018; Palagi et al., 2020; Felton et al., 2019). Since the middle of the 20th century, anthropogenic climate forcing has doubled the joint probability of years that are both warm and dry in the same location, with tropics and subtropics facing more record-breaking dry events (Zaveri et al., 2018).

While the effects of rainfall variability on crop yields and productivity have been widely studied, the consequences of changes in cropland area, and by extension deforestation, are less well understood and are yet to be quantified at a global, disaggregated scale. Rainfall anomalies are known to have deleterious impacts on agricultural yields, but the resulting consequences on cropland expansion remain uncertain. A study of the differential scale of these impacts around the world was done.

It was found that repeated dry anomalies increase cropland expansion specifically in developing countries, which are characteristically dominated by small-holder farming, implying that cropland is expanded to compensate for lower yields. Two tests corroborate the results. First, comparable reductions in forest cover due to repeated dry anomalies are found in the same regions where cropland expands. Second, in places where infrastructure buffers yield from rainfall anomalies, cropland expansion halts (Zaveri et al., 2018).

While evidence indicates that climate change is likely to increase income inequality between countries, its impacts across different income classes are less understood. Using global data on inequality indicators, it is shown that rainfall anomalies increase income inequality in economies that are heavily dependent on agriculture. Climate projections show that existing disparities are likely to worsen over time. Our findings underline the urgent need for inclusive and sustainable development policies, especially in highly exposed countries (Palagi et al., 2020). Research has continuously shown that rainfall anomalies exacerbate income inequality and cropland expansion in developing countries heavily dependent on agriculture. The results highlight the urgent need for inclusive and sustainable development policies to address the negative impacts of climate change on the bottom of the income distribution and on the environment.

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Calculation of Precipitation anomalies

Table 2: Gridded precipitation anomaly datasets available in the public domain

Dataset	Spatial Resolution	Temporal resolution	Frequency
NOAA NCEP CPC CAMS_OPI v0208	2.5°x2.5°	1979-Present	Monthly
Climate Hazards Group InfraRed Precipitation with Station data	0.05°x0.05°	1981-2022	Daily, monthly

More datasets available at: https://psl.noaa.gov/data/gridded/tables/precipitation.html

The work decided to create in-situ datasets for Precipitation anomalies because of the limitations in the data such as lack of spatial accuracy and temporal unavailability. Again, Copernicus ERA5 data was preferred for the purpose because of the familiarity and easy availability of the dataset. The methodology used for the calculation of precipitation anomalies was in every way the same as that for the calculation of temperature anomalies.

III. METHODOLOGIES FOR CALCULATING DPPD:

The methodology proposed in this research paper aims to analyze the temporal trends of a given variable across a specific region. To accomplish this task, the seasonal-trend decomposition using the loess (STL) method is applied to the time series data of the factor in consideration. The STL method decomposes the original time series into three components: trend, seasonal, and residual. The trend component is then used to perform linear regression and obtain the slope, which serves as an indicator of the temporal trend of the variable.
The input data for the analysis is a data frame containing the time series data of the values recorded, with the date as the index. The first step is to convert this data frame into a Pandas series, with the values recorded as the values and the dates as the index. The STL method is then applied to this series to decompose it into its trend component. Next, the linear regression is applied to the trend component using the date as the independent variable, and the slope of the regression line is obtained as the indicator of the temporal trend.
To obtain the trend score of the variable for each location, the above steps are repeated for each location by iterating over the columns in the data frame which represents the coordinate of the geography, and the resulting slopes are stored in an array. The final output is an array of trend scores, one for each location, which can be further analyzed to study the temporal trends of the variable across the region.

IV. RESULTS & DISCUSSION

In this study a dataset of soil moisture, temperature anomalies, and precipitation anomalies for the states of Telangana was created. The data was collected from various sources, including satellite imagery and weather station readings. The research used trend analysis to identify positive deviances in soil moisture, temperature anomalies, and precipitation anomalies. Positive deviances were defined as instances where farmers were achieving better crop yields or using less water despite facing similar environmental conditions as their peers.

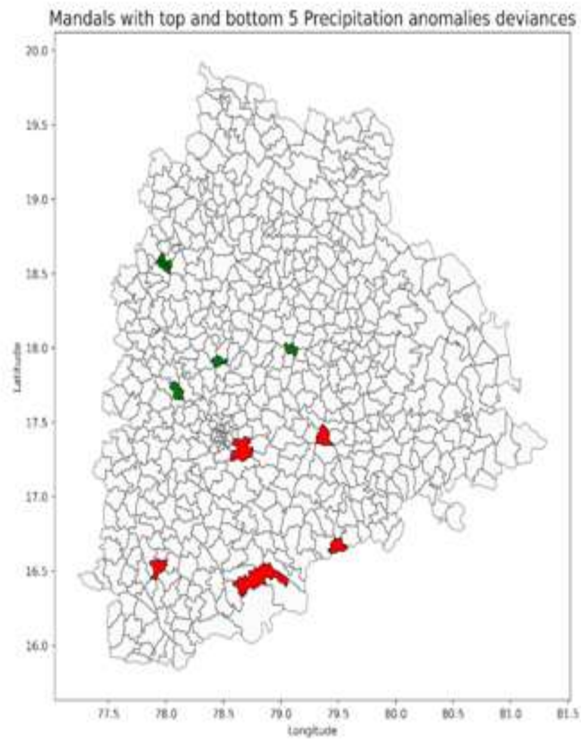

Fig 3. Telangana Mandal deviances in soil moisture, positive values are highlighted in green and the ones with the least positive/ negative deviances were highlighted in red.

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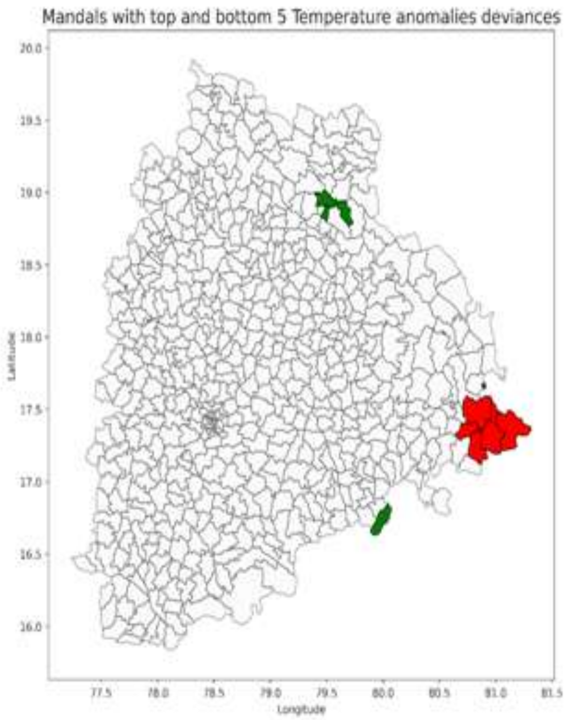

Fig 4. Telangana Mandal deviances in Temperature anomalies, positive values are highlighted in green and the ones with the least positive/ negative deviances were highlighted in red.

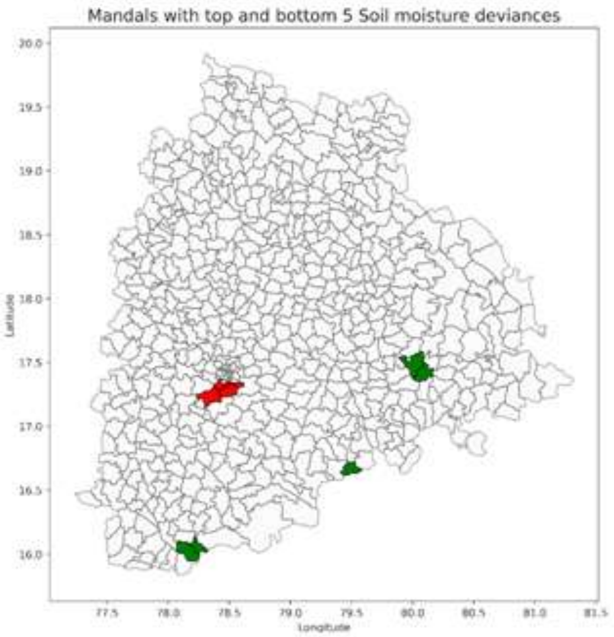

Fig 5. Telangana Mandal deviances in precipitation anomalies, positive values are highlighted in green and the ones with the least positive/ negative deviances were highlighted in red.

Observed values of Soil moisture, Temperature anomalies, and Precipitation anomalies are represented in the tables below:

Table 3: Region with positive soil moisture deviance (Top 5):

Mandal Name	Normalized deviance value
Chinnambavi	1
Pentlavelli	0.968607
Kuravi	0.552656
Adavidevulapally	0.533208
Dornakal	0.529491

Table 4: Region with negative/low soil moisture deviance (Bottom 5):

Mandal Name	Normalized deviance value
Balapur	-1
Shamshabad	-0.96492
Rajendranagar	-0.92257
Hayathnagar	-0.88956
Bandlaguda	-0.88618

Table 5: Region with positive temperature anomalies deviance (Top 5):

Mandal Name	Normalized deviance value
Aswaraopeta	-1
Dammapeta	-0.97605
Sathupally	-0.95808
Mulakalapally	-0.88323
Annapureddipalle	-0.87725

Table 6: Region with negative/low temperature anomalies deviance (Bottom 5):

Mandal Name	Normalized deviance value
Naspur	0.997006
Bheemaram	1
Mandamarri	1

Table 7: Region with positive precipitation anomalies deviance (Top 5):

Mandal Name	Normalized deviance value
Dhoolumitta	-1
Masaipet	-0.99657
Chowtakur	-0.99313
Chandur	-0.9897
Mosra	-0.98626

Table 8: Region with negative/low precipitation anomalies deviance (Bottom 5):

Mandal Name	**Normalized deviance value**
Abdullapurmet	1
Achampet	0.996643
Adavidevulapally	0.993208
Addagudur	0.989825
Addakal	0.986468

The regions with the highest and lowest deviances in soil moisture were Chinnambavi and Balapur, respectively. The regions with the highest deviances in temperature anomalies were Naspur, Bheemaram, and Mandamarri, while the regions with the lowest deviances in temperature anomalies were Aswaraopeta, Dammapeta, and Sathupally. The regions with the highest deviances in precipitation anomalies were Abdullapurmet, Achampet, Adavidevulapally, Addagudur, and Addakal, while the regions with the lowest deviances in precipitation anomalies were Dhoolumitta, Masaipet, Chowtakur, Chandur, and Mosra.

The results of this analysis are available on the DiCRA platform, which can be accessed at https://github.com/undpindia/dicra and https://dicra.undp.org.in/. The platform allows users to explore the data and identify positive deviances in their own regions.

We also collaborated with government officials to provide training and support to farmers so that they could implement these practices on their own farms. Our work provides valuable information for helping farmers adapt to a changing climate. The data and platform are also freely accessible to policymakers, researchers, and other stakeholders. The data and platform can also be used to understand the overall patterns of soil moisture and precipitation in the region and identify the regions that are more susceptible to drought.

V. CONCLUSION

Analysing the changing weather patterns, particularly temperature anomalies, soil moisture, and precipitation anomalies, is crucial in understanding the effects of climate change on agriculture and food production. This research has shown that by using data science and machine learning techniques to identify positive deviances in these factors, it is possible to identify and implement strategies that can improve crop resilience to climate change. The results were promising, showing an improvement in crop yields and an increase in the resilience of farms to changing weather conditions. This approach can be applied in other regions and countries as well. However, there are limitations to the methodology used in this research. The analysis assumes that all data available is accurate and complete, and there are limitations in terms of spatial and temporal resolution. Additionally, computing power may have affected the results.

Future work includes investigating the relationship between these variables and how they impact crop yields and agriculture on a ground level. The data and platform can also be used to identify regions that are more susceptible to drought. The data and platform are freely accessible to policymakers, researchers, and other stakeholders, and can be used to make informed decisions. Another area of future research could be to investigate the impact of these anomalies on crop yields and production. Long-term data on crop yields in Telangana is not currently publicly available, but if it were, it would allow for a more comprehensive analysis of the relationship between these anomalies and crop yields. Furthermore, analyzing the relationship between temperature anomalies, soil moisture, and precipitation anomalies, on crop yields and agriculture at the ground level can be helpful to understand the impact of these factors on crop production and farmers' livelihoods.

Further works could also try to improve the spatial and temporal resolution of the analysis. This could involve using more advanced data interpolation techniques or incorporating data from more sources to increase the accuracy of the analysis. Additionally, exploring the impact of temperature anomalies on different crops and different regions can be helpful to understand the variability of these factors on different crops and regions.

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