DOCTOR OF SCIENCES

High spatial resolution agent-based modelling at the country scale

An application of farming dynamics in Belgium

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Chapter 5 The impact of urban expansion on agricultural dynamics

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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 19th 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 19th 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.

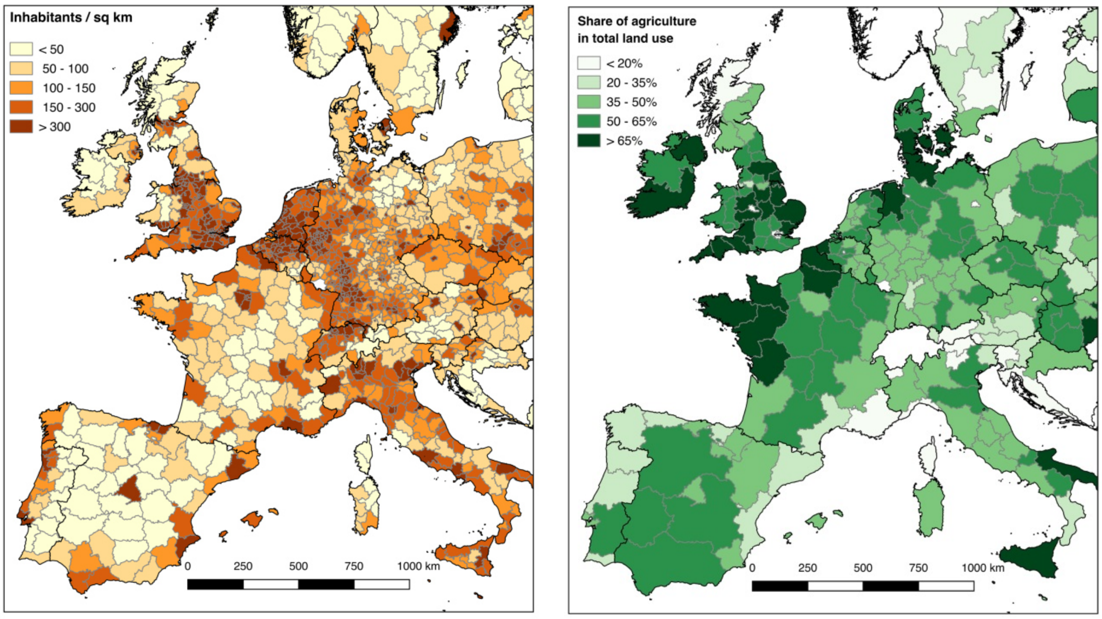


Figure 5.1 – Population density by NUTS3 region in 2015 and percentage of agricultural land by NUTS2 region in Western Europe (European Commission, 2018b)

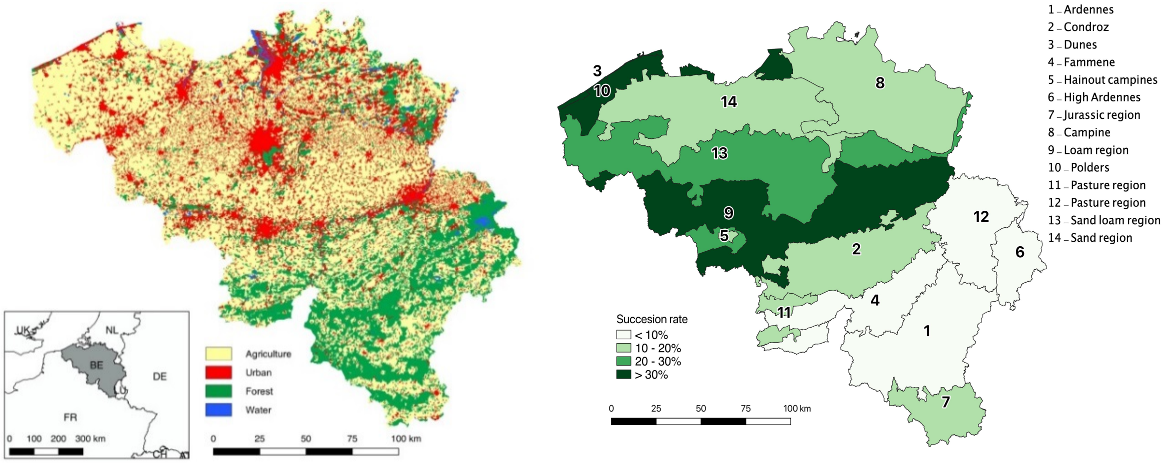


Figure 5.2 – Dominant land use in Belgium based on Corine land cover data (left) (Büttner et al., 2014) and agricultural regions in Belgium with the average farm succession rate (right)(Statistics Belgium, 2018).

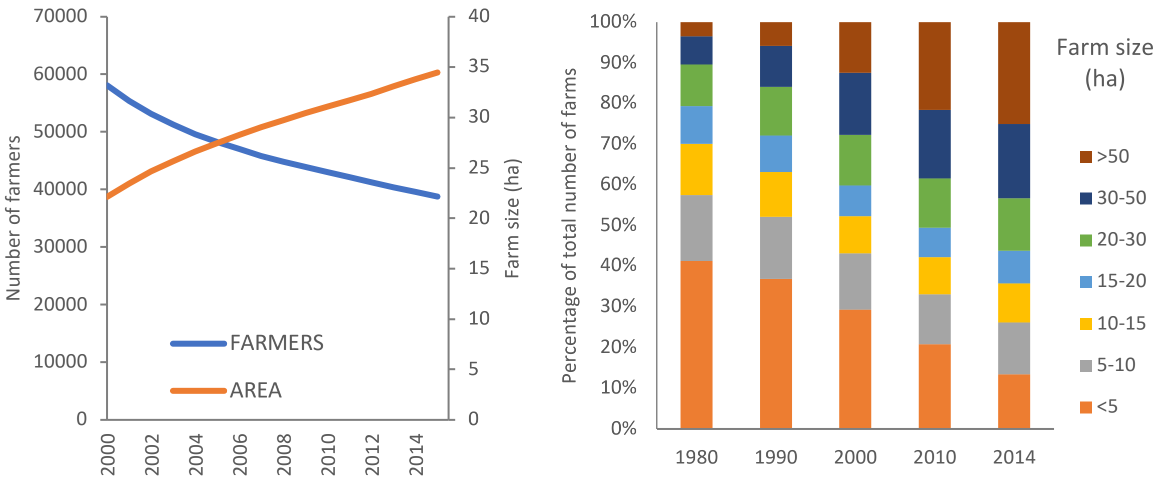


Figure 5.3 – Evolution of the number of farmers and farm size (left) and evolution of the relative proportion of different farm sizes in 2010 (right) (Statistics Belgium, 2018).

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).

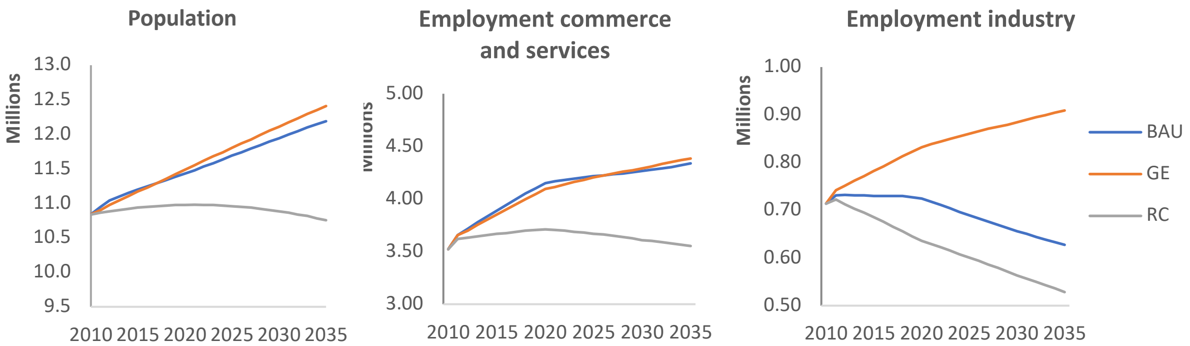


Figure 5.4 – Expectations for population and employment in commerce, services and industry until 2035 under different storylines (Verbeiren et al., 2013).

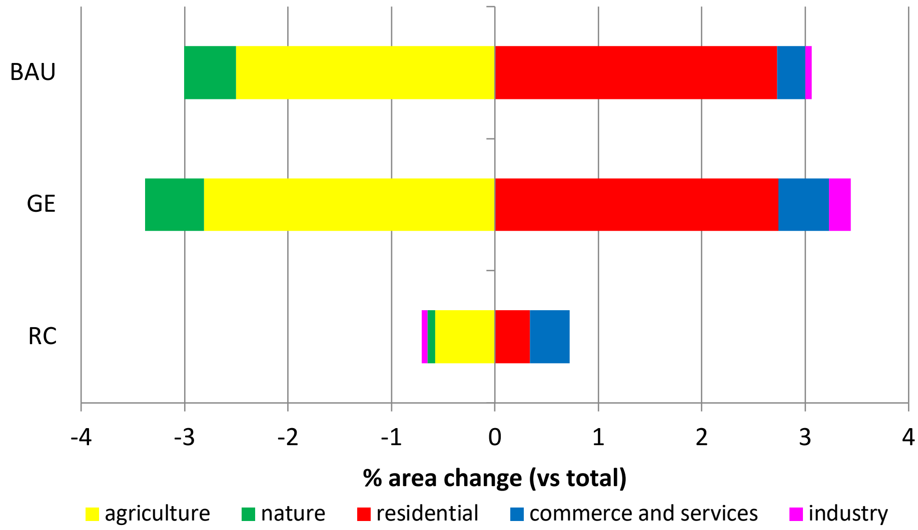


Figure 5.5 – Change in area for each type of land use for the three storylines between 2013 and 2035 (Verbeiren et al., 2013).

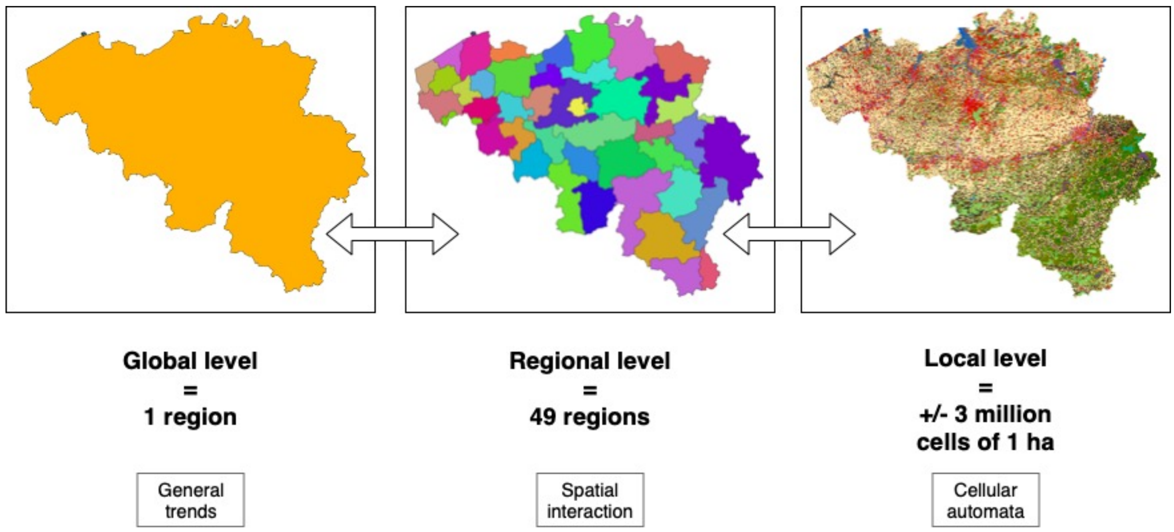


Figure 5.6 – Different levels in the cellular automata land use change scenario modelling: the general trends are defined for the entire study area (the global level), they are translated to specific land demands at the regional level (49 NUTS3 regions), which are used to constrain the land use change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

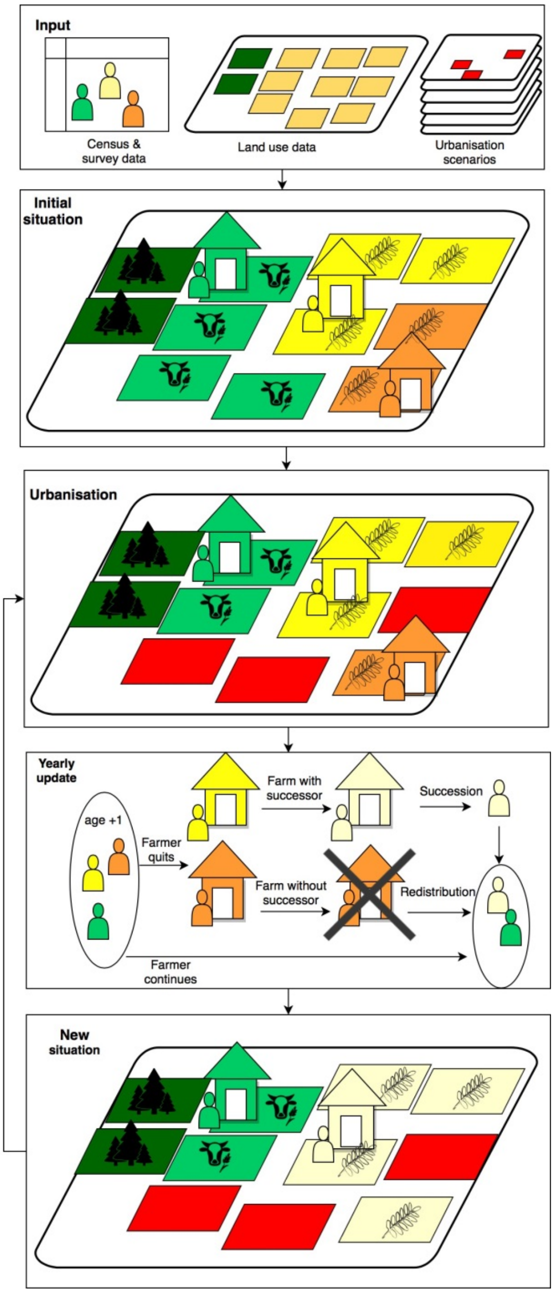


Figure 5.7 – Overview figure of ADAM adapted to include urbanisation.

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.

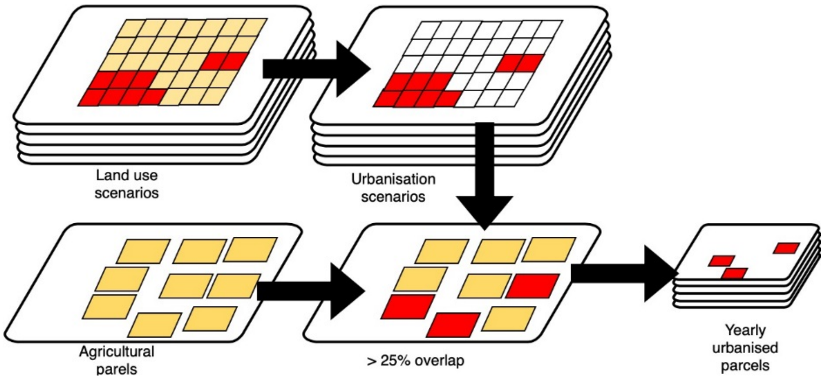


Figure 5.8 – Combining raster-based scenarios with the parcel-based ADAM.

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

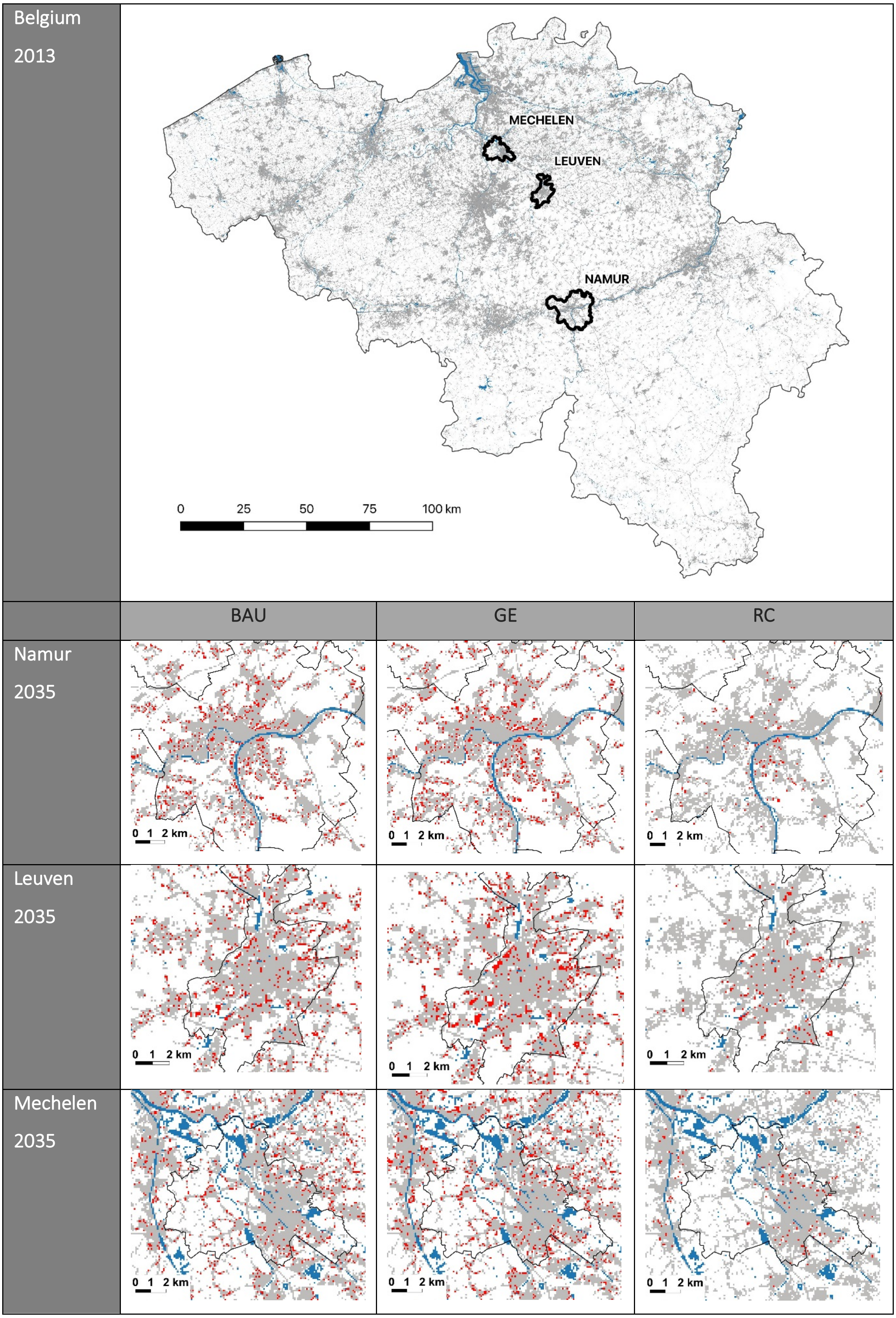


Figure 5.9 – Urban land use for 2013 (grey) and newly urbanised cell in 2035 (red) for all the scenarios for 2035 focussing on three average sized cities.

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

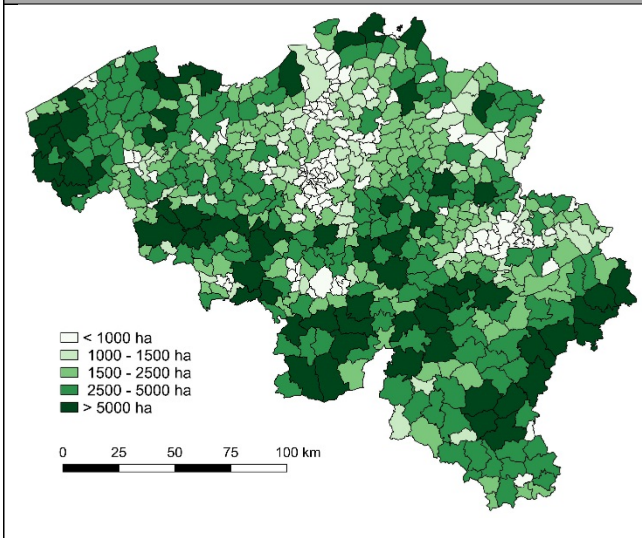
The mismatch in land use data resulting from the combination of rasterized urban expansion data, with vectorized agricultural parcel data, leads to a higher than average loss in the first year modelled. In the first year about 8.5% of parcels is lost through urban expansion. Not unexpectedly, this mostly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

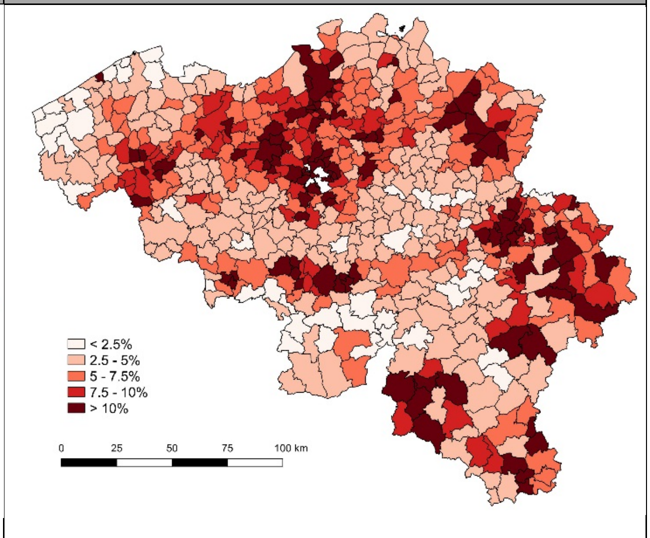
AGRICULTURAL AREA DECREASE

Agricultural area 2013



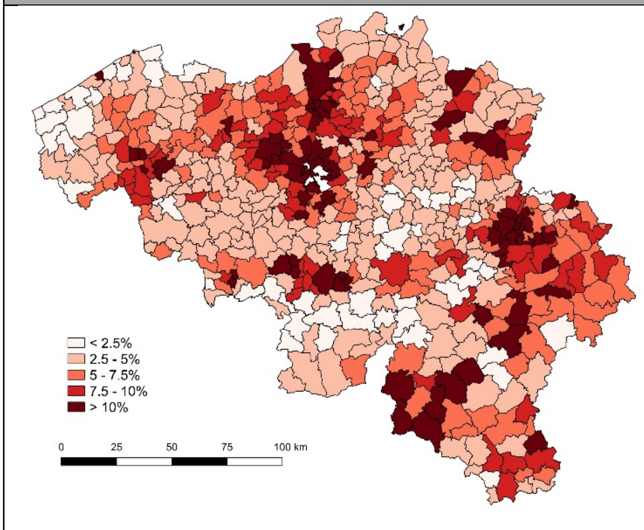
Total: 14 611 km^2

BAU – 2035



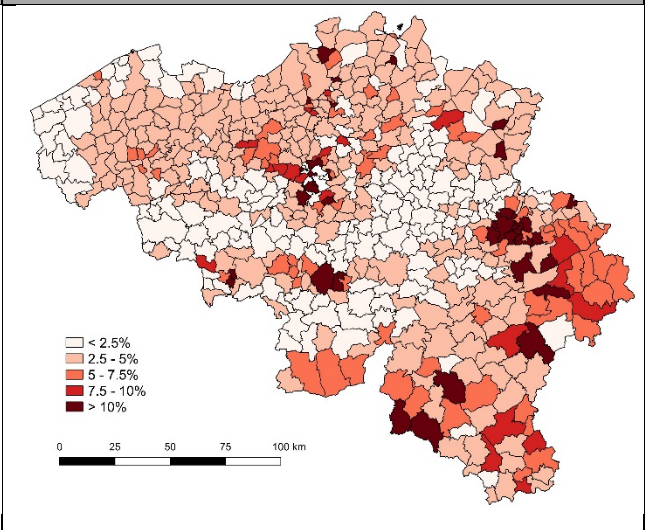
Average total: 13 853 km^2 (SD: 9.72 km^2)

GE – 2035



Average total: 13 881 km^2 (SD: 8.94 km^2)

RC – 2035

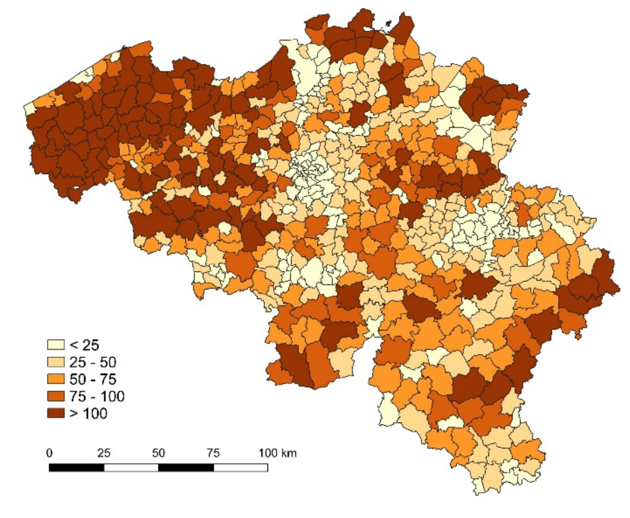


Average total: 14 107 km^2 (SD: 8.75 km^2)

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.

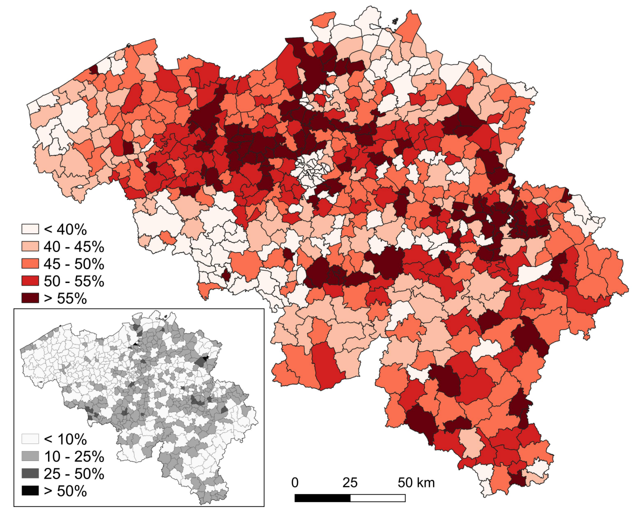
FARMER DECREASE

Farmers 2013



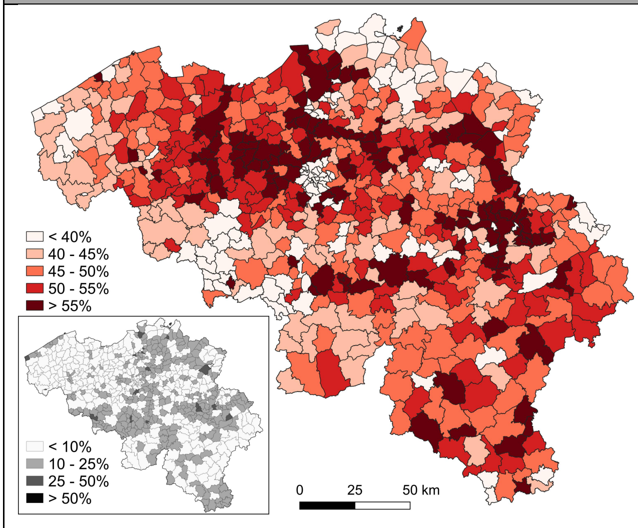
Total: 37 703 farmers

BAU – 2035



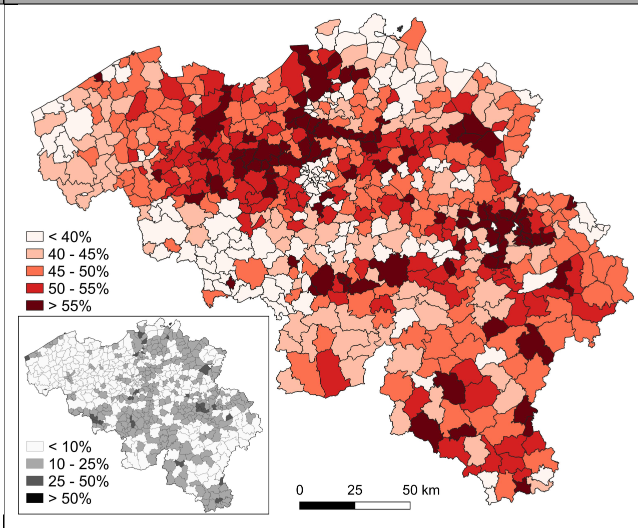
Average total: 15 815 farmers (SD: 65)

GE – 2035



Average total: 15 448 farmers (SD: 78)

RC – 2035

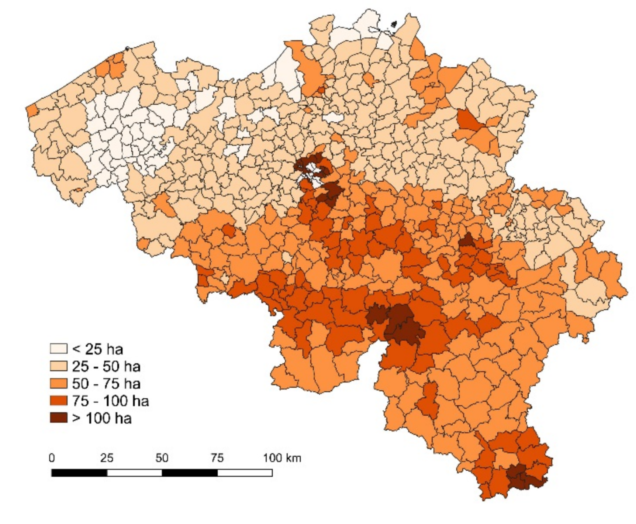


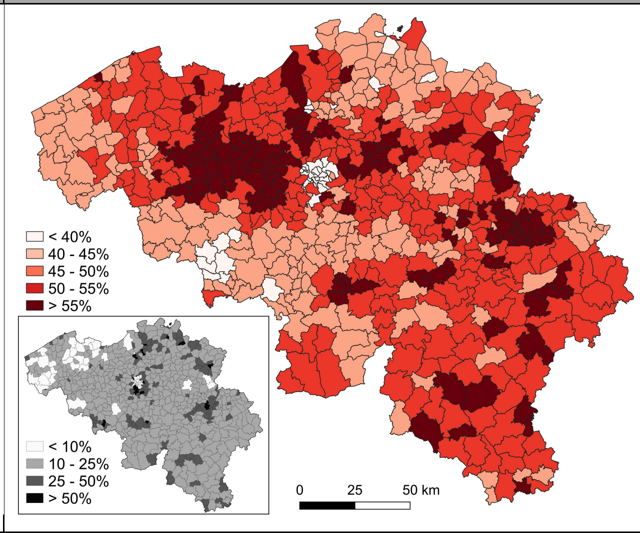
Average total: 16 050 farmers (SD: 78)

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.

FARM SIZE INCREASE

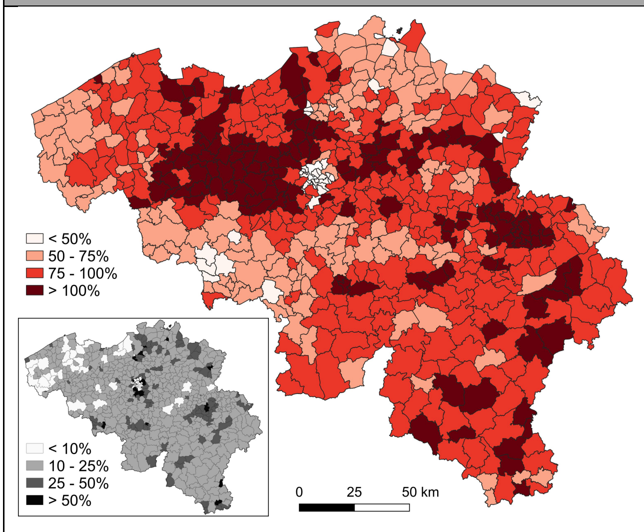
Farm size 2013	BAU - 2035

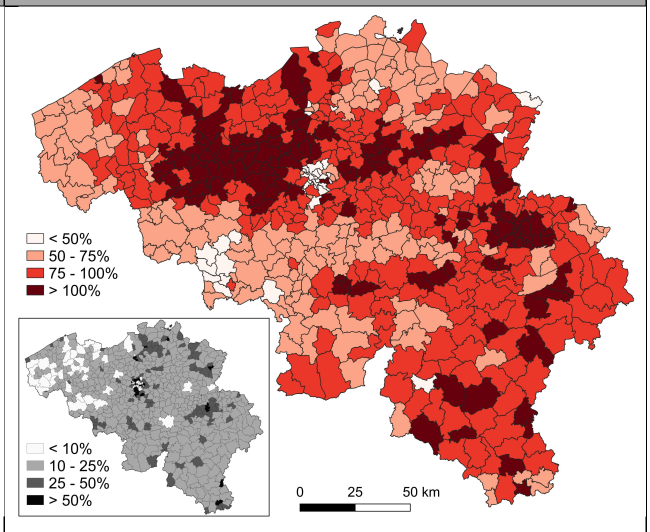




Average: 38.8 ha	Average farm size: 87.9 ha (SD: 0.35 ha)

GE – 2035	RC - 2035





Average farm size: 90.2 ha (SD: 0.45 ha)	Average farm size: 88.2 ha (SD: 0.41 ha)

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 1km^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 1km^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.

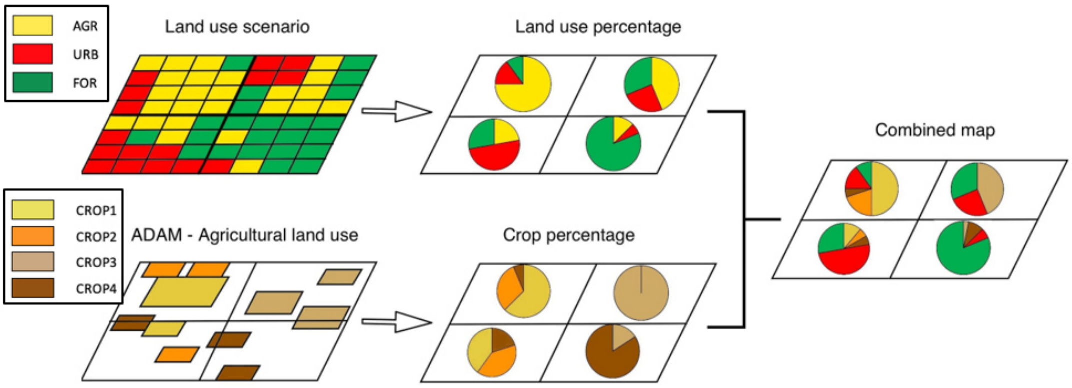


Figure 6.1 – Simplified example of the resampling of the land use data at 1ha resolution and agricultural parcel data from ADAM to the 1km² resolution

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.

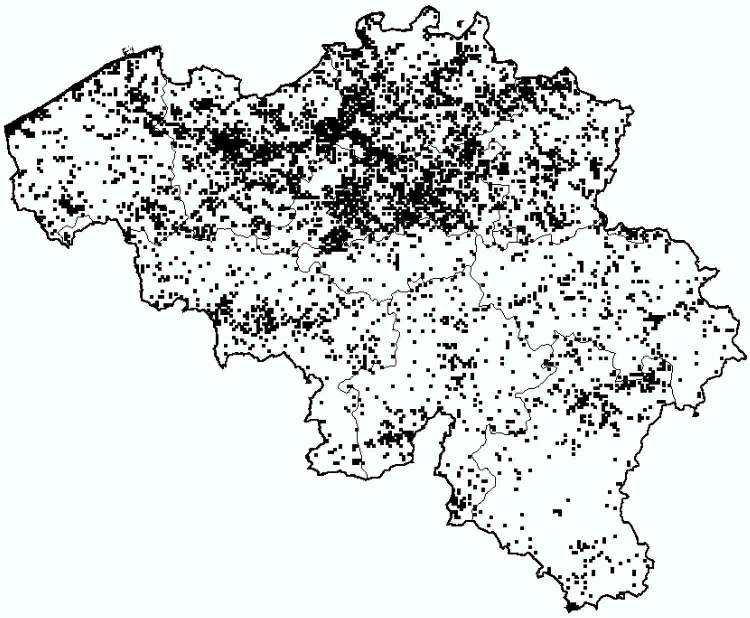


Figure 6.2 – Locations where bumblebees have been sampled in Belgium between 2005 and 2017, used as training data in the SDM and for creating the background sample.

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 • Unregistered agricultural land • Rapeseed • Sugar beet • Potatoes*	• Mixed Forest • Deciduous Forest • Coniferous Forest	• Pasture • Heathland • Semi-natural grassland • Wetland	• Water • Dunes • Military • Greenhouses	• Fruit trees	• Residential • Parks • Recreation • Sealed surfaces • Industry** • Commerce and services** • Infrastructure** • Mining** • 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.

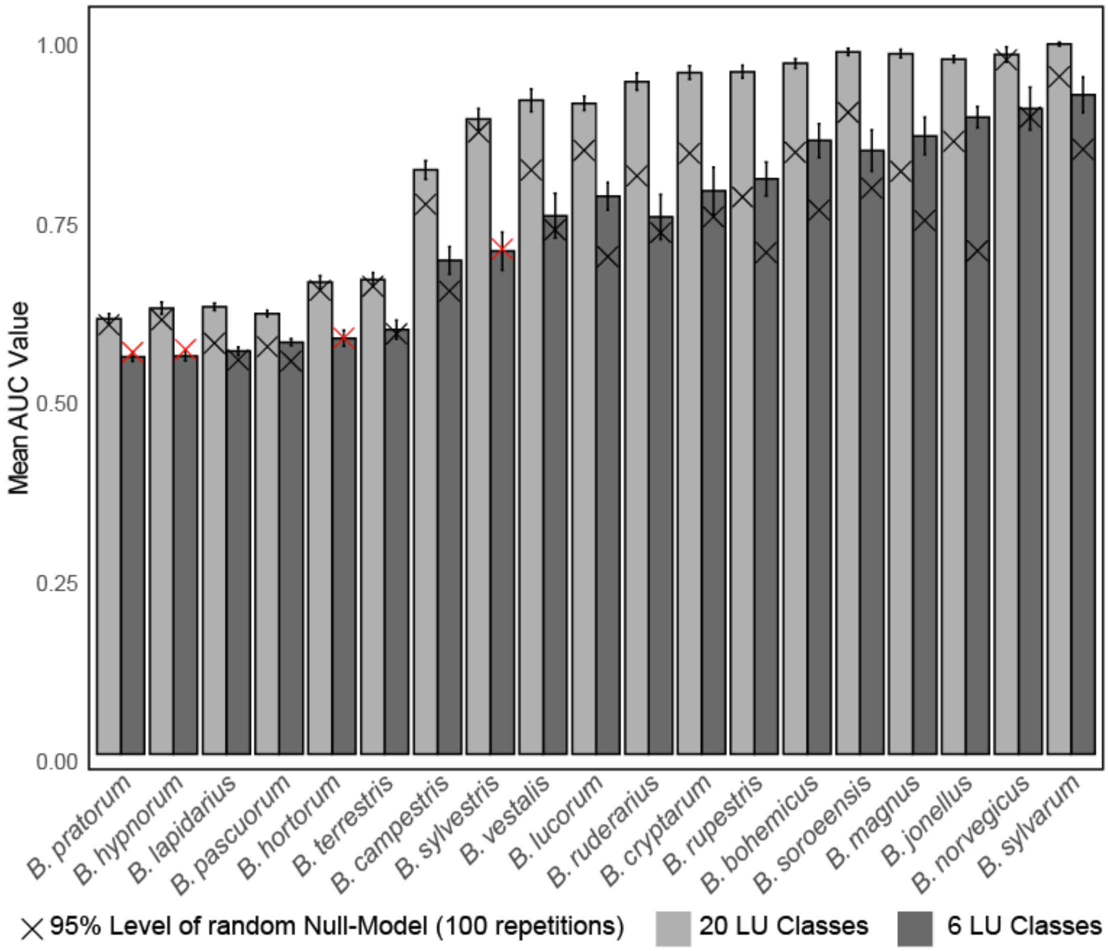


Figure 6.3 – Mean area under the curve (AUC) of the receiver operating curve (ROC) value after 50 runs for 19 Belgian Bumblebee species when modelling with 20 and 6 land use classes. The X indicates the 95th percentile values of AUC from 100 random null models and is used to test model performance. The 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).

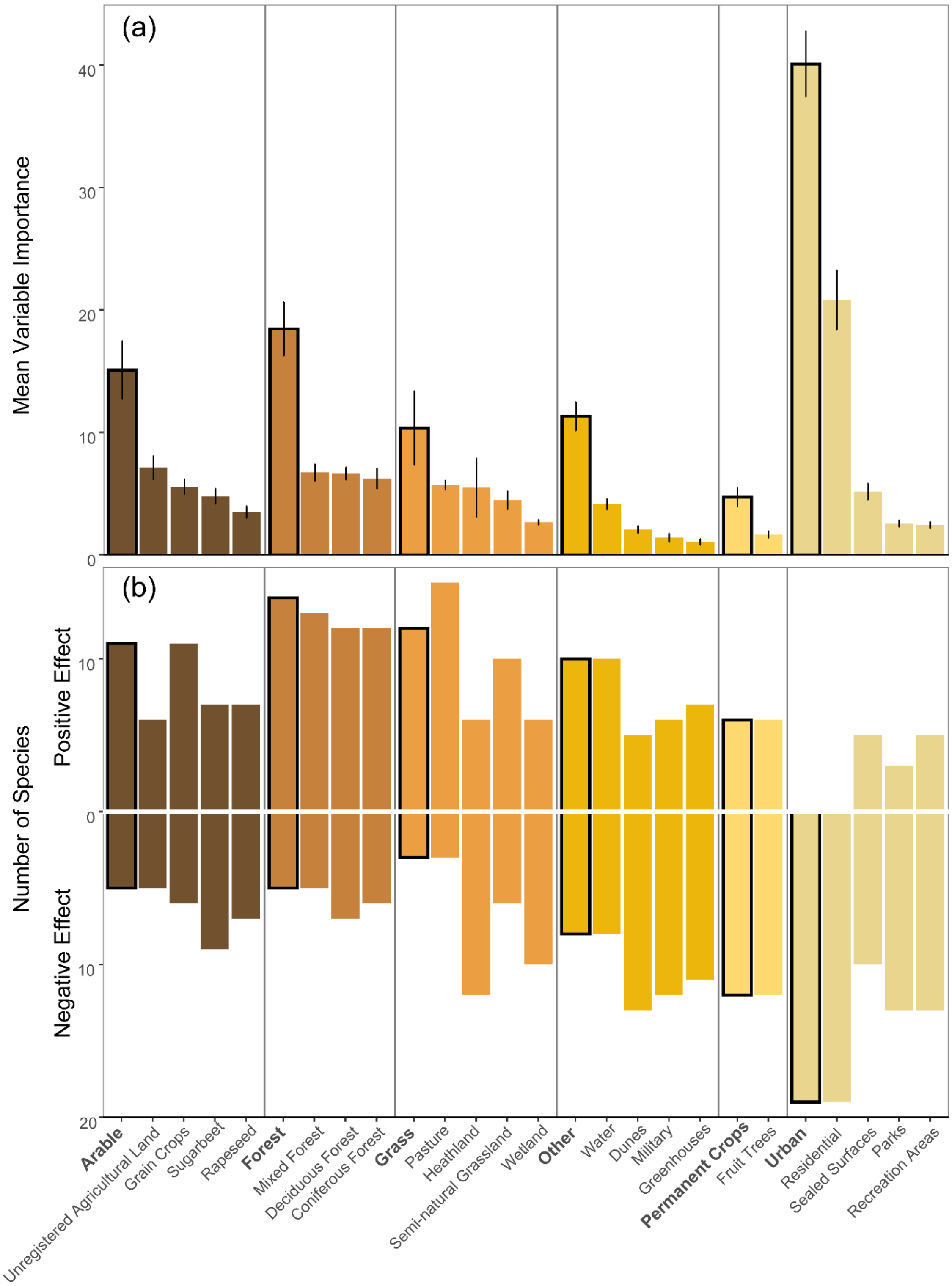


Figure 6.4 – The mean variable importance and the effect of the different land use classes considered, both for the low (framed in black) and the high (framed in white) thematic resolution input.

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.

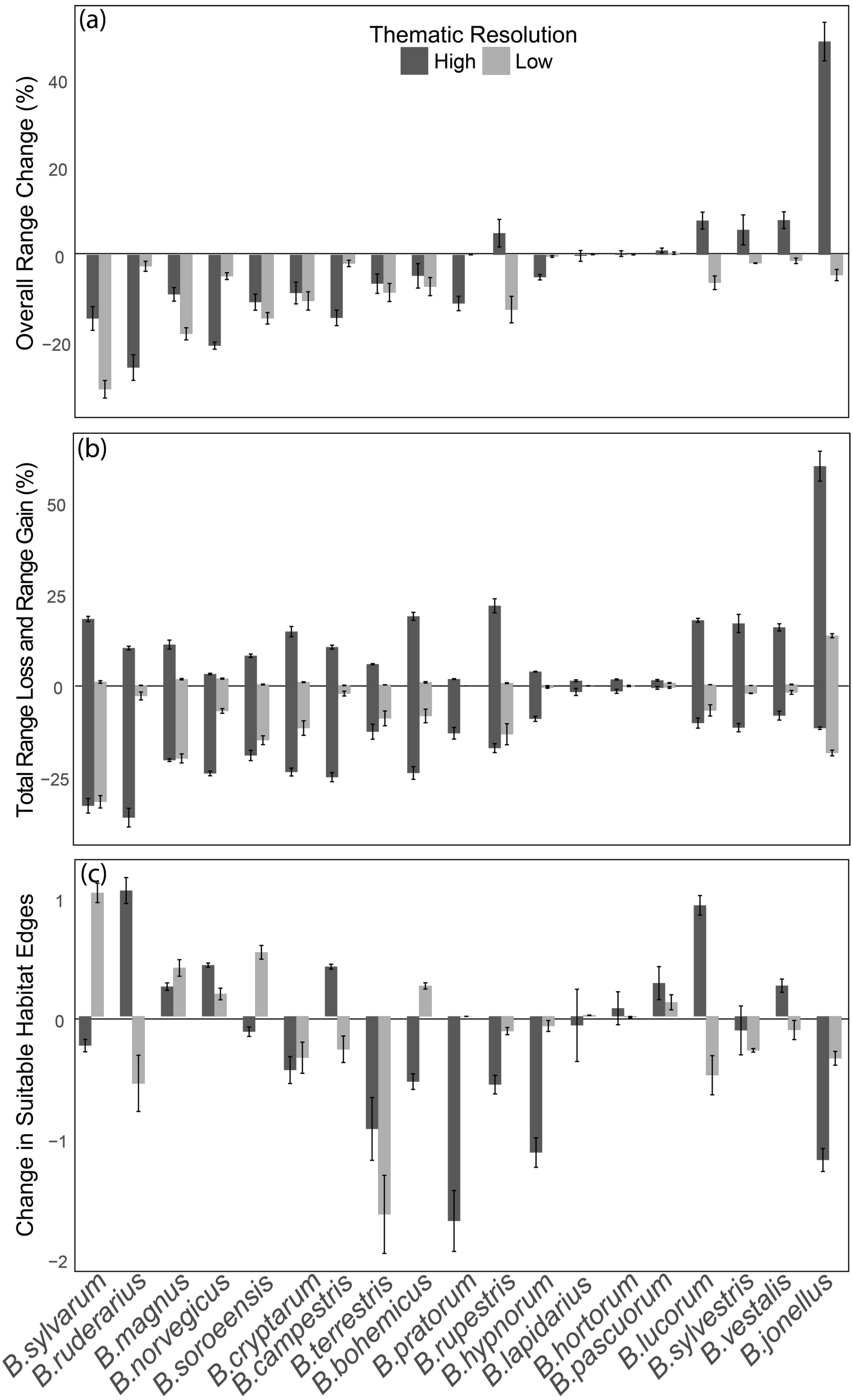


Figure 6.5 – The change in distribution parameters for the different bumblebee species, for both high and low thematic resolution with the differences between the scenarios indicated through a plot of the standard deviation.

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).

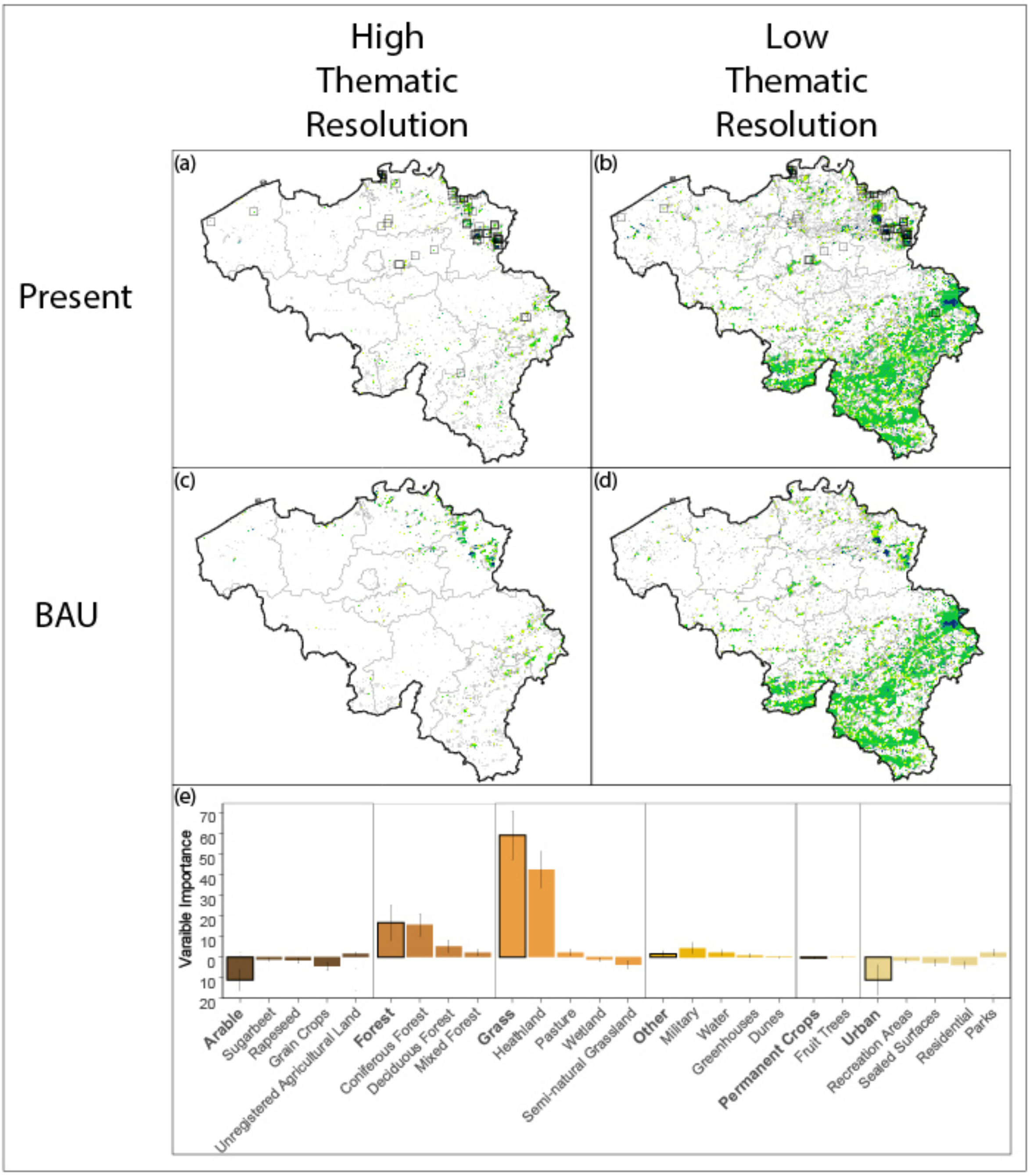


Figure 6.6 – The modelled distribution of B. magnus for both high and low thematic resolution and in the present and for the BAU scenario in 2035, together with the importance of each land use variable to explain the distribution of the species. The inset in figure b shows where the species was collected.

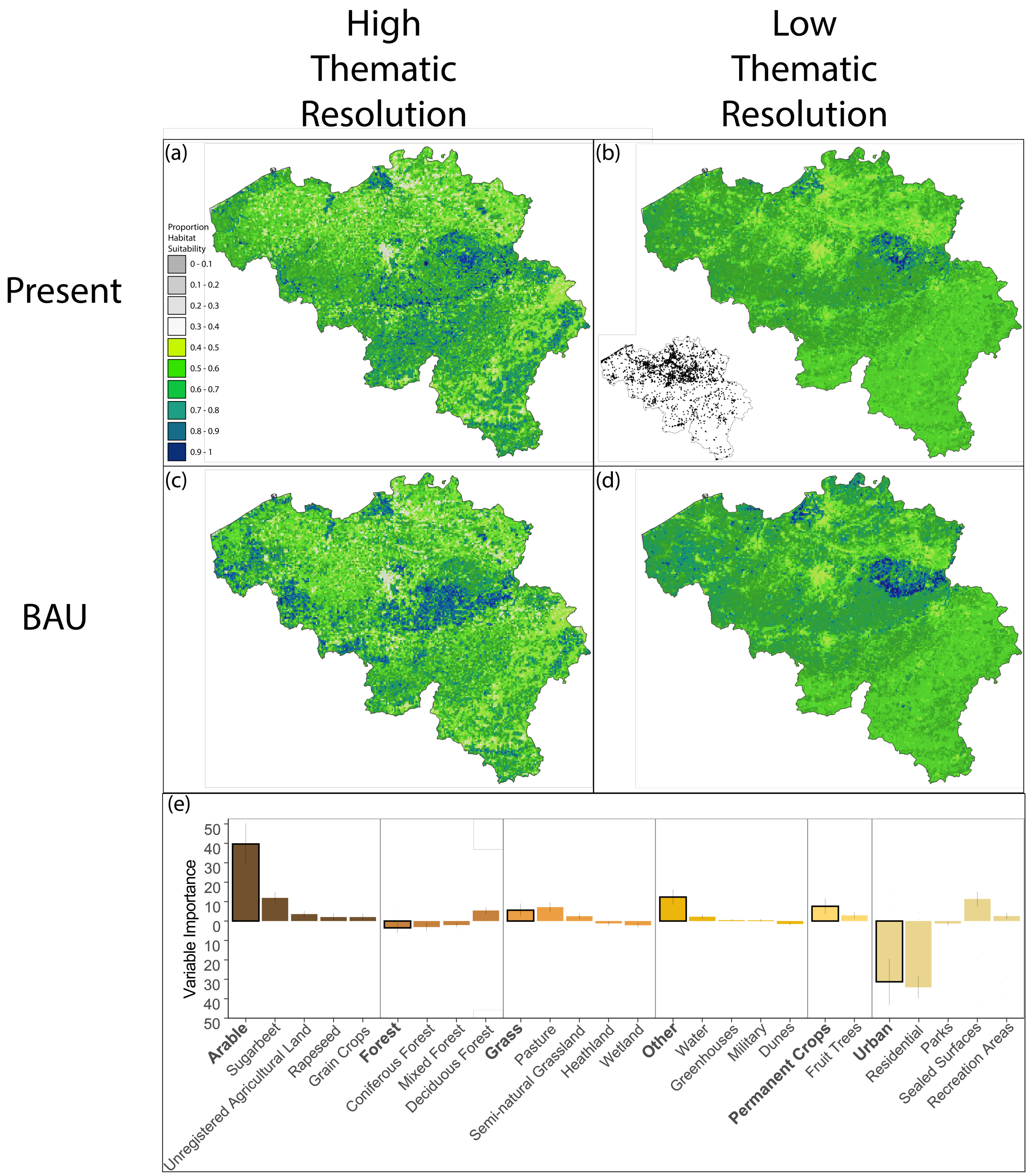


Figure 6.7 – The modelled distribution of B. lapidarius for both high and low thematic resolution and in the present and for the BAU scenario in 2035, together with (e) the importance of each land use variable to explain the distribution of the species. The inset in figure b shows where the species was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