Original Research Article

Agricultural Infrastructure and Agricultural Efficiency Index: A case of Gujarat Agriculture

ABSTRACT

In this research paper, the examination of agricultural infrastructure and agricultural efficiency in Gujarat at the district level for the years 2009-10 and 2019-20 was conducted. The study involved the estimation of Agricultural Infrastructure Index (AII) using Principal Component Analysis (PCA), which considered eleven variables related to agricultural infrastructure to unveil disparities within the districts. Additionally, an Agricultural Efficiency Index (AEI) was also calculated to discern trends in agricultural efficiencyat a disaggregated level in Gujarat. The results of the Agriculture Infrastructure Index (AII) highlighted improvements in the positions of Banskantha, Sabarnaktha, Rajkot and Junagadh in comparison to their 2009-10 AII rankings. Furthermore, the findings related to agricultural efficiency indicated that Rajkot district exhibited a remarkable leap in 2019-20 when compared to its position in 2009-10.

Key words: Agricultural efficiency, agricultural infrastructure, Principal Component Analysis (PCA)

INTRODUCTION

The cues are very appropriate in the context of farmers of developing countries, particularly India, where the size of land holding primarily belongs to the small and marginal farmers and traditional cropping pattern with low productivity remains a momentous concern. In the recent, economic environment, efficiency and competitiveness ought to be the basis of every development strategy of agriculture.The agriculture efficiency is thereby a precursor of agriculture development in India because it is directly related to the productivity of the agriculture sector that can aide in combating such issues.An adequate infrastructure raises farm productivity, reduce farming costs and rapid development accelerates agricultural as well as economic growth rate. Thus, the infrastructure plays a crucial role in producing big multiplier effects in the overall economy with agriculture growth. The social development' and irrigation intensity play positive and significant impact on the composite index of economic development, at the district level(Gulati 1997). Within the 'social-development' factors, the surfaced road length and electricity turned out to be the crucial indicators.Patel (2010) estimated that a 1% increase in the stock of infrastructure will be increase 1per cent in GDP ain the Country. The level of both physical and institutional infrastructure significantly influences the spread of proven and demonstrated yield enhancing agricultural technology. Infrastructural development is used to describe improvement in physical infrastructure which, is important for the country's economic and social development. Infrastructural development is a key driver for economic progress and a critical enabler for productivity (Lokesha and Mahesha, 2016; Lokesha and Mahesha, 2017).Majumdar (2002), indicated that among various physical infrastructures, the transport facilities had significantly affected the agricultural output level and the agricultural development index (ADI). In addition physical infrastructure, social infrastructure had significant and positive impact on the ADI. Llanto and Gilberto (2012) stated that the availability and quality of rural infrastructure are never substitutes to efficient macroeconomic and agriculture-specific policies and the ineffective implementation rural development policies, insufficient infrastructure can be a major constraint to growth and productivity in economic development. Rural infrastructure, like other public investments, raises agricultural productivity, which in turn induces growth in the rural areas, bringing about higher agricultural wages and improved opportunities for nonfarm labour.According to Wharton (1967) classified agricultural infrastructures into three categories capital intensive, capital extensive and institutional. Infrastructure, such as irrigation, watershed development, rural electrification, roads, and markets, in close coordination with institutional infrastructure, such as credit institutions, agricultural research and extension, rural literacy rate determine the nature and the degree of agricultural output in the country.

Agriculture sector is a victim of several gaps. Foremost of these gaps is the Agro-infrastructural. Farmers have little information on the kinds of crops he should grow, how he should grow the crops, what planning he needs to do with respect to his area and soil conditions, and the market infrastructure *etc*. The other gaps included credit gap, productivity gap, marketing gap, price realization gap *etc*. Thus, thestudy through agricultural infrastructure has tried to identify in three broad parameters *viz.,*economic infrastructure in terms of irrigation, electricity, transport and telecommunication *etc.*, institutional infrastructure in terms of agriculture Market, primary agriculture cooperative societies, banks *etc.* and social infrastructure in terms of education and health. Agricultural development or its efficiency is a multi-dimensional phenomenon where different factors and conditions should work together to achieve the potential level of agriculture output. The present empirical study aims to examine the trends of agriculture efficiency index (AEI) and agriculture infrastructure index (AII) in Gujarat.

METHODOLOGY

Database for the Study

The database used for the for the present study from 2009-10 and 2019-20. The data collected on different variables from various secondary data sources *viz.*, Directorate of Economics & Statistics, Government of Gujarat, Land Use Statistics (LUS) prepared by DACNET, Economics & Statistics Division, State Planning Institute Planning Department, Government of Gujarat. The methodology of research has been divided into two sections. The first sub-section elaborates the construction of the Agriculture Infrastructure Index (AII) and the second sub-section spells out the estimation of the Agricultural Efficiency Index (AEI).

Agriculture Infrastructure Index (AII)

Calculation of Agriculture Infrastructure Index (AII) includes three elements *i.e.*, economic, institutional and social infrastructure. Further, these three broad parameters of infrastructure were divided into eleven indicators of infrastructure. These indicators have been selected through the Principal Component Analysis (PCA) on the basis of Eigen value criterion. The list of the parameters and indicators are given in the Table 1.

To arrive at standardized values of variables of agriculture infrastructure, the method of normalization was used. The indicators were normalised using a mini max normalisation method. The mini-max method of each indicator was transformed as follows:

$$I_{qd}^{t} = \frac{X_{qd}^{t} - Min_d\left(X_q^t\right)}{Max_d\left(X_q^t\right) - Min_d\left(X_q^t\right)}$$

Where $Max_d\left(X_q^t\right)$ and – $Min_d\left(X_q^t\right)$ are the maximum and the minimum values of X_{qd}^{t} across all the districts d of Gujarat at time t. In this way the normalized indicators I_{qd}^{t}have values lying between 0 and 1. Thus, the higher the values of I_{qd}^{t}; the higher the district achievement in indicator q.

As earlier stated, PCA and factor analysis were used in order to generate the weights of agricultural infrastructure. This facilitated to construct weights representing the information content of individual indicators without reducing the number of indicators (OECD, 2008). Finally, the following equation was used in order to aggregate the outcomes and arrive at the Agriculture Infrastructure Index (AII) for the all 26 districts of Gujarat from the year 2009-10 to 2019-20.

$$AII = \sum_{q=1}^{Q} w_q I_{qd}$$

$$\text{With } \sum_{q=1}^{Q} \mathrm{w_q} = 1 \text{ and } 0 \leq \mathrm{w_q} \leq 1, \text{for all q} = 1, 2, \ldots.., \mathrm{Q} \text{ and d} = 1, 2, \ldots.,70$$

Estimation of Agricultural Efficiency Index (AEI)

The method of measuring agricultural efficiency has been given by several researchers such as Kendal (1939), Shafi (1960), Khusro (1964), Sharma (1965), Bhatia (1967) and Singh (1979). In this study Bhatia's method is applied to measure agricultural efficiency. The measurement of agricultural efficiency as output per unit area is based on acre yields of crops and a measure for it was evolved by Kendal.

The productivity/yield of selected crops in the component areal units were expressed as a percentage of the corresponding average productivity/yield for the entire region to obtain indexes of productivity/yield efficiency relative to the performance of the crop in the entire selected region. Agricultural efficiency (AE) of the component areal unit relative to the entire region of the study (Bhatia, 1967). As the Agricultural Efficiency Index (AEI) is estimated asfollows; This can be expressed:

$$AEI_i = \frac{I_{ya} \times C_a + I_{yb} \times C_b + \cdots + I_{yn} \times C_n}{\sum_{i=a}^{n} C}$$

Where, $AEI_i$is the agricultural efficiency index, $I_{ya}, I_{yb}, \ldots, I_{yn}$, are the productivity/yield indexes of various crops, and$C_a, C_b, \ldots, C_n$, are percentages of crop area under the different selected crops. For that purpose, 14 major crops selected on the basis of covering 90% of the area in the states. They are Arhar, Bajra, Banana, Castor, Cotton, Gram, Groundnut, Maize, Onion, Potato, Rice, Sesamum, Wheat and Mango which included cereals, pulses, oilseeds, cash crops, fruits and vegetables categories.

RESULT AND DISCUSSION

In order to prepare composite index of Agricultural Infrastructure, step by step procedure is described in following sub-sections.

Normalization of Indicators

As a preliminary step of constructing an index, normalization is required when the data is obtained in different measurement units to convert it into identical measures. Present data on indicators of agricultural infrastructure have the same unit of measurement. But, then also to convert that data into a specified range [here a range of 0 to 1], the given data is normalized by using a 'Linear Scaling Technique' also called 'Min-Max Normalization' (OECD, 2008; Sharpe and Andrews, 2012). Under this technique, minimum value of a variable in its data series is subtracted from the particular value for which normalization is undertaken and the resultant is divided by the range (difference between maximum and minimum value of this particular variable) of its data series. In this way, the normalized data comes up within a limit of 0 to 1.

Principal Component Analysis for Composite Index

Principal component analysis of the normalized data is performed with the help of SPSS (version 20) and resultant output is shown under following headings:

Correlation Matrix, Kaiser-Meyer-Olkin (KMO) Measure and Bartlett's Test

To start the analysis, it is necessary to test that whether present data is adequate for principal component analysis (PCA). In this regard, Correlation matrix (showing scores of correlations among variables), Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy and Bartlett's Test of Sphericity are computed by SPSS system (Kontokosta, 2014).

Since, the PCA method depends on the correlations between sets of variables. Therefore, it becomes imperative to examine the correlation among variables undertaken. More clearly, the correlation scores clarify that whether the PCA willbe meaningful or not. The correlations between individual variables have to be higher than 0.30 for the analysis to provide significant results. However, low scores of some of the correlations do not create problem. But if, most of the correlations score near about zero, then method lose its usefulness (Mooi and Sarstedt, 2011; Hoque, 2014). The correlation matrix which is one of the outputs of PCA, are presented in table 2 and 3 for the year of 2009-10 and 2019-20.

The correlation matrix is a rectangular arrangement of numbers showing the correlation coefficients between one variable and every other variable. It is evident from table 2 and 3 that the all elements on principal diagonal are 1 since correlation coefficient between a variable with itself is always unity. Below this principal diagonal, some correlation coefficients are positive and some are negative thereby implying that some of the variables move in same direction with other variables, some varies oppositely with others.

Next output, Kaiser-Meyer-Olkin (KMO) statistic, a measure of the strength of relationship among variables, indicates whether the correlations between variables can be explained by other variables in the dataset. Its value varies between 0 and 1. The data is considered suitable for PCA if KMO statistic is equal or higher than 0.50. In the present context, the value of KMO 0.681 and 0.734shows that data is significantly suitable for the application of PCA.

Moreover, the Bartlett's test is another indicator of judging that whether original variables are sufficiently correlated. It is used to test the null hypothesis that the correlation matrix is an identity matrix that is, in which diagonal elements are 1 and others are 0. This implies that all variables are perfectly correlated with themselves but uncorrelated with others. Alternatively, correlation matrix is not identity matrix there by implying that there is some degree of correlation between variables. To test the null hypothesis that all correlation coefficients are zero or not significant, chi-square statistic is computed under Bartlett test. The value of approximate chi-square statistic is found to be 277.277 and 245.085 with 55 degrees of freedom, which is significant at 0.000 level of significance which is under the accepted range of level of significance (p-value) 0.05 for both years. On this basis, null hypothesis that is variables are uncorrelated or correlation matrixis an identity matrix is rejected and alternative hypothesis is accepted which means original variables are correlated which is compulsory for the adequacy of PCA. Thus, significant scores of correlation coefficients and results of KMO and Bartlett's test show that principal component analysis is preferable.

Decision for Number of Components

After passing the above tests, next step is to identify the number of factors or principal components or latent variables that can represent all originally undertaken variables. For the same, eigenvalue-one criterion (Kaiser's criterion or latent root criterion), scree plot and total amount of variance extracted are the methods that can be used. But present study adopts eigenvalue-one criterion according to the standard practice of decision as mentioned by OECD (2008) and Sharpe and Andrews (2012). Under, eigenvalue-one criterion, those factors or principal components or latent variables are selected which possess eigenvalues larger than 1, individual variance explained more than 10 per cent; and cumulative contribution to overall variance more than 60 per cent. In table 4 and 5, initial and rotated eigenvalues are presented as another output of PCA.

It is cleared from initial eigenvalues in the table that the number of components is equal to number of variables selected in the study and every component has an eigenvalue showing the variance extracted by itself. But, only first three components are possessing the eigenvalue greater than 1 for 2009-10 (5.773, 2.050, 1.248) and 2019-20 (5.820, 1.687 and 1.065) and thus, eleven indicators are reduced to these three sets of components as shown in table under column extraction sums of squared loadings. For further clarification about retained components, rotation has been applied. It is found that there exist three components with eigenvalues3.758, 2.614 and 2.200 which are some different from initial eigenvalues but their summation is same with initial eigenvalues of first three components.

After rotation, these components individually explain 34.168 per cent, 23.761per cent and 19.998 per cent of variance (well above suggested 10 per cent)but cumulatively explain 77.92 per cent of variance which are notably above the suggested criterion of 60 per cent for 2019-20. With this analysis, three components are retained which are able to represent fourteen variables selected for study.

Component Matrix and Loadings

Table 6 and 7 is a triad for component loadings, squared component loadings and squared loadings scaled to unity sum. Component loadings are the correlations between variables and the latent components. These are used to examine which component is formed with which of the variables. This information is provided by PCA in its output named initial or un-rotated component loading matrix.

In this matrix, sometimes, it becomes difficult to recognize that which variable should be included in which component because various variables load moderately on each component. To overcome this problem, varimax rotation has been applied; as a result of which each original variable tends to be associated with one (or a small number) of retained components, and each component represents only a small number of variables (Abdi and Williams,2010). However, for the sake of simplicity, the rotated component loading matrix is shown in table 6 and 7 In order to check which indicator variable load on which component, a criterion of component loadings greater than 0.5 is employed (Hair *et al.,* 2010). It can be seen from the left side of table that first component is formed by RM, VI, PACS, FPS, EP and PHC in 2009-10 and ES, ST, FPS, EP and VI are in 2019-20, since the component loadings of these variables are high on the first component among three components. Component two is a formation of variables PHC, PACS, DP and VI. On the same notions, component three is a conglomerate of variable namely RL, RM and IR. Now, at the middle of table there are squared component loadings (obtained by squaring the component loadings) which explain the amount of variation of the indicator variables that the latent components explain. Below the matrix of 'squared component loadings' explained variance of three components are displayed. This is attained by adding the square component loadings of components one, two and three respectively. Actually, these are the three eigenvalues, obtained after rotation. Now, total variance is the addition of three values of explained variance [3.758+2.614+2.20]. Explained variance when divided by total variance gives 'component weight'.

Third part of table 'squared loadings scaled to unity sum' is attained by dividing squared loadings in each component by the explained variance of respective component, and the values obtained are entitled as 'domain weight' for all original variables rests under various components. Now, the 'Component weight' and 'domain weight' are used in table 8 and 9 to arrive at the final weights. Similarly, each variable has that component weight in which this variable lies and on this basis column of 'component weight' is prepared. Likewise, all variables have domain weight as well as component weight. As a next step, the 'domain weight' and 'component weight' is multiplied (as shown under column 'Weight Score' in table 8 and 9) and the resultant is divided by summation of multiplication values to arrive at weight scores. In this way, final weights of each variable are obtained and displayed in the last column under:

The heading 'Resulting Weight'. The summation of weights in this column is definitely come out to be 1, and now the weights are ready to be used for a weighed aggregation of variables forgetting a composite index.

Composite Index

To prepare composite index, firstly, each indicator or variable (normalized) for various years is multiplied by its weight (computed in table 8 and 9) and is divided by its standard deviation (obtained from normalized data). In this way all variables will be credited with weighted scores for various years which has to be summated to obtain composite index for every year. To keep the scores of composite indices ranging between 0 and 1, it is necessary to normalize the composite index by subtracting minimum value in the series from each value and then divide the resultant by the difference of maximum and minimum value. In this way, composite index of agricultural infrastructure is constructed and presented in table 12.

Trends of Agricultural Infrastructure (AII)

The trends of Agricultural Infrastructure Index (AII) along with rank allocation at district level for Gujarat are presented in Table 12. It shows that the districts like Ahmedabad, Banskantha, Vadodara, Sabarkantha, Surat, Panchmahal, Rajkot, Junagadh, Kheda and Mehsana have fared quite well and attained the top ranks in terms of Agricultural Infrastructure Index (AII) in the year 2009-10, while, Dang, Porbandar, Narmada, Tapi, Patan, Surendranagar,Kachchh, Dahod,Bharuch and Jamnagar the lowest ten districts in terms of AII rank during the same period.The rest of the districts fell between them. On the other hand, slight variations in the AII rank were observed Trends of Agricultural Infrastructure (AII) in 2019-20. It shows that Banskantha, Sabarnaktha, Rajkot and Junagadhimprove their position with respect to agricultural infrastructure 2009-10. The district like Ahmedabad,Vadoadra, Surat, Panchmahal, Kheda and Mehsana deeps more points in infrastructure index.

Agricultural Efficiency Index (AEI)

Trends of Agricultural Efficiency Index (AEI) The district levels as well as regional level trends of agricultural efficiency index (AEI) of Gujarat are shown in Table 14. It could be seen from the table that, the top 10 performers districts of AEI were found to be Jamnagar, Kachchh, Anand, Gandhinagar, Vadodara, Narmada, Bhavnagar, Banaskantha, Mahesana and Tapi in 2009-10 while the bottom 5 ranks were taken up by Dahod, Amreli, Navsari, Dang, Valsad and Patan during the same period.

However, if one compared the statistics in 2019-20, there were a few new entrants like Amreli, Kheda, Surat, Mahesana, Tapi and Rajkot indicating improved agriculture efficiency during the 10 year span of analysis. However, one also tends to witness new additions of few districts in the race of bottom

Porbandar, Banskantha, Kachchh, Anand and Narmada highlighting falling agriculture efficiency in 2019-20 as compared to 2009-10.

Conclusion

The results of the present study indicate that Vadodara district outperformed in both the Agricultural Infrastructure Index (AII) and Agricultural Efficiency in 2009-10 and 2019-20, whereas Dang lagged behind in both aspects.Notably, Banskantha, Sabarnaktha, Rajkot, and Junagadh demonstrated significant improvements in their Agricultural Infrastructure Index (AII) positions in 2019-20 compared to 2009-10. Regarding Agricultural Efficiency, Gandhinagar maintained the same rank in both years, while Vadodara and Mehsana improved their positions, securing places within the top 10 districts in 2019-20 compared to 2009-10. Remarkably, Rajkot district made a remarkable leap in agricultural efficiency, advancing from the 17^{th}rank in 2009-10 to the 1^{st}rank in 2019-20. On the other hand, some districts like Ahmedabad, Banaskantha, and Sabarkantha exhibited lower agricultural efficiency indexes but performed well in terms of infrastructure. This suggests that these areas may serve as consumer regions and have better accessibility to other markets.Conversely, Dang district requires more focused attention and efforts to enhance its agricultural performance and overall position.

COMPETING INTERESTS DISCLAIMER:

Authors have declared that they have no known competing financial interests OR non-financial interests OR personal relationships that could have appeared to influence the work reported in this paper.

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Table 1: Indicators of Agriculture Infrastructure Index (AII)

Sr.No	Infrastructure Parameters	Indicators of infrastructure	Indicator Description
1	**Economic/ Physical Infrastructure**	Irrigation (IR)	Ratio of Net irrigated area to net sown area in the district
		Transportation (RL)	Road length per 100 square km
		Total veterinary institutes (VI)	Toral number per year working in district
		Storage capacity (ST)	In Metric Tonne
2	**Social Infrastructure**	Health	
		1) Primary Health Centre (PHC)	Total number per year working in district
		2) Dispensaries (DP)	Total number per year working in district
		Education	
		1) Primary (EP)	Total number per year working in district

		2) Secondary (ES)	Total number per year working in district
		Fair price Shop (FPS)	Total number per year working in district
3	**Institutional Infrastructure**	No. of regulated markets (including sub-yards) (RM)	Total number per year working in district
		Primary Agricultural Credit societies (PACS)	Total number per year working in district

Table2: Correlation matrix, KMO and Bartlett's test (2009-10)

	RM	**VI**	**PACS**	**FPS**	**ST**	**IR**	**RL**	**EP**	**ES**	**PHC**	**DP**
RM	1										
VI	0.634	1									
PACS	0.511	0.802	1								
FPS	0.752	0.634	0.596	1							
ST	0.326	0.235	0.293	0.759	1						
IR	0.461	0.128	0.229	0.430	0.229	1					
RL	0.178	-0.351	-0.329	-0.165	-0.122	0.504	1				
EP	0.786	0.763	0.595	0.901	0.596	0.256	-0.185	1			
ES	0.637	0.514	0.452	0.914	0.816	0.346	-0.053	0.846	1		
PHC	0.864	0.762	0.617	0.744	0.266	0.342	-0.027	0.819	0.557	1	
DP	-0.06	-0.220	-0.216	-0.162	-0.064	0.289	0.480	-0.181	0.034	-0.168	1

KMO and Bartlett's test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy	KMO Measure	0.681
Bartlett's Test of Sphericity	Approx. Chi-square	277.277
	Df	55
	Sig.	0.000

Table3: Correlation matrix, KMO and Bartlett's test (2019-20)

	RM	**VI**	**PACS**	**FPS**	**ST**	**IR**	**RL**	**EP**	**ES**	**PHC**	**DP**
RM	1										
VI	0.708	1									
PACS	0.264	0.537	1								
FPS	0.700	0.747	0.451	1							
ST	0.438	0.635	0.353	0.821	1						
IR	0.255	0.072	0.075	0.227	0.153	1					
RL	0.600	0.384	-0.225	0.304	0.224	0.315	1				
EP	0.734	0.840	0.400	0.929	0.753	0.165	0.412	1			
ES	0.478	0.590	0.252	0.884	0.840	0.116	0.281	0.864	1		
PHC	0.697	0.796	0.575	0.679	0.466	0.129	0.317	0.766	0.446	1	
DP	0.236	0.190	0.375	0.232	0.205	-0.265	-0.110	0.256	0.211	0.399	1

KMO and Bartlett's test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy	KMO Measure	0.734
Bartlett's Test of Sphericity	Approx. Chi-square	245.086
	Df	55

	Sig.	0.000

Table 4: Eigenvalues (Initial and Rotated) and Components (2009-10)

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	5.773	52.485	52.485	5.773	52.485	52.485	4.160	37.822	37.822
2	2.050	18.633	71.118	2.050	18.633	71.118	2.881	26.190	64.012
3	1.248	11.344	82.462	1.248	11.344	82.462	2.029	18.45	82.462
4	0.694	6.306	88.768						
5	0.562	5.113	93.880						
6	0.261	2.377	96.257						
7	0.149	1.357	97.615						
8	0.117	1.066	98.680						
9	0.085	0.774	99.454						
10	0.047	0.432	99.886						
11	0.013	0.114	100						

Table 5: Eigenvalues (Initial and Rotated) and Components (2019-20)

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	5.820	52.913	52.913	5.820	52.913	52.913	3.758	34.168	34.168
2	1.687	15.333	68.246	1.687	15.333	68.246	2.614	23.761	57.929
3	1.065	9.680	77.926	1.065	9.680	77.926	2.200	19.998	77.926
4	0.956	8.691	86.618						
5	0.620	5.633	92.251						
6	0.281	2.554	94.805						
7	0.218	1.985	96.790						
8	0.177	1.605	98.395						
9	0.118	1.070	99.466						
10	0.037	0.332	99.797						
11	0.022	0.203	100						

Table 6: Rotated Component Loading Matrices (2009-10)

	Component loading			Squared component loading			Squared Scaled to Unity Sum (Domain Weight)		
	Component			Component			Component		
	1	2	3	1	2	3	1	2	3

RM	**0.823**	0.299	0.289	**0.677**	0.089	0.084	**0.163**	0.031	0.041
VI	**0.877**	0.168	-0.249	**0.769**	0.028	0.062	**0.185**	0.010	0.031
PACS	**0.776**	0.182	-0.226	**0.602**	0.033	0.051	**0.145**	0.011	0.025
FP	**0.623**	0.760	0.017	**0.388**	0.578	0.000	**0.093**	0.200	0.000
ST	0.070	**0.962**	-0.030	0.005	**0.925**	0.001	0.001	**0.321**	0.000
IR	0.338	0.216	**0.729**	0.114	0.047	**0.531**	0.027	0.016	**0.262**
RL	-0.097	-0.129	**0.897**	0.009	0.017	**0.805**	0.002	0.006	**0.396**
EP	**0.733**	0.605	-0.061	**0.537**	0.366	0.004	**0.129**	0.127	0.002
ES	0.420	**0.868**	0.103	0.176	**0.753**	0.011	0.042	**0.262**	0.005
PHC	**0.911**	0.211	0.081	**0.830**	0.045	0.007	**0.200**	0.015	0.003
DP	-0.224	0.009	**0.690**	0.050	0.000	**0.476**	0.012	0.000	**0.234**
Explained variance				4.159	2.881	2.031			
Total variance				9.071					
Explained variance/ total variance (component weight)				0.459	0.318	0.224			

Table 7: Rotated Component Loading Matrices (2019-20)

	Component loading			**Squared component loading**			**Squared Scaled to Unity Sum (Domain Weight)**		
	Component			**Component**			**Component**		
	1	**2**	**3**	**1**	**2**	**3**	**1**	**2**	**3**
RM	0.354	0.490	**0.685**	0.125	0.240	**0.469**	0.033	0.092	**0.213**
VI	0.557	**0.583**	0.390	0.310	**0.340**	0.152	0.083	**0.130**	0.069
PACS	0.254	**0.739**	-0.153	0.065	**0.546**	0.023	0.017	**0.209**	0.011
FP	**0.857**	0.354	0.278	**0.734**	0.125	0.077	**0.195**	0.048	0.035
ST	**0.914**	0.158	0.074	**0.835**	0.025	0.005	**0.222**	0.010	0.002
IR	0.112	-0.191	**0.589**	0.013	0.036	**0.347**	0.003	0.014	**0.158**
RL	0.142	-0.037	**0.867**	0.020	0.001	**0.752**	0.005	0.001	**0.342**
EP	**0.790**	0.424	0.368	**0.624**	0.180	0.135	**0.166**	0.069	0.062
ES	**0.951**	0.112	0.114	**0.904**	0.013	0.013	**0.241**	0.005	0.006
PHC	0.348	**0.772**	0.389	0.121	**0.596**	0.151	0.032	**0.228**	0.069
DP	0.078	**0.715**	-0.272	0.006	**0.511**	0.074	0.002	**0.196**	0.034
Explained variance				3.758	2.614	2.200			
Total variance				8.572					
Explained variance/ total variance (component weight)				0.438	0.305	0.257			

Table 8: Weighted Scores for Variables (2009-10)

Indicators	**Domain weight (1)**	**Component weight (2)**	**Weight score (3=1*2) Total=0.804**	**Resulting weight (4=3/0.804)**
RM	0.163	0.459	0.075	0.093
VI	0.185	0.459	0.085	0.105

PACS	0.145	0.459	0.066	0.083
FPS	0.093	0.459	0.043	0.053
ST	0.321	0.318	0.102	0.127
IR	0.262	0.224	0.059	0.073
RL	0.396	0.224	0.089	0.110
EP	0.129	0.459	0.059	0.074
ES	0.262	0.318	0.083	0.103
PHC	0.200	0.459	0.091	0.114
DP	0.234	0.224	0.052	0.065

Table 9: Weighted Scores for Variables (2019-20)

Indicators	Domain weight (1)	Component weight (2)	Weight score (3=1*2) Total=0.777	Resulting weight (4=3/0.777)
RM	0.213	0.257	0.055	0.070
VI	0.130	0.305	0.040	0.051
PACS	0.209	0.305	0.064	0.082
FPS	0.195	0.438	0.086	0.110
ST	0.222	0.438	0.097	0.125
IR	0.158	0.257	0.040	0.052
RL	0.342	0.257	0.088	0.113
EP	0.166	0.438	0.073	0.094
ES	0.241	0.438	0.106	0.136
PHC	0.228	0.305	0.070	0.089
DP	0.196	0.305	0.060	0.077

Table 10: Weighted Indicators of Agriculture Infrastructure Index (AII) (2009-10)

Sr. no.	Districts	RM	VI	PACS	FPS	ST	IR	RL	EP	ES	PHC	DP
1	Ahmadabad	0.20	0.20	0.14	0.22	0.65	0.14	0.21	0.25	0.44	0.22	0.20
2	Amreli	0.14	0.24	0.11	0.08	0.12	0.07	0.22	0.06	0.10	0.18	0.14
3	Anand	0.18	0.14	0.06	0.11	0.07	0.29	0.36	0.09	0.12	0.24	0.18
4	Banaskantha	0.28	0.41	0.38	0.15	0.17	0.18	0.18	0.20	0.17	0.44	0.28
5	Bharuch	0.24	0.13	0.08	0.08	0.11	0.09	0.20	0.07	0.10	0.19	0.24
6	Bhavnagar	0.17	0.26	0.17	0.12	0.11	0.13	0.17	0.12	0.18	0.24	0.17
7	Dahod	0.14	0.16	0.01	0.10	0.07	0.02	0.20	0.12	0.12	0.34	0.14
8	Gandhinagar	0.13	0.10	0.04	0.04	0.03	0.20	0.54	0.05	0.14	0.10	0.13
9	Jamnagar	0.10	0.24	0.10	0.09	0.13	0.11	0.09	0.13	0.14	0.19	0.10
10	Junagadh	0.18	0.26	0.17	0.12	0.13	0.13	0.19	0.16	0.22	0.32	0.18
11	Kachchh	0.10	0.28	0.10	0.10	0.13	0.10	0.00	0.14	0.11	0.18	0.10
12	Kheda	0.25	0.14	0.06	0.12	0.09	0.24	0.32	0.15	0.14	0.27	0.25
13	Mahesana	0.23	0.18	0.11	0.10	0.05	0.21	0.27	0.08	0.12	0.27	0.23
14	Narmada	0.08	0.06	0.01	0.03	0.04	0.07	0.24	0.03	0.02	0.08	0.08

15	Navsari	0.12	0.09	0.02	0.06	0.13	0.23	0.46	0.05	0.05	0.18	0.12
16	Panchmahals	0.31	0.34	0.05	0.11	0.09	0.06	0.28	0.20	0.19	0.37	0.31
17	Patan	0.08	0.17	0.10	0.07	0.13	0.09	0.17	0.05	0.08	0.13	0.08
18	Porbandar	0.02	0.02	0.00	0.02	0.01	0.04	0.18	0.00	0.02	0.01	0.02
19	Rajkot	0.22	0.26	0.13	0.15	0.18	0.13	0.19	0.20	0.31	0.23	0.22
20	Sabarkantha	0.32	0.41	0.18	0.14	0.11	0.17	0.29	0.23	0.24	0.36	0.32
21	Surat	0.25	0.15	0.03	0.18	0.37	0.23	0.29	0.16	0.33	0.26	0.25
22	Surendranagar	0.12	0.19	0.08	0.09	0.11	0.09	0.15	0.07	0.10	0.15	0.12
23	Tapi	0.05	0.13	0.01	0.03	0.07	0.07	0.23	0.07	0.03	0.14	0.05
24	The Dangs	0.00	0.00	0.00	0.00	0.00	0.00	0.26	0.00	0.00	0.00	0.00
25	Vadodara	0.36	0.25	0.15	0.19	0.18	0.14	0.26	0.25	0.24	0.44	0.36
26	Valsad	0.19	0.09	0.02	0.06	0.10	0.13	0.39	0.07	0.08	0.20	0.19

Table 11: Weighted Indicators of Agriculture Infrastructure Index (AII) (2019-20)

Sr. no.	Districts	RM	VI	PACS	FPS	ST	IR	RL	EP	ES	PHC	DP
1	Ahmadabad	0.16	0.11	0.10	0.44	0.55	0.09	0.25	0.28	0.55	0.11	0.00
2	Amreli	0.12	0.09	0.08	0.16	0.13	0.04	0.09	0.07	0.11	0.11	0.00
3	Anand	0.14	0.05	0.04	0.20	0.13	0.22	0.23	0.10	0.13	0.15	0.00
4	Banaskantha	0.19	0.18	0.43	0.33	0.26	0.11	0.09	0.27	0.24	0.39	0.19
5	Bharuch	0.17	0.08	0.07	0.14	0.10	0.05	0.11	0.09	0.13	0.11	0.19
6	Bhavnagar	0.15	0.08	0.09	0.21	0.21	0.07	0.09	0.14	0.22	0.13	0.00
7	Dahod	0.16	0.07	0.01	0.19	0.16	0.00	0.24	0.16	0.15	0.31	0.19
8	Gandhinagar	0.09	0.03	0.03	0.09	0.07	0.16	0.27	0.07	0.16	0.07	0.00
9	Jamnagar	0.07	0.11	0.04	0.19	0.15	0.12	0.13	0.17	0.19	0.16	0.00
10	Junagadh	0.14	0.12	0.08	0.24	0.46	0.11	0.20	0.18	0.28	0.20	0.19
11	Kachchh	0.07	0.13	0.09	0.20	0.22	0.06	0.00	0.19	0.18	0.20	0.00
12	Kheda	0.16	0.05	0.04	0.20	0.12	0.16	0.17	0.17	0.20	0.17	0.00
13	Mahesana	0.16	0.07	0.09	0.21	0.15	0.15	0.17	0.10	0.08	0.16	0.00
14	Narmada	0.05	0.05	0.02	0.04	0.04	0.06	0.13	0.04	0.03	0.06	0.00
15	Navsari	0.09	0.04	0.01	0.10	0.15	0.15	0.28	0.05	0.07	0.12	0.00
16	Panchmahals	0.25	0.17	0.02	0.25	0.16	0.06	0.49	0.24	0.24	0.25	0.00
17	Patan	0.08	0.06	0.10	0.14	0.20	0.13	0.08	0.06	0.08	0.15	0.00
18	Porbandar	0.00	0.00	0.01	0.04	0.07	0.10	0.07	0.00	0.03	0.01	0.00
19	Rajkot	0.12	0.13	0.07	0.31	0.36	0.10	0.20	0.27	0.48	0.25	0.00
20	Sabarkantha	0.26	0.19	0.08	0.29	0.31	0.18	0.44	0.28	0.25	0.26	0.00
21	Surat	0.17	0.07	0.04	0.33	0.23	0.10	0.15	0.26	0.41	0.16	0.19
22	Surendranagar	0.08	0.06	0.05	0.19	0.15	0.09	0.07	0.08	0.13	0.15	0.00
23	Tapi	0.15	0.06	0.01	0.05	0.12	0.08	0.14	0.05	0.04	0.10	0.00
24	The Dangs	0.00	0.00	0.00	0.00	0.00	0.00	0.13	0.00	0.00	0.00	0.00
25	Vadodara	0.30	0.14	0.07	0.38	0.30	0.14	0.29	0.30	0.29	0.29	0.00
26	Valsad	0.12	0.04	0.01	0.12	0.11	0.12	0.25	0.10	0.11	0.14	0.00

Table 12: Composite Index of Agriculture Infrastructure Index (AII)

Sr. no.	Districts	Composite Index (Aggregation of Weighted Indicators)	Normalized Composite Index	Rank	Composite Index (Aggregation of Weighted Indicators)	Normalized Composite Index	Rank
		2009-10			2019-20		
1	Ahmadabad	2.67	1.00	1	2.62	0.98	2
2	Amreli	1.32	0.44	16	0.99	0.34	22
3	Anand	1.65	0.57	12	1.39	0.49	12
4	Banaskantha	2.56	0.95	2	2.67	1.00	1
5	Bharuch	1.31	0.43	18	1.23	0.43	16
6	Bhavnagar	1.66	0.58	11	1.40	0.50	11
7	Dahod	1.28	0.42	19	1.63	0.59	9
8	Gandhinagar	1.63	0.57	13	1.03	0.35	21
9	Jamnagar	1.31	0.43	17	1.34	0.47	15
10	Junagadh	1.87	0.67	8	2.21	0.82	6
11	Kachchh	1.24	0.41	20	1.34	0.48	14
12	Kheda	1.78	0.63	9	1.45	0.52	10
13	Mahesana	1.75	0.62	10	1.35	0.48	13
14	Narmada	0.66	0.16	24	0.51	0.15	24
15	Navsari	1.40	0.47	14	1.07	0.37	19
16	Panchmahals	2.01	0.72	6	2.13	0.79	7
17	Patan	1.06	0.33	22	1.09	0.37	18
18	Porbandar	0.34	0.03	25	0.33	0.08	25
19	Rajkot	1.99	0.72	7	2.29	0.85	5
20	Sabarkantha	2.45	0.91	4	2.53	0.94	3
21	Surat	2.40	0.89	5	2.11	0.78	8
22	Surendranagar	1.15	0.37	21	1.05	0.36	20
23	Tapi	0.95	0.29	23	0.79	0.26	23
24	The Dangs	0.26	0.00	26	0.13	0.00	26
25	Vadodara	2.45	0.91	3	2.50	0.93	4
26	Valsad	1.34	0.45	15	1.12	0.39	17

Table 14: Trends of Agricultural Efficiency Index

Districts	AEI	Rank	AEI	Rank
	2009-10		2019-20	
Ahmadabad	83.48	20	82.63	19
Amreli	68.31	22	100.06	10
Anand	128.17	3	91.43	14
Banas Kantha	117.10	8	88.62	16
Bharuch	96.78	18	85.49	18

Bhavnagar	117.94	7	100.55	8
Dang	51.87	24	34.72	26
Dahod	69.51	21	75.56	21
Gandhinagar	122.06	4	105.17	4
Jamnagar	132.02	1	108.54	2
Junagadh	114.03	11	92.17	13
Kachchh	130.57	2	77.76	20
Kheda	107.10	14	100.42	9
Mahesana	114.37	9	104.28	6
Narmada	120.62	6	95.01	11
Navsari	52.04	23	59.62	24
Panch Mahals	103.99	15	89.9	15
Patan	45.30	26	68.02	23
Porbandar	112.28	13	73.8	22
Rajkot	97.45	17	112.66	1
Sabar Kantha	102.04	16	93.76	12
Surat	114.02	12	102.48	7
Surendranagar	87.38	19	87.85	17
Tapi	114.19	10	104.76	5
Vadodara	121.59	5	108.42	3
Valsad	46.97	25	40.02	25