Policies for multidimensional poverty reduction: impact simulation and optimization

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Economic and Social Commission for Western Asia

Policies for multidimensional poverty reduction: impact simulation and optimization

United Nations
Beirut

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United Nations publication issued by ESCWA, United Nations House,
Riad El Solh Square, P.O. Box: 11-8575, Beirut, Lebanon.

Website: www.unescwa.org.

2400142E

Key message

- *Building back better from the COVID-19 pandemic and implementing the 2030 Agenda for Sustainable Development require strong policy interventions.*
- *Trends in household deprivations observed through pairs of Arab country surveys show recent improvements across a number of indicators, including age schooling gap, school attendance, mobility assets and overcrowding.*
- *Optimization prescribes that policymakers in Arab middle-income countries prioritize resource allocation to the education sector.*
- *Policymakers in low-income Mauritania should prioritize addressing deprivations in the domains of education, housing and access to public services.*

Contents

Introduction

Persistent poverty remains a prevalent issue in the Arab region, and is characterized by diverse dimensions that include both monetary and non-monetary aspects. Addressing this multifaceted challenge has become a paramount priority for achieving the 2030 Agenda for Sustainable Development.[1] Poverty reduction primarily hinges on the implementation of public programmes and initiatives, which are evident in the allocation of State/government budgets. With Arab middle- and low-income economies dedicating only a minor share of their budgets to poverty alleviation, enhancing the efficiency and effectiveness of resource spending is crucial to maximizing its impact within the allocated funds, particularly in times when economic crises are more frequent and severe, and the pace of recovery is sluggish.

Existing approaches to modeling changes in multidimensional poverty include microsimulation techniques,[2] which estimate the changes induced in household multidimensional deprivation, particularly in response to external economic shocks. The resulting multidimensional deprivation matrix can then be utilized to measure the new index of multidimensional poverty. These simulations, however, rely on several assumptions, including (1) the targeting ability of the simulation, (2) the trickle-down effects of economic shocks and policy responses on relevant indicators and households, (3) the capacity of the State to take effective action, and 4) the interlinkages between the affected indicators. Considering the policy implications of these simulations, it is essential to scrutinize the model assumptions.

The present study makes a formalized effort to contribute to the existing literature, and primarily focuses on how policymakers should allocate scarce resources to achieve a specific degree of multidimensional poverty alleviation. Recognizing the significance of measuring the various dimensions of poverty and deprivation in the Arab region and of continuously monitoring progress towards the Sustainable Development Goals (SDGs)—specifically Target 1, which is aimed at ending poverty in all its forms everywhere—poverty reduction optimization models are applied to five Arab countries (Algeria, Egypt, Iraq, Mauritania and Tunisia), spanning the period from 2010 to 2030. Various models of State intervention are outlined, highlighting the capacity of States to allocate specific resources and the proficiency of policymakers in transferring these resources to households that require them the most.

Four integer linear optimization models are used to calculate optimal resource allocation amid a set of constraints, which are designed to draw the boundaries of policymakers' ability (defined by the

1 United Nations Development Programme (UNDP), 2013; UNDP and Oxford Poverty and Human Development Initiative, 2020.

2 Tsui, 2002; Klasen and Lange, 2012; United Nations Economic and Social Commission for Western Asia (ESCWA), 2017; Makdissi, 2021; ESCWA, 2022; United Nations Children's Fund (UNICEF), 2022; ESCWA, 2023a; ESCWA, 2023b.

maximum resources they can allocate by indicator/policy sector); define and respect the axioms and constraints governing the mathematical formulation of the Alkire–Foster[3] Multidimensional Poverty Index (MPI) definitions; account for the random impact of efforts on household deprivations; and introduce the concept of waste resulting from targeted households not using their allocated resources efficiently. In addition to relying on health survey microdata and their arrangement into a proper deprivation matrix, the analysis also benefits from statistical clustering techniques used to generate statistically homogeneous subgroups of households by taking into consideration common consumption patterns. The more accurately the data clusters are formed, the better the information that can be fed into the optimization model, and the more efficiently policymakers can allocate economic resources in the solution. The logic, assumptions and complete mathematical formulations for the models of MPI reduction are developed and tested against microdata from household surveys. The performance and results are highlighted to support decision makers in setting priorities and identifying effective interventions to reduce the MPI.

The proposed study presents an initial formalized attempt to support national planners in determining the custom-tailored interventions that should be prioritized within a national context to efficiently reduce the MPI. Initial findings of this study suggest that multidimensional poverty reduction models can be successfully characterized and solved, while loosening some of the strong assumptions in micro-simulation regarding States' ability to target poor households and tailor assistance to them, thus enabling policymakers to mobilize resources efficiently. Once applied, these models will inform practitioners on how to avoid resource waste on non-critical dimensions of wellbeing and on non-deprived population groups. Policy scenarios that do not provide policymakers with the ability to accurately target populations and tailor assistance to specific needs achieve much lower efficiency.

The paper is divided into four chapters. Chapter 1 outlines the narrative and rationale of the models. Chapter 2 introduces the methods and mathematical formulations of each model. Chapter 3 presents the results. Chapter 4 includes concluding remarks and policy recommendations.

3 Sen, 1976; Alkire and Foster, 2011; Alkire and Santos, 2014; Alkire and others, 2021.

1. Narrative and rationale for model selection

All four models are designed to assist national planners in identifying priority interventions, relevant indicators/dimensions (such as the education and health sectors), and specific geographic (governorates, caza, etc.) and sociodemographic (gender, age groups, etc.) units that should be prioritized when implementing poverty reduction strategies. In the absence of effective targeting mechanisms, States may enact expensive policy interventions which could pose a potential risk to the achievement of poverty reduction objectives.

In a mathematical context, this entails embracing a bottom-up approach and leveraging an existing household-level deprivation matrix in conjunction with a new target matrix to effectively minimize the MPI while optimizing State efforts. For consistency, “effort” is defined as a combination of resources encompassing fiscal disbursements, manpower, time allocation, and the political and logistical efforts needed to achieve a specific level of MPI reduction. In this paper, specific allocations for indicators will be referred to as “effort”.

Solutions are presented through four integer linear optimization models, each with distinct input requirements, assumptions and targeting approaches. Despite their differences, all models converge on the same objective. They address policy questions, identify priority interventions, and set targeting priorities. The present chapter provides a high-level overview of each model's narrative. The mathematical formulations employed in each model will be explained in the following chapter.

Assumptions and caveats of the models

The models presented in this paper hinge on the following assumptions:

- All normative assumptions established during the design and build-up phase of the MPI framework (in the baseline year preceding the implementation of the poverty reduction strategy) remain constant over time.
- Interventions in one indicator are posited not to impact the deprivation status of households in other indicators, implying the independence of indicators.
- Deprivation status is exclusively lifted for targeted households, with all other households unaffected throughout the entire planning horizon of the poverty reduction strategy.
- It is not mandatory for all indicators to be targeted, as policymakers may find that some sectors do not require consideration for various reasons (for example, the infrastructure may not have been established yet owing to constraints such as budget limitations). These are referred to as non-active indicators. Simulation results may reveal that only a subset of active indicators need

targeting, and achieving MPI reduction targets may be possible by concentrating efforts solely on this subset.

- Efforts required to lift a deprived household out of deprivation in active indicators are assumed to remain constant across additional households (constant marginal cost) or over time (static).
- MPI reduction targets are considered predetermined and unaltered over the planning and implementation horizon. The feasibility of these targets is evaluated in each model.
- Non-poor households are excluded from transitioning into a state of poverty in a multidimensional context.

A. Model 1: Standard no-cost models

This model is commonly referred to as standard because it primarily relies on the poverty measures defined by the Alkire-Foster method. In this sense, poverty can be assessed at the indicator level in a multitude of forms, including:

1. Uncensored headcount: This measures the total number of individuals who are deprived in a specific indicator.
2. Censored headcount: This measures the total number of individuals who are deprived in a specific indicator and are at the same time multidimensionally poor.

While both measures are absolute in nature, a high percentage of deprivation in an indicator may not necessarily translate into a high MPI. Similarly, an indicator with a high concentration of deprived and poor households may not contribute significantly to a high MPI. Hence, the third set of indicator-specific measures introduced by the Alkire-Foster method is considered crucial in the context of MPI.

3. The MPI contribution of an indicator offers insights into relative deprivation within that specific indicator based on its assigned weight (during the design stage of the MPI framework).

Hence, without the need for simulation and solely by analysing the percentage contribution of each indicator to the overall MPI, policymakers can identify the indicators that should be prioritized when setting the poverty reduction strategy. In this scenario, the governing body, typically the Government, would dedicate specific efforts to the identified sector and evaluate the impact of this investment on alleviating deprivation and reducing poverty. In situations where the MPI reduction target is ambitious, efforts could be directed towards multiple contributing indicators, rather than concentrating solely on one.

Focusing on a limited number of indicators throughout the entire period without allocating resources to other indicators may prove inefficient. The rationale behind this lies in the fact that the MPI contribution percentage by indicator is not necessarily static over time. An indicator that is deemed the most influential at the outset of the policy may gradually become the least contributing over the implementation period. Therefore, while prioritizing the most contributing indicator that was initially identified may have seemed valid, this assumption could falter during strategy implementation. It is therefore imperative to adopt a dynamic model.

Model 1 prioritizes the indicator that has the greatest impact on the MPI initially and subsequently targets deprived households within that indicator without additional considerations, such as State effort capacity. The priority of intervention in targeting deprived and poor households within the targeted indicator remains unchanged as long as the indicator continues to be the primary contributor to the MPI during the intervention. Once the contribution of that indicator is surpassed by others and the MPI reduction target is still unmet, the policy intervention will shift to the new indicator with the highest contribution.

Two versions of that model are introduced: one deterministic and another probabilistic. Once the most contributing indicator is targeted, the model proceeds to identify the deprived households. The initial model functions within a deterministic framework and under the assumption that the policymaker can precisely identify deprived households, particularly those facing multiple deprivations across various indicators, essentially representing the poorest households in a multidimensional sense. In contrast, the probabilistic model introduces a more realistic approach where the policymaker's targeting policies are less efficient, making it challenging to precisely locate and target the poorest households. This probabilistic approach acknowledges the inherent inefficiencies in policy implementation, and recognizes that programmes, such as cash-transfer initiatives, may encounter various challenges related to targeting accuracy, corruption, diversion, and misuse by beneficiaries. To simulate this reality, the probabilistic model assumes a random targeting within indicators for deprived households. Consequently, the targeted deprived households may not necessarily represent the poorest in a multidimensional sense.

B. Model 2: Household-level targeting model

Much like model 1 in its deterministic form, model 2 presupposes that the State is equipped with the ability to locate and target deprived and poor households in any given region. It aims to enhance the deprivation status of poor households and achieve an efficient reduction in the MPI without allocating efforts to households that are not categorized as the poorest in a multidimensional sense and are not located within the most MPI-contributing indicators. This model can be conceptualized as allocating conditional cash transfers, while ensuring that the funds are used for targeted indicators and households (or providing in-kind transfers or smart cash-cards that target specific deprivations). A distinguishing feature of this model, in comparison to model 1, is the introduction of the effort dimension. Targeting priority is not solely based on indicators that contribute the most to the MPI, but also considers those requiring the least amount of effort, all while considering the limited supply of efforts a State can allocate for its policy implementation. In this model, the policymaker must consider the efforts needed to lift a deprived household out of deprivation.

It is evident that, by its design, the model focuses on targeting deprived and poor households with the objective of alleviating their deprivation and eliminating their multidimensional poverty status. However, in cases where the MPI reduction target is ambitious, the model will also target deprived and poor households, even if this does not necessarily result in a change in their multidimensional poverty status.

This model is not entirely realistic given its assumptions regarding the State's capacity to target specific households using detailed insights on their deprivations. For instance, according to these assumptions: (1) The State has the necessary resources and capability to remove a single household from deprivation in a single indicator; (2) The State observes the deprivation status of households for the utilities indicators (water and electricity); (3) The State observes the deprivation status of all households and all individual indicators; and
(4) The State can provide access to any tailored resources, and can limit access to only those who are deprived and multidimensionally poor, regardless what infrastructure already exists in the respective region (such as a power plant or water facility). In other words, the State can prevent all inclusion and exclusion errors.

Given that model 2 is deterministic, its results are precise and robust. It is also worth noting that both models 1 and 2 are computationally less demanding, especially when compared with the remaining models.

C. Model 3: Geographic targeting model

Model 3 retains the assumption of model 2 regarding the State's capacity to allocate multidimensional resources efficiently to various households, but it relaxes the restrictive assumption of the State's perfect targeting capacity. The State, accordingly, can intervene in a uniform (or random) manner across all deprived households without the ability to consider their multidimensional poverty status. The State allocates efforts at the geographic level and observes the ex-post societal response. As such, the nature of the model becomes stochastic. The incidence of households being lifted out of deprivation by a certain intervention is random. Only certain deprived households succeed at exiting their state of deprivation, and only some of those manage to exit multidimensional (MD) poverty. This may be because the State is forced to randomly select the targeted deprived households – for lack of information or for its inability to perform better targeting – or because the assistance per household is reduced to provide uniform aid to all those who are deprived. Aid allocation in model 2 can produce changes for the following household types:

- MD poor household becoming MD non-poor.
- MD poor household staying MD poor, despite a subset of indicators switching from a state of deprivation to a state of non-deprivation.
- Non-MD poor household staying as non-MD poor, with a subset of indicators switching from a state of deprivation to a state of non-deprivation.

Therefore, in contrast to model 2, where only multidimensionally poor households can undergo a reduction in deprivations, model 3 permits MPI indicators of non-poor households to transition from a state of deprivation to a state of non-deprivation.

In addition to factoring in the cost of eliminating deprivation in each indicator, the model effectively prioritizes households based on the results of two specific indicator ratios:

$$\mathrm{Ratio}_{1,\mathrm{j}} = \sum_{\mathrm{i}=1}^{\mathrm{N}} \frac{\text{Household i deprived in indicator j and is at the same time MD poor}}{\text{Household i deprived in indicator j}} \tag{1}$$

$(j = 1, \dots, n)$, n being the total number of indicators. The higher the ratio, the more likely that households deprived in indicator j are also MD poor.

$$Ratio_{2,j} = \sum_{i=1}^{N} \frac{Deprived\ and\ MD\ poor\ household\ i\ transitions\ to\ non\ MD\ poor, by\ just\ flipping\ its\ indicator\ j\ from\ 1\ to\ 0}{Household\ i\ deprived\ in\ indicator\ j\ and\ is\ at\ the\ same\ time\ MD\ poor} \tag{2}$$

The greater the value of Ratio 2, the more probable it is for the household poverty status to change by merely adjusting the household's deprivation score in a single indicator.

Thus, under the assumptions of equal costs of deprivation reduction across indicators, and unconstrained resources for deprivation reduction, the model singles out indicators with the highest scores on these ratios. This ensures the selection of households with the highest likelihood of being in a state of multidimensional poverty, and whose multidimensional poverty status changes in association with any change in their deprivation status. If costs vary across indicators, the model also places emphasis on lower-cost indicators. It is worth noting that this targeting priority is estimated for each geographic area, and the higher the number of areas, the more deterministic the model becomes. In simpler terms, when all households are concentrated in a few geographic zones, the ratio can be interpreted as a probability. However, in instances where each household is uniquely situated in just one geographic zone, the ratios will either be zero or one, making the model's targeting approach deterministic in nature (the optimization model path is straightforward: either target the household with a ratio value of 1, or do not target it with a value equal to zero). In a particular case, model 3 becomes analogous to model 2.

D. Model 4: Geographic and demographic targeting model

Now that models 1, 2 and 3 have been introduced, a crucial question arises: Which assumptions are most convincingly supported, considering the State's capacity to address deprived population groups living in geographical areas? How will assistance be allocated to the identified households? Will it take the form of budget allocations to centralized regional administrations (as in model 3), or will it involve personalized aid distributed across different tiers of population groups?

Similar to proxy means testing, which employs information on household characteristics to gauge welfare levels by approximating household income, expenditure or need, it is reasonable to assume that with such information, the State can be empowered to accurately target and address specific indicator deprivations through the strategic deployment of personalized aid transfers. Such indicators are labelled as private good indicators. In our context, the State can likely estimate this proxy using data on income and wealth, typically acquired through a survey.

In contrast, the State may possess significantly less information and capability to address public indicator deprivations among households, especially in the realm of access to utilities and services. To address these deprivations, the State may find it necessary to rely on more detailed information that is normally found in centralized regional administrations (at the level of population group regions or the entire country). This could involve addressing these issues through initiatives like public infrastructure projects. Indicators are classified as either public or private goods based on whether households can obtain or manage them independently (private goods) or if public provision or coordination is necessary (public goods).

The stochastic approach of model 3 is utilized for public good indicators, and concentrates on targeting households at the geographic population-cell level. As for the private good indicators, the household targeting mechanism is reinforced by household cluster identifiers, particularly income-proxy subgroups. This approach achieves a commendable level of targeting efficiency, especially when the clustering method accurately identifies the households experiencing the most significant level of deprivation. Clustering entails grouping data using an unsupervised machine learning technique and partitioning the sample around a given number of median values. The data is the deprivation matrix of the private good indicators, in addition to the income or expenditure vector proxy. This approach is used to identify high incomes (or different consumption patterns) and deprivation levels of distinct groups of households.

The results of the models can be compared and their efficiencies calculated. Efficiency is determined by the post-optimized effort allocation of each model, resulting in an equivalent level of poverty reduction across all models. It is evident that models 1 and 2 are likely to yield the most efficient outcomes, given that a smaller number of deprived households needs targeting to achieve the same level of poverty reduction compared to other models. However, it is crucial to interpret the results with an awareness of the model assumptions and their alignment with reality.

2. Methods and mathematical formulation

A. Model 1: Standard no-cost models

Input variables are categorized into two groups: original and computed variables. Original input variables are those directly provided by the modeler, while computed input variables are additional variables calculated before the optimization routine. Table 1 provides details on variable definitions. Decision variables are classified into two categories: external and internal decision variables. External decision variables are the variables that users can directly observe, and they result from the optimization process.

Internal decision variables are introduced to facilitate the optimization process or to transform logical constraints into linear constraints (further details regarding this transformation can be found in the annex).

Table 1. Nomenclature for models 1 to 4

Original input variables	
I	Set of households
J	Set of individual indicators
k	Poverty threshold
$\forall j \in J, w_j$	Weights of the various indicators (the sum of all weights is 1)
$\forall j \in J, l_j$	Lower bound on the effort spent per indicator
$\forall j \in J, u_j$	Upper bound on the effort spent per indicator
$\forall j \in J, EpF_j$	Effort required to induce a flip per indicator
$\forall i \in I, \forall j \in J, M_{ij}$	Binary deprivation per household and indicator
$\forall i \in I, HS_i$	Household size per household
$\forall i \in I, HW_i$	Statistical weight of household
MPI_s	Starting MPI (pre-optimization)
MPI_r	Reduction required in MPI, continuous variable between 0 and 1
Computed input variables	
$\forall i \in I, \forall j \in J, Mw_{ij}$	Weighted deprivation per household and indicator
$\forall i \in I, P_i$	Binary input variable indicating if a household is originally poor (1) or not (0)

External decision variables	
$\forall i \in I, \forall j \in J, N_{ij}$	Binary decision variable member of the post-optimization deprivation matrix N
$\forall j \in J, E_j$	Effort in the corresponding indicator j
Internal decision variables	
$\forall i \in I, C_i$	Contribution of a household to the post optimization MPI. C_i is a continuous variable with a minimum of zero and is also referred to as weighted deprivation score

First, the household status P_i is defined as

$$'\forall i \in I, \qquad P_i = \begin{cases} 1, & if \sum_J M_{ij} \cdot w_j \geq \text{k} \\ 0, & if \sum_J M_{ij} \cdot w_j < \text{k} \end{cases} \qquad (3)$$

$i.e$, the household is considered poor when $P_i = 1$. The formula used for the C_i contribution of the household to the MPI:

$$\forall i \in I, \qquad C_i = \begin{cases} \sum_J M_{ij} \cdot w_j \cdot HS_i \cdot HW_i, & if\ P_i = 1 \\ 0, & if\ P_i = 0 \end{cases} \qquad (4)$$

Generally, MPI and poverty headcount (H) are defined as:

$$MPI = \frac{\sum_I C_i}{\sum_I HS_i \cdot HW_i} \qquad H = \frac{\sum_I HS_i \cdot HW_i \cdot P_i}{\sum_I HS_i \cdot HW_i} \qquad (5)$$

Finally, the intensity I is obtained by calculating the ratio of MPI to headcount. Uncensored headcount (UH) considers the concentration of deprived households in an indicator: the higher the number of deprived households in an indicator, the higher the uncensored rate. MPI contribution considers the concentration of deprived and poor households in an indicator as well as the weight of the indicator.

$$UH_j = \frac{\sum_I M_i * \text{HW}_\text{i} * HS_i}{\text{HW}_\text{i} * HS_i} \qquad MPI\_Cont_j = \frac{W_j * \sum_{i=1}^{n} M_i * \text{HW}_\text{i} * HS_i * P_i}{\sum_{i=1}^{n} \text{HW}_\text{i} * HS_i} \qquad (6)$$

The MPI contribution can also be normalized, so that the sum of the MPI_Cont_j is equal to 1. This is done to easily locate the most contributing indicator and compute the percentage of its contribution relative to the other indicators.

Model 1 prioritizes addressing the indicator that has the greatest impact on the MPI initially and subsequently targets deprived households within the most contributing indicator, without consideration for cost and budget constraints. This process will be iteratively carried out until the poverty reduction target is achieved, and is outlined as follows:

$$\frac{\sum_I C_i}{\sum_I HS_i \cdot HW_i} \leq MPI_s \cdot (1 - MPI_r) \tag{7}$$

At each iteration, priority is assigned to targeting the indicator with the greatest contribution to the MPI. As noted in the preceding chapter, two configurations of that model have been set up.

In the deterministic model, the policymaker is assumed to have the capability to identify the most contributing indicator and subsequently directs attention to households experiencing severe deprivation, not only in the prioritized indicator but also across all other indicators. In this scenario, households with the highest C_i score are consistently being targeted. In contrast, the probabilistic model identifies the most contributing indicator at the outset but then employs a random targeting approach instead of focusing exclusively on the most deprived households. Consequently, the households selected for targeting may not necessarily have the highest C_i score.

The deterministic version of model 1 can be resolved in a single simulation run. Conversely, the second version lends itself to a probabilistic interpretation accommodating a more realistic scenario, in which the State is assumed to have limited information on the status of deprivation of all households across all indicators. To validate the probabilistic model results and policy recommendations, calculations should be iteratively solved. This approach, known in the literature as the Monte Carlo simulation, generates diverse outcomes by accounting for random variables, specifically within the context of targeting households within selected indicators.

Mathematically, this entails conducting additional tests to assess the robustness of outcomes. Specifically, there is a need to examine the sufficiency of the number of iterations for "random sampling". This involves testing whether the sample size is adequate to accurately represent the mean of the population, which is inherently unknown. To address this, we refer to the Central Limit Theorem (CLT):

Let $E(X) = \mu$ and $Var(X) = \sigma$. Invoking the CLT, we can write:

$$P\left(\left|\frac{\overline{X_n} - \mu}{\sigma/\sqrt{n}}\right| > z_{score}\right) = \text{Threshold} \tag{8}$$

There is approximately a 95 per cent probability that the sample mean $\overline{X_n}$ is within 1.96 $\sigma/\sqrt{n}$ units of the true mean μ. As the degree of precision increases, the threshold decreases, and the needed sample size becomes larger. Depending on the required level of precision, the minimum number of simulations, denoted as *n*, will be calculated. An in-depth interpretation of the n results can then be performed to further assess the uniqueness and robustness of the outcomes and policy recommendations. This involves observing the convergence of simulation-run results towards a consistent policy narrative. Key considerations include determining whether the poverty reduction target is consistently achieved, examining other MPI disaggregation, such as headcount poverty and intensity, and assessing the stability of the ranking of indicators that need to be targeted across all simulation runs. It is also crucial to evaluate consistency in the ranking of geographic regions in the simulation results.

B. Model 2: Household-level targeting model

The three remaining models are classified as integer linear programming given that both the objective function (OBJ) and constraints (Con) follow linear patterns, and certain decision variables take integer values. More specifically, Model 2 aims to minimize the total budget (defined as effort) allocated for poverty reduction purposes:

$$min \sum_{J} E_j \qquad \text{(OBJ 1)}$$

The objective function in those models is bound by the following constraints:

Deprivations can only be diminished and cannot be augmented:

$$\forall i \in I, \forall j \in J, N_{ij} \leq M_{ij} \qquad \text{(Con 1)}$$

Household contribution to the new MPI is then assessed and estimated. In logical form, this means:

$$\forall i \in I, \sum_{J} N_{ij} \cdot w_j \ \geq k \Rightarrow C_i = \sum_{J} N_{ij} \cdot w_j \ \cdot HS_i \cdot HW_i \qquad \text{(Con 2)}$$

$$\forall i \in I, \sum_{J} N_{ij} \cdot w_j \ < k \Rightarrow C_i = 0 \qquad \text{(Con 3)}$$

The value of the optimized allocated budget (effort) by indicator is then estimated:

$$\forall j \in J, E_j = EpF_j \cdot \sum_{I} HW_i \cdot (M_{ij} - N_{ij}) \qquad \text{(Con 4)}$$

The allocated budget is constrained by minimum and maximum thresholds, representing the upper and lower limits on the budget that the State can allocate per indicator:

$$\forall j \in J, E_j \geq l_j \qquad \forall j \in J, E_j \leq u_j \qquad \text{(Con 5 and 6)}$$

The post-optimization MPI is the sum of the contributions to the MPI by all households divided by population (statistically weighted).

$$\frac{\sum_I C_i}{\sum_I HS_i \cdot HW_i} \leq MPI_s \cdot (1 - MPI_r) \qquad \text{(Con 7)}$$

C. Model 3: Geographic targeting model

Model 3 assumes that the effort is exercised at the level of population cells (geographic region). Additional variables are introduced, and are listed in table 2.

Table 2. Nomenclature for additional variables in model 3

Input variables	Description
$\forall i \in I, \forall j \in J, R_{ij}$	A random number between 0 and 1 to determine whether the corresponding entry in the deprivation matrix will be flipped as a result of the effort exerted
D	Set of population cells
$\forall i \in I, d_i$	Population cell
$I[d]$	Set of households belonging to a population cell d (computed input)
Decision variables	Description
$\forall j \in J, \forall d \in D, E_{jd}$	Effort in corresponding indicator j and geographic cell d

Efforts are now computed at the level of population cells and indicators.

$$min \sum_J \sum_D E_{jd} \qquad \text{(OBJ 2)}$$

That function is subject to all constraints listed in model 2, with some adjustments. Most notably, constraint 4 is replaced by:

$$\forall j \in J, \forall d \in D, E_{jd} = EpF_j \cdot \sum_{I[d]} HW_i \cdot (M_{ij} - N_{ij}) \qquad \text{(Con 4*)}$$

Constraints 5 and 6 are replaced as follows:

$$\forall j \in J, \sum_{D} E_{jd} \geq l_j \qquad \forall j \in J, \sum_{D} E_{jd} \leq u_j \qquad \text{(Con 5* and 6*)}$$

Additional constraints have been introduced to address the stochastic impact of efforts E_j on indicator j and its consequential effect on household deprivation scores. The total number of flips that E_{jd} induces is E_{jd}/EpF_j flips in column j of the deprivation matrix. The probability that household i has its indicator j flipped because of effort E_j is:

$$min\left(\frac{E_{jd}/EpF_j}{\sum_{i' \in I[d_i]} M_{i'j}}, 1\right) \qquad (9)$$

Accordingly, given the random matrix R,[4] household i has its indicator j flipped because of effort E_j when the following condition holds:

$$R_{ij} \leq \frac{E_{jd}/EpF_j}{\sum_{i' \in I[d_i]} M_{i'j}} \qquad (10)$$

In logical form, those conditions translate to:

$$\forall i \in I, \forall j \in J, R_{ij} \leq \frac{\frac{E_{jd}}{EpF_j}}{\sum_{i' \in I[d_i]} M_{i'j}} \Rightarrow N_{ij} = 0 \qquad \text{(Con 8)}$$

$$\forall i \in I, \forall j \in J, R_{ij} > \frac{\frac{E_{jd}}{EpF_j}}{\sum_{i' \in I[d_i]} M_{i'j}} \Rightarrow N_{ij} = M_{ij} \qquad \text{(Con 9)}$$

These conditions guarantee that every household witnessing a deprivation in indicator j and located in a certain geographic zone has an equal likelihood of being alleviated from deprivation through an intervention.

D. Model 4: Geographic and demographic targeting model

Model 4 assumes that effort is applied at the geographic cell level for public indicators and at the type of household level for individual indicators, utilizing the same probabilistic approach as employed in model 3. The following variables are added to the list provided in models 2 and 3:

4 Each cell in this matrix is a random number generated from a uniform distribution of the interval [0,1].

Table 3. Nomenclature for additional variables in model 4

Input variables	Description
$\boldsymbol{T}$	Set of type of households
$\forall \boldsymbol{i} \in \boldsymbol{I}, \boldsymbol{t_i}$	Type of household
$\boldsymbol{I}[\boldsymbol{t}]$	Set of households belonging to the type of household t (Computed input from the clustering technique)
Decision variables	**Description**
$\forall \boldsymbol{j} \in \mathbf{U}, \forall \mathbf{t} \in \mathbf{T}, \boldsymbol{E_{jt}}$	Effort in corresponding indicator j and household type t

Let $J = U \cup V$, where U represents the index of individual indicators and V the index for public indicators; I is the index of the set of households; D is the index of the set of regions. T is the index of different types of households.

$$min\left[\sum_{j\in U}\sum_{t\in T} E_{jt} + \sum_{j\in V}\sum_{d\in D} E_{jd}\right] \tag{OBJ 3}$$

That function is subject to all the constraints found in model 2, with some additions. Most notably, the following equation is added to constraint 4*:

$$\forall j \in U, \forall t \in T, E_{jt} = EpF_{jt} \cdot \sum_{i\in I[t]} HW_i \cdot (M_{ij} - N_{ij}) \tag{Con 4**}$$

Constraints 10 and 11 are added to the model:

$$\forall \mathrm{t} \in \mathrm{T}, \forall i \in I[t], \forall j \in \mathrm{U}, \text{if } R_{ij} \leq \frac{\frac{E_{jt}}{EpF_{jt}}}{\sum_{I[t]} M_{ij}} \Rightarrow N_{ij} = 0 \tag{Con 10}$$

$$\mathrm{t} \in \mathrm{T}, \forall i \in I[t], \forall j \in \mathrm{U}, R_{ij} + bigM \cdot (1 - b3_{ij}) > \frac{\frac{E_{jt}}{EpF_{jt}}}{\sum_{I[t]} M_{ij}} \tag{Con 11}$$

3. Results

The revised Arab Multidimensional Poverty Index (MPI) comprises five dimensions and fourteen indicators, all with predefined thresholds designed to consistently capture moderate levels of multidimensional deprivation. The health and education dimensions aim to reflect the social and non-material well-being of individuals, each carrying a 25 per cent weight and consisting of three equally weighted indicators. Both dimensions have enduring impacts on various aspects of well-being, and influence individuals' cognitive abilities, knowledge, school-to-work transition, and employment opportunities. The remaining three dimensions focus on the living standards of individuals, specifically housing, access to services, and assets. These material well-being dimensions are equally weighted (1 over 6) and contribute to the overall multidimensional assessment. In alignment with the 2030 Agenda for Sustainable Development (2030 Agenda), all dimensions and indicators collectively form an integral part of the poverty assessment framework. The classification of multidimensional poverty applies to households with a weighted deprivation score (C_i) exceeding 20 per cent, chosen to better capture moderate forms of poverty. Additional details defining the framework are available in table 4. All 14 indicators are measured across five countries, except for the early pregnancy indicator of Egypt, for which there are no available data from the demographic and health survey conducted in 2014 and the household income and expenditure survey conducted in 2018.

Table 4. Revised Arab MPI framework

Dimension	Indicator	Household is deprived if
Education	School attendance	Any child in the household aged 6–18 years is not attending school and has not completed secondary education.
	Educational attainment	All household members aged 19 years and above have not completed secondary education.
	Schooling gap	Any child aged 8–18 years is enrolled at two grades or more below the appropriate grade for their age.
Access to services	Water	The household lacks any of the following: piped water into a dwelling, piped water into a yard, or bottled water.
	Sanitation	The household lacks access to improved sanitation, either entirely or shares improved facilities with other households.
	Electricity	The household does not have access to electricity.
Health and nutrition	Child mortality	A child in the household has passed away before reaching the age of 5 within the last five years.

Dimension	Indicator	Household is deprived if
	Child nutrition	Any child (0–59 months) is stunted (height for age < -2) or any child is underweight (weight for age < -2).
	Early pregnancy	Any women aged 15–24 years in the household experienced childbirth before reaching the age of 18. (This indicator is omitted in Egypt 2014 and 2018 for lack of data).
Housing	Overcrowding	There are three or more individuals aged 10 years or older per sleeping room in the household.
	Dwelling	The housing situation satisfies at least one of the following conditions: (i) the residence is a place other than a stand-alone house or apartment, (ii) it has a non-permanent floor, or (iii) it has a non-permanent roof.
Assets	Communication assets	The household has no phone (mobile or landline), television or computer.
	Livelihood assets	Despite having access to electricity, the household has no refrigerator, washing machine, any type of heater, or any type of air conditioning or cooler.
	Mobility assets	The household does not own a car/truck, motorbike or bicycle.

Source: Economic and Social Commission for Western Asia (ESCWA), Proposal for a revised Multidimensional Poverty Index for Arab countries, 2020.

The revised Arab MPI framework, unlike the global MPI, focuses on capturing deprivations more specific to Arab middle-income countries rather than acute or extreme poverty. Additionally, Sustainable Development Goal (SDG) target 1.2 mandates that by 2030, Governments must strive to reduce, at least by half, the proportion of men, women and children of all ages living in poverty across all its dimensions, as per national definitions. The global MPI framework is not aligned with this objective, and is especially incongruent in the context of middle-income countries. This misalignment is a significant factor prompting the authors to opt for a revised framework that closely adheres to the SDG definition.

Aligning development policies and programmes with these poverty indices can enhance the design of targeted initiatives and address the severity and multidimensional definition of poverty. Any poverty reduction strategy in the region should prioritize stability and security, and should recognize that recurrent episodes of conflict and violence hinder poverty alleviation efforts. The present study covers four middle-income Arab countries (Algeria, Egypt, Iraq and Tunisia), and one lower-income country (Mauritania).

For each available survey year between 2010 and the outbreak of COVID-19 in 2020, MPI measurements were conducted for each country using the same benchmark framework. Acknowledging the evolving nature of poverty definitions with economic development, the authors opted for an absolute poverty definition, allowing for consistent measurement against the same benchmark over a relatively short period (decade) and across countries. The surveys utilized for calculating the revised Arab MPI for each country are detailed in table 5, with two measurements per country conducted at different time points.

Table 5. Available household surveys per country over the period 2010-2020

Country	Survey year one	Survey year two	MPI year one	MPI year two
Tunisia	Multiple Indicator Cluster 2011	Multiple Indicator Cluster 2018	0.063	0.040
Iraq	Multiple Indicator Cluster 2011	Multiple Indicator Cluster 2018	0.166	0.120
Algeria	Multiple Indicator Cluster 2013	Multiple Indicator Cluster 2019	0.103	0.054
Egypt	Demographic and Health 2014	Household Income, Expenditure and Consumption 2018	0.061	0.044
Mauritania	Multiple Indicator Cluster Survey 2011	Multiple Indicator Cluster Survey 2015	0.458	0.429

Source: ESCWA calculations.

Except for Mauritania, no country conducted a survey in 2015, making it challenging to measure progress in the MPI from 2015 to 2030. To address this issue, the authors advocate for a more pragmatic approach that recognizes the observed changes made in certain countries (e.g., Algeria) beyond 2015. The proposed targets required to meet the SDG target in 2030 for each country, based on the most recent observed survey year, are outlined in table 6. For instance, in Algeria, achieving a 50 per cent reduction in MPI between 2015 and 2030 (considering the newly computed and interpolated MPI in 2015) requires a 20 per cent reduction in the MPI index from 2019 (the latest observed survey in that country) to 2030. This reduction reflects the observed and achieved improvements between 2015 and 2019.

Table 6. SDG 2030 targets by country

Country	MPI in year 2015 (under the assumption of linear interpolation)	MPI reduction by half in 2030 (from baseline year 2015)	Adjusted target (relative change needed from latest observed survey) (per cent)
Tunisia	0.050	0.025	37.85
Iraq	0.139	0.070	41.75
Algeria	0.086	0.043	20.42
Egypt	0.057	0.028	35.96
Mauritania	0.429	0.215	50.00

Source: ESCWA calculations.

In this paper, model 1 is applied to survey data from five countries, and the results presented below reflect the application of this model.

Applying model 1 serves two primary objectives:

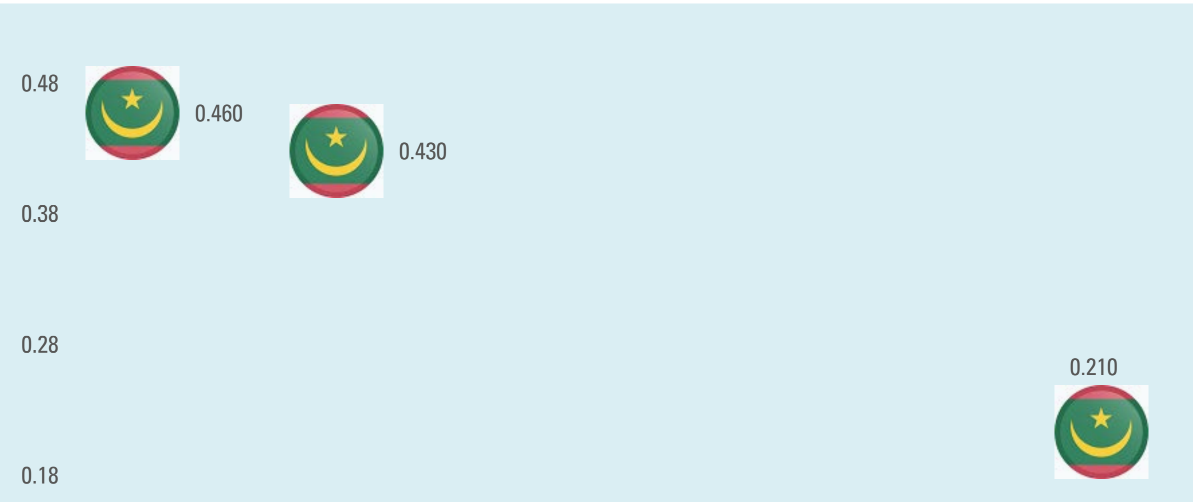
Firstly, the model is applied for out-of-sample testing to evaluate its performance against observed changes. It is applied individually for each country, spanning the period between the two observed survey years. The first observed survey year serves as the baseline year, with the MPI reduction target set to be achieved in the second observed year. Taking Algeria as an example, the MPI index has diminished by 47 per cent in relative terms between the observed years of 2013 and 2019. This reduction renders its MPI value in the year 2019 (where the subsequent survey has been recorded) equal to 0.054, which is the MPI value that should be achieved post-optimization. Out-of-sample testing is typically conducted in forecasting analyses to compare model results with observed data that were not used in parameterizing the model. In this analysis, the observed poverty measures in the second observed year for all countries may not necessarily result from sound policy options applied during the inter-survey period.

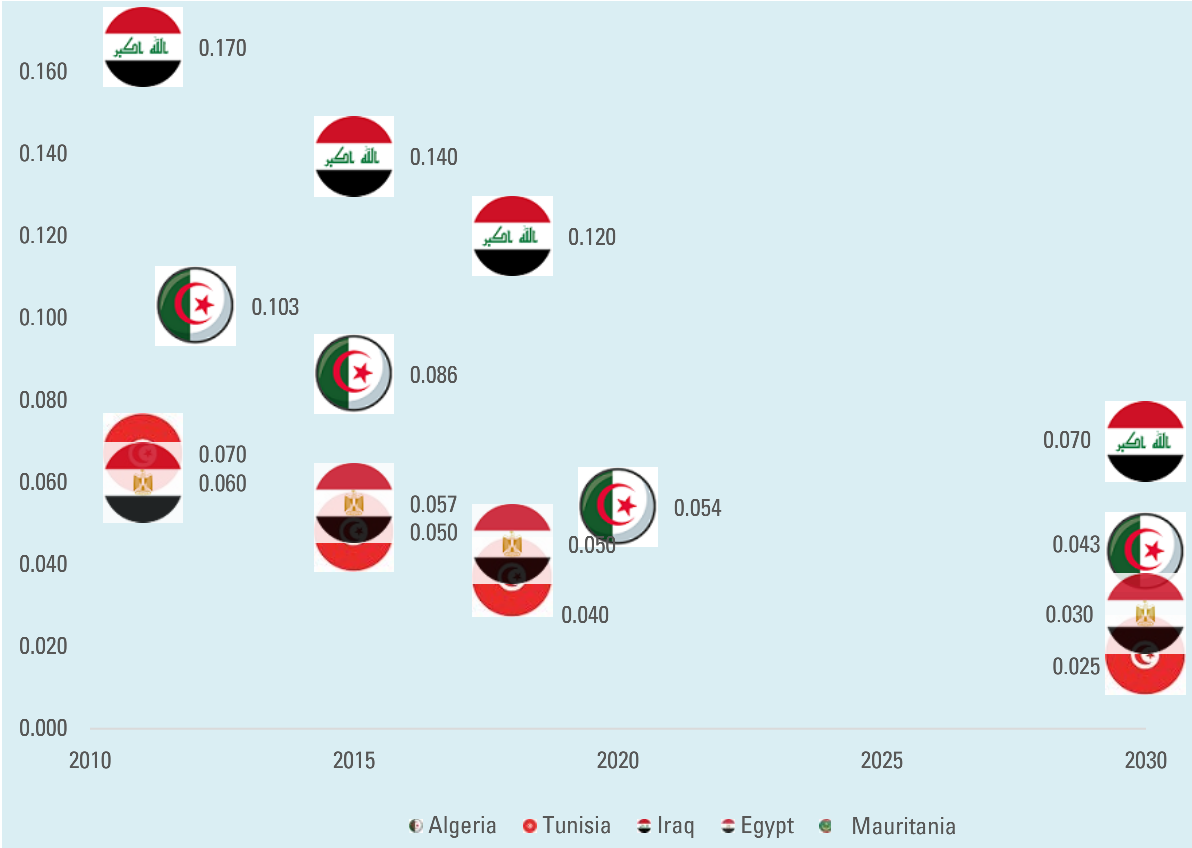
This evaluation helps compare the evolution of the MPI as measured by surveys with the results of the optimization model. In an ideal scenario, which disregards external factors and focuses on the most contributing MPI indicators, the Alkire–Foster method is designed to guide policymakers towards the most optimized approach for reducing MPI.

External factors are fundamentally linked to State capability, resources and efforts at hand (as defined in previous sections in models 2, 3 and 4). Any external factor, such as war or political instability, enforced on the business-as-usual conditions in that country over time, can also impact the results.

Secondly, the optimization routine is also applied to investigate the feasibility of reaching SDG target 1.2 by 2030. This exploration aims to identify the most appropriate targeting paths that policymakers should adopt from the latest observed survey onwards.

Figure 1. MPI time trend





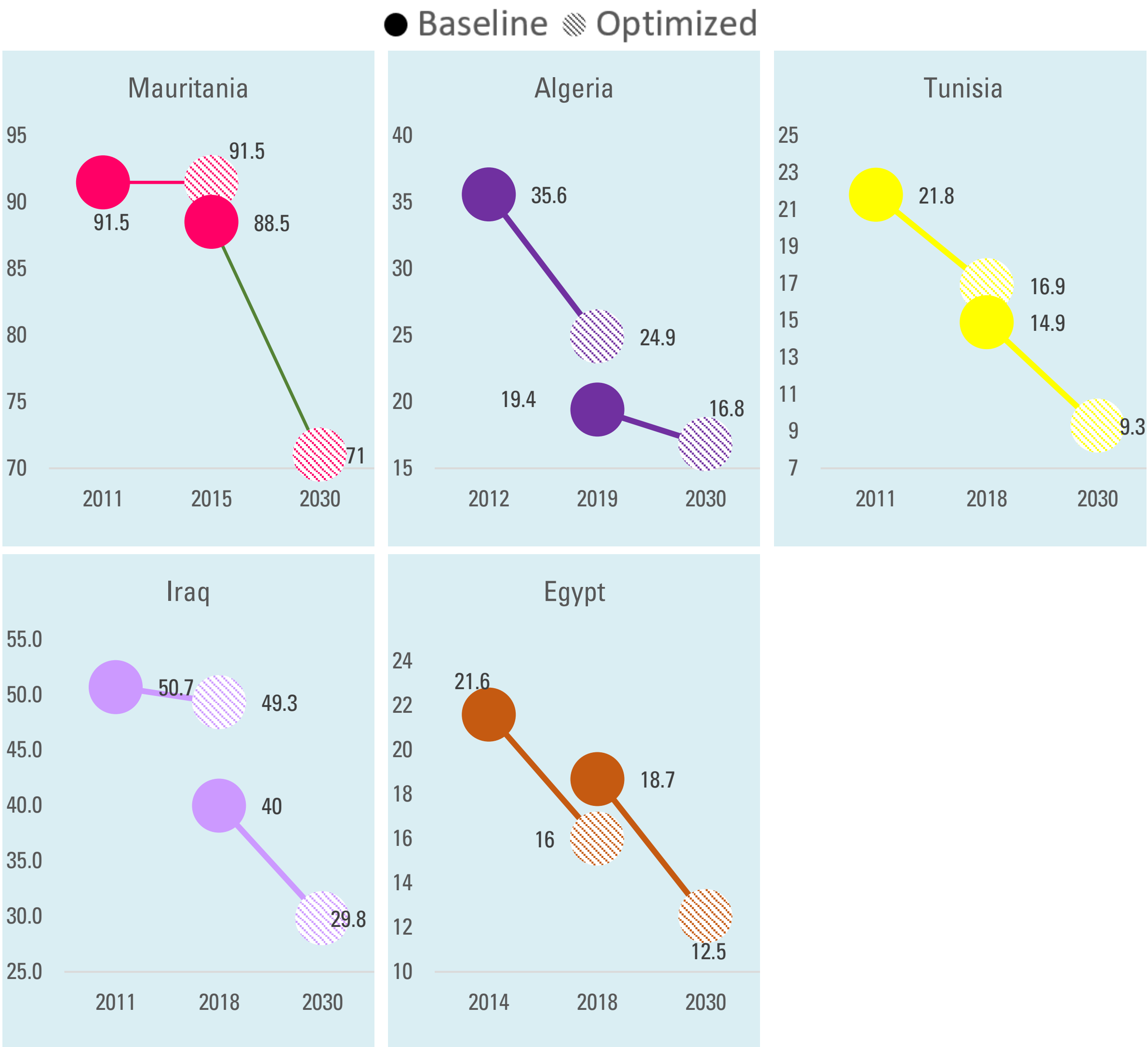
Source: ESCWA calculations.

Comparing results between both observed surveys:

By observing the declining trend in MPI values between the surveyed periods (table 5), it becomes apparent that all five countries have made progress in reducing poverty. While the degree of improvement varies among countries, the percentage change indicates a noticeable reduction in multidimensional poverty, especially in the four middle-income countries: Algeria, Tunisia, Egypt and Iraq, ranked in descending order based on the magnitude of poverty reduction.

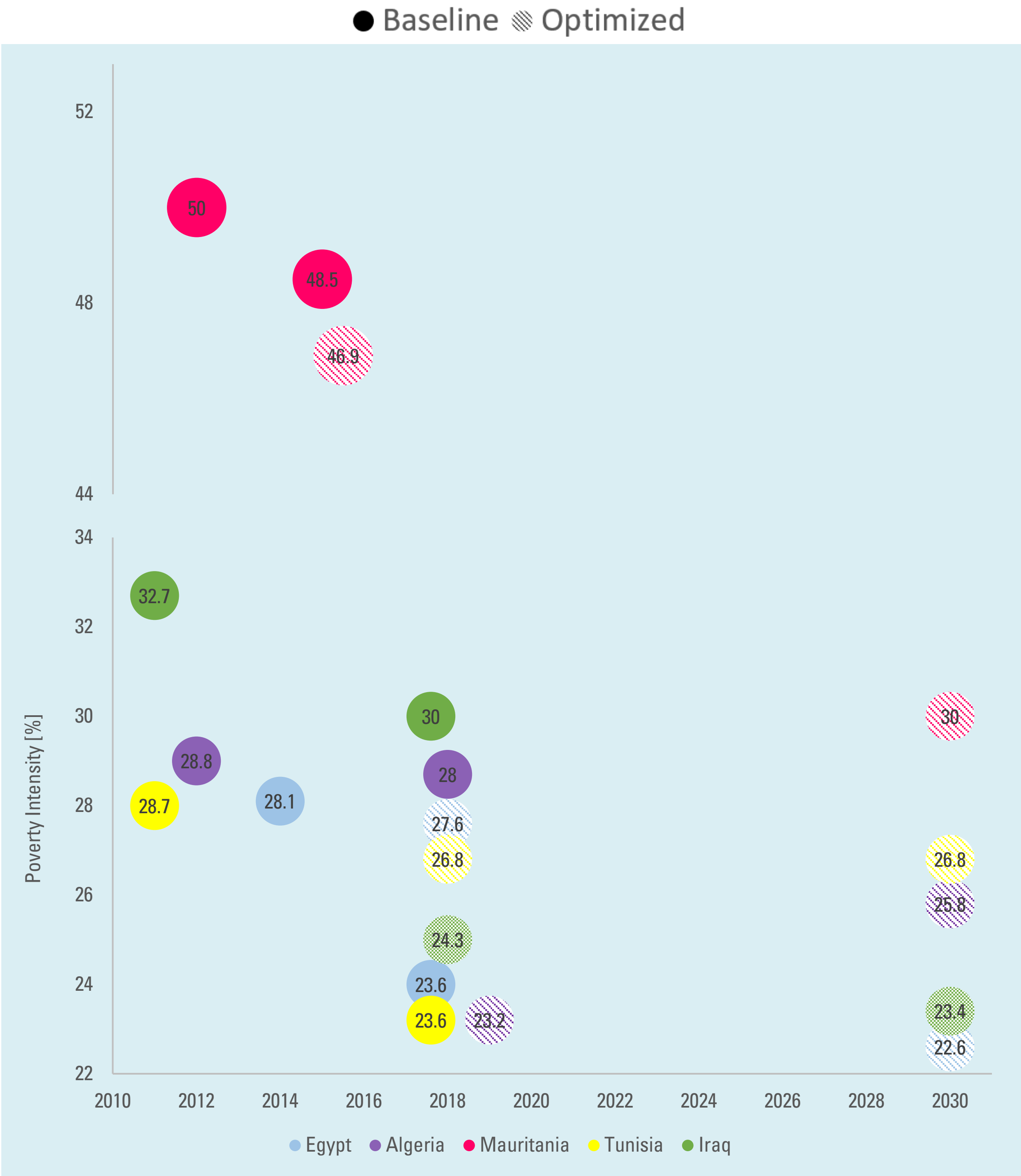
The poverty threshold remains constant throughout the inter-survey period. As previously emphasized, this consistency is vital for comparability purposes and ensures a uniform measurement across space and time. When comparing the levels recorded in the initial year of observation with those in the subsequent year spanning from 2010 to 2020, most countries exhibit a decrease in the poverty headcount ratio (figure 2). In terms of absolute difference, Algeria stands out with the most substantial decline in the headcount ratio, dropping from 35.6 per cent to 19.4 per cent. Algeria has made the most progress in reducing its MPI and headcount values. The narrative takes a nuanced turn when interpreting the evolution of poverty intensity over time (figure 3). Algeria ranks lowest among the five countries in terms of the relative improvement in intensity over the period. This suggests that the majority of the MPI reduction is attributed to individuals transitioning out of poverty. However, those remaining classified as poor have not experienced substantial improvement, and the poverty gap has remained relatively consistent, decreasing only from 28.8 per cent to 28 per cent. Another noteworthy finding is that the reduction in poverty headcount is more significant in relative terms for all countries across time, when compared with the reduction in poverty intensity. Nevertheless, the ongoing reduction in both poverty intensity and headcount ratio throughout this period for all countries remains significant. Operating within the framework of the Alkire-Foster method, where the MPI is the product of both poverty headcount and deprivation intensity, any alteration in the deprivation status of one or multiple households consistently results in a more substantial MPI reduction if it concurrently leads to a change in the households' poverty status.

Figure 2. Poverty headcount time trend - observed vs. simulation (Percentage)



Source: ESCWA calculations.

Figure 3. Intensity of poverty time trend - observed vs. simulation (Percentage)



Source: ESCWA calculations.

Comparing results between out-of-sample results and the first observed survey:

The out-of-sample (optimized) results for the countries' second survey years reveal that nearly all countries, with the exception of Egypt, exhibit higher poverty headcount ratios when compared to the observed results for those survey years (figure 2 and table 7). When comparing the results of both observed years as scenario one, and the optimized results of year 2 against the baseline results of year 1 as scenario two, it becomes evident that Egypt has experienced a more substantial poverty reduction in the second scenario, with a 5.9 per cent reduction in absolute difference terms, in contrast to the 2.9 per cent reduction observed in the first scenario. However, the opposite holds true for the remaining four countries (Algeria, Iraq, Mauritania and Tunisia) (figure 3).

Table 7. Poverty headcount (H) and intensity (I) results for various scenarios across the five countries

Scenario	Country	Mauritania	Egypt	Algeria	Tunisia	Iraq
1	Delta H - observed Y2 vs. observed Y1	-3	-2.9	-16.2	-6.9	-11
2	Delta H - optimized Y2 vs. observed Y1	0	-5.6	-10.7	-4.9	-1
1	Delta I - observed Y2 vs. observed Y1	-1.5	-4.5	-0.8	-1.9	-3
2	Delta I - optimized Y2 vs. observed Y1	-3.1	-0.5	-5.6	-5.1	-8

Source: ESCWA calculations.

This implies that, among the targeted deprived households in Egypt, more often than not (in probabilistic terms), these households are successfully being lifted out of poverty. In the remaining countries, while certain deprivations are alleviated and a reduced level of multidimensional deprivation is recorded among the poor, the probability of successfully transitioning out of poverty is comparatively lower than that recorded in Egypt. One plausible explanation for this phenomenon is that a significant proportion of Egyptian individuals living in poverty are situated near the poverty line threshold. Scrutinizing poverty intensity in all countries at their first survey year baseline shows that Egypt has the lowest intensity. Consequently, even minor changes in the welfare status of these individuals, whether an improvement or regression, directly impact their poverty status, which either results in transitioning out of or descending into poverty.

Taking a closer look at the uncensored headcount time trend, which measures the share of the total population deprived in an indicator across indicators, and comparing the results of the baseline year (first observed survey year) with the optimized results for the second survey year (figures 4 to 8), the following observations can be made:

- For all countries, it is evident that the age schooling gap indicator is consistently being targeted.
- The model consistently targets the indicators of mobility assets, overcrowding and school attendance in middle-income countries.

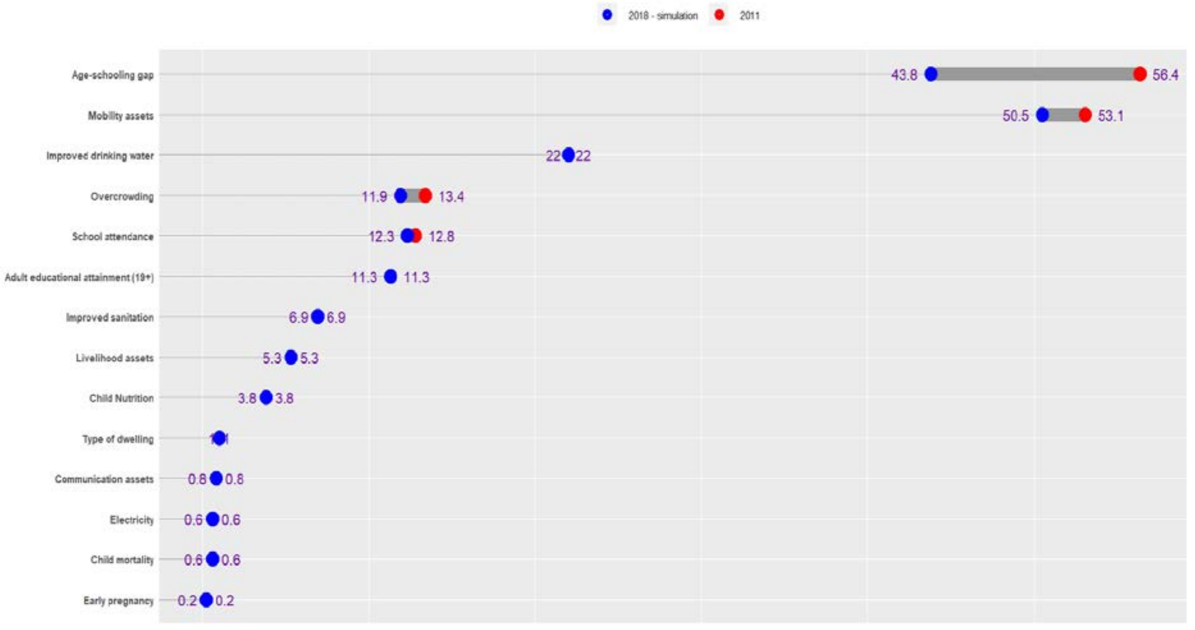
When comparing the results of the uncensored headcount ratios across indicators in the second observed year (figures 9 to 13) and comparing them with the optimized results (figures 4 to 8), the following observation can be made:

- The model almost does not target households that are experiencing deprivations in the dimensions of access to services and health and nutrition. This suggests that the model does not consider household deprivations in indicators such as drinking water, sanitation, electricity, child nutrition, child mortality and early pregnancy. Consequently, there is no change in deprivation levels in those indicators as per the model's targeting approach.

Figure 4. Uncensored headcount changes in Mauritania from 2011 to 2015 – simulation results

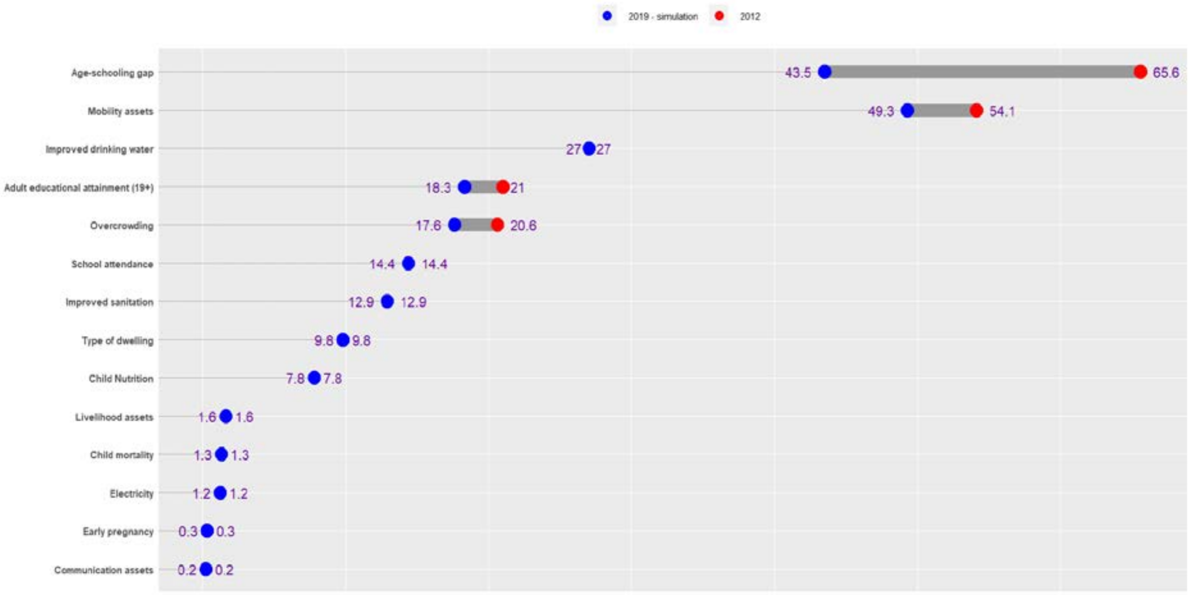
Source: ESCWA calculations.

Figure 5. Uncensored headcount changes in Tunisia from 2011 to 2018 – simulation results



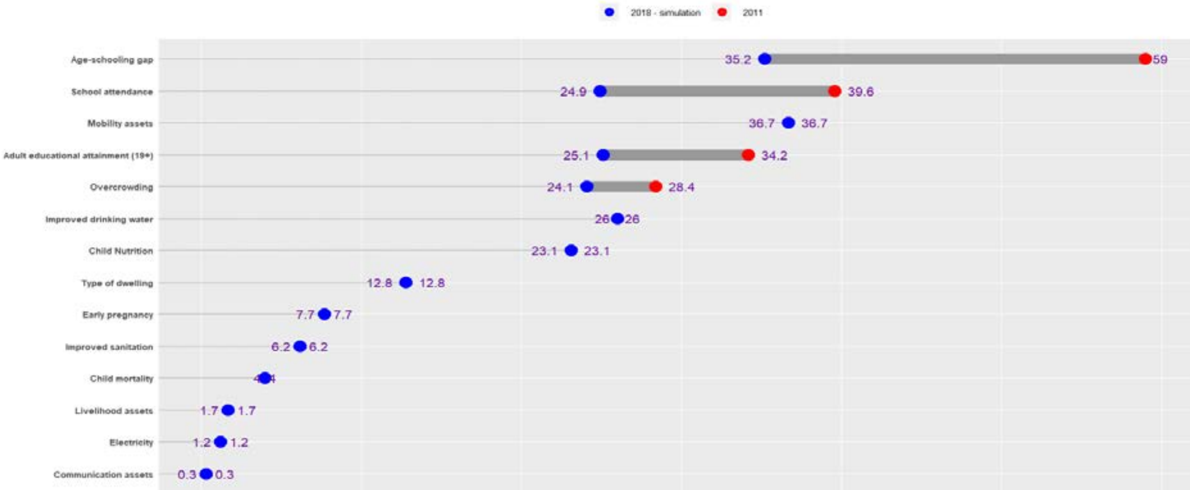
Source: ESCWA calculations.

Figure 6. Uncensored headcount changes in Algeria from 2012 to 2019 – simulation results



Source: ESCWA calculations.

Figure 7. Uncensored headcount changes in Iraq from 2011 to 2018 – simulation results



Source: ESCWA calculations.

Figure 8. Uncensored headcount changes in Egypt from 2014 to 2018 – simulation results

Source: ESCWA calculations.

The primary focus of targeting is concentrated in the education dimension (specifically age schooling gap indicator), followed by the assets and housing dimensions. If the available survey data had allowed for the inclusion of indicators on education quality, deprivations might have increased further. Persistent deficits in the quality of education and knowledge over the years have played a role in widening the skills and knowledge gaps between education and labour market outcomes. The primary reason lies in the design of the model, which directs its indicator targeting approach towards the dimensions/indicators that contribute the most to the MPI. Figure 14 shows that the education dimension is the leading contributor to the MPI in the first survey year across the five countries.

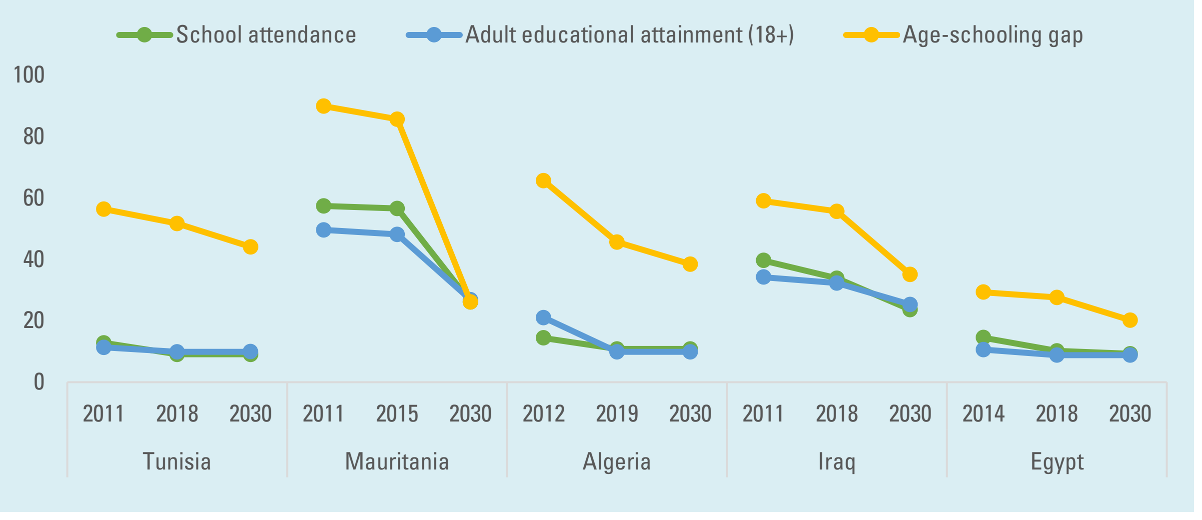
Trends in poverty measures (2010-2030):

Figures 1 to 14 offer valuable insights into crucial metrics such as MPI, poverty headcount ratio, intensity of poverty, uncensored headcount by indicator, and MPI contribution by dimension. These figures span the time frame from 2010 to 2030 and focus on five chosen Arab countries. The country-specific trendline begins with data points that reflect results from the two observed survey years, while the 2030 values correspond to the optimized results.

While MPI, poverty headcount and poverty intensity show a decreasing trend across the observed years for all countries, this is not uniformly reflected in figures 9 to 13. Not all indicator-specific uncensored headcount ratios exhibit a decline over the specified period. In particular, the provision of drinking water poses a persistent nationwide challenge (figure 10) for Tunisia, Algeria and Egypt, with its uncensored poverty headcount experiencing an increase during the initial two periods of the time trend.

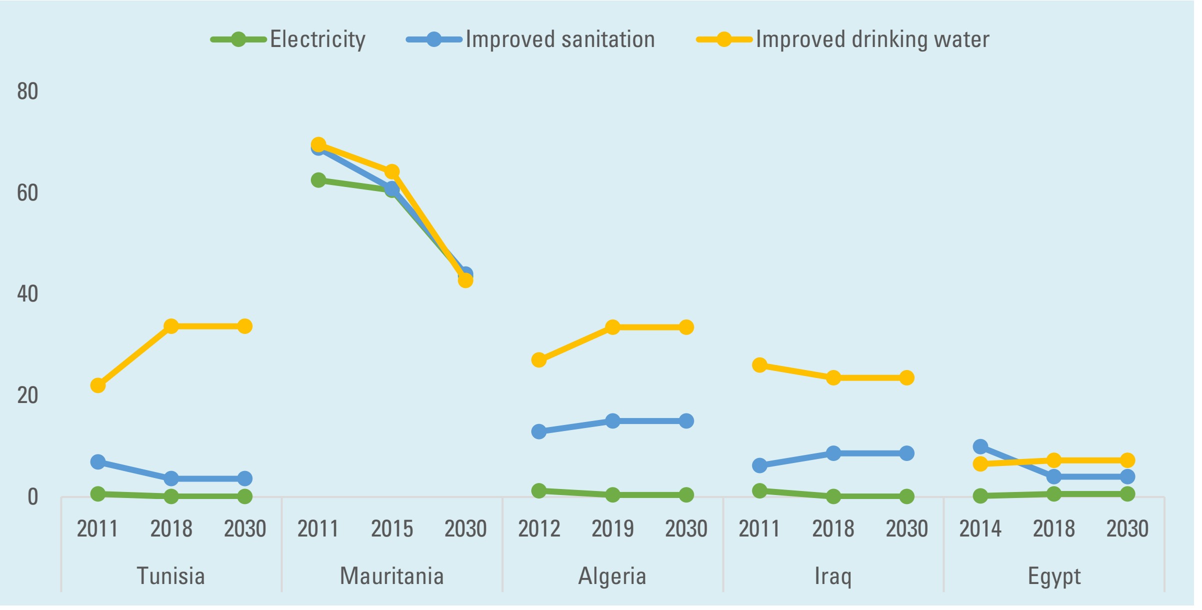
This implies that during the inter-survey period, the sector may have encountered challenges either as a result of insufficient policy and investment emphasis from the respective Governments or due to the fact that it was not considered a policy priority. In either case, some households have witnessed a deterioration in their welfare conditions over this time. However, according to the optimization findings, a decrease in indicator-specific welfare conditions for households cannot technically happen. Welfare levels can only be improved by directing efforts towards deprived households, effectively eliminating their deprivation. Some households might also be considered ineligible for targeting, which would allow their deprivation to persist.

Figure 9. Uncensored headcount time trend by indicator [education dimension] and country - 2011 to 2030



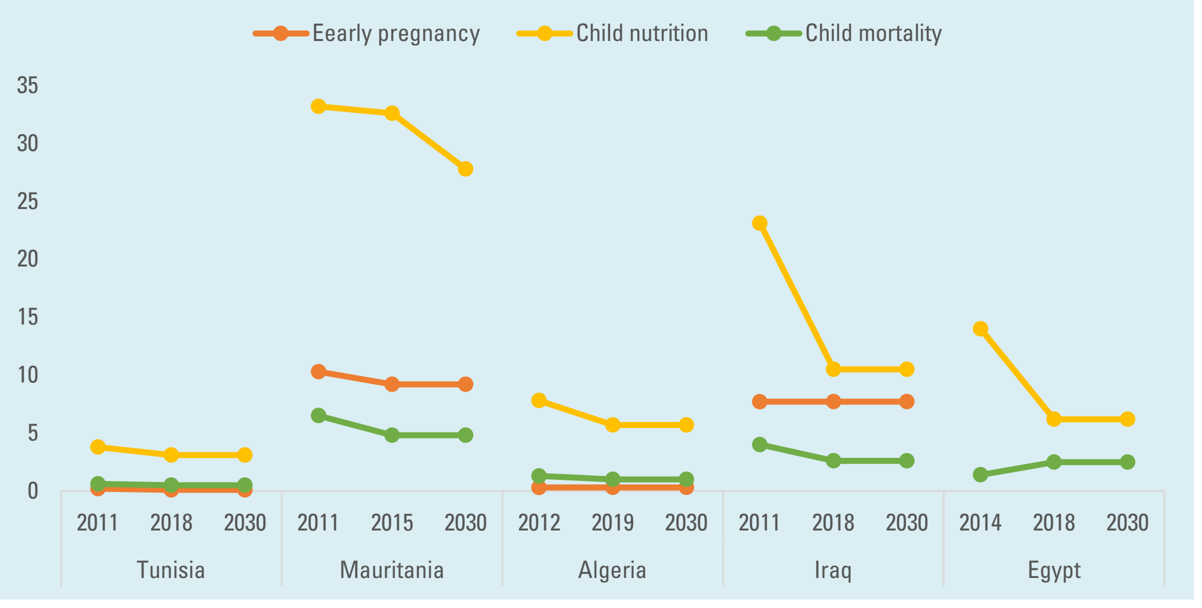
Source: ESCWA calculations.

Figure 10. Uncensored headcount time trend by indicator [access to services dimension] and country - 2011 to 2030



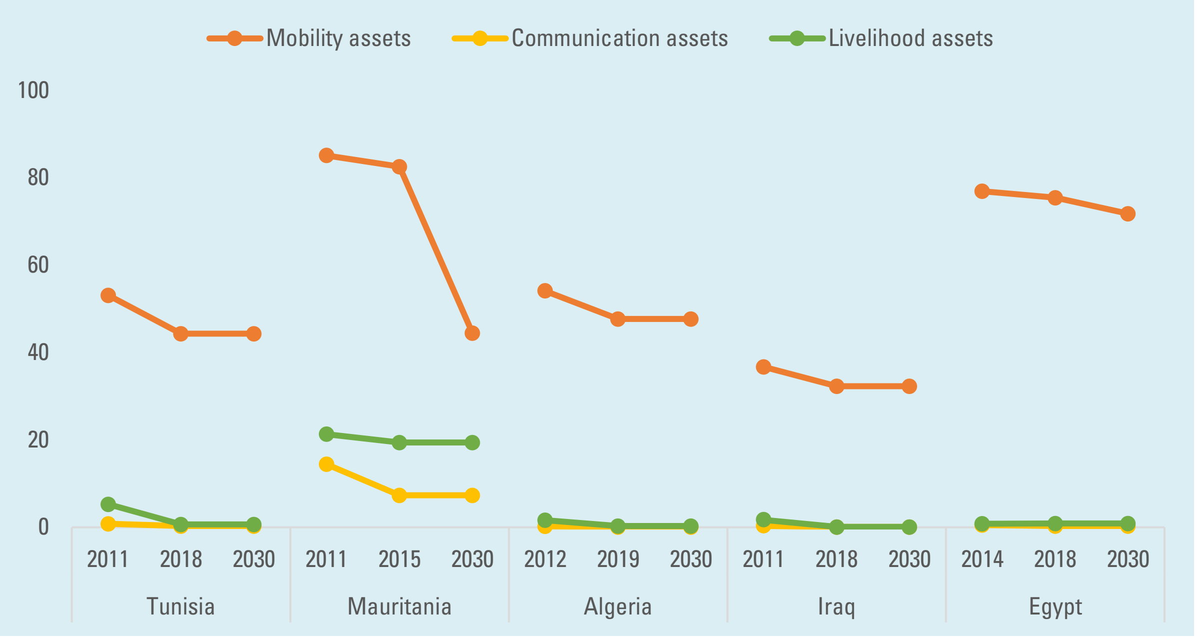
Source: ESCWA calculations.

Figure 11. Uncensored headcount time trend by indicator [health and nutrition dimension] and country - 2011 to 2030



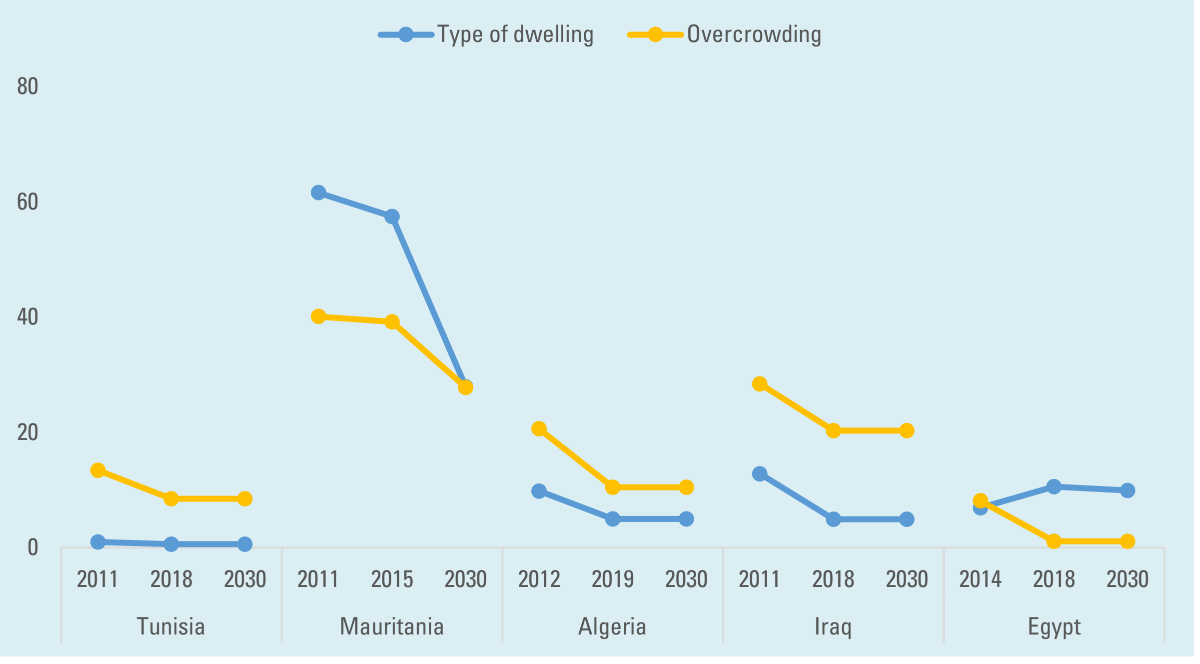
Source: ESCWA calculations.

Figure 12. Uncensored headcount time trend by indicator [assets dimension] and country - 2011 to 2030



Source: ESCWA calculations.

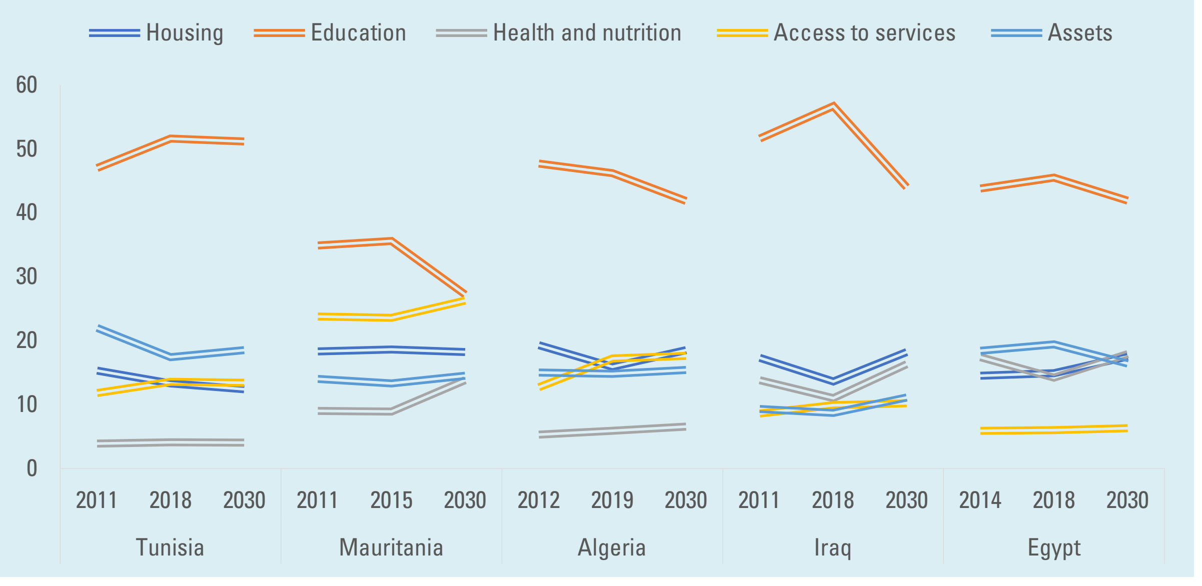
Figure 13. Uncensored headcount time trend by indicator [housing dimension] and country - 2011 to 2030



Source: ESCWA calculations.

The 2030 results appear promising, as they reveal a consistent decreasing trend in all countries and across various poverty measures. Households experiencing deprivations in all three indicators within the education dimension consistently observe a reduction over the period until 2030 in all five countries. This underscores the imperative for policymakers to prioritize the education sector if they aim to achieve SDG target 1.2. The outcomes for the year 2030, as illustrated in figure 14, indicate a decline in the MPI percentage contribution for the education dimension across all countries. This trend is attributed to the optimization model's focused targeting of households deprived of education-related indicators. Notably, this dimension holds the highest contribution to the MPI in both observed survey years for all countries. However, for the lower-income country of Mauritania, enhancement in the education sector alone is insufficient. To achieve their SDG target by 2030, Mauritanian policymakers must address all indicators within the education, housing and access to services sectors/dimensions. They should also focus on enhancing the health and well-being of children, particularly by improving their nutrition. The model also indicates that policymakers in both Egypt and Mauritania should address the mobility assets indicator to ensure the attainment of their SDG targets.

Figure 14. MPI percentage contribution time trend by dimension and country



Source: ESCWA calculations.

4. Conclusion

The present study marks an initial formalized effort to assist national planners in identifying tailored interventions for prioritizing household-level support to tackle multidimensional poverty. Our findings indicate that successful characterization and resolution of new multidimensional poverty reduction models can be achieved to challenge some of the rigid assumptions in micro-simulation regarding States' capacity to target impoverished households and customize assistance. Within the Arab region, the standard no-cost model is applied across five countries with middle and low incomes. For each country, the analysis delves into two observed survey years covering the period from 2010 to the onset of the COVID-19 outbreak in 2020. The MPI measurements are conducted using the revised Arab MPI framework. While acknowledging the evolving nature of poverty definitions, the authors choose an absolute constant poverty definition over time for consistency purposes.

The application of the model serves two primary objectives. The first is to conduct out-of-sample testing and evaluate its performance against observed changes. The model spans the period between the two observed survey years, with the MPI value from the first year serving as the baseline. The level of the MPI value in the second observed year is set as the target for attainment. A second optimization routine is employed to track poverty measurements against SDG target 1.2 by the year 2030, suggesting optimal targeting paths for policymakers to adopt. To the best of the authors' knowledge, this manuscript represents the first attempt in the literature to track multidimensional poverty over the two-decade span from 2010 to 2030.

Comparing results between observed surveys over the first decade reveals a significant reduction in both poverty intensity and the headcount ratio across all countries, albeit at different paces. This consistent observation offers valuable insights and underscores the fact that effective reduction in the MPI is achieved as changes in the deprivation status of households align with shifts in their poverty status. While MPI, poverty headcount, and poverty intensity exhibit a decreasing trend across the observed years for all countries, it is worth noting that not all uncensored headcount ratios by indicator demonstrate a decline. Particularly, access to drinking water remains a persistent challenge, with its uncensored poverty headcount increasing during the initial two periods of the time trend for most middle-income countries.

Analysing out-of-sample results shows that the primary emphasis in targeting is on the education dimension, particularly the schooling gap indicator, followed by the assets and housing dimensions. The model tends to overlook households facing deprivations in access to services, and health and nutrition dimensions, leading to no change in deprivation. This is ascribed to the model's design, which steers its indicator targeting towards dimensions with the greatest contribution to the MPI.

By putting SDG target 1.2 to the test and quantifying the necessary measures to achieve it, the results indicate that all four middle-income countries can efficiently reduce half the proportion of their citizens living in poverty across all dimensions by concentrating solely on the single dimension of education. However, Egypt must also prioritize the mobility asset indicator to ensure the attainment of its target. In contrast, Mauritania must target almost 10 out of the 14 indicators to achieve its target optimally.

Annex. Methods

The linear equivalent for some of the constraints shall be derived. We note the following equivalence:

$A \Rightarrow B \equiv B \vee \neg A$

Therefore enforcing $A \Rightarrow B$ is equivalent to enforcing $B \vee \neg A$. The latter is enforced if at least one of the two sides of the "or" relation is imposed.

Starting with model 1, constraints 2 and 3 are displayed in logical form. Constraint 2 is equivalent to:

$$\forall i \in I, \left(C_i = \sum_J N_{ij} \cdot w_j \ \cdot HS_i \cdot HW_i \right) \vee \left(\sum_J N_{ij} \cdot w_j \ < k \right)$$

which is equivalent to the following three linear constraints, where $b1_i$ refers to binary decision variables and $bigM$ is a sufficiently large number:

$$\forall i \in I, C_i + bigM \cdot b1_i \geq \sum_J N_{ij} \cdot w_j \ \cdot HS_i \cdot HW_i \qquad \text{(Lin 1)}$$

$$\forall i \in I, C_i - bigM \cdot b1_i \leq \sum_J N_{ij} \cdot w_j \ \cdot HS_i \cdot HW_i \qquad \text{(Lin 2)}$$

$$\forall i \in I, \sum_J N_{ij} \cdot w_j - (1 - b1_i) \cdot bigM < k \qquad \text{(Lin 3)}$$

and where $b1_i$ refers to the binary decision variables required to transform logical constraints into linear constraints.

The logic behind this equivalence is the following: When $b1_i = 0$, *(Lin 1)* and *(Lin 2)* are imposed with a neutralized effect of $bigM$, and *(Lin 3)* is always true, this equivalently imposes the first element of the "or" relation in constraint 2 while relaxing the second element. When $b1_i = 1$, *(Lin 1)* and *(Lin 2)* are always true and *(Lin 3)* is imposed with a neutralized effect of $bigM$, this equivalently relaxes the first element of the "or" relation in constraint 2 and imposes the second element.

Constraint 3 is equivalent to:

$$\forall i \in I, (C_i = 0) \vee \left(\sum_J N_{ij} \cdot w_j \ \geq k \right)$$

The above constraint is equivalent to the following two linear constraints, where $b2_i$ refers to binary decision variables and $bigM$ is a sufficiently large number:

$$\forall i \in I, C_i - bigM \cdot b2_i \leq 0 \qquad \text{(Lin 4)}$$

$$\forall i \in I, \sum_J N_{ij} \cdot w_j \ + bigM \cdot (1 - b2_i) \geq k \qquad \text{(Lin 5)}$$

and where $b2_i$ refers to the binary decision variables required to transform logical constraints into linear constraints.

The logic behind this equivalence is the following:

When $b2_i = 0$, *(Lin 4)* is imposed with a neutralized effect of $bigM$ and *(Lin 5)* is always true, this equivalently enforces the first element in the “or” relation in constraint 3 and relaxes the second element. In fact, this imposes $C_i \leq 0$, but given that C_i is defined as a continuous decision variable with a minimum of 0, then this imposes that $C_i = 0$. When $b2_i = 1$, *(Lin 5)* is imposed with a neutralized effect of $bigM$ and *(Lin 4)* is always true, this equivalently enforces the second element in the “or” relation in constraint 3 and relaxes the first element.

Looking at the linear representations of constraints 2 and 3, identified above as *(lin 1 to 5),* one can notice that $b2_i$ can be replaced by $(1 - b1_i)$ to reduce the number of decision variables.

For model 2, in addition to constraints 2 and 3, which are linear equivalents, constraints 8 and 9 must be linearized as follows. Constraint 9 can be written as:

$$\forall i \in I, \forall j \in J, (N_{ij} = 0) \ \vee \left(R_{ij} > \frac{\frac{E_j}{EpF_j}}{\sum_{i' \in I[d_i]} M_{i'j}} \right)$$

This is equivalent to the following two linear constraints where $b2_{ij}$ refers to binary decision variables:

$$\forall i \in I, \forall j \in J, N_{ij} - bigM \cdot b2_{ij} \leq 0 \qquad \text{(Lin 6)}$$

$$\forall i \in I, \forall j \in J, \frac{E_j}{EpF_j \sum_{i' \in I[d_i]} M_{i'j}} - bigM \cdot \left(1 - b2_{ij}\right) < R_{ij} \quad \text{(Lin 7)}$$

Constraint 8 can be written as:

$$\forall i \in I, \forall j \in J, (N_{ij} = M_{ij}) \vee \left(R_{ij} \leq \frac{\frac{E_j}{EpF_j}}{\sum_{i' \in I[d_i]} M_{i'j}} \right)$$

This is equivalent to the following three linear constraints where $b3_{ij}$ refers to binary decision variables and $bigM$ is a sufficiently large number:

$$\forall i \in I, \forall j \in J, N_{ij} + bigM \cdot b3_{ij} \geq M_{ij} \quad \text{(Lin 8)}$$

$$\forall i \in I, \forall j \in J, N_{ij} - bigM \cdot b3_{ij} \leq M_{ij} \quad \text{(Lin 9)}$$

$$\forall i \in I, \forall j \in J, \frac{E_j}{EpF_j \sum_{i' \in I[d_i]} M_{i'j}} + bigM \cdot \left(1 - b3_{ij}\right) \geq R_{ij} \quad \text{(Lin 10)}$$

Looking at the linear representations of constraints 10 and 11, identified above as *(lin 6 to 10)*, one can notice that $b3_{ij}$ can be replaced by $\left(1 - b2_{ij}\right)$ to reduce the number of decision variables.

For model 3, constraints 11 and 12 must be linearized as well, in the same manner as constraints 8 and 9, noting however that the probabilistic narrative is now attributed to the household type cell $I[t]$ instead of the geographic cell $I[d_i]$.

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The Arab region continues to suffer from recurring conflicts and crises, characterized by socioeconomic shocks, such as negative growth, State budget deficits, rise in welfare inequality along various dimensions, and shrinking economy and welfare state. Living standards of various socioeconomic classes are held back along multiple dimensions. Without adequate measurement, policies used to alleviate the problem may lead the society off course, as efforts implemented by policymakers may involve poor targeting, misdirection or over/under-allocation of scarce resources. Recognizing the significance of measuring poverty in the Arab region and the imperative to continuously monitor progress towards the Sustainable Development Goals (SDG)—specifically SDG target 1.2, the application of several optimization models to five Arab countries (Algeria, Egypt, Iraq, Mauritania and Tunisia) is introduced.

Outlined in the present paper are several models of State intervention, encompassing the capacity of States to allocate resources and the proficiency of policymakers in transferring these resources to households that require them the most. We evaluate a standard equal costs model's performance against the observed changes in households' multidimensional deprivations. For each country, the model spans the period between two observed surveys, with the first serving as the baseline and the poverty reduction target set to be achieved by the time of the second survey. The analysis corroborates that the conditions and policies on the ground in each country have been directed towards addressing a number of key challenges, in the areas of age schooling gap, school attendance, mobility assets, and overcrowding. By contrast, the analysis suggests that policymakers in Arab middle-income countries should prioritize directing their resources towards the education sector, while those in lower-income countries such as Mauritania should address deprivations in education, housing and access to public services.

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