Agricultural R&D policy under climate and economic uncertainty

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1 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.

The most important determinants of the demand for food in the future are size of global population and per capita incomes. Developments in these variables in the future are very uncertain. According to the Shared Socioeconomic Pathways (SSPs) (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.

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.

2 Methods

To achieve this goal, we develop a stochastic dynamic model of global land use. 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, adjusted for risk aversion. Utility is derived from land-based goods and services (food, timber, bio-energy and non-market eco-system services) 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. This demand system is very flexible in its description of the evolution of consumer demands with rising incomes, allowing the marginal budget share of staple grains, for example, to fall to zero as 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 analysis, 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. To parameterize this relationship, 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. Following Baldos et al. 2015, information on R&D expenditures for 1948-2007 period is constructed using data available in USDA-ERS (2012) and Huffman and Evenson (2008). The relationship estimated on U.S. data informs relationship between agricultural R&D and productivity at global scale.

To represent uncertainty in future global population and income we use SSP scenarios for population and income growth rates with SSP1 and SSP3 representing lower and upper bounds, respectively, and SSP2 as a median. We allow the growth rates to jump from one scenario to another, producing a Markov chain over the scenarios to represent the uncertainty in population and income. That is, we assume there are several possible pairs of population and income values in each time period within the space defined by the SSP scenarios. Uncertainty in future climate and its impact on agricultural productivity is represented by tipping points. If tipping happens then it will damage agricultural productivity in future periods, and larger R&D spending will be required to achieve level of agricultural productivity that would be observed in the absence of tipping. The stochastic dynamic model is solved using value function iteration method (described in Cai and Judd 2014).

3 Preliminary results and next steps

Preliminary results indicate that the expected optimal annual R&D spending rises to $100 billion in 2050 and to $200 billion in 2100. These figures are much larger than the $36 billion (2000 international $) spent annually in the beginning of the century (Pardey et al. 2006). The range of optimal R&D spending by the end of the century is very wide and depends on sources of the uncertainty included in the stochastic analysis. When only population is source of uncertainty, the range is $150-350 billion annually. When population, income and climate change are stochastic, the range is $100-500 billion annually. The major sources of uncertainty in optimal R&D spending are due to the contributions of population and climate change.

Our current work involves improvement to the specification of the linkages between R&D and TFP under future climate, as well as consideration of alternative objective function specifications. First, the representation of endogenous TFP will be improved by allowing the marginal productivity of R&D expenditures to vary as a function of global mean temperature. As temperature rises, it will take more R&D in order to achieve the same rate of yield gain. In effect, rising temperatures become a drag on productivity growth (IPCC 2014). Information on possible temperature scenarios, together with corresponding population and income, is obtained from the SSPs data base. Secondly, the Markov chain representation of uncertainty requires specification of a transition probability matrix, which is unknown with respect to SSPs scenarios and, thus, requires some assumptions. To avoid this problem, the alternative objective will be defined. We apply a non-Bayesian decision rule, the min-max regret 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.

The outlined study offers a stochastic dynamic framework for analyzing optimal agricultural R&D spending in 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. Failure to incorporate the impact of future uncertainty on optimal decision making is expected to have large impact on the results given the large time lag between the R&D expenditures and the productivity gains at the farm level.

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