How can models foster the transition towards future agricultural landscapes?

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Abstract (245 words)

Modern agriculture faces the twofold challenge 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 to shift towards sustainable, complex and resilient agroecosystems. Modelling is a powerful tool to address these issues since it can inform necessary transformations by simulating the multiscale ecological flows and myriad interactions agroecosystems host as well as multilevel landscape stakeholders' actions and relevant feedbacks. This chapter gives insight on how models can provide guidance on the transition towards future multifunctional agricultural landscapes. We focused on process-based models, which allow for a more thorough comprehension of underlying mechanisms at stake, with the perspective of their beneficial manipulation. We first examined how models can simulate the structure and the dynamics of agricultural landscapes, emphasising the complex mosaic of urban, peri-urban, rural and semi-natural habitats. Then we considered the simulation of biotic and abiotic flows and their complex interactions in such a mosaic of intermingling, contrasted habitats. From the perspective of social sciences, we exemplified contrasted formalisms to integrate human decision-making and actions in landscape models, thereby encompassing a major component in the landscape transformation processes. Finally, we outlined some avenues for future research. We notably focused on expected improvements in landscape representation, and suggested ways to bridge the gap between landscape conception and manipulation, hence providing operational guidance for the transition towards future agricultural landscapes that achieve objectives mentioned above.

1. Introduction

Earth faces changes at an unprecedented pace

Our planet has faced changes at an unparalleled pace over the past three centuries. The impact of humans now competes with natural forces that drive the planet 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 relying on fossil energy, humans have profoundly transformed landscapes worldwide, and inevitably altered the ecological flows and myriad ecological interactions they host (With, 2019). In this context, landscape-scale models are useful tools as they enlighten our knowledge at spatial scales (typically 1 to 1000 km²) at which many ecological processes and linkages are manifest and at which most management decisions have to be made (Keane et al., 2015). Population growth – from 690 million in 1750 to 7.8 billion in 2020 – and urbanisation have resulted in the expansion of cities into the surrounding rural areas and the homogenisation of agricultural landscapes. Concomitantly, intensive 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) contributed to landscape simplification. Such changes have taken up 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 alert on the dramatic decline in biodiversity, species richness and abundance, e.g. birds and mammals (Hallmann et al., 2014; Spooner et al., 2018) or entomofauna (Hallmann et al., 2017; Seibold et al., 2019; Vogel, 2017). Recently, Sánchez-Bayo and Wyckhuys (2019) assessed the main drivers of species declines, which are in order of importance: habitat loss and conversion to intensive agriculture and urbanisation; pollution, mainly that by synthetic pesticides and fertilisers; biological factors, including pathogens and introduced species; and climate change. Additionally, in 2050, agriculture will need to produce 50% more food than in 2012 to meet the need of around 9.73 billion people (Armanda et al., 2019; FAO, 2018).

All these signals urge to alter the systems responsible for this situation, among which farming systems figure prominently since they are held 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 modification is multifaceted since it concerns production systems, socio-economic organisation of labour, crop selection and agricultural practices, but also global diets and food waste.

Reorganising farming areas towards a sustainable agriculture

Today, some 55% of the world's population lives in urban areas, with a global trend towards rising. By 2050, with the urban population more than doubling its current size, nearly 7 of 10 people in the world will live in cities (World Bank, 2020). Concomitantly, rural agricultural land abandonment is the most frequent driver of landscape change in many regions of the world (Plieninger et al., 2016). City regions are thus challenged to plan and design their development in order to deliver green, inclusive, competitive and resilient services including food supply. Furthermore, in Europe, the dichotomy between rural and urban landscapes has lost its relevance since areas classified as peri-urban and characterised by complex landscapes are growing four times faster than urban areas, at a rate which, if continued, would double their area in around 40 years (Piorr et al., 2011). Exhibiting higher structural complexity, future peri-urban landscapes will form mosaics where agricultural, urban and semi-natural habitats intermingle. Maintaining peri-urban agriculture is an essential strategy in ensuring food security and mitigating climate change. This calls for a rethinking of food systems in a farm-to-fork approach going from the farming systems to the consumption modes. Models can foster the transition towards future sustainable complex landscapes by highlighting food production capacity depending on the context of biotic/abiotic/anthropogenic interactions due to local heterogeneities and landscape structure (Tscharntke et al., 2005). This is the issue at stake for supporting the design of new farming systems adapted to local conditions (Duru et al., 2015).

Furthermore, in rural and peri-urban landscapes, semi-natural habitats (composed by hedgerows, ditches and irrigation channels, ponds, grass strips, natural or artificial wetlands, etc.) are of great importance because they are implied in many 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., 2015a; Le Cœur et al., 2002; Power, 2010). Supporting these ecosystem services represents an opportunity to reduce the dependence to agricultural inputs (fertilizers, pesticides, irrigation water, etc.). Favouring diversity in agricultural landscapes is also a condition for the development of biodiversity-based agriculture and functional complementarities between species (Caron et al., 2014), as well as resilience of ecosystems (Chapin III et al., 2000).
Regarding the future of farming, many recent researches pinpoint the importance of considering ecological scales in farming systems (Altieri ad Nicholls, 2012). This direction implies an upscale of the decision and organisation of management practices from the plot or farm levels to the landscape level (Elzen et al., 2012). But whereas the plot and the farm levels are driven by individual decision making in the hand of farmers, managing the landscape is a challenge since it involves a collective decision-making process in the hand of interdependent stakeholders including non-farmers. From a holistic perspective, the landscape can be considered as a system whose properties emerge from its components (e.g. farms). Clearly, organisational, regulatory and technical innovations are needed to make agricultural landscapes more manageable (Hannachi and Martinet, 2019).

Modelling as a central tool to help design future agricultural landscapes

Designing future landscapes with higher complexity, resilience and manageability, requires guidance. Necessary transformations cannot be informed by experiments only, given the system complexity, the scales at stake and the multiple objectives to satisfy. Indeed, examples of projects of agricultural landscape redesign are scarce (Geertsema et al., 2016; Kremen and Merenlender, 2018; Schulte et al., 2017).
Conversely, a wide variety of models is invaluable to get insight on how to guide the transformation of farming systems (Nendel and Zander, 2019) and the associated 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 help predicting the effects of environmental changes on species and ecosystems. Combining models that capture feedbacks between biophysical and socio-economic drivers of land-use change as well as interactions with biodiversity on one hand, and a model of the world economy makes 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 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, multi-objective 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. Using models allows exploring a set of scenarios as a way to cope with uncertainty. By incorporating increase amount of knowledge from various disciplines (physics, chemistry, biology, ecology, economy, sociology, etc.), as well as by coupling components, and considering interactions and feedbacks, models highly contribute to handle complexity. Agricultural landscape models tackle these issues. By providing tools to help understanding and simulate the landscape functioning, they may efficiently inform decision-makers on possible trajectories towards objectives and search options set by the ‘society’. Building reliable tools requires to better couple landscape patterns and process models and account for feedbacks, integrate the decisions of multiple stakeholders, consider the spatial and temporal heterogeneity of data and processes, explore alternative landscape organisations and assess multi-objective performance (Poggi et al., 2018). Myriad of technical issues arises: uncertainty evaluation, model parameter inference, data assimilation, etc. In this paper, we give insight on added value, current development and limitations of such models to provide guidance on the transition towards future desired landscapes.

As much as possible, we focused on process-based models, which allow for a more thorough comprehension of underlying processes at stake, with the perspective of their beneficial manipulation.

Chapter content

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 these evolutions. As previously mentioned, 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, flow models. In section 4, we show how models can generate usable and transformative knowledge for the design of future agricultural landscapes. We attempt to address this issue through social sciences insights about the modelling in some disciplines (e.g. economy, geography), in interdisciplinary modelling (notably between social and natural sciences), and in transdisciplinary modelling (i.e. participatory modelling involving scientists and practitioners). In section 5, we suggest some avenues for future research, identifying needs regarding the multiscale and multilevel representation of agricultural landscapes, as well as their conception (answering the question “which landscape is optimal or suboptimal with respect to given criteria?”) and their manipulation (answering the question “how to operate changes leading to a target landscape?”). Section 6 concludes this chapter.

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

The structure of a given landscape results from cumulative past changes (legacy effect) driven by multi-scale driving forces (Houet et al., 2010). Given current trends, we assume that future landscapes will be more complex, with a strong intermingling between agricultural, semi-natural and urban habitats. Thus, methods and tools that enable to simulate the imbrication between these three types of land cover are of major importance. In this section, we first introduce the way to model the structure and dynamics of agricultural landscapes. We briefly review how to model urban expansion, then focus on peri-urban areas which will become more important with the increasing intermingling between agricultural and urban land uses, and discuss the inclusion of agriculture in cities. Finally, we place the semi-natural habitats as major landscape components, recalling their impact on many ecological and physical processes, and emphasizing the caution with which they should be modelled.

2.1. Current approaches to represent the agricultural landscape structure

Agricultural landscape models describe landscapes as complex 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, i.e. the raster and the vector modes, to model such mosaics, depending on the main goal of the study and how their constitutive units are handled (Bonhomme et al., 2017; Gaucherel et al., 2006b).

Most of the existing models work with raster mode and 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 discretized by a grid, where each grid cell represents the smallest elementary unit containing information about that portion 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, that allowed varying the landscape configuration and composition. The raster-based (or grid-based) approach is particularly suited for modelling gradual landscape dynamics and continuous processes, due to the regular structure of the grid facilitating the operations between contiguous cells.
However agricultural landscapes display a patchy structure made of contiguous polygons delineated with rectilinear boundaries, some polygons having fringe structures such as hedgerows on their borders (Gaucherel, 2008), making the vector-based approach appealing (Gaucherel et al., 2006a, 2006b; Inkoom et al., 2017; Langhammer et al., 2019; Le Ber et al., 2009; Papaïx et al., 2014). For example, Gaucherel et al. (2006a, 2006b) developed a model that simulates the patches and fringe structures. Le Ber et al. (2009) simulated agricultural landscapes defined by two different tessellation methods (Voronoi and rectangular) and two types of cropping pattern distributions (random or stochastic). Papaïx et al. (2014) developed a simple landscape generator that generates the landscape mosaic based on a T-tessellation algorithm developed by Kiêu et al. (2013). Tessellation models have the advantage to be parametric meaning that a set of parameters control the main features of the simulated landscapes. In addition, these models are stochastic thereby producing collections of virtual landscapes with similar landscape metrics (Papaïx et al., 2014). This allows to test for the robustness of the results to the residual landscape variability as landscape metrics are not exhaustive statistics. 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 provide realistic landscape patterns. Combining parametric with nonparametric approaches may enable to bridge this gap (Straubhaar et al., 2011).

2.2. Spread of land uses mixing agricultural and urban covers

As mentioned in the chapter introduction, urban expansion is acknowledged as a global trend (World Bank, 2020). Moreover, in Europe, peri-urban areas characterized by complex landscapes mixing agricultural and urban covers are rapidly growing. Such a context calls for considering the constraints and opportunities offered by urban and peri-urban settings when thinking future agricultural landscapes. This is the purpose of this subsection.

Simulating urban expansion
The simulation of urban land uses in agricultural landscapes relies on 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 first simulated using a cellular automaton (CA) coupled with a geographical information system (GIS) (Couclelis, 1997) to define the neighbourhood effects of various land uses. Then, the temporal dynamics were combined to the CA model using Markovian models, i.e. stochastic process models that describe how one state is likely to change to another state, given the transition probabilities between actual and future land use maps (Sang et al., 2011). According to Guan et al. (2011), the Markov-CA model provides the most suitable approach to study the temporal and spatial changes of land uses.
In the last twenty years, the expansion of urban land uses has been addressed using a variety of models: 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 one hectare to one square kilometre. Main challenges consist in taking account of environmental, spatially explicit variables that constrain urban expansion in space (Figure 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 a large number of land uses and new ones, and the specificities of the transition zone between dense urban and rural areas, namely the peri-urban zone, treated thereafter.

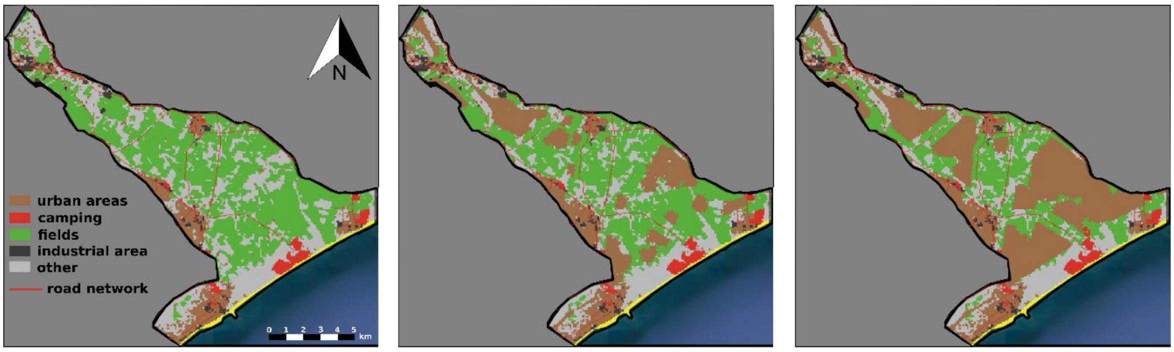

Figure 1: Illustration of urban expansion (from left to right) in a river delta flowing into the Mediterranean Sea, as modelled with a cellular automaton using the NetLogo® platform. The urban areas (brown areas) are constrained by the distance to the road network (red lines) and the distance to the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

Modelling agriculture in complex peri-urban landscapes

Beyond the controversies about the uses of the term peri-urban regarding to its precise location, spatial extent and absent boundaries (Friedmann, 2016), peri-urban agriculture has been defined from a geographical perspective as the farming performed in a defined space close to towns (FAO, 1999). A growing literature characterises the dynamics of rural-urban areas using process-based models but they rarely focus on farming in peri-urban landscapes (Silveira et al., 2006). Statistical approaches applied at the patch scale assess the transition probabilities of the cells from a land-use category to another and notably the impact of urbanisation in the land-use structure of peri-urban areas. For instance, 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 distance from city-centres, in a gradient inspired by the classical Von Thünen's conceptual model (Sinclair, 1967; Von Thünen, 1826). This approach has been used in an agent-based simulation model to generate a wide range of agricultural landscapes, including those of Von Thünen, in a theoretical agricultural society in which agents live in a single settlement and use the surrounding area to produce essential and non-essential goods (Macmillan and Huang, 2008). But distance to a main urban settlement on its own is not enough to characterize agriculture in complex and multi-polarised peri-urban landscapes, which are diverse, plural and dynamic (Sanz Sanz et al., 2017, 2016). Farming systems spatially 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" (i.e. particular spatial structures whose arrangement is identifiable in space resulting in a set of common characteristics, for instance crop plot shape, location of farmstead, border relation between farming and urban zones, etc.). On this basis, agriculture in complex peri-urban areas have recently been modelled by social scientists for the purpose of landscape planning and policy-making by using simple-to-handle 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 NUTS-3 level (**Box 1**).

< Box 1 >

An alternative approach proposed by urban economists in small study areas is to implement accurate peri-urban farm econometric location models based on exhaustive databases at the plot scale and complex mathematical tools. For instance, Geniaux et al. (2011) developed a spatialized hedonic model to estimate land-use change anticipation using Mixed Geographically Weighted Regression (MGWR) techniques with a two-stage model that links agricultural and developable land markets.

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), is considered as the second green revolution (Armanda et al., 2019) that should arise in the future. Despite being studied in many developing countries across the world (Armanda et al., 2019; Dossa et al., 2011; Mawois et al., 2012), intra-urban agriculture suffers from a lack of modelling framework for implementing its spatiotemporal dynamics. This fact is undoubtedly linked to a divergence of spatial scales in land use change models (LUCC) between intra-urban agriculture and traditional agriculture. The intra-urban agriculture acts at a local scale in space-confined cities, sometimes on vertically inclined surfaces such as building walls (Specht et al., 2014). Intra-urban crops are based on short cycles and with wide crop diversity (Mawois et al., 2012).
Nevertheless, the step is almost taken to simulate the spatial allocation of urban agriculture and its temporal dynamics, according to the formalisms presented below. In fact, we could 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 latter model estimates the surface area of each leafy vegetable that depends on plant specificities, amount of resources in the farm, and the sales channel of the 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 semi-natural habitats

Semi-natural habitats have the potential to promote a bundle 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., 2015b). The structure of semi-natural habitats embedded in landscapes dominated by agricultural lands can be highly variable with wild and cultivated elements almost undistinguishable and highly intricately intermeshed such as in tropical agroforestry landscapes (Tscharntke et al., 2011) or strongly separated such as in intensive monoculture landscapes. Even in the latter case, the area and spatial distribution of remnant wildlands can vary greatly (Figure 2).
An enhanced diversity of land cover types, stemming from the inclusion of non-crop and non-managed 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 contrasts between patches affect organism movements and the colonization of neighbouring patches (Perović et al., 2015; Sattler et al., 2010). Moreover, the different land cover types can provide complementary resources along the different stages of an organism's life cycle, thus increasing species diversity and favouring complex trophic network relationships (Dunning et al., 1992; Perović et al., 2015; Tscharntke et al., 2012). Semi-natural habitat cover on farms is generally assessed by national maps to support the planning and implementation of agrienvironmental policies meant for an accurate spatial targeting of biodiversity restoration and preservation (Sullivan et al., 2011). Main approaches

rely on the integration of available datasets, GIS and remote sensing. Remote sensing techniques are often applied being very effective when there is a high contrast between neighbouring habitats, for instance to map scrub on semi-natural 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 semi-natural 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 semi-natural habitats at a regional scale. The main drawbacks of these techniques are 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 by both cultivated and semi-natural patches and their interactions, thereby providing ways to study the relationships between landscape patterns and processes of interest.

Semi-natural habitats distributed as linear corridors following field boundaries (hedgerows or ditches) play a major role because of their important impact on many agroecological processes. However, such fringe structures must be modelled with care due to their low ground coverage and the constraints on the global network they form at the landscape scale. For example, Gaucherel et al. (2006a, 2006b) used models based on Gibbs energy terms to control pairwise interactions between landscape elements and to simulate patches and certain fringe structures. As an alternative, a multilayer network framework can be used to model the interactions between the different geometrical elements of the landscape (**Box 2**). In the previous examples, the fringe structures are constrained by the polygonal meshing of the mosaic of agricultural fields. However, some linear structures hosting natural habitats (e.g. watercourses) are more perennial imposing thus their location to agricultural elements. In that case, Vinatier and Chauvet (2017) developed an interesting framework that they applied to the simulation of road networks. They proposed a hierarchical model based on successive imbrications 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.

< Box 2 >

Spatial-point semi-natural habitats, such as trees, also deserve consideration regarding 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.

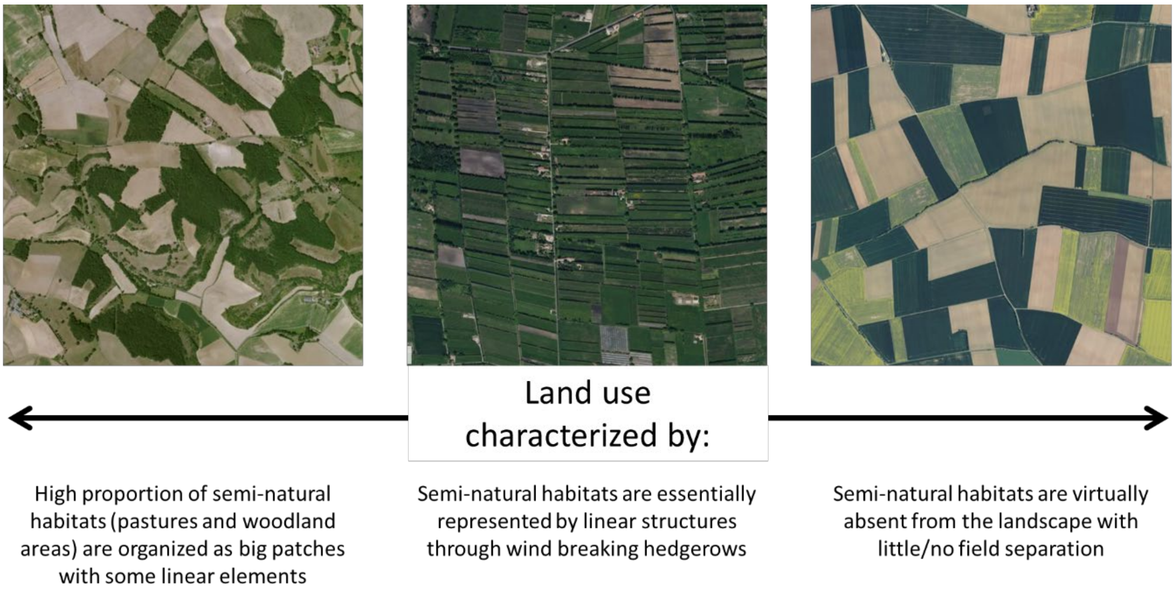

Figure 2: Spatial structure of the agroecological interface across different farming systems. *Source: ©IGN.*

In the future, the debate regarding the notion of aggregation or fragmentation of the semi-natural habitats within territories, i.e. the land-sparing versus land-sharing strategies (Fischer et al., 2008; Mitchell et al., 2015), will certainly remain active. Neutral models as those presented above and those discussed in the section 2.1 may inform the debate. Setting them up considering different constraints may shed light on efficient designs of intermingling configurations of semi-natural habitats in terms of the multifunctionality of agricultural landscapes.

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

In 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 non-cultivated areas (e.g. hedgerows, ditches, ponds, wetlands) at the local or landscape scale (Power, 2010). Interestingly, a better understanding of these interactions may open avenues regarding the deployment of nature-based solutions (Nesshöver et al., 2017; Rey et al., 2015) that 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).
In this section, 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 semi-natural habitats, crops and built areas (see sections 2.2 and 2.3), modelling of spatial flows, e.g. 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, at the scale of an individual such as in random walk models or stochastic differential equations for instance, or at the scale of a population in reaction-diffusion models, but their use in the context of complex environments may involve further developments (see Vinatier et al. (2013) for a review). Fluids, whether water or 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 several scientific disciplines among which ecological, earth and physical sciences. Except in very simple circumstances, modelling approaches are not continuous since there are no general analytical solutions 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 field (e.g. hydraulic conductivity). In the next two paragraphs, 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. For instance, 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) or 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 developing specific models to handle distribution of water inside these infrastructures. For that, the hydrological model MHYDAS (Moussa et al., 2002) and its application to a hydrological network on a hilly landscape opens interesting perspectives. In flatter areas through which linear elements with higher flow rates circulate, e.g. streams or channels, hydraulic models are best suited (Baume et al., 2005; Brunner and Bonner, 1994).

Modelling dispersal of organisms and matters in landscapes comprising agroecological elements with specific geometrical properties (e.g. hedgerows, field borders) needs to be treated cautiously to avoid artefacts, i.e. a misestimation of population densities at the interface between elements. For example, hedgerow networks, which may behave as ecological corridors along which some animal species disperse, but also as barriers, sources or sinks for various organisms, are classically accounted in spatially explicit models by considering position-dependent mobility and reproduction parameters, both at the individual or at the population scale. Depending on various factors such as the size of the population under study or the complexity in individual behaviour that 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 discretised in a regular grid (lattice). When adequate, grid-based population models offer an efficient way to model dispersal because dispersal kernels are easily discretized on a regular, instead of irregular, spatial segmentation (Ricci et al., 2018; Slone, 2011). However, when considering the landscape scale (i.e. a large spatial extent), the limit in the grid spatial resolution makes it difficult to consider elements with low ground coverage, such as linear (e.g. hedgerows or hydrological infrastructures) or point (e.g. trees) 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 in surface and linear elements of the landscape. Indeed, such an approach proves particularly relevant when the presence of a corridor or a barrier (e.g. roads, rivers, hedgerows) may significantly alter the model outcomes. Using the example of the range expansion of *Aedes albopictus* (tiger mosquito) 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 the road network (modelled as 1D corridors with higher diffusion than in the rest of the landscape).

3.2. Simulation of biotic and abiotic interactions in complex landscapes

Simulating biotic-abiotic interrelations requires to handle different scientific disciplines that have independently developed their 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). Within agricultural landscapes, various habitats (e.g. hedgerows, ponds, ditches) are composed of biotic elements (living organisms such as plants, animals, etc.) and abiotic elements (water, air, sediments, nutrients, etc.) in close interaction. Abiotic elements, such as air and water flows, are the physical drivers of the dispersal and growth of living organisms, and vegetation in turn acts as a regulator of water flows, air flows, and matters transported by these flows through diverse mechanisms (for example slowing down of the flow, infiltration, transpiration, physical retention of the matters).

Despite some attempts to unify the biotic and abiotic processes in the same modelling framework (Vinatier et al., 2016), there is still a number of model design, space-time and computational challenges to meet. We highlight these challenges using the functioning of a hydrological man-made network (non-coated 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 whose study relies on a multidisciplinary science such as ecohydrology (Porporato and Rodriguez-Iturbe, 2002). In terms of model design, the simulation of the main abiotic component, i.e. water, that drives the functioning of the hydrographical network, is carried out by privileging 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 view, i.e. a Lagrangian representation. Integrating the biotic component (vegetation) in hydrological infrastructures requires a trait-based approach (Merritt et al., 2010) to consider the whole plant community response to the flows in an aggregated property of the system, instead of considering the aggregation of individual plant-flow interactions. However, such trait-based approach, widely considered in plant community ecology (Violle et al., 2007), is rarely devoted to the specific traits interacting with water flows and requires a large sampling effort for wild plant species found in landscapes.

< Box 3 >

Considering the space-time challenge, dynamics of biotic and abiotic components act at different time scales, thereby requiring to couple short and intense events (e.g. rainfall events and runoff) to more continuous processes (e.g. plant community selection and growth). Keeping in the disciplines of ecology and hydrology, there is a wide range of models susceptible to simulate rainfall and runoff events (see Moradkhani and Sorooshian (2008) for a review), and also a high diversity of models simulating weed community dynamics in agricultural landscapes (see for example Duru et al. (2009); Gardarin et al. (2012)) or riparian communities (García-Arias and Francés, 2016). These two types of models are not easily coupled because the vegetation response to a series of disturbances is poorly known due to the lack of long-term monitoring (Blomqvist et al., 2009), the lack of studies focusing on vegetation response in terms of plant community functional parameters, and the difficulty of disentangling interacting effects of hydrology and agricultural practices. In turn, this poor capacity to model vegetation response to disturbance impairs the correct inclusion of the effect of vegetation on pulses of water fluxes because there are strong uncertainties on the vegetation successions and stages of vegetation development. Fine-scale ecohydraulic models simulating the interaction between a plant

and a Eulerian flow exist (Nepf, 2012), but their complexity entails high computational costs that hinder their use at the landscape scale.
Considering the computational challenge, as it looks for now impossible to model individual plant-flow interactions at the landscape level, we could rely on upscaling methods to move from local observations/modelling/simulations to landscape simulations. High-frequency monitoring procedures could be a way 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 that end, several landscape elements (plots, hedgerows, ponds, etc.) were recently equipped with different sensors to measure all parameters characterizing the system. Continuing on the example of vegetated ditches, biotic parameters were monitored in the field using unmanned aerial system to measure the spatial variability and evolution of plant cover porosity (Rudi et al., 2018; Vinatier et al., 2018). Abiotic parameters could be assessed in controlled conditions in hydraulic flumes with different organisations 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 found at a local scale can in a second time be exploited at the landscape scale (**Box 3**). Another way to meet the computational challenge could be to run several simulations of a fine-scale ecohydraulic model to get, through numerical exploration, the 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). 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 the processes that lead to the natural regulation of pests and diseases are highly needed in low-input agriculture (Macfadyen et al., 2009). In the diversified landscapes of the future, richer plant diversity will be deployed, from basic inter-cropping that mixes two cultivated species, to highly biodiversified patches inside or near the cultivated fields, and up to large patches of natural or semi-natural areas maintained in the landscapes (e.g. forest patches). We assume that in areas with higher plant richness, trophic networks will become more complex. To date there are no multi-scale and multi-trophic 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). It is a suitable approach for simulating the communities from distinct patches, e.g. cultivated fields or semi-natural areas. If flows of individuals (e.g. beneficial predators spreading from diversified patches to cultivated fields) are well described, the metacommunity framework (Figure 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 to simulate innovative landscapes that include new patterns of plant diversification around and inside cultivated fields is to tackle the issue of the zone of influence of these habitats that constitute a potential sink of beneficial organisms. This could be achieved using spatially explicit models where each plant diversified patch has a surrounding area, namely a “foraging zone”, under its influence (Figure3B). The concept of foraging zone was more often used in marine or mammal ecology to represent the area where animals forage (Bailleul et al., 2007; Weimerskirch et al., 2009). In the case of natural enemies, this concept might be helpful to predict the effect of each plant diversified patch on the regulation of pests in the rest of cultivated fields. Foraging zones may be described using differential equation models or, alternatively, simulated using individual based models (Figure 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 is the island ecology theories. This framework is particularly cogent to understand 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). Since Macarthur and Wilson (1967), the diversity of islands is accurately 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. Island ecology concepts are clearly appropriate to the study of plant-diversified patches in an area homogeneously cropped (landscape or field).

Whatever the approach, the parameterisation of metacommunity models is a crucial step to make them available for the design of resilient agroecosystems. Indeed, metacommunity models have been extensively studied from the theoretical perspective, but rarely parameterized with real data. Difficulties are twofold. The first challenge consists in characterizing the dispersal of most important species (pests, natural enemies, alternative preys): data remain scarce. The knowledge of dispersal capacities as well as effect of landscape elements, especially barrier or corridors, are pivotal to optimize the trade-off between fostering the dispersal of beneficial communities and limiting the dispersal of pests. Given the ongoing developments of monitoring tools, e.g. video tracking systems, and increasing performance of signal or image processing using artificial intelligence, there is no doubt that our knowledge regarding the dispersal of pests and other trophic groups will 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 make possible discovering consumption links that are often difficult to observe in the field, especially in arthropod communities. However, such methods are difficult to apply on a dynamic way. The other promising approach that should be particularly valuable to understand the community dynamics and to identify interactions between species arises from the combination of automated imagery applied at the field with artificial intelligence detection algorithms. For instance, the CORIGAN pipeline (Tresson et al., 2019) provides hierarchical classification of the detected species on pictures taken in the field. Such approaches have the advantages (i) to make on-field identifications of taxa at play in communities with a minimal disturbance and (ii) to catch the dynamics of interactions between taxa. It also enables to measure non-trophic interactions (avoidance, cooperation) that are known to be important but still largely underestimated in the understanding of food webs (Loreau and de Mazancourt, 2013; Ohgushi, 2008). Within landscapes, non-trophic interactions should be particularly important at the edges between cultivated habitats and non-cultivated habitats.

Models will certainly be key tools in designing the landscapes of the future. Their relevance for been used in a concrete way will depend on the capacity of the scientific community to realistically parametrize them. The new methodological approaches for characterizing communities and their interactions represent a real opportunity to get multi-scale multi-trophic models out of the research community.

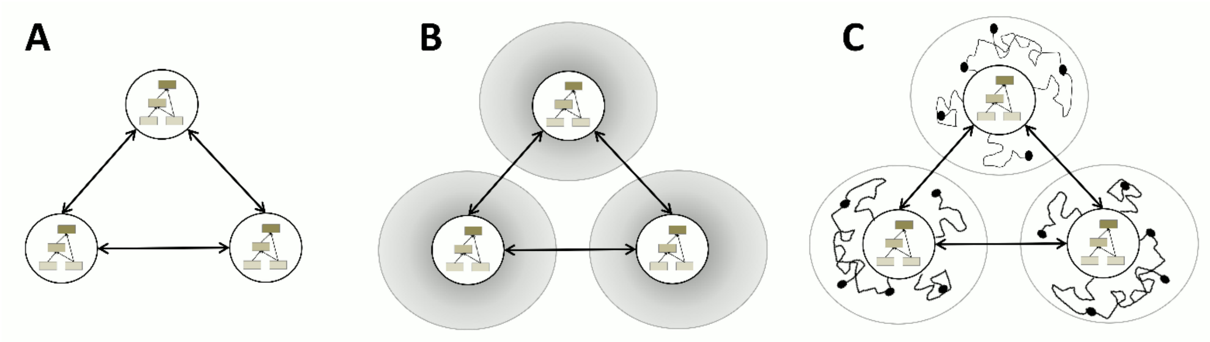

Figure 3: (A) Classical metacommunity model (meta-food web: each community includes a food web model) as emphasized by Massol et al. (2011); (B) metacommunity model with foraging zones; and (C) metacommunity model with Individual Based Model in the foraging zone.

3.4. Measuring and calibrating spatial processes from large spatiotemporal datasets

Gaining more confidence in the spatiotemporal models discussed so far suggest to collect data at multiple spatial and temporal scales, confront them to model simulations, and validate the models 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 can be analysed.

Estimation of dispersal capabilities of organisms is crucial to model consistently their spatiotemporal dynamics but often constitutes a lock. For organisms that disperse passively, observed colonization results from both the actual dispersal and survival, making it complicated 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 spatiotemporal data is essential, either by sampling populations at given locations or by tracking individuals. Regarding biodiversity data, millions of citizen science observations of species have been accumulating over the past decade (e.g. Ries and Oberhauser (2015) or Tulloch et al. (2013)) and provide invaluable sources of knowledge for studies in genetics, trophic ecology, etc. However, they suffer from a number of shortcomings and biases, as they often result from heterogeneous sampling protocols with unknown sampling efforts. Alternatively, data from digital sensors are now being collected at wide spatial scales, leading ecology at the era of Big Data. These digital data offer the advantage that they stem from a survey effort that is intrinsically 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 algorithms (LeCun et al., 2015; Olsen et al., 2019; Wäldchen and Mäder, 2018), provide life sciences data at unprecedented high pace and resolution. Hence, they offer invaluable matter to study 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 offers an efficient framework to achieve 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 is thus convenient to cope with multiple observation processes, operated at different scales, and their related uncertainties and errors. The complexity of hierarchical models, however, can lead

to a class of models whose likelihood function is analytically intractable, meaning that it cannot be solved without the use of simulation or numerical approximation techniques. As reviewed by Clark (2004), the hierarchical Bayesian framework is particularly convenient to deal with heterogeneous data in the case of tractable likelihood functions. It relies on specific estimation algorithms for inferring parameters: the Monte Carlo methods. Note that the 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 variable, the INLA approach is recommended (Illian et al., 2013). Compared to mathematical models, simulation models (e.g. Agent Based Models) offer the possibility of incorporating fine-scale and complex processes more easily but lead to intractable likelihood functions. In that case, approximate Bayesian computation (ABC, Beaumont (2010)) and Pattern-Oriented modelling (POM; Grimm et al. (2005)) are classically used to infer parameters. These methods are based on intensive simulations of the model and the comparison of model outputs to data through summary statistics and a given measure. Although these different methodologies provide interesting and powerful tools to shift 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, however, in the case of spatial models, such methodology is challenging because of the complexity of integrating the landscape as an input factor and the consideration of spatial outputs. Spatial sensitivity analysis assesses how models respond to landscape descriptors. These descriptors do not define a unique landscape but makes it possible to decompose landscape variability into a measurable and controllable component through quantitative variables and a residual variability. It is thus important 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 (e.g. Lamboni et al. (2011)), and summarizing the spatial output in a non-spatial output to use classical sensitivity analysis methods. Another way to explore model outcomes builds on the definition of scenarios, i.e. a set of contrasting initial conditions and parameters. Landscape scenarios can encompass alternative landscape structures and land-use organisations 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 global 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 skepticism towards the social utility of modelling and a perception of models as rather hypothetical than being 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 on the field) to analyze how modelling in general can foster the capacity to change the reality of landscapes (section 4.2).

4.1. Landscape modelling in social sciences

Many research works have been done in social sciences or in interdisciplinarity with 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 comprehending the socio-ecological 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 to better understand the human and social mechanisms backing landscape change. It also enlightens us about the barriers of landscape change. These types of landscape research highlight that, except in the case of non-anthropogenic (i.e. wild ecosystems) and abandoned landscapes, it is never a single driver that is determining the landscape but always a combination of many different drivers that are at stake (Bürgi et al., 2005; Plieninger et al., 2016). This epitomizes the complexity of the landscape as an object of research or action.

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

This second type of researches are generally 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 *in silico* simulations (**Box 4**) and mainly aims at evaluating and designing new instruments or strategies of landscape changes (Martinet, 2013). It is important to note that more and more researches do not focus on a single function and measure (Polasky et al., 2008) but draw attention to the combination of multiple and interconnected functions, measures and human practices within the landscapes (Groot et al., 2009). Such multifunctional landscape modelling researches enable to visualize and understand trade-off 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 enable to 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 landscape with heterogeneous farms. Using an agronomic-ecologic-economic model, the authors 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 control at the landscape scale improves the 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.

< Box 4 >

The main added value of *ex-ante* researches is that they highlight the arbitrations, choices and trade-offs, thereby fostering the public decision toward targetable strategies for the future. Therefore, they are often used as an applied modelling to help decision and action. But the limit of these modelling approaches is that it generally focuses on the state regulator as a key actor and on the subsidies or taxes as the levers for landscape change (Pascual and Perrings, 2007). Putting many stakeholders aside may prevent from understanding the drivers of landscape change. Actually, studies have shown that local cooperatives and agri-production buyers, local agricultural input suppliers (Hannachi and Coléno, 2015), local extension services (Labarthe, 2009), and non-agricultural actors (Cardona, 2012) have levers of action 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.

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

Since the impact of the landscape socio-ecological phenomenon in question is in the hands of many independent land-holders, considering actions and management strategies under direct centralized control ("top-down" process) appears to be a tricky option. In such context, the focus should be on the awareness of stakeholders' interdependence and their visualisation of the social costs and benefits of their actions. In this perspective, approaches for decision-making using multi-agent systems, like Agent-Based Models, 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 (ABM) 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. Thus, they combine elements of game theory, complex systems, computational sociology, and evolutionary programming. ABM can cope with numerous agents, with an individual behaviour, that may interact via cooperation, coordination, competition, and negotiation mechanisms. Such models enable to analyse the effect of individual and collective actions on the environment, and can be seen as "bottom-up" models since they enable to 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). Hence, management strategies can be simulated and evaluated in terms of their impact on the agents and the environment. 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 games (e.g. Becu et al. (2017)), and even in the model conception through participative modelling (Farias et al., 2019; Le Page and Perrotton, 2017). This last option (i.e. incorporating various stakeholders at the conception and simulation steps) seems the best option for inducing socially optimal behaviour in the landscape. Such approach relies on the understanding of the common environmental issue by the diverse 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 when they are developed by those who will bear the consequences. For that reason, 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, the 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 processes in terms of sustainable landscape management (**Box 5**). It has been implemented in a diversity of landscape issues over the world: 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), etc. This approach relies on the formalization of a conceptual model based on iterative interactions between landscape stakeholders' representatives, 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 stakeholder 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 simulation results enables to support a positive confrontation of the different points of view and the reality of the situations. Therefore, here the model is by no means a final product but rather a vector of shared learning.

< Box 5 >

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

The overview of researches in social sciences or in interdisciplinarity with social sciences using landscape modelling reveals a diversity of approaches and aims. But how can these landscape modelling researches impact the reality and drive a landscape change?

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

But are non-participative researches and modelling unable to change landscapes and a vain think to this end? The concept of performativity provides an interesting 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 change 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, that is to say they can create the social reality they are supposed to describe and analyze. 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 thus 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 them to theories or models. But some of them can be applied to theories and models, 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, a

landscape modelling should be enough generic so that it can be applied to managerial 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 at the same time modelling needs to avoid some level of genericity otherwise it becomes too fuzzy and not inspirational 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 if it becomes very 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 socio-material devices that embody the concerned theory's assumptions (Callon, 1998; MacKenzie et al., 2007). Socio-material 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. It is undoubtedly crucial for the performativity of landscape modelling. The third felicity condition for the performativity of landscapes modelling researches is that the practitioners' devices that incorporate the landscape modeling research must be efficient (Muniesa, 2014). It means that they must provide relevant information at the relevant timeline to generate pertinent and efficient decisions enabling the practitioners to reach their objectives.
Finally, the extension of the performativity concept to landscape modelling provides some interesting insights. It leads to the identification of three felicity conditions under which landscape models can foster their capacity to change the reality of landscapes. All these insights are hypotheses that need to be explored and tested but it dresses some features under which a landscape modelling research can be performative and drive landscape effective changes even if it has not produced intentional actionable knowledge.

5. Avenues for future research

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

5.1. Agricultural landscape representation and simulation

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 handles properties that emerge from the interactions (competition, cooperation) between the system's components, and that would not occur under the assumption that elementary components evolve independently.
At the same time, promoting a systemic approach should not lure away from the individual level since individual independence also provides key information regarding the functioning of agricultural

landscapes. For example, Dedeurwaerdere and Hannachi (2019) showed that in a social organization characterized by an anarchy and non-dialogue among farmers about rice seed choices in the Yuanyuang region (China), the independency of farmers enabled a strong autonomy of decision and the absence of conformism pressure on the seed choice. As a consequence, the local cultivated rice diversity was sufficiently large to achieve a sustainable control of rice diseases at the landscape level. Another example, that we mentioned in section 4, regards the farmers 'individual and collective benefits from a landscape-scale management of biological control (Bareille et al., 2020). Using an agronomic-ecologic-economic model that explicitly considered 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 farmers 'benefit'. These inequalities between individuals are a major concern to foster a landscape collective management (e.g. calling for a redistribution of subsidies or specific payment for the vulnerable farmers).
Thus, future research should enhance multilevel and integrated approaches of landscape functioning, but the consideration of all possible processes and their interactions is not possible 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 requires to sustain major efforts in the research agenda.

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., 2019) 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 view of landscapes depicted as a mosaic of discretely delineated 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 available aerial and satellite data provide raw optical and radar multi-modal 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. Further research should produce and/or democratise metrics to characterise continuous surfaces, thereby offering interesting perspectives to link landscape representation (i.e. composition, configuration, connectivity) to ecological processes, and leading to major advances as did the patch mosaic model associated with landscape pattern indices.
Landscapes may also be conceptualised 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.

As regards agricultural landscapes, it is particularly complicated to access to the diversity, sequence and location of crop practices (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) describe 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) propose 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 together 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 in the development of an integrated representation of landscapes, accounting for the multi-scale representation of system organisation 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 highlighted the wide range of landscape models that integrate biophysical processes and stakeholders' views with different levels of complexity. In Figure 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 identified two main research perspectives that we present below: (i) moving towards a conceptualisation of landscape manipulation, and (ii) reconciling theoretical approaches and stakeholders' implication.

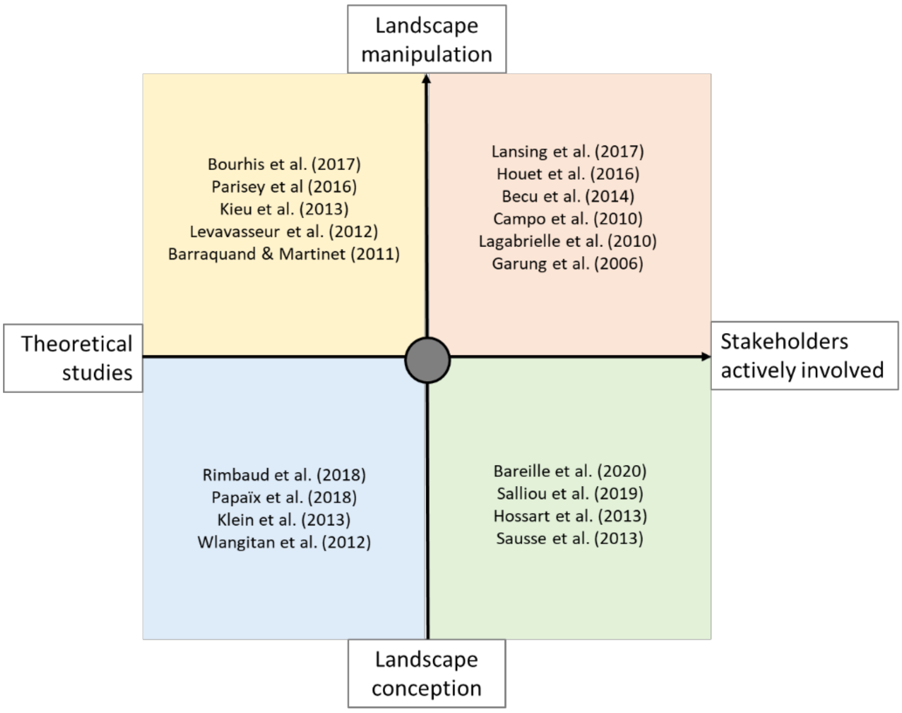

Figure 4: Conceptual classification of landscape planning studies (*lato sensu*). Cited references provide examples of studies falling in different categories, without any claim for exhaustiveness.

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 semi-natural 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 multi-objective regional optimisation for identifying optimum land management adaptations to climate change. Integrating a generic crop model and different climate scenarios they designed a multi-objective 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 provide 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 (Figure 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 inherits from its parental traits but some modifications of these traits can occur through mutations. Thus, the population evolves through the mutation-selection balance. 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.

< Box 6 >

Reconciling theoretical approaches and stakeholders' implication

Figure 4's horizontal axis informs at its left extreme about pure theoretical studies which investigate the effects of spatiotemporal heterogeneities of some landscape features, for example, on biophysical processes or socio-economic outcomes. An example of this category is the previously mentioned work by Bourhis et al. (2017) who examined relevant landscape alterations in terms of minimising the fitness of a crop pest. At the opposite side of the 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-organised cooperative management of rice terraces in Bali achieved a resilient system that both increased and equalised harvests. Naturally, there are studies along the gradient of this axis. Theoretical studies can account implicitly for stakeholders, for example by formalising policies such as incentives and taxation at the national or supranational (e.g. European) scale (Barraquand and Martinet, 2011). At a finer level of integration, 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 farmers' interviews. However, additionally to ongoing research, we promote an enhanced permeation 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 (cooperatives, local extension services, local environmental associations, water catchment managers, etc.) are increasingly demanding to be engaged in planning decisions 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 with various levels of integration. Essentially, they can be involved in the apprehension of the system dynamics, or in the assessment of a set of empirical rules describing agents' behaviours (Becu et al., 2014).

Otherwise, they can be involved in participatory modelling, hence contributing to the model design, the construction of scenarios to be simulated, and the analysis and discussion of model outcomes. The Companion Modelling (see §4.1.3 and Box 5), which exemplifies such a participatory modelling, 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 stakeholders' implication 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 temporality. This issue opens perspectives for meta-modelling that proves useful to convert an overly complex model into a simpler one, preserving the functional link between model inputs and outcomes while speeding up the simulation time. Keeping within the validity domains of input arguments, meta-models, by simplifying the original model and accelerating its computation time, allow to densify the exploration of the variable space and to involve stakeholders, thereby assisting the conception and potentially identifying relevant landscape transformations.

6. Conclusion

Many factors among which the population growth, the urban sprawl, the dependence of modern agriculture 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 required to meet the previously mentioned challenges, solving the necessary trade-offs in the many functions provided by agricultural landscapes (e.g. food production, biodiversity conservation, soil loss mitigation) and that underpin ecosystem services.
Along this chapter, we have shown that a wide range of modelling approaches can be solicited to anticipate and simulate the complexity of future agricultural landscapes. As far as possible, we outlined how spatially explicit and mechanistic models address future landscapes, shedding light on agriculture in expanding cities as well as in rural-urban areas (Box 1). Assuming an increasing complexity of landscapes, characterised by a highly intricate structure, we have illustrated (Box 2) how models can apprehend the agricultural landscape representation and generate virtual but realistic simulations featuring different spatial patterns (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 at stake. Inevitably, modelling spatial flows across complex landscapes is challenging, but it is also an essential step towards the design of resilient landscapes. We 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. Beyond the consideration of landscape heterogeneity, the cautious treatment of organism dispersal, the challenge in inferring key life traits from multiscale spatiotemporal observations, the conceptual and practical difficulty in integrating the landscape as an input in model exploration, we used the functioning of ditch networks in agricultural watershed as a case study (Box 3) to advocate for the reinforcement of multidisciplinary sciences, such as ecohydrology for instance.
The transition process towards future agricultural landscapes puts landscape stakeholders centre stage. A main issue stems from the multiplicity of 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 operate at different spatial and temporal scales. We presented some contrasted examples of formalisms to integrate human actions and decisions in landscape models. Some 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 inescapable to provide guidance on their conception and manipulation, as imperfect and flawed models may be. Many research avenues are open. Landscape representation may call 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 sparse, and if we identified some studies showing potential for solving theoretical landscape planning issues (Figure 4, Box 6), we clearly pinpointed gaps concerning the identification of trajectories – or sequences of landscape modifications – enabling to shift from current agricultural landscapes to novel and more sustainable ones.

We briefly addressed landscape resilience, nonetheless it is an issue that will certainly be increasingly treated in upcoming researches. Over the past decades, and markedly in the last few years, major disturbances (bushfire, drought, flooding, pest outbreak, pandemics) have occurred and caused dramatic damages. This emphasizes that landscapes, more than ever, need be resilient to face such disturbances. It also questions the capacity of models to accommodate perturbations and disruptions, thereby exacerbating the modelling complexity.

Transition towards future agricultural landscapes represents a formidable challenge for scientists of many disciplines and for practitioners, sharing the overarching goal to design landscapes that serve both nature and people.

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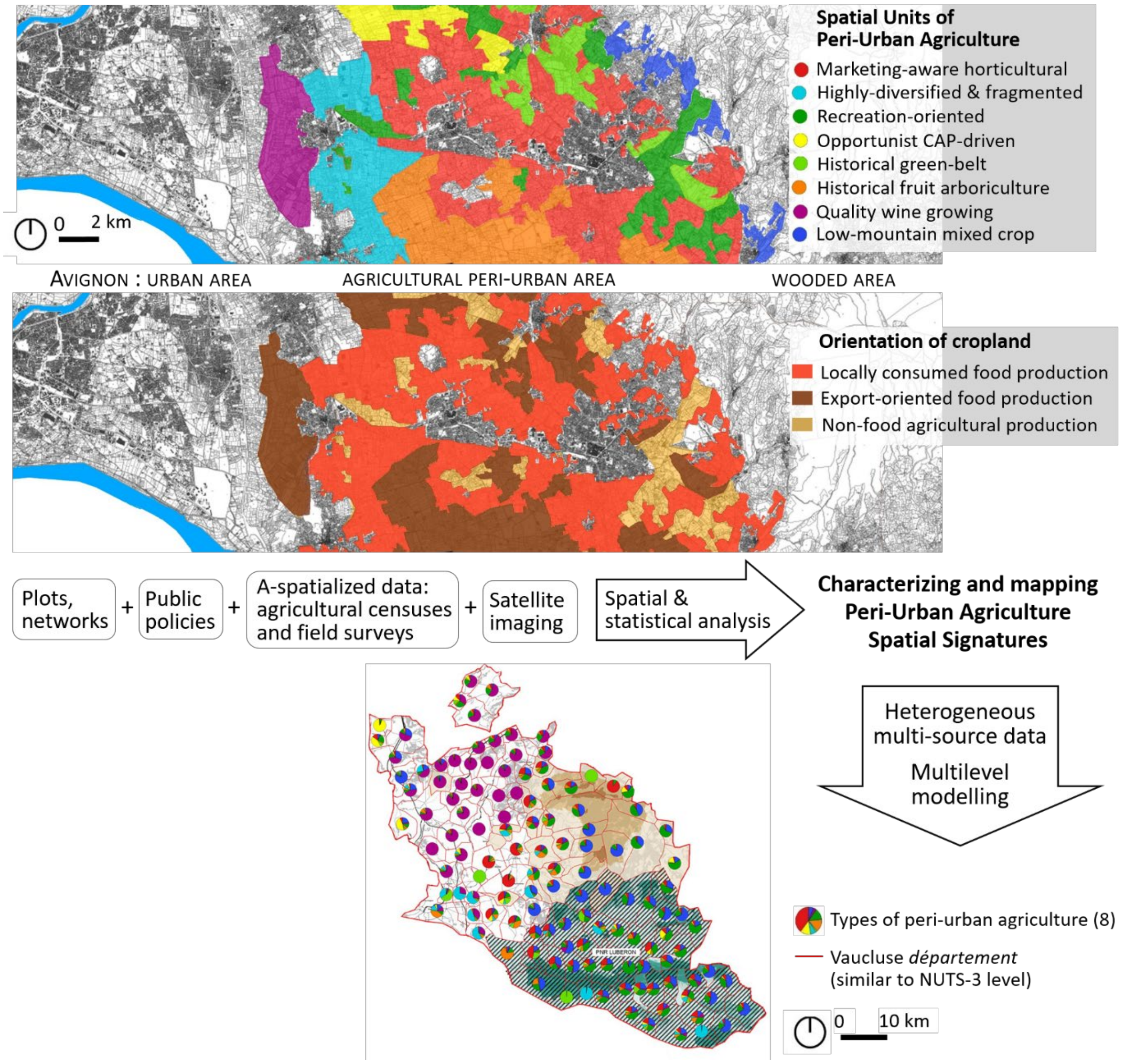
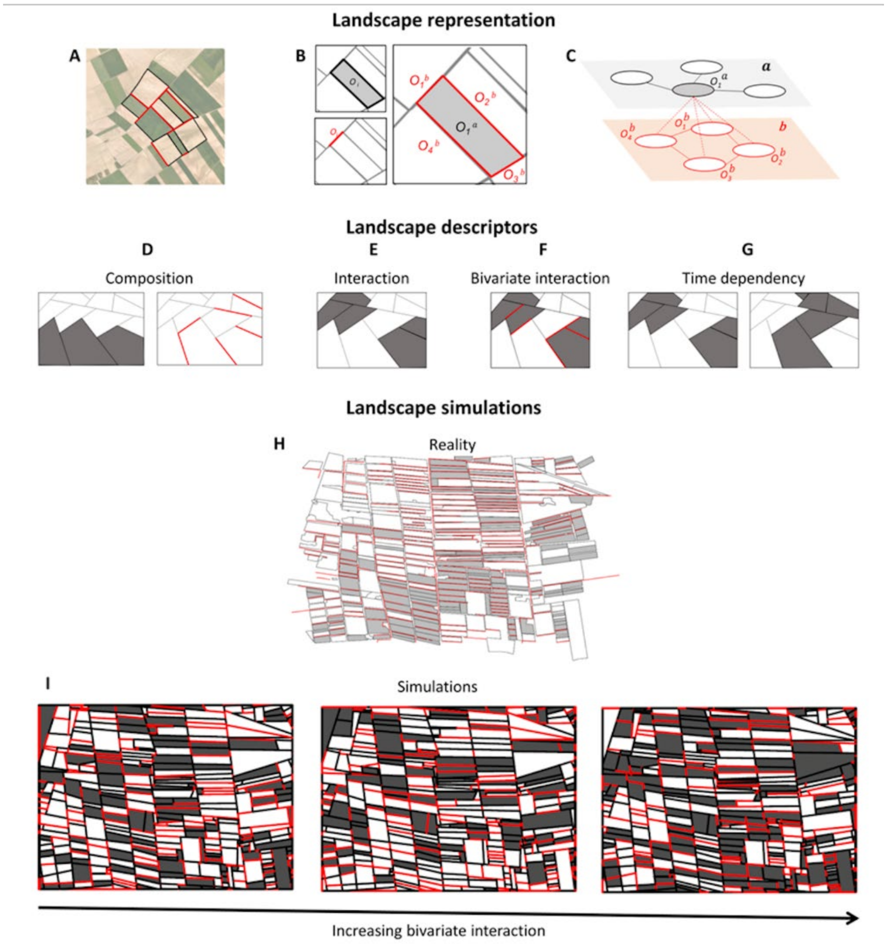
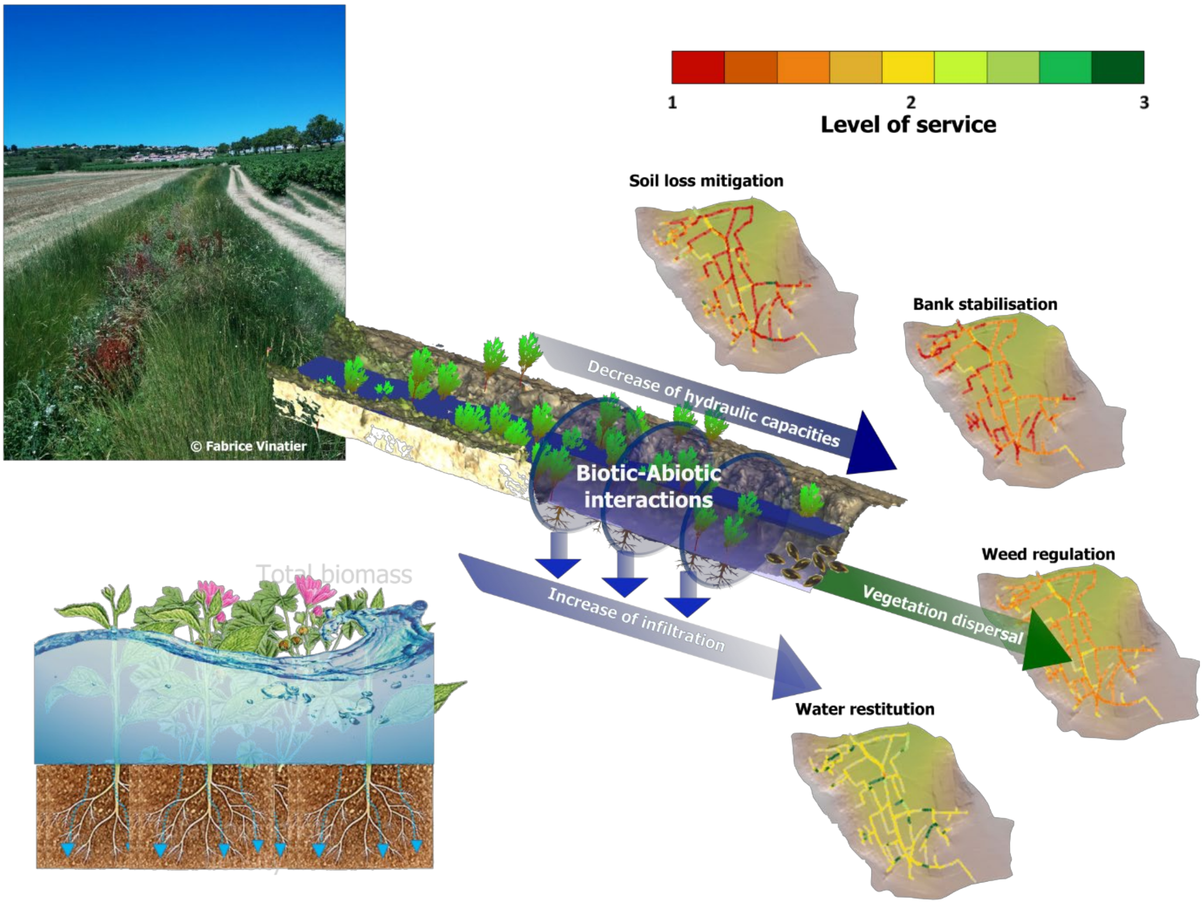


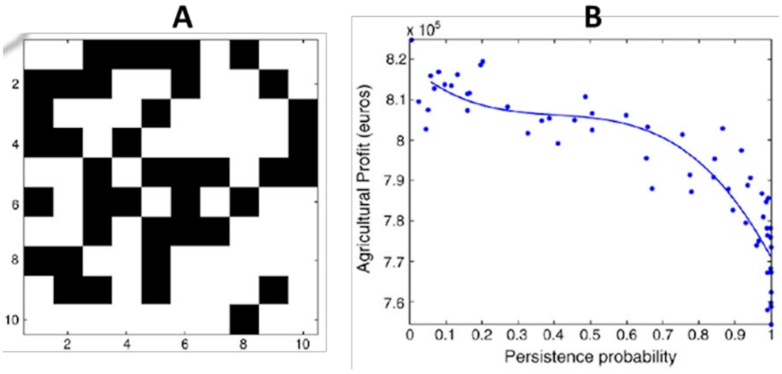
Box 1: Operational modelling of peri-urban farmland in a Mediterranean context. Based on an in-depth analysis of a local case study (Avignon peri-urban area) involving surveys, on-site landscape reading, remote sensing analyses and interviews, Sanz Sanz et al. (2018) classified peri-urban farming into spatial signatures, referred to as spatial units of peri-urban agriculture, using a multivariate statistical approach. 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), to predict the presence and actual proportion of each spatial signature in the total agricultural land of each municipality (151 municipalities). Furthermore, they defined categories of municipality according to the distribution of spatial signatures that open perspectives for public action on peri-urban farming. Beyond fairly reliable predictions regarding peri-urban developments, such a model is simple to handle and hence operational for collective decision-making on 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.



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 crop, natural habitat, etc. Linear segments can be allocated with categories as single-species hedgerow, mixed-species hedgerow or no hedgerow. Spatial or functional relationships among landscape objects are captured by a graphical representation of the landscape. Interactions between objects are modelled through a multilayer network (Boccaletti et al., 2014; Kivela et al., 2013), 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 different types. Landscape descriptors (**D**-**G**) capture important landscape characteristics and features of both patches and linear elements. Typically, three groups of landscape descriptors can be 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 toward 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).

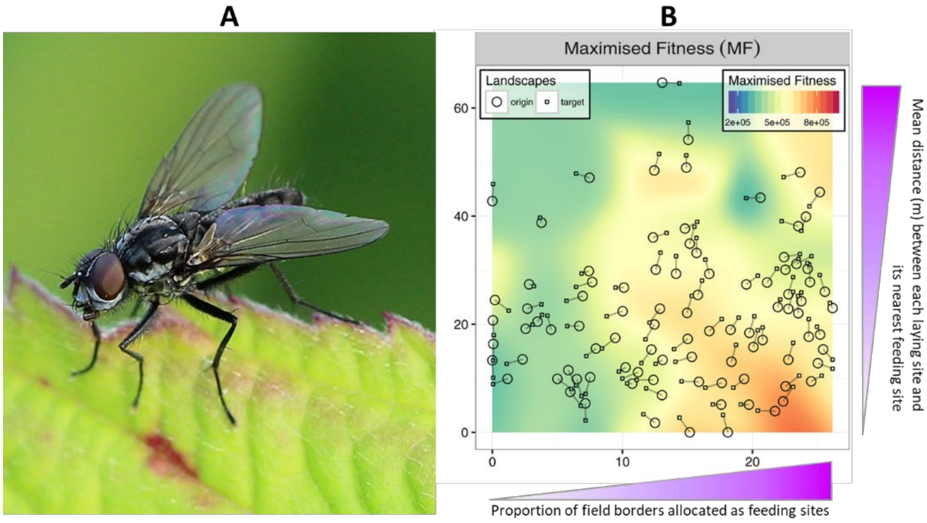


Box 3. Example of a biotic-abiotic coupling using spatially explicit models. In her study, Rudi (2019) aimed to understand to which extent ditch management regimes influence ecohydraulic services provided by vegetation. An explicit representation of the hydraulic network provided by ditches in a Mediterranean watershed was proposed, with a focus on the interactions between vegetation and water, sediments and plant propagules transport through hydrochory. Following a 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.



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 and Martinet (2011).*

Box 5. Application of companion modelling to conflict resolution and organizational innovations. Landscape renewable natural resources 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 improve the farmers' income, which 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 (Raj Gurung et al., 2006). The local deciders chose to use the companion modeling 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 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)*.



Box 6. Illustration of a theoretical landscape planning problem. In their study, (Bourhis et al., 2017) developed a model that built a 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 the ability for high dispersal and directed flight. Foraging strategies hinged on the distribution of two competing resources (feeding and laying sites) affecting (resp. positively or negatively) the pest 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 maximised 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 optimised 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 (notably: constant landscape composition, using field crop – laying sites - rotation as the single lever for changes in landscape configuration), target selection for landscape modification are displayed (squares). This modelling approach shows its potential 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 license. Panel B adapted from Bourhis et al (2017).*