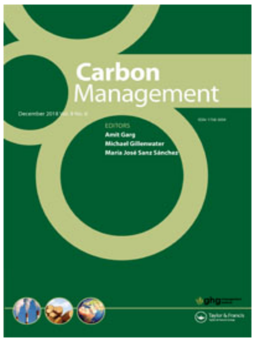

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# Industrial water-use technical efficiency and potential reduction of $CO_2$ emissions: evidence from industry-level data

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**ABSTRACT**
This article analyzes the relationship between industrial water-use efficiency and carbon dioxide for 14 industries from 1998 to 2015 using a true fixed-effects stochastic frontier model. The highest water-use efficiency is that of the rubber products manufacturing industry, approaching 0.62. The average water-use efficiency score across industries is 0.30 for the period. The potential water conservation for the various industries ranges from 4.07 to 212.67 million cubic meters. Further examination of potential reduction for $CO_2$ emissions shows that it ranges from 0.63 to 32.33 million kilograms. The reduction of $CO_2$ emissions for the various industries on average is 12.19 million kilograms. These results exhibit great room for improvement in water-use efficiency; making these improvements will eventually improve $CO_2$ emissions. Water conservation can be viewed as a part of policy to reduce $CO_2$ emissions. The results obtained from this study can help in formulating appropriate policies to face both water supply crises and climate change.

**KEYWORDS**
Industrial water-use efficiency; true fixed-effects stochastic frontier model; $CO_2$ emissions; water conservation; water supply crises

## Introduction

Due to climate change and abnormal weather patterns, serious water shortages during long periods of little rain are being observed by various governments; meanwhile, rivers are gradually becoming increasingly polluted. Against this background, industrial development and economic growth also fuel water crises. Masui *et al*. [1] advocated some substantial ways to handle and solve such difficult situations, including the improvement of energy efficiency and water conservation efforts. Rapid actions in water conservation need to be executed. In addition, all water treatment and transportation consumes energy; hence, saving water equates to carbon reduction. To date, many governments are concerned with the relative risks; the goals are implementing effective initiatives to decrease water waste, to recycle (or reuse) water, and to increase water-use efficiency. This study will focus on industrial water-use efficiency and further investigate the potential reduction of $CO_2$ emissions from water conservation. The following analysis of findings is intended to help various governments make informed decisions regarding water resource waste reduction. In facing scarcity of water and climate change while understanding water efficiency, the evaluation of the latter may help policymakers address both water shortage and $CO_2$ emission challenges.

A core storyline about energy policy for this research lies in water conservation and carbon emissions. As Figure 1 illustrates, there are three steps in investigating the relationship between industrial water use and $CO_2$ emissions: the calculation of industrial water-use efficiency, the goal of water conservation, and computing the potential $CO_2$ emissions reduction. In addition, this study explores water resources and carbon management policy. As Figure 1 shows, first this study calculates industry water-use efficiency and then water waste can be obtained. The majority of previous empirical studies of water-use efficiency applied the stochastic frontier method to perform the empirical analysis. By calculating the water-use efficiency, industries can improve their efficiency through investment in water-saving equipment. In the second step, the goal of water conservation can be obtained from the water-use efficiency in step 1. Using the targets for water conservation and $CO_2$ emissions, the potential $CO_2$ emissions reduction is obtained in the last step. Relatively little attention has been paid to the environmental sustainability of water usage and the potential impacts on $CO_2$ emissions. This study is an attempt

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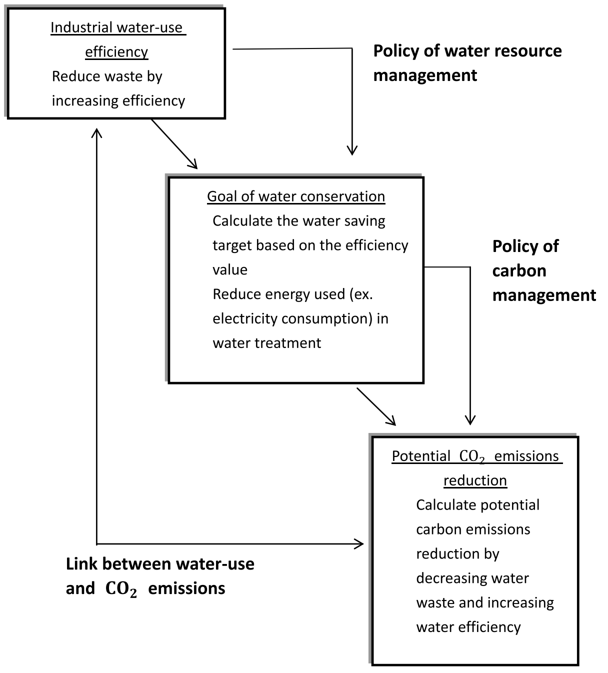

**Figure 1. Water-use efficiency and potential $CO_2$ emissions reduction.**

to fill this gap. The results combine water resource management and carbon management policies. Water-use efficiency is jointly analyzed along with to $CO_2$ emissions. In addition to the abovementioned goals, the empirical model established herein based on efficiency indicators may be applied to other areas of energy efficiency.

There are many research interests related to water-use and consumption explored in the previous literature. Intuitively, environmental economists have been discussing water consumption and sustainability through time series models in recent years; this is because water consumption (demand) is essential for national and regional populations. Investigating water consumption helps us to obtain water pricing schemes and develop water conservation and management programs more efficiently by means of appropriate time series models [2–5]. Another aspect of water use has mainly emphasized the relationship between water use and economic growth. In this context, Kuznets [6] argued that there is an inverted-U relationship between environmental pressures (in this case, water consumption) and economic growth. Many studies have investigated the environmental Kuznets curve (EKC); however, the EKC hypothesis has not yet reached a consistent conclusion. Due to the scarcity of water resources, other research has focused on water-use efficiency, particularly in the agricultural sector. Some scholars have shed light on agricultural commodity export-dominant countries because water resources are vital for their production. For example, the technical efficiency of various agricultural products have been investigated including cotton [7], tea (Hong and Yabe [46]), potatoes [8], rice [9, 10] and dairy products [11]. Studies on the relevance of water-use technical efficiency exist; however, examination of the water-use–$CO_2$ emissions nexus seems to be limited in the literature. This study extends the technical efficiency of water use to link with $CO_2$ emissions, which serves to supplement previous research.

The main contributions of this study are as follows. First, this paper aims to contribute to the estimation of the technological efficiency of industrial water-use for various industries. Understanding water-use efficiency is useful for researchers and planners to guide future directions in water conservation. Every industry can be assigned a goal of water conservation which is then evaluated by achievement rates or efficiency scores. Second, when the water-efficiency figures are known, the potential reduction of $CO_2$ emissions can be calculated. This study provides a helpful reference from the perspective of the stochastic frontier model. Third, because studies rarely use industrial or sectoral data to examine this issue, this study focuses on the linkage between efficient water use and $CO_2$ emissions for 14 industries. Katz [12] argued that a decline in water use per capita could simply be a result of population growth, whereas water use actually remains fixed, or even increases. Therefore, this study uses water consumption by various industries as a more reasonable measure, rather than water use per capita. This study's contributions and results are aimed to help in the further establishment of economic development and water management policies. Based on the empirical analysis, some valuable implications are uncovered for policymakers.

The findings in this study can be summarized as follows. (1) Estimates by this article for 14 Taiwanese industries exhibit that the average water-use efficiency is approximately 0.3. The highest water-use efficiency of 0.62 is found in the rubber products manufacturing industry. The potential water conservation for various industries ranges from 4.07 to 212.67 million cubic meters without sacrifices to output. (2) The estimates reveal that the potential reduction in $CO_2$ emissions ranges from 0.63 to 32.33 million kilograms. The average reduction of $CO_2$ emissions for the various industries is 12.19 million kilograms. In other words, this means that there is still much room for improvement in water-use efficiency;

improvements in water-use efficiency will eventually reduce $CO_2$ emissions. (3) The difference between this and past studies lies in using industry-level data to conduct the empirical analysis instead of using country-level data. In addition, this study applied a true fixed-effects stochastic frontier model to estimate all parameters. It is easy to distinguish the difference between a true fixed-effects stochastic frontier model (proposed by Greene, [15, 16]) and a traditional stochastic frontier model. It is expected that more empirical meaning will be derived from the new approach. The results generated from this study can assist governments in establishing water-management policies in facing water crises in the context of climate change.

The next section of this paper briefly discusses the existing literature. The third section provides the econometric method. The fourth section presents the empirical results. The final section summarizes the conclusions of this study.

## Literature review

As water resources are limited, the study of water-use efficiency continues to develop. The concept of water-use efficiency is a useful tool developed as an indicator to compute the relationship between water input and output. The best interpretation of efficiency is that given certain outputs, the lower the water use, the higher the efficiency; or, in other words, with the same amount of water used, the higher the output, the higher the efficiency of water use. In line with recent studies, stochastic frontier analysis (SFA) and data envelopment analysis (DEA) are usually engaged in estimating water-use efficiency. SFA is a parametric estimation method that assumes a given functional form for the link between inputs and an output, whereas DEA is a nonparametric method that does not assume a functional form. In general, researchers need to present a production function before the SFA efficiency estimation; this is followed by performing statistical tests of the hypothesis regarding the parameter or efficiency scores [13–17]. However, DEA cannot carry out statistical tests of the hypothesis regarding the efficiency scores. Efficiency scores estimated from SFA range between 0 and 1. The production process is technically efficient if and only if the maximum quantity of input(s) can be achieved for a given quantity of input(s). Once the efficiency scores are estimated, a given member can be compared with the other members in the group. In other words, the greater the efficiency scores the greater the magnitude of technical efficiency, and vice versa. SFA has been successfully applied in many fields of efficiency evaluation, such as agricultural studies [10, 14], hospital management [18, 19], R&D efficiency [20, 21] and water efficiency [7, 22, 23].

There is a significant amount of literature estimating agricultural and industrial water-use efficiency. Agricultural water-use efficiency is very important for agricultural export-oriented economies because efficient irrigation is a key determinant for agricultural production. This section takes some agricultural production values discussed in past literature as examples. For cotton production, Watto and Mugera [7] indicated that the average irrigation efficiency under different model specifications for production ranged between 0.55 and 0.81. Shabbir *et al.* [24] found considerable room for improvement in water productivity and efficiency in Pakistan. For tea production, Hong and Yabe [46] found that the water-use efficiency for irrigation ranged from 0.02 to 0.93, whereas the average water-use efficiency was 0.42. According to the results of Hong and Yabe [46] tea farmers could cut water use by 57.81% while maintaining the same output. Karagiannis *et al.* [25] investigated the water efficiency of the vegetable industry and found that the average water-use efficiency was 47.2%; this suggests a further potential for water consumption reductions. For wheat production, Chebil *et al.* [22] found that the average water-use efficiency in the industry was around 41% under constant returns to scale. Their results suggest that large decreases in water use could be realized by using existing irrigation technology. Li and Ma [26] found that industrial water-use efficiency still had room to improve in 30 provinces in mainland China. They also revealed that the efficiency of industrial water use was related to the various industries' technological heterogeneity and the treatment of their water pollution. Shi *et al.* [27] used input–output analysis and found that the water-use efficiency of China's northwest region can be improved by optimizing industrial structure, and that there is room to improve industrial water-use efficiencies.

Water conservation is viewed as an important factor in pursuing the sustainability of water supplies and saving energy to reduce $CO_2$ emissions. In practice, as Ecobug announced, when 1 L of tap water is supplied and treated, this requires around 1.2 kWh of electrical energy and simultaneously creates 0.7 kg of $CO_2$.[1] The Office of National

Statistics in the UK calculated the carbon emissions generated by water supply to be equivalent to 0.452 kg $CO_2$ per cubic meter. Tap water provided by the Taiwan Water Corporation, a monopoly in Taiwan, supplies 23 million people nationwide. According to their calculations, on average, 1 $m^3$ supplied emits approximately 0.152 kg of $CO_2$. Therefore, pursuing water-use efficiency is deemed to be an important channel in reducing $CO_2$ emissions.

## Empirical framework and data

### *Estimation of industrial water-use efficiency*

The definition of energy efficiency traditionally varies with the type of energy source. For example, traditional irrigation efficiency in agriculture is defined by water intensity or the proportion of crop yield to water consumption [28]. However, water intensity or crop yield to water consumption only considers a single input (water), yet the production process could include other inputs (such as labor or physical capital). Hence, this measure does not capture the full picture of the water-use efficiency in agriculture or manufacturing. Coelli *et al.* [29] argued that technical efficiency is defined as the ability of a firm to produce the maximum possible output within the available set of inputs under a given technology. In this paper, water-use efficiency is defined as a ratio of minimum feasible water use to observed water use. On the whole, energy efficiency refers to using less energy to produce the same amount of services or output. Although different studies offer different definitions of energy efficiency, there is a general understanding that water-use efficiency is crucial.

This paper models the production process a using true stochastic frontier model proposed by Greene [15, 16]. The early stochastic frontier method (Battese and Coelli, [30]) [31, etc.] used to model efficiency ignored unobserved unit-specific heterogeneity. The general framework developed by Greene [15, 16] solved the unobserved heterogeneity problem through a time-varying stochastic frontier normal-half model with unit-specific intercepts and by extending fixed- and random-effects models. The literature refers to these as ‘true’ effect models [32]. Consider a given production process with 14 industries which transform inputs ($X_{it}$) to produce output ($Y_{it}$). The specific production frontier function of a given industry is defined as follows:

$$Y_{it} = f(X_{it}, \beta, \alpha_i)\exp(\varepsilon_{it}) = \alpha_i + \beta' X_{it} + \varepsilon_{it} \qquad (1)$$

$$\varepsilon_{it} = v_{it} - u_{it} \qquad (2)$$

$$v_{it} \sim N(0, \sigma_v^2) \qquad (3)$$

$$u_{it} \sim N^+(0, \sigma_u^2) \qquad (4)$$

where $\alpha_i$ and $\beta$ represent the unit-specific intercept and unknown parameters, respectively. $X_{it}$ includes labor, capital and industrial water use. $\varepsilon_{it}$ is the error term, which is composed of $v_{it}$ and $u_{it}$. Specifically, $v_{it}$ is a zero-mean random error, while $u_{it}$ is a stochastic variable measuring the inefficiency effect.

The earliest studies relied upon a Cobb–Douglas functional form. This study adopts a more flexible translog specification to deal with empirical analysis. More specifically, after taking the logarithm of both sides of Equation (1), the translog production frontier can be written as:

$$\begin{aligned} lnY_{it} &= \alpha_i + \beta_1 lnW_{it} + \beta_2 lnL_{it} + \beta_3 lnK_{it} + \beta_{12} lnW_{it} lnL_{it} \\ &+ \beta_{13} lnW_{it} lnK_{it} + \frac{1}{2}\beta_{23} lnL_{it} lnK_{it} + \frac{1}{2}\beta_{11}\left(lnW_{it}\right)^2 \\ &+ \frac{1}{2}\beta_{22}\left(lnL_{it}\right)^2 + \frac{1}{2}\beta_{33}\left(lnK_{it}\right)^2 + v_{it} - u_{it} \end{aligned} \qquad (5)$$

where *ln* denotes the logarithms of the variables, $W_{it}$ is industrial water-use, and $L_{it}$ and $K_{it}$ are labor (measured by employment) and capital inputs (measured by fixed capital formation) for various industries, respectively. As suggested by Coelli [33], the null hypothesis $\gamma = \frac{\sigma_u^2}{\sigma^2} = 0$ is tested, in which $\sigma = \sigma_u^2 + \sigma_v^2$. If the null hypothesis $\gamma = 0$ is rejected, this would indicate the specification with the parameter and estimation is suitable.

According to the empirical framework of Reinhard *et al.* [11] and Hong and Yabe [46], an industry is assumed to have water-use efficiency if it is using the minimum possible irrigation water (indicated as $W_i^*$) while producing the actual output ($Y_i$). When a given industry achieves industrial water-use efficiency, the production function of its efficiency can be written as:

$$\begin{aligned} lnY_{it} &= \alpha_i + \beta_1 lnW_{it}^* + \beta_2 lnL_{it} + \beta_3 lnK_{it} + \beta_{12} lnW_{it}^* lnL_{it} \\ &+ \beta_{13} lnW_{it}^* lnK_{it} + \frac{1}{2}\beta_{23} lnL_{it} lnK_{it} + \frac{1}{2}\beta_{11}\left(lnW_{it}^*\right)^2 \\ &+ \frac{1}{2}\beta_{22}\left(lnL_{it}\right)^2 + \frac{1}{2}\beta_{33}\left(lnK_{it}\right)^2 + v_{it} - u_{it} \end{aligned} \qquad (6)$$

After setting Equations (5) and (6) as equal, the following is obtained:

$$\begin{aligned} \beta_1 lnW_{it} &+ \beta_{12} lnW_{it} lnL_{it} + \beta_{13} lnW_{it} lnK_{it} \\ + \frac{1}{2}\beta_{11}\left(lnW_{it}\right)^2 - u_{it} &= \beta_1 lnW_{it}^* + \beta_{12} lnW_{it}^* lnL_{it} \\ &+ \beta_{13} lnW_{it}^* lnK_{it} + \frac{1}{2}\beta_{11}\left(lnW_{it}^*\right)^2 \end{aligned} \qquad (7)$$

For this investigation, the industrial water-use efficiency index is defined as a function of observed water-use volume and the minimum possible quantity of industrial water-use, therefore resulting in:

$$\mathrm{EE_i} = \frac{\mathrm{W_i^*}}{\mathrm{W_i}} \text{ or } W_{it}^* = \mathrm{EE_i} \times W_{it} \tag{8}$$

where $\mathrm{W_i^*}$ is the minimum possible quantity of industrial water use, and $\mathrm{W_i}$ is the observed water-use volume for a given industry. The water-use efficiency ($\mathrm{EE_i}$) is bounded between 0 and 1. Taking both side of Equation (8), the following is obtained:

$$\ln W_{it}^* = \ln \mathrm{EE_i} + \ln W_{it} \text{ or } \ln \mathrm{EE_i} = \ln W_{it}^* - \ln W_{it} \tag{9}$$

Equations (5) to (9) produce the following:

$$\frac{1}{2}\beta_{11}\left(\ln W_{it}^* - \ln W_{it}\right)^2 + \left[\beta_1 + \beta_{11}\ln W_{it} + \beta_{12}\ln L_{it} + \beta_{13}\ln K_{it}\right]\cdot\left(\ln W_{it}^* - \ln W_{it}\right) + u_i = 0 \tag{10}$$

By substituting Equation (9) into Equation (10) and solving for $\ln \mathrm{EE_i}$, the following is found:

$$\ln \mathrm{EE_i} = \{-(\beta_1 + \beta_{11}\ln W_{it} + \beta_{12}\ln L_{it} + \beta_{13}\ln K_{it}) + [(\beta_1 + \beta_{11}\ln W_{it} + \beta_{12}\ln L_{it} + \beta_{13}\ln K_{it})^2 - 2\beta_{11}u_i]^{\frac{1}{2}}\}/\beta_{11} \tag{11}$$

So it can be calculated that:

$$\mathrm{EE_i} = \exp\left(\frac{\{-(\beta_1 + \beta_{11}\ln W_{it} + \beta_{12}\ln L_{it} + \beta_{13}\ln K_{it}) + [(\beta_1 + \beta_{11}\ln W_{it} + \beta_{12}\ln L_{it} + \beta_{13}\ln K_{it})^2 - 2\beta_{11}u_i]^{\frac{1}{2}}\}}{\beta_{11}}\right) \tag{12}$$

According to Reinhard *et al.* [11], Equation (11) can measure technical and environment efficiency. Water-use efficiency will be analyzed by applying the above efficiency index.

### *Water-use efficiency and $CO_2$ emissions*

After water-use efficiency is estimated, water-saving insights can be provided relative to the various industries. When a given industry does not approach water-use efficiency, this implies that the process of production and operation is not optimal and that there is potential for improvement in this area. Some studies have shown that water supplied through pumped storage reservoirs transports the water resources; this and effluent treatment as well as water re-use are recognized as being relatively energy intensive. The $CO_2$ emissions essentially arise from water supply, the consequent treatment, and wastewater re-use activities. Hence, governments' sustainable and environmental policies for decreasing $CO_2$ emissions should consider the strategy of water saving.

Another goal of this study is to estimate the relationship between water use and $CO_2$ emissions. The estimation of their relationship is based on the following steps. First, as mentioned, the goal of water saving for a given industry is calculated. The water saving goal (WSG) is defined as:

$$\mathrm{WSG} = W_{it} - W_{it}^* \tag{13}$$

in which $W_{it}$ is the observed water use for a given industry; $W_{it}^*$ estimated by SFA represents the volume of optimal water use. The WSG is obtained from Equation (13). If WSG = 0, then the industry is efficient. A smaller value of WSG means that the industry has higher technical efficiency, indicating that little water is wasted in production. Second, based on Equation (13), the WSG can be used to calculate the volume of $CO_2$ emissions reduction. The volume of $CO_2$ emissions reduction is defined as:

$$\mathrm{CO2D} = \mathrm{WSG} * \mathrm{F} = \left(W_{it} - W_{it}^*\right) * F \tag{14}$$

where F is the emissions factor of $CO_2$ emissions and CO2D is the volume of $CO_2$ emissions reduction. In fact, $CO_2$ emissions are calculated by multiplying the emissions factor (i.e. $CO_2$ from various energy sources) with the real volume of energy use; hence, the emission factor is very important. On average, there are 0.152 kg of $CO_2$ emissions per cubic meter of water used, in the official dataset; therefore, F = 0.152.[2] CO2D, is the volume of $CO_2$ emission reduction, which is calculated by multiplying the annual industrial water-use savings by the emission factor (F). Using Equations (13) and (14), the water savings of various industries can be computed; this then leads to the $CO_2$ emissions amount.

## Data

This study uses a balanced dataset from 14 industries in Taiwan for the years 1998 to 2015. These 14 manufacturing industries include beverage and tobacco production; textile mills; leather, fur and related products; pulp, paper, and paper products; chemicals; chemical material products; rubber products; plastic products; non-metallic mineral products; basic metals; fabricated metal products; machinery and equipment; computers, electronics, and optical products; and transportation equipment. The industrial data is collected from the Directorate-General of Budget, Accounting and Statistics, National Statistics and Trade Statistics, the Bureau of Trade in Taiwan. In order to calculate the technical efficiency of industrial water use, this paper specifies industrial employment (measured in thousands of people), capital (measured in millions of NTD), and industrial water use (measured in millions of cubic meters) as inputs; also, the gross domestic product (GDP) of the various industries (measured in million NTD) is designated as an output. The specification of the empirical model and variables include references to previous studies. Summary data for all variables is reported in Table 1.

## Empirical results

The estimates of the parameters are reported in Table 2. Based on these, the first step is to test the validity of the specification of the translog function. If the null hypothesis $H_0 : \beta_{11} = \beta_{12} = \beta_{13} = \beta_{22} = \beta_{33} = \beta_{23} = 0$ is rejected, then the translog production function is preferred. However, if there is enough evidence to reject $H_0$, the Cobb–Douglas production function is suitable. The maximum likelihood-ratio test (hereafter MLRT) should be executed to verify the significance of the null hypothesis. Since the MLRT $= 58.82$, the null hypothesis $H_0 : \beta_{11} = \beta_{12} = \beta_{13} = \beta_{22}= \beta_{23} = \beta_{33}$ is rejected. This result shows that the squared and interactive variables need to be included in the model and the Cobb–Douglas production model (viewed as benchmark model) is rejected. This research uses a translog production function to perform the empirical analysis. The next step is verifying whether there is significant technical efficiency, using the null hypothesis $H_0 : \gamma = \frac{\sigma_u^2}{\sigma^2} = 0$; this tests whether the observed variations in efficiency are random or systematic. Per the estimation results of $\hat{\gamma} = 116.69$, and the test result, this null hypothesis is also rejected.

Empirical studies on the stochastic frontier model have developed through a variety of contributions.[3] Greene [15, 16] extended the SFA to a more flexible specified econometric framework containing *true fixed effects* and *true random effects*. The true fixed-effects model provides a consistent and efficient estimator by the means of the maximum likelihood estimation (MLE) method. The valuable feature of the effort by Greene [15, 16] lies in capturing unobserved heterogeneity among the units of analysis. Based on the estimation of the true fixed-effects model, for simplicity, the efficiency can be classified into three groups, namely low efficiency (efficiency $< 0.25$), middle efficiency ($0.5 >$ efficiency $> 0.25$) and high efficiency (efficiency $> 0.5$). The estimated results of efficiency are reported in Table 3. The results show that seven industries (over 50% of all industries in the present sample) – namely beverages and tobacco; textiles mills; leather, fur and related products; plastic products; fabricated metal products; machinery and equipment; and electronic and optical products – are substantially inefficient, with efficiencies below 0.25. These industries have great room for improvement in water savings. Facing scarcity of water amidst climate change,

**Table 2.** **Parameter estimates.**

| Variable | Coefficient | Standard error |
|---|---|---|
| $InL_{it}$ | $-2.94^{***}$ | 1.13 |
| $InK_{it}$ | $0.97^{***}$ | 0.40 |
| $InW_{it}$ | $2.21^{***}$ | 0.72 |
| $InW_{it}InL_{it}$ | $-0.26^{***}$ | 0.08 |
| $InW_{it}InK_{it}$ | $0.06^{*}$ | 0.04 |
| $InL_{it}InK_{it}$ | $-0.17^{***}$ | 0.06 |
| $\frac{1}{2}(InW_{it})^2$ | $-0.04$ | 0.04 |
| $\frac{1}{2}(InL_{it})^2$ | $0.35^{***}$ | 0.08 |
| $\frac{1}{2}(InK_{it})^2$ | 0.03 | 0.02 |
| $\sigma^2$ | $3.67^{***}$ | 1.64 |
| $\gamma = \frac{\sigma_u^2}{\sigma^2}$ | $116.69^{***}$ | 5.15 |

*Note:* *** and * are significant at the 1% and 10% level, respectively.

**Table 1.** **Summary statistics.**

| Variables | Industrial water use | Employment | Capital | Industrial gross domestic production |
|---|---|---|---|---|
| Mean | 109.1 | 157980.2 | 65412039.9 | 623052.1 |
| Standard deviation | 90.8 | 192373.4 | 160359657.4 | 828857.3 |
| Maximum | 373.6 | 935768.0 | 700673.0 | 4478167.0 |
| Minimum | 10.8 | 27301.0 | 949291379.0 | 20504.0 |
| Unit | Million $m^3$ | Thousand people | Million NT dollars | Million NT dollars |

*Note:* All variables are taken from the official database and collected by the author.

**Table 3.** **Estimation of efficiency.**

| efficiency | Industry |
|---|---|
| $< 0.25$ | Beverages and tobacco manufacturing, textiles mills manufacturing, leather fur and related products manufacturing, plastic products manufacturing, fabricated metal products manufacturing, machinery and equipment manufacturing, electronic and optical products manufacturing |
| $0.5 >$ efficiency $> 0.25$ | Pulp, paper and paper products manufacturing, chemical material manufacturing, chemical products manufacturing, non-metallic mineral product manufacturing, basic metal manufacturing, transportation equipment manufacturing |
| Efficiency $> 0.5$ | Rubber products manufacturing |

**Table 4.** **Volume of water conservation and potential reduction of $CO_2$ emissions.**

| Industry | Water conservation | $CO_2$ reduction |
|---|---|---|
| Beverages and tobacco manufacturing | 212.67 | 32.33 |
| Textiles mills manufacturing | 167.52 | 25.46 |
| Leather fur and related products manufacturing | 4.07 | 0.62 |
| Pulp, paper and paper products manufacturing | 128.95 | 19.60 |
| Plastic products manufacturing | 69.61 | 10.58 |
| Fabricated metal products manufacturing | 78.30 | 11.90 |
| Machinery and equipment manufacturing | 21.31 | 3.24 |
| Electronic and optical products manufacturing | 98.45 | 14.96 |
| Chemical material manufacturing | 179.63 | 27.30 |
| Chemical products manufacturing | 40.71 | 6.19 |
| Non-metallic mineral product manufacturing | 33.52 | 5.09 |
| Basic metal manufacturing | 55.46 | 8.43 |
| Transportation equipment manufacturing | 14.93 | 2.27 |
| Rubber products manufacturing | 17.52 | 2.66 |
| Mean | 80.19 | 12.19 |

*Notes:* The basic unit of water conservation is 1 million cubic meters. The measurement unit of $CO_2$ emissions is 1 million kilograms.

these industries need to implement water conservation plans and promote water-use efficiency.

Six of the industries – namely pulp, paper, and paper products; chemicals; chemical products; non-metallic mineral products; basic metals; and transportation equipment – were located in the middle range of water-use efficiency ($0.5 >$ efficiency $> 0.25$). The water-use efficiency of these six industries is better than that of the above seven industries; however, there is room for improvement. The highest water-use efficiency is found in the rubber products manufacturing industry, approaching 0.62. The average water-use efficiency across all the industries is 0.30 from 1998 to 2015; on the whole, all industries cumulatively have substantially inefficient water use. This evidence suggests that the various industries need to plan and implement water conservation measures and to boost water-use efficiency.

Besides investigating water-use efficiency, this paper also discusses the potential for water conservation by the various industries. Once the water-use efficiencies have been evaluated in the SFA model, the impact of $CO_2$ emissions can be assessed through modeling using Equations (13) and (14). The first step is to compute the potential WSG; these results are reported in the second column of Table 4. The water conservation for the various industries ranges from 4.07 to 212.67 million cubic meters. The potential maximum volume of water savings is found in the beverages and tobacco manufacturing industry, followed by chemicals manufacturing, and textile mills. However, the minimum volume of water conservation exists in the manufacturing of leather, fur, and related products, followed by transportation equipment, and rubber products. According to the present estimation, every industry wastes water resources and can be incentivized to conserve water. The second step of the analysis is to gauge the potential $CO_2$ emissions reductions via water conservation. Following the first step of water conservation calculation, $CO_2$ emissions potential can be expressed using Equation (14). The potential reductions in $CO_2$ emissions for the various industries are revealed in the third column of Table 2. These range from 0.63 to 32.33 million kilograms. The average potential reduction of $CO_2$ emissions for the various industries is 12.19 million kilograms. The goals of $CO_2$ emissions reduction vary across industries. The top three industries for potential $CO_2$ emissions reduction are beverages and tobacco manufacturing, chemicals manufacturing, and textiles mills manufacturing. The results are consistent with the analysis of water-use efficiency: the greater the water-use efficiency, the lower the potential for $CO_2$ emissions reduction. The gain from water-use efficiency implies a significant degree of $CO_2$ emissions reduction. These results support the improved management and conservation of water resources, and can help to inform governments in making decisions to reduce $CO_2$ emissions.

## Discussion

Accelerating economic growth is one of the most important government policies around the world. However, rapid economic development brings environmental degradation, especially in less developed nations. Some evidence in the literature shows that GDP is a substantial factor in $CO_2$

emissions increases [34–36]. In addition to the general positive relationships between GDP and $CO_2$ emissions, in some studies, an inverted-U relationship between economic growth and $CO_2$ emissions was found, showing that initially, economic growth is linked to high $CO_2$ emissions, and tends to decrease as an economy reaches its turning point on the threshold of economic growth [37, 38]. Some determinants of GDP, such as trade openness and foreign direct investment (FDI) are also significantly related to $CO_2$ emissions (He *et al.* [39]) [40]. Trade openness has a positive impact on $CO_2$ emissions [41–43]. In addition, Omri *et al.* [44] argued that FDI inflows raise $CO_2$ emissions by 0.19%, suggesting that FDI flows may have resulted in pollution havens. Loosening environmental regulations may help to attract and retain foreign investment. Similar results are also found in Blanco *et al.* [40]. Those studies show that it is difficult to maintain economic development without worsening environmental quality.

Under the competing pressures of economic growth and environmental quality, it is difficult to deploy and formulate environmental policies. Fortunately, recent studies exploring amelioration strategies such as efficiency upgrades or environmentally friendly investments may be a solution for policymakers who hope to maintain economic development without hurting the environment. Masui *et al.* [1] suggested several approaches to address environmental degradation, one of which is water conservation. Water conservation may be classified into ecosystems of water recycling or water saving given a certain output. Water saving derived from economic change is identified via analysis of input–output efficiency or water-use intensity. Water-use efficiency reveals a firm's operating ability to use and allocate energy input efficiently in a production process. The efficient use of water is important for making progress in the competitiveness of industrial firms, since it results in reduced energy consumption, energy costs and carbon emissions.

Water-use efficiency often appears in agriculture research as a stand-in for irrigation efficiency, in measures such as water withdrawal per unit of GDP. However, this study focuses on the input–output relationship, using parametric approaches to estimate the production frontier. This allows us to find the efficiency score, to improve inputs to reach the frontier, and to decrease water usage. According to the efficiency computation, there remains much room for improvement in water use in many industries, since much inefficiency exists in the sample. In addition, there is considerable space for reduction in $CO_2$ emissions. According to the calculation, water saving induces a reduction in $CO_2$ emissions and maintains output without hurting industrial growth. The policy implications of this study include water resource management and carbon management. The following items are highlighted:

- The maximum performance water-use efficiency.
- A prototype integrated water-use efficiency and carbon emissions framework is laid out to manage resources.

The above arguments illustrate the potential for water-use efficiency and a reduction in $CO_2$ emissions. Environmental damage is generally caused by economic development, which creates great amounts of environmental pollutants. Everyone expects to see a decline in emissions of $CO_2$. This study shows potential approaches to saving water usage, reducing energy demand, and decreasing emissions.

## Conclusions

It is well known that water resource management has become a globally pressing issue due to water resource shortages. Even superpower countries such as the United States, China and India face the risk of water shortage. Formulating policies to conduct mitigation and adaptation is necessary to avoid the negative impacts of water crises. Existing studies have focused on water use or consumption in the context of efficiency and its determinants; however, many are concerned with water efficiency in specific agricultural products or on the frontier of production estimation for a specific city, country or region. There is still a lack of literature which investigates the interdependence of water-use efficiency and $CO_2$ emissions, especially using industry-level evidence. This study addresses that research gap and makes contributions for decision makers and policymakers.

This study estimated industrial water-use efficiency, and found that saving water not only promotes water-use efficiency but can also reduce $CO_2$ emissions through water conservation initiatives. Our conclusions are drawn as follows. First, based on 14 Taiwanese industries, this work finds that the highest water-use efficiency exists within the rubber products manufacturing industry, with a score of 0.62. In addition, the average water-use efficiency of all the scoped industries is approximately 0.30. The water conservation potential for the various industries ranges from 4.07 to 212.67

million cubic meters. These results show that, cumulatively, the industries demonstrate inefficient water-use. There exists much potential for increased water conservation in the majority of industries. Second, according to the estimation using a true fixed-effects stochastic frontier model, the potential for reduction of $CO_2$ emissions ranges from 0.63 to 32.33 million kilograms. The average reduction of $CO_2$ emissions for the various industries is 12.19 million kilograms. In other words, this means that there are increased positive impacts yet to be achieved; there exists great potential for improvement in water-use efficiency which, in tandem, can reduce the $CO_2$ emissions associated with water delivery, treatment and re-use. Policies for water conservation and improvement of water-use efficiency ought to be viewed as a complementary part of $CO_2$ emissions reductions and energy policies. Third, the global economy and population are anticipated to grow and expand, whereby the demand for water (and energy) will also rapidly rise; hence, water crises will continue to become more detrimental. Governments should not limit environmental and energy policies within the narrow scope of carbon emission reductions; close attention should likewise be paid to the significance of water conservation, which in effect is an additional means to curb emissions. Implementing energy- and water-efficiency measures together can achieve greater $CO_2$ emissions reductions; therefore, governments should seek to formulate and implement water-resource policies, reduce resource-consumption incentives, and/or promote water-conservation technologies in order to reach multiple bottom-line results in water and energy savings, for even greater carbon emissions reductions.

## Notes

1. The calculation method and dataset are presented in the following website: http://www.ecobug.com/
2. Taiwan Water Corporation is a monopolistic water supplier in Taiwan. Water supply emissions factors for water use were provided by the Taiwan Water Corporation. The data is available online available at https://www.water.gov.tw/ct.aspx?xItem=1958&ctNode=813&mp=1
3. Reviews of the SFA model can be found in Dorfman and Koop [45] and Coelli *et al.* [46].

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The authors declare that they have no conflict of interest.

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