Prospects for macro-level analysis of agricultural innovation systems to enhance the eco-efficiency of farming in developing countries

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Abstract:

Agricultural innovation is an essential component in the transition to more sustainable and resilient farming systems across the world. Innovations generally emerge from collective intelligence and action, but innovation systems are often poorly understood. This study explores the properties of innovation systems and their contribution to increased eco-efficiency in agriculture. Using aggregate data and econometric methods, the eco-efficiency of 79 countries was computed and a range of factors relating to research, extension, business and policy was examined. Despite data limitations, the analysis produced significant results. Extension plays an important role in improving the eco-efficiency of agriculture, while agricultural research, under current conditions, has a positive effect on eco-efficiency only in the case of less developed economies. These and other results suggest the importance of context-specific interventions rather than a "one size fits all" approach. Overall, the analysis illustrated the potential of a macro-level diagnostic approach for assessing the role of innovation systems for sustainability in agriculture.

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*Keywords***:** Eco-efficiency, data envelopment analysis, agricultural research, extension.

1. Introduction

High-yielding crop varieties, advanced animal breeding, mechanisation, use of agrochemicals and modern management practices have led to large increases in food production and productivity, while slowing the conversion of natural ecosystems to arable land. At the same time, intensive agricultural production puts pressures on the environment in terms of soil degradation, depletion of aquifers, biodiversity loss, nutrient pollution and pesticide contamination (Pretty, 2008; Foley et al., 2011; Tilman et al., 2011). Sustainability and productivity in food systems feature prominently in the UN Sustainable Development Goals. Sustainable agricultural intensification has become a popular concept, but priorities remain controversial (Garnett and Godfray, 2012). Precision farming and modern biotechnologies are advocated as sustainable intensification solutions (World Bank, 2008; Ringler et al., 2014), while other high-level reports suggest a transition in agricultural development from monoculture-based and high external input farming towards diversified and ecologically-intensive systems (IAASTD, 2009; DeSchutter, 2010; UNCTAD, 2013). The UN Food and Agriculture Organization, in its vision for sustainable food and agriculture, sets out clear principles for improving resource use efficiency, agro-ecosystems, livelihoods, resilience and governance (FAO, 2014a), placing strong emphasis on the complementarities among the economic, social and environmental dimensions of sustainability. Nevertheless, trade-offs across these dimensions and over time are not easily overcome. The external costs and benefits of agricultural production often only become apparent in the long run and are rarely accounted for. Innovative solutions are required to maximise synergies that raise agricultural productivity, reduce food loss, improve the ways with which inputs are converted into outputs and conserve scarce resources (OECD, 2011). “The present paradigm of intensive crop production cannot meet the challenges of the new millennium. In order to grow, agriculture must learn to save” (FAO, 2011). This requires a focus on eco-efficiency gains in agriculture.

In addition to increased investments, streamlined policies and enhanced farming and natural resource management practices to enhance eco-efficiency, a successful strategy for sustainable agricultural productivity increases in developing countries involves strengthening agricultural innovation systems (AIS) (World Bank, 2012; FAO, 2014b). An AIS is a network of actors (organisations and individuals) together with supporting institutions (formal and informal) and policies in the agricultural sector that bring existing or new products, processes, and forms of organisation into social and economic use (TAP, 2016). System thinking has a long tradition in agriculture and rural development. Over the last 20 years a widely recognised AIS concept has evolved (Klerkx et al., 2012). Adopting an AIS perspective for agricultural development activities is gaining traction beyond the academic community with international agencies and fora, donors, governments, and research and extension organisations (OECD, 2010; OECD, 2012; World Bank, 2012; FAO, 2014b). Based on a conceptual model proposed by Arnold and Bell (2001) and further refined by Spielman and Birner (2008), four main domains characterise an AIS: (1) Research and education, involving private and public research institutes, universities and vocational training centres; (2) Business and enterprise, involving various value chain actors, agribusiness, producers and consumers; (3) Bridging institutions, involving stakeholder platforms, contractual arrangements and various types of rural advisory services; (4) Enabling environment, involving governance and policies as well as behaviours, mindsets and attitudes. Moving towards sustainable growth in the food and agriculture sectors needs a strong evidence base on what works and what does not (OECD, 2011). However, the complex nature of the AIS concept and innovation processes poses challenges for analytical work in terms of data availability and methodology.

Total Factor Productivity (TFP), the ratio between total outputs and total inputs, has been used to broaden the focus on land or labour productivity and analyse the rate of technical change in agriculture. Growth in TFP is interpreted as increased efficiency of input use (Fuglie and Wang, 2012). However, it rarely accounts for quality improvements in inputs or changes in natural resource stocks. In the context of TFP analysis, considerable attention has been given to the role of research and development (R&D) on agricultural productivity growth (Fan, 2000; Coelli and Rao, 2005; Fuglie, 2012). Mekonnen et al. (2015) complemented R&D related indicators with data on AIS characteristics to examine how they determine levels of technical efficiency in agriculture across developing countries. Using a stochastic production frontier model, the authors found that a range of indicators, such as mobile phone subscriptions or journal publications, positively affects the technical efficiency of agricultural production.

With a focus in the literature on conventional productivity and technical efficiency measures, there is little evidence on what type of innovation system properties can contribute to eco-efficiency. This paper addresses this gap by analysing drivers of eco-efficiency in an innovation system using econometric methods. As Mekonnen et al. (2015) pointed out, the literature on innovation systems in agriculture largely focuses on descriptive methods and avoids the use of formal models (e.g. Hall and Clark, 2010; Klerkx et al. 2010; Schut et al., 2015). The same applies to studies taking an innovation systems perspective towards sustainability issues (e.g. Jacobsson and Bergek, 2011; Chowdhury et al., 2015; Schut et al., 2016). We adopt and extend the more rigorous approach proposed by Mekonnen et al. (2015) to explore the question of how innovation systems can contribute to sustainable agricultural intensification by combining, for the first time, eco-efficiency and innovation systems analysis in a formal model.

The paper starts with a brief overview of the key concepts relevant to the analysis. Subsequently, the data used, coming from a range of sources, the methodological approach and econometric analysis are explained in detail. The Results section presents the efficiency scores by country and shows the determinants of technical and eco-efficiency. The findings are then further scrutinised and discussed in terms of their relevance for policy-making, while also pointing out some limitations of the analysis and the need for more agriculture-specific data.

2. Conceptual frame

We consider eco-efficiency as an essential part of any strategy for sustainable agricultural intensification. It is defined as the ratio between economic value added and a composite indicator of environmental pressures (Kuosmanen and Kortelainen, 2005). With *v* representing value added and P being the pressure function that aggregates environmental pressures into a single score, the eco-efficiency for country *k* is formally expressed as:

$$Eco - efficiency_k = \frac{v_k}{P(p_k)}$$

While eco-efficiency clearly relates to sustainability, improvements in eco-efficiency do not guarantee sustainability (Ehrenfeld, 2004). Pollution levels might still be beyond the carrying capacity of the agro-ecosystem. Nevertheless, their interpretation in relative terms allows for comparison of performance across time and observations. It must also be underlined that measures used for eco-efficiency analysis do not attempt to represent environmental impact of agricultural production in a given country, but rather the environmental pressures associated with it. Following the eco-efficiency definition provided by Kuosmanen and Kortelainen (2005), a country in our study is considered eco-efficient if it is impossible to decrease any environmental pressure without simultaneously increasing another pressure or decreasing the economic value added.

Data Envelopment Analysis (DEA) is widely used for eco-efficiency analysis and has been applied to assess eco-efficiency at the farm level (Picazo-Tadeo et al., 2011; Gomez-Limon et al., 2012). We use DEA in order to obtain eco-efficiency scores for agriculture across 85 low and middle-income countries. Subsequently, we analyse the relationship between innovation system properties and eco-efficiency. While the properties are expected to have a positive effect on technical efficiency, their impact on eco-efficiency is less clear. Therefore this exploratory analysis aims at shedding light on the characteristics of an AIS that can contribute to a transition towards more eco-efficient production, allowing for the identification of specific gaps and the formulation of more targeted research questions. By computing technical efficiency scores to complement the assessment of eco-efficiency, it is then possible to distinguish key differences in what drives either type of efficiency.

More precisely, the overall approach taken in this study can be described as Latent Class Data Envelopment Analysis (LCDEA). We enhance the standard DEA method because countries in our dataset are heterogeneous in terms of technological choice and AIS characteristics. It cannot necessarily be assumed that all Decision Making Units (DMUs) operate under similar technological circumstances and share a single efficiency frontier. For example, Brazil and China tend to use more machinery, capital and fertiliser compared with countries in sub-Saharan Africa, such as Rwanda and Uganda. The use of a latent class model allows us to focus on within class differences by estimating class-specific eco-efficiency and technical efficiency scores. Thereby countries are classified in terms of technology choice rather than geographic location or any other *a priori* criteria unrelated to the analysis. Such arbitrary categorisation has been widely criticised (e.g. Kuosmanen and Kortelainen, 2005; Picazo-Tadeo et al., 2011; Gomez-Limon et al., 2010; Gomez-Limon et al., 2012) because it fails to capture adequately within and between region differences in technology choice and use (Mekonnen et al., 2015). Through the LCDEA approach groups can be created that are more homogeneous in the level and type of technology use. Such classification seems appropriate because production technologies and environmental pressures are closely related. Comparing results among groups and with the pooled data is valuable for identifying relevant policy implications.

3. Data

The availability of comprehensive aggregate data posed a substantial challenge for this type of cross-country analysis. A range of data sources were needed to create a dataset with the necessary information on environmental pressures, agricultural outputs and inputs, as well as

AIS indicators covering 79 low- and middle-income countries and a period ranging from 2004 to 2011. For more recent years insufficient data was available. For inputs, outputs and AIS properties relied on data very similar to those used by Mekonnen et al. (2015). The innovation system characteristics were complemented with additional variables, for instance on research spending in agriculture or foreign aid for agricultural extension. The choice of variables representing AIS characteristics was discussed with subject matter experts and deemed adequate, considering the limited availability of data that is more agriculture-specific or relating to system dynamics. Regarding environmental pressures, we required complete time-series information for eight years, which can be meaningfully used at an aggregate level of analysis. This implies that variables should reflect national pollution levels rather than just average values of point-specific pollution. The analysis focuses on developing countries in Africa (28), Asia (16), Eastern Europe (16) and Latin America (19), where the need for intensification is considerable, while agro-ecosystems are increasingly under threat. Based on the number of countries and the specified time range, with few missing values, we obtained a large dataset of 608 observations for conducting the analysis.

Table 1 gives an overview of the variables used in the eco-efficiency and technical efficiency analyses respectively. Values on total emissions from agriculture and on non-land use and forestry emissions were obtained from the Climate Analysis Indicators Tool (WRI-CAIT, 2014), whereas data on the share of conventional agriculture were taken from FAOSTAT (FAOSTAT, 2016). This variable serves as a proxy for the pressures of intensive high external input production. Environmental contamination by pesticides was measured through the pesticide regulation score, which is part of the Environmental Performance Index (Hsu et al., 2014)[1]. This score quantifies whether countries allow, restrict or ban the 'Dirty Dozen'

[1] The 2014 Environmental Performance Index is a joint project between the Yale Center for Environmental Law & Policy (YCELP) and the Center for International Earth Science Information Network (CIESIN) at Columbia

Persistent Organic Pollutants (POPs) under the Stockholm Convention. Fertiliser use and land under irrigation were included in the eco-efficiency DEA model as proxies for nutrient pollution and water withdrawal by agriculture. They are also part of the technical efficiency analysis, along with labour, land, machinery and annual rainfall variables. The information on productivity enhancing inputs as well as economic value added was available through a dataset compiled for TFP analysis by Fuglie (2012). This dataset (USDA, 2016) is primarily based on annual time series information from FAOSTAT and, in some cases, modified or supplemented with data from other sources (such as national statistical agencies), when they were considered to be more accurate or up-to-date.

Table 1: Summary statistics of variables used in the efficiency analysis.

Efficiency analysis variables	**Mean**	**St. Dev.**	**Min**	**Max**
Output				
Value of agricultural output (1,000 int. dollars)	17,600	57,000	47.2	5,120,000
Eco-efficiency				
Total emissions from agriculture (MtCO2e/ha)	313.13	1,015	0.2	10,304
Total emission from Agriculture, excluding land-use change and forestry (MtCO2e/ha)	275.16	1,027.4	0.21	10,596
Share of conventional agriculture (%)	99	0.7	93	100
Pesticide regulation score (0 to 25)	16.93	7.2	0	24
Both eco-efficiency and technical efficiency				
Fertiliser (tonnes of nutrients)	1,561	6,669	0.001	63,600
Land under irrigation (1,000 ha)	2,882	10,341	0.8	66750
Technical efficiency				
Labour (1,000 people)	14,790	62,934	27	506031
Land (1,000 ha)	11,464	26,363	47	159450
Value of machinery used in agriculture (1,000 int. dollars)	257.7	956.8	0.04	10066.3
Annual rainfall (mm)	1171	837	28	3676
Observations (#)	608			

Table 2 further summarises the information used as determinants of eco-efficiency in the regression analysis. The choice of variables motivated by the AIS concept as specified in key

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reports on the topic (Spielman and Birner, 2008; World Bank, 2012; TAP, 2015). Each variable is attributed to one of the four AIS domains, capturing education and research levels, bridging institutions, business and enterprise development and enabling environment aspects. The variables thus measure the innovation system characteristics of the respective countries. As some variables could capture properties of two domains, we consider them as such, representing them by the overlapping lines in Table 2.

Table 2: Summary statistics of AIS characteristics and their link to the AIS domains.

AIS domains	Explanatory AIS variables	Mean	St. Dev.	Min	Max
Education & research	Quality of the educational system (1=low to 7=high)	3.30	0.68	1.91	5.30
	Primary school enrolment (% gross)	106.00	13.51	51.00	164.50
	Agricultural researchers (FTEs per 100,000 farmers)	912.1	1,007.20	35.00	7520.60
	Agricultural research spending (% of agr. GDP)	0.82	0.89	0.11	7.42
	Foreign aid for agricultural research (% of agr. GDP)	0.013	0.04	0.00	0.37
	Scientific and technical journal articles (#)	1969	7445	1.00	74,019.00
Bridging institutions	University-industry collaboration in R&D (1=minimal to 7=intensive)	3.10	0.64	1.60	4.98
	Foreign aid for extension (% of agr. GDP)	0.02	0.05	0.00	0.45
	Mobile cellular subscriptions (# per 100 people)	62.13	39.30	0.21	189.00
Business & enterprise	Start-up procedures to register a business (#)	9.17	3.22	2.00	18.00
	Time required to start a business (days)	37.0	29.8	2.00	153.00
	Total tax rate (% of commercial profits)	51.45	39.9	14.4	292.40
	Ease of accessing loans (1=low to 7=high)	2.80	0.66	1.38	4.65
	Domestic credit to private sectors (% of GDP)	39.60	29.50	2.70	167.50
Enabling environment	Credit information index (0=low to 8=high)	3.35	2.10	0.00	6.00
	Agricultural policy costs (1=low to 7=high)	3.8	0.57	2.16	5.50
	Legal rights index (0=weak to 12= strong)	4.96	2.18	0.00	10.00
	Foreign aid received (current int. US$ per capita)	52.20	57.40	0.07	672.50
	Gross capital formation (% of GDP)	24.70	7.20	3.03	62.50
	Health expenditures (% of GDP)	6.20	1.81	2.40	12.80

Mekonnen et al. (2015) pointed out that the AIS variables are expected to have a positive influence on the efficiency of agricultural production. For instance, business and enterprise indicators are expected to affect it through their influence on the nature and performance of business and business innovation in the agricultural sector. The quality of institutions and legal systems is assumed to enable innovation in agriculture. Through our study we contend however that all the positive relationships between innovation system characteristics and efficiency postulated by Mekonnen et al. (2015) also apply in the case of eco-efficiency analysis.

Data on the quality of the educational system, on R&D collaborations between university and industry, on the ease of accessing loans, as well as on agricultural policy costs, are available through the Global Competitiveness Report published by the World Economic Forum (WEF, 2012). The variables rank countries on a scale from 1 (low/minimal) to 7 (high/intensive). The Agricultural Science and Technology Indicators (ASTI) database provides information on national agricultural research spending and workforce (ASTI, 2016), while we rely on data collected by the Development Assistance Committee of the Organisation of Economic Cooperation and Development (OECD) for foreign aid statistics related to agricultural research and extension (OECD, 2015). The majority of the figures characterising the properties of a country's innovation system are taken from the World Bank's World Development Indicators (World Bank, 2016a): Rate of primary school enrolment, the number of scientific and journal articles, mobile phone subscriptions, start-up procedures and time to register a business, total tax rate, domestic credit to private sectors, credit information index, legal rights index, foreign aid received, gross capital formation and health expenditures.

4. Methodology

DEA is a non-parametric approach for measuring efficiency of DMUs that uses linear programming techniques to envelop observed input–output vectors for estimating the underlying frontier and efficiency (distance from the frontier). Developing the LCDEA model, we followed two steps to obtain class-specific eco-efficiency and technical efficiency scores. First, we ran a latent class model using technology choice variables to determine class membership. Using estimates of our latent class model, we calculated *a posteriori* probabilities to categorise countries into their respective groups. Second, we performed a DEA to determine class-specific eco-efficiency and technical efficiency scores.

Consider n countries with k combinations of technological choices (such as machinery, labour, irrigation) with many choice possibilities for the above combinations j for a given country in year t to produce output Y. Let the above specific choice combinations be denoted by X_{nkjt}. The latent class model assumes that there are z distinct classes of parameters $\beta = (\beta_{1,} \beta_{2,} \beta_{3,} \dots . \beta_{z)}$ that define countries based on their technological choice. Class membership status of the countries is unknown *a priori* and depends on their technological choice and socio-demographic characteristics.

Classes are not observable and class probabilities are specified by the multinomial logit form:

$$P(z) = \frac{\exp(\theta_{z,} x_{nkt})}{\sum_{z=1}^{Z} \exp(\theta_{z,} x_{nkt})} \quad (1)$$

where X_{nkt} are the socio-economic and technological choice variables that determine class membership. In our setting we used fertiliser use, land under irrigation, pesticide use score, share of conventional agriculture, total emission in CO2 equivalents, total emission excluding land and forestry in CO2 equivalents, gross national income per capita, gross capital formation as a share of GDP, precipitation, arable land and dummy variables for geographic location (Africa, Asia, Eastern Europe, and Latin America and the Caribbean) to determine class membership. After the class membership probabilities had been estimated, each country was assigned to the class for which it had the highest probability. However, in order to assign countries to different classes based on their highest *a posteriori* probability, the number of classes had to be determined. In our case, we apply the Schwarz Bayesian Information Criterion (SBIC)[2].

[2] The latent class model was estimated using the gllamm command in STATA.

After determining the number of classes, we used DEA to estimate class-specific eco-efficiency and technical efficiency scores. We employed DEA and not a stochastic frontier production approach because it allows multiple inputs–outputs relationships without any assumption on the underlying functional relationship linking inputs and outputs (Kuosmanen and Kortelainen, 2005; Picazo-Tadeo et al., 2011). Following Kuosmanen and Kortelainen (2005) and Picazo-Tadeo et al. (2011), we assume that countries produce an output, which is the value of agricultural output (Y) using inputs that may have a detrimental effect on the environment denoted by $D_n = n(n = 1,2,3 \dots \dots N)$. Given our definition of eco-efficiency (EF) as the ratio of economic value added to environmental damage, it is formalised as

$$EF = \frac{Y}{f(D_n)} \quad (2)$$

where $f(.)$ is the damage function that aggregates individual n environmental pressures into a single environmental damage score (Kuosmanen and Kortelainen, 2005). As pointed out by Kuosmanen and Kortelainen (2005) and Picazo-Tadeo et al. (2011), constructing the composite environmental pressure score that aggregates individual environmental pressures is not straightforward, requiring a weighting mechanism that takes into account the relative importance of the different environmental pressures. There are many approaches to calculating weights. These include assigning the same weight to each individual environmental pressure variable or assuming any arbitrary linear combination of the environmental pressure variables:$f(D_n) = \omega_1 d_1 + \omega_2 d_2 \dots \omega_n d_n$, where ω_i is a vector of weights. A natural way of assigning weights in the latter case would be to use Principal Component Analysis (PCA). It transforms a set of environmental pressure variables into a smaller set of uncorrelated principals that represent most of the variation. However, PCA relies on orthogonal transformations of the environmental pressure variables. DEA overcomes the problem of linear combination without requiring an arbitrary combination. It maximises the relative eco-efficiency score of a given DMU compared with the other DMUs in the sample (in our case it maximises the relative eco-efficiency score compared to the class specific scores). Formally, DEA eco-efficiency score of activity *n* can be calculated as

$$\min_{w} EF^{-1} = \sum_{i=1}^{n} \frac{\omega_i D_i}{Y} \tag{3}$$

Subject to

$$\frac{\omega_i D_i}{Y} \geq 1 \tag{4}$$

$$\omega_i \geq 0 \tag{5}$$

The above specification shows that the eco-efficiency score of each country is obtained by taking the inverse of the optimal solution, i.e. the eco-efficiency score measures the level at which the use of environmental pressures can be reduced without reducing output. A higher eco-efficiency score suggests that reducing environmental pressures is more difficult without reducing output. However, DEA takes into account heterogeneities within the observed sample and uses the best performing unit as a benchmark to which other units in the sample are compared. Therefore, the eco-efficiency and technical efficiency scores of countries as obtained from DEA are measured relative to the "best practice" in the sample, which is not necessarily the same as the "best available" technology (Mekonnen et al., 2015).

It is also important to note that the analysis is based on a latent class model, so eco-efficiency and technical efficiency scores of countries are class specific and calculated relative to the best practice in the class to which the sample unit belongs. Under this circumstance, eco-efficiency and technical efficiency scores cannot be directly compared between classes. However, we also estimated results for the pooled dataset, in which efficiency scores are based on a common frontier and are thus comparable across all countries in the dataset.

Once the class-specific eco-efficiency and technical efficiency scores were calculated, we analysed innovation system determinants of efficiency, using a Tobit model specification that takes into account the censored nature of the efficiency scores. Both eco-efficiency and technical efficiency scores are censored at the maximum value of the score, which is one, and at its minimum value, which is zero.

5. Results

In this section, we first explain the efficiency scores computed for each country and then present the determinants of eco-efficiency and technical efficiency.

5.1 Class specific eco-efficiency scores

We provide eco-efficiency scores calculated using the pooled dataset as well as class-specific scores. Based on the SBIC we identified the optimal number of latent classes for estimating efficiency scores, which resulted in a two class model for our specification.

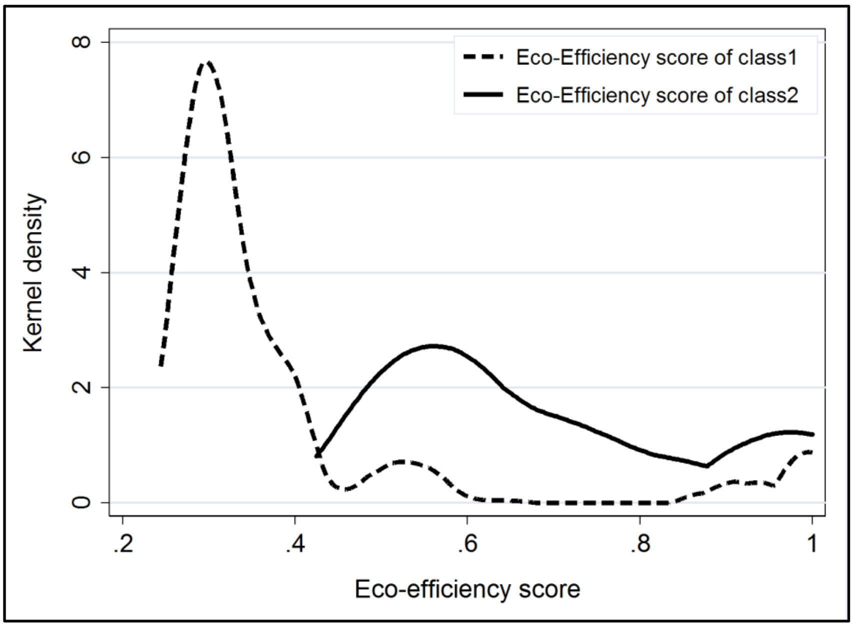

Figure 1: The distribution of class-specific eco-efficiency scores

Figure 1 reports the distribution of eco-efficiency scores for the two classes. The results suggest that countries categorised in class two are more eco-efficient than countries in class one. Table 3 and 4 present the eco-efficiency scores for countries in class one and two for the period spanning 2004 to 2011.

Table 3: Eco-efficiency scores for countries in class one.

Country	2004	2005	2006	2007	2008	2009	2010	2011
Albania	0.50	0.52	0.54	0.56	0.57	0.58	0.57	0.56
Argentina	0.27	0.28	0.28	0.29	0.29	0.29	0.29	0.29
Bangladesh	0.29	0.30	0.30	0.31	0.31	0.31	0.31	0.31
Benin	0.34	0.35	0.35	0.36	0.37	0.37	0.36	0.36
Bolivia	0.31	0.33	0.32	0.33	0.33	0.34	0.32	0.33
Bosnia	0.41	0.42	0.42	0.42	0.43	0.43	0.42	0.41
Botswana	0.38	0.39	0.38	0.39	0.38	0.42	0.38	0.37
Brazil	0.25	0.26	0.26	0.27	0.27	0.27	0.27	0.27
Bulgaria	0.29	0.30	0.30	0.30	0.32	0.32	0.32	0.31
Burkina Faso	0.31	0.33	0.33	0.34	0.34	0.34	0.34	0.33
Cambodia	0.37	0.39	0.37	0.39	0.39	0.40	0.39	0.39
Chad	0.29	0.30	0.31	0.31	0.32	0.32	0.32	0.31
China	0.25	0.26	0.25	0.26	0.26	0.27	0.26	0.26
Colombia	0.28	0.29	0.29	0.30	0.30	0.30	0.29	0.29
Dominican	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Ecuador	0.27	0.28	0.28	0.29	0.29	0.30	0.29	0.29
Egypt	0.28	0.29	0.28	0.29	0.30	0.30	0.29	0.29
Georgia	1.00	1.00	0.92	0.93	0.97	0.94	0.94	0.89
Ghana				0.33	0.33	0.34	0.33	0.33
Guatemala	0.31	0.32	0.33	0.34	0.34	0.34	0.33	0.33
Guyana	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Honduras	0.29	0.30	0.30	0.31	0.32	0.32	0.31	0.31
Hungary	0.29	0.30	0.30	0.31	0.32	0.32	0.31	0.31
India	0.26	0.26	0.26	0.27	0.27	0.27	0.26	0.26
Indonesia	0.24	0.25	0.25	0.26	0.26	0.26	0.25	0.25
Kenya	0.31	0.32	0.32	0.32	0.33	0.33	0.32	0.32
Kyrgyzstan	0.37	0.39	0.49	0.55	0.64	0.55	0.50	0.55
Latvia	0.33	0.34	0.49	0.54	0.52	0.48	0.54	0.48
Lesotho	0.89	0.88	0.93	0.92	0.97	0.96	0.88	0.92
Malawi				0.40	0.40	0.40	0.39	0.39
Malaysia	0.26	0.26	0.27	0.27	0.28	0.28	0.27	0.27
Mauritania	0.32	0.33	0.34	0.35	0.36	0.35	0.35	0.35
Mongolia	0.27	0.28	0.27	0.28	0.29	0.29	0.29	0.29
Morocco	0.31	0.32	0.32	0.32	0.33	0.33	0.32	0.32
Mozambique	0.29	0.29	0.30	0.31	0.31	0.31	0.31	0.31
Nepal	0.30	0.31	0.34	0.35	0.35	0.35	0.34	0.34
Nicaragua	0.39	0.37	0.37	0.31	0.32	0.32	0.31	0.32
Nigeria	0.27	0.28	0.27	0.28	0.29	0.29	0.28	0.28
Panama	0.36	0.37	0.37	0.39	0.38	0.37	0.37	0.36
Paraguay	0.27	0.28	0.28	0.29	0.30	0.30	0.30	0.30
Peru	0.29	0.29	0.29	0.30	0.30	0.30	0.29	0.29
Poland	0.26	0.27	0.27	0.28	0.28	0.29	0.28	0.28
Romania	0.28	0.29	0.29	0.30	0.30	0.31	0.30	0.30
Thailand	0.25	0.26	0.26	0.26	0.27	0.27	0.26	0.26
Tunisia	0.37	0.38	0.38	0.40	0.40	0.40	0.39	0.40
Uganda	0.52	0.54	0.54	0.54	0.50	0.51	0.50	0.50
Tanzania	0.30	0.29	0.30	0.30	0.31	0.31	0.30	0.30
Uruguay	0.40	0.35	0.38	0.39	0.39	0.39	0.40	0.39
Class 1 average	0.37	0.38	0.38	0.39	0.40	0.40	0.39	0.39

Table 4: Eco-efficiency score for countries in class two.

Country	2004	2005	2006	2007	2008	2009	2010	2011
Algeria	0.50	0.59	0.58	0.59	0.59	0.49	0.49	0.50
Armenia	0.81	0.85	0.84	0.86	0.86	0.63	0.63	0.63
Azerbaijan	0.60	0.75	0.76	0.76	0.76	0.70	0.70	0.72
Burundi	1.00	1.00	1.00	1.00	1.00	0.81	0.80	0.81
Cameron	0.48	0.57	0.58	0.58	0.58	0.51	0.52	0.51
Cape Verde						1.00	1.00	1.00
Chile	0.55	0.64	0.64	0.65	0.66	0.52	0.52	0.52
Costa Rica	1.00	1.00	1.00	1.00	1.00	0.70	0.71	0.71
Croatia	0.63	0.69	0.69	0.72	0.73	0.53	0.54	0.54
El Salvador	0.73	0.80	0.80	0.82	0.82	0.60	0.61	0.61
Ethiopia	0.63	0.92	0.79	0.78	0.77	0.75	0.75	0.79
Gambia	0.76	0.78	0.76	0.77	0.79	0.55	0.55	0.54
Jordan	0.61	0.67	0.68	0.69	0.70	0.52	0.52	0.52
Kazakhstan	0.47	0.56	0.56	0.57	0.56	0.49	0.48	0.50
Lebanon						0.53	0.53	0.53
Lithuania	0.64	0.72	0.69	0.71	0.72	0.55	0.55	0.55
Madagascar	0.61	0.68	0.67	0.67	0.68	0.56	0.56	0.56
Mali	0.74	0.93	0.94	0.94	0.94	0.91	0.90	0.93
Mauritius	0.90	0.92	0.87	0.93	0.95	0.59	0.59	0.60
Mexico	0.44	0.55	0.56	0.56	0.56	0.50	0.50	0.52
Namibia	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Pakistan	0.52	0.66	0.67	0.66	0.65	0.59	0.59	0.62
Philippines	0.53	0.64	0.65	0.66	0.67	0.56	0.56	0.57
Russia	0.50	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Rwanda						1.00	1.00	1.00
Senegal			0.99	0.98	1.00	0.99	0.99	1.00
South Africa	0.44	0.54	0.54	0.54	0.55	0.48	0.48	0.49
Turkey	0.42	0.52	0.52	0.52	0.53	0.44	0.44	
Venezuela	0.44	0.53	0.53	0.54	0.54	0.47	0.47	0.48
Vietnam	0.52	0.62	0.63	0.63	0.63	0.52	0.52	0.54
Zambia	0.49	0.57	0.58	0.57	0.57	0.52	0.52	0.52
Class 2 average	0.63	0.73	0.73	0.74	0.74	0.65	0.65	0.66

In terms of the composition of countries, a clear grouping was established. For example, emerging economies such as China, India, Brazil and Thailand are members of class one. The average eco-efficiency scores of countries in this class are generally low and remained constant between 2004 and 2011. While the trend is similar for class two countries, the average eco-efficiency scores remain at a higher level. Despite differences, the results suggest for both classes that most countries can reduce environmental pressures without reducing the value of agricultural output. On average, the most eco-efficient countries in class one include Dominican Republic, Georgia and Guyana, whereas the least eco-efficient countries of class one include Brazil, China, India, Indonesia and Thailand. In class two the most eco-efficient countries include Burundi, Cape Verde, Costa Rica, Namibia and Rwanda, whereas countries such as Kazakhstan, Lebanon, Mexico, South Africa, Turkey and Venezuela are the least eco-efficient countries in class two.

5.2 Determinants of eco-efficiency

Table 5 presents the results of our analysis, using a Tobit regression model to evaluate innovation system determinants of eco-efficiency. The first column shows the coefficients from the regression based on the pooled dataset. Columns two and three contain the coefficients for the variables according to country classes.

The results in Table 5 show diverging effects of public spending on agricultural research, researcher numbers and foreign aid for agricultural research. While the coefficients are significant and positive for class two countries, they are mostly significant, but negative, for those countries in class one. At the same time, foreign aid for agricultural extension has a positive effect for both classes, albeit only being significant for class one. This is in line with the sign of the variable representing overall foreign aid. The positive relationship between foreign aid and eco-efficiency may be a result of conditions in place for the use of such funds. For example, many donors provide loans or grants under terms that stipulate investments in sustainable rural development. The coefficient for scientific publishing, as a bridge between research and other domains, is positive and significant, although its magnitude is very small. However, a clearer positive and significant relationship with eco-efficiency across classes is apparent for the quality of the educational system. The same is true for health expenditures and ease of access to loans. The results further indicate that university-industry collaboration in R&D, the total tax rate, domestic credit to private sectors, gross capital formation, legal rights index, primary school enrolment, and the numbers of start-up procedures to register a business have a statistically significant negative effect on eco-efficiency for one or the other class.

Table 5: Determinants of eco-efficiency.

	Pooled	Class 1	Class 2
	Coef.	**Coef.**	**Coef.**
Quality of the educational system (1=low to 7=high)	0.022*	0.041**	0.039**
	(0.013)	(0.020)	(0.019)
Primary school enrolment (% gross)	-0.002***	-0.001*	-0.002***
	(0.001)	(0.001)	(0.001)
Agricultural researchers (FTEs per 100,000 farmers)	-0.000005	-0.00003***	0.00004**
	(0.00001)	(0.00001)	(0.0001)
Agricultural research spending (% of agr. GDP)	-0.010	-0.038***	0.061***
	(0.013)	(0.012)	(0.016)
Foreign aid for agricultural research (% of agr. GDP)	0.432	-0.188	0.664**
	(0.302)	(0.362)	(0.267)
Scientific and technical journal articles (#)	-0.0001	0.00005***	0.00002***
	(0.0006)	(0.0001)	(0.0001)
University-industry collaboration in R&D	-0.024	-0.106***	-0.020
(1=minimal to 7=intensive)	(0.025)	(0.023)	(0.032)
Foreign aid for extension (% of agr. GDP)	0.828***	0.979***	0.154*
	(0.254)	(0.224)	(0.335)
Mobile cellular subscriptions (# per 100 people)	0.0002	0.001	-0.001***
	(0.0004)	(0.0003)	(0.0002)
Start-up procedures to register a business (#)	-0.013***	-0.014***	-0.009*
	(0.004)	(0.004)	(0.005)
Time required to start a business (days)	-0.0002	-0.0003	0.001
	(0.0003)	(0.0005)	(0.001)
Total tax rate (% of commercial profits)	-0.000	-0.001***	0.0001
	(0.000)	(0.001)	(0.0003)
Ease of accessing loans (1=low to 7=high)	0.009	0.024	0.049**
	(0.022)	(0.020)	(0.024)
Domestic credit to private sectors (% of GDP)	-0.0001	-0.0003	-0.003***
	(0.0002)	(0.0005)	(0.001)
Credit information index (0=low to 8=high)	-0.014**	-0.005	0.011*
	(0.006)	(0.006)	(0.007)
Agricultural policy costs (1=low to 7=high)	0.045**	0.017	0.016
	(0.019)	(0.020)	(0.021)
Legal rights index (0=weak to 12= strong)	-0.023***	-0.008*	-0.006
	(0.005)	(0.005)	(0.007)
Foreign aid received (current int. US$ per capita)	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)
Gross capital formation (% of GDP)	-0.003**	-0.004***	-0.001
	(0.001)	(0.001)	(0.002)
Health expenditure (% of GDP)	0.019***	0.010*	0.048***
	(0.006)	(0.006)	(0.008)
Year 2004	-0.027	-0.016	-0.115**
	(0.048)	(0.043)	(0.054)
Year 2005	0.031	0.005	0.016
	(0.046)	(0.041)	(0.051)
Year 2006	0.014	-0.013	0.029
	(0.044)	(0.039)	(0.049)
Year 2007	0.051	0.004	0.100**
	(0.038)	(0.034)	(0.041)
Year 2008	0.017	-0.004	0.047
	(0.041)	(0.037)	(0.045)
Year 2009	-0.001	0.007	-0.025
	(0.037)	(0.033)	(0.039)
Year 2010	-0.004	-0.001	-0.009
	(0.036)	(0.032)	(0.038)
Observations	608	378	230

The effect of university-industry collaboration in R&D suggests that currently innovations resulting from such collaborations are not geared towards eco-efficiency. As reported in

Table 6, university-industry collaboration in R&D has a significant positive effect on technical efficiency scores of countries in class one. Future collaboration in R&D, in the area of climate smart agriculture for example, can therefore support improving the eco-efficiency of countries, while maintaining levels of technical efficiency. Higher domestic credit to the private sector (as % of GDP) is also associated with lower eco-efficiency scores. This may be because credit allows producers to use more external inputs, such as chemical fertiliser and pesticides, which put pressure on the environment.

5.3 Determinants of technical efficiency

In this section we present the determinants of technical efficiency. As explained in the introduction, the focus of this paper is not on technical efficiency. Nonetheless, we report technical efficiency regression results to explore differences in the magnitude and direction of expected effects of AIS variables on technical and eco-efficiency scores. Certain variables that may improve technical efficiency may not necessarily improve eco-efficiency. The average technical efficiency score lies at 0.93 for countries in both class one and two. This indicates that high technical efficiency scores are not necessarily accompanied by higher eco-efficiency scores. Understanding the expected effects of AIS variables on technical and eco-efficiency respectively will be useful when considering policy objectives.[3] Some striking differences in terms of eco-efficiency trends found among country classes also appear in the case of technical efficiency, e.g. related to agricultural research spending. Overall, these are less pronounced though. Regarding the respective determinants of technical and eco-efficiency, similarities and differences emerge.

[3] Class-specific technical efficiency scores are not reported here due to space limitation but are available from authors upon request.

Table 6: Determinants of technical efficiency

	Pooled	Class 1	Class 2
	Coef.	**Coef.**	**Coef.**
Quality of the educational system (1=low to 7=high)	0.01355**	0.02424***	-0.01224
	(0.007)	(0.007)	(0.010)
Primary school enrolment (% gross)	-0.00042*	0.00026	-0.00101**
	(0.000)	(0.000)	(0.000)
Agricultural researchers (FTEs per 100,000 farmers)	0.00000	0.00001	-0.00004**
	(0.000)	(0.000)	(0.000)
Agricultural research spending (% of agr. GDP)	-0.00006	-0.00008*	0.00026**
	(0.000)	(0.000)	(0.000)
Foreign aid for agricultural research (% of agr. GDP)	0.07366***	0.05316***	0.12440***
	(0.008)	(0.009)	(0.017)
Scientific and technical journal articles (#)	-0.00000**	-0.00000***	0.00001**
	(0.000)	(0.000)	(0.000)
University-industry collaboration in R&D	0.02271***	-0.00627	0.03454***
(1=minimal to 7=intensive)	(0.008)	(0.011)	(0.012)
Foreign aid for extension (% of agr. GDP)	-0.00070	0.00069	-0.00109
	(0.001)	(0.001)	(0.001)
Mobile cellular subscriptions (# per 100 people)	0.00035***	0.00024*	0.00036
	(0.000)	(0.000)	(0.000)
Start-up procedures to register a business (#)	0.00091	-0.00231	0.00315
	(0.001)	(0.001)	(0.002)
Time required to start a business (days)	-0.00053***	-0.00033*	-0.00081***
	(0.000)	(0.000)	(0.000)
Total tax rate (% of commercial profits)	0.00018*	0.00038	0.00015
	(0.000)	(0.000)	(0.000)
Ease of accessing loans (1=low to 7=high)	0.01592**	0.03345***	-0.00040
	(0.007)	(0.008)	(0.010)
Domestic credit to private sectors (% of GDP)	0.00008	-0.00009	-0.00027
	(0.000)	(0.000)	(0.000)
Credit information index (0=low to 8=high)	-0.00110	0.00288	-0.00545*
	(0.002)	(0.002)	(0.003)
Agricultural policy costs (1=low to 7=high)	-0.01263**	-0.01174	-0.00290
	(0.006)	(0.008)	(0.009)
Legal rights index (0=weak to 12= strong)	-0.00549***	0.00037	-0.01118***
	(0.002)	(0.002)	(0.003)
Foreign aid received (current int. US$ per capita)	0.00021***	0.00042***	0.00005
	(0.000)	(0.000)	(0.000)
Gross capital formation (% of GDP)	-0.00063	-0.00012	-0.00101
	(0.000)	(0.001)	(0.001)
Health expenditure (% of GDP)	0.00918***	0.01058***	0.00351
	(0.002)	(0.003)	(0.003)
Year 2004	0.04148***	0.09016***	-0.02143
	(0.016)	(0.019)	(0.023)
Year 2005	0.04229***	0.08947***	-0.01390
	(0.015)	(0.018)	(0.023)
Year 2006	0.04167***	0.07962***	-0.00869
	(0.014)	(0.016)	(0.022)
Year 2007	0.03835***	0.06627***	0.00422
	(0.012)	(0.014)	(0.018)
Year 2008	0.04347***	0.09294***	-0.00884
	(0.014)	(0.016)	(0.020)
Year 2009	-0.00567	0.00084	-0.01526
	(0.012)	(0.013)	(0.017)
Year 2010	-0.00244	-0.00239	-0.00004
	(0.012)	(0.013)	(0.016)
Observations	608	378	230

The results in

Table 6 demonstrate that the quality of the educational system, agricultural research spending, ease of accessing loans, health expenditures as well as foreign aid similarly affect eco-efficiency and technical efficiency. While the variable representing foreign aid dedicated to agricultural research has a highly significant positive effect across both classes, as well as for the pooled dataset when it comes to technical efficiency, the same only applies to countries in class two in the case of eco-efficiency. Unlike for eco-efficiency, foreign aid for extension appears to be of little relevance for technical efficiency. However, university-industry collaborations and mobile phone subscriptions influence technical efficiency positively, but not eco-efficiency.

6. Discussion and conclusions

To date cross-country studies on R&D and AIS have focused on investigating effects on agricultural productivity and technical efficiency. However, little evidence exists on which innovation system properties can support a country's process of sustainable intensification through enhancing eco-efficiency. In the light of the Sustainable Development Goals and the multiple challenges of hunger eradication, poverty reduction, better nutrition and healthier ecosystems, metrics for better understanding policy-relevant issues related to agriculture and the environment need to be explored more widely and deeply. Eco-efficiency can capture potential trade-offs just like win-win situations. It not only takes into account relations between the economic and environmental dimensions, but also the risk of shifting environmental impacts from one area to another. This safeguards against reaching potentially false conclusions when using single metrics, such as carbon footprint or pesticide contamination scores (Uhlman and Saling, 2010). Neither could a composite sustainable agriculture index capture trade-offs.

Eco-efficiency analysis can offer clues on management and decision-making parameters, especially by identifying drivers in a given context, as shown in this study.. Research, extension, business and policy-making are key factors in the intensification and commercialisation of farming systems around the world and their role needs to be better understood. Contrary to the great majority of AIS studies, analysing case-specific innovation processes (Klerkx et al, 2010; Schut et al., 2016), this study uses aggregate data and econometric methods to explore the extent to which innovation system properties relate to eco-efficiency. Data availability poses a challenge though and little evidence from the literature exists for corroborating results found here. Therefore, at this stage, our enquiry remains exploratory rather than allowing for reliable predictions of what system properties determine eco-efficiency in agriculture.

Besides limited availability of time-series data on environmental pressures, the representation of AIS properties constitutes an important constraint in the present analysis. Due to a lack of more specific data at such an aggregate level of analysis on aspects related to e.g. quality of agricultural education and training, public spending on extension services, responsiveness of research to needs of producers or costs of certification procedures in agriculture, many of the variables in the analysis are very broad and rather serve as proxies. With efforts to collect more detailed data for the sector through the Enabling the Business of Agriculture indicators (World Bank, 2016b), the precision in capturing some important elements of a country's AIS will improve, in particular with regard to the business and enterprise domain. However, there is a need to fill data gaps related to research, education and extension, in particular with regard to depicting system qualities. The ASTI database records numbers of researchers and public spending on research in agriculture, but falls short of providing any indicators on the relevance and demand-orientation of agricultural research (IFPRI, 2015). A lack of structured country data is particularly apparent for extension and other institutional arrangements that fulfil the bridging function between education and research actors and value chains actors.

Despite limitations arising from the nature of the data used, the paper produced some significant results. On the whole, eco-efficiency scores among the countries considered in this study are low, while technical efficiency scores are generally high. This suggests that eco-efficiency could be improved for many countries under current conditions. Through the right organisational, institutional, social and financial combinations, existing innovations can be brought into greater use. The AIS indicators explored in this study represent potential parameters to boost innovation processes in support of eco-efficiency. Involving key national and international stakeholders and mainstreaming eco-efficiency criteria within existing development strategies will accelerate the transformation towards more sustainable and resilient rural societies.

While several indicators introduced in the study of Mekonnen et al. (2015) seem not to apply to eco-efficiency, the results for a number of factors, such as the quality of the educational system, agricultural research spending, foreign aid, ease of accessing loans, bureaucratic procedures (either number of steps or time required to start a business) and health expenditures, are consistent for both efficiency types. Reducing bureaucracy in registering innovative business models could, for example, contribute to improving technical efficiency as well as eco-efficiency. However, it transpired that particular AIS properties, such as collaboration between universities and industry in R&D, had a positive effect on technical efficiency only. Possibilities to adjust modalities of collaboration might need to be considered in such instances.

This study underscores that cross-country comparison of eco-efficiency needs to take into account variation among countries. With the aim of providing consistent estimates of eco-efficiency scores, the study employed a latent-class rather than a conventional DEA model.

Important heterogeneities in terms of technological choice and AIS characteristics were thus considered when estimating class-specific eco-efficiency scores. Major emerging economies, including China, India and Brazil, tend to operate at a different technological frontier than developing country economies, such as Rwanda, Uganda and Ethiopia. With exceptions, most emerging economies were attributed to class one, while class two predominantly covers developing country economies. Similarities and differences among classes in terms of the direction and magnitude of the drivers of eco-efficiency are of interest. High quality of education, scientific output, health expenditures and overall foreign aid as well as foreign aid for extension more specifically increase levels of eco-efficiency regardless of class allocation and thus the technological frontier at which countries operate. However, foreign aid for agricultural research, just as for public research spending and researcher numbers, appears to only enhance the eco-efficiency of those countries in class two. These countries could benefit more from investments in research, while countries in class one could boost their eco-efficiency by focusing on extension. In general, the results suggests the need for context-specific interventions instead of a “*one size fits all* “approach.

While this article illustrates the potential of a macro-level diagnostic approach to assessing the role of innovation systems for sustainability in agriculture, it also demonstrates that care is needed when interpreting results. The evidence generated by this type of analysis can provide potential pointers to policy and investment gaps and opportunities, but inferences should be corroborated with concrete case study data in order to draw sound conclusions.

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