GAFSP

global agriculture & food security program

FOOD INSECURITY EXPERIENCE SCALE

Exploration Paper: GAFSP Operationalization and Target Setting

NOVEMBER 2018

This paper summarizes an effort to explore the feasibility of targets for the Food Insecurity Experience Scale (FIES), situated in the broader context of low-income countries eligible for GAFSP funding. It discusses challenges in formalizing FIES targets in lower-income settings using country-level information, as well as sources of divergence arising from considerable differences across regions. The data used for this analysis were provided under the supervision of the Voices of the Hungry (VoH) team at FAO. The GAFSP Coordination Unit is available to explain the results presented in this report; readers should note that the FIES data remain strictly confidential and can be released only at the discretion of the VoH team.

The authors wish to acknowledge valuable inputs and guidance from Carlo Cafiero (Lead Statistician, Voices of the Hungry), Robert Townsend (Lead Economist, Agriculture Global Practice, World Bank), and Paul Christian (Economist, Development Impact Evaluation).

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ACRONYMS AND ABBREVIATIONS

CU	Coordination Unit
DIME	Development Impact Evaluation
FAO	Food and Agriculture Organization of the United Nations
FIES	Food Insecurity Experience Scale
GAFSP	Global Agriculture and Food Security Program
GNI	Gross national income
M&E	Monitoring and evaluation
PPP	Purchasing power parity
SDG	Sustainable Development Goal
SC	Steering Committee
VoH	Voices of the Hungry (FAO)

INTRODUCTION

1. The updated Monitoring and Evaluation (M&E) Plan of the Global Agriculture and Food Security Program (GAFSP) incorporates lessons from experience with M&E for GAFSP to date and explicitly links the collection of information and reporting of results for GAFSP-supported initiatives to the implementation and accountability framework for the **Sustainable Development Goals (SDGs)**. At its January 2016 meeting in Kigali, Rwanda, the GAFSP Steering Committee (SC) reviewed and subsequently endorsed a new set of indicators for GAFSP. The SC determined that given the Program's overarching impact goals—specifically with regard to addressing hunger and food security—the most feasible approach among the various alternatives considered is the **Food Insecurity Experience Scale (FIES)**, a measurement tool for food insecurity developed by the Food and Agriculture Organization (FAO) of the United Nations. The FIES was selected based on the use of extensive external validation criteria that focused principally on whether the indicator: (1) is an SDG indicator and/or correlates highly with the SDG nutrition indicators (such as stunting), (2) has a relatively low cost of information collection, and (3) covers a wide range of countries.

2. Following the SC's endorsement of the FIES as a GAFSP indicator, the GAFSP Coordination Unit (CU) committed to explore and lay out the feasibility and potential approach to estimate an indicative GAFSP target for the FIES, to be shared at the SC meeting in early 2017. This note describes the effort undertaken and provides an update about further analysis.

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3. **The FIES is a tool to measure food access at the individual or household level.** It is an experience-based measure of the severity of the food insecurity condition of a household or an individual respondent (that is, it measures the constraints on the ability to access food). A unique contribution of experience-based food insecurity scales (EBFIS) is that they call attention to elements of deprivation in the diet that are relatively easy to detect via direct personal interviews. Like other existing EBFIS, the FIES underlines aspects of food insecurity linked to anxiety or uncertainty arising from an individual's or household's inability to procure enough food. Although the inability to access food usually results in reduced consumption of food, or in consumption of food of limited nutritional value, the FIES is not intended to provide direct measures of the quantity and quality of actual food consumption or of the nutritional status of respondents.

4. The key assumption behind the FIES is that the severity of food insecurity experienced by an individual or household can be analyzed as a "latent trait"—in other words, a trait that cannot be observed directly but whose magnitude can be inferred from observable conditions. Based on this assumption, the FIES is built on a single-parameter logistic item response theory (IRT) measurement model (commonly known as the Rasch model) that provides a theoretical base and a set of statistical tools to assess the suitability of a set of survey items for scale construction.[1] IRT is founded on the assumption that a quantitative measure of an underlying, unobservable attribute considered as a 'latent trait' can be inferred from a set of dichotomous variables (e.g yes=1; no=0) obtained as the

[1] The FIES creates a scale from the items and compares the performance of the scale in various populations and survey contexts. The model provides the probabilistic basis for estimating the parameters associated with both items and respondents by conducting statistical tests of the strength of association of the responses to the latent trait and of the goodness of fit. Under the Rasch model, the raw score (that is, the simple sum of affirmative responses) is a sufficient statistic to estimate respondents' severity on the scale. Maximum likelihood methods are then used to estimate the item severity and household severity parameters most consistent with the observed responses under the Rasch assumptions.

result of an experiment or test[2]. Measures obtained with the FIES can be used to compute indicators of the prevalence of food insecurity in a population at any level of severity. To monitor food insecurity in a consistent way throughout the world, FAO proposes the use of two different indicators: the percentage of individuals who have experienced **moderate or severe** food insecurity ($FI_{mod+sev}$) and the percentage of individuals who have experienced **severe** food insecurity (FI_{sev}).[3]

5. **The FIES Survey Module (FIES-SM) is composed of eight questions with simple binary responses ("yes"/"no").** Questions can be framed with reference to single individuals or to all individuals living in a household, and are typically applied with a reference (recall) period of 12 months. The FIES also provides an extended version of the questionnaire, with two additional follow-up questions relating to the more severe end of the scale of experiencing hunger, to extend the measured range at the severe end for use in populations where it is important to further discriminate among the severely food insecure. Given the higher prevalence of food insecurity and undernourishment in typical GAFSP recipient countries and locations, it is anticipated that GAFSP projects will roll out the extended version of the FIES for its upcoming cohort of projects.

FIES FOR DEVELOPING COUNTRIES: EXTERNAL VALIDATION

6. **One of the most important characteristics of a strong M&E system is the validity of its indicators.** As part of the process of selecting indicators for GAFSP, the M&E working group undertook a systematic validation exercise for the FIES. The objective was to test the FIES vis-à-vis globally referenced indicators of poverty and human development, and to use the results from the validation analyses to inform the GAFSP Steering Committee (SC) about the suitability of the FIES as the chosen indicator of hunger/food security for the GAFSP. The validation exercise first applied external and cross-country analyses to FIES-based prevalence rates computed by the Voices of the Hungry (VoH) project team.

7. **The results presented here situate the estimated FIES-based measures in the broader context of relevant human development indicators.** FIES-based measures of food insecurity[4] have high correlations with poverty rates, under-five mortality, undernourishment, and stunting. Based on FIES data collected via the Gallup World Poll in 92 developing countries, Table 1 presents the Spearman's rank correlation[5] and Pearson's correlation[6] between the two FIES-based measures – (1) the prevalence of moderate or severe food insecurity in the national adult population ($FI_{mod+sev}$) and (2) the prevalence of severe food insecurity in the adult population (FI_{sev}) – and poverty and health outcomes. Table 2 shows the strength of the relationship between FIES-based indicators and the under-five mortality rate after controlling for extreme poverty, which is positive and significant, estimated for a sample of 69 countries for which complete datasets are available for both dependent and independent variables. Scatterplots (Figure 1 and Figure 2) depict the strength of these correlations. This exercise helped lay the groundwork for further thinking about potential target setting for the FIES at the program level.

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[2] Ballard, T.J., Kepple, A.W. & Cafiero, C. 2013. The food insecurity experience scale: developing a global standard for monitoring hunger worldwide. Technical Paper. Rome, FAO. (available at http://www.fao.org/economic/ess/ess-fs/voices/en/).

[3] A third indicator, the percentage of individuals experiencing moderate levels of food security only (FI_{mod}), can be computed as the difference between $FI_{mod+sev}$ and FI_{sev}. FAO advises against reporting on this third indicator because reductions in FI_{mod} may be due to either a reduction of overall food insecurity (if some of those who used to experience moderate levels of food insecurity improve their condition) or to a worsening situation (when some of them move to severe levels).

[4] The validation is done through publicly available data for FIES-based indicators as of 2014.

[5] Spearman's correlation coefficient presents a non-parametric statistical measure of the strength of a monotonic relationship between paired data.

[6] Pearson's correlation coefficient presents a statistical measure of the strength of a linear relationship between two continuous variables.

Table 1: Spearman and Pearson correlation coefficients between FIES-based measures and other measures of food insecurity/poverty

FIES	Spearman Rank Correlation		Pearson Correlation	
	$FI_{mod+sev}$	FI_{sev}	$FI_{mod+sev}$	FI_{sev}
Poverty line US$1.90	0.7134*	0.6969*	0.6345*	0.6008*
Rural poverty headcount ratio (at US$1.25 PPP a day)	0.5953*	0.5391*	0.6178*	0.5398*
Under-5 mortality rate	0.6999*	0.6751*	0.6336*	0.5678*
Underweight	0.5211*	0.5193*	0.4022*	0.3014*
Stunting	0.6157*	0.5870*	0.6057*	0.5054*
Undernourishment	0.6344*	0.5934*	0.5076*	0.5141*

Source: Publicly available FIES data as of 2014.
Note: * denotes correlation coefficients significant at the 5% level or lower. PPP = Purchasing power parity.

Table 2: Regression analysis of food security and poverty indicators on child mortality rates

	Model 1	Model 2
Coefficients are adjusted for robust standard error		
Log (FLmod+sev)	0.268** (2.47)	–
Log (FLsev)	–	.171** (2.1)
Log (Adjusted poverty headcount)	0.271** (6.94)	.269** (6.58)
Adjusted R-squared	0.7189	0.7183
Number of observations	69	69

Source: GAFSP Coordination Unit and FAO Voices of the Hungry.
Note: Significance of coefficients is denoted as follows: ** p<0.01.

Figure 1: FLmod+sev capturing under-5 mortality rate

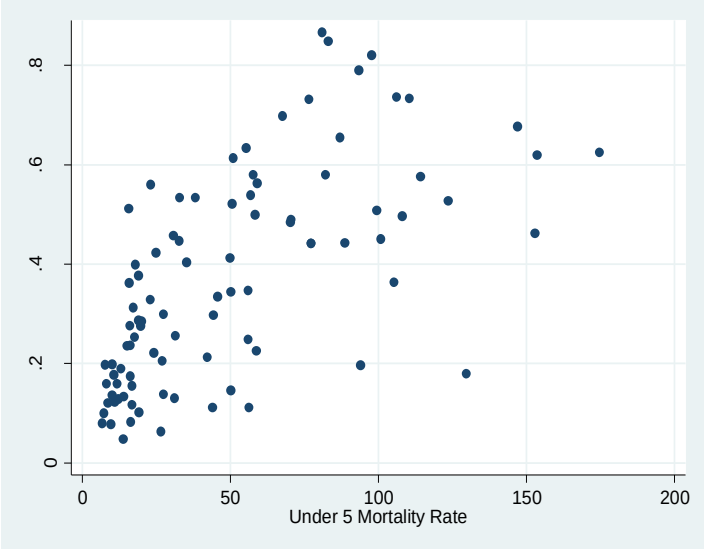
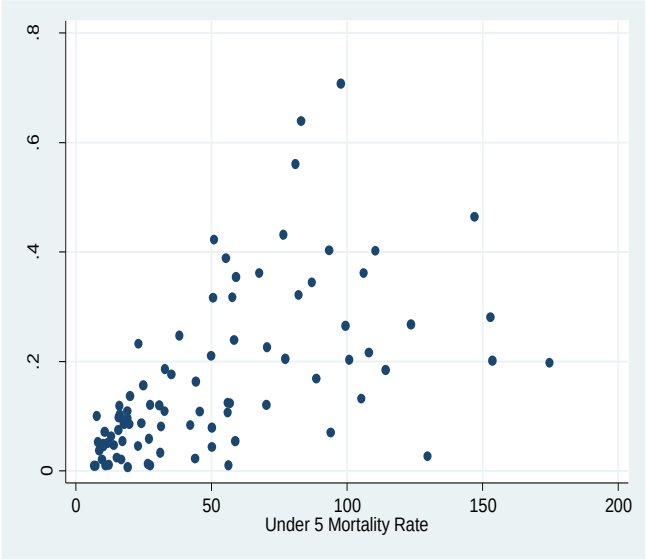


Figure 2: FIsev capturing under-5 mortality rate



Source: GAFSP Coordination Unit and FAO Voices of the Hungry.

FIES FOR GAFSP SAMPLE: TARGET SETTING

8. **Going forward under GAFSP, all new Public Sector Window projects and a sample of existing Private Sector Window projects are expected to use the FIES to track changes in food insecurity among GAFSP beneficiaries.** Given this new M&E policy, it is reasonable for GAFSP to consider what might be an appropriate target percentage change for FI_{sev} to which GAFSP could be expected to contribute.

9. Targets can be estimated based on ex-ante and ex-post approaches. Ex-ante targets typically use structural models or simulations to determine the likely anticipated gains (or not) for an indicator. This paper attempts to predict the change in prevalence of severe food insecurity under GAFSP in response to income changes, based on an ex-ante approach—and with notable limitations, as outlined below.

10. At the time of starting this exercise, a considerable challenge in estimating such a target is that FIES-based measures are only available for two years of data collection at a national level, and for relatively small sample sizes that cannot be further disaggregated. Given the limitation in time series data, there is no way to derive a robust assessment of the magnitude of past annual changes to use as indicators of the magnitude of future changes as the basis for a GAFSP aspirational goal. In consultation with FAO's Voices of the Hungry (VoH) team (VoH is the custodian of the FIES), the GAFSP M&E team has been exploring potential options for deriving a Program-wide FIES-based target. Within the considerable limitations noted, the use of both micro- and macro-level data and statistically grounded methodologies, consistent with country-specific contexts, are presented here.

Objective and Methodology

11. **With the limitations of the FIES data currently available,** an elasticity-based methodology is proposed to derive an indicative change in the prevalence of food insecurity as measured by the FIES for the GAFSP pool of beneficiaries in response to a certain percentage gain in income. **The goal of this exercise is therefore to estimate the change in prevalence of food insecurity, as measured by the FIES,[7] that is implied if GAFSP reaches its poverty reduction target** (Box 1).

> **Box 1: The GAFSP income gain target**
>
> With an additional US$1.5 billion in GAFSP financing, and within five years from the start of implementing associated projects, GAFSP aims to raise incomes by 20 percent of 10 million poor people in rural households in countries furthest from achieving the SDGs (as per the paper presented at the GAFSP SC Meeting in January 2016).

12. The method proposed here is to derive income elasticities of food access, using national-level FIES-based prevalence rates and standardized income. In the absence of time-consistent, household-level income data across all GAFSP-eligible countries, national-level GNI (gross national income) per capita (both Atlas method and PPP-based)[8] and national-level FIES-based prevalence rates were

[7] Moderate or severe food insecurity ($FI_{mod+sev}$) or Severe food insecurity (FI_{sev}).

[8] In calculating GNI in U.S. dollars for certain operational and analytical purposes, the World Bank uses the Atlas conversion factor instead of simple exchange rates. The purpose of the Atlas conversion factor is to reduce the impact of exchange rate fluctuations in the cross-country comparison of national incomes. All models were also tested using GNI per capita, PPP (constant 2011 international

used in the analysis. Using the Atlas method, 29 GAFSP-eligible countries for which two years (2014 and 2015) of FIES and GNI per capita data are available were included (out of 56 total GAFSP-eligible countries; see Annex 2). Using GNI per capita on a PPP basis, the number of countries was reduced further due to lack of data for five GAFSP-eligible countries.

13. **Panel regression analyses suggest that for GAFSP-eligible countries, the prevalence of severe food insecurity (FI_{sev}) is more responsive to changes in income as compared to that for moderate or severe food insecurity ($FI_{mod+sev}$).** Two types of models are tested.[9] A simple Generalized Least Squares (GLS) model is tested and preferred under the assumption that the unobserved variables are uncorrelated with (more strongly, statistically independent of) all the observed variables. The model is repeated under four scenarios using panel and pooled data. An extensive sensitivity analysis is also carried out, given the small size of the sample. Following Buddelmeyer et al. (2008), multiple methods are tested to counter acute fixed effect biases arising from the small sample size.

14. **In all cases, elasticity estimates are derived by regressing the log change in prevalence of food insecurity on the predicted log change in income.** To capture the influence of aggregate time-series trends, an alternative model is also estimated including year dummies[10] under each scenario (see the discussion in the Results section). Because only two years of data are available, the addition of the time dummy had no significant influence on the estimated elasticities.

Results

15. **For GAFSP-eligible countries, the change in the prevalence of food insecurity in response to income, measured by GNI per capita, is estimated to be statistically significant (with p-values of less than 0.05)** (Table 3). The negative values of the estimated elasticities broadly support the hypothesis that higher income is associated with a lower prevalence of food insecurity. In simple terms, the estimates from the first model suggest that for every 10 percent increase in GNI per capita, the prevalence of moderate to severe food insecurity would decline by 4.6 percent, while severe food insecurity would decline by almost 7 percent.

$). GNI PPP is gross national income (GNI) converted to international dollars using purchasing power parity rates. An international dollar has the same purchasing power over GNI as a U.S. dollar has in the United States. GNI is the sum of value added by all resident producers plus any product taxes (less subsidies) not included in the valuation of output plus net receipts of primary income (compensation of employees and property income) from abroad. Data are in constant 2011 international dollars.

[9] Alternative methods (for example, linear regression with panel-corrected standard errors) were also tested and yield statistically significant results, resulting in similar estimates of elasticities.

[10] The rationale for adding time-period specific effects is that it controls for all spatial-invariant variables whose omission could bias estimates in a typical time-series study.

Table 3: Prevalence of food insecurity in response to change in income (GNI per capita, Atlas method)

	$\beta FI_{mod+sev}$^ (p-value in parentheses)	βFI_{sev}^ (p-value in parentheses)
Income elasticity using panel regression	–.46 (0.006)	–.69 (0.016)
Income elasticity using panel regression with year dummy	–.42 (0.013)	–.62 (0.027)
Income elasticity using pooled regression	–.42 (0.001)	–.60 (0.006)
Income elasticity using pooled regression with year dummy	–.42 (0.002)	–.60 (0.007)
Number of observations = 58		

Source: GAFSP Coordination Unit and FAO Voices of the Hungry.
Note: Robust standard errors used to control for heteroskedasticity. P-values lower than 0.05 show a statistically significant relationship.

Table 4: Prevalence of food insecurity in response to change in income (GNI per capita, PPP, constant 2011 international $)

	$\beta FI_{mod+sev}$^ (p-value in parentheses)	βFI_{sev}^ (p-value in parentheses)
Income elasticity using panel regression	–.50 (0.002)	–.84 (0.005)
Income elasticity using panel regression with year dummy	–.50 (0.002)	–.87 (0.004)
Income elasticity using pooled regression	–.52 (0.001)	–.88 (0.001)
Income elasticity using pooled regression with year dummy	–.53 (0.001)	–.88 (0.001)
Number of observations = 58		

Source: GAFSP Coordination Unit and FAO Voices of the Hungry.
Note: Robust standard errors used to control for heteroskedasticity. P-values lower than 0.05 show a statistically significant relationship.

16. After controlling for temporal variation in the dependent variable (year dummy), **a 10 percent income increase (measured by GNI per capita, Atlas method) is estimated to reduce the prevalence of moderate to severe food insecurity by 4.2 percent, while the prevalence of severe food insecurity is estimated to decline by 6.2 percent.** The pooled regression also yields results of similar strength and in the same direction.

17. **The elasticities were estimated to be much higher with GNI per capita PPP** (Table 4). The analysis showed that a 10 percent income increase can reduce the prevalence of moderate or severe food insecurity by 5.0 percent, while the prevalence of severe food insecurity is estimated to decline by 8.4 percent. After controlling for temporal variation in the dependent variable (via the year dummy), a 10 percent income increase (measured by GNI per capita, PPP) is estimated to reduce the prevalence of moderate to severe food insecurity by 5.0 percent, while the prevalence of severe food insecurity is estimated to decline by 8.7 percent. In this case as well, the pooled regression yields results of similar strength and in the same direction.

18. These elasticity estimates can then be used to inform and set a target for the FIES that is consistent with the GAFSP 20 percent income gain target (Box 1). For example, **a 20 percent income gain would imply a 17 percent reduction in the share of people experiencing severe food insecurity** (Income gain

* elasticity = 20 * 0.87 = 17.4 percent); i.e., the corresponding target would be to reduce the share of households experiencing severe food insecurity by 17 percent within five years from the start of implementing associated projects. A big assumption, based on data availability, is that the initial average share of households experiencing severe food insecurity at national level, as reflected by the 2014 FIES data, and the depth of food insecurity, are similar to average shares and the depth of food insecurity among the target participants of GAFSP projects. Arguably, the shares of food insecure households among GAFSP projects would likely be higher given the profile of the project target population.

19. An additional phase in the analysis therefore attempted to test this hypothesis using household-level data on project participants in one country for which such data are newly available (Liberia); the aim was to explore and validate the above findings and the suggested target derived from the macro data (see Annex 4). Baseline data for the GAFSP-financed project in Liberia illustrated higher prevalence rates of food insecurity compared to the rates found using a scale based on nationally representative data: 64.5 percent (+/-2.32 percent) of households are categorized as severely food insecure, and 92.6 percent (+/- 1.53 percent) are categorized as either moderately or severely food insecure, based on a raw FIES score. In other national data for Liberia, 63.9 percent are categorized as severely insecure, and 84.8 percent of households are categorized as moderately or severely food insecure (Cafiero et al., 2016).

20. **Additional micro-level analysis using this data and the model suggest that if the GAFSP-financed project is successful in increasing the income of project participants in Liberia by 20 percent, prevalence of food insecurity would decrease by 8 percent for households identified as severely food insecure and by 6 percent for moderately or severely food insecure households.** While at this stage available only for Liberia, these findings may challenge the assumption that communities and individuals targeted by all GAFSP projects are experiencing food insecurity in a directly comparable way to the national averages. Using macro level data for 58 countries predicts almost double the impacts on reduced food insecurity than the micro level, project-specific data.

21. Should these findings be repeated in other settings, the micro-level data could suggest that at least a 60 percent income gain is needed to help shift the poor in this setting close to a state of food security; this translates into a 25 percent reduction in the prevalence of severe food insecurity and a 16 percent reduction in moderate to severe food insecurity. **The outcome based on household-level impact data for Liberia points to a potentially substantial downward revision of FIES targets set using macro-level data.** It is suggested that additional analysis be carried out, for countries with a variety of socioeconomic structures, to assess whether the suggested GAFSP FIES targets should be revised downward.

Challenges and Caveats

22. **National-level data covering smaller time periods can present many important analytical challenges.** One of the most notable challenges is that only two years of FIES data were available when the macro analysis was conducted. Given these data limitations, variations across countries drove the elasticity estimates more than variations over time. The smaller time series effects limit the robustness of the approach to derive targets for FIES-based indicators. Controlling for the effects of unique country characteristics to isolate the impact of income differences on food insecurity is also a challenge, as discussed below.

23. **It is nearly impossible to validate national-level results with complete household-level estimates.** The Gallup World Poll survey results used by VoH are based on around 1,000 interviews per country,

and are designed to be representative of the national population. Although adjustments are made to reflect the respective shares of urban and rural populations, for many countries the samples drawn from rural areas may be too small to be representative of the rural-based beneficiaries targeted by GAFSP. No way currently exists to assess the extent of these differences, and the associated robustness of using the elasticities derived from national level results as indicative of those for potential GAFSP beneficiaries, as the additional analysis in Annex 4 and summarized above highlighted. Although the GAFSP Coordination Unit (CU) M&E team, through its partnership with the VoH team, has access to micro-level data used to estimate FIES prevalence rates, additional micro-level data for demographic variables (gender, age), employment status, geographic variables (rural/urban), and income corresponding to the same individual/households are needed to carry out additional ex-ante analysis at the household level. Such data are currently only available for a very limited number of countries.

24. **The income variation witnessed in available household (micro-level) data) is much larger than that seen in GNI per capita, which was used as the income variable in the main study.** Also, agricultural income at the household level is subject to large seasonal variation, which in tandem with factors such as intrahousehold distributional effects can dampen the overall impact on reducing the probability of being food insecure. It must also be noted that factors such as variation in household size can play a very important role in dampening the effect of higher income in reducing food insecurity**.**

25. Irrespective of the marginal effect, **the household-level data reiterate the strength of the causal relationship between income and food access as measured by the FIES**. Nonetheless, given that significant shares of households in GAFSP's typical target populations are deeply food insecure and poor, the analysis suggests that change in income would need to be very high to move the needle to bring them close to the poverty line and toward food security in a fragile country such as Liberia.

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ANNEX 1: SELECTED REGRESSION MODELS USING MACRO DATA

```
. xi: xtreg LnFIsev LogGNIpercapita, re r

Random-effects GLS regression                   Number of obs      =        58
Group variable: country1                        Number of groups   =        29


                                                Wald chi2(1)       =      5.77
corr(u_i, X)   = 0 (assumed)                    Prob > chi2        =    0.0163

                                 (Std. Err. adjusted for 29 clusters in country1)
------------------------------------------------------------------------------
             |               Robust
      LnFIsev |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
LogGNIpercapita |   -.693773   .2889366    -2.40   0.016    -1.260078   -.1274676
       _cons |    7.48339   1.891128     3.96   0.000     3.776847    11.18993
-------------+----------------------------------------------------------------
     sigma_u |  .89107274
     sigma_e |  .24444895
         rho |  .93000975   (fraction of variance due to u_i)
------------------------------------------------------------------------------
```

```
. xi: xtreg LnFImodsev LogGNIpercapita, re r

Random-effects GLS regression                   Number of obs      =        58
Group variable: country1                        Number of groups   =        29


                                                Wald chi2(1)       =      7.48
corr(u_i, X)   = 0 (assumed)                    Prob > chi2        =    0.0062

                                 (Std. Err. adjusted for 29 clusters in country1)
------------------------------------------------------------------------------
             |               Robust
   LnFImodsev |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
LogGNIpercapita |  -.4647257   .1698949    -2.74   0.006    -.7977137   -.1317377
       _cons |   6.934508    1.08843     6.37   0.000     4.801223    9.067793
-------------+----------------------------------------------------------------
     sigma_u |  .48260635
     sigma_e |  .14931523
         rho |  .91263835   (fraction of variance due to u_i)
------------------------------------------------------------------------------
```

```
. xi: xtreg LnFImodsev LogGNIpercapita, re r

Random-effects GLS regression                   Number of obs      =        50
Group variable: country1                        Number of groups   =        25


                                                Wald chi2(1)       =      9.15
corr(u_i, X)   = 0 (assumed)                    Prob > chi2        =    0.0025

                                (Std. Err. adjusted for 25 clusters in country1)
------------------------------------------------------------------------------
             |               Robust
   LnFImodsev |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
LogGNIpercapita |  -.5006156   .1654642    -3.03   0.002    -.8249194   -.1763118
       _cons |   7.646186   1.210592     6.32   0.000      5.27347     10.0189
-------------+----------------------------------------------------------------
      sigma_u |  .39170297
      sigma_e |  .16439915
          rho |  .85023088   (fraction of variance due to u_i)
------------------------------------------------------------------------------
```

```
. xi: xtreg LnFIsev LogGNIpercapita, re r

Random-effects GLS regression                   Number of obs      =        50
Group variable: country1                        Number of groups   =        25


                                                Wald chi2(1)       =      7.79
corr(u_i, X)   = 0 (assumed)                    Prob > chi2        =    0.0053

                                (Std. Err. adjusted for 25 clusters in country1)
------------------------------------------------------------------------------
             |               Robust
      LnFIsev |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
LogGNIpercapita |  -.8477126   .3038154    -2.79   0.005     -1.44318   -.2522454
       _cons |   9.288504   2.257139     4.12   0.000     4.864594    13.71241
-------------+----------------------------------------------------------------
      sigma_u |  .80206374
      sigma_e |  .25835915
          rho |  .90599406   (fraction of variance due to u_i)
------------------------------------------------------------------------------
```

ANNEX 2: COUNTRIES ELIGIBLE FOR GAFSP FUNDING

Countries eligible for GAFSP funding are all members of the International Development Association (IDA) that are eligible to receive financing from IDA and not the International Bank for Reconstruction and Development (IBRD) ("IDA-only countries") and that are not in nonaccrual status.[11] When the last GAFSP Public Sector Window Call for Proposals was launched in 2016, that included the 56 countries listed in Table A2.1.

Table A2.1: Countries eligible for GAFSP funding, by region, 2016

Africa *(32 countries)*		**East Asia and the Pacific** *(11 countries)*	**Europe and Central Asia** *(3 countries)*	**Latin America and the Caribbean** *(4 countries)*	**Middle East and North Africa** *(1 country)*	**South Asia** *(5 countries)*
Benin Burkina Faso Burundi CAR Chad Comoros Côte d'Ivoire Djibouti Democratic Republic of Congo Ethiopia Gambia Ghana Guinea Guinea-Bissau Kenya Lesotho Liberia	Madagascar Malawi Mali Mauritania Mozambique Niger Rwanda São Tomé and Principe Senegal Sierra Leone South Sudan Tanzania Togo Uganda Zambia	Cambodia Kiribati Lao PDR Marshall Islands Micronesia, FS Myanmar Samoa Solomon Islands Tonga Tuvalu Vanuatu	Kosovo Kyrgyz Republic Tajikistan	Guyana Haiti Honduras Nicaragua	Yemen	Afghanistan Bangladesh Bhutan Maldives Nepal

[11] Nonaccrual status occurs when the oldest payment arrears are six months overdue. Once all arrears are cleared, all loans to, or guaranteed by, the country are generally restored to accrual status.

ANNEX 3: MICRO-LEVEL VARIABLES

Table A3.1: Definitions and data sources for micro-level variables

Indicator	Definition	Data source
Food Insecurity: Moderate to severe or Severe	The Food Insecurity Experience Scale (FIES) is a measure of food access at the individual or household level. It is a member of the family of experience-based food security measurement scales and measures the severity of the food insecurity condition of a household or an individual respondent (constraints on the ability to access food).	VoH
Income	Annual household income in local currency; per capita income quintiles. Dummy variable that takes the value 1 if the respondent falls in the poorest 40% income group and 0 otherwise.	Gallup
Household Size	Total number of people living in household. Also can be household size squared.	Gallup
Women	Dummy variable that takes the value 1 if the respondent is a woman and 0 otherwise.	Gallup
Age: 15 years and above	Age in years.	Gallup
Age Squared	Age in years, squared.	GAFSP
Marital Status	Dummy variable that takes the value 1 if the respondent is single and 0 otherwise.	Gallup
Education Status: elementary education	Dummy variable that takes the value 1 if the respondent completed elementary education or less (up to 8 years of education) and 0 otherwise.	Gallup
Education Status: secondary education	Dummy variable that takes the value 1 if the respondent completed secondary education and some education beyond secondary and 0 otherwise.	Gallup
Education Status: tertiary education	Dummy variable that takes the value 1 if the respondent completed tertiary education and some education beyond tertiary and 0 otherwise.	Gallup
Employment Status	Dummy variable that takes the value 1 if the respondent is employed, either full- or part-time, and 0 otherwise.	Gallup
Geography	Dummy variable that takes the value 1 if the respondent lives in a rural area and 0 otherwise. According to the World Bank, "rural population" refers to people living in rural areas as defined by national statistical offices. It is calculated as the difference between total population and urban population.	Gallup

Source: This list was prepared based on Cafiero (2013), Gallup (2016), Horton and Hoddinot (2015), Klapper et al. (2016), and Moltedo et al. (2014).

ANNEX 4: VALIDATION OF THE FIES TO ASSESS HOUSEHOLD FOOD INSECURITY IN RURAL LIBERIA: GAFSP EXPERIENCE USING DATA FROM RIGOROUS IMPACT EVALUATION[12]

BACKGROUND

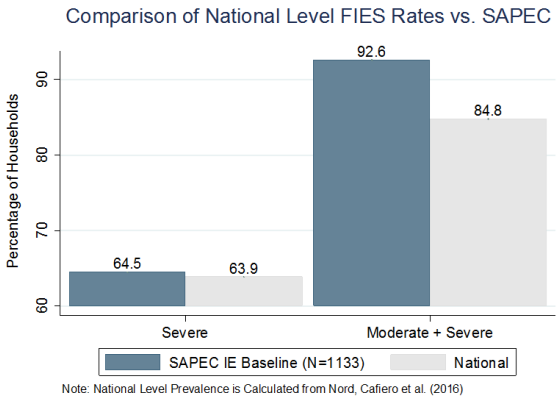
To monitor GAFSP's progress to achieve Sustainable Development Goal 2 (SDG2) of no hunger, validation of FIES targets using ex-post data provides more accurate results about GAFSP targeted beneficiaries than using an ex-ante assessment. This is due to the former's closer proximity to the targeted pool of (project) beneficiaries or participants. In 2017, the GAFSP Steering Committee (SC) endorsed the FIES as a "Tier 1" indicator and set impact-level indicator targets based on macro-level data to guide all GAFSP Public Sector Window investment projects. An elasticity-based methodology was used to derive an indicative change in the prevalence of food insecurity, as measured by the FIES for GAFSP beneficiaries, in response to a certain percentage gain in income. The goal was to estimate the change in the prevalence of food insecurity, as measured by the FIES, that is implied if GAFSP reaches its poverty reduction target.

At the March 2017 Steering Committee meeting, the SC agreed to pursue additional analysis using household-level data to validate the target derived using macro-level data. The GAFSP Coordination Unit (CU) undertook an exercise to validate the income elasticity-based targets using the baseline data collected as part of a rigorous impact evaluation (IE) performed by the World Bank's Development Impact Evaluation (DIME) unit for the GAFSP-financed Public Sector Window project in Liberia. The baseline survey for the IE of the Smallholder Agriculture Productivity Enhancement Commercialization Project (SAPEC)[13] was conducted between June and August 2017. This Annex shares the results of this exercise to estimate the income elasticity for three thresholds set to understand the severity of food insecurity.

[12] The authors wish to acknowledge Michael Adedoyin Sunday Orevba for sharing DIME IE baseline data covering the FIES Survey Module, income module, and socioeconomic variables.

[13] SAPEC received US$46.5 million in grant financing from GAFSP to enhance the income of smallholder farmers, particularly women and youth, through sustainable land expansion and land improvement, increased market access, and strengthened institutional capacities. GAFSP financing in Liberia will support implementation of sustainable medium- and long-term investments in agriculture guided by the Liberia Agriculture Sector Investment Program (LASIP).

Figure A4.1: Comparison of national-level food insecurity rates vs food insecurity of SAPEC participants



DATA

The SAPEC evaluation is the first GAFSP IE to incorporate the FIES, GAFSP's newly-adopted standard for measuring self-reported food insecurity. The baseline survey for the SAPEC IE was conducted between June and August 2017. It covered 97 primary sampling units – in this case, electoral areas – surveyed across all 10 counties where SAPEC operates. The baseline survey covered electoral areas in which SAPEC did not distribute subsidized agricultural inputs in 2017 that were randomly assigned as control communities for the evaluation as well as areas randomly assigned for treatment status during the evaluation where SAPEC did so. Table A4.1 below provides descriptive analysis of income and FIES for GAFSP project participants.

A wide income disparity is estimated across households at different thresholds of food insecurity in Liberia. Table A4.1 shows summary statistics for household income[14] by three different thresholds of food insecurity. Following VoH guidelines (VoH 2016), a set of cutoffs is developed to identify the severity of food insecurity, represented by a set of binary variables based on a raw score cutoff. As defined in the guidelines, the raw score represents the aggregated affirmative responses for eight scales and can be classified as ordinal with the latent trait of food insecurity. The three raw score cutoffs are: (i) a raw score of 1 to 3 is considered "mild food insecurity"; (ii) a raw score of 4 to 6 is considered "moderate to severe" food insecurity; and (iii) a raw score of 7 to 8 is considered "severe food insecurity."

[14] Revenue from sales of all crops minus production costs.

Table A4.1: Mean household income by category of food insecurity, Liberia SAPEC participants

Severe	Total number of households	% of total treatment	Mean annual income (US$)
Male-headed	276	80.2	360.5
Female-headed	141	77.5	304.4
Total	417	79.3	332.5
Moderate to severe			
Male-headed	322	93.6	377.3
Female-headed	161	88.5	327.9
Total	483	91.8	352.6
Mild			
Male-headed	22	6.4	643.9
Female-headed	21	11.5	431.3
Total	43	8.2	537.6

Source: GAFSP Coordination Unit and DIME.

Average annual household income is approximately US$407 for the GAFSP treatment group of project participants, somewhat lower than the national average in Liberia (approximately $458[15]). For beneficiary groups in the *mild* food insecurity category, average annual household income is higher (US$538) than in the other two categories (US$352 and US$332 for households identified as having *moderate to severe* and *severe* food insecurity, respectively). Within the *mild* category, average annual income for male-headed households is 33 percent higher than that of female-headed households (US$644 versus US$431). A similar gap is observed for households identified in the moderate to severe and severe categories.

Figure A4.2a: Average household annual income

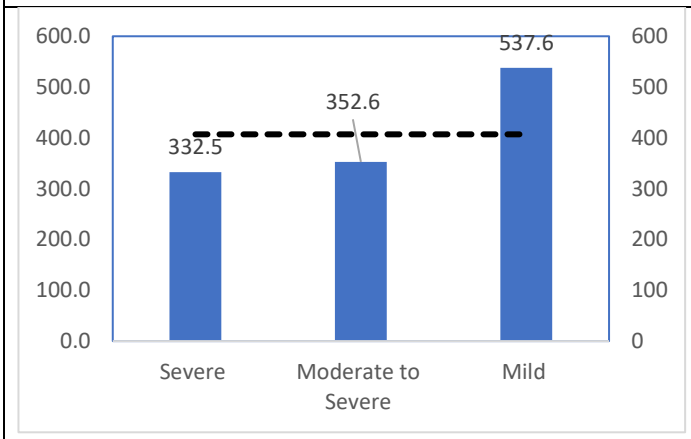
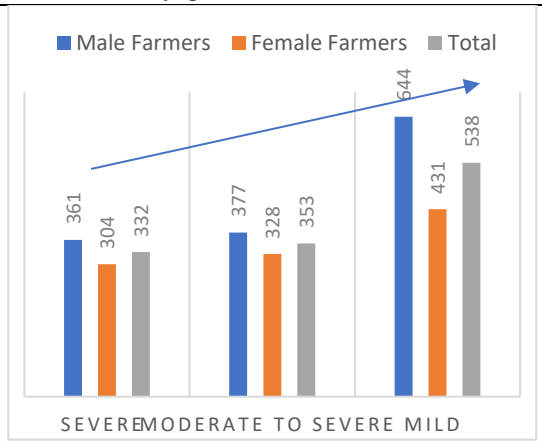


Figure A4.2b. Average household annual income by gender of household head



Source: GAFSP Coordination Unit and DIME. Average income is represented by the dotted line in Figure A4.2a.

EMPIRICAL METHODS

To estimate project level income elasticity (i.e., the effect of income gain on the probability of a household changing its food insecurity status) using household data, a simple logistic regression is used. To understand which category of severity of food insecurity is most strongly associated with a

[15] Measured in terms of GDP per capita.

change in income, a two-step method is deployed, using adjusted predictions estimated by the logit model. The logistic regression can be applied to this problem because it directly estimates the probability of an event occurring for more than one independent variable; that is, for k independent variables. The model is treated as a qualitative response model and can be written as:

$$logit(P_i) = \beta_0 + \beta_i \delta_i + \varepsilon_i \text{ ……………………………………………… (1)}$$

P_i is the probability that the i^{th} household is food insecure. For the empirical analysis, P_i is defined as a categorical variable (can take a value of 0 or 1) using two raw score cutoffs: (i) a raw score of 4 to 6 indicates moderate to severe food insecurity; and (ii) a raw score of 7 to 8 indicates severe food insecurity. δ_i is a vector of explanatory variables describing the i^{th} household (in this case, gender of the household head is the only variable included in the model).

RESULTS AND FIES TARGETING

The first stage of the model uses a logit model to derive the predictive variables for severe (Model 1) and moderate to severe (Model 2) food insecurity (results are in Table A4.2). Using a simple marginal approach, the second stage estimates the impact of a percentage gain in income on households' state of food insecurity. Note that even though the coefficient on income in the moderate to severe food insecurity equation (Model 1) is higher than in the severe food insecurity equation (Model 2), at the margin the impact of every percentage income gain is higher for severely food insecure households relative to the impact on moderately to severely food insecure households.

As indicated in Table A4.1, overall 79 percent of project households are predicted to be severely food insecure (and earn US$333 on average), and 92 percent of project households are predicted to be moderately to severely food insecure (and earn US$353 on average). The marginal effects derived in the second stage indicate that if the income of people in both of those categories increased by 20 percent, food insecurity would decrease by 8 percent for severely food insecure households and 6 percent for moderately to severely food insecure households. The data suggest that an income gain of at least 60 percent is needed to lift poor project households close to a state of food security; this translates to a 25 percent reduction in the prevalence of severe food insecurity and a 16 percent reduction in the prevalence of moderate to severe food insecurity.

In a technical sense, the reason for the smaller effect estimated using micro-level data is probably that a 10 percent increase in income at the mean is actually quite small. For example, a household at 75 percent of the income distribution has an income of US$482, while a household at 25 percent has an income of US$100 - a difference of 382 percent. Given that food insecurity status was modeled based on item response theory , the overall prediction accuracy of the model was high, indicating that the independent variables had a significant impact on explaining food insecurity status. Since a significant share of Liberian households are deeply food insecure and poor, the change in income needs to be very high to move the needle to bring them close to both the poverty and food security line.

This income variation for the Liberia project sample is much larger than that seen when using GNI per capita, the income variable used in the macro-level analysis. Also, agricultural income at the household level is subject to large seasonal variation, which in tandem with factors such as intrahousehold distributional effects can lessen the overall ability of income to reduce the probability of being food insecure. Note also that factors such as variation in household size can play an important role in dampening the effect of higher income in reducing food insecurity. Irrespective of the marginal effect, however, the household-level data reiterate the strength of the causal relationship between income and food access as measured by the FIES instrument.

The state of food insecurity associated with GAFSP project participants due to income and food access constraints is clear. As mentioned above, the data suggest that it would require, on average, an income

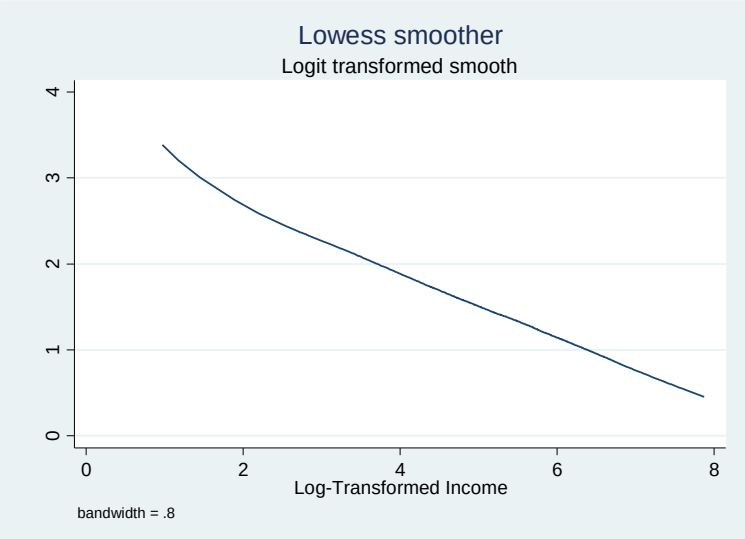
gain of at least 60 percent to pull *severely* food insecure households into mild food insecurity or into a state of food security. Arguably, the wide gap between male and female farmers' income across all three categories of food insecurity points to the need to target interventions at female farmers.

Table A4.2: First-stage logit regression

	(1) FIES Sever	(2) FIES Moderate -to-Severe
main		
log(income)	-0.388***	-0.552***
	(-3.65)	(-3.31)
1.gender	0.218	0.755*
	(0.94)	(2.26)
_cons	3.339***	5.103***
	(5.37)	(5.11)
N	499	499

t statistics in parentheses
* p<0.05, ** p<0.01, *** p<0.001

Figure A4.3: The relationship between income and the state of food insecurity (for severely food insecure households)



Note: A local regression (Lowess) model is used to estimate the change in predicted values of food insecurity in response to income change. The x-axis represents the predictive values of severely food insecure households derived using the Logit Model (Table A4.2)

CONCLUSIONS AND RECOMMENDATION

This study analyzes household-level data derived from a rigorous IE. Overall, estimates from the FIES baseline data exhibit a strong similarity to national-level estimates of the prevalence of food insecurity, reflecting a strong causal relationship between income and the prevalence of food insecurity. However, the estimated effect of income on reducing food insecurity at the margin is lower relative to the estimated effect based on cross-sectional data. Factors such as seasonality and intrahousehold distributional effects may have led to a large variation in income, in effect dampening the overall impact.

The Liberia results are likely to reflect the situation in other low-income fragile countries, as a significant share of the households in GAFSP's typical target populations are deeply food insecure and poor. Any change in income among those poorest populations would likely need to be very high to bring them close to the poverty line and toward food security. It is suggested that additional analysis be carried out, including for other countries with a socioeconomic structure comparable to that of Liberia, to assess whether the suggested GAFSP FIES targets be revised downward.

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