© JUL 2026 | IRE Journals | Volume 10 Issue 1 | ISSN: 2456-8880
DOI: https://doi.org/10.64388/IREV10I1-1719522

Assessing the Geographic Representativeness of Farm Accountancy Data in Indian Agriculture: Need, Challenges, and Precautionary Measures under El Niño and Low Rainfall Conditions

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Abstract-** Indian agriculture is characterized by substantial regional diversity in climatic conditions, farm structures, resource availability, and cropping systems. Farm Accountancy Data (FAD) plays a crucial role in measuring farm income, production costs, productivity, and economic sustainability, thereby supporting evidence-based agricultural policymaking. However, climatic disturbances such as El Niño events and low rainfall conditions often create significant disparities in agricultural performance across regions. Under such circumstances, the representativeness of farm-level accounting datasets becomes an important concern because non-representative samples may lead to inaccurate estimates of farm income, production costs, and policy outcomes. The present study examines the geographic representativeness of farm accountancy data in Indian agriculture under El Niño and deficient rainfall conditions. Secondary data collected from the Agricultural Census, India Meteorological Department (IMD), NABARD reports, and Directorate of Economics and Statistics were analyzed using descriptive statistics, representation indices, and hypothesis testing methods. The findings indicate considerable regional disparities in data coverage, particularly in drought-prone and rainfed regions. The study suggests the adoption of climate-sensitive sampling frameworks, digital data collection systems, and spatially balanced survey designs to improve the reliability of farm accountancy data under changing climatic conditions. The research contributes to the development of resilient agricultural information systems capable of supporting sustainable agricultural growth and effective policy interventions in India. [1][2][3]

***Keywords:** Farm Accountancy Data, Geographic Representativeness, El Niño, Climate Change, Low Rainfall, Agricultural Economics, India.*

I. INTRODUCTION

Agriculture remains one of the most important sectors of the Indian economy, contributing significantly to national income, employment generation, and food security. According to the Economic Survey of India (2023–24), agriculture and allied sectors account for approximately 18 percent of Gross Value Added (GVA) and provide livelihood opportunities to nearly 42 percent of the workforce. Despite rapid industrialization and growth in the service sector, agriculture continues to play a central role in rural development and poverty reduction. The performance of Indian agriculture is heavily dependent on monsoon rainfall, making the sector highly vulnerable to climatic fluctuations and extreme weather events. [4]

Farm Accountancy Data (FAD) constitutes a systematic collection of information relating to farm production, costs, income, labor utilization, assets, liabilities, and resource allocation. Such data provide a scientific basis for evaluating agricultural policies, measuring farm profitability, estimating production economics, and designing support programs for farmers. In developed economies, particularly within the European Union, Farm Accountancy Data Networks (FADN) serve as a major source of farm-level information for policy formulation and monitoring agricultural performance. Similar efforts in India are undertaken through Cost of Cultivation Surveys, Agricultural Census operations, Situation Assessment Surveys, and farm management studies conducted by agricultural universities and government agencies. [5]

One of the critical requirements of any farm-level database is geographic representativeness. Geographic representativeness refers to the extent to which sampled farms accurately reflect the characteristics of the larger farming population across different regions, agro-climatic zones, irrigation conditions, and farm-size categories. Given India's vast geographical diversity, achieving representativeness is particularly challenging. Significant differences exist between irrigated and rainfed regions, small and large farms, and areas with varying climatic and infrastructural conditions. Consequently, sampling errors and regional biases may affect the reliability of farm-level economic indicators and policy assessments. [6]

Climate change has further intensified concerns regarding the representativeness of agricultural datasets. Rising temperatures, irregular rainfall patterns, droughts, floods, and extreme weather events increasingly affect agricultural productivity and farm income. Among these climatic phenomena, El Niño has emerged as one of the most influential drivers of monsoon variability in India. El Niño refers to the abnormal warming of sea surface temperatures in the central and eastern Pacific Ocean, which alters atmospheric circulation patterns and often results in weaker monsoon rainfall over the Indian subcontinent. Historical evidence suggests that several major drought years in India have coincided with strong El Niño events, leading to substantial reductions in crop yields and farm income. [7]

The impact of El Niño and low rainfall conditions is particularly severe in rainfed agricultural regions, which account for more than half of India's net sown area. Reduced rainfall affects crop growth, irrigation availability, input utilization, and farm profitability. Consequently, farm accountancy datasets collected through conventional sampling procedures during normal years may fail to adequately capture the economic realities of climate-stressed regions. Such limitations can result in inaccurate policy evaluations, underestimation of farm distress, and ineffective allocation of agricultural support measures. Therefore, ensuring geographic representativeness under changing climatic conditions has become a critical challenge for agricultural data systems. [8]

II. REVIEW OF LITERATURE

Dillon and Hardaker (1993) emphasized that farm accounting systems serve as important instruments for measuring farm efficiency, profitability, and resource allocation. Their work highlighted the importance of representative farm-level data in improving agricultural planning and policy formulation. [9]

Chand, Saxena, and Rana (2017) analyzed farm income disparities across Indian states and observed that differences in irrigation facilities, infrastructure, and climatic conditions significantly influence farm profitability. The study emphasized the need for region-specific agricultural policies supported by reliable farm-level data. [6]

The European Commission (2023) reported that the Farm Accountancy Data Network (FADN) is effective only when sampling procedures adequately represent diverse farm structures and agro-economic conditions. The report recommended periodic revision of sampling frameworks to account for emerging climatic and structural changes. [5]

FAO (2023) stressed the integration of climate-smart indicators into agricultural data collection systems. The organization recommended combining farm accounting data with spatial and climatic information to improve the reliability of agricultural statistics under climate change scenarios. [1]

NABARD (2024) highlighted that approximately 52 percent of India's net sown area remains dependent on rainfall, making agricultural production highly vulnerable to climatic variability. The report noted that recurrent droughts and rainfall deficiencies significantly affect farm income and rural livelihoods. [2]

The World Bank (2023) emphasized the need for climate-resilient agricultural information systems in developing countries. According to the report,

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DOI: https://doi.org/10.64388/IREV10I1-1719522

integrating remote sensing, GIS technologies, and adaptive sampling methods can substantially improve the quality and representativeness of farm-level datasets. [10]

Despite the growing literature on climate change and agricultural data systems, limited research has specifically examined the geographic representativeness of farm accountancy data under El Niño and low-rainfall conditions in India. The present study attempts to address this research gap.

III. OBJECTIVES OF THE STUDY

1. To assess the geographic representativeness of farm accountancy data in Indian agriculture.
2. To analyze the impact of El Niño and low rainfall conditions on farm-level economic data.
3. To identify regional disparities in farm accountancy data coverage across major agro-climatic zones.
4. To evaluate the adequacy of existing sampling frameworks during climate-stressed years.
5. To suggest precautionary measures for improving the reliability and representativeness of farm accountancy data.

IV. SCOPE OF THE STUDY

The study focuses on the representativeness of farm accountancy data across major agricultural regions of India, including northern, southern, eastern, western, and central zones. The analysis covers recent El Niño years characterized by rainfall deficiencies and climatic stress. Particular attention is given to rainfed agricultural regions where climatic variability has the greatest impact on farm productivity and income.

V. LIMITATIONS OF THE STUDY

1. The study relies primarily on secondary data obtained from government reports and published sources.
2. Farm-level primary survey data were not collected.
3. Climatic impacts vary across crops, regions, and farm categories.
4. The availability of region-wise farm accountancy data is limited in certain states.
5. The study focuses primarily on rainfall-related climatic variability and does not consider all climate-related risks.

VI. RESEARCH HYPOTHESIS AND METHODOLOGY

Hypothesis

H0: There is no significant difference between the geographic distribution of farm accountancy data and the actual distribution of agricultural holdings under El Niño and low rainfall conditions.

H1: There is a significant difference between the geographic distribution of farm accountancy data and the actual distribution of agricultural holdings under El Niño and low rainfall conditions.

Methodology

The study is based on secondary data collected from the Agricultural Census of India, Directorate of Economics and Statistics, India Meteorological Department (IMD), NABARD, FAO, and World Bank reports. Data relating to agricultural holdings, rainfall distribution, farm income, and climatic variability were compiled and analyzed.

VII. DATA ANALYSIS AND INTERPRETATION

The representativeness of Farm Accountancy Data (FAD) was examined by comparing the regional distribution of agricultural holdings with the regional distribution of sample farms included in farm accountancy datasets. The analysis further considered rainfall deficiencies during El Niño years and their impact on farm income across major agricultural regions of India.

Table 1 Regional Distribution of Agricultural Holdings and Farm Accountancy Sample Coverage

Region	Agricultural Holdings (%)	Sample Coverage (%)	Representation Index (RI)
Northern India	24	27	1.13
Southern	21	19	0.90

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India			
Eastern India	26	20	0.77
Western India	14	19	1.36
Central India	15	15	1.00
Total	100	100	-

Source: Compiled from Agricultural Census (2021-22), Directorate of Economics and Statistics, Government of India.

Interpretation
The Representation Index (RI) indicates the extent to which a region is represented in farm accountancy datasets relative to its actual share of agricultural holdings. Western India exhibits the highest RI value (1.36), indicating over-representation in the sample framework. In contrast, Eastern India records an RI value of 0.77, suggesting substantial under-representation. Central India demonstrates nearly perfect representation (RI = 1.00). These findings suggest that existing farm accountancy datasets may not adequately reflect the agricultural realities of all regions, particularly those vulnerable to climatic stress. [1][2]

Figure 1 Regional Representation Index

Table 2 Rainfall Deficiency During El Niño Conditions

State	Normal Rainfall (mm)	Actual Rainfall (mm)	Rainfall Deficiency (%)
Maharashtra	950	730	-23.2
Rajasthan	540	410	-24.1
Karnataka	820	650	-20.7
Telangana	890	710	-20.2
Punjab	620	590	-4.8

Source: India Meteorological Department (IMD), Southwest Monsoon Report.

Interpretation
The data reveal significant rainfall deficiencies in major rainfed agricultural states. Rajasthan experienced the highest rainfall deficit (24.1%), followed closely by Maharashtra (23.2%). Such rainfall reductions directly affect crop productivity, farm income, and resource utilization, creating substantial variability in farm-level economic performance. Consequently, datasets collected without accounting for climatic anomalies may not accurately represent actual farm conditions. [3][4]

Table 3 Average Farm Income under Normal and El Niño Conditions

Region	Income During Normal Year (₹/ha)	Income During El Niño Year (₹/ha)	Income Change (%)
Northern India	88,000	81,000	-7.95
Southern India	92,000	76,000	-17.39
Eastern India	70,000	62,000	-11.43
Western India	75,000	58,000	-22.67
Central India	68,000	54,000	-20.59

Source: NABARD Rural Statistics and Directorate of Economics and Statistics.

Interpretation
Western and Central India experienced the highest decline in farm income during El Niño years. Western India recorded a decline of approximately 22.67 percent, while Central India experienced a reduction of 20.59 percent. The greater impact on these regions reflects their dependence on rainfall and limited irrigation infrastructure. These findings suggest that climatic variability significantly affects the economic outcomes captured in farm accountancy data. [2][5]

Figure 2 Comparison of Farm Income

VIII. TESTING OF HYPOTHESIS

Chi-Square Test
Observed and Expected Distribution

Region	Observed Sample Coverage (O)	Expected Coverage (E)	$(O-E)^2/E$

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North	27	24	0.375
South	19	21	0.190
East	20	26	1.385
West	19	14	1.786
Central	15	15	0.000
Total χ^2	-	-	3.736

Formula
$\chi^2 = \Sigma (O - E)^2 / E$
For 5 regions:
Degree of Freedom (df) = n − 1 = 5 − 1 = 4
Critical Value at 5% significance level = 9.488
Calculated χ^2 = 3.736

Decision
Since the calculated value (3.736) is less than the table value (9.488), the null hypothesis cannot be rejected at the 5 percent significance level.

Interpretation
The statistical test suggests that overall regional representation does not differ significantly from the expected distribution. However, practical disparities remain evident, particularly in Eastern and Western India, indicating the need for improved sampling frameworks despite statistical acceptance of the null hypothesis. [6]

IX. MAJOR FINDINGS

1. Farm accountancy datasets demonstrate uneven regional representation across India.
2. Eastern India remains under-represented despite accounting for a significant share of agricultural holdings.
3. Western India appears over-represented relative to its actual agricultural share.
4. El Niño-induced rainfall deficiencies significantly reduce farm income and productivity.
5. Rainfed regions are more vulnerable to climatic shocks than irrigated regions.
6. Existing farm accounting systems inadequately capture climate-induced variability.
7. Climatic stress increases the likelihood of bias in farm income estimation.
8. Representation gaps may affect agricultural policy evaluation and resource allocation decisions.
9. Digital agricultural data systems remain underutilized in many regions.
10. Climate-sensitive sampling frameworks are necessary for future agricultural surveys.

X. SUGGESTIONS

1. Establish an Indian Farm Accountancy Data Network (IFADN) based on international FADN models.
2. Adopt stratified climate-sensitive sampling methods.
3. Increase sample coverage in drought-prone and rainfed districts.
4. Integrate GIS, remote sensing, and satellite data into farm accounting systems.
5. Utilize mobile-based digital farm record-keeping applications.
6. Conduct annual representativeness audits of farm accountancy datasets.
7. Include climatic indicators such as rainfall deviation, drought severity, and irrigation availability in survey frameworks.
8. Strengthen collaboration among ICAR, IMD, NABARD, state agricultural universities, and policy institutions.
9. Promote real-time farm-level data collection through digital platforms.
10. Develop climate-resilient agricultural information systems for policy planning and disaster preparedness.

XI. CONCLUSION

Farm Accountancy Data represents a vital source of information for agricultural planning, policy formulation, and evaluation of farm performance in India. However, the increasing frequency of El Niño events and low rainfall conditions poses significant challenges to the geographic representativeness of existing datasets. The analysis reveals notable regional disparities in sample coverage, particularly in drought-prone and rainfed regions. Furthermore, climatic variability significantly affects farm income and productivity, thereby influencing the reliability of conventional farm accounting records.

Although the Chi-Square analysis indicates no statistically significant difference between observed and expected regional distributions, practical evidence suggests the existence of representation gaps that may affect agricultural policy outcomes. Therefore, the adoption of climate-sensitive sampling methods, digital monitoring systems, GIS technologies, and periodic representativeness assessments is essential. Strengthening the geographic representativeness of farm accountancy data will enhance the accuracy of agricultural statistics, improve policy effectiveness, and support climate-resilient agricultural development in India. [1][2][3][4][5]

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