Available online at www.isas.org.in/jisas
JOURNAL OF THE INDIAN SOCIETY OF
AGRICULTURAL STATISTICS 66(2) 2012 335-342

Sensitivity Analysis of Various Indicators of Composite Index

Manoj Kumar[1], Tauqueer Ahmad[*2], Anil Rai[2] and Prachi Misra Sahoo[2]
[1]*Central Institute of Agricultural Engineering, Bhopal*
[2]*Indian Agricultural Statistics Research Institute, New Delhi*

Received 25 March 2010; Accepted 09 May 2012

SUMMARY

Sensitivity analysis is the study of how the given composite index depends upon the information fed into it. In this paper, methodological issues for sensitivity analysis of various indicators of composite index have been reviewed and sensitivity analysis using empirical method of variance-based technique has been proposed. The proposed method has been used for sensitivity analysis of indicators and sub indices of Agricultural Development Index (ADI) constructed for all 38 districts of Bihar State. Sensitivity analysis has also been carried out using a software namely SIMLAB, that is especially designed for sensitivity analysis. The results of sensitivity analysis using empirical method of variance-based technique have been compared with the results obtained using SIMLAB software. It has been observed that ADI was highly sensitive to Infrastructure index followed by Output index and Input index as per analysis using both the approaches.

Keywords : Indicator, Composite index, Sensitivity analysis, Variance-based technique.

1. INTRODUCTION

An indicator can be defined as a quantitative or a qualitative measure derived from a series of observed facts that can be used in ranking of performance in a given area. A composite index is formed when several indicators are compiled into a single index on the basis of an underlying model. Narain *et al*. (1991) constructed a composite index of development based on information on important indicators in major states of the country for estimating the potential targets for the underdeveloped states to bring equity in development. Parker (1991) developed environmental problem index by using public opinion as a weighting technique. Kumar (2008) constructed a composite index namely Agricultural Development Index (ADI) for Bihar State using Principal Component Analysis. Sensitivity analysis of the constructed indices has not been done so far in most of the situations. Sensitivity analysis is the study of how the variation in the output can be apportioned, qualitatively or quantitatively, to different sources of variation in the assumption, and of how the given composite indicator depends upon the information fed into it. The purpose of sensitivity analysis is to determine the relationship between uncertainties in independent variables and uncertainties in dependent variables used in an analysis. A sensitivity analysis can help to gauge the robustness of the composite indicator ranking, to increase its transparency and to identify, which districts as per present study are favoured or deteriorated under certain assumptions. Crosetto and Tarantola (2001) proposed uncertainty and sensitivity analysis as tools for GIS-based model implementation. Saltelli and Tarantola (2002) discussed the relative importance of input factors in mathematical models for safety assessment for nuclear waste disposal. Saltelli *et al.* (2000) proposed sensitivity analysis as an ingredient of modelling. A thorough discussion on sensitivity analysis was done by Saltelli *et al.* (2004).

[*] *Corresponding author :* Tauqueer Ahmad
E-mail address : tauqueer@iasri.res.in

There are several techniques available in literature for sensitivity analysis. When several layers of uncertainty are simultaneously present, composite indicators could become a non-linear, possibly non-additive model. As argued by research workers, for non-linear models, robust, "model-free" techniques should be used for sensitivity analysis. Sensitivity analysis using variance-based techniques is model free and displays additional properties convenient for the present analysis. Therefore, in this paper, sensitivity analysis using empirical method of variance-based technique has been proposed. The proposed method has been used for sensitivity analysis of indicators and sub indices of Agricultural Development Index (ADI) constructed for all 38 districts of Bihar State. Sensitivity analysis has also been carried out using a software namely SIMLAB, that is especially designed for sensitivity analysis. The results of sensitivity analysis using empirical method of variance-based technique have been compared with the results obtained using SIMLAB software.

2. EXISTING METHODS OF SENSITIVITY ANALYSIS

A number of techniques are available for sensitivity analysis. Scatter plots offer a qualitative measure of sensitivity. More quantitative measures of sensitivity like Standardized Regression Coefficient (SRC) are based on regression analysis and some sensitivity measures like Partial Correlation Coefficient (PCC) are based on correlation measures. The available techniques of sensitivity analysis are as under:

2.1 Scatter Plots

The generation of scatter plots is undoubtedly the simplest sensitivity analysis technique. This approach consists of generating plots of the points for each independent variable and dependent variable. Scatter plots offer a qualitative measure of sensitivity. Scatter plots may sometimes completely reveal the relationship between model input and model predictions; this is often the case when only one or two inputs dominate the outcome of the analysis. Further, they often reveal non-linear relationships, thresholds and variable interactions, so facilitating the understanding of the model behaviour.

One disadvantage of the method is that it needs generating and inspecting a large amount of plots: at least one per input factor possibly multiplied by the number of time points, if the output is time dependent. Further, scatter plots offer a qualitative measure of sensitivity.

2.2 Spearman Coefficient (SPEA)

Another simple measure of sensitivity is the Pearson product moment correlation coefficient (PEAR) which is the usual linear correlation coefficient computed on X_j; $j = 1, ..., k$ (k being the number of input variables) and Y (output variable). For non-linear models, the Spearman coefficient (SPEA) is preferred as a measure of correlation, which is essentially the same as PEAR, but using the ranks of both Y and X_j instead of the raw values *i.e.*

$$\text{SPEA}(Y, X_j) = \text{PEAR}(\text{R}(Y), \text{R}(X_j))$$

where R(·) indicates the transformation which substitutes the variable value with its rank.

The basic assumptions underlying the Spearman coefficient are:

(a) Both the Y and X_j are random samples from their respective populations.

(b) The measurement scale of both variables is at least ordinal.

2.3 Standardized Regression Coefficients (SRC)

More quantitative measures of sensitivity are based on regression analysis. A multivariate sample of the input x is generated by some sampling strategy (dimension $m \times k$), and the corresponding sequence of m output values is computed using the model under analysis. If a linear regression model is being sought, it takes the form

$$y_i = b_0 + \sum_j b_j x_{ij} + \varepsilon_i$$

where y_i, $i = 1, ..., m$ are the output values of the model, b_j; $j = 1, ..., k$ (k being the number of input variables) are coefficients that must be determined and ε_i is the error (residual) due to the approximation. One common way of determining the coefficients b_j is using the least square method. In this least square approach, b_j's are determined so that the function $F(b) = \sum_i \varepsilon_i^2$ is a minimum. Once, the b_j's are computed, they can be used to indicate the importance of individual input variables

x_j with respect to the uncertainty in the output y. In fact, assuming that b has been computed, the regression model can be rewritten as

$$(y_i - \bar{y})/\hat{s} = \sum_j (b_j \hat{s}_j / \hat{s})(x_j - \bar{x}_j)/\hat{s}$$

where
$$\hat{s} = \left[\sum_i (y_i - \bar{y})^2/(m-1)\right]^{1/2}$$

$$\hat{s}_j = \left[\sum_i (x_{ij} - \bar{x}_j)^2/(m-1)\right]^{1/2}$$

$$\bar{y} = \sum_i y_i/m$$

and
$$\bar{x}_j = \sum_i \bar{x}_{ij}/m$$

The coefficients $b_j \hat{s}_j/\hat{s}$ are called Standardized Regression Coefficients (SRC). These can be used for sensitivity analysis (when x_j are independent) as they can quantify the effect of varying each input variable away from its mean by a fixed fraction of its variance while maintaining all other variables at their expected values. Regression analysis often performs poorly when relationships between input variables are non-linear. The problem associated with poor linear fits to non-linear data can often be avoided with the use of the rank transformation. Standardized Rank Regression Coefficient (SRRC) are the SRC calculated in terms of $R(y_i)$ and $R(x_j)$.

2.4 Partial Correlation Coefficients (PCC)

Another interesting measure of variable importance is given as Partial Correlation Coefficients (PCC). These coefficients are based on the concepts of correlation and partial correlation. For a sequence of observations (X_{ij}, Y_i), the correlation $r_{x_j y}$ between the input variable X_j and the output Y is defined by

$$r_{x_j y} = \frac{\sum_i (x_{ij} - \bar{x}_j)(y_i - \bar{y})}{\left[\sum_i (x_{ij} - \bar{x}_j)^2\right]^{1/2} \left[\sum_i (y_i - \bar{y})^2\right]^{1/2}}$$

where $\bar{y} = \sum_i y_i/m$ and $\bar{x}_j = \sum_i x_{ij}/m.$

The correlation coefficient $r_{x_j y}$ provides a measure of the linear relationship between X_j and Y. The partial correlation coefficient between the output variable Y and the input variable X_j is obtained from the use of a sequence of regression models. First the following two models are constructed:

(i) $\hat{Y} = b_0 + \sum_{k \neq j} b_k x_k$

and (ii) $\hat{X} = c_0 + \sum_{k \neq j} c_k x_k$

Then, the results of these two regressions are used to define the new variables $Y - \hat{Y}$ and $X_j - \hat{X}_j$. The partial correlation coefficient between Y and X_j is defined as the correlation coefficient between $Y - \hat{Y}$ and $X_j - \hat{X}_j$. Thus, the partial correlation coefficients provide a measure of the strength of the linear relationship between two variables after a correction has been made for the linear effects of other variables in the analysis. The PCC can also be computed on the ranks giving the Partial Rank Correlation Coefficient (PRCC).

2.5 Morris Method

Morris method estimates the main effect of a factor by computing a number '*r*' of local measures, at different points x_1, x_2, ..., x_r in the input space, and taking their average (this reduces the dependence on the specific point that a local experiment has). These '*r* ' values are selected such that each factor varied over its interval of experimentation. Morris wishes to determine which factors have negligible effects, linear and additive effects, non-linear or interaction effects.

2.6 FAST Method

FAST is a method used to solve non-linear, non-monotonic problems that are also called non-linear sensitivity analysis. The FAST approach is based on performing numerical calculations to obtain the expected value and variance of a model prediction. The basis of this calculation is a transformation that converts a multidimensional integral over all the uncertain model inputs to a one-dimensional integral. There are also some variations of the basic FAST.

The analysis is divided into four steps: construction of ranges and distributions of the input factors and development of the expected value and variance of Y, transformation of the multidimensional integral, estimation of the expected value and variance of Y and sensitivity analysis. The FAST method can be used with a set of orthogonal factors.

2.7 Variance-based Method

Under this method, a variance based sensitivity measure for a given input factor X_i is computed by fixing factor X_i, e.g. to a specific value x_i^* in its range, and by computing the mean of the output Y averaging over all factors but factor X_i : $E_{X_{-i}}(Y \mid X_i = x_i^*)$. Then, the variance of the resulting function of x_i^* over all possible x_i^* values is taken.

$$V_i = V_{X_i}(E_{X_{-i}}(Y \mid X_i)) \quad (2.7.1)$$

Since, it is known that the following is always true:

$$V_{X_i}(E_{X_{-i}}(Y \mid X_i)) + E_{X_i}(V_{X_{-i}}(Y \mid X_i)) = V(Y) \quad (2.7.2)$$

where the first term of (2.7.2) is called a main effect, and the second one the residual. An important factor should have a small residual, i.e. a small value of $E_{X_i}(V_{X_{-i}}(Y \mid X_i))$. A first order sensitivity index, say S_i, is obtained by normalising the first-order term by the unconditional variance:

$$S_i = \frac{V_{X_i}(E_{X_{-i}}(Y \mid X_i))}{V(Y)} = \frac{V_i}{V(Y)} \quad (2.7.3)$$

One can compute conditional variances corresponding to more than one factor, e.g. for two factors X_i and X_j, the conditional variance would be $V_{X_i X_j}(E_{X_{-ij}}(Y \mid X_i, X_j))$, and the second-order term variance contribution would become:

$$V_{ij} = V_{X_i X_j}(E_{X_{-ij}}(Y \mid X_i, X_j)) - V_{X_i}(E_{X_{-i}}(Y \mid X_i)) - V_{X_j}(E_{X_{-j}}(Y \mid X_j)).$$

where clearly V_{ij} is different from zero only if $V_{X_i X_j}(E_{X_{-ij}}(Y \mid X_i, X_j))$ is larger than the sum of the first-order term relative to factors X_i and X_j. When all k factors are independent from one another, the sensitivity indices can be computed using the following decomposition formula for the total output variance $V(Y)$:

$$V(Y) = \sum_i V_i + \sum_i \sum_{j>i} V_{ij} + \sum_i \sum_{j>i} \sum_{\substack{l>j \\ j>i}} V_{ijl} + \ldots + V_{12\ldots k} \quad (2.7.4)$$

Terms above the first order (equation 2.7.4) are known as interactions. A model without interactions among its input factors is said to be additive. For a non-additive model, higher order sensitivity indices, responsible for interaction effects among sets of input factors, have to be computed. However, higher order sensitivity indices are usually not estimated, as in a model with k factors, the total number of indices (including the S_i's) that needs to be estimated would be as high as $2^k - 1$.

3. PROPOSED EMPIRICAL METHOD OF VARIANCE-BASED TECHNIQUE

When input factors (sub-indices or variables) are correlated, the method of FAST cannot be used for sensitivity analysis. Sensitivity analysis using variance-based techniques is model free and displays additional properties convenient for the present analysis. Thus, in this paper, an empirical variance-based technique has been proposed for sensitivity analysis.

Let, there are several independent variables X_i and one dependent variable Y in the model. In order to calculate sensitivity measure of variable X_i over Y, all values of X_i were arranged in ascending or descending order. The order of Y was also changed as per this arrangement. Then, averages of Y were calculated by taking two values at a time from top to bottom. The variance of these averages was calculated. This yielded $V_{X_i}(E_{X_{-i}}(Y \mid X_i))$. Then, variance of Y was calculated by taking all values of Y at a time, which yielded $V(Y)$. Thus, first order sensitivity measure of a variable over sub index or sub index over composite index was obtained as

$$S_i = \frac{V_{X_i}(E_{X_{-i}}(Y \mid X_i))}{V(Y)} = \frac{V_i}{V(Y)} \quad (3.1)$$

4. ILLUSTRATION

A method of construction of composite index using Principal Component Analysis (PCA) was proposed by Kumar (2008). The proposed method was used for construction of Agricultural Development Index (ADI) and was illustrated with the data of all 38 districts of

Bihar State. The data on many variables in each district of the State were utilized for construction of ADI. The ADI for each districts of Bihar was constructed on the basis of three sub indices, each based on several variables. The three sub indices chosen were Input Index, Output Index and Infrastructure Index. First of all Input Index, Output Index and Infrastructure Index were constructed based on Input variables, Output variables and Infrastructure variables respectively using PCA. These three sub indices were combined to form a composite index (ADI) for each district of Bihar.

The variables, on which secondary data for construction of input index for all districts of Bihar was obtained, were (a) Number of agricultural workers per thousand hectare of cultivated area (NAWPTHCA), (b) Irrigation intensity (II), (c) Fertilizer intensity (FI), (d) Cropping intensity (CI) and (e) Number of tractors per thousand hectare of cultivated area (NTPTHCA).

The variables, on which secondary data for construction of output index for all districts of Bihar was obtained, were (a) Productivity of rice in ton per hectare, (b) Productivity of wheat in ton per hectare, (c) Productivity of maize in ton per hectare, (d) Productivity of pulses in ton per hectare, (e) Productivity of oilseeds in ton per hectare, (f) Productivity of mango in ton per hectare, (g) Productivity of banana in ton per hectare, (h) Productivity of guava in ton per hectare, (i) Productivity of potato in ton per hectare and (j) Productivity of cauliflower in ton per hectare.

The variables, on which secondary data for construction of infrastructure index for all districts of Bihar was obtained, were (a) Number of health centres per thousand villages (NHCPTV), (b) Number of post offices per thousand villages (NPPTV), (c) Number of diesel engines per thousand hectare of cultivated area (NDEPTHCA), (d) Number of villages with paved road per thousand villages (NVPRPTV) and (e) Number of banks per thousand villages (NBPTV).

Sensitivity analysis of Output, Input and Infrastructure indices over ADI was calculated using the proposed empirical variance-based technique. First of all, first order sensitivity measure of input index over ADI was calculated. First order sensitivity measures of output and Infrastructure indices over ADI were also calculated using empirical method discussed as above. The calculated values are presented in the Table 1.

Table 1. First order sensitivity measures of input, output and infrastructure indices over ADI

Factors	Sensitivity
Infrastructure index	0.938
Output index	0.818
Input index	0.805

Similarly, first order sensitivity measures of input variables, output variables and infrastructure variables over input index, output index and infrastructure index were calculated and are presented in the Tables 2, 3 and 4 respectively.

Table 2. Sensitivity measures of input variables over input index

Input variables	Sensitivity
CI	0.83
NAWPTHCA	0.77
I I	0.66
NTPTHCA	0.64
FI	0.61

Table 3. Sensitivity measures of output variables over output index

Output variables	Sensitivity
Mango (ton/ha)	0.94
Guava (ton/ha)	0.92
Banana (ton/ha)	0.82
Maize (ton/ha)	0.78
Rice (ton/ha)	0.72
Pulses (ton/ha)	0.71
Cauliflower (ton/ha)	0.69
Wheat (ton/ha)	0.66
Potato (ton/ha)	0.55
Oilseeds (ton/ha)	0.54

Table 4. Sensitivity measures of infrastructure variables over infrastructure index

Infrastructure variables	Sensitivity
NPPTV	0.86
NBPTV	0.83
NHCPTV	0.68
NVPRPTV	0.65
NDEPTHCA	0.49

5. SENSITIVITY ANALYSIS USING SIMLAB SOFTWARE

Sensitivity analysis can also be carried out using software, SIMLAB (Saltelli *et al.* 2004). SIMLAB 2.2 is a software designed for Monte Carlo based uncertainty and sensitivity analysis. Monte Carlo (MC) methods are used here for pseudo random number generation with emphasis on sampling set of points from joint probability distributions; the designation "sample distribution" is often used.

In general, a Monte Carlo analysis involves the following five steps:

(i) In the first step, range and distribution are obtained for each input variable (input factor). These are used in the next step in the generation of a sample from the input factors. If the analysis is primarily of an exploratory nature, then quite rough distribution assumptions may be adequate.

(ii) In the second step, a sample of points is generated using the distribution of the inputs specified in the first step. The result of this step is a sequence of sample elements. There are many sample generation methods available in Simlab. The sampling generation techniques available in SIMLSB are (a) FAST, (b) Fixed sampling, (c) Latin Hypercube Sampling (LHS), (d) Morris, (e) Random sampling, (f) Replicated Latin Hypercube Sampling (r-LHS) and (g) Sobol.

(iii) In the third step, the model is fed with the sample elements and a set of model outputs is produced. In essence, these model evaluations create a mapping from the space of the inputs to the space of the results. This mapping is the basis for subsequent sensitivity analysis.

(iv) In the fourth step, the results of model evaluations are used as the basis for sensitivity analysis. Under LHS, the sensitivity measures like Partial Correlation Coefficient (PCC), Standardised Regression Coefficient (SRC) and Pearson product moment correlation coefficient (PEAR) are based upon regression analysis. PRCC is rank transformation of PCC.

Accordingly, in order to compute the sensitivity measures of ADI variables i.e. input, output and infrastructure index over ADI, the following information were fed in SIMLAB:

(a) It is known that the ADI was constructed by combining Input, Output and Infrastructure indices. It was found that Input, Output and Infrastructure indices follow Normal distribution with mean '0' and variance '1'. In the first step, the distribution and their parameter estimates for each ADI variables along with obtained correlation matrix of ADI variables while constructing ADI were inputted in SIMLAB.

(b) In the second step, Latin Hypercube Sampling (LHS) was selected as sample generation method. A sample of size 1000 was generated giving the seed value = 23657.

(c) In the third step, the model was specified. Since, ADI was constructed by combining Input, Output and Infrastructure indices, the composite index (CI) constructed using the obtained eigenvalues of variables and principal components is given by

$$\mathrm{CI}_i = \frac{\lambda_1 P_1 + \lambda_2 P_2 + \lambda_3 P_3}{\sum_{j=1}^{3} \lambda_j} \tag{5.1}$$

where CI_i is composite index for i^{th} district, $\lambda_j s$ are eigen values and P_qs are principal components, $i = 1, 2, ..., 38$; $j = 1, 2, 3$; $q = 1, 2, 3$ and

$$P_1 = a_{11}Z_1 + a_{12}Z_2 + a_{13}Z_3$$
$$P_2 = a_{21}Z_1 + a_{22}Z_2 + a_{23}Z_3$$
$$P_3 = a_{31}Z_1 + a_{32}Z_2 + a_{33}Z_3$$

where $Z_q s$ are standardized values of sub index and a_{kq} is an element belonging to k^{th} eigenvector and for q^{th} sub index, $k = 1, 2, 3$; $q = 1, 2, 3$.

Equation (5.1) can be written as

$$\mathrm{CI}_i = \frac{(\lambda_1 a_{11} + \lambda_2 a_{21} + \lambda_3 a_{31})Z_1}{\sum_{j=1}^{3} \lambda_j} + \frac{(\lambda_1 a_{12} + \lambda_2 a_{22} + \lambda_3 a_{32})Z_2}{\sum_{j=1}^{3} \lambda_j} + \frac{(\lambda_1 a_{13} + \lambda_2 a_{23} + \lambda_3 a_{33})Z_3}{\sum_{j=1}^{3} \lambda_j} \tag{5.2}$$

Since, ADI is a composite index, the model is given by

$$ADI_i = C_1Z_1 + C_2Z_2 + C_3Z_3 \quad (5.3)$$

where C_1, C_2 and C_3 are coefficients of Z_1 (Input index), Z_2 (Output index) and Z_3 (Infrastructure index) respectively in Equation (5.2). The calculated value of C_1, C_2 and C_3 were found to be 0.387, 0.179 and 0.516 respectively. Finally, the model given below was fed in SIMLAB:

$$ADI_i = 0.387*Z_1+0.179*Z_2+0.516*Z_3 \quad (5.4)$$

(d) In the fourth step, the SIMLAB software was run after feeding all the above information. Sensitivity analysis was also carried out by taking different sample sizes i.e. 500, 1000 and 2000 but yielded approximately identical results. Therefore, it can be concluded that the selected LHS method works well for sample size greater than 500. Hence, for the sensitivity analysis under the present study, the sample size for generation of sample using LHS was 500. Under LHS, PRCC (Partial Rank Correlation Coefficient) was selected as a measure of sensitivity.

First order sensitivity measures of Output, Input and Infrastructure indices over ADI were calculated and are presented in the Table 5.

Table 5. Sensitivity measures of input, output and infrastructure indices over ADI

Factors	Sensitivity
Infrastructure index	0.96
Output index	0.93
Input index	0.77

Similarly, first order sensitivity measures of input variables, output variables and infrastructure variables over input index, output index and infrastructure index were calculated and are presented in the Tables 6, 7 and 8 respectively.

Table 6. Sensitivity measures of Input variables over Input index

Input Variables	Sensitivity
CI	0.89
NAWPTHCA	0.75
I I	0.57
NTPTHCA	0.45
FI	0.13

Table 7. Sensitivity measures of Output variables over Output index

Output variables	Sensitivity
Guava (ton/ha)	0.88
Mango (ton/ha)	0.85
Banana (ton/ha)	0.80
Cauliflower (ton/ha)	0.70
Maize (ton/ha)	0.59
Potato (ton/ha)	0.49
Rice (ton/ha)	0.44
Pulses (ton/ha)	0.30
Oilseeds (ton/ha)	0.19
Wheat (ton/ha)	0.17

Table 8. Sensitivity measures of Infrastructure variables over Infrastructure index

Infrastructure Variables	Sensitivity
NPPTV	0.83
NBPTV	0.76
NVPRPTV	0.69
NHCPTV	0.67
NDEPTHCA	0.16

6. DISCUSSION

It can be observed from the Tables 1 and 5 that sensitivity of Infrastructure Index over ADI was more in comparison to Output Index and Input Index using empirical method of variance-based technique as well as using SIMLAB software. Therefore, it can be concluded that a change in Infrastructure Index will affect ADI more in comparison to Output Index and Input Index i.e. Infrastructure Index will affect the ranking of districts more rapidly. Similarly, it can be inferred that Output Index affects the ranking of districts more in comparison to Input Index.

The results presented in the Tables 2, 4 and 6, 8 reveal that Input index was highly sensitive to the input variables like Cropping Intensity (CI) and Number of Agricultural Workers per Thousand Hectare of Cultivated Area (NAWPTHCA) but less sensitive to Fertilizer Intensity (FI) whereas, Infrastructure Index was highly sensitive to the infrastructure variables namely, Number of Post Offices per Thousand Villages (NPPTV) and Number of Banks per Thousand Villages

(NBPTV) but less sensitive to Number of Diesel Engines per Thousand Hectare of Cultivated Area (NDEPTHCA) using both the approaches.

It can be observed from the Tables 3 and 7 that the Output Index was highly sensitive to the productivity of fruits (Mango, Guava and Banana) and was very less sensitive to the productivity of Cauliflower, Wheat, Potato and Oilseeds using empirical method of variance-based technique but the Output Index was highly sensitive to the productivity of fruits (Guava, Mango and Banana) but less sensitive to the productivity of Oilseeds and Wheat using SIMLAB software.

Accordingly, it was observed that the results of sensitivity analysis using empirical method of variance-based technique were at par with the results using SIMLAB software.

7. CONCLUSIONS

In this paper, methodological issues for sensitivity analysis of various indicators of composite index have been reviewed and sensitivity analysis using empirical method of variance-based technique has been proposed. The proposed method has been used for sensitivity analysis of various indicators and sub indices of Agricultural Development Index (ADI) constructed for all 38 districts of Bihar State. Sensitivity analysis has also been carried out using SIMLAB software. The results of sensitivity analysis using empirical method of variance-based technique have been compared with the results obtained using SIMLAB software and the results were found to be at par with each other using both the approaches. It has been observed that ADI was highly sensitive to Infrastructure index followed by Output index and Input index as per analysis using both the approaches.

REFERENCES

Crosetto, M. and Tarantola, S. (2001). Uncertainty and sensitivity analysis: tools for GIS-based model implementation. *Int. J. Geogr. Inf. Sc.*, **15(5)**, 415-437.

Kumar, M. (2008). *A study on development indices and their sensitivity analysis*. M.Sc. Thesis, IARI, New Delhi.

Narain, P., Rai, S.C. and Sarup, S. (1991). Statistical evaluation of development on socio-economic front. *J. Ind. Soc. Agril. Statist.,* **43(3)**, 329-345.

Parker, J. (1991). *Environmental reporting and environmental indices*. Ph.D. Dissertation, Cambridge, UK.

Saltelli, A. and Tarantola, S. (2002). On the relative importance of input factors in mathematical models: safety assessment for nuclear waste disposal. *J. Amer. Statist. Assoc.*, **97(459)**, 702-709.

Saltelli, A., Tarantola, S. and Campolongo, F. (2000b). Sensitivity analysis as an ingredient of modelling. *Statist. Sci.*, **15(4)**, 377-395.

Saltelli, A., Tarantola, S., Campolongo, F. and Ratto, M. (2004). *Sensitivity Analysis in Practice: A Guide to Assessing Scientific Models*. John Wiley & Sons, New York.