Article
Linkage of Electricity with Agricultural Growth and Technology Factors: An Illustration of India’s Case

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Abstract: Understanding the relationship between electricity consumption and economic growth is crucial for formulating efficient energy policies for all sectors in general, and for agriculture in particular. To study this, an empirical examination of the long-run co-movement and the causal relationship between electricity consumption and real gross state domestic product (GSDP) from agriculture and its allied sectors is attempted. The agricultural sector involves the use of different input technologies that are further influenced by electricity consumption. To account for this technology-enabling effect of electricity, we further take up an analysis of the relationship between electricity consumption and agricultural technology factors: fertilizer consumption, the share of irrigation, area under cereal, and the extent of mechanization. We use both state (data from 17 states for the period 1993–2017 for the electricity–GSDP relationship) and country-level data (for the period 1980–2018 for the electricity–technology factors relationship) in the analysis. Since short-period time series datasets analysis may yield unreliable and inconsistent results, we employed modern heterogeneous panel co-integration and panel-based error correction model techniques for analyzing the energy–growth linkage. When the heterogeneous states effect is taken into account, the empirical results fully support a positive long-run co-integrated connection between GSDP and electricity consumption. We could detect both long-run and short-run unidirectional causality running from electricity consumption to agricultural growth. Further electricity consumption was also found to augment the use of technology factors in agriculture. This calls for implementing policies and strategies for achieving higher electricity use in agriculture and improved efficiency in its utilization simultaneously.

Keywords: electricity consumption; agricultural growth; panel co-integration; technology

1. Introduction

In today’s world of agriculture, energy is a critical component [1]. Recognizing this, the research on the economics of energy use in agriculture has received considerable attention, especially in developed countries [2]. Here, we try to portray the linkage of energy with agriculture growth and technology factors in India, a developing country that is predominantly agrarian. Energy is an essential factor for agricultural growth in India, and the sector uses energy mainly for land preparation and irrigation [3]. The sector’s energy consumption structure has dramatically shifted from human and animal power to electricity and carbon-based fuels [4]. In recent years, a trend of higher replacement of carbon-based fuels (diesel) by electricity has also been observed, thus suggesting that electricity is the most important energy source for the sector [5]. The electricity consumption of the agriculture sector of India in 2017–2018 was 204 TWh, which is about 18.08 per cent of the country’s total electricity consumption. The series has followed an increasing trend, with a compound annual growth rate of 6.88 per cent between 2008–2009 and 2017–2018 [6].

The policies formulated and implemented by the government of India have played a crucial role in shaping the energy consumption trajectory of the country’s agriculture sector. Free or subsidized electricity for farmers is a specialty in India, which made groundwater
the dominant irrigation source [7]. Unmetered and subsidized electricity, even though it is blamed for having imposed a financial burden on the government as well as power companies, plays a key role in agriculture production [8]. In this context, this study primarily examines the long-run co-movement and the causal relationship between the real gross state domestic product of agriculture and allied sectors (GSDP) and electricity consumption (EC) for agricultural purposes for major Indian states from 1993 to 2017.

The adoption of modern inputs or technologies is crucial for determining the performance of the agriculture sector. The increased use of technological factors, such as fertilizer, irrigation, improved seeds and machines, etc., was part of the transformation of Indian agriculture through the green revolution. With improvements in the availability and use of inputs, the area under cereal cultivation and cereal production also expanded in the country. Further, the direct use of energy in the form of diesel and electricity is believed to be a major driver of improvement in the adoption of other technological factors in Indian agriculture. We test this here by assessing the relationship between energy (electricity consumption) and the technological factors (fertilizer use, area under irrigation, area under cereal, and mechanization) using secondary data for the period 1980–2017. Considering policies, such as subsidized electricity supply for agriculture in several parts of India, and the financial burden that this inflicts on the government, it will be useful to assess the effect of such a measure on technology adoption in the sector. This will help envisage better policies for the sector.

This article aims to answer two research questions. First, it checks whether there is any relationship between electricity consumption and the GSDP from agriculture. Second, it investigates the nature of the relationship between electricity consumption and the adoption of technological factors in agriculture. The methodology followed in this article has several advantages. We used ‘panel unit root tests’ and ‘heterogeneous panel co-integration tests’, which are more powerful and allow us to enhance the degrees of freedom when compared to the cross-sectional approach. Further, to correct the bias introduced by endogeneity and the serial correlation of the regressors in the usual ordinary least squares (OLS) method, we used the fully modified ordinary least squares (FMOLS) technique. We also defined and estimated a dynamic vector error correction model (VECM) for heterogeneous panels that differentiates long-run and short-run causality. Apart from the introduction presented in Section 1, the rest of the article is organized as follows. Section 2 provides a brief literature review on the linkage of electricity with agricultural growth and technology factors. Section 3 describes the data and the analytical techniques used. The results are illustrated in Section 4. Section 5 details the discussion, while the work is concluded in Section 6.

2. Literature on Energy–Growth and Energy–Technology Factor Causality

Several researchers have investigated the causal link between energy consumption and output growth using different econometric approaches, countries, and sample periods [9–11]. The literature has emphasized growth, conservation, neutrality, and feedback hypotheses as to the four possible relationships between energy consumption and economic growth [12]. The growth hypothesis is confirmed if an increase in energy consumption causes an increase in real GDP, whereby the economy is considered to be energy dependent [13,14]. The conservation hypothesis asserts that the positive relationship between energy consumption and output level stems from the positive effects of the output growth rate on energy consumption, and hence policies aimed at conserving energy consumption will have only limited, if any, adverse effects on economic growth [15–17]. As per the neutrality hypothesis, energy consumption and output level are not correlated, and therefore neither energy conservation nor energy promoting policies will affect the economic growth of countries [18–20]. Finally, the feedback hypothesis suggests there is a bidirectional causal relationship between energy consumption and economic growth [21]. The relationship between energy consumption and the adoption of technology factors in agriculture was analyzed by Zaman et al. (2012) [22] for Pakistan. The findings suggested that there is a
bidirectional relationship between tractors and energy demand, but other technological elements backed up the conventional assumption that agricultural technology causes energy consumption in Pakistan. Taking account of these alternative views regarding the relationship between energy consumption and output level, it is evident that discovering the causal linkages between energy consumption and economic growth is vital when designing energy policies for nations.

3. Materials and Methods

3.1. Data

The study uses secondary data from the literature published by various ministries of the government of India. The data on electricity generation and consumption for the period from 1970 to 2017 were compiled from the energy statistics published by the Ministry of Statistics and Programme Implementation. The electricity–agriculture growth co-integrating relationship was analyzed based on annual data for 17 important agricultural states of India. Annual time series data for electricity consumption for agricultural purposes for the period 1993 to 2017 and real gross state domestic product from the agriculture and allied sectors (2004–2005 = 100) were obtained from the Directorate of Economics and Statistics (DES), Ministry of Agriculture and Farmers Welfare, Government of India. The states considered for analysis include Uttar Pradesh, Madhya Pradesh, Maharashtra, Bihar, Andhra Pradesh, Gujarat, Tamil Nadu, Rajasthan, Haryana, Jammu and Kashmir, West Bengal Himachal Pradesh, Karnataka, Kerala, Odisha, Punjab, and Assam. To test the relationship between electricity and the technology factors used in crop production, data are collected from the World Development Indicators, published by the World Bank. Annual time series data on electric power consumption per capita (KWh), the number of tractors per 100 square kilometers of arable land, fertilizer consumption as a percent of fertilizer production, land under cereal production (ha), and agricultural irrigated land as a percent of total agricultural land for the period 1980–2017 were collected.

3.2. Methods

We test the four possible hypotheses presented in Section 2 to assess the causality between agricultural growth (GSDP) and electricity consumption (EC). Three steps were used. First, we check the order of integration in the GSDP and electricity consumption data series. Following that, panel co-integration was used to test for long-run relationships between the two variables. Finally, dynamic panel causality was employed to evaluate the short-run causality direction. Further, we hypothesize a positive relationship between electricity consumption and the technology factors in Indian agriculture, which was tested using the Johansen test for co-integration.

3.2.1. Panel Unit Root Tests

We employed the panel unit root tests proposed by Im et al. (IPS) (2003) [23], Levin et al. (LLC) (2002) [24], as well as the Fisher-ADF and Fisher-PP statistics, to ensure robustness. Panel unit root tests are categorized according to whether the autoregressive process is restricted over cross-sections or series. In contrast to the findings of Levin et al. (2002) [24], which assumes that all cross-sections have the same first-order autoregressive parameters, the Im et al. (2003) [23] test allows for cross-sectional unit heterogeneity.

Consider the following autoregressive condition:

\[ y_{it} = \rho_i y_{i,t-1} + \delta_{it} + \epsilon_{it} \quad (1) \]

where \( i = 1, \ldots, N \) denotes states in the panel; \( t = 1, \ldots, T \) indicates time; \( X_{it} \) denotes exogenous variables in the model, such as fixed effects or the individual time trend; \( \rho_i \) represents autoregressive coefficients, and \( \epsilon_{it} \) are the stationary error terms. If \( \rho_i < 1 \), then \( y_{it} \) is regarded as weakly trend stationary, whereas if \( \rho_i = 1 \), then \( y_{it} \) is nonstationary or contains a unit root.
In the context of dynamic panel data models, recognizing parameter heterogeneity is critical to eliminate any biases that may arise as a result of incorrect specification. As a result of the varying economic and political conditions, as well as the stages of agricultural development in each state, the linkage between agricultural GSDP and electricity consumption for the major states of India is likely to be diverse over time. In light of parameter heterogeneity, the panel unit root test proposed by Im et al. (2003) [23] is preferred, since it allows for heterogeneous autoregressive coefficients. They recommended averaging the augmented Dickey–Fuller (ADF) unit root tests while taking into account varied orders serial correlation, 

\[ e_{it} = \sum_{j=1}^{k_i} \varphi_{ij} e_{it-j} + \varepsilon_{it} \]

Substitution of this expression into Equation (1) yields:

\[ y_{it} = \rho_i y_{it-1} + \sum_{j=1}^{k_i} e_{ij} e_{it-j} + \delta_i X_{it} + e_{it} \]

where \( k_i \) denotes the number of lags in the ADF regression equation. The null hypothesis is that each data series in the panel has a unit root (\( H_0: \rho_i = 1 \forall i \)), i.e., is nonstationary, and the alternative hypothesis is that a minimum of one of the individual series in the panel is stationary (\( H_0: \rho_i < 1 \)). They also defined the following \( t \) statistic as the average of the individual ADF statistics:

\[ t = \frac{1}{N} \sum_{i=1}^{N} t_{\rho_i} \]

where \( t_{\rho_i} \) denotes the individual t-statistic for testing \( H_0: \rho_i = 1 \forall i \) from Equation (2). Under the null hypothesis, the \( t \) statistic is normally distributed with critical values for the given values of different numbers of cross-sections \( N \) and series lengths \( T \). For each cross-section ADF equation, this test statistic requires the number of lags and the deterministic component to be specified. In addition to IPS and LLC, we followed the methods described by Maddala and Wu (1999) [25], who suggested utilizing the Fisher-ADF and Fisher-PP statistics and proposed an easier nonparametric unit root test.

3.2.2. Panel Co-Integration Test

Given the panel’s heterogeneity in both dynamics and error variances, Pedroni (1999, 2004) [12,13] proposed the heterogeneous panel co-integration test, which allows for assessing cross-section inter-dependence with various individual effects, as shown below:

\[ GSDP_{it} = \alpha_{it} + \delta_t t + \gamma_{it} EC_{it} + e_{it} \]

where \( i = 1, \ldots, N \) denotes each state in the panel and \( t = 1, \ldots, T \) represents the time period. The parameters \( \delta_t \) and \( \alpha_{it} \) allow for the possibility of deterministic trends and state-specific fixed effects, respectively. The estimated residuals, which represent departures from the long-run relationship, are denoted by \( e_{it} \). The model parameters \( \gamma^s \) can be regarded as elasticities because all variables are given in natural logarithms. The following unit root test was performed on the residuals to test the null hypothesis of no co-integration \( \rho_i = 1 \):

\[ e_{it} = \rho_i e_{it-1} + u_{it} \]

Pedroni (1999, 2004) [26,27] introduced two sets of panel co-integration tests. These tests are based on the within-dimension approach (i.e., panel co-integration statistics) which contains four statistics: panel \( \rho \)-statistic, panel \( \eta \)-statistic, panel ADF-statistic, and panel PP-statistic. For the unit root tests of the computed residuals, these statistics essentially pool the autoregressive coefficients across multiple states. These statistics account for common time factors as well as state heterogeneity. The group tests use a between-dimension technique (i.e., group mean panel co-integration statistics) which contains three statistics: group PP-statistic, group \( \rho \)-statistic, and group ADF-statistic. The averages of the various autoregressive coefficients associated with the unit root tests of the residuals for each state in the panel are used to generate these statistics. All of these tests were computed and are distributed asymptotically as standard normal.
3.2.3. Causality from Panel Vector Error Correction Model

In the case of co-integrated variables, the following dynamic error correction model was used to estimate a panel vector error correction model to perform Granger causality tests.

\[
\Delta \text{GSDP}_{it} = \alpha_1 + \sum_{q=1}^{k} \theta_{11q} \Delta \text{GSDP}_{it-q} + \sum_{q=1}^{k} \theta_{12iq} \Delta \text{EC}_{it-q} + \lambda_{1i} \epsilon_{it-1} + \epsilon_{1it} \tag{6a}
\]

\[
\Delta \text{EC}_{it} = \alpha_1 + \sum_{q=1}^{k} \theta_{21iq} \Delta \text{GSDP}_{it-q} + \sum_{q=1}^{k} \theta_{22iq} \Delta \text{EC}_{it-q} + \lambda_{2i} \epsilon_{it-1} + \epsilon_{2it} \tag{6b}
\]

where \(\Delta\) is the first-difference operator; \(k\) denotes the lag length, calculated using likelihood ratio tests, and \(\epsilon\) is the serially uncorrelated error term. The short-run causality from energy usage to GSDP was tested using Equation (6a), where the null hypothesis \(H_0 : \theta_{12iq} = 0 \quad \forall \quad i q\), and short-run causality from GSDP to energy usage was tested from Equation (6b), where the null hypothesis \(H_0 : \theta_{21iq} = 0 \quad \forall \quad i q\). In Equations (6a) and (6b), the null hypothesis of no long-run causality was tested by evaluating the significance of the t-statistic for the coefficient on the respective error correction term indicated by \(\lambda\).

3.2.4. Johansen Test for Co-Integration

Johansen (1990) presented a two-step procedure that involved first determining the lag length using either an information criterion or a likelihood ratio test, and then identifying the co-integrating rank using a likelihood ratio test, such as the trace test or the \(\lambda_{\text{max}}\) test. The Johansen co-integration procedure is based upon an unrestricted vector autoregressive (VAR) model, specified in error correction form as follows:

\[
Y_t = A_1 Y_{t-1} + A_2 Y_{t-2} + \ldots + A_k Y_{t-k} + \epsilon_t \tag{7}
\]

\[
\Delta Y_t = \Pi Y_{t-1} + \sum_{i=1}^{k-1} \Gamma_i \Delta Y_{t-i} + \epsilon_t \tag{8}
\]

where \(\Pi = (I - A_1 - A_2 - \ldots - A_k)\) and \(\Gamma_i = (I - A_1 - A_2 - \ldots - A_i), i = 1, \ldots, k - 1\).

\(Y_t\) include all \(P\) variables of the model, which are \(\sim \text{i}(1)\), \(\Pi\) and \(\Gamma_i\) are parameter matrices to be estimated, and \(\epsilon_t\) denotes a vector of random errors that follow a normal distribution with zero mean and constant variance.

The Johansen co-integration approach uses an unconstrained VAR to estimate the matrix \(\Pi\) and then evaluates whether the restriction implied by the reduced rank of \(\Pi\) can be rejected. The trace test and the maximum eigenvalue test are two techniques of testing for the reduced rank of \(\Pi\):

\[
\lambda_{\text{trace}} = -T \sum_{i=r+1}^{n} \ln \left( 1 - \hat{\lambda}_i^2 \right) \tag{9}
\]

\[
\lambda_{\text{max}}(r, r+1) = -T \ln \left( 1 - \hat{\lambda}_{r+1} \right) \tag{10}
\]

where \(\hat{\lambda}_i\) denotes the estimated values of the ordered eigenvalues obtained from the estimated matrix and \(T\) is the number of the observations after the lag correction. If co-integration is found, we use the proper types of causality tests to check for causation.

4. Results

4.1. Overview of the Indian Electricity Sector

India has a total installed capacity of 399,000 MW for electricity generation as of 2018. This total capacity is made up mainly of thermal power plants (70 per cent), followed by renewable sources other than hydro (18 per cent), hydropower (11 per cent), and nuclear energy (1 per cent). Electricity generation in the country has experienced a continuous
increase from 61 TWh in 1970 to 1486 TWh in 2017 (Figure 1a). This increase in production is accompanied by a similar trend in consumption to the tune of 44 TWh and 1130 TWh during the years mentioned. To reach the figures of 2017, electricity generation and consumption grew at a compound annual growth rate of 7.02 per cent and 7.16 per cent, respectively, during the period. Interestingly, the decade of 1980 saw the highest values of growth rates (Figure 1b). Though industrial and domestic sectors are the top consumers of electricity, with a share of 42 per cent and 24 per cent, respectively, our interest is in the consumption of the agriculture sector. Electricity consumption by the agriculture sector, which was as low as 4 TWh in 1970, grew at a rate of 8.47 per cent to reach 204 TWh in 2017. The share of agriculture in total electricity consumption also increased from 7 per cent in 1970 to 18 per cent in 2017. The share reached an overwhelming 31 per cent during the mid-1990s before it subsided to less than 20 per cent during the current decade. Since electricity is mainly used for irrigating the fields, and irrigation was emphasized heavily during the green revolution initiated from the late 1960s, the growth in electricity consumption in the agriculture sector saw the highest growth during the decades of 1970 and 1980. The following decades also witnessed a steady growth in electricity consumption by the sector as irrigation and, hence, electricity has become a key input for agriculture in the country. The growth in the area irrigated by groundwater in the country has been enabled by this steady increase in electricity consumption.

The performance of the agriculture sector is a topic of pertinence for India, as it is the source of livelihood for the majority of its population. To feed and support its increasing population, the country needs to enhance agricultural production every year, which has to be met by utilizing the almost fixed level of arable land and limited rainfall available. Any increase to be achieved in food production thus depends on yield improvements through better irrigation and use of other inputs. Since electricity is used in agriculture mainly for irrigation, it is interesting to explore the relationship between electricity and agricultural growth and between electricity and technology factors. The achievement of India in food grain production so far is remarkable, with an increase from 129 million tonnes in 1980 to 285 million tonnes in 2018 (a compound annual growth rate of 2.1 per cent) (Figure 2). The area under food grains has experienced a marginal decline during this period (∼0.06 per cent); however, this effect was overcome by the 2.15 per cent growth in yield. The per cent share in the irrigated area under food grain during this period increased from 29 per cent to 53 per cent. The consistent growth in the gross value added (gross

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Figure 1. Electricity generation and consumption in India: (a) trends (TWh); (b) decade-wise compound annual growth rate (per cent).

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domestic product adjusted for intermediate consumption) from the agriculture sector is another indicator of its performance. The figures for gross value added from agriculture increased from INR 15,019 billion to INR 18,525 billion between 2011 and 2018. Though the trend in the national level performance of the agriculture sector is promising, the variation could be observed at the regional level (or among different states). The concentration of the green revolution in selected states in its initial years has resulted in a regional disparity. In recent years, deliberate policies are hence being taken by the government to provide better facilities for agriculture in the initially neglected regions (for example, the eastern region of the country).

Figure 2. Performance of the Indian agricultural sector: (a) food grain area and production; (b) food grain yield; (c) share of the irrigated area; (d) value of output from agriculture.

4.3. Electricity Consumption and Agriculture Growth Linkage

We performed panel unit root tests before conducting the co-integration analysis of the EC and GSDP panel data. At the national level, Table 1 displays the results of panel unit root tests with and without the trend. According to the obtained results, both series are nonstationary at the level and stationary at the first difference, i.e., both series are integrated of order one.
Table 1. Panel unit root tests.

| Test                        | GSDP Statistic | GSDP Probability | EC Statistic | EC Probability |
|-----------------------------|----------------|------------------|--------------|----------------|
| Level                       |                |                  |              |                |
| Levin, Lin, and Chu         | −2.17          | 0.014            | 0.24         | 0.595          |
| Im, Pesaran, and Shin       | −1.34          | 0.089            | 1.06         | 0.857          |
| ADF-Fisher Chi-square       | 45.1           | 0.096            | 41.02        | 0.189          |
| PP-Fisher Chi-square        | 55.47          | 0.011            | 32.4         | 0.545          |
| 1st Difference              |                |                  |              |                |
| Levin, Lin, and Chu         | −15.77         | <0.01            | −17.10       | <0.01          |
| Im, Pesaran, and Shin       | −14.21         | <0.01            | −15.6165     | <0.01          |
| ADF-Fisher Chi-square       | 188.78         | <0.01            | 246.164      | <0.01          |
| PP-Fisher Chi-square        | 269.01         | <0.01            | 343.927      | <0.01          |

Granger (1981) [28] shows that if a series becomes stationary only after being differenced once (integrated of order one), it is possible to have linear combinations that are stationary without differencing, and which are hence co-integrated. After establishing that the electricity consumption and GSDP series are first-order integrated, Pedroni’s heterogeneous panel co-integration test, which allows for cross-sectional interdependence with different individual effects, was used to test for the long-run relationship between the two variables. The results of the panel co-integration test at the national level are presented in Table 2. Except for the panel v-statistic, which rejects the null of no co-integration when it has a large positive value, these tests reject the null of no co-integration when they have significant negative values. Pedroni (2004) [27] tabulated the finite sample distributions for the seven statistics using the Monte Carlo simulation.

The results of the tests, as shown in Table 2, reject the null hypothesis of no co-integration for all tests except for the group rho-statistic. In the case of small samples, however, Pedroni (2004) [27] claims that rho-statistics tend to under reject the null hypothesis. As a result, the two variables may be said to be co-integrated. In other words, the findings show that, after controlling for state-specific variables, electricity consumption and real GSDP in India’s key states have a long-run steady-state co-integrating relationship.

Table 2. Panel co-integration test results for different states of India.

| Test                        | Statistic | Probability |
|-----------------------------|-----------|-------------|
| Panel v-Statistic           | 4.52      | <0.01       |
| Panel Rho-Statistic         | −3.01     | <0.01       |
| Panel PP-Statistic          | −5.74     | <0.01       |
| Panel ADF-Statistic         | −4.39     | <0.01       |
| Group Rho-Statistic         | −1.34     | 0.08        |
| Group PP-Statistic          | −5.75     | <0.01       |
| Group ADF-Statistic         | −4.73     | <0.01       |

The next step is to estimate the co-integrated relationship between electricity consumption and real GSDP. For heterogeneous co-integrated panels, the fully modified ordinary least squares (FMOLS) technique is used to determine a long-run connection. Table 3 shows the results of panel FMOLS tests with GSDP as the dependent variable and electricity consumption as the explanatory variable. At the 1% level, all of the coefficients are statistically significant, and the effect is positive. The coefficients can be understood as elasticities because the variables are given in natural logarithms. According to the findings, a 1% increase in power consumption leads to a 0.12% increase in real GSDP in our sample of Indian states. The output from state-specific aggregate productivity shocks tends to rise as electricity demand rises. To summarize, the results of the national-level panel co-integration
test show that there is a co-integrated link between GSDP from the agriculture and allied sectors and electricity consumption in India’s major states.

Table 3. Fully modified ordinary least square estimate.

| Test        | Coefficient | t-Statistic | Probability |
|-------------|-------------|-------------|-------------|
| Panel FMOLS | 0.125       | 2.646       | <0.01       |

We used a panel-based error correction model to analyze short- and long-run causation between electricity consumption and agricultural growth after determining that the two variables are co-integrated. The results of long-run and short-run causality are shown in Table 4. At a 5% level of significance, the estimation of a panel vector error correction model indicates the presence of long-run causation from electricity use to agricultural and allied GSDP. According to the Wald test, there is also short-run causality (Table 4). Electricity consumption has a favorable impact on agricultural growth, implying that energy consumption is vital in the agricultural growth process.

Table 4. Panel causality test (dependent variable: GSDP).

| Long-Run Causality | Short-Run Causality |
|--------------------|---------------------|
|                    | ECT                 | t-Statistics | Probability | t-Statistics | Probability |
| National level     | −0.025              | −2.48923     | 0.013       | 2.646        | 0.008       |

Evidence from across the world available in literature also supports our findings. For example, for the period 1967–2015, Raeeni et al. (2021) [29] evaluated the causal effects of energy consumption on agricultural growth in Iran. They confirmed that there is unidirectional causality from energy usage to agricultural growth. Chandio et al. (2019) [30] empirically examined the linkage between energy consumption and agricultural growth in Pakistan for the period 1984 to 2016. They revealed that, both in the long and short run, gas and electricity usage had a favorable impact on agricultural economic growth. For a panel of 89 nations, Doytch and Narayan (2017) [31] investigated the relationship between energy consumption and economic growth and found mixed causality results i.e., unidirectional, bidirectional and no causality. Karkacier et al. (2006) [32] examined the linkage between energy use and agricultural productivity from 1971 to 2003 in Turkish agriculture. They identified a strong linkage between energy consumption and agricultural output.

4.4. Electricity Consumption and Agriculture Technology Factors Linkage

To assess the linkage between electricity consumption and agricultural technology, we proceeded by undertaking unit root tests to check the stationarity of all the variables considered. We applied both augmented Dickey–Fuller and Phillip–Perron tests for this purpose. As per the result of the analysis, all variables appear to be non-stationary when level, but stationary at the first difference (Table 5). We thus conclude that all the variables are integrated of the order 1, I(1).

After determining the order of integration, we performed the Johansen test for detecting the relationship between electricity consumption and the agricultural technology factors. The determination of the co-integrating rank or the number of co-integrating relations is the first step in the process. For testing the hypothesis that the co-integrating rank is at most r (<k), where k is the number of variables, we use both the trace statistic and max statistic. The alternative hypothesis with the trace statistic is that the rank is k, while in the case of the max statistic, it is that the rank is r + 1 [3]. The results of the Johansen test for co-integration are presented in Table 6. A perusal of the trace statistic and max statistic for testing the relationship between electricity consumption and technology factors suggests the presence of a co-integrating relationship between electricity consumption
and the factors fertilizer, irrigation, and tractors. We could not detect a co-integrating relationship between electricity consumption and area under cereals.

Table 5. Unit root test results.

|                      | Augmented Dickey–Fuller | Phillip–Perron Test |
|----------------------|--------------------------|---------------------|
|                      | t-Statistic | Probability | t-Statistic | Probability |
| Level                |             |             |             |             |
| Electricity         | −1.580     | 0.781       | −1.856     | 0.657       |
| Fertilizer          | −2.179     | 0.486       | −1.832     | 0.669       |
| Irrigation          | −1.381     | 0.850       | −1.119     | 0.912       |
| Cereal              | −0.422     | 0.524       | −1.884     | 0.057       |
| Tractors            | 0.387      | 0.998       | 0.214      | 0.997       |
| 1st difference      |             |             |             |             |
| Electricity         | −5.348     | <0.001      | −5.554     | <0.001      |
| Fertilizer          | −5.039     | <0.001      | −5.027     | <0.001      |
| Irrigation          | −8.049     | <0.001      | −8.806     | <0.001      |
| Cereal              | −9.324     | <0.001      | −12.366    | <0.001      |
| Tractors            | −4.812     | <0.001      | −4.812     | <0.001      |

Table 6. Results of Johansen test for co-integration.

| Electricity vs. | Test Statistic | Probability | Decision |
|-----------------|----------------|-------------|----------|
| Fertilizer      |                |             |          |
| \(\lambda_{\text{trace}}\) |               |             |          |
| \(H_0: r = 0 \text{ vs. } H_1: r \geq 1\) | 11.36         | 0.05       | Co-integrated |
| \(H_0: r \leq 1 \text{ vs. } H_1: r \geq 2\) | 0.90          | 0.39       |          |
| \(\lambda_{\text{max}}\) |               |             |          |
| \(H_0: r = 0 \text{ vs. } H_1: r \geq 1\) | 10.46         | 0.04       | Co-integrated |
| \(H_0: r \leq 1 \text{ vs. } H_1: r \geq 2\) | 0.90          | 0.39       |          |
| Irrigation      |                |             |          |
| \(\lambda_{\text{trace}}\) |               |             |          |
| \(H_0: r = 0 \text{ vs. } H_1: r \geq 1\) | 21.88         | <0.001     | Co-integrated |
| \(H_0: r \leq 1 \text{ vs. } H_1: r \geq 2\) | 1.96          | 0.18       |          |
| \(\lambda_{\text{max}}\) |               |             |          |
| \(H_0: r = 0 \text{ vs. } H_1: r \geq 1\) | 19.92         | <0.001     | Co-integrated |
| \(H_0: r \leq 1 \text{ vs. } H_1: r \geq 2\) | 1.96          | 0.18       |          |
| Cereal          |                |             |          |
| \(\lambda_{\text{trace}}\) |               |             |          |
| \(H_0: r = 0 \text{ vs. } H_1: r \geq 1\) | 8.57          | 0.19       | Not co-integrated |
| \(H_0: r \leq 1 \text{ vs. } H_1: r \geq 2\) | 0.01          | 0.94       |          |
| \(\lambda_{\text{max}}\) |               |             |          |
| \(H_0: r = 0 \text{ vs. } H_1: r \geq 1\) | 8.56          | 0.14       | Not co-integrated |
| \(H_0: r \leq 1 \text{ vs. } H_1: r \geq 2\) | 0.01          | 0.94       |          |
| Tractors        |                |             |          |
| \(\lambda_{\text{trace}}\) |               |             |          |
| \(H_0: r = 0 \text{ vs. } H_1: r \geq 1\) | 17.99         | 0.005      | Co-integrated |
| \(H_0: r \leq 1 \text{ vs. } H_1: r \geq 2\) | 2.79          | 0.11       |          |
| \(\lambda_{\text{max}}\) |               |             |          |
| \(H_0: r = 0 \text{ vs. } H_1: r \geq 1\) | 15.20         | 0.009      | Co-integrated |
| \(H_0: r \leq 1 \text{ vs. } H_1: r \geq 2\) | 2.79          | 0.11       |          |

Though we could detect long-run equilibrium relationships between electricity and technology factors (except for area under cereals), there may be deviations from this
equilibrium in the short run. It is thus important to test whether such dis-equilibrium converges in the long run. Further, it is also necessary to determine the long-run and short-run causality between the variables studied. The results (Table 7) indicate that the coefficient of the error correction term is negative and significant. This suggests the presence of long-run unidirectional causality running from electricity to the technology factors, such as the use of fertilizers, irrigation, and tractors. The value of the error correction coefficients in Table 7 also indicates the rate of convergence to the equilibrium state per year, which is 30 per cent for fertilizer, 20 per cent for irrigation, and 5 per cent for tractors. The results of the Wald test, on the other hand, could not confirm the presence of short-run causality among the co-integrated variables. Zaman et al. (2012) [22] also found a close relationship between energy and technology factors which was bidirectional in the case of Pakistan.

Table 7. Estimates of error correction model (long-run causality) and wald test (short-run causality).

| Electricity vs. | Error Correction Model for Long-Run Causality | Wald Test for Short-Run Causality |
|----------------|---------------------------------------------|----------------------------------|
|                | Parameter Estimated | t-Test | Probability | Chi-Square Test | Probability |
| Fertilizer     | -0.30             | -2.70  | 0.01        | 0.10            | 0.75        |
| Irrigation     | -0.20             | -1.98  | 0.04        | 0.32            | 0.85        |
| Cereal         | -                  | -      | -           | -               | -           |
| Tractors       | -0.05             | -2.97  | <0.001      | 0.78            | 0.37        |

5. Discussion

Energy and its relationship with economic growth and its positive effect on enabling technology is a relevant topic concerning the agriculture sector. The topic has gained attention from scholars across the world who have primarily hypothesized four possible links between economic growth and energy consumption. These are the growth, conservation, neutrality, and feedback hypotheses [12]. Our study for the agriculture sector of India supports the growth hypothesis. The panel co-integration test results provide evidence that the electricity consumption indeed has the effect of increasing the GSDP from agriculture and its allied sectors for the major states of India. Further using the national-level data, we could also detect positive relations of electricity consumption with agricultural technology factors, such as the use of fertilizers, irrigation, and mechanization (the use of tractors). Importantly, we disprove the bi-directional causality hypothesis among electricity and technology factors. The unidirectional causality suggests that electricity use in agriculture drives the use of other inputs as well. Electricity drives irrigation directly, and fertilizer use and mechanization indirectly. Improving the level of electricity consumption by the agriculture sector is thus a useful strategy for achieving both (1) better economic performance in terms of output and (2) better efficiency in terms of the use of improved input technologies. To move to such a state, it is necessary to insulate the sector from the prevailing lacunas and irregularities in electricity supply to farms. The first issue is the measurement of electricity consumption itself. Large numbers of electricity connections for agriculture are thought to be unmetered, making it tough to assess the actual consumption figures. Only 27 per cent of the total agriculture connections were metered in the major agriculture states in 2012–2013 [8]. The next source of concern is the subsidy. In India, the electricity supply to agriculture was metered and charged during the 1970s. Later, when the number of tube wells increased, the companies removed meters and began to charge flat tariffs. The flat tariffs fixed initially could not be increased then due to the populist policies of the governments, which gradually led to a state in which agricultural electricity consumption is now subsidized and unmetered [33,34]. The subsidies are either sourced through state governments or by cross-subsidizing consumers. The subsidy amounted to the tune of approximately INR 500 billion in 2013, which itself is an indicator of the financial burden that it inflicts on the country [8].
As the electricity use in agriculture increased, the sector also experienced a shift in the irrigation sources. The share of canals, the dominant irrigation source during the 1950s and 1960s, gave its position away mainly to groundwater. At present, about 70 per cent of the irrigation in the country is through groundwater [8]. The availability of subsidized and unmetered power has its role in bringing groundwater irrigation to the forefront, but it does not incentivize farmers to use the precious resource efficiently [35]. For the farmers, the subsidies do not come free of cost, as the quality of power that they receive is often poor. It suffers from voltage fluctuations, frequency changes, interruptions, and phase imbalances [33]. This leads to the under-utilization of wells and tube wells, unavoidable expenditure on motor repairs, and the conjunctive use of both electric and diesel pumps. The fact, however, remains that India tops the list of countries in groundwater usage with about 60 per cent of the world’s irrigation and 85 per cent of the rural drinking water supply [35]. The flip side of the coin is the fortunes that electricity used for irrigation has brought in the country in the form of higher agricultural production. Agricultural growth in India has relied on groundwater-based irrigation to a considerable extend. The literature also points to the key role that groundwater irrigation, and hence electricity, has played in high agricultural growth in the different regions of India [36–38].

6. Conclusions

Agriculture growth is largely driven by the use of advanced technologies in the production process. Electricity is one such input that, indeed, has a direct effect on improving both the level of output and the adoption of other complementary inputs. We have tested this relationship between electricity and the agriculture output and technology factors used in crop production. In essence, we examined the energy–growth linkage in Indian agriculture, using electricity consumption and GSDP data for the major states of India. We used new heterogeneous panel co-integration and panel-based error correction model techniques to investigate the relationship between electricity consumption and GSDP across India’s 17 states because time series analyses can produce unreliable and inconsistent results with the short periods typical of some datasets. At the national and regional levels, there is unidirectional causality from energy consumption to GSDP in both the short and long run. Next, we delineated the relationship between electricity consumption and technology factors, which suggested the prevalence of a positive effect of electricity consumption on fertilizer, irrigation, and mechanization in Indian agriculture.

From the policy point of view, the findings of this study support the energy-dependent growth theory, implying that energy consumption is a significant factor impacting agricultural growth both directly and indirectly. Our findings confirm the hypothesis that the amount of energy consumed had a major impact on agricultural growth in India across states. This suggests that greater energy use leads to increased agricultural output. As a result, because GSDP is mostly driven by energy, any energy-saving measures taken at this time may hinder agricultural growth. Furthermore, to achieve inclusive and strong agricultural growth in the country, investment in energy-related infrastructure in the least developed states/regions is required. To sum up, this study provides evidence to support the hypotheses that energy consumption drives growth as well as technology factor use in agriculture. However, the extent to which the energy use in agriculture should be promoted has not been addressed by this study, which is one of its the limitations. Future researchers can take forward this discussion. Further, investigations into the effect of the adoption of improved technology factors on improving energy efficiency in agriculture is also a potential research area for the future. In addition, studies specifically addressing the issue of tackling high energy subsidies in some of the Indian states will provide insights of great utility to policymakers.
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References
1. Unakitan, G.; Türkekul, B. Univariate modelling of energy consumption in Turkish agriculture. *Energy Source Part B* 2014, 9, 284–290. [CrossRef]
2. Pachauri, R.K. Economics of energy use in agriculture. *Indian J. Agric. Econ.* 1998, 53, 213–222.
3. Jha, G.K. Energy growth linkage and strategy for meeting the energy demand in Indian agriculture. *Agric. Econ. Res. Rev.* 2013, 26, 119–127.
4. Jha, G.K.; Pal, S.; Singh, A. Changing energy-use pattern and demand projection for Indian agriculture. *Agric. Econ. Res. Rev.* 2012, 25, 61–68.
5. TERI. *Energy Efficiency Potential in India*; The Energy and Resources Institute: New Delhi, India, 2018. Available online: https://www.energyforum.in/fileadmin/user_upload/india/media_elements/publications/09_Energy_Efficiency_Potential_in_India.pdf (accessed on 30 July 2021).
6. Energy Statistics. Central Statistics Office, Ministry of Statistics and Programme Implementation.Government of India. 2019. Available online: https://www.mospi.gov.in/sites/default/files/publication_reports/Energy%20Statistics%202019-finall.pdf (accessed on 30 July 2021).
7. Swain, A.; Charnoz, O. In Pursuit of Energy Efficiency in India’s Agriculture: Fighting ‘Free Power’ or Working with It? (Vol. 126), AFD Working Paper. 2012. Available online: https://issuu.com/objectif-developpement/docs/energy-efficiency-indian-agriculture (accessed on 24 June 2021).
8. Dharmadhikari, S.; Bhalaria, R.; Dabadge, A.; Sreekumar, N. Understanding the Electricity, Water & Agriculture Linkages, Prayas Energy Group. 2018. Available online: https://www.prayaspune.org/peg/publications/item/395-understanding-the-electricity-water-and-agriculture-linkages.html (accessed on 21 June 2021).
9. Ghosh, S. Electricity consumption and economic growth in India. *Energy Policy* 2002, 30, 125–129. [CrossRef]
10. Shiu, A.; Lam, P.L. Electricity consumption and economic growth in China. *Energy Policy* 2004, 32, 47–54. [CrossRef]
11. Shahbaz, M.; Tang, C.F.; Shahbir, M.S. Electricity consumption and economic growth nexus in Portugal using cointegration and causality approaches. *Energy Policy* 2011, 39, 3529–3536. [CrossRef]
12. Karanfil, F.; Li, Y. Electricity consumption and economic growth: Exploring panel-specific differences. *Energy Policy* 2015, 82, 264–277. [CrossRef]
13. Tang, C.F.; Tan, B.W.; Ozturk, I. Energy consumption and economic growth in Vietnam. *Renew. Sustain. Energ. Rev.* 2016, 54, 1506–1514. [CrossRef]
14. Bekun, F.V.; Emir, F.; Sarkodie, S.A. Another look at the relationship between energy consumption, carbon dioxide emissions, and economic growth in South Africa. *Sci. Total Environ.* 2019, 655, 759–765. [CrossRef]
15. Kula, F. The Long-run Relationship between Renewable Electricity Consumption and GDP: Evidence from Panel Data. *Energy Source Part B* 2014, 9, 156–160. [CrossRef]
16. Magazzino, C. The relationship between CO₂ emissions, energy consumption and economic growth in Italy. *Int. J. Sustain. Energy* 2016, 35, 844–857. [CrossRef]
17. Destek, M.A.; Sarkodie, S.A. Investigation of environmental Kuznets curve for ecological footprint: The role of energy and financial development. *Sci. Total Environ.* 2019, 650, 2483–2489. [CrossRef] [PubMed]
18. Lee, C.C.; Chang, C.P. Structural breaks, energy consumption, and economic growth revisited: Evidence from Taiwan. *Energy Econ.* 2005, 27, 857–872. [CrossRef]
19. Apergis, N.; Payne, J.E. Energy consumption and economic growth in Central America: Evidence from a panel cointegration and error correction model. *Energy Econ.* 2009, 31, 211–216. [CrossRef]

20. Nazlioglu, S.; Kayhan, S.; Adiguzel, U. Electricity Consumption and Economic Growth in Turkey: Cointegration, Linear and Nonlinear Granger Causality. *Energy Source Part B* 2014, 9, 315–324. [CrossRef]

21. Liu, Y.; Hao, Y. The dynamic links between CO2 emissions, energy consumption and economic development in the countries along “the Belt and Road”. *Sci. Total Environ.* 2018, 645, 674–683. [CrossRef]

22. Zaman, K.; Khan, M.M.; Ahmad, M.; Rustam, R. The relationship between agricultural technology and energy demand in Pakistan. *Energy Policy* 2012, 44, 268–279. [CrossRef]

23. Im, K.S.; Pesaran, M.H.; Shin, Y. Testing for unit roots in heterogeneous panels. *J. Econom.* 2003, 115, 53–74. [CrossRef]

24. Levin, A.; Lin, C.F.; Chu, C. Unit root tests in panel data: Asymptotic and finite sample properties. *J. Econom.* 2002, 108, 1–24. [CrossRef]

25. Maddala, G.S.; Wu, S.A. Comparative study of unit root tests with panel data and a new simple test. *Oxf. Bull. Econ. Stat.* 1999, 61, 631–652. [CrossRef]

26. Pedroni, P. Critical values for cointegration tests in heterogeneous panels with multiple regressors. *Oxf. Bull. Econ. Stat.* 1999, 61, 653–670. [CrossRef]

27. Pedroni, P. Panel cointegration: Asymptotic and finite sample properties of pooled time series tests with an application to the PPP hypothesis: New results. *Econom. Theory* 2004, 20, 597–627. [CrossRef]

28. Granger, C.J. Some properties of time series data and their use in econometric model specification. *J. Econom.* 1981, 16, 121–130. [CrossRef]

29. Raeeni, A.A.G.; Hosseini, S.; Moghaddasi, R. How energy consumption is related to agricultural growth and export: An econometric analysis on Iranian data. *Energy Rep.* 2019, 5, 50–53. [CrossRef]

30. Chandio, A.A.; Jiang, Y.; Rehman, A. Energy consumption and agricultural economic growth in Pakistan: Is there a nexus? *Int. J. Energy Sect. Manag.* 2019, 13, 597–609. [CrossRef]

31. Doytch, N.; Narayan, S. An investigation of renewable and non-renewable energy consumption and economic growth nexus using industrial and residential energy consumption. *Energy Econ.* 2017, 68, 160–176.

32. Karkacier, O.; Goktolga, Z.G.; Cicek, A. A regression analysis of the effect of energy use in agriculture. *Energy Policy* 2006, 34, 3796–3800. [CrossRef]

33. Gulati, M.; Pahuja, S. Direct delivery of power subsidy to manage energy–groundwater–agriculture nexus. *Aquat. Procedia* 2015, 5, 22–30. [CrossRef]

34. Bhati, P.; Singh, M.; Jhawar, P. *Silver Bullet: Are Solar Pumps a Panacea for Irrigation, Farmer Distress and Discom Losses?* Centre for Science and Environment: New Delhi, India, 2019. Available online: https://www.indiaenvironmentportal.org.in/content/465429/silver-bullet-are-solar-pumps-a-panacea-for-irrigation-farmer-distress-and-discom-losses/ (accessed on 24 June 2021).

35. Margat, J.; Van der Gun, J. *Groundwater around the World: A Geographic Synopsis*; CRC Press: Boca Raton, FL, USA, 2013.

36. Dharmadhikary, S. Unravelling Bhakra: Assessing the Temple of Resurgent India. 2005. Available online: www.manthan-india.org/wp-content/uploads/2015/04/Unravelling-Bhakra.pdf (accessed on 30 July 2021).

37. Shah, T.; Chowdhury, S.D. Farm Power Policies and Groundwater Markets: Contrasting Gujarat with West Bengal (1990–2015). *Econ. Political Wkly.* 2017, 52, 25–26.

38. Gulati, A.; Rajkhowa, P.; Sharma, P. Making Rapid Strides-Agriculture in Madhya Pradesh: Sources, Drivers, and Policy Lessons (Working Paper). 2017. Available online: https://icrier.org/pdf/Working_Paper_339.pdf (accessed on 15 July 2021).