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Model-based estimation of small area food insecurity measures in Ethiopia using the Fay-Herriot EBLUP estimator

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Abstract. In many countries, including Ethiopia, sample surveys are designed to produce estimates of variables of interest at the national and regional levels due to cost and operational considerations. For example, household food insecurity estimates are needed down at least at the zone level in Ethiopia to offer targeted solutions. However, the sample sizes of sample surveys are often not large enough to produce reliable estimates at the small area (zone) level. This paper remedies some of these shortcomings by estimating household food insecurity in each zone of Ethiopia by linking data from the 2015/16 welfare and monitoring survey and the 2007 population census using a small area estimation (SAE) approach. The results show the zonal level household food insecurity estimates generated by SAE were more efficient and precise compared to the survey-based estimates. Besides, accurate and cost-effective food insecurity statistics at the zonal level were produced without more resources through combining the available data sources. Finally, zonal level household food insecurity estimates could be the recommended tools for monitoring the progress of sustainable development goals (SDGs) in Ethiopia. Because, in the final 2030 Agenda, SDG 2 concentrates entirely on food security, recognizing much of its complex and multi-faceted nature.

Keywords: Ethiopian zones, Fay-Herriot model, food insecurity, population census, weighted estimator

1. Introduction

Food insecurity refers to a lack of food due to lack of resources, not because of illness or voluntary fasting or dieting. It is the state of being without regular access to nutritious and sufficient amounts of food for active and healthy life including normal growth and development [1,2]. Having low monthly income, large household size, low educational level, unemployment among adult members, single female head, inadequate dietary intake, and poor nutritional status are the most common variables related to food insecurity at the household level [3]. In other words, food insecurity is to a large extent related to low socio-economic status.

Based on the latest FAO estimates, about 1.3 billion people in the world consisting of 17.2% of the world population have experienced food insecurity at moderate levels [2]. About 2 billion people in the world consisting of 26.4% of the world population have experienced a combination of moderate and severe levels of food insecurity [2]. Among those affected, the majority live in sub-Saharan Africa (SSA) (22.8%), Southern Asia (15.0%) and Western Asia (12%). The undernourished population is distributed unevenly across regions. For example, in 2018 more than 500 million in Asia and almost 260 million people in Africa are undernourished with 90% living in SSA [2].

Currently, food insecurity and its alleviation are one of the international community's main priorities, especially in SSA [4,5]. According to the latest estimates of the State of Food Insecurity in the World [6], the prevalence of hunger for SSA declined by 31% between 1990 and 2015. Although the prevalence of hunger declined from 75% to 32% in Ethiopia, approximately 26 million people were categorized as food insecure in

2016 [7,8]. During this period, however, the number of hungry people fell from 37 to 32 million [9].

Ethiopia is among the countries affected by food shortages since the 1960s [10]. The country has faced three different famines in the past four decades [7,9]. Consequently, the famines in the 1970s, 80s, and 90s affected much of the country's subsequent food production. It was estimated that close to 58 million people were affected by famine between 1973 and 1986 [11]. However, food insecurity continues to be a challenge to the Ethiopian Government despite the country coming a long way in reducing it [7]. Food insecurity patterns of Ethiopia are linked with rainfall patterns, where hunger trends decline after the rainy seasons [12]. Poverty and hunger were found to be the highest in the rural areas where the majority of the poor live [9].

Ethiopia is among the countries that have achieved the millennium development goals (MDGs) target between 1990 and 2015 [6]. For example, Ethiopia has made progress in reducing food insecurity and malnutrition [13], especially the prevalence of undernourishment reduced from the 60% level seen in the 1990s to 30% in 2015 [14,15]. However, the country has experienced one of the worst droughts in half a century due to the La Niña effect in 2015 [16]. The La Niña effect resulted in low summer rainfall in all parts of the country [16], which is often led the country with food security crises [17]. As a result of the drought, many farmers, herders, and families dependent on agriculture have been forced to migrate and become dependent on humanitarian assistance to rescue themselves from widespread hunger and malnutrition [18].

Given that Ethiopia has experienced high scale famine with the potential for recurrence, it is important to provide adequate information for the Government, stakeholders, policymakers and Nongovernmental Organizations (NGOs) for necessary interventions. This paper aims at contributing to two aspects including:-

- First, food insecurity measures are understudied in the literature compared with poverty, especially in developing countries. This paper presents a set of estimates of food insecurity measures in Ethiopia, underpinned by a method that does not receive much attention in food security literature.
- Second, official estimates of poverty, food insecurity, and so on in Ethiopia are available at the national and regional levels. However, there is a need for geographically disaggregated estimates at the sub-national levels (i.e., zones and regional towns) for making better decisions. The national government, as well as zonal level administrative officials, would like to know how they can prioritize and allocate resources. Because zonal level estimates could be used as a basis for identifying marginalized households and communities to ensure the equitable and inclusive provision of assistance to the ones most in need. Furthermore, zonal level estimates are needed to adequately allocate funds and to be able to assess the effectiveness of their spending [19].

Having this in mind, the aim of this paper is twofold. First, the primary aim is to account for inequality in food insecurity measures at the zone levels in Ethiopia. Second, this paper analyses geographical (spatial) variations of food insecurity measure at the zone levels in Ethiopia.

2. Materials and methods

2.1. The study area

Ethiopia is located in eastern Africa, bordered by Sudan and South Sudan to the west, Kenya to the south, Eritrea to the north, Djibouti to the east and Somalia to the south and east. The GPS coordinates of Ethiopia is 9.1450° N, 40.4897° E [20].

2.2. Data sources

Small area estimation depends on a combination of different datasets such as survey data and census data [19]. The welfare and monitoring survey (WMS) was conducted by the government statistical agency, Central Statistical Authority (CSA) in 2015/16 [21]. The survey covered the population in sedentary areas of the country on a sample basis excluding the non-sedentary population in Afar and Somali Regions. The sampling method considered under this category was a stratified multi-stage cluster sampling with enumeration areas as the second-stage sampling units. In summary, a total of 30,237 households (10,368 in rural and 19,869 in urban areas) were covered. To fill the possible gap in the survey data we used the auxiliary information from the 2007 Ethiopian population census data.

2.3. The Fay-Herriot model and small-area estimators

In particular, since food insecurity measures depend on the binary outcome from the question ("Did the household suffer food shortage during the last 12 months?"), neither linear mixed models nor unit-level model-based estimation approaches can hardly be used [22]. Instead, the Fay-Herriot model gives an easy-to-apply solution [22]. Therefore, the well-known Fay-Herriot model is applied to obtain estimates of food insecurity measures at the zone levels in Ethiopia. This model is useful in cases where auxiliary data are available at the area level or when it is not possible to link the information of the sample units with census data or unit-level data, which might not be available due to confidentiality issues [23,24].

Following [24], the model is described as: let

$$\theta_i = h(\bar{Y}_i) \tag{1}$$

denote the i^{th} small area mean or the area total, where $\bar{Y}_i$ is the unknown population of the target variable y in area i for $i = 1, \ldots, m$, where m is the number of sampled areas, $\boldsymbol{x}_i = (x_{1i}, \ldots, x_{ki})'$ is an area specific data vectors for area i. It is assumed that θ_i is related to the area-specific auxiliary data in the Fay-Herriot model through a linear regression model:

$$\theta_i = \boldsymbol{x}_i'\boldsymbol{\beta} + \nu_i,\ i = 1, \ldots, m. \tag{2}$$

The Fay-Herriot model is therefore expressed as:

$$y_i = \boldsymbol{x}_i'\boldsymbol{\beta} + \nu_i + e_i, \tag{3}$$

where the area specific random effects $\nu_i \overset{\text{ind}}{\sim} N[0, A]$ are independent of the sampling errors $e_i \overset{\text{ind}}{\sim} N[0, \psi_i]$ with known variance ψ_i. The sampling variance, ψ_i represents the sampling variance of y_i to be estimated from the sample survey. The Fay-Herriot area-level model can also be expressed in matrix notation as $\boldsymbol{y} = \boldsymbol{X\beta} + \boldsymbol{\nu} + \boldsymbol{e}$, where $\boldsymbol{X} = (x_1, \ldots, x_m)', \boldsymbol{y} = (y_1, \ldots, y_m)', \boldsymbol{\nu} = (\nu_1, \ldots, \nu_m), \boldsymbol{e} = (e_1, \ldots, e_m)$, the variance-covariance matrix of $\boldsymbol{y}$ is $\boldsymbol{\Sigma} = \text{diag}(\psi_1, \ldots, \psi_m) + A\boldsymbol{I}_m$. We assume that rank $(\boldsymbol{X}) = k$.

2.4. Empirical best linear unbiased predictor (EBLUP) estimator

Small area means or totals can be expressed as linear combinations of fixed and random effects. The best known method for the prediction of mixed effects is the best linear unbiased predictor (BLUP). The BLUP estimator was first originated by [25] and used by many authors in different applications. It is a weighted combination of the direct estimator, y_i and the regression synthetic estimator, $\boldsymbol{x}_i'\hat{\boldsymbol{\beta}}$ [26]. If the parameters β and A are known under the area-level model, the BLUP of θ_i is given by

$$\tilde{\theta}_i^B = (1 - \gamma_i)y_i + \gamma_i \boldsymbol{x}_i'\tilde{\boldsymbol{\beta}},\ i = 1, \ldots, m \tag{4}$$

where $\tilde{\boldsymbol{\beta}} = (\boldsymbol{X}'\boldsymbol{\Sigma}^{-1}\boldsymbol{X})^{-1}\boldsymbol{X}'\boldsymbol{\Sigma}^{-1}y$ and $\gamma_i = \frac{\psi_i}{\psi_i + A}$.

Since $\boldsymbol{\beta}$ and A are unknown, BLUP is not usable until we estimate these model parameters. The best way to estimate θ_i is to replace the unknown parameters $\boldsymbol{\beta}$ and v_i with their respective estimators. There are various ways of estimating the model variance A such as the method of moments obtained by [24,27], Maximum Likelihood (ML) and Restricted Maximum Likelihood (REML) obtained by [28] and so on. For example, the Fay-Herriot moment estimator of A is based on the weighted least squares residual sum of squares. We can get the Fay-Herriot moment estimator of A by simplifying the following equation iteratively:

$$\sum_{i=1}^{m} \frac{(y_i - \boldsymbol{x}_i'\tilde{\boldsymbol{\beta}})^2}{\psi_i + A} = m - p \tag{5}$$

where m is the number of small areas, p is the dimension of the vector of auxiliary variables $\boldsymbol{x}_i$ and

$$\tilde{\boldsymbol{\beta}} = \left\{ \sum_{i=1} \frac{\boldsymbol{x}_i \boldsymbol{x}_i'}{\psi_i + A} \right\}^{-1} \left\{ \sum_{i=1} \frac{\boldsymbol{x}_i y_i}{\psi_i + A} \right\}. \tag{6}$$

The equation is iteratively solved subject to the condition $A \geqslant 0$ [26]. When the unknown parameters are replaced by their estimators, then we will have EBLUP of θ_i which is given by

$$\hat{\theta}_i^{\text{EB}} = (1 - \hat{\gamma}_i)y_i + \hat{\gamma}_i \boldsymbol{x}_i'\hat{\boldsymbol{\beta}},\ i = 1, \ldots, m, \tag{7}$$

where $\hat{\boldsymbol{\beta}} = (\boldsymbol{X}'\hat{\boldsymbol{\Sigma}}^{-1}\boldsymbol{X})^{-1}\boldsymbol{X}'\hat{\boldsymbol{\Sigma}}^{-1}y$ and $\hat{\gamma}_i = \frac{\psi_i}{\psi_i + \hat{A}}$.

When the variance of the area effect, $\hat{A}$ is negative, the EBLUP estimator reduces to synthetic estimator. This makes the contribution of the mean squared error (MSE) estimate assuming all parameters are known becomes zero. To avoid this limitation, an alternative weighted estimator with fixed weights $(1 - w_i)$ and w_i has been proposed by [26,29]. The estimator $\hat{\theta}_i^w$ is a special case of the θ_i with $h_i(y) = -w_i\{y_i - \boldsymbol{x}_i'\tilde{\boldsymbol{\beta}}(\hat{A})\}$. Considering this, for the i^{th} zone, a weighted estimator of θ_i is given by [26,30]:

$$\hat{\theta}_i^w = (1 - w_i)y_i + w_i \boldsymbol{x}_i'\hat{\boldsymbol{\beta}},\ i = 1, \ldots, m, \tag{8}$$

where w_i is a fixed weight $(0 \leqslant w_i \leqslant 1)$. It can be simply be ascertained from past knowledge or simply chosen as $w_i = 1/2$, say.

2.5. Estimation of MSE of EBLUP

In practical applications, we need an estimator of MSE($\hat{\theta}_i^w$) as a measure of variability (or uncertainty) associated with the estimator $\hat{\theta}_i^w$. An asymptotic expression of the MSE($\hat{\theta}_i^w$) which is accurate to the order

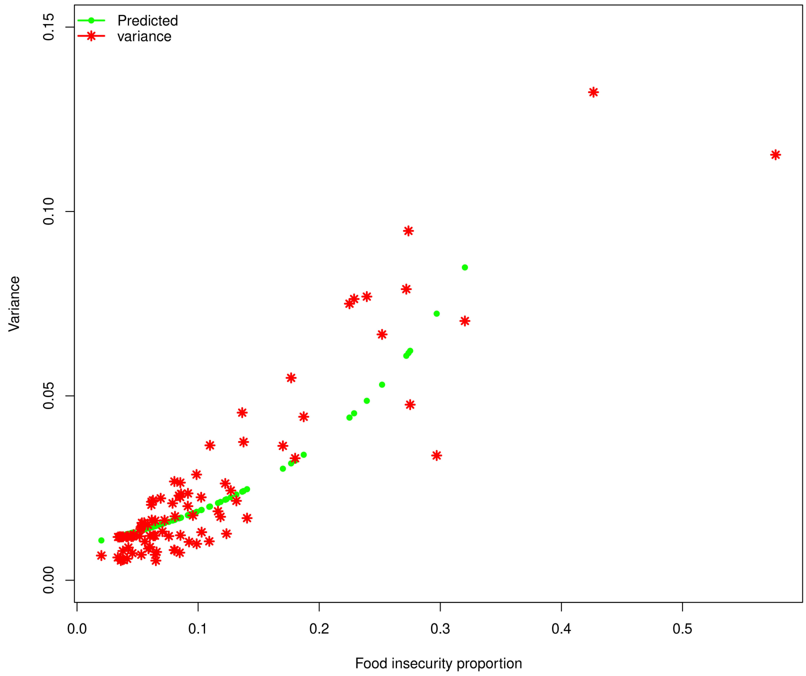

Fig. 1. Dispersion plots for GVF fit for food insecurity estimates.

$o(m^{-1})$ is given by [30]:-

$$\mathrm{MSE}(\hat{\theta}_i^{\,w}) = g_{1i}(A) + g_{2i}(A) + g_{3wi}(A) + o(m^{-1}), \quad (9)$$

where $g_{1i}(A) = \frac{A\psi_i}{A+\psi_i}$, $g_{2i}(A) = \gamma_i^2 x_i'(X'\mathbf{\Sigma}^{-1}X)^{-1} x_i$ and $g_{3wi}(A) = (\gamma_i - w_i)^2\{(A+\psi_i) - \boldsymbol{x}_i'(\boldsymbol{X}'\mathbf{\Sigma}^{-1}(A)\boldsymbol{X})^{-1}\boldsymbol{x}_i\} + o(m^{-1})$.

This estimator accounts for the variability (or uncertainty) associated with the estimation of the regression parameters, random effects, and variance components. According to [30], the $\mathrm{MSE}(\hat{\theta}_i^w)$ can also be expressed as follows: $\mathrm{MSE}(\hat{\theta}_i^w) =: h_{1i}(A) + h_{2i}(A) + o(m^{-1})$. Now, $E[h_{2i}(\hat{A})] =: h_{2i}(A) + o(m^{-1})$ for the REML and FH estimators. In addition, $h_{1i}(A)$ can be expressed as $h_{1i}(A) = \psi_i(1-w_i)^2 + Aw_i^2$.

A nearly unbiased estimator of $\mathrm{MSE}(\hat{\theta}_i^w)$ using the Fay-Herriot estimator $\hat{A}$ is given as follows:-

$$\mathrm{mse}(\hat{\theta}_i^w) =: h_{1i}(\hat{A}) + h_{2i}(\hat{A}) - b_{\hat{A}}(\hat{A})w_i^2, \quad (10)$$

where $b_{\hat{A}}$ is the bias of the FH estimator. Details about $\mathrm{mse}(\hat{\theta}_i^w)$ can be found [30].

Let S represents the set of all people in the survey population for the small area and N represents the number of individuals/households in S. For $k \in S$, the proportion of food insecure households can be obtained as:

$$y_k = \begin{cases} 1 & \text{if person } k \text{ is food insecured} \\ 0 & \text{otherwise} \end{cases} \quad (11)$$

Let $Y = \sum_{k\in S} y_k$, total number of food insecure people in S, the main parameter of interest, $P = \frac{Y}{N}$, proportion of food insecure people in S, food insecurity ratio, $y_i = \frac{\hat{Y}}{\hat{N}}$.

The Akaike information criterion (AIC), Bayesian information criterion (BIC) and log-likelihood function were used to select the auxiliary variables [26]. In general, a desirable model is one that minimizes the AIC or the BIC on the significance tests for each parameter. The model was operationalized using the R statistical software package. Furthermore, the steps and procedures required to obtain small area estimates are discussed by [31].

Furthermore, the generalized variance function (GVF) introduced by [24] was applied to smooth out the uncertainty of the design-based variance estimate in a complex setting. When sample sizes are too small, standard design-based estimators are not precise enough. It is important to have stable estimators for smaller domains. The GVF is used to produce domain-level variance estimators that would be more stable than direct design-based variance estimators. As shown in Fig. 1, the GVF helps to smooth out the unreliable and noisy estimated variance [22].

Table 1
Estimates of the log-transformed FH model parameters

		Estimate	Std error	t-value	p-value
Women	$\hat{\beta}_1$	3.695	1.046	3.532	0.001**
Age less than or equal to 30	$\hat{\beta}_2$	0.515	0.608	0.847	0.399
Single	$\hat{\beta}_3$	0.062	0.161	0.387	0.699
Greater than 12 years of schooling	$\hat{\beta}_4$	−0.186	0.065	−2.859	0.005**
Self employed	$\hat{\beta}_5$	0.319	0.123	2.589	0.011*
Household size less than 5	$\hat{\beta}_6$	−0.703	0.514	−1.368	0.175
Adjusted r-square (adjR^2)			0.95		
AIC			174.35		
BIC			191.93		
Loglik			−80.18		

Note: *significant at 0.05 and **significant at 0.01.

3. Results and discussion

In the usual application of standard small area estimation, data on the variables of interest would be taken from the survey while data on the auxiliary variables would be taken from the census data [26]. The estimated proportion of food-insecure households in Ethiopian zones calculated from the 2015/16 WMS data acts as the response variable in the Fay-Herriot regression model. As auxiliary (i.e., explanatory) variables, we considered the indicators of age, the indicators of sex, the indicators of the different levels of the variable education, the indicators of the categories of the variable employment, indicators of marital status and indicators of household size.

Table 1 reports the estimates of the Fay-Herriot model parameters and the corresponding p-values. The AIC, BIC and log-likelihood values included women, age less than or equal to 30, single marital status, greater than 12 years of schooling, self-employed, and household size less than 5 as best covariates (Table 1). The fitted model also provides the adjusted r-square of 94.50%. This indicates that 94.50% of the variation in household food insecurity measure is explained by auxiliary variables. The findings of this study revealed that women households, households with greater than 12 years of schooling and self-employed households had a statistically significant association with food insecurity. Moreover, food insecurity decreased among households with greater than 12 years of schooling and household size less than 5.

The estimation results for all the zones are shown in Table 2. The smallest zonal level food insecurity estimates ($< 5\%$) were situated in the Addis Ababa sub-cities such as Addis Ketema (2.47%), Nifas Silk (3.18%), Bole (3.30%), Arada (3.50%), Yeka (4.40%), Kirkos (4.83%), Lideta (4.84%), Kolfe (4.89%) and Harari (4.46%). On the other hand, the Ethiopian zones that contain the highest food insecure households ($> 20\%$) were Amaro (20.60%), Konso (26.03%) and Alaba (33.05%). Figure 2 shows the weighted estimates (also known as the model-based estimates) and the survey-based estimates (also known as direct estimates) of the food insecurity measures for each Ethiopian zone. The scatter plots in all cases show that the model-based estimates are less variable than the direct estimates since model-based estimates borrowed information from the population census [23,26].

Once we are confident of our choice of small area model, it is still very important to assess the quality of the small area estimates produced. To do this, the coefficient of variation (CV), root MSE (RMSE) and their corresponding percent improvement were used.

RMSE The performance of the weighted estimate, $\hat{\theta}_i^w$ relative to the direct survey-based estimate y_i was improved by the percent improvement, $PI_{\text{rmsei}} = 100 \times [\text{rmse}(y_i) - \text{rmse}(\hat{\theta}_i^w)]/\text{rmse}(y_i)$, where $\text{rmse}(y_i)$ is the RMSE of direct estimator and $\text{rmse}(\hat{\theta}_i^w)$ is the RMSE of the weighted estimator. The values of PI_{rmsei} were varied from 4.21% for Nefas Silk to 43.41% for Alaba. The average percent improvement was 43.41%. For most zones, the improvement was quite real. Furthermore, Fig. 3 (left) showed the scatter plots of the RMSEs of the weighted estimator and direct estimates against the zones, with zones sorted by increasing CVs of direct estimates. This figure shows that the RMSE of the weighted estimates is smaller than those of the corresponding direct estimates.

CV Another measure of the performance of the weighted estimates, $\hat{\theta}_i^w$ relative to the direct estimate y_i was the percent improvement based on the CV. The percent improvement in this case was $PI_{CVi} = 100 \times [CV(y_i) - CV(\hat{\theta}_i^w)]/CV(y_i)$, where $CV(y_i)$ is the CV of direct estimator and $CV(\hat{\theta}_i^w)$ is the CV of the weighted estimator. In this particular case, the percent

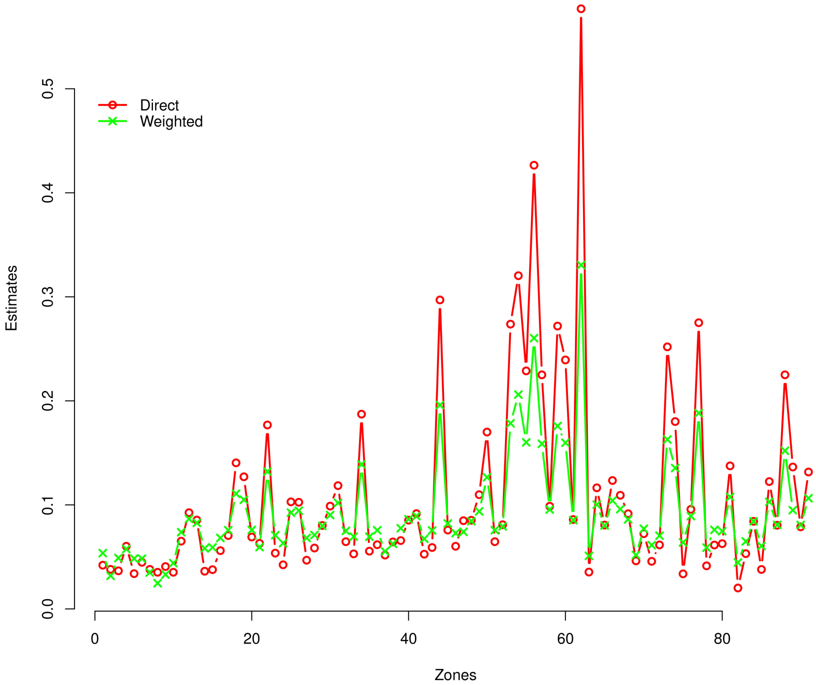

Fig. 2. The EBLUPs and direct estimates for each zone.

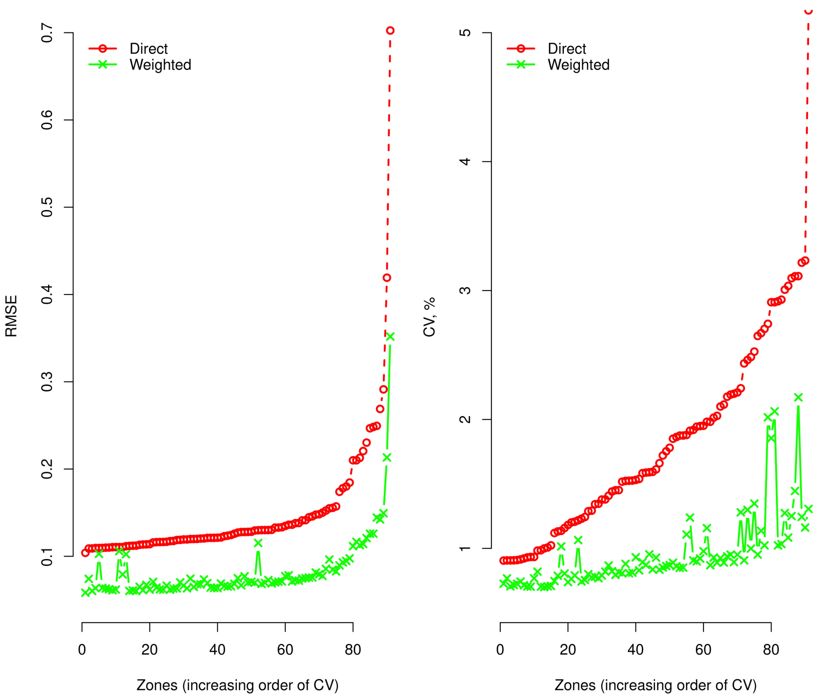

Fig. 3. Plot illustrating the RMSEs (left) and CVs (right) of household food insecurity along the Ethiopian zones in 2015/16.

improvement PI_{CVi} varied from 10.64% for Korahe to 74.75% for Harari. The average percent improvement PI_{CVi} was 43.24%. Moreover, Fig. 3 (right) shows that the scatter plots of the CVs of the weighted estimates and direct estimates against the zones, with zones sorted by increasing CVs of direct estimates. It can be seen

Table 2
Estimates of household food insecurity for the Ethiopian zones. RMSE is the root mean squared error of the estimates. CV is the coefficient of variation of the estimates

Zones	Weighted (%)	RMSE($\hat{\theta}_i^w$)	RMSE(y_i)	$CV(\hat{\theta}_i^w)$	$CV(y_i)$
Akaki	5.36	0.0609	0.1121	1.1363	2.6694
Nifas Silk	3.18	0.1059	0.1106	1.8547	2.9093
Kolfe	4.89	0.0623	0.1100	1.2738	3.0065
Gulele	5.75	0.0665	0.1193	1.1570	1.9818
Lideta	4.84	0.0603	0.1090	1.2441	3.2160
Kirkos	4.83	0.0651	0.1132	1.3476	2.5262
Arada	3.50	0.0792	0.1106	2.0629	2.9093
Addis Ketema	2.47	0.1028	0.1095	2.1715	3.1116
Bole	3.30	0.1024	0.1116	2.0165	2.7418
Yeka	4.40	0.0635	0.1095	1.4453	3.1106
North Gondar	7.37	0.0635	0.1213	0.8614	1.8636
South Gondar	8.65	0.0712	0.1333	0.8228	1.4410
North Wollo	8.27	0.0728	0.1301	0.8798	1.5232
South Wollo	5.82	0.0630	0.1099	1.0837	3.0358
Norths Shewa	5.91	0.0611	0.1104	1.0336	2.9293
East Gojam	6.82	0.0630	0.1176	0.9247	2.1003
West Gojam	7.57	0.0653	0.1236	0.8628	1.7532
Waghmra	11.07	0.0827	0.1571	0.7466	1.1192
Awi	10.49	0.0775	0.1501	0.7384	1.1816
Oromo Zone	7.59	0.0660	0.1230	0.8700	1.7805
Bahirdar	5.94	0.0735	0.1205	1.2390	1.9122
Argoba	13.20	0.0931	0.1780	0.7055	1.0069
West Wollega	7.08	0.0664	0.1167	0.9378	2.1765
East Wollega	6.32	0.0602	0.1123	0.9520	2.6474
Illubabor	9.25	0.0721	0.1381	0.7797	1.3425
Jimma	9.44	0.0725	0.1380	0.7689	1.3459
West Shewa	6.82	0.0618	0.1139	0.9072	2.4347
North Shewa	7.10	0.0632	0.1186	0.8892	2.028
East Shewa	7.98	0.0668	0.1278	0.8365	1.5935
Arsi	9.02	0.0712	0.1362	0.7897	1.3786
West Harerge	10.19	0.0757	0.1458	0.7431	1.2301
East Harerge	7.50	0.0638	0.1211	0.8508	1.8753
Bale	6.95	0.0621	0.1164	0.8933	2.1996
Borena	13.89	0.0977	0.1845	0.7033	0.9854
South West Shewa	6.94	0.0618	0.1174	0.8897	2.1152
Guji	7.56	0.0680	0.1199	0.8993	1.9439
Adama	5.53	0.0708	0.1159	1.2798	2.2417
Jimma Liyu	6.26	0.0693	0.1211	1.1077	1.8798
West Arsi	7.75	0.0688	0.1216	0.8886	1.8507
Kellem Wollega	8.62	0.0696	0.1300	0.8071	1.5246
Horogudru	8.92	0.0709	0.1329	0.7942	1.4509
Gurage	6.74	0.0641	0.1162	0.9513	2.2096
Hadya	7.54	0.0701	0.1188	0.9290	2.0140
Kembata	19.59	0.1423	0.2689	0.7261	0.9053
Sidama	8.21	0.0685	0.1259	0.8344	1.6607
Gedeo	7.28	0.0633	0.1193	0.8692	1.9819
Wolayita	7.41	0.1153	0.1298	0.9307	1.5309
South Omo	8.43	0.0684	0.1300	0.8118	1.5259
Sheka	9.37	0.0750	0.1414	0.8002	1.2881
Kefa	12.65	0.0896	0.1739	0.7084	1.0231
Gamo Gofa	7.57	0.0642	0.1211	0.8487	1.8749
Benci Maji	7.93	0.0708	0.1281	0.8923	1.5836
Yem	17.84	0.1259	0.2482	0.7054	0.9068
Amaro	20.60	0.1494	0.2913	0.7253	0.9093
Burji	16.01	0.1128	0.2128	0.7041	0.9300
Konso	26.03	0.2133	0.4192	0.8192	0.9830
Derashe	15.87	0.1116	0.2100	0.7032	0.9334
Dawro	9.55	0.0783	0.1362	0.8197	1.3797
Basketo	17.58	0.1259	0.2467	0.7162	0.9074

Table 2, continued

Zones	Weighted (%)	RMSE($\hat{\theta}_i^w$)	RMSE(y_i)	$CV(\hat{\theta}_i^w)$	$CV(y_i)$
Konta	15.97	0.1141	0.2206	0.7143	0.9218
Silte	8.53	0.0689	0.1303	0.8072	1.5173
Alaba	33.05	0.3518	0.7025	1.0645	1.2177
Hawassa	5.10	0.0638	0.1096	1.2505	3.0960
North West	10.02	0.0756	0.1447	0.7547	1.2432
Central	8.02	0.0699	0.1280	0.8714	1.5878
Eastern	10.41	0.0795	0.1482	0.7634	1.2011
Southern	9.59	0.0745	0.1411	0.7764	1.2925
Western	8.61	0.0701	0.1329	0.8143	1.4519
Mekelle	5.18	0.0673	0.1137	1.2987	2.4613
Metekel	7.70	0.0656	0.1244	0.8517	1.7205
Asosa	6.13	0.0612	0.1135	0.9983	2.4843
Kemashi	7.04	0.0649	0.1198	0.9214	1.9486
Pawi	16.28	0.1209	0.2303	0.7428	0.9142
Maokomo	13.54	0.0947	0.1801	0.6995	0.9998
Zone1	6.39	0.0742	0.1089	1.1618	3.2324
Zone3	8.92	0.0773	0.1348	0.8673	1.4083
Zone5	18.82	0.1444	0.2494	0.7673	0.9067
Agnuwak	5.89	0.0603	0.1119	1.0234	2.7023
Nuwer	7.60	0.0744	0.1198	0.9784	1.9511
Mejenger	7.47	0.0678	0.1203	0.9067	1.9191
Itang	10.76	0.0847	0.1556	0.7876	1.1313
Harari	4.46	0.0583	0.1040	1.3060	5.1730
Diredawa	6.49	0.0617	0.1164	0.9514	2.1928
Shinle	8.42	0.0698	0.1296	0.8295	1.5386
Giggia	6.05	0.0619	0.1105	1.0234	2.9165
Liben	10.29	0.0814	0.1477	0.7907	1.2069
Degahabur	8.08	0.0771	0.1279	0.9537	1.5903
Fik	15.20	0.1166	0.2100	0.7674	0.9334
Korahe	9.49	0.0963	0.1550	1.0151	1.1360
Gode	8.07	0.0749	0.1272	0.9280	1.6124
Warder	10.64	0.0856	0.1524	0.8045	1.1583

from this plot that the CVs of the weighted estimates are smaller than those of the direct estimates for nearly all zones. Moreover, the reduction in CV tends to be greater for zones with smaller sample sizes [26,32].

Figure 4 shows the distribution of RMSE and the CV of direct and weighted estimators of household food insecurity. From this figure, we can also see that there is an improvement using model-based small area estimates than survey-based estimates (direct).

In the past two decades, food insecurity has received increased attention from various countries because of the severe financial crises [33]. Findings of the Fay-Herriot model analysis showed that women, households with greater than 12 years of schooling and household size less than five were significant determinants of food insecurity.

The relationship between women's households and food insecurity was positive. In other words, for a unit increase on the women households keeping other covariates fixed, the food insecurity increases by 3.695. This result is not surprising in the Ethiopian context, as women have less access to education since they are responsible for domestic chores such as caring for children and the whole family [34]. Further, the majority of women are often forced to rely on casual labour due to their low educational status as better education provides higher chances of gaining better employment [35].

This study found a negative relationship between household heads who attended greater than 12 years of schooling and food insecurity. The study by [36] in Sidama district Southern Ethiopia found that wealth is highly correlated with education. They also found that education is strongly associated with the status of food security and hunger.

Self-employment was also found to be a significant predictor of household food insecurity in Ethiopia. There was a positive relationship with household food insecurity indicating that self-employment is largely a drive out of unemployment rather than being something driven by entrepreneurship [37]. More specifically, [37] reported declining trends in self-employment.

Finally, Fig. 5 shows the spatial mapping of zonal level household food insecurity obtained by the Fay-Herriot weighted approach. This map shows the degree of inequality concerning the distribution of household food insecurity in different zones. It is very crucial in

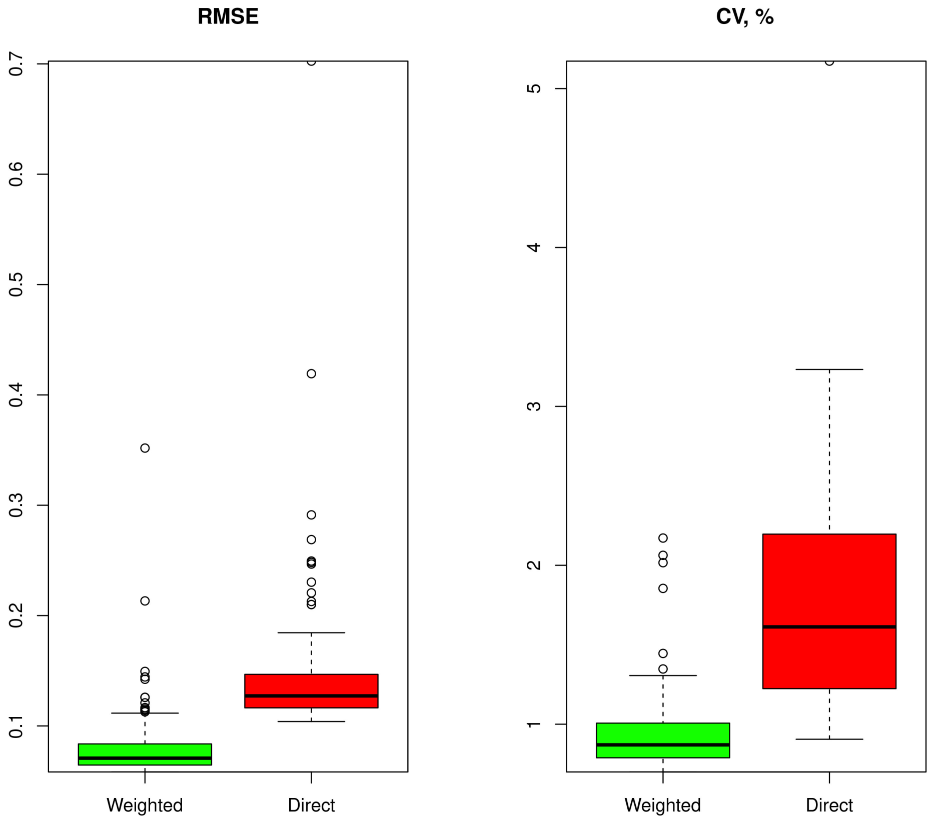

Fig. 4. Distribution of RMSE (left) and CV (right) of weighted and direct estimators of household food insecurity.

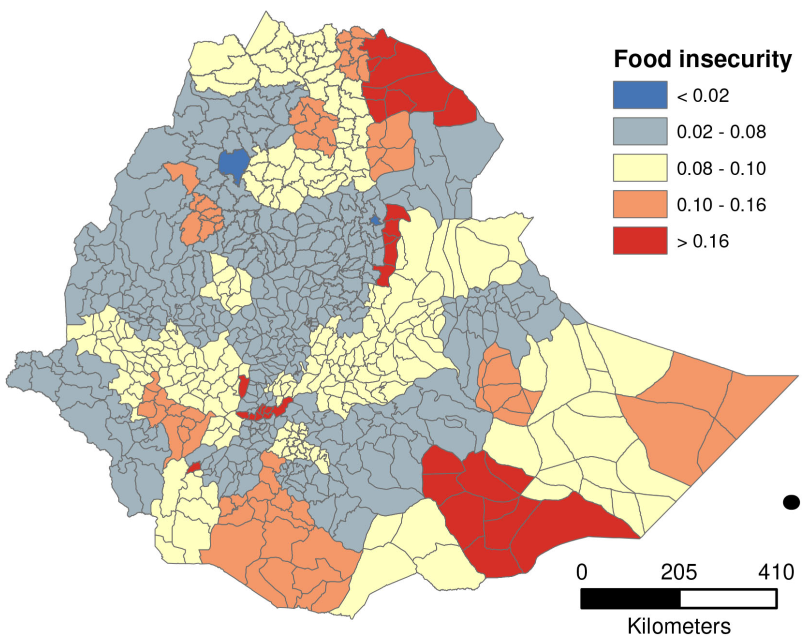

Fig. 5. A map of Ethiopia showing zonal level food insecurity estimates.

identifying the zones and regions with low and high household food insecurity in Ethiopia.

4. Conclusion

Estimation of food insecurity related variables at the small area levels is a challenging statistical problem because sample sizes are too small and simple parametric models may be poorly captured the relationships between these variables [19]. There is a growing demand for accurate, reliable and cost-effective small area household food insecurity statistics among policy and decision-makers, private and public sector administrators using data from different sources. In this context, the Fay-Herriot weighted estimator has the potential to make a real impact. Therefore, this study has attempted to shed some light on the nature of household food insecurity in Ethiopian zones using the Fay-Herriot weighted estimator. This study used the data from the 2015/16 WMS and 2007 population and housing census of Ethiopia. It takes another step forward by reporting estimates of household food insecurity at the zone levels in Ethiopia, for the first time.

The results indicated that Ethiopian zones such as Amaro, Konso and Alaba contain the highest percentage of food-insecure households (above 30%) in 2015/16 and emerge as the most food-insecure zones in Ethiopia. These zones were identified as high priority zones for serious food insecurity and poverty alleviation interventions. In contrast, Addis Ketema, Nifas Silk, Bole, Arada, Yeka, Kirkos, Lideta, Kolfe, and Harari had the least food insecure households (below 5%) in 2015/16. These findings are not surprising since all of these zones except Harari are found in Addis Ababa, the economic hub of the country.

Moreover, the food insecurity map showed how household food insecurity varied by zones across Ethiopia. The map gave reliable information for the guidance of policy, resource allocation, and the planning and evaluation of the food insecurity measure programme. This information can be used by the government of Ethiopia for budget allocation and intervention of targeted zones. Furthermore, this information can also be the recommended tool for monitoring the progress of SDGs, launched in 2015, aim to end hunger, achieve food security and improved nutrition' [2].

In summary, there was an overall clear gain of precision when using the weighted estimates based on the Fay-Herriot model instead of direct estimates. This indicated that weighted estimates of household food insecurity were more efficient and precise than the direct design-based estimates.

Finally, the findings demonstrate that accurate disaggregate household food insecurity statistics at small area level (zones) can be produced without more resources since this paper used the existing WMS and census datasets for this purpose [38]. Future research aimed at applying more advanced small area estimation techniques to improve the precision of household food insecurity estimates even at the fourth administrative levels (Woredas) in Ethiopia.

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