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Enhancing Resilience of Indian Agriculture to Climate Shocks – The Way Ahead

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Summary

Indian agriculture has exhibited remarkable resilience to climate shocks, as evident from the trend increase total production of foodgrains and horticulture crops, yields, and agriculture sector gross value added (GVA) over the years. As the frequency and intensity of climate shocks are expected to increase in the future, however, policies to safeguard and entrench the resilience of agriculture will progressively assume greater importance. Globally, while the adverse impact of climate shocks is already visible, the rising penetration of climate resistant cropping practices and yield enhancing technologies have moderated the impact considerably. In India also, empirical estimates from an Autoregressive Distributed Lag (ARDL) model presented in this paper show that, in the long-run, when temperature rises by 1 per cent (equivalent to about 0.26 degree Celsius in a year), yield of foodgrains declines by 6.5 per cent, which can be contained by increasing the share of irrigated land in total gross cropped area. A one per cent drop in YIELD lowers foodgrain production by 0.65 per cent, which can be partly offset through price based support enabling the terms of trade (ToT) to move in favour of agriculture. If average rainfall drops by one per cent, agri GVA could decline by 0.27 per cent, but better terms of trade and provision of subsidized inputs (such as fertilizer) could moderate the adverse impact. Panel regression results, that capture the state level heterogeneity, validate the sensitivity of foodgrain production to rainfall, if not temperature yet. Recognising the challenge of limited resource availability to support an accelerated green transition path in agriculture, and taking into account insights from the Environmental Kuznets Curve (EKC), adoption of an incremental approach appears suitable for strengthening further the resilience of Indian agriculture. An integrated framework, however, must aim at making gradual progress on all feasible dimensions of greening agriculture, ranging from sifting the household diet pattern in favour of low emissions food to a more balanced and judicious use of water and

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chemical fertilisers, soil conservation, pest and insect management, adoption of organic farming practices, crop diversification recognising the emission intensity of crops, wider use of climate resistant and high yielding seeds, adoption of sustainable animal breeding practices, arresting conversion of forest land and encroachment of mangroves, reducing crop residue burning, promoting carbon sequestration, and reducing food wastes at different stages of the food supply chain.

Introduction

Every plate of food we eat has a slice of the carbon emissions pie, and emissions-induced climate change is progressively endangering future food security. This bi-directional causality – of agriculture as a major source of carbon emissions, and climate change impacting the availability and cost of food – warrant adoption of greener farming practices on the one hand to be able to lower the carbon intensity of farm output and thereby keep the planet liveable, and embracing climate smart farming options, on the other, that can enhance the resilience of the sector to climate events, assuring access to adequate and nutritious food at low-cost in the future. While awareness campaigns about the carbon footprint of a food plate can trigger changes in consumption habits of households, ground level demonstration of the positive impact of climate smart farming methods on farmers' income can propel their wider adoption. For enabling such desirable shifts in consumption habits and farming practices, however, current policies – both fiscal and financial, may need to be realigned so as to effectively disincentivise production and consumption that harm the planet, and incentivising adoption of climate smart farming practices and consumption habits.

Different stages of food – production, distribution, consumption and waste disposal – generate greenhouse gases (GHGs)[2]. Creating awareness about the carbon footprint generated at every stage is the first major step to contain future risks to food security. Input use for the cultivation of crops and the raising of animals, such as fossil fuels for powering farm machineries, fertilizers, and other agricultural inputs increase the carbon footprint. When food is processed and packaged for distribution it leads to carbon emissions. Transportation related emissions could be high when food is transported long distances. Before consumption, energy used during cooking and refrigeration of leftovers also contributes to carbon emissions. At the final leg of the food lifecycle, food waste used for landfills produces methane.

[2] Greenhouse gases that cause climate change include carbon dioxide (CO2) – which enters the atmosphere due to burning of fossil fuels (coal, natural gas, and oil); methane (CH4) – which is emitted during the production and transport of fossil fuels and also by livestock (digestive systems of certain types of livestock called ruminants such as cattle, sheep, goats) and other agricultural practices, and organic waste; and Nitrous oxide (N2O) – which is emitted during farming due to use of fertilizers, treatment of wastewater, and others. The latter two gases are often converted to "carbon dioxide equivalent" (CO2e), based on their relative impact on climate change, *i.e.*, Global Warming Potential (GWP). Methane has a GWP which is 27–30 times that of CO2 over 100 years, and nitrous oxide has a GWP that is 273 times of CO2 (Joiner and Toman, 2023).

Globally, the food system is responsible for approximately 26% of global GHG emissions (Ritchie, 2019), though recent holistic estimates peg the share at about 31% (Sutton *et al*, 2024). The total food system emissions emanate from four major sources: (a) crop production (27%) – of which 21% is from crop production for direct human consumption and 6% from the production of animal feed; (b) livestock (31%) – for meat, dairy, eggs and seafood production, with cattle producing methane through their digestive processes (known as enteric fermentation); (c) land use (24%) – *i.e.*, conversion of forests, grasslands and other carbon 'sinks' into cropland or pasture – of which 16% is for livestock and 8% for crops; and (d) food supply chains (18%) – food processing, transport, packaging and retail, and food wastes (Ritchie, 2019). As per the Sutton *et al*., (2024) estimates, the shares are somewhat different – livestock (25.9%), net forest conversion (18.4%), food wastes (7.9%), household food consumption pattern (7.3%), and the rest due to fertiliser production, soil degradation and rice production. WWF (2024) highlights that the current global food system is responsible for 27% of global GHG emissions, 70% of freshwater withdrawals, 90% of tropical deforestation, with 82% of available agricultural land being used for grazing and producing feedstock for livestock.

The share of agriculture in total GHG emissions by India is pegged at about 14%, despite its large cattle population, milk production and rice exports (PIB, 2023). In India, 60 percent of India's agrifood system emissions, as reported, comes from the farm gate (*i.e.*, crop production and livestock rearing, that include crop residues, on-farm energy use, synthetic fertilisers, rice cultivation, enteric fermentation *etc.*), with the largest contribution coming from enteric fermentation, which is because of the inefficiency of the livestock sector in terms of emission intensity of milk and meat. With land use change (*i.e.*, conversion of forest land for use in agriculture) contributing very little to emissions in India, the remaining close to 40% of emissions are due to pre and post-production emissions (waste disposal, household consumption, food retail, food processing, food transport, input and energy manufacturing for agriculture, and food packaging) (Sutton *et al*., 2024).

Several India specific farm sector sustainability issues have been highlighted in the recent writings on the subject, that require concerted policy efforts to ensure future food security of India. Overuse of urea – as against the recommended ratio of 4:2:1 for nitrogen, phosphorous and potassium (NPK) the actual ratio of 11.8:4.6:1 – has led to air and water pollution, besides soil degradation. Urea subsidy is about 85 to 90 % of cost of production, and urea accounts for 4.3% of India's total GHG emissions (Bhushan, 2024). The distorted fertiliser mix has lowered the response of grains to fertiliser use, from more than 10:1 in the 1970s to 2:1 (Gulati, 2024). Inefficient use of input resources and the resultant GHG emissions from agriculture explains why India is the world's third largest agri food system emitter after China and Brazil (Reddy and Lingareddy, 2024). India's water stress level is fast approaching a flashpoint (Kant, 2024); agriculture may account for as high as 87% of India's water demand by 2030, and the combination of large procurement at assured remunerative minimum support prices (MSPs) has incentivised water-intensive crops like rice, wheat and sugarcane, leading to the depletion of groundwater levels at an alarming rate (Neog and Khanduja, 2024); free power and water programmes have caused considerable damage to the environment (Kaundinya, 2024); and, because of increased water stress, about 150 million women days are used in India in fetching water alone, and most regions of India may experience severe water stress by 2050 (Narayanamoorthy, 2024). India's post-harvest losses are high, reducing income potential for farmers while raising GHG emissions (Gulati and Das, 2024). Increasing incidents of heatwaves also pose the risk of fall in wheat yields and output (Kohli, 2024). Green norms and policy focus on enforcement of these norms in the European countries could hurt India's agri exports (Kumar, 2024).

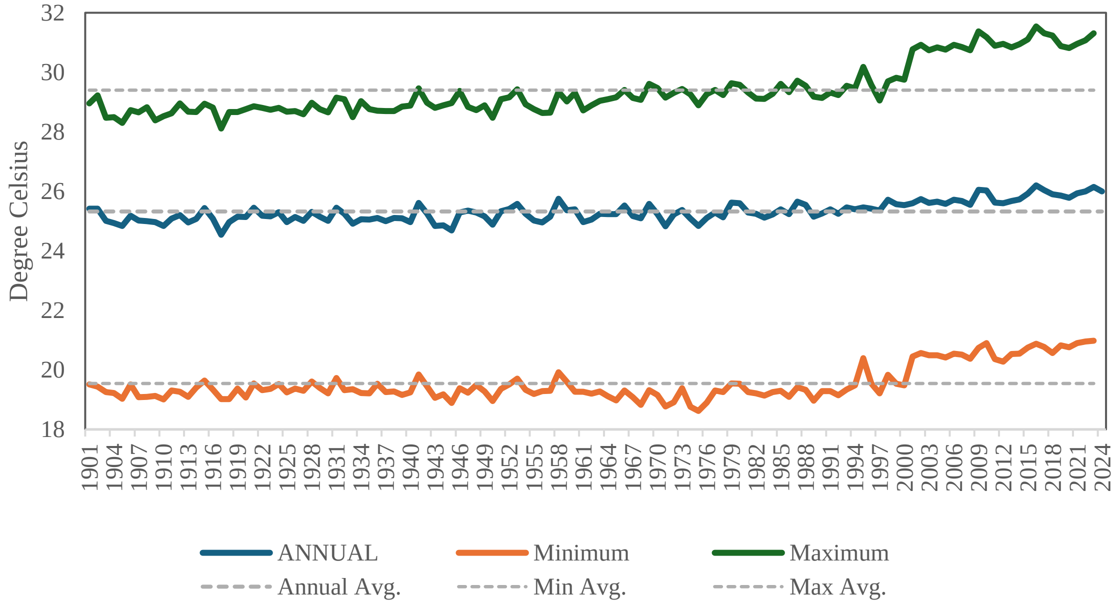
Both adaptation and mitigation agenda for agriculture in India, thus, must recognise that the path to transforming the agrifood system could be expected to be bumpy, because of headwinds from both producers – who have to embrace greener farming practices, and consumers – who have to alter food consumption preferences. Both supply side (such as higher farm productivity backed by climate smart farming practices and reduced post-harvest losses) and demand side (curbing meat demand or substituting it by lab meat) changes would need to be guided through appropriate policy incentives. Dominance of small sized farms and their low margins may not help in promoting large scale adoption of green farming practices (Chateau *et al.*, 2023), unless adoption is preceded by a climate literacy campaign. In a survey of agri-startups, fragmentation of land holdings was reported as a major impediment to adoption of new farming techniques in India (Suganthi *et al.*, 2024). As highlighted in the WWF Living Planet Report, 2024, India's current consumption pattern looks environmentally sustainable (despite high share of food in the consumption basket, and largely due to the low share of meat), unlike many other major economies, but with rising per capita income, the India's consumption pattern may become environmentally less sustainable. Raising awareness about GHG emission intensity of different food items in the consumption basket, and use of tax/subsidy, wherever necessary to drive a shift in demand, may be critical to avoid risks to sustainability. As pre the estimates of the World Bank, globally, the net payoff from altering the agrifood system could be substantially positive – a 16-to-1 return on investment costs, but annual investment needs may have to increase by 18 times. Some part of the higher investment costs could be met by reducing current wasteful subsidies, but a major part may have to be provided as additional resources (Sutton *et al*., 2024). The costs of policy induced changes in the food systems could be dwarfed by the costs of no climate action, as assessed by the ADB (2024) – climate change can reduce gross domestic product (GDP) in Asia and the Pacific by 17% by 2070 (24.7% for India) under a high-end emissions scenario.

Set against this background, this paper makes an assessment of risks to India's future food security based on estimates of the impact of climate shocks on agricultural GVA, foodgrain production and yields, and proposes policy options, recognising the potential of fast evolving tech-enabled solutions for climate risk mitigation and adaptation, and the power of public policy in mitigating climate risks. Section II presents facts on various dimensions of rising climate risks in India. India's agricultural production and consumption patterns are evaluated in Section III form the standpoint of their carbon emissions. Empirical estimates relating to the impact of climate shocks on production of foodgrains, yields and agriculture sector GVA are analysed in Section IV. Available range of policy interventions as the way forward are discussed in Section V, under an integrated greening the agriculture framework. Section V sets out the concluding observations.

Section II: Signs of Climate Change

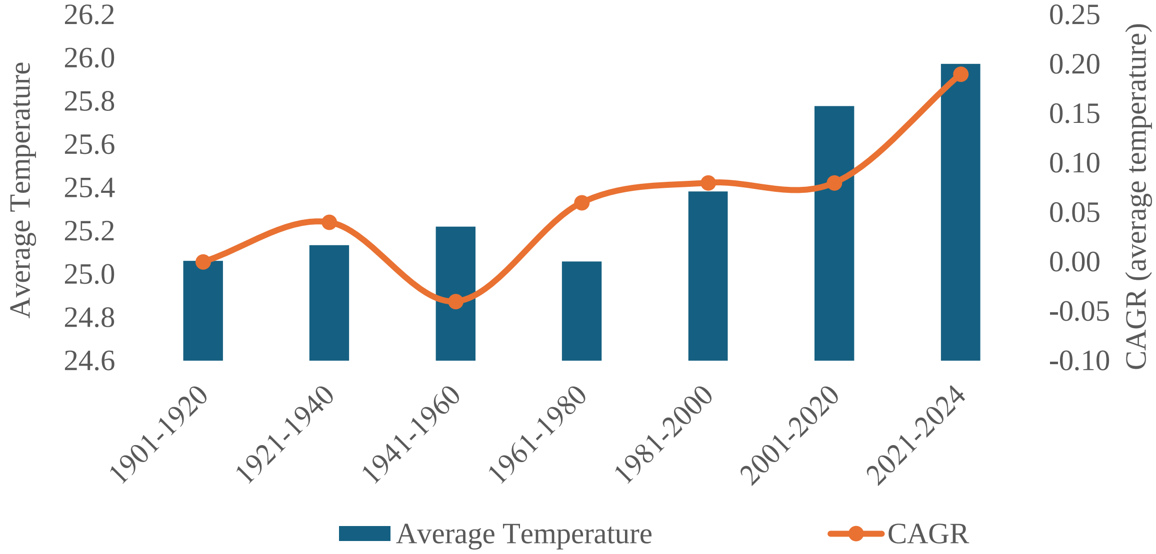
Abnormal rainfall pattern (trend decline in average levels of precipitation, with uneven seasonal and temporal distribution), rising average temperature, and increase in the incidence of extreme weather events such as floods, heatwaves, droughts, cyclones, forest fires, *etc*, are the major signs of climate change, which has raised the importance of climate smart framing practices to enhance the resilience of agriculture. As evident from Figure 1, the annual average, minimum, and maximum temperature in India over the period 1901 to 2024 have gradually edged up. Moreover, the compound annual average growth rate (CAGR) of temperate has been the highest during 2021-24 (Figure 2).

Figure 1: Annual Average, Minimum and Maximum Temperature in India (1901-2024)



Source: Ministry of Earth Science, Govt. of India.

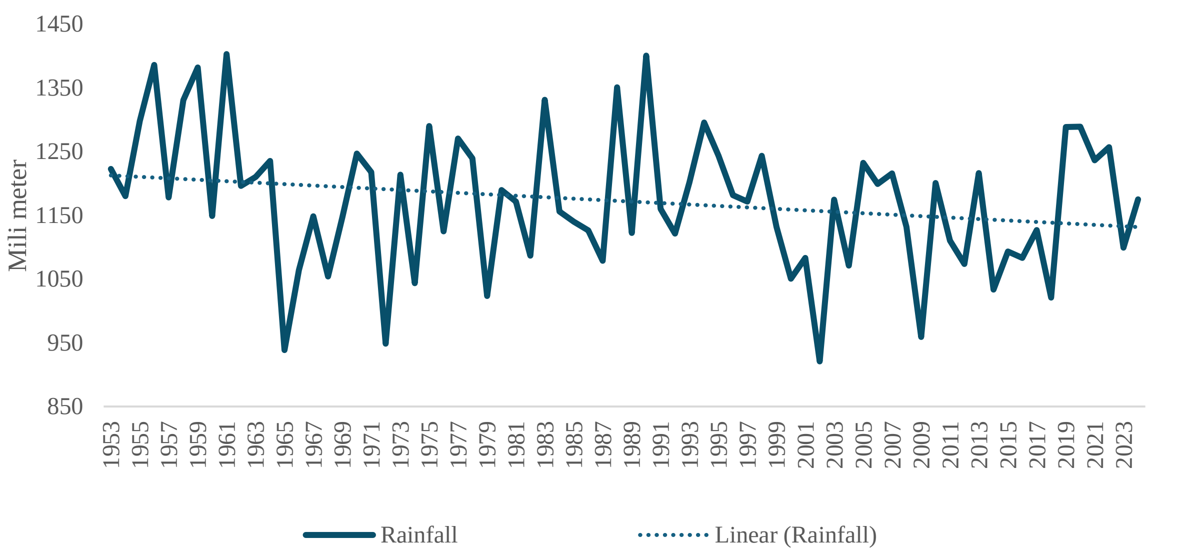
Figure 2: Average Temperature and its Growth Rate (1901-2024)



Source: www.indiastat.com, IMD

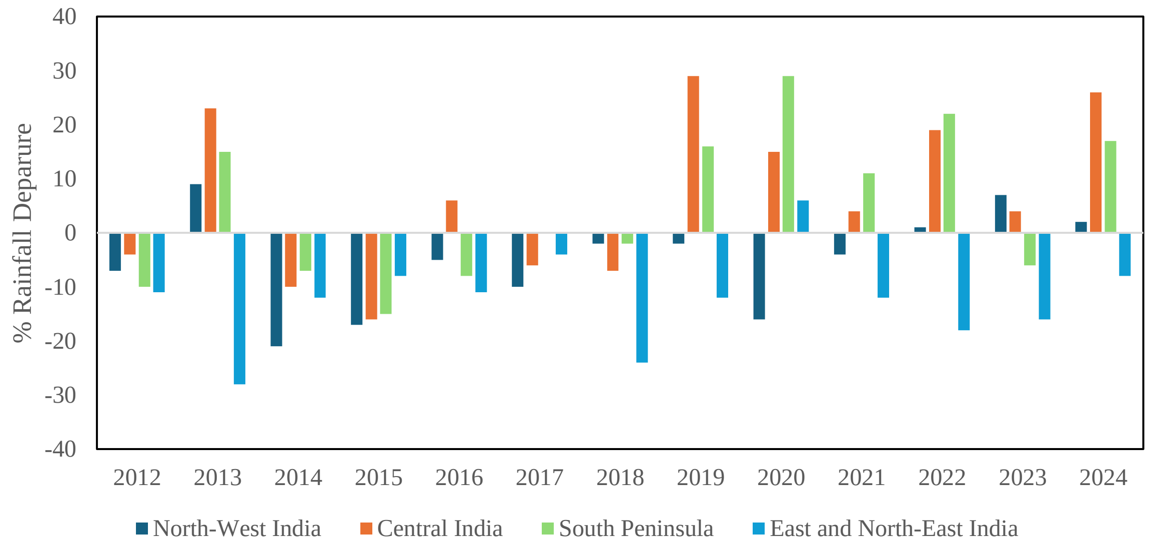
The trend of annual rainfall in India is also moderating over the period 1953 to 2024 (Figure 3). Regional distribution of rainfall also shows that when some regions in a year are in surplus, others may be in deficit, and at times such deviations from the national average may be large (Figure 4). Over time also, the distribution of rainfall is often asymmetric during the crucial four months of the south-west monsoon season (June-September), with both delayed onset and delayed withdrawal, and large unseasonal rains causing crop damage.

Figure 3: Annual Rainfall in India (1953-2024)



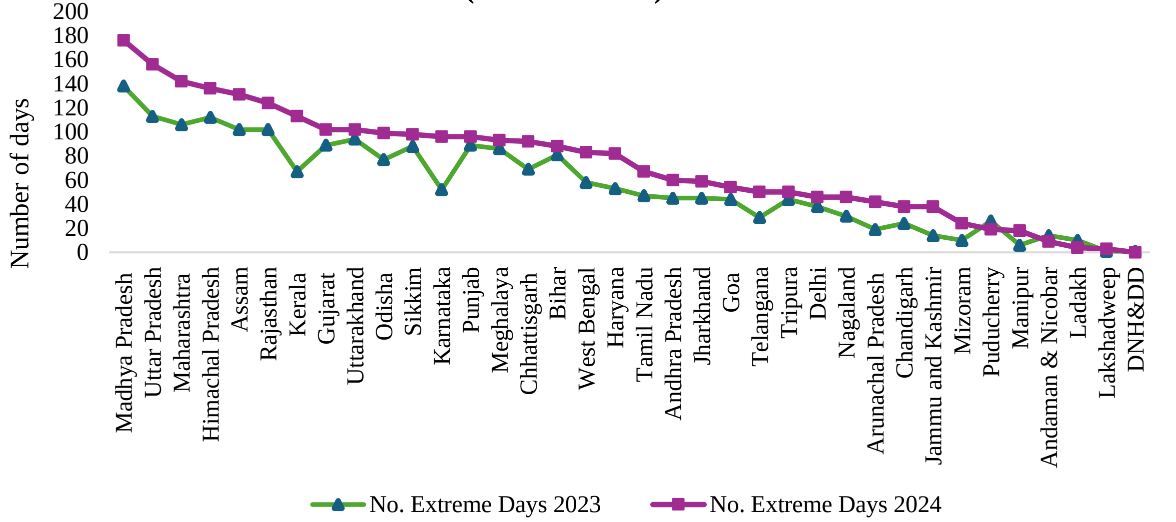
Source: IMD

Figure 4: Region-wise Departure of Rainfall from Normal (%)



Source:IMD

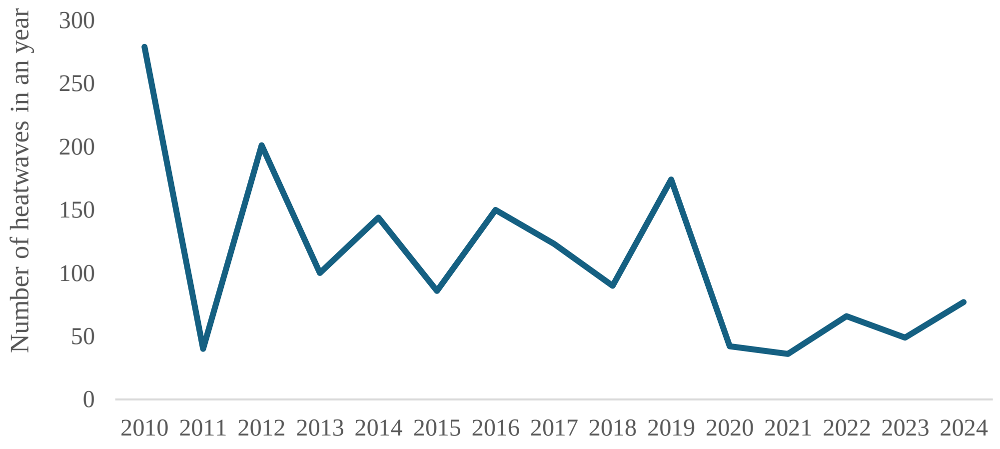
Figure 5: Number of Days of Extreme Weather Events (2023 and 2024)



Source: Climate India 2023 & 2024: Assessment of Extreme Weather Events (DownToEarth)

Extreme events like heavy rains, floods, storms, heatwaves, and cold waves are also becoming more common and severe in India. In 2024, India experienced extreme weather events on 255 out of 274 days (Source: Down-to-earth), impacting several states (figure 5). In 2023 and 2022, extreme weather events occurred on 318 and 314 days, respectively, affecting nearly every part of the country. Heatwaves have become a regular feature of Indian weather system now (Figure 6). For foodgrain production and yield, these weather extremes often pose a major threat. Excessive rains and flooding disrupt sowing and harvesting cycles, cause soil erosion, and damage crops.

Figure 6: Number of Heat-Waves (2010 - 2024)



Source: Indiastat, DownToEarth.

Section III: Greening the Food Production and Consumption Pattern in India

For changing the farm output mix and household consumption pattern – with a view to achieving the goal of sustainable food security for the future, it is important first to identify the carbon emissions intensity of various major food items, and second, to assess risks to sustainability from the composition of domestic agricultural output and household consumption expenditure. It has been assessed in the related literature that a meat-heavy diet, especially with beef, lamb and shellfish, emits more GHGs than a plant-based diet (Table 1). Post-production transportation, storage, cooking for consumption, and wastes also add to emissions generated during the production of food. It has been reported that an average heavy meat eater produces 18.5 pounds of carbon dioxide while an average vegetarian produces 8.4 pounds of carbon dioxide per day (Afrouzi *et al*., 2023). While nuts, tofu, fruits and vegetables have low GHG intensity, poultry meat and eggs produce comparatively less GHGs than red meat.

Table 1: Emission of Greenhouse Gases Due to Production of Food Items

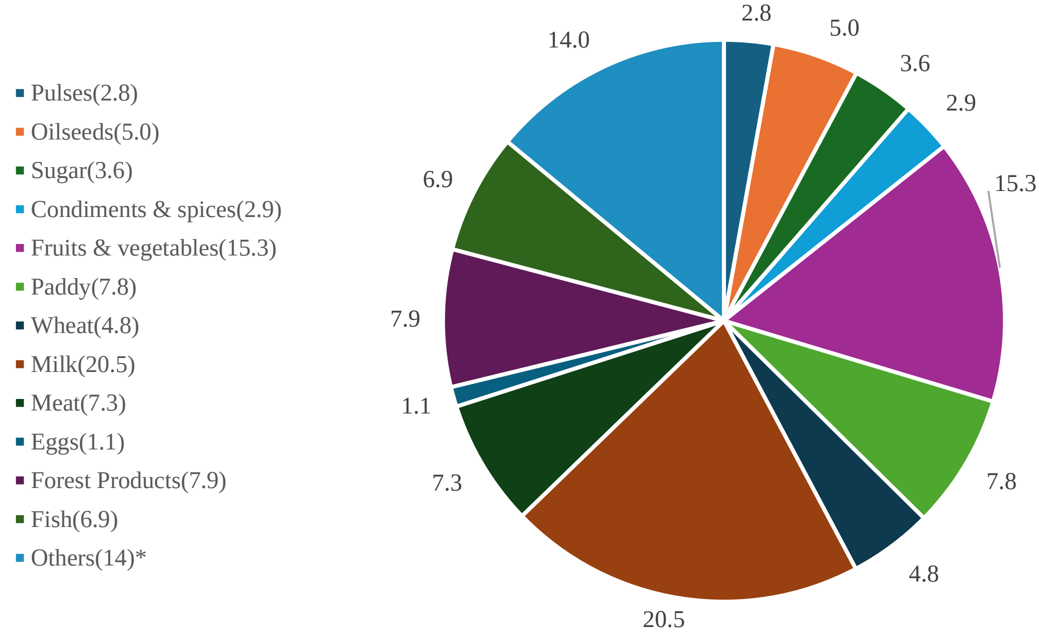
(Kilograms of carbon dioxide equivalents)

Food item	**Per Kilogram of Food**	**Per 100 Grams of Protein**	**Per 1000 Kilocalories**
Beef	70.6	35.5	25.9
Lamb	39.7	19.9	12.5
Shellfish	26.9	18.2	26.1
Cheese	23.9	10.8	6.2
Fish	13.6	6	7.6
Pork	12.3	7.6	5.15
Poultry	9.9	5.7	5.3
Eggs	4.7	4.2	3.2
Rice & Grain	3.6	4.8	0.9
Milk	3.2	9.5	5.25
Tofu	3.2	2	1.2
Legumes	2	0.9	0.5
Breads&Pastas	1.6	1.3	0.6
Fruit	0.9	10.4	1.5
Vegetables	0.7	6.8	3.3
Nuts	0.4	0.3	0.1

Source: UN (2024), "Food and Climate Change: Healthy diets for a healthier planet", https://www.un.org/en/climatechange/science/climate-issues/food. Afrouzi *et al*., (2023) give food item wise emissions of carbon dioxide (CO2), methane (CH4) and nitrous oxide (N2O).

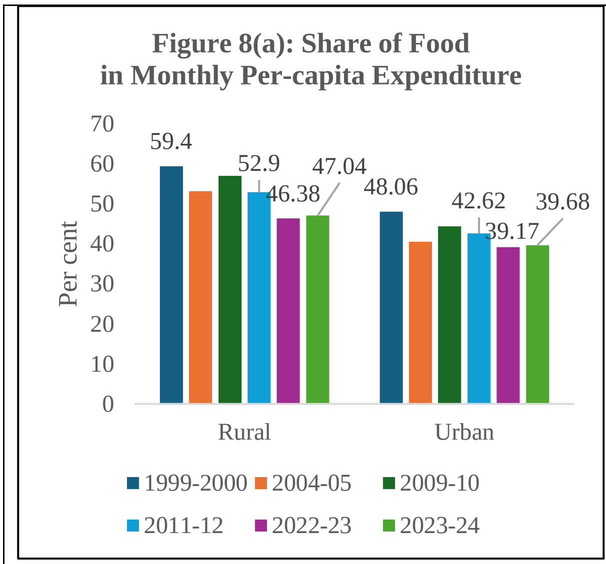
The composition of India's gross value of output (GVO) of agriculture and allied activities (based on latest available data for 2022-23) shows that the share of livestock is 30.9 %, of which milk accounts for 20.5 %, meat only 7.3 %, and the remaining 3.1% by eggs and others (Figure 7). The low share of meat in GVO is a major factor why India's food system GHG missions may have been assessed as still sustainable by the WWF Living Planet Report (2024).

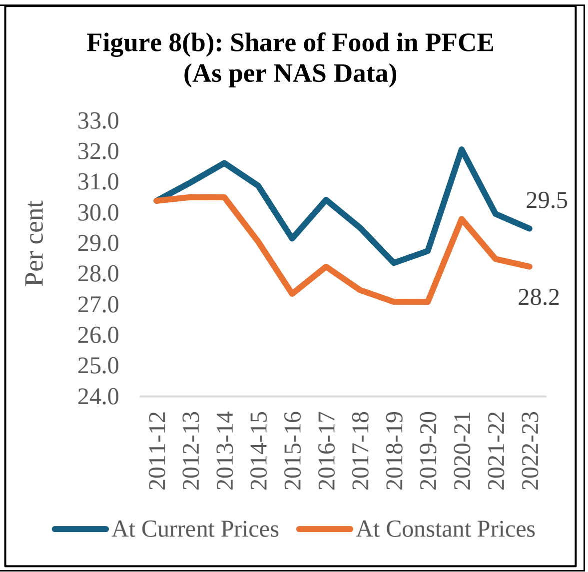
Figure 7: Share in Agri GVO



*Others include maize, bajra, jawar, fibres, drugs and narcotics, kitchen garden, etc.

As regards the food consumption pattern of the households in India, given the continuing high share of food in the consumption basket, greater awareness and sensitivity of households to GHG emissions due to food consumption may have become desirable. For designing a policy induced shift in the consumption pattern, however, one may have to deal with the challenge posed by two sets of available data on the share of food in consumption. While as per national accounts statistics (NAS) the share of food in private final consumption expenditure (PFCE) has dropped to marginally below 30 % in 2022-23 (at both current and constant prices, and remained stable around 30% since 2011-12), as per the Household Consumption Expenditure Survey (HCES) of the National Sample Survey Office (NSSO) the share of food in average monthly consumption in rural and urban areas was still high at 46.38% and 39.17%, respectively, in 2022-23, though showing notable moderation since 2011-12 (Figure 8a and 8b). In 2023-24, the share of food in fact edged up, in both rural and urban areas. The CSO (2015) Report had expressed concerns about the growing divergence between NAS and HCES data sets over time and offered certain recommendations for course correction, but the difference seems to have persisted.





Note: Figure 8(b) presents the share of food in Private Final Consumption Expenditure (PFCE) in “domestic market”, using data from NAS. PFCE, otherwise, includes final consumption expenditure of resident households in the rest of the world and excludes final consumption expenditure of non-resident households in the economic territory. Shares presented in Figure 8(b) change only marginally when PFCE is used as the denominator in place of PFCE in domestic market. Figure 8(a) is based on data from the Household Consumption Expenditure Survey (HCES), including for recent years 2022-23 and 2023-24.

For planning a policy induced shift in the consumption pattern, more than the overall share of food in total consumption, information on the shares of individual major food items in total food consumption is more relevant. Both data sources seem to suggest similar consumption patterns, with high share of milk and milk products in total consumption in both urban and rural areas, but relatively modest share of meat, at almost half that of the total share of fruits and vegetables. But this pattern can be expected to change over the next few decades, with associated potential increase in the carbon footprint of India’s food system.

Global trends of the past suggest that during 1990-2019, food production (measured by available calories) increased by 61 %, as against increase in world population by 45%. While production of grains (in terms of available calories) increased at the same rate as population growth, production of animal products (meat and dairy), vegetable oils and fruits and vegetables increased at a faster pace than population growth, and calories from animal products doubled in China, and nearly doubled in Brazil, though remained still below the level of consumption attained in the US (Sands, 2024). This shows how the consumption pattern may change with higher per capita income. India, as the most populous country in the world, and given its relatively faster pace of increase in per-capita income compared to other major economies, may experience a similar shift in the consumption pattern in the future, which will be environmentally unsustainable, unless checked through right policy interventions.

Table 2: Share of Major Food Items in Total Food Consumption (Per cent)

	NAS-PFCE (2022-23 at Current Prices)	NSSO-HCES (Rural) (2022-23)	NSSO-HCES (Rural) (2023-24)	NSSO-HCES (Urban) (2022-23)	NSSO-HCES (Urban) (2023-24)
Bread, cereals and pulses	20.19	14.92	14.94	12.84	13.00
Meat, Fish, seafood and eggs	12.80	10.59	10.46	9.11	8.97
Milk and milk products	20.84	17.96	17.94	18.43	18.12
Oils and fats	6.21	7.74	5.89	6.05	4.59
Fruits	13.10	8.00	8.18	9.7	9.75
Vegetables	10.96	11.60	12.82	9.7	10.38
Others (non-alcoholic beverages, processed food, sugar, salt, honey, spices, *etc*)	15.90	29.19	29.76	34.16	35.18
Total	100	100	100	100	100

Note: NAS-PFCE item-wise classification has been mapped broadly to NSSO-HCES classification. Unlike the large difference between overall share of food in consumption between NAS-PFCE and NSSO-HCES, the size of differences in item level food shares are relatively lower, and this consumption mix could help in planning for a greener consumption demand pattern in the future.

Section IV: Impact of Climate Change

With the rising adaptation of farming to climate events and adoption of climate-resistant farming practices in India, the impact of climate events on agricultural GVA, foodgrain production and crop yields in the empirical literature has generally been found to be subdued, though positive. Misra *et al*., (2023) reported a positive and statistically significant impact of SWM rainfall on kharif production, with July rainfall appearing to be the most important for production followed by June, September and August rainfall. Excess rainfall, however, negatively impacts foodgrain production. Gupta *et al*., (2023) used a panel regression framework and concluded that the sensitivity (or elasticity) of crop production to SWM has declined, pointing to increasing resilience, which may be due to the counterbalancing influence of rising irrigation coverage. They, therefore, recommended enhanced public spending on irrigation infrastructure to strengthen resilience. Ghosh *et al*., (2023) reported positive and statistically significant causal influence of growth in annual rainfall on agri GVA growth, and rabi and kharif foodgrain production. Gulati *et al.* (2013), in their study for the period 1996-97 through to 2012-13 obtained a relatively stronger impact of rainfall deviation on agri GDP growth, and rainfall was reported as more important than capital formation in agriculture and terms of trade in explaining agri GDP growth. Dilip *et al*, (2023) found that weather conditions influence real economic activity indicators like PMI, IIP, demand for electricity, trade, tourist arrivals, and tractor and automobile sales, and also food inflation, with a stronger impact on vegetable prices. Ghosh *et al* (2021) studied how the coastal states of India are affected by cyclones, floods, droughts and rising sea levels and concluded that natural calamities cause lower growth and a decline in the yields of vegetables and fruits. Tripathi *et al*., (2020) noted that with rising climate events, farmers are learning and adapting, and as a result, resilience is visible across commodities. Advances in technology, increasing awareness, and government-supported programmes are also helping in this observed adaptation to climate change.

In this paper, the impact of climate change – assessed through variations in annual rainfall (millimeter) and annual average temperature (degree Celsius) in India – on agricultural gross value added (GVA), total production of foodgrains, and yield of foodgrains is studied, using annual data for the period 1980-81 to 2023-24. Besides two climate change variables, other explanatory variables such as terms of trade (ToT) derived as the ratio of agri GVA deflator to non-agri GVA deflator, annual fertilizer consumption, irrigated land as per cent of gross cropped area, credit intensity (derived as the ratio of gross annual disbursement of agri credit to annual nominal agri GVA) and annual capital formation in agriculture (CFA) are also used. Three different models are used separately for agriGVA, foodgrains and yield, to estimate their sensitivity to two climate change variables (temperature and rainfall) and five other explanatory variables (ToT, fertilizer, irrigation, credit intensity and CFA). All ten variables seem to have a trend (Annex Figure 1) and enter the model in their natural log form. Stationarity test results suggest that these variables are either I(0), *i.e*., stationary in level form, or I(1), *i.e*., stationary in first difference form (Table 3), and therefore the autoregressive distributed lag (ARDL) model of Pesaran *et al*., (2001) appears appropriate (please refer to Nasrullah *et al*., (2021) for a detailed analysis).

The key steps in applying the ARDL model, given the chosen variables, are: (a) identifying the lag structure using Akaike information criterion (AIC), Schwarz (BIC), Hannan-Quinn (HQ), or the adjusted R^2 criterion; (b) check bounds test results to confirm the presence of cointegration; (c) examine the long-run relationship from the estimated coefficients and their statistical significance in relation to expected/theoretical relationship among variables; (d) check also short-run impact of right hand side variables, besides the sign and size of the error correction model (ECM) coefficient (*i.e.*, whether it is negative and less than 1); (e) diagnostic tests, such as serial correlation LM test (to accept or reject the null hypothesis that the residuals are serially uncorrelated) and Breusch-Pagan-Godfrey heteroscedasticity test (to accept or reject the null hypothesis that the residuals are homoscedastic); and (f) cumulative sum (CUSUM) and cumulative sum of squares (CUSUMSQ) tests for checking the stability of the short-run and long-run coefficients, given the possibility of single/multiple structural breaks in all variables during the sample period.

For L(YIELD), besides two fixed regressors in the form of a constant and a trend, L(TEMPERATURE) and L(IRRIGATED) are used as the key explanatory variables, and other variables are dropped as they turn out to be statistically insignificant in the long-run estimated equation. The ARDL model uses the lag structure of (2, 1 and 0) as per the SIC criterion, and the Bounds test F value at 10.08549 exceeds the critical value at 1%, rejecting the null hypothesis of no equilibrating relationship. As per the Breusch-Godfrey Serial Correlation LM test, F-statistic at 0.013659 with a p value of 0.9864 indicates no problem of serial correlation. As per the Breusch-Pagan-Godfrey heteroscedasticity test, F-statistic at 0.579997 with a p value of 0.7438 suggests that the null of homoscedastic residuals is not rejected. Cumulative sum (CUSUM) and cumulative sum squared (CUSUMSQ) plots of L(YIELD) lie within 5% significance level over time, pointing to stability and good fit of the ARDL model (Figure 9). Long-run estimates (or elasticities, since all variables are in log form) suggest that when temperature rises by 1 per cent (equivalent to about 0.26 degree Celsius in a year), foodgrains yield drops by 6.5 per cent (Table 4). This highlights the risk from sustained increase in average temperature being witnessed in India in recent years. Increasing the share of irrigated land in total gross cropped area by one per cent could raise yields by 0.74 per cent, as per the long run estimated coefficient of L(IRRIGATED). Thus, greater investment on irrigation can help in mitigating to some extent the risks to yield from rising temperature. The estimated coefficient of ECM at -0.699019 is statistically significant, which validates the presence of cointegration, and whenever there is a deviation in the relationship in the short run, the speed of adjustment is high (69% each year) leading to movement towards the long-run equilibrium. Available literature also highlights the adverse impact of rising temperature on crop yields – an increase in global mean temperature by one degree Celsius reduces, on average, global yields of wheat, rice, maize and soybean by 6.0%, 3.2%, 7.4%, and 3.1%, respectively (Zhao, 2017). Past global experience, however, shows that crop yields have increased over time, and climate impact may have only reduced the pace of increase. With rising penetration of climate-resistant cropping practices aided by technology, yields may keep rising in the future, but that would require more investment in innovations and resources to promote greater adoption of temperature and drought-resistant cropping practices (Ritchie, 2024).

It is important to recognise that the impact of temperature on yields may vary from country to country, as high-latitude or temperate countries may experience an increase in yields while those in tropics and subtropics may witness the adverse impact of rising temperature on yields (Ritchie, 2024). In South Korea, for example, where severe cold is a risk to rice yields, the former impact was observed, with a one per cent rise in mean temperature yielding higher rice production by 1.16 per cent (Nasrullah et al., 2021).

Table 3: Stationarity Test Results

Variables	Augmented Dickey-Fuller (Level)	Augmented Dickey-Fuller (First Difference)
L(YIELD)	-3.230381***	
L(FOODGRAINS)	-5.842239*	
L(AGRI GVA)	-4.286806*	
L(TEMPERATURE)	-5.910907*	
L(RAINFALL)	-6.284908*	
L(IRRIGATED)	-2.660761	-9.346309*
L(TOT)	-2.126735	-6.216312*
L(FERTILISER)	-1.236529	-5.850190*
L(CREDIT INTENSITY)	-1.813166	-6.012116*
L(CFA)	-3.071615	-9.286615

*, **, *** indicate significant at 1%, 5 % and 10 % level. All equations have an intercept and a trend.

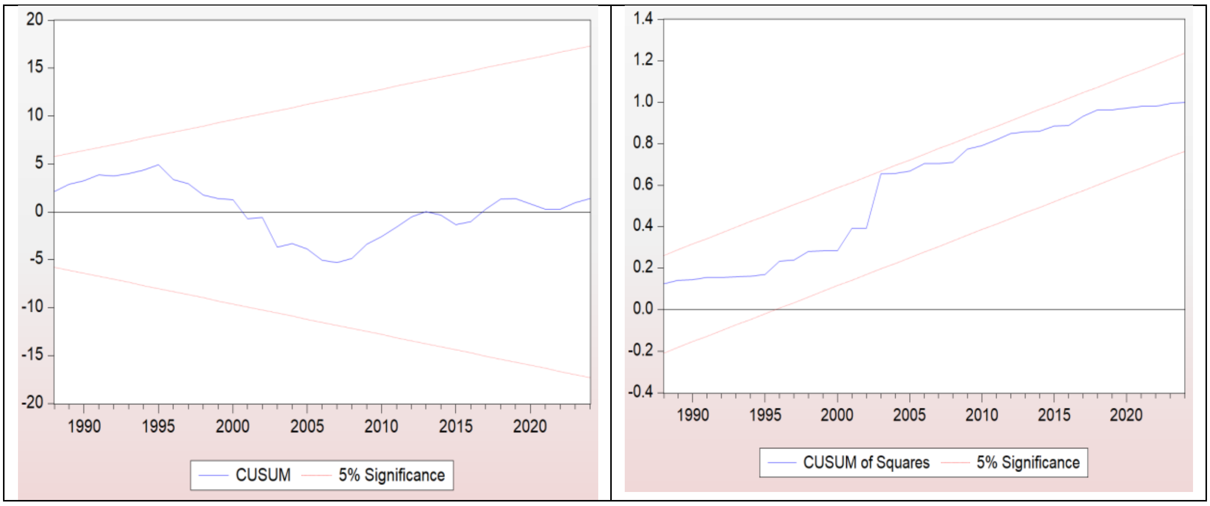
Table 4: Regression Coefficients: Long-run and Short Run

L(YIELD)	Long-run Coefficients	Short-Run Coefficients (Error Correction Equation)
L(TEMPERATURE)	-6.515724 (-3.002346)*	
L(IRRIGATED)	0.735253 (2.417814)**	
ECM		-0.699019 (-5.647295)*

*, **, *** indicate significant at 1%, 5 % and 10 % level. Figures in parentheses are t-values.

Estimated value of adjusted r-squared at 0.983403 shows the ARDL model is a good fit.

Figure 9: Plot of CUSUM and CUSUMSQ for Coefficient Stability



In the ARDL equation for L(FOODGRAINS), besides two fixed regressors in the form of a constant and a trend, L(RAINFALL), L(TOT) and L(YIELD) are used as the key explanatory variables. Other variables are dropped through a sequential check as they turn out to be statistically insignificant in the long-run estimated equation. The ARDL model uses the lag structure of (1, 4, 3 and 1) as per the Hannan–Quinn information criterion (HQC), and the Bounds test F value at 10.69663 exceeds the critical value at 1%, rejecting the null hypothesis of no equilibrating relationship. Cumulative sum (CUSUM) and cumulative sum squared (CUSUMSQ) plots of L(FOODGRAINS) lie within 5% significance level over time, pointing to stability and good fit of the ARDL model (Figure 10). Long-run estimates suggest that when the rainfall rises by 1 per cent, foodgrains production improves by 0.30 per cent (Table 5). While in the first model for L(YIELDS), rainfall was not statistically significant, in the model for L(FOODGRAINS) a decline in rainfall emerges as a risk to production of foodgrains (with a positive and statistically significant coefficient). Moreover, given the adverse impact of temperature on yields in the first model, a 1 per cent drop in YIELDS is estimated to lower foodgrains production by 0.65 per cent. Price based support that could keep the terms of trade (ToT) in favour of agriculture could only partly offset the adverse impact of rainfall deficiency and drop in yield due to rising temperature, because for one per cent improvement in L(TOT), production of foodgrains could rise by only 0.14 per cent. The estimated coefficient of ECM at -0.988115 is statistically significant, which shows that whenever there is a deviation from the long-run relationship, the speed of adjustment is fast (99 % in a year).

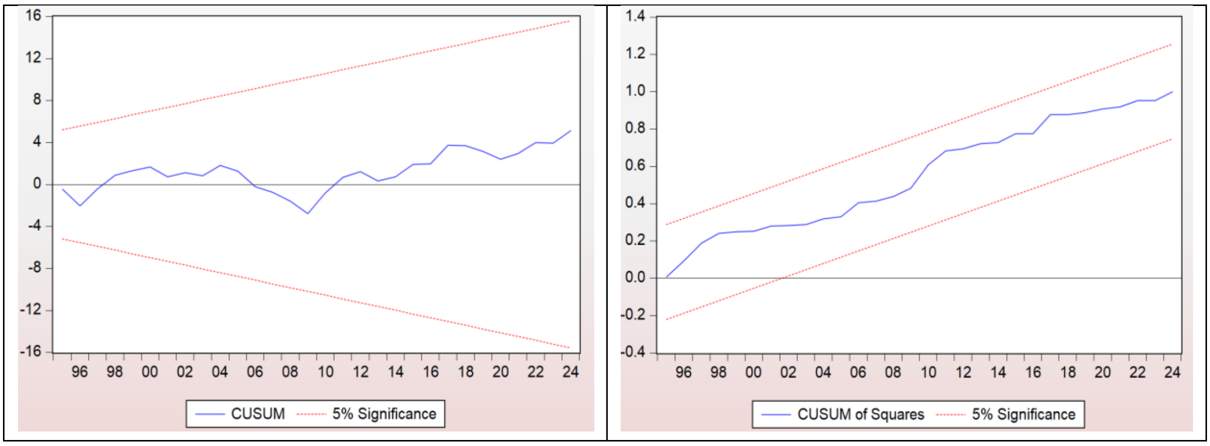
Table 5: Regression Coefficients: Long-run and Short Run

L(FOODGRAINS)	Long-run Coefficients	Short-Run Coefficients (Error Correction Equation)
L(RAINFALL)	0.299992 (4.576973)*	
L(YIELD)	0.645782 (9.624402)*	
L(TOT)	0.141967 (0.037483)*	
ECM		-0.988115 (-6.860405)*

*, **, *** indicate significant at 1%, 5 % and 10 % level. Figures in parentheses are t-values.

Estimated value of adjusted r-squared at 0.966841 shows the ARDL model is a good fit. As per the Breusch-Godfrey Serial Correlation LM test, F-statistic at 0.498209 with a p value of 0.6129 indicates no problem of serial correlation. As per the Breusch-Pagan-Godfrey heteroscedasticity test, F-statistic at 0.830850 with a p value of 0.7438 suggests that the null of homoscedastic residuals is not rejected.

Figure 10: Plot of CUSUM and CUSUMSQ for Coefficient Stability



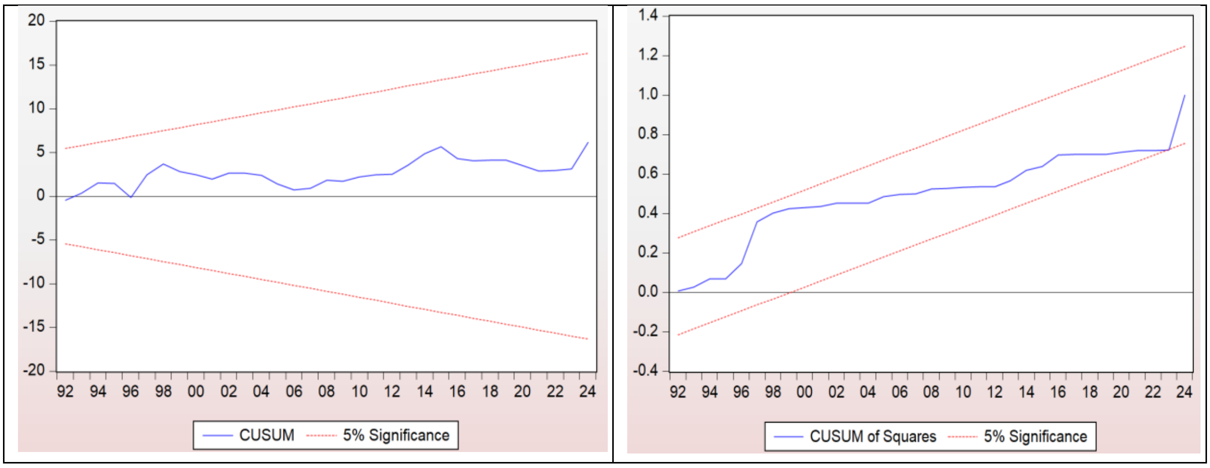
L(AGRI GVA) is modelled as a function of L(RAINFALL), L(TOT) and L(FERTILISER) besides two fixed regressors in the form of a constant and a trend, and other variables are dropped from the model through a sequential search as they turn out to be statistically insignificant in the long-run estimated equation. The ARDL model uses the lag structure of (2, 2, 2 and 0) as per the Hannan–Quinn information criterion (HQC), and the Bounds test F value at 12.94152 exceeds the critical value at 1%, rejecting the null hypothesis of no equilibrating relationship. Cumulative sum (CUSUM) and cumulative sum squared (CUSUMSQ) plots of L(YIELD) lie within 5% significance level over time, pointing to stability and good fit of the ARDL model (Figure 11). Long-run estimates suggest positive and statistically significant impact of rainfall, favourable terms of trade for agriculture, and fertilizer use on agri GVA. If average rainfall drops by one per cent, agri GVA could decline by 0.27 per cent, but better terms of trade and subsidized inputs (such as fertilizer) may be helping in countering the adverse impact of climate shock (Table 6). The estimated coefficient of ECM at -0.897307, which is statistically significant, deviations from the long-run relationship gets corrected by about 90 per cent in a year.

Table 6: Regression Coefficients: Long-run and Short Run

L(AGRI GVA)	Long-run Equation	Short-Run (Error Correction) Equation
L(RAINFALL)	0.268223 (4.128024)*	
L(TOT)	0.370649 (5.203585)*	
L(FERTILISER)	0.079074 (2.117220)**	
ECM		-0.897307 (-7.514792)*

*, **, *** indicate significant at 1%, 5 % and 10 % level. Figures in parentheses are t-values. Estimated value of adjusted r-squared at 0.836254 shows the ARDL model is a good fit. As per the Breusch-Godfrey Serial Correlation LM test, F-statistic at 1.835700 with a p value of 0.1764 indicates no problem of serial correlation. As per the Breusch-Pagan-Godfrey heteroscedasticity test, F-statistic at 1.138775 with p value of 0.3648 suggests that the null of homoscedastic residuals is not rejected.

Figure 11: Plot of CUSUM and CUSUMSQ for Coefficient Stability



State-level Panel Data Regression Results

Unlike time series estimates, use of panel data models helps in capturing heterogeneity across states and examine state-specific effects. Adverse climate shocks, for example, may impact agri output and crop yields of all states (working as common shocks), but state specific developments (like adoption of climate resistant cropping practices, or more investment made by some states to raise yields and productivity) which are unobserved (not captured explicitly in the dataset, i.e., omitted variables) may also influence outcomes in respective states, if not all states. Panel data can minimise estimation biases resulting from aggregating states into a single national level time series data. Depending on the relationship between the unobserved state-specific individual effects and explanatory variables in the model (i.e., whether individual effects are correlated with the independent variables), Hausam test helps in choosing between fixed effects models (where individual effects are controlled for) and random effects models (where individual effects are assumed to be randomly distributed, and no correlation between unobserved effects and independent variables). The null hypothesis for the test is random effects (no correlation) and if the Hausman test statistic is statistically significant, the fixed effects model is considered as more appropriate.

The impact of rainfall and temperature variations on state-wise production of food grains is examined in a panel data model using data for 27 states over the period 2012–13 to 2022-2023. The time period and number of states for the panel dataset is conditioned by the goal of having a balanced panel and data availability. L(Foodgrains) is modelled as a function of L(Rainfall) and L(Temperature). Whie estimating the model, square of the independent variables is also used to capture nonlinearities and thereby test whether larger changes (extreme values in the data) help explain variations in the dependent variable. Levin, Lin, and Chu (LLC) test results suggest that all the three variables in the model are stationary and, therefore, could be used in a panel regression (Table 7). Hausman test, with a p-value of 0.0000 confirms the suitability of a Fixed Effects (FE) model.

Table 7. Levin, Lin, and Chu test for stationarity

Variable	**Statistics (Adjusted t*)**
L(Foodgrains)	-4.91*
L(Rainfall)	-11.40*
L(Temperature)	-17.34*

* Indicates significant at 1% level.

The FE model helps explain how the two climate change variables (both current period and lagged) influence agricultural GVA, while controlling for the unobserved, time-invariant state-specific characteristics. One year lagged rainfall has a positive and statistically significant impact on food grain production, with a coefficient of 0.31 ($p < 0.01$), suggesting that a 1% decline in rainfall in the previous year could cause a 0.31% decrease in the production of foodgrains (Table 8). Unlike the timeseries estimate where the impact of rainfall is contemporaneous, panel regression results support one year lagged effects of rainfall, though the coefficient values are fairly similar. The impact of temperature, even when captured in the non-linear form, does not show any statistically significant impact on production of foodgrains.

Table 8. Results of Fixed Effects Panel Regression

L(Foodgrains)	**Coefficient**	**P>t**
L(Rainfall)	0.03	0.58
L(Temperature)	0.04	0.85
L(Rainfall)L1	0.31*	0.00
L(Temperature)L1	1.43	0.59
L(Temperature)^2 L1	-0.22	0.62
Constant	3.34	0.40
sigma_u	1.89	
sigma_e	0.14	
rho	0.99	

* Indicates significant at 1%.

Section V. The Way Ahead

Both climate adaptation (aimed at reducing vulnerability to and losses from climate events) and mitigation (to reduce GHG emissions from agriculture and to raise carbon sinks) measures are resource intensive, but despite the challenge of financing gap, Indian agriculture has exhibited remarkable resilience, as evident from the increase in yields, total production of foodgrains and horticulture crops and agri GVA over the years. However, as the frequency and intensity of climate shocks are expected to increase in future, policies to safeguard and entrench resilience of agriculture will progressively assume greater importance, given particularly the fact that India is now the most populous country in the world which is also experiencing fast-paced growth in per-capita income, that may create testing conditions for future food and nutrition security. As per the extensive field and crop simulation exercise conducted in India, in the absence of adaptation measures, rainfed rice yields could drop by 20% in 2050 and 47% in 2080; wheat yield could decline by 19.3% in 2050 and 40% in 2080 (PIB, 2023). Given the high share of employment involved in physical outdoor activity in agriculture (and construction, trade and transportation), a further increase in temperature would also lower labour productivity (ILO, 2019).

Recognising the need for a multi-pronged approach to deal with the challenge, India's National Mission for Sustainable Agriculture (NMSA), which is in operation since 2014-15, has placed policy focus on several thrust areas, which include enhancing water use efficiency through technology-enabled interventions in the form of drip and sprinklers under the 'Per Drop More Crop (PDMC)' component of Pradhan Mantri Krishi Sinchayee Yojana (PMKSY); promoting judicious use of chemical fertilizers, including through the "Soil Health Card" scheme that provides information to farmers on soil nutrients; empowering farmers with access to climate -smart farming practices through the National Mission on Agriculture Extension & Technology and National Initiative for Climate Resilient Agriculture (NICRA). Notwithstanding progress being made through the multi-pronged targeted initiatives, an integrated approach, with regular monitoring of progress in a holistic manner, timely course correction depending on periodic performance review of programmes, and regular introduction of new tech-enabled interventions may be required.

In designing an integrated framework, a realistic assessment of technical capabilities, available financial resources relative to the requirement, and clarity on the institutional mechanism that could drive the transformation would be critical. Moreover, location specific, as opposed to a one-size-fits-all approach would also be required based on local agro-climatic conditions and vulnerability to climate shocks. Initial costs incurred may need to be compared against the costs of no action in the medium to long-run, while also recognising that the flow of private capital is generally guided by potential future returns on investment rather than the scale of a problem which is not specific to a firm. The financing gap is likely to keep the green transition process incremental rather than transformative. Compared with a resource-heavy transformative green transition process, the alternative incremental approach that continues to enhance the climate resilience of agriculture gradually may be preferred, to allow available limited resources to pursue the overriding goal of economic growth, at least till technology and external concessional resources which can minimise the "growth and environment sustainability" trade-off becomes more accessible. Even under an incremental approach, however, an integrated framework may need to focus on each of the following multiple levels of interventions for further strengthening of the resilience of Indian agriculture and for a greener sustainable agriculture.

Alter the Consumption Pattern of Food Gradually

Animal-based foods, particularly red meat, dairy, and farmed shrimps generate the highest levels of GHGs in the agriculture and allied sector, as deforestation for expanding grasslands releases carbon dioxide; the cattle population emits methane while digesting grass and plants; use of chemical fertilisers to produce cattle feed leads to emission of nitrous oxide; and destruction of mangroves to create shrimp farms reduces carbon absorbed by mangrove forests. Changing food habits in favour of plant-based food and/or lab meat, through climate literacy campaigns could be necessary, given particularly the risk that with higher per-capita income levels in the future demand for animal food could only increase, as has been the experience of other major economies. Under the climate literacy campaign, consumption of locally produced food may be encouraged to avoid food transportation to far-off places and thereby save associated fuel consumption. As a potential policy tool for use in the future, taxation to discourage high carbon-emitting food may also be explored (as already announced in Denmark for livestock farming). Climate literacy campaigns under the Lifestyle for Environment (LiFE) mission to shift the diet pattern may be the least resource-intensive and also feasible option to encourage adoption of a healthy and sustainable living.

Livestock emissions could also be reduced from the supply side (by modifying animal feeds that reduce methane emissions or by increasing the supply of lab meat) and through technological interventions (such as the use of biogas digesters to convert methane and CO2 to energy).

Reduce the conversion of forest land and encroachment of mangroves

The Global Forest Watch (2023) reported that India lost 2.33 million hectares of tree cover since 2000 (equivalent to a six per cent decrease in tree cover), and between 2001 and 2022 forests in India emitted 51 million tons of carbon dioxide equivalent to a year while removing 141 million tons of carbon dioxide equivalent a year, implying a net carbon sink of 89.9 million tons of carbon dioxide equivalent a year. Reducing forest loss would mean a higher carbon sink (Indian Express, 2024).

As per the State of the World's Mangroves Report, 2024, the expansion of aquaculture has been a major factor driving the destruction of mangroves in India (besides adding to available land for rice cultivation). Mangroves reportedly hold (an average of) 394 tonnes of carbon per hectare in their living biomass and the top meter of soil. The integrated mangrove shrimp aquaculture, particularly the Sustainable Aquaculture in Mangrove Ecosystem

(SAIME) initiative that has already been launched in India could help in limiting risks from mangrove destruction.

India has set a target for carbon sequestration by increasing forest and tree cover to 33 % and pledged under the Paris Agreement to create an additional carbon sink of 2.5 to 3 billion metric tonnes of carbon dioxide (CO2) equivalent by 2030. As per the India State of Forest Report, 2023, the forest and tree cover has increased by 1445 sq km since 2021, but overall it stands at 25.17 % of the geographical area. Blue carbon sinks (like mangroves, salt marshes and seagrasses) could sequester 2.67 times more carbon than afforestation and over 10 times more than grasslands and agriculture, and India highlighted the potential of blue carbon sequestration during its G20 presidency (Rajbanshi, 2023). Moharaj (2024) presents many successful examples in India, across states, contributing to the progress on the carbon sequestration goal, and strategies for effective community participation can help in making further progress.

Soil sequestration or "carbon farming" helps in addressing the challenge emanating from intensive/repetitive tillage and overuse of chemical fertilisers (that release GHGs while reducing organic carbon in soil), and would require perennial crops, cover crops, *etc*., for absorbing CO2 from the air in the soil.

Reduce food wastes

According to the Food Waste Index Report, 2024, India generates an average of 55 kg of food waste per capita annually, implying as high as more than 78 million tonnes in a year. A major part of this waste ends up in landfills, and decomposed food waste leads to methane emissions. Out of thirteen waste treatment solutions, as elaborated by Vijayvergiya (2024), anaerobic digestion, black soldier fly larvae (BSLF) treatment and biochar production rank high, followed by traditional methods like composting and vermicomposting. Besides strengthening the agri supply chain to reduce food waste at different stages, the adoption of preferred techniques may be encouraged, taking into account the pros and cons of each.

Promote organic farming and reduce excess use of chemical fertilisers

Both production and excess as well as imbalanced use of chemical fertilisers emit GHGs. Every tonne of urea produced leads to the emission of five tonnes of CO2 equivalent GHGs, and when urea is applied in fields nitrous oxide (N2O) is released, which is ozone-depleting (Bhushan, 2024). Besides producing green urea from green hydrogen/renewables (instead of imported natural gas), calibrated use of chemical fertilisers using sensors (or precision farming) and selective adoption of natural farming are possibilities for the future.

Technology has expanded the scope for precision farming, particularly Variable Rate Technology (VRT) for precise application of fertilizer; soil sensors for real-time nutrient level monitoring; drone-based fertilizer spraying in hard-to-reach areas; and artificial intelligence (AI)-powered crop models for raising crop yields while improving soil health (Farmonaut, 2024).

It was announced in the Union Budget for 2024-25 that over the next two years, one crore farmers across the country will be initiated into natural farming supported by certification and branding. Currently, under two schemes, namely Paramparagat Krishi VikasYojna (PKVY) and Mission Organic Value Chain Development for the Northeastern Region (MOVCDNER) end-to-end support is provided to farmers engaged in organic farming (training, capacity building, production, processing, certification, marketing and post-harvest management). Both forward linkages (through branding and certification) and backward linkages (through the bio-input resource centres (BRCs)) are critical in natural farming, with certification enabling demarcation of natural farming outputs to fetch a premium and BRCs providing farmers access to bio inputs (Manjula, 2024). Ground-level implementation challenges, arising particularly due to the subsidised provision of chemical fertilisers, would require reforming the fertiliser subsidy regime, for which the strategy adopted by China (setting a net zero growth target in 2015 for both chemical fertilisers and pesticides by 2020, which has been achieved) or direct benefit transfer (DBT) route that can check leakage with better targeting could be explored. To check the overuse of agrochemicals - partly a result of aggressive marketing strategies that emphasise chemicals as a necessity to raise crop yields - the regulatory regime may require an overhaul (Mittal, 2024).

Alter the cropping pattern and stop crop residue burning

High subsidies tend to distort farming practices in India. The way subsidies are currently provided encourages the cultivation of high-emissions rice (for instance, through minimum support prices and procurement by the government) and overconsumption of energy by farms (for instance, through highly subsidized energy and water resources) (Chateau *et al*., 2023). Reducing methane emissions from rice fields would require avoiding the current practice of continuous flooding and adopting controlled and intermittent water application techniques, besides aerobic cultivation (to reduce methane produced by bacteria in waterlogged soils). Micro-irrigation and crop diversification, use of water-efficient drip/sprinkler system, volumetric pricing system for water, and implementation of water efficiency benchmarks (following the constitution of the Bureau of Water Use Efficiency) would need to be pursued, recognising the risk that India's per-capita water availability is likely to reach water scarce scenario by 2050 (Sarkar, 2024). Empirical research for India suggests that drip irrigation reduces water consumption in the range of 39-55 % (for five crops) compared to flood irrigation, improves crop productivity by 33-41%, and increases profit margins of farmers by 53-115 per cent (Narayanamoorthy, 2024). Recognising its potential, the Ministry of Agriculture and Farmer's Welfare has issued detailed operational guidelines for "Per Drop More Crop", which should help in driving deeper penetration of drip/sprinkler systems in the country. Increasing the use of solar agri pumps in India is another positive climate smart trend, given the estimate (Sutton *et al*., 2024) that if one-quarter of India's 8.8 million diesel irrigation pumps are replaced with solar ones that could reduce carbon emissions by 11.5 million tons per year.

Burning of crop residue (in Punjab, Haryana and UP in the winter) is estimated to cause a loss of 1.43 million tonnes of nutrients from the topsoil layer in India, which results from multiple cropping and shortened intervals between crops, greater mechanization of harvesting (that leaves stubble of 10– 30 cm in the field, given that labour shortage/high cost discourages manual harvesting), and low local demand for crop residue for any alternative use other than roofing of houses (CSE, 2017). Besides using crop residues for biofuels, organic fertiliser and packing materials under different schemes, farmer awareness programmes have also been initiated to inform them about the health hazards and loss of soil fertility, which need to be sustained.

VI. Conclusions

The observed resilience of Indian agriculture to climate shocks so far – an outcome of progressive adaptation by farmers and wide-ranging targeted policy interventions of the government – supports the adoption of an incremental approach for achieving the goal of sustainable agriculture. The alternative, an accelerated or a transformative transition approach, would entail "growth *versus* environment sustainability" trade-off costs, which could be contained only when access to affordable green technology and external concessional resources improves in the future. This would be consistent with the Environmental Kuznets Curve (EKC) hypothesis, which recognises the unintended carbon emissions challenge associated with economic growth, and importantly, highlights an observed inverted U shaped pattern globally - that growth-induced carbon emissions tend to decline for a country after a level of per-capita income as it progressively becomes more energy efficient and technologically advanced.

Despite high resilience of Indian agriculture so far, as evident from the trend increase in production of foodgrains, yields and agri GVA, the adverse impact of climate shocks is already visible. Empirical estimates presented in this paper show that in the long-run, when temperature rises by 1 per cent (equivalent to about 0.26 degree Celsius in a year), yield of foodgrains declines by 6.5 per cent, which can be contained by increasing the share of irrigated land in total gross cropped area. A one per cent drop in YIELD lowers foodgrains production by 0.65 per cent, which can be partly offset through price based support enabling the terms of trade (ToT) to move in favour of agriculture. If average rainfall drops by one per cent, agri GVA could decline by 0.27 per cent, but better terms of trade and provision of subsidized inputs (such as fertilizer) could moderate the adverse impact. Panel data estimates, that help capture state level heterogeneity, point to a decline in average rainfall lowering production of foodgrains, but the impact of rising temperature on production is not found to be significant yet. Global experience also shows that despite climate shocks, food production and yields have continued to rise in many countries, though at a slower pace, which is largely possible due to the rising penetration of climate resistant cropping practices and yield enhancing technologies. In the future also, greater investment on drought and temperature resistant cropping practices can limit risks from climate shocks.

Recognising this, India's National Mission for Sustainable Agriculture (NMSA), which is in operation since 2014-15, has been driving targeted interventions across multiple dimensions, for making Indian agriculture more resilient and more environmentally sustainable. As the most populous country in the world which is also experiencing fast-paced growth in per-capita income, to preserve and entrench India's future food and nutrition security, even while adopting an incremental approach, an integrated framework with a focus on making progress across a whole range of targeted interventions will be critical. This must include sifting the household diet pattern in favour of low emissions food; balanced and judicious use of water and chemical fertilisers; soil conservation; pest and insect management; adoption of organic farming practices; crop diversification recognising the emission intensity of crops; wider use of climate resistant and high yielding seeds, particularly by small and marginal farmers; adoption of sustainable animal breeding practices; arresting conversion of forest land and encroachment of mangroves; reducing crop residue burning; promoting carbon sequestration; and reducing food wastes at different stages of the food supply chain. As an integrated approach, there may be due attention to regular organised monitoring of progress in a holistic manner, timely course correction depending on periodic performance review of programmes, and regular introduction of new tech-enabled interventions while also strengthening extension services and climate literacy campaigns to enhance traction.

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Annexe Figure 1: Variables Used in the Model (in Log form)