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## An application of farming dynamics in Belgium

Beckers, Véronique

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**Veronique Beckers**

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Prof. Nicolas Dendoncker
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Dissertation presented in partial fulfilment of the requirements for the degree of Doctor of Science

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# HIGH SPATIAL RESOLUTION AGENT-BASED MODELLING AT THE COUNTRY SCALE

AN APPLICATION OF FARMING DYNAMICS IN BELGIUM

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Dissertation presented in partial fulfilment of the requirements for the degree of Doctor of Science

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# Summary

During the last decades, ongoing economic pressure as a result of increasing specialisation, mechanisation and globalisation have led to a continuous decrease in farmers numbers in many parts of the world. This process is leading to profound changes in the socio-ecological system of rural areas worldwide and confronts policy makers and rural planners with new challenges.

To better understand such complex systems that are, to a certain extent, the outcome of the individual decisions of interacting agents, agent-based modelling (ABM) is a promising simulation tool. Reliable model simulations could provide more insight in current processes and in possible future evolutions in rural areas and could support decision making processes in rural planning.

Since agent-based models (ABMs) require the simulation of the behaviour of every individual agent in the system, they need a large amount of data. Therefore, until now, the application of ABMs has been limited to small regions, or when applied to larger areas, with a great loss of detail due to strong generalization. There is therefore a gap between the level at which ABMs are designed to be used (the detailed, individual level) and the level that is relevant for policy making and planning (the regional or national level).

This research aims to bridge that gap by developing and applying ADAM (Agricultural Dynamics through Agent-based Modelling): a simple agent-based farming model that operates at national scale but with the spatial resolution of individual fields. Belgium, that holds many different agricultural landscapes and farming types on a relatively small area, was used as a case study throughout this dissertation.

In the first part of this work the current situation and trends of agriculture in Belgium were analysed and positioned in a global context. This enabled us to define relevant characteristics and key processes of the farming activities in Belgium.

In the next part, these characteristics and key processes were generalized and put into a conceptual framework that led to the development of ADAM. ADAM firstly estimates the drop-out and succession of farmers depending on both the characteristics of the farmer and his land. Farmlands without a successor are redistributed among neighbouring farmers or abandoned. The evolution of the agricultural population in ADAM was calibrated and validated with data from agricultural

censuses for the period 2000-2010, resulting in a relative RMSE of 4.77 % for the number of farmers and 13.2% for the evolution in the number of farmers when validated at the level of individual municipalities.

The validation process showed an impact of urban expansion processes on the obtained results for Belgium. This impact can be direct through urban expansion on farm land or indirect when the farmland is used for suburban activities such as recreation or hobby farming. To incorporate the impacts of urban expansion, in the third part of this research, the original model was coupled with a constrained cellular automata land use change model.

With this coupled model structure various scenarios on possible futures for Belgium's rural areas in 2035 were run. All scenarios showed a continuous decrease of the number of farms and an increase in average farm size. The simulations showed a very distinct spatial pattern with the highest decrease in farm numbers in the central part of the country and in the east of the country.

In the last part, the results of the scenarios were used as an input for a species distribution model on bumblebees. The use of the high thematic resolution land use data as input allowed for a higher accuracy when modelling the distribution patterns of bumblebees. The added value of using these high thematic resolution land use data as input was seen when modelling more localized species as opposed to widespread bumblebee species, making the added value of the high thematic land use data dependent on the specific use case.

# Samenvatting


Aanhoudende economische druk, als een gevolg van toenemende specialisatie, mechanisatie en globalisatie, hebben de laatste jaren tot een voortdurende afname van het aantal boeren in vele gebieden ter wereld geleid. Dit proces leidt wereldwijd tot verregaande veranderingen in het socio-ecologisch systeem van rurale gebieden en confronteert beleidsmakers en stedenbouwkundigen met nieuwe uitdagingen.

Om een dergelijk complex systeem dat, in zekere mate, de uitkomst is van de individuele beslissingen van interagerende agenten, beter te verstaan wordt agent-gebaseerd modelleren (agent-based modelling; ABM) naar voren geschoven als een beloftevolle simulatietechniek. Betrouwbare modelsimulaties kunnen meer inzicht verschaffen in de huidige processen en mogelijke toekomstige evoluties in rurale gebieden, net zoals de ondersteuning van besluitvormingsprocessen bij ruimtelijke ordening.

Gezien in agent-gebaseerde modellen (agent-based models; ABMs) het gedrag van elke individuele agent in het systeem gesimuleerd wordt, is er nood aan een grote hoeveelheid data. Daardoor is de toepassing van ABMs tot op heden beperkt gebleven tot kleine regio's, of, indien toegepast op grotere gebieden, met een groot verlies aan detail door de sterke generalisatie. Hierdoor is er een zekere kloof tussen het niveau waarop ABMs vooral gemaakt zijn om gebruikt te worden (het gedetailleerde, individuele niveau) en het niveau dat relevant is voor beleidsmakers en ruimtelijke ordening (het regionale en nationale niveau)

Dit onderzoek heeft als doel die kloof te dichten door de ontwikkeling en toepassing van ADAM (Agricultural Dynamics through Agent-based Modelling): een agent-gebaseerd landbouwmodel dat toepasbaar is op nationale schaal maar werkzaam is op het niveau van de individuele boeren en percelen. België, met zijn vele agrarische landschappen en verschillende landbouwtypes op een vrij beperkte oppervlakte, werd gebruikt als studiegebied doorheen dit proefschrift.

In het eerste deel werden de huidige situatie en trends in de landbouw in België geanalyseerd en geplaatst binnen een mondiale context. Dit laat ons toe om de relevante eigenschappen en de sleutelprocessen van de landbouw in België te bepalen.

In het volgende deel werden deze eigenschappen en sleutelprocessen gegeneraliseerd en toegepast in het conceptuele kader dat tot de ontwikkeling van ADAM leidde. ADAM bepaalt eerst het aantal landbouwers dat uitvalt en of ze al dan niet opgevolgd worden, gebaseerd op de kenmerken van de landbouwer en het landbouwbedrijf. Landbouwgronden van bedrijven waar geen opvolger aanwezig is, worden herverdeeld onder de naburige landbouwbedrijven of worden verlaten. De landbouwpopulatie in ADAM werd gekalibreerd en gevalideerd op basis van de data van de landbouwenquêtes tussen 2000 en 2010. Deze analyse resulteerde in een relatieve RMSE van 4.77% voor het aantal landbouwers en een relatieve RMSE van 13.2% voor de evolutie van het aantal landbouwers op gemeenteniveau.

Dit validatieproces toonde de impact van urbanisatie en suburbanisatie op de resultaten voor België aan. Deze impact kan zowel direct zijn door de urbanisatie van landbouwgrond, of indirect indien landbouwgrond wordt gebruikt voor niet-commerciële suburbane activiteiten zoals ontspanning of hobbyboeren. Om deze gevolgen van urbanisatie in rekening te brengen werd ADAM in het derde deel van dit onderzoek gekoppeld aan een cellulaire automaten landgebruiksveranderingsmodel

Op deze manier werden verschillende mogelijke toekomstscenario's voor het landbouwareaal in België tot 2035 doorlopen. Alle scenario's resulteerden in een verdere afname in aantal landbouwbedrijven en een toename in de gemiddelde bedrijfsgrootte. Hierbij toonden de simulaties een zeer duidelijk ruimtelijk patroon, waarbij de grootste afname in aantal landbouwbedrijven te vinden was in het centrale en oostelijke deel van het land.

In het laatste deel werden de resultaten van de scenario's gevoed aan een soortendistributie model gericht op hommels. Het gebruik van landgebruiksdata met een hoge thematische resolutie als invoer voor het modelleren van distributiepatronen van hommels verhoogde de accuraatheid van de modellen. De toegevoegde waarde werd vooral duidelijk bij het modelleren van meer lokale soorten ten opzichte van meer wijdverspreide hommelsoorten. Dit leidde tot de conclusie dat de meerwaarde van modelleren met een hoge thematische resolutie vooral afhankelijk is van de specifieke toepassing.

Résumé

Au cours des dernières décennies, la pression économique actuelle causée par une augmentation de la spécialisation, de la mécanisation et de la mondialisation a conduit à une diminution continue du nombre d'agriculteurs dans de nombreuses régions du monde. Ce processus occasionne de profondes mutations du système socio-écologique des zones rurales de toute la planète et les décideurs et responsables doivent faire face à de nouveaux défis.

La modélisation multi-agents (agent-based models; ABMs) est un outil de simulation prometteur qui nous permet de mieux comprendre de tels systèmes complexes qui sont, dans une certaine mesure, le résultat des décisions individuelles des agents et de leurs interactions. Des simulations fiables de modèle pourraient nous éclairer sur les processus actuels ainsi que sur les éventuelles évolutions futures dans les zones rurales et pourraient étayer les prises de décision de l'aménagement rural.

Étant donné que les ABM doivent simuler le comportement de tous les agents individuels du système, ils ont besoin d'un grand volume de données. En conséquence, jusqu'à présent, l'application des modèles basée sur les agents a été limitée à de petites régions, ou son application à de grandes zones s'est soldée par une perte importante de détails à cause d'une intense généralisation. Il existe ainsi un décalage entre le niveau prévu pour l'utilisation des ABM (niveau détaillé, individuel) et le niveau pertinent pour les décisions et la planification de politiques (niveau régional ou national).

L'objectif de cette recherche est de combler cette lacune par la création et l'application de la modélisation ADAM (Dynamique Agricole grâce à la Modélisation Basée sur les Agents): un ABM parcimonieux et destiné à l'agriculture qui fonctionne à l'échelle nationale avec toutefois la résolution spatiale de champs individuels. La Belgique, dotée de nombreux différents paysages agricoles et types d'agricultures sur une zone de taille relativement petite a été utilisée comme étude de cas dans cette dissertation.

La première partie de cet ouvrage correspond à l'analyse de la situation actuelle et des tendances agricoles en Belgique ainsi qu'à leur place dans un contexte mondial. Cela nous permet de définir les caractéristiques importantes et les processus essentiels des activités agricoles en Belgique.

Dans la partie suivante, ces caractéristiques et processus essentiels ont fait l'objet d'une généralisation et ont été placés dans un cadre conceptuel qui a abouti au développement de ADAM. Dans un premier temps, ADAM estime les abandons et successions d'agriculteurs en fonction des caractéristiques de l'agriculteur et de ses terres. Les terres agricoles sans successeur sont redistribuées parmi les exploitants agricoles voisins ou abandonnées. L'évolution de la population agricole dans ADAM a été calibrée et validée grâce à des données de recensements agricoles pour la période 2000-2010 et donne le résultat suivant : un RMSE relative de 5.11% pour le nombre d'agriculteurs et 46,4% pour l'évolution du nombre d'agriculteurs lorsque la validation se fait au niveau des municipalités individuelles.

Ce procédé de validation a démontré l'impact de l'urbanisation et de la périurbanisation sur les résultats obtenus pour la Belgique. Cet impact peut être direct en cas d'urbanisation des terres agricoles ou indirect lorsque les terres agricoles sont utilisées pour des activités telles que l'agriculture d'agrément à la périphérie urbaine. Dans la troisième partie de cette recherche, le modèle original a été associé à un modèle d'automates cellulaires sur l'utilisation des sols, pour incorporer les impacts de l'urbanisation.

Grâce à cette structure de modèle associé, plusieurs scénarios d'avenirs possibles pour les zones rurales en Belgique en 2035 ont été examinés. Tous les scénarios indiquent une diminution continue du nombre d'exploitations agricoles et une augmentation de la taille moyenne des exploitations agricoles. Ces simulations dénotent un modèle spatial très net avec la plus forte diminution du nombre d'exploitations agricoles au centre et à l'est du pays.

Dans la dernière partie, les résultats des scenarios ont été utilisés comme données d'entrée pour un modèle de distribution d'espèces de bourdons. Le recours à des données d'utilisation de sol à fine résolution thématique en tant que données d'entrée nous a apporté une meilleure précision pour la modélisation de distribution des bourdons. La valeur ajoutée du recours à ces données d'utilisation des terres à fine résolution thématique comme données d'entrée a été démontrée lors de la modélisation d'espèces plus localisées par opposition à une espèce de bourdon plus largement répandue. Cela rend la valeur ajoutée des données d'utilisation de terres à fine résolution thématique tributaire des cas spécifiques d'utilisation.

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| | |
|---|---|
| ABM | *Agent-based modelling* |
| ABMs | *Agent-based models* |
| ADAM | *Agricultural Dynamics through Agent-based Modelling* |
| AUC | *Area under the curve* |
| BAU | *Business-as-usual* |
| CA | *Cellular Automata* |
| CCA | *Constrained cellular automata* |
| CI | *Confidence interval* |
| DVM | *Dynamic vegetation modelling* |
| EU | *European Union* |
| EU-CAP | *European Union Common Agricultural Policy* |
| FAO | *Food and Agriculture Organization of the United Nations* |
| GE | *Global Economy* |
| GIS | *Geographical information system* |
| IACS | *Integrated Administration and Control System* |
| IPBES | *Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services* |
| IPCC | *Intergovernmental Panel on Climate Change* |
| LCU | *Local currency unit* |
| LULC | *Land use and land cover* |
| LULCC | *Land use and land cover change* |
| MAP | *Mest Actie Plan* |
| MAUP | *Modifiable Areal Unit Problem* |
| NIS | *National Institute of Statistics of Belgium* |
| ODD | *Overview – Design concepts – Details* |
| PGDA | *Programme de Gestion Durable de l'Azote* |
| RC | *Regional Communities* |
| ROC | *Receiver Operating Characteristic* |
| RRMSE | *Relative root mean square error* |
| SD | *Standard deviation* |
| SDM | *Species distribution model* |
| SDMs | *Species distribution models* |
| SGM | *Standard gross margin* |
| SIGEC | *Système intégré de gestion et de contrôles* |
| SO | *Standard output* |
| WTO | *World Trade Organisation* |

# Chapter 1 Introduction

## 1.1 A complex world

The world we are living in is complex. To better understand it and to gain insight into how it may evolve in the future, models have been created as schematic representations of reality. Modelling has become a widespread technique in research on weather, climate change, soils, economy etc. As soon as living beings get involved however, modelling gets more complex. Living beings interact with each other and the environment, influencing each other's decisions and reacting differently to the same situation. In order to model the interactions between all these individuals, agent-based models (ABMs) are often used as a modelling approach. By modelling every individual actor involved, unexpected results may emerge as the sum of individual actions. ABMs are now increasingly used to model complex ecological, economic and societal systems. The fact that in such ABMs the behaviour of every individual actor is modelled makes it difficult to create models that are applicable to large areas with a large number of agents. Therefore, until now, most ABMs have been applied either on a small community or region (Acosta-Michlik and Espaldon, 2008; Bakker et al., 2015; Fontaine et al., 2013; Happe et al., 2009; Le et al., 2008; Vermeiren et al., 2016), or have started from hypothetical situations, without real-world application (Ligtenberg et al., 2004; Murray-Rust et al., 2014). Therefore, a challenging question is: can we create applicable, large scale

ABMs, useful in scenario analysis and for decision making and, if so, what can be the added value of these detailed large-scale ABMs for other research fields?

To address these questions, the case study of agriculture was chosen. The agricultural system is an ideal example of a system where individuals, i.e. farmers, take individual decisions, based on the (socio-economic, biophysical and political) environment and their own characteristics, and thereby shape the agricultural landscape. At the same time, the agricultural sector is an interesting case since it is currently facing many challenges and would therefore benefit of gaining some insights on future developments under different scenarios.

This introduction will first describe the agricultural sector and the many challenges it is facing at present, after which, the current state-of-the-art research in agricultural modelling is presented. The research questions will then be further detailed in relation to the agricultural case study. The chapter will conclude with an overview of the dissertation's structure, and on the different chapters that will be introduced.

## 1.2 Agriculture: a sector in crisis

Agriculture as a mean to produce food has been an important part of our society since the Neolithic (Figure 1.1), having an ever increasing impact on the environment (DeFries, 2014; Ehrlich and Holdren, 1971) and thereby becoming the most important land use in Europe (Verburg et al., 2006).

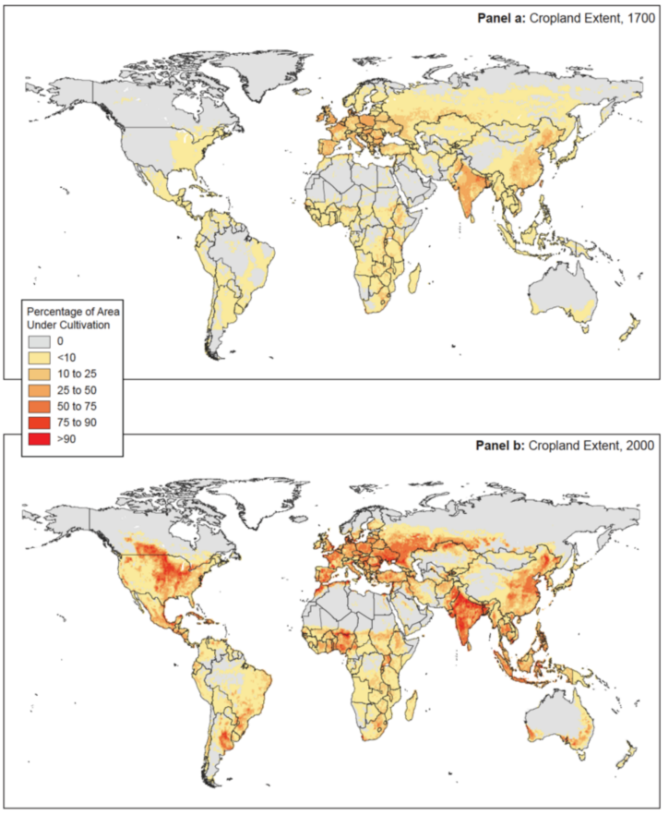



*Figure 1.1 – Percentage of land in use for crop production in 1700 and 2000 based on SAGE data (Alston et al., 2010).*

The continuous population growth led to phases of deforestation that, together with innovations, increased the output of agricultural systems. Growth continued, until limits to the system were reached and a crisis emerged. New techniques and developments, allowed for new phases of growth, until limits were reached again

(DeFries, 2014; Mazoyer and Roudart, 2006). This continuing cycle of crises and revolutions resulted in an unprecedented demographic, economic and urban expansion, and to the current system of highly intensive farming with high inputs and high outputs per hectare where continuously less labour is needed (Figure 1.2). At the same time, the advancements in transportation opened up the world, putting farmers into global competition. As a result, the worldwide export of agricultural products has increased from 187 billion real USD in 1962 to 1.6 trillion real USD in 2016 (FAO, 2018; Würtenberger et al., 2006).

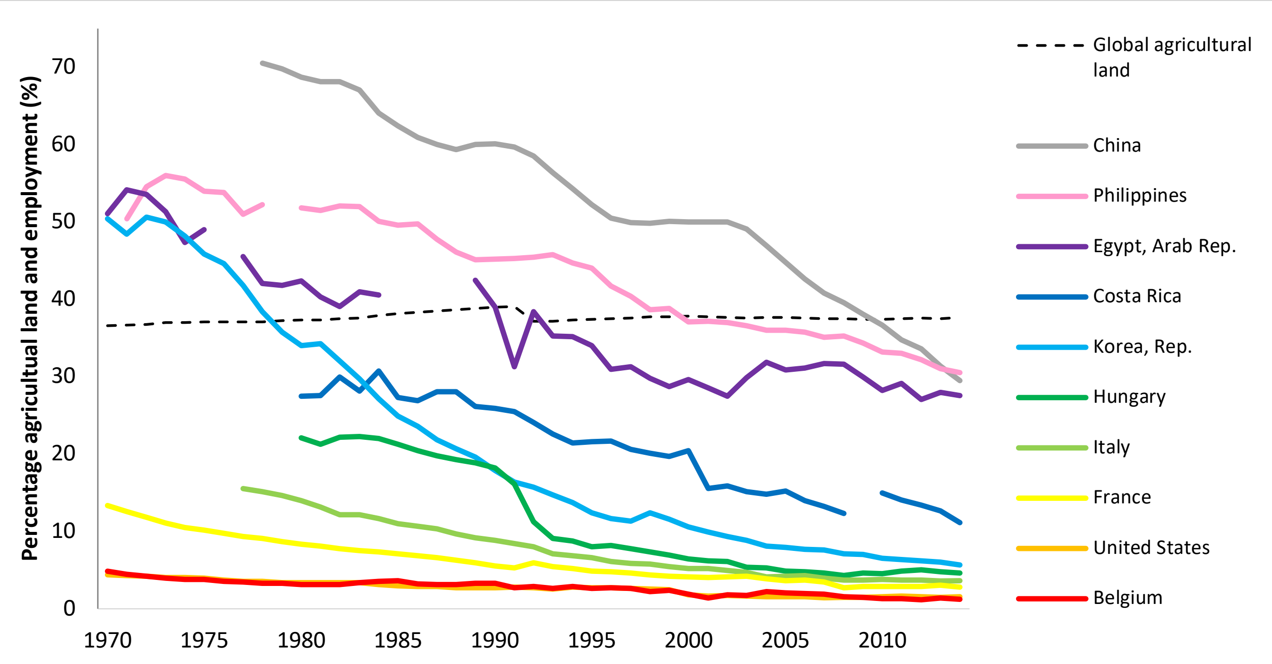



*Figure 1.2 – Evolution of the percentage of employment in agriculture (The World Bank, 2017) and the evolution of the total percentage of agricultural land (The World Bank, 2019) from 1970 to 2015.*

Globalisation of the agricultural market creates opportunities for farmers, but also puts them under pressure. The continuous fall of real agricultural prices in the last century as a consequence of technological advancement and thus declining product costs together with global over-production and increased competition reduces the gross margins of farmers. This requires them to continuously find ways to stay competitive, often resulting in further specialization and increasing farm size (Mazoyer and Roudart, 2006). Other farmers focus on increasing gross margins by selling through short chain markets or selling products that customers are willing to pay higher prices for (organic products, products of certified origins or with quality labels) (Mathijs and Relaes, 2012). Farmers that do not find a way to stay competitive, might fail to find a successor and disappear from the agricultural population. This has, from halfway the 19th century until today, resulted in a strong and continuing decrease in the farmers' population, notably in developed countries (The World Bank, 2008). At the same time, these trends in agriculture have an impact on the environment and the landscape (Harms et al., 1984; Ihse, 1995; Poudevigne and Alard, 1997). With agriculture managing to stay relatively competitive in comparison to other land uses, often helped by laws through spatial planning or subsidies, the decrease of agricultural land is minimal and therefore farms grow in size (European Commission, 2016; USDA, 2017).

Apart from this economical pressure, from the 1960s and 1970, agriculture has become increasingly associated with different environmental problems like eutrophication from fertilization (Withers et al., 2014), soil erosion (Montgomery, 2007), climate change through the emission of greenhouse gasses (Cole 1997) and biodiversity losses (Díaz et al., 2019) with some of the declining species having a crucial role as the pollinator of certain crops (Aguirre-Gutiérrez et al., 2017).The future of agriculture remains uncertain: the overproduction in some regions in the world together with the declining production costs, lead to a structural fall in real agricultural prices, outcompeting and impoverishing other regions (Mazoyer and Roudart, 2006), while at the same time, around 10% of the world population is currently still undernourished (FAO et al., 2018). Until 2050, the global population is projected to further increase, plateauing at around 9 billion (Godfray et al., 2010), possibly resulting in a doubled global grain demand (Tilman et al., 2002). Combined with the issues that might result from climate change (Schmidhuber and Tubiello, 2007) and biodiversity losses (Díaz et al., 2019), the necessary adaptations resulting from a diminishing fossil fuel reserve (Shafiee and Topal, 2009) and the further urban expansion onto agricultural lands (Du et al., 2014; Rounsevell et al., 2006), it is clear that many challenges are arising, or will arise in order to feed the entire global population in a healthy and sustainable way. These evolutions will further lead to changes in agriculture, the (agricultural) landscape, the management of the land and the ecosystem services it provides. In heavily urbanised countries, the long period of human presence has a large impact on the current landscape, often resulting in a fragmented landscape that limits the current possibilities of agriculture (for example in) Western-Europe. In the future, similar issues might arise in countries that are heavily urbanised but also experience a continuous urban expansion, such as China, Brazil and some African countries. There is as such a need to obtain a deeper understanding on how and why these trends occur and how they may evolve in the future.

## 1.3 Research in agricultural systems

The agricultural system can be seen as the result of the combination of different processes occurring in, and impacting, the physical, the socio-economic and the political environment (Figure 1.3). Agriculture is a key sector where humans interact with their biophysical environment: humans are being limited by the specifics of the biophysical environment (topography, climate, soil type) and have, wantingly and unwantingly, an important impact on it (both negative through erosion, soil degradation, pollution, habitat destruction, and positive through agro-ecology, preservation of specific ecosystems…), and on the ecosystem services it provides. Humans are however, completely dependent on these ecosystem services for their living and well-being and for the conservation of the socio-economic environment. Since agriculture has a strong impact on the workings of our society, in Europe, it is heavily regulated through different policy measures. These policies focus both on the environmental (e.g. erosion measures) as well as on the socio-economic impacts (e.g. through subsidy measures).

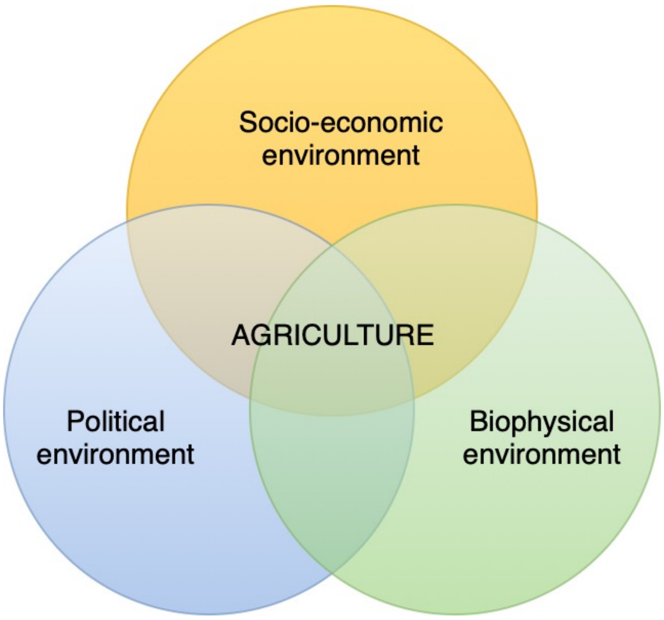



*Figure 1.3 – Agricultural system studies, at the centre of different research fields.*

Although there is a strong interaction between these three environments impacting agriculture, the highly complex nature of the agricultural system results in most agricultural studies reverting to a reductionistic approach, thereby focussing on only one of these research fields. Related to the biophysical environment, research has looked at different aspects ranging from the impact of agriculture on biodiversity (Bengtsson et al., 2005; Gabriel et al., 2013; Koh and Wilcove, 2008), surface run-off and erosion processes (Basic et al., 2004; Dilshad et al., 1996; Langdale et al., 1992; Montgomery, 2007; Prosdocimi et al., 2016; Reganold et al., 1987), eutrophication (Sharpley and Rekolainen, 1997; Ulén et al., 2007; Withers et al., 2014; Withers and Haygarth, 2007) and soil quality (Hamza and Anderson, 2005; Horn et al., 1995; Raper, 2005), to the impact of different aspects of the environment, like climate, climate change, soil fertility and soil type on agriculture itself. Studies from a socio-economic point of view on agriculture focus on different aspects of rural poverty (Datt and Ravallion, 1998; Meert et al., 2005), technological diffusion (Boserup, 1965), and farming networks (Hoang et al., 2006; Stain et al., 2008). In the field of political research on agriculture, the focus is on the effect of different policy measures on agriculture, for example the effects of measures in the European Union's Common Agricultural Policy (EU-CAP) (Ciaian et al., 2010; Knudsen, 2009; Weyerbrock, 1998).

Some research however, also investigates the overlap between thematic fields. In the overlapping fields of socio-economic research and research on the biophysical environment, examples can be found on agricultural intensification (Harms et al., 1984; Stoate et al., 2001; Van Meijl et al., 2006), on the impact of urban expansion on agriculture (Delbecq and Florax, 2010; Verhoeve et al., 2015), and on the different links between rural poverty and the environment (Reardon and Vosti, 1995). Agricultural research on the overlap between political and biophysical research can be found in studies on the impact of the EU-CAP measures on the environment, like the fallowing of fields (Van Rompaey et al., 2001) or the effects of creation of grass strips (Borin et al., 2010; Dorioz et al., 2006) both due to policy measures on erosion reduction or the impact of the EU-CAP on ecosystem services (Hauck et al., 2014). Studies on the impact of different policy measures specifically aimed at helping rural, disadvantages areas (Lasanta and Marín-Yaseli, 2007; Rahoveanu and Rahoveanu, 2013; van Berkel and Verburg, 2011) can be positioned on the overlap between political and socio-economic research.

## 1.4 Modelling agriculture dynamics at the rural-urban fringe

Due to the complexity and multi-disciplinarity of research in agriculture, research adopting a systemic approach is rare. A systemic approach, whereby components from different disciplines are combined and interact, is needed to study and understand complex systems like the agricultural system (Bawden, 1991; Jones et al., 2017). Approaching agriculture from a modelling point of view, allows adopting a systematic stance. Modelling allows for a better understanding of the different processes and their future outlook, together with the expected environmental and socio-economic impact, using a systemic approach.

Throughout the years, different modelling techniques and frameworks have been developed within the field of agricultural modelling (Bakker et al., 2015; Britz and Wieck, 2014; Fontaine and Rounsevell, 2009; Malawska and Topping, 2016; Rounsevell et al., 2006, 2005; Spangenberg et al., 2010; Valbuena et al., 2010; Verburg and Overmars, 2009; Westhoek et al., 2006; Yamashita and Hoshino, 2018) and land use change (Berger, 2001; Lambin et al., 2000; Qiang and Lam, 2015; Verburg et al., 2004; Yalew et al., 2016). As such, modelling has become a frequently applied technique to gain insight in the complex processes related to agriculture, agricultural land use and land use change. It has led to a wide variety of models, with different goals, starting from different thematic backgrounds, methodological origins and paradigms. With the abundance of proposed modelling techniques, different classifications have been proposed (Azadi et al., 2016; Heistermann et al., 2006; Lambin et al., 2000). Based on this research and for this dissertation, three types of spatially explicit land-use models can be distinguished: statistical models, probabilistic models and optimization models.

### 1.4.1 Spatially-aggregated statistical models

Lambin et al. (2000) define *empirical-statistical models* as models that focus on explicitly identifying the correlation between land-cover changes and a wide variety of variables through the use of multivariate analyses in order to define the contribution of these different external variables to the empirically-derived change rate. The nature of these models, however, allows to only explain the land use change patterns that are present in the original data set and without a certainty of causality. An example is research on the relationship between land cover and land use change in relation to population growth (López et al., 2001) or the importance of incorporating spatial autocorrelation in modelling land use (Dendoncker et al., 2007). Another well-known example is the link between agricultural intensification and population growth by Boserup (1981, 1965).

### 1.4.2 Probabilistic models

Probabilistic or stochastic models try to define the transition probability of a certain location, combined with the expected amount of land, covered by different types of land cover or land use. Similar as for the empirical-statistical models, only transitions that have been observed in the dataset can be applied in the model and they provide only a limited insight in the motivation of land users (Lambin et al., 2000). Examples of probabilistic models in agricultural modelling can be found in the different variations of the CLUE model (Veldkamp and Fresco, 1996; Verburg et al., 2002; Verburg and Overmars, 2009), but also in the study of Van Rompaey et al. (2002) looking at the impact of agricultural land use change on erosion, the study of Mustafa et al. (2018a, 2018b) on modelling urban expansion, and in the downscaling of aggregated land use data and scenarios (Dendoncker et al., 2006).

### 1.4.3 Optimisation models

*General overview*

Optimisation models, often used in economics, focus on optimisation at the microeconomic level or general equilibrium models at the macroeconomic scale. These models assume entities to steer their behaviour based on economic optimisation.

One of the first and best-known models on economic optimisation in agriculture is the model proposed by Von Thünen, combining economic theories linked to the physical environment to explain the agricultural patterns near urban areas. The theory states that the intensity of agricultural land use decreases with the distance from a city, given that the primary force is the transport cost to the market (Von Thünen, 1826). This results in different agricultural land uses shaped as rings around a single, central, isolated market (Figure 1.4). Although this theory has its value (e.g. pedagogical), it is considered outdated in many advanced industrialized countries. While Von Thünen saw the city as a static entity, with set boundaries, Sinclair (1967) states that the rural land use is affected even before the expansion of the built up area. This has little to do with the market situation in the city but is more related to the urban and rural land prices, the flexibility offered through different modes of transportation and the preferences of the people using the land. The assumptions made by Von Thünen, that demand of products exceeds supply, that transport costs are an important part of the total cost and that the concerned area is an isolated commercial settlement (Alonso, 1964), can no longer be applied to today’s cities in the global north. Also the improvement of transportation techniques and transportation modes made the model less relevant.

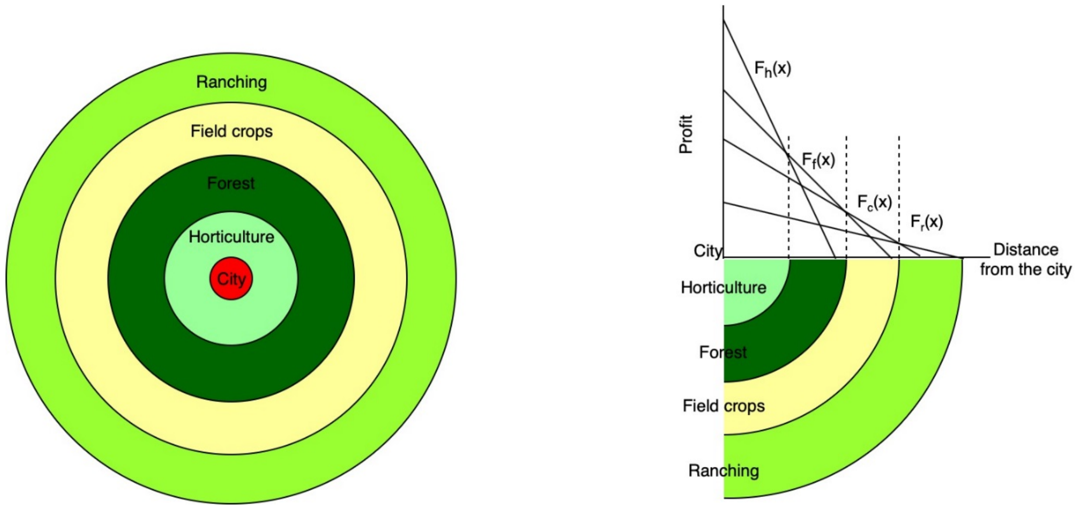



*Figure 1.4 – Representation of the Von Thünen model with different rings of production around a central market (left) with different profit functions for each product in function to their distance to the city (adapted from Von Thünen, 1826).*

### *Agent-based models*

A more recent modelling approach based on the optimisation idea, is agent-based modelling (ABM). ABM relies on the creation of virtual objects that define individual agents representing real-world actors, with autonomous behaviour and decision-making strategies based on their environment and their specific characteristics (Rounsevell et al., 2012). It allows for a spatially explicit systemic approach, and the inclusion of heterogeneity in the population and the environment.

According to Hare and Deadman (2004) and Matthews et al. (2007), the advantages of ABMs are their capability to (1) incorporate decision-making at the individual level, (2) combine social and environmental models and (3) allow the emergence of unexpected results from the aggregated behaviour at the macro-scale level. Parker et al. (2002b) also mention the possibility to combine decision-making processes at different levels and the modelling of adaptive behaviour as an advantage.

Axelrod (1997) argues that ABM is a combination of deductive and inductive approaches, since it starts from assumptions, deducted from perceptions of the phenomena taking place, and uses them to generate data that are to be analysed inductively. The different advantages of ABM make Rounsevell et al. (2012) conclude that the ability to introduce heterogeneity in an agent population that results into different outcomes, sets it apart from equation-based models. It makes it an appropriate technique to model human decision processes, especially for researching the land system. With the possibility of a one-to-one mapping between the virtual and real-world entities allowing for calibration, validation and explorative future modelling of complex systems through scenarios.

As such, ABM, with its ability to link sociological and environmental systems (Huber et al., 2018), and with the decisions being affected by the environment, which then also impact the environment, combined with the capability to look at the emerging patterns from the aggregated behaviour at the macro level, is a relevant approach for modelling agricultural dynamics.

Although ABM seems an ideal modelling approach that allows the integration with different models, across different disciplines, ABMs are rarely linked to different models in different research fields. The problem is that for linking models, developed with different purposes in mind, the spatial and temporal scales do not always align (Parker et al., 2002b; Veldkamp et al., 2001). Not only do processes sometimes take place on different temporal or spatial scales, but sometimes the models are also restricted by the resolution at which the underlying data are available. When this is not at the level at which the actor's decision making is taking place, results might need to be aggregated causing a loss of information or loss of heterogeneity.

## 1.5 Research gap and research questions

The previous overview shows the possibilities of the application of ABMs for modelling agricultural dynamics: they can be used to incorporate the social, economic and political landscape, as well as the biophysical environment and they can be used in scenario testing. ABMs suffer, however, from a few shortcomings that hamper their use. ABMs are mostly defined for very specific detailed (small scale) cases, reducing the reusability. They are also rarely combined with other existing models in other thematic fields.

This research gap can be translated into the following research questions, that will be the main focus of this dissertation.

**RQ1: To what extend can agent-based models simulate farmers decision at country scale?**

As mentioned above, ABM allows the modelling of human decision-making behaviour in its relation to its socio-economic, political and physical environment (Hare and Deadman, 2004; Parker et al., 2002b; Rounsevell et al., 2012), making it an interesting approach to look into modelling agriculture in a systemic way. The goal is to see whether a framework for a basic, generic agricultural agent-based model that incorporates the relevant thematic fields can be developed, permitting adaptation to allow modelling in different contexts and needs. Agricultural ABMs have been created before (e.g. Bakker et al., 2015; Happe et al., 2009). However, due to the high level of detail and their focus at very specific regions, they are less relevant for policy makers and hardly replicable in other settings. In order to use the model in other regions and to make them politically relevant, it is important to create ABMs for larger regions (Rounsevell et al., 2012). It is however crucial for an agent-based model to operate at the level at which the actors take their decisions, to consider the local conditions and heterogeneities (Berger and Troost, 2014). Therefore, the model needs to be applicable for a larger region (e.g. the country level), even though the modelling of the decision-making is to take place at the smallest spatial unit relevant for farmers decision-making: the agricultural parcel.

In order to allow the model to be adapted and used relatively easily in regions that currently experience similar agricultural developments, it is important to work with data that is generally available for many regions, without the necessity to gather extra data in the field.

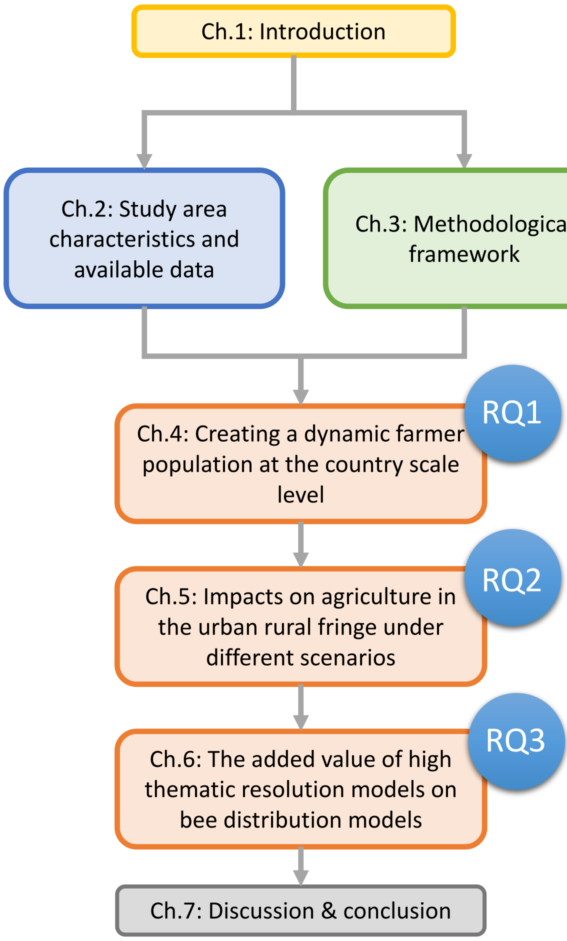
**RQ2: What is the possible impact of different scenarios on the future of farming**?

A model of agricultural dynamics might provide better insights in the processes that resulted in the current outlay of the agricultural sector. Such a model becomes even more relevant if it can be used to compare different scenarios for the future. The possible impact of continued urban expansion following different scenarios together with changes in agricultural subsidies is especially relevant for agriculture in a highly urbanised and fragmented landscape. The outcome of such scenarios allows an insight in the possible impacts of different choices in policy making. The proposed model will therefore be combined with different policy scenarios to look at the possible impacts these might have on the agricultural sector.

**RQ3: What is the added value of high thematic resolution ABMs in combination with models from other research fields (e.g. ecological modelling)?**

ABMs require a high amount of input data and a high time investment in order to set up and execute the model. Apart from the usefulness of the model on its own, this high investment could be further justified if the model can be integrated and prove its usefulness for other research applications and models. As previously mentioned, ABMs are in general seldom linked to models in other research fields because of the incompatibilities in the spatial and temporal resolution (Parker et al., 2002b; Veldkamp et al., 2001). Given the impact of agriculture on the environment and biodiversity it would be interesting to investigate the possibilities of linking the proposed model with an ecological model. Past research has shown the importance of (agricultural) land use change in species distribution modelling of pollinator species (Aguirre-Gutiérrez et al., 2017). This makes it an interesting case study for looking into the added value of highly detailed agricultural land cover modelling on models in other research areas.

To summarize: the aim of this dissertation is to create a reusable model, at the national scale level, incorporating the core mechanisms relevant for agricultural dynamics at the rural-urban fringe. The model should allow the testing of different scenarios and the combination with models stemming from other thematic fields.




## 1.6 Thesis outline

A case study area is required to tackle these research questions. In this research, the country of Belgium was chosen as an interesting case study due to the high dynamics currently present in agriculture and the large diversity in the (agricultural) landscape. It is a highly urbanised country, with a fragmented landscape, leading to a strong interwoven land use, posing many challenges on the agricultural sector. Furthermore, it is representative for European countries in terms of data and data availability. This is important since the aim is to create a model that is reusable in regions or countries undergoing similar dynamics. The study area will be further discussed in the next chapter.

The dissertation will follow the structure visualised in Figure 1.5. In the next chapter, the study area in all its relevant aspects is presented together with an overview of the different datasets available and useful in the process of modelling agriculture. Chapter 3 focusses on the methodological background, looking into the history of ABM, its applications in agriculture and some of its current shortcomings. Based on the background gathered in chapter 2 and 3 and in relation to our first research question, an agent-based model is developed and presented in chapter 4. The major achievements and the remaining limitations are thereby further discussed. Chapter 5 focusses on the second research question and looks into the possibilities of using the model for testing different scenarios on urban expansion and farm subsidies as a result from different storylines. Chapter 6 is related to the third research question, linking the agent-based model to a bee distribution model to assess the added value of the proposed, detailed type of modelling to other research fields. The last chapter, chapter 7, discusses the results, based on the initially defined research gap and research questions, before concluding.

This dissertation is mostly based on papers that have been published or are submitted to international peer-reviewed journals. There is therefore sometimes some overlap between chapters.

# Chapter 2 Study area characteristics and available data

## 2.1 Available data to create an agricultural agent-based model

Since the aim is to create a large-scale model, applicable to a large set of industrialized countries, it is important to work with data that are in general already available, so no own collection of data for large regions is necessary. With our case study of Belgium, a country part of the European Union (EU), the aim is to make use of datasets that the EU requires to be collected. The main datasets used are the yearly agricultural survey, the agricultural parcel dataset from the Integrated Administration and Control System (IACS), the mortality rate, a time series of crop prices and data on average yield for a limited number of crops. These data are later combined with scenarios on urban expansion.

### 2.1.1 Agricultural survey

Belgium has a large collection of socio-economic data on agriculture. The first surveys were organized in 1846, after which they were held every 10 to 20 years. In 1970 the National Institute on Statistics (NIS) started with yearly surveys, to gain insight on the amount of cattle and pigs, the sowing plans for winter, and expected production volumes. To reduce the burden of this yearly survey on farmers, the survey was simplified and connected to existing datasets. This resulted in the yearly obligatory survey being replaced by a sample, covering 75% of farmers from 2008 onwards and whereby every farmer would be requested to fill in the survey at least every two years. This was combined with a large consecutive simplification of the survey from 2011 until 2014, reducing the number of questions. These surveys are now also obligatory by the European Union (EU) (Eurostat, 2015a) and information on the number of farms, farm size, farm types and farmer characteristics at the NUTS2 level can, for most countries, be found in the Farm Structure Survey and the Agricultural census of the EU on a three yearly basis. For Belgium, the aggregated data of the agricultural survey is available yearly at the municipality level. Although largely simplified in recent years, these survey data give an interesting insight into the evolution of different aspects of farm characteristics. The full survey contains 900 variables but not all variables are available for all years or for all aggregation levels. The available data can be found on the website of Statbel (statbel.fgov.be).

### 2.1.2 Agricultural parcel data

The agricultural land use data is derived from the *Système intégré de gestion et de contrôles* (SIGEC) and *Landbouwgebruikspercelen* dataset for respectively Wallonia and Flanders-Brussels. These datasets are collected yearly as required by the EU in the IACS dataset in order to distinguish, identify and measure the main crop production areas in Europe and check the validity of farmers' applications for EU subsidies (European Commission, 2018a). The dataset contains the agricultural parcels with the main crop being cultivated that year as well as data on pools, wood edges, farm yards and barns, sheds and other agricultural buildings as vector data and without any information on ownership or right of use. The dataset also provides information on crop rotations when creating a timeseries for the crops for each parcel in consecutive years for the parcel dataset. Based on this sequence the probability that one crop is followed by another crop can be defined.

### 2.1.3 Other datasets

*Mortality*

To model the demographic component, the model uses the data on the mortality rates for the male Belgian population in 2000 for each age, from 18 until 105 according to the Belgian statistical office (Statistics Belgium, 2019a). At 105 the probability of decease is set to 100%.

*Crop prices*

For the economic data on the prices per ton for each crop, the yearly real producer prices in local currency unit (LCU) per tonne are used. They were extracted from the database of the Food and

Agricultural Organization of the United Nations (FAO) for Belgium-Luxembourg from 2000 to 2015 (whereby the years 2000 and 2001 are converted from Belgian francs to euro by dividing them by 40.3399) (Food and Agriculture Organization, 2019).

*Yield data*

Data on expected yield for Belgium were obtained from the Dynamic Vegetation Model (DVM) CARAIB (CARbon Assimilation In the Biosphere) (Jacquemin et al., 2017). For the main Belgian crops (winter wheat, barley, maize, sugar beet, rapeseed and potatoes), CARAIB provides yearly the expected yields for the entire country at the spatial resolution of 1km$^2$. These data might not always be available for other study areas, but could be replaced by regional averages for the local main crop types. At the time of model completion, the time series on yield were not available, therefore, yield expectations were kept constant.

## 2.2 Belgium: an urbanised country in the centre of Europe

Belgium is a sovereign state in the densely populated area of Western Europe with an area of 30 528 km$^2$ (11 787 sq. mi), bordered by the Netherlands in the north, Germany in the east and Luxembourg and France in the south. In 2019, Belgium had a total population of about 11.4 million inhabitants (Statistics Belgium, 2019b), resulting in an average population density of about 376.7 inhabitants per km$^2$ (Figure 2.1 & Figure 2.2).

The major cities in Belgium are Brussels (the capital), Antwerp, Charleroi, Ghent and Liège (Figure 2.2). Most cities in Belgium date back to the Middle Ages and started expanding in the 19$^{th}$ century in relation to the developing industries and trade but, at that time, maintaining clear boundaries with the surrounding land. During the second part of the 19$^{th}$ century, under the impulse of increased mobility, cities started to spread out past their initial city boundaries. With the development of the railway system, the richer upper class started escaping the busy unhealthy city centres by moving to the greener countryside. After World War I, the population densities in the historic cities started to decrease, with people moving to the suburban areas, blurring the previously marked boundary between cities and their surroundings. The absence of a well thought out spatial planning, together with increasing mobility options, resulted in a further urban expansion towards the countryside, creating a strongly fragmented landscape (Van Hecke et al., 2010). These evolutions lead to the current spatial configuration of population density (Figure 2.2) and, to some extent, materialize in the current land use map (Figure 2.3): the highest population densities can be found in and around the major cities. Agricultural areas are in the fertile areas around the cities and less productive areas remained or returned forested.

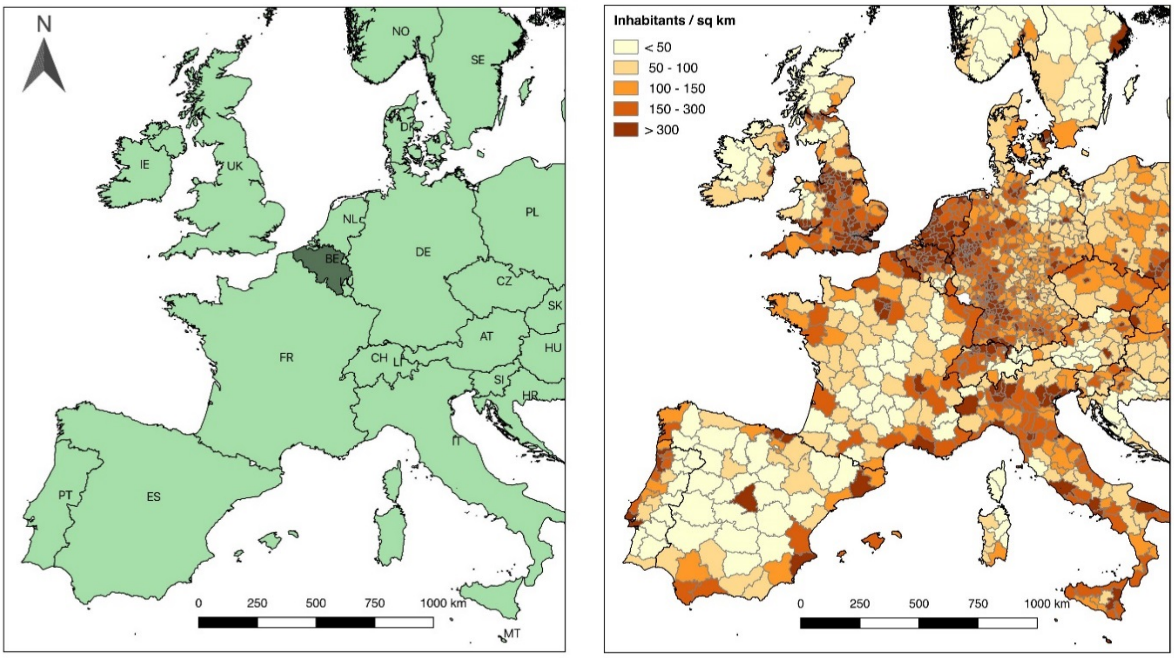



*Figure 2.1 – Belgium situated in Western Europe (left) and population density by NUTS3 region in 2015 (right)(European Commission, 2018b).*

## 2.3 Agriculture in Belgium

### 2.3.1 General overview

The aforementioned evolutions, together with the environmental and regional socio-economic circumstances, resulted in a great diversity of rural landscapes largely shaped by agriculture. Belgium has a maritime temperate climate with regular precipitation throughout the year, allowing for a wide variety of agricultural choices and making the soil specifications one of the most important environmental constraints. Based on the differences in local characteristics, Belgian authorities have delineated 14 agricultural areas, largely following east-west belts (Figure 2.4): the Dunes and Polders in the north-west, the Campine in the north-east, the Sand region in the central north and the Sand Loam and Loam region in the centre, containing the small region of the Hainaut Campines. Further south is the Condroz, followed by the Fagne and Famenne, the Ardennes and finally the Jurassic region in the lower south-east. In the most eastern part of the country are the High Ardennes and the Pasture region of Liège (AGIV, 2013).

The percentage of agricultural land remains the highest in the central loam belt, the most fertile part of Belgium and in the northwest, where agriculture has been historically important and where urban expansion remained relatively low. The percentage is the lowest in the south of the country, where the less fertile Ardennes region is located (Figure 2.5).

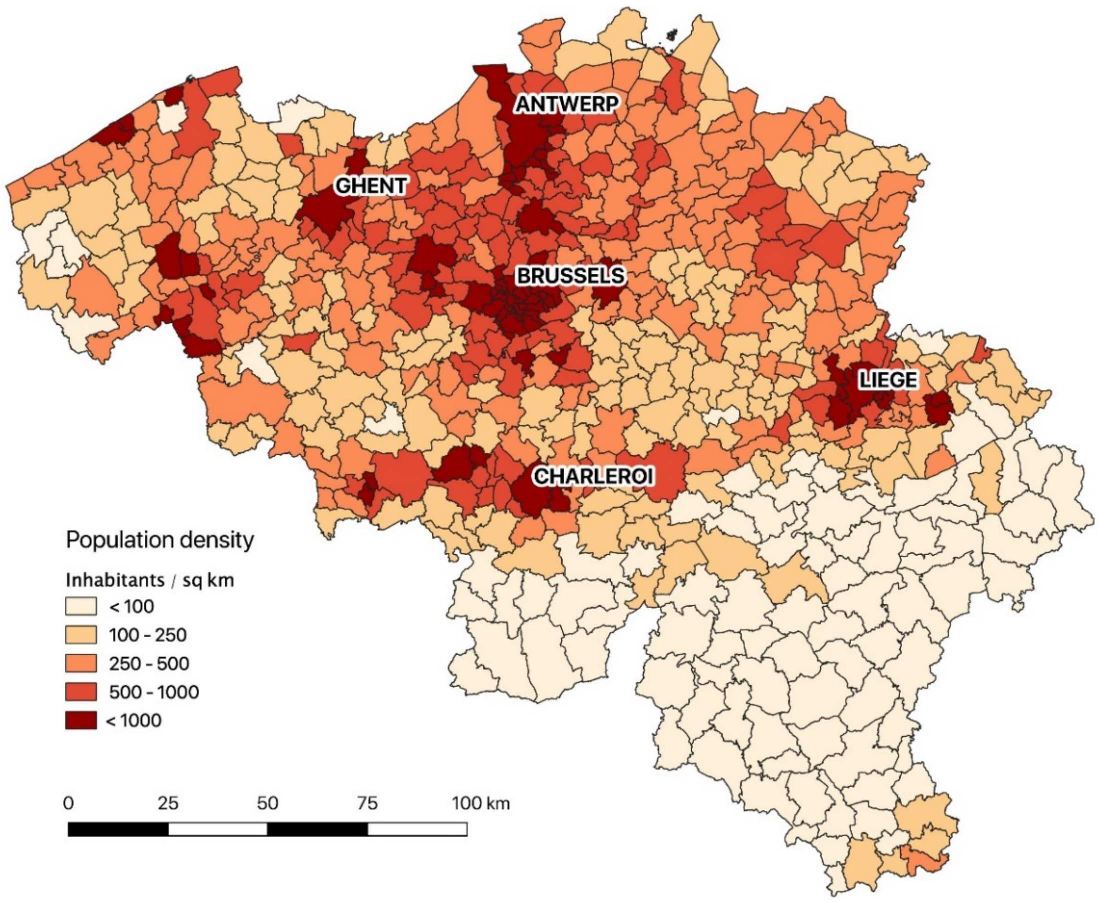



*Figure 2.2 – Population density in 2018 and major cities in Belgium (Statistics Belgium, 2019b).*

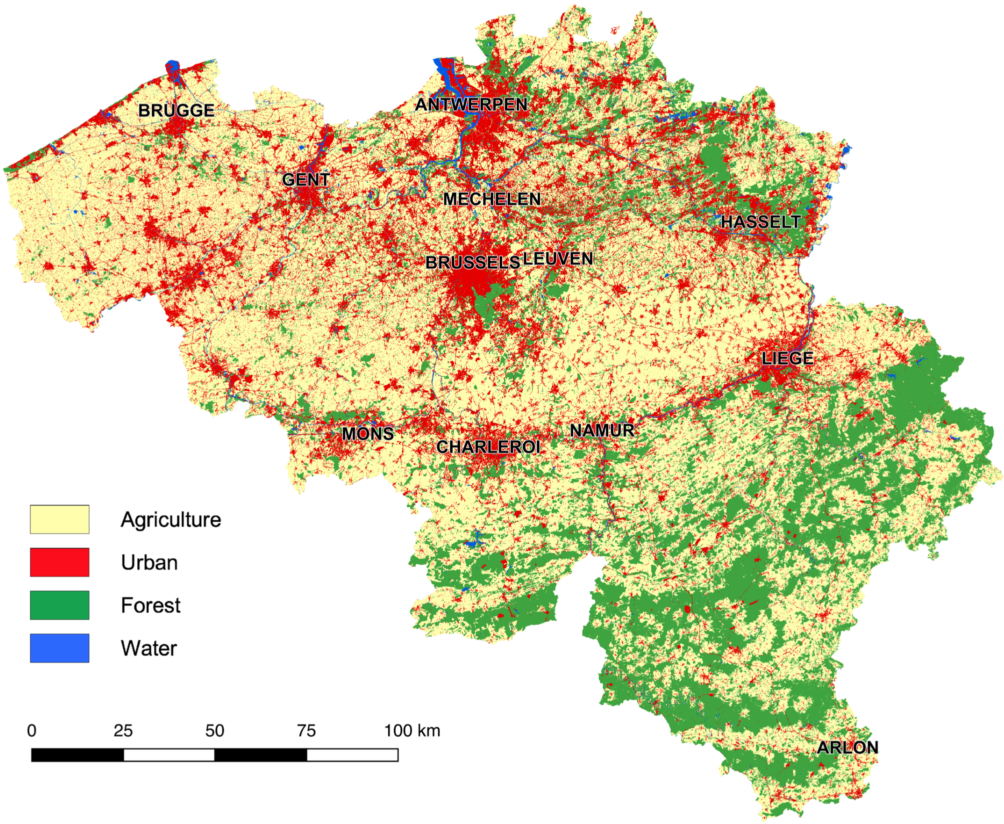



*Figure 2.3 – Dominant land use in Belgium at 1ha resolution based on Corine Land Cover data (Büttner et al., 2014).*

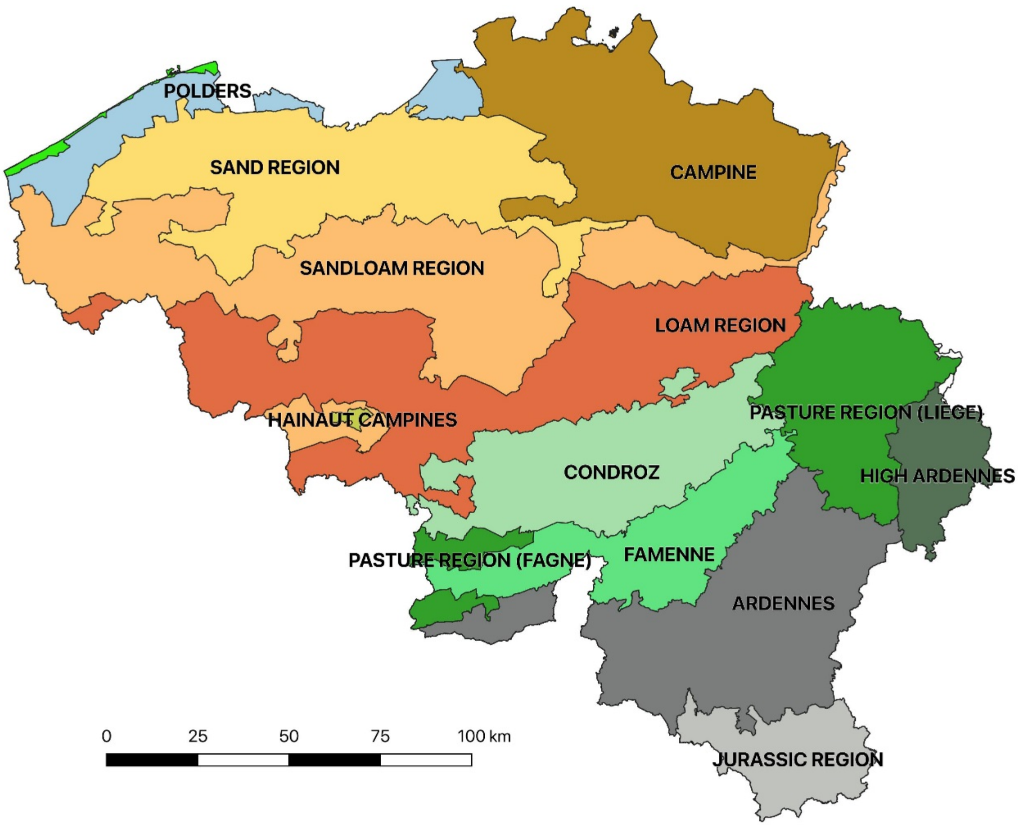



*Figure 2.4 – Agricultural areas in Belgium (AGIV, 2013).*

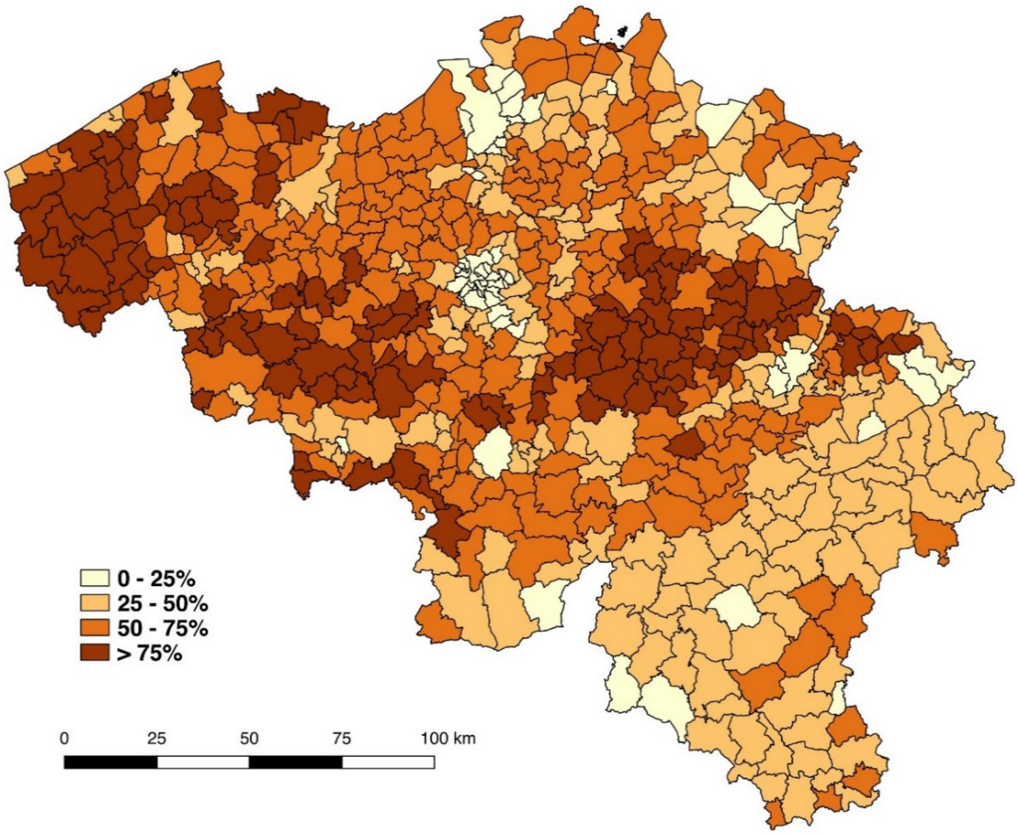



*Figure 2.5 – Percentage agricultural area in every municipality in 2010 according to the land registry (Statistics Belgium, 2019c).*

### 2.3.2 Historical context

Belgium has a long agricultural history, but apart from the specific physical environmental conditions, the roots of the current outlay of Belgian agriculture go back to the 13th century where an increase in the population led to first forms of agricultural intensification and specialisation (Van Hecke et al., 2010). The already higher population density in the north of the country with an important domestic industry resulted into on average smaller farms with more intensified systems in the north and larger farms, with more extensive farming in the south (Figure 2.6).

The situation was further enhanced by the implementation of the Napoleonic inheritance law, where heirs received equal shares of the inheritance, leading to a further fragmentation of the agricultural land (Mathijs and Relaes, 2012).

At the end of the 19th century, the small farms could not compete with the cheap import of grains from America. The combination with upcoming factories, which decreased revenues from domestic industries, led to an agricultural crisis. Especially the north of the country suffered, due to their higher dependence on these activities for their income. It only slowly recovered under the impulse of increased scientific knowledge on agricultural techniques, machinery, biology and chemistry.

After the world wars, the agricultural landscape changed fast. Improvements in mechanisation and automatization led to a reduction in required labour forces, resulting in an urbanisation wave. Change in selection methods, fertilization techniques and knowledge on hygiene and nutrition, increased production for both crops and animal related farming. Many of these new techniques and methods required heavy investments and farms not able to do this, dropped out (Mazoyer and Roudart, 2006). Remaining farms reinvested their income and increased their debts often reducing the farm income.

### 2.3.3 Regional differences leading to the present situation

The historical context set the main scene for agriculture in Belgium, but it was regionally influenced by differences in the social, economic, and physical environment. These differences however, only became clear when the focus of agriculture shifted from self-sufficiency to highly commercialized and market driven production, and when at the same time, transport options improved. At this point, soil properties and the historical context in terms of landscape and population became more pronounced (Van Hecke et al., 2010).

The average farm size per municipality (Figure 2.6) shows a clear north-south distinction: farms in the north of the country are on average much smaller than in the south of the country (an average of 25.4 ha in the north of the country (Flanders) versus 48.9 ha in the south of the country (Wallonia) in 2014), with the largest average farm sizes located in the centre of the country, in the fertile loam area. A high population density, results in smaller farms, and a higher farm density: The highest farm densities can be found in the north-west of the country, the highly urbanised central Antwerp – Brussels axis in the north shows a very low farm density. The farm density further decreases from north to south, with very low farm densities in the less fertile south of the country, where the less favourable pedoclimatic conditions, together with the absence of urban expansion led to more extensive types of farming on large farms (Figure 2.7).

The prevalence of different farm types is a result of the differences in historical context and the opportunities provided by the environmental conditions. These differences show in the specific spatial distribution of the share of the standard gross margin (SGM) of the different farm types in

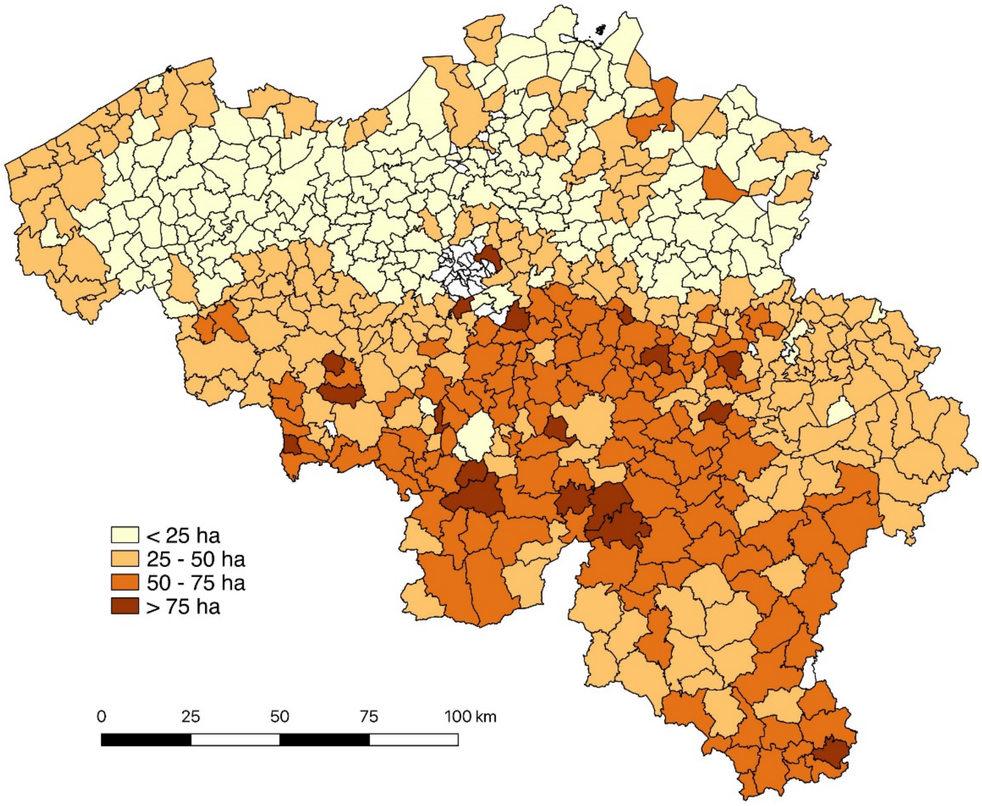



*Figure 2.6 – Average farm size for each municipality in 2010 (Statistics Belgium, 2018).*

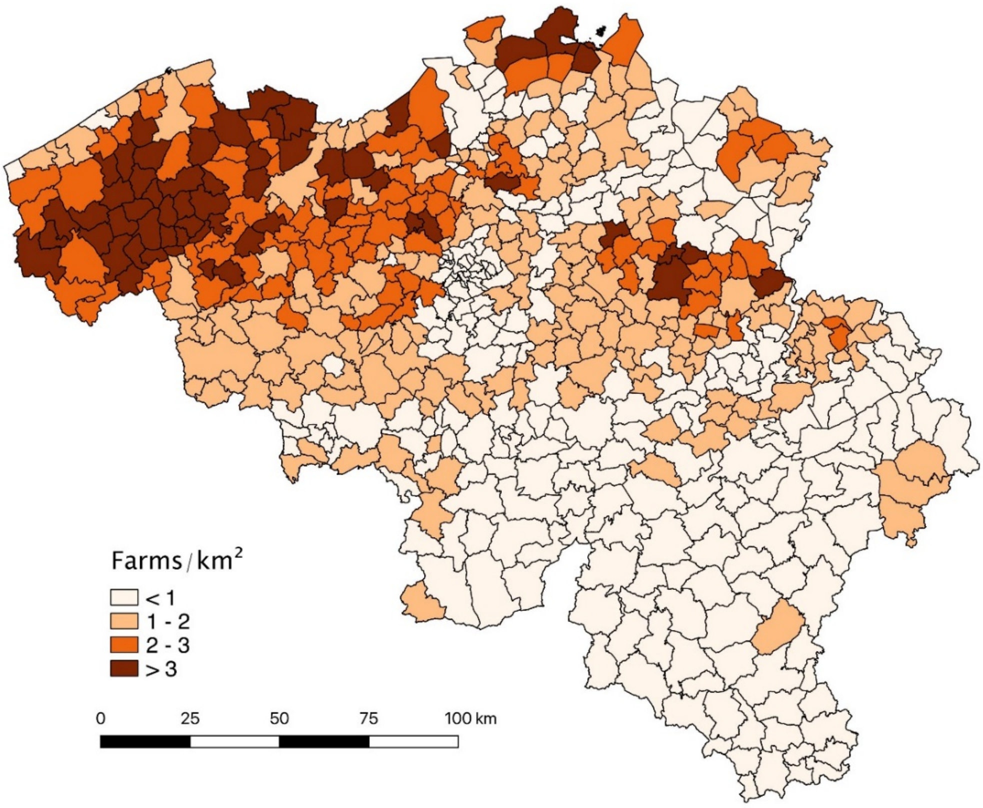



*Figure 2.7 – Number of farms per km² in 2010 (Statistics Belgium, 2018).*

every municipality (Figure 2.9). The SGM is a measure for the business size of a farm, and an approximation of profit, incorporating revenue, subsidies and estimated costs. After direct payments were decoupled from production in 2005, the SGM could be negative without subsidies, making it hard to be used as classification criteria. From 2010 onwards, the SGM was replaced by the EU by a new indicator: the standard output (SO). The SO is the average monetary value of the agricultural output at farm-gate price, in euro per hectare or per head of livestock. Since the new indicator used by the EU, the SO, does not take subsidies nor costs into account, it results in a distorted image due to the large differences in costs between different agricultural sectors. Therefore, and although no longer in use, we preferred to use the SGM for discussing the economic importance of agriculture in Belgium.

The combination of the earlier mentioned changes in the socio-economic conditions from the 19$^{th}$ century onwards together with the local pedoclimatic conditions led to grassland currently being the most dominating agricultural land cover in the Ardennes, the High Ardennes and the Pasture areas on the stony soils in the south, and in the Campine with its sandy soils. Maize can be mostly found in areas with intensive cattle and granivore farming, due to its high nutritional value and high uptake of the overabundant fertilizers (Figure 2.8). The high population density in the north of the country, on the other hand, led to more intensive types of farming that require less space, like horticulture and poultry and pig farming (Figure 2.9). Croplands can be mostly found in the most fertile part of the country, the loam area, which is highly suitable for different grain types and sugar beets (Figure 2.8).

The combination of the different regional characteristics, the historical context and traditions as well as the environmental conditions, results in the current lay-out of Belgian agriculture, summarized through the SGM per hectare and SGM per farm. The SGM per hectare (Figure 2.10) is on average higher in the north than in the south of the country, due to the presence of more intensive types of farming in the former, especially for the areas with a high intensity of horticulture or granivore farming. The SGM per farm (Figure 2.11), on the other hand, shows that the economically most important farms can be found in the central loam area with its large farms on highly fertile fields, and in the north of the country, where the small but intensive horticulture farms also result in a high SGM per farm. The centre of the country, with small farms, less fertile soils and under the pressure of urban expansion of Brussels and Ghent, clearly stands out due to its on average low SGM per farm.

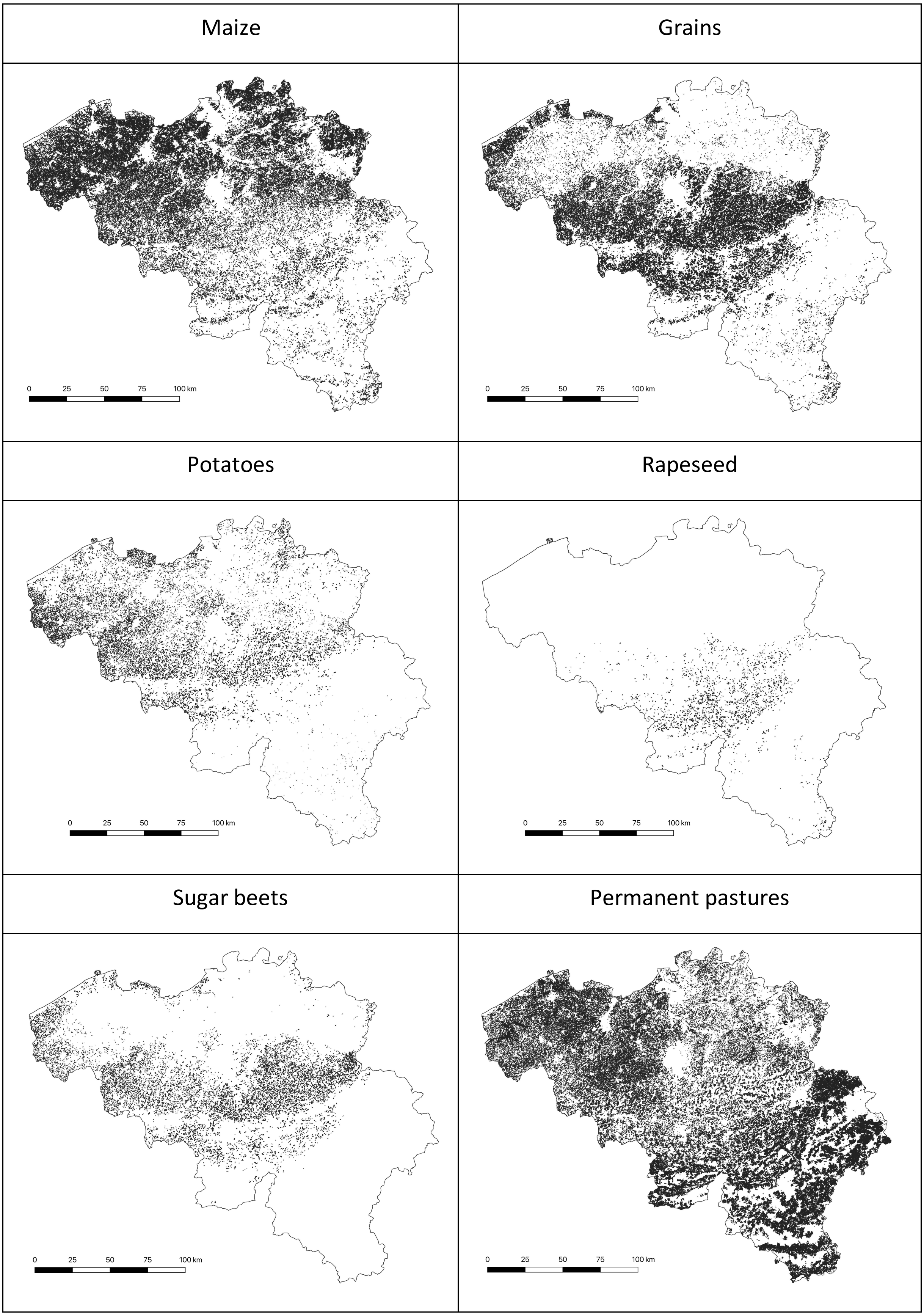



*Figure 2.8 – Presence of Different crops and agricultural land use in 2013 according to the IACS dataset of the European Union (European Commission, 2018a).*

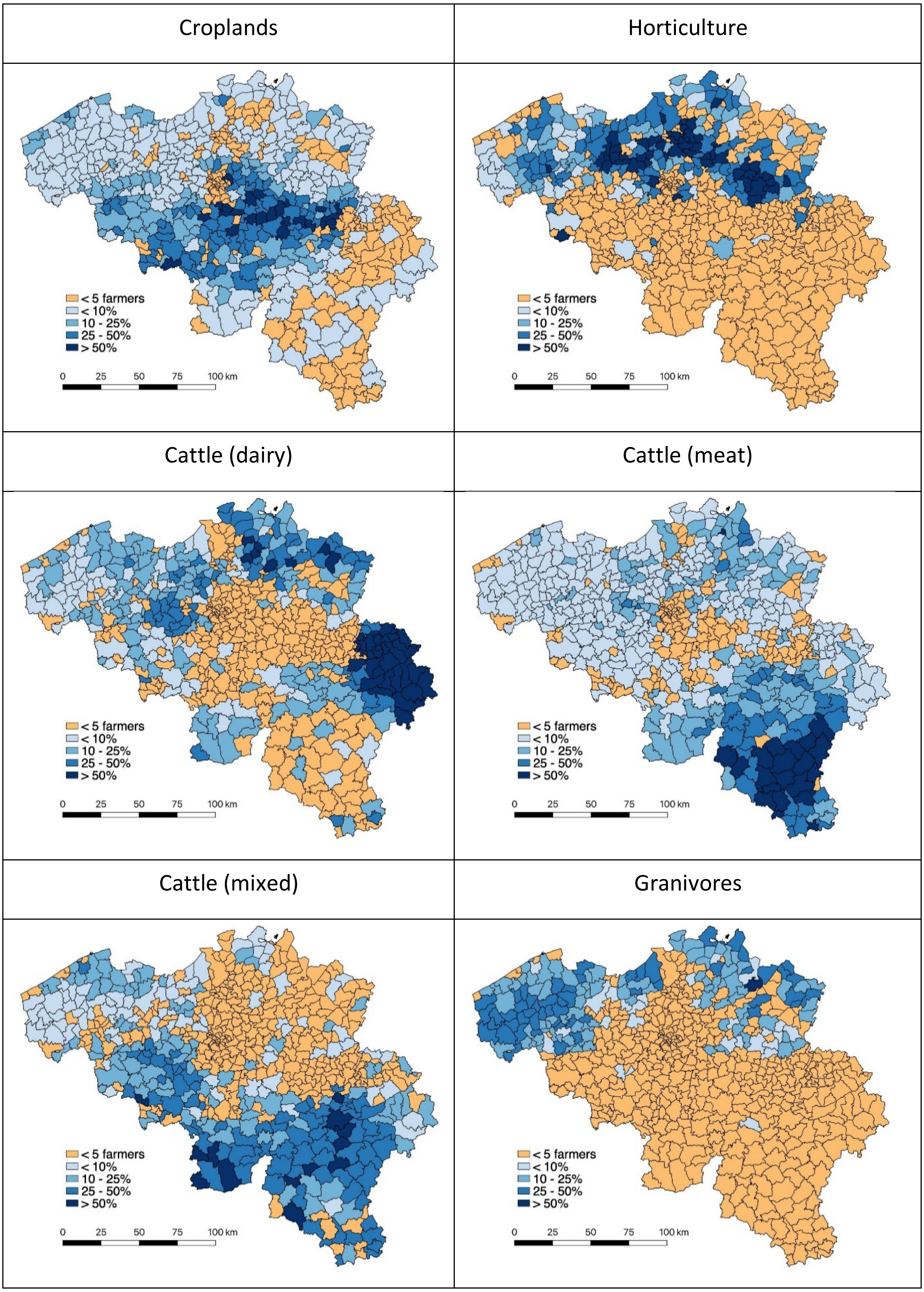



*Figure 2.9 – Share in the standard gross margin of different farm types for the different municipalities. Data for municipalities with less than 5 farmers per type are unavailable due to possible privacy issues. They are marked accordingly (Statistics Belgium, 2018).*

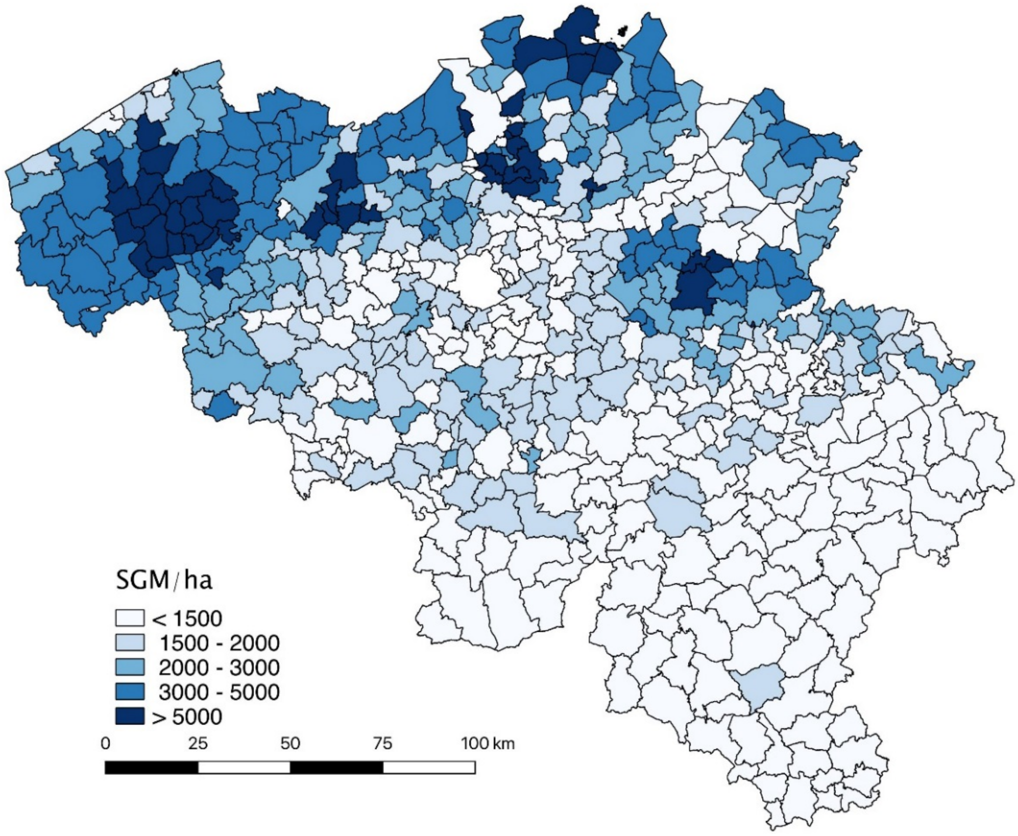



*Figure 2.10 – Standard gross margin per hectare in 2006 (Statistics Belgium, 2018).*

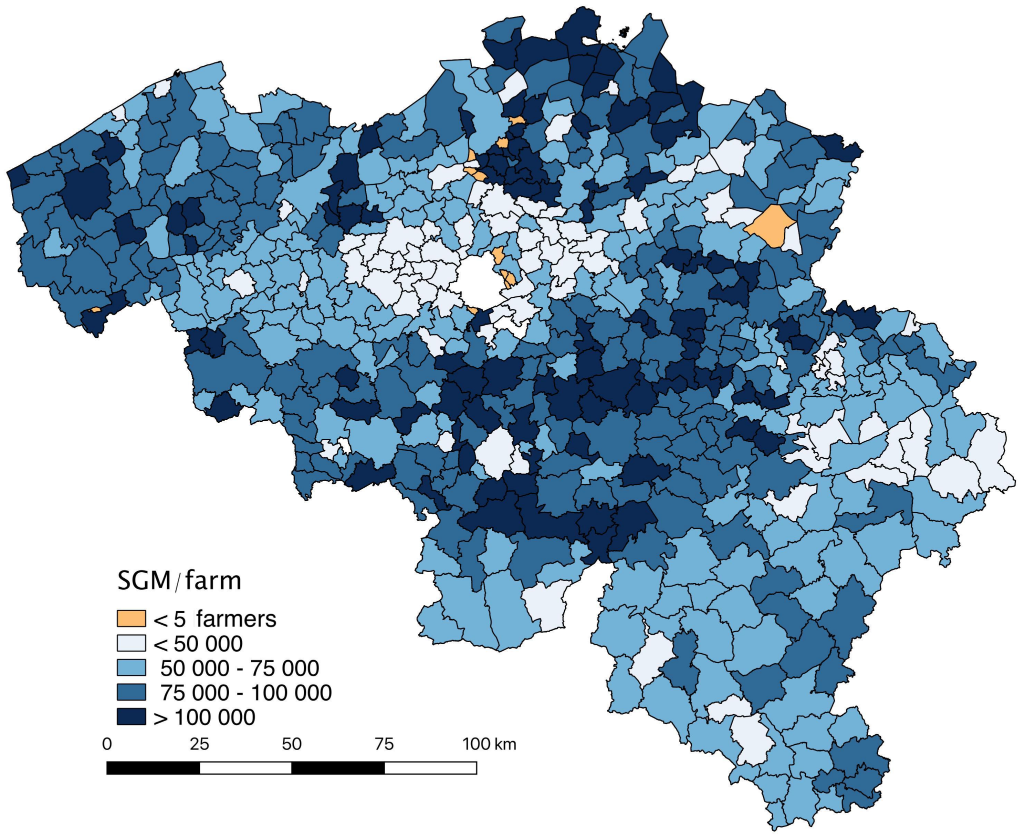



*Figure 2.11 – Standard gross margin per farm in 2006. Data for municipalities with less than 5 farmers per type are unavailable due to possible privacy issues. They are marked accordingly (Statistics Belgium, 2018).*

### 2.3.4 Current trends

Since the 1980s there has been a dramatic decrease in the number of farms in Belgium, with between 1980 and 2010 on average more than 6 farmers a day quitting. Recently, this number is decreasing, with an average of less than 2 farmers a day from 2011 onwards. A trend that can be expected given the diminishing number of farmers remaining. At the same time the average farm size has been increasing from an average of 12.5 ha in 1980 to 36.5 ha in 2015 (Figure 2.12). The decrease in the number of farms is most prominent in the central north of the country (the Flemish Diamond), in the east of the country and in the less fertile south. The regions with a strong agricultural tradition (West-Flanders and the loam belt) experience a much lower decrease (Figure 2.13).

This decrease can be related to the above discussed changes in the agricultural landscape after the world wars and the global trends discussed in the Introduction: the continuously improving techniques and methods require heavy investments, increasing input costs and reducing margins, especially with structurally falling agriculture prices in a globalised market. In order to be more competitive or even merely stay in business, farmers are forced to upscale. Farms that cannot make the required investments fail to stay competitive and leave the agricultural population at some point (Mazoyer and Roudart, 2006). While from an economical point of view, this can be seen as a necessity to increase the competitiveness of the sector in its whole, it also often leads to personal dramas with bankruptcies or (hidden) poverty and social exclusion for the farmer and his family or, together with their families, live in (hidden) poverty (Meert et al., 2005, 2002; Van Hecke, 2001). Studies in different countries have also identified a higher suicide rate in farming than in the general population (e.g. 5.9% vs 3.9% in Québec) (Behere and Bhise, 2009; Klingelschmidt et al., 2018; Roy et al., 2013).

This decrease in number of farmers can also partly be related to the demographic situation of the agricultural population and the succession rate for farms. Belgium, like many European countries, has an old farmer population. 85% of farmers are male, 44.4% of farmers are older than 55 in 2010 and 20% are even older than 65 (Statistics Belgium, 2018). The oldest farmers can be found in the central west of the country (Figure 2.16), the area that was also clearly marked by a low average SGM. Given this aging farmer population and the low average succession rate for farmers over 50 years old (15.6% have a successor, 51.7% do not and 32.7% do not know), a further decrease of the number of farmers can be expected. Differences between succession rates can however be observed between regions and between farm sizes: succession rate is higher in the central loam area, and south of it (Figure 2.17). Succession rate in the north of the country and the southernmost part of the county is clearly lower. Succession rate also relates to farm size: the larger the farm, the higher the succession rate (Figure 2.14). This strong link between farm size and succession rate therefore also results in an over-representation of younger farmers in the farm size categories above 30 and especially 50 hectares. While the older farmers tend to manage smaller farms, up to 20 hectares (Figure 2.15).

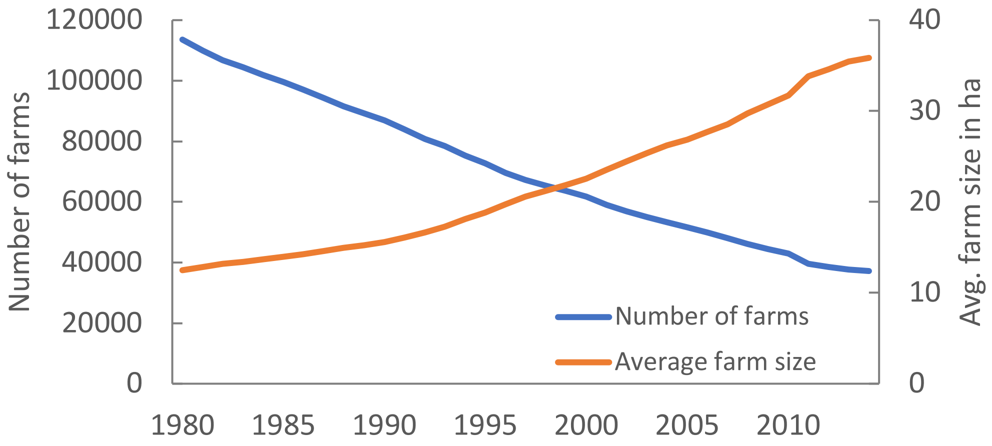



*Figure 2.12 – Evolution of the number of farmers and the average farm size since 1980 (Statistics Belgium, 2018).*

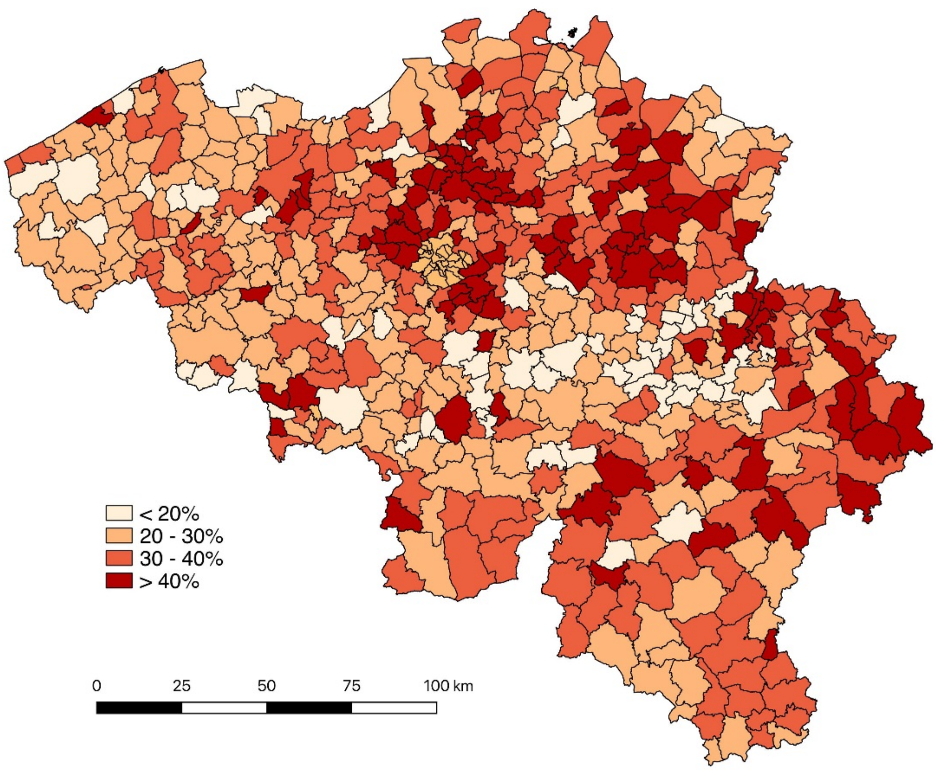



*Figure 2.13 – Relative decrease in the number of farmers between 2000 and 2010 (Statistics Belgium, 2018).*

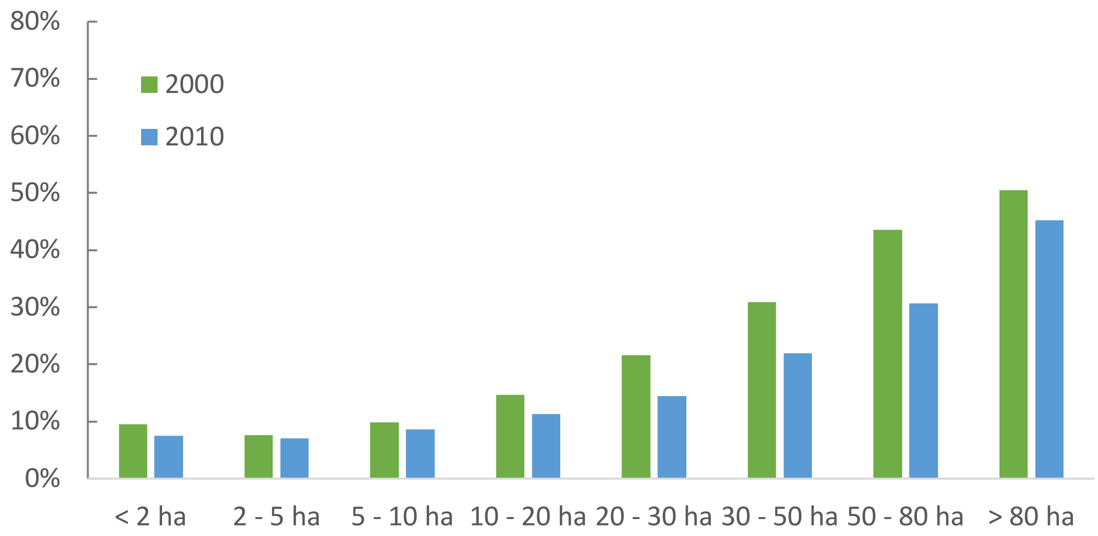



*Figure 2.14 – Percentage of farmers having a successor in function of farm size (Statistics Belgium, 2018).*

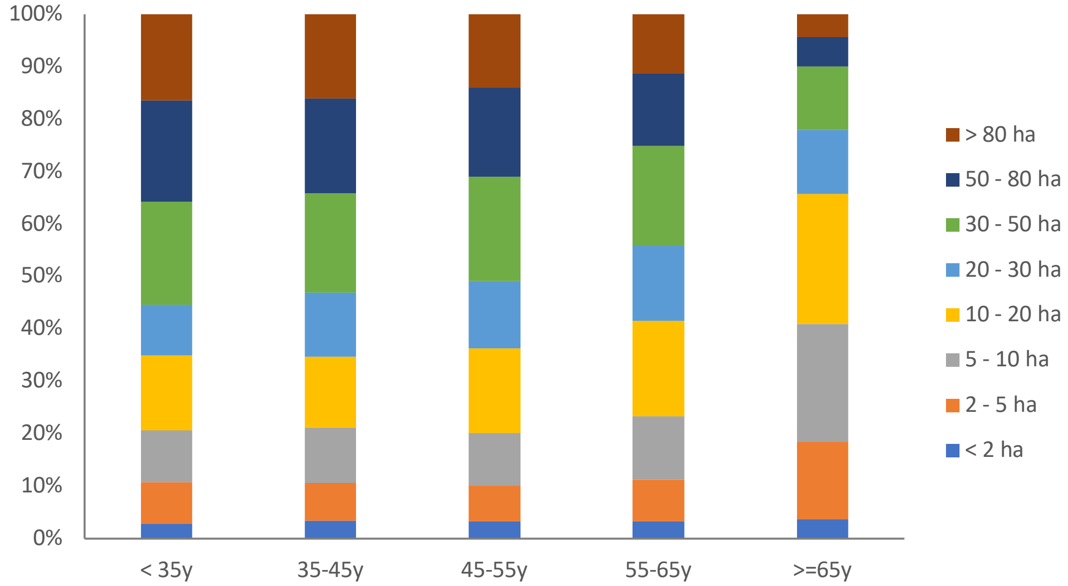



*Figure 2.15 – The relation between the farmer's age and the size of the farm in 2016 (Statistics Belgium, 2018).*

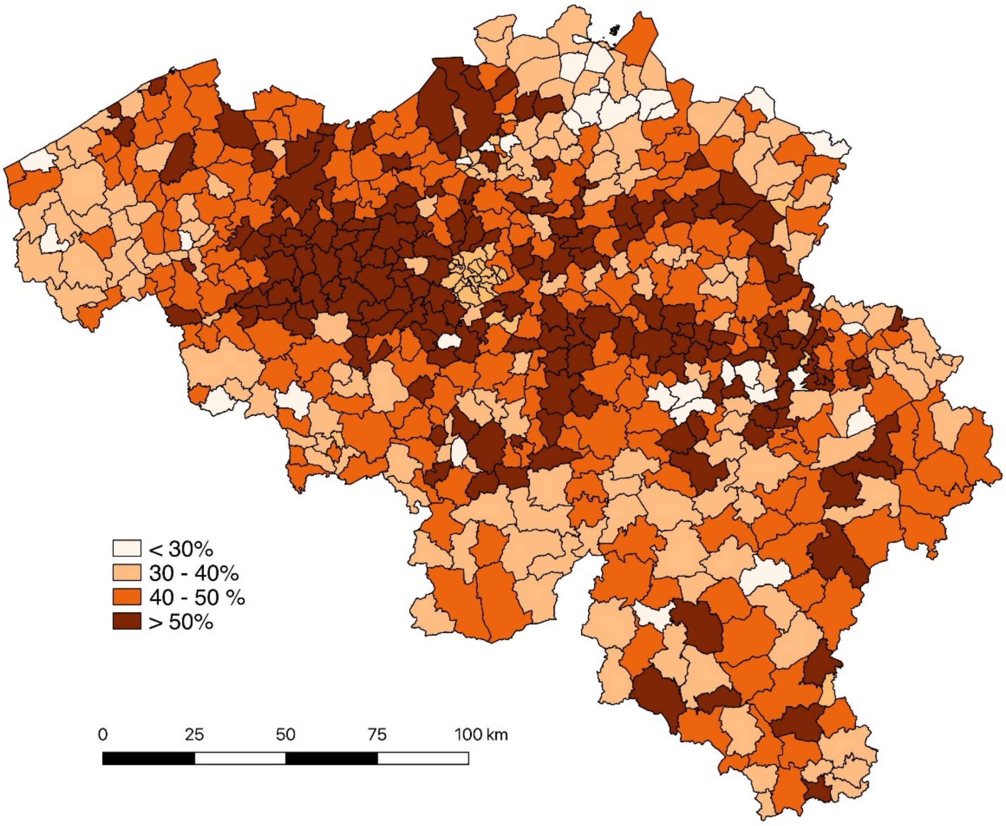



*Figure 2.16 – Percentage of farmers over 55 years old in 2010 (Statistics Belgium, 2018).*

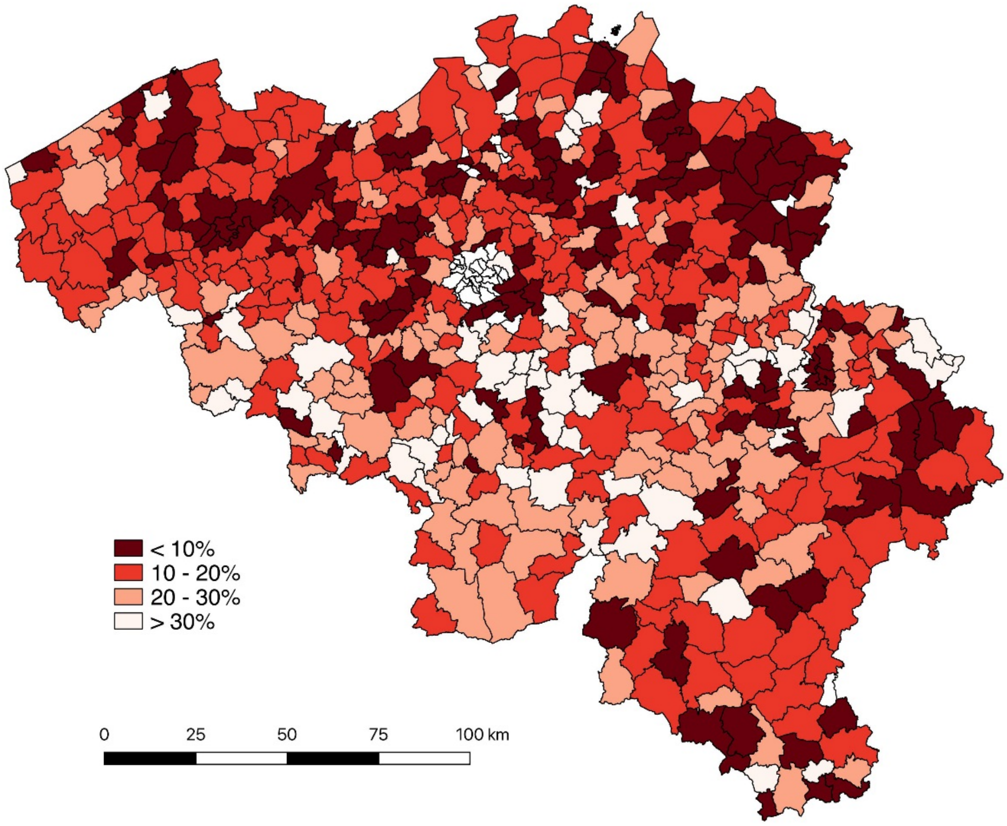



*Figure 2.17 – Percentage of farmers over 50 years old having a successor in 2010 (Statistics Belgium, 2018).*

### 2.3.5 Common Agricultural Policy

Since Belgium is part of the European Union, it falls under the Common Agricultural Policy (EU-CAP) of the EU, a system of income and market support programmes for the agricultural and rural sectors. It sets out the lines of the national agricultural policies of its member states. A first step towards the EU-CAP was already introduced in the Treaty of Rome in 1957, which defined the start of the European Economic Community, the origin of the EU (European Commission, 2012).

The Treaty of Rome mentions the main aims of the EU-CAP as (1) to increase agricultural productivity, (2) to provide a reasonable standard of living for the agricultural population, (3) to stabilize agricultural markets, (4) to provide food security, and (5) to guarantee reasonable prices for customers (Mathijs and Relaes, 2012). These aims led to the creation of the EU-CAP, which was introduced in 1962 and still exists today, undergoing several changes along the way.

The first major period, from 1962 until 1992, was based on 3 basic principles: a single market, community preference and financial solidarity. Production and trade within the EU was regulated through common market organisations to guarantee steady incomes for farmers and steady prices for consumers by regulating supply (quota, import taxes, grubbing-up premiums, temporary storage) and demand (export subsidies, promotional campaigns, buying-in interventions) (European Commission, 2012; Mathijs and Relaes, 2012). the result was a strong increase in agricultural production, moving from an insufficient agricultural production to a situation of overproduction. Guaranteeing prices with overproduction was resolved by heavy export subsidies, requiring an increasingly higher budget. Especially in the dairy sector, budgets were derailing, which led in 1984 to the setting of strict (tradable) quotas for milk (Mathijs and Relaes, 2012). The will to also maintain agriculture in less favourable and less populated regions resulted in a rural development plan, that later became an integrated part of the EU-CAP (the second pillar, market- and income policy being the first).

The derailing of the budgets led to the first important reform in the history of the EU-CAP: the Mc Sharry-reform. With the Mc Sharry-reform, price support was gradually decreased and replaced by income support (per animal or per hectare) independent of production level (Mathijs and Relaes, 2012). According to the reform, farmers were asked to fallow part of their land and were also encouraged to produce more environmentally friendly. After the Mid Term Review in 2003, support was completely decoupled from production level and more subsidies were foreseen for agro-environmental measurements (European Commission, 2012; Mathijs and Relaes, 2012).

In 2013, the EU-CAP was reformed to reduce differences between and within member states. It also focusses on making the payments to farmers more related to environmentally farming practices and more directed towards young farmers, farmers in low income sectors and farmers in unfavourable areas (European Commission, 2013).

In 2018, the European Commission communicated the legislative proposals for the future of the EU-CAP, after 2020. The focus is on making the EU-CAP more responsive to current and future challenges through nine objectives: ensuring fair income for farmers, increasing competitiveness, improve farmers' position in the food chain, climate change action, environmental care, preservation of landscape and biodiversity, supporting generational renewal, vibrant rural areas and protection of food and health quality (European Commission, 2019).

## 2.4 Challenges for agriculture in Belgium in a global context

### 2.4.1 Urban expansion

In the last decades, Belgium, like many western European lands, has been characterized by a remarkable expansion of urbanised areas, at the expense of agricultural lands and nature (Pointereau et al., 2008).

Not only did this evolution reduce the available land for farmers, it also resulted in the loss of the exclusive use of agricultural land by farmers. These lands were increasingly adopted for other functions with a weak or even no link to agricultural production, like horse-riding, agro-tourism, construction or for residents practicing a rural lifestyle (Bomans et al., 2011; Primdahl et al., 2013). In the northern part of the country this led up to 15% of agricultural area not being used for commercial agriculture (Verhoeve et al., 2015).

The urban expansion and fragmentation of the agricultural land in Belgium currently still continues (Crols et al., 2017; Mustafa et al., 2018a; Poelmans, 2010) with the decrease in agricultural land being most pronounced in the north of the country, namely in the highly urbanised Flemish Diamond, and around major Belgian cities (Figure 2.18).

In order to put a stop to the further loss of open space to built-up areas, different policy measures are being proposed (Departement Ruimte Vlaanderen, 2017; SPW, 2018). These plans are however long term (by 2040 and 2050 for Flanders and Wallonia respectively) and are difficult to implement, due to legal difficulties and resistance from the population (Leonardi, 2018; Paelinck, 2019; Rombaut, 2018; Verbergt, 2018).

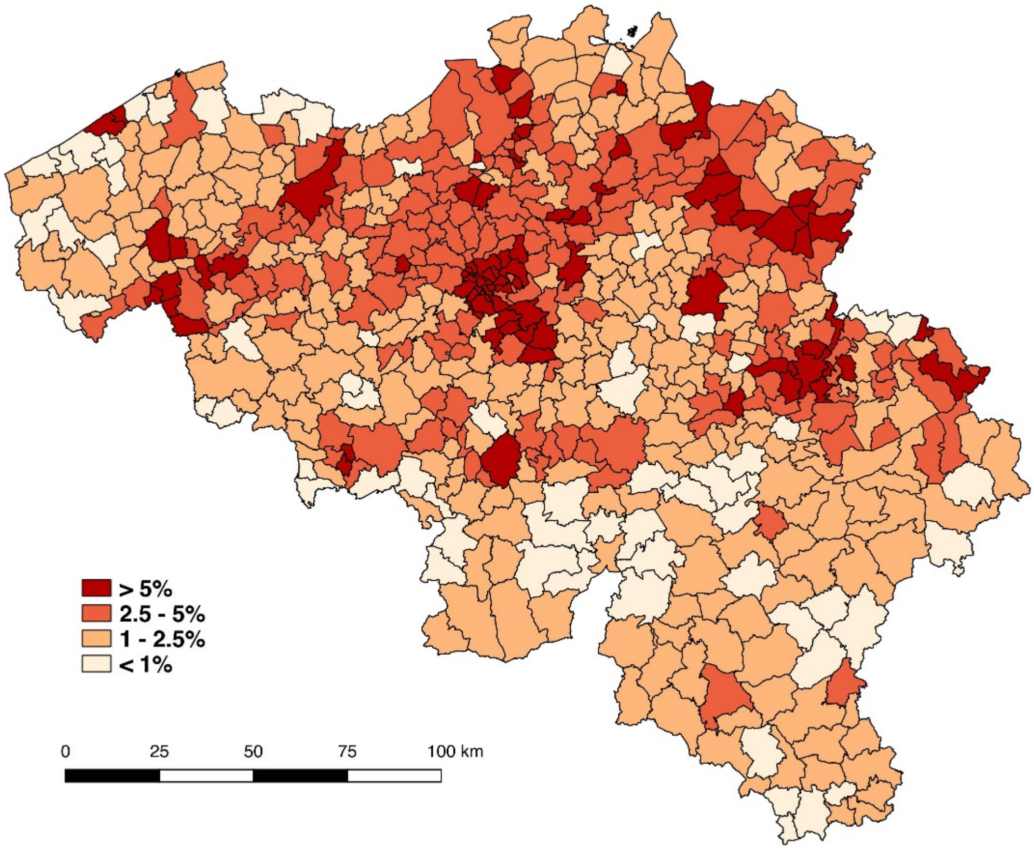



*Figure 2.18 – Relative decrease of the agricultural area between 2000 and 2010 following the land register* (Statistics Belgium, 2019c).

### 2.4.2 Environmental challenges

From the 1960s and 1970s, there has been an increasing interest in the environment and awareness of environmental problems. A first environmental problem related to agriculture is eutrophication. Eutrophication occurs when water becomes very rich in minerals and nutrients, resulting in an increasing growth of plants and algae. These plants increase the turbidity of the water and use large amounts of the available oxygen. These processes alter the water, making it an uninhabitable environment for many other species, living in it. Eutrophication is almost always the result of the discharge of nitrate or phosphate-containing substances in the water (Withers et al., 2014; Withers and Haygarth, 2007), namely the products used and produced by agriculture for fertilizing the land

and as a result of animal farming. In Belgium especially for the northwest of the country, with a high amount and high density of pig farming, this proved to be problematic (Van Hecke et al 2010). To tackle this issue, the EU created the Nitrates Directive in 1991, requiring countries to limit the use of organic and inorganic fertilizers and to monitor all farms in relation to their fertilizer management. This directive was implemented in Belgium through the Mest Actie Plan (MAP) in Flanders and the Programme de Gestion Durable de l'Azote (PGDA) in Wallonia. In 1997, in Flanders, a balance of the amount of fertilizers produced and the amount that could be used, showed a surplus of about 34% of the total nitrogen production and 40% of total phosphate production (Van Hecke et al., 2000). The imbalance resulted is many negotiations between farms over and under the limits and in slurry transportation (sometimes over long distances) between these farms, often at a high cost for overproducing farmers (Van Hecke et al., 2000).

Problems related to erosion are also closely linked to the eutrophication issue. In the first place, soil erosion leads to valuable, high-quality soil to wash away, whereby also impacting the turbidity of the water. Sometimes the high run-off on agricultural lands results in muddy floods impacting residential areas, with a subsequent significant financial cost (Verstraeten and Poesen, 1999). The eroded soil also contains the fertilizers applied to the land (Montgomery, 2007). As such, even with strong restrictions on the amount of applied fertilizer on the land, eutrophic elements still arrive in water bodies. In 2003, for the Mid Term Review of the EU-CAP, the EU included a cross-compliance system, which required farmers to follow a set of rules in order to receive financial support from the EU. The set-out rules included measures to reduce soil erosion, like the use of grass buffer strips, certain land management techniques and the avoidance of bare soil in order to reduce erosion (European Commission, 2018c).

Since halfway the 20$^{th}$ century, agriculture increasingly started using different forms of pesticides to increase agricultural output: organophosphate insecticides in the 1960s, followed by carbamates, herbicides, fungicides and pyrethroids in the 1970s and 1980s (Aktar et al., 2009). The use of these pesticides resulted in an increased pest control and a higher agricultural output but also had an impact on the environment and human health. An estimation in 1999 states that yearly about 1 million deaths and chronic diseases can be linked to pesticide poisoning (Environews Forum, 1999). Through run-off and percolation, these pesticides also contaminate the surface- and groundwater (Hildebrandt et al., 2008). Recent studies have also shown pesticide contamination of air (Socorro et al., 2016) and different non-target organisms (Mancini et al., 2019; Yohannes et al., 2017).

Recently, climate change has become an important environmental concern and might require severe adaptations of current farming techniques. Although there is uncertainty about the impact of climate change on the climate of temperate regions in Europe (Kovats et al., 2014), there is a high certainty on the increase of variability and extreme weather events (Beniston et al., 2007; Lenderink and van Meijgaard, 2008). The impacts of these changes are already showing, for example, in the yield losses for agriculture as a result of the 2018 drought (European Commission, 2018d).

One of the focus points to mitigate climate change is the reduction of the emission of greenhouse gasses. Already in 1997, research pointed to agriculture as an important contributor to greenhouse gas emissions (Cole et al., 1997). Consequently, farmers are required to implement measures and make extra investments to reduce their greenhouse gas emissions. The Effort Sharing Regulation for example requirs a 35% reduction of greenhouse gasses for Belgium by 2030 as compared to 2005 (European Union, 2018).

Last but not least, the 2019 published global assessment report of the Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services (IPBES) (Díaz et al., 2019) indicates the strong, rapidly and accelerating deterioration of biodiversity and ecosystem functions worldwide. Land use change, and more specifically agricultural expansion and intensification, is denoted as having the largest relative negative impact on nature for terrestrial and freshwater ecosystems, with climate change increasingly exacerbating the impact (Díaz et al., 2019). Among species experiencing a rapid decline are some species with a crucial relation to agriculture for their role as pollinator (Aguirre-Gutiérrez et al., 2017). A large extinction wave of pollinating species could ultimately have a dramatic impact on agricultural production.

### 2.4.3 Challenges arising from globalisation

The issues resulting from globalisation, as discussed in the introduction and earlier in this chapter, have a significant impact on Belgian agriculture. Farmers remain in a constant competition with other local farmers, as well as with farmers worldwide. Differences in the socio-economic conditions (e.g. wages and tax systems) and legal obligations (e.g. environmental, social, or animal welfare laws) make it impossible for Belgian farmers to be compete with farmers from countries like Brazil or Argentina. In 2016 Brazil was the most important exporter of prepared meat and comes only second, after the USA, on soy and maize exportation, worldwide the two most important fodder crops (FAO, 2016). This does not only affect the competitiveness of Belgian farmers directly but also indirectly: the carbon footprint of food commodities through greenhouse gases from transportation, together with the large deforestation campaigns to support the production (Barona et al., 2010; Morton et al., 2006) are not taken into account. They have an important impact on climate change and raise questions about the sustainability of the food production (Elgert, 2013; van Berkum and Bindraban, 2008). This has, in turn and as described above, its impact on the environment and biodiversity and thus on farming itself.

## 2.5 Conclusion

Belgium, as other Western Europe countries, has a long agrarian history, shaping the landscape for ages. Together with environmental limitations and historic evolutions, it resulted in the current agrarian landscape of the country. As many Western countries, the agricultural sector in Belgium faces large challenges. These challenges, together with the fact that Belgium is part of the EU, making it representative for other EU countries in terms of data availability, make Belgium an interesting case study area. The listed datasets will be used as an input and starting point for modelling agricultural dynamics. They were specifically chosen on the basis of their availability for other EU countries, allowing making the model transferable to other regions. The analysis of this data however shows that, throughout the years, progressively less data on farming is being collected and made easily accessible, reducing representativeness and hampering the study of time series. The chosen datasets are therefore generally available for many countries within the EU at the time of writing, but no guarantee can be expected for the future.

# Chapter 3 Methodology

## 3.1 Agent-based models

### 3.1.1 History of agent-based models

Agent-based models (ABMs) allow a one-to-one mapping of virtual agents to real world actors in a spatially explicit way (Berger & Troost 2012). The agents can represent a wide range of individual entities, from animals or plants to persons, firms and organisations (Rounsevell et al., 2012). These agents interact both with each other and with their environment. Through the decisions they make, they influence each other and the environment (Ferber, 1999; Matthews et al., 2007; Rounsevell et al., 2012). The nature of this modelling technique allows for a holistic approach (Berger and Troost, 2014) and the ability to investigate the emergence of macro-scale phenomena at the aggregated level as the results of the individual decisions of all agents (Crooks et al., 2008).

Agent-based modelling (ABM) is a relatively new technique that has gained increased attention in the last decades. The first notions of ABM can be traced back to the 1950s with the Von Neumann machine (Burks et al., 1946), a machine capable of self-reproduction. The idea was further developed into the concept of Cellular Automata (CA) through the incorporation of concepts on working with a lattice network that considers neighbours' behaviour (Figure 3.1) (Bialynicki-Birula and Bialynicka-Birula, 2005). CA only became more widespread with the development of Conway's

“Game of Life” in 1970 (Figure 3.2) (Adamatzky, 2010; Gardner, 1970) and Wolfram’s classification of CA rules (Adamatzky, 2010; Wolfram, 1984). A CA is typically represented as a grid, where every cell is in one of a finite number of states. Each cell state can change every timestep according to a given set of rules using information on the current state of the cell and the state of its neighbours. CAs can be seen as a simplistic agent-based model, where every cell is an agent, with the rules being the agent’s behaviour (Macal and North, 2009).

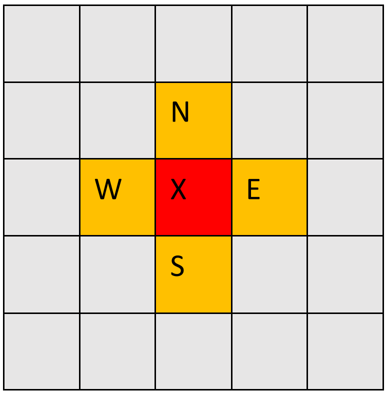



*Figure 3.1 – Neighbourhood lattice for cellular automata*

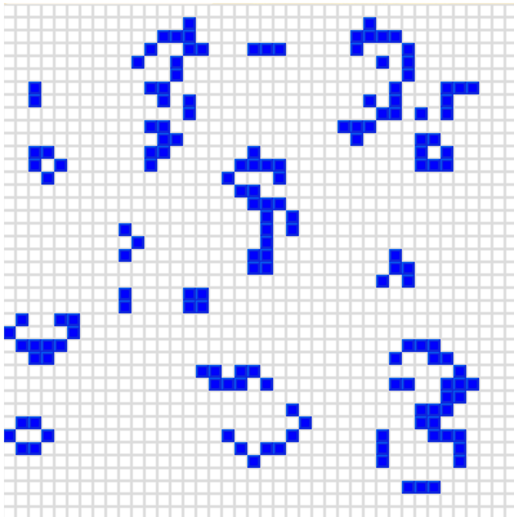
| Generation 0 | Generation 30 |
|---|---|
|  |  |

*Figure 3.2 – Conway’s “Game of Life” simulation, with the initial state, and the state after 30 time steps (dCode, 2019).*

Also in the 1970s, Schelling (1971) proposed a basic model with simple dynamics on segregation in populations, containing both autonomous and interacting agents in a shared environment resulting in an aggregate, emergent outcome. In the 1980s, ABMs became more into use, for example in the field of political science (Axelrod, 1997; Axelrod and Hamilton, 1981) and biology, with Reynolds’ (1987) famous “Boids” simulation on flocking behaviour of animals (Figure 3.3).

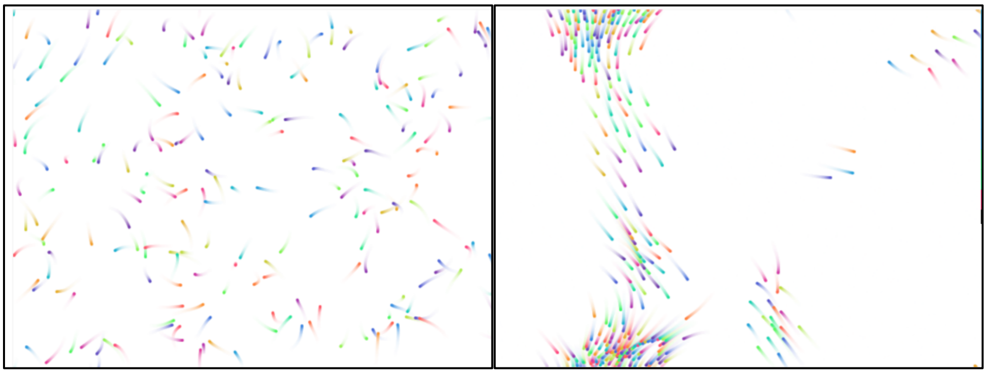


*Figure 3.3 – Boids simulation with initial situation (left) and the situation after a series of time steps (right) (Veltman, 2019).*

Since those first models, ABM has become more complex, often focussing on specific cases, sometimes related to real-world situations, with efforts towards increased empirical grounding (Matthews et al., 2007; Rounsevell et al., 2012) and is now used in a wide variety of domains, from ecology (de Vries and Biesmeijer, 1998; DeAngelis and Mooij, 2005; Grimm and Railsback, 2013) to social sciences (Epstein and Axtell, 1996; Gilbert and Troitzsch, 2005; Macy and Willer, 2002), economics (Axtell, 1999; Farmer and Foley, 2009; Magliocca et al., 2011; Tesfatsion, 2002), demography (Billari et al., 2007, 2006; Wu et al., 2008), epidemiology (El-Sayed et al., 2012; Marshall and Galea, 2014; Roche et al., 2011) and land use change (Bakker et al., 2015; Bousquet and Le Page, 2004; Hare and Deadman, 2004; Matthews et al., 2007; Parker et al., 2002b; Valbuena et al., 2010; Zhang et al., 2013).

ABMs also made their entrance in the domain of agriculture. Balmann (1997), for example, created a simple cellular automata in a hypothetical landscape for analysing structural change in agriculture, while Berger (2001) created an empirically grounded multi-agent/cellular automata focusing on technology diffusion in agriculture. Recently, ABMs in agriculture have become more and more advanced with empirically based real-world agricultural ABMs like AgriPoliS (Happe et al., 2009, 2008), RULEX (Bakker et al., 2015) and a model on structural farm change in Canada by Freeman et al. (2009). A full overview of agricultural ABMs can be found in the review paper of Huber et al. (2018), where an overview is given on the different characteristic elements of the models (purpose, extent, interactions, environment, etc.) together with a comparison on the complexity of the decision-making processes involved. They show that many agricultural ABMs model changes in land-use (16 out of 20), but only a limited number looks at farm structure (5 out of 20), or incorporate farm types (4 out of 20). Interaction between farmers is in most cases limited to interaction through a land market (Huber et al., 2018).

In general, different results produced by ABMs in the domain of land use and land use change can also be estimated through statistical models. This approach, however, estimates the average effect based on the available data, making it only useful for processes that are static and constant over space and time. It does not allow the inclusion of possible feedback mechanisms that can emerge and cannot represent the effects of individual, independent and heterogeneous human decision making on the landscape (Parker et al., 2002b). On top of that, ABM allows an interdisciplinary approach with an empirical grounding.

### 3.1.2 Challenges for ABMs

The research on ABMs in the last years has shown many interesting opportunities, but has at the same time revealed its difficulties, limitations and shortcomings. One of the most encountered issues is related to the high amount of data required to set up an agent-based model. In most ABMs, the representation of actors and their characteristics in space and time is crucial (Crooks et al., 2008). Robinson et al. (2007) compared different approaches to obtain these data and to provide ABMs with an empirical ground, namely sample surveys, participant observation, field and laboratory experiments, companion modelling and GIS and remotely sensed data (Figure 3.4). The research shows that the chosen approach depends heavily on what is expected from ABM and that the final outlay of ABMs is heavily dependent on the available data. The lack of spatial data at the scale relevant for decision-making processes might lead to a need of upscaling and hence the loss of information and the possible loss of spatial heterogeneity (Parker et al., 2002b).

However, Rounsevell et al. (2012) insist that there is a need for ABMs covering larger geographical regions in order to combine them with other models like ecosystem and vegetation models, and to be able to model at the level relevant for policy processes and politics. This problem, together with the high data requirement of ABMs, makes this challenging. They argue that especially social surveys are useful in the empirically grounding of ABMs, allowing the introduction of a degree of heterogeneity in the characteristics of the population, which influences decision-making.

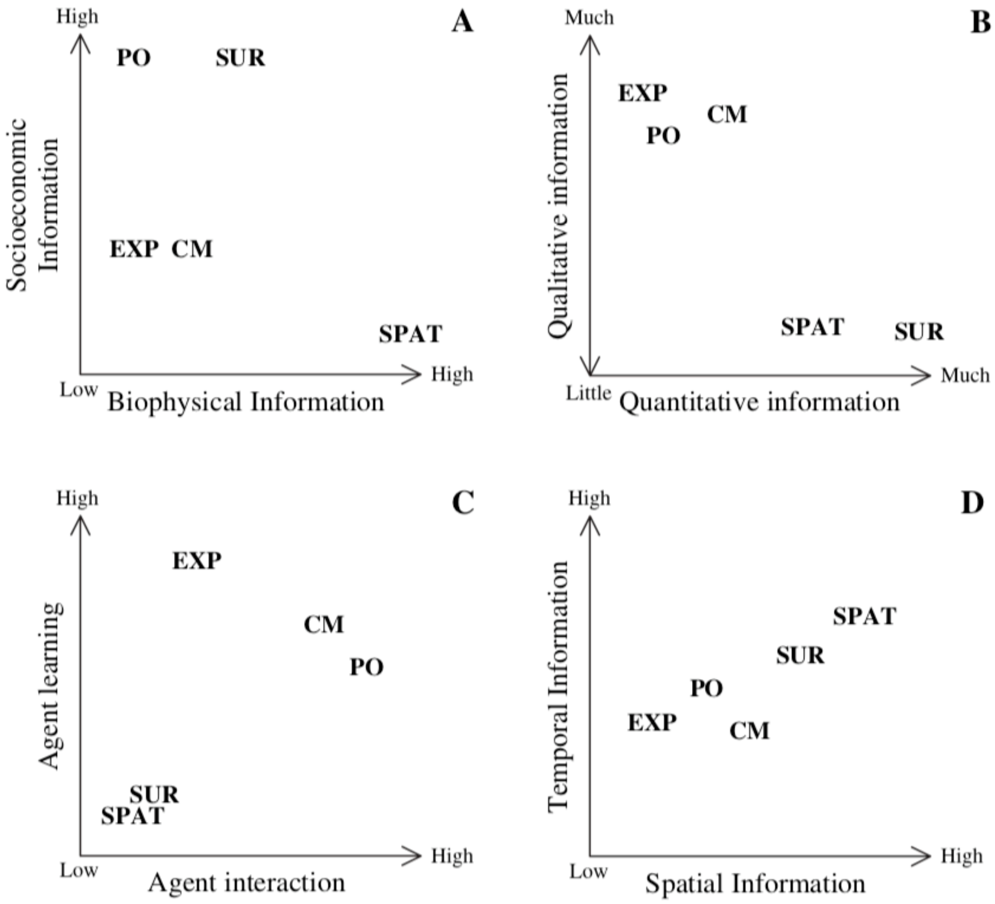



*Figure 3.4 – Comparison of five different empirical approaches for ABM: sample surveys (SUR), participant observation (PO), field and laboratory experiments (EXP), companion modelling (CM), and GIS and remotely sensed spatial data (SPAT) in terms of (A) socioeconomic and biophysical information, (B) qualitative and quantitative information, (C) agent learning and interaction and (D) temporal and spatial information by Robinson et al. (2007).*

A typical characteristic of ABMs is their almost inherent interdisciplinarity (Parker et al., 2002b; Rounsevell et al., 2014), as behavioural sciences provide insights on a decision-making process based on, but also impacting the physical environment (Bithell et al., 2008; Collins et al., 2010). This requires a broad knowledge of the researchers involved or a broad team of researchers, creating new challenges intrinsic to interdisciplinary research. Two main challenges can be identified: the first is the possible desire to unify models, both within ABMs itself and in the outcomes of the ABMs. The models from different disciplines, however, might be initially developed to operate at different spatial and temporal scales. The second challenge is the wide variety of results that might be anticipated from the research, based on the expectations related to a specific discipline (Parker et al., 2002b). For the same agent-based model, researchers might expect economic, ecological, social or geographical results, in relation to their proper field. To cope with this challenge and to avoid confusion on the expected result, it is necessary to clearly define the framework or structure of the model, the expected outcomes and the key factors that will be considered, together with the degree of abstraction that will be applied (Parker et al., 2002b).

Another important reason to define the modelling framework and the boundaries of the model is to not get caught in a never-ending iterative loop, since designing ABMs is typically an iterative process where every modelling step leads to new opportunities for more detail, improvements and refinements (Parker et al., 2002b; Rounsevell et al., 2012). Even with a good fit of the model in relation to reality or theory, there always seems to be missing features (Crooks et al., 2008) and every new finding or new dataset can provide an opportunity to adapt the framework and thus the model (Rounsevell et al., 2012). Due to the iterative nature of ABMs, Rounsevell et al. (2012) conclude that they should be seen more as an approach for scientific analysis than an application tool, making it useful for discussions, formalising assumptions based on the results and as a computational laboratory to experiment with different policies.

Specifically for agent-based land-use models, Matthews et al. (2007) come to a similar conclusion. They state that for decision support, these models have possibly more potential in providing insight to define some simple rules-of-thumb, than for direct decision support based on the results.

### 3.1.3 Creating an agricultural agent-based model

Apart from the aforementioned general challenges in working with ABMs, specific requirements and challenges are present when defining the key components of an agricultural agent-based model. The most important one being collecting the collection or the availability of data to populate and initialize these models. A first work around has been to propose hypothetical ABMs, using artificial data (Ligtenberg et al., 2004; Murray-Rust et al., 2014), allowing to work with detailed datasets that however have no link to the real-world. Another approach was to create very detailed real-world ABMs, whereby the focus is on relatively small regions (Acosta-Michlik and Espaldon, 2008; Bakker et al., 2015; Fontaine et al., 2013; Happe et al., 2009; Le et al., 2008). Efforts to develop large scale ABMs were made, but resulted in less detailed models, working with large grid cells (e.g. Rounsevell et al., 2014). To the best of our knowledge, no further research on improving ABMs over large extents at individual scales has been undertaken over the last few years (see Appendix 1). This results in current agricultural ABMs either losing touch with reality in hypothetical models with artificial data or, losing political relevance in working on small specific regions or losing detail in working on large regions.

The modelling of the relevant actors is crucial for an agricultural agent-based model, namely the farmers, their characteristics, and their decision-making strategies and behaviour. Valbuena et al. (2010) state that farmers' decisions are based on a complex combination of internal and external factors. Internal factors are related to the personal, socio-economic and biophysical factors of the farmer and farming system. Examples are the type of the farm, the presence of a successor but also the possibilities and limitations of the local environment, like local soil quality and land availability. External factors refer to the biophysical and socio-economic context, such as climate, market and policies.

According to Rounsevell et al. (2012), ABMs are ideal to be combined with social survey data. These datasets can be used to create a static or dynamic agent population. When creating a dynamic population, the surveys can provide information on the demography and on the creation and the disappearance of agents. Furthermore, they can be used to obtain information on the characteristics of the agents. After deciding on the most relevant characteristics, they need to be mapped onto the agents, constituting the agents' attributes and as such providing heterogeneity amongst the agents. In the model, these attributes are then used to enable or constrain behaviour, to allow for changes in decisions when attributes change or as a reason to react to the attributes of other agents. Troost et al. (2012) propose to create a synthetic but realistic population by drawing a random sample based on the available data to estimate agent properties. The result is then an agent population with a large degree of variability.

To represent the actual decision-making strategies, different approaches have been proposed. The first and most simple one, is through *heuristics or decisions trees* (Gigerenzer and Todd, 1999; Macal and North, 2010) whereby the decisions are based on a true or false result for a given characteristic or measurement. This allows the decision-making process to be transparent and empirically grounded by using survey data (Rounsevell et al., 2012). A second strategy is based on the concept of utility maximization, assuming that agents make rational decisions to maximize their utility, based on a selection of given options and assuming perfect information (i.e. *Homo economicus*) (Edmonds, 1999; Manson, 2006; Simon, 1997, 1955). Given the fact that most of the time perfect information is not plausible and with humans not being able to process the combinations of the large amount of data involved, ABMs mostly assume bounded rationality. With bounded rationality, agents take their decisions based on a limited number of possible choices (Rounsevell et al., 2012). This adaptation however, still assumes rationality, while human behaviour is often influenced by social comparison, imitation and habits in order to limit cognitive resources and to pursue satisfying instead of optimal behaviour. A third approach is therefore the inclusion of these behavioural traits, creating a *Homo psychologicus* instead of a *Homo economicus*, resulting in a better perspective on human behaviour (Jager et al., 2000). A fourth approach, is the learning and adaptation technique, where agents have a memory and change their behaviour based on what they have learned, linking to the field of artificial intelligence (Promburom, 2010; Reschke, 2001). This technique however often leads to a black box, where transparency and insight is lost (Rounsevell et al., 2012).

### 3.1.4 Implementation strategy

The aforementioned challenges together with possibilities conditioned by the available data, were kept in mind when creating an innovative agricultural agent-based model. This means defining the **boundaries**, the **possibilities and limitations** of the model, the **key components** of the model, and the right **scale of operation**, keeping in mind possibilities to **connect it to other existing models**. Furthermore, choices need to be made on how to **define the agents**: what are the critical elements that define the actors and which are the key components of those actors that need to be incorporated in the model. This will require incorporating some elements from the diverse fields of agricultural economics, environmental sciences, demography and sociology among others. The following choices were made:

1. Modelling boundaries: The aim is to create a nationwide agent-based model that simulates the farmer population, their farms and the changes on the land they manage.
2. Possibilities and limitations: The model allows to look at the evolution of an agricultural population and how these evolutions impact the evolution of farms and the agricultural land use. The model is not able to make any predictions, nor does it pretend to make an exact reproduction of reality. The model is also not capable of simulating the financial situation and long-term strategy of a farm.
3. Key components: The creation of a plausible starting situation, a demographic component, a succession method and a land-use and crop changing method.
4. Scale of operation: The model is set to work at the individual farmer level, managing individual parcels for an entire country.
5. Agent definition: Agents are defined by their age, typology, location and the farm they manage. The location, size and type of their farm impact their succession chance. Their

growth opportunities are dependent on the type and succession changes of other nearby farms.

6. Connection to other models: The model accepts external input and creates external output through open formats (CSV), through which they can be integrated in other models or processes.

These considerations, in combination with the available data, led the development of the model ADAM (Agricultural Dynamics through Agent-based Modelling) which is described briefly below and further discussed in Chapter 4. Full documentation of the initialisation and yearly simulation processes and the different process flows is available in the technical appendix.

*Initialisation*

In order to create a model with widely available data, on a scale relevant for the decision-making process, while at the same time being relevant for policy makers and the possibility to combine it with other models, specific methodological choices need to be made. The agricultural surveys (see Chapter 2) allow to empirically ground the agent population in the model, and for an easy adoptability in other, comparable, regions. To create a heterogenous demographically representative farmer population the data on the number of farmers and their age distribution at the municipality level are used. Farmers are assigned a farm type based on the data on farm typology per municipality (aggregated to yearly crop farmers, permanent crop farmers, greenhouse farmers, land-based animal farmers and non-land-based animal farmers. Since these data are only available for 2006 and 2016, for starting years 2000 and 2013 an extrapolation and interpolation were done respectively, with the help of the total number of farmers per municipality for that year. The succession rate for farmers is also based on the agricultural survey. Since this data is not available at the municipality level, the average succession rate for each agricultural area is used. Lastly, to finish the demographic situation for farmers, the mortality rate for the male Belgian population for each age was used, based on the data from the Belgian statistical office (see Chapter 2). The rationale behind this is that farmers are still mostly male (85% in 2000 (Statistics Belgium, 2018)) and mortality rates are different for sexes at all ages.

The data from the agricultural survey permits to define the model at the national scale, putting it at a level relevant for policy making. The available parcel data (see Chapter 2) allows the model to be set up and run at the level relevant for the decision-making of the agents creating a direct link with the real-world situation. The choice for working with existing parcel datasets results in a closer representation of reality, but at the same time, turns away from the more commonly used technique in ABMs to work with a rasterised presentation of the environment. By combining the location and agricultural land use data in the parcel dataset together with the farmer types initialised at the municipality, farms are created. As a first parcel a farmer is being assigned a parcel with an agricultural building on it in its own municipality, making it its home parcel. From that home parcel the farm grows, by adding neighbouring parcels of an agricultural land use type, that are compatible with the farmers type. The neighbouring parcels of a parcel are arbitrary defined as the 20 most nearby parcels according to a spatial analysis in GIS of the parcel dataset. When this process is not able to allocate all parcels to farmers, the allocation process for a parcel is redone, dropping the neighbouring constraint and looking at all suitable farmers for that parcel within the municipality and the neighbouring municipalities. After this step, the allocation process using the neighbouring constraint is rerun, given that the newly added parcels to the farm, results in new neighbouring parcels. If parcels are still not allocated after this process, they are added to farms of neighbouring parcels while dropping the type restriction. This process creates the farms within the model and defines the size of the farm through the combined size of the parcels.

*Yearly simulation*

The yearly simulations largely result from the evolution of the farmer population, based on their age and mortality rate added with the component of succession, change of parcel ownership, change of agricultural land use and change of crop type. Every time step, the farmers age. If the farmer simply continues farming, nothing changes, apart from the choice for a new crop for the crop rotating farmer type. In that case, the farmer chooses a new crop based on a combination of crop rotation (based on the parcel dataset), yield (from the CARAIB data) and price (from the FAO dataset) (see Chapter 2 for description of the data) combined with a stochastic component to represent non-rational decision making.

If the farmer is below retirement age and dies that year, the age of the farmer is simply reset if he has a successor. Whether or not a farmer has a successor, is based on the combination of the farm size, farm type and farm location, that define the farmers estimated profitability. The higher the profitability, the higher the chance of succession. An average farm profitability will result in the farm having a succession chance according to the average succession change of the agricultural region it is located in, a higher profitability will increase the succession chance, a lower profitability will lower the chance. If there is no successor, the parcels are transferred to farmers managing neighbouring parcels. These farmers preferably have the same or similar farm typology as to reduce the cost of having to change the agricultural land use (for example, not having to change an animal barn to a field for crop farming). If necessary, the agricultural land use of the parcel is changed in function of the farm type of the new farm it belongs to. The home parcel of the farmer that stopped farming is converted to a residential parcel and is no longer available for agriculture.

The same process applies if the farmer decides to retire. A farmer will retire at the legal retirement age if a successor is present (following the decision process on succession above), if not, a farmer continues farming with a reduced farm size. The farm size is reduced according to the average percentage of rented agricultural land in the country. The motivation is that the farmer will only keep the parcels he owns and no longer the parcels that he rents. The rented parcels are reallocated to neighbouring farmers (following the process above).

After retirement age, farmers can still decide to retire. The percentage of farmers retiring after retirement age is unknown and needs to be calibrated (see Chapter 4). If a farmer dies past retirement age, the assumption is made that no successor is present, since in that case, the farmer would have stopped at retirement age.

## 3.2 Cellular Automata model

### 3.2.1 Concepts

In Chapter 5, ADAM is combined with a cellular automata (CA) model to include the impact of urban expansion. As earlier discussed, cellular automata, with a lattice network of cell states, were a precursor to ABM. Every time step, the cell state changes based on a certain set of rules related to the current state of the cell and the state of its neighbouring cells. CA models have a widespread application and have also been used many times for urban modelling (Poelmans, 2010; Sakieh et al., 2015; van Vliet et al., 2009; White et al., 1997). CA models are defined by: (1) the cellular space, (2) the possible states of the cell, (3) the definition of its neighbourhood and (4) the transition rules between different cell states (White and Engelen, 1993).

The *cellular space* is usually a regular 2D grid of square cells (as earlier presented in Figure 3.1). This is however not a necessity. Earlier models have also worked with one-dimensional data (Wolfram,

1984) or, more recently, with a 3D approach which includes building height (Benguigui et al., 2008). Also the use of square cells have been challenged through the use of hexagons (Iovine et al., 2005), Voronoi polygons (Shi and Pang, 2000) or irregular, parcel based polygons (Stevens and Dragićević, 2007). The size of the grid is usually fixed, but other methods are possible, e.g. through the use of a variable grid size, acting at different levels (Crols et al., 2015; van Vliet et al., 2009).

The *cellular state* of a grid cell defines the value of a grid cell which is re-evaluated every time step. These values are usually two or more discrete or categorical values (e.g. the land use type), but some model approaches also use fuzzy membership (Liu and Phinn, 2003) or vectorized states whereby the cell value can also have continuous or mixed values (van Vliet et al., 2012).

The *neighbourhood* is defined as the spatial entities surrounding a cell. In simple regular square cell grids, the neighbourhood is usually defined as the four surrounding cells in cardinal directions (as in the van Neumann machine, Figure 3.1) or through the eight surrounding cells in cardinal and diagonal directions (the Moore neighbourhood) (Birch, 2006). Throughout the years other approaches to define the neighbourhood have been proposed, e.g. a large circular neighbourhood (Engelen et al., 2007) the entire study area (van Vliet et al., 2009) or a dynamic sized neighbourhood (Moreno et al., 2009).

The *transition rules* are the set of rules through which the state of cell is determined every time step. The rules usually take the current state of the cell in account, together with the state of the cells that are defined as the neighbourhood (White and Engelen, 1993).

### 3.2.2 Used approach

The CA model used in Chapter 5 is based on the constrained cellular automata (CCA) model developed by White et al. (1997). First development focussed on the Flanders region (Engelen et al., 2011), afterwards it was extended to the entire country in the GroWaDRISK BELSPO project (Verbeiren et al., 2013).

*Cellular space*

The model works on three hierarchically embedded levels, whereby the lowest level consists of a regular grid of square cells of 1 ha.

*Cell state*

The 1 ha cells represent the dominant land use at the 1 ha resolution. The possible categories for each cell are the following:

1. *grassland*
2. *deciduous forest*
3. *coniferous forest*
4. *mixed forest*
5. *heathland*
6. *dunes*
7. *wetland*
8. *other*
9. *arable land*
10. *orchard*
11. *pasture*
12. *greenhouse*
13. *unregistered arable land*
14. *residential*
15. *commerce and services*
16. *industry*
17. *recreation*
18. *park*
19. *military*
20. *mining*
21. *infrastructure*
22. *harbour*
23. *water*

*Neighbourhood*

For the neighbourhood, a Moore neighbourhood (8 neighbours) is used, nested in increasingly larger supercells relative to the distance of the centre cell allowing long-distance effects (see Crols et al., 2015).

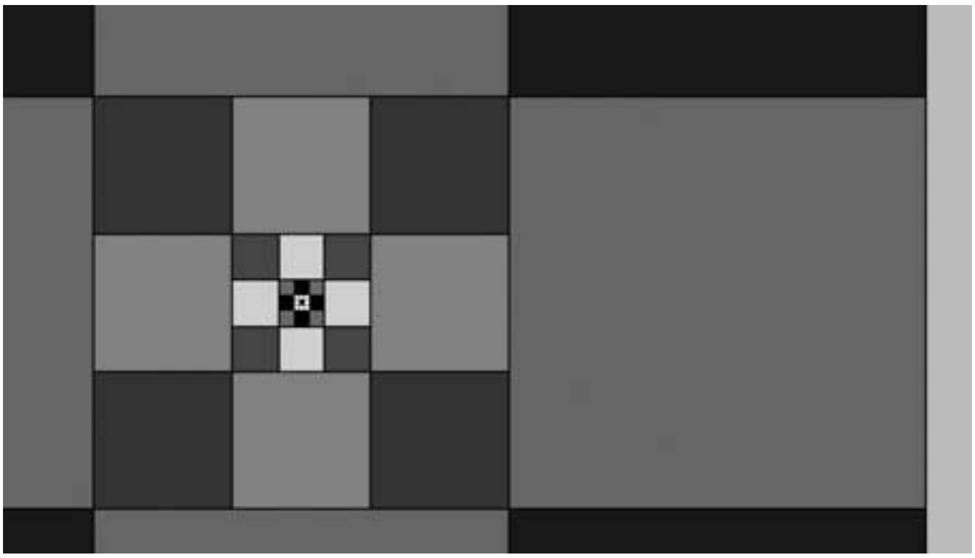


*Figure 3.5 – Variable grid structure with nested Moore neighbourhood in the CCA model* (Crols et al., 2015)

*Transition rules:*

In yearly time steps the transition potential to another land use is calculated based on (1) the cell's current land use, (2) the land-use categories in the neighbourhood of the cell, (3) a number of cell-specific properties, such as the physical characteristics (defining the suitability for each land-use type), the accessibility and the zoning status (based on spatial planning documents), and (4) a stochastic factor (representing the fact of non-rational decisions). The transition potential defines the likeliness that the land use of a cell changes and is calculated every time step *(t)* for every land use *(l)* and every cell *(c)*. The calculation of the transition potential depends on whether the effect of the land use is positive or negative:

If ${}^{t}N_{l,c} \geq 0$

$$ {}^{t}P_{l,c} = ( w_s \cdot S_{l,c} + w_z \cdot {}^{t}Z_{l,c}) \cdot {}^{t}A_{l,c} \cdot {}^{t}N_{l,c} \cdot {}^{t}R_{l,c} $$

If ${}^{t}N_{l,c} < 0$

$$ {}^{t}P_{l,c} = ( w_s + w_z - ( w_s \cdot S_{l,c} + w_z \cdot {}^{t}Z_{l,c}) \cdot {}^{t}A_{l,c} \cdot ( {}^{t}N_{l,c} \cdot {}^{t}R_{l,c}) $$

Thereby, the noise factor ${}^{t}R_{l,c}$ is defined as:

$$ {}^{t}R_{l,c} = - {}^{10}log({}^{t}rand_{l,c})^{a} $$

whereby:

| | |
|---|---|
| ${}^{t}P_{l,c}$ | Transition potential |
| $w_s$ and $w_z$ | Weights for suitability and zoning respectively |
| $S_{l,c}$ | Suitability for a certain LU, a constant factor based on environmental variables |
| ${}^{t}Z_{l,c}$ | Zoning according to policies, a Boolean factor to determine if a LU is allowed or not |
| ${}^{t}A_{l,c}$ | Accessibility of a cell through the transport network |
| ${}^{t}N_{l,c}$ | CA-environmental effect that calculated the interaction between land uses |
| ${}^{t}R_{l,c}$ | Noise factor |
| ${}^{t}rand_{l,c}$ | Random choice from a uniform distribution (0,1) with $P({}^{t}rand_{l,c} < x) = x$ |
| $a$ | Stochastic parameter |

The formulas for each of these individual parameters can be found in the report of Engelen et al. (2011)

The land-use class with the highest transition potential was assigned as new cell state, constrained by the regional land demand for each land-use category. The regional demand is calculated at the NUTS3-level based on scenarios on the evolution of the population and the economy. Once the land demand for a certain land use category is met, the land-use category with the second highest transition potential is attributed to a cell, and so on. A full description of the CCA-based land-use model and its application can be found in White et al. (2015).

## 3.3 Species Distribution Model

In Chapter 6, the results of the combination of the agent-based model ADAM and the Cellular automata (Chapter 5) are used as an input to a species distribution model (SDM) on bumblebees. An SDM is a statistical tool that combines the occurrence of species with the environmental conditions to create an insight into their distribution patterns (Elith and Leathwick, 2009; Franklin, 2010). This allows the projection of the distribution of the species in non-sampled environments and into the future.

### 3.3.1 Occurrence data

To determine the distribution pattern of a species, an SDM requires the input of spatially explicit occurrence observations. Observations are considered to indicate the presence of a species, but surveys are not usually sufficiently detailed to indicate the absence of an animal species (Barbet-Massin et al., 2012), especially for small, mobile, species like bumblebees. Therefore, in SDMs absences of a species can be estimated by randomly defining pseudo-absences (Phillips et al., 2009) of a species. One method to produce pseudo-absences is to only select them from areas where other species have been found (i.e. the target background sample) (Mateo et al., 2010).

To allow the projection to other areas or to an unknown time period, it is also crucial to train the model with as much data as possible to get as near as possible to the entire range of the species that is being modelled (Titeux et al., 2017). Therefore, it is often necessary to take species record with a large temporal range. This allows to work with a larger sample but also results in the loss of knowing the exact conditions of the observation.

### 3.3.2 Maxent algorithm

Different algorithms are available to construct an SDM and statistically represent the relationship between occurrences and the environment. In this research, the Maximum Entropy algorithm (Maxent) is used, since it has been shown to perform well when only presence occurrence records are available and having true absences of a species is not possible (Phillips and Dudík, 2008). Maxent is considered to be one of the best algorithms for working with presence-only data (Elith et al., 2011, 2006; Elith and Leathwick, 2009; Hirzel et al., 2002; Pearce and Boyce, 2006; Phillips et al., 2009). Maxent requires the definition of the covariates that define the habitat and spatially explicit occurrence data of the modelled species to define its presence probability for the given resolution of the dataset. Maxent estimates this presence probability of a certain habitat for the modelled species by comparing the variation in probability density for this habitat to the probability density of a background sample of the same habitat (Elith et al., 2011). Therefore, first the probability density for the covariates of the habitat where a species is present is calculated. Next, the same is done for the total study area. Then, the ratio between both probability densities is used to create the probability distribution for all locations, which can be considered as an estimate of habitat suitability (Elith et al., 2011).

### 3.3.3 Validation

After the training of the model, a validation step is necessary to see if the proposed model is suitable for its purpose. The validation is usually done by splitting the data in a training and a validation set. This cross validation is repeated multiple times with different splits to derive a statistically relevant validation result (Elith and Leathwick, 2009) based on a confusion matrix comparing observed records to predicted occurrences. The confusion matrix provides values on the true positive fraction, the true negative fraction, the false positive fraction and the false negative fraction. Based on these fractions, sensitivity can be calculated as the ratio between true positives and the total number of presences and specificity can be calculated as the ratio between true negatives and the total number of absences (or pseudo-absences) (Fielding and Bell, 1997). In order to obtain this confusion matrix, the data needs to be converted from a habitat suitability into a binary presence or absence prediction. These binary maps not only allow the creation of the confusion matrix, they also allow the analysis of changes in the species distribution when creating future projections. The creation of binary maps is done based on a threshold value. This threshold value is determined by testing different threshold values until the point where the model maximizes the sum of sensitivity and specificity from the confusion matrix as proposed.

The confusion matrix also provides the input to validate the model based on the area under the curve (AUC) of the receiver operating characteristic (ROC; Figure 3.6). The ROC is measured as the rate between false positives and true positives for a range of thresholds. A model is considered accurate when a high number of true positives is combined with a low number of false positives whereby the threshold varies between 0 and 1. In the case where no absences are available, the false positives are determined based on a background of pseudo-absences. This means the AUC measures indicates whether the model indicates a true presence based on a random background (Phillips et al., 2006).

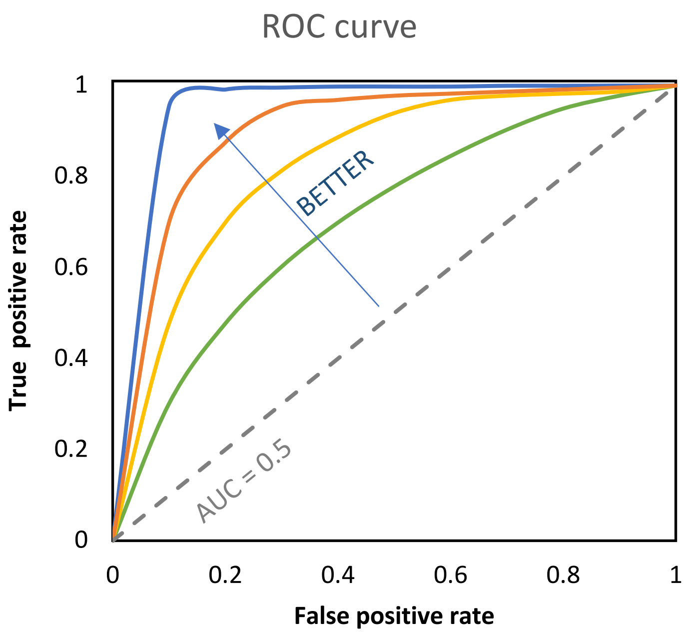



*Figure 3.6 – Receiver operating characteristic (ROC) curve. For the random classifier, the area under the curve (AUC) is 0.5. An increase of the AUC implies an increase in accuracy based on Draelos (2019).*

# Chapter 4 A country scale application of an agent-based model: farm growth in Belgium

*This chapter is based on the paper: Beckers V., Beckers J., Vanmaercke M., Van Hecke E., Van Rompaey A., Dendoncker N. (2018). Modelling farm growth and its impact on agricultural land use: a country scale application of an agent-based model, Land 7, 109.*

## 4.1 Introduction

The ongoing industrialisation of agriculture and the recent globalisation of agricultural markets put pressure on the profitability of farming activities in countries with an above-average population density (Anderson, 2010). The increasing competition among farmers together with the continuous requirement to invest and improve, has resulted in a decrease in the number of farmers. Often, small and uncompetitive farmers are either forced to end their activities or do not find a successor after retirement (FAO, 2000). This may allow the remaining farmers to upscale their activities by taking over the land of their former competitors. This process is often accompanied by specialisation and a change in agricultural management (Altieri, 1998; FAO, 2000) allowing investments in specialised equipment and farming technology. The introduction of these more intensified farming practices increases the productivity and allows the production of more food on less land (Mather et al., 1999; Van Hecke et al., 2010). In the global North, the continuous decrease in agricultural employment (The World Bank, 2008), and the increase in average farm size (European Commission, 2016; USDA, 2017) has been going on for decades.

The agricultural transition has both socio-economic and environmental impacts. Since approximately one fourth of the food produced for human consumption is traded internationally (D'Odorico et al., 2014), prices of food commodities are influenced by events on the global stock market.

In developed countries, a highly efficient cereal farmer sometimes earns the equivalent of the salary of an unskilled worker (FAO, 2000) meaning many farmers and farmer families live in (hidden) poverty (Meert et al., 2002; Van Hecke et al., 2000; Van Hecke, 2001). These farmers are no longer able to invest in the farm, resulting in a gradual decline in competitiveness of those farms in comparison to others. Furthermore, when they cease their farming activities and find no successor, their farms might be taken over by neighbouring expanding farms. Through this process, most farms have disappeared, with only a minority progressing and reaching today's high demands of capital and productivity (Mazoyer and Roudart, 2006). These transitions lead to a disappearance of a large part of the agricultural population. The continuing growth of farms also has a significant impact on the landscape, e.g. through the removal of trees, ditches and hedges, and as such, decreases its ecological value (Björklund et al., 1999; Harms et al., 1984; Ihse, 1995; Poudevigne and Alard, 1997).

This push-out of non-competitive farmers is also noticed at regional scales. Farming systems in flat regions with good environmental conditions that allow for low cost mechanized farming, have (also encouraged by the European Common Agricultural Policy (EU-CAP), see Chapter 2) created large surpluses that can be exported to regions with less favourable environmental conditions, leading to farm and farmland abandonment in these non-profitable regions (FAO, 2000). These evolutions tend to make agriculture a non-attractive sector, which leads to a limited influx of new farmers and a relatively old farmer population with almost a third aged 65 or over, and only 6% younger than 35 in the EU in 2013 (Eurostat, 2015b).

Agriculture has been high on the agenda of regional, national and supra-national policy-makers in order to intervene, support farmers and steer evolutions in specific directions. Examples are the EU-CAP and its various reforms (European Commission, 2012), the New Deal (1933), the Food and Agriculture Act (1965), and the Federal Agriculture Improvement and Reform Act (1996) in the United States (USDA, 2002), all of which have been widely studied.

Existing studies can be categorized in (1) detection studies, exploring the major trends and their related spatial patterns and how they can be monitored (e.g. Alston et al., 2010; Beddow and Pardey, 2015; Eurostat, 2015; Headey, 2016; Lerman et al., 2003); (2) analysis studies, looking at the controlling factors of transitions and the impact of policy (e.g. Alston et al., 2010; FAO, 2017, 2000; Rivers and Schaufele, 2014) and (3) modelling and scenario studies: exploring what future transitions can be foreseen, and to what extent transitions can be steered (e.g. Alexandratos and Bruinsma, 2003; Berger, 2001; Brown et al., 2014; Spangenberg et al., 2010; Westhoek et al., 2006)

The latter domain led to the development of a whole range of agricultural simulation models at various spatial scales (see Appendix 1). These models help in obtaining a macro-scale understanding of how and why certain trends occur and how they may evolve in the future under different scenarios. However, these models provide only limited insights into the decision mechanisms of individual farmers and households that lay at the basis of macro-scale trends. An understanding of the decision mechanisms is important for the development of tailored policies that aim to steer the agricultural sector and its corresponding landscapes in a certain direction.

Recently, agent-based modelling (ABM) has become increasingly popular as an approach for modelling different spatially explicit processes. Agent-based models consist of autonomous decision-making objects, called agents, that act with and react to the environment based on a set of rules (Parker et al., 2002a). These models allow the representation of the decision-making strategy of individual actors related to e.g. agricultural land use change by incorporating the complexity, emergence and cross-scale dynamics of the topic (Bousquet and Le Page, 2004; Parker et al., 2002b, 2001).

The on-going trend of upscaling of farming practices and specialization driven by the non-succession of non-profitable farms is an interesting case to describe with agent-based models since existing statistical models cannot fully capture the complexity of these processes in a spatially explicit way. Therefore, not allowing to see the impact on the landscape. However, the simulation of farmers' behaviour and the evolution of farms is lacking in present-day agent-based agricultural models. Attempts to work with ABM and incorporate the explicit modelling of farmers' population are often synthetic applications (e.g. Murray-Rust et al., 2014, 2011; Schelling, 1971) or are restricted to relatively small study areas (Bakker et al., 2015). As such, a weakness of ABM currently is the lack of convincing real-world applications on a national or sub-continental scale.

The main objective of this chapter is therefore to introduce an agent-based model, capable of working in a real-world situation, allowing to obtain insights in the farmer population and its impact on the agricultural land at the national scale, based on national statistics and cadastral maps, that can be used in scenario analyses.

This chapter presents 'ADAM' (Agricultural Dynamics through Agent-based Modelling), a model that simulates the evolution of a farmers' population, their farms and the corresponding land use on the national scale. The paper starts by describing the proposed model framework in a generic way. Thereafter the model will be set up for the case study area, the country of Belgium. The case study area is discussed, after which we describe how the model is initialised, calibrated and validated for Belgium, then run until 2030 under a business-as-usual scenario. In part 5, the model and the results of the model simulations are further analysed and discussed. The final section provides some concluding remarks and a scope for further research.

## 4.2 Description of the ADAM model framework

For the description of ABMs, often the ODD-protocol (Overview – Design concepts – Details) developed by Grimm et al. (2010, 2006) is used as a means to standardize descriptions of ABMs. It has previously been used by many authors to describe ABMs ever since it was published (e.g. Bakker et al., 2015; Bert et al., 2011; Yamashita and Hoshino, 2018). In this paper however, the model is presented in a descriptive manner, in order to explain the different steps in the model in a more consecutive order. For completeness, a summarized version following the ODD protocol is added in the appendix (Appendix 2) and a full description of the processes, including flow charts, is available in the technical appendix.

The ADAM model is developed to represent the main processes driving agricultural land use change (Figure 4.1). ADAM was created through object-oriented programming (OOP, as almost all ABMs (Heppenstall et al., 2012)) in Java 1.8-se in the Eclipse IDE. It simulates the number of farmers, the size of farms and the corresponding land use at the parcel level, trying to capture the main current processes of farms' abandonment or growth. The model starts from a set of different types of farmers that are combined with agricultural parcels to create farms. The farmers and their farms have different characteristics, listed in Table 4.1: a farm is of a certain type and is managed by a farmer of a certain age. The farm consists of a number of parcels that, combined, form the entire farm and determine its size. The parcels are the agricultural parcels according to the datasets collected yearly as required by the EU in order to distinguish, identify and measure the main crop production areas in Europe and check the validity of farmers' applications for EU subsidies. A combination of internal (farm size, farm type) and external (market, policies and physical environment) properties give the profitability of a farm. For model simplification purposes, farms were considered to be involved in only one of the following farming activities: (1) yearly crop rotation farming, (2) permanent crop farming, (3) greenhouse farming (4) land-based animal farming and (5) barn-based animal farming (The model is driven by the yearly decisions made by individual farmers. The decisions are based on a combination of the characteristics of the farm and define whether a new farm will be created, whether a farmer continues, stops its activities, or takes over an individual parcel or an entire farm. These decisions are steered by external factors such as the availability of new agricultural land, employment alternatives and the reference wage in the region. Furthermore, the survival threshold for a farm, the characteristics of the parcels, the farmers age and the availability of a successor also play a role in these decisions.

Table 4.2). Each farming type was then associated with a specific agricultural land use. The mixed farms, being farms that are involved in two or more of farming activities and which consisted of 13% of the total number of farms in 2016 (Statistics Belgium, 2018), were reduced to a single activity farm by assuming their dominant activity as the single activity. This choice was taken because the inclusion of mixed farms would oversimplify the assignment of parcels to farms in this initialisation phase, since this would allow to assign almost any parcel to these farms. They would also greatly increase complexity in the modelling phase. Furthermore, for Belgium, a continuous decrease in mixed farming can be observed with an increase in monoculture farming systems (Statistics Belgium, 2018).

*Table 4.1 – Description of the different characteristics of farms and farmers in the model.*

| Variable | Description | Variable type | Update |
|---|---|---|---|
| **Farm type** | Type of farming practice (e.g. animal farming, crop farming etc.) | Categorical variable related to the type of farming practice | Farm type can change when new farmer takes over |
| **Age of farmer** | The age of the farmer to create a population with a representative demography. | Descrete numerical variable | Yearly update, changes when farmer is succeeded |
| **Parcel** | Agricultural parcel managed by a farmer, the smallest spatial unit present. | Geographical variable (polygon with location and size) | Farmer and type (agricultural land use) can change if parcels are taken over |
| **Farm size** | The total farm size managed by a farmer, determined by the sum of the size of all parcels. | Continuous numerical variable | Increases when farmer takes over other parcels |

The model is driven by the yearly decisions made by individual farmers. The decisions are based on a combination of the characteristics of the farm and define whether a new farm will be created, whether a farmer continues, stops its activities, or takes over an individual parcel or an entire farm. These decisions are steered by external factors such as the availability of new agricultural land, employment alternatives and the reference wage in the region. Furthermore, the survival threshold for a farm, the characteristics of the parcels, the farmers age and the availability of a successor also play a role in these decisions.

*Table 4.2 – Characteristics of different farm types.*

| Farm type | Main parcel type | Common agricultural product |
|---|---|---|
| **Yearly rotating crop farmers** | Arable land with temporary crops | Wheat, barley, maize, beets, potatoes, rapeseed |
| **Greenhouse farmers** | Greenhouses | Tomatoes, bell peppers, cucumbers, zucchinis, strawberries, flowers |
| **Barn based animal farmer** | Barns and cropland | Meat (pork & poultry) & eggs |
| **Land based animal farmer** | Barns, grassland and cropland | Meat (beef), milk |
| **Permanent crop farmers** | Arable land with permanent crops | Apples, pears, cherries |

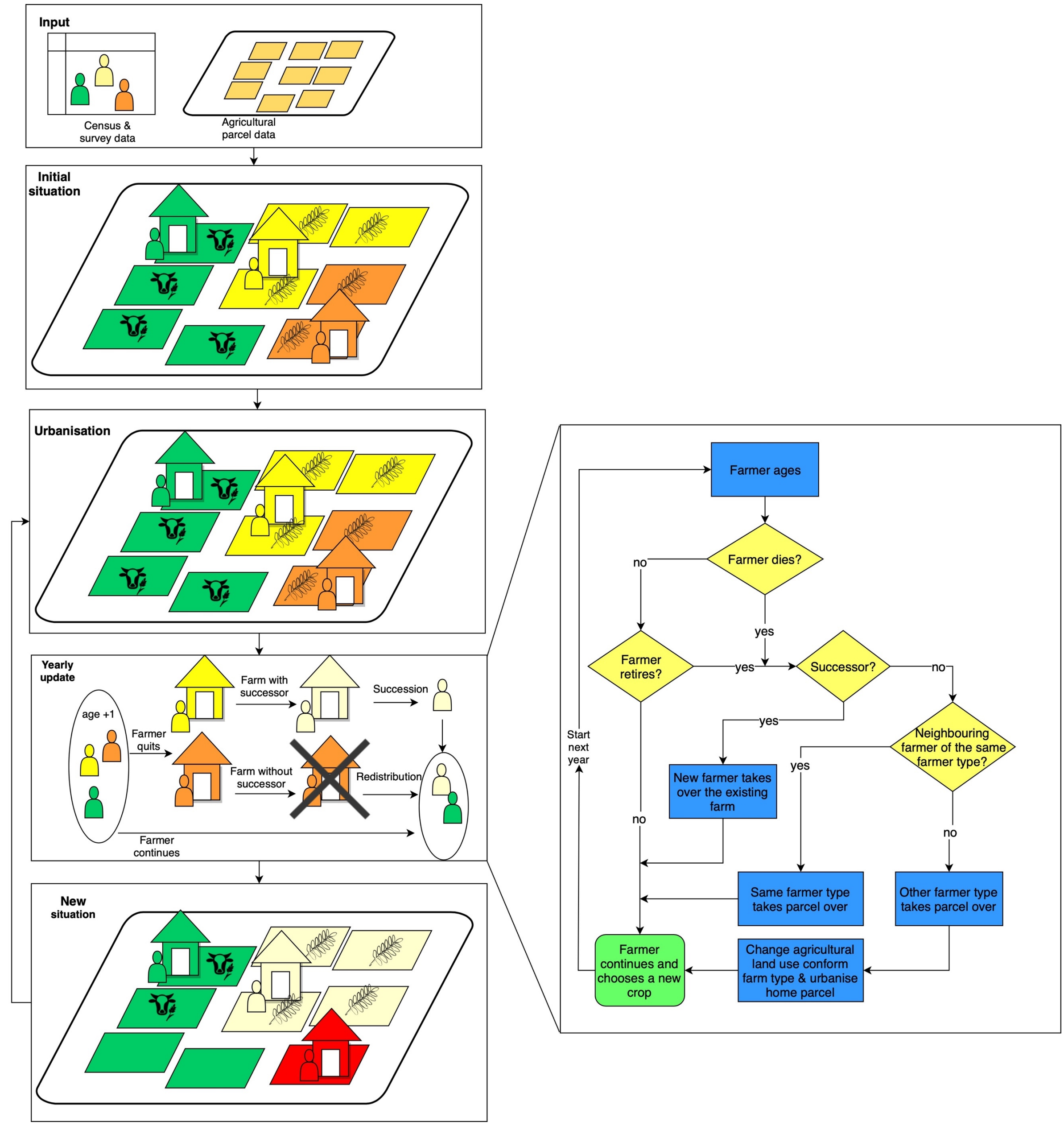



*Figure 4.1 – Overview of ADAM, including urbanisation.*

In the first phase, the land use of agricultural parcels is changed if spatial information is available (urban expansion, nature conservation…). Next, all farmers decide whether they continue or stop farming. A farmer stops farming if he retires or dies or if his farm falls below a survival threshold. The farms of the farmers that stopped are taken over if the farmer has a successor. Whether or not a farm has a successor is stochastically decided (representing the fact of non-rational decisions) based on the succession rate in the region combined with the profitability of the farm. Farms without a successor are split up and the individual parcels are taken over by farmers in the old farmer's network, provided the agricultural land is suitable for the envisioned farming activities (e.g.

fertility, existing infrastructure, local topography, soil characteristics). The farmer's network is defined as the farmers who cultivate the parcels in the vicinity of the parcels of a farmer. The list of parcels in the vicinity of a certain parcel are required as an input. Through spatial analysis in GIS, it can be determined as a certain (limited) number of nearest parcels or all the parcels within a certain distance, whereby the method and parameters are up to the modeller to choose. For the freed-up parcels, priority is given to farmers from the same farming type as the quitting farmer or to a farmer who can easily convert the parcel to a desired agricultural land use (crop land, permanent crops and grassland are easily converted, while greenhouses and agricultural buildings are more difficult and costlier to convert). Currently, the price of the land is not included in this step.

These transformations are part of the last phase of the simulation where the agricultural land use is updated. This agricultural land use change can happen through (1) abandonment of unfavourable agricultural parcels when no new owner can be found, because the parcel is too far away from other parcels, (2) conversion to residential houses of former farm houses, (3) changing cultivated crops on arable land stochastically (representing the fact of non-rational decisions) by combining the probability of crop rotation cycles combined with expected yields for the area and crop prices and (4) converting the land to another type of agricultural land use when a farmer of another type acquires the parcel (e.g. through the removal of permanent crops, the conversion to pasture or the construction of agricultural buildings). This conversion of the land to another agricultural land use is important for the farmer in order to not having to face new investments related to the original agricultural land use (Rounsevell et al., 2003) and engaging in different farming activities could lead to alienation from the farmer's social network (Karali et al., 2014, 2013).In order to apply the model to a certain region, data is needed on (1) the initial total farmer population, the age of these farmers and their farm type (2) the location of all agricultural parcels, the farmer cultivating each parcel and the current use and quality of each parcel (3) a list with for every parcel, the parcels in its vicinity, and (4) the typical crops or crop rotations present in the area together with their expected yield according to the local environmental characteristics.

Furthermore, other parameters need to be determined, namely, (1) the local average retirement age, together with the effective number of retirements at that age, (2) the mortality rate for farmers at every age, (3) the age of new-coming farmers, (4) the survival threshold of the farm and (5) the chance of succession.

## 4.3 A case study for Belgium

### 4.3.1 Study area background

In this section, the model is applied to the country of Belgium, situated in the centre of Western Europe (Figure 4.2). The highest percentages of cultivated areas in the country can be found in the central loam belt of the country and the northwest of the country, the Polders (Figure 4.2 & Figure 4.3). The Polders also has the highest farm density. The Belgian Polder area dates from the Middle ages and is, due to its typical heavy soils, more suitable for animal-based farming (grasslands and fodder crops). Farms in the north-western part of the country are on average smaller than those in the east and south. This is a consequence of the population density before the industrialisation period in the south and the lower fertility of the soil in the east and south. Currently, the relation between population density and farm size is less prevalent (Van Hecke et al., 2010).

Belgium has a long agrarian history, shaping the environment for centuries and leading to a great diversity of rural landscapes. Ever since the implementation of the Napoleonic inheritance law, heirs were to receive equal parts of the inheritance, leading to a strong fragmentation of the agricultural land (Mathijs and Relaes, 2012). The lack of spatial planning led to a rapid urban expansion at the expense of the countryside, increasing pressure on rural areas and open spaces, resulting in a strongly fragmented landscape. Former agricultural lands largely became residential areas, reducing space for farmers. The lack of space to grow encouraged farmers to intensify. This allowed them to keep earning a living on smaller and more fragmented parcels (Mazoyer and Roudart, 2006; Van Hecke et al., 2010).

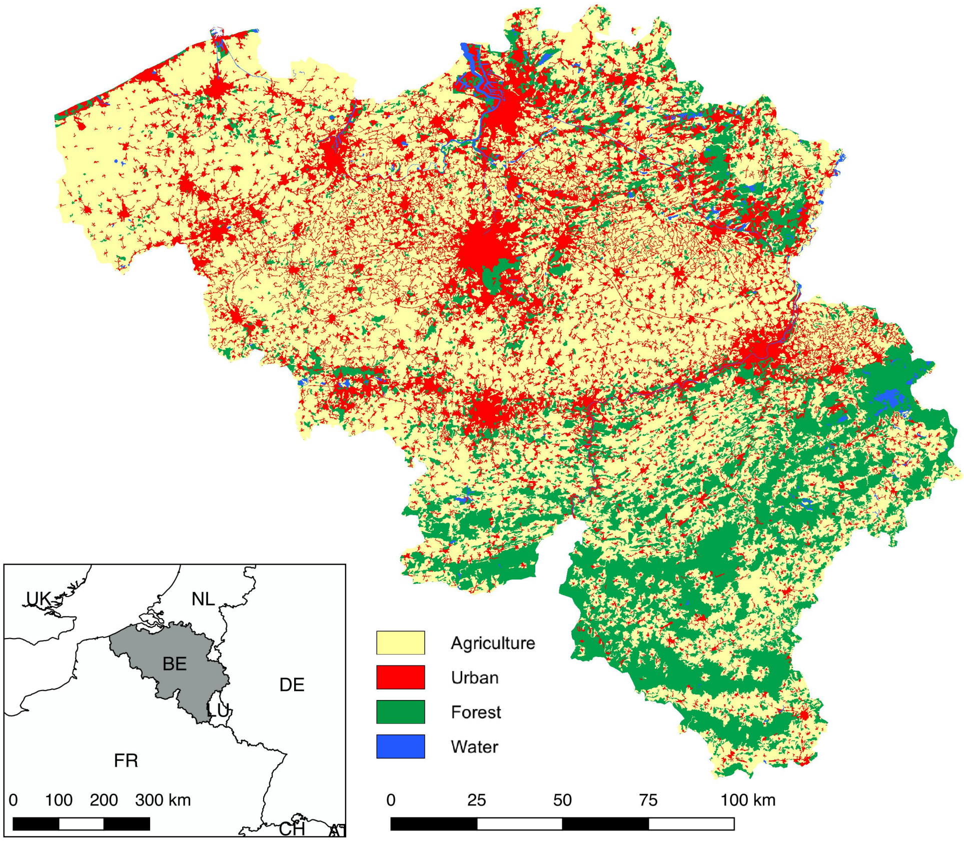



*Figure 4.2 – Land use in Belgium according to classification of Corine Land Cover data (Büttner et al., 2014).*

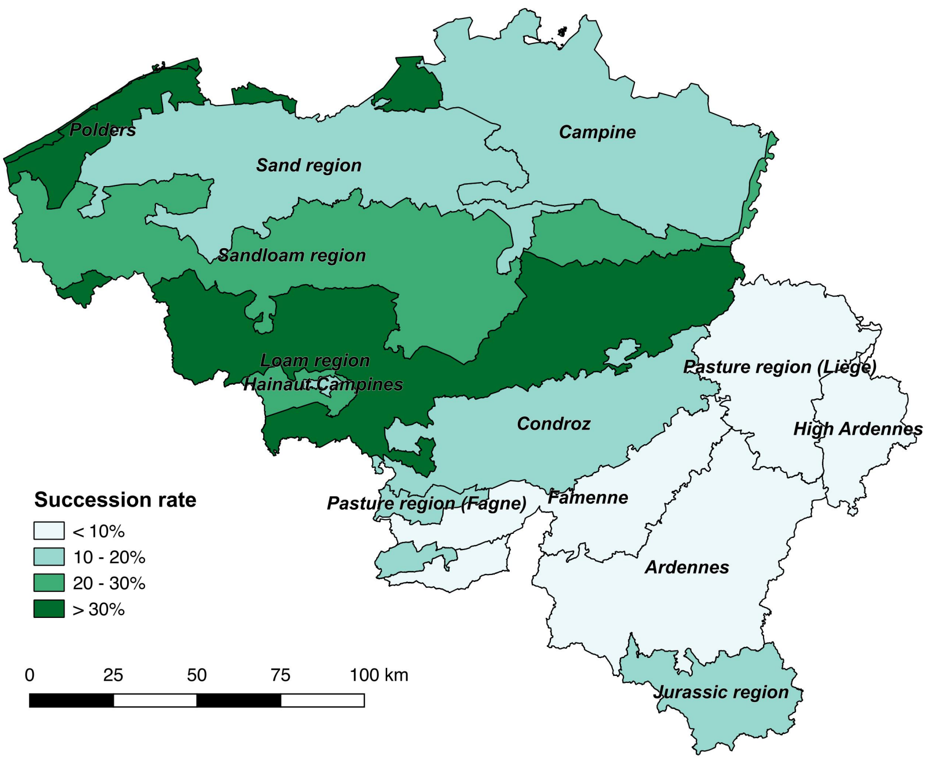



*Figure 4.3 – Succession rate for agricultural regions in Belgium (Statistics Belgium, 2018).*

Despite these difficulties, the second half of the 20th century experienced an agricultural boom in Belgium as a result of technical progress and mechanization, which increased productivity and turnover (Van Hecke et al., 2010). Additional support received through the first Common Agricultural Policy (EU-CAP) of the EU also contributed to this boom. In parallel, non-competitive and small farmers, unable to keep up with new necessary investments were driven out of agriculture. For the farmers that managed to continue farming, the pressure remains: residential land remains an attractive economic alternative to agricultural land, competition might further increase with the further phasing out of some of the trade barriers by the EU-CAP under pressure of the World Trade Organisation (WTO) (Mathijs and Relaes, 2012) and with the further decrease in subsidies from the EU-CAP after 2020 (European Commission, 2018e; European Council, 2013). Moreover, price fluctuations on the market can have a strong and immediate impact, and stricter environmental policies put new constraints on established farming techniques. Additionally, the possible role of climate change remains uncertain (Maertens, 2011; Olesen and Bindi, 2002; Van Hecke et al., 2000; Van Hecke et al., 2010; Van Passel et al., 2017). This requires farmers to constantly adapt and invest thus creating lasting land use changes on agricultural land. This continued pressure caused a further decline of farms of 70% between 1980 and 2015, an average of 6 farms per day (Statistics Belgium, 2018). A simple linear extrapolation of this trend would imply that no more farmers would remain by 2028 (Figure 4.4). Although this linear extrapolation is a simplification as the decrease might tail-off, it still gives a general idea on the speed of the decrease over the last decades and highlights the urgency of the necessity of a policy change, to curb this dramatic decline.

In contrast, total farmland area has only decreased slightly since 1980, resulting in an increase of the average farm size (Figure 4.5). Belgium is dominated by farms focussing on yearly rotating crops and herbivore farming. Greenhouse farming, permanent crop farming and non-land-based farming are mostly found in Flanders, in the north of the country (Figure 4.6). The greenhouse and non-land-based farms can be related to the relatively small farms in the north of the country which is a result of the high population density, pressure from urban expansion, and the overall historical evolution of agriculture.

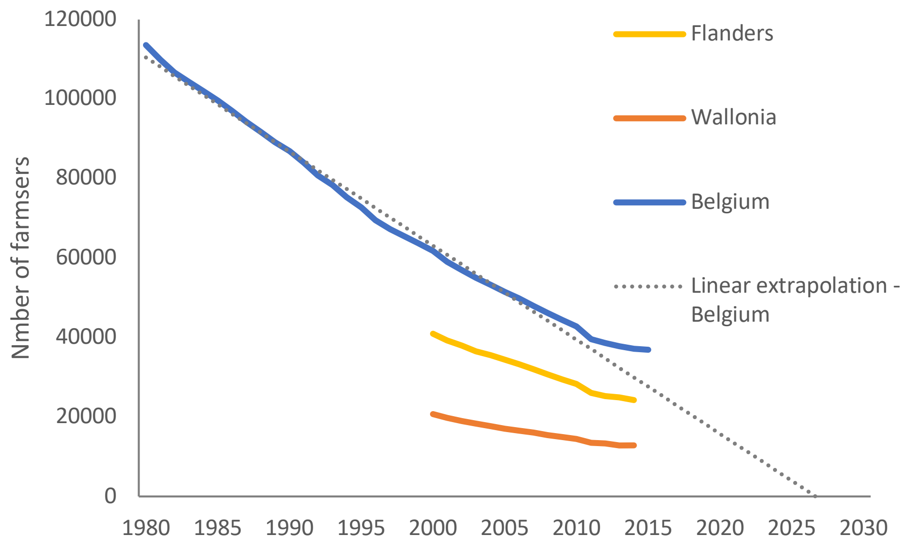



*Figure 4.4 – Evolution of the number of farmers in Belgium between 1980 and 2016 and a linear extrapolation of the trend together with the trend for regions Flanders and Wallonia from 2000 to 2016 (Statistics Belgium, 2018). A change in the trend can be observed after the change in methodology in 2010.*

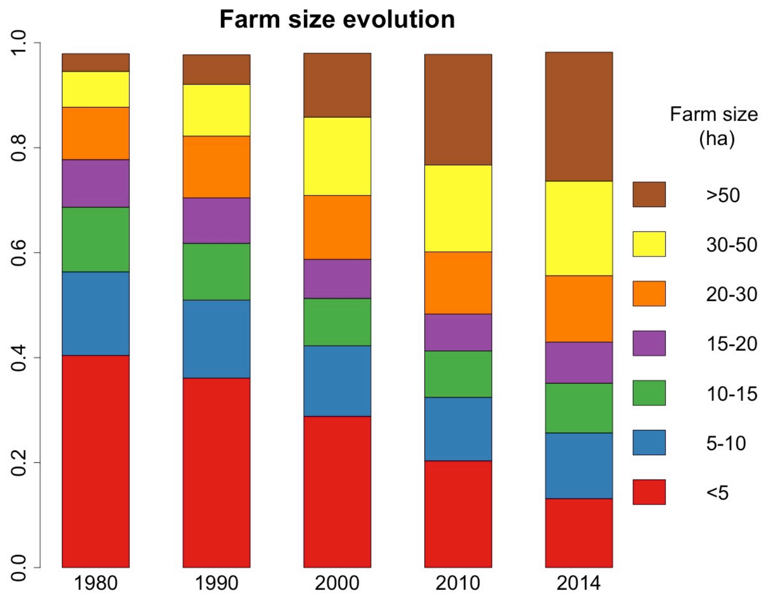



*Figure 4.5 – Evolution of the farm size distribution as a fraction of the total amount of farms from 1980-2014 in Belgium based on data from the agricultural surveys 2010 (Statistics Belgium, 2018).*

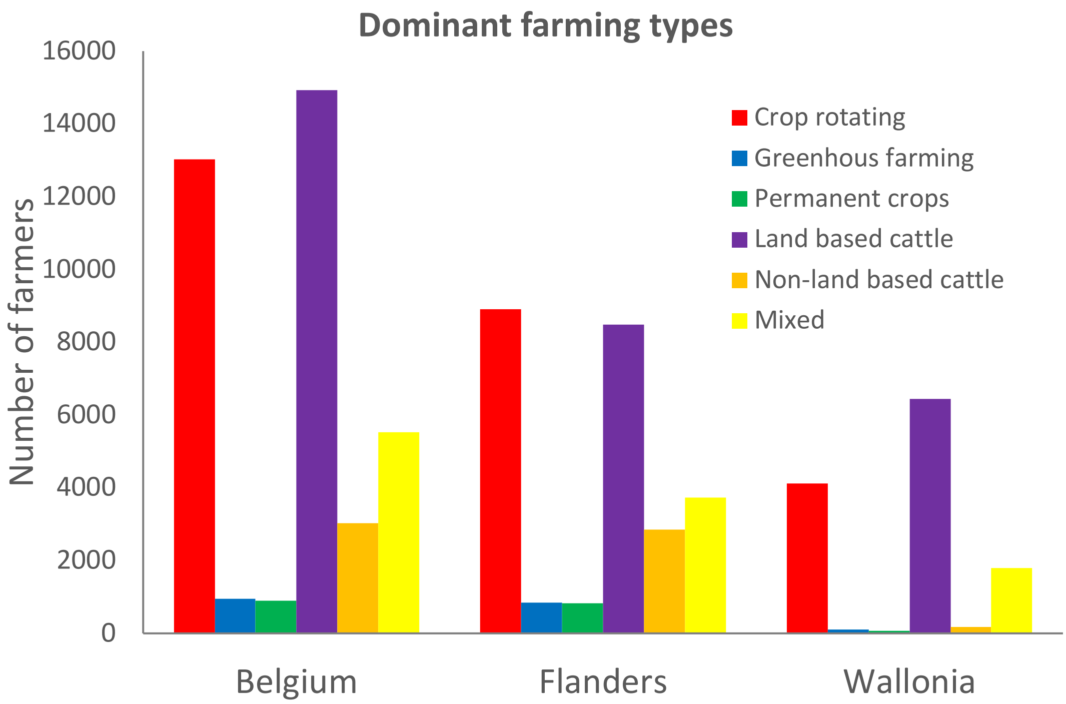



*Figure 4.6 – Number of farmers of each type in Belgium, Flanders and Wallonia 2010 (Statistics Belgium, 2018).*

The sharp decrease in farmers' numbers and large regional variation, characterized by a diverse landscape with diverse farming practices, together with a high competition for space, a high participation in the global market and being part of the EU from the very beginning, makes Belgium representative for the general trends observed in Western-Europe and an interesting case study for the model.

### 4.3.2 Data

Data on the agricultural population was obtained from national agricultural surveys, which were collected on a yearly basis from 1970 onwards by the National Institute of Statistics of Belgium (NIS) (Statistics Belgium, 2018). The data of the survey of 2000 were used to create a realistic farmer population in the initialization phase of the model. The surveys until 2010 were used to calibrate and validate the modelled results.

Agricultural land use data were derived from the *Système intégré de gestion et de contrôles* (SIGEC) and *Landbouwgebruikspercelen* datasets for respectively Wallonia and Flanders-Brussels which are collected yearly as required by the EU (European Commission, 2018a). This yearly collection is done in order to distinguish, identify and measure the main crop production areas in Europe and check the validity of farmers' applications for EU subsidies. The dataset contains the agricultural parcels as vector data, including the size of every parcel but without any information on ownership or right of use. The combined data for the year 2000 of Flanders, Brussels and Wallonia were used to initialize the model.

Prices on the different modelled crops from 2000 to 2015 were obtained from the Food and Agriculture Organization (FAO) dataset on annual producer prices (Food and Agriculture Organization, 2019), were converted to real price and were linearly extrapolated based on the 2000 to 2015 trend.

## 4.4 Model initialisation and calibration

### 4.4.1 Initialisation

As discussed in the last part of the methodology section, in order to apply the model, some initialisation of data and parameters is needed. The initial total farmer population and farmers' type and age are derived from the agricultural surveys. The location, current agricultural land use, typical crops, nearby parcels and crop rotations come from the agricultural parcel dataset. The crop rotations were extracted by creating a timeseries for the crops for each parcel in the available years for the parcel dataset and defining the probability that one crop is followed by another crop (see Appendix 3). These datasets are used to create the initial situation, since no information on the individual farmers and which parcels they cultivate is available. The first step in this initialisation is the creation of the different individual farmers of a certain age, located in a municipality and who will manage a certain farm type with characteristics shown in The model is driven by the yearly decisions made by individual farmers. The decisions are based on a combination of the characteristics of the farm and define whether a new farm will be created, whether a farmer continues, stops its activities, or takes over an individual parcel or an entire farm. These decisions are steered by external factors such as the availability of new agricultural land, employment alternatives and the reference wage in the region. Furthermore, the survival threshold for a farm, the characteristics of the parcels, the farmers age and the availability of a successor also play a role in these decisions.

Table 4.2. These different types of farmers currently only serve the purpose of making a distinction in the profitability and succession rate between different farming types and the resulting agricultural land use. This distinction of farmer types, however, also allows to further refine the

decision-making process in the future by adding differences in characteristics and behaviour. van Vliet et al. (2015) state the importance of the farmer characteristics when looking into agricultural land use change, and processes of intensification and disintensification. They are however found to be less important in the decision making process on whether or not a farmer decides to quit (van Vliet et al., 2015), and there is currently no data available that could be applied on the national scale in order to include this in the model. Once the farmer population is created, each farmer receives a first parcel as their home parcel. This parcel contains agricultural buildings according to the parcel dataset (or a random other parcel if there are not enough parcels with agricultural buildings). From this initial parcel, each farm starts growing by adding an agricultural parcel near the initial farm (arbitrarily defined as the 20 nearest parcels) that suit the farmer's type (barns, grassland, greenhouses, permanent crops, arable land). After each iteration, a new random agricultural parcel from the list of 20 nearest parcels of all parcels defining the farm, is added to the farm. The remaining parcels that could not be allocated to farms through this process, are randomly added to a neighbouring farm.

As mentioned before, apart from the initial dataset, other parameters need to be defined (see last part of methodology section). The local retirement age was set to 65, the legal retirement age in Belgium. Since many farmers continue farming even after they reach the legal retirement age (one third of EU farmers were 65 or older in 2013 (Eurostat, 2015b)), a farmer retires immediately at 65 if there is a successor. If there is no successor, farmers continue, downsizing the farm in the meanwhile by giving up land they lease (about 2/3 of the total farmed area). Since no exact information is available on this chance of continuation after legal retirement age, the percentage is calibrated in the first model run. The mortality rates were defined using mortality statistics for the male Belgian population in 2000, aged 18 to 105, at which point the mortality rate is set to 100%. This dataset was chosen since, in Belgium, farmers are still mostly male (85% in 2000 (Statistics Belgium, 2018)) and mortality rates differ between sexes at all ages. The age of the newcomer taking over a farm is arbitrarily set to a random age normally distributed around 35, with a standard deviation of 5 and a lower limit of 18 years (similar to Bakker et al. (2015)).

For the Belgian case study, it is important to note that population density is high and land is rather scarce (Bouchedor, 2017; Mollen, 2018; Mustafa et al., 2018b; Poelmans and Van Rompaey, 2009). This results in a high demand for land, and farmland is hardly abandoned. There is almost always someone interested in taking over agricultural parcels that become available. If a successor is not found, neighbouring farmers take over the agricultural parcels and the farm house itself is converted to residential land use. The long agricultural history resulted in the most fertile lands being cultivated, while unfavourable plots have been abandoned. As such, the opening up of new agricultural land through for example deforestation, hardly happens in Belgium. Therefore, deforestation was not considered relevant and was not incorporated in the model. Furthermore, two open unstructured interviews with key experts in the government and the agricultural unions revealed that Belgian farmers in general do not quit farming unless they have a successor. When a farm is unsuccessful and falls below the survival threshold, farmers continue farming, even if this means living in poverty. Hence, the following assumptions were made for the Belgian case: newcomers can only enter the system by taking over another farm, a new cultivator can always be found for agricultural land that becomes available and a farmer continues farming at least until the retirement age, even if the farm is unprofitable.

In Belgium, no information is available on succession at the farm level from the Agricultural surveys. These surveys show however that for farmers over 50 years, only 15 to 16% are sure of having a successor, around 50% do not have a successor and the remaining 35% are unsure. These numbers vary greatly between agricultural areas, with higher succession certainty in fertile areas like the Polders and the Loam area (respectively 19% and 23%) and much lower in less fertile areas like the High Ardennes (4% having a successor, 74% having none). The decision for a successor to take over a farm was defined through the profitability of the farm. Defining the profitability of a farm requires complicated calculations and a large amount of specific information that is mostly unavailable. For land-based farming types, the profitability (as defined through the standard gross margins or SGM) is strongly correlated to the size of the farm on the municipality level (examples for cropland and dairy in Figure 4.7). Even though a linear regression between farm size and profitability is a simplification of reality and does not take into account many other factors contributing to the profitability of a farm, the slope of a linear regression between the farm size and the profitability at the municipality level was used as an approximation to define the profitability on the individual farm level (Profitability = farm size * linear regression slope). This profitability, is then compared to the profitability of other farms through the mean and standard deviation. The succession probability ($P_{(succ)}$) is defined according to succession probability for each agricultural region (Figure 4.3) corrected with a factor depending on the relative profitability (Table 4.3). After discussions with experts, this correction factor was based on a discretized logistic curve whereby the most profitable farms see an increase of their survival chance with a factor four, an average farm having a survival chance equal to the regional average and farms with a less than average profitability see their chances being reduced with a factor 2 to 10.

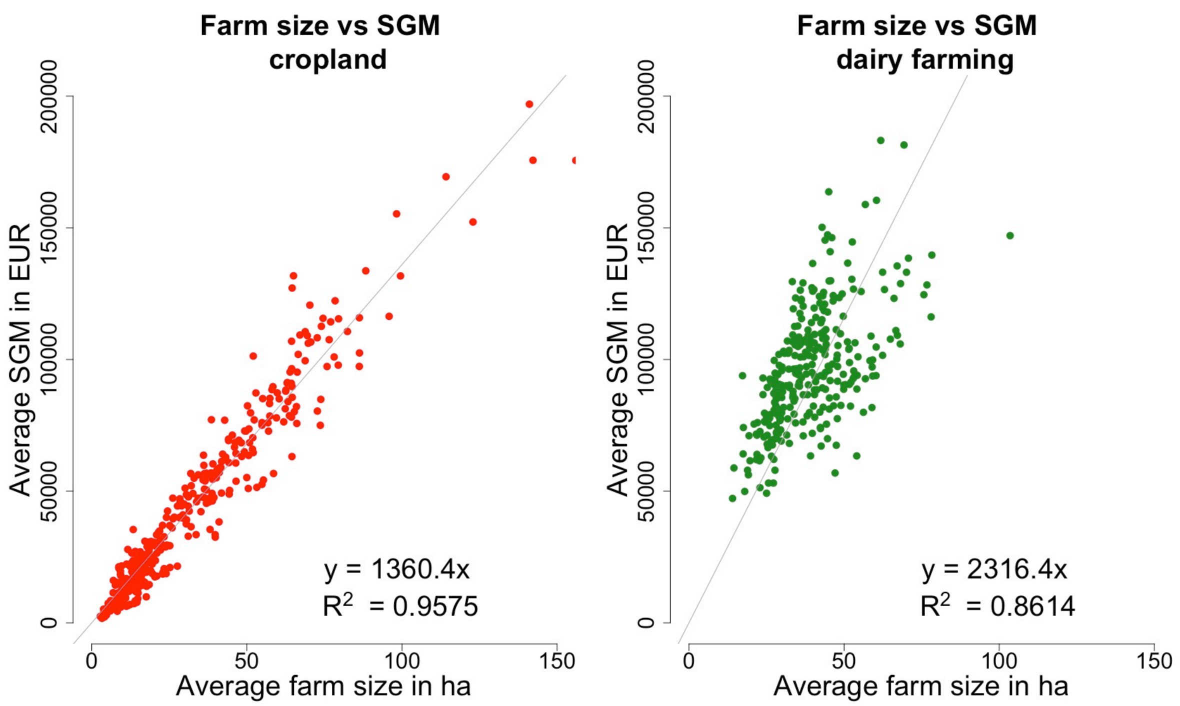



*Figure 4.7 – Relation between average SGM and average farm size for cropland (left) and dairy farming (right) in Belgium on the municipality level 2010 in 2006 (Statistics Belgium, 2018).*

*Table 4.3 – Relation between the profitability and the succession chance.*

| | | |
|---|---|---|
| *Profitability > (μ + SD * 2.5)* | ➔ | *P(succ) = regionalSurvChance * 4* |
| *Profitability > (μ + SD * 1.5)* | ➔ | *P(succ) = regionalSurvChance * 3* |
| *Profitability > (μ + SD * 0.5)* | ➔ | *P(succ) = regionalSurvChance * 2* |
| *Profitability > (μ - SD * 0.5)* | ➔ | *P(succ) = regionalSurvChance * 1* |
| *Profitability > (μ - SD * 1.5)* | ➔ | *P(succ) = regionalSurvChance * 0.5* |
| *Profitability < (μ - SD * 1.5)* | ➔ | *P(succ) = regionalSurvChance * 0.1* |

For non-land-based agriculture, other factors such as the technological advancement and modernity are more important than the size in determining the succession probability. Since no data is available on the subject, for these types of farms, the average succession rate in the region was used, and farm size was not considered. Hence, for each farm, the probability of having a successor was assessed based on a combination of the regional succession probability, the type of farm and, in the case of land-based agriculture, the size of the farm.

An overview of all the mentioned choices and assumptions can be found in Appendix 4.

### 4.4.2 Model calibration

Most model inputs are derived from empirical data or defined through discussions with experts in the field (see above). As previously mentioned, data on the retirement probability after passing the legal retirement age (65) are not available, making it the only parameter requiring calibration. In order to calibrate this percentage, the model was run for Belgium for yearly retirement percentages ranging from 10 to 30%. The yearly predicted results for the farmer population aged 65 and older between 2000 and 2010 were compared to the observed values from the Agricultural Surveys (Statistics Belgium, 2018) for half of the municipalities (the other half was used to validate the results). Results from after 2010 are available but from 2011 onwards, farmers could choose to be registered collectively in the survey. This option was given in order to simplify administrative work, but has led to a direct decrease of the number of farmers and increasing the average farm size, which is derived from the number of farmers (Platteau et al., 2014). This change in methodology makes the comparison between observations and predictions difficult from 2011 onwards.

The predicted and observed data were evaluated by the means of a relative root mean square error (RRMSE):

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(m_i - o_i)^2}$$

$$RRMSE = RMSE \times \frac{100\%}{o_{mean}}$$

with $n$ the number of observations, $m_i$ the modelled value, $o_i$ the observed value and $o_{mean}$ the mean of the observed values. The RRMSE gives insight on the difference between modelled and observed values, the lower the RRMSE value, the better the model performs. The model run with a retirement percentage of 14% was found to produce the lowest RRMSE (2.54%, Figure 4.8). This retirement probability was therefore used for subsequent simulations.

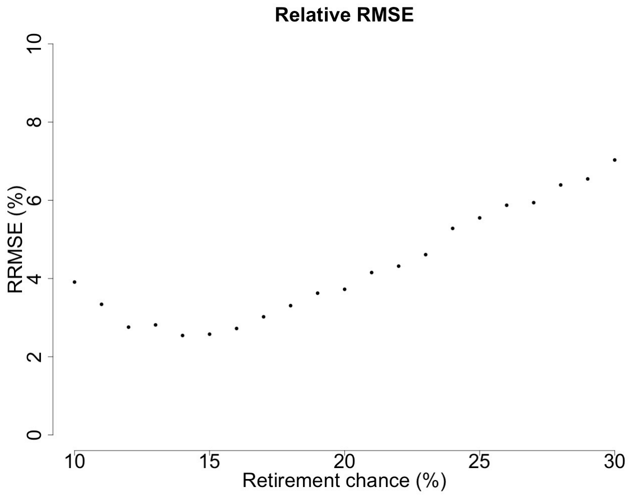



*Figure 4.8 – Calibration through the RRMSE for different percentages of farmers retiring after they passed the legal retirement age.*

## 4.5 Results and discussion

### 4.5.1 Farmer population validation

The initialisation phase resulted in a farm size distribution comparable to the farm distribution in Figure 4.5 for 2000, with an overestimation in the smallest category and an underestimation in the category 5 to 10 ha. The reason for the initial underestimation is linked to the organic growth of farms in the initialisation phase, that does not take the farm size distribution into account. Adding this in the initialisation phase would greatly increase complexity due to the requirement of having to comply with a type as well as a location and a size restriction and possible making it unsolvable.

The model was furthermore validated by comparing, for the other half of the municipalities (see calibration), the predicted number of farmers for the time period ranging from 2000 to 2010 with observed data from the agricultural surveys (Statistics Belgium, 2018) by means of the RRMSE. For the evolution of the total number of farmers in Belgium between 2000 and 2010, an RRMSE of 4.77% was obtained. These are promising results at the level of the entire Belgian farmer population, but possibly conceal discrepancies at the more detailed level of the municipality.

A municipality level comparison between observed and predicted number of farmers in 2010 after 100 model runs results in an RMSE of 11.2. The observed versus predicted evolution of the number of farmers between 2000 and 2010 at the municipality level, results in an RMSE of 13.2%. Figure 4.9 visualises the different over-and underestimations in the evolution of the number of farmers. Highest underestimations (i.e. observed decrease is higher than modelled decrease) can be found in the highly urbanised central north of the country and around the city of Liège, underestimations in the south of the country show a more randomised pattern. Overestimations (i.e. the observed decrease is lower than the modelled decrease) are rarer.

The underestimations in the municipalities in the north and around Liège can most likely be explained by the fact that these municipalities are under pressure of urban expansion, being located in the most urbanised parts of the country (see Figure 4.2). This urban expansion decreases the amount of available agricultural land and as such might make farms smaller (relative to other farms in the region) and therefore less interesting for succession, but is currently not incorporated in the model. The proximity of larger cities might also provide alternative jobs for possible successors, making it harder for farmers to find one. Furthermore, urban expansion may complicate farming indirectly by making some parcels less accessible and through extra regulations to manage negative externalities (for example slow traffic, noise and smells)(Delbecq and Florax, 2010).

Data for validation of the farm types are not available in 2010, this parameter was only included in the surveys of 2006 and 2016 (see part 4.4.2).

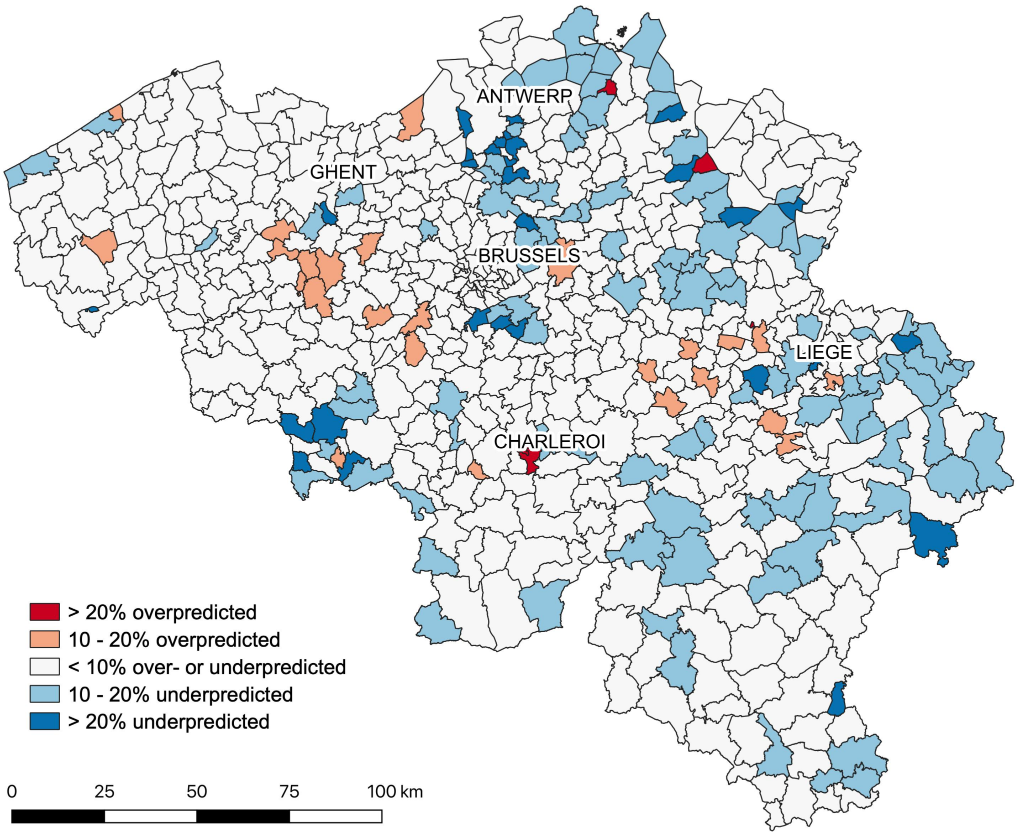



*Figure 4.9 – Average difference between observed and predicted percentage of farmer decrease between 2000 and 2010 after 100 model runs.*

### 4.5.2 Agricultural land use validation

The average percentage of each agricultural land use of the modelled output for 2018 after 100 runs (Table 4.4), is similar to the data found in the agricultural survey (for cropland, grassland, permanent crops and greenhouses) and the cadastral data (agricultural buildings).

For the different crops that are being modelled within the cropland class, a difference with the observed crops for 2018 (agricultural survey) can be observed. Rapeseed, sugar beet and maize are overestimated, while grains, and potatoes are underestimated. A mapping of the most occurring crop on each parcel (the mode) in 2018 after 100 runs is visualised in Figure 4.10. These maps show very similar results to the observed spatial distribution of crops in Belgium (Figure 2.8). The overestimation of rapeseed, is mostly focussed in the west of the country (West Flanders), where, at the same time, potatoes are underestimated. This can be explained when looking at the average yield in West Flanders combined with the average producer price (2013-2018) for these crops. For rapeseed an average of 5.1 ton/ha is to be expected in West Flanders (data from CARAIB (Jacquemin et al., 2017), see Chapter 2), while for potatoes this is 3.6 ton/ha. The prices for both crops between 2013 and 2018 average 218 and 135 euro respectively, resulting in an average of 1121 EUR/ha and 490 EUR/ha . This is not the case in the rest of the country (see Appendix 5).

Given the simplicity of the crop decision module (based on yield, market price crop rotation and a stochastic factor), the found differences are to be expected and can be considered as acceptable. Especially since the different data sources on agricultural land (the land register, the ICAS data and the agricultural survey) lead to different results, since they are made with different purposes in mind. Agricultural LUC models have also shown to have greater amounts of uncertainty in comparison to other LUC models (Alexander et al., 2017).

*Table 4.4 – left: The observed compared to the modelled percentage of agricultural land use for 2018 and right: the observed compared to the modelled percentage of different crops in the cropland class.*

| | *Observed* | *Modelled* |
|---|---|---|
| *Cropland* | 50.15% | 49.34% |
| *Grassland* | 42.04% | 42.19% |
| *Permanent crops* | 1.61% | 0.99% |
| *Greenhouses* | 0.20% | 0.17% |
| *Agricultural buildings* | 2.30% | 2.67% |

| | *Observed* | *Modelled* |
|---|---|---|
| *Grains* | 19.73% | 14.19% |
| *Maize* | 15.75% | 17.36% |
| *Sugar beet* | 5.50% | 9.16% |
| *Rapeseed* | 0.99% | 3.88% |
| *Potatoes* | 8.18% | 4.75% |

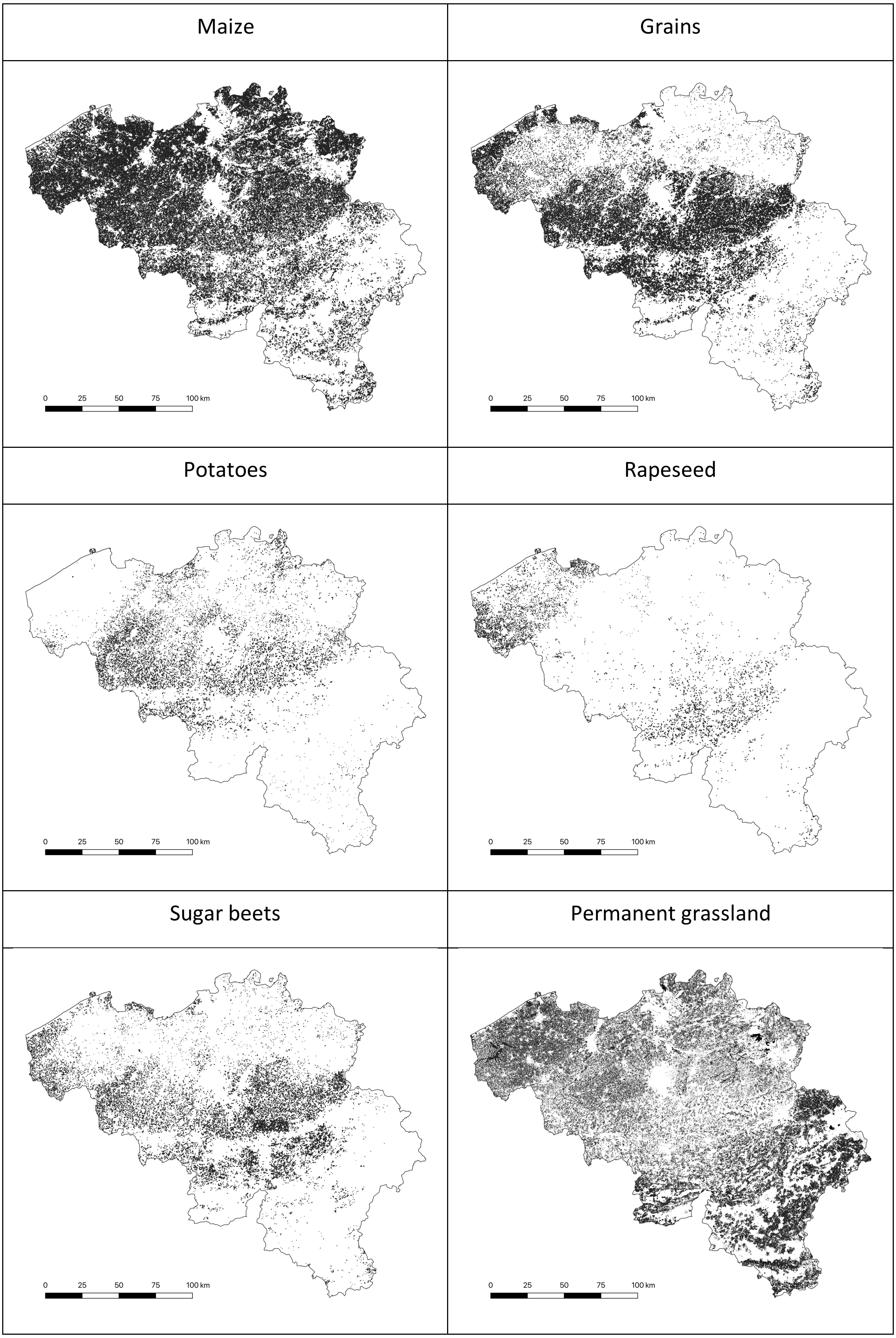



*Figure 4.10 – Most frequently modelled agricultural land use per parcel for 2018 after 100 model runs.*

### 4.5.3 Simulations of a business-as-usual scenario until 2030

After calibration and validation, the model was run from 2013 until 2030 under a business-as-usual (BAU) scenario, under the assumption that current conditions and trends in agriculture would continue in the future. The simulations show that the number of farmers keeps decreasing and that the average farm size continues to increase with small farms leaving the system, by being taken over by bigger farms.

These trends differ throughout the country. Results on the aggregated level of the municipality show that the percental decrease in number of farms is the lowest in the central part of the country and in the loam region (Figure 4.11). The relative size increase is the largest in the south and the central west part of the country. These results can be expected when comparing them with the average succession rate in Belgium for each agricultural region (Figure 4.3), to the percentage of farmers over 55 years old (Figure 2.16) and farmers over 50 years old without successor (Figure 2.17). This is especially clear for the central south of Belgium (the most fertile part of the country, with the largest farms), where the succession rate is relatively high and the central west, with a relatively old farmer population and low succession rates.

The spatial variation in relative increase in farm size, can largely be explained by the current farm sizes in these areas, which have the largest relative growth capacity. The projected change in agricultural land use for 2030 is minimal, with almost all changes in agricultural area per land use type being less then 5% and often less then 1% (see Appendix 6).

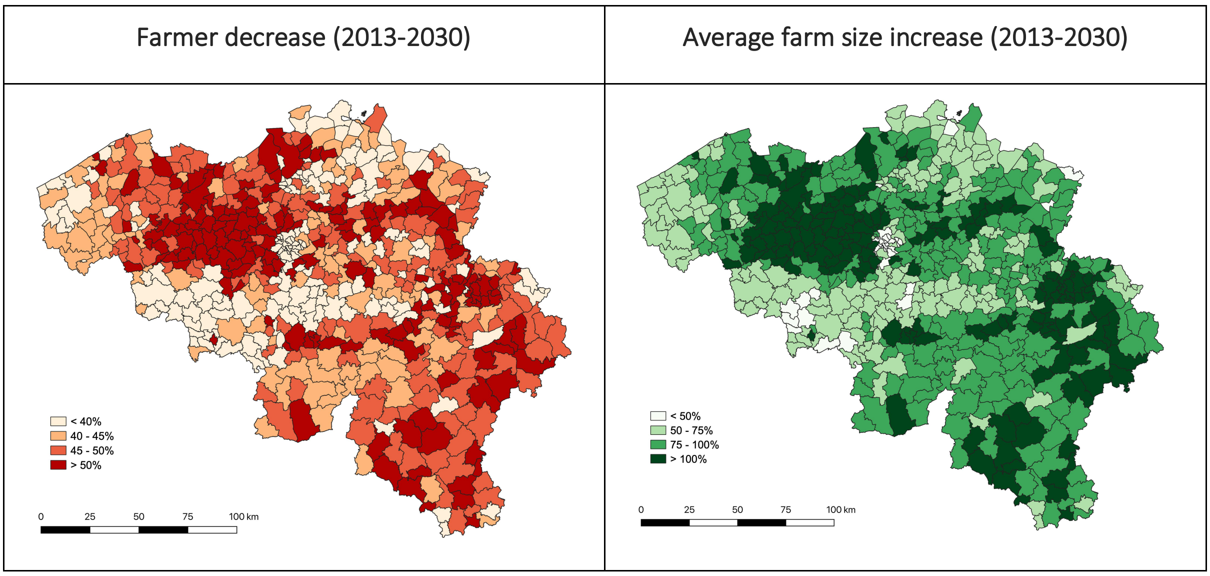



*Figure 4.11 – Percental decrease in farmers (left) and increase in farm size (right)between 2013 and 2030 as the result of 100 runs of the model until 2030*

### 4.5.4 Discussion

Ever since the start of the collection of farm data through agricultural surveys a continuing trend of farmers decrease and farm size increase is observed, together with a decrease in mixed farming and an increase in monoculture farming systems (Statistics Belgium, 2018). The most important driver of this change is the competition between farmers on the local and global level, requiring ever increasing intensification, rationalization and growth.

The results from these BAU scenarios indicate that farm size will continue to increase, with small farms disappearing, confirming the trend of growth for survival that is mentioned by Mazoyer & Roudart (2006). The disappearance of the small farms can lead to more personal dramas in farmer households that often have been living in hidden poverty for many years. The Belgian society could anticipate these changes by offering socio-ecological pathways out of their lock-in situation. The activation of local farming and local food systems could reduce the necessity to increase farm size in order to stay competitive in a global market.

Furthermore, this growth will lead to larger farms, sometimes creating larger parcels whereby parcel boundaries might disappear as a successful farm takes over an adjacent parcel. This upscaling will lead to a decrease in the landscape diversity (Björklund et al., 1999; Harms et al., 1984; Ihse, 1995; Poudevigne and Alard, 1997) and ecological value (Benton et al., 2003; Marshall and Moonen, 2002; Stoate et al., 2001). In current debates on the importance of ecology, ecosystem services and climate mitigation, these changes in landscape caused by current trends in agriculture, require an increased interest from policy makers and the creation of tools that allow the evaluation of different options in policy.

Our results demonstrate that ADAM is able to simulate the evolution of a farmer population (with differences in prediction mostly under 10%) and the agricultural land use. The modelled farmer population and its evolution reproduces the observed trends and simulates a reliable agricultural population, making the model promising for use in future agent-based simulations of agricultural dynamics.

Running the model until 2030 under a BAU scenario shows the expected increase in average farm size throughout the country. Although the largest relative growth is expected in the north west of the country, the largest farms can still be found in the southern part of Belgium. This is due to the lower fertility of the soil, which historically already led to an on average larger farm size and still today results in an on average lower succession rate (Figure 4.12), ultimately leading to less farms being continued and a further growth of the remaining farms.

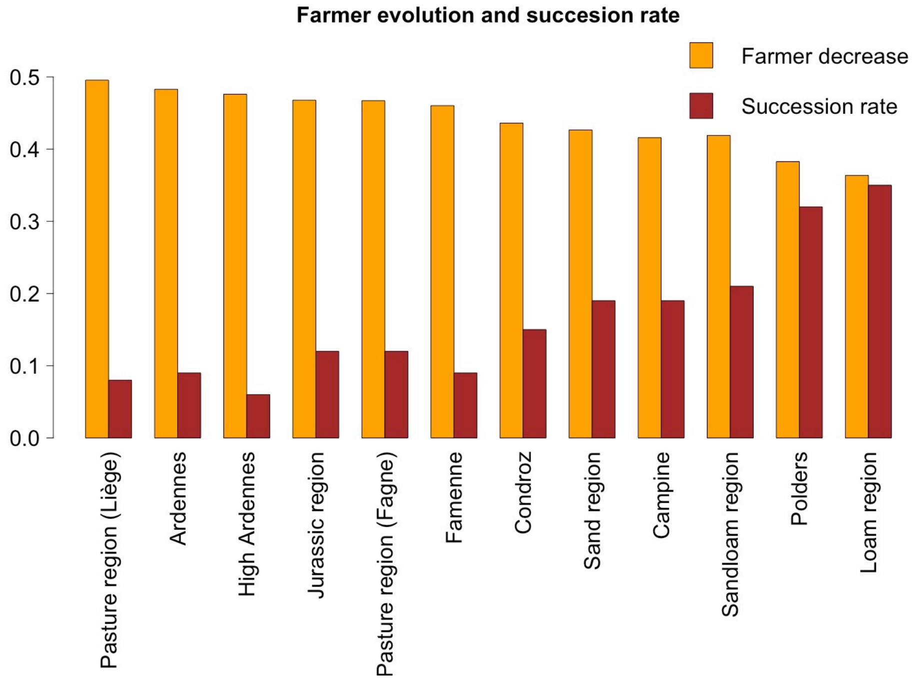



*Figure 4.12 – Percentage decrease of farmers between 2015 and 2030 and the succession rate used for each agricultural region.*

The model currently uses only a limited number of farming types: yearly crop rotation farming, permanent crop farming, greenhouse farming and land-based and non-land-based animal farming. In reality however, some farmers perform agricultural side activities, while others have two or more main activities and are categorized as mixed farms in statistics. Ignoring the reality of mixed farming is another constraint of the model, which might need to be addressed in a next version. Furthermore, results for the agricultural land use could be further refined by improving the farmers decision making process by adding more differences in characteristics and behaviour. A broader range of farming types and greater detail on the agricultural land cover could provide more insights into the impact of the agricultural evolutions on ecosystem services related to agriculture.

Although the loss of agricultural land is limited (4% between 2000 and 2014), results show that local losses of agricultural land due to urban expansion are not negligible and must be included to improve the results of the model. Currently, a parcel containing the farm and the home of the farmer is no longer considered to be agricultural land but becomes a residential parcel and leaves the system. This type of urban expansion does not grasp the full reality of the resulting loss of agricultural land. At the same time, this transformation from a farm to a residential home does not always match reality. Recently these farms have gained the interest of a new type of farmer, i.e. the peri-urban farmer, who produces for (and with) the local community. These farmers are interested in farms close to urban centres (Danckaert et al., 2010). Although this is a recent and still relatively small trend, it might nevertheless be important in the process of urban expansion at the expense of agricultural land. Another interesting phenomenon is the usage of peri-urban farm land for horses by non-farmers. These parcels are also considered to no longer be available for commercial farming.

The current agricultural land use change, (when a different farmer type than the previous takes over an agricultural parcel) does not consider the impact of land ownership versus rented land, even though this might hinder the farmer to alter the agricultural land use. In Belgium, only about 37% of land is owned by the farmer himself. This might have an impact on the agricultural land use change as it is currently presented in the model. During the rental period of the land, the renting farmer is however, protected by laws that allow farmers to have a long-term strategy for the land and their farm.

The aim of creating an agent-based model at the country scale, often with a limited amount of information, required a simplification of the decision-making process of the agents. This is because insights gained on agricultural decision making processes by previous studies (Bakker et al., 2015; De Lauwere, 2005; Fontaine and Rounsevell, 2009; van Vliet et al., 2016; Verburg et al., 2002), are often difficult to apply at country scale. This model framework, however, allows to create a more detailed decision-making process when more information is available.

To summarize, ADAM allows to simulate the evolution of a farmer population. In further research, the model can be used under different scenarios and therefore evaluate the effects of different policies, different economic view-points, and a changing climate on different regions. For example, ADAM could be used to investigate the changes in expected yield as a consequence of different climate change scenarios, or the effect of subsidies on crop prices and to look on the effect these have on the decision-making process of the farmer. Another question that can be investigated by the model is how the farmer population reacts to changes in the legal retirement age or in changes in farmer subsidies, impacting the expected profitability of different farming types.

Despite the fact that ADAM can adequately simulate the evolution of a farmer population, improvements can still be made. This could be achieved by refining the farmers' behaviour together with the farms' typology (e.g. eco-farming and peri-urban farming). Additionally, further including regional differences, and including the impact of urban expansion on the availability of agricultural land would further improve the model.

## 4.6 Conclusion

In this paper, the agent-based model ADAM was presented. ADAM simulates the evolution of a farmer population at country scale, capturing basic farmer's decision-making at the agent level, resulting in a comparable agricultural land use distribution. Thereby ADAM transcends the statistical level. As such, this research shows that it is possible to create ABMs simulating real-world situations at the country level.

The study showed that ADAM performs less well in more densely populated communities. This can be explained by the fact that part of the municipalities with higher population densities are under pressure of urban expansion, especially municipalities located near large cities, but also by the fact that municipalities with higher population densities have less available room for agriculture, making the farms on average smaller and so more likely to disappear. Urban expansion thus leads to more rapid farm abandonment than expected. To address this issue, it would be useful to incorporate data on urban expansion in the model, to see what the effect is on the farms and farmers.

ADAM was developed as a simple model that captures the main processes driving agricultural land use change while excluding other relevant but small-scale processes such as the emergence of urban farming and horsification. ADAM is capable of adequately simulating an agricultural population, useful for further application in agent-based simulation of agricultural land use change. The model is capable of creating farms that evolve over time, outputting information on which agent manages a certain piece of land. As such, ADAM can be used to investigate the impact of different scenarios on the farm evolution and therefore on the profitability and succession rate of a farm. Increasing a farm size for economic reasons (e.g. as a consequence of the reduction of gross margins) is thought to be valid within a broad international context. Since the model uses data sets that are required for EU-reporting, the model can be applied in other EU-countries. The application in other countries will depend on local data availability. Evidently, many assumptions and parameters in the present model application for Belgium are region-specific. Application in other countries would require a recalibration and possibly a re-evaluation of certain assumptions made on farm succession, land availability and land abandonment.

# Chapter 5 The impact of urban expansion on agricultural dynamics

*This chapter is under review as: Beckers V., Poelmans L., Van Rompaey A., Dendoncker N. (2019). The impact of urban expansion on agricultural dynamics: a case study in Belgium, Journal of Land Use Science.*

## 5.1 Introduction

Early European farmers created their first settlements on fertile lands. The most fertile areas prospered, flourished and gave rise to historical cities. Through time, many of these cities continued to grow under an increasing population, resulting in many of the largest cities being built and expanding on the most fertile lands, with often a continuation of this urban growth until today (Du et al., 2014; van Vliet, 2019; van Vliet et al., 2017). As such, farmers close to city centres have often been under pressure of urban expansion. Specifically for Europe this has led to a majority (64%) of regions either having a combination of land highly suitable for agriculture and a high degree of urbanisation or with low suitability for agriculture and low degrees of urbanisation (Primdahl et al., 2013). During the last decades, the transformation of Western European landscapes has mainly been characterised by an expansion of the built-up area at the expense of fertile arable land and natural areas. The loss of these lands under urban expansion has had important environmental and socio-economic impacts (Frumkin, 2016; Johnson, 2001; Lambin et al., 2001). It is expected that urban expansion will continue in the near future (Rounsevell et al., 2006) with an increase from 2.06% of ice-free land being urbanised in 2000 to an estimated 4.71% by 2040 (van Vliet et al., 2017).

Several studies (Archer and Lonsdale, 1997; Cabus and Vanhaverbeke, 2003; Delbecq and Florax, 2010; Livanis et al., 2006; López et al., 2001; Lopez et al., 1988; Verhoeve et al., 2015; Wu et al., 2011) have also shown that the impact of urban expansion on farming practices goes beyond the simple conversion of farming land into urban area. For example Delbecq and Florax (2010) show that the increasing land rent at the urban fringe attracts speculators that buy farming land not for farming but as a strategic investment, anticipating future land development possibilities. This typically leads to an increase of the set-aside land in the urban fringe. Furthermore, the farming land in the urban fringe receives the attention of urban dwellers who want to use the open space for leisure activities such as hobby farming, horse keeping and riding. Bomans et al. (2011) indicated that circa one third of the grassland in the northern part of Belgium (Flanders) is now being used for hobby horse keeping and horse riding, a phenomenon referred to as ‘horsification’. Another factor is that the high rent and the lack of space in the city centres pushes away some industrial and commercial activities for which a new location is found on peri-urban farmland. Verhoeve et al. (2015) made an inventory of non-farming use of farms in Flanders and came to the conclusion that in the last two decades about 20% of the farms were being used for other activities such as the storage of building material, garages for car repair, restaurants and catering, wellness centres and farm tourism.

Finally, the nearby presence of a city stimulates in some cases the development of alternative farming practices such as ecological farming, short supply chain farming, collective farming and self-harvest farms (Renting et al., 2003).

The above mentioned developments in the urban fringe will lead in the coming decades to a complete transformation of the peri-urban landscapes and are expected to have important impact on both the biophysical and social environment (Cabus and Vanhaverbeke, 2003; Power, 2010; Stoate et al., 2001; Zhang et al., 2007). Not surprisingly spatial planning in peri-urban areas is receiving increasing attention from policy makers and land managers (Departement Ruimte Vlaanderen, 2017; SPW, 2018). At present, however, a sustainable spatial planning of the rural-urban fringe is hampered by the lack of integrating theories and integrated models that allow to evaluate the impact of possible policy interventions (Meyfroidt, 2013).

This can partially be explained by the fact that rural studies and urban studies have been clearly distinct academic fields that have evolved differently, neglecting the increasing spatial interactions between rural and urban. Some rural-urban interactions models were developed (Fontaine and Rounsevell, 2009; Rounsevell et al., 2006, 2005; Spangenberg et al., 2010; Valbuena et al., 2010; Verburg and Overmars, 2009; Westhoek et al., 2006), but many of them do not go further than a simple land take procedure in which urban expansion eats away existing farming land.

The aim of this chapter is to assess both the direct and indirect impacts of urban expansion on the agricultural population in the urban fringe. For this assessment a rasterized land use model describing the urban expansion processes and its related land use changes is coupled with an agent-based model simulating the decisions of individual farming households. The model is run for a set of different storylines for future urban development until 2035. Belgium was selected as a case study because the country is characterized by a strong urbanization, with a gradient from the centre towards the periphery and a long agricultural history. Firstly, the study area and its farming practices are described. Secondly, the modelling approach is presented in relation to the study area. Finally, the model is used to simulate the future of farming practices in a business-as-usual scenario and two contrasting policy scenarios.

## 5.2 Study area

Belgium is situated in the densely populated region of Western Europe (Figure 5.1) with an average population density of circa 370 inhabitants per $km^2$. The areas with the highest presence of agriculture can be found in the centre of the country (the Loam region) and the northwest of the country (the Polders) (Figure 5.1). Most cities in Belgium date back to the Middle Ages, but only in the $19^{th}$ century the first important urban expansion took place under the influence of the developing industries and trade. At this point, cities were mostly still clearly delineated from the surrounding land. Increasing urban population first led to a more compact housing, but from the second part of the $19^{th}$ century, urban expansion started to spread out past the initial city boundaries. Increasing urban mobility (e.g. trams) allowed a further expansion of cities. At the same time, the richer upper class started escaping the busy unhealthy city centres, moving to the greener countryside. After World War I, the population density in the historic cities started to decrease, with people moving to the suburban areas. After World War II, the delineation between cities and their surroundings became less and less clear: the lack of spatial planning, together with increasing mobility options and policies promoting home ownership, resulted in a further urban expansion towards the countryside. The result is a strongly fragmented landscape (Paredis, 2015; Van Hecke et al., 2010). Together with this direct effect of urban expansion on the available agricultural land, there is also the indirect effect of losing the exclusive use of agricultural lands by farmers. Agricultural lands became increasingly used for other services, such as horse-riding or residents enjoying a rural lifestyle (Bomans et al., 2011; Primdahl et al., 2013). For Flanders for example, this leads up to 15% of designated agricultural area not being used for commercial agriculture (Verhoeve et al., 2015). The different evolutions in agriculture, urban expansion and forest dynamics led to the current land use configuration in Belgium, with a highly urbanised and fragmented landscape, especially in (but not limited to) the northern part of the country (Figure 5.2) and also had its impact on the agricultural landscape. The agricultural landscape in Belgium is dominated by cropland and land-based animal farming. However, a combination of historic, traditional and environmental factors led to a spatial differentiation of the farming practices in the country. In regions with a relative high population density, labour-intensive farming practices such as greenhouse farming and barn-based animal farming were further developed, resulting in relatively small farm sizes. Rotational crop farming and land-based cattle farming, which are associated with large farm sizes, are relatively more present in regions with a lower population density (Van Hecke et al., 2010).

Despite governmental efforts to put a halt to the further urban expansion at the expense of the countryside (e.g. the ambition to not take up any more open space in Flanders by 2040 (Departement Ruimte Vlaanderen, 2017) and in Wallonia by 2050 (SPW, 2018)), urban expansion and landscape fragmentation is still ongoing in Belgium (Crols et al., 2017; Mustafa et al., 2018a; Poelmans, 2010). In the period 2000-2015 the built-up area in Belgium increased with more than 11%, mainly in the form of ribbon development in the peri-urban zone (Statistics Belgium, 2015). The ongoing urban expansion creates an extra challenge for farmers, which are already under pressure because of (1) the increasing international competition in a globalized market with lower margins and (2) stricter environmental policies resulting in new rules and regulations for the farm management (Maertens, 2011; Mathijs and Relaes, 2012; Van Hecke et al., 2000; Van Hecke et al., 2010). As a result, relatively few Belgian farmers find a successor when they reach their retirement age.

Figure 5.2 shows that the present-day succession rate is in most cases lower than 30%. Especially in the less fertile parts of the country on the sandy soils in the north (Campine and Sand area), and the shallow soils in the south (Condroz, Fagne-Famenne and Ardennes) the number of farmers has been decreasing significantly. At national scale the number of farmers decreased by 70% in the period 1980-2015. Figure 5.3 shows that, over the same period, the area of agricultural land did not decrease at the same rate as the number of farmers, resulting in an average increase of the farm size.

## 5.3 Data & methodology

In order to evaluate the impact of expected future urban expansion on farming practices in the peri-urban and rural settings of Belgium, a two-step methodology was developed. Firstly, existing qualitative storylines on the future of urban expansion and farming in Belgium were explored. Secondly, three storylines were selected and downscaled to quantify the impact of urban expansion on the level of individual farms. This is done by combining the urban expansion from a cellular automata land use change model and an agent-based model to model the individual farms.

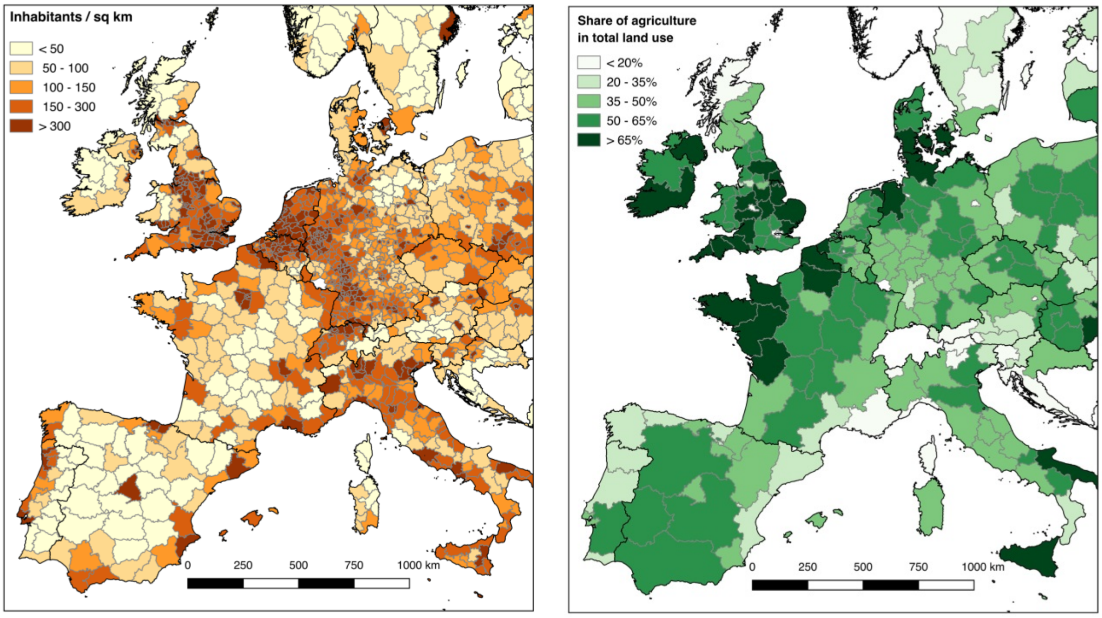



*Figure 5.1 – Population density by NUTS3 region in 2015 and percentage of agricultural land by NUTS2 region in Western Europe (European Commission, 2018b)*

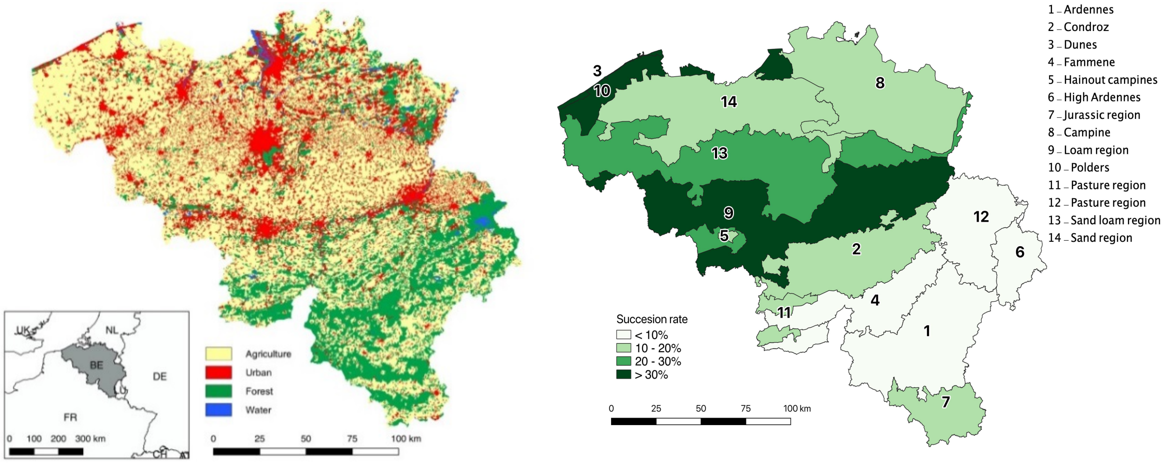


Figure 5.2 – Dominant land use in Belgium based on Corine land cover data (left) (Büttner et al., 2014) and agricultural regions in Belgium with the average farm succession rate (right)(Statistics Belgium, 2018).

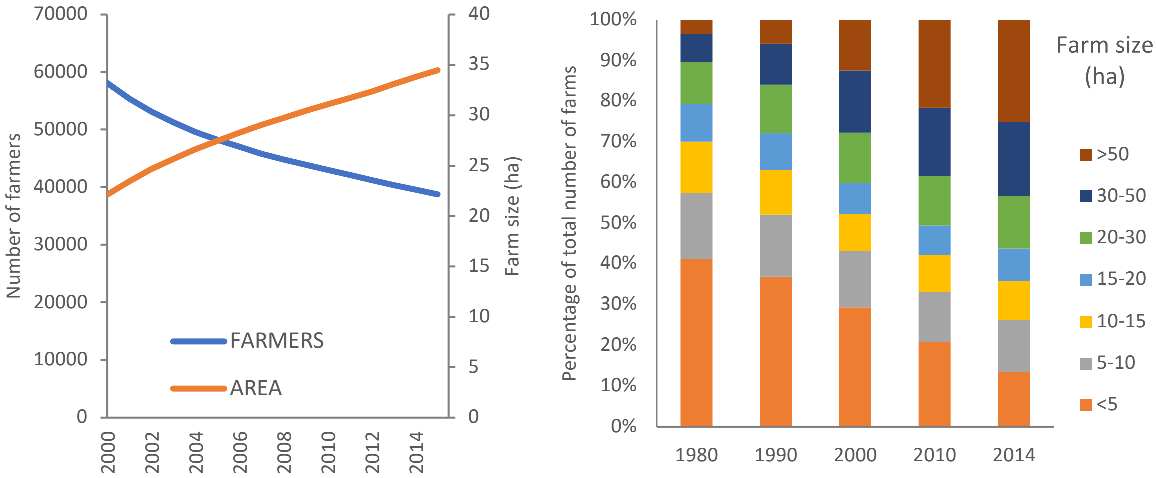


Figure 5.3 – Evolution of the number of farmers and farm size (left) and evolution of the relative proportion of different farm sizes in 2010 (right) (Statistics Belgium, 2018).

### 5.3.1 Storylines on urban expansion & farming

The storylines used to create the scenarios were based on the family of storylines created in the "Welvaart en Leefomgeving" project of the Dutch Planning Bureaus (CPB, MNP, RPB, 2006). The starting point of the storylines from the Dutch Planning Bureaus were two key uncertainties for the future in Europe: the level of international cooperation and the direction of institutional reforms (Lejour, 2003). Variations in these uncertainties led to the creation of 4 storylines: the Strong Europe (SE) storyline (high international cooperation, high importance of public institutions), the Global Economy (GE) storyline (high international cooperation, focus on private initiatives), the Regional Communities (RC) storyline (low international cooperation, emphasis on public institutions) and the Transatlantic Market (TM) storyline (low international cooperation, prominence of private initiatives). Even though these storylines are already relatively old, they are still relevant because of their explorative character, without the ambition to be predictive.

From the set of storylines described above, two contrasting storylines were selected: the GE and the RC storyline. The GE storyline assumes a further urban expansion, increased global competition and reduction of regulations from the EU-CAP to control agricultural supply and demand. The RC storyline assumes a slowing down of the urban expansion rate through a strong regulatory framework and the focus of the EU-CAP on subsidies to small, local and organic farms. These storylines were complemented with a Business-as-usual (BAU) storyline, developed by Engelen et al. (2011) for the Flanders region. The BAU-storyline was based on a continuation of current trends of population growth and changes in population densities combined with a continuation of the current spatial policy and no changes in agricultural policies on the local level or in the EU-CAP. The assumptions behind these 3 storylines were translated into expected impacts on urban expansion in the Belgian context in the BELSPO Growadrisk project (Verbeiren et al., 2013). For this study, they were combined with expected impacts on farming. An overview of the main characteristics for each storyline is shown in Table 5.1.

*Table 5.1 – Overview of the different storylines and their impacts based on the WTO storylines (CPB, MNP, RPB, 2006) that were translated to the Belgian case by Engelen et al. (2011) and in the Growadrisk project (Verbeiren et al., 2013) and combined with the expected impact on farming in this study.*

| Storyline | General assumptions | Impact on urban expansion | Impact on farming |
|---|---|---|---|
| BAU | Continuation of current trends of population and employment growth and current (spatial) policies. | Continued growth, continuing urban expansion. | Continuation of current trends, with same subsidy levels |
| GE | Economic growth with decreased trade barriers. Liberal market with little political interference. | Strong urban expansion due to little spatial planning. Increased competition. | Increased competition in a global market due to the removal of trade barriers and decrease in subsidies received via the EU-CAP. |
| RC | Reduced international trade, focus on social and environmental measures at a regional scale. | Reduced urban expansion. | Small local organic farms are encouraged and subsidised through the EU-CAP and farmers focus on short chain markets. |

Finally, the resulting land demands were used as an input to drive the constrained cellular automata-based land-use model (CCA-model) developed by White et al. (1997). The CCA-model was based on three hierarchically embedded levels: (1) the macroscopic level, represented by the country level in the applied model, (2) the regional level, represented by the 49 EU-NUTS3 entities in Belgium, and (3) the local, cellular level, consisting of a matrix of individually modelled cells with a 1 ha resolution (Figure 5.6). These cells represent the dominant land use at a 1 ha resolution. For every 1 ha cell the model calculated the transition potential to all possible land use categories in yearly time steps. The transition potential was determined by (1) the cell's current land use, (2) the land-use categories in the neighbourhood of the cell, (3) a number of cell-specific properties, such as the physical characteristics (defining the suitability for each land-use type), the accessibility and the zoning status (based on spatial planning documents), and (4) a stochastic factor (representing the fact of non-rational decisions) (see Chapter 3). Each time step, for each cell, the land use class with the highest transition potential was assigned. This process was constrained by the regional land demand (at the NUTS3-level) for each land-use category. This means that once the land demand for a certain land use category is met, the land-use category with the second highest transition potential is attributed to a cell, and so on. A more detailed description of the CCA-based land-use model can be found in Chapter 3 and in White et al. (2015) and (Engelen et al., 2011).

The outputs of the land-use model consist of land-use maps in a raster-GIS format with a spatial resolution of 1 hectare and a temporal resolution of 1 year. For this study, the model was run from 2013 until 2035, so yearly outputs for the period 2013-2035 are available. The results on urban expansion will be used as input in the agent-based model in order to evaluate the impact of urban expansion on the farming practices. The land-use model for all the scenarios show an increase in urbanised area in Belgium by 2035: + 14.3% of the area of urban land for BAU, +16.1% for GE and +3.3% for RC (Figure 5.5).

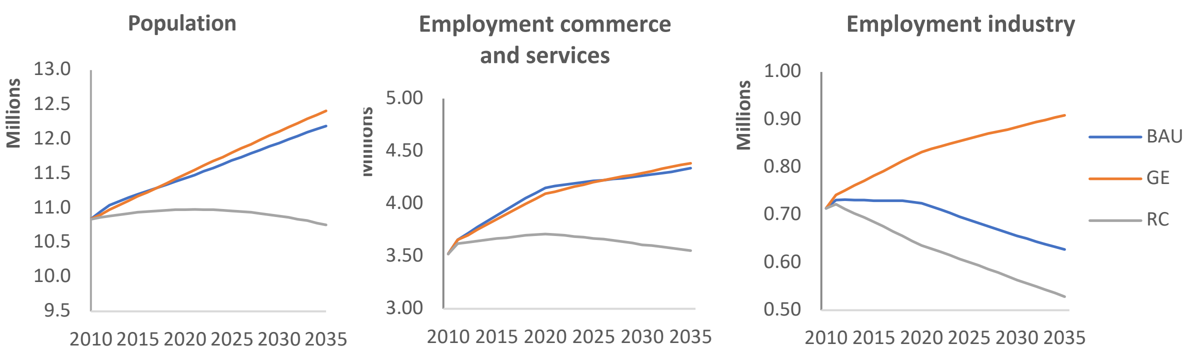



*Figure 5.4 – Expectations for population and employment in commerce, services and industry until 2035 under different storylines (Verbeiren et al., 2013).*

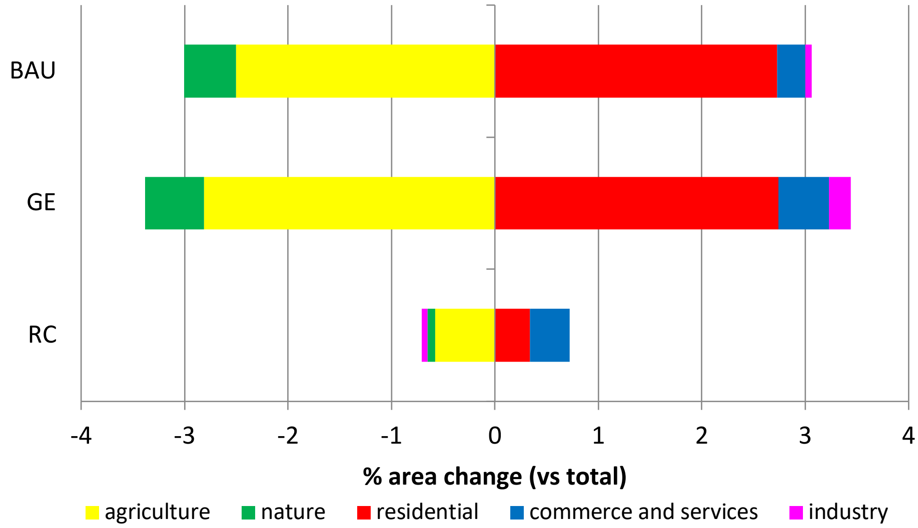



*Figure 5.5 – Change in area for each type of land use for the three storylines between 2013 and 2035 (Verbeiren et al., 2013).*

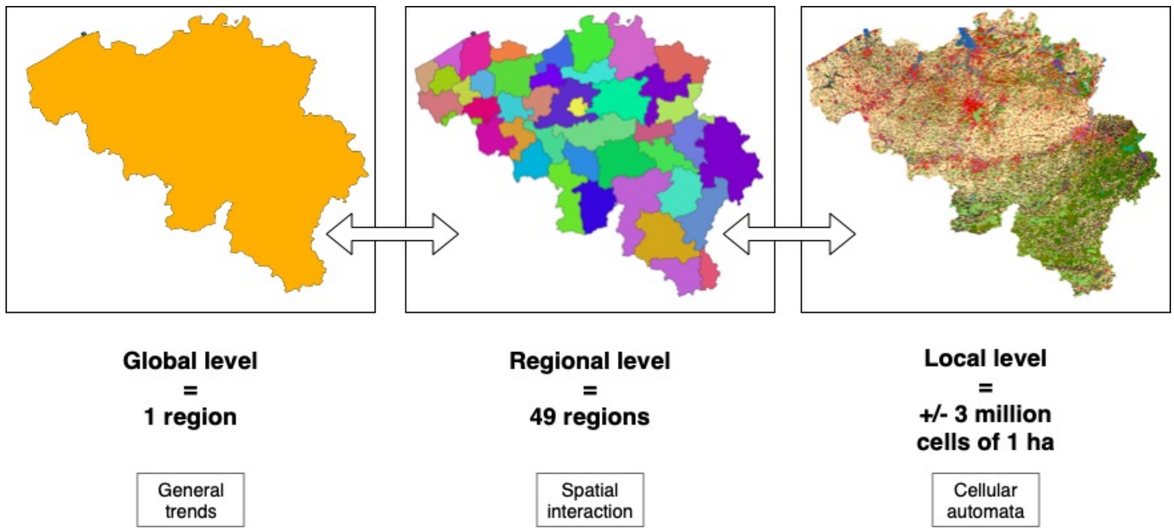



*Figure 5.6 – Different levels in the cellular automata land use change scenario modelling: the general trends are defined for the entire study area (the global level), they are translated to specific land demands at the regional level (49 NUTS3 regions), which are used to constrain the land use change at the local level (1ha cells).*

### 5.3.2 Spatial downscaling of the impacts on farming

Agent-based models (ABMs) allow looking into the evolution of a population at the level of the agent in a spatially explicit way (see Chapter 3 and Chapter 4). These models define autonomous decision making objects, called agents, which act and react to the environment and to the actions of other agents, allowing the representation of the decision-making process of these agents in relation to changes (Bousquet and Le Page, 2004; Parker et al., 2002a, 2002b, 2001).

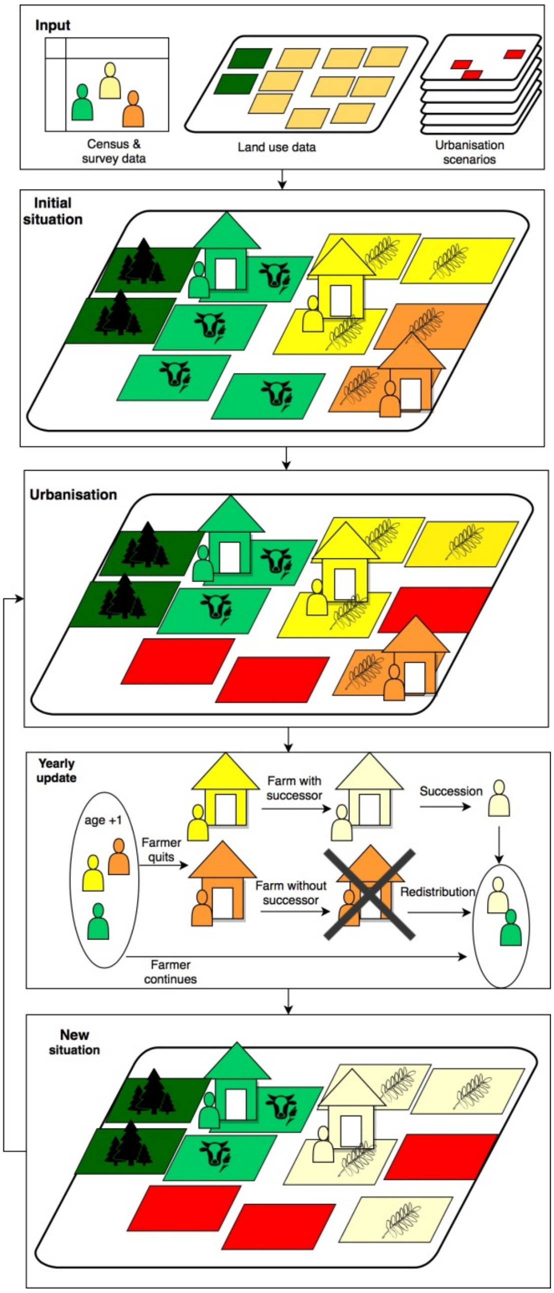



*Figure 5.7 – Overview figure of ADAM adapted to include urbanisation.*

The agent-based model ADAM (Agricultural Dynamics through Agent-based Modelling) that simulates, on a yearly basis, the decisions of the farming population of a whole country (Chapter 3 and 4) is adapted to analyse the impact of urban expansion (Figure 5.7). The demographic component of the model updates the age of the farmers, leading to a possible retirement or decease with or without a successor for the farm. Whether or not a successor is present depends on the farm characteristics: the farm size and type and the characteristics of its parcels. In the case where no successor is found the parcels of the farm are abandoned or taken over by neighbouring farms (Chapter 3 and 4).

In this study, 5 different farm types were considered: (1) yearly rotating crop farmers, (2) permanent crop farmers, (3) greenhouse farmers, (4) land-based animal farmers and (5) barn-based animal farmers. Each of them has different characteristics in terms of profitability, dependence on soil type, and minimum size to survive (Chapter 4).

After the initialisation of ADAM (a parcel-based vector model, see Chapter 3 and Chapter 4), the model is coupled with yearly land-use maps on urban expansion produced by the CCA LUC model (raster model with a spatial resolution of 1 ha, see Chapter 3), to consider the direct and indirect impacts of urban expansion as follows:

1. The direct loss of parcels was included by considering an agricultural parcel as urbanised and lost for farming when it has a 25% overlap with an urbanised raster cell from the land use change scenario (Figure 5.8). As a result, the farm size of affected farmers is decreasing, resulting in a

lower profitability for their farm. An overlap threshold of 25% was chosen since this value resulted in the best correspondence with observed decline in agricultural area in the period 2000-2010. The land lost can thus only be compensated when other land in the area becomes available from other farmers quitting.

2. The indirect impacts of urban expansion on farming activities were taken into account by considering the isolation of farmland due to fragmentation of the landscape. When a farmland parcel was disconnected from other farmland because of urban expansion, the parcel was no longer considered to be profitable for commercial farming and withdrawn from the model's simulation. These parcels were then assumed to be used for non-commercial farming activities such as hobby farming, horse keeping or other leisure activities. A parcel is considered to be disconnected if no other farmland parcel is present in a radius of 1 km or when the 20 nearest neighbours is urbanised.
3. The impact on farming activities as assumed under the different storylines (BAU, RC or GE) were included. This was done because policy measures such as direct subsidies or possible price interventions directly affect the profitability of farms and therefore their survival chances.

- For the BAU-storyline the assumption was made that the profitability of the farms (based on the combination of farm type, farm size and farm location; see Chapter 3 and the technical appendix) will not change and that current trends will persist.
- The GE-storyline assumed a general decrease of profitability of 10% for land-based farming and 10% decrease in succession chance for non-land-based farming, caused by an increased competition in a more globalized market that results from a removal of trade barriers and a decrease in subsidies. These subsidies form an important component of the total income of Belgian farmers: According to an assessment of the EU circa 30% of the income of Belgian farmers in the period 2011-2015 came from subsidies of which 25% in the form of direct payments (European Commission, 2017). Since this scenario assumes a decrease in subsidies and not a complete abolishment, a decrease of 10% in general profitability was assumed.
- The RC-storyline assumed an increase of the agricultural subsidies oriented towards land-based farming with a below-average profitability. In this storyline small local organic farms are seen as an important asset, they are encouraged and subsidised by the government and are able to increase profits due to short chain markets (Pearson et al., 2011) and a higher appreciation from customers (Crowder and Reganold, 2015). This assumption was implemented by raising the profitability of the small land-based farms, being farms with a below average profitability, by 20%. Non-land-based farms, which are considered as not environmentally friendly in this storyline, do not receive subsidies.

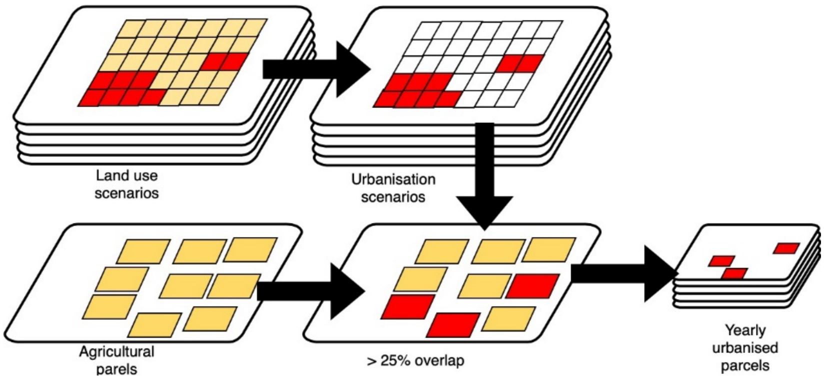



*Figure 5.8 – Combining raster-based scenarios with the parcel-based ADAM.*

### 5.3.3 Model initialization

The model set-up as described above requires a database with the location of all farms and their parcels, the farm type and the age of the farmer. The available Belgian agricultural census data (Statistics Belgium, 2018) do not reveal these data at the level of individual farmers due to privacy regulations. Therefore, the data available at municipality level was downscaled to simulate a realistic farming population and their corresponding farm structure.

The number of farmers per farm type and their age structure at municipal level was extracted from the agricultural surveys of 2013 and 2016 (Statistics Belgium, 2018). This dataset was combined with agricultural parcel databases from 2013 (*Landbouwgebruikspercelen* dataset for Flanders and the *Système intégré de gestion et de contrôles* (SIGEC) dataset for Wallonia (European Commission, 2018a)). These databases contain information in a vector-GIS format with the location and shape of individual farmland parcels.

Both datasets were combined by assigning parcels from the parcel map to the individual farmers in the municipality (or a neighbouring municipality) based on the farm type. The result of this procedure is a farmland distribution that is not the exact farmland distribution but realistic and suitable for model simulations.

## 5.4 Results

### 5.4.1 Simulated urban expansion patterns for 2035

Figure 5.9 shows the expected spatial pattern of urban expansion for the surrounding area of three medium sized cities (with each around 100.000 inhabitants) in Belgium: Namur, Leuven and Mechelen. The BAU and GE scenarios show the largest level of urban expansion with a diffusion

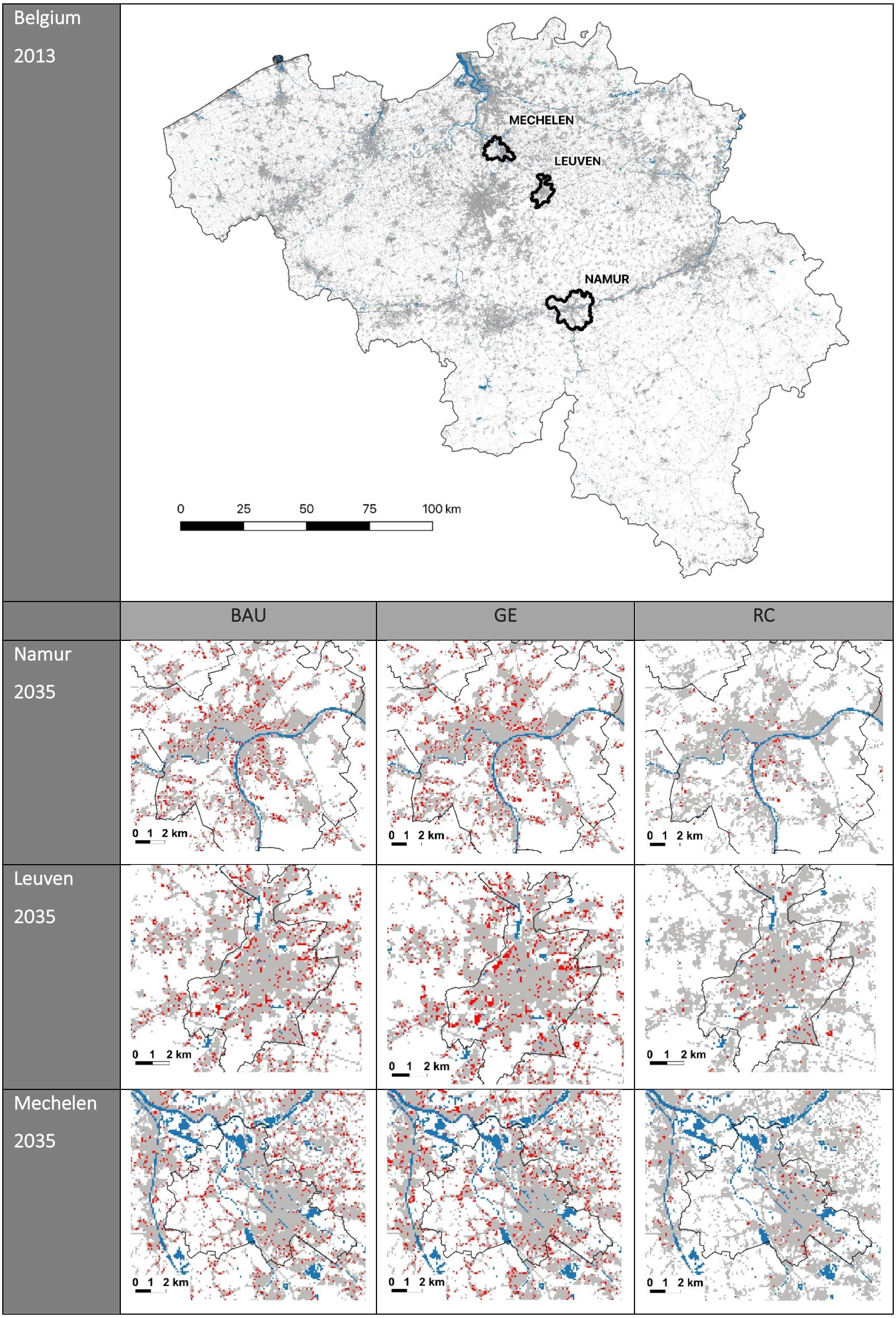



*Figure 5.9 – Urban land use for 2013 (grey) and newly urbanised cell in 2035 (red) for all the scenarios for 2035 focussing on three average sized cities.*

from existing urban area through continuous ribbon development along the major roads. This is a form of urban expansion often referred to as urban sprawl. The RC scenarios, on the other hand, shows the lowest increase in urbanised areas. Moreover, newly urbanised areas are mostly located within the current urbanised areas resulting in a densification of existing centres.

### 5.4.2 Simulated impact on agriculture

The mismatch in land use data resulting from the combination of rasterized urban expansion data, with vectorized agricultural parcel data, leads to a higher than average loss in the first year modelled. In the first year about 8.5% of parcels is lost through urban expansion. Not unexpectedly, this mostly concerns small agricultural parcels resulting therefore in a loss of only 2% of agricultural area (about 32.000 hectares) in total.

Figure 5.10 shows the relative decrease of farmland as a result of urban expansion. Municipalities in the surroundings of cities lose a significant part of their agricultural land (in some cases more than 10%). This is especially the case in the area in the central north of the country, the highly urbanised area of the so-called Flemish Diamond in between the cities Brussels, Antwerp, Ghent and Leuven and in the greater Liège area in the east of the country. Only in the RC-scenario, the loss of farmland is clearly lower, with the loss being the lowest in the central loam belt, south of Brussels. For all scenarios the Standard Deviation (SD) on the estimated agricultural area in 2035 is small (max 9.72 $km^2$ on a total of 13 853 $km^2$ in BAU).

In Figure 5.11 the expected average decrease in number of farmers at the municipality level after 100 model runs is visualised. All scenarios show a high loss of the number of farmers of about 50% over the period 2013-2035 with a similar spatial pattern. The SD on the total is low and similar in all three scenarios, with a maximum of 78 on a total of 15 448 farmers for the GE scenario and 16 050 in the RC scenario. In all three scenarios, the largest relative losses can be found in the north of the country between Antwerp and Brussels, in the central-west of the country to the west of Brussels, and in the south-east of the country around Liège, while the decrease is the least in the centre of the country. The relative decrease of farmers is the highest for the GE scenario, where even in the central loam belt, there is a higher decrease. The SD on the results is low and similar in all three scenarios. The large decreases in the central west of the country, to the west of Brussels, have a low SD in all scenarios. The differences in total number of farmers by 2035 are small, but still noteworthy. The largest decrease can be found in the very competitive GE scenario with on average only 15 448 farmers of the 37 703 farmers that were present in 2013 remaining (Figure 5.11).

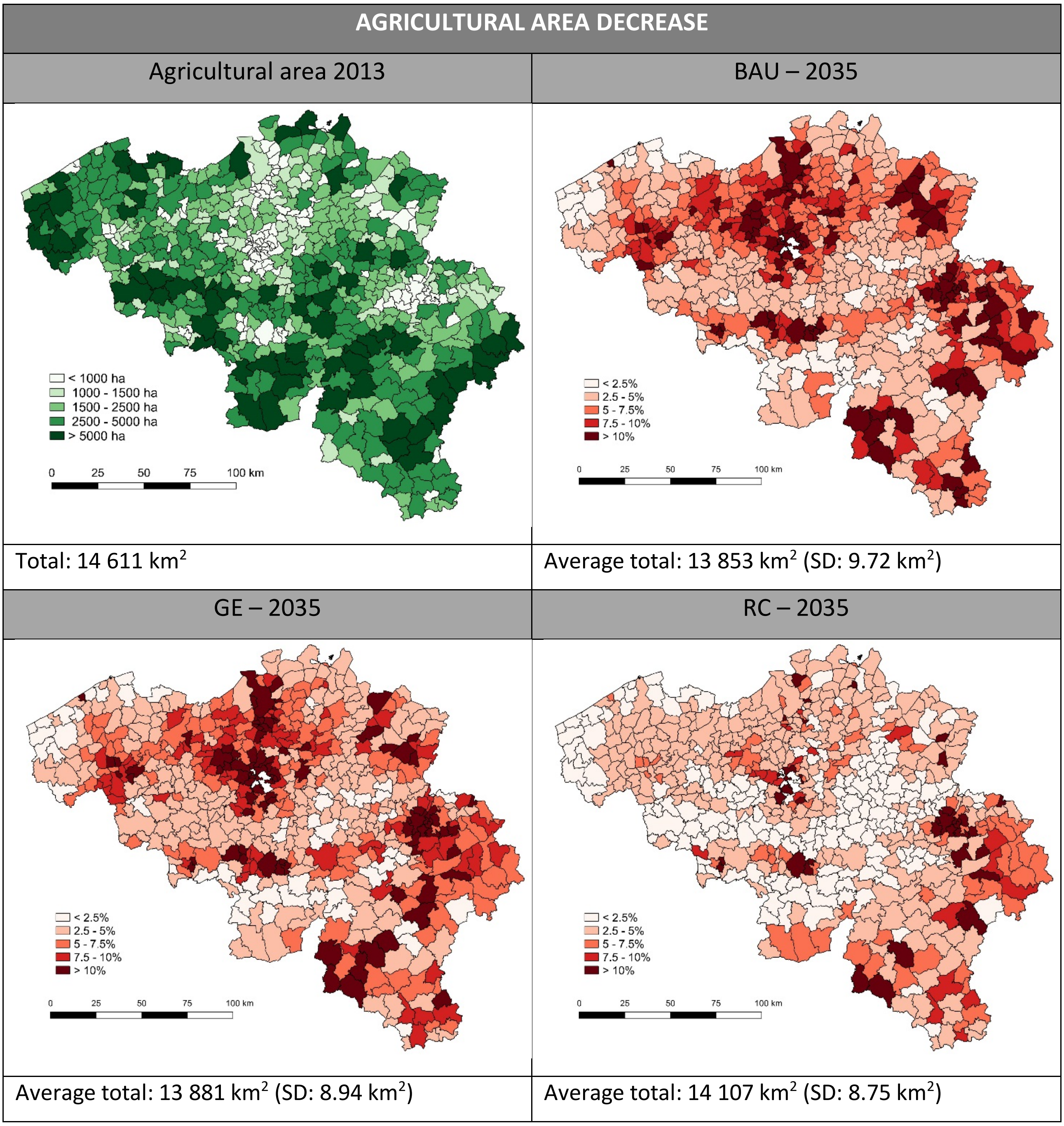



*Figure 5.10 – Total observed agricultural area in 2013 and the average expected decrease by 2035 at the municipality level for the different scenarios after 100 model runs with the standard deviation for each scenario as an inset.*

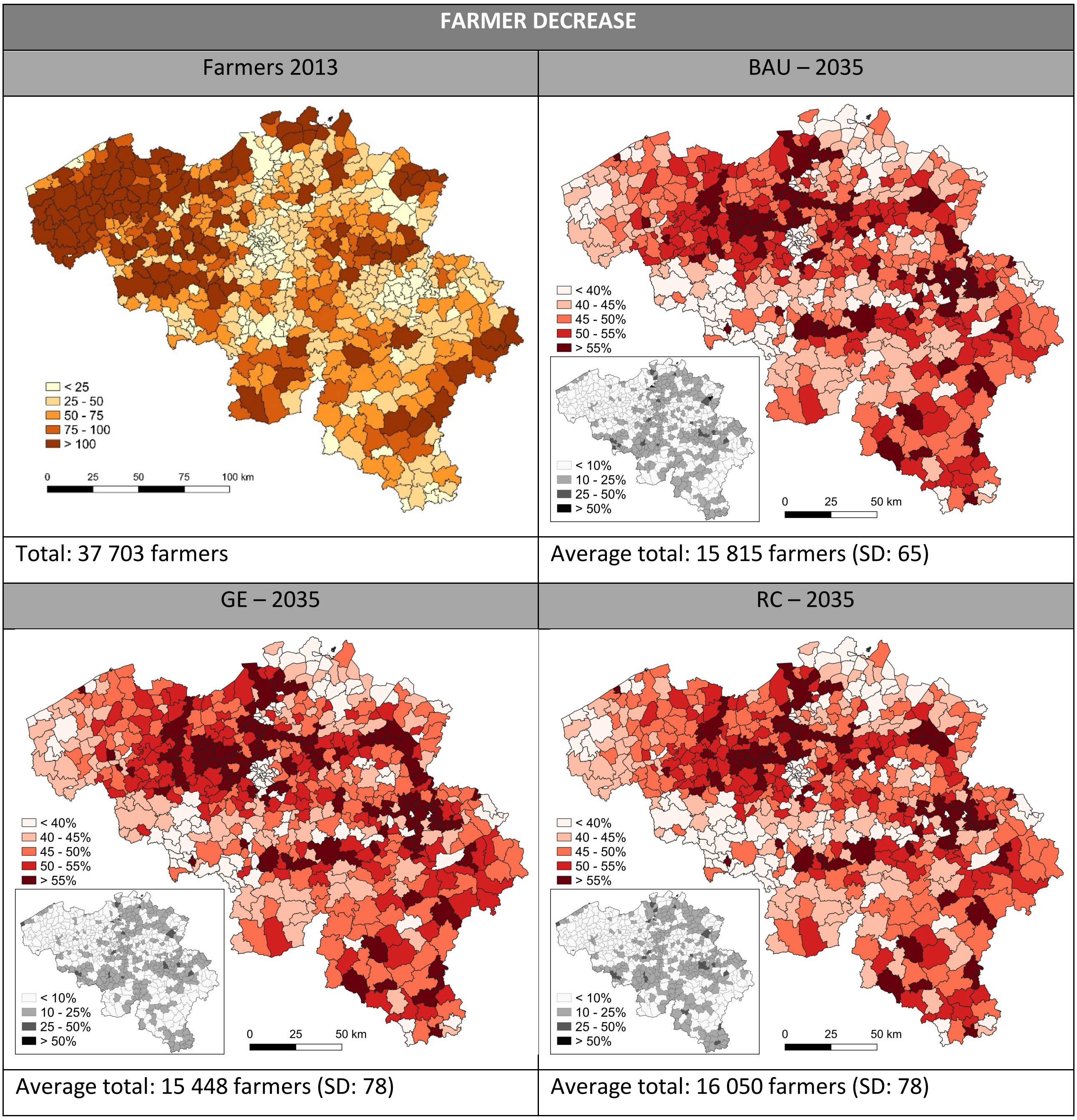



*Figure 5.11 – Average number of farmers in 2013 and the average expected decrease by 2035 for the different scenarios after 100 model runs with the standard deviation for each scenario as an inset.*

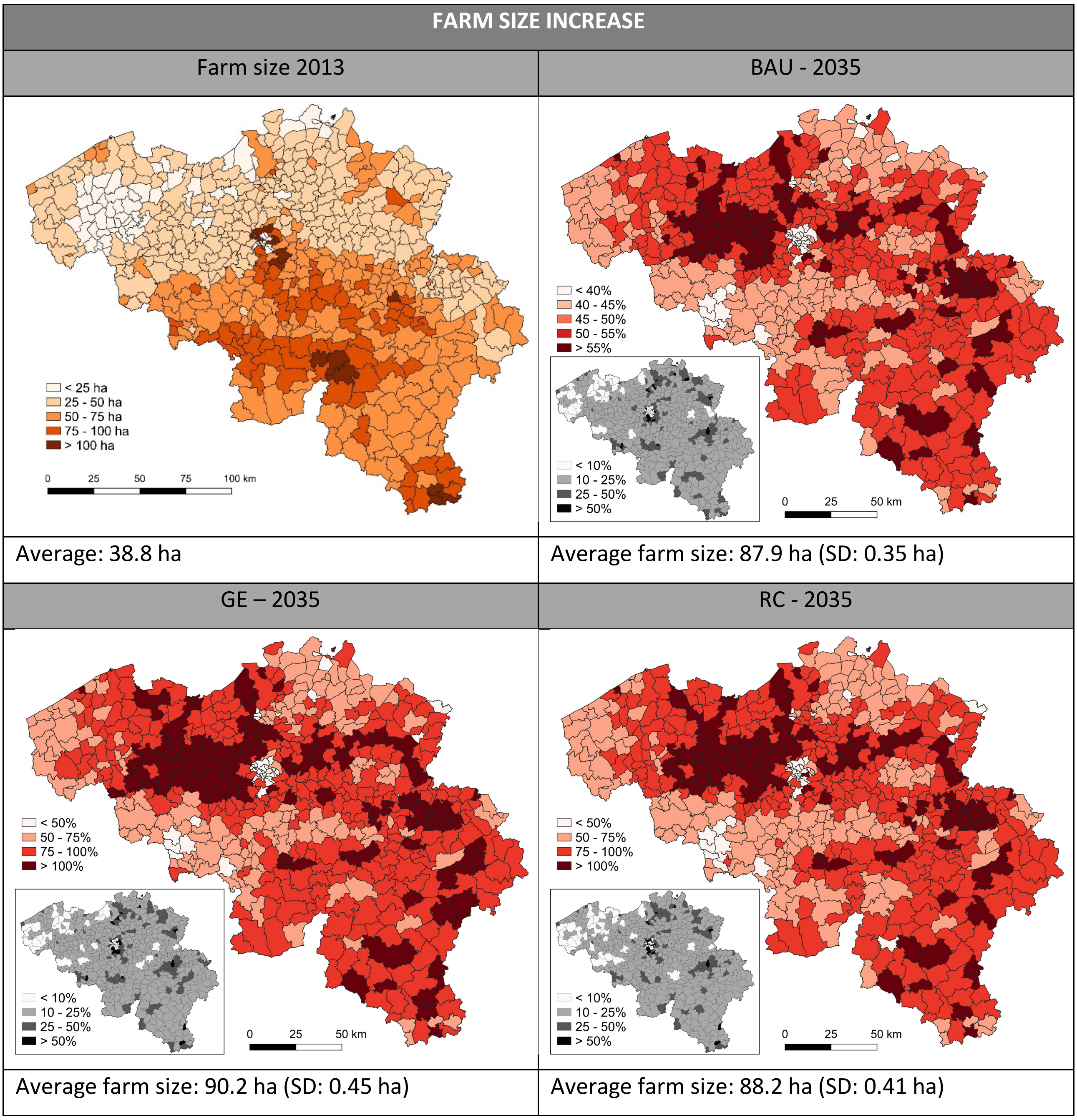



*Figure 5.12 – Average farm size in 2013 and the average expected increase by 2035 for the different scenarios after 100 model runs with the standard deviation for each scenario as an inset.*

Figure 5.12 represents the expected changes in farm size between 2013 and 2035. The GE scenario results in the highest average farm size (90.2 ha), which is slightly higher than the average farm sizes for the BAU and RC scenarios (respectively 87.9 ha and 88.2 ha). The spatial patterns of farm size increase, as well as the SD, are similar in all scenarios with highest increases expected in the Liège area and the area west of Brussels. The increases in the central loam belt are the smallest. The SD is relatively small, with an SD ranging between 0.35 and 0.45 ha on an average between 87.9 and 90.2 ha.

## 5.5 Discussion

Figure 5.10 to 5.12 show the expected changes in agricultural area and the expected number of farmers and farm size for the different scenarios. The results show a further decline of farms and farmland under all selected scenarios and with similar spatial patterns. The continued strong decrease of the number of farmers also leads, in spite of the decrease in farmland area, to a continued increasing average farm size. These findings are in agreement with the model simulations for Saxony and Baden-Württemberg in Germany reported by Happe et al. (2008) that applied the AgriPolis model, an agricultural ABM with a strong economic focus.

The produced maps show three hotspots of change: (1) the area around the city of Liège in the east of the country, (2) the fertile loam belt in the centre of the country and (3) the area to the west of Brussels.

In the Liège area the low succession rate (on average lower than 10%; Figure 2.17 and Figure 5.2), together with a relatively high loss of agricultural area around the city of Liège (often more than 10%; Figure 5.10) leads to a strong decrease in farmers numbers (mostly more than 55%), even though (but also because) the number of farmers is already relatively low in this area (Figure 5.11). The strong increase in farm size (>100%; Figure 5.12) is an obvious consequence of these trends and can also be related to the relatively small farm sizes as the start of the model runs (mostly 25-50 ha).

The fertile loam belt, going from east to west in the central south of the country, is, in agricultural terms, the most productive part of Belgium with a high standard gross margin per farm (Figure 2.11). The succession rate is also, with an average of more than 30 %, one of the highest of the country (Figure 5.2). Not surprisingly, the loss of agricultural land is very limited in this region (Figure 5.10), as well as the decrease in number of farmers (mostly less than 45%; Figure 5.11) and the on average already large farm sizes in 2013 show the least increase in size (often less than 75%; Figure 5.12).

The area to the west of Brussels projects a strong decrease in farmers (>55% %; Figure 5.11) and increase in farm size (up to more than 100%; Figure 5.12) in all scenarios. In the BAU and GE scenarios, a strong decrease in agricultural land is also observed (Figure 5.10). These strong relative changes are a consequence of the relatively small number of farmers and small farm sizes in 2013. But similar trends do not immediately show in other areas with comparable farm size, number of farmers and loss of agricultural land (e.g. the north-east of the country). Both regions even show similar succession rates (Figure 2.17). The difference between both regions shows however in the spatial distribution of farmers over 55 years old, whereby the region west of Brussels stands out with more than 55% of farmers being over 55 years old (Figure 2.16).

The results in the different scenarios show little differences. Although the difference in the loss of agricultural area between the scenarios GE and RC is clear (13 881 vs 14 107 $km^2$), the differences are relatively small for the number of farmers (15 448 vs 16 050) and the average farm size (90.2 vs 88.2 ha). The higher loss of agricultural area in the GE scenario, combined with the relatively higher farmer dropout, results in an on average larger farm size. The BAU scenarios is also characterised by a high loss of agricultural area, but with a lower decrease in the number of farmers compared to the GE scenario. This ultimately leads to a smaller average farm size. Though the differences in the results between the scenarios are there, they show to be much smaller than the difference between the current situation (37 703 farmers and 38.8 ha in 2013) and these simulated results.

The earlier analysis of the different regions, showed the importance of farmer age and succession rate. Therefore, the relatively small differences between the different model outputs can most likely be related to the much stronger inherent demographic mechanisms that result from the initial farmer population. In 2013 20% of farmers were older than 65, 65% were older than 55, and only 4% were younger than 35. This automatically leads to a high number of dropouts due to retirement and decease. The loss of farmland around urban centres is the lowest in the RC-scenario, where small farms are being actively supported through subsidies. This shows the (current) importance of these subsidies (and other financial incentives) in making small farms more viable at the urban fringe, which fits well with the ambition of the Belgian government to slow down or even stop further urban expansion. A possible reorientation of traditional farming practices towards organic farming in the suburban area and the possible promotion of local food and short supply chains could support these farmers and reduce the required level of subsidies.

The trends that are expected under these scenarios can be considered as a logical and necessary upscaling and consolidation of the farming sector in Belgium but also impose an important (social) challenge on society. Without accompanying measures this upscaling process can result in personal bankruptcy of small-scale farmers and their families and in many cases in long-term poverty and social exclusion (Meert et al., 2005, 2002; Van Hecke, 2001). Furthermore, these trends can have a negative impact on biodiversity and ecosystem services. Farms growing in size are expected to continue the trend of parcel consolidation to improve efficiency. This will result in less parcel borders (Robinson and Sutherland, 2002) and a simplification of the agricultural landscape (Bianchi et al., 2006). Agricultural intensification and the reduction of hedges and other small landscape elements have proven to have a negative impact on biodiversity (Bäckman and Tiainen, 2002; Marshall and Moonen, 2002), reduce the ability of natural pest control of the landscape (Bianchi et al., 2006), and allow for increasing soil erosion (Evans, 1996; Ouyang et al., 2010), water run-off and pollution of rivers (Pätzold et al., 2007; Stoate et al., 2009; Withers et al., 2014).

This also implies that if policy makers would want to alter these trends, drastic changes in the current policies and financial system in regard to agriculture would be required. This would require changes that result in a much higher succession rate, thereby encouraging new farmers to start. An issue which was also picked up by the European Commission, resulting in the inclusion of specific measures for young farmers in the revision of the EU-CAP in 2013 (payments between 20 and 90 euro per ha for farmers under 40 for the first 5 years; Bori, 2018; European Commission, 2013) and further continued in the renewed EU-CAP in 2018 (European Commission, 2019).

In other words, if there is an intent to keep the number of farmers at the current level, every retiring farmer needs to have a successor. An enormous challenge given that currently (2016), 28% of farmers are older than 55 and only 16% of farmers over 50 indicate that they have a successor (Statistics Belgium, 2018). Given that the results of the different scenarios are very similar, we can assume that possible measures that alter this trend, would work for all scenarios. The necessity of the implementation of these changes depends of course on the vision and aims that policy makers have on agriculture in the future. These trends can after all also be considered as a logical evolution. In that case, one could argue, that policy makers should make sure the individual impact on these outcompeted farmers is in some way mitigated.

From that prospect, the agent-based model ADAM would further benefit from an improved economic model (or the combination with an external model) and improved behavioural mechanisms (social benefits, appraisal, desire to farm…) to allow the further investigation of trends.

What is currently also not fully included is farmland abandonment in more remote areas. Farmland abandonment is the process where the land of the farm is not sold and cultivation stops. It is present throughout most of the EU (Hatna and Bakker, 2011) and is expected to continue in the next decades

(Hatna and Bakker, 2011; Renwick et al., 2013; Verburg et al., 2010). According to Renwick et al (2013), highest levels of abandonment are to be expected in GE-like scenarios (high global competition, with low levels of EU-CAP support), but also under other scenarios farmland abandonment continues. Though the rate of farmland abandonment in Belgium in the past has mostly been low (<0.5% decrease between 1990 and 2006), with the highest decrease in the south of the country (0.5%-2%; Hatna and Bakker, 2011), including the mechanisms on farmland abandonment might be necessary to create a more complete image on the evolution of agricultural lands and to extend the use of the model to other regions.

The scenarios also do not consider possible changes in crop choices due to changes in trade mechanisms or the existence or not of trade barriers. For example, in 2014 Belgium imported about 1 064 million tons of soybeans, 26% originating from outside the EU (Danckaert, 2016). An important decrease in the possibility to import soybeans could lead to a shift in locally produced crops, in order to provide the necessary crops for fodder.

## 5.6 Conclusion

The aim of this chapter was to gain an insight on the impact of different scenarios on the agricultural population in the urban fringe by coupling a raster-based CCA model on urban expansion with a vectorized agricultural agent-based model in order to gain insight in the different underlying processes.

The results showed that most changes are expected in the area to the west of Brussels and the greater Liège area. But under the current conditions in the model, even the two extreme storylines resulted in a similar loss of farmland and farms both in numbers as in spatial distribution.

The analysis of the results seems to imply that the model is more driven by the demographic process of an ageing population in combination with low succession rates than by the scenario specific economic and policy parameters. We can therefore assume that the current scenarios do not capture the elements that would be necessary to model a shift in the current trends in agriculture in Belgium.

The added value of the results of the different models lies more in the recognition of the persistent spatial pattern of expected changes, showing the areas where most changes are to be expected, and to the conclusion that the current demographic processes have an unavoidable impact on the results in the current model set-up. The different scenarios on urban expansion and changes in farming policies thereby further pronunciation and aggravates these processes. The results herefore also show that the combinations of different models from different backgrounds cannot provide insightful outcomes and are worth further exploring.

# Chapter 6 High thematic resolution land use data in species distribution modelling

*This chapter is under review as: Beckers V., Marshall L., Vray S., Rasmont P., Vereecken N., Dendoncker N. (2019). Increased Thematic Resolution of Land Use Change Models for Biodiversity Scenarios: Case study of Belgian Bumblebees, Journal of Biogeography.*

## 6.1 Introduction

Land use and land use change have an important impact on the physical environment: land use change notably impacts erosion (Van Rompaey et al., 2002), hydrology (Poelmans et al., 2011), climate (Berckmans et al., 2018) and biodiversity (Polasky et al., 2011; Reidsma et al., 2006). Regarding the latter, many studies have shown the importance of land use and land cover change (LULCC) as drivers of species distribution patterns and biodiversity loss (Krauss et al., 2010; Lambin and Meyfroidt, 2011; Luoto et al., 2007; Ostberg et al., 2015; Tscharntke et al., 2005). Species distribution models (SDMs) have become a common approach to provide insights on the current and future distribution of species in relation to climate and land use. They combine the occurrence of species together with environmental conditions, to get an insight on their distribution patterns (Elith and Leathwick, 2009; Franklin, 2010). These studies tend to only use a limited number of land use types, since land use change scenarios are often only available at low spatial and thematic resolution (Titeux et al., 2016; Verburg et al., 2013).

Land use change modelling through agent-based modelling (ABM) has come up as a powerful approach to allow the modelling of fine scale and high thematic-resolution land use change (Rounsevell et al., 2012). The combination of ABM with SDMs is however, rarely done, partly due to differences in spatial and temporal scales used by the different models (Parker et al., 2002b). ABMs are, for example, often being developed to be either very detailed for a small region (Bakker et al., 2015; Happe et al., 2008) or cover large regions losing detailed information in the process (Rounsevell et al., 2014) making them unsuitable for use in SDMs in both cases. The development of ADAM (Agricultural Dynamics through Agent-based Modelling) allows the modelling of a wide variety of agricultural land cover types at a fine resolution and for a large spatial extent. This allows for a greater complexity in predictors to estimate habitat suitability of landscapes in SDMs.

Pollinators' distributions have been highly impacted by LULCC (Kevan, 1999). For example, bumblebees, a well-studied pollinator group, have suffered from loss of habitat for feeding and nesting as a result of changes in agricultural land use and land cover (LULC; Aguirre-Gutiérrez et al., 2017; Vray et al., 2019). Although the importance of LULC on historical bumblebee distributions has been proven (Aguirre-Gutiérrez et al., 2017) and land use and land cover models have shown their added value in bumblebee SDMs for future scenarios (Marshall et al., 2018), most SDMs only include changes in different climate related parameters, or use static LULC data (Titeux et al., 2016). Recently, Marshall et al (2018) showed that projections of loss and gain of bumblebees in the future varied depending on whether land use change scenarios were included in SDMs. However, the scenarios were limited to only six land use classes due to the absence of high thematic resolution LULCC models for Europe. Comparing the results of low thematic resolution SDMs versus high thematic resolution SDMs provides an interesting case study to assess the added value of a thematically detailed, parcel level, national scale agent-based model (like ADAM). Specifically, their potential to improve the quality of biodiversity studies in general. Hence testing the hypothesis put forward by Martin et al. (2013) that increased thematic resolution is a necessity to better capture the effect of land use on species trends. We expect that the increased thematic resolution in land use, and more specifically in agricultural land use will result in less uncertainty in biodiversity projections and a greater detail on the connectivity and fragmentation of species distribution, therefore making models using a high thematic resolution an added value for SDMs on bumblebees. We also expect that the use of high-thematic resolution data will have a greater impact when modelling species with specific habitat preferences.

The main aim of this research is therefore to assess the importance of high thematic resolution land use change projections in SDMs. First, the applied land use scenarios are briefly described, together with an explanation on the SDMs. Next, the results are presented through a comparison of the differences in future distribution patterns between SDMs with both high and low thematic resolution LULCC maps as an input. The obtained results are first presented for all bumblebee species. Subsequently, we specifically look at two bumblebee species: *Bombus magnus*, with specific habitat preferences and *B. lapidarius*, a widespread generalist species. The results are followed by a discussion and concluding paragraph.

## 6.2 Material and methods

### 6.2.1 Land use change scenarios

The development of ADAM showed the possibility of creating ABMs able to model decision-making at the parcel level for a large (national) extent. In ADAM, farmers take yearly decisions on the next agricultural land cover for their land, based on their farming type, the current land cover of the parcel and the combination of rotation practices, crop prices and expected yield for each crop (see Chapter 3, 4 and the technical appendix). The result is a yearly agricultural land cover map of Belgium from 2013 to 2035, for all parcels with a high thematic resolution. In order to use the results in a species distribution model (SDM), a complete LULC map for the entire extent of Belgium is needed. Therefore, ADAM was combined with the Belgian land use change scenarios that resulted from the storylines: Global Economy (GE), Regional Communities (RC) and Business-as-usual (BAU) which were earlier used to define the pressure from urban expansion on farming (see Chapter 5). The land use scenarios based on the work of Engelen et al. (2011, 2007, 2003) produce land use maps with 23 classes at a spatial resolution of 1 ha from 2013 to 2035.

The SDM requires, as input, a grid with for every grid cell the percentage of the land use classes present. Therefore, the 1ha land use maps were aggregated to a grid of 1 $km^2$ resolution with land use percentages for every grid cell (Figure 6.1). A similar process was done with the parcel map with the agricultural land use produced by ADAM. The presence of the different crops was translated into a percentage of the total agricultural land on the 1$km^2$ resolution (Figure 6.1). In a last step, the crop percentages were used to further split up the arable land use class generated from the land use map, by defining the relative share of each crop in the total percentage of arable land on the 1$km^2$ resolution (Figure 6.1). The percentage of arable land was in that way further split up into four agricultural land use classes, namely: grains (containing the modelled amount of wheat, barley and maize), sugar beets, rapeseed and potatoes (Figure 6.1). Together with pasture, these four crop types make up more than 90% of the Belgian agricultural landscape (see Appendix 7). Pasture and fruit trees, are both modelled in ADAM and the CCA LUC model. In the CCA models these classes are part of a map covering all LU, while in ADAM, only agricultural land use is modelled. In order to guarantee a total of 100% for the land use percentages in the aggregated cell at the 1 $km^2$ resolution, the percentages of pasture and fruit trees present in the CCA LU maps were used. With the arable land from the CCA LU map (containing 23 classes, see Chapter 3.2) being split up in 4 crop types, this results in aggregated 1 $km^2$ land use maps containing a total of 26 classes.

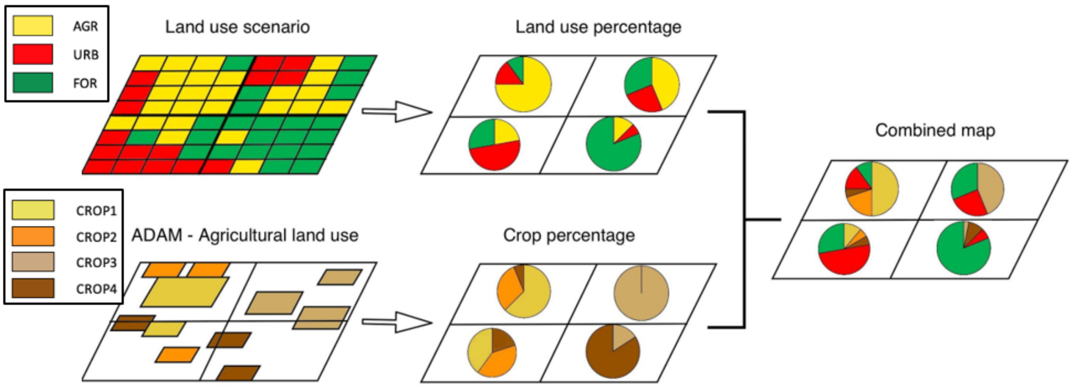



*Figure 6.1 – Simplified example of the resampling of the land use data at 1ha resolution and agricultural parcel data from ADAM to the 1km² resolution*

### 6.2.2 Bumblebee collection records

This study uses bumblebee collection records from Belgium since 2005 until 2017 as they best match the present period given the available land use data (Figure 6.2). Taking a larger range of data allows to have sufficient records to model the species, knowing however that this might mean a loss in knowledge about the exact observation conditions. The data were collated by the University of Mons and are available for view on the Atlas Hymenoptera webpage (Rasmont and Iserbyt, 2012). The data represent museum collection data, validated and verified citizen science data, and data systematically sampled as part of scientific research projects. Overall the data contains 28 252 records for 24 bumblebee species. Five species had less than 15 records and were excluded from the further modelling process to avoid modelling under-sampled species, resulting in 19 remaining bumblebee species.

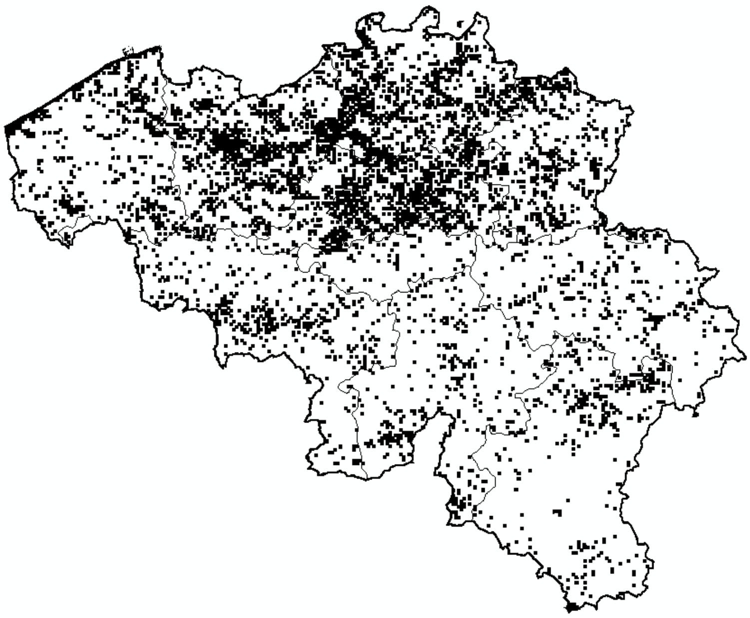


*Figure 6.2 – Locations where bumblebees have been sampled in Belgium between 2005 and 2017, used as training data in the SDM and for creating the background sample.*

### 6.2.3 Bumblebee distribution modelling

In order to model the distribution of Belgian bumblebees we first reduced the 26 LULC classes in the land use data to 21 land use variables (i.e. the predictor variables), since 5 classes (Industry, Commerce and services, Infrastructure, Mining and Harbour) were assumed to be too similar in land cover to be considered as different classes to train the models. These 21 remaining land use predictors were further reduced to 20, due to collinearity between the percentage of potatoes and percentage in grain crops (correlation < -0.7 or > 0.7 in Spearman correlation analysis). This is not entirely unexpected, since both crops have a similar spatial distribution (mostly concentrated in the central loam belt, see Figure 2.8). The 20 remaining land use variables were categorized into 6 aggregated classes to be used as the low thematic resolution input. They were classified according to Table 6.1 in arable, forest, grassland, other, permanent crops and urban. This resulted in two separate sets of predictor variables used for the modelling, high thematic resolution predictors and low thematic resolution predictors. These six classes were chosen so as to be comparable to the previous research comparing future climate and land use change models for bumblebees (Marshall et al., 2018).

*Table 6.1 – Overview of the land use classes used in the high-resolution model and their categorization in 6 aggregated classes.*

| Arable | Forest | Grass | Other | Permanent Crops | Urban |
|---|---|---|---|---|---|
| • Grain crops<br>• Unregistered agricultural land<br>• Rapeseed<br>• Sugar beet<br>• Potatoes* | • Mixed Forest<br>• Deciduous Forest<br>• Coniferous Forest | • Pasture<br>• Heathland<br>• Semi-natural grassland<br>• Wetland | • Water<br>• Dunes<br>• Military<br>• Greenhouses | • Fruit trees | • Residential<br>• Parks<br>• Recreation<br>• Sealed surfaces<br>• Industry**<br>• Commerce and services**<br>• Infrastructure**<br>• Mining**<br>• Harbour** |

** Potatoes was removed due to collinearity (correlation = -0.77).*

*** These classes were aggregated to Sealed surfaces due to high similarity in land cover properties.*

The bumblebee collection is spread over multiple years. To create a single presence map of the countrywide spread of the species for training the model, the presence of the species from 2005 to 2017 are combined. If a species is present at least once in the grid cell during the period, the species is considered present for the training dataset. For the training, this presence map is to be combined with a land use map. Apart from agriculture, percentage of land use of each class for every grid cell is considered to be constant, whereby the year 2010 is taken as the reference. For agriculture, being a class with yearly variation, the average of crop percentages for every cell from 2009 to 2015 was taken from the Integrated Administration and Control System (IACS) dataset, a dataset on agricultural land use and main crop data collected yearly by the EU (European Commission, 2018a). Based on the defined land use classes, the distribution of the 19 bumblebee species of the dataset was modelled using the Maximum Entropy (MAXENT) modelling software (version 3.4-1, see Chapter 3) (Phillips and Dudík, 2008). MAXENT is considered to be one of the best algorithms for working with presence-only data (Elith et al., 2011, 2006; Elith and Leathwick, 2009; Hirzel et al., 2002; Pearce and Boyce, 2006; Phillips et al., 2009). For both the low and high thematic resolution, MAXENT was run 50 times using an 80% training, 20% testing split of the data. These multiple runs allow to validate the runs, measure the uncertainty in the projection and to provide a more robust average of model performance and variable importance.

The model performance with both low and high thematic resolution land use change as input was assessed by looking at the area under the curve (AUC) of the receiver operating characteristic (ROC) curve. The AUC is a commonly used methodology to assess model performance. The value of the AUC, however, is strongly impacted by sampling size and species occurrence. Therefore, the comparison between models on different species is meaningless (Jiménez-Valverde and Lobo, 2007; van Proosdij et al., 2016). Since this evaluation parameter is based on a confusion matrix containing correctly predicted presences and absences (Fielding and Bell, 1997; see section 3.3.3), it requires absence data. True absences are however not available since it is not possible to be completely sure that a bee species is not present during sampling (Barbet-Massin et al., 2012; see Section 3.3.1). To account for this lack of absences, a random background sample (or pseudo-absence) is used (Phillips et al., 2009). This background sample is only taken from areas where other bumblebee species had previously been collected (Figure 6.2), referred to as a target background area (Mateo et al., 2010). This approach accounts for sampling bias by providing a more objective selection of grid cells that may be used to represent absence (Elith et al., 2011; Phillips et al., 2009) and has been shown to produce better performing models (Mateo et al., 2010).

To test the ability of our model to capture the niche requirements of a single species and therefore perform significantly better than random, the average AUC value of all model runs was compared to the expected AUC values of 100 randomizations of a null model (Raes and ter Steege, 2007; van Proosdij et al., 2016). The null model is the result of the SDM based on a randomization of observations within the target background area. Being based on randomised observations, the AUC of the null model will on average be lower than the AUC of the model on true observations, since it will be harder for the SDM to find patterns. A model is performing well if it has a mean AUC value higher than a one-sided 95% confidence interval of the null distribution. If our model performs better than the null-model in 95% of the cases, it indicates a statistically clear difference. This means the model indicates that the bumblebees had specific niche requirements that were captured by the predictors.

The result of the 50 MAXENT model runs for both low and high thematic resolution input, were then used in combination with the average of 100 runs for each of the three future land use change scenarios.

To assess the changes in distribution and to build the confusion matrix for the ROC analysis, binary presence/absence maps are made based on the habitat suitability maps for each species. These maps are created through the selection of a suitability threshold that would result in a maximum of 10% of occurrence records being left out (see Section 3.3.3).

### 6.2.4 Analysis

The variable importance of the different predictors is analysed. Variable importance is thereby defined as the percentage increase in range gain as predictors are being added to the model (Phillips et al., 2006). For each variable a general direction of the effect (i.e positive or negative) of each variable was also determined. If the correlation coefficient between a single predictor and the habitat suitability is greater than 0.5, the effect is positive, if lower then -0.5, the effect is negative.

The results for using the low and high thematic land use data are compared using five change metrics, namely: (1) changes in the distribution patterns analysed through the overall range change, (2) the total loss and (3) gain in range, (4) change in number of edges of suitable habitat and (5) the uncertainty of future model projections. Overall range change is defined as the percentage change in the total number of cells occupied. Loss and gain in range are measured as the total number of cells lost or gained between the present and future projections. These three range change metrics were calculated using the Biomod2 package in R (version 3.3.7; Thuiller et al., 2013). Fragmentation is defined as the edge density of the species distribution and is measured by taking the total number of edges (cells projected as presences that neighbour cells projected as absences) divided by the total area (Belgium). Fragmentation was calculated using the FragStats package in R (version 0.3.1; Hesselbarth et al., 2019). Uncertainty in modelling projections was simply measured as the per grid cell standard deviation in habitat suitability of all 50 projections for each scenario in 2035. To conclude, a widespread species (*B. lapidarius*) was compared to a more localized bumblebee species (*B. magnus*) in terms of variable importance and range change.

## 6.3 Results

### 6.3.1 Model performance

The average of the 50 models using high thematic resolution land use predictors were significantly better than random null models, the AUC value was higher than 95% CI of null distribution (Figure 6.3). In contrast, four species modelled with low thematic resolution land use predictors, had AUC values that were not better than random, (*B. hortorum, B. hypnorum, B. pratorum* and *B. sylvestris*). Additionally, for all species AUC values are clearly higher (0.1 on average) for the models using high thematic resolution land use predictors versus low thematic resolution.

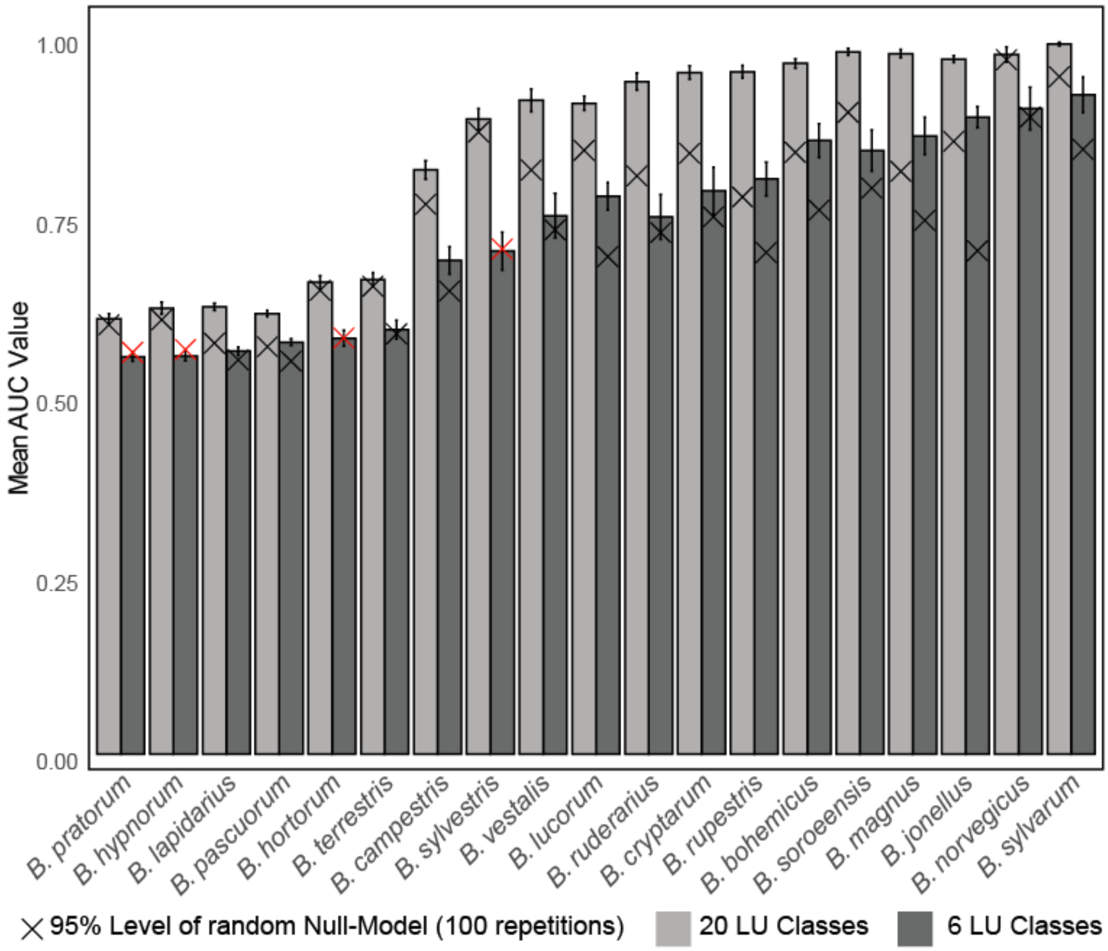



*Figure 6.3 – Mean area under the curve (AUC) of the receiver operating curve (ROC) value after 50 runs for 19 Belgian Bumblebee species when modelling with 20 and 6 land use classes. The X indicates the 95th percentile values of AUC from 100 random null models and is used to test model performance. The red X (n=4) indicates the models with mean AUC values lower than the 95th percentile and that therefore do not show a statistically clear difference.*

### 6.3.2 Variable importance

The mean variable importance (Figure 6.4a) and the number of species on which a variable has a positive or negative effect (Figure 6.4b) allow to compare the added value of using high thematic resolution input for each variable.

The Grass class has a low mean variable importance and the usage of high thematic resolution input has a limited impact on the mean variable importance, with all subclasses showing similar values. The class however, shows a high variability in the effect of subclasses. The subclass Pasture has a positive impact on a large number of species, while both heathland and wetland have a negative impact on a large number of species.

The Urban class has a very high mean variable importance with a strong negative effect. Using high thematic resolution input shows that the impact and effect are the result of the strong negative effect of the Residential class, while other subclasses (Sealed surfaces, Parks and Recreation areas) still have a positive effect on a certain number of species.

Results on the Other class demonstrate the importance of using the high thematic resolution input for this class as it contains an amalgam of subclasses (water, dunes, military and greenhouses) with high differences in effect: The Water class has both positive and negative effects, depending on the species, while Military, Dunes and Greenhouses have a negative effect on more species than a positive.

The impact of using high thematic resolution for the Forest and Permanent Crops class is limited. Forest subclasses show similar mean variable importance (Figure 6.4a) and effect, with a similar number of species for both positive and negative impact (Figure 6.4b).

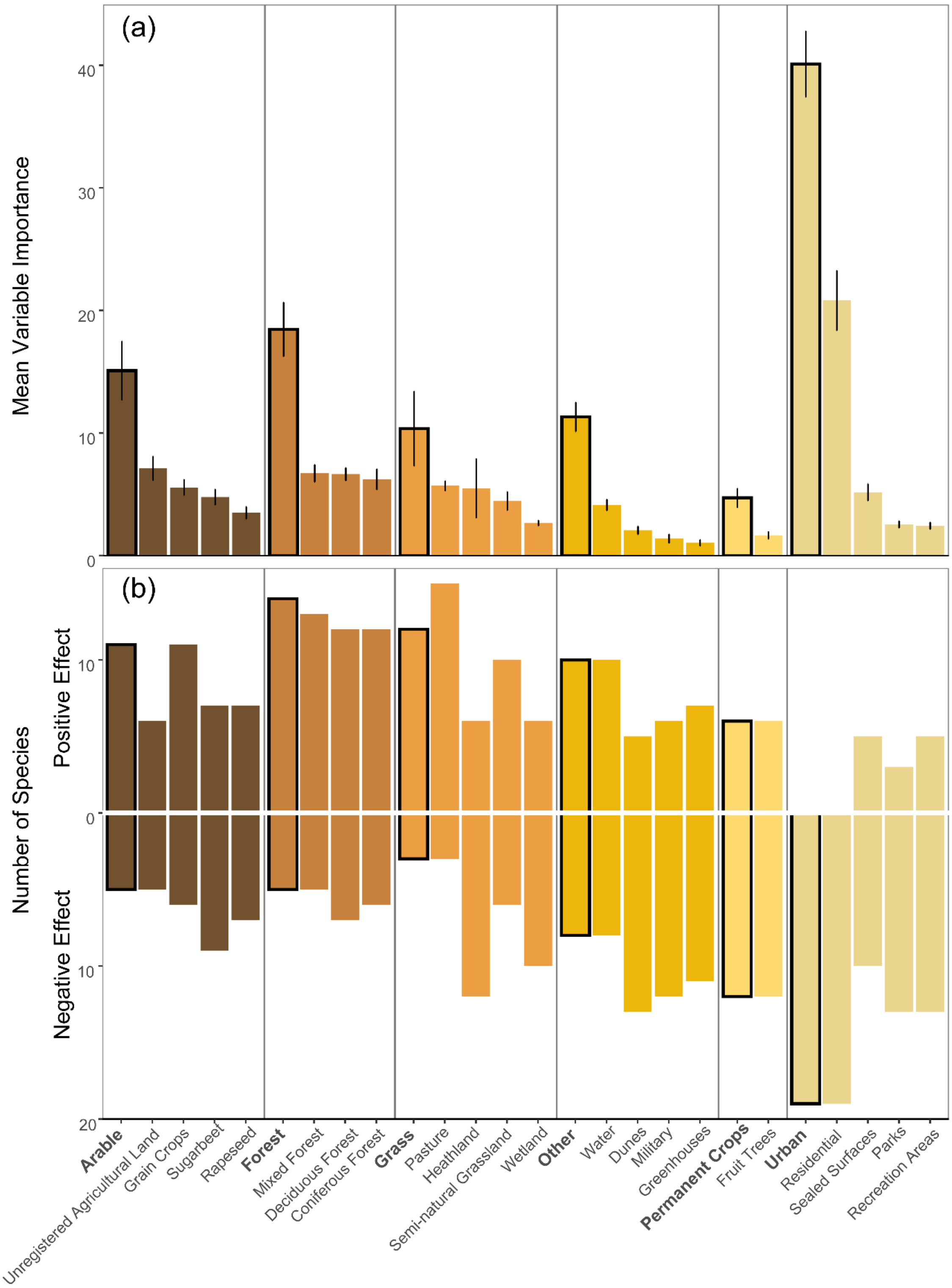



*Figure 6.4 – The mean variable importance and the effect of the different land use classes considered, both for the low (framed in black) and the high (framed in white) thematic resolution input.*

### 6.3.3 Projections

*Distribution Change*

All parameters on distribution change show a strong response to the thematic resolution of the SDMs, while the differences in distribution measures show less difference between the different scenarios. For all measures the differences between the high and low thematic resolution are less pronounced for more widespread species (e.g. *B. pascuorum, B. lapidarius, B. terrestris, B. pratorum, B. hypnorum, B. hortorum, B. lucorum*) (Figure 6.5). The classification of species on being widespread or more localized was based on the current predicted range size (see Appendix 8).

Considering the overall range change, on average, species were predicted to lose 20% more range when using low thematic resolution predictors rather than high (Figure 6.5a). This difference decreases for more widespread species.

The overall pattern shows that modelling with low thematic resolution will result in a larger range loss for species, meaning the total number of cells occupied decreases. The percentage of grid cells lost and gained (Figure 6.5b) shows a more nuanced reality. In total, there is a greater turnover in the number of cells occupied by species on average for the high thematic resolution results. In other words, there is both a greater number of cells projected to be lost and gained when modelling using high thematic resolution. Figure 6.5 also clearly shows that low thematic resolution projects very little or no range gain for almost all species (only *B. jonellus* has a significant range gain). Again, we see that more widespread species will on average lose less grid cells. Fragmentation, in the form of edge density, both with high and low thematic resolution SDMs, increases on average for the species. For most species, there is a large difference between low and high thematic resolution modelling, with sometimes even contrasting results (*B. sylvarum, B. ruderarius, B. soroeensis, B. campestris, B. bohemicus, B. vestalis, B. lucorum*). Considering the more widespread species, edge densities are overall lower, and the results for high and low thematic modelling are more similar.

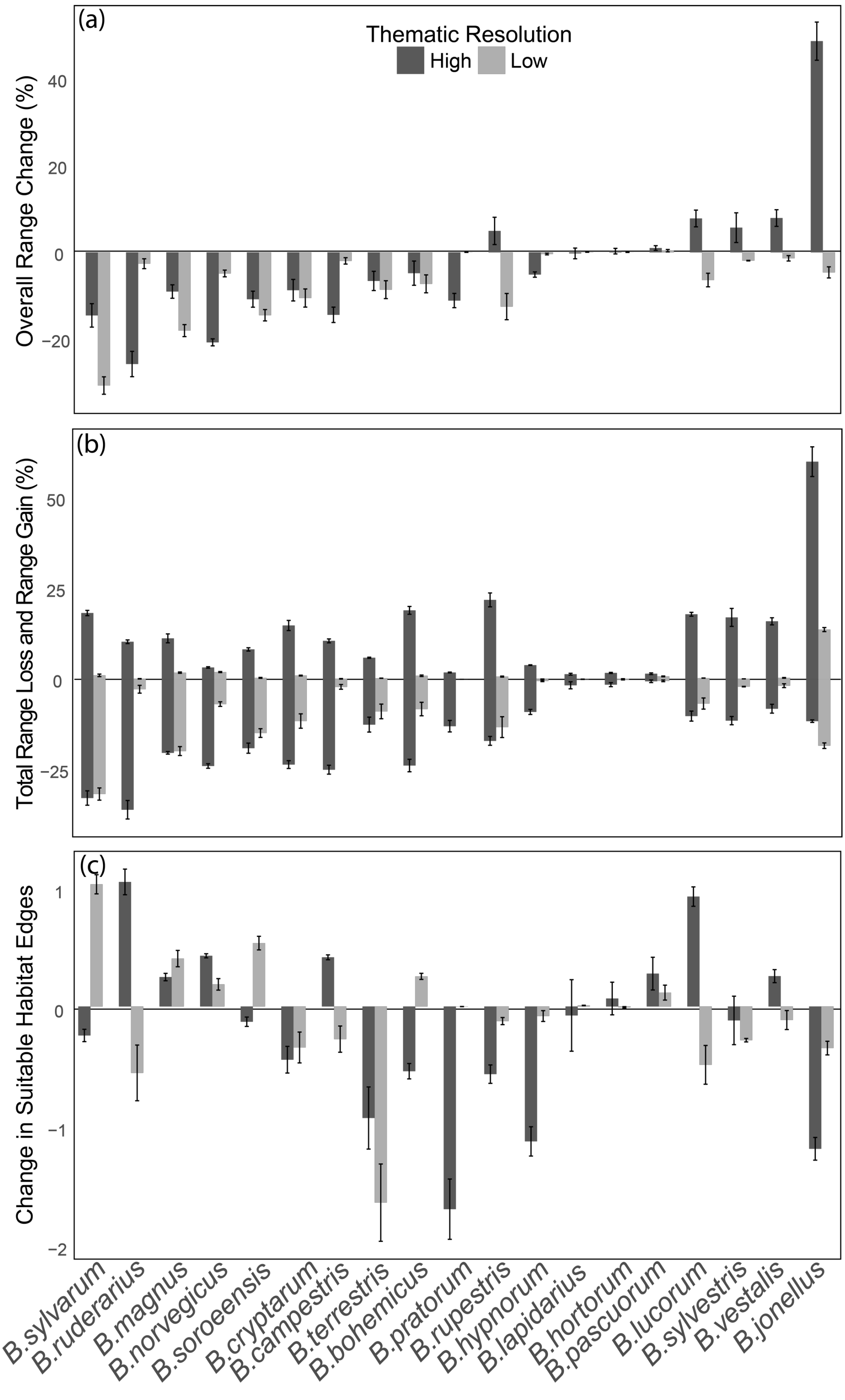



*Figure 6.5 – The change in distribution parameters for the different bumblebee species, for both high and low thematic resolution with the differences between the scenarios indicated through a plot of the standard deviation.*

*Uncertainty*

The uncertainty in the future projections shows that the average standard deviation per cell of projections in the future is greater for high thematic resolution (0.11) than low (0.09). These differences show a statistically clear effect (W = 2173, p-value = 0.002, 95% CI: 0.008, 0.041).

*Focus on two contrasting species*

To look into detail on the effect of using high versus low thematic resolution in SDMs, two species, one widespread and one localised, that showed contrasting results were further examined: *B. magnus*, a very localized species, and *B. lapidarius,* a more widespread species.

For *B. magnus* SDM results with low thematic resolution show the importance of the combination of grassland and forest. For model runs with high thematic resolution the variables heathland and coniferous forest are the most important (Figure 6.6 e). Since the combination of heathland and coniferous forest is limited in Belgium in comparison to the combination of grassland and forest, the current and future expected distribution of the species is much lower for model runs with high thematic resolution (Figure 6.6 a-c) as compared to runs with low thematic resolution (Figure 6.6 b-d).

For *B. lapidarius* the results of the SDM with low thematic resolution show a high and positive importance of the Arable class. For the high thematic resolution results, the Sugar beet class shows the highest importance within the Arable classes (Figure 6.7e). Noteworthy is also the Forest class, that has a slight negative impact on species occurrence in the model with low thematic resolution. Results from the model with high thematic resolution show the negative effect is limited to the Coniferous and Mixed Forest class, whereas the Deciduous Forest class shows a positive effect. With *B. lapidarius* being a widespread species, differences in the mapped results are limited. This can also be observed in the overall range change and the total range loss and gain for this species (Figure 6.5 b-c).

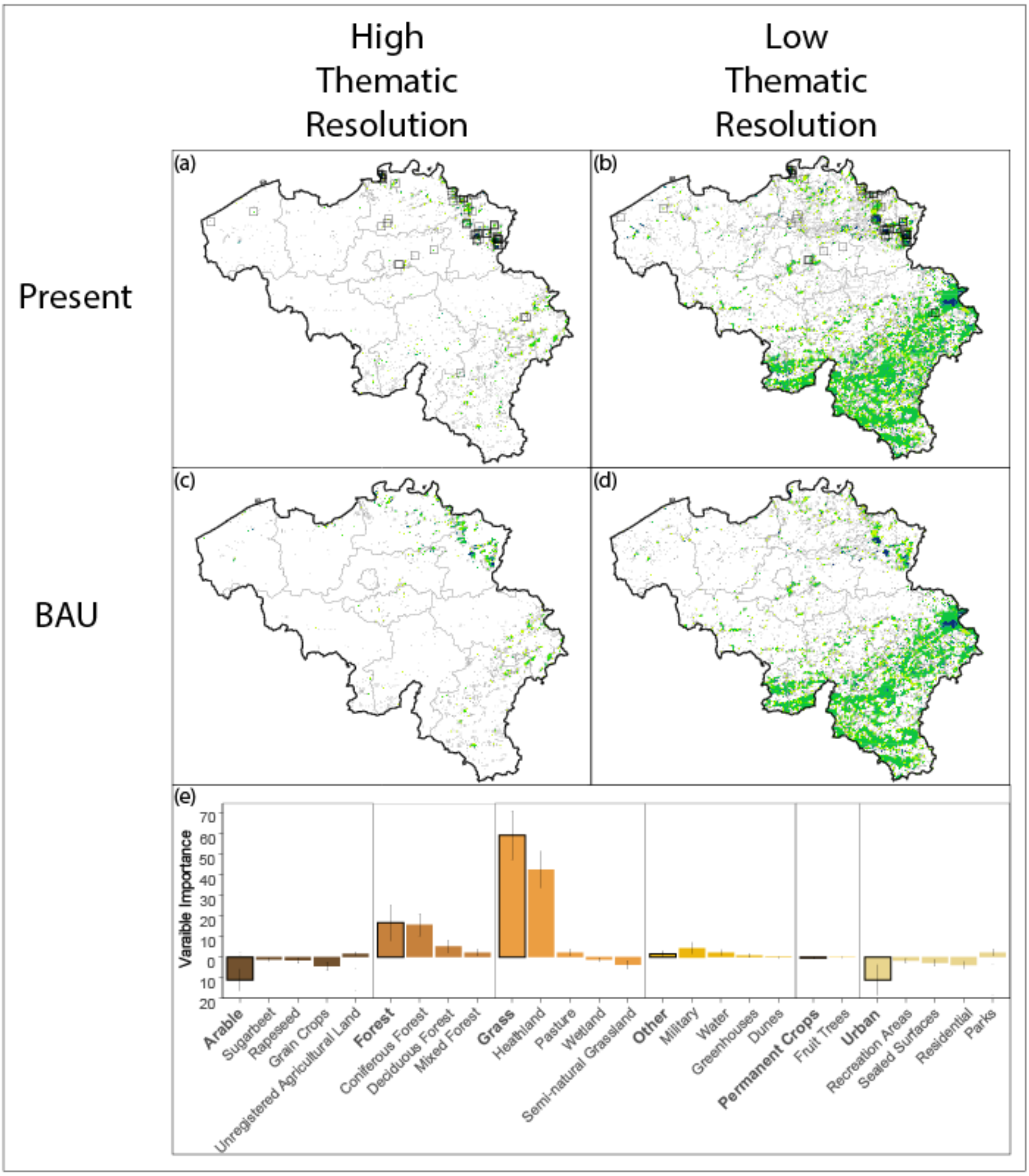



*Figure 6.6 – The modelled distribution of B. magnus for both high and low thematic resolution and in the present and for the BAU scenario in 2035, together with the importance of each land use variable to explain the distribution of the species. The inset in figure b shows where the species was collected.*

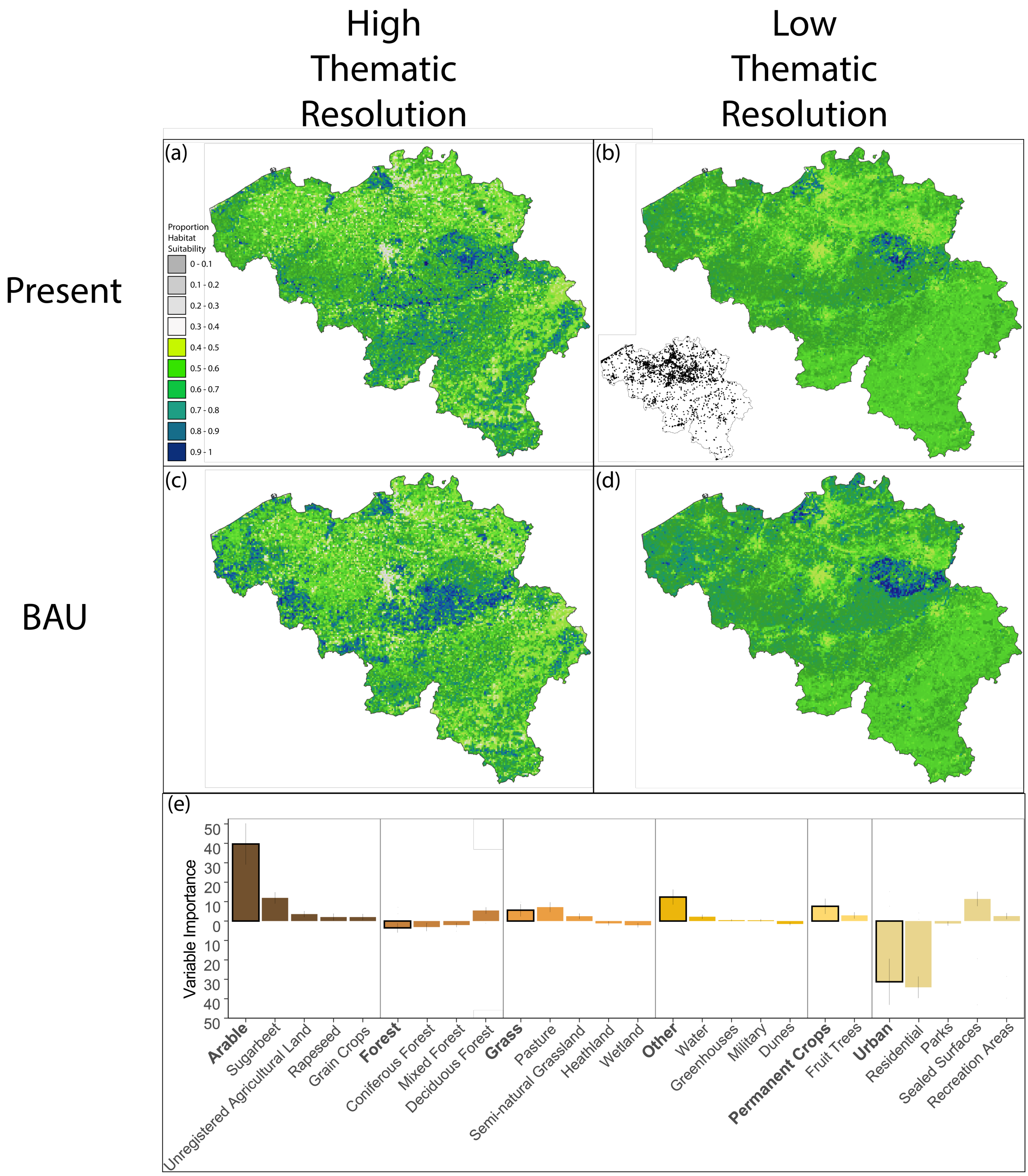



*Figure 6.7 – The modelled distribution of B. lapidarius for both high and low thematic resolution and in the present and for the BAU scenario in 2035, together with (e) the importance of each land use variable to explain the distribution of the species. The inset in figure b shows where the species was collected.*

## 6.4 Discussion and conclusion

Models with high thematic resolution predictors consistently performed better than randomised null models compared to models with low thematic resolution predictors. They also showed a more detailed relationship with the land use predictors which resulted in considerable variation in projected distribution patterns compared to low thematic resolution models. This suggests that the usage of high thematic resolution land use data as an input for SDMs has an added value allowing to better capture species trends, which confirms the hypotheses of this study and of Martin et al. (2013)

The added value of using high thematic resolution land use varies between land use classes. In contrast to expectations, the highest added value of increasing thematic resolution is not related to the agricultural land use classes but rather for the classes Grass, Urban and Other.

The land use class Other contains Military, Dunes, Greenhouses and Water, i.e. classes with little similarities and as such also very different habitats. The improvements when further detailing this land use class are therefore an expectable and logical result. At the same time, some of these classes, like Water, are relatively easy to model in future projections given their stable nature. While other classes, e.g. Military, might be a very hard class to model in future projections and sometimes also harder to sample.

Splitting up the land use class Grass in the subclasses pasture, semi-natural grassland, heathland and wetland adds value to the SDM of bumblebees. For example, heathland has a relatively small distribution in Belgium, has a comparatively high importance, and is shown to be quite a restrictive land cover for many bumblebee species. Heathland is likely to be limiting to those bumblebee species not adapted to the specialized feeding resources present in these habitats (Moquet et al., 2017). The difference in habitat conditions are less pronounced in comparison to the Other class, but are nonetheless important in relation to habitat requirements of certain bumblebee species.

For the Urban class, results show how the Residential sub class is on average very important and also determines to a large extent the effect of the Urban class. This is however more related to a lack of sampling within this land use category (causing a complete absence of bumblebees in this land category) than to reality. This not only shows the importance of the sampling method, but also underlines the importance of using higher thematic resolutions. Using a higher thematic resolution of land use, separating the Residential class from other Urban land use classes, results in the model being able to capture the positive effect of other urban classes such as Parks and Recreational Areas.

The added value of splitting up the Arable class appears to be limited in these results. The high ecological value of Unregistered Agricultural Land results in this class being the most important subclass. It has been shown previously that mass flowering crops such as rapeseed can have a positive influence on the number of bumblebee species (Westphal et al., 2003). We observed that the percentage cover of rapeseed is positively influencing the distribution of six species and negatively influencing six species.

Splitting up the Forest class in Coniferous, Deciduous and Mixed had a limited added value with all classes showing similar importance and similar effect.

The use of high thematic resolution input proved to be especially interesting when modelling less widespread, or localized species, that have specific preferences and niche habitats, in contrast to more widespread species with little specific habitat needs. The benefit was illustrated by comparing the localized species *B. magnus* with the widespread *B. lapidarius*.

The results show that uncertainty increases when using land use maps with high thematic resolution as input, as compared to maps with low thematic resolution. This could be expected, as with increased numbers of predictors the complexity of the landscape is likely to result in more complex model fit and therefore greater ambiguity.

All together we could say that using high thematic resolution land use data as an input in SDMs has an added value, but that it is not equally useful for all land use classes and depends on the species that is modelled. This comes down to how well the species’ habitat requirements are being represented, which is strongly related to whether a localized or widespread species is being modelled. For some species, other indicators may also be more important than the specific land use type, like for example, the management practices on the land. This can be especially relevant for the Arable class, where the added value of using data with a higher thematic resolution was limited. For this class, the added value of a higher thematic resolution in relation to management practices instead of crop types might still lead to significant improvement for capturing species trends. Specifically for bumblebees, their presence has been positively related to the presence of naturally regenerated field margins (Kells et al., 2001) or organic crops (Holzschuh et al., 2008).

As shown with the distribution maps of two specific species (Figure 6.6 & Figure 6.7) the difference between two modelled distributions can be substantial, especially for *B.magnu*s this difference clearly shows. Using only low thematic resolution LUC predictors for SDMs could lead to overpredictions and maybe even show contrasting trends. This might lead to wrong decisions being made in relation to conservation measures (Araújo et al., 2019).

These results should however be treated with caution. As discussed earlier (Chapter 4 & 5), the land use modelling has its limitations and so does the SDM. Many methods for SDMs exist, and changing the model or model parameters might affect results (Aguirre-Gutiérrez et al., 2013). There are also limitations related specifically to the methodology used in this research. Since the main aim of this research is to look at the importance of high thematic resolution land use maps in SDMs, the impact of climate, although known to be an important parameter in SDMs (Rasmont et al., 2015), was not included. Araújo et al. (2019) specifically stresses the importance of considering relevant environmental and biotic variables. This means the resulting projections are not representative of future ranges but do specifically indicate the impact of increased thematic resolution. Another specific limitation results from the methodology of the calibration process. Bumblebee data were collected over a period of a few years and are, in the calibration process, linked to one observation year for land use, and a five-year average for agricultural land use, inconsistencies may arise due to land use change happening during that period. By working with percentages on the 1 km grid cell, the inconsistencies should remain limited. The aggregation to a 1 km grid however, might also impact the results. A shift of the grid or a change in resolution would result in different land use percentages in the grid cell (being derived from land use at the 1 ha resolution) and might also affect the cell to which certain bumblebee observations are appointed. This problem is known as the modifiable areal unit problem (MAUP), which has been proven to possibly induce a statistical bias and can significantly impact the result of statistical tests (Holt et al., 1996; Unwin, 1996; Wong, 2009). Given these limitations, it is important that the results should not be considered as predictions of future bumblebee distributions, but as an explorative study on the added value of high thematic resolution land use data in SDMs.

While the importance of including land use and land use change data in species distribution models has already been identified (Aguirre-Gutiérrez et al., 2017; Marshall et al., 2018), this study further highlights the importance of including high thematic resolution data and high thematic resolution land use change models, showing the added value of models like ADAM, outside their own research context and highlighting the importance of further research in this field. Evaluating for which thematic classes the input of high resolution might be interesting, is an important exercise, given that the relevance is not the same for all classes. The use of climate data was absent in this research. To accurately model the impacts of high-resolution land use change alongside climate and climate change we would need collection records from the whole range of the species with correspondingly high-resolution land use change data, which is currently unavailable. As more detailed land use change models begin to be produced at larger scales, research including climate change might result in projections applicable to and useful in policy making processes. Given the results obtained from using land use change data with a high thematic resolution, it might be interesting to see if similar results might be obtained when using high spatial resolution data in the context of climate change.

# Chapter 7 Discussion and conclusion

## 7.1 Overview

The agricultural sector is worldwide characterized by a rapid transition which brings along many challenges (both social, environmental and economic, see Chapter 2). These challenges are complex, given the many interactions between the socio-economic, the biophysical and the political environment that are inherent to agriculture. For policy makers and rural planner, it is important to be able to get an insight on the possible outcomes of different policy scenarios and possible interventions in order to support the decision-making process. Due to the complexity of the processes involved, many models have showed scenario results that are either very detailed, focussing on smaller regions, or too generalised when focussing on large regions (such as the national scale level). The outcome of both model types offers limited support in a policy development context. The aim of this research was to create a real-world, large scale agent-based model that would be useful for scenario analysis in agriculture. Current trends in the agricultural dynamics in Western-Europe were chosen as a use-case, given the many problems the sector is currently facing. Belgium was taken as a study area, given its central location within Europe, its long agricultural history and high levels of urbanisation, resulting in a strong competition for land.

The starting point was an analysis of the current situation of agriculture in Belgium in a global context. In many ways, the agricultural sector in Belgium faces large challenges, similar to those in other countries in the EU, where competition both locally and globally have led to reduced margins, a low succession rate and thus an old and diminishing agricultural population. This, together with the competition for land and the many environmental challenges that farmers are facing, results in an agricultural sector in crisis, in Belgium, as well as in many other countries.

The methodological chapter provides more insight in the concept of agent-based modelling (ABM), its history, current challenges and best-practices for implementation. Since all agents are modelled individually in a starting point population together with the relevant factors that influence the decision-making process, ABM often requires large data inputs. The result is that it is hard to apply agent-based models (ABMs) to large scale real-world situations. Other reviewed challenges were related to the inherent multidisciplinarity of ABMs and the iterative process that takes place during its development, which might lead to the inclusion of an increasing amount of detail.

Keeping the relevant factors for decision-making processes in mind, ADAM (Agricultural Dynamics through Agent-based Modelling) was created to simulate the evolution of a farmer population at country scale. To allow ADAM to work for large scale real-world simulations, the focus was on creating a simple model simulating the key processes by including basic decision-making with an initialization based on a limited dataset. ADAM proved to be capable of simulating an agricultural system, with farms evolving over time in complex settings. The results of ADAM were less satisfactory in more densely populated communities due to the importance of urban expansion processes in these municipalities. Urban expansion impacts agriculture both directly, by reducing the available land, but also indirectly through land speculation (Delbecq and Florax, 2010) and the use of agricultural land for non-commercial agrarian activities (e.g. hobby farming, horse riding (Bomans et al., 2011)) in the urban fringe.

To include urban expansion in ADAM, the results from a constrained cellular automata (CCA) land use change model, (Engelen et al., 2011) adapted to the case study area of Belgium, were used. Two storylines (Global Economy (GE) and Regional Communities (RC)) were used, together with a business-as-usual (BAU) storyline to simulate the impact of policy changes on urban expansion and farming. This modelling approach was able to simulate the continuous decrease of the number of farms and its spatial pattern for the period 2013 until 2035. A comparison of the model output of the original results of ADAM (Fig 4.10) and the new results, including urban expansion, (Fig 5.10) showed the impact of urban expansion on Belgian farming practices with a clear spatial pattern: In urbanised regions of the Flemish Diamond in the central north of the country and the Liège area in the east, there is a significant loss of agricultural land. The comparison of the results of the GE and RC storylines showed a lower loss of agricultural land (5% versus 3% loss) and farmers (15 448 versus 16 050 farmers remaining).

However, compared to the total decline of the farmer population the differences imposed by the different regional economic development scenarios were small. This implies that the demographic process (the rapid aging of the farmer population and the low succession rates for farms) are more important factors than the economic parameters defined through the scenarios.

In order to evaluate the potential of ADAM in other research fields, for example in the assessment of changing ecosystem services, the results on land use change in the different scenarios, were used as an input for species distribution models on bumblebees. The results showed that using high thematic resolution land use data allows to better capture the species' trends. For the case of bumblebee species in this research, the highest added value was found in land use classes other than the Arable class. The mass flowering crop rapeseed, a crop gaining importance and important for bumblebees (Westphal et al., 2003), did have a positive influence on the distribution of certain species and a negative influence on other species.

## 7.2 Revisiting the research questions

**RQ1: To what extend can agent-based models simulate farmers decision at country scale?**

This research question was mainly tackled in Chapter 4, showing that it is indeed possible to apply an agent-based model at a high spatial resolution at the national scale for the case study of agricultural dynamics in Belgium through the development of ADAM, when accepting certain generalizations (limited to 5 farming types and ignoring the reality of mixed farming) and assumptions (new farmers can only enter the system through the take-over of another farm, a new cultivator can always be found for available agricultural land and farmers continue farming at least until retirement age). ADAM allows to model the individual decision-making process of farmers at the smallest spatial unit (i.e. the parcel level) relevant for farming at a national scale using data sets required for EU-reporting. This allows to model at a scale, relevant for policy makers, using data available in EU-countries, avoiding the need to gather extra data in the field. Although the framework is made based on the data that is required for EU-reporting, application in other countries will depend on local data availability, since requirements are not always met. Also, the assumptions and parameters being used in the current set-up for Belgium (e.g. the succession and retirement rate), are region-specific and might require recalibration and re-evaluation when modelling in other countries.

**RQ2: What is the possible impact of different scenarios on farming practices?**

In Chapter 5, the combination of ADAM with a CCA on land use change was used to run different scenarios on possible futures for the agricultural landscape in Belgium. The results generated more insight in the expected patterns of future urban expansion in Belgium and its expected impact on the agricultural landscape, both in terms of farm size as in the farmer population with clear differences between urbanised and more rural regions and between different agricultural regions. The differences between the outcome of the different scenarios were however relatively small. This led to the conclusion that economic and urban expansion scenarios are surpassed in importance by the underlying demographic processes resulting from an old farmer population with a low succession rate. This research has shown the importance of including the demographic component in agricultural ABMs, while it often has been neglected in the past. ADAM is however more than a simple demographic model given that it is spatially defined up to the finest relevant scale and that the characteristics of the spatial configuration of the environment (e.g. urbanisation pressure, current farm size and farm type configuration as a result of historic processes, specific crop yield as a result of the physical environment) have an impact on the results.

**RQ3: What is the added value of high thematic resolution models in relation to other research fields like ecological modelling?**

Highly detailed agricultural ABMs like ADAM require a high investment in developing and execution time and need a large amount of input data but showed their usefulness in other research areas, as seen in this dissertation with the distribution modelling of bumblebees. The results in Chapter 6 showed that there is indeed an added value of highly detailed land use data as an input for species distribution modelling, but also that it highly depends on the species being modelled. For bumblebees, the added value was much higher for localized species as compared to more widespread species. The added value of high thematic resolution models will thus mostly depend on the specific case. A pre-evaluation is therefore recommended before investing time in the extra effort coming from obtaining and including highly detailed data as input in other models.

## 7.3 Overall discussion

This dissertation proposed ADAM, an agent-based model for agricultural dynamics, modelling farmers at the parcel and farm level, which was applied to the country of Belgium. ADAM is a useful tool for doing research experiments to help define and understand the key processes in agricultural dynamics and study the possible futures by using different storylines and scenarios and showed its added value as input for other models.

Apart from showing the spatial patterns of change that can be expected in the future, Chapter 5 showed that the effect of the different storylines was surpassed by the effect of the current state of the agricultural population (i.e. relatively old with a low succession rate). These characteristics of the farmer population are not limited to Belgium, but are present in most of the European Union (Eurostat, 2018).

In all scenarios the highest losses were also found in the most urbanised regions of the country. The losses were however the lowest in the storyline with low urban expansion rates and where small farms receive extra financial support. This shows the impact urban expansion processes have on their surroundings and on other sectors, like agriculture, that are not directly related to it. The results also show the possible impacts of subsidies (or other financial incentives, like present in the EU-CAP) for small farms in the urban fringe, especially on the short term. In the long term, the reorientation of traditional farming practices towards alternative ways of farming that provide a competitive advantage (like organic farming, rebranding, short supply chains or self-harvest farms) could increase the income of these farmers (Crowder and Reganold, 2015; Pearson et al., 2011) and reduce the required amount of subsidies.

Given the results ADAM can thus be seen as a useful model for the specific goal it was designed for, being the testing of the possibilities of country scale ABM at a fine spatial resolution, allowing the combination with external inputs (e.g. urbanisation scenarios) and other models (e.g. species distribution models). As with many other agricultural ABMs there is always room for the improvement of the decision-making processes. Highly sophisticated models often mostly focus on a specific aspect in order to explain certain trends or explore possible future scenarios, and do not include of full parameterization of the decision-making process (Huber et al., 2018). Increasing the complexity of the representation or the decision-making processes of farmers in agricultural ABMs are not always necessary or meaningful (Sun et al., 2016) therefore, improvements and further detailing are only to be done when the specific aim of the research question requires it. This was also shown through the results in Chapter 6 for the coupling with the bumblebee species distribution model, where the added value of increasing the thematic resolution was highly depended on the specific use case (in this case the specific bumblebee species that was being modelled).

Possible improvements in the model that might be useful are:

- An improved financial and economic module or the combination of ADAM with an external micro-finance model (for example as done by Happe et al. (2009)) when wanting to have more insight in the results of changing market processes and farm accounting. This could allow for a better calculation of income and profit, or other survival strategies at the farm level (e.g. agro-tourism, product upgrading, short chain initiatives, specific acquisitioning strategies…). Adding this could be especially interesting when more insight is wanted in the possible impacts from changes in the EU-CAP.
- Increasing the variety in agents to gain insights on changes in land management (pesticides, fallowing, fertilisation). Currently, the model does not include differences in land management within the same farm type category. An example could be the subdividing of agent types in conventional or green farmer types, or the inclusion of personal preferences (for example as proposed by Murray-Rust et al. (2014)). This would allow changing the process on crop decision making and the amount or type of pesticides and fertilisation leading to a diversification in land management practices.
- Starting the model from the real initial agricultural landscape to further improve the accuracy of the current model. The starting point in the current model was downscaled from aggregated data, which made the starting point of the model simulations in this study realistic but not reality. At the same time, better data would also to improve the calibration and validation process through less uncertainties and more variables that can be validated.
- To get a more detailed insight in the processes that result in the loss of agricultural land, a further refinement of the land abandonment process would be recommended. Farmland abandonment both in remote areas as well as in the urban fringe (e.g. through horsification) is present throughout most of the EU and expected to continue (Hatna and Bakker, 2011; Renwick et al., 2013; Verburg et al., 2010).

## 7.4 Recommendations for future research

### 7.4.1 Recommendations for science

The coupling of ADAM with scenarios on urban expansion, and its combination with a species distribution model on bumblebees, showed ABM at the country scale has an added value. This research also showed that the added value differs between use cases. Further development of high-resolution models that allow to gain insight in the possible future developments of a population or of its impact on the environment is therefore recommended when an initial assessment of the objectives justifies the extra investment in data and time.

In future research ADAM could be tested for regions or countries which experience similar trends and difficulties and with similar data, like other countries in the EU. Also, in areas that differ more from the current case study area, using ADAM might be interesting.

It would also be interesting to link ADAM to other existing models, as was done with the species distribution modelling on bumblebees. It could be used as input for other species distribution models or in combination with other models on micro-economy and finance, climate change, vegetation dynamics, erosion etc.

### 7.4.2 Recommendations for policy makers

The presented research clearly shows the importance of the availability of consistent, extensive and elaborate data on a nationwide scale. This research is subject to an almost yearly reduction of available data, with less variables being registered and less farmers surveyed in order to reduce the administrative burden on farmers. This is understandable, given the high administrative load farmers are already facing, but it also leads to an important loss of information, which makes it harder for policy makers to have a good insight, or follow-up on taken measures. In addition, progressively less data is being published, due to privacy issues: when the number of farmers in a category (municipality, farmer type etc) is lower than five, the data is no longer published. Given the current trend of a decreasing number of farmers, this might result in an almost inexistent dataset in the future. Making further academic research and analysis on this topic more and more difficult. On top of this decreasing data availability, definitions of categories and variables change. The decreasing data availability together with the changing categories and variables, makes trend analysis, model set-up, calibration and validation very difficult. Given the requirement of a high amount of consistent data for this type of research and models, it is in the best interest for research, as well as for policy makers to continue to collect and provide these data. Providing high quality data, while preserving privacy, is however not an easy task, especially in this specific case, with a strong decline in the surveyed population. However, data collection in a continuous, consistent way is beneficial to both researchers and policy makers in order to follow up on trends and look at the impact of certain policies. The most important factors are thereby the consistency in the data at a relevant spatial resolution to allow time series analysis and the validation of model set-ups. Thereby, for this type of research, the frequency of the data is less important than the consistency of the data definitions and the availability of a full dataset on farm numbers, farm size and farm type, age categories and the statistics on succession. To further reduce the administrative burden, the recurrence of some questions in the survey could be reduced to updates every 5 years: The use of a good, complete and consistent dataset at the initialisation of the model, would allow to fill in the data in the years between. This is especially the case for the demographic data and the farm characteristics. For the agricultural land use, a yearly reporting will continue to be necessary, because of the uncertainties in the model on this part and because it remains a requirement by the EU.

For the case study of agriculture, the research showed a further decline in the number of farmers and increase in average farm size in all tested scenarios as a result of the current demographic situation of the farmer population, being an aging population with a low to extremely low succession rate. This can be seen as a logical and necessary trend of farm consolidation that has been going on for years, but it also implies personal dramas for non-competitive farmers with poverty, social exclusion and bankruptcy (Meert et al., 2005, 2002; Van Hecke, 2001) and has a negative impact on biodiversity and ecosystem services (Bäckman and Tiainen, 2002; Bianchi et al., 2006; Evans, 1996; Marshall and Moonen, 2002; Ouyang et al., 2010; Pätzold et al., 2007; Robinson and Sutherland, 2002; Stoate et al., 2009; Withers et al., 2014). This finding might be tackled by policy makers through two types of measures, namely measures that allow to alter this trend and measures that mitigate the effect. These measures are thereby not necessarily mutually exclusive. The changing of this trend will only be possible with a dramatic increase in the succession rate or the rate of new starters. A survey in 2015 requested by the EU showed that the most important needs for young farmers in Belgium, as well as in the rest of the EU, are: access to land (both to buy or to rent), access to loans for example and aid through subsidies (Zondag et al., 2015). Measures that focus on these needs, could make farming more attractive for young farmers by reducing some of the uncertainties inherent to farming. For the mitigation of the effects of these trends policy makers could focus on providing solutions for farmers that would like to stop farming in order to avoid social dramas. An example of support policy makers could provide could start with the services the non-profit organisation *Boeren op een Kruispunt* provides for both personal problems as farm related problems (individual support, psychological help, financial advice, etc). At the same time, the effects on nature, biodiversity and ecosystem services of consolidation processes should be mitigated (for example through stimuli for good agricultural practices). The latest EU-CAP revisions on greening measures and supporting young farmers (European Commission, 2019, 2013), are in that way a good start, and show the awareness among policy makers of the current challenges in agriculture.

## 7.5 Concluding remarks

For decades, researchers from different fields have presented agriculture as a system, as being the result of a combination of processes, being political, socio-economic or environmental in their nature. Research approaching agricultural systems from a systematic approach, are mainly descriptive in nature. This research has tried to translate the present knowledge on the agricultural system, to a practical agent-based model, surpassing previous small-scale attempts. In a way, this research opens up the research world to the use of large-scale systemic models, while using the individual agent as the starting point. This thesis should be considered as a first contribution to the research on highly detailed, large scale systemic models, opening up new perspectives for future research.

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# Appendix

*Appendix 1- Non-exhaustive overview of agricultural simulation models in literature.*

| MODEL NAME | REFERENCE | INSTITUTE | TEMPORAL RESOLUTION | SPATIAL RESOLUTION | EXTENT | MECHANISM |
|---|---|---|---|---|---|---|
| CLUE | (Veldkamp and Fresco, 1996) | Wageningen University, Netherlands | yearly time step | 7 to 32km grid | National - continental level with finer allocation | Empirical model simulating multiple land-use types simultaneously. |
| CLUE-s | (Verburg et al., 2002) | Wageningen University, Netherlands | yearly time step | 1m grid | Combination of national to continental with local to regional extent | Empirical model simulating multiple land-use types simultaneously. |
| DYNA CLUE | (Verburg and Overmars, 2009) | Wageningen University, Netherlands | yearly time step | 1 km grid | Multi-scale applied to the European Union | Empirical model combining top- down allocation of land use change with a bottom-up determination of conversions. |
| FORE-SCE | (Sohl and Sayler, 2008) | US Geological Survey, EROS Centre | yearly time step | 250m grid | Sub regions in the Western Great Plains (USA) | Combining theoretical, statistical, and deterministic modelling techniques to project future land cover change. |
| DINAMICA | (Soares-Filho et al., 2002) | Federal University of Minas Gerais, Brazil & Intelligenesis do Brazil | yearly time step | 100m grid | Small sub-regions in the Amazon basin in Southern Brazil | Stochastic cellular automata model to simulate spatial patterns. |
| (no name) | (Thornton and Jones, 1998) | International Livestock Research Institute, Kenya & International Centre for Tropical Agriculture, Colombia | yearly time step | Plots of land | Hypothetical landscape with 300 parcels and 106 households | Conceptual model |
| LandSHIFT | (Schaldach et al., 2011) | University of Kassel, Germany | 5-year time step | 5 arc-minute grid | Continental to global extent | Empirical model for land use change dynamics based on country-lever inputs |
| GTAP + IMAGE | (Van Meijl et al., 2006) | Wageningen University and Research Centre & Planbureau voor leefomgeving, Netherlands | 10-year time steps | Countries | National to continental level | Non-spatially explicit combination of an economic and biophysical model |

*Appendix 2 - ADAM ODD protocol*

| Overview | |
|---|---|
| Purpose | The spatial simulation of the number of farmers and the size of farms in a real-world setting allowing the testing of different scenarios influencing the profitability of the farm. |
| State variables and scales | The main entity in the model is the farmer. Farmers can be of different types: animal farmer (land based or non-land based), greenhouse farmer, permanent crop farmer or rotational crop farmer. All farmers have an age, use a certain number of agricultural parcels that together form its farm, and belong to a certain municipality (the municipality where their "main" parcel or home is). The spatial unit of the model is the parcel, parcels have a certain size, belong to a farmer and to a municipality and have neighbours. The model is capable of running for larger extends (e.g. regions or countries) and each time step, represents a year. |
| Process overview and scheduling | Every time step (year), farmers die, retire of decide to continue farming. If the farmer dies or retires, a chance for succession is determined based on the location of the farm and its profitability for land-based farming types (crop farming and herbivore farming) or a general succession change for non-land-based farming types (greenhouses and granivore farming). The profitability of the farm is defined by a function which related the revenue of the farm to the total area of the farm. If the farm has no successor, for each of the parcels defining the farm a new farmer is searched in the vicinity of the parcel. If the new farmer is of a different type, the parcel is converted leading to agricultural land use change. |
| Design concepts | |
| Design concepts | Due to stochasticity in different steps of the model, the results will be different after every model run, with changes in the number of farmers and the farm size. The remaining number of farmers and their farm structure are, as such, the main results to obtain from the output. The decision of a farmer to retire and for a new farmer to take over a farm, are strongly depending on the profitability of the farm. Changes in the parameters determining the profitability (e.g. subsidies), will impact the decisions made by the farms. These can be used for future scenario testing. The interaction of farmers is limited to the exchange of parcels when a farmer quits, and the availability of information on expected yield for crops in the region, helping them in the decision-making process on next year's crop. |
| Details | |
| Initialization | Initialization is based on the provided input data from surveys to create a starting situation close to reality for the starting year. The initial farmer population is created based on the number of farmers per spatial entity (e.g. municipality) and further information on farmers' age distribution, farm types and initial agricultural land use of the parcels. This step is not necessary if information about the user of each agricultural parcel is available. |
| Input data | The model requires information on the number of farmers of each modelled type in each entity (e.g. municipality), the age distribution of the famers and the mortality rate at each age. Secondly, it requires the input of a dataset of agricultural parcels and their current agricultural land use, with derived information on location, size and neighbouring parcels and possible changes to the parcel on a yearly basis (urban expansion, conversion to nature). For the crop decision making process, information is required on the current price or expected price evolution of the modelled crops, the expected yield for each crop and information on the rotation of crops. |
| Sub models | First, the land use of parcels changes based on the input data (urban expansion, conversion to nature).<br>Next, farmers leave the system by dying (stochastically determined based on the general mortality rate of the population) or retiring. The farmer retires at the legal retirement age when a successor is present, or at a later age according to a calibrated probability. The decision making of a possible successor to take over a farm or not is stochastically determined according to a probability based on the regional retirement chance available in statistics, which is combined with the profitability of the farm for land-based farming types. Farms without a successor, end activities and parcels are divided among farms cultivating neighbouring parcels. Priority is given to farms of the same type. If not of the same type, the parcel is converted to a suitable agricultural land use for the farm type.<br>Lastly, farms with yearly crop rotations decide on a new crop on their fields based on the expected probability, defined by the combination of the expected yield for the possible crops and the price level for the crop, in combination with the rotation probabilities in the region. |

*Appendix 3 – Cross table for crop rotation succession for main Belgian crops based on the time series (2009-2015) of crops on each parcel in the Système intégré de gestion et de contrôles (SIGEC) and Landbouwgebruikspercelen datasets for respectively Wallonia and Flanders-Brussels.*

| | Winter wheat | Barley | Maize | Sugar beet | Rapeseed | Potatoes | Temp. grassland |
|---|---|---|---|---|---|---|---|
| Winter wheat | 0.90 | 0.02 | 0.01 | 0.02 | 0.01 | 0.01 | 0.03 |
| Barley | 0.02 | 0.90 | 0.02 | 0.01 | 0.01 | 0.01 | 0.03 |
| Maize | 0.02 | 0.02 | 0.90 | 0.01 | 0.01 | 0.01 | 0.03 |
| Sugar beet | 0.01 | 0.01 | 0.02 | 0.90 | 0.01 | 0.02 | 0.02 |
| Rapeseed | 0.01 | 0.02 | 0.01 | 0.02 | 0.90 | 0.01 | 0.03 |
| Potatoes | 0.02 | 0.01 | 0.02 | 0.01 | 0.02 | 0.90 | 0.02 |
| Temp. grassland | 0.01 | 0.02 | 0.01 | 0.02 | 0.01 | 0.02 | 0.91 |

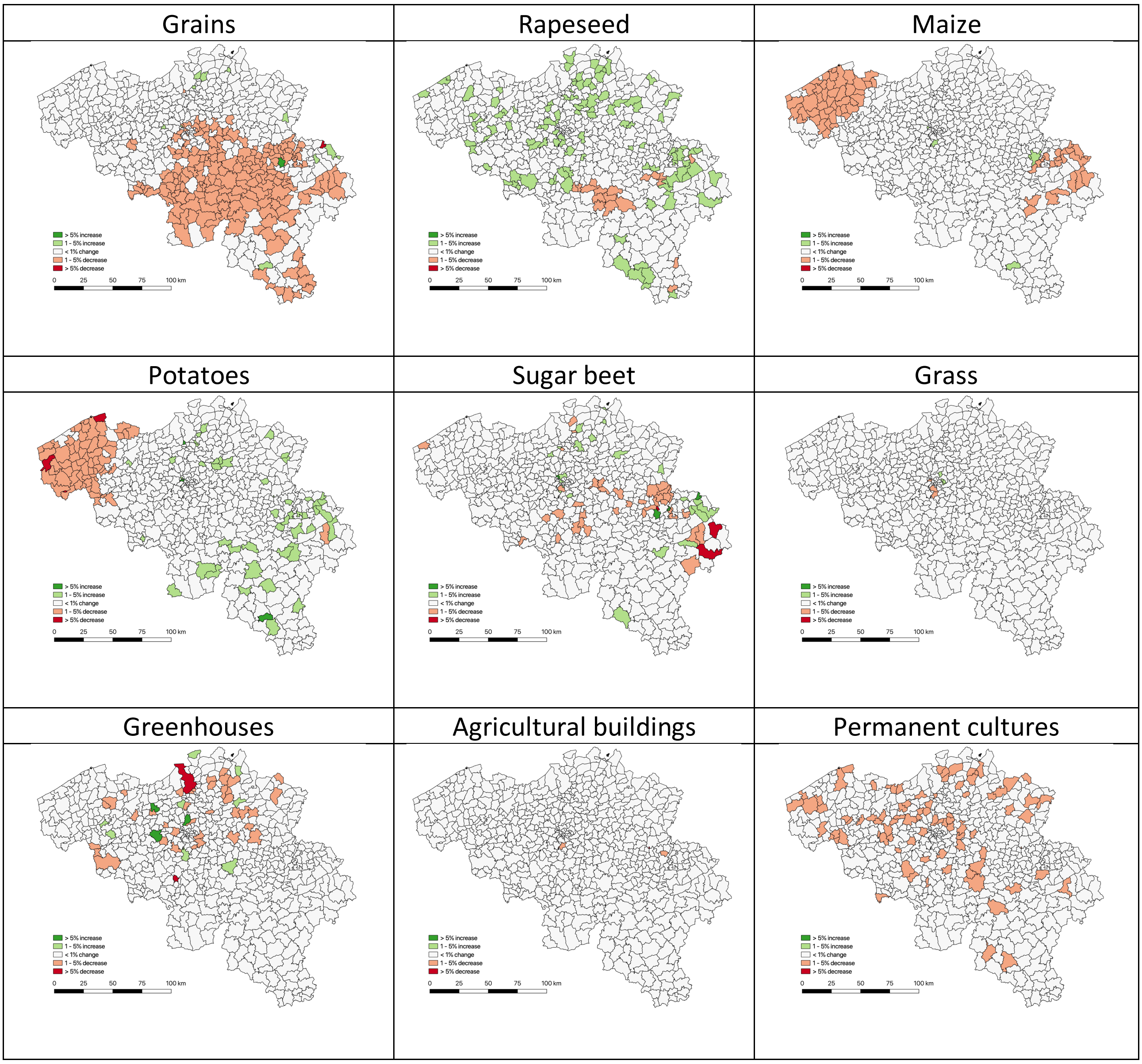
*Appendix 4 – Overview of choices and assumptions made for the Belgian case study based on conversations with experts and gained insights in Belgian agriculture.*

| | |
|---|---|
| Farmer population | - Farmers can live to max. 105 years old<br>- Famers retire at legal retirement age if a successor is present<br>- Farmers without successor continue farmer until finally retiring or passing away<br>- The age of the successor is normally distributed around the age of 35 with a minimum of 18<br>- There are 5 farm types (yearly crop farm, permanent crop farm, greenhouse farm, land-based and non-land-based animal farms), there are no mixed farm types |
| Succession | - For non-land-based farms (greenhouse farms and non-land-based animal farms), succession is based on the regional average succession chance.<br>- For land-based farmers (permanent crop, rotating crop and land-based animal farms) succession chance is related to profitability and the regional average succession chance.<br>- Profitability is thereby calculated as the farm size times the regional average SDM per ha per farm type.<br>- The assumed profitability of a farm is compared to the average profitability for that farm type in the region and results in an adaptation of the average succession chance through a correction factor. The correction factor is based on a discrete logistic curve with steps according to the standard deviation from the average profitability. |
| Parcel dynamics | - If a farmer continues after retirement age, 2/3 of his parcels (i.e. the estimated rate of leased lands) are being redistributed among farmers in the neighbourhood of this parcel.<br>- Parcels are given in preference to farmers that can use the land without land use change (as such avoiding extra costs).<br>- A farmer that receives a parcel that he cannot immediately use given the current agricultural land use, will change the agricultural land use of the parcel.<br>- If a farmer stops without a successor, the farm house becomes a residential parcel.<br>- For farmers that yearly change the crop type, a crop is chosen stochastically from a limited list of popular crops (maize, sugar beet, barley, wheat rapeseed and potatoes) based on the expected yield in combination with the average price per ton for a crop.<br>- If there are no agricultural parcels left within 1km of the parcels, the parcel is abandoned. |
| Neighbours | - The neighbours of a farmer are the farmers that manage the 20 nearest parcels to every parcel that is part of the farmers' farm. |

*Appendix 5 – Average price between 2013 and 2018 (Food and Agriculture Organization, 2019) and the average yield (Jacquemin et al., 2017) and average resulting producer prices per hectare for West Flanders specific, and for Belgium more generally.*

| | | **West Flanders** | | | **Belgium** | | |
|---|---|---|---|---|---|---|---|
| Crop | Average price 2013-2018 *EUR* | Average yield *ton/ha* | SD yield *ton/ha* | Average price/ha *EUR/ha* | Average yield *ton/ha* | SD yield *ton/ha* | Average price/ha *EUR/ha* |
| Wheat | 159.89 € | 6.34 | 1.05 | 1 013.10 € | 7.59 | 0.78 | 1 213.27 € |
| Barley | 147.09 € | 7.04 | 0.98 | 1 035.15 € | 7.97 | 0.70 | 1 172.12 € |
| Maize | 173.44 € | 6.20 | 4.56 | 1 074.84 € | 15.30 | 5.55 | 2 654.32 € |
| Sugar beet | 25.55 € | 19.86 | 8.42 | 507.48 € | 36.28 | 22.06 | 926.99 € |
| Rapeseed | 217.98 € | 5.14 | 0.73 | 1 121.03 € | 5.76 | 0.49 | 1 256.18 € |
| Potatoes | 135.44 € | 3.62 | 4.42 | 490.59 € | 18.56 | 9.21 | 2 514.06 € |

*Appendix 6 – Modelled change in agricultural land use between 2013 and 2030 with increase in green and decreases in orange-red.*



*Appendix 7 – Area of common agricultural crops according to the agricultural survey (Statistics Belgium, 2018)*

| Agricultural land (2018) | 8505 km$^2$ |
|---|---|
| Permanent grassland | 4796 km$^2$ |
| Grains | 3045 km$^2$ |
| Maize | 2337 km$^2$ |
| Potatoes | 933 km$^2$ |
| Sugar beets | 627 km$^2$ |
| Rapeseed | 113 km$^2$ |

*Appendix 8 – Modelled current range as the number of 1km cells with a certain Bombus species present.*

| High thematic resolution | | Low thematic resolution | |
|---|---|---|---|
| Current range (# 1km cells) | Bombus species | Current range (# 1km cells) | Bombus species |
| 2143 | magnus | 6749 | sylvarum |
| 2851 | jonellus | 8413 | norvegicus |
| 3258 | sylvarum | 10308 | jonellus |
| 4202 | norvegicus | 10839 | magnus |
| 5244 | soroeensis | 11567 | soroeensis |
| 8432 | bohemicus | 16151 | bohemicus |
| 8939 | cryptarum | 20907 | rupestris |
| 9841 | rupestris | 24454 | cryptarum |
| 12430 | ruderarius | 26963 | lucorum |
| 15897 | vestalis | 27834 | terrestris |
| 16543 | sylvestris | 28492 | vestalis |
| 16756 | lucorum | 28912 | campestris |
| 20952 | campestris | 29252 | ruderarius |
| 24232 | terrestris | 29668 | pascuorum |
| 26560 | hypnorum | 29825 | sylvestris |
| 28536 | hortorum | 30064 | hortorum |
| 28670 | lapidarius | 30101 | hypnorum |
| 28988 | pratorum | 30407 | lapidarius |
| 29140 | pascuorum | 30430 | pratorum |

# Technical appendix

## TA.1. General introduction

ADAM is an open-source object-oriented framework developed to analyse the evolution of an agricultural population and the agricultural landscape. ADAM is based on two major components: the initialization and the yearly update. In the initialization phase the agricultural landscape is created based on the available input information. In the yearly update, the farmers and their farms evolve over time and change the agricultural land they manage. ADAM was developed from an object-oriented design instead of a procedural program design since this would allow (1) a more easily transferability to other case-study areas, (2) working with a compartmented structure with independent pieces of code and (3) an easier way to further expand the model and increase complexity, without the need to adapt the original code.

This technical documentation starts with an overview of the concepts, choices and assumptions made within the modelling framework followed by an overview of the required input files and parameters. Next, a detailed overview of the initialization and yearly update is given, supported by tables and flow charts when useful. The model overview is followed by an explanation of the different output files. Finally, relevant pieces of code that support the model explanation are added. ADAM is written in Java 1.8-se in the Eclipse IDE. The full code consists of 22 files with a total of 3673 lines of code and is available through Github:

*https://github.com/veroniquebeckers/ADAM*

## TA.2. Concepts

The following concepts were implemented in ADAM:

Agents:

- Farmers retire at legal retirement age only if a successor is present.
- Farmers without successor continue farming until finally retiring or passing away.
- The age of the successor is normally distributed around the age of 35 with a minimum of 18.
- There are 5 farm types (yearly crop farm, permanent crop farm, greenhouse farm, land-based and non-land-based animal farms), there are no mixed farm types.

Farm succession:

- For non-land-based farms (greenhouse farms and non-land-based animal farms), succession is based on the regional average succession probability.
- For land-based farmers (permanent crop, rotating crop and land-based animal farms), succession probability is related to profitability and the regional average succession probability.
- Profitability is thereby calculated as the farm size times the regional average SDM per ha per farm type.
- The assumed profitability of a farm is compared to the average profitability for that farm type in the region and results in an adaptation of the average succession probability through a correction factor. The correction factor is based on a discrete logistic curve with steps according to the standard deviation from the average profitability.

Parcel ownership:

- If a farmer continues after retirement age, he continues farming on the parcels he owns. The parcels he leases are being redistributed among farmers in the neighbourhood of this parcel.
- Parcels that become available are given in preference to farmers that can use the land without land use change (as such avoiding extra costs).
- If a farmer retires without a successor, the farm house becomes a residential parcel.

Land use change:

- For yearly rotating crop farms a crop is chosen stochastically from a limited list of popular crops (maize, sugar beet, barley, wheat, rapeseed and potatoes) based on the expected yield in combination with the average price per ton for a crop.
- A farmer that receives a parcel that he cannot immediately use given the current agricultural land use, will change the agricultural land use of the parcel.

# TA.3. Input

## TA.3.1. Data

<u>Required:</u>

- AgrNeighb.csv: A CSV file indicating the distance between parcels and their twenty most nearby neighbouring parcels. (separator = “,”)
    - InputID: The first parcel
    - TargetID: The second parcel
    - Distance: The distance between the centroids of the first and second parcel in meters
- Market.csv: A CSV file containing expected real producer prices for all the different crops for each year. For each crop, a row is present. (separator = “,”)
    - Fields 1-41: The real producer price for a crop in the year “2000 + FieldNr - 1”
- CropRot.csv: A CSV file describing the probability that crops follow each other each year (separator = “;”)
    - Field 1: First crop
    - Field 2: Second crop
    - Field 3: The probability that second crop follow first crop
- DVM2ABMdict.csv: CSV file specifically made to link the yearly yield output of the CARAIB model (Jacquemin et al., 2017) to ADAM. Each parcel in ADAM is linked to a 1km2 cell that identifies the yield of CARAIB. (separator = “;”)
    - ParcelID: The parcel ID as used by ADAM
    - Longitude: The longitude of the cell in the CARAIB model
    - Latitude: The latitude of the cell in the CARAIB model.
- Municipality.csv: CSV file containing information on the farmer population at the municipality level. (separator = “,”)
    - NIS_CODE: The NIS code of the municipality (the official code of the National Institute of Statistics for all municipalities)
    - NAME: The name of the municipality
    - Fields 3-7: The number of yearly rotating crop farms, permanent crop farms, greenhouse farms, land-based and non-land-based animal farmers
    - Fields 8-12: The number of farmers in age categories [18,35[, [35,45[, [45,55[, [55,65[ and [65,105[.
- Parcels.csv: CSV file containing information on all the parcels that are used by ADAM. (separator = “,”)
    - ADAM_ID: The parcel ID (which allows to link it to the original GIS vector file to visualise the result)
    - LU: The current land use (being 2 for agricultural parcels)
    - CROP: The agricultural land cover for the start year (if known and if being a class being modelled, otherwise 0)
    - AREA: The size of the parcel in hectares
    - ZONE: The zone (a currently not used column that could be used to indicate a zoning (zoning plans, hydrological zones…) for relevant use within the model)
    - NIS: The NIS code

- NAME: The name of the municipality
    - LBS: The agricultural zone it belongs to
- Mortality.csv: A CSV file indicating the mortality rate for farmers. The mortality statistics start at 18 years old and end at 105 years old, where the mortality rate is set to 1. (separator = ";")
    - AGE: The age of the farmer
    - RATE: The mortality rate at the specified age.
- PROD folder: Folder containing yield data for every year being modelled from CARAIB (Jacquemin et al., 2017). The yield input is available through TXT files, with the filename consisting of the word "yield", followed by the year of the yield (e.g. yield2015.txt). Each file contains CSV data with 25 fields without a header. (separator = tab)
    - Field 1: Longitude of the CARAIB cell
    - Field 2: Latitude of the CARAIB cell
    - Field 3: Expected yield in tons per hectare of different types of crop or other vegetations being modelled.
    - Fields 4-18: Not used
    - Fields 19-25: The expected yield for wheat, barley, maize, sugar beet, rapeseed, potatoes and grassland respectively.

Optional:

- ABM2DVMdict.csv: An optional CSV file to aggregate the ADAM output at parcel level to a 1km2 resolution. With this conversion file, the output of ADAM can be used as input for CARAIB. The file consists of 5 columns with a header. The file is required when DVM_output = true in Config.java (separator = ";")
    - ADAM_ID: The parcel ID in ADAM
    - TARGET_FID: The ID of the grid used by CARAIB
    - X: The longitude of the 1km2 grid cell in CARAIB
    - Y: The latitude of the 1km2 grid cell in CARAIB
    - AREA_PERC: the contribution of the parcel identified in the first column to the total land use of the cell in the second column as a rate to a total of 1
- (scenario)_urban.csv: CSV file containing information on when parcels will no longer be used in agriculture as a result of urban expansion. The file is required when urbanisation = true in Config.java (separator = ",")
    - ADAM_ID: The parcel ID in ADAM
    - (scenario)-YEAR: A field for each year that the specific scenario provides data for. The standard value for every combination of parcel and year is 0, from the year a parcel is expected to be lost due to urban expansion, the value becomes 1 and stays 1 for the rest of the years.
- SCENARIO folder: Folder containing CSV files to include a full land use map at a 1km2 resolution as output when required. The file is required when DVM_output = true in Config.java. The names of the files are composed as "ScenarioName_ModelYear.csv". (separator = ";")
    - Field 1: The first column states the land use as an integer according to Table TA.1
    - Field 2: The ID of the DVM grid of CARAIB
    - Field 3: The total area of the DVM grid cells (approx. 1km$^2$)

- Fields 4,5: Longitude and latitude of the cell
- Field 6: The total area of the land use type of the total column into the specific $1km^2$ cell,
- Field 7: Contains the ratio relative to the total area of the $1km^2$ cell

*Table TA.1 – Land use code and land use name as used in the land use input*

| ID | Land use | ID | Land use |
|---|---|---|---|
| 1 | Arable land | 13 | Water |
| 2 | Orchard | 14 | Recreation |
| 3 | Greenhouse | 15 | Park |
| 4 | Pasture | 16 | Residential |
| 5 | Grassland | 17 | Military |
| 6 | Unregistered arable land | 18 | Commerce and services |
| 7 | Deciduous forest | 19 | Industry |
| 8 | Coniferous forest | 20 | Mining |
| 9 | Mixed forest | 21 | Infrastructure |
| 10 | Heathland | 22 | Harbour |
| 11 | Dunes | 23 | Other |
| 12 | Wetland | 9999 | Out of study area |

## TA.3.2. Parameters and configuration

Can be changed in `Config.java`

- basePath: Path to the folder where the input data can be found, relative to where the code source is found.
- outputFolder: Path to the folder where the output data will be written, relative to where the code source is found. When running in batch or shell, this can be added as an argument.
- START_YEAR: The start year of the model run. When running in batch or shell, this can be added as an argument.
- END_YEAR: The end year of the model run. When running in batch or shell, this can be added as an argument.
- Scenario: The scenario that will be used in relation to the input files. When running in batch or shell, this can be added as an argument.
- RETIREMENT_AGE: Legal retirement age in the study area.
- RETIREMENT_CHANCE: Calibrated parameter that defines how many agents retire yearly when continuing after retirement age.
- SUBSIDY: A fixed subsidy that each farmer receives if GENERAL_FARM_SUBSIDY = true. Standard value is 0.
- SUBSIDY_PER_HA: Subsidies a farmer receives per hectare he manages if GENERAL_FARM_SUBSIDY = true. Standard value is 0.

- BSS_IMPACT_FACTOR: Correction factor on the expected total income (SGM) of a farmer if POLICY_BSS_IMACT = true or SMALL_FARM_SUBSIDY = true. Standard value is 1 When below 1, SGM is lowered, when above 1, SGM is increased.
- CROP_SUBSIDY_FACTOR: Correction factor on the expected income per ton for a specific crop indicated in SUBSIDIZED_CROP. Standard value is 1.
- SUBSIDIZED_CROP: Integer referring to the specific crop being subsidized by the CROP_SUBSIDY_FACTOR.
- SMALL_FARM_SUBSIDY: Boolean to indicate if BSS_IMPACT_FACTOR should be applied on farms with farm size below average.
- GENERAL_FARM_SUBSIDY: Boolean to indicate if a general subsidy is to be applied to all farms through the value indicated in SUBSIDY.
- AREA_SUBSIDY: Boolean to indicate if subsidy per hectare should be given according to the factor indicated in SUBSIDY_PER_HA.
- POLICY_BSS_IMPACT: Boolean to indicate if BSS_IMPACT_FACTOR should be applied to all farms.
- CROP_SUBSIDY: Boolean to indicate if subsidy for a certain crop should be given according to the factor indicated in CROP_SUBSIDY_FACTOR for the crop indicated in SUBSIDIZED_CROP.
- Agricultural land use codes
- Succession percentage per agricultural zone
- landOwnershipRate: Rate on the amount of land that is on average owned and not leased in regard to the total.
- BSS_rot_(agricultural zone): Average standard gross margin (SGM) per hectare for yearly rotating crop farmers for each agricultural zone.
- BSS_perm_(agricultural zone): Average standard gross margin (SGM) per hectare for permanent crop farmers for each agricultural zone.
- BSSforLBAF: Average standard gross margin (SGM) per hectare for land-based animal farmers.
- URBANISATION_DISTANCE: Threshold for the minimum distance to another agricultural parcel, before the parcel is considered to be too isolated to be still in use as agricultural parcel.
- UrbanisationTreshold: Threshold for the number of agricultural parcels in the neighbourhood of the parcel (defined through AgrNeighb.csv) underneath which it will be considered as too isolated to be still in use as agricultural parcel.
- startRate(crop): Average rate of every crop in comparison to the total for all cropland. This rate can be used to initialize crops when no start crops are available.

# TA.4. Model overview

## TA.4.1. Initialisation

The initialization procedure (`init()`)is responsible for creating parcels and assigning them to agents. The initialisation phase follows the conceptual flow chart visualised in Chart 1 and is based on the following key methods:

- `MainModel.assignAgents()`
- `MainModel.getFreeParcelForAgent()`
- `MainModel.joinNeighbouringParcelbyFarmer()`
- `MainModel.joinMunicipParcel()`

The method starts with loading in all the input data provided in the different files (see Input), after which it starts the module `MainModel.assignAgents()`.

For all municipalities, all agents get one parcel, considered to be their home parcel through the method `Parcel.getFreeParcelForAgent()`. If there are more farmers in the municipality than available farmers, the neighbouring parcels of the parcels in the municipality are added as potential home parcels for the farmer. This is preferably a parcel listed as an agricultural building. If there are not enough parcels of that type available in the municipality, another type of parcel is randomly assigned to the farmer as its home parcel. When a parcel is appointed to a farmer, it gets the land cover label "farm house" and it becomes part of the agricultural zone in which the farmer is located.

Now that all farmers have at least one parcel, all the parcels that are not assigned to a farmer yet are listed and are assigned through the method `Agent.joinNeighbouringParcelbyFarmer()` using a type restriction. The neighbours are defined through the agrNeighbours.csv (see Input). The type restriction is checked through the function `Agent.canOccupyParcel()` and is defined as follows:

*Table TA.2 – Type of parcels that can be occupied by a certain farmer type*

| Farmer type | canOccupyParcel |
|---|---|
| **Land-based animal farmer** | Grassland & agricultural buildings |
| **Greenhouse farmer** | Greenhouses |
| **Non-land-based animal farmer** | Agricultural buildings |
| **Permanent crop farmer** | Fruit trees & arboriculture |
| **Yearly crop farmer** | Cropland |

The method continues until there are no more parcels to be assigned or until it is no longer possible to find a suitable owner. When there are still unassigned parcels, new owners for these parcels are being searched within the entire municipality through the method `Parcel.joinMunicipParcel()`. When there are still unassigned parcels after this method, the model tries again to assign farmers to parcels through the method `Agent.joinNeighbouringParcelbyFarmer()`, given that the situation might have changed after the previous method. Since parcels are searching for neighbouring parcels that have an agent of the correct type, new neighbouring parcels of the correct type might have been created in the previous iteration. Hence, an iterative approach is needed. When there are still parcels that are not assigned, the method `Agent.joinNeighbouringParcelbyFarmer()` is executed again, now without the type restriction. This continues until all parcels are linked to a farmer, after which the farms are created and the output of the initialisation phase is printed out.

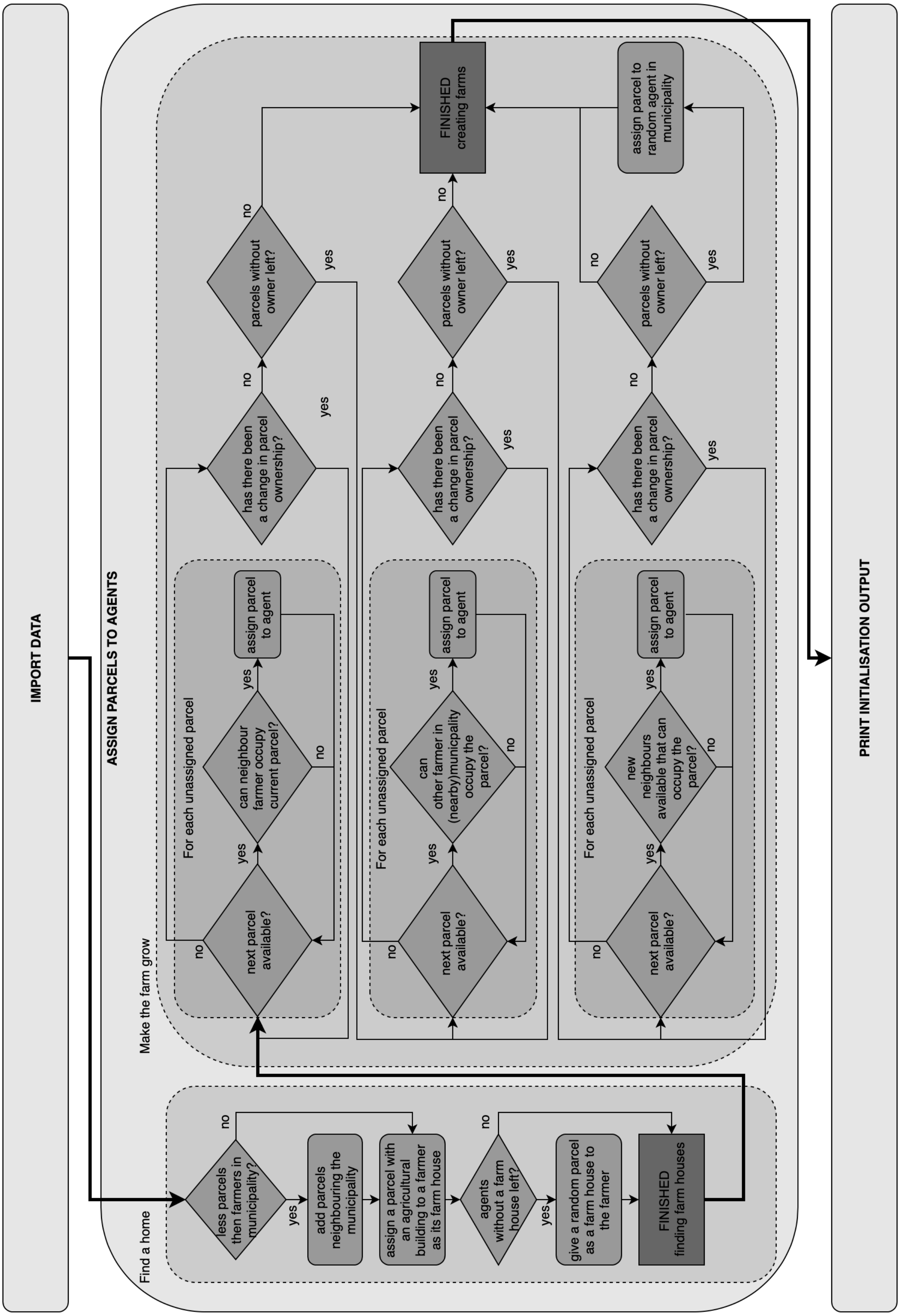



*Chart 1: Flow chart of the initialization phase*

## TA.5. Yearly update

The main program (`MainModel.run()`) covers the yearly update of the farmer population, the farms they own and the agricultural land by yearly calling the method `MainModel.processYear (year)` from the start year until the end year as defined in `Config.java`.

`MainModel.processYear` follows the conceptual flow chart visualised in Chart 2 and is based on the following key methods:

- `MainModel.terminateUncompetitveAgent(year,agent)`
- `MainModel.farmSurvivalChance(agent)`
- `MainModel.reassignParcel(year,parcel)`
- `MainModel.getAverageBSSforType(year,parcel)`
- `Agent.updateParcels(year)`
- `Agent.updateCoverType`

### TA.5.1. General farmer and farm update

Every year, the method starts with loading in the year specific yield data provided in the input (see Input), after which the yearly update of agents and parcels starts.

For every agent the model determines whether it dies this year or not, by a randomized probability based on the mortality rate for its age. If the agent dies:

- If the agent has passed the retirement age, the agent is assumed to have no successor and is immediately terminated through (see Terminating Agents).
- If the agent did not pass the retirement age, the probability of succession and thus survival of the farm is evaluated (see Succession). If there is a successor, the age of the farmer is reset to a random successor age, normally distributed around 35 ($\mu$=35, $\sigma$=5). If there is no successor, the agent and farm are terminated (see Terminating Agents).

If the agent does not die:

- If its age equals the retirement age, a potential successor is identified (see Succession). If there is a successor, the age of the farmer is reset to a random successor age, normally distributed around 35 ($\mu$=35, $\sigma$=5). If there is no successor, the farmer continues to farm, whereby the farm size is reduced by `MainModel.reassignParcel(year,parcel)` until a leftover percentage that equals the average landownership percentage.
- If its age surpasses the retirement age, the probability of retirement is determined by comparing a random probability to the calibrated retirement probability. If the agent retires, it is assumed to have no successor and agent and farm are terminated (see Terminating Agents).

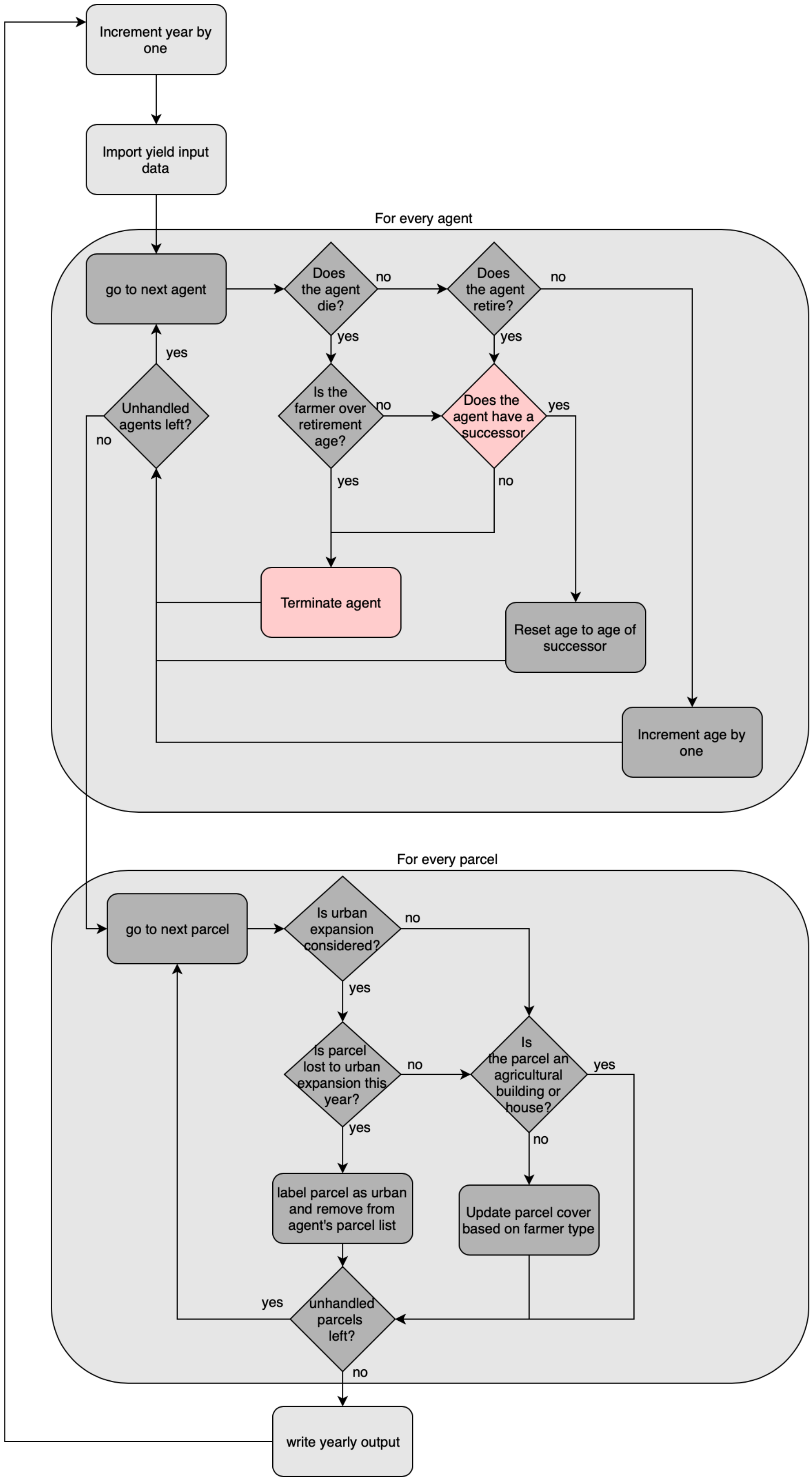



*Chart 2 – Chart with overview of the main model, boxes in red are explained into more detail in their own flow chart*

### *Terminating agents*

When farm and farmer are terminated through `MainModel.terminateUncompetitveAgent(year,agent)` the farm house is converted to residential land and all other parcels are reassigned through `MainModel.reassignParcel(year,parcel)` (Chart 3). This method reassigns a parcel of the terminated agent amongst his neighbours. First the model checks whether the neighbour has not passed retirement age yet. Afterwards it looks for a potential owner among the neighbours of the same Farm Type (`Agent.hasHigherChanceOfTakeOver(neighbour`) (see Table TA.3), unless no farmers of the same Farm Type are available.

*Table TA.3 – Farmer types that have a higher probability of being taken over by a certain farmer type*

| Farmer type | hasHigherChanceOfTakeOver |
|---|---|
| **Land-based animal farmer** | Animal Farmer |
| **Greenhouse farmer** | Greenhouse Farmer |
| **Non-land-based animal farmer** | Animal Farmer |
| **Permanent crop farmer** | Crop Farmer |
| **Yearly rotating crop farmer** | Crop Farmer |

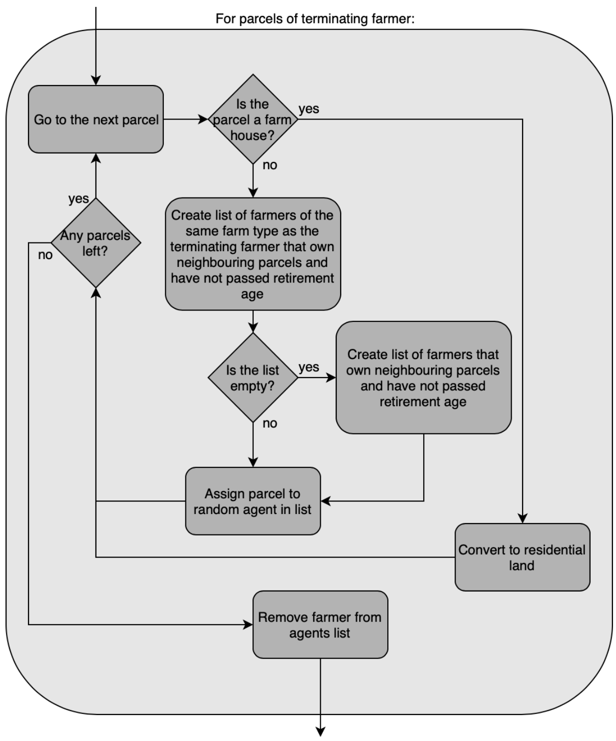



*Chart 3 – Flow chart of the process of `MainModel.terminateUncompetitveAgent(year,agent)`*

*Succession*

The probability that a farm has a successor is defined through `MainModel.farmSurvivalChance(agent)`.

For the types Greenhouse farmer and Non-land-based animal farmer, the probability of succession is determined by the comparison of a random probability to the average succession probability in the agricultural zone of the farmer that is terminating (`Config.getSurvivalPercentageForZone`). A correction factor on the succession probability is applied when this is part of the scenario as determined in `Config.java` (see Input).

For land-based farming types (land-based animal farmers and permanent and yearly rotating crop farmers) the method first defines the average profitability (defined as the bruto standard saldo (BSS)) and standard deviation (SD) for the retiring farmer's farm type in its agricultural zone (`MainModel.getAverageBSSForType`). The BSS is thereby calculated (`Agent.getBss()`, Table TA.4) for every individual farmer of the same farm type in the same agricultural zone. These values are then combined to define the average and the SD. The SGM per hectare is defined as an input parameter (see Input) per agricultural zone for permanent (`BSS_perm`) and yearly rotating crop farmers (`BSS_rot`) and is defined as an average for the country for land-based animal farmers (`BSSforLBAF`).

*Table TA.4 – The calculation of the SGM for the different farmer types.*

| Farmer type | getBSS |
|---|---|
| **Land-based animal farmer** | BSSforLBAf * total farm size |
| **Greenhouse farmer** | 0 |
| **Non-land-based animal farmer** | 0 |
| **Permanent crop farmer** | BSS_perm for zone * total farm size |
| **Yearly rotating crop farmer** | BSS_rot for zone *total farm size |

Next the profitability of the terminating farmer (`Agent.getBSS()`) is corrected if this is part of the scenario determined in `Config.java` (see Input) and compared to the earlier defined regional average profitability and SD according to Table TA.5.

*Table TA.5 – Succession percentage of a farm as based on a comparison to similar farmers*

| From | To | Succession Percentage |
|---|---|---|
| infinity | mean + SD*2.5 | Config.getSurvivalPercentageForZone * 4 |
| mean + SD*2.5 | mean + SD*1.5 | Config.getSurvivalPercentageForZone * 3 |
| mean + SD*1.5 | mean + SD *0.5 | Config.getSurvivalPercentageForZone * 2 |
| mean + SD*0.5 | mean - SD *0.5 | Config.getSurvivalPercentageForZone * 1 |
| mean - SD*0.5 | mean - SD *1.5 | Config.getSurvivalPercentageForZone * 0.5 |
| mean - SD*1.5 | 0 | Config.getSurvivalPercentageForZone * 0.1 |

This adapted survival chance is then compared to a random chance to define whether the farm is being taken over by a successor and thus survives.

The last step in the agent update is the increment of the age of all agents by one.

### TA.5.2. Update of the agricultural land

After the agents have been updated, the method `MainModel.processYear (year)` continues with updating the agricultural land.
If urbanisation of agricultural land is foreseen as input (`Config.urbanisation=true`), the model checks in `agent.updateParcels(year)` for parcels that will change from agricultural (2) to urban (1) land use based on input data on urbanisation and on whether the nearest agricultural parcel is further away than the urbanisation threshold defined in `Config.UrbanisationTreshold`.
For all remaining agricultural parcels that are not labelled as the farm house or as agricultural building, the next agricultural land cover is chosen in `Agent.updateCoverType(year)`, based on the method getNextCoverType(year, parcel area, parcel) (see Table TA.6).

*Table TA.6 – The result of getNextCoverType for each farm type.*

| Farmer type | getNextCoverType |
|---|---|
| **Land-based animal farmer** | If not farm house or building: grassland |
| **Greenhouse farmer** | If not farm house or building: Greenhouse |
| **Non-land-based animal farmer** | If not farm house or building:<br>If cropland: maize<br>If grassland: grassland<br>Else: random maize (20%), grassland(30%) or building (50%) |
| **Permanent crop farmer** | If not farm house or permanent crop: fruit trees |
| **Yearly rotating crop farmer** | If not farm house or building:<br>If grassland: random based on crop productivity & rotation statistics<br>Else: random based on crop productivity, market value & rotation statistics |

After the land update, the different output files are printed.

## TA.6. Output

The output is sorted in 4 folders: agent_dyn, agents, municipality and parcels.

- agent_dyn: contains one CSV file with an overview of the total number of agents for every year of the model run.
- agents: contains one CSV file for every year of the model run, plus one with the data after initialization, with summarized data for every living agent. The data consists of:
    - OWNER_ID: The unique identifier of an agent, which stays the same throughout the entire model run.
    - OWNER_TYPE: The farm type of the agent
    - AGR_ZONE: A numbered code referring to the agricultural zone in which the agent started its farm. The code is the same as the one used in the input files.
    - MUNICIPALITY_NIS: The NIS that refers to the official NIS code of the National Institute of Statistics for the municipality in which the agent started its farm.
    - OWNER_AGE: The current age of the agent.
    - TOTAL_LAND: The total land, or sum of all the parcels, the agent manages.
    - SGM: The calculated SGM based for land-based farming types.
- municipality: contains one CSV file for every year of the model run, plus one with the data after initialization, with summarized data for every municipality. The data consists of:
    - NIS: The NIS that refers to the official NIS code of the National Institute of Statistics for the municipality.
    - NAME: Name of the municipality
    - AVG_SIZE: Average size of the farms in the municipality in hectares.
    - FARMERS_home: Number of farmers that are active and have their home parcel in this municipality.

  - FARMERS_active: Number of farmers that manages one or more parcels in this municipality. Some of them might have their home parcel in another municipality.
  - Agr_area: The total agricultural area in the municipality.
  - 101: Number of hectares of wheat in the municipality.
  - 102: Number of hectares of barley in the municipality.
  - 103: Number of hectares of maize in the municipality.
  - 104: Number of hectares of sugar beets in the municipality.
  - 105: Number of hectares of rapeseed in the municipality.
  - 106: Number of hectares of potatoes in the municipality.
  - 107_91: Number of hectares of grassland in the municipality.
  - 92: Number of hectares of tree nurseries in the municipality.
  - 93: Number of hectares of fruit trees in the municipality.
  - 94: Number of hectares of greenhouses in the municipality.
  - 95: Number of hectares of agricultural buildings in the municipality.
- parcels: contains one CSV file for every year of the model run, plus one with the data after initialization, with the data on every parcel. The data consists of:
  - ID: Unique identifier of the parcel.
  - NIS: The NIS that refers to the official NIS code of the National Institute of Statistics for the municipality in which the parcel is located.
  - AREA: The size of the parcel in hectares.
  - CROP_TYPE: A code referring to the current agricultural land use with:
    - -1: not agriculture, 101: wheat, 102: barley, 103: maize, 104: sugar beet, 105: rapeseed, 106: potatoes, 107: grassland, 91: (permanent) grassland, 92: tree nursery, 93: fruit trees, 94: greenhouses, 95: agricultural buildings
  - LAND_TYPE: A code referring to the current land use with:
    - 1: urban, 2: agriculture, 3: forest, 4: non-commercial agriculture
  - OWNER_ID: ID of the agent currently managing the parcel.
  - OWNER_AGE: Age of the current agent managing the parcel.
  - OWNER_CHANGE: Boolean value that shows whether the parcel did (1) or did not (0) changed owner that year.

## TA.7. Running the script

The script can be run from any IDE suitable for Java.

The code can also be compiled as a JAR-file, with pre-set parameters, allowing direct execution and inclusion in other Java projects.

The JAR-file can also be executed (in a loop) from a batch (Windows) or shell (Linux) file whereby the following arguments are processed: [0] START_YEAR, [1] END_YEAR, [2] FOLDER_NAME and [3] SCENARIO. The build-up of the folder name or other changes in the argument can be preconfigured in `MainModel.main(args)`. Running these batch or shell files from the command line allows the follow up of the script through print-outs.

# TA.8. Code

*MainModel.assignAgents()*

```
/**
* Links agents to parcels, until every parcel is connected to an agent.
* First by giving every farmer one parcel,its home parcel, then by letting
* the farm expand by joining parcels that are close to the home plot.
*/
private void assignAgents() {

	// Loop over all municipalities
	for (Municipality munic : this.municipalityList) {
		// Loop over all agents within municipality
		int nrOfAgents = munic.getAgents().size();
		ArrayList<Agent> agents = (ArrayList<Agent>) munic.getAgents().clone();
		// Find a home plot for every agent
		for (int i = 0; i < nrOfAgents; i++) {
			Agent a = agents.get(i);
			if (a != Agent.INITIAL) {
				Parcel p = getFreeParcelForAgent(munic.getParcels(), nrOfAgents, a);
					p.setAgent(a);
				}
			}
		}

	// All agents now have at least one parcel
	// Get all the parcels still assigned to Agent.INITIAL (i.e. unassigned parcels)
	// and assign the parcel to the owners of neighboring parcels
	int parcelsAtStart;
	ArrayList<Parcel> currentList = (ArrayList<Parcel>)
Agent.INITIAL.getParcelList().clone();

	// As long as something changed, keep assigning parcels
	do {
		currentList = (ArrayList<Parcel>) Agent.INITIAL.getParcelList().clone();
		parcelsAtStart = currentList.size();

		for (Agent a : this.myAgents) {
			joinNeighboringParcelbyFarmer(a, false, true);
		}
	} while (parcelsAtStart != Agent.INITIAL.getParcelList().size());


	// Some parcels are still not assigned to an agent. We try to find a
	// suitable owner for each parcel in the whole municipality
	if (Agent.INITIAL.getParcelList().size() > 0) {
		currentList = (ArrayList<Parcel>) Agent.INITIAL.getParcelList().clone();
		Iterator<Parcel> i = currentList.iterator();
		while (i.hasNext()) {
			Parcel p = i.next();
			joinMunicipParcel(p);
		}
	}

	// We try to assign parcels again looking at neighbours, after looking
	// in the whole municipality for suitable owners
	if (Agent.INITIAL.getParcelList().size() > 0) {
		do {
			currentList = (ArrayList<Parcel>) Agent.INITIAL.getParcelList().clone();
			parcelsAtStart = currentList.size();

			for (Agent a : this.myAgents) {
				joinNeighboringParcelbyFarmer(a, false, true);
```

```
                    }

                } while (parcelsAtStart != Agent.INITIAL.getParcelList().size());
        }

        // Some parcels are still not assigned to an agent. Parcels are now
        // assigned to neighbouring farms without type restrictions until every
        // parcel is linked to an agent (ie. Agent.INITIAL.getParcelList is empty).

        currentList = (ArrayList<Parcel>) Agent.INITIAL.getParcelList().clone();
        while (Agent.INITIAL.getParcelList().size() > 0) {
                currentList = (ArrayList<Parcel>) Agent.INITIAL.getParcelList().clone();
                Iterator<Parcel> i = currentList.iterator();
                while (i.hasNext()) {
                        Parcel p = i.next();
                        joinNeighboringParcel(p, false, false);
                }
                log("Parcels    left    over    after    dropping    type    restriction:    "    +
Agent.INITIAL.getParcelList().size());

        }
        log("Number of final free plots: " + Agent.INITIAL.getParcelList().size());
}
```

*MainModel.getFreeParcelForAgent(parcelList, nrOfAgents, agent)*

```
/**
 * Find a home parcel for every agent. First by looking at parcels that
 * are labeled as agricultural building. Then by giving a random parcel
 * within the municipality.
 * @param parcels - An ArrayList of all parcels within the municipality
 * @param nrOfAgents - The total number of farmers in the municipality
 * @param a - The farmer for which a home parcel is currently sought.
 * @return p - The parcel that is assigned a home parcel for this farmer.
 */
        private Parcel getFreeParcelForAgent(ArrayList<Parcel> parcels, int nrOfAgents, Agent a) {
                // Check if there are enough parcels for the agents within the municpality
                // If not, add the neighbouring parcels of all parcels in the municipality.
                if (parcels.size() < nrOfAgents) {
                        ArrayList<Parcel> addedParcels = new ArrayList<Parcel>();
                        for (Parcel p : parcels) {
                                ArrayList<Parcel> neighbors = p.getNeighboringParcels();
                                addedParcels.addAll(neighbors);
                        }
                        parcels.addAll(addedParcels);

                }
                //Sort parcels according to size
                ArrayList<Parcel> potentials = (ArrayList<Parcel>) parcels.clone();
                Collections.sort(potentials, new Comparator<Parcel>() {
                        @Override
                        public int compare(Parcel a, Parcel b) {
                         return Float.compare(a.getArea(),b.getArea());
                    }
                });
                //Find a parcel that is currently not owned (i.e. Agent.INITIAL) and is
                //labeled as an agricultural building. Make it into the home parcel of the agent.
                for (Parcel p : potentials) {
                        if (p.getAgent() == Agent.INITIAL && p.getCoverType() ==
Config.agr_buildings) {
                                a.setAgrzone(p.getAgricultZone());
```

```
                        p.setCoverType(Config.farm_house);
                        return p;
                }
        }

        // If farmers without parcels are still left, give another parcel than
        // building and set parcel to farm house
        for (Parcel p : potentials) {
                if (p.getAgent() == Agent.INITIAL) {
                        a.setAgrzone(p.getAgricultZone());
                        p.setCoverType(Config.farm_house);
                        return p;
                }
        }
        throw new RuntimeException("Less parcels than farmers in the municipality");
}
```

*MainModel.joinNeighbouringParcelbyFarmer(agent, boolean, boolean)*

```
/**
 * Looks for a parcel in the neighbourhood of the farmer that can be added to the its farm.
 * @param a - The agents that is looking for a new parcel to add to its farm.
 * @param areaCheck - If true, a size restriction applies on the total farm size of the farm
 * @param typeCheck - If true, a typeCheck is performed on the added parcel through
Agent.canOccupyParcel.
 * @return boolean - If true, a parcel has been found and the method is ended.
 */
private boolean joinNeighboringParcelbyFarmer(Agent a, boolean areaCheck, boolean typeCheck) {
        //Create a list of all parcels neighbouring the parcels owned by the farmer
        ArrayList<Parcel> parcels = a.getParcelList();
        ArrayList<Parcel> neighbParcels = new ArrayList<Parcel>();

        for (Parcel p : parcels) {
                ArrayList<Parcel> neighbours = p.getNeighboringParcels();
                neighbParcels.addAll(neighbours);
        }
        Collections.shuffle(neighbParcels);
        int size = neighbParcels.size();
        for (int i = 0; i < size; i++) {
                Parcel potParcel = neighbParcels.get(i);
                //Looks whether the farmer can own the parcel, based on land use if typeCheck=true
                if (potParcel.getAgent() == Agent.INITIAL) {
                        if (!typeCheck) {
                                potParcel.setAgent(a);
                                return true;

                        } else {
                        //Looks whether the farmer can own the parcel based on area if
areaCheck=true
                        if (a.canOccupyParcel(potParcel)) {
                                if (!areaCheck) {
                                        // This owner can take on the given parcel
                                        potParcel.setAgent(a);
                                        return true;
                                } else {
                                        float potArea = potParcel.getArea();
                                        float ownerCanTake = potParcel.getAgent().getMaxLand() -
potParcel.getAgent().getLandArea();
                                        if (areaCheck && ownerCanTake >= potArea) {
                                                potParcel.setAgent(a);
                                                return true;
                                                }
```

```
                                    }
                              }
                        }
                  }
}
                  //The parcel can not be added to the farmer's farm
                  return false;
}
```

*MainModel.joinMunicipParcel(parcel)*

```
/**
* Assign a parcel to any agent within the municipality or the
* neighbouring municipality that can occupy it.
* @param p - A parcel for which an owner is sought.
*/
private void joinMunicipParcel(Parcel p) {
      // List all agents in the municipality of the parcel
      ArrayList<Agent> municipAgents = (ArrayList<Agent>)
p.getMunicipality().getAgents().clone();
      ArrayList<Agent> neighbouringAgents = new ArrayList<Agent>();
      //Add agents in neighbouring municipalities that are not in the list yet.
      for(Parcel potParcel : p.getNeighboringParcels()){
            ArrayList<Agent> neighbourAgents = potParcel.getMunicipality().getAgents();
            for(Agent aa : neighbourAgents)
            {
                  if(!neighbouringAgents.contains(aa))
                  {
                        neighbouringAgents.add(aa);
                  }
            }
      }
      //Find a random agent form the agent list that can occupy the parcel.
      municipAgents.addAll(neighbouringAgents);
      Collections.shuffle(municipAgents);
      int size = municipAgents.size();
      for (int i = 0; i < size; i++) {
            Agent potOwner = municipAgents.get(i);
            if (potOwner != Agent.INITIAL) {
                  if (potOwner.canOccupyParcel(p)) {
                        p.setAgent(potOwner);
                        return;
                  }
            }
      }
}
```

*MainModel.processYear(year)*

```
/**
* Main method that yearly updates the farmer population and its farms, followed
* by an update of the agricultural land.
* @param year - The current year of the model run
*/
private void processYear(int year) {
	// Load new productivity data from input
	myImporter.loadProductivityForYear(this, year);

	int agentsAtStartOfYear = getNumberOfActiveAgents();
	int deadAgents = 0;
	int succsAgents = 0;
	int urbanisedAgents = 0;

	@SuppressWarnings("unchecked")
	ArrayList<Agent> allCurrentAgents = (ArrayList<Agent>) myAgents.clone();

	//1 - AGENT UPDATE
	for (int i = 0; i < allCurrentAgents.size(); i++) {
		Agent agent = allCurrentAgents.get(i);
		int age = agent.getAge();
		double mortalityChance = agent.getMortality(age);

		//Define whether an agent dies
		if (CustomRandom.getDouble() < mortalityChance) {
			// Decide what happens with the agent that died
			if (age > Config.RETIREMENT_AGE) {
				terminateUncompetitiveAgent(year, agent);
				deadAgents++;
			} else if (CustomRandom.getDouble() > farmSurvivalChance(agent)) {
				terminateUncompetitiveAgent(year, agent);
				deadAgents++;
			} else {
				agent.setAge(Config.getSUCCESOR_AGE());
				succsAgents++;
			}
		//For the agents that did not die...
		} else {
			// Check if any agents that did not die will retire
			if (age == Config.RETIREMENT_AGE) {
				//If the agent is retiring, check for successor
				if (CustomRandom.getDouble() < farmSurvivalChance(agent)) {
					agent.setAge(Config.getSUCCESOR_AGE());
					succsAgents++;
				} else {
					//If no successor, farmer continues farming with only its
					// owned parcels, releasing the leased parcels.
					ArrayList<Parcel> rentedParcelList =
agent.getRentedParcels();
					for (int p = 0; p < rentedParcelList.size(); p++) {
						reassignParcel(year, rentedParcelList.get(p));
						}
					}
				}
			//Agents that did not die, but are over retirement age, have a
			//retirement chance based on Config.RETIREMENT_CHANCE
			else if (age >= Config.RETIREMENT_AGE && CustomRandom.getDouble() <=
Config.RETIREMENT_CHANCE) {
				terminateUncompetitiveAgent(year, agent);
				deadAgents++;
			}
		}
		//All living agents age
```

```
            agent.setAge(agent.getAge() + 1);

            // 2 - LAND COVER CHANGE
            if (Config.urbanisation && !agent.isDead()) {
                  //Urbanise parcels according to external data
                  agent.updateParcels(year);
                  //Check if there are now agents without parcels
                  if (agent.getParcelList().isEmpty()) {
                        agent.die();
                        myAgents.remove(agent);
                        urbanisedAgents++;
                  }
            }
      }
      //Update the agricultural land use  of all parcels
      for (int i = 0; i < allCurrentAgents.size(); i++) {
            Agent agent = allCurrentAgents.get(i);
            agent.updateCoverType(year);
      }

      if (agentsAtStartOfYear - deadAgents - urbanisedAgents != this.myAgents.size()) {
            throw new Error("uh oh");
      }

      // 3 loop over all parcels and save their
      // save data for creating history file
      if (Config.ABM_output == true) {
            for (Parcel parcel : myParcels.values()) {
                  parcel.saveCurrentState();
            }
      }

      // Print current crop type percentages to CSV for DVM
      if (Config.DVM_output == true && (year==Config.END_YEAR || year==Config.START_YEAR)) {
            myPrinter.printCropTypePercentage(this, outputMappingDict, year);
      }
      //Print output of the ABM
      if (Config.ABM_output == true) {
            this.agentHistory.add(myAgents.size());
            printParcelsCSV(Integer.toString(year));
            printAgentCSV(Integer.toString(year));
            printMunicpalityInfo(Integer.toString(year));
      }
}
```

*MainModel.terminateUncompetitiveAgent(year, agent)*

```
/**
* Terminates the given agent. This includes redistributing his parcels to
* other Agents
*
* @param agent – The agent that is being terminated
* @param year – The current year of the model run
*/
private void terminateUncompetitiveAgent(int year, Agent agent) {

@SuppressWarnings("unchecked")
//Find new owner for the parcels through reassignParcel
ArrayList<Parcel> parcels = (ArrayList<Parcel>) agent.getParcelList().clone();
for (int i = 0; i < parcels.size(); i++) {
      if (parcels.get(i).getCoverType() != Config.farm_house) {
            //Find a new owner for the parcel
```

```
            reassignParcel(year, parcels.get(i));
        } else {
            //The home parcel becomes residential land
            parcels.get(i).setAgent(agent.LANDLORD);
            parcels.get(i).setLandUse(Parcel.URBAN);
        }
}
agent.die();

// and off he goes
myAgents.remove(agent);
```

*MainModel.reassignParcel(year, parcel)*

```
/**
* Reassigns the given parcel. Currently, this is done by assigning it to a
* random closest neighbor preferably from the same or similar type
*
* @param parcel – The parcel that is being reassigned
* @param year – The current year of the model run
*/
private void reassignParcel(int year, Parcel parcel) {
Agent currentAgent = parcel.getAgent();
Integer landUse = parcel.getLandUse();
ArrayList<Agent> neighbors = parcel.getNeighbors();
ArrayList<Agent> potentialsSameClass = new ArrayList<Agent>();
ArrayList<Agent> potentialsOthClass = new ArrayList<Agent>();

for (int i = 0; i < neighbours.size(); i++) {
        Agent neighbor = neighbours.get(i);

        if (neighbor == currentAgent) {
            // someone can't take over his own parcels
            continue;
        }

        // Check if the given neighbour is able to take over this kind
        // of land (i.e. is it agricultural land?)
        if (!neighbour.canTakeOverLandOfType(landUse)) {
            continue;
        }

        //Is the farmer young enough to expand?
        if (neighbour.getAge() <= Config.RETIREMENT_AGE && neighbour.isFarmer()) {
            if (neighbor.hasHigherChanceOfTakeOver(currentAgent)) {
                potentialsSameClass.add(neighbor);
            } else {
                potentialsOthClass.add(neighbor);
            }
        }
}

if ((potentialsSameClass.size() == 0) && (potentialsOthClass.size() == 0)) {
        parcel.setAgent(Agent.LANDLORD);
        parcel.setLandUse(Parcel.FOREST);
} else {
        if (potentialsSameClass.size() == 0) {
            int random = (int) Math.floor(CustomRandom.getDouble() *
potentialsOthClass.size());
            Agent newOwner = potentialsOthClass.get(random);
            parcel.setAgent(newOwner);
```

```
            parcel.setCoverType(newOwner.getGeneralCover());
        } else {
            int random = (int) Math.floor(CustomRandom.getDouble() *
potentialsSameClass.size());
            parcel.setAgent(potentialsSameClass.get(random));
        }
}
```

*MainModel.farmSurvivalChance(retiringFarmer)*

```
/**
 * The farmSurvivalChance defines the chance a farm has to find a successor based on a
 * regional average survival chances of the farm type and, for land-based farms,
 * based on its SGM (which is related to size) in comparison to similar farm types.
 * The survival chance might be corrected based on scenario inputs from the Config class.
 * @param retiringFarmer - The farmer that is leaving the system
 * @return survivalChance - The chance the farm has that it is taken over by a successor.
 */
       public double farmSurvivalChance(Agent retiringFarmer) {
              //Get the regional average & SD SGM for a certain farm type
              double stats[] = getAverageBSSforType(retiringFarmer);
              double mean = stats[0];
              double SD = stats[1];
              double correctionFactorBSS = 1.0;
              double correctionFactorSurv = 1.0;
              //Define the correction factor if there is an impact on the SGM of policy changes
              if (Config.POLICY_BSS_IMPACT) {
                     correctionFactorBSS = Config.BSS_IMPACT_FACTOR;
                     correctionFactorSurv = Config.BSS_IMPACT_FACTOR;
              }
              //Get the average survival size in the agricultural zone
              double survivalChance =
Config.getSurvivalPercentageForZone(retiringFarmer.getAgrZone());
              // Correct the SGM for small farms if a small farm subsidy is applied
              if (Config.SMALL_FARM_SUBSIDY) {
                      if (retiringFarmer.getBSS() < mean) {
                            correctionFactorBSS = Config.BSS_IMPACT_FACTOR;
                     }
              }
              //The survival chance equals the regional survival chance for non-land-based farms
              if (retiringFarmer.getFarmerType() == "NonLandBasedAnimalFarmer") {
                     return survivalChance* correctionFactorSurv;
              } else if (retiringFarmer.getFarmerType() == "GreenhouseFarmer") {
                     return survivalChance* correctionFactorSurv;
              //The survival chance depends on a comparison between the farms' SGM and the
average
              //SGM in the agricultural zone for the specific farm type.
              } else if (retiringFarmer.getBSS() * correctionFactorBSS  > (mean + SD * 2.5)) {
                     return survivalChance * 4;
              } else if (retiringFarmer.getBSS() * correctionFactorBSS > (mean + SD * 1.5)) {
                     return survivalChance * 3;
              } else if (retiringFarmer.getBSS() * correctionFactorBSS  > (mean + SD * 0.5)) {
                     return survivalChance * 2;
              } else if (retiringFarmer.getBSS() * correctionFactorBSS  > (mean - SD * 0.5)) {
                     return survivalChance * 1;
              } else if (retiringFarmer.getBSS() * correctionFactorBSS  > (mean - SD * 0.75)) {
                     return survivalChance * 0.5;
              }
              return survivalChance * 0.1;
     }
```

*MainModel.getAverageBSSforType(retiringFarmer)*

```
/**
 * Define the average SGM and SDD for similar farms as the retiring farmer
 * in the agricultural zone the farm is located in.
 * @param retiringFarmer
 * @return statistics - Containing the average and SD on the SGM for the
 * farm type of the farmer in the agricultural zone the farm is located in.
 */
public double[] getAverageBSSforType(Agent retiringFarmer) {
	ArrayList<Double> farmBSS = new ArrayList<Double>();
	double totFarmBSS = 0;
	double temp = 0;
	double statistics[] = new double[2];
	for (Agent f : myAgents) {
		//Look for all agents of the same farm type in the same agricultural zone
		if (retiringFarmer.getAgrZone() == f.getAgrZone()
	    && retiringFarmer.getFarmerType() == f.getFarmerType()) {
			//Get the SGM for the found farmer to calculate average and SD on.
			farmBSS.add(f.getBSS());
			totFarmBSS += f.getBSS();
		}
	}
	//Calculate the average
	double mean = (totFarmBSS / farmBSS.size());
	for (double a : farmBSS) {
		temp += (a - mean) * (a - mean);
	}
	//Calculate the SD
	double SD = Math.sqrt(temp / (farmBSS.size() - 1));
	statistics[0] = mean;
	statistics[1] = SD;
	return statistics;
}
```

*Agent.getBSS()*

```
/*
 * The SGM is returned for a farmer based on the farm type and the agricultural
 * zone where the farm is located. For land-based farming types, the SGM depends
 * on the farm size. The average SGM per ha is defined in the Config class.
 *
 */
public double getBSS() {
	double BSS = 0.0;
	if (this.getFarmerType().equals("YearlyCropFarmer")) {
		BSS = Config.getBSSRotForZone(this.getAgrZone()) * totalArea;
	} else if (this.getFarmerType().equals("PermanentCropFarmer")) {
		BSS = Config.getBSSPermForZone(this.getAgrZone()) * totalArea;
	} else if (this.getFarmerType().equals("LandBasedAnimalFarmer")) {
		BSS = Config.BSSforLBAF * totalArea;
	} else {
		BSS = 0;
	}
	return BSS;
}
```

*Agent.updateParcels(year)*

```
/**
	 * Changes the land use of parcels from agriculture (2) to urban (1)
	 * land use based on the input data on urbanisation or based on whether
	 * the nearest agricultural parcels is further away than the UrbanisationTreshold
	 * @param year - The current year of the model run
	 */
	public void updateParcels(int year) {
		for (int i = 0; i < this.parcelList.size(); i++) {
			Parcel p = this.parcelList.get(i);
			ArrayList<Parcel> nearbyNeighbours = p.getNearestParcels();
			ArrayList<Parcel> agriNeighbours = new ArrayList<Parcel>();
			//Check if the parcel is becoming urbanised this year
			if (year == p.getUrbanisationYear()) {
				p.setLandUse(Parcel.URBAN);
				p.setAgent(Agent.LANDLORD);
				p.setCoverType(-1);
			}
			//Check if the parcel still has nearby agricultural neighbours
			for(int j=0; j<nearbyNeighbours.size();j++){
				if(nearbyNeighbours.get(j).getLandUse()==Parcel.AGRI){
					agriNeighbours.add(nearbyNeighbours.get(j));
				}
				if(nearbyNeighbours.size()<=Config.UrbanisationTreshold){
					p.setLandUse(Parcel.AGRI_NONCOMM);
					p.setAgent(Agent.LANDLORD);
				}
			}
		}
	}
```

*Agent.updateCoverType(year)*

```
/**
* Updates the land cover of all agricultural parcels that are not
* farm houses or agricultural buildings
* @param year - The current year of the model run.
*/
public void updateCoverType(int year) {
	for (int i = 0; i < this.parcelList.size(); i++) {
		Parcel p = this.parcelList.get(i);
		if(p.getCoverType()!=Config.farm_house && p.getCoverType()!=Config.agr_buildings){
		int newCrop = getNextCoverType(year, p.getArea(), p);
		p.setCoverType(newCrop);
		}
	}
}
```