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Estimation of Poverty in Somalia Using Innovative Methodologies

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Abstract: Somalia is highly data-deprived, leaving policy makers to operate in a statistical vacuum. To overcome this challenge, the World Bank implemented wave 2 of the Somali High Frequency Survey to better understand livelihoods and vulnerabilities and, especially, to estimate national poverty indicators. The specific context of insecurity and lack of statistical infrastructure in Somalia posed several challenges for implementing a household survey and measuring poverty. This paper outlines how these challenges were overcome in wave 2 of the Somali High Frequency Survey through methodological and technological adaptations in four areas. First, in the absence of a recent census, no exhaustive lists of census enumeration areas along with population estimates existed, creating challenges to derive a probability-based representative sample. Therefore, geo-spatial techniques and high-resolution imagery were used to model the spatial population distribution, build a probability-based population sampling frame, and generate enumeration areas to overcome the lack of a recent population census. Second, although some areas remained completely inaccessible due to insecurity, even most accessible areas held potential risks to the safety of field staff and survey respondents, so that time spent in these areas had to be minimized. To address security concerns, the survey adapted logistical arrangements, sampling strategy using micro-listing, and questionnaire design to limit time on the ground based on the Rapid Consumption Methodology. Third, poverty in completely inaccessible areas had to be estimated by other means. Therefore, the Somali High Frequency Survey relies on correlates derived from satellite imagery and other geo-spatial data to estimate poverty in such areas. Finally, the nonstationary nature of the nomadic population required special sampling strategies.

Keywords: Consumption Measurement, Poverty, Questionnaire Design

JEL classification: C83, D63, I32

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1. Introduction and related literature

Somalia gained independence in 1960. The collapse of Siad Barre's post-independence regime in 1991 led to civil war between local power factions and dismantled the central state completely. Between 1995 and 2000, regional administrations emerged across the country, as security improved and economic development accelerated.[2] The formation of the Transitional Federal Government in 2004 and of its successor, the Federal Government of Somalia, in 2012 marked the return of a significant central state institution. After peaceful elections in 2016, a new government was formed in 2017 committed to embark on a development trajectory (World Bank, 2017).

Though Somalia remains one of the world's poorest countries (World Bank, 2016a, 2015), a vibrant but largely informal private sector sprouted in the absence of government, drove growth in the Somali economy, and took on the provision of services. Several economic activities including telecommunications, money transfer businesses, livestock exports, and localized electricity services grew well during this period (World Bank, 2017). Large-scale out-migration of skilled Somalis who sent back part of their earnings made diaspora remittances essential to the Somali economy, equivalent to between 23 and 38 percent of GDP and outweighing both international aid flows and foreign direct investment (World Bank, 2015).

Despite improvements in political stability, Somalia remains fragile. Parts of southern Somalia are inaccessible due to the presence of Al-Shabaab, which also repeatedly carried out terroristic attacks, and violent clashes between various power factions continue to occur throughout the territory.[3] In addition to conflict, the cyclical El Nino phenomenon caused severe droughts in 1991/92, 2011/12, and 2016/17 which exacerbated preexisting vulnerabilities in the Somali population. Both conflict and drought have led to large-scale internal displacement (World Bank, 2018a). The recent 2016/17 drought led to the displacement of approximately one million Somalis, adding to an existing population of internally displaced persons of 1.1 million (UNHCR, 2018).

As is typical for fragile states, Somalia is highly data-deprived, leaving policy makers to operate in a statistical vacuum (Beegle et al., 2016). Specifically, years of civil war and ongoing conflict have eroded Somalia's statistical infrastructure and capacity, leading to the lack of key macro- and micro-economic indicators, including the poverty rate (Hoogeveen and Nguyen, 2017). The government conducted and published the last full population census in 1975, while Somalia Socioeconomic Survey of 2002 was the last country-wide household survey (UNFPA, 2014). Most recent existing data sources are local FSNAU and FAO food and nutrition surveys, while organizations operating within Somalia implemented a range of smaller surveys. In 2014, UNFPA implemented the first nationwide Population Estimation Survey (PESS) in preparation for a national census, finding the total population to be 12.3 million, of which 42 percent are urban, 23 percent rural, 26 percent nomadic, and 9 percent are internally displaced (UNFPA, 2014).

Funded by the World Bank, Somaliland carried out a household budget survey (SLHS) in 2013, which generated much-needed indicators, including poverty estimates, but the sample was not representative especially for the rural population and did not cover the nomadic and displaced populations. The World Bank conducted the first wave of the Somali High Frequency Survey (SHFS) in the spring of 2016, representative of the accessible urban, rural, and IDP population in 9 of 18 prewar regions as well as

[2] Somaliland self-declared independence in 1991.

[3] See the Armed Conflict Location and Events Database (ACLED), Somalia, for a disaggregated overview.

Mogadishu, providing a baseline data set for monitoring poverty and contributing to other key statistical indicators. However, in addition to large inaccessible areas, the sample excluded nomadic population and households in insecure areas. Furthermore, the rural sampling frame had to be derived ad-hoc with only limited representativeness. Wave 2 of the SHFS, implemented in December of 2017, significantly expanded coverage to urban and rural areas in central and southern Somalia and included the nomadic population for the first time, while a newly derived sampling frame enhanced overall representativeness.

The specific context of insecurity and lack of statistical infrastructure in Somalia posed a number of challenges for implementing a household survey and measuring poverty. First, in the absence of a recent census, no exhaustive lists of census enumeration areas along with population estimates existed, creating challenges to derive a probability-based representative sample. Second, while some areas remained completely inaccessible due to insecurity, even most accessible areas held potential risks to the safety of field staff and survey respondents, so that time spent in these areas had to be minimized. Third, poverty in completely inaccessible areas had to be estimated by other means. Finally, the non-stationary nature of the nomadic population required special sampling strategies. This paper outlines how these challenges were overcome in wave 2 of the SHFS through methodological and technological adaptations in four areas: sampling strategy, survey design, fieldwork implementation, and poverty measurement. In line with the challenges outlined above, this paper contributes to several themes in the literature on poverty measurement and data collection in the context of conflict and fragility, involving hard-to-survey populations.

First, geospatial techniques and high-resolution imagery were used in the SHFS to model the spatial population distribution, build a probability-based population sampling frame, and generate enumeration areas in an effort to overcome the lack of a recent population census (section 2). The SHFS sampling strategy bears resemblance to the strategy proposed by Muñoz and Langeraar (2013), which relies on satellite imagery and grid cells to build a sampling frame in Myanmar. Wardrop et al. (2018) review various efforts to produce spatially disaggregated population estimates based on satellite imagery, in contexts where census data are absent or inaccurate. Barry and Rüther (2005) and Turkstra and Raithelhuber (2004) employ satellite imagery to study informal urban settlements in South Africa and Kenya, respectively, while Aminipouri et al. (2009) estimate various slum populations in Dar-es-Salaam, Tanzania. Himelein et al. (2016) compare the viability of various satellite and area-based sampling methods in second-stage sample selection in Mogadishu, Somalia.

Second, risks to the safety of field staff required spending as little time in enumeration areas as possible. One strategy to address this issue is to call or message respondents on their mobile phones and not visit dangerous areas at all. A growing body of literature explores the use of mobile technology in this context (e.g. Demobynes and Sofia, 2016; Dillon, 2012; Firchow and Mac Ginty, 2016). However, administration of necessary consumption modules to estimate poverty is not feasible via phone surveys.

To address security concerns, the SHFS adapted logistical arrangements, sampling strategy, and questionnaire design to limit time on the ground. In logistical arrangements, a detailed and timely security assessment ensured that the enumeration areas to-be-visited were safe on the day of fieldwork. The fieldwork protocol was designed such that teams would spend as little time as possible in any given region and draw little attention, ensuring enumerator and respondent safety (section 3.2). Concerning sampling strategy, it was not feasible to conduct a full listing of all households in an enumeration area, as this was too time-intensive and may have raised suspicion. Instead, a micro-listing approach was used, which required enumeration areas to be segmented into smaller enumeration blocks using satellite imagery. Enumeration blocks are small enough for enumerators to list and select households immediately before conducting the interview (section 2.2). Himelein et al. (2016) compare this methodology with other second-stage sampling strategies designed for use in fragile and time-sensitive settings.

Complete food and nonfood consumption modules result in an overall questionnaire length that is prohibitive in areas with high insecurity. The length of consumption modules can be reduced by removing rarely consumed items from the module or to combine categories of items (e.g. vegetables) and ask aggregates rather than individual items. Beegle et al. (2012) and Olson Lanjouw and Lanjouw (2001) provide evidence that both approaches lead to an underestimation of consumption and hence an overestimation of poverty. Fujii and Van der Weide (2013) propose an alternative approach which could be adapted for use in fragile settings, by assigning a full consumption module to households in areas without a binding security and time constraint, with only the covariates of consumption administered to households in insecure areas. Consumption and poverty could then be imputed based on those covariates. This approach, however, potentially leads to biases as the assignment of the two different modules depends on security and is not necessarily random. Instead, the Rapid Consumption Methodology (Pape and Mistiaen, 2018) was used to significantly reduce the length of the survey's consumption modules. The Rapid Consumption Methodology used in the SHFS relies on a set of core consumption items administered to all households. The remaining items are algorithmically partitioned into optional modules distributed systematically across households, with multiple imputation techniques used to impute total consumption and poverty. Pape and Mistiaen (2018) show that this design yields reliable poverty estimates (section 4).

Third, the SHFS relies on correlates derived from satellite imagery and other geo-spatial data to estimate poverty in areas that remained completely inaccessible as a result mainly of insecurity. A growing field of research is dedicated to predicting a range of outcomes based on a diverse set of such data sources. Early applications use night-time lights data to predict economic activity. These data are particularly successful at predicting GDP at the country-level (Henderson et al., 2012; Pinkovskiy and Sala-i-Martin, 2016), but appear less well-suited for measuring income and when variation in welfare is desired at a highly disaggregated level (Engstrom et al., 2017; Mellander et al., 2015). More recently, deep learning techniques applied to daytime imagery in order to classify such objects as roof types, roads, tree coverage, and crops has led to advances in measuring welfare at more disaggregated levels (Krizhevsky et al., 2012). Jean et al. (2016) use a convolutional neural network based on daytime satellite features to predict per capita consumption at the level of the enumeration area from living standards measurement surveys. Their model is successful in predicting consumption and explains 46 percent of variation on average across four countries and out-of-sample. Engstrom et al. (2017) provide a recent overview of the state of the literature and use high-resolution satellite features to estimate poverty at the village-level. In the SHFS, estimating poverty in inaccessible areas relied on a linear model with the objective of creating reliable and transparent poverty measures (section 5).

The remainder of this paper proceeds as follows. Section 2 discusses the sampling strategy. Section 3 provides an overview of the data collection process. Section 4 describes the derivation of the consumption aggregate, including the Rapid Consumption Methodology. Section 5 describes the imputation of poverty in inaccessible areas, and section 6 gives an overview of poverty in Somalia.

2. Sampling strategy

Wave 2 of the SHFS employed a multi-stage stratified random sample, ensuring a sample representative of all sub-populations of interest, while optimally balancing cost and precision of estimates. Strata were defined along two dimensions – administrative location (pre-war regions and emerging states) and population type (urban areas, rural settlements, IDP settlements, and nomadic population), leading to a total of 57 strata (Table A.2). Sub-populations in the urban centers of Mogadishu, Baidoa, and Kismaayo, in fisheries livelihood zones in coastal areas (Figure A.1), and IDP host communities were of particular interest and therefore deliberately oversampled.

The total planned sample size was 6,384 interviews, allowing for high-precision consumption estimates with less than 10 percent relative standard errors for key sub-populations and overall. The sample was allocated across strata following optimal (Neyman) allocation, minimizing the global sampling error of the consumption estimates (Neyman, 1934). Optimal allocation is given by

$$n_h = \frac{N_h S_h}{\sum_{h=1}^{H} N_h S_h}, \quad (1)$$

where n_h is the sample size in stratum *h, n* is the total sample size, *H* is the total number of strata, N_h is the total population of stratum *h*, *N* is the total overall population, and S_h is the standard deviation in stratum *h.* Hence, the number of households to be interviewed per stratum is mainly determined by the variability of consumption within the stratum (S_h). S_h was derived from the results of the SHFS Wave 1. The population size only matters for practical purposes in very small strata below 10,000 households. In the absence of a recent population census, the population of each stratum was derived from UNFPA's 2014 Population Estimation Survey (PESS), which contains detailed estimates for each population type and administrative unit of interest.

The optimal allocation of interviews was subject to the following requirements:

(i) 500 expected interviews in IDP settlements and 500 in nomadic populations;
(ii) At least 600 interviews expected per administrative unit;
(iii) Oversampled populations with
  - Mogadishu (urban): 900 interviews, including IDPs;
  - Kismaayo (urban) and Baidoa (urban): at least 500 interviews each;
  - Coastal fisheries livelihood zones: at least 300 interviews;
  - IDP host communities: 500 expected interviews.

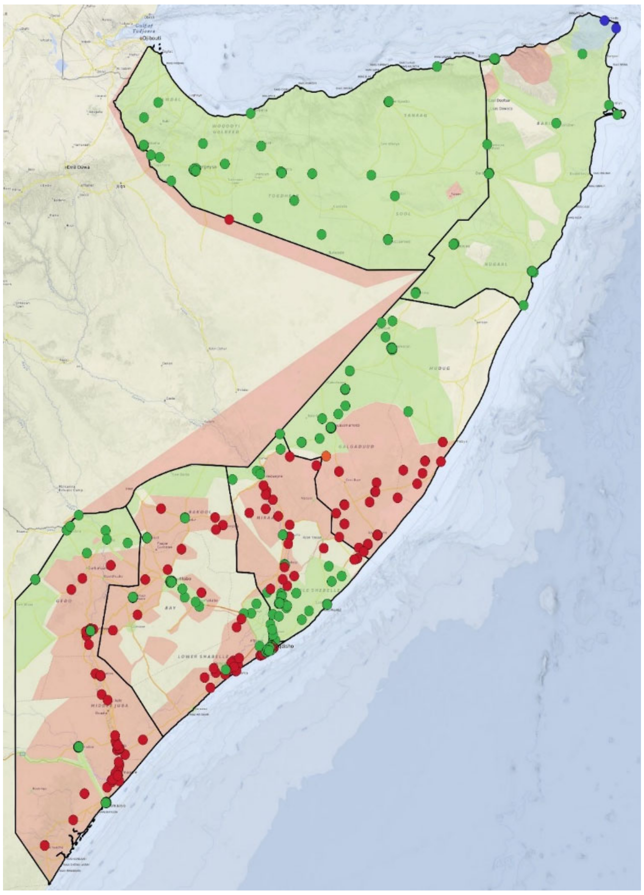
Households are clustered into enumeration areas (EAs), with 12 interviews expected for each selected EA. A larger number of households per enumeration area would only marginally benefit the statistical estimation of indicators because of potential homogeneity among households in geographic proximity. A smaller number of households would result in fewer than 3 observations for each of the four optional modules capturing household consumption based on the Rapid Consumption Methodology, and thus affect the reliability of poverty estimates (see section 4).

The sampling design addressed the challenging security situation on the ground in two ways. First, a security assessment was conducted to exclude areas too dangerous for field teams to visit. Second, a micro-listing approach was used in second-stage sample selection to allow field teams to spend limited time on the ground. Replacement of sampling units during fieldwork followed a transparent and predefined replacement schedule, which was necessary to correctly calculate sampling weights (see Appendix on Replacement of sampling units).

2.1. Incorporating inaccessibility into the sampling frame

A geo-spatial access map depicting accessibility (Figure 1) was created through key informant interviews with security experts and regional fieldwork coordinators based in the field. Publicly available information and incident reports provided by a local security company were used as auxiliary inputs. Finally, the information in the access map was triangulated with security analysts from a security NGO and private security company.

Figure 1: Security assessment access map



Source: Authors' own calculations.
Note: Red color indicates inaccessibility, green color indicates accessibility. Circles represent urban centers.

The security assessment led to the complete exclusion of pre-war region Middle Juba. Several other pre-war regions in south and central Somalia were only partially accessible (Table 1). The security situation differed substantially between different cities, with some completely inaccessible and some at least partially accessible even though they were located in insecure regions. The sampled IDP and nomadic populations fell within safe areas. Survey estimates for these populations were thus considered to be representative.

Table 1: Accessibility rates by pre-war region.

Pre-war region	Percentage of population in accessible areas	
	Urban areas	**Rural areas**
Awdal	100%	94%
Bakool	35%	21%
Banadir	87%	96%
Bari	99%	92%
Bay	86%	46%
Galgaduud	88%	50%
Gedo	100%	43%
Hiraan	44%	28%
Lower Juba	92%	9%
Lower Shabelle	28%	33%
Middle Juba	0%	0%
Middle Shabelle	98%	77%
Mudug	100%	76%
Nugaal	100%	100%
Sanaag	100%	100%
Sool	89%	98%
Togdheer	100%	98%
Woqooyi Galbeed	100%	96%
Overall	89%	48%

Source: Authors' calculations

Low accessibility in south and central Somalia motivated the imputation of poverty in inaccessible areas using geo-spatial information (section 5). The accessibility map was incorporated into the sampling frame to draw EAs only from accessible areas. The resulting sample was thus representative of the entire Somali population within secure areas.

2.2. Sampling frame and sample selection

The sampling frame for wave 2 of the SHFS is the exhaustive list of sampling units for every stage in the multi-stage selection process (denominated according to the stage of selection, i.e. primary sampling units (PSUs) in the first stage, secondary sampling units (SSUs) in the second stage, and so on) employed in the survey's sampling strategy. Sampling units are listed separately by stratum. Each sampling unit must have information concerning the population residing in it to allow for selection proportional to size (United Nations Statistical Division, 2005). In the absence of a recent population census, no readily useable enumeration areas and population estimates existed. To overcome these challenges the SHFS drew from a variety of data sources and GIS techniques to create a population sampling frame, strata boundaries, and a comprehensive list of enumeration areas.

Strata boundaries

In line with stratification at the intersection of administrative regions and population type, the following GIS data sets were combined to spatially demarcate strata boundaries:

(i) Pre-war region boundaries;
(ii) IDP settlement boundaries;

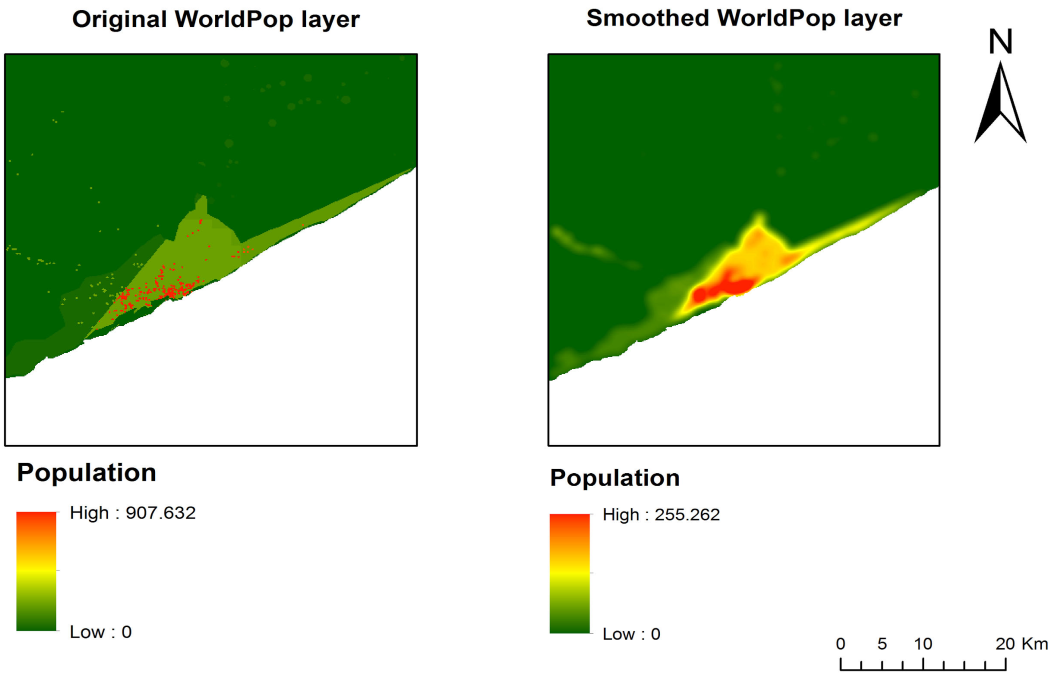
(iii) Urban area boundaries;
(iv) Rural settlement boundaries;
(v) Security assessment access map.

Pre-war region boundaries are available as shapefiles from UNDP. The boundaries of urban areas were defined by the urban enumeration areas previously used in UNFPA's Population Estimation Survey 2014 (PESS). Boundaries of IDP settlements were provided by UNHCR's Shelter Cluster and PESS. The IDP strata boundaries were subtracted from the urban and rural strata to prevent duplicate sampling. The remaining areas outside of the urban and IDP strata were considered as rural strata. Areas determined too dangerous through the security assessment were removed from the sampling frame.

Population sampling frame

In urban and rural strata, population estimates were derived from the 2015 WorldPop data set, detailed in Linard et al. (2010). This data set uses a combination of data sources and methods, including satellite imagery, to derive highly spatially disaggregated population estimates. First, the starting point are 2005 population estimates at the district-level from the UN Office for the Coordination of Humanitarian Affairs (OCHA) for 74 districts. Second, an Africover GIS dataset depicting 22 landcover classes was combined with 2005 Landsat satellite imagery depicting settlement outlines. Third, settlement point location data, based on the efforts of various NGOs and UN agencies, with more than 11,000 settlement points along with some population estimates, including urban and rural areas, and IDP settlements. To achieve higher spatial resolution, the OCHA estimates were disaggregated using the information contained in the settlement points data and the landcover class data. The result is a gridded population dataset at 100m-by-100m spatial resolution. For each 100m-by-100m cell, the data set contains a population estimate, which, aggregated within the PSU, provides a population estimate for each primary sampling unit (PSU) in urban and rural strata, which was later used for sample selection proportional to size. Due to inadequacies of the population density map for the purpose of creating a sampling frame, a set of corrections had to be made to this data set. In the original WorldPop layer, the population values were not always distributed smoothly. For instance, a village might have only one pixel with a high population number creating a sharp contrast, although its coverage area is larger and the transition from sparse to dense population is more progressive. Hence, a Gaussian smoothing kernel technique with standard deviation of 500m was applied. This distributed higher values smoothly in areas surrounding a high-density pixel while preserving close to the total population count in the area (Figure 2).

Figure 2: Gaussian smoothing of the WorldPop population density layer.



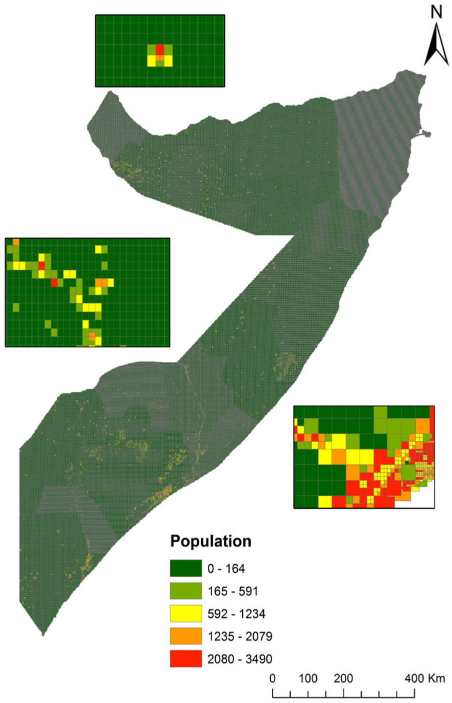
Source: Flowminder / WorldPop.

In IDP strata, population estimates for each PSU were based on the PESS IDP population estimates for each pre-war region.

Primary Sampling Units (PSUs) and first-stage sample selection

PSUs were generated using a variety of techniques depending on the population type. The primary sampling unit (PSU) in urban as well as rural strata was the enumeration area (EA). The boundaries for urban EAs were derived from the enumeration areas used in UNFPA's 2014 Population Estimation Survey (PESS). Overlaps with IDP settlements were removed. The EAs thus obtained were combined with the corresponding population estimates from the 100m-by-100m WorldPop data set to form the sampling frame for urban strata in which each PSU has a positive and known probability of selection. In case a strata boundary cut through any grid cell in the WorldPop data set, the grid cell was split and the population estimates re-calculated weighted by geographical area. In rural strata – defined as those permanently settled areas outside of urban areas and IDP settlements – no list of enumeration areas comparable to the PESS EAs exists. The entire area of rural strata assessed as secure was divided into rectangular grid cells of different sizes using a quadtree algorithm. The approach splits an area into successively smaller quadtratures by checking to see whether the content of each split is greater or less than a prescribed value. In this case, the population map was used as the unit of measure, and was split successively until each square had a population of less than a target population of 3,500. This approach also allowed the definition of each grid cell per a set of combined parameters, specifically geographic extent and population size (Figure 3; see Minasny et al., 2007). Thus, each cell has a minimum estimated population size of 3,500 and a maximum geographical area of 3 km x 3 km. to keep enumeration areas manageable in size for field teams.

Figure 3: Quadtree grids



Source: Flowminder / WorldPop.

For IDP strata, primary sampling units were IDP settlements as defined by UNCHR's Shelter Cluster. PSU boundaries, which, given the choice of PSU, are equivalent IDP settlement boundaries, were derived from UNHCR's GIS shapefiles. In several cases information on settlement boundaries was missing. In these cases, the missing information was drawn from PESS IDP enumeration areas (Table A.1). PESS population data, available at the pre-war region level, were used to obtain population estimates for each IDP settlement. To match the pre-war region IDP population to each IDP settlement in the sampling frame, the following protocol was applied: Whenever there was exactly one IDP settlement per pre-war region, the PESS IDP population for that pre-war region was used as the population estimate for the respective settlement, thus taking the settlement population as representative of the IDP population in its pre-war region. In cases where there is more than one settlement per pre-war region, the PESS IDP population was assigned to each settlement proportional to the geographical area each settlement covers relative to the total area of all settlements in the given pre-war region.

Across all strata, PSUs were selected using a systematic random sampling approach with selection probability proportional to size (PPS), where size is given by the estimated population in each PSU. In PPS sampling, PSUs are selected into the sample based on their size so that large PSUs have a greater chance of being part of the final sample. In urban and rural areas, the EA served was the primary sampling unit.

In IDP strata, PPS sampling is applied at the IDP settlement level, determining how many enumeration areas are to be selected in each settlement. PSUs were drawn separately for each stratum, with at least 20 percent additional PSUs selected to serve as replacements in case one of the main PSUs needed to be replaced (see section 2).

Secondary sampling units (SSUs) and second-stage sample selection

Even in areas deemed accessible per the security assessment, it was critical to the safety of field staff and respondents that teams would spend as little time as possible in each EA. Himelein et al. (2016) discuss and compare several second-stage sample selection strategies for use in contexts such as this one. In wave 2 of the SHFS, a micro-listing approach is used in second- and final-stage sample selection. In micro-listing, enumeration areas are divided into smaller enumeration blocks. Rather than performing a time-consuming full listing of all households in the EA, enumerators list only households in one enumeration block, then select the household to be interviewed, and immediately conduct the interview, greatly reducing the time required in the EA.

Enumeration blocks were generated through different means, depending on the population type. In urban and rural strata, the EAs selected in the first stage were manually segmented into enumeration blocks (EBs) using satellite imagery from Google Earth or Bing, counting the number of structures visible in each. Enumeration blocks served as secondary sampling units (SSUs) in the sampling design. Enumeration blocks were created as per the following general criteria:

- Each selected EA would be comprehensively covered by enumeration blocks.
- Each EA would be delineated into 12 enumeration blocks, expecting one interview per block.
- Each enumeration block would contain at least 1 and at most 12 structures.
- Enumeration blocks in the same EA should have roughly the same number of visible structures.
- Blocks would be drawn to take account of natural boundaries.
- Each block should have a central point from which all structures in the block can be seen.

The general criteria for block delineation allow for several special cases:

(i) If any PSU contained fewer than 12 structures, it would not be possible to delineate 12 blocks of the same size.

(ii) If any PSU contained more than 150 structures, more than 12 blocks were delineated, following the above criteria.

(iii) Given the design features of the sample, a fraction of PSUs was selected more than once. This occurred in two instances: First, given the nature of the first-stage sample selection with PPS, very large PSUs were selected twice or three times. This was especially likely in strata with a relatively short list of PSUs and a relatively large number of required interviews in the stratum. Second, as outlined in the previous section, PSUs were selected more than once if they formed part of one of the oversamples. The number of required interviews and consequently the required number of enumeration blocks was scaled up proportionately in these cases. For instance, if a PSU was selected twice, 12*2=24 interviews and blocks were required, and if a PSU was selected three times, 12*3=36 interviews and blocks were required. All other criteria for block delineation remained in place (Figure 4).

Figure 4: Example of EA delineated into blocks

Source: Flowminder / WorldPop.

Enumeration blocks were selected with equal probability. In the general case of 12 blocks per enumeration area, every single block was selected as 12 interviews per EA were required (and equivalently for PSUs with 24 or 36 required interviews in special case (iii)). In PSUs where more than 12 (or 24, or 36) blocks had been delineated due to the high number of visible structures (special case (ii)), selection of 12 (or 24, or 36) blocks with equal probability was implemented using equal probability random sampling. In PSUs with less than 12 (or 24, or 36) visible structures (special case (i)), two selection mechanisms were possible: First, if field teams found that there were indeed less than 12 structures in the PSU (as the satellite imagery suggested), all structures were interviewed. Second, when field teams found that the number of structures was higher than the satellite imagery suggested, enumerators counted the number of structures and randomly selected 12 (or 24, or 36) households to be interviewed with equal probability.

A similar second-stage sampling strategy was employed for IDP strata. Each IDP settlement was segmented manually into enumeration blocks with approximately 10 structures each. Where sensible, 12 enumeration blocks were combined into one enumeration area. In some cases, however, IDP settlements consisted of geographically dispersed pockets within urban areas, each far away from the next. To keep enumerator travel time in check, facilitate supervision, and ensure safety, the construction of IDP EAs followed these geographical contingencies to some extent. Hence, some EAs were created to contain more than 12 blocks and others contained less than 12.

Several of the most recent IDP settlement boundaries provided by UNHCR were a few years old, while the recent drought caused perturbations to the size, composition, and localization of the IDP population. Thus, each selected IDP enumeration area was inspected to ensure that it was still inhabited by displaced communities. This led to several IDP EAs being dropped and replaced by backup EAs. Enumeration areas served as secondary sampling units and were selected with probability proportional to size, with size given by the number of blocks per EA. The required number of EAs in each IDP settlements was fixed through first-stage sample selection. Then, where there were more or fewer than 12 blocks per IDP EA, blocks were selected with equal probability.

Final-stage sample selection: Households

Except for the special cases discussed in the previous sections, enumerators were expected to interview one household per block in all selected blocks within the enumeration area. The household was selected randomly with equal probability in two stages, following the micro-listing protocol: From a central point in the block, the enumerator listed all residential structures within the current block into the tablet. The enumerator's tablet then randomly selected a residential structure for the enumerator to visit. At the structure, the enumerator recorded the number of households residing in the structure, and the tablet again randomly selected a household to be interviewed.

Oversamples

For Baidoa, Kismaayo, and fisheries areas, a second-stage oversampling strategy was used. In second-stage oversampling, PSUs selected in the first stage and falling into the specified urban centers or coastal areas were selected again to reach the minimum sample size for each oversample. Through this process, PSUs in Kismaayo were selected twice, and PSUs in Baidoa and in fisheries areas were selected a total of three times. Fisheries livelihood zones in coastal areas were defined by FEWSNET and FSNAU (Figure A.1, zones SO7 and SO8). For the host communities oversample, all urban enumeration areas adjacent to IDP settlements were pre-selected as a separate sampling frame. The resulting list was stratified implicitly by pre-war region. 42 enumeration areas were selected with probability proportional to size to reach the desired oversample.

2.3. Sampling of the nomadic population

Nomadic households, who make up around a quarter of the Somali population according to UNFPA's Population Estimation Survey (PESS) of 2014, are inherently difficult to sample because, by definition, they have no permanent place of residence (Kalsbeek, 1986; Soumare et al., 2007). Himelein et al. (2014) use a random geographic cluster sample approach, in which points are randomly selected from a map and all nomadic households within a radius around the point are interviewed. The SHFS followed a different approach. The strategy for sampling nomadic households relied on lists of water points used by nomadic households to water their livestock, which served as the primary sampling units. UNFPA's 2014 PESS took a similar approach to estimate the nomadic population (UNFPA, 2014). The SHFS project deployed 200 purpose-designed tracking devices to nomadic households who gave consent, which track their movements for two years. This will improve the understanding of the patterns of movement of the nomadic population in Somalia, which will facilitate sampling this population in the future.

Nomadic sampling frame

Nomadic strata were defined at the federated member state level (**Error! Reference source not found.**), with the population count for each stratum provided by PESS. The list of water points was divided up by stratum. The list was put together from a combination of two sources. First, the list of water points used in PESS. Second, a regularly updated list of water points kept by the UN Food and Agriculture Organization (FAO). Given this combination of sources, the resulting list of water points used as sampling frame was viewed to be close to or completely exhaustive. The list contained the GPS location and information on type of water point (Berkad, Borehole, Dam, Dug Well, Spring, Other). Other water point characteristics such as the number of households using the water point and the predominant type of cattle watered were available only for an incomplete subset of water points. The list was stratified implicitly by pre-war region (each federated member state encompasses several pre-war regions) and type of water point.

First-stage sample selection

Water points from this list served as primary sampling units. In the absence of reliable estimates of the population size of water points, 42 water points were selected in the first stage with equal probability, with 12 interviews to be conducted at each selected water point. A further challenge in sampling nomadic household peculiar to the timing of SHFS wave 2 was the ongoing drought, which led to many water points having run dry. Therefore, a series of Key Informant Interviews (KIIs) and Focus Group Discussions (FGDs) in each federated member state verified whether each selected water point was currently frequented by nomadic households. In case a selected water point was not currently frequented by nomadic households, it was replaced.

Selection of nomadic households at water points

Selection of nomadic households to interview relied on a listing process at each water point whose aim was to compile an exhaustive list of all nomadic households at the water point. However, the total number of nomadic households at a given water point is not static as nomadic households are not resident at water points, but only stay there for a limited time, and arrive and leave at various times during the day. It was determined in KIIs that nomadic households need to spend a very minimum of two hours at a given water point to water their cattle and that cattle watering would occur during daylight hours. To allow for a complete listing, daylight hours were segmented into two-hour time slots, during each of which enumeration team leaders completed a full listing of all nomadic households at the water point at that time. As not all persons present at water points were members of nomadic households, but may instead be from close-by rural settlements, the listing form contained a number of questions identifying nomadic households. The form also asked for informed consent to be interviewed. Upon completing a two-hour listing period, up to three households were randomly selected from the list of consenting nomadic households gathered during this time slot. Interviews were then scheduled with the selected households at a time and place convenient for the household respondent.[4] Based on this sampling design, sampling weights were calculated after the completion of data collection (see Appendix for the derivation Sampling weights).

3. Data collection

Wave 2 of the Somali High Frequency Survey was implemented using computer assisted personal interviewing (CAPI), whereby enumerators were equipped with tablet computers which contained the survey questionnaire (section 3.1) and would upload completed interviews to the project's Survey

[4] Additional rules applied in special cases: (i) If no nomadic households were found or arrived at a given water point, enumeration teams remained at the water point for three days. If no nomadic household had arrived, the water point was replaced. (ii) If nomadic households were present but arrived at very low frequencies, so that teams struggled to reach the required number of interviews, they would stay for a maximum of 12 days. Then teams would leave whether or not they have reached the required number of interviews. If 3 or fewer (but at least 1) nomadic households arrived during any two-hour listing period, all listed households were interviewed during that period.

Solutions cloud servers daily. The choice of CAPI was guided, on the one hand, by the finding that this technology greatly reduces the number of errors relative to pen-and-paper interviewing (e.g. Caeyers's et al., 2012). On the other hand, this technology was essential to the near real-time monitoring of data collection (section 3.2) and quality control (section 3.3), which were deemed necessary in the Somali context where insecurity and remoteness make close supervision challenging and follow-up visits costly.

3.1. Survey instrument

The consumption modules were the central components of the SHFS wave 2 survey questionnaire. The questionnaire also contained other key components of a multi-topic household survey, particularly those relevant to the Somali context. These included an individual-level module with information on education, employment, and health, household characteristics, remittances, displacement, perceptions and subjective welfare, and shocks. The questionnaire was designed in line with best practices (Deaton and Grosh, 2000) and went through several iterations of internal and external expert revision.

The food consumption module consisted of 114 food items drawn from a list of CPI items provided by statistical authorities. To meet the requirements of the Rapid Consumption Methodology (section 4), items were divided in one core and four optional modules, with most commonly consumed items assigned to the core module. The list of items was highly specific (e.g. apples, pears rather than fruits) and selected to cover the basic food categories and adequately reflect the local diet (Smith et al., 2014; Zezza et al., 2017). The list of food items contained various items for food away from home, accounting for both food bought away from home and consumed at home and food consumed outside of the home. Further, to facilitate food quantity reporting for respondents, a list of non-standard units, along with their conversion to kilograms, was developed for each item, with inputs from regional experts and experience from the accompanying market price survey (Oseni et al., 2017).[5] The questionnaire was designed to capture purchased food, home production, and gifts.

The nonfood consumption module consisted of 90 items, which were assigned to core and optional modules in the same manner as the food items. The choice of nonfood items followed the COICOP classification system, with all relevant COICOP categories represented in the list of nonfood items.

3.2. Fieldwork and monitoring

The fieldwork strategy was designed to facilitate high-quality data collection and safety of field teams.[6] All enumerators and team leaders attended rigorous training sessions and had to sit a final exam to be hired. Forty-five teams were assembled for fieldwork, staffed each with one team leader, three regular enumerators, and two reserve enumerators. The large number of teams was essential, on the one hand, for security reasons. It allowed teams to enter and exit an area swiftly before their presence would draw too much suspicion and endanger their safety and that of survey respondents. On the other hand, this arrangement allowed teams to be composed of enumerators native to the areas which they covered.

The survey was piloted in each region before the beginning of fieldwork. Fieldwork was monitored in near real-time to verify data collection progress, data quality, and enumerator performance. To implement

[5] The Market Price Survey (MPS) is a component of the SHFS. The MPS collects weekly exchange rates and prices of a broad range of 91 products and services as well as exchange rates from 14 key markets across all Somali regions.
[6] The Somali High Frequency Survey was implemented by Altai Consulting in coordination with the respective statistical authorities. The team worked closely with the Directorate of National Statistics, Ministry of Planning, Investment and Economic Development of the Federal Government of Somalia.

near real-time monitoring, field teams uploaded interviews onto the project's Survey Solutions server at the end of each day. An automated pipeline of Stata code downloaded and processed the data, creating a detailed monitoring dashboard in Microsoft Excel, which headquarters reviewed daily. The dashboard tracked the number of submissions meeting the quality standards to be considered acceptable (see section 3.3 for these standards), interview duration, and unit non-response rates separately by EA, enumerator, team, and strata. It further assessed item non-response by listing the number of household members, proportion of missing values, 'No', and 'Don't know' or 'Refused to respond' entries in all modules and several other key questions, which would trigger follow-up questions. Unusually high proportions of missing values, 'No', 'Don't know', or 'Refused to respond' entries indicated possible enumerator shirking, as this behavior would reduce enumerators' workload. For example, entering that a household self-identifies as displaced would trigger an entire module on displacement. Enumerators returning low-quality or displaying suspicious behavior received warnings and follow-up training. If the issues could not be resolved in this way, enumerators were replaced by reserve enumerators from their team. Overall, however, enumerator performance was high, requiring few replacements, while the unit non-response rate was very low at 0.16 percent among urban, rural, and IDP households, and 0.50 percent among nomadic households.

3.3. Submissions quality standards

Each enumerator submission was subject to a set of minimum standards to ensure data quality.
Interviews were classified as valid or invalid based on the criteria listed in the following.

- *Valid EAs*. If the EA was not part of the final sample (i.e. it was replaced), the interview was classified as invalid and thus excluded from the final data set.
- *Valid EBs.* If the EB was not part of the final sample (i.e. it was replaced), the interview was excluded.
- *Duration.* If the duration of the interview did not exceed the minimum threshold of 30 minutes, the interview was excluded.
- *Location.* If the interview did not have GPS coordinates associated with it, the interview was considered invalid. If the GPS coordinates fell outside buffer zone of a 50m+accuracy of GPS (based on the minimum latitude-longitude formula + 50m buffer) around the EA, the interview was excluded.
- *Follow up visits*. If the interview was not conducted in the first visit, the interview for the first visit must be valid except for the minimum duration, and both records must contain matching GPS positions (with a 10m + precision maximum distance), otherwise the interview completed in the follow-up visit was excluded.
- *Replacement interview*. If the interview was from a replaced household, the record of the original household must be valid except for the minimum duration and the reason for no interview must also be valid, otherwise the interview was excluded.

Beyond these criteria, the Survey Solutions CAPI platform allowed to 'reject' submissions on a case-by-case basis and send them back to enumerators to correct whenever headquarters found problems with a submission.

4. Consumption aggregate

The main welfare measure used in this and other analyses using SHFS data is per-capita consumption, rather than income (Deaton and Zaidi, 2002). The SHFS collected data on realized consumption rather than the total money spent on consumption items, as this measured actual realized welfare in a utility-consistent way (Ravallion, 1994). This section discusses the various adjustments made to the SHFS data to construct the consumption aggregate using the Rapid Consumption Methodology. Section 6 discusses the use of the international poverty line and various aggregate poverty measures to perform poverty analysis on the SHFS data.

4.1. Cleaning of consumption data

Before deriving the consumption aggregate, the components of consumption –data on food consumption, nonfood consumption, and durable assets– must undergo a cleaning process to correct outliers and other mistakes (Deaton and Zaidi, 2002).

Food expenditure data are cleaned in a four-step process. First, units for reported quantities of consumption and purchase are corrected. Typical mistakes include recorded consumption of 100 kg of a product (like salt) where the correct quantity is grams. These mistakes are corrected using generic rules (Table A.4). Then, a conversion factor to kg for all units is introduced. For example, a small piece of bread will likely have a different weight than a small piece of garlic. To avoid mistakes, enumerator trainings focused on units and introduced a common understanding of what each unit means for each food item. In addition, the conversion to kilograms was made explicit on the enumerators' tablets (Table A.5). The third step consisted of correcting issues with the exchange rate selected (Table A.6). Finally, outliers in each component of consumption are detected using a set of cleaning rules to correct quantities and prices (see Appendix Cleaning rules for food consumption data). The non-food data set only contains values without quantities and units. First, the same cleaning rules for currencies are applied (Table A.6), followed by a set of specialized cleaning rules (see Appendix Cleaning rules for nonfood consumption data). Likewise, for durables, the same cleaning rules for currencies are applied (Table A.6), and then a set of durables-specific cleaning rules (see Appendix Cleaning rules for durable assets).

4.2. Consumption aggregate using the Rapid Consumption Methodology

The nominal household consumption aggregate is the sum of four components, namely expenditures on food items, expenditures on non-food items, the value of the consumption flow from durable goods, and housing (Deaton and Zaidi, 2002). Without a housing market functioning well enough to derive credible estimates for the cost of housing, the SHFS consumption aggregate is based on the first three components: food consumption, nonfood consumption, and consumption of durable assets.

Food and nonfood consumption in the Rapid Consumption Methodology

The SHFS used the Rapid Consumption Methodology to estimate the consumption aggregate. Pape and Mistiaen (2018) provide a detailed and general exposition of the Rapid Consumption Methodology including an ex-post assessment of the methodology. The methodology is based on dividing food and nonfood consumption items in one core and several optional modules. With each household assigned the core module and one optional module, this methodology reduces the time spent on enumerating the consumption modules. Deriving the consumption aggregate with this methodology is a two-step process. First, core and optional modules are constructed. Core items are selected based on their importance for consumption. The remaining items are partitioned into optional modules. Optional modules are assigned to groups of households. Second, after data collection, consumption of optional modules is imputed for all households. Then, the resulting consumption aggregate is used to estimate poverty indicators.

Module construction

Food and non-food consumption for household *i* are estimated by the sum of expenditures for the full list of consumption items[7]

(2)
$$y_i^f = \sum_{j=1}^{m} y_{ij}^f \text{ and } y_i^n = \sum_{j=1}^{m} y_{ij}^n$$

where y_i^f and y_i^f denote the food and non-food consumption of item *j* in household *i*. As the estimation for food and non-food consumption follows the same principles, the upper indices *f* and *n* are neglected in the remainder of this section. The list of items can be partitioned into M+1 modules each with m_k items:

(3)
$$y_i = \sum_{k=0}^{M} y_i^{(k)} \text{ with } y_i^{(k)} = \sum_{j=1}^{m_k} y_{ikj}$$

For each household, only the core module $y_i^{(0)}$and one additional optional module $y_i^{(k^*)}$are collected.

Item assignment to the core module was designed to maximize the core module's share of total consumption, so that a large share of consumption would be enumerated from each household. Important items were identified by their average food share across households from wave 1 of the SHFS.[8] This strategy relies on the fact that, in Somalia, a few dozen items capture the majority of consumption. The core modules captured 94 percent of food consumption and 79 percent of nonfood consumption, respectively (Table 2). Optional modules were constructed such that items are orthogonal within modules and correlated between modules, using an iterative algorithm (Pape and Mistiaen, 2018).

Table 2: Item partitions and consumption shares in SHFS wave 2.

	Food Items			Non-food Items		
	Number of items	Share Wave 2	Share Wave 2 Imputed	Number of items	Share Wave 2	Share Wave 2 Imputed
Core	38	94%	79%	29	79%	47%
Module 1	21	2%	8%	14	5%	14%
Module 2	18	2%	6%	15	6%	15%
Module 3	19	1%	5%	16	7%	18%
Module 4	18	1%	4%	15	5%	11%

Source: Authors' calculations based on SHFS Wave 2.

[7] The list of consumption items used in wave 2 of the SHFS is discussed in section 3.1.

[8] Generally, previous consumption surveys in the same country or consumption shares of neighboring or similar countries can be used to estimate food shares. In the worst case, a random assignment results in a larger standard error but does not introduce a bias. The assignment of items to modules is very robust and, thus, even rough estimates of consumption shares are sufficient to inform the assignment without requiring a baseline survey.

In fieldwork, a sufficient number of households must be assigned each optional module to obtain a reliable total consumption estimate. In wave 2 of the SHFS, this was ensured by interviewing 12 households per EA allowing for the ideal partition of three items per optional module.

Consumption estimation

Household consumption was then estimated using the core module, the assigned optional module, and estimates for the remaining optional modules

$$\hat{y}_i = y_i^{(0)} + y_i^{(k^*)} + \sum_{k \in K^*} \hat{y}_i^{(k)} \tag{4}$$

where $K^* := \{1, \dots, k^* - 1, k^* + 1, \dots, M\}$ denotes the set of non-assigned optional modules. Consumption of non-assigned optional modules was estimated using multiple imputation techniques taking into account the variation absorbed in the residual term (Pape and Mistiaen, 2018). Multiple imputation was implemented using multivariate normal regression based on an EM-akin algorithm to iteratively estimate model parameters and missing data.[9] The standard errors capture the error distribution of the multiple imputation process. The underlying model is a welfare model relating consumption to key household characteristics thus explaining 71 percent of variation in food consumption and 64 percent in nonfood consumption. The model parameters were household size, share of children in household, share of seniors in household; household head gender, employment, and education; dwelling type, dwelling drinking water access, dwelling floor, and dwelling ownership status; household experience of hunger; receipt of remittances; population type (urban, rural, IDP, nomadic) and a region-population type interaction, as well as each household's core consumption quartile.[10] Pape and Mistiaen (2018) demonstrate that the Rapid Consumption Methodology yields reliable estimates of poverty using an ex-post assessment with household budget data from Hargeisa and mimicking the Rapid Consumption methodology by masking consumption of items that were not administered to households.[11]

Durable consumption flow

The consumption aggregate includes the consumption flow of durables calculated based on the user-cost approach. The consumption flow distributes the consumption value of the durable over multiple years.

[9] Pape and Mistiaen (2018) test various other techniques for imputing total consumption, including OLS and tobit module-wise regression and multiple imputation chained equations, concluding that multivariate normal regression is the preferred technique.

[10] Negative imputed values are corrected by scaling all associated imputed values to an average of zero without affecting the variance.

[11] Pape and Mistiaen (2018) compare the imputation results with consumption estimates from the full consumption modules of the 2013 Somaliland Household Survey. The authors present the performance of the estimation techniques in terms of the relative bias (mean of the error distribution) and the relative standard error. The methodology generally does not perform well at the household level (HH) but improves considerably already at the enumeration area level (EA) where the average of 12 households is estimated. At the national aggregation level, the Rapid Consumption methodology slightly over-estimates consumption by 0.3 percent. Assessing the three standard poverty measures (Foster et al., 1984) including poverty headcount (FGT0), poverty depth (FGT1) and poverty severity (FGT2), the simulation results show that the Rapid Consumption methodology retrieves estimates within 1.5 percent of the reference measure (Figure A.5). Generally, the estimates are robust as suggested by the low standard errors (Figure A.6). Simulations were also run for the complete data set from the Somaliland 2012 household budget survey producing comparable results.

The user-cost principle defines the consumption flow of an item as the difference of selling the asset at the beginning and the end of the year as this is the opportunity cost of the household for keeping the item. The opportunity cost is the difference in the sales price and the forgone earnings on interest if the asset is sold at the beginning of the year.

If the durable item is sold at the beginning of the year, the household would receive the market price p_t for the item and the interest on the revenue for one year. With i_t denoting the interest rate, the value of the item thus is $p_t(1 + i_t)$. If the item is sold at the end of the year, the household will receive the depreciated value of the item while considering inflation. With π_t being the inflation rate during the year t, the household would obtain $p_t(1 + \pi_t)(1 - \delta)$ with the annual physical or technological depreciation rate denoted as δ assumed constant over time.[12] The difference between these two values is the cost that the household is willing to pay for using the durable good for one year. Hence, the consumption flow is:

$$\text{(5)} \qquad \mathrm{y}^d = p_t(1 + i_t) - p_t(1 + \pi_t)(1 - \delta)$$

By assuming that $\delta \times \pi_t \cong 0$, the equation simplifies to

$$\text{(6)} \qquad \mathrm{y}^d = p_t(i_t - \pi_t + \delta) = p_t(r_t + \delta)$$

where r_t is the real market interest rate in period t. Therefore, the consumption flow of an item can be estimated by the current market value p_t, the current real interest rate r_t, and the depreciation rate δ. Assuming an average annual inflation rate π, the depreciation rates δ can be estimated utilizing its relationship to the market price[13]:

$$\text{(7)} \qquad p_t = p_{t-k}(1 + \pi)^k(1 - \delta)^k$$

The equation can be solved for δ obtaining:

$$\text{(8)} \qquad \delta = 1 - \left(\frac{p_t}{p_{t-k}}\right)^{\frac{1}{k}} \frac{1}{(1 + \pi)}$$

Based on this equation, item-specific median depreciation rates are estimated assuming an inflation rate of 0.5 percent, a nominal interest rate of 2.0 percent and, thus, a real interest rate of 1.5 percent (Table A.8).

For all households owning a durable but did not report the current value of the durable, the item-specific median consumption flow is used. For households that own more than one of the durable, the consumption flow of the newest item is added to the item-specific median of the consumption flow times the number of those items without counting the newest item.[14]

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[12] Assuming a constant depreciation rate is equivalent to assuming a “radioactive decay” of durable goods (Deaton and Zaidi, 2002).

[13] In particular, π solves the equation $\prod_{i=t-k}^{t}(1 + \pi_i) = (1 + \pi)^k$.

[14] The SHFS wave 2 questionnaire provides information on a) the year of purchase and b) the purchasing price only for the most recent durable owned by the household.

Deflators

Spatial price indices were calculated using a common food basket and spatial prices to make consumption comparable across regions. The Laspeyres index is chosen as a deflator due to its moderate data requirements. The deflator is calculated by analytical strata areas based on the price data collected in wave 2 of the SHFS. The Laspeyres index (Table 3) reflects the item-weighted relative price differences across products. Item weights are estimated as household-weighted average consumption share across all households before imputation. Based on the democratic approach, consumption shares are calculated at the household level. Core items use total household core consumption as reference while items from optional modules use the total assigned optional module household consumption as reference. The shares are aggregated at the national level (using household weights) and then calibrated by average consumption per module to arrive at item-weights summing to 1. The item-weights are applied to the relative differences of median item prices for each analytical stratum. Missing prices are replaced by the item-specific median over all households.

Table 3: Spatial Laspeyres index

Analytical strata	Foo deflator
IDPs	0.856
Nomads	1.030
Banadir (Urban)	0.910
Nugaal (Urban)	1.058
Bari and Mudug (Urban)	0.976
Woqooyi Galbeed (Urban)	1.181
Awdal, Sanaag, Sool and Togdheer (Urban)	1.181
Hiraan, Middle Shabelle and Galgaduud (Urban)	1.119
Gedo, Lower and Middle Juba (Urban)	0.960
Bay, Bakool and Lower Shabelle (Urban)	0.931
Bari, Mudug and Nugaal (Rural)	0.960
Awdal, Togdheer and Woqooyi (Rural)	0.887
Hiraan, Middle Shabelle and Galgaduud (Rural)	0.925
Bay, Bakool and Lower Shabelle (Rural)	0.945

Source: Authors' calculations.

To obtain the US$1.90 PPP (2011) poverty line and correct for price differences over time, a price index was created –in the absence of a national CPI– using consumption shares from the survey and prices collected by the Market Price Survey (MPS) and by the Food Security and Nutrition Analysis Unit, Somalia (FSNAU).[15] Inflation between 2011 and December 2017 was obtained from the growth in the price index, which was estimated in two steps. First, the price index was calculated from 2011 to February 2016 using data from Wave 1 of the SHFS and prices from FSNAU, and then from February 2016 to December 2017 with data from Wave 2 of the SHFS and prices from the MPS.[16]

In the first step, consumption shares of 109 food and 68 nonfood items were aggregated according to their Classification of Individual Consumption by Purpose (COICOP) code, and then combined with monthly prices from FSNAU for 51 products. As a result, 32 matched COICOP codes were used to calculate

[15] FSNAU collects monthly prices of commodities in 50 markets across all regions. The MPS collects weekly prices of a broad range of products and services as well as exchange rates from 14 key markets across all Somali regions.

[16] The products and services in the MPS are a close match with the food and nonfood items that form part of the consumption module of the Somali High Frequency household survey component. The price survey is implemented using a stringent set of quality standards.

the price index between 2011 and February 2016. In the second step, consumption shares of 114 food and 89 nonfood items were aggregated by COICOP code, in combination with weekly price series from the MPS for 109 products. This resulted in 49 matched COICOP codes that were then used to estimate the price index until December 2017.

4.3. Imputing consumption data in North-East and Jubbaland regions

Despite methodological innovations, field team training, and a stringent security protocol (section 3.2), some challenges with data collection persisted in certain geographic areas. These were mainly related to human resource capacity constraints and remote monitoring to ensure the quality of the data. Specifically, in the Jubbaland and rural North-East regions,[17] the information collected turned out to be only representative of a very small, idiosyncratic part of the population or did not consistently meet the survey's high-quality standards.

Jubbaland

The implementation of Wave 2 of the SHSF required some concessions to the local authorities in terms of the recruitment of field teams. Some enumerators who performed sub-optimally during training and the pilot were recruited as agreed with local authorities in Jubbaland. Likewise, there were some constraints to replace enumerators during the data collection if they were found to underperform. Based on internal discussions and consultations with trusted team leaders, the SHFS team judged that this affected the quality of the data collected in Jubbaland, particularly of the more demanding consumption modules, compared to other regions. Furthermore, insecurity remained widespread in Jubbaland, mainly due to a strong presence of Al-Shabaab. The entire region of Middle Juba was excluded from wave 2 of the SHFS due to security reasons. Likewise, large parts of Lower Juba, and to a lesser extent Gedo were also excluded (see Table 1 for accessibility rates by pre-war region).

In rural Jubbaland, field teams only collected data in areas that were relatively close to main cities (e.g. within a 10-km radius around Kismayo, Afmadow and Dhobley in Lower Juba). This was due to insecurity and because many rural EAs considered in the sampling frame were found to be empty after reviewing the satellite imagery. The EAs sampled for rural Jubbaland were peri-urban areas that correspond to large villages or small cities and thus the information was not representative of the rural population there. In addition, data from teams surveying rural Jubbaland showed signs of inconsistency and relatively low quality (highest percentage of invalid submissions compared to other urban and rural areas (Table 4); largest number of flags in the cleaning process of the consumption modules (Table 6), and large differences in the consumption of many food items relative to other rural areas (Table 7)). Interviews with rural households from this region were therefore entirely excluded from the final data set, and poverty estimated from satellite imagery and other geo-spatial data (section 5).

In urban areas, data collection lasted longer than in any other area covered due to over-sampling. Insecurity also made it more difficult collecting interviews and thus required more time. Team leaders reported that these issues contributed to fatigue on the part of enumerators, presumably impacting the quality of the data collected in urban Jubbaland.

[17] Jubbaland region consists of pre-war regions Gedo, Middle Juba, and Lower Juba (Middle Juba was completely inaccessible). North-East region consists of pre-war regions Nugaal, Bari, and Mudug (Table A.12).

Table 4: Percentage of valid submissions for urban and rural areas

Region	%
Mogadishu (Urban)	99.9
North-east Urban	99.6
North-east Rural	100.0
North-west Urban	99.2
North-west Rural	100.0
Central regions Urban	99.0
Central regions Rural	97.0
Jubbaland Urban	99.3
Jubbaland Rural	94.6
South West Urban	98.6
South West Rural	98.1

Source: Authors' calculations.

Table 5: Percentage of missing values for food items in urban and rural areas

Region	Percentage
Mogadishu (Urban)	54.8
North-east Urban	58.4
North-east Rural	61.2
North-west Urban	58.2
North-west Rural	61.2
Central regions Urban	57.9
Central regions Rural	58.3
Jubbaland Urban	49.8
Jubbaland Rural	49.1
South West Urban	57.5
South West Rural	56.5

Source: Authors' calculations.

Table 6: Number of flags in the cleaning of food items for urban and rural areas

Region	Average number per household
Mogadishu (Urban)	1.0
North-east Urban	0.8
North-east Rural	0.8
North-west Urban	0.9
North-west Rural	0.8
Central regions Urban	1.8
Central regions Rural	1.1
Jubbaland Urban	2.1
Jubbaland Rural	2.6
South West Urban	1.0
South West Rural	0.9

Source: Authors' calculations.

Table 7: Items consumed by 10% more/less households in each region relative to the urban/rural average

Region	Number of core food items
Mogadishu (Urban)	5
North-east Urban	6
North-east Rural	20
North-west Urban	7
North-west Rural	17
Central regions Urban	1
Central regions Rural	13
Jubbaland Urban	20
Jubbaland Rural	20
South West Urban	10
South West Rural	8

Source: Authors' calculations.

While the validity rate of submissions was in line with other regions (Table 4), the consumption data were flagged as outliers more often than in other regions during the review and cleaning process (Table 6). Further, the profile of food consumption for households in urban Jubbaland was different than in other urban areas for 20 of 38 core food items (Table 7). These issues in the consumption modules led to inconsistent poverty rates. Therefore, the information on the consumption modules (food, non-food and assets) was discarded and poverty estimated based on sociodemographic and other household characteristics in a multiple imputation process routine.

Rural North-East

The implementation of the survey also experienced some constraints in the recruitment of field teams in the rural North-East regions. The access of some areas in this region is possible only for team members from certain clans. Thus, enumerators had to be selected and replaced based on this criterion. Some of these candidates might not otherwise have been selected given their performance during training, the pilot, and data collection. This was judged to have affected the quality especially of the consumption data collected.

Moreover, the EAs sampled were spread across a vast territory and mostly in remote areas. They were far from each other, and far from urban centers. NE teams who covered rural areas had to travel up to two days to reach some EAs, longer than teams in any other region. Team leader reports from the field indicate that these large distances and conditions created fatigue among enumerators. Further, direct monitoring of field teams by supervisors was limited due to poor connectivity, and thus sending frequent and timely feedback was more challenging that for other teams. As a result, the performance of teams did not improve as in other regions.

Finally, the consumption profile of most core food items was different to other rural areas, including nearby and ostensibly similar areas covered by other teams (Table 7). Hence, the consumption data (food, non-food and assets) were discarded, and poverty was estimated from a multiple imputation process.

Consumption imputation process

Consumption data in North-East rural and Jubbaland urban were imputed in Stata with Multiple Imputation (MI) techniques. The same multiple imputation process and model described to estimate the consumption of non-assigned optional modules from equation (4) were used to obtain the four consumption components, and thus the total consumption expenditure for households in these regions.

The dependent variable of the model is total consumption expenditure per capita with data from North-East rural and Jubbaland urban set as missing and to be imputed.[18] The independent variables were chosen based on explanatory power with respect to household consumption: household size, share of children in household, share of seniors in household; household head gender, employment, and education; dwelling type, dwelling drinking water access, dwelling floor, and dwelling ownership; household experience of hunger and receipt of remittances; population type (urban, rural, IDP, nomadic) and a region-population type interaction, as well as consumption quartiles. With an R-Squared of 71 percent, this model had high explanatory power.

The model for imputing consumption had two caveats: first, each value or category of the right-hand-side variables of the model must overlap with some non-missing values of the dependent variable. Otherwise, there is no basis for simulating the relationship between consumption and these explanatory variables. This means that the region-population type interaction variable must be modified, as North-East rural and Jubbaland urban are two categories of that variable without overlap with any non-missing consumption values. To do this, the North-East rural category was combined with North-East urban to form a general North-East category. Jubbaland urban was combined in the final specification with adjacent South-West urban (Table 8, column I). Various other specifications were tested in which Jubbaland urban was combined with Central Regions urban, as an assessment of the sensitivity of the final estimates to this choice (Table 8, column III and IV). Second, the model contains consumption quartiles as a key right-hand-side variable. Since the consumption data for North-East rural and Jubbaland urban were inconsistent, consumption quartiles were calculated for North-East rural and Jubbaland urban separately, to include this variable in the final specification. Other specifications excluding the quartile variable were assessed as a sensitivity test as well (Table 8, column II and IV).

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[18] A logarithmic transformation is not feasible in this case due to its singularity at zero. As the core module was constructed to capture maximum consumption shares, many optional modules – almost by definition – obtained zero consumption especially among the poorer households, which have a less diversified diet.

Table 8: Multiple Imputation results.

	(I)	(II)	(III)	(IV)
Region	Poverty rate			
Mogadishu (Urban)	73.67% (69.45%, 77.9%)	72.25% (67.83%, 76.64%)	73.74% (69.54%, 77.94%)	72.28% (67.81%, 76.58%)
North-east Urban	58.78% (43.17%, 74.38%)	56.93% (40.45%, 73.68%)	59.01% (43.54%, 74.49%)	57.21% (40.44%, 73.72%)
North-east Rural	62.46% (62.1%, 62.81%)	64.97% (64.3%, 64.88%)	63.59% (52.36%, 75.21%)	65.01% (64.3%, 64.88%)
North-west Urban	62.71% (51.81%, 73.62%)	61.5% (50.93%, 72.24%)	62.7% (51.83%, 73.68%)	61.48% (50.97%, 72.27%)
North-west Rural	77.3% (67.07%, 87.53%)	75.29% (64.66%, 86.04%)	76.48% (65.52%, 87.4%)	75.41% (64.75%, 86.48%)
IDP Settlements	75.62% (62.35%, 88.88%)	74.55% (61.43%, 88.1%)	75.62% (62.31%, 88.86%)	74.45% (61.4%, 88.03%)
Central regions Urban	59.18% (47.46%, 70.9%)	58.21% (46.2%, 70.24%)	59.18% (47.42%, 70.85%)	58.24% (46.25%, 70.32%)
Central regions Rural	65.06% (27.44%, 102.7%)	64.77% (27.28%, 102.6%)	65.01% (27.41%, 102.5%)	64.81% (27.28%, 102.5%)
Jubbaland Urban	53.34% (42.4%, 64.29%)	59.33% (54.81%, 63.53%)	53.85% (42.51%, 64.31%)	48.81% (44.01%, 54.32%)
South West Urban	62.72% (43.1%, 82.35%)	60.8% (40.43%, 80.96%)	62.39% (42.62%, 82.22%)	60.91% (40.57%, 80.88%)
South West Rural	74.94% (61.43%, 88.44%)	73.61% (59.25%, 88%)	75% (61.52%, 88.45%)	73.53% (59.17%, 88.02%)
Nomadic population	71.61% (63.1%, 80.12%)	70.86% (62.27%, 79.54%)	71.71% (63.18%, 80.22%)	70.87% (62.28%, 79.53%)

Source: Authors' calculations.

Note: (I) final model used to impute consumption and poverty; (II) sensitivity test without income quartiles in imputation model; (III) sensitivity test with Jubbaland urban combined with Central regions instead of South-West; (IV) as (III) but without income quartiles. 95% confidence interval in parentheses

The results from the imputation process are stable and robust considering these different specifications. The imputation process and these results were judged the best alternative to overcome the issues experienced in data collection.

5. Imputing poverty in inaccessible areas using geo-spatial data

Prevalent insecurity and conflict meant that parts of Somalia remained inaccessible for the SHFS field teams (Table 1). In the 10 least accessible urban and rural strata, less than 50 percent of the population could safely be reached.[19] The survey poverty estimates in these regions are therefore insufficiently representative of the regions' entire urban and rural populations. Hence, poverty in each region was predicted making use of correlations between geo-spatial information and survey estimates. The resulting poverty predictions are supplemental to survey estimates and serve as a proof-of-concept for using geo-spatial information alongside on-the-ground data collection. This section describes selection of geo-spatial variables and the model used to impute poverty.

5.1. Selection of variables for poverty predictions

Spatial variables expected to predict poverty well were drawn from three types of sources. First, a custom-derived global database of over 300 spatial covariates from the WorldPop research group at the University of Southampton (see Stevens et al., 2015).[20] Second, spatial variables were computed from geo-tagged data from publicly available sources such as ACLED conflict data or FEWSNET food security data, and OpenStreetMap. Third, population and population type data drawn from a novel population density map using recent data from OpenSteetMap, BMGF / Digital Globe spatial data, UNFPA survey and SHFS data.

[19] Of these 10 strata, 4 were urban and 6 were rural. The survey of IDP and nomadic populations was not subject to similar accessibility problems, so that survey results are considered representative for these populations.

[20] WorldPop "Global high resolution population denominators", project funded by the Bill & Melinda Gates Foundation (OPP1134076).

From these sources, 15 variables were selected based on their correlation with survey poverty estimates at the EA-level. These contained information on the type of land cover (distance to bare land cover, distance to cultivated areas),[21] climate (temperature, precipitation, distance to drought-affected areas), population characteristics (population density, distance to urban areas), infrastructure (distance to major roads, medical sites, schools, water sources, and waterways), conflict and insecurity (distance to conflict incidents, distance to insecure areas), and food security (distance to food insecure areas). A detailed list of the selected variables, their sources, preparation for analysis, illustration (Table A.8), summary statistics (Table A.9), and linear correlations with survey poverty estimates (Table A.11) are available in the Appendix.

5.2. Model selection

The final model to predict poverty was selected in two steps. First, a range of model types was compared based on a five-fold cross validation scheme.[22] The data were randomly partitioned in five folds, four of which made up the training set and one served as the validation set, ensuring that each model was trained and validated on identical data. Models' prediction success in the validation set determined which models were selected, with R-squared and Root mean squared error (RSME) as goodness-of-fit measures. The models were fitted separately for each population type.[23] The survey poverty estimates aggregated at the EA-level served as the response variable.[24] Linear models yielded the best results. Second, the selection of covariates, from the 15 spatial variables presented in Table A.8, was refined using stepwise regression to minimize the RMSE of the linear models and maximize their predictive power. In this process, a sequence of linear combinations of up to 15 covariates, as well as covariate interactions, was iteratively fitted to the response variable with different starting points and criterion for selecting the covariates, using the full data set of survey poverty estimates at the EA-level.[25] The final model for each population type was the one with the lowest AIC and RSME value.[26] Furthermore, the residuals did not present any patterns and, therefore, were treated as random.

Final models for predicting urban and rural poverty

The final model for predicting poverty in urban areas contained 12 covariates and various covariate interactions (Table 9; Figure A.2). Most variables individually, and all variables collectively, are statistically significant in explaining variation in poverty. However, the model's overall explanatory power is limited, with an adjusted R-squared of 52 percent. To check for potential issues with over-fitting, 10 percent of

[21] Variables produced by D. Kerr, H. Chamberlain and M. Bondarenko (WorldPop) in the framework of the WorldPop "Global high resolution population denominators."

[22] Several models in each of the following categories were tested: linear models, random forest models, Support Vector Machine models, and Gaussian Process Regressions.

[23] IDP and nomadic households did not suffer from accessibility problems.

[24] EA-level poverty estimates are preferable to household-level estimates as EAs cover larger areas and contain fewer binary values. Thus, the model was trained and tested at the EA-level and within EA variability was not considered.

[25] The MATLAB function 'fitlm' was used to obtain a first model for EA-level poverty. The MATLAB 'step' function, which implements stepwise regression, was then used to select model terms, including interactions of terms. See https://uk.mathworks.com/help/stats/fitlm.html and https://uk.mathworks.com/help/stats/linearmodel.step.html for the MATLAB documentation of these functions. Goodall (1993) provides the basis for the 'fitlm' fitting algorithm and Draper and Smith (2014) give an overview of stepwise regression on which 'step' is based.

[26] Minimizing the Akaike information criterion (AIC) of a linear model is equivalent to minimizing the cross-validation error. See Shao (1997) and Stone (1977).

the sample was randomly excluded and the model from Table 10 estimated. The process was repeated 1,000 times and Figure A.4 shows the results for the in-sample and out of sample R^2 of this validation.

Table 9: Final model to predict urban poverty.

Coefficients	Coefficient estimate	Standard error	p-value
(Intercept)	-1.946	0.355	0.000
Distance to bare areas	0.165	0.028	0.000
Distance to cultivated areas	0.000	0.008	0.969
Distance to dry areas	0.001	0.000	0.017
Distance to major roads	0.084	0.026	0.002
Distance to medical sites	0.062	0.024	0.011
Distance to schools	0.083	0.028	0.003
Distance to unsafe areas	0.002	0.001	0.001
Distance to urban areas	-0.057	0.021	0.009
Distance to water sources	0.001	0.001	0.147
Distance to waterways	0.001	0.001	0.437
Population density	0.000	0.000	0.001
Temperature	0.084	0.013	0.000
Distance to bare areas x Distance to waterways	0.000	0.000	0.000
Distance to bare areas x Temperature	-0.006	0.001	0.000
Distance to cultivated areas x Distance to waterways	-0.001	0.000	0.012
Distance to dry areas x Distance to schools	0.000	0.000	0.001
Distance to major roads x Distance to schools	-0.010	0.003	0.001
Distance to major roads x Distance to unsafe areas	-0.003	0.001	0.000
Distance to major roads x Distance to urban areas	-0.090	0.024	0.000
Distance to medical sites x Distance to water sources	-0.001	0.000	0.015
Distance to schools x Temperature	-0.002	0.001	0.025
Distance to urban areas x Distance to water sources	0.002	0.000	0.000
Model statistics			
Unit of observation	Enumeration areas		
Observations	252		
Degrees of freedom	229		
R-squared	0.56		
Adjusted R-squared	0.518		
Root mean squared error	19.8		
F-Statistic	13.3		

Source: Flowminder / WorldPop.

The model's relatively low predictive power is likely because the explanatory variables do not vary at a high enough spatial frequency relative to urban poverty estimates, which can vary significantly across a small space. Furthermore, distance explanatory variables could result in relatively smooth predictions across space and not accurately capture small geographical clusters of low/high consumption.[27] For example, in urban settings, poverty levels may be quite different in two EAs which are only several hundred meters apart. In contrast, the same two EAs will have very similar levels of precipitation or,

[27] The same issue can arise with non-distance variables computed within a buffer, such as precipitation, temperature and conflict density.

depending on spatial resolution, may indeed be covered by the same precipitation data point. Predictors such as the density of buildings or building patterns would likely improve the model.

Further, two different sets of night-time lights data were used to improve the predictive power of the urban model, but these turned out to be poorly correlated with survey poverty estimates and did not improve the urban model's predictive power.[28] This failure to improve the model is likely due to the night-time lights data's coarse resolution of 1km and 500m, respectively.

In rural areas, EAs are highly dispersed and poverty levels somewhat more spatially homogenous. Hence, the rural model was more successful at explaining variation in poverty in rural areas, with an adjusted R-squared of 94 percent (Table 10).

The uncertainty from using spatial covariates as explanatory variables was not considered in the estimation of standard errors. However, the data points used in the model were randomly selected to ensure they were taken from places far from each other. The resulting weighted average coefficient of variation (CV) from estimates for urban districts is 0.19 and 0.73 for rural districts. Moreover, EAs were randomly selected for the survey with the multi-stage stratified process described above, which combined with a random selection of data points to estimate the model, aims to derive a sample of EAs with different values within the range of each explanatory variable, similar to the range from the overall EA population.

Table 10: Final model to predict rural poverty.

Coefficients	Coefficient estimate	Standard error	p-value
(Intercept)	2.075	0.320	0.000
Conflicts density	0.000	0.000	0.003
Distance to cultivated areas	0.040	0.008	0.000
Distance to food insecure areas	0.020	0.008	0.018
Distance to major roads	-0.019	0.005	0.001
Distance to medical sites	-0.026	0.004	0.000
Distance to schools	0.034	0.005	0.000
Distance to unsafe areas	-0.009	0.004	0.027
Distance to urban areas	0.011	0.002	0.000
Distance to water sources	0.007	0.002	0.000
Distance to waterways	0.000	0.001	0.830
Precipitations	0.001	0.000	0.001
Temperature	-0.089	0.012	0.000
Conflicts density x Distance to cultivated areas	0.000	0.000	0.005
Distance to cultivated areas x Distance to major roads	0.001	0.000	0.002
Distance to cultivated areas x Distance to medical sites	-0.001	0.000	0.001
Distance to cultivated areas x Distance to schools	-0.002	0.000	0.000
Distance to food insecure areas x Distance to schools	0.000	0.000	0.002
Distance to food insecure areasx Distance to urban areas	0.000	0.000	0.001
Distance to food insecure areas x Distance to water sources	0.000	0.000	0.000
Distance to food insecure areas x Temperature	-0.001	0.000	0.000
Distance to medical sites x Distance to urban areas	0.001	0.000	0.000
Distance to unsafe areas x Distance to water sources	0.000	0.000	0.025
Distance to urban areas x Distance to water sources	0.000	0.000	0.000

[28] The two data sets are from 'Visible Infrared Imaging Radiometer Suite' (VIIRS) and Defense Meteorological Satellite Program (DMSP).

Distance to urban areas x Distance to waterways	0.000	0.000	0.027
Model statistics			
Unit of observation	Enumeration areas		
Observations	92		
Degrees of freedom	67		
R-squared	0.953		
Adjusted R-squared	0.937		
Root mean squared error	11.2		
F-Statistic	56.9		

Source: Flowminder / WorldPop.

Both the urban and the rural model were used to predict poverty at the 100m-by-100m pixel-level for all urban and inhabited rural areas. In order to derive imputed poverty estimates at the pre-war region and district levels, pixels were aggregated using as population weights an updated version of the WorldPop population layer.[29]

6. Poverty in Somalia

Poverty is a complex phenomenon that refers to the deprivation of a person, household, or community in multiple dimensions (Deaton and Zaidi, 2002). In general, it considers whether individuals or households have enough resources to meet their needs. Identifying the poor population or those living below a minimum threshold is a first crucial step for evidence-based planning aimed at alleviating poverty in any country. Profiling the poor and vulnerable is crucial to inform policies, design targeted interventions, as well as to monitor and evaluate the evolution of living standards and poverty reduction efforts (Baker, 2000). This section presents an overview of quantitative measures used to assess poverty and inequality in Somalia using SHFS wave 2 data. The analysis focuses on the monetary dimensions of poverty. The World Bank's forthcoming Somali Poverty Assessment, and therein especially the first chapter, provides a more detailed analysis of poverty and deprivation, including non-monetary dimensions of deprivation.

6.1. Measuring poverty

Three components are required for poverty analysis. First, a measure of welfare. Second, a poverty line that defines a level of welfare at which individuals are either considered poor or not poor. Third, an aggregate poverty measure (Coudouel et al., 2002; Haughton and Khandker, 2009; Ravallion, 2008). The measure of welfare used in this analysis, per-capita consumption, is discussed in detail in Section 4.

Poverty line

There are two types of poverty lines: relative to the overall distribution of consumption in a country, or anchored in an absolute level of what a household should consume to meet basic needs (Beegle, at al., 2016). Many countries define a national poverty line based on the cost of essential food items or a minimum calorie intake in that country, along with an allowance for non-food products. While a national poverty line allows for a precise measure of poverty according to national standards and circumstances, it is not comparable with other countries. Thus, absolute poverty lines are preferred to measure poverty across countries.

This analysis uses the international poverty line which was introduced in the 1990 World Development Report with the aim of measuring poverty consistently across countries (Ravallion et al., 2009). To be

[29] The poverty estimates were obtained using an updated WorldPop population density map of Somalia with the latest data from wave 2 of the SHFS and DigitalGlobe.

representative of poverty in the poorest countries, it was computed using data from national poverty lines of 33 of the poorest countries. The international poverty line is expressed in terms of purchasing power parity (PPP) rather than traditional currency exchange rates to compare both poverty and GDP across countries (Beegle et al., 2016).[30] The value of the poverty line has been revised through the years and adjusted to reflect welfare conditions of low-income countries. In 2008 this international line was estimated at $1.25 per capita per day at 2005 prices. In 2015 the line was updated to its current level at a daily value of US$ 1.90 (2011 PPP) per person (World Bank, 2016b).

Poverty and inequality measures

The poverty measure is primarily based on the three standard poverty measures following Foster, Greer, and Thorbecke (1984). These measures are derived from the following general function:

(9) $$F(\alpha) = \frac{1}{n}\sum_{i=1}^{p}\left[\frac{z-y_i}{z}\right]^{\alpha}$$

Here y_i denotes the consumption of individual i, n the total population, p the poor population and z the poverty line. The poverty headcount ratio is obtained when the parameter α takes the value of 0, the poverty gap and severity when this parameter is set to 1 and 2 respectively. The poverty headcount ratio or poverty incidence is the most common poverty measure. It is the share of population in a given region that is poor by virtue of having a total consumption lower than the poverty line. With $\alpha = 0$, the poverty headcount ratio can be expressed as the sum of poor individuals (p) over the total population (n), such that

(10) $$F(0) = \frac{p}{n}$$

The poverty gap, obtained when α takes the value of 1, measures how far households or individuals are from overcoming poverty, by measuring the distance poor households are from the poverty line. It captures the difference between poor households' current consumption and the poverty line as a proportion of the poverty line. It can be interpreted as the minimum amount of resources that would have to be transferred to the poor, under a perfect targeting scheme, to eradicate poverty (Deaton, 2006). This measure is obtained by adding up all the shortfalls of the poor relative to the poverty line and dividing the total by the population:

(11) $$F(1) = \frac{1}{n}\sum_{i=1}^{p}\left[\frac{z-y_i}{z}\right]$$

The poverty severity index measures the level of inequality among the poor. This measure is estimated as the square of the poverty gap. It attributes a larger weight to the poorest among the poor, with the formula given by:

(12) $$F(2) = \frac{1}{n}\sum_{i=1}^{p}\left[\frac{z-y_i}{z}\right]^{2}$$

[30] The poverty line was derived considering the regression-based PPP estimate for Somalia, which corresponds to a private consumption conversion factor of US$1 PPP (2011) worth 10,731 SSh.

In the context of monetary poverty, equality can be defined as an equal distribution of consumption across the population, with inequality being the departure from that equal distribution. Measures of inequality are thus defined over the entire population, aiming instead to capture the full consumption distribution without depending on the mean of the consumption distribution. It is important to note that measuring inequality with consumption, instead of income, tends to underestimate inequality in the population as consumption-based measures do not consider savings or wealth (Beegle et al., 2016).

The Gini index or coefficient is the primary measure of inequality presented in this analysis. It ranges between 0 and 1, such that a coefficient equal to 0 indicates perfect equality and equal to 1 complete inequality. The Gini index is graphically represented by the Lorenz curve, a visual representation of the distribution of consumption across the population. It plots the cumulative population distribution by consumption percentile against the cumulative consumption distribution. The Gini index is the area between perfect equality, as represented by the 45-degree line, and the Lorenz curve observed from the data, relative to the maximum area that would be attained given perfect inequality (Figure A.7). Formally,

(13)
$$Gini = 1 - \sum_{i=1}^{N}(x_i - x_{i-1})(y_i + y_{i-1})$$

where y denotes the cumulative proportion of the total country-wide consumption expenditure for the *ith* person and x the cumulative proportion of the total population for the *ith* person. An alternative measure of inequality presented below is the Theil index. It is part of a larger family of measures referred to as the general entropy class (Coudouel et al., 2002), with the general formula given by:

(14)
$$GE(\alpha) = \frac{1}{\alpha(\alpha-1)}\left[\frac{1}{N} - \sum_{i=1}^{N}(\frac{y_i}{\bar{y}})^{\alpha} - 1\right]$$

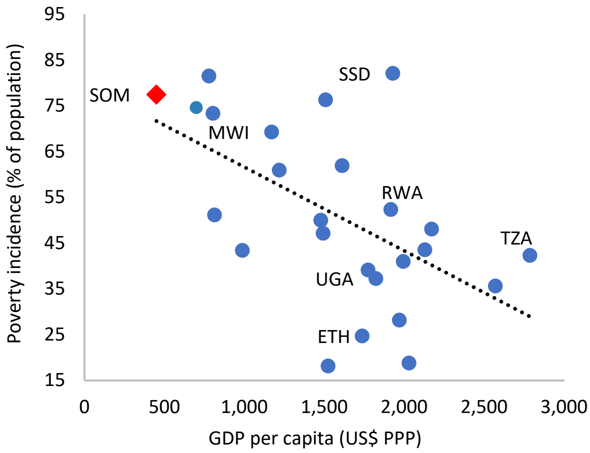
where y_i denotes the total consumption for individual *i,* $\bar{y}$ the mean expenditure per capita and *N* is the total population. The parameter α regulates the emphasis placed on higher or lower incomes. As with the Gini index, higher values of the Theil index represent higher levels of inequality, but unlike the Gini coefficient, this measure is not bounded between 0 and 1. Moreover, the Theil index is sensitive to inequality among the poor, and has the advantage of being additive across different subgroups in the country, allowing to decompose inequality into how much of it is explained by differences within groups and how much by differences between groups.

6.2. Results

As data collection in wave 2 of the SHFS was restricted to accessible areas, survey poverty headcount estimates are representative of only of the population living in these areas (Table 1; Figure 1). The SHFS filled this critical gap by imputing poverty based on data extracted from satellite images for inaccessible areas. Section 5 describes the imputation methodology in detail. Survey and satellite imputation estimates for all population types were combined to compute a poverty headcount rate representing the entire

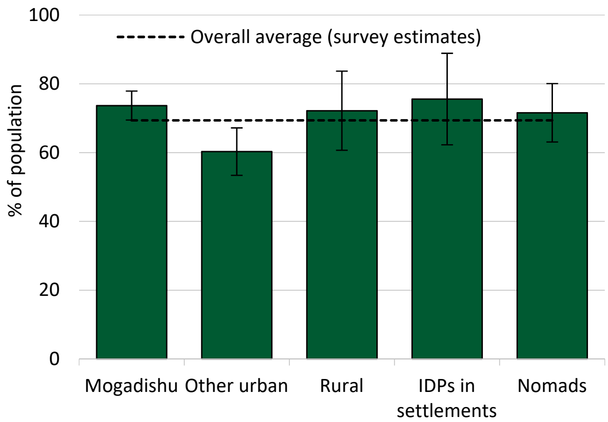
Somali population (Table A.13; Figure 7).[31] Overall, 77 percent of the Somali population lived below the poverty line in December 2017. This poverty incidence was 26 percentage points higher than the unweighted average of low-income countries in Sub-Saharan Africa (51 percent) in 2017. The country has the third-highest poverty rate in the region, after Burundi and South Sudan (Figure 5).[32] The high poverty incidence of Somalia is in line with its low levels of Gross Domestic Production (GDP) per capita, which was estimated at US$450 in 2017 (Figure 5).[33]

Figure 5: Cross-country comparison of poverty and GDP



Source: Authors' calculation and World Bank Open Data.

Figure 6: Poverty incidence



Source: Authors' calculations.

Poverty is somewhat heterogeneous between different population types and regions. Urban areas have a lower poverty headcount rate (60 percent), than the rest of the Somali population (Figure 6; $p<0.01$ vs. Mogadishu, $p<0.05$ vs. IDPs in settlements and nomads, and $p<0.10$ vs. rural areas).[34] This comparison excludes the capital, Mogadishu, whose residents are poorer than in other urban areas (between 72 and 76 percent). This higher poverty rate in Mogadishu compared to other urban areas is likely the result of a

[31] To derive a nation-wide poverty rate, survey and satellite estimates were combined in the following way. For each pre-war region and population type, the satellite prediction was considered if the accessibility rate in wave 2 was 90 percent or less, and the survey estimate was used if accessibility exceeded this threshold.

[32] The countries used for regional comparison are all the African low-income countries as defined by the World Bank: Benin, Burkina Faso, Burundi, Central African Republic, Chad, Comoros, Democratic Republic of Congo, Eritrea, Ethiopia, Guinea, Guinea-Bissau, Liberia, Madagascar, Malawi, Mali, Mozambique, Niger, Rwanda, Senegal, Sierra Leone, South Sudan, Tanzania, Togo, Uganda, and Zimbabwe. For each country, we include the most recent available year for each indicator.

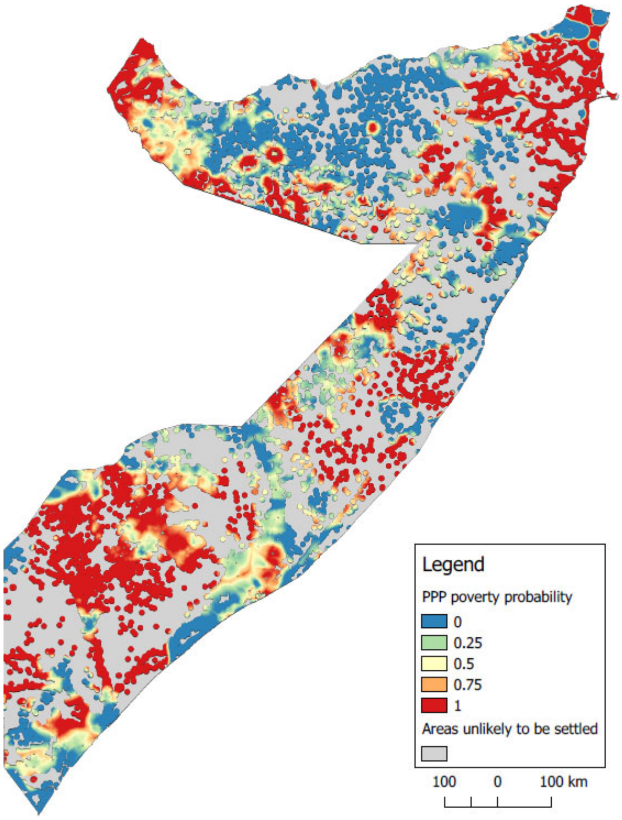
[33] For international comparisons, the poverty rate for Somalia was derived from satellite estimates. In the rest of the section, the figures refer to survey estimates unless explicitly noted.

[34] Urban areas usually benefit from agglomeration effects that result in more economic opportunities and access to services, relative to rural areas (Lall et al., 2017).

larger concentration of the displaced population and the challenges associated with the displacement crisis, which the 2016/17 drought recently exacerbated.[35]

Poverty is also heterogeneous across space. Based on estimates from satellite imputation, the highest levels of poverty are clustered in south-western Somalia, and several districts in northern Somalia (Figure 7).

Figure 7: Map of poverty incidence at the district-level based on satellite imputation[36]

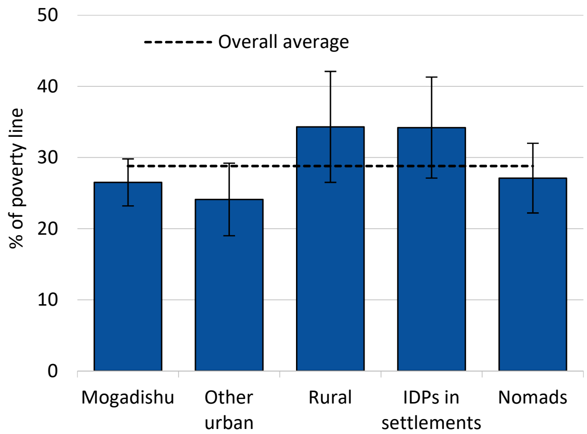


[35] Banadir/Mogadishu concentrates 41 percent of IDPs in settlements and 28 percent of the overall displaced population according to the second wave of the SHFS. The share is similar (22 percent) for the overall displaced population with data from Protection & Return Monitoring Network of the United Nations High Commissioner for Refugees (UNHCR).

[36] The boundaries on the map show approximate borders of Somali pre-war regions and do not necessarily reflect official borders, nor imply the expression of any opinion on the part of the World Bank concerning the status of any territory or the delimitation of its boundaries.

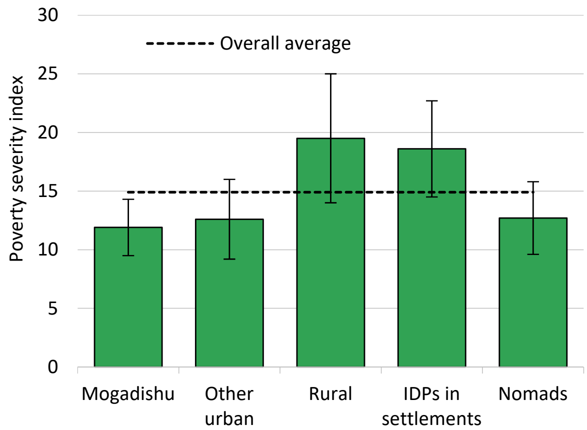
Source: Flowminder / WorldPop.
Note: The poverty incidence of each region does not include IDPs in settlements.

Figure 8: Poverty gap



Source: Authors' calculations.

Figure 9: Poverty severity



Source: Authors' calculations.

The average poverty gap in Somalia was estimated at 29 percent (Figure 8), implying that the average consumption level of a poor Somali is about 71 percent of the international poverty line. Poverty was deeper in rural areas and IDP settlements (34 percent for both), compared to Mogadishu (27 percent, $p<0.1$) and other urban areas (24 percent, $p<0.05$). A large share of Somalis living in poverty, together with a considerable shortfall in their consumption expenditure relative to the poverty line means that a substantial boost in consumption would be necessary to overcome poverty. A transfer of around US$ 1.64 billion per year would lift the poor population out of poverty, assuming a perfect targeting scheme and ignoring administrative and logistical costs.[37] In line with these results, the average poverty severity index is 15 percent pointing to inequalities among the poor. These inequalities were concentrated in rural areas and IDP settlements (Figure 9).

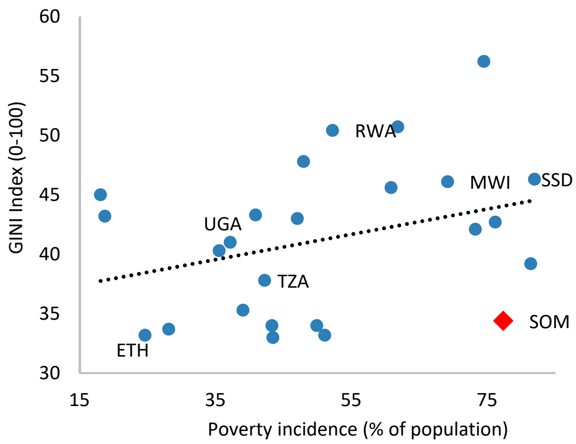
Consumption was relatively homogenous due to the high levels of monetary deprivation shared by most households. Hence, inequality was relatively low with a Gini index of 34 percent in 2017. Other low-income countries in Sub-Saharan Africa with similar levels of poverty tend to have higher levels of inequality. For example, Malawi and South Sudan which have a poverty incidence of 69 and 82 percent respectively, have around a 12 percentage points higher Gini index than Somalia (Figure 10). The Gini index is 41 percent in rural areas, 34 percent in other urban areas and 26 percent in Mogadishu (Figure 11). Donor support concentrated in urban areas due to insecurity and accessibility constraints may help in leveling the consumption of the urban population, leading to lower levels of inequality.

Overall inequality stems largely from differences within regions and population groups, rather than from differences between them. The Theil index indicates that between 98 and 99 percent of total inequality is the result of inequality within groups (Table 11). Differences between households from within the same

[37] Corresponds to an annual value for all the regions, including areas not covered in wave 2 of the SHFS. For these, the same poverty incidence and gap was assumed as in regions covered by the survey.

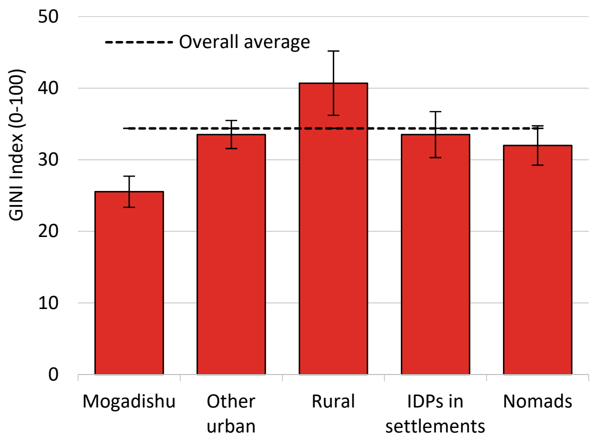
region or population group (Mogadishu, other urban, IDPs in settlements and nomads) largely explain inequality in consumption.

Figure 10: Cross-country comparison of poverty and inequality



Source: Authors' calculations.

Figure 11: Inequality



Source: Authors' calculations.

Table 11: Inequality decomposition

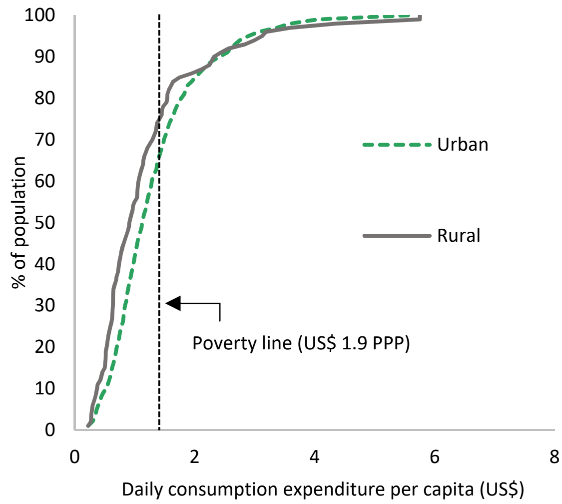
Theil GE(1) inequality index

Decomposition	By population type	By region
Between group	0.002	0.005
Within group	0.208	0.205
Total	0.210	0.210

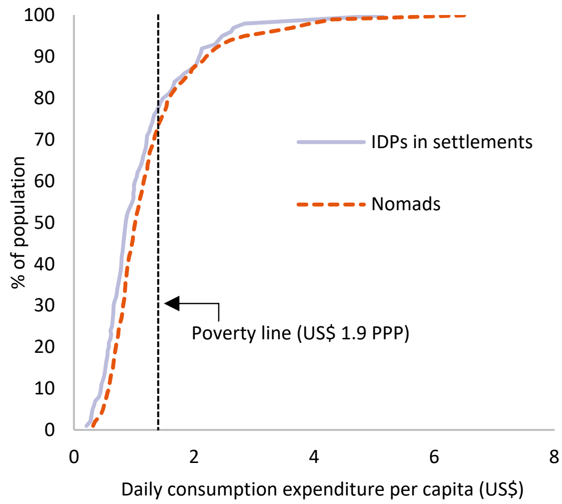
Source: Authors' calculations.

The consumption distributions of the different population groups are relatively similar. The largest differences between rural and urban areas, as well as between IDPs in settlements and nomads, are found below the poverty line (Figure 12). A considerable share of 10 percent of the non-poor population is clustered within 20 percent of the poverty line. This population is susceptible to fall into poverty in case of an unexpected decrease in their consumption levels.

Figure 12: Consumption distribution



Source: Authors' calculations.



Source: Authors' calculations.

7. Conclusions

The lack of data in Somalia poses a risk to evidence-based interventions aimed at alleviating poverty and inequality. To mitigate this risk, the World Bank implemented Wave 2 of the Somali High Frequency Survey to better understand the welfare conditions of the population and to estimate the incidence of poverty. An analysis of the data set has been published as the Somali Poverty and Vulnerability Assessment (World Bank, 2018b).

This paper contributes to several themes in the literature on poverty measurement and data collection in the context of conflict and fragility, involving hard-to-survey populations. It outlines how challenges associated to the context of insecurity and lack of statistical infrastructure in Somalia were overcome through four methodological and technological adaptations: i) building a probability-based population sampling frame; ii) minimizing the time spent in the field using the Rapid Consumption Methodology; iii) estimating poverty in completely inaccessible areas with correlates derived from satellite imagery and other geo-spatial data; and iv) employing a special sampling strategy for the nomadic population.

Further improvements in terms of human resource capacity should be considered to minimize disruptions to the quality of the data, besides field team training and stringent security protocols. Also, future applications should consider refining the model to predict poverty from satellite imagery by incorporating predictors with higher spatial frequencies, as well as data on building footprints, which are likely to improve the estimates. Other alternatives are thresholding some of the distance variables or applying a sigmoid transformation to capture variations in small areas. Furthermore, the accuracy of satellite-based imputations should be assessed based on a reference data set, ideally in a more stable environment.

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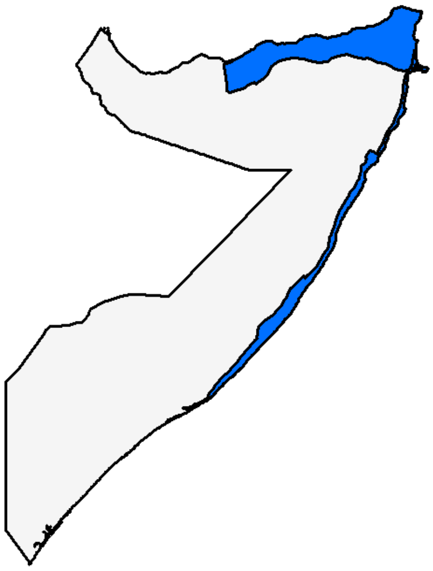
Appendix

Table A.2: Sample overview.

Strata ID	Administrative unit	Population type	Total Interviews	Total EAs
1	Central Regions	IDP	36	3
2	Galmudug	IDP	0	0
3	Jubaland	IDP	84	7
4	Mogadishu	IDP	108	9
5	North East	IDP	192	16
6	North West	IDP	24	2
7	South West	IDP	24	2
8	Central Regions	nomadic	60	
9	Galmudug	nomadic	36	
10	Jubaland	nomadic	84	
12	North East	nomadic	96	
13	North West	nomadic	144	
13	South West	nomadic	84	
25	Hiraan	rural	144	12
26	Hiraan	urban	48	4
27	Middle Shabelle	rural	264	22
28	Middle Shabelle	urban	48	4
29	Galgaduud	rural	144	12
30	Galgaduud	urban	396	33
31	Lower Juba	urban	804	67
32	Gedo	rural	108	9
33	Gedo	urban	48	4
34	Lower Juba	rural	108	9
35	Middle Juba	rural	0	0
36	Middle Juba	urban	0	0
37	Banadir	urban	792	66
38	Bari	rural	48	4
39	Bari	urban	264	22
40	Mudug	rural	24	2
41	Mudug	urban	96	8
42	Nugaal	rural	12	1
43	Nugaal	urban	36	3
44	Awdal	rural	24	2
45	Awdal	urban	36	3
46	Sanaag	urban+rural	72	6
47	Sool	urban+rural	24	2
48	Toghdeer	rural	12	1
49	Toghdeer	urban	108	9
50	Woqooyi Galbeed	rural	36	3
51	Woqooyi Galbeed	urban	156	13
52	Bay	urban	540	45
53	Bakool	rural	48	4
54	Bakool	urban	12	1
55	Bay	rural	180	15
56	Lower Shabelle	rural	204	17
57	Lower Shabelle	urban	48	4
N/A	Host community sample	urban (IDP adjacent)	504	42
	Total		**6,384**	

Emerging state	**Total interviews**
Central Regions	684
Galmudug	576
Jubaland	1,248
Banadir	984
North East	840
North West	732
South West	1,296
Pre-war region	
Hiraan	264
Middle Shabelle	420
Galgaduud	576
Gedo	228
Lower Juba	996
Middle Juba	24
Bari	420
Mudug	324
Nugaal	96
Awdal	84
Sanaag	108
Sool	48
Toghdeer	192
Woqooyi Galbeed	300
Bakool	84
Bay	900
Lower Shabelle	312
Banadir	984
Urban / rural / IDP / nomad	
urban	3,936
rural	1,356
IDP	468
nomad	504
Oversampled populations	
Fisheries	324
Baidoa	540
Kismaayo	612
Mogadishu	900
Host communities	504

Figure A.1: Fishery livelihood zones Somalia



Source: FSNAU and FEWSNET.

Table A.3: Source of IDP settlement boundaries

#	Pre-war region	IDP name	Sources	Year
1	Bay	Baidoa	PESS	2016
2	Hiraan	Beletweyne	UN Shelter Cluster	2016
3	Nugaal	Garowe	UN Shelter Cluster	2016
4	Lower Juba	Kismayo	UN Shelter Cluster	2016
5	Bari	Qardho	UN Shelter Cluster	2016
6	Hiraan	Buloburto	UN Shelter Cluster	2015
7	Hiraan	Maxaas	UN Shelter Cluster	2015
8	Lower Juba	Afmadow, Diff and Dhobley	UN Shelter Cluster	2014
9	Togdheer	Burao	UN Shelter Cluster	2014
10	Mudug	Gaalkacyo North	UN Shelter Cluster	2014
11	Mudug	Gaalkacyo South	PESS	2014
12	Woqooyi Galbeed	Hargeisa	UN Shelter Cluster	2014
13	Middle Shabelle	Jowhar	UN Shelter Cluster	2014
14	Lower Juba	Kismayo	UN Shelter Cluster	2014
15	Gedo	Luuq	PESS	2014
16	Lower Shabelle	Marca	PESS	2014
17	Banadir	Mogadishu	PESS	2014

Replacement of sampling units

Sampling units (EAs, EBs, structures, households) may need to be replaced for a variety of reasons, but their replacement must follow a predetermined schedule that allows each interviewed household to be assigned a sampling weight and to preserve the sample's representativeness.

Replacement of enumeration areas (EAs)

An enumeration area (EA) was replaced only in one of the following scenarios:

(i) The EA was insecure for field teams to conduct interviews.
(ii) The EA could not be accessed for logistical reasons.
(iii) The EA did not contain any residential structures.
(iv) All residential structures in the EA were visited unsuccessfully.

Main EAs were replaced from the pool of replacement EAs drawn for the same stratum during sample selection. All replacement EAs had a replacement rank, thus setting the order of replacement in a replicable way. Replacement occurred both before fieldwork and during fieldwork. All selected EAs (including replacements) were manually checked prior to fieldwork to establish whether they were empty of structures (scenario (iii) above). If an EA was found to be empty, it was replaced with the highest-ranked replacement EA within its stratum. If the replacement EA was also empty, the next highest-ranked replacement EA was used to replace it, and so on (Table A.3). Prior to fieldwork 3 percent of selected urban EAs and 53 percent of selected rural EAs were found to be empty and thus replaced. If an EA needed to be replaced during fieldwork in any of the four scenarios listed above, the same schedule for replacement applied.

Replacements of enumeration blocks (EBs)

An entire EB was replaced in the following scenarios:

(i) The EB was insecure for field teams to conduct interviews.
(ii) The EB was empty or not comprised of inhabited dwellings (e.g. market).
(iii) All residential structures in the EB were visited unsuccessfully.

If an EB needed to be replaced in any of the three scenarios, the enumerator responsible for the EB randomly drew a replacement EB from the list of EBs in the current enumeration area using his/her tablet. Since, in most cases, there were exactly 12 EBs per EA and one interview had to be completed in each EB, EB replacement thus led to two or more households interviewed in the same EB.

Replacement of Households

Once the enumerator randomly selected a household, he/she made contact, trying to find a knowledgeable person in the household (an adult of 15 years or older with good knowledge of the household and its members). Where no knowledgeable person was currently present, enumerators scheduled follow-up visits before replacing the household.

Once contact was made during the first visit, it was possible to arrange a meeting at another time of the day or following day if more convenient for the respondent. However, if no knowledgeable person was at home and no later appointment was scheduled, the enumerator had to go back to the same household a second and a third time. At least 5 hours separated these consecutive visits. A household was replaced in any of the following scenarios:

(i) If the household was deemed unsafe by the enumerator, and this was confirmed by the team leader.

(ii) If someone in the household said that no knowledgeable person was around nor would be in the next 2 days. In this case, the household was replaced, without a second and third visit.
(iii) The household was found to be empty even after three visits to the household.
(iv) The head of household or a person 15 or above who was sufficiently knowledgeable to respond the survey was not available after three visits.
(v) The respondent refused to give his/her consent to continue the interview.
(vi) The interview that was conducted with that household is incomplete (the respondent stopped the interview in the middle or some required fields were not filled in) without the possibility to return to the household to complete the interview.

Sampling weights

The sampling weight of each household is the inverse of its probability of selection. Its probability of selection is the combination of selection probabilities at each stage of sample selection, in line with SHFS wave 2 sampling design discussed in section 2. A household's probability of selection is the probability of selection of the primary sampling unit in which it is located, multiplied by the probability of selection of the secondary sampling unit in which it is located, and so on.

Urban (non-host communities) and rural households

In urban and rural households, the EA was the primary sampling unit and the enumeration block (EB) was the secondary sampling unit. Enumerators followed a micro-listing protocol on the ground, in which they first listed all the structures in the EB, selected a structure, and then listed all the households in the selected structure. Thus, the probability of selection for urban and rural households is the following:

$$P_{hij} = P_1 P_2 P_3 P_4 = \frac{EA_j\, H_i}{H_j}\, \frac{BS_i}{B_i}\, \frac{SS_k}{S_k}\, \frac{HS_m}{H_m},$$

where

P_1: Probability of selecting the EA, given by $\frac{EA_j\, H_i}{H_j}$.

P_2: Probability of selecting the enumeration block, given by $\frac{BS_i}{B_i}$.

P_3: Probability of selecting the structure, given by $\frac{SS_k}{S_k}$.

P_4: Probability of selecting the household, given by $\frac{HS_m}{H_m}$.

EA_j: Number of EAs selected in strata *j.*

H_i: Number of households in the sample frame for the original EA *i.*

H_j: Number of households in the sample frame in strata *j.*

BS_i: Number of blocks selected in EA *i.*

B_i: Total number of blocks in EA *i.*

SS_k: Number of selected structures in block *k.*

S_k: Total structures in block *k.*

HS_m: Number of households selected in structure *m.*

HL_m: Total number of households in structure *m.*

Urban and host communities

Since the host community sample was drawn from a subset of urban enumeration areas, urban households selected in the host communities sample were part of two separate sampling processes. They thus had two positive probabilities to be selected into the final sample. To reflect this, the probability of selection for this group is the following:

$$P_{hij} = P_1 P_2 P_3 P_4 = P_1 \frac{BS_i}{B_i} \frac{SS_k}{S_k} \frac{HS_m}{H_m},$$

where

P_1: Probability of selecting the EA given by two successive sampling processes

$$P_1 = (P_{1\mathrm{a}} + P_{1\mathrm{b}} - P_{1\mathrm{a}} * P_{1\mathrm{b}}),$$

such that,

$P_{1\mathrm{a}} = \frac{EA_j H_i}{H_j}$ and $P_{1\mathrm{b}} = \frac{EA_{host} H_{host}}{H_{host}}$.

EA_j: Number of EAs selected in urban strata *j.*

H_i: Number of households in the sample frame for the original urban EA *i.*

H_j: Number of households in the sample frame in urban strata *j.*

EA_{host}: Number of EAs selected in the host community sample.

H_{host}: Number of households in the sample frame for the original host community EA.

H_{host}: Number of households estimated in the host community sample.

P_2: Probability of selecting the enumeration block, given by $\frac{BS_i}{B_i}$.

P_3: Probability of selecting the structure, given by $\frac{SS_k}{S_k}$.

P_4: Probability of selecting the household, given by $\frac{HS_m}{H_m}$.

BS_i: Number of blocks selected in EA *i.*

B_i: Total number of blocks in EA *i.*

SS_k: Number of selected structures in block *k.*

S_k: Total structures in block *k.*

HS_m: Number of households selected in structure *m.*

HL_m: Total number of households in structure *m.*

IDP households

For IDP settlements, wave 2 of the SHFS employed a slightly different sampling strategy. IDP settlements were first sampled with probability proportional to size to determine the number of enumeration areas to be selected in each settlement. Then, the probability of selection follows the same schema as for urban and rural households, multiplying the first-stage probability of selection with the probability of selecting the EA, which is selected with probability proportional to size, with the size given by the number of equal size enumeration blocks (EBs) in the EA. This is then multiplied by the probability of selection of the EB, the structure, and the household, all of which are selected with equal probability. Thus, the probability of selection of IDP households is given by:

$$P_{hijc} = P_1 P_2 P_3 P_4 P_5 = \frac{C_j\, H_c}{H_j}\ \frac{EA_c\, B_i}{B_c}\ \frac{BS_i}{B_i}\ \frac{SS_k}{S_k}\ \frac{HS_m}{H_m},$$

with

P_1: Probability of selecting the IDP settlement, given by $\frac{C_j\, H_c}{H_j}$.

P_2: Probability of selecting the EA, given by $\frac{EA_c\, B_i}{B_c}$.

P_3: Probability of selecting the enumeration block, given by $\frac{BS_i}{B_i}$.

P_4: Probability of selecting the structure, given by $\frac{SS_k}{S_k}$.

P_5: Probability of selecting the household, given by $\frac{HS_m}{H_m}$.

CA_j: Number of camps selected in strata *j.*

H_c: Number of households in the sample frame for camp *c.*

H_j: Number of households in the sample frame in strata *j.*

EA_c: Number of EAs selected in camp *c.*

B_i: Number of blocks in the original EA *i.*

B_j: Number of blocks in camp *c.*

BS_i: Number of blocks selected in the EA *i.*

B_i: Total number of blocks in EA *I.*

SS_k: Number of selected structures in block *k.*

S_k: Total structures in block *k.*

HS_m: Number of households selected in structure *m.*

HL_m: Total number of households in structure *m.*

Nomadic households

The sampling strategy for nomadic households was based on water points and a listing exercise of households in each of the water points (see above). First, the water point is selected with equal probability. Then, households are selected with equal probability in each listing round. Thus, the probability of selecting a nomadic household is given by:

$$P_{hij} = P_1 P_2 P_3 = \frac{WS_j}{W_j} \frac{LS_r}{L_r} \frac{HS_r}{H_r},$$

with

P_1: Probability of selecting the water point, given by $\frac{WS_j}{W_j}$.

P_2: Probability of selection for the listing round, given by $\frac{LS_r}{L_r}$.

P_3: Probability of selecting the household, given by $\frac{HS_r}{H_r}$.

WS_j: Number of selected water points in strata *j.*

W_j: Total number of water points in strata *j.*

LS_r: Selected number of listing rounds *r.*

L_r: Total number of listing rounds *r.*

HS_r: Number of households selected in listing round *r.*

H_r: Total households listed in listing round *r.*

Of note, since all the listing rounds were always selected, $\frac{LS_r}{L_r}$ = 1 and the probability of selection becomes:

$$P_{hij} = P_1 P_3 = \frac{WS_j}{W_j} \frac{HS_r}{H_r}.$$

Table A.4: Summary of unit cleaning rules for food items.

Unit	Condition	Correction
250 ml/gr units	<=.03	multiply by 4
animal back, ribs, shoulder, thigh, head or leg	>=10 kg	divide by 10
basket or dengu (2 kg)	>=10	divide by 10
kilogram (1 kg)	>=100	divide by 1,000
kilogram (1 kg)	>20	divide by 10
spoonfull (200g)	>=2	divide by 2
faraasilad (12kg)	>12	divide by 12
Gram	<=0.001 (<1 gram) & item is a spice	multiply by 100
Gram	<=0.001 (<1 gram) & item is not a spice	multiply by 1,000
haaf (25 kg)	>=25	divide by 25
heap (750g)	>=7.5	divide by 10
large bag (50 kg)	>=50	divide by 50
spoonfull (4 g)	<0.004	multiply by 25

piece (30 g)	<=0.02	multiply by 3.334
piece (40 g)	<=0.03	multiply by 2.5
piece (50 g)	<=0.04	multiply by 2
piece (60 g)	<=0.05	multiply by 1.6667
piece (75 g)	<=0.065	multiply by 1.3334
piece (100g)	>=10	divide by 100
piece (110g)	>=11	divide by 110
piece (120g)	>=12	divide by 120
piece (125g)	>=12.5	divide by 125
piece (130g)	>=13	divide by 130
piece (150g)	>=15	divide by 150
piece (300g)	>=30	divide by 300
piece (350g)	>=35	divide by 350
piece (400g)	>=40	divide by 400
piece (500g)	>=50	divide by 500
piece (600g)	>=60	divide by 600
piece (800g)	>=80	divide by 800
rufuc/Jodha (12.5kg)	>12.5	divide by 12.5
large bag (10 kg)	>10	divide by 10
large bag (8 kg)	>8	divide by 8
large bag (7 kg)	>7	divide by 7
large bag (6 kg)	>6	divide by 6
large bag (5 kg)	>5	divide by 5
large bag (4 kg)	>=16	divide by 4
large bag (3 kg)	>=9	divide by 3
large bag (2.5 kg)	>=6.25	divide by 6.25
large bag (1.5 kg)	>=2.25	divide by 1.5
large bag (15kg)	>=15	divide by 10
saxarad (20kg)	>=20	divide by 20
large bag (30kg)	>=30	divide by 30
large bag (100kg)	>=100	divide by 100

Table A.5: Conversion factor to Kg for units of food items.

Unit	Conversion factor to 1kg
1 liter tin (about 1 kg)	1
1 meal portion (about 300g)	0.3
250 ml tin (250g)	0.25
250gr tin (250g)	0.25
500 gr tin (500g)	0.5
500 ml tin (500g)	0.5
Animal Back (around 1.5kg)	1.5
Animal leg (around 1.5kg)	1.5
Animal Ribs (around 2kg)	2
Animal Shoulder (around 1kg)	1
Animal Thigh (around 1 kg)	1
Basket (dengu, around 4kg)	4
Bottle (1l)	1
Bottle (2.5l)	2.5
Bottle (350g)	0.35

Bottle (400g)	0.4
Bottle (500g)	0.5
Bottle (600g)	0.6
Bottle (750g)	0.75
Bottle (750ml)	0.75
Bottle (800g)	0.8
Bottle (800ml)	0.8
Breast (130g)	0.13
Cup (100g)	0.1
Cup (125g)	0.125
Cup (1l)	1
Cup (250g)	0.25
Cup (250ml)	0.25
Cup (400g)	0.4
Cup (400ml)	0.4
Cup (500g)	0.5
Cup (500ml)	0.5
Cup (750g)	0.75
Faraasilad (12kg)	12
Gram	0.001
Haaf (25kg)	25
Heap (125g)	0.125
Heap (25kg)	25
Heap (2kg)	2
Heap (300g)	0.3
Heap (350g)	0.35
Heap (500g)	0.5
Heap (5kg)	5
Heap (750g)	0.75
Kilogram	1
Large bag (100kg)	100
Large bag (10kg)	10
Large bag (12kg)	12
Large bag (15kg)	15
Large bag (1kg)	1
Large bag (25kg)	25
Large bag (2kg)	2
Large bag (30kg)	30
Large bag (3kg)	3
Large bag (4kg)	4
Large bag (50kg)	5
Large bag (5kg)	5
Large bag (6kg)	6
Large bag (7kg)	7
Large bag (8kg)	8
Leg (250g)	0.25
Liter	1
Loaf (200g)	0.2
Madal/Nus kilo ruba (0.75kg)	0.75
Mass (1.5kg)	1.5
Packet (1kg)	6
Packet (3kg)	3
Packet (sealed box/container, 1.5kg)	1.5
Packet (sealed box/container, 10kg)	10
Packet (sealed box/container, 12.5kg)	12.5
Packet (sealed box/container, 120g)	0.12
Packet (sealed box/container, 150g)	0.15
Packet (sealed box/container, 15kg)	15

Packet (sealed box/container, 1kg)	1
Packet (sealed box/container, 20kg)	20
Packet (sealed box/container, 250g)	0.25
Packet (sealed box/container, 2kg)	2
Packet (sealed box/container, 300g)	0.3
Packet (sealed box/container, 350g)	0.35
Packet (sealed box/container, 3kg)	3
Packet (sealed box/container, 500g)	0.5
Packet (sealed box/container, 5kg)	5
Packet (sealed box/container, 6kg)	6
Piece (1.5kg)	1.5
Piece (100g)	0.1
Piece (110g)	0.11
Piece (120g)	0.12
Piece (125g)	0.125
Piece (150g)	0.15
Piece (1kg)	1
Piece (200g)	0.2
Piece (250g)	0.25
Piece (2kg)	2
Piece (300g)	0.3
Piece (30g)	0.03
Piece (350g)	0.35
Piece (400g)	0.4
Piece (500g)	0.5
Piece (50g)	0.05
Piece (600g)	0.6
Piece (60g)	0.06
Piece (750g)	0.75
Piece (75g)	0.075
Piece (large)	0.9
Rufuc/Jodha (12.5kg)	12.5
Saxarad (20kg)	20
Small bag (150g)	0.15
Small bag (15kg)	15
Small bag (1kg)	1
Small bag (2.5kg)	2.5
Small bag (250g)	0.25
Small bag (2kg)	2
Small bag (3kg)	3
Small bag (4kg)	4
Small bag (500g)	0.5
Small bag (5kg)	5
Small bag (6kg)	6
Small bag (750g)	0.75
Spoonful (125g)	0.125
Spoonful (200g)	0.2
Spoonful (40g)	0.04
Spoonful (4g)	0.004
Tray (1kg)	1
Tumin (125g)	0.125

Table A.6: Summary of cleaning rules for currency.

Currency	Condition	Correction
Somaliland shillings thousands	Price>1,000 for food and nonfood item Price>10,000 for durable goods	Divide by 1,000 because respondents meant units, not thousands.

Somali shillings thousands	Price>1,000 for food and nonfood items Price>10,000 for durable goods	Divide by 1,000 because respondents meant units, not thousands.
US$	Price >1,000	Replace currency to Somali(land) shillings.

Cleaning rules for food consumption data

- *Rule 1.*
  - Consumption quantities with missing values for items reported as consumed were replaced with item-specific median consumption quantities.
  - Missing purchase quantities and missing prices for items consumed were replaced with item-specific median purchase quantity and item-specific median purchase price.
- *Rule 2.* Records where the respondent did not know or refused to respond if the household had consumed the item, were replaced with the mean value, including non-consumed records.
- *Rule 3.* Records with the same value for quantity consumed or quantity purchased and price are assumed to have a data entry error in the price or quantity and are replaced with the item-specific medians.
- *Rule 4.* Records that have the same value in quantity consumed and quantity purchased but different units are assumed to have a wrong unit either for consumption or purchase. For both quantities, the item-specific distribution of quantities in kg is calculated to determine the deviation of the entered figure from the median of the distribution. The unit of the quantity that is further away from the median is corrected with the unit of the quantity closer to the median.
- *Rule 5.*
  - Missing and zero prices are replaced with item-specific medians.
  - Outliers for unit prices were identified and replaced with the item-specific median. This includes unit prices in the top 10 percent of the overall cumulative distribution (considering all items), and unit prices below 0.07 US$.
- *Rule 6.* The consumption value in US$ was truncated to the mean plus 3 times the standard deviation of the cumulative distribution for each item, if the record exceeded this threshold.

All medians are estimated at the EA level if a minimum of 5 observations are available excluding previously tagged records. If the minimum number of observations is not met, medians are estimated at the strata-level before proceeding to the survey level. In addition, medians greater than 20 kg and smaller than 0.02 kg were not considered for quantities, while medians greater than 20 US$ and smaller than 0.005 US$ were also excluded for unit prices.

Cleaning rules for nonfood consumption data

- *Rule 1.* Zero, missing prices and missing currency for purchased items are replaced with item-specific medians.
- *Rule 2.* Records where the respondent did not know or refused to respond if the household had purchased the item, were replaced with the mean value, including non-consumed records.

- *Rule 3.* Prices that are beyond a specific threshold for each recall period (Table A.7) are replaced with item-specific medians.
- *Rule 4.* Prices below the 1 percent and above the 95 percent of the cumulative distribution for each item are replaced with item-specific medians.
- *Rule 5.* The purchase value in US$ was truncated to the mean plus 3 times the standard deviation of the cumulative distribution for each item, if the record exceeded this threshold.

The item-specific medians were applied at the EA, strata and survey levels as described above.

Table A.7: Threshold for non-food item expenditure (US$).

Recall period	Min	Max
1 Week	0.05	30
1 Month	0.20	95
3 Months	0.45	200
1 Year	0.80	1,200

Cleaning rules for durable assets

- *Rule 1.* Vintages with missing values and greater than 10 years are replaced with item-specific medians.
- *Rule 2.* Current and purchase prices equal to zero are replaced with item-specific medians.
- *Rule 3.* Records that have the same figure in current value and purchase price are incorrect. For both, the item-vintage-specific distribution is calculated to determine the deviation of the entered figure from the median. The one that is further away from that median is corrected with the item-year-specific median value.
- *Rule 4.* Depreciation rates are replaced by the item-specific medians in the following cases:
    - Negative records
    - Depreciation rates in the top 10 percent and vintage of one year
    - Depreciation rates in the bottom 10 percent and a vintage greater or equal to 3 years.
- *Rule 5.* Records with 100 items or more, and those that reported to own a durable good but did not report the number were replaced with the item-specific medians of consumption in US$.
- *Rule 6.* Consumption in the top and bottom 1 percent of the overall distribution were replaced with item-specific medians.
- *Rule 7.* Records where the respondent did not know or refused to respond if the household owned the asset, were replaced with the mean consumption value, including non-consumed records.
- *Rule 8.* the consumption value in US$ was truncated to the mean plus 3 times the standard deviation of the cumulative distribution for each item, if the record exceeded this threshold.

All medians are estimated at the EA level if a minimum of 3 observations are available excluding previously tagged records. If the minimum number of observations is not met, medians are estimated at the strata-level before proceeding to the survey level. Table A.8 presents median expenditure and median depreciation rates for each durable item.

Table A.8: Median consumption and depreciation rate of durable assets.

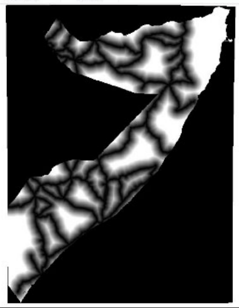
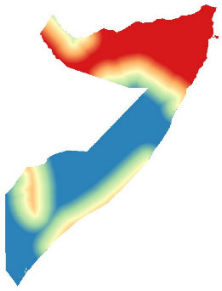
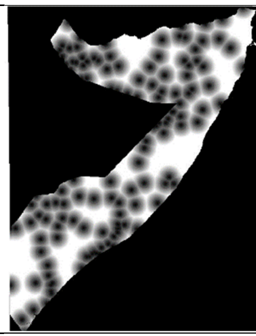
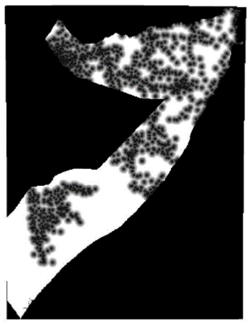
Item	Median consumption (current US$/week)	Median depreciation rate
Air conditioner	0.002	0.264
Bed with mattress	0.092	0.229
Car	0.013	0.159
Cell phone	0.085	0.245
Chair	0.015	0.242
Clock	0.007	0.267
Coffee table (for sitting room)	0.002	0.209
Computer equipment & accessories	0.010	0.182
Cupboard, drawers, bureau	0.019	0.213
Desk	0.001	0.349
Electric stove or hot plate	0.000	0.204
Fan	0.006	0.188
Gas stove	0.005	0.159
Generator	0.017	0.333
Iron	0.007	0.229
Kerosene/paraffin stove	0.000	0.248
Kitchen furniture	0.006	0.296
Lantern (paraffin)	0.000	0.092
Lorry	0.001	0.209
Mattress without bed	0.041	0.267
Mini-bus	0.002	0.248
Mortar/pestle	0.005	0.244
Motorcycle/scooter	0.004	0.229
Photo camera	0.000	0.005
Radio ('wireless')	0.005	0.276
Refrigerator	0.007	0.210
Satellite dish	0.004	0.213
Sewing machine	0.001	0.229
Small solar light	0.002	0.195
Solar panel	0.002	0.188
Stove for charcoal	0.002	0.296
Table	0.014	0.229
Tape or CD/DVD player; HiFi	0.001	0.337
Television	0.056	0.201
Upholstered chair, sofa set	0.021	0.267
VCR	0.000	0.161
Washing machine	0.013	0.210

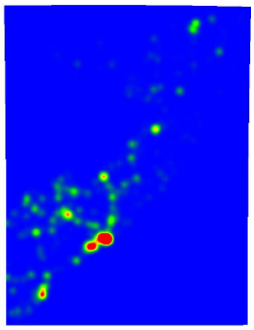
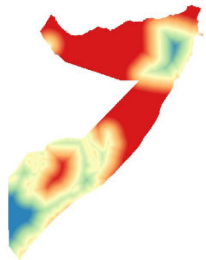
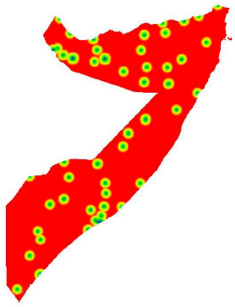
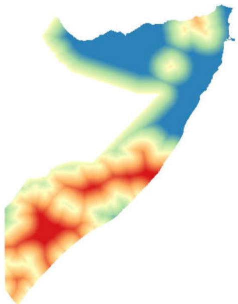
Table A.9: Overview of spatial variables used in poverty imputation.

Variable	Source	Description	Illustration

Distance to bare areas	WorldPop Global covariate dataset[38]. The ESA-CCI 300m annual global landcover dataset was used to produce this layer.	Distance to borders of areas of which land cover was classified as bare. The distance is positive outside of the areas and negative inside.	
Distance to cultivated areas	WorldPop Global covariate dataset[38]. The ESA-CCI 300m annual global landcover dataset was used to produce this layer.	Distance to borders of areas of which land cover was classified as cultivated. The distance is positive outside of the areas and negative inside.	
Temperature	WorldClim v2	Average annual temperature. Original layer from World Clim.	
Precipitations	WorldClim v2	Average annual precipitations. Original layer from World Clim.	

[38] The WorldPop "dist-to" data sets have been produced by D. Kerr, H. Chamberlain and M. Bondarenko in the framework of the WorldPop “Global high resolution population denominators”, project funded by the Bill & Melinda Gates Foundation (OPP1134076).

Distance to major roads	WFP	Distance to primary and secondary roads in km. FM/WP rasterized the original shapefile to 100m and computed the distance transform.	
Distance to drought areas	FAO SWALIM	Distance in km to borders of areas labelled as 'moderate drought' and 'severe drought' (computed by FM/WP). The distance is positive outside of the areas and negative inside.	
Distance to medical sites	UNICEF, FAO SWALIM	Distance to medical sites. FM/WP computed the distance to the points given in the source dataset. 2005	
Distance to schools	UNICEF, FAO SWALIM	Distance to schools. FM/WP computed the distance to the points given in the source dataset. 2004	
Distance to water sources	FAO SWALIM	Distance to strategic water points or sources. FM/WP computed the distance to the points given in the source dataset. 2008	

Distance to waterways	OSM extract	Volunteer-reported vector data of waterway locations. FM/WP rasterized the vectors at 100m and computed the distance transform.	
Conflict density	ACLED	Reports on violent events (e.g. battles, riots) from news outlets. FM/WP computed the spatial average of the number of fatalities from January 2014 to May 2018, within a 25 km radius.	
Distance to food insecure areas	FEWS NET	Food security outcomes for October 2017. FM/WP computed the distance to borders of areas with an IPC phase of 3 or more. The distance is positive outside of the areas and negative inside.	
Distance to urban areas	UNFPA / PESS urban EAs	Distance to borders of urban areas. FM/WP used the UNFPA urban EAs and filled in gaps within urban areas. Then we computed the distance to the urban borders. The distance is positive outside of the areas and negative inside.	
Distance to unsafe areas	World Bank	Distance to areas labelled as unsafe by the World Bank. FM/WP rasterized the shapefile provided at 100m then computed the distance to the unsafe areas border. The distance is positive outside of the areas and negative inside.	

Population density	World Bank / Flowminder	Population density inferred at 100m as part of the work on: Defining a new Somali national sampling frame.	

Source: Flowminder / WorldPop.

Table A.10: Summary statistics of collected spatial variables.

	Urban mean	Urban median	Urban min	Urban max	Rural mean	Rural median	Rural min	Rural max
Conflicts density	1302.29	134	0.11	5697.2	61.24	9.15	0	5688.03
Distance to bare areas	8.89	2.95	-2.72	101.48	22.92	12.27	-10.78	132.95
Distance to cultivated areas	2.95	0.7	-2.69	57.76	10.18	5.19	-12.29	93.15
Distance to dry areas	-15.07	-18.03	-484.27	239.91	-7.02	5.78	-505.07	281.1
Distance to food insecure areas	-80.46	-54.13	-272.25	92.98	-65.2	-41.66	-329.51	171.76
Distance to major roads	1.89	0.9	0	188.74	29.96	17.93	0	237.97
Distance to medical sites	3.17	2.48	0	27.34	35.2	30.51	0	158.01
Distance to schools	8.74	3.34	0	78.34	27.01	21.92	0	165.1
Distance to unsafe areas	37.86	27.4	-107.32	186.93	27.78	16.38	-142.18	262.72
Distance to urban areas	-1.1	-0.8	-4.8	-0.1	52.88	48.91	0	200.32
Distance to water sources	45.82	5.32	0	237.8	31.57	13.26	0	295.61
Distance to waterways	13.76	3.69	0	111.89	25.49	15.34	0	141.71
Population density	78.1	17.57	0.11	978	0.18	0	0	1551.57
Precipitations	358.63	419.07	9.05	551.15	287.98	266.56	9.05	746.43
Temperature	25.04	26.5	17.24	29.88	29.81	26.77	14.57	30.51

Notes: distance to bare, cultivated, drought, food insecure areas, unsafe and urban areas is positive outside these areas and negative inside these areas (e.g. location within unsafe area has negative distance to unsafe areas).
Source: Flowminder / WorldPop.

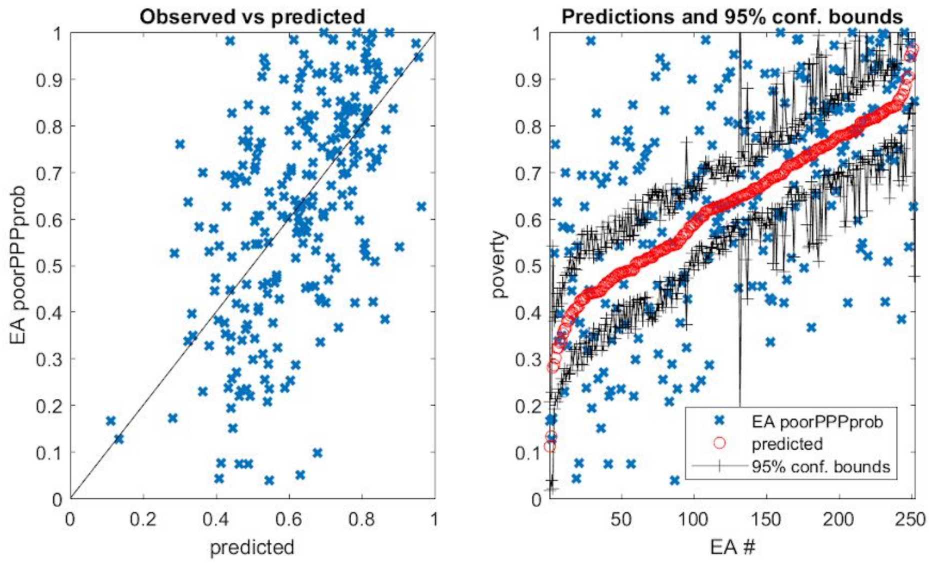
Table A.11: Linear correlations between spatial variables and poverty.

Spatial variables	poverty	Urban poverty	Rural poverty	Nomad poverty	IDP poverty
Conflicts density	0.12	0.18	-0.1	0.2	0.37
Distance to bare areas	-0.12	0.01	0.14	-0.53	0.14

Distance to cultivated areas	-0.08	0.04	-0.08	-0.15	-0.14
Distance to dry areas	-0.21	-0.27	-0.21	-0.26	-0.36
Distance to food insecure areas	-0.1	-0.04	-0.33	-0.34	0.25
Distance to major roads	-0.01	0.02	0.02	-0.08	0.18
Distance to medical sites	-0.02	0.11	-0.22	0.01	-0.27
Distance to schools	0.16	0.29	0.11	0.08	0.34
Distance to unsafe areas	-0.04	0.06	0.29	-0.2	-0.18
Distance to urban areas	-0.22	-0.01	-0.18	-0.61	0.17
Distance to water sources	-0.1	0.13	-0.22	-0.55	0.1
Distance to waterways	-0.28	-0.11	-0.25	-0.58	0.07
Population density	-0.16	0.11	-0.03	-0.11	-0.68
Precipitations	0.06	-0.04	0.08	0.01	0.37
Temperature	-0.06	0.04	-0.19	-0.31	0.14

Notes: distance to bare, cultivated, drought, food insecure areas, unsafe and urban areas is positive outside these areas and negative inside these areas (e.g. location within unsafe area has negative distance to unsafe areas).
Source: Flowminder / WorldPop.

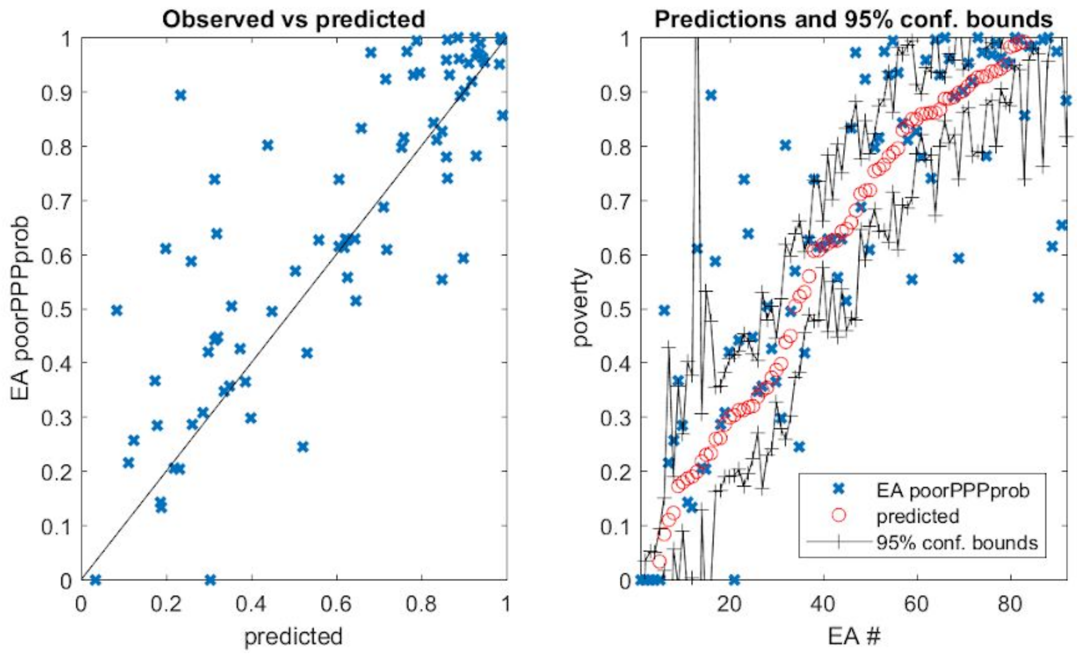
Figure A.2: Visual representation of urban model fit.



Source: Flowminder / WorldPop.

Notes: Blue crosses are urban EAs. The left figure plots the survey estimates against the model predictions for each EA, the black line shows the perfect fit. The right figure shows the model predictions for each EA ordered by increasing poverty (red circles) and compares it to the lower and upper 95% confidence bounds on the predictions (black crosses) and to the survey estimates (blue crosses).

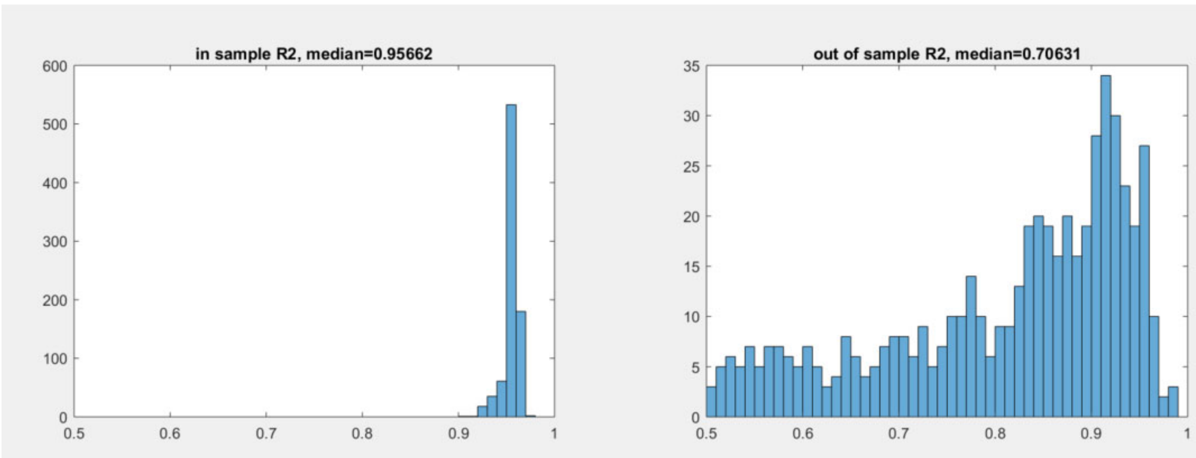
Figure A.3: Visual representation of rural model fit.



Source: Flowminder / WorldPop.

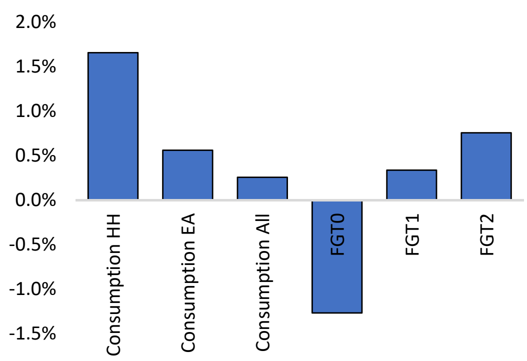
Notes: Blue crosses are rural EAs. The left figure plots the survey estimates against the model predictions for each EA, the black line shows the perfect fit. The right figure shows the model predictions for each EA ordered by increasing poverty (red circles) and compares it to the lower and upper 95% confidence bounds on the predictions (black crosses) and to the survey estimates (blue crosses).

Figure A.4: In and out-of-the sample R-squared.



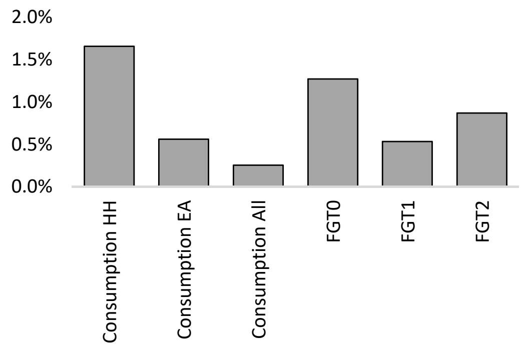
Source: Flowminder / WorldPop.

Figure A.5: Relative bias of simulation results using the rapid consumption estimation.



Source: Pape and Mistiaen (2018).

Figure A.6: Relative standard error of simulation results using the rapid consumption estimation.

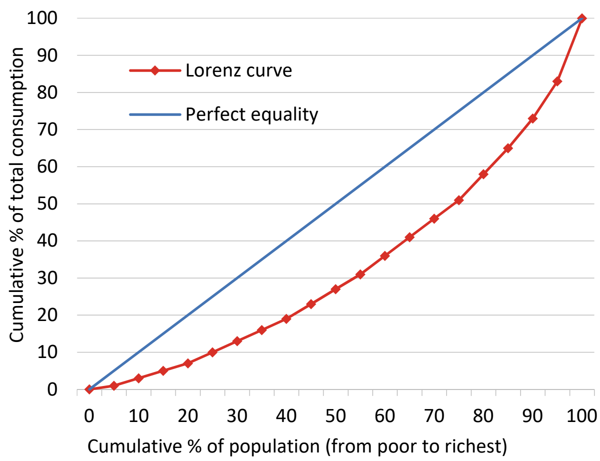


Source: Pape and Mistiaen (2018).

Table A.12: Fieldwork regional breakdown.

Region	Pre-war region
North-West	Awdal, Sanaag, Sool,Togdheer, Woqooyi Galbeed
North-East	Nugaal, Bari, Mudug
Central regions	Hiraan, Middle Shabelle, Galgaduud
Mogadishu	Banadir
Jubbaland	Gedo, Lower Juba
South-West	Bay, Bakool, Lower Shabelle

Figure A.7: Lorenz curve based on SHFS data.



Source: Authors' calculations.

Table A.13: Poverty incidence by pre-war region.

	Poverty incidence (% of population)					
	Urban areas			Rural areas and Nomads		
Pre-war region	Accessibility	Survey	Satellite	Accessibility	Survey	Satellite

	rate	estimate	estimate	rate	estimate	estimate
Awdal	100%	21% (6%, 36%)	23% (14%, 33%)	94%	76% (72%, 79%)	68% (57%, 79%)
Bakool	35%	55% (55%, 5%)	16% (11%, 27%)	21%	26% (13%, 39%)	55% (33%, 78%)
Banaadir	87%	74% (69%, 78%)	69% (61%, 77%)	N/A	N/A	N/A
Bari	99%	77% (58%, 95%)	71% (60%, 81%)	92%	63% (54%, 71%)	84% (76%, 90%)
Bay	86%	83% (80%, 85%)	77% (67%, 88%)	46%	92% (87%, 97%)	73% (57%, 84%)
Galgaduud	88%	49% (42%, 55%)	42% (32%, 56%)	50%	47% (40%, 54%)	75% (61%, 85%)
Gedo	100%	58% (52%, 65%)	66% (55%, 76%)	43%	42% (0%,100%)	60% (47%, 70%)
Hiraan	44%	71% (39%, 100%)	76% (66%, 85%)	28%	18% (0%, 52%)	40% (24%, 61%)
Lower Juba	92%	50% (34%, 66%)	55% (45%, 64%)	9%	N/A	31% (9%, 59%)
Lower Shebelle	28%	50% (20%, 79%)	61% (50%, 72%)	33%	58% (46%, 70%)	41% (30%, 60%)
Middle Juba	0%	N/A	97% (74%, 100%)	9%	N/A	54% (26%, 80%)
Middle Shebelle	98%	72% (38%, 105%)	79% (64%, 92%)	77%	75% (57%, 93%)	47% (33%, 63%)
Mudug	100%	41% (34%, 48%)	45% (35%, 56%)	76%	53% (42%, 64%)	48% (36%, 60%)
Nugaal	100%	48% (35%, 61%)	56% (47%, 65%)	100%	90% (73%, 100%)	72% (52%, 86%)
Sanaag	100%	95% (94%, 95%)	77% (74%, 79%)	100%	100% (N/A)	86% (80%, 92%)
Sool	89%	85% (85%, 85%)	80% (70%, 81%)	98%	79% (61%, 97%)	56% (37%, 75%)
Togdheer	100%	69% (59%, 78%)	60% (50%, 71%)	98%	96% (90%, 100%)	83% (69%, 92%)
Woqooyi Galbeed	100%	64% (49%, 79%)	64% (54%, 74%)	96%	82% (74%, 89%)	58% (43%, 75%)

Source: Authors' calculations and Flowminder / WorldPop.

Note: N/A=not applicable. 95% confidence interval in parentheses.