



Horizon 2020 Societal challenge 5: Climate action, environment, resource efficiency and raw materials

VERIFY

Observation-based system for monitoring and verification of

greenhouse gases

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Changes with respect to the DoA

The deliverable is several months later than in the original DoW. The reasons are twofold. First this work could not start until the time series (D2.2) based on reported emissions up to 2017 were ready, which was in April 2020. The D2.2. was 3 months postponed to include the year 2017, subsequently D2.5 was also scheduled for 3 months later. These changes of delivery dates benefit the ultimate VERIFY goal of having the most reliable dataset for the next synthesis cycle. In this light it was critical that the data were made available to the modelers in July 2020, which was achieved. Second, due to some problems during the internal review process at CEA, the deliverable was only submitted on the EC portal early 2021.

Dissemination and uptake

(Who will/could use this deliverable, within the project or outside the project?)

The data provided with this deliverable are needed for (inverse) modelling efforts within Verify to cover a period up to the present year-1 (T2.3). They also support other tasks by providing emission data for recent periods covered with measurement data gathered in Verify (e.g. T2.2). Additionally, the methodology describe in this deliverable report (and its update following in M38) can be implemented in other projects to support emission verification for more recent years than possible with reported emissions (which lag 2 years behind).

Short Summary of results (<250 words)

In a previous deliverable (D2.4) a first attempt was made to estimate emissions for the two most recent years for which country reports are not yet available. Here, we update our methodology by using activity data or proxies to better estimate the year-to-year variability in emissions per source sector. We estimate emissions for 2018 and 2019, but also for 2016 and 2017 using the same methodology for comparison with reported emissions. We start with the most dominant source sectors and found good activity data for most of them, although often these data are not yet available for 2019. In the testing for 2016 and 2017, the emissions estimates generally approximate the reported emissions because of the large variability and trend in its emission factors. For small countries (such as Malta) the implementation of new technologies can have a large, sudden impact on the emissions that is difficult to take into account. Therefore, (very) small countries show the largest deviations. However, their impact on the total emissions is limited and overall the presented methodology gives a good first estimate of the emissions for recent years. Further effort will be made to include additional source sectors in a next update (D2.6).

Evidence of accomplishment

(report, manuscript, web-link, other)



The results of this work are disseminated to all VERIFY partners and accessible under a SharePoint platform. Besides this report the gridded emission data for 2018 are 2019 are made available through the VERIFY portal under the product pages.



Version	Date	Description	Author (Organisation)
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V0.1	July 2020	Writing/Formatting/Delivery	I.Super, H.A.C. denier van der Gon (TNO)
V1	February 2021	Formatting/Delivery on the Participant Portal	Aurélie Paquirissamy and Philippe Peylin (LSCE/CEA)



1. Glossary	6
2. Executive Summary	7
3. Introduction	8
4. Methodology	9
4.1. Source sector selection	9
4.2. Calculation steps	9
4.2.1. Activity data	10
4.2.2. Emission factors	11
4.3. Generating emission maps	11
5. Results	13
5.1. Predictive value of activity proxy data	13
5.2. Country-level emissions	13
5.3. Total emissions 2000-2019	15
6. Conclusions	16
7. References	17



1. Glossary

Abbreviation / Acronym	Description/meaning
GNFR	National gridded data of emissions by source category
GDP	Gross domestic product
NVMOC	non-methane volatile organic compounds



2. Executive Summary

This report describes a methodology to estimate emissions for the two most recent years for which country reports are not yet available. Compared to the previous attempt (deliverable D2.4) we updated our methodology by using activity data or proxies to better estimate the year-to-year variability in emissions per source sector.

We estimate emissions for 2018 and 2019, but also for 2016 and 2017 using the same methodology for comparison with reported emissions. We start with the most dominant source sectors and found good activity data for most of them, although often these data are not yet available for 2019. In the testing for 2016 and 2017, the emissions estimates generally approximate the reported emissions for 2016 and 2017 satisfactorily, which validate our approach.

However, especially for CO the projected emissions sometimes show deviations with the reported ones because of the large variability and trend in its emission factors. For small countries (such as Malta) the implementation of new technologies can have a large, sudden impact on the emissions that is difficult to take into account. Therefore, (very) small countries show the largest deviations. However, their impact on the total emissions is limited and overall the presented methodology gives a good first estimate of the emissions for recent years. Further effort will be made to include additional source sectors in a next update.



3. Introduction

The emission inventories made by TNO within the Verify project make use of emission reports. Those country-level annual data form the basis of the emission inventory and are spatially and temporally disaggregated for use in the chemical transport models. Although this approach ensures consistency between countries and years, one main disadvantage is the 2-year lag in emission reporting that makes emission verification for the last 1-2 years impossible.

To overcome this limitation we are developing a methodology to estimate emissions for recent years. A first effort was made in D2.4, where we used regression analyses to estimate emissions for 2018. Here, we describe an update and further development of this method to estimate emissions for 2018 and 2019, making use of the correlation between activity data and emissions. Whereas extrapolation based on a regression analysis works well for source sectors with little interannual variability, activity data can help to better estimate emissions from more variable source sectors. The current COVID-19 crisis emphasizes the importance of this approach.

Because validation of emission estimations is difficult, we decided to test the methodology for the two most recent years covered in the reporting, which are 2016 and 2017 (the methodology is described for 2018 and 2019, but the same methodology is adopted for 2016 and 2017). This allows us to compare the emissions from this new methodology to reported emissions. The results from this comparison are discussed in this report.

The emission inventories are delivered for 2018 and 2019 using the same methodology as discussed and illustrated here. The emission inventory covers the entire European domain (Figure 1) at a resolution of $0.1^{\circ} \times 0.05^{\circ}$ (~ 6 km x 6 km) (for more details see D81.1.1.2).



4. Methodology

4.1. Source sector selection

Table 1 shows an overview of the domain-average source sector contributions to the total emissions of CO_2 , CH_4 , CO, NO_x and NVMOC (non-methane volatile organic compounds). Industry and other stationary combustion contribute significantly to most of the gases and are therefore our main point of focus. Public power is also very important for CO_2 and is therefore also included. To ensure that CH_4 is also represented we also consider the agriculture-livestock sector. With this selection we make a first step towards a dynamic approach in emission estimations. The road transport and shipping sectors will be included in the next round (D2.6).

	CO2 ff	$CO_2 bf$	CH4	СО	NO_x	NMVOC
Public power	<u>32</u>	<u>23</u>	2	2	<u>18</u>	1
Industry	<u>25</u>	<u>16</u>	8	<u>18</u>	<u>14</u>	<u>10</u>
Other stat. Comb.	<u>15</u>	<u>44</u>	4	<u>29</u>	6	<u>12</u>
Fugitives	3	0	<u>35</u>	1	1	<u>15</u>
Solvents	0	0	0	0	0	<u>30</u>
Road transport - gasoline	6	1	0	<u>26</u>	3	<u>14</u>
Road transport - diesel	<u>13</u>	4	0	9	<u>29</u>	3
Road transport - LPG	1	0	0	2	1	4
Road transport - non-exhaust	0	0	0	0	0	5
Shipping	2	0	0	1	<u>18</u>	0
Aviation	1	0	0	0	1	0
Off-road	3	0	0	5	8	2
Waste	0	0	<u>24</u>	1	0	1
Agriculture-livestock	0	0	<u>23</u>	0	0	0
Agriculture-other	0	<u>11</u>	5	7	1	3

Table 1. Contribution (%) of each source sector to the total emissions of a gas in 2017. Contributions >10% are bold/underlined.

4.2. Calculation steps

Emissions are usually calculated using a simple equation:

Emission = *activity x emission factor*

The emission factor (the amount of emissions per amount of activity) differs per gas, but in the case of combustion they share the same activity (i.e. the amount of fuel burnt). The activity data also allow us to study whether there are trends in the emission factors that need to be considered. The activity and emission factors are estimated following the methods described next and with



these estimates we can then calculate the emissions. For source sectors that are currently not included, the most recent reported emissions (in this case for 2017) are used.

4.2.1. Activity data

There are two ways to describe the activity:

- Using activity data that can be directly linked to the source sector, such as energy statistics or animal numbers. This is the preferred and most reliable approach.
- Using a generic proxy not directly linked to the source sector to estimate the activity, such as gross domestic product (GDP).

Even if good activity data exist for a specific source sector, sometimes these data are not available for all countries. In that case the second option is used for the missing countries. Moreover, the time series do not always extend to 2019 yet and this can also be resolved using the second option (when activity data are available for 2018 we will use the first option for 2018).

For the second method we first test how well the generic proxy correlates with the activity data for those countries and years that the activity data are available. How far back this time series extends depends on the data availability, but the time series cover between 7 to 13 years. Next, we examine whether a trend exists in the activity/proxy over this period. If the trend is strong enough ($R^2 > 0.3$) we extrapolate the trend to estimate the activity for recent years. If not, we take the average activity/proxy for the entire period. An overview of all the data used is given in Table 2.

	Period covered	Proxy data	Period	
Public power	Electricity generation (non-renewable) ¹	2008-2018	GDP	Up to 2019
Industry: Refineries	Refinery througput ¹	2008-2018	GDP	Up to 2019
Industry: Coal mining	Coal production ¹	2008-2018	GDP	Up to 2019
Industry: Other	Industrial production index (manufacturing) ²	2000-2019	GDP	Up to 2019
Other stat. Comb.	Yearly degree day sum ³	2005-2019		
Agriculture-livestock	Animal numbers (cattle, swine, sheep, other) ⁴	2010-2018		

Table 2. Overview of activity and proxy data used for each source sector.

¹ Source: <u>BP statistics</u>; ² Source: <u>Eurostat</u>; ³ Source: <u>E-OBS gridded mean temperature</u>, converted to yearly degree day sum using the approach described by Mues et al. (2004); ⁴ Source: <u>FAO</u>

For countries and source sectors where there is no data to estimate the activity, an emission estimate will be lacking. Missing emissions will be gap filled using 2017 reported emissions, as mentioned before. This means that the entire agriculture-livestock sector only has emission estimates for 2018 using the approach described here, whereas 2019 is completely copied from 2017.

Please note that there is some uncertainty in the relationship between the activity data and actual fuel consumption (in case of combustion activities). For example, the industrial production index is a generic measure of industrial activity, but the fuel consumption and related emissions depend on the type of industrial activities that take place. Nevertheless, we found these activity data to be the best possible options and we validate the results for 2016 and 2017.



4.2.2. Emission factors

For the emission factors we look at the full period covered by the activity data to see whether a trend exists in the emissions/activity that we can use to calculate the emission factor for recent years (again only if $R^2 > 0.3$). Otherwise, the average value over the full period is used. Note that the activity can also be the estimated activity from the previous step.

4.3. Generating emission maps

The emission inventory contains emissions per GNFR sector (+ a fuel split for road transport), but our emission estimates are sometimes done at a more detailed level. The reason for this is that some source sectors, especially industry and agriculture, show a large diversity in emission sources and putting them all together would make it difficult to find representative activity data. Therefore, we first aggregate the estimated emissions to the GNFR sector level. Second, we determine a scaling factor for each GNFR sector that we apply to the 2017 emissions to get an emission inventory for 2018 and 2019. The scaling factors are year and species specific.

Whereas the TNO_GHG_co emission inventory contains CO emissions from fossil fuel (ff) and biofuel (bf) separately, we only make emission estimates for total CO. The reason is that the CO emissions are relatively variable and uncertain and we assume that the total CO emissions can be predicted more accurately than CO ff and CO bf, separately. The scaling factors for CO are then applied to both CO ff and CO bf. For CO₂ we do calculate separate scaling factors for CO₂ ff and CO₂ bf.

In total 35 countries are included in our calculations and for those countries emissions are updated for 2018 and 2019. For non-included countries and sea regions emissions from 2017 are used.





Figure 1: Spatial domain of the high resolution (~6x6 km) emission inventory.



5. Results

The results discussed here follow the methodology describe before, but then for 2016 and 2017 to allow the comparison to reported emissions.

5.1. Predictive value of activity proxy data

As shown in Table 2 we use GDP as proxy for the activity in the energy and industrial sectors. Here, we examine how well GDP correlates with the actual activity data for these source sectors.

For the energy industry and refineries the average correlations across all countries for which data are available are relatively poor ($R^2 = 0.33$ (N = 18) and $R^2 = 0.27$ (N = 20)). This suggests that GDP is not a good predictor for electricity generation and refinery throughput. The average correlation between GDP and coal production is better ($R^2 = 0.54$ (N = 9)). The best result is found for the industrial production index, which correlates well with GDP ($R^2 = 0.72$ (N = 25)).

5.2. Country-level emissions

The comparison of the estimated emissions with reported emissions shows a good agreement for most countries (Figure 2). Some source sectors are clearly more easy to estimate than others. For example, the public power sector is relatively sensitive to the applied emission factor. In smaller countries the closing of a coal-fired power plant can already have a significant impact on the emission factor and therefore on the estimated emissions. Relatively often, Malta causes the largest deviations because of this.







Figure 2. Emissions of CO₂ and CO for the year 2017 per country and source sector. Left bars are reported emissions, right bars are estimated. Emissions are normalized to the total emissions reported per country.

Also the CO emissions from other industry sometimes shows a large deviation, for example in Belgium and France. Figure 3 shows the temporal variability in the emission factor for this sector in both countries. In our calculations we now used the time series until 2015. For Belgium, this period shows no clear trend. Therefore, the average emission factor is used to calculate the emissions for 2017, which is clearly too high for 2017. In France a sharp decline in the emission factor is visible, but it stabilizes during the last years. Extrapolating the trend based on 2010-2015 will therefore underestimate the emission factor for 2017. These examples illustrate one major difficulty when estimating emissions for recent years based on highly variable data.



Figure 3. CO emission factor (calculated as emissions/activity) for the source sector other industry in Belgium (left) and France (right).

For 2016 deviations are visible for different countries/source sectors than for 2017. The overall performance is somewhat better for 2016, because more often actual activity data is used. A summary of the results for all species and both years is given in Table 3.

Table 3. Statistics of the emission estimates per species. Given are the mean, minimum and maximum normalized emissions compared to the total reported emissions.

	2016			2017			
	Mean	Min	Max	Mean	Min	Max	
CO2	1.01	0.93	1.32	0.99	0.93	1.11	
CO₂ ff	1.00	0.92	1.23	0.99	0.90	1.07	

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CO₂ bf	1.00	0.60	1.20	1.02	0.77	1.26
со	1.02	0.94	1.15	1.01	0.58	1.42
NOx	1.04	0.92	1.22	1.07	0.91	1.51
NMVOC	1.01	0.90	1.09	1.02	0.90	1.10
CH₄	1.00	0.97	1.03	1.00	0.95	1.06

After applying the same methodology to estimate emissions for 2018 and 2019 we can determine the scaling factors needed to build the emission inventory for those years from the 2017 inventory. The scaling factors are determined per country, per GNFR sector and per chemical species for both years. For those source sectors that are not included in our methodology the scaling factors are 1.0, i.e. the emissions from 2017 are copied.

5.3. Total emissions 2000-2019

Finally, we take a look at the domain emissions per species for the full time series (Figure 4). For CO_2 we see some variations, but not a clear trend over the years. The estimated emissions for 2016 and 2017 are also compared to the reported emissions and they agree well. For CH_4 we have seen a slight decrease over the last years. For 2016 and 2017 the decrease is too strong in the estimated emissions. However, for the 2018 and 2019 emission estimates the reported emissions for 2016 and 2017 are included in our trend analyses and this is corrected, resulting in slightly higher estimates for 2018 and 2019.



Figure 4. Time series of emissions of CO₂ and CH₄ per source sector and summed for the whole domain. For years before 2016 emissions are reported; for 2016 and 2017 both the reported (right bars) and estimated (left bars) emissions are given; for 2018 and 2019 emissions are estimated.



6. Conclusions

With the proposed methodology we were able to estimate country-level emissions per source sector for the two most recent years. Comparison of this method with reported emissions (for year 2016 and 2017) shows a relatively good agreement for most countries and species, although large variations can exist.

Several source sectors have not been included yet. Waste and fugitives are important sources of CH4 emissions, but are very difficult to predict. Therefore, the focus in the next round will be on road transport and shipping. Moreover, we plan to look into the degree day sum in more detail. We have used a threshold of 17 °C to calculate the degree day sum, but this may differ depending on the geographical location.



7. References

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