How can models foster the transition towards future agricultural landscapes?

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Advances in Ecological Research
ISSN 0065-2504
https://doi.org/10.1016/bs.aecr.2020.11.004

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Abstract

Modern agriculture faces the dual challenges of feeding a growing human population, while preserving natural resources and slowing current trends in climate change and its impacts. A deep understanding of the functioning of agricultural landscapes appears crucial if we are to move towards sustainable, complex and resilient agroecosystems. Modelling is a powerful tool to address these issues since it can inform these transformations by simulating the multiscale ecological flows and myriad interactions agroecosystems host, and the multilevel stakeholder actions and their feedbacks in landscapes. This chapter shows that models can provide guidance on the transition towards future multifunctional agricultural landscapes. We have focused on process-based models, which allow for a more thorough understanding of the underlying mechanisms and how these may be manipulated. We first examine how models can simulate the structure and the dynamics of agricultural landscapes, emphasizing the complex mosaic of urban, peri-urban, rural and seminatural habitats. Then, we consider the simulation of biotic and abiotic flows and their complex interactions in the mosaic habitats. Using formalisms from the social sciences, we integrate human decision-making and actions into the landscape models, thereby encompassing a major component in the landscape transformation process. Finally, we outline some avenues for future research. We have focused on improvements to landscape representation, and have suggested ways to bridge the gap between future landscape conception and manipulation, thus providing operational guidance for the transition towards future agricultural landscapes that achieve our objectives.

1. Introduction

1.1 Earth faces changes at an unprecedented pace

Our planet has undergone unparalleled change over the past three centuries. The impact of humans now competes with natural forces as a driver of planetary change, justifying the term 'Anthropocene' for the present, human-dominated, geological epoch (Crutzen, 2002). Very few places on Earth have not been affected by humans, either directly or indirectly (Vitousek, 1997). Supported by considerable mechanical and technological developments that rely on fossil–fuel-derived energy, humans have transformed landscapes worldwide and altered, potentially irrevocably, the ecological flows and myriad ecological interactions they host (With, 2019). In this context, landscape-scale models are useful tools to improve our knowledge and guide decision-making at spatial scales (typically 1–1000 km^2) on which

many ecological processes and linkages are manifest (Keane et al., 2015). Ongoing population growth—from 690 million in 1750 to 7.8 billion in 2020—and urbanization have resulted in the expansion of cities into the surrounding rural areas and the homogenisation of agricultural landscapes. Concomitant, intensification of farming practices (land consolidation, shortening of crop rotations, and selection of the most productive cultivars relying on agrichemicals to protect fields from pathogens and pests) has contributed to landscape simplification. Such changes were adopted in answer to the challenge of feeding the increasing world population, but at the expense of the environment as well as animal and human health (Foley, 2005; Rayfuse and Weisfelt, 2012; Tilman, 1999).

Some recent studies spotlight dramatic declines in biodiversity, species richness and abundance, e.g. birds and mammals (Hallmann et al., 2014; Spooner et al., 2018) and entomofauna (Hallmann et al., 2017; Seibold et al., 2019; Vogel, 2017). Sánchez-Bayo and Wyckhuys (2019) assessed and ordered the main drivers of species declines: habitat loss and land use change to intensive agriculture and urbanization; pollution, mainly by synthetic pesticides and fertilizers; biological factors, including pathogens and introduced species; and climate change. By 2050, agriculture will need to produce an additional 50% of food than in 2012 to meet the need of around 9.73 billion people (Armanda et al., 2019; FAO, 2018).

All these signs signal a need to transform the systems responsible for this situation, including farming systems that are responsible for 14.5% of all anthropogenic greenhouse gas emissions (Gerber et al., 2013), pollution of soils (Rodríguez Eugenio et al., 2018) and waters (Carpenter et al., 1998; Mateo-Sagasta et al., 2017), and biodiversity decline (Tilman, 2001; Tsiafouli et al., 2015). Such transformation will have to be multifaceted, since it will modify production systems, socioeconomic organization of labour, crop selection and agricultural practices, but also global diets and food waste.

1.2 Reorganizing farming areas towards a sustainable agriculture

Today, some 55% of the world's population lives in urban areas, and this percentage is rising. By 2050, with the urban population more than doubling its current size, nearly 7 in 10 people in the world will live in cities (World Bank, 2020). The rural agricultural land abandonment that this causes is the most frequent driver of landscape change in many regions of the world (Plieninger et al., 2016). Cities and their surrounding regions will be

challenged to plan and design their development in order to deliver green, inclusive, competitive and resilient services including food supply. In Europe, much of the distinction between rural and urban landscapes has lost because areas classified as peri-urban and characterized by complex landscapes are growing four times faster than urban areas. At this rate, the peri-urban area would double in around 40 years (Piorr et al., 2011). In exhibiting higher structural complexity, future peri-urban landscapes could lead to the formation of mosaics where agricultural, urban and seminatural habitats intermingle. Maintaining agriculture within these peri-urban mosaics will be an essential strategy for ensuring food security and mitigating climate change. This calls for a rethinking of food systems in a farm-to-fork approach linking farming systems to our modes of consumption. Models can foster this transition towards future sustainable complex landscapes by highlighting food production capacities that depend on the context of biotic/abiotic/anthropogenic interactions due to local heterogeneities and landscape structure, and support the design of new farming systems adapted to local conditions (Duru et al., 2015).

Seminatural habitats (composed by hedgerows, ditches and irrigation channels, ponds, grass strips, natural or artificial wetlands, etc.) are of great importance in rural and peri-urban landscapes because they are implicated in ecosystem services such as erosion limitation, water supply and flood regulation, pesticide and nutrient mitigation, weed and pest spreading regulation (Biggs et al., 2017; Burel, 1996; Dollinger et al., 2015; Le Cœur et al., 2002; Power, 2010). These ecosystem services, if supported, presents an opportunity to reduce our dependence on agricultural inputs (fertilizers, pesticides, irrigation water, etc.). Diversity and functional complementarities between species (Caron et al., 2014) is also a condition for the development of biodiversity-based agricultural landscapes, as well as resilience of ecosystems (Chapin et al., 2000).

For this sustainable future of farming, much research points to the importance of considering ecological scales in farming systems (Altieri and Nicholls, 2012). This implies an upscaling of decision and organization of management practices from the plot or farm levels to the landscape level (Elzen et al., 2012). Whereas the plot and the farm levels are driven by individual farmer decision making, managing the landscape is a challenge since it involves a collective decision-making process that includes interdependent stakeholders, including nonfarmers. The landscape can therefore be considered as a system whose properties emerge from its components (e.g. farms). Organizational, regulatory and technical innovations are needed to make agricultural landscapes more manageable (Hannachi and Martinet, 2019).

1.3 Modelling as a central tool to help design future agricultural landscapes

Designing future landscapes with higher complexity, resilience and manageability, requires a modified scientific approach. Transformations across scales cannot be informed by experiments alone, given the complexity of the system, the broad range of spatial scales and the multiple objectives that must be satisfied. Indeed, examples of projects of agricultural landscape redesign are rare (Geertsema et al., 2016; Kremen and Merenlender, 2018; Schulte et al., 2017).

Conversely, the wide variety of models that are available could be used to provide invaluable insight to guide the transformation of farming systems (Nendel and Zander, 2019) and the transition towards future agricultural landscapes. For instance, combining output from global climate models (Hayhoe et al., 2017) and species distribution models (Franklin (2010) and references therein) can predict the effects of environmental changes on species and ecosystems. Combining models that capture feedbacks between biophysical and socioeconomic drivers of land-use change, yet include at the small scale interactions with biodiversity, and at the large scale a model of the world economy, would make it possible to investigate the consequences of reaching equal global production gains by 2030, either by cropland expansion or intensification, and analyse their impacts on agricultural markets and biodiversity (Zabel et al., 2019). More generally, agricultural landscapes provide many ecosystem services (e.g. food production, regulation of water, regulation of greenhouse gases), thereby making it challenging to commit to transformative changes that improve one service without unintended consequences for the others. In that, multiobjective optimisation algorithms (Memmah et al., 2015; Todman et al., 2019) can be helpful, for instance in identifying trade-off frontiers.

Complexity and uncertainty are two cornerstones of modelling. Models allows the exploration of a set of scenarios as a way of exploring uncertainty. By incorporating knowledge from various disciplines (physics, chemistry, biology, ecology, economy, sociology, etc.), coupling components and considering interactions and feedbacks, models contribute to our comprehension of complexity. Here we use agricultural landscape models to tackle these issues of future agricultural landscape design. These tools, in simulating the landscape functioning, can help to inform decision-makers on possible trajectories towards objectives and search options set by "society". Building reliable tools requires a better coupling of landscape patterns and process models to account for feedbacks, integrate the decisions of multiple stakeholders, consider the spatial and temporal heterogeneity of data and processes,

explore alternative landscape organizations and assess multiobjective performance (Poggi et al., 2018). A myriad of technical issues arises when doing this coupling. These include uncertainties of evaluation, model parameter inference, data assimilation, etc. In this paper, we give insights on the added value, current development and limitations of such models to provide guidance on the transition towards future desirable landscapes. Where possible, we focus on process-based models that allow for a more thorough comprehension of the underlying processes at stake and provide our perspective of their beneficial use.

1.4 Chapter structure

In Section 2, we present some major drivers of the modifications of agricultural landscapes, notably urban expansion and sprawl, and highlight the relevance of modelling for forecasting this ongoing evolution. We assume that demographic pressure, demand for food, reduction of fossil energy dependence and environmental requirements will give rise to more complex agricultural landscapes, forming mosaics where contrasted habitat intermingle. In Section 3, we focus on the simulation of biotic and abiotic flows across agricultural landscapes, and the impacts of adding complexity in process-based models of these flows. In Section 4, we show how models can generate transformative knowledge for the design of future agricultural landscapes. We address this issue via insights from the social sciences (e.g. economy, geography), interdisciplinary modelling (notably between social and natural sciences), and transdisciplinary modelling (i.e. participatory modelling involving scientists and practitioners). In Section 5, we suggest some avenues for future research, identifying the need for multiscale and multilevel representations of agricultural landscapes, as well as their conception and their manipulation. Finally, in Section 6 we conclude this chapter with a key set of take-home messages for landscape modelling.

2. Are current models relevant to simulate the complexity of future agricultural landscapes?

The structure of a given landscape results from the accumulation of past changes (legacy effect) driven by multiscale forces (Houet et al., 2010). Given current trends, we assume that future landscapes will be more complex, with a strong intermingling between agricultural, seminatural and urban habitats. Thus, methods and tools that enable the simulation of these three types of land cover, and their interaction, are of major importance.

In this section, we first introduce a way to model the structure and dynamics of agricultural landscapes. We briefly review how urban expansion may be modelled and then focus on peri-urban areas which are likely to become ever more important with the increasing intermingling between agricultural and urban land uses, and discuss the inclusion of agriculture in cities. Finally, we introduce seminatural habitats into the landscape mix, and by recalling their impact on many ecological and physical processes, emphasize the caution that should be exercised when modelling these important habitats.

2.1 Current approaches to represent the agricultural landscape structure

Agricultural landscape models describe landscapes as mosaics of fields having shapes and properties that vary in space and time (Poggi et al., 2018). Different approaches have been proposed for generating landscapes with various structures (i.e. the spatial arrangement of land covers), and for studying biotic or abiotic processes (Langhammer et al., 2019). There are two complementary approaches, raster and vector representations, for modelling such mosaics, depending on the goal of the study and how their constitutive parts are handled (Bonhomme et al., 2017; Gaucherel et al., 2006b).

Most existing models use rasters to simulate cell mosaics (Engel et al., 2012; Gardner, 1999; Pe'er et al., 2013; Saura and Martínez-Millán, 2000; van Strien et al., 2016). The landscape is discrete and played out across a grid, where each grid cell is the smallest elementary spatial unit of the landscape and contains information about that unit of the landscape. Begg and Dye (2015) developed a modelling framework that couples a landscape mosaic generator and a population module to study the interactions between the population dynamics of several crop pests and the cropping system. Engel et al. (2012) designed simple landscape patterns composed by 15 crop types with varying crop proportions and mean field sizes. A more complex approach was developed by van Strien et al. (2016) who generated landscapes integrating different landscape metrics (e.g. number of patches, patch size, patch edge contrast), calculated at the field or class levels, which allowed for variation in the landscape configuration and composition. The raster-based (or grid-based) approach is particularly suited to the modelling of gradual landscape dynamics and continuous processes, due to the regular grid structure facilitating processes operating between contiguous cells.

Real agricultural landscapes display a patchy structure made of contiguous, irregular polygons delineated by rectilinear boundaries, some polygons having border structures such as hedgerows (Gaucherel, 2008), making the

vector-based approach appealing (Gaucherel et al., 2006a,b; Inkoom et al., 2017; Langhammer et al., 2019; Le Ber et al., 2009; Papaïx et al., 2014). For example, Gaucherel et al. (2006a,b) developed a model that simulates tessellated patches and borders structures. Le Ber et al. (2009) simulated agricultural landscapes defined by two different tessellations (Voronoi and rectangular), i.e., the cover of the Euclidian plan by a countable number of geometric shapes, and two types of cropping pattern distributions (random or stochastic). Papaïx et al. (2014) developed a simple landscape generator that generates the polygon landscape mosaic based on a T-tessellation algorithm developed by Kiêu et al. (2013). Tessellation models have the advantage of being parametric, meaning that a set of parameters control the main features of the simulated landscapes. In addition, these models are stochastic, producing collections of replicated virtual landscapes with similar landscape metrics (Papaïx et al., 2014). This allows testing of the robustness of the results to changes in residual landscape variability, as landscape ecological metrics are not sufficient statistically. However, it can prove difficult to reproduce fine grain spatial structures with such approaches as they do not capture the full complexity of landscapes nor do they provide realistic landscape patterns. Combining parametric with nonparametric approaches may enable this gap to be bridged (Straubhaar et al., 2011).

2.2 Spread of land uses mixing agricultural and urban covers

Urban expansion is an increasing global trend (World Bank, 2020). In Europe, peri-urban areas characterized by complex landscapes mixing agricultural and urban covers are growing rapidly. These new contexts call for the constraints and opportunities offered by urban and peri-urban settings to be explored for the purpose of developing future agricultural landscapes.

2.2.1 Simulating urban expansion

The simulation of urban land use within agricultural landscapes relies on an understanding and integration of biophysical and social perspectives (Verburg et al., 2010). The biophysical perspective sets the environmental conditions (e.g. climate, altitude) determining the global change processes. The social perspective encompasses at least the demographic development and rural–urban flows that depend on the territorial context.

The development of cities was initially simulated using a cellular automaton (CA), coupled to a geographical information system (GIS) to define the neighbourhood effects of various land uses (Couclelis, 1997). Subsequently, temporal dynamism was integrated into the CA model using stochastic

process models that describe how one state is likely to change to another state (Markovian models), given the transition probabilities between actual and future land use maps (Sang et al., 2011). Guan et al. (2011) stated that such Markov-CA modelling provides the most suitable approach to study the temporal and spatial dynamics of land use change. Various models have been proposed over the last 20 years: CA models (Barredo et al., 2003), Markov-CA models (Jokar Arsanjani et al., 2013), the Dyna-Clue model (Verburg and Overmars, 2009), the Spacelle (Dubos-Paillard et al., 2003) and Foresight models (Houet et al., 2016) with spatial resolutions spanning from 1 ha to 1 km^2. The main challenges for this modelling have been to take into account spatially explicit, environmental variables that constrain urban expansion in space (Fig. 1), and irregularities in temporal trends that affect transitions from current to future landscapes. In particular, model calibration requires comprehensive and accurate spatial and temporal datasets. Importantly, these modelling approaches do not consider the large number of current land uses or potential new uses, or the specifics of the peri-urban zone in the transition between dense urban and rural areas.

2.2.2 Modelling agriculture in complex peri-urban landscapes

Beyond the ongoing scientific debate about the use of the term peri-urban, its precise location, spatial extent and the definition of boundaries (Friedmann, 2016), peri-urban agriculture can be defined empirically as the farming performed in the space close to towns (FAO, 1999). A growing literature characterizes the dynamics of rural–urban areas using process-based models but these rarely focus on farming in peri-urban landscapes (Silveira et al., 2006). Statistical approaches have been applied at the patch scale to assess the transition probabilities of grid patches from one land-use category to another and notably the impact of urbanization in the land-use patch structure of peri-urban areas. These models are used to assess the loss of cultivated land, and the deterioration of the site conditions of unconverted peri-urban cultivated land due to the fragmentation induced by urban sprawl (Li et al., 2017; Pribadi and Pauleit, 2015). Agriculture in peri-urban landscapes is usually considered in terms of a distance from city-centres, as a distance-gradient inspired by the classical Von Thünen's conceptual model (Sinclair, 1967; Von Thünen, 1826). For Von Thünen, a theoretical agricultural society would be one in which agents live in a single settlement and use the surrounding area to produce essential and nonessential goods. The distance between urban settlements and the areas of agricultural production are therefore extremely important for the placement of these products. This approach has been used

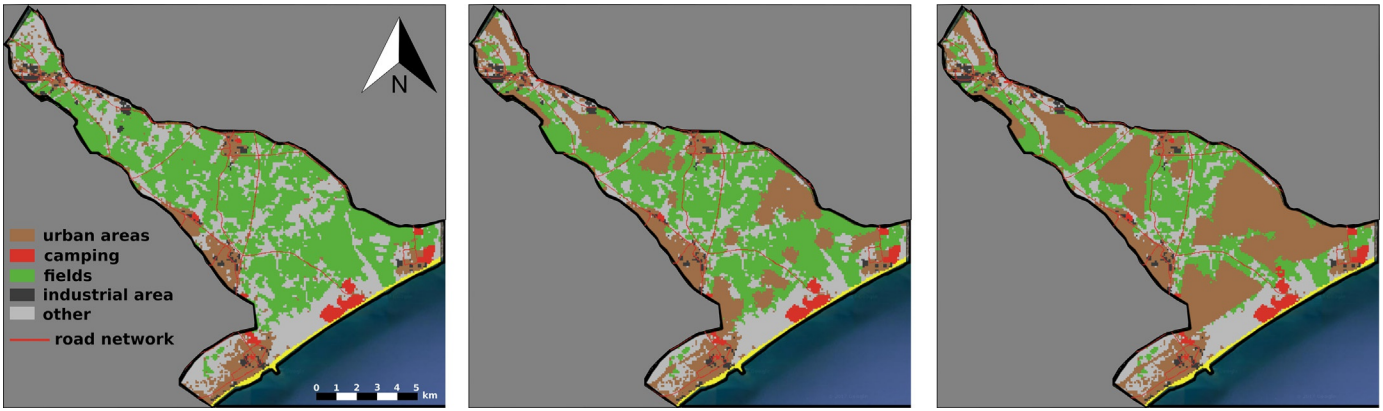


Fig. 1 Illustration of urban expansion (from left to right) in a river delta flowing into the Mediterranean Sea, as modelled with a cellular automaton using the NetLogo® platform. The urban areas (brown areas) are constrained by the distance to the road network (red lines) and the distance to the sea. Land uses derive from a study on the Lower Orb river fluvial plain by Saint-Geours et al. (2015).

in an agent-based simulation model to generate a wide range of agricultural landscapes (Macmillan and Huang, 2008). But, distance to a main urban settlement is, on its own, not sufficient to characterize agriculture in complex and multipolarized peri-urban landscapes, which are diverse, plural and dynamic (Sanz Sanz et al., 2017, 2016). Farming systems connected to cities are indeed characterized by a high degree of complexity related to anthropic developments as well as to the strategies of the different stakeholders (Zasada et al., 2013). This complexity is not integrated in the existing process-based agricultural landscapes generators (Langhammer et al., 2019). Furthermore, landscape change models operating at an aggregated level (including dynamic process-based simulation models) have not been used to predict changes in peri-urban agricultural land use such as intensification, because intensification is a function of the management of physical resources within the context of the prevailing social and economic drivers (Lambin et al., 2000).

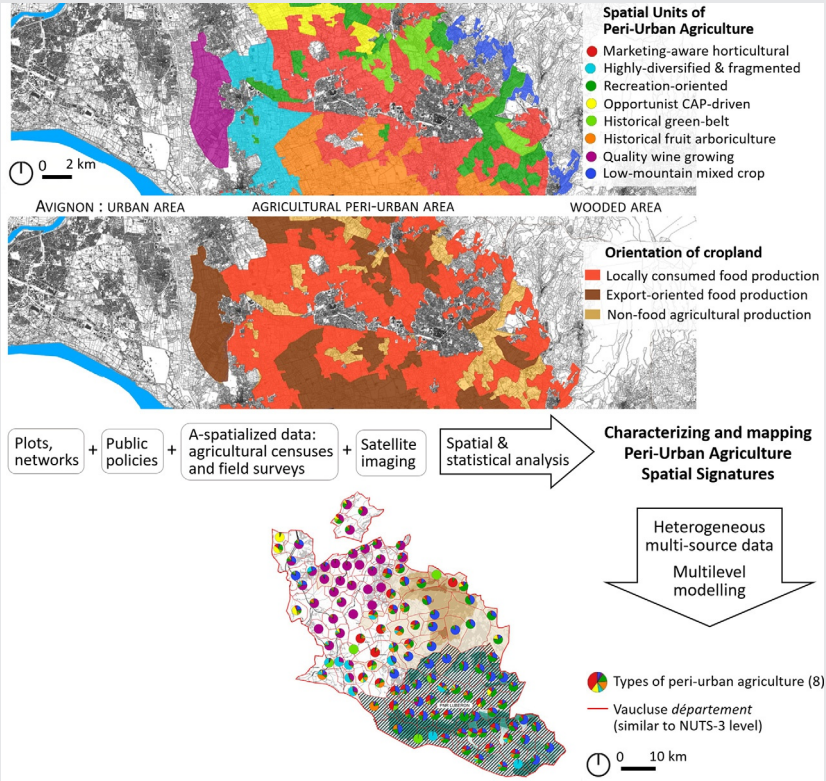
Most attempts to evaluate spatial suitability of agriculture in peri-urban landscapes are partly based on qualitative approaches requiring thorough fieldwork associated with statistical and spatial analysis based on GIS (Thapa and Murayama, 2008). Farming systems shape agricultural landscapes, as observed by Rizzo et al. (2013), and thus every type of peri-urban agriculture has its "spatial signature". These are particular spatial structures whose arrangement is identifiable in space resulting in a set of common characteristics, such as crop plot shape, location of farmstead, border relation between farming and urban zones, etc. Complex peri-urban agriculture has recently been modelled by social scientists for the purpose of landscape planning and policy-making by using simple, predictive probabilistic models based on free available data. Sanz Sanz et al. (2018) classed peri-urban farming into spatial units of peri-urban agriculture (USAPU) and proposed a multivariate statistical modelling approach at the NUTS-3 level, that is a small region defined by the European Union for specific diagnoses and statistics (Box 1).

An alternative approach proposed by urban economists for small study areas has been to use peri-urban farm econometric location models based on exhaustive databases at the plot scale and often complex mathematical tools. Geniaux et al. (2011) developed a spatialized hedonic model to estimate land-use change using mixed geographically weighted regression (MGWR) techniques with a two-stage model that links agricultural and developable land markets.

2.2.3 Inclusion of agriculture in cities

Urban agriculture, which can be defined as the cultivation of crops and rearing of animals for food and other uses within cities (Mougeot, 2000), may

BOX 1



Operational modelling of peri-urban farmland in a Mediterranean context. Sanz Sanz et al. (2018) classified peri-urban farming into spatial signatures, referred to as spatial units of peri-urban agriculture, using a multivariate statistical approach. This was done using an in-depth analysis of a local case study in the Avignon, France, peri-urban area, involving surveys, on-site landscape reading, remote sensing analyses and interviews. The classification obtained from seven municipalities was subsequently used to train a fractional regression model, which was then tested on the rest of this French department (similar to NUTS-3 level; EC European Commission, 2018) to predict the presence and actual proportion of each spatial signature in the total agricultural land of each municipality (151 municipalities). They defined categories of municipality according to the distribution of spatial signatures that open perspectives for public action on peri-urban farming. While providing reliable predictions regarding peri-urban developments, this model proved to be simple and operational for collective decision-making on peri-urban planning. Incorporating this concept of spatial signatures in Markov-CA models (Guan et al., 2011) simulating urban expansion offers promising developments for the study of farming dynamics in the complex peri-urban areas of future landscapes.

lead to a second green revolution (Armanda et al., 2019). Despite being studied in many developing countries (Armanda et al., 2019; Dossa et al., 2011; Mawois et al., 2012), intraurban agriculture suffers from the lack of a modelling framework for elaborating spatiotemporal dynamics. This may be due to the divergence of spatial scales in land use change models (LUCC) between intraurban agriculture and traditional agriculture. In contrast to the relatively large-scale and long-term dynamics of traditional agriculture, intraurban agriculture acts at a local scale in space-confined cities, sometimes on vertically inclined surfaces such as building walls (Specht et al., 2014). Intraurban crops are also based on short cycles and with wide crop diversity (Mawois et al., 2012).

Nevertheless, it is necessary to simulate the spatial allocation of urban agriculture and its temporal dynamics. A potential avenue to explore is to create a specific LUCC model by combining the factors affecting spatial suitability of urban agriculture (Thapa and Murayama, 2008) and the leafy vegetables land use model (LYLU) developed by Mawois et al. (2012). The LUCC model estimates the surface area of each leafy vegetable that depends on plant specificities, amount of resources in the farm, and the sales channel for these products. In the future, such an approach combining LUCC and agronomic models should be able to guide decisions for the estimation of agricultural food supply in urban or peri-urban areas.

2.3 Considering the structure of seminatural habitats

Seminatural habitats have the potential to deliver bundles of desired ecosystem services because of their influence on the community ecology of crop pests and beneficial organisms (Bianchi et al., 2006; Burdon and Thrall, 2008; Chaplin-Kramer et al., 2011), on water flow regulation, soil loss mitigation or pollutant retention and degradation (Dollinger et al., 2015). The structure of seminatural habitats embedded in landscapes dominated by agricultural land can be highly variable. These can range from wild and cultivated elements being almost undistinguishable and intermeshed, such as in tropical agroforestry landscapes (Tscharntke et al., 2011), to being strongly separated such as in intensive monoculture landscapes, with the area and spatial distribution of remnant wildlands varying greatly (Fig. 2).

An enhanced diversity of land cover types, stemming from the inclusion of noncrop and nonmanaged areas of different patch sizes and shapes, can result in higher levels of complexity, both in terms of landscape composition and configuration (Perović et al., 2015). The boundary types (ecotones) and

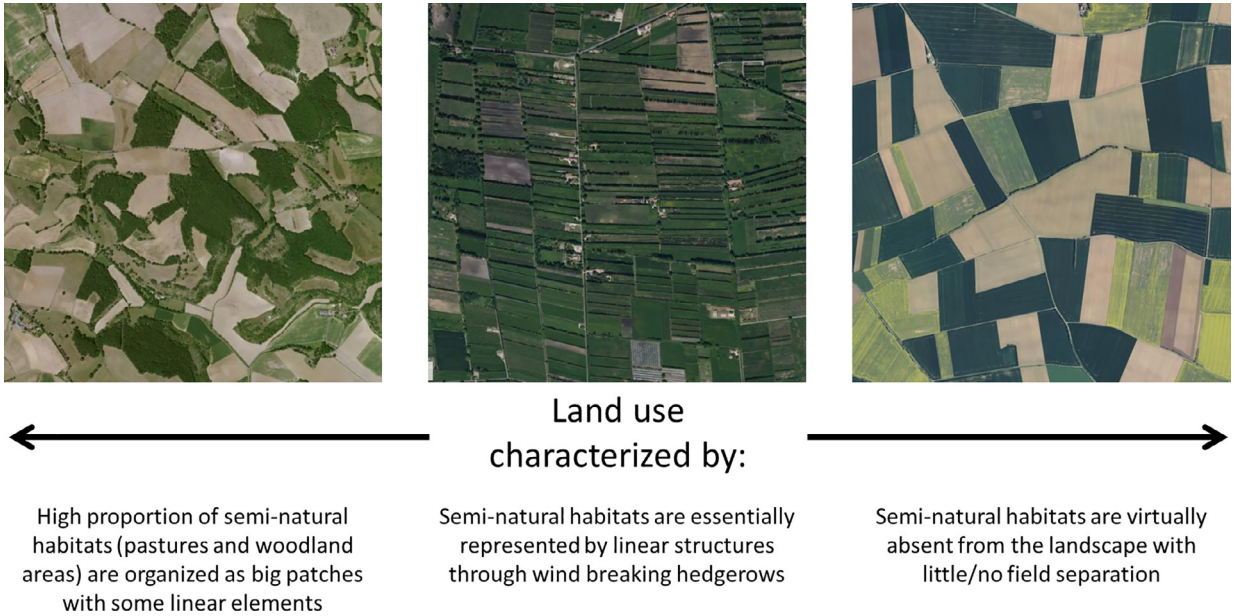


Fig. 2 Spatial structure of the agroecological interface across different farming systems. *Source: ©IGN.*

contrasts between patches affect the dispersal of species and the frequency and probability of colonization of neighbouring patches (Perović et al., 2015; Sattler et al., 2010). These different land cover types can contribute complementary resources during the life cycles of each species, thereby increasing species diversity and favouring complex trophic network relationships (Dunning et al., 1992; Massol et al., 2017; Perović et al., 2015; Philpott et al., 2020; Tscharntke et al., 2012). Seminatural habitat cover on farms is generally assessed by national maps to support the planning and implementation of agri-environmental policies meant for an accurate spatial targeting of biodiversity restoration and preservation (Sullivan et al., 2011). This approach relies on the integration of available datasets, GIS and remote sensing. Remote sensing techniques are very effective when there is a high contrast between neighbouring habitats, for instance to map scrub on seminatural grassland habitats in Ireland (Parr et al., 2006; Sullivan et al., 2011). Based on farm agronomic and economic data and farm practice surveys, broad scale land use classifications have been used to build indicators and identify areas of High Nature Value farmland in France (Pointereau et al., 2007), Belgium (Samoy et al., 2007) and Hungary (Belényesi et al., 2008). Sullivan et al. (2011) developed a model to investigate the relationships between the percent seminatural area and a number of variables that reflect surrounding landscape features and farm management practices. They estimated the likely distribution of hotspots or areas with high cover of seminatural habitats at a regional scale. The main drawbacks of these techniques is that they are site specific and depend on the availability and reliability of landscape data (Pointereau et al., 2007; Sullivan et al., 2011). We show in Section 2.3 that landscape models are appropriate tools to simulate the landscape mosaic composed of cultivated and seminatural patches and their interactions, thereby providing ways to study the relationships between landscape patterns and the landscape processes of interest.

Linear corridor, seminatural habitats, such as field boundaries (hedgerows or ditches), play a major role in the landscape because of their important impact on many agroecological processes. Such border structures should be modelled with care, though, due to their low-ground coverage and the spatiotemporal constraints that they can impose at the landscape scale. For example, Gaucherel et al. (2006a,b) used models based on Gibbs energy terms to control pairwise interactions between landscape elements and to simulate patches and certain border structures. Alternatively, multilayer network frameworks can be used to model the interactions between the different geometrical elements of the landscape (Box 2). In previous examples, the

BOX 2

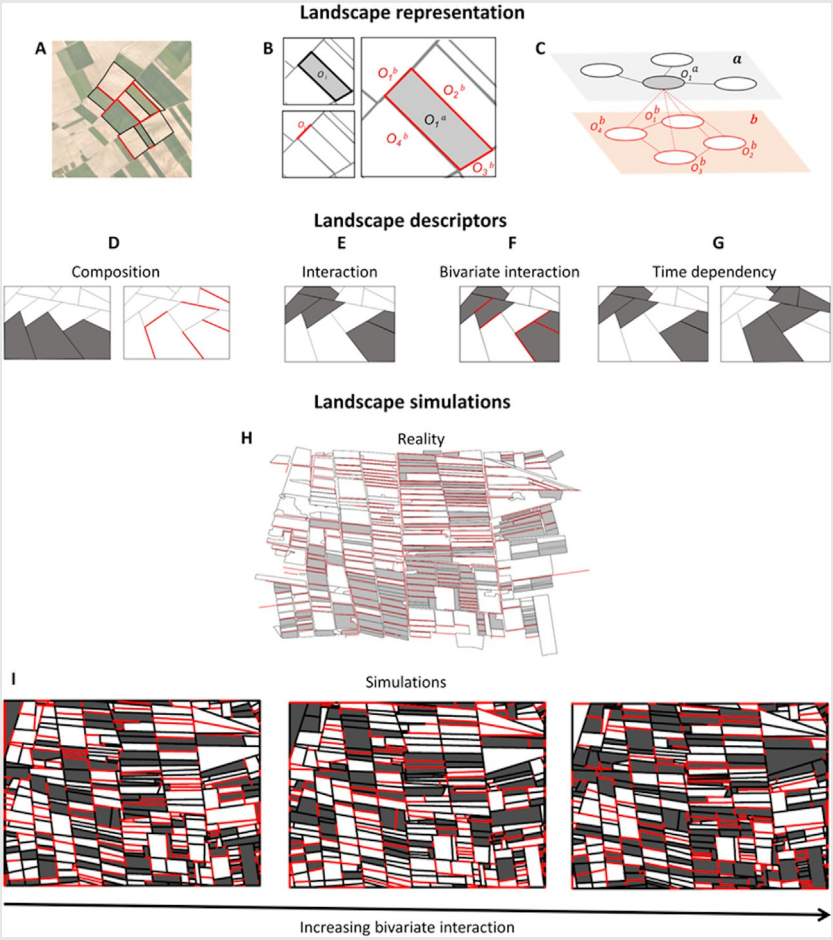


Illustration of a landscape stochastic generator and its parameter statistical inference. The landscape is represented as a collection of *n* geometric objects which can be of different types, such as polygons (i.e. habitat patches such as fields) or linear segments (i.e. linear landscape elements such as rivers or hedges), depicted in (A) and (B). Polygons can be of different categories such as crops, natural habitat, etc. Linear segments can be allocated with categories as single-species hedgerows, mixed-species hedgerows or no hedgerows. Spatial or functional relationships among landscape objects are captured by a graphical representation of the landscape. Interactions between objects are modelled through a

BOX 2—CONT'D

multilayer network (Boccaletti et al., 2014; Kivela et al., 2014), as shown in (C). Each layer corresponds to an object type, and each single-network layer represents the interactions among objects of the same type. Interactions between different network layers represent interactions between objects of the different types. Landscape descriptors (D-G) capture important landscape characteristics and features of both patches and linear elements. Typically, three groups of landscape descriptors are defined (Zamberletti et al., 2020): (i) composition metrics (D) correspond to the contributions of individual objects; (ii) spatial interaction metrics measure the interaction between two adjacent objects of the same type (E) or of different types (F); and, (iii) temporal metrics (G) assess the difference between configurations over two consecutive time steps. These descriptors can be incorporated in a probability measure describing the energy of the current configuration, i.e. a Gibbs energy function (Cressie, 2015; Van Lieshout, 2019), to infer parameters governing the real allocation and perform landscape simulations starting from a given parameter setting. Starting from a real landscape (H), simulations of landscape configurations can be performed using an iterative algorithm (Metropolis-Hastings algorithm) converging towards the stationary distribution of the target model (e.g. Descombes (2013)). The model generates virtual but realistic agricultural scenarios (I) featuring different spatial patterns (e.g. geometry, connectivity) and temporal patterns (e.g. crop rotation).

border structures are constrained by the polygonal meshing of the agricultural fields. However, seminatural habitats (e.g. watercourses) are more perennial imposing their location on agricultural elements. Vinatier and Chauvet (2017) therefore developed an interesting framework that they applied to the simulation of road networks. They proposed a hierarchical model based on successive interleavings of deformed networks, with the deformation being realized on the basis of a reverse Douglas–Peucker algorithm (Douglas and Peucker, 1973). This model could be adapted to account for external variables influencing the network of linear elements such as topography, wind direction, connectivity of habitat patches, etc.

Spatial-point seminatural habitats, such as trees, also deserve inclusion in models due to their potential role in the spread of organisms. For instance, Rossi et al. (2016) simulated the distribution of isolated trees in a landscape using an inhomogeneous Poisson point process model. Remarkably, they discovered that trees outside forests constituted the main source of landscape connectivity for the pine processionary moth, suggesting a potentially huge role in forest insect pest dispersal and invasive species expansion.

In the future, the debate regarding the notion of aggregation or fragmentation of the seminatural habitats within territories, i.e., the land-sparing vs land-sharing strategies (Fischer et al., 2008; Grass et al. , 2021; Mitchell et al., 2015), will continue. Neutral models as those presented above and those discussed in the Section 2.1 may inform this debate. Building such models to consider different landscape constraints may shed light on efficient designs of configurations of seminatural habitats for increasing the multifunctionality of agricultural landscapes.

3. Spatial flows and interactions across agricultural landscapes: Simulation of biotic–abiotic interrelations and trophic networks

For the representation of future agricultural landscapes, complex biotic and abiotic interactions deserve specific attention as many ecosystem services (e.g. erosion limitation, pest regulation) derive from these interactions (de Groot et al., 2010; Fisher et al., 2009). Processes underpinning these interactions can take place in fields or noncultivated areas (e.g. hedgerows, ditches, ponds, wetlands) and at the local or landscape scale (Power, 2010). Interestingly, a better understanding of these interactions may open ways of deploying nature-based solutions (Nesshöver et al., 2017; Rey et al., 2015), which could enhance the resilience of agricultural landscapes against extreme weather events, pest and disease outbreaks, and other anthropogenic stressors, and decrease their dependence on the use of agricultural inputs such as fertilizers and pesticides (Duru et al., 2015).

Here, we first address the modelling of spatial flows in complex landscapes. Then we present how interacting biotic and abiotic flows are currently modelled in agricultural landscapes, and we discuss concepts and models underpinning the simulation of multitrophic interactions in complex landscapes, notably useful to unravel the processes at stake in natural regulation of pests which is pivotal in an agroecosystem favouring biodiversity. Finally, we highlight current trends in measuring and calibrating models of spatial processes based on large spatiotemporal datasets.

3.1 Modelling spatial flows in complex landscapes

In landscapes characterized by a strong intermingling between seminatural habitats, crops and built areas (see Sections 2.2 and 2.3), modelling of spatial flows, such as the movements of individuals, particles, chemicals and fluids (wind, water), between those landscape elements is of primary importance

for a better understanding of landscape resilience. A variety of mathematical tools are available in ecology, such as in random walk models or stochastic differential equations at the scale of an individual for instance or reaction–diffusion models at the scale of a population, but their use in the context of complex environments may require further methodological developments (see Vinatier et al. (2013) for a review). Fluids, such as water and air, are generally considered as three-dimensional continua, characterized by density and velocity fields that vary in space and time. Modelling these fields and their related compartments (atmosphere, vegetation, soil surface, subsurface) at the landscape scale involves uniting approaches from several scientific disciplines, including ecology, and the earth and physical sciences. Except for very simple circumstances, these modelling approaches are not continuous and no general analytical solutions exist to solve the equations representing 3D flow processes (Singh and Woolhiser, 2002). Equations are derived from physical laws (e.g. Darcy laws) and involve parameters that could be measured in the field (e.g. hydraulic conductivity). Here, we present examples of spatial flow representation and modelling in agricultural landscapes in the cases of (i) physical processes and (ii) biological processes.

In landscapes in which increased complexity of geometrical structures stems from the introduction of numerous linear or point elements of significant height, such as hedgerows in bocage landscapes or trees in agroforestry systems, dispersal of airborne propagules may be profoundly affected by different airflows and turbulences between crops cultivated in open lands and crops surrounded by hedgerows or cultivated under shade trees. As an example, tree architecture and its interactions with microclimates may drive the dynamics of fungal diseases in crop fields (Motisi et al., 2019). Spatially explicit models for the simulation of turbulent flows within and above vegetation exist (Dupont and Brunet, 2008), and have already been applied to pollen dispersal (Dupont et al., 2006) and wind gust inside forests during windstorms (Dupont and Brunet, 2006), but their application to highly structured environments covering a large extent with varying height of linear elements remains challenging. The inclusion of hydrological infrastructures forming a high-density network within spatially explicit models also requires the development of specific models to handle the distribution of water within these infrastructures. The hydrological model MHYDAS (Moussa et al., 2002) and its application to a hydrological network on a hilly landscape opens interesting future avenues to explore. In flatter areas through which linear elements with higher flow rates circulate, e.g., streams or channels, hydraulic models are most suited (Baume et al., 2005; Brunner and Bonner, 1994).

Modelling dispersal of organisms and matter in landscapes comprising agroecological elements with specific geometrical properties (e.g. hedgerows, field borders) needs to be treated cautiously to avoid artefactual effects, such as might result from the incorrect estimation of population densities at the interface between elements. Hedgerow networks may act both as ecological corridors along which animal species disperse and as barriers to dispersal, in other circumstances. These source and sink structures for various organisms are classically modelled using spatially explicit models that consider position-dependent mobility and reproduction parameters, at individual and population scales. Depending on various factors such as the size of the population under study or the complexity in individual behaviour that it is necessary to consider, a wide range of mechanistic approaches can be used, from differential equation models to individual-based models (Bourhis et al., 2015; Preisler et al., 2013; Soubeyrand and Roques, 2014; Vinatier et al., 2011). In these models, space is either treated as continuous or as a discrete, regular grid (lattice). Grid-based population models can offer an efficient way to model dispersal because dispersal kernels are easily discretized on a regular lattice (Ricci et al., 2018; Slone, 2011). At the landscape scale (i.e. a large spatial extent), however, the limitations in the grid spatial resolution makes it difficult to consider elements with low grid coverage, such as linear or point elements. In contrast, Roques and Bonnefon (2016) developed a promising approach based on a system coupling two-dimensional (2D) and one-dimensional (1D) reaction-diffusion equations describing the population dynamics of surface and linear elements of the landscape. This approach proved particularly relevant when the presence of a corridor or a barrier (e.g. roads, rivers, hedgerows) significantly alters the model outcomes. Using the example of the range expansion of the tiger mosquito, *Aedes albopictus*, in metropolitan France, the 2D/1D approach provided a better fit and a higher predictive power than a classical 2D reaction-diffusion approach, outlining the importance of considering explicitly corridors such as the road network.

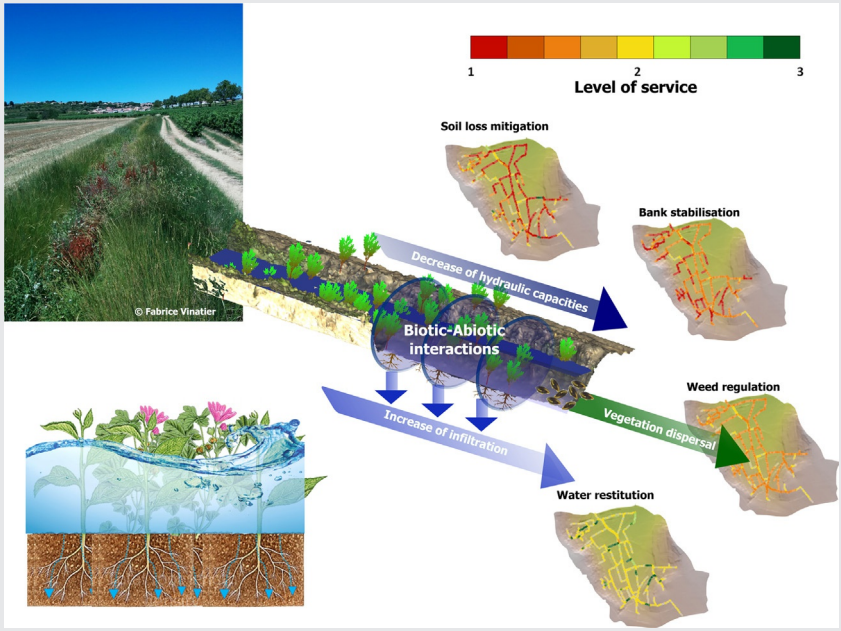
3.2 Simulation of biotic and abiotic interactions in complex landscapes

Simulating biotic-abiotic interrelations requires interdisciplinary approaches. Each discipline may have developed, independently, its own landscape modelling approaches, resulting in an unbalanced representation of biotic, abiotic processes depending on the core discipline of the modellers (Vinatier et al., 2016).

Despite some attempts to unify the biotic and abiotic processes in the same modelling framework (Vinatier et al., 2016), there remain a number

of model design, space-time and computational challenges to be met. We highlight these challenges using the functioning of a hydrological man-made network (noncoated ditches) in an agricultural watershed as a case study (Box 3). Ditches are both hot-spots of plant biodiversity and vectors of water flow transport in agricultural watersheds, thus giving rise to interactions

BOX 3



Example of a biotic-abiotic coupling using spatially explicit models. Rudi (2019) aimed to understand to which extent ditch management regimes influences ecohydraulic services provided by vegetation. An explicit representation of the hydraulic network provided by ditches in a Mediterranean watershed was proposed, with a focussed on the interactions between vegetation and water, sediments and plant propagules transport through hydrochory. Following continuum observation-experimentation-modelling, a spatially explicit model was developed at the grain of a ditch section and the extent of a small watershed, then applied to simulate indicators of service linked to water, weeds and soil regulation. The model, built on concepts from two contrasting disciplines, ecology and hydraulics, is expected to help design nature-based solutions on the basis of plant biodiversity for the regulation of water and soil resources.

whose comprehension relies on the multidisciplinary science of ecohydrology (Porporato and Rodriguez-Iturbe, 2002). In terms of model design, the simulation of the abiotic, water component, which drives the functioning of the hydrographical network, is carried out by assuming an Eulerian representation of the flows. In the Eulerian representation, water is modelled as a continuous quantity following mass conservation laws. In the case of vegetated ditches, the biotic components in direct interaction with the water flow, i.e., the plants and their propagules, are generally modelled as discrete elements by adopting an object-oriented Lagrangian representation. Integrating the biotic component (vegetation) in hydrological infrastructures used a trait-based approach (Merritt et al., 2010) that considers the whole plant community response to the flows as an aggregated property of the system, instead of considering the aggregation of individual plant-flow interactions. However, such trait-based approaches, although widely adopted in plant community ecology (Violle et al., 2007), has rarely been considered in terms of the specific traits of interacting with water flows and this will require a large sampling effort to establish the appropriate traits and their value for the wild plant species found in landscapes.

For the space–time challenge, the complex dynamics of biotic and abiotic components acting at different time scales require a coupled modelling of short, intense events (e.g. rainfall events and runoff) and more continuous processes (e.g. plant community selection and growth). In ecology and hydrology, there are a wide range of models for simulating rainfall and runoff events (see Moradkhani and Sorooshian (2008) for a review), and a diversity of models simulating weed community dynamics in agricultural landscapes (see, for example, Duru et al. (2009); Gardarin et al. (2012)) and riparian communities (García-Arias and Francés, 2016). These two types of models are not readily coupled because the response of vegetation to a series of disturbances is poorly understood, due to the lack of long-term monitoring (Blomqvist et al., 2009), a paucity of vegetation community response parameters and the difficulty of disentangling the underlying effects of hydrology and agricultural practices. This limited capacity to model vegetation response to disturbance impairs the inclusion of the effect of vegetation on pulsed fluxes of water due to uncertainties in our understanding of vegetation succession and development. Fine-scale ecohydraulic models simulating the interaction between a plant and a Eulerian flow do exist (Nepf, 2012), but their complexity entails high computational costs that hinder their use at the landscape scale.

The computational challenge would suggest that it is infeasible to model individual plant-flow interactions at the landscape level. We might,

however, use upscaling methods to scale-up from local observations/modelling/simulations to landscape simulations. High-frequency monitoring procedures could be used to define a phenomenological model of the structure–function relationship of the biotic system and its effect on abiotic processes at a local scale. To this end, several landscape elements (plots, hedgerows, ponds, etc.) were recently equipped with different sensors to measure all parameters characterizing the system. In vegetated ditches, biotic parameters have been monitored using drones to measure the spatial variability and evolution of plant cover porosity (Rudi et al., 2018; Vinatier et al., 2018). Abiotic parameters might also be assessed in controlled conditions in hydraulic flumes with different organizations of vegetation patches to measure the friction exerted by vegetation as a function of flow rates and water height (Vinatier et al., 2017). These parameters and metrics observed at a local scale could then be scaled-up for exploitation at the landscape scale (Box 3). Another way to meet the computational challenge would be to run several simulations of a fine-scale ecohydraulic model to produce a set of relations between biotic/abiotic parameters. The use of machine learning/artificial intelligence to detect, model and predict the structure–function response of the vegetation to flows opens promising perspectives to face the current numerical issues that slow and limit the exploration of these relationships.

3.3 Simulation of multitrophic interactions in complex landscapes

The simulation of interaction/trophic networks among living communities at the landscape scale remains a hard task (Tixier et al., 2013). Most recent advances were made using Bayesian network approaches (Häussler et al., 2020) or path analysis (Beduschi et al., 2015; Jacquot et al., 2019). It is particularly difficult because it encompasses both the interactions between species (or trophic groups) and their dispersal at multiple scales (from within the plot to the landscape scale or even the region). Unravelling these interactions is crucial because identifying the processes that lead to the natural regulation of pests and diseases are sorely needed in low-input agriculture (Macfadyen et al., 2009). In the diversified landscapes of the future, richer plant diversity will be deployed, from basic intercropping that mixes two cultivated species, via highly biodiversified patches inside or near the cultivated fields to large patches of natural or seminatural areas maintained in the landscapes (e.g. forest patches). We hypothesise that in areas with higher plant richness, trophic networks will become more complex. To date there are no multiscale and

multitrophic model able to address comprehensively the issue of optimizing the integration of plant biodiversity at all these scales in order to maximize the services supported by associated communities, and primarily the natural control of pests and diseases or the conservation of biodiversity.

Simulating trophic interactions across heterogeneous landscapes can be done with models based on the metacommunity concept (Leibold et al., 2004; Massol and Petit, 2013) that simulates interactions within and between the communities in distinct patches, e.g., cultivated fields or seminatural areas. If flows of individuals (e.g. beneficial predators spreading from diversified patches to cultivated fields) are well described, the metacommunity framework (Fig. 3A) is powerful to simulate the overall dynamic in patches and within the landscape. To date, metacommunity models have not yet been implemented on concrete cases to answer applied issues. The challenge for simulating innovative landscapes which include new patterns of plant

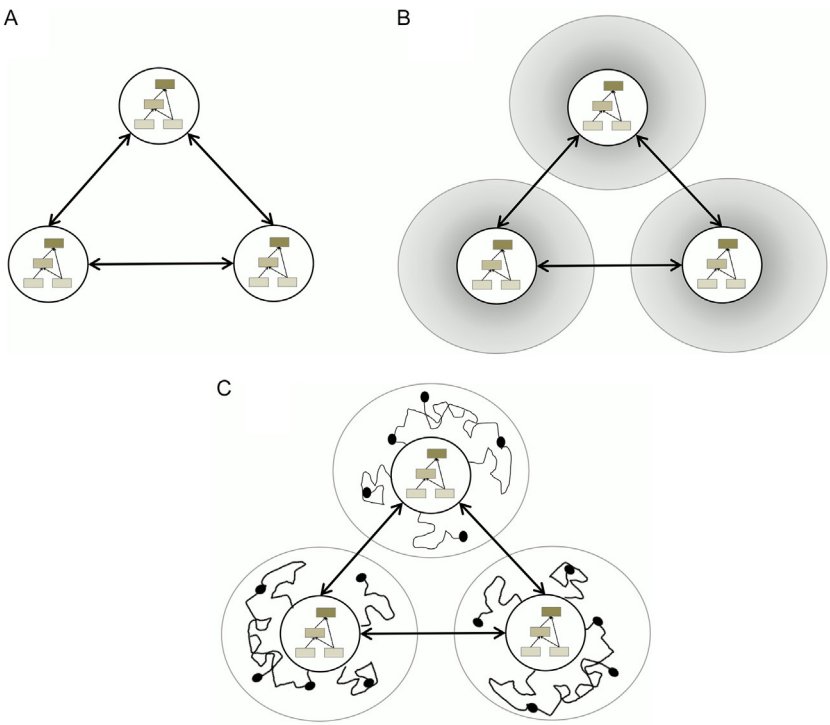


Fig. 3 (A) Classical metacommunity model (meta-food web: each community includes a food web model) as emphasized by Massol et al. (2011); (B) metacommunity model with foraging zones; and (C) metacommunity model with Individual Based Model in the foraging zone.

diversification around and inside cultivated fields is to tackle the issue of the zone of influence of these habitats and their potential as a sink for beneficial organisms. This could be achieved using spatially explicit models where each plant diversified patch has a surrounding "foraging zone" (Fig. 3B). The concept of foraging zone has more often been used in marine or mammal ecology to represent the area where animals can forage (Bailleul et al., 2007; Weimerskirch et al., 2009). In the case of natural enemies, this concept might be helpful for the prediction of the effect of each plant diversified patch on the regulation of pests in the surrounding cultivated fields. Foraging zones may be described using differential equation models or, alternatively, simulated using individual based models (Fig. 3C) which are particularly suitable to simulate species dispersal in heterogeneous environments (Collard et al., 2018). Another concept that could be used to rethink interactions between communities at the landscape scale are "island ecology" theories. This framework is particularly useful for considering the effect of the size of patches and their distance on immigration and extinction rates and finally on species composition of patches (Warren et al., 2015). Macarthur and Wilson (1967) stated that the diversity of islands could be formalized by a diversity-dependent dynamic balance between immigration and extinction. They assumed that the immigration rate for an island falls as the number of species on the island increases and that the rate of extinction of species increases as the number of species increases. Such island ecological concepts may prove useful for the study of plant-diversified patch-islands in a sea of homogeneous cropped land (landscape or field).

Whatever the approach, the parameterisation of metacommunity models is a crucial step towards designing of resilient agroecosystems. While metacommunity models have been extensively studied from the theoretical perspective, they have rarely been parameterized with real data. The difficulties of this are twofold. The first challenge consists in characterizing the dispersal of the most important species (pests, natural enemies, alternative preys), as data remain scarce. The knowledge of dispersal capacities as well as effect of landscape elements, especially barrier or corridors, are pivotal for optimizing the trade-off between the dispersal of beneficial communities and pests. The ongoing developments of monitoring tools, such as video tracking systems, and increases in the performance of signal or image processing using artificial intelligence, our knowledge regarding the dispersal of pests and other trophic groups will undoubtedly improve.

The parameterization of the interaction between trophic groups is the other challenge to take up in order to get realistic and useful food web

models. Recent technological advances of DNA metabarcoding approaches make possible unravelling trophic links between preys and predators (Mollot et al., 2014). These approaches are powerful as they uncover predator-prey consumption links that may be difficult to observe in the field, especially in arthropod communities. However, such methods are difficult to apply in a dynamic way. Another promising approach that could be particularly valuable for understanding community dynamics and identifying interactions is the combination of automated imagery in-field and artificial intelligence detection algorithms. The CORIGAN pipeline (Tresson et al., 2019) provides hierarchical classification of the detected species on pictures taken in the field, for example. Such approaches have the advantage of: (i) making in-field identifications of taxa at play in communities with a minimal disturbance; and, (ii) observing the dynamics of interactions between taxa. They may also enable the measurement of nontrophic interactions (avoidance, cooperation) that are believed to be important but are often not considered in the interpretation of food webs (Loreau and de Mazancourt, 2013; Ohgushi, 2008). Such nontrophic interactions could be particularly important at the edges between cultivated habitats and noncultivated habitats.

Although models will be key tools for designing the landscapes of the future, their relevance will depend on the quality of their parametrization. New methodological approaches for characterizing communities and their interactions represent a real opportunity to parameterize multiscale multitrophic models.

3.4 Measuring and calibrating spatial processes from large spatiotemporal datasets

Investing greater confidence in the spatiotemporal models discussed so far in this paper, will require that we collect data at multiple spatial and temporal scales, test the model simulations against this data and validate the model behaviours regarding variations in their inputs. In this subsection, we focus on the dispersal of organisms as an illustration of the variety of datasets that might be analysed.

Estimation of the dispersal capabilities of organisms is crucial for a consistent model of spatiotemporal dynamics. For organisms that disperse passively, an observed colonization event results from both a dispersal process and the subsequent survival, and it is often difficult to disentangle these processes. For organisms that disperse actively, the behaviour of individuals has to be considered in addition to dispersal and survival. In heterogeneous environments and in complex community structures, heterogeneity in survival

and modification of behavioural strategies can blur the estimation of actual dispersal. To cope with these difficulties, collecting high-resolution spatio-temporal data are essential, either by sampling populations at given locations or by tracking individuals. Citizen scientists have contributed millions of observations of species to databases over the past decade (e.g. Ries and Oberhauser (2015) or Tulloch et al. (2013)) and these provide invaluable sources of information for studies on genetics, trophic ecology, etc. These databases suffer, however, from a number of shortcomings and biases, as they often result from heterogeneous sampling protocols with unknown sampling efforts. Data from digital sensors are also now being collected at wide spatial scales, and these might in the future provide estimates of species dispersal as part of the era of Big Data. These digital data offer the advantage that they are documented, and they can be preserved for later species identity verification (Kays et al., 2020). Recent imagery and tracking systems (Dell et al., 2014; Hodgson et al., 2018; Kays et al., 2015; Steenweg et al., 2017), combined with new developments in machine learning (LeCun et al., 2015; Olsen et al., 2019; Wäldchen and Mäder, 2018), could provide data in real-time and at unprecedented resolution, that will prove invaluable for the study of habitat suitability, ecological interactions, impact of climate change, response to anthropogenic disturbance, effect of conservation policies, etc.

Inference of dispersal parameters from landscape models has to accommodate a diversity of data types (pest occurrence or abundance, crop phenology, agricultural practices, etc.), potentially collected at multiple temporal and spatial scales, some of them massive (Big Data from remote imagery or next-generation sequencing in the case of genetic studies), others possibly sporadic (e.g. field measurements, survey on technical operations), and generally giving access to a partial and indirect observation of the mechanisms under study. In this context, hierarchical modelling approaches offer a framework for parameter inference as it decomposes the model into multiple layers encompassing the set of parameters, the process at stake and the observation process (Cressie et al., 2009). It can cope with multiple, simultaneous observation processes, operating at different scales, and their related uncertainties and errors. The complexity of hierarchical models, however, can lead to models whose likelihood functions are analytically intractable and cannot be solved without the use of simulation or numerical approximation techniques. Hierarchical Bayesian frameworks are particularly convenient when dealing with heterogeneous data (Clark, 2004). These rely on specific estimation algorithms to infer parameters using Monte Carlo methods. We would note, however, that Monte Carlo methods generally require a large number of

iterations, making them difficult to use when the process model takes time to simulate. In that case, classical optimization tools could be more appropriate to find the parameters maximizing the likelihood function even if they render the computation of uncertainty around the estimated values difficult. In the particular case of Gaussian latent variables, the integrated nested Laplace approximation (INLA) approach is recommended (Illian et al., 2013). When compared with mathematical models, simulation models (e.g. individual-based models) offer the possibility of incorporating fine-scale and complex processes but can lead to intractable likelihood functions. Where this is the case, approximate Bayesian computation (ABC; Beaumont (2010)) and pattern-oriented modelling (POM; Grimm et al. (2005)) may be used to infer parameter values. These methods are based on intensive simulations of the model and the comparison of model outputs to data through summary statistics and a measure of quality of fit. Although these different methodologies provide interesting and powerful tools that help us to move from pure correlative data analysis to an integrative analysis explicitly introducing the underlying processes of interest, model complexity and parameter identifiability remain key issues.

Model exploration is classically performed through global sensitivity analysis. In the case of spatial models, however, this is challenging because of the complexity of integrating the landscape as an input factor and the consideration of spatial outputs. Spatial sensitivity analysis evaluates how models respond to landscape descriptors. These descriptors do not define a unique landscape but rather decompose landscape variability into a measurable and controllable component through quantitative variables and a residual variability. It is important therefore to build landscape replicates for each set of descriptors to perform a robust sensitivity analysis (Papaïx et al., 2014). In the literature, three strategies are described to deal with spatial outputs: mapping local sensitivity indices to study correlations with landscape characteristics (Saint-Geours et al., 2014); performing the sensitivity analysis on the components of a multivariate analysis (Lamboni et al., 2011); and, summarizing the spatial output as nonspatial output to use classical sensitivity analysis methods. Other methods to explore model outcomes use scenarios, i.e. a set of contrasting initial conditions and parameters. Landscape scenarios can encompass alternative landscape structures and land-use organizations to explore ways to increase sustainability. They can also help assess the effects of various political decisions, social or environmental contexts, and evolutions of landscape systems. Simulating scenarios provides a viable approach to anticipate the impact of changes on agricultural landscapes and to pinpoint potential pathways to be explored (Tieskens et al., 2017; Verburg et al., 2016).

A major challenge lies in the adoption of such results for policy applications, which essentially demands the correspondence of model output to real world data (Topping et al., 2013).

4. Learnings from social sciences on how landscape models can "transform" reality

"This is just a model!" is sometimes heard when landscape modelling is discussed with practitioners or policymakers. This sentence expresses a scepticism towards the social utility of modelling and a perception of models as rather hypothetical than proper knowledge. But is modelling really a vain thing for action and decision? Can we foster the capacity of models to generate usable and transformative knowledge for future agricultural landscapes? These questions can be addressed via a focus on social sciences insights. We first examine how landscape modelling is used in social sciences to generate knowledge and/or action (Section 4.1). We then use the performativity concept (a concept from social sciences that aims to understand how theory and knowledge can create or shape a new reality in the field) to analyse how modelling in general can foster the capacity to change the reality of landscapes (Section 4.2).

4.1 Landscape modelling in social sciences

Much research has been done in the social sciences and in interdisciplinary science incorporating the social sciences on the subject of landscape modelling. This research is often used by policymakers, practitioners and academics to identify and shape strategies and objectives for public action or to evaluate the state of progress and the incomes of measure implemented. While not claiming to be exhaustive, we identify three main types of landscape modelling involving social sciences according to their approaches and the ultimate aim of the model.

4.1.1 Comprehensive ex-post research on in situ drivers of landscape changes

A great deal of landscape modelling studies focuses on deciphering the trajectory of real landscapes (Benoît et al., 2012; Bieling et al., 2013; Hersperger and Bürgi, 2009; Mignolet et al., 2004; Mottet et al., 2006; Serra et al., 2008; Xiao et al., 2014). The approach is generally based on an analysis of the real landscape historical evolution in terms of land cover (Fuchs et al., 2015) and/or farming practices (Medley et al., 1995) with the aim of understanding

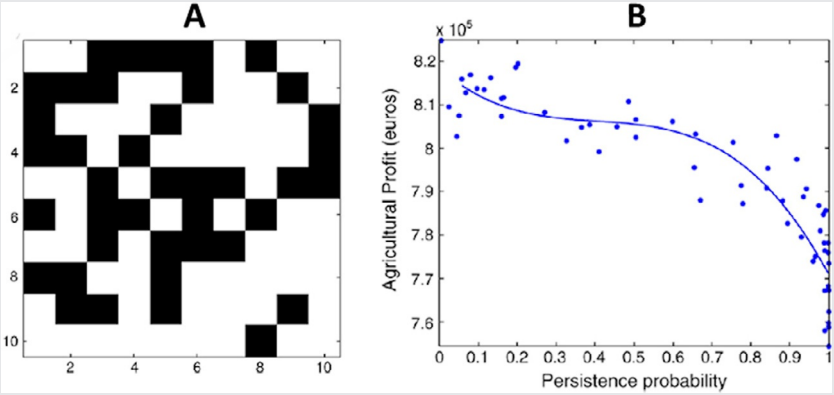
the socioecological drivers of landscape change. The drivers are commonly political (e.g. agricultural policy, subsides or regulations), economic (e.g. markets and commercialization opportunities), cultural (e.g. public attitudes, values and beliefs), technological (appearance and spread of new technologies for the use of natural resources or for cropping), and natural/spatial factors (e.g. soil characteristics, climate change, the spatial configuration of landscape patches).

The main added value of this type of landscape research is that it enables an improved understanding of the human and social mechanisms behind landscape change. It also enlightens us about the barriers to landscape change. These types of landscape research have shown that, except in the case of non-anthropogenic (i.e. wild ecosystems) and abandoned landscapes, there is never a single driver that operates alone to determine landscape change, but rather a combination of many different drivers that come into play (Bürgi et al., 2005; Plieninger et al., 2016). This characterizes the inevitable complexity of the landscape as an object of socioeconomic research and action.

4.1.2 Ex-ante research for in silico evaluation of scenarios or policy measures

Computational, in silico, research has been used to evaluate and simulate public policies or behavioural strategies in spatially explicit or simplified landscapes (Overmars et al., 2007). The approach is based on simulation models (Box 4) and typically evaluates the design of new instruments and strategies of landscape change (Martinet, 2013). It is important to note that increasingly research focusses on the combination of multiple and interconnected functions, measures and human practices within the landscapes (Groot et al., 2009). Such multifunctional landscape modelling research enables the visualization and comprehension of trade-offs between services (Box 4; see also for example co-viability theory (Béné and Doyen, 2008; Doyen and Martinet, 2012)), or ecosystem services (Rossing et al., 2007; Zander et al., 2008). These model-based policy evaluations also reveal possible barriers and impact inequalities of policies. For instance, Bareille et al. (2020) examined farmers' benefits from the coordinated landscape-scale management of biological control in a realistic, heterogeneous farmland landscape. Using an agronomic-ecologic-economic model, Bareille et al. (2020) simulated various strategies from no management to collective landscape-scale management, including situations of individual management. Their results show that if the coordinated management of biological

BOX 4



Effectiveness of public policies for biological conservation in dynamic agricultural landscapes. National or supranational entities (e.g. the European Union with the Common Agricultural Policy) invest significant funding to mitigate the environmental effects of intensive agriculture, calling in turn for an economic evaluation of such expenditure. In their theoretical study, Barraquand and Martinet (2011) developed a framework to examine the effect of monetary incentives on the probability of persistence of a metapopulation used as a proxy for biological conservation. They considered a dynamic mosaic landscape (A) composed of two land uses: grassland (white cells), assumed to favour the local population dynamics, and cropland (black cells), which has a negative effect on population growth. Their ecological-economic model links simulated farmers' behaviour (private land-use decisions in a context of agricultural output price volatility) to the biological population through the resulting dynamic landscape. A set of policy instruments were explored: incentives for implementing habitat favourable to biological conservation, in the form of subsidies to grassland, tax for practices unfavourable to biodiversity such as agricultural input, and their joint effect. Beyond cost-benefit analyses, the authors determined the production possibility frontier of the dynamic landscape in terms of agricultural profit and biological conservation (B), thus the expected trade-off between agricultural and ecological outcomes.

Figures from Barraquand, F., Martinet, V., 2011. Biological conservation in dynamic agricultural landscapes: effectiveness of public policies and trade-offs with agricultural production. Ecol. Econ. 70, 910–920. https://doi.org/10.1016/j.ecolecon.2010.12.019.

control at the landscape scale improves collective benefits, the heterogeneity of farms entails strong inequalities in terms of farmers benefit from the coordination process. In turn, farmers may reject the coordination policy unless specific measures support vulnerable farms.

The main added value of *ex ante* research is that it highlights conflicts, choices and trade-offs, thereby fosters a public decision for targetable strategies for the future. They are often used as an applied modelling exercise to help form decision-making and action. The limit of these modelling approaches, however, is that they generally focus on the state regulator as a key actor and on the subsidies or taxes as the levers for landscape change (Pascual and Perrings, 2007); they are top-down. Excluding many stakeholders in this way may limit the full understanding the drivers of landscape change. Indeed, studies have shown that local cooperatives and agri-production buyers, local agricultural input suppliers (Hannachi and Coléno, 2015), local extension services (Labarthe, 2009), and nonagricultural actors (Cardona, 2012) all have some power to change landscapes. Moreover, this diversity of stakeholders operates at different scales (Poggi et al., 2018). Thus, there is a need to consider, integrate and connect decisions and drivers from multiple stakeholders to make landscapes more "manageable", i.e., to enable the emergence of a multistakeholder's action that allows to collectively plan and control landscapes.

4.1.3 Collective transdisciplinary learning as a tool for the evaluation of future landscapes

Since the impact of the landscape socioecological phenomenon in question is in the hands of many independent land-holders, considering actions and management strategies under direct centralized control (top-down process) will be tricky without parallel changes in political systems. In such context, the focus should be on communication and education to increase the awareness of stakeholders' to their interdependence and their vision of the social costs and benefits of their actions. In this perspective, approaches for decision-making using multiagent systems, like Agent-Based Models (ABM), have flourished (Huber et al., 2018), as they offer an appropriate tool to study the interactions among agents and/or their environment. Agent-based models simulate the actions and interactions of acting agents (be they individuals or collective entities such as organizations or firms) with a view to assessing their effects on the system as a whole. They combine elements of game theory, complex systems, computational sociology and evolutionary programming. ABM can cope with numerous agents, each with an individual behaviour

or personality, that may interact via cooperation, coordination, competition and negotiation mechanisms. Such models enable the exploration of the effects of individual and collective actions on the environment, and can be seen as "bottom-up" models since they simulate emergent phenomena without any a priori assumptions regarding the local agents' cooperation and the aggregate system properties (Brown et al., 2016; Magliocca et al., 2015). The impact on the agents and the environment of management strategies can then be simulated and evaluated. This type of modelling is recognized as a methodology that facilitates collective learning. Therefore, many scientists call for a strong integration of stakeholders in the simulation process, e.g., via role-playing games (e.g. Becu et al. (2017)), and even in model conception through participative modelling (Farias et al., 2019; Le Page and Perrotton, 2017). This last option of incorporating various stakeholders at the conception and simulation steps, appears one of the better options for inducing socially optimal behaviour in the landscape, as it relies on a common understanding of the environmental issue between stakeholders, and not only on the responsiveness of farmers, consumers or any other stakeholder to the policy measures and actions.

It is generally accepted that the best decisions are made by those who will bear the consequences. It is axiomatic, therefore, that the more the agent-based modelling is participative, the more it may formalize and improve the knowledge of a system. Participatory models are particularly recognized for the production of shared and innovative solutions for a problem solving (Voinov and Bousquet, 2010), and thus they have a strong transformative potential for landscape change. Among the different participatory modelling approaches, companion modelling appears particularly suited to engender landscape reality changes (Etienne, 2014). Companion modelling is an approach combining ABM and role-playing games, advocating three major principles: construction of the model with stakeholders, transparency of the process and adaptiveness, with the model evolving as the problems change during the research. Companion modelling aims to support collective decision-making process in terms of sustainable landscape management (Box 5). It has been implemented in a diversity of landscape issues over the world, including management of the erosive runoff in Seine Maritime in France (Souchère et al., 2010), adaptation of extensive grazing strategies to climate change in Uruguay (Dieguez Cameroni et al., 2014), water resource management in Burkina Faso (Daré and Venot, 2018), forest and livestock management in the Larzac in France (Simon and Etienne, 2010). This approach relies on the formalization of a conceptual model based on iterative interactions between landscape stakeholders' representatives,

BOX 5

Application of companion modelling to conflict resolution and organizational innovations. Renewable natural resources at the landscape scale are often the subject of conflicts due to the lack of coordination between stakeholders and insufficient awareness of collective interdependency. It was the case in Lingmuteychu (Bhutan) where conflicts among villages and among farmers had arisen because of the stress for use of water in a rice terraces landscape, particularly during the highland rice transplanting period. The traditional way of working was upset by the adoption of new commercial crops that improved farmer income, but gave rise locally to disputes on the use of water as well as farmers food security issues. The Lingmuteychu watershed was chosen as an experimental site by the local Ministry of Agriculture to explore solutions to the conflict over water management (Gurung et al., 2006). The local deciders chose to use the companion modelling approach as a mediation tool between the nine villages involved. The initiative comprised two rounds. The first round (2003–2004) consisted of the design of a preliminary role-playing game on water sharing between two villages. To this end, surveys, focus groups and literature reviews were done to shape the social, hydrogeological and agricultural outline. This first game was used in many sessions to collectively understand and validate the way of decision making of various types of farmers and the collective consequences in each village and at the whole landscape level. The second round (2005–2006) consisted of the design of a new role-playing game that was more abstract and concerned seven stepped villages sharing water. This second role-playing game was used for many sessions involving differing village representatives according to various play modes in terms of communication (with and

BOX 5—CONT'D

without inter-village communication). This approach raised awareness of the importance of coordination among stakeholders. Along the game session collective debriefs, the players identified the information to share, and when and how to do it. Beyond the conflict resolution locally in Lingmuteychu, the companion modelling method induced the creation of an organizational innovation: a sub-catchment resource management committee where common action plan among villages are set and carried out. Moreover, this case study was used to draw up by-laws of the watershed committee and inspired other regions in Bhutan.

Photographs: ©Guy Trébuil (CIRAD).

scientific experts (notably on the natural or biophysical process) and modellers. This conceptual model combines shared representations among practitioners and researchers. Then, it is used to produce a serious game that is subsequently played with local stakeholders in game sessions. Here the model serves as an intermediary object, in the sense that it helps clarify and formalize the points of view and provide a discussion space. The collective discussion of the simulation that results enables support for a positive confrontation of the different points of view and the reality of the situations. As Skrimizea et al. (2020) argue, such collective learnings are key for the transformative changes required to ensure sustainability in agriculture.

4.2 How to foster the capacity of models to perform reality and change landscapes

But, how can these landscape modelling research impact the reality and drive future landscape change?

One response is that more the modelling research is participative and include stakeholders, the more it has the potential to change stakeholder behaviour, and thus to shape a change within the landscape (Voinov and Bousquet, 2010). Interactions between modellers and stakeholders and practitioners enable a better mutual understanding that can foster the interest of practitioners in the model outcomes. Moreover, a modelling design that includes stakeholders' perceptions, room for manoeuvre and information needs, is a design that is more likely to produce usable knowledge for practitioners and decision-makers.

But is nonparticipatory research and modelling able to change landscapes? The concept of performativity provides a potential response to this question. The concept of performativity stems from the works of Austin on language (Austin, 1962). Austin identified two kinds of utterances: the "constative" utterances, which can be predictive or descriptive and which can be true or false, and "performative" utterances, which have the intrinsic power to change social reality under certain circumstances, as for example, when a judge or a clergyman officiates at a marriage (Austin, 1962). Many researchers in social sciences extended the Austin conception to scientific theories to explore and understand how researchers can change the world via their utterances. According to this perspective, a theory is said to be performative when it contributes to a change in the reality it describes (Callon, 1998; Latour, 2005). Such thoughts and analyses have been applied to economic and financial markets theories (Callon, 1998; MacKenzie et al., 2007) and management theories (Cabantous and Gond, 2011; Muniesa, 2014). These researches have shown that social science theories have the potential to be performative, in that they can create the social reality they are supposed to describe and analyse. This concept of performativity offers a novel and interesting perspective to understand interactions between science and practice development. If we extend the concept of performativity to landscape modelling (which involves social sciences), the question is whether and how it can be performative even if it has been developed in academic contexts (i.e. without being a participative research).

According to Austin (1962), an utterance performs if some conditions, called "felicity conditions", are reached. Felicity conditions refer to the conditions that must be in place and the criteria that must be satisfied to induce and achieve the change in social reality. Many of these felicity conditions strongly relate to the speakers of the utterance and their status, and this makes it difficult to transpose all of them to theories or models. Some can be applied to theories and models, however, and here we attempt to extend them to landscape modelling researches. If we extend the concept of performativity and its felicity conditions to landscape modelling, a first felicity condition, inspired by Latour (1987), can be named as a tripod "generic-explicit-combinable". This condition means that, to perform, landscape modelling should be generic-enough so that it can be applied to management practices and fit in different landscape management or social contexts. In other words, if the model is too specific or linked to a very explicit landscape, this will limit the capacity of the model to influence or drive the reality.

But, the modelling needs also to be sufficiently explicit, otherwise it becomes too intangible and uninspiring for practitioners. Finally, the landscape modelling needs to be combinable so that its statements can be cumulated, aggregated or shuffled with other models and insights, and this can let the practitioners and/or policymakers to adapt and to test it in their contexts, even as it becomes complex.

The second felicity condition relates to theories' performativity. These researches show that a necessary condition of the performativity of a given theory is the existence of sociomaterial devices that embody the theory's assumptions (Callon, 1998; MacKenzie et al., 2007). Sociomaterial devices stands for dashboards, control panels or indicators, etc., i.e., operational devices that can be used in everyday life by practitioners and decision-makers and which may thus shape their routines. This means that to become performative, it is pivotal for landscape modelling research to be incorporated into devices used by landscapes' stakeholders. For example, to cope with the issue of controlling cross pollination between GMO and non-GMO corn crops, French farmers' cooperatives used GMO pollen dispersion models to create geographic information systems and decision systems allowing the management of farmers' production plans at the landscape scale (Hannachi and Coléno, 2015). These systems shaped the cooperatives marketing supply for farmers and allowed cooperatives to play a strategic role, ensuring a relevant spatial distribution of crops and appropriate harvest dates. This step of connecting researchers' models into practitioners' devices is a transdisciplinary issue that builds on the knowledge of multiple scientific disciplines (such as computer sciences, ergonomics, etc.) as well as practitioners' knowledge. This will be crucial for the performativity of landscape modelling. The third felicity condition for the performativity of landscapes modelling research is that the practitioners' devices that incorporate the landscape modelling research must be efficient (Muniesa, 2014). It means that they must provide relevant information on the relevant timeline to generate pertinent and efficient decisions enabling the practitioners to reach their objectives.

The extension of the performativity concept to landscape modelling provides some interesting insights. It leads to the identification of three felicity conditions under which we can increase the capacity of the landscape models to change the reality of landscapes. All these insights are hypotheses that need to be explored and tested but it addresses where landscape modelling research can be performative and drive landscape effective changes even where it has not produced intentional actionable knowledge.

5. Avenues for future research

In previous sections we have outlined the wide range of models available to represent and simulate the complex structure of landscapes (Section 2), to model the interacting biotic and abiotic flows within landscapes (Section 3), and to encompass social sciences to foster the use of models to generate knowledge and transformative actions (Section 4). In this section we suggest some avenues for future research.

5.1 Agricultural landscape representation and simulation

5.1.1 Enhancing a multilevel and integrated approach of landscape functioning

The understanding and management of landscapes should rely on a more systemic approach by considering multiscale biotic and abiotic processes and their interactions, multilevel stakeholder's decision-making and actions, feedbacks between processes and actions. Interestingly, the systemic approach considers explicitly properties that emerge from the interactions (competition, cooperation) between the system's components, which would not normally occur under the assumption that these components evolve independently.

At the same time, promoting a systemic approach should not distract us from the importance of the individual level since individual independence also provides key information regarding the functioning of agricultural landscapes. Dedeurwaerdere and Hannachi (2019), as an example, demonstrated that in a social organization characterized by an anarchy and nondialogue among farmers about rice seed choices in the Yuanyuang region of China. The independence of farmers fostered a strong autonomy of decision-making and nonconformism to pressure on the choice of rice seed. As a consequence, the local cultivated rice diversity was sufficiently large to achieve a sustainable control of rice diseases at the landscape level. Bareille et al. (2020) examined individual farmer and collective benefits from a landscape-scale management of biological control. Using an agronomic-ecologic-economic model of farm system constraints (e.g. allocation of land uses), the authors demonstrated that a landscape-scale management of biological control generates strong inequalities in terms of farmer benefits. These inequalities between individuals are a major cause of concern and conflict in landscape collective management that calls for a redistribution of subsidies or specific payment for the vulnerable farmers.

Thus, future research should enhance multilevel and integrated approaches of landscape functioning. The consideration of all possible processes and their interactions is not possible, however, because the complexity of the resulting model impedes a rigorous analysis of the outcomes. Therefore, despite previous research efforts, these approaches remain a challenge that will require a concerted research effort.

5.1.2 Refining the representation of the agricultural landscape structure

The representation of agricultural landscapes remains challenging, and deserves attention as there is plethora of evidence arguing for the effect of the landscape structure on key processes or phenomena at the core of agriculture sustainability. Among many examples, increasing the heterogeneity of the crop mosaic (crop diversity and mean field size) enhances multitrophic diversity (Sirami et al., 2019), landscape structure impacts agricultural pest suppression (Haan et al., 2020) and biological control in agroecosystems (Thies and Tscharntke, 1999). If large-scale patterns are now commonly integrated in landscape metrics and in models simulating virtual landscapes, fine-scale elements are generally not considered as they require a higher spatial resolution. However, such elements are important as they directly influence the local heterogeneity of the landscape.

The classic but still commonly used patch mosaic paradigm (Forman, 1995; Forman and Godron, 1986; Wiens et al., 1993) essentially adopts a human-centric view of landscapes, which are depicted as a mosaic of discrete, homogeneous cover types characterized by their composition and configuration. Such categorical conceptualisation fails to represent the continuous spatial heterogeneity and may result in the loss of information as most ecological attributes are inherently continuous in their spatial variation (e.g. soil properties, climate, and vegetation index). The gradient concept of landscape structure, as proposed by McGarigal and Cushman (2005), offers a more realistic representation of landscape heterogeneity where landscape structure is described by continuous surface characteristics without arbitrary land-use classification thus avoiding delineation of discrete areas with sharp boundaries (Lausch et al., 2015). Increasingly aerial and satellite data provide raw optical and radar multimodal time series of landscape images that can efficiently feed such continuous representations. A challenge consists in interpreting these images to quantify the properties of landscape elements. For instance, Betbeder et al. (2017) showed that synthetic aperture radar images enabled to estimate the resistance values associated with hedgerows

according to their suitability in terms of canopy cover and landscape grain for forest carabid beetles. Future research should produce metrics that characterize continuous surfaces, which could characterize interesting linkages between landscape representation (i.e. composition, configuration, connectivity) and ecological processes.

Landscapes may also be conceptualized using a graph-theoretical approach where habitat patches are represented by nodes and their functional connections are represented by edges (Urban and Keitt, 2001). Some developments in progress (Box 2) open promising avenues to generate virtual but realistic agricultural landscapes featuring different spatial patterns (geometry, connectivity) and temporal patterns (e.g. crop rotation), thus providing a useful tool to explore the relationships between landscape structure and processes at stake within it.

It is particularly complicated to access to the diversity, sequence and location of crop practices of agricultural landscapes (Leenhardt et al., 2010). Most studies aim at classifying subregions as homogeneous clusters based on datasets of crop practice sequences considering cropping systems as static (Dury et al., 2012). For example, Xiao et al. (2014) described the spatial distribution of crop sequences at a large regional scale mining crop sequences in land survey dataset with hidden Markov models and clustering based on the similarity of occurrence of crop sequences. Such approaches can help identify homogeneous zones in agricultural landscapes and study their characteristics. Conversely, Murgue et al. (2016) proposed an approach that consists in progressively hybridizing databases and local actors' and experts' knowledge to finely model the spatiotemporal distribution of cropping systems. All this, when combined, highlights the importance of defining a typology of crop practices and the need for databases describing fine scale crop practices.

Future research could consider a combination of the patch mosaic, gradient concept, and graph-theoretical paradigms to describe landscapes, as advocated by Frazier and Kedron (2017). Overall, the ultimate goal still consists of the development of an integrated representation of landscapes, accounting for the multiscale representation of system organization and control, and in which changes in the landscape pattern interrelate with the dynamics of the biophysical processes under study.

5.2 Landscape conception and manipulation

Across the different sections of this chapter, we have highlighted the wide range of landscape models that integrate biophysical processes and

stakeholders' views with different levels of complexity. In Fig. 4, we propose a classification of studies reported in the literature of landscape planning (*lato* sensu) according to two axes, without any claim for exhaustiveness but rather seeking to shed light on contrasted modelling approaches. The horizontal axis separates conceptual and theoretical studies from studies in which stakeholders are actively involved in the modelling process. The vertical axis separates studies oriented towards landscape conception (answering the question "which landscape is optimal or suboptimal with respect to given criteria?") from those focusing on landscape manipulation (answering the question "how to operate changes leading to a target landscape?"). From this simple typology we identify two main research perspectives that we present below: (i) moving towards a conceptualisation of landscape manipulation; and, (ii) reconciling theoretical approaches and stakeholders' involvement.

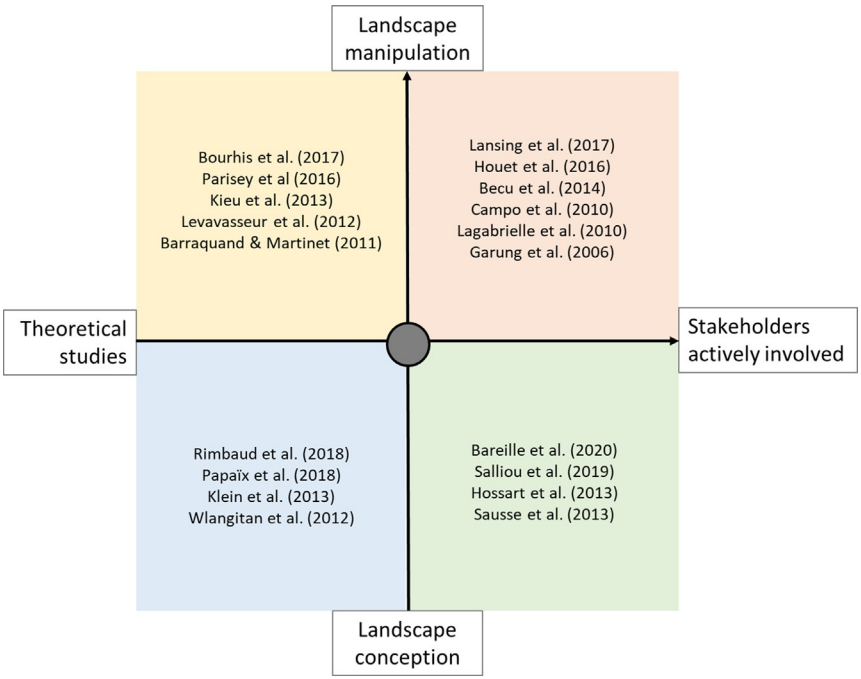


Fig. 4 Conceptual classification of landscape planning studies (*lato* sensu). Cited references provide examples of studies falling in different categories, without any claim for exhaustiveness.

5.2.1 Moving towards a conceptualisation of landscape manipulation

The conception of new landscape configurations relates to the definition of a spatial or spatiotemporal configuration of some landscape characteristics (e.g. crop diversity, structure of seminatural patches) that is considered as optimal or suboptimal with respect to a given, potentially multidimensional, criterion. The conception of new landscape configurations from theoretical approaches is generally based on two different approaches (landscape conception involving the participation of stakeholders is discussed later). The first approach consists in understanding how some landscape characteristics impact a given biophysical process. For example, Papaïx et al. (2018) and Rimbaud et al. (2018) developed a spatially explicit epidemiological model that described the demography and evolution of a pathogen population across a landscape composed of a mosaic of fields where different crop cultivars were grown. The goal of these studies was to understand how the spatiotemporal structure of cultivar deployment at the landscape scale modified the disease spread and the level of adaptation of the pathogen population on each crop cultivar, these measures having direct economic and ecological impacts through yield loss, resistance durability, and the use of pesticides. The key point here is that the analysis is performed globally over the parameter space leading to a general picture of how epidemics proceed in agricultural landscapes. The second approach relies on the optimisation of model outcomes over the landscape characteristics. Optimisation heuristics search for the best combinations of input landscape descriptors to meet multiple output criteria (Memmah et al., 2015). Klein et al. (2013) performed multiobjective regional optimisation for identifying optimum land management adaptations to climate change. Integrating a generic crop model and different climate scenarios they designed a multiobjective optimisation routine and identified conflicts between productivity and environmental goals. In a similar approach, Walangitan et al. (2012) analysed socioeconomic and ecological conflicts in the use of land resources of Lake Tondano (Indonesia).

Modelling approaches allowing the conception of new landscape configurations generally integrate complex outputs and detailed biophysical models. However, such approaches do not generate possible trajectories of a shift from a given landscape towards a more sustainable one. This dynamical aspect describing which trajectory could lead to the desired configuration is what we refer to as landscape manipulation (Fig. 4). Further theoretical and methodological developments are needed to better capture landscape dynamics (Houet et al., 2010) and identify relevant and feasible trajectories with their related costs. Some theoretical studies explicitly focus

on the dynamics describing which modifications have to be done to improve landscape performances regarding some specified outcome. Bourhis et al. (2017), see also Box 6, specifically addressed this issue based on a mechanistic model that fitted the traits of a theoretical flying insect pest. They investigated which modifications impacting the feeding and laying sites of the insect were relevant depending on the characteristics of the initial landscape. In the same way, Parisey et al. (2016) compared different landscape configurations built under agronomic constraints allowing them to propose rearrangements of landscapes that achieved a better biological regulation of weeds. Interestingly, in the specific context where landscapes are defined as a set of polygons forming a T-tessellation, Kiêu et al. (2013) demonstrated that it is theoretically possible to explore all landscape structures using only three geometrical operations modifying the shape of the fields. Another promising perspective to account for the landscape trajectory could be the use of models developed in evolutionary biology to describe the evolutionary trajectory of populations (e.g. Tenaillon (2014)). In these models, an individual is described by a set of phenotypic traits that determines its selective advantage (i.e. its fitness) in a given environment. Individuals can produce offspring that inherit their traits, but some modifications of these traits can occur through mutations. Thus, the population evolves through the mutation-selection balance. When applied to the context of landscape modification, different landscapes with different configurations represent individuals whose selective advantage can be evaluated through a set of criteria. The representation of the fitness landscape could help identify changes associated with elevated costs.

5.2.2 Reconciling theoretical approaches and stakeholders' implication

Fig. 4's horizontal axis shows that purely theoretical landscape studies, which might investigate the effects of spatiotemporal heterogeneities of landscape features on biophysical processes or socioeconomic outcomes, exist towards the extreme left of the abscissa. An example of this category is the work by Bourhis et al. (2017) who examined relevant landscape alterations in terms of minimizing the fitness of a crop pest. At the opposite end of the x-axis lie studies in which stakeholders play a central role in the landscape conception or transformation, including for example works from Hossard et al. (2013), Lagabrielle et al. (2010), Salliou et al. (2019) and Sausse et al. (2013). Lansing et al. (2017) provided a remarkable example showing that a self-organized cooperative management of rice terraces in Bali achieved a resilient system that both increased and equalized harvests. Naturally, there are studies along

BOX 6

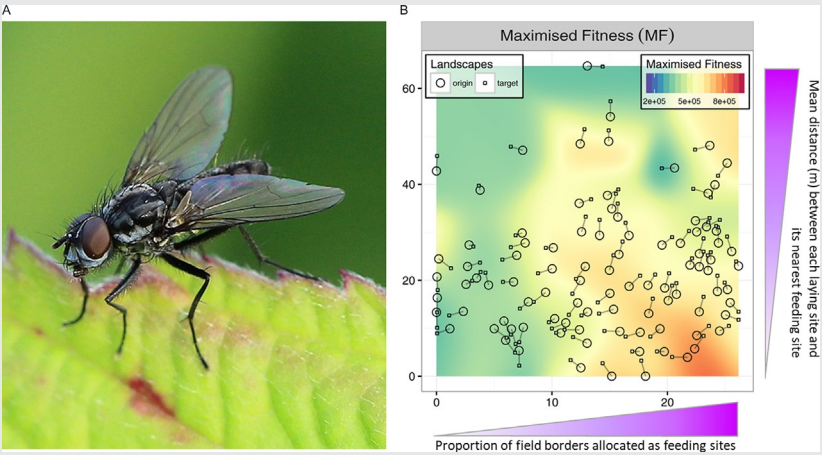


Illustration of a theoretical landscape planning problem. Bourhis et al. (2017) developed a model that made the strong and mechanistic link between the landscape structure and the population dynamics of flying insect pests (e.g. the cabbage root fly, Panel A) with an ability for high dispersal and directed flight. Foraging strategies hinged on the distribution of two competing resources (feeding and laying sites) affecting the pest's energy supply. Two landscape metrics described the competing resources spatial co-occurrence: the interface length (IL) which described the proportion of field borders allocated as feeding sites, and the Euclidean nearest neighbour (ENN) which measured the mean distance between each laying site and its nearest feeding site. A wide variety of landscapes was generated to explore the metric space (IL, ENN). The maximized fitness (MF) of the pest population measured the favourability of each landscape in terms of reproduction success. (Panel B) displays 94 original landscapes (circles) with the corresponding optimized values of fitness (MF) and their interpolated surface (background colormap). The interpolated surface allows an informed navigation in the metric space, in which the landscapes can be relocated to become more suppressive regarding pests. Assuming restrictive constraints, such as a constant landscape composition and using the field crop (laying sites) rotation as a single mechanism for change in the landscape, target selection for landscape modification are displayed (squares). This approach demonstrates the potential of landscape pest modelling for solving theoretical landscape planning problems.

Photo from https://commons.wikimedia.org/wiki/File:Delia_radicum_01.JPG (retrieved on 30-18-2020) licensed under the Creative Commons Attribution-Share Alike 4.0 International licence. *Panel B adapted from Bourhis, Y., Poggi, S., Mammeri, Y., Le Cointe, R., Cortesero, A.-M., Parisey, N., 2017. Foraging as the landscape grip for population dynamics—a mechanistic model applied to crop protection. Ecol. Model. 354, 26–36. https://doi.org/10.1016/j.ecolmodel.2017.03.005.*

the gradient of this axis. Theoretical studies can account implicitly for stakeholders, for example by formalizing policies such as incentives and taxation at the national or supranational (e.g. European) scale (Barraquand and Martinet, 2011). At a finer scale, in their study on farmers' benefits from the coordinated landscape-scale management of biological control in a realistic landscape with heterogeneous farms, Bareille et al. (2020) considered two realistic farm systems ("swine" and "cattle") with specific crop-allocation rules that were calibrated based on interviews with farmers. However, additionally to ongoing research, we advocate for a better mix between theoretical studies and those involving stakeholders.

Pure conceptual or theoretical approaches are essential to explore the relevance of landscape structures regardless of social and economic constraints, as they can potentially bring innovations that were not accessible without isolation from the specific context. But farmers and other landscape stakeholders (e.g. cooperatives, local extension services, local environmental associations, water catchment managers) demand increasingly to play an active role in planning and decision-making that affect them, their communities and the agricultural landscapes they inhabit. They are also increasingly aware of their own capabilities to provide inputs to planning processes, including models (Voinov et al., 2016). Moreover, it is generally agreed that better decisions are implemented with less conflict and more success when they are driven by stakeholders. Consideration of stakeholders can be done at various levels of integration. Stakeholders can either be involved in the conception of the systems' dynamics, or in the assessment of a set of empirical rules describing agent behaviour (Becu et al., 2014). Elsewhere, they can be involved in participatory modelling, contributing to the model design, the construction of scenarios to be simulated and the analysis and discussion of model outcomes. Participatory Companion Modelling (see Section 4.1.3 and Box 5), has successfully been applied to natural resource management issues in spatial entities ranging from the village to the small watershed involving multilevel stakeholders (Campo et al., 2010; Etienne, 2014).

Another challenge in reconciling theoretical approaches and stakeholder involvement stems from the complexity of models. Excessive computation time may limit the exploration of scenarios or impede any direct interaction with stakeholders who are themselves involved in process with a different time frame. This issue opens up possible uses for meta-modelling to convert overly complex models into simpler ones, while preserving the functional link between model inputs and outcomes but markedly improving simulation times and costs; facilitating a wider exploration of the variable space and greater stakeholder involvement.

6. Conclusion

Factors including human population growth, urban sprawl, dependency on modern agriculture and on chemical inputs, and its subsequent impacts on the health and the environment, make it challenging to feed humankind while preserving natural resources and slowing current trends in climate change and its effects. In this context, the understanding and management of landscapes is of utmost importance, as it has become vital to shift towards sustainable agricultural landscapes. Transformative changes are necessary to meet these challenges, and providing solutions to the trade-offs in the many functions provided by agricultural landscapes (e.g. food production, biodiversity conservation, soil loss mitigation) and that underpin ecosystem services.

In this chapter, we have shown that a wide range of modelling approaches can be used to anticipate and simulate the complexity of future agricultural landscapes. Where possible, we have outlined how spatially explicit and mechanistic models address future landscape construction, shedding light on agriculture in expanding cities as well as in rural-urban areas (Box 1). Assuming an increasing complexity of landscapes, characterized by a highly intricate structure, we have illustrated (Box 2) how models can capture aspects of agricultural landscapes and generate virtual but realistic simulations featuring different spatial (e.g. geometry, connectivity) and temporal patterns (e.g. crop rotation).

However, the design of agricultural landscapes faces a daunting prospect: a myriad of processes and their interactions are in play. Inevitably, modelling spatial flows across complex landscapes is challenging, but it is also an essential step towards the design of resilient landscapes. We have attempted to give an overview of the main issues when modelling and simulating biotic and abiotic flows, as well as multitrophic interactions, in complex landscapes. We used the functioning of ditch networks in agricultural watershed as a case study (Box 3) to advocate for the reinforcement of multidisciplinary sciences.

The transition towards future agricultural landscapes puts landscape stakeholders centre stage. However, the multiplicity of stakeholder actors (individual farmers, agricultural cooperatives, local and national regulators, estate owners, etc.) that shape the landscape and whose decision-making are influenced by the landscape patterns, and also who operates at which spatial and temporal scale, presents considerable problems of model formulation.

We presented some contrasted examples of formalisms to integrate human actions and decisions in landscape models. Theoretical models and their simulations consider stakeholders implicitly and address questions such as the evaluation of policies (Box 4), other models actively involve landscape stakeholders to solve natural resource management conflicts and promote institutional innovations (Box 5). The level of model genericity or territory-specificity should be adjusted to the research and action objectives. Independently, we question to which extent the concept of performativity might provide interesting insights on how the research in landscape modelling could drive effective changes in the reality of landscapes even if it has not produced intentional actionable knowledge.

Agricultural landscapes are highly complex systems for which modelling appears an inescapable tool in the toolkit required to provide guidance on their future conception and manipulation. Models open up many possible lines of research. Landscape representation, in models, may lead to further conceptualisation as technological developments (e.g. high throughput data from satellites or drones) and precision agriculture bring increasing information. In terms of landscape conception, building bridges between disciplines underpinning agricultural landscape modelling (e.g. agronomy, geography, ecology, economy and computer science) becomes pivotal. Regarding landscape manipulation, research remains rare, and while we identified some studies showing potential for solving theoretical landscape planning issues (Fig. 4, Box 6), we also pinpointed gaps in the identification of future trajectories—or sequences of landscape modifications—enabling a shift from current agricultural landscapes to novel and more sustainable ones.

While we only briefly addressed landscape resilience, it is an issue that will increasingly become important for future research. Over the past decades, and notably in the last few years, major disturbances (bushfire, drought, flooding, pest outbreak, pandemics) have occurred and caused dramatic damage. Landscapes, more than ever, need be resilient to such disturbance. But, this also calls into question the capacity of models to accommodate perturbations and disruptions, because it exacerbates problems of model complexity and tractability.

The transition towards future agricultural landscapes represents a formidable challenge for scientists of many disciplines and for practitioners. It will require a sharing of the overarching goal to design landscapes that serve both nature and people, and we would argue that landscape modelling has a central role in this goal.

Acknowledgements

S.P., F.V., and J.P. thank the PAYOTE scientific network funded by the French National Research Institute for Agriculture, Food and Environment (INRAE) for fruitful discussions. F.V. and G.R. thank Marc Voltz for his assistance in the redaction of Section 3.1 of this manuscript.

References

Altieri, M.A., Nicholls, C.I., 2012. Agroecology scaling up for food sovereignty and resiliency. In: Lichtfouse, E. (Ed.), Sustainable Agriculture Reviews. Springer Netherlands, Dordrecht, pp. 1–29. https://doi.org/10.1007/978-94-007-5449-2_1.

Armanda, D.T., Guinée, J.B., Tukker, A., 2019. The second green revolution: innovative urban agriculture's contribution to food security and sustainability—a review. Glob. Food Secur. 22, 13–24. https://doi.org/10.1016/j.gfs.2019.08.002.

Austin, J.L., 1962. How to Do Things with Words. Harvard University Press. ed, Cambridge (MA).

Bailleul, F., Charrassin, J.-B., Monestiez, P., Roquet, F., Biuw, M., Guinet, C., 2007. Successful foraging zones of southern elephant seals from the Kerguelen Islands in relation to oceanographic conditions. Philos. Trans. R. Soc. B Biol. Sci. 362, 2169–2181. https://doi.org/10.1098/rstb.2007.2109.

Bareille, F., Boussard, H., Thenail, C., 2020. Productive ecosystem services and collective management: lessons from a realistic landscape model. Ecol. Econ. 169, 106482. https://doi.org/10.1016/j.ecolecon.2019.106482.

Barraquand, F., Martinet, V., 2011. Biological conservation in dynamic agricultural landscapes: effectiveness of public policies and trade-offs with agricultural production. Ecol. Econ. 70, 910–920. https://doi.org/10.1016/j.ecolecon.2010.12.019.

Barredo, J.I., Kasanko, M., McCormick, N., Lavalle, C., 2003. Modelling dynamic spatial processes: simulation of urban future scenarios through cellular automata. Landsc. Urban Plan. 64, 145–160. https://doi.org/10.1016/S0169-2046(02)00218-9.

Baume, J.P., Malaterre, P.O., Belaud, G., Le Guennec, B., 2005. SIC: a 1D hydrodynamic model for river and Irrigation canal modeling and regulation. Método. Numér. Em Recur. Hidr. 7.

Beaumont, M.A., 2010. Approximate Bayesian computation in evolution and ecology. Annu. Rev. Ecol. Evol. Syst. 41, 379–406. https://doi.org/10.1146/annurev-ecolsys-102209-144621.

Becu, N., Raimond, C., Garine, E., Deconchat, M., Kokou, K., 2014. Coupling environmental and social processes to simulate the emergence of a Savannah landscape mosaic under shifting cultivation and assess its sustainability. J. Artif. Soc. Soc. Simul. 17, 1. https://doi.org/10.18564/jasss.2397.

Becu, N., Amalric, M., Anselme, B., Beck, E., Bertin, X., Delay, E., Long, N., Marilleau, N., Pignon-Mussaud, C., Rousseaux, F., 2017. Participatory simulation to foster social learning on coastal flooding prevention. Environ. Model. Software 98, 1–11. https://doi.org/10.1016/j.envsoft.2017.09.003.

Beduschi, T., Tscharntke, T., Scherber, C., 2015. Using multi-level generalized path analysis to understand herbivore and parasitoid dynamics in changing landscapes. Landsc. Ecol. 30, 1975–1986. https://doi.org/10.1007/s10980-015-0224-2.

Begg, G.S., Dye, R., 2015. Exploring trade-offs and synergies between biological pest control and species conservation (Commissioned Report No. 692). Scottish Natural Heritage.

Belényesi, M.B., Podmaniczky, L., Balczo, B., 2008. Delineation of high nature value areas in Hungary. Hung J. Landsc. Ecol., 5.

Béné, C., Doyen, L., 2008. Contribution values of biodiversity to ecosystem performances: a viability perspective. Ecol. Econ. 68, 14–23. https://doi.org/10.1016/j.ecolecon.2008.08.015.

Benoît, M., Rizzo, D., Marraccini, E., Moonen, A.C., Galli, M., Lardon, S., Rapey, H., Thenail, C., Bonari, E., 2012. Landscape agronomy: a new field for addressing agricultural landscape dynamics. Landsc. Ecol. 27, 1385–1394. https://doi.org/10.1007/s10980-012-9802-8.

Betbeder, J., Laslier, M., Hubert-Moy, L., Burel, F., Baudry, J., 2017. Synthetic aperture radar (SAR) images improve habitat suitability models. Landsc. Ecol. 32, 1867–1879. https://doi.org/10.1007/s10980-017-0546-3.

Bianchi, F.J.J.A., Booij, C.J.H., Tscharntke, T., 2006. Sustainable pest regulation in agricultural landscapes: a review on landscape composition, biodiversity and natural pest control. Proc. R. Soc. Lond. B Biol. Sci. 273, 1715–1727.

Bieling, C., Plieninger, T., Schaich, H., 2013. Patterns and causes of land change: empirical results and conceptual considerations derived from a case study in the Swabian Alb, Germany. Land Use Policy 35, 192–203. https://doi.org/10.1016/j.landusepol.2013.05.012.

Biggs, J., von Fumetti, S., Kelly-Quinn, M., 2017. The importance of small waterbodies for biodiversity and ecosystem services: implications for policy makers. Hydrobiologia 793, 3–39. https://doi.org/10.1007/s10750-016-3007-0.

Blomqvist, M.M., Tamis, W.L.M., de Snoo, G.R., 2009. No improvement of plant biodiversity in ditch banks after a decade of agri-environment schemes. Basic Appl. Ecol. 10, 368–378. https://doi.org/10.1016/j.baae.2008.08.007.

Boccaletti, S., Bianconi, G., Criado, R., del Genio, C.I., Gómez-Gardeñes, J., Romance, M., Sendiña-Nadal, I., Wang, Z., Zanin, M., 2014. The structure and dynamics of multilayer networks. Phys. Rep. 544, 1–122. https://doi.org/10.1016/j.physrep.2014.07.001.

Bonhomme, V., Castets, M., Ibanez, T., Géraux, H., Hély, C., Gaucherel, C., 2017. Configurational changes of patchy landscapes dynamics. Ecol. Model. 363, 1–7. https://doi.org/10.1016/j.ecolmodel.2017.08.007.

Bourhis, Y., Poggi, S., Mammeri, Y., Cortesero, A.-M., Le Ralec, A., Parisey, N., 2015. Perception-based foraging for competing resources: assessing pest population dynamics at the landscape scale from heterogeneous resource distribution. Ecol. Model. 312, 211–221. https://doi.org/10.1016/j.ecolmodel.2015.05.029.

Bourhis, Y., Poggi, S., Mammeri, Y., Le Cointe, R., Cortesero, A.-M., Parisey, N., 2017. Foraging as the landscape grip for population dynamics—a mechanistic model applied to crop protection. Ecol. Model. 354, 26–36. https://doi.org/10.1016/j.ecolmodel.2017.03.005.

Brown, C., Brown, K., Rounsevell, M., 2016. A philosophical case for process-based modelling of land use change. Model. Earth Syst. Environ. 2, 50. https://doi.org/10.1007/s40808-016-0102-1.

Brunner, G.W., Bonner, V., 1994. HEC River Analysis System (HEC-RAS) (No. Technical Paper No. 147). US Army Corps of Enginners. Hydrologic Engineer Center.

Burdon, J.J., Thrall, P.H., 2008. Pathogen evolution across the agro-ecological interface: implications for disease management: pathogen evolution in agro-ecosystems. Evol. Appl. 1, 57–65. https://doi.org/10.1111/j.1752-4571.2007.00005.x.

Burel, F., 1996. Hedgerows and their role in agricultural landscapes. Crit. Rev. Plant Sci. 15, 169–190. https://doi.org/10.1080/07352689.1996.10393185.

Bürgi, M., Hersperger, A.M., Schneeberger, N., 2005. Driving forces of landscape change—current and new directions. Landsc. Ecol. 19, 857–868. https://doi.org/10.1007/s10980-005-0245-3.

Cabantous, L., Gond, J.-P., 2011. Rational decision making as performative praxis: explaining rationality's *Éternel Retour*. Organ. Sci. 22, 573–586. https://doi.org/10.1287/orsc.1100.0534.

Callon, M., 1998. The Laws of the Markets. The Sociological Revew/Basil Blackwell. ed, Oxford.

Campo, P.C., Bousquet, F., Villanueva, T.R., 2010. Modelling with stakeholders within a development project. Environ. Model. Software 25, 1302–1321. https://doi.org/10.1016/j.envsoft.2010.01.005.

Cardona, A., 2012. Territorial agri-food systems: relinking farming to local and environmental stakes to change farming systems. In: Producing and Reproducing Farming Systems. New Modes of Organisation for Sustainable Food Systems of Tomorrow. Presented at the Proceedings of the 10th European IFSA Symposium.

Caron, P., Biénabe, E., Hainzelin, E., 2014. Making transition towards ecological intensification of agriculture a reality: the gaps in and the role of scientific knowledge. Curr. Opin. Environ. Sustain. 8, 44–52. https://doi.org/10.1016/j.cosust.2014.08.004.

Carpenter, S.R., Caraco, N.F., Correll, D.L., Howarth, R.W., Sharpley, A.N., Smith, V.H., 1998. Nonpoint pollution of surface waters with phosphorus and nitrogen. Ecol. Appl. 8, 559–568. https://doi.org/10.1890/1051-0761(1998)008[0559:NPOSWW]2.0.CO;2.

Chapin III, F.S., Zavaleta, E.S., Eviner, V.T., Naylor, R.L., Vitousek, P.M., Reynolds, H.L., Hooper, D.U., Lavorel, S., Sala, O.E., Hobbie, S.E., Mack, M.C., Díaz, S., 2000. Consequences of changing biodiversity. Nature 405, 234–242. https://doi.org/10.1038/35012241.

Chaplin-Kramer, R., O'Rourke, M.E., Blitzer, E.J., Kremen, C., 2011. A meta-analysis of crop pest and natural enemy response to landscape complexity. Ecol. Lett. 14, 922–932.

Clark, J.S., 2004. Why environmental scientists are becoming Bayesians: modelling with Bayes. Ecol. Lett. 8, 2–14. https://doi.org/10.1111/j.1461-0248.2004.00702.x.

Collard, B., Tixier, P., Carval, D., Lavigne, C., Delattre, T., 2018. Spatial organisation of habitats in agricultural plots affects per-capita predator effect on conservation biological control: an individual based modelling study. Ecol. Model. 388, 124–135. https://doi.org/10.1016/j.ecolmodel.2018.09.026.

Couclelis, H., 1997. From cellular automata to urban models: new principles for model development and implementation. Environ. Plan. B Plan. Des. 24, 165–174. https://doi.org/10.1068/b240165.

Cressie, N.A.C., 2015. Statistics for Spatial Data, Revised edition. John Wiley & Sons, Inc, Hoboken, NJ.

Cressie, N., Calder, C.A., Clark, J.S., Hoef, J.M.V., Wikle, C.K., 2009. Accounting for uncertainty in ecological analysis: the strengths and limitations of hierarchical statistical modeling. Ecol. Appl. 19, 553–570. https://doi.org/10.1890/07-0744.1.

Crutzen, P.J., 2002. Geology of mankind. Nature 415, 23. https://doi.org/10.1038/415023a.

Daré, W., Venot, J.-P., 2018. Room for manoeuvre: user participation in water resources management in Burkina Faso. Dev. Policy Rev. 36, 175–189. https://doi.org/10.1111/dpr.12278.

de Groot, R.S., Alkemade, R., Braat, L., Hein, L., Willemen, L., 2010. Challenges in integrating the concept of ecosystem services and values in landscape planning, management and decision making. Ecol. Complex. 7, 260–272. https://doi.org/10.1016/j.ecocom.2009.10.006.

Dedeurwaerdere, T., Hannachi, M., 2019. Socio-economic drivers of coexistence of landraces and modern crop varieties in agro-biodiversity rich Yunnan rice fields. Ecol. Econ. 159, 177–188. https://doi.org/10.1016/j.ecolecon.2019.01.026.

Dell, A.I., Bender, J.A., Branson, K., Couzin, I.D., de Polavieja, G.G., Noldus, L.P.J.J., Pérez-Escudero, A., Perona, P., Straw, A.D., Wikelski, M., Brose, U., 2014. Automated image-based tracking and its application in ecology. Trends Ecol. Evol. 29, 417–428. https://doi.org/10.1016/j.tree.2014.05.004.

Descombes, X. (Ed.), 2013. Stochastic Geometry for Image Analysis. John Wiley & Sons, Inc., Hoboken, NJ, USA. https://doi.org/10.1002/9781118601235.

Dieguez Cameroni, F.J., Terra, R., Tabarez, S., Bommel, P., Corral, J., Bartaburu, D., Pereira, M., Montes, E., Duarte, E., Morales Grosskopf, H., 2014. Virtual experiments using a participatory model to explore interactions between climatic variability and management decisions in extensive grazing systems in the basaltic region of Uruguay. Agr. Syst. 130, 89–104. https://doi.org/10.1016/j.agsy.2014.07.002.

Dollinger, J., Dagès, C., Bailly, J.-S., Lagacherie, P., Voltz, M., 2015. Managing ditches for agroecological engineering of landscape. A review. Agron. Sustain. Dev. 35, 999–1020. https://doi.org/10.1007/s13593-015-0301-6.

Dossa, L.H., Abdulkadir, A., Amadou, H., Sangare, S., Schlecht, E., 2011. Exploring the diversity of urban and peri-urban agricultural systems in Sudano-Sahelian West Africa: an attempt towards a regional typology. Landsc. Urban Plan. 102, 197–206. https://doi.org/10.1016/j.landurbplan.2011.04.005.

Douglas, D.H., Peucker, T.K., 1973. Algorithms for the reduction of the number of points required to represent a digitized line or its caricature. Cartogr. Int. J. Geogr. Inf. Geovisualization 10, 112–122. https://doi.org/10.3138/FM57-6770-U75U-7727.

Doyen, L., Martinet, V., 2012. Maximin, viability and sustainability. J. Econ. Dyn. Control 36, 1414–1430. https://doi.org/10.1016/j.jedc.2012.03.004.

Dubos-Paillard, E., Guermond, Y., Langlois, P., 2003. Analyse de l'évolution urbaine par automate cellulaire. Le modèle SpaCelle. In: Espace Géographique Fr. 32, p. 357. https://doi.org/10.3917/eg.324.0357.

Dunning, J.B., Danielson, B.J., Pulliam, H.R., 1992. Ecological processes that affect populations in complex landscapes. Oikos 65, 169. https://doi.org/10.2307/3544901.

Dupont, S., Brunet, Y., 2006. Simulation of turbulent flow in an Urban Forested Park damaged by a windstorm. Bound.-Lay. Meteorol. 120, 133–161. https://doi.org/10.1007/s10546-006-9049-5.

Dupont, S., Brunet, Y., 2008. Influence of foliar density profile on canopy flow: a large-eddy simulation study. Agric. For. Meteorol. 148, 976–990. https://doi.org/10.1016/j.agrformet.2008.01.014.

Dupont, S., Brunet, Y., Jarosz, N., 2006. Eulerian modelling of pollen dispersal over heterogeneous vegetation canopies. Agric. For. Meteorol. 141, 82–104. https://doi.org/10.1016/j.agrformet.2006.09.004.

Duru, M., Adam, M., Cruz, P., Martin, G., Ansquer, P., Ducourtieux, C., Jouany, C., Theau, J.P., Viegas, J., 2009. Modelling above-ground herbage mass for a wide range of grassland community types. Ecol. Model. 220, 209–225. https://doi.org/10.1016/j.ecolmodel.2008.09.015.

Duru, M., Therond, O., Martin, G., Martin-Clouaire, R., Magne, M.-A., Justes, E., Journet, E.-P., Aubertot, J.-N., Savary, S., Bergez, J.-E., Sarthou, J.P., 2015. How to implement biodiversity-based agriculture to enhance ecosystem services: a review. Agron. Sustain. Dev. 35, 1259–1281. https://doi.org/10.1007/s13593-015-0306-1.

Dury, J., Schaller, N., Garcia, F., Reynaud, A., Bergez, J.E., 2012. Models to support cropping plan and crop rotation decisions. A review. Agron. Sustain. Dev. 32, 567–580. https://doi.org/10.1007/s13593-011-0037-x.

EC European Commission, 2018. Regions in the European Union: Nomenclature of Territorial Units for Statistics, NUTS 2016/EU 28: Edition 2018. Publications Office of the European Union, Luxembourg.

Elzen, B., Barbier, M., Cerf, M., Grin, J., 2012. Stimulating transitions towards sustainable farming systems. In: Darnhofer, I., Gibbon, D., Dedieu, B. (Eds.), Farming Systems Research into the 21st Century: The New Dynamic. Springer Netherlands, Dordrecht, pp. 431–455. https://doi.org/10.1007/978-94-007-4503-2_19.

Engel, J., Huth, A., Frank, K., 2012. Bioenergy production and skylark (*Alauda arvensis*) population abundance—a modelling approach for the analysis of land-use change

impacts and conservation options. GCB Bioenergy 4, 713–727. https://doi.org/10.1111/j.1757-1707.2012.01170.x.
Etienne, M., 2014. Companion Modelling: A Participatory Approach to Support Sustainable Development. Springer, Dordrecht.
FAO, 1999. Urban and peri-urban agriculture. In: Committee on Agriculture, 15th Session Urban and Peri-Urban Agriculture.
FAO, 2018. The State of Food and Agriculture. Migration, agriculture and rural development. Food and Agriculture Organization of the United Nations, Rome, p. 2018.
Farias, G., Leitzke, B., Born, M., Aguiar, M., Adamatti, D.F., 2019. Systematic review of natural resource management using multiagent systems and role-playing games. Res. Comput. Sci. 148, 91–102. https://doi.org/10.13053/rcs-148-11-7.
Fischer, J., Brosi, B., Daily, G.C., Ehrlich, P.R., Goldman, R., Goldstein, J., Lindenmayer, D.B., Manning, A.D., Mooney, H.A., Pejchar, L., Ranganathan, J., Tallis, H., 2008. Should agricultural policies encourage land sparing or wildlife-friendly farming? Front. Ecol. Environ. 6, 380–385. https://doi.org/10.1890/070019.
Fisher, B., Turner, R.K., Morling, P., 2009. Defining and classifying ecosystem services for decision making. Ecol. Econ. 68, 643–653. https://doi.org/10.1016/j.ecolecon.2008.09.014.
Foley, J.A., 2005. Global consequences of land use. Science 309, 570–574. https://doi.org/10.1126/science.1111772.
Forman, R.T.T., 1995. Some general principles of landscape and regional ecology. Landsc. Ecol. 10, 133–142.
Forman, R.T.T., Godron, M., 1986. Landscape Ecology. Cambridge University Press, Cambridge.
Franklin, J., 2010. Mapping Species Distributions: Spatial Inference and Prediction. Cambridge University Press, Cambridge. https://doi.org/10.1017/CBO9780511810602.
Frazier, A.E., Kedron, P., 2017. Landscape metrics: past progress and future directions. Curr. Landsc. Ecol. Rep. 2, 63–72. https://doi.org/10.1007/s40823-017-0026-0.
Friedmann, J., 2016. The future of periurban research. Cities 53, 163–165. https://doi.org/10.1016/j.cities.2016.01.009.
Fuchs, R., Verburg, P.H., Clevers, J.G.P.W., Herold, M., 2015. The potential of old maps and encyclopaedias for reconstructing historic European land cover/use change. Appl. Geogr. 59, 43–55. https://doi.org/10.1016/j.apgeog.2015.02.013.
García-Arias, A., Francés, F., 2016. The RVDM: modelling impacts, evolution and competition processes to determine riparian vegetation dynamics: the RVDM: modelling riparian vegetation dynamics. Ecohydrology 9, 438–459. https://doi.org/10.1002/eco.1648.
Gardarin, A., Dürr, C., Colbach, N., 2012. Modeling the dynamics and emergence of a multispecies weed seed bank with species traits. Ecol. Model. 240, 123–138. https://doi.org/10.1016/j.ecolmodel.2012.05.004.
Gardner, R.H., 1999. RULE: map generation and a spatial analysis program. In: Klopatek, J.M., Gardner, R.H. (Eds.), Landscape Ecological Analysis. Springer New York, New York, NY, pp. 280–303. https://doi.org/10.1007/978-1-4612-0529-6_13.
Gaucherel, C., 2008. Neutral models for polygonal landscapes with linear networks. Ecol. Model. 219, 39–48.
Gaucherel, C., Fleury, D., Auclair, D., Dreyfus, P., 2006a. Neutral models for patchy landscapes. Ecol. Model. 197, 159–170. https://doi.org/10.1016/j.ecolmodel.2006.02.044.
Gaucherel, C., Giboire, N., Viaud, V., Houet, T., Baudry, J., Burel, F., 2006b. A domain-specific language for patchy landscape modelling: the Brittany agricultural mosaic as a case study. Ecol. Model. 194, 233–243. https://doi.org/10.1016/j.ecolmodel.2005.10.026.

Geertsema, W., Rossing, W.A., Landis, D.A., Bianchi, F.J., van Rijn, P.C., Schaminée, J.H., Tscharntke, T., van der Werf, W., 2016. Actionable knowledge for ecological intensification of agriculture. Front. Ecol. Environ. 14, 209–216. https://doi.org/10.1002/fee.1258.

Geniaux, G., Ay, J.-S., Napoléone, C., 2011. A spatial hedonic approach on land use change anticipations. J. Reg. Sci. 51, 967–986. https://doi.org/10.1111/j.1467-9787.2011.00721.x.

Gerber, P.J., Steinfeld, H., Henderson, B., Mottet, A., Opio, C., Dijkman, J., Falcucci, A., Tempio, G., 2013. Tackling Climate Change through Livestock: A Global Assessment of Emissions and Mitigation Opportunities. Food and Agriculture Organization of the United Nations (FAO), Rome.

Grass, et al., 2021. The future of European land-sharing/−sparing connectivity landscapes. In: Bohan, D., Vanbergen, A (Eds.), Advances in Ecological Research. Elsevier, p. 64 (this issue).

Grimm, V., Revilla, E., Berger, U., Jeltsch, F., Mooij, W.M., Railsback, S.F., Thulke, H.H., Weiner, J., Wiegand, T., DeAngelis, D.L., 2005. Pattern-oriented modeling of agent-based complex systems: lessons from ecology. Science 310, 987–991.

Groot, J.C.J., Rossing, W.A.H., Tichit, M., Turpin, N., Jellema, A., Baudry, J., Verburg, P.H., Doyen, L., van de Ven, G.W.J., 2009. On the contribution of modelling to multifunctional agriculture: learning from comparisons. J. Environ. Manage. 90, S147–S160. https://doi.org/10.1016/j.jenvman.2008.11.030.

Guan, D., Li, H., Inohae, T., Su, W., Nagaie, T., Hokao, K., 2011. Modeling urban land use change by the integration of cellular automaton and Markov model. Ecol. Model. 222, 3761–3772. https://doi.org/10.1016/j.ecolmodel.2011.09.009.

Gurung, T.R., Bousquet, F., Trébuil, G., 2006. Companion modeling, conflict resolution, and institution building: sharing irrigation water in the Lingmuteychu Watershed. Bhutan. Ecol. Soc. 11 (2), 36 (online) http://www.ecologyandsociety.org/vol11/iss2/art36/.

Haan, N.L., Zhang, Y., Landis, D.A., 2020. Predicting landscape configuration effects on agricultural pest suppression. Trends Ecol. Evol. 35 (2), 175–186. https://doi.org/10.1016/j.tree.2019.10.003.

Hallmann, C.A., Foppen, R.P.B., van Turnhout, C.A.M., de Kroon, H., Jongejans, E., 2014. Declines in insectivorous birds are associated with high neonicotinoid concentrations. Nature 511, 341–343. https://doi.org/10.1038/nature13531.

Hallmann, C.A., Sorg, M., Jongejans, E., Siepel, H., Hofland, N., Schwan, H., Stenmans, W., Müller, A., Sumser, H., Hörren, T., Goulson, D., de Kroon, H., 2017. More than 75 percent decline over 27 years in total flying insect biomass in protected areas. PLoS One 12, e0185809. https://doi.org/10.1371/journal.pone.0185809.

Hannachi, M., Coléno, F.-C., 2015. Towards a managerial engineering of coopetition the findings of the study of the management of GMOs in the French grain merchant industry. Manag. Organ. Stud. 3, p1. https://doi.org/10.5430/mos.v3n1p1.

Hannachi, M., Martinet, V., 2019. In: Petit, S., Lavigne, C. (Eds.), Vers une co-conception de paysages pour la santé des plantes et avec des acteurs du territoire, in: Paysage, biodiversité fonctionnelle et santé des cultures (in French), pp. 185–205.

Häussler, J., Barabás, G., Eklöf, A., 2020. A Bayesian network approach to trophic metacommunities shows that habitat loss accelerates top species extinctions. Ecol. Lett. 23 (12), 1849–1861. https://doi.org/10.1111/ele.13607. ele. 13607.

Hayhoe, K., Edmonds, J., Kopp, R.E., LeGrande, A.N., Sanderson, B.M., Wehner, M.F., Wuebbles, D.J., 2017. Ch. 4: Climate Models, Scenarios, and Projections. Climate Science Special Report: Fourth National Climate Assessment. vol. I U.S. Global Change Research Program. https://doi.org/10.7930/J0WH2N54.

Hersperger, A.M., Bürgi, M., 2009. Going beyond landscape change description: quantifying the importance of driving forces of landscape change in a Central Europe case study. Land Use Policy 26, 640–648. https://doi.org/10.1016/j.landusepol.2008.08.015.

Hodgson, J.C., Mott, R., Baylis, S.M., Pham, T.T., Wotherspoon, S., Kilpatrick, A.D., Raja Segaran, R., Reid, I., Terauds, A., Koh, L.P., 2018. Drones count wildlife more accurately and precisely than humans. Methods Ecol. Evol. 9, 1160–1167. https://doi.org/10.1111/2041-210X.12974.

Hossard, L., Jeuffroy, M.H., Pelzer, E., Pinochet, X., Souchere, V., 2013. A participatory approach to design spatial scenarios of cropping systems and assess their effects on phoma stem canker management at a regional scale. Environ. Model. Software 48, 17–26. https://doi.org/10.1016/j.envsoft.2013.05.014.

Houet, T., Verburg, P.H., Loveland, T.R., 2010. Monitoring and modelling landscape dynamics. Landsc. Ecol. 25, 163–167. https://doi.org/10.1007/s10980-009-9417-x.

Houet, T., Aguejdad, R., Doukari, O., Battaia, G., Clarke, K., 2016. Description and validation of a "non path-dependent" model for projecting contrasting urban growth futures. Cybergeo Eur. J. Geogr. https://doi.org/hal-01326063.

Huber, R., Bakker, M., Balmann, A., Berger, T., Bithell, M., Brown, C., Grêt-Regamey, A., Xiong, H., Le, Q.B., Mack, G., Meyfroidt, P., Millington, J., Müller, B., Polhill, J.G., Sun, Z., Seidl, R., Troost, C., Finger, R., 2018. Representation of decision-making in European agricultural agent-based models. Agr. Syst. 167, 143–160. https://doi.org/10.1016/j.agsy.2018.09.007.

Illian, J.B., Martino, S., Sørbye, S.H., Gallego-Fernández, J.B., Zunzunegui, M., Esquivias, M.P., Travis, J.M.J., 2013. Fitting complex ecological point process models with integrated nested Laplace approximation. Methods Ecol. Evol. 4, 305–315. https://doi.org/10.1111/2041-210x.12017.

Inkoom, J.N., Frank, S., Greve, K., Fürst, C., 2017. Designing neutral landscapes for data scarce regions in West Africa. Eco. Inform. 42, 1–13. https://doi.org/10.1016/j.ecoinf.2017.08.003.

Jacquot, M., Massol, F., Muru, D., Derepas, B., Tixier, P., Deguine, J.-P., 2019. Arthropod diversity is governed by bottom-up and top-down forces in a tropical agroecosystem. Agric. Ecosyst. Environ. 285, 106623. https://doi.org/10.1016/j.agee.2019.106623.

Jokar Arsanjani, J., Helbich, M., Kainz, W., Darvishi Boloorani, A., 2013. Integration of logistic regression, Markov chain and cellular automata models to simulate urban expansion. Int. J. Appl. Earth Obs. Geoinf. 21, 265–275. https://doi.org/10.1016/j.jag.2011.12.014.

Kays, R., Crofoot, M.C., Jetz, W., Wikelski, M., 2015. Terrestrial animal tracking as an eye on life and planet. Science 348, aaa2478. https://doi.org/10.1126/science.aaa2478.

Kays, R., McShea, W.J., Wikelski, M., 2020. Born-digital biodiversity data: millions and billions. Divers. Distrib. 26 (5), 644–648. ddi.12993 https://doi.org/10.1111/ddi.12993.

Keane, R.E., McKenzie, D., Falk, D.A., Smithwick, E.A.H., Miller, C., Kellogg, L.-K.B., 2015. Representing climate, disturbance, and vegetation interactions in landscape models. Ecol. Model. 309, 33–47.

Kiêu, K., Adamczyk-Chauvat, K., Monod, H., Stoica, R.S., 2013. A completely random T-tessellation model and Gibbsian extensions. Spat. Stat. 6, 118–138. https://doi.org/10.1016/j.spasta.2013.09.003.

Kivela, M., Arenas, A., Barthelemy, M., Gleeson, J.P., Moreno, Y., Porter, M.A., 2014. Multilayer networks. J. Complex Netw. 2 (3), 203–271. SSRN Electron. J. https://doi.org/10.2139/ssrn.2341334.

Klein, T., Holzkämper, A., Calanca, P., Seppelt, R., Fuhrer, J., 2013. Adapting agricultural land management to climate change: a regional multi-objective optimization approach. Landsc. Ecol. 28, 2029–2047. https://doi.org/10.1007/s10980-013-9939-0.

Kremen, C., Merenlender, A.M., 2018. Landscapes that work for biodiversity and people. Science 362, eaau6020. https://doi.org/10.1126/science.aau6020.

Labarthe, P., 2009. Extension services and multifunctional agriculture. Lessons learnt from the French and Dutch contexts and approaches. J. Environ. Manage. 90, S193–S202. https://doi.org/10.1016/j.jenvman.2008.11.021.

Lagabrielle, E., Botta, A., Daré, W., David, D., Aubert, S., Fabricius, C., 2010. Modelling with stakeholders to integrate biodiversity into land-use planning—lessons learned in Réunion Island (Western Indian Ocean). Environ. Model. Software 25, 1413–1427. https://doi.org/10.1016/j.envsoft.2010.01.011.

Lambin, E., Rounsevell, M.D., Geist, H., 2000. Are agricultural land-use models able to predict changes in land-use intensity? Agric. Ecosyst. Environ. 82, 321–331. https://doi.org/10.1016/S0167-8809(00)00235-8.

Lamboni, M., Monod, H., Makowski, D., 2011. Multivariate sensitivity analysis to measure global contribution of input factors in dynamic models. Reliab. Eng. Syst. Saf. 96, 450–459. https://doi.org/10.1016/j.ress.2010.12.002.

Langhammer, M., Thober, J., Lange, M., Frank, K., Grimm, V., 2019. Agricultural landscape generators for simulation models: a review of existing solutions and an outline of future directions. Ecol. Model. 393, 135–151. https://doi.org/10.1016/j.ecolmodel.2018.12.010.

Lansing, J.S., Thurner, S., Chung, N.N., Coudurier-Curveur, A., Karakaş, Ç., Fesenmyer, K.A., Chew, L.Y., 2017. Adaptive self-organization of Bali's ancient rice terraces. Proc. Natl. Acad. Sci. U. S. A. 114, 6504–6509. https://doi.org/10.1073/pnas.1605369114.

Latour, B., 1987. Science in Action: How to Follow Scientists and Engineers through Society. Harvard University Press. ed.

Latour, B., 2005. Reassembling the Social-an Introduction to Actor-Network-Theory. Oxford University Press. ed, Oxford.

Lausch, A., Blaschke, T., Haase, D., Herzog, F., Syrbe, R.-U., Tischendorf, L., Walz, U., 2015. Understanding and quantifying landscape structure—a review on relevant process characteristics, data models and landscape metrics. Ecol. Model. 295, 31–41. https://doi.org/10.1016/j.ecolmodel.2014.08.018.

Le Ber, F., Lavigne, C., Adamczyk, K., Angevin, F., Colbach, N., Mari, J.F., Monod, H., 2009. Neutral modelling of agricultural landscapes by tessellation methods-application for gene flow simulation. Ecol. Model. 220, 3536–3545.

Le Cœur, D., Baudry, J., Burel, F., Thenail, C., 2002. Why and how we should study field boundary biodiversity in an agrarian landscape context. Agric. Ecosyst. Environ. 89, 23–40. https://doi.org/10.1016/S0167-8809(01)00316-4.

Le Page, C., Perrotton, A., 2017. KILT: a modelling approach based on participatory agent-based simulation of stylized socio-ecosystems to stimulate social learning with local stakeholders. In: Sukthankar, G., Rodriguez-Aguilar, J.A. (Eds.), Autonomous Agents and Multiagent Systems. Springer International Publishing, Cham, pp. 31–44. https://doi.org/10.1007/978-3-319-71679-4_3.

LeCun, Y., Bengio, Y., Hinton, G., 2015. Deep learning. Nature 521, 436–444. https://doi.org/10.1038/nature14539.

Leenhardt, D., Angevin, F., Biarnès, A., Colbach, N., Mignolet, C., 2010. Describing and locating cropping systems on a regional scale. A review. Agron. Sustain. Dev. 30, 131–138. https://doi.org/10.1051/agro/2009002.

Leibold, M.A., Holyoak, M., Mouquet, N., Amarasekare, P., Chase, J.M., Hoopes, M.F., Holt, R.D., Shurin, J.B., Law, R., Tilman, D., Loreau, M., Gonzalez, A., 2004. The metacommunity concept: a framework for multi-scale community ecology: the metacommunity concept. Ecol. Lett. 7, 601–613. https://doi.org/10.1111/j.1461-0248.2004.00608.x.

Li, W., Wang, D., Li, H., Liu, S., 2017. Urbanization-induced site condition changes of peri-urban cultivated land in the black soil region of Northeast China. Ecol. Indic. 80, 215–223. https://doi.org/10.1016/j.ecolind.2017.05.038.

Loreau, M., de Mazancourt, C., 2013. Biodiversity and ecosystem stability: a synthesis of underlying mechanisms. Ecol. Lett. 16, 106–115. https://doi.org/10.1111/ele.12073.

Macarthur, R.H., Wilson, E.O., 1967. The Theory of Island Biogeography. Princeton University Press. https://doi.org/10.2307/j.ctt19cc1t2.

Macfadyen, S., Gibson, R., Polaszek, A., Morris, R.J., Craze, P.G., Planqué, R., Symondson, W.O.C., Memmott, J., 2009. Do differences in food web structure between organic and conventional farms affect the ecosystem service of pest control? Ecol. Lett. 12, 229–238. https://doi.org/10.1111/j.1461-0248.2008.01279.x.

MacKenzie, D., Muniesa, F., Siu, L., 2007. Do Economists Make Markets? On the Performativity of Economics. Princeton University Press, New Jersey.

Macmillan, W., Huang, H.Q., 2008. An agent-based simulation model of a primitive agricultural society. Geoforum 39, 643–658. https://doi.org/10.1016/j.geoforum.2007.07.011.

Magliocca, N.R., van Vliet, J., Brown, C., Evans, T.P., Houet, T., Messerli, P., Messina, J.P., Nicholas, K.A., Ornetsmüller, C., Sagebiel, J., Schweizer, V., Verburg, P.H., Yu, Q., 2015. From meta-studies to modeling: using synthesis knowledge to build broadly applicable process-based land change models. Environ. Model. Software 72, 10–20. https://doi.org/10.1016/j.envsoft.2015.06.009.

Martinet, V., 2013. Effect of soil heterogeneity on the welfare economics of biofuel policies. Land Use Policy 32, 218–229. https://doi.org/10.1016/j.landusepol.2012.10.013.

Massol, F., Petit, S., 2013. Interaction networks in agricultural landscape mosaics. In: Advances in Ecological Research. Elsevier, pp. 291–338. https://doi.org/10.1016/B978-0-12-420002-9.00005-6.

Massol, F., Gravel, D., Mouquet, N., Cadotte, M.W., Fukami, T., Leibold, M.A., 2011. Linking community and ecosystem dynamics through spatial ecology: an integrative approach to spatial food webs. Ecol. Lett. 14, 313–323. https://doi.org/10.1111/j.1461-0248.2011.01588.x.

Massol, F., Dubart, M., Calcagno, V., Cazelles, K., Jacquet, C., Kéfi, S., Gravel, D., 2017. Island biogeography of food webs. In: Advances in Ecological Research. Elsevier, pp. 183–262. https://doi.org/10.1016/bs.aecr.2016.10.004.

Mateo-Sagasta, J., Zadeh, S.M., Turral, H., Burke, J., 2017. Water pollution from agriculture: a global review. In: Executive Summary (CGIAR Research Program on Water, Land and Ecosystems). International Water Management Institute, FAO, Rome, p. 35.

Mawois, M., Le Bail, M., Navarrete, M., Aubry, C., 2012. Modelling spatial extension of vegetable land use in urban farms. Agron. Sustain. Dev. 32, 911–924. https://doi.org/10.1007/s13593-012-0093-x.

McGarigal, K., Cushman, S., 2005. The gradient concept of landscape structure. In: Issues and Perspectives in Landscape Ecology. Cambridge University Press, pp. 112–119.

Medley, K.E., Okey, B.W., Barrett, G.W., Lucas, M.F., Renwick, W.H., 1995. Landscape change with agricultural intensification in a rural watershed, southwestern Ohio, U.S.A. Landsc. Ecol. 10, 161–176. https://doi.org/10.1007/BF00133029.

Memmah, M.-M., Lescourret, F., Yao, X., Lavigne, C., 2015. Metaheuristics for agricultural land use optimization. A review. Agron. Sustain. Dev. 35, 975–998. https://doi.org/10.1007/s13593-015-0303-4.

Merritt, D.M., Scott, M.L., LeRoy Poff, N., Auble, G.T., Lytle, D.A., 2010. Theory, methods and tools for determining environmental flows for riparian vegetation: riparian vegetation-flow response guilds: Riparian vegetation-hydrologic models. Freshw. Biol. 55, 206–225. https://doi.org/10.1111/j.1365-2427.2009.02206.x.

Mignolet, C., Schott, C., Benoît, M., 2004. Spatial dynamics of agricultural practices on a basin territory: a retrospective study to implement models simulating nitrate flow. The case of the seine basin. Agronomie 24, 219–236. https://doi.org/10.1051/agro:2004015.

Mitchell, M.G.E., Suarez-Castro, A.F., Martinez-Harms, M., Maron, M., McAlpine, C., Gaston, K.J., Johansen, K., Rhodes, J.R., 2015. Reframing landscape fragmentation's effects on ecosystem services. Trends Ecol. Evol. 30, 190–198. https://doi.org/10.1016/j.tree.2015.01.011.

Mollot, G., Duyck, P.-F., Lefeuvre, P., Lescourret, F., Martin, J.-F., Piry, S., Canard, E., Tixier, P., 2014. Cover cropping alters the diet of arthropods in a Banana plantation: a Metabarcoding approach. PLoS One 9, e93740. https://doi.org/10.1371/journal.pone.0093740.

Moradkhani, H., Sorooshian, S., 2008. General review of rainfall-runoff modeling: model calibration, data assimilation, and uncertainty analysis. In: Sorooshian, S., Hsu, K.-L., Coppola, E., Tomassetti, B., Verdecchia, M., Visconti, G. (Eds.), Hydrological Modelling and the Water Cycle. Springer Berlin Heidelberg, Berlin, Heidelberg, pp. 1–24. https://doi.org/10.1007/978-3-540-77843-1_1.

Motisi, N., Ribeyre, F., Poggi, S., 2019. Coffee tree architecture and its interactions with microclimates drive the dynamics of coffee berry disease in coffee trees. Sci. Rep. 9, 1–12. https://doi.org/10.1038/s41598-019-38775-5.

Mottet, A., Ladet, S., Coqué, N., Gibon, A., 2006. Agricultural land-use change and its drivers in mountain landscapes: a case study in the Pyrenees. Agric. Ecosyst. Environ. 114, 296–310. https://doi.org/10.1016/j.agee.2005.11.017.

Mougeot, L., 2000. Urban Agriculture: Definition, Presence, Potentials and Risks. In: Growing Cities, Growing Food: Urban Agriculture on the Policy Agenda. ZEL, Feldafing (GER).

Moussa, R., Voltz, M., Andrieux, P., 2002. Effects of the spatial organization of agricultural management on the hydrological behaviour of a farmed catchment during flood events. Hydrol. Process. 16, 393–412. https://doi.org/10.1002/hyp.333.

Muniesa, F., 2014. The Provoked Economy: Economic Reality and the Performative Turn, first ed. Routledge. https://doi.org/10.4324/9780203798959.

Murgue, C., Therond, O., Leenhardt, D., 2016. Hybridizing local and generic information to model cropping system spatial distribution in an agricultural landscape. Land Use Policy 54, 339–354. https://doi.org/10.1016/j.landusepol.2016.02.020.

Nendel, C., Zander, P., 2019. Landscape models to support sustainable intensification of agroecological systems. In: Burleigh Dodds Series in Agricultural Science. Burleigh Dodds Science Publishing, pp. 321–354. https://doi.org/10.19103/AS.2019.0061.17.

Nepf, H.M., 2012. Hydrodynamics of vegetated channels. J. Hydraul. Res. 50, 262–279. https://doi.org/10.1080/00221686.2012.696559.

Nesshöver, C., Assmuth, T., Irvine, K.N., Rusch, G.M., Waylen, K.A., Delbaere, B., Haase, D., Jones-Walters, L., Keune, H., Kovacs, E., Krauze, K., Külvik, M., Rey, F., van Dijk, J., Vistad, O.I., Wilkinson, M.E., Wittmer, H., 2017. The science, policy and practice of nature-based solutions: an interdisciplinary perspective. Sci. Total Environ. 579, 1215–1227. https://doi.org/10.1016/j.scitotenv.2016.11.106.

Ohgushi, T., 2008. Herbivore-induced indirect interaction webs on terrestrial plants: the importance of non-trophic, indirect, and facilitative interactions. Entomol. Exp. Appl. 128, 217–229. https://doi.org/10.1111/j.1570-7458.2008.00705.x.

Olsen, A., Konovalov, D.A., Philippa, B., Ridd, P., Wood, J.C., Johns, J., Banks, W., Girgenti, B., Kenny, O., Whinney, J., Calvert, B., Azghadi, M.R., White, R.D., 2019. DeepWeeds: a multiclass weed species image dataset for deep learning. Sci. Rep. 9, 2058. https://doi.org/10.1038/s41598-018-38343-3.

Overmars, K.P., Verburg, P.H., Veldkamp, T.A., 2007. Comparison of a deductive and an inductive approach to specify land suitability in a spatially explicit land use model. Land Use Policy 24, 584–599. https://doi.org/10.1016/j.landusepol.2005.09.008.

Papaïx, J., Adamczyk-Chauvat, K., Bouvier, A., Kiêu, K., Touzeau, S., Lannou, C., Monod, H., 2014. Pathogen population dynamics in agricultural landscapes: the Ddal modelling framework. Infect. Genet. Evol. 27, 509–520. https://doi.org/10.1016/j.meegid.2014.01.022.

Papaïx, J., Rimbaud, L., Burdon, J.J., Zhan, J., Thrall, P.H., 2018. Differential impact of landscape-scale strategies for crop cultivar deployment on disease dynamics, resistance durability and long-term evolutionary control. Evol. Appl. 11, 705–717. https://doi.org/10.1111/eva.12570.

Parisey, N., Bourhis, Y., Roques, L., Soubeyrand, S., Ricci, B., Poggi, S., 2016. Rearranging agricultural landscapes towards habitat quality optimisation: in silico application to pest regulation. Ecol. Complex. 28, 113–122. https://doi.org/10.1016/j.ecocom.2016.07.003.

Parr, S., O'Donovan, G., Finn, J., 2006. Mapping the broad habitats of the burren using satellite imagery. End of Project Report, Teagasc.

Pascual, U., Perrings, C., 2007. Developing incentives and economic mechanisms for in situ biodiversity conservation in agricultural landscapes. Agric. Ecosyst. Environ. 121, 256–268. https://doi.org/10.1016/j.agee.2006.12.025.

Pe'er, G., Zurita, G.A., Schober, L., Bellocq, M.I., Strer, M., Müller, M., Pütz, S., 2013. Simple process-based simulators for generating spatial patterns of habitat loss and fragmentation: a review and introduction to the G-RaFFe model. PLoS One 8, e64968. https://doi.org/10.1371/journal.pone.0064968.

Perović, D., Gámez-Virués, S., Börschig, C., Klein, A.-M., Krauss, J., Steckel, J., Rothenwöhrer, C., Erasmi, S., Tscharntke, T., Westphal, C., 2015. Configurational landscape heterogeneity shapes functional community composition of grassland butterflies. J. Appl. Ecol. 52, 505–513. https://doi.org/10.1111/1365-2664.12394.

Philpott, S.M., Lucatero, A., Bichier, P., Egerer, M.H., Jha, S., Lin, B., Liere, H., 2020. Natural enemy–herbivore networks along local management and landscape gradients in urban agroecosystems. Ecol. Appl. 30 (8). https://doi.org/10.1002/eap.2201.

Piorr, A., Ravetz, J., Tosics, I., 2011. Peri-Urbanisation in Europe: Towards European Policies to Sustain Urban-Rural Futures. University of Copenhagen/Academic Books Life Sciences.

Plieninger, T., Draux, H., Fagerholm, N., Bieling, C., Bürgi, M., Kizos, T., Kuemmerle, T., Primdahl, J., Verburg, P.H., 2016. The driving forces of landscape change in Europe: a systematic review of the evidence. Land Use Policy 57, 204–214. https://doi.org/10.1016/j.landusepol.2016.04.040.

Poggi, S., Papaïx, J., Lavigne, C., Angevin, F., Le Ber, F., Parisey, N., Ricci, B., Vinatier, F., Wohlfahrt, J., 2018. Issues and challenges in landscape models for agriculture: from the representation of agroecosystems to the design of management strategies. Landsc. Ecol. 33, 1679–1690. https://doi.org/10.1007/s10980-018-0699-8.

Pointereau, P., Paracchini, M.-L., Terres, J., Jiguet, F., Le Bas, Y., Katarzyna, B., 2007. Identification of high nature value farmland in France through statistical information and farm practice surveys. EUR- scientific and technical research reports.

Porporato, A., Rodriguez-Iturbe, I., 2002. Ecohydrology-a challenging multidisciplinary research perspective/Ecohydrologie: Une perspective stimulante de recherche multidisciplinaire. Hydrol. Sci. J. 47, 811–821. https://doi.org/10.1080/02626660209492985.

Power, A.G., 2010. Ecosystem services and agriculture: tradeoffs and synergies. Philos. Trans. R. Soc. B Biol. Sci. 365, 2959–2971. https://doi.org/10.1098/rstb.2010.0143.

Preisler, H.K., Ager, A.A., Wisdom, M.J., 2013. Analyzing animal movement patterns using potential functions. Ecosphere 4, art32. https://doi.org/10.1890/ES12-00286.1.

Pribadi, D.O., Pauleit, S., 2015. The dynamics of peri-urban agriculture during rapid urbanization of Jabodetabek metropolitan area. Land Use Policy 48, 13–24. https://doi.org/10.1016/j.landusepol.2015.05.009.

Rayfuse, R., Weisfelt, N., 2012. The Challenge of Food Security. Edward Elgar Publishing. https://doi.org/10.4337/9780857939388.

Rey, F., Cécillon, L., Cordonnier, T., Jaunatre, R., Loucougaray, G., 2015. Integrating ecological engineering and ecological intensification from management practices to ecosystem services into a generic framework: a review. Agron. Sustain. Dev. 35, 1335–1345. https://doi.org/10.1007/s13593-015-0320-3.

Ricci, B., Petit, S., Allanic, C., Langot, M., Parisey, N., Poggi, S., 2018. How effective is large landscape-scale planning for reducing local weed infestations? A landscape-scale modelling approach. Ecol. Model. 384, 221–232. https://doi.org/10.1016/j.ecolmodel.2018.06.029.

Ries, L., Oberhauser, K., 2015. A citizen Army for science: quantifying the contributions of citizen scientists to our understanding of monarch butterfly biology. Bioscience 65, 419–430. https://doi.org/10.1093/biosci/biv011.

Rimbaud, L., Papaïx, J., Barrett, L.G., Burdon, J.J., Thrall, P.H., 2018. Mosaics, mixtures, rotations or pyramiding: what is the optimal strategy to deploy major gene resistance? Evol. Appl. 11, 1791–1810. https://doi.org/10.1111/eva.12681.

Rizzo, D., Marraccini, E., Lardon, S., Rapey, H., Debolini, M., Benoît, M., Thenail, C., 2013. Farming systems designing landscapes: land management units at the interface between agronomy and geography. Geogr. Tidsskr.-Dan. J. Geogr. 113, 71–86. https://doi.org/10.1080/00167223.2013.849391.

Rodríguez Eugenio, N., McLaughlin, M.J., Pennock, D.J., 2018. Soil Pollution: A Hidden Reality. FAO, Rome, p. 142.

Roques, L., Bonnefon, O., 2016. Modelling population dynamics in realistic landscapes with linear elements: a mechanistic-statistical reaction-diffusion approach. PLoS One 11, e0151217. https://doi.org/10.1371/journal.pone.0151217.

Rossi, J.-P., Garcia, J., Roques, A., Rousselet, J., 2016. Trees outside forests in agricultural landscapes: spatial distribution and impact on habitat connectivity for forest organisms. Landsc. Ecol. 31, 243–254. https://doi.org/10.1007/s10980-015-0239-8.

Rossing, W.A.H., Zander, P., Josien, E., Groot, J.C.J., Meyer, B.C., Knierim, A., 2007. Integrative modelling approaches for analysis of impact of multifunctional agriculture: a review for France, Germany and the Netherlands. Agric. Ecosyst. Environ. 120, 41–57. https://doi.org/10.1016/j.agee.2006.05.031.

Rudi, G., 2019. Modelling and Analysis of Eco-Hydraulic Services of Ditch and Channel Networks in Mediterranean Agrosystems (in French). Montpellier SupAgro.

Rudi, G., Bailly, J.-S., Belaud, G., Vinatier, F., 2018. Characterization of the long-distance dispersal of Johnsongrass (*Sorghum halepense*) in a vegetated irrigation channel: hydrochorous dispersal of Johnsongrass in a vegetated channel. River Res. Appl. 34, 1219–1228. https://doi.org/10.1002/rra.3356.

Saint-Geours, N., Bailly, J.-S., Grelot, F., Lavergne, C., 2014. Multi-scale spatial sensitivity analysis of a model for economic appraisal of flood risk management policies. Environ. Model. Software 60, 153–166. https://doi.org/10.1016/j.envsoft.2014.06.012.

Saint-Geours, N., Grelot, F., Bailly, J.-S., Lavergne, C., 2015. Ranking sources of uncertainty in flood damage modelling: a case study on the cost-benefit analysis of a flood mitigation project in the Orb Delta, France: ranking sources of uncertainty in flood damage modelling. J. Flood Risk Manage. 8, 161–176. https://doi.org/10.1111/jfr3.12068.

Salliou, N., Vialatte, A., Monteil, C., Barnaud, C., 2019. First use of participatory Bayesian modeling to study habitat management at multiple scales for biological pest control. Agron. Sustain. Dev. 39, 7. https://doi.org/10.1007/s13593-018-0553-z.

Samoy, D., Lambotte, M., Biala, K., Terres, J.M., Paracchini, M.L., 2007. Validation and Improvement of High Nature Value Identification: National Approach in the Walloon Region in Belgium and the Czech Republic (JRC Scientific and Technical Reports). Institute for Environment and Sustainability, Luxembourg.

Sánchez-Bayo, F., Wyckhuys, K.A.G., 2019. Worldwide decline of the entomofauna: a review of its drivers. Biol. Conserv. 232, 8–27. https://doi.org/10.1016/j.biocon.2019.01.020.

Sang, L., Zhang, C., Yang, J., Zhu, D., Yun, W., 2011. Simulation of land use spatial pattern of towns and villages based on CA–Markov model. Math. Comput. Model. 54, 938–943. https://doi.org/10.1016/j.mcm.2010.11.019.

Sanz Sanz, E., Napoleone, C., Hubert, B., 2016. Peri-urban farmland characterisation. A methodological proposal for urban planning. In: Sustainable Urban Agriculture and Food Planning. Taylor and Francis Group, London, pp. 73–90.

Sanz Sanz, E., Napoléone, C., Hubert, B., 2017. A systemic methodology to characterize peri-urban agriculture for a better integrationn of agricultural stakes in urban planning. Espace Géogr. 46, 174. https://doi.org/10.3917/eg.462.0174.

Sanz Sanz, E., Martinetti, D., Napoléone, C., 2018. Operational modelling of peri-urban farmland for public action in Mediterranean context. Land Use Policy 75, 757–771. https://doi.org/10.1016/j.landusepol.2018.04.003.

Sattler, T., Duelli, P., Obrist, M.K., Arlettaz, R., Moretti, M., 2010. Response of arthropod species richness and functional groups to urban habitat structure and management. Landsc. Ecol. 25, 941–954. https://doi.org/10.1007/s10980-010-9473-2.

Saura, S., Martínez-Millán, J., 2000. Landscape patterns simulation with a modified random cluster method. Landsc. Ecol. 15, 661–678. https://doi.org/10.1023/A:1008107902848.

Sausse, C., Le Bail, M., Lecroart, B., Remy, B., Messéan, A., 2013. How to manage the coexistence between genetically modified and conventional crops in grain and oilseed collection areas? Elaboration of scenarios using role playing games. Land Use Policy 30, 719–729. https://doi.org/10.1016/j.landusepol.2012.05.018.

Schulte, L.A., Niemi, J., Helmers, M.J., Liebman, M., Arbuckle, J.G., James, D.E., Kolka, R.K., O'Neal, M.E., Tomer, M.D., Tyndall, J.C., Asbjornsen, H., Drobney, P., Neal, J., Van Ryswyk, G., Witte, C., 2017. Prairie strips improve biodiversity and the delivery of multiple ecosystem services from corn–soybean croplands. Proc. Natl. Acad. Sci. U. S. A. 114, 11247–11252. https://doi.org/10.1073/pnas.1620229114.

Seibold, S., Gossner, M.M., Simons, N.K., Blüthgen, N., Müller, J., Ambarlı, D., Ammer, C., Bauhus, J., Fischer, M., Habel, J.C., Linsenmair, K.E., Nauss, T., Penone, C., Prati, D., Schall, P., Schulze, E.-D., Vogt, J., Wöllauer, S., Weisser, W.W., 2019. Arthropod decline in grasslands and forests is associated with landscape-level drivers. Nature 574, 671–674. https://doi.org/10.1038/s41586-019-1684-3.

Serra, P., Pons, X., Saurí, D., 2008. Land-cover and land-use change in a Mediterranean landscape: a spatial analysis of driving forces integrating biophysical and human factors. Appl. Geogr. 28, 189–209. https://doi.org/10.1016/j.apgeog.2008.02.001.

Silveira, J.J., Espíndola, A.L., Penna, T.J.P., 2006. Agent-based model to rural–urban migration analysis. Phys. Stat. Mech. Appl. 364, 445–456. https://doi.org/10.1016/j.physa.2005.08.055.

Simon, C., Etienne, M., 2010. A companion modelling approach applied to forest management planning. Environ. Model. Software 25, 1371–1384. https://doi.org/10.1016/j.envsoft.2009.09.004.

Sinclair, R., 1967. Von Thünen and urban sprawl. Ann. Assoc. Am. Geogr. 57, 72–87. https://doi.org/10.1111/j.1467-8306.1967.tb00591.x.

Singh, V.P., Woolhiser, D.A., 2002. Mathematical modeling of watershed hydrology. J. Hydrol. Eng. 7, 270–292. https://doi.org/10.1061/(ASCE)1084-0699(2002)7:4(270).

Sirami, C., Gross, N., Baillod, A.B., Bertrand, C., Carrié, R., Hass, A., Henckel, L., Miguet, P., Vuillot, C., Alignier, A., Girard, J., Batáry, P., Clough, Y., Violle, C., Giralt, D., Bota, G., Badenhausser, I., Lefebvre, G., Gauffre, B., Vialatte, A., Calatayud, F., Gil-Tena, A., Tischendorf, L., Mitchell, S., Lindsay, K., Georges, R., Hilaire, S., Recasens, J., Solé-Senan, X.O., Robleño, I., Bosch, J., Barrientos, J.A., Ricarte, A., Marcos-Garcia, M.Á., Miñano, J., Mathevet, R., Gibon, A., Baudry, J., Balent, G., Poulin, B., Burel, F., Tscharntke, T., Bretagnolle, V., Siriwardena, G., Ouin, A., Brotons, L., Martin, J.-L., Fahrig, L., 2019. Increasing crop heterogeneity enhances multitrophic diversity across agricultural regions. Proc. Natl. Acad. Sci. U. S. A. 116, 16442–16447. https://doi.org/10.1073/pnas.1906419116.

Skrimizea, E., Lecuyer, L., Bunnefeld, N., Butler, J.R.A., Fickel, T., Hodgson, I., Holtkamp, C., Marzano, M., Parra, C., Pereira, L., Petit, S., Pound, D., Rodríguez, I., Ryan, P., Staffler, J., Vanbergen, A.J., Van den Broeck, P., Wittmer, H., Young, J.C., 2020. Sustainable agriculture: recognizing the potential of conflict as a positive driver for transformative change. In: Advances in Ecological Research. Elsevier, pp. 255–311. https://doi.org/10.1016/bs.aecr.2020.08.003.

Slone, D.H., 2011. Increasing accuracy of dispersal kernels in grid-based population models. Ecol. Model. 222, 573–579. https://doi.org/10.1016/j.ecolmodel.2010.11.023.

Soubeyrand, S., Roques, L., 2014. Parameter estimation for reaction-diffusion models of biological invasions. Popul. Ecol. 56, 427–434. https://doi.org/10.1007/s10144-013-0415-0.

Souchère, V., Millair, L., Echeverria, J., Bousquet, F., Le Page, C., Etienne, M., 2010. Co-constructing with stakeholders a role-playing game to initiate collective management of erosive runoff risks at the watershed scale. Environ. Model. Software 25, 1359–1370. https://doi.org/10.1016/j.envsoft.2009.03.002.

Specht, K., Siebert, R., Hartmann, I., Freisinger, U.B., Sawicka, M., Werner, A., Thomaier, S., Henckel, D., Walk, H., Dierich, A., 2014. Urban agriculture of the future: an overview of sustainability aspects of food production in and on buildings. Agric. Hum. Values 31, 33–51. https://doi.org/10.1007/s10460-013-9448-4.

Spooner, F.E.B., Pearson, R.G., Freeman, R., 2018. Rapid warming is associated with population decline among terrestrial birds and mammals globally. Glob. Chang. Biol. 24, 4521–4531. https://doi.org/10.1111/gcb.14361.

Steenweg, R., Hebblewhite, M., Kays, R., Ahumada, J., Fisher, J.T., Burton, C., Townsend, S.E., Carbone, C., Rowcliffe, J.M., Whittington, J., Brodie, J., Royle, J.A., Switalski, A., Clevenger, A.P., Heim, N., Rich, L.N., 2017. Scaling-up camera traps: monitoring the planet's biodiversity with networks of remote sensors. Front. Ecol. Environ. 15, 26–34. https://doi.org/10.1002/fee.1448.

Straubhaar, J., Renard, P., Mariethoz, G., Froidevaux, R., Besson, O., 2011. An improved parallel multiple-point algorithm using a list approach. Math. Geosci. 43, 305–328. https://doi.org/10.1007/s11004-011-9328-7.

Sullivan, C.A., Bourke, D., Skeffington, M.S., Finn, J.A., Green, S., Kelly, S., Gormally, M.J., 2011. Modelling semi-natural habitat area on lowland farms in western Ireland. Biol. Conserv. 144, 1089–1099. https://doi.org/10.1016/j.biocon.2010.12.028.

Tenaillon, O., 2014. The utility of Fisher's geometric model in evolutionary genetics. Annu. Rev. Ecol. Evol. Syst. 45, 179–201. https://doi.org/10.1146/annurev-ecolsys-120213-091846.

Thapa, R.B., Murayama, Y., 2008. Land evaluation for peri-urban agriculture using analytical hierarchical process and geographic information system techniques: a case study of Hanoi. Land Use Policy 25, 225–239. https://doi.org/10.1016/j.landusepol.2007.06.004.

Thies, C., Tscharntke, T., 1999. Landscape structure and biological control in agroecosystems. Science 285, 893–895.

Tieskens, K.F., Shaw, B.J., Haer, T., Schulp, C.J.E., Verburg, P.H., 2017. Cultural landscapes of the future: using agent-based modeling to discuss and develop the use and management of the cultural landscape of south West Devon. Landsc. Ecol. 32, 2113–2132. https://doi.org/10.1007/s10980-017-0502-2.

Tilman, D., 1999. Global environmental impacts of agricultural expansion: the need for sustainable and efficient practices. Proc. Natl. Acad. Sci. U. S. A. 96, 5995–6000. https://doi.org/10.1073/pnas.96.11.5995.

Tilman, D., 2001. Forecasting agriculturally driven global environmental change. Science 292, 281–284. https://doi.org/10.1126/science.1057544.

Tixier, P., Peyrard, N., Aubertot, J.-N., Gaba, S., Radoszycki, J., Caron-Lormier, G., Vinatier, F., Mollot, G., Sabbadin, R., 2013. Modelling interaction networks for enhanced ecosystem Services in Agroecosystems. In: Advances in Ecological Research. Elsevier, pp. 437–480. https://doi.org/10.1016/B978-0-12-420002-9.00007-X.

Todman, L.C., Coleman, K., Milne, A.E., Gil, J.D.B., Reidsma, P., Schwoob, M.-H., Treyer, S., Whitmore, A.P., 2019. Multi-objective optimization as a tool to identify possibilities for future agricultural landscapes. Sci. Total Environ. 687, 535–545. https://doi.org/10.1016/j.scitotenv.2019.06.070.

Topping, C.J., Odderskær, P., Kahlert, J., 2013. Modelling skylarks (Alauda arvensis) to predict impacts of changes in land management and policy: development and testing of an agent-based model. PLoS One 8, e65803. https://doi.org/10.1371/journal.pone.0065803.

Tresson, P., Tixier, P., Puech, W., Bagny Beilhe, L., Roudine, S., Pagès, C., Carval, D., 2019. CORIGAN: assessing multiple species and interactions within images. Methods Ecol. Evol. 10, 1888–1893. https://doi.org/10.1111/2041-210X.13281.

Tscharntke, T., Clough, Y., Bhagwat, S.A., Buchori, D., Faust, H., Hertel, D., Hölscher, D., Juhrbandt, J., Kessler, M., Perfecto, I., Scherber, C., Schroth, G., Veldkamp, E., Wanger, T.C., 2011. Multifunctional shade-tree management in tropical agroforestry landscapes—a review: multifunctional shade-tree management. J. Appl. Ecol. 48, 619–629. https://doi.org/10.1111/j.1365-2664.2010.01939.x.

Tscharntke, T., Tylianakis, J.M., Rand, T.A., Didham, R.K., Fahrig, L., Batáry, P., Bengtsson, J., Clough, Y., Crist, T.O., Dormann, C.F., Ewers, R.M., Fründ, J., Holt, R.D., Holzschuh, A., Klein, A.M., Kleijn, D., Kremen, C., Landis, D.A., Laurance, W., Lindenmayer, D., Scherber, C., Sodhi, N., Steffan-Dewenter, I., Thies, C., van der Putten, W.H., Westphal, C., 2012. Landscape moderation of biodiversity patterns and processes—eight hypotheses. Biol. Rev. 87, 661–685. https://doi.org/10.1111/j.1469-185X.2011.00216.x.

Tsiafouli, M.A., Thébault, E., Sgardelis, S.P., de Ruiter, P.C., van der Putten, W.H., Birkhofer, K., Hemerik, L., de Vries, F.T., Bardgett, R.D., Brady, M.V., Bjornlund, L., Jørgensen, H.B., Christensen, S., Hertefeldt, T.D., Hotes, S., Gera Hol, W.H., Frouz, J., Liiri, M., Mortimer, S.R., Setälä, H., Tzanopoulos, J., Uteseny, K., Pižl, V., Stary, J., Wolters, V., Hedlund, K., 2015. Intensive agriculture reduces soil biodiversity across Europe. Glob. Chang. Biol. 21, 973–985. https://doi.org/10.1111/gcb.12752.

Tulloch, A.I.T., Possingham, H.P., Joseph, L.N., Szabo, J., Martin, T.G., 2013. Realising the full potential of citizen science monitoring programs. Biol. Conserv. 165, 128–138. https://doi.org/10.1016/j.biocon.2013.05.025.

Urban, D., Keitt, T., 2001. Landscape connectivity: a graph-theoretic perspective. Ecology 82, 1205–1218. https://doi.org/10.1890/0012-9658(2001)082[1205:LCAGTP]2.0.CO;2.

Van Lieshout, M.N.M., 2019. Theory of Spatial Statistics: A Concise Introduction. CRC Press, Boca Raton, Florida.

van Strien, M.J., Slager, C.T.J., de Vries, B., Grêt-Regamey, A., 2016. An improved neutral landscape model for recreating real landscapes and generating landscape series for spatial ecological simulations. Ecol. Evol. 6, 3808–3821. https://doi.org/10.1002/ece3.2145.

Verburg, P.H., Overmars, K.P., 2009. Combining top-down and bottom-up dynamics in land use modeling: exploring the future of abandoned farmlands in Europe with the dyna-CLUE model. Landsc. Ecol. 24, 1167–1181. https://doi.org/10.1007/s10980-009-9355-7.

Verburg, P.H., van Berkel, D.B., van Doorn, A.M., van Eupen, M., van den Heiligenberg, H.A.R.M., 2010. Trajectories of land use change in Europe: a model-based exploration of rural futures. Landsc. Ecol. 25, 217–232. https://doi.org/10.1007/s10980-009-9347-7.

Verburg, P.H., Dearing, J.A., Dyke, J.G., van der Leeuw, S., Seitzinger, S., Steffen, W., Syvitski, J., 2016. Methods and approaches to modelling the Anthropocene. Glob. Environ. Chang. 39, 328–340. https://doi.org/10.1016/j.gloenvcha.2015.08.007.

Vinatier, F., Chauvet, M., 2017. A neutral model for the simulation of linear networks in territories. Ecol. Model. 363, 8–16. https://doi.org/10.1016/j.ecolmodel.2017.08.022.

Vinatier, F., Tixier, P., Duyck, P.F., Lescourret, F., 2011. Factors and mechanisms explaining spatial heterogeneity: a review of methods for insect populations. Methods Ecol. Evol. 2, 11–22.

Vinatier, F., Gosme, M., Valantin-Morison, M., 2013. Explaining host–parasitoid interactions at the landscape scale: a new approach for calibration and sensitivity analysis of complex spatio-temporal models. Landsc. Ecol. 28, 217–231. https://doi.org/10.1007/s10980-012-9822-4.

Vinatier, F., Lagacherie, P., Voltz, M., Petit, S., Lavigne, C., Brunet, Y., Lescourret, F., 2016. An unified framework to integrate biotic, abiotic processes and human activities in spatially explicit models of agricultural landscapes. Front. Environ. Sci. 4. https://doi.org/10.3389/fenvs.2016.00006.

Vinatier, F., Bailly, J.-S., Belaud, G., 2017. From 3*D* grassy vegetation point cloud to hydraulic resistance: application to close-range estimation of Manning coefficients for intermittent open channels. Ecohydrology 10, e1885. https://doi.org/10.1002/eco.1885.

Vinatier, F., Dollinger, J., Rudi, G., Feurer, D., Belaud, G., Bailly, J.-S., 2018. The use of photogrammetry to construct time series of vegetation permeability to water and seed transport in agricultural waterways. Remote Sens. (Basel) 10, 2050. https://doi.org/10.3390/rs10122050.

Violle, C., Navas, M.-L., Vile, D., Kazakou, E., Fortunel, C., Hummel, I., Garnier, E., 2007. Let the concept of trait be functional! Oikos 116, 882–892. https://doi.org/10.1111/j.0030-1299.2007.15559.x.

Vitousek, P.M., 1997. Human domination of Earth's ecosystems. Science 277, 494–499. https://doi.org/10.1126/science.277.5325.494.

Vogel, G., 2017. Where have all the insects gone? Science 356, 576–579. https://doi.org/10.1126/science.356.6338.576.

Voinov, A., Bousquet, F., 2010. Modelling with stakeholders. Environ. Model. Software 25, 1268–1281. https://doi.org/10.1016/j.envsoft.2010.03.007.

Voinov, A., Kolagani, N., McCall, M.K., Glynn, P.D., Kragt, M.E., Ostermann, F.O., Pierce, S.A., Ramu, P., 2016. Modelling with stakeholders—next generation. Environ. Model. Software 77, 196–220. https://doi.org/10.1016/j.envsoft.2015.11.016.

Von Thünen, J.H., 1826. Von Thünen's Isolated State. Pergamon Press, Glasgow.

Walangitan, H.D., Setiawan, B., Tri Raharjo, B., Polii, B., 2012. Optimization of land use and allocation to ensure sustainable agriculture in the catchment area of Lake Tondano, Minahasa, North Sulawesi, Indonesia. Int. J. Civ. Env. Eng. 12, 68–75. IJCEE-IJENS.

Wäldchen, J., Mäder, P., 2018. Machine learning for image based species identification. Methods Ecol. Evol. 9, 2216–2225. https://doi.org/10.1111/2041-210X.13075.

Warren, B.H., Simberloff, D., Ricklefs, R.E., Aguilée, R., Condamine, F.L., Gravel, D., Morlon, H., Mouquet, N., Rosindell, J., Casquet, J., Conti, E., Cornuault, J., Fernández-Palacios, J.M., Hengl, T., Norder, S.J., Rijsdijk, K.F., Sanmartín, I., Strasberg, D., Triantis, K.A., Valente, L.M., Whittaker, R.J., Gillespie, R.G., Emerson, B.C., Thébaud, C., 2015. Islands as model systems in ecology and evolution: prospects fifty years after MacArthur-Wilson. Ecol. Lett. 18, 200–217. https://doi.org/10.1111/ele.12398.

Weimerskirch, H., Shaffer, S., Tremblay, Y., Costa, D., Gadenne, H., Kato, A., Ropert-Coudert, Y., Sato, K., Aurioles, D., 2009. Species- and sex-specific differences in foraging behaviour and foraging zones in blue-footed and brown boobies in the Gulf of California. Mar. Ecol. Prog. Ser. 391, 267–278. https://doi.org/10.3354/meps07981.

Wiens, J.A., Stenseth, N.C., Horne, B.V., Ims, R.A., 1993. Ecological mechanisms and landscape ecology. Oikos 66, 369. https://doi.org/10.2307/3544931.

With, K.A., 2019. Essentials of Landscape Ecology, first ed. Oxford University Press. https://doi.org/10.1093/oso/9780198838388.001.0001.

World Bank, 2020. Urban development. [WWW Document]. URL https://www.worldbank.org/en/topic/urbandevelopment/overview. (accessed 9.1.20).

Xiao, Y., Mignolet, C., Mari, J.-F., Benoît, M., 2014. Modeling the spatial distribution of crop sequences at a large regional scale using land-cover survey data: a case from France. Comput. Electron. Agric. 102, 51–63. https://doi.org/10.1016/j.compag.2014.01.010.

Zabel, F., Delzeit, R., Schneider, J.M., Seppelt, R., Mauser, W., Václavík, T., 2019. Global impacts of future cropland expansion and intensification on agricultural markets and biodiversity. Nat. Commun. 10, 2844. https://doi.org/10.1038/s41467-019-10775-z.

Zamberletti, P., Papaïx, J., Gabriel, E., Opitz, T., 2020. Landscape Allocation: Stochastic Generators and Statistical Inference. arXiv:2003.02155 Q-Bio Stat.

Zander, P., Groot, J.C.J., Josien, E., Karpinski, I., Knierim, A., Meyer, B.C., Madureira, L., Rambonilaza, M., Rossing, W.A.H., 2008. Farm models and economic valuation in the context of multifunctionality: a review of approaches from France, Germany, the Netherlands and Portugal. Int. J. Agric. Resour. Gov. Ecol. 7, 339. https://doi.org/10.1504/IJARGE.2008.020084.

Zasada, I., Loibl, W., Köstl, M., Piorr, A., 2013. Agriculture under human influence: a spatial analysis of farming systems and land use in European rural-Urban-regions. Eur. Countrys. 5 (1), 71–88. https://doi.org/10.2478/euco-2013-0005.