# IMPACT OF INNOVATION POLICY AND TECHNOLOGY TRANSFER ON LONG-TERM FOOD SECURITY – A CGE ANALYSIS

*Abstract:* In this paper, alternative baseline scenarios of public R&D investment were considered and their impact on agricultural productivity via R&D driven endogenous technical change. The findings showed that R&D growth rates at the level reached in 2000s, particularly those for China would not be expected any longer. Concerning the impact of projected R&D investments on agricultural productivity, it was found that endogenous growth rates of land-augmenting technical change in all R&D scenarios are comparably lower than the standard exogenous rates. This shows that public R&D investments are not able to stimulate agricultural production to the levels that would be expected from the standard baseline outcomes.

*Key Words List:* Public agricultural R&D investments, land-augmenting technical change, agricultural productivity, CGE model, MAGNET, food security.

# 1. INTRODUCTION

Food security is one of the largest challenges facing mankind in the next half century. There are various challenges for reaching long-term sustainable agricultural production and food security: on the one hand there are increased demand pressures resulting from ongoing population growth, improving living standards in developing countries and competition of food with biofuels; on the other hand there are constraints at the production side, due to limited space for expansion of agricultural land and migration of rural labour to urban areas. Recently the FAO estimated that food production needs to be increased with 60 percent to feed the global population of 9 billion people in 2050. Around 80 % of the projected growth will have to come from intensification, predominantly an increase in yields through better use of inputs (Alexandratos and Bruinsma, 2012). Increasing agricultural productivity and crop yield is becoming even more important considering the fact that land and water resources are becoming scarce, which makes extensive agriculture more and more problematic.

Agricultural R&D investments in biotechnologies such as GMO represent a possible solution for the food security challenge, especially in developing countries where cereal yields are still well below the global average level. Continuous investments in R&D are important from the perspective of all food security dimensions. The *availability* dimension is associated with the physical supply of food. According to various scholars (such as Avila and Evenson, 2010, Fuglie, 2012, Pardey et al. 2013, Alston, 2010), investments in R&D are important drivers of agricultural productivity and food availability. As Pardey and Alston (2010) point out, U.S. agricultural R&D has fuelled productivity growth and food supplies not only in U.S. agriculture but also globally via the R&D and technology spillovers.

The *accessibility* dimension of food security looks at the economic determinants of the access to food such as households' income and the evolution and variability of food prices. Particularly for the poor, who spend even 50% of their income on food consumption, changes in the prices of mayor staple crops such as rice, wheat and maize, can have a dramatic impact. The positive occurrence of the period of low agricultural prices in 1980s-1990s was predominantly achieved by R&D investments in better seeds and varieties during the Green Revolution.

The *utilization* dimension refers mostly to the population's ability to obtain sufficient nutritional intake. As highlighted by Mogues, et al. (2012), the potential for agricultural investments to have significant and observable effects on health and nutrition is great. By increasing agricultural productivity, the corresponding farmer income gains can translate into better nutrition through greater calorie consumption and gains in dietary diversity, as well as improved health through a better ability to purchase medicine and access health services.

In view this, the role of R&D investments as a key technology driver in achieving various dimensions food security is undisputable. However, only limited attention is paid to R&D as a key technology driver in most of the leading assessment models that intend to project food security and corresponding changes in food production and prices. Yet, as shown in an experiment performed by Robison et al. (2013), long-term projections of food prices may be highly contradicting under different assumptions of technical change. As a result, their ability to guide policy makers in defining long-term food security strategies is weakened.

This paper aims tackles this limitation by explicitly modelling R&D-driven technical change in agriculture in order to improve insights into the projections of food security. The contribution of this research is twofold: i) methodological, by incorporating a dynamic accumulation of R&D stocks and their links to agricultural productivity in a state-of-the-art CGE model MAGNET, ii) empirical, by

exploring the possible directions of R&D investments worldwide and their impacts on agricultural productivity and consequently food security.

The paper is structured as follows: chapter 2 contains the literature review which served as a basis for incorporating public R&D investments in MAGNET, as described in chapter 3. In chapter 4, outcomes of the model are analysed and chapter 5 concludes.

## 2. LITERATURE REVIEW

## 2.1 PUBLIC AGRICULTURAL R&D INVESTMENTS - HIGH RETURNS BUT LONG LAGS

There is a rich empirical evidence on the effects of R&D investments on productivity with generally significantly positive results. According to the famous meta-analysis of 289 studies conducted by Alston et al. (2000), the average returns on R&D in agriculture reached 82% (mean) and 44% (median). Recently, Hurley, Rao and Pardey (2014) re-examined the rates of return in 372 separate studies from 1958 to 2011 and confirmed the positive evidence of R&D investments, although with lower returns than previously advocated. Similarly, Mogues, Yu, Fan and McBride (2012) presented an updated evidence from country case studies focused on developing countries. They conclude that literature on public investments strongly suggests that returns to research and extension are significant. Next to that they point out three observations – i) higher R&D returns are found in R&D for shorter production cycles, such as field crop ii) higher returns have been found in R&D in Asia and developed countries and iii) R&D is associated with higher returns than are agricultural extension.

Although public R&D investments undisputedly bring large returns, their benefits accrue with considerable lags, contrary to industrial research, which has a more short-term experimental character.<sup>1</sup> Thus, specific approaches must be adopted that allow for alternative accumulation of R&D

<sup>&</sup>lt;sup>1</sup> As Alston et al. (2008) explains research and development might take 5-10 years before the variety is adopted, due to time spent on experimental trials and regulatory approvals. After the variety is adopted, farmers have to learn how to produce it, and consumers have to accept the new product innovation on the market. Therefore, the peak of benefits only comes 15-25 years after the initial investment. Eventually, the variety may become obsolete, as it may be less effective against evolving pests or diseases.

investments to reflect this delay in the construction of knowledge stocks in agriculture. Trapezoidal lag models, polynomial-distributed lagged forms (PDL) and gamma lag distributions are the most common and recommended forms for modelling R&D stocks in agriculture. Thirtle Piesse and Schimmelpfennig (2008) comment, that the gamma distribution is of interest since it offers the smooth form of a trapezoid, which can be estimated rather than imposed. By fitting knowledge stocks calculated from alternative distribution specifications in a TFP regression, Alston (2010) found that in a double log function, a gamma distribution with a maximum 50-year lag and peak after 24 years yields the best result. For the calculation of knowledge stock with this distribution, Alston used the following formulas:

$$RDstock_{i,t} = \sum_{k=0}^{50} b_k \cdot R_{i,t-k} \text{ where } \sum_{k=0}^{50} b_k = 1 \text{ and } b_k = (k+1)^{\frac{\delta}{1-\delta}} \cdot \lambda^k$$
(1-3)

Where  $RDstock_{i,t}$  represents the accumulated knowledge stock per state,  $R_{i,t-k}$  represents the R&D expenditures in lagged period *t-k*,  $b_k$  are gamma weights that sum to one, *k* is the maximum lag of the distribution and  $\lambda$  and  $\delta$  are gamma distribution parameters.

Various studies have adopted the above-mentioned distributions in modelling R&D stocks. Recently, Andersen and Song (2013) quantified the effects of cumulative R&D investments on **US agricultural multi-factor productivity**, adopting Alton's gamma distribution with 50 years lag and found positive evidence, with the elasticity of TFP with respect to R&D ranging around 0.3%. Sheng, Gray and Mullen (2011) tested 10 different alternatives of gamma, trapezoidal and geometric distribution for constructing knowledge stocks in **Australian agriculture** from 1953 – 2007. The authors concluded that the gamma distribution with a peak after 7 years and a lag of 35 years performed the best. Under this distribution, the estimated elasticity of TFP with respect to public R&D knowledge stocks was 0.23%, with an internal rate of return on public R&D reaching 28%. Similarly, Hall and Scobie (2006) found a 17% rate of return on public R&D in **New Zealand** agriculture, using the perpetual inventory method, a Koyck transformation and a polynomial lag structure on annual data from 1927 – 2000. As for the **European agriculture**, similar studies that would quantify the effect of public R&D investments on productivity are scarce. The evidence can be found by Thirtle Piesse and

Schimmelpfennig for UK. The authors applied alternative distributions to gamma distribution with lag of 25 years and their calculated elasticity ranged between 0.1 - 0.3%.

Concerning developing countries, a review of studies and calculated elasticities is presented in Ninn Pratt and Fan (2009) who use a lag of 10 years and elasticities ranging 0.1% to simulate the optimal allocation of R&D investments in across regions of Asia, Africa and Latin America. Their choice of parameters is largely based on a study of Thirtle et al. (2003) that analysed the impact of research-led agricultural productivity growth of poverty reduction and calculated elasticities of R&D driven land productivity in range of 0.3% for Asia, Africa and Americas. A single country study for India was performed by Fan (2002) who modelled R&D investments using PDL functional form with a maximum lag of 13 years and derived an elasticity of 0.255%. Fan found that among all the rural investments considered in his study, agricultural research has the largest impact on urban poverty reduction in India per additional unit of investment. Another evidence from Asia provided Supananachart and War (2011) for Thailand who considered only seven year lag of R&D investments with corresponding elasticities ranging around 0.07%. A shorter lag of R&D investments found is justifiable in developing countries, where research is often closer to extension. As argued by Alene (2009, 2010) much of R&D in African agriculture is of adaptive nature with a shorter gestation lag than would be the case for basic research. Applying a Second Degree PDL function with 16 years lag, Alene quantified elasticity of Sub-Saharan African agricultural productivity with respect to R&D ranging 0.2% (for TFP) and 0.38% (for value added per hectare). Alene concludes that agricultural R&D has significant effects on productivity in African agriculture brining a rate of return of 33% per year and being thus a socially profitable investment in African agriculture. As for Latin America, a similar study was conducted by Bervejillo, Alston, Tumber (2012) who found a gamma distribution with 25 years lag and peak in 24th years to perform the best with corresponding elasticities of TFP with respect to public R&D stock in the range of 0.5%.

Finally, empirical evidence for countries of Central and Eastern Europe and Former Soviet Block is almost non-existent. For **Czech Republic**, Kristkova and Ratinger (2013) found a positive evidence of R&D stocks modelled by gamma distribution with lags ranging from 7 - 15 years. They

argued, that shorter time lags compared to evidence from UK or USA can be explained by the transition period which has seen a rapid upgrading of technologies, likely induced by the urgent need to enhance the competitiveness of agricultural production.

#### 2.2 APPROACHES TO MEASURING INTERNATIONAL R&D SPILLOVERS IN AGRICULTURE

Due to the public goods character of knowledge, it is realistic to assume that newly accumulated knowledge brings benefits outside of the domestic region. For measuring industrial R&D spillovers, transaction matrices composing of input-output and bilateral import shares are typically used (originally proposed by Coe and Helpman, 1995 and later modified by Lichtenberg and van Pottelsberghe de la Potterie, 1998 and Keller, 1998). Alternatively, technology proximity based on patents, FDI or geographic proximity has been proposed in the literature (for instance Verspagen, 1997, Cincera, 2005 or Krammer, 2010).

Nonetheless, all these approaches deal with measuring R&D spillovers resulting from aggregate or industrial R&D. However, for measuring R&D spillovers in agriculture, specific approaches must be adopted and relatively limited number of scholars attempt to quantify their effect. Since agricultural production is especially dependent on natural inputs such as soil and climate conditions which affect the performance of particular crops or production practices, the degree of **agro-ecological similarity** affects the degree to which spill ins can be exploited (Pardey, 2013). Van Meijl and Tongeren (2004) also take into account the **structural similarity**, defined as a share of land to labour rations. The similarity conditions determine a potential R&D stock that can be spilled over between the countries. A second important factor is the **absorption capacity** of farmers to adopt new knowledge. Various factors influence the absorption capacity among which education of farmers, agricultural extension and the distance from technological frontier play the biggest role. Eaton and Kortum (1999, cit. in Hall and Scobie, 2006) show that a **country's level of education** plays a significant role in its ability to absorb foreign ideas. The education level of farmers was as an absorption factor was used for instance by Van Meijl and Tongeren, 2004. Regarding the **distance from the technological frontier**, two contradictory opinions exist. From the convergence theories follows that the larger is the distance from the technology leader, the quicker is the growth towards the frontier (Acemoglu, 2009). On the other hand, in the agricultural literature prevails the opinion that the larger is the distance from the frontier, the more costly is technology adoption (Pardey, 2013). Recently, Eaton and Wurlod (2015) attempted to quantify a productivity convergence in agriculture and found that the distance from the technology frontier slows down the convergence.

## 2.3 AGRICULTURAL R&D POLICY: IS THERE A SLOWDOWN OF R&D INVESTMENTS?

Between 1960 – 2009, the spending on global public research on food and agriculture grew by 3.4 % annually (Pardey, 2013 a,b). However, the regional composition of public spending changed dramatically in favour of middle income countries such as Brazil, China or India. Whereas in 1960s, high income countries accounted for 56% of total R&D spending, in 2009 it was less than 50% with US share dropping from 20% to 13%. Not only rich countries, but also Sub-Saharan Africa's economies and most of Latin American countries lost their shares to Asia, particularly due to expansion of R&D investments in China and India. As quoted by Pardey, "nowadays, China spends more than any other country on public-sector agricultural R&D". This is also reflected in the deceleration of growth rates of public R&D spending in high income countries in the last decade. Yet, sustained investments to R&D are required to prevent productivity from falling which could jeopardize the long-term prospects of global food security. Next to that, productivity enhancing research in farming and food production is gradually directed away to other research targets (Alston and Pardey, 2014).

Another warning is directed towards the poorest countries that are falling even farther behind and that according to Pardey will find it more difficult to benefit from spillovers due to tightening of intellectual property rise and role of private R&D companies. As a conclusion, Pardey argues that the world's future productivity will largely depend on middle income economies for agricultural innovations. In this paper, these considerations are explored in alternative baseline scenarios, which differ by the assumptions on future growth of domestic R&D investments and concern also spillover effects from agricultural R&D from abroad.

#### 3. METHODOLOGICAL APPROACH

#### 3.1 INTRODUCTION OF THE CGE MODEL MAGNET

Whereas various methodological approaches can be used to assess the impact of R&D investments on food security projections, such as structural macro-econometric models, a multicountry computable general equilibrium (CGE) model MAGNET is particularly suitable here, due to the following reasons:

- As a CGE model, MAGNET enables to assess R&D impact in a systematic way capturing various dimensions of food security (mainly availability and accessibility dimension) and at the same time measuring also sustainability aspects (such as land use).
- MAGNET as a multi-country model enables to model interlinkages between all countries in the world and is thus highly equipped for incorporating R&D spillovers and technology transfer.
- MAGNET enables to calculate long-term projections of food security under various assumptions of exogenous drivers such as population, diet preferences, etc.

CGE model MAGNET is an extended and version of the GTAP (Global Trade Analysis Project) model, a widely used tool for global trade analysis (Hertel, 1997). The model has been applied to analyse the medium and long run effects of global and EU agricultural, trade, land, and biofuels policies (Banse et al., 2008; Francois et al., 2005; Van Meijl et al., 2006). MAGNET belongs to the class of global computable general equilibrium (CGE) models, which are able to simulate the behaviour of the total (global) economy, including the interaction of agriculture, manufacturing and services sectors. MAGNET is characterized by an input-output structure that links industries in a value added chain from primary goods, over continuously higher stages of intermediate processing, to the final production of goods and services for consumption. It assumes perfect competition and profit maximizing agents. Demand, supply and international trade are derived by solving the demand, supply and price system of many interacting factor and product markets that together cover the global economy.

For the analysis in this paper, MAGNET uses the GTAP database version 8, final release (Narayanan et al., 2013), which contains data on the economic structure of 140 countries for 2007. The

sectoral division distinguishes 12 agricultural (land using) sectors available in GTAP at the highest level of detail, including paddy rice, wheat and other grains, various other crops and livestock and animal produce sectors as well as a (commercial) forestry sector, a fishing sector, manufacturing and services.

In order to assess the impact of policy shocks in the future, the model is calibrated on exogenous macro-drivers, in particular GDP and population growth. In comparison to the GTAP model, MAGNET has been extended with segmented labour and capital markets, modified consumption structure, improved modelling of the land market. The incorporation of an R&D-driven land augmenting technical change in a new Magnet module is described in the following section.

# 3.2 INCORPORATION OF AN R&D-DRIVEN TECHNICAL CHANGE IN MAGNET

We make a major distinction between private and public R&D activities. In this paper, we focus on public agricultural R&D targeted to major improvements of seeds and varieties in the style of Green revolution, developed in specific publically funded research institutes. Opposed to private agricultural R&D where technology might be developed more "in-house"<sup>2</sup>, public R&D requires a representation of a specific production sector and technology (for instance independent CGIAR institutes developing new varieties). Second distinctive feature from private agricultural R&D is that the effects accrue only after long lags (ranging to 50 years) and explains why public R&D still represents the major financing source of agricultural research. Third, we assume that the nature of public R&D research is mostly targeted to improvements in crop varieties and thus it can be considered as a technology stimulating land-augmenting technical change<sup>3</sup>.

Various approaches exist that incorporate R&D sector into CGE framework, such as linking R&D effects to Total Factor Productivity (TFP), as done earlier by Lejour and Nahuis (2000) in the Worldscan CGE model or Verbic (2007) for Slovenia, or via incorporating a cumulated R&D stock in form of knowledge as a new production factor (as applied for instance by Kristkova, 2013). Fully dynamic Romer based endogenous growth CGE models incorporate effects via R&D production of

<sup>&</sup>lt;sup>2</sup> Such as developing of farm machinery by John Deer or agricultural chemicals by Syngenta.

<sup>&</sup>lt;sup>3</sup> Parallel to this research, empirical estimates have been carried out to quantify the direction of R&D in factoraugmenting technical change. The results on sector level indicate that R&D has mostly labour-augmenting effect (Smeets Kristkova et al., 2015), however, as for agricultural sector, the results are not conclusive due to omission of land from the estimates.

capital varieties with public goods feature were applied by Gosh (2007) for Canada. Finally, the models of directed technical change are further extension of the Romer style CGE models two-variety capital sectors capturing the trade-off between improving productivity of one input versus others, as used by Popp (2004) in ENTICE model or Otto, Löschel, et al (2007).

Given the high level of stylization in most of the above mentioned approaches, we propose an empirically based approach to link R&D with productivity coefficients in CES<sup>4</sup>. We consider factorbiased technical change that consists of exogenous part and endogenous part. The endogenous part depends on domestic cumulative public agricultural R&D investments in all countries and we also consider international diffusion of knowledge (R&D spillovers).

# 3.2.1 R&D DATA USED FOR SAM DISAGGREGATION

Social Accounting Matrix (SAM) is a basic data structure that is used to replicate a CGE model in the benchmark equilibrium. In line with our assumption on a specific R&D production technology, a separate R&D sector was disaggregated from the sector of public services in the SAM. A simple procedure of applying the share of public R&D expenditures in the value of output of public services was applied to all cost components. This means that public R&D sector employs the same share of skilled and unskilled labour as other public services. In most of the regions, the share of skilled labour reaches more than 50%, which is realistic.

In order to implement R&D sector in MAGNET, various data sources were compiled to derive value of public R&D expenditures for all 140 regions, namely i) Asti Public database for most of the developing countries, ii) OECD and EUROSTAT for European countries and iii) UNESCO Database for the remaining countries. Next to that, Pardey InsTepp Database Summary was used to obtain agricultural R&D expenditures for important EU countries which do not share the data with EUROSTAT, such as Germany, France, Spain or Italy. Finally, all values were converted from 2005 PPP dollars to 2007 current Dollars to homogenize with values of other variables in the SAM.

<sup>&</sup>lt;sup>4</sup> Such approach has been used for instance by Carraro and Cian (2013) for modelling the effects of climate change and it is also in line with our empirical estimates on factor-augmenting technical change in CES framework.

# 3.2.2 MODELLING DOMESTIC R&D STOCKS IN MAGNET

Following the empirical evidence on the specific shape of knowledge stocks distribution of the agricultural R&D investments, a gamma distribution function was incorporated to MAGNET for building R&D stocks from the governmental R&D expenditures. In line with the evidence in literature, regions were grouped into six vintage groups. R&D investments in high income regions such as USA exhibit the longest lags corresponding to the nature of the research (basic research prevails). On the other hand, developing regions are allocated to vintage groups with shorter lag due to more adaptive nature of research (Table 1, Figures 1-6). Similarly, the elasticity values vary with vintage group and generally follow the pattern that the longer is the R&D distribution lag, the higher is the return and the elasticity of technical change with respect to R&D.

Given the choice of the vintage groups, R&D stocks in each region were reconstructed backwards from 1960 – 2010 using formulas 1-3. In the process of this calculation, a matrix of R&D vintages is constructed where each row indicates the distribution of annual investment over the production period (depending on the max lag) and each column indicates the contribution of t-k R&D investment to current R&D stock. Comparison of annual R&D investments and calculated cumulative R&D stocks for the case of the USA is demonstrated in Figure 7.

#### <Table 1>

Finally, gamma weights and R&D vintage matrix for the period of the simulation horizon were aggregated according lengths of the simulation periods.

<Figures 1-6>

<Figure 7>

#### 3.2.3 MODELLING INTERNATIONAL R&D SPILLOVERS

In order to reflect the evidence of agricultural R&D spillovers in literature described in chapter 2.2, four spillover indices were constructed and implemented in MAGNET. For expressing *spillover potential*, **production similarity index (PSIN)** is calculated as a correlation coefficient of agricultural production shares and is updated after each simulation period:

$$PSIN_{r,s} = \frac{\sum agr_share_{j,r}*agr_share_{j,s}}{\sqrt{agr_share_{j,r}^2*agr_share_{j,s}^2}}$$
(4)

Calculated values of the Production similarity index in base year (2007) are shown in Appendix 1. Values closer to 1 indicate high similarity of production systems, values approaching zero indicate different productions structures.

The second element of the spillover potential is the similarity of farming conditions, expressed by the **agro-ecological index (GAEZ).** Values for the index were adopted from aggregated figures presented in Pardey and Pingali (2010).

For expressing the *absorption level*, two indices were constructed. The **education index** (**EDUIN**) was calculated as a ratio of total years of schooling per region to the maximum attained level using data of Barro and Lee (2010). Appendix 3 shows that the highest education level was achieved in USA, followed by other high income countries, whereas in Eastern Africa, years of schooling reached only 30% level of the level in USA.

Finally, the **technology gap index (YgIndex)** was calculated as a share of aggregated yield in a given region r and maximum attained yield (values are reported in Appendix 4). Each simulation period, the aggregated yield is updated by growth of land-augmenting technical change in the previous period (aland t-1):

$$\operatorname{YgIndex}_{j,r,t} = \frac{(1 + \operatorname{aland}_{t-1,(j,r)}/100) \operatorname{*Agg_Yield}_{j,r,t}}{\operatorname{Max}_{r}[(1 + \operatorname{aland}_{t-1,(j,r)}/100) \operatorname{*Agg_Yield}_{j,r,t}]}$$
(5)

# 3.2.4 LINKING R&D STOCKS AND LAND-AUGMENTING TECHNICAL CHANGE

Finally, growth of the cumulated R&D stocks from gamma distribution and R&D spillovers are linked to land-augmenting technical change as shown in the following equation:

$$aland_{j,r} = elasRD_r * rdstock_r + if(rdspil_r > 0, * elasRD_r * rdspil_r)$$
 (6)

where *aland* represents land-augmenting technical change parameter, which enters the CES production function, *elasRD* is elasticity of *aland* with respect to R&D growth (values are reported in Table 1) and *rdstock* and *rdspil* are growth rates of domestic R&D stocks and R&D spillovers per each region. The scheme of the linkages between R&D investments and land augmenting technical change is provided below. From governmental expenditures on R&D, real R&D investments are determined which are split over individual period contributions to total R&D stock following the gamma distribution function. In each period, the new value of R&D stock is formed as a sum of the annual contribution and the previously cumulated stock. The new value of R&D stock is spilled over to other regions depending on their production and agroecological similarities. Only certain part of the growth of R&D spillover is absorbed to the other region, depending on the education level and the distance from the technological frontier. The growth of land-augmenting technical change consequently enters the demand equation for land and alters land prices.

## <Scheme 1>

# 4. IMPACT OF PUBLIC R&D INVESTMENTS ON PRODUCTIVITY AND FOOD SECURITY

# 4.1 MODEL AGGREGATION, DEFINITION OF SCENARIOS AND BASELINE ASSUMPTIONS

The production and region aggregation choices applied in MAGNET are provided in Table 2. There are 21 aggregated regions and 25 production sectors, from which 11 are primary agricultural sectors. Industry sectors are aggregated to low and high industry, services contain sectors of business services (oth\_ser), public services (pub\_ser) and public agricultural R&D sector (rd).

#### <Table 2>

The CGE model MAGNET has been applied in three scenarios, that represent alternative baseline scenarios:

- *Baseline VINTAGE*: In this baseline scenario, land-augmenting technical change grows according the growth of domestic R&D stock.
- *Baseline SPILLOVER*: in this baseline scenario, land-augmenting technical change grows according the growth of domestic R&D stock but it also captures productivity effects from the foreign R&D spillovers.
- *Baseline ALEX*: this is the usual baseline in which land-augmenting technical change is determined exogenously based on the historical growth rates of yields, which means there is no R&D-driven technical change in the model.

In all three baselines (Business as usual) scenarios, we use the Shared Socio-economic Pathways (SSPs), which have been recently developed to assess the impact of global climate change (Kriegler et al., 2012; O'Neill et al., 2011, 2014). The SSPs are a set of plausible and alternative assumptions that describe potential future socioeconomic development in the absence of climate policies or climate change. They consist of two elements: a narrative storyline and a quantification of key drivers, mainly population growth and economic development. For the assessment in the paper we only use one of the five SSPs, the so-called Middle of the Road (SSP2) scenario, which reflects a business-as-usual future. In this scenario, trends that are typical of recent decades continue in the future (O'Neill et al., 2011). There will be some progress towards achieving development goals but development of low-income countries proceeds unevenly. Most economies are politically stable with partially functioning and globally connected markets. Per-capita income levels grow at a medium pace on the global average, with slowly converging income levels between developing and industrialised countries. Intra-regional income distributions improve slightly with increasing national income, but disparities remain high in some regions.

The implementation of the first two baseline scenario requires assumptions about the evolution of the R&D investments in each region. Two alternatives are considered here:

- Version A (*RD\_shareGDP*): In this version, R&D investments are determined as a fixed share of agricultural GDP in the base year. This implies that R&D expenditures grow according to agricultural GDP growth.
- Version B (RD\_growth2000s): in this version, R&D investment growth rates copy the historical period growth rate in 2000s.

#### 4.2 EVOLUTION OF R&D INVESTMENTS IN ALTERNATIVE BASELINE SCENARIOS

In this section, the evolution of R&D investments towards 2050 is analysed. Two interesting insights can be derived here – first a comparison of historical and projected growth rates and second an interval in which future R&D investments might oscillate in each region. The evolution of real R&D investments towards 2050 that follow GDP growth in agriculture is displayed in Figure 8. Compared to the historical period (1960-2010), **R&D growth rates of China will be much smaller**,

which is in line with the assumption of gradual slowdown of Chinese GDP growth towards 2050. Regions that might continue with high R&D investment rates are Sub-Saharan African states where rates could exceed 10% growth. This baseline scenario also predicts that R&D investments would be boosted in high income economies like USA and EU-16 which have seen a slowdown of growth R&D rates in the past two decades.

# <Figure 8>

Figure 9 shows how different are these R&D investment growth rates projections compared to the baseline scenario where R&D growth rates follow historical behaviour. Under the assumption that R&D investments will grow according the historical growth rates, regions like South East Asia, Eastern and North Africa, rest of South America but mostly China and EU 12 are better off compared to the rates in Figure 8. Particularly in case of China, R&D growth rates might vary between 2% to 10% depending on the assumption. On the other hand if we believe that R&D investments will follow a constant share in agricultural GDP, most of the high income countries like USA, Canada, Australia and New Zealand (Oceania) but also Brazil are better off. Finally, regions like India, and South Africa enjoy high rates of R&D investments in either scenario. To evaluate how credible either of this stories is, long-term shares of R&D investments in agricultural production are plotted for countries where sufficiently long R&D data series are available. Figure 10 shows that except for India, R&D expenditures seem to follow a constant share in agricultural production, which oscillates between 1% to 4% depending on region. From this can be concluded that for most of the developing countries, **R&D** growth rates at the level reached in 2000s would not be expected any longer (except for India). The same applies for EU-12 that might have enjoyed higher R&D growth rates in 2000s in the process of EU integration. From another perspective, it can be also noted that the divergence of growth rates in high income regions shows that their historical spending was too restrictive and there is much higher room for boosting future R&D investments in agriculture.

# < Figure 9>

< Figure 10>

#### 4.3 ACCUMULATION OF DOMESTIC R&D STOCKS AND R&D SPILLOVERS

The evolution of domestic R&D stocks calculated as a weighted average of all past R&D investments using gamma distribution weights is provided in figure 11. In this Figure, R&D stocks are built from R&D investments following a growth rate of agricultural GDP. Clearly, the biggest volume of R&D stocks would be accumulated in the EU-16, also as the effect of the aggregation of 16 high income economies. It is also visible, that China would catch up with USA and other high income economies within next 20 years and India would reach their level in 2050. This shows that even with a more pessimistic alternative of R&D investments for China where R&D growth rates reach only 2% annually, China will belong to R&D leaders in the upcoming periods.

# < Figure 11>

Until now, only domestic R&D stocks were considered. Figure 12 shows, how domestic R&D stock growth rates are transmitted abroad in form of R&D spillovers. It is clearly visible, that R&D spillovers grow much slower than domestic R&D stocks. At first, comparing domestic R&D stock with *Rdpot* shows that there is generally a low similarity of production structures and agroecological zones between the countries and thus R&D stocks cumulated in one region are difficult to be adopted in another. Next, the potential R&D spillover is further reduced due to the low education level in many developing regions. Finally, only limited part of the absorbed R&D stock is effectively used because of the high technology gap. In fact, three groups of regions can be distinguished: countries where domestic R&D stocks highly exceed the potential growth of R&D spillovers such as Eastern Africa, Western Africa and India. In these countries, growth of productivity would mostly rely on domestic R&D policy. In the second group are countries that could potentially benefit from R&D spillovers as their domestic R&D stocks growth rates are not high enough such as Oceania, China, EU-12, South East Asia and South Africa, but have low absorption capacity due to education levels and distance from technology frontier. Third group represent countries that can fully benefit from R&D spillovers, which are USA, EU-12, High income countries and Brazil. In case of Brazil, productivity growth relies more on foreign R&D policy then on domestic one. Obviously this picture is very much dependent on the assumptions of individual factors that affect R&D spillovers. Also, it should be noted that education level remains constant in the whole period, which may be too restrictive as most of the countries also catch up with total years of schooling. Second, a more empirical evidence on the channels of R&D spillovers and their measurement is needed to have a reliable picture on technology transfer.

#### < Figure 12>

#### 4.4 EVOLUTION OF AGRICULTURAL PRODUCTIVITY WITH R&D-DRIVEN TECHNICAL CHANGE

As explained in the methodological section, we model R&D-driven land augmenting technical change (aland) as a function of growth of cumulated domestic R&D stocks and R&D spillovers. Figure 13 displays the average growth rates of *aland* across all baseline scenarios. This exercise enables to compare endogenous growth rates of aland achieved under alternative R&D investment assumptions with *aland* growth rates that are modelled exogenously in standard baselines. This can also serve as a validation of the productivity growth rates are usually assumed in the ex-ante exercises. First conclusion when inspecting Figure 13 shows that the endogenous growth rates of aland in all **R&D** scenarios are comparably lower than the standard exogenous rates. This can have various interpretations. First, one should take into account that in this exercise, only public agricultural R&D investments stimulate land productivity, leaving other relevant factors such as private R&D reflected in better quality of inputs, extension, and other types of agricultural investments might play important role. Next to that, the exogenous growth rates of *aland* are usually proxied from historical growth rates of yields, which does not correspond to historical growth rates of land augmenting technical change. Therefore, it is not surprising to observe that endogenous *aland* rates are lower. However, for some regions, R&D driven aland is comparable or even exceeds the exogenous rates, which is in case of EU-16, Canada and USA. It can be concluded that for these regions, the exogenous aland underestimates the productivity potential.

# < Figure 13>

Another interesting insight can be drawn from Figure 14 which shows the average growth rates of endogenous yields, calculated ex-post as an aggregated ratio of quantity produced per hectare of agricultural land. It should be noted here that the yield growth reflects not only the effect of land-

augmenting technical change, but also joint effects of labour productivity growth and factor substitution between land and other production factors. Therefore rates observed in Figure 14 are higher than the rates of land-augmenting technical change reported in Figure 13. Comparing endogenous yield growth rates across the alternative baseline scenarios, one can note that for multiple regions, scenarios with R&D driven technical change lead to higher yields than in the standard baseline. This situation occurs in Western Africa, India, Middle East, EU-16 and USA. It can be concluded that in these regions, the predictions of yield growth with R&D driven technical change are more optimistic than the predictions obtained without endogenous R&D investments. On the other hand, case of Brazil shows that yield growth rates could be overestimated. For China, growth of yields are comparable across the scenarios.

## < Figure 14>

## 4.5 PROJECTIONS OF AGRICULTURAL PRODUCTION, PRICES AND CALORIC CONSUMPTION

An important question that arises when inspecting the evolution of yields is how are these developments translated in sustainable agricultural production and food security. Figure 15 shows average growth rates of agricultural production under the alternative baseline scenarios. For all Sub-Saharan regions, it is clearly visible that although the production growth rates are substantial (40% - 60%), **public R&D investments are not able to stimulate agricultural production to the levels that would be expected from the standard baseline outcomes**. This suggests that either R&D public investments in these regions should be strongly boosted, or that our usual assumptions about future growth rates of agricultural production in Sub-Saharan Africa are too optimistic. Looking at the low income Asian regions and Middle East, projections of agricultural growth range about 25% and the gap between the baseline scenarios is smaller. Completely different picture is observed in High income countries, here projections of agricultural growth highly exceed standard baseline projections, particularly in case of Canada, USA and EU-16. This shows that if high income countries would continue investing in public R&D either at the historical rates or at the rates of their agricultural GDP, their production would be largely boosted (provided that R&D investments will contribute to productivity at the same rates as in the past).

Figure 16 shows the average growth rates of agricultural prices. For the **Sub-Saharan regions**, the projections are highly alarming, as agricultural prices could grow from about 60% in case of exogenous aland scenario up to 80% if land-augmenting technical change is driven only by public R&D investments. An exception is the region of Eastern Africa where under the historical growth rates assumption, agricultural prices would raise less but still 60%. An extreme growth of agricultural prices (80%) is also expected in India, but to a much lower extent in China and other regions. Nevertheless, in none of the regions would agricultural prices decline, which is not in line with the projections obtained from standard baseline.

## < Figure 16>

Finally, Figure 17 shows how excessive growth of agricultural prices is projected to total caloric consumption per capita. When inspecting the figures across regions, India emerges as a region with the highest expected growth of caloric intake, irrespective of the baseline scenario. High growth of caloric consumption is expected also for Eastern and North Africa, despite sharp increase in agricultural prices.

# < Figure 17>

# 5. CONCLUSION

In this paper, alternative baseline scenarios of public R&D investment were considered and their impact on agricultural productivity via R&D driven endogenous technical change. The methodological approach was based on the application of the state-of-the art CGE model MAGNET with newly built R&D module.

The findings showed that R&D growth rates at the level reached in 2000s, particularly those for China would not be expected any longer. Regions that might continue with high R&D investment rates are Sub-Saharan African states where rates could exceed 10% growth and India, which would continue investing in R&D expenditures in either R&D scenario and its knowledge stocks would gradually reach levels of USA and China. As for high income countries, simulations showed that historical R&D spending was too restrictive and there is much higher room for boosting future R&D investments in agriculture. This is in line with the arguments of Pardey (2013) who alerted that public support for agricultural science has broadly waned and an increasing share is being directed toward off-farm issues (Pardey, 2013). Pardey, Beddow and Buccola (2014) warn that the increase in new funding directed to research in the New US Farm Bill is insufficient to reverse the dramatic decline in the US share of global public spending. The same applies for the EU, where in spite of the positive effort of increased financing of agricultural research in Horizon 2020 and the new EIP initiative in agriculture, a conflict between objectives of sustainable intensification – parallel advancement in productivity and sustainability in selecting the winning projects of Horizon 2020 exists (Matthews, 2013).

Concerning international technology transfer it was found that public agricultural R&D spillovers grow much slower than domestic R&D stocks mainly due to low similarity of production structures and agro-ecological zones between the countries. For countries where domestic R&D stocks highly exceed the potential growth of R&D spillovers such as Eastern Africa, Western Africa and India, growth of productivity would mostly rely on domestic R&D policy. This is in line with Pardey who warns that some developing countries will find it more difficult to benefit from spillovers due to tightening of intellectual property rise and role of private R&D companies.

Concerning the impact of projected R&D investments on agricultural productivity, it was found that endogenous growth rates of aland in all R&D scenarios are comparably lower than the standard exogenous rates. This shows that public R&D investments are not able to stimulate agricultural production to the levels that would be expected from the standard baseline outcomes. Regarding food prices, projections for Sub-Saharan regions are alarming. This also applies for India which clearly shows that R&D investments are not sufficient to prevent high food prices from rising.

Group	Typical Regions	Max Lag	Lambda	Delta	Elasticity aland to RD	Peak
А	USA	50	0.7	0.9	0.3	24
В	Australia and New Zealand	35	0.7	0.8	0.2	10
С	EU-15 and other High Income	25	0.6	0.85	0.2	10
D	EU-12 and Russian Federation	15	0.4	0.8	0.2	3
Е	Latin America	25	0.7	0.9	0.1	24
F	Asia Pacific and Africa	15	0.5	0.8	0.1	5

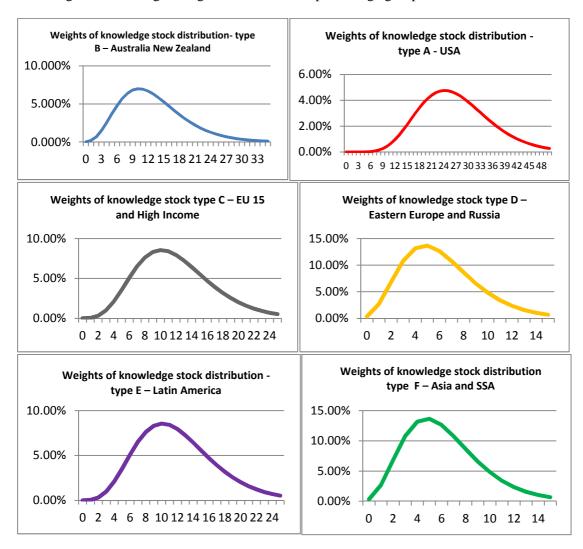
Table 1: Parameters of gamma distribution function of R&D stock accumulation per vintage group

Source: Authors elaboration

Table 2: Desc	ription	of regions,	pro	oduction	sectors	and	periods	applie	d in M	AGNET

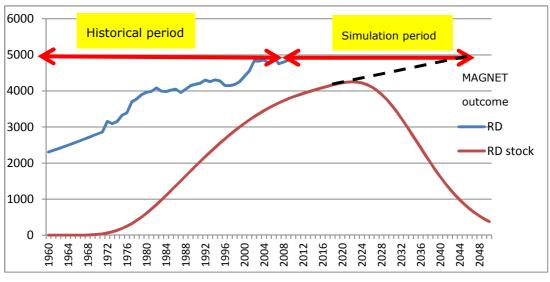
PROD. SECTORS	PERIODS					
1 pdr *	1 p[1]	2007-2010				
2 wht*	2 p[2]	2010-2020				
3 grain*	3 p[3]	2020-2030				
4 oils*	4 p[4]	2030-2040				
5 sug*	5 p[5]	2040-2050				
6 hort*						
7 crops*						
8 cattle*						
9 pigpoul*						
10 milk*						
11 cmt						
12 omt						
13 dairy						
14 sugar						
15 vol						
16 ofd						
17 fish						
18 lowind						
19 oth_ser						
20 oagr*						
21 pub_ser						
22 highind						
23 rd						
24 fossilfuel						
25 CGDS						
Total	_					
	1 pdr * 2 wht* 3 grain* 4 oils* 5 sug* 6 hort* 7 crops* 8 cattle* 9 pigpoul* 10 milk* 11 cmt 12 omt 13 dairy 14 sugar 15 vol 16 ofd 17 fish 18 lowind 19 oth_ser 20 oagr* 21 pub_ser 22 highind 23 rd 24 fossilfuel 25 CGDS Total	1 pdr * 1 p[1]   2 wht* 2 p[2]   3 grain* 3 p[3]   4 oils* 4 p[4]   5 sug* 5 p[5]   6 hort* 5 p[5]   6 hort* 5 p[5]   7 crops* 8   8 cattle* 9   9 pigpoul* 4   10 milk* 4   11 cmt 4   12 omt 4   13 dairy 4   14 sugar 4   15 vol 4   16 ofd 4   17 fish 4   18 lowind 4   19 oth_ser 4   20 oagr* 4   21 pub_ser 4   22 highind 4   23 rd 4   24 fossilfuel 4   25 CGDS 4				

Note: primary agricultural sectors are noted with\*. Sector description follows GTAP terminology (see sector listing at: <u>https://www.gtap.agecon.purdue.edu/databases/v9/v9\_sectors.asp</u>)

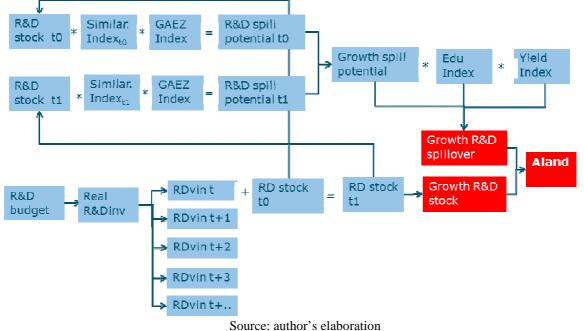


Figures 1-6: Weights of gamma distribution per vintage group

Figure 7: Agricultural R&D investments and R&D stocks - case of USA



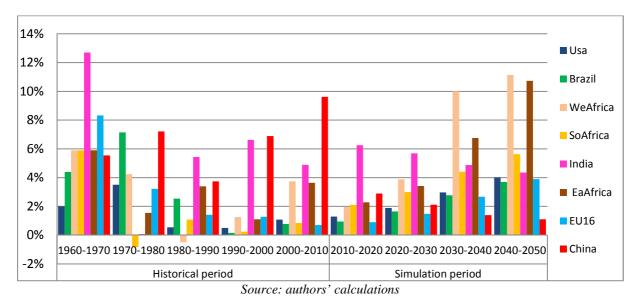
Source: authors' calculation



Scheme 1: Linkages between R&D investments and land-augmenting technical change

Source. aution's elaboration

Fig 8: Historical and projected annual growth rates of real R&D investments (Baseline VINTAGE version RD\_share GDP)



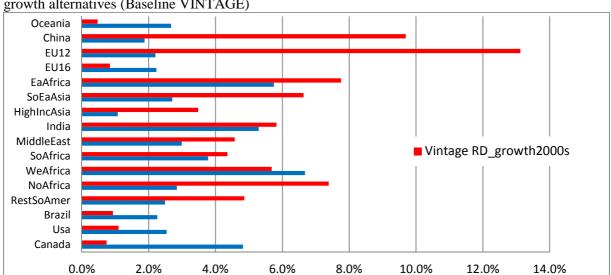
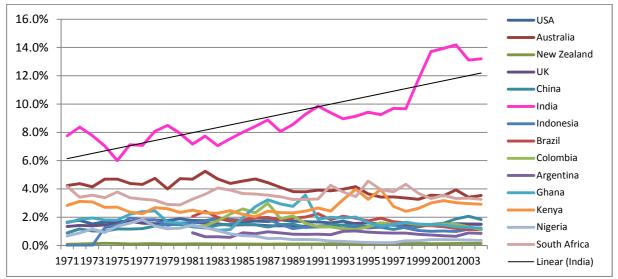


Figure 9: Comparison of annual growth rates of R&D investments over 2010 - 2050 in two R&D growth alternatives (Baseline VINTAGE)

Source: authors' calculations

Fig 10: Long-term evolution of share of agricultural R&D expenditures in Gross Agricultural Output



Note: R&D data compiled from various sources, data for Gross Agricultural Output taken from Fuglie dataset (2012)

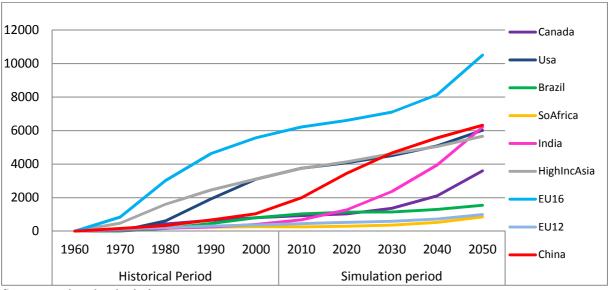
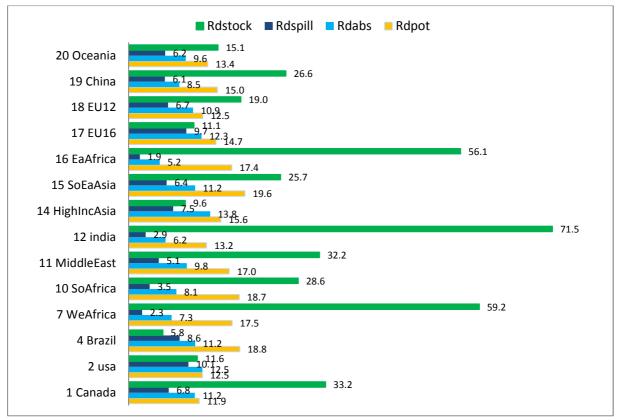


Fig. 11: Evolution of knowledge stocks in Baseline VINTAGE (R&D grows according agricultural VA)

Source: authors' calculations

Fig 12: Comparison of mean growth rates of R&D stocks and R&D spillovers for 2010-2050 (Baseline VINTAGE)



Source: authors' calculations

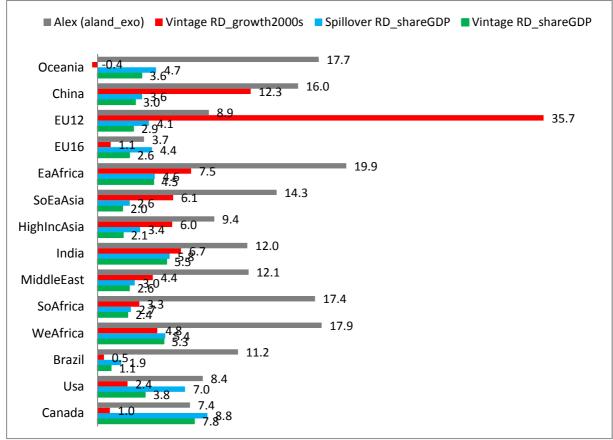
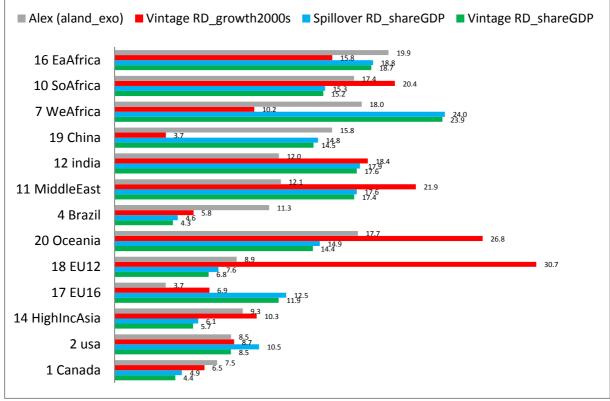


Fig 13: Average growth of aland across baselines (mean 2010-2050)

Source; authors' calculation





Source; authors' calculatio

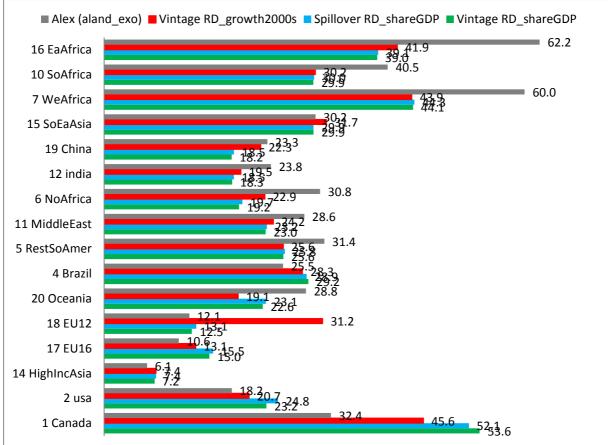
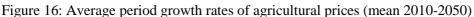
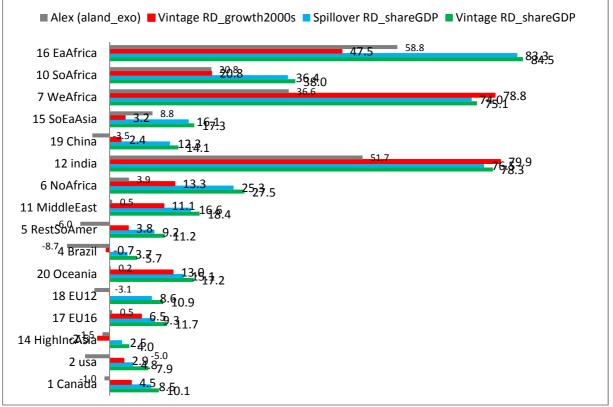


Figure 15: Average period growth rates of agricultural production quantity (mean 2010-2050)

Source; authors' calculation





Source; authors' calculation

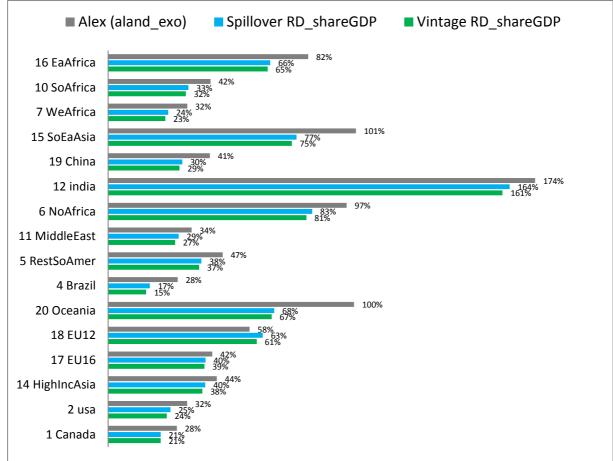


Figure 17: Growth of consumption of calories per capita between 2000 and 2050

Source; authors' calculation

Appendix 1: Production similarity index for regions included in the assessment (base year 2007)

	1		3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21
PsIndex	Canad	2 usa	Centr	Brazil	RestS	NoAfri	WeAfr	REaEu	RWeE	SoAfri	Middl	india	ReSoA	HighIn	SoEaA	EaAfri	EU16	EU12	China	Ocean	Russi
1 Canada	0	0.88	0.72	0.72	0.82	0.58	0.54	0.87	0.84	0.72	0.7	0.72	0.64	0.61	0.62	0.74	0.83	0.87	0.6	0.85	0.7
2 usa	0.88	0	0.89	0.68	0.83	0.73	0.81	0.92	0.79	0.9	0.86	0.78	0.62	0.74	0.69	0.87	0.84	0.89	0.75	0.8	0.8
3 CentrAmer	0.72	0.89	0	0.71	0.8	0.8	0.9	0.88	0.69	0.95	0.87	0.87	0.72	0.91	0.76	0.93	0.88	0.91	0.84	0.66	0.7
4 Brazil	0.72	0.68	0.71	0	0.84	0.34	0.51	0.66	0.68	0.75	0.43	0.7	0.72	0.61	0.68	0.72	0.83	0.81	0.4	0.64	0.4
5 RestSoAmer	0.82	0.83	0.8	0.84	0	0.64	0.73	0.79	0.63	0.83	0.7	0.81	0.74	0.7	0.89	0.84	0.83	0.85	0.61	0.69	0.6
6 NoAfrica	0.58	0.73	0.8	0.34	0.64	0	0.87	0.77	0.44	0.81	0.92	0.75	0.65	0.74	0.65	0.81	0.64	0.67	0.77	0.63	0.7
7 WeAfrica	0.54	0.81	0.9	0.51	0.73	0.87	0	0.79	0.48	0.91	0.9	0.82	0.67	0.78	0.71	0.87	0.74	0.74	0.74	0.56	0.7
8 REaEurope	0.87	0.92	0.88	0.66	0.79	0.77	0.79	0	0.86	0.89	0.9	0.92	0.77	0.77	0.63	0.9	0.9	0.9	0.66	0.89	0.9
9 RWeEurope	0.84	0.79	0.69	0.68	0.63	0.44	0.48	0.86	0	0.66	0.68	0.76	0.59	0.66	0.43	0.65	0.84	0.81	0.55	0.9	0.7
10 SoAfrica	0.72	0.9	0.95	0.75	0.83	0.81	0.91	0.89	0.66	0	0.85	0.86	0.79	0.83	0.75	0.97	0.87	0.86	0.71	0.72	0.78
11 MiddleEast	0.7	0.86	0.87	0.43	0.7	0.92	0.9	0.9	0.68	0.85	0	0.85	0.64	0.8	0.63	0.84	0.78	0.79	0.82	0.74	0.9
12 india	0.72	0.78	0.87	0.7	0.81	0.75	0.82	0.92	0.76	0.86	0.85	0	0.84	0.81	0.69	0.86	0.92	0.88	0.62	0.8	0.8
13 ReSoAsia	0.64	0.62	0.72	0.72	0.74	0.65	0.67	0.77	0.59	0.79	0.64	0.84	0	0.74	0.72	0.85	0.77	0.71	0.45	0.65	0.65
14 HighIncAsia	0.61	0.74	0.91	0.61	0.7	0.74	0.78	0.77	0.66	0.83	0.8	0.81	0.74	0	0.77	0.84	0.81	0.82	0.88	0.58	0.63
15 SoEaAsia	0.62	0.69	0.76	0.68	0.89	0.65	0.71	0.63	0.43	0.75	0.63	0.69	0.72	0.77	0	0.81	0.64	0.68	0.69	0.45	0.46
16 EaAfrica	0.74	0.87	0.93	0.72	0.84	0.81	0.87	0.9	0.65	0.97	0.84	0.86	0.85	0.84	0.81	0	0.83	0.84	0.69	0.71	0.75
17 EU16	0.83	0.84	0.88	0.83	0.83	0.64	0.74	0.9	0.84	0.87	0.78	0.92	0.77	0.81	0.64	0.83	0	0.97	0.66	0.81	0.78
18 EU12	0.87	0.89	0.91	0.81	0.85	0.67	0.74	0.9	0.81	0.86	0.79	0.88	0.71	0.82	0.68	0.84	0.97	0	0.74	0.78	0.7
19 China	0.6	0.75	0.84	0.4	0.61	0.77	0.74	0.66	0.55	0.71	0.82	0.62	0.45	0.88	0.69	0.69	0.66	0.74	0	0.47	0.6
20 Oceania	0.85	0.8	0.66	0.64	0.69	0.63	0.56	0.89	0.9	0.72	0.74	0.8	0.65	0.58	0.45	0.71	0.81	0.78	0.47	0	0.8
21 RussiaStan	0.79	0.85	0.75	0.48	0.64	0.79	0.76	0.91	0.79	0.78	0.9	0.82	0.65	0.63	0.46	0.75	0.78	0.77	0.62	0.89	

Source: authors calculation

EDIN	EduIndex
1 Canada	0.93
2 usa	1
3 CentrAmer	0.63
4 Brazil	0.6
5 RestSoAmer	0.67
6 NoAfrica	0.51
7 WeAfrica	0.42
8 REaEurope	0.84
9 RWeEurope	0.94
10 SoAfrica	0.43
11 MiddleEast	0.58
12 india	0.47
13 ReSoAsia	0.41
14 HighIncAsia	0.88
15 SoEaAsia	0.57
16 EaAfrica	0.3
17 EU16	0.84
18 EU12	0.87
19 China	0.57
20 Oceania	0.72
21 RussiaStan	0.83

Appendix 2: Education Index per each region included in the assessment

Source: authors calculation

Appe	ndix	3:	Yield	gap	index	in	the	base	year	(2007	)

	Canad		CentrA		RestSo	NoAfric	WeAfri	REa Eur	RWeEu	SoAfric	Middle	12	ReSoAs	HighIn	SoEaAs	Ea Afric	17	18	19	Oceani	Russia
Ygindex	а	2 usa	mer	4 Brazil	Amer	а	са	ope	rope	а	East	india	ia	cAsia	ia	а	EU16	EU12	China	а	Stan
1 pdr	0	0.96	0.35	0.32	0.35	1	0.15	0.66	0	0.16	0.03	0.27	0.32	0.19	0.38	0.29	0.65	0.32	0.54	0.7	0
2 wht	0.49	0.48	0.58	0.36	0.48	0.18	0.16	0.54	0.96	0.34	0.3	0.2	0.16	0.52	0.14	0.35	1	0.67	0.5	0.26	0
3 grain	0.46	1	0.27	0.39	0.48	0.3	0.12	0.37	0.56	0.2	0.22	0.12	0.14	0.37	0.34	0.16	0.62	0.44	0.51	0.2	0.
4 oils	0.65	0.94	0.89	0.81	0.73	0.33	0.22	0.53	0.94	0.28	0.72	0.34	1	0.41	0.83	0.12	0.75	0.92	0.62	0.43	0.3
5 sug	0.76	0.83	0.79	1	0.89	0.6	0.15	0.47	1	0.52	0.57	0.8	0.55	0.84	0.64	0.5	0.93	0.68	0.88	0.82	0.4
6 hort	0.57	0.94	0.42	0.61	0.55	0.47	0.35	0.6	0.92	0.34	0.42	0.23	0.25	1	0.47	0.27	0.63	0.58	0.67	0.58	0.4
7 crops	0.1	0	0.83	0.98	0.47	0.79	0.19	0.18	0.53	0.5	0.48	0.21	0.43	0.1	0.46	0.16	1	0.25	0.6	0.18	0.1
8 cattle	0.87	0.85	0.86	0.86	0.84	0.82	0.81	0.84	0.88	0.86	0.77	1	0.66	0.85	0.99	0.9	0.85	0.82	0.86	0.86	0.8
9 pigpou	0.81	0.83	0.81	0.88	0.83	0.85	0.79	0.74	0.81	0.84	0.88	0.96	0.75	0.78	1	0.8	0.81	0.78	0.85	0.86	0.8
10 milk	0.63	0.63	1	0.68	0.6	0.66	0.6	0.74	0.66	0.65	0.74	0.67	0.86	0.64	0.67	0.63	0.64	0.72	0.9	0.6	0.6
20 oagr	0	0.54	0.05	0.63	0.25	0.11	0.22	0.1	0	0.26	0.39	0.18	0.25	0.01	0.18	0.26	0.13	0.21	0.66	1	0.2

Source: authors calculation

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