Research Paper

# Relative importance of factors in explaining fluctuations in India's agricultural production

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**ABSTRACT**

This study examines the relative importance of irrigated area, non-irrigated area, fertilizer use, rainfall, and temperature in explaining agricultural output fluctuations in India during 1960–61 to 2022–23. The analysis uses the True Relative Importance (TRI) framework based on orthopartial and simple correlation. Rainfall emerges as the most important factor when agricultural fluctuations are analyzed without separating trend and de-trended components. Agricultural output remains highly sensitive to monsoon variability. After decomposition, the trend components explain only about 2 percent of total fluctuations. This indicates that factors such as irrigation expansion, fertilizer use, and technological progress mainly influence long-run agricultural growth and stability. The de-trended components account for nearly 65 percent of total fluctuations, showing that agricultural instability is driven largely by short-run factors. Irrigated area is the largest contributor, explaining about 34.7 percent of fluctuations. Rainfall ranks second with 16.6 percent, followed by fertilizer with 9.9 percent. The effects of non-irrigated area and temperature remain relatively small.

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## 1. INTRODUCTION

Agriculture has been an important sector of the Indian economy for many decades. It contributes significantly to national income. A large number of people are employed in this sector. For many rural households, agriculture remains the main source of livelihood. Food grains, horticulture, livestock, fisheries, and forestry are included within the agricultural sector. India produces several major agricultural commodities and is considered one of the leading producers in the world. However, its performance varies from region to region and also across years.

Although agriculture plays a vital role in the economy, many challenges still exists. A large share of cultivated land depends on rainfall. This makes agricultural production highly sensitive to weather conditions. Crop output can be affected by changes in rainfall and temperature. In some years, the effect becomes very severe. Agricultural instability is therefore often observed. Production levels do not remain same every year.

Many policy measures have been adopted over time to support the sector. Irrigation facilities were expanded in different parts of the country. Crop insurance schemes were also introduced. Efforts were made to improve agricultural marketing systems and related infrastructure. Productivity has increased because of these initiatives. At the same time, several issues remain unresolved. Not all problems have been fully addressed. As a result, short-term fluctuations in agricultural performance still continue to occur.

Indian agriculture therefore exhibits both growth and instability. Long-term growth has been supported by technology, institutional changes and policy interventions. On the other hand, fluctuations are generated by climatic uncertainty, uneven input use and infrastructure related constraints. The contribution of these factors may not be same at all times. Therefore, understanding their relative importance is necessary for framing better agricultural policies and development strategies.

Thus, the primary aim of this study is to analyse the relative significance of various factors influencing the variability of Indian agriculture and to isolate the factors which are responsible for the fluctuations in agriculture in the country.

## 2. RELATED WORK

The concept of relative importance of predictors has changed over time. This happened mainly because traditional regression methods often face problems when explanatory variables are correlated. [1] Introduced a hierarchical partitioning approach. This method considers all possible orders of variables when estimating their contribution. [2] Later proposed Proportional Marginal Decomposition (PMD) based on cooperative game theory. Shared explanatory power among predictors was allocated through this approach. [3] Discussed the problem of multicollinearity. Correlated variables were observed to explain more variation jointly than separately. As a result, the interpretation of regression coefficients becomes difficult. [4] Introduced orthopartial correlation to address this issue. A clearer separation of the independent effects of predictors was possible through this method. Later, permutation-based signed $R^2$ decomposition approaches were developed, providing more stable estimates of relative importance. These methods have been applied in many empirical studies. [5] Examined the role of structural changes, including break-in-trend, in agricultural output modelling. Short-term fluctuations, however, continued to remain. [6] Analysed Indian GDP growth using relative importance techniques. Openness contributed more than crude oil prices in their analysis. The outcome differed from those obtained through conventional regression models.

[7] Introduced dominance analysis as a procedure for evaluating predictor importance across all possible subset models. [8] Drew attention to the need for robust statistical techniques, particularly in the presence of highly correlated predictors. [9] Expanded the practical application of dominance analysis. Stata-based tools became available and the implementation process became easier for researchers. Additional developments were reported [10]. Improvements were discussed from both conceptual and empirical perspectives. [11] Combined logistic regression with relative importance analysis. Key drivers of urban growth were identified through this framework. [12] Earlier discussed the LMG variance decomposition method. The method proved useful, although it generally assumes linear relationships among variables and correct model specification.

[13] Further developed dominance analysis by providing formal definitions of dominance. Bootstrap procedures were also incorporated to improve reliability. [14] Examined the long-term influence of the Green Revolution on agricultural productivity. Governance and agricultural development were later

analysed [15]. Different levels of contribution from governance factors were observed across sub-periods. Agricultural instability was also investigated [16]. Subsequently [17] examined the principal determinants of agricultural GDP growth using relative importance methods. [18] Employed fuzzy logic models in agricultural productivity analysis and demonstrated the applicability of advanced modelling approaches.

Applications of relative importance methods are not limited to economics and agriculture. [19] Employed the RII method to identify productivity constraints in the construction sector. [20] Used structured decision-making techniques in the assessment of maternal healthcare determinants. [21] Extended relative importance analysis to logistic regression settings, allowing its use with categorical outcomes. In another study [22], they recommended that relative importance measures should be interpreted together with conventional regression results, particularly when multicollinearity is present.

[23] Developed an R package for calculating different measures of relative importance. The use of bootstrap procedures for improving estimation accuracy was also recommended. [24] Discussed limitations associated with standardized coefficients and partial correlations. Greater attention was given to the need for reliable decomposition techniques. [25] Compared dominance analysis with relative weight methods. Relative weights required less computational effort, especially in high-dimensional datasets.

## 3. METHODOLOGY

### 3.1. Data

This study is based on annual time-series secondary data on India's agricultural Gross Domestic Product (GDP) covering the period 1960–61 to 2022–23, measured at constant prices with base year 2011–12. In addition to agricultural GDP, the analysis incorporates key explanatory variables, namely non-irrigated area, irrigated area, fertilizer use, rainfall, and temperature.

Data on agricultural GDP, total cultivated area, and irrigated area were obtained from the Central Statistics Office (CSO), the Directorate of Economics and Statistics, Ministry of Agriculture, and various editions of the Statistical Abstract published by the Government of India. Data on fertilizer consumption was sourced from the Department of Fertilizers and the Department of Agriculture & Farmers Welfare. Climatic variables, including rainfall and temperature, were obtained from the Indian Meteorological Department (IMD). The non-irrigated area was computed as the difference between total cultivated area and irrigated area.

The analysis is conducted in two phases. In Phase I, we assess the relative importance of the factors in explaining the stochastic component of log Agricultural GDP. In Phase II, we deepen the analysis by decomposing the factors into their respective trend and detrended (residual) components. This enables us to consider separately the contribution of the long-term evolution of these and the short-term variability of these to agricultural volatility as shown in the Figure 1.

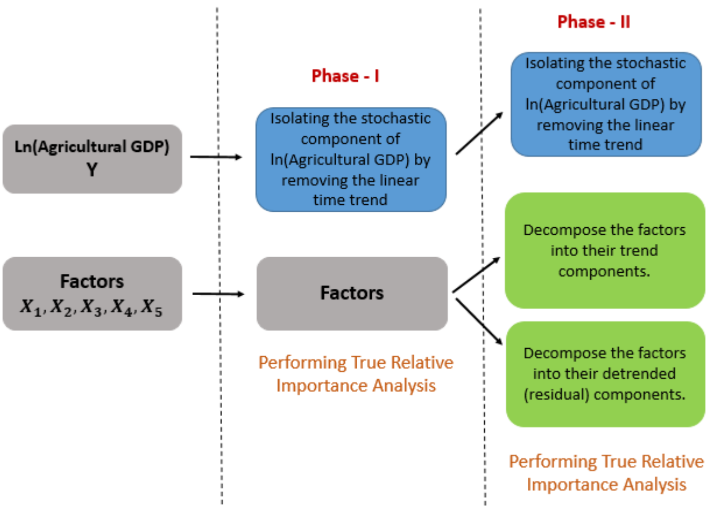


Figure 1. Framework for Multi-Phase Factor Decomposition Analysis

### 3.2. Method of True Relative Importance Analysis

True Relative Importance (TRI) framework is adopted for the evaluation of contribution of the predictors. The analysis starts by establishing a linear relationship between a variable Y which is modeled against a set of n variables$X = \{X_1, X_2, \dots, X_n\}$, such that$Y = X\beta + \varepsilon$. The algorithm will generate all possible (n-1)! Combinations of the predictors, where n is the number of predictors.

The direct effect is calculated using regression of Y on X base for a particular predictor X base. to obtain the coefficient of determination $R^2_{Y \sim X_{base}}$. To handle multi-collinearity and partial contributions, the logic generates residual terms, known as e-terms. For any subset of predictors $S \subset X \setminus \{X_{base}\}$, the residual $e_{base}.S$ is defined as the remaining variance of $X_{base}$ that cannot be explained by the variables in S. Formally, this residual is obtained as $e_{base}.S = X_{base} - \hat{X}_{base|S}$, where $\hat{X}_{base|S}$ denotes the fitted values from regression $X_{base}$ on S. This residual represents the unexplained variance of $X_{base}$ and forms the basis of orthopartial correlation as introduced by Mondal (2008). According to Mondal (2008), the regression coefficient in this context has two distinct interpretations:

1. The degree of variation in the specific segment of Y that is not affected by other explanatory variables, resulting from a one-unit alteration in the corresponding portion of X that is also not accounted for by other explanatory variables.
2. The extent of change in Y when there is a one-unit change in the section of $X_j$ that is not accounted for by other explanatory variables.

The correlation obtained in the first regression is frequently referred to as "partial correlation" in literature, but it is not truly partial because it does not fully isolate the effects of the other independent variables. The true partial correlation is obtained in the second regression where the effect of the other explanatory variables is removed. This measure, therefore, was called orthopartial correlation by Mondal (2008) since it is correct and completely isolated.

The orthopartial contribution is a regression of Y on the residual e_base.S using Ordinary Least Squares (OLS) with the residual vector being: $e_{base}.S = Y - X\hat{\beta}$.

The algorithm then builds up a full contribution path for each variable, step-by-step, along each permutation path, so that the R^2 contribution for each variable can be determined at each level of factor complexity. The matrix form of estimation of parameters is given below: $\beta = (X^T X)^{-1} X^T Y$.

The $R^2$ values associated with these paths are signed according to the t-statistic of the regression coefficient to distinguish between synergistic and antagonistic effects. Specifically, if the t-value is negative, the $R^2$ is treated as a negative contribution in the signed analysis. The raw path-wise contributions are then aggregated into two primary metrics for each variable $X_j$. The overall unsigned average is defined as the arithmetic mean of the absolute values of all $R^2$ contributions across the $m = (n-1)!$ generated paths, given by $\frac{1}{m}\sum_{i=1}^{m}|R_i^2|$, which reflects the magnitude of influence irrespective of direction. The overall signed average is defined as $\frac{1}{m}\sum_{i=1}^{m} R_i^2$, capturing the net directional effect of the predictor.

The Final Adjusted Relative Importance is the result of a last refinement. This is done by taking a weighted normalized sum of the interaction terms. For n predictors, the weight for each path component is given as:

$$w = \frac{1}{(n-1)!}$$

During the adjustment phase the normalization multiplier is 2/n, which means that only the relevant positive or negative interaction terms are added and weighted (selectively) according to the signed average. The final absolute importance of predictor $X^j$ is then calculated as:

$$\text{Final Adjusted Importance} = |\text{Signed average}| + \left|\text{Normalized Sum}_{weighted}\right|$$

This value is the actual contribution of the predictor to the variance in the data, after adjusting for the complex covariances among the data values.

## 4. RESULTS AND DISCUSSION

The fluctuation component of agricultural production is broken down in a first stage of the analysis (Phase I) using the True Relative Importance (TRI) framework. The number of possible decomposition paths of each explanatory variable is (5-1)! = 24, as five variables are considered. Further each path is hierarchicalized into five groups according to the number of variables that contribute to the path: orthopartial, up to two joint, up to three joint, up to four joint, up to five joint. These sections are representing successive amounts of common explanatory power of the predictors.

The absolute values of the degree of joint contribution is added up for all 24 paths for each section and compared between variables. The results indicate that there is a definite and consistent dominance of rainfall at each level of decomposition. In the orthopartial section, 82 per cent of the total contribution is due to rainfall alone. Its dominance further increases to 85 percent in the up to two joint section, remains high at 74 percent in the up to three joint section, and continues to explain 64 percent in the up to four joint section. In the up to five joint section, rainfall again emerges as overwhelmingly dominant, accounting for nearly 90 percent of the total contribution, as illustrated in Figure 2.

In contrast, the contribution of non-irrigated area remains comparatively small across all sections. Its share ranges from about 4 percent in the orthopartial component to a maximum of around 14 percent in the up to four joint section. Similarly, across the intermediate joint sections, the contribution of non-irrigated area varies between 5 and 13 percent. The remaining variables, irrigated area, fertilizer, and temperature, also exhibit relatively limited shares in each section when compared to rainfall.

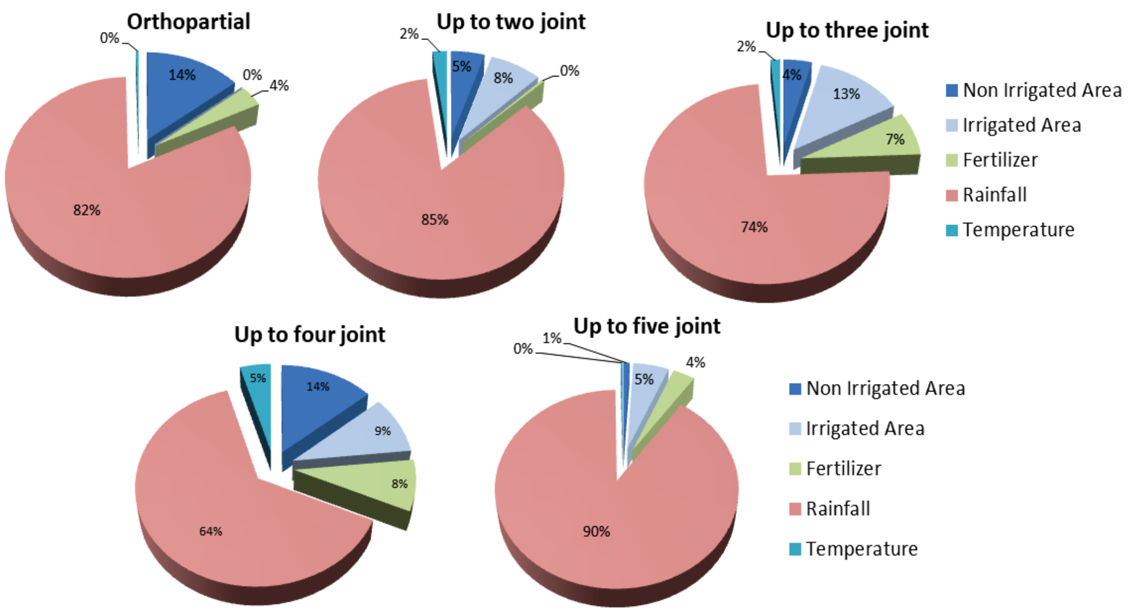


Figure 2. Distribution of Orthopartial and Higher-Order Joint Shares across Variables

However, the decomposition process reveals substantial negative overlap among the predictors across the 24*5=120 paths. A total of 158 instances of sign changes are observed when examining all decomposition points across the five variables. These sign changes indicate the presence of enhancement–synergism and antagonistic interactions among the explanatory variables. In other words, the contribution of a factor is not uniform across paths; it varies depending on the order and combination in which other variables enter the decomposition process. Such behaviour confirms the existence of multicollinearity and overlapping explanatory power among the determinants.

To address this issue, the adjustment mechanism embedded in the True Relative Importance framework is applied. This procedure takes into account sign changes and evenly distributes overlapping effects. These adjustments are then made to get the final relative importance values. The values show the proportion of the total coefficient of determination (R^2) from the multiple regression of Agricultural GDP in logs on these factors. The final adjusted measures then make sure that the total of the individual contributions is exactly the total of explained variation.

The TRI analysis takes three situations into account. The Unsigned Average is an average of the magnitude of contribution but not direction. The Signed Average is a method that takes into account both positive and negative overlaps, and it records the direction of the net effect. The Adjusted Signed Average is a final/experimental corrected measure that adjusts for sign reversals and interaction effects.

The results indicate that Irrigated Area is related to agricultural output with an Unsigned Average value of 0.01273, which accounts for around 1.2 per cent of the overall variation. The signed and adjusted measures also help support the fact that the irrigated area does not aggravate variability, but instead helps stabilize agricultural production in India. This means that despite irrigation, the variability will be reduced instead of increased. The stabilizing effect is found due to irrigation reducing the reliance on rainfall and providing a more consistent, and reliable, supply of water to crops. This leads to greater crop certainty and less climate risk for crops. Therefore, irrigated area is mainly responsible for stabilizing agricultural output, as opposed to its volatile component, as is illustrated in Figure 3.

Rainfall, however, is the most important agricultural fluctuation factor, compared to the other factors. The Adjusted Signed Average value of rainfall is 0.204247 which shows that variation in agricultural production due to rainfall is about 20.42 percent of the total fluctuation in the production. This overwhelming contribution is an indication of the importance of the role of inter-annual rainfall variability in the Indian agriculture. In India, a substantial proportion of cultivated land is rain-fed and hence the agricultural production is very much dependent on changes in monsoon patterns. In addition to the spatial variability of rainfall across the region, India is also plagued by temporal uncertainty of rainfall. Lack of rainfall may result in drought and loss of crops while heavy rainfall may result in flooding and water logging, which have negative impacts on productivity. This results in a considerable impact of rainfall fluctuations on agricultural production fluctuations. Improved water infrastructure, water management and crop diversification to mitigate vulnerability to rainfall shocks.

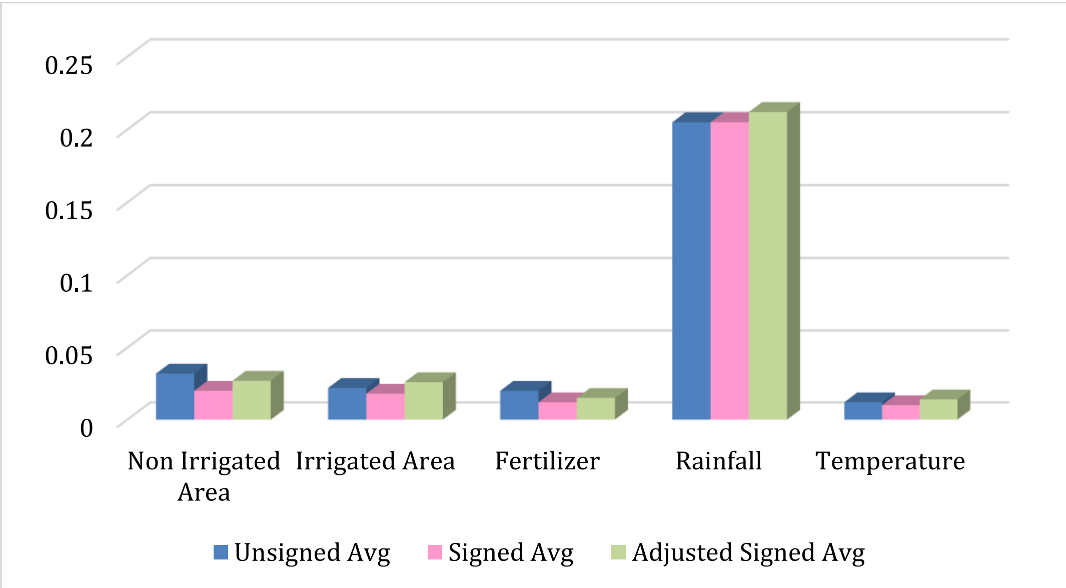


Figure 3. Decomposition of Agricultural Output Fluctuations by Major Determinants in India

The analysis then reveals that the contribution of Fertilizer to agricultural fluctuations is not large in terms of Adjusted Signed Average with value of 0.004152 or about 0.4 per cent fluctuations. The quantitative contribution of this to the variation in yield is rather low in comparison to that of rainfall, but fertilizer use is still a factor of high importance for yield variation. In India, soil fertility varies from one place to another and farmers often use less than the recommended amount of fertilizer or fertilizers that are not recommended for the specific soil type, which can result in poor crop yields. Fertiliser application is a balance between having enough and too much; too little will grow the crop while too much will decrease soil quality and lower long term productivity. So, the mismanagement of fertilizers may lead to a higher variability in output. Balanced nutrient management is a key to optimize the use of fertilizer and thus to promote productivity without compromising soil health. Temperature also impacts on the variability of agricultural production but to a lesser degree than rainfall. The Adjusted Signed Average value (≈0.006041) implies that the fluctuation is caused by temperature, which is approximately 0.6%. Any deviation from the optimum temperature may influence the growth and productivity of crops and high temperatures can also cause yield losses. Though it has a limited impact, temperature is still a key climatic variable affecting agriculture.

The study utilizes annual information on agricultural GDP of India for the time period 1960-61 to 2022-23, which is characterized by significant changes in agricultural structures and various policy measures, technological development and institutional changes. Factors are separated into trend and residual components to avoid giving misleading results due to long-term trends. The first stage accounts for long-term variation due to structural and policy change, while the second stage accounts for short-term variation, including climatic changes, market unpredictability and agricultural instability as illustrated in Figure 1.

### 4.1. How Agricultural Fluctuation is Influenced by Policy-Driven Trends (Phase-I)

The regression analysis for the trends in agricultural output shows that only 2% of the variations in the output of agriculture can be attributed to the regression analysis components. That is, the variation in agricultural production is very small and caused by only a small proportion of long-run structural and policy-induced changes. This indicates that the instability in agriculture in India is of a short run or even irregular nature rather than of a gradual change in the policy. This breaks down into 5 factors of TRI, and does not show significant contribution. In this policy–trend framework, rainfall is also the biggest contributor in terms of trend components as shown in Figure 4 by the highest adjusted signed average value. This means that changes in agricultural activity are affected even by a long-term trend in precipitation, perhaps representing a slow, long-term change in climate. The magnitude is not very large compared to the overall variation, though.

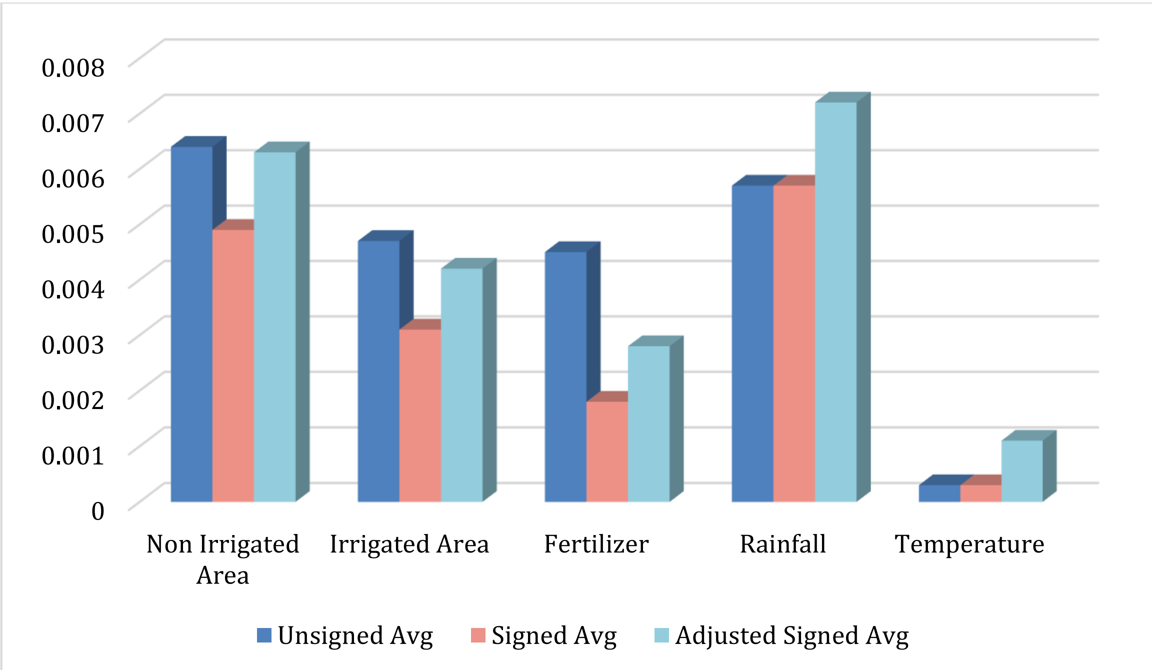


Figure 4. Contribution of Trend-Predicted Factors to Agricultural Output Fluctuations in India

In contrast, the temperature contribution is very small in this trend decomposition. This means that the effect of the long-run temperature trend on the fluctuations in agricultural production over the study period is not significant. The observed rise in temperature seems to affect agricultural productivity more by short-term fluctuations and/or extreme events than by a deterministic trend. Likewise, irrigated area and non-irrigated area as well as fertilizer use exhibit weak trends in trend components implying that policy-driven changes in irrigation and fertilizer use primarily drive structural growth and stability and less output volatility.

There is a significant difference between the sum of the absolute averages and the signed averages, signifying that there are positive and negative trends in the variables. Unsigned measures are not direction sensitive, which makes them tend to overestimate the overall contribution. Hence the necessity to make an adjustment so as to be able to achieve the desired consistency of decomposition.

### 4.2. How Agricultural Fluctuation is Influenced by Detrended (Residual) Components (Phase-II)

Absolute contribution shares of the different variables across the different decomposition paths, based on the absolute value of the contribution sums across all 24 paths, are shown here by section. In every section these factors are all significant and the irrigated area has the largest proportion of the explained variation at every hierarchical level. It is dominant in the orthopartial, up to two joint and simple components, suggesting that the irrigated area is a significant influence not only on its own, but also in combination with other components. Rainfall and fertilizer share moderate shares and have a higher proportion of interaction effects in higher-order joint components indicating that rainfall and fertilizer affect fluctuations in agriculture more through interaction effects than pure effects. In comparison, all sections have relatively small contributions from non-irrigated area and temperature, as shown in Figure 5.

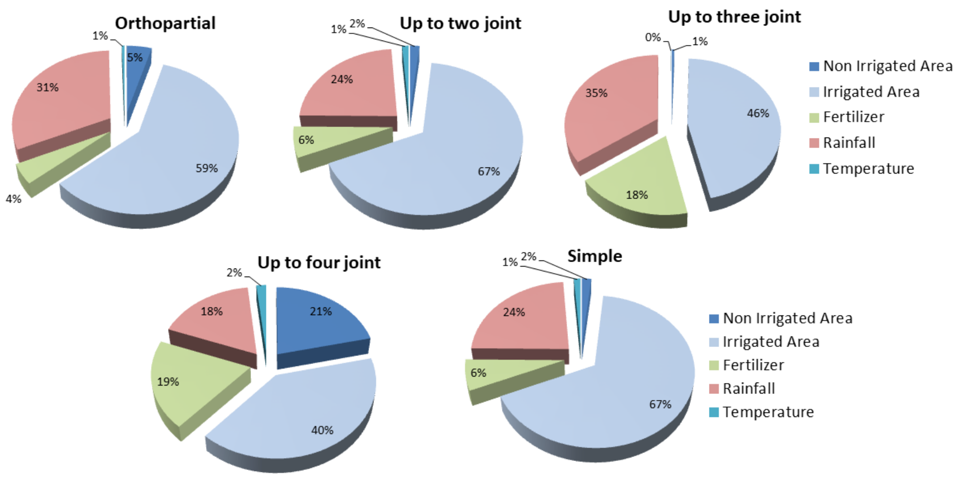


Figure 5. Absolute Joint Contribution Shares by Hierarchical Section

The multiple regression results show that the de-trended or irregular components explain about 65 percent of the total fluctuations in agricultural output, which is substantially higher than the contribution of the policy-driven trend component. This is clearly indicates that agricultural fluctuations in India are predominantly driven by non-policy factors. The decomposition is internally consistent, as the sum of the adjusted signed average contributions exactly equals the total explained variation, thereby confirming the validity of the True Relative Importance framework. In the TRI analysis process, a total of 52 points have been adjusted, as they represent points of sign change, as reported in Table 1 and Table 2. These sign changes are observed in the paths of two factors, namely $X_1$ and $X_5$. After adjusting these points, the Adjusted Signed Average is obtained.

Table 1. Total of 24 Paths for Factor$X_1$, with 26 Colored Markers Representing Points of Sign Change. The Markers are Adjusted with Respect to Factors $X_2$ (Light Green), $X_3$ (Light Blue), $X_4$ (Light Yellow), and $X_5$ (Light Orange)

| Orthopartial | Up to Two Joint | Up to Three Joint | Up to Four Joint | Simple |
|---|---|---|---|---|
| -0.01406 | -0.08918 | -0.17417 | -0.01741 | -0.01888 |
| -0.01406 | -0.08918 | -0.17417 | -0.21162 | -0.01888 |
| -0.01406 | -0.08918 | -0.00096 | -0.01741 | -0.01888 |
| -0.01406 | -0.08918 | -0.00096 | 0.001344 | -0.01888 |
| -0.01406 | -0.08918 | -0.08116 | -0.21162 | -0.01888 |
| -0.01406 | -0.08918 | -0.08116 | 0.001344 | -0.01888 |
| -0.01406 | -0.02127 | -0.17417 | -0.01741 | -0.01888 |
| -0.01406 | -0.02127 | -0.17417 | -0.21162 | -0.01888 |
| -0.01406 | -0.02127 | 0.005082 | -0.01741 | -0.01888 |
| -0.01406 | -0.02127 | 0.005082 | 7.63E-05 | -0.01888 |
| -0.01406 | -0.02127 | -0.04774 | -0.21162 | -0.01888 |
| -0.01406 | -0.02127 | -0.04774 | 7.63E-05 | -0.01888 |
| -0.01406 | 0.00833 | -0.00096 | -0.01741 | -0.01888 |
| -0.01406 | 0.00833 | -0.00096 | 0.001344 | -0.01888 |
| -0.01406 | 0.00833 | 0.005082 | -0.01741 | -0.01888 |
| -0.01406 | 0.00833 | 0.005082 | 7.63E-05 | -0.01888 |
| -0.01406 | 0.00833 | 0.006013 | 0.001344 | -0.01888 |
| -0.01406 | 0.00833 | 0.006013 | 7.63E-05 | -0.01888 |
| -0.01406 | -0.02229 | -0.08116 | -0.21162 | -0.01888 |
| -0.01406 | -0.02229 | -0.08116 | 0.001344 | -0.01888 |
| -0.01406 | -0.02229 | -0.04774 | -0.21162 | -0.01888 |
| -0.01406 | -0.02229 | -0.04774 | 7.63E-05 | -0.01888 |
| -0.01406 | -0.02229 | 0.006013 | 0.001344 | -0.01888 |
| -0.01406 | -0.02229 | 0.006013 | 7.63E-05 | -0.01888 |

Table 2. Total of 24 Paths for Factor$X_5$, with 26 Colored Markers Representing Points of Sign Change. The Markers are Adjusted with Respect to Factors $X_1$ (Salmon Pink), $X_2$ (Light Green), $X_3$ (Light Blue) and $X_4$ (Light Yellow)

| Orthopartial | Up to Two Joint | Up to Three Joint | Up to Four Joint | Simple |
|---|---|---|---|---|
| 0.001452 | 0.009682 | 0.000316 | 0.038494 | 0.002517 |
| 0.001452 | 0.009682 | 0.000316 | -0.01724 | 0.002517 |
| 0.001452 | 0.009682 | 0.032354 | 0.038494 | 0.002517 |
| 0.001452 | 0.009682 | 0.032354 | 0.007111 | 0.002517 |
| 0.001452 | 0.009682 | 1.6E-06 | -0.01724 | 0.002517 |
| 0.001452 | 0.009682 | 1.6E-06 | 0.007111 | 0.002517 |
| 0.001452 | -0.00833 | 0.000316 | 0.038494 | 0.002517 |
| 0.001452 | -0.00833 | 0.000316 | -0.01724 | 0.002517 |
| 0.001452 | -0.00833 | -0.00105 | 0.038494 | 0.002517 |
| 0.001452 | -0.00833 | -0.00105 | -0.00105 | 0.002517 |
| 0.001452 | -0.00833 | -0.01685 | -0.01724 | 0.002517 |
| 0.001452 | -0.00833 | -0.01685 | -0.00105 | 0.002517 |
| 0.001452 | 0.005883 | 0.032354 | 0.038494 | 0.002517 |
| 0.001452 | 0.005883 | 0.032354 | 0.007111 | 0.002517 |
| 0.001452 | 0.005883 | -0.00105 | 0.038494 | 0.002517 |

| | | | | |
|---|---|---|---|---|
| 0.001452 | 0.005883 | -0.00105 | -0.00105 | 0.002517 |
| 0.001452 | 0.005883 | 0.012117 | 0.007111 | 0.002517 |
| 0.001452 | 0.005883 | 0.012117 | -0.00105 | 0.002517 |
| 0.001452 | 0.002319 | 1.6E-06 | -0.01724 | 0.002517 |
| 0.001452 | 0.002319 | 1.6E-06 | 0.007111 | 0.002517 |
| 0.001452 | 0.002319 | -0.01685 | -0.01724 | 0.002517 |
| 0.001452 | 0.002319 | -0.01685 | -0.00105 | 0.002517 |
| 0.001452 | 0.002319 | 0.012117 | 0.007111 | 0.002517 |
| 0.001452 | 0.002319 | 0.012117 | -0.00105 | 0.002517 |
| 0.001452 | 0.002387 | 0.004481 | 0.006829 | 0.002517 |

The Adjusted Signed Average reveals that the key variable is irrigated area which accounts for around 34.7% (0.347353) of the variations in agricultural activity. This means that short-run fluctuations in irrigation supply rather than long run growth in irrigation supply are significant in causing instability in output. These variations are attributed to changes in water supply, infrastructure performance, groundwater availability and regional differences in irrigation access. The second largest contributor is Rainfall with a contribution of about 16.6 per cent (0.165949) of fluctuations. This confirms the importance of the variability of rainfall as a major factor contributing to agriculture instability particularly in the rain-fed areas. The variability of monsoon patterns, the spatial variability of rainfall and extreme events directly influence crop yields and are related to the irrigation constraints, which further exacerbate the volatility in crop yields as shown in Figure 6.

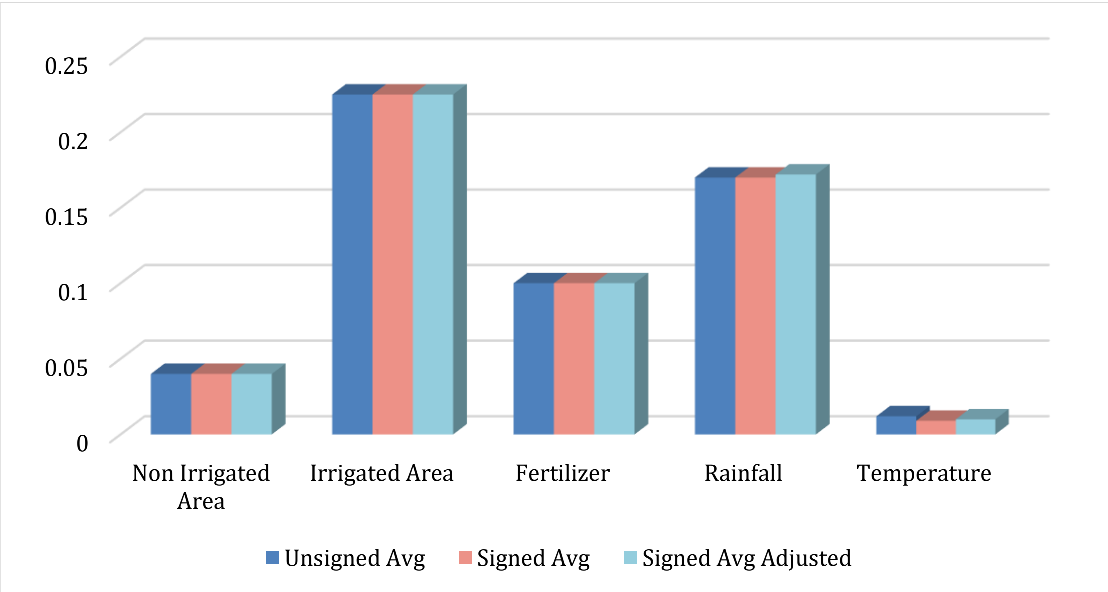


Figure 6. Relative Importance of Detrended (Residual) Components in Explaining Agricultural Output Fluctuations in India

Fertilizer accounts for almost 9.9 percent (0.099208) of agriculture fluctuations, showing that the need for fertilizer, the price of fertilizer, constraints on fertilizer supply and regional variations in soil nutrient conditions are important factors affecting performance. Inconsistencies in the application of fertilizer can also lead to variations in yield, although it is a means towards improving productivity. The Non-Irrigated Area contribution has a relatively small impact accounting for around 3.5 per cent (0.034529) of fluctuations. This implies that the variability in the area seeded to rain-fed crops is a source of output instability, but its effect is less than that of irrigation and rainfall effects. Finally, the contribution of Temperature is almost negligible (0.03 percent or 0.003781) in the fluctuations in agriculture in the residual component. This means that the effects of temperature are either slow and/or can be taken up by adapting to them or are expressed only indirectly through interactions with the rains and availability of water, not as an independent short-run influencer.

## 5. CONCLUSION

This study examined the factors responsible for fluctuations in agricultural output in India.The analysis used the True Relative Importance (TRI) methodology.Long-run data from 1960–61 to 2022–23 were used for the study. Unlike conventional regression approaches that rely on standardized coefficients or partial correlations, the TRI method combines orthopartial and simple correlations. It decomposes the explained variation into all possible paths of interaction. The findings lead to three major conclusions.
First, when the detrended components are not separated from the data, rainfall emerges as the most important factor behind agricultural output fluctuations. Its adjusted signed contribution remains high. Monsoon variability continues to play a major role in agricultural instability. Agricultural production remains highly sensitive to changes in rainfall.

Second, a clear distinction appears when the explanatory variables are divided into trend and de-trended components. The trend component represents long-run structural changes. The de-trended component captures short-run irregular movements. The trend components explain only about 2 percent of total agricultural fluctuations. Factors such as irrigation expansion, fertilizer use, and technological progress mainly influence long-term agricultural growth and stability. Their contribution to short-run fluctuations remains relatively small.

Third, and most importantly, the residual or de-trended components account for nearly 65 percent of total agricultural fluctuations. Agricultural instability in India is therefore driven largely by short-run non-policy factors. Within this group, irrigated area emerges as the most important contributor. It explains around 34.7 percent of the fluctuations. Short-term changes in irrigation availability have a stronger effect on output instability than rainfall itself. These changes may be linked to water shortages, groundwater fluctuations, uneven water distribution, or inefficiencies in irrigation systems.

Rainfall ranks second and accounts for about 16.6 percent of the fluctuations. Monsoon irregularities continue to affect agricultural production, especially in rain-fed areas. Fertilizer explains nearly 9.9 percent of the fluctuations. Variations in fertilizer availability and usage also contribute to output instability. The short-run effect of non-irrigated area remains relatively small. Temperature contributes very little to agricultural output fluctuations during the study period.

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### Author Contributions Statement

| Name of Author | C | M | So | Va | Fo | I | R | D | O | E | Vi | Su | P | Fu |
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| Rajib Kumar Dolai | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | | ✓ | |
| Debasish Mondal | ✓ | ✓ | | ✓ | | ✓ | | ✓ | ✓ | ✓ | | ✓ | ✓ | |

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

### Conflict of Interest Statement

The authors declare that there is no conflict of interest regarding the publication of this paper.

### Data Availability

All data used in this study are collected from secondary sources and are publicly available. Detailed information on data sources is provided in the methodology section.

### Informed Consent

Informed consent was not required for this study, as it does not involve human participants.

### Ethical Approval

This study does not involve human participants or animals; therefore, ethical approval was not required.

## REFERENCES


[1] A. Chevan and M. Sutherland, ‘Hierarchical Partitioning’, The American Statistician, 45(2), pp. 90–96, 1991. doi.org/10.1080/00031305.1991.10475776.

[2] B. E. Feldman, 'Relative importance and value', SSRN Electron. J., 2005. doi.org/10.2139/ssrn.2255827

[3] D. Hamilton, 'Sometimes R 2> r 2 yx 1+ r 2 yx 2: Correlated variables are not always redundant', Am Stat, vol. 41, no. 2, pp. 129-132, 1987. doi.org/10.1080/00031305.1987.10475460

[4] D. Mondal, 'On the test of significance of linear multiple regression coefficients', Commun. Stat. Simul. Comput., vol. 37, no. 4, pp. 713-730, Feb. 2008. doi.org/10.1080/03610910701753853

[5] D. Mondal and R. Dolai, 'Necessity of incorporating break-in-trend in aggregate time series data: Evidence from agricultural GDP in India', PRAGATI: Journal of Indian Economy, vol. 11, no. 2, pp. 27-38, Oct. 2024. doi.org/10.17492/jpi.pragati.v11i2.1122402

[6] D. Pradhan and D. Mondal, 'Relative importance of Openness Index and Crude Oil Price in explaining growth of India's GDP during 1970-71 to 2019-20', Int. J. Innov. Res. Eng. Manag., vol. 10, no. 6, pp. 60-65, Dec. 2023. doi.org/10.55524/ijirem.2023.10.6.9

[7] D. V. Budescu, 'Dominance analysis: A new approach to the problem of relative importance of predictors in multiple regression', Psychol. Bull., vol. 114, no. 3, pp. 542-551, Nov. 1993. doi.org/10.1037/0033-2909.114.3.542

[8] J. Bi, 'A review of statistical methods for determination of relative importance of correlated predictors and identification of drivers of consumer liking', J. Sens. Stud., vol. 27, no. 2, pp. 87-101, Apr. 2012. doi.org/10.1111/j.1745-459X.2012.00370.x

[9] J. N. Luchman, 'Determining relative importance in Stata using dominance analysis: domin and domme', Stata J., vol. 21, no. 2, pp. 510-538, June 2021. doi.org/10.1177/1536867X211025837

[10] J. M. Lebreton, R. E. Ployhart & R. T. Ladd, ‘A Monte Carlo comparison of relative importance methodologies’, Organizational Research Methods, 7(3), 258-282, 2004. doi.org/10.1177/1094428104266017

[11] L. N. Kantakumar, S. Kumar, and K. Schneider, 'What drives urban growth in Pune? A logistic regression and relative importance analysis perspective', Sustain. Cities Soc., vol. 60, no. 102269, p. 102269, Sept. 2020. doi.org/10.1016/j.scs.2020.102269

[12] P. K. Sen, R. H. Lindeman, P. F. Merenda, & R. Z. Gold, ‘Introduction to Bivariate and Multivariate Analysis’, Journal of the American Statistical Association, 76(375), 752, 1981. doi.org/10.2307/2287559

[13] R. Azen and D. V. Budescu, 'The dominance analysis approach for comparing predictors in multiple regression', Psychol. Methods, vol. 8, no. 2, pp. 129-148, June 2003. doi.org/10.1037/1082-989X.8.2.129

[14] R. Dolai and D. Mondal, 'Agricultural growth in India: A comparative analysis of sub-periods from 1960-61 to 2019-20', PRAGATI: Journal of Indian Economy, vol. 10, no. 2, pp. 1-13, Dec. 2023. doi.org/10.17492/jpi.pragati.v10i2.1022301

[15] R. K. Dolai and D. Mondal, 'Endogenous Breaks in India's Agricultural GDP and the Role of Good Governance', Journal of Agriculture Research and Technology, vol. 51, no. 2, pp-208-219, 2026. doi.org/10.56228/JART.2026.51211

[16] R. K. Dolai and D. Mondal, 'Cointegration between agricultural GDP and inputs in India: An empirical analysis', Sch. J. Econ. Bus. Manag., vol. 10, no. 05, pp. 118-129, June 2023. doi.org/10.36347/sjebm.2023.v10i05.003

[17] R. K. Dolai and D. Mondal, 'Relative importance of agricultural factors on India's GDP growth', Farming Manag., vol. 10, no. 1 (JUNE) 2025, June 2025. doi.org/10.31830/2456-8724.2025.FM-158

[18] R. K. Dolai and P. Das, 'Analysing Rice Productivity in India using a Fuzzy Logic Model based on Soil Quality Parameters', Spec. Eng. Man. Sci., vol. 4, no. 1, pp. 15-28, Jan. 2026. doi.org/10.31181/sems41202656d

[19] S. Dixit, S. N. Mandal, J. V. Thanikal, and K. Saurabh, 'Study of significant factors affecting construction productivity using relative importance index in Indian construction industry', E3S Web Conf., vol. 140, p. 09010, 2019. doi.org/10.1051/e3sconf/201914009010

[20] S. Sreekumar and K. S. Kumar, 'Determination of the relative importance of factors affecting maternal healthcare in India', in PROCEEDINGS OF THE INTERNATIONAL ENGINEERING RESEARCH CONFERENCE - 12TH EURECA 2019, Selangor Darul Ehsan, Malaysia, 2019. doi.org/10.1063/1.5120231

[21] S. Tonidandel and J. M. LeBreton, 'Determining the relative importance of predictors in logistic regression: An extension of relative weight analysis', Organ. Res. Methods, vol. 13, no. 4, pp. 767-781, Oct. 2010. doi.org/10.1177/1094428109341993

[22] S. Tonidandel and J. M. LeBreton, 'Relative importance analysis: A useful supplement to regression analysis', J. Bus. Psychol., vol. 26, no. 1, pp. 1-9, Mar. 2011. doi.org/10.1007/s10869-010-9204-3

[23] U. Grömping, 'Relative importance for linear regression inR: The package relaimpo', J. Stat. Softw., vol. 17, no. 1, 2006. doi.org/10.18637/jss.v017.i01

[24] W. Kruskal and R. Majors, 'Concepts of relative importance in recent scientific literature', Am Stat, vol. 43, no. 1, pp. 2-6, 1989. doi.org/10.1080/00031305.1989.10475596

[25] Y.-C. E. Chao, Y. Zhao, L. L. Kupper, and L. A. Nylander-French, 'Quantifying the relative importance of predictors in multiple linear regression analyses for public health studies', J. Occup. Environ. Hyg., vol. 5, no. 8, pp. 519-529, Aug. 2008. doi.org/10.1080/15459620802225481


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