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Sample Application of Impact Modeling to Agricultural Development in Sub-Saharan Africa & South Asia

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CAMBER COLLECTIVE

Illustration of Application & Generated Insights

Social impact funders in the ag development sector, as in others, need to make tough decisions about where to invest their limited grant dollars, influence, and staff time to maximize impact. For funders seeking to reduce global poverty through improvements to the livelihoods of smallholder farm households in Sub-Saharan Africa and South Asia, the rationale for investing in agricultural development is clear. The best paths through which to do so, however, are less well-defined. To help ensure every philanthropic dollar spent on agricultural development had the largest impact on poverty reduction, we, in conjunction with a leading philanthropy, developed (i) a new decision framework, (ii) reliable dataset, and (iii) widely applicable **Revenue and Income Impact Model (RIIM)** to improve investment decisions to better benefit the 70% of the world's poorest who, according to the World Bank, derive some or most of their annual income from agriculture.

Camber has engaged clients to jointly pursue multiple projects involving impact modeling. The thinking discussed in this paper was largely developed with a major funder who aimed to reduce poverty through agricultural development. We worked hand-in-hand with the client to develop the underlying framework, gather the data, build the impact models, and agree on the implications of those outputs for agricultural development programming.

The new foundational framework, **Figure 1,** which links changes in income impact to changes in farm productivity includes key variables, such as *changes in cost to farmer, future changes in commodity price, changes in realized yield, and percentage of households adopting an intervention*. Figures associated with these variables are specific to each commodity and are further tailored to four different segments within the smallholder farm household population. These segments, based on land agricultural potential and household proximity to input (e.g. fertilizer) market, allow for the output of more refined total estimates. RIIM, illustrated in **Figure 2** and replaced with representative dummy data, represents the ex-ante impact model constructed and can be used by funders at the strategic and portfolio levels across multiple geographies, commodities, and beneficiary segments to project expected beneficiary impact and aid decision-making.

Figure 1. Revenue and Income Impact Model (RIIM) Framework

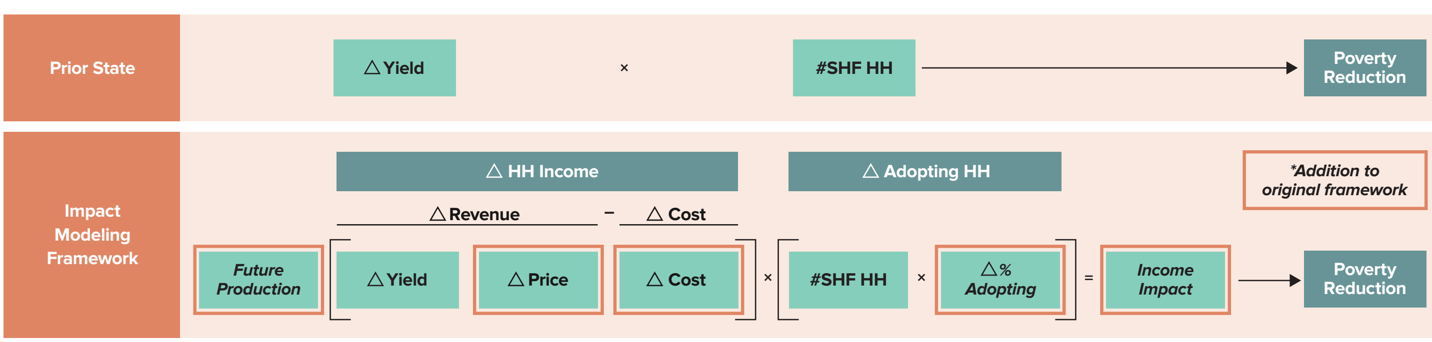
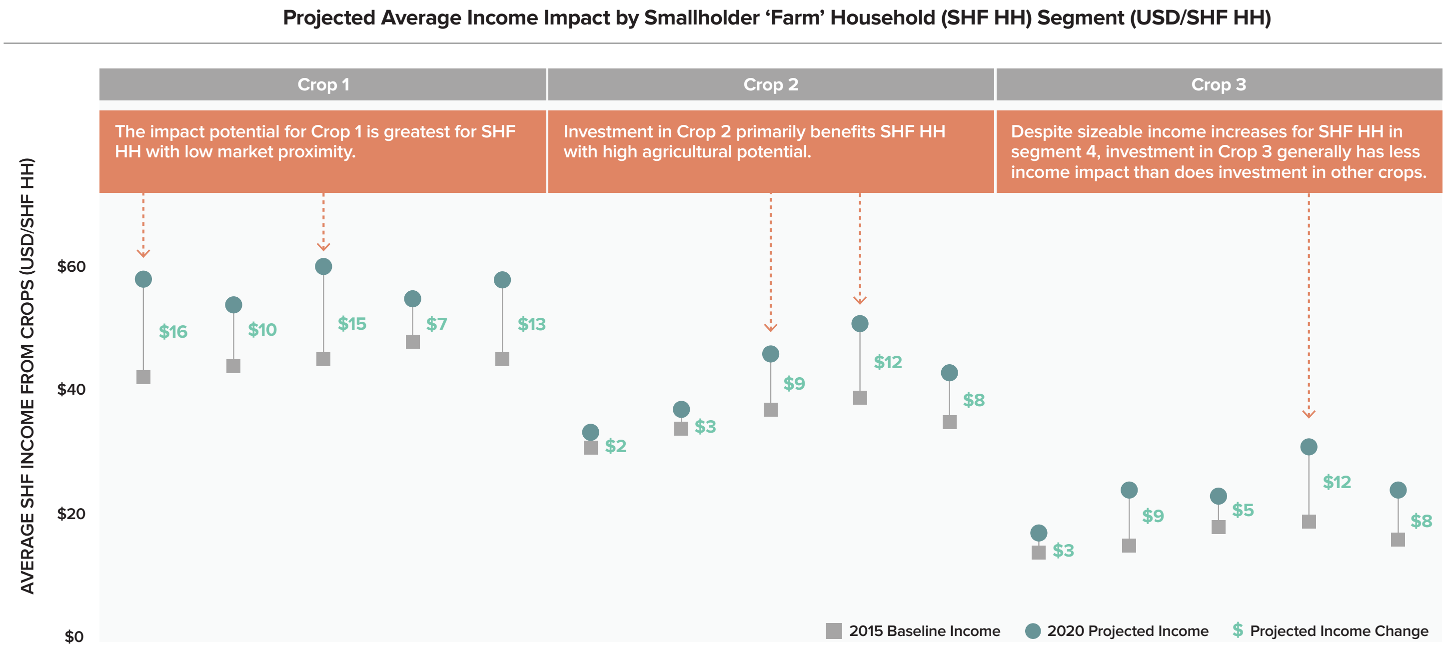


Figure 2. Revenue and Income Impact Model (RIIM)

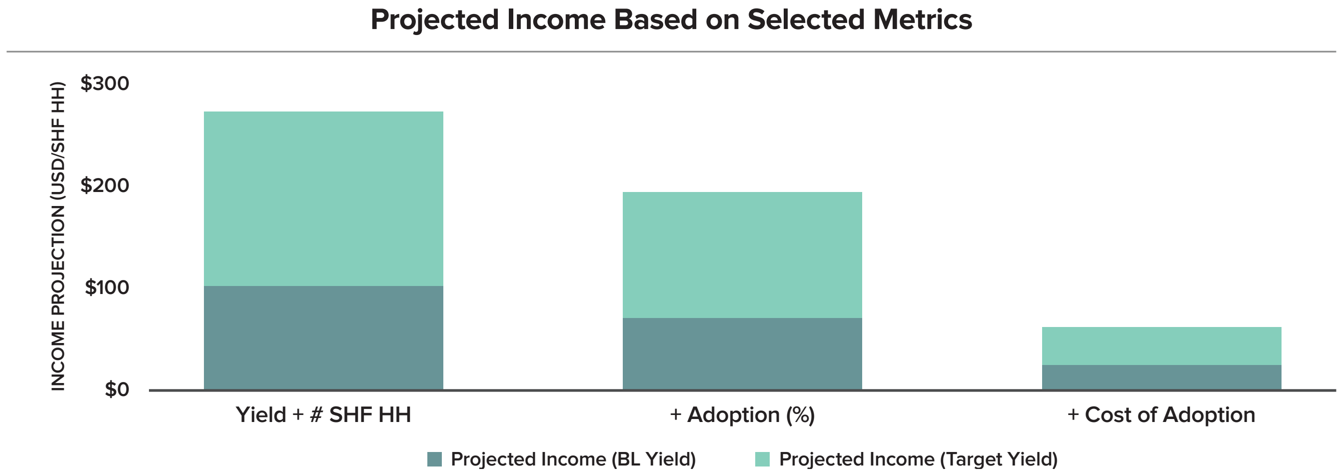


SHF HH Segment	1	2	3	4	TOTAL	1	2	3	4	TOTAL	1	2	3	4	TOTAL
Ag Pot	Lo	Lo	Hi	Hi	-	Lo	Lo	Hi	Hi	-	Lo	Lo	Hi	Hi	-
Mkt Prox	Lo	Hi	Lo	Hi	-	Lo	Hi	Lo	Hi	-	Lo	Hi	Lo	Hi	-

Through RIIM's construction, we uncovered key insights and confirmed the value of right-sized impact modeling, illustrating how it could dramatically improve the consistency and rigor with which key strategy and investment decisions are made by major funders, including philanthropies, multinational agencies, donors, and local governments.

For example, **misalignment exists between the agricultural commodities focused on by most funders based off traditional relationships, expert opinion, and experience and some of the commodities suggested by the more consistent, data-backed RIIM.** Maize (corn), for example, has been the primary investment focus in Sub-Saharan Africa for many of Ag's largest funders. In Ethiopia, over 7 million of 12 million smallholder farm households (SHF HH) grow maize. When examined through RIIM, which features other variables (e.g. expected # and cost of adoption) contributing to any smallholder income change associated with maize investments, however, maize clearly offers far less promise for poverty reduction than most funders had thought.

Figure 3. Projected Income Impact Based on Inclusion of estimated # of adopters and $ of adoption



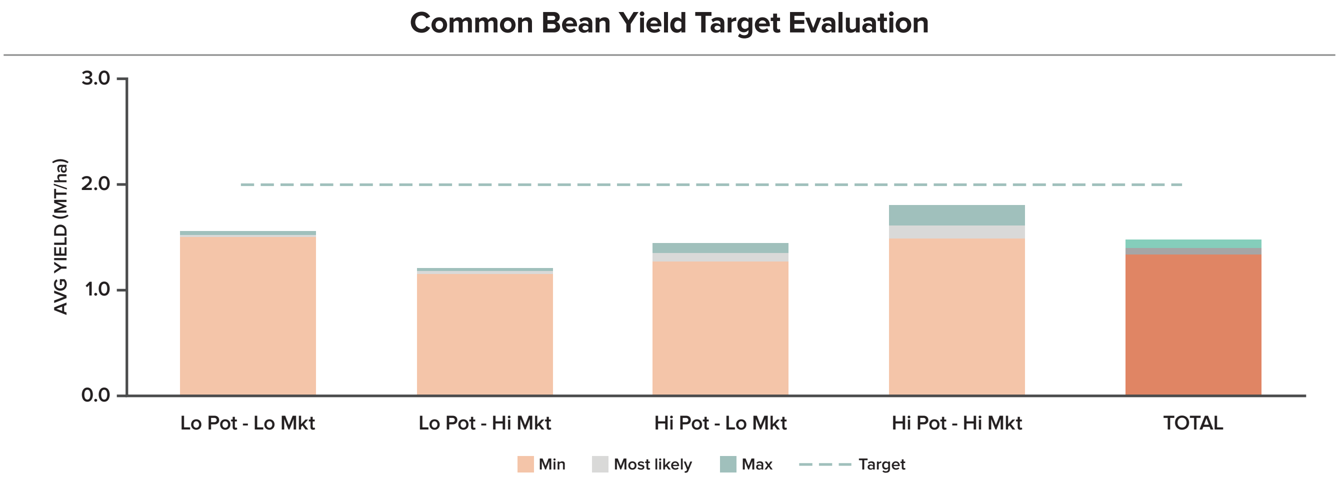
RIIM reveals that despite maize's ubiquity on smallholder farms, its higher intervention costs, low adoption numbers, and relatively low sale price mean that it is a far less attractive commodity for poverty reduction than originally assumed. Using baseline data values for farm gate value ($225/metric ton), 2020 target yield values (1.6 metric tons/hectare), and expert opinion of a 2020 reduction to intervention package costs to households ($67/metric ton of production) results in a substantially smaller return toward income than was initially believed.

Additionally, RIIM highlights how some commodities with fewer growers by comparison but still significant presence on smallholder farms are excluded from many investors' focus. When evaluated on the basis of their contribution to smallholder farm household income and the impact of a yield increase on income, these crops emerge as key points of investment leverage. According to baseline data in Ethiopia, maize's annual income contributions equate to $24 per smallholder farm household across all smallholder farm households, maize-growing or not. Teff, by contrast, is grown by just under 6 million smallholder farm households, and its income contributions of $40 per household are 68% higher than maize's, primarily due to the higher farm gate price. Even with the anticipated 18% increase in yield values from baseline data, maize's projected income contribution jumps only to $37 per smallholder farm household.

Understandably, factors aside from revenue potential (e.g. a commodity's impact on gender equality or nutrition) are worthy of consideration in the selection of focus crops. RIIM calls attention to the discrepancies between the recommended focus crops and suggests that income and revenue play a larger role in those decisions.

Current investments are not structured to reach future goals. Separating smallholder farm households into four distinct segments based on proximity to input (e.g. fertilizer) markets and farm-land quality shows us the current yields achieved by each segment. In many cases, we see that *every* farmer segment would need to experience a yield increase in order to reach overall target goals, an unlikely outcome given the difficulty and higher costs of reaching households in more remote segments. In other cases, expert opinion about the magnitude of the most likely yield increases across segments indicate that previous targets are not at all feasible, even if a significant portion of every segment is reached. Expert-informed

Figure 4. Evaluation of Estimated Realized Yields by Segment



2020 yield and adoption assumptions for common bean in Ethiopia, for example, reveal that even in the most optimistic scenario, the yield values are expected to be low enough in each segment that overall target achievement is nigh impossible. Such discoveries encourage reexamination of the goals and of the investment portfolio and suggest that other investments, for example in rural roads and infrastructure, may be necessary before commodity-specific interventions can have their hoped-for impact.

Downstream investment in the supply chain may be as or more important than R&D. Historically, investment by some major funders have primarily prioritized R&D and other technologies aimed at increasing yields. Though research has shown that the products of those investments offer significant productivity gains to *adopting* smallholder farmers, the magnitude of their potential impact has generally not yet been realized due to low adoption rates. Our analysis of baseline data indicates that use of potential intervention package components such as fertilizer or hybrid seed, though varying across segments, tends low and is of high cost to farmers. Adoption rates are often lowest in the low-proximity-to-market farmer segments, who often have the largest theoretical on-farm gains to realize.

RIIM underscores an already very strong argument that addressing low adoption rates, rather than further investing solely in improved crops and inputs, is more likely to generate the nationwide yield increases that have been assumed but not yet realized by smallholder farmers. Adding more new technology to a downstream pipeline of farmers unable or unwilling to adopt them is alone unlikely to produce desired results.

A More Detailed Review of Impact Model Design

Model Construction for Investors in the Agricultural Development Sector

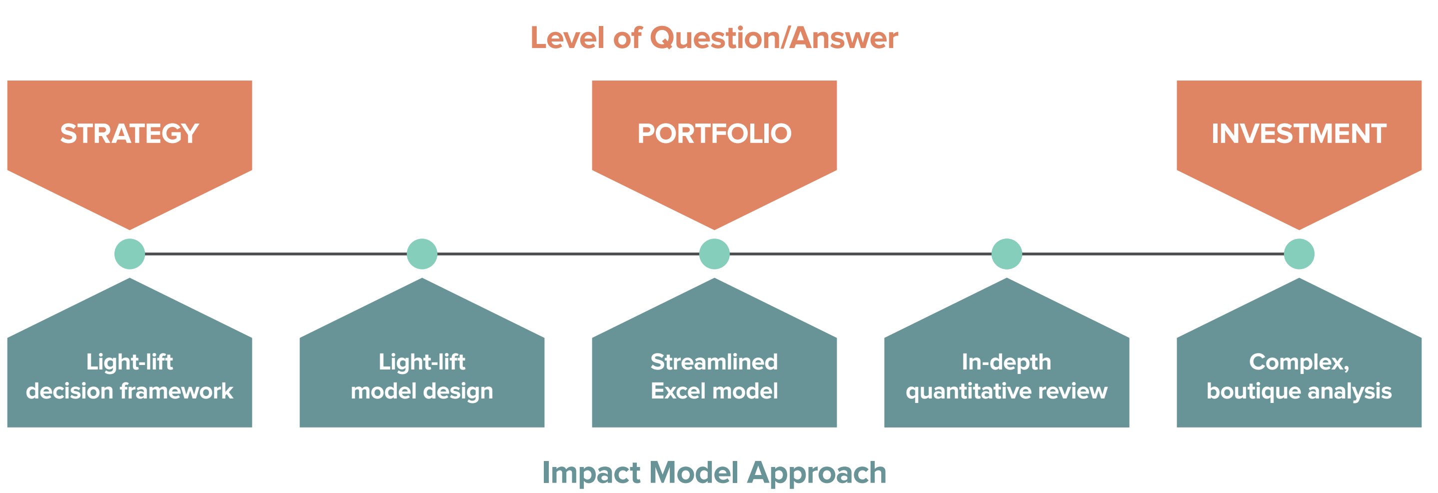
A Progression of Impact Modeling Approaches

Complex, data-driven impact modeling is not right for every circumstance or every actor. In some cases, more qualitative methods may be a better fit. **In all cases, the nature of the questions an organization wishes to answer should drive the choice as to which approach is best.** In situations where impact modeling is used, the model should always be "right-sized" for the organization and investment need it supports, as well as combined with other decision tools and processes. Impact modeling is not a one-size-fits-all solution, nor a silver bullet. Once the organization's purpose-driving questions have been identified and the type and level of appropriate answer have been determined, the organization may then consider two additional factors: (i) the extent to which the answers the organization seeks will improve as a model becomes *more complex* and (ii) *the resources* (e.g. time, funding, available data, and quantitative expertise) available to design, execute, and apply the impact model.

Upon closer examination, a progression of analytical modeling approaches emerges. Organizations can determine which impact modeling approach is best suited to their needs by (i) identifying the level of questions facing the organization, (ii) determining the added value of increased model complexity, and (iii) defining resource availability.

For high-level strategy decisions, a light-lift decision framework often proves most useful. A lack of clarity or alignment on the decision-making process compels adoption of a light-lift decision framework. With varying degrees of qualitative and quantitative research, this approach emphasizes conceptual frameworks and expert opinion to most quickly improve strategy-level decisions. Rapidly approaching internal strategy reviews or board reviews may warrant this approach, which requires less time (e.g. 1-2 months) and lighter data input requirements.

Figure 5. Conceptual Framework: Choosing the best-suited impact model approach



For mid-level portfolio decisions, streamlined Excel models may be more useful. The adoption of a middle ground approach with rapid prototyping of impact models often complements situations where the development and implementation of a more complex impact model add value to an organization's decision-making process. This requires increased access to more relevant datasets (not just expert opinion), confidence in the validity of those data, and development of an actual model (e.g. in Excel), as opposed to simply a conceptual framework. However, this added complexity and effort help answer more and more detailed tradeoff decisions. Commonly employed at the portfolio level, we find this is a good sweet spot between too much simplicity and complexity, as it brings additional rigor but can be executed in 3-6 months and usually draws from a level of widely available data that can be applied to decisions across diverse geographies and beneficiary segments – a key requirement of major funders like leading philanthropies, multinational agencies, and local governments. We also find this is often the last level of analysis that is widely approachable and useable for most philanthropic program officers and/or government policymakers. If data requirements and/or model complexity progress further, the models outputs generally become less widely applicable and/or the logic model becomes less approachable.

For individual investment decisions, complex, boutique analyses typically offer the greatest insight but do so at a higher cost. When analysis beyond the development of basic impact models is necessary, highly complex models that present answers to the most specific questions tend to work best. This resource-intensive approach often requires years of refinement and data collection but also offers a nuanced look at a particularly focused area (e.g. a particular farmer type growing a specific crop in a sub-region of one country). This level of specificity and complexity is well-suited for occasions where the additional knowledge provided by more extensive modeling improves decision-making capacity. More often than not, however, this approach's applicability is severely limited due to the absence of quality data at such a granular level across a broad range of interventions, beneficiary segments, and/or target geographies. Onerous data requirements and a need for patience further limit the number of adopters of this approach and the number of occasions on which we would actually recommend it. Only a small subset of experts (rarely policymakers) with deep knowledge of statistics and health or development economics are likely to understand the complex mechanics of the resulting models. For investment-level tradeoff decisions aimed at answering specific questions, however, complex, boutique analyses, have their place.

A logical framework backed by data offers social impact funders increased opportunity for maximized returns at any level, though right-sizing the approach is key. **Although other, more complex options offer greater return in select scenarios, for most funders, light-lift decision frameworks or streamlined Excel models are a great step forward.** In fact, an overly-detailed focus on data or highly complex econometric models often stalls the global development sector's decision-making process and leaves funders ill-positioned to make actionable investment decisions. Our experience has shown that the best investment decisions and decision-making tools are those that depend on relevant and timely data and have simpler designs that allow them to be understood, and used, by a wider set of actors, particularly grant- and policymakers.

Once an organization can clearly articulate the level of necessary answers and has identified the appropriate approach, the task switches to determining how available resources may best be allocated within the context of that decision. Low availability of quality data, for example, may dictate that data procurement be limited to the first two weeks of a four-month engagement. Similarly, abundant time and internal capacity resources paired with a desire for future iterations of an annual investment-level model may allow for an extended period of data procurement, cleaning, and analysis.

We developed a decision-making framework to inform an investment portfolio focused on reducing global poverty through agricultural growth. To be most useful to major funders, we needed a framework with wide-ranging applicability as a decision-making tool across multiple countries, a host of agricultural commodities, and different segments of smallholder farmers. Highly specific analysis depending on boutique datasets limited to specific geographies, commodities, or beneficiary segments would be of little strategic use. We determined that a middle option combining an Excel-based impact model with widely applicable data provided the best balance of rigor and applicability. Once we began to build the model, we identified places where increased complexity would substantially improve output accuracy. For these, we shifted slightly toward the right side of our spectrum but remained cognizant and aligned with our final goal.

We identified three prominent design needs: (i) an improved proxy showing potential for poverty reduction; (ii) broad, comparable baseline data; and (iii) an ex-ante impact model comparing investment tradeoffs. We met these needs by (i) designing the Revenue and Income Impact Model (RIIM), (ii) consolidating and cleaning baseline data from multiple sources, and (iii) separating smallholder farmers into four segments using proximity to markets and land quality.

To create a practical set of recommendations for major agricultural development funders, we ultimately had to answer:

- Which countries need to be focused on?
- Which crop or animal commodities need to be invested in?
- Which farmer segments need to be served?

Prematurely seeking to answer these questions based off expected yield increase and total number of farmers only, however, would leave funders unable to optimize investments.

Constructing the Impact Model

We brought together new baseline data and multiple stages of analytics to address the identified design needs and produce a functional decision-making tool. We shifted investors’ focus from their former state to one where they could make portfolio-level tradeoff decisions among countries, commodities, and farmer segments based on projections of future income impact, a still imperfect but much improved proxy for poverty reduction.

Our process emphasized three critical steps: (i) designing a revenue and income impact model and its necessary components, (ii) consolidating, organizing, and aggregating baseline data, and (iii) engaging in beneficiary segmentation.

Designing the Revenue and Income Impact Model (RIIM)

Major funders need a better way to project which strategies best promote poverty reduction for smallholder farmers. Yield change and number of famers alone have tenuous links to poverty reduction and, to **better estimate income impact,** funders need an improved proxy. The conceptual framework we developed includes several additional variables that add substantial predictive power without overwhelming complexity. These key components form the basis of the **Revenue and Income Impact Model (RIIM)** to inform funders of any disconnect between where the largest opportunities for impact lie and their current strategy and investments.

Figure 6. Revenue and Income Impact Model (RIIM) Framework

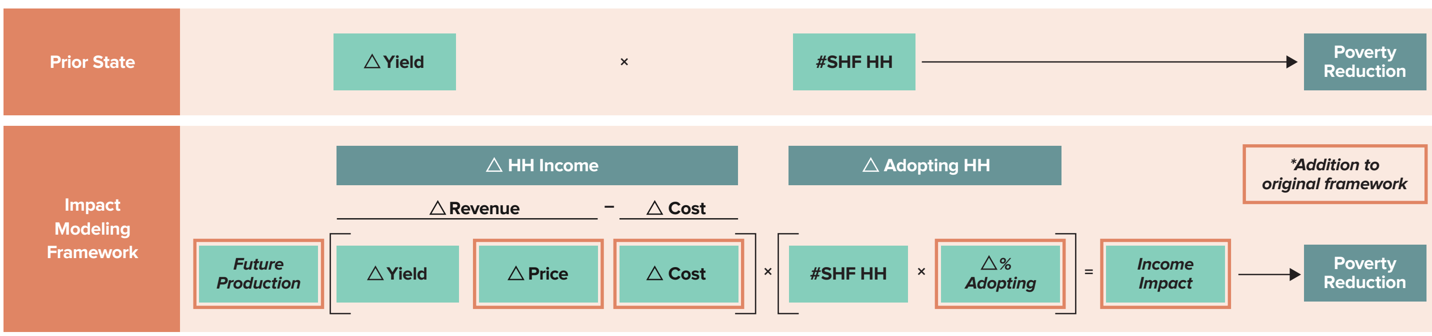
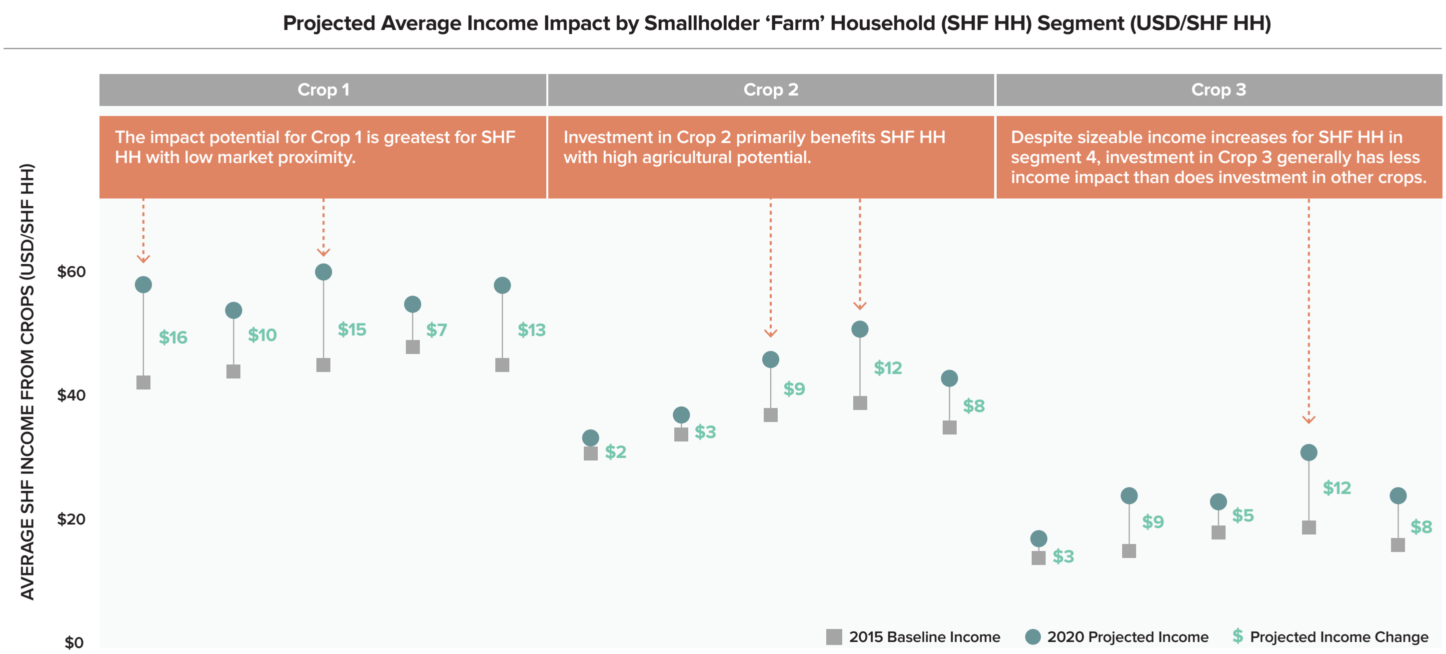


Figure 7. Revenue and Income Impact Model (RIIM)



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RIIM relies on available measures and data but also adds previously unexamined fields with essential ties to revenue and income. Yield, a variable of significant importance, had previously been examined as a measure of goal progress alongside only the gross number of smallholder farmer households growing a crop. In this prior framework, an increase in realized yields represented an increase in production and was consequently assumed to be accompanied by increased income. Only farmers adopting technologies affording yield bumps experience these gains, however, and the costs of those technologies lessen the net gain when estimating income. A prominent example of this is hybrid maize (corn), which at first glance appears to be a great bet to increase smallholder incomes due to (i) its potential to increase yields and (ii) the large number of smallholder farmers in Sub-Saharan Africa already growing maize. However, when we layer on the costs of adoption (annual seed and fertilizer purchases), the relatively low price for the sale of maize, and the difficulty of anyone but high-proximity-to-market smallholders accessing these new varieties, the national-level income impacts look far less appealing.

RIIM's logic is largely linear. Income impact is the product of the *change in household income* and *the change in the number of adopting households. Change in household income* is the difference between the *change in revenue* and the *change in cost,* each of which is affected by the anticipated *future production. Change in revenue* is influenced predominantly by *change in yield* and *change in price per unit* (e.g. metric tons of crop or units of a particular livestock byproduct). *Change in cost* depends on the *cost* of the intervention package.

The *change in revenue,* however, is experienced only by adopters of the agricultural technologies offered through the investment intervention packages. Funders' previous decision-making frameworks generally considered the *total number of smallholder farm households* but did not incorporate the *percentage of adopting households,* a moderator variable with significant influence on income impact. The *change in revenue* due to an anticipated increase in production from a *change in yield* is also accompanied by a *change in cost* associated with technology adoption, which is, again, a factor that often reduces the income impact of any strategy or intervention.

RIIM compares the five-year change in revenue and income attributable to yield increases due to the adoption of investment-supported technologies across commodities within and between geographies. The resulting income impact output display presents the anticipated effect on income due to investments in different commodities.

Gathering & Consolidating Baseline Data

Once the key components of RIIM had been identified, we compiled and organized the **broad, comparable baseline data** needed to calculate RIIM's outputs.

Multiple years of panel data from approximately 5,000 household surveys run by the World Bank (WB) in each of the Sub-Saharan Africa geographies and from nearly 8,600 households surveyed by the Government of India (IG) provided the bulk of these figures. Additional data from the Commonwealth Scientific and Industrial Research Organization (CSIRO) served as supplement, providing estimates for otherwise missing variables, such as total animals owned or livestock byproduct yield. Separate datasets, through the assignment of unique identifiers, allowed household-level data to be linked to plot-level data, which provided additional information about the use of agricultural inputs specific to particular crops. The farm gate value, or price, for each crop or animal byproduct sold by each household was also available in these datasets, as were recorded yield figures, area planted values, and herd sizes. The data for many of the variables in RIIM existed in these panel datasets, but they had not previously been analyzed for smallholder farm households and seldom, if ever, applied to an income impact model.

Procuring and cleaning these figures provided the broad comparability across commodities and geographies required for a high-level investment decision-making team. Prior to our work, although much of this data was theoretically available to anyone who wanted it, its raw form meant few used it. For example, we found it was not uncommon for two investment proposals focused on the same country to use radically different estimates of simple data points, such as the number of smallholders in a given region growing a specific crop. Improved baseline data was critical for RIIM, and it also provided a common set of standards for other decision-making processes (e.g. individual grant proposals and review).

Figure 8. Sample of included variables

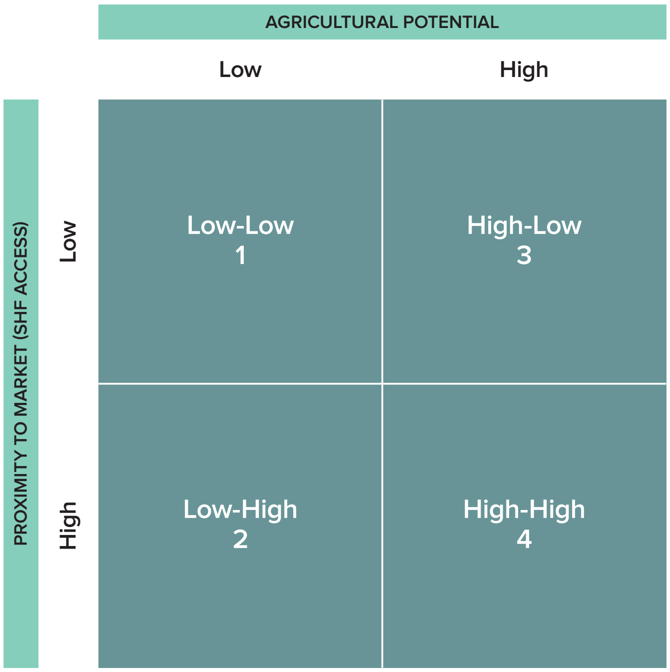
Example Variable	SHF HH Classification	Harvest/ Production	Area Planted	Commodity Yield	Farm Gate Price	Ag Input Use	Ag Input Cost	# of Animals
Source	Calculation	WB/IG/CSIRO	WB/IG/CSIRO	Calculation	WB/IG/CSIRO	WB/IG	WB/IG	CSIRO
Description	Designation based on survey assignment as farming HH and area operated	Amt. of crop harvested or byproduct produced	Amt. of land planted with crop	Amt. of commodity produced per unit of production (per hectare or per animal)	Unit value per produced unit	Binary indicator of ag input use (e.g. fertilizer, improved seed)	Cost of ag input use	No. of animals by type raised by HH

Improving Investment Strategy through Segmentation

For each of the households in each national survey, we assigned **segment classification,** which addressed the persistent need to identify primary beneficiaries of interventions and the ease of reaching those beneficiaries. The segmentation divides households into four segments (or groups) based on (i) **the agricultural potential of their land** and (ii) their **proximity to an urban input market.** Since each segment realizes different yields and adopts intervention packages at different rates, future yield and adoption rate estimates can be tailored to each segment to better evaluate the impact of investment across the population at large. Segmentation also allows for tailored costs of adoption. Since planting hybrid seeds, for example, requires annual seed purchases (in order to maintain favorable genetic traits) and requires fertilizer purchase, few households pursue this expense fully. Segmentation accounts for this and remains a key factor in our process, primarily because it addresses the likely scale of any investment impact.

As an example of the significance of segmentation's inclusion, we point again to hybrid maize. With more households growing maize than any other crop, distributing hybrid maize seeds with higher yields to smallholder farmers

Figure 9. Segmentation Methodology



seems to offer a revenue promise greater than any other. Segmentation and a closer look at baseline data reveal, however, that adoption of hybrid maize seed trends low for low-proximity-to-market households and that those adoption figures are difficult to improve due to the need for hybrid seed to be purchased annually and receive very specific and timely applications of fertilizer. Based on this, we see the introduction of new technologies alone as unlikely to produce significant increases in adoption rates or resulting in the expected yield increases realized on demonstration plots. Examining the *per hectare* costs of agricultural inputs further decreases the income impact due to the cost of adoption and relatively small numbers of farmers that can be expected to make that change.

Segmentation highlights another key concern about funder targets. Yield targets for 2020 had already been set before we began, but it became clear through our work that even in the most optimistic cases those national-level yield targets were unlikely to be met.

The analysis reveals that poverty reduction goals are unreachable without drastically expanding the beneficiaries targeted, a process that would require new strategies and investments to reach far more low-proximity-to-market smallholders traditionally left out of many agricultural development efforts.

Because of the adopted segmentation scheme, intervention package adoption costs can also be tailored to each segment. This additional step to the bottom-up build addresses the need to more effectively evaluate the true costs and impacts of multiple investment opportunities. Segment-specific population numbers, yield figures, and cost assumptions produce a uniform output for yields and costs, which consider the relative proportion of farmers in each segment and their respective yields and expenses.

Improving Model Accuracy through Additional Sophistication

Aggregating these data and expert opinion gave way to a bespoke national-level **ex-ante impact model** predicting the relative income impacts of different country, agricultural commodity, and farmer segment combinations.

RIIM accommodates preferences for alternative datasets by allowing user-defined yield and cost assumptions to be inputted. Though, RIIM's design produces the income and revenue outputs necessary to evaluate ROIs at a high level, we wanted to add sophistication to the model that would improve its accuracy without adding too much complexity. We revisited the segmentation scheme and incorporated agricultural potential ratings specific to particular crops in recognition that land that is great for one crop may be far less so for another. A household that previously had been designated as having low agricultural potential due to infrequent rains and shallow soil may, for example, have been reclassified as having high agricultural potential when examined solely for sweet potato, a crop that tolerates mediocre growing conditions such as poor soil and dry spells. These nuanced segmentation assignments enabled more useful yield parameter estimates from subject matter experts.

Similarly, though we knew it was unlikely we could incorporate a fully functional and easily understood econometric model in our design, we recognized the value of including a future price prediction factor since market prices for particular commodities fluctuate over time, altering the total revenue smallholder farm households might receive from sale. If production increases are large enough, for example, new markets for export may open or prices may plummet. To this end, we included future national production and consumption estimates and incorporated an elasticity function to the model, which allows users to modify future prices.

Additionally, though household-level panel data provide agricultural baseline figures, it was noted early on that the survey weighting assigned by the administering organization was likely assigned based on total population counts and was therefore not necessarily consistently representative of agricultural demographics in each focus geography. To account for this, we included census multipliers that align the smallholder farm household counts derived from the panel data with the total smallholder farm household counts derived from the agriculture portion of each country's census survey.

Small additions such as these provide additional sophistication that enable more predictive model outputs.

Applying Impact Modeling More Broadly

RIIM represents an application of impact modeling to the agricultural development sector. With more than two billion people worldwide relying on smallholder farms for their livelihood and dozens of impact-seeking investment actors in the space, identifying the appropriate impact metrics and building ex-ante models that produce meaningful outcomes using those metrics can dramatically improve the consistency and rigor with which key strategy and investment decisions are made, thereby increasing the income gains for millions.

Beyond internal use by major funders, impact models can also, in some cases, be used as tools to influence and align entire fields around a common way of evaluating and making tough tradeoff decisions between different strategies and groups of investments. The Lives Saved Tool (LiST) developed by John Hopkins with funding from multiple foundations, for example, has become the gold standard for estimating the impact of scaled-up nutrition and health interventions. Now in its 14th year, LiST's start in an academic institution with funding from a private philanthropy has transformed to a tool used by implementing NGOs, Ministries of Health, international development agencies, multinational orgs like the UN and WHO, and academic institutions for strategic and investment planning. If incorporated more broadly into the agricultural development and poverty reduction sectors at large, RIIM and similar models could provide comparable benefits outside the field of health.

Paired with clear goals, impact modeling offers social impact funders a way to predict and compare the effects of their investments *before* making them. LiST and RIIM illustrate the value of impact models and demonstrate how they can enable actors in the social impact sector to benefit from the same sorts of tools already more widely employed in the private sector to great effect.