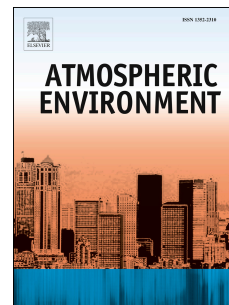


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A complete rethink is needed on how greenhouse gas emissions are quantified for national reporting

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1 **A complete rethink is needed on how greenhouse gas emissions are**
2 **quantified for national reporting**

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14 **A complete rethink is needed on how greenhouse gas emissions are**
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17

18 The 2015 Conference of the Parties (COP21) in Paris has for the first time agreed that both
19 developed and developing countries need to reduce greenhouse gas (GHG) emissions to
20 maintain a global average temperature ‘well below’ 2°C and aim to limit the increase to less
21 than 1.5°C above pre-industrial temperatures. This requires more ambitious emission
22 reduction targets and an increased level of cooperation and transparency between countries.
23 With the start of the second Kyoto Commitment period in 2013, and the 2015 Paris
24 Agreement, it is, therefore, timely to reconsider how GHG emissions are determined and
25 verified.

26 The policy agenda is currently centred on GHG emission estimates from bottom-up
27 inventories (see box 1a). This includes annual national reporting of GHG emissions (e.g. to
28 the United Nations Framework Convention on Climate Change (UNFCCC) and defining
29 emission reduction targets. However, bottom-up emission estimates rely on highly uncertain
30 and, in some cases, sparse input data and poorly characterized emission factors.

31 In order to enhance accuracy, cost-efficiency and transparency of the process to assess
32 progress towards the national emissions reduction targets, we call for a rethink of the current
33 reliance on ‘bottom-up’ inventories for reporting national and global anthropogenic GHG
34 emissions.

35 Climate scientists employ atmospheric observations (in the so-called ‘top-down’ approach,
36 see box 1b) to assess and verify national bottom-up emission inventories of non-CO₂ GHGs,

37 principally nitrous oxide (N₂O) and methane (CH₄). Top-down approaches use atmospheric
38 concentration (or mole fraction) measurements in conjunction with models of atmospheric
39 transport (i.e. atmospheric inversions) to provide a mass balance constraint on the total
40 emissions. For CO₂, the net flux between the atmosphere and the Earth's surface (land
41 biosphere and ocean) amount to approximately half of the global anthropogenic emission and
42 thus also need to be accounted for. It is currently a burning research question, how to
43 accurately discern anthropogenic emissions versus land biosphere and ocean fluxes using top-
44 down constraints, and a number of additional atmospheric tracers to achieve this have been
45 proposed (e.g. ¹⁴C, CO, and O₂). With present knowledge, it is pertinent that top-down
46 approaches are incorporated in national reporting and policy for non-CO₂ GHGs and, in the
47 future when the methods are fully developed, also for CO₂.

48 The use of top-down approaches is particularly relevant for CH₄ and N₂O (the second and
49 third most important GHGs after CO₂, respectively). Both gases are predominately of
50 microbial origin and, therefore, characterized by high spatial and temporal variability. This
51 makes it very challenging to parameterize and up-scale their emissions to regional or national
52 totals. Employing top-down approaches to quantify emissions of these GHGs can provide a
53 cost-effective strategy for assessing reduction targets and would deliver several benefits by:
54 (i) focusing on climate relevant data, i.e., the concentration of radiative forcers in the
55 atmosphere, (ii) overcoming the problem of limited accuracy in bottom-up estimates, (iii)
56 better integration of national estimates into a global framework, making emission estimates
57 more transparent and independently verifiable, and (iv) providing a framework to focus
58 investigations on emission hotspots using bottom-up methods.

59 If maximum accuracy of GHG emissions (i.e., across all source categories) and emission
60 trends are the most important goals for international climate policy, then top-down
61 approaches offer numerous advantages over bottom-up ones. Namely, by frequently

62 measuring atmospheric GHG concentrations, a physical constraint on total emissions and
63 emission trends can be provided; and, by resolving the atmospheric transport using models,
64 constrained emission estimates can be reported regionally. Thereby problems of sparse and
65 unreliable activity data, poorly characterized emission factors, and unaccounted-for emissions
66 are avoided. Furthermore, by measuring concentration changes with time, the effect of
67 mitigation can be more directly related to radiative forcing and thus to the expected global
68 warming. Atmospheric observation networks will also serve to alert the policy maker of
69 changing biogenic emissions in response to changing climate or unexpected disturbances.

70 While top-down approaches are better suited to detect the success or failure of countries and
71 regions to reduce GHG emissions, they cannot give indications where future mitigation
72 policies will be most effective. Therefore, it will be important for countries to supplement
73 top-down data with targeted sophisticated bottom-up measurement and model approaches for
74 hotspot sources and regions. It will not be necessary to improve existing basic inventories
75 over the entire territory and for all sectors and any resulting financial savings should be
76 channelled into improving the inventory for hotspots and optimizing mitigation.

77 We, therefore, suggest a paradigm shift from bottom-up to top-down approaches for emission
78 estimation as a basis for policy, whilst maintaining bottom-up approaches in the role of
79 planning mitigation strategies and for providing future emission scenarios. Tier 1 bottom-up
80 estimates would also be used as prior information for top-down emission quantification.

81 Furthermore, top-down estimates could be validated in meso-scale studies in which the
82 inversions are performed for a given region with high observation density and the results
83 compared to flux measurements (e.g. Eddy Covariance) or a flux data product (see Fig. 1).

84 The top-down approach requires spatially and temporally dense observation networks,
85 complemented by future satellites missions. This includes existing surface measurement

86 networks, such as those emerging in Europe, North America and now also in Asia. Satellite
87 observations of GHGs are currently available for CH₄ and CO₂. Current projects such as
88 those promoted by the Copernicus Atmosphere Monitoring Service (CAMS¹) and the
89 Integrated Carbon Observation System (ICOS²) demonstrate the feasibility of the approach.
90 In Europe, where the density of atmospheric observation sites is relatively high, and where
91 the natural sources of N₂O are nearly negligible, inverse models are already capable of
92 providing good estimates of the total anthropogenic N₂O emissions for individual countries¹⁻
93 ³. Furthermore, inverse models were able to detect regional trends in emissions such as for
94 N₂O in Asia⁴. And inverse models have been able to constrain emissions of CH₄ in China,
95 where the inventories were found to significantly overestimate emissions in the 2000s^{5,6}, or in
96 the U.S. corn belt finding an underestimation of N₂O emissions if estimated with IPCC
97 approaches⁷. Complications in detecting trends in anthropogenic emissions arise, however,
98 when the natural emissions are changing as a response to climate forcing. Developing
99 methods to discriminate different emission sources is a continuing area of research and
100 include multiple tracer approaches, e.g., for CH₄ stable isotopes (¹³C and D) can help
101 discriminate microbial and fossil fuel sources⁸.

102 Considerable effort, however, is still needed to further develop and integrate surface
103 networks, with emphasis on tropical and southern hemisphere countries⁹. Clearly, a shift in
104 emphasis to top-down approaches will require significant investment to improve the capacity
105 and capability of atmospheric measurements and modelling. We calculate that for 500

¹ <http://atmosphere.copernicus.eu>

² <https://www.icos-ri.eu>

106 stations globally, which would provide a good in-situ network sufficient to resolve most
107 countries, an investment of about \$500M would be required over the next 20 years. For
108 comparison, in the UK a programme to improve the GHG inventory for agriculture required
109 investment of about \$20M, thereof \$10M for specific measurements of N₂O emissions at
110 different scales (Luke Spadavecchia, personal communication, Feb. 2016). The development
111 of Tier 2 and Tier 3 methodologies¹⁰ has shown that the cost of developing high-quality
112 national bottom-up methodologies is substantial.

113 It is paramount that atmospheric concentration measurements and inversion modelling results
114 will be internationally freely available. This not only will guarantee high quality (and lower
115 uncertainty) of the emission estimates, but also allow countries that are not able to run their
116 own inverse models to delegate the reporting of their national emissions to other countries or
117 (international) research institutes. Therefore, such a paradigm shift will allow all countries to
118 assess their progress towards their target, without the need to build their own national
119 emission inventory, whilst at the same time providing highest possible transparency. Quality
120 assessment and control would need to be carried-out: (i) on the in-situ measurements and (ii)
121 by model inter-comparisons. This would be a significant simplification compared to the
122 review system currently in place at the UNFCCC.

123 Our suggested approach for science and policy-relevant emissions estimates is summarized as
124 follows (see Figure 1):

- 125 • Develop GHG emission estimates, spatially and temporally resolved, from inversions
126 using atmospheric concentration measurements. These will be informed by prior flux
127 estimates provided by global Tier 1 GHG emission inventories or from national data, if
128 available. A (global) network of atmospheric observation sites provides high accuracy
129 and frequency concentration data for use in inverse models yielding national-scale

- 130 optimized emissions, which will be the appropriate data to be submitted to e.g. the
131 UNFCCC.
- 132 ● Use Tier 2 and Tier 3 bottom-up inventories for hot-spot areas and source categories for
133 future emission scenarios, and to inform and monitor climate change mitigation
134 policies.
 - 135 ● Cross-check regional inversion-based emission estimates using meso-scale inversions
136 (resolution of $\sim 10 \text{ km}^2$, nested in a larger regional inversion system) with flux
137 measurements (e.g. from Eddy Covariance and chambers) to “close the gap” between
138 top-down estimates and bottom-up ones based on field-scale flux measurements (see
139 Fig. 1).

140 Our suggestion to move to top-down-based GHG emission estimates is motivated by the fact
141 that for the assessment of compliance with emission reduction targets, anthropogenic
142 emission trends need to be determined at the highest possible accuracy. Detailed knowledge
143 of emissions from individual source categories is not required for this purpose. However, a
144 profound understanding of processes and interactions is still needed to identify the most
145 suitable and cost-effective mitigation approaches at national and sub-national scales.

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180 Author Contributions

181 AL conceived the idea for this manuscript, all authors contributed equally to the development
182 of the proposal and to the writing of the manuscript.

183

184 **Figure Legend**

185 Figure 1: Schematic showing how a GHG emission assessment system could be designed. (a)

186 Prior flux estimates provided by global Tier 1 GHG emission inventories or from national

187 data, if available. (b) A (global) network of atmospheric observations for use in inverse

188 models yielding national-scale optimized emissions, which will be submitted to e.g. the

189 UNFCCC. (c and d) Validation of the results using nested meso-scale inversions (resolution

190 of $\sim 10 \text{ km}^2$), which will be compared to flux measurements (e.g. Eddy Covariance and

191 chambers). Meso-scale experiments could also be employed in emission hot-spots to test

192 mitigation strategies and could help with the verification of process-based models.

193 Improvements to bottom-up estimates will be used to revise the GHG emission inventories.

194

195

196 **Box 1:** Explanation of a) bottom-up and b) top-down methods for estimating GHG emissions

197 a) Bottom-up methods

198 In its simplest form bottom-up emission inventories are the mandatory annual GHG
199 emissions reporting for all signatory countries of the UNFCCC declaration to reduce national
200 GHG emissions. The main GHGs (CO₂, CH₄, N₂O and CFCs) from all anthropogenic sectors:
201 energy, industry, solvent and other product use, agriculture, land use, land-use change and
202 forestry, and waste, need to be reported. To standardize this process, the expert panel of the
203 Intergovernmental Panel for Climate Change (IPCC) has developed guidelines on how to
204 calculate emissions using a three-tier approach ([http://www.ipcc-](http://www.ipcc-nggip.iges.or.jp/public/2006gl/)
205 [nggip.iges.or.jp/public/2006gl/](http://www.ipcc-nggip.iges.or.jp/public/2006gl/)). These guidelines reflect the current state-of-the-art for
206 estimating anthropogenic emissions. The most commonly used Tier 1 approach employs
207 universally applicable emission factors (EFs), Tier 2 employs country specific EF's, or
208 simple regression equations, and Tier 3 employs process-based models. Tier 2 and 3
209 calculations can take into account variability of climate and mitigation activities, but require
210 much more data than the Tier 1 approach. Tier 2 or Tier 3 methodologies do not necessarily
211 reduce the uncertainty of the emission estimates^{11,12}, but can provide more effective
212 monitoring of mitigation measures and, therefore, should be used for emission hotspots.

213 Bottom-up methodologies provide estimates for certain sources that are scaled-up assuming
214 representativeness of the EFs applied to activity data (e.g. nitrogen fertiliser rate, livestock
215 type, megawatts produced from coal power plants). For national emission inventories, the
216 more the activities that are disaggregated into e.g. geographic entities or production systems,
217 the more confidence is assumed in the estimated fluxes. However, this requires that for each
218 disaggregate activity data have to be collected, and appropriate EFs determined. At country
219 level, and for emission sources that are characterized by a high level of spatial and temporal

220 variability, high accuracy can only be achieved on the basis of a high number of observations
221 at prohibitive costs.

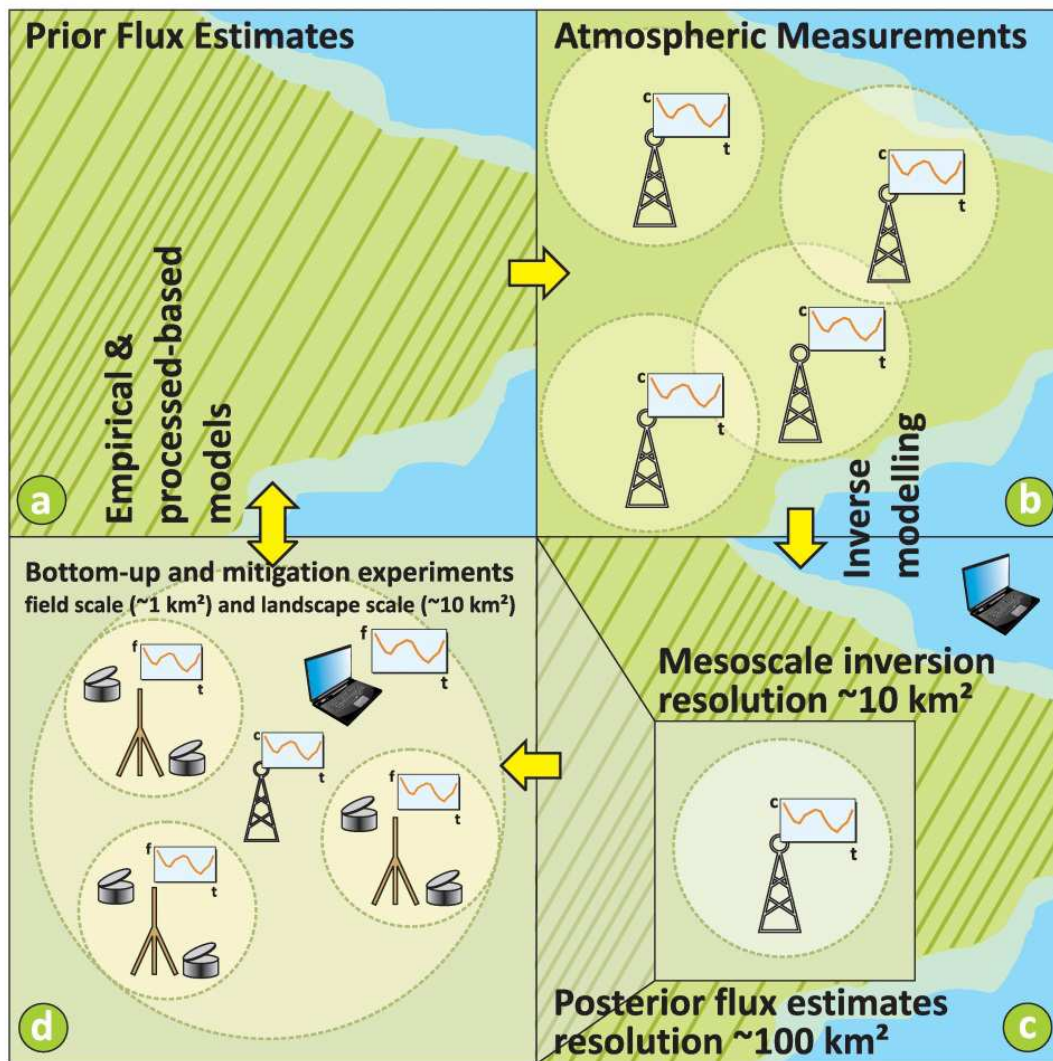
222 b) Top-down methods







223 Gases emitted into the atmosphere are dispersed through atmospheric turbulence and
224 transported by winds while large-scale circulation patterns mix gases at the global scale.
225 Atmospheric transport is modelled by numerical “atmospheric transport models” driven by
226 meteorological data. Atmospheric transport models can be used to simulate changes in
227 atmospheric concentrations given the surface fluxes and taking into account deposition and
228 atmospheric chemistry. Some atmospheric transport models can also be run in a backwards in
229 time mode, reversing the direction of transport and other processes, to determine the
230 sensitivity of change in concentration to surface fluxes resolved in space and time. In this
231 way, atmospheric concentrations can be related to surface fluxes and forms the basis of
232 inverse modelling. Using time series of atmospheric concentrations from many locations, and
233 prior information about the expected fluxes to further constrain the problem, inverse
234 modelling can be used to provide optimized estimates of the fluxes. The inverse modelling
235 approach can be used at different scales to provide estimates of emissions at landscape,
236 national or continental scale, depending on the number and distribution of atmospheric
237 observations. Increased computer capacity, advances in numerical algorithms, improved
238 transport models and a greater number of atmospheric observations have all contributed to a
239 recent leap forward in this method. The accuracy of the spatial distribution of the emissions
240 from inversions is strongly dependent on the observation frequency and density of the
241 network. How well the observations constrain the emissions is reflected in the posterior
242 uncertainty (i.e, the emission uncertainty after assimilating atmospheric observations). Future
243 improvements will arise through using atmospheric observations of multiple tracers (e.g.
244 isotopes and gases which are co-emitted in different processes), combining different

245 observation streams (e.g. ground-based and satellite) and by using ensembles of transport
246 models to better quantify uncertainties.

247

ACCEPTED MANUSCRIPT

**Key:**

-  Flux chamber
-  Eddy covariance tower/site
-  Atmospheric measurement site
-  Flux
-  Timeseries of observation: c = concentration; f = flux
-  Flux sensitivity area