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VERIFY

Observation-based system for monitoring and verification of greenhouse gases

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Changes with respect to the DoA
Dissemination and uptake **(Who will/could use this deliverable, within the project or outside the project?)**
This report is a summary document relevant to all VERIFY project partners, practitioners engaged in GHG inventory analysis, the scientific research community and the public. This report can help set the future research agenda for the scientific research community and its funders to support the needs of different climate policy actors.
Short Summary of results (<250 words)
The VERIFY project has identified and documented many ways to reduce the uncertainty of GHG flux estimates through the provision of new datasets and modelling methods. To achieve reliable verification of climate policy in a useful timeframe, additional work is required and VERIFY scientists have outlined some of the necessary approaches through reports, published literature and in responses to the survey conducted in this deliverable. While several steps have begun to be implemented, others could be in the near future. Some of the required steps are specific to an individual work package while others apply throughout. The body of this report summarises these approaches. **Attention is often focussed upon methodological differences, including variation in input data, as well as the implementation of three main approaches: bottom-up (BU) process-based models; top-down (TD) inversions; and national greenhouse gas inventories (NGHGI). A clear finding of the report is that each of the approaches serve an important role and therefore uncertainty can be minimised by planning how best to combine each approach to achieve an optimal estimate. However, continued enhancement of communication and collaboration between scientific research communities and the inventory community will help to reduce uncertainty. In addition, there is a clear need for collection of better-quality data at higher spatial and temporal resolution (both in-situ and remotely sensed) and in areas that are not currently well covered. Tackling those gases and sectors with the highest uncertainty that can impact emissions at the national scale, should have the largest impact on reducing current uncertainty levels.**
Evidence of accomplishment **(report, manuscript, web-link, other)**
The content of this report represents the accomplishment of the work.

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1. Glossary

Abbreviation / Acronym	Description/meaning
AD	Activity Data
AFOLU	Agriculture, Forestry and Other Land-Use
APO	Atmospheric Potential Oxygen
BU	Bottom-Up
^{13}C, ^{14}C	Carbon isotopes
CH_4	Methane
CIF	Community Inversion Framework
CO	Carbon Monoxide
CO_2	Carbon Dioxide
CO2M	Copernicus CO_2 Monitoring
CRF	Common Reporting Format
DGVM	Dynamic Global Vegetation Model
EF	Emissions Factor
EU	European Union
FAOSTAT	Food and Agriculture Organisation Statistics
fCO_2	Carbon Dioxide Fugacity
$ffCO_2$	Fossil Fuel-derived Carbon Dioxide
pCO_2	Carbon Dioxide Partial Pressure
GCB	Global Carbon Budget
GCP	Global Carbon Project
GHG	Greenhouse Gas
Gt	Giga tons
HCHO	Formaldehyde
IAM	Integrated Assessment Model
IPCC	Intergovernmental Panel on Climate Change
IPPU	Industrial Processes and Product Use
LULUCF	Land-Use, Land-Use Change and Forestry
MS	Member State
NGHGI	National Greenhouse Gas Inventory
N_2O	Nitrous Oxide
222Rn	Radon isotope
TD	Top-Down
Tg	Terra grams
TROPOMI	TROPospheric Ozone Monitoring Instrument
UK	United Kingdom
UNFCCC	United Nations Framework Convention on Climate Change
VOC	Volatile Organic Compound

2. Executive Summary

This report outlines significant causes of uncertainty in the verification of estimates of anthropogenic and natural GHG emissions and sinks in Europe and globally. It summarises work undertaken during the VERIFY project to address and minimise these uncertainties as well as research priorities to address those that remain. The uncertainties and priorities of greatest relevance to each work package are discussed in each section of the report. The information presented in this report is summarised from VERIFY reports and published literature, integrated with the results of a survey of VERIFY scientists and inventory compilers. The survey was conducted in spring 2022 and received 16 responses. Results from the survey are included in the report as "*anonymous quotes*" and are listed in Appendix A.

Extensive feedback was received for each work package and key elements are summarised in Figure 1, under 4 themes that transcend work package boundaries. Within this report and the literature summarised, attention is often focussed upon methodological differences, including variation in input data, as well as the implementation of three main approaches: BU process-based models; TD inversions; and NGHGI. A clear finding of the report is that each of the approaches serve an important role and therefore uncertainty can be minimised by planning how best to combine each approach to achieve an optimal estimate.

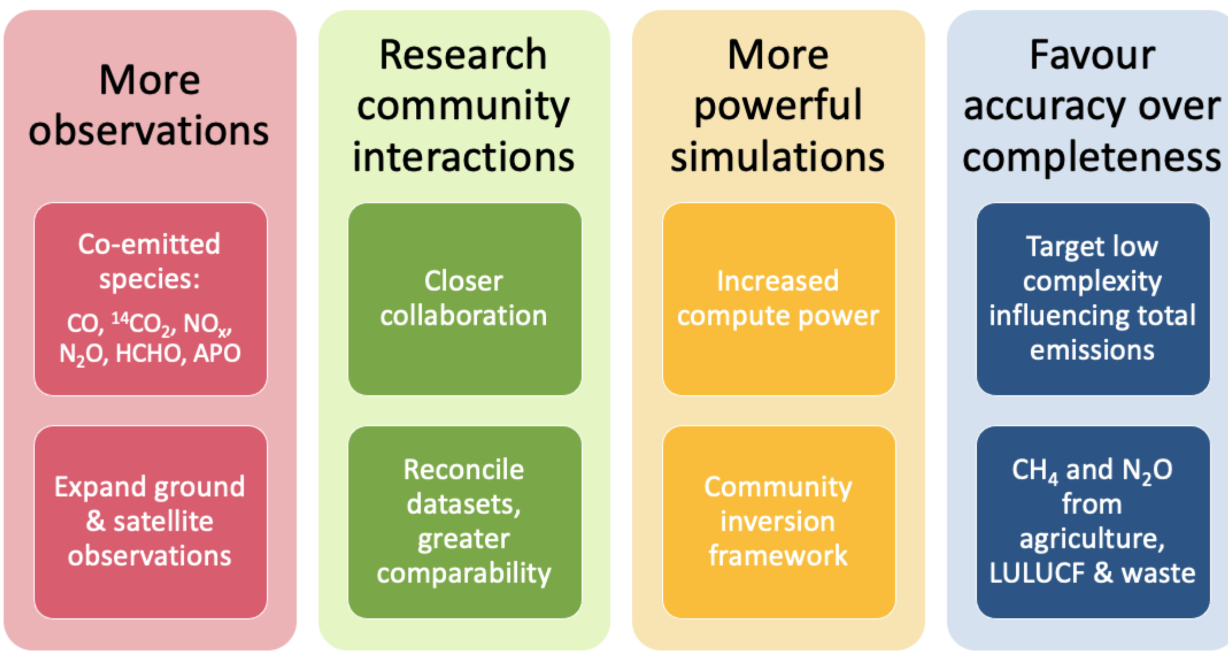

Figure 1: summary of key research priorities to minimise uncertainty in the verification of GHG fluxes.

However, it is widely acknowledged that continued enhancement of communication and collaboration between scientific research communities and the inventory community will help to reduce uncertainty. In addition, there is a clear need for collection of better quality data at higher spatial and temporal resolution (both in-situ and remotely sensed) and in areas that are not currently well covered. For example soil carbon dynamics are acknowledged by VERIFY scientists as an area where further research is required to better understand and characterise uncertainty in terrestrial GHG fluxes. Tackling those gases and sectors with the highest uncertainty that can impact emissions at the national scale should have the largest impact on reducing current uncertainty levels. The remainder of this report outlines findings in more detail, addressing each work package in an individual chapter.

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3. Uncertainty in observation and verification of GHGs

3.1. WP1: National monitoring, reporting and verification

3.1.1. Sources of uncertainty

VERIFY project deliverables in WP1 and published papers have outlined numerous sources of uncertainty within and between inventories and climate science inversions, used for reporting and monitoring of GHG sources and sinks. NGHGIs follow the UNFCCC and IPCC guidelines to produce CRF tables that detail sources and sinks of emissions in a standard format across each country and administration. Inventories from 2016 had total emissions uncertainty estimates between 3% and 50%, while the trend uncertainty ranged between 1.4% and 34% (Kiesow et al., 2019 [D1.3]).

Comparing BU activity data AD that are summed in NGHGI and TD inversions used in climate science research reveals a number of sources of uncertainty in how emissions and removals of GHG are estimated. These can be grouped into three categories, namely methodological differences; system boundary effects; and terminology (Pellis et al., 2019 [D1.1]):

- **Methodological differences** include the very specific sector levels that NGHGI are reported under that may not be resolvable by climate science research, making it hard to attribute emissions for specific processes in equivalent reporting processes. For example, EF used in NGHGI are not used in climate science research. Direct and indirect emissions and GHG precursors are reported separately in NGHGIs but not in climate science inversions as they may not be resolved by satellite observations or ground monitoring. NGHGI and climate science methods may vary in their consideration of which emissions and removals are significant, or they may differ in their definition of anthropogenic and biogenic emissions.
- **System boundary differences** include different spatial and temporal scales: TD inversion models are conducted at regional or global scales, with data also incorporated from local-scale projects, while NGHGIs are ordered at the country-scale which may be a different resolution. NGHGI are reported at annual time-scales, yet AD and inversion data use time-scales varying between monthly and daily. This complicates efforts to make direct comparisons between approaches.
- **Terminology differences** impact comparisons between NGHGI and climate science estimations for the Agriculture and LULUCF sectors. Models can define flux estimates in different ways depending on the scope of the individual model, increasing uncertainty in terrestrial source and sink estimates (Pongratz et al., 2014). Examples include anthropogenic effects, where IPCC AR5 considered only emissions and removals from direct human activities, whereas the [2006 IPCC guidelines for National GHGI]() consider the effects of all human interventions to production, ecological or social function. The definition of managed land is not prescriptive in the 2006 IPCC guidelines, complicating equivalent estimations. NGHGIs focus on land-use whereas climate science research focuses on land-cover classification by remote sensing. Furthermore the 2006 IPCC guidelines allow for international variation in land

use definitions and modifications to carbon pool definitions, complicating verification. In addition, there are different methods for defining the soil organic carbon stock, using either soil mass or soil depth, which may be defined as the upper 30cm or 1m of soil column. [D1.1].

A common theme reported by survey respondents is that the Energy sector (CRF1 - Common Reporting Format) is "*responsible for the majority of total emissions (78%), however the uncertainty range is small*", especially for CO_2, due to the "*availability of high quality energy statistics*" among EU member states and many other developed countries. For example, fuel combustion (CRF 1A) has the lowest uncertainty estimate for CO_2 at ~1%, although the highest uncertainty estimates (18.4%) come from N_2O and CH_4 fugitive emissions from fuel production (CRF 1B). The IPPU sector (CRF 2) has the second or third highest emissions yet "*quite small uncertainty estimates due to the availability of reliable plant-specific data and country-specific methods*" [D1.1., D1.3].

A number of survey responses noted that the Agriculture, LULUCF and Waste sectors are "*characterised by very large uncertainty estimates of 45.5%, 32.6% and 51.4%, respectively*" (Pellis et al., 2019 [D1.1]), due to their "*emission and removal estimations being based on a number of variable parameters*". Within the Agriculture sector, the largest emissions sources of N_2O are from manure management (CRF 3B) and agricultural soils (CRF 3D) and of CH_4 from enteric fermentation (CRF 3A). Uncertainty of N_2O emissions from agricultural soils dominates uncertainty estimates in this sector, though they vary widely between countries, likely due to different subjective judgements during estimation rather than different conditions (Rypdal & Winiwarter, 2001). Uncertainty estimated for enteric fermentation "*is relatively small due to the sophisticated methodology available*." For the LULUCF sector, CO_2 emissions and removals are estimated for six different environments, with the methodology varying between countries, even among EU member states, relying upon country-specific data with relatively low uncertainty, or IPCC default emission factors that carry higher relative uncertainty estimates [D1.1., D1.3].

In the Waste sector, "*almost all member states report CH_4 emissions from solid waste disposal in landfills using a Tier 2 methodology*", which samples the uncertainty estimate from AD and EF using a probability distribution function and Monte Carlo simulation. In contrast, other waste subsectors use the more accurate Tier 1 methodology of combining and aggregating individual uncertainty estimates for each AD and EF. In addition, the Waste sector uncertainty estimate is influenced by "*high uncertainty in the amount of solid waste deposited*", with organic matter decomposition producing CH_4.

Feedback from national inventory compilers presented to the VERIFY General Assembly, May 2022, suggests that multiple countries appreciate the wealth of data prepared by VERIFY that has helped to put NGHGI into perspective regionally. There is reasonable agreement between NGHGI and other approaches for many member states at the total emissions level. However, there are a number of examples where individual gases or sectors show a significant miss-match between TD inversion estimates or BU book-keeping models and NGHGI that are yet to be well explained. This is particularly the case for any individual year, where the mean of each approach can vary considerably within overlapping uncertainty ranges. Despite this, when averaged over a time series of multiple years, the mean of each approach converges. While the uncertainty within GHG assessments is now better described, more information is required before all of this data can be properly incorporated into national inventory reports. In particular, for numerous EU member states, the large interannual variability of the terrestrial LULUCF CO_2 flux represented by TD inversions is not represented by NGHGI, while the anthropogenic CH_4 flux significantly exceeds NGHGI. These discrepancies need further investigation and explanation to assist national inventory compilers.

3.1.2. Priorities for resolving uncertainty

Reducing uncertainties in monitoring and verification of GHG sources and sinks can be achieved through improvements to measurements and data. GHG monitoring networks should be sensitive to and representative of GHG throughout the entire region, which can be simulated by atmospheric modelling. Increasing the density and precision of observations will reduce uncertainty. Current satellite observations are too sparse to usefully resolve atmospheric chemistry in cloudy or small regions, impacting locations such as the UK or the Netherlands. Next generation satellites are expected to improve upon this limitation. Combining satellite and airborne observations has improved verification in locations such as India (House et al., 2019 [D1.4]). Measurement of radiocarbon and co-released tracer compounds (CO, NO_x) can enable inversions to identify anthropogenic and natural CO_2 emissions, for example [D1.4].

Further model refinement is required to reach closer agreement and limit uncertainty, which in some cases exceed the theoretical uncertainty range. As an example the atmospheric transport model may be improved by modelling radon transport, which is well resolved by detectors. Developing standards for the comparison of global inversions and ground observations could aid verification for countries without their own inversion model or ground network. [D1.4].

Close collaboration among inversion modellers and inventory analysts can improve the quality of both results, with evidence of this having occurred in Australia and the UK [D1.4]. As one survey respondent noted, this should aid with "*reconciling various methods (ground-based monitoring, default reporting, remote sensing and modelling)*".

Priorities for reducing uncertainty from survey responses include targeting research input to "*gases and sectors (e.g. N_2O and CH_4 for agriculture and waste) where countries use a low level of complexity and accuracy in their estimation methods… constraining inventory compilers to implement IPCC default values*" (Perugini et al., 2021). Prioritising research input on "*key categories that have a significant influence on a country's total emissions*" should minimise potential uncertainty. Additional research focus on "*those sectors with the highest percentage uncertainties in input data*" (Waste (51.5%), Agriculture (47.0%), LULUCF (34.3%)) would likely further reduce uncertainty estimates of country emissions (Perugini et al., 2021). "*Higher frequency surveys of domestic waste composition*" would improve the accuracy of "*related emissions estimates*".

Additional research input could help to reduce uncertainty estimates for developing countries that currently can be large and poorly defined because non-annex I countries aren't required to report them. This can lead to frequent revisions, sometimes with large anomalies between different estimates, even for energy statistics, which are very reliable in developed countries (Perugini et al., 2021). For example, two preliminary coal use estimates for China in 2014 included a -2.9% reduction and a +0.9% increase, having a significant impact on predicted global CO_2 emissions (Korsbakken et al., 2016). While the agriculture and LULUCF sectors represent a more significant proportion of total emissions in developing countries (Perugini et al., 2021), with emissions from agriculture increasing ~1% per year (1990-2010), exceeding emissions from LULUCF by 2010, which declined ~1% per decade over the same period, driven by declining deforestation (Tubiello et al., 2015). The average uncertainty (1990-2015) for emissions from deforestation driven by agriculture in the tropics is ±62.4% (Carter et al., 2017), which shows the large potential to reduce uncertainty through additional data availability and research.

One survey response identified that "*the requested spatially explicit approach for LULUCF inventories, starting with the 2023 reporting, should improve the LULUCF inventories and reduce their uncertainties*." Furthermore "*improved estimation of GHG fluxes outside forest biomass (e.g. agricultural soils, organic soils, non-forest biomass) is also needed to resolve uncertainty of fluxes for the LULUCF sector.*" Regarding the waste sector, which has high uncertainty at the EU27+UK level, one survey response recommended "*more detailed data and statistics to better refine the related emission estimations, e.g. higher frequency of surveys for domestic waste compositions*."

3.2. WP2: National fossil CO_2 emissions

3.2.1. Sources of uncertainty

Estimates of CO_2 emissions from fossil fuels ($ffCO_2$) can be derived from atmospheric CO_2 concentrations and co-emitted species, such as NO_x, CO, $^{14}CO_2$, measured through ground-networks and satellite observations. However the "*lack of dedicated CO_2 observation networks*" noted in a survey response, mean the spatial density of such observations is limited, resulting in uncertainty. Experimental analyses from southwest Germany combined contemporaneous in-situ and remotely sensed co-emitted species measurements to attribute variations in their abundance to different local sectoral emissions of industry, traffic and residential heating (Jäschke et al., 2021 [D2.7]). Remotely sensed variability in co-emitted proxy gases was damped by 3-4 times compared to in-situ measurements, but correlations were nonetheless clear. However, to reliably quantify source-sector attribution will require calculation of the NO_x lifetime, potentially requiring new improvements to atmospheric chemistry-transport models and auxiliary measurements of ozone and VOC [D2.7].

Further work using TROPOMI observed co-emitted species (CO, NO_2 and HCHO) as proxy observations reflecting (incomplete) combustion emission of CO_2. This work found that incorporating CO_2:CO error correlations reduced uncertainty in estimated CO_2 combustion across Europe by around an average of 15%, as well as improvements in estimated natural CO_2 and CO fluxes (Palmer et al., 2021 [D2.14]).

Uncertainty analysis for the dynamical inventory model used monte carlo simulation of individual parameters per sector, fuel and country (Super et al., 2019 [D2.9]). An example for 2015 shows relatively small (a few %) uncertainty ranges for CO_2 emissions across most sectors, with the largest uncertainty often relating to small sectors. The uncertainty range for the spatial distribution of co-emitted CO is much larger due to the lognormal shape of the uncertainty distribution for CO emission factors. For CO_2 the largest uncertainty is derived from the emission factors for power plants and industry. Attention should be focussed on reducing these uncertainties to improve the emissions inventory.

Another factor contributing to uncertainty in $ffCO_2$ (and other GHG) estimates is the static emissions threshold applied to the European Pollutant Release and Transfer Register. For example, power plants have been able to emit amounts less than 100,000 tonnes per year of CO_2 without those emissions being registered. The sum of these emissions is potentially detected by TD inversions but missing from book-keeping models and NGHGI. Similar thresholds are set for other GHG likely resulting in similar discrepancies.

As noted by one survey respondent, further uncertainty arises from attempting to relate "*satellite observations of co-emitted species*" to national "*inventories at relevant spatial, sectoral and temporal resolution.*"

3.2.2. Priorities for resolving uncertainty

Survey responses and VERIFY reports (e.g. D2.7) point to "*improvements in atmospheric chemistry-transport models*" in order to develop atmospheric inversion models, for example to resolve NO_x lifetime and other proxy species, as priority research areas in the next 5 years to reduce current uncertainties. Furthermore, the "*upgrade of observation networks and products, especially with the launch of CO2M*" should also underpin research efforts to reduce $ffCO_2$ uncertainty estimates. CO2M is the European Space Agency's latest Copernicus CO_2 monitoring mission that will observe atmospheric CO_2 released from human activities. A fully automated permanent urban GHG column sensor network in Munich (Dietrich et al., 2021) has demonstrated the ability to record urban emissions (CO_2, CO, CH_4) with a data density favourable for input to an inversion framework. Development of networks in other key cities could help refine estimate techniques by adding accuracy above BU estimates and by validating satellite observations (Dietrich et al., 2021).

The impact of atmospheric aerosol concentrations on the verification of GHG fluxes was not a focus of the VERIFY project, though it is acknowledged as a potentially important factor. The upcoming AVENGERS and PARIS research projects will each investigate this through a work package focussed on aerosols such as black carbon.

3.3. WP3: National & regional terrestrial CO_2 fluxes

3.3.1. Sources of uncertainty

CO_2 net fluxes from LULUCF carry quite significant uncertainty, which require spatially resolved estimates and high temporal resolution data to be better resolved (Janssens-Maenhout et al., 2021 [D6.1]). The relatively large uncertainty estimates for these net flux estimates stem, in part, from the use of complicated terminology, such as six land use classes (forest, cropland, grassland, wetlands, settlements and harvested wood products), multiple flux definitions and differing system boundaries between BU activity data, TD inversion estimates and NGHGHI (Pongratz et al., 2014; Janssens-Maenhout et al., 2021; Petrescu et al., 2021a).

TD inversion models sample uncertainty related to interannual variability, parametrisation within each model and structural differences between model variants, with total uncertainty derived from model spread (Petrescu et al., 2021a). For the EU27 + UK, the mean of the 2019 NGHGIs for fossil CO_2 emissions was 2624 $TgCO_2$ in 2014, while the mean of 7 BU process models was 2588 ±463 $TgCO_2$ and for TD inversions it was 2700 ±480 $TgCO_2$ (Petrescu et al., 2021a). While there is reasonable agreement in the mean of each approach, model spread and uncertainty are too large to enable verification (Petrescu et al., 2021a).

The State-of-the-art-database (Kuhnert et al., 2022 [D3.3]) has aided substantial improvement of prior estimates input to TD inversions, reducing uncertainty. This includes improvement to biomass and carbon content data, climate forcing data, land-use and land-cover data and ocean and coastal flux data [D3.1, D3.2, D3.3]. This database was used in an ensemble of BU model simulations to determine carbon fluxes and stock estimates for natural and managed terrestrial (croplands, grasslands & forests) and marine (including coastal/shallow) ecosystems throughout Europe (McGrath et al., 2022 [D3.6]). Further analysis (Pongratz & Gazenmüller, 2021 [D3.9]) indicates that differences between model runs due to input data or parameterisation add only small uncertainty to European land-use emissions. However, the uncertainty is larger for component fluxes such as emissions from cropland and pasture expansion, or carbon uptake from agricultural abandonment. Repeated transitions are not currently captured by land-use datasets, yet have significant impact on component fluxes (Pongratz & Gazenmüller, 2021 [D3.9]).

The CIF (Berchet et al., 2021a [D3.10]) provides a means for flexible and inclusive combinations of inversion systems from different research labs, to optimally estimate fluxes of different GHG species. The CIF enables simple switching between choices of atmospheric transport model, observation data, inversion configuration and data assimilation method. This enables a much more reliable assessment of the overall uncertainty (Berchet et al., 2021b), as well as individual uncertainties from isolated components (Berchet et al., 2021a [D3.10]).

Survey responses highlight areas of ongoing uncertainty in LULUCF flux estimation as relating to a "*divide between data-driven and modelling approaches*", and differences in "*definition/terminology*", along the lines of the discussion for WP1 and WP2. Additional difficulties representing the "*forest sink in terms of soil carbon dynamics*" were noted [D3.9], including "*forest management options, mitigation options along the whole forest wood chain, impacts of climate change on forest disturbance, tree growth rates*" and mortality. Another respondent pointed out the "*benefit of estimating uncertainty due to model structure, through the processes represented, e.g. a dynamic nitrogen cycle, forest management, tree mortality due to hydraulic failure in a drought*". Conversely, they noted that there is additional uncertainty regarding the "*validity of parameterising models at the site-level and then running simulations at resolutions of a couple of hundred square kilometre grid cells; where different processes may be more important. As an extreme example, consider an individual tree. Once every few hundred years, a tree will die. In most places, however, 250 square kilometres of forests will not die simultaneously every 200-300 years.*"

Multiple survey responses mentioned "*uncertainty due to input data*" quality, including "*regional data gaps*" and differing "*spatial and temporal resolution making different products vary substantially*". The development of permanent city observatories combining ground-network and remote sensing observations, such as Dietrich et al. (2021), were highlighted as a benefit to "*closing the scale gap between in-situ and spaceborne observations*"; however their limited availability on only a "*demonstration level for a few cities*", hinders the scale of uncertainty reduction currently achievable.

While the next two points were raised in survey responses for WP3 they could equally be applied to WP2 and WP4. It was suggested that "*field experiments of land use change or management are not long enough and are limited more by funding cycles than experimental need. For example there are very few long term flux measurements or soil carbon measurements in Europe. In addition many flux towers are only in position for up to 5 years*." As well as "*many projects include both measurements and model development, however the data is only available at the end of the project and so the modelling is not benefiting from the later data.*" Increased funding cycle lengths would enable more model development to be undertaken after initial results are gathered, with the benefit of newly acquired data.

3.3.2. Priorities for resolving uncertainty

Research priorities aimed at reducing uncertainty in the LULUCF sector net flux include developing new and better methods to incorporate spatial datasets at different resolutions, as well as pursuing "*increasingly finer spatial* [and temporal] *resolution*." Continued and better integration of atmospheric observations via BU and TD approaches through close collaboration, to reconcile differences, would provide better understanding of uncertainty and hopefully reduce the range (Janssens-Maenhout et al., 2021).

A number of survey responses suggest continued "*investment in better quality datasets.*" These include "*combining ground based and remote sensing techniques*" to better define emissions from human processes, including LULUCF; "*extension of observation networks such as CO_2M*" and expansion of permanent city observations to "*at least a representative subset of large cities*" on each continent. Some of these improvements to input data are anticipated to occur within the next five years.

Another survey response suggests that research to "*improve the inversion scheme to overcome atmospheric transport model uncertainties*" will feasibly achieve improvements within the next five years. Lastly, should "*improvements to compute power achieve an order of magnitude increase in computing speed, that would help us get closer to being able to characterise the uncertainty of a single land-surface model by running thousands of perturbed simulation experiments. So far this has not been done, hence why people revert to inter-model comparisons.*" With regard to field experiments of land use change being too short, it was suggested to lengthen funding cycles to allow experiments to be maintained for longer duration. It was also suggested to gather complementary data from old experiments and incorporate in new model development. Research into soil carbon dynamics was not a focus of VERIFY and so is an important component of future research.

3.4. WP4: National & regional CH_4 and N_2O fluxes

3.4.1. Sources of uncertainty

European (EU27 + UK) CH_4 and N_2O emissions are estimated from national BU estimates combining input AD and EF from one process-based and two statistical models, with the uncertainty propagating to regional or global estimates as the squared sum of the AD uncertainty and the EF uncertainty. Uncertainties are then summed by sector sub-categories and cross-country tables (Leip et al., 2021 [D4.2]). Following IPCC guidelines of assigning lower and upper bound uncertainties based on a country's level of development, this results in a large uncertainty range for each gas across sectors (CO_2: 4.8% – 43.6%; CH_4: 14.5% – 39.9%; N_2O: 12.9% – 298%) (Leip et al., 2021 [D4.2]). The Emissions Database for Global Atmospheric Research (EDGAR) model estimates human-induced CH_4 and N_2O emissions and also derives structural uncertainty from both AD and EF components, meaning uncertainty varies by country, sector and GHG. Solazzo et al. (2021) estimated the combined (CO_2, CH_4, N_2O) global uncertainty range for 2015 at between -15% and +20% (95% confidence interval or a log-normal distribution).

The natural CH_4 flux is determined from wetlands and terrestrial water bodies and remaining sources of uncertainty include the distribution of peatland soils and the mineral soil flux estimate, both of which can be further constrained by more and better quality observations (Aalto et al., 2021 [D4.5]). As outlined in greater detail by Petrescu et al. (2021b), TD inversions contain both anthropogenic and natural emissions, whereas NGHGIs do not, making their direct comparison more complex. For N_2O, the difference between inversion and NGHGI emissions is greater than the estimate of natural N_2O emissions. The spread in CH_4 emissions from inversion results is large and further research is needed to explain the cause (Petrescu et al. (2021b).

The seasonality of CH_4 emissions from wetlands and N_2O emissions, especially in the form of agricultural fertiliser application, need to be better constrained by observations that feed into BU process models and TD inversions in order to reduce currently large uncertainties (Petrescu et al., 2021). TD inversion estimates of CH_4 and N_2O fluxes have reduced uncertainty by up to 75%,

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compared to BU process estimates alone, constraining European (EU27 + UK) emissions and also reducing uncertainty in NGHGIs (Thompson et al., 2021a [D4.8]).

Survey responses have identified a number of ways in which remaining uncertainty in estimation of CH_4 and N_2O fluxes could be investigated and hopefully reduced. Once again "*atmospheric transport models, especially boundary layer dynamics and vertical mixing, such as stratosphere-troposphere exchange*" and poor input data quality in regions with "*poor spatial coverage, particularly in southern and eastern Europe*", are identified as contributing to uncertainty in current estimation methods. Improved atmospheric transport models could also help to reduce uncertainty in inventory methods as well, by reducing "*uncertainties in emission factors and a lack of knowledge about their variability due to e.g. technology level and environmental factors*", as described by Thompson et al. (2014; 2021).

Another survey response noted "*uncertain boundary conditions in inversions, where regional CH_4 & N_2O models need constraining with global model output*". An example was given where "*switching global models resulted in substantial changes in European CH_4 emissions*", indicating higher EU27+UK CH_4 emissions than previous estimates (Thompson et al., 2021b [D4.9]). In addition, "*another major source of uncertainty is the model representation error (which includes model transport errors), which is difficult to define. Different choices for this error (or how it is modelled) have quite a strong impact on estimated CH_4 fluxes. Better ways of describing this uncertainty are needed, which account for the dependence of the error on the meteorological situation.*" Another survey response described the atmospheric transport model as a "bottleneck" given the "*increasing coverage and quality of satellite and ground-based observations*", suggesting that "*we are lacking robust methods to quantify transport model uncertainties*."

3.4.2. Priorities for resolving uncertainty

Survey responses indicated priority areas for new research in the next 5 years include expanding "*the number of atmospheric monitoring stations across Europe and especially southern and eastern Europe*", as well as "*improved atmospheric chemistry transport models to better constrain boundary layer dynamics, vertical mixing*" and, "*for methane, better constraints on OH concentrations*" (Zhao et al., 2020). It was suggested better validation of atmospheric models could be achieved "*using radon (222Rn) boundary layer height measurements and aircraft measurements.*" While another survey response advocates investment in "*large-scale*" deliberate tracer release experiments to "*calibrate atmospheric transport models*" using a variety of tracer compounds (e.g. Simmonds et al., 2021) that would "*provide a great return on investment.*"

To address uncertainty in boundary conditions between regional models, another survey response suggests "*concentration levels simulated by different global CH_4 data assimilation products should be compared and the influence of their differences on regional CH_4 inversions should be studied (also with respect to trends). To reduce the dependence on global boundary conditions, regional models should optimise not only emission fluxes but also boundary conditions*", which it is suggested, should be straightforward to implement within the next 5 years. A capability currently under development and likely to be achieved in the next 5 years is "*flow-dependent model representation errors derived from ensembles of CH_4 tracers driven by a meteorological ensemble*."

A new ground-based measurement of APO to quantify the regional ffCO2 component of atmospheric CO_2 has reported greater accuracy at identifying reductions in the UK linked with reduced emissions during the COVID-19 pandemic (Pickers et al., 2022). The method separates anthropogenic and biogenic atmospheric CO_2 signals from continuous measurements, using machine learning, enabling high-frequency and near real-time quantification of relative emissions. Further research of this method and collection of these measurements across an extended European network and incorporating results in TD inversion, could be a step to enable better verification of atmospheric CO_2 concentration, in response to climate change policy.

3.5. WP5 & WP6: Global GHG synthesis products and policy-relevant verification

3.5.1. Sources of uncertainty – CO_2

A detailed description and mostly quantitative comparison of different sources of global CO_2 emissions data are outlined in D5.1 (Peters & Andrew, 2019). Emissions uncertainty can be divided into 'structural uncertainties' stemming from methodological choices, such as deciding which emissions are included/excluded, and 'parametric uncertainties' such as variations in the input data selected. Structural uncertainties often arise from differences in the system boundaries used to define the estimate, including the choice of administrative or geographic definition of a territory (accounting for ±1-2% of emissions); the inclusion of fossil fuel emissions, land-use change and carbonate decomposition; the difference between combustion or oxidation (of a product); time periods; bunker fuels; sector definitions & approach; inventories covering geographic areas (e.g. energy balances) or accounts covering economic activities (e.g. energy accounts).

As has been described for earlier work packages, CO_2 emissions estimates vary at the European level and a significant number of other countries, for the AFOLU and LULUCF sectors, from a combination of system boundary and methodological variations (Dolman et al., 2019 [D5.9]; Dolman et al., 2021 [D5.3]; Petrescu et al., 2020). It is important to note that agreement between estimates may reflect similarities in their method or input data, rather than confirming the accuracy of the estimate. Remaining gaps in understanding include the differences between FAOSTAT and UNFCCC and between DGVMs and bookkeeping models (Petrescu et al., 2020; Petrescu et al., 2021a).

Comparison between a fast-track inversion product (based on satellite CO and N_2O) and BU process models reveals that the inversion produces more credible values with a larger uncertainty estimate of ~17% (Dolman et al., 2021 [D5.3]). Progress is being made to reconcile differences between BU and TD methods, but they continue to show greater variability than NGHGI methods.

The net LULUCF CO_2 flux uncertainty estimate from BU approaches can be smaller than the BU model-spread, while the model-spread for TD estimates is much larger and can be used to estimate uncertainty (Petrescu et al., 2021a; Janssens-Maenhout et al., 2020 [D6.1]). The interannual variability of the LULUCF CO_2 flux is higher from TD estimates than BU estimates, which are higher than NGHGI estimates, despite broadly similar multi-annual mean values (Petrescu et al., 2021a; Janssens-Maenhout et al., 2020 [D6.1]).

The **global carbon budget** (GCB 2021) (Friedlingstein et al., 2022) prepared by the Global Carbon Project compares observations and estimates of CO_2 fluxes based on multiple approaches. In agreement with the reports and papers summarised already, the GCB 2021 found a large and persistent uncertainty in the estimation of LULUCF CO_2 emissions; low agreement between different estimation approaches for the magnitude of the terrestrial CO_2 flux in the northern extra-tropics; as well as low agreement between approaches for the strength of the ocean sink over the last decade (Friedlingstein et al., 2022). The major sources of uncertainties in the global carbon budget 2021 are outlined in Table 9 (Friedlingstein et al., 2022, pp. 1953) and discussed throughout the text and highlighted references. In particular, large sources of uncertainty include estimating CO_2 emissions from LULUCF and estimating the Southern Hemisphere ocean CO_2 sink, due to the sparsity of fCO_2 (non-ideal gas corrected pCO_2) observations in the Southern Ocean (Friedlingstein et al., 2022).

The significant impact of variations between different methods of estimating the global LULUCF CO_2 flux are highlighted by Grassi et al. (2021) who describe a method for adjusting the cumulative emissions budget to achieve international climate targets (net zero, 1.5^o or 2^{o}C). The adjustment is required because global land-use fluxes derived from integrated assessment models (IAM) exceed NGHGI by around 5.5 $GtCO_2yr^{-1}$ (2005-2015), reducing original IAM carbon budgets by 120-192 $GtCO_2$. The majority (4.5 $GtCO_2yr^{-1}$) of this difference comes from anthropogenic CO_2 removals, most of which occurs in forests. Around ⅔ of the potential causes of this difference are difficult to assess and represent a slowly diminishing uncertainty over time as (hopefully) models and NGHGIs improve (Grassi et al., 2021).

In harmony with the summary from VERIFY reports and published literature, survey responses highlight "*inconsistent or unclear definitions and system boundaries. Inversions & inventories are reporting different things, though this is not always obvious.*" "*Data is not reported in a way to help comparisons, for example AD and EFs may not be separated, or sector definitions are different*". Fundamentally, NGHGI have a different agenda from BU models or TD inversions, the former focuses on "*country accuracy and inventory reporting*", while the latter focuses on "*global consistency and scientific analysis*". A different survey response refers to this as a problem ensuring "*the famous apples-to-apples comparison*."

Survey responses also identified "*missing or heterogeneous information as inputs* [are] *bottom-up* [and there are] *no political country borders of the top down estimates. While progress has been made on more complete and homogeneous info in time, the measurements will remain representative for a certain region and will not allow to solve political country borders*." In addition to "*uncertainty on the changes*" of GHG concentrations, there is also "*uncertainty on the attribution of this change to human activities and implementation of GHG measures. With the*

COVID 'experiment' great progress was made but the relatively small GHG decrease under lockdown shows the huge emissions source which seem relatively fixed in our backpack and carried over from year to year."

3.5.2. Sources of uncertainty – CH_4 N_2O

A synthesis of European CH_4 and N_2O emissions (Petrescu et al., 2021b) identified CH_4 emissions for the period 2011-2015 are estimated by NGHGI to be 18.9 ±1.7 $TgCH_4$ yr^{-1}, which compares well with two BU mean estimates of 20.8 $TgCH_4$ yr^{-1} and 19.0 $TgCH_4$ yr^{-1}. Due to the inclusion of natural emissions TD inversion estimates are higher with a mean of 28.8 $TgCH_4$ yr^{-1} for high resolution models and 23.3 - 24.4 $TgCH_4$ yr^{-1} for coarse resolution models. Natural emissions are estimated to be 5.2 $TgCH_4$ yr^{-1}. For the same period, N_2O emissions are estimated by NGHGI to be 0.9 ±0.6 TgN_2O yr^{-1}, which compares well with two BU mean estimates of 0.8 TgN_2O yr^{-1} and 0.9 TgN_2O yr^{-1}. The average for global and regional TD inversions was 1.3 ±0.4 and 1.3 ±0.1 TgN_2O yr^{-1}. Natural and anthropogenic emissions cannot be separated in TD inversions, preventing direct comparison to BU estimates (Dolman et al., 2021 [D5.3]), however, natural emissions do not explain the difference of 452 kt N_2O between BU and TD estimates, so this discrepancy needs further research (Petrescu et al., 2021b).

Further comparisons between BU, TD and NGHGI estimates reveal that, for CH_4, the uncertainty range of BU estimates is around half the spread of TD estimates, while TD estimates exceed BU estimates by an average +22% (Petrescue et al., 2021b). For N_2O, the uncertainty range of BU estimates almost doubles the spread of N_2O estimates, while the average emissions from TD estimates exceeds BU estimates by +37% (Petrescue et al., 2021b). Declining trends in CH_4 and N_2O emissions from BU estimates is not supported by TD estimates, while BU estimates result in higher energy and waste emissions than NGHGI estimates (Petrescu et al., 2021b).

While significant development of global observation systems and TD inversion methods are required to support verification of policies implemented under the Paris Agreement, TD inversion methods are an important tool to independently verify (or at least compare to) NGHGI. Their ability to quantify anthropogenic emissions and natural sources/sinks is particularly important (Petrescu et al., 2021b).

With progress being made to reduce the highest emitting sectors, the contribution from smaller sources with broader uncertainty (e.g. fugitive CH_4 emissions from fossil fuel extraction/production, or N_2O emissions from leaching and run-off from landfill) will become more significant (Janssens-Maenhout et al., 2021). In future, much greater attention should also be paid to the seasonality of CH_4 and N_2O emissions, which may help to better quantify uncertainty within specific sectors, particularly agriculture and natural wetland emissions (Petrescu et al., 2021b).

The **global methane budget** (Saunois et al., 2020) identified natural CH_4 sources as the most important source of uncertainty, particularly wetlands and inland waters. Emissions from wetlands and geological processes are smaller than previous budgets by around 35 $TgCH_4yr^{-1}$ and

8 $TgCH_4yr^{-1}$ respectively. However uncertainty ranges for different emissions sources are in the order of 20-35% for sector inventories of anthropogenic emissions (e.g. agriculture, waste, fossil fuels); around 50% for biomass burning and natural wetland emissions; around 100% for natural emissions from inland waters and geological sources (Saunois et al., 2020). The primary atmospheric methane sink through OH reduction carries an uncertainty range between 10-15%. Regional uncertainty in emissions can be in the order of 40-60% in parts of South America, Africa, India, China and Siberia and other high-latitudes.

Reducing uncertainty in the size of methane sources needs to overcome four problems (Saunois et al., 2020):

(i) The broad range of both natural and anthropogenic methane sources, including biogenic, thermogenic and pyrogenic emissions classes, as well as point and diffuse sources (such as leakage from fossil fuel production), means data from a very broad range of scientific and industrial communities must be integrated.

(ii) Removal of atmospheric methane by hydroxyl free-radicals with extremely short life-times (~1 sec) requires global, high resolution spatio-temproal OH measurements and modelling.

(iii) Only net methane concentration (source – sink) is constrained by reliable atmospheric growth-rate observations, leaving uncertainty in sum of source and sum of sink estimates.

(iv) Limited observational constraint for: models of wetland extent and emissions; inland water sources; anthropogenic emissions inventories; and atmospheric inversions at global/regional-scales. In particular, for tropical and southern latitudes. Though the improving quality and density of modern satellite observations, as well as bias correction techniques for older satellite data, are reducing these observation gaps.

The **global nitrous oxide budget** (Tian et al., 2020) identified uncertainty in TD inversion estimates of global N_2O fluxes is derived from systematic errors in the modelled atmospheric transport and stratospheric loss of N_2O, as well as an over-dependence on prior flux estimates. They're also susceptible to gaps in observations, particularly for Africa, southeast Asia, southern South America and the global oceans. Uncertainty can be reduced by improved atmospheric transport models, prior flux estimates and additional atmospheric N_2O observations.

BU process-based estimates are susceptible to uncertainties in the estimation of land and ocean sources, resulting from both model configuration and parameterisation. Uncertainty could be reduced by the inclusion of additional processes, such as freeze-thaw cycles and ecosystem disturbance, in terrestrial biospheric models. N_2O emissions from permafrost thaw and peatland degradation are a particularly important source of uncertainty in global terrestrial flux estimates. Better quality observations of the timing and scale of agricultural nitrogen application and spatio-temporal variation in the distribution of natural versus agricultural land, would further reduce uncertainty in soil emissions (Tian et al., 2020).

Input data for all tiers of inventory approach for estimating agricultural N_2O sources (fertiliser use; livestock manure management; nutrient, crop and soil management) are particularly uncertain, especially for tier approaches using emission factors (Tian et al., 2020). For the oceans, a key uncertainty is the contribution of N_2O flux derived from tropical low oxygen zones (e.g. eastern equatorial Pacific) with high-yield N_2O formation processes such as denitrification and

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enhanced nitrification. Regional observational studies have suggested models may under-predict the N_2O produced in these regions. Global/regional ocean biogeochemical models that better represent ocean circulation and BGC fluxes would reduce this uncertainty. N_2O emission factors and long-term flows from marine or freshwater aquaculture are also very uncertain due to a lack of representative input data (Tian et al., 2020).

Survey responses discussing uncertainty in CH_4 and N_2O emissions estimates focussed on "*the assimilation of different observation data sets (satellite versus in-situ, different combinations of in-situ stations). Other differences are the use of different transport models, a priori inventories, a priori uncertainties, and inversion approaches. In order to make progress, the influence of these factors on the results need to be investigated more systematically.*"

3.5.3. Priorities for resolving uncertainty

Priorities for reducing uncertainty in the global methane budget include (Saunois et al., 2020):

(i) A global, high resolution map of water-saturated soils classified into emitting habitats (wetlands, ponds, lakes, reservoirs, streams, rivers, estuaries, and marine systems).

(ii) Development of process-based models of emissions from inland waters.

(iii) Improved density of methane observations to constrain bottom-up models at local scale (e.g. FLUXNET–CH_4) and urban-scales, as well as regional-scale (e.g. surface networks – GOSAT, GOSAT-2 – airborne observations – TCCON, Aircor – or satellite monitoring – TROPOMI) to improve atmospheric inversions.

(iv) Improved atmospheric transport models representing photochemical sinks in top-down atmospheric inversions, particularly vertically. This includes a more robust representation of the OH field in both space and time.

(v) Improved source partitioning via 3D variational inversion driven by isotopic and/or co-emitted species (e,g, ethane, carbon monoxide).

Survey responses suggest "*greater communication between inventory and inversion researchers*" as well as "*more transparency and organisation from modelling groups to allow for WP5 to more easily know what they are comparing*." "*The tendency is to report aggregated numbers, and in a range of formats. Reaching greater harmonisation in what is reported and how, while allowing and encouraging independent estimates, is important.*" This should include identifying "*best methods of comparing estimates, how to weight different estimates* [and] *how to statistically compare with UNFCCC inventories*."

While a number of responses focus on work to "*improve the precision/accuracy of inversions*" that are a priority for reducing uncertainty. This includes the "*development of a joint inversion framework like CIF*" (Community Inversion Framework, Berchet et al., 2021 [D3.10]), which "*will help disentangle the influence of different factors (satellite versus in-situ data, different combinations of in-situ stations, the use of different transport models, a priori inventories, a priori uncertainties, and different inversion approaches) on inversion results. This will help identify priorities for future improvements and reduce the currently large spread between inversion* *results.*” Another survey response mentioned “*reconciling ground based and remote sensing* [data] *for forests*” and “*improving real time assessments*” as priority areas.

Lastly, two survey responses suggested focussing on efforts “*to monitor the change*” or “*growth rate over absolute values*” and the “*uncertain attribution to potential drivers*” should be a priority. One of these scientists believes that “*the blueprint for verifying GHGs in Europe will be to have a good handle on the level and its change over 5 yrs* [trend] *for Europe as a whole. This needs to be extrapolated to the entire globe, which will increase the uncertainty but also the value!*” Ongoing work “*dealing with the spatial and temporal profiles helping to deconvolute the measured signals*” is an important component of this.

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4. Conclusions

The VERIFY project has identified and documented many ways to reduce the uncertainty of GHG flux estimates through the provision of new datasets and modelling methods. In order to achieve reliable verification of climate policy in a useful timeframe, additional work is required and VERIFY scientists and inventory compilers have outlined some of the necessary approaches through reports, published literature and in their survey responses.

While a number of steps have begun to be implemented, others could be in the near future. Some of the required steps are specific to an individual work package while others apply throughout. The body of this report summarises these approaches, referring to original reports for further detail, while highlights are presented in Table 1 under four themes that transcend all work packages. Attention is often focussed upon methodological differences, including variation in input data, as well as the implementation of three main approaches: BU process-based models; TD inversions; and NGHGI. A clear finding of the report is that each of the approaches serve an important role and therefore uncertainty can be minimised by planning how best to combine information from each approach to achieve an optimal estimate.

More observations	Research community interactions
"Expanding satellite & insitu observations of co-emitted species [CO, $^{14}CO_2$, NO_x, N_2O, HCHO] using e.g. CO2M."	*"Closer collaboration & better communication*".
"Significant development of global observation systems."	*"Making sure the datasets being compared are actually predicting the same thing (compare 'apples-to-apples')."*
Expand *"the number of atmospheric monitoring stations across Europe."*	*"Reconcile ground-based and remote sensing data for forests and improve real-time assessments."*
"Extension of observation networks such as Copernicus Carbon Dioxide Monitoring."	
More powerful simulations	**Favour accuracy over completeness**
"I*mproved atmospheric chemistry transport models to better constrain boundary layer dynamics, vertical mixing, OH concentrations."*	Target *"gases and sectors with low level of complexity & accuracy in estimation methods."*
More compute power would help *"characterise the uncertainty of a single* [model] *by running thousands of perturbed simulations."*	Prioritise *"key categories that significantly influence country-level total emissions."*
"Community inversion framework to disentangle influence of different factors".	Recurrent example: CH4 and N2O from agriculture, LULUCF, waste.

Table 1: key research priorities for verification grouped by themes applying to multiple work packages.

However, continued enhancement of communication and collaboration between scientific research communities and the inventory community will help to reduce uncertainty. In addition, there is a clear need for collection of better-quality data at higher spatial and temporal resolution (both in-situ and remotely sensed) and in areas that are not currently well covered. For example soil carbon dynamics are acknowledged by VERIFY scientists as an area where further research is required to better understand and characterise uncertainty in terrestrial GHG fluxes. Tackling those gases and sectors with the highest uncertainty that can impact emissions at the national scale should have the largest impact on reducing current uncertainty levels.

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6. Appendix: Survey Responses

WP1	
Sources of Uncertainty	**Priorities for resolving uncertainty**
The WP analyzed the uncertainty of the national GHG inventories (D1.1.). Uncertainty assessment is a fundamental requirement, and it can help the inventory compilers in prioritizing future GHG inventories improvements. In order to obtain total uncertainties per sector or a final one for the total inventory, it is necessary to propagate the uncertainties of the input data (i.e. activity data and emission factors) used for emission/removal estimations. Main propagation techniques focus on uncertainty combinations (for Tier 1 level) and on Monte Carlo simulations (for Tier 2 level). Differences in the uncertainty levels among inventories and among different sectors can be substantial. Deliverable 1.3 gives an overview of 26 EU Member States (MS) (all EU MS with the exception of Sweden and Czech Republic) uncertainties considering both sector and main GHGs subdivision. Deliverable results indicate that the reported uncertainty level in the total emissions of greenhouse gas inventories for 2016 ranges between 3% and 49.9%. The reported trend uncertainty in the total emissions of greenhouse gas inventories for 2016 ranges between 1.4 – 34%. The countries with the lowest uncertainties are the Netherlands (level uncertainty) and Spain (trend uncertainty), and the countries with the highest uncertainties are Lithuania (level uncertainty) and Finland (trend uncertainty). In addition, the uncertainty analysis shows a clear trend on uncertainties among different sectors. This trend appears in almost all EU MS equally (see D 1.3, Annex). Deliverable 1.3 suggests that Energy (CRF 1) is the most relevant sector in terms of emissions in all countries (except for Iceland) and that, overall, it is responsible for 78% of the total emissions. However, its uncertainty level is lower with respect to that of the other sectors because of the generally solid data based on national energy statistics. Overall, the lowest	Although developing countries have acquired extensive experience in measuring, reporting and verifying their GHG emissions and removals. However, there are still some gases (e.g., CH_4, N_2O) with high uncertainty levels in the inventories and sectors (e.g., waste and agriculture) where countries use a low level of complexity and accuracy in the estimation methods. Priority for improvement if GHG inventories and research input should focus on key categories, which are those that have a significant influence on a country's total emissions. Generally, rather high uncertainty levels occur when inventory compliers do not have country- or sector-specific data and methodologies and, therefore, they are constrained to applying IPCC default values (Tier 1 level). When country-specific values are available, but there are large uncertainties in the input data, this can lead to uncertainty in emissions estimates. As an example, we report here the case of the EU-27 plus United Kingdom and Iceland (Fig. 1). Although Energy is the sector with the highest total emissions, the estimate of its percentage uncertainty is nearly negligible (1.1 %). Therefore, a greater effort could be focused on refining or improving the estimates of other sectors characterised by higher percentage uncertainties such as Waste, Agriculture, LULUCF and IPPU, where uncertainties are 51.5%, 47.0%, 34.3% and 11.8 %, respectively (Fig. 1a). Similarly, efforts could be more targeted to reduce the uncertainties of N_2O emission estimates (even higher than ± 90 %) rather than those for CH_4 (10.1 %) (Fig. 1b). This does not mean that the reduction of uncertainty for Energy sector is not necessary, but that, in an expected future scenario of GHGs emission reduction from Energy, the proportional role of other sectors and gases could increasingly affect the total relative and absolute uncertainty of emissions estimates for the EU. Although difficult to assess, developing countries may have different uncertainty reduction needs as non-annex I countries are currently not required to

uncertainty level refers to the CO_2 emissions estimation, while those referring to N_2O and CH_4 are higher with respect to the previous one because several MS have adopted IPCC defaults factors for these gasses. Fuel combustion (1 A) is characterised by the lowest estimation uncertainties (0.9%). On the other opposite, the highest uncertainties have been estimated for N_2O and CH4 (18.4% UNFCCC, 2018) in the Fugitive emissions from fuels (subsector 1 B) subsector. Generally, IPPU (CRF 2) is the second or third sector for GHG emissions. Its uncertainties are quite small because emission estimations are usually based on plant-specific data and country-specific methods. CO_2 estimations are more accurate than those of N_2O and CH_4. In contrast to Energy and IPPU, the other sectors (Agriculture, LULUCF and Waste) are characterised by very high uncertainty percentages (45.5, 32.6 and 51.4%, respectively). A main common reason is that these sectors are characterised by GHG emission/removal estimations based on a number of variable factors and parameters, which make it harder to measure them accurately and because these sectors (with the exception of LULUCF) are characterised by mainly non-CO_2 GHGs emission.

Considering Agriculture sector, the main emitting sources for CH_4 are the different subcategories of enteric fermentation (3 A) and for N_2O the different subcategories of both manure management (3 B) and agricultural soils (3 D). Generally, lower uncertainty is associated to the CH_4 emissions from enteric fermentation from cattle, because almost all MS calculate corresponding emission with very sophisticated methods.

Considering LULUCF sector, the key categories for CO_2 emission and removals estimation are Forest Land, Cropland, Grassland, Wetlands, Settlements and Harvested Wood Products. Different MS adopt different methods for their emission/removal estimations. These methods can be country specific (low uncertainties) or based on IPCC default factors (high uncertainties). According to Rypdal & report the uncertainties for their estimates. For example, in China, where well-developed statistical methods have been adopted, the CO_2 emissions estimates from coal are frequently revised and, often, they contain large anomalies between revisions, thus suggesting high uncertainty in the Energy categories and sub-categories (Korsbakken et al., 2016). LULUCF and Agriculture emissions represent a large portion of many developing countries' total emissions (Tubiello et al., 2015), thus the uncertainties in those sectors need to be overcome. Uncertainty is a fundamental measurement for scientific and research outputs, giving inventory compilers a quantitative indication of the reliability of mean estimates and data for assessing inventory uncertainties. When uncertainty measurements are reported, the type of uncertainty methodology used (e.g., standard error or standard deviation of the mean) the number of observations (or replicates) considered needs to be defined. When the data source lacks an uncertainty value or its related information is not clearly defined, inventory compliers are obliged to adopt assumptions for uncertainty estimates which, in turn, add uncertainty to the reliability of the estimates (Carter et al., 2018; Herold et al., 2019).

[Source of the text above: Perugini, L., Pellis, G., Grassi, G., Ciais, P., Dolman, H., House, J. I., ... & Peylin, P. (2021). Emerging reporting and verification needs under the Paris Agreement: How can the research community effectively contribute?. Environmental science & policy, 122, 116-126.]

Winiwarter (2001), there is an incomplete understanding of GHG dynamics from soil (which represents the largest contribution to national uncertainty assessments). This represents the main reason for overall highly uncertainty estimations in addition to the extension of the land use and management change. Regarding Waste sector, almost all MS report CH_4 emissions from solid waste disposal on managed and unmanaged landfills using a Tier 2 methodology. In all other source categories in the waste sector, the share of MS using a higher Tier method is much lower than in the previous case. Important contributions to the overall uncertainty are generally high uncertainties about the amount of solid waste (organic material that decomposes to produce CH_4) that is deposited.	
E.g. cf. Verify deliverable 1.3 "Consolidated reporting requirement assessment", chapter 5. Recommendation: "For almost all EU MS, uncertainty analysis/fact sheets reveal that uncertainties in agriculture sector, LULUCF sector and waste sector are highly variable and uncertain -> VERIFY should focus on this. On EU level, waste sector is most uncertain sector".	Concerning LULUCF, the requested spatially explicit approach for LULUCF inventories for MS, in the frame of the UE LULUCF regulation starting with the 2023 reporting, should improve the LULUCF inventories and reduce their uncertainties. Improved estimation of GHG fluxes outside forest biomass (e.g. agricultural soils, organic soils, non-forest biomass…) is also needed to resolve uncertainty of fluxes for the LULUCF sector. Concerning agriculture, in France, year after year more country specific data/parameters and approaches are implemented, but still need to be further developed in relation with research activities. Concerning the waste sector, still more efforts are necessary for more detailed data and statistics to better refine the related emission estimations, e.g. higher frequency of surveys for domestic waste compositions.
	Reconciling various methods (ground based, default reporting, remote sensing, modelling).
WP2	
Sources of Uncertainty	**Priorities for resolving uncertainty**
For $FFCO_2$ atmospheric inversions: lack of dedicated CO_2 observation networks, uncertainties in satellite observation of co-emitted species and in atmospheric chemistry-transport modelling, and the challenges of characterizing the uncertainties in the	Upgrade of the observation networks and products (should be very important in the next 5 years, especially with the launch and operation of CO2M); progress in the inversion configurations to overcome part of these uncertainties (will be significant within the next 5 years).

inventories at relevant spatial, sectoral & temporal resolution.	
WP3	
Sources of Uncertainty	**Priorities for resolving uncertainty**
There are considerable uncertainties around land use change CO2 fluxes, including just the terminology (https://doi.org/10.5194/esd-5-177-2014). Individual model uncertainty for land-surface models are generally estimated by using ensembles, such as those found by TRENDY (used in the first VERIFY paper, https://doi.org/10.5194/essd-13-2363-2021). Ensemble simulations have the benefit of estimating the uncertainty due to model structure (such as the processes represented, e.g. a dynamic nitrogen cycle, forest management, tree mortality due to hydraulic failure in a drought), but this misses uncertainty due to input data, model parameters, and the initial state of the model. There is also a big question of the validity of parameterizing models at the site-level and then running simulations at resolutions of a couple hundred square kilometre grid cells; different processes may be more important. As an extreme example, consider an individual tree. Once every few hundred years, a tree will die. In most places, however, 250 square kilometres of forests will not die simultaneously every 200-300 years.	This has been the debate for decades: given limited resources, where do we focus our attention to have the biggest gains? I can't say I have concrete convictions on the subject. I think we need to keep attacking all fronts (improved data assimilation, increasingly finer spatial resolution, incorporation of more realistic processes including human activities). I do not think we will see any major progress in the next five years, though the biggest hope seems to be a revolution in computing power that gives us an order of magnitude increase in computing speed. That would help us get closer to being able to characterize the uncertainty of a single land-surface model by running thousands of perturbed simulation experiments (which so far has not yet been done, and hence why people revert to inter-model comparisons).
For CO_2 ecosystem flux inversions: uncertainties in transport models, limitations in the observation coverage.	Need for improving the inversion scheme to overcome the transport model uncertainties (feasible within the next 5 years); extension of the observation networks (will be done, in particular with the launch of CO2M, within the next 5 years).
Forest sink estimation, dealing with regional data gaps, divide between data-driven and modeling approaches.	Investing in better datasets, and data driven discoveries.
Permanent city observatories using ground-based remote sensing equipment for closing the scale gap between in-situ and spaceborne observations are only available on a demonstration level for a few cities today -as this one amt.copernicus.org/articles/14/1111/2021.	At least a representative subset of large cities (in North and South America, Western and Eastern Europe, Africa, Asia) should be equipped with permanent observational infrastructure.
Forest soil carbon balance irt to management options; mitigation options along whole forest wood chain in the EU; impacts of climate change	Experimental research, combining ground based and remote sensing techniques.

on forest disturbances; impacts of climate change on tree and forest growth rates.	
1) Land use forcing: underlying data sources, spatial resolution make different products vary substantially. 2) Definition/terminology: National GHG inventories report differently than global carbon cycle models, but their estimates are frequently compared.	1) Better monitoring of land use and land cover change, including degradation effects -- combined with methodological approaches to separate natural from anthropogenic drivers. 2) Mapping/translation of different approaches (see Friendlingstein et al., 2021 Global Carbon Budget 2021, Tab. A8 based on Grassi et al 2021).
Land use and land cover change (LULCC) data as forcing for bookkeeping models and DGVMs (Deliverable D3.9); Spatial explicit information on vegetation and soil carbon densities and dynamics (work in progress).	Increased integration of information from remote sensing products in LULCC datasets. Focus on the importance of LULCC data for emission estimates is increasing. Substantial improvements are likely in the next years with the increased integration of new data products in LULCC datasets.
The main source of uncertainty is the using data sets of different spatial and temporal resolutions in many different models all of which do not cover all the driving explanatory variables or processes. In reality the parameterization of these models is limited as the field experiments of the trials of land use changes or management are not long enough and are limited more by funding cycles than experimental need. For example there are very few long term flux measurements or soil carbon measurements in Europe. In addition many flux towers are only in position for up to 5 years. Soil carbon measurements are very sparse and not in terms of time series. Another limitation is that many projects include both measurements and model development, however the data is only available at the end of the project and so the modelling is not benefiting from the later data.	Land use and land cover change (LULCC) data as forcing for bookkeeping models and DGVMs (Deliverable D3.9); Spatial explicit information on vegetation and soil carbon densities and dynamics (work in progress).
WP4	
Sources of Uncertainty	**Priorities for resolving uncertainty**
From atmospheric inversions, important uncertainties for global inversions are uncertain atmospheric loss (due to OH), uncertain atmospheric transport, and for regional inversions uncertain boundary conditions, uncertain atmospheric transport. For inventory approaches (e.g IPCC Tier 1 and 2 methods), uncertainties are largely due to uncertainties in emission factors and lack of knowledge about	Improved atmospheric chemistry transport models, for methane, better constraints on OH concentrations.

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their variability (due to e.g. technology level and environmental factors). (doi: 10.1098/rsta.2020.0443; doi:10.5194/acp-20-9525-2020)	
Regional CH_4 models need to be constrained at the borders by the output of a global CH_4 model to determine background CH_4 concentrations. Switching from one global model to another resulted in substantial changes in European CH_4 emissions (see Deliverable D4.9). Another major source of uncertainty is the model representation error (which includes model transport errors), which is difficult to define. Different choices for this error (or how it is modeled) have quite a strong impact on estimated CH_4 fluxes. Better ways of describing this uncertainty are needed, which account for the dependence of the error on the meteorological situation.	The concentration levels simulated by different global CH_4 data assimilation products should be compared and the influence of their differences on regional CH_4 inversions should be studied (also with respect to trends). To reduce the dependence on global boundary conditions, regional models should optimize not only emission fluxes but also boundary conditions. Implementing this possibility is straightforward. Flow-dependent model representation errors may be derived from ensembles of CH_4 tracers driven by a meteorological ensemble. We are currently developing this capability. Both advances are very likely to be achieved in a 5 year time frame.
Major sources of uncertainty of top-down estimates by inverse modelling: - atmospheric transport in atmospheric models, especially boundary layer dynamics and vertical mixing; - coverage atmospheric network (especially southern and eastern Europe); - limited accuracy (and poorer spatial coverage) of atmospheric N_2O measurements.	- improve modelling of atmospheric transport in atmospheric models, especially boundary layer dynamics and vertical mixing - need to better validate atmospheric models (e.g. using 222Rn, boundary layer height measurements and aircraft measurements) - need to further increase number of atmospheric monitoring stations across Europe (especially southern and eastern Europe).
With the increasing coverage and quality of satellite and ground-based observations the quality of the transport models are increasingly becoming a bottleneck. We are lacking robust methods to quantify transport model uncertainties.	The only way to "calibrate" atmospheric transport models is through tracer release experiments with exactly known emissions at exactly known places and times. The last large-scale experiment (ETEX) dates back almost 30 years and was very limited in scope (two releases only). Several publications advocated such experiments (e.g. https://doi.org/10.1016/j.atmosenv.2020.118074). Investments in such an experiment would be considerable (several million Euro) but only a tiny fraction of current investments in measurement infrastructure and would provide a great return on investment.
WP5 & WP6	
Sources of Uncertainty	**Priorities for resolving uncertainty**

In the synthesis of European CH_4 and N_2O emissions by Petrescu et al. (10.5194/essd-13-2307-2021) results from many different global and regional models were combined. An important source of differences between model results is probably the assimilation of different observation data sets (satellite versus in-situ, different combination of in-situ stations). Other differences are the use of different transport models, a priori inventories, a priori uncertainties, and inversion approaches. In order to make progress, the influence of these factors on the results need to be investigated more systematically.	The development of a joint inversion framework like CIF will help disentangle the influence of different factors (see above) on inversion results. This will help identify priorities for future improvements and reduce the currently large spread between inversion results. This should be achievable in the next 5 years.
WP5 is a synthesis work package, and as such it seems to rely on WP2-4 supplying uncertainty information. Perhaps I am mistaken? They do grab some information outside of VERIFY to incorporate as well, but to my knowledge they do not carry out any modeling or data analysis themselves. Thinking about it, the biggest uncertainty is WP5 is making sure the datasets being compared are actually predicting the same thing (the famous "apples-to-apples" comparison).	There needs to be more transparency and organization from modelling groups to allow for WP5 to more easily know what they are comparing. This is something achievable in five years, I think.
1. Missing information or heterogeneous information as input bottom-up and no political country borders of the top down estimates. While progress has been made on more complete and homogeneous info in time, the measurements will remain representative for a certain region and will not allow to solve political country borders. 2. The uncertainty on the changes and the uncertainty on the attribution of this change to human activities and implementation of GHG measures. With the COVID "experiment" great progress was made but the relative small GHG decrease under lockdown shows the huge emissions source which seem relatively fixed in our backpack and carried over from year to year.	The greatest priority is to monitor the change itself now and in the future with its uncertainty and the uncertain attribution to potential drivers. In 5 yrs from now, the level should have changed but probably (looking back to the trend over last 30 years) might not have changed much. As such, I believe that the blueprint for verifying GHGs in Europe will be able to have a good handle on the level and its change over 5 yrs for Europe as a whole. This needs to be extrapolated to the entire globe, which will increase the uncertainty but also the value! Of course, I am happy that there are follow-up projects, dealing with the spatial and temporal profiles helping to deconvolute the measured signals.
Wide ranges of results when synthesizing the results from ensemble of inversions from different groups or system configurations.	Improvement of the precision/accuracy of inversions (should be significant in the next 5 years).
* Inconsistent or unclear definitions, system boundaries, etc. Inversions & different	* Greater communication between inventory and inversion researchers

inventories are reporting different things, though this is not always obvious * Different foci: global consistency versus country accuracy, inventory reporting versus scientific analysis, etc. * How to easily compare estimates, data is not reported in a way to help comparisons, for example AD and EFs may not be separated, sector definitions are different, etc.	* Clear communication and detail. The tendency is to report aggregated numbers, and in a range of formats. Reaching greater harmonisation in what is reported and how, while allowing and encouraging independent estimates, is important. * Best methods of comparing estimates, how to weight different estimates, how to statistically compare with UNFCCC inventories, etc * More focus on growth rates over absolute values?
	Reconciling ground based and remote sensing for forests, improving real time assessments.

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