International Journal of Web of Multidisciplinary Studies
( Peer-Reviewed, Open Access, Fully Refereed International Journal )
website: https://ijwos.com
Volume 3 Issue 2 , Feb 2026
OPEN ACCESS
E-ISSN : 3049-2424
DOI: https://doi.org/10.71366/ijwos

# Regional Disparities and Convergence in the Agricultural Sector: Evidence from Indian States in the 21st Century

Bikash Ranjan Sethy[1], Dr Murari Behera[2]
[1] *Research Scholar, PhD in Economics, DSEP, SSS, Central University of Gujarat, Kundhela-391107, Vadodara, Gujarat, India*
[2] *Assistant Professor, School of Business and Management, Institute of Advanced Research, Gandhinagar, Koba Institutional Area, Gandhinagar-382426, Gujarat.*

***Article Info***

***Article History:***

*Published:24 Feb 2026*

***Publication Issue:***
*Volume 3, Issue 2*
*February-2026*

***Page Number:***
*405-415*

***Corresponding Author:***
*Dr Murari Behera*

***Abstract:***

This study investigates regional convergence in India's agricultural sector from 2001 to 2020, focusing on whether states with lower initial levels of per capita agrarian income are catching up with more affluent counterparts. Using dynamic panel data pooled in five-year intervals for 18 major states, the analysis employs fixed-effects estimation to assess absolute and conditional β-convergence. The methodology incorporates initial income levels, lagged income growth, and structural controls, including population growth, electricity usage, irrigation density, fertiliser input, and human capital, while addressing potential endogeneity through the augmented Solow framework. The study aims to examine the existence of absolute β-convergence in per capita agricultural income, evaluate conditional convergence by accounting for structural and demographic influences, and explore how incorporating dynamic factors such as lagged growth affects convergence patterns. The findings reveal weak evidence of absolute convergence, with marginal statistical significance, but demonstrate strong support for conditional convergence once key variables are included. Electricity usage consistently shows a significant positive effect on growth, while population growth and price instability exert adverse effects. Traditional inputs, such as irrigation and fertiliser, display either weak or adverse effects, suggesting inefficiencies in their deployment. An accompanying σ-convergence analysis shows a decline in income disparities between 2001 and 2012, followed by increasing divergence through 2020, indicating that while some convergence is occurring, it is neither widespread nor sufficient to reduce overall regional inequality. These results emphasise that various structural and demographic factors conditionally influence convergence in Indian agriculture.

***Keywords:*** Regional Disparities, Convergence, Agricultural Sector, Growth, Investment

## 1. Introduction

Agriculture remains a cornerstone of India's economy and a critical source of livelihood for over half of its population. Despite its foundational role, the sector exhibits significant regional disparities in productivity, income levels, infrastructure, access to modern technology, and market integration. These disparities reflect differences in agroclimatic conditions and resource endowments, as well as the uneven distribution of public investments, institutional capacity, and policy implementation across states. As India aspires toward inclusive and sustainable development, understanding and addressing these regional agricultural imbalances has become increasingly urgent.

Historically, the 1960s and 1970s Green Revolution catalysed significant agricultural transformation, but it was concentrated mainly in the northwestern states, such as Punjab and Haryana. While these regions benefitted from adopting high-yielding varieties (HYVs), assured irrigation, and better access to credit and markets, several eastern and central Indian states were left behind. This selective impact has created long-standing disparities in agricultural outcomes, which persist despite decades of subsequent reforms and investments.

In recent years, convergence has gained traction as a framework for analysing whether economically and agriculturally lagging regions are catching up with more advanced ones. Convergence in agriculture implies narrowing regional gaps in productivity, income, and infrastructure, either through accelerated growth in underdeveloped areas or a harmonisation of growth trajectories across regions. This convergence can take several forms, including beta convergence, where lower-performing regions grow faster, sigma convergence, where disparities in outcomes reduce over time, and club convergence, where subsets of areas with similar characteristics converge.

Understanding the patterns and drivers of convergence is essential for designing effective regional and sectoral policies. It can reveal whether national growth strategies translate into equitable development or exacerbate existing inequalities. Furthermore, convergence analysis can help identify the structural, institutional, and socio-economic barriers that prevent lagging regions from realising their agricultural potential.

This study explores the regional disparities and convergence dynamics within Indian agriculture. It investigates whether convergence occurs across Indian states and districts, the pace and nature of that convergence, and the key determinants influencing the process. In doing so, it aims to contribute to the ongoing discourse on regional development and provide insights that can inform more balanced and inclusive agricultural policies in India.

## 2. Conceptual Framework: Understanding Convergence

Convergence in the agricultural context refers to the reduction of differences in farm productivity and income across regions over time. It can be categorised into three main types. Beta Convergence occurs when poorer areas with lower initial levels of productivity or income grow faster than richer regions, thereby closing the gap over time. Sigma Convergence indicates a reduction in the dispersion of productivity or income across states. Club Convergence implies that subsets of regions converge toward similar steady-state levels, forming “clubs” of convergence. These concepts provide a framework for evaluating the changing dynamics of Indian agriculture and have been central to recent empirical studies.

Beta convergence has been a dominant focus in empirical studies. A significant number of researchers report evidence that states with lower agricultural income levels have experienced relatively higher growth, indicating beta convergence. For instance, Shahabaz et al. (2024) found evidence of absolute and conditional beta convergence, particularly highlighting that less developed states have been catching up to their more developed counterparts in terms of agricultural income. Their study used longitudinal data to estimate convergence rates and identified policy interventions as a key factor supporting growth in lagging regions. Similarly, Balaji & Gopinath (2023) presented evidence of conditional beta convergence across Indian districts. However, they noted that convergence speed has decelerated over the past decade due to widening infrastructural and market access gaps. Their findings stress the importance of physical and institutional factors that condition convergence. The notion of conditional beta convergence suggests that convergence is not automatic but is influenced by contextual factors such as infrastructure, education, and market integration.

While beta convergence suggests catching up, sigma convergence assesses whether disparities are shrinking. The empirical evidence on sigma convergence in Indian agriculture presents a more pessimistic picture. Singh (2022) argued that sigma convergence remains elusive in the agricultural sector. His analysis revealed no consistent decline in the standard deviation of per capita agrarian income across states, indicating that disparities persist despite some states experiencing faster growth than others. Chatterjee (2017) also concluded that while beta convergence exists, sigma convergence is lacking. The persistence of high dispersion in agricultural income implies that faster growth in lagging regions is insufficient to reduce disparities across the board. These findings underscore the need for caution in interpreting beta convergence as a comprehensive indicator of equitable growth. The lack of sigma convergence suggests that broader structural and systemic barriers continue to limit inclusive agricultural development.

The phenomenon of club convergence introduces an additional layer to the convergence debate, indicating that groups of states may converge to different steady states. Shahabaz et al. (2024) identified two convergence clubs in Indian agriculture: one comprising three states that converged to the national average, and another comprising 12 states that did not. This differentiation highlights structural differences among state economies that influence their convergence paths. Akram & Ali (2021) extended this analysis to sectoral convergence, finding that agriculture and industry lagged behind the services sector in forming cohesive convergence clubs. Their study suggested that agricultural convergence is slower and more fragmented than convergence in the service sector. These findings indicate that convergence may not be a uniform process nationwide, but rather one shaped by region-specific factors, including agroclimatic conditions, policy environments, and institutional capacities.

## 3. Factors Influencing Convergence

Infrastructure is widely recognised as a critical driver of convergence. States with better irrigation, roads, power supply, and market access are more likely to achieve higher agricultural productivity. Chatterjee (2017) emphasised that investments in infrastructure, especially irrigation and rural roads, significantly contributed to agricultural output convergence. Similarly, Balaji and Gopinath (2023) found that physical infrastructure facilitated agricultural growth and reduced spatial income inequalities. Infrastructure enables farmers to access markets, inputs, and information more effectively, which is crucial for sustained agrarian growth in lagging regions.

Education and skill development are vital in driving convergence. Educated farmers are more likely to adopt modern practices, access institutional credit, and diversify their income sources. Chatterjee (2017) found a strong correlation between rural literacy rates and agricultural growth convergence. He argued that states with higher human capital have experienced faster convergence because they are better able to absorb agrarian innovations. Balaji and Gopinath (2023) also emphasised that investments in human capital can help reduce income disparities by enabling rural populations to participate in high-value farm activities and related sectors.

Adopting new technologies, such as high-yielding varieties, modern irrigation systems, and mechanisation, has played a transformative role in agricultural convergence. Mukhopadhyay & Sarkar (2019) examined convergence in food grain productivity and found that states that adopted modern inputs experienced faster productivity growth. Similarly, Reddy (2015) demonstrated that convergence in rice yields was driven by convergence in the use of fertilisers, irrigation, and machinery. These studies collectively suggest that the diffusion of technology is essential for narrowing regional disparities in agricultural productivity.

Public policy is a significant determinant of convergence, particularly in a diverse federal structure like India's. Banerjee & Kumar Kuri (2015) highlighted the uneven distribution of public and private agricultural investments, reinforcing regional inequalities. Their findings suggest that states receiving more targeted investment and policy support tend to grow faster. Kaur & Dhillon (2017) emphasised that reforms such as land redistribution, irrigation support, and minimum support price mechanisms contributed to agricultural income convergence in selected states. These findings underscore the importance of well-targeted public interventions to achieve convergence and reduce rural poverty.

## 4. Agricultural Diversification and Structural Change

### *a. Diversification as a Strategy for Convergence*

Agricultural diversification, which involves shifting from traditional cereal crops to high-value crops, livestock, and allied sectors, has emerged as a key strategy for reducing regional disparities. Anwer et al. (2019) argued that diversification offers income-enhancing and risk-reducing benefits, especially for smallholders in lagging regions. However, they also found that diversification levels have declined over time, particularly in areas with poor infrastructure. Diversification is an economic strategy and a pathway to nutritional security, environmental sustainability, and livelihood resilience.

### *b. Determinants of Diversification*

The key drivers of diversification include rising per capita income, urbanisation, market development, and improved transport infrastructure. Anwer et al. (2019) found that urbanisation-related dietary shifts created new markets for fruits, vegetables, and animal products. However, the lack of cold storage facilities and agro-processing units hindered diversification efforts, particularly in eastern and central India. Therefore, adequate diversification requires a supportive ecosystem of policies, institutions, and infrastructure to translate market signals into viable farm-level decisions.

### *c. Convergence in Diversification Patterns*

The evidence on convergence in agricultural diversification remains inconclusive. While diversification presents opportunities to reduce disparities, studies suggest a growing divergence in diversification patterns. Anwer et al. (2019) concluded that divergence in diversification levels has exacerbated regional disparities in agricultural incomes. They also emphasised that promoting diversification through public investment and institutional reforms could catalyse inclusive growth.

## 5. Research Gap, Questions and Objective

While many studies have analysed income convergence across Indian states, few have specifically addressed convergence in the agricultural sector using dynamic panel models with five-year pooled data. The existing literature often overlooks the role of structural variables (e.g., irrigation, fertiliser use, human capital) in shaping regional agricultural growth patterns. Moreover, most studies use static models, potentially ignoring the role of past growth in explaining current outcomes. There is a need to robustly fill this gap by using dynamic, fixed-effects models that account for initial income and region-specific growth inertia to test for absolute and conditional β-convergence in agriculture.

To fill the gap, the work has followed the following questions;

*a.* Is there evidence of absolute β-convergence in the per capita agricultural income among Indian states during 2001–2020?

*b.* To what extent do structural and socio-economic factors, such as irrigation, electricity use, fertiliser input, and human capital, influence conditional convergence in the agricultural sector?

*c.* How does incorporating past income growth (dynamic effects) change the convergence pattern compared to static models?

To answer the question, the work has set the following objectives;

*a.* To examine the presence of absolute β-convergence in per capita agricultural income across Indian states using a dynamic panel fixed-effects model.

*b.* To assess conditional convergence by incorporating structural and demographic variables that may influence agricultural growth across regions.

*c.* To evaluate the importance of dynamic factors, such as lagged income growth, in shaping regional convergence in the agricultural sector.

## 6. Methodological framework

To test for absolute β-convergence, the fixed-effects model regresses income growth on initial income; the work used the following equation,

$$g_{i,t,t-\tau} = \alpha + \beta ln(y_{i,t-\tau}) + \varepsilon_{i,t}$$

Where $g_{i,t,t-\tau}$ is the average growth rate of per capita NSDP, and $\beta ln\left(y_{i,t-\tau}\right)$ is the initial income level. A negative, significant β indicates convergence, suggesting that poorer regions grow faster. Fixed effects control for time-invariant regional heterogeneity.

For conditional β-convergence, the model includes control variables

$g_{i,t,t-\tau}=(ln(y_{i,t})-ln(y_{i,t-\tau}))/\tau=\alpha+\beta ln(y_{i,t-\tau})+\sum\theta_j in(X^j{,}_{t-\tau})+\epsilon_{i,t}$

Here, $X^j{,}_{t-\tau}$ represents factors like human capital and infrastructure. Convergence is supported if β < 0, holding these factors constant.

OLS estimation is subject to omitted-variable bias and endogeneity. To address this, the augmented Solow model (Mankiw, Romer, and Weil, 1992) adds fixed effects and a dynamic component;

$ln(y_{it})-ln(y_{it-\tau})=(1+\beta)\ ln(y_{it-\tau})+\psi X_{it}+\eta_i+\mu_t+\epsilon_{it}$

Dynamic panel methods with fixed effects account for unobserved heterogeneity and enhance the reliability of estimation in convergence analysis.

In the context of σ-convergence analysis using the log of per capita income in the agricultural sector, income dispersion across regions is measured by the variance and standard deviation of the logarithms of income. The variance at time t is calculated using the equation;

$$var_t = \frac{1}{N}\sum_{i=n}^{n}(lny_{i,t} - \overline{lny_t})^2$$

Where $lny_{i,t}$ represents the natural logarithm of per capita income for region i and $\overline{lny_{i,t}}$ is the mean of these log values across all N regions at time t. The standard deviation, denoted $\sigma_t$, is the square root of the variance and is given by:

$$\sigma_t = \sqrt{\frac{1}{N}\sum_{i=n}^{n}(lny_{i,t} - \overline{lny_t})^2}$$

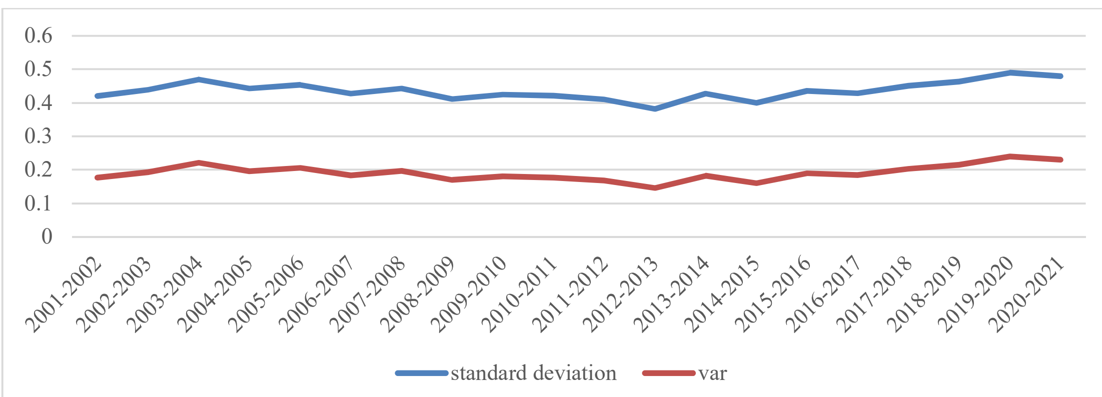
These measures capture the extent of income dispersion. A decline in standard deviation over time indicates σ-convergence, suggesting a reduction in regional disparities, while an increase implies σ-divergence. If the data represent a sample rather than the full population, the denominator N is replaced by N-1 to obtain an unbiased estimate.

Data are primarily collected from EPW Research Foundation, CMIE State of India, Census of India, MoSPI, and Indiastat.

## 7. Evidence of sigma convergence

The analysis of σ-convergence in the agricultural sector, measured through the standard deviation and variance of the log of per capita agrarian income, offers insights into the evolution of regional income disparities over time. σ-convergence implies a reduction in the dispersion of log per capita incomes across regions, indicating that areas are becoming more homogeneous in terms of income levels. Between 2001–2002 and 2012–2013, the standard deviation of the log of per capita agricultural income declined from 0.4206 to 0.3817, signalling a period of σ-convergence where regional income inequality in the agricultural sector decreased. However, the standard deviation rose from 2012 to 2013 onward, peaking at 0.4898 in 2019–2020 before slightly declining in 2020–2021. This upward trend in dispersion suggests a phase of σ-divergence, in which regional disparities in agricultural income widened. Despite early signs of convergence, the later years reflect divergence, indicating no sustained long-term σ-convergence in the agricultural sector based on the log of per capita income.

**Figure 1: Evidence for sigma convergence/divergence for the agricultural sector from 2001 to 2020**




*Sources: Estimated by using the EPWRF Database*

## 8. Evidence of Beta Convergence

In Model 1, which employs a fixed-effects specification, the coefficient on lny is -3.854, indicating absolute convergence, although the p-value of 0.077 suggests marginal statistical significance. This initial result supports the idea of convergence but indicates that income alone does not fully explain the growth dynamics, suggesting that additional explanatory variables are needed.

**Table 1: Estimation of beta convergence in the agricultural sector from 2001 to 2020**

| **Model** | **Model 1** | |
|---|---|---|
| **variables** | **coeff** | **p-value** |
| | **t-stat** | |
| **c** | 37.701 | |
| | 19.948 | 0.064 |

| | | |
|---|---|---|
| **lny** | -3.854 | |
| | 2.139 | 0.077 |
| **R-squared** | 0.506 | |
| **Adjusted R-squared** | 0.338 | |
| **F-statistic** | 3.010 | |
| **Durbin-Watson stat** | 2.573 | |

*Sources: Estimated by using the EPWRF Database.*

In Model 4, a fixed-effects model incorporating these controls, we observe conditional convergence. The coefficient on ln y remains negative and becomes statistically significant at –2.191, indicating that initial income continues to harm growth even when other growth determinants are taken into account. The explanatory variables introduced include cgn (population growth rate), lndef (log of the agricultural deflator as a proxy for price instability), elec (electricity used in agriculture), irri (irrigation density), lnnpk (N+P+K fertiliser use per hectare), and ln ger (gross enrolment ratio at the upper primary level as a proxy for human capital). Notably, cgn has a significant adverse effect, reflecting how rapid population growth can strain agricultural resources and dilute income gains. The variable elec is positive and significant, suggesting that access to electricity boosts agrarian productivity. However, variables such as irri and ln npk show negative coefficients, which could signal inefficient use or diminishing marginal returns in traditional, input-intensive agriculture.

Building on Model 4, Model 5 continues with the fixed-effects framework and updates the measurement of variables or the time-period influences. The conditional convergence effect strengthens further as the coefficient on ln y becomes more negative and statistically robust. The model's explanatory power also improves, with the R-squared increasing to 0.804 and the adjusted R-squared to 0.716. Variables such as cgn and elec exhibit significant effects in the expected directions, reaffirming the importance of demographic pressure and infrastructure. Interestingly, irri becomes statistically significant with a negative coefficient, possibly indicating over-reliance on outdated or inefficient irrigation techniques. The fertiliser variable lnnpk maintains a negative and significant coefficient, further supporting the view that mere input intensification may not lead to sustainable growth unless accompanied by efficiency improvements. The education variable ln ger remains statistically insignificant, perhaps because the link between educational attainment and agricultural productivity was weak or lagged during the sample period.

**Table 2: Estimated conditional convergence for the agricultural sector from 2001 to 2020.**

| **Model** | **Model 2** | | **Model 3** | | **Model 4** | | **Model 5** | | **Model 6** | |
|---|---|---|---|---|---|---|---|---|---|---|
| **variables** | **coeff** | | **coeff** | | **coeff** | | **coeff** | | **coeff** | |
| | **t-stat** | **p-value** | **t-stat** | **p-value** | **t-stat** | **p-value** | **t-stat** | **p-value** | **t-stat** | **p-value** |
| **c** | 21.981 | | 27.300 | | 60.985 | | 43.900 | | 31.952 | |
| | 13.276 | 0.103 | 2.294 | 0.025 | 2.591 | 0.013 | 3.187 | 0.003 | 2.308 | 0.025 |
| **lny** | -1.881 | | -1.783 | | -6.243 | | -4.574 | | -3.213 | |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | -1.385 | 0.171 | -1.384 | 0.171 | -2.191 | 0.033 | -2.813 | 0.007 | -2.116 | 0.040 |
| **cgn** | -1.015 | | -1.120 | | -0.908 | | -1.011 | | -0.963 | |
| | 0.258 | 0.000 | -4.492 | 0.000 | -3.081 | 0.003 | -5.228 | 0.000 | -5.658 | 0.000 |
| **lndef** | -0.924 | | | | | | | | -1.015 | |
| | 0.658 | 0.166 | | | | | | | -4.866 | 0.000 |
| **elec** | 2.419 | | 2.492 | | 3.408 | | 3.022 | | 3.684 | |
| | 0.710 | 0.001 | 3.622 | 0.001 | 3.159 | 0.003 | 3.522 | 0.001 | 7.709 | 0.000 |
| **irri** | -0.998 | | -1.069 | | -1.532 | | -1.341 | | -1.599 | |
| | 0.490 | 0.046 | -2.240 | 0.029 | -2.348 | 0.023 | -3.180 | 0.003 | -6.942 | 0.000 |
| **lnnpk** | -1.590 | | -2.016 | | -0.520 | | -0.111 | | | |
| | 0.986 | 0.112 | -2.236 | 0.029 | -0.333 | 0.741 | -0.113 | 0.911 | | |
| **lnger** | 1.341 | | | | | | | | | |
| | 1.450 | 0.359 | | | | | | | | |
| **R-squared** | 0.387 | | 0.373 | | 0.662 | | 0.804 | | 0.887 | |
| **Adjusted R-squared** | 0.320 | | 0.326 | | 0.510 | | 0.716 | | 0.837 | |
| **F-statistic** | 5.766 | | 7.862 | | 4.361 | | 9.150 | | 17.523 | |
| **Durbin-Watson stat** | 2.294 | | 2.283 | | 2.805 | | 2.726 | | 2.692 | |

*Sources: Estimated by using EPWRF, CMIE State of India, Indiastat, Database.*

Building on Model 4, Model 5 continues with the fixed-effects framework and updates the measurement of variables or the time-period influences. The conditional convergence effect strengthens further as the coefficient on ln y becomes more negative and statistically robust. The model's explanatory power also improves, with the R-squared increasing to 0.804 and the adjusted R-squared to 0.716. Variables such as cgn and elec exhibit significant effects in the expected directions, reaffirming the importance of demographic pressure and infrastructure. Interestingly, irri becomes statistically significant with a negative coefficient, possibly indicating over-reliance on outdated or inefficient irrigation techniques. The fertiliser variable lnnpk maintains a negative and significant coefficient, further supporting the view that mere input intensification may not lead to sustainable growth unless accompanied by efficiency improvements. The education variable ln ger remains statistically insignificant, perhaps because the link between educational attainment and agricultural productivity was weak or lagged during the sample period.

Model 6 represents the most comprehensive specification under the fixed effects framework, incorporating the complete set of explanatory variables to account for the multifaceted growth environment in Indian agriculture. The coefficient on ln y remains negative and statistically significant, confirming conditional convergence, which implies that even after controlling for differences in inputs, infrastructure, demographic trends, and human capital, states with lower initial income levels in agriculture tend to grow faster. The model exhibits the highest explanatory power among all specifications, with an R-squared value of 0.887 and an adjusted R-squared value of 0.837. The control variables reinforce previous findings; cgn is strongly negative, indicating that unchecked population growth impedes per capita agricultural income growth; ln def is also significantly negative, highlighting the destabilising impact of price fluctuations. Elec exhibits the strongest positive association across all models, underscoring the transformative role of rural electrification.

Meanwhile, irri remains significantly negative, suggesting an overreliance on inefficient or unsustainable irrigation methods. Interestingly, ln npk becomes statistically insignificant in this fully specified model, possibly due to over-saturation effects. Finally, ln ger continues to lack statistical significance, suggesting that improvements in education do not have an immediate or direct impact on agricultural growth or that the benefits are absorbed outside the sector (e.g., via rural-urban migration). Across the fixed-effects models (Models 1, 4, 5, and 6), diagnostics further validate the robustness of the results. The F-statistics increase progressively, reaching a maximum of 17.523 in Model 6, indicating the joint significance of the explanatory variables. The Durbin-Watson statistics remain within the acceptable range (2.573–2.805), suggesting no serious autocorrelation issues in the residuals. From absolute convergence to increasingly sophisticated conditional convergence models, the sequential improvements in model specification reflect the growing ability to explain interstate variations in agricultural income growth. This reinforces the central claim that convergence exists but is conditional upon key structural and demographic factors.

## 9. Conclusion

The convergence analysis of the Indian agricultural sector, using both σ-convergence and β-convergence frameworks, reveals a complex, evolving pattern of regional inequality. The examination of σ-convergence, which measures the dispersion of the log of per capita agricultural income across states, provides only limited optimism. From 2001–2002 to 2012–2013, the standard deviation declined, indicating a period of σ-convergence during which regional disparities in agricultural income gradually narrowed. It may be attributed to initial gains from targeted development programs, infrastructure investments, and increased technology adoption in underperforming regions. However, from 2012 onward, the standard deviation rose consistently, peaking in 2019-2020 and then declining only slightly thereafter. This rise signifies a phase of σ-divergence, indicating that disparities have not only persisted but also widened in recent years, despite earlier progress. This trend suggests that while some regions have made progress, others have been left behind, resulting in regional inequalities.

Complementing this, the results from the β-convergence analysis provide a somewhat more encouraging picture, albeit with caveats. The regression results indicate the presence of both absolute and conditional β-convergence, meaning that states with lower initial levels of agricultural income tended to grow faster than their wealthier counterparts. In the absolute convergence model (Model 1), the negative coefficient of initial income suggests convergence, though the statistical significance is marginal. When additional control variables are introduced in Models 4 through 6, such as population growth, electricity usage, irrigation, fertiliser use, and human capital, the convergence relationship becomes more robust and statistically significant. These models suggest that convergence is conditional, meaning it is significantly influenced by structural factors such as infrastructure quality, demographic pressures, and access to productive inputs. For example, electricity use in agriculture emerges as a strong positive driver of growth, while rapid population growth and unstable agricultural prices act as deterrents to growth. Notably, irrigation and fertiliser use show adverse or insignificant effects, highlighting possible inefficiencies or diminishing returns in traditional input-intensive agriculture.

Together, the σ- and β-convergence results reveal a nuanced reality. While the faster growth of poorer states (β-convergence) offers hope for catching up, the persistence or even increase in income dispersion (lack of σ-convergence) suggests that this growth has not been widespread or deep enough to reduce regional inequalities substantially. In other words, growth is occurring, but not uniformly or equitably across all areas. The disconnect between the two forms of convergence highlights the need to address deeper structural constraints that hinder inclusive development.

A comprehensive and multidimensional policy approach is necessary to address these challenges and foster meaningful convergence. First, enhancing rural infrastructure is critical. States lagging in agricultural development need targeted investments in irrigation systems, rural roads, electricity, storage facilities, and market connectivity. Improved infrastructure raises productivity, links farmers to broader markets, and reduces post-harvest losses. Second, investing in human capital through education, agricultural training, and extension services can empower farmers to adopt innovations, diversify their production, and engage more effectively with market systems. Enhancing education and skills in rural areas facilitates movement into higher-value agricultural and allied sectors.

Third, technology diffusion should be prioritised. Government support should promote the adoption of precision farming, climate-resilient practices, and sustainable input use. However, this requires ensuring affordability and regional appropriateness, especially in agroecologically disadvantaged areas. Fourth, agricultural market reforms must be accelerated to improve price realisation and risk management. Policies should support farmer-producer organisations (FPOs), contract farming, agro-processing, and cold chain development to facilitate the shift from subsistence to commercial agriculture. Additionally, diversification of agricultural production into high-value crops, livestock, and non-farm rural activities can enhance incomes, reduce risks, and encourage sustainable land use. Public support for diversification should include access to finance, insurance, infrastructure, and training tailored to local needs.

Fifth, central and state governments must ensure equitable distribution of public resources. Historically, richer states have attracted more public investment, perpetuating disparities. A more balanced intergovernmental fiscal framework that allocates resources based on need and performance can help level the playing field. Finally, policies must recognise the heterogeneity of Indian agriculture. One-size-fits-all approaches are unlikely to succeed; instead, convergence strategies should be region-specific, based on local agro-climatic conditions, socio-economic structures, and institutional capacities.

While the presence of β-convergence suggests that poorer states are catching up in terms of growth, the lack of sustained σ-convergence indicates that income disparities remain entrenched. Achieving genuine and inclusive agricultural convergence in India requires facilitating growth in lagging regions and addressing the foundational inequities in infrastructure, human capital, market access, and institutional support. Only through such a holistic and differentiated strategy can India ensure that agricultural development becomes a driver of balanced regional progress and rural prosperity.

## References

1. Akram, V., & Ali, J. (2021). Output convergence at sector level across Indian states: Evidence from weak sigma and club convergence analysis. Journalof International Development, 33(7), 1166–1188. https://doi.org/10.1002/jid.3571
2. Anwer, M. E., Sahoo, B. K., & Mohapatra, S. (2019). Spatio-temporal variations in agricultural diversification in India: Determinants and convergence. Journal of Agribusiness in Developing and Emerging Economies, 9(5), 476–502. https://doi.org/10.1108/JADEE-11-2018-0161
3. Balaji, S. J., & Gopinath, M. (2023). Spatial growth and convergence in Indian agriculture. Agricultural Economics (United Kingdom), 54(6), 761–777. https://doi.org/10.1111/agec.12807
4. Banerjee, A., & Kumar Kuri, P. (2015). Agricultural Growth and Regional Disparity in India: A Convergence Analysis. Sri Lankan Journal of Agricultural Economics, 16(1), 61. https://doi.org/10.4038/sjae.v16i1.4605
5. Chatterjee, T. (2017). Spatial Convergence and Growth in Indian Agriculture: 1967–2010. Journal of Quantitative Economics, 15(1), 121–149. https://doi.org/10.1007/s40953-016-0046-3
6. Kaur, P., & Dhillon, S. S. (2017). Disparities in Agriculture Income Across the Indian States. Changing Contours of Indian Agriculture Investment, Income and Non-Farm Employment, 133–148. https://doi.org/10.1007/978-981-10-6014-4_8
7. Mukhopadhyay, D., & Sarkar, N. (2019). CONVERGENCE OF FOODGRAINS PRODUCTIVITY IN INDIAN AGRICULTURE.
8. International Journal of Food and Agricultural Economics (IJFAEC), 7(3), 229–241. https://doi.org/10.22004/AG.ECON.292487
9. Reddy, A. A. (2015). Regional disparities in profitability of rice production: Where small farmers stand? Indian Journal of Agricultural Economics, 70(3), 259–271. https://www.scopus.com/inward/record.uri?eid=2-s2.0- 85047525216&partnerID=40&md5=fa48c16a85663e5287a45fc7d8845aeb
10. Shahabaz, B. M., Shaheen, M., Rizvi, S. A., & Tarique, M. (2024). Regional Disparity in the Growth Performance of the Agricultural Sector: Evidence from Indian States. Indian Journal of Economics and Development, 20(1), 20–27. https://doi.org/10.35716/IJED-23032
11. Singh, T. (2022). Economic growth and the state of poverty in India: sectoral and provincial perspectives. Economic Change and Restructuring, 55(3), 1251–1302. https://doi.org/10.1007/s10644-021-09345-5