Agricultural R&D Policy

in the Face of Climate and Economic Uncertainty

by

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Introduction

Despite abundant and affordable food throughout developed world, currently 12.9 percent of population in developing countries is undernourished (World Food Program 2016). By 2050, world population is expected to increase by 33 percent, from 7.3 to 9.7 billion (United Nations 2015). When coupled with increases in income and changing diets, this may translate into a very substantial rise in the demand for agricultural production, by 70 percent (Bruinsma 2009). Studies looking at the future supply and demand of food indicate that meeting this demand may pose some challenges for the current food and environmental systems (Piesse and Thirtle 2010). The extent of environmental pressure and the resulting food price changes will hinge critically on the evolution of productivity growth in agriculture (Hertel 2015).

Since the 1950s, increased agricultural productivity has allowed food supply growth to outpace demand on a global scale, resulting in a downward trend in world prices. Public and private investments into agricultural research and development (R&D) have been the foundation for this achievement. Studies have shown that public investment in agricultural research has resulted in large economic benefits with annual rates of return between 20 and 60 percent (USDA-ERS 2015a). These results are generally taken as evidence of underinvestment in agricultural R&D and suggest that increasing investment will further increase agricultural output. The rate of growth in global public agricultural R&D spending was declining over 1976-2000 and became negative in developed countries over the 1991-2000 decade (Peisse and Thirtle 2010). However, global R&D picked up strongly, rising by 22% over the 2000-2008 period, with accelerated spending in China and India accounting for close to half of the increase (Beintema et al. 2012). Several studies report estimates of additional investment in agricultural R&D needed to meet projected increases in demand by 2050 (Beintema and Elliot 2009, von Braun et al. 2008, Rosegrant et al. 2008). It is likely that increasing part of the R&D expenditures in coming decades will be targeted at counteracting disasters related to new pests and diseases which may be amplified by climate change.

While investments into agricultural R&D play critical role in improvements of agricultural productivity, the time lag involved in translating agricultural research expenditures into realized productivity gains is extremely long. This means that research planning and expenditures cannot simply be adjusted in the middle of 21st century if the world finds itself in food shortfall at that point in time. Long run planning is required. However, this must be done in an environment of uncertain future population, per capita incomes, and changes in climate. According to the Shared Socioeconomic Pathways (SSPs) (O'Niell et al. 2014, IIASA 2015), the spread between low and high global population levels in 2100 is about 5.8 billion people, and average global per capita income ranges between 22 and 138 thousand 2005USD. On the supply side, future agricultural productivity plays a critical role in determining ability to meet increasing demands for food, fiber and bioenergy. Agricultural productivity, as well as effectiveness with which agricultural R&D spending translates into increased productivity growth, are also influenced by climate change, the impacts of which are highly uncertain (Rosenzweig et al. 2014).

The goal of this analysis is to understand impacts of uncertainty in future population, income and climate change on optimal level of global investment in agricultural R&D over the 21st century, taking into account the long lag in agricultural productivity response to R&D.

Methodology

To achieve this goal, we develop a dynamic model of global land use, following earlier work of Steinbuks and Hertel (2013). In the model, a social planner maximizes sum of discounted payoffs, subject to endowments and production function constraints. The social planner's payoff in each period takes into account size of global population and per capita utility. Utility is derived from goods and services produced by the land-based economy, including food, timber and bio-energy, as well as other goods and services. Consumer preferences are represented with An Implicit, Directly Additive Demand System (Rimmer and Powell 1996) which has been estimated on international cross-section data (Reimer and Hertel 2004). This demand system is very flexible in its description of the evolution of consumer demands as per capita incomes rise.

Studies that quantify changes in agricultural productivity over time consider different measures of productivity, including: physical crop yield, land and labor productivity, as well as total factor productivity (TFP). TFP accounts for input substitution. Piesse and Thirtle (2010) point out that although yield growth has slowed in aggregate and labor productivity growth varies by region, TFP has improved in most regions. Studies on contributions of agricultural research and extension to productivity growth often use TFP as a measure of agricultural productivity. These studies highlight that technological innovation – from new technologies to commercial development and transmission to farmers – takes time, and represent TFP as a function of a weighted sum of R&D expenditures over some number of past years (Alston et al. 2010).

In our dynamic model of land use, both TFP and R&D are endogenous variables, with increases in the global stock of R&D driving growth in TFP. The diffusion of innovations in agriculture takes many years, so there is a lag between the R&D expenditures and the productivity gains at the farm level that can be 25 to 40 years (Piesse and Thirtle, 2010). In the model with decadal time step, current agricultural TFP is a concave function of agricultural R&D expenditures 10, 20, 30 and 40 years ago (I_{t-i}) , as well as historical productivity level (TFP_{t-3}):

$$TFP_{t+1} = \sum_{i=0}^{3} c_i \sqrt{I}_{t-i} + \phi TFP_{t-3} \qquad (1)$$

Lagged TFP is included to prevent current TFP and agricultural production from falling to zero in a situation of zero lagged R&D spending. In fact, a significant share of the R&D expenditures is spent to support research aimed at preventing agricultural productivity from declining in the face of co-evolving pests and diseases (Alston et al. 2009). To parameterize relationship (1), we use U.S. annual time series data on agricultural TFP and R&D expenditures. We employ USDA-ERS (2015b) data on U.S. agricultural TFP growth over 1948-2007. Information on R&D expenditures for this time period is constructed using data available in USDA-ERS (2012) and Huffman and Evenson (2008). When estimating equation 1, regression coefficients on lagged R&D expenditure are restricted according to the Bayesian lag weights estimated in Baldos et al. (2015). The relationship estimated on U.S. data informs relationship between agricultural R&D and productivity at global scale over the coming century. Specifically, we assume that U.S. investments, when scaled up to the global level, are capable of bringing a level of global TFP comparable to that in the U.S.

Agricultural output depends on inputs used and overall level of technology, represented by TFP, where TFP today depends on past investments into agricultural research according to equation (1). Meta-analysis of crop impacts of climate change (Challionor et al. 2014) shows that global yields will be damaged by global warming with yields dropping on average 4.9% per 1ºC increase in temperature. To reflect the impact of climate change on crop yields in the model, we multiply variable TFP_t by (1- ηT_t) with η =0.049, where T_t is change in global surface temperature relative to beginning of the 21st century. This results in an outcome whereby past R&D become less efficient in delivering agricultural output under warmer climate. In effect, rising temperatures become a drag on productivity growth (IPCC 2014).

To represent uncertainty in future global population, income and change in global surface temperature we use SSP1-5 scenarios (IIASA 2015) (Table 1). SSP2 is dubbed the ‘middle of the road’ scenario, since population and income growth rates are based on business-as-usual (BAU) conditions. SSP1 is the ‘sustainability scenario’ in which population growth peaks at mid-century and the global mean temperature rise from today is just 2.5 degrees Celsius. SSP3 contrasts sharply with these scenarios, with ‘fragmentation’ of the world economy leading to low income growth and population reaching nearly 13 billion at the end of the century. SSP5, ‘conventional development’ scenario, is characterized by high income growth and the highest temperature increase of all -- almost +4 ºC above current levels by 2100. SSP4, the ‘inequality scenario’, has lower rates of income growth with slightly higher population in 2100 than SSP2.

One way to represent uncertainty in the dynamic model of land use is to build a Markov chain over the SSPs, and then determine a range of optimal R&D paths and, by maximizing expected value of objective function, find optimal path of R&D expenditures. This representation, however, requires specification of a transition probability matrix, which is unknown with respect to the SSPs scenarios. The alternative pathways represented by the SSPs are just alternative storylines intended to encompass a wide range of possible future states of the world. There are no associated probabilities, although some, like the middle of the road, appear more likely than others. The essential challenge in this decision making problem boils down to the following: what if we choose the optimal R&D action today with one SSP in mind, and then discover that the world economy is, in fact, following a different SSP? Given the long lag between R&D expenditures and productivity, it would be impossible to boost agricultural productivity by investing more into agricultural R&D at the time food shortages are realized. A natural approach to decision making under this type of uncertainty is to avoid choosing a path which is tailored to just a single SSP. To find optimal path of investments into agricultural R&D, we apply a non-Bayesian decision rule, the min-max regret (MMR) method (Cai and Sanstad 2016). It yields an optimal solution reflecting a form of robustness to the uncertainty: the solution is an acceptable outcome irrespective of which candidate scenario may be correct, and ameliorate the conservatism of the min-max criterion's dependence upon the worst scenario.

Results

Optimal global R&D spending in the beginning, middle and end of the 21st century and the resulting TFP for each of five SSPs are presented in figures 1a and 1b. Global annual spending starts at around $36 billion observed at the beginning of the 21st century (Pardey et al. 2006). SSP3 (high population) and SSP5 (high income) show the highest rates of R&D spending over the first half of the century. In the second half of the century, SSP3 is surpassed by the SSP2. By the end of the century, SSP5 shows the highest optimal level of R&D. The lowest R&D spending is observed for the sustainability scenario, SSP1, which has both lower increases in global average temperature and population growth, along with medium income per capita growth (Table 1). Overall, optimal agricultural R&D spending in 2100 varies by a factor of 2.5 in 2100 – ranging from about $260 billion to nearly $660 billion, depending on the SSP scenarios. Depending on scenario, optimal growth rate in global annual R&D spending is from 3.4 % to 4.4% in the first half and from 0.6% to 2.3% in the second half of the century. In the end of the century, pattern of optimal TFPs across scenarios (figure 1b) follows the one observed for R&D

spending, with highest TFP increase observed in SSP5 and lowest in SSP1. We also plot historical TFP over 1964-2004 period using information presented in Fuglie (2010). Our results indicate that optimal TFP in 21st century should grow faster, from 1% (SSP1) to 1.3% (SSP5) per year, than it was observed historically, on average at 0.98% per year in the second half of the last century.

We employ MMR method to find robust decisions regarding how much to invest into agricultural R&D, given uncertainty in future global population, income and change in surface temperature. First, we consider one source of uncertainty at a time. For example, with SSP2 chosen as a reference case, when looking at the effect of uncertainty in population, we keep global income and change in temperature at levels suggested by SSP2 and vary only population path according to the five SSPs. Figure 2 shows the optimal MMR paths of TFP and R&D spending for models with only population uncertainty, only income uncertainty, or only climate uncertainty, where the other two exogenous paths are chosen to be SSP2. The optimal MMR path falls within the extreme solutions based on individual SSPs. Income uncertainty is, individually, the greatest source of R&D uncertainty, although population is more important as a driver of R&D under the MMR formulation. Uncertainty in climate change play a relatively small role in the optimal investment decisions within our framework. When compared to the demand-side uncertainty emanating from population and income, the supply side impacts of temperature changes envisioned under the SSPs are modest. Population in 2100 varies by a factor of nearly 2, while the ratio of high to low per-capita income in 2100 is almost 5. Against this backdrop, the 1.5ºC temperature difference in 2100 between the most extreme SSPs is quite modest.

Finally, we include all three sources of uncertainty into the MMR analysis. MMR solutions for R&D spending and TFP are shown in figures 1a and 1b, respectively (last set of columns). MMR path of R&D spending involves ramping up spending strongly at the beginning of the century, but moderating this growth rate after mid-century. Optimal rate of growth in R&D spending is 3.8% per year to 2050 and then 1.3% until the end of the century. Note also that the MMR path lies between the extremes of the deterministic paths, although at mid-century it brushes up against the maximum R&D spending obtained when individual SSPs are treated as being certain.

Conclusions

The outlined study offers a dynamic framework for analyzing optimal agricultural R&D spending in the 21st century factoring in uncertainty in future population, incomes and climate change. The feature that makes this problem interesting in the dynamic context is that investment into agricultural productivity pays off with a lag. Most of the current projections of future R&D spending are undertaken using deterministic framework and can only incorporate uncertainty in the form of parametric sensitivity analysis (e.g. elasticity of output with respect to R&D) or alternative scenarios. By drawing on techniques from the robust decision analysis literature, we extend this earlier work, taking explicit account of the underlying sources of uncertainty in determining the optimal path for future agricultural R&D.

This paper finds the optimal path of agricultural R&D spending over the 21st century for each SSP. The global annual spending starts at about 36 bill USD in the beginning of the century and grows to 260-660 bill USD, depending on scenario. Then, the maximum regret is minimized to find a robust optimal R&D pathway that factors in key uncertainties and the long lag in productivity response to R&D. The growth rate in global R&D was at 2.2% per year over 2000-2008 period (Beintema et al. 2012). Our analysis indicates that this strong growth in R&D spending should continue and even increase to 3.8% per year up to 2050, and then slow down averaging at 2.6% over the course of the century. The central finding in this paper is that society should move quickly to higher levels of R&D spending up to mid-century, thereafter moderating this growth rate.

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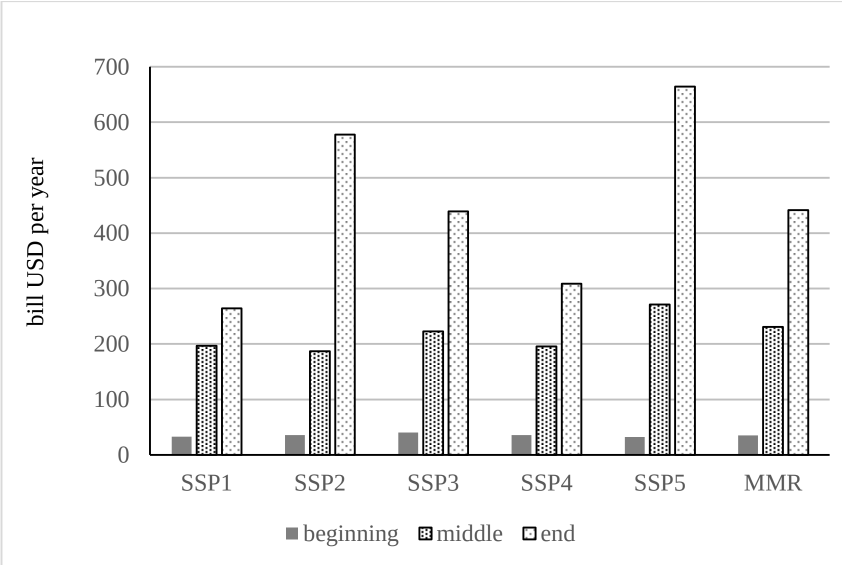

Figure 1a Optimal global agricultural R&D spending in the beginning, middle and end of the 21st century.

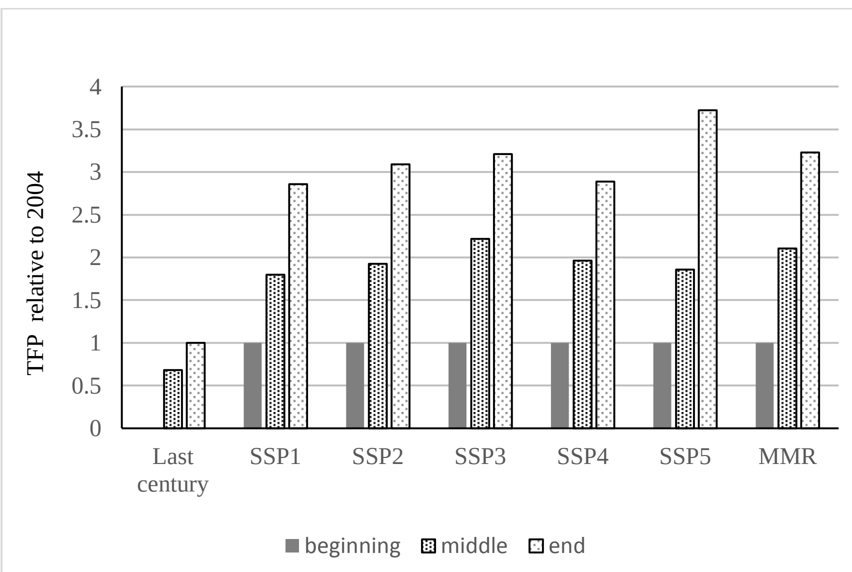

Figure 1b Historical and optimal global TFP in agriculture in the beginning, middle and end of the 21st century (TFP in 2004 =1)

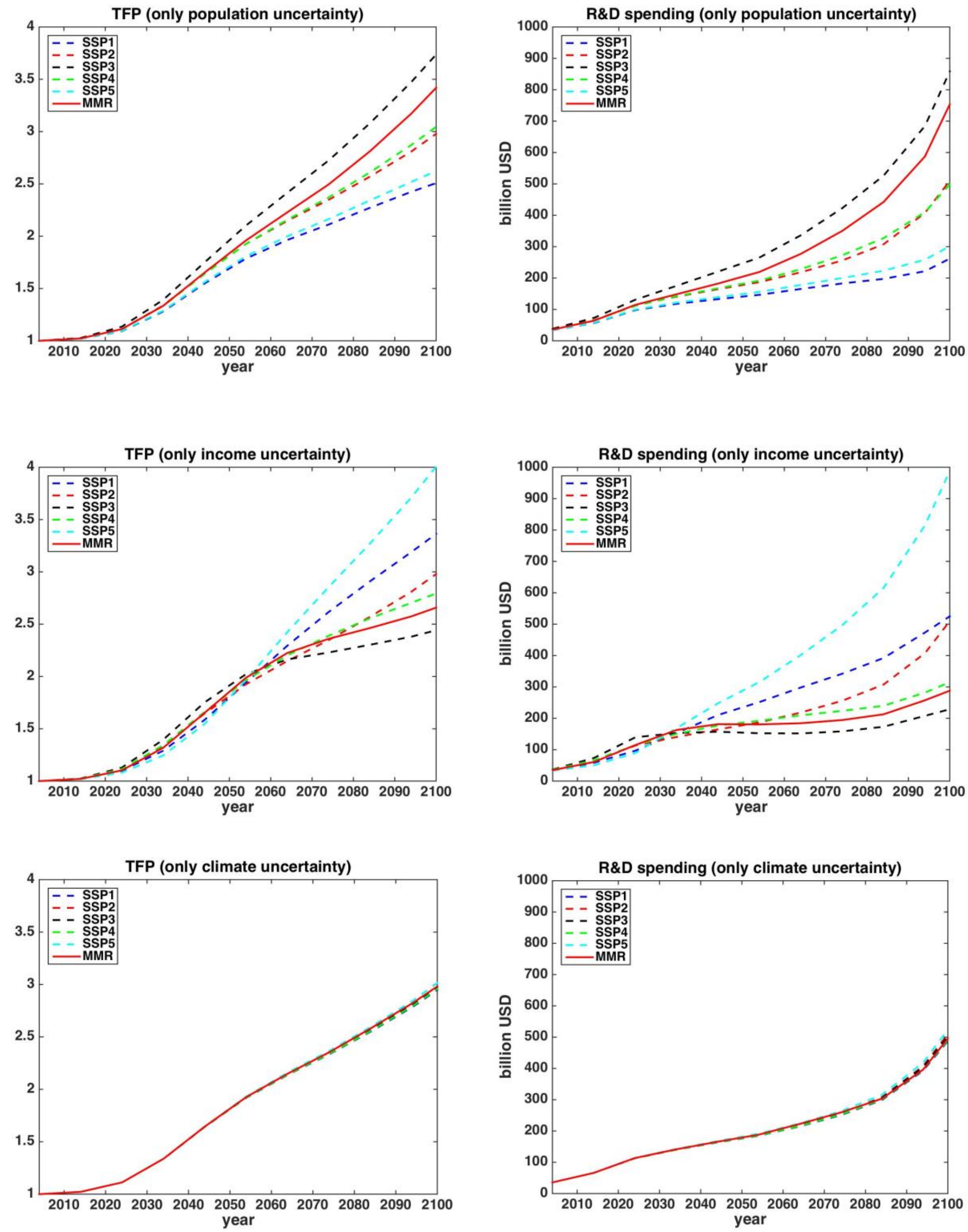

Figure 2 Optimal paths of TFP and R&D spending for only population uncertainty, only income uncertainty, and only climate uncertainty

Table 1. Population, global income and their associated per capita income, and change in global surface temperature in five SSPs

	2000	2050	2100
Population, bill			
SSP1	6.0	8.5	6.9
SSP2	6.0	9.2	9
SSP3	6.0	10.0	12.7
SSP4	6.0	9.1	9.4
SSP5	6.0	8.6	7.4
Global World Product (GWP) per year, trill US$2005			
SSP1	48	286	566
SSP2	48	231	539
SSP3	48	179	279
SSP4	48	221	354
SSP5	48	363	1018
Per capita annual GWP, 1000 US$2005			
SSP1	8	34	82
SSP2	8	25	60
SSP3	8	18	22
SSP4	8	24	38
SSP5	8	42	138
Global surface temperature change relative to beginning of the 21st century, ^{o}C			
SSP1	0	1.2	2.5
SSP2	0	1.3	3.2
SSP3	0	1.3	3.2
SSP4	0	1.3	2.7
SSP5	0	1.5	4.0

Source: SSP database, 2012-1015. Population and GWP information presented in the table is based on OECD Env-Growth model, change in global surface temperature correspond to reference scenarios based on GCAM4.