Chapter 9: Scaling point/plot measurements of greenhouse gas fluxes, balances and intensities to whole-farms and landscapes

Todd S. Rosenstock, Mariana C. Rufino, Ngonidzashe Chirinda, Lenny Bussel, Pytrik Reidsma, Klaus Butterbach-Bahl

Abstract

Measurements of nutrient stocks and greenhouse gas (GHG) fluxes are typically collected at very local scales (< 1 to 30 m^2) and then extrapolated to estimate impacts at larger spatial extents (farms, landscapes, or even countries). Translating point measurements to higher levels of aggregation is called *scaling*. Scaling fundamentally involves conversion of data through combination or interpolation and/or simplifying or nesting models. Model and data manipulation techniques to scale estimates are referred to as scaling methods. In this chapter, we first discuss the necessity and underlying premise of scaling and scaling methods. Almost all cases of GHG impact research relies on disaggregated data, either spatially or by activity, as a fundamental input of scaling. So, we then assess the utility of using empirical and process-based models with disaggregated data, specifically concentrating on the opportunities and challenges for their application to diverse smallholder farming systems in tropical regions. We describe key advancements needed to improve the confidence in results from these scaling methods in the future. Resources to familiarize readers with the scientific theory underlying scaling methods—e.g., hierarchy theory in ecology—as well as to help implement the approaches surveyed in the text are available on the website associated with this chapter.

6.1 Why estimate GHG impacts at whole-farm and landscape level?

There is an urgent need for information on GHG balances and the GHG intensity of agricultural products (e.g., emission per unit product) at levels where livelihood and environmental impacts occur and management decisions are being made. But even in smallholder farming systems where decisions are taken on fields and farms that are usually less than one hectare, this decision-scale is substantially greater than the scale at which changes in GHG fluxes take place or are measured, often that of microns and meters (Butterbach-Bahl et al., 2013). For example, soil moisture affects oxygen available to microbes at the soil aggregate level driving denitrification (the conversion of NO_3^- to N_2O principally by facultative anaerobic bacteria) but the percentage of water filled pore space is regulated by precipitation and soil tillage—events correlated at greater spatial extent. On the other hand, decomposing residues from the previous harvest may form hotspots for denitrification and N_2O formation at the cm scale, thereby triggering the magnitude of fluxes even at plot scale (Groffman et al., 2009). In practice, land-based mitigation actions require a lower resolution of information than that needed to explain the processes driving GHG emissions at the soil-plant-atmosphere interface.

Furthermore, GHG fluxes are typically measured at locations or 'points', intended to be representative of a larger area. Independent of source, sink or molecule, GHG measurements – for example chamber measurements of fluxes - are conducted on only a fraction of the area or a few of the landscape units because of costs and complexity (Rufino et al. Chapter 2;

Butterbach-Bahl et al. Chapter 5). When attempting to understand landscape or regional GHG fluxes or consider mitigation options, it is therefore necessary that these point measurements are translated to larger extents where effective and meaningful mitigation actions can be taken.

'Scaling' GHG flux measurements or data on atmospheric concentrations underlies GHG accounting (e.g., national inventories), and forms the basis for policy analysis (e.g., marginal abatement cost curves), development strategies (e.g., low emission development), and even simple testing of mitigation options (e.g., comparing impacts of one practice versus an alternative). Thus, it is important to understand basic principals and terminology that pertain to scales and scaling, to avoid confusion in discussions and analysis. *Scale* refers to the spatial or temporal dimension of a phenomenon (van Deldon et al. 2011; Ewert 2004). It is not a property of objects. There is no such thing as a plot scale or landscape scale. Plots or landscapes can be described at various scales. *Scaling* refers to the transfer of information between scales or organizational levels (Blöschl and Sivapalan 1995). *Scaling methods* refer to tools required to accomplish scaling. This chapter is concerned with understanding the theory and practice behind scaling methods as applied to GHG measurements and impacts.

6.2 Scaling methods

Most scaling methods are grounded in ecological hierarchy theory. Hierarchy theory provides a conceptual framing for scaling in that it structures systems as nested levels of organization (Holling, 1992). Components are arranged within higher levels; for example, a field is part of a farm that can be thought of as part of a landscape (Figure 1). Scaling methods rely on this conceptual framing to infer relationships between attributes and to translate values derived from point measurements into estimates of across scales.

Scaling methods can be categorized into two groups: (1) manipulation of data or (2) manipulation of models (Volk & Ewert, 2011). Approaches that manipulate data extrapolate, interpolate, or average sampled input data (i.e., point measurements) or output data to generate estimates at larger scales (Table 1). National Greenhouse Gas Inventories that use IPCC Default Tier 1 Emissions Factors (IPCC 2006) are an example of a scaling method that use a data manipulation approach, namely aggregation or disaggregation. Agriculture is disaggregated into farming activities and their extents (e.g., size of cattle population or tons of nitrogen fertilizer applied) for which a coefficient derived from point measurements of the relationship between that activity and GHG flux (i.e., empirical model) is then used to calculate emissions at national levels. Data manipulation approaches are among the simplest approaches to implement, especially in regions and for production conditions where data are sparse. However, heterogeneity in underlying processes is neglected and thus estimates may not represent fluxes well (Figure 2). But in most cases for developing countries, the accuracy of using such methods is unknown because there are insufficient data to evaluate the variation of source events (input data) or the accuracy of outputs. The ability to generate accurate predictions at larger scales by manipulating data depends on (1) representative sampling of the disaggregated GHG source/sink activities and (2) the availability of a reasonable model, empirical or process-based to scale input data. Recently, more sophisticated approaches to

disaggregation of national, landscape or farm components can help improve estimates because of the better representation of the heterogeneity (Hickman et al. 2015, Rufino et al. Chapter 2).

The alternative to manipulating data is to modify underlying models to be relevant at larger spatial scales. This has been successfully done for national scale soil carbon monitoring in the US, where an integrated data collection and biogeochemical process-based model (DAYCENT) predicts changes in soil carbon stocks (Spencer *et al.*, 2011). But other examples for agricultural GHG impact assessments remain scientific exercises (see Perlman *et al.*, 2013 for national scale N_2O assessment). Approaches to manipulate models change model structure to account for the availability and resolution of input data and to make them computationally tractable. Key processes that link impacts across scales are preserved and represented in the revised form. Reformulation of model structure can result in a reduction of parameters (e.g., macroecological models of functional traits) or simplified model functional forms (e.g., empirical equations derived from multiple runs of process-based models).

Theory supporting the manipulation of data and models as well as potential errors/uncertainties in outcomes is reviewed in the integrated assessment literature (e.g., Ewert *et al.*, 2011; Volk & Ewert, 2011). The process of selecting representative sampling points by various stratification methods (e.g., spatially, land cover, farming activity, etc.) are covered in Chapter 2 and measurements techniques for various fluxes and productivity are covered in Chapters 3-9 and thus in the next section here, we discuss the two methods most commonly used to *scale up* point measurements of disaggregation/aggregation data using empirical and process-based models. Empirical models are usually relatively simple statistical functions constructed based on relationship between occurrence of activities, farming or otherwise, and monitored responses in the magnitude and temporal and spatial variability of greenhouse gas fluxes. By contrast, process-based models are built upon our current theoretical understanding and best representation of complex processes and interactions to simulate the mechanisms that control GHG fluxes, though part of the algorithms is often still empirical. Unlike empirical models that require calibration each time they are used this is not always necessary with process-based models unless they are being used in a different agro-ecological regime for which they have not previously been calibrated. In the following, we briefly describe these two approaches, their applicability for smallholder systems, representation of the landscape units, technical demands of the process, and sources of uncertainty.

6.3 Using empirical and process-based models with disaggregated data

Empirical models

Empirical models for scaling GHGs are based on statistical functions that relate land management 'activities' such as extent of a land cover type, amount of fertilizer applied, or the number of head of livestock to nutrient stocks, stock change to GHG emissions or sequestration. Carbon stock, stock changes, and greenhouse gas fluxes can then be calculated based on two types of input data: (1) that describes the occurrence of activities (so called 'activity data') and (2) the average effect that activity has on a nutrient stock or flux in question ('emission factors') (eq 1).

$$GHG = \sum_i^n A_i * EF_i \quad (1)$$

where, *GHG* equals the stock (mass) or flux (rate: mass per unit time), sequestration or balance in units of C, N or an integration of the two (CO_2 eq); *A* represents the extent (area) over which an activity occurs and *EF* is an emissions factor (e.g., a constant rate relative to the specific activity: mass per unit time per unit area). Summation of GHG fluxes or stock changes across *N* activities (sources/sinks) generates a cumulative balance for the selected area. This approach is analogous to a linear aggregation scaling method based on measurements or estimates values.

The most widely applied empirical models for scaling GHGs are contained within the IPCC Guidelines for Greenhouse Gas Accounting (IPCC, 2006c). The IPCC Guidelines define global (Tier 1) and, sometimes regional emissions factors (Tier 2) for GHG sources and sinks such as the methane produced by enteric fermentation per head of cattle or the amount of nitrous oxide resulting from application of nitrogenous fertilizers. Persons interested in GHG quantification can multiply these values and the provided equations with locally relevant data on farm and landscape management activities to generate estimates of individual source and sink strength or cumulative GHG balance. Application of emission factors and empirical models is the foundation of national greenhouse gas inventories and data (Tubiello *et al.*, 2013) and is becoming more common for landscape GHG accounting including *ex-ante* climate change mitigation project impact assessments (Colomb & Bockel, 2013).

IPCC Tier 1 default emission factors are based on both empirical data and expert opinion. In some cases, emissions factors are derived from analysis of 100s or even 1 000s of measurements of the source activity and the rates of emissions. For instance, IPCC default emissions factor for nitrous oxide emissions from nitrogen fertilizer use (1%) are based on the database of nearly 2 000 individual measurements from studies conducted around the world (De Klein et al., 2006; Stehfest & Bouwman, 2006), though distribution of studies are biased toward measurement campaigns conducted in Europe and North America. But this is not true for all activities. Other emission factors are estimated based on very limited data (e.g., single values for carbon stocks in agroforestry systems) or expert opinion, (e.g., emission factor for methane emission from enteric fermentation is based on modeled results not measurements for Africa) (IPCC, 2006a, 2006b). Global default emissions factors are published in the National Guidelines for Inventories while other regionally relevant emissions factors are available in the IPCC Emissions Factor database, peer reviewed literature and in the future will be made available through the joint Global Research Alliance on Greenhouse Gas Emissions (GRA) and SAMPLES web platform.

Empirical models are typically thought to generate reasonable approximations of GHG fluxes at higher levels of organizations and large spatial extent (Del Grosso et al., 2008), presuming the activity data are well constrained. This is because it is thought that at large scales such as across countries, the departure of actual fluxes—because edaphic conditions driving variability—from average emissions factor values will average out with aggregation of multiple land units. But for

any local scale—e.g., farms, where local environmental and management heterogeneity of conditions are not well represented in the global datasets, applying empirical models and emissions factors may represent a significant departure from actual fluxes (Rosenstock et al. 2014, Richards et al. *in review*).

The relevance of using empirical models for farm-scale estimates of greenhouse gas balances is untested and perhaps spurious, especially for developing country farming systems. IPCC guidelines using Tier 1 default factors were not designed for this purpose. Tier 1 approaches were intended to be used when the source activity was relatively inconsequential to total GHG budgets, perhaps contributing less than five percent of the total. Furthermore, significant variation in GHG flux rates occur between point locations due to edaphic mechanisms that control biological emission processes. Because observations of GHG fluxes for tropical smallholder farming systems are scarce or nearly missing in available databases, Tier 1 default factors may considerably misrepresent flux rates for such systems. In view of the low use of N fertilizers, it is therefore not surprising that many of the N2O fluxes currently being measured in sub-Saharan Africa are 1/3 to 1/2 than the Tier 1 IPCC emission factors would suggest (Hickman *et al.*, 2014). In consequence, using IPCC standards would currently lead to overestimate the impact of agriculture in Africa on the global atmospheric N2O budget. A comprehensive evaluation of Tier 1 emissions factors relating to GHG impacts measured in tropical regions is currently lacking. Despite these concerns, disaggregation of whole-farms into component activities and applying available empirical models remains perhaps the only way to estimate relative impacts of smallholder farming activities at the whole-farm level (Seebauer, 2014) and at minimum can be used to understand uncertainties around GHG balances and intensities and can generate hypotheses to identify important research gaps.

Emissions from livestock production in the tropics, namely from enteric fermentation and manure management, present their own challenges due to data scarcity. Similarly to soil fluxes, emissions from both sources are poorly constrained and data are nonexistent in Africa. Yet in many countries, these sources are thought to be substantial fractions of the total GHG budgets. For example in Africa, methane from enteric fermentation and emissions from manure deposited on pasture represents roughly 40% and 28% of annual GHG emission (FAO 2015). However, there are no data that quantify emissions from either source despite our knowledge that the drivers of emissions (e.g., feed quality and quantity and C and N content of manure) are known to differ significantly from where emissions factors have been produced.

An additional issue—besides poorly constrained emissions factors—is limited knowledge of farm management practices (*A* in equation 1) and limits the use of empirical relationships and models for calculating fluxes. Many developing countries have poorly defined reporting schemes about e.g. organic and inorganic fertilizer use, manure management, crop rotations etc. and record keeping and so there is little accurate information on the extent of land management decisions (Ogle *et al.*, 2013). This adds in another source of uncertainty (in addition to emission factors themselves). In most cases, there are no uncertainty estimates around activity data. Valentini et al. (2014) report that estimates of the extent of various land

cover in Africa can be from 2.5% to 110% different depending on the data source, either using inventory sources or satellite imagery (Valentini *et al.*, 2014). Other evidence from data collection methods suggests that the uncertainty in activity data is similar to that of emission, 30 to 80% (Figure 3, Seebauer, 2014). New best practices have been developed to help developing countries better represent the activities on-going in their agricultural landscapes (Tubiello et al. 2013). However, incentives to improve and standardize data collection and archiving efforts are limited.

Simplicity and transparency are the largest benefits of using data (dis)aggregation techniques and empirical models for scaling GHG estimates. The models represent relationships that are easy to understand and implement, which makes them accessible to next users without requiring much technical expertise. This has led to a wide range of greenhouse gas calculators being created, including: Cool Farm Tool, Carbon Benefits Tool, etc. (Colomb & Bockel, 2013). These tools make it possible for non-specialist to perform calculations and generate estimates of greenhouse gas balances with relatively little data or effort. The question, that remains to be answered, is whether the estimates produced by such tools provide robust values—either in terms of absolute or terms of relative changes between two systems and at what scales.

Process-based models

Empirical models are only one way to scale manipulated data, however. Process-based models are also used. For example Bryan et al. (2011) average household data for seven counties and four agroecological zones in Kenya and use a process-based model to predict changes in methane emissions from enteric fermentation and revenue with improved feeding practices (Table 2). Process-based models consist of equations implementing current scientific understanding of the mechanisms determining system properties. Even though microbial and physic-chemical processes involved in GHG emissions from soils are implemented in various levels of detail in different biogeochemical models, equations are often based on empirical observations or represent apparent changes in production rates or microbial activity due to, for example, changes in environmental conditions such as changes in moisture and temperature. Thus, models describe a system consisting of components such as soil physics and energy fluxes, vegetation biomass development, or soil microbial C and N turnover and their interactions, which are represented by the equations describing states and rates at different points in time (temporal resolution). Process-based GHG models are designed run at source scale (e.g., site or animal) after being calibrated based on observed relationships in controlled experiments and monitoring data. Because the equations represent principal microbial, biogeochemical and physical-chemical processes underlying ecosystem-atmosphere exchange processes and the emission of GHG's the models are suitable to simulate GHG dynamics under diverse environmental and management conditions even outside the range they have been calibrated for. I.e. it makes them a widely used predictive tool in global change studies and they might be suitable as well to account for fine scale heterogeneity in the farming context, which is not possible with the current empirical models.

The accuracy of a process-based model is related to errors due to model structure or errors due

to the accuracy of data inputs, parameter uncertainty and input uncertainty, respectively. Errors related to model structure are based on incomplete understanding and knowledge of the fundamental relationships that are driving GHG fluxes and the representation of them in the model. These errors can be quantified statistically by comparing the model's predicted GHG fluxes to measured GHG fluxes; for instance, with correlation coefficients. Errors related to input uncertainty take place because the input data describing a particular system is not well known. This may be particularly problematic in developing countries when the detailed climate, soils, and land use data are not available at a high degree of resolution. Parameter uncertainty can be estimated using Bayesian calibration and Monte Carlo simulations (e.g. Van Oijen et al., 2011; Rahn et al., 2011).

Process-based models are available for the majority of GHG sources and sink but are mostly sectorial. I.e. models for predicting atmosphere-biosphere exchange of greenhouse gases and change of soil C and N stocks at ecosystem scale as well as models for livestock GHG emissions (e.g., Giltrap, Li, & Saggar, 2010; Thornton & Herrero, 2010). E.g., DAYCENT or Landscape DNDC (Haas et al., 2013) were developed to simulate biomass production and soil processes, including simulation of soil GHG fluxes and soil C/N stock changes, while the process based RUMINANT model simulates CH_4 emissions from livestock and are mainly applied in the US and in Europe (Rotz et al., 2012; Duretza et al., 2011). These models are reasonable when evaluating the soil carbon sequestration potential at large scales or emissions of N2O from monoculture fields (Babu *et al.*, 2006)., or changes in herd management (Pathak *et al.*, 2005; Bryan *et al.*, 2013; Perlman *et al.*, 2013) but perhaps less so when trying to characterize the GHG impacts of smallholder systems at the whole farm level or landscape scale accounting.

Smallholder farming systems comprise multiple types of farming activities, often combining trees, animals, and crops in interconnected systems. Human management alters nutrients flows, potentially mitigating or exacerbating emissions from parts of the system, and thus applying sectorial process-based models to whole farms may oversimplify the complex interactions taking place (Tittonell *et al.*, 2009). As of yet, few modeling approaches have been adapted for farm level modeling of GHG impacts in mixed crop-livestock systems (Schils *et al.*, 2007; Del Prado *et al.*, 2013) and to our knowledge none have been applied to smallholder conditions of tropical developing countries (note Farm Design model integrates coefficients into a process-based model).

As a first step the models need to be tested for most locales dominated by smallholder farming, which requires the availability of respective test datasets, since calibration and utilization of process-based models requires significant input and validation data. Data on site-specific factors such as soil properties, cropping sequences, and fertilizer use are required, information which is often unavailable in many developing countries. In terms of enteric fermentation, the challenge is both a lack of information on animal numbers, feeding regimes, indigenous breeds as well as the quality of feeds and forages even though the models are based on the presumption that the chemical reactions that occur in the rumen are fairly standard and tend to go to completion. However, emission factors, which have been obtained

so far, don't consider that livestock production in developing countries often involves periods of severe under nutrition with feed qualities being far lower than tested in experiments in OECD countries. It is obvious that there is a great need to generate data that can be used for model parameterization and evaluation for smallholder conditions. Until now, only limited information has been available to independently assess the validity of the emissions models for developing country conditions casting doubt on the reliability of any results generated from process-based models.

Until process-based models have been adapted, calibrated and evaluated to account for diversity and complexity characteristic of smallholder farming, their use for GHG quantification at the whole-farm level in mixed systems such as the crop-livestock systems of Africa remains a challenge and requires a tight coupling of sectorial models and a whole system understanding.

6.4 Conclusion

The complexity and scale that is characteristic of smallholder farming and the general lack of data presents significant challenges for scaling GHG emissions with much certainty. Significant efforts and investments are needed to improve systems representation so that collected data are used to improve either empirical or process based models. Moreover, conducting detailed monitoring campaigns can address the challenge of complexity and heterogeneity, and provided data that can be used to scale up representative systems with greater confidence.

Besides concerns over accuracy, technical demands in terms of data availability, model calibration and human capital all limit the utility of process-based models as a scaling method for GHG fluxes in agricultural systems of tropical developing countries at this time. However, given the costs of monitoring programs, it becomes an imperative to establish programs that can adapt and improve process-based models for quantification as they provide a means to test hypotheses of mitigation options and GHG accounting. This will require a number of investments in climate monitoring, scientific capacity building, and GHG measurements to evaluate the models for smallholder conditions. We estimate that a 10 year program of targeted measurements—those for key sources and sinks spanning heterogeneous conditions—is needed before use of process-based models becomes a viable solution for GHG quantification in smallholder systems at either farm or landscape scales.

6.5 References

Babu YJ, Li C, Frolking S, Nayak DR, Adhya TK (2006) Field Validation of DNDC Model for Methane and Nitrous Oxide Emissions from Rice-based Production Systems of India. *Nutrient Cycling in Agroecosystems*, 74, 157–174.

Blöschl, G. and M. Sivapalan (1995). "Scale issues in hydrological modelling: a review." Hydrological Processes 9(3-4): 251-290.

Bryan E, Ringler C, Okoba B, Koo J, Herrero M, Silvestri S (2013) Can agriculture support climate change adaptation, greenhouse gas mitigation and rural livelihoods? insights from Kenya. *Climatic Change*, 118, 151–165.

Colomb V, Bockel L (2013) Selection of appropriate calculators for landscape-scale greenhouse gas assessment for agriculture and forestry. *Environmental Research Letters*, 015029.

Duretz, S, Drouet JL, Durand P, Hutchings NJ, Theobald MR, Salmon-Monviola J, Dragosits U, Maury O, Sutton MA, Cellier P (2011) Nitroscape: a model to integrate nitrogen transfers and transormations in rural landscapes. Environmental Pollution, 159, 3162-70

Ewert F, van Ittersum MK, Heckelei T, Therond O, Bezlepkina I, Andersen E (2011) Scale changes and model linking methods for integrated assessment of agri-environmental systems. *Agriculture, Ecosystems & Environment*, 142, 6–17.

Ewert, F. (2004). Modelling changes in global regionalized food production systems under changing climate and consequences for food security and environment – development of an approach for improved crop modelling within IMAGE, Plant Production Systems Group, Department of Plant Sciences, Wageningen University & Netherlands Environmental Assessment Agency (MNP), National Institute for Public Health and Environment (RIVM).

Giltrap DL, Li C, Saggar S (2010) DNDC: A process-based model of greenhouse gas fluxes from agricultural soils. *Agriculture, Ecosystems & Environment*, 136, 292–300.

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

Hickman JE, Scholes RJ, Rosenstock TS, Garcia-Pando CP, Nyamangara J (2014) Assessing non-CO2 climate-forcing emissions and mitigation in sub-Saharan Africa. *Current Opinion in Environmental Sustainability*, 9-10, 65–72.

Ogle SM, Buendia L, Butterbach-Bahl K et al. (2013) Advancing national greenhouse gas inventories for agriculture in developing countries: improving activity data, emission factors and software technology. *Environmental Research Letters*, 8, 015030.

Pathak H, Li C, Wassmann R (2005) Greenhouse gas emissions from Indian rice fields: calibration and upscaling using the DNDC model. *Biogeosciences*, 2, 113–123.

Perlman J, Hijmans RJ, Horwath WR (2013) Modelling agricultural nitrous oxide emissions for large regions. *Environmental Modelling & Software*, 48, 183–192.

Potter C, Klooster S, Myeni R,Genovese V, Pang-Ning, T, Vipin K, (2003) Continental-scale comparisons of terrestrial carbon sinks estimated from satellite data and ecosystem modeling 1982-1998. Global and Planetery Change, 39, 201-213.

Del Prado a, Crosson P, Olesen JE, Rotz C a (2013) Whole-farm models to quantify greenhouse gas emissions and their potential use for linking climate change mitigation and adaptation

in temperate grassland ruminant-based farming systems. *Animal : an international journal of animal bioscience*, 7 Suppl 2, 373–85.

Rahn KH, Butterbach-Bahl K, Werner C, 2011, Selection of likelihood parameters for complex models determines the effectiveness of Bayesian calibration. Ecological Informatics 6, 333-340.

Schils RLM, Olesen JE, del Prado A, Soussana JF (2007) A review of farm level modelling approaches for mitigating greenhouse gas emissions from ruminant livestock systems. *Livestock Science*, 112, 240–251.

Seebauer M (2014) Whole farm quantification of GHG emissions within smallholder farms in developing countries. *Environmental Research Letters*, 9, 035006.

Spencer S, Ogle SM, Breidt FJ, Goebel JJ, Paustian K (2011) Designing a national soil carbon monitoring network to support climate change policy: a case example for US agricultural lands. *Greenhouse Gas Measurement and Management*, 1, 167–178.

Thornton PK, Herrero M (2010) Potential for reduced methane and carbon dioxide emissions from livestock and pasture management in the tropics. *Proceedings of the National Academy of Sciences of the United States of America*, 107, 19667–72.

Tittonell P, van Wijk MT, Herrero M, Rufino MC, de Ridder N, Giller KE (2009) Beyond resource constraints – Exploring the biophysical feasibility of options for the intensification of smallholder crop-livestock systems in Vihiga district, Kenya. *Agricultural Systems*, 101, 1–19.

Tubiello FN, Salvatore M, Rossi S, Ferrara A, Fitton N, Smith P (2013) The FAOSTAT database of greenhouse gas emissions from agriculture. *Environmental Research Letters*, 8, 015009.

Valentini R, Arneth A, Bombelli A et al. (2014) A full greenhouse gases budget of Africa: synthesis, uncertainties, and vulnerabilities. *Biogeosciences*, 11, 381–407.

Van Delden, H., et al. (2011). "Comparison of scale and scaling issues in integrated land-use models for policy support." Agriculture, Ecosystems & Environment 142(1-2): 18-28.

Van Oijen M, Cameron DR, Butterbach-Bahl K, Farahbakhshazad N, Jansson PE, Kiese R, Rahn KH, Werner C, Yeluripati JB, 2011, A Bayesian framework for model calibration, comparison and analysis: Application to four models for the biogeochemistry of a Norway spruce forest. Agricultural Forest Met., 151

Volk M, Ewert F (2011) Scaling methods in integrated assessment of agricultural systems—State-of-the-art and future directions. *Agriculture, Ecosystems & Environment*, 142, 1–5.