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Making the CAADP BR Forward Looking

A Decision Support Tool for Transforming African Agrifood systems

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INTERNATIONAL FOOD POLICY RESEARCH INSTITUTE

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ABSTRACT

This paper presents an Excel-based interactive decision-support tool that policymakers and development practitioners can use to evaluate policy options to achieve targeted outcomes of the Malabo Declaration at the country level. The tool is based on a partial equilibrium simulation model that allows the user to simulate different scenarios based on the desired level of change in one outcome or more. For each scenario that is created, the simulated results provide information on the level of change required in each of the policies included in the model, the level of change in the other outcomes included in the model, and the allocation of the resources provided, including reallocation of some of the existing resources. A prototype of the tool that is developed using the fourth biennial review (BR) data on Ghana, which has some quality issues, is presented to demonstrate the potential features and utility of the tool.

Limitations of the model and further work that is required to develop the actual tool for reliable policy evaluation are discussed. The latter includes using accurate data on the various indicators and expanding it to cover more years, in addition to developing a web-based interactive version of the tool.

Keywords: CAADP, decision support, Malabo declaration, policy evaluation, public expenditure

ACKNOWLEDGEMENTS

Funding for this work is from the Bill and Melinda Gates Foundation via the Akademiya2063-IFPRI joint project on Biennial Review and Data Systems Strengthening. The motivation for this work dates to the early years of CAADP and in the mid-2000s when I, considering myself an applied econometrician, had joined IFPRI and was part of a small group of researchers, mostly computable general equilibrium (CGE) modelers, that provided technical support to countries in the development of their national agricultural investment plan (NAIP). My colleagues, using CGE modeling, would analyze the options for achieving the CAADP target of six percent agricultural growth as well as the first Millennium Development Goal (MDG1) of halving poverty by 2015. Then, using expenditure-growth elasticities, I would estimate how much public agriculture expenditure must increase to make those options viable and achieve the CAADP agricultural growth and poverty reduction targets.

It seemed that the policy implications of the two analyses could be reinforced by integrating the analyses to increase the coherence between the causative objectives of the econometric models and the predictive objectives of the CGE models. This realization led to the publication of a couple of reports on how we could carry out a holistic assessment of the economy-wide, growth and poverty reduction impacts of public investments in agriculture and rural areas to be used for budgeting, monitoring, and evaluating policies and strategies to achieve stated development outcomes. Thus, I am grateful to my colleagues for sharing ideas and co-authoring the reports that allowed me to advance several of the ideas leading to the development of this decision support tool (DST).

In 2020, with dedicated funding from the Bill and Melinda Gates Foundation via the Akademiya2063-IFPRI joint project on Biennial Review and Data Systems Strengthening, the dream to develop the DST came to life and a plan to get it done was put in place. It has been four years since. At times, it seemed futile as the plan was not going well for various reasons especially when some of the initially planned expertise did not materialize. Over time, I have ventured into areas that I had not initially anticipated, including machine learning regression methods, visual basic for applications and programming in Excel, and user interactive modules. I am grateful to several people who provided invaluable input during the early stages of the research and development of the tool. They include Sunday Odjo on brainstorming how to create the objective function and constraints of the simulation model, John Ulimwengu on setup of the simulation model in Excel and compilation of data on the unit cost of policies, and Mahamadou Tankari on estimation of the parameters of the simulation model using the kernel-based regularized least squares estimator. I am also grateful to the many people that entertained my ideas on the tool and provided encouragement to keep going.

As the tool is a demo or proof of concept, this only marks the end of the beginning.

ABBREVIATIONS AND ACRONYMS

AATS	Africa Agricultural Transformation Scorecard
AU	African Union
BR	biennial review
CAADP	Comprehensive Africa Agriculture Development Programme
DST	decision support tool
GDP	gross domestic product
KRLS	kernel-based regularized least squares
LRR	lasso regularized regression
NAIP	national agricultural investment plan
OLS	ordinary least squares
SVR	support vector regression

1. INTRODUCTION

In 2014, African leaders adopted the Malabo Declaration for the continent's 2025 vision of shared prosperity and improved livelihoods through accelerated agricultural growth and transformation (AU 2014). This is implemented within the framework of the Comprehensive Africa Agriculture Development Programme (CAADP, AU-NEPAD 2003) toward the achievement of Africa's Agenda 2063 (AUC 2015). Since then, the African Union (AU) has conducted four biennial reviews (BRs) and released as many reports as possible, including the accompanying Africa Agricultural Transformation Scorecard (AATS) that tracks progress in implementing the Declaration. Thus, the results of the BR and AATS serve as a performance record and identifies the areas which countries, subregions, and the continent as whole have made progress as well as areas still in need of improvement (AUC 2022, 2024).

However, as the fifth round of the BR process is underway and the next report is expected in January 2026, the question of how the BR report and results can be used to inform the design of policies and investments to accelerate agricultural growth and transformation, reduce poverty and hunger, and improve nutrition and resilience of livelihoods, for example, remains. Currently, the BR and AATS mainly provide information on whether a country is "on-track" or "not-on-track" to achieve the Malabo Declaration commitments, which is based on a scorecard of the progress made by the country in 58 indicators against a specified benchmark or milestone for the review period. Countries with a score from 0 to 10 at or above the benchmark are classified as being on-track, whereas those below are classified as being not-on-track. There is no analysis or information on what actions (policies, investments, programs, etc.) can be taken to achieve desired outcomes, or how any one action may affect different outcomes, including those that may not be desirable.

The 58 indicators currently tracked in the BR capture various components of agricultural transformation pathways, from the upstream (for example, policies, public investment, governance, and mutual accountability) through the midstream (for example, value chain decisions and behavior such as input use and on-farm investment, and intermediate results such as agricultural productivity and prices) to the downstream (for example, broader development goals such as poverty reduction, food security, nutrition, and environmental health) (AUC 2023). As these indicators are interconnected and interact with each other in complex ways, a change in one will cause a change in others. Take the indicator on government agriculture expenditure measured as a percentage of total government expenditure, for example. The average for African countries has persistently declined over time from more than six percent per year in the 1980s to a little over two percent in 2020 (Benin 2022), which is far below the CAADP target of 10 percent. As such, many people, in addition to the recommendations in the BR reports, have been advocating for governments to increase the share of their budget that is allocated to agriculture to address the slow agricultural productivity growth on the continent, with about one-half of the countries on the continent achieving a negative annual average agricultural total factor productivity growth rate (Steensland 2021). However, increasing the share of the government budget allocated to agriculture will necessarily reduce the share allocated to other sectors, which may lead to tradeoffs between agricultural productivity and nutrition outcomes, for example, depending on how the change in the budget shares effects overall incomes and food consumption.

Such tradeoffs may derive from conflicting policy objectives at various levels. At the macroeconomic level, for example, economic growth versus environmental health is a well-known conflict as economic growth can generate production and consumption externalities in the form of pollution and other forms of environmental degradation (Arrow et al. 1995). Another is full employment versus low inflation: expansionary fiscal policy to create jobs can also cause an increase in prices (Karanassou et al. 2010). Policy conflicts at the sector level, too, are common. For example, public sector investment crowding out private sector investment instead of crowding in, which may come about through public sector borrowing that can drive up long-term interest rates (Barry and Devereux 1992).

By assessing the impacts and tradeoffs of policies and investments (represented by the BR indicators in the upstream) on agrifood systems, value-chain actors, and households (represented by the BR indicators in the midstream and downstream), the policy reforms needed to achieve desired development goals and outcomes will become more logical. This will help increase the utility of the BR for policy decision-making and planning purposes.

The objective of this paper is to present an Excel-based interactive decision-support tool (DST) that policymakers can use to evaluate policy options for optimizing their impacts and tradeoffs on the multiple outcomes of the Malabo Declaration at the country level. Based on a partial equilibrium simulation model, the DST can be used for making two broad categories of evaluations: (1) What is the effect of an increase or decrease in the implementation of a policy (e.g., government expenditure on agriculture, trade facilitation, food safety laws and standards, or social protection) on different outcomes (e.g., agricultural growth, income, resilience of households, or child nutrition)? and (2) What are the most cost-effective policies to consider to achieve a specified target of an outcome? The two categories of questions are essentially interrelated. However, the first category of questions helps to understand or know how different policies affect different outcomes—impacts and tradeoffs—without considering the cost of implementing the policies, whereas the second considers the cost of implementation and helps evaluate the cost-effectiveness of the policies with respect to each outcome.

As such, the DST will provide a powerful tool for a variety of stakeholders (policymakers, development agents, researchers, analysts, etc.) interested in agrifood systems. For example, those in charge of preparing the BR reports can use the DST to provide more rigorous and reliable policy implications countries can use to help accelerate implementation of the Malabo Declaration, which seems to be getting farther out of countries' reach over time (AUC 2024). With the development of the new ten-year CAADP Strategy and Action Plan (2026–2035) underway and expected to be unveiled at the AU Summit in January 2025, the importance of the DST will continue into the post-Malabo period. Because the accuracy and reliability of DST simulations will depend on the accuracy and reliability of the data used in estimating the parameters (i.e., the relationship between policies and outcomes), improving the BR data quality will be critical.[1] While the DST cannot solve the BR data quality issues, it can be used to advocate for improving the quality of the BR data as well as for evaluating the relevance of various indicators and their measures.

As the DST is based on a partial equilibrium simulation model, it considers the effects of the policies only on the outcomes that are analyzed and ignores the effects of the policies on other outcomes in the economy, in addition to any second-round effects that might affect the variables treated as exogenous in the model.

In the next section, we present the conceptual framework for the model for optimizing the impacts and tradeoffs of policies on outcomes. This is followed by the methods and the data used to estimate the parameters for the optimization in section 3. Using Ghana as a case study to demonstrate the model, estimated parameters and results are presented in section 4 and 5, respectively, and conclusions and next steps in section 6.

[1] See Benin et al. (2018, 2020, 2022) and AUC (2024) for a discussion of the BR data quality issues.

2. CONCEPTUAL FRAMEWORK

The conceptual framework for optimizing the impacts and tradeoffs of policies on outcomes is based on a cost-minimization partial equilibrium model where the objective is to minimize the cost of implementing various policies to achieve different targeted outcomes. From the perspective of using public spending for stimulating growth and reducing poverty, this framework is situated in the literature on the cost of the Millenium Development Goals (Kakwani and Son 2006, Fan and Rosegrant 2008) and the method developed by Benin, Fan, and Johnson (2012) to estimate the amount of total agricultural expenditure required to achieve certain agricultural growth rates, considering economy-wide growth and poverty reduction impacts of public investments in agriculture and rural areas (Benin et al. 2008). The framework is captured mathematically in equations 1 to 5. A policy (P_j) is defined as a controllable decision variable that policymakers can use to induce change in an outcome (O_i). This definition can be broadened to include public interventions such as investments, programs, regulations, and governance, among others. In the objective function, equation 1, the idea is to implement the policies decided on in a country as close to their CAADP targets as possible, where w_j and $\tilde{P}_j$ are the weight and target for the *j*th policy, respectively. In equation 2, with as many sub-equations as the number of outcomes, the policies affect the different outcomes determined by the functional relationships (b_{ij}), given the vector of other factors ($\boldsymbol{H}_l$) and its effect on the outcomes (δ_{il}). The target for each *i*th outcome is $\tilde{O}_i$. Equation 3 is a budget constraint, where c_j is the unit cost of implementing the *j*th policy, B is the budget, and C is the total cost of implementing the policies. Equations 4 and 5 are closure conditions where the policy weights add up to one and a policy is non-negative. A policy with a value of zero indicates that it is not implemented.

$$\min_{P_j} \sum_j w_j \cdot (P_j - \tilde{P}_j)^2, \quad \forall j = 1, 2, \dots, J \qquad \dots\dots 1$$

Subject to:

$$O_1 = f_1\big(P_1,\ P_2,\ \dots,\ P_J; \boldsymbol{H}_l \,\big|\, b_{11},\ b_{12},\ \dots,\ b_{1J}; \boldsymbol{\delta}_{1l}\big) \le \tilde{O}_1,\ \forall l = 1, 2, \dots, L \qquad \dots\dots 2.1$$

$$O_2 = f_2\big(P_1,\ P_2,\ \dots,\ P_J; \boldsymbol{H}_l \,\big|\, b_{21},\ b_{22},\ \dots,\ b_{2J}; \boldsymbol{\delta}_{2l}\big) \le \tilde{O}_2,\ \forall l = 1, 2, \dots, L \qquad \dots\dots 2.2$$

$$\vdots \qquad \vdots \qquad\qquad\qquad\qquad \vdots \quad \vdots \qquad\qquad \vdots$$

$$O_M = f_M\big(P_1,\ P_2,\ \dots,\ P_J; \boldsymbol{H}_l \,\big|\, b_{M1},\ b_{M2},\ \dots,\ b_{MJ}; \boldsymbol{\delta}_{Ml}\big) \le \tilde{O}_M,\ \forall l = 1, 2, \dots, L \qquad \dots\dots 2.M$$

$$C = \sum_j c_j \cdot P_j \le B \quad \forall j = 1, 2, \dots, J \qquad \dots\dots 3$$

$$\sum_j w_j = 1 \quad \forall j = 1, 2, \dots, J \qquad \dots\dots 4$$

$$P_j \ge 0 \quad \forall j = 1, 2, \dots, J \qquad \dots\dots 5$$

Calibrated model

The optimum solution to the model is represented by (P_j^*, O_i^*, C^*). At an initial state or baseline (P_j^0, O_i^0, C^0, w_j^0, c_j^0, B^0, H_l^0), $\hat{b}_{ij}$ and $\hat{\delta}_{il}$ represent the unique set of relationships between the policies and outcomes and between the other factors and outcomes, respectively, such that the model converges (i.e., $P_j^* = P_j^0$, $O_i^* = O_i^0$, and $C^* = C^0$) when the targets and budget are set to their respective initial state (i.e., $\tilde{P}_j = P_j^0$, $\tilde{O}_i = O_i^0$, and $B = C^0$). The $\hat{b}_{ij}$ and $\hat{\delta}_{il}$ at which the model converges—wherein the optimum solution is identical to the initial observed state—represents the calibrated model that can be used to conduct the simulations and evaluate the most cost-effective policies to achieve a specified target of an outcome.

The assumptions and data on $\hat{b}_{ij}$ and $\hat{\delta}_{il}$ will be critical in determining how realistic the calibrated model is. As this is a cost-minimization partial equilibrium model, there may be other policies, factors, or sectors of the economy affecting the outcomes analyzed which may not be captured in $\hat{b}_{ij}$ and $\hat{\delta}_{il}$. Therefore, the effect of any changes in the excluded policies, factors, or sectors resulting from changes in the policies and outcomes associated with the policy simulations are assumed to remain unchanged from the baseline. Another implication of the partial equilibrium model is that the results of the simulations are useful to the extent that they involve marginal changes around the initial or baseline values or within a reasonable range of the mean of the observed values of P_j and O_i that $\hat{b}_{ij}$ and $\hat{\delta}_{il}$ were estimated from. The above assumption and implication of the model distinguishes it from those based on computable general equilibrium models which consider the whole economy and conduct farther futuristic scenarios (e.g., Diao and Thurlow 2012).

However, a useful property of the model is that it protects against simulating extreme counterfactuals or values of P_j and O_i that lie far from all the observed data points used in the estimation of $\hat{b}_{ij}$ and $\hat{\delta}_{il}$. Typically, models that simulate extreme counterfactuals are conducted as though the assumed linear trajectory continues indefinitely, which creates a risk of producing highly implausible predictions (King and Zeng 2006). From a Bayesian perspective, the model presented here also seems sensible, considering that the expected value for extreme counterfactuals converges to the mean of the observed values (Kimeldorf and Wahba 1970).

Simulations and interpretation of results

Using the calibrated model, policy simulations or scenarios can be conducted by setting the target of one outcome or more to a desired level. Suppose that the third outcome O_3 is food security (measured as the proportion of the population that are food secure) and we are interested in knowing the cost-effective policy options to increase the outcome in the baseline by 5 percent (or the equivalent in percentage points). This may be implemented by setting the target for the third outcome accordingly (i.e., $\tilde{O}_3 = O_3^0 * 1.05$), changing the inequality sign in to an equal sign in the relevant equation, and then running the calibrated model to obtain the optimum solution (P_j^*, O_i^*, C^*), while keeping the other parameters and factors at their baseline values (w_j^0, c_j^0, B^0,

H_l^0). Note that in this scenario, the result of the third outcome will be equivalent to the set target (i.e., $O_3^* \equiv \tilde{O}_3 = O_3^0 * 1.05$).

By comparing the optimum solution (P_j^*, O_i^*, C^*) to their initial or baseline value (P_j^0, O_i^0, B^0), the results will show: (1) how much each policy must change, either increase or decrease, to achieve the desired target of the third outcome, which is to increase food security by 5 percent; (2) how much the other outcomes will change, either decrease or increase, in response to the change in the policies; and (3) how the existing budget should be reallocated across the policies, which will reflect the inefficiencies of the allocation in the baseline scenario. The share or percentage of the budget allocated to the *j*th policy is determined by $(c_j^0 * P_j^* * C^*)/100$. Optimum policies that show a decrease from their baseline value (i.e., $P_j^* < P_j^0$) will have budgets taken away from them and given to policies that show an increase from their baseline value (i.e., $P_j^* > P_j^0$).

Under each policy simulation or scenario, several permutations can be conducted to deepen the evaluation of the policy options by relaxing or tightening several of the constraints in the baseline scenario (i.e., P_j^0, O_i^0, B^0, c_j^0, w_j^0).

Budget and unit cost permutations

As the entire or a substantial part of the current budget may be difficult to reallocate in real life, a more realistic case would be to increase the budget by *x* percent (i.e., set $B = B^0 + B^0 * \frac{x}{100}$ in equation 3). Then, the optimum total cost (C^*) will reflect a combination of reallocating a part of the existing budget in addition to the injection. An option to use up the full budget or allow for a surplus may be implemented by replacing the inequality sign in equation 3 with an equal sign or maintaining it, respectively. Because different policies have different weights, unit costs, and outcome effects, slightly changing the budget in each permutation will reveal how the cost-effectiveness of one policy relative to others may change with different budget sizes. For example, a policy that is very effective but also very costly may not be prioritized until some high budget threshold is reached.

The unit cost (c_j) is perhaps the next most important parameter in the model after $\hat{b}_{ij}$ and $\hat{\delta}_{il}$. It embodies the efficiency of the policy simulations and thus permutations within a scenario can be made by changing the values to, for example, determine the range within which the relative cost-effectiveness of a policy remains the same. In this model, it is key that P_j is incremental enough that it allows a cost to be assigned for one unit.

Permutations on constraining change in other outcomes

Another set of permutations under a policy simulation or scenario may be implemented by constraining the extent to which an *i*th outcome (aside from the one(s) for which the target has been set for the simulation) may change by resetting the respective values of $\tilde{O}_i$ in equation 2 of the calibrated model. Continuing with the above scenario, if, for example, each of the other outcomes do not increase by more than 2 percent from their baseline value, then this may be implemented by setting $\tilde{O}_i = O_i^0 * 1.02\ \forall i \neq 3$ and maintaining the inequality signs in the respective equation. Because each outcome is a function of all the policies, we expect that a change in any one policy will likely cause some change in each of the outcomes depending on the magnitude of the effect of the policy determined in matrix $\hat{b}_{ij}$. As such this permutation is important for the convergence of the model under each of the policy simulations. Here too, slight changes to the constraints in each permutation will help deepen analysis of the tradeoffs. For example, a desired outcome can be influenced by few or ineffective policies and may be difficult to achieve until change in other outcomes are restricted or change in the desired outcome is significantly relaxed.

Permutations on constraining change in policies

Here, the idea is to constrain the extent to which an ith policy may change by resetting the relevant non-negativity closures in equation 5. Because an optimum policy (P_j^*) may be any positive value including less than or greater than the target ($\tilde{P}_j$), another permutation may be made by constraining some of the policies to a desired level. Suppose that the solution for the second policy should be positive but not surpass the target (i.e., $0 < P_2^* \leq \tilde{P}_2$), and the fourth policy should equal the target (i.e., $P_4^* = \tilde{P}_4$). Then, assuming $P_2^* = 3.5$ and $P_4^* = 7.8$, these may be implemented by resetting the respective constraints in equation 5 as $P_2 > 0$, $P_2 \leq 3.5$, and $P_4 = 7.8$. Such permutations may be useful when some policies seem to be more favored (or not) in the simulation because their unit cost is unrealistically low (or high), for example.[2]

Policy weight permutations

Permutations under a policy simulation or scenario may also be conducted by changing the weights (w_j) associated with the policies, reflecting preference of some policies over others. In general, the preferences may depend on political economy factors such as ideology of the ruling political party of government, type of government, and lobbying by interest groups, among others (Andersen et al. 2013). They may also depend on socio-economic and natural or environmental factors. For example, preference for certain policies may increase when there are shocks, as experienced with the recent COVID-19 pandemic on social safety nets (Gronbach et al. 2022) or with the high prices and financial crisis of 2008/2009 and the well-known bailouts. However, because these preferences may be captured in the data used in the estimation of $\hat{b}_{ij}$ and $\hat{\delta}_{il}$, the weights may be the least important component of the model and may not be needed. Nevertheless, weights are included to make the model complete from a normative perspective and to provide the option for those that may have good data with which to form the weights and assess their implications on the cost-effectiveness of the policies.

Permutations on the calibration (estimated relationships and initial values)

In a typical simulation model, the estimated relationships (in this case, $\hat{b}_{ij}$ and $\hat{\delta}_{il}$) used to calibrate the model is an average effect over a time series, and the simulations use a normal year

[2] Having more realistic unit cost at the outset is always better.

or situation as the reference or baseline scenario. As the variables used in estimating the relationships are usually evolving in different directions and at different speeds over time, the average effect seems inherently biased to the extent that the unmodeled effects of some observed variables (collinear variables that are dropped in the estimation with ordinary least squares estimation, for example) or data points (outliers) are mistakenly attributed to other observed variables or data points (Hainmueller and Hazlett 2014). Also, the concept of a normal year or situation can be misleading in the sense that what may seem normal for most of the variables in one year may not be for others in the same year. Similarly, what may be normal for some variables in one year may not be for the same variables in another year. Together, these mean that the variables may be like or unlike each other in any given period, resulting in positive effects among some variables in some years and negative effects in others.

What if $\hat{b}_{ij}$ and $\hat{\delta}_{il}$ can be estimated for every year in the time series (or pointwise partial derivatives)? Then, the model can be calibrated for each year of the data, and the observed value on the variables for respective years can be used as the reference or baseline scenario. The simulation model includes this feature, which is useful for analyzing cost-effective policies for getting out of periods affected by different types of shocks (floods, drought, widespread diseases such as the COVID-19 pandemic, etc.).

Limitations of the model

The DST is based on a partial equilibrium simulation model and, therefore, considers the effects of the policies only on the outcomes that are analyzed. It ignores the effects of the policies on other outcomes of the economy, in addition to any second-round effects that might affect the budget constraint, which is treated as exogenous in the model. Regarding the second-round effects, for example, we know that national budgets and government expenditure are financed primarily from tax revenues, loans, and aid, which may depend on the outcomes. Therefore, a change in the outcomes may cause a change in the budget constraint, which will in turn influence the policies. Such dynamics or second-round effects involving the exogenous variables (B, c_j, w_j, and some elements of $\boldsymbol{H}_l$), which are likely to be more important when simulating extreme counterfactuals of P_j and O_i, are not considered in the model. By keeping the outcome(s) to be simulated within a small range of the baseline value, such second-round effects can be assumed to be small. The estimators ($\hat{b}_{ij}$ and $\hat{\delta}_{il}$) used in developing the model also protects against simulating extreme counterfactuals of P_j and O_i (more on this later).

3. ESTIMATING THE PARAMETERS

3.1. Relationship between outcomes and polices

3.1.1. Estimation method and issues

The main parameters to estimate are b_{ij}, which captures the relationship between the outcomes (O_i) and the policies (P_j), and δ_{il}, which captures the relationship between the outcomes and other factors (H_l). Because the main purpose of the parameters is prediction, as opposed to causation, a regression method and estimator that has a high predictive accuracy is used. We use machine-learning regularized regression methods, which has become increasingly attractive in economics and applied econometrics (Varian 2014, Mullainathan and Spiess 2017, Athey 2019, and Kleinberg et al. 2018). Like ordinary least squares (OLS), regularized linear regression minimizes the sum of squared deviations between observed and model-predicted values but imposes a regularization penalty aimed at limiting model complexity. Although regularized regressions typically do not produce estimates that can be interpreted as causal, their predictive strength is derived from the bias-variance tradeoff, where the variance of the estimated predictor increases with the model complexity and the bias decreases with model complexity. By reducing model complexity, regularized regression methods tend to outperform OLS in terms of out-of-sample prediction performance and address the common problem of overfitting (Ahrens, Hansen, and Schaffer 2020).

We consider three methods that have available packages in STATA: kernel-based regularized least squares (KRLS) (Hainmueller and Hazlett 2014, Ferwerda, Hainmueller, and Hazlett 2014 2014), support vector regression (SVR) (Chang and Lin 2011, Guenther and Schonlau 2016), and lasso regularized regression (LRR) (Frank and Friedman 1993, Tibshirani 1996, and Ahrens, Hansen, and Schaffer 2020). The KRLS method is suitable for small datasets and generates estimates like the OLS which can be interpreted as causal partial derivatives. The other two methods are suitable for larger datasets, with the SVR having linear and non-linear estimation options. The LRR is suitable for cases where the number of explanatory variables may be greater than the number of observations and variable selection is ideal. It is also suitable for time series and fixed-effects estimation, among others. Here, we present the details for the KRLS method only and how the results are used in developing the simulation model. Later, and in the discussion of the results of the KRLS estimation and its accuracy of in-sample prediction, we compare it to those from the SVR and LRR estimators.[3]

Let X_t= (P_{jt}, H_{lt}) and β_i = (b_i, δ_i), where $t = 1, 2, \ldots, T$ represents the unit of observation. The KRLS is applied to estimate the following *M* reduced-form equations[4] (one for each outcome):

$$O_{it} = f_i(X_t|\beta_i) \qquad \ldots\ldots 6$$

[3] In the final DST, the simulation model will be developed using the parameters from the three estimators (KRLS, SVR, and LRR) and the user can select any one of them to conduct the simulations.

[4] Reduced form may also be referred to as treatment effect, as opposed to structural (Chetty 2009).

As with the various machine-learning methods, fitting a kernel function that can be treated as providing a measure of similarity between the covariate vectors of two observations of the form is fundamental:

$$K = \begin{bmatrix} k(X_{1t}, X_{1t}) & \cdots & k(X_{1t}, X_{Nt}) \\ \vdots & \ddots & \vdots \\ k(X_{Nt}, X_{1t}) & \cdots & k(X_{Nt}, X_{Nt}) \end{bmatrix} \quad \text{......7}$$

Where *N*=*J*+*L* and the Gaussian kernel is used and defined as:

$$k(X_{dt}, X_{gt}) = e^{-\frac{\|X_{dt}-X_{gt}\|^2}{\sigma^2}} \quad \text{......8}$$

$\|X_{lt} - X_{dt}\|$ is the Euclidean distance between the covariate series and σ^2 is the bandwidth of the kernel function. The solution ($\tilde{\beta}_j$) is determined by fitting the model at each observation, considering both empirical fit and model complexity in the following matrix notation that is like in the case of OLS:

$$\tilde{\beta}_i = (K + \lambda_i I)^{-1} O_i \quad \text{......9}$$

λ determines the tradeoff between model fitness and complexity, with larger values of λ indicating complexity over fitness and lower values indicating fitness over complexity. Therefore, σ and λ are tuning parameters in KRLS that deal with the bias-variance tradeoff and determine the accuracy of prediction.[5] While the results of KRLS can be interpreted as those of generalized linear regression models, deriving pointwise marginal effects is an appealing property and is given by:

$$\tilde{\beta}_{int} \equiv \frac{\partial O_i}{\partial X_{nt}} = \frac{-2}{\sigma^2} \sum_n \beta_{it} e^{-\frac{\|X_{dt}-X_{gt}\|^2}{\sigma^2}} (X_{dt} - X_{gt}) \quad \text{......10}$$

This means that variables with similar time series will also have similar marginal effects, which is logical. With linear regression models, for example, variables that have similar time series may present multicollinearity problems, and the marginal effect cannot be estimated or will lack precision if estimated (Greene 1993).

Because we are estimating reduced-form models of the outcome equations, the estimated marginal effects do not provide any inference on the channels through which a policy influences an outcome, which a structural model may be required for. The estimated marginal effects from the reduced-form equations are sufficient for reliable policy counterfactuals (Lumsdaine et al. 1992).

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[5] Suppose we can write the prediction estimator of the SVR loosely as: $\tilde{O}_{it} = \hat{\beta}_i + \sum_t \hat{\alpha}_{int}\, O_{it} \gamma_i K(X_{idt}, X_{igt}) - \epsilon_i$, where $0 \leq \alpha_i \leq C$ and ϵ is a loss function, then γ, ϵ, and C are the main tuning parameters (Guenther and Schonlau 2016). The LRR minimizes the mean squared error subject to a penalty (ψ) on the absolute size of coefficient estimates: $\tilde{\beta}_{in}(\lambda) = \arg\min \frac{1}{T}\sum_t (O_{it} - X'_{int}\beta_{in})^2 + \frac{\lambda_i}{T}\sum_n \psi_{in}|\beta_{in}|$, then λ and ψ are the tuning parameters (Ahrens, Hansen, and Schaffer 2020).

The estimation was carried out in STATA (StataCorp 2024) using the KRLS command (Ferwerda, Hainmueller, and Hazlett 2014). The equations were estimated independently or one at a time because the KRLS package does not include an option for estimating the equation jointly. To the extent that some of the outcomes are related, joint estimation has potential efficiency gains (Zellner 1963). However, as the main objective is to obtain consistent estimates of the relationship between the outcomes and the policies and other factors (i.e., $\tilde{\beta}_{int}$) to use as priors for $\hat{b}_{ijt}$ and $\hat{\delta}_{ilt}$ in the simulation model, the lack of efficiency gains in the error terms without the joint estimation is trivial.

3.1.2. Variables, data, sources, and issues

To make the simulation model appealing to the CAADP stakeholders, we use the indicators in the BR as the variables for the estimation. Therefore, the main data used in the estimation comes from the CAADP BR database on the 58 indicators tracked in the reviews, which we have categorized into policies (20 indicators), intermediate results (32 indicators), and outcomes (17 indicators) as shown in Table 1. The indicators are measured at the national level and the data are annual from 2015 to 2022. There are several data quality issues, with the most severe ones being missing observations and outliers or unrealistic spikes and dips in many of the series (AUC 2024, Benin et al. 2018, 2020, 2022). As such, there are few countries in the current database with reliable annual data on many of the indicators, especially those in the policy and outcome categories of interest in this study.

Table 1: CAADP BR indicators by category (policy, intermediate result, and outcome)

Number	Description	Variable	Category		
			P	*IR*	*O*
1.1	CAADP Process Completion Index	CAADPRO	x		
1.2	Quality of multi-sectorial and multi-stakeholder coordination	MSCOORD	x		
1.3	Evidence-Informed Policies and corresponding human resources	EVIDPOL	x		
2.1i	Government agriculture expenditure as % of total government expenditure	GAETOT	x		
2.1ii	Government agriculture expenditure as % of agriculture value added	GAEVAD	x		
2.1iii	Official development assistance for agriculture, disbursement as % of commitment	AGODA		x	
2.2	Ratio of domestic private sector investment to agriculture value added, %	DOMPRIV		x	
2.3	Ratio of foreign private direct investment to agriculture value added, %	FDIPRIV		x	
2.4	Proportion of men and women engaged in agriculture with access to financial services, %	ACCFINS		x	
3.1i	Fertilizer consumption (kilogram per hectare of arable land)	FERTCON		x	
3.1ii	Growth rate of the size of irrigated areas from its value of the year 2000	IRRIGGR		x	
3.1iii	Growth rate of the ratio of supplied quality agriculture inputs (seed, breed, fingerlings) to the total national inputs requirements for the commodity	INPUTGR		x	
3.1iv	Proportion of farmers having access to Agricultural Advisory Services	ACCEXT		x	
3.1v	Total Agricultural Research Spending as % of agriculture value added	GAERES	x		
3.1vi	Proportion of adult agricultural population with ownership or secure land rights over agricultural land	ACCLAND		x	
3.1vii	Percentage increase in the proportion of evaluated and certified locally adapted livestock seed, by species/breed/ecotypes annually used in a country (Livestock Seed)	LVSTGR	x	x	
3.1viii	Seed Sector Performance Index (Seed Sector Performance Index)	SEEDSPI		x	
3.2i	Growth rate of agriculture value added, in constant US dollars, per agricultural worker	VADWKGR		x	x

Number	Description	Variable	Category		
			P	*IR*	*O*
3.2ii	Growth rate of agriculture value added, in constant US dollar, per hectare of agricultural land	VADLDGR		x	x
3.2iii	Growth rate of yields for the 5 national priority commodities, and possibly for the 11 AU agriculture priority commodities	YIELDGR		x	
3.3	Reduction rate of Post-Harvest Losses for (at least) the 5 national priority commodities, and possibly for the 11 AU agriculture priority commodities	PHLGR		x	
3.4	Budget lines (%) on social protection as percentage of the total resource requirements for coverage of the vulnerable social groups	SOCPROT	x		
3.5i	Prevalence of stunting (% of children under 5 years old)	STUNTING			x
3.5ii	Prevalence of underweight (% of children under 5 years old)	UNDWGHT			x
3.5iii	Prevalence of wasting (% of children under 5 old)	WASTING			x
3.5iv	Prevalence of undernourished (% of the country's population)	UNOURSH			x
3.5v	Growth rate of the proportion of Minimum Dietary Diversity-Women	MDDW			x
3.5vi	Proportion of 6-23 months old children who meet the Minimum Acceptable Diet	MADCH			x
3.5vii	Reduction in the prevalence (%) of adult individuals (15 years or older) found to be food insecure	FDINSGR			x
3.5viii	Cost of a healthy diet as a % of household food expenditure	COHDIET		x	
3.5ix	Percentage (%) of population overweight or obese (adult population)	OBESITY			x
3.6i	Sanitary and Phytosanitary Systems Index	SPSSI	x		
3.6ii	SPS Health Index, %	SPSHI		x	x
3.6iii	SPS Trade Index, %	SPSTI		x	
3.7	Africa Biofortification Progress Index	ABPI	x	x	
4.1i	Growth rate of the agriculture value added, in constant US dollars (ţAgVA)	VADTGR		x	x
4.1ii	Agriculture contribution to the overall poverty reduction target	AGRPOV			
4.1iii	Reduction rate of poverty headcount ratio, at national poverty line (% of population)	NAPOVGR			x
4.1iv	Reduction rate of poverty headcount ratio at international poverty line (% of population)	INPOVGR			x
4.1v	Reduction rate of the gap between the wholesale price and farmgate price	FGWPGR		x	
4.2	Number of priority agricultural commodity value chains for which a PPP is established with strong linkage to smallholder agriculture	NUMPPP		x	
4.3	Percentage of youth that is engaged in new job opportunities in agriculture value chains	YTHJOBS		x	
4.4	Proportion of rural women that are empowered in agriculture	EMPOWER		x	
5.1i	Growth rate of the value of trade of agricultural commodities and services within Africa, in constant US dollars	ATRGR		x	
5.1ii	Diversification index for the intra-Africa trade of agricultural commodities and services.	ATRDVI		x	
5.2i	Trade Facilitation Index	ATRFCI	x		
5.2ii	Indicator of Food Price Anomalies (IFPA) applied to the Food Consumer Price Index (food CPI)	IFPAFPI		x	
5.3i	Tariff rate, weighted average applied tariff rate (%)	ATRTFR	x		
5.3ii	Index of non-tariff measures related to intra-Africa trade of agricultural commodities and services	ATRNTR	x		
5.3iii	Index for enabling institutional environment for AfCFTA implementation	ATRINST	x		
6.1i	Percentage of farm, pastoral, and fisher households that are resilient to climate and weather-related shocks	FRMRESIL		x	x
6.1ii	Share of agriculture land under sustainable land management practices	LNDSLM		x	x
6.1iii	Total Green House Gas (GHG) emissions from agriculture	AGGHG		x	x
6.2	Existence of government budget-lines to respond to spending needs on resilience building initiatives	GAERBI	x		
7.1	Index of capacity to generate and use agriculture statistical data and information	ASCI	x	x	
7.2	Existence of inclusive institutionalized mechanisms for mutual accountability and peer review	MUTACC	x		
7.3	Country Biennial Report submission	BRRSUB	x		

Number	Description	Variable	Category		
			P	*IR*	*O*
7.4	Country BR results dissemination	BRRDIS	x		
7.5	Country BR results Utilization	BRRUTL	x	x	
	Total number of indicators		**20**	**32**	**17**

Source: Author's illustration based on CAADP BR technical guidelines (AUC 2023).

Notes: For the categories, *P* = policy, *IR* = intermediate results, and *O* = outcome. AfCFTA = African Continental Free Trade Area.

To demonstrate how we would estimate the parameters for the simulation model, we use the BR data on Ghana for the indicators in the policy and outcome categories that have observations on all the years (2015–2022). This results in 4 and 11 of the indicators in the policy and outcome categories, respectively. These are supplemented with data from other sources on variables representing H_{kt}, made up of government nonagricultural expenditure as a percentage of gross domestic product (GNAGEXP), gross domestic product (GDP) per capita (GDPPCAP), and rainfall (World Bank 2024a, 2024b). All the variables used in the estimation, and the summary statistics are shown in Table 2, and the full annual data are provided in the annex (Table A1). Because GNAGEXP and GDPPCAP may depend on the outcomes, we use their lagged values in the estimation.

Table 2: Variables and summary statistics of the data on Ghana, 2015–2022

Variable (BR indicator number)	Mean	Standard deviation
Outcome indicators (O_i)		
VADWKGR (3.2i)	9.89	1.13
VADLDGR (3.2ii)	2.17	0.17
STUNTING (3.5i)	16.90	1.75
WASTING (3.5ii)	6.05	0.96
UNOURSH (3.5iv)	5.90	1.58
MDDW (3.5v)	41.92	22.21
MADCH (3.5vi)	20.97	12.73
FDINSGR (3.5vii)	7.51	3.45
OBESITY (3.5ix)	14.46	2.39
INPOVGR (4.1iv)	11.77	0.74
LNDSLM (6.1ii)	26.64	8.94
Policy indicators (P_j)		
GAEVAD (2.1ii)	4.77	1.52
GAERES (3.1v)	0.67	0.60
SOCPROT (3.4)	17.25	10.60
ASCI (7.1)	66.37	2.25
Other factors (H_l)		
GNAGEXP	8.06	1.25
GDPPCAP	1853.71	125.16
RAINFALL	1183.50	24.09

Source: Econometric model results using data from AUC (2024) and World Bank (2024a, 2024b).

Notes: The variables representing the outcome and policy indicators are from the BR database, with the BR indicator number in parenthesis and described in Table 1. For other variables, GNAGEXP is government nonagricultural expenditure as a percentage of gross domestic product (GDP), GDPPCAP is GDP per capita in 2015 constant prices, and RAINFALL is precipitation measured in mm.

Other issues with the data and model specification are the short time series (2015–2022) and omitted variables. On the length of the time series, for example, it is known that the effect of policies and investments take time to yield results or have impact, with different magnitudes of effect over time. Regarding omitted variables, although we are estimating reduced-form models of the outcomes, the choice of explanatory variables, especially H, must represent the exogenous variables from the structural model for each outcome. The CAADP BR outcomes cover a range of development objectives and goals in the areas of production and productivity, growth, food security, nutrition, poverty, gender and inclusion, resilience, and environmental health, among others. The purpose of the paper is to demonstrate how we would estimate the parameters and test their predictive strength. Therefore, we do not dwell on these issues as they are unnecessary to achieving the objectives of the paper. Yet, the parameters of the estimated models must be interpreted with caution.

3.1.3. Estimated marginal effects ($\widetilde{\boldsymbol{\beta}}_{int}$)

The estimated average and pointwise marginal effects using the KRLS method are shown in Tables 3 and 4, respectively. Here, we focus primarily on showing the appeal of using the KRLS method in terms of differentiating the average and the pointwise marginal effects, considering the model fit tests, rather than the interpretation of the estimated effects or their policy implications given the issues of potentially omitted variables and the short time series of the data.

There are differences in the overall model fit and in the marginal effects for the different policies and other factors across the various outcomes. As λ determines the tradeoff between model fitness and complexity, with larger values of λ indicating complexity over fitness and lower values indicating fitness over complexity, the model fit is good for VADWKGR, STUNTING, UNOURSH, INPOVGR, and LNDSLM compared to VADLDGR, WASTING, MDDW, MADCH, FDINSGR, and OBESITY (Table 3). These results are consistent with the variance between the predicted and observed values of the outcome variables in Table 4, which is smaller for those that the model fits well (i.e., smaller values of λ), compared to those that the model does not fit well (i.e., larger values of λ).

The results in Table 3 are the average marginal effects, which can be interpreted like those of a generalized linear regression model. The results in Table 4 on the pointwise marginal effects show that the average effects hide important information on the variation of the effects over time: some are positive in some years while others are negative. Even with the outcomes where the overall model fit is relatively lower (i.e., VADLDGR, WASTING, MDDW, MADCH, FDINSGR, and OBESITY as shown in Table 3), the differences in the variance between the predicted and observed values of the outcome variable over time suggest that the main issue is with MDDW for 2015/2016, which reflects the huge jump in data for the following years (Table 4) and point to data quality issues. More on this to come.

Table 3: KRLS estimated parameters and average marginal effects of outcomes with respect to policies and other factors in Ghana, 2015–2022

Outcome	For policy indicators ($\tilde{b}_{ij}$)			For other factors ($\tilde{\delta}_{il}$)				λ	R^2
	GAEVAD	GAERES	SOCPROT	ASCI	GNAGEXP	GDPPCAP	RAINFALL		
VADWKGR	0.07261 ***	-0.03641 **	-0.00942 ***	-0.08281 ***	0.04319 **	-0.00129 ***	0.00307 **	0.00712	1.000
VADLDGR	-0.00311	0.01032	-0.00030	0.01162	-0.00452	0.00015 *	-0.00016	0.33440	0.927
STUNTING	0.10557 ***	0.23983 ***	-0.02149 ***	-0.10110 ***	0.16610 ***	-0.00147 ***	-0.00250 **	0.00272	1.000
WASTING	-0.09829	-0.10135	0.00422	0.03724	-0.05842	0.00059	0.00139	0.41330	0.881
UNOURSH	0.04635 ***	-0.10332 ***	-0.02060 ***	-0.06876 ***	-0.07222 ***	-0.00151 ***	0.00721 ***	0.00272	1.000
MDDW	-0.69460	0.52560	0.10232	1.11946	-0.90178	0.01654	-0.12177	0.54100	0.837
MADCH	0.21311 **	1.91935 ***	-0.02019 **	0.10997 **	0.77577 ***	0.00625 ***	-0.01611 **	0.00440	1.000
FDINSGR	-0.09206 **	0.29381 ***	0.05551 ***	-0.00999	0.42152 ***	0.00225 ***	-0.01312 **	0.00712	0.999
OBESITY	-0.02374 **	0.26309 ***	0.01407 ***	0.06167 ***	0.11520 ***	0.00231 ***	-0.00075 *	0.00440	1.000
INPOVGR	-0.09449 ***	-0.05117 ***	-0.00034	-0.06061 ***	0.08813 ***	-0.00074 ***	0.00541 ***	0.00712	1.000
LNDSLM	-0.08186 *	1.23851 ***	-0.04777 ***	0.25874 **	0.16875 **	0.00565 ***	-0.03291 **	0.00712	1.000

Source: Econometric model results using data from AUC (2024) and World Bank (2024a, 2024b).
Notes: The bandwidth of the kernel function (σ^2) = 7. λ is a parameter that determines the tradeoff between model fit and complexity and R^2 is the r-squared. *, **, and *** indicate statistical significance at the 10, 5, and 1 percent level, respectively.

Table 4: KRLS estimates of the pointwise marginal effects of outcomes with respect to policies and other factors in Ghana, 2015–2022

Outcome/year	Weight ($\tilde{\beta}_{it}$)	For policy indicators ($\tilde{b}_{ijt}$)			For other factors ($\tilde{\delta}_{ilt}$)				Value of outcome		
		GAEVAD	GAERES	SOCPROT	ASCI	GNAGEXP	GDPPCAP	RAINFALL	Predicted	Observed	% difference
VADWKGR											
2015	1.95285	-0.00335	-0.09007	-0.00815	-0.08707	0.03362	-0.00137	0.00441	11.83170	11.84741	-0.133
2016	1.00119	0.23399	0.08493	-0.01226	-0.07009	0.06834	-0.00102	0.00232	10.99880	11.00686	-0.073
2017	-0.70950	0.27179	0.09402	-0.00510	-0.08535	0.20808	-0.00116	0.01732	10.51253	10.50682	0.054
2018	0.08371	0.02221	-0.10558	-0.01824	-0.12703	0.04670	-0.00217	0.00283	9.83655	9.837226	-0.007
2019	-0.72673	0.02706	-0.14402	-0.03229	-0.16474	-0.03682	-0.00298	-0.00112	9.28530	9.279452	0.063
2020	-0.43525	-0.01327	-0.12883	0.01713	-0.04226	0.00841	-0.00022	0.00161	8.97615	8.972652	0.039
2021	-0.54432	0.04470	0.04457	-0.00520	-0.03251	-0.02339	-0.00102	-0.00815	8.89919	8.894809	0.049
2022	-0.64605	-0.00228	-0.04631	-0.01122	-0.05338	0.04054	-0.00036	0.00531	8.76602	8.760825	0.059
VADLDGR											
2015	-1.19412	0.00726	0.01781	0.00083	0.01435	-0.00209	0.00021	-0.00032	1.98821	1.91995	3.555
2016	-0.87796	-0.01755	-0.00269	0.00101	0.01128	-0.00573	0.00014	-0.00003	2.02256	1.97237	2.544
2017	0.26964	-0.01919	-0.00290	0.00035	0.01470	-0.02261	0.00018	-0.00184	2.07946	2.09487	-0.736
2018	0.07639	0.00793	0.02340	0.00131	0.01956	-0.00369	0.00030	-0.00006	2.19265	2.19702	-0.199
2019	0.95810	0.00128	0.03038	-0.00107	0.01900	0.00086	0.00023	-0.00021	2.24463	2.29940	-2.382
2020	-0.59238	0.00308	0.02509	-0.00480	0.00500	-0.00180	-0.00003	-0.00039	2.16770	2.13384	1.587
2021	0.23652	-0.00801	-0.01618	0.00019	0.00336	0.00262	0.00016	0.00193	2.30074	2.31426	-0.584

Outcome/year	Weight ($\tilde{\beta}_{it}$)	For policy indicators ($\tilde{b}_{ijt}$)			For other factors ($\tilde{\delta}_{ilt}$)				Value of outcome		
		GAEVAD	GAERES	SOCPROT	ASCI	GNAGEXP	GDPPCAP	RAINFALL	Predicted	Observed	% difference
2022	0.97542	0.00033	0.00768	-0.00019	0.00568	-0.00375	0.00003	-0.00040	2.35466	2.41041	-2.313
STUNTING											
2015	1.14079	0.09743	0.20247	-0.01392	-0.10810	0.18966	-0.00122	0.00149	18.49457	18.50000	-0.029
2016	0.79963	0.13810	0.10924	-0.01751	-0.16878	0.19307	-0.00207	0.00919	17.59619	17.60000	-0.022
2017	-0.68749	0.22831	0.19219	-0.01132	-0.17975	0.27264	-0.00189	0.01480	16.80327	16.80000	0.019
2018	-0.34390	0.01242	0.19464	-0.03445	-0.08793	0.20221	-0.00191	-0.00547	15.90164	15.90000	0.010
2019	-0.63338	0.14347	0.25411	-0.07411	-0.14901	0.02633	-0.00322	-0.00251	15.00302	15.00000	0.020
2020	-1.30555	0.03034	0.14582	0.01646	-0.03999	0.16149	0.00037	-0.00258	14.20621	14.20000	0.044
2021	1.28979	0.03720	0.10142	-0.00868	-0.02744	0.06425	-0.00018	-0.00069	19.19386	19.20000	-0.032
2022	0.14086	0.15728	0.71875	-0.02842	-0.04784	0.21915	-0.00162	-0.03419	17.99933	18.00000	-0.004
WASTING											
2015	-1.28029	-0.14619	-0.12066	0.00555	0.04857	-0.08272	0.00054	-0.00112	5.20911	4.70000	10.832
2016	-0.30566	-0.11587	-0.06167	0.00421	0.07418	-0.10593	0.00084	-0.00700	6.12155	6.00000	2.026
2017	0.86161	-0.18037	-0.11576	0.00533	0.07757	-0.10008	0.00076	-0.00456	6.45738	6.80000	-5.039
2018	0.32923	-0.06926	-0.08546	0.00817	-0.00945	-0.07302	0.00032	0.00163	6.66908	6.80000	-1.925
2019	0.44182	-0.11577	-0.06804	0.01322	0.05636	-0.01236	0.00093	-0.00066	6.62431	6.80000	-2.584
2020	0.37179	-0.02651	-0.01255	-0.01166	0.01371	-0.03779	-0.00015	0.00012	6.65216	6.80000	-2.174
2021	-1.33866	-0.04273	-0.08162	0.00248	0.01429	-0.00927	0.00047	0.00571	5.03233	4.50000	11.829
2022	0.45277	-0.08960	-0.26502	0.00644	0.02268	-0.04620	0.00101	0.01701	5.81996	6.00000	-3.001
UNOURSH											
2015	0.92094	-0.17633	-0.23904	0.00157	-0.01165	-0.08165	-0.00056	0.00903	7.69603	7.70000	-0.052
2016	0.86689	0.23398	0.06417	-0.01176	-0.01333	-0.05325	-0.00036	0.00044	7.59627	7.60000	-0.049
2017	-0.10448	0.20947	0.03222	0.00177	-0.06221	0.16289	-0.00077	0.02371	7.10045	7.10000	0.006
2018	-0.17681	0.09975	-0.14621	-0.01558	-0.18875	-0.06497	-0.00238	0.01545	6.40076	6.40000	0.012
2019	0.84066	-0.00356	-0.25756	-0.07742	-0.15984	-0.26897	-0.00447	0.00336	6.09638	6.10000	-0.059
2020	-1.52672	-0.01274	-0.20321	-0.03205	-0.04274	-0.19370	-0.00187	0.00375	4.10658	4.10000	0.160
2021	-0.75835	0.05423	0.08908	-0.00785	-0.02625	-0.04580	-0.00129	-0.01214	4.10327	4.10000	0.080
2022	-0.69801	-0.03403	-0.16600	-0.02346	-0.04530	-0.03230	-0.00036	0.01405	4.10301	4.10000	0.073
MDDW											
2015	-1.06864	0.46824	1.33071	0.02226	1.02378	-0.92081	0.01490	-0.15047	20.04206	7.20000	178.362
2016	-1.22459	-2.34283	-0.78837	0.06522	1.10535	-1.81626	0.01362	-0.16710	21.91613	7.20000	204.391
2017	0.83202	-2.55398	-0.75267	-0.03517	1.57605	-3.73863	0.01771	-0.37289	37.20138	47.20000	-21.184
2018	0.16358	-0.43443	1.21416	0.13164	1.47982	-1.19549	0.02339	-0.17090	45.23417	47.20000	-4.165
2019	0.10417	-0.29604	1.71847	0.45385	2.17558	0.42173	0.03921	-0.06212	45.94819	47.20000	-2.652
2020	0.48839	0.16778	1.52197	-0.02770	0.61920	0.30701	0.00886	-0.03849	53.93087	59.80000	-9.815
2021	0.39276	-0.62191	-0.84072	0.05788	0.33457	0.11462	0.01063	0.08817	55.08013	59.80000	-7.893
2022	0.36458	0.05643	0.80124	0.15059	0.64132	-0.38641	0.00399	-0.10035	55.41879	59.80000	-7.326
MADCH											

Outcome/year	Weight ($\tilde{\beta}_{it}$)	For policy indicators ($\tilde{b}_{ijt}$)			For other factors ($\tilde{\delta}_{ilt}$)				Value of outcome		
		GAEVAD	GAERES	SOCPROT	ASCI	GNAGEXP	GDPPCAP	RAINFALL	Predicted	Observed	% difference
2015	-0.56792	1.09386	2.38306	-0.00045	0.11510	0.93049	0.00692	-0.02391	13.03181	13.00000	0.245
2016	-0.34687	-1.02973	0.16954	0.02379	-0.51453	0.68105	-0.00258	0.04323	12.61943	12.60000	0.154
2017	0.05631	-0.79371	0.49071	-0.03190	-0.60541	-0.45625	-0.00195	-0.08862	12.59685	12.60000	-0.025
2018	-0.61342	0.31702	2.58311	0.00121	0.72822	0.94572	0.01293	-0.04521	13.03436	13.00000	0.264
2019	0.13483	1.19280	3.88899	-0.04031	0.66338	1.23478	0.01584	0.01438	16.89245	16.90000	-0.045
2020	-0.48713	0.50998	2.80626	-0.09163	0.17057	1.24031	0.00629	-0.02821	16.92729	16.90000	0.161
2021	0.98081	-0.40337	-0.68482	0.00820	0.12231	0.69984	0.01366	0.16154	41.34506	41.40000	-0.133
2022	1.20590	0.81801	3.71793	-0.03044	0.20016	0.93025	-0.00115	-0.16207	41.33245	41.40000	-0.163
FDINSGR											
2015	-0.32235	0.41876	0.57552	-0.01953	-0.21468	0.40545	-0.00148	-0.01803	5.00796	5.00000	0.159
2016	-0.25818	-0.46111	-0.09775	0.01605	-0.21484	0.37523	-0.00184	0.00715	5.00637	5.00000	0.127
2017	-0.20743	-0.35423	-0.00104	-0.01231	-0.14557	-0.01124	-0.00130	-0.03394	5.00512	5.00000	0.102
2018	-0.00660	-0.42908	0.26393	0.01505	0.23930	0.41193	0.00250	-0.04280	5.00016	5.00000	0.003
2019	-1.91537	0.06004	0.67250	0.20990	0.15090	0.93949	0.00946	-0.00565	5.04727	5.00000	0.945
2020	2.12068	0.01697	0.50521	0.15720	0.03863	0.77246	0.00642	-0.00765	11.64766	11.70000	-0.447
2021	0.76085	-0.10161	-0.17277	0.01802	0.02543	0.17478	0.00302	0.03039	11.68122	11.70000	-0.160
2022	0.84308	0.11379	0.60488	0.05972	0.04090	0.30403	0.00118	-0.03441	11.67919	11.70000	-0.178
OBESITY											
2015	-1.04905	0.19048	0.39604	0.00583	0.04768	0.11936	0.00181	-0.00632	11.91103	11.90000	0.093
2016	-0.68744	-0.30465	-0.02255	0.01553	-0.04538	0.06799	0.00037	0.00393	12.30723	12.30000	0.059
2017	0.34755	-0.30394	-0.00983	-0.00159	-0.06606	-0.22920	0.00029	-0.02749	12.69635	12.70000	-0.029
2018	-0.59308	0.01760	0.42046	0.02115	0.18757	0.12528	0.00370	-0.00864	13.10623	13.10000	0.048
2019	0.10248	0.17806	0.72274	0.05744	0.21053	0.35925	0.00597	0.00498	14.49892	14.50000	-0.007
2020	0.38002	0.09044	0.54691	-0.01142	0.05513	0.25301	0.00176	-0.00440	15.69601	15.70000	-0.025
2021	0.34338	-0.12209	-0.25658	0.00859	0.03874	0.12551	0.00334	0.04008	17.19639	17.20000	-0.021
2022	1.49218	0.06418	0.30756	0.01702	0.06514	0.10042	0.00122	-0.00811	18.28432	18.30000	-0.086
INPOVGR											
2015	0.07858	-0.18406	-0.12275	-0.00080	-0.07252	0.07120	-0.00103	0.00648	11.99958	12.00000	-0.003
2016	2.84138	-0.08705	-0.05305	-0.00153	-0.06672	0.09569	-0.00090	0.00704	13.28492	13.30000	-0.113
2017	-0.86654	-0.12470	-0.07773	0.00625	-0.08368	0.22061	-0.00107	0.02103	12.30460	12.30000	0.037
2018	-0.01095	-0.17245	-0.12489	-0.00813	-0.11534	0.10097	-0.00171	0.00548	11.70006	11.70000	0.000
2019	-1.16802	-0.11888	-0.10284	-0.01087	-0.09330	0.03511	-0.00147	0.00246	11.10620	11.10000	0.056
2020	-0.23989	-0.04703	-0.05576	0.01755	-0.03166	0.06118	0.00011	0.00118	11.20127	11.20000	0.011
2021	-0.46284	0.00727	0.06775	-0.00114	-0.00395	0.02954	-0.00011	-0.00301	11.30246	11.30000	0.022
2022	-0.17471	-0.02903	0.05995	-0.00406	-0.01770	0.09077	0.00025	0.00264	11.30093	11.30000	0.008
LNDSLM											
2015	-0.98538	0.30850	1.44000	-0.00023	0.35557	0.21345	0.00756	-0.04449	18.86280	18.80010	0.333
2016	-0.83417	-0.95357	0.02466	-0.00547	-0.00904	-0.21039	0.00137	-0.02867	19.55312	19.50004	0.272

Outcome/year	Weight ($\tilde{\beta}_{it}$)	For policy indicators ($\tilde{b}_{ijt}$)			For other factors ($\tilde{\delta}_{ilt}$)				Value of outcome		
		GAEVAD	GAERES	SOCPROT	ASCI	GNAGEXP	GDPPCAP	RAINFALL	Predicted	Observed	% difference
2017	0.63825	-0.93083	0.15237	-0.03237	0.01874	-0.97673	0.00263	-0.11530	23.12417	23.16479	-0.175
2018	-0.39380	0.10930	1.77258	-0.02449	0.45483	0.20962	0.00902	-0.05636	24.22506	24.20000	0.104
2019	0.40421	0.52114	2.68458	-0.13035	0.71119	0.40631	0.01051	-0.01507	24.40699	24.43271	-0.105
2020	-0.89761	0.30647	2.04530	-0.13968	0.19499	0.66329	0.00318	-0.02770	21.61415	21.55704	0.265
2021	0.81105	-0.43043	-0.70285	-0.00070	0.12280	0.44066	0.01050	0.12627	40.19174	40.24335	-0.128
2022	1.34906	0.41453	2.49144	-0.04884	0.22085	0.60376	0.00041	-0.10195	41.15750	41.24335	-0.208

Source: Econometric model results using data from AUC (2024) and World Bank (2024a, 2024b).

Notes: The % difference is calculated as (Predicted-Observed)×100/Predicted. The statistical significance of the pointwise marginal effects has been excluded as they require manipulation of large matrixes (variance-covariance) to calculate the *t*-statistics.

3.1.4. Comparing in-sample prediction of KRLS, SVR, and LRR

The results in Table 5 show that the three machine-learning estimators do well with the in-sample predictions, with an average prediction for all the outcomes ranging from -6.8% to 1.5% of the observed values. There are differences in the pointwise predictions, with KRLS performing the best overall, followed by LRR and then SVR. Considering the average predictions, however, LRR performs the best, followed by KRLS and then SVR. These suggest that it will be valuable to have separate simulation models developed using the estimates from the LRR and SVR as well for the user of the tool to have a comprehensive evaluation of the policies.

Table 5: Prediction outcomes using KRLS, SVR, and LRR methods, 2015–2022

Outcome	Observed	Predicted					
		KRLS		SVR		LLR	
		Value	% difference	Value	% difference	Value	% difference
VADWKGR							
2015	11.847	11.832	-0.13	11.812	-0.30	11.767	-0.68
2016	11.007	10.999	-0.07	11.162	1.41	11.030	0.21
2017	10.507	10.513	0.05	10.551	0.42	10.552	0.43
2018	9.837	9.837	-0.01	9.617	-2.24	9.748	-0.91
2019	9.279	9.285	0.06	9.497	2.34	9.410	1.41
2020	8.973	8.976	0.04	8.663	-3.46	8.930	-0.48
2021	8.895	8.899	0.05	9.131	2.66	8.940	0.50
2022	8.761	8.766	0.06	8.636	-1.43	8.729	-0.37
Average	9.888	9.888	0.00	9.883	-0.05	9.888	0.00
VADLDGR							
2015	1.920	1.988	3.56	2.020	5.23	1.926	0.31
2016	1.972	2.023	2.54	2.014	2.11	1.974	0.09
2017	2.095	2.079	-0.74	2.015	-3.79	2.085	-0.49
2018	2.197	2.193	-0.20	2.121	-3.47	2.207	0.45
2019	2.299	2.245	-2.38	2.199	-4.38	2.290	-0.43
2020	2.134	2.168	1.59	2.234	4.70	2.139	0.22
2021	2.314	2.301	-0.58	2.214	-4.32	2.316	0.06
2022	2.410	2.355	-2.31	2.313	-4.04	2.407	-0.15
Average	2.168	2.169	0.05	2.141	-1.22	2.168	0.00
STUNTING							
2015	18.500	18.495	-0.03	18.552	0.28	18.324	-0.95
2016	17.600	17.596	-0.02	17.380	-1.25	17.398	-1.15
2017	16.800	16.803	0.02	17.013	1.27	17.017	1.29
2018	15.900	15.902	0.01	15.871	-0.18	15.988	0.55
2019	15.000	15.003	0.02	14.994	-0.04	15.035	0.24
2020	14.200	14.206	0.04	14.219	0.13	14.339	0.98
2021	19.200	19.194	-0.03	18.961	-1.25	18.889	-1.62
2022	18.000	17.999	0.00	18.059	0.33	18.209	1.16
Average	16.900	16.900	0.00	16.881	-0.11	16.900	0.00
WASTING							
2015	4.700	5.209	10.83	4.665	-0.74	4.708	0.16
2016	6.000	6.122	2.03	6.215	3.58	6.125	2.08
2017	6.800	6.457	-5.04	6.638	-2.38	6.614	-2.73
2018	6.800	6.669	-1.93	6.873	1.07	6.838	0.56
2019	6.800	6.624	-2.58	6.792	-0.12	6.826	0.38
2020	6.800	6.652	-2.17	6.848	0.70	6.798	-0.02
2021	4.500	5.032	11.83	4.727	5.05	4.675	3.90

Outcome	Observed	Predicted					
		KRLS		SVR		LLR	
		Value	% difference	Value	% difference	Value	% difference
2022	6.000	5.820	-3.00	5.948	-0.86	5.815	-3.08
Average	6.050	6.073	0.38	6.088	0.63	6.050	0.00
UNOURSH							
2015	7.700	7.696	-0.05	7.711	0.14	7.691	-0.12
2016	7.600	7.596	-0.05	7.694	1.23	7.547	-0.69
2017	7.100	7.100	0.01	7.020	-1.13	7.201	1.42
2018	6.400	6.401	0.01	6.310	-1.40	6.383	-0.27
2019	6.100	6.096	-0.06	5.989	-1.82	5.992	-1.77
2020	4.100	4.107	0.16	4.199	2.41	4.160	1.48
2021	4.100	4.103	0.08	3.987	-2.75	4.043	-1.39
2022	4.100	4.103	0.07	4.198	2.40	4.182	2.01
Average	5.900	5.900	0.01	5.888	-0.20	5.900	0.00
MDDW							
2015	7.200	20.042	178.36	7.059	-1.96	8.430	17.09
2016	7.200	21.916	204.39	7.771	7.94	8.222	14.20
2017	47.200	37.201	-21.18	23.344	-50.54	44.271	-6.20
2018	47.200	45.234	-4.16	46.977	-0.47	49.217	4.27
2019	47.200	45.948	-2.65	47.306	0.22	45.659	-3.26
2020	59.800	53.931	-9.81	60.043	0.41	60.574	1.29
2021	59.800	55.080	-7.89	60.183	0.64	60.154	0.59
2022	59.800	55.419	-7.33	60.001	0.34	58.871	-1.55
Average	41.925	41.846	-0.19	39.086	-6.77	41.925	0.00
MADCH							
2015	13.000	13.032	0.24	13.229	1.76	13.494	3.80
2016	12.600	12.619	0.15	6.722	-46.65	12.703	0.82
2017	12.600	12.597	-0.03	13.084	3.84	11.639	-7.62
2018	13.000	13.034	0.26	17.466	34.35	13.870	6.69
2019	16.900	16.892	-0.04	16.290	-3.61	16.463	-2.59
2020	16.900	16.927	0.16	17.372	2.79	17.316	2.46
2021	41.400	41.345	-0.13	40.676	-1.75	41.938	1.30
2022	41.400	41.332	-0.16	41.469	0.17	40.377	-2.47
Average	20.975	20.972	-0.01	20.788	-0.89	20.975	0.00
FDINSGR							
2015	5.000	5.008	0.16	5.042	0.83	4.719	-5.62
2016	5.000	5.006	0.13	5.027	0.55	5.310	6.19
2017	5.000	5.005	0.10	5.063	1.25	4.891	-2.18
2018	5.000	5.000	0.00	4.665	-6.70	4.749	-5.03
2019	5.000	5.047	0.95	6.070	21.40	5.644	12.88
2020	11.700	11.648	-0.45	11.294	-3.47	11.371	-2.81
2021	11.700	11.681	-0.16	12.083	3.27	12.047	2.96
2022	11.700	11.679	-0.18	11.570	-1.11	11.369	-2.83
Average	7.513	7.509	-0.04	7.602	1.19	7.512	0.00
OBESITY							
2015	11.900	11.911	0.09	11.937	0.31	11.977	0.65
2016	12.300	12.307	0.06	12.171	-1.05	12.324	0.19
2017	12.700	12.696	-0.03	12.678	-0.18	12.565	-1.06
2018	13.100	13.106	0.05	13.318	1.67	13.231	1.00
2019	14.500	14.499	-0.01	14.291	-1.44	14.371	-0.89
2020	15.700	15.696	-0.03	16.030	2.10	15.761	0.39
2021	17.200	17.196	-0.02	16.975	-1.31	17.217	0.10
2022	18.300	18.284	-0.09	18.426	0.69	18.253	-0.26
Average	14.463	14.462	0.00	14.478	0.11	14.462	0.00
INPOVGR							

Outcome	Observed	Predicted					
		KRLS		SVR		LLR	
		Value	% difference	Value	% difference	Value	% difference
2015	12.000	12.000	0.00	12.151	1.26	12.007	0.06
2016	13.300	13.285	-0.11	13.174	-0.95	13.277	-0.17
2017	12.300	12.305	0.04	12.446	1.19	12.312	0.10
2018	11.700	11.700	0.00	11.638	-0.53	11.710	0.08
2019	11.100	11.106	0.06	11.189	0.80	11.093	-0.06
2020	11.200	11.201	0.01	11.305	0.93	11.201	0.01
2021	11.300	11.302	0.02	11.187	-1.00	11.285	-0.13
2022	11.300	11.301	0.01	11.197	-0.91	11.315	0.13
Average	11.775	11.775	0.00	11.786	0.09	11.775	0.00
LNDSLM							
2015	18.800	18.863	0.33	19.038	1.27	19.309	2.71
2016	19.500	19.553	0.27	18.908	-3.03	19.923	2.17
2017	23.165	23.124	-0.18	23.506	1.47	21.954	-5.23
2018	24.200	24.225	0.10	28.005	15.72	25.034	3.45
2019	24.433	24.407	-0.11	23.786	-2.65	23.796	-2.61
2020	21.557	21.614	0.26	22.228	3.11	21.877	1.48
2021	40.243	40.192	-0.13	39.531	-1.77	40.390	0.36
2022	41.243	41.158	-0.21	41.361	0.28	40.860	-0.93
Average	26.643	26.642	0.00	27.045	1.51	26.643	0.00

Source: Econometric model results using data from AUC (2024) and World Bank (2024a, 2024b).
Notes: The % difference is calculated as (Predicted-Observed)×100/Predicted.

3.2. Unit cost and weight of policies

To find the unit cost, we first determine the unit of measurement of the indicator and then estimate the cost associated with one unit of the indicator. The basic expenditure and cost data are taken from the 2022 annual financial report of the government of Ghana (CAGD 2022). This is straightforward for GAEVAD, GAERES, and GNAGEXP because expenditure and GDP values are already associated with them. For these three indicators, the unit cost is one percent of the Ghanaian Cedi (GHS) equivalent of the value of the indicator in 2022, which is the default baseline for the simulation model. The results are shown in Table 6.

For SCOPROT, this is measured as budget lines (%) on social protection as the percentage of the total resource requirements for coverage of vulnerable social groups across four components: food and cash reserves, emergency food supplies, school feeding, and other protective services. To simplify, we used government expenditure on social benefits as the GHS equivalent of the indicator (17.2 percent) and then one percent of that as the unit cost.

For ASCI, it is an index of the capacity to generate and use agriculture statistical data and information. We first estimated the budget or expenditure allocated to the Ghana Statistical Service for agriculture (assuming that 0.5 percent is related to agriculture)[6] and the Ministry of Food Agriculture's Monitoring and Evaluation Department, Program Planning & Budget Department and Statistics Research and Information Department. This was divided by the value of the indicator (68) to get an estimate of the unit cost (Table 6).

[6] This is share of total government expenditure that is spent on agriculture in general (CAGD 2022).

For the weight of policies ($\widehat{w}_j$), we assume that the preferences for one policy over another are captured in the data used in the estimation of $\widehat{b}_{ijt}$ and $\hat{\delta}_{ilt}$ as well as in the unit cost of policies. Therefore, we assign equal weights to the policies in the baseline and the simulations. Users of the tool will have the option of assigning different weights as they wish.

Table 6: Unit cost and weight of policies in Ghana, 2022

Parameter	GAEVAD	GAERES	SOCPROT	ASCI	GNAGEXP
Unit of measurement	%	%	%	Number	%
Value of indicator	5.66	1.48	17.20	68	10.05
Unit cost, million GHS ($\hat{c}_j$)	234.57	61.46	0.70	0.13	1,975.08
Weight ($\widehat{w}_j$)	1	1	1	1	1

Source: Author's calculation and assumptions based on data from CAGD (2022).

Notes: GHS = Ghanaian Cedi.

4. SIMULATION MODEL

4.1. Calibration

With the parameters from the KRLS estimation ($\tilde{\beta}_{it}$, $\tilde{\lambda}_i$), the function (f_i) of relationship between outcomes (O_i) and policies and other factors (X_n) in the simulation model presented in the conceptual framework are constructed using conditional expectation function of the KRLS model that produces fitted values or out-of-sample predictions of the outcome ($\hat{O}_i$) for varying levels of X_n. Suppose the desired prediction is for X_n^*, then the predicted outcome is derived from:

$$\hat{O}_i^* = K(X_n^*, X_{nt}|\tilde{\lambda}_i) \cdot \tilde{\beta}_{it} \qquad \ldots\ldots 11$$

In the KRLS estimation, the outcome equations were estimated one at a time, and $\tilde{\beta}_{it}$ was estimated independently. In the simulation model, all the outcomes are predicted together. As a result, $\tilde{\beta}_{it}$ is not precise in a joint model. To address this, the simulation model, which is constructed in Excel and uses the generalized reduced gradient nonlinear solver, was first calibrated to obtain $\hat{\beta}_{it}$, which is $\tilde{\beta}_{it}$ plus a scalar ($\tilde{\beta}_i^s$), at which the model converges, or the predicted values are identical to the initial state of observed values that represent the baseline. Assuming the baseline is 2022, then the calibrated model is $\tilde{\beta}_{i,2022}^s$ at which $\hat{O}_i^* = O_{i,2022}$ when $X_n^* = X_{n,2022}$, which is represented by:

$$O_{i,2022} = \left[K\left(X_{n,2022}, X_{nt}\middle|\tilde{\lambda}_i\right) \cdot \tilde{\beta}_{it}\right] + \tilde{\beta}_{i,2022}^s \qquad \ldots\ldots 12$$

Tables 7 and 8 show the calibrated models for the case of Ghana using 2022 and 2019 as examples for the baseline, respectively. The relatively high scalars, with respect to the outcomes on WASTING and MADCH in Table 7 (baseline = 2022) and the outcomes on WASTING, MADCH, and LNDSLM in Table 8 (baseline = 2019), suggest that the models are more complex than estimated.

Table 7: KRLS-based calibrated simulation model, baseline = 2022

Outcome	$K\left(X_{n,2022}, X_{nt}\middle|\tilde{\lambda}_i\right) \cdot \tilde{\beta}_{it}$								$\tilde{\beta}_{i,2022}^s$
	2015	2016	2017	2018	2019	2020	2021	2022	
VADWKGR	-0.65065	-0.32235	-0.07038	-0.14677	0.01023	-0.02917	0.04161	0.16995	0.00000
VADLDGR	-0.10392	-0.03649	0.01109	-0.09579	0.00934	0.19350	0.14007	1.30161	0.00000
STUNTING	-0.21111	-0.12792	-0.04204	-0.02827	0.03323	0.14124	0.09928	0.76382	0.00000
WASTING	-0.79276	-0.11142	0.01882	-0.43199	0.01529	0.04025	0.17402	0.07144	-0.92789
UNOURSH	-0.24687	-0.41336	-0.76041	0.16978	-0.02161	-0.00430	0.03603	0.08015	-0.03926
MDDW	-0.09300	-0.05089	0.03421	0.02000	0.02104	0.07897	0.23259	0.56181	-0.00016
MADCH	-0.01442	0.00232	-0.05338	-0.06943	-0.09838	0.02180	0.71414	0.98512	-1.47993
FDINSGR	-0.02805	-0.01073	-0.00853	-0.00081	-0.38684	0.34291	0.45058	0.84908	0.00000
OBESITY	-0.09130	-0.02857	0.01429	-0.07250	0.02070	0.06145	0.20335	1.49875	0.00000
INPOVGR	-0.23590	-0.03879	-0.27409	-0.17595	-0.00134	0.00684	-0.03563	0.11809	0.00000
LNDSLM	-0.08576	-0.03467	-0.14514	0.02624	-0.04814	0.08164	0.48031	1.35867	-0.00001

Source: Model simulation results.

Notes: See Table 1 for a detailed description of the outcome variables.

Table 8: KRLS-based calibrated simulation model, baseline = 2019

Outcome	$K(X_{n,2019}, X_{nt}\|\tilde{\lambda}_i) \cdot \tilde{\beta}_{it}$								$\tilde{\beta}^s_{i,2019}$
	2015	2016	2017	2018	2019	2020	2021	2022	
VADWKGR	-0.13048	-0.03435	-0.23906	-0.73190	0.03955	-0.13804	0.21927	0.47636	0.00000
VADLDGR	-0.29128	-0.19228	0.05246	-0.32537	0.03609	1.27849	0.01493	0.19700	-0.00693
STUNTING	-0.71708	-0.63510	-0.16246	-0.13376	0.17513	0.02845	0.27827	0.08140	0.00000
WASTING	-0.08449	-0.31230	0.09916	-0.06173	0.07233	0.15553	1.21772	0.24267	0.48428
UNOURSH	-0.83856	-0.04405	-0.15316	0.84295	-0.08353	-0.02033	0.18986	0.22465	0.00000
MDDW	-0.26067	-0.26820	0.16188	0.07728	0.16052	0.26825	0.02479	0.07363	0.00000
MADCH	-0.07597	0.01096	-0.14963	-0.26829	-0.48927	0.07405	0.07611	0.19809	-3.62663
FDINSGR	-0.07863	-0.05654	-0.04036	-0.00312	-1.92900	1.16480	0.04802	0.17027	-0.01649
OBESITY	-0.25590	-0.15056	0.06762	-0.28017	0.10293	0.20873	0.02167	0.30137	0.00000
INPOVGR	-1.17633	-0.13176	-0.02921	-0.03529	-0.00517	0.01917	-0.16859	0.62229	-0.07038
LNDSLM	-0.24036	-0.18269	-0.49302	0.12418	-0.18603	0.40708	0.05119	0.27246	-0.23260

Source: Model simulation results.

Notes: See Table 1 for a detailed description of the outcome variables.

4.2. Scenarios and permutations

As presented in the section on the conceptual framework, the calibrated model can be used to simulate policy changes required to bring about a desired change in an outcome. This is done by first deciding on the baseline year of the calibrated model to use, setting the level of one outcome or more to the desired level, and then running the model to solve for the optimum policies, given the levels of other parameters, constraints, and external factors (i.e., w_j, c_j, B, and H_l) that have also been selected.

As such, there is an infinite number of scenarios and permutations that can be simulated with the model. For purposes of demonstration, we use the model that is calibrated at the 2019 and 2022 baseline to simulate two scenarios with respect to a desired or target outcome: (1) reduce WASTING (prevalence of wasting in children under five years old) by 2 percent from the baseline value and (2) reduce WASTING by 1 percent and increase FDINSGR (reduction in the prevalence of adults that are food insecure) by 1 percent from the baseline value. Under each scenario, we conduct several permutations as illustrated in Table 9. Overall, there are four main permutations that we demonstrate: restricting the extent of change in the non-target outcomes (with a minimum or maximum level of change) or not; cost neutral or relative cost of policies; providing additional budget or not; and allowing the external factors (H_l) to change or not. In all the scenarios, the policies have equal weights and there are no restrictions on the policy solutions. The results are presented in the next section.

Scenario 1 demonstrates a basic case that targets one outcome (in this example, reduce WASTING by 1 percent), assuming the unit cost of policies are identical and external factors are allowed to change. In Scenario 1a, change in the other outcomes are not restricted, compared to Scenario 1b where change in the other outcomes is capped at 3 percent. In Scenario 2, which targets two outcomes, 2a is like 1b in the permutations and 2b relaxes the change in the other outcomes to a maximum of 5 percent. In 2c to 2f, the other factors (GDPPCAP and RAINFALL) are fixed at the baseline value, and the actual and differential unit cost of policies is considered.

In 2c, no additional budget is provided, and any inefficiencies will be taken care of by reallocating some of the existing resources from one or more policies to others. In 2d, an additional budget that is equivalent to 0.5 percent of total government expenditure (TGOVEXP) is provided, which is doubled in 2e and 2f. Change in other outcomes is capped at 5 percent, except in 2f where there is no restriction.

As the model protects against simulating extreme counterfactuals of O_i and P_j, it is important to keep simulated outcomes and other parameters within a reasonable range of their respective baseline values. The model will not converge and there will be no solution when "extreme" values are set. Because there are several outcomes and parameters to create different scenarios, we do not know what may be considered "extreme" a priori. This is left for the user to experiment with.

Table 9: Examples of policy simulation scenarios to achieve specified levels of outcomes

Permutation	Scenario: target outcome (desired % change from baseline)							
	1. WASTING (-2%)		2. WASTING (-1%) and FDINSGR (1%)					
	1a	1b	2a	2b	2c	2d	2e	2f
Restriction on change in other outcomes, $\hat{O}^*_{i \neq target}$	None	≤3%	≤3%	≤5%	≤5%	≤5%	≤5%	None
Restriction on $\hat{P}^*_j$	P_i≥0	P_i≥0	P_i≥0	P_i≥0	P_i≥0	P_i≥0	P_i≥0	P_i≥0
w_j	$1 \forall P_j$	$1 \forall P_j$	$1 \forall P_j$	$1 \forall P_j$	$1 \forall P_j$	$1 \forall P_j$	$1 \forall P_j$	$1 \forall P_j$
c_j	$0 \forall P_j$	$0 \forall P_j$	$0 \forall P_j$	$0 \forall P_j$	$\hat{c}_j$	$\hat{c}_j$	$\hat{c}_j$	$\hat{c}_j$
Restriction on H_l	None	None	None	H_l^0	H_l^0	H_l^0	H_l^0	H_l^0
Additional budget B, GHS mil.	None	None	None	None	None	978.5	1975.0	1975.0

Source: Author's assumptions and illustration.

5. SIMULATION RESULTS

The policy simulation results are presented in Table 10. In order to achieve a desired level of change in one outcome or more in each scenario, the results show: (1) the level of change in each of the policies (and other variables where relevant); (2) the level of change in the other outcomes; and (3) where relevant, the allocation of the resources provided, including the reallocation of some existing resources. The changes in the outcomes and policies are presented as the percentage change from their respective baseline value.

Using Scenario 2c as an example of how the results may be interpreted, to reduce WASTING by 1 percent and increase FDINSGR by 1 percent from the 2022 baseline, GAERES, SOCPROT, and ASCI must be increased by 15.51, 1.00, and 0.20 percent, respectively, whereas GAEVAD and GNAGEXP must be decreased by 0.16 and 0.06 percent, respectively. Doing these will lead to an increase in VADLDGR (0.08 percent), STUNTING (0.70 percent), MDDW (0.29 percent), MADCH (1.97 percent), OBESITY (0.37 percent), INPOVGR (0.14 percent), and LNDSLM (1.20 percent), as well as a decrease in VADWKGR by 0.13 percent and UNOURSH by 0.72 percent. These will involve a reallocation of GHS 14.28 million of the existing budget taken from GAEVAD (GHS 2.07 million) and GNAGEXP (GHS 12.21 million) and given to GAERES (GHS 14.14 million or 99.04 percent of the total), SOCPROT (GHS 0.12 million or 0.84 percent), and ASCI (GHS 0.02 million or 0.13 percent).

When an additional budget of GHS 987.50 million is provided, represented by Scenario 2d and using 2022 as the baseline, GAEVAD, GAERES, GNAGEXP must be increased by 3.62, 3.11, and 4.72 percent, respectively, whereas SOCPROT and ASCI must be decreased by 0.91 and 0.26 percent, respectively. Doing so will lead to an increase in VADWKGR (0.35 percent), STUNTING (0.75 percent), MADCH (1.56 percent), OBESITY (0.25 percent), INPOVGR (0.39 percent), and LNDSLM (0.84 percent), as well as a decrease in VADLDGR by 0.09 percent and MDDW by 0.55 percent. There is no change with UNOURSH. Including the additional budget, these will also involve a reallocation of GHS 0.13 million of the existing budget taken from SOCPROT (GHS 0.91 million) and ASCI (GHS 0.26 million), which together is given to GAEVAD (GHS 48.04 million or 4.86 percent of the total), GAERES (GHS 2.84 million or 0.29 percent), and GNAGEXP (GHS 936.76 million or 94.85 percent).

Note that the results are different for each baseline year that the simulation model is calibrated, which is expected. The user can choose the baseline year and define the scenarios and permutations as they wish. Also, as the main purpose of the paper is to demonstrate how we would build the simulation model to develop the tool, these results must be interpreted with caution because of data and model specification issues.

Table 10: Policy simulation results based on the KRLS estimated parameters

Indicator	Baseline = 2019									Baseline = 2022									
	Value in 2019	Scenario: target outcome (% change from baseline)								Value in 2022	Scenario: target outcome (% change from baseline)								
		1. WASTING (-2%)		2. WASTING (-1%) and FDINSGR (1%)							1. WASTING (-2%)		2. WASTING (-1%) and FDINSGR (1%)						
		1a	1b	2a	2b	2c	2d	2e	2f		1a	1b	2a	2b	2c	2d	2e	2f	
		% change from baseline									% change from baseline								
Outcome (O_i)																			
VADWKGR	9.28	-0.728	1.051	0.286	-0.195	-0.200	0.563	0.206	0.200	8.76	0.09	0.22	-0.02	-0.02	-0.13	0.35	0.72	0.72	
VADLDGR	2.30	0.782	-0.167	-0.006	0.299	0.296	-0.201	0.045	0.048	2.41	0.05	-0.01	0.03	0.03	0.08	-0.09	-0.15	-0.15	
STUNTING	15.00	1.358	1.559	0.668	0.665	0.654	0.667	0.861	0.858	18.00	1.410	1.364	0.697	0.698	0.695	0.747	0.898	0.898	
WASTING	6.80	-2.000	-2.000	-1.000	-1.000	-1.000	-1.000	-1.000	-1.000	6.00	-2.000	-2.000	-1.000	-1.000	-1.000	-1.000	-1.000	-1.000	
UNOURSH	6.10	-1.385	1.945	0.102	-0.344	-0.348	0.424	0.300	0.293	4.10	-0.718	-0.408	-0.582	-0.578	-0.724	0.001	0.765	0.765	
MDDW	47.20	1.175	-2.901	-0.806	0.282	0.297	-1.805	-1.756	-1.739	59.80	-0.042	-0.271	0.103	0.100	0.291	-0.547	-1.231	-1.231	
MADCH	16.90	12.195	3.000	3.000	5.000	5.000	2.224	5.000	5.018	41.40	3.436	3.000	1.820	1.821	1.966	1.563	1.669	1.669	
FDINSGR	5.00	3.947	-3.646	1.000	1.000	1.000	1.000	1.000	1.000	11.70	1.656	1.350	1.000	1.000	1.000	1.000	1.000	1.000	
OBESITY	14.50	2.773	0.226	0.548	1.096	1.097	0.340	1.062	1.068	18.30	0.586	0.425	0.318	0.318	0.375	0.254	0.354	0.354	
INPOVGR	11.10	-0.582	-0.315	-0.169	-0.317	-0.329	-0.072	0.046	0.041	11.30	0.364	0.262	0.177	0.178	0.141	0.391	0.800	0.800	
LNDSLM	24.43	6.804	1.458	1.178	2.830	2.807	0.071	1.714	1.728	41.24	2.048	1.691	1.049	1.051	1.197	0.839	1.090	1.090	
Policy (P_j)																			
GAEVAD	5.33	3.945	10.688	4.605	2.738	2.874	8.465	7.565	7.594	5.66	5.377	7.998	0.642	0.648	-0.156	3.617	4.877	4.877	
GAERES	0.43	87.771	27.554	19.796	46.784	47.018	-48.59	-82.23	-82.28	1.48	26.01	20.60	10.797	10.864	15.508	3.114	6.501	6.501	
SOCPROT	21.47	-0.121	-0.721	-0.210	-0.165	0.043	-0.613	-0.491	-0.492	17.20	-0.169	-0.688	0.226	0.227	0.997	-0.909	-1.338	-1.338	
ASCI	68.00	-0.096	-0.779	-0.290	-0.091	-0.096	-0.272	-0.209	-0.203	68.00	-0.095	-0.541	0.045	0.045	0.199	-0.258	-0.409	-0.409	
Other factors (H_l)																			
GNAGEXP	7.04	2.133	-0.654	0.717	-0.226	-0.347	6.430	13.673	13.671	10.05	1.531	0.649	1.185	1.192	-0.062	4.721	9.599	9.599	
GDPPCAP	1899.81	0.000	-0.001	0.000	0.000	0.000	0.000	0.000	0.000	2014.71	0.000	-0.001	0.000	0.000	0.000	0.000	0.000	0.000	
RAINFALL	1208.61	-0.001	-0.002	-0.001	0.000	0.000	0.000	0.000	0.000	1181.23	-0.008	-0.010	-0.001	0.000	0.000	0.000	0.000	0.000	
Budget (GHS mil.)																			
Total	n.a.	n.a.	n.a.	n.a.	n.a.	48.26	1000.3	1996.6	1996.7	n.a.	n.a.	n.a.	n.a.	n.a.	14.28	987.63	1975.2	1975.2	
New	n.a.	n.a.	n.a.	n.a.	n.a.	0.00	987.50	1975.0	1975.0	n.a.	n.a.	n.a.	n.a.	n.a.	0.00	987.50	1975.0	1975.0	
Exiting	n.a.	n.a.	n.a.	n.a.	n.a.	48.26	12.85	21.65	21.66	n.a.	n.a.	n.a.	n.a.	n.a.	14.28	0.13	0.20	0.20	
Distribution																			
GAEVAD	n.a.	n.a.	n.a.	n.a.	n.a.	35.93	105.85	94.59	94.95	n.a.	n.a.	n.a.	n.a.	n.a.	-2.07	48.04	64.78	64.78	
GAERES	n.a.	n.a.	n.a.	n.a.	n.a.	12.32	-12.73	-21.55	-21.57	n.a.	n.a.	n.a.	n.a.	n.a.	14.14	2.84	5.93	5.93	
SOCPROT	n.a.	n.a.	n.a.	n.a.	n.a.	0.01	-0.09	-0.07	-0.07	n.a.	n.a.	n.a.	n.a.	n.a.	0.12	-0.11	-0.16	-0.16	
ASCI	n.a.	n.a.	n.a.	n.a.	n.a.	-0.01	-0.02	-0.02	-0.02	n.a.	n.a.	n.a.	n.a.	n.a.	0.02	-0.02	-0.04	-0.04	

Indicator	Baseline = 2019									Baseline = 2022								
	Value in 2019	Scenario: target outcome (% change from baseline)								Value in 2022	Scenario: target outcome (% change from baseline)							
		1. WASTING (-2%)		2. WASTING (-1%) and FDINSGR (1%)							1. WASTING (-2%)		2. WASTING (-1%) and FDINSGR (1%)					
		1a	1b	2a	2b	2c	2d	2e	2f		1a	1b	2a	2b	2c	2d	2e	2f
		% change from baseline									% change from baseline							
GNAGEXP	n.a.	n.a.	n.a.	n.a.	n.a.	-48.25	894.50	1902.1	1901.7	n.a.	n.a.	n.a.	n.a.	n.a.	-12.21	936.76	1904.5	1904.5
Distribution (%)																		
GAEVAD	n.a.	n.a.	n.a.	n.a.	n.a.	74.45	10.58	4.74	4.76	n.a.	n.a.	n.a.	n.a.	n.a.	0.00	4.86	3.28	3.28
GAERES	n.a.	n.a.	n.a.	n.a.	n.a.	25.54	0.00	0.00	0.00	n.a.	n.a.	n.a.	n.a.	n.a.	99.04	0.29	0.30	0.30
SOCPROT	n.a.	n.a.	n.a.	n.a.	n.a.	0.01	0.00	0.00	0.00	n.a.	n.a.	n.a.	n.a.	n.a.	0.84	0.00	0.00	0.00
ASCI	n.a.	n.a.	n.a.	n.a.	n.a.	0.00	0.00	0.00	0.00	n.a.	n.a.	n.a.	n.a.	n.a.	0.13	0.00	0.00	0.00
GNAGEXP	n.a.	n.a.	n.a.	n.a.	n.a.	0.00	89.42	95.26	95.24	n.a.	n.a.	n.a.	n.a.	n.a.	0.00	94.85	96.42	96.42

Source: Model simulation results.

Notes: n.a. = not applicable. See Table 8 for detailed description of the scenarios, assumptions, and permutations.

6. CONCLUSIONS AND FURTHER WORK

CAADP has elevated the importance of evidence-based planning and implementation as fundamental to addressing Africa's development challenges and achieving its development goals and objectives. This is reflected in the CAADP Country Implementation Guide and NAIP toolkit, for example, which are intended to help countries determine and formulate detailed and precise sets of actions (policies, investments, programs, etc.) that fit their local context to address their challenges and translate into achieving their national goals and objectives. The importance of evidence-based planning and implementation is also reflected in the conduct of regular reviews for course (re)direction at various levels, including joint sector reviews at the country level and the CAADP partnership platform and BR at the continental level.

Yet, reliable information on which actions (policies, investments, programs, etc.) to take to achieve desired outcomes and how taking those actions may affect other outcomes, including those that may not be desirable, has been sorely lacking. To help address this gap, this paper demonstrated an Excel-based interactive decision-support tool that policymakers and development practitioners can use to evaluate policy options and optimize their impacts and tradeoffs on the multiple outcomes of the Malabo Declaration at the country level. The current CAADP BR database has 58 indicators, which were categorized into 20 policy indicators (covering public spending, governance, and trade facilitation, for example), 32 intermediate result indicators (covering areas such as access to and use of agricultural inputs and services, prices, and postharvest losses), and 17 outcome indicators (productivity, growth, poverty, food security, nutrition, and environmental health, among others) that are measured at the national level from 2015 to 2022.

Machine-learning regression methods are used to estimate the relationship between the outcome and policy indicators, and the estimated parameters are then used to develop a partial equilibrium simulation model in Excel. This forms the core of the tool, which can be used to simulate an infinite number of scenarios based on the desired level of change in one or more outcomes. For each scenario on the desired level of change, the simulated results will show: (1) the level of change required in each of the policies included in the model; (2) the level of change in the other outcomes included in the model; and (3) the allocation of the resources provided, including reallocation of some of the existing resources. The changes in the outcomes and policies are presented as the percentage change from their respective baseline value. A prototype of the tool has been developed using the BR data on Ghana to demonstrate the features and utility of the tool.[7]

The tool will be useful for a variety of stakeholders (policymakers, development agents, researchers, analysts, etc.) interested in agrifood systems. For example, those in charge of preparing the BR reports can use the tool to provide more rigorous and reliable policy implications that countries can use to help accelerate implementation of the Malabo Declaration.

Because the accuracy and reliability of the simulations of the tool will depend on the accuracy and reliability of the data used in estimating the model parameters (the relationship between

[7] The prototype tool can be downloaded from here (https://hdl.handle.net/10568/152192).

policies and outcomes), improving the quality of the BR data will be critical. Therefore, while the tool cannot solve the BR data quality issues, it requires the data used in building the underlying simulation model to be of high quality. Otherwise, as the adage goes, garbage in, garbage out. By demonstrating the potential features of the tool to evaluate policy choices and analyze their tradeoffs, it can be used to advocate for improving the quality of the BR data.

As the DST is based on a partial equilibrium simulation model, it considers the effects of the policies only on the outcomes that are analyzed and ignores the effects of the policies on other outcomes in the economy, in addition to any second-round effects that might affect the budget constraint, for example, which is treated as exogenous in the model.

It is imperative to build simulation models for as many countries as possible, depending on the availability of reliable data on the BR indicators that also extends backward to 2000. Extending the time series of the data is critical because the effect of policies and public investments, for example, take time to yield results or have impact, with different magnitudes of impact over time. As the CAADP BR outcomes cover a wide range of development objectives, the policies and other factors used in estimating the parameters for the simulation model must be exhaustive to avoid omitted variables problems. For each outcome indicator considered, its structural model must first be developed to ensure that all the exogenous variables that matter are included in the estimation of the reduced-form models, the estimated parameters of which are used in building the simulation model of the tool.

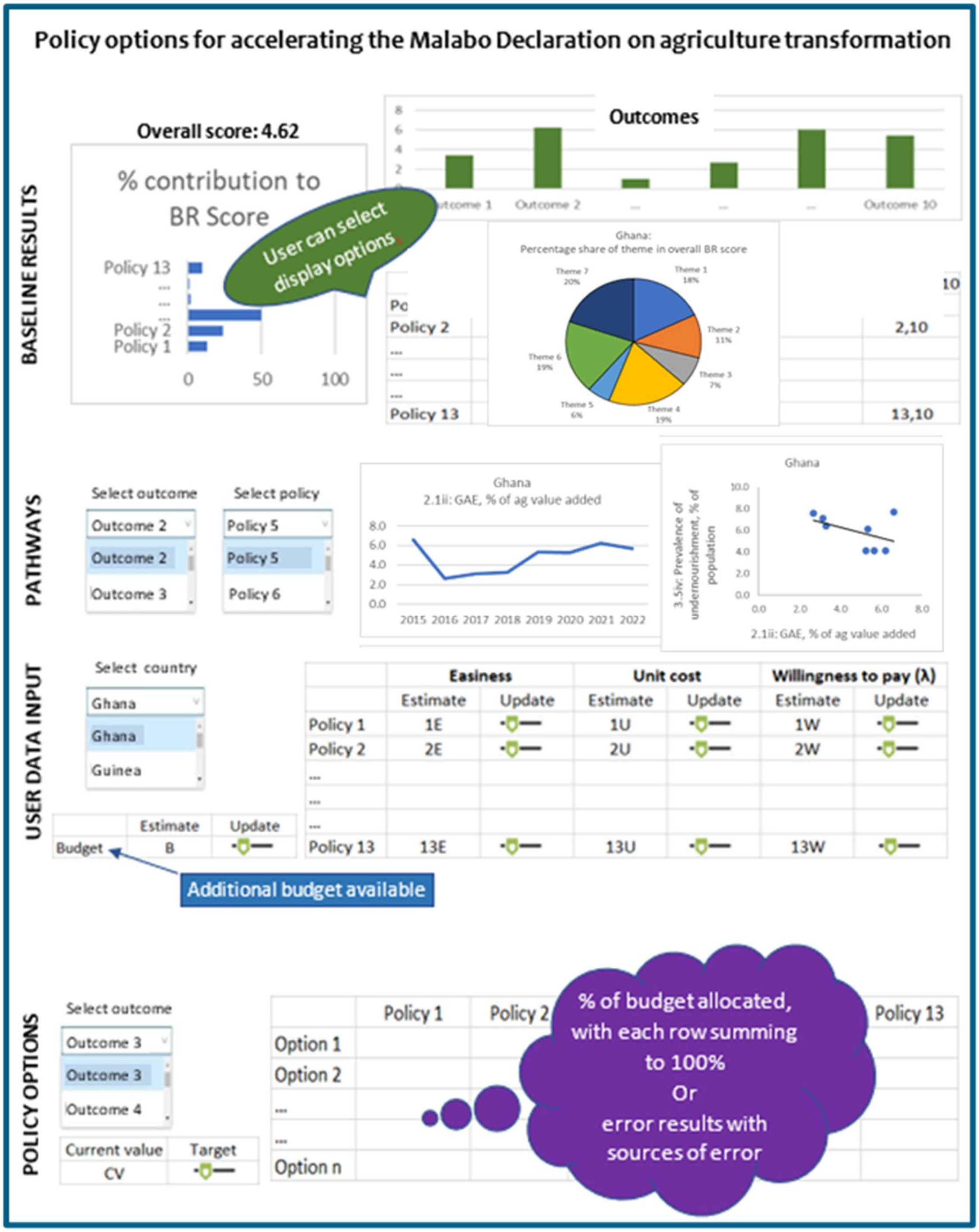
For each country completed, the tool will be made available on the internet for download in Excel. A web-based interactive version will also be developed, and users will be able to do the simulations online. This will be accompanied by other analytics related to the BR scores, as illustrated below in Figure 1 with an envisaged user interface of the online version.

The top panel of the interface will include a decomposition of the overall BR score by theme, performance category, and indicator. The decomposition will show, for example, the percentage share of the theme (or performance category or indicator) in the overall BR score. To display the information of choice, the user will select the country and type of chart/results (e.g., pie, bar, stacked bar).

The middle panel will allow the user to examine indicator trends as well as their correlations to one another. The user will select the country and the indicators from three categories (policies, intermediate results, and outcomes) to display. These will include a trend or line chart over time and a correlation and scatter plot of two variables at a time. To help improve the quality of the data, the user will be requested to provide feedback on abnormal values of the indicators and suggested correct data and sources.

The bottom panel will simulate the policies to achieve the specified target of one outcome or more, as presented in this paper. The user will select the country and the scenario (i.e., value of target outcome(s), baseline year, restrictions on change in other outcomes or variables, unit cost and weight of policies, budget, and estimated parameters used in the calibration—KRLS, SVM, or LRR). The results will be displayed as percentage change in policies and outcomes relative to baseline, and allocation of budget by policy.

Figure 1. Envisaged interface of the online version of the CAADP BR decision support tool



Source: Author's illustration.

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ANNEX TABLES

Table A1: Data on Ghana used in the econometric analysis to estimate the marginal effect of policies and other factors on outcomes, 2015-2022

Variable	2015	2016	2017	2018	2019	2020	2021	2022
Outcomes (O_j)								
VADWKGR	11.85	11.01	10.51	9.84	9.28	8.97	8.89	8.76
VADLDGR	1.92	1.97	2.09	2.20	2.30	2.13	2.31	2.41
STUNTING	18.50	17.60	16.80	15.90	15.00	14.20	19.20	18.00
WASTING	4.70	6.00	6.80	6.80	6.80	6.80	4.50	6.00
UNOURSH	7.70	7.60	7.10	6.40	6.10	4.10	4.10	4.10
MDDW	7.20	7.20	47.20	47.20	47.20	59.80	59.80	59.80
MADCH	13.00	12.60	12.60	13.00	16.90	16.90	41.40	41.40
FDINSGR	5.00	5.00	5.00	5.00	5.00	11.70	11.70	11.70
OBESITY	11.90	12.30	12.70	13.10	14.50	15.70	17.20	18.30
INPOVGR	12.00	13.30	12.30	11.70	11.10	11.20	11.30	11.30
LNDSLM	18.80	19.50	23.16	24.20	24.43	21.56	40.24	41.24
Policies (P_i)								
GAEVAD	6.61	2.66	3.14	3.29	5.33	5.24	6.22	5.66
GAERES	0.53	0.21	0.25	0.26	0.43	0.42	1.76	1.48
SOCPROT	7.32	12.98	9.32	11.80	21.47	40.90	16.99	17.20
ASCI	63.50	63.50	64.00	68.00	68.00	68.00	68.00	68.00
Other factors (H_k)								
GNAGEXP	7.68	7.89	6.96	7.10	7.04	7.83	9.95	10.05
GDPPCAP	1715.82	1711.27	1728.10	1827.27	1899.81	1981.61	1951.07	2014.71
RAINFALL	1185.40	1203.96	1167.38	1172.95	1208.61	1209.32	1139.16	1181.23

Source: Compiled from AUC (2024) and World Bank (2024a, 2024b).

Notes: The variables representing the outcome and policy indicators are from the BR database and described in Table 1. For other variables, GNAGEXP is government nonagricultural expenditure as a percentage of gross domestic product (GDP), GDPPCAP is GDP per capita in 2015 constant prices, and RAINFALL is precipitation measured in mm.

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