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Parameter Uncertainty Analysis of the Life Cycle Inventory Database: Application to Greenhouse Gas Emissions from Brown Rice Production in IDEA

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Abstract: The objective of this paper is to develop a simple method for analyzing the parameter uncertainty of the Japanese life cycle inventory database (LCI DB), termed the inventory database for environmental analysis (IDEA). The IDEA has a weakness of poor data quality because over 60% of datasets in IDEA were compiled based on secondary data (non-site-specific data sources). Three different approaches were used to estimate the uncertainty of the brown rice production dataset, including the stochastic modeling approach, the semi-quantitative DQI (Data Quality Indicator) approach, and a modification of the semi-quantitative DQI approach (including two alternative approaches for modification). The stochastic modeling approach provided the best estimate of the true mean of the sample space and its results were used as the reference for comparison with the other approaches. A simple method for the parameter uncertainty analysis of the agriculture industry DB was proposed by modifying the beta distribution parameters (endpoint range, shape parameter) in the semi-quantitative DQI approach using the results from the stochastic modeling approach. The effect of changing the beta distribution parameters in the semi-quantitative DQI approach indicated that the proposed method is an efficient method for the quantitative parameter uncertainty analysis of the brown rice production dataset in the IDEA.

Keywords: semi-quantitative DQI approach; GHG emissions; parameter uncertainty analysis; brown rice production; inventory database for environmental analysis (IDEA)

1. Introduction

Life cycle assessment (LCA) has been used widely for assessing the environmental impact of a product. Oftentimes, an LCA result is reported as a single value of the environmental impact for a given functional unit [1,2]. However, a single value without an uncertainty range can never represent the true mean of the environmental impact. Every measurement has uncertainty. As such, a single value should not be used in expressing LCA results [1,2].

Concepts and types of uncertainties had been defined previously in risk assessment and policy analysis fields. Types of uncertainties were classified into data, model, and completeness in the risk assessment field [3]. In the policy analysis area, uncertainty was classified into scenario, parameter, and model uncertainty [4]. Huijbregts classified uncertainty into parameter, model, and choices, along with temporal, spatial, source, and object variabilities [1]. Of the three types of uncertainties (parameter, scenario, and model) in LCA, parameter uncertainty a more significant effect on the results, and is the

most frequently addressed and commonly recognized form of uncertainty compared to that of the model or choices [5,6]. However, the importance of the type of uncertainty depends on the purpose of the uncertainty analysis. For instance, uncertainties in forecasting the result focused on the scenario uncertainty [7], while uncertainties in estimating potential human exposure to toxic pollutants focused on the model dimensions and assumptions [8]. Therefore, the purpose of the uncertainty analysis dictates the type of uncertainty considered. In this paper, a parameter uncertainty analysis is chosen for the qualification of uncertainty from the datasets of the life cycle inventory (LCI) database (DB) because parameter uncertainty is a more significant issue than others in the LCI DB.

In Japan, over 60% (including the AIST (National Institute of Advanced Industrial Science and Technology)-LCA database and IDEA) of LCA research works adopt the Inventory Database for Environmental Analysis (IDEA). The IDEA has more than 3400 life cycle inventory (LCI) datasets encompassing the whole industry in Japan. The datasets were developed from 2008 to 2014 (IDEA ver.1 and IDEA ver.2 [9,10]). Datasets include input and output data of the unit processes, system boundary, and various decision rules such as allocation, cut-off, and open loop recycling, among others. Users can modify the data, system boundary, as well as various decision rules, which are common features in any LCI dataset [11]. However over 60% of datasets in the IDEA were compiled based on secondary data (non-site-specific data sources), such as the Economic Input Output Table and industry statistics) [10,12]. This means that the IDEA has the weakness in data quality of the datasets because most (over 60%) of the datasets are compiled using the non-site-specific data sources.

Parameter uncertainty is the error of the parameter. The parameter error occurs because no two measurements of the parameter produce exactly the same value. The magnitude of the error is described by the standard deviation of the measured data and more precisely by the confidence interval of the parameter. This indicates that parameter uncertainty or error is closely linked to data quality, and it thus follows that the IDEA exhibits a weakness in its poor data quality.

Researchers have analyzed the parameter uncertainties of the LCI database to improve the reliability of the LCA results [13–16]. The parameter uncertainty analysis of the LCI data can be classified into quantitative analysis and semi-quantitative analysis. The former is based on the statistical methods (e.g., classical statistics, stochastic modeling, and fuzzy theory) [13–17], while the latter is based on the data quality indicator (DQI) method such as a definition of probability density function (PDF) from DQI results [18–22].

In the quantitative analysis, statistical methods are used to quantitatively assess the uncertainty of the LCI database [13–17,23]. Error propagation based on the Taylor series expansion method was used to identify key factors [13]. Citroth et al. proposed a combined model for error propagation formulas and Monte Carlo simulation [23]. Sonnemann et al. [17] and Maurice et al. [15] performed uncertainty analysis using the Monte Carlo simulation.

However, many researchers have pointed out disadvantages of the quantitative uncertainty analysis. Maurice et al. reported that quantitative uncertainty analysis is too time-consuming [15]. Lloyd and Ries reported that current quantitative uncertainty analysis does not address important contributors to the uncertainty of the LCA results because of the complexity of the LCA models [6]. Additionally, the collection of data samples from non-site data is too time-consuming, leading to literature references within insufficient data in LCI datasets. This is one of the reasons why many studies have used the semi-quantitative uncertainty analysis approach [18,19,24–26]. Therefore, assessing the applicability of the quantitative analysis and the semi-quantitative DQI approach for the uncertainty analysis of the input parameters of the datasets in the IDEA is necessary. Furthermore, the development of a simple method for uncertainty analysis is required.

Of the semi-quantitative uncertainty analysis methods, the semi-quantitative DQI approach [18,19,21,22,26] based on a qualitative data quality assessment [27] is worthy of consideration because of its common use in the LCA field. The DQI approach can be classified into qualitative and semi-quantitative approaches. The qualitative approach assesses the data quality in terms of qualitative descriptors such as good, fair, and poor data quality, which depends on rather

subjective judgment. Typically, the Pedigree method falls under the qualitative approach [27,28]. The semi-quantitative approach adopts a numerical rating system when assessing the data quality. Here, the assigned quality rating is processed to produce a single score of the data quality based on beta probability distribution [18]. Frischknecht et al. suggested a framework for the uncertainty analysis of the LCI database [21]. There are basic uncertainty factors of input and output in the LCI based on expert judgments and default uncertainty factors from DQI results.

There are no truly quantitative data quality assessment methods. Often the semi-quantitative method is mistakenly termed a quantitative assessment method. The logic here is to convert the qualitative analysis results into numerical scores with a limited number of data points. Weidema and Wesnaes [27] and Weidema [28] pointed out that even if the DQI score does not represent any degree of data quality, many researchers have studied the possibility of converting the DQI scores into quantitative uncertainty analysis results [19,21,22,28,29]. Weidema and Wesnaes [27] suggested the conversion of input data points to random variables using the DQI approach.

Attempts have been made to integrate the semi-quantitative DQI approach with a statistical method or a modification of the data quality assessment method. Muller et al. carried out the application of the DQI approach to investigate the distribution based on this framework [22]. However, there are difficulties in applying this method to other LCI databases such as the IDEA because of the limitation in the modification of the two factors based on expert judgments. Kennedy et al. [26] and Wang et al. [20] proposed the DQI weighting method related to the data quality assessment. Wang et al. [29] proposed a procedure to relate stochastic modeling to the semi-quantitative DQI approach for the building material industry. Canter et al. [19] performed a stochastic modeling study based on the semi-quantitative DQI approach and they did not attempt to modify the parameters in beta distribution to decide the ranges of the input parameter.

However, it is not possible to apply the above approach to other industry sectors. This is because this approach is based on the beta distribution parameters for specific industry databases, such as the beverage delivery or building material industry, and thus cannot be applied directly to the datasets of the other industry sectors, such as the agricultural product in the IDEA. Specifically, the above approach does not consider specific conditions inherent to the agricultural product production in Japan. Thus, modification of the beta distribution parameters (endpoint range, shape parameter) is required.

A review of the existing literature indicates that there is a need to develop a specific parameter uncertainty analysis method applicable to the IDEA. The method should be based on the semi-quantitative DQI approach proposed by Kennedy et al. [18], focused on the modification of the beta distribution parameters in the semi-quantitative DQI approach. Brown rice production, which is a typical agriculture LCI dataset in Japan, was chosen for the parameter uncertainty analysis. Therefore, the objectives of this paper are to:

- i. assess the applicability of the semi-quantitative DQI approach and the stochastic modeling approach to the parameter uncertainty analysis of the brown rice production and compare the uncertainty analysis results from both approaches;
- ii. develop a method for the parameter uncertainty analysis of the agricultural DB in the IDEA.

2. Materials and Methods

2.1. Brown Rice Production in the IDEA

In order to manage 3400 datasets of the inventory data, classification with a hierarchical structure was developed to manage all of the datasets in the IDEA, as shown in Figure 1. The IDEA has three tiers of classifications, where the six-digit classification represents a specific product such as brown rice, wheat, or tomato. These are the target datasets (six-digit classification) for the parameter uncertainty analysis in this research. A dataset consists of input and output data of the processes involved in that dataset. It includes many processes and relations among the processes. The system boundary of

datasets as well as various rules such as allocation, cut-off, treatment of recycling, and data quality issues are part of the dataset.

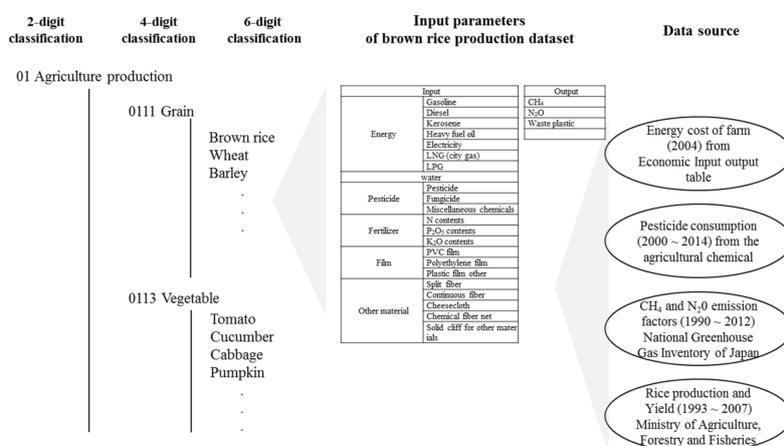


Figure 1. The hierarchical structure of the IDEA (inventory database for environmental analysis) and input parameters of brown rice production.

All data in the brown rice production dataset were the Japanese national average and its base year was 2010. The functional unit is 1 kg brown rice produced. The system boundary includes field preparation, crop management, harvest, and storage; thus, the production of energy, pesticides, fertilizers, films, other materials, and emissions of CH₄, N₂O from the agricultural land were included, but emissions from buildings and equipment and the CO₂ sinking of rice production (plants) were excluded. The allocation of the rice straw was not considered because of its low economic value.

2.2. Overview of the Parameter Uncertainty Analysis

In order to develop a simple method for the parameter uncertainty analysis of the dataset in the IDEA, we formulated two hypotheses. First, the proposed method for the parameter uncertainty analysis should be simple method. In this sense, a simple method such as the semi-quantitative DQI approach with relevant modification may be applicable to over 3400 datasets in the IDEA or 259 datasets of the agricultural industry. Second, the modification of the semi-quantitative DQI approach should be based on a comparison of the differences in the uncertainty analysis results between the stochastic modeling approach and the semi-quantitative DQI approach.

A comparison of the two different uncertainty analysis approaches was made for the brown rice production dataset. The two approaches are: the stochastic modeling approach and the semi-quantitative DQI approach adopting beta probability distribution (hereafter termed beta distribution) [18]. The same system boundaries with the same decision rules were used in both approaches.

The stochastic modeling approach used here is the modified version of the approach by Maurice et al. [15]. The modifications included: (i) simplifying the procedure for selecting input parameters for the uncertainty analysis; (ii) estimating probability density function (PDF) of a parameter in a process, using data points of the parameter. The semi-quantitative DQI approach adopting beta distribution was also modified. The modifications included: estimating weight of the DQIs based on pair-wise comparison of the DQIs [30], calculating the aggregated DQI (ADQI) using the weight, and determining the shape parameters and range endpoints of the beta distribution based on the ADQI using the transformation matrix. The transformation matrix provides link between the beta distribution parameter and the DQIs.

We considered two assumptions for the comparison: (i) the analysis focused on the uncertainty of the input parameters of the processes in the dataset of the IDEA; and (ii) the target environmental

impact chosen was climate change because it is considered most significant in today's world [31]. Characterization factors of the climate change impact category were the 100-year GWP (global warming potential) values [32].

Based on the comparison between the two approaches, we proposed a simple method for the parameter uncertainty analysis of the agricultural dataset in the IDEA by modifying the semi-quantitative DQI approach. In order to apply the method to the agriculture dataset, the beta distribution parameters (endpoint range, shape parameter, and ADQI scales) of the semi-quantitative DQI approach was modified. Figure 2 shows the flow of the parameter uncertainty analysis method with the specific steps involved.

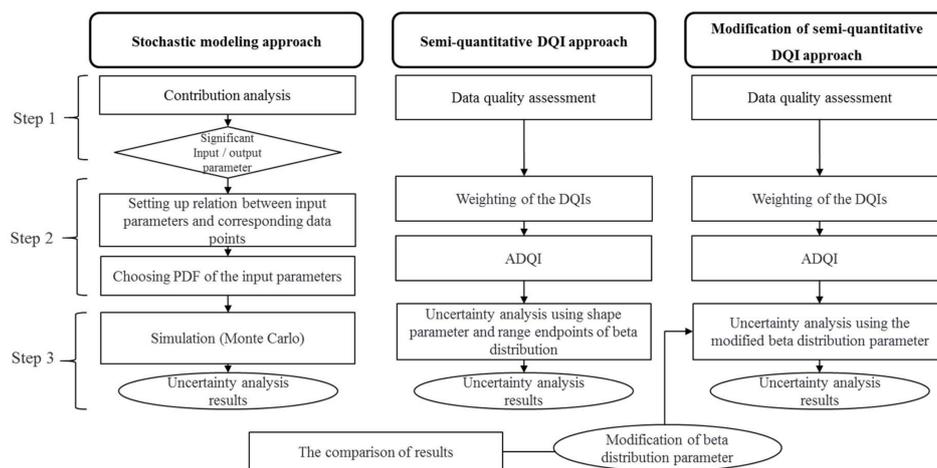


Figure 2. Flow of the stochastic modeling, the semi-quantitative DQI (data quality indicator) approach, and modification of the semi-quantitative DQI approach.

2.3. Stochastic Modeling Approach

The stochastic modeling approach, in particular Monte Carlo simulation (MCS), is a common method for quantitative uncertainty analysis in LCA [6,15–19,33]. Application of the stochastic modeling approach such as MCS requires information of the PDF of input parameters. The stochastic modeling approach was carried out in three steps, as shown in Figure 2: (i) contribution analysis; (ii) choosing the PDF; and (iii) performing the Monte Carlo simulation.

2.3.1. Step 1. Contribution Analysis

Contribution analysis in LCA is used for identifying key issues or environmentally weak points of a product system. Characterized environmental impact and weighted environmental impact can be used for identification of the key issues [34]. In this paper, conventional contribution analysis method was applied in selecting input parameters for the uncertainty analysis.

2.3.2. Step 2. Choosing Probability Density Function

Probability distribution of the selected input parameters should be determined. To estimate the PDF, at least 15–30 data points are required. In general, it is difficult to collect a sufficient number of data points of the input parameters in LCA. In order to estimate the PDF by the goodness-of-fit test, the relation between input parameter and data points (raw data) was identified by an empirical formula. The three types (energy, pesticide use, and CH₄ from land) of input parameter contribute about 80% to the GHG (Greenhouse Gas) emissions produced from brown rice production (see case study; Section 3). Here, as an example, we defined three formulas that were related on the input

parameter; energy, pesticide use, and CH₄ from land for the brown rice production (*k*th product) as shown in Equations (1)–(3).

$$Energy_{(i,k)} = \frac{Energy_{farm(k)} \times W_{e(i)}}{Production_{farm(k)}} \quad (1)$$

where $Energy_{(i,k)}$: amount of the *i*th energy (gasoline, diesel, kerosene, heavy fuel oil, electricity, LNG (liquefied natural gas), and LPG (liquefied petroleum gas)) in the *k*th product, kg or L/f.u. (1 kg rice production); $W_{e(i)}$: contribution of the *i*th energy consumption to the total energy consumption, %; $Energy_{farm(k)}$: operation cost (total energy cost of a farm) of the *k*th product, ¥/60 kg, statistical data (1993–2007) [35]; $Energy_{cost(i)}$: cost of the *i*th energy, ¥/ith energy unit (kg or L) [36]; $Production_{farm(k)}$: base amount of the *k*th production of farm in statistical data [35], 60 kg.

$$Pesticide_{(i,k)} = \frac{Pesticide\ consumption_{(i,k)}}{Production_{(k)}} \quad (2)$$

where $Pesticide_{(i,k)}$: amount of the *i*th pesticide (pesticide, disinfectant, and miscellaneous chemicals) in the *k*th product, kg/f.u. (1 kg rice production), $Pesticide\ consumption_{(i,k)}$: amount of the *i*th pesticide of the *k*th product, kg/year [37]; $Production_{(k)}$: amount of the *k*th product production, kg/year, 2004–2007 [35].

$$CH_4(k) = \sum_{i=1}^2 \frac{E_{CH_4(k)}}{Area\ of\ Rice\ paddy_{(i,k)}} \times W_{(i)} \quad (3)$$

where $CH_4(k)$: amount of the methane emission from land in the *k*th product, kg/f.u. (1 kg rice production) $Production_{(i,k)}$: amount of the *i*th type (dry-field plant and deep water) in the *k*th product production, kg/year (2004–2007) [35]; E_{CH_4} : methane emission factor of the *k*th product production, kg CH₄/m² [38]; $Area\ of\ Rice\ paddy_{(i,k)}$: area of the *i*th type (dry-field plant and deep water) in the *k*th product production, m²; $W_{(i)}$: contribution of *i*th type (dry-field plant and deep water), 1993–2007, % [35].

Several methods can be used to estimate the PDF. They include the Chi-square test, Kolmogorov-Smirnov (K-S) test, and Anderson Darling test, among others [39–41]. The K-S test used in this study is based on the comparison of the empirical cumulative distribution function (ECDF) and the assumed theoretical cumulative distribution function (TCDF) for the data points of the input parameter [42].

$$D_n = \max|F_X(x) - S_n(x)| \quad (4)$$

where D_n is the statistic (random variable), $F_X(x)$ is the theoretical CDF (cumulative distribution function), and $S_n(x)$ is the ECDF based on the collected input parameter. D_n is tested for the critical value of the D_n distribution. If D_n^a is the critical value from the K-S table at the significance level of α , then the probability of $P(D_n \leq D_n^a)$ equal to $(1 - \alpha)$ can be computed. If D_n is less than or equal to D_n^a , then the collected input parameter is a good fit with the assumed cumulative distribution function, $F_X(x)$.

2.3.3. Step 3. Monte Carlo Simulation

Once the PDF of the input parameters are determined, the effect of the input parameters on the GHG emissions is estimated by performing the Monte Carlo simulation (MCS). Monte Carlo simulation is a technique generally used to estimate the confidence interval of the environmental impact results [43].

MCS, a stochastic method for estimating the model output (here, GHG emissions) requires a method for generating input data of each input parameter and calculating the model output using the generated input data. The principal steps of the MCS include selecting or assuming the PDF of each input parameter, X_i , followed by generating the random deviate from the PDF of X_i . Here, the transformation method that transforms the uniform deviate of the uniform distribution to the random deviate of the assumed distribution is used. The next step is to compute the model output using the

random deviates, to obtain the relevant statistics [39]. The model output, z , from the Monte Carlo simulation can be expressed as shown in Equation (5):

$$z = \sum w_i x_i \quad (5)$$

where w_i : the sensitivity coefficient; x_i : the input parameters; and z : the model output.

Random deviates of the input parameter vector, X , and coefficients vector, W , and the model output vector from the Monte Carlo simulation, z , are given by Equations (6)–(8):

$$X = \begin{bmatrix} x_1(1) & \cdots & x_n(1) \\ \vdots & \ddots & \vdots \\ x_1(N) & \cdots & x_n(N) \end{bmatrix} \quad (6)$$

$$W = [w_1 \quad \dots \quad w_n] \quad (7)$$

$$z = (w^T \cdot X^T)^T, \text{ or } \begin{pmatrix} w^T \cdot \rightarrow \\ x(1) \\ \dots \\ w^T \cdot \rightarrow \\ x(N) \end{pmatrix} \quad (8)$$

where N = number of iteration(run).

Crystal Ball 11.1.2 was used as a tool for the Monte Carlo simulation [44].

2.4. Semi-Quantitative DQI Approach

The semi-quantitative DQI approach can be used when it is difficult to carry out the uncertainty analysis using the statistical modeling approach. This approach was developed by Kennedy et al. for use when there is an insufficient number of data points for a parameter [18]. Canter et al. applied this approach to the transformation matrix on the emissions of inventory parameters such as carbon dioxide and nitrogen oxide [19]. Wang et al. carried out a hybrid procedure to integrate the semi-quantitative DQI approach with the Monte Carlo simulation [29].

Here, the transformation matrix means a list of values for the beta distribution parameter that is linked to the DQIs, as was proposed by Kennedy et al. [18]. The term “transformation matrix” was coined by Wang et al. [29].

Figure 2 shows steps of the semi-quantitative DQI approach with two modifications of the original approach (Kennedy et al. [18]). The modified approach consists of three steps: (i) a data quality assessment to obtain the DQI; (ii) an aggregated DQI (ADQI) calculation; and (iii) an uncertainty analysis using the transformation matrix including the shape parameter and range endpoints of beta distribution.

2.4.1. Step 1. Data Quality Assessment (DQA)

The qualitative data assessment was performed using the data quality indicator (DQI) of the Pedigree matrix data assessment method [27,28]. A score between 1 and 5 was given to five different DQIs, which are reliability, completeness, temporal correlation, geographical correlation, and technological correlation. Score 1 denotes the highest data quality, while score 5 indicates the lowest data quality.

The Pedigree method was proposed for the data quality assessment at the input parameter level; however, in this research the DQA was performed at the unit process level, while each input parameter has different data sources. This is because all IDEA datasets do not provide the DQA results at the input parameter level. The level of the DQA chosen here is an attempt to apply the semi-quantitative DQI approach as a practical and simple means for parameter uncertainty analysis.

2.4.2. Step 2. Aggregated DQI (ADQI)

An ADQI is the sum of the five weighed DQIs. It is required for the determination of the shape parameters as well as range endpoints of the best distribution in the transformation matrix, as shown in Table 1. Maurice et al. determined the ADQI using the Pedigree matrix method. They first obtained the weight of each input parameter by assigning scores between 1 and 5 to each of the five DQIs [15]. Then the DQI value was multiplied by the weight of each DQI and these values were summed up. Of the five DQIs, three (reliability, temporal correlation, and completeness) were given a weight of 0.167 each, and two (geographical correlation and technological correlation) were given a weight of 0.25 each. This approach known as ADQI has been used widely in the LCA field [15,20].

Table 1. The transformation matrix for the semi-quantitative DQI approach.

| Aggregated DQI Scores | Beta Distribution Parameter | |
|-----------------------|--------------------------------------|---------------------|
| | Shape Parameters (α, β) | Range Endpoints (%) |
| 1 | 5, 5 | 10 |
| 1.5 | 4, 4 | 15 |
| 2 | 3, 3 | 20 |
| 2.5 | 2, 2 | 25 |
| 3 | 1, 1 | 30 |
| 3.5 | 1, 1 | 35 |
| 4 | 1, 1 | 40 |
| 4.5 | 1, 1 | 45 |
| 5 | 1, 1 | 50 |

Although the ADQI method is considered by giving a weight to different DQIs, there is no consistent basis for the weighting. In this research a weighting factor was determined based on the pairwise comparison of the DQIs, named the AHP (Analytic Hierarchy Process) method [45,46]. The weight of the DQIs determined in the dairy cow case was used in this research [30]. This is because the dairy cow system and brown rice system are similar in nature, as both belong to the agricultural industry. The weight of the five DQIs including reliability, completeness, temporal, geographical correlation, and technological correlation was 0.473, 0.241, 0.147, 0.072, and 0.067, respectively.

2.4.3. Step 3. Uncertainty Analysis Using the Transformation Matrix

Beta distribution and transformation matrix have been used to perform uncertainty analyses [18–20,26,29]. Kennedy et al. argued that virtually any shape probability distribution can be presented with the beta distribution [18]. This indicates that beta distribution is flexible, and as such it is a useful modeling tool. It is often used a priori for a parameter in the interval of [0, 1] and as a connection to other distributions. The rationale for choosing beta distribution is that it can represent various types of distribution, ranging from normal to uniform using the shape parameter (α, β). The transformation matrix proposed by Kennedy et al. was based on the “rule of thumb” and they chose beta distribution when the actual distribution of the input parameters’ data was unknown [18]. The PDF of the beta distribution random variable X is given by Equation (9) [18,47].

$$f(x, \alpha, \beta, a, b) = \left[\frac{1}{b-a} \right] \left[\frac{\gamma(\alpha + \beta)}{\gamma(\alpha) \cdot \gamma(\beta)} \right] \left[\frac{x-a}{b-a} \right]^{\alpha-1} \left[\frac{b-x}{b-a} \right]^{\beta-1} \quad (9)$$

where α and β distribution are shape parameters; a and b are range endpoints, %.

The ADQI result can be converted into the shape parameter and range endpoint by the transformation matrix, as shown in Table 1. Kennedy et al. [18], Canter et al. [19], and Wang et al. [20] indicated that the highest data quality or score of DQI is 5, while the lowest is 1; however, this scoring scale is contradictory to that of the general Pedigree matrix data assessment method [22,24,25]. As such, we defined in this research that score 1 is the highest data quality and score 5 lowest.

2.5. Modification of the Semi-Quantitative DQI Approach for IDEA

The proposed method is based on two approaches: the stochastic modeling approach and semi-quantitative DQI approach. Modification of the stochastic modeling approach was made by simplifying the procedure for selecting input parameters for the uncertainty analysis, and estimating the probability distribution of the input parameter. Modification of the semi-quantitative DQI approach was also made. It included the development of a procedure for the estimation of the weight of the DQIs based on the pair-wise comparison [30], calculation of the aggregated DQI (ADQI) using the weight and transformation matrix, and calculation of the beta distribution parameters (range of variable, shape parameter, and lower/upper bounds) relevant to the specific target dataset.

3. Results

3.1. Stochastic Modeling Approach

Key parameters derived from the result of the contribution analysis were determined by the percent contribution of the parameter to the total GHG emissions of the brown rice production. A total of 11 input parameters were included in the 95% contribution of the parameters to the GHG emissions, while there are 25 parameters in the brown rice production. However, four parameters (nitrogenous fertilizer, 5.12%; phosphate fertilizer, 4.98%; potassic fertilizer, 3.31%; and nitrous oxide from land, 2.85%) out of 11 were excluded from the target parameters for the uncertainty analysis because of an insufficient number of data points. Therefore, seven parameters with the assumed PDF were chosen as the target parameters, there are methane from land, miscellaneous chemicals, diesel, kerosene, electricity, liquefied petroleum gas and pesticides. The seven target parameters combined contributed to 81.3% of the total GHG emissions.

In the IDEA, the PDF of the parameters were estimated from the relation between the parameter and data points using Equations (1)–(3). Table 2 shows the information of the parameters in Equations (1)–(3) such as the range of value and reference.

Table 2. The data points of parameters in Equations (1)–(3) for estimating the PDF (probability density function).

| Parameters in Equations (1)–(3) | | Number of Data Points | Range of Value | Reference |
|---------------------------------|---------------------------------------|-----------------------|-------------------------------------|-----------|
| Energy | $Energy_{farm(k)}$ | 15 | 5.57–7.75 yen/kg | [35,36] |
| | Diesel | 15 | 19.09–81.11 yen/L | [35,36] |
| | $Energy_{cost(i)}$ | 15 | 15.15–88.43 yen/L | [35,36] |
| | Electricity | 15 | 14.01–16.30 yen/kwh | [35,36] |
| | LPG | 15 | 39.06–72.85 yen/kg | [35,36] |
| Pesticides | $Pesticide_{consumption(i,k)}$ | 15 | 13,344–37,000 ton/year | [37] |
| | Miscellaneous chemicals Pesticides | 15 | 47,459–75,000 ton/year | [37] |
| Rice production | Amount of brown rice production | 18 | 7,791,500–11,980,700 ton/year | [35] |
| Methane (land) | $CH_4(k)$ | 9 | 15.85–16.17 g $CH_4/m^2 \cdot year$ | [38] |

An example of estimating the PDF of methane from land involves assuming that the beta distribution density function is its PDF. Then the values of the range endpoints with minimum and maximum and the shape parameters of alpha and beta from the data points are determined using the relation as shown in Equations (1)–(3). Next, the K-S test goodness-of-fit method is used to check the validity of the assumed beta distribution to this parameter according to Equation (4) and the critical value from the K-S table [42]. If the assumed PDF fails to pass the K-S text, a different PDF is assumed and the process is repeated. The above steps are repeated for all seven parameters. Table 3 shows the assumed PDF of the parameters based on the above PDF estimation procedure.

Table 3. Assumed PDF of the parameter.

| Parameter | Input | PDF | Stochastic Parameter |
|--|--------------------|-----------|--|
| Methane (land) | 0.03100 (kg/f.u.) | Beta | Minimum = 0.02793, Maximum = 0.03414, Alpha = 2.0, Beta = 3.0 |
| Miscellaneous chemicals (insect-fungicide) | 0.01060 (kg/f.u.) | Beta | Minimum = 0.00645, Maximum = 0.015900, Alpha = 2.09, Beta = 4.28 |
| Diesel | 0.04850 (L/f.u.) | Beta | Minimum = 0.03200, Maximum = 0.09100, Alpha = 0.64, Beta = 1.72 |
| Kerosene | 0.02290 (L/f.u.) | Beta | Minimum = 0.02061, Maximum = 0.02520, Alpha = 2.0, Beta = 3.0 |
| Pesticides | 0.00483 (kg/f.u.) | Lognormal | Mean = 0.00388, Std. Dev. = 0.00124, Location = 0.000270 |
| Electricity | 0.07227 (kwh/f.u.) | Pareto | Location = 0.06456, Shape = 9.44472 |
| Liquefied petroleum gas | 0.00008 (kg/f.u.) | Lognormal | Mean = 0.00008, Std. Dev. = 0.00001, Location = 0.00007 |

In the Monte Carlo simulation, data points were artificially generated for all selected input data parameters, and then the GHG emissions were calculated. The result of the stochastic modeling shows that the GHG emissions of the brown rice production have the mean, 95% confidence interval, standard deviation, and coefficient variation (CV) of 1.32 kg CO₂ eq/f.u., 1.24~1.43 kg CO₂ eq/f.u., 0.05 kg CO₂ eq/f.u., and 3.95%, respectively, as shown Figure 3.

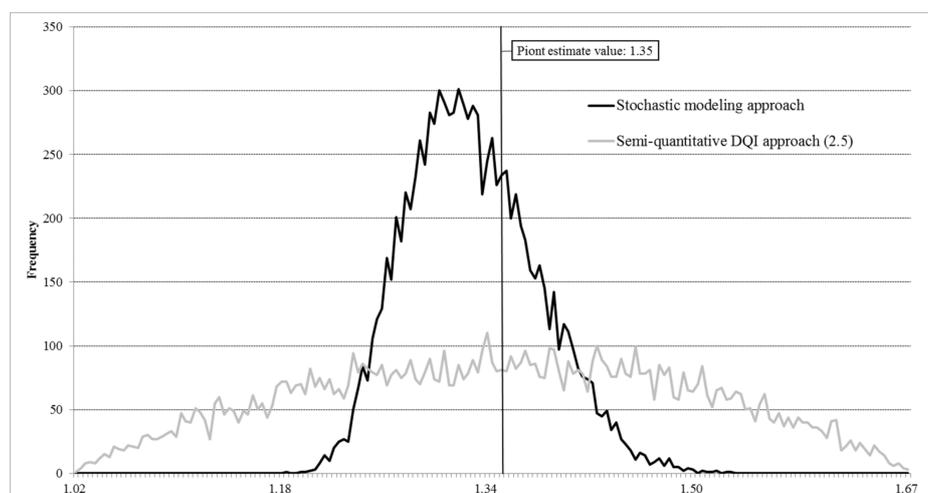


Figure 3. Comparison of the probability distribution of the GHG (greenhouse gas) emissions between the semi-quantitative DQI approach and the stochastic modeling approach.

In the stochastic modeling approach, the number of available data points for methane, each type of energy, and pesticides were 45, 30, and 30, respectively, for the estimation of the PDF. Although seven out of the 25 parameters represent a significant portion of the total GHG emissions, nonetheless the number of data points required for the uncertainty analysis poses a major challenge in using the stochastic modeling approach. Therefore, we conclude that the stochastic modeling approach is not practical to apply to the uncertainty analysis of the IDEA. As such, there is a need for the development of a simple method for the parameter uncertainty analysis of the agriculture industry DB in the IDEA.

3.2. Semi-Quantitative DQI Approach

The semi-quantitative DQI approach was applied to the uncertainty analysis of the brown rice production dataset in the IDEA. The DQA and ADQI score of brown rice production was calculated according to the Section 2.4. The ADQI score of the brown rice production was estimated to be 2.615. Since the ADQI score in Table 1 does not have 2.615, 2.5 was chosen in lieu of 2.615 for the application of the ADQI score to the transformation matrix. The shape parameters and range endpoints of the beta distribution from the transformation matrix were chosen using Table 1 and Equation (9). Table 4 shows the results of the DQA and ADQI for the semi-quantitative DQI approach to the analysis of the brown rice production.

Table 4. The result of DQA (data quality assessment) and ADQI (aggregated data quality indicator) for the semi-quantitative DQI (data quality indicator) approach to the analysis of the brown rice production.

| DQI | DQA | Weighting Factor | ADQI | Beta Distribution Parameter |
|---------------------------|-----|------------------|--|--|
| Reliability | 3 | 0.473 | 2.615 (assume 2.5 to apply to the beta distribution) | Shape parameters ($\alpha, \beta; 2, 2$); range endpoint, $\pm 25\%$) |
| Completeness | 2 | 0.241 | | |
| Temporal correlation | 3 | 0.147 | | |
| Geographical correlation | 1 | 0.072 | | |
| Technological correlation | 3 | 0.067 | | |

There are limitations to the comparison between the two approaches. In the stochastic modeling approach, seven parameters out of 25 were used, while the semi-quantitative DQI approach used comprehensive DQA at the unit process level. However, seven input parameters can cover the entire brown rice production because they represent most of the impacts of the dataset.

The result of the semi-quantitative DQI approach shows that the mean, 95% confidence interval, standard deviation, and coefficient of variation of GHG emissions of the brown rice production were 1.34 kg CO₂ eq/f.u. (functional unit), 1.07~1.62 kg CO₂ eq/f.u., 0.15 kg CO₂ eq/f.u., and 11.2%, respectively. The 95% confidence interval of the stochastic approach and that of the semi-quantitative DQI approach around the mean were (1.24 < mean = 1.32 < 1.43) and (1.07 < mean = 1.34 < 1.62), respectively. The relative difference in the absolute value between the single value (point estimate value) (1.35 kg CO₂ eq/f.u., see Figure 3) and the upper and lower bounds of the confidence interval were 5.9% (0.08 kg CO₂ eq/f.u.), 8.2% (0.11 kg CO₂ eq/f.u.) in the stochastic modeling approach, and 20.7% (0.27 kg CO₂ eq/f.u.), 20.0% (0.28 kg CO₂ eq/f.u.) in the semi-quantitative DQI approach, respectively. This result indicates that point estimate cannot represent the true mean, but rather the confidence interval of the two approaches should be discussed for the development of the simple method for the parameter uncertainty analysis of the agricultural dataset in the IDEA.

Figure 3 also shows that variance of the stochastic modeling approach is much smaller than that of the semi-quantitative DQI approach. It is obvious that the semi-quantitative DQI approach needs improvement, while the stochastic modeling approach is too time-consuming to be practical for use on routine basis.

3.3. Modification of the Semi-Quantitative DQI Approach for the Agriculture Dataset in the IDEA

For the improvement of the semi-quantitative DQI approach as a newly proposed approach for the agriculture DB in the IDEA, two alternative parameters (modification of the semi-quantitative DQI approach) including the shape parameter (α, β) and the range endpoint of the beta distribution for the agriculture dataset in the IDEA were suggested.

From the case study, the difference between the stochastic modeling approach and semi-quantitative DQI approach of the 95% confidence interval were 13.71% (1.07 kg CO₂ eq/f.u. and 1.24 kg CO₂ eq/f.u.) at the lower bounds and 13.29% (1.62 kg CO₂ eq/f.u. and 1.43 kg CO₂ eq/f.u.) at the upper bounds. A similar observation has been made in other research works as well,

where the semi-quantitative DQI approach overestimated the uncertainty [29,48,49]. In particular, the shape parameter and range endpoint appearing in the beta distribution may not be universally applicable; therefore, the beta distribution parameters (shape parameter and range endpoint) should be determined for the agricultural LCI dataset in the IDEA. The two alternative approaches (modification of semi-quantitative DQI approach), alternative approach A and B, were proposed in order to reduce the difference between the two approaches.

Based on the above analysis, we made three modifications to the beta distribution parameters for the proposed approaches, termed alternative A and alternative B. The modifications included: (i) setting up range points for the reduction of difference from the stochastic modeling result as 15% and 10% lower than the initial endpoint range (endpoint range, see Table 1) (exception, 5% and 7.5% in the ADQI 1 and 1.5)—this assumption was based on the difference (about $\pm 13\%$) between the stochastic modeling and semi-quantitative DQI approaches; (ii) subdividing the ADQI scale in order to consider the attributes of the IDEA (agriculture, livestock, and fish industrial datasets, 259 datasets) that have similar results as the ADQI result (of the 97.9%, 2.5 (ADQI) and 3 (ADQI) in agriculture and livestock DB are 31.1% and 66.8%, respectively). As shown in Table 5, the classification of the ADQI between 2 (ADQI result) and 4 (ADQI result) were increased from four scale points (see Table 1) to eight scale points (see Table 4); (iii) modification of the shape parameter to get closer to the stochastic modeling result. The shape parameters α , β were modified such that α is smaller than β , as shown in Table 5, following the definition of beta distribution [18,47]. In beta distribution, if α and β are the same, as shown in Table 1 (initial parameter), the beta distribution appears to be a normal distribution (when α and $\beta > 1$). If α is bigger than β , the shape of the distribution (mean and distribution) is closer to the low value, such as in lognormal, gamma, and pareto distributions.

Table 5. Two alternative approaches A and B for the semi-quantitative DQI approach for the agriculture DBs (data bases) in the IDEA.

| ADQI | Beta Distribution Parameter | | | |
|------|---|----------------------------|-------------------|-------------------|
| | Shape Parameters (α , β) | Initial Endpoint Range (%) | Alternative A (%) | Alternative B (%) |
| 1 | 4, 5 | 10.00 | 5.00 | 2.50 |
| 1.5 | 4, 5 | 15.00 | 7.50 | 3.75 |
| 2 | 3, 4 | 20.00 | 10.00 | 5.00 |
| 2.25 | 3, 4 | - | 12.50 | 7.50 |
| 2.5 | 3, 4 | 25.00 | 15.00 | 10.00 |
| 2.75 | 2, 3 | - | 17.50 | 12.50 |
| 3 | 2, 3 | 30.00 | 20.00 | 15.00 |
| 3.25 | 2, 3 | - | 22.50 | 17.50 |
| 3.5 | 1, 2 | 35.00 | 25.00 | 20.00 |
| 3.75 | 1, 2 | - | 27.50 | 22.50 |
| 4 | 1, 2 | 40.00 | 30.00 | 25.00 |
| 4.5 | 0, 1 | 45.00 | 35.00 | 30.00 |
| 5 | 0, 1 | 50.00 | 40.00 | 35.00 |

The alternative approaches A and B were proposed for the semi-quantitative parameter uncertainty analysis of the agriculture DB in the IDEA based on the semi-quantitative DQI approach put forth by Kennedy et al. [18]. As shown in Table 5, the key features of the alternative approaches A and B are: (i) 15% and 10% lower than the initial range points [18]; (ii) the eight different scales between the ADQI scores of 2 and 4; and (iii) α is 1 and smaller than β , as shown in Table 5.

4. Discussion

In order to assess the effect of the modified semi-quantitative DQI approach (the alternative approaches A and B), a comparison of the alternative approaches A and B, the initial semi-quantitative DQI approach, and the stochastic modeling approach was conducted. The 95% confidence interval of GHG emissions from the brown rice production were calculated for the four approaches, as shown

in Figure 4. In particular, the results of the proposed alternatives A and B were estimated based on Equation (9) and Table 5. The alternative approaches A and B have eight ADQI scales from 2 (ADQI) to 4 (ADQI) and the applied ADQI score is not 2.5 but 2.75 from the ADQI result (2.68), achieved by subdividing the ADQI scales. Figure 4 shows that the 95% confidence interval of alternative approach B is much closer to the reference, the stochastic modeling approach, than alternative approach A and the semi-quantitative DQI approach.

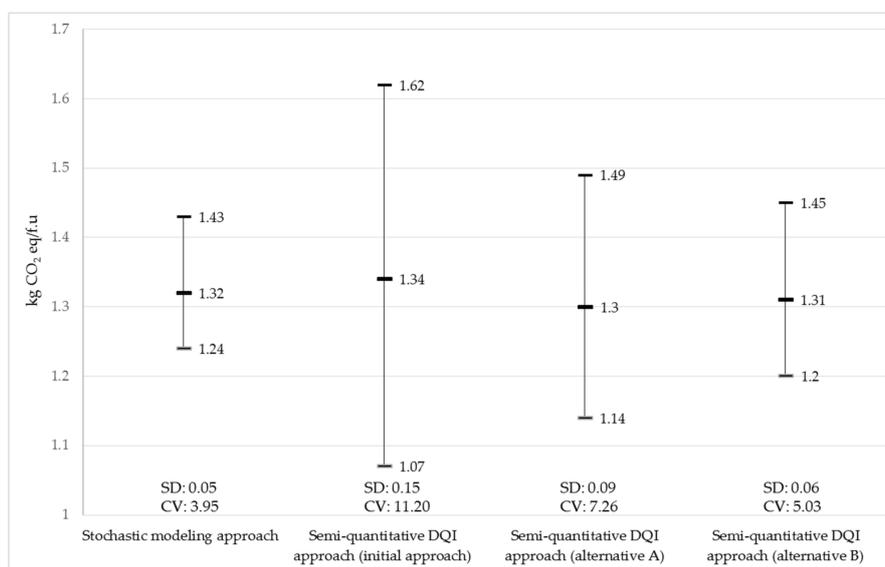


Figure 4. Comparison between the stochastic modeling approach and three semi-quantitative DQI approaches of the brown rice production in the IDEA (kg CO₂-eq/f.u.), SD: Standard Deviation, kg CO₂ eq/f.u.; CV: Coefficient Variation, %.

The comparison indicates that: (i) the difference of the 95% confidence interval ranges (upper/lower bounds) in comparison to that of the stochastic modeling approach is -13.29% (0.19 kg CO₂ eq/f.u.), 13.71% (0.17 kg CO₂ eq/f.u.) in the initial approach, -4.20% (0.06 kg CO₂ eq/f.u.), 8.06% (0.10 kg CO₂ eq/f.u.) in alternative approach A, and -1.40% (0.02 kg CO₂ eq/f.u.), 3.23% (0.04 kg CO₂ eq/f.u.) in alternative approach B; (ii) the difference of standard deviation is 200% (initial approach), 80% (alternative approach A), and 20% (alternative approach B), respectively. In addition, the difference of CV (Coefficient Variation) presents similar results, as shown Figure 4. This indicates that alternative B is closest to the stochastic modeling of the brown rice production.

Alternative approach B was chosen as the simple method for the uncertainty analysis of the agriculture dataset in the IDEA when there is an insufficient number of data points available. While it is risky to generalize that alternative approach B from one case (brown rice) is applicable to all agriculture datasets in the IDEA, there are justifications for this generalization based on two observations: (i) the brown rice production dataset represents typical agricultural practices in Japan because it adopted same data processing procedure, same data collection period, same year of data collection, and same data sources as other agricultural products in Japan; and (ii) the brown rice production has the same data source and system boundary for the energy consumption per farm, pesticide consumption per product, operation cost of a farm, and adopted the same estimation method for CH₄ emissions as stipulated in the guide for the agriculture datasets in the IDEA, shown in Figure 1, and thus same empirical equations such as Equations (1)–(3) can be applicable to other types of agricultural products.

The stochastic modeling approach tested in this research, which is a typical quantitative uncertainty analysis method, required at least 15 data points of each input parameter to estimate the PDF. Therefore, 45 data points of raw data for methane (which required three raw data points, see Equation (3)), 30 data points in each type of energy (which required two raw data points,

see Equation (1)), and 30 data points in pesticides (which required two raw data points, see Equation (2)) were used to estimate the PDF. In this case study, at least seven different PDFs are required for the seven different input parameters. In order to apply the stochastic modeling approach, more than 210 data points are required. The number of datasets in the IDEA is about 3400. Therefore, the adoption of the stochastic modeling approach in the IDEA is practically impossible.

As a result, many researchers have asserted that a lot of time and resources are needed for quantitative uncertainty analyses such as stochastic modeling [6,15,18,19]. Research works related to the range endpoints of the input parameter have begun, as Finnveden and Lindfors [50] carried out research on the range endpoints of the input parameter as minimum (x/factor) and maximum ($x \times \text{factor}$) and the factor varied from 2 to 100 based on the “rule of thumb”. In addition, Hedbrant and Sorme [51] proposed the ranges of the five data quality levels from $x/1$ to $x \times 10$ related to the data collection in the heavy metal industry. Here, X is the amount of input parameter in the life cycle inventory and the factor was varied by the authors from 2 to 100. Meier [52] proposed four data quality levels for the site-specific process data, with a coefficient of variation of 2%, 10%, 20%, and 30% based on the measurements of emissions. Saur et al. [53] proposed the standard deviation of the input parameter (process data) of $\pm 2.5\%$, $\pm 5\%$, $\pm 7.5\%$, $\pm 10\%$, $\pm 15\%$, $\pm 20\%$, and $\pm 25\%$ related to the data source and representativeness.

However, it is difficult to apply the above approaches to agricultural product datasets such as those in the IDEA. This is because the above approaches do not consider specific conditions inherent to the agricultural product production in Japan. Thus, attempts were made to modify the existing semi-quantitative DQI approach by developing new range endpoints from the actual measurements (including an expert judgment) or the site-specific data.

In theory, the site-specific approach [50–53] is required for the uncertainty analysis of the IDEA; however, the collection of data, measurements, and specific statistical data of each parameter is not practical. From the comparative study of the uncertainty results with the stochastic modeling approach, alternative approach B was developed in this research. The alternative approach B adopted $\pm 2.5\text{--}\pm 35\%$ endpoint range and a shape parameter (α is smaller than β) based on the stochastic modeling result, as shown in Table 5.

The proposed alternative approach B indicates that it is necessary to modify the beta distribution parameters in the semi-quantitative DQI approach when applying it to other industry sectors' LCI DB. The alternative approach B solves the apparent underestimation of the uncertainty estimated by the conventional semi-quantitative DQI approaches by other researchers [29,48,49].

In principle, the proposed methodology can be applied to other industrial sectors. For instance, the method for modifying the beta distribution parameters including transformation matrix, endpoint range, and shape parameter as well as the method for generating aggregated DQI and ADQI scales are examples of the application of the proposed methodology to the development of datasets from other industrial sectors.

5. Conclusions

This study aimed to modify the beta distribution parameters in the semi-quantitative DQI approach for parameter uncertainty analysis in the other industry sectors' LCI DB. The feasibility of the parameter uncertainty analysis for the agricultural industry dataset in the IDEA was assessed by comparing two different approaches, stochastic modeling and semi-quantitative DQI. The difference between the two led to the development of the modified semi-quantitative approach for the parameter uncertainty analysis of the agriculture dataset of the LCI DB. Major conclusions are:

- i. A simple method for the parameter uncertainty analysis of the agriculture industry dataset was proposed by modifying the beta distribution parameters (transformation matrix including the endpoint range, shape parameter, and aggregated DQI (ADQI) scales) in the semi-quantitative DQI approach based on the stochastic modeling result.

- ii. The stochastic modeling approach provides the best estimate of the true mean of the sample space; however, because of the excessive requirements for the number of data points, its use in uncertainty analyses is not practical.

Author Contributions: Chun-Youl Baek collected data and performed the uncertainty analysis, Kyu-Hyun Park interpreted results and helped draft the manuscript, Kiyotaka Tahara conceived the research, while supervising the IDEA.

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