Environmental Efficiency Assessment of the U.S. Pulp and Paper Industry Using an SBM-DEA Model

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The pulp and paper industry contributes to the economic development of the U.S., producing goods that meet primary needs. However, this sector must operate in a balance with the environment to ensure ecological preservation. Proposing a non-radial slacks-based measure – data envelopment analysis (SBM-DEA) approach, this study assessed the environmental efficiency of the pulp and paper industry in the U.S. from 2015 to 2018. External environmental impacts and random interferences on efficiency assessment were explored by using a stochastic frontier approach (SFA) regression. This study revealed that the U.S. pulp and paper industry was highly non-eco-efficient in the period evaluated, presenting an average environmental efficiency value of 0.509. Also, it is suggested that a total of 2.967 million metric tons of CO_{2eq} emissions were in excess of those that were estimated based on an assumption of perfect environmental efficiency from 2015 to 2018 in the U.S. pulp and paper Industry. Based on the analysis of input and output slacks and the external environmental factors which reflect the environmental features of each decision-making unit (DMU), these facilities should substantially reduce CO_2eq emissions and enhance the resources-allocation efficiency for improving the environmental efficiency of the U.S. PPI.

Keywords: Environmental efficiency; Carbon emissions reduction; P & P industry; Slack-based measure; Data envelopment analysis

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INTRODUCTION

The effects of climate change are seen globally on a large-scale. Climate change affects society and ecosystems in different ways, such as severe temperatures, flooding, and changes in the quality of the air. As climate change concerns grow, a series of actions to combat the problem have emerged to understand and reduce its causes. Recently, the Climate Action Summit, held in September 2019, had as a central purpose to develop plans to reduce greenhouse gas emissions by 45% over the coming decade, and net to zero by 2050 (United Nations 2019). The presence of greenhouse gases (GHGs) in the atmosphere, such as carbon dioxide, methane, nitrous oxide, and chlorofluorocarbons, leads to the global warming effect. Global warming potential (GWP) relates how much energy will be absorbed by one ton of emissions of these gases over a period of time, compared to one ton of carbon dioxide. Thus, when considering different gases of increasing GWP, the more they will warm the earth in contrast to carbon dioxide (EPA 2017).

The U.S. energy demand is mainly satisfied by fossil fuel combustion, which causes massive carbon dioxide (CO_2) emissions (U.S. EIA 2018). Although CO_2 is the main contributor to GHGs, accounting for about two thirds, other gases such as methane (CH_4)

and nitrous oxide (N_2O) are also generated during fuel combustion and contribute to GHGs emissions (EPA 2018). According to the most recent data from the Global Carbon Project 2018, the U.S. is the second-largest emitter of CO_2. Also, for the sources of GHG emissions, in 2017, the US total emissions were estimated to be 6.5 billion metric tons of CO_{2eq}, with a breakdown of 82% coming from CO_2, 10% from CH_4, 6% from N_2O, and 3% from other fluorinated gases. For the U.S. pulp and paper Industry, the GHGs emissions have been estimated to be 35.5 million metric tons of CO_{2eq} (EPA 2017). Therefore, to reduce the environmental impact, it is worthwhile to estimate the GHGs emissions and assess the environmental efficiency in the U.S. pulp and paper industry, which may provide useful information for researchers who are likely to investigate in this field.

Few studies have analyzed efficiency by using cross-sectional data instead of panel data in the U.S. pulp and paper industry from a productivity efficiency perspective. Many previous studies have preferred to apply radial programs into the efficiency analysis, which cannot estimate all the technical inefficiencies of greenhouse gas emissions. Thus, the purpose of this study is to fill in the gap by using a slack-based efficiency approach with non-radial measure for estimating the environmental efficiency of the U.S. pulp and paper industry and exploring its slacks of inputs and outputs to determine the optimal values for capital, labor, energy usage, and CO_{2eq} emissions.

Literature Review

The assessment of environmental performance has been the focus of research worldwide in the past several decades. Shephard (1970) firstly introduced the concept of "environmental efficiency". Since then, there have been various measurements and evaluations of environmental efficiency analyzed by scholars. Some researchers prefer to assess environmental efficiency by using an environmental performance index (EPI) (Färe and Grosskopf 2004; Kortelainen 2008; Vachon 2012). Life Cycle Assessment (LCA) methods have been also applied into estimate carbon dioxide equivalents (CO_2eq) in certain sectors. This approach accounts for contributions to pollution from the cradle to landfill, and it also has been used to evaluate CO_2eq emissions as the input indicator of environmental efficiency (Miettinen and Hämäläinen 1997; Lozano *et al.* 2010; Olander 2012; Poeschl *et al.* 2012; Hawkins *et al.* 2013; Vázquez-Rowe and Iribarren 2015; Carvalho *et al.* 2014).

Environmental efficiency analysis often employs the data envelopment analysis model (DEA). The DEA method is a non-parametric approach that can achieve an optimal linear combination of multiple inputs and outputs, which has the advantage of ignoring the imposition of a function form (Zhu 2004). Therefore, DEA could make the estimation of efficiency easier. DEA was first designed by Charnes *et al.* (1978) and called the CCR model as a combination analysis tool of input and output based on relative efficiency. It is different from the radial models, which have been widely employed, as it applies the parametric approach into efficiency assessment. Wei *et al.* (2007) estimated the energy efficiency of China's specific industry using DEA models. However, conventional DEA in the application may only take the desirable outputs into account. Conventional DEA does not consider environmental efficiency analysis results from "bad" or "pollutants" as inputs to the model. For instance, it may cause biased results on the assessment of the environmental efficiency due to ignoring the impacts of undesirable gaseous outputs such as CO_2 or SO_2 as well as pollutants in the treated wastewater (He *et al.* 2013; Chen *et al.* 2015).

In this context, the slacks-based measure (SBM) models were introduced by Tone

(2001) and Pastor *et al.* (1999). The SBM-DEA model is a non-radial measurement under the constant returns-to-scale (CRS) and the variable returns-to-scale (VRS) assumption. It allows inputs, undesirable outputs, and desirable outputs by individuals to obtain factor efficiencies based on non-uniform inputs and outputs. Shi *et al.* (2010) applied DEA under the constant returns-to-scale (CRS) and the variable returns-to-scale (VRS) models to estimate the industrial environmental efficiency in some provinces of China, considering waste gases as undesirable outputs. Park *et al*. (2016) estimated environmental and carbon efficiency of the U.S. transport sector by using a lack-based data envelopment method. Chen and Jia (2017) selected sulfur dioxide emissions and industrial solid waste as undesirable outputs and made the environmental efficiency evaluation of China's industry. Guo *et al.* (2011) analyzed the environmental efficiency and reduction of carbon dioxide emission in 30 provinces of China through SBM-DEA methods. Wang *et al.* (2011) analyzed CO_2 emissions for China with an expanded DEA efficiency measurement. Zhang *et al.* (2008) assessed the industrial environmental efficiency of large provinces in China, considering CO_2, CH_4, SO_2, and other emissions as input for a DEA model with variable returns to scale. Ramanathan (2005) estimated the energy efficiency of the transport sector in India by using the DEA model. Önüt and Soner (2006) assessed the energy efficiency in 32 five-star hotels in the Antalya Region of Turkey while employing DEA with the non-function linear programming model. Lee *et al.* (2014) evaluated the environmental efficiency of port cities and considered input of input, desirable output of GDP, and undesirable outputs of pollutant emissions as indicators of the SBM-DEA model. Chang *et al.* (2014) expanded upon an SBM model with the weak disposability assumption to analyze the economic and environmental efficiency of international airlines. Some researchers adjusted the SBM-DEA model with advanced SBM-DEA software to analyze the internal process of DMUs (Tone and Tsutsui 2009; Cook *et al.* 2010; Tone and Tsutui 2010; Li *et al.* 2017; Wu *et al.* 2019).

As for the Pulp and Paper Industry (PPI), a number of researchers have estimated PPI's environmental efficiency. For instance, Yu *et al.* (2016) assessed the environmental efficiency of 16 provinces' PPI in China and compared the disparity between efficient and inefficient DMUs by using SBM-DEA and ML methods. Ashrafi *et al.* (2013) applied a simulated model and analyzed PPI's GHG emissions with the removal of excess nitrogen in the wastewater plants. Hubbe *et al.* (2016) reviewed comprehensive approaches for wastewater treatment, which could help the PPI to eliminate higher levels of pollutant by proposing advanced treatment and improve environmental efficiency.

The goal of the present work was to analyze the impacts of the external environment and random factors on sustainable development in the U.S. PPI. In this study, the Stochastic Frontier Analysis (SFA) proposed by Aigner *et al.* (1977) was used to assess environmental efficiency more accurately by accounting for external environmental variables and removing random interference factors. The traditional SBM-DEA model does not take external environmental and random factors impact into account, leading to deviations in the adjustment of inputs slack and undesirable output slack (Zhang and Bu 2017). In addition, the waste factors have extent effects on the U.S. PPI sustainable practice.

As shown by the review of the literature, SBM software and SFA regression have been widely used to evaluate the environmental efficiency of the models involving undesirable outputs. Few pieces of research have been applied to the evaluation of the environmental efficiency of PPI facilities from a micro perspective. Given the scenarios of the environmental impact of the U.S. pulp and paper industry, CO_2eq emissions should be specifically treated as undesirable outputs. This conforms to the realistic production process of PPI from manufacturing, fuel combustion, and landfill, and the efficient result will be more convincing to reveal the true environmental performance of the U.S. PPI. In this study, the DEA model was expanded based on the output-oriented slacks-based measurement (SBM) approach under the variable returns to scale (VRS) assumption, to estimate the environmental efficiency of the U.S. pulp and paper Industry. This study explored the excess in inputs and undesirable outputs that could potentially lead to reducing the carbon emissions of this sector. Additionally, the impacts of external environmental factors on the slacks of inputs and outputs by using SFA method was explored. It is expected that the results reflect the actual pulp and paper industry development in the U.S. and provide policy implications relative to CO_2eq emissions reduction while maximizing benefits.

EXPERIMENTAL

Methodology

This study developed a framework for measuring the environmental efficiency of 130 pulp and paper facilities in the U.S. from 2015 to 2018 *via* slack-based measurement (SBM) with undesirable outputs and explored the influences of the external environment and random factors on slack of inputs and outputs.

Slacks-based Measure for DEA

Following Zhou *et al.* (2006), Chang *et al.* (2013), and Hong and Shi (2014), this paper proposes and expands an SBM-DEA framework by using the undesirable outputs as an objective function and the restricted function. It has three variations, *i.e.*, input-oriented, output-oriented, and non-oriented, which can be estimated under constant returns-to-scale (CRS) and the variable returns-to-scale (VRS) assumption (Tone 2001; Tone and Sahoo 2003). While considering a bad output in the model, it is noted that the efficiency value of each decision-making unit (DMU) could be improved by increasing the desirable output, reducing the excess in inputs, or decreasing the undesirable outputs (Zhang *et al.* 2011; Chang *et al.* 2014).

Suppose that a system has $\mathrm{k} = \{1,\dots,\mathrm{n}\}$ decision DMU and that each “k” uses “j” inputs to produce “e” desirable outputs and generate “f” undesirable outputs. The vectors of inputs, desirable outputs and undesirable outputs for each DMU, are given by$(x\epsilon R^{j})$, $(y^{g}\epsilon R^{e})$, and $(y^{b}\epsilon R^{f})$, respectively. The matrices are defined as follows:

$$X = \left[x_{1,\dots,}x_{n}\right]\epsilon R^{j\times n}, \tag{1}$$

$$Y^{g} = [y_1^{g},\dots,y_n^{g}]\epsilon R^{e\times n}, \tag{2}$$

$$Y^{b} = [y_1^{b},\dots,y_n^{b}]\epsilon R^{f\times n}, \tag{3}$$

Assume that all data on $X, Y^{g}, and\ Y^{b}$ are positive. The set (P) as production $-$ possibility can be designed as follows,

$$P = \{(x, y^{g}, y^{b})|xcanproduce(y^{g}, y^{b}), x \geq X\lambda, y^{g} \leq Y^{g}\lambda, y^{b} = Y^{b}\lambda, \lambda \geq 0\} \tag{4}$$

where λ denotes the positive intensity vector. And the production efficiency and technical efficiency based on the slacks-based directional distance function exhibits variable returns to scale (VRS). This study uses an SBM paradigm that can incorporate undesirable outputs into both the objective function and an additional restriction. The SBM-DEA equation set with output-oriented model could be explained in Model 1 below (Lu *et al.* 2013),

$$\theta^* = \frac{1-\frac{1}{j}\sum_{i=1}^{j}\frac{s_i^-}{x_i}}{1+\frac{1}{e+f}(\sum_{r_1=1}^{e}\frac{s_{r_1}^g}{y_{r_1}^g}+\sum_{r_2=1}^{f}\frac{s_{r_2}^b}{y_{r_2}^b})} \tag{5}$$

$s.t.$

$$x_0 = X\lambda + s^- \tag{6}$$

$$y_0^g = Y^g\lambda - s^g \tag{7}$$

$$y_0^b = Y^b\lambda + s^b \tag{8}$$

$$s^- \geq 0, s^g \geq 0, s^b \geq 0, \lambda \geq 0, \tag{9}$$

where θ^* is each DMU's value [0.1]; i is the index of inputs (1,2 ...,m); j is the number of inputs; r_1 is the index of desirable outputs; r_2 is the index of undesirable outputs; e is the number of desirable outputs; f is the number of undesirable outputs; s^- is the slack of inputs; s^g is the slack of desirable outputs; and s^b is the slack of undesirable outputs.

The DMU is regarded as being efficient if θ^* is equal to 1, which means that all the slack values, s^-, s^g, and s^b are equal to 0. If θ^* is less than 1, then the DMU is considered as out of efficiency, and it could be improved by proper adjusting the ratio of the slacks in inputs and undesirable outputs and augmenting the desirable outputs. But Eq. 2 is not a linear function. As proposed by Tone (2001), a convertible model is used, and the result is seen as:

$$r^* = min\, c - \frac{1}{j}\sum_{i=1}^{j}\frac{s_i^-}{x_i} \tag{10}$$

$s.t.$

$$1 = c + \frac{1}{e+f}\left(\sum_{r_1=1}^{e}\frac{s_{r_1}^g}{y_{r_1}^g} + \sum_{r_2=1}^{f}\frac{s_{r_2}^b}{y_{r_2}^b}\right) \tag{11}$$

$$x_0 c = X\varphi + s^- \tag{12}$$

$$y_0^g c = Y^g\varphi - s^g \tag{13}$$

$$y_0^b c = Y^b\varphi + s^b \tag{14}$$

$$s^- \geq 0, s^g \geq 0, s^b \geq 0, \varphi \geq 0, c \geq 0 \tag{15}$$

The best solution of the linear program model (Eqs. 10 to 15) can be found, and the optimal solution is found to be $(r^*, c^*, \varphi^*, s^{-*}, s^{g*}, s^{b*})$, where $\theta^* = r^*, \lambda^* = \frac{\varphi^*}{c^*}, s^{-*} = \frac{s^{-*}}{c^*}, s^{g*} = \frac{s^{g*}}{c^*}, s^{b*} = \frac{s^{b*}}{c^*}$ from the linear program model. The solution to $c^*, \varphi^*, s^{-*}, s^{g*}$and s^{b*}can be generated through the linear program model with $c^* \geq 0$.

Stochastic Frontiers Analysis (SFA)

SBM-DEA and stochastic frontiers are two alternative methods for estimating frontier functions and thereby measuring the efficiency of production. The input-output slacks are assumed to analyze the initial inefficiency, which is classified as external environmental factors, government regulations, and stochastic interference (Coelli *et al.* 2005). The traditional SBM-DEA model cannot accurately reflect the optimal adjustment on slacks of inputs and outputs which have been influenced by the external environment and random errors on the environmental efficiency evaluation. Different from SBM-DEA software, which involves the use of non-linear programming, SFA involves the use of econometric regression functions (Coelli *et al.* 1998). The main objective of using the SFA method is to decompose the slack variables into the above external environmental effects by SFA regression, where the slack variables are used to be explained by the environment variables and the mixed error items (Herrala and Goel 2012). The regression equation is as follows:

$$S_{ij} = \alpha_{ij} + x_i\lambda_i = 1,2,\cdots\cdots m, j = 1,2,\cdots\cdots n \tag{16}$$

$$S_{ij} = f^i(z_j;\beta_i) + \nu_{ij} + \mu_{ij} \tag{17}$$

Among the above equations, S_{ij} explains the slack variable of input_i or output_i of DMU_j, and $z_j = [z_{1j}, z_{2j}, \cdots, z_{kj}]$, β_i explains the external environment parameter to be estimated, $\nu_{ij} + \mu_{ij}$ are comprehensive errors term, where it is supposed that ν_{ij} and μ_{ij} are independent of each other, and also that they are independent of the k external environment variables. Therefore, the aforementioned SFA regression needs to be designed as follows,

$$\gamma = \sigma_\mu^2/(\sigma_\nu^2 + \sigma_\mu^2) \tag{18}$$

$$\sigma^2 = \sigma_\nu^2 + \sigma_\mu^2 \tag{19}$$

where σ_ν^2 and σ_μ^2 explain the variances of the comprehensive error term, and γ indicates the ratio of the variance of the inputs and outputs inefficiency to the total variance. When γ approaches 1, this indicates that the environmental efficiency of each DMU is different, and the stochastic factor seem small. When γ approaches 0, it indicates that the environmental efficiency difference between the DMUs is not significant and the stochastic difference seems large. Thus, one needs to estimate the parameter by using the maximum likelihood method. The results of each parameter can be estimated and inputs and outputs slack could be adjusted by analyzing its coefficient so that all of the DMUs are taken into consideration for the environmental efficiency.

Data

To analyze the characteristics of the U.S. pulp and paper industry, the data of 130 facilities were collected from the Environmental Protection Agency (U.S. EPA, 2018)) and FisherSolve databases for 2015 to 2018. The number of facilities was selected based on an optimal collection and data availability of inputs and outputs. These 130 facilities account for 75.83% of the GHGs emissions (million metric tons) of the pulp and paper industry in the U.S in 2018 (U.S. EPA 2018). Therefore, empirical results derived from these data could substantially reflect the U.S. pulp and paper industry. The models described in Section 3 have been applied to study the environmental efficiency of these 130 facilities.

According to Cooper (1978), the number of DMUs should follow Eq. 20 below. This means that the number of DMUs could be appropriate when it is more than 30 subjects. In this study ($m + p$) is the sum of input and output variables.

$$N \geq \max_{\substack{m>0 \\ p>0}}\{5(m + p)\} \tag{20}$$

The information described in the framework was collected (Table 1). The data on capital and production were obtained from FisherSolve database (FisherSolve, 2015-2018).

Based on the availability of the data, the inputs for energy (mmBTU) and labor (number of employees) were estimated by using the information of 2019, and adjusting for 2015-2018 through the change in price of energy (U.S. EPA 2018) and Employment Cost Index respectively (U.S. Bureau of Labor Statistics 2015-2018). The energy use, selected as an input, includes all gas usage and electricity usage from the pulp and paper industry. The official data of GHGs emissions for each facility, selected as undesirable output, are available in the U.S. EPA database as part of the Greenhouse Gas Reporting Program (U.S. EPA 2018), specifically, the Facility Level Information on Greenhouse Gases Tool (FLIGHT), which includes CO_{2eq} from stationary combustion, pulp and paper manufacturing, and industrial waste landfills (Myhre *et al.* 2013). One advantage of the non-parameter slack measure method is that the desired output of the model not only can be selected as the profit but also as the quantity produced.

Because it would be difficult to present each DMU's result based on each facility throughout the paper, the data were grouped by the states of the U.S., covering 31 states. The average environmental efficiency of each state was estimated based on the environmental efficiency of each facility within the state. Therefore, this study assesses the environmental efficiency of the U.S. pulp and paper industry at a state-level from 2015 to 2018. The data descriptions are presented in Table 1. The degree of variations in all selected variables across each facility from 2015 to 2018 is shown from the standard deviations in Table 2.

Table 1. Input and Output Variables and Data Sources, 2015–2018

Indicators	Definition	Unit	Data Source
Input	Capital	Millions USD	FisherSolve
	Energy	mmBTU	
	Labor	Employees	
Desirable Output	Production	MT	
Undesirable Output	GHG emissions (CO_{2eq})	MMT	EPA

Note: Unit (MT): Metric Tons; Unit (MMT): Million Metric Tons.

Table 2. Descriptive Statistics of Inputs and Outputs, 2015-2018. (N=520)

Inputs & Outputs	Variable	Unit	Min	Max	Mean	Std.dev.
Non-energy inputs	Capital	Millions USD	6.70	468.40	126.62	86.05
	Labor	Employees	41.19	1,435.10	399.19	246.98
Energy inputs	Energy Use	mmBTU	182,905	26,782,117	5,305,867	4,233,380
Desirable output	Produc-tion	MT	386,46	1,605,349.00	424,086.13	299,592
Undesirable output	CO_{2eq}	MMT	0.022	1.350	0.215	0.211

RESULTS AND DISCUSSION

Environmental Efficiency Assessment

In terms of environmental efficiency (EE), the performance from 2015 to 2018 of the U.S. pulp and paper industry (PPI) shows that only one state (Vermont) was found to be relatively environmentally efficient with an EE score of 1. The scores from the remaining 30 states, gathered in Table 3, performed inefficiently, ranging from 0.27 to 0.93.

Table 3. Environmental efficiency of the U.S. PPI

State	2015	2016	2017	2018	Mean	Returns to Scale
Alabama	0.578	0.591	0.656	0.633	0.614	Increasing
Arkansas	0.406	0.454	0.466	0.505	0.458	Increasing
California	0.622	0.605	0.651	0.786	0.666	Increasing
Connecticut	0.590	0.617	0.652	0.989	0.712	Increasing
Florida	0.502	0.518	0.528	0.582	0.532	Increasing
Georgia	0.615	0.616	0.670	0.675	0.644	Increasing
Idaho	0.443	0.451	0.435	0.471	0.450	Increasing
Indiana	0.305	0.313	0.301	0.314	0.308	Increasing
Kansas	0.209	0.311	0.311	0.319	0.287	Increasing
Kentucky	0.510	0.517	0.529	0.662	0.554	Increasing
Louisiana	0.586	0.614	0.682	0.761	0.661	Increasing
Massachusetts	0.311	0.350	0.281	0.406	0.337	Increasing
Maine	0.390	0.441	0.462	0.473	0.442	Increasing
Michigan	0.411	0.428	0.455	0.456	0.438	Increasing
Minnesota	0.396	0.429	0.443	0.459	0.432	Increasing
Mississippi	0.896	0.901	0.964	0.956	0.929	Increasing
North Carolina	0.243	0.278	0.322	0.435	0.320	Increasing
New Hampshire	0.325	0.282	0.307	0.311	0.306	Increasing
New York	0.705	0.698	0.676	0.729	0.702	Increasing
Ohio	0.394	0.387	0.371	0.394	0.386	Increasing
Oklahoma	0.596	0.603	0.607	0.652	0.614	Increasing
Oregon	0.557	0.589	0.615	0.655	0.604	Increasing
Pennsylvania	0.248	0.275	0.250	0.297	0.268	Increasing
South Carolina	0.535	0.490	0.561	0.553	0.535	Increasing
Tennessee	0.365	0.445	0.436	0.482	0.432	Increasing
Texas	0.540	0.570	0.629	0.616	0.589	Increasing
Virginia	0.428	0.451	0.488	0.604	0.493	Increasing
Vermont	1.000	1.000	1.000	1.000	1.000	Constant
Washington	0.388	0.421	0.468	0.430	0.427	Increasing
Wisconsin	0.274	0.305	0.310	0.322	0.303	Increasing
West Virginia	0.292	0.310	0.354	0.361	0.329	Increasing
Mean	0.473	0.492	0.512	0.558	0.509	

Specifically, there were 17 states with an environmental efficiency score below 0.5 on average. Thus, there is considerable room for improvement in the environmental efficiency of the PPI. Instead of analyzing the efficiency of the PPI in a purely economic measurement, the environmental efficiency of PPI was assessed including an undesirable output into the SBM-DEA model, so that the contribution of CO_{2eq} emissions to the inefficiency and potential CO_{2eq} reduction could be analyzed (Table 4). These emissions are produced during the pulp and paper manufacturing process, fuel combustion, and delivery waste into landfills. Combusting paper products results in emissions of both carbon dioxide (CO_2) and nitrous oxide (N_2O) (U.S. EPA 2016). When paper products are landfilled, anaerobic bacteria can slowly degrade the materials, producing CH_4, and CO_2 over time (U.S. EPA 2016). The sustainable practice must be implemented by the P&P Industry from the process of production to landfills. In sum, the U.S. PPI needs improvement in environmental efficiency and sustainable development.

Potential Carbon Equivalents Emission Reduction of PPI

As the results of Environmental efficiency show, most states are not performing efficiently in the PPI, with the exception of Vermont.

Table 4. Potential CO_{2eq} Reduction (MMT)

State	2015	2016	2017	2018	Mean
Alabama	(0.17)	(0.17)	(0.15)	(0.15)	(0.16)
Arkansas	(0.18)	(0.17)	(0.17)	(0.17)	(0.17)
California	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)
Connecticut	(0.05)	(0.05)	(0.05)	(0.01)	(0.04)
Florida	(0.19)	(0.18)	(0.16)	(0.14)	(0.17)
Georgia	(0.18)	(0.16)	(0.15)	(0.16)	(0.16)
Idaho	(0.14)	(0.16)	(0.17)	(0.13)	(0.15)
Indiana	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Kansas	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Kentucky	(0.05)	(0.04)	(0.04)	(0.03)	(0.04)
Louisiana	(0.18)	(0.19)	(0.18)	(0.16)	(0.18)
Massachusetts	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Maine	(0.16)	(0.17)	(0.15)	(0.15)	(0.16)
Michigan	(0.10)	(0.10)	(0.11)	(0.11)	(0.10)
Minnesota	(0.07)	(0.07)	(0.07)	(0.06)	(0.07)
Mississippi	(0.04)	(0.02)	(0.02)	(0.02)	(0.03)
North Carolina	(0.09)	(0.09)	(0.08)	(0.07)	(0.08)
New Hampshire	(0.01)	(0.08)	(0.07)	(0.07)	(0.06)
New York	(0.06)	(0.06)	(0.07)	(0.03)	(0.06)
Ohio	(0.13)	(0.24)	(0.20)	(0.18)	(0.19)
Oklahoma	(0.12)	(0.12)	(0.13)	(0.13)	(0.12)
Oregon	(0.07)	(0.07)	(0.08)	(0.07)	(0.07)
Pennsylvania	(0.11)	(0.10)	(0.08)	(0.08)	(0.09)
South Carolina	(0.15)	(0.19)	(0.12)	(0.12)	(0.14)
Tennessee	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)
Texas	(0.08)	(0.08)	(0.08)	(0.09)	(0.08)
Virginia	(0.24)	(0.24)	(0.23)	(0.24)	(0.24)
Vermont	0.00	0.00	0.00	0.00	0.00
Washington	(0.08)	(0.08)	(0.07)	(0.07)	(0.08)
Wisconsin	(0.11)	(0.09)	(0.08)	(0.08)	(0.09)
West Virginia	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)

In Table 4, the average result indicates that the total cumulative growth of CO_{2eq} emissions (31 states) in the PPI should have been reduced by 2.967 MMT to be environmentally efficient, with a range from a minimum 0.01 MMT to a maximum 0.24 MMT by one state from 2015 to 2018. As a general summary, the findings indicate that CO_{2eq} emissions need to be cut considerably.

Among the 31 states, Virginia showed the most potential for CO_{2eq} emissions cut by 0.24 MMT, followed by Ohio with 0.19 MMT and Louisiana with 0.18 MMT. Almost every state had a relatively lower environmental efficiency score and excess of CO_{2eq} emissions, which suggests that a reduction of CO_{2eq} emissions can contribute to the improvement of environmental efficiency in the U.S. PPI. Besides, recycling could reduce CO_{2eq} emissions significantly more than landfilling or combustion (U.S. EPA 2020). However, recycling, as a pathway to reduce GHG emissions, costs significantly more than combustion or landfilling. The state government need to encourage recycling by imposing subsidies and incentive programs on recycling compared to landfilling or combustion.

Analysis of Slack Variables

From the result of environmental efficiency (EE) scores, all 31 states performed inefficiently with low-efficiency values. Therefore, each state within pulp and paper facilities should seriously consider the slack values of the inputs and outputs each year. The purpose of assessing efficiency and slack value is to achieve the slack value of excess input, while considering undesirable outputs, so that each inefficient DMU can find the optimal implementations and actions in maintaining and operating a sustainable PPI system.

The best target values and the estimated slack values are shown in Table 5. Each slack value with the negative value from Table 5 explains the proportion of potential input and undesirable output cuts for each state from 2015 to 2018. For each state, to achieve an EE score of 1, the capital needs to be cut by the estimated slack value shown in Table 4. Besides, the excess carbon emissions output needs to be reduced by the corresponding slack value. The situation just mentioned does not apply for the highly eco-efficient state, Vermont, which has non-slacks in the capital, energy, and labor input and also has non-excess in the CO_{2eq} emissions. Among the more environmentally efficient ranked states, the highest-ranked state Mississippi could increase its environmental efficiency growth by 7% on average per year while cutting its carbon emissions by 0.03 MMT per year and reducing its capital, energy, labor inputs by 22.33 Million USD, 0.52 mmBTU and about 60 employees respectively. For this state, it is estimated that the target value of capital, energy, and labor input and CO_{2eq} emissions that could achieve the optimal environmental efficiency value is 67.07 million USD, 2.29 mmBTU, 181 employees, and 0.05 MMT respectively per year. On the other hand, the lowest-ranked state of Pennsylvania should reduce 30.67 million USD, 1.18 mmBTU, and about 116 employees, as well as 0.09 MMT of emissions. This shows that Pennsylvania has more than 73.2% needs for improvement until its environmental efficiency score reaches a peak value. Comparing the findings from Tables 3 to 5, the excess capital, energy, and labor input, and potential CO_{2eq} emissions output had an inhibiting effect on environmental efficiency in the U.S. PPI. Achieving a balance between adequate pulp and paper production provisions and reducing GHGs emissions has been a challenging task. The slack results show that the environmental efficiency performances in the PPI through each through each facility's environmental efficient allocation of inputs and sustainable practices on the reduction of CO_{2eq} emissions can be potentially improved.

Table 5. Summary of Average Excess in Inputs and Shortfall in Outputs, 2015–2018 (31 States)

State	Input Excess						Undesirable Outputs (Excess)		Desirable Outputs (Shortfalls)
	Capital (Millions USD)		Energy (mmBTU)		Labor (Employees)		CO_2eq (Million MT)		Production (MT)
	Slack (Percentage)	Target Value	Slack (Percentage)	Target Value	Slack (Percentage)	Target Value	Slack (Percentage)	Target Value	Slack (Percen-tage)
Alabama	-37.08%	49.77	-24.86%	2.31	-33.63%	136.06	-55.22%	0.01	0%
Arkansas	-39.23%	36.94	-42.53%	1.26	-36.31%	114.84	-55.92%	0.01	0%
California	-46.27%	8.96	-21.57%	0.96	-17.40%	59.19	-56.50%	0.01	0%
Connecticut	-45.26%	9.08	-8.36%	0.99	-13.67%	54.77	-44.51%	0.01	0%
Florida	-40.98%	34.04	-36.62%	2.34	-34.38%	111.28	-55.13%	0.01	0%
Georgia	-33.10%	44.51	-30.01%	2.39	-34.95%	132.68	-52.79%	0.02	0%
Idaho	-37.27%	67.21	-28.87%	2.52	-40.95%	163.55	-53.65%	0.02	0%
Indiana	-51.11%	3.82	-47.77%	0.25	-40.95%	42.84	-50.76%	0.01	0%
Kansas	-52.26%	1.68	-48.81%	0.17	-39.20%	28.45	-48.56%	0.01	0%
Kentucky	-45.57%	34.25	-34.20%	0.89	-23.97%	89.23	-48.31%	0.01	0%
Louisiana	-28.83%	64.29	-25.37%	3.53	-31.54%	149.10	-54.12%	0.02	0%
Massachusetts	-50.66%	13.58	-38.68%	1.60	-45.85%	77.21	-36.96%	0.01	0%
Maine	-47.84%	28.52	-34.79%	1.89	-40.29%	97.63	-56.18%	0.01	0%
Michigan	-47.98%	17.09	-30.91%	1.68	-39.64%	75.97	-55.91%	0.01	0%
Minnesota	-43.43%	34.72	-35.00%	1.31	-38.96%	113.99	-50.63%	0.01	0%
Mississippi	-13.63%	67.07	-11.10%	2.46	-14.85%	182.67	-22.19%	0.05	0%
North Carolina	-53.15%	6.95	-35.75%	0.60	-44.25%	41.85	-54.94%	0.01	0%
New Hampshire	-49.87%	9.40	-41.91%	0.98	-46.88%	60.40	-53.78%	0.01	0%
New York	-31.30%	52.16	-17.69%	1.32	-20.48%	154.06	-41.70%	0.02	0%
Ohio	-47.49%	10.84	-44.71%	0.44	-41.67%	62.43	-57.78%	0.01	0%
Oklahoma	-30.15%	97.68	-3.42%	3.90	-4.05%	145.12	-54.16%	0.01	0%
Oregon	-49.98%	22.81	-21.22%	1.85	-27.12%	84.94	-53.84%	0.01	0%
Pennsylvania	-54.07%	4.86	-41.56%	0.52	-45.80%	35.91	-57.59%	0.01	0%
South Carolina	-41.90%	31.06	-25.91%	2.80	-40.67%	110.79	-56.03%	0.01	0%
Tennessee	-51.42%	18.73	-36.75%	1.21	-36.74%	72.00	-54.18%	0.01	0%
Texas	-42.69%	23.09	-22.82%	1.92	-37.05%	89.20	-54.15%	0.01	0%
Virginia	-43.77%	22.14	-27.68%	1.60	-37.07%	98.70	-58.27%	0.01	0%
Vermont	0.00%	118.28	0.00%	1.90	0.00%	315.61	0.00%	0.02	0%
Washington	-47.72%	16.70	-40.04%	0.77	-38.95%	78.49	-53.66%	0.01	0%
Wisconsin	-54.08%	5.07	-45.10%	0.36	-45.73%	39.87	-57.15%	0.00	0%
West Virginia	-52.28%	10.50	-42.82%	1.27	-41.58%	53.37	-45.87%	0.01	0%

For further analysis, this study analyzes specific Pulp and Paper facilities within two states above with environmental efficiency ratings from the highest (Mississippi) to lowest (Pennsylvania). In Mississippi, it was shown that Georgia Pacific contributes the most shares to the state's optimal environmental efficiency. Georgia Pacific Company has been focusing on sustainable practice, not only on the economic stability of the company but also on protecting environmental resources to minimize GHG emissions (Georgia-Pacific 2018). G-P LLC plans to estimate that approximately $80 million sustainability investments will be invested to help the mill to reduce nitrous oxide emissions by 67 percent (Georgia-Pacific 2020).

Two other mills, International Paper's Columbus Mill and Vicksburg Mill, have not been as efficient as Georgia Pacific (Monticello) in terms of the allocation and utilization of capital, labor, and energy. However, the International Paper mills had less (0.01 and 0.02) slack of CO_2eq MMT, respectively, while G-P had excess CO_2eq at 0.11 MMT from 2015-2018 due to the different size of mills.

Table 6. Summary of Average Excess in Inputs and Shortfall in Outputs, 2015–2018 (Representative Facilities)

State		Input Excess			Undesirable Outputs (Excess)	Desirable Outputs (Shortfalls)
		Capital (Millions USD)	Energy (mmBTU)	Labor (Employees)	CO_2eq (Million MT)	Production (MT)
		Slack	Slack	Slack	Slack	Slack
Mississippi	GEORGIA PACIFIC MONTICELLO LLC	0.00	0.00	0.00	0.00	0.00
	INTERNATIONAL PAPER - COLUMBUS MILL	-38.16	-1.56	-109.2	-0.06	0.00
	INTERNATIONAL PAPER - VICKSBURG MILL	-28.82	-0.57	-88.95	-0.01	0.00
Pennsylvania	CASCADES TISSUE GROUP PA RANSOM PLT	-10.96	-0.84	-43.06	-0.01	0.00
	DOMTAR PAPER COMPANY, LLC	-62.98	-0.92	-157.4	-0.17	0.00
	NGC INDUSTRIES INC	-12.71	-0.67	-29.73	-0.02	0.00
	NEWMAN & CO	-6.90	-0.29	-64.70	-0.02	0.00
	PIXELLE SPECIALTY LLC	-15.79	-1.56	-44.69	-0.32	0.00
	WESTROCK LLC – STROUDSBURGE MILL	-74.50	-2.78	-355.2	-0.01	0.00

In Pennsylvania, input and output slack results of six mills have been reported in Table 6. The reason for the lowest environmental efficiency ranking of the State is mainly due to which five of the six mills, including Cascades, Domtar, NGC, Pixelle, and West Rock, have not been equipped with high efficiency in the usage of capital, energy, and labor, resulting in the slack of resources, making it difficult to achieve the dual goals of the economy and environmental protection.

It is undeniable that some facilities have been doing a good job in protecting our environment, resulting in less CO_2eq redundancy at range from 0.01 to 0.02 MMT from 2015 to 2018, such as WestRock, it business strategy has been in connection with matters relating to environmental compliance (WestRock 2016, 2019). Based on these results, it can be concluded that for the sustainable development of PPI, more attention needs to be paid to environmental practices as well as efficient allocation of labor, energy, capital, and other resources in the production process.

The Influence of External Environmental Factors on the Slack of Input and Unexpected Output

Table 7. Stochastic Frontier Analysis (SFA) Regression Results

	Capital Slack		Energy Slack		Labor Slack		CO_{2e} Slack	
	Coef.	t-value test	Coef.	t-value test	Coef.	t-value test	Coef.	t-value test
Industrial Waste Landfill	0.61	44.12***	0.54	1.45*	0.61	23.00***	0.38	1.26*
Wastewater Treatment	-0.28	2.31***	-0.28	0.91*	-0.13	8.03***	-0.31	-1.29*
Solid Waste Combustion	0.15	0.56	0.04	0.20	0.25	2.80***	-0.21	-0.99*
Constant	1.92	29.34***	0.55	3.14***	2.33	1.93***	-1.18	-2.14***
Sigma-squared	0.24***		0.22***		0.34***		0.13***	
Gamma	0.983		0.962		0.991		0.989	
Log likelihood	-141.49		-39.98		-176.82		-46.85	
LR Test of the one-side Error	19.82***		8.74***		21.71***		6.38***	

Note: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$ The values in parentheses are the corresponding estimated T-statistics.

Through the calculation of the SBM-DEA model (Table 5), it was found that the slack on production output of each state was estimated as having a 0 value, and all inputs and the undesired output CO_2eq emissions had a certain degree of slack, indicating that insufficient production in the production process is not a contributor to environmental inefficient in the U.S. PPI. In addition, the main reasons for the loss of environmental efficiency are contributed by the capital, energy, labor input, and CO_2eq emissions. By applying Frontier 4.1 software, a regression analysis was carried out on all inputs and undesirable outputs. The results are shown in Table 7. The gamma value was greater than 0.95, indicating that proposing SFA was reasonable in this study, and the likelihood ratio (LR) test results of 19.82, 8.47, 21.71, and 6.38 were located outside of the 99% confidence interval, explaining that external environment inefficiency was present. The slack of inputs and CO_2eq output could be reduced by cutting external environmental variables. And, if external environmental variables are negatively correlated with inputs and CO_2eq emissions, it indicates that the increase of external environmental variables will reduce the slack amount of the input and undesirable output variable. In other words, the external environmental factor will be conducive to the environmental efficiency of U.S. PPI and *vice versa*.

In this study, external environmental variables were selected from the amount of Industrial Waste Landfills, Wastewater Treatment Plants, and Solid Waste Combustion of each state which represent variables of IWL, WWT, and SWC, respectively (U.S. EPA, 2018). From the table, firstly it can be seen that the amount of Industrial Landfills is significantly positively correlated with the slack value of capital, energy, labor input, and CO_2eq emissions. This shows that the larger the number of industrial waste landfills in each state, the larger the scale of IWL, which may indirectly lead to inefficient use and distribution of capital, energy, and labor, and also contribute to increasing CO_2eq emissions. This result indicated that the loss of the environmental efficiency of the U.S. PPI. (U.S. EPA 2018). Secondly, the variable of wastewater treatment is significantly negatively correlated with the slack value of capital, energy, labor input, and CO_2eq emissions. This result showed that wastewater treatment plants (WWTPs) have been widely applied to the P&P industry, and supplementary treatments have positive effects on the cost-effective inputs of capital, labor, and energy in the PPI. The P&P industry has been a big contributor to the usage of water as process water (Savant *et al.* 2006; Hubbe *et al.* 2016). Although traditional WWTPs may generate nitrogen due to chemical and energy use (Bani Shahabadi *et al.* 2009), more advanced treatment, such as anaerobic wastewater treatment can be used to convert extra CO_2eq to methane as fuels in other places which can help reduce CO_2eq emissions and energy input (Sanusi and Menzes 2014; Meyer and Edwards 2014). These results also showed that WWTPs are currently focusing on environmental efficiency using environmentally friendly treatment methods instead of the traditional one to decrease CO_2eq emissions for the PPI. Therefore, the more advanced WWTPs in a state, the more optimized wastewater treatments could provide those pulp and paper mills with producing more sustainable and environmental products. Thirdly, the variable of solid waste combustion is positively correlated with the slack of capital, energy, and labor input, but has no significant impact on capital and energy slack. This shows that the waste-paper treatment methods of the PPI mainly include recycling, combustion, and landfills. With the implementation of the National Sword Policy, China banned imports of solid waste including recovered papers by the end of 2017 (Paben 2017). Consequently, the U.S. MRFs have suspended the recycling of solid wastes, and the available treatments of solid waste were largely chosen as combustion and landfill (Staub 2017). The regression result shows that due to the larger the scale of solid waste combustion, it may adversely affect the effective use of capital, energy, and labor, and ultimately lead to the ecological inefficiency of the PPI. However, the variable is significantly negatively correlated with the relaxation value of CO_2eq emissions. This may be dependent on whether the CO_2eq emissions estimated in this study were mainly collected from the PPI manufacturing, combustion, and landfill. The combustion could reduce GHG emissions by transforming methane to carbon dioxide. And the combusted residue could be used as agricultural fertilizers (US EPA 2020).

CONCLUSIONS

1. Based on the analysis, 31 states had an average environmental efficiency (EE) score of 0.509 from 2015 to 2018, indicating that these states considerably have a potential room for improvements of environmental efficiency and have the potential to reduce CO_{2eq} emissions and inputs. And for the CO_{2eq} potential reduction analysis, the estimation results showed that the U.S. Pulp and Paper Industry (PPI) had a large potential range to cut the excess CO_{2eq} emissions, with a wide range from a minimum 0.01 MMT to a maximum of 0.24 MMT from 2015 to 2018 in the U.S. PPI. Therefore, P&P facilities need to implement more sustainable practices from the process of production to landfills. Also, recycling was shown to be a promising pathway to minimizing greenhouse gas (GHG) emissions. This indicates that state governments should encourage recycling by imposing less tax on recycling compared to landfilling or combustion.

2. When assessing the slacks of inputs and outputs by using a non-radial slacks-based measure – data envelopment analysis (SBM-DEA) model, the result of excess inputs and undesirable output can explain that each state has responsibility for the cutting of excess

capital, energy and labor input cost, respectively, by the estimated input slacks. In addition, the excess carbon equivalents emissions output needs to be reduced. The slack results indicates that environmental efficiency performances in the PPI through each facility's environmental efficient allocation of inputs and sustainable practices on the reduction of CO_{2eq} could be potentially improved.

3. In terms of the differentiated performance of the environmental efficiency of the PPI in each state, each U.S. state’s government and relevant environmental authorities are promoting sustainable industrial development and implementing active ecological incentive policies. It is necessary to take into account the difference both on quantity and quality of industrial waste landfills, wastewater treatment, and solid waste combustion in each state and put forward target requirements that match each state's developmental stage and waste management capability. Also, more attention needs to be paid to the issue of environmental efficiency in the development of the PPI and improve the environmental efficiency of the U.S. PPI.

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