Global agricultural trends: impact and role for Australian agricultural and agronomic research

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Abstract
Over the past 50 years public agricultural research has contributed enormously to humanity, enabling the supply of food to grow faster than demand in spite of a rapidly growing population, income growth, and shrinking natural resources. Recent trends suggest a reversal of the long run tendencies with new price increases for staple food crops signaling that the demand for food is now growing faster than supply. A fundamental question is whether or not changes in the global food markets in the past few years are transitory or represent structural shifts in these markets. Behind these more evident changes, in many countries we see waning public support for agricultural R&D, especially in Africa, a diversion of research resources from farm productivity towards other agendas, and early warning signs of a slowdown in agricultural productivity. One response is to revitalize global investments in agricultural research. Another, often complementary response, is make better use of the available research resources. In this paper we highlight important changes in global R&D investment trends and describe the new, spatially explicit, methods being developed to evaluate the prospective agronomic and economic consequences of R&D as a means of improving the efficient use of the resources committed to agricultural research.

Keywords
Productivity, geo-spatial crop, pest and disease models, economic benefits, geographical information systems

Introduction
In the past half-century, agricultural science achieved a great deal. Since 1960, the world's population has more than doubled, from 3.1 billion to 6.7 billion, and real per capita income has nearly tripled (U.S. Census Bureau 2008).[1] Over the same period, total production of cereals grew faster than population, from 878 million metric tons in 1961 to over 2,221 million metric tons in 2006, and this increase was largely due to unprecedented increases in crop yields (FAOSTAT 2008 and Pardey et al. 2007). The fact that the Malthusian nightmare has not been realized over the past 50 years is attributable in large part to improvements in agricultural productivity achieved through technological change enabled by investments in agricultural R&D.

Agricultural R&D is at a crossroads. The close of the 20th century marked changes in policy contexts, fundamental shifts in the scientific basis for agricultural R&D, and shifting funding patterns for agricultural R&D in developed countries. Even though rates of return to agricultural research are demonstrably very high, we have seen a slowdown in spending growth and a diversion of funds away from farm productivity enhancement. Together these trends suggest a slowdown in farm productivity growth at a time when the market has begun to signal the beginning of the end of a half-century and more of global agricultural abundance. It is a crucial time for rethinking national policies and revitalizing multinational approaches for financing and conducting agricultural research.

Research Investment Trends at the Global Scale [2]
In 2006, about $887 billion (2000 international) dollars, or 1.7 percent of global GDP, was spent on *all* the sciences worldwide (Pardey, Dehmer and El Feki 2008).[3] Patterns of R&D spending have changed significantly in the past two decades. Global spending on R&D has more than doubled in real (2000 international dollar) terms between 1980 ($374 billion) and 2006 ($887 billion).

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[1] In 2000-based U.S. dollars, per capita income increased from $2,169 in 1962 to $6,389 in 2006 (World Bank 2007).

[2] This section draws heavily on Pardey, Alston and James (2008), Pardey, Dehmer and El Fekkie (2008) and Alston, Andersen, James and Pardey (2008), which contain much more complete descriptions and assessments of these research investment trends.

[3] This figure includes the total spending by public and private entities across *all* areas of science (i.e., including agricultural, medical, and engineering R&D, the information technology and social sciences, and so on).

The United States accounted for 31 percent of the world's science spending in 1980, and 33 percent in 2006. Collectively the high-income countries (those with per capita incomes in excess of $10,726) accounted for 80 percent of the world's R&D in 2006.[4] The developing-country share of the world total has grown over time; from 5 percent in 1980 to 15 percent in 2006. Notably, China, India, and Brazil account for a growing share of this developing-country total—61 percent of the developing world's total R&D spending in 1980, increasing to 83 percent in 2006. China now ranks 3rd, behind the United States and Japan, in terms of total science spending (denominated in international dollars); South Korea ranks 6th, India 12th, and Australia (with just $12.4 billion of total science spending) ranked 15th.

Agriculture's share of total R&D is generally modest. In 2000 (the latest year for which comparable global agriculture R&D and all-of-science data are available), only 3.2 percent of total R&D spending by rich countries was oriented towards agriculture. The corresponding developing-country share was 6.0 percent. As a share of public R&D spending, agricultural has remained steady among the developed countries at around 7 percent in both 1981 and 2000. In contrast, among developing countries the share of public research spending directed to agriculture declined from 22 percent in 1981 to 15 percent in 2000, albeit still more than double the corresponding rich-country share.

Worldwide, public investment in agricultural R&D increased by 35 percent in inflation-adjusted terms between 1981 and 2000, from an estimated $14.2 billion to $20.3 billion in 2000 international dollars (Table 1). The developing world now accounts for about half of global public-sector spending—up from an estimated 41 percent share in 1980. However, developing countries account for about one third of the world's total agricultural R&D spending when private investments are included. Public spending on agricultural R&D is highly concentrated, with the top 5 percent of countries in the data set (i.e., 6 countries in a total of 129 underlying Table 1) accounting for approximately half of the spending, and the top 20 percent of countries accounting for 80 percent of spending.

Among the regions of the world, the developing countries in the Asia and Pacific region have gained considerable ground, accounting for an ever-larger share of the world and developing country total since 1981 (25.1 percent of the world total in 2000, up from 15.7 percent in 1981). In 2000, just two countries from this region, China and India, accounted for 29.1 percent of *all* expenditure on public agricultural R&D by developing countries, a substantial increase from their 15.6 percent combined share in 1981.

If the conduct of agricultural R&D globally continues to become much more spatially concentrated (like R&D spending generally), and if the growth in investments in agricultural R&D continues to slow (if not stall or slide) much greater efficiencies in the conduct of the R&D will be required to face continuing growth in demand for food, feed and fiber worldwide. This in turn will require a better match of the available R&D resources to the production problems and opportunities, crops, and agro-ecologies confronting global agriculture.

The HarvestChoice initiative funded by the Bill and Melinda Gates Foundation is developing and deploying new data sets and analytical tools to assess the prospective (economic) payoffs to agricultural research as a means of improving the productivity and livelihood outcomes arising from that research. To acomplish this, HarvestChoice is developing geo-referenced data sets concerning agroecological, production system, infrastructure, and market attributes along with new global atlases of crop geographies for use in spatially explicit crop and pest modelling and economic simulation tools that are being applied at regional scales. Using these bio-economic models, HarvestChoice is assessing the magnitude of the productivity and economic tradeoffs involved in prioritizing a given line of research over another as a means of informing choices among competing research investment options. The general approach being taken by HarvestChoice is usefully illustrated by the specific data collection and assessment efforts underway to evaluate the payoffs to ameliorating the production and economic losses arising from crop pest and disease complexes.[5] A distinguishing feature of the HarvestChoice approach is its use of an explicitly georeferenced framework to

[4] The per capita income classes used here come from World Bank (2007). Countries classified by the World Bank as either Low or Lower-Middle income countries were here considered as "developing countries."

[5] More comprehensive information on the HarvestChoice project and much of the project generated data can be obtained at www.HarvestChoice.org.

capture important agroecological variation when evaluating research impacts at the regional scales deemed relevant for making research investment decisions.

Table 1. Public and private spending on agricultural R&D, 1981 and 2000

Country or Region	Public Spending	Private Spending	Private Share of Country / Region Total	Country / Region Share of World Public Total	Rank by Total Public Spending	Public Agricultural R&D Spending	
						Per $100 Ag GDP	Per Capita
	millions international dollars (2000)		*percent*				
1981							
United States	2,568.7	2,495.0	49%	18%	1	1.68	10.99
Japan	1,821.3	1,048.5	37%	13%	2	2.64	15.47
Germany	547.4	701.1	56%	4%	5	1.85	7.01
Australia	522.0	32.6	6%	4%	7	3.36	35.41
United Kingdom	533.4	676.5	56%	4%	6	3.08	9.56
Canada	520.7	109.2	17%	4%	8	2.54	21.02
France	478.5	377.7	44%	3%	10	1.17	8.84
Total OECD	*8,339.8*	*6,478.4*	*44%*	*59%*		*1.62*	*10.97*
Brazil	628.0			4%	3	0.91	5.05
China	586.9			4%	4	0.41	0.58
India	332.4			2%	12	0.18	0.47
Total Developing	*5,903.2*			*41%*		*0.49*	*1.81*
World Total	*14,243.0*			*100%*		*0.84*	*3.55*
2000							
United States	3,882.2	4,118.8	51%	19%	1	2.65	13.62
Japan	1,646.2	2,331.8	59%	8%	3	3.62	12.96
Germany	758.2	877.6	54%	4%	6	3.22	9.21
Australia	588.6	193.9	25%	3%	7	3.38	30.73
United Kingdom	495.5	1,244.6	72%	2%	9	3.57	8.41
Canada	474.3	244.5	34%	2%	10	2.54	15.41
France	341.9	1,009.2	75%	2%	15	0.91	5.77
Total OECD	*10,267.6*	*12,184.5*	*54%*	*51%*		*2.36*	*12.01*
Brazil	928.8	36.8	4%	5%	5	1.43	5.41
China	1,762.8	73.5	4%	9%	2	0.40	1.37
India	1,159.5	128.8	10%	6%	4	0.34	1.14
Total Developing	*10,030.7*	*686.5*	*6%*	*49%*		*0.50*	*2.13*
World Total	*20,298.3*	*12,871.1*	*39%*	*100%*		*0.84*	*3.65*

Source: Alston et al (2008).

Mapping Biotic Constraints at Regional Scales

The ways in which pests, diseases and weeds, collectively known as "biotic stressors," affect the lives of the world's poorest farmers is a primary concern of the HarvestChoice project. Biotic stressors decrease agricultural yields, raise production costs (due to managing these stressors), and limit the storability and marketability of food. They also raise the riskiness of farming as a livelihood strategy or a commercial enterprise. As living organisms, biotic stressors exhibit complex behavior, leading to difficulties in understanding where they might be found, and what their crop productivity impacts might be. HarvestChoice and its partners are conducting spatially-explicit assessments of the prospective productivity and economic gains from ameliorating the effects of these biotic stressors on crop production, with special emphasis on the biotic cropping constraints confronting agricultural systems on which the world's poor most heavily depend.

Nature of the Problem

Pest, disease and weed problems have strong site- and time-specific dimensions. The crop loss impacts of one particular pest on a particular crop growing in a particular location may be entirely different from the losses incurred by the same pest on the same crop in other locales. Further, pest population dynamics, migration, invasion and damage are driven by local conditions, such as temperature and rainfall. Thus, a crucial first step in determining where, when and how agricultural systems might be affected by biotic constraints is to determine where pests, weeds and diseases might be. Earlier efforts by Hill (1983, 1987), the Center for Agricultural and Biosciences International, CABI (2006), Oerke and colleagues (1994) and others have provided important information about the distribution of biotic stressors worldwide. Unfortunately, most of the available data and information on pest, weed and disease occurrence are relatively coarse. CABI, for example, provides maps of pest occurrence, but these show only that a pest or disease occurred in a country at some, usually unknown, time in the past. The spatial extent and severity of the infestations are also not typically recorded, meaning such data and information are not sufficiently spatially or temporally explicit to capture the important local conditions that drive biotic constraint problems.

Survey and Simulated Occurrence Data

The paucity of pest, disease and weed data of sufficient granularity to develop the spatially referenced occurrence data required to support spatially explicit modeling methods that assess the economic benefits from reduced pest, disease and weed problems spurred a search for a rapid, but replicable and reasonably reliable, survey technique to reveal and codify occurrence data. Recognizing that much of these data are held as tacit unpublished knowledge, often by those with local expertise, an on-line survey instrument dubbed V-GET™ (Virtual Georeferenced Elicitation Tool) was developed and is presently in use by HarvestChoice and a range of project partners to build better maps of presumptively important pest, disease and weed occurrences worldwide.

V-GET™ is a web-enabled survey tool that facilities elicitation of spatially explicit data on the known location and frequency of occurrence of specific pests and diseases from geographically disperse respondents. V-GET™ uses the Google Maps application programming interface (API), which allows for manipulation and distribution of map data via Google's servers while incorporating the mapping functionality into a structured survey. Respondents provide spatial data by clicking a displayed map using a natural interface. V-GET™ was designed with the HarvestChoice pest and disease assessments in mind, but is programmed in ways that make it readily adaptable to web-enabled surveys of many other spatially explicit data layers where available data are scarce, such as geo-referenced information on production systems, agricultural inputs, and technology adoption). Of particular importance is the use of a gridded data entry interface, allowing for direct collection of medium-resolution raster data instead of point or polygon data that are not useful in the present case due to their statistical properties.

To calibrate HarvestChoice efforts to model the spatial likelihood of occurrence for its initial targeted group of 62 pests and diseases, an on-line survey of their frequency of occurrence is being conducted in collaboration with a group of key collaborators. Information from a knowledgeable set of more than 100 respondents from around the world is being used to calibrate efforts jointly undertaken by HarvestChoice and its partners to estimate the likely spatial occurrence of the pests and diseases worldwide

The V-GET™ surveys from a plurality of experts combined with compilations from (published) secondary sources are yielding partial spatial distributions of the occurrence of key pests and diseases. A variety of pest models can then use this known distribution, along with geo-referenced climate data to infer a plausible spatial distribution of specific biotic constraints. Such models rely on either statistical analysis of observed locations or population ecology to derive the plausible distribution. While mapping approaches using statistical approaches are probably more widely used, population ecology models may yield a more valid estimation of the potential spatial distribution of pests and diseases outside the areas of reported occurrences (see, for example, Sutherst and Bourne (forthcoming)). After a comprehensive investigation of modeling options, HarvestChoice opted to deploy the CLIMEX population ecology model to map the likelihood of occurrence of key crop pests, diseases, and, perhaps, weeds. HarvestChoice is working with the developers of CLIMEX to add additional functionality to make it possible to better assess the temporal aspects of biotic stresses and thus support more formal analyses of the production risk, as well as productivity, consequences of crop pests and diseases.

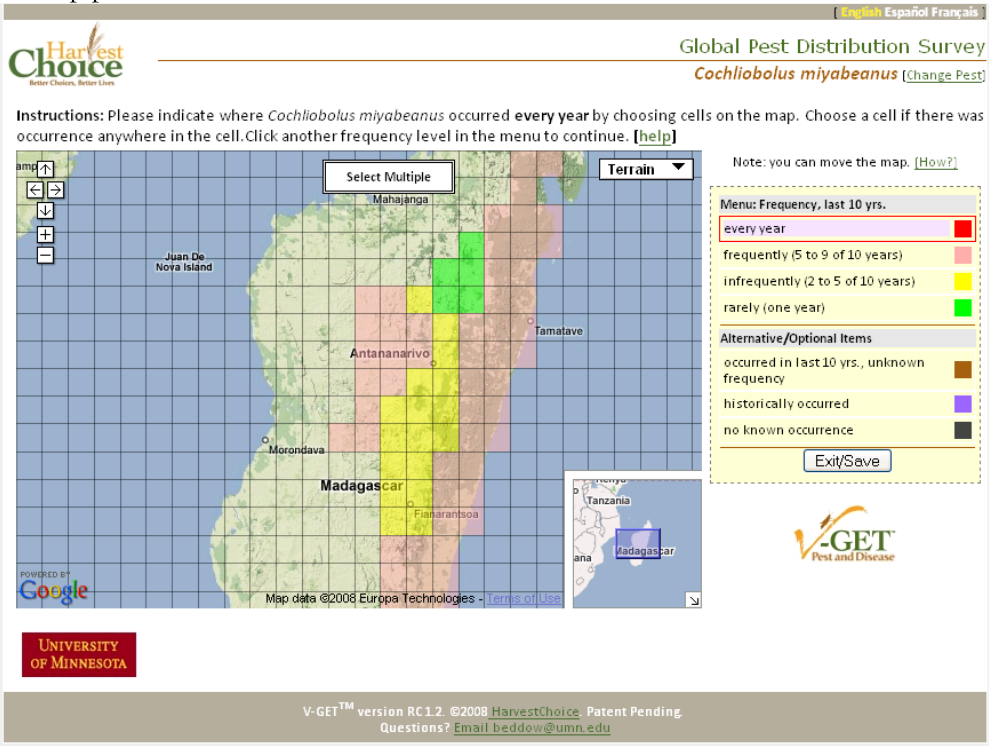

Figure 1. Interface for survey page on the Virtual Georeferenced Elicitation Tool (V-GET™)

Applying Crop Models at Regional Scales

Complex crop systems models, such as DSSAT (Jones et al. 2003) mathematically describe the growth and development of a crop interacting with environment, including weather, soils, and human management of the production process. Crop systems models have been used with great success in many studies and across disciplines to improve our understanding of environmental and management influences on the dynamics of cropping systems. Recent examples include estimating soil carbon sequestration potential (Koo et al. 2007), assessing regional climate change impacts (Xiong et al. 2008), gene-based modeling to simulate yield responses to environmental changes (Messina et al. 2006), optimizing irrigation strategy (Peake et al. 2008), nutrient management (Jing et al. 2007), seasonal yield forecasting (de Wit and van Diepen 2007), and quantifying yield potential (Wu et al. 2006).

The large majority of applications of process-based, dynamic, crop systems models are on comparatively small unit areas (e.g., a block of experimental plots), which are typically assumed to be homogeneous in terms of crop growth performance, environmental conditions, and management (or treatment) regimes. The potential benefits (and pitfalls) of increasing the spatial scales of analysis to which dynamic crop system models are applied have been discussed and tested ((e.g., Jones and Thornton 2003; Liu et al. 2007; Stehfest et al. 2007). However, in most cases, the choice of model or the scenarios to be modeled at larger spatial scales have been relatively simple and limited in scope, in part due to the computational cost of running these models over large spatial scales, the incomplete, spatially-explicit knowledge of the crop system attributes required to deploy these models, and a lack of sufficiently high-resolution data at the regional or global scales required to run such models.

Despite these data and modeling challenges, HarvestChoice and its partners have launched a major effort to overcome these modeling limitations. The objective is to utilize a suite of well tested and reasonably well calibrated crop models to assess the productivity or other (agronomic and biophysical) consequences of spatially explicit changes to cropping systems (Koo and Wood 2008). The regional scale results from the geo-referenced aggregation of "pixel scale" crop simulations are not only of intrinsic interest and value for setting research priorities, they can also be creatively juxtaposed with spatially explicit crop pest, disease, and weed occurrence data to promote more informed judgments about the likely agronomic and economic consequences of mitigating the effects of these biotic stressors through management, technological or other means.

To provide input to and calibration of this bio-economic modeling platform, HarvestChoice is developing (typically geo-referenced) data pertaining to a range of variables, including:

- the biophysical as well as the socio-economic characteristics of farming systems based on a blend of macro (i.e., national/sub-national) and micro (i.e., household) level data,
- highly-disaggregated baseline distributions of crop geography, cropping systems, and their production performance, and
- newly compiled information on the distribution and severity of key biotic/abiotic constraints in the systems.

Based on harmonized compilations of these various data layers, the crop systems modeling approach provides an experimental test-bed for biophysically assessing the likely productivity and regional crop production impacts of technology and management innovations under different scenarios of innovation, investment, technology access, and farm-scale adoption. The results of these analyses are used to calibrate the accompanying economic evaluations.

The initial version of this crop systems modeling capacity in HarvestChoice is being developed to simulate baseline crop productivity of 13 key staple crops at a 5-arcminute spatial resolution in all sub-Saharan Africa countries. Scientists in multiple CGIAR centers are collaborating to characterize cropping systems across the region and develop common templates for model input datasets, including weather, soils, cropping patterns, crop variety, planting window, water and nutrient managements, and residue management. Figures 2 and 3 provide preliminary outputs from proof-of-concept simulations designed to assess spatially-explicit maize yield potentials and responses to a range of management options.

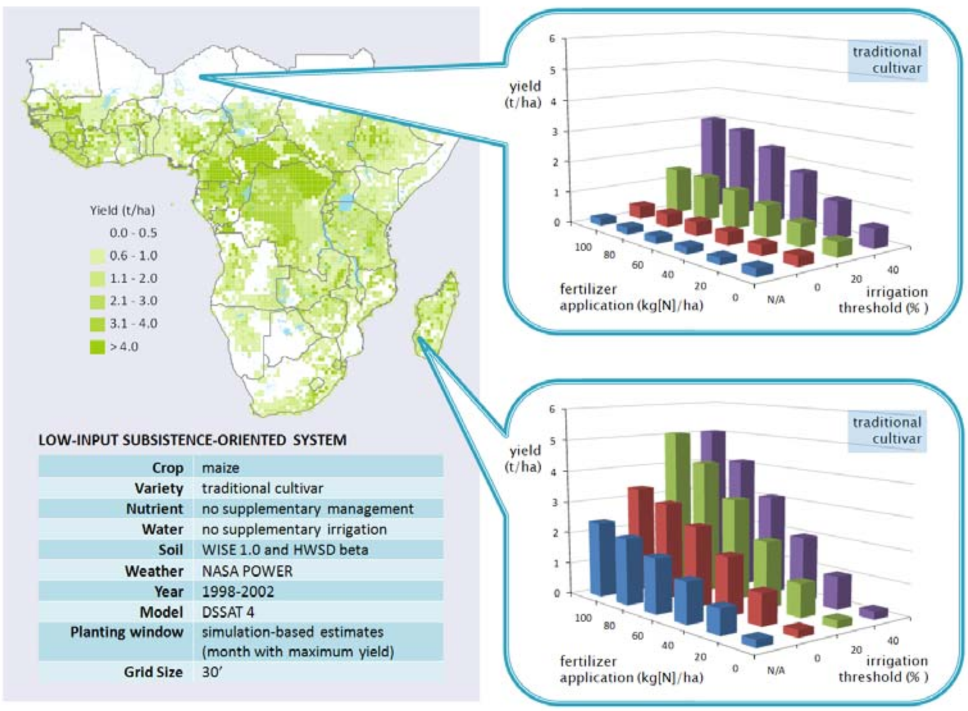

Figure 2. Regional and site-specific simulated maize yield potential

Four different crop models are currently being used: DSSAT, APSIM, WOFOST, and ORYZA. The choice of model is conditioned by the goal of the analysis, the conceptual design of the crop growth model, and the operational versatility of each model, as well as by the experience and creativity of the analyst. Some models perform better than others in specific contexts, e.g., when applied to particular climates, crops, cropping patterns/rotations, soil quality indicators, and potential management interventions. Importantly, a common data, and where feasible, parameterization, platform is being tapped irrespective of the model choice to maximize the comparability of the crop specific simulation results.

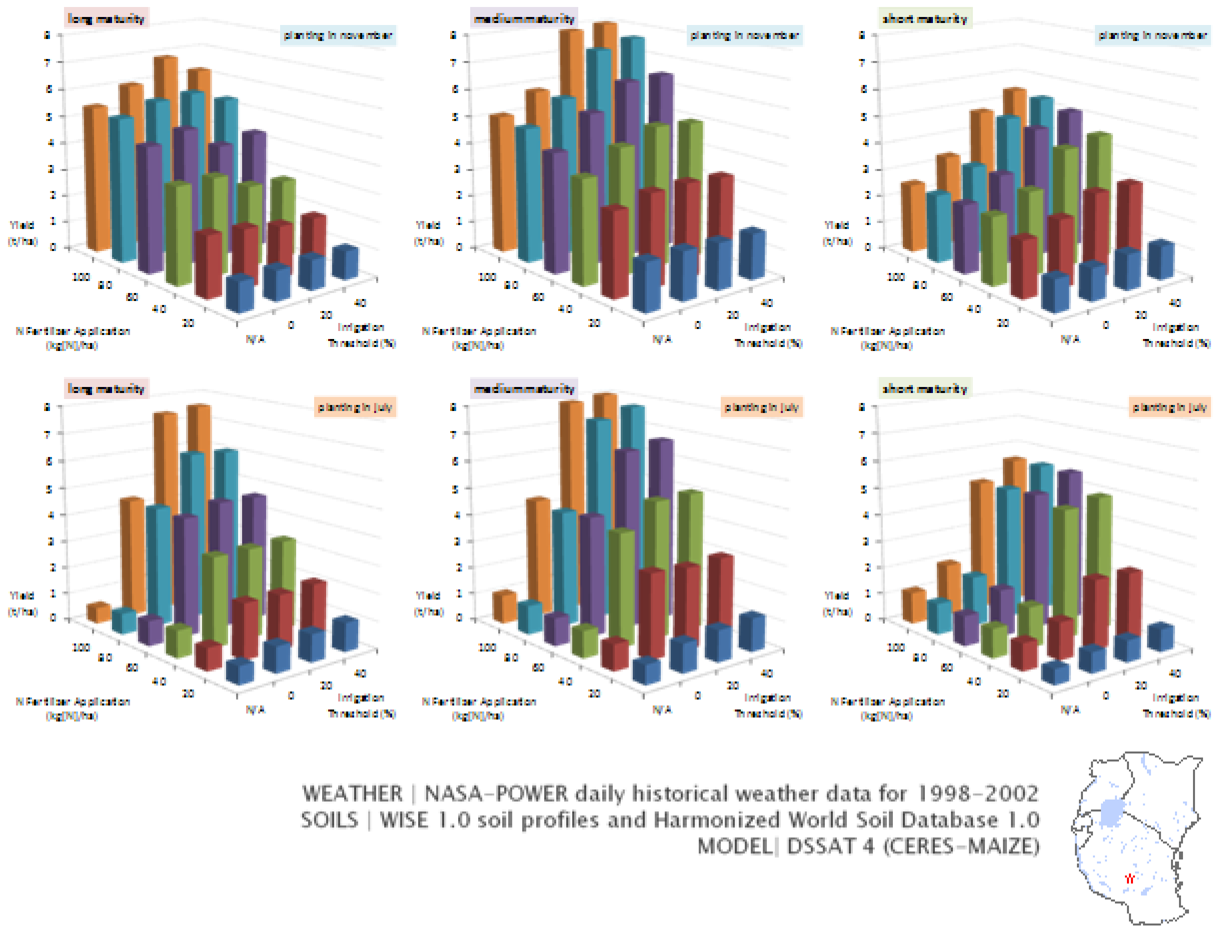

Figure 3. Simulated site-specific maize yield potential under different variety choices, planting windows, and nutrient and water regimes

The performance of crop models may be compromised if the environmental or production conditions of interest differ markedly from those used during the development and evaluation of the models. In new use contexts, therefore, adjustments in model structure or parameters may be necessary. As part of this crop growth modeling work, HarvestChoice is designing and implementing processes to assess and improve the reliability of the models for the primary geographies and cropping systems of interest. Such validation will be critical in gaining the confidence of scientists, analysts, investors, and policymakers.

The spatial application of these models is soon to span to areas outside Africa. Technological spillovers combined with the interrelatedness of commodity markets via trade and regulatory realities means that the effects of a technological intervention can spread well beyond the location at which that technology is developed or used. Moreover, providing differential access to new technologies in commercial versus non commercial settings can segment markets in creative ways that incentivize public and private interests to sell or share new technologies and maximize the global gains from those technologies. Developing a spatially calibrated sense of the magnitude and distribution of the potential gains from using new technologies is one way of helping to facilitate collective action to address global food security concerns.

Linking Pests and Plants

As plant pathologists often say, "Plants get sick too (Esnard 2003)." The minimal use of resistant varieties, pesticides, herbicides and other management practices designed to ameliorate the production losses due to biotic stresses means that low-input, smallholder farmers in developing countries are especially susceptible to the vagaries of crop pests and diseases. Crops are especially susceptible to biotic stresses when they are also experiencing water and nutrient stresses, limiting their ability to sustain immunity and recover from infection. The double jeopardy of simultaneous biotic and abiotic stresses are prevalent in many subsistence-oriented or low-input cropping systems. These stresses not only limit yield on average they also increase the risks associated with farming. Absent due consideration of these vulnerabilities, estimating crop production potentials in low-input cropping systems may generate unrealistic and even implausible crop productivity potentials. Plausible estimates of the productivity *changes* from changing the pest and disease complexes affecting agriculture are key to generating plausible estimates of the prospective economic benefits attributable to new technologies or changes in crop management practices.

HarvestChoice is testing the practicality and plausibility of various analytical methods that link pest prevalence evidence to crop productivity effects. One option under consideration is the use of "coupling points;" specific variables in crop growth models that can be used to simulate the effects of crops pests and diseases on crop growth. Examples of coupling points include leaf mass/area, stem mass, root mass, root length volume, seed mass/number, shell mass/number, and whole plant number in a plot. This concept was first introduced by Boote and colleagues in 1983, and 10 years later implemented via a pest module in the DSSAT model by Batchelor and colleagues. The pest module allows users to input field observations and scouting data on insect damage, disease severity, and physical damage to plants or plant components (e.g., grains or leaves) to simulate the effects of specified pest and diseases on growth and yield.

For a specific type of damage to be simulated, one needs to provide information on the destruction pathway, which defines how much damage occurs on which parts of a plant on daily basis in either a relative (e.g., 1% leaf area reduction per day) or an absolute (e.g., 10g seed destruction per day) sense. The types of damage that can be simulated include leaf mass or area destruction, stem mass destruction, root mass destruction, number or percentage of plants or seeds destructed, and the rate of assimilation reduction. Depending on the specific characteristics of pest or disease effects being modeled, damages can be expressed in single or multiple pathways. For example, in the United States, a corn earworm is known to damage susceptible maize via the following pathways:

- Destroying up to 10 small seeds per day per worm
- Destroying up to 2.5 large seeds per day per worm
- Destroying up to 50 cm^2 of leaf area per day per worm

Assuming a scenario of sudden pest infestation on maize about two months after planting, Figure 4 provides an example of the crop yield effects of a simulated range of leaf damage and consequent canopy developments at a pixilated scale throughout Tanzania. Although the damaged maize crop continued to grow (except for the case of complete damage), the plant did not recover from the initial infection and overall leaf growth was permanently compromised. As the more detailed ecological information concerning pest infestations becomes available, more realistic crop growth scenarios can be modeled (e.g., damages with or without crop stress, extreme weather events, tolerant cultivars, and flexible planting windows) to assess the pest impacts on crop production. In principle (if sufficient data were available) this modeling framework could be used to design more efficient integrated pest management strategies (e.g., Willocquet et al. 2002).

Recognizing the data realties in the near term, more reduced form approaches to linking pest occurrence (and severity) to crop performance are being tested. The choice of modeling methods to be deployed will hinge on a number of considerations, including the evaluation questions being addressed. The HarvestChoice approach is to release versions of data and results, all the time improving the coverage, reliability, and spatial resolution of the underlying data and fitting the modeling approach to the data realities. The reality is that major research investment decisions are continuing to be made with little understanding of the opportunity costs of these decisions. Research resources are scarce. Thus, for example, investing large sums in developing drought tolerant maize varieties implies less or no funding to pursue, say, research designed to develop cassava varieties or management practices that ameliorate the yield suppressing effects of cassava mosaic virus. Understanding the likely economic trade-offs implicit in these research priority decisions is the ultimate objective of HarvestChoice. Plausible agronomic and economic assessments at the spatial scales required for policy and investment choices, which also recognize the site-specificity of these technological and crop management interventions, is key to better calibrating these research and related investment choices.

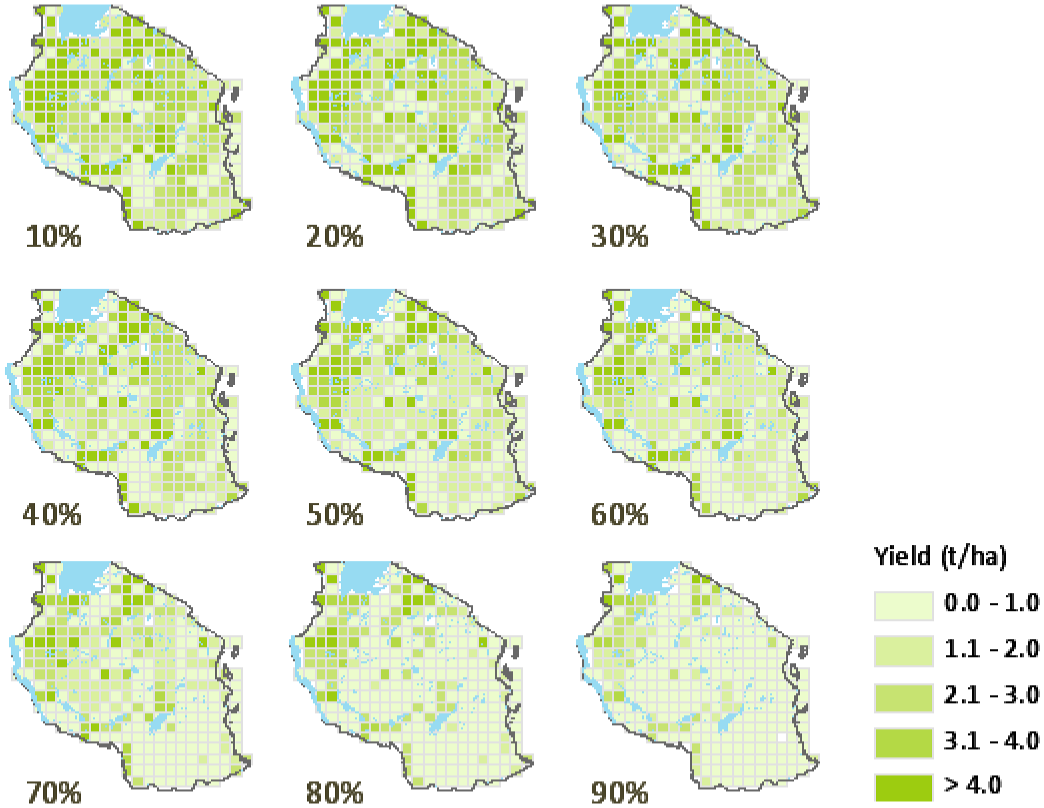

Figure 4. Simulated impacts of leaf-damaging pest infestation on maize yield at regional scale (30-arcminute grids in Tanzania). A range of leaf damages on Day 60 was implemented through a leaf area coupling point in the DSSAT model.

Conclusion

In the past 50 years, productivity growth played a crucial role in increasing food supplies, enabling agriculture to more than keep pace with the growing demand for food fuelled by population growth and per capita income growth, and helping to reduce the global problems of chronic hunger and poverty. A fundamental driver of this productivity growth has been the technical changes from improved inputs such as seeds, fertilizers and production practices that stem directly from investments in R&D. The next 50 years will call for even more of the same kinds of technological changes and productivity growth. This will be necessary not just to meet the present demand and to reduce the chronic hunger experienced by an estimated 854 million people worldwide (Wiesmann et al. 2007), but also to address the future growth in demand for farm commodities for food and fuel in the face of a shrinking natural resource base. The lags between investing in R&D and realizing a return from that investment are long, matters of decades not months or years. Getting the policies and investment priorities right to stimulate the required public and private provision of new agricultural technologies requires a commensurate long-term timeframe.

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