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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11 in agriculture. Using aggregate data and econometric methods, the eco-efficiency of 79

12 countries was computed and a range of factors relating to research, extension, business and

13 policy was examined. Despite data limitations, the analysis produced significant results.

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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.

48   In addition to increased investments, streamlined policies and enhanced farming and natural

49   resource management practices to enhance eco-efficiency, a successful strategy for sustainable

50   agricultural productivity increases in developing countries involves strengthening agricultural

51   innovation systems (AIS) (World Bank, 2012; FAO, 2014b). An AIS is a network of actors

52   (organisations and individuals) together with supporting institutions (formal and informal) and

53   policies in the agricultural sector that bring existing or new products, processes, and forms of

54   organisation into social and economic use (TAP, 2016). System thinking has a long tradition

55   in agriculture and rural development. Over the last 20 years a widely recognised AIS concept

56   has evolved (Klerkx et al., 2012). Adopting an AIS perspective for agricultural development

57   activities is gaining traction beyond the academic community with international agencies and

58   fora, donors, governments, and research and extension organisations (OECD, 2010; OECD,

59   2012; World Bank, 2012; FAO, 2014b). Based on a conceptual model proposed by Arnold and

60   Bell (2001) and further refined by Spielman and Birner (2008), four main domains characterise

61   an AIS: (1) Research and education, involving private and public research institutes,

62   universities and vocational training centres; (2) Business and enterprise, involving various

63   value chain actors, agribusiness, producers and consumers; (3) Bridging institutions, involving

64   stakeholder platforms, contractual arrangements and various types of rural advisory services;

65   (4) Enabling environment, involving governance and policies as well as behaviours, mindsets

66   and attitudes. Moving towards sustainable growth in the food and agriculture sectors needs a

67   strong evidence base on what works and what does not (OECD, 2011). However, the complex

68   nature of the AIS concept and innovation processes poses challenges for analytical work in

69   terms of data availability and methodology.

70   Total Factor Productivity (TFP), the ratio between total outputs and total inputs, has been used

71   to broaden the focus on land or labour productivity and analyse the rate of technical change in

72   agriculture. Growth in TFP is interpreted as increased efficiency of input use (Fuglie and Wang,

73   2012). However, it rarely accounts for quality improvements in inputs or changes in natural

74   resource stocks. In the context of TFP analysis, considerable attention has been given to the

75   role of research and development (R&D) on agricultural productivity growth (Fan, 2000; Coelli

76   and Rao, 2005; Fuglie, 2012). Mekonnen et al. (2015) complemented R&D related indicators

77   with data on AIS characteristics to examine how they determine levels of technical efficiency

78   in agriculture across developing countries. Using a stochastic production frontier model, the

79   authors found that a range of indicators, such as mobile phone subscriptions or journal

80   publications, positively affects the technical efficiency of agricultural production.

81   With a focus in the literature on conventional productivity and technical efficiency measures,

82   there is little evidence on what type of innovation system properties can contribute to eco-

83   efficiency. This paper addresses this gap by analysing drivers of eco-efficiency in an innovation

84   system using econometric methods. As Mekonnen et al. (2015) pointed out, the literature on

85   innovation systems in agriculture largely focuses on descriptive methods and avoids the use of

86   formal models (e.g. Hall and Clark, 2010; Klerkx et al. 2010; Schut et al., 2015). The same

87   applies to studies taking an innovation systems perspective towards sustainability issues (e.g.

88   Jacobsson and Bergek, 2011; Chowdhury et al., 2015; Schut et al., 2016). We adopt and extend

89   the more rigorous approach proposed by Mekonnen et al. (2015) to explore the question of

90   how innovation systems can contribute to sustainable agricultural intensification by combining,

91   for the first time, eco-efficiency and innovation systems analysis in a formal model.

92   The paper starts with a brief overview of the key concepts relevant to the analysis.

93   Subsequently, the data used, coming from a range of sources, the methodological approach and

94   econometric analysis are explained in detail. The Results section presents the efficiency scores

95   by country and shows the determinants of technical and eco-efficiency. The findings are then

96   further scrutinised and discussed in terms of their relevance for policy-making, while also

97   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

122   to a transition towards more eco-efficient production, allowing for the identification of specific

123   gaps and the formulation of more targeted research questions. By computing technical

124   efficiency scores to complement the assessment of eco-efficiency, it is then possible to

125   distinguish key differences in what drives either type of efficiency.

126   More precisely, the overall approach taken in this study can be described as Latent Class Data

127   Envelopment Analysis (LCDEA). We enhance the standard DEA method because countries in

128   our dataset are heterogeneous in terms of technological choice and AIS characteristics. It

129   cannot necessarily be assumed that all Decision Making Units (DMUs) operate under similar

130   technological circumstances and share a single efficiency frontier. For example, Brazil and

131   China tend to use more machinery, capital and fertiliser compared with countries in sub-

132   Saharan Africa, such as Rwanda and Uganda. The use of a latent class model allows us to focus

133   on within class differences by estimating class-specific eco-efficiency and technical efficiency

134   scores. Thereby countries are classified in terms of technology choice rather than geographic

135   location or any other *a priori* criteria unrelated to the analysis. Such arbitrary categorisation

136   has been widely criticised (e.g. Kuosmanen and Kortelainen, 2005; Picazo-Tadeo et al., 2011;

137   Gomez-Limon et al., 2010; Gomez-Limon et al., 2012) because it fails to capture adequately

138   within and between region differences in technology choice and use (Mekonnen et al., 2015).

139   Through the LCDEA approach groups can be created that are more homogeneous in the level

140   and type of technology use. Such classification seems appropriate because production

141   technologies and environmental pressures are closely related. Comparing results among groups

142   and with the pooled data is valuable for identifying relevant policy implications.

143   **3. Data**

144   The availability of comprehensive aggregate data posed a substantial challenge for this type of

145   cross-country analysis. A range of data sources were needed to create a dataset with the

146   necessary information on environmental pressures, agricultural outputs and inputs, as well as

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147 AIS indicators covering 79 low- and middle-income countries and a period ranging from 2004

148 to 2011. For more recent years insufficient data was available. For inputs, outputs and AIS

149 properties relied on data very similar to those used by Mekonnen et al. (2015). The innovation

150 system characteristics were complemented with additional variables, for instance on research

151 spending in agriculture or foreign aid for agricultural extension. The choice of variables

152 representing AIS characteristics was discussed with subject matter experts and deemed

153 adequate, considering the limited availability of data that is more agriculture-specific or

154 relating to system dynamics. Regarding environmental pressures, we required complete time-

155 series information for eight years, which can be meaningfully used at an aggregate level of

156 analysis. This implies that variables should reflect national pollution levels rather than just

157 average values of point-specific pollution. The analysis focuses on developing countries in

158 Africa (28), Asia (16), Eastern Europe (16) and Latin America (19), where the need for

159 intensification is considerable, while agro-ecosystems are increasingly under threat. Based on

160 the number of countries and the specified time range, with few missing values, we obtained a

161 large dataset of 608 observations for conducting the analysis.

162 Table 1 gives an overview of the variables used in the eco-efficiency and technical efficiency

163 analyses respectively. Values on total emissions from agriculture and on non-land use and

164 forestry emissions were obtained from the Climate Analysis Indicators Tool (WRI-CAIT,

165 2014), whereas data on the share of conventional agriculture were taken from FAOSTAT

166 (FAOSTAT, 2016). This variable serves as a proxy for the pressures of intensive high external

167 input production. Environmental contamination by pesticides was measured through the

168 pesticide regulation score, which is part of the Environmental Performance Index (Hsu et al.,

169 2014)[1]. This score quantifies whether countries allow, restrict or ban the 'Dirty Dozen'

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[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

170 Persistent Organic Pollutants (POPs) under the Stockholm Convention. Fertiliser use and land

171 under irrigation were included in the eco-efficiency DEA model as proxies for nutrient

172 pollution and water withdrawal by agriculture. They are also part of the technical efficiency

173 analysis, along with labour, land, machinery and annual rainfall variables. The information on

174 productivity enhancing inputs as well as economic value added was available through a dataset

175 compiled for TFP analysis by Fuglie (2012). This dataset (USDA, 2016) is primarily based on

176 annual time series information from FAOSTAT and, in some cases, modified or supplemented

177 with data from other sources (such as national statistical agencies), when they were considered

178 to be more accurate or up-to-date.

179 *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			

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181 Table 2 further summarises the information used as determinants of eco-efficiency in the

182 regression analysis. The choice of variables motivated by the AIS concept as specified in key

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

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194   business and business innovation in the agricultural sector. The quality of institutions and legal

195   systems is assumed to enable innovation in agriculture. Through our study we contend however

196   that all the positive relationships between innovation system characteristics and efficiency

197   postulated by Mekonnen et al. (2015) also apply in the case of eco-efficiency analysis.

198   Data on the quality of the educational system, on R&D collaborations between university and

199   industry, on the ease of accessing loans, as well as on agricultural policy costs, are available

200   through the Global Competitiveness Report published by the World Economic Forum (WEF,

201   2012). The variables rank countries on a scale from 1 (low/minimal) to 7 (high/intensive). The

202   Agricultural Science and Technology Indicators (ASTI) database provides information on

203   national agricultural research spending and workforce (ASTI, 2016), while we rely on data

204   collected by the Development Assistance Committee of the Organisation of Economic

205   Cooperation and Development (OECD) for foreign aid statistics related to agricultural research

206   and extension (OECD, 2015). The majority of the figures characterising the properties of a

207   country's innovation system are taken from the World Bank's World Development Indicators

208   (World Bank, 2016a): Rate of primary school enrolment, the number of scientific and journal

209   articles, mobile phone subscriptions, start-up procedures and time to register a business, total

210   tax rate, domestic credit to private sectors, credit information index, legal rights index, foreign

211   aid received, gross capital formation and health expenditures.

212   **4. Methodology**

213
214   DEA is a non-parametric approach for measuring efficiency of DMUs that uses linear

215   programming techniques to envelop observed input–output vectors for estimating the

216   underlying frontier and efficiency (distance from the frontier). Developing the LCDEA model,

217   we followed two steps to obtain class-specific eco-efficiency and technical efficiency scores.

218   First, we ran a latent class model using technology choice variables to determine class

219   membership. Using estimates of our latent class model, we calculated *a posteriori* probabilities

220   to categorise countries into their respective groups. Second, we performed a DEA to determine

221   class-specific eco-efficiency and technical efficiency scores.

222   Consider n countries with k combinations of technological choices (such as machinery, labour,

223   irrigation) with many choice possibilities for the above combinations j for a given country in

224   year t to produce output Y. Let the above specific choice combinations be denoted by X_{nkjt}.

225   The latent class model assumes that there are z distinct classes of parameters $\beta =$

226    $(\beta_1, \beta_2, \beta_3, \dots. \beta_{z)}$ that define countries based on their technological choice. Class membership

227   status of the countries is unknown *a priori* and depends on their technological choice and socio-

228   demographic characteristics.

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

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

230
231   where X_{nkt} are the socio-economic and technological choice variables that determine class

232   membership. In our setting we used fertiliser use, land under irrigation, pesticide use score,

233   share of conventional agriculture, total emission in CO2 equivalents, total emission excluding

234   land and forestry in CO2 equivalents, gross national income per capita, gross capital formation

235   as a share of GDP, precipitation, arable land and dummy variables for geographic location

236   (Africa, Asia, Eastern Europe, and Latin America and the Caribbean) to determine class

237   membership. After the class membership probabilities had been estimated, each country was

238   assigned to the class for which it had the highest probability. However, in order to assign

239   countries to different classes based on their highest *a posteriori* probability, the number of

240   classes had to be determined. In our case, we apply the Schwarz Bayesian Information Criterion

241   (SBIC)[2].

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

242 After determining the number of classes, we used DEA to estimate class-specific eco-efficiency

243 and technical efficiency scores. We employed DEA and not a stochastic frontier production

244 approach because it allows multiple inputs–outputs relationships without any assumption on

245 the underlying functional relationship linking inputs and outputs (Kuosmanen and Kortelainen,

246 2005; Picazo-Tadeo et al., 2011). Following Kuosmanen and Kortelainen (2005) and Picazo-

247 Tadeo et al. (2011), we assume that countries produce an output, which is the value of

248 agricultural output (Y) using inputs that may have a detrimental effect on the environment

249 denoted by $D_n = n(n = 1,2,3 \dots \dots N)$. Given our definition of eco-efficiency (EF) as the ratio

250 of economic value added to environmental damage, it is formalised as

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

251

252 where $f(.)$ is the damage function that aggregates individual n environmental pressures into a

253 single environmental damage score (Kuosmanen and Kortelainen, 2005). As pointed out by

254 Kuosmanen and Kortelainen (2005) and Picazo-Tadeo et al. (2011), constructing the composite

255 environmental pressure score that aggregates individual environmental pressures is not

256 straightforward, requiring a weighting mechanism that takes into account the relative

257 importance of the different environmental pressures. There are many approaches to calculating

258 weights. These include assigning the same weight to each individual environmental pressure

259 variable or assuming any arbitrary linear combination of the environmental pressure

260 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

261 assigning weights in the latter case would be to use Principal Component Analysis (PCA). It

262 transforms a set of environmental pressure variables into a smaller set of uncorrelated

263 principals that represent most of the variation. However, PCA relies on orthogonal

264 transformations of the environmental pressure variables. DEA overcomes the problem of linear

265 combination without requiring an arbitrary combination. It maximises the relative eco-

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266 efficiency score of a given DMU compared with the other DMUs in the sample (in our case it

267 maximises the relative eco-efficiency score compared to the class specific scores). Formally,

268 DEA eco-efficiency score of activity n can be calculated as

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

269   Subject to

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

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

270 The above specification shows that the eco-efficiency score of each country is obtained by

271 taking the inverse of the optimal solution, i.e. the eco-efficiency score measures the level at

272 which the use of environmental pressures can be reduced without reducing output. A higher

273 eco-efficiency score suggests that reducing environmental pressures is more difficult without

274 reducing output. However, DEA takes into account heterogeneities within the observed sample

275 and uses the best performing unit as a benchmark to which other units in the sample are

276 compared. Therefore, the eco-efficiency and technical efficiency scores of countries as

277 obtained from DEA are measured relative to the "best practice" in the sample, which is not

278 necessarily the same as the "best available" technology (Mekonnen et al., 2015).

279 It is also important to note that the analysis is based on a latent class model, so eco-efficiency

280 and technical efficiency scores of countries are class specific and calculated relative to the best

281 practice in the class to which the sample unit belongs. Under this circumstance, eco-efficiency

282 and technical efficiency scores cannot be directly compared between classes. However, we also

283 estimated results for the pooled dataset, in which efficiency scores are based on a common

284 frontier and are thus comparable across all countries in the dataset.

285 Once the class-specific eco-efficiency and technical efficiency scores were calculated, we

286 analysed innovation system determinants of efficiency, using a Tobit model specification that

287   takes into account the censored nature of the efficiency scores. Both eco-efficiency and

288   technical efficiency scores are censored at the maximum value of the score, which is one, and

289   at its minimum value, which is zero.

290   **5. Results**

291   In this section, we first explain the efficiency scores computed for each country and then

292   present the determinants of eco-efficiency and technical efficiency.

293   **5.1   Class specific eco-efficiency scores**
294
295   We provide eco-efficiency scores calculated using the pooled dataset as well as class-specific

296   scores. Based on the SBIC we identified the optimal number of latent classes for estimating

297   efficiency scores, which resulted in a two class model for our specification.

298
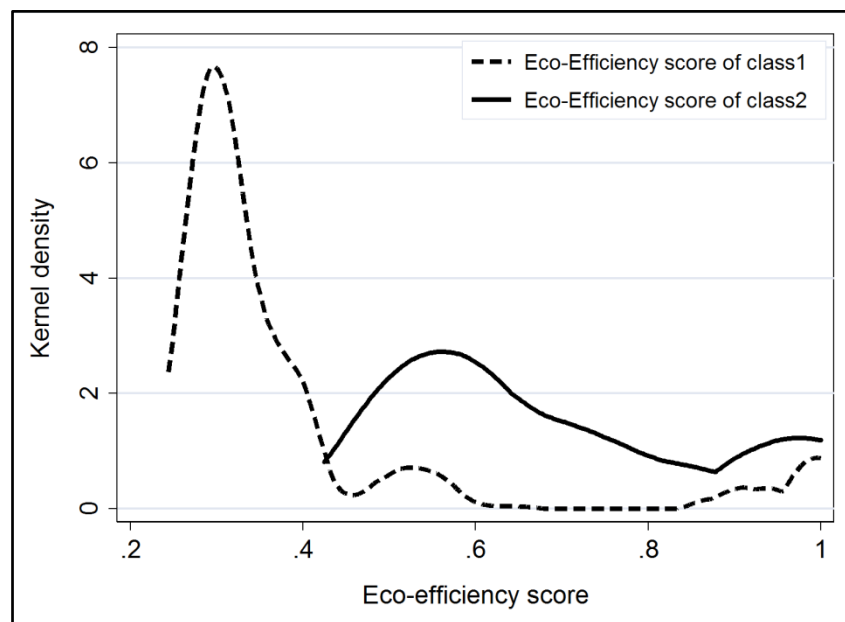299   *Figure 1: The distribution of class-specific eco-efficiency scores*
300
301   Figure 1 reports the distribution of eco-efficiency scores for the two classes. The results suggest

302   that countries categorised in class two are more eco-efficient than countries in class one. Table

303   3 and 4 present the eco-efficiency scores for countries in class one and two for the period

304   spanning 2004 to 2011.

305

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

308 *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

309
310 In terms of the composition of countries, a clear grouping was established. For example,

311 emerging economies such as China, India, Brazil and Thailand are members of class one. The

312 average eco-efficiency scores of countries in this class are generally low and remained constant

313 between 2004 and 2011. While the trend is similar for class two countries, the average eco-

314 efficiency scores remain at a higher level. Despite differences, the results suggest for both

315 classes that most countries can reduce environmental pressures without reducing the value of

316 agricultural output. On average, the most eco-efficient countries in class one include

317 Dominican Republic, Georgia and Guyana, whereas the least eco-efficient countries of class

318   one include Brazil, China, India, Indonesia and Thailand. In class two the most eco-efficient

319   countries include Burundi, Cape Verde, Costa Rica, Namibia and Rwanda, whereas countries

320   such as Kazakhstan, Lebanon, Mexico, South Africa, Turkey and Venezuela are the least eco-

321   efficient countries in class two.

322   **5.2   Determinants of eco-efficiency**

323   Table 5 presents the results of our analysis, using a Tobit regression model to evaluate

324   innovation system determinants of eco-efficiency. The first column shows the coefficients from

325   the regression based on the pooled dataset. Columns two and three contain the coefficients for

326   the variables according to country classes.

327   The results in Table 5 show diverging effects of public spending on agricultural research,

328   researcher numbers and foreign aid for agricultural research. While the coefficients are

329   significant and positive for class two countries, they are mostly significant, but negative, for

330   those countries in class one. At the same time, foreign aid for agricultural extension has a

331   positive effect for both classes, albeit only being significant for class one. This is in line with

332   the sign of the variable representing overall foreign aid. The positive relationship between

333   foreign aid and eco-efficiency may be a result of conditions in place for the use of such funds.

334   For example, many donors provide loans or grants under terms that stipulate investments in

335   sustainable rural development. The coefficient for scientific publishing, as a bridge between

336   research and other domains, is positive and significant, although its magnitude is very small.

337   However, a clearer positive and significant relationship with eco-efficiency across classes is

338   apparent for the quality of the educational system. The same is true for health expenditures and

339   ease of access to loans. The results further indicate that university-industry collaboration in

340   R&D, the total tax rate, domestic credit to private sectors, gross capital formation, legal rights

341   index, primary school enrolment, and the numbers of start-up procedures to register a business

342   have a statistically significant negative effect on eco-efficiency for one or the other class.

17

343   *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 (1=minimal to 7=intensive)	-0.024	-0.106***	-0.020
	(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

344

345 *The effect of university-industry collaboration in R&D suggests that currently innovations*
346 *resulting from such collaborations are not geared towards eco-efficiency. As reported in*
347
348 Table 6, university-industry collaboration in R&D has a significant positive effect on technical

349 efficiency scores of countries in class one. Future collaboration in R&D, in the area of climate

350 smart agriculture for example, can therefore support improving the eco-efficiency of countries,

351 while maintaining levels of technical efficiency. Higher domestic credit to the private sector

352 (as % of GDP) is also associated with lower eco-efficiency scores. This may be because credit

353 allows producers to use more external inputs, such as chemical fertiliser and pesticides, which

354 put pressure on the environment.

355 **5.3   Determinants of technical efficiency**

356 In this section we present the determinants of technical efficiency. As explained in the

357 introduction, the focus of this paper is not on technical efficiency. Nonetheless, we report

358 technical efficiency regression results to explore differences in the magnitude and direction of

359 expected effects of AIS variables on technical and eco-efficiency scores. Certain variables that

360 may improve technical efficiency may not necessarily improve eco-efficiency. The average

361 technical efficiency score lies at 0.93 for countries in both class one and two. This indicates

362 that high technical efficiency scores are not necessarily accompanied by higher eco-efficiency

363 scores. Understanding the expected effects of AIS variables on technical and eco-efficiency

364 respectively will be useful when considering policy objectives.[3] Some striking differences in

365 terms of eco-efficiency trends found among country classes also appear in the case of technical

366 efficiency, e.g. related to agricultural research spending. Overall, these are less pronounced

367 though. Regarding the respective determinants of technical and eco-efficiency, similarities and

368 differences emerge.

369

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

21

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

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

422   data is particularly apparent for extension and other institutional arrangements that fulfil the

423   bridging function between education and research actors and value chains actors.

424   Despite limitations arising from the nature of the data used, the paper produced some

425   significant results. On the whole, eco-efficiency scores among the countries considered in this

426   study are low, while technical efficiency scores are generally high. This suggests that eco-

427   efficiency could be improved for many countries under current conditions. Through the right

428   organisational, institutional, social and financial combinations, existing innovations can be

429   brought into greater use. The AIS indicators explored in this study represent potential

430   parameters to boost innovation processes in support of eco-efficiency. Involving key national

431   and international stakeholders and mainstreaming eco-efficiency criteria within existing

432   development strategies will accelerate the transformation towards more sustainable and

433   resilient rural societies.

434   While several indicators introduced in the study of Mekonnen et al. (2015) seem not to apply

435   to eco-efficiency, the results for a number of factors, such as the quality of the educational

436   system, agricultural research spending, foreign aid, ease of accessing loans, bureaucratic

437   procedures (either number of steps or time required to start a business) and health expenditures,

438   are consistent for both efficiency types. Reducing bureaucracy in registering innovative

439   business models could, for example, contribute to improving technical efficiency as well as

440   eco-efficiency. However, it transpired that particular AIS properties, such as collaboration

441   between universities and industry in R&D, had a positive effect on technical efficiency only.

442   Possibilities to adjust modalities of collaboration might need to be considered in such instances.

443   This study underscores that cross-country comparison of eco-efficiency needs to take into

444   account variation among countries. With the aim of providing consistent estimates of eco-

445   efficiency scores, the study employed a latent-class rather than a conventional DEA model.

446   Important heterogeneities in terms of technological choice and AIS characteristics were thus

447   considered when estimating class-specific eco-efficiency scores. Major emerging economies,

448   including China, India and Brazil, tend to operate at a different technological frontier than

449   developing country economies, such as Rwanda, Uganda and Ethiopia. With exceptions, most

450   emerging economies were attributed to class one, while class two predominantly covers

451   developing country economies. Similarities and differences among classes in terms of the

452   direction and magnitude of the drivers of eco-efficiency are of interest. High quality of

453   education, scientific output, health expenditures and overall foreign aid as well as foreign aid

454   for extension more specifically increase levels of eco-efficiency regardless of class allocation

455   and thus the technological frontier at which countries operate. However, foreign aid for

456   agricultural research, just as for public research spending and researcher numbers, appears to

457   only enhance the eco-efficiency of those countries in class two. These countries could benefit

458   more from investments in research, while countries in class one could boost their eco-efficiency

459   by focusing on extension. In general, the results suggests the need for context-specific

460   interventions instead of a "*one size fits all* "approach.

461   While this article illustrates the potential of a macro-level diagnostic approach to assessing the

462   role of innovation systems for sustainability in agriculture, it also demonstrates that care is

463   needed when interpreting results. The evidence generated by this type of analysis can provide

464   potential pointers to policy and investment gaps and opportunities, but inferences should be

465   corroborated with concrete case study data in order to draw sound conclusions.

466

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