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Abstract: Implementing the United Nations 2030 Agenda for Sustainable Development requires the expansion of green agriculture through updating low-carbon agricultural technologies. This study extends the definition of technological progress by introducing undesirable outputs into the calculation of global and local technological progress in the context of the by-production model. Convex and nonconvex models are applied to calculate the distance function, and then the Luenberger productivity indicator is obtained and decomposed into economic and environmental performance. This study then calculates the contribution of global and local innovation forces to technological progress with consideration for environmental factors. Finally, it tests the beta-convergence of productivity and identifies innovators. In the investigation of global and local technological changes in the agricultural sector in developing economies, the results show improvements in the Luenberger green productivity, efficiency changes, and technological progress, with technological progress in the environmental dimension contributing the most to performance improvement. Moreover, 14 sample countries experience global and local technological progress, and global and local innovation forces contribute equally. But the countries' agricultural green development did not converge. Therefore, developing economies should pay more attention to environmental technological innovation and agricultural cooperation.

JEL Codes: D24

Keywords: Global and local technological change; by-production model; Luenberger productivity indicator; convex and nonconvex

1. Introduction

Developing economies have committed to building a green Belt and Road and have made it official through the Memorandum of Understanding in 2016 (Solheim, 2017) to implement the United Nations 2030 Agenda for Sustainable Development. Given that agriculture not only plays an important role in these developing economies, but also contributes substantially to greenhouse gas emissions in the world (Cassman, Dobermann, Walters, & Yang, 2003), it is necessary to study green agriculture development in these countries.

In fact, developing countries are generally confronted with pressing environmental challenges in agricultural production. For instance, widely-used puddling and transplanting technique for rice in South Asia will not only consume intensive irrigation water and energy (Kumar et al., 2018), but also reduce rice yield by 8–10% (Kumar & Ladha, 2011). Consequently, significant efforts have been made in all aspects of agricultural production to improve agricultural performance in developing countries.

Impressive technological progress in agriculture across developing countries contributes to green performance improvement to a large extent. On the one hand, global technological progress is promoted in many developing economies and helps to improve productivity. For instance, pest management technique has not only increased the average yield of crops by 40.9%, but it also decreases the use of pesticides by 30.7% (Pretty & Bharucha, 2015). On the other hand, local technological progress has taken place in a single country because of the force of local innovation, such as India who has developed intensive techniques and become an example of rapid development of sustainable agriculture (Emerick, De Janvry, Sadoulet, & Dar, 2016).

Therefore, identifying the main contributor to performance improvement and technological progress helps to seek a path to sustainable development of agriculture in developing economies. What are the main drivers of changes in agricultural green productivity in developing countries? Do global and local innovation forces drive technological progress in the same way? Are the levels of green development in agriculture in these countries convergent? Which country is the innovator? The answers to these questions offer empirical evidence and policy implications for the development of sustainable agriculture in developing countries.

Correspondingly, the first goal of this study is to examine the role of economic and environmental performance in agricultural green productivity change in the 2000–2019 period through convex and nonconvex models. Next, we aim to distinguish global and local technological change combined with performance decomposition in the context of the by-production model. Finally, we investigate performance convergence and identify innovators. Although a few studies have investigated agricultural technological changes in developing countries, no empirical studies have quantified global and local technological progress in agriculture among developing countries with consideration for undesirable outputs.

This study makes three key contributions to the existing literature. First, to the best of our knowledge, this study is the first to explore green productivity of agricultural sector across Belt and Road countries. Second, the identification of global technological progress (GTP) and local technological progress (LTP) in agriculture is helpful in identifying the driving factors of green agricultural development among developing countries and extends the operational definition of these technological properties to undesirable outputs. Third, further discussions are of great significance to fostering deep cooperation on sustainable agricultural development in these developing countries. Our study may be also of certain reference for the green Belt and Road construction.

2. Literature Review

2.1 Green Productivity Estimation

A large body of literature has been conducted to extend the measurement of productivity with consideration for environmental inputs and outputs. For example, the Malmquist productivity index is utilized to model the joint production of desirable and undesirable outputs (Färe, Shawna, & Carl A., 2001), but its weak disposability assumption does not meet the conservation laws of matter (Coelli, Lauwers, & Van Huylenbroeck, 2007). Chambers (2002) proposed the Luenberger productivity indicator (LPI) by using the directional distance function (DDF), which has also been extended to include pollutants as undesirable outputs. However, it fails to analyze the economic or environmental contributions to green productivity gains because of its lack of additive completeness.

To address these issues, Murty, Russell, and Levkoff (2012) construct a by-production (BP) model in which pollutants meet cost disposability and other outputs satisfy free disposability. The model decomposes performance into economic and environmental changes using two sub-technologies. The combination of LPI and the

BP model creates a model with three appealing properties: (i) it meets the material balance conditions; (ii) it can be decomposed into economic and environmental changes; and (iii) it can be made to relax the convexity assumption. This approach has been applied to the estimation of economic and environmental production performance in some countries or regions, such as the European Union (Beltrán-Esteve & Picazo-Tadeo, 2017) and China (Shen, Vardanyan, Balezentis, & Wang, 2021; Wang & Wei, 2016). However, it has rarely been used to investigate the economic and environmental performance of Belt and Road countries (Yuan, Balezentis, Shen, & Streimikiene, 2021; Zhu, Dai, Balezentis, Streimikiene, & Shen, 2022).

2.2 Convex and Nonconvex Technologies

In the past, productivity growth is typically calculated by parametric specification approaches, but a lot of recent studies have adopted nonparametric approaches that allow for a dynamic analysis based only on technical information without input and output price data. Data envelopment analysis (DEA) _ENREF_13with a convex production frontier and Free disposal hull (FDH) with a nonconvex production frontier are two typical nonparametric methods (Charnes, Cooper, & Rhodes, 1978; De Borger & Kerstens, 1996; Deprins, Simar, & Tulkens, 1984). The convex production frontier is a piecewise linear curve composed of actual decision-making units (DMUs), and its outward expansion requires a global shift in the production frontier. By contrast, the nonconvex production frontier is composed of actual DMUs without strict convex shape constraints, and its outward expansion allows for a local shift in the production frontier.

It has a long debate over whether the production frontier is convex. The traditional view generally holds that production technology satisfies the convexity theorem. However, production activities carry the complex factors such as widespread setup and lead times that challenge the convexity axiom (Coviello, Ichino, & Persico, 2014). In addition, the indivisibility of production factors, the increasing returns to scale and well-known externalities of production violate the convexity axiom and should also be carefully considered (Baumol & Bradford, 1972; Romer, 1990; Scarf, 1994). Therefore, the nonconvex model is proposed and further extended to the case of variable returns to scale, aiming to provide a benchmark for inefficient DMUs (Deprins et al., 1984; Kristiaan Kerstens & Eeckaut, 1999; McFadden, 1978). But there are still several disputes over the application of nonconvex technology such as scale defects (Cesaroni, Kerstens, & Van de Woestyne, 2017).

Nevertheless, a growing body of evidence supports the superiority of nonconvex models over convex models. Tone and Sahoo (2003) argue that nonconvex techniques embedded in FDH models can help reveal the inseparability caused by task-specific processes. Balaguer-Coll, Prior, and Tortosa-Ausina (2007) explain that the nonconvex production frontier contains more efficient observations. Furthermore, Copeland and Hall (2011, p. p. 246, p. 246) show that the per vehicle cost is 4.36% higher under nonconvex model than that under convex model in the car manufacturing case. Kristiaan Kerstens and Van de Woestyne (2021) reveal that cost estimations under convexity are on average between 21% and 38% lower than those under nonconvexity.

All this logical and empirical evidence points to the need to reconsider the convexity assumption in green productivity estimates. Because land is generally indivisible in agricultural production (Krautkraemer, 1994), performance evaluations under convexity may not be accurate (Ang & Kerstens, 2021; Kim, Chavas, Barham, & Foltz, 2012). Thus, we aim to provide more empirical analysis for the application of nonconvex models as well as evidence in support for the comparison of the convexity and nonconvexity assumptions.

2.3 Global and Local Technological Change

The original concept of local technological change dates to the seminal research by Atkinson and Stiglitz (1969). Although these authors did not provide a formal definition of LTP, they compare the concept of technological progress that transfers the entire production function outward with that of local technological progress that transfers part or different parts of the production function outward to different degrees.

Following this initial contribution, empirical studies have emerged. Bernard, Cantner, and Westermann (1996) examine innovators and technological changes in the French machinery industry using a nonparametric approach under a convex production technology. They find that local technological change has significant impacts on firm performance and that innovators promote LTP in a particular field. Timmer and Los (2005) investigate labor productivity growth in Asian countries and show that technological innovation is localized in the agricultural and manufacturing sectors. López-Pueyo and Mancebón (2010) report that LTP makes a significant contribution to performance improvements in the information and communication technology industry. However, all of the above works have not provided operational identification.

K. Kerstens and Managi (2012) conduct the first attempt to provide an operational definition of global and local technological change (GTP and LTP) within the context of convex and nonconvex technologies. In one of their empirical studies on oil field drilling in the Mexican Gulf, they conclude that approximately 62.8% more observations satisfy the conditions for LTP than GTP. Barros, Fujii, and Managi (2015) report the opposite case in Chinese commercial banks and show more observations fitting GTP rather than LTP. Fujii et al. (2015) analyze 16 sectors in the Japanese manufacturing industry and showe that the relative importance of GTP and LTP varies by sector and period. Therefore, the assumption of convex and nonconvex technologies is of great significance in distinguishing global and local technological changes. However, undesired outputs have not been introduced to the quantification of GTP and LTP, which would need empirical testing in agricultural production.

3. Methodology

Initially, we model an environmental technology that is related to convex and nonconvex specifications in the context of the BP model, followed by a rough illustration. Next, we decompose the LPI for detailed measurements. In this second step, we explicitly define the distinction between global and local technological changes in green production performance, with consideration for undesirable outputs. In the third step, we investigate whether green performance development would show a beta-convergence that refers to a process in which poor regions grow faster than rich ones and therefore catch up on them. We also identify innovators. Next, we provide a detailed description of the data used. The details of the nonparametric estimation strategies for the convex and nonconvex models appropriate for the BP model are presented in the Appendix.

3.1 Modeling environmental technology

We apply a By-production technology that could be illustrated by a dual frontier (T1, T2) (Murty et al., 2012). We assign K DMUs that corresponded to the agricultural sectors in each developing country in our case. To account for environmental performance, we separate inputs into two groups, namely the "clean" inputs (x^n), the consumption of which does not produce pollutants, and the "dirty" inputs (x^p), which generate pollution in production activities. The "dirty" inputs generate undesirable outputs (z), whereas both types of inputs produce desirable outputs (y). Accordingly, the desirable output production process could be modeled by one subset of technology that describes the efficient economy, T_{eco}, whereas the polluting production process is defined by another subset of technology that focuses on the green environment, T_{env}. Production technology sets (T_{BP}) are defined as follows:

$$\begin{aligned}
T_{BP} &= T_{eco} \cap T_{env} \\
&= \left\{ (x^n, x^p, y, z) \in R_+^{N+P+M+J} : (x^n, x^p) \text{ can produce } y \text{ ; } x^p \text{ can generate } z \right\} \\
T_{eco} &= \left\{ (x^n, x^p, y) \in R_+^{N+P+M} \mid f(x^n, x^p, y) \leq 0 \right\} \\
T_{env} &= \left\{ (x^p, z) \in R_+^{P+J} \mid g(x^p) \leq z \right\}
\end{aligned} \tag{1}$$

where f and g are used to model the sub-technologies related to economic and environmental performance, respectively. Thus, we conceive the BP model as the intersection of the two sub-technologies, both of which satisfy closedness, variable returns to scale, and strong disposability under the premise of continuous differentiability. We should note that no convexity axiom was imposed.

To distinguish these two output groups, we assume free disposability (A_{eco}) in T_{eco} that employs all inputs to obtain desirable outputs—the supplied inputs can yield fewer outputs. We also assume the cost disposability (A_{env}) in T_{env} associated with "dirty" inputs and undesirable outputs, signifying the difficulty in abandoning the undesirable outputs as easily as disposing of desirable outputs. The specific formal requirements for A_{eco} and A_{env} are as follows:

$$\begin{aligned}
&A_1: \textit{ if } (x^n, x^p, y, z) \in T_{eco}, \\
&\textit{then } (\tilde{x}^n, \tilde{x}^p, \tilde{y}, \tilde{z}) \in T_{eco} \textit{ for all } (-\tilde{x}^n, -\tilde{x}^p, \tilde{y}) \le (-x^n, -x^p, y). \\
&A_2: \textit{ if } (x^p, z) \in T_{env}, \\
&\textit{then } (\tilde{x}^p, \tilde{z}) \in T_{env} \textit{ for all } (\tilde{x}^p, -\tilde{z}) \le (x^p, z).
\end{aligned} \tag{2}$$

In our empirical application, we presume that the good agricultural outputs are generated by using "clean" inputs, such as labor and capital. Moreover, to assess the environmental performance, we presume that the undesirable output at the national level of carbon equivalent emissions is generated by the "dirty" inputs, including land, energy, fertilizers, and pesticides. Although pedoclimatic conditions (e.g., soil quality, sunshine, rainfall, and temperature) play a major role in agricultural production processes (Deligios, Carboni, Farci, Solinas, & Ledda, 2019), we do not consider them in the study for the sake of brevity.

We employ a non-radial directional distance function (DDF) for the nonparametric estimation to assess the potential for progress compared with the relevant production frontier. As in previous work (Chung, Färe, & Grosskopf, 1997; Färe, Grosskopf, Noh, & Weber, 2005), one can expand the desirable outputs and reduce the undesirable outputs simultaneously, i.e.:

$$D(x,y,z;g_x,g_y,g_z)=\max\left\{\delta,\theta\in R_+:(x,y+\delta g_y,z-\theta g_z)\in T\right\} \tag{3}$$

where δ and θ are inefficiency scores, scalar δ is a symbol of the potential expansion of desirable outputs, and scalar θ refers to the possible reduction in pollutants along the direction indicated by the direction vector (g_y, g_z). Thus, an evaluated country with scalar $\delta=0$ or $\theta=0$ at the optimum can be regarded as a benchmark in a certain field.

3.2 Productivity measurement

The green LPI focuses on the distances between the frontier and each observation during the timeline from t to t+1 such that changes in the environmental productivity gains can be measured (Chambers, Fāure, & Grosskopf, 1996). The output-oriented green LPI formulation comparing the base period t with the following period t+1 and that keeps the input amounts the same is given by:

$$LPI^{t,t+1}=\frac{1}{2}\begin{bmatrix} D^t\left(x^t,y^t,z^t;0,g_y^t,g_z^t\right)-D^t\left(x^{t+1},y^{t+1},z^{t+1};0,g_y^{t+1},g_z^{t+1}\right) \\ +D^{t+1}\left(x^t,y^t,z^t;0,g_y^t,g_z^t\right)-D^{t+1}\left(x^{t+1},y^{t+1},z^{t+1};0,g_y^{t+1},g_z^{t+1}\right)\end{bmatrix} \tag{4}$$

This output-oriented green LPI can be decomposed to evaluate the disparity between efficiency and technological contributions_ENREF_10. First, efficiency change (or the catch-up effect) quantifies the change in distance between observations and their benchmark for a given period and evaluates the potential for improvement through more efficient resource utilization. Second, technological change measures a frontier shift over the period t to t+1, which indicates higher productivity owing to technological innovations in the case of a positive frontier shift. Combining the four output-directional distance functions from (4), both of these additive components of the environmental LPI can be formulated as follows:

$$EC^{t,t+1} = D^t\left(x^t, y^t, z^t; 0, g_y^t, g_z^t\right) - D^{t+1}\left(x^{t+1}, y^{t+1}, z^{t+1}; 0, g_y^{t+1}, g_z^{t+1}\right),$$

$$TP^{t,t+1} = \frac{1}{2}\left[\begin{array}{l} D^{t+1}\left(x^t, y^t, z^t; 0, g_y^t, g_z^t\right) - D^t\left(x^t, y^t, z^t; 0, g_y^t, g_z^t\right) \\ +D^{t+1}\left(x^{t+1}, y^{t+1}, z^{t+1}; 0, g_y^{t+1}, g_z^{t+1}\right) - D^t\left(x^{t+1}, y^{t+1}, z^{t+1}; 0, g_y^{t+1}, g_z^{t+1}\right) \end{array}\right]. \quad (5)$$

The LPI inefficiency scores can be further dissected into economic and environmental sub-scores (θ^m and θ^j) using a mix of DDFs and the BP technology (Shen et al., 2021). Therefore, the economic and environmental decomposition of the LPI can be summarized as:

$$\begin{aligned} LPI_{green}^{t,t+1} &= \frac{1}{2}(LPI_{eco}^{t,t+1} + LPI_{env}^{t,t+1}) \\ LPI_{eco}^{t,t+1} &= \frac{1}{2}(EC_{eco}^{t,t+1} + TP_{eco}^{t,t+1}) \quad (6) \\ LPI_{env}^{t,t+1} &= \frac{1}{2}(EC_{env}^{t,t+1} + TP_{env}^{t,t+1}) \end{aligned}$$

3.3 Global and local technological progress

To provide an identification strategy for distinguishing between GTP and LTP in a green productivity context, we follow K. Kerstens and Managi (2012) who elaborate on the properties of technological progress using productivity estimates in connection with convex and nonconvex assumptions. Because the BP model distinguishes the contributions of economic and environmental progress separately, the definition of GTP or LTP is based on the analysis of efficiency scores relative to the corresponding sub-frontiers, which allows distinguishing between the origins of technological progress. The BP model is suitable for convex and nonconvex technologies (Murty, 2015). If we define global and local technological change in terms of economic and environmental performance as shifts toward the economic and environmental frontiers, then the definitions of K. Kerstens and Managi (2012) can be extended to the BP setting where undesirable outputs are included.

GTP is defined as arising from an outward shift of the convex frontier that occurs to efficient observations associated with the same frontier from year t to year t+1. This puts forward three constraints on the observations: (i) technological progress during the period, (ii) efficiency compared with the initial convex frontier, and (iii) efficiency compared with the final convex frontier. However, they are so strict that only a few observations fit. Therefore, it is desirable to apply a more relaxed definition. Given that progress is a relative concept, it is not necessary to require observations to remain efficient on a convex frontier at the two time periods. Thus, if we relax one of the constraints on efficient observations and adhere to the constraint of positive technological change related to either the convex or nonconvex frontier, then more suitable observations can be obtained in the context of these relaxed definitions. The three definitions of GTP are as follows:

$$
\begin{aligned}
&TP1_C^{t,t+1} = \{(x,y): D_C^t(x_t,y_t)=0 \cap D_C^{t+1}(x_{t+1},y_{t+1})=0 \cap TP_C^{t,t+1}>0\} \\
&TP2_C^{t,t+1} = \{(x,y): D_C^t(x_t,y_t)>0 \cap D_C^{t+1}(x_{t+1},y_{t+1})=0 \cap TP_C^{t,t+1}>0\} \quad (7) \\
&TP3_C^{t,t+1} = \{(x,y): D_C^t(x_t,y_t)=0 \cap D_C^{t+1}(x_{t+1},y_{t+1})>0 \cap TP_C^{t,t+1}>0\}
\end{aligned}
$$

LTP is introduced as the product of an outward shift of the nonconvex frontier, where observations are regarded as efficient relative to nonconvex frontiers but inefficient for convex frontiers throughout the year. Observations have three constraints as well: (i) technological progress during the period relative to the nonconvex frontier, (ii) having to remain on the nonconvex frontier over the years, and (iii) having to remain in the interior relative to the convex frontiers over the years. We can define weaker versions of the same definitions, whereby an observation could only be efficient in one of the two time periods considered. The following three definitions of LTP are obtained:

$$\begin{aligned}
TP1_{NC}^{t,t+1} &= \{(x,y): D_{NC}^{t}(x_t,y_t)=0 \cap D_{NC}^{t+1}(x_{t+1},y_{t+1})=0 \\
&\quad \cap D_{C}^{t}(x_t,y_t)>0 \cap D_{C}^{t+1}(x_{t+1},y_{t+1})>0 \cap TP_{NC}^{t,t+1}>0\} \\
TP2_{NC}^{t,t+1} &= \{(x,y): D_{NC}^{t}(x_t,y_t)>0 \cap D_{NC}^{t+1}(x_{t+1},y_{t+1})=0 \\
&\quad \cap D_{C}^{t}(x_t,y_t)>0 \cap D_{C}^{t+1}(x_{t+1},y_{t+1})>0 \cap TP_{C}^{t,t+1}>0\} \\
TP3_{NC}^{t,t+1} &= \{(x,y): D_{NC}^{t}(x_t,y_t)=0 \cap D_{NC}^{t+1}(x_{t+1},y_{t+1})>0 \\
&\quad \cap D_{C}^{t}(x_t,y_t)>0 \cap D_{C}^{t+1}(x_{t+1},y_{t+1})>0 \cap TP_{C}^{t,t+1}>0\} \quad (8)
\end{aligned}$$

Figures 1 A and B illustrate the difference between GTP and LTP in the “clean” input and desirable output space, and in the “clean” input and undesirable output space, respectively. The broken line represents the convex technology, and the full line indicates the nonconvex technology. The production possibility sets are given by the area inside these frontier curves.

Focusing on year t, the frontier has four DMUs—A, B, D, and F—for both technology specifications, reflected in the 0% inefficiency score. C and E fail to be efficient under the convex assumption, but are efficient under the nonconvex one. If their economic inefficiency scores are 1%, then they can increase their desirable outputs by 1% without increasing inputs. If their environmental scores are 1%, then they can decrease their undesirable outputs by 1% without decreasing inputs.

One year later, the position of A stays the same, which means that no GTP and LTP have occurred. Productivity is relatively stagnant during the period. By contrast, B, D, and F reach a higher frontier for both assumptions in the year t+1: an indicator of global technological progress. By contrast, C and E are inside the convex frontier in year t+1, and such a shift is regarded as LTP, regardless of how perfect they are on the nonconvex frontier.

Here, we offer two other manifestations of local technological progress. In Figure 1A, if a shift towards the upper left direction occurs to E in year t+1, but the new position of E is still far from both convex and nonconvex frontiers, then E can be presumed to experience economic LTP. In Figure 1B, if a shift towards the bottom right direction occurs to a DMU that was within the frontier in year t, and the later position is on the frontiers of year t+1, then the change can be described as LTP.

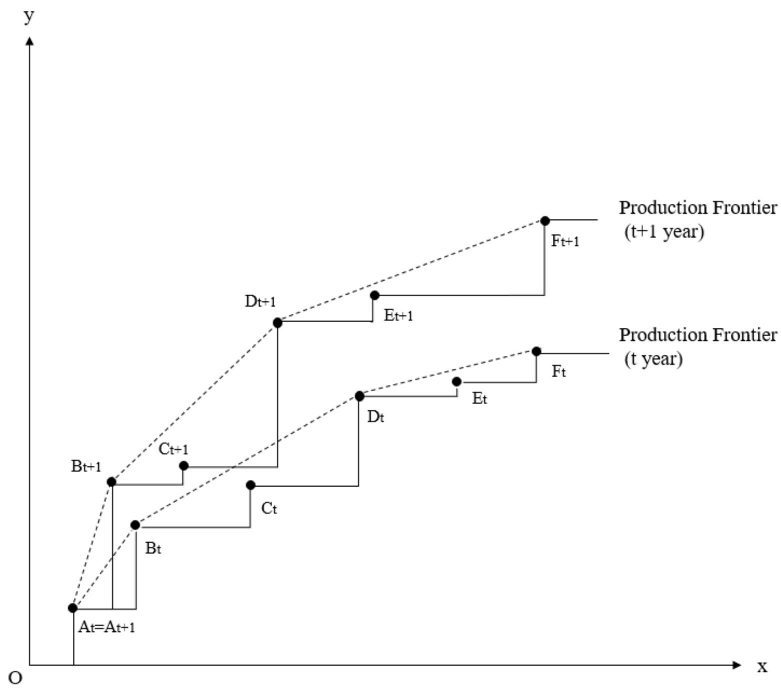


Figure 1A. Production frontier of T_{eco}

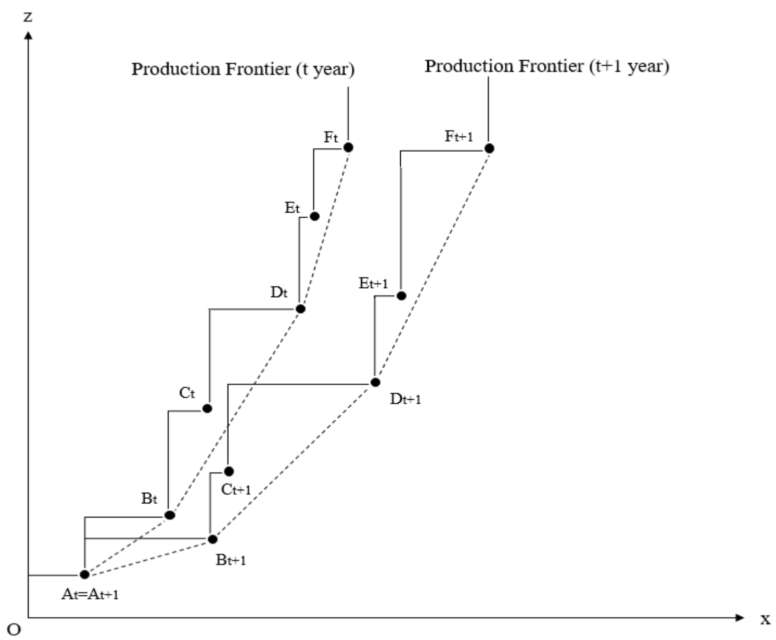


Figure 1B. Production frontier of T_{env}

3.4 Growth convergence and innovator identification

To gain deeper insight into green performance change, we refer to Barro and Sala-i-Martin (1992) in presenting estimates for the beta-convergence model. It measures whether countries with low initial productivity experience faster growth, implying a convergence trend between efficient and inefficient countries. We establish a regression model using a simple unconditional convergence velocity equation (Steger, 2000):

$$\Delta \ln y_{it(i)} = \alpha + \beta \ln y_{i0} + e_i \quad (9)$$

where β can be interpreted as convergence flexibility; $\Delta \ln y_{it(i)}$ is a symbol of the indicator that covers a range of performance changes, such as average green productivity change, efficiency change (EC), and technological progress (TP) between these two time periods; and $\Delta \ln y_{i0}$ represents the initial level of the same indicators. Error terms are shown in e_i. All the estimated results of the indicators relative to convex and nonconvex technologies are regressed in the formulation. In addition, average green productivity growth can be easily decomposed into economic and environmental changes in the context of the BP approach.

We intend to determine if a high starting production performance of one observation can be sustained and if a low initial production performance of one observation can, with time, catch up with the frontier. If the estimated value of β is significantly negative, then poorer observations gradually narrow the gap with better observations. In other words, the β-convergence hypothesis is applicable under these conditions. By contrast, a positive value of the β-estimate can refute the validity of the convergence hypothesis.

The LPI framework also contributes to identifying the most innovative countries. Innovative countries are defined as efficient observations that push the production frontier upward to a location with greater efficiency scores owing to technological progress during that period. These countries tend to have great potential for performance improvements and strong radiation effects in the region. We use three criteria to identify innovative countries (Beltrán-Esteve & Picazo-Tadeo, 2017; Färe, Grosskopf, Norris, & Zhang, 1994):

$$TI\left(\left(x_t, y_t\right)\left(x_{t+1}, y_{t+1}\right)\right) = \left\{\begin{array}{c} TP^{t,t+1} > 0 \\ \cap D^t\left(x_k^{t+1}, y_k^{t+1}, z_k^{t+1}; 0, g_y^{t+1}, g_z^{t+1}\right) < 0 \\ \cap D^{t+1}\left(x_k^{t+1}, y_k^{t+1}, z_k^{t+1}; 0, g_y^{t+1}, g_z^{t+1}\right) = 0 \end{array}\right\} \quad (10)$$

In other words, innovative countries experience positive technological changes and move from an inefficient to an efficient position.

3.5 Data

Our data sample covers 53 developing countries across the Belt and Road, namely, Armenia, Azerbaijan, Bangladesh, Belarus, Bhutan, Bosnia and Herzegovina, Brunei Darussalam, Bulgaria, Cambodia, China, Croatia, Cyprus, Czechia, Egypt, Estonia, Georgia, Greece, Hungary, India, Indonesia, Iran, Iraq, Israel, Jordan, Kazakhstan, Kuwait, Kyrgyzstan, Laos, Latvia, Lebanon, Lithuania, Malaysia, Maldives, Mongolia, Nepal, Oman, Pakistan, Palestine, the Philippines, Poland, Romania, Russia, Saudi Arabia, Slovakia, Slovenia, Sri Lanka, Tajikistan, Thailand, Turkey, Turkmenistan, Ukraine, Vietnam, and Yemen. The period covered is from 2000 to 2019.

We describe the products of agricultural production activities by one desirable output (gross production value) and one undesirable output (carbon dioxide emissions). The inputs to the production process are classified into two categories. The group of "clean" inputs consists of agricultural employment and gross fixed capital formation capital. The group of "dirty" inputs consists of agricultural land[1], energy consumption, fertilizer use, and pesticide use. Undesirable outputs can only be produced by "dirty" inputs.

All data are collected from the Food and Agriculture Organization (FAO) database. The capital stock and gross production values are converted to the value of the 2015 price as the base period via the subtraction method. Fertilizer dosage data are obtained by aggregating the volume of the three main elements of nitrogen, phosphorus, and

[1] Agricultural land is a contributor of total emissions. When the soil is turned over by growing crops, carbon forms in the soil and is gradually released into the atmosphere.

potassium, for a unified calculation. Table 1 provides a brief description of the input and output variables and offers descriptive statistics.

Table 1. Data description

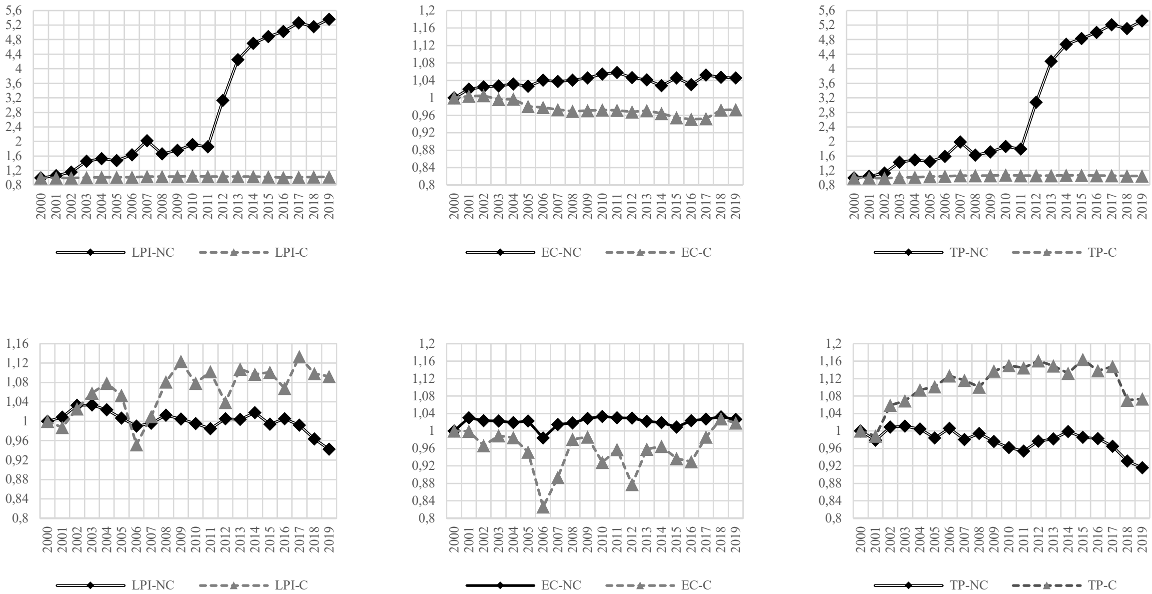
Variable	Unit	Mean	Std. Dev	Min	Max
Agricultural Employment	1000 persons	11,904.7	42,237.7	1.1	307,213.1
Gross Fixed Capital Formation	million$	4,150.1	15,282.7	1.9	142,570.9
Agricultural Land	1000 ha	35,849.8	86,266.4	5.6	529,038.6
Energy Consumption	Terajoule	88,054.1	242,716.8	91.2	1,940,192.5
Fertilizers Use	tonnes	1,994,983.7	7,228,750.6	18.0	55,612,825.0
Pesticides Use	tonnes	39,264.7	222,449.3	1.0	1,815,690.0
Gross Production Value	thousand$	38,586.9	147,967.1	3.3	1,257,561.8
CO_2 eq Emissions	kilotonnes	75,747.9	194,553.2	46.8	1,439,537.3

4. Results and discussion

4.1 Productivity growth and its decomposition

Figure 2 displays the cumulative LPI scores in terms of green productivity, economic performance, and environmental performance over the past two decades in the sample of countries. We divide the changes into three components for both convex and nonconvex technologies: aggregated indicator scores, efficiency change, and technological change. The results show more variations in aggregate green LPI, efficiency change, and technological change by nonconvex technologies than by convex technologies. Moreover, the aggregate green LPI, efficiency change, and technological change by nonconvex techniques were higher than those by convex techniques. The environmental performance of LPI, efficiency change, and technological change presents similar trends to aggregate green productivity—more variation and higher values of LPI, EC, and TP by nonconvex techniques compared to convex techniques. Regarding economic productivity, the LPI and TC calculated by convexity are higher than those computed by nonconvexity, whereas the EC calculated by convexity is lower than that calculated by nonconvexity. These results suggest that the cumulative LPI under nonconvexity is higher and that TP is the major driving force of green productivity.

The scores of the green LPI and its TP component slowly increase during the initial period of 2000–2011. From 2012 to 2019, they experience a striking increase of 160%. The turning point is 2011, which coincides with the proposal of the Belt and Road construction. The growth pattern of TP is similar to that of green LPI. In addition, changes in overall productivity over the years are strongly due to pedoclimatic conditions.



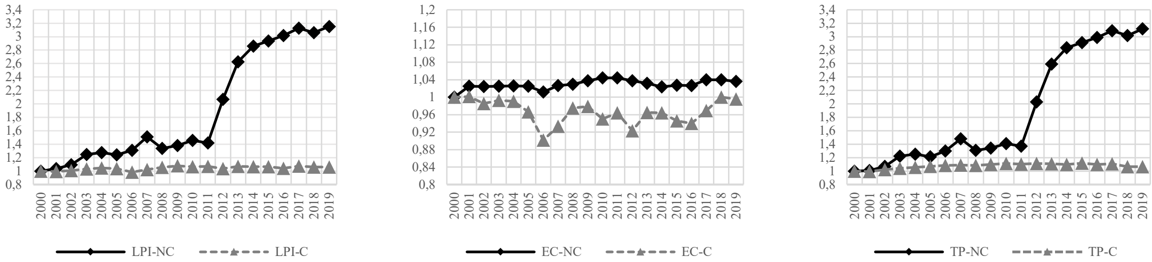


Figure 2. Accumulative LPI change

Note. NC is for nonconvex model, whereas C stands for convex model. LPI refers to green Luenberger productivity indicator, EC refers to efficiency change, and TP refers to technological advancement.

The annual changes in the LPI scores, including overall change, efficiency change, and technological change, among the 53 developing countries are presented in Table 2. We observe substantial disparities in the estimation results for convex and nonconvex technologies. First, agricultural green productivity and its components EC and TP are higher in terms of environmental performance under nonconvexity than under convexity, whereas the values of all the components are lower in terms of economic performance under nonconvexity than under convexity. Second, most of the average change rates in all elements are positive; only the values of environmental EC under convexity and economic LPI and TP under nonconvex are negative. The contradictory estimates under the convex and nonconvex models may have been affected by the difference in the characteristics of returns to scale between the two models (Cesaroni et al., 2017).

Table 2. Descriptive statistics of green productivity change

Descriptive Statistics	Convex						Nonconvex					
	LPI		EC		TP		LPI		EC		TP	
	Eco	Env	Eco	Env	Eco	Env	Eco	Env	Eco	Env	Eco	Env
Mean	0.005	0.001	0.001	-0.001	0.004	0.003	-0.003	0.846	0.001	1.545	-0.004	1.235
Standard deviation	0.265	0.080	0.258	0.054	0.158	0.065	0.128	3.138	0.097	0.098	0.135	3.138
Minimum	-2.484	-0.493	-2.938	-0.285	-1.892	-0.493	-0.789	-8.842	-1.545	-0.729	-0.842	-8.842
Maximum	4.244	0.728	3.972	0.740	1.467	0.491	0.846	9.795	1.545	0.738	1.235	9.795

Note. LPI stands for green productivity, EC for efficiency improvement, and TP for technological development; Eco and Env stand for the economic and environmental performance of LPI scores, respectively.

4.2 Global and local technological progress

Owing to the large number of production units involved, the growth of technological change is often a localized and diffused dynamic process. Technological progress is mainly reflected in frontier shift, which is subject to a certain input space in the output-oriented BP model. If the convexity assumption is imposed on the technology, then the actual technological progress may be covered. In other words, local technological change is aggregated in global technological change, and even significant progress is likely to be overestimated. In the light of the aforementioned empirical findings, a higher performance score under the assumption of a nonconvex technology suggests local instead of global technological change over time.

Table 3. Global and local technological progress identification

Country	Global technological progress	Local technological progress

	TP1		TP2		TP3		TP1		TP2		TP3	
	Eco	Env	Eco	Env	Eco	Env	Eco	Env	Eco	Env	Eco	Env
Armenia	0	0	0	0	0	0	0	2	2	1	1	2
India	4	0	0	1	0	0	0	0	0	2	0	0
Azerbaijan	0	0	0	1	0	0	0	2	0	1	0	1
China	0	2	0	0	0	0	0	0	0	3	0	0
Bulgaria	0	0	0	1	0	0	2	0	0	0	1	0
Georgia	0	0	1	1	0	0	1	0	1	0	0	0
Pakistan	0	0	1	0	0	0	0	0	1	1	0	1
Sri Lanka	0	0	1	1	0	0	0	0	1	0	1	0
Hungary	0	0	0	1	0	0	0	0	1	0	1	0
Cyprus	0	0	0	0	1	1	0	0	0	0	0	0
Malaysia	0	0	0	1	0	0	0	0	1	0	0	0
Oman	0	0	1	1	0	0	0	0	0	0	0	0
Russia	0	0	0	1	0	0	0	0	0	0	0	1
Tajikistan	0	0	1	1	0	0	0	0	0	0	0	0
In total	4	2	5	10	1	1	3	4	7	8	4	5

Note. TP1, TP2 and TP3 denote the first identification strategy with strict conditions, the second one with one form of relaxed conditions, and the third one with the other form of relaxed conditions of global and local technological progress separately; Eco and Env designate technological progress presented in economic efficiency and environmental protection respectively.

Table 3 shows the annual frequency and distribution of GTP and LTP in developing countries over the past two decades as defined in (7) and (8). Fourteen countries, or approximately 26% of the sample countries, experience some form of GTP or LTP. In particular, the frequency of GTP does not exceed LTP based on any of the three definitions, indicating that the technological progress of developing countries generally comes from local technological progress. In particular, the second identification strategy captures a larger number of GTP and LTP signals. This is likely due because the method of TP2 relaxes the identification conditions.

Armenia shows a lead in frequent technological change; every technological progress was localized. The results of TP2 show that Armenia experiences two times of economic LTP and environmental LTP. Thus, local technological innovations promote Armenia's success in agriculture. Agriculture in Armenia has been suffering from poor infrastructure and insufficient facilities in the early 21st century [53, 54]. Local governments adopted a combination of incentive and assistance strategies. Since 2011, the Armenian government has exempted agricultural technology products from value-added tax while importing agricultural machinery from neighboring countries, such as Belarus, for leasing (see Armenia Economic and Commercial Affairs Office[2]).

India and Azerbaijan follow in terms of the frequency of GTP and LTP. Over the past 20 years, India has made more global technological progress and fewer local technological changes. Local technological changes in agricultural production have occurred more frequently in Azerbaijan and are reflected in the improvement of its environmental productivity.

China, as the country proposing the Belt and Road initiative, has also experienced GTP and LTP several times. Specifically, China's agricultural green production technology has undergone three local changes over the past 20 years, all of which are reflected in the improvement in environmental productivity. Bulgaria, Georgia, and Pakistan show fewer overall and local technological advances. Finally, countries such

[2] For more information, see http://am.mofcom.gov.cn/index.shtml.

as Sri Lanka, Hungary, Cyprus, Malaysia, Oman, Russia, and Tajikistan stagnated after one or two GTP and LTP in agricultural green production technology have occurred in certain periods.

4.3 Convergence and Innovator Recognition

Table 4. Testing β-convergence of productivity changes

	LPI		EC		TP	
	Eco	Env	Eco	Env	Eco	Env
Convex						
β	0.229***	0.175	3.221***	0.340***	0.427**	0.444***
	(4.49)	(1.29)	(4.37)	(4.13)	(2.55)	(8.71)
R^2	0.100	0.017	0.124	0.013	0.072	0.197
Nonconvex						
β	0.443***	0.752***	11.884	0.309***	0.095	0.575***
	(7.21)	(9.78)	(0.60)	(3.85)	(1.56)	(8.50)
R^2	0.152	0.250	0.109	0.149	0.028	0.185

Note. () means t-value; *Significant at the 10% level. **Significant at 5% level. ***Significant at 1% level. LPI stands for green productivity, EC for efficiency improvement, and TP for technological development; Eco and Env represent the development of economic and environmental performance.

Table 4 reports the convergence results of our parameter estimation in productivity changes, efficiency changes, and technological progress in 53 developing countries. The results show that regardless of the convex and nonconvex models, the coefficients of agricultural green productivity and its two components in economic and environmental dimensions are all positive, most of which were significant at the 1% level. As such, the performance of agricultural green productivity and its two components in economic and environmental dimensions does not converge. These developing countries are in different stages of agricultural development, whereas the initial level of agricultural green productivity is significantly different. Although green agriculture productivity has improved in all countries in the past 20 years, the speed of development green agriculture has failed to make up for the low agricultural green productivity in lagging countries. Developing countries with higher agricultural green productivity have maintained their good performance through their effective allocation of resources and advanced technology.

Table 5. Number of periods countries appeared as innovators, 2000–2019

Country	Number of periods	Initial period	Last period
Azerbaijan	4	2011-2012	2018-2019
Armenia	3	2008-2009	2011-2012
India	3	2001-2002	2010-2011
Egypt	1	2007-2008	-
Pakistan	1	2012-2013	-

Table 5 provides the detailed results for innovative countries from 2000 to 2019 according to definition (10). We also report the number of times each country is identified as an innovator, as well as the first and last periods in which this occurs. Azerbaijan has been identified as the most frequently innovative country during the period 2000–2019. It becomes an innovator in 2011 and maintained this position until 2019. Armenia and India follow Azerbaijan. Armenia appears as an innovator among developing countries for three consecutive years since 2008, whereas India becomes an innovative country three times in 2001–2011. Countries such as Egypt and Pakistan have become innovators in agricultural green production for some time. Pakistan becomes an innovative country during 2012–2013 when biotechnology spread throughout the country. Biotechnology has made a significant contribution to agricultural green development in Pakistan. Pakistan grew 2.8 million hectares of biotech cotton in 2013, which significantly reduced the use of pesticides (James, 2013).

5. Conclusions and policy implications

This study introduces undesirable outputs into the calculation of global and local technological progress and expands the definition of both to green productivity. First, we calculate the green performance of agriculture in Belt and Road countries based on the by-production model using the convex and nonconvex methods. Second, we distinguish the sources of agricultural technological progress in Belt and Road countries. Using the extended definitions, we explore the extent to which global and local innovation forces have contributed to agricultural technological progress in developing countries. Third, we examine whether the agricultural green performance of countries in the Belt and Road region converged and we also identify which countries play the role of innovators, to provide a reference for promoting agricultural cooperation in the region.

The key findings are summarized as follows. First, Belt and Road countries show improvements in their agricultural green productivity, efficiency changes, and technological progress from 2000 to 2019. The 2011–2019 period witnesses rapid development of green agriculture, and environmental technological progress is the driving force of growth under the nonconvex model. However, the cumulative change rate of green productivity indicators obtained by the nonconvex method is higher than that calculated by the convex method, which provides evidence from agriculture for the inference of the previous literature supporting the nonconvex FDH method. The nonconvex frontier is likely to offer a better depiction of agricultural activities and of the actual situation. Second, 14 of the sample countries demonstrate GTP and LTP between 2000 and 2019, and the contributions of global and local innovation power are about the same. However, the local innovation force is relatively weak in terms of environmental performance. Overall, the loose definition of TP2 is the most applicable definition for the agricultural sector in Belt and Road countries. Third, we find no convergence in the green development of agriculture in the Belt and Road region. Some of the countries continue to push the production frontier in the Belt and Road region upward with higher agricultural green production performance. Azerbaijan is shown to be the most innovative country.

The results have several policy implications. First, developing countries must pay more attention to environmental technological innovation. To reduce carbon emissions from agricultural production, each country should increase investment in agricultural technology and promote low-carbon production technologies to give full play to the power of local innovation. Second, Belt and Road construction must consider the gaps in agricultural development among countries and implement more agricultural cooperation projects. To narrow the gaps in sustainable agricultural development, regional organizations should promote the widespread dissemination of advanced technologies and experiences within the region and encourage innovative countries to help backward countries improve their agricultural green performance.

This study has some limitations. First, more research is needed to examine the validity of convexity imposed on production technology in general, especially when the true empirically estimated technology may be nonconvex. Second, we only investigate the agricultural sector of 53 developing countries, and further research could be conducted with larger samples.

Appendix. Estimation Strategy

A set of linear programs that involves comparing observations with their sample must be solved to compute the Luenberger productivity indicator (4) and its components. Provided that the production technology is convex, the output-oriented DEA model can be applied. The specific directional distance function with given constraints is given by:

$$D(x,y,z;0,g_y,g_z) = \max \frac{1}{2}\left(\sum_{m=1}^{M} \delta^m / M + \sum_{b=1}^{B} \theta^j / J\right)$$

$$\begin{aligned}
s.t.\ & \sum_{k=1}^{K} \lambda_k y_k^m \geq y_{k'}^m + \delta^m g_y^m,\ m = 1,\ldots,M \\
& \sum_{k=1}^{K} \lambda_k x_k^n \leq x_{k'}^n,\ n = 1,\ldots,N \\
& \sum_{k=1}^{K} \lambda_k x_k^p \leq x_{k'}^p,\ p = 1,\ldots,P \\
& \sum_{k=1}^{K} \lambda_k = 1,\ \lambda_k \geq 0,\ k = 1,\ldots,K \\
& \sum_{k=1}^{K} \sigma_k z_k^b \leq z_{k'}^b - \theta^b g_z^b,\ b = 1,\ldots,B \\
& \sum_{k=1}^{K} \sigma_k x_k^p \geq x_{k'}^p,\ p = 1,\ldots,P \\
& \sum_{k=1}^{K} \sigma_k = 1,\ \sigma_k \geq 0,\ k = 1,\ldots,K
\end{aligned} \quad \text{(LP-C)}$$

where both λ_k and σ_k are weight variables. The former weight variable is associated with desirable outputs, "clean" inputs, and "dirty" inputs rendered by sub-technology T_{eco}. The latter weight variable represents the impact of sub-technology T_{env}. that employs "dirty" inputs and generates undesirable outputs. It is noticeable that all the constraints on the left reflect the performance of the benchmark unit while the other side expressions reveal the real performance of each DMUS. In the current setting, we strike a balanced expansion whereby desirable outputs can be expanded and undesirable outputs can be contracted simultaneously.

In a similar manner, if we discard the convexity assumption in favor of a non-convex technology, then our FDH program for calculating the distance function is shown by:

$$
\begin{aligned}
D(x,y,z;\,0,g_y,g_z) \;=\; & \max \frac{1}{2}\left(\sum_{m=1}^{M}\delta^m / M + \sum_{b=1}^{B}\theta^j / J\right) \\
s.t.\; & \sum_{k=1}^{K}\lambda_k y_k^m \geq y_{k'}^m + \delta^m g_y^m,\ m=1,\ldots,M \\
& \sum_{k=1}^{K}\lambda_k x_k^n \leq x_{k'}^n,\ n=1,\ldots,N \\
& \sum_{k=1}^{K}\lambda_k x_k^p \leq x_{k'}^p,\ p=1,\ldots,P \\
& \sum_{k=1}^{K}\lambda_k = 1,\ \lambda_k \geq 0,\ k=1,\ldots,K \\
& \sum_{k=1}^{K}\sigma_k z_k^b \leq z_{k'}^b - \theta^b g_z^b,\ b=1,\ldots,B \\
& \sum_{k=1}^{K}\sigma_k x_k^p \geq x_{k'}^p,\ p=1,\ldots,P \\
& \sum_{k=1}^{K}\sigma_k = 1,\ \sigma_k \in \{0,1\},\ k=1,\ldots,K
\end{aligned}
\tag{LP-NC}
$$

where λ_k and σ_k have only two possible binary integer values, which ensures that the peer unit on the production frontier must be a real observation. If one observation result is dominated by at least one other observation, then it can be declared invalid. We think that the continuing debate surrounding convex and non-convex technologies stems from the point that the units on the curve connecting each vertex point in the convex frontier are not included in the nonconvex frontier. Because a nonconvex frontier is only composed of a few actual observations, the nonconvex model tends to offer a more conservative evaluation of production possibility sets than does the convex one.

References

Ang, F., K. Kerstens (2021) Energy Productivity and Greenhouse Gas Emission Intensity in Dutch Dairy Farms: A Hicks-Moorsteen By-Production Approach under Nonconvexity, Lille, IESEG School of Management (Working paper 2021-EQM-07), 22 pp.

Atkinson, A. B., & Stiglitz, J. (1969). A new view of technological change. The Economic Journal, 79(315), 573-578.

Balaguer-Coll, M. T., Prior, D., & Tortosa-Ausina, E. (2007). On the determinants of local government performance: A two-stage nonparametric approach. European Economic Review, 51(2), 425-451.

Barro, R. J., & Sala-i-Martin, X. (1992). Convergence. Journal of Political Economy, 100(2), 223-251.

Barros, C., Fujii, H., & Managi, S. (2015). How scale and ownership are related to financial performance? A productivity analysis of the Chinese banking sector. Journal of Economic Structures, 4(1), 1-14.

Baumol, W. J., & Bradford, D. F. J. E. (1972). Detrimental externalities and non-convexity of the production set. 39(154), 160-176.

Beltrán-Esteve, M., & Picazo-Tadeo, A. J. (2017). Assessing environmental performance in the European Union: Eco-innovation versus catching-up. Energy Policy, 104, 240-252.

Bernard, J., Cantner, U., & Westermann, G. (1996). Technological leadership and variety: A Data Envelopment Analysis for the French machinery industry. Annals of Operations Research, 68(3), 361-377.

Cassman, K. G., Dobermann, A., Walters, D. T., & Yang, H. (2003). Meeting cereal demand while protecting natural resources and improving environmental quality. Annual Review of Environment and Resources, 28(1), 315-358.

Cesaroni, G., Kerstens, K., & Van de Woestyne, I. (2017). Global and local scale characteristics in convex and nonconvex nonparametric technologies: A first empirical exploration. European Journal of Operational Research, 259(2), 576-586.

Chambers, R. G. (2002). Exact nonradial input, output, and productivity measurement. Economic Theory, 20(4), 751-765.

Chambers, R. G., Fāure, R., & Grosskopf, S. (1996). Productivity growth in APEC countries. Pacific Economic Review, 1(3), 181-190.

Charnes, A., Cooper, W. W., & Rhodes, E. (1978). Measuring the efficiency of decision making units. European Journal of Operational Research, 2(6), 429-444.

Chung, Y. H., Färe, R., & Grosskopf, S. (1997). Productivity and undesirable outputs: a directional distance function approach. Journal of Environmental Management, 51(3), 229-240.

Coelli, T., Lauwers, L., & Van Huylenbroeck, G. (2007). Environmental efficiency measurement and the materials balance condition. Journal of Productivity Analysis, 28(1), 3-12.

Copeland, A., & Hall, G. J. J. o. A. E. (2011). The response of prices, sales, and output to temporary changes in demand. 26(2), 232-269.

Coviello, D., Ichino, A., & Persico, N. J. A. E. R. (2014). Time allocation and task juggling. 104(2), 609-623.

De Borger, B., & Kerstens, K. (1996). Cost efficiency of Belgian local governments: A comparative analysis of FDH, DEA, and econometric approaches. Regional science and urban economics, 26(2), 145-170.

Deligios, P. A., Carboni, G., Farci, R., Solinas, S., & Ledda, L. (2019). The Influence of Herbicide Underdosage on the Composition and Diversity of Weeds in Oilseed Rape (Brassica napus L. var. oleifera DC) Mediterranean Fields. Sustainability, 11(6). doi:10.3390/su11061653

Deprins, D., Simar, L., & Tulkens, H. (1984). Measuring labor-efficiency in post offices. In M. M., P. P., & T. H. (Eds.), The Performance of Public Enterprises : Concepts and Measurement (pp. 243-267): Amsterdam Elsevier.

Emerick, K., De Janvry, A., Sadoulet, E., & Dar, M. H. (2016). Technological innovations, downside risk, and the modernization of agriculture. American Economic Review, 106(6), 1537-1561.

Färe, R., Grosskopf, S., Noh, D.-W., & Weber, W. (2005). Characteristics of a polluting technology: theory and practice. Journal of Econometrics, 126(2), 469-492.

Färe, R., Grosskopf, S., Norris, M., & Zhang, Z. (1994). Productivity growth, technical progress, and efficiency change in industrialized countries. The American Economic Review, 66-83.

Färe, R., Shawna, G., & Carl A., P. (2001). Accounting for air pollution emissions in measures of state manufacturing productivity growth. Journal of Regional Science, 41(3), 381-409.

Fujii, H., Edamura, K., Sumikura, K., Furusawa, Y., Fukuzawa, N., & Managi, S. (2015). How enterprise strategies are related to innovation and productivity change: an empirical study of Japanese manufacturing firms. Economics of Innovation and New Technology, 24(3), 248-262.

James, C. (2013). Global Status of Commercialized Biotech/GM Crops: 2013: ISAAA Brief No. 46: International Service for the Acquisition of Agri-biotech Applications (ISAAA).

Kerstens, K., & Eeckaut, P. V. (1999). Estimating returns to scale using non-parametric deterministic technologies: A new method based on goodness-of-fit. European Journal of Operational Research, 113(1), 206-214.

Kerstens, K., & Managi, S. (2012). Total Factor Productivity Growth and Convergence in the Petroleum Industry: Empirical Analysis Testing for Convexity. International Journal of Production Economics, 139(1), 196-206.

Kerstens, K., & Van de Woestyne, I. (2021). Cost functions are nonconvex in the outputs when the technology is nonconvex: convexification is not harmless. Annals of Operations Research, 1-26.

Kim, K., Chavas, J. P., Barham, B., & Foltz, J. J. A. E. (2012). Specialization, diversification, and productivity: a panel data analysis of rice farms in Korea. 43(6), 687-700.

Krautkraemer, J. A. J. J. o. D. E. (1994). Population growth, soil fertility, and agricultural intensification. 44(2), 403-428.

Kumar, V., Jat, H. S., Sharma, P. C., Gathala, M. K., Malik, R. K., Kamboj, B. R., . . . Sharma, D. (2018). Can productivity and profitability be enhanced in intensively managed cereal systems while reducing the environmental footprint of production? Assessing sustainable intensification options in the breadbasket of India. Agriculture, ecosystems & environment, 252, 132-147.

Kumar, V., & Ladha, J. K. (2011). Direct seeding of rice: recent developments and future research needs. Advances in Agronomy, 111, 297-413.

López-Pueyo, C., & Mancebón, M.-J. (2010). Innovation, accumulation and assimilation: Three sources of productivity growth in ICT industries. Journal of Policy Modeling, 32(2), 268-285.

McFadden, D. (1978). Cost, revenue, and profit functions. Histoy of Economic Thought Chapters, 1.

Murty, S. (2015). On the properties of an emission-generating technology and its parametric representation. Economic Theory, 60(2), 243-282.

Murty, S., Russell, R. R., & Levkoff, S. B. (2012). On modeling pollution-generating technologies. Journal of Environmental Economics and Management, 64(1), 117-135.

Pretty, J., & Bharucha, Z. P. (2015). Integrated pest management for sustainable intensification of agriculture in Asia and Africa. Insects, 6(1), 152-182.

Romer, P. (1990) Are nonconvexities important for understanding growth?, American Economic Review, 80(2), 97–103.

Scarf, H. (1994). The allocation of resources in the presence of indivisibilities. Journal of Economic Perspectives, 8(4), 111-128.

Shen, Z., Vardanyan, M., Balezentis, T., & Wang, J. (2021). Analyzing the Tradeoff Between the Economic and Environmental Performance: The Case of the Chinese Manufacturing Sector. Ieee Transactions on Engineering Management. doi:10.1109/tem.2021.3118275

Solheim, E. (2017). A Green Belt and Road [Press release]

Steger, T. (2000). Economic growth with subsistence consumption. In Transitional

Dynamics and Economic Growth in Developing Countries (pp. 21-60): Springer.

Timmer, M. P., & Los, B. (2005). Localized innovation and productivity growth in Asia: an intertemporal DEA approach. Journal of Productivity Analysis, 23(1), 47-64.

Tone, K., & Sahoo, B. K. (2003). Scale, indivisibilities and production function in data envelopment analysis. International Journal of Production Economics, 84(2), 165-192.

Wang, K., & Wei, Y.-M. (2016). Sources of energy productivity change in China during 1997-2012: A decomposition analysis based on the Luenberger productivity indicator. Energy Economics, 54, 50-59. doi:10.1016/j.eneco.2015.11.013

Yuan, Q., Balezentis, T., Shen, Z., & Streimikiene, D. (2021). Economic and environmental performance of the belt and road countries under convex and nonconvex production technologies. Journal of Asian Economics, 75. doi:10.1016/j.asieco.2021.101321

Zhu, N., Dai, X., Balezentis, T., Streimikiene, D., & Shen, Z. (2022). Estimating production gains from international cooperation: Evidence from countries along the Belt and Road. Economic Change and Restructuring, 55(2), 715-736. doi:10.1007/s10644-021-09325-9