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Sectoral performance analysis of national greenhouse gas emission inventories by means of neural networks

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Abstract

Annual greenhouse gas emissions have increased more than threefold between 1950 and 2014, posing a major threat to the integrity of the entire earth system and subsequently to humankind. Consequently, roadmaps towards low-carbon pathways are urgently needed. Our study contributes to a more detailed understanding of the dynamics of country based emission patterns and uses them to discuss prospective low-carbon pathways for countries. As availability of databases on sectoral emissions substantially increased, we employ machine learning techniques to classify emission features and pathways. By doing so, 18 representative emission patterns are derived. Overall emissions from seven sectors and for 167 countries covering the time span from 1950 to 2014 have been used in the analyses. The following significant trends can be observed: a) increasing per capita emissions due to growing fossil fuel use in many parts of the world, b) a decline in per capita emissions in some countries, and c) a shift in the emission shares, i.e., a reduction of agricultural and land use contributions in certain regions. Using the emission patterns, their dynamics, and best performing countries as role models, we show the possibility for gaining a decent human development without significantly increasing per capita emissions.

Keywords: emissions, mitigation, human development, self-organizing map, machine learning, climate change

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1. Introduction

The consumption of fossil fuels is the major source of emissions followed by deforestation and agriculture (Gütschow et al., 2016). While the increasing global trend of greenhouse gas emissions is still unbowed, large differences exist in terms of emission drivers and how certain sectors contribute to emission profiles of different countries (IPCC, 2014).

Today, countries are usually grouped according to spatial and political criteria for a global analyses (IPCC, 2014; UNEP, 2017) and together with sectoral information these groups are used to analyze the global emission dynamics, i.e., changes in emission quantities and sources over time (Olivier et al., 2017; Timilsina, 2016; UNEP, 2017). However, such analysis neglects the characteristics of countries and may therefore blur their emission quantities and sources. Moreover, it is difficult to understand why some countries perform better in terms of emissions although they are characterized by similar development stages. Despite recent progress in the analysis of trends in national emission dynamics, these are mostly carried out for selected countries only, e.g. Emission Gap Report 2017 (UNEP, 2017) and are of limited use for gathering global solutions. Hence, comprehensive understanding on the global emission dynamics based on national emission time series is still required.

With more than 20 years of efforts policymakers agreed to limit global warming to well below 2 °C as ratified in the Paris Agreement in 2015 (UN, 1992; UNFCCC, 2015). Nevertheless, actual climate policy and agreed reduction ambitions, as expressed in Nationally Determined Contributions (NDCs), are yet far away from a reliable climate protection target (Roelfsema et al., 2018; Rogelj et al., 2016). Consequently, roadmaps to guide human civilizations towards low-carbon pathways are urgently needed (Rockström et al., 2017). An approach for identifying the pathways is to look for countries, which are performing best, to act as role models and set best-practice standards. So far two attempts exist to rate and rank countries according to their emissions and NDC ambitions (Burck et al., 2017; Climate Action Tracker, 2017). Climate Action Tracker

(2017) analyzed how compatible are a country's current policies, NDC, long-term targets, and 2020 pledges to meet the Paris Agreement. Similarly, Burck et al. (2017) evaluated the climate protection performances of countries based on their emissions, renewable energies, energy use, and climate policy. However, these studies cover only 56 (Burck et al., 2017) and 33 (Climate Action Tracker, 2017) countries, i.e., they cannot provide a global overview. In addition, they do not consider differences in the origin of emissions and thus disparate endeavors for countries facing mitigation needs are neglected.

To contribute to the above discussion we provide a data driven classification of emission patterns, based on both sectoral and national emission time series data. To our knowledge underlying trends of these emission dynamics have never been studied using machine learning techniques, despite their application in many other studies in the environmental field e.g. Hsieh (2009); Kanevski et al. (2009). In the short term it is rather unlikely to obtain sufficient knowledge about the intrinsic country dynamics and how this may materialize in emission profiles. Moreover, in case of an inadequate a priori knowledge system components are being determined by many unknown and nonlinear interactions between their sectoral components, inductive methods may supply valuable results for understanding the behavior of systems in a more qualitative context. Especially in complex modeling problems or in the context of analysis and forecasting of whole systems, elucidation of knowledge from data sets therefore has advantages. Thus, in the first step we identify emission patterns by using a self-organizing neural network approach. In the second step national and temporal changes in emission profiles have been examined for the last six decades. This approach enables us to examine national and sectoral emission dynamics with machine learning techniques in order to identify underlying trends. The analyses have been complemented by the identification of best practice countries as role models in terms of low emissions and desirable human development to explore future low-carbon pathways.

2. Data and methods

2.1. Data sources and preprocessing

We used sectoral emission data version 1.1 from Gütschow et al. (2017) for this study. Gütschow et al. (2017) aggregated sectoral emissions on country scale from multiple publicly available sources through an extensive process of prioritization and extrapolation. The dataset covers all Kyoto gas emissions from each UNFCCC member state and different non-UNFCCC territories for the period 1850 to 2014. The data is available for seven sectors: "Total Energy", "Industrial Processes", "Solvent and other product use", "Agriculture", "Land Use, Land Use Change, and Forestry (LULUCF)", "Waste", and "Other" (Gütschow et al., 2016). Population data is needed to convert national emissions into per capita emissions (UN, 2015), which is available for 233 countries and for the period 1950 to 2015. The sectoral emissions were selected according to their global warming potential based on the fourth Assessment Report of the IPCC and the period covered by the population dataset, i.e., from 1950 to 2014 (Gütschow et al., 2017).

In the first step sectoral national emissions have been converted into sectoral per capita emissions using the population data. In a second step all countries with data gaps in the emission data were excluded, because handling data gaps would impose a slightly different analytical method. As the performance of emission sources and emission savings should be analyzed, LULUCF are defined as zero if this sector is a net emission sink that is indicated by negative numbers. In addition sectoral per capita emissions for "Total Energy" and "Solvent and other product use" reveal some extreme values, providing unstable results. Therefore, we exclude countries that are characterized by sectoral per capita emissions in the top 99^{th} quantile in these sectors.

The final aggregated input dataset used for neural network analysis consists of 10,855 data points and includes per capita emission time series for seven sectors and 167 countries for the period 1950 to 2014 (Table S1). These 167 countries emitted approx. 52 Gt CO_2eq and were responsible for 98.7% of the global emissions in 2014. The sectoral per capita emissions of a country for a year is considered as a data point. In the input data, the total emissions per capita range between 0.3 t CO_2eq/cap/yr and 65.8 t CO_2eq/cap/yr with a mean value of 8.54 t CO_2eq/cap/yr.

As there exists a dependency between human development and carbon dioxide emissions (Costa et al., 2011; Reusser et al., 2013), we also considered data on the human development index (HDI) (UNDP, 2017). Consequently, low emissions combined with a high HDI can be characterized as best practice examples. We selected the HDI data for the countries that belong to the final emission dataset (Table S2). The selected HDI data contains yearly values for 132 countries in 1990, with an over time increasing coverage to 161 countries in 2014.

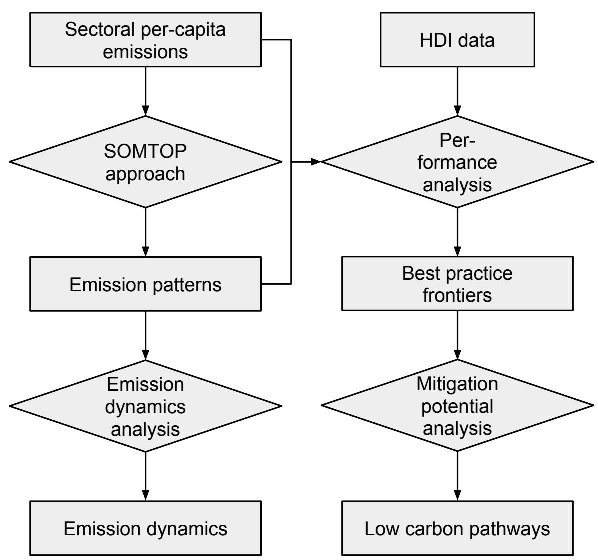

Figure 1: An overview of the applied methodology. The data on sectoral per capita emissions is analyzed by applying the Self-Organizing Map with Topographical Product (SOMTOP) to identify emission patterns and transitions. This is supplemented by an performance analysis using the Human Development Index (HDI) to estimate mitigation potentials.

2.2. Methodological approach

An overview of the applied methodological approach is given in Figure 1. Assuming that data are representative for a system under investigation, complex signal processing tasks can be solved by an appropriate encoding of the relevant information of the underlying data set on an object. Consequently, this motivates the use of Self-organizing map (SOM), an artificial neural network, together with topographical product (TOP). This approach has several advantages against classical methods, e.g., a low susceptibility against noisy data and can immanently discover salient features in a data distribution and categorize each pattern according to these features.

2.2.1. Self-organizing map (SOM)

Self-organizing map (SOM) extracts in a self-supervising way structural information from numerical data as opposed to memorizing all of it (Kohonen, 2001). Thus, SOM's are capable of displaying both the phenomenological pattern hidden in an input data set and the neighborhood relations between the structural units. The interpretation of the information stored in the trained network provides cross-sectional phenomena of the system being observed. It has been applied frequently in environmental systems analysis, i.e. landscape analysis or anthropogenic structures, which are complex and characterized by an inadequate a priori knowledge on processes occurring within and between different system components or noisy data.

During the learning it maps an m-dimensional continuous input space V onto an n-dimensional discrete space A, representing the structural information of the input data (clusters, types). The SOM learning process can be formulated as follows (Astudillo and Oommen, 2014; Kropp, 1998; Skupin and Agarwal, 2008):

1. The weight vectors ω_i of the nodes in the output space A are initialized by the assignment of random values.
2. With each iteration t an input vector v from the input space V is stochastically selected and than presented to A, where all nodes compete to best represent v.

3. Step (2) is repeated until a predefined threshold of the average changing rate of the map, or the mapping error, or number of iterations is reached. To ensure high quality results the topological distortion of the mapping is measured in addition and used as an evaluation criteria (cf. section below). All three measure together has been used a termination criteria (Table S3).

The data are finally represented by a "hyperplane" of lower dimensionality, which is embedded within data space. Therefore, the approach can be interpreted as a clustering and non-linear dimensionality reduction technique (e.g., in the sense of a non-linear principal component analysis) (Skupin and Agarwal, 2008). The technique offers a convenient method to reduce the amount of information as well as to form an implicit model, without having to develop a traditional physical model of the underlying problem. The major advantage of a SOM is that it can preserve the topological order in the input data set (cf. below). This is of particular relevance for the analyses as we compare countries, which show regional interdependencies in terms of their geographical distribution or in regard to similar HDI values.

2.2.2. Topographical Product (TOP)

It might happen, due to unsuitable experimental settings, that the network training would produce topological distortion, e.g., in terms for twisted output networks. To avoid this, the network is combined with an algorithm which can quantify neighborhood distortions (Bauer and Pawelzik, 1992). The combined SOMTOP approach is applied to classify representative emission patterns based on the sectoral per capita emissions of 167 countries for the period 1950 to 2014. This approach has been used in several studies (Kropp, 1998; Kropp and Schellnhuber, 2008; Pradhan et al., 2013).

As the SOMTOP training consumes a considerable amount of computational time it is worth to know an upper boundary for the embedding dimension of the data set. For this purpose the principal component analysis (PCA) has been used. Although the PCA is a linear approach it can be assumed that the obtained value provides an upper boundary for the SOMTOP learning.

2.3. Analysis of emission dynamics

Since emission patterns are identified for the period 1950-2014 across the world, sectoral emissions of a country can belong to different emission patterns at different years. We capture the emission dynamics for the last six decades by analyzing frequencies and likelihoods of observed emission transitions. By the means of the generated emission patterns a transition of a country can be observed as a change in emission patterns. Thus, we define a transition as the change of a country from one emission pattern to another and staying in the new pattern for at least three years. The three year restriction is introduced to only capture significant transitions, as some countries yearly alternated between two patterns without displaying major changes in emissions. The likelihood is calculated for each transition possibility, and describes the statistically observed chance of a country in one pattern to move to another specific pattern.

2.4. Performance analysis

We applied a performance analysis to identify the best practice frontiers, using per capita emissions as input and HDI as output. Performance analysis in connection with artificial neural networks have been carried out in different studies, e.g., in context of greenhouse gas emissions from agricultural production, operational and environmental efficiency of primary sectors, and human well-being (Carboni and Russu, 2015; Vlontzos and Pardalos, 2017a,b). Our analysis considered that a country's objective is to maximize its HDI and to minimize its per capita emissions. By doing this, we were able to estimate hypothetical emissions of countries to achieve their HDIs if they were on the best practice frontier (Section 2.5). Our analysis has two assumptions: i) constant returns to scale, i.e., a linear relation between input and output at any scale; and ii) the best practice countries have a decent standard of living with high human development, i.e., HDI ≥ 0.7 (UNDP, 2016). Therefore, the best practice frontiers were represented by straight lines with the slope derived based on ratios between HDI and per capita emissions.

We identified the frontiers considering two different scenarios to understand variations between the best practices within the emission patterns and worldwide. In Scenario A the frontiers were determined for each emission pattern, while in Scenario B they were estimated for each year from 1990 to 2014. We first calculated the ratio between HDI and per capita emissions for each country and year (henceforward country entry). The larger the value of the ratio, the better the country entry is in attaining higher HDI with lower emissions. Afterwards, we identified the three country entries with the largest HDI and emission ratios within the respective peer group (pattern and year). The best practice frontiers were estimated by taking an average of these three ratios within each pattern (Scenario A) and each year (Scenario B) so that the frontiers were not only influenced by an extremely best performer.

2.5. Analysis of mitigation potentials

The mitigation potentials were calculated for each country based on the performance analysis (Figure S1). We defined the mitigation potential as the difference between the country's emissions and the hypothetical emissions of the country to achieve its HDI if the country were on the best practice frontier. The hypothetical emissions were estimated by multiplying country's population with the per capita emissions obtained by dividing the slope of the frontier by the country's HDI. Similar to the performance analysis only countries with an HDI of at least 0.7 were considered to estimate the mitigation potential. By doing so, we reserved a fair emission path for developing countries to proceed with their development as suggested by Costa et al. (2011).

For both scenarios A and B, we estimated the hypothetical emissions for each country for the period 1990 to 2014. Here scenario A represented the emissions of a country if the country were as efficient as the best examples within its emission pattern in obtaining higher HDI with lower emissions. Whereas scenario B provided country's emissions if the country were as efficient as the best examples worldwide for the particular year. Afterwards, we obtained the global hypothetical emissions for the period 1990 to 2014 by summing up the emissions for each country.

3. Results

3.1. Emission patterns

The sectoral per capita emissions for the period 1950 to 2014 can be explained by 18 emission patterns that consist of different amount and composition of emissions (Figure 2). We obtained these patterns by applying the SOMTOP approach that suggests 18 nodes (a two-dimensional network: 6x3) as the best representation of the emission data with the topographical product being closest to zero (Table S3). Our PCA also indicated a two dimensional network as two PCs explained the majority of variation in the data (Table S4). We used the linear approach based on the PCA to estimate an upper bound of the dimensionality reduction for the SOMTOP approach that is a clustering in addition to non-linear dimensionality reduction technique. For a brief discussion, we categorized the emission patterns into four groups according to the quantity of per capita emissions: low (A–C), moderate (D–J), high (K–P), and very high (Q and R) emitters.

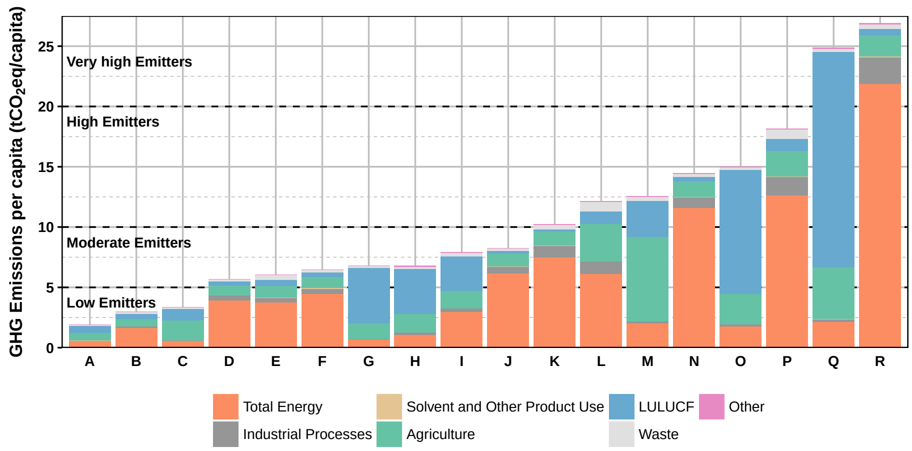

Figure 2: The 18 emission patterns identified by the SOMTOP approach. The patterns are categorized in low, moderate, high and very high emitters according to quantity. The sectoral composition is mostly dominated either by the energy (D, E, F, J, K, N, P, R), or the Land Use, Land Use Change, and Forestry (LULUCF) (G, H, O, Q) sector, or a mixed sources (A, B, C, I, L, M).

Low emitters, A–C with emissions up to 5 $t\,CO_2eq/cap/yr$, are present on every continent, with Africa and Asia being core areas (Figure 2). Among the low emitters, B and C have higher emissions mainly coming from energy and agricultural sector, respectively. Patterns D, E, F, and J are energy dominated moderate emitters (5 to 10 $t\,CO_2eq/cap/yr$), which existed mainly in Europe, as well as in China in more recent years (1995–2014). Other member countries of the moderate emitters (G, H, I) have large shares of emissions from LULUCF and agricultural sectors, and are mostly located in tropical regions. High emitters (10 to 20 $t\,CO_2eq/cap/yr$) are dispersed worldwide. They have either large shares of emissions from energy (K, L, N, P), agricultural (M) or LULUCF (O) sectors. Very high emitters (>20 $t\,CO_2eq/cap/yr$) belong to either LULUCF (Q) or energy (R) dominated patterns.

The 18 emission patterns show that emission mitigation potentials need to be explored in the energy, the LULUCF, and the agricultural sector (Figure

2). The energy sector is the biggest emission contributor for almost half of the patterns. Similarly, the LULUCF sector has the largest emission share in three patterns. Within the six patterns of mixed sources, emissions are mainly coming from two of the three sectors (energy, LULUCF, and agriculture).

Globally, only a small number of countries had high and very high per capita emissions (Figure 3). The highest number of countries belongs to the low emitter A, followed by the LULUCF dominated moderate emitter G. The data points belonging to other patterns range between 324 (Pattern R) and 791 (Pattern B). Altogether, the majority of country entries are rather low and moderate emitters. In addition, the patterns of mixed source composition (I, L, M) tend to contain less data points than especially energy dominated patterns (e.g. D, J, K, N).

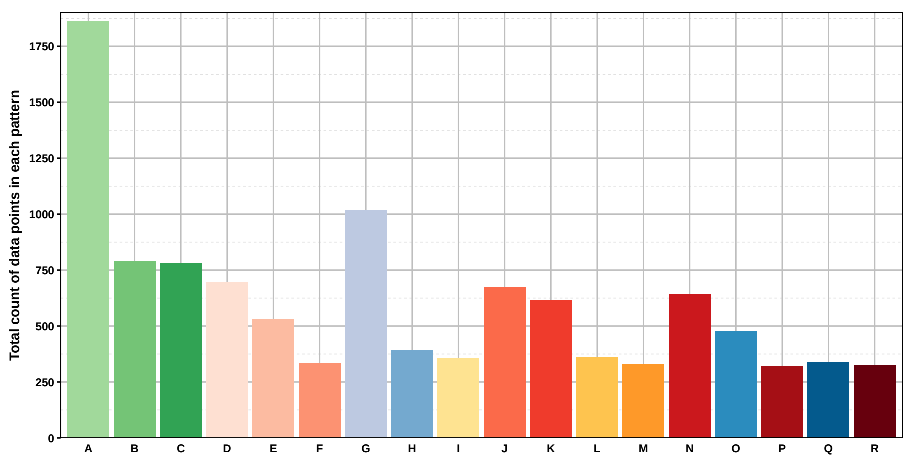

Figure 3: The number of data points in the emission pattern. The pattern with the lowest per capita emissions (A) has by far the most country entries (1864), while the pattern with the highest per capita emissions (R) contains the least (324). In general, low emitting patterns (<5 t CO_2eq/cap/yr) have more country entries than higher emitting patterns.

3.2. Spatial variation of emission patterns

The emission patterns vary widely among continents and over time (Figure 4). In Asia, most countries from the Middle East, the former Soviet Union, and East Asia become energy dominated high and very high emitters over time. South East Asia mostly transforms from moderate LULUCF dominated to high energy dominated or mixed source emitters. This trend goes along with an increase in HDI values in the respective countries. On the contrary, South Asia remain low emitters, although HDI values increase steadily but at low rates.

Emission patterns in Africa are quite diverse. Countries in the Sahel and East Africa are predominantly low emitters. In the Congo basin, countries tend towards LULUCF dominated patterns of very high emitters in the beginning of 1950s, which has reduced later on. In addition, a few African countries are high emitters with a large share of emissions from the agriculture or the energy sector.

North America is split in two parts throughout the study period. Canada and the USA are characterized as energy dominated high and very high emitters. While Central American countries are low and moderate emitters with LULUCF dominated or mixed sources.

Countries in South America are mostly moderate and high emitters with LULUCF dominated or mixed sources. While LULUCF dominated emitters predominate in the beginning of 1950s, most countries start emitting from mixed sources over time. Further, an increase in number of energy dominated emitters is observed by 2014. The changes in emission sources in most countries go conjointly with an increase in their HDIs.

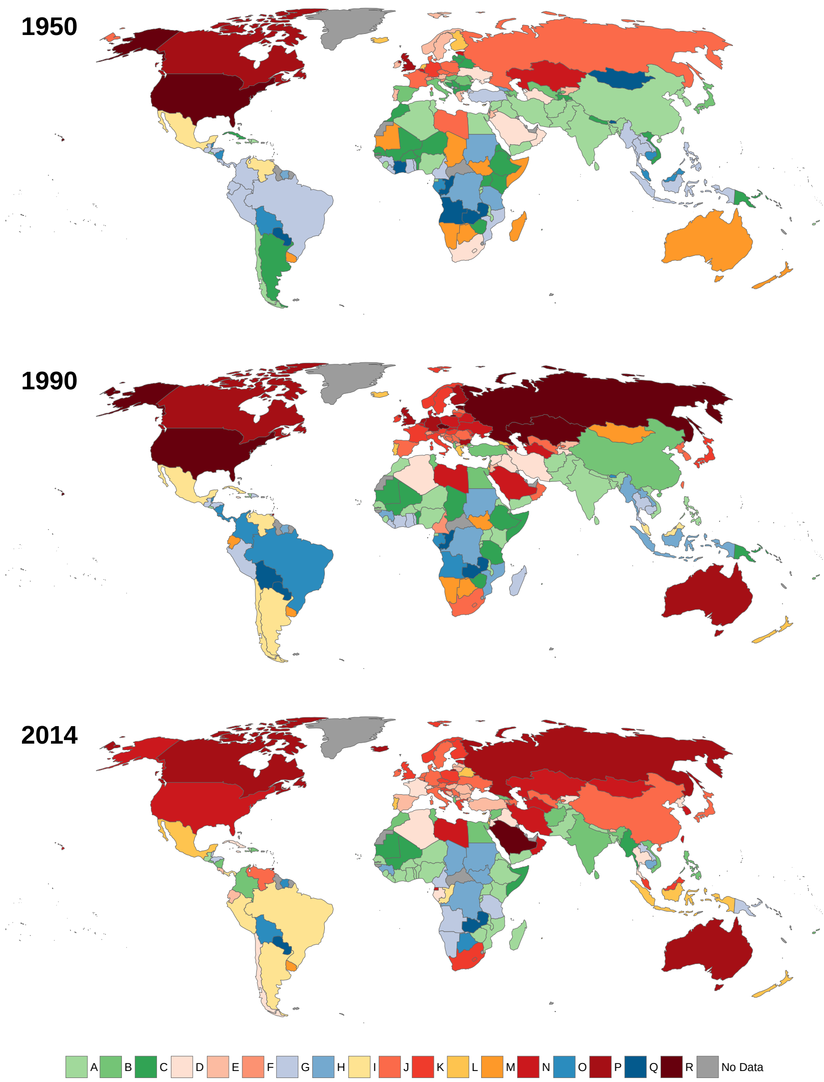

Figure 4: Spatial distribution of emission patterns in 1950, 1980, and 2014. China and Australia undergo great changes towards energy dominated patterns. Sub-Saharan Africa, with the exception of South Africa, show land use and agriculture dominated patterns, while countries in Northern Africa and the Middle East mostly move towards energy dominated patterns. Countries in South East Asia change from Land Use, Land Use Change, and Forestry (LULUCF) to mixed or energy dominated patterns. North America and Russia stay in energy dominated classes.

In Europe different energy dominated emitters prevail. In the 1950s, Center, West, and North Europe are moderate and high energy dominated emitters, while countries in the Mediterranean and the former Eastern Block are mainly low energy dominated emitters. By 1990 almost all countries transform to high energy dominated emitters. Overall, per capita emissions are increasing in most European states in the first half of the study period, and then decrease again in the second half. Reasons for the decline are technological changes and fuel switches (Henriques and Borowiecki, 2017), and economical changes in the former Soviet states after 1990s (Brizga et al., 2013).

In Oceania three widely different emission categories exist. New Zealand and Australia are high emitters with emissions from mixed and energy dominated sources, respectively. All other countries are low or moderate emitters.

3.3. Emission dynamics

In the last six decades, many countries have shifted from low to higher per capita emissions, mainly due to an increase in fossil fuel use (Figure 5). In particular, the number of the low emitters has reduced by almost one third. The number of the high emitters more than doubled until 2004 and fell slowly afterwards. In contrast, the number of countries with large shares of emissions from the LULUCF and agricultural sectors has decreased until 2014. The global emissions from the LULUCF and agricultural sectors has recently reduced (IPCC, 2014).

Contrary to the number of countries associated with low emitters, population in this group almost doubled from around 1.5 to 2.9 billion in the past six decades (Figure S2). This is mainly due to high population growth rates in member countries of this group. More interestingly, we observe considerable increase in population associated with moderate and high emitters, mainly in energy dominated or mixed source patterns. These patterns represent a small number of population in the beginning, however, it has grown to almost half of the world population by 2014. A reason for such increase is China became a moderate emitter from a low emitter between 1950 and 2014.

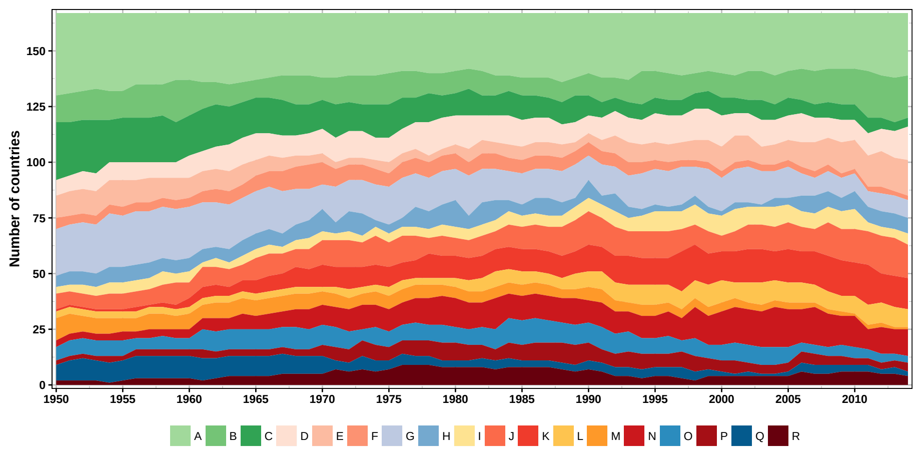

Figure 5: Changes in the size of the emission patterns over time in terms of country entries. The size of low emitters (A–C) and Land Use, Land Use Change, and Forestry (LULUCF) dominated emitters (G, O, Q) have decreased. Contrary, most energy dominated patterns has increased (D, J, K, N). This reflects the shift from low to higher per capita emissions in many countries due to growing fossil fuel uses.

We observe the highest frequencies for the transition from low to moderate energy dominated emitters (Figure 6). The connections A→B→D→J build a transition pathway, which is characterized by the highest observed frequencies and high likelihoods (Table S5 and S6). This pathway or parts of it are mostly taken by countries in Europe and Asia, e.g., Spain, Croatia, China, India, South Korea. Another pathway, reflecting a decrease in LULUCF related per capita emissions, is highlighted by Q→O→G. This is mainly present in tropical countries, e.g., Brazil, Colombia, Angola, Côte d'Ivoire, Malaysia. Although LULUCF dominated per capita emissions decrease over time, this does not reflect the increase in total emissions from LULUCF in most of the tropical countries, with Brazil and Mexico being exceptions (Zarin et al., 2016).

We find pattern G (a LULUCF dominated moderate emitter) as an interesting intersection, with the most connections to other patterns. A country, transiting from pattern G, becomes either low or moderate emitter with mixed

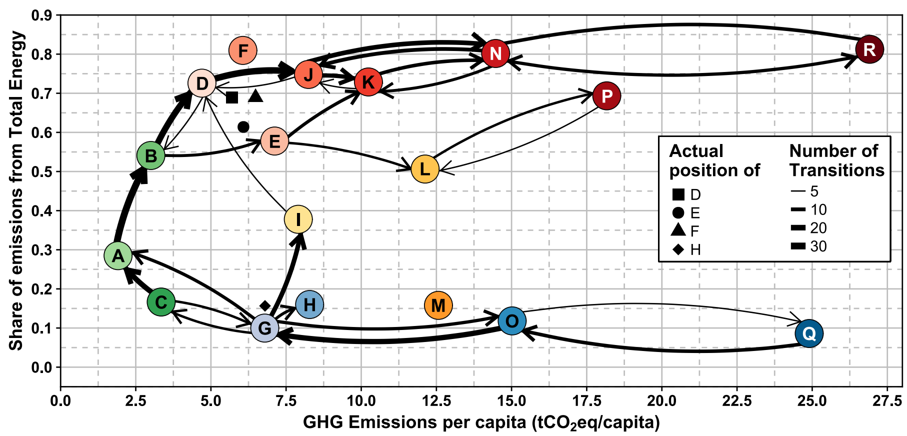

Figure 6: Prominent transitions from one emission pattern to another (only transitions of at least 5 times are shown). Most frequent transitions are observed from A to B (30 times), D to J (27 times), B to D (25 times), C to A (18 times), and O to G (18 times). In general, transitions often occurred from low to moderate energy dominated, moderate to high energy dominated, and high to moderate LULUCF emitters.

(e.g., I and H) or LULUCF dominated sources (O). Most frequently observed transition is from G to I that reflects an increase of per capita emissions from the energy sector with progress in human development. For examples, Brazil, Colombia, and Panama recently moved from G to I pattern. We also observe frequent transitions from G to A and C (low emitters), which translates in a decrease of LULUCF related per capita emissions mainly in Asia and Africa. This can be linked to population growth and a decrease in deforestation in some Asian and Africa countries in the last two decades (Mayaux et al., 2013).

3.4. Best practice frontiers

Looking at ratios between countries' HDI and per capita emissions, we found that the best practice frontiers show huge differences among the patterns in the plane (Table 1 and Figure S3). The best practice frontiers are represented by straight lines with slopes defined by the ratios. The larger the ratio is the better a country performs in achieving higher HDI with lower emissions. In general, the frontier slopes of low and moderate energy dominated or mixed source emitters are larger than those of high, very high, and LULUCF dominated emitters. Countries that are energy dominated high and very high emitters, also have relatively larger HDI. This indicates that improvements in HDI might be achieved through activities that use fossil energy. HDIs and per capita emissions from fossil fuel combustion shows the existence of a positive and time-dependent correlation (Costa et al., 2011). On the contrary, the HDIs of LULUCF dominated emitters are relatively low. This reflects that emissions from LULUCF do not contribute much to countries for reaching very high human development. For achieving a higher gross domestic product (GDP), an important component of the HDI, a country needs to transform its economy from agriculture to industries and services (Lutz et al., 2013).

Sri Lanka (pattern A and B), Georgia (pattern E), and Armenia (pattern F) are example countries showing high ratios between HDI and per capita emissions of greater than 0.26. This is because of multiple reasons. In terms of HDI, these countries have a) above average life expectancies (WHO, 2016), b) high school enrollment rates (Lamb, 2016), and c) a midfield ranking in GDP per capita (The World Bank, 2018). In terms of low emissions, Sri Lanka and Georgia have large shares of renewable energies, and Armenia obtains much of its energy from a nuclear power plant (IEA, 2018). Renewable energy plays an important role in lowering countries GHG emissions, which can also be observed for Sweden, a best performer in pattern J and K. More than 70% of Swedish energy supply comes from renewable sources including nuclear power (IEA, 2018). Additionally, the economic recession following the collapse of the former Eastern Block plays an important role in the emission development of Georgia and Armenia (Brizga et al., 2013). In Sri Lanka the service orientation of the economy might be a further reason for its low per capita emissions (Jayasooriya, 2017).

We found that the yearly best practice frontiers improved unevenly over time (Table S7 and Figure S4). Between 1990 and 2002 the frontier slopes remain almost stable and then escalate significantly for four years with a slightly drop afterwards. Overall, members of low and moderate energy dominated patterns

Table 1: Best practice countries in each pattern from 1990 to 2014. No best practice country could be identified for pattern C, as no country reached an HDI of 0.7. *VCT is Saint Vincent and the Grenadines.

Pattern	Best performance	2nd best performance	3rd best performance	Frontier slope
A	Sri Lanka (2005)	Sri Lanka (2003)	Sri Lanka (2004)	0.26
B	Sri Lanka (2007)	Sri Lanka (2006)	Sri Lanka (2008)	0.52
C	NA	NA	NA	NA
D	Jamaica (2012)	Jamaica (2010)	Jamaica (2013)	0.20
E	Georgia (2007)	VCT* (2014)	Georgia (2006)	0.26
F	Armenia (2006)	Armenia (2007)	Armenia (2008)	0.26
G	Panama (2004)	Panama (2005)	Panama (2003)	0.10
H	Grenada (2011)	Grenada (2010)	Grenada (2012)	0.23
I	VCT* (2010)	VCT* (2006)	VCT* (2008)	0.16
J	Sweden (2014)	Sweden (2012)	Sweden (2013)	0.15
K	Croatia (2013)	Sweden (2006)	Sweden (2005)	0.12
L	Mauritius (2013)	Mauritius (2004)	Mauritius (2005)	0.18
M	Uruguay (2000)	Uruguay (2001)	Uruguay (2002)	0.06
N	Japan (2006)	Japan (2007)	Japan (2001)	0.08
O	Belize (2011)	Suriname (2011)	Belize (2013)	0.06
P	Israel (2007)	Israel (2005)	Israel (2004)	0.07
Q	Belize (2010)	Belize (2009)	Belize (2006)	0.03
R	Luxembourg (2013)	Luxembourg (2014)	USA (2011)	0.04

represent the yearly top performers, with two exceptions (Mauritius in 2004 and 2005). One of the frequent best practice countries was Hong Kong until 2002, which can be attributed to its high life expectancy (UNDP, 2017) and a high share of service sectors in its GDP (To and Lee, 2017). Some countries with low per capita emissions meet the high human development threshold after 2002 (e.g., Sri Lanka, Georgia, Armenia, etc.), defining the frontier. This shows the possibility to gain a decent human development without significantly increasing per capita emissions. Recently, some countries with very high human development (e.g., Sweden, Switzerland, and France) are lowering their per capita emissions but not enough to be the global best performer.

3.5. *Low carbon pathways*

Global greenhouse emissions could be reduced if the countries were as efficient as the best frontiers without undermining their HDIs (Figure 7), i.e., move in the plane along the HDI axis (Figure S1). However, this is not the case as shown by the differences between the historical and the hypothetical emissions for both scenarios. Under scenario A, the differences, so called mitigation potentials, alter between 5.5 Gt CO_2eq and 7.7 Gt CO_2eq from 1990 to 2010, and then rise to 16.8 Gt CO_2eq by 2014. In comparison, the differences vary between 11.3 Gt CO_2eq and 13.6 Gt CO_2eq from 1990 to 2002, under scenario B and then increase to 29.8 Gt CO_2eq by 2014. The large growth in the differences after 2002 are due to improved best practice frontiers with higher values and China hitting the high human development threshold of 0.7 in 2010. Similar to the performance analysis, the hypothetical emissions were only estimated for countries with an HDI of at least 0.7.

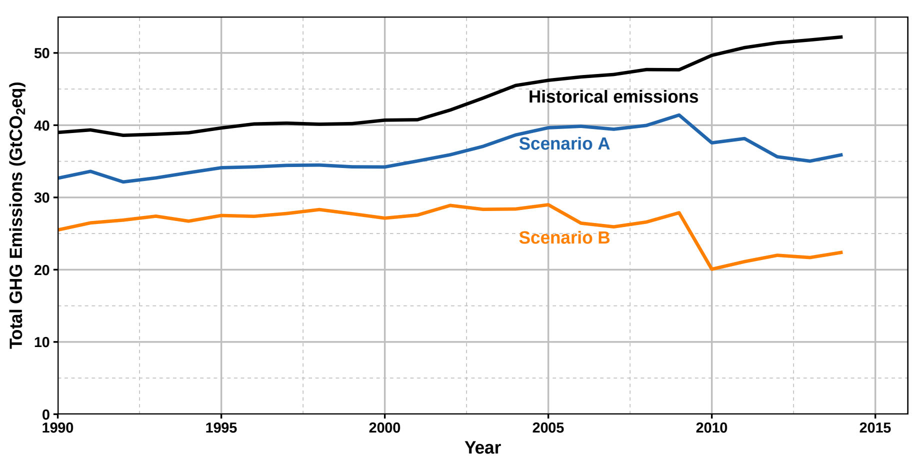

Figure 7: Emissions mitigation potentials under scenarios A and B. The differences between the total emissions (black line) and the hypothetical emissions (blue and orange lines) provide the mitigation potential. The large decrease in the hypothetical emissions after 2010 is due to consideration of China as it obtained an HDI of 0.7 in 2010.

The above results show that the best practice frontiers can act as inspirations for transitions towards low-carbon development pathways. Countries may attempt to be as efficient as the frontiers within their emission patterns (Scenario A) to mitigate climate change. However, following this pathway might not be ambitious enough to meet the Paris Agreement because of the limited mitigation potential (Figure 7). To limit the global warming well-below 2 °C, the world needs to reach net-zero emissions by 2050 (Rockström et al., 2017). An ambitious low-carbon development pathways would be to become more efficient than the global frontiers (Scenario B), regardless of their current development status. Strategies for such low-carbon pathways consists of multiple dimensions, including increased share of renewable energy, reduced deforestation, diversified economy, and holistic development beyond economic growth.

4. Discussion

Our discussion focuses on several key findings this study presents on the interplay of emission patterns, their dynamics, and mitigation potentials. First, our study identifies the 18 emission patterns that represent the sectoral emissions from 1950 to 2014 based on a neural network approach. These patterns are motivated by the structure and composition of the emission data in contrast to spatial and political categories [e.g., IPCC (2014); Timilsina (2016); UNEP (2017)]. The identified patterns also enable us to capture emission dynamics that reflect countries' transitions from one pattern to another.

Second, we observe three striking emission trends. In the last six decades, per capita emissions have increased in most countries, mainly due to growing fossil energy use. This trend has also been reported by previous studies (IPCC, 2014; Olivier et al., 2017). In comparison to these studies, we additionally highlight a fossil energy dependent development pathway taken by Japan, South Korea, and some European countries that have very low per capita emissions in the 1950s. Recently, China is also following the similar trajectory. This opens up the question of how current low per capita emitters can leapfrog towards a low-carbon development pathway (Kainuma et al., 2017).

Additionally, we identify distinctive tendencies towards decreasing per capita emissions in certain regions. These findings are similar to different regional studies, e.g., Brazil (Song et al., 2015), the former Eastern Block (Brizga et al., 2013), Europe, and the USA (Henriques and Borowiecki, 2017). However, our study also highlights decreasing per capita emissions in African and Asian countries, due to much higher growth of their population in comparison to their emissions.

Another novel trend is shifting emission compositions in South East Asia, and South and Central America. While existing studies usually focus on emissions from LULUCF activities in these regions [e.g., Pearson et al. (2017); Zarin et al. (2016)], we additionally highlight an increasing emission share from the energy sector. Hence, these regions are facing a twofold mitigation challenge: i) to halt deforestation and ii) to curb increasing fossil energy use.

Third, we provide a global overview of best practice countries and frontiers in terms of emissions and human developments in comparison to other studies [e.g., (Climate Action Tracker, 2017) and (Burck et al., 2017)]. These studies covered only 56 (Burck et al., 2017) and 33 (Climate Action Tracker, 2017) countries. The top performers of these studies have either HDI below 0.7 (e.g., Morocco, Bhutan, Ethiopia, India) or are not on our best frontiers according to their HDI emission ratios (e.g., Norway, UK, Finland). Nevertheless, Costa Rica and Sweden are top ranked by Climate Action Tracker (2017) or Burck et al. (2017) and also marked as best performers in our analysis. These countries have special geographical and economic characteristics, e.g., use of hydro-power in both countries (Hoes et al., 2017; MINAE, 2015), nuclear power in Sweden (Qvist and Brook, 2015), and a large tourism industry in Costa Rica (Vanegas et al., 2015). Although nuclear power produces electricity with low emissions, it is controversial due to associated threats to people and the environment.

We additionally discuss the need of adopting and exceeding the global best frontiers to meet the Paris Agreement. The latest Emissions Gap Report shows that the gap between current policy scenarios and 1.5 °C pathways could be closed with technically and economically feasible measures by 2030 (UNEP, 2017). However, achieving the best frontiers within own emission pattern might not be ambitious enough to limit global warming well below 2 °C. A far-reaching transformation is needed to get there (Rockström et al., 2017; Schellnhuber et al., 2016).

Although our study provides clear findings, they come along with some caveats, implied from the data sources and chosen methodology. On the data side, there might be inconsistencies because Gütschow et al. (2016) compiled the emission data from multiple sources, which are produced using different methodologies. However, all datasets are reviewed to produce a reliable and comprehensive emission database (Gütschow et al., 2016). Further, the applied IPCC emission categories might not be ideal for reflecting differences in major emission sources. Nevertheless, currently Gütschow et al. (2016) offers the best temporal and spatial coverage among publicly available emission dataset.

On the method side, it might be impossible to entirely avoid misclassification while identifying the emission patterns. Such errors can occur in the stochastic learning procedure, through unsuitable learning parameters or the differences in the dimensionality of input and output nodes (Kropp and Schellnhuber, 2008). However, we limit such errors to a minimum by applying the SOM in connection with the TOP and the concise finding of best learning parameters. Further, the performance analysis is a simplified model that relies only on two indicators and other relevant factors to characterize a role model country in terms of emission mitigation might have been neglected. Nevertheless, HDI is the composite index of life expectancy, education, and per capita income, and we provide a transparent and comprehensive method, open for further development.

In summary, our study provides a more detailed understanding of the dynamics of country based emission patterns and uses them to discuss prospective low-carbon pathways. The findings contribute to the discussions on mitigation potentials by showing the possibility to follow and exceed the global best frontiers for meeting the Paris Agreement. However, further research is needed to identify and to implement best practice solutions. For example, emissions from the agriculture and the land use sector can be reduced by avoiding food loss and waste (Hiç et al., 2016) and consuming less animal products (Pradhan et al., 2013; Reusser et al., 2013). Accordingly, valuable insights could be gained by analyzing emission dynamics at sub-national scale. Moreover, a further development of the performance analysis could include additional characteristics of role model countries, considering Sustainable Development Goals (SDGs). Low carbon-development pathways that reduce material and environmental footprints (e.g., GHG emissions) will play a crucial role in the successful implementation of the 2030 development agenda (Pradhan et al., 2017).

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