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Accounting for resource accumulation in Japanese prefectures: an environmental efficiency analysis

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Abstract

This study analyzed the environmental efficiency of production activities based on the accumulated resources (i.e., buildings and roadways), factor inputs (i.e., labor and private capital stock), and CO_2 emissions of 46 Japanese prefectures during the period ranging from 1992 to 2008. The major findings were as follows: (1) A decline in environmental efficiency was observed in many prefectures from 1992 to 1999, whereas a rapid increase in environmental efficiency was observed from 2000 to 2008 as a result of technical change (14%), (2) although the increase in population has positively impacts the environmental efficiency, the expansion of tertiary industries reduces the environmental efficiency due to the lower per worker GDP for the retail, lodging, and transportation industries compared with the manufacturing industries, (3) the total CO_2 emission reduction potential of all environmentally inefficient prefectures identified in this study increased from 127 to 179 million t-CO_2 (41%) over the 17-year period between 1992 and 2008.

1 Background

In 2013, the Japanese Ministry of the Environment issued the "Third Fundamental Plan for Establishing a Sound Material-Cycle Society" (Ministry of the Environment 2013). The plan explains that, in order to create a sound material-cycle society, it will be necessary not only to focus on societal material flow and improve resource productivity, but also to focus on societal material stock, to utilize stock more efficiently, and to accumulate stock that will increase social welfare (Ministry of the Environment 2013).

A seminal study focusing on material flow is by Wolman (1965). Walman's study described cities as organisms that have a metabolism: Materials and energy are fed into cities, while waste matter is discharged. By examining the process of inputs and outputs in a socioeconomic system, Wolman (1965) showed the importance of quantifying the amount of resources (e.g., food, fuel, and electricity) needed to sustain lives or production activities, and of analyzing the interactions between material and energy flows and their associated environmental problems.

Fischer-Kowalski (1998) conducted a seminal study that considered the metabolism of cities from many different perspectives, such as biology, ecology, social theory, cultural anthropology, and social geography, and pointed out the importance of analyzing material and energy flows in a socioeconomic system. Inspired in part by this prior research, a variety of studies in recent years have analyzed the flows of energy, water, resources, waste matter, and even greenhouse gas emissions in a socioeconomic system (e.g., Haberl 2001; Duchin and Levine 2013; Minx et al. 2013; Ding and Xiao 2014; Nakamura et al. 2014).

In addition to these flow analyses, dynamic studies that consider the accumulation of materials in a city are also very important for analyzing the metabolism of cities (Zhang et al. 2015). An example of a study aimed at estimating the stock of resources accumulated in a society is Hashimoto et al. (2007). They found that the estimated quantity of building waste in 2000 greatly exceeded the actual stock of building waste, and this gap was designated as "missing stock." Furthermore, Tanikawa et al. (2015) used four-dimensional geographic information system (4D-GIS) and prefecture-level data to construct long-term time-series data on the stock of accumulated resources in Japan resulting from the construction of buildings and infrastructure (e.g., roadways, railways, airports, dams, sewerage systems, and sea ports). A number of other studies attempting to estimate the stock of accumulated resources in a society have also been performed around the world in recent years (e.g., Tanikawa and Hashimoto 2009; Zheng et al. 2012; Pauliuk et al. 2014; Fishman et al. 2014; Reyna and Chester 2015).

In addition to material flow and stock analyses, it is also important to quantitatively analyze the environmental efficiency of a city in order to assess the sustainability of a city's metabolism (Zhang et al. 2015). Huppes and Ishikawa (2007) classified environmental efficiency into the following four indicators: (1) environmental productivity (i.e., production or consumption value per unit of environmental impact), (2) environmental intensity (i.e., environmental impact per unit of production or consumption value), (3) environmental improvement cost (i.e., cost per unit of environmental improvement), and (4) environmental cost-effectiveness (i.e., environmental improvement per unit of cost). In an environmental efficiency analysis based on the indicators shown above, for example, Browne et al. (2009) considered the second indicator, environmental intensity, and estimated the ratio of waste discharge to product consumption in Limerick, Ireland. In addition, Zhang et al. (2013) considered the second indicator and estimated the ratio of waste displacement to resource displacement within an area of Beijing, China. However, these studies did not consider desirable outputs (GDP, etc.) generated by production activity and the factor inputs required the production activity and they did not analyze economic efficiency based on the input–output data.

On the other hand, data envelopment analysis (DEA) is well known as an input minimization modeling technique (i.e., input-oriented DEA model) and an output maximization modeling technique (i.e., output-oriented DEA model) to estimate the efficiency of decision making units (Cooper et al. 2007). Tyteca (1996) provided a comprehensive overview related to environmental performance indicators and recommended using DEA that could simultaneously consider input, desirable output, and undesirable output to evaluate environmental performance. That study marked a turning point, and environmental efficiency analyses using DEA approaches have become very active in recent years (e.g., Färe et al. 2004; Kumar 2006; Sueyoshi and Goto 2012; Eguchi et al. 2015; Halkos et al. 2016; Emrouznejad and Yang 2017; Sueyoshi et al. 2017).

Regarding an analysis that estimated the productive efficiency using a DEA approach in Japan, Nakano and Managi (2010) applied a DEA framework considering CO_2 emissions as an undesirable output to analyze the environmental efficiency of production resulting from labor and the private capital stock of Japanese prefectures from 1991 to 2002. Using data for private capital stock in the *monetary* base, they found that environmental efficiency decreased over the analysis period. Another example of production efficiency analysis considering prefectural-level CO_2 emissions includes a study by Hashimoto and Fukuyama (2017). However, when providing an effective policy guidance for urban planning, what is needed is production efficiency analysis using *physical*- rather than *monetary*-base private and social capital stock data.

On the other hand, Eguchi (2017) analyzed changes in production efficiency resulting from the labor force and accumulated resources in Japan during the study period of 1970–2010. He found that although production efficiency increased in almost all of the prefectures between 1970 and 1990, it declined in approximately 80% of Japan's prefectures, including highly populated prefectures such as Tokyo and Osaka, between 1990 and 2010. However, the environmental efficiency of production activities based on accumulated resources in the cities of Japan has not yet been analyzed because the DEA framework used in Eguchi (2017) does not account for the associated environmental burden. According to the Paris Agreement, Japan is obligated to reduce CO_2 emissions by 26% relative to 2013 levels by 2030 (United Nations 2016). As such, conducting environmental efficiency analyses of CO_2 emissions associated with production activities is very important.

With this motivation, this study compares a "conventional" environmental efficiency indicator (i.e., production per unit of environmental impact) with a "DEA-based" environmental efficiency indicator and examines how the efficiency indicators obtained by the "simplified" efficiency analysis differ from those endogenously determined by the DEA analysis based on economic theory (Cooper et al. 2007). This study estimates the environmental efficiency of production activities based on the accumulated resources of 46 Japanese prefectures during the period ranging from 1992 to 2008. The accumulated resources in the *physical* base and CO_2 emissions associated with the production activities in the 46 Japanese prefectures are taken into consideration.

This study further analyzes changes in environmental efficiency of production activities based on the accumulated resources in Japan during the same period, and identifies prefectures where environmental efficiency had increased or decreased in order to explore possible ways of sustainable development in relation to resource accumulation.

This paper is organized as follows. The methodology is described in Sect. 2, the data and results are presented in Sect. 3, and concluding remarks are given in Sect. 4.

2 Methods

2.1 Conventional environmental efficiency indicator

Using an indicator from Huppes and Ishikawa (2007), "conventional" environmental efficiency indicator (*CEEI*) in Prefecture z can be defined as follows (environmental efficiency indicator provided by Huppes and Ishikawa (2007)):

$$CEEI_z = \frac{y_z}{b_z} \tag{1}$$

where y_z represents the real gross regional product (GRP) in Prefecture z and b_z represents the CO_2 emissions associated with the final energy consumption. Thus, $CEEI_z$ is an environmental indicator representing production per unit of CO_2 emissions in Prefecture z. A higher $CEEI_z$ value corresponds with better environmental performance.

2.2 DEA-based environmental efficiency indicator

This study also calculates the "DEA-based" environmental efficiency indicator (*DEEI*) using the directional distance function, which can evaluate efficiency accounting for inputs, desirable outputs, and undesirable outputs simultaneously (Färe et al. 2001). If I denote inputs by $\mathbf{x} \in \mathbb{R}_+^N$, desirable outputs by $\mathbf{y} \in \mathbb{R}_+^M$, and undesirable outputs by $\mathbf{b} \in \mathbb{R}_+^I$, output set $P(\mathbf{x})$ can be defined as follows:

$$P(\mathbf{x}) = \left\{ \left(\mathbf{y}, \mathbf{b}\right):\mathbf{x} \text{ can produce}\left(\mathbf{y}, \mathbf{b}\right) \right\}, \quad \mathbf{x} \in \mathbb{R}_+^N \tag{2}$$

Then, let $\mathbf{g} = \left(\mathbf{g}_y, -\mathbf{g}_b\right)$ be a direction vector, and the directional distance function is given by

$$\vec{D}_o\left(\mathbf{x}, \mathbf{y}, \mathbf{b}; \mathbf{g}_y, -\mathbf{g}_b\right) = \sup\left[\beta:\left(\mathbf{y} + \beta\mathbf{g}_y, \mathbf{b} - \beta\mathbf{g}_b\right) \in P(\mathbf{x})\right] \tag{3}$$

In this case, the desirable and undesirable outputs are treated asymmetrically. Therefore, β is determined as the value that gives the maximum expansion of the desirable outputs and contraction of the undesirable outputs for a given level of inputs.

Figure 1 illustrates the directional distance function used in this study. The output set is represented by $P(\mathbf{x})$, and output vector $\left(\mathbf{y}, \mathbf{b}\right)$ belongs to the output set. Based on the direction of $\mathbf{g} = \left(\mathbf{g}_y, -\mathbf{g}_b\right)$, the directional distance function takes the same output vector from Z to Z'. At point Z' on the output set $P(\mathbf{x})$, the output vector is $\left(\mathbf{y} + \beta^*\mathbf{g}_y, \mathbf{b} - \beta^*\mathbf{g}_b\right)$, where $\beta^* = \vec{D}_o\left(\mathbf{x}, \mathbf{y}; \mathbf{g}_y, -\mathbf{g}_b\right)$. Therefore, $\beta^*\mathbf{g}_y$ has been added to the desirable output $\mathbf{y}$, and $\beta^*\mathbf{g}_b$ has been subtracted from the undesirable output $\mathbf{b}$. The directional distance function $\vec{D}_o\left(\mathbf{x}, \mathbf{y}, \mathbf{b}\right)$ is nonnegative and equals zero if and only the observation vector $\left(\mathbf{y}, \mathbf{b}\right)$ is on the production possibility frontier.

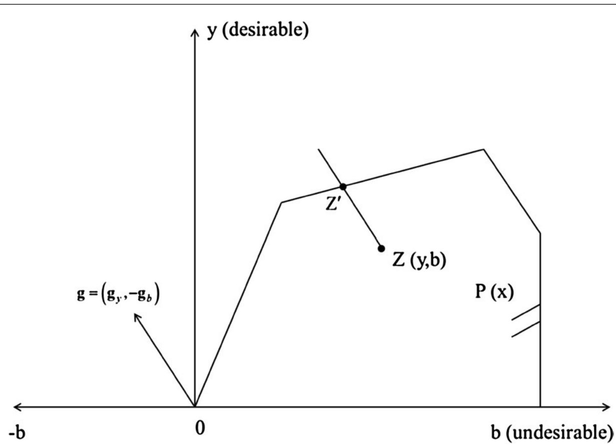

Fig. 1 Illustration of the directional distance function

Using this directional distance function, the *DEEI* is calculated as follows if the DEA framework described in Mandal and Madheswaran (2010) is introduced:

$$
\begin{aligned}
&\vec{D}_o\left(\mathbf{x}_k, \mathbf{y}_k, \mathbf{b}_k; \mathbf{y}_k, -\mathbf{b}_k\right) = Max\ \beta \\
&s.t. \\
&\sum_{k=1}^{K} \lambda_k y_{km} \geq (1+\beta) y_{zm} \quad m = 1, \ldots, M \\
&\sum_{k=1}^{K} \lambda_k b_{ki} \leq (1-\beta) b_{zi} \quad i = 1, \ldots, I \\
&\sum_{k=1}^{K} \lambda_k x_{kn} \leq x_{zn} \quad n = 1, \ldots, N \\
&\sum_{k=1}^{K} \lambda_k = 1 \\
&\lambda_k \geq 0, \quad k = 1, \ldots, K
\end{aligned}
\tag{4}
$$

where y_{zm} is the output vector for desirable output m in Prefecture z, b_{zi} is the output vector for undesirable output i, and x_{zn} is the input vector for input n. Furthermore, y_{km}, b_{ki}, and x_{kn} are the output matrix for desirable output m, the output matrix for undesirable output i, and the input matrix for input n in Prefecture k, respectively. In addition, λ_k is a weight vector for Prefecture k determined endogenously by solving Eq. (4). In this study, $M = 1$, $I = 1$, $N = 4$, and $K = 46$ because I assume one desirable output (real GRP), one undesirable output (CO_2 emissions), and four inputs (buildings, roads, private capital stock, and labor).

In Eq. (4), β necessarily takes a value between 0 and 1. The environmental efficiency in Prefecture z is considered efficient when $\beta = 0$ and inefficient when $\beta > 0$. Furthermore, the production frontier is constructed by the line that connects the prefectures where $\beta = 0$. In addition, since a variable returns to scale (VRS) DEA model is employed for analysis in this study, environmental efficiency is measured under all conditions, namely constant, decreasing, and increasing returns to scale (see Banker et al. 1984).

Although numerous DEA analyses have used the directional distance function, some of these studies, such as Chung et al. (1997) and Färe et al. (2001), imposed a weak disposability assumption on undesirable outputs through equality constraint. Weak disposability means that undesirable outputs cannot be reduced without lowering the production level of desirable outputs (see Kuosmanen 2005). This study, however, assumes that undesirable output (CO_2 emissions) can be reduced with no limit, and thus imposes a free (strong) disposability assumption on undesirable output using the inequality constraint in Eq. (4). In other words, under a strong disposability condition, the reduction of CO_2 emissions in each prefecture could be achieved without assuming certain costs (see Mandal and Madheswaran 2010; Oggioni et al. 2011). Given that this study targets reduction of CO_2 emissions while increasing production levels, it assumes strong disposability.

2.3 Malmquist–Luenberger (ML) index

In this study, changes in environmental efficiency over time are estimated using the Malmquist–Luenberger (ML) index (e.g., Chung et al. 1997; Färe et al. 2001). Using the directional distance function, the ML index with the technology of year t as the reference technology is defined as follows:

$$ML^t = \frac{\left[1 + \vec{D}_o^t\left(\mathbf{x}^t, \mathbf{y}^t, \mathbf{b}^t;\ \mathbf{y}^t, -\mathbf{b}^t\right)\right]}{\left[1 + \vec{D}_o^t\left(\mathbf{x}^{t+1}, \mathbf{y}^{t+1}, \mathbf{b}^{t+1};\ \mathbf{y}^{t+1}, -\mathbf{b}^{t+1}\right)\right]} \tag{5}$$

where $\vec{D}_o^t\left(\mathbf{x}^t, \mathbf{y}^t, \mathbf{b}^t;\ \mathbf{y}^t, -\mathbf{b}^t\right)$ in the numerator expresses the environmental efficiency of a specific region of year t evaluated by the production possibility frontier of year t, and $\vec{D}_o^t\left(\mathbf{x}^{t+1}, \mathbf{y}^{t+1}, \mathbf{b}^{t+1}; \mathbf{y}^{t+1}, -\mathbf{b}^{t+1}\right)$ in the denominator expresses the environmental efficiency of a specific region of year $t+1$ evaluated by the production possibility frontier of year t.

Similarly, the ML index with the technology of year $t+1$ as the reference technology is defined as follows:

$$ML^{t+1} = \frac{\left[1 + \vec{D}_o^{t+1}\left(\mathbf{x}^t, \mathbf{y}^t, \mathbf{b}^t;\ \mathbf{y}^t, -\mathbf{b}^t\right)\right]}{\left[1 + \vec{D}_o^{t+1}\left(\mathbf{x}^{t+1}, \mathbf{y}^{t+1}, \mathbf{b}^{t+1};\ \mathbf{y}^{t+1}, -\mathbf{b}^{t+1}\right)\right]} \tag{6}$$

where $\vec{D}_o^{t+1}\left(\mathbf{x}^t, \mathbf{y}^t, \mathbf{b}^t; \mathbf{y}^t, -\mathbf{b}^t\right)$ in the numerator expresses the environmental efficiency of a specific region of year t evaluated by the production possibility frontier of year $t+1$, and $\vec{D}_o^{t+1}\left(\mathbf{x}^{t+1}, \mathbf{y}^{t+1}, \mathbf{b}^{t+1};\ \mathbf{y}^{t+1}, -\mathbf{b}^{t+1}\right)$ in the denominator expresses the environmental efficiency of a specific region of year $t+1$ evaluated by the production possibility frontier of year $t+1$.

In order to avoid the arbitrary choice of the reference technology, the ML index expressing the change in environmental efficiency between years t and $t+1$ is computed using the geometric mean of Eqs. (5) and (6):

$$ML_t^{t+1} = \left(ML^t \times ML^{t+1}\right)^{1/2} \tag{7}$$

here, if $ML_t^{t+1} > 1$, then the environmental efficiency of Prefecture z improves between years t and $t+1$. If $ML_t^{t+1} = 1$, then there is no change in the environmental efficiency of Prefecture z. If $ML_t^{t+1} < 1$, then there is a decline in the environmental efficiency of Prefecture z.

Following Färe et al. (2001), Eq. (7) can be decomposed into relative efficiency change in Prefecture z and shift in the production possibility frontier as follows:

$$ML_t^{t+1} = MLEFFCH_t^{t+1} \times MLTECH_t^{t+1} \tag{8}$$

where $MLEFFCH_t^{t+1}$ expresses the change in relative efficiency of Prefecture z between years t and $t+1$, and $MLTECH_t^{t+1}$ expresses the shift in the production possibility frontier between years t and $t+1$. $MLEFFCH_t^{t+1}$ and $MLTECH_t^{t+1}$ can be further decomposed and calculated as follows:

$$MLEFFCH_t^{t+1} = \frac{\left[1 + \vec{D}_o^t\left(\mathbf{x}^t, \mathbf{y}^t, \mathbf{b}^t, \mathbf{y}^t, -\mathbf{b}^t\right)\right]}{\left[1 + \vec{D}_o^{t+1}\left(\mathbf{x}^{t+1}, \mathbf{y}^{t+1}, \mathbf{b}^{t+1}, \mathbf{y}^{t+1}, -\mathbf{b}^{t+1}\right)\right]} \tag{9}$$

$$MLTECH_t^{t+1} = \left\{ \frac{\left[1 + \vec{D}_o^{t+1}\left(\mathbf{x}^t, \mathbf{y}^t, \mathbf{b}^t, \mathbf{y}^t, -\mathbf{b}^t\right)\right]\left[1 + \vec{D}_o^{t+1}\left(\mathbf{x}^{t+1}, \mathbf{y}^{t+1}, \mathbf{b}^{t+1}, \mathbf{y}^{t+1}, -\mathbf{b}^{t+1}\right)\right]}{\left[1 + \vec{D}_o^t\left(\mathbf{x}^t, \mathbf{y}^t, \mathbf{b}^t, \mathbf{y}^t, -\mathbf{b}^t\right)\right]\left[1 + \vec{D}_o^t\left(\mathbf{x}^{t+1}, \mathbf{y}^{t+1}, \mathbf{b}^{t+1}, \mathbf{y}^{t+1}, -\mathbf{b}^{t+1}\right)\right]} \right\}^{1/2} \tag{10}$$

here, if $MLEFFCH_t^{t+1} > 1$, then the relative distances from Prefecture z to the frontier approach each other between years t and $t+1$, indicating that relative efficiency is increasing (in other words, there is a "catch-up" in efficiency). If $MLEFFCH_t^{t+1} = 1$, then there is no change in relative efficiency. Lastly, if $MLEFFCH_t^{t+1} < 1$, then relative efficiency is decreasing.

If $MLTECH_t^{t+1} > 1$, then there is a shift in the production frontier around Prefecture z in the direction of "more desirable output and less undesirable output" between years t and $t+1$; in other words, the frontier technology improves. If $MLTECH_t^{t+1} = 1$, then there is no shift in the frontier, that is, no technological improvement. If $MLTECH_t^{t+1} < 1$, then there is a shift in the frontier in the direction of "less desirable output and/or more undesirable output" between years t and $t+1$.

In addition, in order to reduce the incidence of infeasible LP problems, I employ multi-year "window" data as the reference technology. All of the production possibility frontiers are constructed from that year plus the previous 2 years. Therefore, the reference technology for year t consists of observations from years $t-2$, $t-1$, and t (see Färe et al. 2001; Kumar 2006).

2.4 Estimating the change in environmental efficiency by undesirable output

If we call the ML index based on the DEA model of Eq. (4) ML_{all}, it should be noted that any increase in desirable output or decrease in undesirable output for a given input level will increase ML_{all} (Kaneko and Managi 2004). If we also call the ML index calculated by the DEA model that excludes the constraint for undesirable output from Eq. (4), ML_{des}, following Kaneko and Managi (2004), ML_{env} that provides the measure of the change in environmental efficiency due to the undesirable output is estimated by the following equation:

$$ML_{env} = ML_{all}/ML_{des} \tag{11}$$

If $ML_{env} > 1$, then the undesirable output contributes to improving the environmental efficiency in Prefecture z. Conversely, if $ML_{env} < 1$, then the undesirable output leads to lower environmental efficiency. In this study, I identified the prefectures that gained environmental efficiency due to the change in CO_2 emissions by using Eq. (11). Thus, Eq. (11) is the "modified" Malmquist–Luenberger index.

3 Data and results

3.1 Data

In this study, I assumed four inputs, one desirable output, and one undesirable output. For the inputs in this study, I used the accumulated quantity (stock) of buildings and roads in *physical* terms (million tonnes), the private capital stock in *monetary* terms (billion JPY), and the total number of workers (million people) for 46 Japanese prefectures (Okinawa was excluded due to a lack of data). Geographic information for Japanese prefectures and regions is provided in Additional file 1: Fig. S1.

For desirable and undesirable outputs, I used the real GRP (billion JPY) and the amount of CO_2 emissions associated with final energy consumption (thousand t-CO_2) consisting of the manufacturing, non-manufacturing, residential, and transportation sectors for the 46 prefectures, respectively. In economic theory, labor and private capital stock are important input factors for production activities. In addition, both buildings and roads emit CO_2—the former as commercial buildings and factories in which production activities take place, and the latter via motor vehicle transportation activity—thereby impacting environmental efficiency. For the data on the accumulated quantity of buildings and roads, I make use of the estimates from Tanikawa et al. (2015). For the data on private capital stock, total number of workers, and real GRP, I use the R-JIP Database 2014 (Research Institute of Economy, Trade and Industry 2014). Real GRP and private capital stock are based on 2000 prices. Finally, data on CO_2 emissions associated with final energy consumption are obtained from data on the Energy Consumption Statistics (Agency for Natural Resources and Energy 2016). The study period covers the 17 years from 1992 to 2008. *Monetary*-base private capital stock data also include buildings such as factories and office buildings owned by companies. As such, it is possible that these will be double-counted in *physical*-base building data. However, data for facilities owned by private companies are included only in private capital stock data, and data for public facilities are included only in building-related accumulated resource stock data. Accordingly, it is not possible to analyze the environmental efficiency of urban production activities by taking only private capital stock into account. Given the difficulty in differentiating these factors, in this study, I treat the *monetary*-base private capital stock data and building-related *physical*-base accumulated resource stock data as separate items. Furthermore, to be able to analyze the environmental efficiency of production activities at the city but not the prefectural level, it is necessary to have more detailed production, CO_2 emission, and private capital stock data at the city level. Thus, I did not perform city-level analysis in this study because of the problems with data availability. These are limitations of the present study as well as challenges for future research.

Table 1 shows the descriptive statistics of the variables used in this study in 1992 and 2008. In Table 1, we can see that the accumulated quantities of buildings and roads in Japan increased by approximately 1480 and 1360 million tonnes, respectively, from 1992 to 2008. Private capital stock also increased by approximately 270 billion JPY. On the other hand, the total number of workers decreased by 2.1 million during the same period. Regarding output factors, the real GRP of desirable output increased by 94 billion JPY and the amount of CO_2 emissions of undesirable output increased by 92 million t-CO_2.

Table 1 Descriptive statistics of the variables used in this study in 1992 and 2008

Year	Statistics	Input				Desirable output	Undesirable output
		Buildings	Roads	Private capital stock	Number of employees	Real gross regional product	CO_2 Emissions
		Million tonnes	Million tonnes	Trillion JPY	Million	Trillion JPY	Million t-CO_2
1992	Sum	7881.37	4612.81	894.77	65.78	425.78	832.44
	Mean	171.33	100.28	19.45	1.43	9.26	18.10
	Max.	892.37	427.13	121.65	9.12	73.07	58.12
	Min.	38.01	33.63	3.89	0.35	1.80	3.53
	SD	168.49	66.27	21.83	1.54	12.09	15.75
2008	Sum	9361.67	5971.92	1164.15	63.61	519.33	924.45
	Mean	203.51	129.82	25.31	1.38	11.29	20.10
	Max.	1067.50	532.54	134.23	8.72	87.79	65.97
	Min.	43.20	43.64	5.29	0.31	2.26	4.57
	SD	203.94	82.06	25.34	1.50	14.32	17.95

Table 2 shows the percent change of each variable in 46 Japanese prefectures from 1992 to 2008. Regarding the increase rate of the accumulated quantity of buildings during the 17-year period, Saitama Prefecture in the Kanto region shows the highest value (33.3%), whereas Kyoto Prefecture in the Kinki region shows the highest value (66.5%) for the increase rate of the accumulated quantity of roads. Conversely, the increase rate of the accumulated quantity of buildings in Wakayama Prefecture in the Kinki region is only 1%, which is the lowest value among the 46 prefectures. Interestingly, regarding the increase rate of the accumulated quantity of roads, Tokyo, the capital of Japan, shows the lowest value (7.2%). Furthermore, although the number of workers decreased in 38 of the 46 prefectures, it increased by 11.6% in Shiga Prefecture in the Kinki region.

When looking at the output factors, real GRP increased in all prefectures. The increase rate in Mie Prefecture in the Kinki region is highest (55.4%), whereas it is lowest (4.4%) in Hokkaido Prefecture. The amount of CO_2 emissions associated with final energy consumption increased in every prefecture except for Toyama, Ishikawa, Tokushima, Kagawa, Ehime, and Fukuoka, where it decreased. In Toyama Prefecture in the Chubu region, the amount of CO_2 emissions in 2008 substantially decreased by 16.8% compared with 1992. As we can see, the changes in variables differ greatly over prefectures; however, how these changes affect environmental efficiency, which accounts for resource accumulation in Japanese prefectures, remains unclear.

3.2 Comparison between CEEI and DEEI

Table 3 shows the results of the two indicators, *CEEI*, calculated based on the ratio of real GRP to CO_2 emissions, and *DEEI*, estimated using the DEA framework in this study (Eq. (4)), and rankings of the 46 prefectures in regard to these indicators for 1992 and 2008. The DEA was performed by the MATLAB. Note that the *CEEI* represents higher environmental efficiency as it takes a higher value, whereas the *DEEI* necessarily takes a

Table 2 Percent change in variables from 1992 to 2008

Region	Prefecture	Input				Desirable output	Undesirable output
		Buildings	Roads	Private capital stock (%)	Number of employees (%)	Real gross regional product (%)	CO_2 emissions (%)
Hokkaido	Hokkaido	20.4	24.7	32.3	−7.5	4.4	24.9
Tohoku	Aomori	18.4	25.5	75.1	−9.4	23.6	14.4
	Iwate	17.1	30.5	44.9	−12.6	23.8	7.7
	Miyagi	22.0	40.9	38.2	−5.3	21.8	23.0
	Akita	17.1	30.5	47.6	−16.0	32.1	17.6
	Yamagata	14.1	30.6	41.2	−11.6	38.1	11.4
	Fukushima	18.5	22.0	24.4	−11.2	36.0	15.5
Kanto	Ibaraki	22.2	24.5	36.8	−2.0	35.0	15.4
	Tochigi	23.1	31.0	31.4	−2.7	36.1	20.1
	Gunma	18.9	25.7	38.7	−3.3	18.9	15.7
	Saitama	33.3	21.3	44.9	10.7	23.7	18.5
	Chiba	28.8	20.4	33.6	6.7	16.1	11.4
	Tokyo	19.6	7.2	10.3	−4.4	20.1	20.9
	Kanagawa	27.2	62.6	14.1	4.1	18.2	14.8
Chubu	Niigata	11.7	23.5	25.4	−9.2	20.7	11.8
	Toyama	14.7	25.5	26.5	−6.8	22.1	−16.8
	Ishikawa	15.3	25.0	49.8	−3.8	23.1	−2.0
	Fukui	9.9	21.6	21.7	−8.4	27.7	7.2
	Yamanashi	24.3	24.2	40.8	−5.1	42.0	29.4
	Nagano	16.4	29.4	26.4	−7.2	42.9	18.4
	Gifu	17.1	26.1	49.1	−4.5	20.6	8.3
	Shizuoka	14.9	15.6	38.8	−2.4	43.8	2.7
	Aichi	16.0	41.9	41.8	4.7	32.2	13.5
Kinki	Mie	20.8	31.9	58.6	1.6	55.4	5.4
	Shiga	23.7	30.1	45.2	11.6	41.1	10.1
	Kyoto	10.6	66.5	30.8	−3.9	22.5	11.6
	Osaka	14.2	50.5	15.8	−9.1	6.6	1.9
	Hyogo	23.0	39.3	27.6	−1.2	9.9	13.0
	Nara	15.3	29.7	37.5	2.7	16.6	31.2
	Wakayama	1.0	29.1	9.1	−10.9	6.9	2.9
Chugoku	Tottori	13.7	27.1	36.3	−10.1	30.1	29.7
	Shimane	13.8	38.3	77.7	−12.4	19.1	13.8
	Okayama	12.6	27.4	24.7	−5.0	10.3	13.8
	Hiroshima	12.1	44.7	24.3	−5.1	23.4	10.6
	Yamaguchi	5.6	19.2	22.5	−11.1	8.5	9.3
Shikoku	Tokushima	6.4	35.7	64.2	−11.5	32.8	−6.3
	Kagawa	16.5	30.0	41.3	−8.4	9.6	−4.6
	Ehime	8.9	40.5	26.2	−8.6	15.7	−2.1
	Kochi	14.9	27.0	37.8	−14.6	9.6	0.8
Kyushu	Fukuoka	22.0	54.7	43.8	1.5	19.9	−4.1
	Saga	24.3	27.7	36.4	−2.4	39.6	9.8
	Nagasaki	13.0	25.5	34.6	−7.9	21.3	2.7
	Kumamoto	20.8	44.7	44.7	−4.0	30.8	17.0
	Oita	12.8	33.1	54.1	−5.5	32.1	0.1
	Miyazaki	15.1	28.1	45.5	−5.7	28.1	2.6
	Kagoshima	15.9	22.4	38.9	−5.6	37.4	11.9
	Total	18.8	29.5	30.1	−3.3	22.0	11.1

value between 0 and 1, and represents higher environmental efficiency as it takes a value closer to 0.

If we look at the results of the *CEEI* in 1992, Tokyo shows the highest value (1.341), followed by Kyoto (0.863) and Osaka (0.842). Conversely, Oita Prefecture in the Kyushu region shows the lowest value (0.172) in 1992 (see Table 3).

On the other hand, looking at the results of the *DEEI* in 1992, it is zero in Akita, Tokyo, Yamanashi, Shiga, Kyoto, Osaka, Nara, Tottori, Tokushima, and Kochi. In other words, the production possibility frontier in 1992 is constructed by these 10 prefectures (see Table 3). In addition to Tokyo and Osaka, relatively small prefectures such as Akita in the Tohoku region and Tottori in the Chugoku region, where the population density is less than 200 people per km^2, also construct the frontier because this study introduced a VRS DEA model, and the *DEEI* is estimated in consideration of the difference in scale of such prefectures.

Comparing the results of the *CEEI* and *DEEI* in 1992, high-ranking prefectures in terms of the *CEEI* such as Tokyo, Kyoto, and Osaka construct a production possibility frontier based on the results of the *DEEI* (see Table 3). However, Gunma Prefecture in the Kanto region, the sixth-ranking prefecture in terms of the *CEEI*, contrastingly ranks 37th in terms of the *DEEI* (see Table 3). A ranking gap is also apparent between the two indicators in Nagano, Tochigi, and Saitama Prefectures. The reason for this ranking gap is that the *CEEI* ignores input factors used by production activities, whereas the *DEEI* does not. In addition, using Spearman's rank correlation coefficient (ρ), the rank correlations between *CEEI* and *DEEI* are calculated as $\rho = 0.198$ and $\rho = 0.444$ in 1992 and 2008, respectively. From these results, it can be said that there is only a low-rank correlation between *CEEI* and *DEEI*. It should be noted that while DEA is able to account for inputs, the number of factors used and assumptions regarding the returns to scale (e.g., whether they are constant or variable returns to scale) substantially impact the estimated efficiency. Furthermore, whereas the *CEEI* yields absolute estimates, the *DEEI* yields relative estimates. As can be seen from the above, each estimated value has its own characteristics. However, *DEEI* estimates take input factors into account and represent the environmental efficiency of production activities that take the accumulated resources in each prefecture into account.

3.3 Changes in environmental efficiency from 1992 to 2008

Figure 2 shows the changes in the geometric mean of the ML index (ML_{all}), the efficiency change index ($MLEFFCH_{all}$), and the technical change index ($MLTECH_{all}$) from 1992 to 2008. Because ML_{all} consistently declined from 1992 to 1999, it can be said that Japan suffered a decline in environmental efficiency during this period. On the other hand, after 2000, we can see a rapid increase in ML_{all}, as well as a 10.8% increase from 1992 to 2008. The rapid increase in environmental efficiency after 2000 is a result of substantially higher $MLTECH_{all}$ growth (14%) (see Table 1). In other words, the growth in environmental efficiency in the prefectures that constructed a production possibility frontier contributed to improving the environmental efficiency of Japan after 2000.

Here, it should be noted that the growth in ML_{all} can be achieved by an increase in desirable output (real GRP) and/or a reduction in undesirable output (the amount of CO_2 emissions) for a given input level. By using Eq. (11), we can estimate changes in

Table 3 Comparison between the "conventional" environmental efficiency indicator (*CEEI*) and the "DEA-based" environmental efficiency indicator (*DEEI*)

Region	Prefecture	1992				2008			
		CEEI	Rank	*DEEI*	Rank	*CEEI*	Rank	*DEEI*	Rank
Hokkaido	Hokkaido	0.457	28	0.303	44	0.382	39	0.474	46
Tohoku	Aomori	0.372	36	0.302	43	0.402	36	0.395	45
	Iwate	0.450	30	0.257	40	0.517	31	0.297	39
	Miyagi	0.531	21	0.304	45	0.526	29	0.312	40
	Akita	0.562	19	0	1	0.631	19	0	1
	Yamagata	0.569	13	0.159	32	0.706	11	0.132	23
	Fukushima	0.568	15	0.279	42	0.669	15	0.099	15
Kanto	Ibaraki	0.345	39	0.273	41	0.404	35	0.180	28
	Tochigi	0.628	8	0.176	35	0.711	10	0.093	14
	Gunma	0.648	6	0.199	37	0.666	16	0.237	35
	Saitama	0.609	9	0.196	36	0.635	17	0.327	43
	Chiba	0.313	40	0.129	25	0.326	41	0.315	41
	Tokyo	1.341	1	0	1	1.332	1	0	1
	Kanagawa	0.562	18	0.098	19	0.579	24	0.219	31
Chubu	Niigata	0.498	26	0.365	46	0.538	28	0.318	42
	Toyama	0.380	34	0.116	23	0.557	25	0.115	17
	Ishikawa	0.584	11	0.107	21	0.733	7	0.117	18
	Fukui	0.509	24	0.061	12	0.606	20	0.009	10
	Yamanashi	0.737	5	0	1	0.809	4	0	1
	Nagano	0.648	7	0.253	39	0.782	5	0.176	27
	Gifu	0.536	20	0.064	14	0.596	22	0.287	38
	Shizuoka	0.516	23	0.240	38	0.723	8	0.091	13
	Aichi	0.478	27	0.114	22	0.557	26	0.113	16
Kinki	Mie	0.354	38	0.154	31	0.523	30	0	1
	Shiga	0.605	10	0	1	0.776	6	0	1
	Kyoto	0.863	2	0	1	0.946	2	0.081	12
	Osaka	0.842	3	0	1	0.881	3	0.191	29
	Hyogo	0.409	33	0.099	20	0.398	38	0.251	36
	Nara	0.786	4	0	1	0.699	12	0	1
	Wakayama	0.308	41	0.150	30	0.320	42	0.226	32
Chugoku	Tottori	0.508	25	0	1	0.510	32	0	1
	Shimane	0.452	29	0.094	18	0.474	33	0.126	19
	Okayama	0.199	45	0.126	24	0.193	46	0.252	37
	Hiroshima	0.254	43	0.141	28	0.283	43	0.131	21
	Yamaguchi	0.199	44	0.064	13	0.198	45	0.126	20
Shikoku	Tokushima	0.417	32	0	1	0.590	23	0.008	9
	Kagawa	0.520	22	0.007	11	0.597	21	0.165	25
	Ehime	0.297	42	0.144	29	0.352	40	0.228	33
	Kochi	0.369	37	0	1	0.401	37	0.056	11
Kyushu	Fukuoka	0.378	35	0.078	16	0.472	34	0.358	44
	Saga	0.566	16	0.077	15	0.720	9	0	1
	Nagasaki	0.582	12	0.084	17	0.688	14	0.135	24
	Kumamoto	0.568	14	0.168	33	0.635	18	0.231	34
	Oita	0.172	46	0.138	26	0.227	44	0.132	22
	Miyazaki	0.432	31	0.140	27	0.539	27	0.207	30
	Kagoshima	0.566	17	0.172	34	0.694	13	0.174	26
	Mean	0.511		0.127		0.576		0.161	

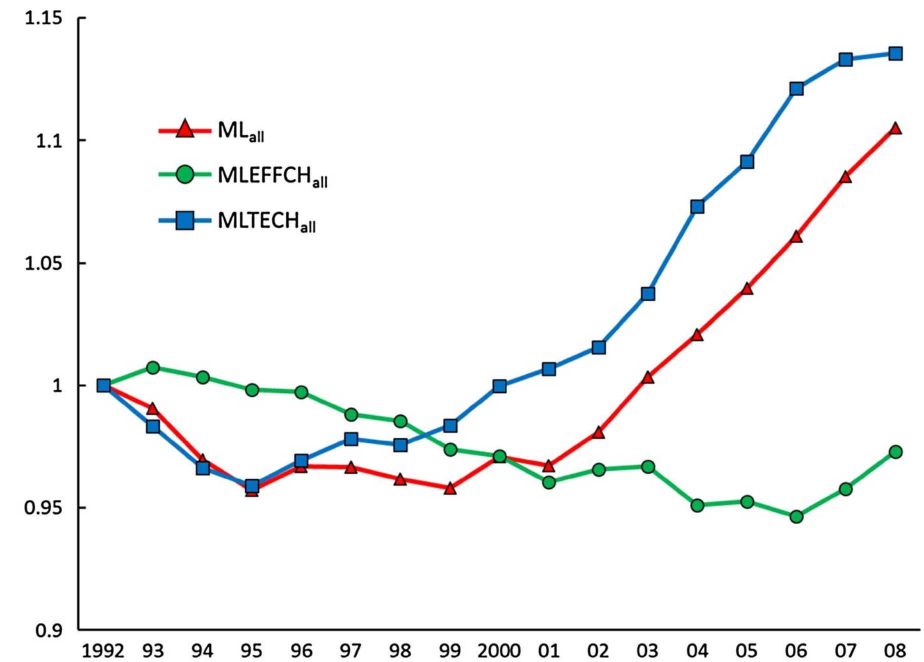

Fig. 2 Changes in decomposition effects of environmental efficiency based on the standard Malmquist–Luenberger index decomposition technique. Note that the value of unity on the vertical axis shows the baseline index at 1992

environmental efficiency (ML_{all}) due to undesirable output. Looking at the results of ML_{env}, $MLEFFCH_{env}$, and $MLTECH_{env}$ shown in Fig. 3, we can see how the amount of CO_2 emissions contributed to the changes in environmental efficiency (ML_{all}). Although each index (ML_{env}, $MLEFFCH_{env}$, and $MLTECH_{env}$) shows almost no change during the

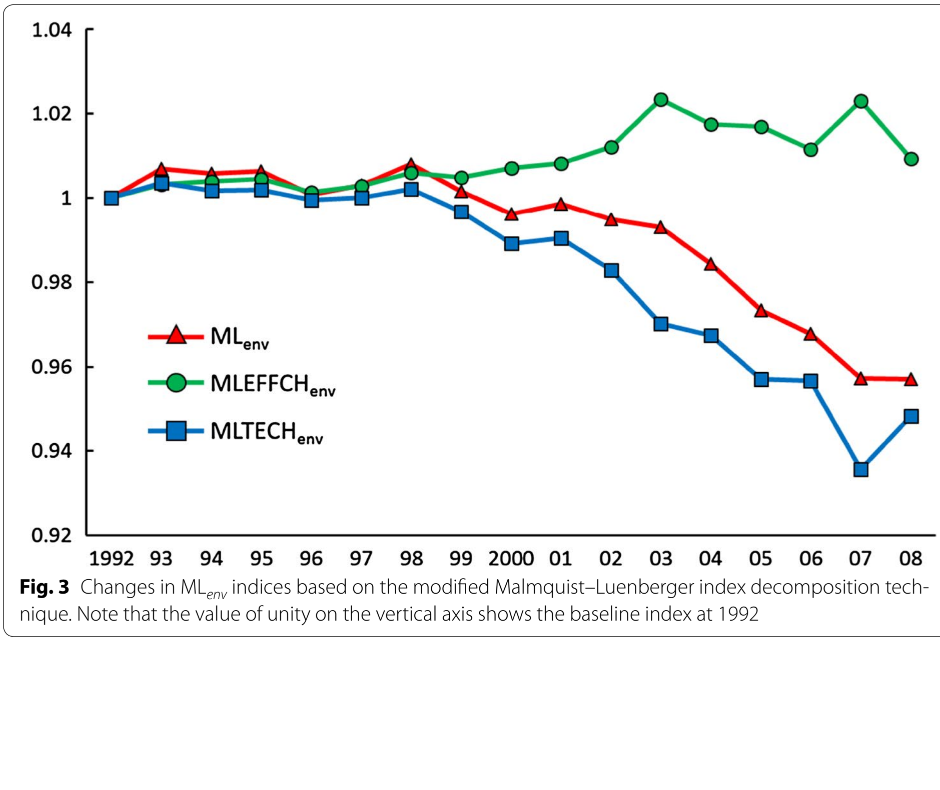

Fig. 3 Changes in ML_{env} indices based on the modified Malmquist–Luenberger index decomposition technique. Note that the value of unity on the vertical axis shows the baseline index at 1992

period of 1992 to 1999, when there is a consistent decline in ML_{all}, ML_{env} and $MLTECH_{env}$ substantially declined and consistently took values under unity after 2000, when ML_{all} greatly improved (see Fig. 3). From these results, it can be concluded that the substantial improvement in environmental efficiency (in other words, the substantial increase in ML_{all}) after 2000 is brought about by the increase in the real GRP for a given input level, not by the reduction in the amount of CO_2 emissions. Results for ML_{des} can be found in Additional file 1: Fig. S2.

Table 4 shows the main results regarding changes in environmental efficiency among the 46 prefectures. Although I employed multi-year "window" data as the reference technology, due to infeasible LP problems, I could not obtain results for Tottori Prefecture in the Chugoku region and Kochi Prefecture in the Shikoku region. During the study period, the largest increase in environmental efficiency (ML_{all}) is observed in Mie Prefecture in the Kinki region, followed by Fukushima in the Tohoku region and Shizuoka in the Chubu region. Environmental efficiency increased by more than 40% during the study period in these prefectures. On the other hand, although Kyoto and Osaka can be found on the production possibility frontier in 1992 (see Table 3), these prefectures suffered the most serious declines in environmental efficiency (18 and 17%, respectively) during the study period of 1992–2008. Regarding the changes in inputs of Kyoto and Osaka from 1992 to 2008, the rates of road construction in these prefectures increased 66.6 and 50.4%, respectively, which are far higher values than average (29.5%) (see Table 2). However, the real GRP rates of Kyoto and Osaka are 22.5 and 6.6%, respectively (see Table 2). Therefore, the relatively smaller increase in real GRP compared to that in road construction led to a substantial decline in environmental efficiency of these prefectures during the study period. Furthermore, looking at the highly populated prefectures of Saitama, Chiba, Tokyo, Kanagawa, Aichi, Osaka, and Fukuoka, where the population density is over 1000 people per km^2, environmental efficiency in Tokyo, Kanagawa, and Aichi increased more than average over the study period; by contrast, it decreased in Saitama, Osaka, and Fukuoka.

In addition, if we look at the results of ML_{env} in Table 4, we see that ML_{env} took a value less than unity in 75% of the prefectures. In other words, the change in the amount of CO_2 emissions in these prefectures led to a decrease in environmental efficiency (ML_{all}). Furthermore, if we focus on the results regarding Osaka, which shows the second largest decline in terms of ML_{all}, the rate of CO_2 emissions increased below the average (1.9%) (see Table 2), but the change in CO_2 emissions contributed to decreased environmental efficiency during the study period from 1992 to 2008 because the value of ML_{env} is 0.931 (see Table 4). When we look at the change in CO_2 emissions in Osaka by sector, the rate of CO_2 emissions from the transportation sector increased 59.1%, which is a relatively higher value and ranks 13th out of 46 prefectures (Agency for Natural Resources and Energy 2016). As previously mentioned, since the rate of increased road construction in Osaka is very high (see Table 2), it is possible that the accumulated roads might have caused the increase in traffic volume, as well as the further increase in CO_2 emissions from the transportation sector. On the other hand, although the change in the amount of CO_2 emissions contributed to improved environmental efficiency in some prefectures, the positive effect is under 1% in all prefectures. From these results, it can be said the

Table 4 Changes in environmental efficiency in the 46 prefectures

Region	Prefecture	ML_{all}	$MLEFFCH_{all}$	$MLTECH_{all}$	ML_{env}	$MLEFFCH_{env}$	$MLTECH_{env}$
Hokkaido	Hokkaido	1.125	0.884	1.273	0.998	1.004	0.993
Tohoku	Aomori	1.092	0.934	1.170	0.921	1.000	0.921
	Iwate	1.026	0.969	1.059	0.899	1.034	0.870
	Miyagi	1.148	0.994	1.155	0.957	1.016	0.942
	Akita	1.230	1.000	1.230	0.972	1.000	0.972
	Yamagata	1.036	1.024	1.012	0.823	0.984	0.837
	Fukushima	1.444	1.164	1.241	0.985	1.006	0.979
Kanto	Ibaraki	1.381	1.079	1.281	0.995	1.000	0.995
	Tochigi	1.293	1.076	1.202	0.967	1.001	0.966
	Gunma	1.093	0.969	1.128	0.976	1.054	0.926
	Saitama	0.922	0.901	1.023	0.902	1.074	0.840
	Chiba	1.099	0.858	1.281	1.000	1.000	1.000
	Tokyo	1.198	1.000	1.198	0.996	1.000	0.996
	Kanagawa	1.147	0.900	1.274	0.999	1.000	0.999
Chubu	Niigata	1.223	1.035	1.181	0.913	0.997	0.916
	Toyama	1.260	1.001	1.258	1.003	1.013	0.991
	Ishikawa	1.127	0.991	1.138	0.981	1.064	0.922
	Fukui	1.280	1.051	1.218	0.946	1.000	0.946
	Yamanashi	1.150	1.000	1.150	0.860	0.939	0.915
	Nagano	1.129	1.065	1.060	0.796	0.903	0.881
	Gifu	0.927	0.827	1.121	0.946	1.007	0.939
	Shizuoka	1.425	1.137	1.253	0.995	1.002	0.994
	Aichi	1.277	1.001	1.276	0.999	0.999	1.000
Kinki	Mie	1.466	1.154	1.271	1.003	1.000	1.003
	Shiga	1.221	1.000	1.221	1.009	1.000	1.009
	Kyoto	0.820	0.925	0.887	0.975	1.066	0.914
	Osaka	0.829	0.840	0.987	0.931	1.011	0.921
	Hyogo	1.125	0.878	1.281	1.000	1.000	0.999
	Nara	1.015	1.000	1.015	1.060	1.000	1.060
	Wakayama	1.178	0.938	1.255	1.000	0.999	1.000
Chugoku	Tottori	na	na	na	na	na	na
	Shimane	1.052	0.971	1.083	0.894	1.061	0.842
	Okayama	1.103	0.899	1.227	0.999	0.999	0.999
	Hiroshima	1.226	1.008	1.216	1.000	0.999	1.000
	Yamaguchi	1.184	0.945	1.253	1.000	1.000	1.000
Shikoku	Tokushima	1.149	0.999	1.151	0.987	1.004	0.983
	Kagawa	0.989	0.865	1.143	0.960	1.024	0.937
	Ehime	1.033	0.932	1.108	1.000	1.000	1.000
	Kochi	na	na	na	na	na	na
Kyushu	Fukuoka	0.909	0.794	1.145	1.000	0.999	1.000
	Saga	1.110	1.077	1.031	0.836	1.072	0.780
	Nagasaki	0.862	0.955	0.903	0.975	1.025	0.951
	Kumamoto	0.924	0.949	0.974	0.946	1.059	0.893
	Oita	1.226	1.005	1.219	0.999	1.000	0.999
	Miyazaki	0.864	0.944	0.916	0.893	1.025	0.872
	Kagoshima	0.953	0.998	0.955	0.887	1.007	0.880
	Geometric mean	1.108	0.972	1.140	0.957	1.010	0.948

decoupling of economic growth and CO_2 emissions is not achieved during the study period. Results for ML_{des} can be found in Additional file 1: Fig. S2.

3.4 Comparative analysis between the present study and Hashimoto and Fukuyama (2017)

In this section, I compare the results of this study with the results of production analyses conducted by Hashimoto and Fukuyama (2017), which take prefectural-level CO_2 emissions into account. Hashimoto and Fukuyama (2017) performed static production efficiency analyses for each prefecture, taking labor input, capital input, energy input, intermediate goods input, production output, and CO_2 emissions in each prefecture into account for the period from 2006 to 2009. Their analyses identified Tokyo and Kyoto as having the highest and Mie as having the lowest production efficiency. Comparing our results with those above, in this study, Tokyo was found to be one of the prefectures located at the frontier in 1992 and 2008, which is consistent with the results reported by Hashimoto and Fukuyama (2017) (Table 3).

With respect to Kyoto, although Kyoto was identified in our study as a highly efficient prefecture on the frontier in 1992, its efficiency has steadily declined since 1992 (Tables 3, 4). In terms of the treatment of capital inputs in the two studies, whereas Hashimoto and Fukuyama (2017) used the *monetary*-base sum of private capital stock and social capital stock as capital inputs, this study uses *monetary*-base private capital stock and *physical*-base accumulation of buildings and roads as capital inputs. As previously discussed, this study revealed that although Kyoto accumulated a large number of roads between 1992 and 2008, because these excessively accumulated roads have not been effectively used for production activities, Kyoto's environmental efficiency has fallen dramatically. As can be seen from the above, performing efficiency analysis based on physical resource inputs enables more detailed analysis of the relationship between social infrastructure and production efficiency.

3.5 How have socioeconomic factors affected the efficiencies?

Industrial structure and population differ among prefectures, affecting the efficiencies of individual prefectures. Nakano and Managi (2010) pointed out that regional differences in the proportion of energy-intensive industries (e.g., chemicals) affect the environmental efficiencies of different regions, while Hashimoto and Fukuyama (2017) analyzed how regional differences in population density, the proportion of tertiary industries, the share of energy consumption by manufacturing industries, and the share of energy consumption by non-manufacturing industries affect differences in environmental efficiency.

Taking the results of these previous studies (Nakano and Managi 2010; Hashimoto and Fukuyama 2017) into consideration, in this study, I selected the following dependent and independent variables to analyze the impact of socioeconomic factors on efficiency: dependent variables (1) ML_{all} and (2) ML_{des}; independent variables (1) annual change in population (*POPULATION*), (2) annual change in the share of GRP accounted for by tertiary industry production (*TERTIARY*), (3) annual change in the share of energy consumption accounted for by manufacturing industries (*ENE_MANUFACTURING*), (4) annual change in the share of energy consumption accounted for by non-manufacturing industries (*ENE_NONMANUFACTURING*), (5) annual change in building stock (*BUILDINGS*), (6) annual change in road stock (*ROADS*), and (7) a Kyoto Protocol dummy (*KYOTO*). The two dependent variables, ML_{all} and ML_{des}, represent values estimated in Sect. 3.3. I obtain the data on population from the Population by Prefecture and Sex (Ministry of Internal Affairs and Communications 2016). The share of GRP accounted for by tertiary industry production is calculated based on the data provided by the R-JIP Database 2014 (Research Institute of Economy, Trade and Industry 2014), and the shares of energy consumption accounted for by manufacturing and non-manufacturing industries are calculated based on the data provided by Energy Consumption Statistics (Agency for Natural Resources and Energy 2016). For calculating the annual change in building and road stocks, I make use of the estimates from Tanikawa et al. (2015).

By adding annual changes in *physical*-base building and road stocks to the pool of independent variables used by Nakano and Managi (2010) and Hashimoto and Fukuyama (2017), this study is able to estimate how changes in building and road stocks impact production efficiency via their effect on production and transportation activities. The Kyoto Protocol dummy is assigned a value of 0 for observations from 1992 to 1997 and a value of 1 for observations from 1998 and later. It should be noted that Japan ratified the Kyoto Protocol on climate mitigation in 1997. A total of 704 observations are used for regression analysis, including data for 44 prefectures, excluding Tottori and Kochi, for which ML indices could not be calculated, over the 16-year period from 1992 to 2008 ($704 = 16 \times 44$).

The results show that *POPULATION* significantly impacts ML_{all} and ML_{des} and that population accumulation increased the environmental efficiency and economic efficiency of production activities (Table 5). In contrast, *TERTIARY* is found to negatively impact ML_{all} and ML_{des}, indicating that the expansion of tertiary industries reduces the environmental and economic efficiency of production activities (Table 5). This is due to the fact that, in Japan, per worker GDP is substantially lower for the retail, lodging, and transportation industries compared with the manufacturing industries (Ministry of Economy, Trade and Industry 2014). Accordingly, to increase environmental efficiency, it is necessary to shift to an industrial structure with a greater share of tertiary industries while increasing per worker GDP in tertiary industries.

Table 5 Results of the regression analysis

Independent variable	ML_{all}	ML_{des}
POPULATION	0.714*** (2.95)	0.474** (2.10)
TERTIARY	−1.073*** (−15.59)	−1.378*** (−21.51)
ENE_MANU	−0.158*** (−2.89)	0.091* (1.78)
ENE_NONMANU	0.678*** (4.16)	0.052 (0.34)
BUILDINGS	−0.509*** (−3.31)	−0.443*** (−3.09)
ROADS	−0.167*** (−2.77)	−0.165*** (−2.89)
KYOTO	0.006** (2.18)	0.010*** (3.97)
Constant	1.531*** (5.21)	2.380*** (8.70)
Number of observations	704	704
Adjusted R^2	0.422	0.557

Values in parentheses are *t* values

*** indicates a variable is significant at the 1% level, ** indicates a variable is significant at the 5% level, and * indicates a variable is significant at the 10% level

ENE_MANUFACTURING and *ENE_NONMANUFACTURING* are found to negatively and positively, respectively, impact ML_{all} (Table 5), which is consistent with the results presented by Nakano and Managi (2010) and Hashimoto and Fukuyama (2017). Both *BUILDINGS* and *ROADS* are observed to negatively impact ML_{all} and ML_{des} (Table 5), probably due to the excessive input of social capital stock in regions with low productivity, as pointed out by Nakano and Managi (2010). Finally, although KYOTO is found to positively impact ML_{all} and ML_{des} (Table 5), the magnitude of its impact is not so large. Thus, Kyoto Protocol was not effective for improving environmental and economic efficiencies.

It should be noted that we need to be careful about a serial correlation among the estimated efficiencies pointed out by Simar and Wilson (2007). Although the present study focuses on the socioeconomic factors, it does not consider the serial correlation problem. This problem should be more investigated in the future work.

3.6 CO_2 emission reduction potentials in 1992 and 2008

One of the advantages of DEA analysis is that it allows prefectures with low environmental efficiency to use the production frontier to estimate optimal input, production, and emissions levels under optimal production conditions. The results of this study indicate that in 1992, 36 of the 46 prefectures were engaged in production activities with low environmental efficiency (Table 3). Using the production frontier constructed by production activities of environmentally *efficient* prefectures, the CO_2 emission reduction potential of environmentally *inefficient* Prefecture k is easily estimated as $\beta_k \times b_k$ and the total CO_2 emission reduction potential for all 36 environmentally inefficient prefectures is estimated as $Q = \sum_{k=1}^{36} \beta_k b_k$.

Figure 4 shows the total CO_2 emission reduction potential of all environmentally inefficient prefectures in 1992 and 2008. The total CO_2 emission reduction potential in Japan in 1992 is estimated to be 127 million t-CO_2, corresponding to 13.1% of the total CO_2 emissions in Japan in the same year. This study also identifies regions with substantial emission reduction potential consisting of the top five prefectures shown in Fig. 4, which have a combined CO_2 emission reduction potential of 38.2 million t-CO_2, accounting for 35% of the total 127 million t-CO_2 reduction potential.

Next, total CO_2 emission reduction potential increased from 127 to 179 million t-CO_2 (41%) over the 17-year period between 1992 and 2008. The combined CO_2 emission reduction potential of the top five prefectures (Hokkaido, Chiba, Fukuoka, Hyogo, and Kanagawa) in 2008 is 78 million t-CO_2, corresponding to about 6% of Japan's total CO_2 emissions (1.286 billion t-CO_2) in 2008 (Ministry of the Environment 2016). This marks a rapid (greater than twofold) increase over the 17-year period from 1992 to 2008, which is an important finding.

Although it is important to formulate macroscale emission reduction measures at the national level, it is even more important to formulate emission reduction measures at the prefecture level that are tailored to the specific region and therefore more effective. We are able to use an environmental efficiency analysis to identify prefectures whose production activities, based on each prefecture's accumulated resources (i.e., physical stock) and other factor inputs, are environmentally inefficient; however, it is not possible to formulate emission reduction measures solely on the basis of the level of environmental

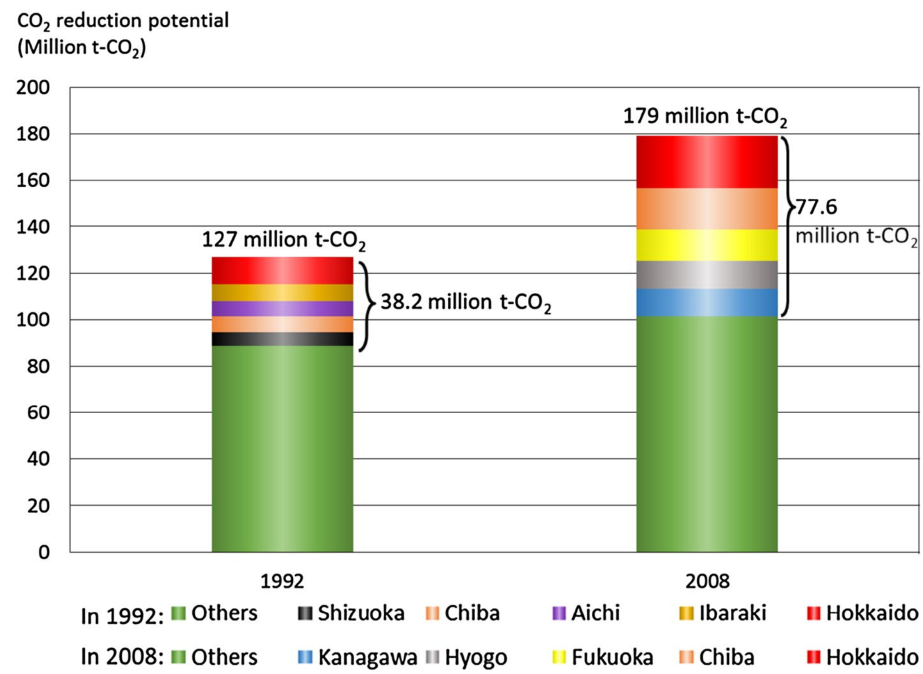

Fig. 4 CO_2 reduction potential in 1992 and 2008

efficiency. The important point is to improve environmental efficiency while also reducing CO_2 emissions. This study revealed that, as of 2008, five prefectures—Hokkaido, Chiba, Fukuoka, Hyogo, and Kanagawa—are not only engaged in low-environmental-efficiency production activities, but also have substantial CO_2 emission reduction potential (Fig. 4). Taking the results presented in Sect. 3.5 into consideration, in addition to avoiding investment in useless buildings and roads, the key to improving environmental efficiency of production activities at the regional level is to shift to an industrial structure with a greater share of tertiary industries while achieving greater value-added in tertiary industries (Ministry of Economy, Trade and Industry 2014).

4 Conclusions

In this study, I comparatively analyzed the *CEEI* and *DEEI* and examined the gap between these two indicators. From the results, I can conclude that the *DEEI*, which accounts for resource accumulation in Japanese prefectures, is more desirable as an environmental performance indicator because the *CEEI* (calculated by real GRP per CO_2 emissions) does not account for input factors used by the production activities.

Based on the analysis on changes in environmental efficiency using the ML index, environmental efficiency was shown to have consistently declined from 1992 to 1999; however, a rapid increase in environmental efficiency was seen after 2000, and an increase of 10.8% was observed from 1992 to 2008. One reason for this increase in environmental efficiency was the substantial improvement in frontier technology; that is, the growth in environmental efficiency in the prefectures that constructed a production possibility frontier contributed to improving the environmental efficiency of Japan after 2000.

By looking at the ML index in each prefecture, we could identify the prefectures where environmental efficiency substantially increased (Mie, Fukushima, and Shizuoka). On the other hand, looking at the highly populated prefectures of Saitama, Chiba, Tokyo, Kanagawa, Aichi, Osaka, and Fukuoka, where the population density is over 1000 people per km^2, environmental efficiency in Tokyo, Kanagawa, and Aichi increased more than average, whereas that in Osaka significantly declined during the study period. In addition, looking at how changes in the amount of CO_2 emissions contributed to changes in environmental efficiency, in 75% of the prefectures, a change in the amount of CO_2 emissions led to a decrease in environmental efficiency. There were very few prefectures where environmental efficiency increased while the amount of CO_2 emissions decreased for a given input level.

In this study, I analyzed factors affecting efficiency by performing regression analysis with ML_{all} and ML_{des}, estimated using DEA and the Malmquist–Luenberger index decomposition method, as dependent variables and socioeconomic factors as independent variables. Population accumulation was found to be a key factor for increasing the environmental and economic efficiency of production activities, whereas the expansion of tertiary industries was found to reduce the environmental and economic efficiency of production activities. The latter result is due to the low per worker GDP in tertiary industries in Japan. Furthermore, increasing building and road stocks was found to reduce the environmental and economic efficiency of production activities owing to excessive investment in social infrastructure in regions with low productivity.

In addition, on the basis of efficiency scores estimated by DEA analysis, it is apparent that the CO_2 emission reduction potential of the low-environmental-efficiency prefectures identified in this study increased substantially from 127 million t-CO_2 in 1992 to 179 million t-CO_2 in 2008. Therefore, the key to achieving effective emission reduction in Japan lies in proactively improving the environmental efficiency of the five prefectures—Hokkaido, Chiba, Fukuoka, Hyogo, and Kanagawa—identified in this study. To improve the environmental efficiency of production activities in the prefectures identified above, it is necessary to avoid excessive investment in social infrastructure and to shift to an industrial structure with a greater share of tertiary industries while increasing per worker GDP in tertiary industries.

Additional file

Additional file 1. Supplementary information.

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Competing interests

The author declares that he has no competing interests.

Availability of data and materials

Data sources of the independent variables in the regression analysis are provided in Additional file 1: Table S2.

Ethics approval and consent to participate
The author declares that this study does not involve human subjects, human material, and human data.

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