

APPLICATION OF RESPONDENT DRIVEN SAMPLING TO ESTIMATE THE NUMBER OF IDPS IN A HOST COMMUNITY IN BIU LOCAL GOVERNMENT AREA OF BORNO STATE, NIGERIA.

^{1*}Anjikwi, Y., ²Agog, N.S., ³Buba, C.P

¹ Department of Agricultural Economics, University of Maiduguri, Borno-Nigeria.

² Department of Mathematical Sciences, Kaduna State University, Kaduna-Nigeria.

³ Department of Mathematical Sciences, Gombe State University, Gombe-Nigeria.

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ABSTRACT

The escalating crisis of internal displacement in north-eastern Nigeria, driven primarily by Boko Haram insurgency, has generated a large and largely hidden populations of Internally Displaced Persons (IDPs) residing in host communities. Estimating the size and characteristics of this population is methodologically challenging due to the absence of a formal sampling frame and the concealed nature of IDPs in host settings. This study applied Respondent-Driven Sampling (RDS) to recruit 650 IDPs across three communities; Miringa, Biu, and Buratai in Biu Local Government Area, Borno State, Nigeria. Two estimators were employed: the Naïve estimator (Heckathorn, 1997), grounded in with-replacement sampling assumptions, and a Weighted RDS estimator developed under without-replacement sampling assumptions. The study estimated displacement status, socio-demographic profiles, types of support received, and food insecurity experiences. Results revealed that 97.6% of respondents were confirmed IDPs, with conflict and violence as the primary driver of displacement (94.5%). The majority had been forcibly displaced more than five times (63.2%) and were living in severely inadequate shelter conditions. Food insecurity was pervasive, with 97.6% worried about food sufficiency and 94.3% having skipped meals in the past 30 days. Only 60.6% had received any form of post-displacement support, predominantly food assistance. Weighted estimates consistently differed from unweighted figures, confirming the importance of accounting for differential sampling probabilities in RDS-based studies of hidden populations.

1. Introduction

On a global scale, the number of individuals compelled to abandon their homes due to natural disasters or conflicts resulting in violence, loss of life, and human rights violations has exceeded 40 million (World Bank, 2015). Whether displaced within their own country as internally displaced persons (IDPs) or seeking refuge outside their nation as refugees, these individuals face immense challenges (World Bank, 2015). Particularly in Africa, various crises across the continent have displaced approximately 3.2 million individuals (World Bank, 2015). Internally Displaced Persons (IDPs) are individuals or groups of people who have been forced to flee their homes or places of habitual residence due to conflicts, violence, human rights violations, natural disasters, or other reasons, but remain within the borders of their own country (Olaoye, 2022). According to the UNHCR (UNHCR, 2020), internally displaced persons (IDPs) are those who have been compelled to escape their homes because of violence or war but are still inside their nation's borders. International normative frameworks and national policies aimed at protecting IDPs, internally displaced persons in Nigeria, especially in Biu local government area (LGA), Borno state's informal camps, continue to face systemic neglect, inadequate service delivery, and poor access to essential services such as healthcare. In the Nigerian context, the protection of IDPs is further complicated by legal and institutional deficiencies. The National Policy on Internally Displaced Persons (2012; revised 2021) represents a state-level attempt to domesticate global protection standards, yet its operationalization has remained inconsistent and largely symbolic (IDMC, 2023).

The increase in conflict-induced displacement and natural disasters has led to a significant rise in the number of

* Corresponding author: +2348036267312

E-mail address: y.anjikwi@gmail.com

Internally Displaced Persons (IDPs) worldwide. These individuals and families seek refuge in host communities, often facing numerous challenges related to their displacement (Adamu, 2019). The impact of IDPs on host communities is a multifaceted issue that requires in-depth analysis to understand the social, economic, and environmental consequences. Borno State, located in north-eastern Nigeria, has experienced a significant influx of internally displaced persons due to various factors, particularly the insurgency carried out by the Boko Haram terrorist group. This has led to the displacement of thousands of individuals and families within the state's borders. As a result, Biu LGA has become a host to a considerable number of IDPs who have fled their homes in neighbouring villages such as Azir, Sabon Gari, and Wajirko. Therefore, a thorough understanding of the IDPs' movement patterns is required to identify potential solutions that will avoid host community conflict with the IDPs. IDPs had to deal with a wide range of issues, such as subpar housing, inadequate healthcare, dangerous employment, the susceptibility of human trafficking and sexual mistreatment, discrimination based on gender, class, religion, or ethnicity, and a breakdown in social relations (Nweke, 2019; Ajayi *et al.*, 2019; Cantor *et al.*, 2021). However, a limited comprehensive study has been carried out to assess the impact of IDPs on the host communities, due to the lack of a sampling frame and the hidden nature of the IDPs in the host communities, which makes it difficult to apply standard sampling techniques (random sampling). This gap suggests a need for using an alternative method, a convenient sampling technique such as respondent-driven sampling (RDS).

RDS illustrates a constructive sampling method that leverages social networks to recruit individuals from hard-to-reach populations that lack formal sampling frameworks. This technique has shown considerable success in reaching marginalized or underrepresented communities, providing a way to connect with those who are often excluded by traditional research methods. In medical research, RDS has effectively recruited individuals from a variety of high-risk groups, including intravenous drug users, men who engage in sexual relationships with other men, and those experiencing homelessness (Card *et al.*, 2017; Heckathorn & Cameron, 2017; Lyons *et al.*, 2017; White *et al.*, 2015). The RDS procedure begins with the selection of individuals known as "seeds," chosen from a convenience sample of the larger target population. These seeds take part in a survey, which can be conveniently administered online or offline to enhance accessibility. Following the completion of their surveys, seeds invite a limited number of their contacts, referred to as "peer-recruited participants," who also belong to the targeted population. To efficiently manage this recruitment process, RDS employs a coupon system that monitors relationships among participants and encourages individuals to share information about their social networks within the target group. Through this progressive recruitment approach, RDS expands the sample size over multiple recruitment waves, decreasing reliance on the initial convenience sample while increasing study diversity. Participants are motivated through a dual rewards system, obtaining incentives for completing the survey as well as for successfully recruiting additional respondents. This strong incentivization strategy significantly enhances engagement among both seed participants and their referrals, leading to heightened participation and a more diverse pool of respondents, as noted by researchers like Gile & Handcock (2010) and White *et al.* (2015).

Furthermore, the RDS approach is crucial in facilitating recruitment for necessary health interventions, enabling researchers to reach individuals who might not otherwise seek health services. Its effectiveness goes beyond healthcare, aiding efforts to engage with migrant communities in various environments (Górny & Napierała, 2016; Keygnaert *et al.*, 2014). The method's distinct ability to generate reliable population estimates with favorable statistical properties, along with its practical use in real-world contexts, has led to a significant rise in the number of RDS studies carried out globally in recent years (Johnston *et al.*, 2016). This growth underscores the importance of RDS in enhancing our understanding of hidden populations and addressing their particular needs. This study therefore, applied RDS to recruit members of IDPs in a host community of Biu LGA, estimate their IDP displacement status, type of support received, and their food experience.

2. Methods

2.1 Method of Data Collection

Respondent-driven sampling (RDS) was used to collect data from 650 IDPs in Miringa, Biu, and Buratai in 2026. Initial 8 key recruits, known as "seeds," who were well known in the IDPs host community, were recruited. Each of the 8 seed was given 2 coupons (a unique code that allowed researchers to track recruitment) to invite their associates, friends, relatives, and acquaintances who were also displaced due to the activities of insurgency in the area.

These individuals then recruited their associates and so on, until the desired sample size was reached. Each consenting participant answered a detailed questionnaire about demographics, impact of insurgency attack, loss of family member, properties, and the number of attacks. Also, their degree network (an individual's own direct contacts). These questions were asked by a trained interviewer at a designated centre. As is typical in RDS, the recruitment process was assumed to resemble a Markov chain in which the stationary distribution was reached after 12 waves or referrals, which was key in defining the sample size of 650. The recruitment tree is depicted in Figure 1

Recruitment Tree

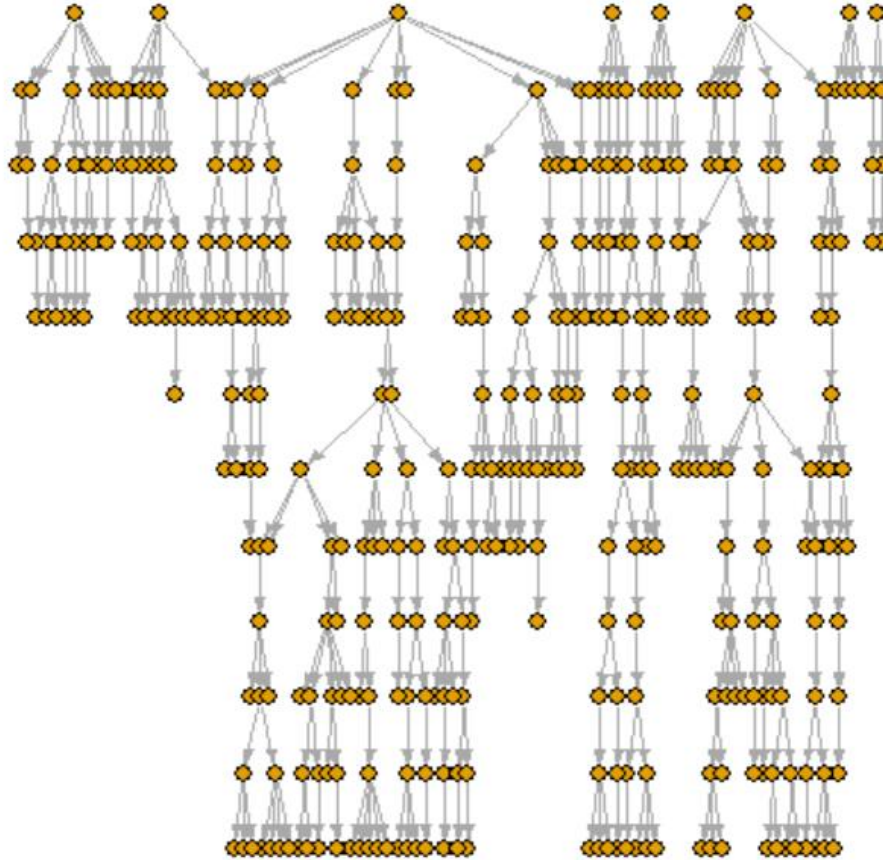


Figure 1: RDS Recruitment Tree

2.2 Model of Data Analysis

This study employed the naïve estimator of Heckathorn (1997), based on the assumption of sampling with replacement, and the weighted RDS estimator proposed by Anjikwi *et al.* (2026), which assumes sampling without replacement.

2.2.1 The Naïve Estimator.

The Naïve estimator was proposed by Heckathorn (1997) and was simply the proportion of infected individuals found in the sample.

$$\hat{\mu}_{NV} = \frac{\phi_A}{\phi_A + \phi_B} \quad (1)$$

where,

$\hat{\mu}_{NV}$ was the population proportion, ϕ_A was the number of recruits in group A, and ϕ_B was the number of recruits in group B.

Equation (1) indicated that when equal sampling probabilities were observed for individuals in both group A and group B, it acted as a generalized Hansen-Hurwitz estimator for the parameter of interest.

The Assumptions of the Naïve Estimator were:

- i. Respondents recruited peers from their social contacts with equal probability.
- ii. Sampling was done with replacement.
- iii. The degree of respondents was normally distributed.
- iv. The social network of the population was undirected. The population formed a connected network.

2.2.2 Weighted RDS estimator

Estimation of inclusion probability

The idea of probability proportional to size without replacement (PPSWOR) was extended to an RDS estimator to sample a hidden population (Anjikwi *et al.*, 2026). Since a node was recruited into an RDS sample with a probability proportional to its degree. The inclusion probability was specified as follows:

$$\lambda_{i_{weighted}} = \sum_{s \in S} P(s) \times I(i \in s) \quad (2)$$

where,

$P(s)$ was the probability of selecting sample s

$I(i \in s)$ was an indicator function (1 if $i \in s$, 0 otherwise)

For the RDS sample without replacement, $P(s)$ can be modelled as:

$$P(s) = P(i_1) \prod_{k=2}^n P(i_k | i_{k-1})$$

where,

$P(i_1)$ was the probability of selecting the seed node i_1 (often not random, or usually 1).

$P(i_k | i_{k-1})$ was the probability that node i_k was recruited by node i_{k-1} :

$$P(i_k | i_{k-1}) = \frac{D_{i_k}}{\sum_{j \in N(i_{k-1}) - \{i_1, i_2, \dots, i_{k-1}\}} D_j} \quad (3)$$

where,

$N(i_{k-1})$ the set of neighbors of i_{k-1} , not yet recruited

Substitute $P(s)$ into equation (2)

$$\lambda_{i_{weighted}} \approx \sum_{s \in S} \left(\prod_{k=2}^n \frac{D_{i_k}}{\sum_{j \in N(i_{k-1}) - \{i_1, i_2, \dots, i_{k-1}\}} D_j} \right) \times I(i \in s) \quad (4)$$

Simplify the expression in the equation

$$\lambda_{i_{weighted}} \approx \frac{D_i}{(\sum_{j \in U} D_j)} \quad (5)$$

where,

$I(i \in s)$ was equal to 1 if i belonged to S

U was the total number of nodes.

$\lambda_{i_{weighted}}$ can be approximated as

$$\lambda_{i_{weighted}} \approx \frac{D_i}{E} \quad (6)$$

where,

E was the total number of edges in the network.

$$E \approx \sum_{j \in U} D_j \quad (7)$$

Estimation of mean degree ($D_{weighted}$)

The weighted mean degree ($D_{weighted}$) of a node i can be estimated as:

$$\hat{D}_{weighted} = \frac{\left(\frac{\sum_{i \in S} \frac{d_i}{D_i}}{\frac{1}{E}} \right)}{\sum_{i \in S} \frac{1}{D_i}} \quad (8)$$

Simplify equation (8)

$$\hat{D}_{weighted} = \frac{\left(\frac{E \sum_{i \in S} \frac{d_i}{D_i}}{E \sum_{i \in S} \frac{1}{D_i}} \right)}{\quad} \quad (9)$$

$$\widehat{D}_{weighted} = \frac{(\sum_{j \in S} \frac{d_i}{D_i})}{(\sum_{j \in S} \frac{1}{D_i})} \quad (10)$$

Estimation of cross-group edges ($S_{g_a g_b}$)

Let $S_{g_a g_b}$ be the number of cross-group edges, that is, from group g_a to group g_b ,
Then the probability of a cross-group edge being reported can be modelled as:

$$P(\text{edge } (i, j) \text{ was reported}) = \frac{D_i}{E} \times \left(\frac{1}{D_i}\right) + \frac{D_j}{E} \times \left(\frac{1}{D_j}\right) \quad (11)$$

where,

$i \in g_a$ and $j \in g_b$ (or vice versa)

D_i was the degree of node i

D_j was the degree of node j

E was the total number of edges in the network

Equation (11) can be simplified as:

$$\begin{aligned} P(\text{edge } (i, j) \text{ is reported}) &= \frac{1}{E} + \frac{1}{E} \\ &= \frac{2}{E} \end{aligned} \quad (12)$$

Estimate $S_{g_a g_b}$ using the reported cross-group edges.

$$\begin{aligned} E[S_{g_a g_b}] &= \sum_{\{i \in g_a, j \in g_b\}} P(\text{edge}(i, j) \text{ is reported}) \\ &= \frac{S_{g_a g_b}}{E} \end{aligned} \quad (13)$$

Estimation of population proportion

The weighted RDS estimator was specified for the case of estimating the proportion of individuals with a particular trait in an RDS network setting. Specifically, if $S_{g_a g_b}$ denotes the total number of observed links (edges) from group g_a to group g_b , λ_1 and λ_0 are the respective inclusion probabilities for individuals with and without the trait, D_1 and D_0 are their respective degrees, the estimator was modelled as:

$$\begin{aligned} \widehat{RDS}_{weighted} &= \frac{\left(\frac{S_{g_a g_b}}{\lambda_1}\right)}{\left(\frac{S_{g_a g_b}}{\lambda_1} + \frac{S_{g_b g_a}}{\lambda_0}\right)} \quad (14) \\ &= \frac{\left(\frac{S_{g_a g_b}}{D_1}\right)}{\left(\frac{S_{g_a g_b}}{D_1} + \frac{S_{g_b g_a}}{D_0}\right)} \\ &= \frac{\left(E * \frac{S_{g_a g_b}}{D_1}\right)}{\left(E * \frac{S_{g_a g_b}}{D_1} + E * \frac{S_{g_b g_a}}{D_0}\right)} \\ &= \frac{\left(\frac{S_{g_a g_b}}{D_1}\right)}{\left(\frac{S_{g_a g_b}}{D_1} + \frac{S_{g_b g_a}}{D_0}\right)} \\ &= \frac{(D_0 * S_{g_a g_b})}{(D_0 * S_{g_a g_b} + D_1 * S_{g_b g_a})} \end{aligned} \quad (15)$$

The assumptions of the weighted RDS estimator model are:

- i. Respondents recruit peers from their social contacts with equal probability (random).
- ii. Each recruitment consists of only one peer (throughout the sampling period).
- iii. Sampling are done without replacement.
- iv. The degree of respondents reported has a negligible error.
- v. The network is directed.

- vi. The population forms a connected network.
- vii. The population size N is unknown.

3. Results and Discussion

3.1 Sociodemographic Profile of Internally Displaced Persons

The results in Table 1 present the sociodemographic profile of internally displaced persons (IDPs) identified in the host community survey in Miringa, Biu, and Buratai in Borno State, North-eastern Nigeria, which reveals several notable patterns that were compared between the weighted and unweighted estimates.

Table 1: IDPs Characteristics

Variables	Number	Unweighted	Weighted (lower-upper)
Age			
under 18	18	2.7	2.3(1.2-3.2)
18-38	222	34.2	32.6(27.3-39.6)
39-59	268	41.3	39.1(32.3-43.2)
60 or above	142	21.9	19.4(15.4-23.4)
level of education			
No education	163	25.1	24.3(18.2-27.6)
Qur'anic	228	35.1	32.3(28.3-38.4)
Primary	126	19.4	16.5(13.3-24.3)
Secondary	90	13.8	12.5(9.2-15.4)
Tertiary	43	6.6	5.1(2.3-8.7)
Marital status			
Married	519	79.9	76.7(68.7-83.4)
Never married	16	2.5	2.1(1.2-3.2)
Divorced/Separated	55	8.4	7.9(4.3-8.7)
Widowed	60	9.3	8.3(5.4-10.2)
Household Size			
1—3	55	8.4	7.6(5.6-11.2)
4—6	134	20.6	19.4(14.3-23.4)
7---10	441	67.8	65.7(57.6-71.2)
>10	21	3.2	2.7(1.2-3.2)
no of children <6			
1—3	104	16.0	14.3(9.2-18.5)
4—6	179	27.5	25.4(21.9-29.3)
7---10	196	30.2	28.6(21.3-32.1)
>10	171	26.3	25.4(19.2-31.9)
Occupation			
Farming	476	73.2	72.1(65.7-82.1)
Civil servant	37	5.7	4.8(2.1-5.3)
Trading	72	11.1	10.4(8.5-14.1)
Hand craft	66	10.1	9.5(7.3-15.4)

Source: Field Survey, 2026

Age Distribution

The unweighted results in Table 1 indicated that the largest proportion of respondents fell within the 39–59 age group (41.3%), followed by the 18–38 age group (34.2%), with persons aged 60 and above accounting for 21.9%, and those under 18 comprising only 2.7%. However, the estimates with weights to correct for differential sampling probabilities and non-response, a consistent downward shift was observed across all age groups. The weighted estimate for the 39–59 group declined to 39.1% (95% CI: 32.3–43.2), the 18–38 group to 32.6% (95% CI: 27.3–39.6), those aged 60 and above to 19.4% (95% CI: 15.4–23.4), and those under 18 to 2.3% (95% CI: 1.2–3.2). This downward adjustment

across all age groups following weighting suggests that younger and older age groups may have been slightly overrepresented in the raw sample, likely due to the convenience of accessing household respondents during field visits.

The predominance of working-age adults (18–59 years) in this IDP community, accounting for over 70% of the weighted sample, contrasts with findings from national-level IDP surveys. The National Bureau of Statistics (NBS) / International Organization for Migration (IOM). (2018). reported that the majority of IDPs are children, with 57 percent of IDPs being children under age 15. Similarly, the NBS IDP Survey found that among IDPs, 50.3 percent were mainly minors and below the age of 18 years. The underrepresentation of children under 18 in the present study (weighted: 2.3%) may reflect the household-based sampling design, which typically targets adult household heads or representatives as primary respondents, thereby structurally excluding children from direct enumeration. This is an important methodological distinction that must be acknowledged when interpreting age-related findings.

level of education

The educational profile of the surveyed IDPs reflects deep-seated deprivation. The weighted estimates show that 24.3% had no formal education, 32.3% had only Quranic education, 16.5% had primary-level education, 12.5% had secondary education, and only 5.1% had attained tertiary education. After weighting, a general reduction in the proportions was observed across all educational categories, with the most notable decline in the Quranic education category (35.1% unweighted vs. 32.3% weighted). This convergence upon weighting suggests that individuals with Quranic-only education were slightly oversampled in the raw data, possibly reflecting their higher availability at home during data collection. These findings are consistent with the broader literature on IDP educational disadvantage in north-eastern Nigeria. The destruction of schools and the disruption of educational systems by the Boko Haram insurgency have been widely documented as key drivers of low educational attainment among displaced populations. Studies have noted that most school-age children in Adamawa, Borno, and Yobe have had their opportunities for schooling severely constrained, with at least 338 schools damaged or destroyed by attacks (Tarasuk & Mitchell 2020). Furthermore, the NBS and IOM (2018) found that IDPs have lower school enrolment rates, with many IDP children not having attended school for three years or more since their displacement. The combined proportion of IDPs with no education or only Quranic schooling (approximately 56.6% weighted) in the present study underscores the magnitude of this educational deficit and its potential long-term implications for livelihood recovery and community resilience.

Marital Status

The overwhelming majority of respondents were married (79.9% unweighted; 76.7% weighted, 95% CI: 68.7–83.4), with widowed persons accounting for 9.3% unweighted and 8.3% weighted, and divorced or separated persons accounting for 8.4% unweighted and 7.9% weighted. The downward shift in the married category following weighting (from 79.9% to 76.7%) may reflect a correction for the oversampling of married household heads, who are more likely to be present and accessible during household surveys. The proportion of widowed respondents (8.3% weighted) is noteworthy and is consistent with findings from IDP studies elsewhere in Nigeria; a study among IDPs in Kaduna found that 20.5% were widowed, a higher figure likely attributable to the more acute conflict exposure in that setting. The high proportion of married respondents in the present study may reflect the household community setting, where family units are more intact compared to camp-based IDP populations.

Household Size

The distribution of household sizes reveals a predominantly large-household structure among the surveyed IDPs. The majority of households had 7–10 members (67.8% unweighted; 65.7% weighted, 95% CI: 57.6–71.2), followed by households with 4–6 members (20.6% unweighted; 19.4% weighted), and only 8.4% (7.6% weighted) had 1–3 members. Households with more than 10 members were rare (3.2% unweighted; 2.7% weighted). The consistent downward adjustment across all categories after weighting indicates a modest overrepresentation of large households in the raw sample, which may reflect higher visibility and accessibility of larger households in community settings. These findings align with the broader literature documenting overcrowding as a defining characteristic of IDP living conditions. The NBS and IOM (2018) noted that IDPs suffer from overcrowding in terms of housing and sanitation, and that severe overcrowding reduces living standards, contributes to the spread of communicable diseases, and increases the risk of gender-based violence. Large household sizes in the context of displacement are particularly concerning, given the limited resources and space available to displaced families, and may compound vulnerabilities related to food insecurity, hygiene, and child welfare.

Number of Children Under Six

A striking feature of the data is the high number of children under six years per household. The weighted proportions show that 14.3% of households had 1–3 such children, 25.4% had 4–6, 28.6% had 7–10, and 25.4% had more than 10 children under six. The near-symmetrical distribution across the middle and upper categories, and the minimal change between unweighted and weighted estimates, suggests that this variable was relatively uniformly sampled across the

population. The high fertility and child dependency burden reflected in these figures is consistent with the sociodemographic profile of rural northern Nigeria and aligns with evidence that female-headed IDP households tend to have higher dependency ratios.

Occupation

Agriculture dominated the occupational profile of the surveyed IDPs, with 73.2% unweighted (72.1% weighted, 95% CI: 65.7–82.1) engaged in farming, followed by trading (11.1% unweighted; 10.4% weighted), handicraft (10.1% unweighted; 9.5% weighted), and civil service (5.7% unweighted; 4.8% weighted). The slight downward revision of the farming proportion following weighting is consistent with a marginal overrepresentation of farming households in the raw sample, possibly reflecting their greater availability during daytime data collection. These occupational patterns are broadly consistent with findings from the NBS and IOM (2018), which reported that approximately 70 percent of IDP households rely primarily on agriculture for their livelihoods, noting that IDPs may rent land from host communities to maintain agricultural activities even after losing their own land. This reliance on agriculture, despite displacement-related land loss, reflects both the limited livelihood diversification options available to IDPs in north-eastern Nigeria and the deeply agrarian character of the region.

3.2 Displacement Status and Classification

The results in Table 2 present the displacement status and classification, based on types of residence, duration of residence at current location, reasons for displacement, duration since arrival at current location, frequency of forced movement, and shelter condition.

Table 2: IDPs Displacement Status

Items	Number	Unweighted	Weighted (lower-upper)
Type of Residence			
Recent migrant not forcefully displaced	11	1.7	1.4(0.2-2.1)
Internally displaced person (IDP)	639	98.3	97.6(85.4-99.3)
Duration of Residence at Current Location			
Yes	169	26.0	25.6(19.2-29.3)
No	481	74.0	73.2(65.4-85-3)
Reasons for Displacement			
Security reasons, conflicts, and violence	621	95.6	94.5(87.3-98.4)
Natural or man-made disaster [e.g., drought, floods]	16	2.5	2.3(1.2-3.7)
Human rights/fear of personal persecution	13	2.0	1.9(1.1-2.3)
Duration Since Arrival at Current Location			
less than six months	196	30.2	29.3(21.3-33.7)
More than six months	454	69.8	68.7(57.4-74.2)
Frequency of Forced Movement			
1-5	231	35.6	34.2(25.4-38.4)
>5	419	64.4	63.2(54.3-72.1)
Shelter Conditions			
Apartment/house, damaged/destroyed, in bad condition	214	32.9	31.4(28.3-38.4)
Unfinished or abandoned building	160	24.6	23.1(19.2-28.3)
Tent/makeshift shelter	142	21.9	20.5(17.3-28.4)
Container/caravan	37	5.7	4.5(2.1-5.6)
Public building or collective shelter	81	12.5	11.4(8.5-13.2)
Other shelter [garage, farm building]	16	2.5	2.1(0.9-3.2)

Source: Field Survey, 2026

The vast majority of respondents (IDPs) in this study were confirmed internally displaced persons (IDPs), accounting

for 98.3% of the unweighted sample and 97.6% on the weighted estimate (95% CI: 85.4–99.3). Only 1.7% (weighted: 1.4%, 95% CI: 0.2–2.1) were classified as recent migrants who had not been forcefully displaced. The near-total dominance of IDPs in the sample is consistent with the household community setting from which respondents were recruited, which was deliberately selected to capture the displaced population. The wide confidence interval for the non-IDP category (0.2–2.1) reflects the very small cell size ($n = 7$) and should be interpreted with caution. Nonetheless, the finding confirms that the study population is overwhelmingly composed of forcibly displaced individuals, lending validity to subsequent displacement-specific analyses.

Duration of Residence at Current Location

A substantial proportion of respondents, 74.0% unweighted and 73.2% weighted (95% CI: 65.4–85.3), had resided at their current location for less than two years, while 26.0% (weighted: 25.6%, 95% CI: 19.2–29.3) had lived there for more than two years. This finding suggests that the majority of IDPs in the surveyed community are in a relatively recent phase of displacement, which has significant implications for their humanitarian needs, livelihood recovery, and social integration. The modest downward adjustment between unweighted and weighted estimates is consistent with the general pattern observed across the table, suggesting a slight overrepresentation of more recently arrived IDPs in the raw sample.

Reasons for Displacement

Security-related reasons encompassing conflicts and violence were overwhelmingly the primary driver of displacement, cited by 95.6% of respondents (weighted: 94.5%, 95% CI: 87.3–98.4). Natural or man-made disasters accounted for only 2.5% (weighted: 2.3%), and human rights violations or fear of personal persecution for 2.0% (weighted: 1.9%). The weighted estimates for the non-conflict categories carry narrow and overlapping confidence intervals, reflecting their small sample sizes and the limited precision of estimates in these subgroups.

Duration Since Arrival at Current Location

When asked specifically how long ago they arrived at their current place of residence, 30.2% (weighted: 29.3%, 95% CI: 21.3–33.7) had arrived less than six months prior, while 69.8% (weighted: 68.7%, 95% CI: 57.4–74.2) had arrived more than six months ago. This distribution, read alongside the two-year residence variable, indicates a heterogeneous displacement population: a core of relatively settled IDPs (more than six months but less than two years) and a significant subgroup of newly arrived individuals (less than six months), the latter representing approximately three in ten respondents. The consistent downward shift in weighted estimates across both categories suggests mild oversampling of both very recent and more established arrivals in the raw data.

Frequency of Forced Movement

A striking and important finding is the high frequency of forced movement reported by respondents. The majority, 64.4% unweighted and 63.2% weighted (95% CI: 54.3–72.1), had been forcibly displaced more than five times, while 35.6% (weighted: 34.2%, 95% CI: 25.4–38.4) had been displaced between one and five times. The weighted estimates are marginally lower than the unweighted figures, suggesting a slight overrepresentation of multiply displaced individuals in the raw sample, though the differences are small and the confidence intervals confirm that the majority of the IDP population in this community has experienced repeated displacement.

Shelter Conditions

The shelter profile of the surveyed IDPs reflects severe housing deprivation. The largest category of shelter was damaged or destroyed apartments and houses in bad condition (32.9% unweighted; 31.4% weighted, 95% CI: 28.3–38.4), followed by unfinished or abandoned buildings (24.6% unweighted; 23.1% weighted), tents or makeshift shelters (21.9% unweighted; 20.5% weighted), public buildings or collective shelters (12.5% unweighted; 11.4% weighted), containers or caravans (5.7% unweighted; 4.5% weighted), and other informal structures such as garages or farm buildings (2.5% unweighted; 2.1% weighted). Across all shelter categories, weighted estimates were consistently lower than unweighted figures, reflecting the general pattern of mild oversampling of more visible or accessible households. The confidence intervals for the smaller shelter categories particularly containers/caravans (2.1–5.6) and other shelters (0.9–3.2) are wide, indicating limited precision in these estimates.

3.3 Type of Support Received by IDPs

The results in Table 3 present the Type of Support Received by IDPs, such as cash, shelter, food, training, and inputs.

Table 3: IDPs Type of Support Received

Items	Number	Unweighted	Weighted (lower-upper)
Have you received any support since your displacement?			
Yes	401	61.7	60.6(54.3-71.3)
No	249	38.3	37.6(27.3-45.3)
Who has supported you			
Cash	122	18.7	17.6(14.3-24.3)
Shelter	38	5.9	5.2(3.2-6.7)
Foods	369	56.8	55.8(45.3-58.1)
Training	49	7.6	7.3(4.3-11.2)
Input (seed, fertilizer, pesticide etc)	72	11.1	10.5(7.3-13.2)

Source: Field Survey, 2026

The data reveal that 61.7% of respondents (weighted: 60.6%, 95% CI: 54.3–71.3) reported receiving some form of support since their displacement, while 38.3% (weighted: 37.6%, 95% CI: 27.3–45.3) reported receiving no support at all. The weighted estimates are marginally lower than the unweighted figures across both categories, consistent with the general pattern of mild oversampling of supported individuals in the raw data. The relatively wide confidence intervals, particularly for the "No" category (27.3–45.3), reflect sampling variability and suggest that the true proportion of unsupported IDPs in the broader community population could range from just over a quarter to nearly half of all displaced persons. This uncertainty itself is a finding of significance, underscoring the need for more precise enumeration of unmet support needs in this setting.

Type of Support

Among those who received support, food assistance was overwhelmingly the dominant type, cited by 56.8% of all respondents (weighted: 55.8%, 95% CI: 45.3–58.1). This was followed by cash (18.7% unweighted; 17.6% weighted, 95% CI: 14.3–24.3), input (seed, fertilizer, pesticide etc) (11.1% unweighted; 10.5% weighted, 95% CI: 7.3–13.2), training (7.6% unweighted; 7.3% weighted, 95% CI: 4.3–11.2), and host community (5.9% unweighted; 5.2% weighted, 95% CI: 3.2–6.7). Across all support categories, weighted estimates were consistently lower than unweighted values, with the most notable absolute difference in the food assistance category (56.8% vs. 55.8%), suggesting a slight overrepresentation of food-assisted households in the raw sample, possibly because such households are more visible and accessible during field data collection.

3.4 Food Insecurity

The Results from Table 4 shed light on the prevalent issues of food insecurity among households, and when compared with existing literature, they reinforce the findings of numerous studies on the adverse effects of limited access to food.

Table 4: Food Experience by IDPs

Items	Number	Unweighted	Weighted (lower-upper)
During the last 30 days, Does your household experience the following			
Worried about not having enough food to eat	639	98.3	97.6(78.2-99.1)
Unable to eat healthy and nutritious food	566	87.0	86.5(67.3-93.2)
Ate only a few kinds of foods	406	62.4	61.5(54.2-74.3)
Had to skip a meal	618	95.1	94.3(81.2-97.2)
Ate less than you thought you should	479	73.7	72.7(67.8-89.1)

No food to eat of any kind in your house	240	36.9	35.4(22.3-44.1)
Go to sleep at night hungry	80	12.3	11.3(6.2-19.2)
Go a whole day and night without eating anything at all	16	2.5	2.1(0.4-3.8)

Source: Field Survey, 2026

The results in Table 4 revealed that about (98.3%) indicated that they were worried about food sufficiency. This alarming rate of respondents who felt worried about not having enough food reflects findings from the literature, which stress that anxiety related to food insecurity is common and can have profound effects on mental health. According to a study by Ella *et al.* (2020), the psychological stress from worrying about food availability is ubiquitous among food-insecure populations and can lead to chronic stress and related health issues.

Similarly, the majority (87.0%) of the IDPs indicated that they are inability to eat nutritionally. The high percentage of individuals unable to eat healthy foods correlates with research showing that socio-economic barriers often restrict access to nutritious foods. Walker *et al.* (2010) emphasizes that living in food desert areas with limited access to affordable and nutritious food contributes heavily to this phenomenon. Furthermore, food insecurity is often linked to higher consumption of low-cost, calorie-dense, nutrient-poor foods (Gundersen & Ziliak, 2015).

Limited Food Variety (62.4%): The finding that a significant portion of respondents ate only a few kinds of foods aligns with Ruel's (2003) research. Limited dietary diversity is frequently observed in food-insecure households, which is concerning as it can lead to poor nutritional outcomes and micronutrient deficiencies.

Meal Skipping (95.1%): The extremely high figure of respondents who had to skip meals resonates strongly with the conclusions of Cook *et al.* (2013), who found that food insecurity is strongly associated with irregular eating patterns. Skipping meals is a common coping strategy among food-insecure individuals, but it carries health implications, including increased risk for negative physical and mental health outcomes.

Eating Less Than Needed (73.7%): This statistic illustrates a significant concern regarding self-perception of food intake. Studies have shown that individuals facing food insecurity often report feeling hungry despite having some food (Holben, 2016), suggesting a large gap between actual food availability and individuals' perceptions of their needs.

Lack of Food at Home (36.9%): The proportion of respondents with no food to eat at all is particularly troubling. Research by Gundersen and Ziliak (2015) highlights that this extreme level of food insecurity can lead to severe health consequences, especially among at-risk populations, including children, who are more susceptible to the effects of malnutrition.

Going to Sleep Hungry (12.3%): While this figure is lower than many other statistics, it still indicates a significant population dealing with hunger at night. Literature emphasizes that going to bed hungry is linked to both mental and physical health struggles, particularly affecting sleep quality and overall well-being (Micha *et al.*, 2018).

Fasting for a Whole Day (2.5%): The reported cases of going a whole day and night without eating represent severe food insecurity, which is directly correlated with acute malnutrition and negative health outcomes, as noted by Tarasuk and Mitchell (2020). This extreme form of food deprivation highlights the urgent need for effective interventions to prevent physical and mental health deterioration.

4. Conclusion

Based on the results of these findings, it was concluded that this study demonstrates the utility of RDS as a viable and effective methodology for estimating the size and characteristics of IDPs residing in host communities where conventional sampling frames are unavailable. Future research should extend the RDS framework to larger and more geographically diverse IDP populations, and policymakers should prioritize the identified gaps in shelter, food security, and livelihood support to address the chronic and multidimensional vulnerabilities facing displaced communities in Borno State.

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