



Meghnad Desai
Academy of Economics

Dissertation Title:

**How Climate Change Affects Food
in India: Case study.**

Dissertation Mentor:

Dr. Niranjana Rajadhyaksha

Swastika Pandey

PGD Economics, Meghnad Desai Academy of Economics

Acknowledgements

First, I would like to thank my mentor, Dr. Niranjana Rajadhyaksha, for his invaluable guidance and support throughout my dissertation, from the very initial conception of the idea to its final execution. His insights and encouragement have been instrumental in shaping this work, and this would not have happened without his guidance.

I am also deeply grateful to all the amazing faculty at Meghnad Desai Academy of Economics for their thoughtful discussions and feedback, and for always hearing me out which significantly enriched my research.

Additionally, I extend my heartfelt thanks to the administration at the academy for their assistance with logistical arrangements, ensuring a smooth and efficient process. This dissertation would not have been possible without their collective support!

Abstract

Agriculture in India saw the Neolithic era, the Indus Valley Civilization, the Iron Age, the Middle Ages, and the colonial period. It witnessed dynasties come and go and is now witnessing climate change. This study examines the impact of climate change on food security in India, focusing on agricultural yields and climate patterns over the past five decades. Utilizing data from ICRISAT and ERA5-Land, a time series analysis was conducted to assess the effect of climate variables on agricultural yields. Wheat, Rice and Pulses were studied in district Sehore of Madhya Pradesh.

Keywords: Climate Change.

Table of Contents:

<u>Abstract</u>	<u>2</u>
<u>Introduction</u>	<u>4</u>
<u>Literature Review</u>	<u>6</u>
<u>Methodology</u>	<u>11</u>
<u>Result</u>	<u>12</u>
<u>Discussion</u>	<u>24</u>
<u>Citation</u>	<u>25</u>

Introduction

Indian agriculture—safe to say one of the first in the world—began independently around 9000 BCE in the northwest, revolutionizing human civilization and neurology forever. This is the first time the human brain learned to save and understand the concept of planning beyond the near future. Pioneers—our ancestors.

Agriculture in India saw the Neolithic era, the Indus Valley Civilization, the Iron Age, the Middle Ages, and the colonial period. It witnessed dynasties come and go. Fast forward to now, in the post-colonial period, India has been extremely focused on growing more crops (cash and food) within the country with policies that were introduced to fill the void left by colonial practices. Since Independence, India has become one of the largest producers of wheat, edible oil, potatoes, spices, rubber, tea, fish, fruits, and vegetables in the world.

In the context of India, temperatures all around the country are reaching all-time highs. Places like the western Himalayas, Punjab, Haryana, Delhi, Rajasthan, and Uttar Pradesh have seen decadal and all-time temperature rises. There are increasing occurrences of heatwaves throughout the country that are causing forest fires and affecting the vast majority of the nation (Indian Meteorological Department, 2022). Precipitation, although not varying too much in quantity in a given area, varies significantly in the timing throughout the year, affecting sowing patterns.

These changes in climatic conditions are making agriculture increasingly challenging. Time and time again, the IPCC and other researchers have highlighted the harms of a warming planet—hotter temperatures, unreliable weather, increased instances and intensity of climate-induced natural disasters, rising oceans, loss of biodiversity, climate injustice, and the possibility of a global rise in hunger and poor nutrition. An increase in atmospheric carbon accelerates crop growth, but the crops tend to lack nutrients. Food security had been consistently rising for several years due to neo-Malthusian policies adopted around the globe, but in recent times, food security has stalled and even started to decline. In our project, we explore whether climate change plays a role in this trend in the Indian context.

Food Security is a situation that exists when all people, at all times, have physical, social, and economic access to sufficient, safe, and nutritious food that meets their dietary needs and food preferences for an active and healthy life.

- FAO, 2001

There are four dimensions of food security. Availability, Access, Utilization, and Stability. The Availability(National/International) dimension of food security deals with the supply side of the food security problem. There should be enough food produced internally and imported by the nation to have enough food determined by the level in stock and net trade. Then comes Access(Household). This refers to the economic and physical access to food. Now if there is National/International Availability of food, then comes the factor of physical and economic accessibility. These are the two dimensions we are mainly focusing on in this study. Furthermore, there is Utilization(individual). This dimension is concerned with how the body makes use of the food provided to it, and if the food is nutritious. The next dimension is Stability, and it is all of the above dimensions over time. Meaning the food availability, access and utilization should be somewhat constant over time. Moreover, there are two kinds of hunger. One kind is apparent when somebody's calorie intake is not being met. Another kind is what's called hidden hunger, where the calorie intake is seemingly met but the nutritional requirements of an individual aren't being met.

To speak of the Intersectionality of climate change, food production, and food security; Climate change as earlier mentioned causes harsher climatic conditions and thus makes for scarce agricultural yields, increased carbon dioxide levels cause crops to grow quicker and have lower nutritional value. Not only that but increases in temperatures and erratic rainfall patterns can cause produce to spoil quickly and the world faces vastly more quantities of food loss (supply side) and food waste(demand side). In case there isn't discarded food on either end of the food supply chain, spoiled food might cause people food poisoning. Increased crops also increase pests' resistance to heat requiring farmers to use more pesticides. Increasing temperatures also harm agricultural workers livestock and pollinators that can not adapt to the heat. There are mitigation strategies but they only go so far. The consequences of farmers using more resources and producing yield with less nutritional output mean that consumers pay more for the same quantity of food with even less nutritional intake, increasing the food insecurity problem, even though there is more food on the planet than ever.

Literature Review

(Cole et. al., 2018) By 2050 the world population will grow to 9.7 billion people and require 70% (127×10^{15} kcal) more food available for human consumption than currently available. There are 5 “megatrends” that are going to affect the food industry significantly in the next few decades:

- **A less predictable planet**

This is because of climate change, fewer resources and more people sharing them.

- **Health conscious people**

This is because of an ageing population around the globe.

- **Choosey consumers**

Improving wealth and lifestyle choices may lead to a pull from the demand side for high quality.

- **One world**

Increasing globalisation may lead to well-connected value chains and increased competition (and risk)

- **Smarter food chains**

Improved value chains because of big data and enhanced e-commerce platforms.

Food loss is prevalent in developing countries where a large proportion of food is lost during production, processing and/or transportation, and food waste is a big problem in developed countries where retailers and consumers throw food away, so mitigation strategies aimed at reducing the effects of climate should target different areas in different regions. To remove food insecurity, one must focus on both “human and planetary health”.

(NASA et. al., March 2020) The current food system (production, transport, processing, packaging, storage, retail, consumption, food loss, food waste) feeds a majority of the world’s population and gives livelihood to 1 billion people. Agriculture generates up to 60% of the GDP in countries (a world average of 4% in 2017). Since 1961, the world has seen tremendous increases in food production per capita (30%), nitrogen fertilisers (300%) and water (100%). Since carbon has increased in the atmosphere, crops tend to grow faster. This might seem productive on paper, but the produced grains have significantly less nutritional value unless combined with increased nitrogen and water in the soil which helps mitigate a significant amount of loss from climate change. Climate change is also causing the world to

experience more natural disasters like floods, droughts, storms, and heat waves; which, studies suggest as the temperature increases will only get more prolonged, more intense, and more likely to occur. This is detrimental to food production and livelihoods of countries with a majority of the population earning their livelihood in the agricultural sector. Climate change not only affects crop and fruit/vegetable production; but also fisheries and livestock all over the world because of increased instances of floods and heatwaves respectively. There are steps during the production phase and the processing phase that will help mitigate climate change and reduce potential food waste by increasing the shelf life of the produce, but the mitigation strategies can only do so much. They also add a lot more resources needed to produce food. There is also a need for increased public opinion on climate change and wanting to consume food that does not have immensely negative consequences for climate and foods that will not go bad soon. This will affect the supply side by a “pull” from the demand side of the food production mechanism. Food production has a very strange relationship with climate change because not only is it a major contributor to climate change but also incredibly susceptible to it.

There will be a need to produce 50% more food to feed the world’s population (UNFAO, 2018). This will lead to a loss in biodiversity and forest cover for food production. This will also lead to a huge increase in GHG emissions. Climate change affects all four pillars of food security: Availability, Access, Utilization, and Stability. Low-income producers and consumers are likely to be most affected because of a lack of resources to invest in adaptation and diversification measures (UNCCD 2017; Bailey et al. 2015).

Climate Change and Availability of Food: Climate Change affects the availability of food because it increases food prices. It leads to a reduction in crop and livestock yields, reduces pollinators, reduces food quality, and disrupts storage and supply chain networks.

93% of the world’s calories, including crop and animal products, which are being traded more than ever are produced on land. The world has observed an increase in oil crops, fruits, vegetables, cereals, and animal products and as a result- there was a decrease in underweight individuals and an increase in overweight individuals until the 2014-15 fiscal year. Post that the prevalence of hunger is increasing as well as instances of overweight individuals. This goes to say that disparities in who and what places get good quality food are prevalent. This gives a sort of dual aspect to the problem of food security. On the one hand, some people are malnourished, and on the other hand, some people are obese/overweight, and now that we are producing more food than ever (a 30% increase in per capita production as discussed) food

insecurity is on the rise.

Apart from that, there is also the problem of “hidden hunger”. This problem worsens in Africa and improves elsewhere when a person eats enough calories but not enough nutrients as per their requirements. This is because of the increased production of calorie-dense crops. The increase in said crops contributes to a “food desert” where people have hidden hunger. So, a place (usually in the developed world) a place that has high-calorie food often leads to a decline in nutritional status of the area and an increase in obesity and other problems that come with being overweight.

Climate change, it is found, has particularly adverse effects on rural areas. A study in rural Mexico observed a 1.4% reduction in employment locally.

Climate change also affects human health through utilisation, in the sense that it reduces shelf life, and makes food less nutritious. Food insecure people are more likely to be affected by heat, employment-wise- since they will be more susceptible to falling sick.

There is also an angle of gender in food insecurity due to climate change, because women have different nutritional requirements throughout their lives, such as when pregnant or breastfeeding. Women also tend to reduce their consumption as food insecurity hits the area/family relative to other community members. Additionally, the urban poor experience more exacerbated food insecurity because of climate change because they have lesser access to resources to produce food than the urban rich or rural poor, and climate-induced floods cause water contamination and as a result, food poisoning and diarrhoea.

Increasing concentrations of Short Lived Climate Pollutants (SLCPs) like ozone and black carbon affect crop yield directly. Ozone affects cell metabolism and is associated with increases in temperatures. C3 crops (maize, soybean, barley, peppers, etc.) are highly and C4 crops (Sorghum, Sugarcane, Giant Millet, etc.) are moderately affected by the ozone increase.

On the production pillar, There is glaring evidence that the increase in climate change affects food production. Studies on existing climate variables indicate that a temperature rise will seriously affect crop production in the future (Mavromatis 2015, Innes et al. 2015). A counterfactual analysis proved that climate change between the years 1981 and 2010 decreased produce yields in maize (4.1%), wheat (1.8%), and soybean (4.5%) resultantly (this is relative to pre-industrial climate, after taking into account the effect of CO₂ fertilisation and other mitigation strategies). Drylands- which are 40% of the world’s land area, and home to 2.5 billion people are the most susceptible to effects on production by climate change since they have deficient capacities for dealing with decreasing crop yields (FAO et al. 2011).

Asia has observed increased rice yields in China (because of the increasing temperatures) (Shi et al. 2013), positive in northern China and negative in Southern China. (Tao et al. 2014). India, however, has seen a decrease in yields by 5.2% from 1981 to 2009 because of the warming despite mitigation efforts (Gupta et al. 2017). The Hindu-Kush Mountains are particularly affected by the lack of infrastructure and resulting isolation. They are also particularly affected by Glacial Lake Flood Outbursts (GLFOs), making them even more vulnerable to climate-induced food insecurity. They experience more intense extremes in weather and often occurring floods and droughts. Agriculture in Pakistan has seen similar effects due to climate change, and it frequently changes the phenology of the crop in question (Tariq et al. 2018).

Large shifts in land use and the choice of crops planted will be required to keep feeding the world by 2050 because climate change reduced attainable yields (Pugh et al. 2016). Vegetables see a similar effect (Bisbis et al. 2018).

An increase in heat may increase production in some cases but can seriously alter plant biology and the nutrients in the food. This will increase food loss and waste, and people will need more food to get the same nutrients.

On the access pillar, it has been found, by a series of AgMIP style analyses that were conducted on several RCP (Representative Concentration Pathways) and SSP (Shared Social Pathways) scenarios by 2050. (SSP (Shared Social Pathways) are 5 pathways devised on quantitative factors like GDP, population, urbanization, education for countries and 5 narratives are given 1 being sustainability and 5 being fossil fueled growth. Depending on what a country chooses the SSP forecasts the future, so to speak. These SSPs are then used as inputs for integrated emission models RCPs (Representative Concentration Pathways) are forecasted concentrations of trajectories of greenhouse gasses throughout the years. AgMIP (Agricultural Model Intercomparison and Improvement Project) aims to assess the interconnectivity between agriculture and climate change scenarios and vice versa.) In the study conducted mentioned above, cereal prices may increase 1-29% in certain areas of the world due to climate change, with the median remaining 7% across the globe even in SSP 1, 2 and 3 (where the RCP is 6.0). Declining food availability due to climate change is projected to raise food costs, impacting global consumers, especially low-income groups. Higher prices reduce demand, decreasing calorie intake and micronutrient availability, leading to poorer diets and increased diet-related mortality. Models predict a rise in hunger risk, with millions more facing insufficient energy intake because of climate change (Hasegawa et al. 2018).

Climate change is also likely to increase in land use globally(Nelson et al. 2014) and that 7 out of 8 models suggest an increase in land use due to decreased productivity (climate-induced) by 2050 . The study also shows that south asia is likely to lose significant amounts of its grassland cover in SSP 2 and SSP 3.

On the utilisation pillar, climate change can increase risk of contamination due to increased temperatures and erratic rainfall. Intensification of the crop to battle climate change may also make them more susceptible to such attacks (Tirado et al. 2010). There are small-scale experiments that suggest that rising co2 levels and temperature changes affect physiological processes in photosynthetic organisms (like maize) and thus make crops more susceptible to aflatoxins which are responsible for some kinds of cancer. (Medina, Vaughan et al. 2016)

Methodology

Quantitative analysis was done on secondary data taken from ICRISAT and ERA5-Land monthly averaged data from 1950 to the present from Climate Data Store, Copernicus, which has a lot of climatic datasets on the EU as well as the world. The analysis was done in Python. A few images were exported from Google Earth Engine.

ICRISAT has agricultural data from 20 agriculture-heavy states in India, including Chhattisgarh, Madhya Pradesh, Andhra Pradesh, Telangana, Karnataka, Tamil Nadu, Maharashtra, Gujarat, Rajasthan, Punjab, Haryana, Uttar Pradesh, Uttarakhand, Assam, Himachal Pradesh, Kerala, Orissa, West Bengal, Bihar, and Jharkhand. This dataset encompassed 308 districts across the country and spans nearly five decades, from 1966 to 2015.

The primary focus of our study was on evaluating various agricultural parameters such as fertilizer consumption and the APY (Area, Produce, Yield) of multiple crops. Sowing and irrigation patterns were also examined to comprehensively understand agricultural practices across these states. This rich dataset was sourced from a collaborative repository maintained by the TATA Cornell Institute (TCI) and the International Crops Research Institute for the Semi-Arid Tropics (ICRISAT).

Geospatial data was integrated by adding geocodes to the datasets using Python. This enhancement allowed for the inclusion of spatial dimensions, climate data, including temperature and precipitation metrics, as well as information on water resources, was incorporated. This data was sourced from Google Earth and seamlessly integrated into the Python environment.

The districts in the ICRISAT were plotted on the GEE interface, along with minimum and maximum temperature (mean) over the 50 years of study.

To assess the impact of climate on agriculture, a time series analysis was conducted to see how temperature affects agricultural yields on the district of Sehore, then the state of Madhya Pradesh.

Results

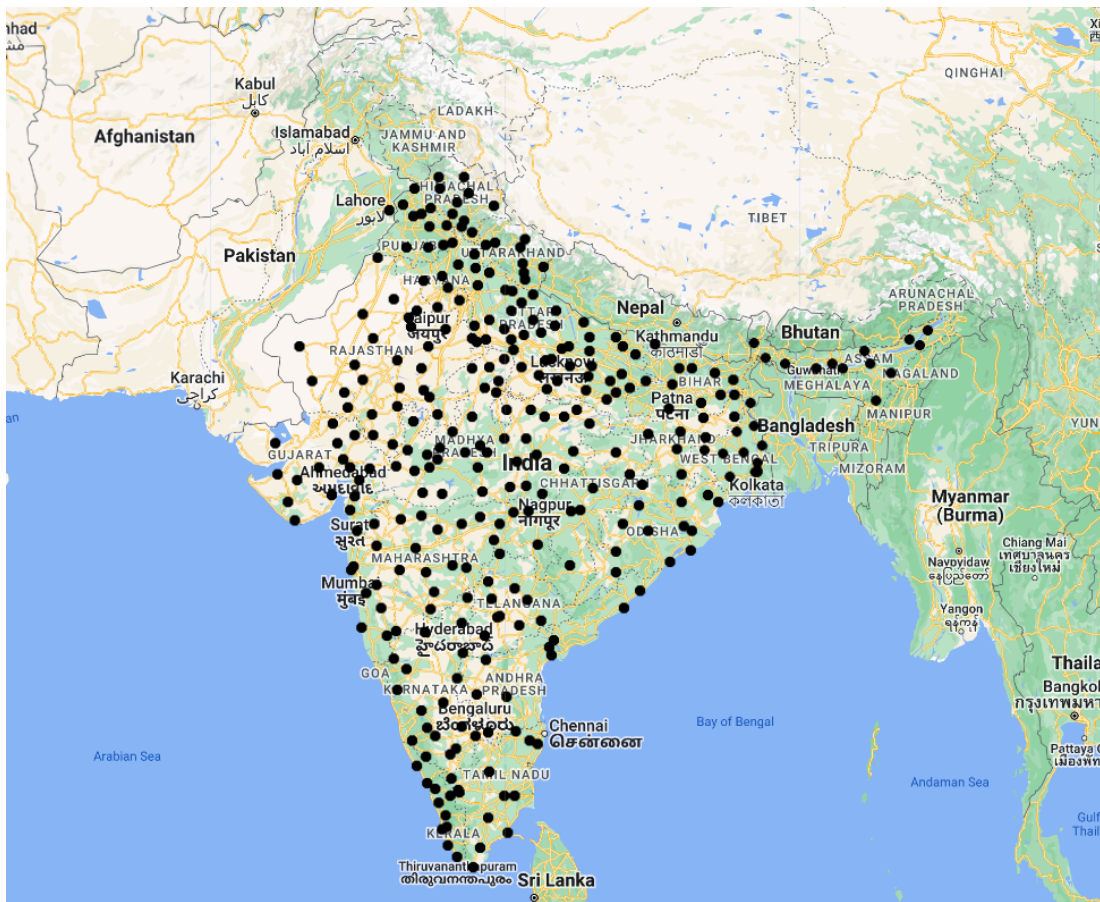


Image 1: Districts

Extracted from: Google Earth Engine

The above are the districts with available data.

This is the data of Mean maximum temperatures for the duration of our study

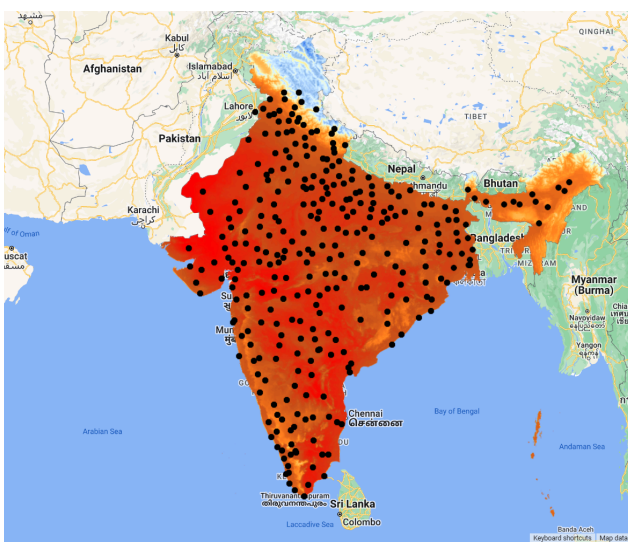


Image2: Maximum Temperature

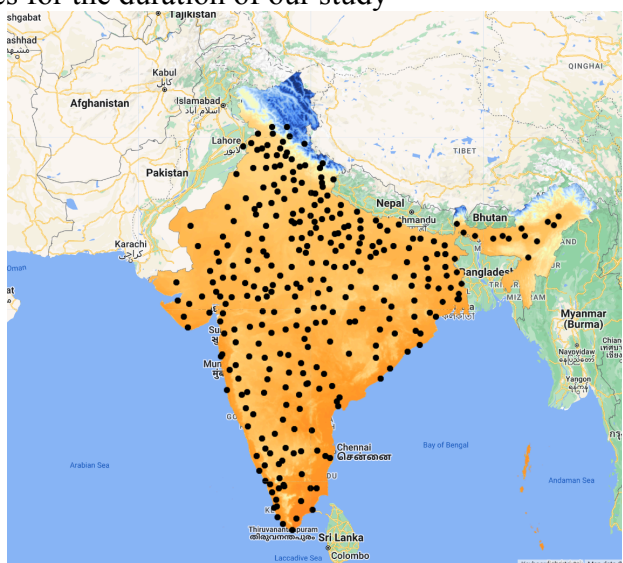


Image3: Minimum Temperature

Temperature and Precipitation data was taken from TERRAClimate and analysed statewise.

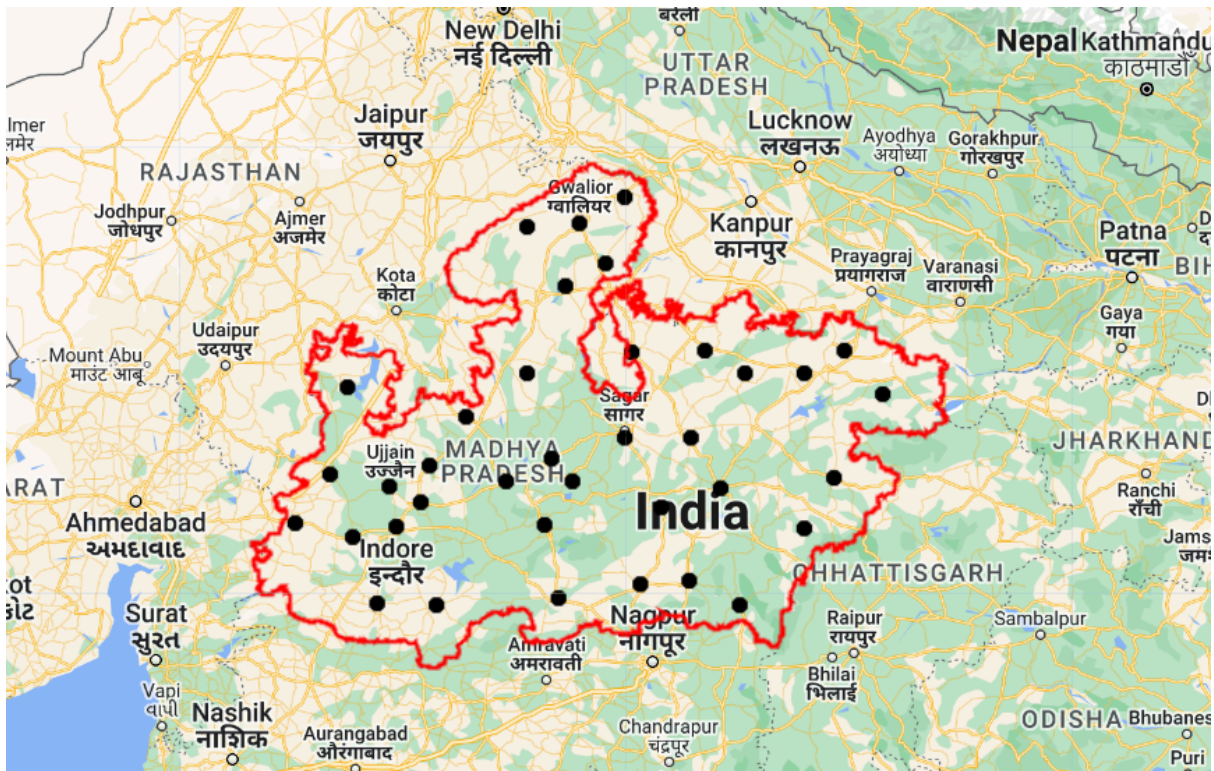


Image 4: Districts in MP in the ICRISAT data

First, we take Sehore, a district right next to Bhopal famous throughout the country for its crop produce, particularly wheat.

The APY was further divided into wheat, rice, and pulses as they constitute most of the Indian diet.

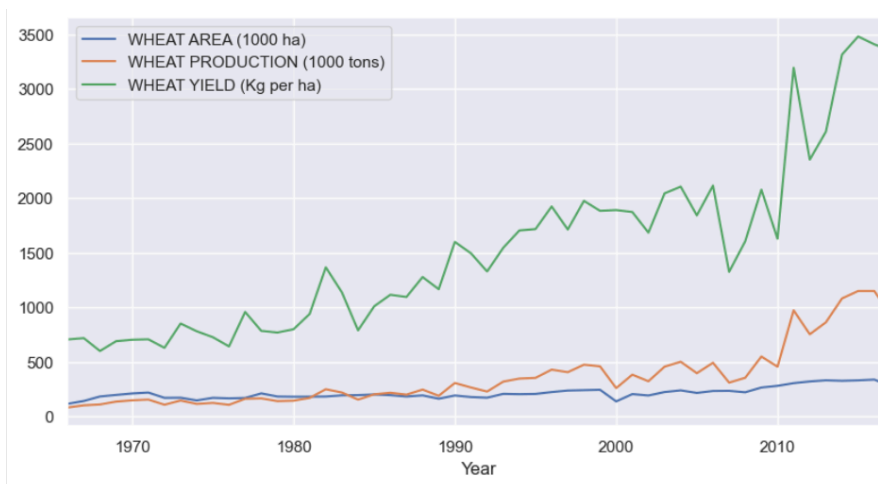


Image 5: Wheat APY in Sehore through 1966 to 2016.

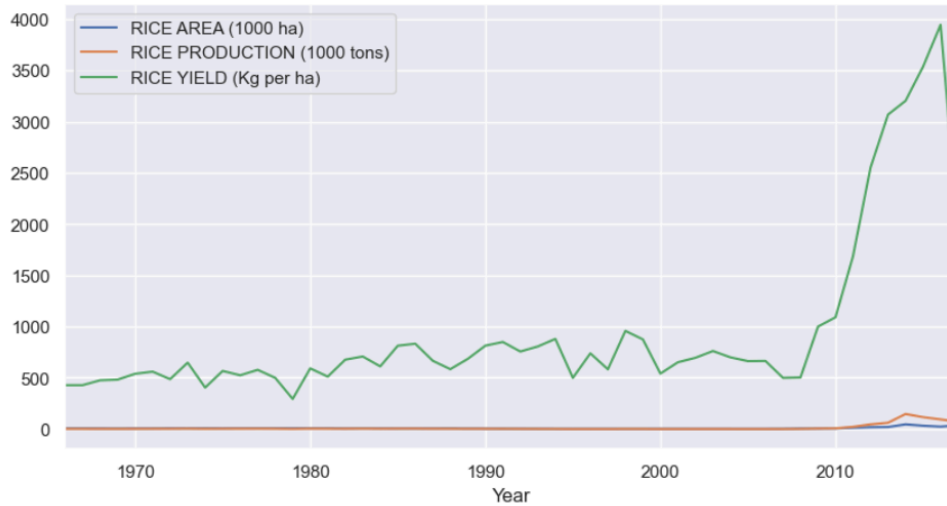


Image 6: Rice APY in Sehere through 1966 to 2016.

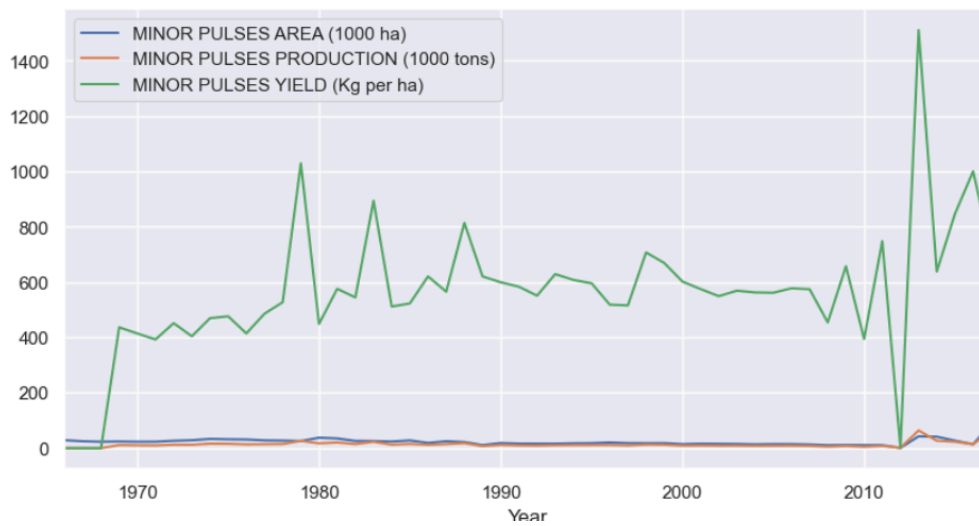


Image 7: Wheat APY in Sehere through 1966 to 2016.

There is seemingly an increase in wheat after 2010, probably owing to technological advances or a regional change in Sehere/Madhya Pradesh.

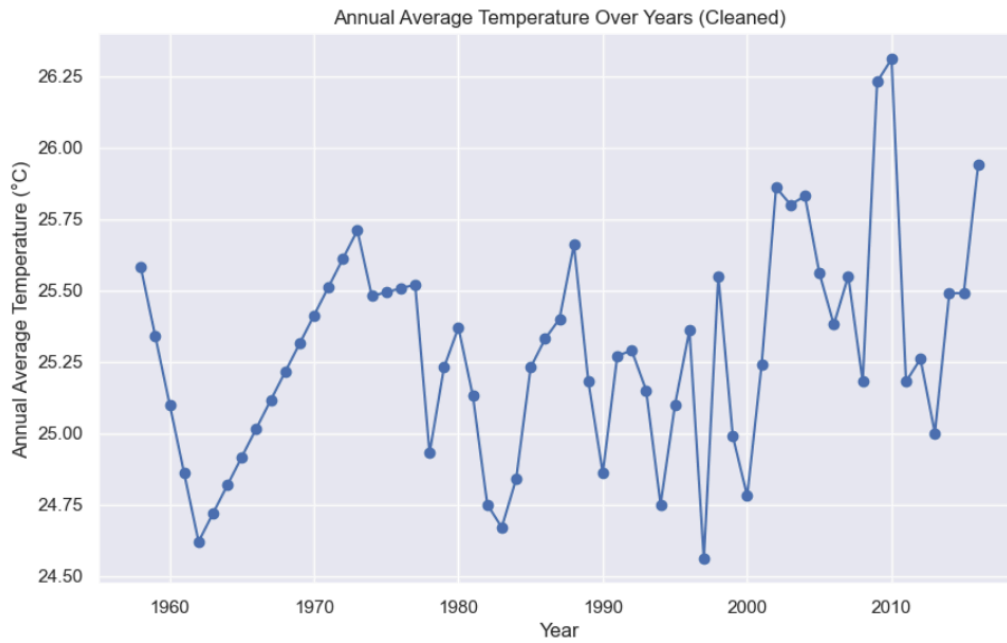


Image 8 : Temperature from NASA's Bhopal Station over the years 1956 to 2016

One can observe the rise in temperature in this graph throughout the years. This is the annual average temperature recorded by GISS Surface Temperature Analysis (v4); NASA's station in Bhopal, a district adjacent to Sehore. Below, in image 9, is a seasonally decomposed representation of the same climate data, and there is a clear upward trend of 0.5, which is not as small as it sounds; and is also of course, seasonal.

Images 10 and 11 are summer and winter plots respectively. Now, there seems to be a rise in seasonal summer temperatures every year, the winter temperatures (when the kharif crops are sown) rise too but not as much as the summer ones do.

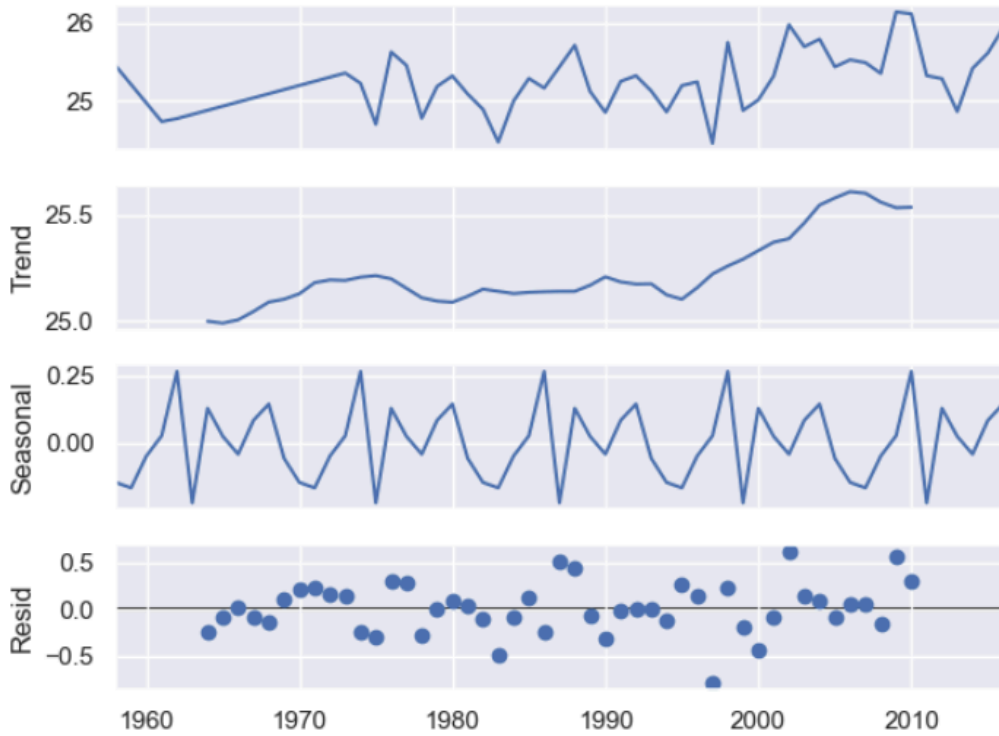


Image 9: Seasonal Decomposition of Month-wise Temperature Data

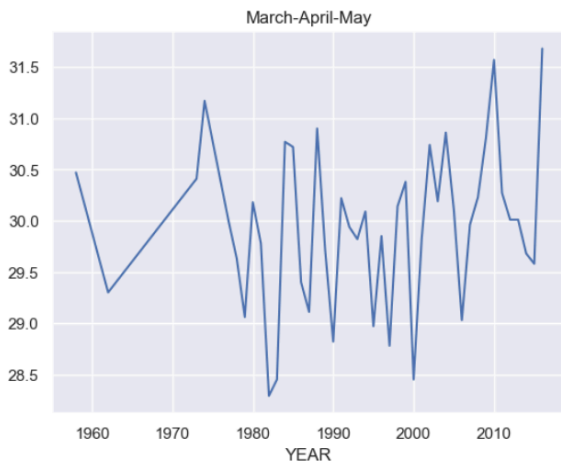


Image 10: Summer Temperature 1966-2016

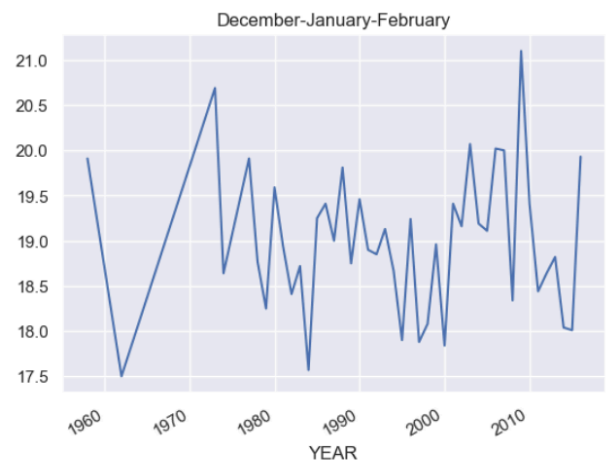


Image 11: Winter Temperature 1966-2016

Now, we perform Augmented Dickey Fuller on our Sehere: Rice, Wheat, and Pulses APY.
We find:

	Test Statistic	p-value	Lags Used	Number of Observations	Critical Values	IC Best
RICE AREA (1000 ha)	-1.613414	0.476183	5	46	('1%': -3.5812576580093696, '5%': -2.926784912...	230.957074
RICE PRODUCTION (1000 tons)	-2.885212	0.047095	4	47	('1%': -3.5778480370438146, '5%': -2.925338105...	283.911985
RICE YIELD (Kg per ha)	-1.973486	0.298318	6	45	('1%': -3.584828853223594, '5%': -2.9282991495...	583.301327

Image 12: ADF on Rice APY of Sehore

Rice Area, Production, and Yield, as we saw in the graphs above are not stationary. Lags used are 5,4, and 6 which means data from those lags is affecting the stationarity.

	Test Statistic	p-value	Lags Used	Number of Observations	Critical Values	IC Best
WHEAT AREA (1000 ha)	-1.437308	0.564266	1	50	('1%': -3.568485864, '5%': -2.92135992, '10%':...	378.401548
WHEAT PRODUCTION (1000 tons)	0.328343	0.978608	1	50	('1%': -3.568485864, '5%': -2.92135992, '10%':...	499.111042
WHEAT YIELD (Kg per ha)	1.058049	0.994842	2	49	('1%': -3.5714715250448363, '5%': -2.922629480...	582.944595

Image 13: ADF on Wheat APY of Sehore

Wheat Area, Production, and Yield are also non-stationary.

	Test Statistic	p-value	Lags Used	Number of Observations	Critical Values	IC Best
MINOR PULSES AREA (1000 ha)	-1.370505	0.596332	4	47	('1%': -3.5778480370438146, '5%': -2.925338105...	298.985536
MINOR PULSES PRODUCTION (1000 tons)	-1.602876	0.482149	4	47	('1%': -3.5778480370438146, '5%': -2.925338105...	305.398058
MINOR PULSES YIELD (Kg per ha)	-6.549548	0.0	0	51	('1%': -3.5656240522121956, '5%': -2.920142229...	543.167836

Image 14: ADF on Pulses APY of Sehore

Pulses Area and Production are non-stationary.

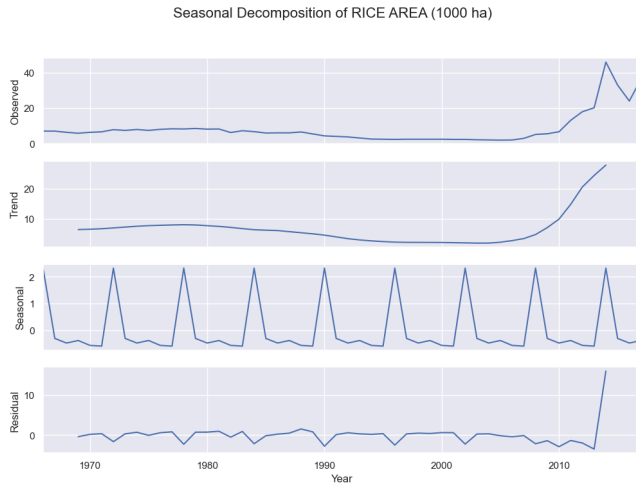


Image 15: SD of Rice Area in Sehare.

In all of the trend decompositions, there is an increase in the APY. (in wheat, rice and pulses).

Then, there is of course seasonality in the data of all of the seasonal decompositions.

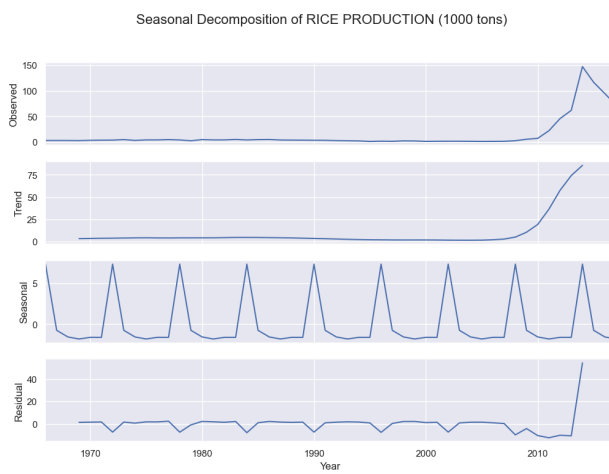


Image 16: SD of Rice Production in Sehare.

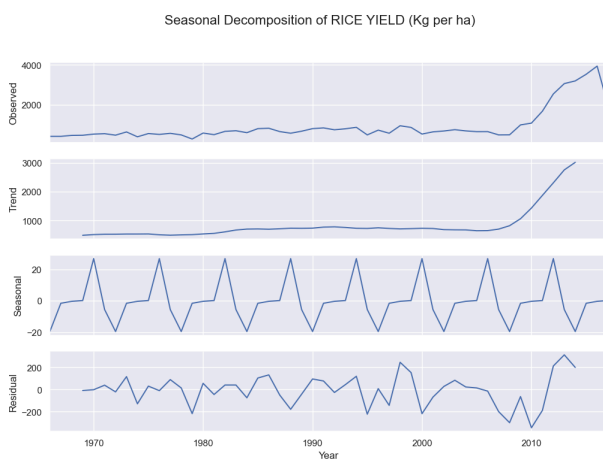


Image 17: SD of Rice Production in Sehare.

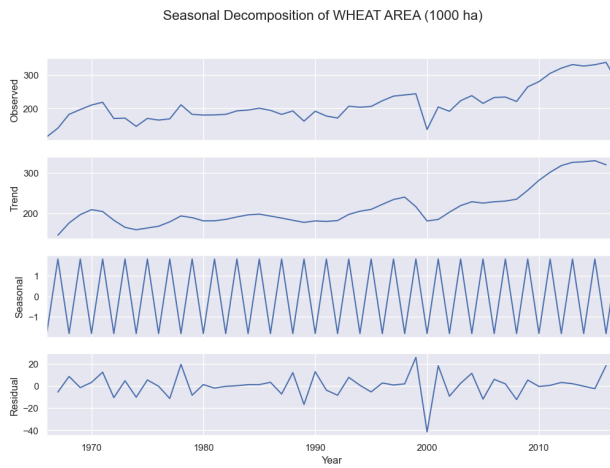


Image 18: SD of Wheat Area in Sehore.

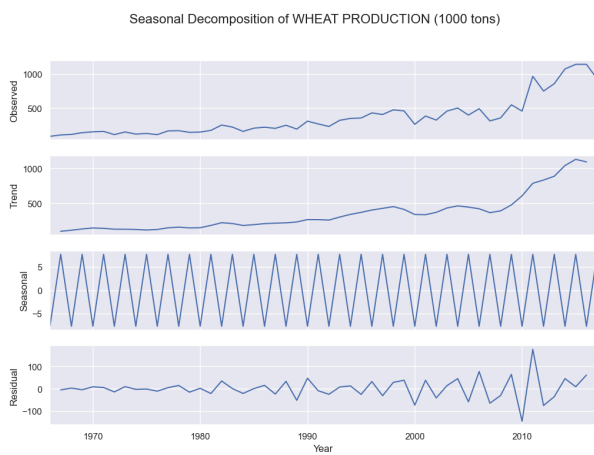


Image 19: SD of Wheat Area in Sehore.

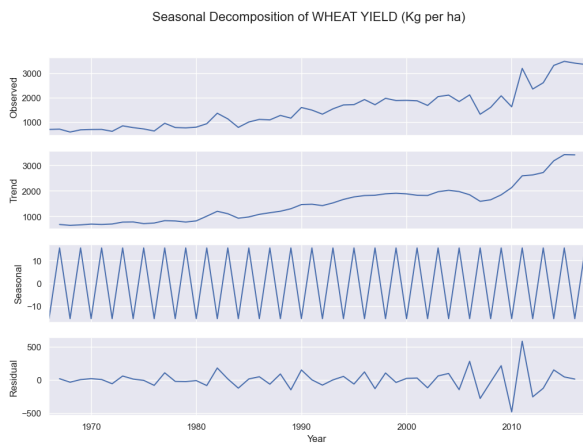


Image 20: SD of Wheat Area in Sehore

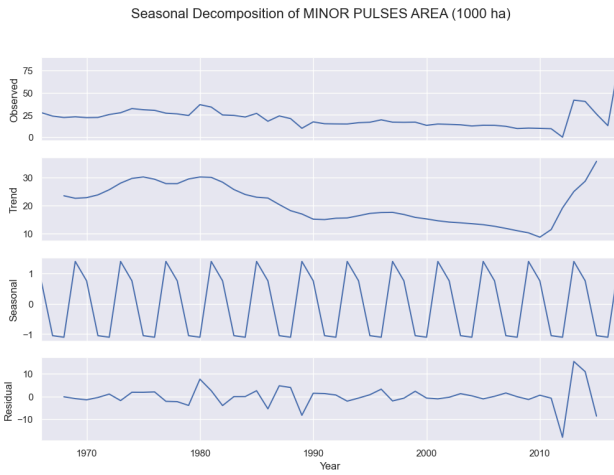


Image 21: SD of Pulses Area in Sehore.

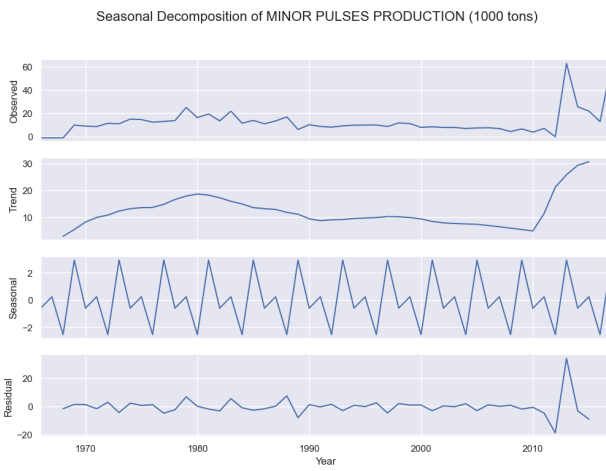


Image 22: SD of Pulses Production in Sehore.

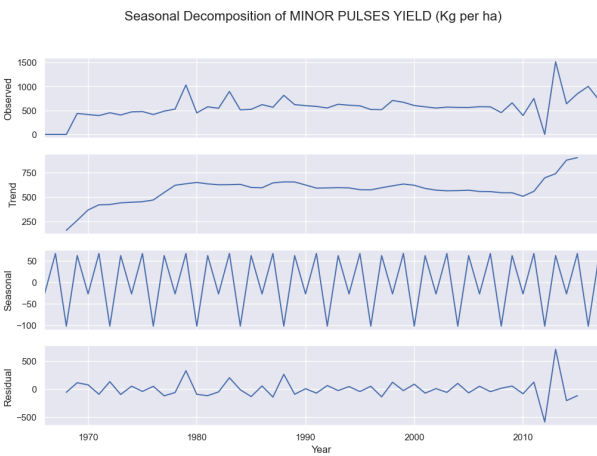


Image 23: SD of Pulses Area in Sehore.

OLS Regression Results

```

=====
Dep. Variable:   WHEAT YIELD (Kg per ha)   R-squared:         0.882
Model:          OLS                       Adj. R-squared:    0.858
Method:         Least Squares             F-statistic:       36.46
Date:           Thu, 11 Jul 2024          Prob (F-statistic): 9.12e-16
Time:           04:45:45                  Log-Likelihood:    -334.23
No. Observations: 48                     AIC:               686.5
Df Residuals:   39                       BIC:               703.3
Df Model:        8
Covariance Type: nonrobust
=====

```

	coef	std err	t	P> t	[0.025	0.975]
const	5142.1497	3271.594	1.572	0.124	-1475.273	1.18e+04
WHEAT AREA (1000 ha)	0.8651	2.083	0.415	0.680	-3.349	5.079
TOTAL CONSUMPTION (tons)	-5.092e-05	0.006	-0.009	0.993	-0.012	0.012
WHEAT IRRIGATED AREA (1000 ha)	6.3811	1.583	4.032	0.000	3.180	9.583
metANN	0.2568	365.837	0.001	0.999	-739.718	740.231
D-J-F	-57.3624	98.777	-0.581	0.565	-257.159	142.434
M-A-M	-115.0071	121.763	-0.945	0.351	-361.296	131.282
J-J-A	10.2955	103.024	0.100	0.921	-198.090	218.681
S-O-N	-12.9206	83.357	-0.155	0.878	-181.527	155.686

```

=====
Omnibus:         5.892   Durbin-Watson:      1.799
Prob(Omnibus):   0.053   Jarque-Bera (JB):    5.328
Skew:            -0.504   Prob(JB):            0.0697
Kurtosis:        4.284   Cond. No.            3.80e+06
=====

```

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 3.8e+06. This might indicate that there are strong multicollinearity or other numerical problems.

Image 24: Regression on Sehere Dependent Variable: Wheat Yield

Although none of the variables are significant (possibly attributable to a small dataset), wheat seems to be enjoying the heat. This could also be because it is famous for wheat production and there are other factors at play the regression does not address.

OLS Regression Results

```

=====
Dep. Variable:   RICE YIELD (Kg per ha)   R-squared:         0.974
Model:          OLS                       Adj. R-squared:    0.969
Method:         Least Squares             F-statistic:       185.8
Date:           Thu, 11 Jul 2024          Prob (F-statistic): 1.37e-28
Time:           04:02:17                  Log-Likelihood:    -302.64
No. Observations: 48                     AIC:               623.3
Df Residuals:   39                       BIC:               640.1
Df Model:        8
Covariance Type: nonrobust
=====

```

	coef	std err	t	P> t	[0.025	0.975]
const	3691.4285	1649.271	2.238	0.031	355.462	7027.395
RICE AREA (1000 ha)	-45.2440	9.521	-4.752	0.000	-64.503	-25.985
TOTAL CONSUMPTION (tons)	-0.0032	0.002	-2.008	0.052	-0.006	2.35e-05
RICE IRRIGATED AREA (1000 ha)	162.0892	13.623	11.899	0.000	134.535	189.643
metANN	-310.0132	190.989	-1.623	0.113	-696.324	76.298
D-J-F	80.1341	52.213	1.535	0.133	-25.477	185.745
M-A-M	67.3867	63.703	1.058	0.297	-61.464	196.238
J-J-A	54.3914	52.416	1.038	0.306	-51.630	160.413
S-O-N	1.3345	42.956	0.031	0.975	-85.551	88.220

```

=====
Omnibus:         4.159   Durbin-Watson:      1.563
Prob(Omnibus):   0.125   Jarque-Bera (JB):    4.302
Skew:            -0.110   Prob(JB):            0.116
Kurtosis:        4.450   Cond. No.            3.70e+06
=====

```

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 3.7e+06. This might indicate that there are strong multicollinearity or other numerical problems.

Image 25: Regression on Sehere Dependent Variable: Rice Yield

Here, again the pattern repeats, more or less and keeps repeating for all Sehere OLS outputs.

OLS Regression Results

```

=====
Dep. Variable:   MINOR PULSES YIELD (Kg per ha)   R-squared:         0.325
Model:          OLS                       Adj. R-squared:    0.187
Method:         Least Squares             F-statistic:       2.350
Date:           Thu, 11 Jul 2024          Prob (F-statistic): 0.0362
Time:           04:53:17                  Log-Likelihood:    -315.69
No. Observations: 48                     AIC:               649.4
Df Residuals:   39                       BIC:               666.2
Df Model:        8
Covariance Type: nonrobust
=====

```

	coef	std err	t	P> t	[0.025	0.975]
const	3194.2457	2171.942	1.471	0.149	-1198.922	7587.414
MINOR PULSES AREA (1000 ha)	7.1016	4.180	1.696	0.098	-1.369	15.572
TOTAL CONSUMPTION (tons)	0.0010	0.002	0.556	0.575	-0.003	0.005
MINOR PULSES IRRIGATED AREA (1000 ha)	9.1262	6.614	1.380	0.175	-4.252	22.504
metANN	-220.8309	248.881	-0.887	0.380	-724.241	282.579
D-J-F	47.3967	67.759	0.699	0.488	-89.660	184.453
M-A-M	11.0428	82.808	0.133	0.895	-156.453	178.539
J-J-A	26.9520	69.662	0.387	0.701	-113.953	167.857
S-O-N	32.0731	56.364	0.569	0.573	-81.934	146.080

```

=====
Omnibus:         8.236   Durbin-Watson:      2.814
Prob(Omnibus):   0.016   Jarque-Bera (JB):    16.487
Skew:            -0.128   Prob(JB):            0.000263
Kurtosis:        5.860   Cond. No.            3.71e+06
=====

```

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 3.71e+06. This might indicate that there are strong multicollinearity or other numerical problems.

Image 26: Regression on Sehere Dependent Variable: Rice Yield

Pulses seem to have a negative effect on the total annual mean temperature as well, but not seasonally.

State OLS

OLS Regression Results						
Dep. Variable:	RICE YIELD (Kg per ha)	R-squared:	0.837			
Model:	OLS	Adj. R-squared:	0.807			
Method:	Least Squares	F-statistic:	27.70			
Date:	Thu, 11 Jul 2024	Prob (F-statistic):	1.41e-14			
Time:	07:53:43	Log-Likelihood:	-512.59			
No. Observations:	52	AIC:	1043.			
Df Residuals:	43	BIC:	1061.			
Df Model:	8					
Covariance Type:	nonrobust					
	coef	std err	t	P> t	[0.025	0.975]
const	2.445e+04	1.14e+04	2.136	0.038	1370.119	4.75e+04
RICE AREA (1000 ha)	-1.6850	8.275	-0.204	0.840	-18.373	15.003
RICE IRRIGATED AREA (1000 ha)	39.7673	10.568	3.763	0.001	18.455	61.080
TOTAL CONSUMPTION (tons)	0.0068	0.002	3.335	0.002	0.003	0.011
metANN	-4355.4366	6432.699	-0.677	0.502	-1.73e+04	8617.338
D-J-F	2454.5145	1789.967	1.371	0.177	-1155.298	6064.327
M-A-M	1991.5051	2193.085	0.908	0.369	-2431.273	6414.283
J-J-A	1485.5551	1813.431	0.819	0.417	-2171.578	5142.688
S-O-N	-1794.1755	1490.939	-1.203	0.235	-4800.940	1212.589
Omnibus:	12.689	Durbin-Watson:	1.363			
Prob(Omnibus):	0.002	Jarque-Bera (JB):	13.324			
Skew:	-1.048	Prob(JB):	0.00128			
Kurtosis:	4.324	Cond. No.	1.59e+07			

Image 27: Regression on Madhya Pradesh Dependent Variable: Rice Yield

OLS Regression Results						
Dep. Variable:	WHEAT YIELD (Kg per ha)	R-squared:	0.956			
Model:	OLS	Adj. R-squared:	0.948			
Method:	Least Squares	F-statistic:	117.1			
Date:	Thu, 11 Jul 2024	Prob (F-statistic):	1.23e-26			
Time:	07:59:15	Log-Likelihood:	-519.48			
No. Observations:	52	AIC:	1057.			
Df Residuals:	43	BIC:	1075.			
Df Model:	8					
Covariance Type:	nonrobust					
	coef	std err	t	P> t	[0.025	0.975]
const	3.383e+04	9756.374	3.468	0.001	1.42e+04	5.35e+04
WHEAT AREA (1000 ha)	2.4053	3.001	0.801	0.427	-3.647	8.458
WHEAT IRRIGATED AREA (1000 ha)	15.7836	3.476	4.540	0.000	8.773	22.794
TOTAL CONSUMPTION (tons)	-0.0079	0.006	-1.243	0.221	-0.021	0.005
metANN	-8960.0979	7322.865	-1.224	0.228	-2.37e+04	5807.867
D-J-F	1641.3011	1990.511	0.825	0.414	-2372.947	5655.550
M-A-M	2872.6409	2493.817	1.152	0.256	-2156.620	7901.901
J-J-A	2972.0474	2121.259	1.401	0.168	-1305.880	7249.974
S-O-N	384.5557	1682.799	0.229	0.820	-3009.131	3778.243
Omnibus:	0.329	Durbin-Watson:	1.170			
Prob(Omnibus):	0.848	Jarque-Bera (JB):	0.028			
Skew:	-0.034	Prob(JB):	0.986			
Kurtosis:	3.091	Cond. No.	1.18e+07			

Image 28: Regression on Madhya Pradesh Dependent Variable: Wheat Yield

OLS Regression Results						
=====						
Dep. Variable:	MINOR PULSES YIELD (Kg per ha)	R-squared:	0.666			
Model:	OLS	Adj. R-squared:	0.603			
Method:	Least Squares	F-statistic:	10.70			
Date:	Thu, 11 Jul 2024	Prob (F-statistic):	4.01e-08			
Time:	08:05:35	Log-Likelihood:	-505.89			
No. Observations:	52	AIC:	1030.			
Df Residuals:	43	BIC:	1047.			
Df Model:	8					
Covariance Type:	nonrobust					
=====						
	coef	std err	t	P> t	[0.025	0.975]

const	-1.558e+04	7737.033	-2.014	0.050	-3.12e+04	23.403
MINOR PULSES AREA (1000 ha)	14.0816	2.566	5.487	0.000	8.906	19.257
MINOR PULSES IRRIGATED AREA (1000 ha)	-10.6424	18.428	-0.578	0.567	-47.806	26.521
TOTAL CONSUMPTION (tons)	0.0043	0.003	1.381	0.175	-0.002	0.011
metANN	-670.6759	5646.318	-0.119	0.906	-1.21e+04	1.07e+04
D-J-F	554.1070	1547.700	0.358	0.722	-2567.127	3675.341
M-A-M	-450.6061	1937.246	-0.233	0.817	-4357.434	3456.222
J-J-A	1084.8365	1596.692	0.679	0.501	-2135.200	4304.873
S-O-N	-36.6642	1291.119	-0.028	0.977	-2640.454	2567.125
=====						
Omnibus:	5.348	Durbin-Watson:	1.207			
Prob(Omnibus):	0.069	Jarque-Bera (JB):	6.550			
Skew:	0.205	Prob(JB):	0.0378			
Kurtosis:	4.690	Cond. No.	1.23e+07			
=====						

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

[2] The condition number is large, 1.23e+07. This might indicate that there are strong multicollinearity or other numerical problems.

Image 29: Regression on Madhya Pradesh Dependent Variable: Pulses Yield

In Image 27, the yield of wheat was significant in irrigated areas but not fertilizers and areas. Though none of the seasonal variables were significant either, an increase in annual mean and autumn temperatures in a year causes it to decrease.

In Image 29, the Annual temperature coefficient, Summer and Autumn are negative but insignificant again.

Discussion

Overall, increasing land temperatures do affect agriculture, which did not show up too well in Sehore's case, and if there were more data points present in the ols the regression would have turned out a lot more fruitful. Such as when the OLS of data points of the whole state are taken, a few more things come forth.

Although the study finds huge coefficients speaking of the negatives of the effects of climate (increased land temperature) on crop produce, but only during harvesting season in the Indian Kharif and Rabi sowing patterns. Temperature increases during the sowing season in our model are positive for crop yields.

In the future, larger data with more varied crops and regions can be taken to analyse the effects of not only surface temperature but also erratic rainfall, and the presence of harmful gasses in the environment like NO₂ and CO that harm crop life.

Citation

NTRS-NASA (Mbow, Cheikh et al.), 2020, Special Report: Special Report on Climate Change and Land, 20200001724, <https://ntrs.nasa.gov/citations/20200001724>

FAOSTAT, Food and Agriculture Organizations of the United Nations, <https://www.fao.org/statistics/en/>

Cole, M.B., Augustin, M.A., Robertson, M.J. et al. The science of food security. npj Sci Food 2, 14 (2018). <https://doi.org/10.1038/s41538-018-0021-9>

Ruedy, R., M. Sato, and K. Lo. 2015. NASA GISS Surface Temperature (GISTEMP) Analysis. In Trends: A Compendium of Data on Global Change. Carbon Dioxide Information Analysis Center, Oak Ridge National Laboratory, U.S. Department of Energy, Oak Ridge, Tenn., U.S.A. doi: 10.3334/CDIAC/cli.001.

ICRISAT, District Datasets, CGIAR Research Programs, 2020 <http://data.icrisat.org/dld/src/about-dld.html>