A travel time-based variable grid approach for an activity-based cellular automata model

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Urban growth and population growth are used in numerous models to determine their potential impacts on both the natural and the socio-economic systems. Cellular automata (CA) land-use models became popular for urban growth modelling since they predict spatial interactions between different land uses in an explicit and straightforward manner. A common deficiency of land-use models is that they only deal with abstract categories, while in reality several activities are often hosted at one location (e.g. population, employment, agricultural yield, nature…). Recently, a multiple activity-based variable grid CA model was proposed to represent several urban activities (population and economic activities) within single model cells. The distance-decay influence rules of the model included both short- and long-distance interactions, but all distances between cells were simply Euclidean distances. The geometry of the real transportation system, as well as its interrelations with the evolving activities, were therefore not taken into account. To improve this particular model, we make the influence rules functions of time travelled on the transportation system. Specifically, the new algorithm computes and stores all travel times needed for the variable grid CA. This approach provides fast run times, and it has a higher resolution and more easily modified parameters than the alternative approach of coupling the activity based CA model to an external transportation model. This paper presents results from one Euclidean scenario and four different transport network scenarios to show the effects on land-use and activity change in an application to Belgium. The approach can add value to urban scenario analysis and the development of transport- and activity-related spatial indicators, and constitutes a general improvement of the activity based CA model.

Keywords: cellular automata; activity-based modelling; land-use change; urban growth; multimodal transportation networks

1. Introduction

Population growth and urbanisation put increasing pressure on both natural resources and the quality of the urban environment. This phenomenon occurs predominantly in rapidly developing countries (United Nations 2013), as well as in suburban areas with a poor

spatial planning history (Ravetz et al. 2013). Therefore, urban modelling continues to be a key research topic not only at the global scale (Lambin and Geist 2006), but also at the regional scale in land-use modelling (e.g. Barredo et al. 2003, de Kok et al. 2012), and in all sorts of environmental studies (e.g. Geertman and Stillwell 2009, Van Steertegem et al. 2009, Hansen 2010).

Many types of models have been developed (Batty 2005, Haase and Schwarz 2009), including land-use and transport interaction (LUTI) models (Wegener 2004, Chang 2006, Iacono et al. 2008), multi-agent systems (MAS) (Bura et al. 1996, Parker et al. 2003, Matthews et al. 2007, Gilbert 2008) and cellular automata (CA) models. CA models have become popular for studies of land-use change in urbanised areas because of their simplicity and flexibility (Santé et al. 2010) and their ability to simulate realistic urban patterns by incorporating path dependence and self-organisation (Poelmans and Van Rompaey 2010). Recent applications include Engelen et al. (2007), Almeida et al. (2008), Stanilov and Batty (2011), de Kok et al. (2012), Aljoufie et al. (2013), and Fuglsang et al. (2013).

Most urban models, including CA models, focus on the rather abstract and categorical concept of land-use change. Each unit is in one dominant land-use state at each time step in the simulation interval. However, in the real world, many urban zones are characterised by mixed land uses (e.g. residential and commercial functions). In regions with extensive urban sprawl, like Flanders, Belgium, where ribbon development is common, urban and non-urban functions also become mixed, turning agricultural and natural areas into highly fragmented landscapes (Poelmans and Van Rompaey 2009). MAS capture the interaction between different types of activities in a direct way, but need a huge amount of data to realistically represent the agents and their spatial behaviour (Parker et al. 2003). They are also computationally very heavy, especially for running

simulations on large study areas, which can only be solved by aggregating agents into 'super-individuals' and resorting to parallel computing (Parry and Bithell 2012). A more straightforward solution for this is to introduce activities and their interactions into the simple but efficient grid structure of a CA model. Then a list of all activities that are present in each cell of the model provides an appropriate description of the complexity of land use in both dense urban areas and regions with urban sprawl.

Urban CA models rely in the first place on distance-dependent interactions among land uses to predict the future development of urban regions. These are captured in the neighbourhood effect. The neighbourhood effect is calculated by means of influence functions that define the effect of each cell in the neighbourhood on the cell for which the neighbourhood effect is being calculated — i.e. the focal cell — where that effect depends on both the distance and the state of the cell. The contributions of all cells in the neighbourhood are summed to get the neighbourhood effect on the focal cell. A neighbourhood effect is calculated for each possible state that the focal cell could have. Traditionally, neighbourhoods are small and only capture short-distance effects up to a maximum of 1 km. Some modellers tackle this problem by coupling the CA component to a regional gravity-based spatial interaction model of the economy and population (e.g. Engelen et al. 1995, White and Engelen 2000, Engelen et al. 2007, Lauf et al. 2012). However, the coupling of such a macro model with a CA model has several disadvantages: additional parameters are needed to link the models, the regions may be large but each is represented by a single point, typically the centroid, not all levels of spatial interaction are represented, and finally it is still impossible to have several activities in a single CA cell (White et al. 2012). A solution is to change the topology of the CA model, which has an influence on its dynamics (Baetens et al. 2013), so that long-distance effects can be efficiently included.

Andersson et al. (2002a, 2002b) introduced a variable grid representation of the cell neighbourhood in order to make it computationally feasible to expand the neighbourhood to include the entire modelled area, so that all cells could have an effect on the possible land use of each individual cell. White (2006) extended the variable grid approach by including activities in it: both land uses and their associated activities are represented and forecasted for each individual cell. For the purpose of calculating the neighbourhood effect, cells, and their associated land uses and activities, are aggregated into increasingly large supercells the greater the distance from the focal cell. The expansion factor is three, which gives a set of nested Moore neighbourhoods. In other words, supercells consist of 3^{2L} unit cells and have a resolution of 3^L times the resolution of the modelling grid, where L, an integer, is the level number of the variable grid (Figure 1). In the cell neighbourhood, only the cells belonging to the immediate Moore neighbourhood (L = 0) have the unit cell resolution. This approach keeps calculations fast and simple.

[Figure 1 about here]

Other work further developed these concepts: van Vliet et al. (2009) discuss the use of a variable grid approach for land-use change only, van Vliet et al. (2012) tested an activity-based model without a variable grid, while White et al. (2011) applied the full approach to the Dublin region. In van Vliet et al. (2012) and White et al. (2011), only one activity type is considered in each cell, consistent with the dominant land use. White et al. (2012) introduced a multiple-activity CA model that can really deal with multifunctional land use, where each cell has values for all activity types considered in the model. Initial results obtained with this model seem promising, yet some challenges remain unsolved. One striking simplification in all variable grid approaches proposed to date is that simple Euclidean distances are used in the influence rules of a neighbourhood

with a size of sometimes several hundred kilometres instead of travel times generated by a transport model component.

Many studies have shown that transport and land use are strongly interrelated systems, but the nature of the relation is often debated. Both the road system and the public transport system influence and are influenced by the land-use characteristics of urban areas and their related activity patterns. The standard work of Newman and Kenworthy (1989) suggested a negative relationship between population density and energy use in transportation. Although this work has been criticised as being simplistic (van de Coevering and Schwanen 2006), other authors have also found statistical relationships between the urban structure, activities, access to public transport and commuting patterns (e.g. Sohn 2005, Schwanen and Mokhtarian 2005, Næss 2010, Fuglsang et al. 2011). Attitudes (e.g. Handy et al. 2005) as well as socio-economic characteristics of a country or region, such as income and fuel prices (Giuliano and Dargay 2006), have also been found to be important. Hansen (2009) used a raster-based approach to show that many new residential and industrial areas in Northern Denmark have high accessibility to existing towns, and for industry also to motorway exits. In regions with much sprawl, however, it is almost impossible to build a public transport network with a high competitiveness and efficiency; nevertheless, public transport can influence dynamics within and between city centres (Camagni et al. 2002). The reality is without any doubt complex, and to some degree specific to countries or regions.

Over the past decades, a considerable number of LUTI models have been developed. According to Wegener (2004), most of these models describe the link between slowly changing systems (land use, networks and buildings), fast changing systems (activities) and immediate changes (transport as such). Hagen-Zanker (2012) compared the standard CA model of White et al. (1997) with well-known examples of LUTI models

— in particular MEPLAN (see e.g. Echenique 2004) and UrbanSim (Waddell 2002). He concluded that although these three modelling strategies are fundamentally and computationally different, all of them may lead to similar results if their weaknesses are overcome. Unlike LUTI models, most CA models do not have an intrinsic economic or transport component. An activity-based model includes economic activities, but should still be improved by taking transport into account.

Some LUTI models are linked to a stand-alone transport model, others have their own transport subsystem. Aljoufie et al. (2013) coupled a CA-based land-use model, developed with the Metronamica framework and thus based on the work of White et al. (1997), to a stand-alone transport model for the city of Jeddah. The resulting generalised cost of the transport model is used as an input for the accessibility component of the land-use model. Nevertheless, the accessibility component does not directly influence the distance between cells in the influence rules. Blečić et al. (2011) incorporated distance effects directly into their CA model. They represented the short-distance CA neighbourhood effect and a long-distance accessibility effect separately in what they call a 'wave model'. Two different signals of land-use influences are propagated between cells to simulate vicinity and accessibility. Vicinity is here represented by a small-neighbourhood Euclidean influence function. Accessibility is modelled as an influence signal that gets weaker with increasing distance.

In this study, we use the model of White et al. (2012) to test how travel times can be integrated into the variable grid neighbourhood rules (except for the close neighbourhood) and show how this impacts modelling results. We define different transport network scenarios to compute these travel times with a road-based or a multimodal network. The remainder of the paper starts with a short description of the multiple activity-based variable grid CA in section 2. Next, in section 3, we explain our

methodology to define travel time-based distances for the influence rules of the model. In section 4, we apply this methodology to the case of Belgium, and define a 'Euclidean scenario' and four 'network scenarios'. In section 5, we compare the results obtained with the various transport scenarios. This is followed by a discussion in section 6, including suggestions for future research, and a short conclusion in section 7.

2. A multiple activity-based variable grid cellular automaton

The modelling approach proposed by White et al. (2012) constitutes a multiple activity-based cellular automaton. It makes use of active, passive and static land uses. Active land uses change directly as a result of CA dynamics as forced by exogenous demands: these are land uses such as residential, industrial or commercial. Passive land uses, such as various agricultural or natural land-cover states, change as a consequence of the dynamics of the active land uses — they are taken over or abandoned by active land uses. Static land uses, like water and parks, cannot change state and are not subject to the CA dynamics, though may affect it. By definition, there exists a one-to-one relationship in the model between active land-use types and activity types. In an active land-use cell, primary activities are defined as those associated with the dominant land use (e.g. population in residential land use). However, each cell can also have non-zero values for activities that are primarily associated with other land uses (e.g. employment in residential land use). Such activity is referred to as secondary activity. Passive and static land-use categories have no associated primary activity, but may host secondary activities; for example, agriculture cells may have a resident population.

Several factors are incorporated in the model to determine future activity values, with the neighbourhood effect being the most important one. Within the variable grid approach this effect contains the influence on a cell of all activities throughout the entire study area. The Euclidean distance d_{ij} between the centroid of a focal unit cell i, for which

the neighbourhood effect is being calculated, and the centroid of one of its variable grid neighbour cells j can only have specific discrete rook or bishop values since the resolution of variable grid cells increases by a factor of 3 for each level. Therefore d_{ij} can only be R, $\sqrt{2}$ R, 3R, $3\sqrt{2}$ R, etc., with R being the resolution of the CA grid — i.e. the size of a unit cell in the grid. Next, the weights W of the influence functions (Figure 2) are expressed in the model as functions of log-base 3 cell distances L_{ij}:

$$L_{ij} = \log_3(d_{ij}/R) \tag{1}$$

$$W_{JK,dij} = f_{JK}(L_{ij}) \tag{2}$$

where $W_{JK,dij}$ is the weight given by the influence function f_{JK} for the influence of activity J on activity K at distance d_{ij}. The possible rook or bishop values of L_{ij} are then 0, 0.315, 1, 1.315, etc.

 [Figure 2 about here]

The activity potential V_{Ki} for an activity K on a cell i for the next time step is calculated as:

$$V_{Ki} = r \ Z_{Ki} \ X_{Ki} \ S_{Ki} \ N_{Ki} \tag{3}$$

where r is a random perturbation term, Z_{Ki} is the zoning status for activity K on cell i, X_{Ki} is a measure of accessibility to the transport network for activity K on cell i, S_{Ki} is the suitability of cell i for activity K, and N_{Ki} is the neighbourhood effect. The random perturbation, which is necessary to account for the possible differences in actor behaviour, is drawn from a highly skewed distribution, so that most perturbations are very small. A fixed seed is used in the random generator to make different scenarios comparable. The neighbourhood effect N_{Ki} on cell i for activity K is a function of the influence weights:

$$N_{Ki} = \Sigma_J \Sigma_j W_{JK,dij} (A_{Jj} / A_J) \qquad (4)$$

where A_{Jj} is the total activity J on cell j, and A_J is the total activity J in the study area.

Next, the land-use transition potential VT_{Ki} for the associated active land use U_K on cell i is calculated as:

$$VT_{Ki} = D_{Ki} (V_{Ki})^{mK} + I_K \qquad (5)$$

where D_{Ki} is a factor representing diseconomies of agglomeration, accounting for the effect of congestion and high land prices on location decisions, m_K is a parameter to be calibrated for each activity K, and I_K is the inertia value for activity K, representing the tendency of land uses and activities to remain fixed because of relocation costs. Cells are ranked based on their largest land-use transition potential, and subsequently get the land use for which they have the highest potential until the number of cells demanded by the input scenario for each land use U_K is met.

The input scenario also defines the total amount of activity K to be located at each time step. A parameter Q_K determines the proportion to be distributed as primary activity on the associated land use U_K. The allocation of primary activity to the cells with the associated land use is in proportion to the activity potential V_{Ki}. The remainder of activity K is distributed to cells of the other land uses as secondary activity on the basis of activity potentials, as modified by compatibility factors representing the compatibility of activity K with the various land uses. Several rescaling operations are necessary to keep all activity totals and proportions consistent. For a full description of the model, the reader is referred to White et al. (2012).

3. Travel time computations within the Variable Grid CA

White et al. (2012) observed that the calibrated neighbourhood influence rules in their

activity-based variable grid CA model divide naturally into two parts: an inner zone with a radius of approximately 1 km, where the influence weights decrease rapidly with increasing distance, and the rest of the study area, where the weights decrease slowly as a function of distance. This can be seen in Figure 2. Therefore, in incorporating network-based distances in the activity-based CA model, we decided to deal with the immediate neighbourhood of a location and more distant areas in different ways. In our approach, the classic Euclidean concept of vicinity still holds for distances within the range of a local CA neighbourhood of approximately 1 km radius, as used in the MOLAND modelling framework (Engelen et al. 2007). For long-distance interactions, however, we introduce time distances through the network. To make this dual approach compatible with the variable grid, the point at which the transition between Euclidean and network distances occurs needs to be between two levels of the variable grid. The level at which the network distances are introduced will be referred to as the network grid level or level L_{NG}.

This approach, tailored to the specific requirements of the variable grid CA, is more effective than the alternative of coupling the variable grid CA to a transportation model to provide the required travel time distances. It can offer higher resolution than a typical transport model and thus more accurate distances, while requiring fewer distances to be stored in memory. As an internal algorithm it gives fast run times if updates are desired during the simulation, or if the modeller wants to execute a full model calibration, including transport-related parameters.

Nevertheless, calculating travel times and simulating travel behaviour between a number of widely separated points involves a reasonable amount of computation time. For polygon-based modelling approaches, adaptive zoning can be an alternative approach (Hagen-Zanker and Jin 2012, 2013). This technique groups polygons systematically and

thereby develops a new zone map for each origin with small zones nearby and larger zones further away, based on the idea that exact locations are less important for long-distance interactions. Essentially, the same reasoning lies at the basis of the variable grid approach. Some studies have even investigated whether network distances, represented by a weighted l_p norm, are just mathematical functions of Euclidean distances (e.g. Berens 1988, Brimberg et al. 2007). Although these studies led to interesting results for some regions, especially for cities with rectangular road patterns, we believe that these results are not relevant to our model, which must be applicable to a wide variety of network configurations.

Therefore, we define a fixed grid zone system that consists of supercells of a specific level, L_{NG}, but unlike the template of supercells in the variable grid itself, it is not displaced as we move from one unit cell to another. We call this the network grid, or NG, and its cells the network grid cells, or NG cells. It has resolution $R_{NG} = 3^{L_{NG}} R$, where R is the resolution of the unit cell grid. Note that the resolution R_{NG} is equal to the size of the immediate neighbourhood in which the Euclidean distance calculation is applied.

The network time distance between a unit (L = 0) cell within a fixed NG cell and the centroid of a distant supercell (L $\geq$ L_{NG}) is then taken to be the network distance between the centroid of the NG cell containing the unit cell and the centroid of the NG cell containing the centroid of the supercell (Figure 3). We call the NG cell containing the unit cell the origin of the transport computation, and we call the NG cell containing the centroid of the supercell the destination. As already indicated, we only have to store network distances between specific needed combinations of NG cells. The only needed 'destinations' for an 'origin' NG cell are exactly the centroids of all the variable grid neighbour cells of the central unit cell of an NG cell with L $\geq$ L_{NG}. Therefore, the results can be stored as an $8 \times (L_{max} - L_{NG} + 1) \times N_{NG}$ matrix, where 8 is the number of possible

directions (top, top right…), L_{max} is the highest needed level number of the variable grid, and N_{NG} is the total number of NG cells. The storage size is significantly smaller than a N_{NG} x N_{NG} matrix, since the value of L_{max} is, even for large regions, often only 6 or 7.

[Figure 3 about here]

Some supercells will lie partly outside the area being modelled. Since it does not make sense to calculate distances to points outside the study area, an algorithm was developed to determine the centroid of that part of the supercell that is within the study area. The NG cell containing that centroid is then used to determine the network distance.

For the sake of generality and realism the network used to calculate travel times can be a multimodal one. The one used here has two components: the road network, and public transport — specifically rail in the current application (Figure 4). Both components can be combined to generate weighted time distances, or one specific component can be selected. If roads only are used, the weights are respectively 1 and 0. For public transport, however, displacements are always multimodal since the road network must in general be used to reach a station. These access times by road are calculated with the road network component. Finally, a Euclidean displacement corresponding to a low speed, which we call the Euclidean speed, is added to reach the nearest point in the road network. Note that this Euclidean travel time is treated as part of the network distance. To this are added the Euclidean travel times from the origin unit cell to the centroid of the origin NG cell, and from the centroid of the destination NG cell to the centroid of the destination variable grid supercell. The road network itself has known speeds for all road segments, while the public transport network is characterized by an origin-destination travel time matrix, with the origins and destinations being stations on the network.

[Figure 4 about here]

In the road network component, we calculate network travel times with the shortest path algorithm of Dijkstra (1959), applied to all needed origins. We verify whether travelling on a straight line between the two NG centroids at low speed — the 'Euclidean speed' — is indeed slower than travelling to and then through the network. This verification is especially important in cases where the road network consists of major roads only, and the Euclidean distance can be used to represent a more direct route using minor roads that are not included in the network.

The public transport component is mainly designed for rail travel but can also be used for local public transport. In either case, the calculation of effective travel times through the network requires data on (1) average travel time, and (2) frequency of service between each pair of stations on the network. Frequency of service is defined as the total number of possible connections between the stations per hour, either direct or indirect, but earlier departures should not result in later arrivals. The frequency is used to add a penalty to the average travel time, where the penalty is inversely proportional to the frequency. Finally, the road network travel times to reach the stations from the origin and destination centroids in the network grid are added. Thus the multimodal travel time is given by:

$$t_{m,ij} = t_{p,ab} + C / f_{ab} + t_{r,ia} + t_{r,bj} \qquad (6)$$

where $t_{m,ij}$ is the multimodal transport time between two NG cells i and j, $t_{p,ab}$ is the average public transport travel time between the departure station a and the arrival station b, C is the frequency penalty parameter, f_{ab} is the frequency of service between stations a and b, $t_{r,ia}$ is the road travel time from the origin NG cell i to the departure station a, and $t_{r,bj}$ is the road travel time from the arrival station b to the destination NG cell j.

As already indicated, the travel time distance is a weighted average of the various travel times — specifically road and multimodal in the present case. We include the

possibility of giving more weight to the fastest mode with the introduction of a parameter F. If $F > 0$, then it will increase the weight of the fastest mode between two NG cells, and decrease the weight of the slowest mode. Hence, the parameter introduces the option of developing scenarios where the existence of one fast travel mode between certain locations suffices to make the associated cells relatively more attractive for activities. The weighted network time t_{ij} between NG cells i and j is then calculated as follows:

$$t_{ij} = t_{m,ij} \, \frac{w_m \left(t_{r,ij}\right)^F}{w_m \left(t_{r,ij}\right)^F + w_r \left(t_{m,ij}\right)^F} + t_{r,ij} \, \frac{w_r \left(t_{m,ij}\right)^F}{w_m \left(t_{r,ij}\right)^F + w_r \left(t_{m,ij}\right)^F} \tag{7}$$

where $t_{m,ij}$ is the multimodal network time between i and j, $t_{r,ij}$ the road network time between i and j, w_m the multimodal weight, and w_r the road weight (with $w_r = 1 - w_m$). The public transport component is fully optional: by choosing $w_m = 0$, only the road network is used. If $w_r = 0$, then travelling by road towards stations is still possible, but a straight displacement at low 'Euclidean speed' is used when no station is located near one of the NG cells. This is of course a rather theoretical option to test the abilities of the model. The maximum road distance to reach a station can be specified, and it can be different for major and minor stations. A nearby major station overrides a minor one, except in a specified smaller zone around the minor station.

Travelling via a multimodal network is often slower than travelling by road, thus t_{ij} is often larger than $t_{r,ij}$, which would have an illogical effect on activity potentials of cells close to stations. Therefore, when w_m and w_r are between 0 and 1, equation (7) is only used to calculate the weighted travel time for combinations of NG cells where both cells are close to a station. For all other combinations of cells, the calculated road time is penalised proportionally to the importance of multimodal travelling:

$$t_{ij} = \frac{P}{P - w_m} \, t_{r,ij} \tag{8}$$

where P ≥ 1 is a parameter that defines how much the road time has to be penalised: the smaller the value of P, the larger the increase of the road time.

The final time distance t_{ij} can subsequently be used as an input to determine the weights in the influence functions of the CA neighbourhood effect, except for the close neighbourhood where distances are still Euclidean. This division between the close and the far neighbourhoods generates a continuity problem. The weights of the influence functions are dependent on log-base 3 cell distances, as specified by equations (1) and (2). The distance d_{ij} of equation (1) is still Euclidean if it is shorter than R_{NG}. For the longer distances, we obviously have to convert the travel time t_{ij} into a relative distance d_{ij} that is comparable with Euclidean distances since we do not want influence functions that are in two different intervals dependent on two different quantities. Because the influence weights are values that have to be calibrated for each possible cell distance, it makes sense to work with a continuous range of cell distances. Consequently, we set the shortest calculated travel time between any unit cell in the modelling area and one of its variable grid neighbours equal to the network grid resolution R_{NG}, since R_{NG} is the upper boundary of the range of Euclidean distances. Next, all the other travel times are scaled proportionally as follows:

$$d_{ij} = t_{ij} \left(R_{NG} / t_s \right) \tag{9}$$

where d_{ij} is the relative network distance between NG cells i and j, t_{ij} the calculated network travel time between i and j, R_{NG} the resolution of the network grid NG, and t_s the shortest calculated network travel time in the study area. Finally, all distances are converted with equation (1) to be expressed in logarithmic cell distances L, so that these cell distances can be used to find the corresponding neighbourhood influence weights from equation (2). For the short Euclidean distances ($L < L_{NG}$), L can only have Euclidean rook or bishop values (0, 0.315, etc.), while for the longer network distances ($L \geq L_{NG}$),

any value of L is possible. An example of a mixed Euclidean distance-decay and time distance-decay influence function can be seen in Figure 5.

[Figure 5 about here]

4. Study area and implementation

This study is a continuation of the work of White et al. (2012), which focused on the Belgian case. Hence, in this study too, we applied and tested the adapted activity-based CA model to Belgium (map: see Figure 6). Several studies have discussed the problem of urban sprawl in Belgium (e.g. Poelmans and Van Rompaey 2009, De Decker 2011) and the link between urban land use and the transport network (e.g. Vandenbulcke et al. 2009, Boussauw et al. 2012). Low land prices together with the dense road network in the northern part of Belgium have led to large areas of urban sprawl, and more specifically ribbon development along the roads (Antrop 2000). Meanwhile, the average commuting distance continues to increase because the population growth in many peri-urban municipalities is much higher than the growth of jobs, while the opposite is true for cities (Boussauw et al. 2011).

[Figure 6 about here]

Studies of both home-to-work travel and general travel in Belgium indicate that individual car travel is far more common than any other transport mode (Thys and Andries 2011, Vandenbulcke et al. 2009). A survey by the Belgian Federal Department of Transport and Mobility indicates that 67% of Belgian employees commute individually by car. Train travel is the second most used mode with 9.5%. It is especially popular for long distances (> 30 km) and for travel to large cities (Thys and Andries 2011). Thus, a road-based approach seems the most relevant for simulating distance-based interactions

in a realistic way, yet train travel towards the most important stations can improve the model significantly. As local public transport, mostly by bus, is less popular except in some cities, we have not yet included it in our analysis. Hence, we compare five different scenarios for determining distance: (1) the Euclidean distance approach of White et al. (2012); (2) road-based network distances; (3) a 'congestion' scenario, which uses road-based network distances with congestion effects in the central area of Belgium; (4) a rather theoretical 'train only' scenario with multimodal weight $w_m = 1$, which means that Euclidean paths with low speeds are used when train travel is not possible; and (5) a 'choice' scenario with road weight $w_r = 0.7$, and multimodal weight $w_m = 0.3$.

Road data come from the NAVSTREETS database for Belgium, the Netherlands and northern France, made available by the Flanders Geographical Information Agency, AGIV. We exclude the least important local roads (functional class 5) and estimate average speeds on the basis of legal maximum speeds for all road segments as provided in the database (Table 1). The 'Euclidean speed' is given a low value of 5 km/h. The 'congestion' scenario is largely based on a report of the Flemish Traffic Study Centre (Vlaams Verkeerscentrum: Hoornaert et al. 2014). It generally assumes lower speeds in the central area of Flanders between Ghent, Antwerp, Brussels and Leuven, and lower motorway segment speeds based on saturation statistics.

[Table 1 about here]

An origin-destination train time matrix could not be provided by the Belgian National Railway Company (NMBS/SNCB); therefore we reconstructed it from their website for the most important origin-destination pairs. The resulting matrix contains average travel time and frequencies per hour for weekday connections in 2013, between the 18 largest major stations (> 8000 users per weekday in 2009) and all 116 stations (major and minor) with more than 1000 users per weekday in 2009. The data can be used

to start model runs from the year 2000, since there were no major changes in the train schedule during the period 2000-2013. All missing links are handled as origin-destination pairs where travel by train is not possible. Since train commuting is mainly towards the big cities, we believe that this limited matrix covers the vast majority of the important train connections for a land-use model. After initial tests, and following observations by Thys and Andries (2011), we used a maximum distance of 10 km for the access and egress legs by car to and from train stations in multimodal travelling. A major station overrides a minor one except in the NG cell of the minor station itself.

Land-use data come from the Corine land-use / land-cover data set for 2000, which was aggregated to a 300 m grid (Figure 6). Activity maps for population and employment were reused from White et al. (2012). There are three urban categories in the Corine map that were associated with primary activities: the discontinuous urban fabric (associated with population), the continuous urban fabric (associated with 'urban' employment: wholesale, retail, hotels and catering, and finance), and industrial or commercial units (associated with all other employment). As our main aim is to assess the impact of different transport scenarios on the model outcome, and compare the results that are obtained with a simple Euclidean scenario, we ran simulations from 2000 to 2060 with the same parameters, rules, land-use area changes, and population and employment growth (Table 2) as those used in White et al. (2012), even though that paper indicated that this growth is somewhat excessive, especially for the discontinuous urban land use. However, a large land-use growth helps to visualise transport scenario differences.

Since the modelling resolution is 300 m, we could have used $L_{NG} = 1$ so that the boundary between Euclidean and network travel would be 900 m, which is close to the 'ideal' boundary of 1 km. However, in order to keep the computation time reasonable for our large study area, we chose $L_{NG} = 2$, which means that $R_{NG} = 2700$ m. With these

settings and with a 64-bit version of the software, the calculation of all needed network distances takes +/- 10 min on an Intel® Core™ i5-2520M CPU. Using another distance algorithm could still reduce the run time. The network distance calculations are normally only performed once; if the network or link speeds do not change between simulations the calculations do not need to be repeated. The land use and activity calculations take approximately 2 min for 15 years of simulation without updating the network distances. The program uses about 500 MB of RAM memory.

Initial tests were done to determine suitable values for the parameters C, F and P in equations (6), (7) and (8). We chose C = 20 min, F = 5 and P = 2, yet these choices proved to have only a limited influence on the model results. Only for extreme values, or when the parameters are omitted (C = 0 min, F = 0, P → + ∞) do the results differ significantly: yet, even then, differences are still slightly smaller than between the transport scenarios (at most, about 500 cells have a different land use; most population differences are below 1 person/km²).

[Table 2 about here]

5. Results

Land use and activities were modelled for the five transport scenarios for 2000 to 2060. To make the comparison of the resulting land-use and activity patterns of the alternative transport scenarios easier, we defined an accessibility index to produce maps of the effort needed to travel from each network grid cell towards the centroids of its variable grid neighbours in a specific transport scenario. For the network scenarios, we first calculate two sums: (1) the sum of all possible network times t_{ij} from an origin NG cell i to all the NG cells j containing the centroids of its variable grid neighbours, and (2) the sum of the associated Euclidean distances. We then define the accessibility to be the ratio of these

network and Euclidean distance sums. The very long distances towards the high-level variable grid neighbours ($L \geq 5$) were not included in the index to avoid boundary effects. Moreover, the neighbourhood effect weights for these levels are very small. To arrive at a standardised index, we replace the smallest value in the study area by 1: this is the most accessible NG cell. All larger values (less accessible NG cells) are scaled proportionally. The results for the four network scenarios can be seen in Figure 7.

[Figure 7 about here]

In the 'road-based' scenario, the north of Belgium has the best accessibility values, especially in the large cities and along the motorways (Figure 7a). The 'congestion' scenario produces a rather different pattern, with lower accessibility values in the central part of Flanders and around Brussels (Figure 7b); the best values are now situated along the motorways west and south of this region. The 'train only' scenario has a very distinct accessibility map with the best accessibility values around the most important stations, especially around Brussels (Figure 7c). The accessibility map of the multimodal scenario has a fairly similar pattern to that of the 'road-based' scenario, but logically, values are clearly worse where there is no major station nearby (Figure 7d).

In general, the predicted land-use change patterns between 2000 and 2060 are rather similar for all the network scenarios. The discontinuous residential area grows significantly in the central area of Flanders between Brussels, Antwerp and Ghent, as well as in the southwest of Flanders. This is shown for the 'road-based' scenario in Figure 8. The differences between the 'road-based' and most other scenarios are distinct but less pronounced than the overall growth pattern in all scenarios (Figures 9, 11, 13). The differences between the scenarios stand out more strongly in the activity values, especially in the population difference maps (Figures 10, 12, 14).

[Figure 8 about here]

In the road network-based model the urban growth in the central areas is slightly higher in 2060 than in the Euclidean model and vice versa for the peripheral areas (Figure 9). Most interestingly, some of the more accessible cells in the peripheral areas also become residential. Although the general pattern in the population difference map is harder to discern, the population values are somewhat higher next to major roads as well as in the centres of the major cities (Figure 10).

[Figure 9 about here]
[Figure 10 about here]

The residential land-use difference map between the scenarios without and with congestion clearly shows that the model is sensitive to network speed differences (Figure 11). The population growth is also smaller in the suburban regions of central Belgium in this 'congestion' scenario (Figure 12). The 'train only' scenario leads to some remarkable but logical differences, with much more residential growth in central areas that are more accessible to rail stations (Figure 13). The differences in population compared with the 'road-based' scenario show a reasonable pattern with more population not only in the 'train only' scenario in big cities but also around smaller stations with good connections to big cities. Rural areas, as well as some areas near smaller stations lacking good connections with the centre of Belgium (e.g. in West Flanders), gain less population (Figure 14). The 'choice' scenario produces growth patterns similar to those of the 'road-based' scenario. Only some slight differences can be noted, such as somewhat higher population values in big cities.

[Figure 11 about here]
[Figure 12 about here]

[Figure 13 about here]

[Figure 14 about here]

6. Discussion

The transport component of the activity based CA model discussed in this paper is a useful extension of the original version of White et al. (2012) for studying the influence of existing and evolving transport networks on land-use dynamics. The accessibility measure used in the original model, X_{Ki} in equation (3), was based on a weighted Euclidean distance to reach the network from a cell, and thus represented only a cell's accessibility to the transport network, rather than its general accessibility to the region. The new model individually computes the anisotropic accessibility of a unit cell towards its supercells and saves it in a structure adapted to the variable grid. The structure of the distance grid is more independent of urban development than a population-based zone system, as often used in transport models (e.g. the model of the Flemish Traffic Study Centre). This is an advantage in less-populated areas, which are important for future development, but can be a disadvantage in current urban areas. Nevertheless, more detailed zones are possible in our model with a lower network grid level L_{NG}. Moreover, we define useful parameters to enhance an easy definition of long-term transport scenarios with different modes within an activity and land-use modelling context.

The transport scenarios indeed generate different results, both in terms of land use and activity patterns. The 'congestion' and the 'train only' scenarios lead to pronounced differences compared with the 'road-based' scenario. In places where the value of the accessibility index is clearly higher for the 'congestion' scenario (worse accessibility), less land is converted to urban land uses, and the population growth is significantly smaller (Table 3). Cells that have slightly worse accessibility in the central areas seem to attract more people and urban land use. This is logical as the population and land-use

growth were fixed, and other mechanisms in the model normally produce the largest growth in those central areas. The same conclusions largely hold for the 'train only' scenario in comparison with the 'road-based' scenario (Table 4). The best locations in the 'train only' scenario are those close to large stations, and those are often already built-up. New space for urban development is limited. Nevertheless, the model predicts substantial densification, since almost 100,000 extra people (or 160 per km²) are allocated to these areas, compared to the 'road-based' scenario. The regions around these areas also gain extra residential land use and population, while there is clearly less growth in remote areas far from stations. Obviously, the 'choice' scenario is, by definition, much more realistic than the theoretical 'train only' scenario, yet its results do not differ much from those of the 'road-based' scenario (Table 5). This is clearly caused by the values of the modal weights w in the 'choice' scenario, but we chose these values because it is reasonable that the road network plays the most important role in allocating new land uses, especially in the many suburban villages and ribbon developments of Belgium. In comparison with the 'road-based' scenario there is a slightly higher population growth near the most important stations. On the contrary, residential land-use growth is slightly greater near the edge of these cities in less accessible cells of this scenario. This may seem contra-intuitive but it is caused by the attraction effects of the model since there is no space for urban growth very close to major stations.

[Table 3 about here]
[Table 4 about here]
[Table 5 about here]

Although the variable grid provides a good computational framework for activity predictions in large study areas, network distance calculations can be further improved. Firstly, in the approach described in section 3, distances are measured between centroids

of NG cells, of which one may represent the centroid of a larger variable grid supercell. The latter might not be representative of the location of the activities within the supercell. Hence, the logical next step is to represent each supercell by a centre that reflects the actual distribution of activity within the supercell. Initial tests of this approach are generally positive, but more work is necessary to define the best way of implementing it. Secondly, the access and egress legs in the multimodal computations can be made more realistic, since in home-to-work travel there is often a very short leg at the work end of the displacement (Thys and Andries, 2011). Because of the symmetry of the variable grid, such an asymmetric approach has not yet been implemented.

Extra details could also be included in an improved transport-based model, such as different modal weights w for different regions of the study area, or transport networks evolving over time. The functionality to introduce changes to the network at specified time steps during a simulation is already implemented, but has not been used due to a lack of data. Since Belgium already has a dense network, there are likely to be few additions to the network, but a growing population and increased congestion could reduce travel speeds in the future, and road characteristics could change. Congestion scenarios of transport models can therefore provide useful input for the model. It would be an interesting exercise to couple our activity based CA model directly to a transport model in order to get simultaneous predictions of activities, land uses and transport for the future. On the other hand, we fear that a direct coupling would increase the computation time drastically.

Finally, in a more complete and general sensitivity analysis it would be interesting to examine how parameters, rules and functions of the activity based CA could be adapted, added or removed to improve the model. For instance, the accessibility component of the earlier CA models using Euclidean distances seems to have less

influence in the network-based implementation, and so it might be redundant. Additionally, it would be interesting to use a generalized cost measure of distance. Such a measure would enable the model to be used to investigate the effects of a subsidised, and hence cheaper, public transport in comparison with congestion pricing schemes for the road network.

7. Conclusion

The activity-based CA model of White et al. (2012) was a big step forward in comparison with earlier CA models, since every cell is modelled as a truly multifunctional environment where people live and work. Future versions of this model could even include agricultural yield or natural activities as a complement to the current, predominantly urban activities. In this study, we developed an activity-based CA model with travel time-based interaction rules for long-distance interactions, and simple Euclidean distance-based rules for the local vicinity interactions. The network-based rule sets for the model are clearly more realistic and provide the possibility to test different transport scenarios. The impacts of road congestion and public transport usage on land-use and activity futures can be evaluated with the proposed approach, and possibly new spatial indicators could be derived to clearly display these impacts.

Nevertheless, the new version of the model still has some shortcomings. The variable grid could be adapted by defining activity centres as the representative locations of large variable grid cells, of which some can only be reached by road and others both by road and public transport. Furthermore, more critical assessment, calibration and sensitivity analysis are needed to confirm that all its current components are useful and necessary, and to update parameters and rule sets.

The application to Belgium is interesting since the country could benefit from more public transport usage to reduce future urban sprawl. Therefore, we intend to

continue this work with a historical calibration exercise to validate and improve the model. Enhanced model versions could be used to promote sustainable land-use scenarios and provide the relevant decision-makers with better insights into the coupled problems of growing congestion and urban sprawl.

Acknowledgements

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Table 1. Average modelling speeds for road segments in km/h.

Link type	Legal max. speed (reality)	Average speed (model)
Motorway	120	100
Express road, urban motorway	90-100	85
Major road	90	70
Secondary road	70	55
Local road	50	40
Urban low speed zone	30	30
'Euclidean speed'	-	5

Table 2. Land-use and activity growth scenarios, and parameter values of the application to Belgium that were copied from White et al. (2012).

Active land use or activity	Value in 2000	Value in 2060
Discontinuous urban fabric (cells)	56,051	101,741
Continuous urban fabric (cells)	527	570
Industrial or commercial units (cells)	5540	6000
Population	10,251,249	12,662,761
'Urban' employment	855,822	891,061
Other employment	3,140,781	3,850,000

Table 3. Comparison in 2060, in terms of discontinuous residential land use and population, between the 'road-based' scenario ('R') and the 'congestion' scenario ('C'). The classes are defined by relative accessibility index values (division of 'congestion' and 'road-based' index values).

Relative accessibility (C / R)	Total area (km²)	Population density difference ((C – R)/km²)	Discontinuous residential in 2060 (cells)		
			R only	Both scenarios	C only
< 0.97	9493	3.11	192	12911	222
0.97 – 1	6731	9.80	89	19349	516
1 – 1.15	8746	8.03	572	36577	1276
> 1.15	5692	- 29.11	1806	30245	645

Table 4. Comparison in 2060, in terms of discontinuous residential land use and population, between the 'road-based' scenario ('R') and the 'train only' scenario ('T'). The classes are defined by relative accessibility index values (division of 'train only' and 'road-based' index values).

Relative accessibility (T / R)	Total area (km²)	Population density difference ((T – R)/km²)	Discontinuous residential in 2060 (cells)		
			R only	Both scenarios	T only
< 1	597	160.62	5	4140	384
1 – 2	5774	53.96	551	24242	2370
2 – 3	14408	- 11.13	4325	41484	5163
> 3	9881	- 25.01	3962	23032	926

Table 5. Comparison in 2060, in terms of discontinuous residential land use and population, between the 'road-based' scenario ('R') and the 'choice' scenario ('Ch'). The classes are defined by relative accessibility index values (division of 'choice' and 'road-based' index values).

Relative accessibility (Ch / R)	Total area (km²)	Population density difference ((Ch − R)/km²)	Discontinuous residential in 2060 (cells)		
			R only	Both scenarios	Ch only
< 1	2012	4.80	200	12352	8
1 – 1.04	4241	0.98	289	20446	89
1.04 – 1.08	8984	- 1.02	303	37163	376
> 1.08	15424	- 0.30	100	30888	419

Figure 1. Structure of the variable grid.
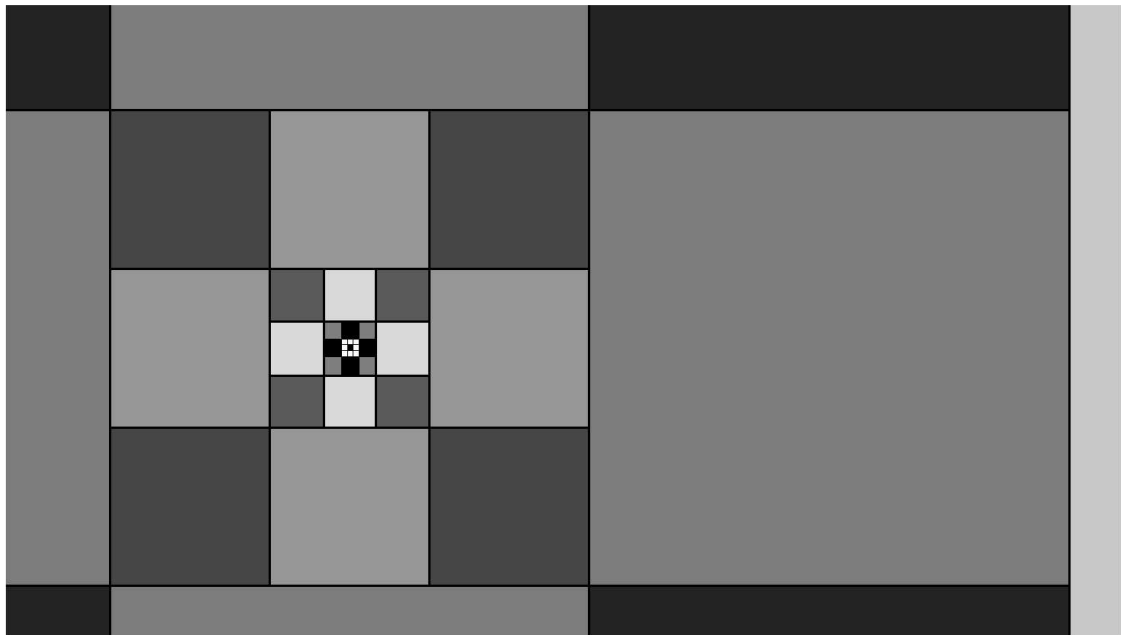
Figure 2. Example of a neighbourhood influence function for the variable grid activity based CA model.
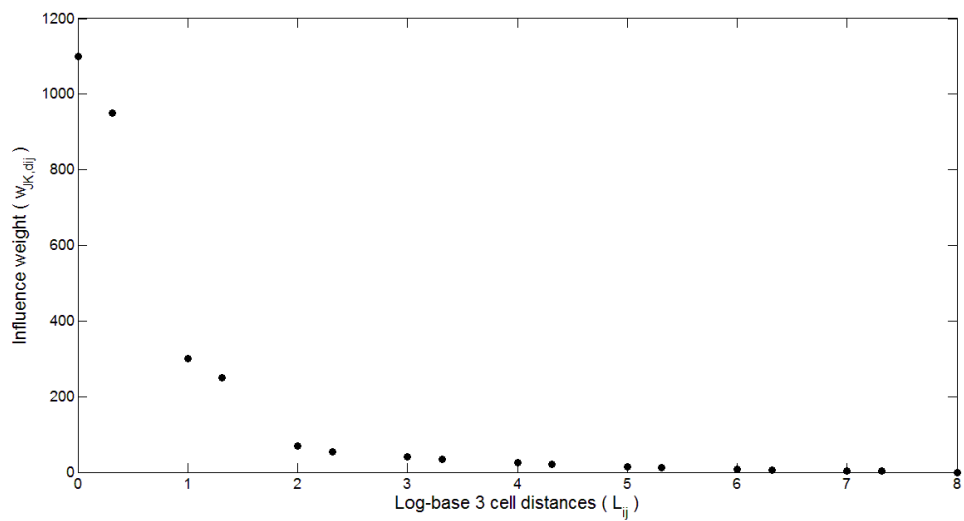
Figure 3. Detail of a fixed 'network grid' (NG) with resolution 3^{2R}. The model cells with resolution R are shown within one NG cell. When the distance is needed from a black unit cell to the centroid of its black variable grid neighbour, the distance from the red centroid of the fixed NG cell containing the black unit cell towards the centroid of the red NG cell containing the centroid of the black variable grid neighbour is used.
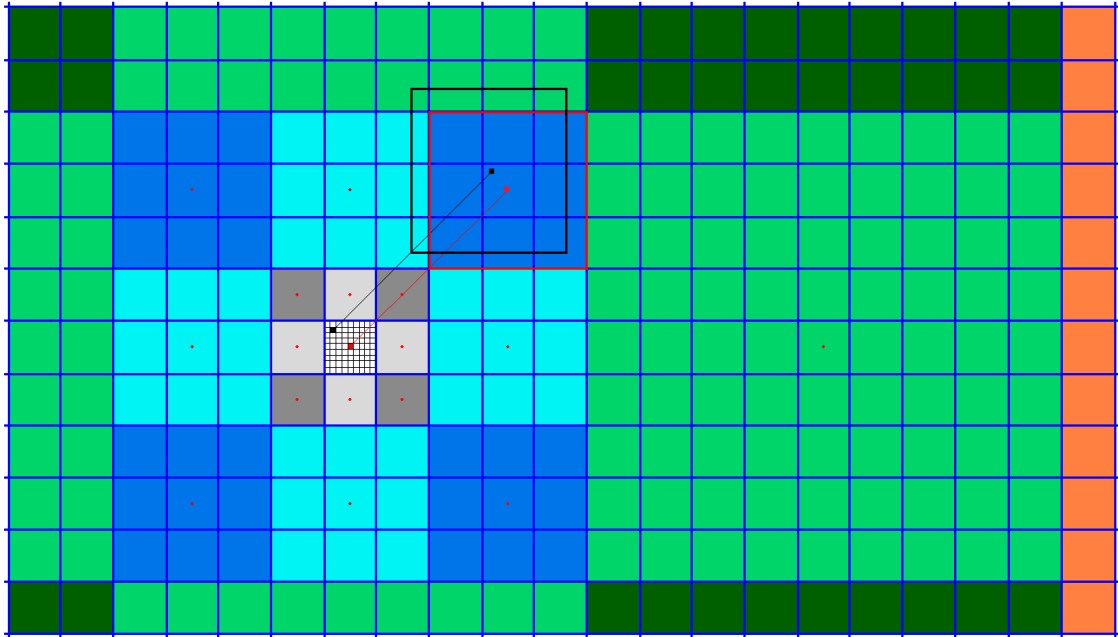
Figure 4. The road component and the public transport component can be combined or used separately to generate time distances.
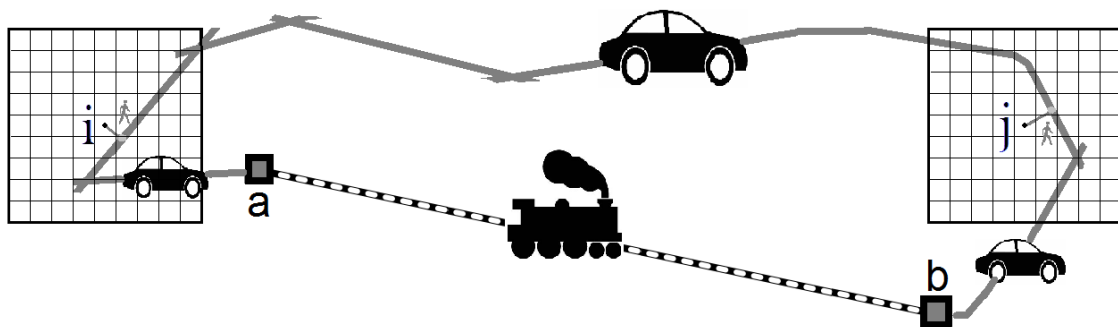
Figure 5. Example of a neighbourhood influence function with a Euclidean part for local interactions and a network time-distance part for long-distance interactions. The cell distance axis is made continuous with equation (9).
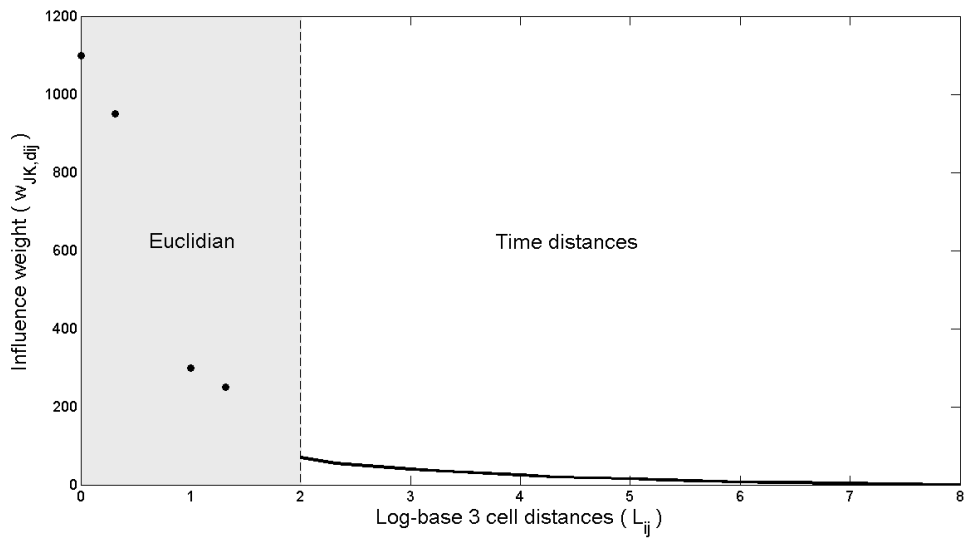
Figure 6. CORINE land-use map of Belgium in 2000, with an indication of the regions (Flanders, Wallonia and the Brussels Capital Region (B)) and the largest cities (Brussels (B), Antwerp (A), Ghent (G), Leuven (Le), Liège (Li), and Charleroi (C)).
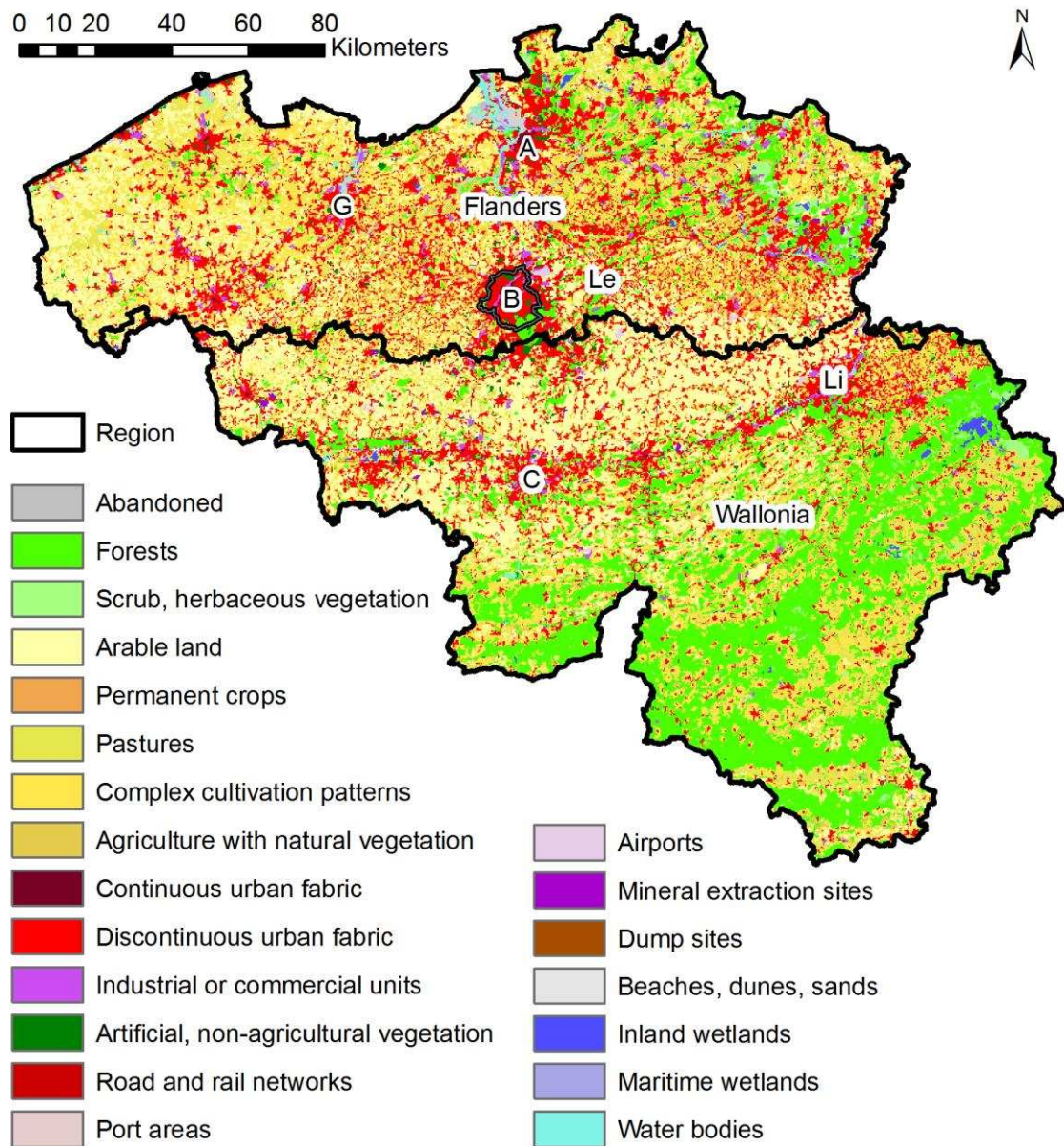
Figure 7. Accessibility index for different transport scenarios in Belgium: (a) the standard 'road-based' scenario, (b) the 'congestion' scenario, (c) the 'train only' scenario, and (d) the 'choice' scenario.
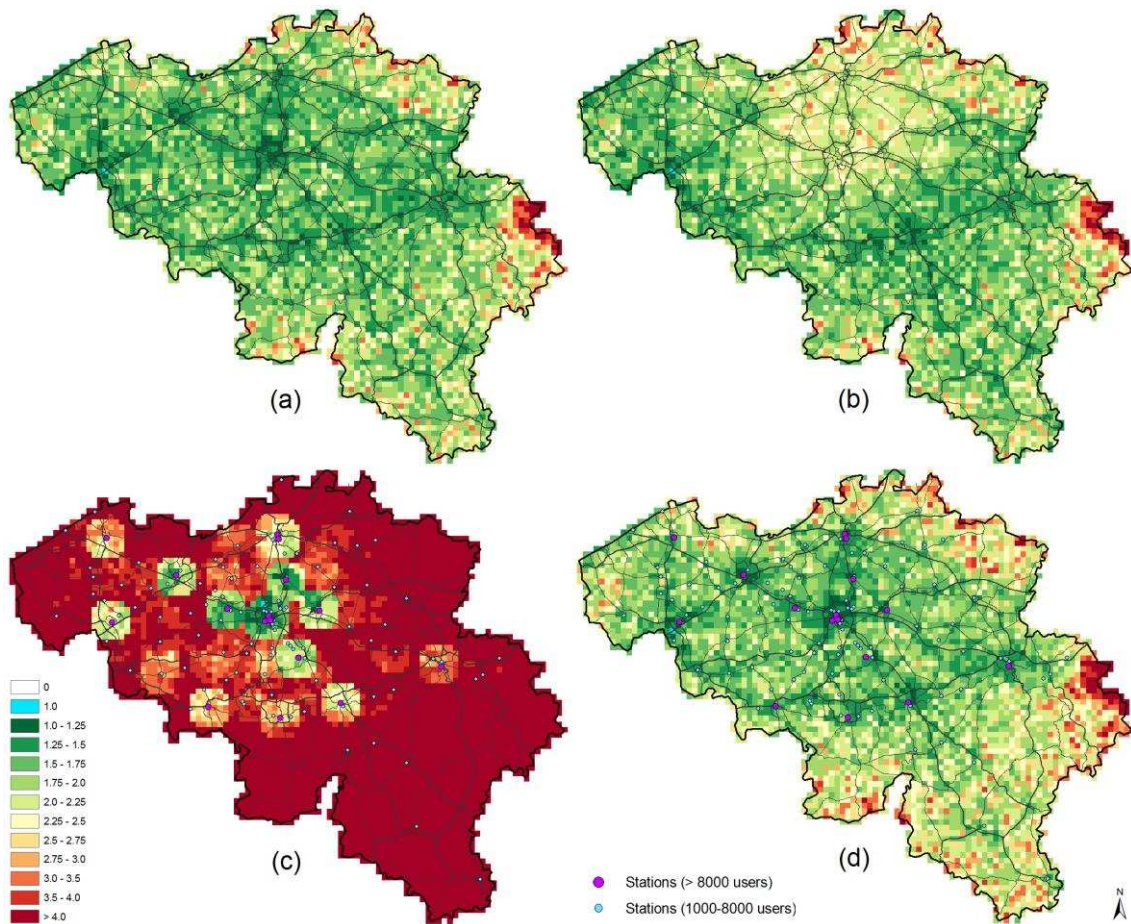
Figure 8. New discontinuous residential development in Belgium in the road-based scenario between 2000 and 2060. The rectangle shows the extent of the zooms in the next figures.
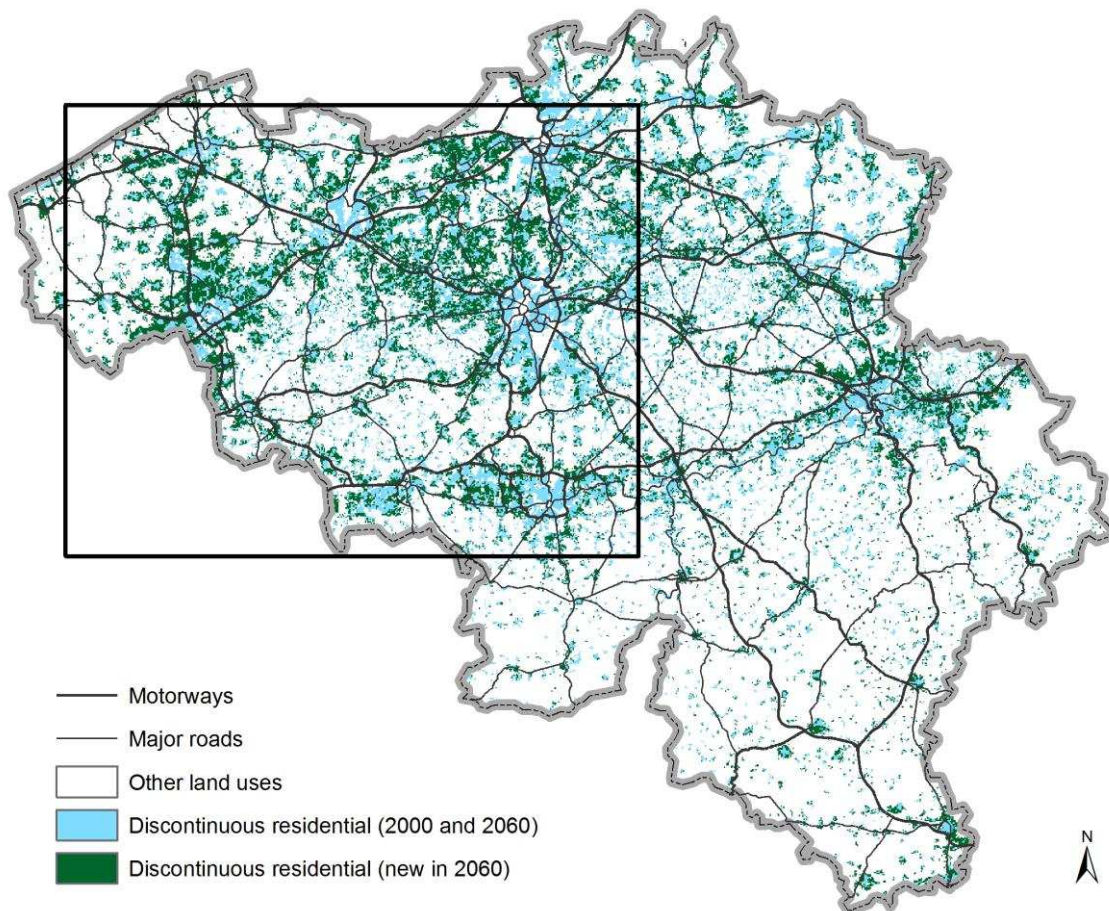
Figure 9. Differences in residential development between the Euclidean and the 'road-based' scenarios in 2060.
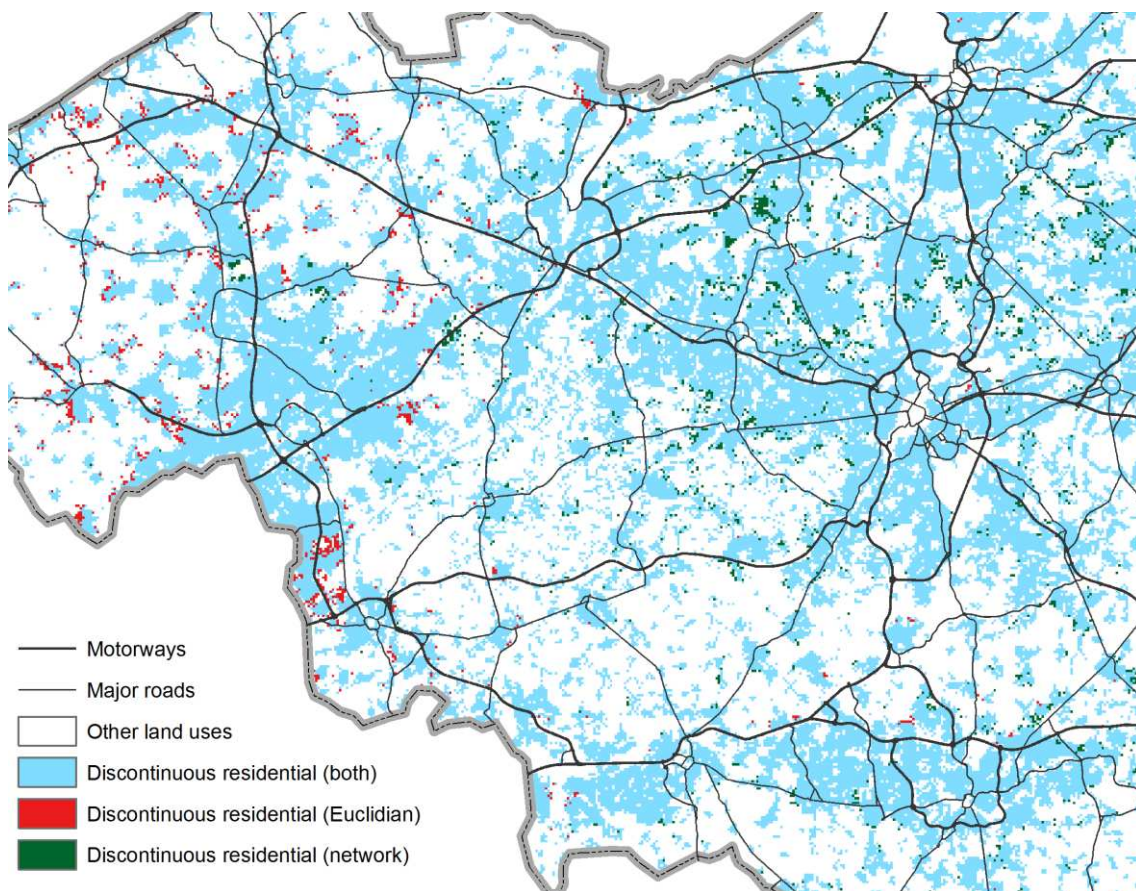
Figure 10. Differences in population values between the Euclidean and the 'road-based' scenarios in 2060.
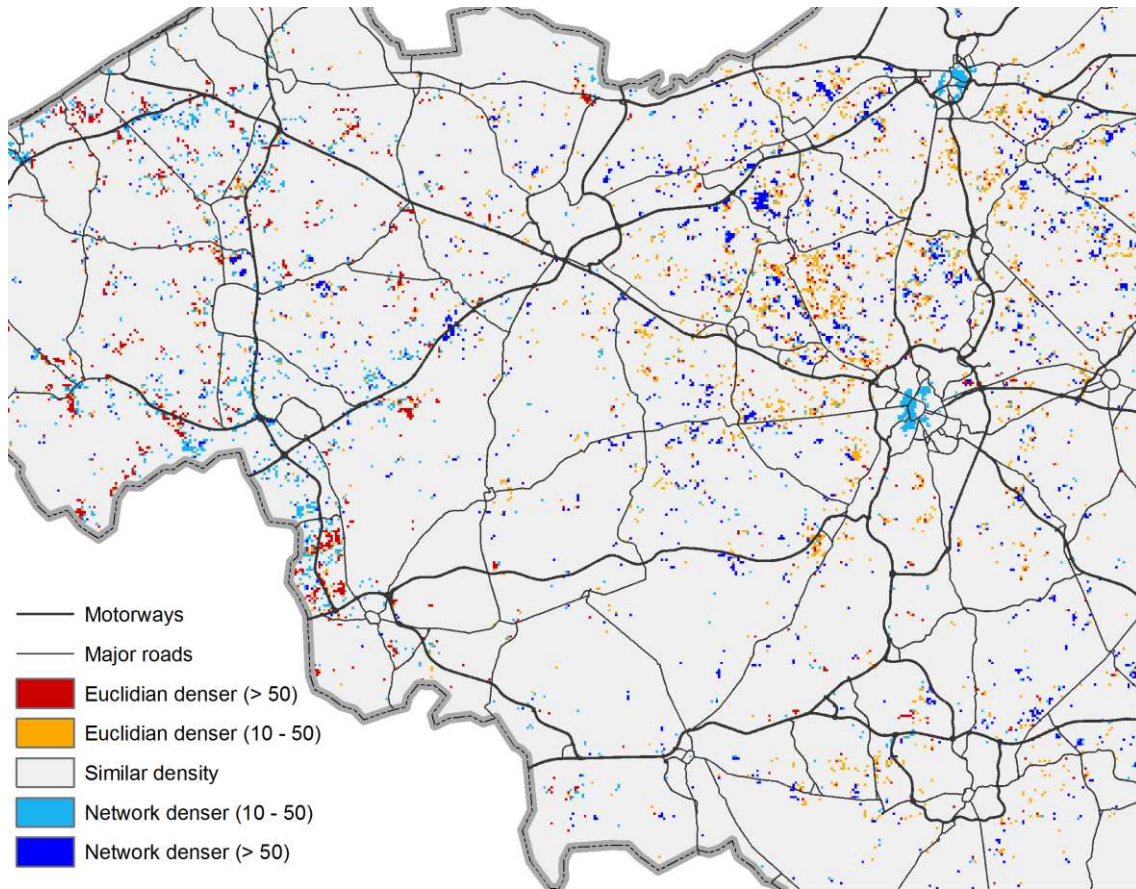
Figure 11. Differences in residential development between the 'road-based' and the 'congestion' scenarios in 2060.
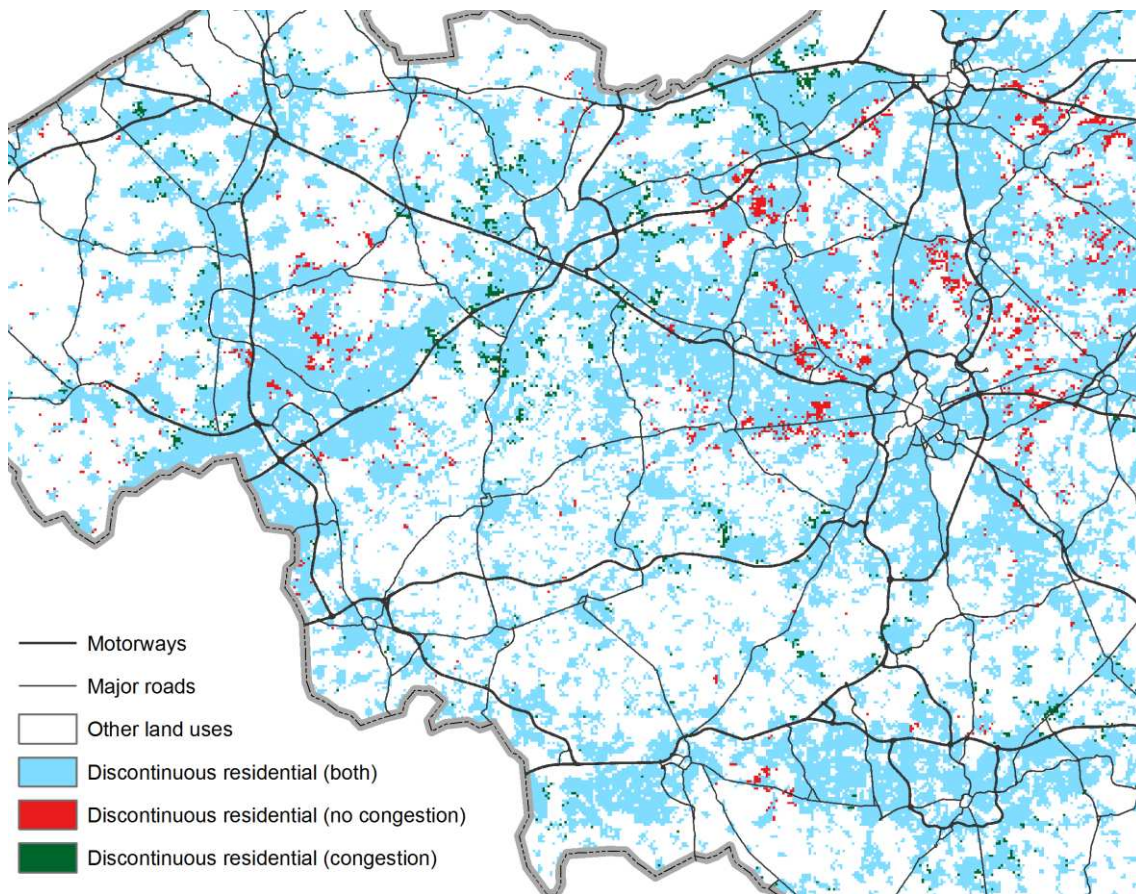
Figure 12. Differences in population values between the 'road-based' and the 'congestion' scenarios in 2060.
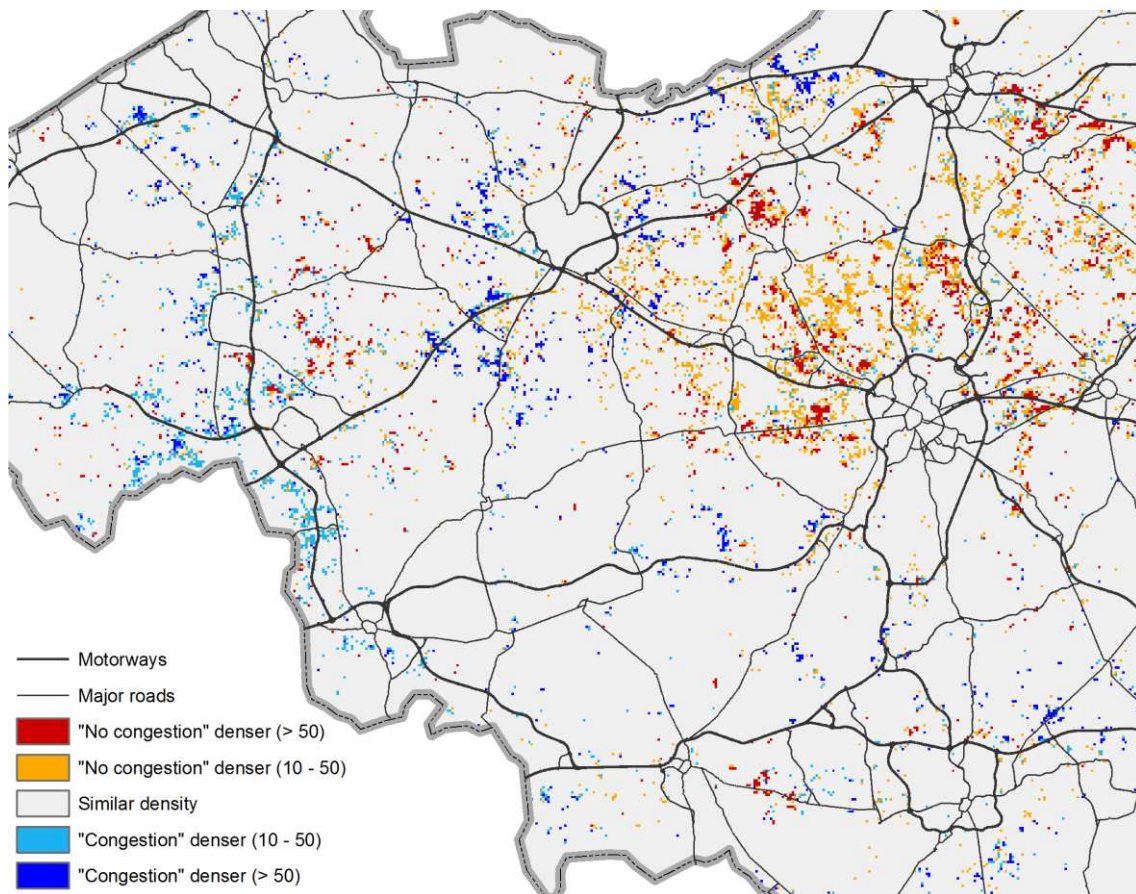
Figure 13. Differences in residential development between the 'road-based' and the 'train only' scenarios in 2060.
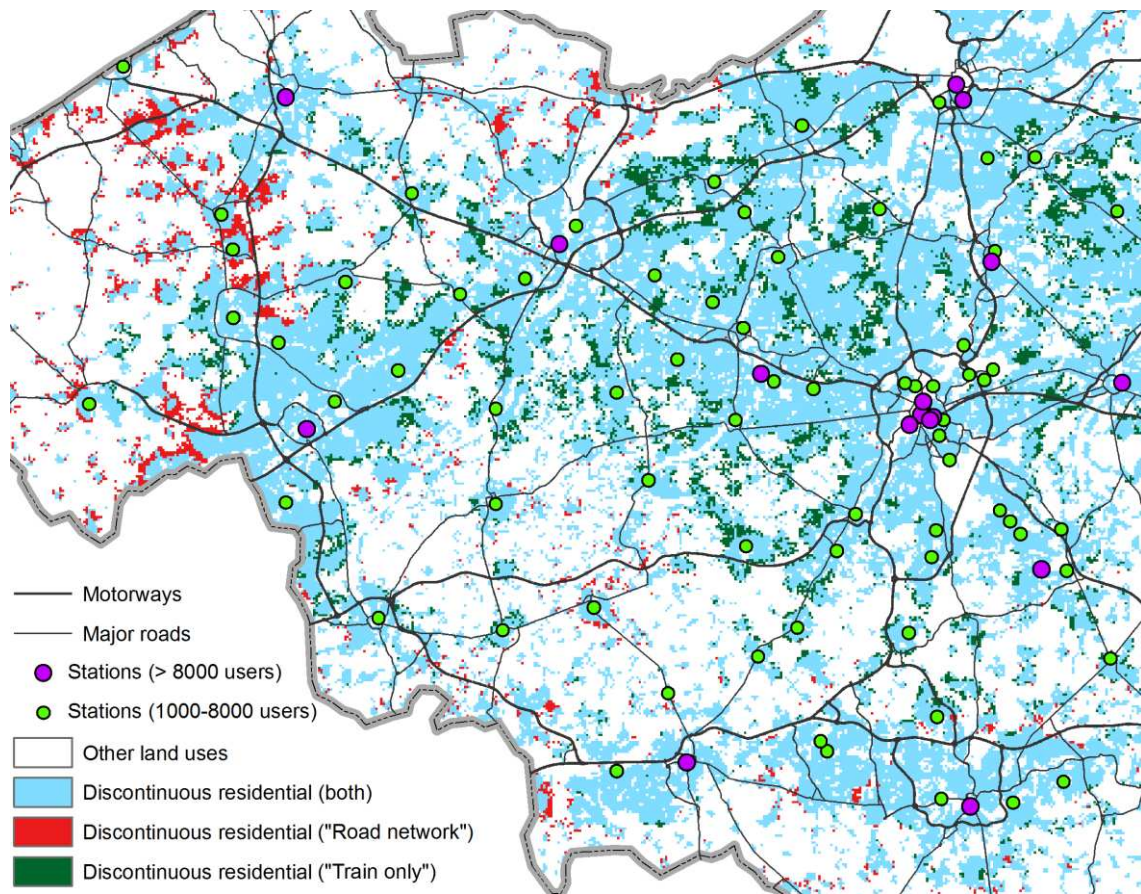
Figure 14. Differences in population values between the 'road-based' and the 'train only' scenarios in 2060.