Evaluating the Mutual Relationship between IPAT/Kaya Identity Index and ODIAC-Based GOSAT Fossil-Fuel CO₂ Flux: Potential and Constraints in Utilizing Decomposed Variables

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Abstract: The IPAT/Kaya identity is the most popular index used to analyze the driving forces of individual factors on CO₂ emissions. It represents the CO₂ emissions as a product of factors, such as the population, gross domestic product (GDP) per capita, energy intensity of the GDP, and carbon footprint of energy. In this study, we evaluated the mutual relationship of the factors of the IPAT/Kaya identity and their decomposed variables with the fossil-fuel CO₂ flux, as measured by the Greenhouse Gases Observing Satellite (GOSAT). We built two regression models to explain this flux; one using the IPAT/Kaya identity factors as the explanatory variables and the other one using their decomposed factors. The factors of the IPAT/Kaya identity have less explanatory power than their decomposed variables and comparably low correlation with the fossil-fuel CO₂ flux. However, the model using the decomposed variables shows significant multicollinearity. We performed a multivariate cluster analysis for further investigating the benefits of using the decomposed variables instead of the original factors. The results of the cluster analysis showed that except for the M factor, the IPAT/Kaya identity factors are inadequate for explaining the variations in the fossil-fuel CO₂ flux, whereas the decomposed variables produce reasonable clusters that can help identify the relevant drivers of this flux.

Keywords: IPAT/Kaya identity; GOSAT; CO₂ flux; correlation; hierarchical cluster analysis

1. Introduction

IPAT/Kaya identity is used to analyze the input factors of CO₂ emissions. The IPAT identity estimates the human impact on the environment, and the Kaya identity represents the CO₂ emissions as the product of five factors such as, for example, the gross domestic product (GDP) and population. It plays a crucial role in the construction of preliminary and future emission scenarios [1]. In addition to its simplicity, IPAT/Kaya identity is very useful to find the most effective and critical criteria for implementing carbon dioxide (CO₂) emission reduction targets as it identifies the driving forces with regard to CO₂ emissions from anthropogenic activities [2,3]. According to the United Nations Framework Convention on Climate Change (A/AC.237/18 (Part II)/Add.1 and Corr.1), CO₂ emissions can be defined as the release of CO₂ and their precursors into the atmosphere over a specified area and period of time. CO₂ emissions can be expressed in terms of either inventory measurements or flux. The IPAT/Kaya identity uses the inventory CO₂ emissions as environmental impacts. Inventory CO₂
emissions present the quantity of CO$_2$ estimated indirectly using the emission factors in units of weight. They contain information about CO$_2$ emitted into the atmosphere by an individual, an organization, a process, a product, or an event from within the boundaries of a specific country [4]. Inventory CO$_2$ emissions fluctuate depending on a variety of variables, such as the collection and reporting system of the country’s energy statistics, data definition and data processing, level of detail, and specific local conditions. Besides, accuracy, transparency, and uncertainty of inventory CO$_2$ emission data vary among countries owing to the differences in proficiency and level of development of statistics [5]. Thus, documented inventory CO$_2$ emissions sometimes show large discrepancy with the actual CO$_2$ directly emitted to the atmosphere [6,7].

1.1. Benefits of IPAT/Kaya Identity

In previous studies, the (linear) correlation between all five factors of IPAT/Kaya identity and inventory CO$_2$ emissions was empirically established and examined on a global scale [8]. At face value, IPAT/Kaya identity suggests that inventory CO$_2$ emissions grow linearly with the increases in these factors. However, the driving forces of IPAT/Kaya identity are often not instructive because of the great heterogeneity among countries. Examples are differences in demographics, economics, resources, and technology with respect to inventory CO$_2$ emissions [1,9]. A global aggregated correlation analysis between the inventory CO$_2$ emissions and IPAT/Kaya identity isolates the spatial and temporal heterogeneity, particularly with respect to the distinctions between industrial and developing countries [10]. Therefore, to ascertain the true driving forces of IPAT/Kaya identity for actual CO$_2$ emissions, the correlation between IPAT/Kaya identity and the standardized CO$_2$ directly emitted to the atmosphere on a regional scale should be evaluated.

1.2. The Fossil-Fuel CO$_2$ Flux

The CO$_2$ flux represents the transfers of CO$_2$ among different reservoirs of CO$_2$ [11]. An example is the combustion of fossil fuel: the fossil CO$_2$ flux indicates the amount of CO$_2$ transferred from one reservoir (fossil fuel) to another (atmosphere). CO$_2$ fluxes are usually expressed as a rate, that is, as an amount of substance being transferred over a certain period of time in a certain area; in this case the unit would be kgC km$^{-2}$ year$^{-1}$. Thus, the fossil-fuel CO$_2$ flux indicates the intensity of CO$_2$ directly emitted to the atmosphere in standardized units. Unlike inventory CO$_2$ emissions, the fossil-fuel CO$_2$ flux is the footprint and absolute data. It is a measure of the direct CO$_2$ emissions from CO$_2$ sources on the ground to the atmosphere. Thus, this flux is objective with regard to the heterogeneity of populations and environments of individual countries and considers only the existence and locations of CO$_2$ sources related to fossil-fuel combustion in a country.

1.3. Characteristics of the GOSAT Fossil-Fuel CO$_2$ Flux

In the inversion frameworks, the fossil-fuel emissions are the most important reference for analyzing the carbon budget among the three CO$_2$ fluxes, namely, the biospheric and oceanic fluxes and the fossil-fuel flux. The fossil-fuel emissions are given as known quantities, and these values cannot be corrected via optimization because fossil fuel emissions are already measured on the basis of the survey [12]. In this regard, literature suggests the application of satellite-observed CO$_2$ data that have a denser spatial coverage. Emission inventory with high spatiotemporal resolution is essential for accurate inversion. The inventory CO$_2$ emission data in national inventory reports (NIRs) contain the net CO$_2$ emission data only within a given national boundary. These data are not sufficient to calculate regional fluxes. In contrast, satellite-based fossil-fuel CO$_2$ flux data contain large amounts of information on near-ground CO$_2$ sources. The Japan Aerospace Exploration Agency Greenhouse Gases Observing Satellite (GOSAT) fossil-fuel CO$_2$ flux has high spatial resolution and employs the Carbon Monitoring for Action (CARMA), which is a global database of CO$_2$ emissions from power plants and nighttime satellite imagery. The GOSAT fossil-fuel CO$_2$ flux provides CO$_2$ emissions in terms of locations of CO$_2$ sources and provides a measure of the direct exchange of CO$_2$ between
in situ CO$_2$ sources and the atmosphere over CO$_2$ sources located within an area. [13,14]. Thereby, the satellite-based fossil-fuel CO$_2$ flux has the advantage of monitoring and comparing the average flux from the CO$_2$ sources located in heterogeneous countries because the satellite measures the CO$_2$ flux all over the world with the same standardized method and unit. Evaluating mutual relationships between the factors of IPAT/Kaya identity and the satellite fossil-fuel CO$_2$ flux can offer tangible evidence to validate the actual driving forces of these factors with regard to the CO$_2$ directly emitted to atmosphere. Thus, the CO$_2$ fossil flux is a simple, robust diagnostic property of the CO$_2$ directly emitted to the atmosphere. It can provide an independent validation reference to evaluate the mutual correlation between the IPAT/Kaya identity and the CO$_2$ directly emitted into the atmosphere from ground CO$_2$ sources [15,16].

1.4. Scope of this Paper

Nonetheless, the mutual correlation of the fossil-fuel CO$_2$ flux with IPAT/Kaya identity is yet to be validated. Raupach et al. [17] used the extended form of Kaya identity based on the airborne fraction of CO$_2$ to assess the relative effects of changes in the airborne fractions and anthropogenic drivers of CO$_2$ emissions on CO$_2$ growth. They concluded that the growth of per capita income and the decline in negative growth in the carbon intensity of the economy is greatly responsible for the accelerated growth (post 2000) in the airborne fraction of CO$_2$. Zhang et al. [18] demonstrated the influence of subannual variations in fossil-fuel CO$_2$ emissions, which were estimated using the Kaya identity and used as the flux boundary condition, on simulated CO$_2$ concentration and suggested that inversion studies should consider these variations in the affected regions. Garrett [19] remarked about the substantially narrowed visions of future emission scenarios for implementation in global circulation models, which provide projections for future climate warming based on the evolution of the factors of the Kaya identity, from a thermodynamic perspective. However, literature on the analysis of the mutual correlation between the IPAT/Kaya identity and the CO$_2$ fossil-fuel flux is lacking. This study addresses this lacuna in research. Our objective is to identify the realistic driving forces of IPAT/Kaya identity on the actual CO$_2$ emitted to the atmosphere.

2. Materials and Methods

2.1. Study Area

The certainties and accuracy of the energy consumption data and CO$_2$ emission data in NIRs are relatively high for the countries listed in Annex 1 of the United Nations Framework Convention on Climate Change (UNFCCC) due to their well-developed statistical systems and capacity to use higher-tier methods [20]. Europe is the second-smallest continent in the world after Australia. As 44 countries are densely located in this region, it is an ideal region for studying carbon emissions among countries. Europe is also ideal for investigating the correlation between fossil-fuel CO$_2$ flux and IPAT/Kaya identity owing to the diversity in structure of the energy consumption, population, industry, and economic scale [21]. To guarantee the accuracy of fossil-fuel CO$_2$ flux data, a high accuracy of preliminary data for CO$_2$ emission is required. Analysis of the sum of Annex I reported emissions as well as some independent estimates and inverse modeling results found an uncertainty of 6 percent for fossil-fuel CO$_2$ [20]. In this regard, GOSAT fossil-fuel CO$_2$ flux is calibrated with accurate CO$_2$ emissions data. From the list of Annex 1 countries, we selected 30 European countries excluding the smallest and most remote ones. For example, we excluded Iceland, Monaco, Liechtenstein, and Malta because these countries are either too far from the European continent or too small for using a $1^\circ \times 1^\circ$ scale GOSAT fossil-fuel CO$_2$ flux data.
2.2. IPAT/Kaya Identity

2.2.1. Description of IPAT/Kaya Identity

The IPAT identity is widely used to examine the drivers of CO₂ emissions. The identity \( I = P \times A \times T \) states that the human impact on the environment \( I \) is the product of population \( P \), affluence \( A \), and technology \( T \). As shown in Equation (1), the Kaya identity distinguishes the factors of \( P \), \( A \), and \( T \) with respect to CO₂ emissions into four: (1) the size of the population, (2) GDP per capita, (3) energy intensity of the GDP, and (4) carbon footprint of energy \([1,22]\). In Equation (1) we additionally split up the factor \( T \) into energy divided by the GDP and CO₂ divided by energy.

\[
\text{CO}_2 \text{ emissions} = \frac{\text{Population}}{\text{Population}} \times \frac{\text{GDP}}{\text{GDP}} \times \frac{\text{Energy}}{\text{Energy}} \times \frac{\text{CO}_2 \text{ emissions}}{\text{EC}}
\]

Using Equation (1), many studies extended the IPAT identity to the Kaya identity to explore the energy sector in detail, as explained in Equation (2) \([22–25]\):

\[
\text{CO}_2 \text{ emissions} = \frac{\text{Population}}{\text{Population}} \times \frac{\text{GDP}}{\text{GDP}} \times \frac{\text{TEC}}{\text{TEC}} \times \frac{\text{EC}}{\text{EC}} \times \frac{\text{CO}_2 \text{ emissions}}{\text{EC}}
\]

where \( P \) is the population size; GDP, the gross domestic product; TEC, the total energy consumption; and EC, the fossil fuel energy consumption. In this equation, \( E (\text{CO}_2/\text{EC}) \) is the CO₂ emission coefficient related to fuel sources; \( M (\text{EC}/\text{TEC}) \), the portion of fossil-fuel consumption from the total energy consumption; \( I (\text{TEC}/\text{GDP}) \), the energy intensity; \( G (\text{GDP}/P) \), per capita GDP; and \( P \), population size \([22]\).

In this study, we used the Kaya identity as described in Equation (2).

2.2.2. Data Sets for Computing the Decomposed Variables of IPAT/Kaya Identity

The International Energy Agency (IEA) collects energy supply and demand data not only for the member countries of the Organization for Economic Cooperation and Development (OECD), but also for non-OECD countries \([26,27]\). The original data are submitted by national administrations of the OECD, European Union (EU), and United Nations Economic Commission for Europe (UNECE) member states. The (final) joint IEA/OECD–Eurostat–UNECE questionnaire is the result of aggregating a set of five individual questionnaires (for coal, oil, gas, electricity, and renewable energy) \([28]\). Then, the basic energy statistics with over 60 energy types in physical energy units such as ton and m³ are converted into energy units (ktoe). This disaggregated energy balance is combined into 13 energy types (coal, crude oil, biofuels, nuclear, etc.). The sum of these 13 energy types gives the total energy consumption \([29,30]\). We used the total final consumption sections from the IEA energy balance data for TEC and the EC to calculate the I, M, and E factors of the Kaya identity from 2010 to 2017 \([31]\). The GDP and population data were acquired from World Bank data to calculate G, I, and P in the IPAT/Kaya identity from 2010 to 2017 \([32]\).

An NIR contains detailed qualitative and quantitative information and tables in a common reporting format (CRF) for all Kyoto Protocol, such as carbon monoxide (CO), nitrogen oxides (NOₓ), non-methane volatile organic compounds, and sulfur dioxide (SO₂) \([33,34]\). The GOSAT Level 4a fossil-fuel CO₂ flux exclusively provides the annual CO₂ flux derived from fossil-fuel combustions with \(1° \times 1° \) spatial resolution. It is generally acknowledged that CO₂ accounts for the most significant portion of greenhouse gases, and the term CO₂ is often used interchangeably with greenhouse gas. To perform a correlation analysis between factors in the Kaya identity and GOSAT fossil-fuel CO₂ flux data, we used direct CO₂ emissions (CRF Table 10s2 submitted to UNFCCC in 2018) from 2010 to 2017. We excluded the CO₂ emissions from land use, land use change, and forestry sectors since they are associated with the variations in CO₂ uptakes and emissions from the net CO₂ sink (i.e., forests).

The a priori flux dataset for the GOSAT fossil-fuel CO₂ flux data inversion comprises monthly fossil-fuel CO₂ emissions with the Open-source Data Inventory of Anthropogenic CO₂ emissions
where

\[ \sigma = \frac{\text{Standard Deviation}}{\text{Mean}} \]

which is the result of dividing the standard deviation of a data set by its mean. Hence, the CV indicates the variation in relation to the average level of the respective factor. As displayed in Table 1, we see that the standard deviations of both the P factor and population are larger than those of other factors. However, considering the CV values, EC and TEC show the highest values. This is reasonable as, in this study, we used data from 30 quite heterogeneous European countries. For examples, the Netherlands (1.74 ktoe/km²) have the 29 times larger TEC than Latvia (0.06 ktoe/km²).

In order to compare the factors’ fluctuations, we computed the coefficient of variation (CV), which is the result of dividing the standard deviation of a data set by its mean. Hence, the CV indicates the variation in relation to the average level of the respective factor. As displayed in Table 1, we see that the standard deviations of both the P factor and population are larger than those of other factors. However, considering the CV values, EC and TEC show the highest values. This is reasonable as, in this study, we used data from 30 quite heterogeneous European countries. For examples, the Netherlands (1.74 ktoe/km²) have the 29 times larger TEC than Latvia (0.06 ktoe/km²).

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| Category                        | Min  | Max  | Mean  | STDEV | CV (%) |
|---------------------------------|------|------|-------|-------|--------|
| **Kaya identity**               |      |      |       |       |        |
| G factor (MM $/person)          | 0.00 | 0.10 | 0.03  | 0.02  | 0.70   |
| I factor (kt/OMM $)             | 0.03 | 0.56 | 0.11  | 0.09  | 0.81   |
| M factor (kt)                   | 0.34 | 0.80 | 0.62  | 0.11  | 0.18   |
| E factor (kt CO₂ Equation/ktoe) | 0.41 | 14.76| 5.22  | 2.22  | 0.42   |
| F factor (MM person)            | 1.32 | 82.66| 21.68 | 24.50 | 1.13   |
| **Decomposed variables of Kaya identity** |      |      |       |       |        |
| GDP (MM $/km²)                  | 0.16 | 26.80| 4.49  | 5.89  | 1.31   |
| Population (person/km²)        | 13.39| 507.89|123.32| 104.24| 0.85   |
| TEC (kt/OMM km²)               | 0.05 | 1.93 | 0.30  | 0.37  | 1.22   |
| EC (kt/OMM km²)                | 0.02 | 1.54 | 0.21  | 0.29  | 1.40   |
| CO₂ emission (kt CO₂ Equation/km²) | 0.10 | 5.40 | 0.88  | 1.03  | 1.17   |
| Fossil-fuel CO₂ flux (gC m⁻² day⁻¹) | 0.06 | 3.79 | 0.68  | 0.78  | 1.14   |

Min: Minimum, Max: Maximum, Mean: Average, CV: coefficients of variation, STDEV: Standard deviation, TEC: total energy consumption, EC: fossil fuel energy consumption.

2.3. Multiple Regression and Cluster Analysis

To evaluate the mutual dependencies in our data sets, that is, the dependencies between the factors of the IPAT/Kaya identity (or the corresponding decomposed variables of these factors), we established a regression of the GOSAT fossil-fuel CO₂ flux above-mentioned factors. The corresponding multiple regression models are shown in Equations (3) and (4). They were calibrated using ordinary least squares optimization:

\[
\text{Fossil-fuel CO}_\text{₂} \text{ flux} = \alpha_0 + \alpha_1 \times P + \alpha_2 \times G + \alpha_3 \times I + \alpha_4 \times M + \alpha_5 \times E + \epsilon_1, \tag{3}
\]

\[
\text{Fossil-fuel CO}_\text{₂} \text{ flux} = \beta_0 + \beta_1 \times \text{Population} + \beta_2 \times \text{GDP} + \beta_3 \times \text{TEC} + \beta_4 \times \text{EC} + \beta_5 \times \text{CO}_\text{₂} \text{ emissions} + \epsilon_2 \tag{4}
\]

where \( \alpha_i, \beta_j \in \mathbb{R}, i, j = 1, \ldots, 5 \), and \( \epsilon_1 \) and \( \epsilon_2 \) are Gaussian distributions with zero mean and standard deviation \( \sigma > 0 \). Equations (3) and (4) show the regression models based on the five factors and the decomposed variables of the factors in the IPAT/Kaya identity. The pairs of data per country are eight years’ data from 2010 to 2017 and we used 240 samples per individual variable. Note that, in order to be able to merge the datasets of these eight individual years to one large sample, we had to demand the absence of autocorrelation. With autocorrelation we mean (partial) dependence of a data set on its own past, that is, there is a correlation on the time axis. For this purpose, we applied
the Durbin–Watson test. Autocorrelation might also occur if the functional form of the model itself is incorrect. The Durbin–Watson statistic is an indicator of autocorrelation in the residuals of a regression model: values greater than 0 but less than 2.0 indicate positive correlation; values close to 2.0 indicate no autocorrelation; values from 2 to 4 indicate negative autocorrelation [38]. For the regression models in Equations (3) and (4), the values of the test statistic are 2.13 and 2.07, respectively, and hence, both satisfy the assumptions regarding the autocorrelation of the error term. Hence, we can fit both models from Equations (3) and (4) using the merged dataset. Thereby, the decomposed variables are fitted to annual net amounts, and the fossil-fuel CO\textsubscript{2} flux is fitted to annual mean values.

Cluster analysis is an exploratory approach that intends to identify structures within a dataset by segmenting it into disjoint sub-groups of similar (possibly multivariate) observations. Cluster analysis methods can be applied to binary, nominal, ordinal, and scale (interval or ratio) data. Some of the commonly used methods are hierarchical clustering, k-means, clustering large applications (CLARA), or the Ward algorithm [39]. Thereby, cluster analysis is often used in conjunction with other methods such as discriminant analysis. After clustering, the members within a group should have similar properties and features, while those in different groups should have highly dissimilar properties and features. This is achieved using certain distance measures. For example, in Ward’s method, a hierarchical approach, analysis of variance is performed to evaluate the distances between the cluster centroids; this method optimizes the minimum variance within clusters by using the sum of squared deviations within the individual groups to evaluate cluster membership. Thereby, a meaningful data structure can be applied to various types of data without prior information about the internal structure of the dataset.

Note that a clustering algorithm does not distinguish between dependent and independent variables. Hence, to use it in our study, we applied Ward’s method to multivariate observations obtained by combining the country-specific fossil-fuel CO\textsubscript{2} flux value with the input factors, that is, the independent variables from Equations (1) and (2). We obtained various sets of multivariate observations and performed a cluster analysis for each variable to explore the unknown patterns and characteristics of both dependent and independent variables that influence the results of the multiple regressions from Equations (1) and (2). If these variables have high positive correlation, the different groups will be linearly located on the trend lines with distinctive range between different groups. Thus, by performing a cluster analysis, we obtained more information about the structures and characteristics of different groups of independent variables (i.e., the factors of IPAT/Kaya identity and the decomposed variables of IPAT/Kaya identity) and their influence on the dependent variable, that is, the fossil-fuel CO\textsubscript{2} flux.

3. Model Estimation and Evaluation of Results

We employed the methods described in Section 2.3. and the variables derived in Section 2.2.: we fit the multiple regression models from Equations (3) and (4) and applied Ward’s clustering.

3.1. Model Calibration

The data in Table 2 show that the multiple regression model from Equation (3) has a relatively low explanatory power with an R\textsuperscript{2} of 0.38. Correlation and regression coefficient values are also relatively low, except for the M factor. From the p-values of the regression coefficients, we see that among the five factors of the Kaya identity (hereinafter, Decomposition 1), the coefficients of I and E are statistically insignificant. Hence, their influence on the fossil-fuel CO\textsubscript{2} flux cannot be proven using the model in Equation (3). This is remarkable as the E factor, that is, the CO\textsubscript{2} emissions from fossil fuel/EC, was expected to be strongly and positively related to the fossil-fuel CO\textsubscript{2} flux. However, the p-value indicates the factor’s insignificance, and the correlation coefficient shows only a small negative influence.
Table 2. Results of the multivariate linear regression and Pearson correlation coefficients between GOSAT fossil-fuel CO₂ flux and the five factors of the Kaya identity.

| Category | Standardized Coefficient | VIF   | T-Statistics | Pearson Correlation Coefficient |
|----------|--------------------------|-------|--------------|---------------------------------|
| G        | 0.26 **                  | 1.80  | 3.84         | 0.18 **                         |
| I        | 0.03                     | 1.63  | 0.41         | -0.15 **                        |
| M        | 0.66 **                  | 1.44  | 10.68        | 0.56 **                         |
| E        | 0.03                     | 1.31  | 0.56         | -0.23 **                        |
| Population | -0.13 *                | 1.29  | -2.18        | 0.16 **                         |

R: 0.62; R²: 0.38; Durbin–Watson: 2.13; F-value (p-value): 29.22 (0.00); *: p ≤ 0.05, **: p ≤ 0.01.

In contrast, we see that the explanatory power of the multiple regression model based on the decomposed variables of IPAT/Kaya identity factors (hereinafter, Decomposition 2) is comparatively high (R² = 0.83). In addition, the correlation coefficients between Decomposition 2 and the fossil-fuel CO₂ flux (0.64 to 0.90) are higher than the corresponding values of Decomposition 1 (~0.23 to 0.56). The results for all the models are listed in Table 3. Interestingly, some factors of the IPAT/Kaya identity and their decomposed variables differ in terms of the significance (p-value) of their regression models. For example, the E factor in the model based on Equation (3) is insignificant with a p-value of 0.58. However, its decomposed variables, namely, EC and CO₂ emissions from fossil fuels, individually are significant (p ≤ 0.01) in the model from Equation (4). The I factor is insignificant (p = 0.66) in the first regression model, but the GDP, which is a component of the I factor, is significant (p ≤ 0.01) in the second model. The TEC value, again, which is another decomposed variable of the I factor, is statistically insignificant due to its large p-value of 0.66. It is the only insignificant variable in the second model. This finding suggests that changes in the TEC are not associated with changes in the response of the fossil-fuel CO₂ flux. An explanation may be that TEC contains the energy consumptions from 13 energy types, from fossil fuels to nuclear and renewable energies, all converted to the energy units (ktoe). Hence, the proportion of nonfossil fuels accounts for about 20% (Netherlands) to 67% (Sweden) in TEC. However, as fossil fuel accounts for over 50% in the energy mix of all countries except for Estonia, Finland, Latvia, Norway, and Sweden (from our data for 2010–2017), we still see a fairly positive correlation of 0.64 with the fossil-fuel CO₂ flux. This example proves that computing the correlation is often not enough, and additional insight is gained by calibrating the model in Equation (4).

3.2. Using Cluster Analysis to Handle the Problem of Multicollinearity

Despite this knowledge gained by calibrating the model in Equation (4), a challenge persists: we see significant multicollinearity, that is, the decomposed factors of the IPAT/Kaya identity are not independent of each other. This fact has been well established in previous research [1,40,41]. We used the variance inflation factors (VIFs) as indicators of multicollinearity. The general rule of thumb is that VIFs > 4 warrant further investigation, while VIFs > 10 are signs of serious multicollinearity requiring correction [3]. In the first model, the VIF values are all far below 10, whereas in the second model, three out of five factors exceed 10. Multicollinearity is commonly observed along with high R², as observed in Table 3. Besides, when analyzing the correlation between the individual factors of Decomposition 2,
we see some substantial interdependencies between the factors TEC and EC or between the population and GDP (Table 4). These interdependencies make it difficult to interpret the results given in Table 3. Hence, further analysis is required to support our deductions.

Table 4. Correlation between the decomposed factors of the IPAT/Kaya identity.

| Category          | CO₂ Emission | GDP   | Population | TEC   | EC    |
|-------------------|--------------|-------|------------|-------|-------|
| CO₂ emission      | 1.000        | 0.325 | 0.037      | -0.086| -0.221|
| GDP               | -            | 1.000 | 0.430      | -0.196| -0.300|
| population        | -            | -     | 1.000      | -0.091| -0.307|
| TEC               | -            | -     | -          | 1.000 | -0.834|
| EC                | -            | -     | -          | -     | 1.000 |

For this purpose, we performed a multivariate cluster analysis for both Decomposition 1 and 2. The individual cluster pattern was derived based on a bivariate dataset (over all 30 countries and years) consisting of the fossil-fuel CO₂ flux on the one side and one of the five factors of the IPAT/Kaya identity or their decomposed factors on the other side. Then, we could explore the disparity of the results in Tables 2 and 3 without assuming a specific model. The property of multicollinearity is also observed in the results of the cluster analysis performed using Ward’s method (see Section 2.3.). Details of the clustering are provided in Tables A1 and A2, but the major results can be also obtained by examining Figures 1 and 2, which show colored maps to visualize the clustering. In Figure 1a1,b1, we show the resulting clusters for G and I, respectively, while in Figure 1a2,b2, we show the resulting clusters for the corresponding decomposed variables. Each color represents a different cluster.

Figure 1. Distribution map of country clusters on the basis of fossil-fuel CO₂ flux, Kaya identity (G and I factors), and decomposed variables of G and I factor (GDP, population, TEC). (a1) Country cluster with the fossil-fuel CO₂ flux and G factor. (a2) Country cluster with the fossil-fuel CO₂ flux and decomposed variables of G factor (GDP and population). (b1) Country cluster with the fossil-fuel CO₂ flux and I factor. (b2) Country cluster with the fossil-fuel CO₂ flux and decomposed variables of I factor (GDP and TEC).
Figure 2. Distribution map of country clusters on the basis of the fossil-fuel CO₂ flux, Kaya identity (M, E, and P factors), and decomposed variables of M, E, and P factors (EC, TEC, CO₂ emissions from fossil fuel, and population). (a1) Country cluster with the fossil-fuel CO₂ flux and M factor. (a2) Country cluster with the fossil-fuel CO₂ flux and decomposed variables of M factor (EC, and TEC). (b1) Country cluster with the fossil-fuel CO₂ flux and E factor. (b2) Country cluster with the fossil-fuel CO₂ flux and decomposed variables of E factor (CO₂ emissions from fossil fuel and EC). (c1) Country cluster with the fossil-fuel CO₂ flux and P factor. (c2) Country cluster with the fossil-fuel CO₂ flux and decomposed variables of P factor (population).

The maps on the left side show no clear structure or specific pattern, whereas the maps on the right side indicate (strong) positive correlation, and we see reasonable clusters such as Central Europe and Eastern Europe. Let us, for example, consider the clusters based on the factors G and I (for details, see Table A1). Norway, Ireland, and Switzerland belong to the first cluster with the highest G factor values among the sample (0.07–0.08 MM $/person). However, the corresponding fossil-fuel CO₂ flux values are not the highest in the sample (which would indicate a positive dependence). Besides, considering again the G factor-based clustering, the fossil-fuel CO₂ flux values in Cluster 1 show a considerably large range (0.08–0.70 gC m² day⁻¹) which fully contains all values of Cluster 4.
was produced elsewhere (leading to a higher carbon footprint). Thus, the direct CO2 flux within national boundaries. It does not consider the CO2 flux from imports and exports of goods and services that entail CO2 emissions produced within national boundaries. It does not consider the CO2 emissions conveyed through international trade. For instance, if oil is imported for electricity generation, this results in an increase in emissions in the importing country. Whereas, if electricity as such is imported, it is not counted as emissions in the importing country. In countries like Switzerland, Sweden, Austria, the United Kingdom, or France, over 30% of consumption-based emissions were imported, with net imports to many Europeans of over 4 tons of CO2 per person in 2004[42]. TEC includes the imported energy from other countries. European countries may have a low production of electricity but consume much more electricity that was produced elsewhere (leading to a higher carbon footprint). Thus, the direct CO2 emissions may not

(0.25–0.37 gC m² day⁻¹). Cluster 2, again, has a considerably large range of fossil-fuel CO2 flux values comprising the smallest and the largest values (0.05–3.80 gC m² day⁻¹). Hence, we cannot derive any relation between the G factor and the fossil-fuel CO2 flux from this clustering result. Considering the decomposed factors of the G factor, again we see more evidence for a relation. The Netherlands show the highest values for GDP (24.66 MM $/km²), population (507.89 person/km²), and fossil-fuel CO2 flux (2.48 gC m² day⁻¹). With decreasing GDP, we also have tendentially a decreasing fossil-fuel CO2 flux, whereby there is a certain range in each cluster. Looking at the I factor, we have an (on average) increasing pattern of fossil-fuel CO2 flux values from Cluster 1 (0.05–0.49 gC m² day⁻¹) to Cluster 4 (2.48–3.80 gC m² day⁻¹). The I factor values are slightly decreasing, whereas the ranges of values within the individual cluster are fairly large and overlap each other. As a consequence, we can hardly see any interdependency between the I factor and the fossil-fuel CO2 flux.

Similar conclusions can be drawn by analyzing Figure 2a1–c1, where we compare the clusters for M, E, and P with the clusters of their decomposed variables (for details see Table A2). The ranges of M factor values in all clusters overlap more or less, whereas the fossil-fuel CO2 flux values are decreasing. E factor values, again, are decreasing where ranges of the cluster values hardly overlap. However, the corresponding fossil-fuel CO2 flux values do. The fossil-fuel CO2 flux values of Cluster 3 range from 0.08 gC m² day⁻¹ to 1.73 gC m² day⁻¹, which completely includes the range of Cluster 2 (0.25–0.36 gC m² day⁻¹). In addition, considering the E factor, Germany, Norway, and Finland are in the same group as Turkey, Belarus, and Romania, which have a lower efficiency of generating electricity and where coal-fired power plants are dominant (Figure 2b1). The corresponding decomposed values offer a more concrete clustering, however the fossil-fuel CO2 flux value increases from the first to the second cluster. Apart from that, all input values as well as fossil flux values decrease, hence we see a clear positive relationship. Most of the clusters identified based on the individual decomposed variables show a distinctive pattern with quite homogeneous groups and fairly large distances between the individual clusters. This reflects the heterogeneous characteristics of the individual countries in Europe. Belgium, for example, always belongs to Cluster 1, in which the decomposed variables and the fossil-fuel CO2 flux show the highest values among all four clusters; Germany and UK are always in the same cluster. Northern and eastern European countries usually belong to the same Cluster as well (Figure 1a2,b2, Figure 2a2,c2).

Thus, the results of the cluster analysis indicate that Decomposition 2 has a stronger explanatory power for the fossil-fuel CO2 flux than Decomposition 1. Besides, except for the M factor and its decomposed variables, the cluster results on the left side of Figures 1 and 2 differ significantly from those on the right side (which are based on the decomposed variables). Note that the M factor is a proportional factor that indicates the share of fossil fuels in total energy consumption [22]. Unlike other factors of the IPAT/Kaya identity, the M factor has the same cluster members in both models, that is, the model considering the correlation of M with the fossil-fuel CO2 flux and that considering the correlation between its decomposed variables (EC and TEC) and the fossil-fuel CO2 flux.

3.3. Discussion

Consumption-based CO2 emissions differ from conventional production-based inventories due to imports and exports of goods and services that entail CO2 emissions either directly or indirectly. However, the CO2 emissions in the Kaya identity account for only those CO2 emissions produced within national boundaries. The Kaya identity does not consider the CO2 emissions conveyed through international trade. For instance, if oil is imported for electricity generation, this results in an increase in emissions in the importing country. Whereas, if electricity as such is imported, it is not counted as emissions in the importing country. In countries like Switzerland, Sweden, Austria, the United Kingdom, or France, over 30% of consumption-based emissions were imported, with net imports to many Europeans of over 4 tons of CO2 per person in 2004[42]. TEC includes the imported energy from other countries. European countries may have a low production of electricity but consume much more electricity that was produced elsewhere (leading to a higher carbon footprint). Thus, the direct CO2 emissions may not
agree well with the energy consumed. In this study, we do not involve the net effect of CO₂ emissions embodied in trade. This incongruence is not discussed in the current manuscript.

Besides, in the EU, 71% of the total energy is consumed by the end users. Transformation and distribution losses account for 24% of the EU’s primary energy and about 5% by the energy sector’s own consumption of energy. A 2% increase of transformation efficiency in traditional power plants, given the same fuel mix, would save about 50 million tons of CO₂ emissions per year in the EU [43]. In this regard, we need further research about the driving forces of Kaya identity factors and decomposed variables according to variations of efficiency in energy transformation and distribution.

4. Potential and Constraints in Utilizing Decomposed Variables

The hypothesis of the IPAT/Kaya identity is that its five factors can be used to discuss the primary driving forces of inventory CO₂ emissions [40]. However, in reality, these five factors are often not instructive for discussing the primary driving forces on the CO₂ directly emitted to the atmosphere. Alternatively, as described in Section 3, the five factors of IPAT/Kaya identity can be decomposed into five subcomponents, GDP, TEC, EC, CO₂ emissions from fossil fuel, and population. However, the multiple regression model based on these five subcomponents shows significant multicollinearity. This limits the application of this model. Owing to the interdependencies among the decomposed variables, the influence of each decomposed variable on the fossil-fuel CO₂ flux may be overestimated.

A further drawback of the five decomposed variables is that, unlike the identity factors themselves, the decomposed variables are not adequate for prioritizing targets to mitigate the domestic CO₂ emission [1]. The decomposed variables cannot be used to identify specific categories of anthropogenic activities such as social, economic, industrial, and biophysical activities. For instance, GDP and TEC themselves do not provide any insights about the “targets” for reducing CO₂ emissions because the absolute numbers of both decomposed variables depend on population, economic scales, energy mix, industrial structures, and so forth. Thus, the decomposed variables of IPAT/Kaya identity are not adequately indicative of the major sectors that may help to mitigate the resulting CO₂ emissions in individual countries [44].

On the other hand, the decomposed variables have the advantage that they can be used to explain and describe the heterogeneous country-specific characteristics and levels of CO₂-emitting activities. The decomposed variables contain instructive information about the anthropogenic CO₂-emitting activities. Many authors, for example, demonstrated that atmospheric CO₂ concentrations grow linearly with the five decomposed variables (GDP, TEC, EC, population, and CO₂ emissions from fossil fuel) [45–47]. They are the representative parameters related to the direct CO₂ emitted from anthropogenic activities. Thus, the decomposed variables facilitate a comparison of the intensities of CO₂-emitting anthropogenic activities from individual countries.

As described, the IPAT/Kaya identity is a concept of splitting up the inventory CO₂ emissions into five factors. Hence, the growth rates of the components are additive, that is, the total growth rate of the inventory CO₂ emissions related to energy is the sum of the growth rates of the individual factors. When predicting future CO₂ emissions, the inferred growth rates of the individual IPAT/Kaya identity factors serve as input for predicting future CO₂ emissions or designing various emission scenarios. Thus, one of the important caveats of applying IPAT/Kaya to emission scenarios is that the five factors of IPAT/Kaya identity on the right side of Equation (2) should not be considered as the fundamental driving forces themselves [1]. The IPAT/Kaya identity assumes that each factor has the same importance in explaining the driving forces behind inventory CO₂ emissions. The fossil-fuel CO₂ flux is a footprint originating from the same CO₂ sources as in the inventory CO₂ emissions. Thus, the five factors of the IPAT/Kaya identity should be positively correlated with this flux. However, in this study, all factors of the IPAT/Kaya identity, except for the M factor, show low correlation with the fossil-fuel CO₂ flux. In contrast, four out of five decomposed variables show a high correlation with the flux. According to this study, variations in the individual IPAT/Kaya identity factors do not always positively lead to changes in the CO₂ directly emitted to the atmosphere. The IPAT/Kaya identity factors are calculated by
dividing two specific decomposed variables. This calculation process eliminates the multicollinearity among the decomposed variables and reduces the influences of the decomposed variables on the fossil-fuel CO$_2$ flux. Ignoring the correlations of the decomposed variables with this flux during the construction of the emission scenarios may lead to incorrect predictions of the actual CO$_2$ emissions, which reflect the variations in the CO$_2$ directly emitted to the atmosphere. Therefore, the correlation coefficients of the decomposed variables must be considered when building CO$_2$ emission scenarios in order to find realistic reduction targets for atmospheric CO$_2$.

5. Conclusions

The evaluation of the mutual correlation between the factors of the IPAT/Kaya identity and their decomposed variables with the fossil-fuel CO$_2$ flux, which is the CO$_2$ emitted from the in situ fossil-fuel CO$_2$ sources to the atmosphere, showed disparity between the two datasets. The decomposed variables of the IPAT/Kaya identity have a substantially higher correlation with this flux than the factors of the IPAT/Kaya identity. In addition, the individual factors of the IPAT/Kaya identity are statistically insignificant when used in a regression model to explain this flux. In contrast, the decomposed variables of the IPAT/Kaya identity are statistically significant, but show multicollinearity, when considering their regression to explain the fossil-fuel CO$_2$ flux. These results show that the influences and multicollinearity of individual decomposed variables on actual CO$_2$ emissions are not reflected in the factors of the IPAT/Kaya identity and multiplicative calculations. However, the factors of IPAT/Kaya identity are still important for policymakers since the decomposed variables cannot provide policy-wise targets for reducing CO$_2$ emissions at the national level. There are limitations to generalizing the results of this study owing to the relatively short period of 8 years of (annual) observations and the confined study area. Therefore, further research with a longer period of observations and worldwide data is necessary to generalize the results of this study. In particular, a longer period of 20–25 years (or even longer if possible) should be considered for the generalization of the results; many similar studies have considered such longer periods.

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Abbreviations

| Acronym  | Description                                                      |
|----------|------------------------------------------------------------------|
| CARMA    | Carbon Monitoring for Action                                      |
| CV       | Coefficient of variation                                         |
| DMSP-OLS | Defense Meteorological Program—Operational Line-Scan System      |
| EC       | Fossil-fuel energy consumption                                    |
| E        | CO$_2$ emissions/EC                                              |
| G        | GDP/P                                                            |
| GDP      | Gross domestic product                                           |
| GOSAT    | Japan Aerospace Exploration Agency Greenhouse Gases Observing Satellite |
| I        | TEC/GDP                                                          |
| IEA      | International Energy Agency                                      |
| M        | EC/TEC                                                           |
| Acronym | Description |
|---------|-------------|
| NIR     | National inventory report |
| ODIAC   | Open-source Data Inventory of Anthropogenic CO₂ emissions |
| OECD    | Organization for Economic Cooperation and Development |
| P/Pop   | Population size |
| TEC     | Total energy consumptions |
| UNFCCC  | United Nations Framework Convention on Climate Change |
| UNECE   | United Nations Economic Commission for Europe |
Appendix A

Table A1. Results obtained by the Ward methods in the hierarchical cluster analysis and comparisons of the members in individual cluster groups in terms of factors of the Kaya identity (G and I factors) and the decomposed variables of the Kaya identity (GDP, population, and TEC). G factor: MM $/person, I factor: ktoe/MM $, GDP: MM $/km², Pop (Population): MM person/km², TEC: ktoe/km², Fossil-fuel CO₂ flux: gC m² day⁻¹.

| Cluster Level. | Cluster 1 | Cluster 2 | Cluster 3 | Cluster 4 |
|----------------|-----------|-----------|-----------|-----------|
| Decomposed Variables of G Factor | GDP: 24.66 | GDP: 16.61–17.21 | GDP: 4.72–11.02 | GDP: 0.27–2.80 |
| G Factor | Pop: 507.89 | Pop: 213.88–375.67 | Pop: 69.78–273.05 | Pop: 14.45–137.16 |
| | Fossil-fuel CO₂ flux: 2.48 | Fossil-fuel CO₂ flux: 0.70–3.80 | Fossil-fuel CO₂ flux: 0.33–1.73 | Fossil-fuel CO₂ flux: 0.08–1.32 |

| Countries Belonging to the Cluster | NET | BEL, SWI | AUS, FRA, GER, IRE, ITA, UK | BEL, BUL, CRO, CZE, EST, FIN, GRE, HUN, LAT, LIT, NOR, POL, ROM, SI, SK, SPA, SWE, TUR, UKR |
|----------------|-----------|-----------|-----------------------------|-----------------------------|
| G Factor | G: 0.07–0.08 | G: 0.04–0.06 | G: 0.01–0.03 | G: 0.00–0.01 |
| | Fossil-fuel CO₂ flux: 0.08–0.70 | Fossil-fuel CO₂ flux: 0.05–3.80 | Fossil-fuel CO₂ flux: 0.09–1.32 | Fossil-fuel CO₂ flux: 0.25–0.37 |

| Countries Belonging to the Cluster | NOR, IRE, SWI | AUS, BEL, DEN, FIN, FRA, GER, NET, SWE, UK | CRO, CZE, EST, GRE, HUN, ITA, LAT, LIT, POL, POR, SI, SK, SPA | BLR, BUL, ROM, TUR, UKR |
|----------------|----------------|-----------------------------|-----------------------------|-----------------------------|
| Decomposed Variables of I factor | GDP: 24.66 | GDP: 16.61–17.21 | GDP: 4.72–11.02 | GDP: 0.27–2.80 |
| | TEC: 1.74 | TEC: 0.47–1.34 | TEC: 0.16–0.65 | TEC: 0.06–0.35 |
| | Fossil-fuel CO₂ flux: 2.48 | Fossil-fuel CO₂ flux: 0.70–3.80 | Fossil-fuel CO₂ flux: 0.33–1.73 | Fossil-fuel CO₂ flux: 0.08–0.35 |

| Countries Belonging to the Cluster | NET | BEL, SWI | AUS, FRA, GER, IRE, ITA, UK | BLR, BUL, CRO, CZE, EST, FIN, GRE, HUN, LAT, LIT, NOR, POL, ROM, SI, SK, SPA, SWE, TUR, UKR |
|----------------|-----------|-----------|-----------------------------|-----------------------------|
| I Factor | I: 0.05–0.54 | I: 0.04–0.15 | I: 0.06–0.13 | I: 0.08–0.09 |
| | Fossil-fuel CO₂ flux: 0.05–0.49 | Fossil-fuel CO₂ flux: 0.58–0.77 | Fossil-fuel CO₂ flux: 1.10–1.73 | Fossil-fuel CO₂ flux: 2.48–3.80 |

| Countries Belonging to the Cluster | BEL, BUL, CRO, DEN, EST, FIN, GRE, HUN, IRE, LAT, LIT, NOR, POR, ROM, SPA, SWE, TUR, UKR | AUS, FRA, ITA, POL, SI, SK, SWI | CZE, GER, UK | BEL, NET |
Table A2. Results obtained by the Ward methods in the hierarchical cluster analysis and comparisons of the members in individual clusters in terms of the factors of the Kaya identity (M, E, and P factors) and decomposed variables of the Kaya identity (GDP, population, TEC, EC, and CO₂ emission from fossil fuel). M factor: ktoe, E factor: kt CO₂ Equation/ktoe, P factor: MM person, GDP: MM $/km², Pop (Population): MM person/km², TEC: ktoe/km², EC: ktoe/km², CO₂ emission from fossil fuel: kt CO₂ Equation/km², Fossil-fuel CO₂ flux: gC m² day⁻¹.

| Cluster Level | Cluster 1 | Cluster 2 | Cluster 3 | Cluster 4 |
|---------------|-----------|-----------|-----------|-----------|
| Decomposed Variables of M Factor | EC: 1.03–1.37 | EC: 0.22–0.45 | EC: 0.15–0.30 | EC: 0.02–0.16 |
| | TEC: 1.34–1.74 | TEC: 0.35–0.65 | TEC: 0.22–0.47 | TEC: 0.06–0.33 |
| | Fossil-fuel CO₂ flux: 2.48–3.80 | Fossil-fuel CO₂ flux: 1.10–1.73 | Fossil-fuel CO₂ flux: 0.49–0.77 | Fossil-fuel CO₂ flux: 0.08–0.41 |
| Countries Belonging to the Cluster | BEL, NET | GER, UK, CZE | HUN, AUS, FRA, ITA, POL, SI, SK, SWI | DEN, IRE, BLR, BUL, CRO, EST, FIN, GRE, LAT, LIT, NOR, POR, ROM, SPA, SWE, TUR, UKR |
| M Factor | M: 0.77–0.79 | M: 0.63–0.75 | M: 0.59–0.68 | M: 0.34–0.75 |
| | Fossil-fuel CO₂ flux: 2.48–3.80 | Fossil-fuel CO₂ flux: 1.10–1.73 | Fossil-fuel CO₂ flux: 0.49–0.77 | Fossil-fuel CO₂ flux: 0.08–0.41 |
| Countries Belonging to the Cluster | BEL, NET | GER, UK, CZE | HUN, AUS, FRA, ITA, POL, SI, SK, SWI | DEN, IRE, BLR, BUL, CRO, EST, FIN, GRE, LAT, LIT, NOR, POR, ROM, SPA, SWE, TUR, UKR |
| Decomposed Variables of E Factor | EC: 1.37 | EC: 0.22–0.45 | EC: 0.22–0.45 | EC: 0.02–0.30 |
| | CO₂: 4.88 | CO₂: 1.37–2.9 | CO₂: 0.12–1.10 | CO₂: 0.08–0.77 |
| | Fossil-fuel CO₂ flux: 2.48 | Fossil-fuel CO₂ flux: 1.10–1.73 | Fossil-fuel CO₂ flux: 0.49–0.77 | Fossil-fuel CO₂ flux: 0.08–0.41 |
| Countries Belonging to the Cluster | NET | BEL | CZE, GER, UK | AUS, BEL, BUL, CRO, DEN, EST, FIN, FRA, GRE, HUN, IRE, ITA, LAT, LIT, NOR, POL, POR, ROM, SI, SK, SPA, SWE, SWI, TUR, UKR |
| E Factor | E: 13.44 | E: 7.11–8.47 | E: 4.75–6.59 | E: 0.48–4.26 |
| | Fossil-fuel CO₂ flux: 0.32 | Fossil-fuel CO₂ flux: 0.25–0.56 | Fossil-fuel CO₂ flux: 0.08–1.73 | Fossil-fuel CO₂ flux: 0.06–3.80 |
| Countries Belonging to the Cluster | EST | BUL, GRE, UKR | BLR, CZE, DEN, FIN, GER, IRE, NOR, POL, POR, ROM, SI, SK, SPA, TUR | AUS, BEL, BUL, BUL, CRO, HUN, ITA, LAT, LIT, NET, SWE, SWI, UKR |
| Decomposed Variables of P Factor | Pop: 375.67–507.89 | Pop: 205.81–273.05 | Pop: 69.78–137.16 | Pop: 18.13–46.81 |
| | Fossil-fuel CO₂ flux: 2.48–3.80 | Fossil-fuel CO₂ flux: 0.70–1.73 | Fossil-fuel CO₂ flux: 0.25–1.32 | Fossil-fuel CO₂ flux: 0.05–0.32 |
| Countries Belonging to the Cluster | BEL, NET | GER, ITA, SWI, UK | AUS, BUL, CRO, CZE, DEN, FRA, GRE, HUN, IRE, POL, POR, ROM, SI, SK, SPA, TUR, UKR | BLR, EST, FIN, LAT, LIT, NOR, SWE |
| P Factor | P: 81.10–82.66 | P: 60.54–66.87 | P: 37.97–46.59 | P: 1.32–19.59 |
| | Fossil-fuel CO₂ flux: 0.37–1.73 | Fossil-fuel CO₂ flux: 0.58–1.10 | Fossil-fuel CO₂ flux: 0.25–0.76 | Fossil-fuel CO₂ flux: 0.08–3.80 |
| Countries Belonging to the Cluster | GER, TUR | FRA, ITA, UK | POL, SPA, UKR | AUS, BEL, BLR, BUL, CRO, CZE, DEN, EST, FIN, GRE, HUN, IRE, LAT, LIT, NOR, POR, ROM, SI, SK, SWE, SWI |
References

1. IPCC. Special Report on Emissions Scenarios; IPCC: Cambridge, UK, 2000.

2. Aye, G.C.; Edoja, P.E. Effect of economic growth on CO2 emission in developing countries: Evidence from a dynamic panel threshold model. *Cogent Econ. Financ.* 2017, 5, 1379239. [CrossRef]

3. Tavakoli, A. A journey among top ten emitter country, decomposition of “Kaya Identity”. *Sustain. Cities Soc.* 2018, 38, 254–264. [CrossRef]

4. Pandey, D.; Agrawal, M.; Pandey, J. Carbon footprint: Current methods of estimation. *Environ. Monit. Assess.* 2011, 178, 135–160. [CrossRef] [PubMed]

5. Hwang, Y.; Um, J.-S. Performance evaluation of OCO-2 XCO2 signatures in exploring casual relationship between CO2 emission and land cover. *Spat. Inf. Res.* 2016, 24, 451–461. [CrossRef]

6. Gurney, K.; Liang, J.; Patarasuk, R.; O’Keefe, D.; Huang, J.; Hutchins, M.; Lauvaux, T.; Turnbull, J.; Shepson, P. Reconciling the differences between a bottom-up and inverse-estimated FFCCO2 emissions estimate in a large US urban area. *Elem. Sci. Anth.* 2017, 5, 44. [CrossRef]

7. Hwang, Y.-S.; Lee, J.-J.; Park, S.-I.; Um, J.-S. Exploring explainable range of in-situ portable CO2 sensor signatures for carbon stock estimated in forestry carbon project. *Sens. Mater.* 2019, 31, 3773. [CrossRef]

8. Chertow, M.R. The IPAT equation and its variants. *J. Ind. Ecol.* 2000, 4, 13–29. [CrossRef]

9. Jia, B.; Tsau, J.; Barati, R. A review of the current progress of CO2 injection EOR and carbon storage in shale oil reservoirs. *Fuel* 2019, 236, 404–427. [CrossRef]

10. Lutz, W. Population and environment—What do we need more urgently: Better data, better models, or better questions? In *Environment and Population Change;* Zaba, B., Clarke, J., Eds.; Derouaux Ordina Editions: Liege, Belgium, 1994.

11. USGCRP. *Second State of the Carbon Cycle Report (SOCCR2): A Sustained Assessment Report*; U.S. Global Change Research Program: Washington, DC, USA, 2018.

12. Gurney, K.R.; Law, R.M.; Denning, A.S.; Rayner, P.J.; Baker, D.; Bousquet, P.; Bruhwiler, L.; Chen, Y.-H.; Ciais, P.; Fan, S.; et al. Towards robust regional estimates of CO2 sources and sinks using atmospheric transport models. *Nature* 2002, 415, 626–630. [CrossRef]

13. Hwang, Y.; Um, J.-S. Evaluating co-relationship between OCO-2 XCO2 and in situ CO2 measured with portable equipment in Seoul. *Spat. Inf. Res.* 2016, 24, 565–575. [CrossRef]

14. Hwang, Y.; Um, J.-S. Exploring causal relationship between landforms and ground level CO2 in Dalseong forestry carbon project site of South Korea. *Spat. Inf. Res.* 2017, 25, 361–370. [CrossRef]

15. Turnbull, J.C.; Keller, E.D.; Norris, M.W.; Wiltshire, R.M. Independent evaluation of point source fossil fuel CO2 emissions to better than 10%. *Proc. Natl. Acad. Sci. USA* 2016, 113, 10287–10291. [CrossRef] [PubMed]

16. Avitabile, V.; Schultz, M.; Herold, N.; de Bruin, S.; Prathast, A.K.; Manh, C.P.; Quang, H.V.; Herold, M. Carbon emissions from land cover change in Central Vietnam. *Carbon Manag.* 2016, 7, 333–346. [CrossRef]

17. Raupach, M.R.; Canadell, J.G.; Le Quéré, C. Anthropogenic and biophysical contributions to increasing atmospheric CO2 growth rate and airborne fraction. *Biogeosciences* 2008, 5, 1601–1613. [CrossRef]

18. Zhang, X.; Gurney, K.R.; Rayner, P.; Baker, D.; Liu, Y.P. Sensitivity of simulated CO2 concentration to sub-annual variations in fossil fuel CO2 emissions. *Atmos. Chem. Phys.* 2016, 16, 1907–1918. [CrossRef]

19. Garrett, T.J. Are there basic physical constraints on future anthropogenic emissions of carbon dioxide? *Clim. Chang.* 2011, 104, 437–455. [CrossRef]

20. National Research Council. *Verifying Greenhouse Gas Emissions: Methods to Support International Climate Agreements;* The National Academies Press: Washington, DC, USA, 2010; p. 124. [CrossRef]

21. Andrejeiová, M.; Grincová, A.; Marasoviňová, D. Study of the percentage of greenhouse gas emissions from aviation in the EU-27 countries by applying multiple-criteria statistical methods. *Int. J. Environ. Res. Public Health* 2020, 17, 3759. [CrossRef]

22. Jung, S.; An, K.-J.; Dob diba, G.; Fujita, T. Regional energy-related carbon emission characteristics and potential mitigation in eco-industrial parks in South Korea: Logarithmic mean Divisia index analysis based on the Kaya identity. *Energy* 2012, 46, 231–241. [CrossRef]

23. Ma, M.; Cai, W. What drives the carbon mitigation in Chinese commercial building sector? Evidence from decomposing an extended Kaya identity. *Sci. Total Environ.* 2018, 634, 884–899. [CrossRef]

24. Mahony, T.O. Decomposition of Ireland’s carbon emissions from 1990 to 2010: An extended Kaya identity. *Energy Policy* 2013, 59, 573–581. [CrossRef]
25. Lima, F.; Nunes, M.L.; Cunha, J.; Lucena, A.F.P. A cross-country assessment of energy-related CO₂ emissions: An extended Kaya index decomposition approach. *Energy* **2016**, *115*, 1361–1374. [CrossRef]

26. IEA. *Energy Statistics of OECD Countries* 2015; OECD Publishing: Paris, France, 2015. [CrossRef]

27. IEA. *Energy Statistics of Non-OECD Countries* 2015; IEA: Paris, France, 2015. [CrossRef]

28. Fujimori, S.; Matsuoka, Y. Development of method for estimation of world industrial energy consumption and its application. *Energy Econ.* **2011**, *33*, 461–473. [CrossRef]

29. IEA. *Energy Balances of OECD Countries* 2015; OECD Publishing: Paris, France, 2015. [CrossRef]

30. IEA. *Energy Balances of Non-OECD Countries* 2015; IEA: Paris, France, 2015. [CrossRef]

31. IEA. Available online: https://www.iea.org/data-and-statistics/data-tables?country=WORLD (accessed on 13 April 2020).

32. World Bank. Available online: https://data.worldbank.org/ (accessed on 13 April 2020).

33. Gernaat, D.E.H.J.; Calvin, K.; Lucas, P.L.; Luderer, G.; Otto, S.A.C.; Rao, S.; Strefer, J.; van Vuuren, D.P. Understanding the contribution of non-carbon dioxide gases in deep mitigation scenarios. *Glob. Environ. Chang.* **2015**, *33*, 142–153. [CrossRef]

34. Yılmaz, G.; Bilgili, A.V. Modeling seasonal variations of long-term soil CO₂ emissions in an orchard plantation in a semiarid area, SE Turkey. *Environ. Monit. Assess.* **2018**, *190*, 486. [CrossRef]

35. Oda, T.; Maksyutov, S. A very high-resolution (1 km × 1 km) global fossil fuel CO₂ emission inventory derived using a point source database and satellite observations of nighttime lights. *Atmos. Chem. Phys.* **2011**, *11*, 543–556. [CrossRef]

36. Andres, R.; Gregg, J.; Losey, L.; Marland, G.; Boden, T. Monthly, global emissions of carbon dioxide from fossil fuel consumption. *Tellus B* **2011**, *63*, 309–327. [CrossRef]

37. Maksyutov, S.; Takagi, H.; Belikov, D.A.; Saito, M.; Oda, T.; Saeki, T.; Valsala, V.K.; Saito, R.; Ito, A.; Yoshida, Y.; et al. *Algorithm Theoretical Basis Document (ATBD) for the Estimation of CO₂ Fluxes and Concentration Distributions from GOSAT and Surface-Based CO₂ Data*; NIES: Tsukuba, Japan, 2014.

38. Chen, Y. Spatial autocorrelation approaches to testing residuals from least squares regression. *PLoS ONE* **2016**, *11*, e0146865. [CrossRef]

39. Rodríguez, M.Z.; Comin, C.H.; Casanova, D.; Bruno, O.M.; Amancio, D.R.; Costa, L.d.F.; Rodrigues, F.A. Clustering algorithms: A comparative approach. *PLoS ONE* **2019**, *14*, e0210236. [CrossRef]

40. Kaya, Y.; Yokobori, K. *Environment, Energy, and Economy: Strategies for Sustainability*; United Nations University Press: Tokyo, Japan, 1997.

41. European Union. *Analysis of Greenhouse Gas Emission Trends and Drivers*; European Commission: Luxembourg, 2013.

42. Davis, S.J.; Caldeira, K. Consumption-based accounting of CO₂ emissions. *Proc. Natl. Acad. Sci. USA* **2010**, *107*, 5687–5692. [CrossRef]

43. Agency, E.E. Are Energy Losses in Transformation and Distribution Declining in Europe? Available online: https://www.eea.europa.eu/data-and-maps/indicators/energy-efficiency-in-transformation/are-energy-losses-in-transformation (accessed on 13 April 2020).

44. Alcamo, J.; Bouwman, A.; Edmonds, J.; Grubler, A.; Morita, T.; Sugandhly, A. *An Evaluation of the IPCC IS92 Emission Scenarios*; IIASA: Cambridge, UK, 1995.

45. Blanco, G.; Gerlagh, R.; Suh, S.; Barrett, J.; de Coninck, H.C.; Diaz Morejon, C.F.; Mathur, R.; Nakicenovic, N.; Ofou Ahenkora, A.; Pan, J.; et al. Drivers, trends and mitigation. In *Climate Change 2014: Mitigation of Climate Change. Contribution of Working Group III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*; Edenhofer, O., Pichs-Madruga, R., Sokona, Y., Farahani, E., Kadner, S., Seyboth, K., Adler, A., Baum, I., Brunner, S., Eickemeier, P., et al., Eds.; Cambridge University Press: Cambridge, UK; New York, NY, USA, 2014.

46. Friedlingstein, P.; Andrew, R.M.; Rogelj, J.; Peters, G.P.; Canadell, J.G.; Knutti, R.; Luderer, G.; Raupach, M.R.; Schaeffer, M.; van Vuuren, D.P.; et al. Persistent growth of CO₂ emissions and implications for reaching climate targets. *Nat. Geosci.* **2014**, *7*, 709–715. [CrossRef]

47. Varotsos, C.A.; Mazei, Y.A. Future temperature extremes will be more harmful: A new critical factor for improved forecasts. *Int. J. Environ. Res. Public Health* **2019**, *16*, 4015. [CrossRef] [PubMed]