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Data Quality Assessment of the Uncertainty Analysis Applied to the Greenhouse Gas Emissions of a Dairy Cow System

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Abstract: The results of an uncertainty analysis are achieved by the statistical information (standard error, type of probability distributions, and range of minimum and maximum) of the selected input parameters. However, there are limitations in identifying sufficient data samples for the selected input parameters for statistical information in the field of life cycle assessment (LCA). Therefore, there is a strong need for a consistent screening procedure to identify the input parameters for use in uncertainty analysis in the area of LCA. The conventional procedure for identifying input parameters for the uncertainty analysis method includes assessing the data quality using the pedigree method and the contribution analysis of the LCA results. This paper proposes a simplified procedure for ameliorating the existing data quality assessment method, which can lead to an efficient uncertainly analysis of LCA results. The proposed method has two salient features: (i) a simplified procedure based on contribution analysis followed by a data quality assessment for selecting the input parameters for the uncertainty analysis; and (ii) a quantitative data quality assessment method is proposed, based on the pedigree method, that adopts the analytic hierarchy process (AHP) method and quality function deployment (QFD). The effects of the uncertainty of the selected input parameters on the LCA results were assessed using the Monte Carlo simulation method. A case study of greenhouse gas (GHG) emissions from a dairy cow system was used to demonstrate the applicability of the proposed procedure.

Keywords: data quality assessment; uncertainty analysis; greenhouse gas (GHG) emissions; dairy cow system; life cycle assessment (LCA); data quality indicator (DQI)

1. Introduction

The livestock sector is the largest global source of methane (CH_4) and nitrous oxide (N_2O), at 39% of anthropogenic CH_4 emissions and 65% of anthropogenic N_2O emissions, with the main sources being enteric fermentation and manure in livestock product production (on-farm) and fertilizers in feed production (pre-farm) [1,2]. This means that the livestock sector plays a significant role in global climate change, which makes it necessary to estimate the greenhouse gas (GHG) emissions within livestock products including enteric fermentation and manure treatment (on-farm) and feed production (pre-farm). Hence, life cycle assessments (LCA) have been widely used by many studies to assess the environmental impact of dairy cow systems [3–9].

LCA is a useful method for the identification of significant issues, such as key life cycle stages, or activities, such as weak points of a product and/or service from the environmental perspective, thus providing specific information to policy and decision makers. The results of an LCA are, however, often reported as a single point estimate (value) of the environmental load for a given functional unit. Thus, this value can be viewed as having ideally zero uncertainty even though uncertainties are ignored or unknown. It is difficult to specify the LCA results using this type of ideal value [10,11], as making decisions based on the LCA results of one single point estimate (without considering the uncertainties) can mislead decision makers.

There are various types of uncertainties which occur when performing LCAs. Funtowicz and Ravetz [12] classified the types of uncertainty into data, model, and completeness. Firestone et al. [13] classified the types of uncertainty into scenario, parameter, and model. Huijbregts [10] classified them into parameter, model, and choices, and the variability of temporal, spatial, sources, and objects. All these classifications, despite differences in terminology, are the same in nature. In this paper, we adopted the terminology introduced by Firestone et al. [13]. There are three types of uncertainties, and it is clear that the uncertainty of the LCA results originates from the uncertainties in the input parameter values, and the chosen scenarios associated with entire life cycle stages including the end-of-life stage, and models employed for the calculation of the LCA results.

Parameter uncertainty is the major source of uncertainty in the output results [14]. Scenario uncertainty includes choices regarding the functional unit, valuation and weighting factors, time horizons, geographical scales, natural contexts, allocation procedures, waste-handling scenarios, use of environmental thresholds and expected technology trends [14]. Model uncertainty includes models for deriving emissions and characterization factors [14]. The scenario can be considered as part of the input data, as the scenario consists of assumed activities where the input data is entered in each activity. The error or uncertainty propagates through the transformation process from the input data via the model to the output results. Therefore, this paper focuses mainly on the input parameter uncertainty.

There are several methods for calculating the uncertainties from the parameter based on statistical methods. Lloyd and Ries [14] classified the types of calculating uncertainty in the LCA field; they include stochastic modeling, analytical uncertainty propagation, interval calculating, fuzzy data sets and others. Those methods can be further classified into two groups: one is the stochastic simulation approach such as Monte Carlo simulation (MCS), and the other is the mathematical (analytical) approach, such as error propagation. The stochastic simulation approach has been widely used to calculate parameter uncertainty in the last two decades [14–18]. Although the mathematical approach has limitations in applying to complex models with large uncertainties, its application in LCA, for instance, in the global sensitivity analysis [19–21], is currently gaining momentum as it can help to give more insight into the robustness of the result. The global sensitivity analysis based on the mathematical approach addresses the contribution of the individual input parameter to the variance of the output (result). The proposed method in this paper showed a similar approach as the key input parameter is screened by the contribution approach, but adopts the conventional contribution analysis for screening input parameters and the stochastic simulation approach for calculating the uncertainty from the parameters.

Many researchers have pointed out the disadvantages of parameter uncertainty analysis based on statistical methods. Maurice et al. [22] reported that quantitative uncertainty analysis was too time consuming, and Lloyd and Ries [14] suggested that current uncertainty analysis did not address important contributors to the uncertainty of the LCA results due to the complexity of the LCA models and insufficient data points for statistical information in the LCI database.

Some studies, thus, are focused on screening or simplified methods for uncertainty analysis in the LCA field [22–26]. Maurice et al. [22] proposed the procedure for selecting key data parameters for the uncertainty analysis as it is based on integrating the results of the contribution analysis and the data quality assessment results. Kenndy et al. (1996) [25] and Canter et al. (2002) [26] suggested a simplified method for uncertainty analysis based on the data quality assessment. In order to apply the data quality assessment for the screening method, the weighting of five DQIs (data quality indicator) is necessary. Maurice et al. [22] chose to weight the five DQIs based on almost equal weighting by assumption, while Wang et al. [24] derived the DQI weighting using the AHP method, but it was not studied on the basis of weight. Therefore, a consistent screening procedure is necessary for identifying input parameters for uncertainty analysis.

Therefore, the objectives of this paper are twofold: the first objective is to propose a simplified procedure for selecting input parameters based on contribution analysis followed by data quality assessment; and the second is to propose a quantitative data quality assessment method based on the modified pedigree method using a weight for data quality indicators (DQI) in order to reflect the inherent characteristics of the product system using the analytic hierarchy process (AHP) and quality function deployment (QFD) methods. Here, a pair-wise comparison of the data quality assessment criteria based on AHP and weighting procedure based on the QFD approach were used. A case study of GHG emissions from a dairy cow system was used to demonstrate the applicability of the proposed method for uncertainty analysis.

2. Materials and Methods

2.1. *Simplified Procedure for Selecting Key Parameters*

The proposed procedure for selecting key parameters for uncertainty analysis was a modification of the method described by Maurice et al. [22], which is based on integrating the results of contribution analysis and the data quality assessment results for GHG emissions. While this method is useful in selecting key input data parameters for uncertainty analysis, too many input data parameters for data quality assessment are involved in implementing this method. However, if it is deemed practical, the proposed method can reduce the total number of input data parameters involved as the method selects significant input parameters identified first by the contribution analysis, and then by the data quality assessment. In other words, the proposed method enables LCA practitioners to identify key parameters among others, and concentrate on the decisive parameters in terms of data quality, and their contributions to the LCA results. The procedures by Maurice et al. [16] and our proposed method are shown in Figure 1. Figure 1 shows how the proposed method is expected to reduce the number of input parameters involved at each step.

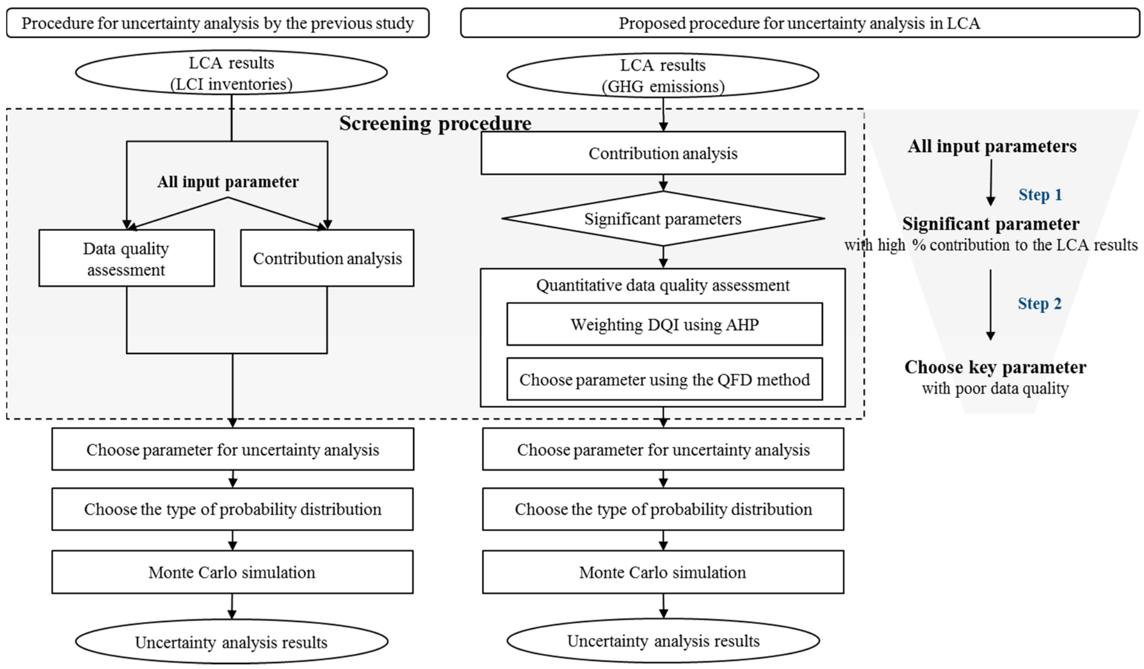


Figure 1. Proposed procedure and previous study [22] for uncertainty analysis in life cycle assessment (LCA).

The pedigree method proposed by Weidema and Wesnaes [23] used five data quality indicators in the data quality assessment. The input parameters were assessed qualitatively according to the DQI in the pedigree matrix, and represented by the quantitative scores. In general, the data quality assessment was performed using the data quality indicators and by assigning a score to the input parameter for each DQI. A score between one and five was assigned to the five different DQIs, which consisted of reliability, completeness, temporal correlation, geographical correlation, and technological correlation.

The original pedigree method implicitly assumes that all DQIs are equally important, however, this does not reflect the inherent characteristics of the product system. Each product system is different in nature as each product has unique attributes and behaves differently across its entire life cycle stages. Unilateral or automatic assignment of equal weight to each DQI cannot reflect the unique attributes of the product system. The weight of each DQI should be different among different types of product, thus, there is a strong need to develop a scheme that assigns weight to the DQI.

Maurice et al. [22] used the pedigree method to determine the data quality of the input parameter by assigning input parameter with scores for each DQI, and then summing them up. At this stage, relative importance was given to the DQIs. Among the five DQIs, three (reliability, temporal correlation, completeness) were given a relative importance of 16.7% each, and two (geographical correlation, technological correlation) had 25% each. This approach is known as the aggregated data quality indicator (ADQI), and has been used in various studies [22,24]. Although the method by Maurice et al. [22] considered assigning different relative importance to different DQIs, there was no consistent basis for the weighting of relative importance.

Thus, our method used a pairwise comparison in the AHP method [27,28], when assigning relative importance to the assessment criteria. In addition, a comparison of the input parameters to select the key input parameters was made by the QFD Phase I matrix approach [29].

2.2. Overview of the Proposed Method

2.2.1. Step 1: Contribution Analysis and Choice of Significant Parameters

Contribution analysis in LCA has been used for identifying the significant parameters or environmentally weak points of a product system as characterized environmental impact, weighted environmental impact, or inventory analysis results can be used for the identification of key issues [7]. Conventional contribution analysis of parameters to GHG emissions was conducted in this step as shown in Figure 1. Parameters included input data and activity data; furthermore, the choice of key parameters was determined by the percent contribution of the parameter to the GHG emissions result of the product system.

2.2.2. Step 2: Quantitative Data Quality Assessment

In Step 2, the study fundamentally used the data quality indicators (five DQIs) of the pedigree matrix [17] such as reliability, completeness, and temporal, geographical, and technological correlation. To select the input parameters for the uncertainty analysis, it was necessary to obtain the relative importance (weights) of each DQI. In this study, AHP (analytic hierarchy process) was used to obtain the relative importance of each DQI. AHP is a multi-criteria evaluation method that decomposes a complex decision problem into a number of subsystems [28–30]. In particular, pairwise comparison is widely used for comparing multiple indicators [31]. Thus pairwise comparison was used to obtain the relative importance of each DQI. Next, QFD (quality function deployment) was used to make a decision for selecting the input parameter based on the relative importance and the score of the input parameter using the pedigree matrix.

To avoid confusing terminology during this step, this paper used two terminologies for the weighting procedure. The first was to describe the relative importance of weighting the five DQIs in AHP; and the second was the relative weights of selecting of key input parameters for the uncertainty analysis in the QFD method.

Construction of Reciprocal Matrix

To reflect the inherent characteristics of the product system using AHP, the construction of a reciprocal matrix was the first step [27,28]. In the 5 × 5 matrix, A = (a_{ij}) was used for five DQIs as shown in the matrix (1). A survey was necessary to identify the values (weight) among the five DQIs from experts in the field of LCA and livestock, using a nine-point scale of the reciprocal matrix for pairwise comparison [27,28]. For instance, when ith DQI and jth DQI are of equal importance the value is 1 in the matrix. When ith DQI is more importance that jth DQI the value is 3 (weakly) to 9 (very strongly) in the matrix. In order to check the consistency of the survey's results, the calculation of the consistency ratio (CR) of survey from each expert was necessary. The consistency ratio (CR) is the ratio to measure how consistent the judgements have been relative to large samples of purely random judgments. Saaty [27,28] suggested a consistency ratio based on the consistency index (CI) and the random consistency index (RI), where if the value of the consistency ratio is smaller or equal to 0.1, the inconsistency is acceptable.

$$\begin{pmatrix} 1 & a_{12} & \cdots & a_{15} \\ \frac{1}{a_{12}} & 1 & \cdots & a_{25} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{1}{a_{15}} & \frac{1}{a_{25}} & \cdots & 1 \end{pmatrix} \tag{1}$$

Estimation of Relative Importance of the Five DQIs

The values of the elements in each row of the reciprocal matrix (1) were summed, and each value in the row was divided by the sum column to produce a normalized matrix that enabled a comparison between the elements. Next, the mean value of each column was calculated using the values of the elements in each column of the normalized matrix [31]. The relative importance (w_i) of the five DQIs was estimated using this step.

The consistency of this result may be weak when obtaining the relative importance (weights) of each DQI, as it is based on the survey results from the pair-wise comparison in the 5 × 5 matrix. Saaty et al. [27] recommended that comparison matrices no larger than 6 × 6 in dimension should be used, because it is difficult to be consistent when answering too many comparisons from the survey. Hence, this study excluded survey results that had a higher consistency ratio (CR) than 0.1 in the case study.

Choose Input Parameter for Uncertainty Analysis Using the QFD Method

To apply the QFD method, the five DQIs with their relative importances (w_i) from the AHP method and the significant input parameters from the contribution analysis were required. Here, a five-point scale was used to assess the relationship between the criteria (DQI) and input parameters instead of the conventional scale employed in the QFD (e.g., blank, 1, 3 and 9).

$$w_{ij=\sum w_i \times d_{ij}} \tag{2}$$

$$s_j = \frac{w_{ij}}{\sum w_{ij}} \times 100 \tag{3}$$

where s_j is the relative weight of the input parameter; w_{ij} is the raw score for the relative weight of the input parameter; w_i is the relative importance of the DQIs from the AHP; and d_{ij} is the score of the input parameter using the pedigree matrix [23].

To assess data quality using the pedigree matrix, all entries (including the method used to collect the field data), and all considerations regarding the calculation and verification of the data should be recorded. Furthermore, the references of all literary data, system boundaries (target area, technology and processes), and all other related information should also be recorded.

The input parameters for the uncertainty analysis were selected through the relative weights shown in Equations (2) and (3). Input parameters for uncertainty analysis can be easily selected using the QFD method, and input parameters with a higher relative weight were chosen for the uncertainty analysis, as 'the higher the score, the better the selection' [29].

2.2.3. Step 3: Choice of Probability Distribution and Monte Carlo Simulation

The Monte Carlo simulation requires the specific probability distribution of a selected input parameter for uncertainty analysis. Uniform distribution, triangular distribution, normal distribution, and log-normal distribution are frequently used in the Monte Carlo simulation. For selecting the probability distribution, at least 15–30 samples are required to represent the population, although the number can vary case by case [9,32]. However, it is difficult to collect a sufficient number of data samples to represent the population that can be applied to determine the probability distribution in the actual LCA. Therefore, statistical data were used to estimate the probability distribution of the selected input parameter. For instance, a normal distribution with a mean and standard deviation was acquired on the basis of site-specific data and dairy statistical data [33] using the Crystal Ball 11.1.2 software [34] based on the Anderson–Darling goodness-of-fit method [35].

Once the probability distribution of the input parameter was determined, the Monte Carlo simulation was performed. The Monte Carlo simulation was used to analyze the propagation of uncertainty when estimating the GHG emissions. Input parameters were artificially produced by generating random numbers at two intervals (minimum and maximum values) for all input data parameters, and then GHG emissions were calculated. The Monte Carlo simulation was performed using the Crystal Ball software [34] on the basis of 10,000 trials with a 95% confidence level. In the process of performing the simulation, the propagation of uncertainty by the object system was derived, and, as a result, statistics such as the probability distribution, mean, standard deviation, coefficient of variation, standard error of mean and confidence interval of the accumulated results were obtained.

2.3. Case Study

A dairy cow farm in Korea was chosen for the case study to demonstrate the feasibility of the proposed approach for the uncertainty analysis of GHG emissions from a dairy cow system. The functional unit (f.u.) of a dairy cow system and the reference flow were 1 kg of raw milk FPMC (fat and protein corrected milk where the fat and protein content were 4% and 3.3%, respectively) and one dairy cow farm, respectively. The system boundary of the dairy cow system used in this study is shown in Figure 2. The product life cycle of the cow system was divided into the following three stages: feed production, dairy cow (product) production, and manure management. The dairy cow production stage consisted of feeding, enteric fermentation, and farm operation. This study did not include the distribution, use and end-of-life stages of the livestock products. Table 1 shows the particulars of the targeted dairy cow farm used in this study.

Table 1. Information on the dairy cow farm.

Category	Contents
Number of cow heads	90
Head per growth phase	Calf: 10, growing heifers: 27, heifers: 14, lactating cows: 36, dry cows: 3
Farm size	Large-scale (>80)
Manure treatment system	Solid storage (composting settled solids)
Milk production	1450 kg/day
Functional unit	1 kg raw milk FPCM (fat and protein corrected milk) (fat content = 4%, protein contents = 3.3%)

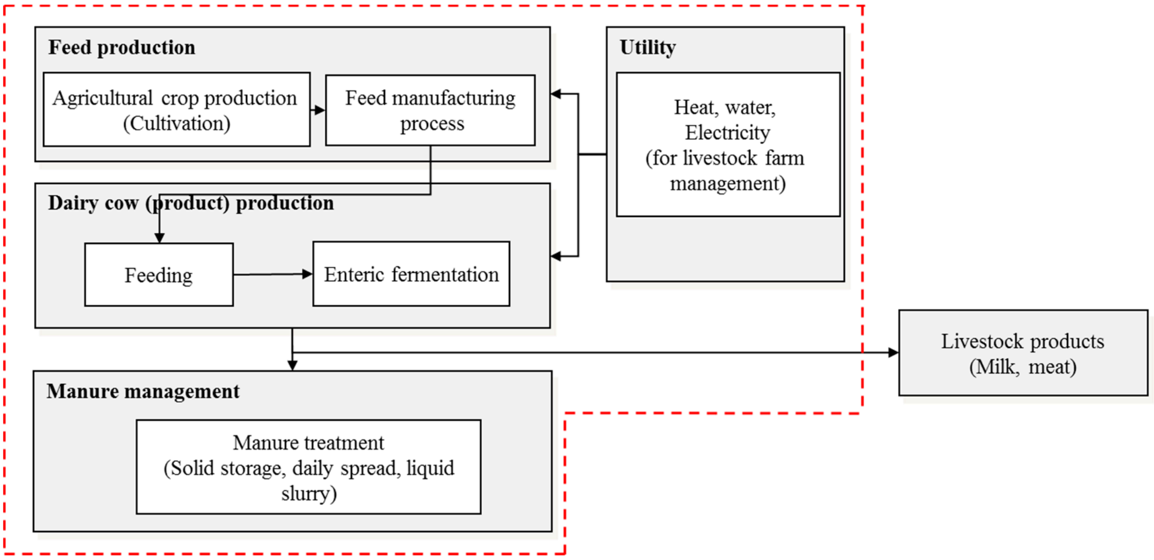


Figure 2. System boundary of the dairy cow system.

3. Results

3.1. Step 1: Contribution Analysis and Choice of Significant Parameters

The total number of parameters involved were 68 in the case study. The specific parameters were as follows.

- In the feeding activity: the total number of parameters were 19; they include the number of feed intakes (two feeds such as roughage and concentrated feed), head (five in the growth phase) and the emissions factors (EF) (emission factors for 12 feedstuffs).
- In the enteric fermentation activity: the total number of parameters were 20; they include the number of feed intakes (two feeds), heads (five in the growth phase), methane conversion factors, Y_m and the EF and Growth Energy (GE) (12 feedstuffs).
- In the farm operation: the total number of parameters were 14; they include the types of energy (seven types of energy consumption) and EFs of energy (seven types such as coal, diesel, electricity, etc.).
- In the manure management: the total number of parameters were 27; they include the number of heads (five in the growth phase), daily volatile solid excreted in five growth phases, and others (see Baek et al. [9] for further details).

To identify the key activities and parameters that contributed significantly to the GHG emissions of the dairy cow system, a contribution analysis was performed for activities such as feeding (including the feed production stage), enteric fermentation, farm operation, and manure management. Figure 3 shows the contribution of each activity to the GHG emissions of the dairy cow system. The feeding activity and enteric fermentation activities in the dairy cow production stage were dominant representing 41.2%, and 39.0%, respectively (Figure 3).

Another contribution analysis was performed for the GHG emissions from the feeding and enteric fermentation activities to identify specific parameters contributing to GHG emissions of the dairy cow system. Significant input parameters identified from this analysis became the target for the data quality assessment.

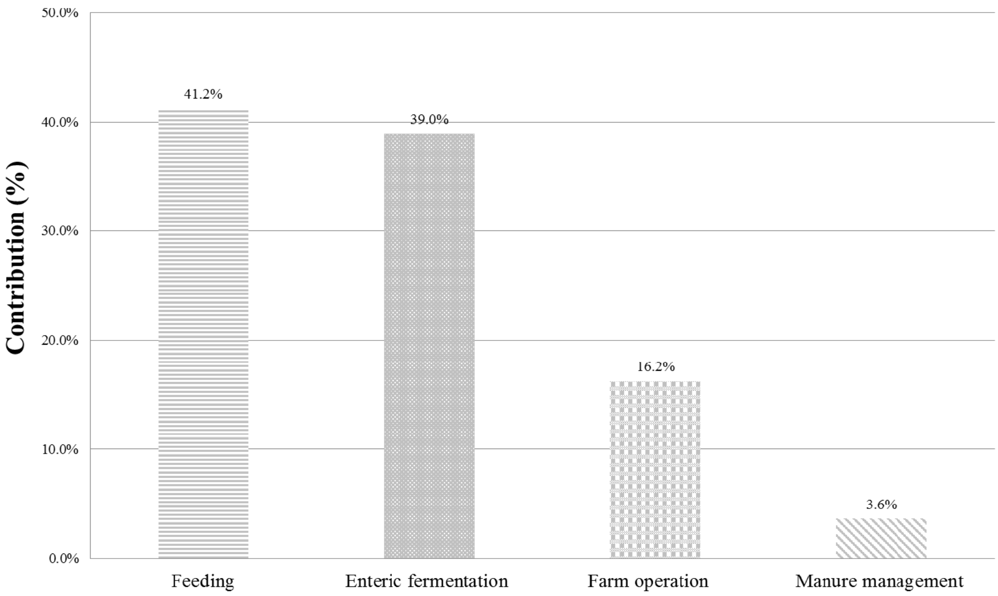
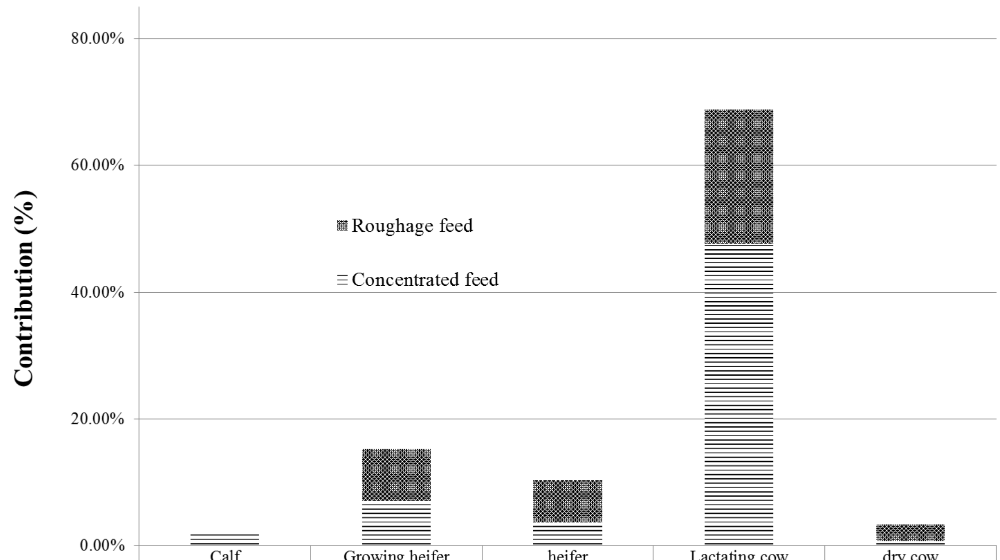


Figure 3. Contribution analysis of the dairy cow system.

First, the contribution analysis in the feeding activity was performed as shown in Figure 4. The feeding activity for the lactating cow was the significant input parameter. The portion of feed for the lactating cow, which comprised of roughage feed and concentrated feed, represented a contribution of 68.85% of GHG emissions in the feeding activity, where roughage feed and concentrated feed represented 21.18% and 47.67%, respectively (Figure 4).



	Calf	Growing heifer	heifer	Lactating cow	dry cow
Roughage feed	0.00%	8.18%	6.67%	21.18%	2.57%
Concentrated feed	2.19%	7.11%	3.67%	47.67%	0.76%

Figure 4. Contribution analysis of the feeding activities.

The contribution of feedstuff to the GHG emissions of the feeding activity is illustrated in Figure 5, and shows the relative contribution of the significant feedstuffs including soybean cake (27.91%), maize (23.76%), silage maize (15.96%), green barley (15.17%), alfalfa (6.11%) and cotton seed meal

(3.81%). The six feedstuffs were identified as significant parameters based on the cut-off criteria that their contributions accounted for over 95% of the impact from the feeding activity.

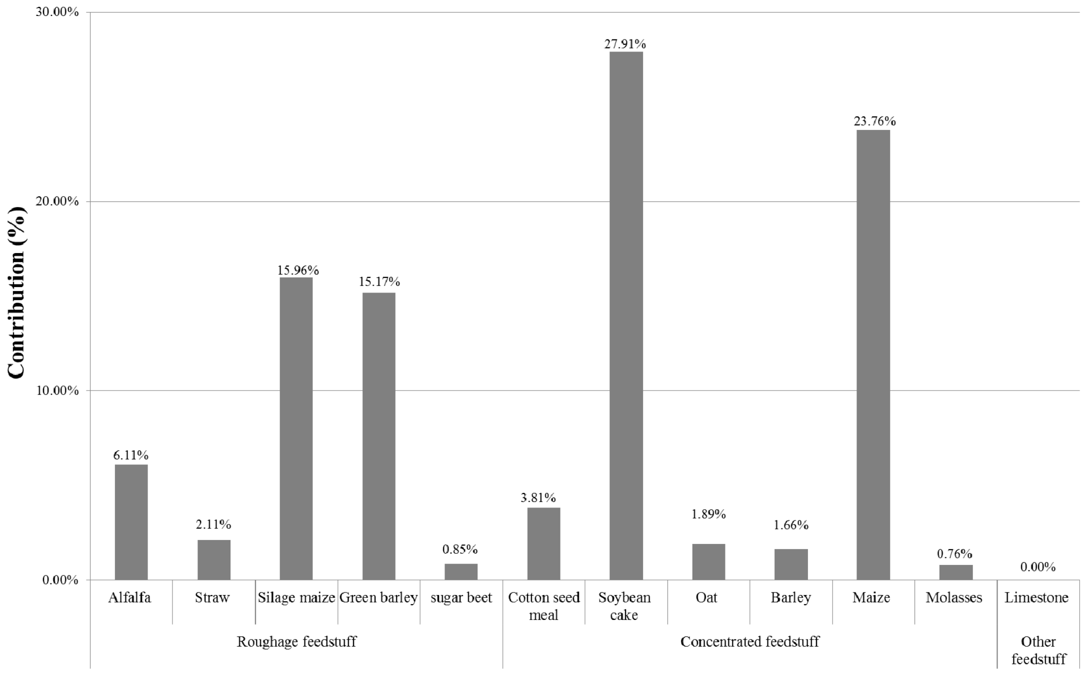


Figure 5. Contribution analysis of the feedstuffs.

Second, the enteric fermentation activity of a cow in the dairy cow production stage was the second highest contribution with 39.0% of the total GHG emissions (Figure 3). In the enteric fermentation activity, the GHG emissions of the lactating cows were 67.41%. These results were caused by lactating cows, which were more than 40% of the total heads of cows on the farm. The lactating cows take 2.5 times more concentrated feedstuff and 1.5 times more roughage feedstuff than the average intake of five growth phases. Feedstuffs influence the GHG emissions of both feeding and enteric fermentation activities, which are the significant stages and activities for the GHG emissions. EF and GE, are also influenced by feedstuff in contributing to the GHG emissions.

In summary, the dairy cow product production stage was the significant issue (stage), and at the activity level, feeding and enteric fermentation were the key issues. Both the feeding and enteric fermentation activities for the lactating cows were significant issues. Thus, the significant parameters associated with the feeding and enteric fermentation activities for lactating cows were identified as: the feed intake of the lactating cow; the methane conversion factor (Y_m); and the EF (emissions factor) and GE (gross energy) of the six feedstuffs (alfalfa, silage maize, green barley, cotton seed meal, soybean cake, and maize). These parameters are the elements of the calculation method (see Baek et al. [9] for further details) for the GHG emissions from the feeding and enteric fermentation activities of lactating cows.

3.2. Step 2: Quantitative Data Quality Assessment

The survey was collected from 20 experts related to the livestock and LCA fields for reflecting the inherent characteristics of the dairy cow system in Korea. The expert panel consisted of 10 people from the Animal Environment Division at the National Institute of Animal Science of Korea, which is related to the livestock field. In the LCA field, the panel included 10 academic experts from Ajou University and the Korea Institute of Industrial Technology.

In this study, a 5 × 5 matrix was used to identify the weight of five DQIs based on the survey. However, Saaty (1980) recommends that comparison matrices no larger than 6 × 6 in dimension be used, because it is difficult to be consistent when answering too many comparisons in the survey [27]. In order to check the consistency of the survey results, the calculation of the consistency ratio (CR) of the survey from each expert was necessary. For the case study, 15 survey results (seven experts in the livestock and eight experts in the LCA fields) were finally chosen, excluding five survey results that had a higher consistency ratio (CR) than 0.1. To aggregate the 15 survey results, the aggregating individual priorities (AIP) method was used [36].

The survey results were split into two sub-groups: the livestock field and LCA field groups. The weight of each sub-group was set at 0.4 (livestock field) and 0.6 (LCA field), given the difference in the understanding of the data quality assessment between the two sub-group. Table 2 shows the values aggregated from the survey results, as well as the normalized relative importance (w_i) due to the five DQIs.

Table 2. Reciprocal matrix for assigning relative importance (w_i) to the five data quality indicators (DQIs).

Reciprocal Matrix							
DQI	**Reliability**	**Completeness**	**Temporal**	**Geographical**	**Technological**	**Sum**	**CR: 0.073**
Reliability	1	4.400	3.667	4.333	5.100		
Completeness	0.227	1	3.073	3.320	4.220		
Temporal	0.273	0.325	1	2.745	2.833		
Geographical	0.231	0.301	0.364	1	0.983		
Technological	0.196	0.237	0.353	1.02	1		
Sum	1.927	6.264	8.457	12.415	14.137	43.200	
Normalization Matrix							
DQI	**Reliability**	**Completeness**	**Temporal**	**Geographical**	**Technological**	**Sum**	**Relative importance (*wi*)**
Reliability	0.519	0.702	0.434	0.349	0.361	2.365	0.473
Completeness	0.118	0.160	0.363	0.267	0.299	1.207	0.241
Temporal	0.142	0.052	0.118	0.221	0.200	0.733	0.147
Geographical	0.120	0.048	0.043	0.081	0.070	0.361	0.072
Technological	0.102	0.038	0.042	0.082	0.071	0.334	0.067

The data quality assessment of the identified significant parameters was conducted by the criteria of the pedigree matrix [23]. The data quality assessment of the parameters was estimated based on the report of the Korea LCI(Life Cycle Inventory) feedstuffs database (for EF of feedstuffs) [37], the Intergovernmental Panel on Climate Change (IPCC) guidelines (for Y_m) [38] and statistics provided by the Ministry of Food, Agriculture, Forestry and Fisheries (for GE of feedstuffs) [39]. The relative weight of the input parameter was calculated using Equations (2) and (3). From Table 3, the input parameters for the next step (uncertainty analysis) were selected by relative weight. The input parameters for the uncertainty analysis can be easily selected by relative weight, and the input parameters with a higher relative weight were chosen for the uncertainty analysis, as 'the higher the score, the better the selection' as described in the material and methods Section 2.2.2 [29]. Thus, the subjective judgment criteria (threshold) were applied where parameters with relative weights greater than 0.08 were considered significant and became input parameters for the simulation, these being soybean cake, maize, alfalfa, silage maize, and Y_m.

Table 3. Data quality assessment of the identified significant parameters.

DQI		Significant Parameters												
		Feeding Activity						Enteric Fermentation Activity						
	Relative Importance (w_i)	$EF_{(i)}$						Y_m	GE					
		Alfalfa	Silage Maize	Green Barley	Cotton Seed Meal	Soybean Cake	Maize		Alfalfa	Silage Maize	Green Barley	Cotton Seed Meal	Soybean Cake	Maize
Reliability	0.473	3	3	2	2	3	3	4	4	3	3	3	4	4
Completeness	0.241	3	3	2	3	3	3	4	4	3	2	3	3	3
Temporal	0.147	3	3	2	3	3	3	3	3	4	2	3	4	4
Geographical	0.072	4	4	2	4	4	4	5	5	5	4	4	4	4
Technological	0.067	4	4	3	3	4	4	3	3	5	3	3	3	3
raw score (w_{ij})		3.14	3.14	2.07	2.60	3.14	3.14	3.86	3.86	3.42	2.68	3.07	3.69	3.69
relative weight (s_j)		0.08	0.08	0.05	0.06	0.08	0.08	0.09	0.09	0.08	0.06	0.07	0.09	0.09

3.3. Step 3: Choice of Probability Distribution and Monte Carlo Simulation

Probability distribution, as per the data distribution, was estimated by using the site-specific and literature data of the input parameter based on the goodness-of-fit method, as shown in Table 4. As described previously, this corresponded to the insufficient data sample in the LCA study, and the estimation of the probability distribution was mainly through the literature data and the statistical data of the input parameter, although site-specific data were used.

Table 4. Input parameter and assumed probability distribution.

Significant Parameter	Input Parameter (Random Variable)		Stochastic Assumption	Probability Distribution
Feeding	$EF_{(i)}$ (kg CO_2 eq/kg)	Soybean cake	Mean: 0.712, Std. Dev.: 0.090	Normal distribution
		Maize	Mean: 0.744, Std. Dev.: 0.084	Normal distribution
		Alfalfa	Mean: 0.326, Std. Dev.: 0.029	Normal distribution
		Silage Maize	Mean: 0.224, Std. Dev.: 0.071	Normal distribution
	$Feeding_{(j,\ lactating\ cow)}$ (kg DM/yr head)	Concentrated feed	Likeliest: 4803, Scale: 493	Maximum Extreme distribution
Enteric fermentation		Roughage feed	Likeliest: 6226, Scale: 639	Maximum Extreme distribution
	$GE_{(i)}$ (Mcal/kg DM)	Soybean cake	Mean: 4.713, Std. Dev.: 0.519	Normal distribution
		Maize	Mean: 4.447, Std. Dev.: 0.441	Normal distribution
		Alfalfa	Mean: 4.08, Std. Dev.: 0.410	Normal distribution
		Silage Maize	Mean: 4.14, Std. Dev.: 0.401	Normal distribution
	Methane conversion factor Y_m (%)		Minimum: 5.5%, Likeliest: 6.5%, Maximum: 7.5%	Triangular distribution

Note: DM (dry matter).

For instance, in the feeding activity, the probability distribution of the feed consumption (feeding) for the lactating cows were derived from the 15 data samples based on statistics provided by the Ministry of Food, Agriculture, Forestry and Fisheries [39]. The probability distribution of the GHG emissions factor for the four feedstuffs was assumed to be normal, and the stochastic assumption was derived from the process data associated with seeding, fertilizer, use of machine, harvesting, and transport of feedstuff, developed as for the Korean LCI feedstuffs database [37].

In the fermentation activity, the gross energy (GE) of the four feedstuffs for the enteric fermentation activity was derived from the statistics of the input feed [40]. Furthermore, the methane conversion factor was calculated based on the standard deviation range proposed by the IPCC guidelines [39].

Based on the probability distribution of the input parameter in Table 4, the Monte Carlo simulation using the Crystal Ball software was performed with 10,000 trials and a 95% confidence level. The results of the uncertainty analysis for the feeding and enteric fermentation activities are listed in Table 5. The GHG emissions of the feeding and enteric fermentation activities had mean values of 0.43 kg CO_2 eq/1 kg of FPCM (CO_2 equivalent/functional unit) and 0.41 kg CO_2 eq/1 kg of FPCM, and 95% confidence interval ranges of 0.38–0.49 kg CO_2 eq/1 kg of FPCM and 0.38–0.44 kg CO_2 eq/1 kg of FPCM, respectively. The amount of GHG emissions (0.43 kg CO_2 eq/1 kg of FPCM) in the feeding (derived from the case study) corresponded to around 50% of the entire probability distribution area, and the amount of emissions by enteric fermentation was 0.41 kg CO_2 eq/1 kg of FPCM, which corresponded to around 50% of the entire probability distribution area.

Table 5. Results of the uncertainty analysis.

Parameter	The GHG Emissions (kg CO_2-eq/1 kg of FPCM)			
	The Proposed Method		The Existing Method	
	Feeding	Enteric Fermentation	Feeding	Enteric Fermentation
Point estimate	0.43	0.41	0.43	0.41
Mean	0.44	0.42	0.43	0.41
Standard Deviation	0.04	0.02	0.04	0.03
Coefficient of Variation (%)	6.67	4.17	8.64	7.83
95% confidence interval	<0.38, 0.49>	<0.38, 0.44>	<0.36, 0.51>	<0.35, 0.48>

Besides the results of the uncertainty analysis by the proposed method, the results from the existing method by Maurice et al. [22] are also shown in Table 5. However, the results were derived from the 14 parameters (intake of the lactating cow, methane conversion factor (Y_m), the EF (emissions factor) and GE (gross energy) of the 12 feedstuffs) selected only by the contribution analysis of the existing method. GHG emissions of the feeding and enteric fermentation activities from the control method have 95% confidence interval ranges of 0.36–0.51 kg CO_2 eq/1 kg of FPCM and 0.35–0.48 kg CO_2 eq/1 kg of FPCM, respectively. From the comparison, we can assume that the uncertainty result of the proposed method is similar to the result of the existing method, although the proposed method was focused on the simplified procedure for selecting the input parameters in the uncertainty analysis.

In order to make a clear the difference between the two results in this case study (A farm) and the previous study (B farm) (Baek et al. (2014) [9], we note that the two farms have three differences. First, milk productive capacity: A farm (14,701 kg FPCM/head of lactating cow/year) has 25% higher productive capacity than B farm (11,774 kg FPCM/head of lactating cow/year). Second, A farm has 10% (40%, 36/90 heads) less than B farm (50%, 93/185 heads) in terms of lactating cows. Last is the composition of the feedstuff. According with three differences, the GHG emissions of feeding and enteric fermentation activities from A farm is 20% and 15% lower than B farm, respectively.

4. Discussion

An uncertainty analysis is indispensable for LCA practitioners or decision makers to assure the reliability of the LCA results so that the results can be verified. Concerning the trade-offs between accuracy and the costs of implementation, determining the significant contributors to uncertainty in the LCA results assists in the efficient use of the available resources and time. In that sense, many studies have introduced and used the concept of contribution to determine the important data, thus estimating uncertainty based on the key data [22,25,26,41]. For instance, the procedure by Maurice et al. [22] was based on integrating the results of the contribution analysis and data quality assessment results. While this method was useful in selecting key data parameters for the uncertainty analysis, there were too many input data parameters for the data quality assessment involved in implementing the method. Therefore, the major departure of this study from previous studies was the proposal of a step-by-step procedure for selecting input parameters: first, the contribution analysis, and second, the data quality assessment.

The DQI method has been used to analyze the uncertainty of LCA results in many studies [22–27,42]. The proposed quantitative data quality assessment is similar to the approaches suggested by Maurice et al. [22] and Wang and Shen [42] in that selecting the input parameters is its objective, while it is different in that the method is based on the pedigree method [23] and DQI weighting [22,24]. Weidema and Wesnaes [23] mentioned that the DQI should not be aggregated, but Maurice et al. [22] and Wang et al. [24] decided to use a DQI weighting as an intermediate indicator for the identification of the data used in the uncertainty analysis. For this same purpose, the relative importance of the DQIs was derived on the basis of the weighting to reflect the characteristics of the product system.

The proposed method showed a difference in the weight derivation method in weighing the DQIs. Maurice et al. [22] chose to give the DQIs an almost equal weighting, giving the same weight to the three indicators related to reliability, and to the two indicators related to appropriateness, for simplification. Wang et al. [24] derived the DQI weightings using the AHP method, but it was not studied on the basis of weight.

In contrast, in this study, the basis of the weighting was calculated by a pairwise comparison in the AHP method to reflect the characteristics of the target system, which was a dairy cow system. As shown in the case study, the relative importance of the five DQIs in the dairy cow system for estimating the GHG emissions was shown to be reliability (47.3%) and completeness (24.1%). These results were calculated by a pairwise comparison in the AHP method based on the survey between the LCA and livestock experts, and meant that these two DQIs (reliability and completeness) were more significant indicators than the three other DQIs for estimating the GHG emissions from the dairy cow system. This can lead us to believe that the five DQIs may have differently weighted values in other product systems. For instance, technical changes to an electronic product occur faster than for agricultural products, so the technological and temporal correlation for electronic products may be estimated to be more important than the other DQIs by the expert survey. For a furniture product, however, geographical correlation is more important than the other criteria given that furniture manufacturing is a raw-material-oriented industry.

In addition, the relative importance of the five DQIs obtained from the case study can be a representative default value for selecting input data parameters during a data quality assessment in the livestock sector. It means that once the value of the five DQIs is identified in a certain area, the survey and AHP procedures can be skipped, thus it can save the consumption of time and resources in the data quality assessment. Furthermore, the resulting DQIs in the case study led practitioners and decision makers to develop a better understanding of the analysis of uncertainty in LCA results, especially for GHG emissions in the livestock sector.

The main contribution of this study was that the proposed method showed an efficient way to analyze the uncertainty of LCA results. As shown in Figure 1, the qualitative analysis (data quality assessment) and contribution analysis were processed at the same time in the existing method, but in the proposed method, those two analyses were processed by a step-by-step screening procedure. Thus, the total number of input parameters involved for the data quality assessment could be reduced.

For instance, the total number of input parameter was 68 parameters (see Section 3.1 Contribution Analysis) If we use the existing method's screening procedure for data quality assessment, at least more than 68 input parameters need to be assessed during the data quality assessment step. This also means that 340 evidentiary materials are required for assessing a score using a pedigree matrix (68 input parameters and 340 materials are 68×5 (five DQIs)). In contrast, the proposed method could assess 12 key input parameters identified using 60 materials (EF and GE from six feeds for five DQIs).

The proposed method enables LCA practitioners to find decisive parameters for the LCA results, and focus more on these parameters in terms of data quality. Thus, the LCA practitioners could know to which extent the decisive parameter with poor data quality influences the LCA results. This method filters trivial parameters (contributing to the final results) out of the procedure, thus finally involving less input parameters for the uncertainty analysis, compared to the existing method (Figure 1).

The proposed method could require considerable time and effort to conduct a series of processes for quantitative data quality assessment. The processes involved are, for instance, making and processing the surveys, conducting AHP and QFD, and calculating the consistency ratio. Nonetheless, once the scores of the DQIs are created through the process, this can save time for future work, as the resulting DQIs can be used as representative values in a certain sector.

The proposed method might have a weak point in obtaining consistent results for the relative importance (weights) of each DQI, as it is a survey result from the pair-wise comparison in a 5×5 matrix. Saaty et al. [19] recommended that comparison matrices no larger than 6×6 in dimension be used since it is difficult to be consistent when answering too many comparisons from the survey. This could be avoided, however, by excluding the five survey results that had a higher consistency ratio (CR) than 0.1.

The screening procedure also has the potential to underestimate the uncertainties (output) by excluding important parameters for the uncertainty analysis. LCA practitioners need to pay attention to the significant parameters for the uncertainty analysis by using consistent cut-off criteria or in-depth analysis of each parameter such as global sensitivity analysis.

5. Conclusions

The objective of the proposed procedure and method described in this paper was to overcome the following problems mentioned:

- Parameter uncertainty is the major source of uncertainty of LCA results, but it is difficult to quantify all types of uncertainty in the input parameter.
- The DQI indicators used to generate the aggregated DQI scores were treated with equal weight, or in two types of weight based on an abstract basis.

The proposed method solving the problems has two features:

(i) A simplified procedure based on a contribution analysis followed by a data quality assessment was proposed for selecting input parameters for the uncertainty analysis, and
(ii) A quantitative data quality assessment method based on the modified pedigree method was proposed, which adopted the AHP (analytic hierarchy process) method and QFD (quality function deployment).

The proposed method was used on a case study of the GHG emissions from a dairy cow system, demonstrating the applicability of this approach. By proposing a simplified approach for selecting the significant input parameters for uncertainty, the efficiency and reliability of the uncertainty assessment increased. Furthermore, the combination of two techniques, AHP and QFD, for scoring DQIs addressed the limitation that needed improvement regarding the reliability of the existing DQI method [34], from the perspective that DQIs were given different weights.

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References

1. Gerber, P.J.; Steinfeld, H.; Henderson, B.; Mottet, A.; Opio, C.; Dijkman, J.; Tempio, G. *Tackling Climate Change through Livestock: A Global Assessment of Emissions and Mitigation Opportunities*; Food and Agriculture Organization of the United Nations (FAO): Washington, DC, USA, 2013.
2. Bailey, R.; Froggatt, A.; Wellesley, L. *Livestock—Climate Change's Forgotten Sector*; Global Public Opinion on Meat and Dairy Consumption; The Royal Institute of International Affairs: London, UK, 2014.
3. Cederberg, C.; Mattsson, B. Life cycle assessment of milk production—A comparison of conventional and organic farming. *J. Clean. Prod.* **2000**, *8*, 49–60. [CrossRef]
4. Haas, G.; Wetterich, F.; Köpke, U. Comparing intensive, extensified and organic grassland farming in southern Germany by process life cycle assessment. *Agric. Ecosyst. Environ.* **2001**, *83*, 43–53. [CrossRef]

5. Ogino, A.; Kaku, K.; Osada, T.; Shimada, K. Environment: Environmental impacts of the Japanese beef-fattening system with different feeding lengths as evaluated by a life-cycle assessment method. *J. Anim. Sci.* **2004**, *82*, 2115–2122. [CrossRef] [PubMed]
6. Halberg, N.; van der Werf, H.M.; Basset-Mens, C.; Dalgaard, R.; de Boer, I.J. Environmental assessment tools for the evaluation and improvement of European livestock production systems. *Livest. Prod. Sci.* **2005**, *96*, 33–50. [CrossRef]
7. International Organization for Standardization (ISO). *Technical Committee ISO/TC 207, Environmental Management. Subcommittee SC 5, Life Cycle Assessment. Environmental Management: Life Cycle Assessment: Requirements and Guidelines*; International Organization for Standardization (ISO): Geneva, Switzerland, 2006.
8. Thomassen, M.A.; van Calker, K.J.; Smits, M.C.; Iepema, G.L.; de Boer, I.J. Life cycle assessment of conventional and organic milk production in the Netherlands. *Agric. Syst.* **2008**, *96*, 95–107. [CrossRef]
9. Baek, C.Y.; Lee, K.M.; Park, K.H. Quantification and control of the greenhouse gas emissions from a dairy cow system. *J. Clean. Prod.* **2014**, *70*, 50–60. [CrossRef]
10. Huijbregts, M.A. Application of uncertainty and variability in LCA. *Int. J. Life Cycle Assess.* **1998**, *3*, 273–280. [CrossRef]
11. Heijungs, R.; Huijbregts, M.A. A review of approaches to treat uncertainty in LCA. In Proceedings of the IEMSS Conference, Osnabrück, Germany, 14–17 June 2004.
12. Funtowicz, S.O.; Ravetz, J.R. *Uncertainty and Quality in Science for Policy*; Springer Science & Business Media: Berlin, Germany, 1990; Volume 15.
13. Firestone, M.; Fenner-Crisp, P.; Barry, T.; Bennett, D.; Chang, S.; Callahan, M.; Barnes, D. *Guiding Principles for Monte Carlo Analysis*; US Environmental Protection Agency: Washington, DC, USA, 1997.
14. Lloyd, S.M.; Ries, R. Characterizing, Propagating, and Analyzing Uncertainty in Life-Cycle Assessment: A Survey of Quantitative Approaches. *J. Ind. Ecol.* **2007**, *11*, 161–179. [CrossRef]
15. Huijbregts, M.A.; Gilijamse, W.; Ragas, A.M.J.; Reijnders, L. Evaluating Uncertainty in Environmental Life-Cycle Assessment. A Case Study Comparing Two Insulation Options for a Dutch One-Family Dwelling. *Environ. Sci. Technol.* **2003**, *37*, 2600–2608. [CrossRef] [PubMed]
16. Basset-Mens, C.; Kelliher, F.M.; Ledgard, S.; Cox, N. Uncertainty of global warming potential for milk production on a New Zealand farm and implications for decision making. *Int. J. Life Cycle Assess.* **2009**, *14*, 630–638. [CrossRef]
17. Chen, X.; Corson, M.S. Influence of emission-factor uncertainty and farm-characteristic variability in LCA estimates of environmental impacts of French dairy farms. *J. Clean. Prod.* **2014**, *81*, 150–157. [CrossRef]
18. Flysjö, A.; Henriksson, M.; Cederberg, C.; Ledgard, S.; Englund, J.-E. The impact of various parameters on the carbon footprint of milk production in New Zealand and Sweden. *Agric. Syst.* **2011**, *104*, 459–469. [CrossRef]
19. Groen, E.A.; Bokkers, E.A.; Heijungs, R.; de Boer, I.J. Methods for global sensitivity analysis in life cycle assessment. *Int. J. Life Cycle Assess.* **2017**, *22*, 1125–1137. [CrossRef]
20. Mutel, C.L.; de Baan, L.; Hellweg, S. Two-step sensitivity testing of parametrized and regionalized life cycle assessments: Methodology and case study. *Environ. Sci. Technol.* **2013**, *47*, 5660–5667. [CrossRef] [PubMed]
21. Saltelli, A.; Ratto, M.; Andres, T.; Campolongo, F.; Cariboni, J.; Gatelli, D.; Saisana, M.; Tarantola, S. *Global Sensitivity Analysis: The Primer*; John Wiley & Sons: Hoboken, NJ, USA, 2008; pp. 157–158.
22. Maurice, B.; Frischknecht, R.; Coelho-Schwirtz, V.; Hungerbühler, K. Uncertainty analysis in life cycle inventory. Application to the production of electricity with French coal power plants. *J. Clean. Prod.* **2000**, *8*, 95–108. [CrossRef]
23. Weidema, B.P.; Wesnæs, M.S. Data quality management for life cycle inventories—An example of using data quality indicators. *J. Clean. Prod.* **1996**, *4*, 167–174. [CrossRef]
24. Wang, E.; Shen, Z.; Neal, J.; Shi, J.; Berryman, C.; Schwer, A. An AHP-weighted aggregated data quality indicator (AWADQI) approach for estimating embodied energy of building materials. *Int. J. Life Cycle Assess.* **2012**, *17*, 764–773. [CrossRef]
25. Canter, K.G.; Kennedy, D.J.; Montgomery, D.C.; Keats, J.B.; Carlyle, W.M. Screening stochastic life cycle assessment inventory models. *Int. J. Life Cycle Assess.* **2002**, *7*, 18–26. [CrossRef]
26. Kennedy, D.J.; Montgomery, D.C.; Quay, B.H. Data quality. *Int. J. Life Cycle Assess.* **1996**, *1*, 199–207. [CrossRef]
27. Saaty, T.L. *The Analytic Hierarchy Process*; McGraw-Hill: New York, NY, USA, 1980.

28. Saaty, L.T. How to make a decision: Analytic hierarchy process. *Eur. J. Oper. Res.* **1994**, *48*, 9–26. [CrossRef]
29. Chuang, P.T. Combining the analytic hierarchy process and quality function deployment for a location decision from a requirement perspective. *Int. J. Adv. Manuf. Technol.* **2001**, *18*, 842–849. [CrossRef]
30. Saaty, L.T. Decision making with the analytic hierarchy process. *Int. J. Serv. Sci.* **2008**, *1*, 83–98. [CrossRef]
31. Macharis, C.; Springael, J.; De Brucker, K.; Verbeke, A. PROMETHEE and AHP: The design of operational synergies in multicriteria analysis: Strengthening PROMETHEE with ideas of AHP. *Eur. J. Oper. Res.* **2004**, *153*, 307–317. [CrossRef]
32. Vose, D. *Quantitative Risk Analysis—A Guide to Monte Carlo Simulation Modeling*; Wiley: Hoboken, NJ, USA, 1996; pp. 103–117.
33. Mon, J.P.; Korea Dairy Committee and Ministry of Agriculture; Food and Rural Affairs. Dairy Statistical Yearbook 2010, 121–128. Available online: http://ebook.dairy.or.kr/autoalbum/view.html (accessed on 20 September 2017).
34. Anderson, T.W.; Darling, D.A. Asymptotic theory of certain goodness-of-fit criteria based on stochastic processes. *Ann. Math. Stat.* **1952**, *25*, 193–212. [CrossRef]
35. Oracle. *Crystal Ball 11.1.2 User's Guide*; Oracle: Redwood, CA, USA, 2012.
36. Aull-Hyde, R.; Erdogan, S.; Duke, J.M. An experiment on the consistency of aggregated comparison matrices in AHP. *Eur. J. Oper. Res.* **2006**, *171*, 290–295. [CrossRef]
37. Lee, K.M.; Park, K.H. Development of carbon tracing system for livestock agriculture. In *Development of LCI DB and Estimation of Greenhouse Gas from Feedstuff*; Research Report; National Institute of Animal Science of the Republic of Korea: Jeonju, Korea, 2012.
38. Intergovernmental Panel on Climate Change (IPCC). *IPCC Climate Change Fourth Assessment Report: Climate Change*; Intergovernmental Panel on Climate Change (IPCC): Geneva, Switzerland, 2007.
39. Park, B.H. *Food, Agriculture, Forestry and Fisheries Statistical Yearbook*; Ministry of Agriculture, Food and Rural Affairs: Guelph, ON, Canada, 2011; pp. 128–129.
40. Lee, S.J. *Korean Feeding Standard for Dairy Cattle*; National Institute of Animal Science: Jeonju, Korea, 2007; pp. 250–255, 374–429.
41. Heijungs, R. Identification of key issues for further investigation in improving the reliability of life-cycle assessments. *J. Clean. Prod.* **1996**, *4*, 159–166. [CrossRef]
42. Wang, E.; Shen, Z. A hybrid Data Quality Indicator and statistical method for improving uncertainty analysis in LCA of complex system—Application to the whole-building embodied energy analysis. *J. Clean. Prod.* **2013**, *43*, 166–173. [CrossRef]