Chapter 2
Innovative Sample Designs for Studies of Refugees and Internally Displaced Persons

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2.1 Introduction

The United Nations High Commissioner for Refugees (UNHCR) estimates that nearly 71 million people in the world were forcibly displaced at the end of 2018, amounting to 1 of every 108 people globally (UNHCR, 2019b). Of the more than 20 million refugees, two-thirds come from five countries—Syria, Afghanistan, South Sudan, Myanmar, and Somalia—and many of these people have been displaced for more than 5 years. Half are younger than 18, including approximately 138,600 unaccompanied minors. There are an estimated 41 million Internally Displaced Persons (IDPs), a 50% increase over the last decade. The nature of displacement has also changed: fewer people live in dedicated camps in rural areas and more in urban areas, especially in wealthier host countries (UNHCR, 2019b). This shift has led the international community to reevaluate its understanding of displacement from a humanitarian crisis to a development challenge, and donor portfolios are increasingly focused on new initiatives to aid these vulnerable groups.

With increased aid programming, however, has come the need for better quality and more rigorous data with which to design, implement, and monitor these projects. Probability samples should be the foundation of high-quality data about refugees and IDPs (or any population). Unfortunately, many or even most studies of these vulnerable populations use nonprobability methods to select cases, and some studies do not describe the selection process at all (Enticott et al., 2017; Jacobsen & Landau, 2003; Kuhnt et al., 2019). Changes in the number and situations of displaced persons necessitate a rethinking of sampling approaches. In addition, digital technology such

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S. Pötzschke, S. Rinken (eds.), *Migration Research in a Digitized World*, IMISCOE Research Series, https://doi.org/10.1007/978-3-031-01319-5_2

as satellite photos and computer vision has led to the development of new sampling options. This chapter reviews nine probability sampling methods that have been or could be applied to refugee and IDP populations.

We focus in this chapter on samples for surveys about the living conditions of refugees and IDPs—their health, well-being, employment, etc. Such studies provide the data that guide relief and development efforts (Brown et al., 2008). We do not discuss studies which seek to count displaced persons moving into, out of, or through a given area, although such studies are important too (see Global Migration Group, n.d.; Hughes et al., 2016; Lu et al., 2016; Williams et al., 2015). The sampling methods we have chosen to highlight are those that result in probability samples (each case has a known probability of selection) and can be carried out in developing countries to study refugees and IDPs. We further focus on face-to-face surveys, although telephone and app-based surveys are also possible (Hoogeveen et al., 2019; Keusch et al., 2019).

Before describing the sampling methods, Sect. 2.2 reviews coverage error in surveys and how under- and overcoverage on a sampling frame can introduce bias into survey data. The sampling methods are then organized by the living situations of the population of interest. Section 2.3 discusses sample selection methods appropriate for populations in camps or other settlements. In the settlements, all or nearly all households or persons are eligible for the survey (absent targeting by country of origin). Because refugees and IDPs are increasingly living in urban areas rather than settlements, Sect. 2.4 considers approaches suitable for urban environments where the populations of interest live among the host population. Section 2.5 presents options for selecting migrants while they are on the move, although researchers should carefully consider the ethics of interviewing people in unstable situations. Throughout the chapter, we draw on our years of experience designing samples and conducting studies around the world with hard-to-reach and vulnerable populations (Eckman & Himelein, 2019; Himelein et al., 2014, 2017).

2.2 Coverage Error in Surveys

Several sources of error can affect surveys of refugees and IDPs, such as sampling and measurement error and bias due to nonresponse. Those designing surveys should be aware of all sources and seek to minimize them as much as possible.[1] We focus in this chapter on coverage error because it is less well known and relevant to studies of refugees and IDPs.

Coverage error refers to bias that arises in survey estimates due to under- or overcoverage on a sampling frame. Undercoverage occurs when some members of the target population cannot be selected. The cases do not appear on the frame—the list from which the sample is selected. Undercoverage happens for many reasons:

[1] For more information on error sources in surveys, see Biemer et al. (2017). For a review of errors in studies of migrants specifically, see Jacobsen and Landau (2003).

perhaps the target population is homeless, and the survey selects cases through households; perhaps the list from which dwelling are selected is outdated; or perhaps a survey excludes a province from the frame because of violence in the area.[2]

Just like nonresponse, undercoverage can lead to bias in survey estimates. Because we have no data for undercovered cases, the estimate of, for example, a mean is made only on the covered cases: $\bar{y}_c$. The amount of undercoverage bias in estimates of a mean, $bias(\bar{y}_c)$, is related to the size of the undercovered population and the difference in the mean of interest for the registered and unregistered population:

$$bias(\bar{y}_c) = (1 - CR) * [\bar{y}_c - \bar{y}_{uc}]$$

where:

CR is the proportion of the population that is covered,
$\bar{y}_c$ is the mean among the covered cases, and.
$\bar{y}_{uc}$ is the mean among the uncovered cases.

For example, a researcher might be interested in estimating the proportion of school-aged refugee children who attend school. If there is a large difference between the true rate of school enrollment in the registered and unregistered populations (that is, $\bar{y}_c - \bar{y}_{uc}$ is large), then even a small rate of undercoverage $(1 - CR)$ could lead to large bias (Lessler & Kalsbeek, 1992).

The converse of undercoverage is overcoverage—the inclusion on the frame of cases that are not members of the target population. Overcoverage is not necessarily a problem and does not always lead to bias. For example, a survey may be interested in interviewing only households with children, but the frame from which the sample is selected includes all households. In such cases, studies often screen cases to determine which are eligible. Screening involves short interviews, usually done with any available household adult, about the characteristics of those living in the household. Screening can help identify an eligible subpopulation for a study, but it does increase costs, because ineligible households must still be interviewed and screened out (Kalton, 2014; Lavallée, 2014). We discuss screening in the context of surveys of refugees and IDPs in Sect. 2.4.1.

In the following sections, we describe each sampling method and comment on its vulnerability to under- and overcoverage. Researchers should carefully consider these issues and think through whether a given sampling approach is likely to lead to coverage bias in their data.

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[2]Note that undercoverage is not the same as nonresponse. Undercovered cases have no chance to participate in the survey, even if they would like to, because they are never selected. Nonrespondent cases are those that are selected and do not participate because of noncontact or refusal. We avoid the term representative because it often conflates undercoverage and nonresponse.

2.3 Living in Settlements

Many IDP and refugee populations live apart from other groups, perhaps in camps specifically built to house them. In such situations, researchers can often adapt sampling methods more commonly used for general population household surveys.

2.3.1 Registration Lists

The World Bank can often access official camp registration lists maintained by the UNHCR. For example, in the study Enquête Harmonisée Sur Les Conditions de Vie des Ménages in Chad (2018–2019), camps were selected with probability proportional to size, where the size was determined from the registration lists. Households in the selected camps were then selected directly from the registers (World Bank, forthcoming). This approach has the advantage that camp administrators are often able to assist with fieldwork by introducing the interviewers to residents.

When registers of camp residents are available to researchers, selecting samples from these lists is often a good choice. The registers often contain additional variables, such as gender, age, ethnicity, place of origin, and date of arrival, which can be used for explicit or implicit stratification. Because these variables likely correlate with the variables measured by the survey, stratification reduces the variance of sample estimates (Eckman & West, 2016).

Any persons or households that are not on the official registers will be undercovered by this approach (Lebanon Humanitarian INGO Forum, 2014). Such unregistered refugees face unique challenges earning money and accessing health care (HelpAge International and Handicap International, 2014). Because unregistered refugees have different characteristics, concerns, and outcomes than do those who are registered, a survey relying only on registration lists may produce biased estimates due to undercoverage and lead to poor policy conclusions.

Overcoverage can occur with this method if the lists include persons who are no longer in the camp. This type of overcoverage can increase data collection costs, because interviewers will spend time looking for the selected people who are not available, but it is unlikely to introduce bias. Another source of overcoverage in the registers is fraudulent registration (Lodinová, 2016). The most common issue with fraud would be multiple registrations by the same household as members try to increase their rations. Another issue is people living in the surrounding communities claiming to be IDPs to receive goods and services. When people who are not refugees or IDPs register, they may be selected and interviewed. Because they are not truly eligible, the data they give should not be part of the data set. Because those who commit fraud are likely different from those who are appropriately registered, the data collected from fraudulent registrants can introduce overcoverage bias.

Aside from coverage issues, a logistical concern with sampling from camp registration lists is that not all researchers can access the lists (Martin-Shields et al., 2019). Although the approach of sampling from official registration lists can work well, alternatives are needed. We now turn to a discussion of these alternatives.

2.3.2 In-Field Listing

When registration lists are not accessible or not of high quality, in-field listing can be used. This method of frame creation is common in household surveys around the world. Clusters are first selected in one or more stages. Within the smallest clusters, field staff are sent to create a list of all households or dwellings. This process, called listing, produces a frame from which a sample can later be selected (Grosh & Muñoz, 1996; Harter et al., 2010). Although listing is commonly used for general population surveys, it can be adapted for studies of refugees and IDPs. A 2014 World Bank study in Uganda used listing to create a frame of households in refugee settlements (World Bank, 2019).

Although it may seem straightforward to create an accurate list of dwellings while walking around a selected cluster, errors of both undercoverage and overcoverage are common in listing (Eckman & Kreuter, 2013). To avoid undercoverage and other sources of bias, listing work should be done before any interviewing, preferably by different staff than those who will do the interviewing (Eckman & Koch, 2019; Manheimer & Hyman, 1949; Stoop et al., 2010). However, that approach necessitates two visits to the camps—one to do the listing and another to do the interviewing—increasing costs and introducing a delay in the data collection schedule. Another drawback to the listing approach is that it increases the amount of time that field staff spend in the camp. Listing involves walking systematically around an area, often with a tablet computer or laptop. This behavior can expose field staff to theft or even kidnapping and assault. Interviewing, because it involves travel from one randomly selected household to another, may be less dangerous (Himelein et al., 2017).

2.3.3 Sampling from Satellite or Aerial Images

When camp registration lists are not available or are out of date, and listing is too dangerous, alternatives are needed. Fortunately, the availability and resolution of satellite photos has increased in recent years. Many companies and governments have launched satellites to orbit the earth and take pictures of the land and ocean. The images range from high-resolution pictures, taken less frequently, to low resolution pictures, available at higher frequency. Unmanned aerial vehicles (UAVs, or drones) can also take aerial pictures, at lower cost and higher resolution. Some satellite and aerial images are available online at low or no cost, although availability and recency vary across countries. If the images are recent and high-resolution, they can be used to select a sample of dwellings in a refugee or IDP camp.

Consider the satellite images of an IDP camp in Haiti, shown in Fig. 2.1. The top image is from March 8, 2010, and the second is from April 29, 2010. Both are from Google Earth and were downloaded at no cost. The images show the development of a temporary settlement for IDPs. Between the two dates, the dwellings have been improved, perhaps because of the arrival of humanitarian aid. Let's say it is 2010 and we want to conduct a study of persons displaced by the earthquake in Haiti and living in temporary settlements such as this one. We could review satellite images to find the areas where people have resettled and then manually identify and label the dwellings and select a sample of them. We might then prepare paper or electronic copies of the satellite image with the selected dwellings marked for interviewers.

Rather than identifying dwellings manually in images, we could train an algorithm to identify them. Spectacular progress has been achieved in recent years in computer vision, the branch of computer science involved in detecting and identifying objects in images and videos. This progress is the result of three advancements: the development of advanced methods of artificial intelligence, such as deep learning and convolutional neural networks; the release of open-source machine-learning frameworks like Google's TensorFlow; and the availability of inexpensive computing resources that can run these models in hours rather than weeks. Using these tools, computers can learn to identify tents or buildings in satellite images. Wang et al. (2015) and Quinn et al. (2018) used computer vision methods to count tents in Vietnam and Turkey, with Wang et al. reporting 81% accuracy. These approaches could also be used to select a sample of tents for interviewing.

The accuracy of the computer vision detection is affected by the resolution and spectral characteristics of the images. Some dwellings are also easier to detect than others. The computer vision approach would likely work better on the dwellings in the second image in Fig. 2.1 than the first, because those in the second image are more uniform in size, shape, and color (Wang et al., 2015). With further development, these algorithms may be faster, cheaper, and more accurate than manual identification of dwellings from images.

New dwellings that have been built since the satellite photo was taken will be undercovered by both the manual and the computer vision approaches to identifying camp dwellings from imagery. If the satellite image is old or change is occurring rapidly, which is sometimes the case with refugee and IDP populations, the situation on the ground may not look like the photo at all. Unfortunately, there is no set schedule for how often satellite photos are taken and released. In times of crisis, however, satellite photos may be taken more often, to support aid efforts and reconnaissance. If updated images are not available, one solution is to use UAVs to create up-to-date photos just before they are needed (Eckman et al., 2018), although researchers should always be cautious about how UAVs would be perceived by refugees and IDPs. Another method for dealing with older images is to use a missed housing unit procedure to detect and select undercovered dwellings (Harter & English, 2018). However, these procedures are challenging to implement in the field (Eckman & O'Muircheartaigh, 2011). Overcoverage can also occur with this design if the selected cases are not dwellings or no longer exist.

Fig. 2.1 Displaced persons settlement in Haiti: March 8, 2010, and April 29, 2010. (Source: Google, Maxar Technologies)

2.4 Living in Urban Areas

Refugee and IDP populations are becoming increasingly urban. At the start of the twenty-first century, most refugees were in camp-based and rural settings. Now, more than 60% of displaced persons live in urban areas. This urbanization of refugees is particularly prevalent in middle- and high-income host countries, where nearly all refugees report living in private accommodation (UNHCR, 2019b).

Surveying these urban populations can be particularly challenging, especially if the displaced are cohabitating with established family members. However, several of the previously discussed techniques can be used or adapted to study urban refugees. For example, if high-quality registration lists such as those discussed in Sect. 2.3.1, are available, then they remain an option. However, in urban areas, it is easier to live without registering with the host country government or a nongovernmental organization. Therefore, we suspect that the share of refugees and IDPs who are missing from registration lists is larger in urban areas than in camps, and those who are registered are likely to have out-of-date information. In this section, we discuss other approaches that can capture unregistered refugees and IDPs in urban areas.

2.4.1 Household Selection with Screening

In-field listing and selection from satellite images, discussed in Sect. 2.3, are also options for surveys of refugees and IDPs living in urban areas. In-field listing was used in the Syrian Refugee and Host Community Surveys in 2015–2016 in Lebanon (Aguilera et al., 2020). Because listing methods are well-documented elsewhere (Grosh & Muñoz, 1996), we here discuss selection from satellite images in more detail. Several studies have selected buildings or dwellings from satellite and aerial images. Across sites in Senegal, South Africa, Sudan, and Zambia, Baker et al. (2019) and Lowther et al. (2009) selected buildings from images by manually marking the images. Lowther et al. found that more than 98% of the buildings they identified could be located by field workers. Dreiling et al. (2009) used a similar approach in the rural U.S.

Results from these studies point to several challenges. Undercoverage is certainly a concern, due to out-of-date images or miscoding by staff. Local staff may be better able to identify buildings from images than those who are less familiar with the area. Overcoverage was a concern in all three studies. In urban areas, many buildings contain no dwellings. Locating and inspecting these buildings for dwellings can substantially increase field costs. Dreiling et al. (2009) used trained persons with local knowledge to code buildings in images as containing dwellings or not. Most dwellings (91%) were correctly identified with about equal rates of overcoverage (structures thought to be dwellings which were not) and undercoverage (missed dwellings).

However, removing buildings which appear to contain no dwellings can also lead to undercoverage. Refugees and IDPs may be forced by circumstances to live in buildings that are not intended to be dwellings. Thus, we recommend that studies sample a portion of these buildings so that persons living there are not undercovered. Researchers could stratify buildings into those more and less likely to contain dwellings and sample at different rates from each stratum.

Another concern is that urban residential buildings may contain more than one dwelling, and it is often not possible to tell from a satellite image how many dwellings are in a building. Interviewers can be trained to select one or more dwellings from multi-unit buildings. They might use a table of random numbers[3] or (if the study uses tablet or laptops) a selection program. However, such procedures allow interviewer influence on the selection process, which can introduce bias (Eckman & Koch, 2019). In-field listing is better able to handle multi-unit buildings, because the field staff can list each dwelling separately if they are able to determine how many there are. In addition, a dwelling may be home to more than one household. Interviewers need guidance on how to handle these cases as well.

Once a sample of households is selected, the next step is to screen the selected households to determine which contain refugees or IDPs. Researchers should craft screening questions carefully. Information about how long household members have been in the country and their legal status may be considered sensitive. Respondents may be reluctant to mention household members who lack a valid residence permit and may even deliberately not report them. Any misreporting at the screener stage can lead to undercoverage bias.

The Migration and Remittances Household Surveys in Burkina Faso, Kenya, Nigeria, Senegal, South Africa, and Uganda used screening to find households where immigrants and returned migrants lived. In 2009, that survey screened approximately 56,000 households to interview about 10,000 (Plaza et al., 2011). Such large ratios between the number of households screened and the number of eligible households identified are not unusual and can increase data collection costs. To increase the efficiency of screening, researchers can stratify the sample of households into areas more and less likely to contain the population of interest. This stratification can be based on field staff observation or information from community organizations serving the population (Singh & Clark, 2013). However, some buildings or households should be selected in the strata where eligibility is expected to be low to avoid undercoverage bias.

2.4.2 Time-Location Sampling

Another technique that is available when refugees and IDPs live in host country communities is to select them through the community centers or organizations that

[3] See Figure 2a in Singh and Clark (2013) for an example.

they visit, if such organizations exist (Lee et al., 2014). This approach is known as intercept-point sampling, center sampling, or time-location sampling (Baio et al., 2011; McKenzie & Mistiaen, 2009).

This approach can result in a probability sample, if several conditions are met. First, the probabilities of selection of the organizations themselves must be known. That is, a convenience sample should not be used. Researchers should make a list of organizations where the population of interest can be found and select a sample, or select all of them, if there are not too many. They should record the probabilities of selection at this stage (for example: three organizations selected out of seven). Second, respondents should be selected from the organizations' members or visitors with known probability. Researchers should randomly select a time to visit the location and observe who is there, selecting a sample of visitors. It is important not to select only those who look approachable, to avoid biasing the sample. Third, respondents must accurately report which organizations they visit, and how often, so that weights can adjust for the higher probability of selecting those who are frequent visitors or who visit more than one organization. See Baio et al. (2011) for details on the development of weights and a discussion of an application in Italy.

Time-location sampling undercovers any members of the target population who are not members or visitors of any of the known organizations. Depending on the type of organizations, the undercovered population might include the sick and disabled, who have a harder time leaving their homes. Furthermore, any error in the reports of respondent visits to organizations will lead to inaccurate weights and thus biased estimates. We are not aware of any research into how accurately respondents can report these behaviors. One advantage to this method, however, is its low cost: in a review paper, McKenzie and Mistiaen (2009) found that surveys conducted via time-location sampling cost about half as much as surveys conducted via listing and screening.

In terms of data quality, the McKenzie and Mistiaen (2009) comparison study determined that time-location sampling overrepresented those migrants who were more connected to the community organizations and weighting only partially removed this overrepresentation. Even after weights, the survey results were biased (McKenzie & Mistiaen, 2009). However, some bias may be tolerable, given the cost savings.

2.4.3 Respondent-Driven Sampling

When a population is difficult to find in the field, but the members are well connected, respondent-driven sampling may be a good choice. This method begins with a nonprobability sample of seeds, who are members of the target population known to researchers. The seeds complete the survey and then recruit additional members to complete the survey and recruit additional members. The process continues, each seed creating a recruitment chain.

Under certain assumptions, probabilities of selection can be calculated for all cases recruited though this method (Heckathorn, 2002; Salganik & Heckathorn, 2016; Volz & Heckathorn, 2008), making it superior to snowball sampling and other methods of uncontrolled network sampling. The crucial assumptions are (1) that relationships are reciprocal (i.e., if person A recruits person B, then person B would have recruited person A, had person B been recruited first); and (2) that all respondents can accurately report how many members of the population are in their network. However, these assumptions do not always hold (Gile & Handcock, 2010). In addition, estimation works best when recruitment chains are long, but in practice, short chains are more common (UNHCR, 2019a).

Several studies have used respondent-driven sampling to study refugees (Liu et al., 2018; UNHCR, 2019a). The World Food Program used this approach to study refugees in Turkey. The results indicate the importance of the recruitment chains to the success of the project. Respondents tend to recruit others like them (from the same ethnic group, for example). To achieve a diverse sample, the seeds should represent the breadth of the population of interest (Bozdag & Twose, 2019). The book *Applying Respondent Driven Sampling to Migrant Populations: Lessons from the Field* (Tyldum & Johnston, 2014) offers practical advice to researchers who wish to implement this approach.

Undercoverage can occur with respondent-driven sampling if some members of the population are not connected to others. Unless a seed is chosen in that community, no persons can be recruited or interviewed. Thus, researchers should take care to recruit a diverse set of seeds with large networks that span different subgroups within the population of interest. For example, a study of immigrants to the United States from El Salvador, Guatemala, and Honduras should take care of recruit seeds from each country and from different demographic groups (age, gender, legal status, etc.) (Abuelafia et al., 2019).

Overcoverage can also occur with respondent-driven sampling. Because of the presence of an incentive for responding and the ability to earn a higher incentive for recruiting additional respondents, some people may claim to be population members when they are not. This type of overcoverage can introduce bias into survey data if the responses from the ineligible respondents are different from the responses of those who are truly eligible (Wright & Tsao, 1983).

2.4.4 Adaptive Sampling

This approach takes advantage of the fact that people tend to live near those who are like them. If we can identify one member of our target population, others are likely to be nearby. The adaptive cluster approach comes from wildlife surveys: where we find one zebra, we are likely to find many others (Thompson, 1990). Take the example of a survey of Syrian refugees living in a city in Turkey. It is likely that the refugees are not randomly distributed throughout the city but clustered together so that they can support each other and build a community. We first screen a random

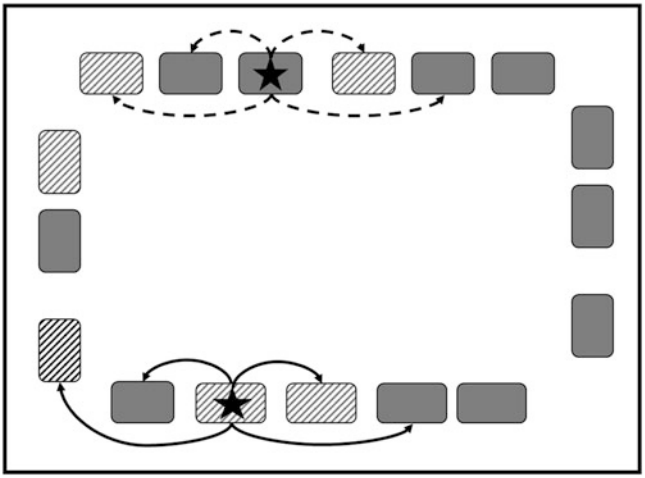

Fig. 2.2 Adaptive cluster sampling in household survey
Hatched boxes are eligible households; stars indicate those in initial sample. The lines show the additional selections that occur (solid lines) or would occur (dashed lines) when eligible households are found

sample of persons or households throughout the city, as in Sect. 2.4.1, to find a few Syrian refugees. We then put more resources into screening in the areas where we found Syrians.

The adaptive cluster approach was used by the European Union Agency for Fundamental Rights (2017) to sample Roma in the second wave of the European Union Minorities and Discrimination Survey. Figure 2.2 illustrates how the technique worked in that study. In the figure, each square represents an address. The two starred addresses are part of the initial sample and are screened. If a starred address is eligible, then the two addresses before and after it are also selected and screened. The starred address at the bottom of Fig. 2.2 is eligible, as indicated by the grey and white hatching. Because it is eligible, its four neighbours will also be screened, as shown with the solid arrows. Two of those addresses are also eligible. The starred address at the top of the figure is not eligible, so its four neighbours are not selected or screened (shown with dashed arrows). Even though two of its neighbours are eligible, they will not be screened. However, those addresses do have a probability of selection and thus are not undercovered: they have a chance to be part of the initial sample.

The European Union Minorities and Discrimination Survey found that the adaptive approach more than doubled the eligibility rate in two of the three countries where it was implemented, resulting in meaningful cost savings (European Union Agency for Fundamental Right, 2017). The efficiency gains from the approach are related to how clustered the target population is in the larger population.

Each household in Fig. 2.2 has a chance to appear in the initial sample, and many have an additional chance to be selected as the sample expands. Researchers should calculate analysis weights for each case that account for all chances that a case has to be selected. Verma (2014) discusses weighting, and many other technical aspects of implementation of adaptive cluster sampling, in detail, including how large the neighborhood around each eligible household should be, how to introduce stratification, and when to stop expanding the sample.

We are not aware of a study using adaptive cluster sampling to study refugees or IDPs. However, the technique seems to be a good choice for populations that live in clustered urban areas. The tendency for under- and overcoverage with this approach should be the same as in any other household survey with screening (see Sect. 2.4.1).

2.5 On the Move

Although most studies of displaced populations take place once persons have settled, even temporarily, in a new location, some circumstances may require sampling mobile populations. Researchers may wish to understand the factors that compel people to continue traveling or understand how they protect themselves and maintain their livelihoods while in transit. Temporary collection areas, such as welcome centres, may offer a limited opportunity to conduct interviews or to develop a sampling frame that can be used later to recontact populations (World Bank, 2018). Below, we present two options for identifying and selecting migrants while they are on the move. However, we urge researchers interested in doing studies of migrants to carefully consider the ethics of their approaches. People who have left their homes and countries may not be in the best position to give informed consent to a survey interview.

2.5.1 Random Geographic Cluster Sampling

Random geographic cluster sampling is a method borrowed from forestry and wildlife surveys. Himelein et al. (2014) describe the method in detail and discuss an application to the Afar region of Ethiopia where livestock owners travel with their animals in search of water and food. To implement this method, we first selected random geographic points in the survey area. Geographic information system software can perform this random selection. Second, we created circles around the selected points. In the Afar implementation, the circles had radii of 0.1–5 km, with smaller radii in strata with higher likelihoods of finding people. Third, field workers travelled around inside the selected circles and interviewed all persons within them. To help guide interviewers to the selected areas and determine who was inside and outside, the points and circles were loaded onto handheld GPS devices.

This method captures persons wherever they happen to be at a given time, which makes it particularly useful for populations without permanent dwellings, such as refugees on the move, the homeless, or pastoralists. These populations are commonly undercovered by surveys (Carr-Hill, 2013). The approach is cost-effective and can be implemented quickly, although it does require some technical sampling and mapping skills to calculate the probabilities of selection (see Himelein et al., 2014 for details). However, we are not aware of any studies using this method to sample refugees or IDPs.

All land in the target area is available for selection with this method, unless there are safety or accessibility issues. However, undercoverage of some housing units or persons can occur if interviewers do not canvass the entire circle thoroughly. As discussed with other methods, reliance on interviewers to perform selection is not ideal and opens the door to interviewer-induced undercoverage. For this reason, the circles should be kept small, 500-m radius or so. Himelein et al. (2014) had some success using Viewshed analysis to estimate how much of the selected circle interviewers observed and thus how much undercoverage there might be.

Overcoverage is also a concern; if persons travel during the field period, they can be found in more than one circle. To mitigate this issue, the field period should be short. If it is known that the population is generally traveling in a given direction (for example, from north to south), then the selected circles could be worked from south to north.

2.5.2 Mobile Phone Trace Data

Many refugees use smartphones and other mobile devices to coordinate travel and stay in touch with friends and family (Economist, 2017; Jones, 2019). Digital trace data generated by these devices can help researchers identify where the refugees are and thus where to sample for a face-to-face survey. Smartphones communicate through towers, and each tower keeps a record of the devices with which it communicates. Researchers can gain access to these call detail records, with some privacy protections applied. Most of the studies using call record data to study refugees count the stocks and flows of refugees (see, for example, Pastor-Escuredo et al., 2019). These studies often do not involve a survey—that is, they do not select and contact respondents for in-depth interviews about their living conditions, health, employment status, etc.

However, we are aware of one study that has used call detail records to design a face-to-face sample of refugees. The World Bank study of Venezuelans in Ecuador worked with a telecommunications company to obtain call detail records for each tower. They first determined which mobile phones were likely to be owned by Venezuelans: those which had made or received a call or text message from a Venezuelan number or accessed a website of interest to Venezuelans. All numbers with 30 or more such events in the prior 30 days were flagged. The towers used by those mobile phones between 8 p.m. and 6 a.m. were then identified as neighborhoods where Venezuelans lived. Neighborhoods were stratified into low, medium, and high concentrations of Venezuelans. Within selected neighborhoods, the study used in-field listing of dwellings and screening (Muñoz et al., 2020).

With this method, the goal is not to interview the holders of the phone numbers in the call detail records—the records simply help identify where the refugees are. In fact, access to actual phone numbers is not required for this approach, which helps preserve respondent privacy. The locations of the cell towers can also be coarsened to protect privacy (Pastor-Escuredo et al., 2019).

This method seems to be a promising approach for future studies of refugees; however, it does face several challenges. Call detail records are difficult to acquire and are often maintained by several companies within a country. Researchers may need to negotiate data use agreements separately with each company; the study of Venezuelans was unable to obtain records from the largest telecommunications company in Ecuador (Muñoz et al., 2020). Any delay in receiving and processing the data may mean that the persons of interest have moved on. However, the method described above, which used the records only to identify neighborhoods where refugees are, is likely somewhat less vulnerable to changes over time—neighborhoods change less quickly than individuals' residences.

Undercoverage should be about the same as it is in any other survey using in-field listing and screening (see Sect. 2.4.1). Although there may be refugees who do not have mobile phones, or whose mobile phones are not flagged, those individuals are not undercovered, because the call data are used only for stratification, not selection. IDPs, however, would likely be harder to identify with this method, because their call, text, and browsing habits may be similar to other country residents who are not displaced.

2.6 Discussion

We have discussed nine sample selection methods for studies that wish to conduct face-to-face surveys of refugees and IDPs. For each approach, we have reviewed previous studies and summarized the advantages and disadvantages. We have also discussed the patterns of undercoverage and overcoverage that may result from each method.

The best approach for a given study will depend on the situation of the population of interest, the data collection budget, and the tolerance for under- and overcoverage bias. The highest quality surveys will use a high coverage method such as in-field listing with screening but they will also be the most expensive. Respondent-driven and time-location sampling can be logistically and statistically challenging but are generally faster and less expensive. Adaptive sampling, random geographic cluster sampling, and sampling from images using computer vision may be best for studies with technical staff.

We have not discussed surveys of host communities in this chapter, mostly due to space constraints. However, some of the studies we have cited also involved surveys with members of the host communities, to understand how they were affected by the presence of refugees and IDPs. Often innovative designs are not needed for studies of the host community because they are well captured by census data and are the majority of the residents in their neighborhoods.

We foresee many more studies of refugees and IDPs in the coming years, as their numbers unfortunately continue to grow. We hope that the discussion in this chapter helps researchers in designing future studies. We also encourage continued methodological development to improve sample selection and survey data quality as new data sources and data collection methods become available. Survey researchers can help to improve the conditions of refugees and IDPs by collecting high-quality data about their living situations, which can support policy and aid responses.

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