

Original Research Article

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

ABSTRACT

Background : : Gujarat is a diversified Agricultural Economy. The State agricultural economy has witnessed a shift towards high value crops like cotton, groundnuts, fruits, vegetables, condiments and spices from low value cereals and other crops. The Agricultural Growth table at 9.6% was catch the national wide attention, the one cause behind it was improvement in Agricultural infrastructure which leads to increase agricultural efficiency.

Method : To 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 efficiency at a disaggregated level in Gujarat.

Result : The revealed that 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 efficiency Index, Agricultural infrastructure Index, Principal Component Analysis (PCA),

INTRODUCTION

The indications are very suitable in the context of farmers of developing countries, in India, where the size of land holding primarily belongs to the small and marginal farmers, traditional cropping pattern and low productivity remains a momentous concern. As of now, 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 sect and it can aide in combating related issues. It leads to

raises adequate infrastructure. farm productivity, reduce farming costs and rapid development accelerates agricultural as well as economic growth rate country. 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) projected that a 1 percent increase in the stock of infrastructure will be increase 1per cent in GDP a in the country. For the enhancing agricultural technology. the level of physical and institutional infrastructure were significantly influences the spread of proven and demonstrated yield. 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 (Loksha and Mahesha, 2016; Loksha 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; Primary of these gaps found in the Agro-infrastructurel. Farmers face many farms decision related problems due to have little information on the kinds of crops should grow, how should be grow, what planning needs to do with respect to area and soil conditions, and the market infrastructure *etc.* With this, the other important slits included credit gap, productivity gap, marketing gap, price realization gap *etc.* Thus, the study identifies three broad parameters of agricultural infrastructure viz., economic infrastructure (ie.irrigation, electricity, transport and telecommunication *etc.*), institutional infrastructure (ie. agriculture Market, primary agriculture cooperative societies, banks *etc.*) and social infrastructure (ie. 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 the secondary data sources viz., Directorate of Economics & Statistics, Government of Gujarat, Land Use Statistics (LUS), Economics & Statistics Division, State Planning Institute, Government of Gujarat.

Agriculture Infrastructure Index (AII)

Agriculture Infrastructure Index (AII) includes three elements *i.e.*, economic, institutional and social infrastructure. These three parameters of infrastructure were estimated with help eleven indicators of infrastructure. These indicators were selected through the Principal Component Analysis (PCA) with help of Eigen value criterion and rotated component loading metrics . Table 1 represent the list of the parameters and its indicators.

the method of normalization was used, to calculate at standardized values of variables of agriculture infrastructure under studies. The indicators were normalised by using a mini-max normalisation method and transformed as follows:

$$I_{qd}^t = \frac{X_{qd}^t - \text{Min}_d(X_q^t)}{\text{Max}_d(X_q^t) - \text{Min}_d(X_q^t)}$$

Where $\text{Max}_d(X_q^t)$ and $-\text{Min}_d(X_q^t)$ are the maximum and the minimum values of X_{qd}^t across all the districts (d) of Gujarat at time t. The normalized indicators I_{qd}^t have values lying between 0 and 1. Means, the higher the values of I_{qd}^t ; shows the higher the district attainment in indicator q.

The PCA was 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). After that, the below mentioned equation was used to calculate the Agriculture Infrastructure Index (AII) for the all 26 districts of Gujarat from the year 2009-10 to 2019-20.

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

$$\text{With } \sum_{q=1}^Q w_q = 1 \text{ and } 0 \leq w_q \leq 1, \text{ for all } q = 1, 2, \dots, Q \text{ and } d = 1, 2, \dots, 26$$

Estimation of Agricultural Efficiency Index (AEI)

The estimation of agricultural efficiency as the output per unit area is based on per acre yields of crops was evolved by Kendal. The methodology of estimation of agricultural efficiency were given by several researchers ie. Kendal (1939), Shafi (1960), Khusro (1964), Sharma (1965), Bhatia (1967) and Singh (1979). But we applied Bhatia's method to estimate the agricultural efficiency.

The productivity of 14 major crops in the areal units were expressed as a percentage of the corresponding average productivity for the entire region is to obtain the indexes of productivity 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 as follows; This can be expressed:

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

Where, AEI_i is the agricultural efficiency index, $I_{ya}, I_{yb}, \dots, I_{yn}$, are the productivity/yield indexes of various crops, and C_a, C_b, \dots, 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

Normalization of Indicators

The normalization is required when the data is obtained in different measurement units to convert it into identical measures was the first step of constricting index, which convert the data on indicators of agricultural infrastructure in the same unit of measurement and in the specified 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). This method, minimum the 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. Then, the normalized data comes up within a limit of 0 to 1.

Principal Component Analysis

Principal component analysis of the normalized data is performed with the help of SPSS (version 20).

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

The Correlation matrix, Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy and Bartlett's Test of Sphericity are computed to test that whether present data is adequate for principal component analysis (PCA). It can be done by SPSS system (Kontokosta, 2014).

The PCA technique depends on the correlations between sets of variables. Hence, the correlation scores clarify that whether the PCA will be meaningful or not. If the correlations between individual variables are higher than 0.30 percent then the analysis gives the significant results. Even though, low scores of the correlations do not create problem. With the condition that the correlations score near to zero, the method lose its utility (Mooi and Sarstedt, 2011; Hoque, 2014). The correlation matrix is 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.

The Kaiser-Meyer-Olkin (KMO) statistic, a measure of the strength of relationship among variables, which indicates that the correlations between variables can be explained by other variables in the dataset or not. The data is considered appropriate for PCA application if KMO value is equal or higher than 0.50. In the study, the value of KMO was 0.681 and 0.734, shows that data is significantly suitable for the application of PCA.

The Bartlett's test is another indicator of judging that whether original variables are sufficiently correlated. The null hypothesis for the test was that the correlation matrix is an identity matrix, in which the diagonal elements are 1 and others are 0. It means that all variables are perfectly correlated with themselves but uncorrelated with others. Whereas, correlation matrix is not identity matrix then there is some degree of correlation between variables under study. To test the null hypothesis that all correlation coefficients are zero or not significant, chi-square statistic is computed under Bartlett test. From the table 2 and 3 shows that chi-square statistic was calculated 277.277 and 245.085 with 55 degrees of freedom with significant at 0.000 level of significance considered as accepted range of level of significance

(p-value) 0.05 for both years. Reject the null hypothesis that the variables are uncorrelated or correlation matrixes is 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 eigenvalues 3.758, 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, 23.761 per 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 Junagadh improve 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 13. 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 17thrank in 2009-10 to the 1strank 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:

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)	Total 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
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
		Fair price Shop (FPS)	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)

Comp onent	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumula tive %
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						
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Table 5: Eigenvalues (Initial and Rotated) and Components (2019-20)

Comp onent	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
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	Component			Component			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 13: 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
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