Input-Output 2010
18th International Input-Output Conference
20-25 June 2010 • Sydney Australia

http://www.isa.org.usyd.edu.au/io_2010/

Uncertainty and sensitivity analysis in MRIO modelling – some empirical results with regard to the carbon footprint of the Netherlands

Harry C. Wilting

Netherlands Environmental Assessment Agency (PBL)
P.O. Box 303, 3720 AH Bilthoven, The Netherlands
Phone +31 30 274 4274. Fax +31 30 274 4435. E-mail: Harry.Wilting@pbl.nl

Abstract

Environmental multi-regional input-output (MRIO) models require huge amounts of economic and environmental data. Furthermore, assumptions have to be made in constructing the MRIO table. In order to gain an understanding of the effects of uncertainties in the data on the uncertainties in the outcomes, an uncertainty analysis seemed to be useful. Such an uncertainty analysis was carried out for an IO model for the calculation of the Dutch carbon footprint (CF). The model is a full MRIO model with feedback loops in trade between 12 world regions and the Netherlands. The uncertainty analysis concerned a Monte Carlo analysis based on probability distributions around the IO and emission coefficients in the model. The analysis showed a low uncertainty in the total Dutch CF; uncertainties in the emissions allocated to regions, sectors and chains were far higher. Furthermore, a sensitivity analysis was performed to investigate which of the IO coefficients were the most important in the calculation of the Dutch CF. Coefficients in the domestic blocks and in the Dutch import blocks showed the highest effects on the CF. Non-diagonal blocks concerning the imports of foreign regions played a minor role in the outcomes and therefore a partial MRIO analysis may be sufficient in certain cases.

Keywords: Multi-regional input-output analysis, carbon footprint, uncertainty analysis, sensitivity analysis

1. Introduction

The use of input-output (IO) analysis in industrial ecology and life-cycle applications is very common nowadays (Suh, 2009). IO analysis has been applied in the energy field since the 1970s and later on in environmental applications, e.g. in assessing environmental pressures or material flows. Nowadays it is used in footprint analyses, which include total environmental pressure over the whole supply chain of products. A special issue of Economic Systems Research, e.g., confirmed the role of IO analysis in determining the carbon footprint (CF) of countries and products (ESR, 2009). Not only the applications developed in time, but also the models. A long period only single-country models were used in which it was assumed that imported goods and services were produced with the same technology as the domestic technology. However, there are differences in production technologies, efficiencies and output mixes in the same sector between countries. Multi-regional models were developed in order to account for these differences. First, the main trading partners of the country under consideration were included in so-called partial multi-regional input-output (MRIO) models. After that full MRIO models covering the global economy were introduced including all the trade flows between regions (Wiedmann *et al.*, 2007). The increasing availability of international data sets covering multiple countries stimulated the building of more detailed MRIO models.

The advantage of an MRIO model is that information on region-specific technologies is included in the calculations. Furthermore, MRIO models are very useful in investigating where production takes place along supply chains. However, MRIO models have their drawbacks (Lutter *et al.*, 2008). Since complete MRIO tables are not available, they are constructed from national/regional IO tables and bilateral trade data between countries or regions. Especially, the blocks corresponding with the trade flows between regions at the sectoral level are estimated then. Considering these data issues, an analysis of an MRIO model seems to be useful. Such a model analysis consists of an uncertainty analysis and a sensitivity analysis, and is needed for getting an impression of the plausibility and reliability of the outcomes of the model (Janssen *et al.*, 1990). The uncertainty analysis investigates the uncertain aspects of the model and the effects of these uncertainties on the outcomes of the model. The sensitivity analysis investigates the influence of variations in the input parameters of the model on the outcomes. Quantitative model analyses are rather scarce in IO modelling. In the 1970s, some uncertainty and sensitivity analyses were carried out for the single-region model (Sebald, 1974; Viet, 1980). Wilting and Biesiot (1993) applied the available methods in the field of energy analysis in models on energy intensities and household energy requirements. An example of an uncertainty analysis of the outcomes of a full MRIO model is the study by Lenzen *et al.* (2010) on the time series of the UK carbon footprint.

In this paper, an uncertainty and sensitivity analysis is described for an MRIO model that was developed for the calculation of the CF of Dutch private and public consumption (Wilting, 2008). This model enables the investigation of chains from the consumption perspective providing insights in the role of sectors and regions all over the world in producing for Dutch consumption. The model analysis concerned an analysis of the effects of the uncertainties in the model parameters (technical coefficients matrix, greenhouse gas (GHG) emissions and final demand) and the sensitivity of the CF for changes in these model parameters. The non-diagonal foreign trade blocks in the full MRIO model received extra attention in the model analysis, since these blocks are additional compared to partial MRIO models.

2. Carbon footprint of the Netherlands

In this section, the model and data for calculating the Dutch CF are described and the outcomes are presented for the year 2001.

2.1 Methodology

The MRIO model for determining the CF for Dutch (private and public) consumption is straight-forward. The equations are analogous to the equations in common IO models for single-country analyses. The following relationship between production **x** and final demand **y** exists for an **n**-region economy:

$$\begin{bmatrix} \mathbf{x_1} \\ \vdots \\ \mathbf{x_n} \end{bmatrix} = \begin{bmatrix} \mathbf{A_{11}} & \cdots & \mathbf{A_{1n}} \\ \vdots & \ddots & \vdots \\ \mathbf{A_{n1}} & \cdots & \mathbf{A_{nn}} \end{bmatrix} \begin{bmatrix} \mathbf{x_1} \\ \vdots \\ \mathbf{x_n} \end{bmatrix} + \begin{bmatrix} \mathbf{y_{11}} + \sum_{j \neq 1} \mathbf{y_{1j}} \\ \vdots \\ \mathbf{y_{nn}} + \sum_{j \neq n} \mathbf{y_{nj}} \end{bmatrix} \quad \textbf{(1)}$$

where $\mathbf{x_i}$ is the vector of production in region *i*, $\mathbf{A_{ii}}$ is the matrix of domestic input coefficients of region *i*, $\mathbf{A_{ij}}, _{i \neq j}$ is the matrix of import coefficients of region *j* importing from region *i*, $\mathbf{y_{ii}}$ is the vector of domestic final demand of region *i*, and $\mathbf{y_{ij}}, _{i \neq j}$ is the vector of imported final demand of region *j* importing from region *i*.

The domestic and import coefficients depict the intermediate input requirements per unit output for each sector and summed up they form the technical coefficients matrix per region. The model in (1) is a complete multi-regional model with feedback loops (according to the terminology in Wiedmann *et al.*, 2007). Setting

$$\mathbf{x} = \begin{bmatrix} \mathbf{x_1} \\ \vdots \\ \mathbf{x_n} \end{bmatrix}, \ \mathbf{A} = \begin{bmatrix} \mathbf{A_{11}} & \cdots & \mathbf{A_{1n}} \\ \vdots & \ddots & \vdots \\ \mathbf{A_{n1}} & \cdots & \mathbf{A_{nn}} \end{bmatrix}, \ \mathbf{y} = \begin{bmatrix} \mathbf{y_{11}} + \sum_{i \neq 1} \mathbf{y_{1i}} \\ \vdots \\ \mathbf{y_{nn}} + \sum_{i \neq n} \mathbf{y_{ni}} \end{bmatrix},$$

the MRIO model is:

$$\mathbf{x = A\,x + y} \qquad \mathbf{(2)}$$

The standard IO model for calculating sectoral output **x** for a certain final demand **y**, e.g. consumption, is derived by solving this equation for **x**:

$$\mathbf{x = (I - A)^{-1}\,y} \qquad \mathbf{(3)}$$

where $\mathbf{(I - A)^{-1}}$ is the Leontief inverse matrix. Matrix **I** is the identity matrix. The IO model for calculating the total GHG intensities is:

$$\mathbf{e = d\,(I - A)^{-1}} \qquad \mathbf{(4)}$$

with $\mathbf{d} = [\mathbf{d_1} \ \cdots \ \mathbf{d_n}]$, where $\mathbf{d_i}$ is a row vector of direct GHG intensities of region *i* (depicting the emissions of one unit of production for all sectors), and $\mathbf{e} = [\mathbf{e_1} \ \cdots \ \mathbf{e_n}]$, where $\mathbf{e_i}$ is a row vector of total GHG intensities of region *i*. Assuming that the row vector of GHG intensities **e** defines the supply-chain GHG emissions per unit of output for all industries, the IO model for calculating the CF related to domestic final demand in region *i*, $\mathbf{E_i}$, is:

$$\mathbf{E_i = e\,y_i + D_i} \qquad \mathbf{(5)}$$

with $\mathbf{y_i} = \begin{bmatrix} \mathbf{y_{1i}} \\ \vdots \\ \mathbf{y_{ni}} \end{bmatrix}$, and $\mathbf{D_i}$ is the direct GHG emission of final demand in region *i*.

The model described in equations 4 and 5 was also used for determining the regions and sectors in which emissions occur, and the supply-chain emissions of specific consumption categories (in final demand), like dairy products or cars.

2.2 Data sources and processing

2.2.1 Economic data

Economic data were derived from the GTAP database, version 6, which concerns the global economy in 2001 (Dimaranan, 2006). This database contains IO data (national and imports) and bilateral trade data of 87 regions and 57 sectors. By using the GTAP aggregation tool GTAPAgg (Horridge, 2006) the 87 regions were aggregated to 13 regions, viz. 12 aggregated world regions and the Netherlands[1]. The sectors were not aggregated. In Appendix A an overview is given of the aggregation scheme from 87 GTAP regions to the 13 world regions in the MRIO model. The sectors that were distinguished in the model are listed in Appendix B.

The GTAP 2001 data for the Netherlands differ substantially from the original IO data for the Netherlands on which the GTAP data were based. These differences were caused by the adjusting and updating procedures applied by GTAP in order to balance import and export flows between countries (McDougall, 2008). Especially the volume data of Dutch imports were too high in the GTAP database. Since this led to an overestimation of emissions related to Dutch consumption abroad, the data for the Netherlands in GTAP were replaced by the original IO data (compiled by Statistics Netherlands and the Agricultural Economics Research Institute; Koole and Van Leeuwen, 2006).

Final demand consisted of private and public consumption in 13 regions. Investments were moved from final demand to the intermediate matrix in order to account for the GHG emissions related to capital investments in the supply chains. Only the replacement investments should be assigned to the production chains, but since the GTAP database did not distinguish replacement and extension investments, all investments were added to the intermediate matrices. The deliveries to the investments were, for each sector, assigned to the inputs in the intermediate matrices (domestic and imports) on the basis of depreciation per sector.

Starting from the domestic and import tables and final demand in 13 regions, a full MRIO table was constructed. In the construction procedure, the matrix of imports per region was split up over regions on the basis of the bilateral trade data of the 57

[1] See Wilting (2008) for a further description of the aggregation procedure and the treatment of imports in the aggregation process.

sectors. The application of the procedures mentioned resulted in an MRIO table of 13 regions and 57 sectors per region. The calculated production per region on the basis of the full MRIO table by using equation 3 was compared with the original data on production in the GTAP database. Since for more than 90% of the sector-region combinations, the differences in total production were less than 1%, it was assumed that the imports and exports were translated in bilateral trade flows between regions in a sound way and no further balancing procedures were applied.

2.2.2 GHG emission data

Data on greenhouse gas emissions (CO_2, CH_4, N_2O and F-gases) for the 12 world regions were derived from the EDGAR 3.2 Fast Track 2000 dataset (Van Aardenne et al., 2005) and the GTAP/EPA databases (Lee, 2005; Rose and Lee, 2008). Furthermore, data on GHG emissions for region 13, the Netherlands, were obtained from Dutch NAMEA (CBS, 2007). The GTAP/EPA databases, which are compatible with the GTAP 6 regions and sectors, were more detailed at the sectoral level than the EDGAR dataset. On the other hand, the EDGAR 3.2FT dataset contains more emission sources than the GTAP/EPA databases. Emission sources included in the calculation of the Dutch footprint are fossil-fuel related CO_2 emissions and process emissions, e.g. in the production of concrete, and emissions related to biomass burning. Emission sources that were not included in the calculations are e.g. the CO_2 emissions allocated to non-energy use and chemical feedstock, which are not actually emitted, and the emissions caused by tropical forest fires for deforestation. CH_4 and N_2O emissions from forests, savannah, shrubs and grassland fires were also excluded. See Wilting (2008) for a description of the allocation of GHG emissions to sectors. Residential emissions including private transport were allocated as direct emissions of final demand. Methane emissions related to landfills were allocated to direct emissions too, since it was difficult to allocate them to industrial sectors or households.

2.3 Carbon footprint outcomes

Total CF of Dutch private and public consumption calculated with the MRIO model was 256 Mton of CO_2-equivalents in 2001. Slightly more than 50% of GHG emissions related to Dutch consumption took place abroad (see Figure 1). These gases were mainly emitted in OECD Europe, but East Asia, the former Soviet Union and North America had substantial contributions too.

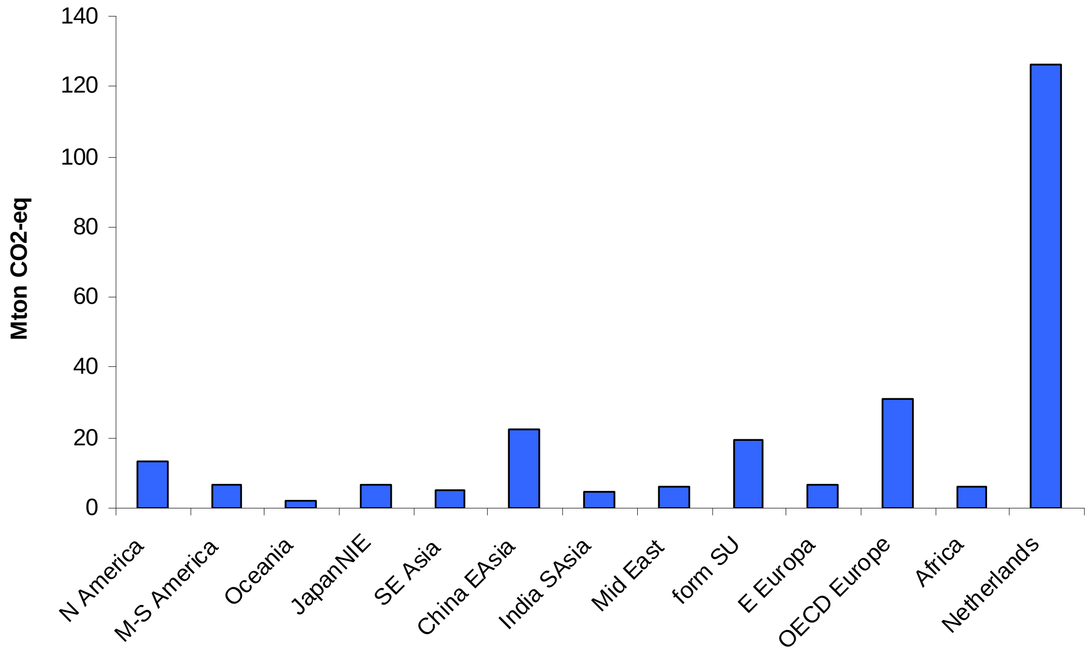

Figure 1 Contribution in CF of the Netherlands per region, in 2001.

In each region, emissions related to Dutch consumption were allocated to the individual sectors. Figure 2 shows the emissions per sector summed up over all regions. Direct GHG emissions of household and government consumption and landfills contributed almost 20% (48 Mton CO_2-eq.) in total Dutch CF. Furthermore, the production of electricity was a main contributor to the CF since electricity use is essential in many production processes. The electricity sectors in the Netherlands, OECD Europe, East Asia, former Soviet Union and North America, all had an important contribution (is not visible in the figure). Other important sectors in the Dutch CF were the food-related sectors and transport.

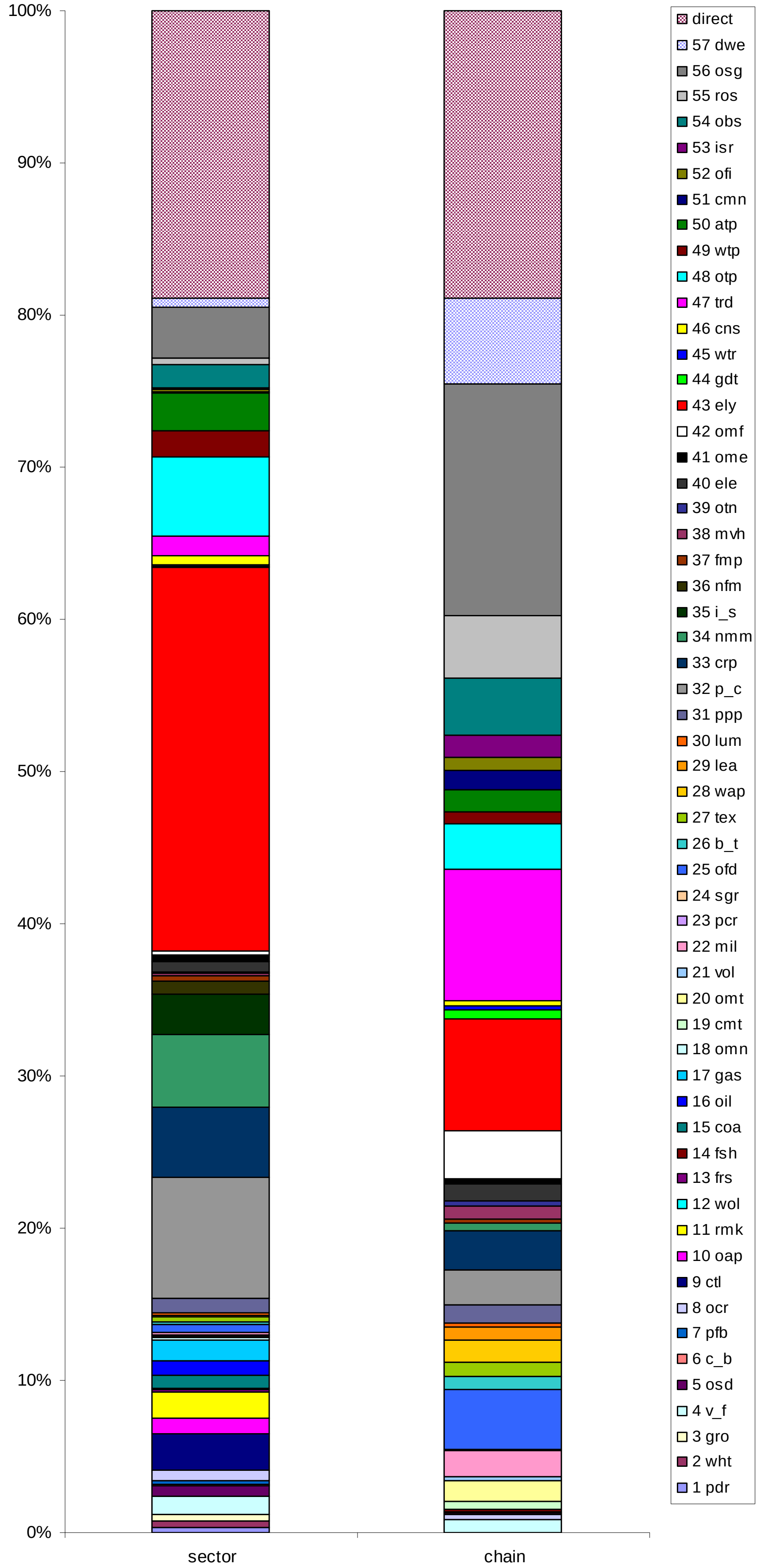

Figure 2 Contributions in Dutch CF per sector and per chain, in 2001.

Figure 2 also shows the contribution of supply chains in the Dutch CF from the perspective of consumption. Chains were considered until the final producing industry delivering to final demand. Trade and transport margins were not assigned to the different consumption categories (as was done in Wilting, 2008), but kept separately. The GHG emissions of chains are the combined effects of the volumes in consumption and the total emission intensities for the whole chain. Chains with an important contribution in the CF have a high share in consumption, like services, or have high emission intensities, like electricity and food products.

3. Uncertainty analysis

Starting from equations 4 and 5, an uncertainty analysis was carried out in order to investigate the reliability of the Dutch CF. On the basis of uncertainty intervals around the elements of the model parameters, viz. the direct GHG intensities **d**, the technical coefficients matrix **A**, consumption vector **y**, and direct GHG emissions **D**, conclusions were drawn on the uncertainty of the total CF and the more detailed outcomes. These uncertainty intervals around the parameters were based on assumptions on the uncertainties in the underlying data and data construction. E.g. the uncertainty intervals around the technical coefficients were based on the uncertainties in the original IO tables (domestic and imports), total production, the trade data and the assumptions in constructing the MRIO table from all these data. Since it was too laborious to determine the uncertainty interval for each coefficient, some general assumptions were made for groups of coefficients. In order to gain better understanding of the propagation of uncertainties through matrix inversion, first, only uncertainties in the technical coefficients matrix were considered. After that, uncertainties in all model parameters were considered in order to investigate the overall uncertainties in the CF results.

3.1 Uncertainties in the technical coefficients matrix

Due to lack of information on the uncertainties in the technical coefficients, uniform distributions were assumed for all coefficients. Given boundaries for the uncertainty intervals for all technical coefficients, both the theoretical maximum uncertainties in the CF were determined as well as more realistic uncertainties in a Monte Carlo approach.

3.1.1 Maximum uncertainties

Starting from certain uncertainty intervals around the elements of the technical coefficients matrix, Sebald (1974) determined analytically upper and lower bounds for the uncertainties in the Leontief inverse matrix. He assumed that each element of the technical coefficients matrix, $\mathbf{A_{ij}}$, lies in a specific interval $[\boldsymbol{\alpha_{ij}}, \boldsymbol{\beta_{ij}}]$ around the nominal value (with $\boldsymbol{\alpha_{ij}} <= \mathbf{0}$, $\boldsymbol{\beta_{ij}} >= \mathbf{0}$). The selection of values from these intervals leads to an unlimited number of technical coefficients matrices $\mathbf{A^n}$. For each matrix $\mathbf{A^n}$, the Leontief inverse matrix, $\mathbf{B^n = (I\text{-}A^n)^{-1}}$, can be calculated[2]. For each element of the original Leontief inverse matrix, $\mathbf{B_{ij}}$, there exists an interval $[\boldsymbol{\gamma_{ij}}, \boldsymbol{\delta_{ij}}]$, $\boldsymbol{\gamma_{ij}} <= \mathbf{0}$, $\boldsymbol{\delta_{ij}} >= \mathbf{0}$, that contains all possible values of the corresponding element in $\mathbf{B^n}$. Sebald (1974) raised the question what the intervals for the elements of $\mathbf{B}$ should be, so that for all possible matrices $\mathbf{B^n}$, all elements lie in these intervals[3]. He demonstrated that for each $\mathbf{A}$ there exists one specific $\mathbf{A^n}$, so that for each element of $\mathbf{B}$ the difference with the corresponding element of $\mathbf{B^n}$ has its maximum value. This 'bad' case arises when all technical coefficients have their extreme deviations in the same direction. The elements of $\mathbf{B^n}$ have their maximum value, $\boldsymbol{\delta_{ij}}$, if for all elements of $\mathbf{A^n}$ the value $\boldsymbol{\beta_{ij}}$ is chosen. The elements of $\mathbf{B^n}$ have their minimum value, $\boldsymbol{\gamma_{ij}}$, if for all elements of $\mathbf{A^n}$ the value $\boldsymbol{\alpha_{ij}}$ is chosen.

Wilting and Biesiot (1993) carried out empirical investigations for a Dutch 1987 IO table in which the same deviation was assumed for all elements of $\mathbf{A}$. For all elements of $\mathbf{B^n}$ the maximum positive and negative relative deviations according to the elements in $\mathbf{B}$ were calculated. The results of these investigations were:

- the relative deviations in the elements of $\mathbf{B^n}$ were much higher than the original deviations in the elements of $\mathbf{A^n}$;
- elements of $\mathbf{B}$ with a high value showed low values in the matrix of relative deviations between $\mathbf{B}$ and $\mathbf{B^n}$;
- the absolute values of the negative deviations were smaller than those of the positive deviations (Bullard and Sebald (1977) concluded the same);

---

[2] In case the newly derived technical coefficients matrix still suffices certain conditions.
[3] Sebald called this problem the tolerance problem.

- a comparison of the outcomes of the calculations for different values of $\boldsymbol{\beta_{ij}}$, viz. 1%, 5%, and 10%, showed that the deviations in the elements of $\mathbf{B^n}$, $\boldsymbol{\delta_{ij}}$, grew more than proportionally with higher deviations $\boldsymbol{\beta_{ij}}$ in $\mathbf{A^n}$.

These investigations showed that the elements of the Leontief inverse matrix were not equally influenced by the same deviations in the technical coefficients.

As a first exercise for determining the uncertainties in the Dutch CF we assumed an uncertainty of 10% for all technical coefficients. After calculation of the Leontief inverse matrices with the maximum deviations, the effect of the changes in these matrices on the CF was calculated. The boundaries of the uncertainty interval for the CF were -20% and +34%. So, the matrix inversion enlarged the boundaries of the outcomes. For the emissions allocated to regions, the maximum boundaries on the basis of uncertainties of 10% in all technical coefficients were more extreme. Especially the GHG emissions allocated to the Chinese region and the former Soviet Union showed large intervals with positive boundaries of more than 80%. The boundaries of the interval for the contribution of the domestic emissions in the Netherlands were -7% and +9%. These values are low, since the direct emissions of consumption, which were not affected by changes in the technical coefficients matrix, were included in the CF. For emissions allocated to sectors, the average maximum boundary in GHG emissions was 37% with maximum values over 80%. For the GHG emissions allocated to chains, the average maximum boundary was 32% with for no chain boundaries higher than 67%.

Emissions allocated to sectors and regions are based on production which is based on the technical coefficients in rows. The emissions allocated to chains are based on total GHG intensities which are based on technical coefficients in columns. All the calculations demonstrated the amplifying effect of the Leontief multipliers to the uncertainties.

3.1.2 Uncertainties based on Monte Carlo analysis

Above, upper and lower bounds were determined for the Dutch CF given boundaries for the technical coefficients. It is emphasized that these maximum boundaries occur in the most unfavourable case, in which all technical coefficients had a maximum deviation in the same direction. However, in practice, not all deviations in the technical coefficients matrix lie in the same direction. Since the sum and column totals of the intermediate matrix are determined on the basis of other data too, the uncertainties in these totals will be low. So, the probability that all technical coefficients deviate in the same direction is low too (Bullard and Sebald, 1977). Therefore, a stochastic approach was recommended, which assumes random uncertainties around the coefficients, expecting much lower uncertainties in the Leontief inverse matrix. Bullard and Sebald (1988) confirmed this expectancy. For the Dutch CF, a stochastic analysis was carried out via a Monte Carlo simulation in which the CF and related outcomes were calculated many times.

Similar to the maximum approach in the previous section an uncertainty interval with a uniform distribution was assumed around each element of the technical coefficients matrix, **A**. The random draw of a value in that interval for all elements of **A** generated a new matrix $\mathbf{A}^n$ for which the Leontief inverse matrix was determined. Subsequently, by using this new Leontief inverse matrix and the other parameters in equation 5, the CF was calculated. By repeating this procedure several times a number of CF's was generated. In this research, the described computation was carried out 10000 times[4]. At the end, the mean and the standard deviations around these values were calculated. The standard deviation of the outcomes of the simulation gives insights in the uncertainties of the CF.

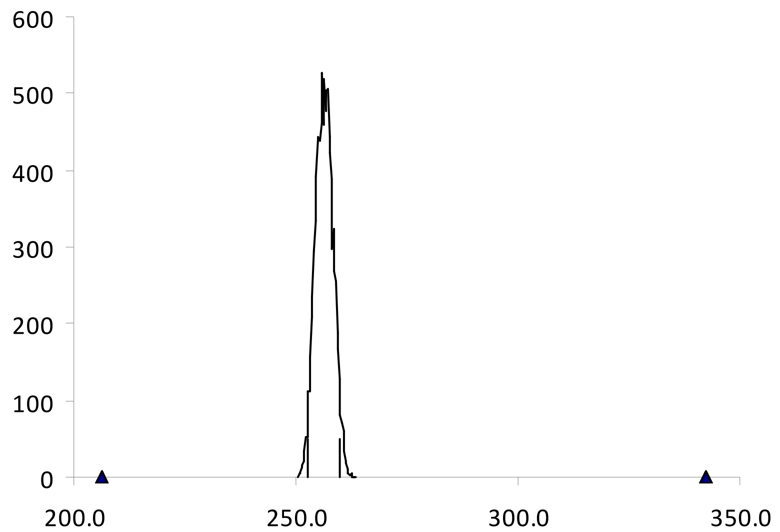

Figure 3 Distribution around total CF (10000 simulations) with 95% (line) and maximum (triangle) confidence intervals.

[4] A disadvantage of a stochastic approach is the large number of matrix inversions that has to be carried out. Computer time at a standard laptop was almost seven hours for 10000 iterations (2.5 second per iteration).

Figure 3 shows the results for all outcomes (10000) of the calculations of the CF. For all outcomes, the calculated values were much smaller than the maximum boundaries calculated in the previous section. The 95% confidence interval based on the distribution of the outcomes of the Monte Carlo analysis was between 252.6 and 260.0 Mton (-1.4% and 1.5%). In case of a normal distribution, the 95% confidence interval can be calculated with the so-called Student's t distribution (the t-value is 1.96) and the standard deviation. The 95% confidence interval based on the standard deviation was 1.5% too.

Table 1 shows for the five supply chains with the highest uncertainties the outcomes of the Monte Carlo simulation. The table shows the mean value of the emissions (based on the iterations), the theoretical minimum and maximum deviations and the 95% confidence intervals based on the distributions around the mean values. The 95% confidence intervals around the GHG emissions allocated to chains were about 7% at the most and until a factor 50 smaller than the maximum intervals. The last column shows the 95% boundary of the GHG emissions calculated on the basis of the t-value and the standard deviation (assuming a normal distribution). In case of normal distributions, the confidence intervals calculated in this way are quite similar to the intervals based on the Monte Carlo simulation. In case of more uniform distributions, the confidence intervals based on the distribution are smaller than the confidence intervals based on the standard deviation. In general, confidence intervals calculated with the t-value seem to be good upper estimations of the uncertainties in the GHG emissions.

Table 1 ***GHG emissions of 5 supply chains based on 10000 draws (with uncertainties in the technical coefficients). Mean emissions (from model and iterations), maximum positive (max) and negative deviations (min) and 95% confidence intervals based on distribution (95-dis) and standard deviation (95-std).***

	model Mton	MC Mton	min %	max %	95-dis %	95-dis %	95-std %
43 ely	18.97	19.00	-9.5	13.3	-5.8	6.3	7.2
22 mil	4.57	4.57	-19.0	28.5	-6.1	6.2	7.0
44 gdt	1.49	1.49	-26.9	46.0	-5.6	5.7	6.1
57 dwe	14.58	14.58	-33.3	61.3	-4.8	5.1	5.3
23 pcr	0.04	0.04	-14.4	18.6	-4.7	4.7	5.2

In the previous section, the same uncertainties were assumed for all technical coefficients. In practice, not all elements of an IO table have the same reliability. In general, the deliveries to industrial sectors are better known than the deliveries to service sectors. Further, IO data are more precise for those economic sectors that consist of only a few companies. These sectors are fully investigated, while the investigations of sectors with many companies are based on samples. Due to these differences in input characteristics, two groups of sectors were distinguished with different uncertainties in their inputs from other sectors:

A. manufacturing, construction and energy sectors (sectors 15-46);

B. agriculture, trade and services (sectors 1-14; 47-57).

Furthermore, the imports are more uncertain than the domestic inputs of sectors, since the import blocks were constructed in the compilation of the technical coefficients matrix on the basis of bilateral trade data. The considerations stated above led to a division in uncertainties in the technical coefficients matrix (Table 2). Since there was no information available about the probability distribution function, uniform distributions were assumed for the technical coefficients again.

Table 2 Assumptions on uncertainties (%) in technical coefficients (columns) for two groups of sectors in the Monte Carlo analysis.

	Group A	**Group B**
Domestic inputs from A	5	10
Domestic inputs from B	10	20
Imports from A	10	20
Imports from B	20	40

The Monte Carlo simulation based on the uncertainties in table 2 resulted in a 95% confidence interval for the Dutch CF of only 1.2%. Despite of the higher uncertainties in the imports, the uncertainties in the emissions allocated to chains are lower or in the same order as in the previous case in which no groups of sectors were distinguished. So, the import blocks are of less importance in the calculation of the CF.

3.2 Uncertainties in all model parameters

The other parameters of the MRIO model, viz. GHG intensities, final demand and direct emissions from consumption and landfills, will have uncertainties too. In a complete uncertainty analysis, the effects of uncertainties in all model parameters were investigated. Uncertainties in direct GHG intensities per sector were based on the uncertainties in GHG emissions and production per sector. Uncertainties in emissions are different for the specific greenhouse gases. Monitoring data on CO_2 emissions, e.g., are far more reliable than data on the other GHG emissions. Detailed information was available on uncertainties at the level of processes for the emissions in the Netherlands (Olivier *et al.*, 2009). This information was not available for the data on emissions abroad (in the EDGAR database), but it was expected that the emissions reported in the EDGAR database were more uncertain than the emissions reported for the Netherlands. Furthermore, the foreign emissions were reported at a higher aggregation level, so that emissions had to be distributed over sectors. Therefore, we distinguished uncertainties in Dutch emissions and uncertainties in emissions in other regions. For each greenhouse gas, the same uncertainty was assumed for all sectors and direct emissions of (household and government) consumption and landfills (see Table 3). The probability distribution functions were based on normal distributions (Olivier *et al.*, 2009). By using assumptions on uncertainties in production per sector and error propagation rules for normal distributions, uncertainty intervals for GHG intensities were calculated. The uncertainties for production and final demand of economic sectors are listed in Table 4.

Table 3 Assumed uncertainties (%) in GHG emissions per gas in the Netherlands (NL) and abroad (95% confidence intervals).

	CO_2	CH_4	N_2O	F-gases
NL	3	25	50	50
Other regions	6	50	75	75

The uncertainties in the direct GHG intensities, the technical coefficients matrix, the final demand vector and direct GHG emissions were combined in a Monte Carlo simulation of 10000 runs in which in each run values were drawn randomly from the confidence intervals around the values given the probability distributions. The 95%-confidence interval (based on distribution and standard deviation around the mean) for the Dutch CF was about 3.5% (9 Mton CO_2 eq.) which is remarkably higher than in the previous simulations based on uncertainties in technical coefficients only.

Table 4 Assumed uncertainties (%) in production and final demand for 2 groups of sectors in the Netherlands (NL) and abroad (95% confidence intervals).

	Production	Final demand
NL - group A	3	5
NL - group B	6	10
Other regions - group A	6	10
Other regions - group B	12	20

Uncertainties were higher for emissions allocated to specific regions, sectors and chains. Table 5 shows for the contributions of all regions in Dutch CF the uncertainties as 95% confidence intervals. Regions with a high share in non-CO_2 GHG emissions show the highest uncertainties. These regions contributed to the Dutch footprint mainly through agriculture. The minimum and maximum values in the table concern the minimum and maximum values that appeared in the Monte Carlo analysis (and are different from the minimum and maximum values in the previous section).

Table 5 Outcomes of Monte Carlo analysis concerning GHG emissions per region. Mean, minimum, maximum and 95% confidence interval based on 10000 simulations.

	mean Mton	min %	max %	95-std %
N America	13.3	-13.5	14.1	6.8
M-S America	6.8	-27.9	29.6	15.5
Oceania	2.0	-18.1	17.5	9.3
JapanNIE	6.9	-12.8	11.4	6.0
SE Asia	5.1	-13.4	14.0	7.1
China EAsia	22.1	-12.0	15.3	6.6
India SAsia	4.4	-13.3	14.0	7.1
Mid East	6.3	-11.9	13.8	6.8
form SU	19.5	-12.9	12.7	7.0
E Europa	6.5	-10.2	10.5	5.4
OECD Europe	31.1	-10.4	11.4	5.8
Africa	6.1	-20.7	21.0	10.4
Netherlands	126.1	-9.2	9.4	4.9

Table 6 shows the uncertainties at the sectoral and chain level. Uncertainties allocated to sectors varied from 4% to 50%. Sectors with the highest uncertainties were sectors like agricultural sectors with a high contribution of non-CO_2 GHG emissions. Uncertainties allocated to chains varied from 4% to slightly more than 30%. Chains with high uncertainties were agricultural and food products.

Table 6 Outcomes of Monte Carlo analysis concerning GHG emissions per sector and chain. Mean, minimum, maximum and 95% confidence interval based on 10000 simulations.

	sector				chain			
	mean Mton	min %	max %	95-std %	mean Mton	min %	max %	95-std %
1 pdr	0.9	-44.5	53.0	26.3	0.0	0.0	0.0	0.0
2 wht	1.1	-93.4	96.5	47.1	0.0	0.0	0.0	0.0
3 gro	1.1	-81.1	98.1	44.2	0.0	0.0	0.0	0.0
4 v_f	2.9	-44.8	50.9	23.0	2.2	-39.1	41.6	19.8
5 osd	1.8	-91.2	102.2	50.1	0.0	0.0	0.0	0.0
6 c_b	0.3	-74.8	77.9	34.9	0.0	0.0	0.0	0.0
7 pfb	0.5	-75.9	75.9	39.5	0.0	0.0	0.0	0.0
8 ocr	1.9	-62.5	59.6	32.3	0.8	-39.7	42.4	20.4
9 ctl	6.1	-35.1	37.4	17.8	0.0	0.0	0.0	0.0
10 oap	2.5	-48.2	49.8	25.0	0.2	-48.5	48.3	25.2
11 rmk	4.4	-48.6	59.0	27.6	0.1	-53.6	68.0	31.6
12 wol	0.0	-21.7	25.7	13.2	0.0	0.0	0.0	0.0
13 frs	0.3	-41.2	51.3	23.0	0.3	-22.3	23.8	12.7
14 fsh	0.3	-14.6	16.0	8.2	0.4	-14.9	17.3	10.7
15 coa	2.1	-43.3	46.0	21.7	0.0	0.0	0.0	0.0
16 oil	2.4	-37.7	36.1	19.9	0.0	0.0	0.0	0.0
17 gas	3.7	-31.7	40.5	17.7	0.0	-16.3	18.0	9.5
18 omn	0.4	-10.3	10.2	5.1	0.1	-6.9	7.1	4.0
19 cmt	0.1	-9.8	10.7	5.7	1.2	-35.7	38.0	17.6
20 omt	0.1	-9.4	11.5	5.3	3.6	-21.8	27.3	12.4
21 vol	0.1	-11.4	12.2	6.2	0.6	-26.6	24.4	13.7
22 mil	0.4	-12.3	12.6	6.2	4.6	-34.2	46.4	19.8
23 pcr	0.0	-9.4	12.2	5.0	0.0	-41.9	56.3	23.8
24 sgr	0.1	-8.0	9.7	4.4	0.1	-51.0	51.9	24.5
25 ofd	1.4	-10.8	11.1	5.9	10.0	-15.6	17.1	9.2
26 b_t	0.3	-10.0	11.2	5.6	2.3	-13.2	14.3	7.4
27 tex	0.9	-8.2	8.1	4.3	2.2	-8.1	8.6	4.9
28 wap	0.2	-7.6	8.1	4.6	3.9	-9.7	10.1	5.3
29 lea	0.1	-8.3	8.3	4.8	2.1	-18.6	22.5	11.2
30 lum	0.3	-10.5	11.0	5.6	0.7	-8.1	8.4	4.9
31 ppp	2.4	-9.0	12.5	5.4	3.0	-8.6	9.4	5.6
32 p_c	20.4	-8.9	10.3	5.1	5.9	-10.5	12.0	6.4
33 crp	11.9	-15.6	18.3	8.1	6.7	-14.0	12.1	6.2
34 nmm	12.1	-10.3	13.6	5.3	1.2	-8.0	8.3	5.3

35 i_s	6.8	-9.5	10.1	5.2	0.0	-11.0	11.0	7.0
36 nfm	2.3	-21.5	21.5	10.6	0.0	-44.8	43.8	22.7
37 fmp	0.9	-10.8	11.2	5.6	0.7	-9.0	9.2	5.4
38 mvh	0.4	-13.2	13.9	7.0	2.2	-11.0	12.1	9.3
39 otn	0.2	-11.8	11.3	5.7	0.9	-6.8	7.6	4.1
40 ele	1.8	-50.6	56.2	25.6	2.9	-10.3	12.2	5.7
41 ome	1.0	-10.4	10.5	5.4	0.9	-7.4	7.3	4.5
42 omf	0.8	-10.2	10.5	5.7	8.0	-11.0	10.5	6.1
43 ely	64.6	-8.9	10.1	5.3	19.0	-14.6	16.8	8.7
44 gdt	0.4	-7.9	9.2	4.7	1.5	-11.3	12.5	7.6
45 wtr	0.2	-20.7	22.9	11.2	0.7	-10.9	11.3	6.8
46 cns	1.5	-13.7	18.1	8.5	0.8	-9.8	10.4	6.5
47 trd	3.3	-17.7	19.6	10.6	22.1	-15.1	16.4	11.9
48 otp	13.3	-10.7	12.6	6.1	7.7	-14.4	16.9	11.0
49 wtp	4.5	-12.5	11.6	6.4	1.9	-13.1	13.8	8.5
50 atp	6.4	-16.3	16.9	8.8	3.8	-16.3	14.9	8.8
51 cmn	0.2	-16.7	18.4	8.9	3.2	-18.0	22.6	12.9
52 ofi	0.4	-18.5	19.9	9.5	2.2	-21.2	20.9	13.5
53 isr	0.2	-16.7	19.7	10.2	3.6	-18.1	21.2	13.6
54 obs	3.9	-19.8	22.9	11.4	9.6	-12.4	14.4	8.0
55 ros	1.1	-17.4	18.8	11.2	10.7	-17.8	21.5	13.2
56 osg	8.5	-21.8	22.9	13.7	38.8	-15.7	16.7	12.1
57 dwe	1.7	-20.4	23.6	13.2	14.6	-17.1	18.6	12.8

4. Sensitivity analysis

Generally, sensitivity analysis is used to investigate for the parameters of a specific model the effect of a variation in those parameters on the model outcomes. In this way, the most important elements of the model parameters, which have the largest effects on the model outcomes, can be determined. Sensitivity analyses have been performed before in economic IO analysis (Sebald, 1974; Viet, 1980). These analyses concerned the effect of variations in one element of the technical coefficients matrix on the Leontief inverse matrix. Van der Linden and Oosterhaven (1995) investigated changes in columns of the technical coefficients matrix corresponding with technological change. Sonis and Hewings (1992) presented a general approach to investigate coefficient changes in single elements, all element in a row or column, or all elements in the technical coefficients matrix. Viet (1980) compared two methods of sensitivity analysis: the Sebald method and the Sekulic method. Both methods differ in the way in which they identify the most important elements (see below). Sekulic (described by

Viet, 1980) also investigated the effects on sectoral production. Wilting and Biesiot (1993) extended the methods presented by Sebald and Viet to energy analysis. In the research described in this paper, sensitivity analysis was applied to CF analysis by considering the effects of changes in the technical coefficients matrix on the Dutch CF. Both effects of changing whole blocks as individual coefficients were considered. Effects of changes in the direct GHG intensities and final demand were not investigated. Equation 4 was the basis for the investigations of the effect on the GHG intensities. The effect on the CF was analysed with equation 5.

4.1 Changes in regional blocks of technical coefficients

As a variation of the uncertainty analysis in which for all elements an uncertainty of 10 was assumed (section 3.1), a sensitivity analysis was carried out in which all 3249 (= 57 * 57) elements per (domestic or trade) block were given a 10% change. This gives insights in the sensitivity of the model outcomes per block of coefficients. Figure 4 shows for each of the 169 (= 13 * 13) blocks in the technical coefficients matrix the effects on total CF.

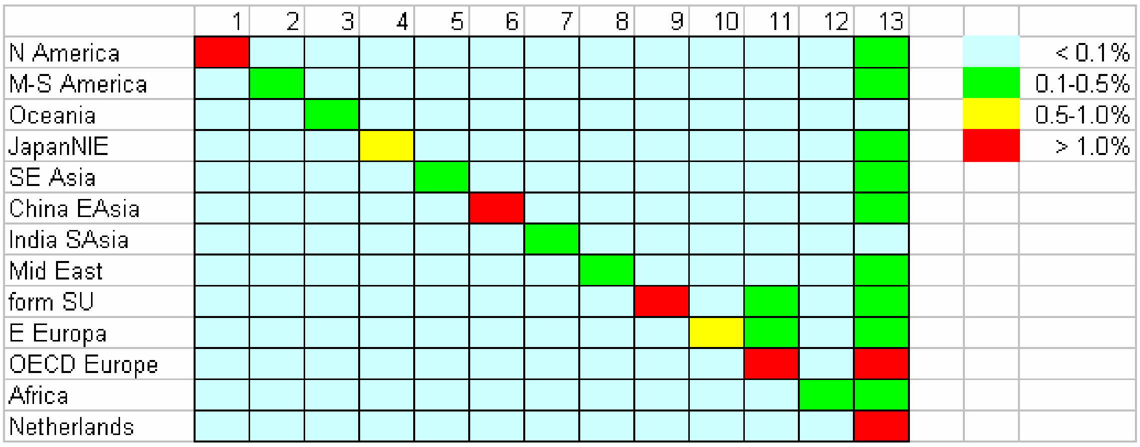

Figure 4 Effect on Dutch CF (%) as a result of a 10% change in all elements per block.

Most important blocks were the domestic blocks concerning the Netherlands (7.9%), the Chinese region (4.3%) and OECD Europe (3.4%). Furthermore, most of the import blocks of the Netherlands and some of OECD Europe were important. The effect on CF summed up over all blocks was 29%. Due to combined effects, this value is lower than the maximum effect of 34% which was calculated as the effect of a 10% change in all technical coefficients together (in section 3).

For individual chains, the pattern may be different. Figure 5, as an example, shows the important blocks in the CF of motor vehicles and parts (chain 38). High effects on the outcomes have the domestic blocks of those regions that produce cars for the Dutch market and some of their main import blocks. Another example of a chain with high contributions of import blocks in other regions is the clothes chain (sector 28 wearing apparel).

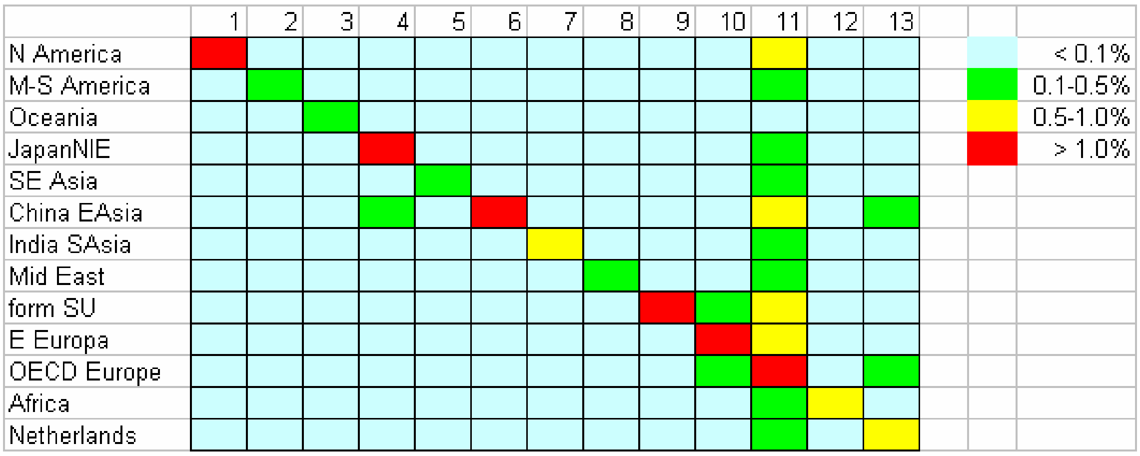

Figure 5 Effect on the CF of cars (chain 38) consumed in the Netherlands as a result of a 10% change in all elements per block.

4.2 Changes in single technical coefficients

This section investigates the effects of a change in one element of the technical coefficients matrix on GHG intensities and CF. For technical coefficient $\mathbf{A_{ij}}$, a deviation $\boldsymbol{\varphi}$ is assumed[5]. The other technical coefficients remain unchanged. The matrix $\mathbf{A^n}$ is defined as:

$$\mathbf{A^n = A + F} \tag{6}$$

All elements of $\mathbf{F}$ are zero except $\mathbf{F_{ij}}$ is equal to $\boldsymbol{\varphi}$. Based on the new technical coefficients matrix $\mathbf{A^n}$, the changes in the GHG intensity vector are determined under the assumption that the direct GHG intensities remain unchanged. The notation for the change in the intensities as a result of the change in $\mathbf{A_{ij}}$ is $\mathbf{h^{ij}}$. So, $\mathbf{h^{ij}}$ is defined as:

$$\mathbf{h^{ij} = e^n - e} \tag{7}$$

Viet (1980) gives a derivation for the change in total production as a result of the change in the technical coefficients matrix. Similarly, Wilting and Biesiot (1993)

[5] Oositive changes in the coefficients are assumed; equations for negative values are derived analogously.

derived an equation for the change in energy intensities (see Appendix C). This equation was used for the change in the GHG intensity vector **h**:

$$h_k^{ij} = \frac{e_i F_{ij} B_{jk}}{1 - F_{ij} B_{ji}}, \forall k = 1, .., n \tag{8}$$

where $\mathbf{h_k^{ij}}$ is the change in the GHG intensity of sector *k* as a result of a change in technical coefficient $\mathbf{A_{ij}}$. The calculation of the changes in the GHG intensities only requires the GHG intensity vector, **e**, and the Leontief inverse matrix, **B**. The equation is very practical, since only one matrix has to be inverted to calculate the effects for all individual coefficients. Given the effects of a change in a single technical coefficient on the GHG intensities, the effect on the Dutch CF can be determined as follows:

$$\Delta^{ij} = \sum_{k=1}^{n} h_k^{ij} y_k \tag{9}$$

with $\mathbf{\Delta^{ij}}$ the total change in CF as a result of the change $\boldsymbol{\varphi}$ in technical coefficient $\mathbf{A_{ij}}$ of the s matrix. In this way the effect of a change on CF can be calculated for all technical coefficients in order to determine the importance per technical coefficient.

Equations 8 and 9 were applied to investigate the sensitivity of the CF for changes in single technical coefficients. Totally, there are 549081 (= 13*57*13*57) technical coefficients in the MRIO model of which 126500 are zero. For the remaining 422581 coefficients the effect of a 10% change on total CF was calculated. The average effect was about 0.12 kton CO_2-eq. which is very small compared to the total footprint of 256 Mton. Slightly more than 20000 coefficients showed an effect higher than the average. The coefficient corresponding with the intra-sectoral deliveries in the Dutch electricity sector showed the highest effect (about 1% of the CF). Some other coefficients in the Dutch domestic part of the technical coefficients matrix showed high effects too.

All effects of the changes were ordered with the elements with the highest changes on top and the top 5000 of the ordered list were considered. More than 70 of these 5000 elements belonged to the diagonal blocks of the technical coefficients matrix, which were based on the domestic IO tables of the 13 regions. Figure 6 shows for all regions the number of important elements in the domestic block and in the import blocks. Only the import blocks of the Netherlands and in some extent those of OECD Europe consist of a considerable number of important coefficients. The trade blocks related to Dutch imports with the highest number of important coefficients concern the imports from OECD Europe, Japan and the new industrializing economies, and North America. For most regions, only the coefficients in the domestic block were important for the Dutch CF.

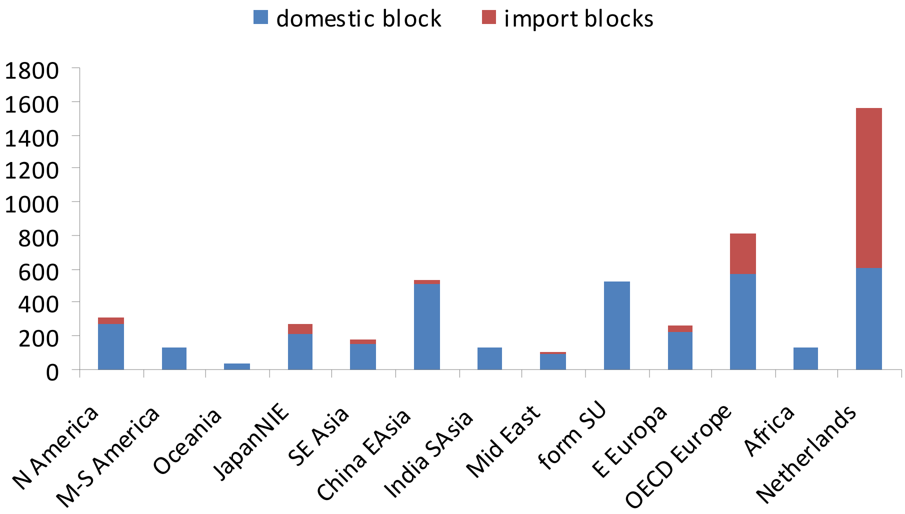

Figure 6 Number of important coefficients in domestic blocks and trade blocks per region (for the 5000 most important coefficients).

4.3 Identification of important coefficients for chains

In the previous section, the most important parameters were defined as the coefficients that cause the largest change in the CF. An additional investigation concerned the determination of important coefficients in relation to the GHG emissions of chains. The investigation is based on the method that Sebald applied in investigating the effect of changes in the technical coefficients matrix on the Leontief inverse matrix (Sebald called this the ‘Most Important Parameter’ problem). He calculated for a specific change in technical coefficient $\mathbf{A}_{ij}$ all changes in the Leontief inverse matrix $\mathbf{B}$. He defined $\mathbf{A}_{ij}$ as important compared to element $\mathbf{B}_{kl}$ of $\mathbf{B}$ in case the change in $\mathbf{A}_{ij}$ effects at least a certain percentage change in $\mathbf{B}_{kl}$. The importance of coefficient $\mathbf{A}_{ij}$ was determined by counting the elements of $\mathbf{B}$ for which $\mathbf{A}_{ij}$ was important. Most important wee those technical coefficients which were most often important compared to the elements of $\mathbf{B}$[6].

[6] Sekulic determined the most important elements differently. He started from the opposite: how much may an element change at most, so that no element of the total production vector changes with more than a fixed percentage.

Now, the effect of a change in each single coefficient on the GHG emissions of 47 chains was calculated[7]. A coefficient was defined as important for a specific chain when the change in the coefficient resulted in a certain effect in the chain (in our case 0.005% of the GHG emissions of the chain). So, a change in a coefficient may be important for some of the 47 chains. For each coefficient, it was counted for how many chains the coefficient was important. By repeating this procedure for all coefficients, 21 coefficients were found that were important for all 47 chains (Figure 7). All of these coefficients belonged to the domestic coefficients of other regions: 9 in the Chinese region, 6 in the former Soviet Union and 6 in OECD Europe. The energy sectors and basic industries (chemicals, minerals, metals) were some of the sectors that played a role in all chains. None of the coefficients in the Dutch domestic part of the table was important for all chains. On the other hand, 5657 coefficients were important for the emissions of only one chain and more than half a million coefficients were important for no chain at all (in case of a effect of 0.005% in the chain emissions).

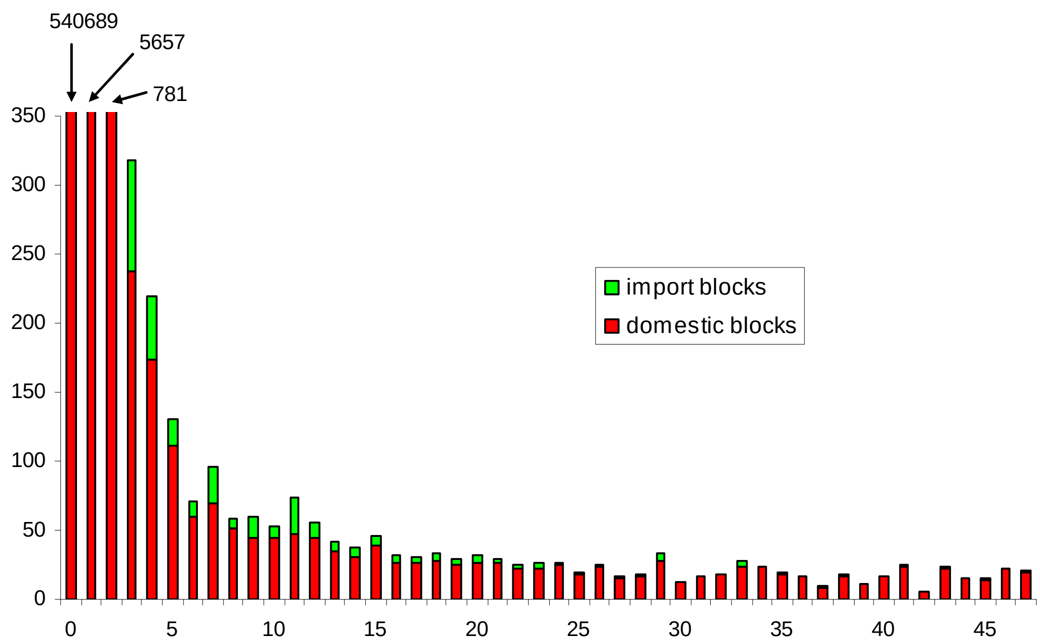

Figure 7 Number of times that coefficients are important for chains.

Figure 7 also shows that most important coefficients for chains belonged to the diagonal blocks, which correspond to the domestic IO tables of the 13 regions. Most non-

[7] For 10 chains, emissions were zero, since consumption was zero.

diagonal block coefficients that were important belonged to the import blocks of the Netherlands.

5. Partial MRIO versus full MRIO

It can be concluded from the sensitivity analysis and in some sense of the uncertainty analysis that the import blocks of the foreign regions (exclusive the Netherlands) in the MRIO table were of less importance for the total Dutch CF. Therefore, it may be conceivable that a partial MRIO analysis will be sufficient for calculating the CF. So, a partial MRIO analysis was carried out starting from the full MRIO table. A partial MRIO table was constructed by adding the import blocks of the foreign region to the domestic blocks per region. The import blocks of the foreign regions were set to zero. In this way, the supply chains are truncated in the regions that export to the Netherlands and for the imports of these regions it was assumed that they were produced in those regions (with the region-specific technologies). Only the import blocks of the Netherlands remained unchanged.

The total Dutch CF calculated with the partial MRIO model was 258.4 Mton, which was less than 1% higher than the CF based on the full MRIO. The calculated value even lies in the 95% uncertainty interval of the CF calculated in section 3. Differences between the outcomes of the partial and full MRIO analysis were small too for most GHG emissions allocated to sectors and chains. At the sectoral level, the sectors concerning extraction of energy sources like coal, oil and natural gas showed the largest differences since the use of specific energy sources is region-specific. Since, chains were truncated in the partial model and the region-specific information was lost. The partial model overestimated the GHG emissions of clothes (with 22%) and electric equipment (with 11%) and underestimated the CF of motor vehicles (with 21%). The differences in GHG emissions were much smaller for other chains. A partial MRIO analysis is less appropriate for allocating emissions to regions of course, since chains are truncated. E.g. the emissions allocated to Eastern Europe were more than 75% higher and emissions allocated to Oceania were more than 30% lower in the partial analysis compared to the full MRIO analysis due to truncation.

In practice, differences in outcomes based on both MRIO methods may be larger. In this study, the partial MRIO table was based on the full MRIO table, which was not re-balanced after allocating the trade flows to regions. The re-balancing process may cause larger differences between both approaches. Furthermore, in partial MRIO modeling, data may be collected that was not made consistent at the global level.

6. Conclusions and recommendations

In this paper, some empirical results were described of an uncertainty and sensitivity analysis of an MRIO model for calculating the Dutch CF. Some conclusions and recommendations are:

- The Monte Carlo simulation concerning the uncertainties in the technical coefficients showed low uncertainties in the model outcomes. The inclusion of uncertainties in final demand and GHG emissions in the analysis resulted in higher uncertainties, but these uncertainties were still at an acceptable level. Especially sectors and chains with high shares in non-CO_2 GHG emissions showed high uncertainties in emissions. The technical coefficients in the non-diagonal blocks were assigned higher uncertainties, but this seemed to have little influence on the overall uncertainties.

- Due to lack of information the uncertainty analysis started from the technical coefficients with uncertainty intervals estimated by the author. The availability of insights in uncertainties in 'raw' IO and trade data might enable a more complete uncertainty analysis including the uncertainties in the construction of the technical coefficients matrix.

- Both the sensitivity analysis per block of coefficients as the sensitivity analysis per coefficient showed the importance of the diagonal blocks in the technical coefficients matrix. Changes in these coefficients had the largest effects on total carbon footprint and emissions of chains. Furthermore the import blocs of the Netherlands showed a considerable effect in the Dutch CF. For specific chains, import blocs of regions with high exports to the Netherlands were recognized as important. So, it may be concluded that in improving IO tables and data, the coefficients in the domestic tables and the imports to the region under consideration should require most attention.

- The differences between the Dutch CF based on a partial and full MRIO analysis were small. Therefore, for some applications, e.g. the trend in the CF of a nation, as carried out by Lenzen *et al.* (2010) for the UK, a partial analysis may be sufficient. For specific purposes, like a regional distribution of the GHG emissions or a detailed supply-chain analysis, a full MRIO analysis is still recommended.

- All outcomes apply for the Dutch CF based on the Dutch situation, i.e. production structure, trade structure and emissions. Since it is not clear in advance if the conclusions hold for other regions or environmental pressures further empirical analyses will be useful.

References

Bullard, C.W., Sebald, A.V. (1977), Effects of parametric uncertainty and technological change on input-output models, **Review of Economics and Statistics**, 59, pp. 75-81.

Bullard, C.W., Sebald, A.V. (1988), Monte Carlo sensitivity analysis of input-output models, **Review of Economics and Statistics**, 70, pp. 708-712.

CBS (2007) **Milieurekeningen 2006** (Voorburg, Statistics Netherlands).

Dimaranan, B.V., ed. (2006) **Global Trade, Assistance, and Production: The GTAP 6 Data Base** (West Lafayette, Center for Global Trade Analysis).

ESR (2009), Special Issue: Carbon Footprint and Input-Output Analysis, **Economic Systems Research**, pp. 175-335.

Horridge, M. (2006) GTAPAgg Data Aggregation Program, in: Dimaranan, B.V., ed. (2006) **Global Trade, Assistance, and Production: The GTAP 6 Data Base** (West Lafayette, Center for Global Trade Analysis).

Janssen, P.H.M, Slob, W., Rotmans, J. (1990), **Gevoeligheidsanalyse en onzekerheids-analyse: een inventarisatie van ideeën, methoden en technieken**, report no. 958805001 (Bilthoven, RIVM).

Koole, B., van Leeuwen, N. (2006) The Netherlands, in: Dimaranan, B.V., ed. (2006) **Global Trade, Assistance, and Production: The GTAP 6 Data Base** (West Lafayette, Center for Global Trade Analysis).

Lee, H.-L. (2005) **An Emissions Data Base for Integrated Assessment of Climate Change Policy Using GTAP**. GTAP Resource #1143 (West Lafayette, Center for Global Trade Analysis).

Lenzen, M., Wood, R., Wiedmann, T. (2010) Uncertainty analysis for Multi-region input-output models – a case study of the UK's carbon footprint, **Economic Systems Research,** 22, pp.43-63.

Lutter, S., Wilting, H., Wiedmann, T., Palm, V. and Giljum, S. (2008) Interim Report on the results of the evaluation of methodologies assessed with the RACER framework. ERANET SKEP Project EIPOT (Development of a methodology for the assessment of global environmental impacts of traded goods and services). http://www.eipot.eu.

McDougall, R.A. (2008) **Personal communication** (West Lafayette, Center for Global Trade Analysis).

Olivier, J.G.J., Brandes, L.J., te Molder, R.A.B. (2009) **Uncertainty in the Netherlands' greenhouse gas emissions inventory; Estimation of the level and trend uncertainty using the IPCC Tier 1 approach**, Netherlands Environmental Assessment Agency (Bilthoven, PBL).

Rose, S.K., Lee, H.-L. (2008) Non-CO2 Greenhouse Gas Emissions Data for Climate Change Economic Analysis, in: T. Hertel, S. Rose & R. Tol (eds.) **Economic Analysis of Land Use in Global Climate Change Policy** (Routledge).

Sebald, A.V. (1974) **An analysis of the sensitivity of large scale input-output models to parmatric uncertainties**, CAC-doc. No. 122 (Urbana, University of Illinois, Center for Advanced Computation).

Sherman, J., Morrison, W.J. (1950) Adjustment of an inverse matrix corresponding to a change in one element of a given matrix, **Annals of Mathematical Statistics**, 21, pp. 124-127.

Sonis, M., Hewings, G.J.D. (1992), Coefficient Change in Input-Output Models: Theory and Applications, **Economic Systems Research**, 4, pp. 143-157.

Suh, S., ed. (2009) Handbook of Input-Output Economics in Industrial Ecology, (Dordrecht, Springer).

van Aardenne, J.A., F.D. Dentener, J.G.J. Olivier, J.A.H.W. Peters and L.N. Ganzeveld (2005) **The EDGAR 3.2 Fast Track 2000 dataset (32FT2000)**, downloaded from http://www.mnp.nl/edgar/model/v32ft2000edgar.

van der Linden, J.A., Oosterhaven, J. (1995) **Fields of influence of technological change in EC intercountry input-output tables, 1970-80**, SOM research report 95D17 (Groningen, University of Groningen).

Viet, V.Q. (1980) **Sensitivity analysis in input-output: theory and application**, Ph.D. thesis (New York, New York University).

Wiedmann, T., M. Lenzen, K. Turner and J. Barrett (2007) Examining the global environmental impact of regional consumption activities — Part 2: Review of input–output models for the assessment of environmental impacts embodied in trade, **Ecological Economics**, 61, pp. 15-26.

Wilting, H.C. (2008), Analysis of the Sustainability of Supply Chains with a Multi-Region Input-Output Model, paper presented at the International Input-Output Meeting, 9-11 July, Seville, Spain.

Wilting, H.C., Biesiot, W. (1993) **Het berekenen van energie- en CO_2 emissie-intensiteiten met behulp van input-outputanalyse: berekeningen voor het jaar 1987**, IVEM report no. 64 (Groningen, University of Groningen).

Appendix A World regions based on the GTAP 6 regions

World region No.	Code	Description	GTAP 6 region No.	Code	Description
1	NAm	North America	21	can	Canada
			22	usa	United States
			24	xna	Rest of North America
2	CSAm	Central and South America	23	mex	Mexico
			25	col	Colombia
			26	per	Peru
			27	ven	Venezuela
			28	xap	Rest of Andean Pact
			29	arg	Argentina
			30	bra	Brazil
			31	chl	Chile
			32	ury	Uruguay
			33	xsm	Rest of South America
			34	xca	Central America
			35	xfa	Rest of FTAA
			36	xcb	Rest of the Caribbean
3	Oc	Oceania	1	aus	Australia
			2	nzl	New Zealand
			3	xoc	Rest of Oceania
4	JNIE	Japan and New Industrializing Economies	5	hkg	Hong Kong
			6	jpn	Japan
			7	kor	Korea
			8	twn	Taiwan
			13	sgp	Singapore
5	SEA	Southeast Asia	10	idn	Indonesia
			11	mys	Malaysia
			12	phl	Philippines
			14	tha	Thailand
			15	vnm	Vietnam
			16	xse	Rest of Southeast Asia
6	EA	East Asia	4	chn	China
			9	xea	Rest of East Asia
7	SA	South Asia	17	bgd	Bangladesh
			18	ind	India
			19	lka	Sri Lanka
			20	xsa	Rest of South Asia
8	ME	Middle East	71	tur	Turkey
			72	xme	Rest of Middle East
9	FSU	Former Soviet Union	69	rus	Russian Federation
			70	xsu	Rest of Former Soviet Union
10	EEU	Eastern Europe	54	xer	Rest of Europe
			55	alb	Albania
			56	bgr	Bulgaria
			57	hrv	Croatia
			58	cyp	Cyprus
			59	cze	Czech Republic
			60	hun	Hungary
			61	mlt	Malta
			62	pol	Poland

			63	rom	Romania
			64	svk	Slovakia
			65	svn	Slovenia
			66	est	Estonia
			67	lva	Latvia
			68	ltu	Lithuania
11	OEU	OECD Europe	37	aut	Austria
			38	bel	Belgium
			39	dnk	Denmark
			40	fin	Finland
			41	fra	France
			42	deu	Germany
			43	gbr	United Kingdom
			44	grc	Greece
			45	irl	Ireland
			46	ita	Italy
			47	lux	Luxembourg
			49	prt	Portugal
			50	esp	Spain
			51	swe	Sweden
			52	che	Switzerland
			53	xef	Rest of EFTA
12	Af	Africa	73	mar	Morocco
			74	tun	Tunisia
			75	xnf	Rest of North Africa
			76	bwa	Botswana
			77	zaf	South Africa
			78	xsc	Rest of South African CU
			79	mwi	Malawi
			80	moz	Mozambique
			81	tza	Tanzania
			82	zmb	Zambia
			83	zwe	Zimbabwe
			84	xsd	Rest of SADC
			85	mdg	Madagascar
			86	uga	Uganda
			87	xss	Rest of Sub-Saharan Africa
13	Nld	Netherlands	48	nld	Netherlands

Appendix B Sectors/commodities in GTAP 6

1	PDR	Paddy rice
2	WHT	Wheat
3	GRO	Cereal grains nec
4	V_F	Vegetables, fruit, nuts
5	OSD	Oil seeds
6	C_B	Sugar cane, sugar beet
7	PFB	Plant-based fibers
8	OCR	Crops nec
9	CTL	Bovine cattle, sheep and goats, horses
10	OAP	Animal products nec
11	RMK	Raw milk
12	WOL	Wool, silk-worm cocoons
13	FRS	Forestry
14	FSH	Fishing
15	COA	Coal
16	OIL	Oil
17	GAS	Gas
18	OMN	Minerals nec
19	CMT	Bovine meat products
20	OMT	Meat products nec
21	VOL	Vegetable oils and fats
22	MIL	Dairy products
23	PCR	Processed rice
24	SGR	Sugar
25	OFD	Food products nec
26	B_T	Beverages and tobacco products
27	TEX	Textiles
28	WAP	Wearing apparel
29	LEA	Leather products
30	LUM	Wood products
31	PPP	Paper products, publishing
32	P_C	Petroleum, coal products
33	CRP	Chemical, rubber, plastic products
34	NMM	Mineral products nec
35	I_S	Ferrous metals
36	NFM	Metals nec
37	FMP	Metal products
38	MVH	Motor vehicles and parts
39	OTN	Transport equipment nec
40	ELE	Electronic equipment
41	OME	Machinery and equipment nec
42	OMF	Manufactures nec
43	ELY	Electricity
44	GDT	Gas manufacture, distribution
45	WTR	Water
46	CNS	Construction
47	TRD	Trade
48	OTP	Transport nec
49	WTP	Water transport
50	ATP	Air transport
51	CMN	Communication
52	OFI	Financial services nec
53	ISR	Insurance
54	OBS	Business services nec
55	ROS	Recreational and other services
56	OSG	Public Administration, Defense, Education, Health
57	DWE	Dwellings

Appendix C

This appendix describes the derivation of the model of the determination of the effect of a change in one technical coefficient on the total GHG intensities (equation 8). The equations were obtained from Wilting and Biesiot (1993) and are in line with the equation that expresses the changes in the inverse of a matrix as a result of the change of one element in that matrix (Sherman and Morrison, 1950).

Starting from the model:

$$\mathbf{e}' = \mathbf{e}'\ \mathbf{A} + \mathbf{d}' \tag{C.1}$$

with **e'** is the row vector of total GHG intensities and **d'** is the row vector of direct GHG intensities. Assuming a new technical coefficients matrix, $\mathbf{A}^{\mathbf{n}}$:

$$\mathbf{A}^{\mathbf{n}} = \mathbf{A} + \mathbf{F} \tag{C.2}$$

with all coefficients of **F** are zero, except coefficient $\mathbf{F}_{\mathbf{ij}} = \boldsymbol{\varphi}$. The vector with changes in the GHG intensities is **h**:

$$\mathbf{e}^{\mathbf{n}} = \mathbf{e} + \mathbf{h} \tag{C.3}$$

Model C.1 also holds for the changed total intensities:

$$(\mathbf{e}^{\mathbf{n}})' - (\mathbf{e}^{\mathbf{n}})'\ \mathbf{A}^{\mathbf{n}} = \mathbf{d}' \tag{C.4}$$

The derivation of **h** starts as follows:

$$(\mathbf{e}^{\mathbf{n}})' - (\mathbf{e}^{\mathbf{n}})'\ (\mathbf{A} + \mathbf{F}) = \mathbf{d}' \tag{C.5}$$

$$(\mathbf{e}^{\mathbf{n}})'\ (\mathbf{I} - \mathbf{A}) = \mathbf{d}' + (\mathbf{e}^{\mathbf{n}})'\ \mathbf{F} \tag{C.6}$$

$$(\mathbf{e}^{\mathbf{n}})'\ (\mathbf{I} - \mathbf{A}) - \mathbf{d}' = (\mathbf{e} + \mathbf{h})'\ \mathbf{F} \tag{C.7}$$

Multiplication of C.7 both sides with $(\mathbf{I} - \mathbf{A})^{-1}$ gives:

$$(\mathbf{e}^{\mathbf{n}})' - \mathbf{d}'\ (\mathbf{I} - \mathbf{A})^{-1} = (\mathbf{e} + \mathbf{h})'\ \mathbf{F}\ (\mathbf{I} - \mathbf{A})^{-1} \tag{C.8}$$

$$\mathbf{e}' + \mathbf{h}' - \mathbf{d}'\ (\mathbf{I} - \mathbf{A})^{-1} = (\mathbf{e} + \mathbf{h})'\ \mathbf{F}\ (\mathbf{I} - \mathbf{A})^{-1} \tag{C.9}$$

Since $\mathbf{e}' - \mathbf{d}'\ (\mathbf{I} - \mathbf{A})^{-1} = \mathbf{0}$:

$$\mathbf{h' = (e + h)' F (I - A)^{-1} = (e + h)' F B} \tag{C.10}$$

with $\mathbf{B = (I - A)^{-1}}$. The k-th element of vector h, $\mathbf{h_k}$, is now:

$$\mathbf{h_k = (e_i + h_i) F_{ij} B_{jk}} \tag{C.11}$$

In case **k=i** then:

$$\mathbf{h_i = (e_i + h_i) F_{ij} B_{ji}} \tag{C.12}$$

Solving for $\mathbf{h_i}$ gives (under the condition that $\mathbf{1 - F_{ij} B_{ji} \neq 0}$):

$$\mathbf{h_i = \frac{e_i F_{ij} B_{ji}}{1 - F_{ij} B_{ji}}} \tag{C.13}$$

Entering of C.13 in C.11 gives:

$$\mathbf{h_k = \left[e_i + \frac{e_i F_{ij} B_{ji}}{1 - F_{ij} B_{ji}} \right] F_{ij} B_{jk}} \tag{C.14}$$

Further elaboration of this equation gives the final result:

$$\mathbf{h_k^{ij} = \frac{e_i F_{ij} B_{jk}}{1 - F_{ij} B_{ji}}, \forall k = 1, .., n} \tag{C.15}$$

This result holds for all elements in the total GHG intensity vector.