BURLEIGH DODDS SERIES IN AGRICULTURAL SCIENCE

Achieving sustainable cultivation of oil palm

Volume 2: Diseases, pests, quality and sustainability

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E-CHAPTER FROM THIS BOOK

burleigh dodds
SCIENCE PUBLISHING

Modelling environmental impacts of agriculture, focusing on oil palm

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1 Introduction

Most people involved in the production, use and consumption of agricultural products, including palm oil, are interested in reducing or eliminating adverse environmental impacts of cultivation while maintaining or improving productivity. To do that we need to know what the impacts are, and predict how they will respond to changes in land use and management. Environmental impacts occur through movement and transformations of energy and materials. In an ideal world, we might monitor all these processes, but that is simply not feasible. We therefore need to estimate them, and this involves models.

Models are simple abstractions of complex systems and always involve a trade-off between complexity and comprehensibility. All of our understanding and knowledge of the environment is in fact in the form of models, because we must simplify the system to make sense of it. The better we understand systems, that is, the better our conceptual models, the more likely we can quantify them and describe them with mathematical relationships. A theoretically ideal model for a question might describe all the important processes mechanistically across space and time, be initialised with easily measured parameters and

http://dx.doi.org/10.19103/AS.2017.0018.24

Chapter taken from: Rival, A. (ed.), *Achieving sustainable cultivation of oil palm Volume 2: Diseases, pests, quality and sustainability,* Burleigh Dodds Science Publishing, Cambridge, UK, 2018, (ISBN: 978 1 78676 108 8; www.bdspublishing.com)

be simple to process. However, that ideal is not realistic because of the complexity of the environment.

What we have is a large and growing collection of models that are useful for many purposes. Available models simulate some but not all processes and ignore, simplify or assume others. They also overlap in diverse ways. Many can serve as useful tools for tackling scientific and practical questions, if their scope and limitations are understood. The optimal model for any particular purpose is one that includes sufficient complexity to explain the processes of interest, but no more. The nature of models reflects the purpose for which they were designed. There are various typical but overlapping purposes related to environmental impact: developing a fuller understanding of environmental processes, helping managers make decisions, producing indicators for reporting against environmental certification criteria, informing policy to help officials plan and regulate industry, and communication.

Here, we look at modelling of the ways in which cultivation of oil palm influences the biophysical state of the environment within the field itself and in the wider environment, in particular via exchanges with the atmosphere and hydrosphere (Fig. 1). Understanding the environmental impacts of oil palm is essential because it is a globally important crop, especially in the humid tropics, and is rapidly expanding (Sayer et al., 2012). The area of oil palm plantations grew by 680 000 ha/year worldwide over the 2005–2013 period (FAOSTAT, Accessed 2016) and further expansion is expected (Corley, 2009). To put that growth in context, it is slower than soybean and rice (2 311 000 and 1 306 000 ha/year over the same period), but faster than rubber and cocoa (224 000 and 220 000 ha/year), which are crops grown in similar areas.

The key issues for modelling environmental impacts of agriculture, including oil palm cultivation, are choice of modelling approach, definition of the system and key parameters (Section 2), providing useful outputs through integration of our understanding (Sections 3 and 4) and accurate modelling of the causal processes (Section 5). Finally, we summarise the information and make some suggestions about future trends in research and where to look for further information (Sections 6 and 7). We focus on process-based models that have been used in oil palm, but also touch on conceptual and empirical models and relevant models that have not yet been applied to oil palm but could be.

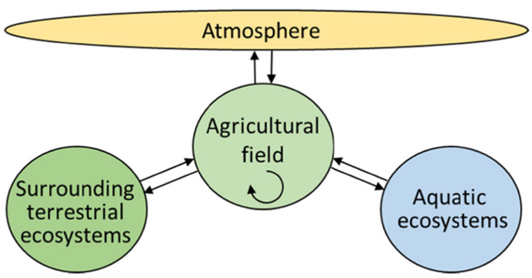

Figure 1 Cultivation of crops, including oil palm, impacts upon the environment through movement of energy, materials and organisms (arrows) between the field and the atmosphere, aquatic ecosystems and surrounding terrestrial ecosystems, and within the field itself.

2 Characteristics of models and the system

Environmental impacts of agriculture, and oil palm cultivation in particular, are diverse. Therefore, when modelling, it is important to be clear about the question being asked. Different questions must be tackled in different ways. Modellers have considered different dimensions and scales of time and space, and used different conceptual and numerical approaches, depending on their emphasis, the availability of data and the understanding of the processes. Several authors have provided useful procedures for selecting environmental models and evaluating their performance (Jakeman et al., 2006; Makowski et al., 2009; Bennett et al., 2013; Kelly et al., 2013; Harmel et al., 2014).

There are two main types of numerical model. On the one hand, there are statistical or empirical models, which describe relationships between data sets, and range from simple regressions to neural networks. They are useful for making predictions but because they are a 'black box', not relying on mechanisms or causality, they are limited in their predictive capacity outside of the conditions under which they were developed. On the other hand, there are 'physically based', 'deterministic', 'mechanistic' or 'process-based' models, which are usually also 'dynamic', having a temporal dimension. They are based on understood causal relationships. The predictive capacity of models generally increases as they become more complex and incorporate more parameters (Fig. 2). The two must go together. There is no point in measuring many parameters if they cannot be incorporated into a model, nor is there any point having a complex model if there are insufficient data to run it.

For problems involving a high degree of uncertainty, models that incorporate probability functions can be useful (Aguilera et al., 2011). For example, Bayesian networks, which are based on probability of one event leading to another, have been used to model ecosystem services (Landuyt et al., 2013), nutrient exports from agricultural areas (Nash et al., 2013;

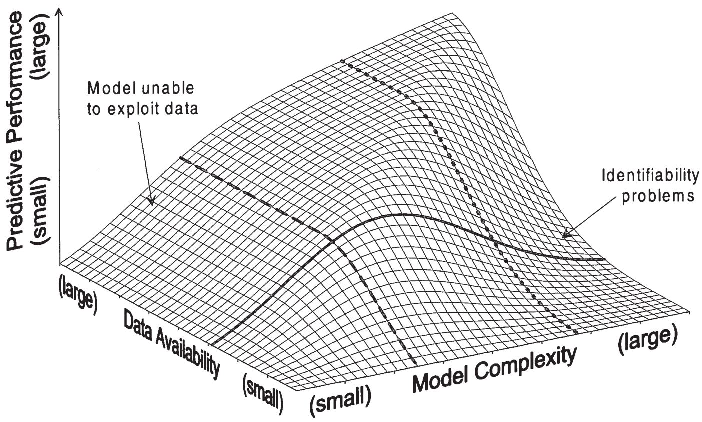

Figure 2 Schematic diagram of the relationship between model complexity, data availability and predictive performance (reproduced from R. Grayson and G. Blöschl, *Spatial Patterns in Catchment Hydrology*, Cambridge University Press, 2001, with permission from Cambridge University Press).

Lucey et al., 2014) and habitat suitability (Hamilton et al., 2015). However, in this chapter we focus on numerical rather than probability-based models.

No matter how sophisticated numerical process-based models are, or how well they model a particular set of circumstances, they are never a perfect representation of reality. Process-based models commonly incorporate relationships that were determined empirically. There is also error involved in determining correct values for parameters. Therefore, for any particular problem and situation, we might expect an optimal model complexity (Fig. 3). Complex models are constructed by combining simpler models, and it follows that model accuracy will be limited by the weakest component.

Models can operate in one, two or three dimensions and at different temporal resolutions. Those operating in two or three dimensions are often called 'distributed' or 'lumped'. Distributed models explicitly model lateral or vertical processes, whereas lumped models assume processes are uniform within given areas. For both, the scale should match the problem being tackled. As for time, some problems might be tackled adequately at coarse timescales such as a year, but others need daily or finer resolution to provide a useful representation of reality.

Impacts on the atmosphere are felt at a global scale because of the relatively well-mixed nature of the atmosphere. Consequently, global climate models and earth system models operate in two or three dimensions across the earth's surface. However, they derive inputs from, or link to, agricultural systems via one-dimensional models of the soil–plant–atmosphere continuum operating with lateral resolution of fields to regions.

Impacts on aquatic ecosystems occur in the field, downstream of it and perhaps also upstream, due to effects on the movement of organisms. Thus, aquatic ecosystem impact models may operate at various scales and dimensions, from one-dimensional to three-dimensional. In general, the effects of agricultural land use tend to accumulate downstream due to an increase in proportion of water that has passed through agricultural fields. However, the impact of disturbance at points (e.g. road crossings and mill outfalls) may diminish downstream and, once the estuary is reached, the effect of the sea becomes important. The direct effect of shading is essentially one-dimensional,

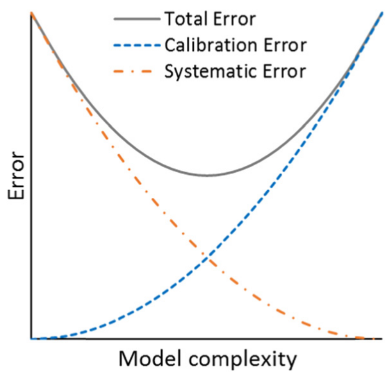

Figure 3 As models become more complex, systematic error (i.e. error from the assumptions made) tends to decrease and calibration error (resulting from limited knowledge about the necessary parameters) tends to increase.

although distributed along stream reaches, whereas nutrient movements and effects must be modelled in two or three dimensions due to downward leaching through the soil, lateral movement through groundwater and discharge into surface water bodies. Quality and ecology of the groundwater may also be important, especially when it is used for drinking water.

Terrestrial impacts are felt in surrounding ecosystems and in the field itself (Fig. 1). Impacts on the surrounding ecosystems tend to be proportional to size and distribution of agricultural fields, reaching negligible levels at distances from fields that are beyond the movement range of organisms and groundwater. Therefore, such models tend to be two- or three-dimensional. Models of in-field soil processes and quality tend to operate in the one-dimensional soil–plant–atmosphere continuum, but lateral variability and movement of materials and organisms may also be taken into account.

Models need parameters that adequately describe the characteristics of the environment, crop and management practices. The greater the availability of data and the more complex the model, the greater the predictive power (Fig. 2). To satisfactorily define parameters, modellers need to know and understand the key factors controlling the processes of interest. Or, on the other hand, models may help researchers find out which are the most important parameters. Models differ in the types of parameters they require, the ways in which the parameters are measured or estimated, and the ways in which they have been calibrated and evaluated (Mulligan and Wainwright, 2013a).

To define characteristics of the oil palm system, it is helpful to recognise that it has some characteristics in common with other cropping systems and others that are unique. Characteristics of oil palm systems are described in detail by Corley and Tinker (2016), but we briefly outline some key features here.

Key climatic characteristics of the system are related to the high temperature and water requirements of oil palm. Radiation tends to be high due to low latitude, although cloud cover can reduce it significantly. Day length varies little, but may affect flowering. Seasonal and daily temperature ranges are also limited, but are important for regulating the rate of processes (e.g. Wang et al. 2014), especially at higher altitudes or latitudes. Rainfall is usually greater than evapotranspiration for much of the year, leaving considerable surplus water available for surface run-off or deep drainage. High-intensity rainfall events mean timescales for modelling generally need to be short to adequately model water-related processes. Irrigation is practised in some places where long periods of water deficit impact on production. While appropriate historical climate data is an essential requirement for modelling, the availability and quality of such data is often limiting.

Key physical characteristics of the system are mostly determined by the climate and topography of tropical lowlands chosen for plantations (Paramananthan, 2011). Topography tends to be flat, often with shallow water table. However, steeper areas are also planted and topography is important for processes such as erosion. The maximum recommended slope is around 20–25°, although steeper slopes have been planted. Terracing is generally practised on slopes steeper than 6–10°.

Soils are typically deep, highly weathered and acidic, with low nutrient holding capacity and high permeability. However, there is also considerable variation, with excessively or poorly drained, shallow, stony, saline, sodic or acid sulphate conditions all existing in plantations. These soil characteristics all affect environmental processes. Most soils are 'mineral' soils with topsoil organic matter contents typically <10%. However, organic soils or peats, which occur in waterlogged areas and have organic matter contents >65%, are also important because of the extensive areas planted with oil palm in Malaysia and Indonesia. Koh et al. (2011) demonstrated that 6% (or ≈880 000 ha) of tropical peatlands in the region had been converted to oil palm plantations by the early 2000s. Appropriate geomorphological and soil data are an essential requirement for modelling many processes.

Infrastructure, especially drainage and road systems, is also an important feature of the physical environment. Networks of earth and gravel roads are relatively dense in oil palm systems, and have a large influence on the movement of water and wildlife, as do drains. Road density and related erosion tends to increase with slope.

The oil palm crop itself has particular key features. It comprises palms at a density of 120–150 ha^{-1}, groundcover vegetation and areas kept bare for harvesting and access. The palms are planted as seedlings, grown to maturity (full canopy cover) by about five years of age and then continued to grow until they are cut down at about 25 years of age. Most oil palm is the ‘tenera’ type of *Elaeis guineensis* Jacq., a hybrid between ‘dura’ and ‘pisifera’ types. However, hybrids between *E. guineensis* and *E. oleifera* are increasingly planted in America (Corley and Tinker, 2016). Corporate plantations are generally managed in field blocks of 25–30 ha, surrounded by roads, whereas smallholder fields may be as small as 2 ha. Intercropping is common in smallholder fields during the immature phase but is not common in corporate plantations. The land use preceding oil palm is also important for many environmental processes. The previous crop may be oil palm, but due to the rapid expansion of the industry, most current oil palm was preceded by a different land use, typically forest, grassland, food crops or other commodity crops such as cocoa, rubber or coconuts.

Finally, models must consider key management practices. The most intensive management is undertaken during the establishment phase, which involves clearing and windrowing (sometimes burning) the existing vegetation, and forming of roads, drains and terraces. Considerable amounts of soil and surface organic matter can be eroded during this phase. The fields are then planted with palms and legume cover crop. The main materials applied are fertiliser (mostly urea or ammonium-based fertilisers and potassium chloride), the palm oil mill by-products–empty fruit bunches (especially around young palms and in fields close to the mill), liquid effluent and increasingly compost, and herbicides (to the harvest paths and weeded circles). Fruit bunches are removed in regular harvests, and old fronds are pruned regularly and placed in heaps between planting rows.

3 Integrated environmental impact modelling approaches

The main approach to quantifying all environmental impacts of the production of a particular agricultural product such as palm oil is life cycle assessment (LCA) (Fig. 4). LCA is, in a sense, an integrated model of environmental impacts, so we discuss it here. As for dynamic process-based models, ‘earth system models’ are in principle the most integrated. However, earth system models tend to focus on the atmosphere and do not yet incorporate many of the processes that are important in agricultural systems. Models that do so can be classified as ‘agricultural (eco)system’ models, ‘catchment process’ models or ‘ecological’ models. All these integrated approaches incorporate or couple

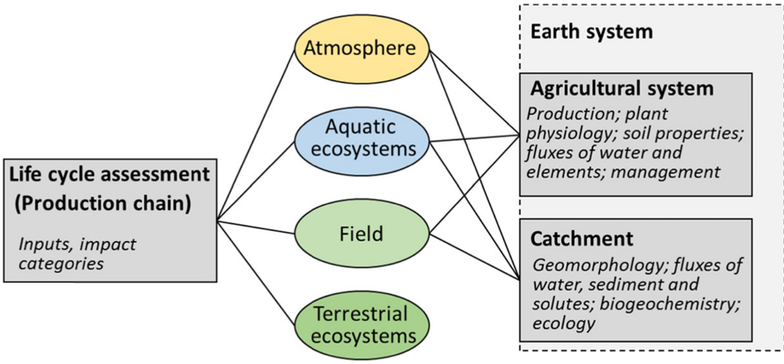

Figure 4 Integrated biophysical modelling of environmental impacts of agriculture can be categorised into different approaches: life cycle assessment on the one hand, or dynamic process-based modelling of the earth system, agricultural systems or catchment processes on the other. Boxes represent typical system boundaries and modelling focus, and lines represent the principal environmental impacts modelled.

simpler models, which we discuss further in subsequent sections. Ecological models tend to focus on the surrounding terrestrial ecosystems or the field itself so we also discuss them later.

The challenge of integrating diverse data types, approaches and models increases even more if social dimensions are included (Granell et al., 2013). Examples include the SEAMLESS and Forest Land Oriented Resource Envisioning System (FLORES) projects. The SEAMLESS modelling project, developed in Europe using the MODCOM framework, is designed to facilitate development of policy (Brouwer and Ittersum, 2010; Ewert et al., 2011). Agricultural systems are simulated using its Agricultural Production and Externalities Simulator (APES) approach (Donatelli et al., 2010). The FLORES model also analyses complex spatial, environmental and social processes (Vanclay et al., 2003). FLORES was developed within the SIMILE graphical modelling environment (Muetzelfeldt and Massheder, 2003) to assist in model development and transparency. Within FLORES, land use decisions are made by ‘actors’ who can be individuals or groups of individuals who collaborate as families, clans, associations and corporations. These actors can make decisions to maximise benefits or minimise risks. Outputs are calculated from models within a spatial context, allowing users to explore impacts at a landscape scale. Socio-ecological systems have a high degree of uncertainty, so they lend themselves to modelling approaches based on probability and expert judgement, such as Bayesian networks (Ropero et al. 2016).

3.1 Life cycle assessment

LCA involves assessment of a suite of environmental impacts throughout the commodity chain, from raw material production to end-of-life of the product or service, with respect to a functional unit (e.g. 1 kg of palm oil). As LCA assesses environmental performance across multiple impacts, such as climate change, acidification and ozone layer destruction, the weightings can be documented and trade-offs assessed. LCA has become a worldwide standard method (ISO 14040 series 2000–2006) for reporting on environmental impacts of production, and is the baseline modelling approach of various greenhouse gas (GHG) inventory guidelines (IPCC, 2006; European Commission, 2009).

LCA of oil palm products enables assessment of palm cultivation together with other parts of the production chain. It also facilitates comparisons between production of palm oil and alternatives (Schmidt, 2015). While palm oil generally performs worse than other oil crops on climate change impact, due in particular to land use change from high carbon stock systems, it performs better than rapeseed oil regarding eutrophication, acidification, ozone depletion and photochemical ozone impacts (Schmidt, 2010).

About 70 full or partial LCAs of palm oil products have been published over the last decade. Most of the published studies were on palm oil as biofuel, and focused on GHG emissions (or climate change impact) and energy balance (or fossil resource depletion) (Bessou et al., 2013; Manik and Halog, 2013). They mostly assessed the life cycle for palm methyl ester or biodiesel, that is, including all processes from background input production (e.g. fertiliser manufacture) up to the vehicle tank, assuming total combustion or including engine efficiency, to calculate final energy and GHG indicators.

Palm oil LCAs have indicated that the agricultural phase is the main contributor to most of the impact, except for human toxicity or respiratory impacts, to which boiler emissions are the main contributor (Stichnothe and Schuchardt, 2011). Climate change impact is strongly influenced by fertilisers, especially nitrogen fertilisers, and also by carbon stock

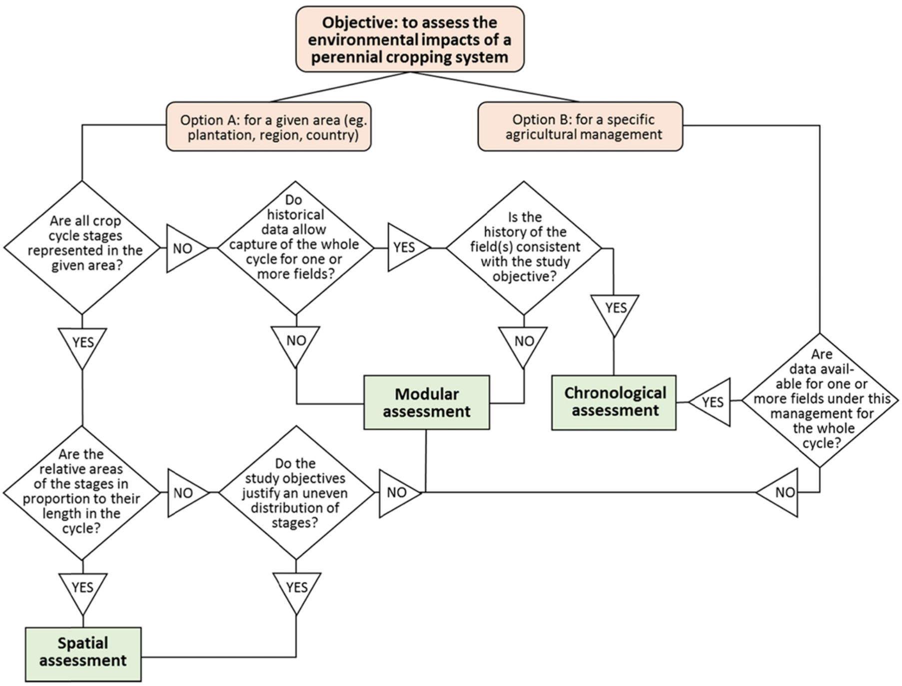

Figure 5 Decision tree for life cycle assessment of a perennial crop system. 'Field' means a unit of plantation with a unique and homogenous planting date, genotype, climate and soil type. 'Crop cycle stages' generally encompass immature phase, most productive phase and declining production phase. From Bessou et al. (2013).

changes in case of land use change or peat drainage (Bessou et al., 2014). Eutrophication impact is driven by nitrogen- and phosphorus-compound emissions, although mill emissions can also contribute. The main eutrophication factors at the agricultural stage are nitrate leaching, and phosphorus and nitrate run-off. The acidification and photochemical ozone impact categories are also influenced by fertilisers, especially due to their influence on nitrogen compound emissions. The largest uncertainties relate to cultivation of peat and emissions of N_2O (Schmidt, 2015).

Impacts originating outside the field are also influenced by in-field management practices, in particular the use of fertiliser. Significant GHG emissions are generated in the production of nitrogen fertiliser (10–30% of total emissions from fertilisers, compared to 70–90% generated in the field), in palm oil mill effluent treatment ponds, especially CH_4 (Wicke et al., 2008; Bessou et al., 2014). Emission factors for the manufacture and transport of inputs are usually taken from databases such as ecoinvent (Nemecek and Kägi, 2007, http://esu-services.ch/data/ecoinvent/).

LCA uses various process models to evaluate impacts, and these are discussed below. Nitrogen management is critical for several impact categories. Perennial cropping systems can be evaluated in different ways, depending on the objectives and the data available (Fig. 5).

Several LCA impact indicators remain to be more widely explored in palm oil production systems. Given the large contribution of fertilisers to environmental impact of the agricultural phase, the eutrophication and acidification impacts related to nitrogen and phosphate inputs need to be further investigated. Other indicators that are little studied include the impacts of herbicides on terrestrial or freshwater ecotoxicity, and the impact of irrigation systems on water depletion.

3.2 Earth system modelling

Earth system models generally focus on the atmosphere and climate, but are increasingly including soil–plant–atmosphere and catchment processes (e.g. Krinner et al., 2005; Fatichi et al., 2012a,b; Oleson et al., 2013; Shen et al., 2013). For example, the Community Earth System Model (CESM) models climate together with land use, vegetation and catchment processes in its Community Land Model (CLM) component (Hurrell et al., 2013; Oleson et al., 2013). A palm growth module incorporating carbon and water cycling was recently developed for the CESM and tested on oil palm (Fan et al., 2015).

Integrating process-based models to larger scales involves a range of challenges. Such integration is aided by software platforms that facilitate data exchange between models while maintaining model transparency for developers and users. For example, The Invisible Modelling Environment (TIME) (Rahman et al., 2003) uses the features of modern software techniques (Rahman et al., 2004) to simplify the communications interface between model components within its spatial modelling framework for issues such as catchment hydrology.

3.3 Agricultural system modelling

Dynamic agricultural system models provide a means for exploring environmental impacts related to water, carbon and nutrient cycles and agrochemicals, especially where several drivers of the system may interact in complex ways. A series of dynamic simulation models are used extensively around the globe for various cropping systems. Examples include Decision Support System for Agrotechnology Transfer (DSSAT-CSM) (Jones et al., 2003), CropSyst (Stockle et al., 2003), Simulateur mulTIdisciplinaire pour les Cultures Standard (STICS) (Brisson et al., 2003), APES (Donatelli et al., 2010) and Agricultural Production Systems Simulator (APSIM) (Holzworth et al., 2014).

These agricultural system models have been developed over several decades to capture an increasing number of environmental interactions. This development involved a shift of focus from the crop to the soil resource base and the cropping system. The shift allowed individual crops to come and go, finding the soil in one state and leaving it in another (McCown et al., 1995). This move towards a stronger focus on soils was a major step from plant models to environmental impact models and application to more complex systems, including perennial crops.

New applications required the modelling of crop management decisions (Moore et al., 2014). These capabilities also allowed the inclusion of livestock models, and simulations of farms with multiple fields (Holzworth et al., 2014). This journey has seen a change in focus such that model use was no longer aimed just at research, but also for management of production systems and exploration of options for farming systems at various scales (van Ittersum and Donatelli, 2003).

The APSIM model (Holzworth et al., 2014) is an example of a modern integrated environmental model that has been applied to oil palm systems. APSIM is developed and maintained within the APSIM community source framework, which provides a freely available open source platform for collaborative development. The software design allows models from different modelling teams and problem domains to be integrated within a single modelling environment. Furthermore, the framework includes software and processes, such as the APSIM Plant Modelling Framework (Brown et al., 2014), that assist in the development of new models.

The APSIM-Oil Palm model (Huth et al., 2014) was developed to communicate with previously developed and tested models for water, nitrogen and carbon cycling (Probert et al., 1998), GHG emissions (Thorburn et al., 2010), surface organic matter dynamics (Probert et al., 1998; Probert et al., 2005) and agricultural management (Moore et al., 2014), in one dimension. The addition of an oil palm model within existing model capabilities improved model reliability and facilitated the capturing of complex environmental issues. For example, soil carbon stocks and nitrogen losses (leaching of nitrate and gaseous emission of N_2O), along with fruit production, can be estimated in a dynamic manner, taking into account soil type, climate and management (Fig. 6). This capacity allows trade-offs between production and environmental impacts to be assessed (Pardon et al., 2017). APSIM-Oil Palm has been validated for growth and yield at several sites (Huth et al., 2014).

Another agricultural system model that has been applied to oil palm is WaNuLCAS (Noordwijk et al., 2011), which used a different approach to the APSIM-Oil Palm model. WaNuLCAS was formulated within the STELLA graphical modelling environment. Development of the oil palm module benefitted from the group's experience in modelling agroforestry systems. WaNuLCAS focuses on interactions between crop species and can incorporate lateral variability in the form of up to four zones.

Adding complexity to dynamic simulation models comes with costs associated with increased data requirements and calibration error, and decreased ease of use and model transparency (Soltani and Sinclair, 2015). Many of these concerns are now being addressed using modern modelling and software engineering processes that ensure model integrity during ongoing development (Holzworth et al., 2011), encourage collaboration by simplifying model reuse (Holzworth et al., 2010) and assist model accessibility and

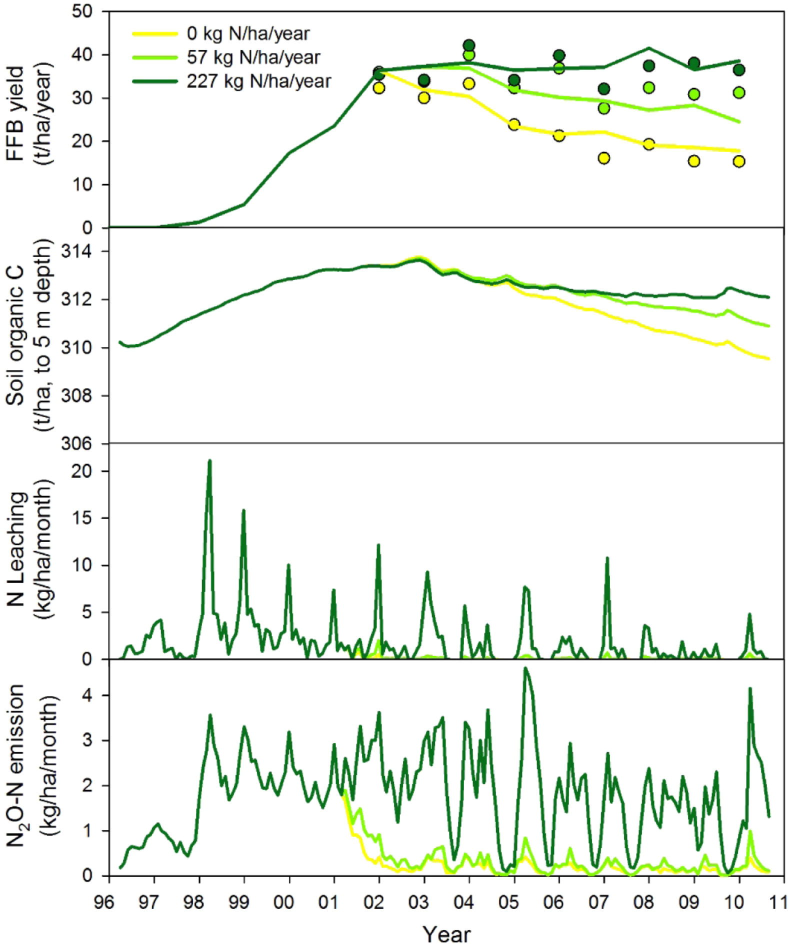

Figure 6 Measured fresh fruit bunch (FFB) yield (points), modelled yield, soil C stock, N leaching and N_2O emission (lines) of oil palm at three nitrogen fertiliser rates, over the course of a crop cycle in Sangara, Papua New Guinea. Modelling was carried out using the agricultural system model APSIM-Oil Palm.

transparency through well-designed user interfaces and automated documentation (Dietze et al., 2011; Brown et al., 2014).

3.4 Catchment process modelling

Catchment (or 'drainage basin' or 'watershed') process models are important tools for examining environmental impacts related to movement water and solutes (e.g. nutrients and pesticides) and erosion of soil. These processes directly impact on conditions of the field, groundwater and downstream aquatic ecosystems. These models couple hydrological models with sediment and solute/contaminant models, and in some cases biogeochemical and ecological models.

The hydrology of oil palm plantations differs to that of other vegetation types, and changes through the crop cycle. Hydrological changes are particularly large during establishment, due to clearing of vegetation, use of heavy machinery, compaction, loosening and creation of bare areas during formation of terraces and roads. Changes are also large, although less dramatic, during the immature phase, when palm canopies and root systems are growing. The presence of roads and oil palm waste from factories and human settlements in plantations also contribute to water quality degradation in these areas (Comte et al., 2012).

Physically based catchment-scale models are 'distributed', dividing the catchment into elements. This distribution is discussed below, in the discussion of the underlying hydrological models. A variety of integrated catchment models have been developed and used (Table 1), and the field is rapidly developing (Robson, 2014a; Paniconi and Putti, 2015). Most of the models do not consider redistribution of soil within the landscape, although some do like LandSoil (Ciampalini et al., 2012).

An integrated surface water and groundwater model such as MIKE SHE/MIKE 11 simulates the major hydrological processes at different levels of spatial distribution and complexity within the catchment. Groundwater, surface water, recharge and evapotranspiration are represented by MIKE SHE, whereas channel flow is represented by the MIKE 11 component of the model. The model also predicts solute transport in the unsaturated and saturated zones. This involves modelling advection and dispersion of solutes in the unsaturated and saturated zone, sorption and desorption processes, erosion and sediment transport (coupled with a sediment transport model), geochemistry reactions for groundwater transport (Geochemistry module) and agricultural applications such as crop yield and nitrogen consumption (MIKE SHE DAISY module).

Complex process-based catchment models such as MIKE SHE require large amounts of data, which is often not available, so simpler catchment models are often used. For example, the SedNet/ANNEX model, developed for catchments of the Great Barrier Reef in Australia, models flux of sediment, N, P and herbicides using a modular empirically based approach (McKergow et al., 2005; Waters et al., 2014; Wilkinson et al., 2014). Sediment sources are apportioned to hill slope erosion (using the Revised Universal Soil Loss Equation, RUSLE), gully erosion and stream bank erosion, and solutes are apportioned to point and diffuse dissolved sources. Budgets are calculated for subcatchments and stream links. SedNet/ANNEX is being used to model the effects of changed agricultural management practices on pollutant loads (Hateley et al., 2014).

So far, published literature on hydrological and solute/sediment modelling of oil palm plantations are few and limited to hydrological impacts. Modelled oil palm run-off yields have been compared with tropical rainforest run-off yields using the HEC-HMS model (Yusop et al., 2007). The Soil and Water Assessment Tool model (SWAT) was used to model run-off yield changes in oil palm at different stages of growth (Majid and Rusli, 2014) and to compare run-off with other biofuel crops (Babel et al., 2011). Integrated hydrological and sediment/solute models such as SWAT and MIKE/SHE provide opportunities to better understand the hydrological and water quality impacts of oil palm plantations, and there is potential to couple them with agricultural system models such as APSIM to model impacts of different management practices.

Table 1 Commonly used field-to-catchment-scale erosion and coupled hydrological sediment/solute models

Model	Spatial scale	Process representation	Spatial representation	Temporal scale	Water quality[1]	GIS[2]	Comments
RUSLE2	Plot	Empirical	Lumped	Annual	S		Improved version of the USLE
WEPP	Catchment	Physical	Distributed	Continuous	S	✓	GIS version (GEOWEPP)
EUROSEM	Field + small catchment	Conceptual	Distributed	Event	S		Linked to hydrological models; KINEROS and MIKE SHE
SHESED	Catchment	Physical	Distributed	Continuous	S		Linked to SHE model (MIKE SHE)
EPI C/APEX	Field	Empirical	Distributed	Continuous	SNP		APEX is the updated version of EPIC
AGNPS/ AnnAGNPS	Catchment	Physical	Lumped/Distributed	Event-based/ Continuous	SNP	✓	Includes stream routing, stream temperature and so on
ANSWERS	Small catchment (<100 km^2)	Physical	Distributed	Continuous	SN	✓	
CREAMS	Field	Physical	Lumped	Continuous	SNP		And GLEAMS (groundwater version)
SWAT	Small to large catchments	Physical	Distributed	Continuous	SNP	✓	Also includes capability for water quality parameters such as DO, BOD, pathogens. Can be linked to MODFLOW for surface groundwater modelling
MIKE SHE/ MIKE 11	Small to medium-sized (up to 5000 km^2)	Physical	Distributed	Continuous	SNP	✓	See text

S= sediment, N=nutrients, P=pesticides.
GIS = geographic information system-based.

4 Modelling impacts of cultivation on components of the environment

Integrated environmental impact models usually couple models focused on particular components of the environment (Fig. 7). Concerns about climate change have driven development of increasingly comprehensive and sophisticated models of atmospheric impacts, highly integrated in terms of the processes modelled. Modelling of impacts on aquatic ecosystems, surrounding terrestrial ecosystems and the field itself is not so developed, but our understanding of the processes is rapidly improving.

4.1 Modelling impacts on the atmosphere

Atmospheric impacts are felt via the net emission of the greenhouse gases CO_2, N_2O and CH_4; ozone; and haze-causing volatile organic compounds, smoke, dust and other particulates. Here, we do not consider ozone or haze, which originates mostly from burning during forest clearing, but focus on GHGs. Atmospheric impacts are modelled so as to better understand effects on climate. Conversion of land to agriculture may directly influence climate through decreased evapotranspiration and hence reduced rainfall. However, this effect is unlikely to be significant with oil palm because its transpiration rate is similar to intact forest (Henson, 1994), so the main concerns are related to GHG emissions.

To meet the requirements of the United Nations Framework Convention on Climate Change (UNFCCC) treaty, countries must report their annual GHG emissions. That accounting is based on the Intergovernmental Panel on Climate Change (IPCC) methods and thus involves various models. Most of the countries with an oil palm industry are classed

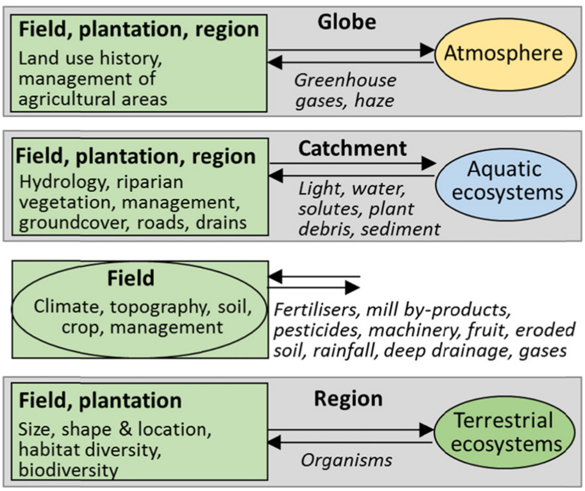

Figure 7 Modelling may simulate processes impacting upon a particular component of the environment (ellipses). That involves different system boundaries and characteristics (rectangles) and different types of exchanges (arrows and italic labels).

as developing economies and are given special status under the treaty as 'non-annex' parties. Nevertheless, palm oil producing countries such as Indonesia and Malaysia are developing carbon accounting procedures (INCAS and MYCarbon, respectively).

Parallel to, and sometimes contributing to, the development of global accounting systems, numerous process-based models have also been developed to simulate effects of land use on the atmosphere. The global earth system models have been compared in the Climate Modelling Intercomparison Project Phase 5 (CMIP5) and reviewed in the fifth Assessment Report of the IPCC (Flato et al., 2013). In some cases they assess management practices as well as land use, by incorporating various crop system, carbon and nitrogen models, discussed in subsequent sections.

GHG emissions are usually modelled using the guidelines of the IPCC (IPCC, 2003, 2006, 2014). The IPCC approach offers several methodological approaches, which differ in complexity. The 'Tier 1' methodology, the one most commonly employed in oil palm LCAs, uses a coarse spatial scale for land use, specified emission factors and a specified timeframe for amortisation if land use changes, that is, an empirical linear model. 'Tier 2' involves locally relevant emission factors, and 'Tier 3' methods involve the use of more sophisticated models (discussed in Section 5, under carbon and nitrogen models), if data are available.

The two main considerations in GHG emission models are whether or not land use change is incorporated and whether cultivation occurs on drained peat soils or mineral soils. Net CO_2 and N_2O emission take place when there is a net decrease in organic matter in the soil–plant system, which occurs most dramatically where oil palm replaces vegetation with higher biomass and net primary production, such as forest, or when it is established on peat soils. The amount of carbon in above-ground biomass is about 3–10 t ha^{-1} in annual crops and grasslands, 37–42 t ha^{-1} in oil palm (average over cycle) and 50–300 t ha^{-1} in tropical forests (Lewis et al., 2013; Lucey et al., 2014; Khasanah et al., 2015a). Establishment on peat entails drainage, which results in net mineralisation of the peat and release of huge quantities of CO_2. On the other hand, there is net sequestration of CO_2 when oil palm replaces vegetation with lower net primary production, such as grassland (Goodrick et al., 2015).

The effects of land use change on GHG emissions have been modelled in different ways. Some studies that do not model it directly nevertheless provide information on the 'carbon debt' or 'payback time'. This carbon debt, initially developed in the context of bioenergy, considers the time needed for a bioenergy value chain to compensate for the initial land use change-related GHG emissions, given its GHG savings compared to the fossil equivalent (Fargione et al., 2008; Gibbs et al., 2008). It ranges from 8 to 169 years for palm biodiesel, with mean and median values of 54 and 43 years, respectively (Fargione et al., 2008; Wicke et al., 2008; Pleanjai et al., 2009; Achten et al., 2010; de Souza et al., 2010; Harsono et al., 2012). The type of previous land use can determine the final GHG balance.

The IPCC approach to modelling effects of land use change assumes that the net flux of CO_2 to the atmosphere equals the difference between the original stock of carbon in biomass and soil and the stock in the new land use. The first-order approximation (Tiers 1 and 2) is to multiply the original stock, which depends on soil and climate type, by 'emission factors' specific to the type of land use and land management. The method operates on the annual time scale required for national reporting of GHG emissions, but measurements or estimates might be done less frequently. There are additional guidelines for calculating N_2O and CH_4 emissions.

GHG emissions from conversion of peatlands to plantations consist of both CO_2 and N_2O emissions, due to the large amounts of organic carbon and nitrogen that are microbially mineralised when oxygen enters the drained peat. Changes in aeration may also affect methanogenic processes. The IPCC provided guidelines for modelling emissions of GHGs from converted peats and other wetlands in its 2013 supplement (IPCC, 2014). There is a linear relationship between water table depth and carbon loss from drained peats, although other factors are also important (Carlson et al., 2015).

After land use change, the second largest contributor to GHG emissions are N_2O emissions. They are largely related to nitrogen inputs to the soil–plant system, especially fertiliser. For emission of N_2O unrelated to land use change, the IPCC (2006) provides Tier 1 factors for 'direct emissions' from the field and 'indirect emissions', which occur elsewhere, after the nitrogen has left the field. For direct emissions the factor of 1% is multiplied by the amount of nitrogen applied in fertiliser or crop residues. The same emission factor is applied irrespective of soil type or other factors. This emission factor was derived from a statistical analysis based on several hundreds of field measurements across the world and it hides large variability in practices and emissions.

However, tropical and perennial crops were poorly represented within the field measurements used for the statistical analysis (Bouwman et al., 2002a,b; Stehfest and Bouwman, 2006), so the factor does not take into account important characteristics of perennial cropping systems such as oil palm (Bessou et al., 2013; Pardon et al., 2016a).

For indirect N_2O emissions the factors are modified to account for nitrogen lost from the field via volatilisation and leaching. The proportion of nitrogen volatilised is set at 10% for synthetic fertiliser and 20% for organic fertiliser. The proportion of nitrogen leached is set at 30% unless specific conditions of water stress or precise irrigation can be demonstrated. The indirect N_2O emissions from these sources are then calculated as 0.75% of the leached nitrogen and 1% of the volatilised nitrogen.

In PalmGHG, a GHG calculator designed especially for the oil palm system, GHG emissions are calculated along the value chain according to the LCA approach, that is, emissions from fertiliser production and transport, land use change and peat drainage, field and mill fuel and electricity use, fertiliser application and palm oil mill effluent (Chase et al., 2012; Bessou et al., 2014). Land use change and fertiliser application-related emissions, as well as N_2O emissions from peat drainage, are calculated based on the IPCC Tier 1 method. In contrast, CO_2 emission from peat drainage is based on an emission factor related to the water table level (Hooijer et al., 2010), which allows more sensitivity to drainage practices than the IPCC Tier 1 method.

Although we focus here on the effects of oil palm cultivation, it is worth briefly mentioning other atmospheric impacts in the palm oil production chain. The impact of palm oil mill effluent treatment on the overall GHG emissions has been investigated by several authors (Yacob et al., 2005; Vijaya et al., 2009; Basri et al., 2010). Methane emissions vary greatly depending on seasonal variations in fruit quality and technical features of mill operations and ponds. GHG assessments mostly rely on derived emission factors based on a few published studies (Yacob et al., 2005; Schmidt, 2007). Based on UNFCCC equations, methane emissions may also be derived from on-site measurements of the chemical oxygen demand reduction during treatment. Considerable emphasis has been placed on reducing these emissions by capturing the biogas at the mill (Choo et al., 2011; Harsono et al., 2014) or by using raw or partially treated effluent in the composting process (Singh et al., 2010; Stichnothe and Schuchardt, 2010).

The impact of fossil fuel use is generally not significant, being 0–5% and 0–2% of total emissions at the field and mill levels, respectively (Bessou et al., 2014). This low impact is due to a low level of mechanisation in the plantations and the use of mill by-products for generating heat and electricity. Most field fuel use is dedicated to fruit transport from plantations to the mill, and its relative contribution varies according to logistics and geography. The high ratio of energy output:input in oil palm systems is matched by very few other agricultural systems (Henson, 1994).

4.2 Modelling impacts on aquatic ecosystems

Impacts on aquatic ecosystems are challenging to model because they involve a complex of processes and events that occur in both nearby and remote ecosystems (Robson, 2014a; Davis et al., 2017). They are influenced by conditions and activities upstream, which are moderated by normal stream discharge and flood events. They are also influenced by connectivity to downstream ecosystems and the marine environment via the migrations of fish and invertebrates up- and downstream. These biological and physical connections between aquatic systems need to be considered before impacts from surrounding terrestrial environments can be modelled.

The riparian zone along the banks of watercourses directly influences the physical characteristics of streams. Natural riparian zones are generally heavily vegetated, due to reliable water supply, and they provide many key services to aquatic ecosystems (Fig. 8), so maintaining their biodiversity and biomass is critical to maintaining near-natural functioning of streams in oil palm landscapes (Singh et al., 2015). Riparian vegetation modifies the flow of water from the land to produce a complex of abiotic and biotic outcomes (Gurnell et al., 2012; Zhang et al., 2012). Sediment and nutrient transport and their delivery to streams are modified (Cooper et al., 1987; Zhang et al., 2003), and plant root systems help bind stream banks and reduce erosion (Kui et al., 2014). The shade provided by overhanging vegetation acts as a major moderator of stream temperature (Moore et al., 2005; Kristensen et al., 2013) and influences the pattern of light and temperature in the water column, which in turn increases in-stream habitat diversity (Naiman et al., 1993) by producing a mosaic of water conditions.

Riparian vegetation also provides vital sources of food and habitat for in-stream fauna via detritus, fruit and insects that fall into streams (Gregory et al., 1991) and through

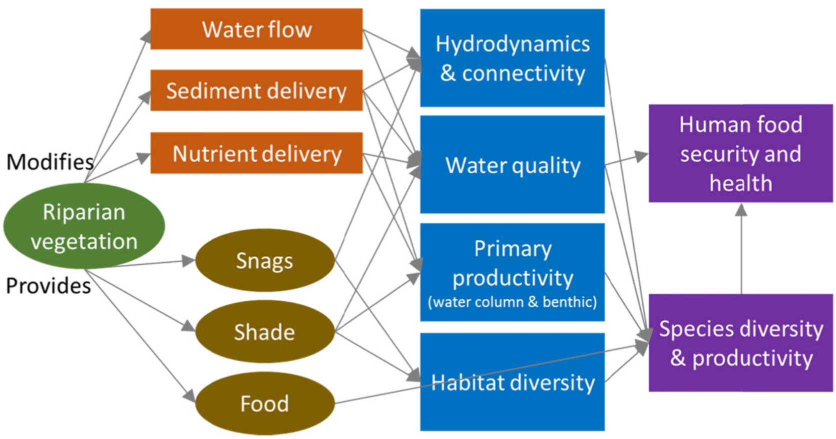

Figure 8 Summary of the services provided by riparian zones to aquatic ecosystems.

the feeding migrations of aquatic fauna into riparian areas during overbank flooding (Welcomme, 1988; De Graaf, 2003). This provision of food helps support high faunal diversity (Gregory et al., 1991). Fallen trees from the riparian zone are vital contributors to in-stream structure (Acuña et al., 2013), substantially enhancing the health and diversity of stream ecosystems (Boyer, 2003). Fallen timber provides structural complexity in streams (Caddy, 2008) and furnishes vital habitat for structure-dependent species (Sheaves, 1996; Valente-Neto et al., 2015), and traps and retains detritus in high-flow streams (Wantzen and Junk, 2000).

While intact and sufficient riparian buffer zones are critical to isolating aquatic systems from many of the impacts of oil palm, their value is circumvented where they are too damaged or narrow to be effective (Singh et al., 2015), or where drains flow directly to streams from plantation mill effluent outfall systems. Similarly, their value is reduced where drainage works lead to the loss of swamps, peatlands and ephemeral wetlands (Anderson, 2008; Comte et al., 2012).

While there have been relatively few investigations of physical processes specific to the oil palm–aquatic ecosystem link, individual physical processes have been quantified in particular locations. For instance, Carlson et al. (2014, 2015) showed that some streams draining oil palm plantations have elevated temperatures and increased total suspended solids concentrations. Such quantitative data are amenable to modelling, at least on a parameter-by-parameter basis. However, such results are likely to be very site- and situation-specific (Chew and Goh, 2015), limiting the value of any models constructed.

Most quantitative models of physical processes that are relevant to the oil palm–aquatic ecosystem situation have been developed in other systems or other parts of the world. Where oil palm-specific studies have been conducted, the majority have been at the local scale (Comte et al., 2012), with a few studies conducted at a watershed scale (but see Yusop et al., 2008 for an example of a small-scale watershed study). Relevant studies generally focus on the volume and quality of water moving into surface water bodies and the physico-chemical nature of those water bodies (e.g. Comte et al., 2012).

Modelling becomes more complex with movement away from simple parameter-by-parameter models to more realistic modes that include the diverse interactions among physical processes, and between physical and biological factors (Robson, 2014a,b; Janssen et al., 2015). Examples of these interactions include the simple effect of riparian vegetation shading on water temperature (Moore et al., 2005; Kristensen et al., 2013), and the impact of converting riparian zones from natural forest to oil palm on surface hydrology, which in turn changes the type and amount of sediment, woody debris and terrestrial-derived food (insects, fruit, leaves) and nutrients entering aquatic food webs (Bruijnzeel, 2004; Comte et al., 2012). This complexity is exacerbated by substantial and unquantified spatio-temporal variation (Comte et al., 2012; Chew and Goh, 2015).

Biological understanding of the effect of oil palm on aquatic ecosystems is in its infancy. There have been studies of impacts on aquatic insects in Malaysian rainforest streams (Mercer et al., 2014) and fish in Papua New Guinea (Nelson et al., 2010b), but little or no generalisation across oil palm areas. Therefore, ecological models of the relationship between oil palm cultivation and aquatic environments are qualitative and mostly based on studies from other parts of the world. Although tropical systems are unique in many respects (Gupta, 2011), most of the broader ecological understanding of streams and their riparian zones probably still applies (Boulton et al., 2008). Holistic models are needed that take into account characteristics of the environment, characteristics of the oil palm, the human dimension and management practices.

There are aquatic ecosystem impacts of palm oil production other than those resulting from cultivation practices. They include direct impacts, such as degraded water quality at mill outfalls and eutrophication in streams resulting from excess nutrient inputs, and less direct effects such as road crossings and gravel extraction for road building, which can greatly increase turbidity in streams.

These impacts reduce the habitat quality of streams for key parameters such as turbidity (Henley et al., 2000) and dissolved oxygen (Wannamaker and Rice, 2000). Other indirect impacts stem from the food and space requirements of local human populations, which are increased by oil palm developments. These impacts are manifested in harvesting of edible aquatic organisms and clearing of riparian zones for cropping.

To effectively model the impacts of oil palm cultivation on aquatic ecosystems it is critical that more extensive, more spatially representative and more holistic data are amassed. Developing empirical models without substantive underpinning data is dangerous because there is no way to understand either sources of error or spatio-temporal variability (Harris and Heathwaite, 2012) or identify tractable components of the causal thicket underpinning outcomes (Levin and Stunz, 2005). In the data-poor meantime, probability-based models show promise for modelling some impacts on aquatic ecosystems (Death et al., 2015).

4.3 Modelling impacts on surrounding terrestrial ecosystems

Oil palm plantations influence the ecology of nearby terrestrial ecosystems, mainly through their effects on populations and movement of organisms (Fig. 1). The degree of effect is related to the relative size and positions of plantations, natural areas and human activity (Foster et al., 2011), which determine size, quality and connectivity of habitat. There is much debate about how conservation and agricultural productivity can be optimised within landscapes (Sayer et al., 2012). Modelling of the interactions suggests that fewer more contiguous areas of oil palm and natural vegetation have a less detrimental effect on biodiversity than finer-scale mosaics of agricultural land and natural habitat (Phalan et al., 2011; Lee et al., 2014).

At a global level, several conceptual models have been proposed to understand the nature of these types of interactions (Tscharntke et al., 2012). It is clear that effects differ between types of organisms (Phalan et al., 2011; Newbold et al., 2014). Such modelling should also include the effects of increased human populations associated (directly or not) with oil palm developments, especially their hunting, fishing and clearing of surrounding forest for food crop cultivation.

Oil palm plantations can also affect nearby terrestrial ecosystems via their effect on movement of groundwater and gases. Lowering of the water table with drains in low-lying plantations can lower the water table in neighbouring ecosystems, but mitigation of the effects using dams is possible. The effects can be modelled using standard hydrology models (Jaenicke et al., 2010), but the high permeability of peat must be taken into account (Baird et al., 2017). Concern has also been raised that terrestrial ecosystems downwind of oil palm plantations might be adversely affected by ozone produced by the reaction of N_2O and volatile organic compounds produced in the plantations (Hewitt et al., 2009).

4.4 Modelling impacts on in-field environmental quality

In-field environmental quality can be described as the abundance, diversity and nature of organisms (above- and below-ground) and the physico-chemical condition of the soil. High quality can be defined as soil conditions and organisms that are conducive to abundant and diverse plant growth and have no negative impact on other components of the environment (Fig. 9). There are no models that integrate all the effects of agricultural management on in-field environmental quality, but there are many modelling approaches for various processes.

As for all agricultural systems, oil palm plantations have less biodiversity than the natural systems they have replaced. Species richness and biomass at all trophic levels is lower than primary forest due to lower net primary productivity and plant diversity (Henson, 1994; Sayer et al., 2012; Barnes et al., 2014). Empirical modelling of bird, beetle and ant populations showed that the larger-bodied species of higher trophic levels are most reduced in oil palm compared to forest, whereas the relatively few species that are more abundant in plantations tend to be smaller and from lower trophic levels (Senior et al., 2013). However, ant populations and species numbers are also much reduced (Fayle et al., 2010).

The abundance and diversity of organisms are determined by energy inputs and habitat. For above-ground organisms, such as insects and arthropods, habitat diversity within the plantation, especially epiphytes and groundcover, appears to be a significant driver of diversity (Koh, 2008; Fayle et al., 2013). The amount and proximity of natural forest in the surrounding landscape is important for more mobile organisms like butterflies, birds and mammals (Koh, 2008; Jennings et al., 2015; Prescott et al., 2016). The ecology and management of weeds, pests and diseases, which is much better studied, is discussed further in this book.

Abundance and diversity of soil organisms are determined by inputs of plant residues and physico-chemical properties of the soil (Carron et al., 2015a,b, 2016; Wakelin et al.,

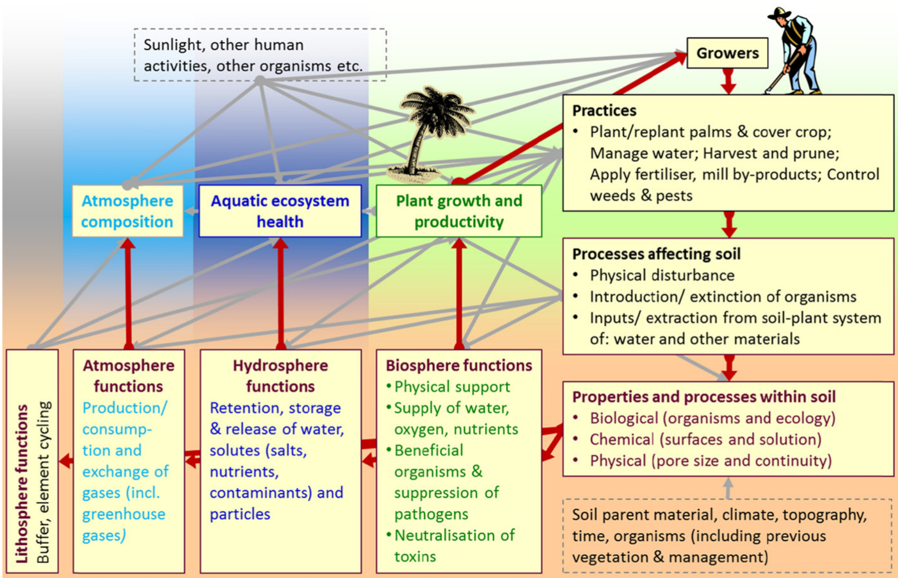

Figure 9 Key interactions (dark red arrows) between oil palm growers, cultivation practices, soil properties and soil functions. Soil is the place where there is a maximum degree of interaction between the lithosphere, hydrosphere, atmosphere and biosphere.

2016). Soil physico-chemical condition can be quantified by fairly stable properties such as texture and mineralogy, and by more dynamic characteristics such as the organic matter content, pH, structure and content of toxic contaminants. Soil organic matter (or carbon) content, accumulation of pesticides and other toxic materials and erosion are discussed in other sections, so here we focus on soil structure and pH. Measurements of soil condition in oil palm plantations must take into account the large spatio-temporal variability inherent in them, and methods are now available to do that efficiently (Nelson et al., 2015a).

Soil structure is enhanced by the faunal activity associated with high inputs of organic matter and is degraded by erosion and compaction. Compaction processes have been modelled but the models have limited applicability in complex heterogeneous systems (Hamza and Anderson, 2005), and simple, well-known empirical relationships can be applied to management. Compaction and sealing can be minimised by minimising the number of passes by machinery; reducing pressure on soil either by decreasing axle load and/or increasing the contact area of wheels with the soil; confining traffic to fixed tracks (using uniform axle widths); and maximising plant growth, including groundcover, and inputs of residues.

Soil pH tends to decline naturally in wet climates but the decline can be accelerated by agricultural management practices. Oil palm is tolerant to low pH, and the associated high availability of aluminium and low availability of calcium, magnesium and potassium. Therefore, accelerated acidification is not necessarily noticed or of concern in oil palm plantations. Nevertheless, it can be considered a detrimental environmental impact. The main drivers of soil acidification in oil palm are nitrate leaching and the off-take of non-acidic cations in harvested fruit (Kee et al., 1995; Nelson et al., 2010a; Dubos et al., 2016). Crop system models simulate these processes, so they are potentially useful for modelling soil acidification (Nelson et al., 2015b).

5 Modelling causal processes

Environmental impact models are based on models of causal processes. Energy enters the field as light, which is used to convert CO_2 and water to organic compounds, and eventually dissipates as heat. Energy transfer processes are discussed in the sections on crop growth models and carbon models. Energy also enters the field in the form of potential energy in water, which is mostly converted to kinetic energy (movement) of water. The water cycle and the associated movement of solutes and soil particles (erosion) are discussed in the section on hydrology models. Apart from carbon and water, a material of particular environmental interest is nitrogen, which is discussed in the section on nitrogen models. Finally, the input of pesticides has particular environmental interest.

Models of elements with less environmental impact than carbon or nitrogen are not considered here, although a range of other elements may be environmentally significant. For example, phosphorus is important in terms of resource depletion and eutrophication (Robson, 2014b), but it tends not to be a major environmental problem in oil palm growing areas, partly because tropical soils tend to have high phosphate retention capacity and also because the amounts of phosphorus fertiliser applied are relatively small. Potassium and chloride are important for oil palm because the quantities taken up are similar to nitrogen. Potassium and chloride have little direct environmental impact, but modelling their cycling in oil palm systems may become important in the future because of their large effect on palm growth.

5.1 Crop growth models

Crop models are not directly focused on environmental impacts, but can be used as a component of integrated models. Early development of OPSIM, an oil palm growth model (van Kraalingen et al., 1989), provided a model of photosynthesis, growth of organs and canopy development, and how these responded to climate and basic management actions such as planting population. After a conspicuously long delay compared to other agricultural domains, other models were developed to capture a wider range of impacts.

Models such as OPRODSIM (Henson et al., 2007), ECOPALM (Combres et al., 2013) and PALMSIM (Hoffmann et al., 2015) added the capacity to model the effect of water supply on crop growth through the incorporation of relatively simple soil water balance models (Table 2). Perhaps more importantly, these models brought a stronger physiological basis to the modelling of oil palm development. The more recent models provided a more detailed description of frond and inflorescence production, which, in the case of ECOPALM, has allowed exploration of the impact of water supply and photoperiod on fruit dynamics. PALMSIM (Hoffmann et al., 2014) is somewhat simpler in some aspects, but this has allowed it to be used in spatial analyses of potential production across climatic regions. CLM-Palm (Fan et al., 2015) is also quite simple but is designed to integrate, via the CLM (Oleson et al., 2013), with the global climate-focused CESM (Hurrell et al., 2013).

A wider range of crop and soil processes can be simulated by the models APSIM-Oil Palm (Huth et al., 2014) and WaNuLCAS (Van Noordwijk et al., 2011). These more detailed models provide opportunities for studying environmental impacts such as GHG emissions, hydrology, erosion and nutrient leaching and understorey management, as discussed in this chapter.

However, crop growth models do not yet represent many characteristics of the oil palm system, such as the presence of shallow groundwater or other soil constraints, or pests and diseases.

5.2 Hydrology, erosion and solute/sediment transport models

Water is the driver of sediment and solute/contaminant transport. Modelling the hydrological cycle and processes (Fig. 10) is important for applications such as water use and management, and water pollution. Hydrological models range in their complexity

Table 2 Oil palm crop models and the processes captured within them

	Model components					
Model	Growth and yield	Water	Soil C&N	Understorey	Management	Reference
OPSIM	●				●	van Kraalingen et al. (1989)
OPRODSIM	●	●			●	Henson et al. (2007)
WaNuLCAS	●	●	●	●	●	van Noordwijk et al. (2011)
ECOPALM	●	●				Combres et al. (2013)
PalmSIM	●	●			●	Hoffman et al. (2014)
APSIM	●	●	●	●	●	Huth et al. (2014)
CLM-Palm	●	●				Fan et al. (2015)

from simple 'black box' models developed from empirical data to powerful process-based computer models that are based on laws of mass, momentum and energy conservation (e.g. Richards equation and Darcy's equation). These models require huge data inputs but can provide distributed predictions of hydrological processes on a continuous timescale.

The development of hydrological models incorporating the interaction between surface water and groundwater provides opportunities to study water flows and contaminant transport between various parts of the hydrological system. Surface and subsurface flows can be modelled in one to three dimensions depending on the type of model. The MIKE SHE model simulates unsaturated flow in one dimension (Richards equation), surface flows in two dimensions (St. Vernant's equation) and groundwater flows in three dimensions (Boussinesq's equation). In addition, many hydrological models now include components to model erosion and solute transport at various levels of complexity (Table 1). Good examples of these coupled hydrological models include the SWAT and the MIKE models.

Erosion of soil is one of the most destructive environmental impacts of poor cultivation practices (Corley and Tinker 2016). Soil erosion is generally low in oil palm plantations due to low slope gradients, permeable soils and permanent ground cover (Lal, 1990; Labrière et al., 2015; Corley and Tinker, 2016). However, erosion can be large in times and places when the soil is exposed, especially during establishment and on steep slopes.

Erosion models simulate the detachment, transport and deposition of sediment in sheetflow, rills, gullies and within stream channels. The simplest empirical sediment transport model is the Universal Soil Loss Equation and its more recent modification, the Revised Universal Soil Loss Equation (Morgan and Nearing, 2011). Other commonly used soil erosion and sediment transport models are process-based, mostly modelling the erosion process in one or two dimensions where the erosion process and resultant

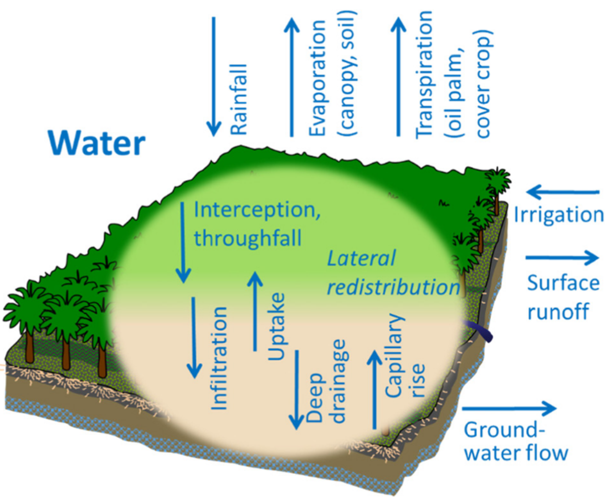

Figure 10 Fluxes of water into, out of and within the field. Water movement has direct impacts on aquatic ecosystems, as well as carrying other materials with their own impacts. Rainfall embodies a significant input of kinetic and potential energy to the system, driving processes such as erosion. Some water molecules are split during photosynthesis and created during mineralisation of organic matter but the amounts are insignificant compared to the fluxes shown.

sediment loads can be predicted either on an event or on a continuous basis. De Vente et al. (2013, 2014) recently made a useful evaluation of regional scale erosion models.

Solute transport models predict the transport of solutes through advection and/or dispersion, sorption/desorption and other geochemical reactions such as aqueous complexation, ion exchange, precipitation/dissolution and oxidation/reduction reactions in subsurface transport. Most of these models simulate solute transport processes in one or two dimensions, although three-dimensional modelling for the saturated zone is increasingly possible with improved computational power. The HYDRUS model simulates water, heat and solute movement in one to three dimensions in variably saturated media and can be linked to the groundwater model MODFLOW. Other examples of solute transport models include MT3DMS (3D multi-species transport model), SUTRA and HST3D (Maliva and Missimer, 2012).

5.3 Carbon models

The carbon cycle is fundamentally important for productivity, sustainability and environmental impacts of agricultural systems. Those modelling the cycle are concerned mostly with simulating the amounts of carbon in the atmosphere (as CO_2 and CH_4), plant biomass and soil (as organic matter), and the fluxes between those three pools. We considered modelling of atmosphere–plant exchanges above ('Atmospheric impact models' and 'Crop growth models'). Therefore, in this section we focus on the cycling of carbon through soil, the largest pool of the three.

Carbon cycling through soil depends on dynamic and incompletely understood interactions between organisms (all Kingdoms), substrates, availability and movement of water and oxygen, temperature, supply of other elements, especially nitrogen, and surface and solution chemistry (mineralogy and pH in particular). Carbon enters the soil mostly as plant-derived organic matter, which then decomposes (Fig. 11). Decomposition involves eventual loss of most or all of the carbon as CO_2, but along the way biomass and organic compounds are formed, especially by microorganisms.

Some organic materials decompose slower than others due to chemical recalcitrance, interactions with inorganic materials or physical inaccessibility to decomposing organisms and enzymes. Overall, if there are no fresh inputs, soil carbon becomes less biologically available over time, although organic matter stabilised by interactions with the mineral phase may originate from initially labile plant components (Haddix et al., 2016). Significant amounts of carbon may also arrive and leave via soil erosion and deposition at some locations and times. Losses of carbon by leaching are generally insignificant compared to the other fluxes.

Large changes in soil organic carbon stocks occur during and following land use change, and these have been modelled using an empirical conversion factor approach. The IPCC default values for soil organic carbon loss following change from forest to cropland are 0.69 (31% soil organic carbon loss) for the dry tropics and 0.58 (42% soil organic carbon loss) for the wet tropics (IPCC, 2003). The meta-analysis of Don et al. (2011) indicated about 30% loss following conversion of primary forest to perennial cropland, but more recent studies have suggested up to half may be lost after conversion (Bruun et al., 2013; Straaten et al., 2015). Much of the loss happens very quickly. However, within the oil palm crop, soil organic carbon stocks have shown no consistent decline, or even an increase over time (Henson, 1994; Haron et al., 1998; Law et al., 2009; Smith et al., 2012; Frazão et al., 2013; Goodrick et al., 2015; Khasanah et al., 2015a). Bahr et al. (2014) showed a

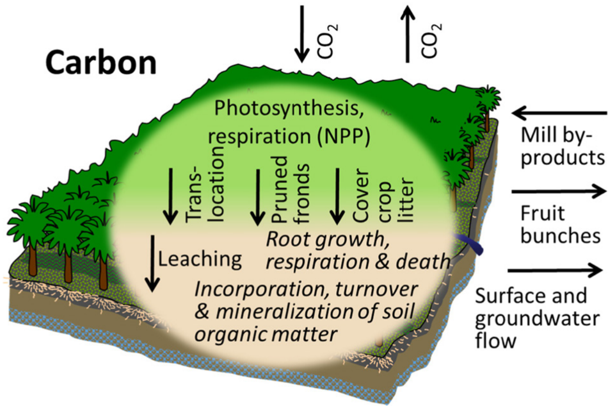

Figure 11 Fluxes of carbon into and out of the field, and transformations of carbon compounds. Carbon represents the main flow of energy through the system. Energy from radiation is converted to chemical bonds during photosynthesis, and used to drive all the biological processes in the system. Net primary production (NPP) is the net amount of organic matter produced in the system, or photosynthesis minus plant respiration.

pattern of decrease immediately after conversion, increase during the perennial cropping phase and then a decrease towards the end of the phase. Modelling with APSIM-Oil Palm shows a similar pattern (Fig. 6) and suggests it is due to inputs to the soil being high initially (from the preceding oil palm crop in the case of the modelling) and then reaching a steady state or declining depending on nitrogen supply.

Process-based models of change in soil carbon during land use change should focus on the key processes, which are redistribution due to erosion and a change in inputs due to the change in vegetation. This is usually achieved by combining erosion models with carbon cycling models (Lacoste et al., 2015). We discussed erosion models above, and now we discuss carbon cycling models.

There are three main approaches to modelling carbon cycling within a particular land use (Smith, 2006). The first two are substrate-based, treating substrates either as several discrete pools or as one continually changing pool. The third is ecologically or food web based.

Substrate-based models that categorise soil organic carbon into several discrete pools are the most used and developed of soil carbon models. In these models, carbon is lost from each pool according to first-order kinetics, and each pool has a different rate coefficient (or 'constant'). Pools comprise plant residue inputs (one or several pools), microbial biomass (one or several pools) and dead organic matter (several pools). The dead organic matter pools have the lowest rate coefficients and some models have an inert pool that does not decompose at all. Carbon lost from each pool is routed into another pool (usually biomass pool or a pool with lower slower rate constant) or lost as CO_2, with the proportions specified by 'carbon use efficiency' factors.

Microbial carbon use efficiency factors are a fundamental component of carbon models but are simply treated in most models. Geyer et al. (2016) have recently defined the concepts involved in a way that will be useful for future advances in carbon modelling.

The most well-known and used multi-pool models are CENTURY (Parton, 1996) and its daily time-step version DAYCENT (Grosso et al., 2001), and Roth-C (Coleman and Jenkinson, 2014). Other examples include APSIM (Probert et al., 1998), Biome-BGC (Thornton and Rosenbloom, 2005), Candy (Franko, 1996), CN-SIM (Petersen et al., 2005), DAISY (Mueller et al., 1996), DNDC (Li et al., 1994; Li, 2007), MIMICS (Wieder et al., 2014), NCSOIL (Molina et al., 1997) and ORCHIDEE (Krinner et al., 2005). Some of these models model nitrogen as well as carbon. Their structure and assumptions have been reviewed by Molina and Smith (1998) and Smith (2006).

Multi-pool models can successfully simulate soil organic carbon contents (Smith et al., 1997), but there are limitations to applying them. One problem is how to initialise the model and another is how to measure or validate pool sizes, rate decay coefficients and efficiency factors. Those things have been done by measuring the quantity of carbon in physically separated fractions and then either a) using the measured fractions as values for the pools and calculating rate coefficients or efficiency factors by fitting the model (Skjemstad et al., 2004), or b) using existing coefficients and splitting the measured pools to match the model pools (Zimmermann et al., 2007). However, the parameters derived in those ways for those situations are not necessarily applicable in other situations. Petersen et al. (2005) showed that a seven-pool model could satisfactorily simulate soil organic carbon contents for several sites using the same parameters, but the sites had similar climate, soil properties and management. Alternatively, chemically characterised pools have shown promise for modelling (Corbeels et al., 2005a,b). Application of multi-pool models within earth system models has resulted in widely varying fits with observed values, so there is considerable scope for improvement (Todd-Brown et al., 2013; Wang et al., 2014; Luo et al., 2016).

The second substrate-based approach to modelling soil carbon cycling is to treat each addition of plant residues as a cohort or single pool that changes with time, rather than assigning all soil carbon to several discrete pools (Bosatta and Ågren, 1995; Yang and Janssen, 2000; Manzoni et al., 2012). In these models the decomposition rate coefficient of each cohort decreases continually with time. This approach is attractive compared to multi-pool models because it reflects the continuously variable nature of substrates and because it requires less parameters. Mono-pool models can be used to simulate soil organic carbon dynamics with a similar degree of accuracy to multi-pool models (Manzoni et al., 2012). However, single- and multi-pool approaches both suffer from the difficulty of measuring pools that correspond with the conceptual pools, determining parameters (decay coefficients in particular) that can be transferred from one situation to another, and initialisation.

Food web-based models have been reviewed by Smith (2006) and Luo et al. (2016). They simulate the decomposing activities of soil organisms in various ways, usually focusing on microbial biomass or components of it, or production and activity of enzymes. For example, Kaiser et al. (2015) showed that soil organic matter accumulation is influenced by interactions between microorganisms that produce catabolic enzymes and those that do not. Food web-based models are able to simulate some aspects of carbon cycling that substrate-based approaches cannot, such as the priming effect and responses to wet-drying cycles. However, they require much more information than substrate-based models. Furthermore, they may not provide much better descriptions of reality because decomposition tends to be limited by substrate supply and physico-chemical conditions, and microbial populations adapt accordingly.

All models modify decomposition rate or decomposer activity according to environmental variables. The most important variables are temperature and the availability of water and oxygen. Their effects are modelled using empirically derived factors, such as an Arrhenius function for temperature and an optimal response function for water content (Luo et al., 2016). The function for water content commonly uses a parameter such as water-filled pore space, which to some extent integrates effects of water film thickness and oxygen supply on microbial activity. Responses to pH, availability of other nutrients, litter quality, litter layer thickness and clay content may also be modelled. Mineralogy, structure and structural stability, particularly pore size distribution, are not included in most models, even though they are known to affect stabilisation of organic matter.

Finally, we need to mention depth and management. The most commonly used models initially focused on a topsoil layer, assumed to be uniform. Only recently has the distribution of processes with depth been incorporated (Jenkinson and Coleman, 2008). Carbon inputs and environmental parameters change with depth, and carbon is moved vertically by fauna. In a similar vein, addition or loss of soil through erosion and deposition, a process that occurs in three dimensions, influences soil depth and the distribution of carbon with depth. Management factors may be included in some carbon models, or their effect on carbon cycling may be accounted for in agricultural system models.

Of the soil carbon modelling approaches, the only one that has been adapted to oil palm systems is the multi-pool substrate-based approach. It is used to model carbon and nitrogen cycling in litter and soil in the agricultural system models APSIM and WaNuLCAS (Probert et al., 1998; Noordwijk et al., 2011). APSIM uses a simplified approach, wherein all soil carbon in the deepest soil layer is assumed to be inert, and the size of the inert pool is assumed to be the same in all layers. It has successfully simulated long-term soil organic carbon contents in other crops (O'Leary et al., 2016). When carbon models are incorporated into crop system models they must realistically simulate not only soil organic carbon contents, but also the mineralisation and immobilisation of nitrogen and its supply to the plant.

The ability of carbon models to simulate soil organic carbon contents in oil palm plantations has not yet been tested. This is mostly because there are no long-term data sets of soil carbon content under oil palm. Such model testing would be very useful, given the peculiarities of oil palm systems. For example, none of the current carbon and nitrogen models mechanistically model the spatio-temporal variability in cycling processes in oil palm plantations, which may or may not be important. Temporal variability in carbon and nitrogen cycling processes is mostly related to the large input of organic matter at the end of the cycle and presence of legume cover crop at the start of the cycle. Spatial variability is largely due to placement of pruned fronds into concentrated stacks, root distribution, weeding and placement of mill by-products (Haron et al., 1998; Nelson et al., 2014; Carron et al., 2016; Goodrick et al., 2016).

5.4 Nitrogen models

The nitrogen cycle is fundamentally important for production and environment, but is complex and challenging to model. The main potential and observed environmental impacts are pollution of ground and surface waters and emission of GHGs, especially N_2O (Choo et al., 2011; Comte et al., 2012). For instance, during the cultivation period, 48.7% of the GHGs emitted to produce 1 t of palm oil fruit are due to nitrogen fertilisation (Choo et al., 2011). The main inputs of nitrogen to the field are manufactured fertilisers, palm oil mill by-products and biological fixation by legume cover crops (Fig. 12).

The largest losses of nitrogen from the field are due to leaching of mineral nitrogen (nitrate in particular) and volatilisation of NH_3, but the magnitude of these and other losses is highly uncertain (Pardon et al., 2016a). In their review, Pardon et al. (2016a) also emphasised that internal nitrogen fluxes in oil palm are large and important compared to other agricultural systems. As measurement of nitrogen losses is difficult and expensive, modelling is useful to help identify management practices that could reduce losses.

The most commonly used process-based models of nitrogen cycling are the same models used for carbon cycling, for example, CENTURY (Parton, 1996), DAYCENT (Grosso et al., 2001), DNDC (Li et al., 1994; Li, 2007) and DAISY (Mueller et al., 1996). They generally model mineralisation and immobilisation of nitrogen based on the C:N ratio of the pools, in the one-dimensional soil–plant–atmosphere continuum, at the scale of the soil profile or the field. Modelling nitrogen cycling is generally more complex than modelling carbon cycling, and several dissolved and gaseous nitrogen compounds are important for plant growth and the environment. In addition to the comprehensive nitrogen cycling models, some models focus on specific fluxes, such as the emission of N_2O (Henault et al., 2005). The concepts and challenges for modelling N_2O emissions have been discussed by Farquharson and Baldock (2008) and Butterbach-Bahl et al. (2013).

When the aim is to identify practices to mitigate environmental impacts, process-based nitrogen models suffer the same limitations as all complex models; they require precise soil and climate input data to function, they tend be not very sensitive to management practices and they are generally calibrated for temperate climate and annual crops and not easily adaptable to other conditions. In the case of nitrogen loss modelling, few models are available for tropical crops, and even fewer for perennial tropical crops such as oil palm (Cannavo et al., 2008; Pardon et al., 2016a,b).

In this context, simpler empirical agri-environmental indicators, such as the INDIGO® method (Bockstaller et al., 2008), may be useful for environmental impact modelling. Indicators combine quantitative and qualitative data based on expert knowledge and are hence suitable in situations where data is limited (Girardin et al., 1999). Their structure is adaptable to new cropping systems, allowing for the accounting of context-specific practices. For instance, Thiollet (2003) developed an indicator of nitrogen losses for vineyards, which might be adapted for oil palm systems.

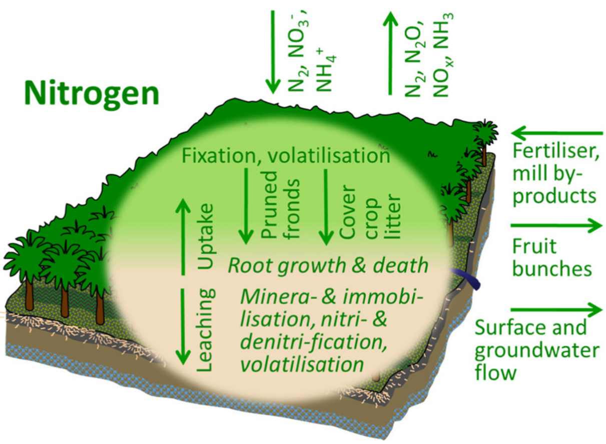

Figure 12 Fluxes of nitrogen into and out of the field, and transformations of nitrogen compounds. Nitrogen-containing compounds are important for many environmental impacts.

In a recent study, Pardon et al. (2016b) compared estimates of nitrogen losses from oil palm plantations made by 11 models and 29 sub-models. Three of the 11 models were process-based cropping system models [WaNuLCAS (Noordwijk et al., 2011); SNOOP (Barros, 2012); APSIM (Huth et al., 2014)], but only APSIM-Oil Palm was validated for production. Two models used a nitrogen budget approach at the scale of the field (Banabas, 2007; Schmidt, 2007). The others were simpler static models that calculate nitrogen losses using empirical relationships (Mosier et al., 1998; Roy et al., 2005; IPCC, 2006; Nemecek and Kägi, 2007; Brockmann et al., 2014; Meier et al., 2014).

The models were compared using the same scenario, a plantation in the Riau region of Sumatra, on a typical Ultisol, over a 25-year growth cycle, using standard management practices. Estimates of total nitrogen losses differed substantially between models, ranging from 21 to 139 kg N ha^{-1} yr^{-1} (Fig. 13). Leaching was the most important pathway, accounting for about 80% of the losses. On average, 31% of the losses occurred during the first three years, which represents 12% of the cycle duration. Losses of nitrogen through leaching and run-off seemed to be overestimated by some models and underestimated by others, with no clear relationship between the complexity or comprehensiveness of models and the magnitude of the losses predicted. All models seemed to underestimate NH_3 volatilisation compared to measured values. Modelled N_2O emissions were similar to field measurements, although the minimum modelled emissions were higher than the minimum losses measured in the field. The most influential variables across the three pathways were related to leaching losses, that is, soil clay content, rooting depth, and nitrogen uptake by the palms. A recent sensitivity analysis using APSIM-Oil Palm identified nitrogen fertiliser rate, drainage and fraction of legume in groundcover vegetation as the factors having most influence on nitrogen losses (Pardon et al., 2017).

Several challenges for modelling nitrogen losses were identified by Pardon et al. (2016b). First, estimation of any one flux depends on accurate estimation of all other fluxes, because they are interdependent. For example, the amount of nitrogen fixed biologically has a large influence on losses, but there is surprisingly little data and only very simple models. Legumes can regulate nitrogen fixation rates depending on the mineral nitrogen content of the soil (Giller and Fairhurst, 2003). Hence, it could be useful to model legume fixation with a rate of nitrogen fixation changing according to the soil mineral N content, such as in the EPIC crop model for soybean (Bouniols et al., 1991). Similarly, the amount of nitrogen released in the soil by residue decomposition is significant, and the way it is modelled has a large influence on losses. Indeed, residue decomposition can be accompanied by temporary immobilisation of nitrogen in the litter and soil organic matter, and the magnitude and timing of losses depend on whether or not the nitrogen immobilisation is considered.

Another challenge is to find parameters that accurately reflect the most influential factors, such as soil water retention and conductivity. The availability of appropriate climate data is also an important limitation.

5.5 Pesticide and contaminant fate models

The use of pesticides is limited in oil palm plantations, but their fate must be considered (Henson, 1994). Herbicides are used to keep the weeded circle and harvest path clear and to control woody weeds. Usually the compounds used rapidly degrade or become inactivated on contact with soil. Insecticides are occasionally used to control outbreaks of pests, in conjunction with biological control methods. The most preferred method of

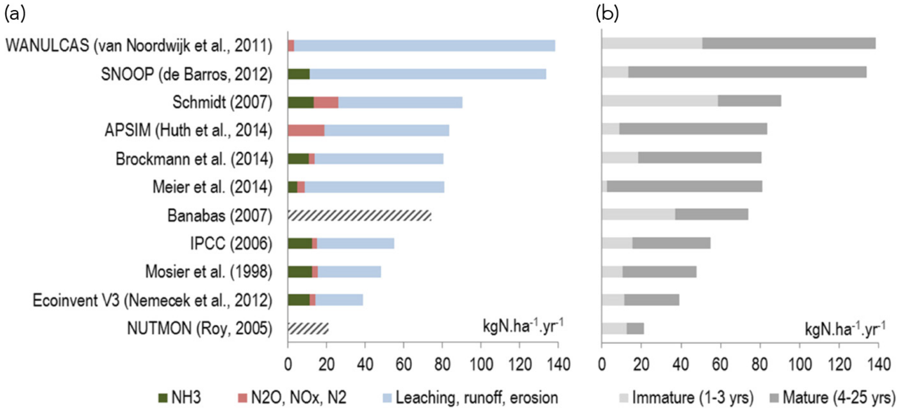

Figure 13 Estimates of N losses from an oil palm field in Sumatra by 11 models. (a) Distribution of the annual average losses between three loss pathways. The hatched bars represent estimates in which separate pathways were not distinguished. (b) Distribution of the annual average losses between the immature and the mature phases (Reproduced from Pardon et al. 2016b, *Biogeosciences* 13, 5433–5452).

application for most insect pests is trunk injection, so opportunities for movement into soil and water are limited. The site of most intense insecticide use, and also fungicides and herbicides, is in nurseries. Rodenticides may also be used in plantations, although alternatives such as encouragement of barn owls through deployment of nesting boxes, is common practice.

To ensure the non-target impact of the pesticides is minimised, several questions must be answered. These include: which pesticide to use, when, where and how? Will these pesticides move offsite (Fig. 14) and if so, what potential impact they may have on the ecosystem and human health?

What best management practices can be adopted/adapted to minimise such impacts? Models and other decision support tools, for example risk indicators, can help answer such questions and assist decision makers (Kookana et al., 2007).

A plethora of models with various degrees of complexity and comprehensiveness have been developed to assess the fate and behaviour of pesticides in the environment. Many have been designed for a specific purpose or with a focus on certain transport pathways (e.g. surface water or groundwater transport, and macropore flow). Therefore, while choosing the model it is important to match the specific question or purpose the user has in mind with the strength of the model.

Pesticide fate models may be classified, on the basis of their intended use and complexity, into categories such as screening, research and management models (e.g. Addiscott and Wagenet, 1985). Screening models are used to compare likely pesticide behaviour under different conditions, or to categorise them into classes differing in potential mobility or toxicity. These are often simple (e.g. analytical solutions) with low data requirement. Risk indicators used in Europe and elsewhere (Reus et al., 2002; Kookana et al., 2007) are this type of model. Research models are designed to quantitatively estimate pesticide transport and transformations. They tend to be comprehensive in terms of fate processes and commensurately hungry for input data. Management models are designed to assess

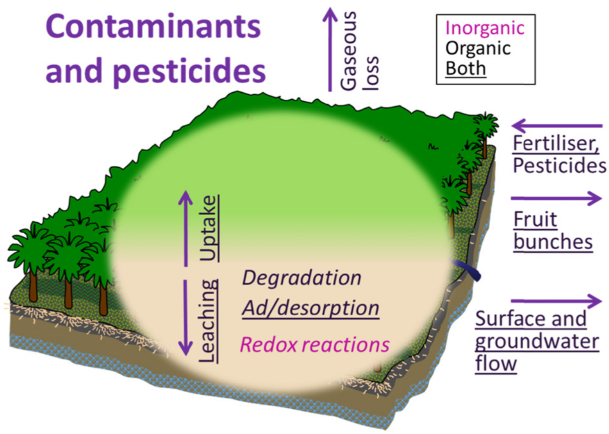

Figure 14 Fluxes and transformations of contaminants and pesticides in the field.

the effect of management practices on pesticide behaviour in field conditions (Bockstaller et al., 2008). The input data requirement of such models is generally somewhere between the research and screening models. A description of some of the models from these categories and their potential uses are described in Table 3.

The fate and behaviour of pesticides in tropical conditions can differ substantially from that in temperate conditions. Currently the database on pesticide behaviour in tropical regions is not well developed and most models rely on pesticide fate data from temperate regions, which may not accurately reflect pesticide behaviour in the tropics. For example, pesticides degrade many times faster in tropical than temperate conditions (Laabs et al., 2000; Kookana et al., 2010). The nature of tropical soils also needs to be considered.

Highly weathered tropical soils, rich in iron and aluminium (hydr)oxides, carry variable charge and may have significant anion exchange capacity at ambient pH (Uehara and Gillman, 1981). Some ionisable pesticides have been found to be substantially sorbed on such soils (Regitano et al., 2000). Soil physical properties are also important. Some tropical soils tend to have substantial macroporosity (biopores), so pesticides may bypass the soil matrix in percolating water. Such preferential flow can result in significant leaching, despite high degradation rates (Laabs et al., 2000). Even if only a very small fraction of applied pesticide (e.g. 0.1%) reaches groundwater, it may breach stringent groundwater standards such as the one used in Europe (0.1 µg/L for any pesticide).

It is therefore important that as much as possible the local data on pesticide fate are used in the models. For degradation, correction factors for persistence based on temperature may need to be applied. For pesticide sorption, techniques such as mid- or near-infrared spectroscopy, together with chemometrics, may allow a rapid and cost-effective estimate of pesticide sorption coefficients (K_d) in a large number of soils (Forouzangohar et al., 2008; Kookana et al., 2014). Ismail and Ooi (2012) found, for a variety of Malaysian soils, adsorption of metsulfuron-methyl was related to soil organic matter and clay content, which are readily estimated.

Some models have been applied and/or tested in tropical conditions (Table 3), but mostly in annual cropping systems. For example, Bannwarth et al. (2014) used a SWAT hydrological model (Table 3) coupled with ANSLEM to simulate the fate of three

Table 3 Some examples of different types of models developed for predicted fate and impact of pesticides from non-point sources

Model name	Class	Processes covered	Intended application	Comments
BAM (Jury et al. 1987)	Screening	Transport, sorption, degradation, volatilisation	To compare behaviour under specific conditions	Useful in grouping pesticides in behavioural classes
PIRI(Kookana et al. 2005)	Screening	Risk indicator integrating mobility, toxicity, application rate and method, topography, soil and environmental conditions	To group pesticides mobility and toxicity to non-target organisms	Useful for identifying relative risk of different pesticides
PRoMPT (Whelan et al. 2007)	Screening	Leaching to groundwater based on a simple water balance model	To identify areas prone to pesticide leaching	Applied in oil palm in Kenya by Unilever
PEARL (Leistra et al. 2000)	Research/ regulatory	Inputs, transport, sorption, degradation, volatilisation, leaching, uptake, transformation	To assess groundwater contamination at regional and local scale	Used for regulatory purposes in Europe
LEACHM (Wagenet and Hutson 1989)	Research	Transport, sorption, transformation, degradation, volatilisation, plant uptake, management	To assess groundwater contamination under cropping systems	Does not cover surface run-off, foliar wash-off, erosion and preferential flow
MACRO (Larsbo and Jarvis 2003)	Research	Specially designed to incorporate the preferential flow paths for pesticide leaching	To assess leaching in soils with macropores	
SWAT (Arnold et al. 2011)	Research/ management	Surface and subsurface hydrological processes. Fate and transport of pesticides is modelled based on GLEAMS model (Leonard et al. 1987)	To predict concentrations in rivers at daily time step	Performed well in tropical northern Thailand (Bannwarth et al. 2014)
PRZM (Suárez et al. 2005)	Regulatory/ management	Surface run-off, foliar wash-off, erosion losses and plant uptake. Not volatilisation	To assess effects of management practices	
PESTFADE (Clemente et al., 1991)	Management	Transport via run-off, erosion and leaching (unsaturated homogenous soil). Includes nutrients	To assess effects of management practices on transport at field, farm and watershed scale	Evaluated in tropics, in Thailand (Shrestha and Datta, 2015)
RZWQM (Ahuja et al. 2000)	Management	Transport via run-off, erosion and leaching (unsaturated homogenous soil). Includes nutrients	To assess effects of management practices on transport at field scale	Evaluated in tropics, in Thailand (Shrestha and Datta, 2015)
I-Phy (Bockstaller et al. 2008)	Management	Leaching, run-off, erosion, drift, volatilisation	To assess effects of management practices on transport at field scale	Being evaluated for glyphosate in oil palm (Marichal et al. 2016)

pesticides in a mountainous catchment of northern Thailand. The predicted daily pesticide concentrations in the river water over two seasons (2008 and 2010) matched the observed concentrations reasonably well, despite the complexity involved at the catchment scale. In terms of sensitivity of different parameters, the percolation parameter was identified as a key parameter.

Reliability of data on pesticide application rate and timing in the catchment is important in such simulations. For pesticide leaching through a soil profile, Shrestha and Datta (2015) evaluated the performance of two models (RZWQM and PESTFADE) for fate and transport of metribuzin herbicide under field conditions in Thailand. While they were generally satisfied with both models, they observed that RZWQM performed better in simulating water content of the soil profile, whereas PESTFADE was better at simulating the herbicide residue. Pesticide transport models are generally not well developed for plantation systems in tropical regions.

Risk indicators are being increasingly used in decision making by pesticide users, natural resource managers and regulators (Kookana et al. 2007). Some of the advantages of risk indicators over comprehensive models are their simplicity, ease of use and usability when input data are scarce. Risk indicators are helpful in assisting (i) growers to choose pesticides that are likely to be more environmentally acceptable, thereby also facilitating adoption of and compliance with integrated pest management or environmental management systems; (ii) growers and regulators to compare risk management options, identify potential hot spots, evaluate management practices and develop appropriate monitoring programmes; (iii) researchers to prioritise pesticides for greater understanding of their environmental fate and toxicology; and (iv) regulators and policy makers to analyse risk trends and develop appropriate policy interventions.

Risk indicators are often classified into two broad types (Reus et al., 2002; Feola et al., 2011). The first type uses simple algorithms such as a scoring table developed based on expert judgement, while the second type employ an exposure-to-toxicity ratio (ETR), that is, comparing the predicted exposure concentration to the toxicity parameter for organisms (e.g. LC_{50}). In the context of potential utility of risk indicators in emerging economies, Feola et al. (2011) used a case study based on small agricultural holdings in Colombia to assess the suitability of a set of indicators drawn from the ETR group (POCER, EPRIP and PIRI) and the non-ETR group (EIQ and PestScreen). They concluded that user-friendly ETR indicators were better suited than non-ETR indicators for reliably estimating environmental risk.

Several risk indicators have been used in tropical tree crops, including oil palm. One recommended risk indicator, PIRI (Kookana et al., 2005) (Table 3), has been promoted over the last decade for use in several tropical countries of South America, Asia and Africa by the joint division of FAO and IAEA on Food and Environment. For a comparative risk assessment of pesticides in papaya plantations, Hernández-Hernández et al. (2007) used SYNOPS risk indicator (an ETR-type risk indicator) and ranked 15 pesticides in terms of their chronological biological risk index. The authors recommended SYNOPS_2 for potential use in other tropical fruit plantations. The INDIGO® risk indicator for pesticides, I-Phy (Bockstaller et al., 2008), is being adapted for oil palm plantations and evaluated for glyphosate (Caliman et al., 2006; Marichal et al., 2016).

In addition to pesticides, trace metals and metalloids such as cadmium, mercury and lead can contaminate soil and water due to inputs as trace contaminants of fertiliser. Although heavy metal contamination has not been detected in oil palm planted soils (Sulaiman et al., 2016), it is a possible threat depending on the source of fertilisers and other amendments applied. The behaviour of trace metals in soils can be modelled to some extent using geochemical models, but soil- and situation-specific parameters are needed (Michel et al., 2007; Jacques et al., 2008; Selim and Zhang, 2013).

6 Conclusions and research directions

There are a variety of approaches and tools available for numerically modelling the environmental impacts of agriculture, including oil palm cultivation. They range from models of a single process or impact to models integrating many processes and impacts. In terms of operation, they range from simple empirical relationships to complex process-based dynamic models, operating at different scales and in different dimensions. For any particular purpose and situation, different models may be useful, but the unknowns and uncertainties must be kept in mind. Agricultural system modelling approaches such as APSIM are useful because they enable comparison of the effects of management changes or environmental factors on productivity and several environmental impacts. Such comparison allows managers to assess possible trade-offs between the two.

Environmental modelling is a rapidly developing field and there is still much to do to make models more accurate and useful for growers, researchers and regulators. Models developed for agricultural systems other than oil palm may be applicable, but peculiarities of the oil palm system need to be taken into account. As for other crops, the most important factors are the climatic, topographic and soil conditions, the nature of the prior and surrounding ecosystems, and the ways in which crop establishment, water, pests, nutrition and harvesting are managed. There is great need for more data on these factors to drive and accompany development of better models.

The type, structure and use of environmental models are changing rapidly in response to pressing needs. Focusing modelling on specific, practical problems of interest can guide optimal selection of measurements, advance our understanding of processes, and improve the integration of science into management and policy decisions. Current and likely future research falls into five main themes.

Representing complexity

As our understanding of biological, chemical and physical processes improves, the attendant complexity must somehow be represented in models. There are many ways this is being or could be tackled, including development of more mechanistic process-based models, integration of existing models, assimilation of data into models, or 'model data fusion' (Keenan et al., 2011; Dietze et al., 2013), hybridisation of statistical and probability-based models with process-based models (Aguilera et al., 2011) and alternative ways of modelling complex self-organising systems, such as cellular automata (Favis-Mortlock, 2013). 'Traditional (and still open) challenges in developing reliable and efficient models are associated with heterogeneity and variability in parameters and state variables; non-linearities and scale effects in process dynamics; and complex or poorly known boundary conditions and initial system states' (Paniconi and Putti, 2015).

Representing the oil palm system

Many models are not well suited to the nature of oil palm systems but could be applied to them, given some evaluation using data from the field, or modifications to the models.

Enhancing usability

Much can be done to incorporate sufficient complexity into models but make them operationally simple, accessible, up-to-date and relevant for managers and the broader community.

Evaluation of models

Evaluation of models, including sensitivity and uncertainty analysis, is becoming increasingly important. There is great scope for evaluation of existing models in oil palm systems and for development of better evaluation techniques.

Data from monitoring and experiments

There is a pressing and growing need for data to inform and evaluate environmental impact models. Essential input data on climate and soil are available globally as estimates from remote sensing and ground observations. However, data scarcity in many oil palm growing regions means their accuracy is often untested and may be poor. There is also much scope for exploiting data from new satellite- and ground-based sensors and other sources such as palm oil mills. Long-term monitoring plots, especially those with experimental treatments, have been valuable for calibrating and validating models and would be very useful for oil palm. Finally, urgently needed data on many key processes could also be obtained by shorter-term experiments.

7 Where to look for further information

The main scientific journals focusing on the topic of this chapter are *Environmental Modelling & Software* and *Ecological Modelling*. Relevant conferences include those of the International Environmental Modelling & Software Society' (http://www.iemss.org/society/). Some references that provide a comprehensive treatment of various aspects of the topic in this chapter follow:

- The oil palm system, including modelling and environmental aspects: Corley and Tinker (2016).
- Environmental modelling: Granell et al. (2013), Wainwright and Mulligan (2013).
- Evaluation of environmental models: Jakeman et al. (2006), Bennett et al. (2013), Kelly et al. (2013).
- Life cycle assessment: ISO 14040 series 2000–2006 and the International Reference Life Cycle Data System Handbook http://eplca.jrc.ec.europa.eu/?page_id=86
- Earth system modelling: Heavens et al. (2013).
- Agricultural system (oil palm) modelling: Huth et al. (2014).
- Catchment process modelling: Mulligan and Wainwright (2013b), Paniconi and Putti (2015), Fatichi et al. (2016).

- Atmospheric impact modelling: IPCC (2003, 2006, 2014).
- Aquatic ecosystem modelling: Robson (2014a).
- Terrestrial biodiversity impacts: Foster et al. (2011), Phalan et al. (2011), Lee et al. (2014).
- Soil quality and erosion: Lal and Stewart (2013), Labrière et al. (2015).
- Erosion modelling: Morgan and Nearing (2011).
- Carbon and nitrogen cycle modelling: Molina and Smith (1998), Smith (2006), Cabrera et al. (2008), Campbell and Paustian (2015).
- Nitrogen environmental impact modelling: Cannavo et al. (2008), Pardon et al. (2016b).
- Nitrous oxide emission modelling: Chen et al. (2008), Butterbach-Bahl et al. (2013).
- Pesticide risk modelling: Kookana et al. (2007).

8 References

Achten, W. M. J., Vandenbempt, P., Almeida, J., Mathijs, E. and Muys, B. (2010). Life cycle assessment of a palm oil system with simultaneous production of biodiesel and cooking oil in Cameroon. *Environ. Sci. Technol.* 44, 4809–15.

Acuña, V., Díez, J. R., Flores, L., Meleason, M. and Elosegi, A. (2013). Does it make economic sense to restore rivers for their ecosystem services? *J. Appl. Ecol.* 50, 988–97.

Addiscott, T. and Wagenet, R. (1985). Concepts of solute leaching in soils: A review of modelling approaches. *J. Soil Sci.* 36, 411–24.

Anderson, J. M. (2008). Eco-friendly approaches to sustainable palm oil production. *J. Oil Palm Res.* 127–42.

Babel, M., Shrestha, B. and Perret, S. (2011). Hydrological impact of biofuel production: A case study of the Khlong Phlo Watershed in Thailand. *Agric. water manag.* 101, 8–26.

Bahr, E., Zaragocin, D. C. and Makeschin, F. (2014). Soil nutrient stock dynamics and land-use management of annuals, perennials and pastures after slash-and-burn in the Southern Ecuadorian Andes. *Agric. Ecosyst. Environ.* 188, 275–88.

Baird, A. J., Low, R., Young, D., Swindles, G. T., Lopez, O. R. and Page, S. (2017). High permeability explains the vulnerability of the carbon store in drained tropical peatlands. *Geophys. Res. Lett.* 44, 1–7. doi:10.1002/2016GL072245.

Banabas, M. (2007). Study of nitrogen loss pathways in oil palm (*Elaeis guineensis* Jacq.) growing agro-ecosystems on volcanic ash soils in Papua New Guinea, PhD thesis, Massey University, Palmerston North, New Zealand.

Bannwarth, M., Sangchan, W., Hugenschmidt, C., Lamers, M., Ingwersen, J., Ziegler, A. and Streck, T. (2014). Pesticide transport simulation in a tropical catchment by SWAT. *Environ. Pollut.* 191, 70–9.

Barnes, A. D., Jochum, M., Mumme, S., Haneda, N. F., Farajallah, A., Widarto, T. H. and Brose, U. (2014). Consequences of tropical land use for multitrophic biodiversity and ecosystem functioning. *Nat. Commun.* 5, 5351.

Barros, I. D. (2012). SNOOP: A simulation model for the dynamics of water and nitrogen in oil palm. In 'V Congresso Brasileiro de Mamona/II Simpósio Internacional de Oleaginosas Energéticas & I Fórum Capixaba de Pinhão Manso, Guarapari (ES) – 2012'.

Basri, M. F., Yacob, S., Hassan, M. A., Shirai, Y., Wakisaka, M., Zakaria, M. R. and Phang, L. Y. (2010). Improved biogas production from palm oil mill effluent by a scaled-down anaerobic treatment process. *World. J. Microbiol. Biotechnol.* 26, 505–14.

Bennett, N. D., Croke, B. F. W., Guariso, G., Guillaume, J. H. A., Hamilton, S. H., Jakeman, A. J., Marsili-Libelli, S., Newham, L. T. H., Norton, J. P., Perrin, C., Pierce, S. A., Robson, B., Seppelt, R., Voinov, A. A., Fath, B. D. and Andreassian, V. (2013). Characterising performance of environmental models. *Environ. Model. Softw.* 40, 1–20.

Bessou, C., Basset-Mens, C., Tran, T. and Benoist, A. (2013). LCA applied to perennial cropping systems: A review focused on the farm stage. *Int. J. Life Cycle Assess.* 18, 340–61.

Bessou, C., Chase, L. D. C., Henson, I. E., Abdul-Manan, A. F. N., Milà i Canals, L., Agus, F., Sharma, M. and Chin, M. (2014). Pilot application of PalmGHG, the Roundtable on Sustainable Palm Oil greenhouse gas calculator for oil palm products. *J. Clean. Prod.* 73, 136–45.

Bockstaller, C., Guichard, L., Makowski, D., Aveline, A., Girardin, P. and Plantureux, S. (2008). Agri-environmental indicators to assess cropping and farming systems. A review. *Agron. Sustain. Dev.* 28, 139–49.

Bosatta, E. and Ågren, G. I. (1995). The power and reactive continuum models as particular cases of the q-theory of organic matter dynamics. *Geochim. Cosmochim. Acta* 59, 3833–5.

Boulton, A. J., Boyero, L., Covich, A. P., Dobson, M., Lake, S.and Pearson, R. (2008). Are tropical streams ecologically different from temperate streams? In Dudgeon, D. (Ed) *Tropical Stream Ecology*. Elsevier: London, UK, pp. 257–84.

Bouniols, A., Cabelguenne, M., Jones, C. A., Chalamet, A., Charpenteau, J. L. and Marty, J. R. (1991). Simulation of soybean nitrogen nutrition for a silty clay soil in southern France. *Field Crops Res.* 26, 19–34.

Bouwman, A. F., Boumans, L. J. M. and Batjes, N. H. (2002a). Emissions of N_2O and NO from fertilized fields: Summary of available measurement data. *Global Biogeochem. Cycles*, 16, 6-1 – 6-13.

Bouwman, A. F., Boumans, L. J. M. and Batjes, N. H. (2002b). Modeling global annual N_2O and NO emissions from fertilized fields. *Global Biogeochem. Cycles* 16, 28-1 – 28-9.

Boyer, K. (2003). Riparian mangement for wood in rivers. *Am. Fish. Soc. Symp*. 37, 407–20.

Brisson, N., Gary, C., Justes, E., Roche, R., Mary, B., Ripoche, D., Zimmer, D., Sierra, J., Bertuzzi, P., Burger, P., Bussière, F., Cabidoche, Y., Cellier, P., Debaeke, P., Gaudillère, J., Hénault, C., Maraux, F., Seguin, B. and Sinoquet, H. (2003). An overview of the crop model STICS. *Eur. J. Agron.* 18, 309–32.

Brockmann, D., Hanhoun, M., Négri, O. and Hélias, A. (2014). Environmental assessment of nutrient recycling from biological pig slurry treatment – Impact of fertilizer substitution and field emissions. *Bioresour. Technol.* 163, 270–9.

Brouwer, F. M., Ittersum, M. V. (Eds) (2010). *Environmental and Agricultural Modelling. Integrated Approaches for Policy Impact Assessment*. Springer: Dordrecht.

Brown, H. E., Huth, N. I., Holzworth, D. P., Teixeira, E. I., Zyskowski, R. F., Hargreaves, J. N. G. and Moot, D. J. (2014). Plant Modelling Framework: Software for building and running crop models on the APSIM platform. *Environ. Model. Softw.* 62, 385–98.

Bruijnzeel, L. A. (2004). Hydrological functions of tropical forests: Not seeing the soil for the trees? *Agric. Ecosyst. Environ.* 104, 185–228.

Bruun, T. B., Egay, K., Mertz, O. and Magid, J. (2013). Improved sampling methods document decline in soil organic carbon stocks and concentrations of permanganate oxidizable carbon after transition from swidden to oil palm cultivation. *Agric. Ecosyst. Environ.* 178, 127–34.

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

Caddy, J. F. (2008). The importance of 'Cover' in the life histories of demersal and benthic marine resources: A neglected issue in fisheries assessment and management. *Bull. Mar. Sci.* 83, 7–52.

Caliman, J. P., Wohlfahrt, J., Carcasses, R., Girardin, P., Perel, N., Wahyu, A., Pujianto, Dubos, B. and Verwilghen, A. (2006). Agri-environmental indicators for sustainable palm oil production. *In* 'XV International Oil Palm Conference', Cartagena de Indias, Colombia.

Cannavo, P., Recous, S., Parnaudeau, V. and Reau, R. (2008). Modeling N dynamics to assess environmental impacts of cropped soils. *Adv. Agron.* 97, 131–74.

Carlson, K. M., Curran, L. M., Ponette-González, A. G., Ratnasari, D., Lisnawati, N., Purwanto, Y., Brauman, K. A. and Raymond, P. A. (2014). Influence of watershed-climate interactions on stream temperature, sediment yield and metabolism along a land use intensity gradient in Indonesian Borneo. *J. Geophys. Res. Biogeosci.* 119, 1110–28.

Carlson, K. M., Curran, L. M., Ponette-González, A. G., Ratnasari, D., Lisnawati, N., Purwanto, Y., Brauman, K. A. and Raymond, P. A. (2015). Consistent results in stream hydrology across multiple watersheds: A reply to Chew and Goh. *J. Geophys. Res. Biogeosci.* 120, 812–17.

Carlson, K. M., Goodman, L. K. and May-Tobin, C. C. (2015). Modeling relationships between water table depth and peat soil carbon loss in Southeast Asian plantations. *Environ. Res. Lett.* 10. doi:10.1088/1748-9326/10/7/074006.

Carron, M. P., Auriac, Q., Snoeck, D., Villenave, C., Blanchart, E., Ribeyre, F., Marichal, R., Darminto, M. and Caliman, J. P. (2015a). Spatial heterogeneity of soil quality around mature oil palms receiving mineral fertilization. *Eur. J. Soil Biol.* 66, 24–31.

Carron, M. P., Auriac, Q., Snoeck, D., Villenave, C., Blanchart, E., Ribeyre, F., Marichal, R., Darminto, M. and Caliman, J. P. (2016). Do the impact of organic residues on soil quality extend beyond the deposition area under oil palm? *Eur. J. Soil Biol.* 75, 54–61.

Carron, M. P., Pierrat, M., Snoeck, D., Villenave, C., Ribeyre, F., Suhardi, Marichal, R. and Caliman, J. P. (2015b). Temporal variability in soil quality after organic residue application in mature oil palm plantations. *Soil Res.*, 53, 205–15.

Chase, L. D. C., Henson, I. E., Abdul-Manan, A. F. N., Agus, F., Bessou, C., Milà i Canals, L. and Sharma, M. (2012). *The PalmGHG Calculator: The RSPO greenhouse gas calculator for oil palm products, Beta-version.* The Roundtable for Sustainable Palm Oil – RSPO: Kuala Lumpur, Malaysia.

Chen, D. L., Li, Y., Grace, P. and Mosier, A. R. (2008). N_2O emissions from agricultural lands: A synthesis of simulation approaches. *Plant Soil* 309, 169–89.

Chew, P. S. and Goh, K. J. (2015). Comment on 'Influence of watershed-climate interactions on stream temperature, sediment yield and metabolism along a land use intensity gradient in Indonesian Borneo'. *J. Geophys. Res. Biogeosci.* 120, 809–11.

Choo, Y. M., Muhamad, H., Hashim, Z., Subramaniam, V., Puah, C. W. and Tan, Y. (2011). Determination of GHG contributions by subsystems in the oil palm supply chain using the LCA approach. *Int. J. Life Cycle Assess.* 16, 669–81.

Ciampalini, R., Follain, S. and Bissonnais, Y. L. (2012). LandSoil: A model for analysing the impact of erosion on agricultural landscape evolution. *Geomorphology* 175–176, 25–37.

Coleman, K. and Jenkinson, D. S. (2014). *RothC – A Model for the Turnover of Carbon in Soil*. Model description and users guide (Windows version) (updated June 2014). Rothamsted Research: Harpenden, UK.

Combres, J.-C., Pallas, B., Rouan, L., Mialet-Serra, I., Caliman, J.-P., Braconnier, S., Soulie, J.-C. and Dingkuhn, M. (2013). Simulation of inflorescence dynamics in oil palm and estimation of environment-sensitive phenological phases: A model based analysis. *Funct. Plant Biol.* 40, 263–79.

Comte, I., Colin, F., Whalen, J. K., Grünberger, O. and Caliman, J.-P. (2012). Agricultural Practices in Oil Palm Plantations and Their Impact on Hydrological Changes, Nutrient Fluxes and Water Quality in Indonesia: A Review. *Adv. Agron.* 116, 71–124.

Cooper, J., Gilliam, J., Daniels, R. and Robarge, W. (1987). Riparian areas as filters for agricultural sediment. *Soil. Sci. Soc. Am. J.* 51, 416–20.

Corbeels, M., McMurtrie, R. E., Pepper, D. A. and O'Connell, A. M. (2005a). A process-based model of nitrogen cycling in forest plantations: Part I. Structure, calibration and analysis of the decomposition model. *Ecol. Model.* 187, 426–48.

Corbeels, M., McMurtrie, R. E., Pepper, D. A. and O'Connell, A. M. (2005b). A process-based model of nitrogen cycling in forest plantations: Part II. Simulating growth and nitrogen mineralisation of Eucalyptus globulus plantations in south-western Australia. *Ecol. Model.* 187, 449–74.

Corley, R. H. V. (2009). How much palm oil do we need? *Environ. Sci. Policy* 12, 134–9.

Corley, R. H. V. and Tinker, P. B. (2016). *The Oil Palm*. 5th Ed. Wiley-Blackwell: Oxford.

Davis, A. M., Pearson, R. G., Brodie, J. E. and Butler, B. (2017). Review and conceptual models of agricultural impacts and water quality in waterways of the Great Barrier Reef catchment area. *Mar. Freshwater Res.* 68, 1–19.

de Graaf, G. (2003). Dynamics of floodplain fisheries in Bangladesh, results of 8 years fisheries monitoring in the Compartmentalization Pilot Project. *Fish. Manag. Ecol.* 10, 191–9.

de Souza, S. P., Pacca, S., de Ávila, M. T. and Borges, J. L. B. (2010). Greenhouse gas emissions and energy balance of palm oil biofuel. *Renew. Energy* 35, 2552–61.

de Vente, J. d., Poesen, J., Verstraeten, G., Govers, G., Vanmaercke, M., Rompaey, A. V., Arabkhedri, M. and Boix-Fayos, C. (2013). Predicting soil erosion and sediment yield at regional scales: Where do we stand? *Earth-Sci. Rev.* 127, 16–29.

de Vente, J. d., Poesen, J., Verstraeten, G., Govers, G., Vanmaercke, M., Rompaey, A. V., Arabkhedri, M. and Boix-Fayos, C. (2014). Corrigendum to 'Predicting soil erosion and sediment yield at regional scales: Where do we stand?' [*Earth-Sci. Rev*. 127 (2013) 16–29]. *Earth-Sci. Rev.* 133, 94.

Don, A., Schumacher, J. and Freibauer, A. (2011). Impact of tropical land-use change on soil organic carbon stocks – a meta-analysis. *Global Change Biol.* 17, 1658–70.

Donatelli, M., Russell, G., Rizzoli, A. E., Acutis, M., Adam, M., Athanasiadis, I. N., Balderacchi, M., Bechini, L., Belhouchette, H., Bellocchi, G., Bergez, J.-E., Botta, M., Braudeau, E., Bregaglio, S., Carlini, L., Casellas, E., Celette, F., Ceotto, E., Charron-Moirez, M. H., Confalonieri, R., Corbeels, M., Criscuolo, L., Cruz, P., Guardo, A. d., Ditto, D., Dupraz, C., Duru, M., Fiorani, D., Gentile, A., Ewert, F., Gary, C., Habyarimana, E., Jouany, C., Kansou, K., Knapen, R., Filippi, G. L., Leffelaar, P. A., Manici, L., Martin, G., Martin, P., Meuter, E., Mugueta, N., Mulia, R., Noordwijk, M. v., Oomen, R., Rosenmund, A., Rossi, V., Salinari, F., Serrano, A., Sorce, A., Vincent, G., Theau, J.-P., Thérond, O., Trevisan, M., Trevisiol, P., Evert, F. K. v., Wallach, D., Wery, J. and Zerourou, A. (2010). A Component-based framework for simulating agricultural production and externalities. In Brouwer, F. M. and Ittersum, M. K. (Eds), *Environmental and Agricultural Modelling: Integrated Approaches for Policy Impact Assessment*. Springer Science+Business Media B.V., pp. 63–108.

Dubos, B., Snoeck, D. and Flori, A. (2016). Excessive use of fertilizer can increase leaching processes and modify soil reserves in two Ecuadorian oil palm plantations. *Exp. Agric.*, 53, 255–68.

European Commission (2009). Directive 2009/28/EC of the European parliament and of the council of 23 April 2009 on the promotion of the use of energy from renewable sources and amending and subsequently repealing Directives 2001/77/EC and 2003/30/EC. *Official Journal of the European Union*, L140, 16–62.

Ewert, F., Ittersum, M. K. v., Heckelei, T., Therond, O., Bezlepkina, I. and Andersen, E. (2011). Scale changes and model linking methods for integrated assessment of agri-environmental systems. *Agric. Ecosyst. Environ.* 142, 6–17.

Fan, Y., Roupsard, O., Bernoux, M., Maire, G. L., Panferov, O., Kotowska, M. M. and Knohl, A. (2015). A sub-canopy structure for simulating oil palm in the Community Land Model (CLM-Palm): Phenology, allocation and yield. *Geosci. Model Dev.* 8, 3785–800.

FAOSTAT (Accessed 2016). http://www.fao.org/faostat/en/#data.

Fargione, J., Hill, J., Tilman, D., Polasky, S. and Hawthorne, P. (2008). Land Clearing and the Biofuel Carbon Debt. *Science* 319, 1235–8.

Farquharson, R. and Baldock, J. (2008). Concepts in modelling N2O emissions from land use. *Plant Soil* 309, 147–67.

Fatichi, S., Ivanov, V. Y. and Caporali, E. (2012a). A mechanistic ecohydrological model to investigate complex interactions in cold and warm water-controlled environments: 1. Theoretical framework and plot-scale analysis. *J. Adv. Model. Earth Syst.* 4, M05002.

Fatichi, S., Ivanov, V. Y. and Caporali, E. (2012b). A mechanistic ecohydrological model to investigate complex interactions in cold and warm water-controlled environments: 2. Spatiotemporal analyses. *J. Adv. Model. Earth Syst.* 4, M05003.

Fatichi, S., Vivoni, E. R., Ogden, F. L., Ivanov, V. Y., Mirus, B., Gochis, D., Downer, C. W., Camporese, M., Davison, J. H., Ebel, B., Jones, N., Kim, J., Mascaro, G., Niswonger, R., Restrepo, P., Rigon, R., Shen, C., Sulis, M. and Tarboton, D. (2016). An overview of current applications, challenges and future trends in distributed process-based models in hydrology. *J. Hydrol.* 537, 45–60.

Favis-Mortlock, D. (2013). Non-linear dynamics, self-organisation and cellular automata models. In Wainwright, J. and Mulligan, M. (Eds), *Environmental Modelling: Finding Simplicity in Complexity*. John Wiley & Sons, Ltd., pp. 45–67.

Fayle, T. M., Turner, E. C., Snaddon, J. L., Chey, V. K., Chung, A. Y. C., Eggleton, P. and Foster, W. A. (2010). Oil palm expansion into rainforest greatly reduces ant biodiversity in canopy, epiphytes and leaf-litter. *Basic Appl. Ecol.* 11, 337–45.

Fayle, T. M., Turner, E. C. and Foster, W. A. (2013). Ant mosaics occur in SE Asian oil palm plantation but not rain forest and are influenced by the presence of nest-sites and non-native species. *Ecography* 36, 1051–7.

Feola, G., Rahn, E. and Binder, C. (2011). Suitability of pesticide risk indicators for less developed countries: A comparison. *Agric. Ecosyst. Environ* 142, 238–45.

Flato, G., Marotzke, J., Abiodun, B., Braconnot, P., Chou, S. C., Collins, W., Cox, P., Driouech, F., Emori, S., Eyring, V., Forest, C., Gleckler, P., Guilyardi, E., Jakob, C., Kattsov, V., Reason, C. and Rummukainen, M. (2013). Evaluation of Climate Models. In Stocker, T. F., Qin, D., Plattner, G.-K., Tignor, M., Allen, S. K., Boschung, J., Nauels, A., Xia, Y., Bex, V. and Midgley, P. M. (Eds), *Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge University Press: Cambridge, United Kingdom and New York, NY, USA.

Forouzangohar, M., Kookana, R. S., Forrester, S. T., Smernik, R. J. and Chittleborough, D. J. (2008). Midinfrared spectroscopy and chemometrics to predict diuron sorption coefficients in soils. *Environ. Sci. Technol.* 42, 3283–8.

Foster, W. A., Snaddon, J. L., Turner, E. C., Fayle, T. M., Cockerill, T. D., Ellwood, M. D. F., Broad, G. R., Chung, A. Y. C., Eggleton, P., Khen, C. V. and Yusah, K. M. (2011). Establishing the evidence base for maintaining biodiversity and ecosystem function in the oil palm landscapes of South East Asia. *Phil. Trans. R. Soc. B.* 366, 3277–91.

Franko, U. (1996). Modelling approaches of soil organic matter turnover within the CANDY system. In Powlson, D. S., Smith, P. and Smith, J. U. (Eds), *Evaluation of Soil Organic Matter Models Using Existing, Long-Term Datasets*. Springer-Verlag: Berlin, pp. 247–54

Frazão, L. A., Paustian, K., Pellegrino Cerri, C. E. and Cerri, C. C. (2013). Soil carbon stocks and changes after oil palm introduction in the Brazilian Amazon. *Glob. Change Biol. Bioenergy* 5, 384–90.

Geyer, K. M., Kyker-Snowman, E., Grandy, A. S. and Frey, S. D. (2016). Microbial carbon use efficiency: accounting for population, community and ecosystem-scale controls over the fate of metabolized organic matter. *Biogeochemistry* 127, 173–88.

Gibbs, H. K., Johnston, M., Foley, J. A., Holloway, T., Monfreda, C., Ramankutty, N. and Zaks, D. (2008). Carbon payback times for crop-based biofuel expansion in the tropics: The effects of changing yield and technology. *Environ. Res. Lett.* 3, 034001.

Giller, K. E. and Fairhurst, T. H. (2003). Legume cover plants. In Fairhurst, T. H. and Härdter, R. (Eds), "*Oil Palm. Management for Large and Sustainable Yields*". Potash & Phosphate Institute/Potash & Phosphate Institute of Canada and International Potash Institute: Singapore, pp. 151–61.

Girardin, P., Bockstaller, C. and Werf, H. v. d. (1999). Indicators: Tools to evaluate the environmental impacts of farming systems. *J. Sustainable Agric.* 13, 5–21.

Goodrick, I., Nelson, P. N., Banabas, M., Wurster, C. M. and Bird, M. I. (2015). Soil carbon balance following conversion of grassland to oil palm. *Glob. Change Biol. Bioenergy* 7, 263–72.

Goodrick, I., Nelson, P. N., Nake, S., Webb, M. J., Bird, M. I. and Huth, N. (2016). Tree-scale spatial variability of soil carbon cycling in a mature oil palm plantation. *Soil Res.* 54, 397–406.

Granell, C., Schade, S. and Ostländer, N. (2013). Seeing the forest through the trees: A review of integrated environmental modelling tools. *Comput. Environ. Urban Syst.* 41, 136–50.

Grayson, R. and Blöschl, G. (2001). *Spatial Patterns in Catchment Hydrology*. Cambridge University Press: Cambridge, UK.

Gregory, S. V., Swanson, F. J., McKee, W. A. and Cummins, K. W. (1991). An ecosystem perspective of riparian zones. *BioScience*, 41, 540–51.

Grosso, S. J. D., Parton, W. J., Mosier, A. R., Hartman, M. D., Brenner, J., Ojima, D. S. and Schimel, D. S. (2001). Simulated interaction of carbon dynamics and nitrogen trace gas fluxes using the DAYCENT model. In Shaffer, M. J., Ma, L. and Hansen, S. (Eds), *Modeling Carbon and Nitrogen Dynamics for Soil Management*. CRC Press: Boca Raton, USA, pp. 303–32.

Gupta, A. (2011). *Tropical Geomorphology*. Cambridge University Press: Cambridge, UK.
Gurnell, A. M., Bertoldi, W. and Corenblit, D. (2012). Changing river channels: The roles of hydrological processes, plants and pioneer fluvial landforms in humid temperate, mixed load, gravel bed rivers. *Earth-Sci. Rev.* 111, 129–41.
Haddix, M. L., Paul, E. A. and Cotrufo, M. F. (2016). Dual, differential isotope labeling shows the preferential movement of labile plant constituents into mineral bonded soil organic matter. *Global Change Biol*. 22, 2301–12.
Hamza, M. A. and Anderson, W. K. (2005). Soil compaction in cropping systems: A review of the nature, causes and possible solutions. *Soil Tillage Res.* 82, 121–45.
Harmel, R. D., Smith, P. K., Migliaccio, K. W., Chaubey, I., Douglas-Mankin, K. R., Benham, B., Shukla, S., Muñoz-Carpena, R. and Robson, B. J. (2014). Evaluating, interpreting and communicating performance of hydrologic/water quality models considering intended use: A review and recommendations. *Environ. Model. Softw.* 57, 40–51.
Haron, K., Brookes, P. C. Anderson, J. M. and Zakaria, Z. Z. (1998). Microbial biomass and soil organic matter dynamics in oil palm (*Elaeis guineensis* Jacq.) plantations, West Malaysia. *Soil Biol. Biochem.* 30, 547–52.
Harris, G. P. and Heathwaite, A. (2012). Why is achieving good ecological outcomes in rivers so difficult? *Freshwater Biol.* 57, 91–107.
Harsono, S. S., Grundmann, P. and Soebronto, S. (2014). Anaerobic treatment of palm oil mill effluents: Potential contribution to net energy yield and reduction of greenhouse gas emissions from biodiesel production. *J. Clean. Prod.* 64, 619–27.
Harsono, S. S., Prochnow, A., Grundmann, P., Hansen, A. and Hallmann, C. (2012). Energy balances and greenhouse gas emissions of palm oil biodiesel in Indonesia. *GCB Bioenergy* 4, 213–28.
Hateley, L. R., Ellis, R., Shaw, M., Waters, D. and Carroll, C. (2014). Modelling reductions of pollutant loads due to improved management practices in the Great Barrier Reef catchments – Wet Tropics NRM region, Technical Report, Volume 3. Queensland Department of Natural Resources and Mines: Cairns, Queensland.
Heavens, N. G., Ward, D. S. and Natalie, M. M. (2013). Studying and Projecting Climate Change with Earth System Models. *Nature Education Knowledge* 4, 4.
Henault, C., Bizouard, F., Laville, P., Gabrielle, B., Nicoullaud, B., Germon, J. C. and Cellier, P. (2005). Predicting in situ soil N2O emission using NOE algorithm and soil database. *Global Change Biol*. 11, 115–27.
Henley, W. F., Patterson, M. A., Neves, R. J. and Lemly, A. D. (2000). Effects of Sedimentation and Turbidity on Lotic Food Webs: A Concise Review for Natural Resource Managers. *Rev. Fish. Sci.* 8, 125–39.
Henson, I. E. (1994). *Environmental Impacts of Oil Palm Plantations In Malaysia*. Palm Oil Research Institute of Malaysia: Kuala Lumpur, Malaysia.
Henson, I. E., Yahya, Z., Noor, M. R. M., Harun, M. H. and Mohammed, A. T. (2007). Predicting soil water status, evapotranspiration, growth and yield of young oil palm in a seasonally dry region of Malaysia. *J. Oil Palm Res.* 19, 398–415.
Hernández-Hernández, C. N., Valle-Mora, J., Santiesteban-Hernández, A. and Bello-Mendoza, R. (2007). Comparative ecological risks of pesticides used in plantation production of papaya: Application of the SYNOPS indicator. *Sci. Total* Eenviron. 381, 112–25.
Hewitt, C. N., MacKenzie, A. R., Carlo, P. D., Marco, C. F. D., Dorsey, J. R., Evans, M., Fowler, D., Gallagher, M. W., Hopkins, J. R., Jones, C. E., Langford, B., Lee, J. D., Lewis, A. C., Lim, S. F., McQuaid, J., Misztal, P., Moller, S. J., Monks, P. S., Nemitz, E., Oram, D. E., Owen, S. M., Phillips, G. J., Pugh, T. A. M., Pyle, J. A., Reeves, C. E., Ryder, J., Siong, J., Skiba, U. and Stewart, D. J. (2009). Nitrogen management is essential to prevent tropical oil palm plantations from causing ground-level ozone pollution. *Proc. Natl. Acad. Sci. USA* 106, 18447–51.
Hoffmann, M., Donough, C., Oberthür, T., VERA, A. C., van Wijk, M., Lim, C., Asmono, D., Samosir, Y., Lubis, A. and Moses, D. (2015). Benchmarking yield for sustainable intensification of oil palm production in Indonesia using PALMSIM. *Planter* 91, 81–96.

Hoffmann, M. P., Castaneda Vera, A., van Wijk, M. T., Giller, K. E., Oberthür, T., Donough, C. and Whitbread, A. M. (2014). Simulating potential growth and yield of oil palm (Elaeis guineensis) with PALMSIM: Model description, evaluation and application. *Agric. Sys.* 131, 1–10.

Holzworth, D. P., Huth, N. I. and deVoil, P. G. (2011). Simple software processes and tests improve the reliability and usefulness of a model. *Environ. Model. Softw.* 24, 510–16.

Holzworth, D. P., Huth, N. I., deVoil, P. G., Zurcher, E. J., Herrmann, N. I., McLean, G., Chenu, K., Oosterom, E. J. v., Snow, V., Murphy, C., Moore, A. D., Brown, H., Whish, J. P. M., Verrall, S., Fainges, J., Bell, L. W., Peake, A. S., Poulton, P. L., Hochman, Z., Thorburn, P. J., Gaydon, D. S., Dalgliesh, N. P., Rodriguez, D., Cox, H., Chapman, S., Doherty, A., Teixeira, E., Sharp, J., Cichota, R., Vogeler, I., Li, F. Y., Wang, E., Hammer, G. L., Robertson, M. J., Dimes, J. P., Whitbread, A. M., Hunt, J., Rees, H. v., McClelland, T., Carberry, P. S., Hargreaves, J. N. G., MacLeod, N., McDonald, C., Harsdorf, J., Wedgwood, S. and Keating, B. A. (2014). APSIM – Evolution towards a new generation of agricultural systems simulation. *Environ. Model. Softw.* 62, 327–50.

Holzworth, D. P., Huth, N. I. and Voil, P. G. d. (2010). Simplifying environmental model reuse. *Environ. Model. Softw.* 25, 269–75.

Hooijer, A., Page, S., Canadell, J. G., Silvius, M., Kwadijk, J., Wösten, H. and Jauhiainen, J. (2010). Current and future CO2 emissions from drained peatlands in Southeast Asia. *Biogeosciences* 7, 1505–14.

Hurrell, J. W., Holland, M. M., Gent, P. R., Ghan, S., Kay, J. E., Kushner, P. J., Lamarque, J.-F., Large, W. G., Lawrence, D., Lindsay, K., Lipscomb, W. H., Long, M. C., Mahowald, N., Marsh, D. R., Neale, R. B., Rasch, P., Vavrus, S., Vertenstein, M., Bader, D., Collins, W. D., Hack, J. J., Kiehl, J. and Marshall, S. (2013). The community earth system model. A framework for collaborative research. *Bull. Am. Meteorol. Soc.* 94, 1339–60.

Huth, N. I., Banabas, M., Nelson, P. N. and Webb, M. (2014). Development of an oil palm cropping systems model: Lessons learned and future directions. *Environ. Model. Softw.* 62, 411–19.

IPCC (2003). '*Good Practice Guidance for Land Use, Land-Use Change and Forestry*'. Edited by J. Penman, M. Gytarsky, T. Hiraishi, T. Krug, D. Kruger, R. Pipatti, L. Buendia, K. Miwa, T. Ngara, K. Tanabe and F. Wagner. Intergovernmental Panel of Climate Change (IPCC) National Greenhouse Gas Inventories Programme, Japan.

IPCC (2006). '*2006 IPCC Guidelines for National Greenhouse Gas Inventories*', Prepared by the National Greenhouse Gas Inventories Programme, Eggleston, H.S., Buendia, L., Miwa, K., Ngara, T. and Tanabe, K. (eds). Intergovernmental Panel of Climate Change (IPCC) National Greenhouse Gas Inventories Programme: Japan.

IPCC (2014). '*2013 Supplement to the 2006 IPCC Guidelines for National Greenhouse Gas Inventories: Wetlands*', Hiraishi, T., Krug, T., Tanabe, K., Srivastava, N., Baasansuren, J., Fukuda, M. and Troxler, T.G. (Eds). Intergovernmental Panel on Climate Change: Switzerland.

Ismail, B. S. and Ooi, K. E. (2012). Adsorption, desorption and mobility of metsulfuron-methyl in soils of the oil palm agroecosystem in Malaysia. *J. Env. Biol.* 33, 573–7.

Jacques, D., Šimůnek, J., Mallants, D. and Genuchten, M. T. v. (2008). Modelling coupled water flow, solute transport and geochemical reactions affecting heavy metal migration in a podzol soil. *Geoderma* 145, 449–61.

Jakeman, A. J., Letcher, R. A. and Norton, J. P. (2006). Ten iterative steps in development and evaluation of environmental models. *Environ. Model. Softw.* 21, 602–14.

Janssen, A. B. G., Arhonditsis, G. B., Beusen, A., Bolding, K., Bruce, L., Bruggeman, J., Couture, R.-M., Downing, A. S., Elliott, J. A., Frassl, M. A., Gal, G., Gerla, D. J., Hipsey, M. R., Hu, F., Ives, S. C., Janse, J. H., Jeppesen, E., Jöhnk, K. D., Kneis, D., Kong, X., Kuiper, J. J., Lehmann, M. K., Lemmen, C., Özkundakci, D., Petzoldt, T., Rinke, K., Robson, B. J., Sachse, R., Schep, S. A., Schmid, M., Scholten, H., Teurlincx, S., Trolle, D., Troost, T. A., Dam, A. A. V., Gerven, L. P. A. V., Weijerman, M., Wells, S. A. and Mooij, W. M. (2015). Exploring, exploiting and evolving diversity of aquatic ecosystem models: A community perspective. *Aquatic Ecol.* 49, 513–48.

Jenkinson, D. S. and Coleman, K. (2008). The turnover of organic carbon in subsoils. Part 2. Modelling carbon turnover. *Eur. J. Soil Sci.* 59, 400–13.

Jennings, A. P., Naim, M., Advento, A. D., Aryawan, A. A. K., Ps, S., Caliman, J.-P., Verwilghen, A. and Veron, G. (2015). Diversity and occupancy of small carnivores within oil palm plantations in central Sumatra, Indonesia. *Mammal Res.* 60, 181–8.

Jones, J. W., Hoogenboom, G., Porter, C. H., Boote, K. J., Batchelor, W. D., Hunt, L. A., Wilkens, P. W., Singh, U., Gijsman, A. J. and Ritchie, J. T. (2003). The DSSAT cropping system model. *Eur. J. Agron.* 18, 235–65.

Kaiser, C., Franklin, O., Richter, A. and Dieckmann, U. (2015). Social dynamics within decomposer communities lead to nitrogen retention and organic matter build-up in soils. *Nat. Commun.* 6, 1–10.

Kee, K. K., Goh, K. J. and ChewChew, P. S. (1995). Effects of NK fertiliser on soil pH and exchangeable K status on acid soils in an oil palm plantation in Malaysia. In Date, R., Grundon, N., Rayment, G. and Probert, M. (Eds), *Plant-Soil Interactions at Low pH: Principles and Management*. Kluwer: Amsterdam, pp. 809–15.

Kelly (Letcher), R. A., Jakeman, A. J., Barreteau, O., Borsuk, M. E., ElSawah, S., Hamilton, S. H., Henriksen, H. J., Kuikka, S., Maier, H. R., Rizzoli, A. E., van Delden, H. and Voinov, A. A. (2013). Selecting among five common modelling approaches for integrated environmental assessment and management. *Environ. Model. Softw.* 47, 159–81.

Khasanah, N. M., Noordwijk, M. v., Ningsih, H. and Rahayua, S. (2015a). Carbon neutral? No change in mineral soil carbon stock under oil palm plantations derived from forest or non-forest in Indonesia. *Agric. Ecosyst. Environ.* 211, 195–206.

Koh, L. P. (2008). Can oil palm plantations be made more hospitable for forest butterflies and birds? *J. Appl. Ecol.* 45, 1002–9.

Koh, L. P., Miettinen, J., Liew, S. C. and Ghazoul, J. (2011). Remotely sensed evidence of tropical peatland conversion to oil palm. *Proc. Natl. Acad. Sci.* 108, 5127–32.

Kookana, R., Holz, G., Barnes, C., Bubb, K., Fremlin, R. and Boardman, B. (2010). Impact of climatic and soil conditions on environmental fate of atrazine used under plantation forestry in Australia. *J. Environ. Manag.* 91, 2649–56.

Kookana, R. S., Ahmad, R. and Farenhorst, A. (2014). Sorption of pesticides and its dependence on soil properties: Chemometrics approach for estimating sorption. In Chen, W., Sabljic, A., Cryer, S. A. and et. al. (Eds), *Non-First Order Degradation and Time-Dependent Sorption of Organic Chemicals in Soil*, Volume 1174. American Chemical Society: Washington, DC, pp. 221–40.

Kookana, R. S., Correll, R. L. and Miller, R. B. (2005). Pesticide impact rating index–A pesticide risk indicator for water quality. *Water Air Soil Pollut.* 5, 45–65.

Kookana, R. S., Kumar, A., Oliver, D. P. and Correll, R. L. (2007). Pesticide risk indicators: Their role in minimizing off-site impacts of pesticides on water quality. In *American Chemical Society Symposium Serie*, Vol. 966. Oxford University Press: Oxford, UK. pp. 37–52.

Krinner, G., Viovy, N., de Noblet-Ducoudré, N., Ogée, J., Polcher, J., Friedlingstein, P., Ciais, P., Sitch, S. and Prentice, I. C. (2005). A dynamic global vegetation model for studies of the coupled atmosphere-biosphere system. *Global Biogeochem. Cycles* 19.

Kristensen, P. B., Kristensen, E. A., Riis, T., Baisner, A. J., Larsen, S. E., Verdonschot, P. and Baattrup-Pedersen, A. (2013). Riparian forest as a management tool for moderating future thermal conditions of lowland temperate streams. *Hydrol. Earth Syst. Sci. Discuss.* 10, 6081–106.

Kui, L., Stella, J. C., Lightbody, A. and Wilcox, A. C. (2014). Ecogeomorphic feedbacks and flood loss of riparian tree seedlings in meandering channel experiments. *Water Resources Research* 50, 9366–84.

Laabs, V., Amelung, W., Pinto, A., Altstaedt, A. and Zech, W. (2000). Leaching and degradation of corn and soybean pesticides in an Oxisol of the Brazilian Cerrados. *Chemosphere* 41, 1441–9.

Labrière, N., Locatelli, B., Laumonier, Y., Freycon, V. and Bernoux, M. (2015). Soil erosion in the humid tropics: A systematic quantitative review. *Agric. Ecosyst. Environ.* 203, 127–39.

Lacoste, M., Viaud, V., Michot, D. and Walter, C. (2015). Landscape-scale modelling of erosion processes and soil carbon dynamics under land-use and climate change in agroecosystems. *Eur. J. Soil Sci.* 66, 780–91.

Lal, P. (1990). *Soil Erosion in the Tropics – Principles and Management*. McGraw-Hill: New York.

Lal, R. and Stewart, B. A. (2013). *Principles of Sustainable Soil Management in Agroecosystems*. CRC Press: Boca Raton, USA.

Law, M. C., Balasundram, S. K., Husni, M. H. A., Ahmed, O. H. and Harun, M. H. (2009). Spatial variability of soil organic carbon in oil palm. *Int. J. Soil Sci.* 4, 93–103.

Lee, J. S. H., Garcia-Ulloa, J., Ghazoul, J., Obidzinski, K. and Koh, L. P. (2014). Modelling environmental and socio-economic trade-offs associated with land-sparing and land-sharing approaches to oil palm expansion. *J. Appl. Ecol.* 51, 1366–77.

Levin, P. S. and Stunz, G. W. (2005). Habitat triage for exploited fishes: Can we identify essential 'Essential Fish Habitat?'. *Estuar. Coast. Shelf Sci.* 64, 70–8.

Lewis, S. L., Sonke, B., Sunderland, T., Begne, S. K., Lopez-Gonzalez, G., Heijden, G. M. F. v. d., Phillips, O. L., Affum-Baffoe, K., Baker, T. R., Banin, L., Bastin, J.-F. o., Beeckman, H., Boeckx, P., Bogaert, J., Cannie`re, C. D., Chezeaux, E., Clark, C. J., Collins, M., Djagbletey, G., Noe¨, M., Djuikouo, K., Droissart, V., Doucet, J.-L., Ewango, C. E. N., Fauset, S., Feldpausch, T. R., Foli, E. G., Gillet, J.-F. o., Hamilton, A. C., Harris, D. J., Hart, T. B., Haulleville, T. d., Hladik, A., Hufkens, K., Huygens, D., Jeanmart, P., Jeffery, K. J., Kearsley, E., Leal, M. E., Lloyd, J., Lovett, J. C., Makana, J.-R., Malhi, Y., Marshall, A. R., Ojo, L., Peh, K. S.-H., Pickavance, G., Poulsen, J. R., Reitsma, J. M., Sheil, D., Simo, M., Steppe, K., Taedoumg, H. E., Talbot, J., Taplin, J. R. D., Taylor, D., Thomas, S. C., Toirambe, B., Verbeeck, H., Vleminckx, J., White, L. J. T., Willcock, S., Woell, H. and Zemagho, L. (2013). Above-ground biomass and structure of 260 African tropical forests. *Phil. Trans. R. Soc. B.* 368, 20120295.

Li, C. (2007). Quantifying greenhouse gas emissions from soils: Scientific basis and modeling approach. *Soil Sci. Plant Nutr.* 53, 344–52.

Li, C., Frolking, S. and Harriss, R. (1994). Modeling carbon biogeochemistry in agricultural soils. *Global Biogeochem. Cycles*, 237–54.

Lucey, J., Hill, J., Meer, P. v. d., Reynolds, G. and Agus, F. (2014). Change in carbon stocks arising from land-use conversion to oil palm plantations. A science-for-policy paper for the Oil palm Research-Policy Partnership Network.

Luo, Y., Ahlström, A., Allison, S. D., Batjes, N., Brovkin, V., Carvalhais, N., Chappell, A., Ciais, P., Davidson, E. A., Finzi, A., Georgiou, K., Guenet, B., Hararuk, O., Harden, J. W., He, Y., Hopkins, F., Jiang, L., Koven, C., Jackson, R. B., Jones, C. D., Lara, M. J., Liang, J., McGuire, A. D., Parton, W., Peng, C., Randerson, J. T., Salazar, A., Sierra, C. A., Smith, M. J., Tian, H., Todd-Brown, K. E. O., Torn, M., Groenigen, K. J. v., Wang, Y. P., West, T. O., Wei, Y., Wieder, W. R., Xia, J., Xu, X., Xu, X. and Zhou, T. (2016). Toward more realistic projections of soil carbon dynamics by Earth system models. *Global Biogeochem. Cycles* 30, 40–56.

Majid, M. R. and Rusli, N. (2014). Hydrological impact of large scale conversion of rubber to oil palm plantation. *In* "2014 International SWAT Conference", Pernanbuco, Brazil.

Makowski, D., Tichit, M., Guichard, L., Keulen, H. V. and Beaudoin, N. (2009). Measuring the accuracy of agro-environmental indicators. *J. Environ. Manag.* 90, S139–46.

Maliva, R. G. and Missimer, T. M. (2012). *Arid Lands Water Evaluation and Management*. Springer Science & Business Media.

Manik, Y. and Halog, A. (2013). A meta-analytic review of life cycle assessment and flow analyses studies of palm oil biodiesel. *Integr. Environ. Assess. Manag.* 9, 134–41.

Manzoni, S., Piñeiro, G., Jackson, R. B., Jobbágy, E. G., Kim, J. H. and Porporato, A. (2012). Analytical models of soil and litter decomposition: Solutions for mass loss and time-dependent decay rates. *Soil Biol. Biochem.* 50, 66–76.

Marichal, R., Sionita, R., Wholfahrt, J., Bessou, C. and Caliman, J. P. (2016). Validation of I-Phy palm, an indicator of pesticide pollution risk: method and preliminary results. *In* "5th International Conference on Oil Palm and Environment (ICOPE)", Bali, Indonesia.

McCown, R. L., Hammer, G. L., Hargreaves, J. N. G., Holzworth, D. and Huth, N. I. (1995). APSIM – An agricultural production system simulation model for operational research. *Math. Comput. Simul.* 39, 225–31.

McKergow, L. A., Prosser, I. P., Hughes, A. O. and Brodie, J. (2005). Sources of sediment to the Great Barrier Reef World Heritage Area. *Marine Poll. Bull.* 51, 200–11.

Meier, M. S., Jungbluth, N., Stoessel, F., Schader, C. and Stolze, M. (2014). Higher accuracy in N modeling makes a difference. *In* "Proceedings of the 9th International Conference on Life Cycle Assessment in the Agri-Food Sector" (R. Schenck and D. Huizenga, eds.). ACLCA, Vashon, WA, USA, San Francisco.

Mercer, E. V., Mercer, T. G. and Sayok, A. K. (2014). Effects of forest conversions to oil palm plantations on freshwater macroinvertebrates: A case study from Sarawak, Malaysia. *J. Land Use Sci.* 9, 260–77.

Michel, K., Roose, M. and Ludwig, B. (2007). Comparison of different approaches for modelling heavy metal transport in acidic soils. *Geoderma* 140, 207–14.

Molina, J.-A. E. and Smith, P. (1998). Modeling carbon and nitrogen cycling processes in soils. *Adv. Agron.* 62, 253–98.

Molina, J. A. E., Crocker, G. J., Grace, P. R., Klír, J., Körschens, M., Poulton, P. R. and Richter, D. D. (1997). Simulating trends in soil organic carbon in long-term experiments using NCSOIL and NCSWAP models. *Geoderma* 81, 91–107.

Moore, A. D., Holzworth, D. P., Herrmann, N. I., Brown, H. E., Voil, P. G. d., Snow, V. O., Zurcher, E. J. and Huth, N. I. (2014). Modelling the manager: representing rule-based management in farming systems simulation models. *Environ. Model. Softw.* 62, 399–410.

Moore, R., Spittlehouse, D. and Story, A. (2005). Riparian microclimate and stream temperature response to forest harvesting: A review. *J. Am. Water Resour. Assoc.* 41, 813–34.

Morgan, R. P. C. and Nearing, M. A. (2011). *Handbook of Erosion Modelling*. Wiley-Blackwell.

Mosier, A., Kroeze, C., Nevison, C., Oenema, O., Seitzinger, S. and Cleemput, O. v. (1998). Closing the global N2O budget: Nitrous oxide emissions through the agricultural nitrogen cycle. *Nutr. Cycl. Agroecosy.* 52, 225–48.

Mueller, T., Jensen, L. S., Hansen, S. and Nielsen, N. E. (1996). Simulating soil carbon and nitrogen dynamics with the soil-plant-atmosphere system model DAISY. In Powlson, D. S., Smith, P. and Smith, J. U. (Eds), *Evaluation of Soil Organic Matter Models Using Existing, Long-Term Datasets*. Springer-Verlag: Berlin, pp. 275–81.

Muetzelfeldt, R. and Massheder, J. (2003). The Simile visual modelling environment. *Eur. J. Agron.* 18, 345–58.

Mulligan, M. and Wainwright, J. (2013a). Modelling and Model Building. In Wainwright, J. and Mulligan, M. (Eds), *Environmental Modelling: Finding Simplicity in Complexity*. John Wiley & Sons, Ltd., pp. 7–26.

Mulligan, M. and Wainwright, J. (2013b). Modelling catchment and fluvial processes and their interactions. In Mulligan, M. and Wainwright, J. (Eds), *Environmental Modelling: Finding Simplicity in Complexity*. John Wiley & Sons, Ltd., p. 183.

Naiman, R. J., Decamps, H. and Pollock, M. (1993). The role of riparian corridors in maintaining regional biodiversity. *Ecol. Appl.* 3, 209–12.

Nelson, P. N., Banabas, M., Goodrick, I., Webb, M. J., Huth, N. I. and O'Grady, D. (2015a). Soil sampling in oil palm plantations: a practical design that accounts for lateral variability at the tree scale. *Plant Soil* 394, 421–9.

Nelson, P. N., Banabas, M., Huth, N. I. and Webb, M. J. (2015b). Quantifying trends in soil fertility under oil palm: practical challenges and approaches. In Webb, M. J., Nelson, P. N., Bessou, C., Caliman, J.-P. and Sutarta, E. S. (Eds), *Sustainable Management of Soil in Oil Palm Plantings. ACIAR Proceedings No. 144*. Australian Centre for International Agricultural Research: Canberra, Australia, pp. 60–4.

Nelson, P. N., Berthelsen, S., Webb, M. J. and Banabas, M. (2010a). Acidification of volcanic ash soils under oil palm in Papua New Guinea: effects of fertiliser type and placement. In Gilkes, R. J. and Prakongkep, N. (Eds), *Proceedings of the 19th World Congress of Soil Science; Soil Solutions for a Changing World*. International Union of Soil Science: Brisbane, Australia, pp. 8–11.

Nelson, P. N., Webb, M. J., Banabas, M., Nake, S., Goodrick, I., Gordon, J., O'Grady, D. and Dubos, B. (2014). Methods to account for tree-scale variability in soil- and plant-related parameters in oil palm plantations. *Plant Soil* 374, 459–71.

Nelson, P. N., Webb, M. J., Orrell, I., van Rees, H., Banabas, M., Berthelsen, S., Sheaves, M., Bakani, F., Pukam, O., Hoare, M., Griffiths, W., King, G., Carberry, P., Pipai, R., McNeill, A., Meekers, P., Lord, S., Butler, J., Pattison, T., Armour, J. and Dewhurst, C. (2010b). Environmental sustainability of oil palm cultivation in Papua New Guinea. *ACIAR Technical Report No. 75*. The Australian Centre for International Agricultural Research: Canberra, Australia.

Nemecek, T. and Kägi, T. (2007). Life cycle inventories of agricultural production systems. Ecoinvent Report No.15. ecoinvent Centre: Switzerland.

Newbold, T., Hudson, L. N., Phillips, H. R. P., Hill, S. L. L., Contu, S., Lysenko, I., Blandon, A., Butchart, S. H. M., Booth, H. L., Day, J., Palma, A. D., Harrison, M. L. K., Kirkpatrick, L., Pynegar, E., Robinson, A., Simpson, J., Mace, G. M., Scharlemann, J. P. W. and Purvis, A. (2014). A global model of the response of tropical and sub-tropical forest biodiversity to anthropogenic pressures. *Proc. R. Soc. B.* 281: 20141371.

Noordwijk, M. v., Lusiana, B. and Khasanah, N. m. (2011). *WaNuLCAS 3.01. Background on a Model of Water, Nutrient and Light Capture in Agroforestry Systems*.

O'Leary, G. J., Liu, D. L., Ma, Y., Li, F. Y., McCaskill, M., Conyers, M., Dalal, R., Reeves, S., Page, K., Dang, Y. P. and Robertson, F. (2016). Modelling soil organic carbon 1. Performance of APSIM crop and pasture modules against long-term experimental data. *Geoderma* 264, 227–37.

Oleson, K. W., Lawrence, D. M., Bonan, G. B., Drewniak, B., Huang, M., Koven, C. D., Levis, S., Li, F., Riley, W. J., Subin, Z. M., Swenson, S. C., Thornton, P. E., Bozbiyik, A., Fisher, R., Heald, C. L., Kluzek, E., Lamarque, J.-F., Lawrence, P. J., Leung, L. R., Lipscomb, W., Muszala, S., Ricciuto, D. M., Sacks, W., Sun, Y., Tang, J. and Yang, Z.-L. (2013). *Technical Description of version 4.5 of the Community Land Model (CLM)*. National Center for Atmospheric Research: Boulder, Colorado.

Paniconi, C. and Putti, M. (2015). Physically based modeling in catchment hydrology at 50: Survey and outlook. *Water Resour. Res.* 51, 7090–129.

Paramananthan, S. (2011). Soil requirements and land evaluation for oil palms for high yields. In Goh, K. J., Chiu, S. B. and Paramananthan, S. (Eds), *Agronomic Principles and Practices of Oil Palm Cultivation*. Agricultural Crop Trust: Selangor Darul Ehsan, Malaysia.

Pardon, L., Bessou, C., Nelson, P. N., Dubos, B., Ollivier, J., Marichal, R., Caliman, J.-P. and Gabrielle, B. (2016a). Key unknowns in nitrogen budget for oil palm plantations. A review. *Agron. Sustain. Dev.* 36, 1–21.

Pardon, L., Bessou, C., Saint-Geours, N., Gabrielle, B., Khasanah, N. m., Caliman, J.-P. and Nelson, P. N. (2016b). Quantifying nitrogen losses in oil palm plantations: Models and challenges. *Biogeosciences* 13, 5433–52.

Pardon, L., Huth, N., Nelson, P. N., Banabas, M., Gabrielle, B. and Bessou, C. (2017) Yield and nitrogen losses in oil palm plantations: main drivers and management trade-offs determined using simulation. *Field Crops Res.* 210, 20–32.

Parton, W. J. (1996). The CENTURY model. In Powlson, D. S., Smith, P. and Smith, J. U. (Eds), *Evaluation of Soil Organic Matter Models Using Existing Long Term Datasets*. Springer-Verlag: Berlin, Germany.

Petersen, B. M., Berntsen, J., Hansen, S. and Jensen, L. S. (2005). CN-SIM – a model for the turnover of soil organic matter. I. Long-term carbon and radiocarbon development. *Soil Biol. Biochem.* 37, 359–74.

Phalan, B., Onial, M., Balmford, A. and Green, R. E. (2011). Reconciling Food Production and Biodiversity Conservation: Land Sharing and Land Sparing Compared. *Science* 333, 1289–91.

Pleanjai, S., Gheewala, S. H. and Garivait, S. (2009). Greenhouse gas emissions from the production and use of palm methyl ester in Thailand. *Int. J. Global Warm.* 1, 418–31.

Prescott, G. W., Gilroy, J. J., Haugaasen, T., Uribe, C. A. M., Foster, W. A. and Edwards, D. P. (2016). Reducing the impacts of Neotropical oil palm development on functional diversity. *Biol. Conserv.* 197, 139–45.

Probert, M. E., Delve, R. J., Kimani, S. K. and Dimes, J. P. (2005). Modelling nitrogen mineralization from manures: Representing quality aspects by varying C:N ratio of sub-pools. *Soil Biol. Biochem.* 37, 279–87.

Probert, M. E., Dimes, J. P., Keating, B. A., Dalal, R. C. and Strong, W. M. (1998). APSIM's water and nitrogen modules and simulation of the dynamics of water and nitrogen in fallow systems. *Agric. Sys.* 56, 1–28.

Rahman, J. M., Seaton, S. P. and Cuddy, S. M. (2004). Making frameworks more useable: using model introspection and metadata to develop model processing tools. *Environ. Model. Softw.* 19, 275–84.

Rahman, J. M., Seaton, S. P., Perraud, J. M., Hotham, H., Verrelli, D. I. and Coleman, J. R. (2003). It's TIME for a new environmental modelling framework. *Proceedings of MODSIM* 4, 1727–32.

Regitano, J., Alleoni, L., Vidal-Torrado, P., Casagrande, J. and Tornisielo, V. (2000). Imazaquin sorption in highly weathered tropical soils. *J. Environ. Qual.* 29, 894–900.

Reus, J., Leendertse, P., Bockstaller, C., Fomsgaard, I., Gutsche, V., Lewis, K., Nilsson, C., Pussemier, L., Trevisan, M. and Van der Werf, H. (2002). Comparison and evaluation of eight pesticide environmental risk indicators developed in Europe and recommendations for future use. *Agric. Ecosyst. Environ* 90, 177–87.

Robson, B. J. (2014a). When do aquatic systems models provide useful predictions, what is changing and what is next? *Environ. Model. Softw.* 61, 287–96.

Robson, B. J. (2014b). State of the art in modelling of phosphorus in aquatic systems: Review, criticisms and commentary. *Environ. Model. Softw.* 61, 339–59.

Roy, R. N., Misra, R. V., Lesschen, J. P. and Smaling, E. M. (2005). *Evaluation du bilan en elements nutritifs du sol. Approches et methodologies*. FAO: Rome.

Sayer, J., Ghazoul, J., Nelson, P. and Boedhihartono, A. K. (2012). Oil palm expansion transforms tropical landscapes and livelihoods. *Glob. Food Sec.* 1, 114–19.

Schmidt, J. H. (2007). Life assessment of rapeseed oil and palm oil. Ph. D. thesis, Part 3: Life cycle inventory of rapeseed oil, Aalborg University: Denmark.

Schmidt, J. H. (2010). Comparative life cycle assessment of rapeseed oil and palm oil. *Int. J. Life Cycle Assess.* 15, 183–97.

Schmidt, J. H. (2015). Life cycle assessment of five vegetable oils. *J. Clean. Prod.* 87, 130–8.

Selim, H. M. and Zhang, H. (2013). Modeling Approaches of Competitive Sorption and Transport of Trace Metals and Metalloids in Soils: A Review. *J. Environ. Qual.* 42, 640–53.

Senior, M. J., Hamer, K. C., Bottrell, S., Edwards, D. P., Fayle, T. M., Lucey, J. M., Mayhew, P. J., Newton, R., Peh, K. S. H., Sheldon, F. H. and Stewart, C. (2013). Trait-dependent declines of species following conversion of rain forest to oil palm plantations. *Biodivers. Conser.* 22, 253–68.

Sheaves, M. (1996). Habitat-specific distributions of some fishes in a tropical estuary. *Mar. Freshwater Res.* 47, 827–30.

Shen, C., Niu, J. and Phanikumar, M. S. (2013). Evaluating controls on coupled hydrologic and vegetation dynamics in a humid continental climate watershed using a subsurface-land surface processes model. *Water Resour. Res.* 49, 2552–72.

Shrestha, S. and Datta, A. (2015). Field measurements for evaluating the RZWQM and PESTFADE models for the tropical zone of Thailand. *J. Environ. Manag.* 147, 286–96.

Singh, M., Malhi, Y. and Bhagwat, S. (2015). Aboveground biomass and tree diversity of riparian zones in an oil palm-dominated mixed landscape in Borneo. *J. Trop. Forest Sci.* 27, 227–39.

Singh, R., Ibrahim, M., Esa, N. and Iliyana, M. (2010). Composting of waste from palm oil mill: A sustainable waste management practice. *Rev. Environ. Sci. Bio.* 9, 331–44.

Skjemstad, J. O., Spouncer, L. R., Cowie, B. and Swift, R. S. (2004). Calibration of the Rothamsted organic carbon turnover model (RothC ver. 26.3), using measurable soil organic carbon pools. *Austral. J. Soil Res.* 42, 79–88.

Smith, D. R., Townsend, T. J., Choy, A. W. K., Hardy, I. C. W. and Sjögersten, S. (2012). Short-term soil carbon sink potential of oil palm plantations. *Glob. Change Biol. Bioenergy* 4, 588–96

Smith, P. (2006). Organic matter modelling. In Lal, R. (Ed.), *Encyclopedia of Soil Science*. CRC Press: Boca Raton, pp. 1196–202.

Smith, P., Smith, J. U., Powlson, D. S., McGill, W. B., Arah, J. R. M., Chertov, O. G., Coleman, K., Franko, U., Frolking, S., Jenkinson, D. S., Jensen, L. S., Kelly, R. H., Klein-Gunnewiek, H., Komarov, A. S., Li, C., Molina, J. A. E., Mueller, T., Parton, W. J., Thornley, J. H. M. and Whitmore, A. P. (1997). A comparison of the performance of nine soil organic matter models using datasets from seven long-term experiments. *Geoderma* 81, 153–225.

Soltani, A. and Sinclair, T. R. (2015). A comparison of four wheat models with respect to robustness and transparency: Simulation in a temperate, sub-humid environment. *Field Crops Res.* 175, 37–46.

Stehfest, E. and Bouwman, L. (2006). N2O and NO emission from agricultural fields and soils under natural vegetation: summarizing available measurement data and modeling of global annual emissions. *Nutr. Cycl. Agroecosys.* 74, 207–28.

Stichnothe, H. and Schuchardt, F. (2010). Comparison of different treatment options for palm oil production waste on a life cycle basis. *Int. J. Life Cycle Assess.* 15, 907–15.

Stichnothe, H. and Schuchardt, F. (2011). Life cycle assessment of two palm oil production systems. *Biomass Bioenergy* 35, 3976–84.

Stockle, C. O., Donatelli, M. and Nelson, R. (2003). CropSyst, a cropping systems simulation model. *Eur. J. Agron.* 18, 289–307.

Straaten, O. v., Corre, M. D., Wolf, K., Tchienkoua, M., Cuellar, E., Matthews, R. B. and Veldkamp, E. (2015). Conversion of lowland tropical forests to tree cash crop plantations loses up to one-half of stored soil organic carbon. *PNAS* 112, 9956–60.

Sulaiman, F. R., Mustaffa, N. F. S. and Mohd Khazaai, S. N. (2016). Preliminary assessment of selected metals in agricultural soils in Jengka, Pahang, Malaysia. *Environ. Earth Sci.* 75, 1–9.

Thiollet, M. (2003). *Construction des indicateurs viti-environnementaux de la méthode INDIGO*. INRA: Colmar.

Thorburn, P. J., Biggs, J. S., Collins, K. and Probert, M. E. (2010). Using the APSIM model to estimate nitrous oxide emissions from diverse Australian sugarcane production systems. *Agric. Ecosyst. Environ.* 136, 343–50.

Thornton, P. E. and Rosenbloom, N. A. (2005). Ecosystem model spin-up: estimating steady state conditions in a coupled terrestrial carbon and nitrogen cycle model. *Ecol. Model.* 189, 25–48.

Todd-Brown, K. E., Randerson, J. T., Post, W. M., Hoffman, F. M., Tarnocai, C., Schuur, E. A. and Allison, S. D. (2013). Causes of variation in soil carbon simulations from CMIP5 Earth system models and comparison with observations. *Biogeosciences* 10, 1717–36.

Tscharntke, T., Tylianakis, J. M., Rand, T. A., Didham, R. K., Fahrig, L., Batáry, P., Bengtsson, J., Clough, Y., Crist, T. O., Dormann, C. F. and Ewers, R. M. (2012). Landscape moderation of biodiversity patterns and processes-eight hypotheses. *Biolog. Rev.* 87, 661–85.

Uehara, G. and Gillman, G. (1981). *The Mineralogy, Chemistry and Physics of Tropical Soils with Variable Charge Clays*. Westview Press: Boulder, Colorado.

Valente-Neto, F., Koroiva, R., Fonseca-Gessner, A. A. and de Oliveira Roque, F. (2015). The effect of riparian deforestation on macroinvertebrates associated with submerged woody debris. *Aquatic Ecol.* 49, 115–25.

van Ittersum, M. K. and Donatelli, M. (2003). Modelling cropping systems – highlights of the symposium and preface to the special issues. *Eur. J. Agron.* 18, 187–97.

van Kraalingen, D. W. G., Breure, C. J. and Spitters, C. J. T. (1989). Simulation of oil palm growth and yield. *Agric. Forest Meteorol.* 46, 227–44.

van Noordwijk, M., Lusiana, B., Khasanah, N. and Mulia, R. (2011). *WaNuLCAS version 4.0: Background on a Model of Water, Nutrient and Light Capture in Agroforestry Systems*. World Agroforestry Centre (ICRAF): Bogor, Indonesia.

Vanclay, J. K., Sinclair, F. L. and Prabhu, R. (2003). Modelling Interactions amongst People and Forest Resources at the Landscape Scale. *Small-scale Forest Econ. Manag. Policy* 2, 117–20.

Vijaya, S., Ma, A. N. and Choo, Y. M. (2009). A gate to gate assessment of environmental performance for production of crude palm kernel oil using life cycle assessment approach. *Am. J. Environ. Sci.* 5, 267–72.

Wainwright, J. and Mulligan, M. (2013). *Environmental Modelling: Finding Simplicity in Complexity*. John Wiley & Sons, Ltd.

Wakelin, S. A., Gerard, E., van Koten, C., Banabas, M., O'Callaghan, M. and Nelson, P. N. (2016). Soil physicochemical properties impact more strongly on bacteria and fungi than conversion of grassland to oil palm. *Pedobiologia* 59, 83–91.

Wang, X., Piao, S., Ciais, P., Friedlingstein, P., Myneni, R. B., Cox, P., Heimann, M., Miller, M., Peng, S., Wang, T., Yang, H. and Chen, A. (2014). A two-fold increase of carbon cycle sensitivity to tropical temperature variations. *Nature* 506, 212–15.

Wannamaker, C. M. and Rice, J. A. (2000). Effects of hypoxia on movements and behavior of selected estuarine organisms from the southeastern United States. *J. Exp. Mar. Biol. Ecol.* 249, 145–63.

Wantzen, K. M. and Junk, W. J. (2000). The importance of stream-wetland-systems for biodiversity: a tropical perspective. In Gopal, B., Junk, W. J. and Davies, J. A. (Eds), *Biodiversity in Wetlands: Assessment, Function and Conservation*, pp. 11–34. Backhuys: Leiden, The Netherlands.

Waters, D. K., Carroll, C., Ellis, R., Hateley, L., McCloskey, G. L., Packett, R. ... and Fentie, B. (2014). Modelling reductions of pollutant loads due to improved management practices in the Great Barrier Reef catchments – Whole of GBR, Technical Report, Volume 1. Queensland Department of Natural Resources and Mines: Toowoomba, Queensland.

Welcomme, R. (1988). Concluding remarks I: On the nature of large tropical rivers, floodplains and future research directions. *J. N. Am. Benthol. Soc.* 7, 525–6.

Wicke, B., Dornburg, V., Junginger, M. and Faaij, A. (2008). Different palm oil production systems for energy purposes and their greenhouse gas implications. *Biomass Bioenergy* 32, 1322–37.

Wieder, W. R., Grandy, A. S., Kallenbach, C. M. and Bonan, G. B. (2014). Integrating microbial physiology and physio-chemical principles in soils with the MIcrobial-MIneral Carbon Stabilization (MIMICS) model. *Biogeosciences* 11, 3899–917.

Wilkinson, S. N., Dougall, C., Kinsey-Henderson, A. E., Searle, R. D., Ellis, R. J. and Bartley, R. (2014). Development of a time-stepping sediment budget model for assessing land use impacts in large river basins. *Sci. Total Environ.* 468–469, 1210–24.

Yacob, S., Hassan, M. A., Shirai, Y., Wakisaka, M. and Subash, S. (2005). Baseline study of methane emission from open digesting tanks of palm oil mill effluent treatment. *Chemosphere* 59, 1575–81.

Yang, H. S. and Janssen, B. H. (2000). A mono-component model of carbon mineralization with a dynamic rate constant. *Eur. J. Soil Sci.* 51, 517–29.

Yusop, Z., Chan, C. and Katimon, A. (2007). Runoff characteristics and application of HEC-HMS for modelling stormflow hydrograph in an oil palm catchment. *Water Sci. Technol.* 56, 41–8.

Yusop, Z., Hui, C. M., Garusu, G. J. and Katimon, A. (2008). Estimation of evapotranspiration in oil palm catchment by short-time period water-budget method. *Malays. J. Civ. Eng.* 20, 160–74.

Zhang, G.-H., Liu, B.-Y., Liu, G.-B., He, X.-W. and Nearing, M. (2003). Detachment of undisturbed soil by shallow flow. *Soil. Sci. Soc. Am. J.* 67, 713–19.

Zhang, G., Liu, G., Wang, G. and Wang, Y. (2012). Effects of patterned Artemisia capillaris on overland flow velocity under simulated rainfall. *Hydrol. Process.* 26, 3779–87.

Zimmermann, M., Leifeld, J., Schmidt, M. W. I., Smith, P. and Fuhrer, J. (2007). Measured soil organic matter fractions can be related to pools in the RothC model. *Eur. J. Soil Sci.* 58, 658–67.