

#### **RESEARCH BRIEF, JULY 2022**

# COMPARING METHODS FOR TARGETING WATER SUBSIDIES TO THE POOREST HOUSEHOLDS

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With funding from the Conrad N. Hilton Foundation (CNHF), The Aquaya Institute (Aquaya) supports government agencies in selected districts of Ghana and Uganda in their efforts to achieve 100% coverage of safe, sustainable, and equitable drinking water supplies. As part of this effort, Aquaya collaborates with Safe Water Network to develop a blueprint for implementing targeted subsidies at rural water systems.

#### **MOTIVATION**

In Ghana, the poorest households tend to have lower access to safe drinking water, in part due to the cost of improved sources such as piped water systems. Subsidizing safe water services for the poorest can help to address these inequities, but water subsidies are commonly ineffective due to the financial constraints of service providers and unsuccessful targeting that benefits high-income groups. It is critical to find appropriate targeting methods that can accurately identify household poverty, are acceptable to community members and other stakeholders, and can be scaled efficiently.

### **RESEARCH QUESTION**

#### WHAT IS THE BEST METHOD TO IDENTIFY POOR AND VULNERABLE HOUSEHOLDS FOR WATER SUBSIDIES?

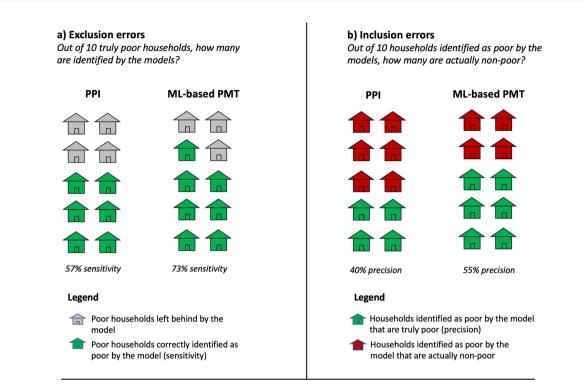
In this study, we compared the performance of five methods for targeting the poorest for water subsidies, identified through the literature and existing practice in Ghana (Table 1).

### **METHODS**

| National poverty<br>definition                                    | Description  |  |  |  |  |  |
|---|--|--|--|--|--|--|
| Consumption-based<br>poverty line                                 | The Government of Ghana defines poverty as a function of household consumption expenditures. Estimating annual expenditures requires a multihour long survey. In the 2016-2017 Ghana Living Standards Survey (GLSS 7), households with an annual consumption of less than 1,760.80 GHS (~425 UD) per adult equivalent were defined as poor. Using this definition, 23% of households in the nationally-representative GLSS 7 dataset were under the poverty line.  |  |  |  |  |  |
| Targeting methods   | Description  |  |  |  |  |  |
| Demographic and<br>Health Survey (DHS)<br>wealth index            | The DHS Wealth Index is an existing proxy means test (PMT) producing an index<br>value for each household based on answers to 13 survey questions. A PMT<br>predicts household poverty status by collecting easily quantifiable proxy indicators<br>for wealth through surveys. Households in the bottom 20% of the national index<br>are typically considered as poor.  |  |  |  |  |  |
| Poverty Probability<br>Index (PPI)                                | The PPI is an existing PMT that consists of 10 country-specific questions about<br>household characteristics and asset ownership, and the responses are used to<br>calculate a household's likelihood of falling below the national poverty line. For<br>consistency with the DHS method, we considered as poor the 20% of households<br>with the highest poverty probabilities.   |  |  |  |  |  |
| ML-based proxy<br>means test (PMT)                                | As part of this research, Aquaya developed a new PMT using machine learning<br>techniques and data from the 2016-2017 Ghana Living Standards Survey (GLSS<br>7) to predict household poverty status relative to the Ghana national poverty<br>line. This approach resulted in a survey with 30 questions to predict poverty. For<br>consistency with the DHS method, we considered as poor the 20% of households<br>with the highest poverty probabilities.  |  |  |  |  |  |
| Community<br>consultation   | Community members come together in a meeting to agree on a definition<br>of poverty and designate households that meet this definition. In this study,<br>consultation meetings typically lasted one hour with 40-120 participants in<br>attendance. Members defined poor households as (i) households that could not<br>feed themselves year-round, or (ii) households that contained an elderly person,<br>a person with a severe disability or chronic illness, a widow, or an orphan and did<br>not receive support from relatives. In our study areas, community consultations<br>identified 12% of households as poor. |  |  |  |  |  |
| Livelihood<br>Empowerment<br>Against Poverty (LEAP)<br>enrollment | Ghana's existing LEAP program uses a combination of proxy means testing and<br>community consultation to identify poor households for cash transfers and free<br>health insurance. Other interventions (such as water subsidies) may consider<br>targeting households that LEAP has already identified. In our study areas, only 4%<br>of households were beneficiaries of the LEAP program.   |  |  |  |  |  |

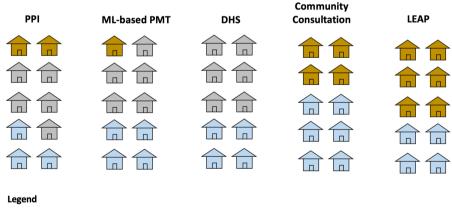
 Table 1. Ghana's official poverty definition and the five targeting methods assessed in this study

This study took place in three small towns in the Ahafo and Ashanti Regions of southwestern Ghana. We held six community consultation meetings in neighborhoods within these towns, and surveyed all 818 households in these communities. Surveys included questions to assess eligibility with respect to all three proxy-means tests (PMT) and enrollment in the Livelihood Empowerment Against Poverty (LEAP) program. To assess the acceptability of each method, we also conducted qualitative interviews with nine households identified as poor through community consultation, eight households not identified as poor, and six local government officials. We also tracked the costs of implementing each approach.



#### c) Field assessment: characteristics of households identified

Out of 10 households identified as poor, how many have observable vulnerability or wealth characteristics?



Households identified as poor that have observable vulnerability characteristics

Households identified as poor that neither have observable vulnerability or wealth characteristics

1 Households identified as poor that have observable wealth characteristics

**Figure 1.** Comparison of five targeting methods with respect to exclusion errors (a), inclusion errors (b), and characteristics of households identified (c). To compute inclusion and exclusion errors, we compared model predictions with true poverty status (relative to the national poverty line) in the GLSS 7 dataset. We could only compute these for the PPI and ML-based PMT.

# **COMPARING PERFORMANCE**

We evaluated the accuracy of the PPI and Aquaya's ML-based PMT by comparing their predictions with true poverty status (relative to the national poverty line) for 2500 households in the GLSS 7 dataset. The ML-based PMT made slightly more accurate predictions that the PPI (87% of the time compared to 81% for the PPI). **Importantly, it made fewer exclusion errors, leaving out 27% of truly poor households as opposed to 43% for the PPI (Figure 1a). It also made fewer inclusion errors: 55% of households predicted to be poor were truly poor, compared to only 40% for the PPI (Figure 1a).** 

### **FIELD ASSESSMENT**

All five methods identified households that seemed on average more vulnerable than the rest. For example, they more often had a female, elderly, disabled, or chronically ill household head, or reported not being able to feed themselves all year round without support from relatives. They also more seldom owned expensive assets such as refrigerators or televisions. The DHS method, followed by the ML-based PMT, were the most successful at identifying households with observable vulnerability characteristics while leaving out households with observable wealth characteristics (Figure 1c).

**Interestingly, the five methods identified different subsets of households as being poor**, with limited overlap between methods. Among all households identified as poor by any method, 58% (190/330) were identified by two methods or more. There was some overlap (40%) between the PPI, ML-based PMT, and DHS, which all rely on surveys about assets, expenditures, and demographics, but very little (4%) between survey-based methods and community consultation.

## **COMPARING ACCEPTABILITY**

Community members overwhelmingly preferred PMT methods, because they felt that people would be more honest in a survey, whereas during community consultation, vulnerable households may be afraid to share their true poverty status, or others may forget to include them. Local officials were split between preferring PMT surveys or community consultation, being concerned about the possibility of lying or bias with each method. No local officials would rely on the LEAP program, largely echoed by interviewed community members, who perceived this method as being influenced by politics and as leaving behind vulnerable households.

National stakeholders such as the Community Water & Sanitation Agency (CWSA) noted that their first priority would be targeting accuracy (i.e., few inclusion and exclusion errors), but that it would also be important to have transparent targeting criteria. This transparency condition may be difficult for PMT methods to meet, as they often rely on combining a large number of household characteristics using "black-box" models. National stakeholders also stated they would prioritize accuracy over cost, noting the possibility of using multiple methods together to better identify eligible households.



Image 1 & 2. Community consultation meetings in Asutifi North.

# **COMPARING COSTS**

Targeting methods involving PMT surveys were the most expensive and time-consuming (Table 2) due to the need to survey every household. A shorter survey such as the PPI may be somewhat more efficient with respect to time and cost, if more surveys can be completed each day, but the cost also depends on the spatial distribution of households (e.g., a lower household density will result in higher logistical costs and time requirements). In contrast, using existing LEAP enrollment would be least expensive (in areas where the LEAP program has been rolled out), as it would simply require obtaining the LEAP household lists from local government offices.

| Method   | Time<br>(days) | Targeting<br>Cost (USD) | One year of water<br>subsidies (USD) |  |
|--|----------------|-------------------------|--------------------------------------|--|
| ML-based PMT   | 7              | \$760                   | \$1,720                              |  |
| PPI  | 7              | \$760                   | \$1,720                              |  |
| DHS  | 7              | \$760                   | \$1,720                              |  |
| LEAP   | 7              | \$89                    | \$340                                |  |
| Community<br>Consultation                                  | 3              | \$412                   | \$1,030                              |  |
| ML-based PMT +<br>Community<br>consultation in<br>parallel | 9              | \$1,172                 | \$2,745                              |  |

**Table 2.** Average cost and time requirements per neighborhood (75-300 households) for each targeting method during this study. The potential costs associated with one year of consumption subsidies reflect the cost of the water only, without any additional implementation or logistical costs.

However, targeting expenses tend to be relatively small compared with the potential costs of providing a water subsidy. For example, one year of consumption subsidies providing for free 20 liters per person per day (exclusive of any implementation expenses) would cost 2-7 times as much as the targeting itself (Table 2), depending on the method and the number of households identified. The cost of subsidies would be higher for the three PMTs, which identified a larger proportion of the population (20%) as poor, compared to community consultation and LEAP, which identified a smaller proportion (4%-12%) as poor.

| Rank (Best=1, worst=5)                   |                 |     |     |                        |      |  |  |  |
|--|-----------------|-----|-----|------------------------|------|--|--|--|
|  | ML-based<br>PMT | PPI | DHS | Community consultation | LEAP |  |  |  |
| Characteristics of households identified |                 |     |     |                        |      |  |  |  |
| Few exclusion and                        | 2               | 3   | NA  | NA                     | NA   |  |  |  |
| inclusion errors                         |                 |     |     |                        |      |  |  |  |
| Identified households more               | 2               | 4   | 1   | 3                      | 5    |  |  |  |
| vulnerable than the rest                 | (A)             |     |     |                        |      |  |  |  |
| Acceptability                            |                 |     |     |                        |      |  |  |  |
| Perceived fairness                       | 1               | 1   | 1   | 3                      | 5    |  |  |  |
|  |                 |     |     |                        |      |  |  |  |
| Perceived transparency                   | 2               | 2   | 2   | 1                      | 5    |  |  |  |
| Scalability                              |                 |     |     |                        |      |  |  |  |
| Ease of implementation                   | 5               | 3   | 4   | 2                      | 1    |  |  |  |
| Targeting affordability<br>(=low cost)   | 4               | 4   | 4   | (B) <sup>2</sup>       | 1    |  |  |  |

Figure 2. Comparison of the five targeting methods with respect to predictive performance, acceptability among community members and local and national stakeholders, and scalability.

#### Recommendation:

(A) If prioritizing ability to identify the most vulnerable: ML-based PMT

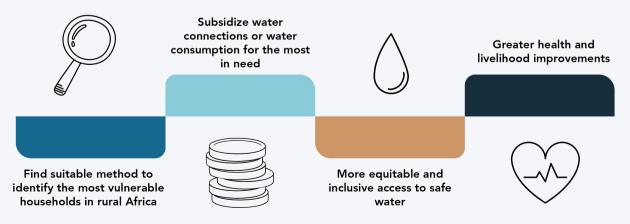
(B) If prioritizing acceptability and scalability: community consultation

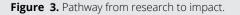
### **TARGETING RECOMMENDATIONS**

There are tradeoffs across the five methods (Figure 2), so a singular recommendation would depend on a stakeholder's top priorities. **If ability to identify the most vulnerable households is the main priority, survey methods (particularly the ML-based PMT) may be the best approach, while community consultation would likely provide better transparency and scalability, with clear eligibility criteria**. **If stakeholders are open to using multiple methods (regardless of cost), a combination of the ML-based PMT and community consultation may be especially effective**. Selecting households identified by either method would result in good performance, with relatively low risks of including non-poor households (inclusion errors) and excluding truly vulnerable households (exclusion errors). Implementing both methods would likely be costlier than any single method (Table 2), but it could also provide a good balance of performance and acceptability, especially if communities participate in the validation of results from the ML-based PMT selection. It is also possible to include households enrolled in the LEAP program in the final list that would be generated from this hybrid approach.

A next step may involve conducting a pilot study in collaboration with Safe Water Network to implement the ML-based PMT and community consultation as a combined approach. Households identified through the survey, community consultation, and LEAP enrollment could be included in the list. Such a pilot would help provide evidence regarding the feasibility, acceptability, and scalability of this combined approach before implementation at large scale. Furthermore, if the combination of the ML-based PMT and community consultation performs well in the field, it could represent one approach for refining the LEAP selection process as it is rolled out nationally.

#### WHY DOES THIS RESEARCH MATTER?





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