Available online at www.sciencedirect.com

ScienceDirect

Current Opinion in Environmental Sustainability

From research to policy: optimizing the design of a national monitoring system to mitigate soil nitrous oxide emissions

Stephen M Ogle[1,2], Klaus Butterbach-Bahl[3], Laura Cardenas[4], Ute Skiba[5] and Clemens Scheer[3]

Nitrous oxide (N_2O) emissions from agricultural soils are a key source of greenhouse gas emissions in most countries. In order for governments to effectively reduce N_2O emissions, a national inventory system is needed for monitoring, reporting and verifying emissions that provides unbiased estimates with the highest precision feasible. Inventory frameworks could be advanced by incorporating experimental research networks targeting key gaps in process understanding and drivers of emissions, with a multi-stage survey to collect data on agricultural management and N_2O fluxes that allow for development, parameterization and application of models to estimate national-scale emissions. Verification can be accomplished with independent estimation of fluxes from atmospheric N_2O concentration data. A robust monitoring system would provide accurate emission estimates, and allow policymakers to develop programs to more sustainably manage reactive N and target mitigation measures for reducing N_2O emissions from agricultural soils.

Addresses
[1] Natural Resource Ecology Laboratory, Colorado State University, Fort Collins, CO 80523, USA
[2] Department of Ecosystem Science and Sustainability, Colorado State University, Fort Collins, CO 80523, USA
[3] Institute for Meteorology and Climate Research (IMK-IFU), Karlsruhe Institute of Technology, Garmisch-Partenkirchen, Germany
[4] Rothamsted Research, Sustainable Agricultural Sciences, North Wyke, Okehampton, EX20 1UW, UK
[5] UK Centre for Ecology and Hydrology, Bush Estate, Penicuik, Midlothian, UK

Corresponding author: Ogle, Stephen M (Stephen.Ogle@colostate.edu)

Current Opinion in Environmental Sustainability 2020, **47**:28–36

This review comes from a themed issue on **Climate change, reactive nitrogen, food security and sustainable agriculture**

Edited by **Klaus Butterbach-Bahl**, **Clemens Scheer**, and **David E Pelster**

Received: 13 April 2020; Accepted: 29 June 2020

https://doi.org/10.1016/j.cosust.2020.06.003

Introduction

Climate shapes the world around us and has a profound impact on society. The anthropogenic influence of greenhouse gas (GHG) emissions on climate is growing with various lines of scientific evidence demonstrating regional impacts such as increased frequency of heat waves, droughts, and heavy precipitation events [1]. In turn, there has been sea level rise, greater risk of catastrophic fires, increased flooding episodes, impacts on food supplies, changes in species migrations and ranges, and increased health risk, among a variety of other impacts that vary regionally [1]. With growing recognition of impacts, there is the possibility of limiting warming by 2°C or possibly 1.5°C through the Paris Agreement [12].

Nitrous oxide (N_2O) is one of three main GHGs emitted through anthropogenic activity, and more than half of global N_2O emissions are from agricultural soil management associated with reactive forms of N [2]. These practices include applications of synthetic mineral N and livestock manure N; crop residue N inputs to soils; enhanced mineralization of N from soil organic matter due to continuous cultivation of land or change in land use to cropland from grassland, forest or wetlands; as well as increased cultivation of N-fixing legume species. There are opportunities to more sustainably manage reactive N in agricultural lands and reduce soil N_2O emissions by optimizing nitrogen-use efficiency (NUE) of crops with a greater proportion of available mineral N incorporated into crop growth [3,4]. In fact, overapplication of N, which decreases NUE, has been shown to exponentially increase N_2O emissions [5], although not all studies have found an exponential increase in emissions with higher application rates [6]. Moreover, the relationship between NUE and soil N_2O emissions may vary due to the complexity of processes driving emissions [4]. For example, improving NUE may not always equate with less N_2O emissions because a larger proportion of crop N uptake may be achieved by a reduction in other N losses, such as ammonia (NH_3) volatilization and emissions of other nitrogen gases (NO_x, N_2), as well as leaching of nitrate and dissolved organic matter. Similarly, the system's response to a combination of N sources, that is, (mineral and organic fertilizer N, and crop residue N), is also complex and not necessarily linear [7,8]. Nonetheless there are opportunities to reduce emissions by improved N management that targets N application rates, timing, placement and type of fertilizers [3,4,9].

With knowledge about ways to reduce N_2O emissions from agricultural soils, there are opportunities to incorporate agricultural soil management into national mitigation plans [10]. However, robust monitoring, reporting and verification programs are needed to support climate change policy. In general, GHG inventories provide the basis for monitoring national emissions, and assessing progress in reducing emissions with mitigation programs. The Intergovernmental Panel on Climate Change (IPCC) has developed inventory guidelines for monitoring national emissions [11,12,13•]. Improving inventories is largely predicated on developing country-specific emission factors (categorized as Tier 2 methods by the IPCC) or model-based approaches for deriving dynamic emission factors both spatially and temporally (categorized as Tier 3 methods by IPCC), as well as improving activity data collection [14,15]. Approximately half of Annex I countries (Table 1) and less than 10% of non-Annex I countries [15] are using country-specific emission factors (Tier 2) and/or model-based approaches (Tier 3) for reporting soil N_2O emissions to the UN Framework Convention on Climate Change. Three Annex I countries have developed Tier 3 methods that are used in combination with Tier 1 and/or 2 methods to estimate soil N_2O emissions, including Iceland [16], Switzerland [17], and USA [18].

Our objective is to describe an inventory framework for monitoring soil N_2O emissions at the national scale that meets the overarching goal of the IPCC guidance, that is, to produce accurate estimates that are as precise as feasible [19], and thus provide a basis for governments to develop and implement policy to more sustainably manage reactive N and reduce N_2O emissions (Figure 1). The components of the framework include a) an experimental research network; b) multi-stage survey of land use, management practices, and emissions measurements; c) model selection and parameterization using N_2O measurements from the survey; d) model implementation to estimate emissions and uncertainties using land use and management data from the survey and scaling to the national level; and e) verification of emissions using atmospheric N_2O concentration data or other independent measurements of N_2O emissions. This framework is primarily focused on direct N_2O emissions from agricultural soils although adding reactive N to agricultural lands creates a cascade effect where N_2O is also emitted indirectly as reactive N is transferred to other locations in the environment [20]

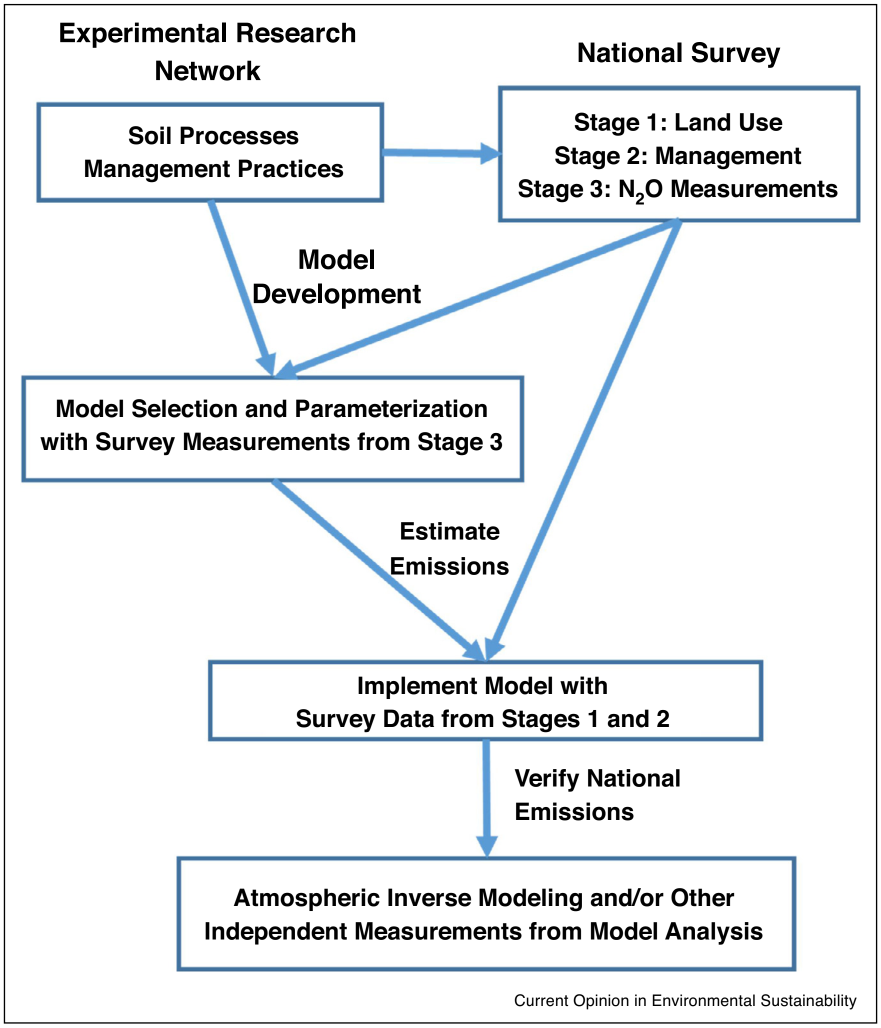
Table 1

Soil N_2O inventory methods that are used by Annex I Parties for reporting to the UN Framework Convention on Climate Change (Convention Reporting)

Country	Tier 1	Tier 2	Tier 3
Australia	X	X	
Austria	X		
Belarus	X		
Belgium	X		
Bulgaria	X	X	
Canada	X	X	
Croatia	X		
Cyprus	X		
Czechia	X	X	
Denmark	X	X	
Estonia	X		
Finland	X	X	
France	X	X	
Germany	X	X	
Greece	X		
Hungary	X		
Iceland	X		X
Ireland	X		
Italy	X		
Japan		X	
Kazakhstan	X	X	
Latvia	X		
Liechtenstein	X		
Lithuania	X		
Luxembourg	X		
Malta	X	X	
Monaco			
Netherlands	X	X	
New Zealand	X	X	
Norway	X		
Poland	X		
Portugal	X	X	
Romania	X		
Russian Federation	X	X	
Slovakia	X		
Slovenia	X		
Spain	X	X	
Sweden	X	X	
Switzerland	X		X
Turkey	X		
Ukraine	X	X	
United Kingdom of Great Britain and Northern Ireland	X	X	
United States of America	X		X

The Tier 1 method applies equations and default emission factors provided by the Ref. [11], the Tier 2 method utilizes the equations provided by the Ref. [11] with country-specific emission factors, and the Tier 3 method is based on country specific equations and emissions factors. Data extracted from Common Reporting Format Tables for the 2019 National GHG Emissions Inventory Submissions to the UN Framework Convention on Climate Change (https://unfccc.int/process-and-meetings/transparency-and-reporting/reporting-and-review-under-the-convention/greenhouse-gas-inventories-annex-i-parties/national-inventory-submissions-2019)

Figure 1



National inventory framework for monitoring N_2O emissions from agricultural soil management.

Inventory framework for monitoring N_2O emissions from soils

Experimental research network

Experiments provide the basis for understanding the N cycle and microbial transformations that lead to soil N_2O emissions, and inform the design of monitoring networks and model development. Experiments are also useful for evaluating feedbacks on N_2O emissions associated with climate change that may require refinements to mitigation strategies and updates to inventory frameworks in the future. Field and laboratory experiments address questions about factors driving emissions [21]. For example, experiments can evaluate effects of microbial community composition and activity on N_2O production and consumption, as well as trade-offs leading to different levels of gaseous N emissions (NH_3, NO_X, N_2O, N_2) related to management and soil conditions. In the field, automated static chamber systems or eddy-covariance techniques capture inherent temporal and spatial variability with 'high-frequency' measurements that have significantly improved flux estimates [22,23]. To characterize and quantify production and consumption processes of N_2O, various tools have been developed, including flow-through methods to directly measure N_2O emissions [24], use of inhibitors (e.g. acetylene), and different stable isotope techniques [25,26•,27,28]. Portable highly sensitive laser spectroscopy and chamber technologies [29] have been used to explore spatial variability in N_2O fluxes from sites to landscape scales [30]. Furthermore, field and laboratory methods have been combined to better understand processes and drivers of N_2O emissions [31,32]. Generalizations can be made by analyzing experimental data from multiple studies via meta-analysis [33•,82].

Experiments have demonstrated that soil N_2O emissions are primarily generated by microbial processes of nitrification and denitrification, although various other microbial and physico-chemical processes may be involved [34]. Soil O_2 concentrations are critical in determining the prevailing process, with nitrification requiring aerobic conditions, while denitrification occurs in anaerobic conditions. Oxygen does not diffuse well in water, approximately four magnitudes slower than in air, and therefore soil O_2 concentrations are controlled by variables influencing water content, including soil relative water content, soil texture and pore size. Together these variables are expressed as water-filled pore space (WFPS) [35], or similar measurements such as volumetric water content and air-filled porosity, and it is assumed that nitrification leads to more N_2O production at lower WFPS, while denitrification leads to more N_2O at higher WFPS. However, recent research has shown that there is considerable complexity underlying the relationship between these processes and WFPS, particularly finer scale microbial dynamics and gas diffusion through the soil matrix, which is leading to a more in-depth understanding of emission patterns [34].

Nitrous oxide emissions from soils exhibit pulses over time and space, referred to as hot moments and hot spots of emissions, respectively [36]. Emission pulses can occur following fertilization in agricultural fields [37], and with changing soil conditions associated with drying-wetting and freeze-thaw cycles [38,39••]. The periodicity in emissions requires sufficient sampling frequencies to ensure pulses are not missed, with more continuous measurements using automated chambers or tower-based eddy covariance measurements [40,41].

Experimental research networks provide a basis for understanding how management influences N_2O emissions [42], and generate new technologies and management options for reducing emissions. Research networks span across national boundaries and through international collaboration among scientists (i.e. https://globalresearchalliance.org/GRA; https://initrogen.org/), providing greater efficiency in making new discoveries about N_2O emissions, and should be encouraged through international organizations (e.g. IPCC, UN-FAO, UNEP, and OECD).

National survey

Based on experimental research, it is known that crop management affects the timing and magnitude of soil N_2O emissions (e.g. Refs. [9,42,43]). Therefore, collection of management activity data is a key component of a national monitoring system and can be accomplished with remote sensing data, questionnaires and expert knowledge [14]. Surveys can use remote sensing data in combination with questionnaires for management information, and can include measurements of N_2O emissions at survey locations. Surveys are cost-effective because data collection is focused on a subsample of locations that are randomly selected from the entire population of the agricultural land base, rather than 'wall-to-wall' data collection from the entire domain using a census approach. Data could be collected using a hierarchical framework with several stages in the survey to increase sampling efficiency and reduce costs.

First, data are needed on the managed land base and underlying area of land use and land use change [11]. Land use data should be collected at all survey locations as the first stage in the sample. Remote-sensing data are the most cost-effective approach for collecting these data, and the information would serve the broader GHG inventory for land use activities [11,12]. Data collection must also address uncertainty in the area estimation based on the underlying survey design [44].

Second, data need to be collected on management activities such as fertilizer management, livestock and manure management, tillage practices, crop selection (including legumes), cover crops, residue management, and other related activities. These data could be collected from a subsample of the survey locations in a second stage of sampling, and may include use of remote sensing technologies to reduce costs at least for some practices such as tillage management [45]. Other data may be collected through questionnaires to capture management information that cannot be collected with remote sensing technologies, such as the type, rate, timing and placement of fertilizer. For efficiency, the data collected through questionnaires may be a subset of the locations in the second stage of sampling (effectively another stage in the sample design). Data collection could also involve crowd-sourcing methods to reduce costs associated with personnel time to deliver a survey. It is likely that some training is needed when collecting data through crowdsourcing to ensure the responses are accurate, reflecting the information and classifications that are used in the inventory [46].

It may not be possible to collect all management data from the survey, and so supplemental data from a regional/national census or other surveys may be used in the inventory (e.g. UK countryside survey, https://countrysidesurvey.org.uk). However, it is important to recognize that this will introduce additional uncertainty. Ogle *et al.* [47] conducted an inventory by modeling emissions based on land use and management histories for survey locations that are tracked by the US Department of Agriculture (USDA) [48]. The USDA survey did not include all management practices needed for the inventory, but additional information was compiled in other datasets. To address uncertainty, Ogle *et al.* [47] used a Monte Carlo simulation approach to estimate emissions multiple times representing variation in the likely practices at each USDA survey location based on the supplemental datasets. Even though it is possible to combine data from different sources, collecting the majority of management data at the survey locations will minimize uncertainty. Other data may be needed to model N_2O emissions, such as meteorological data and soil characteristics [14], which may be part of the survey, but could be based on other data sources introducing some additional uncertainty into the inventory.

Third, an optimal survey supporting the monitoring system would include measurements of N_2O emissions to select and parameterize the best model for the inventory. Data collection could also include other components of the N cycle, such as volatilization of other N gases, losses of N through leaching and overall water flows, plant N uptake and microbial immobilization, as well as N inputs from fertilization, N fixation and deposition. While experimental research will inform model development about key processes and management activities, emission measurements are often a limiting factor in developing and parameterizing models, leading to a large source of overall uncertainty in model predictions (e.g. Ref. [49]). Therefore, measurement data could be collected in a third stage of sampling, that is, a subsample of the second stage, with accepted protocols, for example, Global Research Alliance [81] or the ICOS network protocols [51]. Given that annual N_2O emissions are often dominated by a single or a few emission events, for example, due to soil freeze-thaw, soil-rewetting and fertilization events, reliable emission estimates require continuous daily or even subdaily measurements [41]. Recent advances in micro-meteorological measurements of N_2O fluxes, such as eddy covariance or gradient methods, can capture short-term emission pulses and long-term emission trends at high temporal resolution and integrate fluxes at the field and landscape scales [52]. Automated and static chamber measurements are also an option for capturing emissions at specific sample locations in a survey design (e.g. Ref. [53]). Regardless of the measurement technology, these data will only capture the total net fluxes of N_2O and cannot provide direct inferences on the impact of individual sources of N inputs on N_2O emissions. This requires an experimental design with control and treatments in which the N input from a specific source is modified to understand the impact of a practice. However, the N_2O emission data are informative for parameterizing models that are predicting total net N_2O fluxes.

Model selection and parameterization

Estimation of national emissions could be inferred directly from the measurements in the survey if there is sufficient spatio-temporal sampling resolution to represent the country's geoclimatic variability, and if resulting estimates meet expected levels of precision under government policy programs. However, this level of sampling may be prohibitively expensive in which case a model can be used to scale the information in the measurement data from the third stage to the entire survey sample for estimation of national emissions. Models that are used to predict soil N_2O emissions for inventory assessments are either empirically based statistical models or process-based models. These models are typically designed to quantify the impact of management practices on N_2O emissions, such as application of nitrification inhibitors (e.g. Refs. [54,55]), which is critical for advancing mitigation strategies and verifying outcomes in policy frameworks.

Empirical models are derived from measurement data using statistical methods and can be as simple as a single emission factor derived from the survey measurement data, or can be more complicated functions such as regression models [56–59]. Empirical models are useful in estimating emissions at regional and national scales, and in some cases are more accurate than more complex process-based models [60]. However, well-tested process-based models are likely to capture more drivers of emissions leading to greater accuracy [61•]. In addition, process-based models can be applied to predict emissions for mitigation and future climate scenarios, while empirical models may not be adequate for this purpose if future conditions are different from conditions that were used to derive the empirical functions. Several process-based models have been developed and are currently used to estimate soil N_2O emissions at regional and larger scales, such as DayCent [62], DNDC [63], LandscapeDNDC [64], Dynamic Land Ecosystem Model [65], and SPACSYS [66]. Recent inter-comparisons of process-based models have been conducted to assess predictability of N_2O emissions [67••,68•].

A subset of measurement data from the survey can be used to derive an empirical model with statistical methods, or to parameterize a process-based model using optimization [69] or Bayesian methods [70•,71–73]. Models can be evaluated with independent measurement data from the survey that are not used in model development and parameterization. Final model selection can be made using objective evaluation criteria including conventional statistics, such as root mean square error and bias statistics, or Bayesian model selection [74].

Estimate emissions and uncertainty

The selected model is applied to estimate emissions with the activity data on land use and management practices from the survey, possibly with supplemental datasets. For example, a process-based model simulates the histories over the inventory time period given the crop types, fertilization management, residue management, tillage practices, and other relevant management information. The uncertainty in estimates can be derived by applying the model several times with multiple iterations in a Monte Carlo analysis [19,47,49,75]. In each iteration, model parameters are randomly selected given parameter distributions, possibly from a Bayesian analysis, and a random selection of survey weights that can be estimated based on the survey design. If an empirical model approach is used for the inventory, then uncertainty can be propagated using a Monte Carlo analysis based on probability distribution functions for the emission factors or parameters in the empirically derived functions [19].

Verifying national emissions

National emissions could be verified with N_2O emission measurements from a subsample of sites in the monitoring survey. However, this would only be valid if the subsample of measurement sites were not used in the development or parameterization of the model that was used to estimate national emissions. Alternatively, national GHG emission inventories could be verified using atmospheric N_2O concentrations and associated isotopic signatures from tall towers, aircraft campaigns and possibly remote sensing in the future [76,77]. Globally, atmospheric concentration samples are available through the National Oceanic and Atmospheric Administration Carbon Cycle Cooperative Global Air Sampling Network and the Commonwealth Scientific and Industrial Research Organization Network) [78••], and at regional scales from large tower measurements (i.e. TV towers) [79•]. Combining these data with atmospheric inversion approaches enables comparisons of 'top down' atmospheric measurements with 'bottom-up' GHG emissions inventories [80••]. Such an analysis has shown good agreement between the two methods for UK N_2O emissions [79•]. At the global scale, inverse modelling results identified increasing trends of N_2O emission from 2000 to 2015 for countries such as China and Brazil, whereas emissions from Europe and the USA remained stable [78••]. Although inverse modelling methods are still under development, the results can already provide useful information for verifying N_2O emission inventories, leading to improved confidence that reported emissions are accurate, provided that estimated emissions are consistent between the two approaches. Furthermore, inconsistencies in emission estimates can lead to identification of errors and improvements in the inventory.

Conclusions

Implementation of policy to reduce N_2O emissions needs a robust inventory monitoring framework that is developed and adapted over time with the latest scientific findings from an experimental research network. A survey approach with application of a model is an optimal, cost-effective design for collecting data through remote sensing, questionnaires, crowd-sourcing, as well as N_2O measurements and related data to constrain N budgets. With the reliable, useful and credible soil N_2O emission data, the monitoring system could inform development of mitigation programs for reducing soil N_2O emissions, and be used to monitor emissions ensuring mitigation targets are met. This would give national governments the confidence to include more sustainable management of reactive N as part of their national GHG mitigation plans under the Paris agreement [10]. In turn, this would lead to a larger portfolio of mitigation strategies that is likely needed to achieve the goal of limiting warming to 2°C or less.

Conflict of interest statement

Nothing declared.

Acknowledgements

This paper was developed from discussions at a workshop, 'Climate Change, Reactive Nitrogen, Food Security and Sustainable Agriculture', held at the Karlsruhe Institute of Technology in Garmisch-Partenkirchen, Germany on 15-16 April 2019. The workshop was sponsored by the OECD Co-operative Research Programme: Biological Resource Management for Sustainable Agricultural Systems, which made it possible for the authors to participate in the workshop. The work was supported by the US Environmental Protection Agency and USDA Forest Service (Agreement Number 18-CR-11242305-109); and the German Federal Ministry of Education and Research (BMBF) under the 'Make our Planet Great Again – German Research Initiative', implemented by the German Academic Exchange Service (DAAD) (Grant number 306060); and funding from the Biotechnology and Biological Sciences Research Council (BBSRC) for Rothamsted Research (BBS/E/C/00010320).

References and recommended reading

Papers of particular interest, published within the period of review, have been highlighted as:

- • of special interest
- •• of outstanding interest

1. IPCC: In *Climate Change 2014: Synthesis Report. Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change.* Edited by Pachauri RK, Meyer LA. Geneva, Switzerland: Intergovernmental Panel on Climate Change; 2014.

2. Paustian K, Lehmann J, Ogle S, Reay D, Robertson GP, Smith P: **Climate-smart soils**. *Nature* 2016, **532**:49-57.

3. Reay DS, Davidson EA, Smith KA, Smith P, Melillo JM, Dentener F, Crutzen PJ: **Global agriculture and nitrous oxide emissions**. *Nat Clim Change* 2012, **2**:410-416.

4. Venterea RT, Halvorson AD, Kitchen N, Liebig MA, Cavigelli MA, Grosso SJD, Motavalli PP, Nelson KA, Spokas KA, Singh BP *et al.*: **Challenges and opportunities for mitigating nitrous oxide emissions from fertilized cropping systems**. *Front Ecol Environ* 2012, **10**:562-570.

5. Shcherbak I, Millar N, Robertson GP: **Global metaanalysis of the nonlinear response of soil nitrous oxide (N_2O) emissions to fertilizer nitrogen**. *Proc Natl Acad Sci U S A* 2014, **111**:9199-9204.

6. Hergoualc'h K, Akiyama H, Bernoux M, Chirinda N, del Prado A, Kasimir A, MacDonald JD, Ogle SM, Regina K, van der Weerden TJ *et al.*: **N_2O emissions from managed soils, and CO_2 emissions from lime and urea application**. In *2019 Refinement to the 2006 IPCC Guidelines for National Greenhouse Gas Inventories.* Edited by Calvo Buendia E, Tanabe K, Kranjc A, Baasansuren J, Fukuda M, Ngarize S, Osako A, Pyrozhenko Y, Shermanau P, Federici S. Switzerland: Intergovernmental Panel on Climate Change; 2019.

7. Cardenas LM, Thorman R, Ashlee N, Butler M, Chadwick D, Chambers B, Cuttle S, Donovan N, Kingston H, Lane S, Dhanoa MS *et al.*: **Quantifying annual N_2O emission fluxes from grazed grassland under a range of inorganic fertiliser nitrogen inputs**. *Agric Ecosyst Environ* 2010, **136**:218-226.

8. Xu C, Han X, Ru S, Cardenas L, Rees R, Wu D, Wu W, Meng F: **Crop straw incorporation interacts with N fertilizer on N_2O emissions in an intensively cropped farmland**. *Geoderma* 2019, **341**:129-137.

9. Xia L, Lam SK, Wolf B, Kiese R, Chen D, Butterbach-Bahl K: **Trade-offs between soil carbon sequestration and reactive nitrogen losses under straw return in global agroecosystems**. *Global Change Biol* 2019, **24**:5919-5932.

10. Kanter DR, Ogle SM, Winiwarter W: **Building on Paris: integrating nitrous oxide mitigation into future climate policy**. *Curr Opin Environ Sustain* 2020, **47**:1-6.

11. IPCC: In *2006 IPCC Guidelines for National Greenhouse Gas Inventories. Prepared by the National Greenhouse Gas Inventories Programme.* Edited by Eggleston HS, Buendia L, Miwa K, Ngara T, Tanabe K. Japan: Intergovernmental Panel on Climate Change, IGES; 2006.

12. IPCC *et al.*: In *Global Warming of 1.5°C. An IPCC Special Report on the Impacts of Global Warming of 1.5°C above Pre-industrial Levels and Related Global Greenhouse Gas Emission Pathways, in the Context of Strengthening the Global Response to the Threat of Climate Change, Sustainable Development, and Efforts to Eradicate Poverty.* Edited by Masson-Delmotte V, Zhai P, Pörtner H-O, Roberts D, Skea J, Shukla PR, Pirani A, Moufouma-Okia W, Péan C, Pidcock R. Intergovernmental Panel on Climate Change; 2019.

13. • IPCC: In *2019 Refinement to the 2006 IPCC Guidelines for National Greenhouse Gas Inventories. Prepared by the National Greenhouse Gas Inventories Programme*, , vol 2019. Edited by Calvo Buendia E, Tanabe K, Kranjc A, Baasansuren J, Fukuda M, Ngarize S, Osako A, Pyrozhenko Y, Shermanau P, Federici S. Switzerland: Intergovernmental Panel on Climate Change; 2019.
This report provides updated guidelines that will be used by national governments for reporting greenhouse gas emissions to the UN Framework Convention Climate Change. The guidance provides the basis for developing a national monitoring system for soil N_2O emissions that national governments follow for reporting emissions.

14. Ogle SM, Buendia L, Butterbach-Bahl K, Breidt FJ, Hartman M, Yagi K, Nayamuth R, Spencer S, Wirth T, Smith P: **Advancing national greenhouse gas inventories for agriculture in developing countries: improving activity data, emission factors and software technology**. *Environ Res Lett* 2013, **8**:015030.

15. Ogle SM, Olander L, Wollenberg L, Rosenstock T, Tubiello F, Paustian K, Buendia L, Nihart A, Smith P: **Reducing greenhouse gas emissions and adapting agricultural management for climate change in developing countries: providing the basis for action**. *Global Change Biol* 2014, **20**:1-6.

16. Keller N, Stefani M, Einarsdóttir SR, Helgadóttir ÁK, Guomundsson J, Snorrason A, Þórsson A, Tinganelli L: *National Inventory Report: Emissions of Greenhouse Gases in Iceland from 1990 to 2017*. The Environment Agency of Iceland, Submitted under the United Nations Framework Convention on Climate Change and the Kyoto Protocol; 2019.

17. FOEN: *Switzerland's Greenhouse Gas Inventory: 1990-2017*. Federal Office for the Environment, Swiss Confederation, Submitted under the United Nations Framework Convention on Climate Change and the Kyoto Protocol; 2019.

18. US-EPA: *Inventory of Greenhouse Gas Emissions and Sinks: 1990-2017*. United States Environmental Protection Agency, EPA 430-R-19-001; 2019.

19. Paciornik N, Gillenwater M, De Lauretis R, Romana D, Monni S, Ogle SM, Kareinen T, Alsaker C: **Uncertainties**. In *Refinement to the 2006 IPCC Guidelines for National Greenhouse Gas Inventories*, , vol 2019. Edited by Calvo Buendia E, Tanabe K, Kranjc A, Baasansuren J, Fukuda M, Ngarize S, Osako A, Pyrozhenko Y, Shermanau P, Federici S. Intergovernmental Panel on Climate Change, Switzerland; 2019.

20. Galloway JN, Aber JD, Erisman JW, Seitzinger SP, Howarth RW, Cowling EB, Cosby BJ: **The nitrogen cascade**. *BioScience* 2003, **53**:341-356.

21. Garcia-Marco S, Ravella SR, Chadwick D, Vallejo A, Gregory AS, Cardenas LM: **Ranking factors affecting emissions of GHG from incubated agricultural soils**. *Eur J Soil Sci* 2014, **65**:573-583.

22. Scheer C, Rowlings D, Firrell M, Deuter P, Morris S, Riches D, Porter I, Grace P: **Nitrification inhibitors can increase post-harvest nitrous oxide emissions in an intensive vegetable production system**. *Sci Rep* 2017, **7**:43677.

23. Fuchs K, Hörtnagl L, Buchmann N, Eugster W, Snow V, Merbold L: **Management matters: testing a mitigation strategy for nitrous oxide emissions using legumes on intensively managed grassland**. *Biogeosciences* 2018, **15**:5519-5543.

24. Cárdenas LM, Hawkins JMB, Chadwick D, Scholefield D: **Biogenic gas emissions from soils measured using a new automated laboratory incubation system**. *Soil Biol Biochem* 2003, **35**:867-870.

25. Castellano-Hinojosa A, Loick N, Dixon E, Matthews GP, Lewicka-Szczebak D, Well R, Bol R, Charteris A, Cardenas L: **Improved isotopic model based on ^{15}N tracing and Rayleigh-type isotope fractionation for simulating differential sources of N_2O emissions in a clay grassland soil**. *RCMS* 2019, **33**:449-460 http://dx.doi.org/10.1002/rcm.8374.

26. • Wu D, Well R, Cárdenas LM, Fuß R, Lewicka-Szczebak D, Köster J, Brüggemann N, Bol R: **Quantifying N_2O reduction to N_2 during denitrification in soils via isotopic mapping approach: model evaluation and uncertainty analysis**. *Environ Res* 2019, **179**:108806.
This publication presents a method to better quantify the reduction of N_2O to N_2 gas in soils based on a 'mapping approach' with isotopic ratios of ^{15}N to ^{18}O. This is an example of ongoing research to improve models with the latest experimental research.

27. Denk TR, Mohn J, Decock C, Lewicka-Szczebak D, Harris E, Butterbach-Bahl K, Kiese R, Wolf B: **The nitrogen cycle: a review of isotope effects and isotope modelling approaches**. *Soil Biol Biochem* 2017, **105**:121-137.

28. Denk TRA, Kraus D, Kiese R, Butterbach-Bahl K, Wolf B: **Constraining N cycling in the ecosystem model LandscapeDNDC with the stable isotope model SIMONE**. *Ecology* 2019 http://dx.doi.org/10.1002/ecy.2675. ECY2675.

29. Cowan N, Norman P, Famulari D, Levy P, Reay D, Skiba U: **Spatial variability and hotspots of soil N_2O fluxes from intensively grazed grassland**. *Biogeosciences* 2015, **12**:1585-1596.

30. Hensen A, Groot TT, Van Den Bulk WCM, Vermeulen AT, Olesen JE, Schelde K: **Dairy farm CH_4 and N_2O emissions, from one square metre to the full farm scale**. *Agric Ecosyst Environ* 2006, **112**:146-152.

31. Kravchenko AN, Toosi ER, Guber AK, Ostrom NE, Yu J, Azeem K, Rivers ML, Robertson GR: **Hotspots of soil N_2O emission enhanced through water absorption by plant residue**. *Nat Geosci* 2017, **10**:496-500.

32. Balaine N, Clough TJ, Beare MH, Thomas SM, Meenken ED: **Soil gas diffusivity controls N_2O and N_2 emissions and their ratio**. *Soil Sci Soc Am J* 2016, **80**:529-540.

33. • López-Aizpún M, Horrocks CA, Charteris AF, Marsden KA, Ciganda VS, Evans JR, Chadwick DR, Cárdenas LM: **Meta-analysis of global livestock urine-derived nitrous oxide emissions from agricultural soils**. *Global Change Biol* 2020, **26**:2002-2013.
This review summarizes current knowledge on N_2O emissions from urine patches. It also highlights the need for better metadata and uncertainty reporting in the published studies, in addition to the limited geographical extent of investigations in general, which are mostly in temperate regions. This study implies that systematic measurements throughout a domain of interest is critical for estimating soil N_2O emissions.

34. Butterbach-Bahl K, Baggs EM, Dannenmann M, Kiese R, Zechmeister-Boltenstern S: **Nitrous oxide emissions from soils: how well do we understand the processes and their controls?** *Philos Trans R Soc B* 2013, **368** 20130122.

35. Smith KA, Ball T, Conen F, Dobbie KE, Massheder J, Rey A: **Exchange of greenhouse gases between soil and atmosphere: interactions of soil physical factors and biological processes**. *Eur J Soil Sci* 2018, **69**:10-20.

36. Kuzyakov Y, Blagodatskaya E: **Microbial hotspots and hot moments in soil: concept & review**. *Soil Biol Biochem* 2015, **83**:184-199.

37. Hernandez-Ramirez G, Brouder SM, Smith DR, Van Scoyoc GE: **Greenhouse gas fluxes in an Eastern Corn Belt soil: weather, nitrogen source, and rotation**. *J Environ Qual* 2009, **38**:841-854.

38. Wagner-Riddle C, Congreves KA, Abalos D, Berg AA, Brown SE, Ambadan JT, Gao X, Tenuta M: **Globally important nitrous oxide emissions from croplands induced by freeze-thaw cycles**. *Nat Geosci* 2017, **10**:279-283.

39. •• Congreves KA, Wagner-Riddle C, Si BC, Clough TJ: **Nitrous oxide emissions and biogeochemical responses to soil freezing-thawing and drying-wetting**. *Soil Biol Biochem* 2018, **117**:5-15.
This publication presents key mechanisms driving pulses of emissions during the freeze-thaw and dry-wet cycles that are critical to predicting annual emissions of soil N_2O. The authors highlight key differences in the drivers of emissions between the freeze-thaw and dry-wet cycles and discuss key uncertainties that need further research. Understanding the drivers of these cycles is critical for modeling N_2O emissions as part of a monitoring system.

40. Chadwick D, Cardenas L, Misselbrook TH, Smith KA, Rees RM, Watson CJ, McGeough KL, Williams JR, Cloy JM, Thorman RE, Dhanoa MS: **Optimizing chamber methods for measuring nitrous oxide emissions from plot-based agricultural experiments**. *Eur J Soil Sci* 2014, **65**:295-307 http://dx.doi.org/10.1111/ejss.12117.

41. Barton L, Wolf B, Rowlings D, Scheer C, Kiese R, Grace P, Stefanova K, Butterbach-Bahl K: **Sampling frequency affects estimates of annual nitrous oxide fluxes**. *Sci Rep* 2015, **5**:16912.

42. Zhou M, Zhu B, Brüggemann N, Dannenmann M, Wang Y, Butterbach-Bahl K: **Sustaining crop productivity while reducing environmental nitrogen losses in the subtropical wheat-maize cropping systems: a comprehensive case study of nitrogen cycling and balance**. *Agric Ecosyst Environ* 2016, **231**:1-14.

43. Abdalla M, Hastings A, Cheng K, Yue Q, Chadwick D, Espenberg M, Truu J, Rees RM, Smith P: **A critical review of the impacts of cover crops on nitrogen leaching, net greenhouse gas balance and crop productivity**. *Global Change Biol* 2019, **25**:2530-2543.

44. Olofsson P, Foody GM, Herold M, Stehman SV, Woodcock CE, Wulder MA: **Good practices for estimating area and assessing accuracy of land change**. *Remote Sens Environ* 2014, **148**:42-57.

45. Bégué A, Arvor D, Bellon B, Betbeder J, De Abelleyra D, Ferraz RPD, Lebourgeois V, Lelong C, Simões M, Verón SR: **Remote sensing and cropping practices: a review**. *Remote Sens* 2018, **10**:99.

46. See L, Comber A, Salk C, Fritz S, van der Velde M, Perger C, Schill C, McCallum I, Kraxner F, Obersteiner M: **Comparing the quality of crowdsourced data contributed by expert and non-experts**. *PLoS One* 2013, **8**:e69958.

47. Ogle SM, Breidt FJ, Easter M, Williams S, Killian K, Paustian K: **Scale and uncertainty in modeled soil organic carbon stock changes for US croplands using a process-based model**. *Global Change Biol* 2010, **16**:810-820.

48. USDA-NRCS: *Summary Report: 2015 National Resources Inventory*. Natural Resources Conservation Service, Washington, D.C., and Center for Survey Statistics and Methodology, Iowa State University, Ames, Iowa; 2019 https://www.nrcs.usda.gov/Internet/FSE_DOCUMENTS/nrcseprd1422028.pdf.

49. Del Grosso SJ, Ogle SM, Parton WJ, Breidt FJ: **Estimating uncertainty in N_2O emissions from U.S. cropland soils**. *Global Biogeochem Cycles* 2010, **24**:GB1009 http://dx.doi.org/10.1029/2009GB003544.

51. Pavelka M, Acosta M, Kiese R, Altimir N, Brümmer C, Crill P, Darenova E, Fuβ R, Gielen B, Graf A *et al.*: **Standardization of chamber techniques for CO_2, N_2O and CH_4 flux measurements from terrestrial ecosystems**. *Int Agrophys* 2018, **32**:569-587.

52. Bureau J, Grossela A, Loubet B, Laville P, Massad R, Haas E, Butterbach-Bahl K, Guimbaud C, Hénault C: **Evaluation of new flux attribution methods for mapping N_2O emissions at the landscape scale**. *Agric Ecosys Environ* 2017, **247**:9-22.

53. De Rosa D, Rowlings DW, Biala J, Scheer C, Basso B, Grace PR: **N_2O and CO_2 emissions following repeated application of organic and mineral N fertilizer from a vegetable crop rotation**. *Sci Total Environ* 2018, **637-638**:813-824.

54. Li Y, Shah SHH, Wang J: **Modelling of nitrification inhibitors and its effects on emissions of nitrous oxide (N_2O) in the UK**. *Sci Total Environ* 2020, **709**:136156.

55. Grant RF, Lin S, Hernandez-Ramirez G: **Modelling nitrification inhibitor effects on N_2O emissions after fall- and spring-applied slurry by reducing nitrifier NH_4^+ oxidation rate**. *Biogeosciences* 2020, **17**:2021-2039.

56. Gerber JS, Carlson KM, Makowski D, Mueller ND, Garcia de Cortazar-Atauri I, Havlík P, Herrero M, Launay M, O'Connell CS, Smith P, West PC: **Spatially explicit estimates of N_2O emissions from croplands suggest climate mitigation opportunities from improved fertilizer management**. *Global Change Biol* 2016, **22**:3383-3394.

57. Yue Q, Wu H, Sun J, Cheng K, Smith P, Hillier J, Xu X, Pan G: **Deriving emission factors and estimating direct nitrous oxide emissions for crop cultivation in China**. *Environ Sci Technol* 2019, **53**:10246-10257.

58. Cowan N, Levy P, Drewer J, Carswell A, Shaw R, Simmons I, Bache C, Marinheiro J, Brichet J, Sanchez-Rodriguez AR *et al.*: **Application of Bayesian statistics to estimate nitrous oxide emission factors of three nitrogen fertilisers on UK grasslands**. *Environ Int* 2019, **128**:362-370.

59. Wang Q, Zhou F, Shang Z, Ciais P, Winiwarter W, Jackson RB, Tubiello FN, Janssens-Maenhout G, Tian H, Cui X *et al.*: **Data-driven estimates of global nitrous oxide emissions from croplands**. *Natl Sci Rev* 2020, **7**:441-452.

60. Leip A, Busto M, Corazza M, Bergamaschi P, Koeble R, Dechow R, Monni S, de Vries W: **Estimation of N_2O fluxes at the regional scale: data, models, challenges**. *Curr Opin Environ Sustain* 2011, **3**:328-338.

61. • Yue Q, Cheng K, Ogle S, Hillier J, Smith P, Abdalla M, Ledo A, Sun J, Pan G: **Evaluation of four modelling approaches to estimate nitrous oxide emissions in China's cropland**. *Sci Total Environ* 2019, **652**:1279-1289.
This publication presents a comparison of model predictions of N_2O emissions for empirical and process-based models using datasets from China. The results suggest that models produce more accurate predictions for fertilized systems than unfertilized. In general, the process-based models performed better with less error and bias than the empirical methods.

62. Parton WJ, Hartman MD, Ojima DS, Schimel DS: **DAYCENT: its land surface submodel: description and testing**. *Global Planet Change* 1998, **19**:35-48.

63. Li C, Frolking S, Frolking TA: **A model of nitrous oxide evolution from soil driven by rainfall events: 2. Model applications**. *J Geophys Res* 1992, **97**:9777-9783.

64. Haas E, Klatt S, Fröhlich A, Kraft P, Werner C, Kiese R, Grote R, Breuer L, Butterbach-Bahl K: **LandscapeDNDC: a process model for simulation of biosphere-atmosphere-hydrosphere exchange processes at site and landscape scale**. *Landscape Ecol* 2013, **28**:615-636.

65. Tian H, Xu X, Liu M, Ren W, Zhang C, Chen G, Lu C: **Spatial and temporal patterns of CH_4 and N_2O fluxes in terrestrial ecosystems of North America during 1979–2008: application of a global biogeochemistry model**. *Biogeosciences* 2010, **7**:2673-2694.

66. Abalos D, Cardenas LM, Wu L: **Climate change and N_2O emissions from South West England grasslands: a modelling approach**. *Atmos Environ* 2016, **132**:249-257.

67. •• Ehrhardt F, Soussana J-F, Bellocchi G, Grace P, McAuliffe R, Recous S, Sándor R, Smith P, Snow V, de Antoni Migliorati M *et al.*: **Assessing uncertainties in crop and pasture ensemble model simulations of productivity and N_2O emissions**. *Global Change Biol* 2018, **24**:e603-e616.
This article presents an approach and results for an intercomparison of models that are used to predict soil N_2O emissions for crop and grassland ecosystems. The findings show that model ensembles could produce accurate results for N_2O emissions by applying 3 models in an ensemble although the actual ensembles vary depending on the crop types and grassland.

68. • Tian H, Yang J, Xu R, Lu C, Canadell JG, Davidson EA, Jackson RB, Arneth A, Chang J, Ciais P *et al.*: **Global soil nitrous oxide emissions since the preindustrial era estimated by an ensemble of terrestrial biosphere models: magnitude, attribution, and uncertainty**. *Global Change Biol* 2019, **25**:640-659.
Recent study quantifying long-term N_2O emissions from global soils based on the effects of multiple anthropogenic and natural factors on

soil N_2O emissions. The results are for the period 1861–2016 and used a standard simulation protocol with seven process-based terrestrial biosphere models to predict N_2O emissions.

69. Necpálová M, Anex RP, Fienen MN, Del Grosso SJ, Castellano MJ, Sawyer JE, Iqbal J, Pantoja JL, Barker DW: **Understanding the DayCent model: calibration, sensitivity, and identifiability through inverse modeling**. *Environ Model Softw* 2015, **66**:110-130.

70. Myrgiotis V, Williams M, Topp CFE, Rees RM: **Improving model**
• **predictions of soil N_2O emissions through Bayesian calibration**. *Sci Total Environ* 2018, **624**:1467-1477.
This study presents a Bayesian calibration of the Landscape-DNDC model with the Metropolis-Hastings algorithm, and reduced uncertainty in model predictions of soil N_2O emissions by 33%. Bayesian parameterization methods are a key method for integrating measurements with models that is needed for monitoring soil N_2O emissions.

71. Xu T, White L, Hui DF, Luo YQ: **Probabilistic inversion of a terrestrial ecosystem model: analysis of uncertainty in parameter estimation and model prediction**. *Global Biogeochem Cycles* 2006, **20**:GB2007.

72. Rahn KH, Butterbach-Bahl K, Werner C: **Selection of likelihood parameters for complex models determines the effectiveness of Bayesian calibration**. *Ecol Inf* 2011, **6**:333-340.

73. Rahn KH, Werner C, Kiese R, Haas E, Butterbach-Bahl K: **Parameter-induced uncertainty quantification of soil N_2O, NO and CO_2 emission from Höglwald spruce forest (Germany) using the LandscapeDNDC model**. *Biogeosciences* 2012, **9**:3983-3998.

74. Houska T, Kraft P, Liebermann R, Klatt S, Kraus D, Haas E, Santabarbara I, Kiese R, Butterbach-Bahl K, Müller C, Breuer L: **Rejecting hydro-biogeochemical model structures by multi-criteria evaluation**. *Environ Model Softw* 2017, **93**:1-12.

75. Werner C, Butterbach-Bahl K, Haas E, Hickler T, Kiese R: **A global inventory of N_2O emissions from tropical rainforest soils using a detailed biogeochemical model**. *Global Biogeochem Cycles* 2007, **21**:GB3010.

76. Gålfalk M, Olofsson G, Bastviken D: **Approaches for hyperspectral remote flux quantification and visualization of GHGs in the environment**. *Remote Sens Environ* 2017, **191**:81-94.

77. Garkusha AS, Polyakov AV, Timofeyev YM: **Analysis of capabilities for satellite monitoring of atmospheric gaseous composition using IRFS-2 instrument**. *Izvestiya Atmos Ocean Phys* 2017, **53**:1016-1018.

78. Thompson RL, Lassaletta L, Patra PK, Wilson C, Wells KC,
•• Gressent A, Koffi EN, Chipperfield MP, Winiwater W, Davidson EA *et al.*: **Acceleration of global N_2O emissions seen from two decades of atmospheric inversion**. *Nat Climate Change* 2019, **9**:993-998.
This publication shows that global N_2O emissions in the last decade increased much faster than estimated by the IPCC emission factor approach. It also highlights that East Asia was a driver of the observed acceleration of global atmospheric N_2O increases. Moreover, the authors point out that the global emission factor as calculated by atmospheric inversion is $2.3 \pm 0.6\%$ rather than 1.375% as indicated by the IPCC Tier 1 approach.

79. Ganesan AL, Manning AJ, Grant A, Young D, Oram DE,
• Sturges WT, Moncrieff JB, O'Doherty S: **Quantifying methane and nitrous oxide emissions from the UK and Ireland using a national-scale monitoring network**. *Atmos Chem Phys* 2018, **15**:6393-6406.
This publication presents an ambitious study to utilize atmospheric greenhouse gas concentration measurement data for estimating greenhouse gas fluxes in the United Kingdom. The study incorporates data from a variety of sensors, transport models and inverse modeling methods, and provides a basis for other countries to develop atmospheric-based flux estimates.

80. Leip A, Skiba U, Vermeulen A, Thompson R: **A complete rethink is**
•• **needed on how greenhouse gas emissions are quantified for national reporting**. *Atmos Environ* 2018, **174**:237-240.
This publication recommends using atmospheric greenhouse gas measurements as the basis for reporting greenhouse gas emissions under the Paris agreement. The inversions would be informed by simple Tier 1 method developed by the IPCC with more complex Tier 2 or 3 methods where there are hotspots of emissions.

81. de Klein C, Harvey M (Eds): *Nitrous oxide chamber methodology guidelines: Version 1*. New Zealand: Global Research Alliance, Ministry of Primary Industries; 2018.

82. Xia L, Lam SK, Chen D, Wang J, Tang Q, Yan X: **Can knowledge-based N management produce more staple grain with lower greenhouse gas emission and reactive nitrogen pollution? A meta-analysis**. *Global Change Biol* 2017, **23**:1917-1925.