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Title

Integrated modelling of urban spatial development under uncertain climate futures: A case study in Hungary

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Abstract

To provide fundamental decision support information for climate risk assessment in Hungary, an urban spatial development model of land cover change and population age structure dynamics was developed and applied to local integrated scenarios of climate change and stakeholder-derived socio-economic change. The four integrated scenarios for Hungary produced contrasting projections for urban patterns to 2100, but peri-urbanisation around Budapest was estimated to occur under all scenarios, together with a decline in working age population in the centres of the capital and major towns. This suggests that future urban planning needs to take into consideration the potential for underutilised urban infrastructure in the centre of the capital and pressures for social service provisioning in its outskirt. The integrated scenarios and model developed can be used in future studies to test the effectiveness of inter-sectoral policy responses in adapting urban planning to multiple climate and socio-economic challenges.

Keywords

Integrated modelling; Urban land cover change; Population distribution; Integrated socioeconomic and climate change scenarios; Stakeholder; Hungary;

Highlights

- An integrated model was developed of urban land cover change and population dynamics.
- The model was applied to four integrated climate and socio-economic scenarios for Hungary.
- Local stakeholders were closely involved and this ensured the plausibility and credibility of model projections.
- Contrasting projections for urban patterns were produced to aid climate risk management.
- Recommendations on good practices in collaborative environmental modelling were made.

1 Introduction

Public and scientific concern about the threat of climate change to urban areas and urban residents has become increasingly widespread: the world's urban population (over half of the total population) is expected to face more complex and often inter-related problems related to water scarcity (Schewe et al., 2014), energy demand (Christenson et al., 2006), public health (McMichael et al., 2006), amongst others. Many of these problems occur together, or are closely related to one another, in urban environments and so, it is important to understand how urban and residential development patterns might evolve in the future, and how this affects the consequences of climate change on cities.

Effective policy responses to climate change need to take account of, and coordinate, different perspectives, knowledge and interests across sectors and governance levels (Adger et al., 2005; Hurlimann and March, 2012). Knowing the role of regional and local-level actors is essential in understanding responses to policy, socio-economic and environmental drivers in cities (Antonson et al., 2016; Eikelboom and Janssen, 2013; Kumar and Geneletti, 2015). Targeted responses may be required at regional to local levels to tackle 'vulnerability hotspots' where climate change impacts are particularly significant (Rannow et al., 2010). The capacity of, and interplay between, regional and local level institutions often plays a role in the functioning of multilevel governance and actions to promote such targeted policy (Hanssen et al., 2013; Vedeld et al., 2016). These considerations have resulted in a rapidly growing number of initiatives to develop lower level climate change responses, e.g., the 'Mayors Adapt' (http://mayors-adapt.eu/) and the '100 Resilient Cities initiative' (http://www.100resilientcities.org/). However, such ambitions remain beyond the capacity of most local governments, owing to inadequate local-level information to support decisions and a lack of technical knowledge exchange across levels and sectors (c.f. Kumar and Geneletti (2015), and references therein). Assessments exploring urban development in response to climate change are urgently needed, in order to help support local governments in developing adaptation plans.

Scenario-based model projections of future land cover change are one way of supporting decision-making for adapting to climate change (Harrison et al., 2016; Prestele et al., 2016). Scenario analysis provides information about future uncertainties in a structured and consistent manner, which can support decision-makers in evaluating policy alternatives towards robust decisions (Krueger et al., 2012; Schwarz, 1991). A long-term time scale (decades or centuries) is often required in developing scenarios related to climate change and land use change, as the climate system itself responds slowly to changes in greenhouse gas concentration (Moss et al., 2010). Furthermore, urban planners often need to consider longer time horizons in establishing infrastructure projects. Engaging local stakeholders in the co-creation of scenarios provides qualitative insight into future changes that are plausible and relevant. The co-creation of scenarios has been widely adopted in other studies, e.g. Reginster and Rounsevell (2006), Volkery et al. (2008), Harrison et al. (2015) and Kok and Pedde (2016). Resources, knowledge and expertise brought by stakeholders can help to build trust and strengthen the feasibility of adaptation policies (Moss et al., 2010; Tompkins et al., 2008; Voinov and Bousquet, 2010; Voinov et al., 2016). Neglecting the engagement of stakeholders in climate change assessments may limit the effectiveness of policy responses and potentially result in policy failure (Vogel and Henstra, 2015).

Understanding how cities adapt to climate change is at least partly dependent on knowing where people will live in the future. Hence, projecting plausible long-term trends in both fine-grained urban land cover and population distribution can contribute to improving the assessment of climate risks, and support the development of effective integrated mitigation and adaptation solutions. Existing urban models have focused mostly on projecting land use/cover changes using geostatistical models (Cheng and Masser, 2003; Dendoncker et al., 2007; Jokar Arsanjani et al., 2013b; Poelmans and Van Rompaey, 2009; Verburg et al., 2004; Westervelt et al., 2011), or cellular automata (CA) and agent-based models, in which the decision-making processes of residents and/or policy-makers are embedded (Brown and Robinson, 2006; Fontaine and Rounsevell, 2009; He et al., 2008; Jokar Arsanjani et al., 2013a; Verburg et al., 2002; Vliet et al., 2009). Population is usually treated as an input and a higher level driver of land cover change, while the possible effects of land cover change on the distribution of population at lower (or cell) levels have largely been ignored. White et al. (2012) describe one of the few examples where transition rules about people's spatial activities were embedded within a CA framework to model both land cover and population at the same resolution.

A multi-scale modelling approach is important for supporting urban decision-making across different governance levels. A fine resolution model has greater flexibility in scaling-up local-level projections of urban pattern to higher levels and downscaling the effects of existing climate policies and action plans, most of which are long-term and have been developed for national or higher scales. In this study, we focus the model development on projecting long-term urban development patterns for an entire country (Hungary) at a spatial resolution that is fine enough to represent each local administrative unit. This goes beyond most existing urban models that have been developed for smaller regions, such as a province (Verburg et al., 2002), a river delta (Weng, 2002) or a city (Cheng and Masser, 2003; He et al., 2008). Nationwide studies with fine resolution applications are rare, with studies in the Netherlands (Verburg et al., 2004) and Belgium (Dendoncker et al., 2007) being notable exceptions.

Including the impacts of climate change in modelling urban development has rarely been undertaken previously because of a lack of understanding of how climate change affects either urban land cover or population distribution (Black et al., 2011b; Vari et al., 2003). For example, some extreme weather events, such as floods and landslides, can cause direct damage to urban infrastructure. However, properties and populations may remain in hazard prone areas because people have insurance cover, rely on the government to mitigate their risks, decide to stay as the risks do not outweigh the benefits of a more favourable location, or simply cannot bear the costs of relocation. Droughts and heatwaves may have less direct impacts on urban land cover and are less likely to elicit migration/relocation, as they could possibly be managed or people could change their behaviour to adjust to these challenges (Black et al., 2011a; Fielding, 2011). In this study, given the time period considered (up to 2100), short-lived and localised extreme weather events were not modelled explicitly. However, their aggregated effects on the regional economy through time were considered. Empirical evidence has shown that frequent extreme weather events are likely to cause significant damage to the national economy (Brown et al., 2013), which may influence urban development at some level (Reginster and Rounsevell, 2006).

The main purpose of this study is to provide scenario-based future projections of urban land use and population distribution patterns at a fine spatial resolution for the whole of Hungary. At the local level, the challenges arising from climate change are already apparent, with some parts of Hungary suffering from flooding, storms, heatwaves, and water shortages (Li et al., 2017). Information about the range of plausible, but uncertain, futures facing Hungary is fundamental in supporting multi-level climate change adaptive decision-making and cooperative land use management. To this end, we developed a model that integrates advances in urban development modelling. A set of integrated scenarios of potential long-term climate and socio-economic changes (up to 2100) were co-created with local stakeholders. The stakeholders also participated in reviewing the model structure and evaluating the accuracy and usefulness of model projections. We analysed the projections obtained under different scenarios and identified those parts of Hungary that are likely to face similar challenges in urban development regardless of the scenario.

2 An integrated model for urban development

2.1 Model structure and workflow

This study is based on an integrated model that simulates the spatial dynamics of urban land use/cover change (including residential, commercial and urban green surface areas) and population dynamics for Hungary (named ALLOCATION). The ALLOCATION model consists of three sub-models operating at/across different spatial scale levels i.e., the national, regional and local levels (Figure 1, note: the NUTS3 and LAU1 levels are only for display purposes and have not been used in the current study). The general workflow is described in Figure 2. The model is based on a 1 km^2 cellular grid, has a baseline year of 2010 and simulates urban land cover change with decadal time steps up to 2100. The 1 km resolution was chosen so that each town, village and district of Budapest could be represented by at least 1 cell. At the beginning of each time step, the model calls the economic change sub-model (section 2.2.1) to calculate changes in the NUTS2-level social, economic and demographic factors. The urban land cover change sub-model (section 2.2.2) then executes to: (i) estimate changes in the extent of the NUTS2-level artificial land cover based on the outputs from the economic change sub-model; and, (ii) allocate these projected changes to the 1 km cells. After the cell-level land cover extents are calculated, the population distribution sub-model (section 2.2.3) simulates residential preferences for different age groups based on the distribution of artificial land covers and redistributes the NUTS2-level population.

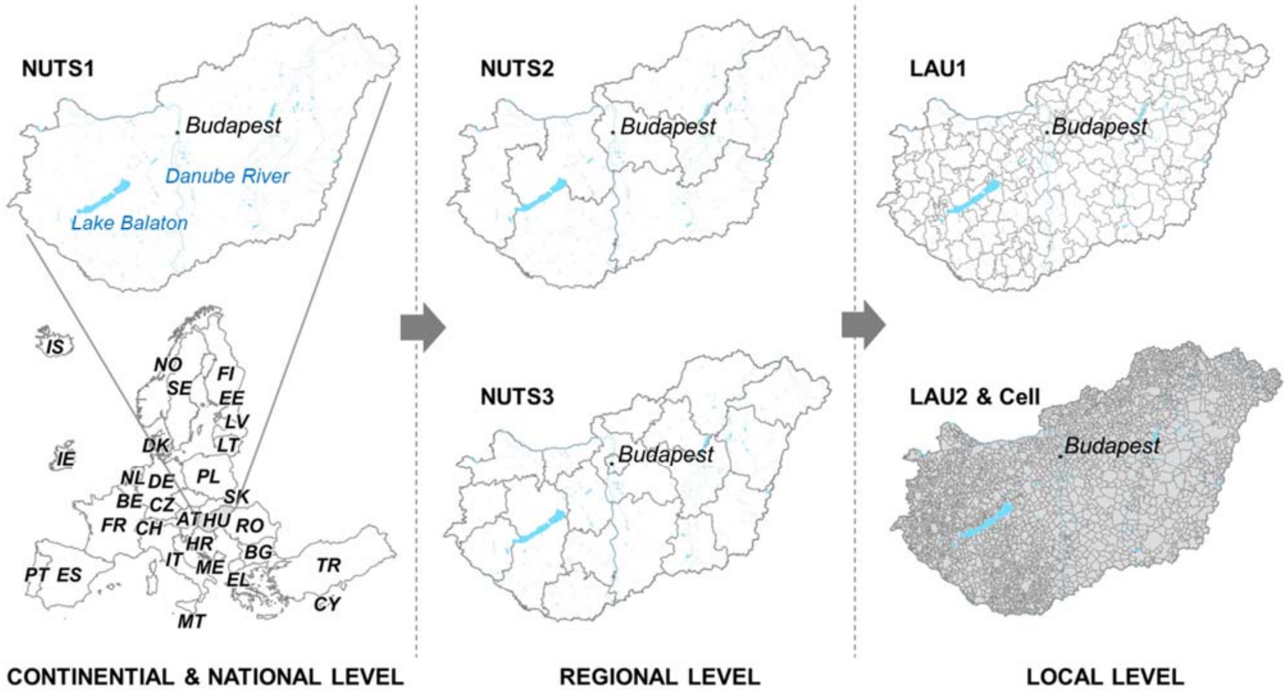


Figure 1 Study region and definition of levels

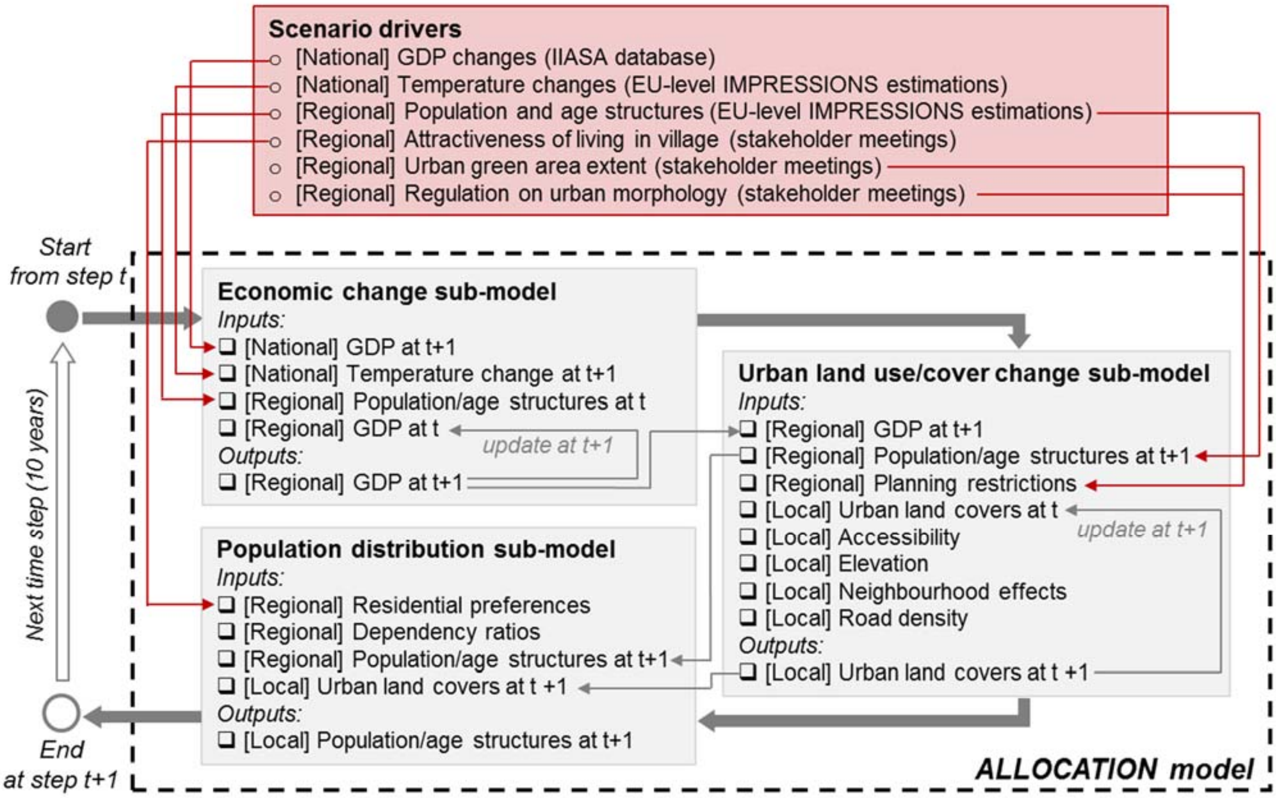


Figure 2 Model structure, parameters and linkages to scenario drivers

2.2 Model components

2.2.1 Economic change

The population distribution sub-model uses the national-level GDP data to estimate the ratio of climate change damage to GDP ($D(T(t))$) using Nordhaus's temperature damage function:

$$D(T(t)) = 1 - 1 /(1+0.0028388*(T^2 (t)), \quad (1)$$

where $T(t)$ is the mean temperature increase above the pre-industrial level at time step t (Golosov et al., 2014). The sub-model next disaggregates the revised GDP to the NUTS2 level using a simple empirical function derived from a linear regressive model based on the national and NUTS2-level GDP and population data from 2000 to 2010 (from the Hungarian Central Statistics Office, KSH). The GDP of a NUTS2 region in time step t is estimated as: $GDP\%(t) = 0.8899 * GDP\%(t-1) + 0.9348 * (Pop\%(t-1)*Pop\%(t)$ (adjusted R-squared = 0.99), where $GDP\%(t)$ is the ratio of the GDP of the NUTS2 region to the GDP of the whole of Hungary and $Pop\%(t)$ is the ratio of the population of the NUTS2 region to the population of Hungary at time step t.

2.2.2 Urban land cover change

This sub-model simulates cell-level urban land cover changes based on changes in NUTS2-level economic and demographic factors. It was developed using the CORINE land cover datasets (CLC) at 100m resolution for 2000, 2006 and 2012 (from the European Environment Agency, EEA, and the Hungarian Institute of Geodesy, Cartography and Remote Sensing, FÖMI). Three types of urban land cover were distinguished: (i) residential ('Urban fabric', CLC class 111-112), (ii) commercial/industrial ('Industrial or commercial units', CLC class 121) and (iii) urban green/leisure ('Green urban areas', CLC class 141 and 'Sport and leisure facilities', CLC class 142). The grid reference system was based on the European Environment Agency (EEA) 1 km^2 reference grid and used to extract the selected CLC land cover classes. The changes in these CLC datasets across time slices were analysed to develop the main empirical functions.

Function 1 This function estimates changes in the NUTS2 level demand for urban area based on changes in GDP and population, following the methods and assumptions used in (Reginster and Rounsevell, 2006). Three regressive functions were developed to project the changes in the three urban land cover types. Additional GDP and population data were collected from the KSH census database. In the functions for residential (adjusted R-squared = 0.99) and industrial/commercial (adjusted R-squared = 0.96) land cover changes, per capita GDP and the extent of existing urban land cover in the region are the key positive predictors. In the function for green/leisure land cover change (adjusted R-squared = 0.99), the extent of industrial/commercial land cover, children (0-14) and working age (15-64) populations are negative predictors.

Function 2 This function estimates a cell's potential to be developed into different urban land cover types. Logistic regressive functions were calculated, which have been widely used in the development of previous urban growth models e.g., in Hu and Lo (2007), Jokar Arsanjani et al. (2013b) and Verburg et al. (2004). A wide range of explanatory variables were collected from various sources to describe (i) the accessibility (to urban centres, lakes and rivers), elevation, and neighbourhood urban composition of the cell, and (ii) the local (LAU2, municipality or equivalent unit, Figure 1) urbanisation level and densities of roads and railways. We examined the collinearity in the spatial database and subdivided it for function development and evaluation. To account for spatial autocorrelation, two additional steps were taken. First, the cell-level geographical coordinates were included as explanatory variables, as spatial autocorrelation can be alleviated to some extent by introducing location into the function (Hu and Lo, 2007). Second, following Cheng and Masser (2003) and Verburg et al. (2004), a restricted spatial sampling scheme was designed to ensure that the sub-dataset used for function development contained minimum spatial autocorrelation between the independent variables. The predictive performance of the logistic functions was evaluated using AUC (the area under the curve) values. Cut-off values to divide predicted probabilities of land cover increase into occurrence or non-occurrence were set when the sum of the logistic function's sensitivity and specificity was maximised (Liu et al., 2005). We built functions for each of the three urban land covers in each of the seven NUTS2 regions in Hungary. Different sets of predictors are included in the final models for different regions and land cover types (see the Electronic Supplementary Materials 1 for the explanatory variables and coefficients). The AUC values of the final models were mostly (26 out of 27) greater than 0.8, indicating good predictive power.

Function 3 This function was built to test the theoretical effects of planning regulations on urban morphology. In real world cases, compact development may be pursued by local authorities to increase residential urban density and prioritise developments close to the urban core, in order to reduce travel distances and save energy (e.g., the concept of "Compact City") (Reginster and Rounsevell, 2006). This type of planning regulation is introduced as $C_i = {\rho_i}^{\delta}$, where $\rho_i \in [0,1]$ is the proportion of the land cover in a cell i's neighbourhood (3km x 3km), and $\delta \geq 0$ is the parameter describing the intensity of the effect of planning on compactness. Thus, δ = 0 indicates no regulation, and; as δ increases the urban patterns' shift from sprawled to compact. The parameter can also be regarded as an abstraction of the "optimal neighbourhood density" concept explained in previous studies (Caruso et al., 2007; Caruso et al., 2005), representing a preferred level of residential density (relative to non-urban area) in the neighbourhood, which can be affected by spatial planning regulations. In Hungary, suburbanisation has been strong from the mid-1990s to around 2005, following a shift in the government's strategy towards more compact development to meet the demand for public services by a growing population (Stanilov and Sýkora, 2014). The outskirts of the Budapest region, however, remained popular for residential developments even after 2005, based on changes observed between CLC datasets. Despite the introduction of a major initiative to prevent suburban sprawl in 2005 in the 'Act LXIV on Spatial Planning in the Agglomeration of Budapest', the seven-year long negotiation to pass this law has still allowed a steady conversion of green and agricultural land into urban areas in the suburban periphery of Budapest. Based on these facts, in the model the initial value of δ for 2000-2010 was set to 0.6 (medium sprawl, unsuccessful planning regulation) for the NUTS2 region of central Hungary (including Budapest, the capital, and Pest county, which surrounds the capital, Figure 1) and to 0.8 (slight sprawl) for the other regions. The regulation of urban compactness was assumed to influence both residential and commercial/industrial areas.

Thus, this sub-model allocates the projected changes in the extents of the NUTS2-level land covers (estimated by Function 1) to the cell-level based on the cells' growth potential *G*, which is a multiplication of the developmental potential *P* (estimated by Function 1) by the strength of planning regulation on compactness *C* (estimated by Function 2). The spatial allocation rules allow more rapid development in cells with greater growth potential (details in the Electronic Supplementary Materials 1). Only increases are considered for residential and commercial/industrial areas. For urban green/leisure areas, both increases and decreases are allowed, as these areas are managed and can usually be converted into other land cover types. The model projects greater decreases from cells with lower growth potential for urban green/leisure areas, and with greater growth potential for residential and commercial/industrial areas.

2.2.3 Population distribution

This sub-model disaggregates the NUTS2 level, age-structured populations onto the 1km grid. It is based on a disaggregation model (Li et al., 2016b) which integrates residential preferences originating from regional economic theories and takes advantage of recent dasymetric modelling approaches. In the first step, this sub-model allocates working age populations (aged 15-29, 30-49 and 50-64) to inhabitable cells (where residential land is present) based on their age-specific weights given to the different residential preference types. The residential preference (*P*) is approximated as a function of land cover density in a cell's neighbourhood, for which the projections from the urban land cover change sub-model are used. Three types of preferences are considered for the social, economic and urban greenery amenities, which are estimated by residential, commercial/industrial and urban green/leisure land cover density in a cell's neighbourhood, respectively. Another set of weights for territorial types is applied to reflect the relative attractiveness of living in the capital (a_C), a town (a_T) and a village (a_V). The second step is based on the pattern projected in the first step. Thus, the allocation of the dependent populations (aged 0-14 and 65+) is driven by their dependency rates (D) to different groups of working age population residing in areas of different territorial types.

Following the data-driven parameterisation method developed by Li et al. (2016b), the model was re-calibrated using the CORINE 2012 database and the LAU2 level population and age structure data from the KSH for each of the NUTS2 regions. The following general rules were applied to redistribute working age populations: (i) all population groups give high preferences to social amenities; (ii) senior adults (50-64) have relatively lower preferences for economic amenities, which is in line with decreased purchasing power found in the literature, and relatively high preferences for urban green amenities, and; (iii) the attractiveness of villages decreases (relative to the capital and towns) as age-class increases. For the dependent populations: (i) children (0-14) depend heavily on young adults (15-29) in the capital and towns, on middle-aged (30-49) populations in towns and villages, and on senior-aged working population (50-64) in the capital, and; (ii) the elderly (65+) depend relatively more on young adults (15-29) in the capital, and on the senior working age population (50-64) in towns and villages (see the Electronic Supplementary Materials 1 for detailed residential preference weights and dependency ratios).

2.3 Model development and evaluation

The integrated model was developed using the Repast Simphony toolkit (version 2.1) and scripted in the Java programming language (North et al., 2013). This toolkit has been widely used in developing cell-based and agent-based models. The empirical functions of the model were developed using the R statistical language (R Core Team, 2012) before integration. Based on the guidance suggested in Bennett et al. (2013), an evaluation scheme was designed for the model which combines both quantitative and qualitative measures. Quantitatively, the model was run for one time step (10 year) with the land cover and population data of 2000 and these projections, i.e., urban land cover extents and age class-specific populations, were compared with observational data around 2010. Predicted changes in land cover extents were compared with the CORINE 2012 data from three perspectives: (i) up-scaled comparisons at the LAU2 (NUTS5) level, (ii) visual comparisons at the cell level, and, (iii) summarised comparisons using distance-density plots (see details in the Electronic Supplementary Materials 2). Projected changes in population and age structure were compared with the KSH's 2011 census data at the LAU2-level only, as finer resolution observations were not available. Qualitatively, stakeholders assessed the overall model structure and the usefulness of model projections during several stakeholder workshops that took place between 2014 and 2016 (introduced in section 3.1, and Figure 3).

2.4 Sensitivity analysis

In this study, the major source of uncertainty lies within the scenarios, due to the inherent uncertainty of future political, socio-economic and technological conditions. A secondary source is related to model uncertainty, which is dependent on the performance of the different model components and the relationships among them. A sensitivity analysis of the integrated model was performed to determine the robustness of our model projections and reveal which parameters are likely to be most effective as drivers for future projections (section 3.2). A simple one-at-a-time sensitivity analysis was performed to examine to what extent the model outcomes are influenced by changes in different parameters. Thus, the projection for the baseline condition was compared with those obtained by tuning each of the selected model parameters (by +10% in this study), while leaving the others unchanged. We firstly compared the key model outputs, i.e., extents of land cover classes and populations of age groups in the capital, towns and villages. Then, following suggestions by (Barreira González et al., 2015), further comparisons were made at the cell level for (i) cell-to-cell agreements, and (ii) the shape, fragmentation and heterogeneity of projections on both urban land cover and population distributions. A detailed explanation of the settings for the analysis and selection of matrices for spatial comparisons is provided in the Electronic Supplementary Materials 3.

3 Scenario development and analysis

3.1 Developing integrated scenarios with stakeholders

Local scenarios for Hungary were based on global Representative Concentration Pathways (RCPs) and Shared Socio-economic Pathways (SSPs). The RCPs describe potential trajectories for atmospheric concentrations of key greenhouse gases over time (van Vuuren et al., 2011), which are used as input to global and regional climate models to produce climate scenarios (see Madsen et al. (2016) for further details). The SSPs describe alternative narratives of future societal development (Kriegler et al., 2012). A set of scenario combinations (expressed as SSP x RCP) were selected (i) to cover both high-end and intermediate climate change, and (ii) to capture the extremes of socio-economic development pathways. The climate scenarios selected were RCP4.5 and RCP8.5, which cover greenhouse gas concentrations from +4.5 to +8.5 W/m^2 and were estimated to lead to global mean temperature increases from the pre-industrial levels by 2 – 4.3 °C and 4 – 7.8 °C by 2100, respectively. Four socio-economic scenarios were selected: SSP1, which emphasises a sustainable future, SSP3, whose central features are international fragmentation and regional rivalry, SSP4, with both across- and within-country inequality, and SSP5, which describes a future of fossil-fuelled development and accelerated globalisation (O'Neill et al., 2015). A final set of four SSP x RCP scenario combinations were selected: (1) SSP1 x RCP4.5, (2) SSP4 x RCP4.5, (3) SSP3 x RCP8.5, and (4) SSP5 x RCP8.5. The background and rationales to these selections are discussed in detail by Kok et al. (2015b).

The integrated scenarios were co-created with local stakeholders following principles developed by Gramberger et al. (2015) and Harrison et al. (2015). Figure 3 shows the general timeline of model and scenario development and how stakeholders were engaged. Two exploratory workshops focusing on the overall design of the study and to discuss and gain feedback on the model structure took place in December 2014 involving 9-12 key stakeholders from the public, civil and private sectors for each workshop. The stakeholders helped to provide sources of up-to-date data, expressed their opinion on the general acceptance of the model structure, and suggested model components to be included to address issues of local interest (i.e., population distribution and age structure). These were followed by a larger workshop on scenario development in July 2015 involving 25 participants. At this workshop, stakeholders were provided with information about the global integrated scenarios for future climate and socio-economic changes as a starting point. Then, with guidance from professional facilitators, they worked together to qualify and localise these scenarios for Hungary for the three time periods of 2010-2040, 2040-2070 and 2070-2100. Progress in the development of the model was reported for discussion leading to further model refinement to include factors of interest to the stakeholders (e.g., the attractiveness of living in villages to account for urban out-migration). The local scenarios were reviewed and extended by a subset of stakeholders at another workshop held in March 2016. The resulting local scenarios provide consistent and plausible descriptions of how events could unfold over time in major Hungarian sectors such as the economy, demographics, politics, urban development, agriculture, health, etc. These four integrated scenario were then applied to the ALLOCATION model, and the model results presented and discussed with stakeholders in a further workshop held in July 2016 involving 34 participants and later at two in-between workshops in December 2016 with 9 and 10 participants, respectively. The objectives of these workshops were to further evaluate whether the model projections were understandable and to use the projections to stimulate stakeholders' discussion on potential policy responses to climate and socio-economic change.

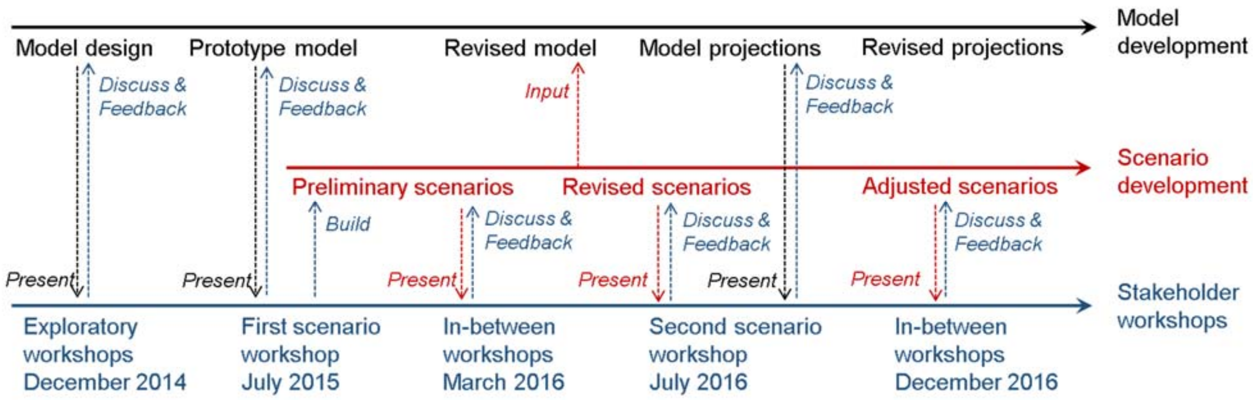


Figure 3 A timeline and interactions of model development, scenarios developments and stakeholder workshops.

3.2 Quantifying scenario drivers for urban development simulations

The localised scenario storylines were quantified for those potential drivers of future urban development which can be represented through the model parameters (Figure 2). Six scenario drivers were selected for quantification based on the availability of data on future projections, the level of interest to local stakeholders and the effort required for their quantification (Table 1). The quantification of these drivers follows the logic of the Story-and-Simulation approach (Alcamo, 2001, 2008); an iterative procedure to link narratives and quantification in scenario exercises. Two, out of the six, scenario drivers were directly quantified by stakeholders in the scenario workshops (i.e., attractiveness of living in villages and the extent of urban green areas), since these were considered to reflect the expertise of the stakeholders. The other scenario drivers were quantified from downscaling existing databases or models or through expert interpretation of the scenario narratives by the modelling team.

Economy National-level GDP data were downloaded from the SSP Database (tntcat.iiasa.ac.at/SspDb) of the International Institute for Applied Systems Analysis (IIASA). The dataset provides future trends of GDP up to 2100, projected under different SSP scenarios. In the ALLOCATION model these projections were prepared as inputs for the economic change sub-model to be downscaled and passed on to the urban land use/cover change sub-model for land demand estimation.

Climate. Projections of temperature were based on bias-adjusted and downscaled projections from global and regional climate models (Madsen et al., 2016). Temperature projections were extracted for Hungary under the RCP4.5 and RCP8.5 scenarios from the HadGEM Earth System Model downscaled with the RCA regional model. In ALLOCATION, temperature is an input to the economic change sub-model which affects GDP.

Demographics. National-level population projections from IIASA's SSP Database were statistically downscaled to the NUTS2 level for Europe (Terama et al., In press). Decadal population data up to 2100 for Hungary (Terama, 2016) were extracted for the present study as input to all three ALLOCATION sub-models: the economic change sub-model (to downscale national-level GDP to NUTS2 level); the urban land use/cover change sub-model (to estimate changes in demand for urban land), and the population distribution sub-model (to be distributed onto the 1 km grid).

Preferences. The driver, attractiveness of living in a village (versus living in more urbanised areas such as towns or the capital) is considered as a driver of urban out-migration. Possible changes in this factor under the four SSP x RCP scenarios were quantified in the stakeholder workshop using Fuzzy Set Theory (Kok et al., 2015a). In the model, attractiveness of living in villages is a factor in the population distribution sub-model which shapes the cell-level distribution of working age groups and, consequently, that of the children and the elderly.

Urban planning. Scenario drivers considered in this sector include the extent of urban green area and regulation of urban compactness. Urban green area (or infrastructure) can play an important role in the pursuit of high quality sustainable development in terms of delivering improved quality of life, promoting healthy communities and creating high quality environments for a competitive economy (Kambites and Owen, 2006). Future planning directions and rates of change in urban green area under the four SSP x RCP scenarios were discussed and analysed during the quantification exercises in the stakeholder workshops using the Fuzzy Set Theory approach. In the model, the rates of planned change in urban green area, growth or shrinkage, are applied for the urban land use/cover change sub-model to estimate the cell-level changes in the extent of green/leisure land. These changes further influence cells' residential preference and population sizes. The driver of planning regulations represents government efforts towards delivering compact urban development constrained by the specific SSP x RCP scenario. As an abstract concept, this driver was discussed during the stakeholder workshop for qualitative trends only, i.e., more compact or sprawled development trends at a low or high level compared to the baseline (sprawled). In the model, the low and high levels were converted to 30-year changes in δ by 33% and 67% (Function 3, the urban land cover change sub-model, an increasing δ indicates changes towards compactness).

The ALLOCATION model was run by assigning scenario-specific values to these scenario drivers. By using the CORINE land cover data 2012 as an approximation for a baseline land cover map, the projected changes by 2100 are compared across the different integrated climate and socio-economic scenarios. The results for the overall extent of urban land cover and population density (inhabitants per km2 residential areas) are mapped at the LAU2 level (as defined in Figure 1) for a better visualisation of the general trends. Projections for different urban land cover types and population age classes are summarised using the KSH's territorial typology, by which LAU2-level administrative units are classified into five types, namely, capital (districts), town (county seat or with county rights), town, large village and village.

Table 1 Scenario settings and estimation for model variables

Class	Scenario driver	Period	Integrated climate and socio-economic scenarios [a]				Source	Estimation method
			SSP1 x RCP4.5	SSP4 x RCP4.5	SSP3 x RCP8.5	SSP5 x RCP8.5		
Economy	GDP	2010-2040	+85.10%	+63.74%	+50.63%	+116.91%	Database	IIASA SSP Database
		2040-2070	+40.61%	+15.95%	-2.18%	+94.74%		
		2070-2100	+29.64%	+4.64%	-8.43%	+81.09%		
Climate	Temperature	2010-2040	+1.3°C	+1.3°C	+1.4°C	+1.4°C	Model	IMPRESSIONS EU Integrated Assessment Platform
		2040-2070	+1.0°C	+1.0°C	+1.8°C	+1.8°C		
		2070-2100	+0.5°C	+0.5°C	+2.3°C	+2.3°C		
Demographics	Population (and age structure)	2010-2040	-5.24%	-10.79%	-16.47%	+1.09%	Model	IMPRESSIONS EU Integrated Assessment Platform
		2040-2070	-6.99%	-17.72%	-27.39%	+6.10%		
		2070-2100	-12.21%	-24.82%	-32.71%	+3.54%		
Preferences		2010-2040	-36.33%	-18.33%	0%	-36.33%		

	Attractiveness of living in village (urban out-migration)	2040-2070	0%	-36.33%	+22.17%	-57.67%	Stakeholder workshop	Quantification using Fuzzy Set Theory
		2070-2100	-36.33%	0%	+22.17%	-36.33%		
Urban planning	Urban green area extent	2010-2040	+11.67%	0%	-8%	-8%	Stakeholder workshop	Quantification using Fuzzy Set Theory
		2040-2070	+11.67%	-8%	-8%	-24%		
		2070-2100	+11.67%	-8%	-8%	-24%		
Urban planning	Regulation on urban morphology	2010-2040	compact	compact	sprawl	sprawl+	Stakeholder workshop	Qualitative interpretations of the integrated scenarios
		2040-2070	compact	sprawl	sprawl+ [b]	sprawl+		
		2070-2100	compact	compact	n/a [c]	sprawl+		

[a] Changes between the start and end of the time period.
[b] Indicating a more sprawled development trend at a high level compared to the baseline.
[c] Expansion of urban area stops in 2070-2100 under SSP3 x RCP8.5, according to the qualitative scenarios.

4 Results

4.1 Model performance

The LAU2-level comparison of the modelled and observed urban land cover suggests good model performance, as the Coefficient of Determination (R-squared) was found to be greater than 0.97 for all three urban land cover types. Visual and distance-density plot comparisons also suggest satisfactory model performance in predicting urban land cover changes at the cell level. The predictive power for population distribution was also found to be good at the NUTS5 level, as the R-squared was greater than 0.83 for all five age groups. More details of the results of the quantitative model evaluation are provided in the Electronic Supplementary Materials 2.

Qualitative evaluations by stakeholders suggest general acceptance of the model structure and usefulness of model projections. In the initial stakeholder workshops (Figure 3), an in-depth discussion was conducted to clarify the model's structure and to ensure factors of stakeholders' interest (e.g., the attractiveness of living in villages to account for urban out-migration) were included. In the final workshop, the projected results under the four integrated scenarios were presented to promote discussion of climate change adaption responses that would represent progress towards the vision of a sustainable future by 2100 to the extent allowed by the logic of a given SSP and RCP. In a post-workshop survey with participants, 20 out of the 23 responses rated the question "How useful were the modelling results in discussing possible responses?" as "very positive" or "positive", with the remainder rating them "satisfactory".

4.2 Model sensitivity

The results of the sensitivity analysis suggest that the ALLOCATION model is relatively stable in projecting urban development patterns and, hence, has the potential to be useful for scenario planning (Hewitt and Díaz-Pacheco, 2017). In general, projected extents and spatial patterns of urban land cover were found to be sensitive to changes in the national-level GDP, regional-level population and planning restrictions towards compact urban development. Consequently, population distributions, which depend highly on urban land cover distribution in the model, were also sensitive to these parameters. Projected population distributions were also found to be sensitive to changes in residential preference on proximity to social amenities and on desire to live in the capital, towns or villages.

4.3 Future urban development trends in Hungary

4.3.1 Urban land use/cover change

The differences in the projected extents of urban areas are driven by GDP and population (sections 2.2.1 & 2.2.2). The spatial pattern is driven by the planning regulation parameter (section 2.2.2) and the potential of a cell to be developed further for urban land use, e.g., residential and commercial/industrial, which is calculated using the same set of rules. In general, a cell's development potential is greater with an urban land cover element, and if its neighbourhood has a higher proportion of urban area. Thus, under all scenarios, new development of urban area was projected to be mainly around the capital and regional centres (towns as county seats and towns with county rights), as shown in Figure 4. Rapid urban development was projected under the SSP5 x RCP8.5 scenario due to a large increase in both GDP and population (Table 1), despite a rise in temperature of up to 5.5°C causing an averaged decadal 2.55% damage to the GDP by 2100 (from 0.30% in 2010-2020 to 7.90% in 2090-2100). A growing GDP and a relatively stable population (albeit decreasing) were projected to contribute to a moderate increase in urban areas under the SSP1 x RCP4.5 scenario. By 2100, a temperature rise of 2.8°C is projected to cause an averaged decadal 1.05% damage to the GDP (from 0.28% in 2010-2020 to 2.18% in 2090-210). In the capital region, more rapid development was projected due to policy regulation of urban compactness to meet the targets of sustainability and reduce energy demand. Although the projected patterns under the SSP4 x RCP4.5 and SSP3 x RCP8.5 scenarios seem to be similar, two differences should be noticed: (i) the former scenario led to an overall greater increase in urban areas (hence the darker colours), as better economic conditions were assumed for SSP4 and; (ii) the latter scenario led to a more widespread pattern of urban area increase, because spatial planning regulations within a de-globalising SSP3 are assumed to focus on local security which results in sprawl. In addition, some decreases in urban areas were projected (grey areas, e.g., around the Lake Balaton region), because urban areas in these regions were mainly composed of green/leisure type, and green/leisure areas were expected to decrease under these scenarios (Table 1).

While residential land was projected to have the greatest absolute increase among the three types of land cover considered (result not shown), commercial/industrial land was projected to have the greatest growth *rate* (Figure 6). This result was found for all scenarios and for all territorial types, as a consequence of increasing per capita GDP. As mentioned previously, changes in green/leisure land were set to be driven by the scenario settings (Table 1) and hence, were projected to be only positive within SSP1 x RCP4.5. Comparing the projections between territorial types, it was interesting to find that large villages had the greatest increase rate in both residential and commercial/industrial land under all scenarios, except for the SSP3 x RCP8.5 and SSP5 x RCP8.5 combinations within which a greater increase rate of commercial/industrial land was found for villages, owing to a sprawl-oriented regulation policy. These large villages were mostly (i) located close to the capital, not far away from rivers, or distant from major towns, (ii) had a greater proportion of land available for future development than capital districts and the majority of towns, and (iii) had a greater extent of existing urban land covers and road density than most villages. For most NUTS2 regions, these characteristics indicated a good developmental potential for both residential and commercial/industrial uses.

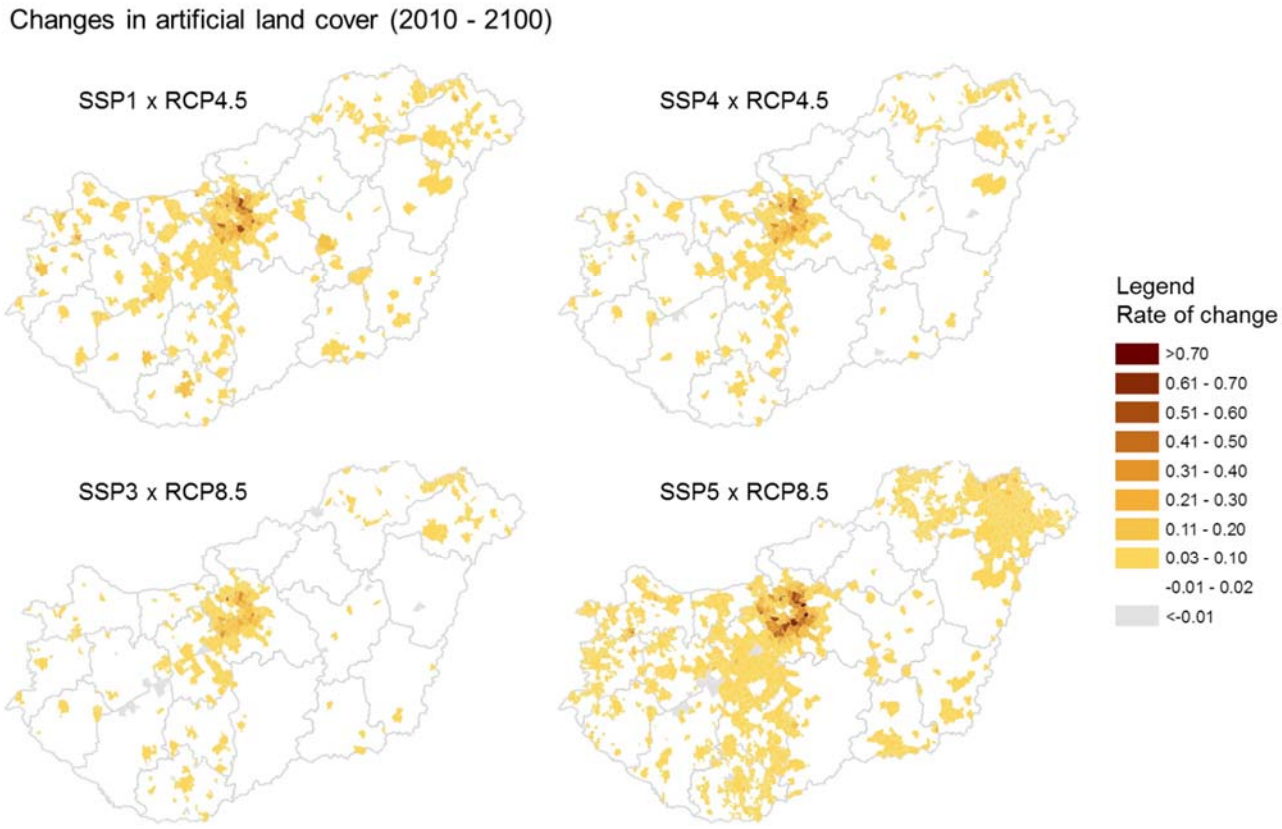


Figure 4 Simulated changes in total urban areas (2010-2100) under the four integrated scenarios.

4.3.2 Population and age structure patterns

The potential of an inhabitable cell to attract residents is a function of urban land cover densities in its neighbourhood (as residential preferences) and preference weights given to different territorial types (section 2.2.3). A major population flow in central Hungary was projected under all scenarios, caused by peri-urbanisation around Budapest: the population was expected to move to the fringe areas of the capital. In Figure 5, it can be seen that fringe areas either increase or maintain their populations under SSP1 x RCP4.5 and SSP4 x RCP8.5 scenarios. Under the other two scenarios, in which population was expected to decline considerably (Table 1), Budapest's fringe areas were projected to have a relatively lower rate of population decrease than the Central Hungary region (results not shown). In the fringe areas of the capital, where the cells' developmental potential for residential, commercial/industrial and urban green/leisure uses were all high, the newly developed residential areas were projected to have relatively high residential preference for residents. Moreover, these new residential cells were capital cells, and in central Hungary a greater residential preference weight is given to the capital cells by the working age groups. As a result, these new residential areas in the fringe areas of Budapest attracted population from the centre of the capital and from the surrounding villages and towns in Pest County. The model further projected several areas at risk of losing population (dark red areas in Figure 5) under all four integrated scenarios, including those in Central Hungary (western Pest County), Northern Great Plain (western Jász-Nagykun-Szolnok County and northern Hajdú-Bihar County) and Southern Great Plain (northern Békés County). Under the SSP4 x RCP8.5 scenario, even though national population and GDP were expected to increase, urban land cover in these regions remained unlikely to expand (Figure 4), owing to low neighbourhood densities of baseline urban land covers and low local road densities. Hence, population was projected to migrate to other areas with greater residential preferences (i.e., better access to social and economic amenities, as new residential and commercial/industrial lands were developed).

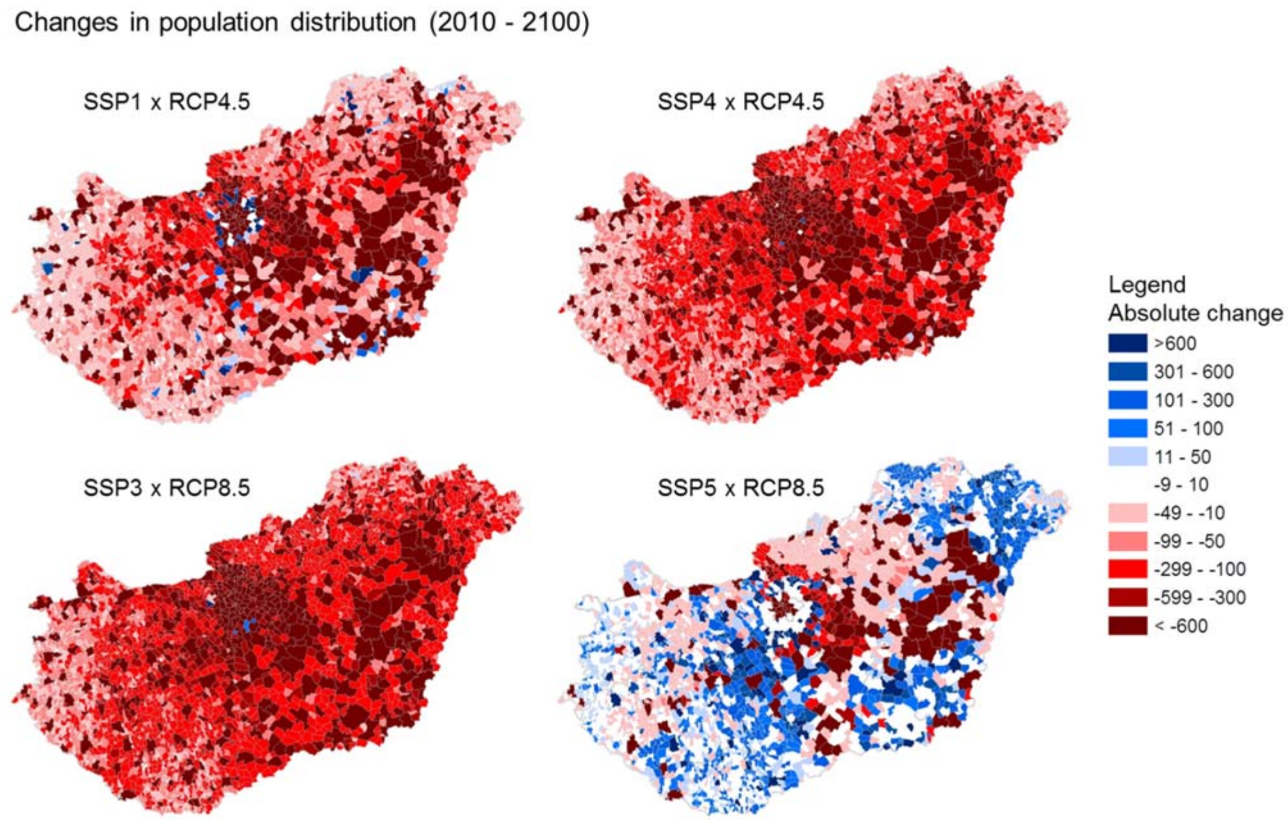
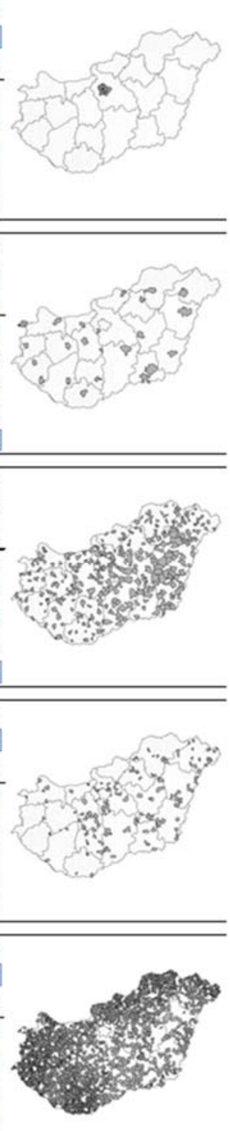


Figure 5 Simulated changes (2010-2100) in population density under the four integrated scenarios.

Some general trends for the projected changes in age structure were found under all scenarios (Figure 6): population aging and sub-replacement fertility were estimated to become a national problem, and the capital and major towns (those with county seats/with county rights) were projected to lose a significant number of the working age population. The changes in age structure further varied across territorial types, as a consequence of differences in the development potential of a cell and in the attractiveness of territorial types. Increasing urban land cover was projected to lead to better residential preferences in the cells in the capital and major towns than in the other territorial types. In theory, this could attract population from other areas, leading to a lower decrease rate of working age population in the capital and major towns under all scenarios. However, under the SSP3 x RCP8.5 scenario, differences in the rate of decrease of the working age population were projected to be similar across territorial types. This was due to the effect of residential preferences in the capital and towns being diluted by an increased attractiveness of living in villages as expected within the scenario. While under the SSP1 x RCP4.5 and SSP4 x RCP8.5 scenarios, the attractiveness of living in villages was assumed to decline, as a consequence the relative attractiveness of the capital and towns increased. This led to more population migrating from villages to more urbanised areas, and, hence, a lower decrease rate of the working age population in the capital and towns. Finally, urban sprawl under the SSP5 x RCP8.5 scenario resulted in more cells becoming inhabitable (and having residents), in particular for large villages and villages. Although, to some extent, this helped to sustain the total size of the working age population in rural areas, the decline of population density in these areas was projected to be more dramatic than in more urbanised areas (results not shown) where residents preferred to remain, as assumed in the scenario.



			SSP1xRCP4.5	SSP4xRCP4.5	SSP3xRCP8.5	SSP5xRCP8.5
Capital district	Land cover change%	Residential	18%	15%	10%	21%
		Commercial/industrial	118%	112%	70%	153%
		Green/leisure	30%	-13%	-21%	-50%
	Population change %	Child (0-14)	-46%	-65%	-71%	-8%
		Working age (15-29)	-64%	-75%	-79%	-41%
		Working age (30-49)	-48%	-61%	-67%	-25%
		Working age (50-64)	-41%	-51%	-59%	-24%
		Elderly (65+)	106%	36%	-15%	131%
Town (county seats /with county rights)	Land cover change%	Residential	27%	19%	11%	28%
		Commercial/industrial	79%	53%	25%	43%
		Green/leisure	47%	-18%	-23%	-41%
	Population change %	Child (0-14)	-53%	-71%	-77%	-16%
		Working age (15-29)	-59%	-73%	-78%	-34%
		Working age (30-49)	-52%	-65%	-71%	-30%
		Working age (50-64)	-31%	-44%	-54%	-12%
		Elderly (65+)	130%	51%	-8%	145%
Town	Land cover change%	Residential	29%	22%	12%	40%
		Commercial/industrial	99%	94%	57%	161%
		Green/leisure	39%	-18%	-20%	-43%
	Population change %	Child (0-14)	-54%	-71%	-76%	-3%
		Working age (15-29)	-60%	-72%	-77%	-25%
		Working age (30-49)	-52%	-64%	-70%	-20%
		Working age (50-64)	-33%	-44%	-54%	-2%
		Elderly (65+)	130%	56%	-4%	181%
Large village	Land cover change%	Residential	52%	39%	22%	78%
		Commerial/Industral	124%	98%	72%	267%
		Green/leasure	52%	-12%	-13%	-37%
	Population change %	Child (0-14)	-55%	-72%	-77%	10%
		Working age (15-29)	-59%	-70%	-75%	-17%
		Working age (30-49)	-46%	-57%	-64%	-2%
		Working age (50-64)	-31%	-40%	-50%	8%
		Elderly (65+)	195%	123%	39%	257%
Village	Land cover change%	Residential	18%	11%	16%	47%
		Commerial/Industral	92%	63%	86%	279%
		Green/leasure	61%	-8%	-10%	-27%
	Population change %	Child (0-14)	-67%	-81%	-78%	-18%
		Working age (15-29)	-67%	-77%	-75%	-33%
		Working age (30-49)	-60%	-69%	-66%	-27%
		Working age (50-64)	-45%	-53%	-48%	-11%
		Elderly (65+)	128%	23%	84%	185%

Figure 6 Projected changes (2010-2100) in urban land cover and population under different integrated scenarios, summarised by territorial types.

5 Discussion

Under the risk-based framework of climate change impact management introduced in an IPCC special report (Cardona et al., 2012), vulnerability is defined as the susceptibility of “exposed elements” being adversely affected by hazardous climate events. Urban infrastructure and population are most commonly regarded as “exposed elements” and their distribution is key to the assessment and management of climate change impacts. It is within this context that the current study was conceived. The ALLOCATION model is a product of combining existing empirical approaches to land use/cover change modelling with population mapping. Two characteristics make the model unique: (i) it is able to make fine resolution projections over a large area, and; (ii) it generates a variety of outputs including the extents of multiple urban land cover types, and age-structured populations. Since the main objective is to model a complex system for a large geographical extent and temporal frame, a top-down modelling approach was selected with careful design of the model components to balance model specificity, computational burden, data requirement, relevance and ease of communication to stakeholders from different sectors. Integration in this modelling study is achieved from different perspectives, including integration of multiple disciplines (e.g., economics, urban/rural land use, and demographics), integration with stakeholders (in scenario and model development), and integration of scales of considerations (i.e., from national to local levels). The model developed can be classified as a coupled component model, based on the five common approaches for integrated environmental modelling summarised by Kelly et al. (2013). Even though the model was developed and calibrated for Hungary, the modelling framework has considerable flexibility and can easily be applied elsewhere. This is because the construction of the model functions only requires open access land cover data and census data at the local administrative levels both of which are increasingly available.

The plausibility of the model projections can be supported in several ways. Firstly, the conceptual model structure was developed based on a combination of three sub-components that are all based on existing empirical approaches with a certain level of realism. The selection of a top-down approach enabled parameterisation with observation data and the adoption of parameters with clear performance criteria (e.g., R-squared and AUC). Secondly, the interests and concerns of local stakeholders were used to guide development of the model and selection of impact and output measurements. This made the model appropriate and of relevance for its end-users. Thirdly, the integrated scenarios depicting the plausible futures of socio-economic and climate conditions were developed through engaging closely with stakeholders. This ensured credibility and salience of these scenarios in supporting policy decisions within the local context. Fourthly, the model performance was found satisfactory with a good accuracy of baseline projections. Finally, the local stakeholders found the projections explainable in the context of the integrated scenarios and useful in stimulating discussions on potential policy responses to climate and socio-economic change.

Rises in temperature under intermediate (RCP 4.5) and higher-end (RCP 8.5) climate change scenarios were projected to cause up to 2.18% and 7.91% damages to the GDP of Hungary by 2100. However, their influence on the urban spatial development patterns was estimated to be marginal by the model. Comparing the projections presented in this paper with those produced without considering GDP damage (not shown), the differences in residential and industrial/commercial area estimates were found to be less than 0.1% for all the NUTS2 regions under all integrated scenarios. This was because the functions to estimate changes in urban land covers (Function 1, section 2.2.2) used the per capita GDP and existing land covers in the region as key indicators, with the latter dominating (see the Electronic Supplementary Materials 2). Moreover, in both climate scenarios, the damage was estimated not to exceed 1% before 2050. Provided both GDP and population were projected to change dramatically, such a small reduction in GDP was inadequate to cause any obvious changes in per capita GDP and its consequent impact on the urban land cover change was negligible. At this scale of modelling, most of the other model factors selected for Hungary were related to socioeconomics and physical urban environments which could not be directly linked to climate change. Thus it was not surprising that the projected results suggested a negligible effect of climate change on urban development through causing damages to the national GDP. Given the current objectives and context of integrated scenarios, further modelling efforts to quantify the impacts of climate change on urban development may integrate sub-models accounting for land cover changes in other sectors, e.g. forestry and agriculture, that can directly influence urban development (through competition for land) and have a clearer link to climate impacts (White and Engelen, 1997). Finally, it should be noted that, different results may be gained when applying the modelling framework to other countries, as the factors selected, coefficients estimated and evolutions of GDP and population projected may all be different.

Applying the model to climate and socio-economic scenarios to simulate a range of plausible futures of urban development provides useful information for stimulating discussions related to climate change adaptation options. This has been frequently emphasised in the literature (van Ruijven et al., 2014) and was confirmed by local stakeholders involved in this study. In general, two types of scenario products can be distinguished: (i) qualitative narratives that contain detailed descriptions of events and complexity that cannot be easily captured in modelling approaches and are generally stakeholder-led, and; (ii) quantitative trends described in numerical forms that are needed as model input and which are often modeller-led (Pedde et al., In revision). The two types of scenario products are often combined in the Story-And-Simulation (SAS) approach (Alcamo, 2008), which refers to an iterative, stepwise process to link narratives and quantifications. The inherent difference between the two scenario types poses great challenges to their integration in the SAS approach (Houet et al., 2016). Several methods have been developed to address this issue by jointly considering research objectives, scales and desired level of participation in the scenario process (c.f. Mallampalli et al. (2016) for an overview). In this study, we applied an approach known as ‘hardwiring’ of the two scenario types (Houet et al., 2016). Thus, scenario drivers are quantified without violating the background climate and socio-economic settings of each scenario, and they consist of both quantitative model estimations (i.e., national GDP, population and temperature) and qualitative information generated through the participation of stakeholders (i.e., residential preferences and planning regulations on urban green infrastructure and urban morphology). Quantifying the drivers in strict obedience to the underlying assumptions helped to retain the internal consistency of each scenario. It further helped to reduce the overall subjectivity of the scenario driver set by limiting the entry of qualitative scenario drivers to higher levels, on which the quality of model estimations was likely to be more profound. The final four localised scenarios were used to set the socio-economic and climatic conditions for model simulation. These scenarios were developed based on combinations of the SSPs and RCPs from the IPCC-related global scenario framework. Extending, downscaling and applying a common scenario framework is likely to increase the chance of our predictions being useful for future climate change risk management studies in the same region, as well as them being comparable with relevant studies in other regions or at a higher level.

An important lesson learnt from this study was the need for optimising the level of efforts required from stakeholders. In this study, stakeholders were closely engaged with both the scenario and model development processes (Figure 3) and provided location-specific knowledge to fill gaps in data, simplify model structure and evaluate model outputs for their acceptance and usefulness. To ease the burden, engaging stakeholders in other technical tasks, such as quantitative evaluation, was avoided. It was, thus, the responsibility of modelling experts for to perform a detailed verification and validation exercise to strengthen the technical soundness of the model (c.f. the quantitative evaluation results in the Electronic Supplementary Materials 2). Moreover, due to the diversity of stakeholders' background, the qualitative evaluation of the model structure was conducted through discussion only. It may be beneficial to include a more structured approach in such discussion, for example, by using a questionnaire to evaluate the model construction, operation and output, and by modelling experts working more closely with the stakeholders in the workshops (Bennett et al., 2013). Another lesson learnt was the need for effective communication among scenario scientists, modelling experts and stakeholders. In our post-workshop survey with stakeholders, it was found important to include a small group of resource persons who engaged with both scenario and model developments in the stakeholder meetings to ensure the transparency of the development processes. In line with Booth et al. (2016), this study highlighted the importance of having research team members capable of working comfortably across disciplines and being capable of understanding both aspects of scenario construction and modelling. Good communication also contributes to interests between the research team and stakeholder community being more balanced. For instance, several modifications of model structure took place to include factors of local interests (e.g., urban/rural out-migration). It should be further mentioned that in our workshops, a few stakeholders with scientific background or modelling skills unexpectedly volunteered in answering questions to the research team raised by the other stakeholders. This facilitated the acceptance of, and enhanced the confidence in, the modelling approach within the stakeholder community.

This study has several limitations, for which future research directions need to be suggested. Firstly, the model lacks explanatory power on the complex underpinning processes of land cover conversion and residential mobility. Future studies which aim to better explain their mechanisms, and interactions with climate conditions, may benefit from linking a bottom-up approach under an agent-based modelling framework. Such models can be developed for smaller geographical regions to better meet the demand of geospatial data, and at finer spatio-temporal scales to enable individual households, life course events and decision-making processes to be represented explicitly (Fontaine and Rounsevell, 2009). They may also be better applied to specific issues, such as international migration flows related to changes in suitability and/or preference for living next to the coast. Secondly, when focusing on smaller research areas, or on a specific set of sectors, building a wider range of localised and sectoral scenarios, may be more informative and helpful in establishing well-targeted policy responses. An example can be found for the fine level simulation of urban growth (Houet et al., 2016), in which the authors utilised a novel six-step method to generate a set of seven contrasting scenarios for climate adaption. Moreover, lower-end climate change scenarios need further attention following the ambition set in the Paris Agreement of limiting the global temperature increase to 1.5°C above pre-industrial levels. Thirdly, more scenario drivers may be included when more qualitative information is available in future studies. One interesting example is the size of neighbourhood being used to estimate a cell's residential preferences in the population distribution sub-model. This parameter is related to the distance travelled for commuting and leisure purposes, which can be influenced by climatic conditions, time use, lifestyle, transport efficiency and planning, etc. (Koetse and Rietveld, 2009; Li et al., 2015; Li et al., 2016a). Many of these factors are likely to cause contrasting patterns of change within the scenarios used in this study. Fourthly, according to qualitative feedback from stakeholders understanding local context and working in the local language are critical factors in reducing the risk of miscommunication during facilitated engagement sessions and may help avoid the need for making corrections later.

6 Conclusion

An integrated model was developed, evaluated and applied to predict fine-level urban development for the whole of Hungary. The model projected contrasting patterns of urban land cover and age-structured population under the four integrated scenarios, which revealed several societal challenges that Hungary may need to face in the future.

Under the scenarios combined with intermediate climate change (RCP 4.5), urban development paths were projected to be different between the two socio-economic conditions describing (i) a sustainable future with less inequality (SSP1), and (ii) an unequal future of increased social, economic and political disparities (SSP4). Under the former integrated scenario, the country was predicted to have moderate and compact urban growth around the capital and regional centres, accompanied with steady rural out-migration and depopulation. Under the latter scenario, a slow urban growth rate in a compact-sprawl-mixed fashion was predicted, with strong national depopulation which is greatest in rural areas. More distinct future urban patterns were projected under the higher-end climate changes (RCP8.5) which were associated with two other socio-economic scenarios. In a de-globalising future of low-level economic growth and a seriously degraded environment (SSP3), the country was projected to have slow and sprawled urban growth across the territory. The capital region was estimated to lose a significant amount of population and newly developed residential areas around the capital were likely to be underutilised. In contrast, in an economically driven future which is highly industrialised and fossil-fuel based (SSP5), the country was projected to have a rapid and sprawled urban growth and an overall growth in population. Strong domestic migration was projected to occur in order to occupy the newly developed residential areas. This was likely to result in a more unevenly distributed population pattern. Despite the differences in shape and speed, the peri-urbanisation of the Budapest region and out-migration from the centres of the capital and major towns were projected to occur under all scenarios. This suggests that future local urban policies should take into the consideration the potential underutilisation of urban infrastructure in the capital centre, and the pressure of social service provisioning in its outskirt.

Our modelling experiments revealed the inadequacy of approximating the impacts of climate change on urban land cover change through GDP only, and suggested further integration with land cover change sub-models for other land cover types that not only affect urban developments but also respond directly to climate changes. Co-learning with stakeholders in both scenario and model developments contributed to the originality of this study. To achieve effective collaboration between scenario scientists, modelling experts and stakeholders, the study pointed out the importance of objectively deciding upon the division of work load between the stakeholders and research term, and in ensuring consistency between the two. Having participants in both groups who work comfortably across disciplines and are thoroughly familiar with the local context also supported good communication and collaboration. The projected results may provide fundamental decision support information for assessing the vulnerability of Hungarian cities to climate change. The integrated model can further be used to test the effectiveness of response options for climate change adaptation.

Software and data availability

No specific software has been developed. This paper uses R version 3.2.0 (R Foundation for Statistical Computing, Austria) for statistical analysis and empirical function construction, ArcGIS version 10.2 (ESRI Inc., USA) for spatial data management and final output visualisation, and Repast Simphony version 2.1 (Argonne National Laboratory, USA) for model development and integration. The data used for model development (section 2) and scenario configuration (section 3) are either open access or freely available upon request from the corresponding author. The final projected patterns of urban land covers and population age structures for Hungary by 2040, 2070 and 2100 are also available upon request from the corresponding author.

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Electronic Supplementary Material 1 - Supplemental data and methods

1 Rules for spatially allocating the changes in artificial land cover

Parameters and their sources are listed in Tables S1.1-S1.3. At time step *t*, for each NUTS2 region:

➔ ***Step 1*** – The regional demands of each artificial land class (E_{RES}, E_{COM} and E_{GRE}) are calculated by $\Delta E_t = E_t - E_{t-1}$ (Table S1.4 and the main text) or predefined in scenarios as ΔS_t:

- ***Step 1.1*** – For E_{RES} and E_{COM}, if growth in demand of any land types is predicted ($\Delta E_t > 0$) in the region, then identify those increased land classes and go to ***Step 2***; else if no growth is predicted, then go to ***Step 4***.
- ***Step 1.2*** - For E_{GRE}, if growth ($\Delta S_t > 0$) is predefined in scenario settings, then go to ***Step 2***; else if decrease ($\Delta S_t < 0$) is predefined, then go to ***Step 3***; else if no change is predefined, then go to ***Step 4***.

➔ ***Step 2*** – The growth of cell-level artificial land cover is estimated using following steps:

- ***Step 2.1*** – For each cell *i* in the region, calculate the cell-level development potential *Pi* for each land cover type using the logistic regressive functions (Tables S1.5-S1.7): $ln\ (P_i/(1-P_i)) = a + \sum_{j=0}^{V} b_j * var_{ij}$, where a is the intercept and *b* is the coefficient of the variable *var* from the collection of all explanatory variables $\{V\}$. Use the predefined cut-off value (Tables S1.5-S1.7) to identify a pool of candidate cells $\{M\}$ (if P_i > cut-off value) for further growth estimation.
- ***Step 2.2*** – For each cell *k* in the candidate pool *M*, calculate the potential of growth (G_k) for each land cover type using $G_k = P_k \cdot C_k$, where C_k is the force of policy on compact urban development (see main text).
- ***Step 2.3*** – Estimate the cell-level growth for each land class using $D_k = \Delta E_t * G_k / \sum_{m \in M} G_m$, where *m* refers to the *m*th cell from *M*. Total cell-level demand of artificial land ($\widehat{D}_k$) is calculated by summing *D* for all land classes concerned.
- ***Step 2.4*** – If the available land (AVL_k) is limited and competition between land cover types exists ($\widehat{D}_k < AVL_k$), then go to ***Step 2.5***; otherwise, increase each land cover type by its predicted D_k and go to ***Step 2.6***.
- ***Step 2.5*** – Check the development priority for each land cover type:
  - If no priority, then increase the extent of the land cover by its relative demand: $AVL_k * D_k/\widehat{D}_k$;
  - If any land cover type is prioritised, then increase its extent by D_k if ($D_k \leq AVL_k$). Convert the rest of AVL_k to the classes not prioritised according to their relative predicted demands. If ($D_k > AVL_k$), convert all AVL_k into the prioritised land class.
  - Update AVL_k for *M*, calculate unallocated ΔE_t and go to ***Step 2.6***
- ***Step 2.6*** – If ΔE_t for each land class is all allocated, then go to ***Step 2.7***; else repeat ***Steps 2.2-2.5***.
- ***Step 2.7*** – End for the region.

➔ ***Step 3*** – The decrease in cell-level urban green/leisure land cover is estimated using following steps:

- ***Step 3.1*** – For each cell *i* in the region, calculate the cell-level development potential *Pi* for urban green/leisure use using the logistic regressive functions (Tables S1.7): $ln\ (P_i/(1-P_i)) = a + \sum_{j=0}^{V} b_j * var_{ij}$, where *a* is the intercept and *b* is the coefficient of the variable *var* from the collection of all explanatory variables $\{V\}$. Use the predefined cut-off value (Tables S1.7) to identify a pool of candidate cells $\{M\}$ (if P_i > cut-off value) for further decrease estimation.
- ***Step 3.2*** – For each cell *k* in the candidate pool *M*, calculate the potential of decrease in urban green/leisure area (R_k) using $G_k = (1 - P_k) \cdot C_k$, where C_k is the multiplication of the cell's development potentials for residential and commercial/industrial uses.
- ***Step 3.3*** – Estimate the cell-level urban green/leisure decrease using $D_k = \Delta S_t * R_k / \sum_{m \in M} R_m$, where *m* refers to the *m*th cell from *M*.
- ***Step 3.4*** – Check the existing urban green/leisure for each cell:
  - If the existing urban green/leisure land is not smaller that D_k, then turn all D_k from the existing area to available land (AVL_k);
  - If the existing urban green/leisure land is smaller that D_k, then turn all exiting urban green/leisure land to available land (AVL_k);
  - Update AVL_k for *M*, calculate unallocated ΔS_t and go to ***Step 3.5***.
- ***Step 3.5*** – If ΔS_t is all allocated, then go to ***Step 3.6***; else repeat ***Steps 3.3-3.5***.
- ***Step 3.6*** – End for the region.

➔ ***Step 4*** – End for the region.

Table S1.1 Explanatory variables at NUTS2 level – socio-economics and demographics

Variable	Source	Symbol
GDP in million HUF at time step *t*	KSH[1]; IMPRESSIONS IAP[2]	*GDP(t)*
GDP per capita in million HUF at time step *t*	KSH[1]; IMPRESSIONS IAP[2]	*GDP_PC(t)*
Population aged < 15 at time step *t*	KSH[1]; IMPRESSIONS IAP[2]	*CHILD(t)*
Population aged 15 – 64 at time step *t*	KSH[1]; IMPRESSIONS IAP[2]	*WORK(t)*
Population aged > 65 at time step *t*	KSH[1]; IMPRESSIONS IAP[2]	*RETRIED(t)*
Unemployment rate at time step *t*	KSH[1]; IMPRESSIONS IAP[2]	*UNEPLY(t)*

[1] The Hungarian Central Statistical Office (KSH) datasets were used for constructing functions, www.ksh.hu/.
[2] The IMPRESSIONS IAP (under construction) predictions were used for scenario analysis, www.impressions-project.eu/.

Table S1.2 Explanatory variables at the cell level

Variable	Source	Symbol
X coordinate in ETRS_1989_LAEA_L52_M10 spatial reference system	EEA[1]	*X*
Y coordinate in ETRS_1989_LAEA_L52_M10 spatial reference system	EEA[1]	*Y*
Distance to the centre of capital (Budapest) in meters	OpenStreetMap[2]	*D2CAPITAL*
Distance to historical town centre in meters	OpenStreetMap[2]	*D2TOWN*
Distance to historical village centre in meters	OpenStreetMap[2]	*D2VILLAGE*
Distance to lake in meters	CORINE[3]	*D2LAKE*
Distance to river in meters	CORINE[3]	*D2RIVER*
Averaged elevation in metres	SRTM[4]	*ELEV*
Variation (standard deviation) of elevation	SRTM[4]	*ELEV_STD*
Proportion of available land at time step *t*	Estimation[5]	*AVL(t)*[*]
Proportion of residential area in baseline in cell at time step *t*	CORINE[6]	*RES(t)*
Proportion of commercial and industrial in cell at time step *t*	CORINE[7]	*COM(t)*
Proportion of urban green and leisure area in cell at time step *t*	CORINE[8]	*GRE(t)*
Proportion of residential area in 3x3 neighbourhood at time step *t*	CORINE[6]	*RES_N1(t)*
Proportion of commercial and industrial in 3x3 neighbourhood at time step *t*	CORINE[7]	*COM_N1(t)*
Proportion of urban green and leisure area in 3x3 neighbourhood at time step *t*	CORINE[8]	*GRE_N1(t)*

[1] European Environment Agency (EEA) reference grid at 1 km^2, www.eea.europa.eu/data-and-maps/data/eea-reference-grids-2.
[2] OpenStreetMap data produced by Geofabrik for locations of centres, www.geofabrik.de/data/download.html.
[3] CORINE land cover classes from EEA, www.eea.europa.eu/data-and-maps/data/clc-2006-vector-data-version-3, and from Hungarian Institute of Geodesy, Cartography and Remote Sensing (FÖMI), www.fomi.hu/.
[4] SRTM (Shuttle Radar Topography Mission) data from the USGS EROS Data Center, http://www2.jpl.nasa.gov/srtm/.
[5] *AVL(t)* = 100% - *RES(t)* - *COM(t)*- *GRE(t)* – *Water body*% - *Protected area(t)*%, where protected area was estimated based on the Natura2000 (2014), http://www.eea.europa.eu/data-and-maps/data/natura-7, and CDDA (2014), www.eea.europa.eu/data-and-maps/data/nationally-designated-areas-national-cdda-8, from the European Environment Agency (EEA).
[6] Residential area - "Urban fabric" (CLC 111-112).
[7] Commercial and industrial area – "Industrial or commercial units" (CLC 121).
[8] Green and leisure area – "Green urban areas" (CLC 141) and "Sport and leisure facilities" (CLC142).

Table S1.3 Explanatory variables at the NUTS5 level

Variable	Source	Symbol
Proportion of residential area at time step *t*	CORINE[1]	*MEAN_RES(t)*
Proportion of commercial and industrial area at time step *t*	CORINE[2]	*MEAN_COM(t)*
Proportion of urban green and leisure area at time step *t*	CORINE[3]	*MEAN_GRE(t)*
Railway density (length in km per km^2)	OpenStreetMap[4]	*DEN_RAIL(t)*
Motorway density (km per km^2)	OpenStreetMap[4]	*DEN_MOTOW(t)*
Primary/Secondary/Tertiary road density (km per km^2)	OpenStreetMap[4]	*DEN_OTHRD(t)*
Region is capital	OpenStreetMap[5]	*IS_CAPTIAL*
Region is town	OpenStreetMap[5]	*IS_TOWN*
Region is village	OpenStreetMap[5]	*IS_VILLAGE*

[1] Residential area - "Urban fabric" (CLC 111-112).
[2] Commercial and industrial area – "Industrial or commercial units" (CLC 121).
[3] Green and leisure area – "Green urban areas" (CLC 141) and "Sport and leisure facilities" (CLC142).
4 OpenStreetMap data for transportation networks.
5 OpenStreetMap data for administrative boundaryies.

Table S1.4 Estimating the extent of urban land class in NUST2 regions at year *t*

Outcome	Expression	R^2	Adj. R^2
$E_{RES}(t)$	$0.987553 * E_{RES}(t-1) +2446.195814 * \Delta GDP\_PC(t) + 627.270153$	0.997	0.997
$E_{COM}(t)$	$1.037425 * E_{COM}(t-1) + 1032.750659 * \Delta GDP\_PC(t) - 113.107198$	0.964	0.960
$E_{GRE}(t)$	$1.113059 * E_{GRE}(t-1) - 0.095884 * E_{COM}(t-1) -0.012262 * \Delta CHILD(t) -7.9137E-8 * \Delta WORK(t)^2 + 134.101485$	0.999	0.999

Table S1.5 Logistic functions to predict residential land cover (P_{RES}) growth for each NUTS2 region.

		HU10 Central Hungary	**HU21** Central Transdanubia	**HU22** Western Transdanubia	**HU23** Southern Transdanubia	**HU31** Northern Hungary	**HU32** Northern Great Plain	**HU33** Southern Great Plain
Cell-level	*X*		1.875e-05				-3.561e-05	-4.358e-06
	Y	-8.998e-06		4.296e-06		2.881e-05		
	D2CAPITAL	-4.712e-05	1.555e-05	7.685e-06			3.527e-05	
	D2TOWN	-1.631e-04	-1.058e-04	-3.966e-05				-3.874e-05
	D2VILLAGE	-2.188e-04	-4.107e-04	-1.277e-03	-6.859e-04	-5.811e-04	-2.062e-04	-1.941e-04
	D2LAKE			2.608e-05		-7.699e-05	-3.367e-05	2.832e-05
	D2RIVER		1.316e-05		-8.345e-06		1.564e-05	
	ELEV		-2.633e-03	6.631e-03			1.438e-02	-3.484e-02
	ELEV_STD			-2.833e-02	2.180e-02	-2.216e-02		
	AVL(t)	1.846e-02	1.473e-02		1.765e-02	4.492e-03	1.325e-02	2.039e-02
	RES(t)	2.441e-02	2.090e-02		2.990e-02	1.255e-02	1.194e-02	2.841e-02
	COM(t)	4.291e-02				-1.248e-01		3.577e-02
	GRE(t)	2.227e-02			4.984e-02			5.443e-02
	RES_N1(t)	2.111e-03	7.233e-03	7.923e-03	8.261e-03	6.893e-03	7.606e-03	6.733e-03
	COM_N1(t)	-5.038e-03		9.390e-03			-5.941e-03	
	GRE_N1(t)	4.619e-03		1.313e-02				
NUTS5-level	*MEAN_RES(t)*	-2.939e-02			-1.952e-01	-4.787e-02	-5.466e-02	
	MEAN_COM(t)	5.234e-02	1.188e-01		1.884e-01		2.539e-01	
	MEAN_GRE(t)	-6.328e-02						
	DEN_RAIL(t)	-2.793e-04	-1.344e-03					
	DEN_MOTOW(t)	5.246e-04		1.025e-03				-3.625e-03
	DEN_OTHRD(t)	7.567e-04						3.376e-03
	IS_CAPTIAL							
	IS_TOWN			1.309e+00	1.219e+00	1.169e+00	4.008e-01	
	IS_VILLAGE							
Intercept		2.279e+01	-9.742e+01	-1.570e+01	-3.908e+00	-8.473e+01	1.716e+02	1.860e+01
AIC		1196.1	1157.9	1586.7	1593.8	1196.1	1570.1	1251.1
AUC		0.8270114	0.8296137	0.8152192	0.8238422	0.8410751	0.8336033	0.8708228
Cutoff[1]		0.06644128	0.03104071	0.05375403	0.03386196	0.02119745	0.02282712	0.02028611

[1] Cutoff value = where the sum of the model sensitivity and specificity is the greatest

Table S1.6 Logistic functions to predict commercial & industrial land cover growth (P_{COM}) for each NUTS2 region.

		HU10 Central Hungary	**HU21** Central Transdanubia	**HU22** Western Transdanubia	**HU23** Southern Transdanubia	**HU31** Northern Hungary	**HU32** Northern Great Plain	**HU33** Southern Great Plain
Cell-level	*X*		1.25E-04		1.36E-04		3.63E-04	
	Y						8.35E-05	-7.33E-05
	D2CAPITAL	-6.38E-05			-1.40E-05		-4.01E-05	
	D2TOWN	-1.84E-04	-3.43E-04	-3.73E-04	-3.09E-04	-2.95E-04	-1.32E-04	-1.14E-04
	D2VILLAGE		1.64E-04					
	D2LAKE	4.38E-05	-7.40E-05				4.20E-05	-3.88E-05
	D2RIVER		1.66E-05	2.78E-05				4.48E-05
	ELEV					-6.22E-02	-2.15E-02	-5.68E-02
	ELEV_STD	-7.05E-02		-1.37E-01				
	AVL(t)		1.27E-02	1.62E-02	1.28E-02	1.54E-02	1.90E-02	6.62E-02
	RES(t)	-1.73E-02					2.37E-02	4.39E-02
	COM(t)	1.61E-02	5.82E-02	6.55E-02		1.57E-02	7.46E-02	1.25E-01
	GRE(t)							
	RES_N1(t)				3.88E-03			5.21E-03
	COM_N1(t)	5.61E-03			2.09E-02			
	GRE_N1(t)			8.75E-03				
NUTS5-level	*MEAN_RES(t)*						1.22E-01	
	MEAN_COM(t)	6.94E-02	1.23E-01	3.16E-01				3.61E-01
	MEAN_GRE(t)	-5.70E-02					6.42E-01	-4.06E-01
	DEN_RAIL(t)	-4.73E-04	-1.28E-03					

	DEN_MOTOW(t)				-6.77E-03			
	DEN_OTHRD(t)		2.92E-03					-1.41E-03
	IS_CAPTIAL							
	IS_TOWN			-1.67E+00			3.85E-01	
	IS_VILLAGE							
Intercept		-3.11E-01	-6.77E+01	-4.90E+00	-7.02E+01	-4.36E+00	-2.09E+02	1.43E+01
AIC		780.52	522.86	254.54	408.12	333.94	900.91	907.24
AUC		0.8374454	0.895711	0.918099	0.854678	0.865272	0.796618	0.819756
Cutoff[1]		0.0491122	0.014451	0.013794	0.007486	0.007966	0.010754	0.014735

[2] Cutoff value = where the sum of the model sensitivity and specificity is the greatest

Table S1.7 Logistic functions to predict green & leisure land cover (P_{GRE}) growth for each NUTS2 region.

		HU10 Central Hungary	**HU21** Central Transdanubia	**HU22** Western Transdanubia	**HU23** Southern Transdanubia	**HU31** Northern Hungary	**HU32** Northern Great Plain	**HU33** Southern Great Plain
Cell-level	*X*		5.98E-04	8.85E-04				
	Y	3.00E-04	4.51E-04	3.29E-04				
	D2CAPITAL		1.03E-04	9.80E-05				
	D2TOWN	-7.55E-05	2.33E-04	-2.50E-04	-1.58E-04	2.38E+02	-2.06E-04	
	D2VILLAGE							
	D2LAKE	-1.78E-04					-1.70E-04	
	D2RIVER					8.37E-05	-5.22E-05	
	ELEV	-8.35E-03						-5.62E-02
	ELEV_STD	3.44E-02					3.71E-01	2.28E-01
	AVL(t)	1.88E-02			2.98E-02	-6.17E-02		2.10E-02
	RES(t)				3.96E-02		2.95E-02	
	COM(t)			5.31E-02				5.18E-02
	GRE(t)	3.86E-02		5.34E-02		2.38E+02	8.07E-02	4.26E-02
	RES_N1(t)	5.44E-03			7.69E-03			
	COM_N1(t)			-1.16E-02		3.97E-02	-2.11E-02	8.57E-03
	GRE_N1(t)		1.12E-02					2.07E-02
NUTS5-level	*MEAN_RES(t)*	-3.40E-02			-2.93E-01		2.79E-01	
	MEAN_COM(t)		1.84E-01	2.82E-01				
	MEAN_GRE(t)		1.89E-01		3.34E-01			
	DEN_RAIL(t)				-4.48E-03		6.16E-03	
	DEN_MOTOW(t)						8.28E-03	-0.00788
	DEN_OTHRD(t)						-9.18E-03	
	IS_CAPTIAL							
	IS_TOWN							-1.00E+00
	IS_VILLAGE							
Intercept		-8.61E+01	-4.34E+02	-5.39E+02	-7.21E+00	-2.36E+04	-5.41E+00	-3.90E+00
AIC		415.1	256.06	271.19	204.27	49.949	211.3	225.31
AUC		0.8091564	0.876377	0.783115	0.807328	0.966114	0.938917	0.820256
Cutoff[1]		0.0143627	0.014363	0.003603	0.002762	0.002911	0.003392	0.002891

[1] Cutoff value = where the sum of model sensitivity and specificity is the greatest

2 Rules for spatially allocating age-structured population

A full description of the background theory is available in the following paper:

Li, S., Juhász-Horváth, L., Harrison, P.A., Pintér, L., Rounsevell, M.D.A., 2016. Mapping population and age structure in Hungary: A residential preference and age dependency approach to disaggregate census data. J Maps 12(sup1), 560-569. doi: 10.1080/17445647.2016.1237898

At time step *t*, for each NUTS2 region:

➔ ***Step 1*** – Read population data from the software system.

➔ ***Step 2*** – Allocating population for working age classes (aged 15-29, 30-49 and 50-64):

- ***Step 2.1*** – Calculate the neighbourhood density of a cell i ($\hat{\rho}_i$) is calculated using a distance decay function, $\hat{\rho}_i = \sum_{n \in N}\left(1 - ((d_n - 1)/\tilde{d})^2 \cdot U(n)\right)$, where N is a collection of the cells in the cell i's rectangular neighbourhood, d_n is the distance from cell n to the cell i, and $\tilde{d}$ is the maximum distance considered in the neighbourhood. The $\tilde{d}$ for social and urban greenery preference is set 3km and for economic preference is assumed in different categories (0-5, 5-15, 15-25 and 25-50 km, Table S1.8).
- ***Step 2.2*** – Calculate the local preference LX using: $LX = e^{w1*\hat{\rho}_S + w2*\hat{\rho}_C + w3*\hat{\rho}_G}$, where $w1$, $w2$, and $w3$ represent the weights given by residents to social (*S*), economic (*C*), and urban greenery (G) preferences (values in Table S1.9). Residential ($\hat{\rho}_S$), commercial/industrial ($\hat{\rho}_C$) and green urban/leisure ($\hat{\rho}_G$) land densities are used for the social (*S*), economic (*C*), and urban greenery (*G*) preferences.
- ***Step 2.3*** – Classify cell-level LX into capital (LX^C), town (LX^T) and village (LX^V) according to the geographical location and territorial types. The local preferences of a cell i is then estimated as $f_w = a_1 * LX^C + a_2 * LX^T + a_3 * LX^V$, where a_1, a_2 and a_3 are the weights given to territorial types (values in Table S1.9).
- ***Step 2.4*** – For an inhabitable cell i in a NUTS2 region m, the number of population of each working population group (W) is calculated as $W_i = \frac{a_1*lx_i^C + a_2*lx_i^T + a_3*lx_i^V}{\sum_{k \in M_t}(a_1*lx_k^C + a_2*lx_k^T + a_3*lx_k^V)} \cdot W_m$, where lx_i^C, lx_i^T, and lx_i^V are the three local preferences of cell i ($i \in M_t$). M_t denotes the collection of all inhabitable cells in region m in time step t. Parameter k refers to the kth cell from M_t. W_m is the population in region m to be redistributed.

➔ ***Step 3*** – Allocating populations for children (0-14) and the elderly (65+): the dependent populations (D) are estimated based on the working populations (W) predicted in ***Step 2***, as: $D_i = \frac{\sum_{j=1}^{R} b_{ji}*W_{ji}}{\sum_{k \in M_t}(\sum_{j=1}^{R} b_{jk}*W_{jk})} \cdot D_m$, where W_{ji} ($W_{ji} \in R$) is predicted the population of a working age group (15-29, 30-49 or 50-64) of cell i ($i \in M_t$). The coefficient b indicates the strength of dependency on W (values in Table S1.10). M_t is a collection of all inhabitable cells in region m in time step t. Parameter k refers to the kth cell from M_t. D_m is the dependent population in region m to be redistributed.

➔ ***Step 4*** – End for the region.

Table S1.8 Frequency (%) of commuting distance in Hungary

	Home worker (otthon dolgozik)	**0–5 km**	**5–15 km**	**15–25 km**	**25–50 km**	**50 km +**	**Other**
Town (Város)	5.3	55.7	19.6	7.6	6.4	5	..
Village (Község)	5.9	31.8	23.6	18.5	12.7	6.8	..
Budapest	5.5	28.7	40.4	17.1	6.8	1.6	..
All (Összesen)	5.5	42.9	24.8	12.9	8.5	4.9	0.4

Table S1.9 Weights for local preference estimation and coefficients for population redistribution function

	Age class	**w1**	**w2**	**w3**	**a1**	**a2**	**a3**	**R-squared**	**RMSE**
HU10	15-29	0.98	0.98	0.94	5070.876	1874.304	462.7677	0.719	2866.179
	30-49	1	0.96	0.92	8259.81	3314.214	807.5729	0.785	4060.033
	50-64	1	0.96	0.92	5361.809	2061.233	532.7279	0.821	2407.333
HU21	15-29	1	1	0.7	0	3164.574	233.3811	0.857	627.919
	30-49	1	1	0.6	0	5164.616	382.6156	0.870	977.873
	50-64	1	1	0.7	0	3716.433	278.401	0.884	695.072
HU22	15-29	1	0.96	0.92	0	4938.67	133.0202	0.916	484.489
	30-49	1	0.4	1	0	8141.008	235.2779	0.922	808.666

	50-64	1	0.04	0.92	0	5848.673	171.7724	0.933	583.131
HU23	15-29	1	0.96	0.08	0	6339.051	300.1142	0.830	650.735
	30-49	1	0.2	0	0	8870.262	493.8941	0.843	934.779
	50-64	1	0.02	0.12	0	6739.412	404.64	0.843	746.989
HU31	15-29	1	0.92	0.04	0	4927.736	188.9237	0.880	681.845
	30-49	1	0.88	0.02	0	7315.161	280.0909	0.887	990.358
	50-64	1	0.2	0	0	5674.714	221.2271	0.887	763.918
HU32	15-29	1	0.98	0.88	0	5931.873	275.3658	0.901	906.767
	30-49	1	0.98	0.88	0	8185.784	403.0809	0.931	1024.495
	50-64	1	0.96	0.92	0	5723.21	299.3604	0.935	734.918
HU33	15-29	0.98	0.94	0.98	0	4549.193	265.9332	0.832	1224.588
	30-49	0.98	0.94	0.98	0	6606.067	434.5498	0.891	1348.229
	50-64	1	0.88	0.98	0	4652.226	352.2766	0.912	878.553

w1 – social preference (S)
w2 – economic preference (C)
w3 – urban greenery preference (G)
a1 – weight of local preference in capital
a2 – weight of local preference in town
a3 – weight of local preference in village

Table S1.10 Coefficients for population redistribution function

	Age class	**b1**	**b2**	**b3**	**b4**	**b5**	**b6**	**b7**	**b8**	**b9**	**R-squared**	**RMSE**
HU10	0-14	0	0.039	0.094	0	0.488	0.501	0.659	0.017	0	0.867	1391.745
	65+	0.625	0.196	0	0	0	0	0.388	0.574	0.725	0.808	2351.728
HU21	0-14	0	0	0.442	0	0.447	0.202	0	0	0.030	0.882	467.835
	65+	0	0.035	0	0	0	0.003	0	0.728	0.677	0.880	536.831
HU22	0-14	0	0.207	0	0	0.312	0.529	0	0	0	0.918	384.752
	65+	0	0.191	0	0	0.163	0.005	0	0.382	0.714	0.927	462.987
HU23	0-14	0	0	0.667	0	0.207	0.033	0	0.351	0.042	0.839	504.464
	65+	0	0.138	0	0	0.547	0	0	0	0.719	0.846	572.849
HU31	0-14	0	0.073	0.918	0	0	0	0	0.578	0	0.891	595.788
	65+	0	0	0	0	0.015	0	0	0.824	0.776	0.882	615.542
HU32	0-14	0	0	0.938	0	0.468	0	0	0	0	0.945	592.229
	65+	0	0.409	0	0	0	0	0	0.286	0.751	0.914	618.028
HU33	0-14	0	0	0.204	0	0.475	0.387	0	0	0	0.904	608.739
	65+	0	0.214	0	0	0	0	0	0.573	0.815	0.906	742.134

b1 – dependency on population aged 15-29 in capital
b2 – dependency on population aged 15-29 in town
b3 – dependency on population aged 15-29 in village
b4 – dependency on population aged 30-49 in capital
b5 – dependency on population aged 30-49 in town
b6 – dependency on population aged 30-49 in village
b7 – dependency on population aged 50-64 in capital
b8 – dependency on population aged 50-64 in town
b9 – dependency on population aged 50-64 in village

Electronic Supplementary Material 2 - Supplemental model evaluation

We ran the model with baseline data for 2000 (based on the CORINE 2000 dataset) for one time step, i.e. 10 years, and compared the predicted results with observed results. The observed land cover changes were based on the CORINE 2012. The observed population and age structure were based on the 2011 census data provided by the Hungarian Central Statistical Office (KSH).

1 Artificial land cover

Firstly, predicted extents of the three artificial land cover types in 2010 were compared with observed extents at the LAU2 level (Figure S2.1). We roughly estimated the urban land extent for 2010 as: (extent in 2000) + (change in extent between 2000 and 2012) * 5/6. The Coefficient of Determination (R-squared) values were computed, with all higher than 0.97, indicating an excellent model performance on predicting. However, this could also be due to the relative small increase (5%) in the urban area between 2000 and 2010.

Secondly, visual comparisons were performed to assess the general accuracy of the predicted cell-level increases in artificial land covers (Figure S2.2). The results are overall satisfactory for the total artificial area which is dominated by the residential and commercial/industrial land cover types. However, the results for green/leisure land cover seems inaccurate, possibly due to the situations that this land cover type is more influenced by policy plans and that it is also likely to be converted into other (artificial) land cover types.

Thirdly, distance-density plots were produced to compare the cell-level predictions on the increases in total artificial with observed increases. Mean value and standard deviation of cell-level increase were calculated for different “distance to (capital/town/village) centre” groups, with an interval of 1 km (Figure S2.3A-C). In general, the standard deviations of the predicted cell-level increases were lower than that of the observed, suggesting the observed increases were more unevenly distributed.

2 Population and age structure

A comparison between the predicted population age structure and observed (census data 2011) was performed. The results were examined at the LAU2 level, see Figure S2.4 for the scatter plots between the observed and predicted populations for the whole of the country. The overall predictive power was satisfactory (all R-squared > 0.82). In general, the predictions seemed to be lower than the observations (all slope < 1).

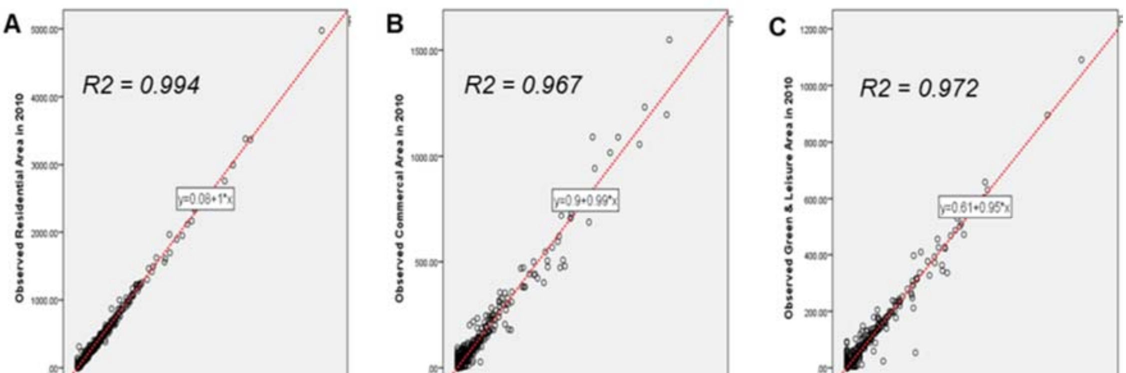

Figure S2.1 Scatterplot: Predicted vs. observed urban land class extent at LAU2-level: (A) residential, (B) commercial & industrial and (C) green & leisure.

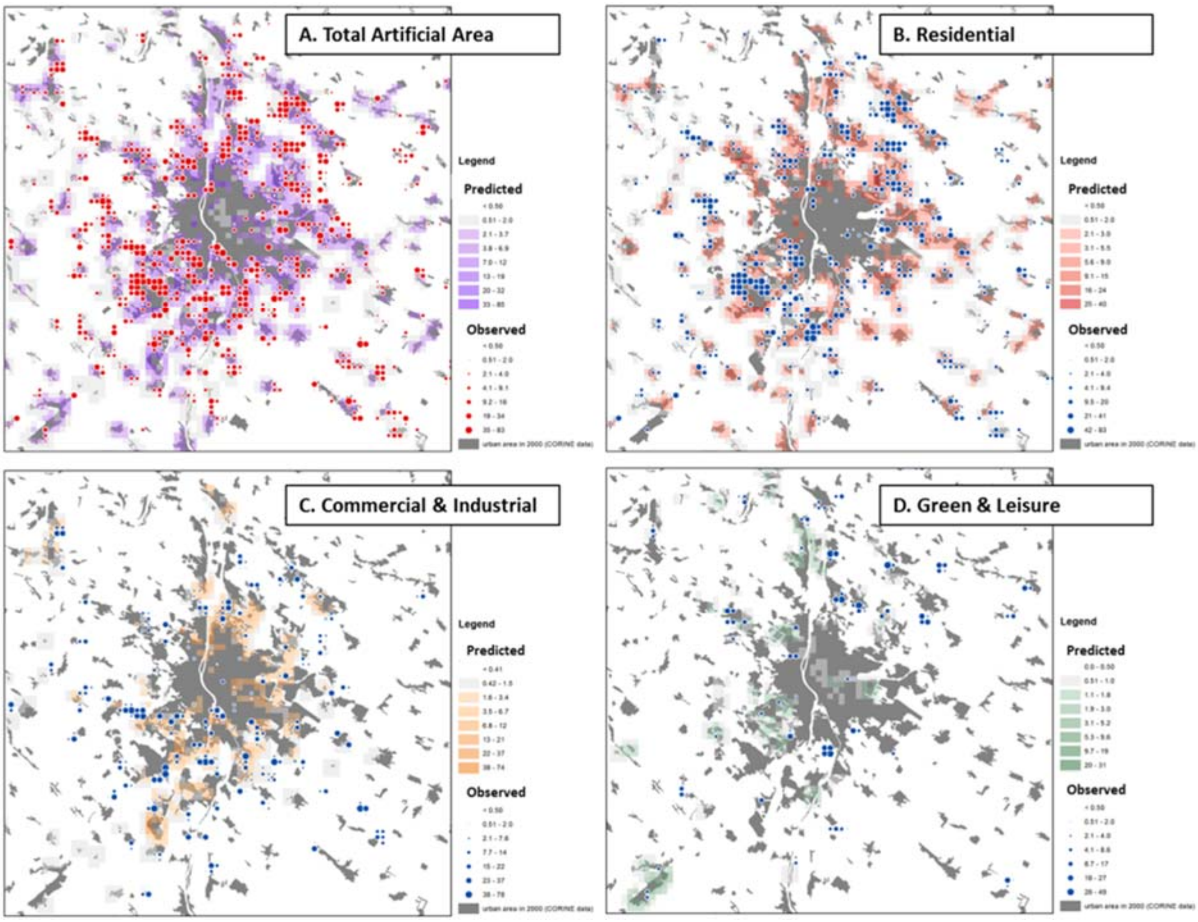

Figure S2.2 Visual comparison between predicted and observed urban area increases (ha/cell) in Budapest region. Total artificial area = sum of residential, commercial/industrial and green/leisure areas.

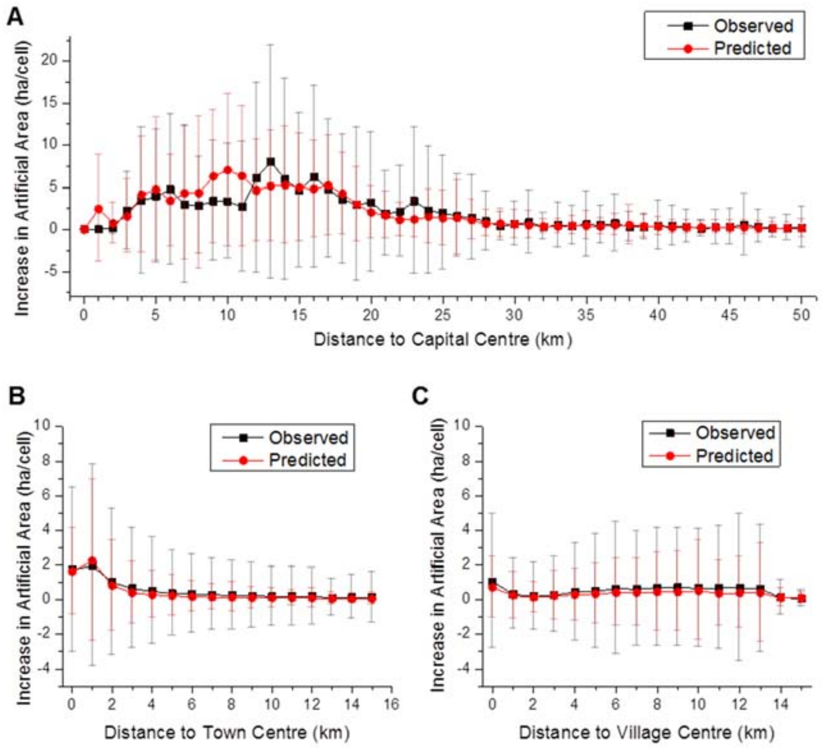

Figure S2.3 Mean and std. of cell-level urban area increase in different "distance to capital centre" (A), "distance to town centre" (B) and "distance to village centre" (C) groups.

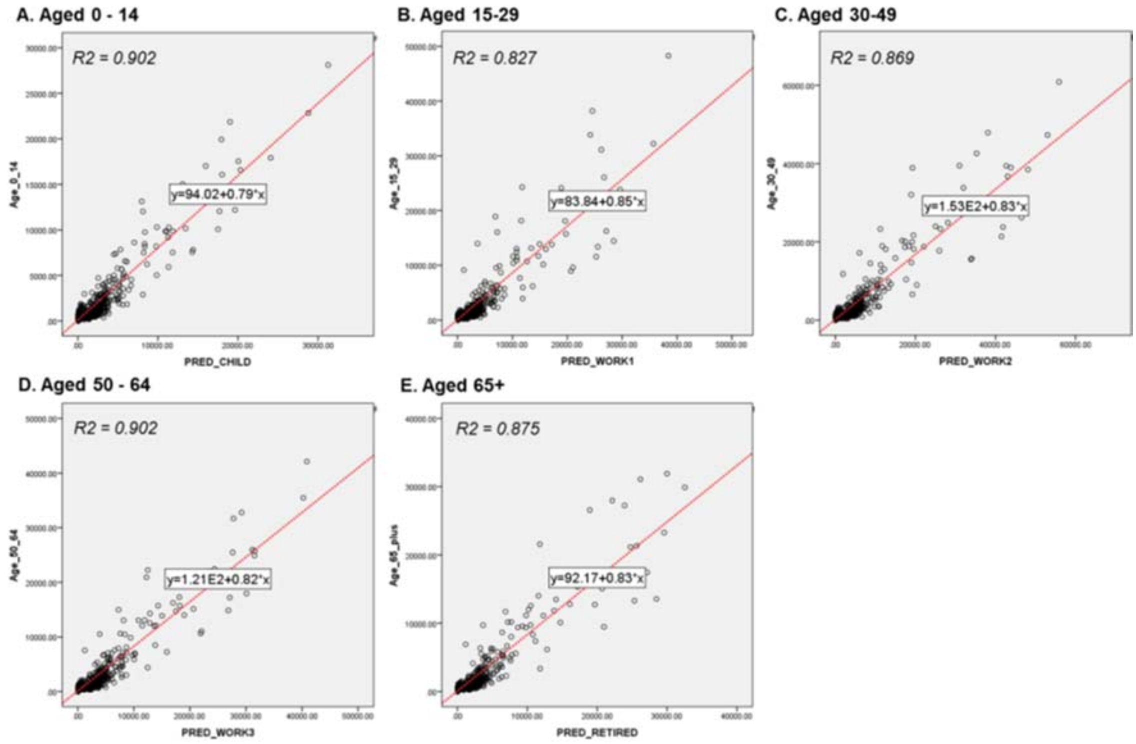

Figure S2.4 Comparison between predicted and observed distributions of population and age-structure at the LAU2 level.

Electronic Supplementary Material 3 - Supplemental sensitivity analysis

A sensitivity analysis was performed to examine how sensitive the changes in model parameters may influence the model outcomes. The most common one-at-a-time (OAT) approach was used, thus different model outputs were obtained by tuning one model parameter, leaving the others unchanged. The analysis was performed to test with the dataset prepared for model validation for which model was executed for one time step for projections at 2010.

A sensitivity index (SI) was calculated as: log10(Yi/Y0)/log10(Pi/P0), where Y0 is the default model output projected using the default parameter values P0 (i.e., the outputs generated for model validation), and Yi is the projection obtained when the parameter value is changed from its default value to Pi (i.e., by +10% for all regions/cells). High absolute SI values indicate a strong effect of the change in the parameter on the model output. Values of 1/−1 refer to positive/negative linear effects.

Not all of the model parameters were included in the sensitivity analysis. The developmental potentials for different urban land cover types (Function 1 Section 2.2.2, main text) were included in the sensitivity analysis, instead of testing their inputs, i.e. the local-level parameters listed in Tables S1.5-S1.7, supplemental data and method, electronic supplementary material 1 (esm1). Since the influence of these parameters on developmental potentials is directly related to their coefficients in the logistic regression models, the consequences of the changes of these parameters on the model outcomes can be inferred. Another set of the excluded parameters were the regional-level dependency ratio of the child and elderly populations listed in Table S1.10, esm1, for population distribution mapping. These parameters are operating at the final step of the model workflow. They are not connected to other model components and their effects on population distribution are based on simple relations to the working age populations, which are rather straightforward.

The targeted model outputs include those general ones of research interests (extents of land cover class and populations of age group in the capital, towns and villages). The cell-level predictions were also compared between the default and OAT induced projections, using a set of matrices accounting for (i) cell-to-cell agreements, and (ii) changes in the shape and heterogeneity of predictions. For urban land cover, model outputs were converted to binary maps of urban area distribution by assigning cells with total urban land cover > 1 ha as presence (1). The Kappa coefficient (≤1) was used to determine the cell-to-cell agreement. The Kappa for the default projection was 1. A SI of Kappa between -2 and 0 would suggest a very good agreement (Kappa > 0.8). The landscape shape index (LSI, a standardised measure of total edge density for the size of the urban landscape) was used to compare the overall shape of outputs. A negative SI of LSI would suggest a more compact shape and a positive value suggests a more irregular shape. The standard deviation shape index (SSI, the standard deviation of the shape indexes calculated for each isolated urban area) was used to compare the variation in the shape indexes for all urban land cover patches. A negative SI of LSI would suggest a more even (positive for uneven) distribution of shape indexes. For population distribution, Pearson’s R was calculated for the cell-to-cell agreement, with that of the default projection being 1. A greater negative SI of R indicates a smaller difference. Skewness and Kurtosis were further computed for the distribution of cells’ population. Skewness (SK) measures the symmetry of the distribution (SK=0 if symmetrical) and positive/negative SIs indicate more/less symmetrical distributions of the population. Kurtosis (KU) measures the amount of probability in the tails of distribution (KU=3 if normal distribution) and positive/negative SI indicate more/less in the tails.

The results of sensitivity analysis are presented in Tables S3.1 and S3.2. The extent and shape of urban land cover projections were sensitive to the national-level GDP, the regional-level population of age group and planning restrictions. Population distributions of age group were further sensitive to residential preference on proximity to social amenities and on whether to live in the capital, towns or villages. The main reasons for a marginal influence of the developmental potentials are due to the settings of the experiment to (i) increase their value for all cells simultaneously and (ii) run the model for only one time step.

Table S3.1 Model's sensitivity to change in a selected set of parameters (symbol definition in Table S3.2)

Sub-model	Parameters (test with +10%) ([N] = national level; [R]=regional level; [L] = local level)	Sensitivity index of model ouput																													
		Urban land cover												Population																	
		Residential			Commercial			Urban green			Total urban area distribution			Child (0-14)			Work1 (15-29)			Work2 (30-49)			Work3 (50-64)			Elderly (65+)			Total population distribution		
		EC†	ET	EV	EC	ET	EV	EC	ET	EV	K	LSI	SSI	PC	PT	PV	PC	PT	PV	PC	PT	PV	PC	PT	PV	PC	PT	PV	R	SK	KU
Economic change	[N] GDP	↗	↗	↗	↗	↗	↗	→	→	→	↘	→	→	→	→	→	→	→	→	→	→	→	→	→	→	→	→	→	→	↘	↘
	[N] Temperature increase	→	→	→	→	→	→	→	→	→	→	→	→	→	→	→	→	→	→	→	→	→	→	→	→	→	→	→	→	→	→
	[R] Child population (0-14)	→	→	→	↘	→	→	↘	↘	↘	→	→	→	↗	↗	↑	→	→	→	→	→	→	→	→	→	→	→	→	→	→	→
	[R] Working population 1 (15-29)	→	→	→	↘	→	↘	↘	→	→	→	→	→	→	→	↗	↗	↑	↑	→	→	→	→	→	→	↗	→	↘	→	→	↗
	[R] Working population 2 (30-49)	→	→	→	↘	↘	↘	↘	→	→	→	→	→	↘	↗	↘	→	→	→	↗	↗	↑	→	→	→	→	→	↘	→	→	→
	[R] Working population 3 (50-64)	→	→	→	↘	→	↘	↘	↗	→	→	→	→	↗	↘	↘	→	→	→	→	→	→	↗	↑	↑	↘	→	↗	→	→	↗
	[R] Elderly population (65+)	→	→	→	→	→	→	→	→	→	→	→	→	→	→	→	→	→	→	→	→	→	→	→	→	↑	↗	↑	→	→	↗
Land cover change	[R] Planning towards compactness	↘	↘	↘	↓	↓	↓	↘	↘	↘	↘	→	↘	→	→	↗	→	→	↗	→	→	↗	→	→	↗	→	→	↗	→	↗	↗
	[L] Potential for residential area	→	→	→	→	→	→	→	→	→	→	→	→	→	→	→	→	→	→	→	→	→	→	→	→	→	→	→	→	→	→
	[L] Potential for rommercial area	→	→	→	→	→	→	→	→	→	→	→	→	→	→	→	→	→	→	→	→	→	→	→	→	→	→	→	→	→	→
	[L] Potential for urban green area	→	→	→	→	→	→	→	→	→	→	→	→	→	→	→	→	→	→	→	→	→	→	→	→	→	→	→	→	→	→
Population distribution	[R] Social preference	→	→	→	→	→	→	→	→	→	→	→	→	↗	→	↘	↗	→	↘	↗	→	↘	↗	→	↘	↗	→	↘	→	↗	↑
	[R] Economic preference	→	→	→	→	→	→	→	→	→	→	→	→	→	→	→	→	→	→	→	→	→	→	→	→	→	→	→	→	→	↘
	[R] Urban greenery preference	→	→	→	→	→	→	→	→	→	→	→	→	→	→	→	→	→	→	→	→	→	→	→	→	→	→	→	→	→	→
	[R] Weight of preference in capital	→	→	→	→	→	→	→	→	→	→	→	→	↘	↘	↗	↘	↘	↗	↘	↘	↗	↘	↘	↗	↘	↘	↗	→	→	→
	[R] Weight of preference in town	→	→	→	→	→	→	→	→	→	→	→	→	↘	↗	↘	↘	↗	↘	↘	↗	↘	↘	↗	↘	↘	↗	↘	→	↘	↘
	[R] Weight of preference in village	→	→	→	→	→	→	→	→	→	→	→	→	↗	↘	↘	↗	↘	↘	↗	↘	↘	↗	↘	↘	↗	↘	↘	→	↗	↗

† EC = extent of land cover class in capital; ET = extent of land cover class in towns; EV = extent of land cover class in villages; K = kappa index; LSI = landscape shape index; SSI = standard deviation shape index; PC = population of age class in capital; PT = population of age class in in towns; PV = population of age class in villages; R = Pearson's R; SK = Skewness; KU = Kurtosis

Table S3.2 Definition of sensitivity index symbols in Table S3.1

Symbol	Range of sensitivity index (SI)	Definition - effect of parameter change on the model output
↑	SI ≥ 1	Positive (equal or stronger than linear effect)
↗	0.05 < SI < 1	Weak positive (weaker than linear effect)
→	-0.05 ≤ SI ≤ 0.05	Marginal or no effect
↘	-1 < SI < -0.05	Weak negative (weaker than linear effect)
↓	S1≤ -1	Negative (equal or stronger than linear effect)