



Food poverty assessment in Ghana: A closer look at the spatial and temporal dimensions of poverty

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ABSTRACT

The multifaceted nature of poverty in terms of its duration or chronicity, systematic changes, seasonality, variation, and risk or vulnerability makes its measurement and analysis complicated, especially in lower-income countries. In Ghana, data show that absolute poverty remains prevalent, and inequality has been rising. Despite the gradual decline in poverty, spatial income inequality has also become a concern in Ghana. This study develops a Foster-Greer-Thorbecke Poverty Measure based spatiotemporal model to investigate the variation in food poverty in Ghana. Application to population-based surveys fielded in 2012/13 and 2016/17 indicate that considerations of temporal and spatial dimensions of poverty have implications for gaging the level of deprivation among households and the potential allocation of scarce resources via policy to achieve poverty alleviation objectives. A model that jointly considers both the spatial and intra-annual dynamics arguably considered the most accurate and flexible but data-intensive one, resulted in the mean unconditional food poverty rate of 50%, with the lowest rate being the Northern Region in March (45%) and the highest rate being in the Upper West Region in June (54%). Overall, cost-wise, this flexible model also results in the highest potential cost savings.

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Introduction

Poverty is a spatiotemporal dynamic and persistent phenomenon: while some households remain in poverty, others move in and out of it. The dynamics of poverty include multiple dimensions (i.e., duration or chronicity, systematic changes, seasonality, variation, and risk or vulnerability) [1]. The measurement and analysis of poverty are, therefore, complicated by the spatiotemporal and dynamic aspects of deprivation: especially in lower-income countries including Ghana. The analysis of the dynamics of poverty has revealed an uneven distribution of poverty alleviation outcomes in many developing countries. For example, based on nationally representative data, the proportion of poor Ghanaians has almost halved from 40% in 1990 to 23.4% in 2017 [2,3]. However, absolute poverty remains prevalent, and inequality has been on the rise in the country

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[4,5]. Despite the gradual decline in poverty, spatial income inequality has become a concern in Ghana over the years. Particularly, in 2016/17, the poverty rate was higher in rural areas (39.5%) compared to urban areas (7.8%); poverty rates were also observed to be higher in three regions (Upper West [70.9%], Northern [61.1%], and Upper East [54.8%]) compared to the rest of the country [6]. Generally, previous studies present a static picture of the poverty and inequality situation prevalent in Ghana.

Since the innovative study of poor households in York [7], the quantitative measurement of poverty has taken several turns, including Sen's seminal contribution to the quantitative unidimensional poverty measures [8]. Several authors have developed and extended different methods to identify and measure the various dimensions of poverty [1,9–11]. This study seeks to investigate the variation in food poverty in Ghanaian households based on spatial and temporal dimensions using the Ghana Living Standards Surveys (GLSS) data. Specifically, the paper aims to examine whether food poverty parameters and outcomes vary spatially and/or temporally. This is followed by evaluating the performance of spatial and temporal specifications in terms of poverty assessment compared to the widely used static approach of poverty assessment. The study applies the Foster-Greer-Thorbecke Poverty Measures (FGT) [12,13] to the two most recent GLSS data fielded in 2012/13 and 2016/17.

The paper contributes to the literature in two distinct ways. First, it develops a spatiotemporal model specification after extracting specific weekly household food consumption panels from food expenditure measures collected at various intervals in a year based on the GLSS data. Thus, the sample constitutes the largest in terms of food expenditure variation for the periods 2012/13 and 2016/17 for any single household in Ghana and is also nationally representative. Second, the paper makes it possible to empirically evaluate the performance of the existing static model vs. the proposed models for empirical poverty assessment. As such the approach proposed in this study provides the avenue to empirically understand not just the spatial but also the intra-annual disparities of food poverty among Ghanaian households and hence allows more information for objective welfare comparisons and targeted welfare-enhancing interventions.

The results indicate that considerations of temporal and spatial dimensions of poverty have important implications for detecting the level of deprivation among households as well as for the allocation of scarce resources to achieve poverty alleviation objectives. The alternative models developed result in different poverty lines across time and space dimensions, which in turn correspond to variations in the level and intensity of food poverty in Ghana. At the aggregate level, all models predict a robust food poverty rate of 50% for the entire country. However, the SPATIOTEMPORAL MODEL considered the most flexible but data-intensive framework, estimated the lowest for Northern Region in March (45%) and highest for Upper West Region in June (54%). In terms of poverty targeting, results show that the STATIC MODEL, the most widely used model indicative of the status quo, is associated with the lowest risk of not correctly identifying the poor, at the expense of the highest risk of over-identifying the non-poor. Across the three alternatives to the SPATIOTEMPORAL MODEL, the SPATIAL MODEL has the lowest risk of wrong diagnoses of poverty regardless of the true poverty status. Overall, the results indicate that both the SPATIOTEMPORAL MODEL and SPATIAL MODEL have the highest potential cost savings, followed by the STATIC MODEL and then the INTRA-ANNUAL MODEL.

In contributing to the Africa Union's Agenda 2063, this study falls under the priority area of reducing poverty, inequality, and hunger of goal 1(a high standard of living, quality of life, and wellbeing for all citizens) and aspiration 1 (a prosperous Africa, based on inclusive growth and sustainable development). Our results show that temporal and spatial dimensions of poverty affect household poverty levels and influence resource allocations toward attaining poverty alleviation objectives. Policymakers can, thus, explore strategic ways to target variables with poverty reduction potential. Furthermore, our research indicates that the temporal and spatial nature of poverty affect household poverty levels (including income and food) and influence resource allocations as well as contribute toward attaining target 1.2 (reducing, at least, by half the proportion of men, women, and children of all ages living in poverty in all its dimension according to national definitions by 2030) of SDG 1 (end poverty in all its forms everywhere).

The rest of the paper is organized as follows: the next section reviews relevant literature. This is followed by the data section detailing the specific steps used to develop weekly consumption patterns and prices, among others. Section 4 presents the empirical strategy used. Section 5 presents estimation results and discussions of the key findings. The paper wraps up with conclusions and limitations and proposes possible further extensions.

Literature review

Measuring and decomposing poverty

Several methods have been employed to identify and measure the various dimensions of poverty, including methodologies developed to address issues of vulnerability and chronic poverty using cross-sectional, panel, or synthetic panel datasets. Oduro [11] provides a discussion of some key methodologies designed for such analyzes: the Spells approach - using Shorrocks mobility index [9,10] - and the Components approach which categorizes poverty based on the concept of permanent consumption or income. Also, Porter and Quinn [1] provide a rigorous discussion of the connections between properties and the form of temporal poverty measures.

Poverty is a multifaceted concept; thus, multiple factors (including access to health, education, and other social amenities; adequate food consumption; housing; and general economic welfare) are needed to present a fair view of the poverty status of an individual or household under study. The most common poverty measure has been based on defining a cer-

tain minimum welfare function needed by an individual to meet basic food and/or clothing/shelter requirements normally referred to as the poverty line [14]. Thus, individuals with per capita expenditure or income below this poverty line are classified as poor. Globally, the most used poverty measure in the absence of survey data is gross domestic product (GDP). Also, missing data may be interpolated between surveys and extrapolated using the preceding or latter years of the previous and latest surveys [15]. However, GDP data, especially in the developing world, may be unreliable as they could underestimate actual poverty rates within a country. For example, Ghana moved from a low-income to a lower-middle-income country category after its 2010 GDP rebasing. Similarly, Nigeria, after rebasing in 2014, outpaced South Africa as the largest African economy. Since GDP constitutes much more than household consumption, calculating poverty based on GDP growth may be problematic. The assumption that growth is evenly distributed is weak since growth may be driven by capital-intensive sectors such as mining and oil production [16], which are likely to overstate the level of poverty reduction.

Several national, household and individual-level studies have been conducted to understand the nature and dynamics of poverty (e.g. [17–20]). Most of these studies examined country-level poverty profiles using quantitative measures and examined dynamics in poverty as well as the consequences of growth on poverty. However, the concept of poverty in Africa is often treated as an event (i.e., static) or as a trend (i.e., differences in severity over time) [11]. Static poverty measures are deficient in distinguishing between an individual who has been in poverty all her life, and another who happens to have had a misfortune during the measurement year [21]. There is relatively little work on analyses of poverty as a dynamic intertemporal concept: i.e., analyzing the welfare transition of individuals or household's overtime. While the intertemporal analysis of poverty may provide useful insights into the determinants of poverty (and its persistence among certain households), the narrative is different, particularly, due to the paucity of specific types of survey data required for such analyses.

Poverty may be decomposed into transient and chronic components. Research on welfare mobility finds that the determinants of transient poverty are different from those of chronic poverty [22]. While chronic poverty may be considered a state of being poor over a long period, the transient poor are those who enter and exit poverty over a period under study [11]. According to Beegle et al. [23], the estimation of poverty dynamics using panel data suggests a somewhat huge variation between chronic and transient poverty rates with the latter being higher. For instance, the median chronic and transient poverty rates are 21% and 32%, respectively. Using synthetic panel data, Dang and Dabalen [24] show a similar situation in Ghana where chronic and transient poverty rates were approximately 20% and 33%, respectively. This implies that a household is more likely to be poor sometimes compared to being always poor [23]. The report further states that shocks related to health, the labor market, conflict, and the weather constitute the major drivers of poverty transitions.

Poverty in Ghana

Ghana experienced a steady increase in economic growth (about 7% per year on average) from 2005 to 2010. Cooke et al. [5] report that income from offshore oil reserves created double-digit growth for 2011 and accompanying income growth has been a rapid reduction in monetary poverty from 51.7% in 1992 to 24.2% of the population by 2013; helping Ghana achieve the Millennium Development Goal (MDG) of cutting extreme poverty and hunger by half target. Compared to the rest of the country, poverty rates are highest in three regions (Northern, Upper East, and Upper West) [25] and, especially, among children since poorer households have large sizes with a larger number of children [5].

The analysis of poverty transcends the identification of who is poor to examine the nature and key determinants of poverty. In this regard, an individual's vulnerability (i.e. the probability or risk of being in poverty today) or tendency of being chronically poor in the future is worth analyzing [14]. Therefore, economic and social issues (including income-generating activities, education, etc.) that affect welfare are important in modeling the factors determining the likelihood of being poor [26–28]. The literature shows varied factors that affect food poverty in Ghana. For example, it has been suggested that income, fertility and maturity indices, age, sex, and education significantly explain household calorie gaps in Ghana [27]. Analysis using the third Ghana Living Standards Survey (GLSS3) shows that poverty incidence varied by locality (urban/rural), region, educational level of household heads, and employment status and category (whether private/ public sector) [29]. Although there is a general improvement in the welfare of the population over the years, later GLSS reports still point to a higher incidence of poverty among rural residents with Adjasi and Osei [14] concluding that poverty in Ghana is a rural phenomenon.

In an analysis of trends in consumption and non-monetary outcomes in Ghana, a decline in mortality of children under five years since the 1990s was observed [30]. However, over the same period, the weight-for-height indicator did not improve significantly while spatial inequality in both monetary and non-monetary outcomes widened. McKay et al. [30] conclude that improvements in Ghana's economic growth have not propelled a faster reduction in the poverty rate due to issues of inequality. This demonstrates that marginal increases in inequality are likely to reduce the decline in poverty contributed by increases in economic growth; and in fact, inequality is increasing in Ghana [5]. This corroborates another study showing that rising average income may not reduce extreme poverty but may cause it to persist if income inequality is high [31]. Therefore, in an increasingly unequal society like Ghana, the concept of inclusive growth, i.e. growth that benefits the poorest proportionately more, is of interest [5].

Data

Data sources

Data for the study come from two sources: i.e., household consumption data retrieved from the Ghana Living Standards Survey round 6-2012/13 (GLSS6) and round 7-2016/17 (GLSS7); and price data from the GLSS, Ghana's Ministry of Food and Agriculture (MOFA), Ghana Statistical Service (GSS), and ESOKO (<https://esoko.com/>).

The GLSS is Ghana's customized version of the Living Standards Measurement Study (LSMS) initiated by the Policy Research Division of the World Bank in the 1980s. The GLSS is a nationally representative survey based on a two-stage stratified sampling designed to produce nationally and regionally representative indicators of households' demographics, socioeconomics, employment, and income-generating activities. The first stage selects enumeration areas (EA) as the primary sampling units (PSU) within Ghana's administrative regions using a probability proportional to population size approach. Fifteen households are then randomly drawn from each of the PSUs from a list of households in each selected EA to form the secondary sampling units (SSUs). Across the two surveys used in this study, there were a total of 18,000 [1,200] and 14,009 [1,000] households [EAs] for GLSS6 and GLSS7, respectively. The population size covered by these surveys is estimated at 26.3 and 27.9 million, respectively. In-depth discussions on the organization, sampling, and data collection are published by the Ghana Statistical Service (GSS) alongside the data in their National Data Archive.

Weekly panel construction

New households were sampled for each GLSS, so the pooled data over multiple rounds do not constitute a panel of households. However, since the surveys are implemented over 12 months to ensure tracking of household consumption and expenditures as well as changes occurring thereof, the study can construct a panel for each household over the periods they were interviewed. Tsiboe [32] developed an algorithm that exploits this survey structure to construct a weekly consumption panel for GLSS7. Here we replicate it for each GLSS.

In the said GLSS surveys, key respondents from each household provided information on the household's frequent consumption (i.e., over one week) from expenditure and own production 7–11 times at 3–5-day intervals over a 33–35 days cycle. On the first visit, the key respondents provided information on the consumption value (from expenditure and own production) of selected items for the entire household over the past week before the first visit. On subsequent visits, the key respondents provided the same information but only for the number of days since the last visit. Given this information, the Tsiboe [32] algorithm utilizes a simple two-step process to construct daily household consumption value over the week dates of the interview. First, the mean daily consumption value for each interview day was calculated as the recorded value divided by the days of recall. Second, the mean daily consumption value for a given week date was taken as the mean recall value for all dates that fall within that week date. Table S1 in the appendix illustrates rice and egg. In this study we use the GLSS specific weekly household consumption panel constructed by Tsiboe [32]. The final sample used in this study comprised 109,121 weekly observations from 26,945 households. Furthermore, the population size covered by the final sample is about 23.98 million, representing about 80% of Ghana's population at the time of the surveys.

District-level prices

The GLSS collected data on household-level prices (where possible) and community-level prices for selected commodities. However, not all the households in the final sample were successfully paired with a complete set of prices for all frequently consumed items. One major reason for this is that most of the community-level prices lacked date assignments so it was difficult to pair them with the weekly panel. Additionally, the usefulness of the GLSS prices (either household or community level) was constrained because they were measured in unstandardized units (e.g., "PIECE", "BULB", "BALL", etc.) that are not easily convertible into standard units such as kilograms and liters. Tsiboe [32] overcame the price issues by applying a four-step process to price data from the GLSS and national/private institutions to construct district-level weekly price series for all commodities and then merged it into the constructed weekly panel. This process essentially converts the daily entries for all commodities recorded in the GLSS that were in local units to standard units, based on similar methods described in the literature for the case of Ghana [33,34].

Given district-level prices per kilogram and liter for a given week date ($p_{i,d,t}$) from the application above, the study then calculates the price of calories for each district and week date ($P_{i,d}$) via the equation $P_{i,d,t} = \sum_{i \in A} [w_i(p_{i,d,t}/c_i)]$. Where the subscripts i , d , and t are for commodity, district, and week date; c_i is the amount of calories in the i^{th} commodity; and w_i is the consumption share of the i^{th} commodity in the total consumption value for all commodities in the set A . The set A included the most consumed food items in Ghana with a complete price from the steps above.¹ The household consumption values were then divided by the district-level prices per kilocalorie to get the calories consumed by the household for a given week.

¹ In no order, these included rice, maize, millet, sorghum, cowpea, groundnut, cassava, yam, plantain, eggplant, okra, onion, chili peppers, tomato, orange, pineapple, palm nuts, chicken meat and egg, beef, chevon, pork, and mackerel.

Table 1
Household summary statistics.

Variable	Mean (SD)	Difference (%)	
		Period (base=2012/13)	Locality (base=urban)
<u>Household</u>			
Size (AE)	4.443 (2.876)	-0.013 [1.188]	16.956* [1.353]
Dependency ratio	1.331 (1.737)	-3.712* [1.710]	-1.618 [1.800]
Household wealth index	0.054 (2.696)	-490.866 [461.171]	-162.075* [2.813]
Food consumption (GHC/AE/week)	34.14 (27.96)	16.227* [2.024]	-6.280* [1.558]
Food consumption (kcal/AE/Week)	3852 (4350)	-19.543* [2.145]	12.120* [2.588]
Caloric price (GHC/kcal)	0.013 (0.010)	74.660* [2.729]	-20.076* [1.376]
<u>Decision-makers</u>			
Size (AE)	2.041 (0.830)	4.284* [0.792]	6.561* [0.803]
Female (ratio)	0.556 (0.328)	5.019* [0.927]	-3.568* [0.897]
Head (ratio)	0.679 (0.248)	-1.597* [0.615]	-5.938* [0.605]
Age (year/AE)	37.83 (15.42)	-0.624 [0.662]	5.540* [0.740]
Education (year/AE)	5.397 (4.747)	13.450* [1.979]	-37.218* [1.175]
Farm work (ratio)	0.617 (0.438)	-10.685* [1.453]	85.842* [4.670]
Non-farm business work (ratio)	0.280 (0.379)	-3.863 [2.527]	-38.716* [1.714]
Wage work (ratio)	0.674 (0.404)	28.582* [1.965]	-5.479* [1.356]

Aside from the expenditure, consumption, and price, weekly invariant characteristics of the households were also retrieved from GLSS and analyzed. Tsiboe [35] presents an in-depth detail of the construction of these variables and their harmonization across all waves of the GLSSs. The summary statistics of the household characteristics are presented in Table 1 and the seasonal patterns in household consumption indicators in Ghana are shown in Fig. 1.

Descriptive statistics of the data

Table 1 presents the summary statistics on key variables collected during the surveys. Overall, the average household size in adult male equivalence (AE) is about four persons while the household dependency ratio is about 1.3. The latter implies a somewhat greater financial burden on household members within the working age (i.e., 15–64 years) by those of non-working age (i.e., below 15 years and above 64 years). On average, there are about two decision-makers per household: with the majority being household heads (about 68%) and female (about 56%). The household decision-makers have a mean age of about 38 years and have approximately five years of education. On average, 62% of the household decision-makers engage in household agricultural production while about 28 and 67% engaged in household non-farm business and outside wage work, respectively. Across the two surveys (i.e., 2012/2013 and 2016/2017), Table 1 shows that while household size has statistically remained unchanged, the number of decision-makers per household has increased. Also, decision-makers are more likely to be female, play lesser roles as household heads, be more educated, less engaged in household farm or non-farm businesses, and be more likely to be engaged in outside wage work. Comparing rural and urban localities, households in the former are bigger, and their household decision-makers are less likely to be female, are older, less educated, less likely to be household heads, more likely to engage in household agricultural production, and less likely to engage in household non-farm business or outside wage work.

The mean food consumption value is GHC 34 per AE/week, and this has increased by about 16% from 2012/2013 to 2016/2017. It can also be observed that compared to urban areas, food consumption value in rural areas is about 6% lower. The mean caloric price is estimated at 0.013 GHC/kcal across the entire sample, and it has increased by about 75% from 2012 to 2017, and calories are about 20% less expensive in rural areas. Mean calorie consumption is 3852 kcal/AE/week, and this has decreased by about 20% from 2012 to 2017. Compared to urban dwellers, Table 1 also shows that rural dwellers are better off in terms of calorie consumption by about 12%. This is partly due to the low caloric price driven by the closeness to the breadbasket. The plots of household consumption indicators in Fig. 1 show that calorie consumption is low mid-year from May to August. Within the same period, caloric price is also higher.

Empirical methods

The study used the Foster-Greer-Thorbecke Poverty Measures (FGT) [12,13] to measure the food poverty level of households. The FGT uses information on the cost of food and caloric consumption to estimate a cost-of-calories function of the form $\ln X_h = \alpha_1 + \alpha_2 C_h$; where X_h and C_h represent daily food consumption value and daily calorie consumption per AE for household h , respectively. An essential assumption for the cost-of-calories function is that the food basket across all households contains the same items, with the only variations being the quantities of individual food items consumed, which depends on household taste and preferences, and income. Additionally, households are assumed to face the same level of food prices. Using the parameter estimates from the cost-of-calories function and the Recommended Daily Allowance (RDA) of calories, the food poverty line Z is estimated as $Z = e^{\hat{\alpha}_1 + RDA \cdot \hat{\alpha}_2}$. Any household is classified as food poor if its average cost of daily calorie consumption is lower than Z . The classification can then be used to estimate the headcount

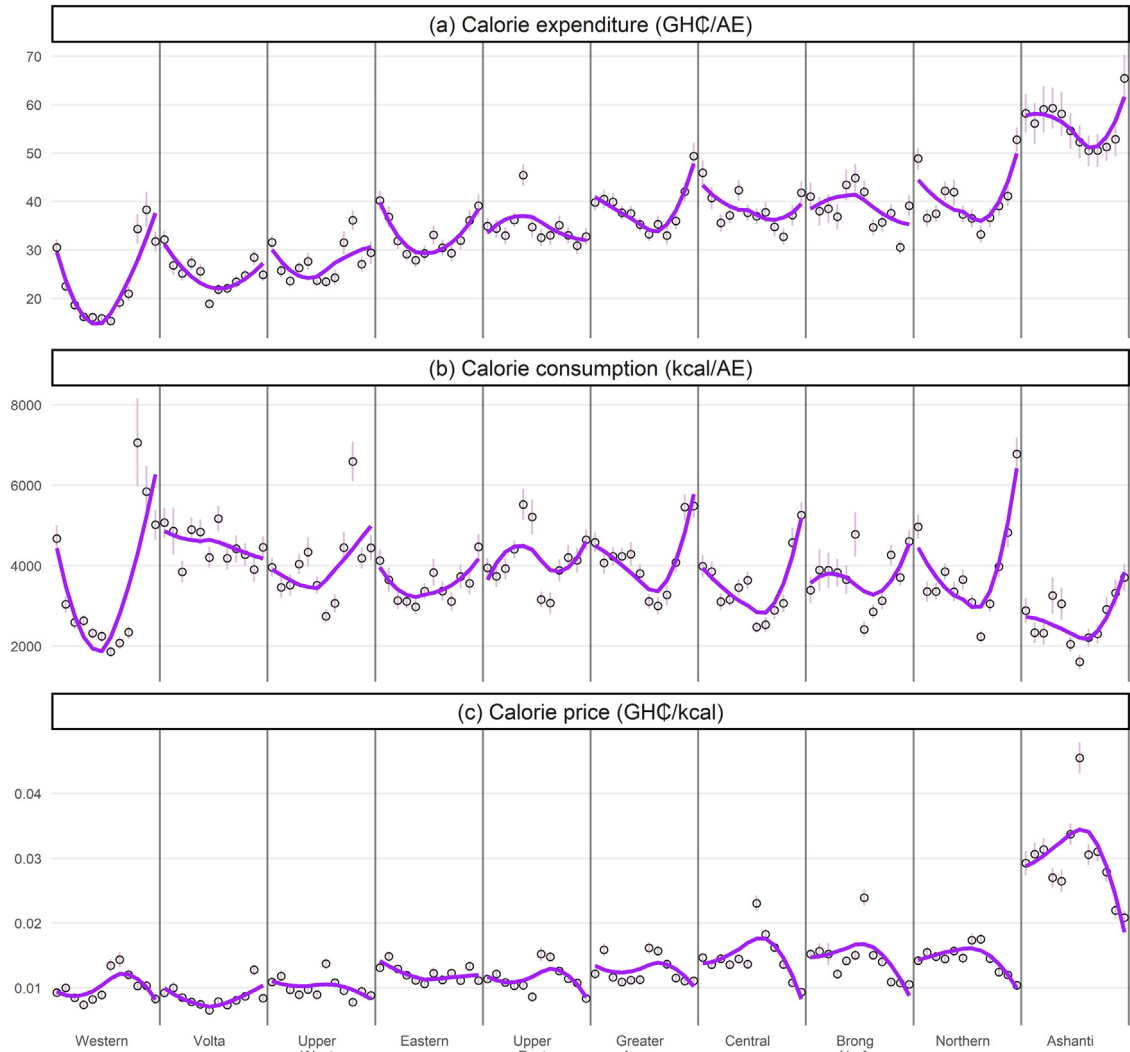


Fig. 1. Dynamics in household consumption indicators in Ghana (2012–2017).

index (P_0); the simplest aggregate measure of food poverty as the proportion of the population that is counted as poor ($P_0 = \frac{1}{N} \sum_{h=1}^N I(X_h < Z)$); where N is the total population (or sample) and $I(\cdot)$ is the food-poor indicator function which takes on the value of unity if the $X_h < Z$ is true. Since the headcount index implies a discontinuity at the poverty line, it fails to indicate the depth of poverty for a given household and cannot respond to instances where households delve deeper into poverty or make marginal improvements towards the poverty line. Additionally, the headcount index cannot assess the severity of poverty because two populations can have very different numbers of food-poor households but have the same headcount index. A relatively better measure of poverty that takes account of the extent of deprivation is the food poverty gap index (P_1).

The food poverty gap index is the mean of the extent to which households fall short of the food poverty line ($G_h = I(X_h < Z) \times (X_h - Z)$) as a share of the poverty line. The household-level index $\frac{G_h}{Z}$ is also referred to as the relative monetary food shortfall and it has an analogous nutritional measure termed the relative caloric shortfall ($C_h = \varepsilon \cdot G_h$). The coefficient $\hat{\beta}_2$ is the estimate of β_2 in the Engel curve for calories defined as $C_h = \beta_1 + \beta_2 \ln X_h$; where $\ln X_h$ is the natural logarithm of the household's food expenditure; and ε is the elasticity of caloric demand with respect to food expenditure. The poverty gap index (P_1) is represented as $\frac{1}{N} \sum_{h=1}^N \frac{G_h}{Z}$ and it gives a measure of the cost of poverty elimination (relative to the poverty line). Particularly, it indicates transfers to the poor needed to bring them to the poverty line. Provided such transfers can be made efficiently and equitably, summing up the monetary food shortfall gives an estimate of the minimum cost of eliminating food poverty. Alternatively, policymakers with no information on who is food poor can incur a maximum cost

of eliminating food poverty by just transferring an amount that is exactly equal to Z to everyone. Taking the ratio of the minimum cost to the maximum cost gives the potential savings from targeting. This implies that these potential savings from proper targeting (for example using surveys to target benefits and programs) are decreasing in the poverty gap index, i.e., as the poverty gap index increases, the benefit of targeting disappears.

The poverty gap index (P_1) outperforms the headcount index (P_0) because it does not imply a discontinuity at the poverty line, however, it cannot pick up signals of inequality among the poor. The measure - poverty severity index (P_2) - accounts for this to an appreciable extent by taking a weighted average of the relative monetary food shortfall. Here the weights are the relative monetary food shortfall themselves, so it puts more weight on the poorest of poor households. Formally, the FGT measure can be generalized as $P_\delta = \frac{1}{N} \sum_{h=1}^N \left[\frac{C_h}{Z} \right]^\sigma$; where σ indicates the sensitivity of the index to poverty and $\delta = 0$ reduces P_σ to the headcount index (P_0), $\sigma = 1$ reduces P_δ to the poverty gap index (P_1), and $\delta = 2$ reduces P_σ to the poverty severity index (P_2). For $\sigma > 0$, P_σ is strictly decreasing in the living standard of the poor so a household is poorer if their standard of living is lower and for $\sigma > 1$, P_σ has the additional property of a relatively higher increase in measured poverty if the poorer experienced a loss in standard of living. These properties make P_σ strictly convex in income with the key exception that it is weakly convex for $\sigma = 1$. Finally, P_σ can be disaggregated for sub-groups in a population and the contribution of each group to the population poverty can be estimated. This study uses a disaggregated approach to the FGT to ascertain what dynamics to consider in household food poverty assessment.

Previous studies focusing on Ghana have generally estimated the various FGT indicators for the entire country or its regions [27,33,34,36–40]. Unlike the previous ones, this study considers four models with varying levels of data requirements and parameter restrictions. The first model [i.e., STATIC MODEL] has the least data requirement and implements the FGT for a given survey and is indicative of the status quo of analyzing poverty as an annual static process. For a given household, the data for the STATIC MODEL is the mean of their weekly X_h and C_h values across the sample. The second model [i.e., SPATIOTEMPORAL MODEL] is the most data-intensive and implements the FGT for every month/region combination for a given survey and is a flexible method of analyzing poverty as an intra-annual dynamic process with regional heterogeneities. For a given household, the data for the SPATIOTEMPORAL MODEL is all their weekly X_h and C_h values across the sample. The other two models collapse each household's data by region [i.e., SPATIAL MODEL] and month [i.e., INTRA-ANNUAL MODEL] and implement the FGT by region and month for a given survey, respectively. The purpose of the SPATIAL and INTRA-ANNUAL MODELS is to isolate the spatial and intra-annual dimensions of the flexible SPATIOTEMPORAL MODEL such that one can appreciate the accurate assessment of the significance of each dimension, especially when data are limited.

The four models are first estimated separately for each GLSS survey and then for each parameter by model, the two respective survey-specific estimates are combined into a pooled estimate by taking their average. The pooled results from the alternatives are then compared to ascertain any statistical differences in their estimated indicators. For statistical inference, the study used bootstrapping, with 1000 replications of the pooled results, by using 1000 survey-specific bootstrap samples from the original samples.

One of the main reasons for measuring poverty is to adequately identify the poor and then target them with policy interventions to lift them out of poverty. In the context of this study and to some extent in practice, there is an inherent risk in the disconnect between the poverty measure employed and the actual poverty status of the individuals/households being evaluated. In practice, this can translate into two situations: (1) classifying a household as non-poor when in fact they are poor, and thus are missed in policy targeting, (2) classifying a household as poor when in fact they are not poor, which can lead to oversubscription of policy which has implications on policy budgeting. With this potential policy targeting and budgeting risks in mind, the study evaluates the poverty classification performance of the forgoing models next.

The implicit assumption made is that the SPATIOTEMPORAL MODEL is close to the benchmark model. The other three models are a special case of the SPATIOTEMPORAL MODEL where certain parameters are constrained to be zero. Particularly, the INTRA-ANNUAL MODEL is the SPATIOTEMPORAL MODEL with all spatial and cross-temporal-spatial parameters constrained to zero. The SPATIAL MODEL is the SPATIOTEMPORAL MODEL with all temporal and cross-temporal-spatial parameters constrained to zero. For the STATIC MODEL, all spatial and temporal parameters, and their cross-products thereof are constrained to zero. In addition to being the most flexible, the study justifies the assumption that the SPATIOTEMPORAL MODEL is close to the benchmark model by using both in- and out-of-sample measures of the predictive accuracy of the cost-of-calories and Engel curve functions. Mean squared error and cross-validation using ten approximately equal-sized subsamples (folds) are used for the in- and out-of-sample measures, respectively. For all models, both measures are reported relative to the SPATIOTEMPORAL MODEL, with values below one indicating better performance over the SPATIOTEMPORAL MODEL. The results for the predictive accuracy exercise shown in Fig. 2, justify the assumption that the SPATIOTEMPORAL MODEL is close to the benchmark model as Fig. 2a shows that all the other models lead to increased predictive inaccuracy across both the cost-of-calories and Engel curve functions. However, when each function is considered individually, the SPATIOTEMPORAL MODEL does poorly in terms of the cost-of-calories function (Fig. 2b) but is better for the case of the Engel curve function (Fig. 2c).

For the SPATIOTEMPORAL MODEL, suppose $\delta = 1$ indicates poor status, while $\delta = 0$ indicates non-poor status, and for a given alternative model let the same be represented as $\hat{\delta} = 1$ and $\hat{\delta} = 0$, respectively. Given this notation, several classification performance measures were estimated. The crucial ones are (1) False Negative Probability (FNP) amongst the poor [$Pr(\hat{\delta} = 0 | \delta = 1)$]; (2) False Positive Probability (FPP) amongst the non-poor [$Pr(\hat{\delta} = 1 | \delta = 0)$]; and (3) Correct Classification

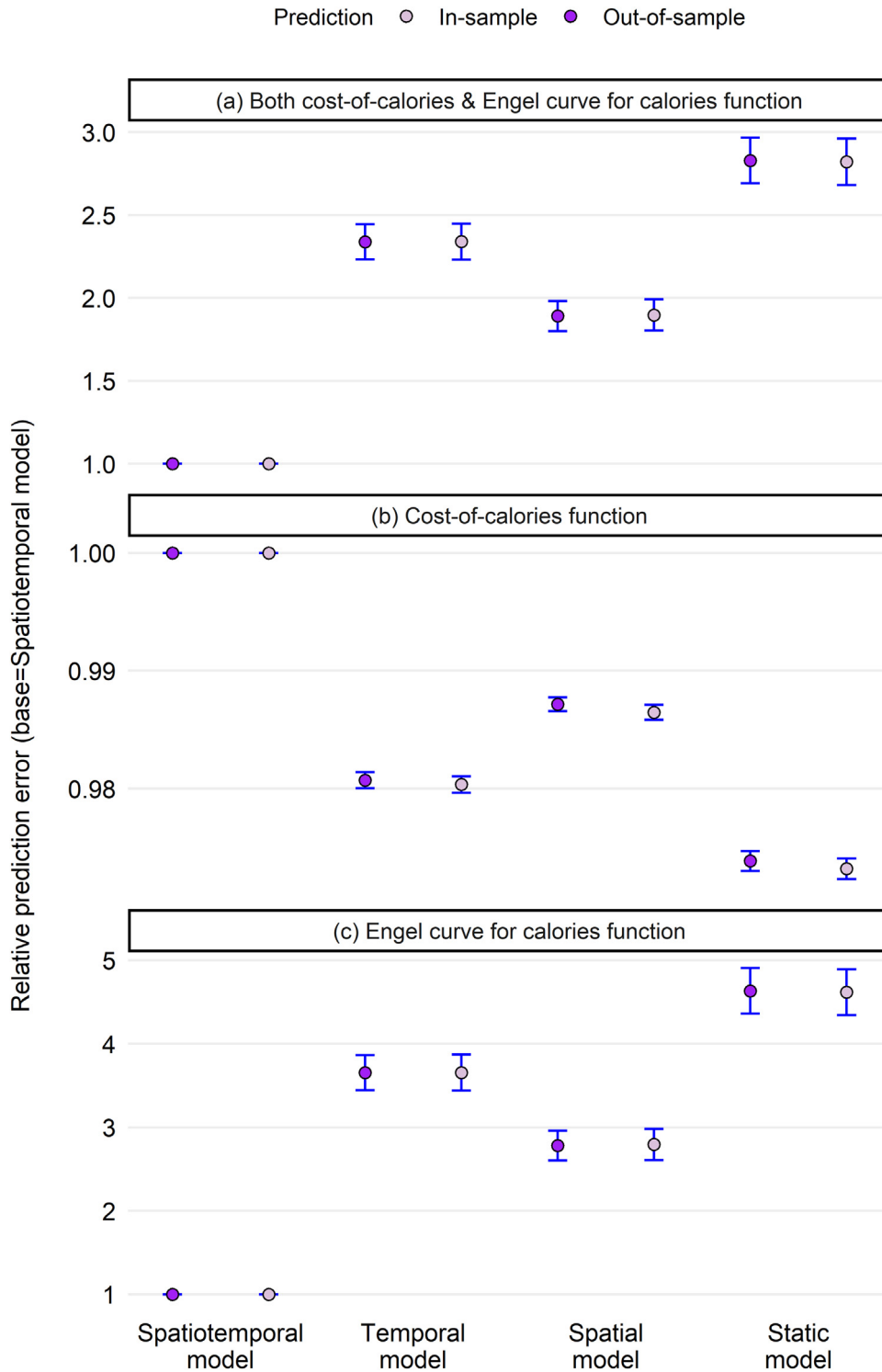


Fig. 2. Predictive performance of alternative models for predicting household cost-of-calories and Engel curve functions.

Probability (CCP) in the sample $[\sum_{i \in (0,1)} Pr(\hat{\delta} = i | \delta = i)]$. The FNP measures the risk of missed policy targeting, and the FPP measures the risk of funds misappropriation for poverty alleviation.

Generally, whilst it is interesting to ascertain the level of measured poverty and to identify the poor, it is equally if not more interesting to know what the conditional distribution of the measured poverty is. This is accomplished by estimating the FGT measures for different subgroups defined by demographic and or location covariates. However, this can face a mul-

dimensionality curse as the number of covariates and their combination thereof increases or become increasingly scalar. To overcome this, the general practice is to regress a dummy for poverty classification ($I(X_h < Z)$), relative monetary food shortfall ($G_h = I(X_h < Z) \times (X_h - Z)$), or relative caloric shortfall ($C_h = \varepsilon \cdot G_h$) at the household level on selected covariates for inference on how these indicators change after controlling for those covariates. If these covariates change the indicators in a desirable but predictable way, then the policy can be targeted at the variables to improve food poverty. For example, it has been shown that non-farm income or participation has a positive influence on food expenditure, food poverty, food poverty vulnerability, nutrient availability, and food security [33,34,41–44]. Furthermore, interventions aimed at improving child/household nutrition, and poverty alleviation consider women's empowerment as a key pathway to achieve impact, so they target women as their main beneficiaries. This is because women's empowerment has been shown to have a positive multiplier effect on those development indicators as well as closely related ones [38,45–49]. Given these empirical facts, the study regressed the dummy for poverty classification ($I(X_h < Z)$) from the competing models to assess its conditional distribution. Again, taking the conditional distribution from the SPATIOTEMPORAL MODEL as the benchmark, the study assesses how those from the competing models deviate from this model. Covariates included in the models included (1) household size and dependency; (2) decision makers gender, age, education, headship within the household, work (farming, off-farm business, or wage work); (3) survey fixed effect for structural changes in poverty; (4) location fixed effects by region and rurality; and (5) monthly fixed effects.

Results and discussion

The pooled regression results across the two surveys are presented in the main text and the disaggregated results from the surveys are presented as supplementary material in the Appendix. All tables and figures in the supplementary material have a leading S.

Foster-Greer-Thorbecke (FGT) poverty measure

The pooled results for key FGT estimates/indicators for the alternative models are illustrated in Fig. 3 while those at the survey level are illustrated in Fig. S2(i) and (ii).² Fig. 3a–d are the primary estimates of the FGT whereas Figs. 3e and 2f are the secondary indicators constructed based on the primary estimates. Fig. 3 shows that: (1) all estimates/indicators show a strong spatial variation although, for a given indicator, the intra-annual variation is similar across different locations; and (2) in terms of magnitude, there exist similarities between the INTRA-ANNUAL MODEL estimates/indicators and the STATIC MODEL as well as between the SPATIAL and the SPATIOTEMPORAL MODEL estimates.

Focusing on the poverty classification threshold (Fig. 3f), the STATIC MODEL estimates the poverty line at 32 GHC/AE/day, and it is constant throughout the year. For the INTRA-ANNUAL MODEL, the mean was 29 GHC/AE/day with a minimum and maximum of 27 and 36 GHC/AE/day in July and December, respectively. The mean poverty line for the spatial model was 38 GHC/AE/day with a minimum and maximum of 18 and 48 GHC/AE/day in the Western and Ashanti regions, respectively. Finally, for the SPATIOTEMPORAL MODEL, the mean poverty line was 28 and GHC/AE/day with a minimum and maximum of 12 and 53 GHC/AE/day for Western in July and Ashanti in December, respectively. The interesting dynamic here is that given a particular dimension (temporal or spatial), the respective specialized model predicts the region/months of high poverty lines as the SPATIOTEMPORAL MODEL does, but they fail to predict the magnitudes of the respective poverty lines. A similar pattern is observed for food poverty rates, food poverty severity, and elasticity of caloric demand.

The national-level food poverty rate (i.e., the proportion of the population that is food poor) for each of the four models across the entire sample is shown in Fig. 4. In terms of increasing order, the food poverty rate for the entire country was estimated at 49.34%, 49.65%, 49.96%, and 50.36% for the INTRA-ANNUAL, STATIC, SPATIOTEMPORAL, and SPATIAL MODEL, respectively. It can be observed that the SPATIAL and INTRA-ANNUAL MODEL rates are statistically different but all the rates from the three alternative models are not statistically different from that of the SPATIOTEMPORAL MODEL. Thus, at the aggregate level, all models predict a robust food poverty rate of 50% for the entire country.

The national food poverty rate of 50% estimated from the current research provide comparable rates with those from existing studies conducted in Ghana in the past decade. Tsiboe et al. [34] estimated food poverty lines by region and found that the percentage of households below these lines for Brong Ahafo, Northern, Upper East, and Upper West were 57, 71, 84, and 57%, respectively. Using the average food poverty line of \$2.6/day, Zereyesus et al. [33] estimated a food poverty rate of 55.1% at the household level for a sample of households in Northern Ghana. Zereyesus et al. [33] also found a food poverty vulnerability rate of 58.6% across the Northern Ghana region. Their study also found varying rates of food poverty rates by region. The estimated food vulnerability rates for Brong Ahafo, Northern, Upper West, and Upper East Regions were 15.9, 54.5, 81.1, and 84.3%, respectively. Similarly, by modeling food poverty vulnerability, Addai et al. [39] further showed that 36.11% of a sample of households in Northern Ghana were food poor and concurrently at high risk of food poverty which implied that they were more likely to continue to be food poor in the future. They also found another 37.89% to belong to transitory food poverty, i.e., they can break out of food poverty soon. They found only 13.56% of households to have a stable

² Across the two surveys and four models, the study estimated a total of 6636 unique FGT parameters. Thus, in order not to flood the paper with lots of tables the study utilizes Figures to illustrate selected parameters to draw key insights, but all 6,636 parameters can be provided by the corresponding author upon request.

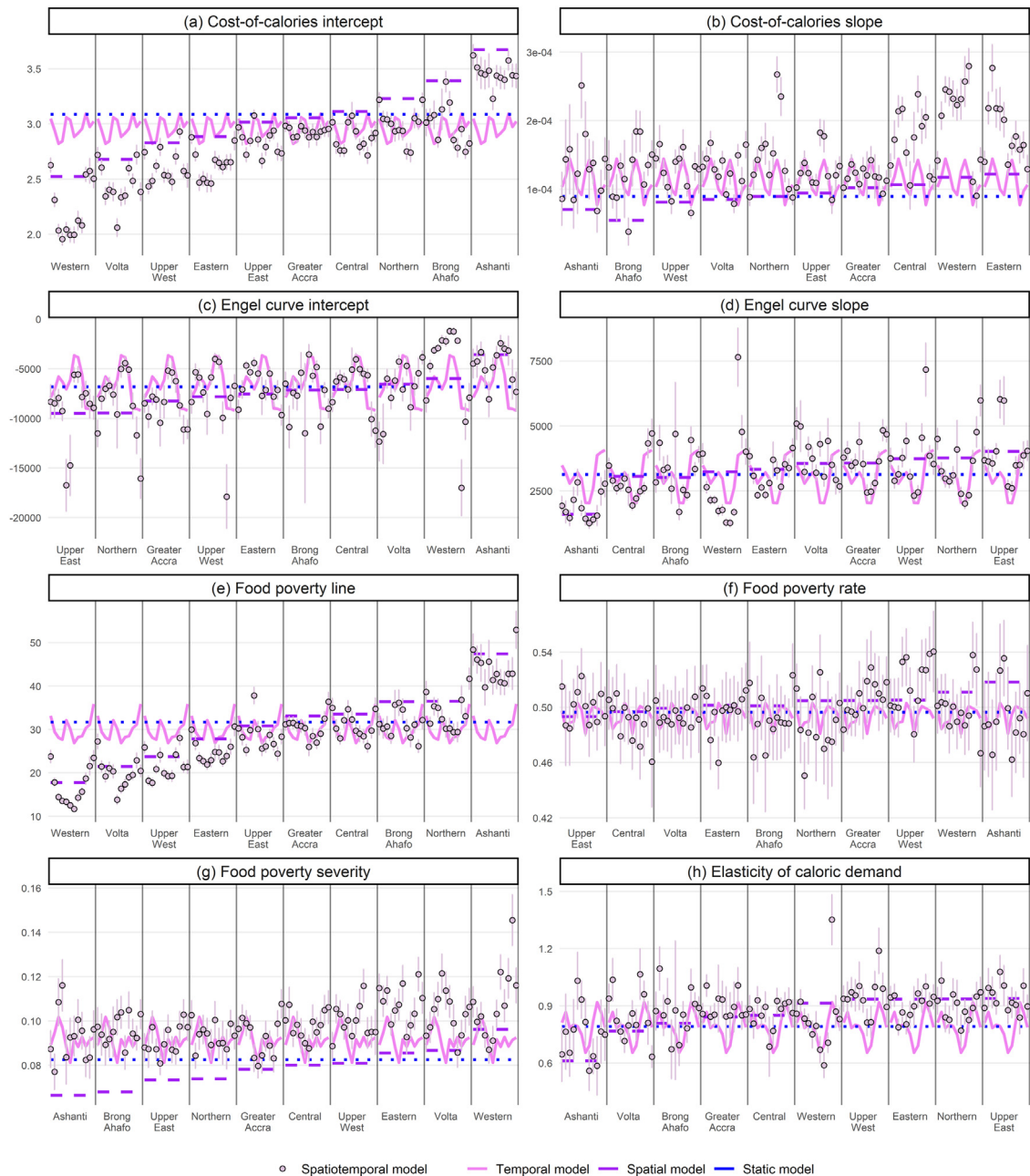


Fig. 3. Dynamics in key food poverty parameters in Ghana from 2012 to 2017.

state of food poverty, i.e., they are food non-poor and at the same time not vulnerable to it. Addai et al. [39] estimated a poverty rate of 74% for their sample when classified using the international poverty line of \$1.9/day as the standard.

These existing studies show that food poverty cannot only be transitional but also vary spatially. By relaxing the static assumption of one poverty line this study more formally shows that there are some heterogeneities along the spatial and temporal domains. Particularly, for the SPATIOTEMPORAL MODEL, the lowest is estimated for Northern Region in March (45%) and the highest for Upper West Region in June (54%). Contrary to the food poverty rate, the predicted food poverty severity for the entire country was not the same for all four models. In terms of increasing order, the food poverty severity for the entire country was estimated at 7.73, 8.25, 9.24, and 9.56% for the SPATIAL, STATIC, INTRA-ANNUAL, and SPATIOTEMPORAL MODEL, respectively. Unlike the poverty rates, the severity rates are all statistically different from each other. In terms of heterogeneities along the spatiotemporal domain, the lowest food poverty severity is estimated for Ashanti Region in February (16%) and the highest for Western Region in November (28%).

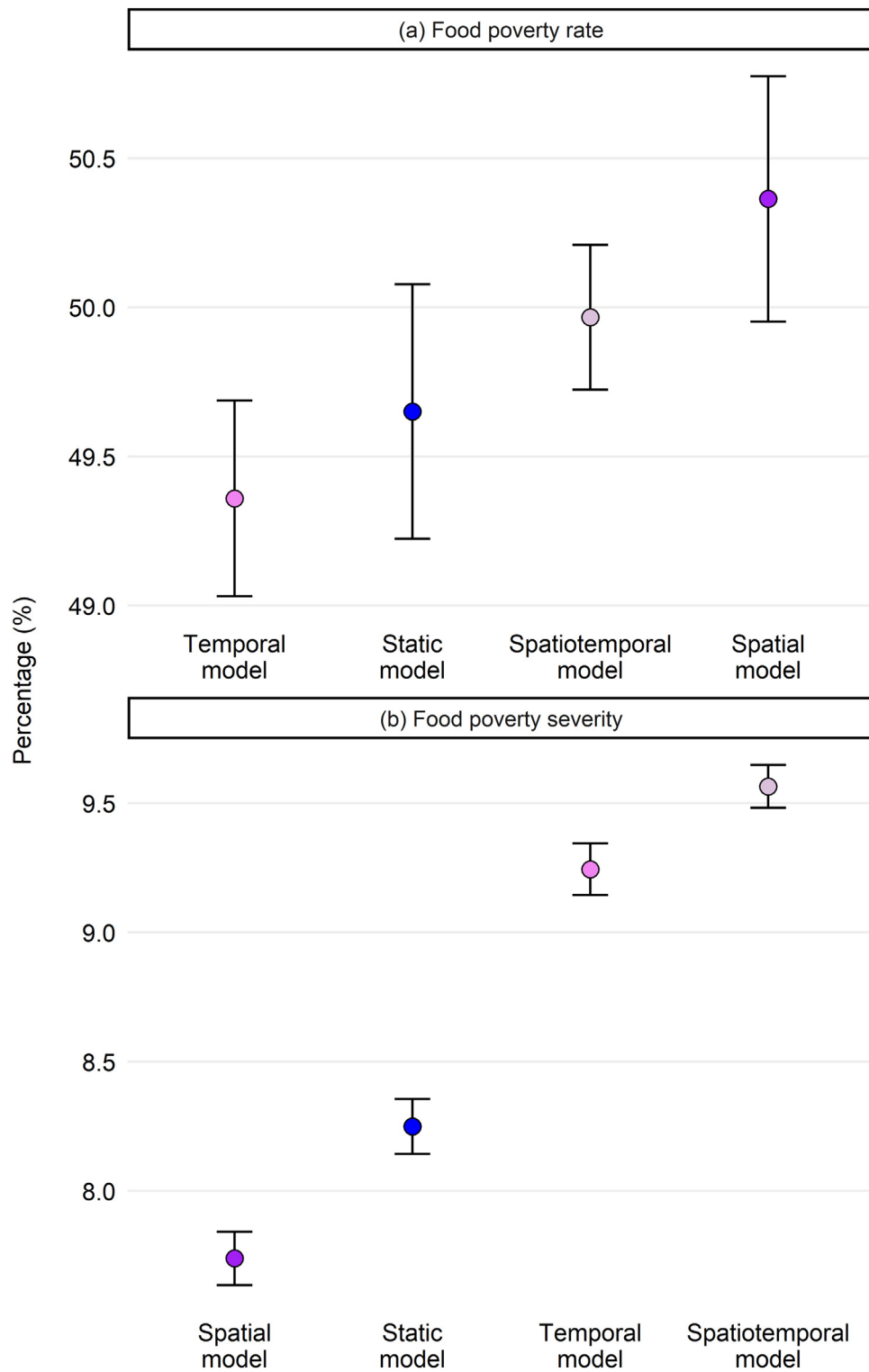


Fig. 4. National level food poverty rate and severity in Ghana from 2012 to 2017.

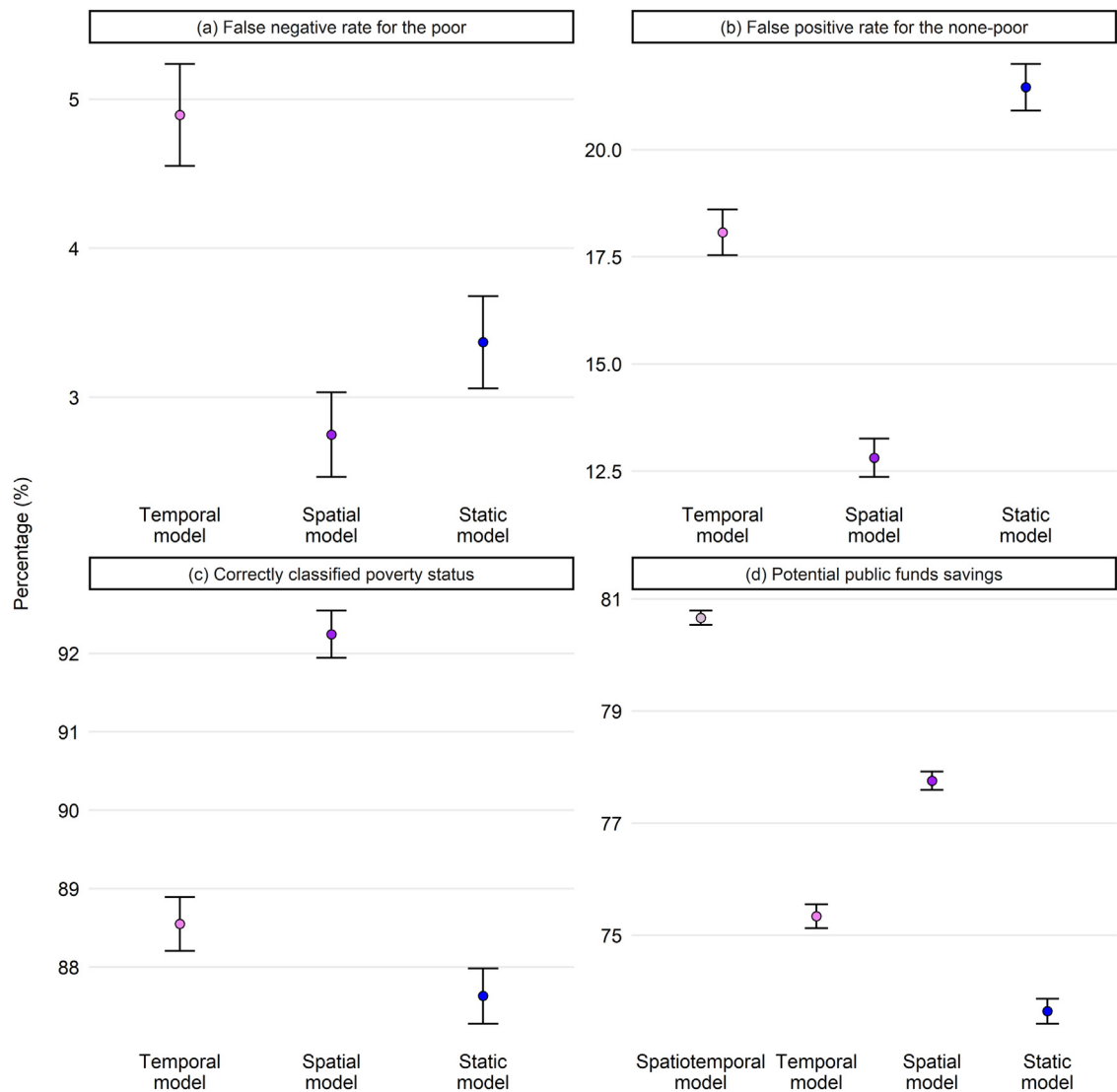


Fig. 5. Classification and program cost performance of household food poverty models.

Countries aiming to identify and deal with poverty are faced with a constrained budget. The question is whether temporal or spatial aspects of poverty (based on the temporal or spatial models) are of primary interest and what will the tradeoffs be in relation to the forgone benefits due to the assessments based on the SPATIOTEMPORAL MODEL. The choice of model will determine the data requirements needed for diagnoses.

Poverty classification performance

The results for the poverty classification performance of the alternative models are illustrated in Fig. 5. Here, the SPATIOTEMPORAL MODEL is assumed to be the benchmark. From Fig. 5, it can be observed that the SPATIAL MODEL is associated with the lowest risk of not correctly identifying the poor. The SPATIAL MODEL is also associated with the lowest risk of over-identifying the non-poor. Whilst the STATIC MODEL has a relatively low risk of not correctly identifying the poor when compared to the INTRA-ANNUAL MODEL, it also performs poorly in identifying the non-poor when compared to the INTRA-ANNUAL MODEL. In practice, these relative differences in the risk of not correctly identifying the poor and over-identifying the non-poor suggest that the SPATIAL MODEL has the potential to adequately diagnose poverty. Furthermore, the relative differences in the misidentification risks suggest that the use of the STATIC MODEL, which is indicative of the status quo, comes at the expense of the higher risk of oversubscribing poverty to the non-poor, which may lead to the misappropriation of poverty alleviation funds. Across the three alternatives to the SPATIOTEMPORAL MODEL, the SPATIAL MODEL has the lowest risk of wrong diagnoses of poverty regardless of the true poverty status. These dynamics suggest that the STATIC MODEL

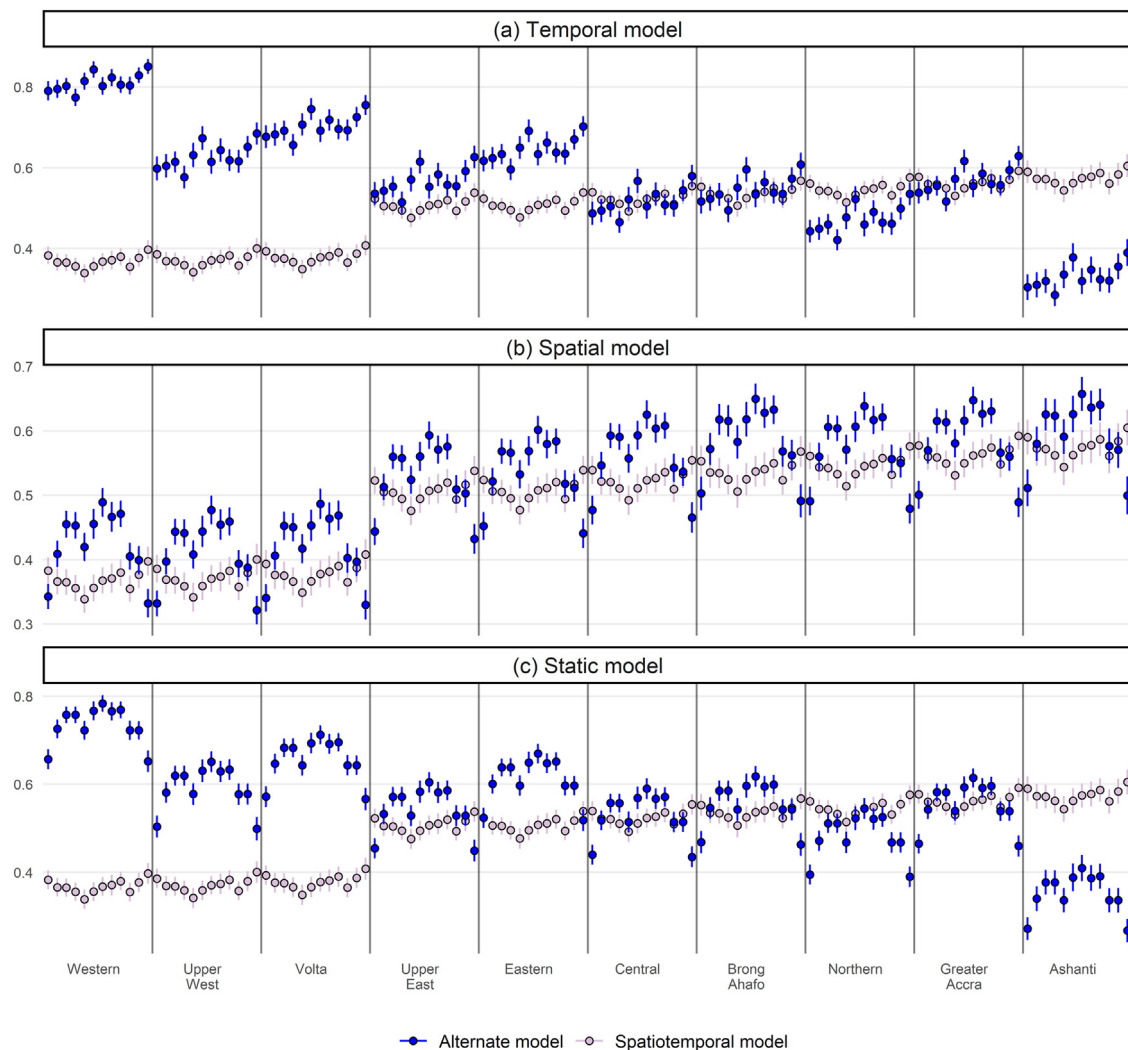


Fig. 6. Dynamics in conditional food poverty in Ghana from 2012 to 2017.

will work best for the case when poverty is pervasive, however, as poverty becomes less pervasive, the SPATIAL MODEL is likely to do a good job at diagnosing the residual poverty without exerting a lot of pressure on limited public funds. Overall, Fig. 5d shows that both the SPATIOTEMPORAL MODEL and SPATIAL MODEL have the highest potential cost savings, followed by the INTRA-ANNUAL MODEL and then the STATIC MODEL.

Conditional poverty dynamics

The conditional poverty rates for every region-month combination after controlling for household characteristics are shown in Fig. 6. Notably, it can be observed that the INTRA-ANNUAL MODEL and SPATIAL MODEL independently mimic their respective specialized dynamics as the SPATIOTEMPORAL MODEL does. On the contrary, the STATIC MODEL fails to mimic either the spatial or the temporal dynamics as depicted by the SPATIOTEMPORAL MODEL. Focusing on the SPATIOTEMPORAL MODEL, households in the Ashanti Region generally have the highest rates of food poverty, followed by Greater Accra, Northern, Brong Ahafo, Central, Eastern, Upper East, Volta, Upper West, and then Western. Food poverty does vary within a given year, a result that is not new in and of itself, but a confirmation of the challenges that households face during the year. Generally, the odds of households falling into food poverty for close months are not significantly different from each other. Notably, it can be observed that the odds of households experiencing food poverty are highest in January and December and is lowest in April, May, and June. The low food poverty odds months are typically the harvest period of the major season for most staple crops; the high odds months reflect periods when the stock of staples may have been depleted either through consumption or sale. The last quarter of the year also begins the minor production season for many crops and begins a long dry spell characterized by food shortage in Ghana.

Conclusion

Research shows that poverty has multiple dimensions and, thus, its measurement and analysis are complicated by the spatiotemporal and dynamic aspects of deprivation. The analysis of the dynamics of poverty reveals an uneven distribution of poverty alleviation outcomes in many developing countries, including Ghana. The current study investigated the variation in food poverty in Ghanaian households based on spatial and temporal dimensions using Ghana Living Standards Surveys (GLSS) data. Specifically, the paper aimed to examine whether food poverty parameters and outcomes vary spatially and/or temporally. This is followed by evaluating the performance of spatial and temporal specifications in terms of poverty assessment compared to the widely used static approach of poverty assessment. The study applied the Foster-Greer-Thorbecke Poverty Measures (FGT) to the two recent GLSS data fielded in 2012/13 and 2016/17.

Our results indicate that considerations of temporal and spatial dimensions of poverty indeed affect both the level of deprivation among households as well as influence the allocation of scarce resources to achieve poverty alleviation objectives. The models developed in the study lead to varying food poverty lines across time and space dimensions, implying distinctly different levels and intensities of food poverty in Ghana. The SPATIOTEMPORAL MODEL arguably considered the most flexible but data-intensive model, resulted in the mean unconditional food poverty rate of 50%, with the lowest record being in the Northern Region in March (45%) and the highest record being in the Upper West Region in June (54%).

When it comes to the question of allocating scarce resources for poverty targeting, results show that the STATIC MODEL which uses a one size fits all poverty measure is associated with the lowest risk of incorrectly identifying the poor, at the expense of the highest risk of over-identifying the non-poor. Across the three alternatives to considering jointly both the spatial and intra-annual dynamics of poverty assessment, considering only the spatial dimension has the lowest risk of wrong diagnoses of poverty regardless of the true poverty status. Overall, cost-wise, results indicate that both the ideal consideration and considering only the spatial dimension have the highest potential cost savings, followed by the one size fits all and then the consideration of only the intra-annual dimension.

In closing, some caveats to the analysis worth mentioning include the use of a somewhat synthetic intra-survey household panel consumption and the non-consideration of non-food items. By not considering non-food items, the analysis falls short of addressing the full spectrum of poverty in general, although the implications from this food poverty study are directly applicable to overall poverty assessment. Subsequent studies can overcome these by expanding the scope of this study to include non-food items with the analysis done with household-level data that is consistently collated throughout the year. However, it should be noted that the availability of household-level panel data required is quite limited and costly. Notwithstanding these caveats, the paper's attempt to answer whether the food poverty estimates based on the standard static FGT measurement overestimate the poverty rates is worth paying closer attention to. It is also important to consider the budget ramifications of poverty alleviation measures, especially when temporal and spatial dimensions of food poverty are clear evidence in a country such as Ghana. The approach proposed in this study provides an empirical basis to understand not just the spatial but also the intra-annual disparities of food poverty among households in Ghana. Consequently, the study's approach gives more information for objective welfare comparisons and targeted welfare-enhancing interventions. A future extension of the current study, at least using the generated data, worth highlighting includes the causal identification of the drivers of food poverty under a spatiotemporal framework as this is missing in the case of Ghana.

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at [doi:10.1016/j.sciaf.2022.e01518](https://doi.org/10.1016/j.sciaf.2022.e01518).

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