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Potential Application of Population Models in the European Ecological Risk Assessment of Chemicals II: Review of Models and Their Potential to Address Environmental Protection Aims

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ABSTRACT

Whereas current chemical risk assessment (RA) schemes within the European Union (EU) focus mainly on toxicity and bioaccumulation of chemicals in individual organisms, most protection goals aim at preserving populations of nontarget organisms rather than individuals. Ecological models are tools rarely recommended in official technical documents on RA of chemicals, but are widely used by researchers to assess risks to populations, communities and ecosystems. Their great advantage is the relatively straightforward integration of the sensitivity of species to chemicals, the mode of action and fate in the environment of toxicants, life-history traits of the species of concern, and landscape features. To promote the usage of ecological models in regulatory risk assessment, this study tries to establish whether existing, published ecological modeling studies have addressed or have the potential to address the protection aims and requirements of the chemical directives of the EU. We reviewed 148 publications, and evaluated and analyzed them in a database according to defined criteria. Published models were also classified in terms of 5 areas where their application would be most useful for chemical RA. All potential application areas are well represented in the published literature. Most models were developed to estimate population-level responses on the basis of individual effects, followed by recovery process assessment, both in individuals and at the level of metapopulations. We provide case studies for each of the proposed areas of ecological model application. The lack of clarity about protection goals in legislative documents made it impossible to establish a direct link between modeling studies and protection goals. Because most of the models reviewed here were not developed for regulatory risk assessment, there is great potential and a variety of ecological models in the published literature. Integr Environ Assess Manag 2010;6:338–360. © 2010 SETAC

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INTRODUCTION

The current field of ecological risk assessment (ERA) of chemicals is characterized by a limited amount of integrated ecological theory. Lower tiers of ERA are based on the results of standard tests which assess the toxicological effects on individual organisms, while effects on higher organizational levels are not routinely taken into account. The protection aims of the various ERA schemes, however, are rarely directed toward individuals, and are more commonly assumed to focus on populations, communities or entire ecosystems (EC 2002; Hommen et al. this issue). Therefore, during previous years, the international field of ERA recognized the need for more population-level oriented approaches (Barnthouse et al. 2007). A full understanding of the impacts of pollutants at higher levels of biological organization requires an understanding of fundamental ecology and the integration of more ecological data into toxicological studies. Various frameworks have been proposed to include more ecology in the decision-making process (Chapman 2002; Brock et al. 2006). Attempts to combine toxicology and ecology have been more numerous in recent years, both in experimental and modeling studies (van den Brink 2008). The development of mesocosm studies (Campbell et al. 1998; Giddings et al. 2001; van den Brink et al. 2006) allows the effects of substances (mostly pesticides) on seminatural communities to be assessed. However, some important ecological processes, such as dispersal and recolonization, are not included in these experimental systems, nor are large species like predators, such as fish, which might play a central role in the community.

Our understanding of the way populations and systems function and interact with their environment, as well as the development of ecological theories, has greatly benefited from mathematical modeling (Malthus 1798; Lotka 1924; Volterra 1926). In recent decades, models are increasingly used for management purposes, especially in fisheries and wildlife management (Starfield 1997). Computational and technological progress enables researchers to model very different scales of biological and spatial organization, ranging from very detailed processes, such as the accumulation of chemicals in

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individuals, to simulating population dynamics on a landscape scale. In the field of ERA, a major advantage of ecological models is that they are able to integrate various ecological and toxicological concepts and processes, allowing extensive scenario testing without the accompanying high costs of, e.g., additional experimental setups (Forbes et al. 2008). Their potential in ERA has been recognized and has resulted in an ongoing development of various types of models for assessing risks of chemicals to populations, communities and ecosystems (Bartell et al. 2003; Pastorok et al. 2003).

The field of pesticide ERA is especially benefiting from these developments, because assessing and quantifying risks to nontarget organisms constitute the major part of the pesticide authorization process. Various stakeholders have acknowledged the added value that ecological models bring to ERA, resulting in, for instance, the LEMTOX workshop (Forbes et al. 2009; Thorbek et al. 2010) held in 2007, where representatives of academia, governmental bodies and industry identified advantages, caveats and ways forward, through a combination of presentations and discussions. The 2 eLINK workshops also held in 2007 focused on the problem of extrapolating effects measured for 1 specific exposure pattern to the variety of exposure patterns predicted by FOCUS step 3 models (Brock et al. 2010; Hommen et al. 2010a). Both workshops specifically discussed the role of ecological models in the ERA of pesticides under the 91/414/EC directive (EC 1991).

With regard to legislation, protecting against adverse effects of chemicals, the authorization and registration of chemical substances in the European Union (EU) is governed by different regulatory frameworks. The directives refer to the uses of chemicals, e.g., as plant protection products, biocides, pharmaceuticals or industrial chemicals. In addition, substances are evaluated in terms of the protection of environmental compartments. Within the European Water Framework Directive (EC 2000), for example, environmental quality standards have been set up for 33 priority substances.

Hommen et al. (this issue) compared different EU directives referring to the ecological effects of chemicals, and analyzed their environmental protection goals, data requirements and risk characterization. They also defined 5 application areas within RA that would benefit particularly from various models:

1) relevance of effects observed on individuals for the population level,
2) extrapolation of effects of a tested exposure pattern to other, untested, exposure patterns,
3) extrapolating recovery processes, from individual to population level recovery, including recolonization,
4) analysis and prediction of possible indirect effects in communities, and
5) bioaccumulation and biomagnification within food chains or food webs.

The main objective of this study was to search for existing ecological, mainly population, models that have been or can be readily used to assess risks of chemicals to nontarget organisms. The aim was to understand whether they can help in addressing the protection requirements of relevant EU directives, and to establish which model types are appropriate for different application areas.

We do not attempt to present an exhaustive review of all models, because Bartell et al. (2003) and Pastorok et al. (2003) have already provided excellent reviews of ecological models and their potential use in the risk assessment of chemicals, together with their relative strengths and weaknesses. To our knowledge, however, no previous attempts have been made to assess the role and potential position of ecological models in regulatory RA, more specifically to determine whether they can address the requirements of protection goals in various EU chemical directives. In addition, our extensive literature search allowed us to obtain and assess more recent publications than previous studies did. To illustrate our point and highlight the link with protection goals for the reader, we provide case studies for each of the above-mentioned areas of application. Lastly, the database with all models reviewed, their potential areas of application, and their description using general and more technical criteria is made available as additional information with this publication (Supporting Information S1).

MODEL ASSESSMENT

Ecological models, or model applications, published in peer-reviewed journals were brought together in a database by means of a literature search using simple keywords relating to ecotoxicology and risk assessment (e.g., ecological models, populations, toxicants, stress, risk), using all major search engines, such as Web of Science, CAB Abstracts, and Scopus. The majority of references related to chemical fate or exposure models, which were excluded from further evaluation. Ecological models that included toxicological effects on organisms were preferred, but purely ecological models were also taken into account when they were considered to be potentially useful and chemical effects could be integrated in a relatively straightforward manner.

In total, we assessed 148 publications and institutional reports, grouping publications dealing with the same model or slightly modified versions of it. This resulted in 90 evaluated entries in our model database, with additional entries that were not evaluated but were characterized as having potential value for users (Supporting Information S1). These were either models relating to integrated pest management (Liu et al. 2005; Tang et al. 2005; Holt and Cooper 2006) or model reviews (Koelmans et al. 2001; Ares 2003; Stark and Banks 2003). To evaluate the published models, we defined 5 groups of descriptors: model identification, model focus, model characterization, potential areas of application and model evaluation.

Model identification lists the name of the publication and/or model and the main reference. When multiple publications deal with the same model, the whole list is given in a separate sheet in the database.

Model focus presents general information on the focal group of organisms modeled, the habitat type considered and the level of organization, i.e., whether it is an individual-, population-, community-, or ecosystem-level model.

Model characterization provides information on the formalism of each model, discriminating between different levels of spatial and biological organization by using 4 different model types: scalar or unstructured, matrix, physiologically structured, and individual-based models. Furthermore, it notes whether the model includes any type of toxicological effects, how exposure is considered and which chemical (or type of chemical) is evaluated. The classification of the exposure–effects link is based on eLINK documents (Brock et al. 2010) and includes direct link models, toxicokinetic–toxicodynamic models, simple population models, complex population models, and food-web and/or ecosystem models. Finally, this category indicates the spatial and temporal scales used and whether stochastic events are included.

Potential areas of application indicates which areas can be addressed by the model. These areas are summarized in the *Introduction* and will be explained further in the *Case Studies* section.

Model evaluation summarizes more technical details of a model, such as the ease with which parameters can be estimated, whether and how validation, calibration, uncertainty and sensitivity analyses have been carried out, model flexibility, and availability of the program or code. Finally, the type of output is provided, as well as, in the case of a purely ecological model, its potential for use in the ERA of chemicals.

MODEL DATABASE ANALYSIS

In total, we evaluated 63 models that included exposure to and effects of toxicants and can or have been already directly used in chemical ERA, while 27 models included only ecological processes. Most (77%) of the 90 models assessed and described are population-level models, with the exception of a few individual- and ecosystem-level models. Model focus ranged from accurate description of specified species' life cycles to general representations of various systems. Consequently, some models were developed to describe specific habitats and species, while others could be applied to a range of habitats and species. The majority of the models describe aquatic, mostly freshwater, habitats, while some models relate to the marine environment (Chen and Liao 2004; Raimondo and McKenney 2006). Around a quarter of the models describe terrestrial systems (e.g., Sherratt and Jepson 1993; Kjaer et al. 1998; Wennergren and Stark 2000).

We primarily grouped models according to their biological level of organization, i.e., individual, population, metapopulation, and community and/or ecosystem models (Tables 1–4). In the following sections, we present some examples for each biological level. Additionally, we discuss a subset of individual-, population-, and metapopulation-level models where spatial aspects are explicitly considered; these are also summarized in Tables 1 to 4.

Individual-level models

Several publications in the database addressed exclusively individual responses to toxicant exposure (Table 1). Apart from lethal effects, most of these individual models also address sublethal effects acting through impaired growth or maturation. A recent example describing the impact of exposure to a toxicant (Methyl-Hg) on behavior was presented in Murphy et al. (2008). In their model, a chemically induced decrease in larval swimming speed resulted in impaired larval growth and thus increased stage duration, with increased predation risk. Klanjscek et al. (2007) developed an individual-level model, based on Dynamic Energy Budgets (Kooijman 2000), assessing the uptake, elimination and bioaccumulation of PCBs in a marine mammal, the right whale. Their model also serves as a potential platform for the assessment of population-level responses. The work by Ashauer et al. (2007a) focuses on establishing a mechanistic link between different exposure regimens of various chemicals and their effects on the survival of *Gammarus pulex*. These types of models are referred to as toxicokinetic-toxicodynamic (TK-TD) models, a class of models that mechanistically account for time-varying exposure, and, consequently, effects of chemicals on individuals (Lee et al. 2002; Lee and Landrum 2006; Ashauer et al. 2006, 2007, 2007a). Ashauer and Brown (2008) provide a review on this group of models, more specifically on the toxicodynamic part, linking dynamic exposure and effects, including assumptions, data requirements, advantages, and constraints of these approaches. Most TK-TD models account for lethal effects, but some can model effects of toxicants on various other endpoints, such as growth or reproduction, i.e., sublethal effects (Billoir et al. 2007). They are usually implemented on the level of individuals or groups, according to age, stage, size, etc. Subsequently, these mechanistic links can be integrated into population models to assess effects at the population level (Pery et al. 2004, 2006; Ducrot et al. 2007).

Population-level models

Table 2 provides a list of publications that describe population models. Within the table we evaluate the suitability of models to address questions in 1 or more of the proposed application areas.

Approximately 21% of all evaluated population models describe unstructured populations, in which all individuals are identical in terms of their life-history details, and simple processes like births and deaths determine the dynamics of the population or group. Even though they are very simple and include only the most basic processes in a population, they add more realism to ERA by assessing the effects of pollutants on cumulative demographic rates and, consequently, on projected abundance or population growth rate. Some examples in our database include Adams et al. (2005), in which simple models, in the form of ordinary differential equations (ODEs), were fitted to data for population dynamics of aphids in broccoli fields repeatedly sprayed with pesticides. Ecosystem models (Traas and Aldenberg 1992; Hanratty and Stay 1994; Naito et al. 2002) are usually a combination of unstructured models for each of the functional groups.

More than half (53%) of all population models evaluated are structured population models. These models tend toward a higher level of realism, because individuals of 1 species have different characteristics in different stages of their life cycle. Furthermore, effects of environmental stressors tend to be expressed differently in different life stages. Classes or groups in structured models are based on stage, age, physiological condition, size, or any other demographically relevant criterion. Most common are matrix models, with distinct stage or age classes combined with a discrete time approach. Matrix models can be used to calculate the population growth rate, λ, for a given set of life cycle data (e.g., age dependent survival and fecundity). The sensitivity of the growth rate to changes in the life table data can be evaluated analytically with a so-called elasticity analysis (for more information on matrix models, see Caswell 2000). Events and parameters are usually deterministic, which makes matrix models suitable for projecting population growth, i.e., assessing abundance or growth rate in the future based on current values. The parameters of matrix models and the impact of toxicants on these parameters are both defined directly from life table data. Half of the matrix model applications in our database

Table 1. Reviewed individual-level ecological models

				Potential application area					
Nr	**Model name**	**Main reference**	**Toxicity included?**	**1**	**2**	**3**	**4**	**5**	**Space considered?**
1	Threshold Damage Model	Ashauer et al. 2007	Y		X	X		X	N
2	Habitat and exposure modeling for ecological risk assessment: A case study for the raccoon on the Savannah River Site	Chow et al. 2005	Y (exposure only)					X	Y
3	A model for energetics and bioaccumulation in marine mammals with applications to the right whale	Klanjscek et al. 2007	Y					X	N
4	On the dynamics of chemically stressed populations - the deduction of population consequences from effects on individuals	Kooijman & Metz 1984	Y	X	X			x	N
5	Modeling larval fish behavior: Scaling the sublethal effects of methyl-mercury to population-relevant endpoints	Murphy et al. 2008	Y	X		X			N
6	A partially specified dynamic energy budget model	Nisbet et al. 2004	N	X		X			N
7	Use of habitat-contamination spatial correlation to determine when to perform a spatially explicit ecological risk assessment	Purucker et al. 2007	Y (exposure only)					X	Y
8	Modeling the influence of environmental heterogeneity on heavy metal exposure concentrations for terrestrial vertebrates in river floodplains	Schipper et al. 2008	Y (exposure only)					X	Y

Table 2. Reviewed population-level ecological models

					Potential application area					
Nr	**Model name**	**Main reference**	**Model type**	**Toxicity included?**	**1**	**2**	**3**	**4**	**5**	**Space considered?**
1	Plant-insect herbivore-pesticide interactions	Adams et al. 2005	Unstructured	Y	X	X				N
2	Assessing ecological risk to night heron	An et al. 2006	Matrix	Y	X					N
3	Application of individual growth and population models of *Daphnia pulex* to other daphnid species	Asaeda & Acharya 2000	Stage structured	N	X		X	X		N
4	Logistic growth model and recovery times	Barnthouse 2004	Unstructured	N			X			N
5	Impact of pesticides on lumbricids	Baveco & De Roos 1996	Structured (PDE), IBM	Y	X	X	X			N
6	Angling and life history effects on bluegill size structure	Beard and Essington 2000	IBM	N	X		X			N
7	Mosquitofish population dynamics	Beaudouin et al. 2008	IBM	N	X		X			N
8	Effects of toxic compounds on population dynamics of *Daphnia magna*	Billoir et al. 2007	Matrix (DEB)	Y	X					N
9	PC-BEEPOP	Bromenshenk et al. 1991	Stage structured	Y	X	X	X			N
10	Endocrine disrupting chemicals in perch populations	Brown et al. 2005	Stage structured	Y	X	X	X			N
11	Synchronous versus asynchronous treatments for control of dispersing insect pests	Byers & Castle 2005	Unstructured	Y	X		X			Y
12	Mosquitofish responses to Genapol OXD-080	Cabral et al. 2001	Structured	Y	X		X			N

13	Risk assessment on the basis of simplified life-history scenarios	Calow et al 1997	Matrix	Y	X		X			N
14	Life cycle testing and Leslie matrix	Chandler et al. 2004	Matrix	Y	X	X	X			N
15	Food availability and *Chironomus riparius*	Charles et al. 2004	Matrix (DEB)	N	X					N
16	Aggregation methods and toxicant effects in spatial systems	Chaumot et al. 2002	Matrix	Y	X					Y
17	Farmed abalone exposed to waterborne zinc	Chen & Liao 2004	Matrix	Y	X	X			X	N
18	Slug IBM	Choi et al. 2006	IBM	N	X		X			Y
19	Effects of temperature and soil moisture on collembolan species	Choi et al. 2006a	Matrix	Y	X	X	X			N
20	Mark-recapture and simulation modeling of saddlebacks	Davidson & Armstrong 2002	IBM	N	X		X			N
21	Density-dependent dynamics in smallmouth bass populations	De Angelis et al. 1991	IBM	N	X		X			N
22	Demographic analysis of continuous-time life-history models	De Roos 2008	Structured (Lotka’s integral eq.)	N	X		X			N
23	DEB and population effects of zinc-spiked sediments in a gastropod	Ducrot et al. 2007	Matrix (DEB)	Y	X					N
24	Bayesian modeling of aphid dynamics	Fabre et al. 2006	Unstructured	N	X					N
25	Chlorpyrifos in aquatic environments	Giesy et al. 1999	Matrix	Y	X	X	X			N
26	GETLAUS01	Gosselke et al. 2001	Physiologically structured	N	X		X	X		N

(*Continued*)

Table 2. (*Continued*)

Nr	Model name	Main reference	Model type	Toxicity included?	Potential application area 1	2	3	4	5	Space considered?
27	Development and application of bioaccumulation models to assess persistent organic pollutant temporal trends in Arctic ringed seal (*Phoca hispida*) populations	Hickie et al. 2005	IBM	N					X	N
28	RA of the Victorian southern rock lobster fishery	Hobday & Punt 2001	Sex and size structured	N	X		X	X		N
29	Multiple endpoints in life-cycle toxicity	Jager et al. 2004	Unstructured	Y	X					N
30	Two modes of action of cpf in the springtail *Folsomia candida*	Jager et al. 2007	Structured (Euler-Lotka eq.)	Y	X					N
31	PCB effects on young-of-the-year largemouth bass	Jaworska et al. 1997	IBM	Y	X					N
32	Estuarine striped bass population	Kimmerer et al. 2001	Stage structured	Y	X		X	X		N
33	Insecticide effects on chrysomelid beetles	Kjaer et al. 1998	Stage structured	Y	X					Y
34	Integrating DEB into matrix models	Klanjscek et al. 2006	Matrix (DEB)	N	X					N
35	*Lumbricus rubellus* in a polluted field soil: possible consequences for the godwit	Klok et al. 2006	Matrix (DEB)	Y	X					N
36	DEB and Bayesian approaches for *Dendrobaena octaedra*	Klok et al. 2007	Matrix (DEB)	Y	X					N
37	Toxicological effects on *Lumbricus rubellus*	Klok & de Roos 1996	Matrix	Y	X	X	X			N
38	Environmental and chemical stressors on *Daphnia*	Koh et al 1997	Physiologically structured	Y	X	X				N
39	Mysid toxicity test data and population modeling techniques	Kuhn et al. 2000	Matrix	Y	X					N

40	Hard clam susceptibility to Hg-stressed birnavirus	Liao & Yeh 2007	Matrix with epidemiological SIM models	Y	X				N
41	Bioenergetics-based matrix population model of tilapia	Liao et al. 2006	Matrix (DEB)	Y	X			X	N
42	Establishing predicted NOECs for population-level ERA	Lin 2005	Matrix	Y	X				N
43	DEBtox models in Leslie models	Lopes et al. 2005	Matrix (DEB)	Y	X				N
44	Accumulation of PCBs by Lake Trout	Madenjian 1993	IBM	Y	X	X	X	X	N
45	Heavy-metal pollution of fish populations	Mastala et al. 1993	Structured	N (only accumulation)				X	N
46	Endocrine disruptors and fathead minnow populations	Miller & Ankley 2004	Matrix (with logistic eq.)	Y	X	X	X		N
47	Herring gull populations and DDT exposure	Nakamaru et al. 2002	Matrix with canonical extinction model	Y	X	X		X	N
48	WORMDYN	Pelosi et al. 2008	Matrix (Leslie)	N	X		X		N
49	*Chironomus riparius* in ecotoxicological risk assessment	Pery et al. 2004	Matrix (DEB)	Y	X				N
50	*Chironomus riparius* and heavy metals	Pery et al. 2006	Unstructured (kinetics, DEB based) and matrix	Y	X	X			N
51	IDamP	Preuss, Hammers-Wirtz, et al. 2009	IBM	Y (see Case Studies)	X	X	X	X	N
52	Modeling aquatic toxicity data	Raimondo & McKenney 2006	Matrix	Y	X	X			N
53	Diel vertical migration of *Daphnia*	Rinke & Petzold 2008	IBM	N	X		X		N

(*Continued*)

Table 2. (*Continued*)

Nr	Model name	Main reference	Model type	Toxicity included?	Potential application area 1	2	3	4	5	Space considered?
54	Temperature and food concentration effects on *Daphnia*	Rinke & Vijverberg 2005	Physiologically structured	N		X		X		N
55	Cadmium exposure of the freshwater gastropod, *Biomphalaria glabrata*	Salice & Miller 2003	Matrix	Y		X	X			N
56	DANIO	Schäfers et al. 1993	IBM	Y		X	X	X		N
57	GamMod	Schmidt 2003	IBM	Y		X		X		N
58	Population parameters for 3 salmon species	Spromberg & Meador 2006	Matrix	Y		X		X		N
59	MORPH	Stillman 2008	IBM	N		X		X		Y
60	Insect growth-regulating insecticides on honeybees	Thompson et al. 2005	Stage structured	Y		X		X		N
61	Insecticide-contaminated dung and the abundance and distribution of dung fauna	Vale & Grant 2002	Stage structured	Y		X	X	X		Y
62	Piscator - IBM to analyze dynamics of lake fish communities	van Nes et al. 2002	IBM	N		X		X	X	N
63	CHARISMA	van Nes 2003	IBM	N		X		X	X	Y
64	Sympatric populations of brown and rainbow trout	Van Winkle et al. 1998	IBM	N		X		X		Y
65	Behavior under food limitation and crowding and the effect on population cycling in *Daphnia*	Vanoverbeke 2008	IBM	N		X		X		N

66	The dynamics of pest-parasitoid-insecticide interactions	Waage et al. 1985	Unstructured, matrix	Y	X		X	X	N
67	Population dynamics of thrips	Wang & Shipp 2001	Physiologically structured	Y	X	X	X		N
68	Beyond just counting dead animals	Wennergren & Stark 2000	Matrix	Y	X	X	X		N

incorporated a TK-TD model to describe mechanistically how effects depend on the body burden changing over time. Often an energy budget model simulating individual growth and reproduction, that is, a Dynamic Energy Budget (DEB) model (Kooijman 2000) is integrated (Lopes et al. 2005; Liao and Chiang 2006; Ducrot et al. 2007). When combined with a model for individual growth and reproduction, such matrix models can easily account for sublethal impacts on reproduction and development.

The next class of population models regards individuals as unique, and these are therefore termed individual-based population models (IBMs, sometimes also called agent-based models); they make up 26% of all the population models in our review. Within IBMs, population properties are a result of keeping track of individuals' intraspecific and interspecific interactions, as well as their interactions with the environment. Their great advantage is their flexibility, because in principle each aspect, including complex behavior, can be included into the model. Furthermore, inclusion of individual variability in the form of distributions from which parameter values are derived allows a direct simulation of demographic stochasticity or probabilistic behavior. One of the disadvantages of such an approach is that, in most cases, assumptions and data used in IBMs are both exhaustive and very species-specific, so their development is very data hungry, requiring a lot of computing power to keep track of all individuals in a population, and their analysis can become very complex and cumbersome. This puts them in the highest levels of realism and makes them suitable for use in case-specific studies in higher tiers of ERA. Early examples of IBMs are predominantly fish models, with non-ERA examples in our database including De Angelis et al. (1991) and Beard and Essington (2000). Examples of nonspatial (fish) IBMs used in ecotoxicological studies are Jaworska et al. (1997) and Madenjian (1993). More recent examples of nonspatial IBM applications outside the field of ERA are mostly aquatic. Rinke and Petzoldt (2008) and Vanoverbeke (2008) focused on *Daphnia*, while Beaudouin et al. (2008) and the Piscator model (van Nes et al. 2002) modeled fish. Recent uses of IBMs in ERA include a *Gammarus* (Schmidt 2003) and *Daphnia* model (Preuss, Hammers-Wirtz, et al. 2009), mostly to refine higher tiers of the pesticide registration process. Terrestrial examples are provided in Baveco and de Roos (1996) and Davidson and Armstrong (2002), who used an IBM to assess the impact of a brodifacoum, a mouse poison, on an island population of New Zealand saddlebacks.

Ecosystem models

A small fraction of the evaluated models address the higher level of biological organization, such as food webs, communities, and ecosystems (Table 3). Within ERA, they have been applied mainly to freshwater ecosystems, e.g., SWACOM (O'Neill et al. 1982), LERAM (Hanratty and Stay 1994), CATS-4 (Traas et al. 1998), CASM (Naito et al. 2002), C-COSM (Traas et al. 2004), and AQUATOX (Park et al. 2008). An early version of the CATS model was also applied to meadow ecosystems (Traas and Aldenberg 1992) and was chosen as one of the case studies discussed below. CASM is an expanded version of SWACOM, while LERAM is a version of CASM adapted to littoral ecosystems. The definition of aquatic food web components differs slightly between these models, with phytoplankton, zooplankton, omnivorous and piscivorous fish, and macroinvertebrates being among the

Table 3. Reviewed community/ecosystem-level ecological models

					Potential application area					
#	**Model name**	**Main reference**	**Model type**	**Toxicity included?**	**1**	**2**	**3**	**4**	**5**	**Space considered?**
1	A food web bioaccumulation model for organic chemicals in aquatic ecosystems	Arnot & Gobas 2004	Unstructured	Y					X	N
2	Deriving water quality criteria	De Laender 2007	Unstructured	Y	X		X	X		N
3	EcoWin	Ferreira 1995	IBM	N	X					N
4	LERAM	Hanratty & Stay 1994	Unstructured	Y	X	X	X	X		N
5	CASM	Naito et al. 2002	Unstructured	Y	X	X	X	X		N
6	SWACOM	O'Neill et al. 1982	Unstructured	Y	X			X		N
7	AQUATOX	Park et al. 2008	Unstructured	Y	X	X		X	X	N
8	C-COSM	Traas et al. 2004	Unstructured	Y	X	X	X	X		N
9	CATS	Traas & Aldenberg 1992	Unstructured	Y	X	X		X	X	N
10	Recovery of macroinvertebrates following a pulse-disturbance in river	Watanabe et al. 2005	Unstructured	Y	X		X	X		N

constant factors. Dynamics of various compartments are usually represented by a set of differential equations, representing the lack of structure within a compartment, and application is usually accompanied by a sensitivity or uncertainty analysis using Monte Carlo simulation. Spatial heterogeneity, apart from heterogeneity in 1 dimension (depth of the water layer), is usually not taken into account.

Spatial models

There is a small subset of individual-level models that include detailed spatial exposure patterns, combining spatial foraging models with food web or food chain accumulation models, but without the resulting effects on groups or individual organisms; for example, Schipper et al. (2008) evaluated the effects of heavy metal exposure on a river floodplain. For terrestrial vertebrates, exposure is integrated over individual home ranges, assuming, e.g., random walk movement and spatial heterogeneity in diet and contaminant exposure (see also Purucker et al. 2007) (Table 1).

Early analyses of the potential impact of spatial structure for population-level ERA are presented in the following papers. Maurer and Holt (1996) analyzed the effect of chronic pesticide stress on populations, based on simple, demographically unstructured, spatially implicit metapopulation models. Spromberg et al. (1998) extended the analysis by including temporal dynamics in exposure in a simple unstructured population model incorporating diffusion

Table 4. Reviewed metapopulation-level ecological models[a]

					Potential application area					
#	**Model name**	**Main reference**	**Model type**	**Toxicity included?**	**1**	**2**	**3**	**4**	**5**	**Space considered?**
1	Carabid metapopulation model	Sherratt & Jepson 1993	Unstructured	Y	X	X	X	X		Y
2	Metapopulation dynamics: indirect effects and multiple distinct outcomes	Spromberg et al. 1998	Unstructured	Y	X		X	X		Y
3	ALMaSS (potential)	Topping et al. 2003	IBM	N	X		X	X		Y
4	MASTEP (potential)	van den Brink et al. 2007	IBM	Y	X		X			Y

[a] Note that not all models are metapopulation models in the classical sense, but have potential to address population level issues from a metapopulation perspective.

between a limited number (3) of patches. Sherratt and Jepson (1993) analyzed 2 simulation models, 1 stochastic model with random walk movement between 16 fields and another deterministic one including predator and prey dynamics and simple diffusion-like dispersal. These studies were mostly theoretical, providing insights and identifying potential mechanisms like action at a distance. This means that local population dynamics in unexposed patches are affected indirectly by stress, through their links (dispersal) with exposed patches. Table 4 lists reviewed publications where metapopulations are modeled. Vale and Grant (2002) provide another example of a simple spatial, stage-structured model, to assess the impact of insecticides on (hypothetical) species of dung fauna.

Later studies have attempted to assess the risk posed to specific organisms in specific areas (spatially explicit ERA). To this end, structured population model approaches have been extended to include both a population and a spatial structure. Chaumot et al. (2002) used a ''multi-region'' Leslie matrix approach to model the impact of Cd on trout populations in a network of waterways. Recent examples show how spatial IBMs can be used to study population recovery in a spatial context (see van den Brink et al. 2007, in the *Case Studies* section below). The ALMaSS system (Topping et al. 2003) is an extensive IBM at the landscape level, including landscape dynamics (management) and multispecies interactions. Topping et al. (2005) and Sibly et al. (2005) compared the results of this IBM with those obtained using a matrix approach to assess the risks posed to skylarks by an imaginary insecticide. Other examples of spatial IBMs in the database, however, do not include an ecotoxicological component, but were developed for pest and wildlife management purposes. For instance, Choi et al. (2006) modeled slug population dynamics, Van Nes (2003) modeled submerged aquatic macrophyte population dynamics, and Van Winkle et al. (1998) modeled trout population dynamics in streams. These studies serve as examples of approaches taking into account both biological and spatial structure, which might be extended to incorporate toxicant effects.

CASE STUDIES ON POTENTIAL AREAS OF APPLICATION OF ASSESSED MODELS

Models were also assessed for their potential use in the application areas (Hommen et al. this issue) (Figure 1). Some models were suitable for use in only 1 or 2 of these areas, others in up to 4. None of the models had the potential to be used in all 5 application areas, which was to be expected because the main purpose of the models is to answer questions that vary greatly between the areas. The following section elaborates on all of these application areas and provides examples of modeling approaches to address each of them. The sections start with a short introduction on the application area including a brief summary of case studies, followed by a detailed description of the case studies.

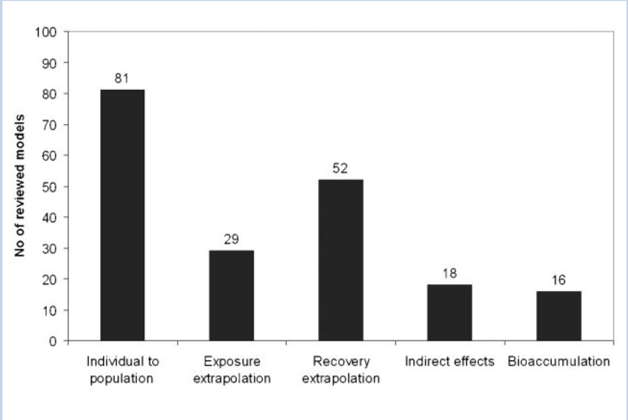

Figure 1. Distribution of the reviewed modeling studies across the proposed application areas.

Population-level relevance of individual-level effects

The first application area relates to assessing population-level responses to individual-level effects, because most directives aim to protect local populations, rather than individuals (with the exception of vertebrates). It is clear that species-specific life-history traits are highly relevant when assessing risks of chemicals to nontarget species. For example, some chemical effects are expressed differently in juveniles and adults and to account for these differences, at least some life history needs to be included for the population-level risk assessment (Sibly et al. 2005). Our review showed that of the 90 model entries in the database, 81 (90%) could be used for extrapolating effects from the individual to the population level (Figure 1). The most commonly used method to estimate effects of chemicals on populations and their growth rates uses data on vital rates from life table response experiments or toxicity tests (Kuhn et al. 2000; Chandler et al. 2004). Vital parameters derived from stressed individuals as well as from the control group are then projected using a population model and compared with an unstressed situation (Klok and de Roos 1996; Salice and Miller 2003). The type of model most commonly used for this form of extrapolation is that of matrix models. There are also models that link toxicant effects in a more mechanistic manner (Naito et al. 2002; van den Brink et al. 2007), and models based on DEB theory (Jager et al. 2004; Billoir et al. 2007; Ducrot et al. 2007).

The following case studies have been chosen to cover the range of approaches, focal organisms, and output that can be used for ERA. The first publication, on susceptibility of biological agents to pesticide stress (Stark et al. 2004), is a clear and simple example of how integrating basic life-history traits in a matrix model results in different outcomes for the species considered. It emphasizes that it is not only the species-specific susceptibility to toxicants that is important in risk assessment, but also the ecology of the species itself. In this sense, it is the exemplar of the integration of ecology into toxicology and risk assessment. The model clearly shows that the pest predator, the lady beetle, is more susceptible due to its higher number of preadult stages, i.e., needs a longer development time before reaching a reproductive stage that ensures population persistence. The second publication, on population-level effects of individual growth of earthworms in Cu-polluted soil (Klok and de Roos 1996), was chosen to demonstrate a somewhat more complex matrix model, one that takes into account individual processes such as growth and some basic calculations of energetics, and projects them to population level responses using a matrix model. Toxicant effects are not explicitly modeled but are implicit in the datasets from polluted soils. Rather than explaining the mechanisms, it concentrates on more specific processes in an organism, considering the distribution of acquired energy among various individual-level processes, and the effects of toxicants on this distribution.

Although the model shows that individual earthworms do grow even after the concentration of Cu in the soil exceeds the safe concentrations, one must be careful in accepting it as harmless, as the trapping of individuals in a subadult stage has obvious consequences for the total population and even for the food chain or ecosystem.

Finally, the individual-based model of a largemouth bass population and the effects of PCBs on young-of-year clearly demonstrates the amount of data and ecological functions needed for such a modeling approach (Jaworska et al. 1997). Constructing an individual-based fish population model requires many variables to be considered, from life-history traits and metabolic processes to lethal and sublethal effects of a specific toxicant. This is often very disadvantageous, because much of this kind of data is still not available, while many processes or aspects of species behavior might not be known either. However, even with the clear difficulties faced when constructing an IBM, the advantages of investigating emergent processes and results that reflect natural behavior may outweigh the problems. The largemouth bass population, for instance, shows an increased juvenile mortality by the presence of PCB. This results in less competition within the cohort for zooplankton, leading to increased weight and length of the surviving individuals. Nevertheless, to understand individual-based models and interpret the results correctly, their processes and assumptions need to be properly understood, as well as the temporal and spatial scales. This is also emphasized by the authors themselves.

Susceptibility of biological control agents to pesticides—Stark et al. (2004) investigated the role that life-history differences play in population responses to pesticides. It focused on mortality and reduction of fecundity (as the sublethal effect), and the influence of population structure on the dynamics of 3 species with different life-history traits: a predatory lady beetle, *Coccinella septempunctata*; its prey, the pea aphid, *Acyrthosiphon pisum*; and a common aphid parasitoid, *Diaeretiella rapae*. This combination of species represents an important predator-prey complex in biological control. Entries for the age-structured Leslie projection matrix (Leslie 1945) model are life-history parameters, such as survivorship in different stages and fecundity of the population.

Although the toxicant used in this study was only hypothetical and its effects were mimicked by decreasing fecundity and survival, it was shown that differences between species in even a small number of life-history parameters greatly impacts the population susceptibility to pesticides. Equal levels of mortality or reduction of fecundity have different impacts on different species The predatory lady beetle shows the greatest response, due to its higher number of life stages, which suggests a longer development time before reaching reproductive age, and a lower reproductive output than the other 2 species modeled.

Toxicological effects of Cu *on individual growth and reproduction in earthworm populations*—Klok and de Roos (1996) developed a model to assess the impact of Cu-polluted soil on earthworm (*Lumbricus rubellus*) populations. The model consists of 2 levels, an individual level describing growth and fecundity of earthworms, and a stage-structured matrix model that projects population-level effects of individual growth and reproductive output in Cu-stressed conditions.

The *individual-level model* follows the dynamic energy budgets theory (Kooijman 2000), the central assumption being that maintenance and growth compete more directly with each other than with reproduction. Energy requirements for maintenance always take priority over growth and reproduction. Food intake is proportional to the surface area, while growth and maintenance are proportional to the wet weight (W) of the individual organism. The surface area is assumed to be proportional to $W^{2/3}$ and reproduction is assumed to start after a certain threshold size (adult size) has been reached. Under constant food conditions, individuals are assumed to grow according to the von Bertalanffy growth curve.

The *population-level model* is a matrix projection model, based on 4 stages, namely the cocoon, juvenile, subadult, and adult stages. Entries in the matrix represent the following transitional probabilities: the probability of remaining in the same stage, the probability of developing into the next stage and reproductive output, which is a property only of the adult stage. Values of all these entries are determined by the model for individual growth and reproduction.

This study investigated 3 possible toxicity scenarios: decrease in energy assimilation, increased maintenance costs for detoxification, and a best-fit scenario (increased maintenance costs and extra energy for cocoon production). The results show that, in all scenarios, individuals get trapped in the subadult stage and are thus incapable of reproduction. The authors suggest that data on the duration of juvenile stages, rather than only on hampered reproduction, might be a better estimate of toxic effects at a population level.

Individual-based modeling of PCB effects on largemouth bass—Because individual-based models generally demand a lot of data and ecological functions, we limit ourselves to describing only the most relevant processes in the model.

Jaworska et al. (1997) developed an individual-based model that simulates the daily development, growth, and survival of largemouth bass, *Micropterus salmoides*, from the egg stage, set at 1 April, to the end of their first growing season, set at 15 October. Nest creation, growth (through consumption), and egg mortality are temperature-dependent. The modeled environment represents a strip of shoreline where bass construct their nests and young-of-the-year (YOY) life stages are usually found. Reproduction starts with nest construction by male spawners, whose numbers and length distribution are specified by the user/modeler. Number of eggs is a function of male length, because it is assumed that larger males attract larger females and fecundity depends on female size. The timing of nest creation and the development rate from the egg to the swim-up larval stage is temperature dependent. After hatching, yolk-sac larvae are assumed to have a constant growth rate until they reach the initiation size of the swim-up larval stage. Daily consumption depends on an individual's random encounters with zooplankton, benthos and shad prey types, the first 2 of which are represented by multiple size classes, while shad prey is represented by 18-week cohorts. Mortality of YOY stages is a combination of constant rates, size-dependent rate, nest desertion and starvation. PCB exposure levels are expressed as TCDD (tetrachlorodibenzo-*p*-dioxin) concentrations in muscle tissue, ranging from 6 to 20 ppm, and no uptake or depuration of PCBs is simulated. Toxic effects of accumulated PCBs include increased mortality of post-egg life stages and reduced growth of swim-up larvae and juveniles. PCB-induced mortality of fish decreases with their age. Growth reduction is a function of toxicant concentration that starts from zero level at NEC and reaches one at the concentration causing 100% growth inhibition, which is modeled by a hyperbolic function and arises from the increased metabolic costs due to processing PCBs and reduced feeding.

The results showed that density-dependent survival was operating, as density and biomass density leveled off with increasing spawner density. The mean length visibly decreased with spawner density due to higher consumption of zooplankton and shad prey by the bass population. Lower growth resulted in lower survival as smaller fish experience a higher mortality rate. PCB effects were apparent but rather small relative to the natural variation in the model predictions. Density, biomass density, mean condition factor, and survivorship all decreased, while the mean length increased slightly with increasing PCB levels. Interestingly, at the lower spawner densities at the 6 and 10 ppm PCB levels, predicted density and biomass density were higher for the chronically stressed population. The most important input affecting densities and survivorship of the bass population was zooplankton carrying capacity. However, the study did not include other possible density-dependent mechanisms that might potentially have a large influence on system behavior.

Extrapolation of effects across exposure patterns

One of the biggest challenges in pesticide ERA is how to deal with exposure regimens that vary in time and extrapolate effects observed after 1 peak exposure in the laboratory to multiple exposures in the field that occur due to spray drift, runoff, or drainage. For nonpesticides, e.g., industrial chemicals or pharmaceuticals, usually a more constant, chronic exposure can be assumed. Techniques that can account for effects of variable temporal exposure include ecological modeling. Focusing on pesticides, the eLINK workshop provided some recommendations on this issue (Brock et al. 2010). In our database, 29 (32%) models include the extrapolation of effects across different exposure patterns. Due to their straightforward construction, matrix models can easily incorporate data on vital parameters from different constant concentrations (Miller and Ankley 2004). However, they only include dose–response functions relating the survival of organisms based on external concentrations, which is a simple form of linking exposure with effects. For a more mechanistic coupling of exposure and effects using internal concentrations TK-TD models can be used. Because these models require extensive laboratory studies for model parameterization, they are still scarce and focus mostly on individuals. The following case study demonstrates how TK-TD models can be linked to population models, and how this can significantly improve the possibilities to predict population level responses at different exposure levels and regimens.

Extrapolating population-level effects of Daphnia magna across exposure patterns—The individual-based model of *D. magna* is described in detail in Preuss, Hammers-Wirtz, et al. (2009) Each daphnid in the model follows its life-cycle, including feeding on algae, aging, growing, developing, and—when maturity is reached—reproducing. The modeled life-cycle is driven by the amount of ingested algae and the density of the *Daphnia* population: at low algal densities, the population dynamics are mainly driven by food supply, whereas at high algal densities, the limiting factor is crowding (a density-dependent mechanism due to chemical substances released by the animals or physical contact, but independent of food competition). Thus, the parameters of the model are the coefficients of different functions describing the life-cycle traits, while individual age, developmental stage, body length, feeding rate, and brood size serve as the state variables of the models. Population dynamics emerge directly from the life cycle of individual daphnids.

The parameterization of the model was based on several life-cycle studies with *D. magna* with different food conditions under flow-through conditions. The model was not only able to predict the total abundance of the population over time but also predicted the size structure in good agreement with observations.

While Preuss, Hammers-Wirtz, et al. (2009) describe the model without considering the effects of toxicants, the model has also been applied to a situation with constant exposure to 3,4-dichloroaniline and nonylphenol (Preuss et al. 2008). To be able to model acute effects of variable toxicant concentrations on *Daphnia* populations, 3 different submodels to link exposure and effects were tested, namely direct link, time-weighted averages (TWA), and the damage assessment model (DAM). A direct link model is a dose–response mortality curve, in this case after a 48-h exposure. In the TWA model, effects depend on the time-weighted average of the external concentration over the individual's lifespan. Finally, the DAM model explicitly models toxicokinetics and toxicodynamics. Uptake and elimination are described by first-order kinetics (and thus by 2 parameters, the uptake and elimination rates [k_{in} and k_{out}]) to describe the body burden (C_B), while survival depends on the internal damage, which is also described by 2 rate constants (the killing rate k_k and the recovery rate k_r). Details of the DAM can be found in Lee et al. (2002) and Ashauer et al. (2006). The model was tested on the data from 12 population experiments with different exposure patterns (different numbers of pulses, different magnitudes of the pulse exposure, and different intervals between pulses). In most of the cases (9 of 12), it was the DAM which produced the best fit to the data. In 3 cases, the simplest model, which assumes a direct link between the actual concentration in the water and the effect, seemed to be the best submodel.

Preuss et al. (2008) concluded that the direct link model can only be used for scenarios with 1 or 2 peaks, while more complex exposure scenarios require choosing an appropriate effect model. The TWA approach does not produce better predictions than the direct link model and is therefore not suitable for the prediction of population dynamics in complex exposure scenarios. The DAM, however, predicts the population dynamics for complex exposure scenarios quite well. Where it does not, its predictions are protective.

Extrapolation of recovery processes

Population recovery after chemical stress has become especially interesting for the risk assessment of plant protection products because Annex VI (the Uniform Principles (EC 1991; Hommen et al. this issue) offers the option of effects being acceptable if recovery within a few weeks after exposure can be demonstrated experimentally or if the likelihood of recovery under field conditions is shown to be high. In fact, the extrapolation of recovery processes was the second best represented application area in our database, with 52 model entries (58%). Recovery at the individual level includes recovery by internal mechanisms (through repair and elimination processes)(Ashauer et al. 2007; Klanjscek et al. 2007), while the population recovers through reproduction and/or recolonization of stressed habitats and subsequent reproduction (Watanabe et al. 2005; van den Brink et al. 2007). Until now, the focus is on the recovery of the population, so very few models integrate toxicokinetic and/or toxicodynamic models with population modeling (Chen and Liao 2004).

The following case study was chosen as an example of a more complex approach to answering the question whether a population will recover and when. Barnthouse (2004) provides examples of simple population models, based on the logistic growth equation, used for assessing population recovery. IBMs offer the possibility to include processes which are of importance for studying population recovery and that could not be (or could be with more difficulty) implemented in other modeling approaches, such as dispersal and both intra- and interspecific interactions. This advantage also means that the number of processes and parameters increases greatly, all of which require additional data. Also, a great deal of computing power is required to simulate all individuals and keep track of their status. More complex modeling approaches also require more research time and resources and are therefore recommended for answering more specific questions in high tiers of risk assessment. An additional asset of using IBMs is that of identifying the type of data that is missing from the parameter set, thus making future research more focused and using fewer resources.

Predicting spatial population dynamics of aquatic invertebrates after pesticide contamination using a complex model—Van den Brink et al. (2007) developed an individual-based model, whose main purpose was to quantify population effects and recovery of the water louse, *Asellus aquaticus*, after pesticide exposure and especially to examine the relation between population recovery and the spatial configuration of the habitat.

The basic modeled unit is a female. The habitat is modeled using a grid representation of the water bodies in the landscape. For a fully aquatic species like the water louse, the water bodies were connected. Processes modeled included reproduction, mortality, and movement or dispersal. All processes were stochastic and modeled as events; timing of these events was drawn from probability distributions. Three FOCUS (Forum for Co-Ordination of Pesticide Fate Models and Their Use 2001) scenarios are described in the publication, namely the ditch, stream, and pond scenario. In the stream scenario, a movement event was sometimes turned into a drift event, involving movement to a downstream cell much further away. Mortality by insecticides was induced at a rate depending on the exposure concentration, expressed as predicted environmental concentration (PEC). The model focused on a single annual cycle of a NW European water louse, comprising 2 generations, the first of which consisted of individuals born in the previous year. To keep the model generic and combinable with mesocosm studies under a variety of conditions, only the bare minimum of detail on the species' life history has been incorporated. Survival at a given peak concentration in the water was defined by a dose–response curve based on data from a hypothetical mesocosm study. Some model parameters were estimated with a high degree of certainty, using published data on water louse ecology. Parameters quantifying density dependence were however highly uncertain.

Results show that, for the pond scenario, differences between the runs were small, while the ditch and stream scenarios showed a larger variation. The highest treatment level resulted in a distinctly lower summer peak than the other treatments. Initial responses for the stretch that was treated were very similar in both the stream and ditch scenarios. Empty cells in the ditch were recolonized by walking and reproducing, but both processes were quite slow, with the exception of the lowest treatment level simulated. Recovery, defined as a complete return to nontreatment densities, did not occur until autumn. The treated part of the stream exhibited a very fast recovery, showing drift to be an important factor in water louse population recovery. The difference between the stream and ditch scenarios was clearly demonstrated: very little water flow caused localized pesticide effects, while the water flow in the stream caused effects throughout the stretch. In a 2-dimensional system, such as a pond, recolonization took place much faster than in a 1-dimensional system, such as a ditch or a stream.

Indirect effects of chemicals in food webs

Identifying indirect effects based only on standard laboratory tests is an impossible task. Most commonly such indirect effects include effects between different trophic levels based on altered predation pressure, differing sensitivities to toxicants, effects of parasites, etc. In some instances, indirect effects can result in trophic cascades (for a review of trophic cascades, see Polis et al. 2000) and substantially change the structure and functioning of a community or ecosystem. The use of experimental multispecies systems, such as mesocosms, allows for the expression of indirect effects due to toxicant contamination. Performing these tests is, however, time and resource consuming, whereas the use of ecosystem models could be a cheaper alternative or addition. Although models describing the impact of chemicals on food webs do exist, microcosms and mesocosms are currently the only ecosystem-level tools used routinely in the risk assessment of chemicals (van den Brink et al. 2006). Complete replacement of mesocosm studies by food-web models seems unrealistic for the near future, because they are rather seen as tools providing additional lines of evidence. Such models can be used to interpret effects observed in cosm experiments, while insights into indirect effects could also be improved by the further development of food-web or ecosystem models, using the wealth of information available from cosm experiments for hypothesis generation and validation (Traas et al. 2004). Our search yielded 18 models that could be used to assess indirect effects in systems (Table 3). Although in the following case study, the precise ecological role of individual species was largely unspecified, food-web models can predict quite well the indirect effects of chemicals like pesticides. If calibrated to a specific study, interpolation or extrapolation of food-web effects between exposure patterns might also be possible, although this greatly depends on the toxicokinetics and toxicodynamics, i.e., the mode of action of the compound under study.

Predicting direct and indirect effects of chemicals in aquatic food webs—The case study is based on the study by Sourisseau et al. (2008a), describing the model development in detail, including sensitivity analysis, calibration, and validation, while Sourisseau et al. (2008b) present the application of the model to a deltamethrin experiment in artificial streams.

The specific model of the community in the artificial streams was implemented in AQUATOX 6.21 (http://www.epa.gov/waterscience/models/aquatox/), which has been developed by the USEPA (Park and Clough 2004; Park et al. 2008). AQUATOX is not a single model but offers equations and standard parameter sets to build bioenergetics models that simultaneously simulate several state variables, such as the biomass of various groups of organisms (e.g., phytoplankton, zooplankton, periphyton, macrophytes, zoobenthos, and fish) as well as detrital compartments, toxicants, and other abiotic variables, e.g., nutrient concentrations.

Sourisseau et al. (2008a) modeled the food webs by first deciding on the level of aggregation of the food web: ''The modeling efforts focused on a simplified (aggregated) food web with 7 biological compartments: 3 for the producers (phytoplankton, periphyton, and filamentous algae), 2 for the herbivores (zooplankton and benthic grazers), 1 for the benthic detritus feeders, and 1 for the predatory invertebrates. In addition, detritus were split into 2 pools (suspended and sediment detritus).'' Values from a literature review were used to replace, where possible, the default AQUATOX parameters (which are mainly based on North American conditions) with parameters more appropriate for Central European conditions. Experimental data from 1 control artificial stream (no toxicant applications) monitored over 2 months in 2005 were used to calibrate the model. The biota were sampled 4 times within this period. The model parameters were modified manually, but goodness-of-fit was assessed by various quantitative measures. Of the 32 parameters that significantly affected the model outcome, the most important ones were found to be maximum photosynthetic rate and optimal temperature for periphyton and filamentous algae, and the optimal temperature, temperature response slope, and maximum consumption rate for predatory invertebrates.

Deltamethrin effects were expressed as risk quotients based on the probability of, e.g., a 20% decrease in a population under treatment compared with control conditions. Only short- (96 h) and medium-term (240 h) effects were considered, due to the rapid degradation of deltamethrin. The results show that direct effects were predicted according to the assumed sensitivities of different groups. The model was also able to predict an indirect effect for a dose-related probability of increased periphyton biomass.

Prediction of bioaccumulation

Chemicals released into the environment are often taken up and accumulated in organisms, in the process known as bioaccumulation. Both bioconcentration and biomagnification result in accumulation of chemicals in organisms. An essential difference between bioconcentration and biomagnification is the trophic level where these processes take place: bioconcentration occurs within a trophic level and is the increase in concentration of a substance in an individual's tissues due to uptake from the surrounding environment, while biomagnification is the increase in the concentration of a substance in an organism due to food uptake. It is especially for the investigation of biomagnification that ecological models could be very useful to assess the risks posed to different trophic levels in a food web. They could be used as tools to refine experimental studies and identify the most critical compartments in an ecosystem in terms of the effects of various chemicals.

In our database of models, only 16 include bioaccumulation and/or biomagnification processes. These are either food-web or ecosystem models (Traas and Aldenberg 1992; Arnot and Gobas 2004; Park et al. 2008), or models mainly dealing with PCBs or heavy metals in aquatic populations (Madenjian 1993; Chen and Liao 2004). In several studies (Mastala et al. 1993; Klanjscek et al. 2007) bioaccumulation processes are examined in more detail at the individual level, including toxicant dilution through reproduction. By further developing the threshold damage model (TDM), Ashauer et al. (2007) examined the accumulation and depuration of various substances in *Gammarus pulex*. After a critical internal threshold has been reached, there is a certain probability that an individual will die. We also found a few terrestrial models looking into exposure and bioaccumulation, but they disregard effects of toxicants to populations and their dynamics (Chow et al. 2005; Schipper et al. 2008).

The model in the following case study was developed to study the response of a meadow ecosystem to continued loading with the persistent contaminant Cd (Traas and Aldenberg 1992). The probabilistic treatment of the model resulted in probability distributions of all relevant model outputs. It was, therefore, possible to calculate the probabilities of exceeding given environmental standards, following different Cd loadings. This type of modeling study is useful to obtain a general overview of the system and provides a rough estimate of critical compartments in a food web with regard to metal loads.

A model for predicting contaminant Cd accumulation in meadows—The model belongs to the CATS group of models (Contaminants in Aquatic and Terrestrial Systems) and was developed for the ecological risk assessment of Cd accumulation in a meadow system, on a moist, nutrient-rich peat soil in the lowland peat district in the Netherlands.

A major feature of this model is the conceptual separation of the biomass and toxicant cycles. Only bioaccumulation is modeled, without any effects on the biomass/nutrient cycle. The model considers spatial structure only in the vertical direction (i.e., soil layers, vegetation), while the area is considered to be homogeneous. Modeled species are grouped into functional groups based on their role with respect to nutrient cycling. Presence and abundance of specific vertebrates, such as raptors or carnivorous mammals, are usually considered to reflect the health of the ecosystem. Their feeding habits are quite accurately known, while ecological details of soil fauna feeding habits are much less known. Because the goal of this model was not to predict true population dynamics in the field but to study the principal effect of emission reduction, the more phenomenological approach of logistic growth was chosen to embed mass balance principles. The major feature of the toxicant cycle is the principal role of pollutant equilibria determining the amount of Cd bound to the litter or SOM or Cd dissolved in interstitial pores. A high binding constant means that the dissolved Cd concentration is quite low and vice versa. Cadmium enters the system by deposition from manure brought in from outside the system and bird immigration, while it leaves the system through percolation of dissolved Cd in excess rain water to deeper soil layers, with crop harvesting, meadow bird emigration, and the deaths of cows and birds.

Biomass fluxes in the model follow similar paths for all groups: all animal functional groups consume food either from 1 or several sources. Food is assimilated with a certain efficiency, and is partitioned into growth, reproduction, and respiration, while nonassimilated food is egested. Toxic fluxes in animal groups include Cd uptake from their food or from the soil solution. The nonassimilated fraction of Cd in the food is egested with nonassimilated biomass and is returned to litter or soil organic matter, depending on the animal's habitat. The group loses Cd by mortality, excretion and predation, where Cd excretion is modeled as a first-order process.

Simulations show that a steady state is reached within 3 y for all functional groups, as well as for organic matter pools and all accumulation scenarios. The authors conclude that Cd accumulation shows the same dependence on topsoil concentration for all compartments, and that steady-state concentrations will be reached somewhere in the year 2300. Given that this is a model with no feedback between accumulation level and the biomass cycle, an almost linear relation seems to exist between soil concentrations and concentrations in all functional groups. Results also show that environmental quality criteria for the food of birds are exceeded at the same loading scenarios, for the years 2015 and 2050. In other scenarios, where Cd load is smaller, there is no real risk to bird food. However, when it comes to food for mammals, it seems that in 2015, even with 1/8 of the current load, the standard will be exceeded by 2.4%. By 2050, the quality standards will be exceeded even if they are as high as half of the present load.

DO THE MODELS REVIEWED ADDRESS THE REQUIREMENTS FOR PROTECTION GOALS IN LEGISLATIVE DOCUMENTS?

Hommen et al. (this issue) reviewed protection goals, data requirements, and risk characterizations within European chemical directives and concluded that the risk assessment approach in different directives is very similar because they are all based on a quotient of predicted or measured environmental concentrations and an ecological threshold value. Protection goals are broadly defined in both spatial and temporal terms, e.g., local versus regional population protection and defining acceptable recovery period for affected nontarget organisms. Hommen et al. (this issue) linked the proposed areas of model application to protection principles, as defined by Brock et al. (2006) and European chemical directives. This linkage can be used to relate model output to protection goals, with the most common output types being population abundances, biomass (more used in ecosystem models), and population growth rates. To translate the output of standard laboratory tests to these higher levels of organization, such as populations and ecosystems, which are often the level of protection, ecological models offer excellent tools.

Linking reviewed models to potential areas of application

Some of the case studies show that more than 1 modeling approach can be used within 1 area of application, but also the potential of the evaluated models to cover more than just 1 application area. Because usually not 1 endpoint, but a combination of endpoints, is of interest in chemical risk assessment, it is reasonable to expect that models will belong to more than 1 application area. For example, integration of a detailed exposure–effects link, such as a TK-TD model, with a population model will produce a more realistic description of effects of time-varying exposure on field populations. Such models can also give information about effects at the individual level, due to the TK-TD component, and about population-level recovery, due to recovery-relevant vital parameters, such as survival and reproduction. Consequently, such a model can be used in 3 application areas.

Given the levels of biological organization (individual, population, metapopulation, and community or ecosystem) addressed by various models and the relatively narrow set of questions and interests for the risk assessment process, only some biological levels are likely to be relevant and appropriate when addressing each of the proposed application areas. Table 5 summarizes our assessment about useful combinations between the level of biological organization (individual, population, metapopulation, and community or ecosystem), modeled entities within these levels (from internal concentrations, stages, individuals to functional groups), and potential areas of application they could address. Assumed useful combinations are denoted as grey areas, while numbers represent the findings from our review of the models and show the numbers of existing models for each of the combination. We obtained 2 modeling studies that focus on effects of toxicants on energy budgets in individuals that do not yet address the population levels. There is, however, a high potential in these studies to do so in the future. Not surprisingly, models at the population level generally suffice when the focus is on population-level effects. Preferably, populations in these models would be structured at least at the level of stage or age. Exposure extrapolation can be performed at either the individual or the population level. If population-level effects of time-varying or multipeak exposure are of interest, a TK-TD type of submodel can be used to assess the effects at the individual level. On the other hand, in cases with a single peak or constant exposure, a detailed TK-TD model is not needed, and a direct link between exposure and effects can be used to model effects on individuals. Because recovery processes encompass individual- to community-based processes, all levels might be appropriate. For instance, individual recovery might be more important for vertebrates, whereas for invertebrates the focus will usually be on the population level. Because indirect effects are defined as feedbacks among functional groups or trophic levels in a food web, the food web/community/ecosystem level is the relevant one for a modeling study. Finally, bioconcentration processes are best investigated at the individual level, and this was most commonly found in published studies, while at least a simple food chain is required for biomagnification. If necessary, both levels can be combined in 1 study. Just as with application areas, and depending on the questions asked, models relating to different biological levels of organization can be combined.

Table 5. Proposed levels of biological organization and modeled entities that are relevant when addressing different application areas of ecological models[a]

			Model application areas				
Modeled level of biological organization	**Modeled entity**	**Model types (examples)**	**Extrapolation from individual to population level effects**	**Extrapolation between exposure patterns**	**Extrapolation of recovery processes**	**Analysis and prediction of indirect effects**	**Prediction of bioaccumulation**
Individual	Energy budgets, internal conc.	TK/TD models, Debtox	2	▨ 2	▨ 3	0	▨ 7
Population	Unstructured population	Lotka-Volterra type models	5	▨ 1	3	0	0
	Age/stages	Matrix and other stage structured models	▨ 44	▨ 17	▨ 22	5	4
	Individuals	IBMs	▨ 17	▨ 4	▨ 15	2	2
Metapopulation	Patches (sub-populations)	Spatial explicit population models	4	1	▨ 4	3	0
Community/food web	Functional or taxonomical groups	System of unstructured pop. models	9	5	5	▨ 8	▨ 3

[a] Gray areas denote our suggestions, whereas the figures denote the number of modeling studies per application area found in our review. One modeling study was considered on more than 1 biological level.

When it comes to spatial structure, our review found a very small fraction of spatially explicit models, probably due to the high computing and data demands of such models, and because exposure is not yet commonly modeled in a spatially explicit manner. We did, however, find several modeling studies where exposure is explicitly modeled, but the effects and dynamics of exposed individuals and populations are not.

OUTLOOK

Due to the imprecision of protection goals, researchers and risk assessors rely on different sources of guidance to bridge the gap between measurement endpoints and protection goals. These include technical documents (EC 2002; SANCO 2002) and reports from workshops where all the stakeholders (academia, regulating authorities, and industry) are brought together (Campbell et al. 1998; Giddings et al. 2001; Barnthouse et al. 2007; Forbes et al. 2009; Thorbek et al. 2010). So, even though the protection aims in European legislation are very broadly defined, their focus and the level of protection have been interpreted into more manageable terms. Ecological models have proven to be able to provide a strong link between measured data and foci of protection. Further development and improvement of ecological models in RA greatly depends on the needs identified by industry and regulators. During the last few years, for instance, recovery of affected species has become very important for the registration of pesticides. The fact that recovery cannot be studied for all species, even in field studies, e.g., mesocosm studies, has stimulated the development of recovery models (van den Brink et al. 2007). Furthermore, with progress in computing, explicit consideration of space in exposure and effects is becoming more common and is a vital part of a realistic ecological risk assessment process. Interestingly, almost half of the spatially explicit models in our database are also individual based, thus representing the high ends of both biological and spatial structures, while the other half are based on biologically unstructured populations. The development of spatially explicit and spatially realistic (GIS-based) models is expected to increase for future chemical ERA purposes.

An additional advantage of modeling studies is that they allow deficiencies in existing datasets to be identified, thus making future experimental research more focused. One of the challenges that might be faced in this field is the proper link between exposure and effects in the field. This topic was covered by the eLINK workshop (Brock et al. 2010) that should produce tools that correctly address the effects of extrapolation within a species, i.e., extrapolation to population-level response, as well as from the lab to field conditions. Because the emphasis is on realistic ERA, reliable data will be required on life-history traits of the species of interest, their life-cycle parameters and, in the case of spatially explicit environments, their movement and dispersal patterns. Effects of chemicals need to be looked at for all levels, including sublethal effects, so the resulting risk is not overestimated or underestimated.

This study represents one of the steps in addressing the potentials and pitfalls of ecological models published in the last 2 decades for the field of regulatory risk assessment. The range of modeling studies identified in our review reveals a need for more coherent modeling approaches relating to chemical risk assessment, an issue put forward by the LEMTOX workshop (Forbes et al. 2009). The workshop identified obstacles to a wider use of models in risk assessment of plant protection products, as well as ways forward. One of these was the development of Good Modeling Practice, an approach that would include recommendations and information on all parts of the modeling process, including design, testing, application, documentation, and reporting. Model development relies heavily on the focal species or ecosystem and questions that are more or less similar in the risk assessment schemes for different types of chemicals, which clearly suggests that a more unified approach is definitely feasible. A big step forward for the field of ecological models in chemical RA is the establishment of an advisory group within SETAC, called MemoRisk, which focuses on mechanistic models in chemical risk assessment (Preuss, Hommen, et al. 2009). Furthermore, the establishment of the CREAM EU (Grimm et al. 2009) project, whose main goal is to develop a suite of well-tested and validated mechanistic ecological effect models for an array of species and ecosystems relevant to chemical risk assessments, is probably the biggest leap in the right direction.

It is relatively easy to be impressed by the vast possibilities of ecological models, and we want to caution against the urge to apply them to any system, without extensive prior considerations. Ecological models are very useful, integrative tools with a high potential for extrapolation. However, it is very important to bear in mind that model output should always be regarded in a relative sense and no absolute conclusions should be drawn. The error propagation in model results arises from errors in data sampling and accumulation, false assumptions, and omission of potentially relevant processes. Bartell et al. (2003) rightly state that the focus of risk assessors should be on the relative strengths of each modeling approach, which should be chosen based on the question at hand and protection aims.

In conclusion, the published literature offers a variety of modeling approaches that have been developed to answer various questions related to effects of chemicals. Most of them are presented as academic exercises rather than for registration purposes, although many of them have a high potential for regulatory risk assessment. Brock et al. (2006) mention the potential use of modeling studies in the highest tiers of RA of chemicals under the WFD and 91/414/EC directives, following standard species tests as the first, species sensitivity distributions as the second and the model ecosystem approach as the third tier. Only in the third and higher tiers, modeling studies are considered as tools for RA refinement. But even in the highest tiers of RA, some models are more generic, easier to parameterize and, thus, useful to obtain preliminary results on the effects of chemicals on populations in question. Models that include only the basic life-history of the species, e.g., unstructured or structured such as Euler-Lotka based or matrix models, could be used for an initial screening process. These modeling studies can give an overview of adverse effects and/or most sensitive life-stages, requiring a limited effort. For more specific cases and questions, more complex models including more detailed life histories of focal species, such as IBMs, spatial structure, and different exposure patterns could be more appropriate. Our review, including the database of models, represents a starting point for gaining an overview of published ecological models used to assess the effects various chemical substances have on different species. Furthermore, the case studies serve as examples of the possibilities and added value of various ecological modeling approaches for the field of chemical ERA. Finally, easily obtainable information on focal species, habitats, and chemical substances, and more specific details on technical aspects of the models reviewed here, might facilitate the decision-making process for end-users.

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SUPPORTING INFORMATION

Supporting Information S1. Data on the models reviewed. (68 KB DOC)

REFERENCES

Adams BM, Banks HT, Banks JE, Stark JD. 2005. Population dynamics models in plant-insect herbivore-pesticide interactions. *Math Biosci* 196:39–64.

An W, Hu JY, Yao F. 2006. A method of assessing ecological risk to night heron, Nycticorax nycticorax, population persistence from dichlorodiphenyltrichloroethane exposure. *Environ Toxicol Chem* 25:281–286.

Ares J. 2003. Time and space issues in ecotoxicology: Population models, landscape pattern analysis, and long-range environmental chemistry. *Environ Toxicol Chem* 22:945–957.

Arnot JA, Gobas FAPC. 2004. A food web bioaccumulation model for organic chemicals in aquatic ecosystems. *Environ Toxicol Chem* 23:2343–2355.

Asaeda T, Acharya K. 2000. Application of individual growth and population models of *Daphnia pulex to Daphnia magna, Daphnia galeata* and *Bosmina longirostris*. *Hydrobiologia* 421:141–155.

Ashauer R, Boxall A, Brown C. 2006. Predicting effects on aquatic organisms from fluctuating or pulsed exposure to pesticides. *Environ Toxicol Chem* 25:1899–1912.

Ashauer R, Boxall ABA, Brown CD. 2007. Simulating toxicity of carbaryl to Gammarus pulex after sequential pulsed exposure. *Environ Sci Technol* 41:5528–5534.

Ashauer R, Boxall ABA, Brown CD. 2007a. New ecotoxicological model to simulate survival of aquatic invertebrates after exposure to fluctuating and sequential pulses of pesticides. *Environ Sci Technol* 41:1480–1486.

Ashauer R, Brown CD. 2008. Toxicodynamic assumptions in ecotoxicological hazard models. *Environ Toxicol Chem* 27:1817–1821.

Barnthouse LW. 2004. Quantifying population recovery rates for ecological risk assessment. *Environ Toxicol Chem* 23:500–508.

Barnthouse LW, Munns WR, Sorensen MT. 2007. Population-level ecological risk assessment. Boca Raton (FL): SETAC. 337 p.

Bartell SM, Pastorok RA, Akcakaya HR, Regan H, Ferson S, Mackay C. 2003. Realism and relevance of ecological models used in chemical risk assessment. *Hum Ecol Risk Assess* 9:907–938.

Baveco JM, De Roos AM. 1996. Assessing the impact of pesticides on lumbricid populations: An individual-based modeling approach. *J Appl Ecol* 33:1451–1468.

Beard TD, Essington TE. 2000. Effects of angling and life history processes on bluegill size structure: Insights from an individual-based model. *Trans Am Fish Soc* 129:561–568.

Beaudouin R, Monod G, Ginot V. 2008. Selecting parameters for calibration via sensitivity analysis: An individual-based model of mosquitofish population dynamics. *Ecol Model* 218:29–48.

Billoir E, Pery ARR, Charles S. 2007. Integrating the lethal and sublethal effects of toxic compounds into the population dynamics of Daphnia magna: A combination of the DEBtox and matrix population models. *Ecol Model* 203:204–214.

Brock TCM, Arts GHP, Maltby L, van den Brink PJ. 2006. Aquatic risks of pesticides, ecological protection goals, and common aims in European Union Legislation. *Integ Environ Assess Manag* 2:20–46.

Brock T, Hommen U, Ashauer R, van den Brink PJ, Caquet T, Ducrot V, Lagadic L, Ratte T. 2010. Linking aquatic exposure and effects in the registration procedure of plant protection products. Boca Raton (FL): SETAC. 410 p.

Bromenshenk JJ, Doskocil J, Olbu GJ, DeGrandi-Hoffman G, Roth SA. 1991. Pc Beepop, an ecotoxicological simulation-model for honey-bee populations. *Environ Toxicol Chem* 10:547–558.

Brown AR, Riddle AM, Winfield IJ, Fletcher JM, James JB. 2005. Predicting the effects of endocrine disrupting chemicals on healthy and disease impacted populations of perch (*Perca fluviatilis*). *Ecol Model* 189:377–395.

Byers JA, Castle SJ. 2005. Areawide models comparing synchronous versus asynchronous treatments for control of dispersing insect pests. *J Econ Entomol* 98:1763–1773.

Cabral JA, Marques JC, Nielsen SN. 2001. Modeling mosquitofish (*Gambusia holbrooki*) responses to Genapol OXD-080, a nonionic surfactant, in rice fields. *Ecological Engineering* 16:537–544.

Calow P, Sibly RM, Forbes V. 1997. Risk assessment on the basis of simplified life-history scenarios. *Environ Toxicol Chem* 16:1983.

Campbell PJ, Arnold DJS, Brock TCM, Grandy NJ, Heger W, Heimbach F, Maund SJ, Streloke M. 1998. Guidance document on Higher tier Aquatic Risk Assessment for Pesticides (HARAP). Brussels (BE): SETAC-Europe. 179 p.

Caswell H. 2000. Matrix population models: Construction, analysis, and interpretation. Sunderland (MA): Sinauer Associates. 727 p.

Chandler GT, Cary TL, Bejarano AC, Pender J, Ferry JL. 2004. Population consequences of fipronil and degradates to copepods at field concentrations: An integration of life cycle testing with Leslie matrix population Modeling. *Environ Sci Tech* 38:6407–6414.

Chapman PM. 2002. Integrating toxicology and ecology: Putting the 'eco' into ecotoxicology. *Mar Pollut Bull* 44:7–15.

Charles S, Ferreol M, Chaumot A, Pery ARR. 2004. Food availability effect on population dynamics of the midge *Chironomus riparius*: a Leslie modeling approach. *Ecol Model* 175:217–229.

Chaumot A, Charles S, Flammarion P, Garric J, Auger P. 2002. Using aggregation methods to assess toxicant effects on population dynamics in spatial systems. *Ecol Appl* 12:1771–1784.

Chaumot A, Charles S, Flammarion P, Auger P. 2003. Ecotoxicology and spatial modeling in population dynamics: An illustration with brown trout. *Environ Toxicol Chem* 22:958–969.

Chen B, Liao C. 2004. Population models of farmed abalone Haliotis diversicolor supertexta exposed to waterborne zinc. *Aquaculture* 242:251–269.

Choi WI, Moorhead DL, Neher DA, Il Ryoo M. 2006a. A modeling study of soil temperature and moisture effects on population dynamics of *Paronychiurus kimi* (Collembola : Onychiuridae). *Biol Fertil Soil* 43:69–75.

Choi YH, Bohan DA, Potting RPJ, Semenov MA, Glen DM. 2006b. Individual based model of slug population and spatial dynamics. *Ecol Model* 190:336–350.

Chow TE, Gaines KF, Hodgson ME, Wilson MD. 2005. Habitat and exposure modelling for ecological risk assessment: A case study for the raccoon on the Savannah River Site. *Ecol Model* 189:151–167.

Davidson RS, Armstrong DP. 2002. Estimating impacts of poison operations on non-target species using mark-recapture analysis and simulation modeling: An example with saddlebacks. *Biol Conserv* 105:375–381.

De Laender F. 2007. An ecosystem modelling approach for deriving water quality criteria. *Water Sci Technol* 56:19–27.

De Roos AM. 2008. Demographic analysis of continuous-time life-history models. *Ecol Lett* 11:1–15.

De Angelis DL, Godbout L, Shuter BJ. 1991. An individual-based approach to predicting density-dependent dynamics in smallmouth bass populations. *Ecol Model* 57:91–115.

Ducrot V, Pery ARR, Mons R, Queau H, Charles S, Garric J. 2007. Dynamic energy budget as a basis to model population-level effects of zinc-spiked sediments in the gastropod valvata piscinalis. *Environ Toxicol Chem* 26:1774–1783.

[EC] European Commission. 1991. Council Directive 91/414/EEC of 15 July 1991 concerning the placing of plant protection products on the market. Official Journal L 230; p 1–32.

[EC] European Commission. 2000. Directive 2000/60/EC of the European Parliament and of the Council of 23 October 2000 establishing a framework for Community action in the field of water policy. Official Journal of the European Communities L 327.

[EC] European Commission. 2002. Guidance document on aquatic toxicology in the context of the Directive 91/414/EEC. Working Document of the European Commission Health and Consumer Protection Directorate-General. Brussels, Belgium.

Fabre F, Pierre JS, Dedryver CA, Plantegenest M. 2006. Barley yellow dwarf disease risk assessment based on Bayesian modelling of aphid population dynamics. *Ecol Model* 193:457–466.

Ferreira JG. 1995. ECOWIN - An object-oriented ecological model for aquatic ecosystems. *Ecol Model* 79:21–34.

Forbes VE, Calow P, Sibly RM. 2008. The extrapolation problem and how population modeling can help. *Environ Toxicol Chem* 27:1987–1994.

Forbes VE, Hommen U, Thorbek P, Heimbach F, van den Brink PJ, Wogram Jr, Thulke H-H, Grimm V. 2009. Ecological models in support of regulatory risk assessments of pesticides: Developing a strategy for the future. *Integr Environ Assess Manag* 5:167–172.

Forum for Co-Ordination of Pesticide Fate Models and Their Use. 2001. FOCUS Surface Water Scenarios in the EU Evaluation Process under 91/414/EEC. Brussels, Belgium.

Giddings JM, Brock TCM, Heger W, Heimbach F, Maund SJ, Norman SM, Ratte HT, Schafers C, Steloke M. 2001. Community - Level aquatic system studies - interpretation criteria. Pensacola (FL): SETAC. 44 p.

Giesy JP, Solomon KR, Coats JR, Dixon KR, Giddings JM, Kenaga EE. 1999. Chlorpyrifos: ecological risk assessment in North American aquatic environments. *Rev Environ Contam Toxicol* 160:1–129.

Gosselke U, Triltsch H, Rossberg D, Freier B. 2001. GETLAUS01: The latest version of a model for simulating aphid population dynamics in dependence on antagonists in wheat. *Ecol Model* 145:143–157.

Grimm V, Ashauer R, Forbes V, Hommen U, Preuss TG, Schmidt A, van den Brink PJ, Wogram J, Thorbek P. 2009. CREAM: A European project on mechanistic effect models for ecological risk assessment of chemicals. *Environ Sci Pollut Res* 16:1–14.

Hanratty MP, Stay FS. 1994. Field-evaluation of the littoral ecosystem risk assessment models predictions of the effects of chlorpyrifos. *J Appl Ecol* 31:439–453.

Hickie BE, Muir DCG, Addison RF, Hoekstra PF. 2005. Development and application of bioaccumulation models to assess persistent organic pollutant temporal trends in arctic ringed seal (*Phoca hispida*) populations. *Sci Total Environ* 351:413–426.

Hobday D, Punt AE. 2001. Size-structured population modelling and risk assessment of the Victorian southern rock lobster, *Jasus edwardsii*, fishery. *Mar Freshw Res* 52:1495–1507.

Holt J, Cooper JE. 2006. A model to compare the suitability of locust hopper targets for control by insecticide barriers. *Ecol Model* 195:273–280.

Hommen U, Ashauer R, van den Brink PJ, Caquet T, Ducrot V, Lagadic L, Ratte T. 2010a. Tools for extrapolating effects between exposure patterns. In: Brock T, Alix A, Brown CD, Capri E, Gottesburen BFF, Heimbach F, Lythgo CM, Schulz R, Streloke M, editors. Linking aquatic exposure and effects in the registration procedure of plant protection products. Report on the ELINK workshops. Pensacola (FL): SETAC. 410 p.

Hommen U, Baveco JM, Galic N, van den Brink P. 2010b. Potential application of ecological models in the European environmental risk assessment of chemicals: I. Review of protection goals in EU directives. *Integr Environ Assess Manag* (this issue).

Jager T, Crommentuijn T, Van Gestel CAM, Kooijman S. 2004. Simultaneous modeling of multiple end points in life-cycle toxicity tests. *Environ Sci Technol* 38:2894–2900.

Jager T, Crommentuijn T, van Gestel CAM, Kooijman S. 2007. Chronic exposure to chlorpyrifos reveals two modes of action in the springtail *Folsomia candida*. *Environ Pollut* 145:452–458.

Jaworska JS, Rose KA, Brenkert AL. 1997. Individual-based modeling of PCBs effects on young-of-the-year largemouth bass in southeastern USA reservoirs. *Ecol Model* 99:113–135.

Kimmerer WJ, Cowan JH, Miller LW, Rose KA. 2001. Analysis of an estuarine striped bass population: Effects of environmental conditions during early life. *Estuaries* 24:557–575.

Kjaer C, Elmegaard N, Axelsen JA, Andersen PN, Seidelin N. 1998. The impact of phenology, exposure and instar susceptibility on insecticide effects on a chrysomelid beetle population. *Pestic Sci* 52:361–371.

Klanjscek T, Caswell H, Neubert MG, Nisbet RM. 2006. Integrating dynamic energy budgets into matrix population models. *Ecol Model* 196:407–420.

Klanjscek T, Nisbet RM, Caswell H, Neubert MG. 2007. A model for energetics and bioaccumulation in marine mammals with applications to the right whale. *Ecol Appl* 17:2233–2250.

Klok C, Hout Av-d Bodt J. 2006. Population growth and development of the earthworm *Lumbricus rubellus* in a polluted field soil: possible consequences for the godwit (*Limosa limosa*). *Environ Toxicol Chem* 25:213–219.

Klok C, Holmstrup M, Damgaard C. 2007. Extending a combined dynamic energy budget matrix population model with a Bayesian approach to assess variation in the intrinsic rate of population increase. An example in the earthworm *Dendrobaena octaedra*. *Environ Toxicol Chem* 26:2383–2388.

Klok C, de Roos AM. 1996. Population level consequences of toxicological influences on individual growth and reproduction in *Lumbricus rubellus* (Lumbricidae, Oligochaeta). *Ecotoxicol Environ Saf* 33:118–127.

Koelmans AA, Van der Heijde A, Knijff LM, Aalderink RH. 2001. Integrated modelling of eutrophication and organic contaminant fate and effects in aquatic ecosystems. A review. *Water Res* 35:3517–3536.

Koh LH, Hallam TG, Ling Lee H. 1997. Combined effects of environmental and chemical stressors on a model Daphnia population. *Ecol Model* 103:19–32.

Kooijman SALM. 2000. Dynamic energy and mass budgets in biological systems. Cambridge (UK): Cambridge Univ. 444 p.

Kooijman SALM, Metz JAJ. 1984. On the dynamics of chemically stressed populations: The deduction of population consequences from effects on individuals. *Ecotoxicol Environ Saf* 8:254–274.

Kuhn A, Munns WR Jr, Poucher S, Champlin D, Lussier S. 2000. Prediction of population-level response from mysid toxicity test data using population modeling techniques. *Environ Toxicol Chem* 19:2364–2371.

Lee J-H, Landrum PF. 2006. Application of multi-component damage assessment model (MDAM) for the toxicity of metabolized PAH in *Hyalella azteca*. *Environ Sci Technol* 40:1350–1357.

Lee J-H, Landrum PF, Koh C-h. 2002. Prediction of time-dependent PAH toxicity in *Hyalella azteca* using a damage assessment model. *Environ Sci Technol* 36:3131–3138.

Leslie PH. 1945. On the use of matrices in certain population mathematics. *Biometrika* 33:183–212.

Liao C-M, Chiang K-C, Tsiang J-W. 2006. Bioenergetics-based matrix population modeling enhances life-cycle toxicity assessment of tilapia *Oreochromis mossambicus* exposed to arsenic. *Environ Toxicol* 21:154–165.

Liao C, Yeh C. 2007. Hard clam *Meretrix lusoria* to Hg-stressed birnavirus susceptibility revealed through stage-structured disease transmission dynamics. *Aquaculture* 264:101–118.

Lin B. 2005. Approaches for establishing predicted-no-effect concentrations for population-level ecological risk assessment in the context of chemical substances management. *Environ Sci Technol* 39:4833–4840.

Liu Y, Guo H, Fan Y, Wang L. 2005. Research advance on lake ecosystem dynamic models. *Chin J Appl Ecol* 16:1169–1175.

Lopes C, Pery ARR, Chaumot A, Charles S. 2005. Ecotoxicology and population dynamics: Using DEBtox models in a Leslie modeling approach. *Ecol Model* 188:30–40.

Lotka AJ. 1924. Elements of physical biology. Baltimore (MD): Williams and Wilkins. 495 p.

Madenjian C. 1993. Accumulation of PCBs by lake trout (Salvelinus namaycush) - An individual-based model approach. *Can J Fish Aquat Sci* 50:97–109.

Malthus TB. 1798. First essay on population (an essay on the principle of population as it affects the future improvement of society with remarks on the speculation of Mr. Godwin M. Condorcet and other writers). London (UK): Macmillan.

Mastala Z, V-Balogh K, Perenyi M. 1993. A model for heavy-metal pollution of fish populations and exploited fish. *Ecol Model* 70:263–276.

Maurer BA, Holt RD. 1996. Effects of chronic pesticide stress on wildlife populations in complex landscapes: Processes at multiple scales. *Environ Toxicol Chem* 15:420–426.

Miller DH, Ankley GT. 2004. Modeling impacts on populations: Fathead minnow (Pimephales promelas) exposure to the endocrine disruptor 17[beta]-trenbolone as a case study. *Ecotoxicol Environ Saf* 59:1–9.

Murphy CA, Rose KA, Alvarez MadC, Fuiman LA. 2008. Modeling larval fish behavior: Scaling the sublethal effects of methylmercury to population-relevant endpoints. *Aquat Toxicol* 86:470–484.

Naito W, Miyamoto K, Nakanishi J, Masunaga S, Bartell SM. 2002. Application of an ecosystem model for aquatic ecological risk assessment of chemicals for a Japanese lake. *Water Res* 36:1.

Nakamaru M, Iwasa Y, Nakanishi J. 2002. Extinction risk to herring gull populations from DDT exposure. *Environ Toxicol Chem* 21:195–202.

Nisbet RM, McCauley E, Gurney WSC, Murdoch WW, Simon NW. 2004. Formulating and testing a partially specified dynamic energy budget model. *Ecology* 85:3132–3139.

O'Neill RV, Gardner RH, Barnthouse LW, Suter GW, Hildebrand SG, Gehrs CW. 1982. Ecosystem risk analysis: A new methodology. *Environ Toxicol Chem*:167–177.

Park RA, Clough JS. 2004. AQUATOX: Modeling environmental fate and ecological effects in aquatic ecosystems. Vol 2. Technical documentation. Washington (DC): US Environmental Protection Agency, Office of Water.

Park RA, Clough JS, Wellman MC. 2008. AQUATOX: Modeling environmental fate and ecological effects in aquatic ecosystems. *Ecol Model* 213:1–15.

Pastorok RA, Akcakaya HR, Regan H, Ferson S, Bartell SM. 2003. Role of ecological modeling in risk assessment. *Hum Ecol Risk Assess* 9:939–972.

Pelosi Cl, Bertrand M, Makowski D, Roger-Estrade J. 2008. WORMDYN: A model of *Lumbricus terrestris* population dynamics in agricultural fields. *Ecol Model* 218:219–234.

Pery ARR, Geffard A, Garric J. 2006. Mechanistic models to perform population risk assessment with the midge *Chironomus riparius*: Application to heavy metals. *Environ Sci Technol* 40:6026–6031.

Pery ARR, Mons R, Garric J. 2004. Energy-based modeling to study population growth rate and production for the midge *Chironomus riparius* in ecotoxicological risk assessment. *Ecotoxicology* 13:647–656.

Polis GA, Sears ALW, Huxel GR, Strong DR, Maron J. 2000. When is a trophic cascade a trophic cascade? *Trends Ecol Evol* 15:473–475.

Preuss TG, Hammers-Wirtz M, Hommen U, Rubach MN, Ratte HT. 2008. Prediction of effects from variable exposure scenarios to populations of *D. magna* - Application of an individual-based population model. SETAC-Europe Annual Meeting, Warsaw, Poland.

Preuss TG, Hammers-Wirtz M, Hommen U, Rubach MN, Ratte HT. 2009. Development and validation of an individual based *Daphnia magna* population model: The influence of crowding on population dynamics. *Ecol Model* 220:310–329.

Preuss TG, Hommen U, Alix A, Ashauer R, van den Brink P, Chapman P, Ducrot V, Forbes V, Grimm V, Schafer D, Streissl F, Thorbek P. 2009. Mechanistic effect models for ecological risk assessment of chemicals (MEMoRisk) - A new SETAC-Europe Advisory Group. *Environ Sci Pollut Res* 16:250–252.

Purucker ST, Welsh CJE, Stewart RN, Starzec P. 2007. Use of habitat-contamination spatial correlation to determine when to perform a spatially explicit ecological risk assessment. *Ecol Model* 204:180–192.

Raimondo S, McKenney CLJ. 2006. From organisms to populations: Modeling aquatic toxicity data across two levels of biological organization. *Environ Toxicol Chem* 25:589–596.

Rinke K, Petzoldt T. 2008. Individual-based simulation of diet vertical migration of *Daphnia*: A synthesis of proximate and ultimate factors. *Limnologica* 38:269–285.

Rinke K, Vijverberg J. 2005. A model approach to evaluate the effect of temperature and food concentration on individual lifehistory and population dynamics of Daphnia. *Ecol Model* 186:326–344.

Salice CJ, Miller TJ. 2003. Population-level responses to long-term cadmium exposure in two strains of the freshwater gastropod *Biomphalaria glabrata*: Results from a life-table response experiment. *Environ Toxicol Chem* 22:678–688.

[SANCO] Santé des Consommateurs. 2002. Guidance document on aquatic toxicology in the context of the Directive 91/414/EEC. Working Document of the European Commission Health and Consumer Protection Directorate-General. Brussels, Belgium. 62 p.

Schafers C, Oertel D, Nagel R. 1993. Effects of 3,4-dichloroaniline on fish populations with differing strategies of reproduction. In: Braunbeck T, Hanke W, Segner H, editors. Fish: Ecotoxicology and ecophysiology. Weinheim (DE): VCH. p 133–146.

Schipper AM, Loos M, Ragas AMJ, Lopes JPC, Nolte BT, Wijnhoven S, Leuven RSEW. 2008. Modeling the influence of environmental heterogeneity on heavy metal exposure concentrations for terrestrial vertebrates in river floodplains. *Environ Toxicol Chem* 27:919–932.

Schmidt J. 2003. Wirkung von Umweltchemikalien auf *Gammarus fossarum*: Populationsexperimente und individuenbasiertes Reproduktionsmodell [PhD thesis]. Dresden (DE): TU Dresden.

Sherratt TN, Jepson PC. 1993. A metapopulation approach to modeling the long-term impact of pesticides on invertebrates. *J Appl Ecol* 30:696–705.

Sibly RM, Akcakaya HR, Topping CJ, O'Connor RJ. 2005. Population-level assessment of risks of pesticides to birds and mammals in the UK. *Ecotoxicology* 14:863–876.

Sourisseau S, Basseres A, Perie F, Caquet T. 2008a. Calibration, validation and sensitivity analysis of an ecosystem model applied to artificial streams. *Water Res* 42:1167–1181.

Sourisseau S, Basseres A, Perie F, Caquet T. 2008b. Stochastic simulation of aquatic ecosystem models for the ecological risk assessmentof chemicals. Warsaw, Poland: SETAC Europe. 2008.

Spromberg JA, John BM, Landis WG. 1998. Metapopulation dynamics: Indirect effects and multiple distinct outcomes in ecological risk assessment. *Environ Toxicol Chem* 17:1640.

Spromberg JA, Meador JP. 2006. Relating chronic toxicity responses to population-level effects: A comparison of population-level parameters for three salmon species as a function of low-level toxicity. *Ecol Model* 199:240–252.

Starfield AM. 1997. A pragmatic approach to modeling for wildlife management. *J Wildl Manag* 61:261–2270.

Stark JD, Banks JE. 2003. Population-level effects of pesticides and other toxicants on arthropods. *Annu Rev Entomol* 48:505–519.

Stark JD, Banks JE, Acheampong S. 2004. Estimating susceptibility of biological control agents to pesticides: Influence of life history strategies and population structure. *Biol Control* 29:392–398.

Stillman RA. 2008. MORPH-An individual-based model to predict the effect of environmental change on foraging animal populations. *Ecol Model* 216:265–276.

Tang S, Xiao Y, Chen L, Cheke RA. 2005. Integrated pest management models and their dynamical behaviour. *Bull Math Biol* 67:115–135.

Thompson H, Wilkins S, Battersby A, Waite R, Wilkinson D. 2005. The effects of four insect growth-regulating (IGR) insecticides on honeybee (*Apis mellifera* L.) colony development, queen rearing and drone sperm production. *Ecotoxicology* 14:757–769.

Thorbek P, Forbes V, Heimbach F, Hommen U, Thulke HH, van den Brink P, Wogram J, Grimm V. editors. 2010. Ecological models for regulatory risk assessments of pesticides: Developing a strategy for the future. Pensacola (FL): SETAC-CRC. p 127.

Topping CJ, Hansen TS, Jensen TS, Jepsen JU, Nikolajsen F, Odderskær P. 2003. ALMaSS, an agent-based model for animals in temperate European landscapes. *Ecol Model* 167:65–682.

Topping CJ, Sibly RM, Akcakaya HR, Smith GC, Crocker DR. 2005. Risk assessment of UK skylark populations using life-history and individual-based landscape models. *Ecotoxicology* 14:925–936.

Traas TP, Aldenberg T. 1992. CATS 1: A model for predicting contaminant accumulation in meadows. The case of cadmium. Bilthoven (NL): RIVM. Report 719103001.

Traas T, Janse J, Aldenberg T, Brock T. 1998. A food web model for fate and direct and indirect effects of Dursban® 4E (active ingredient chlorpyrifos) in freshwater microcosms. *Aquat Ecol* 32:179–190.

Traas TP, Janse JH, van den Brink PJ, Brock TCM, Aldenberg T. 2004. A freshwater food web model for the combined effects of nutrients and insecticide stress and subsequent recovery. *Environ Toxicol Chem* 23:521–529.

Vale GA, Grant IF. 2002. Modelled impact of insecticide-contaminated dung on the abundance and distribution of dung fauna. *Bull Entomol Res* 92:251–263.

van den Brink PJ. 2008. Ecological risk assessment: From book-keeping to chemical stress ecology. *Environ Sci Technol* 42:8999–9004.

van den Brink PJ, Baveco JM, Verboom J, Heimbach F. 2007. An individual-based approach to model spatial population dynamics of invertebrates in aquatic ecosystems after pesticide contamination. *Environ Toxicol Chem* 26:2226–2236.

van den Brink PJ, Blake N, Brock TCM, Maltby L. 2006. Predictive value of species sensitivity distributions for effects of herbicides in freshwater ecosystems. *Hum Ecol Risk Assess* 12:645–674.

van Nes EH. 2003. Charisma: A spatial explicit simulation model of submerged macrophytes. *Ecol Model* 159:103.

van Nes EH, Lammens E, Scheffer M. 2002. PISCATOR, an individual-based model to analyze the dynamics of lake fish communities. *Ecol Model* 152:261–278.

Van Winkle W, Jager HI, Railsback SF, Holcomb BD, Studley TK, Baldrige JE. 1998. Individual-based model of sympatric populations of brown and rainbow trout for instream flow assessment: Model description and calibration. *Ecol Model* 110:175–207.

Vanoverbeke J. 2008. Modeling individual and population dynamics in a consumer-resource system: Behavior under food limitation and crowding and the effect on population cycling in Daphnia. *Ecol Model* 216:385–401.

Volterra V. 1926. Variations and fluctuations of the numbers of individuals in animal species living together. In: Chapman R, editor. Animal ecology. NY (NY): McGraw Hill. p 409–448.

Waage JK, Hassell MP, Godfray HCJ. 1985. The dynamics of pest-parasitoid-insecticide interactions. *J Appl Ecol* 22:825–838.

Wang K, Shipp JL. 2001. Simulation model for population dynamics of *Frankliniella occidentalis* (Thysanoptera: Thripidae) on greenhouse cucumber. *Environ Entomol* 30:1073–1081.

Watanabe K, Yoshimura C, Omura T. 2005. Stochastic model for recovery prediction of macroinvertebrates following a pulse-disturbance in river. *Ecol Model* 189:396–412.

Wennergren U, Stark J. 2000. Modeling long-term effects of pesticides on populations: Beyond just counting dead animals. *Ecol Appl* 10:295–302.