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Integrated Economic Modeling of Global and Regional Micronutrient Security

Siwa Msangi[1], Timothy B. Sulser[1], Andrew Bouis[2], Daniel Hawes[1], and Miroslav Batka[1]

ABSTRACT

In this paper, we examine the implications of alternative country-specific scenarios for biofortification on the reduction of micronutrient deficiency prevalence in under-fives. The scenarios are implemented within a long-term projections model of agriculture production and consumption, given the timeframe needed to develop and implement biofortification of crops and the need to account for changing diets over time. The effectiveness of the various biofortification strategies is largely determined by the evolution of regional dietary patterns over time, which show continued reliance on staple food crops among the poor. It suggests that cereal grain-focused biofortification is likely to be most effective in South Asia, while targeting roots and tubers is most effective in Sub-Saharan Africa.

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I. OBJECTIVES OF THE STUDY

Biofortification is emerging as a new intervention to address micronutrient malnutrition. Its advantage is that it is based on enhancing the micronutrient content of staple foods that most impoverished people consume. Yet, as the global economic environment is changing rapidly, so are diets. Therefore, an understanding of the long term impact of interventions such as biofortification requires an assessment of how diets will change in the future and how reliance on staples foods will change in particular, which in turn has implications for the success of the biofortification strategy. This provides the context of this study, which attempts to account for the impact of global socioeconomic drivers on agricultural production and the availability of micronutrient demands to poor, rural, and food-insecure households and to make projections of staple food and micronutrient intakes into the future. In order to accomplish this, we have undertaken to modify the simulation structure of IFPRI's International Model for Policy analysis of Agricultural Commodities and Trade (IMPACT) model to simulate the specific demands for food and micronutrients across a variety of socioeconomic classes. The disaggregation of rural and urban consumers among their various income classes allows us to look more closely at how patterns of consumption of staples, meats, and key fruit and vegetable commodities evolve over time and how changes in diet due to income changes compare with the changes in nutrient availability that biofortification can provide.

The broad objectives of the study are:

- Develop a methodology to disaggregate food and derived micronutrient demand by socioeconomic strata;
- To incorporate the ability to represent the policy impacts from the IMPACT model and simulation results relating to micronutrient demand under various policy scenarios at the appropriate spatial scale;
- In a subset of countries, provide forecasts of staple food and micronutrient intakes into the future, disaggregated by rural and urban areas and by income group, so as to better inform biofortification priority setting over time; and
- Use these forecasts to simulate changes in prevalence of inadequate intakes from the successful implementation of biofortification.

In the rest of this paper, we describe the various activities that were undertaken in order to meet these objectives. Starting from the basic compilation and analysis of household-level consumption and expenditure data, we constructed algorithms that could estimate household food demands so that a modified IMPACT model could be linked to the disaggregated demand system. This program of work embodied the efforts of a number of research staff who are listed in the Appendix 1.

II. JUSTIFICATION AND LIMITATIONS

Here we address a number of issues that will arise regarding the appropriateness of the methodology employed in this study, the way in which certain limitations were handled within the scope of this study, and issues that will need to be addressed in future work. Among the top issues are those of (1) using a partial-equilibrium framework versus an economy-wide or general-equilibrium approach; (2) the extent to which actual intake values are considered in the analysis versus market-level availability; and (3) comparisons to other interventions.

Partial- versus General-Equilibrium Modeling Approaches

The work on food security and poverty impacts arising from agricultural policy changes or shocks to the economy or environment have been examined within a variety of country- and global-level studies at IFPRI, as well as other policy research institutions. The researchers' choice of modeling framework is often driven by the particular research questions being asked and the most readily-available and appropriate analytical framework suited to address those questions. The choice between adopting a partial- or general-equilibrium approach to modeling economic markets and their role in mediating socioeconomic impacts usually depends on whether the researcher believes the particular shock being investigated has implications just within the sector being considered or is likely to have implications that cut across a variety of markets and sectors within the wider economy. Partial-equilibrium models in either single- or multi-market form have the general characteristic of not fully endogenizing all of the relevant markets, especially those which might mediate the scarcity of fixed factors such as land. If in addition to the pricing of these factors, there are important feedbacks between the markets for productive factors (like labor) and household income and expenditure levels, especially where the interventions and responses of the government matter, then a general-equilibrium framework may be more appropriate.

While partial-equilibrium markets can be extended to cover the interactions across several output and input markets, there are some sectors of the economy that are not considered, such as those which represent high levels of capital intensity, which rely on movement in financial and capital markets to regulate the accumulation and investment activities that happen over time. An economy-wide general-equilibrium model fully endogenizes the prices of productive factors and captures the flow of revenues, costs, and rents within the various agents of the economy (including the government, households of various socioeconomic classes, and other relevant decisionmaking agents within the productive sectors of the economy producing intermediate or final consumption goods). This works well when dealing with issues of growth, investment, macroeconomic stability, and policymaking, where the tax, trade, and other socioeconomic policies of the government are important in the balance of payments of the country, and when the income and welfare effects are felt at the household level for various socioeconomic groups. The flow of consumption and production goods within these general equilibrium models are typically represented in terms of value (i.e., money), since that is the unit of measurement that is most easily extracted from national accounts.

When dealing with issues of nutrition, however, the flow of capital and investment is not as important to track as the actual quantities (in kilograms or calories) of consumption that are happening within the countries across household types. This is where partial equilibrium methods have a distinct and clear advantage in being able to focus analysis on the food sector and represent interactions in terms of actual quantities (hectares of land, kilos per hectare of yield, cubic meters of water applied, and kilograms per capita of consumption). This is where IMPACT and other models like it have found their greatest strength lies—in terms of their ability to represent agricultural commodities in as disaggregate a level as possible and to be specific about utilization of those commodities and in terms of human food, animal feed, or other uses. This type of distinction has allowed this project to focus on those particular food goods that are important for nutrition and amenable to biofortification interventions.

Modeling Food Availability versus Food Intake

Given the advantages we have described above that argue in favor of a partial-equilibrium modeling approach, we still confront a methodological challenge when dealing with issues of food intake and nutrition. Macrolevel market-equilibrium models, in general, tend to be focused on linking primary production activities to final demand on a fairly aggregate regional level, although different levels of subnational or socioeconomic disaggregation are possible. Some models tend to be better about modeling intermediate production activities that transform primary products, raw cotton for instance, into intermediate products like cloth, which can then be made into the final consumption products, e.g., clothes, that are available on the market at given levels of prices. This level of market availability is somewhat different, however, from what actual intake levels might be at the household level, which is particularly important for nutrition. In the case of clothes, even ignoring the process of manufacturer-to-retail pass-through and mark-up, what the consumer buys at the retail outlet is more or less what is consumed at the household level as ready-to-wear clothing.

In the case of food, however, there is a further process of transformation that can happen at the processor level before reaching the retail-level point-of-sale, which also extends to the household itself where foods are prepared and transformed (through cooking) into its final form before consumption and intake.

These kind of farm-gate-to-home-plate representations of food systems are lacking at anything more than the most detailed household-level models, which represent the production and consumption linkages of many rural farm households who consume part of what they produce and use both marketed and nonmarketed inputs (like household labor) to prepare such goods for household consumption. This kind of model does not exist on the global scale, and we are not able to model the transformative process that takes store-bought food items and show the pathway through which they are changed into a form where nutrients are released and taken into the body. While it is a long-term research goal to make progress on a framework that can directly tie global-to-regional market-level effects with outcomes that are specific to nutrition and food quality at the household level, we were not able to make use of such a model for this project. Therefore, we have assumed that the levels of micronutrient deficiency prevalence and availability, which are described in Tables 6 and 7, move in proportion to the levels of food availability (in total and per capita terms) that are directly modeled by IMPACT. In other words, we assume a proportional relationship between the change in availability $(\Delta Avail)$ and the change in nutrient intake $(\Delta Intk)$ specific to the scenarios that hold the transformative process (that is not explicitly modeled and represented by α below) constant across scenarios.

$$\Delta Intk \propto \Delta Avail \quad \rightarrow \quad \Delta Intk = \alpha \cdot \Delta Avail$$

This proportionality is represented in the relationship above and should be kept in mind as being implicitly in operation within the modeling framework of this project.

Comparison to Other Micronutrient Interventions

Given that the objective of this study is to show the effectiveness of biofortification in enhancing nutrient intake across socioeconomic groups, the question of how it compares to other possible methods of enhancing micronutrient content of foods (like direct fortification or supplementation) might very well arise. The inability to directly model fortification (where micronutrients are added to the food commodities in the processing stage before reaching the retail-level point-of-sale) and supplementation (where nutrient supplements/pills are taken at the household level, in addition to direct food consumption and intake of food-bound nutrients) arises due to the same modeling gaps that were pointed out in the previous subsection. We do not model the food processing sector and do not have a sense of how the costs of implementing a biofortification scheme compare to fortification in order to do a direct cost-and-benefit comparison. At this point, we have not accounted for the research costs of biofortification that would be necessary for this comparison, but it is within the workplan of the HarvestPlus program to carry out that analysis for target countries where they are working. Furthermore, we do not account for the fact that the bioavailability of micronutrients in fortified foods once prepared and cooked may differ from that of biofortification, which makes a difference in the implicit market-level availability of nutrients at the retail level and/or probably requires a different α parameter when considering the relationship $\Delta Intk = \alpha \cdot \Delta Avail$ and how the transformative process differs at the household level.

While this comparison would greatly enhance the appreciation of how biofortification "performs" relative to other interventions and how its cost-effectiveness compares to other methods, we can only offer this as a first-step towards that kind of comprehensive analysis and leave it for future work (based on this study and others) to carry forward.

III. OVERVIEW OF PROJECT ACTIVITIES

The activities that were undertaken in the course of this project have mainly been data-related, as the micronutrient consumption patterns must be inferred from household-level consumption and expenditure surveys. In order to obtain the widest possible coverage of countries for the global modeling, we undertook a massive empirical exercise, which entailed obtaining the base datasets themselves in collaboration with the World Bank, as well as analyzing them to obtain the commodity-specific consumption patterns. A detailed description of the data that we used is given in a later section.

Parallel to the collection and analysis of household consumption and expenditure data, the IMPACT model was undergoing a variety of modifications in order to accommodate a new baseline for year 2000 and allow for a much higher level of spatial resolution than before—going from 69 spatial units in the base-year 1995 model to 281 total spatial units in the present one. This, combined with the addition of several new crops to the model, primarily those of dryland pulses and grains, caused the final completion of the model to be delayed from what was originally planned. Once the process was complete the simulation of micronutrient availability for socioeconomic strata was carried out with a new set of baseline results and simulations. A more detailed description of IMPACT and how it is linked to the disaggregated food demand system created by the project activities will be given in a later section.

The linking of a disaggregated demand system to IMPACT was done to account for various income strata within the regions and the proportion of rural and urban consumers of various commodities. The estimation of this disaggregated demand system was accomplished with the use of the household consumption data for the target countries and was implemented using the Food Characteristic Demand System (FCDS) framework of Bouis (1996, 1997). The FCDS methodology was chosen because of its relative simplicity and ease of applicability to the nature of the household consumption data that we are analyzing. The FCDS methodology was translated from FORTRAN into the GAMS programming language to allow for greater facility in manipulating it with the new consumption data that was used. A more detailed description of the FCDS methodology is given in a later section of this report.

In order to make the demand system derived from the FCDS approach consistent with the simulation framework of IMPACT, a number of modifications and additional calibration had to be done. Among these were the following:

- A systematic retuning of demand parameters to conform to theoretical properties of curvature and adding-up and
- Calculation of country-level income and population levels among the various strata in order to remain consistent with the IMPACT baseline, as well as with available information on country-level poverty and inequality.

IV. ANALYSIS OF HOUSEHOLD DATA

Overview

A large part of the data for this study is derived from household survey datasets. In particular, household survey data for 21 countries provide our analysis with average food consumption estimates for 37 food items over 6 different social strata for a total of 21 countries. The relevant strata for our calculations are three urban and three rural income groups based on the per capita income of each household. Food consumption in this analysis is expressed as per capita kg consumption per day and in terms of per capita kcal per day. Additionally, we calculate the relative price of each food item (indexed to the least expensive item in each survey), as well as the average household size and average nonfood budget share in each of the six strata.

Table 1 shows a generic data matrix for this analysis.

Table 1: Generic Matrix of Data Extracted for this Study

			kg/capita and day			cal/capita and day			Price (relative to most expensive crop)	Average HHsize (adult equivalent)	Average non-food budget share
			Crop1	…	Crop41	Crop1		Crop41			
Country1	urban	richest		…			…				
		medium		…			…				
		poor		…			…				
Country1	rural	richest		…			…				
		medium		…			…				
		poor		…			…				
…	…	…		…			…		…	…	…
…	…	…		…			…		…	…	…
…	…	…		…			…		…	…	…
Country22	urban	richest		…			…				
		medium		…			…				
		poor		…			…				
Country22	rural	richest		…			…				
		medium		…			…				
		poor		…			…				

The datasets used in this study were collected from various sources and for varying purposes; therefore, they do not necessarily contain the entire spectrum of variables necessary for our analysis. Specifically, none of the household surveys contain data entries regarding all 37 commodities of our analysis. Furthermore, total income (which is the basis for the division into rural/urban income terciles) must be approximated from total expenditure figures, and food/calorie consumption needs to be approximated from food/calorie availability.

Data Challenges and Assumptions

Appreciation of the challenges and concerns regarding the underlying data of our analysis is essential for interpreting our model results correctly. These challenges and concerns can be summarized under the following headings:

a) Coverage of food items within countries
b) Conversion from specific food items to primary products
c) Conversion from quantities to calories
d) Approximation of total income from total expenditure
e) Approximation of consumed quantities from acquired quantities

Coverage of Food Items within Countries
As mentioned above, none of the available datasets exactly cover all of the 37 food commodities used in IMPACT. Because of this, we were forced to assume the consumed quantities of these missing items to be proportional to others in the dataset. For example, the strata-specific quantities of consumed, low-value fish are assumed to be proportional to the quantities of high-value fish, or the quantities for pigeon peas are assumed to be proportional to those for other legumes. An alternative method would have been to estimate missing values for a specific food item from calculations made for other similar countries. However, this second alternative requires that at least one data entry be available for a commodity within a group of similar countries; a requirement that is not always fulfilled. Hence, we estimate consumption of missing items as simple proportions of the consumption of similar food items within the same country.

To give the reader a sense of the coverage within the datasets that we considered, Table 2 shows the proportion of commodities with the broad food categories shown that were missing in the nationally representative household datasets that were used for the study. From this, we see that the coverage of meat commodities is very good, while that of cereals is variable with a higher number missing in South Asia[1]. The preference of roots and tubers for food in Sub-Saharan Africa is evident from the relatively low share of missing commodity types within this category in those countries, and the coverage of fruits is relatively good. Since the most important commodities considered in the biofortification scenarios of this study are well-covered for the particular countries of interest, we do not think the coverage issue will have any effect on the qualitative or quantitative outcomes of our simulations. Milk, eggs, and vegetables were covered within the data for all countries, so those commodities are not shown here.

[1] It should be noted, though, that our cereal category includes millet and sorghum, separately, which are generally used for animal feed in Asia, whereas they are still important grains for human consumption in Sub-Saharan Africa.

Table 2: Proportion of Commodities within the Broad Food Types Missing in Household Data

	Non-fish meat	Cereals	Roots & tubers	Fruits	Pulses	All categories
Bangladesh	0.20	0.50	0.80	0.21	0.75	0.49
Ethiopia	0.03	0.00	0.40	0.67	0.25	0.28
Ghana	0.00	0.14	0.23	0.29	0.50	0.28
India	0.00	0.17	0.60	0.00	0.75	0.30
Indonesia	0.00	0.33	0.20	0.21	0.50	0.26
Kenya	0.00	0.00	0.00	0.50	0.50	0.28
Malawi	0.00	0.17	0.33	0.21	0.50	0.25
Malaysia	0.00	0.33	0.20	0.21	0.50	0.26
Mozambique	0.20	0.33	0.10	0.25	0.50	0.32
Pakistan	0.40	0.33	0.80	0.21	0.50	0.49
Rwanda	0.20	0.17	0.20	0.21	0.50	0.35
Sri Lanka	0.60	0.50	0.60	0.71	0.75	0.56
Tanzania	0.00	0.00	0.20	0.00	0.50	0.23
Uganda	0.00	0.17	0.40	0.29	0.50	0.33
Zambia	0.33	0.17	0.40	0.50	0.75	0.43

Conversion from Specific Food Items to Primary Products

IMPACT models food items in terms of primary products (wheat, rice, maize, etc.). Many of the available surveys, however, feature food items in terms of processed products (breakfast cereals, pasta, bread, flour, etc.).

Generally, we convert the quantities of processed products into their primary product equivalents using the technical conversion factors listed by the UN Food and Agricultural Organization (See: http://www.fao.org/es/ess/tcf.asp)

Since the error that occurs from assuming processing technology and ratios of ingredients to be constant within and among countries is assumed to be smaller than the accepted error margin that accompanies the underlying survey data estimates, the conversion method meets the precision requirements of our study.

Greater concern regarding the conversion from processed variants to primary products arises from the implicit assumption that a survey actually covers the complete set of processed variants that describe a primary product—an assumption that is by definition extremely unlikely to be fulfilled. To further illustrate this concern, one may picture the following extreme scenario: Imagine three surveys (A, B, & C), where Survey A asks respondents plainly for the amount of wheat (in any form) purchased, while survey B asks for the amounts of bread, wheat flour, wheat malt, wheat-based breakfast cereals, alcohol, pasta, and pastries that were consumed. Survey C in comparison asks only for pasta. In this scenario, we would rate survey A the most accurate measure of total wheat consumption, followed by Survey B and finally Survey C. In particular, we might assume that survey C, due to its omission of other major wheat-based food categories, significantly underestimates total wheat consumption.

Fortunately, the surveys in our analysis more closely resemble Survey B than Survey C of our example, and while they may not cover every single source of each of the 37 primary products used in IMPACT, we find them to cover the main categories. Awareness of this possible underestimation of consumption should, however, be kept in mind when comparing our survey data to national totals as reported by FAO and other sources, for example.

Conversion from Quantities to Calories

Conversion from quantities to calories was undertaken at the level of the reported product (as opposed to the level of the primary equivalent), using the World Food Programs calorie conversion tables.[2]

Again, we realize that caloric conversion of any food item is dependent on a number of regionally specific factors (such as variety of the food item and the preparation method used), yet we accept that the minor inaccuracy can be disregarded given the error margin and scope (i.e., global modeling within IMPACT) of our data use.

Approximation of Total Income from Total Expenditure

While it is not uncommon in economic studies to infer total income from total expenditures, this procedure deserves some additional consideration in the case of our analysis because total expenditure is in itself an inferred value in our datasets and not an actual observation. Total expenditure is an inferred value for many of the datasets in that these datasets do not feature it as a distinct observation, but we must calculate it as sum of all expenditures listed. In the same manner in which we observed that a surveyed list of processed varieties may omit significant sources of a primary product, we can argue that the sum of all item-specific expenditures may fall short of the actual value for total overall expenditures. Moreover, we cannot readily assume that omitted sources of expenditures are distributed equally among the six strata, thereby possibly leading to some methodological inconsistencies in our analysis.

[2] See: http://www.fao.org/infoods/software_worldfood_en.stm

However, a closer analysis of the distribution of food consumption over different strata for the selected countries showed that the inconsistencies arising from leaving this issue unaddressed do not disturb the overall consumption trends known to be present in developing countries and are mirrored by our data. On a provisional basis, we therefore leave this issue unaddressed in our analysis but expect to improve our data sources as the modeling work progresses and new survey data becomes available.

Approximation of Consumed Quantities from Acquired Quantities
Regarding the estimation of consumed quantities, our study makes two major assumptions: (1) acquired quantities provide a sufficient approximation of available quantities, and (2) average available quantities are a sufficient proxy for average consumed quantities.

A recent study working with many of the same datasets as our study suggests that the second assumption holds true because any availability-consumption gap represents random error when our population samples reach a large enough size. In other words, if the likelihood of drawing down on stocks is equal to the likelihood of accumulating food stocks, acquired and consumed quantity measures will exhibit the same means (Smith et al. p.17 ff). One may argue, however, that the main assumption underlying this statement (i.e., an equal likelihood of stock accumulation and stock depletion) depends on population composition and the populations spread around the minimum necessary consumption amounts. Explicitly we find that the same reasoning that Smith et al. apply to show that such an assumed lack of bias does not apply to estimates of food energy deficiency holds true also for the availability-consumption gap because the minimally necessary consumption amounts must be interpreted as a cut-off value according to which stocks may be drawn down on or increased.

It remains a task for future iterations of this study, therefore, to investigate the extent to which the reported acquired quantities in our surveys match actual consumed quantities. In support of this provisional iteration, we again point to the overall consistency of the results of our data analysis with previous studies on consumption patterns in developing studies.

V. MODIFICATION OF IMPACT SIMULATION FRAMEWORK

Basic Modeling Framework of IMPACT
The International Model for Policy analysis of Agricultural Commodities and Trade (IMPACT) was created in the 1990s to address a lack of a long-term vision and

consensus about the actions that are necessary to feed the world in the future, reduce poverty, and protect the natural resource base.

IMPACT covers 32 commodities that account for virtually all world food production and consumption, including all cereals, soybeans, roots and tubers, meats, milk, eggs, oils, meals, vegetables, fruits, sugar and sweeteners, and fish in a partial equilibrium framework. It is specified with a system of supply and demand equations covering 115 countries and regions, which are all linked at the commodity-level through trade. In order to explore food security effects, IMPACT projects the percentage and number of malnourished preschool children (0 to 5 years old) in developing countries as a function of average per capita calorie availability, the share of females with secondary schooling, the ratio of female to male life expectancy at birth, and the percentage of the population with access to safe water. A wide range of factors with potentially significant impacts on future developments in the world food situation can be modeled based on IMPACT. They include: population and income growth; the rate of growth in crop and livestock yield and production; feed ratios for livestock; agricultural research, irrigation, and other investments; commodity price policies; and changes in dietary trends. For any specification of these underlying factors, IMPACT generates projections for crop area, yield, production, demand for food, feed and other uses, prices, and trade; and for livestock numbers, yield, production, demand, prices, and trade.

In 2002, the model was expanded to IMPACT-WATER with the inclusion of a Water Simulation Model, as water was perceived as one of the major constraints to future food production and human well-being (Rosegrant, Cai and Cline 2002).

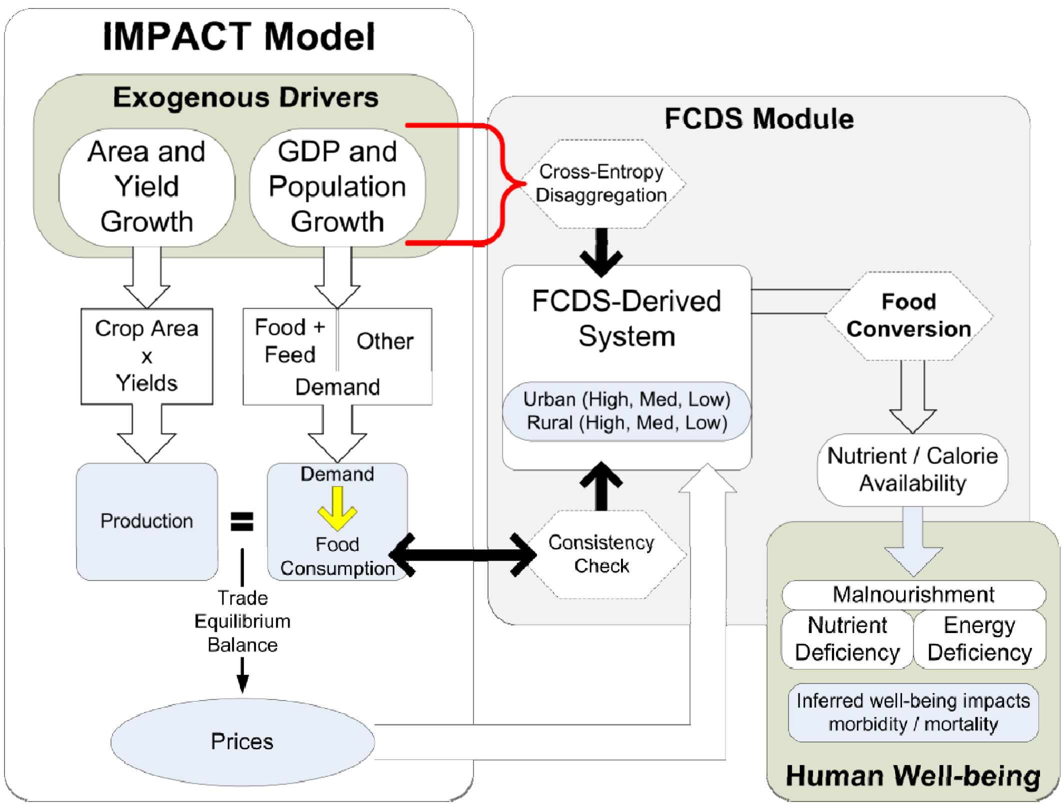
Generating Parameters of the Disaggregate Demands

Following the logic laid forward in the work of Bouis (1995, 1996) and Bouis and Novenario-Reese (1997), we undertook a numerical implementation of the Food Characteristic Demand System (FCDS) estimation procedures to obtain a set of disaggregated food demands that conform to theory and that are consistent with the food consumption and expenditure data that we described in the previous section. The FCDS approach takes such kind of data and allows one to compute a complete demand system for the countries and food commodities being studied.

In deriving the estimates for the demand parameters, we made use of data that had both expenditure as well as actual quantities of consumption. This helps to address the possible bias in demand parameter estimates pointed out by Bouis (1994), which arises from the systematic deviations between recorded expenditures and actual intakes. Because our estimation of demand parameters did not purely depend on expenditure data (given the design of the AFINS data collected by IFPRI and partners), we feel that we have overcome this issue. Other issues related to the estimation of total expenditure at the household level, however, remain and are noted in the appendix section that describes the FCDS estimation.

The linkage between IMPACT and the FCDS-derived disaggregate demand system for food commodities is shown in Figure 1, and highlights the key connections between the model-based price and demand, its demographic drivers, and the ultimate links to human well-being that are made. The disaggregation of consumption patterns allow for specific nutrient intakes to be inferred for each of the socioeconomic strata in the model regions.

Figure 1: Linkage of IMPACT to Disaggregated Demand System



The details on the FCDS demand system and the estimation of its parameters are included in Appendix 2.

Deriving the Distribution of Population and Income

In order to link the analysis of household data to the global modeling framework of IMPACT, a number of key linkages had to be made. First, the FCDS-derived demand parameters had to be associated with the targeted economic regions of IMPACT in order to simulate the changes in consumption in each of those spatial units at the appropriate level of disaggregation. Since the countries for which we had household-level consumption and expenditure data were much fewer than the number of economic regions in the model, we had to 'map' the FCDS estimates to all the spatial units of the model. For this report, the focus is on a few key countries of interest for the HarvestPlus program, shown in Table 3.

Table 3: Target Crops, Nutrients, and Countries for Biofortification Scenarios

Target Nutrients	**Iron**	**Zinc**	**Vitamin A**
Countries			
Uganda			Sweet Potato
Mozambique			Sweet Potato, Maize
Rwanda	Beans		
Kenya		Maize	
Zambia			Maize
India	Pearl millet	Rice, wheat	
Pakistan		Wheat	
Ghana		Maize	
Bangladesh		Rice	
Nigeria			Cassava
Niger	Pearl millet		
DR Congo	Beans		Cassava

Second, in order to relate the rural and urban socioeconomic strata within each of the target IMPACT regions, we had to derive a distribution of income and population that is (1) consistent with the existing aggregate, country-level database of IMPACT and (2) consistent with existing data on country-level inequality, rural/urban population shares, and poverty (at the national, urban, and rural levels). The split of rural and urban populations in each IMPACT region is straightforward to obtain from the UN Population Statistics Division[3]. The information on inequality (in the form of a Gini coefficient) and the poverty ratios at the national, urban, and rural poverty lines were available from the World Bank[4].

One of the principle challenges facing the simulation structure we have chosen is to simulate the changes in demographic composition between the socioeconomic classes over time. Rather than holding the initial distribution of income and population across socioeconomic groups to be constant over time, we allow for the proportions of the total population to vary across the income and urban/rural classes. We do this, however, without explicit graduation or demotion out of one income class and into another through a transition-type matrix structure, which means that we cannot be specific

[3] For which we use the medium-variant projections of the 2004 revision.
[4] World Development Indicator database (see: http://devdata.worldbank.org/data-query/)

about the movements between socioeconomic groups. Nonetheless, we are able to use this approach to move beyond the partial-equilibrium nature of IMPACT, which does not allow for consumer income to be solved for endogenously by the model[5]. In order to further refine the income projections, we will have to make assumptions using our approach on how the Gini coefficients and the poverty rates across national, urban and rural lines change over time. We hope to receive some guidance on how these might plausibly change over the 2000–2030 period from one of the global modeling groups that works on this (such as the LINKAGE model at the World Bank). At present, the MIRAGE model of IFPRI does not do these kinds of poverty simulations.

The remaining challenge was to reconcile these various pieces of data so that we obtain three income classes in both the urban and rural populations that give the same overall income, population, and per capita income as in the existing IMPACT database. In order to do this, we employed cross-entropy-based techniques to derive unknown distributions from fairly limited data and included one's own prior beliefs on the underlying nature of the distribution where possible. Cross entropy methods have been used successfully in many types of statistical analyses in both the physical and social sciences and have even been used in IFPRI's own work, such as balancing the social accounting matrix (SAM) of a computable general equilibrium model (Robinson et al., 2000) or in calculating the distribution of irrigated and rainfed crops based on global data from a variety of sometimes inconsistent datasets (You and Wood, 2004).

By solving this cross-entropy problem across all of the model regions, we were able to derive the population and income distributions shown in Figures 2 to 4. The urban share of total population over time for each of the focus regions is shown in Figure 2, while the distributions of these country populations among the six strata are shown in Figure 3. The overall rates of urbanization shown in Figure 2 come from the medium-variant UN population projections and are disaggregated into the corresponding socioeconomic strata according to the entropy algorithm described previously. Across all countries, with the exception of Uganda, the urban-low and urban-middle strata are the fastest growing segments of the population. This shows the strong trends of urbanization that are common to many of the developing regions of the world, in which rural jobseekers become part of the lower income strata of the urban areas to which they migrate. There is slow to declining growth in the rural population except for in Uganda and Niger (Figures 3a and 3k, respectively). Figure 4 shows that on a per capita basis

[5] It should be noted, however, that even computable general equilibrium (CGE) models do not typically disaggregate consumer income across socioeconomic classes. The usual assumption for carrying out poverty impact simulations within such aggregate models is that 'unskilled agricultural wages' approximate for the income that accrues to the poor. This has strong assumptions and can only be improved upon by microsimulation techniques (Davies, 2004; Savard, 2003).

the upper strata of the urban populations have the highest per capita income levels for each country, as was required by the constraints of the cross-entropy problem. Uganda and Niger have the greatest income disparities initially, but all countries face growing gaps in income per capita out to 2030.

Figure 2: Urban Shares of Total Population within Selected Countries

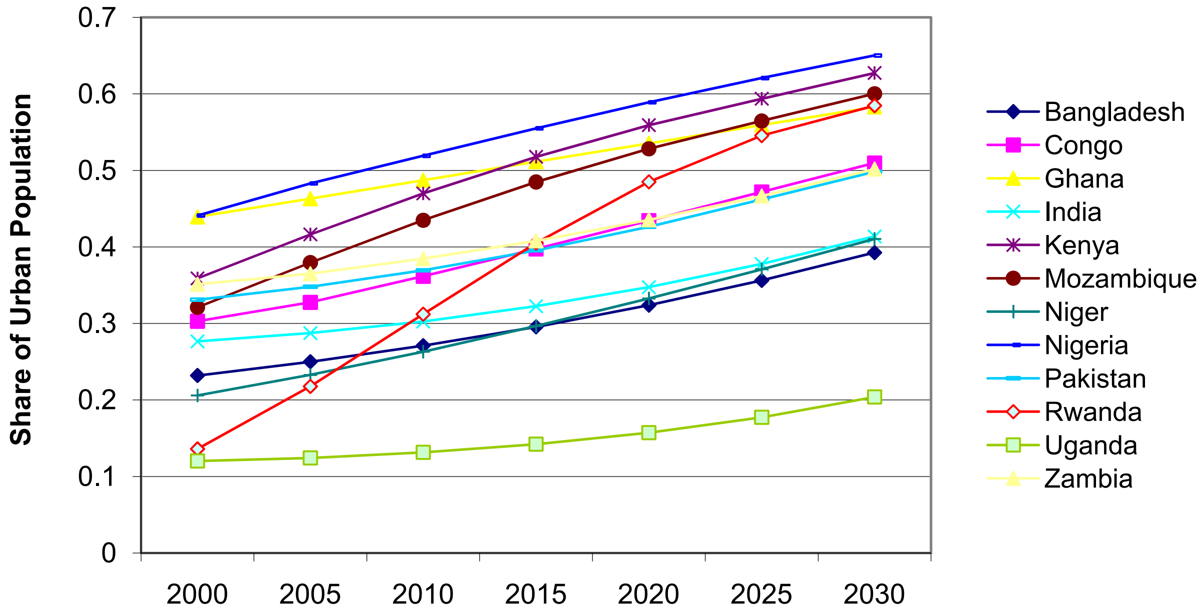
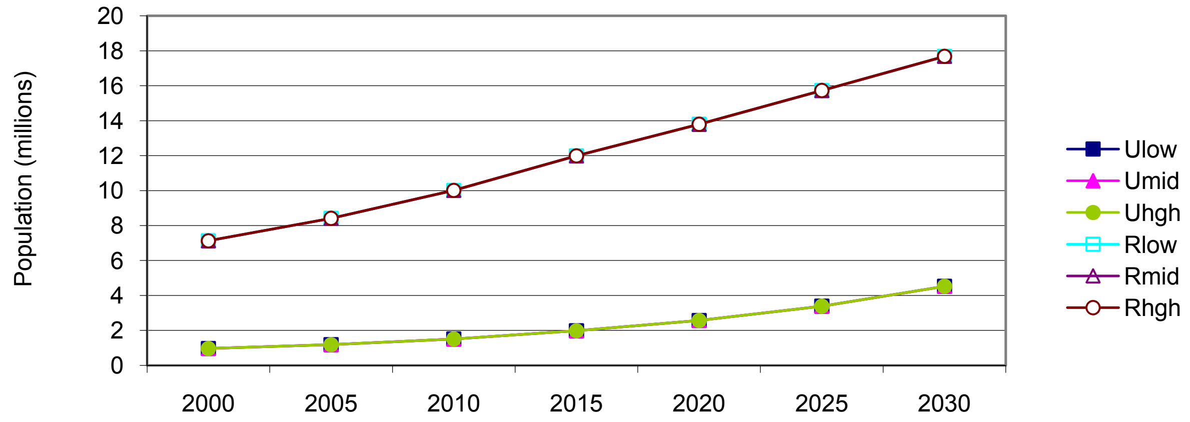
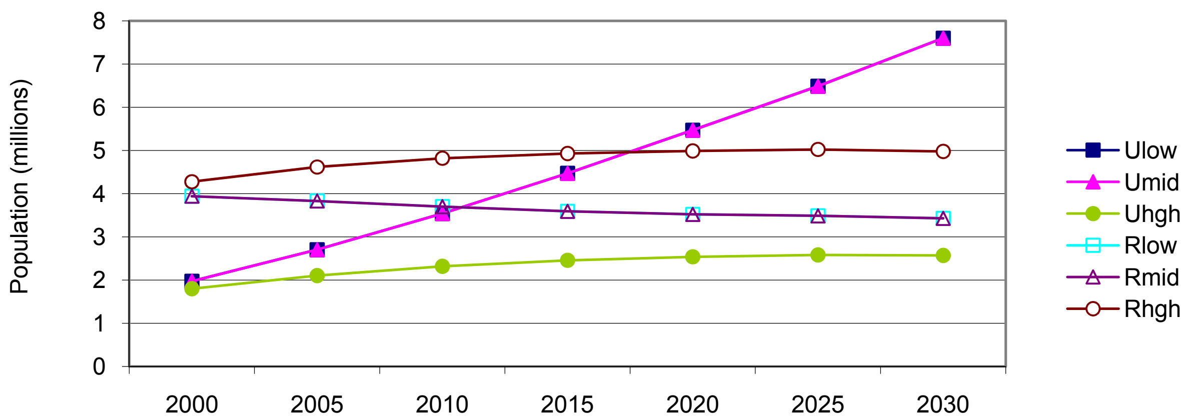


Figure 3: Shares of Low, Middle, and High Income Populations in Urban and Rural Areas of Selected Countries

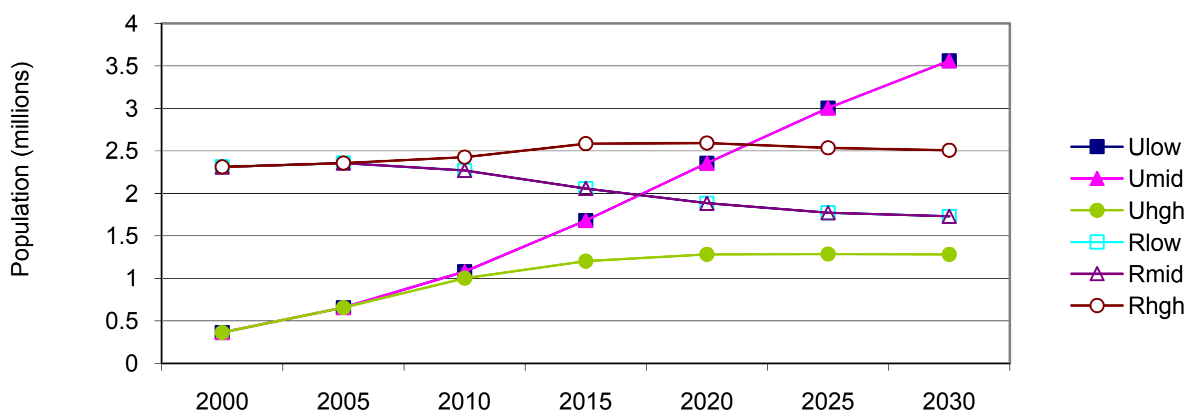
(a) Uganda



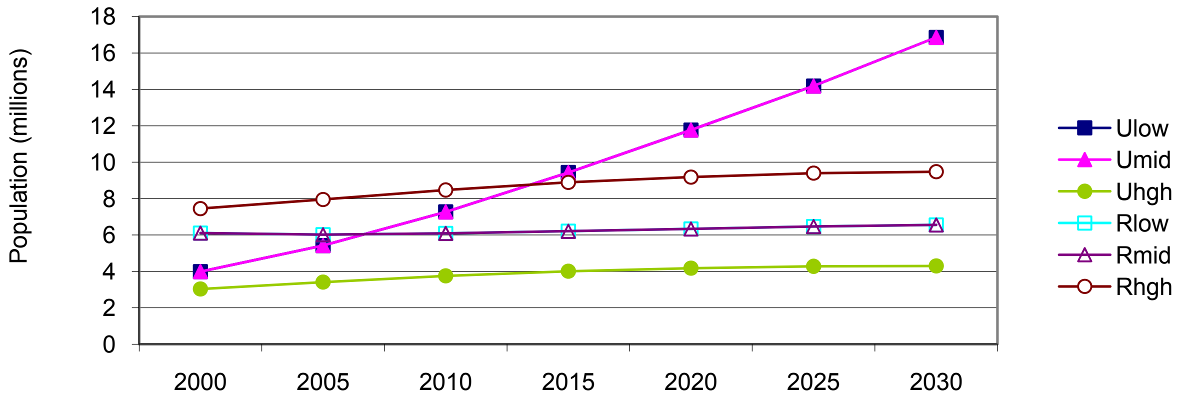
(b) Mozambique



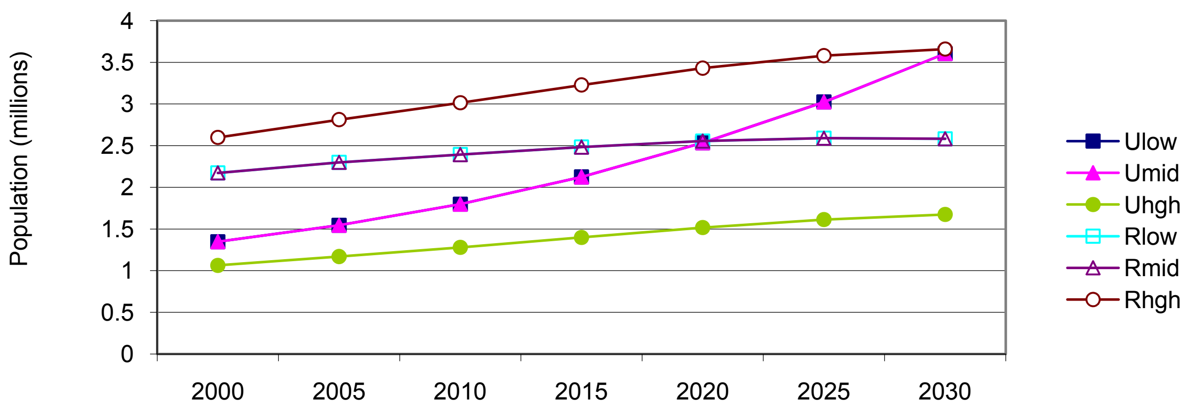
(c) Rwanda



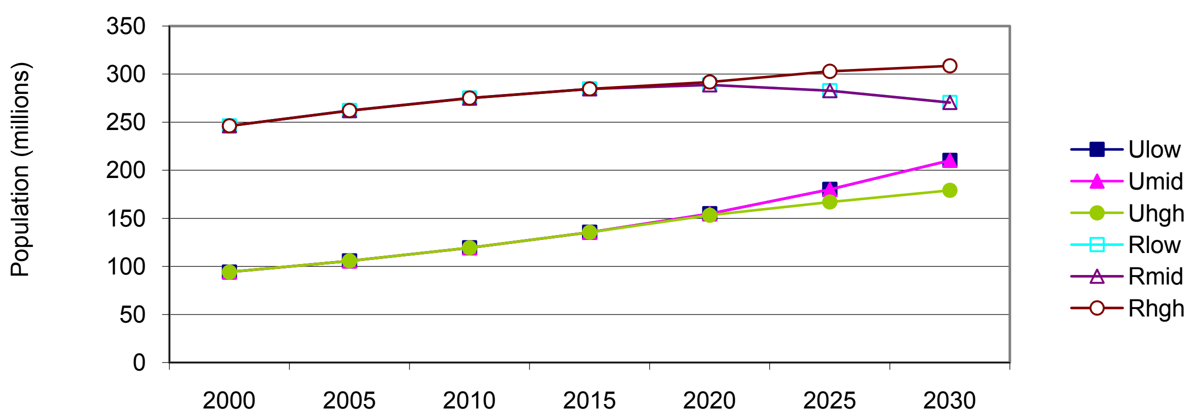
(d) Kenya



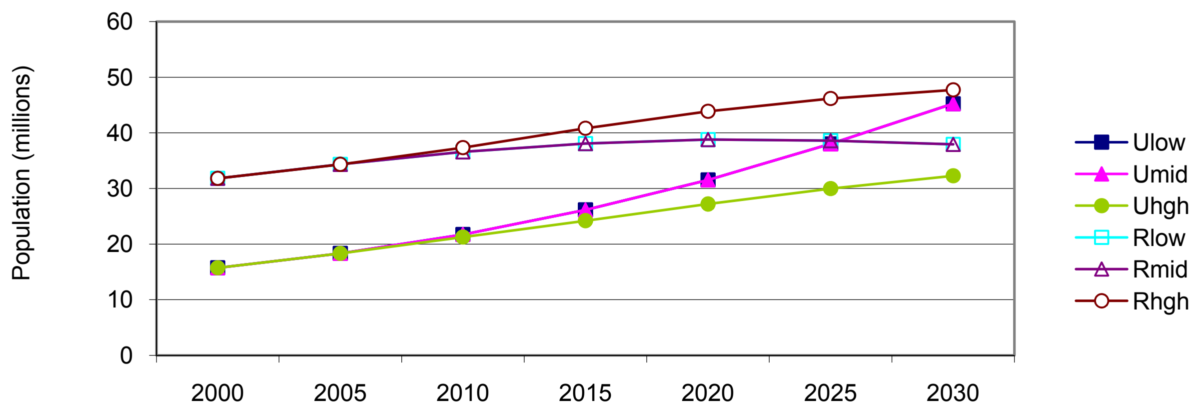
(e) Zambia



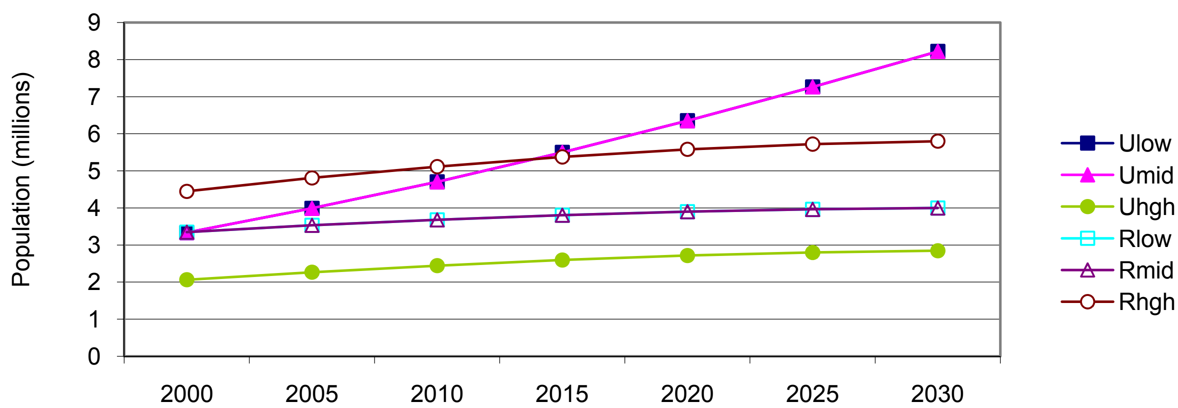
(f) India



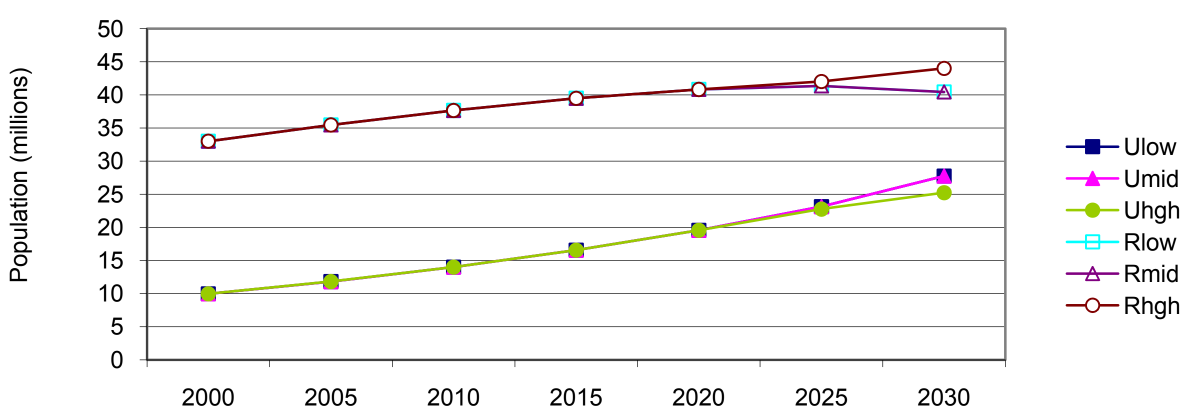
(g) Pakistan



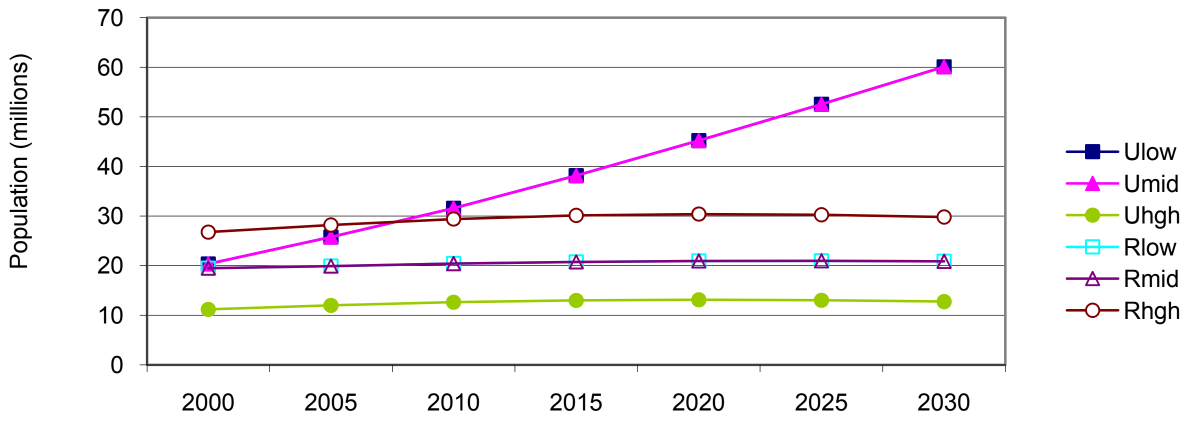
(h) Ghana



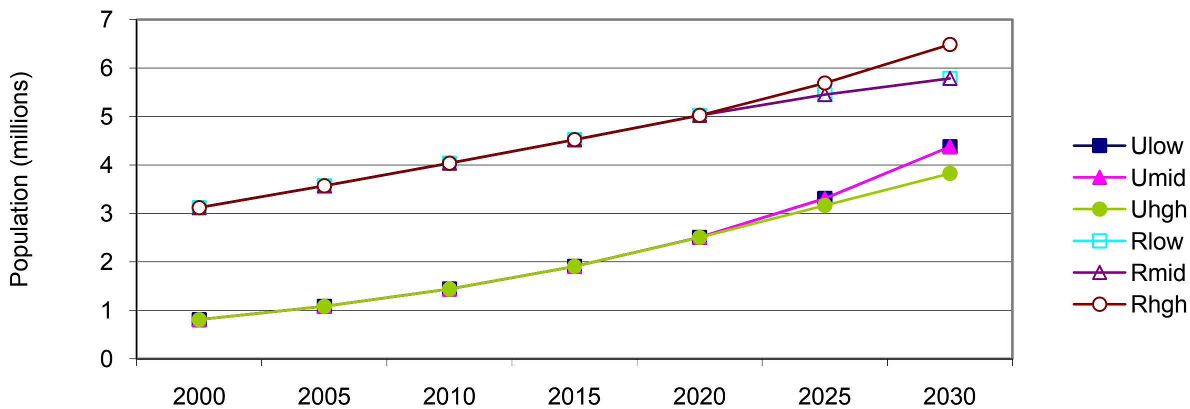
(i) Bangladesh



(j) Nigeria



(k) Niger



(l) DR Congo

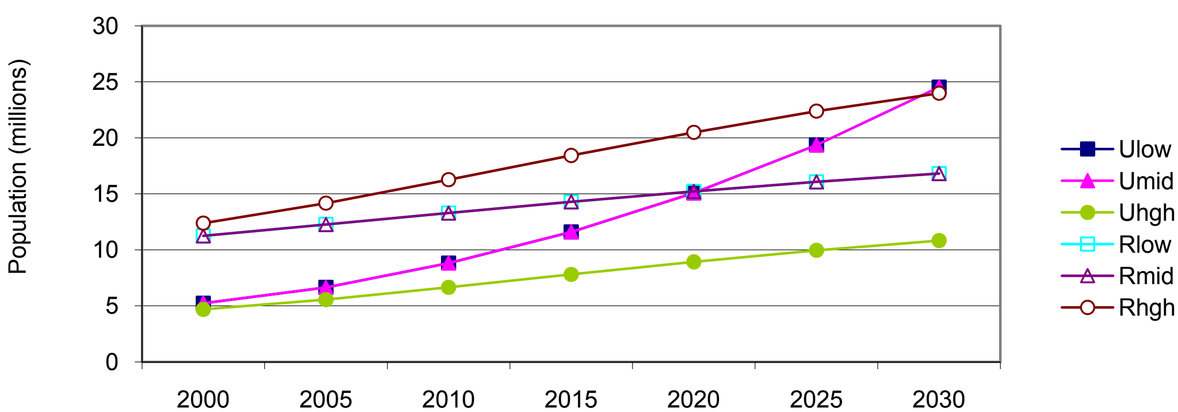
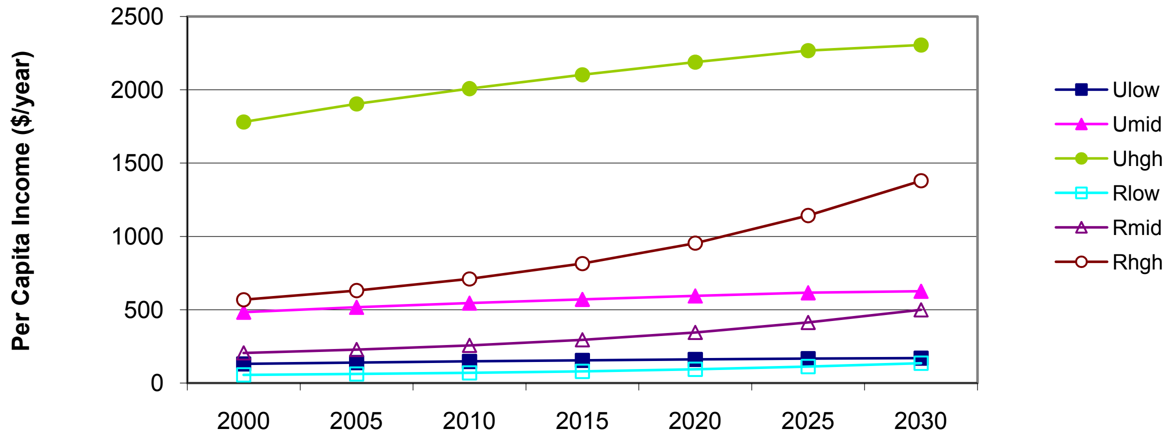
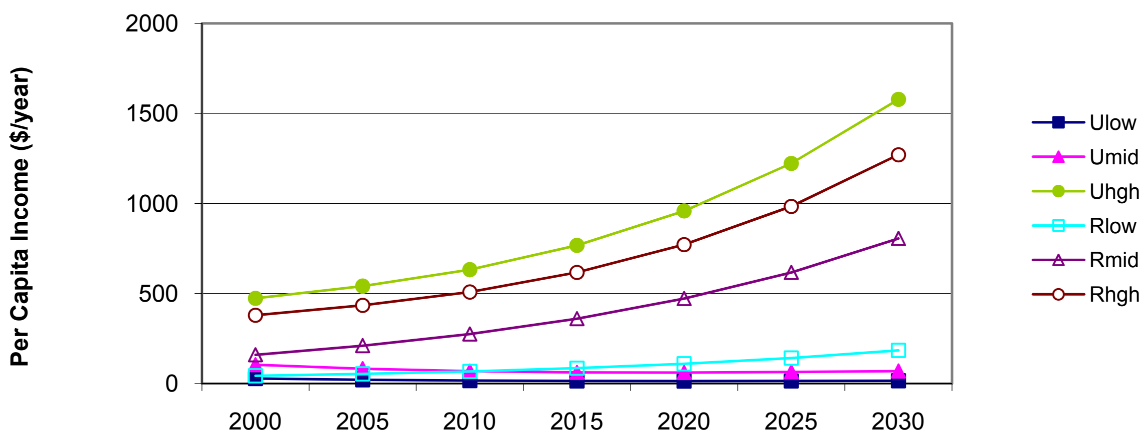


Figure 4: Per Capita Income across Low, Middle and High Income Populations in Urban and Rural Areas of Selected Countries

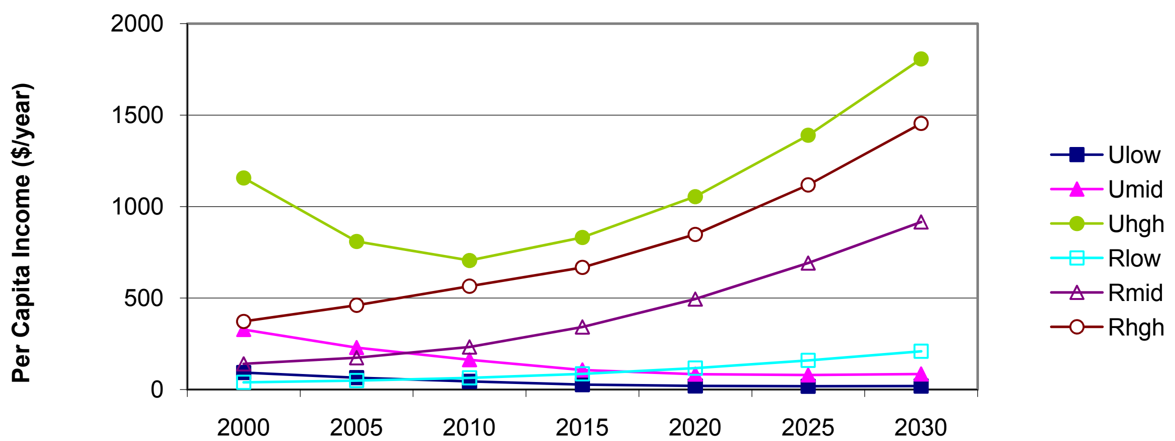
(a) Uganda



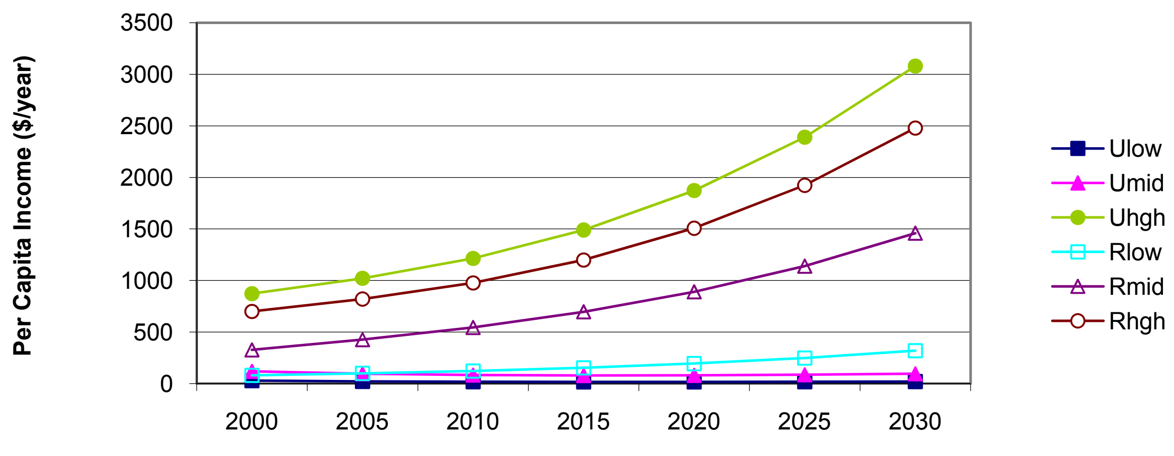
(b) Mozambique



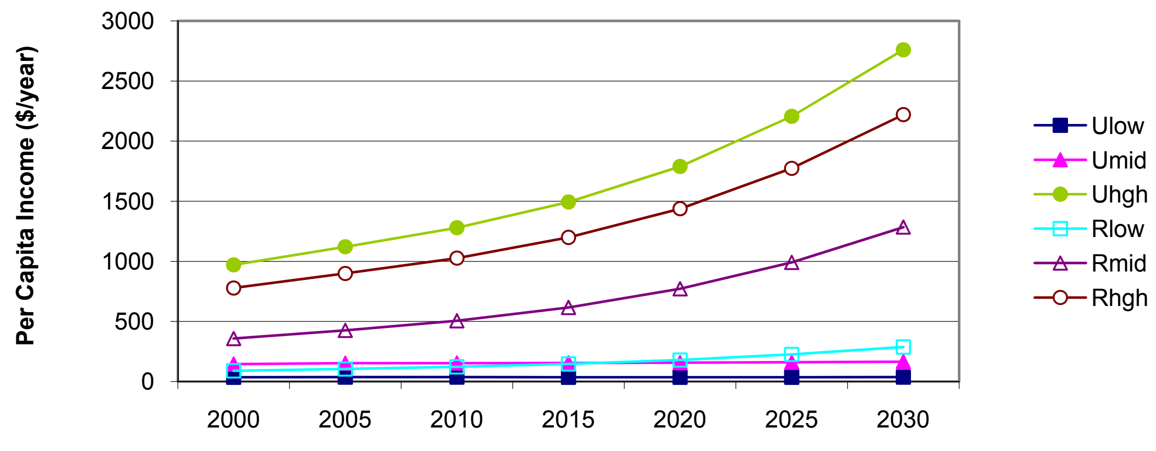
(c) Rwanda



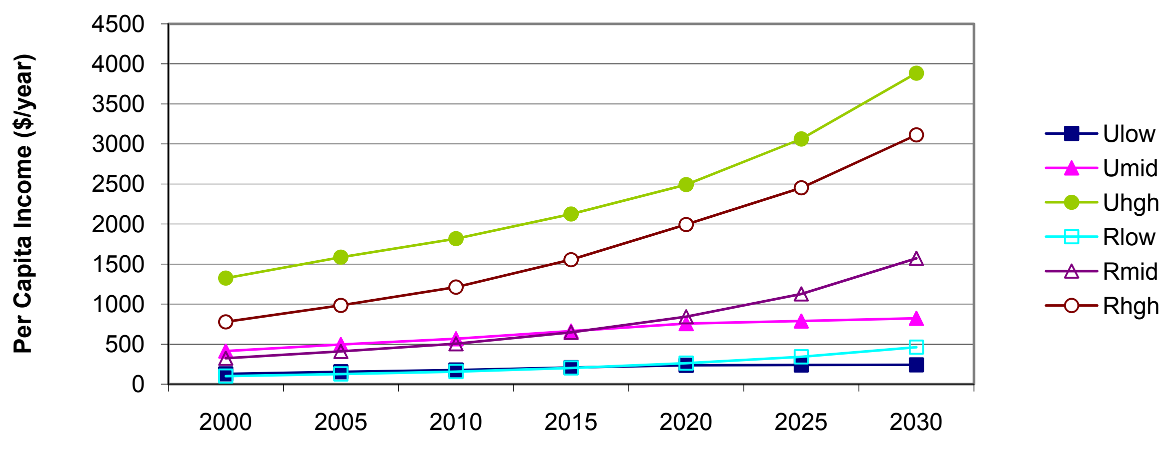
(d) Kenya



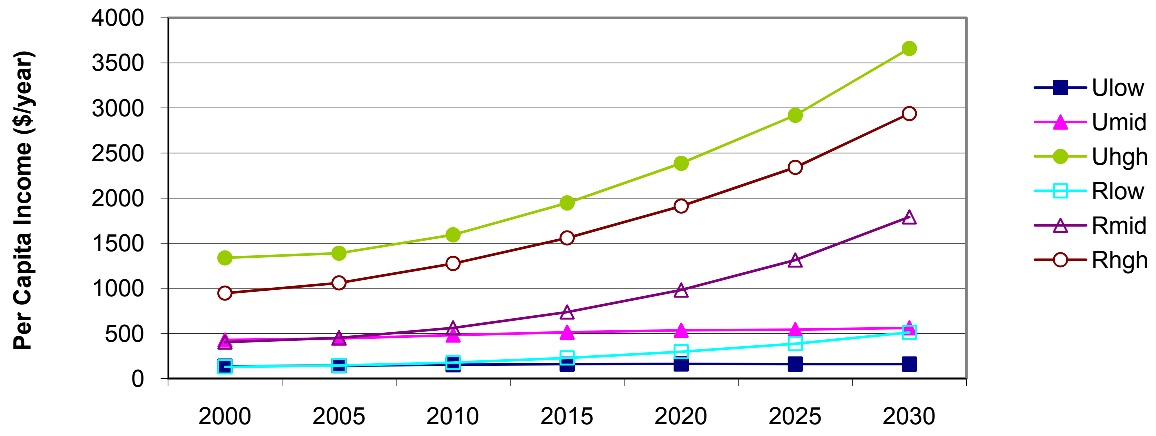
(e) Zambia



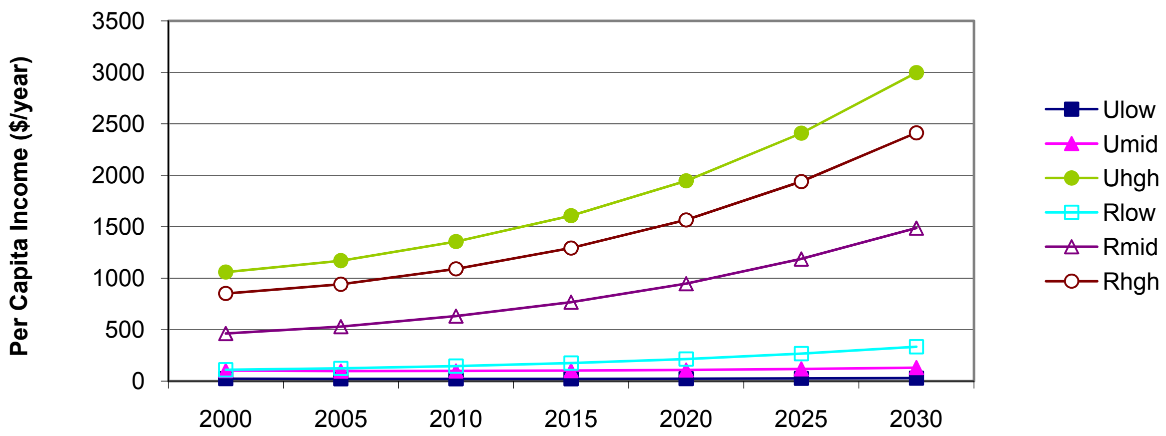
(f) India



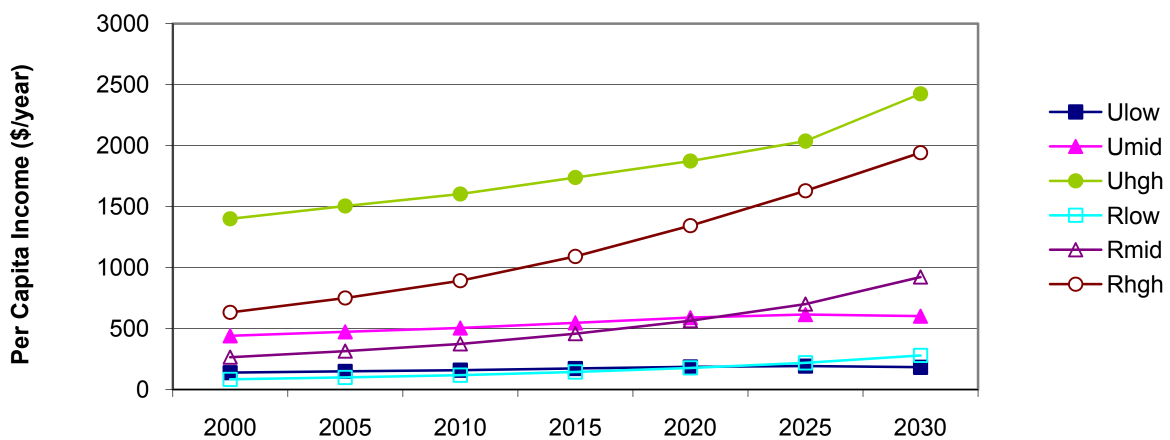
(g) Pakistan



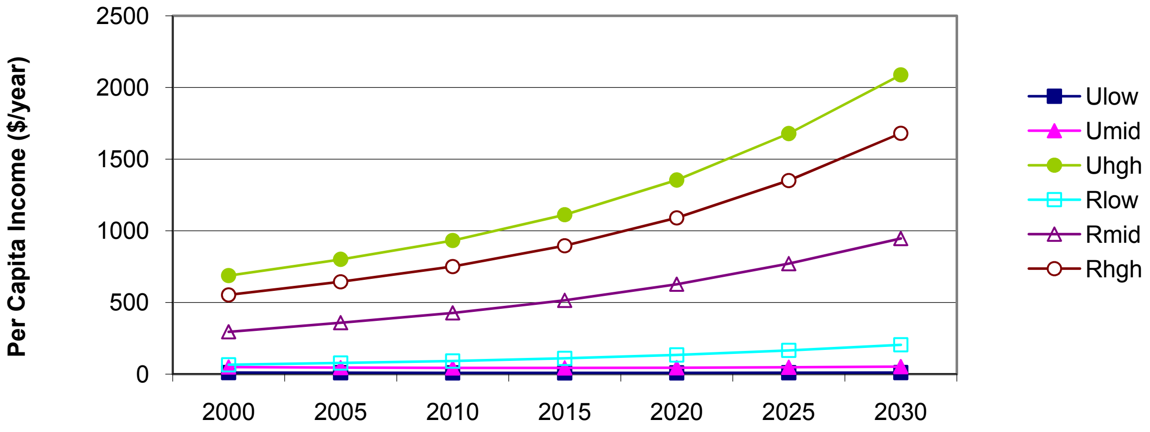
(h) Ghana



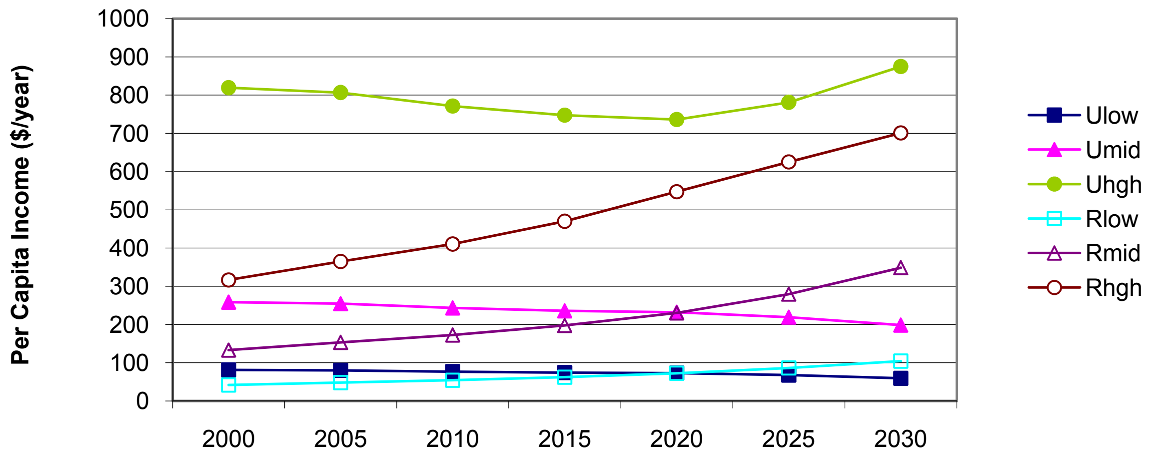
(i) Bangladesh



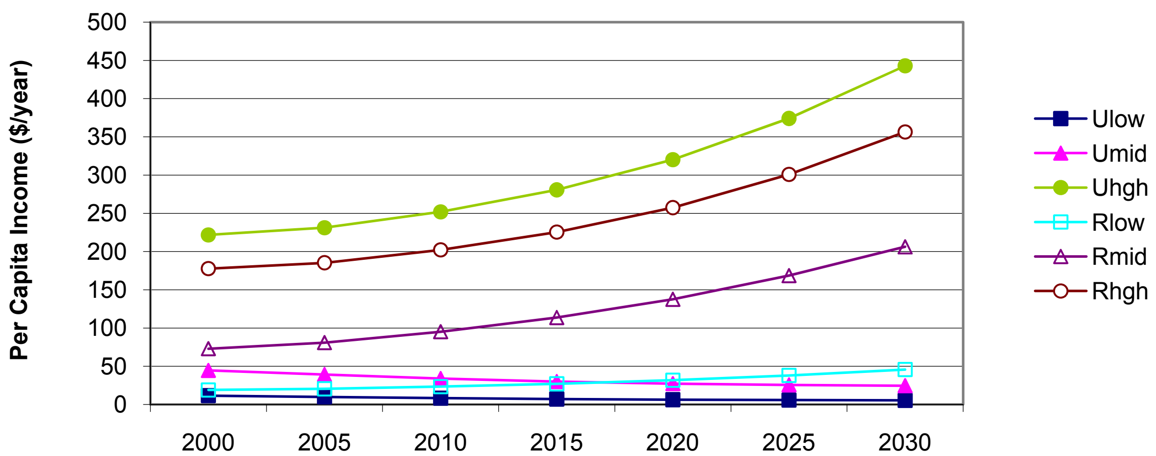
(j) Nigeria



(k) Niger



(l) DR Congo



Using these kind of distributions for populations and incomes in all countries, we then proceeded to simulate the disaggregate demand system within the IMPACT model, making modifications that are described in the next subsection.

VI. INCORPORATING THESE COMPONENTS INTO IMPACT

The policy modeling framework of IMPACT is being modified to meet the requirements of the micronutrient demand project being funded by the HarvestPlus Challenge Program. In particular, the following enhancements are being made to the model structure:

1) A direct linkage is being made between the aggregate demand relationships for the food commodities already in the model to disaggregated food demand relationships estimated from household-level consumption data for a range of countries. This disaggregation is done with respect to income levels as well as urban or rural status.
2) Consumption preferences change both with changing income and in response to other external factors—such as contact with other cultures through globalization—over time. These aggregate trends found in the IMPACT model are also used to evolve the diet preferences embodied in the disaggregated elasticities (Table 4 shows selected examples of elasticity trends).
3) A greater degree of commodity disaggregation in order to focus on HarvestPlus high priority food crops, so that we achieve (for example):
    a. Cassava separate from other roots and tubers,
    b. Sweet potato separate from yams, and
    c. Phaseolus beans separate from aggregated vegetables.
4) A link between the food consumption patterns observed in aggregate at the country level and the availabilities of specific micronutrients in the diet to better capture the changes in the composition of micronutrients in projected consumption patterns.

Table 4: Disaggregated Income and Own-price Elasticity Trends for Selected Target Countries and Crops

Income Elasticities			**Years**						
Region	**Crop**	**Strata**	**2000**	**2005**	**2010**	**2015**	**2020**	**2025**	**2030**
Bangladesh	Rice	Ulow	-0.0608	-0.0773	-0.0901	-0.1000	-0.1076	-0.1135	-0.1181
		Umid	-0.0909	-0.1074	-0.1202	-0.1301	-0.1377	-0.1436	-0.1482
		Uhgh	-0.0738	-0.0903	-0.1030	-0.1129	-0.1206	-0.1265	-0.1311
		Rlow	-0.0117	-0.0282	-0.0410	-0.0509	-0.0585	-0.0645	-0.0690
		Rmid	-0.0530	-0.0695	-0.0823	-0.0922	-0.0998	-0.1057	-0.1103
		Rhgh	-0.0758	-0.0923	-0.1051	-0.1150	-0.1226	-0.1285	-0.1331
Niger	Millet	Ulow	-0.2003	-0.2313	-0.2552	-0.2737	-0.2881	-0.2992	-0.3003
		Umid	-0.1137	-0.1447	-0.1686	-0.1872	-0.2015	-0.2126	-0.2137
		Uhgh	-0.0317	-0.0626	-0.0866	-0.1051	-0.1194	-0.1305	-0.1317
		Rlow	-0.0926	-0.1235	-0.1475	-0.1660	-0.1803	-0.1914	-0.1926
		Rmid	-0.1193	-0.1503	-0.1742	-0.1927	-0.2071	-0.2182	-0.2193
		Rhgh	-0.0382	-0.0691	-0.0931	-0.1116	-0.1259	-0.1370	-0.1382
Zambia	Maize	Ulow	0.2407	0.216	0.1968	0.182	0.1705	0.1616	0.1548
		Umid	0.2159	0.1912	0.172	0.1572	0.1457	0.1368	0.1300
		Uhgh	0.2954	0.2707	0.2515	0.2367	0.2252	0.2163	0.2095
		Rlow	0.2495	0.2247	0.2056	0.1907	0.1793	0.1704	0.1635
		Rmid	0.1637	0.139	0.1198	0.105	0.0935	0.0846	0.0778
		Rhgh	0.1564	0.1316	0.1124	0.0976	0.0861	0.0773	0.0704
Own-price Elasticities									
Bangladesh	Rice	Ulow	-0.4885	-0.4803	-0.4739	-0.4689	-0.4651	-0.4622	-0.4599
		Umid	-0.4822	-0.4739	-0.4675	-0.4626	-0.4587	-0.4558	-0.4535
		Uhgh	-0.4965	-0.4882	-0.4818	-0.4769	-0.4731	-0.4701	-0.4678
		Rlow	-0.4945	-0.4862	-0.4799	-0.4749	-0.4711	-0.4681	-0.4658
		Rmid	-0.4892	-0.4809	-0.4745	-0.4696	-0.4658	-0.4628	-0.4605
		Rhgh	-0.4834	-0.4751	-0.4687	-0.4638	-0.4600	-0.4570	-0.4547
Niger	Millet	Ulow	-0.7233	-0.7078	-0.6958	-0.6865	-0.6794	-0.6738	-0.6695
		Umid	-0.6819	-0.6664	-0.6545	-0.6452	-0.6380	-0.6325	-0.6282
		Uhgh	-0.6870	-0.6715	-0.6595	-0.6503	-0.6431	-0.6376	-0.6333
		Rlow	-0.6756	-0.6601	-0.6481	-0.6388	-0.6317	-0.6261	-0.6218
		Rmid	-0.7216	-0.7061	-0.6942	-0.6849	-0.6777	-0.6722	-0.6679
		Rhgh	-0.6934	-0.6780	-0.6660	-0.6567	-0.6496	-0.6440	-0.6397
Zambia	Maize	Ulow	-0.9866	-0.9742	-0.9646	-0.9572	-0.9515	-0.9470	-0.9436
		Umid	-1.0808	-1.0685	-1.0589	-1.0515	-1.0457	-1.0413	-1.0379
		Uhgh	-0.8981	-0.8857	-0.8761	-0.8687	-0.8630	-0.8585	-0.8551
		Rlow	-0.8337	-0.8214	-0.8118	-0.8044	-0.7986	-0.7942	-0.7908
		Rmid	-0.9381	-0.9257	-0.9161	-0.9087	-0.9030	-0.8986	-0.8951
		Rhgh	-0.9324	-0.9201	-0.9105	-0.9031	-0.8973	-0.8929	-0.8895

By using this modified structure, we are able to generate simulation results around specific policy recommendations and scenarios in order to address the appropriate investment, development, and mitigation strategies for improving nutritional and health outcomes in regions that will be hardest hit by the projected global demographic trends and trade reforms. The policy recommendations will be targeted at specific income groups that are likely to be most affected by projected long-term changes in global economic policy regimes.

Incorporating Impacts of Biofortification

In order to represent the effects of biofortification on availability of micronutrients for the target countries and crop commodities, we undertook a number of steps in the modification of our computational scheme, including:

- Linking the per capita consumption quantities of the food groups to their constituent nutrients and representing them at the level of the socioeconomic strata,
- Linking the country and crop-specific scenarios for biofortification enhancement to the food commodities being modeled, such that the nutrient content is enhanced appropriately for the given scenario over time,
- Linking the biofortification-driven enhancement of micronutrient content to health outcomes, such as prevalence of deficiency among vulnerable groups over time under the various scenarios, and
- Using these as a basis for judging the comparative effectiveness of biofortification across the target countries.

The target countries and crops that we considered for this analysis are shown in Table 3.

Once the consumption paths of the targeted crop commodities were identified and simulated using the derived FCDS parameters, the implied nutrient content from the various foods could be attributed with the use of the IML[6] nutrition tables, which describe the micronutrient content per unit weight of food product.

In order to show the impacts of biofortification on the availability of key nutrients to the socioeconomic strata, some scenarios were constructed, as described below:

- The introduction of biofortified crops will be implemented at a point in the time horizon that seems most plausible from the perspective of breeding, field testing, and release—beginning in 2010.
- The spread of area (i.e., coverage) of biofortified crop will be phased in over a period of time (10 years), and the added nutrient content will be incrementally introduced into the nutrition balance of a target country. The

[6] IML = the International Minilist (IML), which was developed as part of the World Food Dietary Assessment System in 1988–1992 and contains 195 basic food ingredients that are representative of ingredients consumed in many developing countries.

process of adoption will have a logistical adoption profile over time (Figures 13a and 13b).

- The changes in availability of nutrients for consumers in the target countries can occur according to either an optimistic or pessimistic scenario, which are then compared to the changes from the baseline to determine if biofortification has had an appreciable effect in improving the nutrient availabilities within these countries and which types of food crop were most effective in accomplishing this. The scenario coverage and enhancements are shown in Table 5.
- The socioeconomic strata that are most directly affected by biofortification are the low- and middle-income groups of the urban and rural regions. The population of vulnerable, nutrient-deficient people who benefit from biofortification are assumed to be distributed between the socioeconomic strata in the proportions shown in Table 6. The population of deficient persons is obtained from national-level statistics.

Table 5: Coverage and Micronutrient Enhancement under Biofortification Scenarios

Target Nutrients	**Iron**			**Zinc**		**Vitamin A**		
Countries	Beans	Pearl millet	Maize	Rice	Wheat	Sweet potato	Maize	Cassava
Uganda						32/32 (0.4/0.2)		
Mozambique						32/32 (0.4/0.2)	20/10 (0.4/0.2)	
Rwanda	60/40 (0.4/0.2)							
Kenya			43/31 (0.4/0.2)					
Zambia							20/10 (0.4/0.2)	
India		25/19 (0.6/0.3)		22/11 (0.6/0.3)	24/6 (0.6/0.3)			
Pakistan					24/6 (0.6/0.3)			
Ghana			43/31 (0.4/0.2)					
Bangladesh				22/11 (0.6/0.3)				
Nigeria								20/10 (0.4/0.2)
Niger		25/19 (0.4/0.2)						
DR Congo	60/40 (0.4/0.2)							20/10 (0.4/0.2)

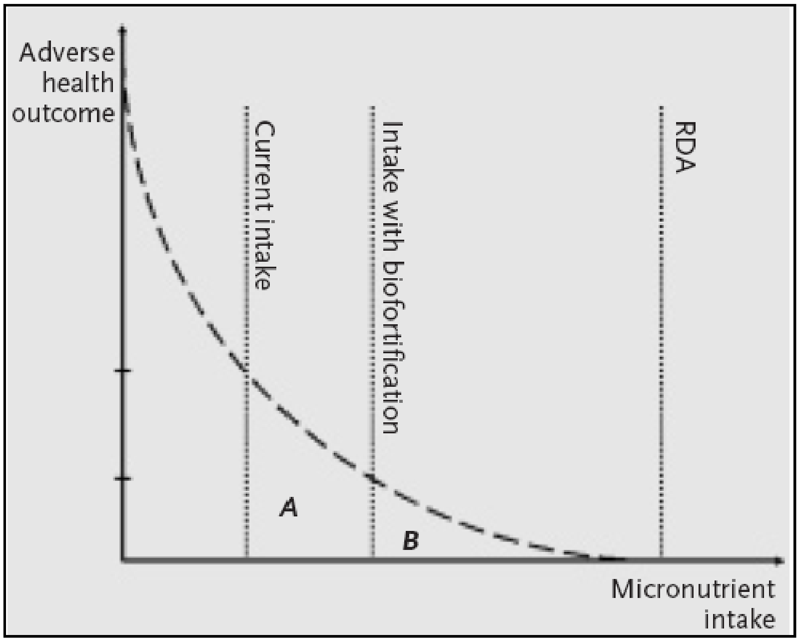
Note: Optimistic/pessimistic enhancement is in parts per million, while optimistic/pessimistic coverage is in parentheses below. Also, vitamin A numbers are specified here as provitamin A which are converted to retinol equivalents by dividing by 12 and then further adjusted to account for food processing losses by multiplying the maize and cassava retinol equivalents by 0.6 and 0.4 for the optimistic and pessimistic scenarios, respectively.

Table 6: Assumptions on Distribution of Micronutrient Deficiency Prevalence

	Share of Prevalence at aggregate National level		Share of Prevalence within Urban/Rural Group
Socioeconomic Strata			
		Urban-Middle	0.2
Urban	0.4	**Urban-Low**	0.8
Rural	0.6	**Rural-Middle**	0.3
		Rural-Low	0.7

The resulting impacts on human well-being were measured in terms of decreases in the prevalence of micronutrient deficiency among young children (aged 0 to 5) using the dose-response approach suggested by Stein et al. (2005) for measuring the impacts of biofortification on health outcomes. This method takes the deviation of the current micronutrient levels from target availability levels under biofortification, as well as that between current levels and the minimum intake requirements for certain countries, so that a proportional boost can be calculated for health outcomes. Using this approach, a country that is farther away from satisfying the minimum requirements will get a larger improvement in health outcomes from a unit increase in nutrient driven by biofortification than one in which most of the population is close to the minimum daily requirements. Figure 5 shows the curve-based relationship upon which the efficacy of the intervention can be calculated. As the ratio of area *A* over *A* plus *B* increases, the efficacy of biofortification improves and is able to bring about a stronger impact on health outcomes. The improvement in health or human well-being can also be measured in other terms, such as the loss of Disability Adjusted Life Years (DALYs). Since the statistics on deficiency prevalence were readily available for our target countries, we chose this method for this analysis.

Figure 5: Relationship between Micronutrient Intake and Health Outcomes Based on Dose-Response Relationship



Source: Zimmermann and Qaim (2004) in Stein et al. (2005)

In the following section, we show the results of our numerical simulations that combine the disaggregation of socioeconomic drivers and food demand from IMPACT with the linkage to biofortification and improvements in human well-being.

VII. MODEL SIMULATIONS AND RESULTS

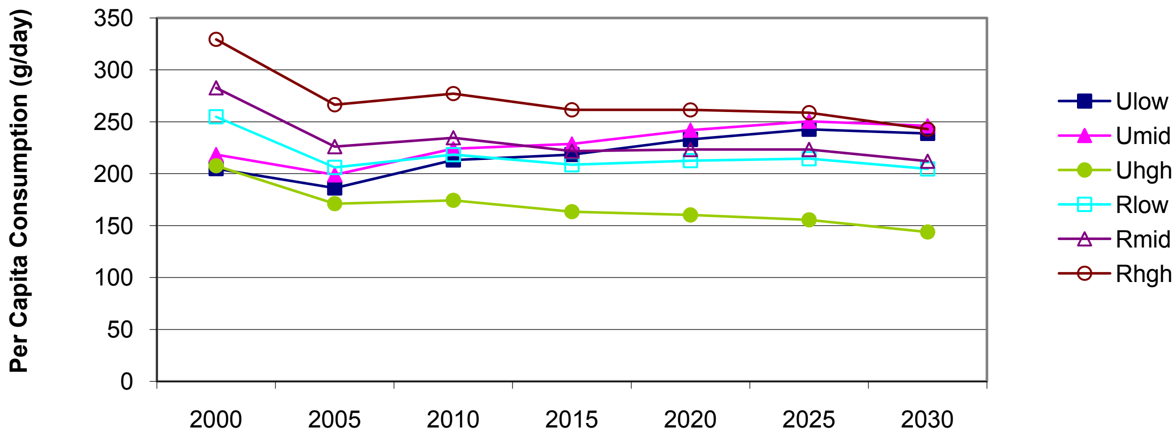
Consumption Results across Groups

In order to look more closely at micronutrient intake, we must first model the consumption of the key target food commodities we want to consider. Using the FCDS-derived demand system as a vehicle for modeling the changes in per capita consumption over time, we also reconciled the consumption patterns across demographic groups with the national totals that are simulated within IMPACT. The differences that are observed in the per capita consumption patterns are driven by changes in per capita income across the various strata (with some growing faster than others), as well as the differences among the response parameters of consumption to income changes (i.e., the elasticities). It is not possible, in all cases, to definitively distinguish the influence of each of these factors in the evolution of consumption patterns that is observed since we have not done controlled experiments to isolate the effect of one factor from the other. To the extent possible, however, we will try to explain the trends observed over the projection horizon in terms of the influences we can account for.

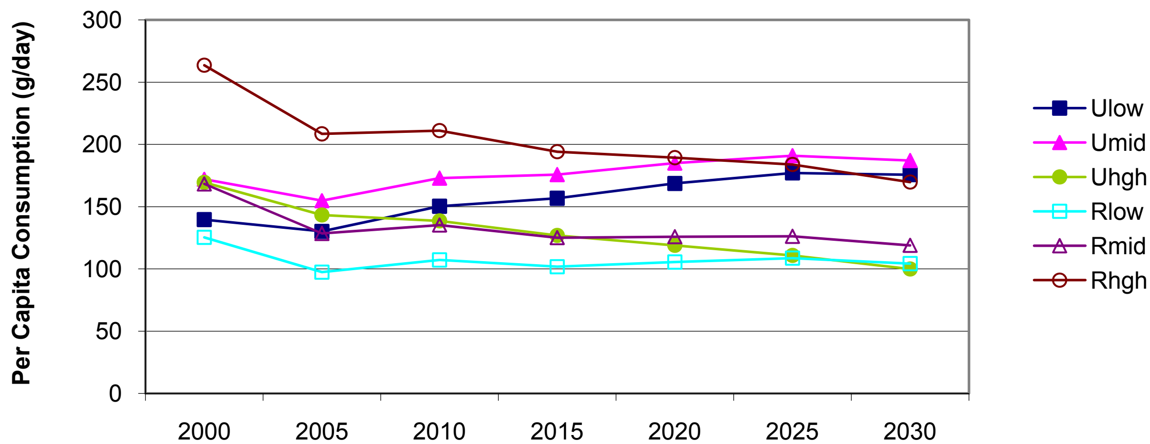
Figure 6 shows the consumption patterns of maize across the countries that were targeted for maize-based biofortification. Zambia (Figure 6d) shows the highest levels of per capita consumption for maize across the countries and shows the rural strata consuming more maize than those who reside in urban areas. Kenya shows a similar pattern across socioeconomic groups (Figure 6a), with somewhat lower per capita levels of consumption on average. The rural and urban patterns of consumption in Mozambique (Figure 6b) do not separate out across time as neatly as in the other countries, and even though Ghana (Figure 6C) has the lowest overall per capita consumption levels, these levels conform to the patterns seen in Zambia and Kenya.

Figure 6: Per Capita Demand for Maize across Socioeconomic Strata

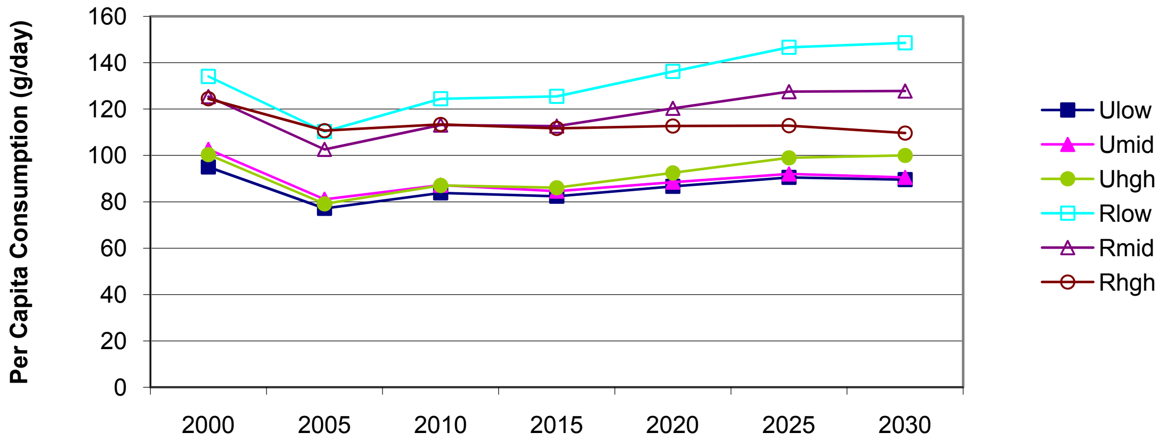
(a) Kenya (Maize)



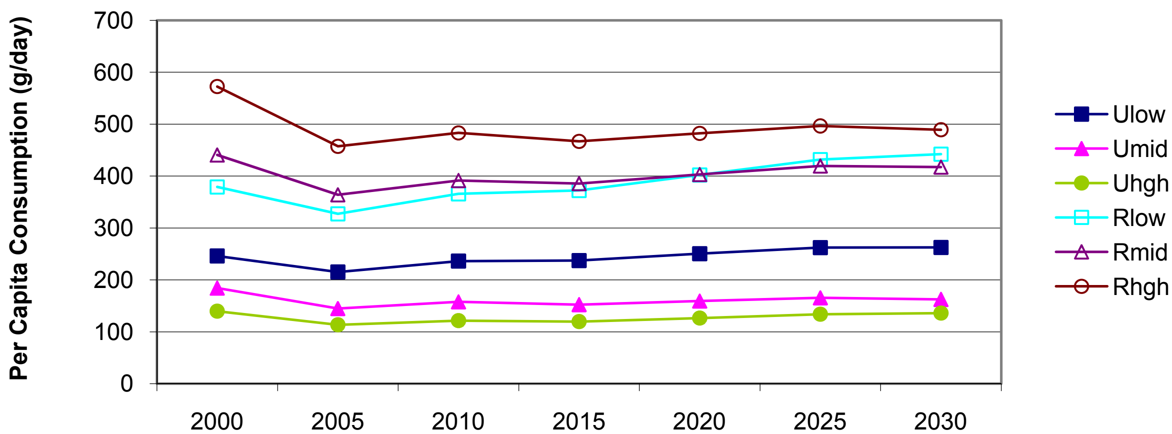
(b) Mozambique (Maize)



(c) Ghana (Maize)



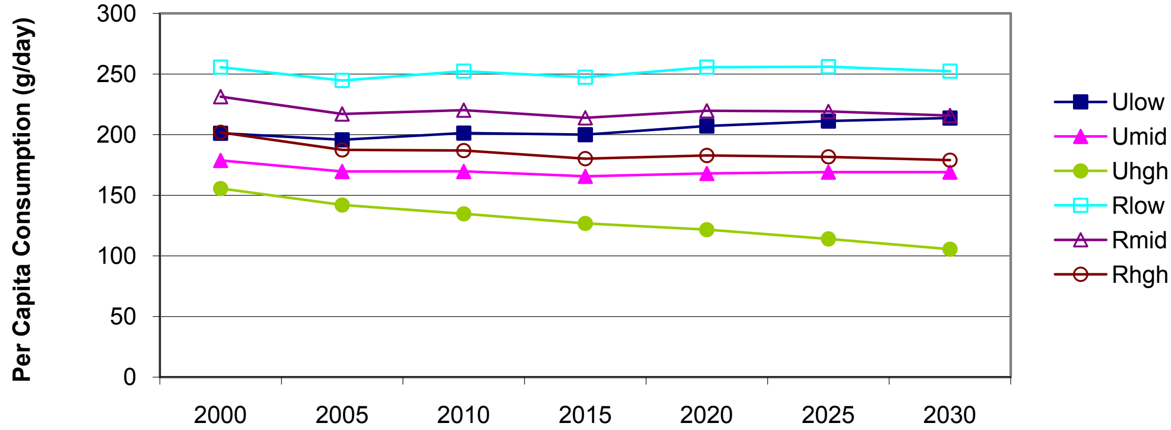
(d) Zambia (Maize)



The patterns of rice consumption in India (Figure 7a) and Bangladesh (Figure 7b) show higher levels of per capita intake in Bangladesh, with better distinction between the socioeconomic classes in the initial periods. Over time, however, the consumption patterns in Bangladesh tend towards convergence, whereas those in India start to diverge over the course of the simulation. The patterns of wheat consumption in India (Figure 8a) also show increasing divergence over time, whereas those in Pakistan (Figure 8b) tend to converge and show higher per capita levels of consumption throughout.

Figure 7: Per Capita Demand for Rice across Socioeconomic Strata

(a) India (Rice)



(b) Bangladesh (Rice)

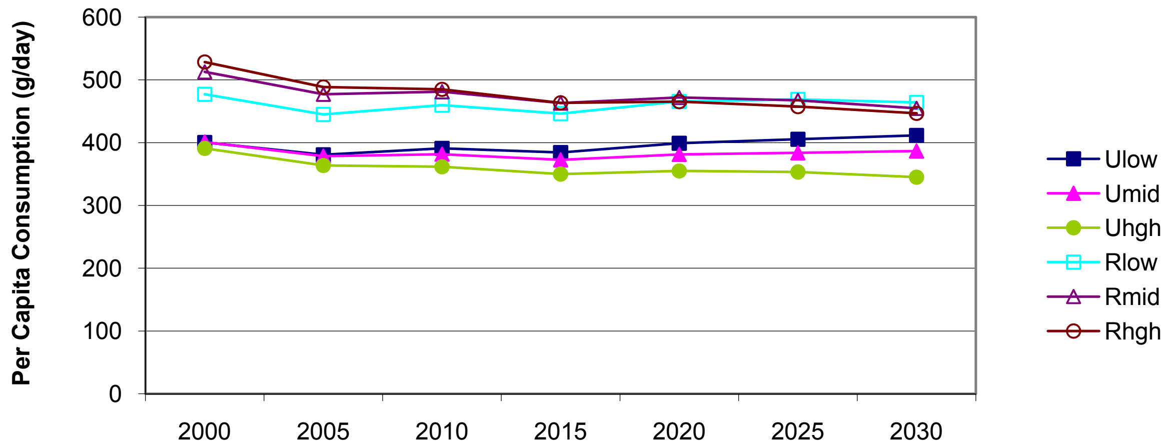
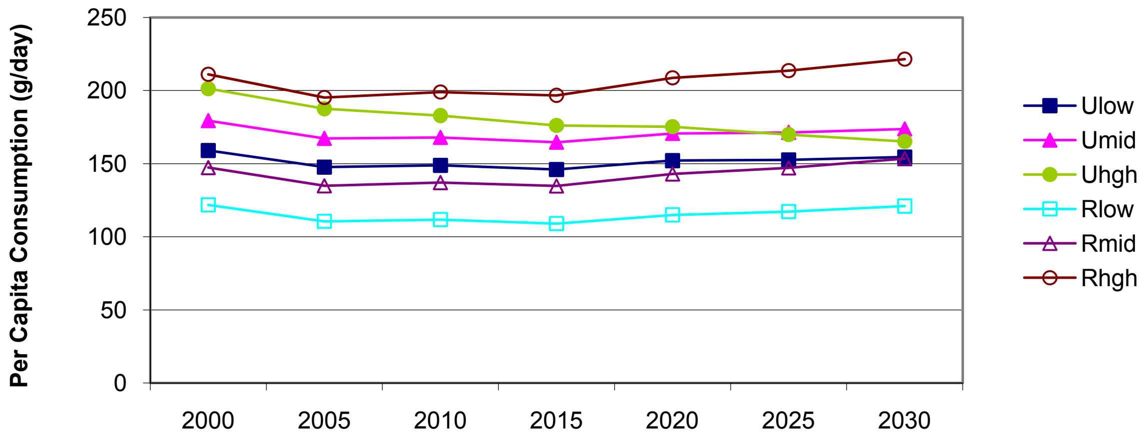
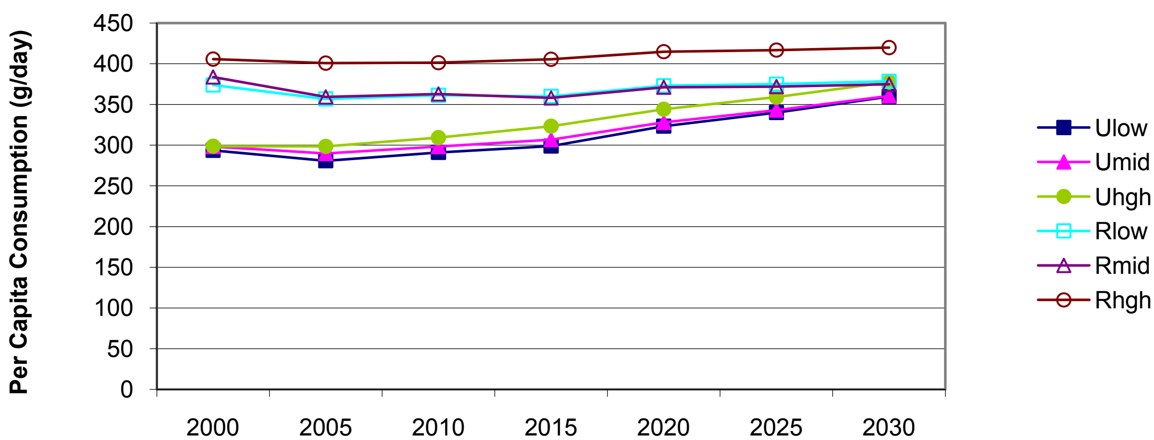


Figure 8: Per Capita Demand for Wheat across Socioeconomic Strata

(a) India (Wheat)



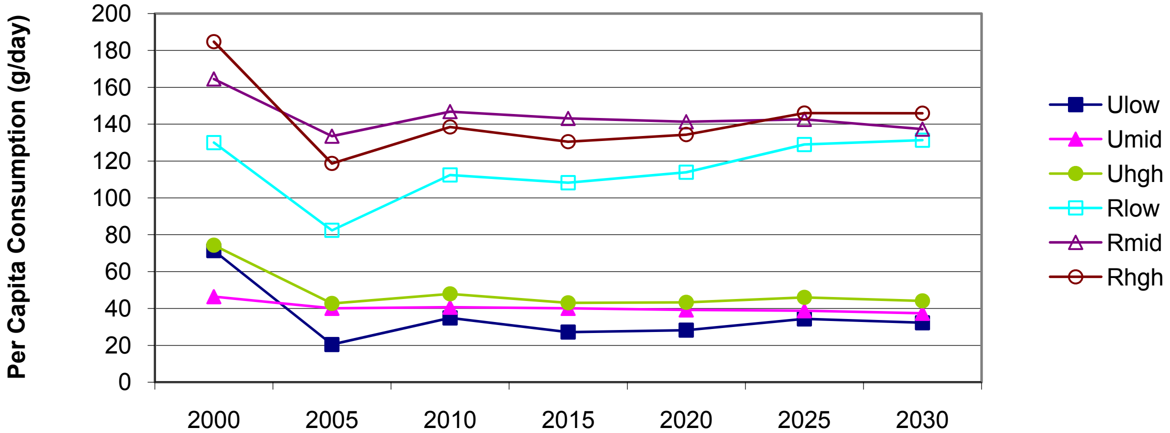
(b) Pakistan (Wheat)



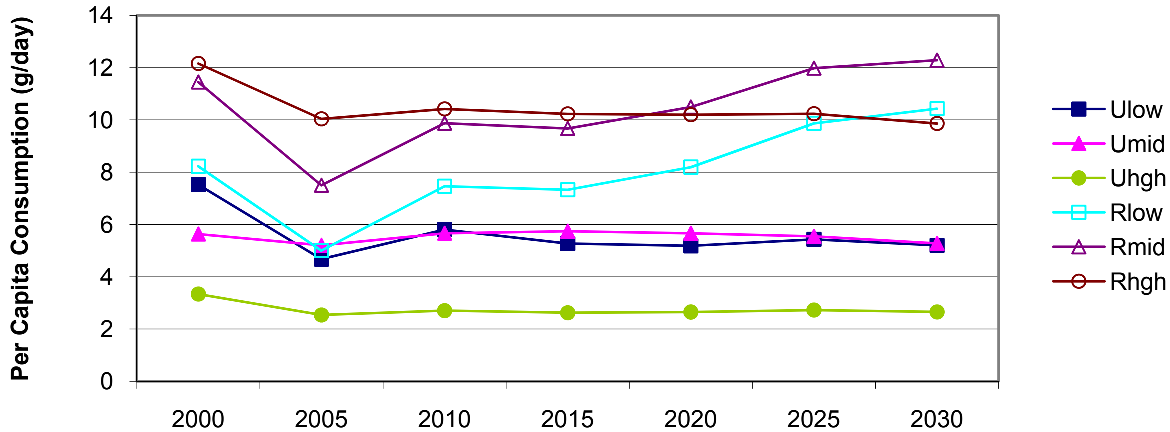
Looking at the patterns of consumption for root and tuber commodities, we see that Uganda (Figure 9a) has a much higher level of sweet potato consumption compared with Mozambique (Figure 9b) and shows more convergence among the consumption patterns of urban and rural groups over time. The consumption of cassava in DR Congo (Figure 9d) is much higher than that seen in Nigeria (Figure 9c). Both countries show, however, a general convergence in the consumption patterns among the rural groups, whereas those of the urban groups tend to diverge slowly over time.

Figure 9: Per Capita Demand for Sweet Potato and Cassava across Socioeconomic Strata

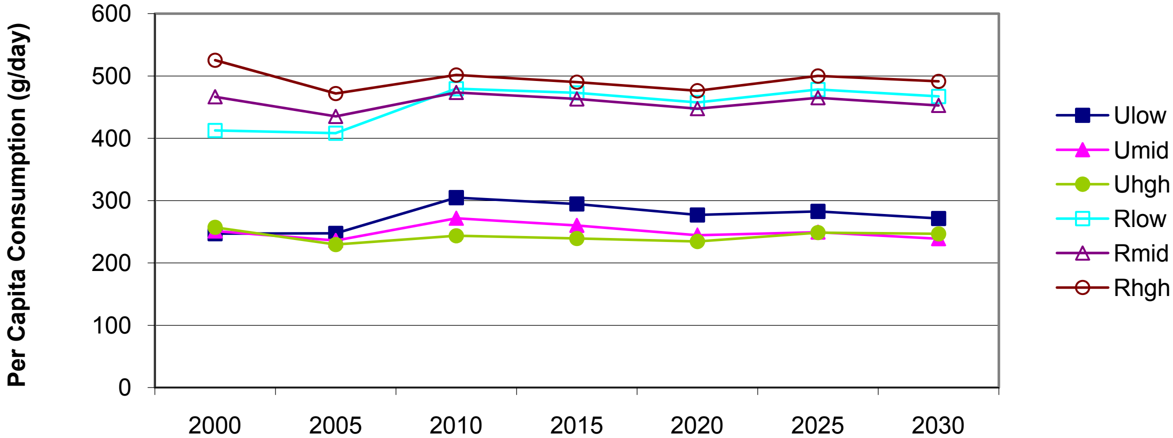
(a) Uganda (Sweet Potato)



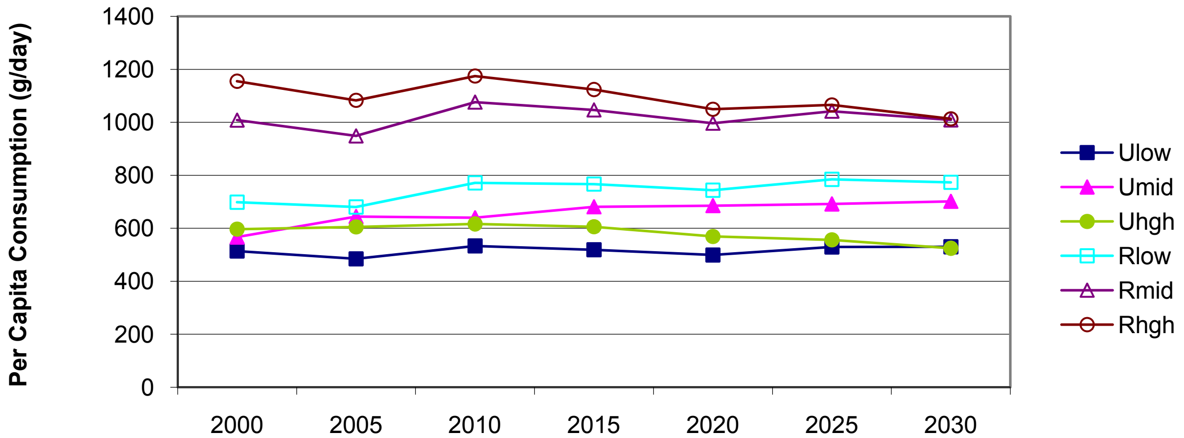
(b) Mozambique (Sweet Potato)



(c) Nigeria (Cassava)



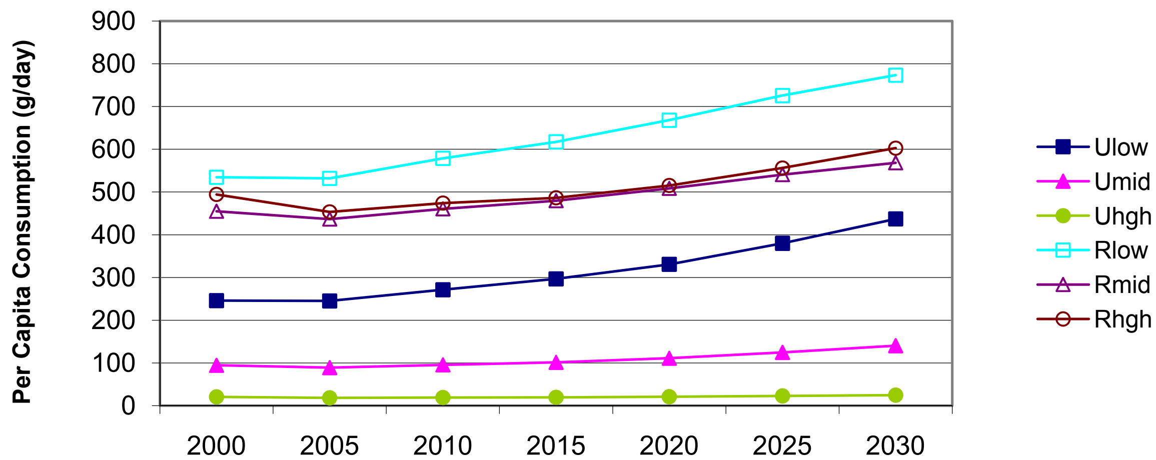
(d) DR Congo (Cassava)



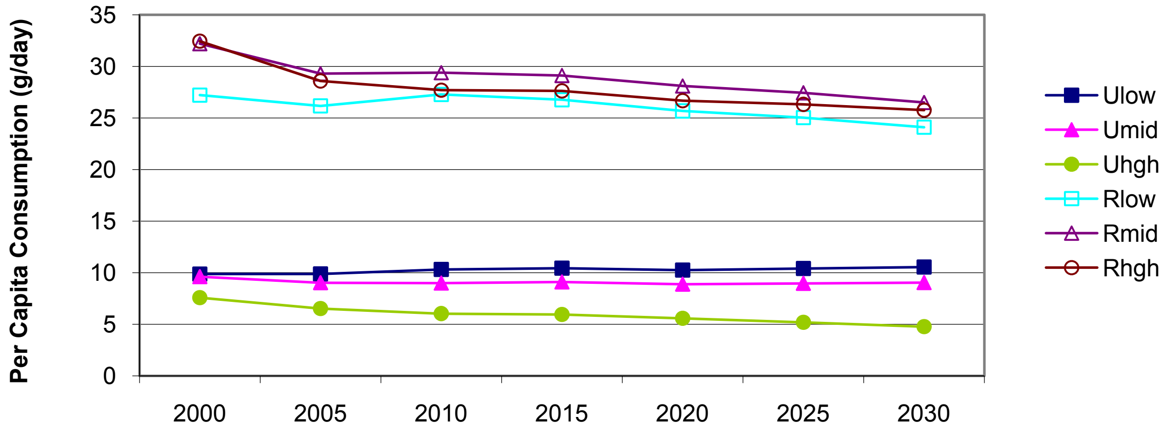
The difference between the per capita consumption levels of millet in Niger (Figure 10a) and India (Figure 10b) reflect the stronger preference in Sub-Saharan Africa to consume millet for human food, whereas it is preferred for animal feed in Asian countries. The same is true for sorghum, which is a key dryland grain crop that is grown throughout the semiarid tropics of Africa and Asia (Ryan and Spencer, 2001). The decreasing preference for dryland grains as food is partly due to the shift towards rice and maize, which are targeted for subsidies through government policies (Gulati and Kelly, 1999).

Figure 10: Per Capita Demand for Millet across Socioeconomic Strata

(a) Niger (Millet)



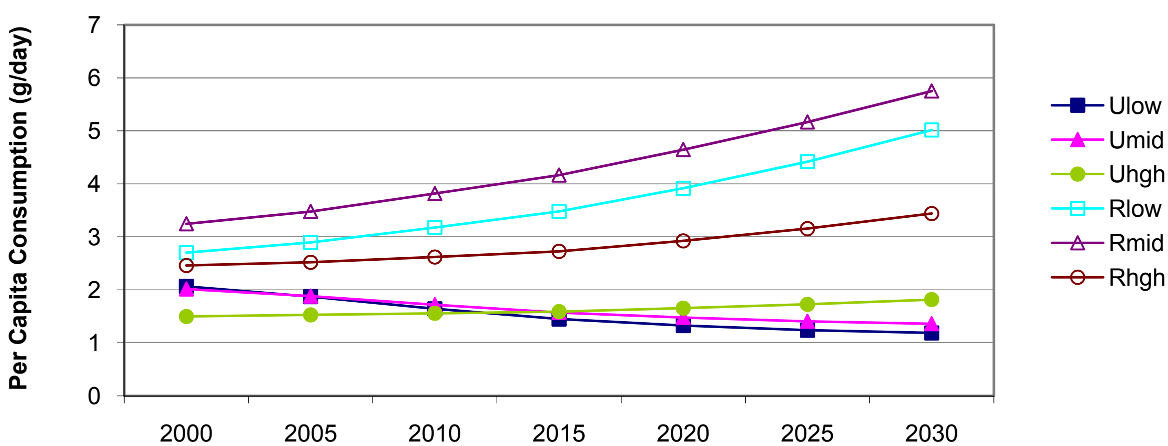
(b) India (Millet)



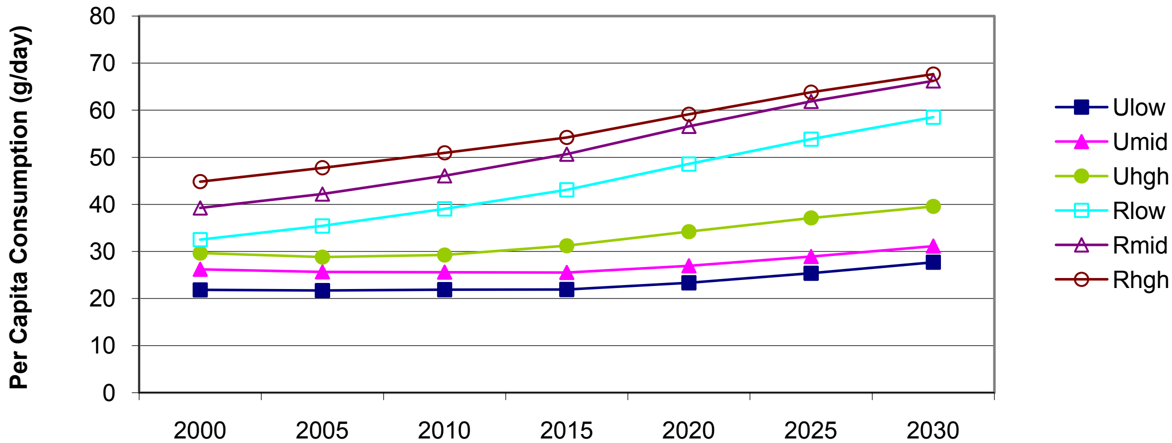
The consumption of beans in DR Congo (Figure 11a) and Rwanda (Figure 11b) is distinguished by an order of magnitude, in terms of per capita consumption levels. The already low levels of consumption in DR Congo continue to decline among the middle and lower urban strata. The consumption strata in Rwanda show a steadily increasing and gradually convergent pattern over time with consumption being highest among the rural poor and falling in order of increasing income levels.

Figure 11: Per Capita Demand for Beans across Socioeconomic Strata

(a) DR Congo (Beans)



(b) Rwanda (Beans)



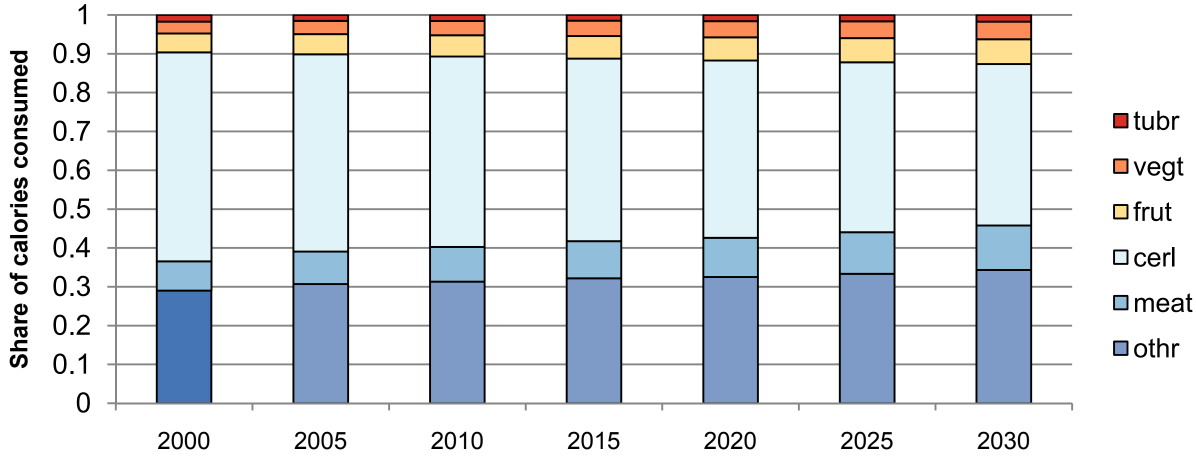
Nutrient Intake across Groups

Given the per capita levels of consumption that are modeled for the socioeconomic groups over time, we can now translate those into levels of nutrient availability, given the intrinsic nutritional properties of each of the food groups considered. The patterns of food consumption across selected socioeconomic strata and countries are shown in Figure 12 in terms of the relative composition of total food consumption across broad commodity groups. The patterns of consumption in urban and rural India (Figures 12a and 12b) show that cereals constitute by far the largest share of diets in terms of calorie intake with a higher proportion of calorie consumption from cereals among the rural groups. The high-income, urban group in India, by contrast, has a slightly higher proportion, which is made up of animal products (both meat and milk). The consumption patterns seen in Rwanda (Figures 12c and 12d), by contrast, show that a larger share of the calorie intakes comes from fruit[7] and root and tuber commodities (sweet potato, cassava, yams, etc.), whereas a relatively small share is made up of animal products or cereals. The calorie consumption from cereals is much lower among both urban and rural groups in Rwanda compared with India, and the consumption of animal products among the lowest income rural group in Rwanda is increasing over time, although it is much smaller than that of the high-income, urban group.

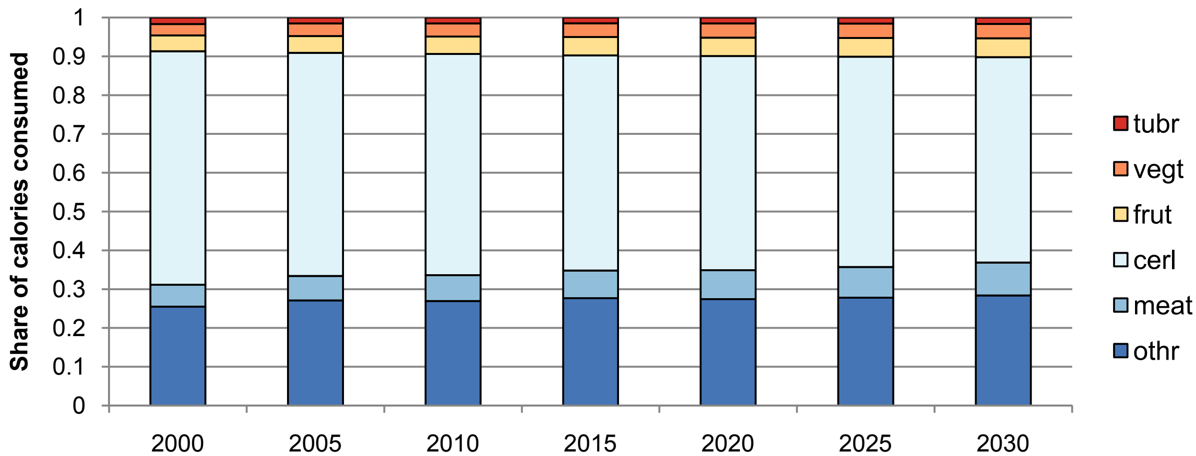
[7] The fruit category in IMPACT includes plantains, which might better be included as a staple in Sub-Saharan Africa.

Figure 12: Diet Composition for Selected Countries and Socioeconomic Strata over Time

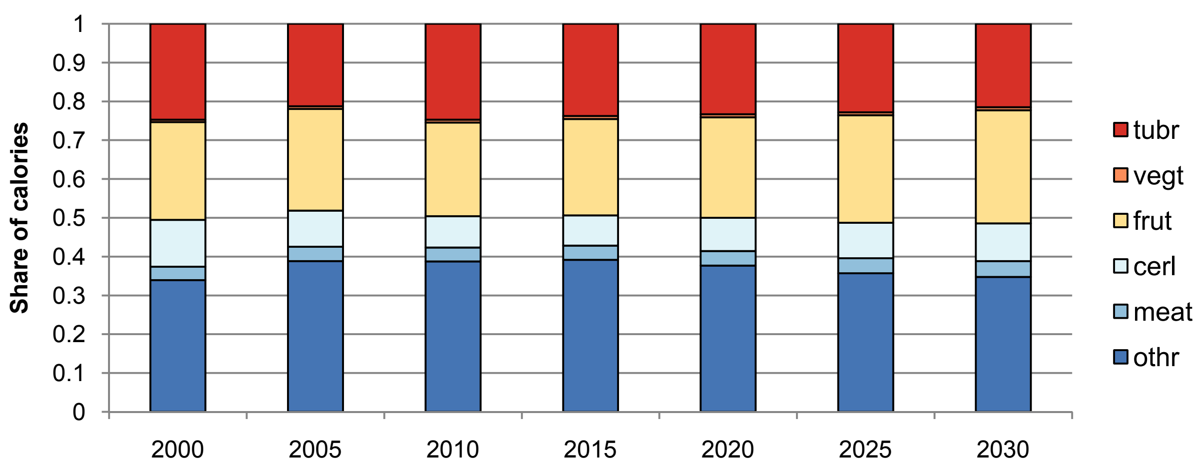
(a) Urban High Income Strata in India



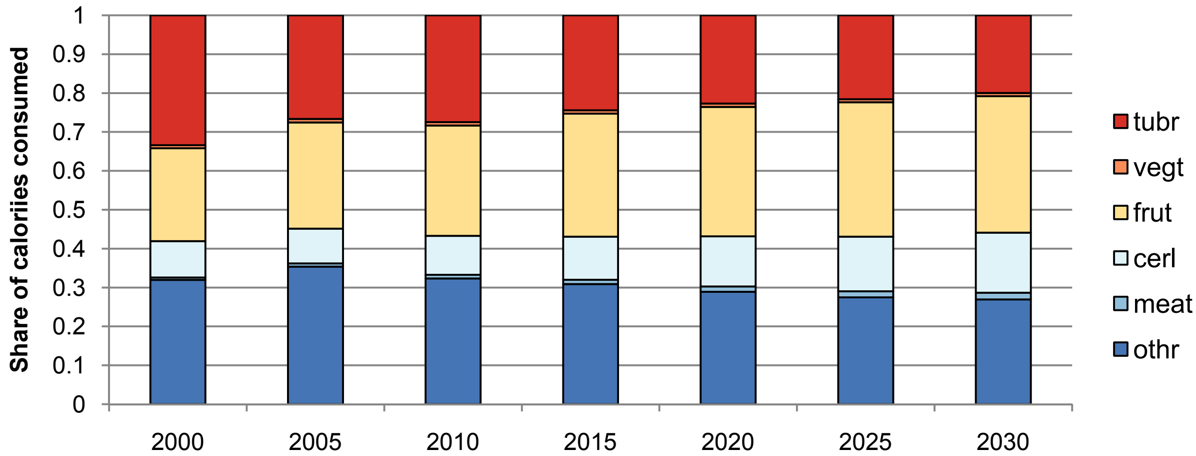
(b) Rural Low Income Strata in India



(c) Urban High Income Strata in Rwanda



(d) Rural Low Income Strata in Rwanda



Translating these patterns into total intake of nutrients, we get the profile over time, shown in Table 7, where we see intakes for the lower urban and rural groups that are relevant to the biofortification scenarios. In some regions, we see the intake levels of nutrients in the low-income, urban populations decrease suggesting that concentrations of urban poverty are likely to decrease, as is seen in Rwanda and DR Congo where the per capita income levels of the urban poor are projected to decrease over time (Figures 3a and 3l, respectively) and where high rates of urbanization are expected (as in Rwanda, Figure 1). This suggests that those population groups would benefit from biofortification to supplement their intake levels that would otherwise fall with their income levels and worsening of diets.

Table 7: Micronutrient Intake under Baseline Case

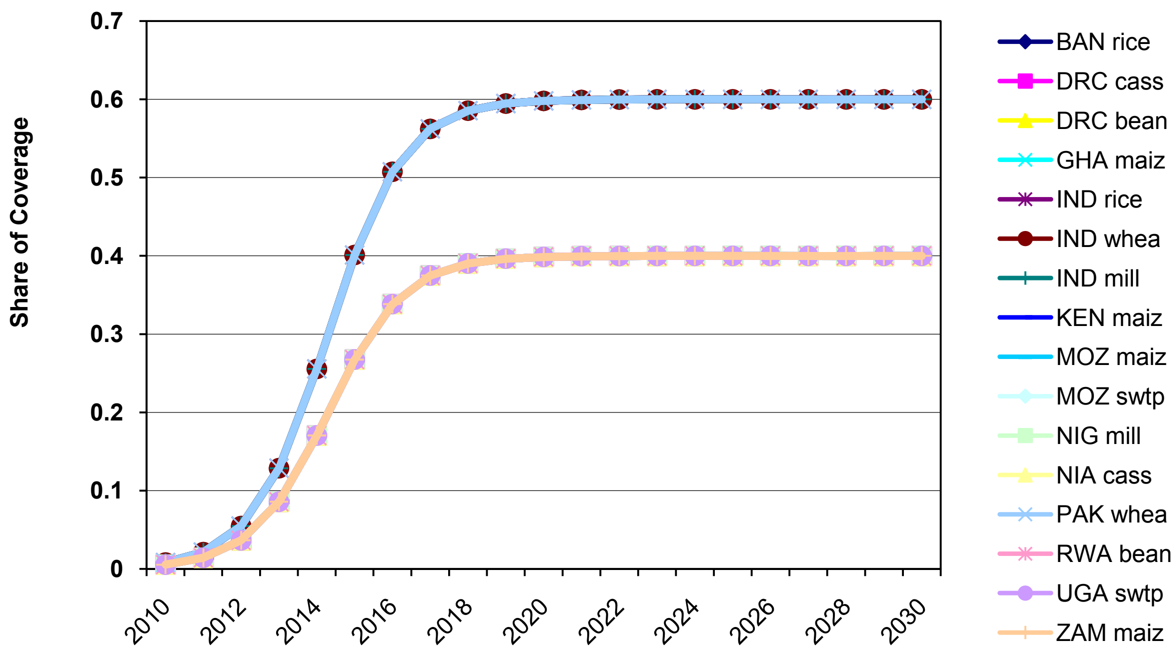
Target Nutrients		Urban Low		Urban Middle		Rural Low		Rural Middle	
Countries		2000	2030	2000	2030	2000	2030	2000	2030
Uganda	Vitamin A	93.1	108.3	101.8	117.0	80.2	104.34	85.1	109.6
Mozambique	Vitamin A	214.7	218.4	294.8	319.6	104.7	259.12	149.3	319.6
Zambia	Vitamin A	90.8	114.0	105.9	129.1	67.8	112.3	79.7	127.4
Nigeria	Vitamin A	301.3	361.1	318.4	380.5	271.3	374.0	282.2	382.4
DR Congo	Vitamin A	130.5	105.6	148.0	123.2	105.0	161.5	126.1	187.0
	Iron	5.4	5.01	5.8	6.1	6.3	7.3	8.2	8.7
Niger	Iron	7.7	11.1	5.4	6.3	12.3	17.0	11.2	13.9
Rwanda	Iron	4.1	3.5	4.4	3.8	3.9	5.4	4.3	5.9
India	Iron	6.4	7.7	6.7	7.9	6.4	8.0	6.8	8.5
	Zinc	3.4	4.2	3.6	4.3	3.4	4.5	3.6	4.8
Bangladesh	Zinc	1.9	2.0	2.0	2.1	1.9	2.2	2.1	2.4
Kenya	Zinc	4.5	5.1	4.7	5.2	4.5	5.4	4.9	5.7
Ghana	Zinc	4.3	4.5	4.5	4.6	4.9	5.8	4.9	5.8
Pakistan	Zinc	4.3	4.9	4.6	5.3	4.3	5.8	4.7	6.2

Note: Units of iron and zinc intake are in mg per capita per day. Vitamin A is given in RE (retinol equivalent) units per capita per day. All intakes reflect that of children under 6 years of age.

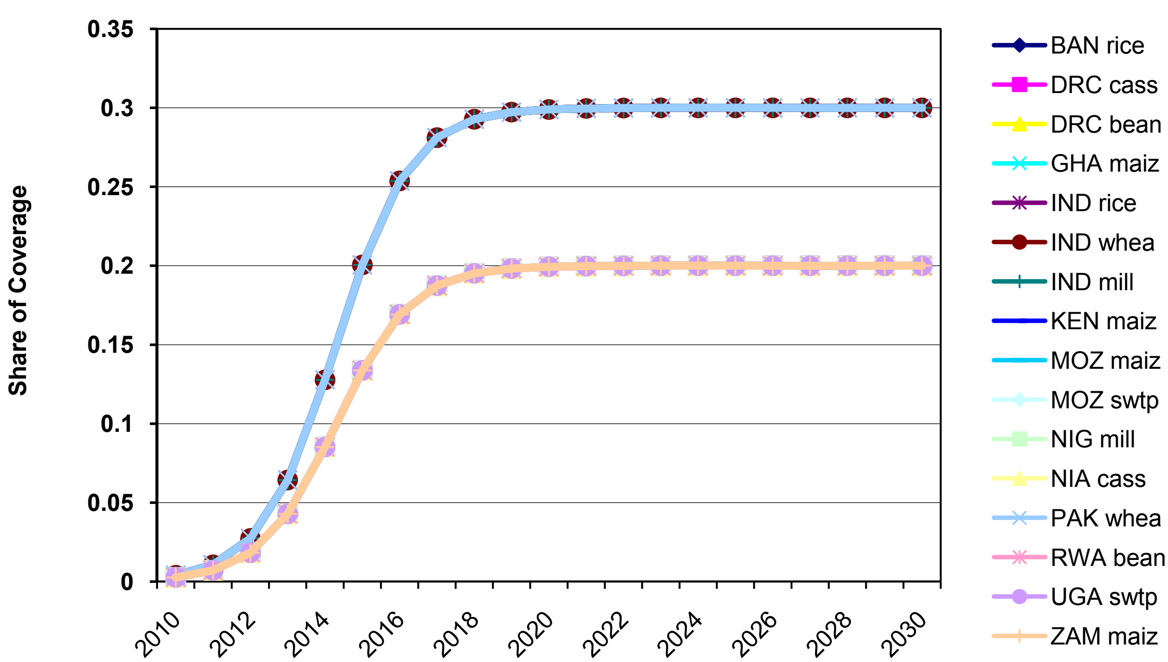
Once the micronutrient content of the foods represented by these consumption patterns is taken into account, we can use standard nutrition tables to model the enhancement of micronutrient content through biofortification. By modeling the process of enhancement with a logistic curve, we obtain the profile of biofortification coverage shown in Figure 13, for both the optimistic (Figure 13a) and pessimistic (Figure 13b) cases. The patterns of maximum coverage that are shown conform to the scenario design that was described earlier in Table 5.

Figure 13: Profile of Micronutrient Adoption and Coverage over Time

(a) Optimistic Scenario for Coverage



(b) Pessimistic Scenario for Coverage



Biofortification Scenario Results

Given the representation of nutrient availability and biofortification coverage that were modeled for each of the target countries and nutrients (Table 3), we can now show the impacts of biofortification on the prevalence of micronutrient deficiency in the general population and among specific socioeconomic strata. Table 8 summarizes the results for the biofortification simulations across all target cops and micronutrients under both optimistic and pessimistic assumptions for coverage and micronutrient enhancement.

Table 8: Percentage Prevalence of Micronutrient Deficiency under Biofortification Scenarios.

Target Nutrients	**Iron**			**Zinc**			**Vitamin A**		
Countries	2000	2020	2030	2000	2020	2030	2000	2020	2030
Uganda							*66*	37/45	33/40
Mozambique							*26*	15/18	10/12
Rwanda	*69*	60/66	51/66						
Kenya				*33*	13/22	10/18			
Zambia							*66*	27/45	23/37
India	*75*	51/52	42/43	*26*	7/16	6/14			
Pakistan				*11*	3/8	2/6			
Ghana				*21*	13/17	11/14			
Bangladesh				*53*	14/33	13/31			
Nigeria							*25*	6/14	2/7
Niger	*57*	32/36	27/28						
DR Congo	*58*	56.8/57.2	50.5/50.9				*58*	18/45	16/41

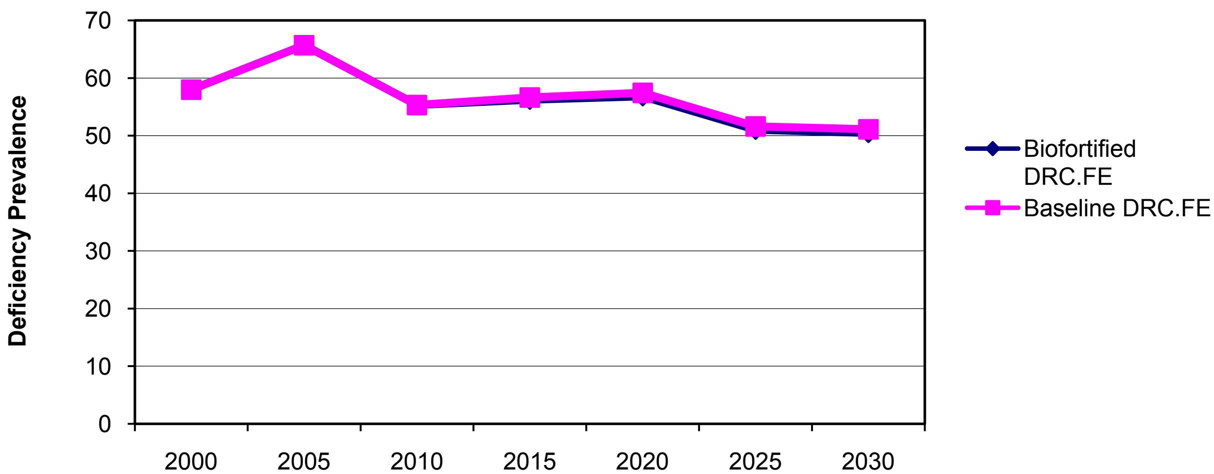
Note: Percentage changes under optimistic and pessimistic scenarios are given in " / " format above, and base year 2000 values are italicized for comparison.

Besides showing the relative effectiveness of the various biofortification strategies in reducing prevalence levels from their initial values, it also shows the difference that the assumptions on coverage and nutrient enhancement have on the long-run levels of prevalence. The results in this table, however, do not give a good comparison of biofortification to the change in micronutrient deficiency prevalence that would occur according to changes in dietary composition over time as a baseline case. To see this comparison, we turn to Figures 14 to 16, which describe the baseline and optimistic levels of micronutrient deficiency prevalence for the target countries and micronutrients.

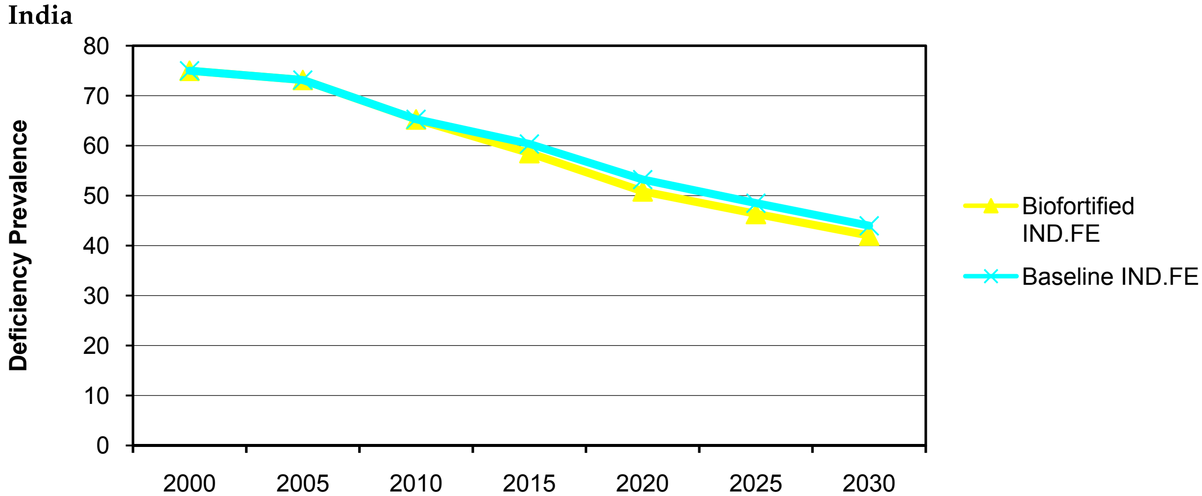
Beginning with overall levels of deficiency among the population of preschool children, we look at the profile across countries targeted for iron biofortification in Figure 14 compared with the changes that would occur from diet change over time without biofortification (the baseline case). Looking across the countries used in the simulation of biofortification effects for iron, we see that the impact on iron deficiency is much stronger for pearl millet in Niger (Figure 14c) and beans in Rwanda (Figure 14d) than for beans in DR Congo or pearl millet in India (Figures 14a and 14b, respectively). These relative differences in effectiveness are a reflection of the contrasting consumption patterns of the target crops that serve as the vehicles for iron biofortification. The consumption of beans is nearly an order of magnitude lower in DR Congo (Figure 11a) than in Rwanda (Figure 11b) and does not offer comparable levels of per capita intake that would lead to the kind of increases in iron intake that would be possible in Rwanda. Similarly, the intake of millet in India (Figure 10b) is much lower than that seen in Niger (Figure 10a) and is stagnant or decreasing over time as compared with Niger. Therefore, when compared with Niger, the effectiveness of iron biofortification in India is diminished in the later time periods when the levels of adoption have reached their maximum potential.

Figure 14: Iron Deficiency Prevalence under Optimistic Scenario (%, children 5 & under)

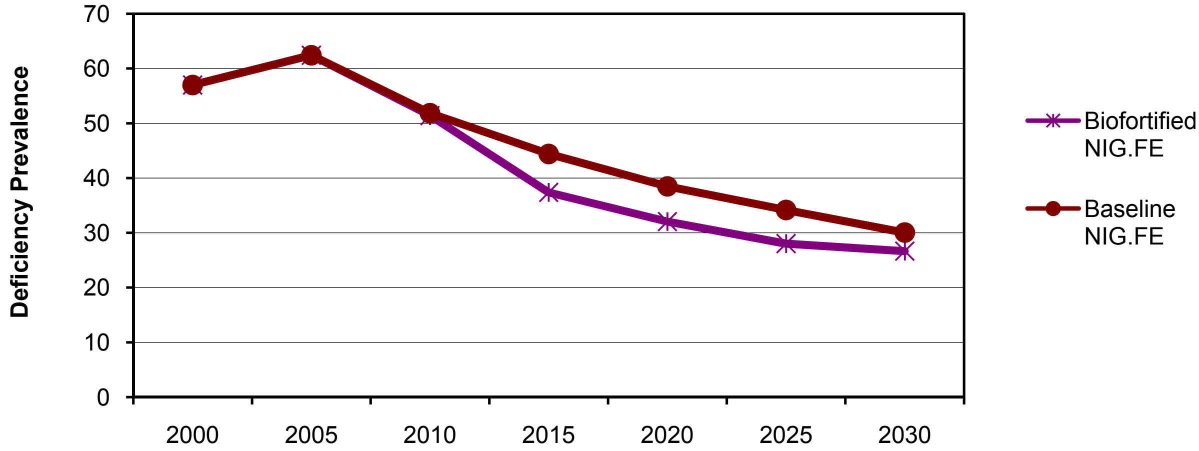
(a) DR Congo



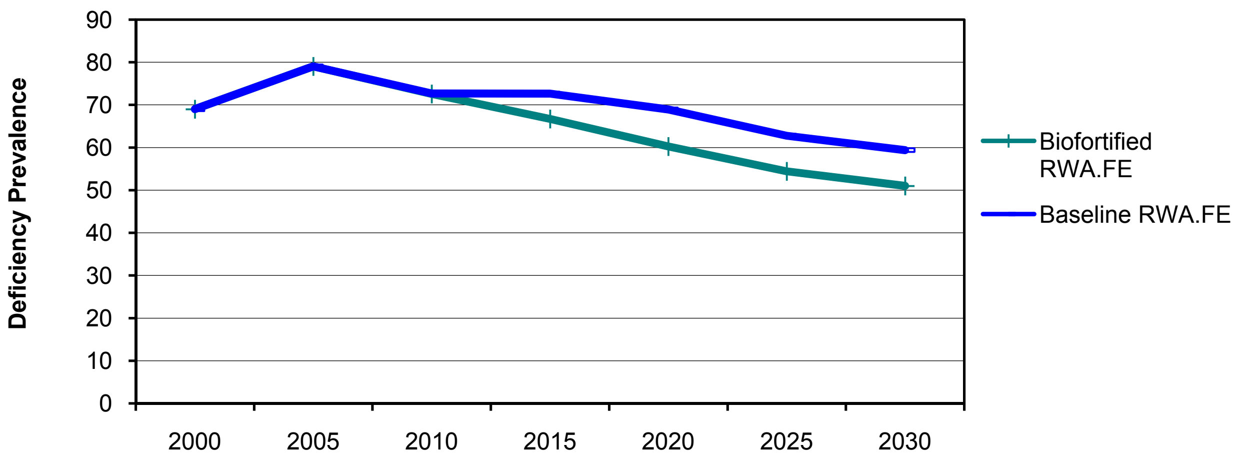
(b) India



(c) Niger



(d) Rwanda



There is a modeling issue here, however. The limited impact of scenarios for iron biofortification of pearl millet in India and beans in DRC is driven by the low national average consumption levels of these crops. This in turn is a reflection of the country-level unit of analysis used by IMPACT and the aggregation biases that are inherent in working with country-level data. For example, in eastern Kivu provinces of DR Congo, bean consumption is reported at over 200 grams per capita, but the national average is only around 9 grams per capita. Similarly, in the semiarid central states in India, pearl millet consumption is over 200 grams per capita, but the national average is only about 25 grams per capita. Iron biofortification strategies in the localized areas could have much more impact than was possible to model in this research.

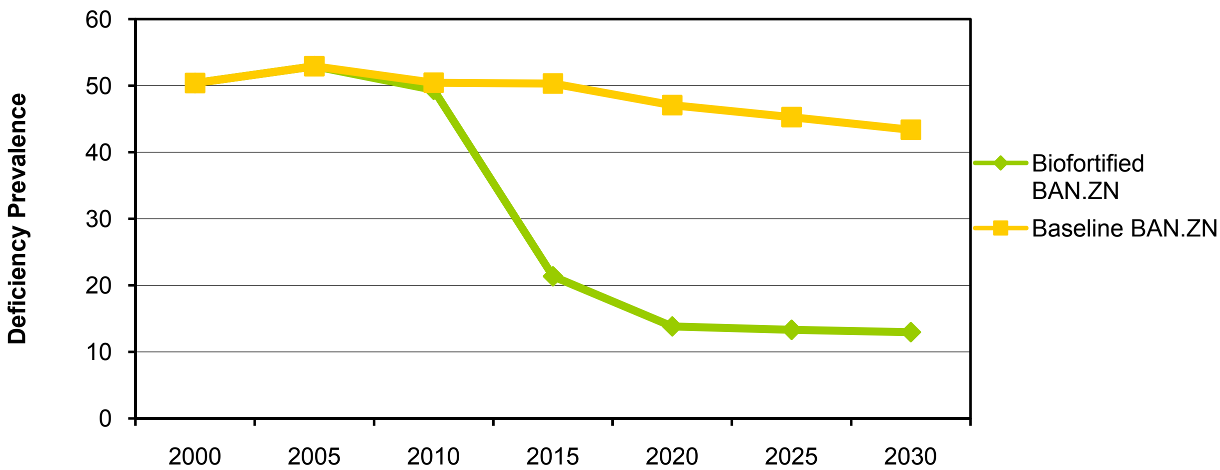
Turning to the scenarios for zinc biofortification, we see much stronger impacts on the level of prevalence among preschool children across the target countries (Figure 15).

Here we see impressive impacts on the levels of prevalence in South Asia, such as that for Bangladesh (Figure 15a) where the levels of prevalence are halved by 2015 and level off at just below a third of their original levels by 2020. The levels of prevalence reduction are also rapid for India (Figure 15c) and Pakistan (Figure 15e), which are able to reach single digit levels of deficiency by the year 2020 and proceed at a steady pace thereafter. The profile for India reflects the simultaneous biofortification of rice and wheat for zinc whose relative effectiveness is shown in Figure 16. The relatively larger share of micronutrient deficiency reduction that is ascribed to rice biofortification under both scenarios is due to the higher per capita levels of rice consumption (Figure 7a) compared with that of wheat (Figure 8a)[8]. The increased weight given to rice in the pessimistic scenario for zinc biofortification is because the assumptions for possible micronutrient enhancement in wheat drop to one-fourth of the optimistic level compared with one-half for rice (Table 5).

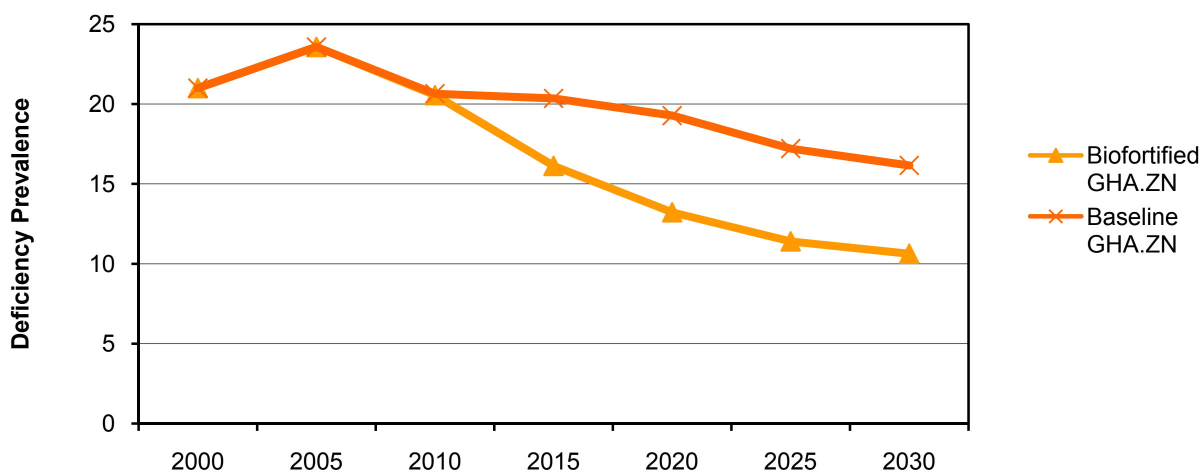
[8] This would appear differently if we did a subregional disaggregation of rice and wheat consumption patterns in India. This, however, was not possible from the national consumption data that we had available.

Figure 15: Zinc Deficiency Prevalence under Optimistic Scenario (%, children 5 & under)

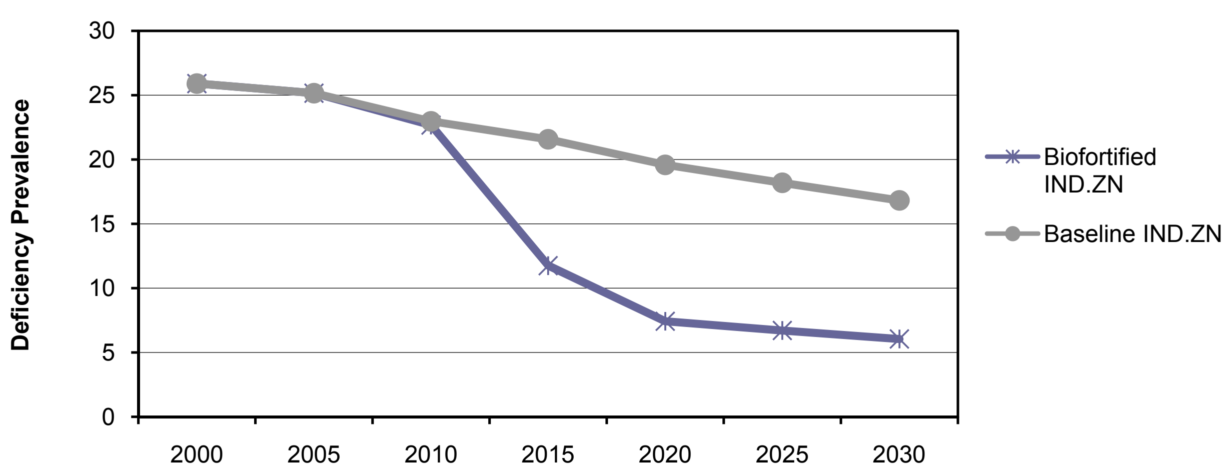
(a) Bangladesh



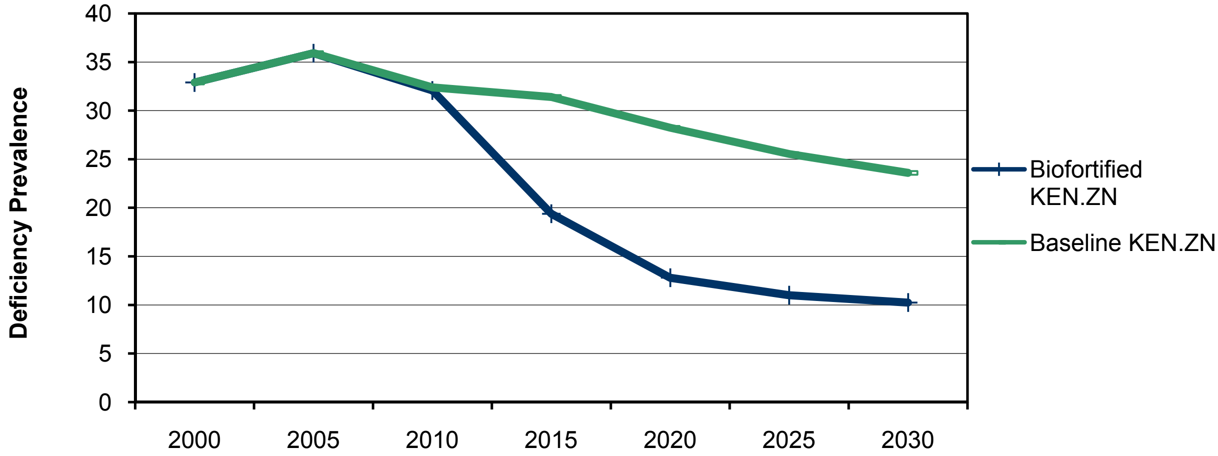
(b) Ghana



(c) India



(d) Kenya



(e) Pakistan

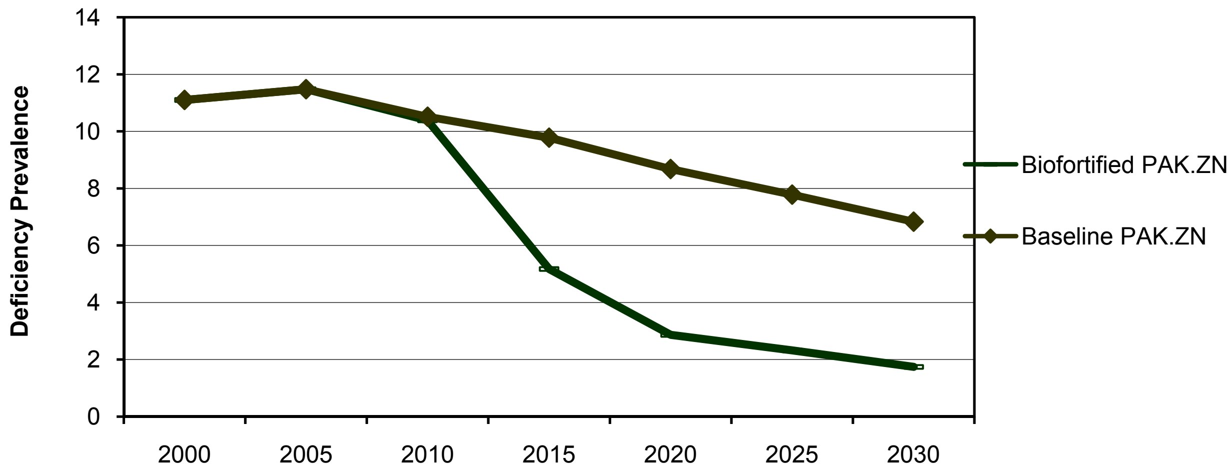
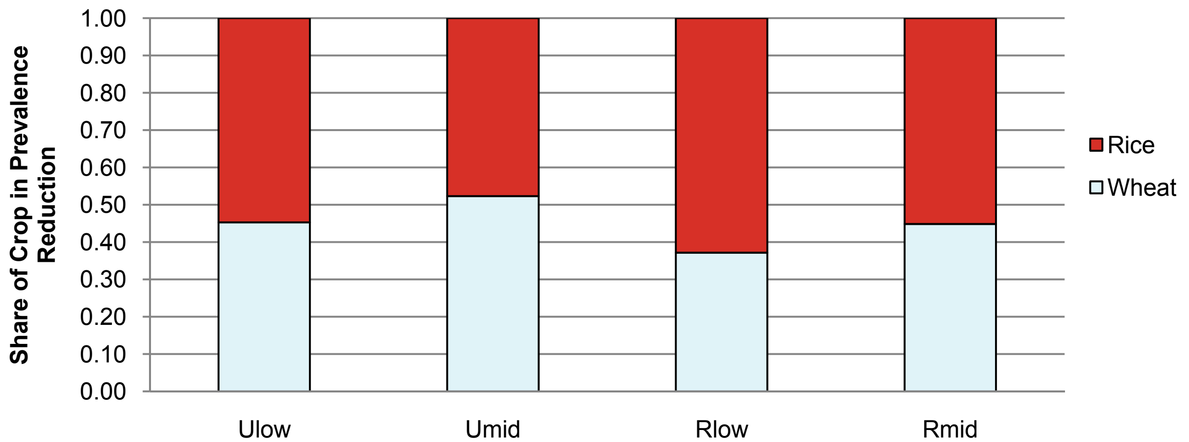
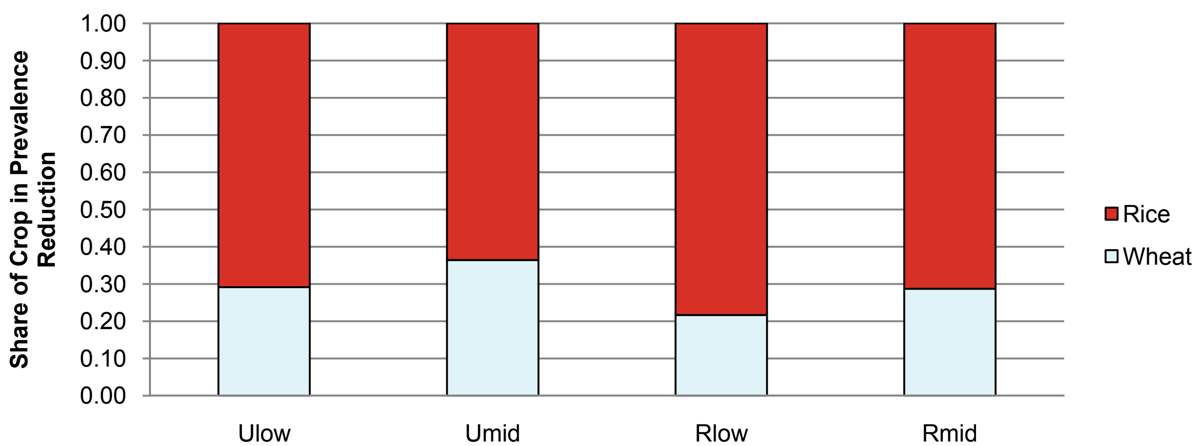


Figure 16: Attribution to Crops in Prevalence Reduction from Baseline due to Biofortification with Zinc in India

(a) Optimistic Scenario



(b) Pessimistic Scenario

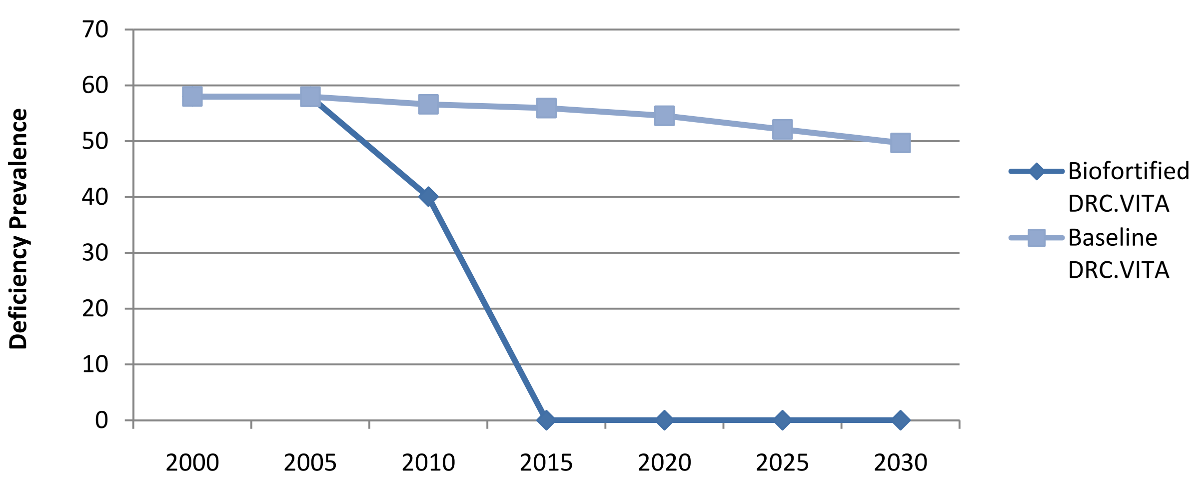


The rate of prevalence reduction in Kenya (Figure 15d) is more rapid than that seen in Ghana (Figure 15b), having started from a higher level of initial deficiency prevalence and reaching about the same level by 2030. Nonetheless, both profiles show that a significant decrease in micronutrient deficiency prevalence is possible from biofortification when compared with the rate that would otherwise occur from diet changes over time in the baseline case. The reason underlying the difference between the impact of biofortification can be seen by comparing maize consumption in both countries, which shows the consumption in Ghana (Figure 6c) being roughly half that in Kenya (Figure 6a) and reflects the contrast between East and West African diets and their preference for alternative staple starches.

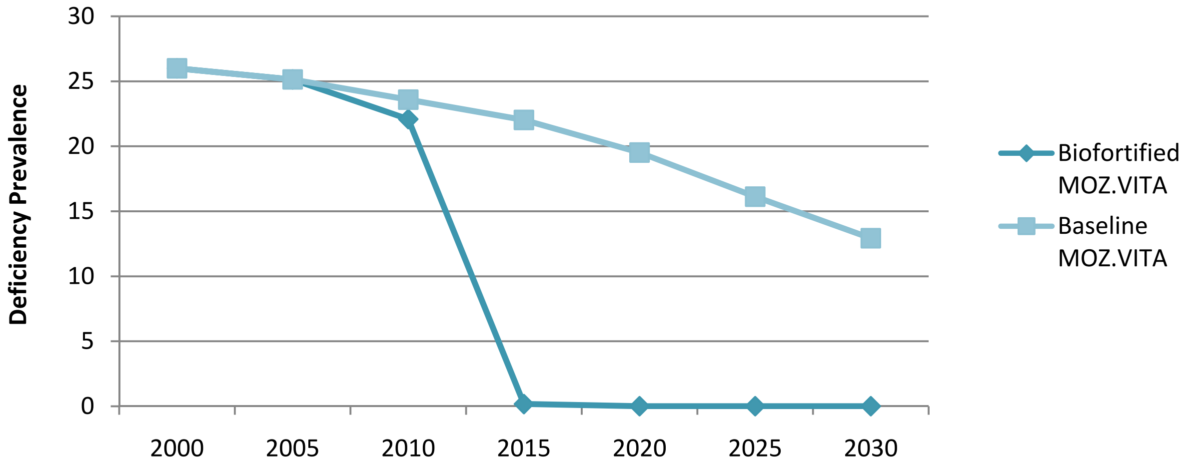
The simulations for vitamin A biofortification give the most impressive reduction in micronutrient deficiency prevalence (Figure 17) and show Mozambique (Figure 17b) being able to reduce its deficiency prevalence level to below 10 percent, DR Congo (Figure 17a) to below 20 percent, and Nigeria (Figure 17c) to below 5 percent by 2030. The fact that DR Congo is able to achieve twice the prevalence level reduction of Nigeria in the same time period is due to the fact that its levels of cassava consumption are much higher (Figure 9d) than those in Nigeria (Figure 9c). Uganda starts from a fairly high level of initial prevalence (Figure 17d) and is able to reduce its levels of deficiency prevalence to less than a half by 2020 through the biofortification of sweet potato for which its consumption levels are high (Figure 9a) in comparison with those in Mozambique (Figure 9b). Compared with Uganda and DR Congo, Mozambique starts with lower levels of prevalence and benefits from the simultaneous biofortification of both sweet potato and maize. Figure 18 shows that the reduction in vitamin A deficiency in Mozambique comes mostly from maize, especially for the urban socioeconomic groups, given that the consumption of maize is much higher than for sweet potato (Figure 6b and 9b) across all groups and is comparable with that seen in Kenya (Figure 6a). Zambia’s high consumption of maize (Figure 6d) makes it a good target for vitamin A fortification and accounts for the rapid reduction of vitamin A deficiency prevalence that is seen there.

Figure 17: Vitamin A Deficiency Prevalence under Optimistic Scenario (%, children 5 & under)

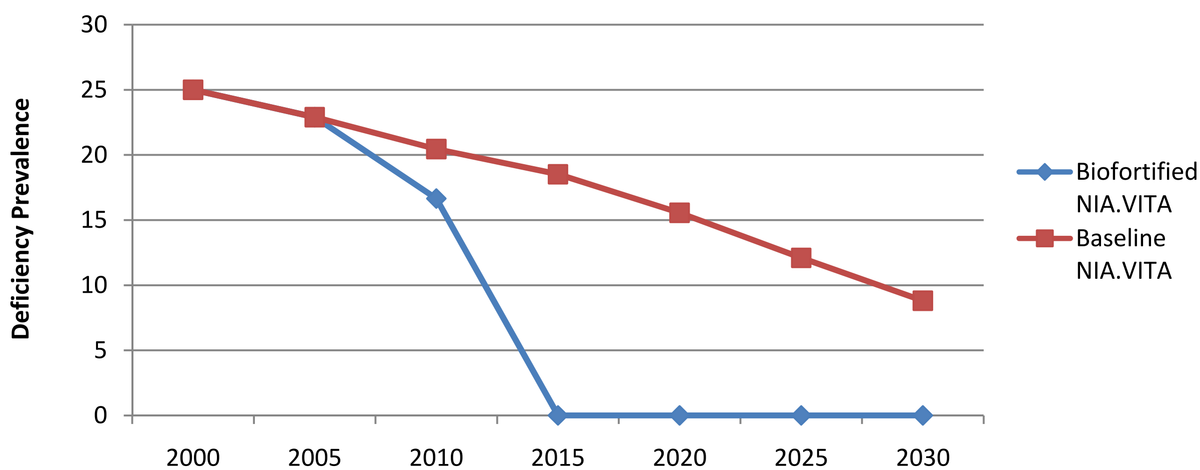
(a) DR Congo



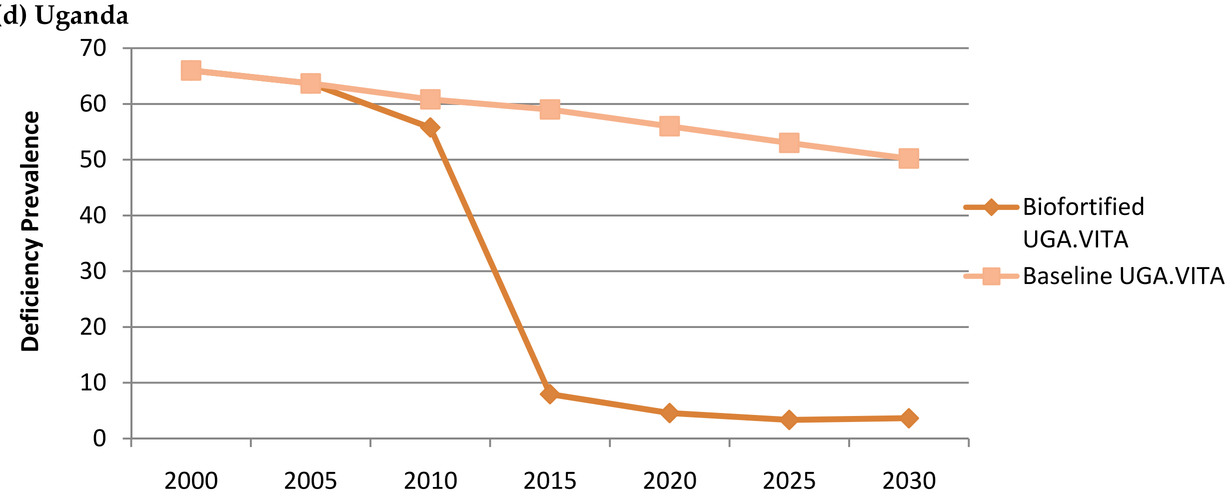
(b) Mozambique



(c) Nigeria



(d) Uganda



(e) Zambia

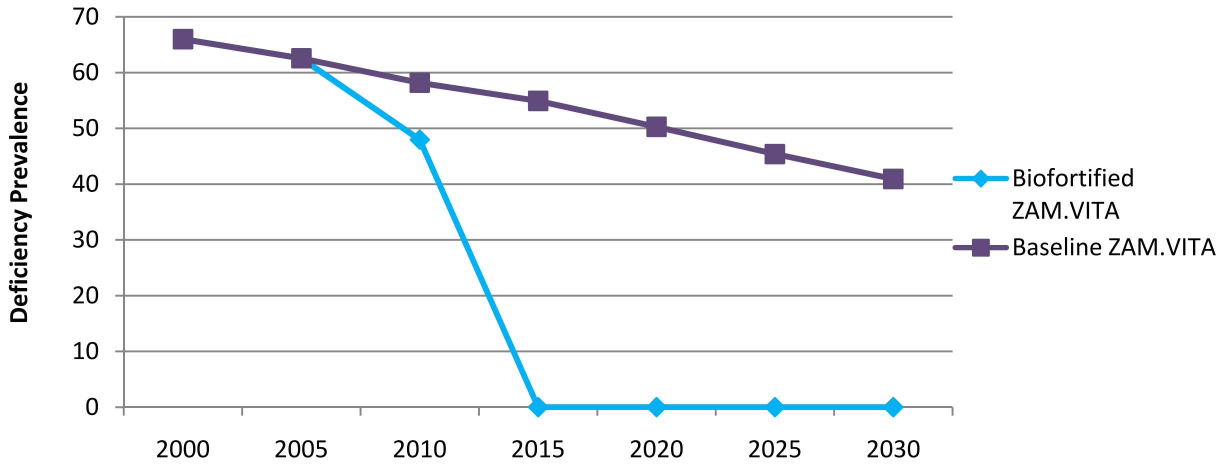
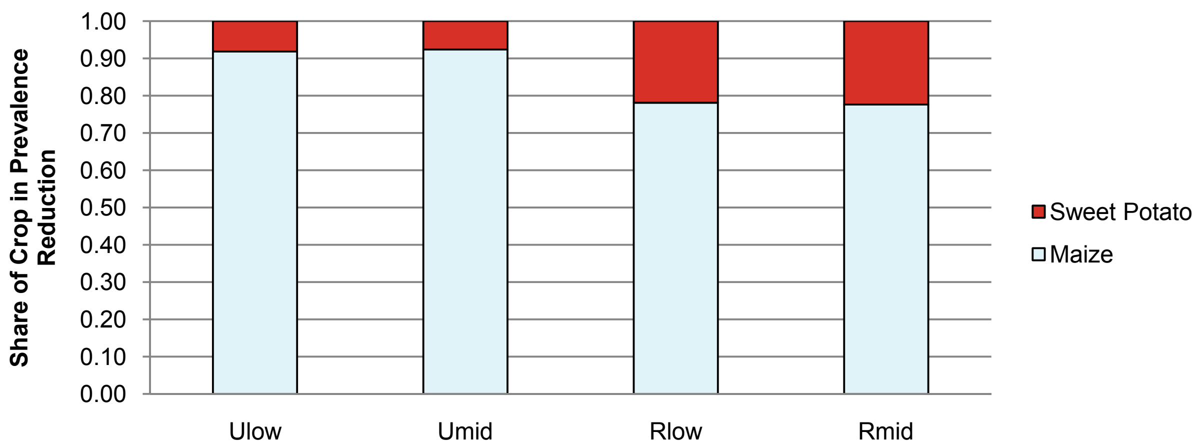


Figure 18: Attribution to Crops in Prevalence Reduction from Baseline due to Biofortification with Vitamin A in Mozambique

(a) Optimistic Scenario



(b) Pessimistic Scenario

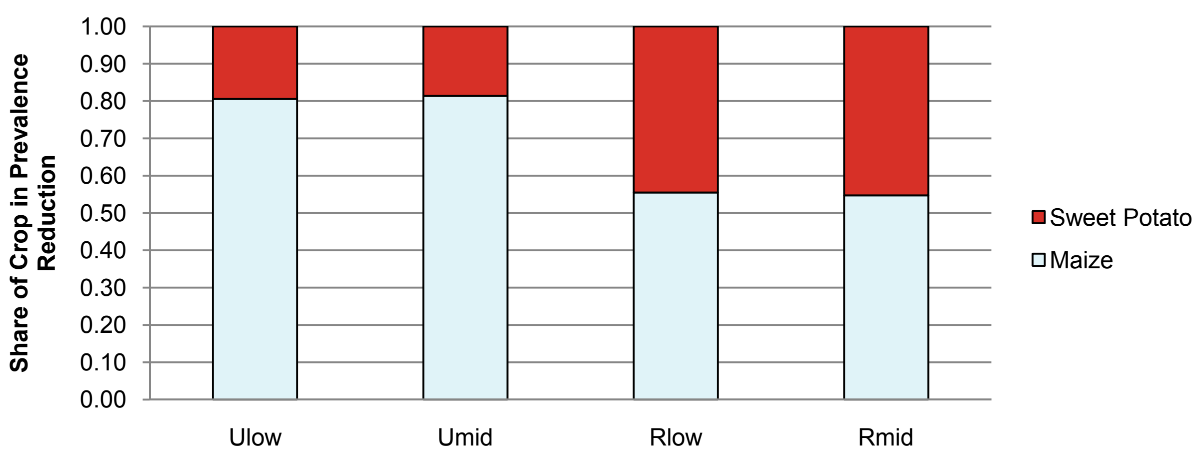
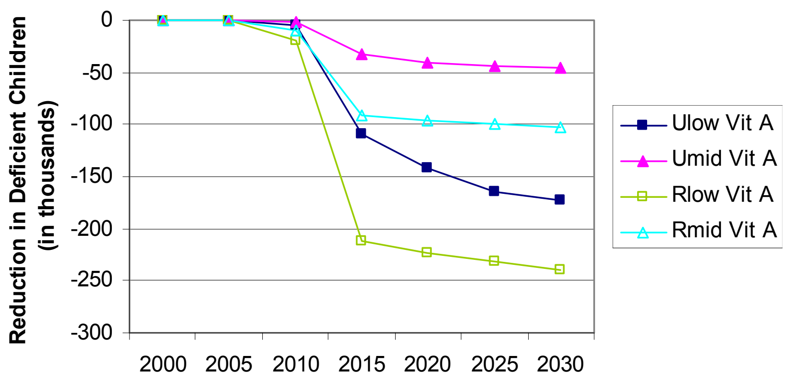


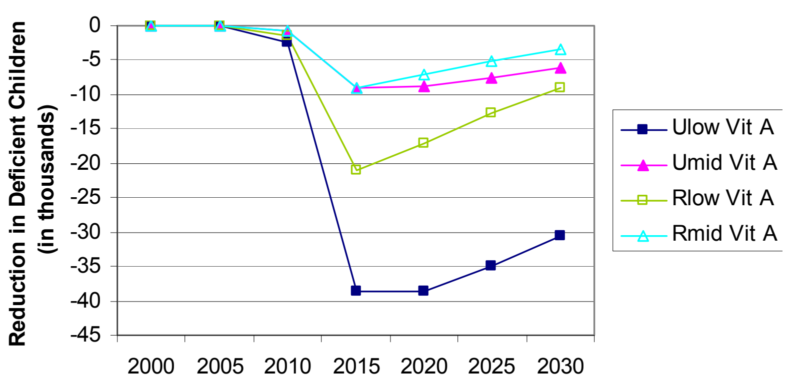
Figure 19 shows the relative impact of the biofortification scenarios across the socioeconomic classes in terms of the additional reduction in the total numbers of micronutrient-deficient children under the optimistic scenario compared to baseline levels of reduction in prevalence over time[9]. Given the assumptions in ascribing national levels of micronutrient deficiency prevalence across socioeconomic groups (Table 6), we see larger numbers for the rural groups compared with the urban groups, in general. The differences across countries and nutrients, however, reflect the relative effectiveness of the biofortification strategy and the differences in food consumption for the target crops represented.

Figure 19: Reduction in the Number of Deficient Children (in thousands) between Baseline and Optimistic Scenario

(a) Uganda

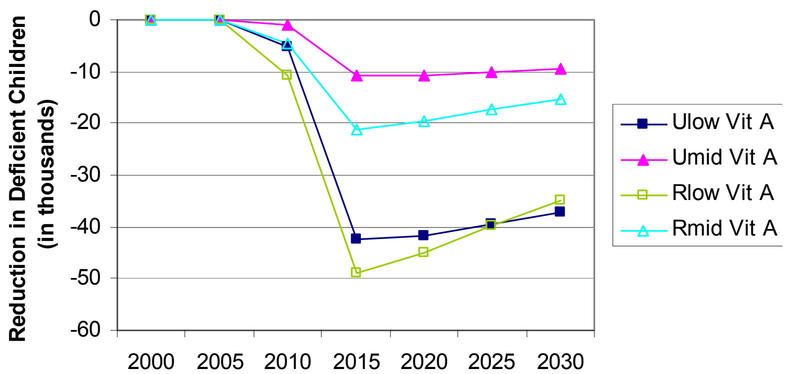


(b) Mozambique

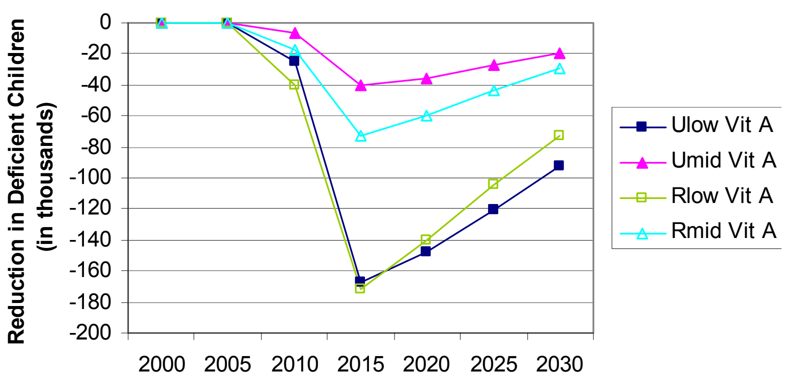


[9] The values in Figure 19 denote the difference between the optimistic and baseline cases – (optimistic – baseline), such that a negative number is an improvement, as the number of deficient children is lowered relative to the baseline case.

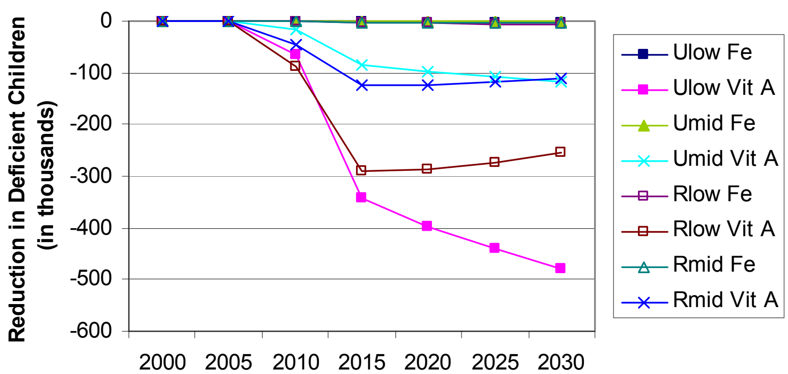
(c) Zambia



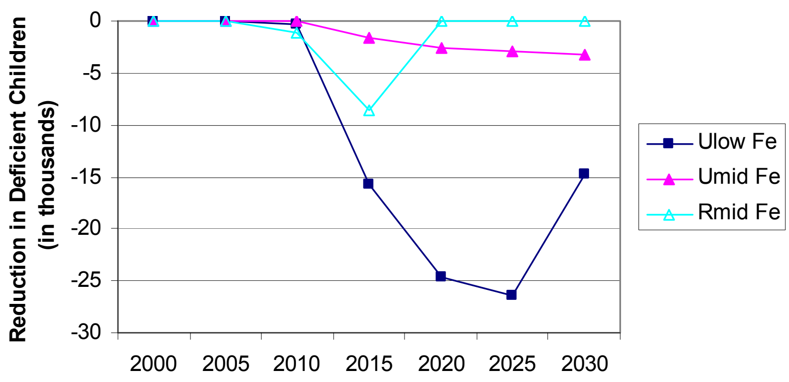
(d) Nigeria



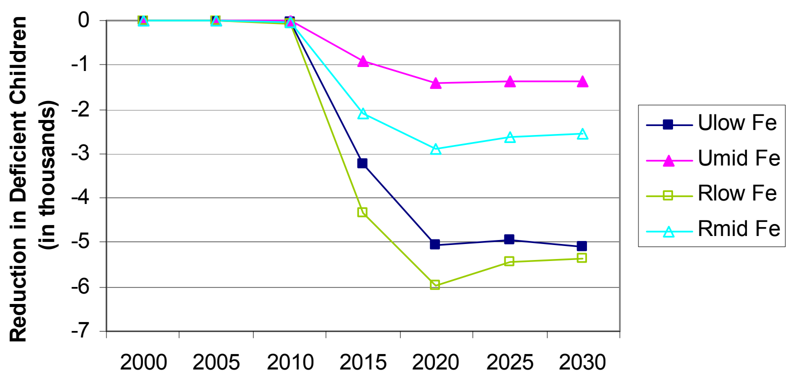
(e) DR Congo



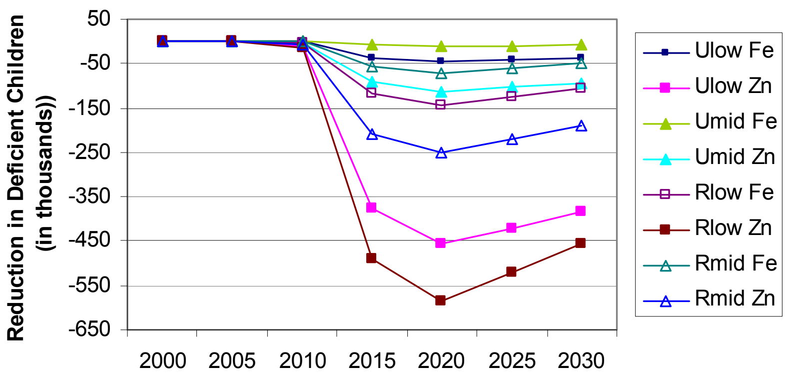
(f) Niger



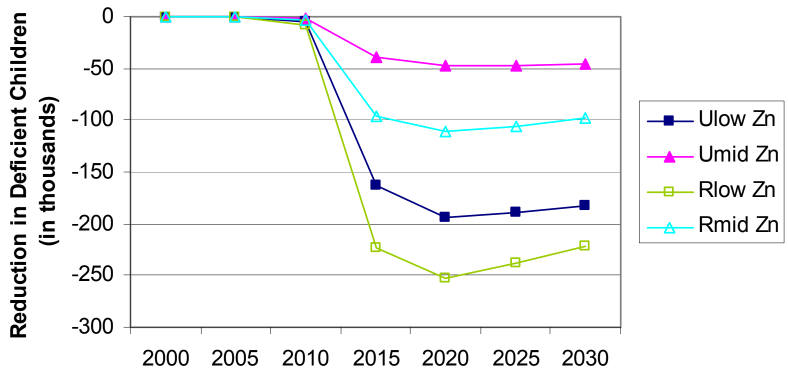
(g) Rwanda



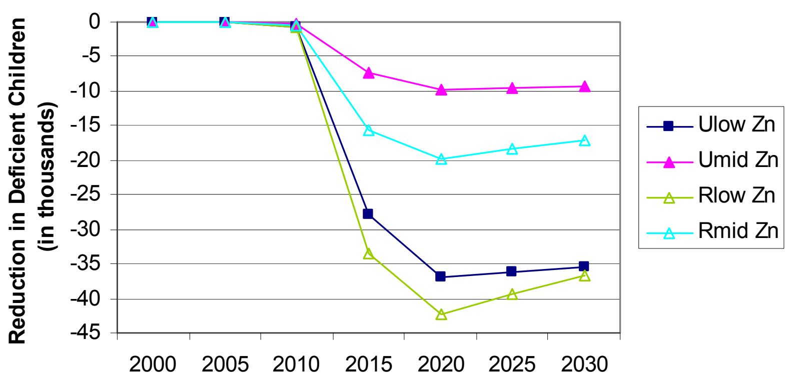
(h) India



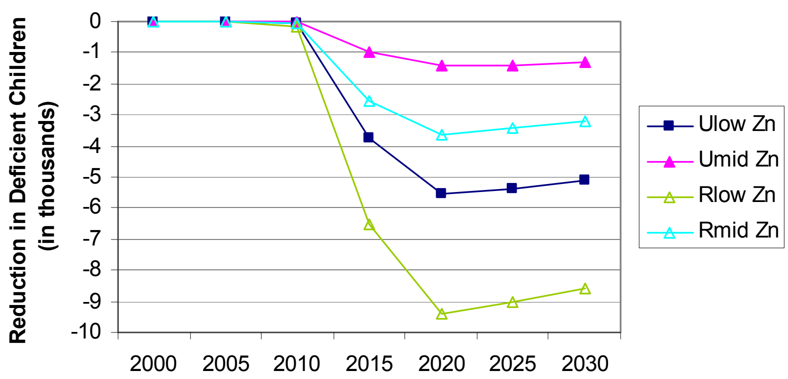
(i) Bangladesh



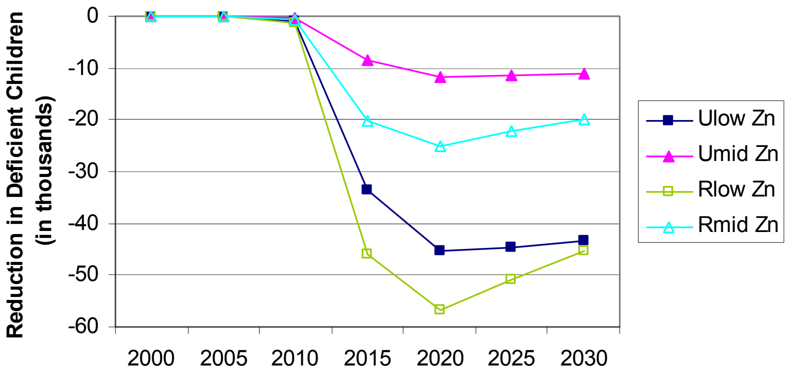
(j) Kenya



(k) Ghana



(l) Pakistan



The large impact seen for Uganda (Figure 19a) and Nigeria (Figure 19d) for vitamin A reflects the dietary dominance of the tuber crops that were targeted for biofortification in those countries compared with the lower intake levels of maize in Zambia and Mozambique where the impact for vitamin A was less. DR Congo (Figure 19e) also shows considerable gains in prevalence reduction over the baseline case through vitamin A biofortification of cassava compared with iron biofortification of beans. The profiles of differential impact over baseline shown in these countries also differ with respect to the rate at which the effect increases or decreases over time once it nears the maximal rates of coverage in the 2015 to 2020 period. The reason behind the difference between Nigeria and DR Congo for vitamin A biofortification is reflected by the difference in the levels of cassava consumption (Figures 9c and 9d, respectively).

The impacts of iron biofortification in Niger (Figure 19f) is "deeper" than that in Rwanda (Figure 18g) but is seen to taper off more quickly than the plateau that is reached in the differential effect of iron biofortification compared to the baseline case. This difference also reflects the contrast between these countries in terms of their profiles of population growth with Niger showing steady growth across all socioeconomic groups (Figure 2k), while Rwanda levels off for the rural and urban-high groups and increases rapidly for the urban-lower and middle income groups (Figure 2c).

The effectiveness of zinc biofortification in South Asia is reflected in the reduced number of zinc-deficient children in India, Bangladesh, and Pakistan as seen in Figures 19h, 19i and 19l, respectively. The amount of tapering is relatively small and shows sustained levels of added deficiency reduction, as is also seen in the results for Kenya (Figure 19j) and Ghana (Figure 19k). The difference between Ghana and Kenya is parallel to that seen when considering the relative reduction in aggregate levels of deficiency prevalence (Figures 15b and d, respectively) and reflects the same difference in the consumption preference for maize as a staple starch.

Table 9 summarizes the overall effectiveness of biofortified crops in terms of the magnitude of reductions in nutrient-deficient children if the optimistic conditions of the scenarios are realized. It shows that the effectiveness of strategies for reducing deficiencies in vitamin A and zinc are quite good for most of the countries that were examined. In those cases where highly consumed staple starch crops were chosen as the vehicle for biofortification (as in DR Congo, Nigeria, Mozambique, and Zambia), there were appreciable reductions in micronutrient deficiency prevalence over time. In choosing between alternative crops for the same micronutrient, the impact of sweet potato dominates that of maize for Mozambique, and the impact of rice appears to be greater than that of wheat in India, especially when the conditions of the pessimistic scenario prevail.

Table 9: Relative Effectiveness of Biofortification across Target Countries and Nutrients

Effectiveness	**Strong**	**Medium**	**Weak**
Target Nutrients			
Iron		Niger	India Rwanda DR Congo
Zinc		Pakistan Ghana Bangladesh Kenya India	
Vitamin A	DR Congo Mozambique Nigeria Zambia	Uganda	

The limited impact of iron biofortification that was observed in Sub-Saharan Africa was mostly due to the relatively low consumption levels of the chosen target crop, whereas that of millet in Niger proved more promising due to the popularity of dryland crops like millet in the semiarid zones of the Sahelian region. Whereas millet also thrives in the semiarid tropics of India, its popularity as a food staple is not as high as Sahelian Africa. The fact that we are considering the average effect on India, however, may be masking the added effectiveness that it might be having in particular regions of this vast and diverse country.

By evaluating the relative effectiveness of biofortified crops over time, we are able to see where such interventions are likely to have the most effect and which countries will need to rely more on growth-induced changes in diet rather than targeted biofortification efforts to change nutrient incomes. The fast-growing economies of South Asia are more likely to increase their intake of nutrients from higher intakes of high-value fruits, vegetables, and animal products, compared with the slower-growing economies of Sub-Saharan Africa where persistent levels of inequality and urban and rural poverty will make for slower changes in diet composition. The heavy reliance on dryland coarse grains and root and tuber crops for staple starch intake in those Sub-Saharan African countries will make these commodities increasingly attractive vehicles for biofortification intervention and will be helped by their inherent robustness to the agronomic and environmental conditions for which they have been bred.

VIII. SUMMARY

In this report, we have described the methodological approach that we used to simulate the intake of critical foods and micronutrients across socioeconomic groups so as to better represent the distribution of nutritional impacts that biofortification interventions can have at the country level. By doing so, we have been able to go beyond the usual limits of macrolevel economic models that can only represent the impact of policy simulations in terms of the population average without resorting to more detailed household data for microsimulation analysis. Our results have demonstrated the relative strength of biofortification impacts across target nutrients and countries in order to evaluate their effectiveness and prioritize their deployment across possible candidate crops. The differences in scenario impacts that we observe originate from differences in the consumption patterns in these individual countries and the relative importance of the candidate biofortified crops in the overall diets of household consumers. The higher consumption of cereal grains (rice, wheat) in India makes those crops effective biofortification crops, whereas roots and tubers are particularly effective in Sub-Saharan Africa. While we have not done a cost-benefit analysis of these interventions, such an exercise would be straightforward once a common metric of health benefit and intervention cost is obtained.

In particular, we have established that despite the urbanization and income growth associated with globalization, diets of the rural poor, who are the focus for micronutrient interventions, will continue to be based on staple foods. To this extent, biofortification will continue to be relevant to poor rural populations in the years to come, as their incomes will still be far too low to afford a more diversified diet.

Through this work and continued refinements to the model framework and data, we hope to gain a better understanding of the dynamics of micronutrient deficiency at a global level and of the underlying drivers of those trends. By doing so, we can identify potential hotspots for nutrient deficiency and work toward designing better and more cost-effective interventions for both agricultural and health policy, as well as for crop research.

This report has laid out the basic approach that we have utilized in addressing the important question of micronutrient availability and the impacts of biofortification on food insecure and nutrient-deficient populations. While ongoing work will necessitate some changes to the simulation results that we have presented here, the overall philosophy and orientation of our work will remain the same.

APPENDIX 1: RESEARCH STAFF PARTICIPATING IN PROJECT

Researcher	Affiliation	Activities Undertaken
Claudia Ringler	Research Fellow, EPTD[10]	Project management
Siwa Msangi	Research Fellow, EPTD	Research management, simulation analysis and model modifications
Timothy Sulser	Research Analyst, EPTD	Model modifications, simulation analysis, demand estimation
Daniel Hawes	Senior Research Assistant, EPTD	Data collection and analysis, demand estimation
Joe Green	Senior Research Assistant, EPTD	Data collection and analysis
Miroslav Batka	Research Assistant, EPTD	Data collection and analysis
Uttam Sharma	Intern/Consultant	Literature review, data collection and analysis
Andrew Bouis	Consultant	Design of FCDS estimation procedure

[10] EPTD is the Environment and Production Technology Division at the International Food Policy Research Institute (IFPRI)

APPENDIX 2: FOOD CHARACTERISTIC DEMAND SYSTEM (FCDS)

General Overview

Following the logic laid forward in the work of Bouis (1995, 1996) and Bouis and Novenario-Reese (1997), we undertook a numerical implementation of the Food Characteristic Demand System (FCDS) estimation procedures to obtain a set of disaggregated food demands that conform to theory and that are consistent with the food consumption and expenditure data that we described earlier in the report. The FCDS approach takes such data and allows one to compute a complete demand system for the countries and food commodities being studied.

To illustrate, we take a simple five-good example (four food goods, and one nonfood good). The bordered Hessian[11] of the demand system can be represented very simply by the (sparse) matrix shown below, which contains both the prices (*p*) and the second derivatives of the parameters in the FCDS utility function (f_{ij})

$$\begin{bmatrix} f_{11} & 0 & 0 & 0 & 0 & -p_1 \\ 0 & f_{22} & 0 & 0 & 0 & -p_2 \\ 0 & 0 & f_{33} & 0 & 0 & -p_3 \\ 0 & 0 & 0 & f_{44} & 0 & -p_4 \\ 0 & 0 & 0 & 0 & f_{55} & -p_5 \\ -p_1 & -p_2 & -p_3 & -p_4 & -p_5 & 0 \end{bmatrix}$$

where for f_{55} we have $f_{55} = \lambda \frac{p_5}{q_5} \frac{\phi}{\eta_5}$, where λ is an implied shadow value in the demand relationship, ϕ is a price flexibility, q_5 is the quantity consumed of the nonfood good, and η_5 is the non-food income elasticity.

Since we know p_5 and q_5 from data, we get values of λ , ϕ .

[11] The bordered Hessian is a matrix of second derivatives that comes from the assumption of utility maximization through food and nonfood good consumption that underlies all economic demand studies. See Henderson and Quandt (1980), Dixit (1990), or Takayama (1993) for more details.

More generally, this can be stated as:

$$\begin{bmatrix} E_{11}+V_{11}+T_{11} & E_{12}+V_{12} & E_{13}+V_{13} & E_{14}+V_{14} & 0 & -p_1 \\ E_{21}+V_{21} & E_{22}+V_{22}+T_{22} & E_{23}+V_{23} & E_{24}+V_{24} & 0 & -p_2 \\ E_{31}+V_{31} & E_{32}+V_{32} & E_{33}+V_{33}+T_{33} & E_{34}+V_{34} & 0 & -p_3 \\ E_{41}+V_{41} & E_{42}+V_{42} & E_{43}+V_{43} & E_{44}+V_{44}+T_{44} & 0 & -p_4 \\ 0 & 0 & 0 & 0 & f_{55} & -p_5 \\ -p_1 & -p_2 & -p_3 & -p_4 & -p_5 & 0 \end{bmatrix}$$

where

(Energy) $E_{ij} = 2w_e e_3 z_i z_j < 0$

(Taste) $T_{ii} = w_{ti}\left(1/q_i \right)^2 < 0$

(Variety) $V_{ij} = \dfrac{2w_v M}{T^3} > 0$

Which relate to the first-order conditions of the underlying utility maximization problem:

(FOC): $$p_i = \frac{w_e}{\lambda}\left[\underbrace{e_2 z_i}_{w_e e_2 z_i} + \underbrace{2e_3 z_i E}_{2w_e e_3 z_i E}\right] + \frac{w_v}{\lambda}\left[-\frac{M}{T^2}\right] + \frac{w_{ti}}{\lambda}\left[\frac{1}{q_i}\right]$$

In Bouis and Novenario-Reese (1997), the suggested sequence of computation, is described as follows:

(1) given $w_e e_3$ → get E_{ij}

(2) given w_v → get V_{ij}

(3) with E_{umx} and $\mathrm{w_e} e_3$ → solve for $\mathrm{w_e} e_2$

(4) given $\mathrm{w_e} e_2$, $\mathrm{w_e} e_3$ and $\mathrm{w_v}$ → get $\mathrm{w_{ti}}$ (by solving the FOC) → then get T_{ii}

(5) given ϕ / η_{nf} → get f_{55}

As described in Bouis (1995, 1996), given the bordered hessian matrix of the utility function described earlier, it is possible to derive an (n+1) by (n+2) matrix of demand elasticities where n is the number of food items. The explicit form of the equations needed to fill in the hessian are also as shown above; however, there are 4 variables (hereafter called parameters) whose values are hard to estimate from data. The approach then is to prespecify four "target" elasticities and solve for the four parameters that reproduce these targets. It has been hypothesized that prespecifying at least four elasticities will constrain the parameters to one solution in the sense that a linearly independent system of four equations and four unknowns has only one solution. Given this unique parameter solution, it is then possible to calculate the complete matrix of demand elasticities.

Estimating the FCDS Parameters

In this project, the solution procedure for finding the parameters has been approached as an iterative optimization problem, whereby a parameter vector in R^4 is mapped to a distance value in R^1, and the goal is to minimize the distance. Note that given an arbitrary parameter vector (values for the parameters in equation 1), the bordered hessian can be filled and elements in the elasticity matrix that correspond to the target elasticities can be computed. Therefore, the distance function is the sum of the squared residuals of the elasticities computed using this vector and their corresponding target elasticities. Unfortunately, computing elasticties on each iteration is a costly operation as it involves calculating determinants according to Cramer's rule (see equations 2–30 and 2–31, Henderson and Quandt, 1980).

The Fortran program that was used previously by Bouis and Novenario-Reese attempted a brute-force iteration of the parameter space, which quickly becomes impractical to implement if all four parameters are to be varied simultaneously. This becomes obvious if we assume (generously) that 100 different values are tried for each parameter. This means that there are 10^8 iterations each of which calculate several determinants (an operation requiring approximately n^3 calculations). In total, there are approximately $10^8 \times n^3$ calculations. More efficient gradient-based optimization algorithms, specifically gradient descent and BFGS, have been implemented in GAMS. In preliminary tests using data and results produced by the Fortran program (n=10), both algorithms converge to the correct solution in a matter of minutes. Using current Uganda data with n=29, a solution that falls within 1.6×10^{-3} could be found within an hour.

FCDS Computation Sequence

A schematic showing the computational sequence is given in Figure A-1 of this annex and is described below:

1) *FCDS.gms* runs the FCDS methodology on one dataset, meaning one rural or urban tertile. This file will execute *init_dataGDX.gms* to read in data and then execute one of the descent algorithms to solve for the parameters and compute the entire demand elasticity matrix.

2) *Init_dataGDX.gms* uses excel GDX to read in household data and create a text file with a list of goods in the system, as well as two GDX files to be read by *hhdata_input.inc.* Following the format of the 'Philippines' or 'Uganda' sheet in fcds_hhDataEdit.xls, the user must prespecify the excel file name and range to read in the food set, foodData parameter, and groupData parameter. This file must also specify values for the nonfood budget share, average family size, and adult equivalent.

   The extra overhead of calling a separate program to read input is caused because *hhdata_input.inc* contains a static set whose elements ('nonfoods' and 'income') are referenced explicitly in the code. This cannot be done during runtime, so *hhdata_input.inc* must $include '*hessianSet.put*' at compile time.

3) The 'algo_' files use gradient-based algorithms to solve for the FCDS parameters. The *gDescent.gms* file is more reliable and better documented. *BFGS.gms* still needs refinement.

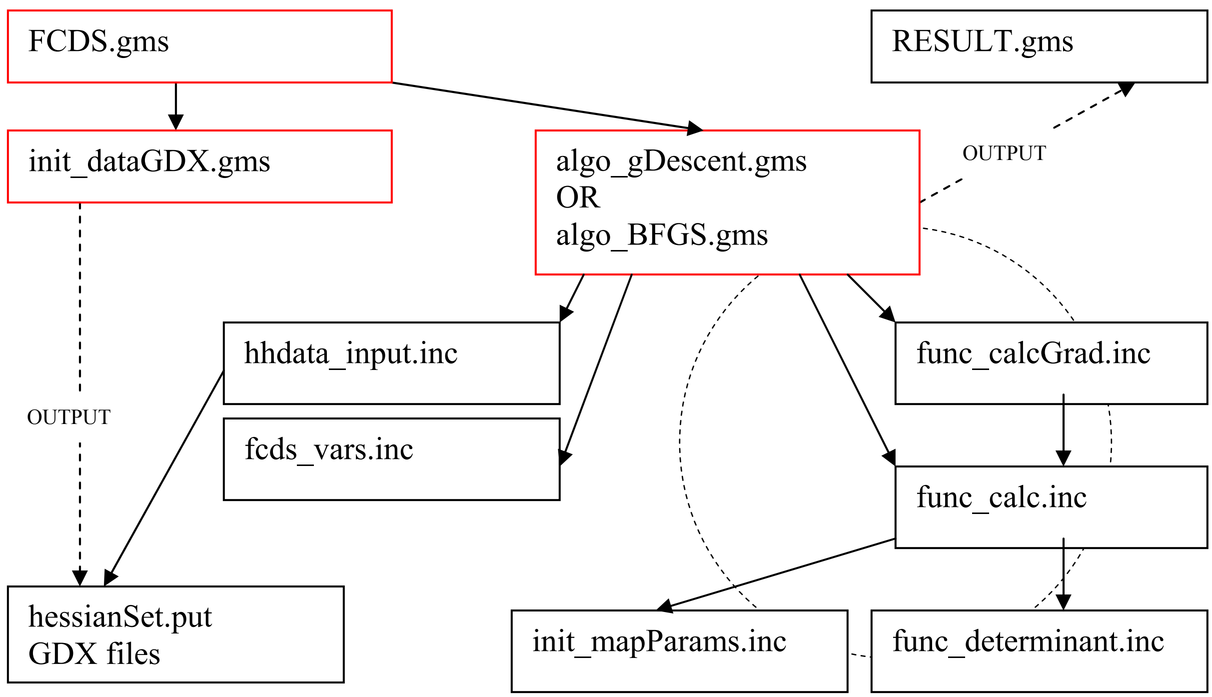
First, household data is initialized in *hhdata_input.inc* via *init_dataGDX.inc* as described in (2). *Fcds_vars.inc* declares the variables used in the FCDS methodology. The algorithm then goes on to manipulate the parameters in such a way as to minimize the distance function. This occurs through loops that continually call the files shown in the dashed circle.

a. Virtually all computation occurs in *func_calc.inc*. This file carries out the FCDS methodology: given arbitrary values for the parameters, the explicit second order equations are calculated to fill in the bordered hessian, and from that compute the elasticities that correspond to the targets. The squared residuals between the computed elasticities and the target elasticities is the mapping from a parameter vector to distance (targetDiff). Basically, the algorithm calls this piece of code over and over with different values for the parameters until it finds a combination that produces elasticities that match the pre-specified, target elasticities.
b. *func_gradient.inc* perturbs each parameter by +/- epsilon and calls *func_calc.inc* each time in order to estimate the slope of the distance curve with respect to each parameter (the gradient) at the current point. Therefore it calls *func_calc.inc* (2 * # of parameters) times.
c. *func_determinant.inc* calculates the determinant of the matrix currently stored in parameter 'a' through Gaussian elimination. Determinants are used in the computation of elasticites.

d. *init_mapParams.inc* specifies the mapping from the parameter set in the algorithm (x1,x2,…xn) to the parameters in the FCDS utility function (we3,we2,…). The user must initialize this mapping.

Files prefixed with "init_" require values to be pre-specified by the user. In addition, the initial values for the parameters as well as certain optimization variables can be set in the "algo_" files. (The naïve starting values of -1, 1, 1, -1 seem to work well though).

Figure A-1: Flow Chart of Computation Sequence and Data Usage



Algorithm Optimization

Optimizing the speed of the algorithm mostly depends on the Armijo constants, aCoef and bCoef, and the size of the kArm set. In the worst case, the total iterations of *gDescent.gms* is:

card(long)*card(short)*card(k)*card(kArm)

for *BFGS.gms*,
card(long)*card(short)*card(reset)*card(k)*card(kArm),

But much of the iterations in kArm can be avoided if bCoef ^{kArm} is near the threshold of the Armijo condition within the first few iterations of kArm. The vast majority of iterations are spent on "plateaus" where the Armijo linesearch algorithm is forced to take very small step sizes. The trick is to take a step size that is often too big, violating the Armijo condition and breaking out of the kArm loop but also small enough that it does not vastly overshoot. bCoef = .7 and kArm = 15 seems fairly stable. For highly sensitive areas, values such as bCoef = .6 and kArm = 15 are more stable.

With card(short) = 2, card(k) = 10, and card(kArm) = 15, reasonable solutions are usually found within card(long) = 50. After that, significant computation time is used for relatively small gains.

Parameter Solutions and Mappings
Parameter solutions are valid under the following constraints:
1) 2 < (we2 / 2*we3) < 3.5; we2 > 0, we3 < 0.
2) -3.5 < incomeFlex < -0.5

The current mapping of the 'param' set in the algorithm files to the fcds parameters is (x1 -> we3), (x2 -> we2), (x3 -> wv), (x4 -> incomeFlex). x5 .. xn correspond to sub-group weights if they are used.

Further Adjustments
In order to make sure that the demand system derived by the FCDS computational procedure that was just described is well-behaved and meets the expectations of economic theory in both form and function, we did a post-estimation retuning procedure to make sure the demand system has the appropriate curvature. We used the Cholesky decomposition to ensure curvature of the Slutsky matrix and also imposed the expected adding-up condition between price and income elasticities with respect to each consumption good.

The Cholesky decomposition equates the solution matrix of price elasticities of demand (*S*) to the quadratic form such that $L^T DL = S$, where we make sure that the diagonal elements of D are non-positive. The adding-up constraint on the price and income elasticities of demand come directly from the implications of a linear budget constraint for household consumption and can be summarized as $\sum_j \varepsilon_{ij} + \eta_i = 0$, where ε_{ij} are the price elasticities of demand for each good i (and j) and where η_i is the income elasticity of demand for good *i.* These are implied directly by Engel and Cournot aggregation in microeconomic consumer theory and can be explained further in Henderson and Quandt (1980).

Deriving the Distribution of Population and Income

The cross-entropy method is built upon the same information theoretic principles that underlie the principle of maximum entropy that was introduced by Shannon (1948a, 1948b) to describe the degree to which a distribution differs from a uniform and uninformative profile—thereby capturing the "surprise" that is embodied in a (random) outcome. In juxtaposition to Shannon's entropy measure $H = \sum_n -p_n \log(p_n)$ for n discrete, random events, we can also express the cross-entropy of a distribution by the measure $CE = \sum_n -p_n \log\left(\frac{p_n}{\bar{p}_n}\right)$, which includes the *prior* distribution of weights (or probabilities) $\{\bar{p}_n\}$ that can be assigned for each random outcome. As shown by Kullback (1959), the maximization of the Shannon criterion with respect to the adding up constraint $\sum_n p_n = 1$ is equivalent to the minimization of the cross-entropy criterion, similarly constrained, if the prior distribution is uniform (i.e., assigns an equal likelihood to each outcome). The divergence of a calculated distribution from prior beliefs as calculated by the cross-entropy criterion conveys information content in a similar way to that calculated by the Shannon measure of information (Kullback and Liebler, 1951).

In applying this method to the inference of the underlying population and income distribution in the various IMPACT regions, we constructed a cross-entropy estimation with the following features:

- The inferred income distribution among the six socioeconomic strata should have a Gini-coefficient that is as close as possible to the WDI-based regional value.
- The split of urban and rural population is completely consistent with UN data.
- There is a continuous distribution of incomes and populations across all classes (otherwise the algorithm might bunch up populations in fewer strata)—i.e., all strata are populated and all populations have income.
- The per capita income of the highest urban stratum is at least as great as that of the highest rural stratum.
- The per capita incomes of within-urban and within-rural strata follow a ranking (such that $pcI_{high} \geq pcI_{mid} \geq pcI_{low}$); however, there could be crossing between urban and rural strata such that $pcI_{high}^{rural} \geq pcI_{low}^{urban}$.
- All of the population below the national, urban, and rural poverty lines in each country comes from the bottom two strata of the urban and rural populations (in some proportion to be determined from the data).

The implementation of these conditions within a cross-entropy framework gave rise to the optimization problem given below, which we solve for all regions in the model

$$S(p) = \min_{\left\{\begin{matrix}\pi_i, \theta_k^{urb}, \theta_j^{rur} \\ \alpha^u, \alpha^r, \beta^u, \beta^r \\ \delta, \delta_1^{urb}, \delta_2^{urb} \\ \delta_1^{rur}, \delta_2^{rur}\end{matrix}\right\}} \left[\begin{matrix} \sum_i \pi_i \cdot \ln\left(\frac{\pi_i}{\hat{\pi}_i}\right) + \sum_k \theta_k^{urb} \cdot \ln\left(\frac{\theta_k^{urb}}{\hat{\theta}_k^{urb}}\right) + \sum_j \theta_j^{rur} \cdot \ln\left(\frac{\theta_j^{rur}}{\hat{\theta}_j^{rur}}\right) \\ +\alpha^u \cdot \ln\left(\frac{\alpha^u}{\hat{\alpha}^u}\right) + \alpha^r \cdot \ln\left(\frac{\alpha^r}{\hat{\alpha}^r}\right) + \beta^u \cdot \ln\left(\frac{\beta^u}{\hat{\beta}^u}\right) + \beta^r \cdot \ln\left(\frac{\beta^r}{\hat{\beta}^r}\right) \\ +\delta \cdot \ln\left(\frac{\delta}{\hat{\delta}}\right) + \delta_1^{urb} \cdot \ln\left(\frac{\delta_1^{urb}}{\hat{\delta}^{urb}}\right) + \delta_2^{urb} \cdot \ln\left(\frac{\delta_2^{urb}}{\hat{\delta}^{urb}}\right) + \delta_1^{rur} \cdot \ln\left(\frac{\delta_1^{rur}}{\hat{\delta}^{rur}}\right) + \delta_2^{rur} \cdot \ln\left(\frac{\delta_2^{rur}}{\hat{\delta}^{rur}}\right) \end{matrix}\right]$$

$$s.t. \qquad Gini = \tfrac{1}{n}\left[(n+1) - 2\left(\frac{\sum_i (n+1-i)\, y_i}{\sum_i y_i}\right)\right]$$

$$\pi_i = \frac{y_i}{Y_{tot}}, \sum_{i\in\{1,..,6\}} \pi_i = 1 \quad \rightarrow \quad Y_{tot} = \sum_i y_i$$

$$p^{urb} + p^{rur} = P_{tot} \quad and \quad p^{urb} = \sum_{k\in\{1,..,3\}} p_k^{urb},\ p^{rur} = \sum_{j\in\{1,..,3\}} p_j^{rur} \quad and \quad \theta_k^{urb} = \frac{p_k^{urb}}{p^{urb}} \in [0,1] \quad \theta_j^{rur} = \frac{p_j^{rur}}{p^{rur}} \in [0,1]$$

$$PovRate_{urban} = \frac{\alpha^u p_1^{urb} + (1-\alpha^u)\, p_2^{urb}}{\sum_{k\in\{1,..,3\}} p_k^{urb}}, \quad \alpha^u \in [0,1] \quad PovRate_{rural} = \frac{\alpha^r p_1^{rur} + (1-\alpha^r)\, p_2^{rur}}{\sum_{j\in\{1,..,3\}} p_j^{rur}}, \quad \alpha^r \in [0,1]$$

$$PovRate_{nat'l} = \frac{\left(\beta^r p_1^{rur} + (1-\beta^r)\, p_2^{rur}\right) + \left(\beta^u p_1^{urb} + (1-\beta^u)\, p_2^{urb}\right)}{\left(\sum_{k\in\{1,..,3\}} p_k^{urb} + \sum_{j\in\{1,..,3\}} p_j^{rur}\right)}, \quad \beta^r, \beta^u \in [0,1]$$

$$\frac{y_1}{p_1^{urb}} \geq \frac{y_4}{p_1^{rur}} \cdot (1+\delta) \qquad \delta \in (0,1)$$

$$\frac{y_1}{p_1^{urb}} \geq \frac{y_2}{p_2^{urb}} \cdot (1+\delta_1^{urb}) \qquad \delta_1^{urb} \in (0,1) \quad , \quad \frac{y_2}{p_2^{urb}} \geq \frac{y_3}{p_3^{urb}} \cdot (1+\delta_2^{urb}) \qquad \delta_2^{urb} \in (0,1)$$

$$\frac{y_4}{p_1^{rur}} \geq \frac{y_5}{p_2^{rur}} \cdot (1+\delta_1^{rur}) \qquad \delta_1^{rur} \in (0,1) \quad , \quad \frac{y_5}{p_2^{rur}} \geq \frac{y_6}{p_3^{rur}} \cdot (1+\delta_2^{rur}) \qquad \delta_2^{rur} \in (0,1)$$

Given that we solve for the weights $\pi_i, \theta_k^{urb}, \theta_j^{rur} \alpha^u, \alpha^r, \beta^u, \beta^r, \delta, \delta_1^{urb}, \delta_2^{urb}, \delta_1^{rur}, \delta_2^{rur}$, which represent shares of income and population and percentage differences in per capita income[12], we are able to recover the population $\left(p_j^{rur}, p_k^{urb}\right)$ and income (y_i) values for

[12] Note that the subscripts for income (y) 1, 2, and 3 correspond to the urban income strata, while 4, 5, and 6 correspond to those strata within rural populations.

each strata as well. The parameters α^u, α^r represent the share of the lowest income group (within the urban and rural strata, respectively) that belongs to the headcount of poor according to the urban and rural poverty line measures. β^u, β^r, on the other hand, represent the shares of the lowest urban and rural strata that belong to the headcount of poor according to the national poverty line. The priors for these parameters were specified as $\alpha^u = \beta^u = 0.8$, $\alpha^r = \beta^r = 0.9$ across all regions. The virtue of the cross-entropy algorithm is that it stays as close as possible to the priors that are specified by the user (so as to achieve minimum entropy or distance) and only deviate to the extent that is warranted by the data. In the absence of informative data, the problem will converge to the prior values for all the parameters or otherwise find a solution as close to the prior values that remains consistent with the observed data.

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