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RESEARCH

Global and Local Technological Changes with Environmental Factors: Analysis of the Agricultural Sector in the Belt and Road Countries

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Abstract
The United Nations 2030 Agenda for Sustainable Development necessitates the expansion of green agriculture, which entails the adoption of low-carbon technologies. This study expands the understanding of technological progress by incorporating the consideration of undesirable outputs within the by-production model framework. Convex and nonconvex models are applied to calculate the distance function, from which the Luenberger productivity indicator is obtained and decomposed into economic and environmental efficiencies. Then, this study assesses the contribution of global and local innovation forces to technological progress, taking environmental factors into account. Additionally, it examines the beta-convergence of productivity and identifies some countries as innovators. Analyzing the technological changes in the agricultural sector across 53 Belt and Road nations, the findings indicate advancements in green productivity, efficiency changes, and technological progress, with technological progress in the environmental dimension contributing the most to efficiency improvement. Moreover, 14 out of 53 sample countries experience both global and local technological progress, with global and local innovation forces contributing equally. However, agricultural green development in these countries does not converge. Therefore, the findings of this study suggest that the Belt and Road countries should prioritize environmental technological innovation and agricultural cooperation to foster sustainable development.

Keywords Global and local technological change · By-production model · Luenberger productivity indicator · Convex and nonconvex

1 Introduction

The Belt and Road Initiative (BRI) is an expansive infrastructure and economic development project initiated by the Chinese government in 2013 with the aim of enhancing trade and investment connectivity between China and various countries in Asia, Europe, and Africa. However, concerns have been raised that certain BRI projects may exert adverse effects on the environment. In response, several developing countries have established the Green Belt and Road Initiative to mitigate these potential environmental impacts. This commitment is solidified through the signing of a Memorandum of Understanding in 2016, which also reaffirms these countries' dedication to upholding the United Nations' 2030 Agenda for Sustainable Development. As a result, these countries are endeavoring to advance environmentally conscious and sustainable practices within the framework of BRI projects in alignment with the global Sustainable Development Goals (SDGs), which encompass reducing carbon emissions, safeguarding

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ecosystems, and fostering clean energy. Given the pivotal role of agriculture within the BRI countries and its substantial contribution to global greenhouse gas emissions [11], there is a pressing need for a targeted examination of green agricultural development in these regions.

Agricultural practices employed within the Belt and Road countries are frequently confronted with substantial environmental impediments. For instance, the prevalent practice of puddling and transplanting in rice cultivation within South Asia necessitates an extensive consumption of irrigation water and energy [34], while simultaneously resulting in a decrease in rice yields by 8–10% [35]. Consequently, there is a multifaceted endeavor underway to augment agricultural productivity in the Belt and Road countries.

Advancements in agricultural technology within the Belt and Road countries have markedly improved their environmental credentials. On the one hand, global technological breakthroughs, propelled by numerous developing economies participating in the BRI, have significantly increased agricultural productivity. For instance, innovations in pest management have led to a 40.9% increase in crop yields while simultaneously reducing the application of pesticides by 30.7% [40]. On the other hand, local technological advancements driven by local innovation efforts, such as the intensive agricultural practices in India, demonstrate the rapid progression towards sustainable agricultural practices [23].

Therefore, identifying the primary factors contributing to efficiency enhancement and technological advancement is pivotal for mapping a trajectory of sustainable agriculture within the Belt and Road countries. What are the main drivers of changes in agricultural green productivity across the Belt and Road 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 promoting sustainable agricultural practices across the Belt and Road countries. Specifically, this study analyzes the impact of technical and environmental performance on changes in agricultural green productivity across the Belt and Road countries from 2000 to 2019 employing both convex and nonconvex models. Furthermore, we distinguish between global and local technological transformations within the by-production model framework, incorporating a performance decomposition. We conclude with an examination of performance convergence and the identification of innovative countries. This study fills a gap in the literature by being the first to quantify the interplay of global and local technological progress in agriculture among the Belt and Road countries, while simultaneously accounting for undesirable output considerations.

2 Literature Review

2.1 Green Productivity Estimation

Numerous studies have contributed to the advancement of productivity measurement by incorporating environmental factors into both inputs and outputs. The Malmquist productivity index, for instance, has been employed to represent the co-production of beneficial and detrimental outcomes [26]. Nonetheless, its reliance on the weak disposability assumption does not align with the conservation principles of matter [17]. Chambers [13] introduces the Luenberger productivity indicator (LPI) via the directional distance function (DDF), which has been further adapted to account for pollutants as undesirable outputs. Despite this extension, the LPI remains limited in its ability to decompose the economic and environmental contributions to green productivity improvements due to its lack of additive completeness [39].

To address these issues, Murty, Russell, and Levkoff [38] develop a by-production (BP) model that ensures pollutants adhere to costly disposability while other outputs are subject to free disposability. This model breaks down performance into economic and environmental components using two distinct sub-technologies. The integration of the LPI with the BP model results in a framework that possesses three desirable features: (i) it satisfies the material balance conditions,(ii) it allows for the decomposition of economic and environmental changes; and (iii) it can relax the assumption of convexity. This methodology has been employed to assess economic and environmental production performance in various countries or regions, including the European Union [8] and China [43, 48]. However, the application of this approach to assess the economic and environmental performance across the Belt and Road countries is not widespread [50, 52]. This study focuses on productivity analysis of the agricultural sector alone in these Belt and Road economies, providing a level of specificity that surpasses the broader focus of prior studies. Therefore, this study serves as a valuable complement to the existing research.

2.2 Convex and Nonconvex Technologies

Productivity growth is often estimated through parametric specification methods. However, there is a growing trend among recent studies to employ nonparametric approaches. These methods enable dynamic analysis without the need for input and output price data, relying solely on technical information. Two prevalent nonparametric techniques are data envelopment analysis (DEA), which employs a convex production frontier, and free disposal hull (FDH), which utilizes a nonconvex production frontier [15, 20, 22]. A convex production frontier is a piecewise linear curve constructed from actual decision-making units (DMUs), and its outward extension requires a global shift in the production frontier. In contrast, a nonconvex production frontier is made up of actual DMUs without a stringent convexity constraint, allowing for local shifts in the production frontier to accommodate outward expansion.

The debate over the convexity of the production frontier has been a topic of significant discussion. The traditional view generally holds that production technology satisfies the convexity axiom. However, real-world production processes introduce complexities like widespread setup costs and variable lead times, which can challenge the assumption of convexity [19]. Furthermore, the indivisibility of production factors, the presence of increasing returns to scale, and the well-documented externalities of production all contravene the axiom of convexity and necessitate careful consideration [7, 41, 42]. In response to these complexities, researchers have developed a nonconvex variable return-to-scale model, which has been further refined to accommodate cases of constant, nonincreasing, and nondecreasing returns to scale. These models aim to serve as a standard for assessing inefficiencies among DMUs [22, 29]. Despite this progress, there remains an ongoing debate regarding the application of nonconvex technologies, particularly with regard to scale effects that may diverge under convexity and nonconvexity [12].

Nevertheless, a growing body of evidence supports the superiority of nonconvex models over convex models. For instance, Tone and Sahoo [47] argue that nonconvex techniques embedded in FDH models can help reveal the inseparability caused by task-specific processes. Balaguer-Coll, Prior, and Tortosa-Ausina [3] explain that the nonconvex production frontier contains more efficient observations. Copeland and Hall [18] show that per vehicle cost is 4.36% higher under a nonconvex model than that under a convex model in the car manufacturing case. Kerstens and Van de Woestyne [31] reveal that cost estimations under convexity are on average between 21 and 38% lower than those under nonconvexity.

All empirical evidence points to the necessity of reevaluating the convexity assumption in green productivity estimates. Given that land is generally indivisible in agricultural setting [33], performance evaluations under convexity may fall short in accuracy [1, 32]. Thus, this study aims to provide empirical analysis for the application of nonconvex models in agriculture (e.g., Ang, Kerstens and Sadeghi [1] summarize evidence on nonconvexities in agriculture) as well as evidence in support for the further comparison of the convexity and nonconvexity assumptions.

2.3 Global and Local Technological Change

The concept of local technological change (LTC) originates in the pioneering work of Atkinson and Stiglitz [2]. Although these authors do not formally define LTC, they do contrast LTC with the idea of global technological change (GTC). GTC refers to shifts that affect the entire production function, whereas LTC refers to shifts that affect only part or different parts of the production function to varying degrees.

Following this foundational work, a series of empirical studies have emerged. Bernard, Cantner, and Westermann [9] use a nonparametric approach within a convex production technology framework to study innovators and technological change in the French machinery industry. They conclude that LTC has a significant impact on firm performance and that innovators play a key role in driving local technological change within their field. Timmer and Los [46] investigate labor productivity growth in Asian countries and show that technological innovation is localized in the agricultural and manufacturing sectors. López-Pueyo and Mancebón [36] report that LTC significantly contributes to performance enhancements in the information and communication technology industry. However, despite these various empirical insights, the literature has not yet provided a clear method for operationalizing the identification of LTC.

Kerstens and Managi [30] make an initial effort to establish operational definitions for global technological productivity change (GTP) and local technological productivity change (LTP) within the frameworks of both convex and nonconvex technologies. In their empirical investigation of oil field drilling in the Mexican Gulf, they find that there are approximately 62.8% more observations that met the criteria for LTP than for GTP. In contrast, Barros, Fujii, and Managi [6] study Chinese commercial banks and observe more instances of GTC than LTC. Fujii et al. [27] examine 16 sectors within the Japanese manufacturing industry and demonstrate that the prevalence of GTP and LTP differs across sectors and over time. These findings highlight the importance of considering the assumptions of convex and nonconvex technologies when distinguishing between global and local technological changes. However, the inclusion of undesirable outputs in the quantification of GTP and LTP has not been investigated, which underscores the need for further empirical research, particularly in the context of agricultural production.

3 Methodology

To begin, we develop a model of environmental technology that accommodates both convex and nonconvex specifications within the bounds of the BP model. This is followed by a rough illustration of the model. We then proceed to decompose the Luenberger Productivity Index (LPI) for more precise measurements. In the second stage, we delineate the difference between global and local technological changes as they pertain to green production performance, taking into account the presence of undesirable outputs. In the third stage, we explore whether green performance improvements exhibit beta-convergence, which is the phenomenon where less developed regions grow at a faster pace than more developed ones, enabling them to narrow the gap. Additionally, we aim to identify instances of innovation. Subsequently, we offer a comprehensive description of the data employed in our analysis.

3.1 Modeling Environmental Technology

We apply a by-production technology that can be illustrated by a dual frontier [38]. We assign K DMUs that correspond 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^t, the consumption of which does not produce pollutants, and the "dirty" inputsx_p^t, which generate pollution in production activities. The "dirty" inputs generate undesirable outputs z_j^t, whereas both types of inputs produce desirable outputs y_m^t. In brief, similar to Murty et al. (38: pp. 121–122), in period t, the desirable output production process is modeled by one subset of technology that describes the conventional technology, T_{eco}^t, whereas the polluting production process is defined by another subset of technology that focuses on the green environment, T_{env}^t. Production technology sets (T_{BP}^t) in period t are defined as follows:

$$
\begin{aligned}
T_{BP}^t &= T_{eco}^t \cap T_{env}^t \\
&= \left\{ (x_n^t, x_p^t, y_m^t, z_j^t) \in \mathbb{R}_+^{N+P+M+J} : (x_n^t, x_p^t) \textit{ can produce } y_m^t; x_p^t \textit{ can generate } z_j^t \right\} \\
T_{eco}^t &= \left\{ (x_n^t, x_p^t, y_m^t) \in \mathbb{R}_+^{N+P+M} | f(x_n^t, x_p^t, y_m^t) \le 0 \right\} \\
T_{env}^t &= \left\{ (x_p^t, z_j^t) \in \mathbb{R}_+^{P+J} | g(x_p^t) \le z_j^t \right\}.
\end{aligned} \tag{1}
$$

where *f(.)* and *g(.)* are used to model the sub-technologies related to economic and environmental inefficiency, 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 is imposed.

To distinguish these two output groups, we assume free disposability (A_{eco}) in T_{eco}^t that employs all inputs to obtain desirable outputs—the supplied inputs can yield fewer outputs. We also assume the costly disposability (A_{env}) in T_{env}^t 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:

$$
\begin{aligned}
&A_{eco} : \textit{if } (x_n^t, x_p^t, y_m^t) \in T_{eco}^t, \\
&\textit{then } (\tilde{x}_n^t, \tilde{x}_p^t, \tilde{y}_m^t) \in T_{eco}^t \textit{ for all } (-\tilde{x}_n^t, -\tilde{x}_p^t, \tilde{y}_m^t) \le (-x_n^t, -x_p^t, y_m^t). \\
&A_{env} : \textit{if } (x_p^t, z_j^t) \in T_{env}^t, \\
&\textit{then } (\tilde{x}_p^t, \tilde{z}_j^t) \in T_{env}^t \textit{ for all } (\tilde{x}_p^t, -\tilde{z}_j^t) \le (x_p^t, z_j^t).
\end{aligned} \tag{2}
$$

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.

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 in period t. As in previous work [16, 24], one can expand the desirable outputs and reduce the undesirable outputs simultaneously, i.e.:

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

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^t,g_z^t). Thus, an evaluated country with scalar $\delta = 0$ or $\theta = 0$ at the optimum can be regarded as an efficient 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 [14]. The output-oriented green LPI formulation comparing the base period t with the next period $t+1$ and that keeps the input amounts the same is given by:

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

where $D^t(.)$ denotes the DDF in the time period t and $D^{t+1}(.)$ denotes the DDF in the time period $t+1$. The terms in parentheses $\left(x^t, y^t, z^t; 0, g_y^t, g_z^t\right)$ and $\left(x^{t+1}, y^{t+1}, z^{t+1}; 0, g_y^{t+1}, g_z^{t+1}\right)$ in (4) represent the inputs and outputs of the evaluated unit, while $D^t(.)$ and $D^{t+1}(.)$ denote the time period of the production technology (or frontier) with regard to which the evaluated unit is projected. By using the evaluated units and production frontiers from two different periods, a total of four different DDFs can be constructed to define the LPI: i.e., two own time period DDFs $D^t\left(x^t, y^t, z^t; 0, g_y^t, g_z^t\right)$ and $D^{t+1}\left(x^{t+1}, y^{t+1}, z^{t+1}; 0, g_y^{t+1}, g_z^{t+1}\right)$ as well as two mixed time period DDFs $D^{t+1}\left(x^t, y^t, z^t; 0, g_y^t, g_z^t\right)$ and $D^t\left(x^{t+1}, y^{t+1}, z^{t+1}; 0, g_y^{t+1}, g_z^{t+1}\right)$. The details of the nonparametric estimation strategies for the convex and nonconvex models appropriate for the BP model are presented in the Appendix.

This output-oriented green LPI can be decomposed to evaluate the disparity between efficiency change ($EC^{t,t+1}$) and technological change ($TP^{t,t+1}$) contributions. 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:

$$\begin{aligned} LPI^{t,t+1} &= EC^{t,t+1} + TP^{t,t+1} \\ EC^{t,t+1} &= D^t\left(x^t, y^t, z^t; 0, g_y^t, g_z^t\right) - D^{t+1}\left(x^{t+1}, y^{t+1}, z^{t+1}; 0, g_y^{t+1}, g_z^{t+1}\right), \\ TP^{t,t+1} &= \frac{1}{2}\left[\begin{array}{c} D^{t+1}\left(x^t, y^t, z^t; 0, g_y^t, g_z^t\right) - D^t\left(x^t, y^t, z^t; 0, g_y^t, g_z^t\right) \\ +D^{t+1}\left(x^{t+1}, y^{t+1}, z^{t+1}; 0, g_y^{t+1}, g_z^{t+1}\right) - D^t\left(x^{t+1}, y^{t+1}, z^{t+1}; 0, g_y^{t+1}, g_z^{t+1}\right) \end{array}\right], \end{aligned} \tag{5}$$

where EC represents efficiency change and TP represents technological change. Efficiency change denotes the alteration in the relative efficiency of a production unit over a specific period of time. Specifically, EC measures the improvement or deterioration in the utilization of resources in the production process of this unit. If EC is positive, then it indicates that the production unit has improved in relative efficiency and is utilizing resources more efficiently. If EC is negative, then the efficiency of the production unit is relatively reduced, and resource utilization becomes less efficient than before. Technological change represents a change in the production method or technical level of the production unit during a specific period of time. If TP is positive, then it indicates that the production unit has adopted a more advanced technology and that it has increased the output level. If TP is negative, then it suggests that the technology or production method of the production unit has become less advanced than before, and the output level has decreased. By combining EC and TP, the LPI can be used to measure the overall productivity change of a production unit, taking into account relative efficiency and technological progress.

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 [43]. Therefore, the economic and environmental decomposition of the LPI can be summarized as:

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

3.3 Global and Local Technological Productivity Change

To provide an identification strategy for distinguishing between GTP and LTP in a green productivity context, we follow Kerstens and Managi [30] 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 [37]. If we define global and local technological change in terms of economic and environmental efficiency as shifts towards the economic and environmental frontiers, then the definitions of Kerstens and Managi [30] can be extended to the BP setting where undesirable outputs are included.

To begin with, we define global technological progress as efficient observations between time periods t and $t+1$ relative to the convex production frontier. In contrast, we define local technological progress as efficient observations between time periods t and $t+1$ relative to a nonconvex production frontier, where these observations are inefficient relative to the convex production frontier but indeed exhibit positive technological changes relative to the nonconvex production frontier.

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, these constraints 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 with respect to 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. Therefore, the three definitions of GTP are as follows:

$$
\begin{aligned}
TP1_C^{t,t+1} &= \{(x^{t,t+1}, y^{t,t+1}) : D_C^t(x^t, y^t) = 0 \wedge D_C^{t+1}(x^{t+1}, y^{t+1}) = 0 \wedge TP_C^{t,t+1} > 0\} \\
TP2_C^{t,t+1} &= \{(x^{t,t+1}, y^{t,t+1}) : D_C^t(x^t, y^t) > 0 \wedge D_C^{t+1}(x^{t+1}, y^{t+1}) = 0 \wedge TP_C^{t,t+1} > 0\} \\
TP3_C^{t,t+1} &= \{(x^{t,t+1}, y^{t,t+1}) : D_C^t(x^t, y^t) > 0 \wedge D_C^{t+1}(x^{t+1}, y^{t+1}) > 0 \wedge TP_C^{t,t+1} > 0\}
\end{aligned}
\tag{7}
$$

where the subscript c indicates the convex frontier. $TP1_C^{t,t+1}$ refers to the original definition of GTP with strict constraints. We now envisage two different definitions in which the requirements for efficiency are gradually relaxed during these two periods. First, observations are required to be efficient in the second period $t+1$, but not necessarily in the first period t, while obtaining a positive technological change relative to the nonconvex frontier between the two time periods, which leads to a slightly looser definition of global technological progress, $TP2_C^{t,t+1}$. Second, observations are required to be efficient in the first period t, but not necessarily in the second period $t+1$, again requiring a positive technical progress between the two time periods relative to the nonconvex production frontier. This results in another slightly relaxed way to define global technological progress, $TP3_C^{t,t+1}$.

LTP is introduced as the product of an outward shift of the nonconvex frontier, where observations are regarded as efficient relative to the nonconvex frontiers but inefficient for the 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. Therefore, the following three definitions of LTP are obtained:

$$
\begin{aligned}
TP1_{NC}^{t,t+1} &= \{(x^{t,t+1}, y^{t,t+1}) : D_{NC}^t(x^t, y^t) = 0 \wedge D_{NC}^{t+1}(x^{t+1}, y^{t+1}) = 0 \\
&\quad \wedge D_C^t(x^t, y^t) > 0 \wedge D_C^{t+1}(x^{t+1}, y^{t+1}) > 0 \wedge TP_{NC}^{t,t+1} > 0\} \\
TP2_{NC}^{t,t+1} &= \{(x^{t,t+1}, y^{t,t+1}) : D_{NC}^t(x^t, y^t) > 0 \wedge D_{NC}^{t+1}(x^{t+1}, y^{t+1}) = 0 \\
&\quad \wedge D_C^t(x^t, y^t) > 0 \wedge D_C^{t+1}(x^{t+1}, y^{t+1}) > 0 \wedge TP_C^{t,t+1} > 0\} \\
TP3_{NC}^{t,t+1} &= \{(x^{t,t+1}, y^{t,t+1}) : D_{NC}^t(x^t, y^t) = 0 \wedge D_{NC}^{t+1}(x^{t+1}, y^{t+1}) > 0 \\
&\quad \wedge D_C^t(x^t, y^t) > 0 \wedge D_C^{t+1}(x^{t+1}, y^{t+1}) > 0 \wedge TP_C^{t,t+1} > 0\}
\end{aligned}
\tag{8}
$$

where $TP1_{NC}^{t,t+1}$ refers to the original definition of LTP with strict constraints. $TP2_{NC}^{t,t+1}$ and $TP3_{NC}^{t,t+1}$ are two relaxed definitions that gradually relax the requirements for efficiency in the same way that GTP does.

Figure 1A 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 convex 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 DMU 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 convex frontier for both assumptions in the year $t+1$: an indicator of global

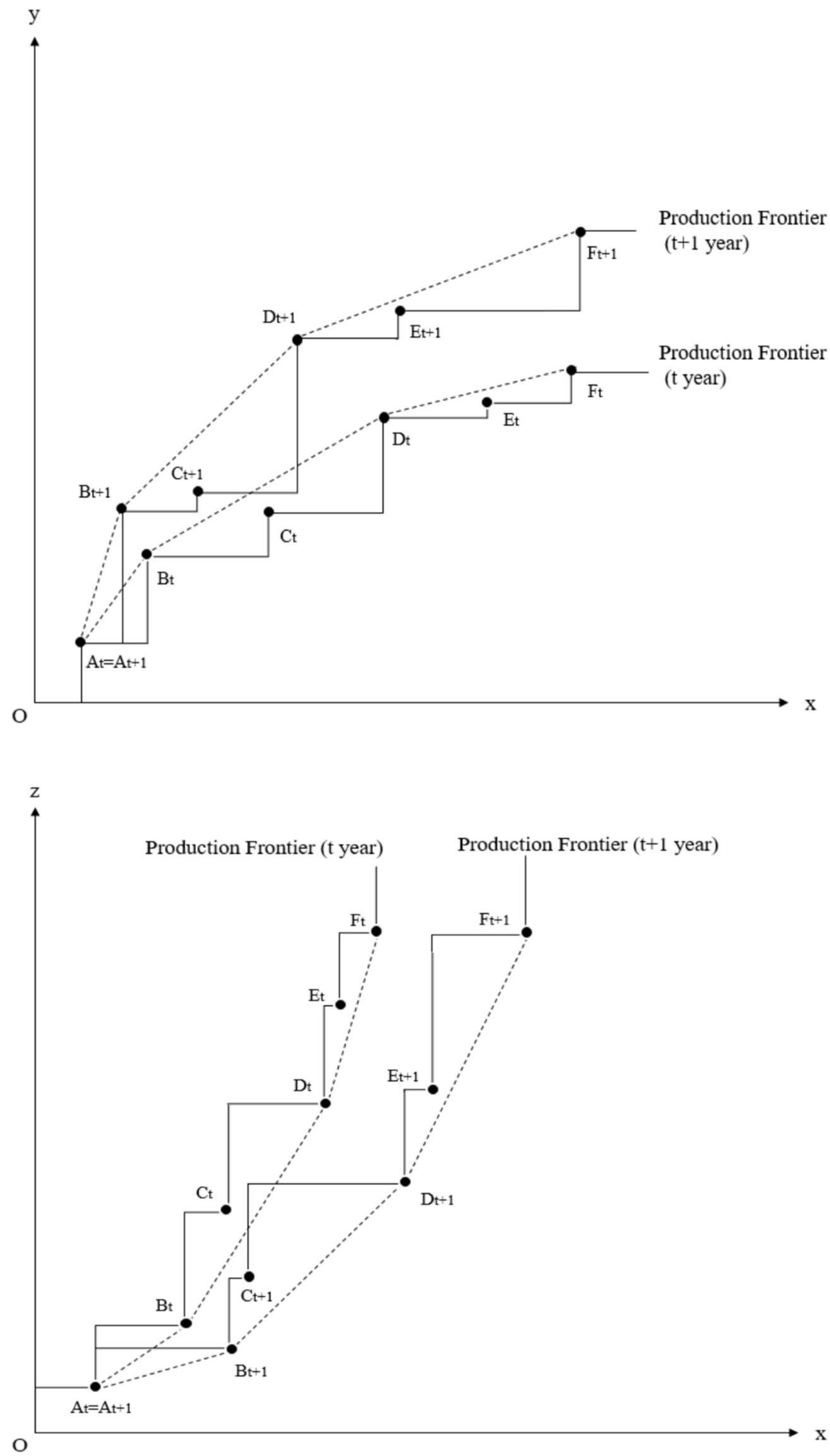


Fig. 1 **A** Production frontier of T_{eco}. **B** Production frontier of T_{env}

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 Fig. 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 Fig. 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 this change can be described as LTP.

3.4 Growth Convergence and Innovator Identification

To gain deeper insight into green efficiency, we refer to Barro and Sala-i-Martin [5] in presenting estimates for the beta-convergence model. This model 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 [45]:

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

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 $\ln y_{i0}$ 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.

What we intend to do is to analyze whether the initial productivity level moves in the opposite direction to the productivity change level: if the β estimate is significantly negative, this indicates growth convergence in the sample of countries. Conversely, if the β estimates are significantly positive, then there is no convergence in GTFP changes for at least the sample countries over the studied period.

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. We use three criteria to identify innovative countries [8, 25]:

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

where TI refers to technological innovators. Those countries who experience positive technological change and whose observations move from an inefficient to an efficient position are called technological innovators. For example, $TP^{t,t+1} > 0$ suggests that technological progress appears between the periods t and $t+1$, $D^{t+1}(x_k^{t+1}, y_k^{t+1}, z_k^{t+1}; 0, g_y^{t+1}, g_z^{t+1}) = 0$ implies that the evaluated DMU is efficient at period $t+1$, and $D^t(x_k^{t+1}, y_k^{t+1}, z_k^{t+1}; 0, g_y^{t+1}, g_z^{t+1}) < 0$ guarantees that the frontier at period $t+1$ is above that at period t. Thus, the technological innovators inherit these specific characteristics.

3.5 Data

Our data sample covers 53 developing countries engaged in the BRI, including 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 sample spans the years from 2000 to 2019.

Following Balezentis et al. [4] and Shen et al. [44], we characterize agricultural production activities by categorizing their outputs into two distinct classes: desirable output, represented by the gross output value at constant prices adjusted for purchasing power parity and undesirable output, which is embodied by carbon dioxide emissions. Similarly, the inputs into the agricultural production process are divided into two categories. The "clean" inputs encompass agricultural employment and the gross fixed formation of capital, while the "pollution-generating" inputs include agricultural land,[1] energy consumption, and the use of fertilizers and pesticides. It is important to note that undesirable outputs can only be generated through the use of pollution-generating inputs.

The data for this study are sourced from the databases of the Food and Agriculture Organization (FAO) database. The monetary variables of capital stock and gross output values used are in constant prices of 2015 and adjusted for purchasing power parity. Data on fertilizer use were obtained by aggregating the volume of the three main elements of nitrogen, phosphorus, and potassium, for a unified calculation. Table 1 provides a brief description of the input and output variables and offers descriptive statistics.

4 Results and Discussion

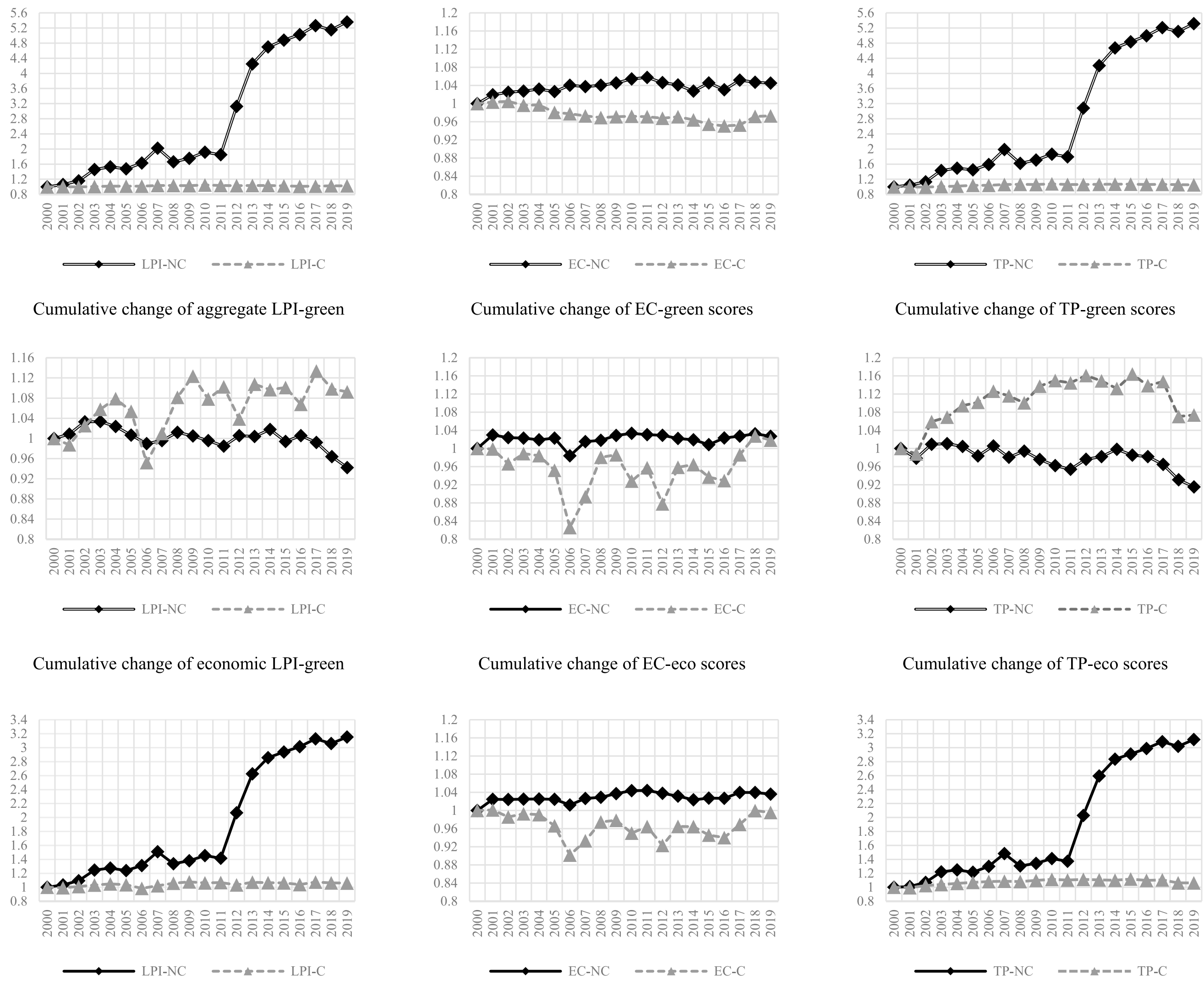
4.1 Productivity Growth and Its Decomposition

Figure 2 illustrates the cumulative LPI scores in terms of green productivity and technical and environmental

[1] Agricultural land is a contributor of total emissions. Note that during the process of agricultural cultivation, both land tillage and post-harvest activities can result in carbon emissions or greenhouse gas emissions. For instance, during the tillage process, methane produced from underground fermentation enters the atmosphere. After harvest, many farmers opt to burn crop residues or bury them underground, leading to fermentation and the generation of methane and other gases (see, e.g., West & Marland [49] or Yun et al. [51]).

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$	4150.1	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 output 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



Cumulative change of aggregate LPI-green

Cumulative change of EC-green scores

Cumulative change of TP-green scores

Cumulative change of economic LPI-green

Cumulative change of EC-eco scores

Cumulative change of TP-eco scores

Cumulative change of environmental LPI-green

Cumulative change of EC-env scores

Cumulative change of TP-env scores

Fig. 2 Cumulative LPI change. Note. NC stands for the nonconvex model, whereas C stands for the convex model. LPI refers to green Luenberger productivity indicator, EC refers to efficiency change, and TP refers to technological progress. Eco and Env stand for the economic and environmental performance of LPI scores, respectively performance for a selected group of countries over the past two decades. 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 the aggregate green LPI, efficiency change, and technological change for nonconvex technologies compared to convex technologies. Moreover, the aggregate green LPI, efficiency change, and technological change by nonconvex techniques exhibit higher values than those linked to convex techniques.

In terms of environmental performance, the trends for LPI, efficiency change, and technological change mirror those of aggregate green productivity—there is more fluctuation and generally higher values for LPI, EC, and TP when nonconvex technologies are considered. When examining economic productivity, the LPI and TC calculated using convexity are higher than those using nonconvexity. Conversely, the efficiency change calculated with convexity is lower than that with nonconvexity. These findings suggest that the cumulative LPI under nonconvex technologies is generally higher, and technological progress is a significant driver of green productivity improvements.

The scores of the green LPI and its TP component slowly increased 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 initiative. 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.

The annual changes in the LPI scores, including overall change, efficiency change, and technological progress, among the 53 developing countries, are presented in Table 2. Notable differences emerge in the estimation outcomes for convex and nonconvex technologies. Specifically, agricultural green productivity and its components EC and TP exhibit higher environmental performance under nonconvexity than under convexity, but in terms of technical performance, the values of all components are lower under nonconvexity. Furthermore, the majority of average change rates for all elements are positive. However, there are exceptions: the values for environmental efficiency change under convexity, and economic LPI and technological progress under nonconvexity are negative. The discrepancies in estimates between the convex and nonconvex models may be attributed to differences in the characteristics of returns to scale inherent in each of the models. These variations could explain the conflicting findings, highlighting the importance of considering the distinct dynamics of returns to scale when analyzing productivity change [12].

4.2 Global and Local Technological Productivity Change

Due to the vast array of production units involved, the advancement of technological change typically manifests itself as a localized and spreading phenomenon. Technological progress is primarily manifested through shifts in the production frontier, which is constrained within a certain input space in the output-oriented by-production model. If the convexity assumption is imposed on technology, then the true technological progress can get masked. In other words, local technological progress is mistaken for global technological progress, and even major local technological breakthroughs may be overlooked. The above empirical results suggest that a higher performance score under the assumption of a nonconvex technology indicates local technological change over time, rather than global technological change. Conversely, a higher performance score under the assumption of a convex technology often corresponds to global technological progress, rather than local technological progress.

Table 3 shows the annual frequency and distribution of GTP and LTP in developing countries over the past two decades as defined in Eqs. (7) and (8). Fourteen countries, or approximately 26% of the sample countries, experience some form of GTP or LTP. In particular, the incidence of GTP does not exceed LTP based on any of the three definitions, indicating that the technological progress in developing countries is predominantly driven by a local

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

Table 3 Frequency of global and local technological progress

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

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 (see (7)-(8)); Eco and Env designate technological progress presented in economic efficiency and environmental production, respectively

technological progress. Moreover, the second identification strategy appears to capture a larger number of GTP and LTP signals. This is likely due to the fact that method TP2 relaxes the identification conditions.

As shown in Table 3, Armenia emerges as the leader in terms of the frequency of technological change, with its technological progress being entirely local. Throughout the early twenty-first century, Armenia's agricultural sector has faced challenges due to subpar infrastructure and a lack of necessary facilities. To get out of the dilemma, local governments adopted a combination of incentive and support 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]). These policies have served as a catalyst for individual farmers to innovate in agricultural production techniques. Consequently, Armenia has been able to become an explosive ground for local technological changes in agriculture among the Belt and Road countries.

India and Azerbaijan rank second and third 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. By contrast, Azerbaijan has experienced more frequent local technological shifts in agricultural production, which are evidenced by improvements in its environmental productivity. This suggests that the technological dynamics in these countries differ somewhat, with India focusing more on global progress and Azerbaijan seeking more localized advancements in its agricultural sector.

As the originator of the BRI, China has itself 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. In contrast, countries such as Bulgaria, Georgia, and Pakistan show fewer overall and local technological advances. These countries have not experienced as frequent or significant technological changes in their agricultural green production technologies. Additionally, a subset of countries such as Sri Lanka, Hungary, Cyprus, Malaysia, Oman, Russia, and Tajikistan has stagnated following one or two instances of GTP and LTP in agricultural green production technology during certain periods. This indicates that these countries have not seen further technological progress in this domain, suggesting potential challenges or limitations in fostering ongoing technological advancements in agricultural green production.

4.3 Convergence and Innovator Recognition

Table 4 reports the convergence results of our parameter estimation of the unconditional convergence velocity Eq. (9)

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

Table 4 Testing β-convergence of productivity changes

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

in productivity changes, efficiency changes, and technological progress across 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, with the majority of these coefficients being statistically significant at the 1% level. This indicates that there is no convergence in the performance of agricultural green productivity and its two components in economic and environmental dimensions. These developing countries are in different stages of agricultural development, and the initial level of agricultural green productivity is significantly different. Despite improvements in the agricultural green productivity across all countries in the past 20 years, the pace of growth in green agriculture has not been sufficient to offset the relatively low levels of agricultural green productivity in lagging countries. Countries with higher agricultural green productivity have maintained their good performance through their effective allocation of resources and advanced technology.

Table 5 provides the detailed results for innovative countries from 2000 to 2019 according to definition (10). We also report the frequency of innovation for each country, as well as the initial and terminal years in which they were recognized as innovators. Azerbaijan stands out as the most consistently innovative country throughout the period 2000–2019, emerging as an innovator in 2011 and maintaining this status until 2019. Armenia and India follow closely behind, with Armenia being identified as an innovator among developing nations for three consecutive years starting in 2008 and India achieving this status three times between 2001 and 2011. Other countries, such as Egypt and Pakistan, have also demonstrated one period of innovation in agricultural green production. Pakistan becomes an innovative country during 2012–2013, which aligns with the widespread adoption of biotechnology in 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 [28].

5 Conclusions and Policy Implications

This study introduces undesirable outputs into the measurement of global and local technological progress, while broadening its scope to include green productivity. First, we calculate the green performance of agriculture in the Belt and Road countries employing both the convex and nonconvex approaches within the by-production model. Second, we distinguish the sources of agricultural technological progress within these countries, utilizing expanded definitions to investigate the impact of global and local innovation drivers on agricultural advancements in developing countries. Third, we examine whether the agricultural green performance of countries within the Belt and Road region has converged and identify those countries that have acted as innovators.

The key findings are summarized as follows. First, the Belt and Road countries show improvements in their agricultural green productivity, efficiency changes, and technological progress from 2000 to 2019. Notably, the period from 2011 to 2019 has witnessed a surge in the development of green agriculture, with environmental technological progress playing a pivotal role in driving growth under the nonconvex model. However, the nonconvex method yields a higher cumulative change rate for green productivity indicators compared to the convex method. This finding provides agricultural evidence supporting previous literature that endorses the nonconvex FDH method (see, e.g., the survey in Ang, Kerstens and Sadeghi [1]). In the realm of agricultural performance evaluation, it is often more feasible for each DMU to have a unique benchmark, rather than multiple benchmarks. For example, in our empirical analysis where countries serve as DMUs, it is more reasonable for one country to be benchmarked against another existing country. In this sense, the nonconvex frontier likely offers a better depiction of agricultural activities and the actual situation.

Second, out of the sample countries, 14 have exhibited GTP and LTP between 2000 and 2019, and these types of technological progress are thought to have occurred equally often in overall performance. Notably, when comparing environmental GTP along the Belt and Road with environmental LTP, the latter is found to be less likely to occur independently in specific Belt and Road countries.

Third, the convergence coefficient is significantly positive, indicating that the gap in agricultural green productivity performance and its economic and environmental dimensions is widening among the 53 Belt and Road countries. In fact, some countries continue to promote the upward movement of the production frontier within the Belt and Road region, with notable improvements in their agricultural green production performance. Furthermore, Azerbaijan stands out as the most innovative country.

The findings have several policy implications. To further promote the sustainable development of global agriculture, more efforts should be invested in optimizing the agricultural green production performance of the Belt and Road countries. Firstly, strengthening agricultural technical cooperation among the Belt and Road countries is the key to the sustainable development of regional agriculture. This can be achieved by improving the allocation of resources and encouraging the expansion of large-scale farming initiatives. Such measures will facilitate the rapid development of high-quality crop varieties, boost research and development in production technologies, and establish a robust environmental-friendly agricultural management framework. Secondly, the BRI should take into account the varying levels of agricultural development across countries. It is essential to execute more collaborative agricultural projects to bridge the gaps in sustainable agricultural development. Regional organizations have a vital role to play in spreading advanced technologies and best practices within the area. Moreover, innovative countries should be encouraged to support less developed nations in enhancing their agricultural green performance, thereby contributing to a more equitable and sustainable agricultural landscape along the Belt and Road countries.

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 Belt and Road countries, and further research could be conducted with larger samples. Third, although pedoclimatic conditions (e.g., soil quality, sunshine, rainfall, and temperature) play a major role in agricultural production processes [21], we do not consider them in this study for the sake of brevity. These limitations of the current study should ideally be investigated in future work to assess the robustness of our empirical results.

An avenue for future research is to transpose these definitions of GTP and LTP from a production context to a value function framework. Indeed, it is conceivable to define a cost or revenue function-based productivity index or indicator and perform a similar analysis, since the convex and nonconvex cost and revenue function are known to be different except under stringent conditions (see [10], [31]). For the profit function matters are more complicated since the convex and nonconvex long run profit function coincides: but this is not the case for any restricted (e.g., short run) profit function. Another avenue for future research is to try disaggregating the fertilizer use to have a clearer picture of the contribution of each input.

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 $D^t(x^t, y^t, z^t; 0, g_y^t, g_z^t)$ with given input and output constraints specified in the BP model is given by:

$$
\begin{aligned}
D^t(x^t, y^t, z^t; 0, g_y^t, g_z^t) &= \max \tfrac{1}{2}\left(\textstyle\sum_{m=1}^{M} \delta^m / M + \sum_{b=1}^{B} \theta^j / J\right) \\
s.t.\ & \textstyle\sum_{k=1}^{K} \lambda_k y_{km}^t \geq y_{k'm}^t + \delta^m g_{ym}^t, m = 1, ..., M \\
& \textstyle\sum_{k=1}^{K} \lambda_k x_{kn}^t \leq x_{k'n}^t, n = 1, ..., N \\
& \textstyle\sum_{k=1}^{K} \lambda_k x_{kp}^t \leq x_{k'p}^t, p = 1, ..., P \\
& \textstyle\sum_{k=1}^{K} \lambda_k = 1, \lambda_k \geq 0, k = 1, ..., K \\
& \textstyle\sum_{k=1}^{K} \sigma_k z_{kb}^t \leq z_{k'b}^t - \theta^b g_{zb}^t, b = 1, ..., B \\
& \textstyle\sum_{k=1}^{K} \sigma_k x_{kp}^t \geq x_{k'p}^t, p = 1, ..., P \\
& \textstyle\sum_{k=1}^{K} \sigma_k = 1, \sigma_k \geq 0, k = 1, ..., K,
\end{aligned}
\tag{11}
$$

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}^t. The latter weight variable represents the impact of sub-technology T_{env}^t 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. The alternative own period DDF $D^{t+1}\left(x^{t+1}, y^{t+1}, z^{t+1}; 0, g_y^{t+1}, g_z^{t+1}\right)$ is obtained by replacing the time superscript t everywhere in (11) by the time superscript $t+1$. The mixed period DDF $D^{t}\left(x^{t+1}, y^{t+1}, z^{t+1}; 0, g_y^{t+1}, g_z^{t+1}\right)$ is obtained by replacing the evaluated observations on the RHS of the inequalities and equalities in (11) by the time superscript $t+1$, while the observations defining the technology on the LHS of the inequalities and equalities in (11) maintain the time superscript t. Finally, the other mixed period DDF $D^{t+1}\left(x^{t}, y^{t}, z^{t}; 0, g_y^{t}, g_z^{t}\right)$ is obtained by replacing the observations defining the technology on the LHS of the inequalities and equalities in (11) by the time superscript $t+1$, while the evaluated observations on the RHS of the inequalities and equalities in (11) preserve the time superscript t.

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

$$\begin{aligned}
&D^t(x^t, y^t, z^t; 0, g_y^t, g_z^t) = max\tfrac{1}{2}\left(\textstyle\sum_{m=1}^{M} \delta^m/M + \sum_{b=1}^{B} \theta^j/J\right)\\
&s.t.\ \textstyle\sum_{k=1}^{K} \lambda_k y_{km}^t \geq y_{k\prime m}^t + \delta^m g_{ym}^t, m = 1, ..., M\\
&\textstyle\sum_{k=1}^{K} \lambda_k x_{kn}^t \leq x_{k\prime n}^t, n = 1, ..., N\\
&\textstyle\sum_{k=1}^{K} \lambda_k x_{kp}^t \leq x_{k\prime p}^t, p = 1, ..., P\\
&\textstyle\sum_{k=1}^{K} \lambda_k = 1, \lambda_k \in \{0,1\}, k = 1, ..., K\\
&\textstyle\sum_{k=1}^{K} \sigma_k z_{kb}^t \leq z_{k\prime b}^t - \theta^b g_{zb}^t, b = 1, ..., B\\
&\textstyle\sum_{k=1}^{K} \sigma_k x_{kp}^t \geq x_{k\prime p}^t, p = 1, ..., P\\
&\textstyle\sum_{k=1}^{K} \sigma_k = 1, \sigma_k \in \{0,1\}, k = 1, ..., K,
\end{aligned} \tag{12}$$

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. The binary activity variables ensure that the benchmark is unique for each evaluated DMU in each sub-technology. We argue that the ongoing debate about convex and nonconvex technologies arises from the fact that the units on the curve connecting each vertex point in the convex frontier are not included in the nonconvex frontier. Since a nonconvex frontier consists only of a series of actual observations, the nonconvex model provides a more conservative evaluation of production possibility sets compared to the convex frontier. The definition of the alternative own period DDF as well as the definition of both mixed period DDFs can be derived in a way similar to the ones commented upon in the convex case (11) above.

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