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Modelling the impacts of land system dynamics on human well-being: Using an agent-based approach to cope with data limitations in Koper, Slovenia

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ABSTRACT

To cope with data limitations and to provide insight into the dynamics of LUCC for local stakeholders in the Municipality of Koper, Slovenia, we constructed an ABM (loosely defined) that integrates utility theory, logistic regression, and cellular automaton-like rules to represent the decision-making strategies of different agents. The model is used to evaluate the impact of LUCC on human well-being, as represented by the provision of highly productive agricultural soil, the extent of noise pollution, and quality-of-life measurements. Results for the Municipality of Koper show that, under a range of model assumptions, (1) high quality agricultural soils are disproportionately affected by urban growth, (2) aggregate resident quality of life increases non-linearly with a change in development density, (3) some drivers of residential settlement produce non-linear preference responses, and (4) clustering industrial development had a beneficial impact on human well-being. Additional novel contributions include the incorporation of noise pollution feedbacks and an approach to empirically inform agent preferences using a conjoint analysis of social survey data.

1. Introduction

Agent-based modelling (ABM) has been used to investigate land-use science research questions for nearly two decades (Parker, Manson, Janssen, Hoffman, & Deadman, 2003). These models typically represent the drivers that affect human decision-making and lead to land-use and land-cover change (LUCC). Among those drivers, modellers include demographics (An, Linderman, Qi, Shortridge, & Liu 2005), population growth (Axtell et al., 1999), and land markets (Filatova, van der Veen, & Parker, 2009). Among the decision-making strategies represented, modellers use decision trees (Deadman, Robinson, Moran, & Brondizio, 2004), utility theory (Evans & Kelley, 2004), statistical models (Brown et al., 2008), and evolutionary processes (Reschke, 2001) among other representations. Frequently, the land-use decisions and changes in ABM of LUCC are then based upon the heterogeneous actors represented as agents and the different socio-ecological contexts at a given location and time (Rounsevell, Robinson, & Murray-Rust, in press).

The application of ABM to LUCC research is growing at an increasing rate (Rindfuss et al., 2008). This is partly due to the ability of ABM to represent heterogeneity in actor characteristics and contexts along with feedbacks, thresholds, path dependence, and interaction among other processes (Holland, 1995). As a result of these and other advantages, ABM is widely used to investigate complex land-change research questions (e.g. Heckbert, Baynes, & Reeson, 2010). This expanded use and application of ABM is reviving discussions about what is an appropriate application of ABM (e.g. O'Sullivan, Millington, Perry, & Wainwright, 2012) because when incorrectly applied its credibility for scientific enquiry may be weakened.

A strictly defined ABM, with strong notions of preferences, autonomy, learning etc. is not applicable in all cases. However, the relevancy and applicability of ABM can be broadened when the strict ideals are loosened and instead ABM is used as an integrated approach to study complex land-use systems. While we can represent the micro-level actors and their aggregate system behaviours that produce regional LUCC, we may also use the concept of an agent to encapsulate a specific type or group of actors that make similar land-use decisions and changes, but for which we have no empirical data to inform their behaviour.

We present an agent-based approach to represent urban growth in an area of Eastern Europe known that has little available data and is undergoing extensive LUCC. To overcome data limitations we use logistic regression and cellular automata to represent decision-making outcomes from agents for which we have no behavioural information. By combining these modelling paradigms we are able to increase the number of land uses and land covers modelled. More importantly, we are able to represent land-use

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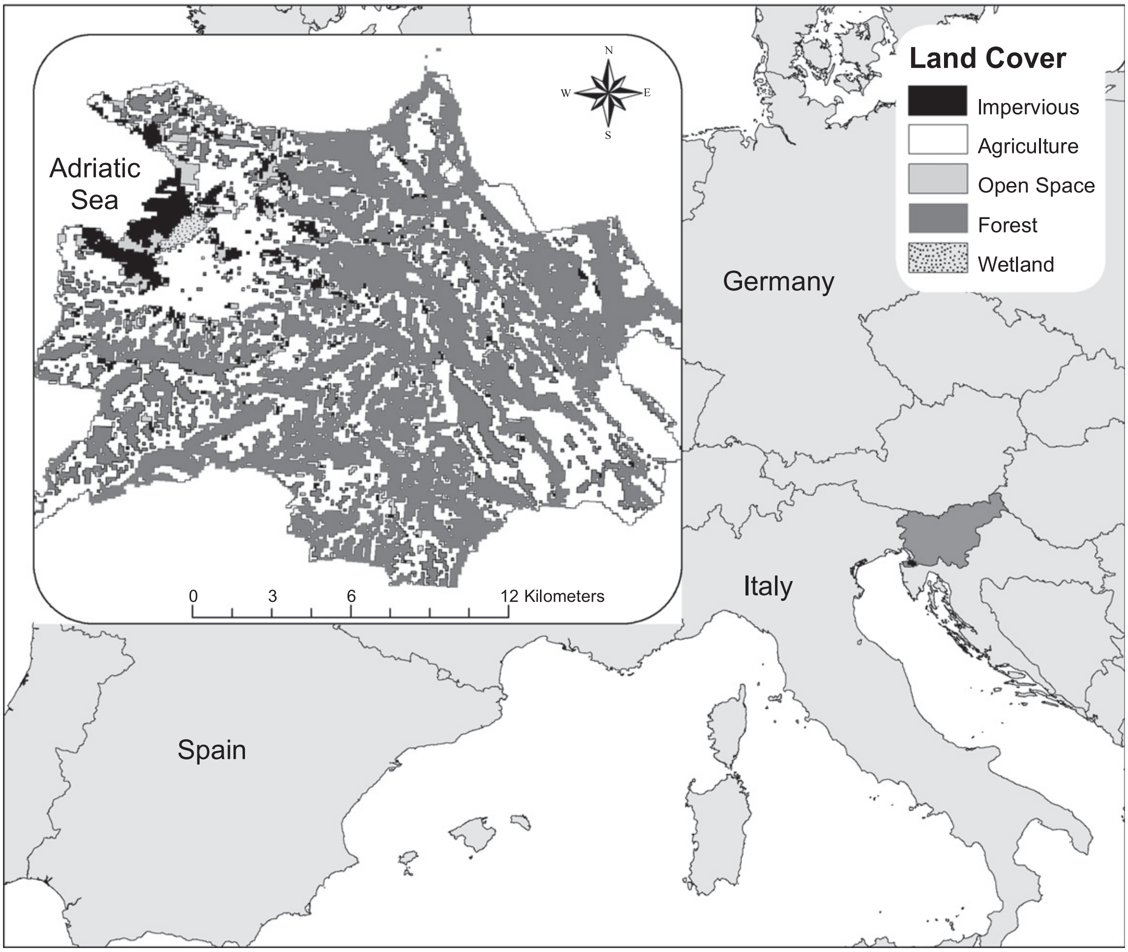

Fig. 1. Republic of Slovenia (dark grey) in Europe (light grey). Inset: The Municipality of Koper, with the city of Koper located along the coast of the Adriatic Sea.

and land-cover characteristics that influence agent decision-making.

Based on requests from of our Slovenian research partners, who were representing local governing interests, we present and use an ABM in a series of computational experiments to evaluate the impacts of LUCC on the provision of productive agricultural soils, the extent of noise pollution, and quality of life in the Municipality of Koper, Slovenia. Through the modelling process we achieve a number of conceptual and technical advances. First, we empirically inform residential-household agents using a conjoint analysis. While others have reviewed methods to empirically inform ABMs (Janssen & Ostrom, 2006; Robinson et al., 2007), conjoint analysis has not been adopted within land-change research. Second, we model settlement density gradients, which are rarely incorporated in LUCC models but are known to influence ecosystem function (Hutyra, Byungman, & Alberti 2010). Third, a number of sub-models are used to represent the impact-response cycle within the human system by representing such processes as the creation and avoidance of noise pollution.

The remainder of this paper is organized as follows. Section 2 describes the study area, the components of the ABM, and the impact measurements used to evaluate model outcomes. Section 3 outlines a series of computational experiments that are used to investigate the role of LUCC on the human and environmental impacts within the Municipality of Koper. Section 4 presents the results from these computational experiments using the presented ABM. The broader impacts and limitations of the results and model are discussed in Section 5, including the policy implications and the applicability of the presented research to other study areas. Lastly, Section 6 concludes the article by reiterating some of our findings and suggesting that ABMs can be used as an integrative tool to represent coupled human–environment systems.

2. Data and methodology

2.1. Study area

A case study approach is used to model land-use dynamics in the peri-urban area of the Municipality of Koper, Slovenia (N45°32′05″ and E13°45′05″). Located in southwest Slovenia with 17.6 km of coastline along the Adriatic Sea (Fig. 1), the 311.2 km^2 study area has experienced an extensive amount of urban growth over the past 50 years. Comprising 105 administrative units, the population of the Municipality of Koper increased from 29,932 in 1961 to 49,827 in 2006 (~66%; Statistical Office of the Republic of Slovenia, 2010). Population growth has been due to local and national interests to expand the Port of Koper and commercial and industrial development as well as tourism within the region. Pressure from urban and economic expansion threatens the cultural and natural landscape of the region and consequently new policy actions are desired to preserve soils with medium, high, and very high agricultural productive capacity and nature protected areas. In the face of multiple and conflicting land-use demands, little data, and few if any process-based applications of LUCC within the region, local governments and their representatives at academic institutions are interested in understanding the potential impacts of future growth on both human and natural systems.

2.2. Model

We present an ABM that represents the process of urban growth as driven by different land uses and land-cover transitions in peri-urban areas. The ABM is initialised with year 2000 land-use and -cover (LUC) data and a rate of LUCC (Appendix A). We model peri-urban land-use change from 2000 to 2030 using annual time-steps. The ABM comprises three broad types of agents: residential households, residential developers, and non-residential developers. We implement three types of residential developer agents, which differ only in the quantity of land they develop and the density of their developments (i.e. low density, high density, and town centre mixed residential and commercial developments; Section 2.4.3). Lastly, we implement three non-residential developer agents that apply LUC transitions to industrial, commercial, and forest (i.e. land abandonment; Section 2.4.4).

2.2.1. ABM process flow and scheduling

Each time step of the model begins with residential developer agents (RDA) polling a subset (i.e. 30)[1] of residential household agents (RHAs) to evaluate undeveloped lands for potential settlement. RDAs average RHA evaluations at each location to create a demand surface for residential settlement. RDAs then develop locations with the highest demand values in the order of town-centre, high-density, and low-density residential developments until a development quantity is reached for each type.

Next, land-use transitions in the order of commercial, industrial, and forest occur – based on the actions of their respective agents. Each of these three agents evaluate all available cells within the landscape to determine preferred locations for transition (Section 2.5.2). Cells are evaluated based on their geographic, biophysical, and neighbourhood characteristics and the quantity of LUC transitions are determined by a transition matrix (see Appendix A). After all land-use transitions have been carried out, new RHAs enter the model. These new RHAs, as well as any who have been displaced by development, evaluate a subset (i.e. 20)[2] of residential land-use cells with available capacity for settlement and settle in the residential development that maximizes their utility.

In addition to the sequence of actions taken by the different agent types described above, each RHA acts asynchronously and in a different random order for each model run. All other agents act in a deterministic manner to identify the most suitable locations for LUCC.

2.3. Landscape

2.3.1. Land-use and land-cover data

Coarse scale remote sensing products of the Municipality of Koper show little-to-no change in LUC prior to year 2000 (e.g. CORINE). Therefore to identify the rate of change (and the location of change for some LUCs) we acquired regional LUC data from Harpha Sea Limited for the years 2000 and 2007. This proprietary product combines existing digital LUC data (MAFF, 2007) with cadastral data (MESP, 2008) from the Slovenian government to create a digital data set that consisted of 25 land-use and land-cover classes. Using additional air photo imagery, we manually corrected misclassifications in these data and reclassified their 25 classes to seven land-use and four land-cover classes (Table 1). The classes were aggregated because (1) the scale of representation in our model is unable to utilise the fine grain detail of 25 LUC classes, (2) the new classes represent a simplified set of LUCs that is manageable to model under significant data constraints, (3) the new classes represent the land uses and land covers of interest to the Koper research and governance partners, and (4) they include the main land-uses or land covers driving development within the region.

Using the 11 LUC classes, we initialise the landscape as a grid of cells, where each cell has a single LUC type. In the absence of

Table 1
Land-use and land-cover classes and area (ha) aggregated from Harpha data.[a]

ABM classes	Original Harpha classes	Year 2000	Year 2007	Change
Agricultural	Arable			
	Permanent crops			
	Pasture			
		13,761	11,007	−2754
Commercial	Commercial			
	Services			
	Touristic objects			
		166	181	15
Forest	Forest	14,711	17,416	2705
Industry	Industry production			
	Infrastructure and public utilities			
	Port			
	Parking			
	Parking house			
	Parking that can be built upon			
		340	435	95
Low density residentia1	Individual houses	615	755	140
High density residential	Multi-dwelling buildings			
	Special residential buildings			
		122	131	9
Mineral extraction	Mineral Extraction	59	63	4
Open space	Open space			
	Vacant			
	Leisure green			
	Graveyard			
	Non-built areas			
		1118	921	−197
Town center	Continuous urban fabric	35	39	4
Water	Water	63	42	−21
Wetland	Wetland	120	120	0
	Rail[a]			
	Road[a]			
	Total number of cells	31,110	31,110	

[a] Classes were removed from the data set during vector to raster conversion using maximum combined area of classes within the grid cell to be created and setting the priority for conversion to zero. Remaining road or rail cells (7 in year 2007) were due to digitization errors and were reclassified to open space.

[1] Sensitivity to change in the demand surface decreased with increasing sample size of evaluating RHAs used in its creation. Thirty agents provided a sample that was relatively stable with low computational overhead; however, any number of agents may be specified by the model user.

[2] To represent the lack of perfect information, RHAs evaluate 20 locations for settlement. This number may be altered by the model user; however, as it moves closer to 1 the site selection process becomes random. As the number of evaluated locations approaches the number of available locations the RHAs approach perfect information. Our choice of 20 provided a relatively large sample that assumed agents had some site selection information available to them (e.g. house listing) but not perfect information.

household census data, housing capacity for each residential land-use type was estimated by regressing the number of cells of each residential land-use type against administrative unit population.[3] The resulting population capacities of 28, 103, and 353, for low density residential, high density residential, and town-centre residential land uses, were then divided by the average household size (2.6 people per household, SORS, 2002a, 2002b) to estimate household capacities of 11, 40, and 136 for each land-use type, respectively.

2.3.2. Features and attributes

Landscape features influence RHA location decisions and subsequent LUCC patterns. Using the available data we were able to include: public transportation nodes (i.e. bus stops), roadways, railway lines, coastline, greenspace, and sea ports.[4] We initialize existing features to their year 2000 locations; however, some features are created endogenously within the model. For example, the model creates local road and bus-stop features when new town centre land uses are created. Similarly, greenspace dynamically comprises areas where recreation may take place, which includes forests, wetlands, open space, and water. All features exist as Boolean presence-or-absence variables in each cell. Features are accessible to agents as a set of attributes in each cell that include: distance to certain LUC types (including composites such as "greenspace"), distance to landscape features and human impact values (e.g. noise pollution).

2.4. Agents

We opted to use a separate agent type for each of the land-uses undergoing significant change within the Municipality of Koper. In the remainder of this section we describe these agents given their best possible representation under a range of constraints that include data limitations, model development constraints, requirements to include multiple LUC types, and the need to produce a model that could provide some insight into land-use dynamics within the Municipality of Koper.

2.4.1. Residential-household agents

RHAs evaluate their expected quality of life at a future location based on their preferences for a range of indicators. Because defining the quality of life for any one individual or household is subjective (GDRC, 2009) we operationalise the evaluation at a location (i.e. cell) using utility theory, henceforth we use the term "utility". It is possible to use other behavioural models (Rounsevell et al., in press), such as heuristics (e.g. Deadman et al., 2004), neural networks, genetic programming (e.g. Manson, 2006), or cultural-theory (Janssen & Carpenter, 1999). However, these alternative behavioural models require either different types of data that were unavailable for the presented work or are unsuitable for location based decisions.

RHAs perform two actions. First, a subset of RHAs is polled to evaluate their expected utility from all undeveloped cells. These values are averaged at each location to create a demand surface, which is later used by developer agents. Second, each new RHA evaluates 20 residential land-use cells with available capacity for settlement and settles at the location that maximizes its utility (i.e. a bounded rational approach). RHAs interact indirectly with each other and other agents by (1) occupying space that could be occupied by other agents, (2) consuming greenspace that is desired by other RHAs, and (3) providing information to residential-developer agents via the demand surface.

2.4.2. Empirically informing residential household agents

We empirically inform RHAs' location preferences using results from an adaptive conjoint analysis (Bell, Affonso, & Montarzino, 2010). To accommodate different relative perceptions of location-attribute values and a lack of precision in recording minor perception differences, conjoint analysis discretises responses into a form analogous to poor, good, and best for each location attribute. Conjoint analysis forces respondents to make preference trade-offs through a series of pair-wise attribute-bundle comparisons. The approach more closely mimics household decision-making under real-world contexts (Aspinall, 2007) when compared to other survey approaches and analyses (e.g. Likert scale approaches).

The conjoint analysis was conducted in Koper Municipality, Slovenia – May 2010, $n = 150$. Respondents chose among three quality levels for the following location attributes (Table 2): accessibility to greenspace, accessibility to public transport, accessibility to shops, and the level of noise. These attributes were chosen as a representative subset of the larger set of Sustainable Communities Indicators (SCI) that was compiled in Canada to measure the impacts of urban sprawl (Ditor, O'Farrel, & Wayne, 1999). Results of the analysis were partial utilities for each discretised location–attribute value for each respondent. The sum of the partial utilities for an attribute is zero and negative partial utility does not imply a negative valuation (Orme, 2010).

For RHAs to evaluate the utility of a given location it is necessary to first map the underlying attribute values (e.g. distance) to the categorical values used in the conjoint analysis (e.g. short, long, far). Using literature we define access to greenspace within a short walk as being less than 300 m, a long walk being between 300 and 600 m, and beyond 600 m requiring public transportation. The initial threshold of 300 m is based on the recommendation of Natural England that access to 2 ha of greenspace should be found within 300 m (Harrison, Burgess, Millward, & Dawe, 1995). This distance is supported by Nielsen and Hansen (2007) who observed a steep decline in greenspace usage when distances from residence extended beyond 100–300 m. Likewise, Grahn and Stigsdotter (2003) found usage declines of 4, 2.7, and 1 visit per week for distances below 50, 300, and 1000 m, respectively. They also report a sharp decline in usage after 300 m. Coles and Bussey (2000) also confirm a sharp decline in the use of urban woodland beyond a 5 min walk or 100–400 m distance.

The second threshold of 600 m is defined based on the perceived distance individuals estimated frequent usage (Schipperijn, Stigsdotter, Randrup, & Troelsen, 2010; Schipperijn et al., 2010), which is also the distance at which greenspace has been shown to influences people's exercise levels (Duncan & Mummery, 2005). Other research provides a similar estimate of most park users being drawn from within 500 m (Giles-Corti et al., 2005).

Because the aforementioned distance thresholds are well documented and corroborated amongst multiple literature sources, we apply the same threshold values for access to public transport and make a slight modification when accounting for access to shops. We define access to shops as many when they are within 300 m, few when their presence is between 300 and 1600 m, and not accessible when beyond the 1600 m limit. The upper limit is based on commonly used interpretations of neighbourhood walk-ability of 1 mile (1609 m, Braza, Showmaker, & Seeley, 2004; Frank, Andersen, & Schmid, 2004; Jago, Baranowski, & Harris, 2006; Pikora et al., 2002).

Conjoint partial-utility values are normalized [−0.5…0.5] using the total importance of all attributes evaluated by the agent. Importance values are defined as the range of partial utility values

[3] The linear regression formula: $y = 28.415 * x1 + 103.114 * x2 + 352.554 * x3$, where y = population, $x1$ = number of low density residential cells, $x2$ = number of high density residential cells, $x3$ = number of town centre cells. $R^2 = 0.9968$, Adjusted $R^2 = 0.9966$, and p-value < 2.2 e^{-16}.

[4] There are no airports within the Koper case study region. Bus-stop locations were acquired from Survey and Mapping Authority of the Republic of Slovenia. Sea port data were derived from air photo interpretation.

Table 2
Mapping model attribute values to resident-agent partial utilities.

Attribute	Attribute thresholds	Attribute category	Conjoint partial utility	Importance values	Normalized partial utility
Access to green space requires	<300 m	Short walk	0.454		0.072
	301–600 m	Long walk	0.010	0.928	0.002
	>600 m	Transport	−0.474		−0.075
Public transport is	<300 m	Very convenient	0.604		0.096
	301–600 m	Convenient	0.265	1.483	0.042
	>600 m	Inconvenient	−0.879		−0.140
Access to shops[b]	<300 m	Many	0.629		0.100
	301–1600 m	Few	0.313	1.581	0.050
	>1600 m	None	−0.952		−0.151
Noise pollution is	<65 dB[a]	None	0.979		0.155
	66–75 dB[a]	Moderate	0.338	2.305	0.054
	>75 dB[a]	Intense	−1.326		−0.211

[a] Noise values from Berglund, Lindvall, and Schwela (1999) were used but adjusted upward by 20 dB to recognize the dampening effects of building facades to those within and other surfaces.
[b] We interpret the number of shops within proximity as access to shops.

for each of the four attribute levels. The total utility for any location can be predicted for an agent using the following utility function:

$$u_{r(x,y)} = \frac{\sum_{i=0}^{n}\alpha_i}{n} \tag{1}$$

where agent r calculates utility u for location (x,y) as the additive outcome of factors i $\{1\ldots n\}$, α is the utility an agent places on one of the three values (i.e. high, medium, low) for attribute i. The function is then divided by the total number of attributes n to normalize the final utility. Other survey analysis or data reduction techniques (e.g. principal components or factor analysis) can be used to derive relative preference weights (e.g. Brown & Robinson, 2006; Filatova et al., 2009). However, these approaches also require the definition of a preferred attribute value (e.g. within 100 m of shops), which is provided explicitly by the conjoint analysis.

In the absence of a clear inductive delineation of respondent types we opted to use a proportional approach to up-scale the survey results (as described in Smajgl, Brown, Valbuena, & Huigen, 2011) to the agent population.[5] To empirically inform agent preferences, we randomly draw agents (with replacement) from the respondent sample to create an agent population, which creates a distribution of agent preferences for the four location-based attributes similar to the social survey. The lack of distinctive respondent groups in the data provides further evidence for the use of agent-based approaches that are capable of representing the variability among actors and decision-makers.

2.4.3. Residential developer agents

Agent-based modellers of LUCC have only recently acknowledged the crucial role of developer's in land-use change (e.g. Morgan, 2010; Mohamed, 2009; Monticino, Acevedo, Callicott, Cogdill, & Lindquist, 2007; Robinson & Brown, 2009).We implement three different residential developer agents (RDAs) that each create a different density of residential land use: low-density (11 households), high-density (40 households), and town centre (a mixture of residential and commercial uses with capacity for 136 households). RDAs first select a number of RHAs to evaluate undeveloped locations for settlement. RDAs average the RHA evaluations at each location to create a demand surface. RDAs then rank locations from, and development proceeds from, those with the highest demand until a specified quantity of development is reached.

[5] Clustering (Hierarchical clustering, k-means and Expectation Maximization clustering) and classification and regression tree techniques were unable to identify well defined types of respondents with shared preferences structures or significant association (Chi Square test) among preferences with 14 respondent characteristics (e.g. marital status, age, income, etc.).

Table 3
Logistic regression coefficients for independent variables contributing to the development of industrial and commercial land uses as well as new forest expansion.

Land use, cover, or feature	Industrial developer	Commercial developer	Forest expansion
Neighbourhood court			
Industrial	1.164000		
Commercial		1.864966	
Agriculture		1.115878	
Open space	0.187005	0.802314	
Forest			0.302547
Wetland	−0.413990		
Distance from			
Industrial	−0.000505		
Commercial		−0.002976	
Agriculture			−0.009932
Open space			0.000269
Forest			−0.003415
Local roads	0.000754		
Main roads		0.001053	
All roads			0.000652
Elevation			0.000650
Intercept	−0.957758	−2.255870	0.330816
Percent correct			
Absence	90.0	92.5	39.9
Presence	79.8	92.1	93.6
Overall	85.2	92.3	77.7
Pseudo R^2			
Nagelkerke	0.532	0.846	0.298
Cox and Snell	0.398	0.635	0.210

2.4.4. Industrial, commercial, and farm agents

The use of regression to represent agent-behaviour is not new (e.g. Manson, 2006). In the absence of survey data to inform decisions about land-change, a logistic regression approach provides an adequate method to represent land-use change. The approach involves deriving a number of potential biophysical, geographic, and adjacency characteristics that may influence land change (Table 1, Section 2.3.2). Then a series of regressions are performed to produce location evaluation equations for industrial and commercial developer agents as well as for transition to forest (Table 3).

Using year 2000 and 2007 land-use data, each regression procedure uses a stepwise variable selection with forward Likelihood Ratio testing to find the most predictive subset of independent variables. We compute the goodness-of-fit using the coefficient of determination (i.e. R^2) as defined by Cox and Snell (1989) and Nagelkerke (1991), which are approximate methods for R^2 as used

Table 4
Study area (ha) by agricultural production capability class.

Class description	Year 2000	Year 2007
Impervious or no agricultural production capability	1608	1817
Very low agricultural production capability	5336	5335
Low agricultural production capability	12,866	12,810
Medium agricultural production capability	3566	3533
High agricultural production capability	2094	2092
Very high agricultural production capability	5640	5523
Total	31,110	31,110

in linear regression models. The overall predictive accuracy of the logistic regression in representing absence or presence of transitions was high for industrial (85%), commercial (92%), and forest (78%) land uses and covers (Table 3). We compute the overall percent correct on a held-out subset of "unseen" cases (test set) using cross validation. For a discussion of overall model validation see Appendix B.

2.5. Impacts

2.5.1. Soil suitability for agricultural production

Farming provides a valued livelihood to an ageing rural population facing urbanization pressures, within the Municipality of Koper. Agricultural land holdings are relatively small in the municipality (4.2 ha on average, Statistical Office of the Republic of Slovenia (SORS), 2000) compared to average Slovenian (10.6 ha) and European sizes (e.g. Germany 40.5 ha, UK 70.9 ha, FAO-WCA, 2000). Due in part to their size and associated histories, agricultural lands hold cultural and aesthetic value to residents and tourists visiting the region (Perpar, 2009). Using available soil data created to estimate the suitability of land for agricultural production in Slovenia (classified into six categories Table 4,[6] Vrščaj, Prus, & Lobnik, 2005; Vrščaj, Prus, & Lobnik, 1998), we measure the area and location of productive agricultural soil loss.

2.5.2. Noise pollution

Despite a paucity of research on the impacts of noise pollution, it is recognized to have significant socio-economic effects. The estimated annual cost of noise pollution in England was in excess of £7 billion per annum, with "£3–£5 billion in annoyance costs, adverse health cost of around £2–£3 billion and productivity losses of another £2 billion" (Department for Environment Food, 2008). We concern our impact measurements with the role of noise as a location-based nuisance because it is the most widely recognized impact affecting resident's quality of life and it is directly accounted for in our social survey analysis of residential location preferences.

We take a simplified approach to noise modelling using known levels for human induced noise sources (Table 5), existing noise maps, and equations for noise propagation and summation. We ignore temporal variation in noise creation and do not incorporate factors that may affect noise prediction values, such as friction and reflectance by ground, building, and other surfaces. For details and equations on the representation of noise pollution and comparative results with EU Directive noise maps see Appendix C.

2.5.3. Quality of life

We measure the quality-of-life of the residential population based on their derived overall and partial utility values. Utility values provide a way to derive a numeric rank-ordering of preferences for location attributes that are difficult to represent along a single dimension (e.g. monetary value, Marshall & Oliver, 1995). While classical economic theory restricts the comparison of utility values, our normalisation procedure assigns equal weightings to each individual, which when combined with all RHAs using the same utility function provide a common base from which we can measure aggregate utility. Aggregate utility calculations are sometimes referred to as Utilitarian measurements because the interest lies in evaluating the betterment of society rather than a single individual (Dolan, 2001). We apply the same approach to the partial utilities for each of the four location attributes (Table 2) to understand how different location attributes affect agent aggregate utility levels.

[6] Soil data acted as the template to which all other raster data (e.g. LUC) were matched such that cells corresponded across datasets. Cell resolution is 100 m, therefore the number of hectares is equal to the number of cells in each class.

Table 5
Noise levels in dBA for land uses and features. All measurements were recorded or assumed to have been acquired at a distance of 10 m.[a]

Land use or feature type	Decibel level (A)
Road type	
Motorways	80
Main roads	75
Regional roads	70
Local roads	65
Public paths	60
Rail	97
Industry/Seaport	75
Commercial	60

[a] Values derived from a combination of literature and extrapolation from existing noise maps for other regions (e.g. Scottish Noise Mapping Initiative conducted by AECOM and Hamilton & McGregor). Other sources included: FICN (1992), IPPC (2002), Jones (2005), FEHRL (2006a, 2006b), www.nonoise.org, and www.chchearing.org/noise-center.

3. Computational experiments

Our goal is to improve understanding about the potential impacts of various actors and processes driving LUCC in the Municipality of Koper, which may provide insight to local decision makers interested in guiding LUCC through land-policy initiatives. To progress towards this goal we conduct a number of computational experiments to verify model behaviour and to gain an understanding about land-change and the impacts of development on human well-being under severe data constraints. For all soil quality, noise pollution, and quality-of-life impact measurements we test for significant differences among experiments using Student-*T* test based on the average and standard deviation of 30 model runs (for each experiment).

3.1. Business as usual

Using the rates of LUCC from the year 2000 and 2007 data (Appendix A), we run the model forward from the year 2000 to 2030. In this Business As Usual (BAU) experiment all agent behaviours are active and actions by one agent influence the actions of others. Also, because the transition rate from open space and agriculture to forest is very high (Table 6), we implement forest transitions in proportion to the amount of existing area of open space and agriculture. The BAU experiment offers a reference point to which we compare the other computational experiments.

3.2. Residential development constraints

One method of interaction among agents is through the process of substitution. When one developer agent creates a land-use at a location, that location is no longer available for other agents who are then forced to substitute less preferred locations for development. To unpack these effects among residential developments

Table 6
Computational experiment outputs of average and standard deviation for agricultural production capacity soils (ha), noise pollution (ha), partial utilities, and total aggregate population utility levels at 2030. Mean values with a + are not significantly different from the BAU experiment and those with a # are not significantly different from the random model (Appendix B, $p = 0.01$, df = 29, t-test).

Paper section	Original values	Computational experiments											
		Business as usual 4.1		Low density residential only 4.2		High density residential only 4.3		Town centre residential only 4.4		Clustered commercial 4.5		Clustered industrial 4.6	
		Mean	Sd	Mean	Sd	Mean	Sd	Mean	Sd	Mean	Sd	Mean	Sd
Impacts													
Agricultural production capability (ha)													
Very high	5988	5046.70	14.29	4866.83	17.43	5286.03	14.14	5419.33	12.96	5067.86	19.90	5104.00	25.32
High	2113	1995.90 #	11.75	1965.50	8.16	2051.90	5.09	2070.50	6.50	2001.69 #+	7.49	1990.50 +	12.17
Medium	3681	3374.60	12.87	3323.67	12.00	3467.23	11.69	3494.97	9.29	3381.59 +	11.34	3368.30 +	14.55
Low	12941	12469.60	19.99	12315.20	21.72	12691.20	10.75	12750.17	9.86	12455.72	12.84	12429.00	28.66
Very low	5344	5308.30	10.89	5302.57 +	5.44	5327.80	2.94	5329.73	2.69	5311.83	9.77	5276.60	19.11
None	565	252.77	8.57	249.83 +	8.18	259.57	6.16	264.53	7.36	226.07	7.59	276.73	6.43
Impervious	713	2662.13	9.17	3086.40	13.51	2026.27	8.78	1780.77	6.37	2665.24 +	10.23	2664.87 +	10.47
Noise (ha)													
⩾75 dB	2998	3225.10	8.42	3224.23 +	10.75	3231.33	8.08	3231.43	7.42	3225.62 +	10.33	3239.70	11.12
>65 and <75 dB	3294	3225.23	8.05	3223.93 +	8.22	3228.23 +	6.79	3232.90	6.08	3228.66 +	8.61	3253.07	8.26
<65 dB	24818	24659.67	11.61	24661.83 +	12.15	24650.43	8.80	24645.67	8.56	24655.72 +	10.44	24617.23	13.31
Quality of life (partial utilities)													
Greenspace	0.0897	0.0930 #	0.0023	0.0916 #+	0.0024	0.0952	0.0021	0.0961	0.0017	0.0922 #+	0.0019	0.0944 #+	0.0023
Public transport	0.0597	0.0568	0.0018	0.0459	0.0022	0.0600	0.0026	0.0773	0.0006	0.0566 +	0.0018	0.0578 +	0.0035
Shops	0.0536	0.0543	0.0023	0.0625	0.0014	0.0618	0.0013	−0.0037	0.0016	0.0556 +	0.0024	0.0526 +	0.0034
Noise	0.0750	0.1198	0.0005	0.1209	0.0002	0.1201	0.0002	0.1201 +	0.0007	0.1199 +	0.0007	0.1200 +	0.0007
Total	0.2780	0.3238	0.0026	0.3209	0.0025	0.3371	0.0031	0.2898	0.0024	0.3243 +	0.0026	0.3248 +	0.0029
Land use and land cover													
Industrial	340	647.27 #	2.95	647.13 #+	2.91	647.90 #+	2.98	648.27 #+	2.48	647.86 #+	2.77	648.43 #+	2.16
Commercial	166	257.40 #	9.03	251.27 #+	13.59	258.07 #+	5.54	259.57 #+	1.91	258.79 #+	5.05	258.03 #+	8.53
Agriculture	13761	4873.33	15.02	4756.40	13.40	5015.17	12.52	5080.90	8.78	4907.45	11.80	4847.70	14.67
Open space	1118	830.37	13.10	785.00	14.32	895.47	11.16	937.70	9.75	799.76	12.34	920.47	12.07
Forest	14711	22502.17	19.48	22240.20	20.48	22931.10	11.69	23068.63	7.98	22495.55	15.07	22434.97	23.01
Low density residential	615	1516.93	4.69	2031.00	1.72	578.07	4.01	607.23	2.43	1518.31 +	5.75	1517.00 +	4.22
High density residential	122	189.50 #	2.46	122.00	0.00	507.23	1.77	118.63	1.75	188.76 #+	3.03	189.17 #+	2.94
Town centre	35	51.03 #	2.57	35.00	0.00	35.00	0.00	147.07	2.61	51.52 #+	2.59	52.23 #+	3.29

we conduct several experiments that constrain development to low-density residential (LDR), high-density residential (HDR), or town-centre land-use types. Within all experiments the rate of population change is constant and the area of each type of development is calculated based on its capacity to house incoming residents.

3.3. Commercial and industrial development constraints

Similar to the previous experiment, we evaluate the individual impacts of commercial and industrial development in this experiment. We alter their behaviours by implementing a constrained cellular-automata approach to location decisions, which forces commercial and industrial developments to occur adjacent or as close as possible to existing commercial and industrial development, respectively. Indicative of enforced planning controls, this experiment provides one approach to investigate how planning controls may alter development and subsequently the consumption of highly productive agricultural soils, the creation of noise pollution, and the quality of life of the municipality's residents.

4. Results

4.1. Business As Usual (BAU)

In this experiment development of impervious surfaces consumes a large area of productive agricultural soils. The area in very high agriculturally productive soil is disproportionately affected by urban expansion as 48% (1001 ha) of new impervious surfaces occur on this soil designation (Table 6). Expanding to those soils classified as medium, high, and very high agricultural productive capacity we find that 70% of new impervious areas consume these soil classifications.

A 7.6% increase in high noise area is observed under BAU, which is due to the expansion of commercial and industrial land uses across the landscape. This expansion increases the area classified as high noise by 227 ha (on average) over the 30 years of the model run (Table 6). Noise levels between 65 and 75 dB decrease on average (69 ha) over model runs, but the majority of high noise expansion is into areas less than 65 dB (156 ha), which suggests greater expansion of industrial and commercial

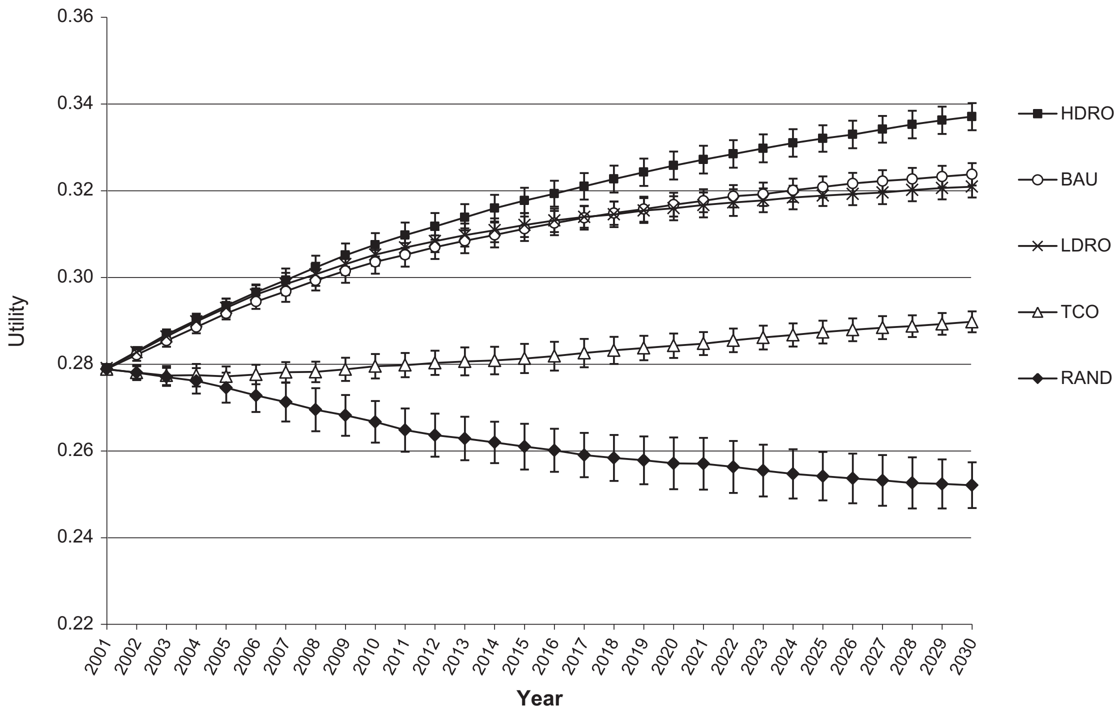

Fig. 2. Average aggregate resident utility for computational experiments. CCD and CID experiments are not plotted, but follow the BAU utility curve closely.

areas in locations non-adjacent to existing land uses of the same type.

The areas affected by high and medium noise have a significant influence on the quality of life of RHAs since their partial utilities related to noise conditions are larger than the other three factors (i.e. access to shops, greenspace, and public transport). Due in part to the doubling of population over thirty years and their settlement in less dense and less noisy peri-urban areas, the higher utility acquired by new residents relative to that of established residents causes an increase in the average utility of the population (Figs. 2 and 4, Table 6). Settlement in peri-urban areas also increases access to greenspace and pulls the average aggregate utility upward (Fig. 2). Access to public transport and shops maintain a relatively constant average partial utility.

4.2. Low Density Residential Only (LDRO)

By constraining new development to LDRO the total area developed increases (i.e. holding population constant, Fig. 3). The result is an increase in the loss of very high agriculturally productive soils relative to the BAU experiment. A loss of 19% occurs which comprises 47% of 2373 ha of new impervious surface. The loss of medium, high, and very high agriculturally productive soils collectively is 14% (12% for BAU).

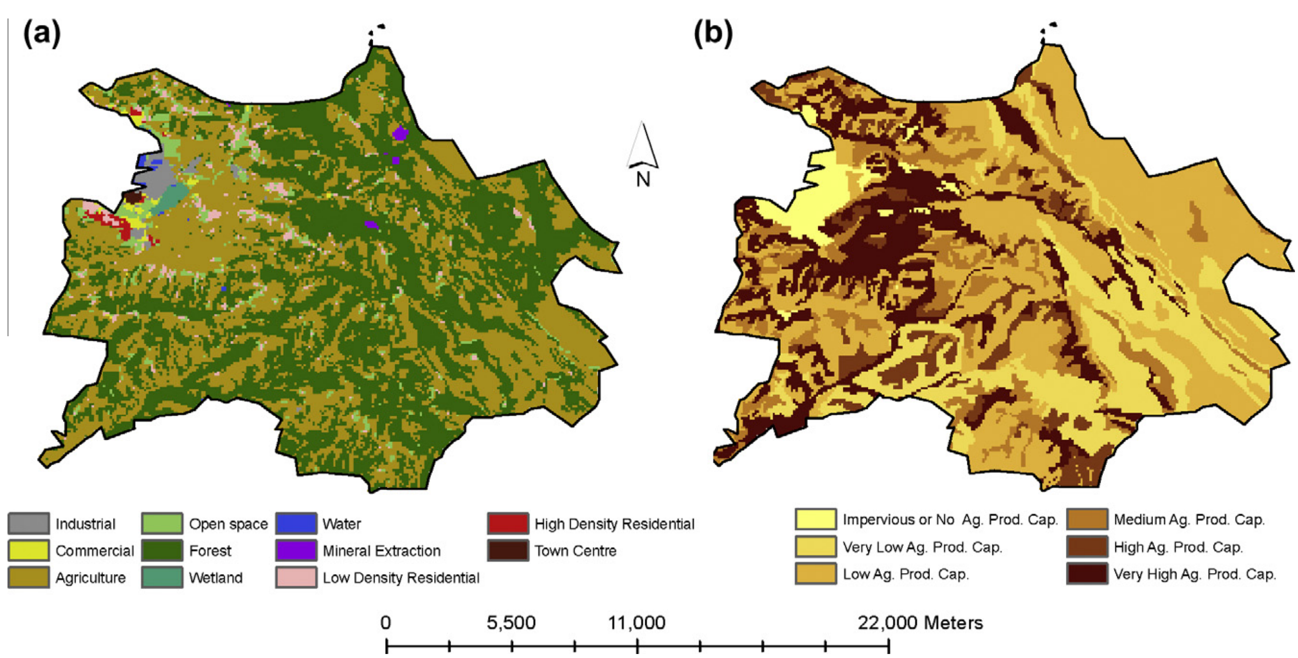

Fig. 3. Map of original land use and land cover for year 2000 (a) and soil agricultural productive capacity (b) for the Municipality of Koper, Slovenia.

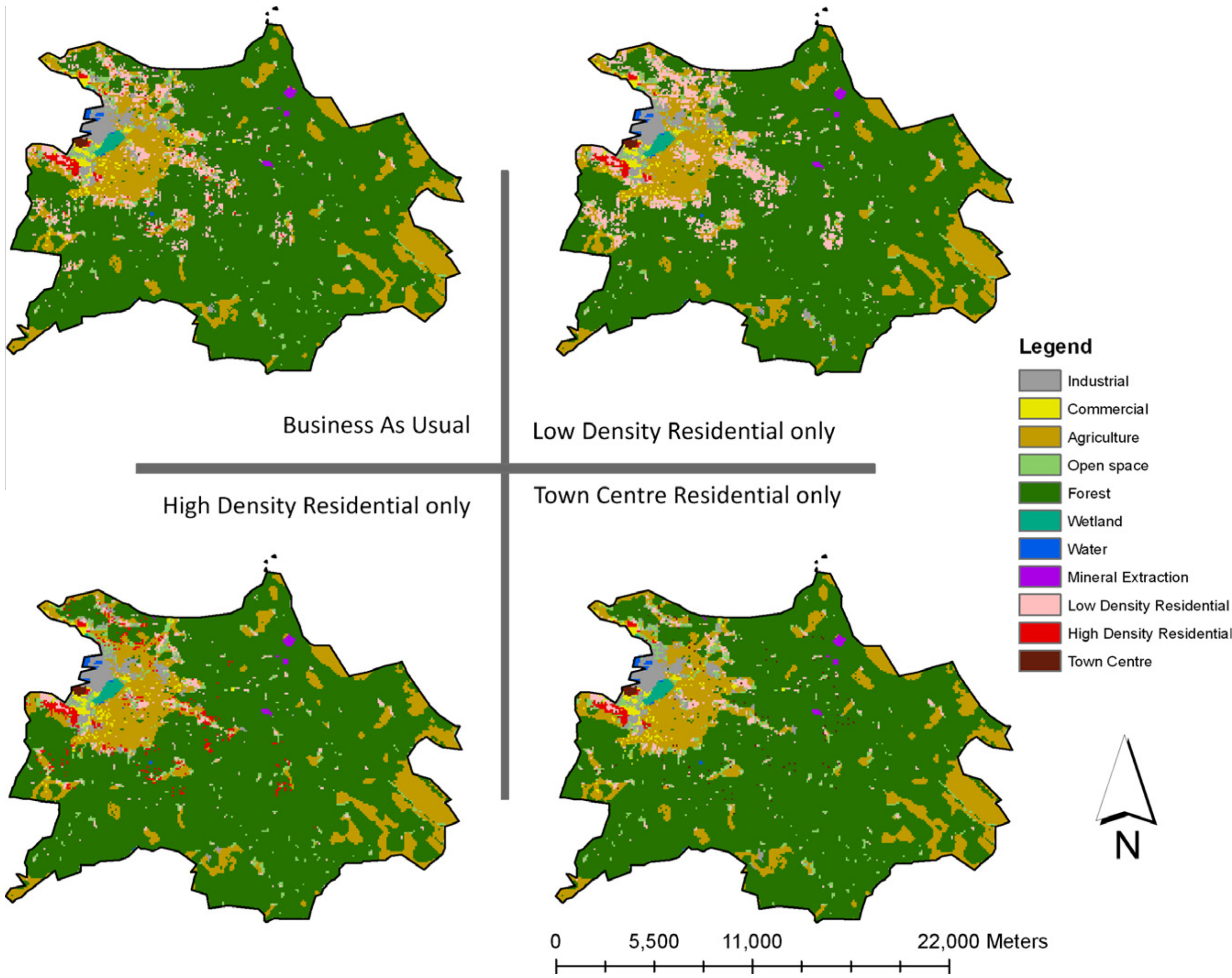

Fig. 4. Maps of typical land use and land cover for the Municipality of Koper, Slovenia, in 2030 from the ABM.

In this experiment noise pollution does not significantly differ to BAU results. Similar to the BAU experiment, partial utility from low noise levels provides the largest partial utility (0.1209 on average, Table 6). In this experiment RHAs have the highest average aggregate utility from low noise levels compared to the other experiments. Relative to the BAU experiment, residents also receive more utility from their proximity to shops (0.0625) since shops are forced to move into the urban periphery due to constraints imposed by the location of available land. The result is a positive feedback as commercial developments act as attractors for some residential developments, which collectively infill or consume the greenspace sought by residential agents. Therefore, while partial utilities from greenspace increase initially they level off toward the end of the 30 year simulation run (Fig. 5). Associated with the amount of sprawl are decreases in the average partial-utility for reduced access to public transportation (0.0459). The collective result is an increase in the aggregate average utility (Fig. 2), which levels off slightly below the BAU aggregate utility.

4.3. High Density Residential Only (HDRO)

The high level of housing density reduces the amount of developed area and better preserves the amount of very high agriculturally productive soils relative to the LDRO and BAU experiments (Fig. 4). The overall average loss of very-high, high, and medium agriculturally productive soils was 701, 61, and 213 ha, respectively. These results represent a loss of 12% of the area in very high agricultural productive soils and an aggregate loss of 8% of the area in these three classifications. Seventy-four percent of the 1313 ha of new impervious surface occurs on these three soil classifications.

The spread of noise pollution is higher in the HDRO experiment when compared to the BAU and LDRO experiments. Areas classified as low (<65 dB) and medium (i.e. >65 dB and <75 dB) noise pollution decrease by 167 ha and 66 ha, respectively, while high noise areas increase by 233 ha or 8%. The degree of variance is also slightly higher indicating that HDR land uses were choosing locations also preferred by industrial and commercial developers.

The average aggregate utility of the population is highest in this experiment, due in part to a large increase in residents' access to greenspace (Fig. 2). A lack of available locations within the town of Koper forces new development to the periphery that mixes well with greenspace and does not experience the infilling that occurs in the LDRO experiment. Consequently, settlement of new residents in quiet areas near these greenspaces also pushes the average partial-utility from a lack of noise pollution upward. Partial-utility from access to shops increases over time. The only partial-utility factor to experience a decrease over time is access to public transportation.

4.4. Town Centre Only (TCO)

By restricting residential development to TCO we impose strong population density constraints that limit the area of residential

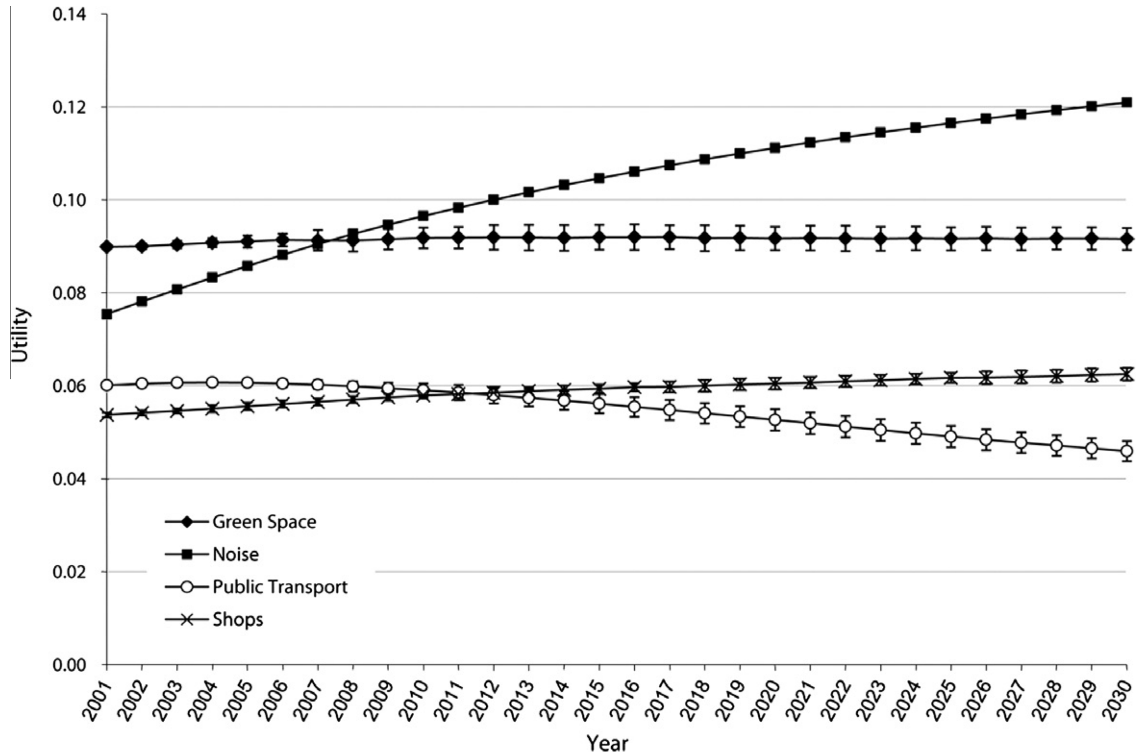

Fig. 5. Mean partial-utilities for LDRO experiment. Error bars denote one standard deviation.

development (Fig. 4). In this experiment, ~9% of the very high agriculturally productive soils is lost and 7% of the area collectively classified as very high, high, and medium agriculturally productive soils are lost (Table 6). The total amount of new impervious surface is lowest in this experiment, of which 74% consumes these beneficial agricultural soils.

Imposing TCO development significantly reduces the overall quality of life relative to other experiments (Fig. 2, Table 6). While the overall quality of life (i.e. aggregate average utility) does increase slightly over model runs, the final level is consistently lowest. Slight increases in partial utilities for noise, greenspace, and public transportation are outweighed by decreases in partial utilities for access to shops.

4.5. Clustered Commercial Development (CCD)

The impact of forcing commercial development adjacent to existing commercial land uses leads to a slight preservation of very high agriculturally productive soils (loss of 15%) relative to the BAU (loss of 16%) and LDRO (loss of 19%), the impact is worse than that attained by the HDRO and TCO experiments that suffer a loss of 12% and ~9%, respectively. The impact on medium, high, and very high productive capacity soils is slightly less (i.e. 1%) than that achieved from the BAU experiment. The CCD results in the smallest area affected by high noise levels; however, the difference is minor relative to other experiments. Household quality-of-life measurements follow closely to the BAU experiment, but aggregate average utility finishes slightly higher (Table 6).

4.6. Clustered Industrial Development (CID)

When we force industrial land uses to cluster adjacent to existing industrial areas, with all else being equal to the BAU experiment, the outcome is a 15% loss of area in very high productive agricultural soils (on average, Table 6). The area affected by high noise (12% above year 2000 levels) is the highest (362 ha) of all experiments; however, the area affected by noise levels >65 dB and <75 dB is the lowest within all experiments. Overall, CID improves aggregate quality of life. Small increases in access to greenspace, public transport, and improvements in exposure to noise pollution allow this experiment to achieve the second highest aggregate utility – HDRO produces the highest aggregate utility of all experiments.

5. Discussion

5.1. Coupled natural-human systems of land change

In addition to illustrating the integrative capabilities of ABM to combine statistical and process models and different types of data to represent the coupled natural-human land-use system, we also showed an approach to represent a new endogenous impact from the human system by creating a noise pollution model. We represented the dynamic nature of noise pollution through the new emission of noise by commercial and industrial developments and its interaction with existing and neighbouring noise emitting land uses, land covers, and landscape features. Although our representation of noise pollution was relatively simple, it provided one endogenous driver of the human system that may add insight into the spatial distribution of other pollutants (e.g. air pollution is moderately correlated to noise pollution).

On a request basis from our Koper constituents, we focused our analysis of ecological impacts on the loss of soils with medium, high, and very high agricultural productive capacity. Due in part to the nominal nature of the soil data they provided, we focused on the loss of soil types to impervious surface resulting from residential and business expansion. Acquisition of quantitative soil quality variables (e.g. depth, texture, soil organic matter) would permit the incorporation of degradation and enhancement processes (e.g. erosion or fertilization) that would allow soil quality to transition among soil types.

5.2. Computational experiments

We evaluated the impacts of different development mechanisms on the provision of highly productive agricultural soils, noise pollution levels, and human quality of life. While the computational experiments were designed to explore and evaluate model mechanisms, parameterisation of the model to the Municipality of Koper provided some insight into the potential development trends and types of policies or planning efforts that could decrease the impact of urban growth on both human and natural systems.

5.2.1. Soil quality

In the absence of residential density constraints, our BAU, CCD, and CID experiments suggest that almost half of urban expansion is likely to take place on very high quality agricultural soils (Table 6). Low density residential development was shown to be the primary consumer of these lands and policies that increase the amount of LDR development will likely cause an accelerated loss of high quality soils. Our results also suggest that a reduction in the loss of very high quality soil will result from constraining development to higher residential densities.

We also found a reduction in the loss of high quality soil by constraining industrial development to adjacent industrial areas. This outcome was due to the existing spatial pattern of soil types and industrial areas in the year 2000. Since the initial industrial areas were not typically located adjacent to high quality agricultural land, initial clustered development did not consume preferred soils at first, but started to penetrate the rich agricultural lands to the southeast of the city over time. Therefore, a combination policy addressing a slight increase in residential development densities and industrial clustering may effectively conserve areas of high quality agricultural soils.

5.2.2. Noise pollution

In contrast to the improvements in soil preservation, increasing residential development density caused an increase in the area classified as high noise (Table 6). However, the increased area affected by high noise did not have a corresponding decrease in the partial-utility values attained by RHAs. In this case, increased noise pollution affected natural areas more than residential areas. Similarly, CID around existing industrial areas produced the highest amount of area affected by high noise of all the experiments ($\sim$15 ha more than the BAU). This too had little impact on residential quality-of-life, which is likely due to prior planning regulations that drove industrial development north of the town and residential development to the centre and south.

The contrasting effects of changing development density on the availability of high quality soils and residential exposure to noise pollution illustrates the trade-offs associated with jointly mitigating impacts on the human and natural systems. Providing general conclusions and insight into the role of development density is difficult as the location attributes providing utility have different effects on different households. However, typically noise acts as a repellent and greenspace and public transport act as attractors.

5.2.3. Quality of life

Quality of life for the RHA population did not increase immediately for all experiments. Initially it (i.e. aggregate utility) decreased in the TCO experiment because of a non-linear distribution for preferences near shops. The majority of agents (and survey respondents) had lower preferences for having access to many shops and no access to shops and had a higher preference for having access to only a few shops. Because each town centre development is a mixture of commercial and residential and agents were not able to sort themselves (i.e. relocate), the result was a significantly lower partial utility for access to shops compared to all other experiment outcomes.

The situation of residential settlement relative to industrial areas also influenced residential quality of life. The impact of clustered industrial development around existing industrial areas had a positive impact. The separation of some land-use types is the foundation of zoning laws (Nelson, 1989) and our results corroborate some of their intended benefits.

Our quality of life measurements are also interesting because aggregate agent utility increased in all experiments except in TCO. This result was due in part to the social survey outcome that residents' placed more importance on noise pollution than on access to greenspace, shops, or public transport. For all experiments, except the TCO, average residential exposure to noise pollution decreased and the decreased residential density that ensued provided additional access to greenspace. These results suggest that either (1) sprawling development guided by resident preferences may improve their quality of life, (2) the model may be missing factors that act as attractors to urban areas and improve quality of life, or (3) the model over-represents the impact of noise pollution (e.g. our simple model did not include noise dampening factors other than distance).

5.2.4. Policy implications

While the quantity and exact locations of our LUCC results are specific to the Municipality of Koper, our results may provide general insight to planners, developers, and local governance agencies in other cities and municipalities that face similar trade-offs between reducing environmental impacts and accommodating urban growth requirements. In many cases, cities are similarly situated within high agricultural quality soil regions since many cities formed partly-due to increased agricultural productivity at those locations. As a result of the spatial patterns (autocorrelation) of soil types, peri-urban areas also often consist of high quality agricultural soils. For example, 25% of Australia's agricultural production occurs in the peri-urban fringe (Houston, 2005). High quality agricultural soils have also been found to positively influence peri-urban development in the Greater Yellowstone Area of the United States (Gude, Hansen, Rasker, & Maxwell, 2006), and urban growth in many Canadian cities has been found to consume large areas of prime agricultural land (Hathout, 2002).

In contrast to the agricultural livelihoods provided by high quality soils, residential households often have preference structures that can lead to sprawling residential development and a depreciation of public goods (e.g. greenspace). However, our results showed that despite individual preferences that can lead to sprawl, aggregate population utility had a non-linear response to our residential density experiments such that aggregate utility of TCO < L-DRO < BAU < HDRO. The increased residential density in our HDRO experiment produced a higher aggregate utility due to improved access to greenspace and public transport. Analogous to the tragedy of the commons (Hardin, 1968), whereby individual decisions can lead to the collapse of a common-pool resource, we find that policy-based density constraints can have a win–win outcome that increases aggregate utility and preserves highly productive agricultural soils.

Our results suggest that there is room to manipulate residential density constraints to moderate the behaviour of individuals for the greater good of society (i.e. reduce environmental impacts and provide improvements to the quality of life of residents). Further empirical research to identify resident satisfaction levels and quality-of-life indicators, stratified by residential density, would provide interesting results. With the aid of LUCC models like the one presented here, we may be able to experiment to identify the optimal residential density level, or distribution of residential density levels, that maximizes agent utilities and mitigate their environmental impact. Similarly other common policy approaches may be investigated (e.g. purchase and transfer of development rights, conservation easements, minimum lot-size zoning, and alteration of property taxes among others).

5.3. Limitations

The development and application of an ABM to a specific-case study with little data forces modellers to make trade-offs between simplicity of design and complexity of representation. We struck a balance between these objectives by developing a working ABM that suggested that LDR development is the most influential driver threatening highly productive agricultural land in the Municipality of Koper. The model provides a useful framework for an iterative modelling process that can focus data collection and research efforts on the behavioural mechanisms missing from the statistical agents. For example, transitions to forest were not well represented and should be the focus of future work; loss of agricultural land to forest indicates land abandonment, which calls for further investigation of the need to protect high quality agricultural soils for cultural and food production purposes and an analysis of approaches to support farming in addition to controlling development. Furthermore, acquisition of process-based data would increase interaction among agents and provide a fuller representation of land-use dynamics.

One approach to systematically extend the presented research is to develop a series of hybrid agents that are based on both statistical and process-based information. For example, the town centre developer agent's location decisions could include both logistic regression information (i.e. neighbourhood counts and distances to LUC) and process-interaction derived information (e.g. demand as represented by occupation of a development, Section 2.2).

While additional data and understanding of actors driving LUCC in the Municipality of Koper can improve our ability to evaluate the impact of land-use dynamics on human and natural systems, it is worth noting that data provide a fixed representation of a system that could produce an infinite number of outcomes. Extrapolating data, as was done under the assumptions of temporal and spatial stationarity in the BAU experiment, led to unlikely population trajectories and land-use transitions to forest. Because the future is uncertain and stochastic events in both natural and human systems can lead to unforeseen outcomes, the creation of coherent, plausible, and internally consistent scenarios can be useful to evaluate the impacts of potential futures (e.g. Rounsevell et al., 2006). Future research into the development of scenarios would not only provide useful narratives for constricting the parameter space of the model, but when used amongst multiple case-study locations or research projects they may provide an approach to unify research efforts by providing a baseline for comparison.

6. Conclusions

Faced with data constraints, we developed and used an agent-based approach to evaluate the impact of LUCC on human well-being in Koper, Slovenia, as represented by the provision of highly productive agricultural soil, the extent of noise pollution, and quality-of-life measurements. Through a series of computational experiments results for Koper showed, under a range of model assumptions, that (1) high quality agricultural soils were disproportionately affected by urban growth, (2) aggregate resident quality of life increased non-linearly with a change in development density, (3) some drivers of residential settlement produced non-linear preference responses, and (4) clustering industrial development had a beneficial impact on human well-being.

As the community moves forward to continue to include additional natural and human processes in coupled natural-human land-use systems, ABM will need to be broadened to act as an integrative approach to address new land-use science research questions. The combined use of different modelling paradigms should not be seen as a hindrance or disadvantage to ABM, but instead ABM should be embraced for its ability to integrate different types of data, models, and impact metrics.

Acknowledgements

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Appendix A. Supplementary material

Supplementary data associated with this article can be found, in the online version, at doi:10.1016/j.compenvurbsys.2011.10.002. These data include Google maps of the most important areas described in this article.

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