Uncertainty and Sensitivity Analysis: Robustness check for Vulnerability to Food Insecurity Index

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Abstract

This paper systematically evaluates the effect of some methodological or assumptions on the robustness of Vulnerability to Food Insecurity Index. The focus was to examine how data type, weight scheme, normalisation method and exclusion/inclusion of variable affect the model of the index using uncertainty and sensitivity analysis. The paper used two approaches: One-at-a-time and global sensitivity approach for the analysis. Using one-at-a-time approach, we explore how the VFII output response to different weighting scheme, normalisation method and inclusion/exclusion of variable. For the global approach, we used Sobol' first-order index and total effect index to explore the uncertainty and sensitivity of VFII. The result of the robustness analysis indicated that VFII performance is stable to changes in the variables and normalisation method when equal weight is applied. Using the min-max normalisation method produces a highly robust estimate. The shock variable was the primary input factor that influences the variation in the output of the VFII. This implies that the VFII is highly sensitive to shocks, therefore better capturing the vulnerability component of food security.

Keywords: Food security, vulnerability, food vulnerability index, sensitivity, robustness, first-order, total-effect

1.0 Introduction

Several assumptions have been used to construct the Vulnerability to Food Insecurity Index (VFII). Notably assumptions in the selection of indicators, the normalisation of indicators, the weighting of the indicators, the aggregation method used, and categorising the index. These assumptions can have a significant impact on the output and reliability of the Vulnerability to Food Insecurity Index. Therefore, sensitivity and uncertainty analysis are needed to establish the robustness of the methodology and the assumptions made in the construction of the VFII (Esty et al., 2006). We will also use sensitivity and uncertainty analysis to test if a useful conclusion can be made from Vulnerability to Food Insecurity Index. The sensitivity analysis will numerically quantify how variation or uncertainty in the VFII output can be apportioned to diverse sources in model input while the uncertainty analysis will focus on quantifying the uncertainty in the VFII output only (Saltelli, 2017). The accuracy and precision of the VFII depend on the following factors: the computational method for estimating missing data, the mechanism for inclusion and exclusion of variables, the transformation of variables when constructing the index, type of normalisation method, amount of missing data, weighting scheme adopted, the level and choice of aggregation method used. Using uncertainty and sensitivity analysis this research will systematically evaluate the effect of some of the above methodological processes on the robustness of the Vulnerability to Food Insecurity Index scoring and ranking. The following questions will be investigated:

1. How does the output of the VFII rank compare to different assumptions?
2. What is the major source of uncertainty in the VFII ranking?
3. What are the most influential input factors that cause this uncertainty in VFII ranking?

We use two main approaches to conduct uncertainty and sensitivity analysis namely: One-at-at-time (OAT) and global sensitivity analysis approach. Using one-at-time approach, we change one assumption or factor at a time and then compare the output. We use OAT to carry out only uncertainty analysis for some assumptions because it was the most suitable method to used base on our model. Although the uncertainty analysis using the OAT approach is criticised as being non-conservative (Saltelli,2007). Global sensitivity approach is widely preferred in literature because it explores the entire effect of each factor or assumptions on the model output and numerically quantifies the effect of different source of uncertainty in the model input (Saltelli et al., 2004).

This paper is organised into sections. The next section (section 2) presents a thorough discussion on the research methodology applied. Section three discusses the result/insight from findings and section four present the conclusion.

2.0 Methodology

2.1 Structure of Vulnerability to Food Insecurity Index

The VFII is a mathematical model derived from contextual vulnerability concept. The contextual approach, view's household vulnerability as a multidisciplinary system consisting of the biophysical and socio-economic environment (Fellmann, 2012). These two-system interaction influences household food vulnerability. Using the vulnerability lens to unpack the meaning and operationalise vulnerability measurement regarding food security. We discovered that vulnerability has three main components (Cardona et al., 2012; IPPC, 2007). These components are the exposure, sensitivity and adaptive capacity. In this paper, we define exposure as those food-related shocks that affect households access to safe and nutritious food. Using the theme derived from conceptual vulnerability, that household vulnerability is affected by its socio-economic and biophysical condition; we selected indicators and variables for the exposure component (Fellmann, 2012; Adger, 2006). The sensitivity component of our VFII represents the previous or accumulative experience of food insecurity within the household such as stunting, child mortality and hunger (Hahn et al., 2009a). Household ability to successfully adjust to the effect of food shocks using the livelihoods assets means that they have strong adaptive capacity (Woller et al., 2013). Households with a strong and more liquid livelihood asset will be less vulnerable to food insecurity. We used this conceptual underpinning to select the indicators and variable for the VFII, shown in Figure 1. A summary of indicators and variables are presented in Table 1. More detail information about these indicators are included in the appendix (see Appendix VII)

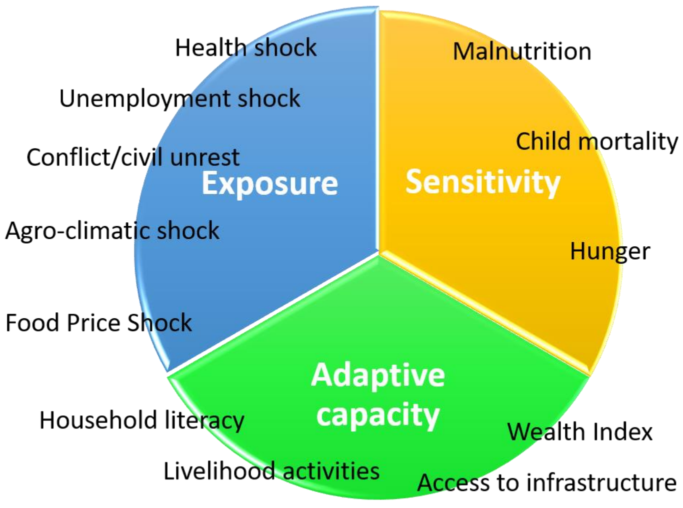

Figure 1: Vulnerability to Food Insecurity Index components and indicators

Table 1: Indicators and variables used for the Vulnerability to Food Insecurity Index

Index Dimension	**Indicators**	**Description of variables**
Exposure *(probability of covariate shocks occurring)*	Health shock	Illness of income earning member
	Unemployment shock	Job loss
	Civil conflict shock	Theft of crops, cash, livestock or other
		Kidnapping/Hijacking/robbery/assault
	Agro-climatic shock	Poor rain that caused harvest failure
		Flooding that caused harvest failure
	Food price shock	Increase in price of major food items consumed
Sensitivity *Previous/accumulative experience of food insecurity*	Malnutrition	Length/height-for-age (stunting)
	Child mortality	Total number of children dead in each household
	Hunger	Total number of days' households gone without eating any food.
Adaptive Capacity *how household respond, exploit opportunities, resist or recover from food insecurity shocks*	Wealth Index	Household assets used to assess information
		Mobility assets used in households
		Livelihood assets own by households
		Housing structure characteristics
	Access to infrastructure	Household distance to nearest major road (km).
		Household distance to nearest market (km).
		Time taken to walk one way to the water source from household dwelling (minutes).
	Livelihood activities	Total income from savings, rental of properties and other types of income.
		Estimated revenue from non-farm enterprises
		Total yield of crops harvested (kg)
	Household literacy	Cumulative years of schooling for household heads or closest individual in the household.

Note: The Closest individual is the next individual in the household if education is missing for the household head, who has the highest level of education, and at least five years of schooling. If educational qualifications are the same for more than one individual, the most senior individual in age is used.

2.1.1 Construction of the VFII

We developed a conceptual framework and selected indicators for the index (see Figure 1). Then we generated weight, either PCA or equal weight for variables and then each component of VFII; normalised these variables using either min-max or z-score method (see equation 3 and 4) and used the aggregation formula in equation (1) to generate the index scores (OECD, 2008).

$$VFII_i = \sum AC_i - \left(\sum E_i + \sum S_i\right) \qquad (1)$$

Where $VFII_i$ is the score for Vulnerability to Food Insecurity Index for i household, AC_i is adaptive capacity, E_i is exposure and S_i is sensitivity. The $VFII_i$ score are then used to rank and categorize household vulnerability to food security. The higher values, the more households are less the vulnerable to food insecurity.

2.2 Data Source

The dataset used for this research is the General Household Survey Panel (GHS-Panel), which is a Living Standard Measurement Study (LSMS) survey from the World Bank. The dataset contains a panel component (GHS-Panel) which is a randomly selected sub-sample of 5,000 households from a cross-sectional survey of 22,000 households carried out annually throughout the country. The dataset contains information on human capital, economic activities, access to services and resources, food security and additional information on agricultural activities and household's consumption is collected from the panel households. The GHS-Panel has two waves: the first wave (2010-2011) and second wave (2012-2013). In each wave, visits are carried out within two periods to panel households. The first period is the post-planting visit in August-October 2010 (wave 1) while September - November 2012 (for wave 2) and the second period is the post-harvest visit in February-April 2011 & 2013 for both waves respectively. A onetime visit is carried out for the cross-section along with the post-harvest visit to the panel households (NBS, 2015; NBS and LSMS, 2015; World-Bank and NBS, 2015; World-Bank and NBS, 2014; Corral et al., 2015).

2.3 Normalization and Weighting Method

The normalisation method used in the construction of Vulnerability to Food Insecurity Index (VFII) variables are based on the Min-Max (equation 3) or standardise (equation 4) value method. Consider the $VFII$ value of selected states in Nigeria $c, c = 1, \dots . . M$,

$$VFII_c = f_{rs}\left(I_{1,c}, I_{2,c}, \dots I_{Q,c}, w_{s,1}, w_{s,2,}, \dots . w_{s,Q}\right), \dots \dots \dots \dots (2)$$

$$where \begin{cases} I_{q,c} = \dfrac{x_{q,c} - min(x_q)}{range(x_q)} \dots \dots \dots \dots \dots \dots (3) \\ I_{q,c} = \dfrac{x_{q,c} - mean(x_q)}{std(x_q)} \dots \dots \dots \dots . . . (4) \end{cases}$$

The weighing method f_{rs}, where the index r refer to the linear aggregation scheme used, and index s refers to the weighting scheme (PCA weight and equal weights). The index is based on Q normalised individual indicators $I_{1,c}, I_{2,c}, \dots I_{Q,c}$ for states in Nigeria and scheme-dependent weights $w_{s,1}, w_{s,2,}, \dots . w_{s,Q}$ for the individual indicators. $I_{Q,c}$ is the normalised and $x_{q,c}$ is the raw value of the individual indicator x_q for states in Nigeria.

2.4 Uncertainty and sensitivity analysis model

We used two approaches to carry out our uncertainty and sensitivity analysis, namely one-at-a-time and global sensitivity approach. The methods adopted from these approaches are explained in this section.

2.4.1 One-at-a-time-approach

This approach tests the effect of a single input or factor on the output one at a time. We used this method to test the performance of the VFII on different weighting method, normalisation method and excluding/including a variable. We applied two types of data in this approach for comparison purpose and to test the robustness of our VFII. Using dataset with missing or incomplete observations and data set that had complete observation. To get a complete data, we used multiple imputation method, running a multiple regression with observable household characteristics variables to impute those variables that had missing data.

2.4.2 Uncertainty analysis

To know the primary source of variability in the ranking of states by the VFII, we carried out an uncertainty analysis. This focus on quantifying uncertainty in the model output (Saltelli et al., 2008). We investigated the difference between the output ($VFII_{BE}$) of two states (Bayelsa and Edo state) composite score as shown in the equation 5.

$$VFII_{BE} = \left(VFII_{Edo\ state} - VFII_{Bayelsa\ state} \right) \qquad (5)$$

In the first step, we must ascertain the presence of uncertainty in the input factors used to produce the output in equation 2 and equation 5. Our main area interest will be on the following assumptions that can introduce uncertainty in our output variables:

a. The selection of variables
b. The normalisation method
c. The weighting schemes
d. Exclusion and inclusion of variable(s)

The input factors defined as everything that causes a variation or uncertainty in the output of the model (Saltelli et al., 2008), is presented in Table 2. These are 12 weighted variables with their probability distribution function (PDF). Also included are additional three trigger variables to represent the type of normalisation (either min-max or z-score), weighting scheme (equal or unequal (PCA) weight) and exclusion or inclusion of variable (either child mortality or distance-to-water-source).

We use the Global approach to perform the uncertainty analysis (Saltelli, 2017). Using Monte Carlo analysis, which is based on using the probabilistic value of the model input to estimate multiple model evaluations and then using these evaluations to determine (1) the uncertainty in the model prediction and (2) the input factors that caused the uncertainty. We followed the following procedures as laid out by (Saltelli et al., 2004; Saltelli et al., 2008):

I. Determine the probability distribution function (mean and standard deviation see table in Appendix VI) of each input factor parameters. X_1, X_2, and X_3 are triggers to select the weighting method, normalization method and variables excluded or included.
II. From each of these input factors, we produce a set of row vectors in such a that the vectors are sampled from the PDF of input factor parameter.
III. Then we compute the model for all vectors, thereby producing a set of N values for the model output in equation 1 and 5.
IV. From these, we can now compute the average output, standard deviation, quartiles distribution, confidence bounds and plot these distributions.
V. To compute the number of simulation for a model with k factors, only $N(k+2)$ model runs were needed. Where k is the total number of input factors and N =1024 is quasi-random sample scheme (Sobol', 1967).

Table 2: Uncertainty input factor probability distribution function

Input factor	Description	PDF	Range
SH	Weighted shock	Normal	-
CM	Weighted child mortality	Normal	-
ST	Weighted stunting	Normal	-
HU	Weighted hunger	Normal	-
WI	Weighted wealth index	Normal	-
DR	Weighted distance-to-road	Normal	-
DM	Weighted distance-to-market	Normal	-
DW	Weighted distance-to-water	Normal	-
IS	Weighted income-savings	Normal	-
NI	Weighted non-farm-income	Normal	-
CY	Weighted crop yield	Normal	-
HL	Weighted household literacy	Normal	-
X_1	Weighting method (either equal weight or unequal (PCA) weight	Discrete	[0,1] where [0,0.5] =equal weights and (0.5,1] =PCA weight
X_2,	Normalization method (min-max or z-score values)	Discrete	[0,1] where [0,0.5] =min-max and (0.5,1] = z-score
X_3	Inclusion-Exclusion (either excluding child mortality and distance-to-water source or including child mortality and excluding distance-to-water-source	Discrete	[0,1] where [0,0.5] = excluding child mortality and distance-to-water source and (1, 0.5] = including child mortality and excluding distance-to-water-source

2.4.3 Sensitivity analysis

We applied the variance-based sensitivity method for our analysis. We are looking at how the overall uncertainty in the input factors affects the output rather than testing one input at a time. Using the variance-based sensitivity method we can decompose the uncertainty in input factors according to their variance and show how output depends on this variance (Saisana et al., 2005; Saltelli et al., 2008). Our primary objective is to look for those factors or groups of factors that when fixed to it true value will reduce the variance of VFII. The reduction in the output variance is highly desirable, and this will mean that the VFII is reliable and robust. We used Sobol' sensitivity indices (Sobol', 1996), which are the first-order and total effect sensitivity indices for our sensitivity analysis.

First-order sensitivity Index

The sensitivity index of an input factor X_i can be measure by comparing the contribution of it variance to a model output due to uncertainty in X_i (Saisana et al., 2005). Looking at the generic model in equation 6.

$$Y = f(X_1, X_2, \ldots., X_k) \qquad (6)$$

Each X in equation 6 has a certainty degree of uncertainty or variation, we want to determine what will happen to the uncertainty of Y if we could fix an input factor. Assuming a fixed factor X_i, at any value be x_i^*. This result to the conditional variance depending on X_i which is be fixed to x_i^*. Let $V_{X_{-i}}(Y|X_i = x_i^*)$, which is the resulting variance of Y taken over by all other factors except X_i. There are two problems to this approach: (1) it is impractical because the sensitivity measure will depend on the position of the point x_i^* and (2) the conditional variance will be greater than the unconditional variance. Instead of taking sensitivity measure at a fixed point, we rather take average of all possible points x_i^*. Then the dependence on x_i^* will be remove. Rewriting this as $E_{X_i}(V_{X_{-i}}(Y|X_i))$. This is always lower or equal to output variance $V(Y)$, and

$$E_{X_i}\left(V_{X_{-i}}(Y|X_i)\right) + V_{X_i}\left(E_{X_{-i}}(Y|X_i)\right) = V(Y) \qquad (6.1)$$

A small $E_{X_i}\left(V_{X_{-i}}(Y|X_i)\right)$, or a large $V_{X_i}\left(E_{X_{-i}}(Y|X_i)\right)$, will imply that X_i is an important factor. The conditional variance $V_{X_i}\left(E_{X_{-i}}(Y|X_i)\right)$ is called the first-order effect of X_i on Y and the sensitivity measure:

$$S_i = \frac{V_{X_i}\left(E_{X_{-i}}(Y|X_i)\right)}{V(Y)} \qquad (6.2)$$

S_i is known as the first-order sensitivity index. S_i is a number that ranges between 0 and 1. A higher value denote an important variable. It represent the main effect contribution of each input to the output variance singly (Homma and Saltelli, 1996). When a model first-order term do not add up to one such model is called nonadditive model $(i.e. \sum_{i=1}^{r} S_i \le 1)$. Alternatively, first-order term add up to one or equal to one, such a model is an additive model (Saltelli et al., 2008).

Total-effect sensitivity index

First-order sensitivity index measures the effect of individual input on the variance of the output not considering the interaction. Thus, total effect index account for the total contribution to the output variation due to factor X_i. It is the combination of first-order effect and higher-order effect due to interactions.

Total effect can be computed by decomposing unconditional variance into main effect and residual:

$$V(Y) = V\big(E(Y|X_i)\big) + E\big(V(Y|X_i)\big) \qquad (6.3)$$

Alternatively, total effect can be computed by decomposing the output variance into the main effect and residual, conditioning this with time with respect to all factors but one, i.e $X_{\sim i}$:

$$V(Y) = V\big(E(Y|X_{-i})\big) + E\big(V(Y|X_{-i})\big) \qquad (6.4)$$

The measure $V(Y) - V\big(E(Y|X_{-i})\big) = E\big(V(Y|X_{-i})\big)$ is remaining variance of Y that would be left, on average, if $X_{\sim i}$ true values could be determine" (Saltelli et al., 2008). $X_{\sim i}$ are uncertainty input factors and their true values are unknown. To obtain the total effect index for X_i, we divide by $V(Y)$:

$$S_{T_i} = \frac{E\big(V(Y|X_{-i})\big)}{V(Y)} = 1 - \frac{V\big(E(Y|X_{-i})\big)}{V(Y)} \qquad (6.5)$$

Total effect index (S_{T_i}) provide an answer to the question: "which factor can be fixed anywhere over its range of variability without affecting the output?" If $S_{T_i} = 0$, this means X_i has meet the condition of not being an influential factor. If $X_i \cong 0$, then X_i can be fixed at any range without affecting value of the output variance $V(Y)$ (Tarantola et al., 2007).

3.0 Result and Discussion

The primary results presented in this section are guided by the questions raised in section 1.0. This section using the methods described earlier in section 2.0 present the results and the discussion.

3.1 How do the VFII ranks compare under different weighting schemes, the normalisation method, and data types?

This section uses one-at-a-time approach to explore the sensitivity of the index to changes in data type, normalisation method, weighting scheme and exclusion and the inclusion of variable.

3.1.1 Using Unequal Weight

Using principal component analysis, we estimated the weights for each variable used to design the Vulnerability to Food Insecurity Index (VFII) (see Appendix V, for unequal weight). PCA gave each component of the index different weight. Weight for exposure, sensitivity and adaptive capacity was 0.0871, -0.5645and 1.1322 respectively. Using these weights, we estimated the VFII score for each state using variables with missing data and variable with imputed data. In each scenario, we applied two type of normalisation method (min-max or z-score method). The results are shown in Table 3 and Figure 2. These shows that irrespective of the data type or normalisation method applied, the VFII produces inconsistence ranking of states in South-South region of Nigeria when unequal weight is applied. The level of inconsistencies in ranking was higher when using missing data to estimate the VFII (Table 3). Only Cross River State maintain the same ranking while other states are ranked differently. The implication of using unequal weight means that it does produce a biased estimate of each state performance in terms of food security and vulnerability. This is because of how the VFII component was constructed. The sensitivity and adaptive capacity component have more than one variables compared to the exposure component. Due to data used in designing the index, all the variables in the exposure component were aggregated into one variable, and this made it have a lesser weight compared to another component.

To test the robustness of different VFII specification as shown in Table 4, we computed their pairwise correlation coefficient. Table 4 shows that all the correlation coefficients were significant at 5% level and most relationships were negatively correlated. Only the combination of VFII with missing data and different normalisation method; and VFII with complete data and different normalisation method had a positive correlation coefficient of 0.85 and 0.69 respectively. With a negative correlation coefficient, we cannot conclude that using PCA weight or unequal with the index can produce a robust estimate.

Table 3: VFII ranking of states in South-South region of Nigeria using unequal weight and different normalisation methods

States	VFII_missing-min-max	VFII_missing-z-score	VFII_complete-min-max	VFII_complete-z-score
Akwa Ibom	4	5	4	5
Bayelsa	3	1	1	1
Cross River	6	6	3	2
Delta	2	2	5	4
Edo	5	3	2	3
Rivers	1	4	6	6

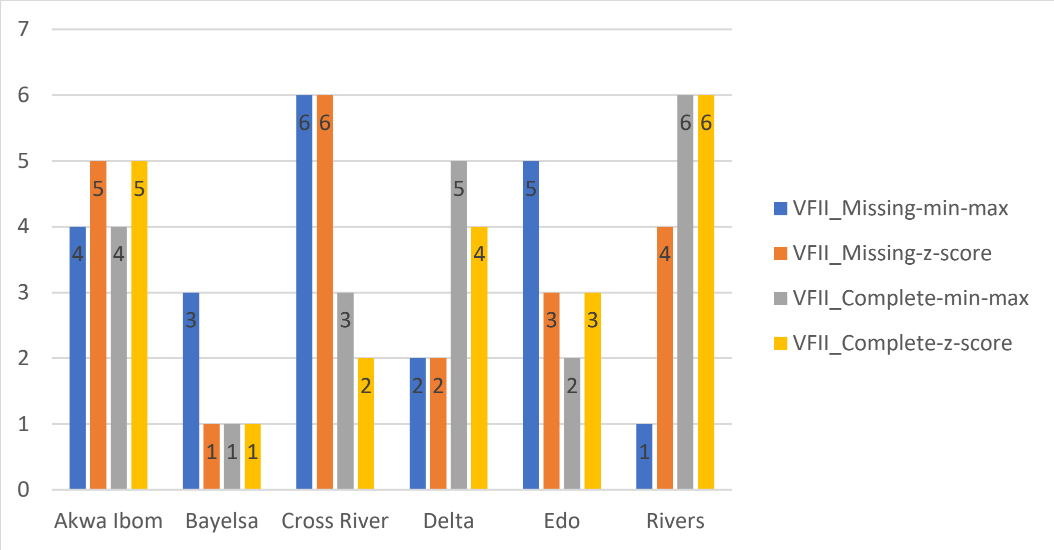

Figure 2: VFII ranking of States when unequal weight and different normalisation method is used

Table 4: All combinations of VFII pairwise correlation result using unequal weight and different normalisation method

Correlation Specifications	VFII_missing-min-max	VFII_missing-z-score	VFII_complete-min-max	VFII_complete-z-score
VFII_missing-min-max	1.00			
VFII_missing-z-score	0.85***	1.00		
VFII_complete-min-max	-0.70***	-0.47***	1.00	
VFII_complete-z-score	-0.63***	-0.56***	0.69***	1.00

3.1.2 Equal Weighting

We decided to apply equal weight to each component of the index to compare its output. Each of the components was given a weight of 0.33, and these weights were equally shared among the variables in each component (see Appendix IV). Using different data types and normalisation method the result is present in Table 5 and Figure 3. These results show that applying equal weight to the Vulnerability to Food Insecurity Index produce a consistent output and ranking of state, irrespective of the data or normalisation method used. The result supports the notion that using equal weight across the index component produces estimates that are unbiased. According to this result, households in Bayelsa state are highly vulnerable to food insecurity whereas households in Edo state are least or not vulnerable to food insecurity.

To test the robustness of this ranking, we estimated a pairwise correlation coefficient for each specification as shown in Table 6. Across the table, the correlation coefficient exceeded 0.87 and was highly significant at 5% level. This suggests that VFII ranking using equal weight are highly robust in its estimate (Alkire and Santos, 2014) unlike using unequal weight as explained in section 3.1.1. Using either min-max or z-score normalisation method for the index will still produce the same output, but the min-max method will produce a better result because it had a correlation coefficient of 0.97. Based on this finding, we adopted equal weight and min-max normalisation method for our VFII.

Table 5: VFII ranking of states in the South-South region of Nigeria using equal weight and different normalisation methods

State	VFII_missing-min-max	VFII_missing-z-score	VFII_complete-min-max	VFII_complete-z-score
Akwa Ibom	5	5	5	5
Bayelsa	6	6	6	6
Cross River	2	2	2	2
Delta	3	3	3	3
Edo	1	1	1	1
Rivers	4	4	4	4

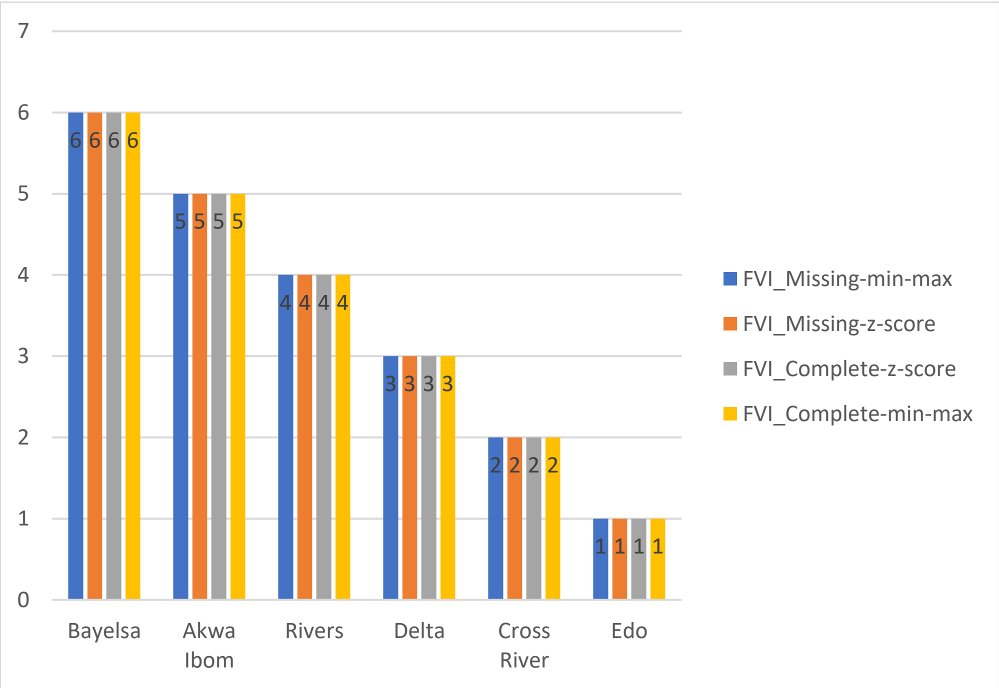

Figure 3: VFII ranking of States when equal weight and different normalisation method is used

Table 6: VFII pairwise correlation result applying equal weight to the index

	VFII_missing-min-max	VFII_missing-z-score	VFII_complete-min-max	VFII_complete-z-score
VFII_missing-min-max	1.00			
VFII_missing-z-score	0.87***	1.00		
VFII_complete-min-max	0.97***	0.89***	1.00	
VFII_complete-z-score	0.91***	0.93***	0.94***	1.00

3.1.3 Inclusion and Exclusion of variables

Finally, we went further to test the effect of excluding or including any variable on the index. To determine what variable(s) to be excluded, we estimated the squared multiple correlations of all the variables used in the VFII as shown in Table 7. The squared multiple correlation coefficient shows the interaction of each variable with all other variables. The larger the coefficient, the stronger the interaction of the variable. From Table 7, child mortality and distance-from-water-source were the two variables with the least correlation of 19.71% and 19.54%. Therefore, we used these variables to carry out the test of either excluding or including them. The result of this test is shown in Figure 4 and Table 8. Using equal weight (see appendix for each component weight), Figure 4 and Table 8 shows the robustness of the VFII output. Three specifications were explored: excluding child mortality only; excluding both child mortality and distance-to-water-source; and including child mortality and excluding distance-to-water source. Irrespective of any specification used the VFII ranking was stable across all specification. Comparing the result in Figure 4 and Figure 3, three states -Edo, Cross River, and Delta maintain the same ranking of first, second and third position. Akwa Ibom, Rivers and Bayelsa state ranking differs. For instance, Bayelsa state ranks sixth when using equal weighting method without excluding any variable. Alternatively, when child mortality and distance-to water-source were excluded/included, Bayelsa state ranked third. This slight alteration is expected because of the effect of excluding or including either child mortality or distance-to-water-source on the VFII. However, the overall performance of the VFII remains robust.

Table 7: Squared multiple correlations of variables with all other variables

Variable	Smc
Shock	0.3640
Stunting	0.5032
Child mortality	0.1971
Hunger	0.4113
Wealth index	0.5893
Road distance	0.2663
Market distance	0.3515
Distant-to-water-source	0.1954
Income source	0.3691
Non-farm Revenue	0.4725
Crop yield	0.4248
Household literacy	0.4836

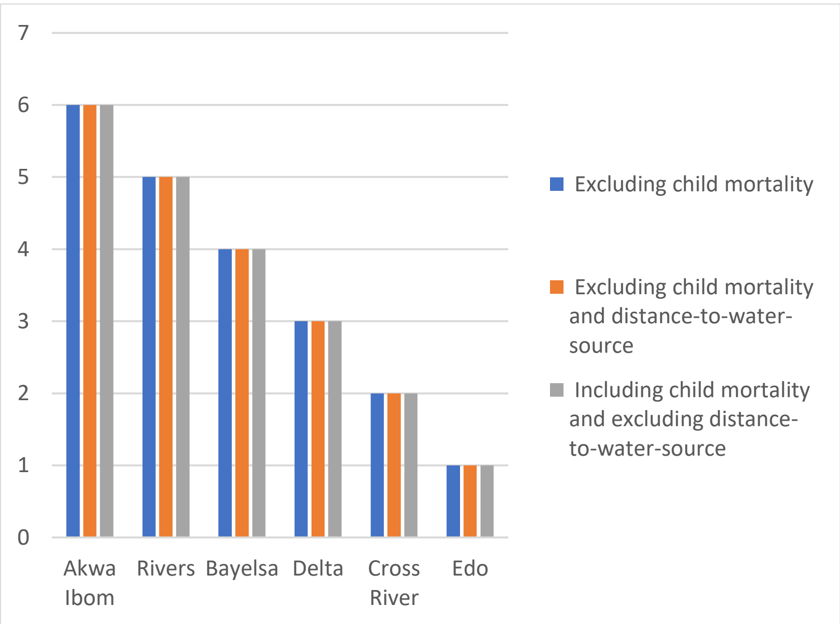

Figure 4: VFII ranking when excluding or including variables

Table 8: VFII ranking of state when excluding or including child mortality or distance-to-water-source.

State	Excluding child mortality	Excluding child mortality and distance-to-water-source	Including child mortality and excluding distance to water source
Akwa Ibom	6	6	6
Bayelsa	4	4	4
Cross River	2	2	2
Delta	3	3	3
Edo	1	1	1
Rivers	5	5	5

3.2 Global Sensitivity Approach

This section discusses how variation or uncertainty in the output of the VFII can be apportioned to the input factors using global sensitivity analysis as described in section 2.4.2 and section 2.4.3. The area of interest investigated are:

a) What are the major sources of uncertainty in the VFII ranking?
b) What are the most influential input factors that cause this uncertainty in VFII ranking?

The total number of Monte Carlo model execution estimated for the Sobol sensitivity measures – first order and total effect sensitivity indices is 29,696 (1024 *(27+2)), where 1024 is sample size adopted by quasi-random scheme (Sobol', 1967), 27 is the total number of input factor used for estimating the model.

3.2.1 Uncertainty Analysis -what are the most influential input factors that cause overlap in two state ranking?

To find out the primary cause of overlap in the VFII ranking, we compare the composite score output of two states – Bayelsa state and Edo state. These two states were selected because Edo is the best-performing state in term of having least food insecurity and vulnerability while Bayelsa state had the highest level of food security and vulnerability. Figure 5 presents the histograms of uncertainty analysis of the differences between the composite scores of these states, which correspond to 29,696 Monte Carlo runs. The left-hand region of Figure 5 shows that Edo state performs better than Bayelsa state in 60% of the cases. This implies that households in Bayelsa state are more vulnerable to food insecurity compare to Edo state. We must find out which uncertainty drive this result. To do this, we estimated the First order (S_i) and Total effect (S_{Ti}) sensitivity indices for Bayelsa and Edo state present in Table 9.

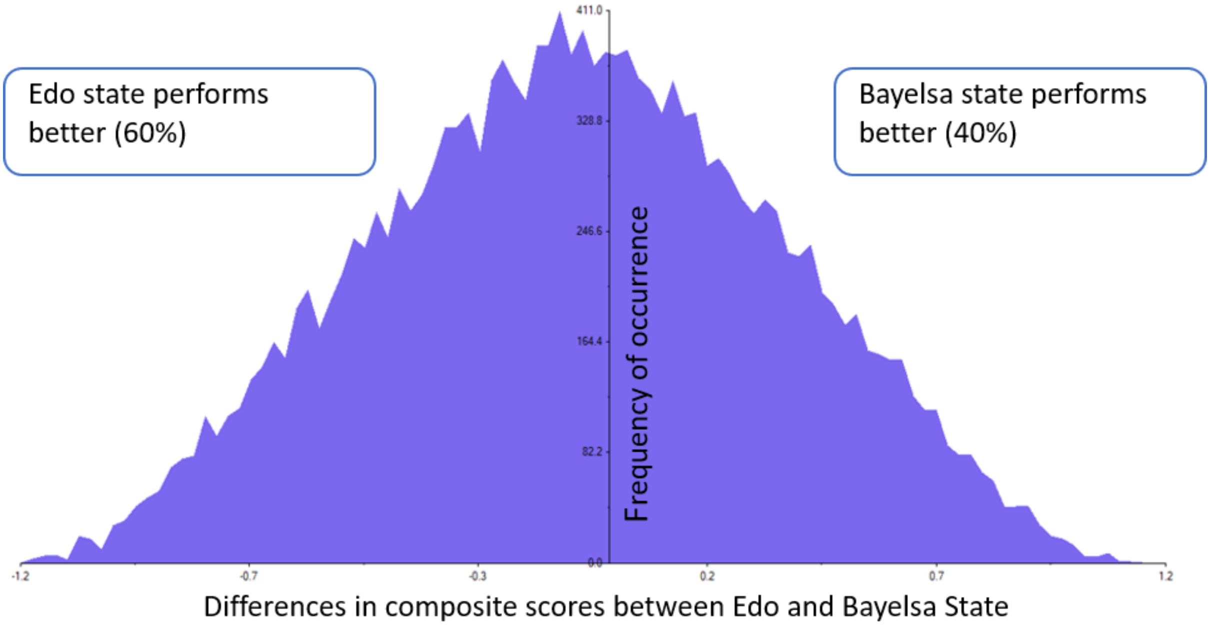

Figure 5: Uncertainty analysis of the difference in composite score between Edo and Bayelsa State. (Uncertainty input factors: 24 weighted indicator values, 3 triggers – weighting, normalisation, inclusion/exclusion)

3.2.2 Sensitivity Analysis

When interpreting Sensitivity analysis result, we are looking for important input factors that influence the output. When this input factor is fixed singly, it will reduce the variance of the output significantly. To determine which input factor is important the S_i >0.10, meaning that the input factor explains more than 1/k of the output variance (Saltelli, 2017).

Table 9 shows the result of the first order sensitivity S_i. It shows the individual interaction and the main effect between the input factors and the output of Edo and Bayelsa state. Individually, none of the triggers, i.e. weighting scheme, normalisation scheme and inclusion/exclusion of variables had any effect on the output variance of the two states. In contrast, for Bayelsa state, the shock variable was the primary source of uncertainty in its composite score. Similarly, in Edo state, the primary source of uncertainty is from the shock variables. For both state, the individual influence between the input factors, do have an impact on the output variance as the total S_i is above 100%. The impact is mainly cause by the shock variable. This implies that the VFII is highly sensitive to shocks. The VFII is a food security indicator that incorporate vulnerability component. It is highly desirable that this index should be able to pick up the effect of the vulnerability component. As the index is highly sensitive to shocks, it proves that the index is reliable and meet the purpose for which it was design. Generally, input factors with a major contribution to variance of the VFII are: shock, child mortality stunting, hunger, wealth index, distance-to-road, distance- to-market and household literacy. Input with lesser contributions are: distance-to-water-source, income source, non-farm income, and crop yield.

The sum of the first order sensitivity index for the two states is greater than 1, implying that the VFII model is an additive model. A model is said to be additive when it is possible to decompose the variance of its input factor quantitatively. The entire input factor taken singly explain more than 100% of the output variance.

The total effect index represents the difference between the two state composite index score. It also measures how much an input factor interacts with other input factors. Our total effect sensitivity index S_{Ti} is less than S_i, this means that the input factors do interact with other input factors. However, the interaction between the input factors was low (-15.6%) due to the influence of the shock variable. The difference between the two states composite scores is mostly attributed to the shock variable of each state with a high score of 0.90 and 0.10 respectively. The triggers had a lesser effect of the output variance of the two state.

Table 9: Sobol sensitivity indices for composite scores of two states in South-Nigeria

Input Factors	First- order (S_i-Bayelsa)	First-order (S_iEdo)	Total effect (S_{Ti} Edo -Bayelsa)
$Shock_b$	1.06651	0	0.903442
$Child\ Mortality_b$	0.02805	0	0.019396
$Stunting_b$	0.004535	0	0.007513
$Hunger_b$	-0.000784	0	0.00163
$Wealth\ Index_b$	0.007421	0	0.00418
$Dist-to-Road_b$	0.069542	0	0.052796
$Dist-to-Water_b$	0.001171	0	0.001117
$Dist-to-Market_b$	0.001643	0	-0.00266
$Income\ Source_b$	0.000129	0	0.00042
$Non\ farm\ Income_b$	0.004479	0	0.002208
$Crop\ Yield_b$	-0.00108	0	-0.00109
$Household\ Literacy_b$	-0.0253	0	-0.0222
$Shock_e$	0	0.857508	0.107939
$Child\ Mortality_e$	0	0.033099	0.000859
$Stunting_e$	0	0.049124	-0.000146
$Hunger_e$	0	0.038877	-0.00287
$Wealth\ Index_e$	0	0.078605	0.011006
$Dist-to-Road_e$	0	0.037927	0.005205
$Dist-to-Water_e$	0	-0.00209	0.005037
$Dist-to-Market_e$	0	0.020292	-0.00434
$Income\ Source_e$	0	0.005667	0.00061
$Non\ farm\ Income_e$	0	-0.00402	-0.000326
$Crop\ Yield_e$	0	-0.000695	0.000996
$Household\ Literacy_e$	0	0.039294	-0.0247
Weighting	0	0	-5.55E-17
Normalization	0	0	-5.55E-17
Inclusion/Exclusion	0	0	-5.55E-17
Sum	1.156316	1.153588	1.066022

4.0 Conclusion

This paper investigated the robustness of the Vulnerability to Food Insecurity Index. We carried out a robust check using sensitivity and uncertainty analysis on the following assumptions used to design the index:

a) alternative data type (missing data or complete data)
b) alternative weighting scheme (equal or unequal weight)
c) alternative normalization scheme (min-max or z-score method)
d) excluding or including variables.

Using these assumptions, we collectively investigate the performance and the sources of uncertainty to the VFII, focusing on the following questions:

a) How does the output of the VFII rank compare to different assumptions?
b) What is the major source of uncertainty in the VFII ranking?
c) What are the most influential input factors that cause this uncertainty in VFII ranking?

The result of the analysis showed that: VFII result is stable to changes in variables and normalisation method when equal weight is applied. Using the min-max normalisation method produces highly robust estimate compare to using the z-score method. The major source of input that introduces uncertainty to the VFII output was shock variable. Implying that the VFII is highly sensitive to shock, therefore better capturing the vulnerability component of food security. We conclude that the index is fit for purpose and will perform better than other indicators of food security in terms of vulnerability.

Appendix

Appendix I: VFII score for each state using unequal weighting

States	VFII_Missing-min-max	VFII_Missing-z-score	VFII_Complete-min-max	VFII_Complete-z-score
Akwa Ibom	0.677	-0.047	-0.130	-0.456
Bayelsa	0.689	0.309	0.033	0.834
Cross River	0.574	-0.360	-0.051	0.668
Delta	0.731	0.162	-0.166	0.069
Edo	0.666	0.072	-0.036	0.418
Rivers	0.739	0.012	-0.225	-0.610

Appendix II: VFII score for each state using equal weighting

State	VFII_missing-min-max	VFII_missing-z-score	VFII_complete-min-max	VFII_complete-z-score
Bayelsa	-0.096	-0.153	-0.093	-0.118
Akwa Ibom	-0.092	-0.103	-0.093	-0.075
Rivers	-0.092	-0.021	-0.091	-0.037
Delta	-0.072	0.007	-0.082	0.007
Cross River	-0.072	0.041	-0.065	0.077
Edo	-0.047	0.168	-0.041	0.153

Appendix III: VFII score for excluding or including a variable

State	Excluding child mortality	Excluding child mortality and distance-to-water-source	Including child mortality and excluding distance to water source
Akwa Ibom	-0.121	-0.110	-0.082
Rivers	-0.120	-0.109	-0.080
Bayelsa	-0.113	-0.098	-0.078
Delta	-0.107	-0.096	-0.071
Cross River	-0.088	-0.077	-0.054
Edo	-0.069	-0.056	-0.028

Appendix IV: Equal-weight used in designing VFII

VFII component	Indicators	Individual weight	Excluding child mortality	Excluding distance-to-water source	Excluding child mortality and distance to water source	Overall weight
Exposure	Shocks	0.33	0.33	0.33	0.33	0.33
Sensitivity	Stunting	0.11	0.165	0.11	0.165	0.33
	Child mortality	0.11	-	0.11	-	
	Hunger	0.11	0.165	0.11	0.165	
Adaptive Capacity	Wealth Index	0.04125	0.0412	0.0471	0.0471	0.33
	Road distance	0.0412	0.0412	0.0471	0.0471	
	Market	0.0412	0.0412	0.0471	0.0471	
	Water source	0.0412	0.0412	-	-	
	Income savings	0.0412	0.0412	0.0471	0.0471	
	Revenue non-farm	0.0412	0.0412	0.0471	0.0471	
	Crop Harvested	0.0412	0.0412	0.0471	0.0471	
	Literacy	0.0412	0.0412	0.0471	0.0471	

Appendix V: Unequal weight used in designing VFII

VFII component	Indicators	Individual weight	Overall weight
Exposure	Shocks	0.0871	0.0871
Sensitivity	Stunting	-0.0058	-0.5645
	Child mortality	-0.2628	
Adaptive Capacity	Hunger	-0.2959	1.1322
	Wealth Index	0.5363	
	Road distance	0.0907	
	Market	0.0607	
	Water source	-0.3767	
	Income savings	0.4437	
	Revenue non-farm	-0.0593	
	Crop Harvested	-0.0035	
	Literacy	0.4403	

Appendix VI: Distributions (μ, σ) for inputs and triggers for inclusion-exclusion, missing data, weighting and normalisation method

			Weighed Variables										
State	Distribution	Shock	Stunting	Child Mortality	Hunger	Wealth Index	Distance-to-water	Income Savings	Non-farm-income	Crop yield	Household Literacy	distance-to-road	Distance-to-market
AKS	Mean	0.10888	0.06182	0.00521	0.00440	0.02054	0.00168	0.00823	0.03502	0.00101	0.01587	0.00256	0.01482
	Std. Dev.	0.08529	0.00687	0.01329	0.01446	0.00729	0.00365	0.00491	0.00157	0.00140	0.00893	0.00249	0.00367
Bayelsa	Mean	0.12178	0.06255	0.01194	0.00052	0.02179	0.00021	0.00333	0.03455	0.00154	0.01827	0.01603	0.01814
	Std. Dev.	0.10662	0.00616	0.02100	0.00325	0.00879	0.00027	0.00222	0.00492	0.00191	0.00902	0.01275	0.00384
CRS	Mean	0.07619	0.06225	0.00948	0.00207	0.01474	0.00090	0.00597	0.03543	0.00482	0.01441	0.00532	0.02819
	Std. Dev.	0.03425	0.00563	0.01774	0.00630	0.00743	0.00129	0.00169	0.00053	0.00797	0.00997	0.00503	0.00505
Delta	Mean	0.09919	0.06064	0.00574	0.00148	0.02501	0.00074	0.00499	0.03524	0.00576	0.01664	0.00770	0.00949
	Std. Dev.	0.04676	0.00614	0.01547	0.00451	0.00779	0.00208	0.00146	0.00272	0.00742	0.00986	0.00566	0.00581
Edo	Mean	0.07355	0.06039	0.00385	0.00208	0.02295	0.00114	0.00466	0.03529	0.00458	0.01618	0.00302	0.02419
	Std. Dev.	0.03225	0.00534	0.01006	0.00870	0.00975	0.00280	0.00115	0.00067	0.00549	0.00857	0.00319	0.00478
Rivers	Mean	0.10764	0.06048	0.00299	0.00303	0.02355	0.00131	0.00692	0.03435	0.00185	0.01992	0.00400	0.00651
	Std. Dev.	0.09240	0.01066	0.01212	0.00961	0.00782	0.00409	0.00133	0.00204	0.00380	0.00843	0.00406	0.00454

Appendix VI: Detailed description of indicators and variables

Index components	Indicators	Variables description and rationale
Exposure *probability of covariate shocks occurring*	Health shock	From the household dataset "illness of income earning member" was selected and used as Health Shock in the Vulnerability to Food Insecurity Index.
	Unemployment shock	"Job loss" is used as a variable to represent unemployment shock in the Vulnerability to Food Insecurity Index. Job loss reduces the ability of households to buy food, get clean water and medicines because of loss of income, therefore increasing household food insecurity and vulnerability (FAO and WHO, 1996).
	Civil conflict shocks	From the household survey data, the variable used to represent Civil conflict shock are: "Theft of crops, cash and livestock" and "kidnapping/Hijacking/robbery/assault".
	Agro-climatic shocks	Agro-climatic shocks have the potential for increasing food insecurity and malnutrition. Based on the household's survey data the variables used for agro-climatic shocks are: "poor rain that caused harvest failure" and "flooding that caused harvest failure.
	Food price shock	From the household survey data, the variable used to represent food price shock is "increase in price of major food items consumed".
Sensitivity previous or accumulative experience of food insecurity	Malnutrition	Malnutrition is the most widely accepted and policy relevance variable commonly used are wasted, stunted, and underweight (Klennert, 2005). However, this research prefers to use stunting as an indicator of malnutrition. Stunting was preferred because it shows inadequate nutrition over a prolonged period (Young and Jaspars, 2006).
	Child mortality	Child mortality, defined as the total number of dead children in each household was derived by adding "number of male children" and/or "female children" reported dead in each household.
	Hunger	This research refers hunger to the physical discomfort caused by a lack of food (Bickel et al., 2000; Barrett, 2010) and not as a result of dieting or being too busy to eat. As such it represents hidden hunger, that is micronutrient deficiencies (Jones et al., 2013a). Thus, hunger is a severe stage of food insecurity. To derive this indicator, the research adopts the Household Hunger Scale (HHS) methodology with a little modification due to inadequate data availability.
	Wealth Index	The wealth index is a measure of economic status of households to ascertain their relative wealth (Ruststein and Johnson, 2004; Fry et al., 2014). The wealth index used in this research uses various household asset such as information assets, mobility assets, livelihood assets, and housing characteristics to design the index. The following variable were used in designing the wealth index: **Livelihood assets:** Tables, mattress, bed, mat, fridge, freezer, sofa set, chair, sewing machine, kerosene stove, other assets, generator, size of agricultural land, broiler chicken, cockerel, local chicken, goat, pig, duck and sheep. **Mobility assets:** Bicycle, motorbike, cars and other vehicles. **Information asset:** Radio, TV set, computer, satellite dish, DVD player, GSM mobile phone/landline, cassette recorder. **Housing structure characteristics:** Outer wall, roof materials, floor material, members per room, lighting fuel, cooking fuel, access to electricity, main source of drinking water during dry season, main source of drinking water during the wet season, type of toilet facilities, type of user who shared toilet facilities, and refuse disposal facilities.

Adaptive capacity *how household respond, exploit opportunities, resist or recover from food insecurity shocks*	Access to infrastructure	This research uses distance to major roads, distance to markets and time taken to get to nearest water source to represent a single indicator called "assess to infrastructure".
	Livelihood activities	Income sources, revenue from non-farm enterprises and agricultural activities are used as variable to represent livelihood activities. These are three major sources of livelihood identified in the LSMS household survey data.
	Household literacy	Cumulative years of schooling of household head or closet individual is one of the main criteria used in defining household literacy. Years of schooling are used as a proxy for literacy and level of understanding of household members, including household heads. An individual is considered literate if he or she has at least five years of education (Dotter and Klasen, 2014). Only post-planting season data were used to derive this indicator because it contains information on household head needed to represent literacy level of the household. In rare cases where there was no data on household head, the *closest individual* in educational achievement that has at least five years of schooling is used as a replacement for household head. If educational qualifications are the same for more than one individual, the most senior individual in age is used.

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