Computers, Environment and Urban Systems 50 (2015) 1–14

Contents lists available at ScienceDirect

Computers, Environment and Urban Systems

journal homepage: www.elsevier.com/locate/compenvurbsys

A utility-based suitability framework for integrated local-scale land-use modelling

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ARTICLE INFO

Article history:
Received 3 June 2014
Received in revised form 9 October 2014
Accepted 12 October 2014

Keywords:
Land-use modelling
Economic theory
Land suitability
Model validation

ABSTRACT

Models that simulate land-use patterns often use either inductive, data-driven approaches or deductive, theory-based methods to describe the relative strength of the social, economic and biophysical forces that drive the various sectors in the land system. An integrated framework is proposed here that incorporates both approaches based on a unified assessment for local land suitability following a monetary, utility-based logic. The framework is illustrated with a hedonic pricing analysis of urban land values and a net present value assessment for agricultural production system in combination with statistics-based assessments of land suitability for other sectors.

The results show that limited difference exists between the most commonly applied inductive approaches that use either multinomial or binomial logistic regression specifications of suitability. Land-use simulations following the binomial regression based suitability values that were rescaled to bid prices (reflecting relative competitiveness) perform better for all individual land-use types. Performance improves even further when a land value based description of urban bid prices is added to this approach. Interestingly enough the better fitting description of suitability for urban areas also improves the ability of the model to simulate correct locations for business estates and greenhouses.

The simulation alternatives that consider the net present values for agricultural types of land use show the relevance of this approach for understanding the spatial distribution of these types of land use. The combined use of urban land values and net present values for agricultural land use in defining land suitability performs best in our validation exercise. The proposed methodology can also be used to incorporate information from other research frameworks that describe the utility of land for different types of use.

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1. Introduction

Local land-use changes are driven by a wide range of social, economic and biophysical forces. These forces have a different impact on the various societal sectors that influence the land-use system. Urbanisation is typically driven by factors such as economic development, accessibility and spatial planning, agriculture is strongly influenced by general agro-economic and local biophysical conditions, while changes in natural areas generally result from (the presence or lack of) agricultural perspective and policy interventions. Obviously the strength of these forces varies across time and space. Land-use models can be used to better understand the interplay between these forces and provide information on the possible future state of the land system (Verburg, Schot, Dijst, & Veldkamp, 2004). Such models apply a wide range of theories and methods to explain the magnitude and location of change (see, for example, Koomen & Stillwell, 2007, chap. 1). A crucial component in most land-use models is the definition of local suitability of land for various types of use that is normally done by statistical analysis or expert judgement (Lesschen, Verburg, & Staal, 2005; Verburg, Schot et al., 2004). The latter approach is prevalent in multi-criteria evaluation or related analytical hierarchy process applications that rely on structured combinations of many different spatially explicit data sets (Collins, Steinder, & Rushman, 2001; Malczewski, 2004). However, the causal relations that link the underlying decision making processes to the observed changes in land use are generally poorly represented in statistics- and

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http://dx.doi.org/10.1016/j.compenvurbsys.2014.10.002
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expert-based approaches (Munroe & Muller, 2007). Yet, data-driven inductive approaches are popular because they tend to perform better in reproducing existing spatial patterns (Overmars, Verburg, & Veldkamp, 2007). Overmars et al. argue, however, that a deductive theory-induced approach should be better equipped to understand causal relations and ongoing processes. Attempts to introduce a deductive approach to land-use modelling are relatively scarce and tend to focus on land-use changes that relate to single-sector processes such as agricultural practices (Overmars, De Groot, & Huigen, 2007) or residential development (Ettema, De Jong, Timmermans, & Bakema, 2007, chap. 14). This is due to the fact that reproducing observed land-use patterns (the typical procedure in validating model outcomes) following a deductive approach is much harder in models that simulate multiple land-use change processes (Van Schrojenstein Lantman, Verburg, Bregt, & Geertman, 2011, chap. 3). The preference for using either an inductive or a deductive approach is also related to the disciplinary background of the researchers involved. Geographers usually focus on spatial patterns and typically rely on inductive, data-driven approaches to describe and explain them, whereas economists – that emphasise processes – normally rely on deduction from theoretical principles.

We propose an integrated approach that can be used to simulate local land-use changes for multiple societal sectors simultaneously. In fact, we will follow the invitation of Overmars, De Groot et al. (2007) to seek the interaction between inductive and deductive work. Our framework aims to combine the strengths of the available concepts, approaches and techniques of different disciplines such as geography and economics (as advocated by Verburg, Schot et al., 2004). A crucial issue here is to come to a unified assessment framework for land suitability that incorporates the local potential for different types of use (urban, agricultural and natural) based on, for example, market preferences, land use related policy measures and biophysical conditions that change over time.

The proposed suitability framework is implemented in an operational land-use model and applied to a challenging case study area where economic processes, planning restrictions and biophysical conditions interact and that is characterised by considerable dynamics in multiple sectors. The Netherlands fulfil these criteria and have the additional advantage that the necessary large amounts of spatial data are available. Especially micro-level data related to land values that have recently become available allow us to pixelise the social as suggested by Geoghegan et al. (1998, chap. 3) and help to reinforce the economic rationale in land-use modelling.

To assess the merits of the proposed suitability framework the resulting simulations are compared with model runs based on inductive, statistically inferred land-use suitability definitions. All simulations are performed using the same base data and cover a period for which actual land-use observations exist to allow for a proper validation of model outcomes.

2. Methodology

2.1. Conceptualising the land suitability framework

Land-use changes follow from the decisions that actors (e.g., farmers, nature managers, real estate developers) make in managing land. Major changes normally follow from the buying or renting of land and a subsequent conversion process. We therefore take the land market as foundation for our approach and model the factors that are relevant to the decision makers on this market. For each of the groups of actors representing a societal sector that influences land use we express their willingness to buy or rent a location in a spatially explicit bid price map. These actor-specific bid-prices are then used as a measure of local suitability to start an iterative competition process to fulfil the (predefined) demand for land of the various actors. Local land suitability is defined following a monetary (utility-based) framework in the tradition of the seminal theoretical work of Alonso (1964) and others. Suitability for a particular type of land use is calculated as the net profit for that use, in line with bid-rent theory and the host of literature on land markets and land evaluation. This utility-based approach has the advantage that it allows for a unified assessment of land suitability that can be directly linked to human behaviour and can, potentially, be defined in a relatively objective way. It provides a common reference scale for the definition of suitability that allows for straightforward interpretation, direct comparison between different types of land use and regions, and a framework for the inclusion of future changes in location characteristics. It thus offers the possibility to insert discontinuities, policy alternatives or anticipated scenario-based changes. These advantages are lacking in alternative approaches such as pure statistical techniques, multi-criteria analysis or the analytical hierarchy process.

Utility-based approaches are commonly applied to add behavioural logic to land-use models, but this is normally confined to the modelling of a single land conversion process (e.g. urbanisation or deforestation) that is steered by economic logic. Typical examples include the well-known spatially explicit economic models for deforestation (Chomitz & Gray, 1996) and urbanisation (Irwin & Geoghegan, 2001) and more recent micro-simulation or multi-agent models that apply utility functions to steer location choice of various urban actors (e.g. Filatova, Parker, & Van der Veen, 2009; Ligtenberg, Bregt, & Van Lammeren, 2001; Waddell et al., 2003). We address multiple land-use change processes simultaneously in our conceptual framework and incorporate the different rationales that underlie, for example, residential development, construction of new offices and industries, nature development and changes in agricultural systems.

Our land suitability definition approach essentially calls for developing bid price maps for all types of land use used in simulation. These bid prices can be generated by different methods and we will test the merits of the following approaches:

- A statistics-based approach that defines spatial variation in land suitability by linking observed bid prices per land-use type with an explanatory analysis of land-use patterns.
- Utility-based approaches that define suitability for specific land-use types. In this paper we applied a sales comparison approach (hedonic pricing analysis of house prices) for urban land and an income approach (net present value) for agricultural land. Other approaches can be selected dependent on locally available knowledge and data.

The resulting spatially explicit and land-use specific bid price maps are then used to define local suitability for all land-use types in several validation runs that aim to simulate 1996 and 2008 land-use patterns. These validation runs will be compared with simulation efforts that only rely on a statistical explanation of observed land-use patterns. As advocated by, amongst others, Pontius et al. (2008) we only use spatial information that was available at or before the 1996 base year of simulation wherever possible, thus allowing a proper validation of the specification of suitability in all cases.

2.2. Statistics-based definitions of land-use specific bid price patterns

The statistics-based approach to define spatial variation in land-use specific bid prices entails the following three steps that are described in more detail below:

1. Establishing bid prices per land-use type.
2. Statistically explaining spatial variation in land-use patterns from a range of driving forces.
3. Linking observed bid price per land-use type with their explained spatial patterns.

2.2.1. Establishing bid prices per land-use type

Bid prices per land-use type are based on an analysis of the agricultural land market by the Dutch Agricultural Economics Institute (LEI, see: Kuhlman, Luijt, Van Dijk, Schouten, & Voskuilen, 2010). This analysis is based on a selection of transactions on the land market and only includes parcels of agricultural land that: (1) were sold in 1998; (2) are located outside existing urban areas; (3) do not include buildings or other property; (4) are without lease contracts; and (5) have a value below 3 million Euro per hectare. Subsequently, these transactions were segmented based on the profession of the buyer indicating the likely use to which the land will be put. Table 1 indicates clear bid price differences between different types of land users. The lowest prices are paid by those who aim to use the land for forest, nature or agriculture. The latter type of use includes both grassland and arable farming and no systematic price difference has been observed between these types of use (Kuhlman, personal communication). Land used for horticulture has a higher price and includes several sub classes: flower bulbs, fruit cultivation, orchards, market gardening and greenhouse horticulture. The latter type of use is associated with the highest land prices and determines to a large extent the relatively high price observed for the aggregated horticulture class.

Land that is likely to be put to urban types of use is sold for the highest price. It is good to note, however, that these land prices are inferred from the selling of agricultural land without buildings or property. The observed values reflect the expectation that the land may be transformed into urban use and thus hint at spillovers from the urban land market into the rural land market; two segments that are created by the relatively strict Dutch spatial planning regulations (Dekkers & Koomen, 2011, chap. 9). The price-increasing effect due to potential agro-urban land use change (Malpezzi & Wachter, 2002) is, however, not fully captured in these transactions as in many cases the land is resold by non-farmers (e.g. middlemen) and therefore absent in the analysed agricultural land transactions. The observed values are thus substantially below those for land with a non-agricultural use, such as building lots and other serviced land that is legally designated to become urban. Such land prices are typically ten or more times higher as is evidenced in the reconstructed land prices of, for example, De Groot (2011) that are further discussed in Section 2.3.

Table 1
Average price for agricultural land as paid by buyers from selected sectors in 1998.

Expected use (based on profession of buyer)	Land price (€/m^2)
Agriculture (grassland and arable farming)	2.5
Horticulture	5.5
Forest and nature	1.7
Mining	3.2
Recreation	6.4
Urban	10.6
Transport	4.0
Average transaction price	3.8

Source: Based on Kuhlman et al. (2010).

2.2.2. Statistically explaining spatial variation in land-use patterns

To explain spatial variation in the land-use patterns observed in our case study area, we apply binomial logistic regression analysis. This approach essentially explains the probability that a location is being used for a specific land-use type:

$$P_{cj} = e^{(\alpha+\beta*X_{cj})}/(1 + e^{(\alpha+\beta*X_{cj})}) \quad (1)$$

In which:

P_{cj} is the probability for cell c being used for land-use type j.
α is a constant.
β is a vector of estimation parameters for all variables X.
X_{cj} is a set of location factors (explanatory variables) for cell c for land-use type j.

Binomial logistic regression is commonly applied in land-change analysis to explain the presence of individual land-use types, often as a first step to build a spatially explicit model of land-use change (Geoghegan, Schneider, & Vance, 2004; Hoymann, 2010; Lesschen et al., 2005; Verburg, Ritsema van Eck, De Nijs, Dijst, & Schot, 2004). In such statistics-based models the term $\alpha + \beta * X_{cj}$ is commonly referred to as land suitability.

As explanatory factors we use a set of spatially explicit variables that capture the most important forces behind land-use change. Following general literature on the forces driving land-use change (e.g. Bürgi, Hersperger, & Schneeberger, 2004) and prior studies into the determinants of land-use change patterns in the Netherlands (Verburg, Ritsema van Eck et al., 2004) we include variables related to policy measures, economic drivers and biophysical conditions important for agricultural production (Table 2). This set is by no means complete but allows for a reasonable explanation of observed land-use patterns. The explained variance (Nagelkerke pseudo R^2) differs considerable for the different land-use types: the presence of nature (0.68) and urban area (0.50) can be explained reasonably well, business estates and agricultural land-use types less so (0.29–0.21) and recreation hardly at all (0.08). The poor performance of the latter type of use may be due to its dispersed, infrequent occurrence (claiming 0.8% of the total land area) and heterogeneous character (e.g., including campsites and theme parks). We have refrained from directly incorporating reference to land use in neighbouring cells – that is a powerful approach to reproduce land-use patterns (De Nijs & Pebesma, 2010; Hagoort, 2006; Van Vliet et al., 2013; Verburg, Ritsema van Eck et al., 2004; Zhou & Kockelman, 2008) – as this would enforce spatial autocorrelation on simulation results and possibly obscure the differences resulting from the methods applied here to define local land suitability. Annex 1 provides a summary of the statistical results.

2.2.3. Linking observed land-use specific bid prices with explained spatial patterns

In the final step of our statistics-based approach to define spatial patterns in land-use specific bid prices we assume that the most attractive locations for a particular land-use type also represent the locations with the highest economic value for the actors that are associated with it. This is a fundamental principle underlying the land appraisal process. So a location that is very likely to be developed into residential land will most probably also have a land price close to the observed prices for land transactions in that land market segment as listed in Table 1. This implies that suitability for a particular type of land use (described as $\alpha + \beta * X_{cj}$ in our regression analysis) is equivalent to the observed bid price for that type of use. We apply this assumption to redefine the probability that a location is being used for a specific land-use type:

$$P'_{cj} = e^{\min\{B_j*(\alpha+\beta*X_{cj}),B_j\}} / \left(1 + e^{\min\{B_j*(\alpha+\beta*X_{cj}),B_j\}}\right) \quad (2)$$

In which:

P'_{cj} is the bid-price related probability for cell c being used for land-use type j.
B_j is the bid price for land-use type j as listed in Table 1.

The minimum value of either $B_j * (\alpha + \beta * X_{cj})$ or B_j is selected to make sure that the suitability values for a particular type of land use do not exceed the bid prices for that land-use type. By way of example, the left hand side of Fig. 1 shows the local land suitability values for urban areas as based on the reconstructed bid price for urban land following the statistics-based approach described in this section. The next section will describe alternative utility-based methods to define spatial patterns in bid prices.

2.3. Utility-based definitions of land-use specific bid price patterns

Suitability values for different types of land use can also be inferred from economic analysis that describes the utility of land for specific purposes, for example, by revealing the investment behaviour of real estate developers or farmers. Currently available micro-level data offer interesting opportunities to link local bid prices for different types of land to spatially explicit land-use models (Dekkers & Rietveld, 2011, chap. 9). In this paper, we use a hedonic analysis of house prices to describe spatial variation in expected bid prices (and thus suitability) for urban land and apply the net present value method to define the value of location for agricultural land.

To obtain a bid price for urban land that is closely related to observed (residential) land values we have calculated implicit residential land values using the approach described by De Groot (2011), De Groot, Marlet, Teulings, and Vermeulen (2010). This local land value is calculated following a hedonic pricing analysis of house transactions (i.e. excluding apartments) for the Netherlands in the period 1993–1999 using transaction data provided by the Dutch Association of Real Estate Brokers (NVM). The hedonic pricing method is a regression technique that allows distinguishing the contribution of separate product components to the total product price (Rosen, 1974). We use it to obtain the contribution of location to the total transaction price of each sold object by controlling for structural house characteristics. The price impact of location is obtained as a region-specific fixed effect for each of the circa 4000 four-digit zip code areas in the country. Based on that, the land value is computed by dividing the location component of the transaction price by the plot size of the sold property. These individual land values are then averaged per four-digit zip code area weighting each transaction for its plot size. For the current analysis real transaction prices for 1999 are used, meaning that we correct for an overall increase of house prices in the period 1993–1999. The resulting urban land values are then used to define suitability for urban area as a bid price following two more steps. First, the land values – that at some inner city locations incidentally exceed 500 €/m^2 – are rescaled to a maximum of 50 €/m^2 to prevent numerical overflow errors in the subsequent simulation process. Second, we add conversion costs to non-built-up land to account for the costs that are involved in preparing land for buildings. These costs are estimated at 40 €/m^2 following a recent national report on land production costs related to housing development projects (Keers, Van 't Hof, & Scheele-Goedhart, 2013). The addition of local conversion costs introduces spatial detail to the otherwise homogeneous zip code areas that are used to calculate the average local land value. Fig. 1 (at right) shows the resulting spatial pattern next to a representation of bid prices that is inferred from a spatial explanation of the occurrence of urban areas as was discussed in Section 2.2. Their overall patterns are similar, but they differ in spatial detail and absolute values. Note that negative values can occur in both approaches at specific locations. In the utility-based approach they arise when construction costs are higher than average residential land values in a region. In the statistics-based approach to define bid price patterns they result from a local dominance of explanatory variables that have a negative influence on the occurrence of urban areas. While such negative bid prices will not occur in reality they do reflect locations where urban development is unlikely due to limited or even negative net benefits.

To describe agricultural land values we apply the net present value (NPV) approach. This is a standard method to calculate the expected net economic benefits of long-term projects by measuring discounted time series of expected cash flows. The net present

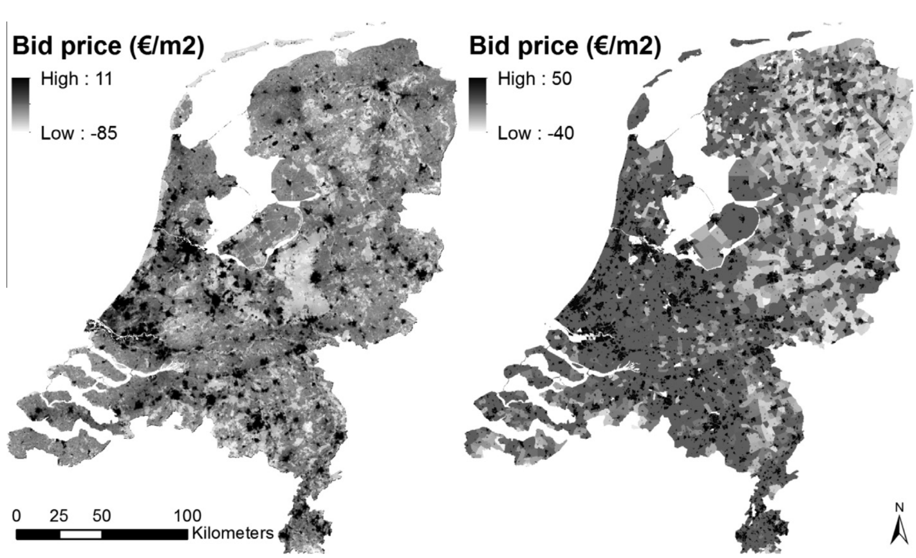

Fig. 1. Suitability for urban area described as bid-price linked to the spatial explanation of the occurrence of this land-use type (left) and as bid price inferred from residential land values and a conversion cost on non-built-up land.

value that a farmer can expect by producing a certain commodity on a land parcel depends on the specific costs to produce that commodity, the market prices of products and co-products and the yields that can be obtained. The yields are related to the biophysical properties of that parcel. When confronted with the decision to buy land for a particular type of use, the net present value can be considered to represent the maximum price a farmer can bid for land without making a loss. This idea is similar to the classic agricultural economic theories of Ricardo (1817), Von Thünen (1826) that state that the land rent at a certain location is equal to the yearly net profit at that location. Farms can be regarded as long-term economic enterprises, involving capital budgeting decisions according to required investment (e.g. in facilities and commodity-specific machinery) and expected future revenues (Barlowe, 1972; Plantinga, Lubowski, & Stavins, 2002; Schatzki, 2003; Van der Hilst et al., 2010). Therefore, instead of considering a single yearly rent we now aggregate the total profits over the life time of a production system to come to a bid price.

In this study we calculate the net present value of agricultural production systems (in our case corresponding to types of agricultural land use) as follows:

$$NPV_{cj} = -Inv_{cj} + \sum_{y=0}^{n} \frac{R_{cjy-C_{cjy}}}{(1+r)^y} \quad (3)$$

In which:

NPV_{cj} is the net present value derived from land-use j in cell c in year 0.
Inv_{cj} are the initial investment costs (e.g. land, new machinery, buildings and facilities) of production system j in cell c in year 0.
R_{cjy} are the annual gross revenues of production system j in cell c in year y.

C_{cjy} are the annual total costs of production system j in cell c in year y consisting of field operation costs, input costs, fixed costs, storing costs and transportation costs.
r is the discount rate.
n is the lifetime of the project in number of years.

To come to a location-specific assessment of the potential gross revenues for a specific production system (R_{cjy}) this approach relies on a cell-based description of biophysical suitability in combination with the maximum attainable yields per hectare and commodity prices:

$$R_{cjy} = \sum_{k=1}^{n} ym_k * yr_{ck} * p_k \quad (4)$$

In which:

k is a commodity produced in production system j.
n is the total number of commodities produced in production system j.
ym_k is the maximum attainable yield of commodity k under optimal biophysical conditions.
yr_{ck} is the yield reduction of commodity k in cell c.
p_k is the market price of commodity k

To describe local yield reduction per commodity (yr_{ck}) we follow the most recently described relationships between soil type, groundwater table and agricultural production for the Netherlands (Van Bakel, Van der Waal, De Haan, Spruyt, & Evers, 2007). These relationships are applied to detailed soil and groundwater level data sets and express the fraction of the maximum attainable yield that can be obtained at locations where biophysical conditions are not optimal for that commodity. These maps are also applied in the regression analyses that explain land-use patterns (Table 2). We considered an annuity time period of 20 years as this is a common time horizon in other cash-crop studies (Kuhlman, Diogo, & Koomen, 2013; Stonehouse, Kay, Baffoe, & Johnston-Drury, 1988; Van der Hilst et al., 2010). Furthermore a discount rate of 5.5% is assumed, which is considered to be a realistic interest rate for farmer loans (De Wolf & Van der Klooster, 2006).

2.4. Implementing the suitability definitions in a land change model

The proposed suitability definitions are applied in Land Use Scanner, a local land change model rooted in economic theory that has been applied in a large number of policy-related research projects in the Netherlands and abroad. (Hilferink & Rietveld, 1999; Koomen and Borsboom-van Beurden, 2011). The model is particularly useful for this purpose as it provides an integrated outlook on land use and has a very flexible framework that allows different model specifications to be tested. This makes it possible to cover a range of urban, natural and agricultural land-use types simultaneously and centre the modelling process on the different definitions of suitability for the distinguished types of land use. The model's basics and recent calibration have been described exten-

Table 2
Explanatory variables used in regression analysis including descriptive statistics.

Variable	Unit	Range	Mean
Economics (location preference and externalities)			
Attractivity of surrounding landscape (expert judged; Roos-Klein Lankhorst et al. (2002))	Scalar	1–11	7.7
Urban facility level (presence of cultural facilities, retail outlets, hotels, restaurants, bars and historic houses in 2002 in 500 m grid)	Index	0–87	0.5
Euclidean distance any station 2002 (cut off at 10 km in analysis)	km	0–34.0	7.2
Euclidean distance IC stations 2004 (cut off at 25 km in analysis)	km	0–46.4	14.3
Euclidean distance highway exits 1991 (cut off at 5 km in analysis)	km	0–40.0	7.7
Travel distance to Amsterdam airport based on 500 m grid (cut off at 25 km)	km	0–226.2	119.8
Travel distance to Rotterdam harbour based on 500 m grid (cut off at 25 km)	km	0–268.2	126.3
Biophysical conditions			
Soil subsidence due to peaty soil	Scalar	0–10	0.3
Yield loss agricultural production (for grassland; Van Bakel et al. (2007))	Scalar	0–20	3.9
Policy			
Inside National Ecological Network (defined in 1990; this policy concept is discussed by De Jong (2009))	Dummy	(0/1)	0.4
Inside Green Heart restrictive policy zone VROM (1989)	Dummy	(0/1)	0.2
Inside Buffer zone restrictive area (VROM (1989); the objectives and effectiveness of Green Heart and Buffer zones are discussed by Koomen, Dekkers, and Van Dijk (2008))	Dummy	(0/1)	0.1

sively elsewhere (Koomen, Hilferink, & Borsboom-van Beurden, 2011, chap. 1; Loonen & Koomen, 2009).

The model employs a logit-type approach – derived from discrete choice theory and equivalent to the setup of logistic regression analysis – that allows modelling the choices made by actors between mutually exclusive alternatives (McFadden, 1978). When considering land-use related decisions, this approach explains the probability that a certain use is chosen for a particular location, based on the utility of that location for that specific type of use, in relation to the total utility for all possible uses. In land-use modelling the economics-based concept of utility is generally replaced by the more general term suitability. This suitability is a combination of positive and negative factors that are usually combined using statistical analysis, expert knowledge or scenario-based assumptions. We now define suitability as an actual utility in terms of approximate benefits and costs. In this way suitability can be interpreted as the bid price a potential user is willing to offer for a location.

This basic model is constrained by the overall demand for each land-use function, and the amount of land that is available. Imposing these two conditions results in a doubly-constrained logit model in which the expected amount of land in cell c that will be used for land-use type j is essentially described by the formula:

$$M_{cj} = a_j * b_c * e^{(\beta * S_{cj})} \tag{5}$$

In which:

M_{cj} is the amount of land in cell c expected to be used for land-use type j.
a_j is the demand balancing factor that ensures that the total amount of allocated land for land-use type j equals the sector-specific claim.
b_c is the supply balancing factor that ensures that the total amount of allocated land in cell c does not exceed the amount of land that is available for that particular cell.
S_{cj} is the suitability of cell c for land-use type j based on, for example, local physical properties and operative policies.
β is a scaling parameter that specifies the importance of the suitability value that is usually left at a value of one.

An iterative process is followed to find the appropriate a_j values that meet the demand of all land-use types as is described in detail elsewhere (Dekkers & Koomen, 2007, chap. 20; Hilferink & Rietveld, 1999). In fact, this iterative approach simulates a bidding process between competing land users (or, actually, land-use classes). Each use will try to get its total demand satisfied, but may be outbid by another category that derives higher benefits from the land. In a simplified way, the model thus mimics the land market. The land-use specific bid prices (B_j) included in Eq. (2) to rescale the statistics-derived suitability values for specific land-use types fit very well with this approach and can be considered as a land-use specific replacement of the β scaling parameter described above. Thus, by connecting bid price based suitability definitions and a discrete choice theory-based algorithm, it is possible to describe the land market clearing process: a land seller compares alternative bids and sells to the actor with the highest bid, thus maximizing both revenue of sellers and utility of buyers (Martinez, 1992).

The model application used for testing the various definitions of land suitability has a resolution of 100 m and distinguishes 11 types of land use of which 7 are endogenous (location simulated by model) and 4 exogenous (location is fixed). Land-use model applications tend to limit the number of land-use types in simulation to those main categories that characterise spatial diversity, are expected to show changes, have relevance to the topic of a specific study (e.g. climate adaptation, flood risk or environmental impact) and are manageable in terms of model specification and performance. The selected seven endogenous land-use types (listed, for example, in Table 5) are representative of typical Land Use Scanner applications and range from urban area, business estates, through three types of agriculture to recreation and nature. Their developments are driven by a range of different driving forces, providing an interesting case study for our validation of different methods to define land suitability. As we use the exact amounts of land per type of use as exogenous input for both years of our simulation (1996 and 2008) we only validate the spatial pattern of the allocation process. While interpreting the validation outcomes it is important to note that simulation does not directly prescribe current land use at specific locations, although reference to local land use is implicitly incorporated in several explanatory variables and the specification of conversion costs. The simulation process basically starts using a blank map and directly tries to find optimal locations for each land-use type for the selected year.

In essence, our approach aims to mimic a land market in which land-use classes fulfil the role of buyers, yet it differs from agent-based models that simulate the behaviour and interactions of actors on the land-use system. Typically, the unit of analysis in such models represents a farm, plot or census tracts that matches with the assumed agents of land-use change. The advantage of that approach is the ability to incorporate social processes and non-monetary influences on decision-making and to dynamically link social and environmental processes, thus expressing the co-evolution of the human and landscape systems based on the interactions between human actors and their environment (Le, Park, Vlek, & Cremers, 2008; Matthews, Gilbert, Roach, Polhill, & Gotts, 2007; Parker, Manson, Janssen, Hoffmann, & Deadman, 2003). These models are well-equipped to analyse the impact of socio-economic processes at the level of individual actors, for example, to characterise processes of change in farm structure or concentration of production (Bert et al., 2011). However, large amounts of data are required to build a well-parameterized model of decision-making for large areas and since the number of potentially interacting agents and environmental factors is extremely large, calibration is often too complex and quantitative validation procedures can become intractable (Batty, Desyllas, & Duxbury, 2003; Brown, Page, Riolo, Zellner, & Rand, 2005; Li, Brimicombe, & Li, 2008; Robinson et al., 2007). Therefore, agent-based models have thus far mainly been implemented in simulating local to regional land-use change processes (e.g. Castella & Verburg, 2007; Le et al., 2008; Schreinemachers & Berger, 2011; Valbuena, Verburg, Bregt, & Ligtenberg, 2010).

2.5. Evaluating the different land suitability frameworks

To assess the performance of the proposed monetary suitability framework in reproducing observed land-use patterns, the simulations resulting from this approach are compared with two model runs that are based on statistically inferred land-use suitability definitions common to many land-use models. A pixel-by-pixel based map-comparison method is applied to assess the degree of correspondence of the different simulated land-use patterns with observed patterns.

The statistics-based definitions of land suitability that are used as reference points in our assessment follow binomial logistic regression analyses and multinomial logistic regression analysis. Both approaches are applied to explain the presence of a land-use type at a certain location based on the explanatory factors listed in Table 2. Tables 3 and 4 summarise the results of both regression analyses. Compared to binomial regression analysis, multinomial regression has the advantage of describing the relative importance of suitability factors across different land-use

Table 3
Binomial regression results.

Nagelkerke pseudo R^2	Urban area 0.496		Business estate 0.293		Recreation 0.079		Grassland 0.258		Arable farming 0.209		Greenhouses 0.279		Nature 0.675	
Variable in equation	B	S.E.	B	S.E.	B	S.E.	B	S.E.	B	S.E.	B	S.E.	B	S.E.
Constant	1.982	0.036	−0.195	0.061	−8.796	0.116	−8.246	0.036	0.282	0.027	3.678	0.111	−9.875	0.086
Attractivity landscape	−0.553	0.001	−0.443	0.002	0.681	0.006	0.389	0.001	0.044	0.001	−0.187	0.003	0.856	0.003
Urban facility level	0.149	0.001	−0.089	0.001	0.053	0.003	−0.204	0.002	−0.186	0.002	−0.268	0.006	−0.003**	0.003
Dist. any station (<5 km)	−0.085	0.001	−0.057	0.002	0.012	0.002	−0.070	0.000	0.115	0.001	−0.005**	0.004	0.028	0.001
Dist. IC station (<25 km)	−0.023	0.000	0.000**	0.001	0.010	0.001	−0.023	0.000	0.037	0.000	−0.101	0.002	0.014	0.000
Dist. motorway exit (<5 km)	−0.089	0.002	−0.155	0.003	−0.123	0.005	0.076	0.001	−0.013	0.001	0.249	0.007	−0.080	0.002
Dist. Amsterdam airport	−0.006	0.001	−0.026	0.002	−0.077	0.004	0.152	0.001	−0.099	0.001	−0.154	0.002	−0.020	0.003
Dist. Rotterdam harbour	0.001**	0.001	−0.027	0.001	−0.035	0.002	0.058	0.001	−0.021	0.000	−0.179	0.001	−0.002**	0.001
Soil subsidence in peat area	−0.204	0.004	−0.244	0.008	−0.189	0.008	0.281	0.001	−0.089	0.002	−0.138	0.014	−0.425	0.003
Yield loss Grassland	0.024	0.001	−0.010	0.002	0.136	0.003	0.062	0.001	−0.234	0.001	−0.343	0.007	0.223	0.001
Nat. ecological network (1)	−1.382	0.014	−1.949	0.045	−2.159	0.026	−1.959	0.004	−1.664	0.006	−3.439	0.175	3.875	0.006
Green heart (1)	−0.162	0.012	0.210	0.023	−0.719	0.034	0.947	0.007	−0.652	0.008	1.064	0.033	−1.474	0.018
Buffer zone (1)	0.195	0.019	−0.691	0.057	0.553	0.041	0.226	0.012	−0.043	0.016	−0.196	0.045	0.375	0.022

Coefficients indicated with ** are not significant, all others are significant at 0.01% level.

Table 4
Multinomial regression results using grassland as reference category – Nagelkerke pseudo R^2: 0.660.

	Urban area		Business estate		Recreation		Arable farming		Greenhouses		Nature	
Variable in equation	B	S.E.	B	S.E.	B	S.E.	B	S.E.	B	S.E.	B	S.E.
Constant	9.621	0.053	8.444	0.096	−4.819	0.126	5.455	0.040	11.761	0.197	−5.312	0.092
Attractivity landscape	−1.121	0.002	−1.234	0.003	0.568	0.007	−0.305	0.001	−0.945	0.004	0.755	0.003
Urban facility level	0.273	0.002	0.191	0.002	0.204	0.004	0.038	0.002	0.01**	0.006	0.102	0.004
Dist. any station (<5 km)	−0.042	0.001	−0.043	0.002	0.044	0.002	0.108	0.001	0.024	0.004	0.051	0.001
Dist. IC station (<25 km)	−0.010	0.000	0.002*	0.001	0.020	0.001	0.034	0.000	−0.079	0.002	0.022	0.000
Dist. motorway exit (<5 km)	−0.121	0.002	−0.205	0.003	−0.148	0.005	−0.04	0.001	0.163	0.007	−0.096	0.002
Dist. Amsterdam airport	−0.106	0.002	−0.125	0.002	−0.168	0.004	−0.166	0.001	−0.243	0.003	−0.086	0.003
Dist. Rotterdam harbour	−0.043	0.001	−0.064	0.001	−0.062	0.002	−0.051	0.001	−0.204	0.001	−0.024	0.001
Soil subsidence in peat area	−0.273	0.004	−0.366	0.009	−0.257	0.008	−0.147	0.002	−0.218	0.014	−0.451	0.003
Yield loss Grassland	−0.014	0.001	−0.031	0.002	0.106	0.003	−0.205	0.001	−0.361	0.006	0.183	0.001
Nat. ecological network (0)	0.506	0.016	1.171	0.046	0.838	0.026	0.332	0.006	2.543	0.175	−3.762	0.006
Green Heart (0)	0.519	0.013	0.276	0.024	0.972	0.034	0.854	0.008	−0.548	0.033	1.583	0.017
Buffer zone (0)	0.054*	0.022	0.908	0.058	−0.365	0.042	0.338	0.017	0.264	0.046	−0.307	0.022

Coefficients indicated with * are significant at 0.05 level, ** indicates not significant, all others are significant at 0.01% level.

types (Chomitz & Gray, 1996; Dendoncker, Bogaert, & Rounsevell, 2007, chap. 7; Lesschen et al., 2005). It has the following basic formulation that is essentially the same as the logit formulation underlying the Land Use Scanner model:

$$P_{cj} = e^{(\alpha+\beta*X_{cj})} \Big/ \sum_{i=1}^{n} e^{(\alpha+\beta*X_{ci})} \tag{6}$$

In which:

P_{cj} is the probability for cell c being used for land-use type j.
α is a constant.
β is a vector of estimation parameters for all variables X.
X_{cj} is a set of location factors (explanatory variables) for cell c for land-use type j.
X_{ci} is a set of location factors for cell c for all (n) land-use types i.

The suitability maps resulting from multinomial logistic regression are related and essentially follow the same scaling. Binomial regression lacks this advantage, but is more flexible in its application: different factors can be applied per land-use type and for the (renewed) analysis of a new land-use type it is not necessary to assess all other land-use types as well. Because binomial regression provides separate equations that each describe the most probable location for a particular type of land use, this approach is also used in this study in combination with different utility-based approaches to define suitable locations for specific types of land use.

As measure of comparison we calculate a degree of correspondence C_j that compares the ratios of simulated and observed land use per cell as follows:

$$C_j = 100 - 100\left(\frac{\Sigma_c|M_{cj} - O_{cj}|/2}{\Sigma_c O_{cj}}\right) \tag{7}$$

In which:

C_j is the degree of correspondence for land-use type j expressed as percentage.
M_{cj} is the simulated amount of land in cell c for land-use type j.
O_{cj} is the observed amount of land in cell c for land-use type j.

The degree of correspondence equals 100% when the amount of allocated land is equal to the observed amount in every cell. Conversely, the degree equals zero when none of the allocated amount of land is present in the corresponding cells with observed land use. If we would have considered all allocation differences here without dividing them by two, the share of correspondence could theoretically range to −100% when all allocation would take place at wrong locations. In addition a weighted average degree of correspondence is computed that takes the relative importance of each land-use type into account in terms of its share in the total amount of observed land. This simple map comparison measure is easier to comprehend than other more complex comparison methods that deliver, for example, (Fuzzy)Kappa statistics or use the probabilities underlying the land-use patterns (De Pinto & Nelson, 2006; Hagen, 2003; Munroe & Muller, 2007; Pontius, Huffaker, & Denman, 2004; Visser & De Nijs, 2006). The use of such simple, intuitive measurements for assessing location disagreement was recently advocated by one of the initiators of kappa-indices (Pontius & Millones, 2011).

3. Validation results

We compare the performance of Land Use Scanner in simulating land-use patterns according to different specifications of local land suitability with observed land use for 1996 and 2008. Figs. 2, 3 and 4 provide a spatial representation of selected simulation results including a comparison of simulated and observed land use. Table 5 lists the degree of correspondence between simulated and observed land use for the various model specifications and shows that the land-use types whose spatial distribution can be explained reasonably well with statistical analysis (e.g., urban area and nature) are also simulated reasonably well by the model. Other land-use types, especially those that are dispersed across the country and/or that occur less frequently (e.g., business estates, areas for recreational use and greenhouses) are more difficult to simulate correctly. A possible solution would be to subdivide these categories into internally more consistent types of land use that have a less ambiguous spatial distribution. For example in the case of

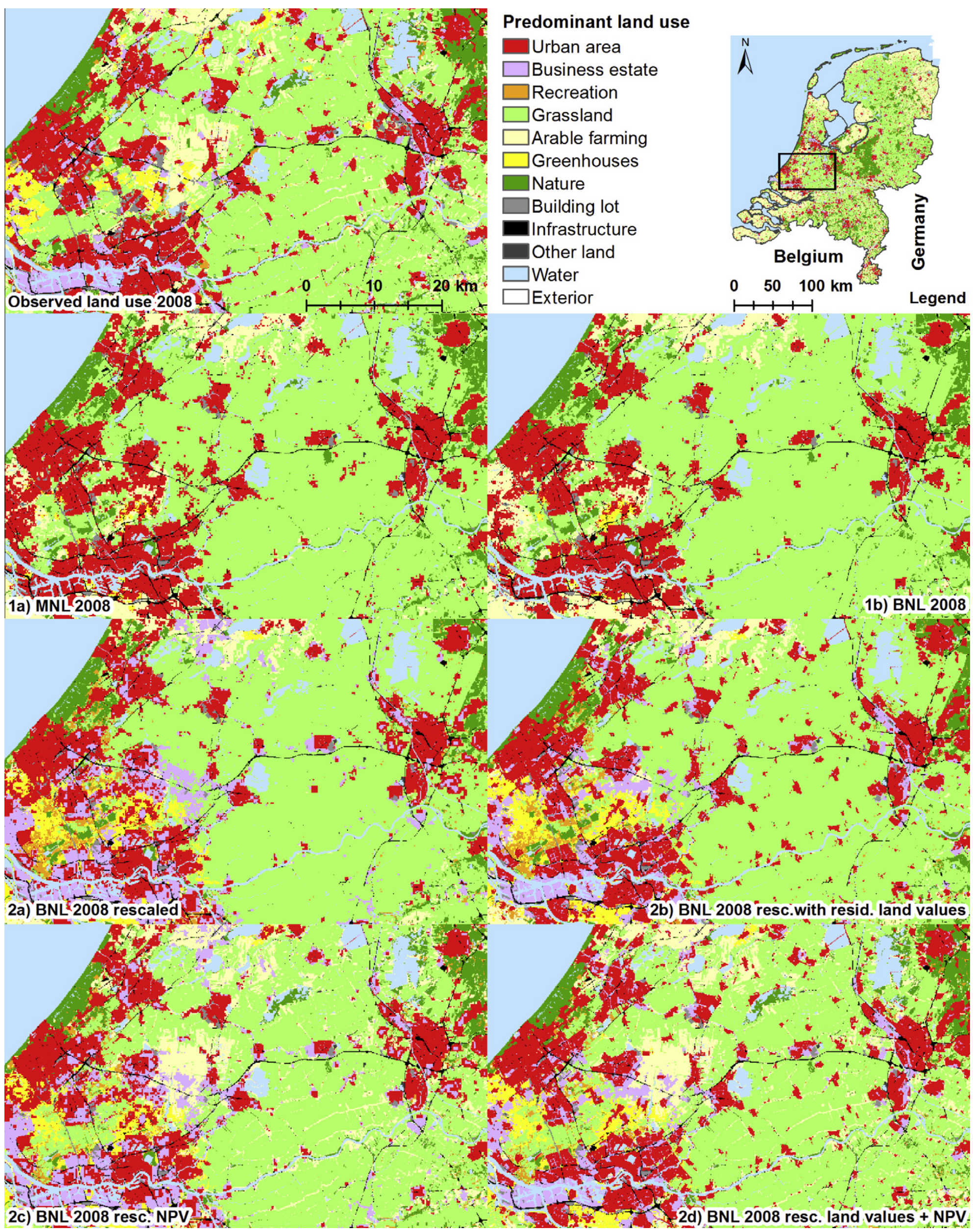

Fig. 2. Depiction of simulated and observed land use for 2008 for part of the Netherlands. The maps show predominant land use per grid cell for the six alternative suitability definitions listed in Table 5. This representation simplifies the underlying data that describe an amount of land per cell for each of the 11 land-use types distinguished in the model. In theory, the dominant type of use may cover only slightly more than 1/11 = 0.09 hectares. Land-use types that, on average, cover most, but not all of a cell (such as urban area or grassland) are overrepresented. Hence, we use land-use type specific simulation results per cell to evaluate model performance as is illustrated in the subsequent figures.

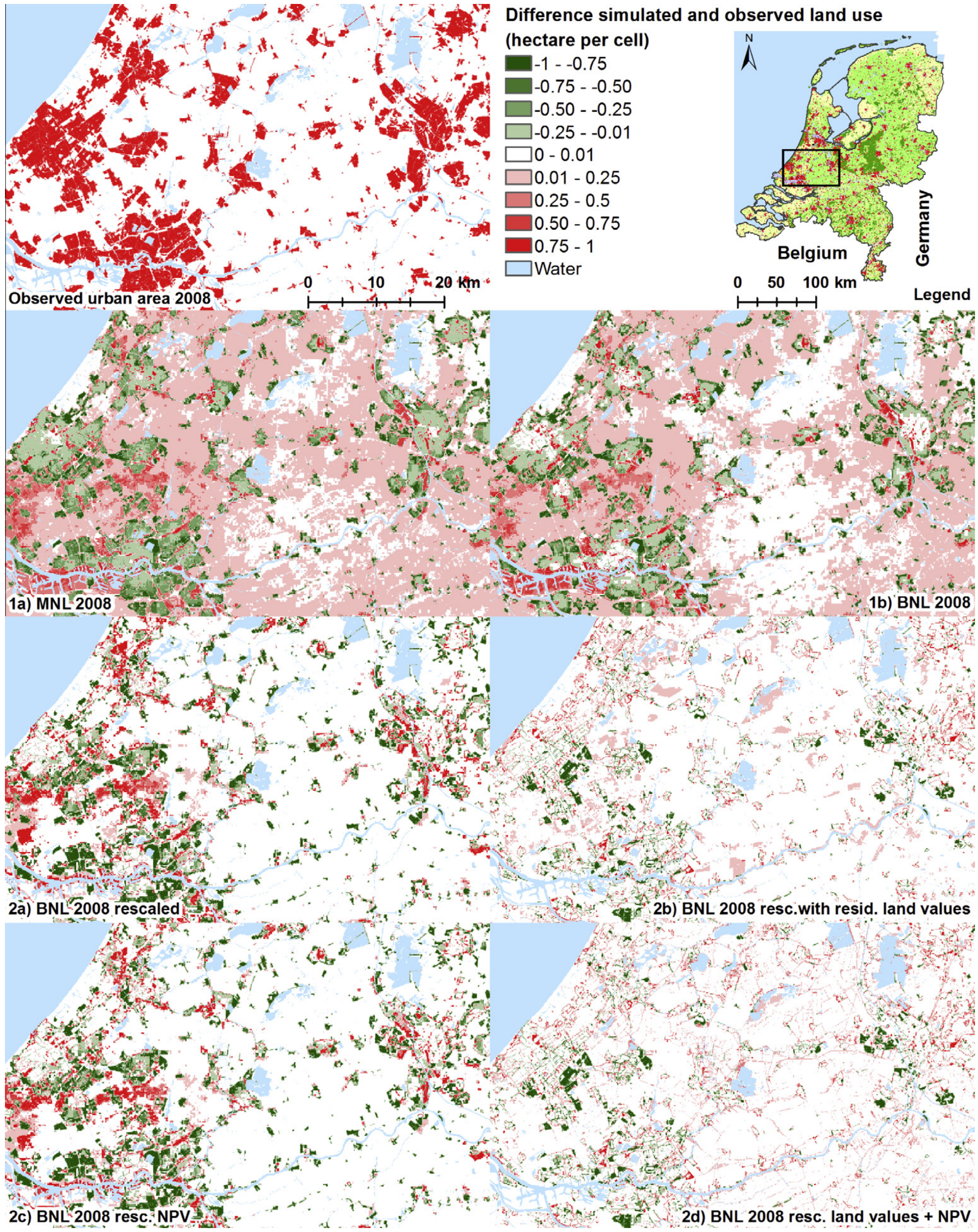

Fig. 3. Comparison of simulated and observed urban area for 2008. The maps show where simulation results in more (red) or less (green) urban area than the 2008 reference map included in the top-left corner. The latter map also contains a fraction per cell and applies the same colour representation as the difference maps on the observed amount of urban area in 2008. Yet, the observed urban area has a very distinct appearance: cells are either mostly urban, or not urban at all. The simulation results following the bid price based suitability definitions (2a–2d) correspond more to this representation than the statistics-based suitability definitions (1a and 1b). The maps, furthermore, highlight spatial differences between the various suitability map definitions that relate to the inclusion of specific elements. Alternatives 2b and 2d, for example, include reference to residential land values which – compared to the other simulation alternatives – leads to less deviation from the observed urban area. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

business estates distinguish between industrial sites, logistic centres at harbour locations and area that primarily consist of offices. This might improve the explanation of their current spatial distribution (and hence their performance in simulation) but introduces additional complexity in defining future developments in terms of changes in total area and preferred location for these more detailed types of use; a prerequisite for typical model application studies. Table 5 also makes clear that limited difference exists between the multinomial and binomial logistic regression specifications of suitability. This is somewhat surprising as the multinomial logistic regression results were expected to better capture the relative importance of suitability factors for different types of land use. Another obvious conclusion from the table is that performance decreases over time; based on statistical analysis it is more difficult to correctly simulate land-use patterns for a future year (2008) than for the year on which the description of suitable locations is based (1996).

When we look at the performance of the land-use simulations following the binomial regression based suitability values that were rescaled to bid prices (alternative 2a in Table 5) we find that this approach performs better for all individual land-use types. So apparently the relative competitiveness of these land-use types as reflected in observed bid prices is a useful criterion to include in their simulation. Performance improves even further when a land

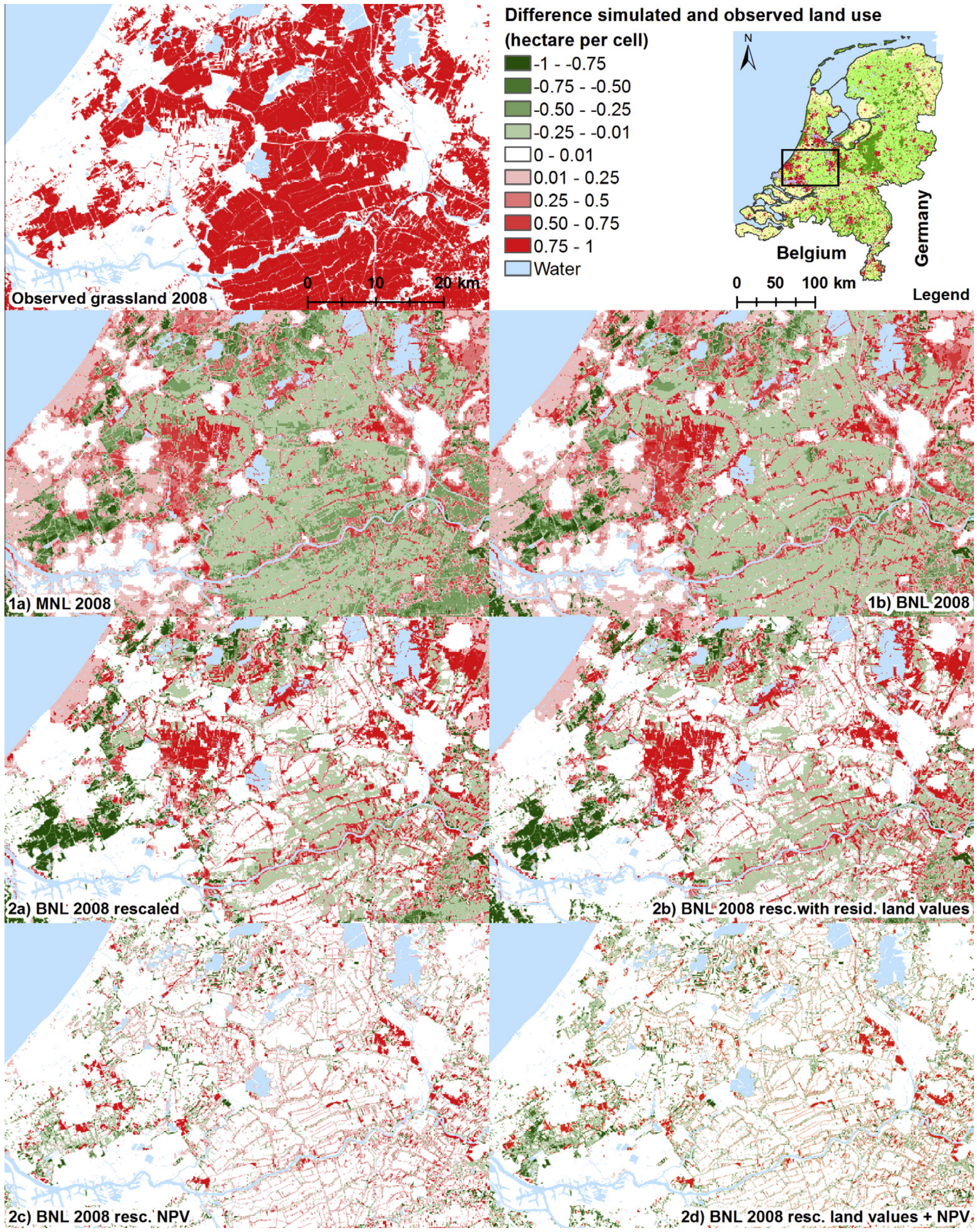

Fig. 4. Comparison of simulated and observed grassland for 2008. The figures show that the simulation results based on suitability definitions that include a net present value assessment for agricultural production systems (2c and 2d) correspond best to observed grassland.

value based description of urban bid prices is added to this approach. Interestingly enough the better fitting description of suitability for urban areas also improves the ability of the model to simulate correct locations for business estates and greenhouses. So by pinpointing more correct locations for urban area the model is better able to locate these other land-use types at their actual location, indicating that these types of land use compete for similar locations in the simulation process. The simulation alternatives that consider the net present values for agricultural types of land use (alternatives 2b and 2c in Table 5) show the relevance of this approach for understanding the spatial distribution of these types of land use. Especially for grassland the current description of the net present values for this type of farming seems to be well-related to its spatial distribution. At the same time the performance of other land-use types that compete for 'green' space (nature and recreation) improves. The combined use of urban land values and net present values for agricultural land-use in defining land suitability (alternative 2d in Table 5) performs best in our validation exercise leading to degrees of correspondence of about 90% for the simulated patterns of several types of land use in 1996. Similar to the statistics-based definition of suitability, the performance drops considerably for when 2008 land-use patterns are simulated. This indicates that the current implementation of the factors that steer land-use change is not complete. Yet, we believe that the proposed methodology offers a good starting point to incorporate more relevant factors. Also the simulation of recreation and greenhouses deserves further attention as their degrees of correspondence are only around 20–30%. The final section of this paper provides some more general reflections on the presented results and discusses potential improvements to the proposed methodology.

Table 5
Comparison of simulated and observed land use for 1996 and 2008 expressed as degree of correspondence.

Statistics-based suitability definitions		Urban area	Business estate	Recreation	Grassland	Arable farming	Greenhouses	Nature	Weighted average
(1a) Multinomial logistic regression	1996	52.4	16.9	2.9	64.1	49.2	11.8	67.6	57.9
	2008	50.2	17.0	2.7	61.5	48.9	9.9	67.0	55.3
(1b) Binomial logistic regression	1996	54.4	11.0	2.7	65.4	50.6	10.0	70.9	59.4
	2008	52.3	11.1	2.5	62.8	50.1	8.4	70.2	56.7
Bid price based suitability definitions									
(2a) Binomial regression based suitability rescaled to bid prices	1996	60.6	22.1	6.8	67.2	53.3	13.1	72.0	61.9
	2008	59.3	20.2	6.6	64.8	52.7	10.5	71.4	59.5
(2b) As 2a with urban area bid price based on residential land values	1996	91.2	52.8	7.4	68.5	54.7	24.3	72.2	66.5
	2008	83.0	49.3	7.0	66.0	54.1	20.2	71.5	63.6
(2c) As 2a with arable farming and grassland bid price based on NPV	1996	66.0	23.3	18.5	93.6	84.6	18.2	86.6	85.2
	2008	63.8	21.4	16.4	82.8	69.1	12.3	83.7	74.0
(2d) As 2a with urban area, arable farming and grassland bid prices	1996	91.8	60.3	20.7	94.0	86.6	36.8	86.7	89.2
	2008	83.4	54.6	17.5	82.8	71.0	24.3	83.5	77.5

4. Conclusion and discussion

The objective of this paper was to bring together different approaches to explain land-use patterns and test the merits of a new integrated utility-based approach to define local land suitability by comparing its performance in reproducing observed land-use patterns with often applied statistics-based methods. From the presented validation exercise that simulated 1996 and 2008 land-use patterns in the Netherlands we conclude that the proposed bid-price related definitions of land suitability outperform classic, purely statistics-based definitions. So integrating inductive and deductive analysis indeed holds promise for improving land-use modelling performance as was suggested by other scholars that experimented with combining these different types of analysis (Castella & Verburg, 2007; Overmars, Verburg et al., 2007). Adding investment costs on land-use conversion to define the change resistance of existing land-use patterns greatly helped to improve the performance of our simulations as was also found by, for example, De Pinto and Nelson (2009). Such references are less specific (but certainly not absent) in our statistics-based suitability
specification. Land-use inertia is incorporated in our approach in a transparent, motivated and flexible manner that allows for an informed combination with other references to the costs and benefits of land-use change. Other approaches to describe resistance to land-use change (often referred to as conversion elasticity) following, for example, semi-automated procedures and expert judgement (Engelen & White, 2008; Koomen, Koekoek, & Dijk, 2011; Verburg & Overmars, 2009) or observed past transitions (following the idea of Markov chains put forward by Bell, 1974) are more difficult to combine with different aspects of land suitability in a consistent and meaningful way.

This paper illustrated the potential of our utility-based, multi-sector framework for local-scale land-use modelling with assessments of urban land value and net present values for agricultural production systems only. But it is also possible to incorporate information from other research frameworks describing the utility of land for different types of use relying on, for example, ground rent capitalisation or capital asset pricing methods in an urban context (Mills & Hamilton, 1994), alternative economic land evaluation methods for agricultural types of use (Rossiter, 1995), empirical-statistical explanatory models of rural or commercial land values (Buurman, 2003; Downing, 1973) or willingness to pay estimates derived from stated preference experiments when monetary prices are scarce or absent (e.g. for natural areas, see Ruijgrok, 1999). An additional advantage of the possibility to include monetary information in the definition of suitability for different land-use types is that it also allows for the assessment of the spatial impacts of specific financial policy instruments. The applied monetary scaling allows for a more meaningful interpretation of suitability and can be used to refer to, for example, the implementation of local taxes on urban development or subsidies for specific biofuel crops as was explored in a previous study (Kuhlman et al., 2013).

Economic rationale is certainly not the only aspect that steers land-use change. While most land users will want to maximise utility, various factors may complicate this decision making process. Issues related to basic assumptions in economics-based approaches (e.g. fully informed actors, perfect competition, presence of equilibrium between supply and demand) are inherently difficult to solve, but other factors that interfere with the economic rationale can be addressed in utility-based approaches using recently developed methods. Some empirical studies have shown, for example, that farmers do not always convert land to the most profitable production option (e.g., Isik & Yang, 2004; Plantinga et al., 2002; Schatzki, 2003) partly because they are averse of risk and have to deal with many uncertain factors (e.g. arising from climate sensitivity, market price volatility, political commitment to specific targets). Option valuation methods might help to monetise land-use conversion decision-making under uncertainty (Isik & Yang, 2004; Schatzki, 2003; Song, Zhao, & Swinton, 2011) and can be used in combination with net present value approach discussed in this paper. Planning regulations that formalise societal ambitions or preferences (e.g. in the form of zoning regulations or development plans) are another important factor in land-use change processes that interfere with a purely utility-driven assessment of land change processes. Such interventions can be incorporated in our integrated approach to define suitability by describing their expected impact on the utility of a location (e.g. in terms of a fine when a preferred use is not allowed following zoning regulations) or by including spatially explicit regulations as explanatory variables in the statistical analyses that describe spatial variation in land-use patterns (as was, for example, done with the plan for a National Ecological Network in the definition of suitable areas for nature).

Another option to expand our utility-based framework is by incorporating specific reference to spatial proximity and clustering in land-use patterns. In many land-use models this neighbourhood effect is expressed in spatially-explicit neighbourhood rules that help simulate realistic patterns (Van Vliet et al., 2013). Such rules offer a powerful, albeit mechanistic way to add spatial realism to simulation. It is possible, however, to incorporate this concept more formally in the statistics-based definitions of suitability discussed in Section 2.2 by applying the spatial econometric methods that are commonly used to control for spatial autocorrelation (see, for example, Anselin, 1988; Jacobs-Crisioni, Rietveld, & Koomen, 2014). Adding the neighbourhood effect to land-use specific utility-based definitions of suitability (as introduced in Section 2.3) would also call for a quantified description of the underlying logic in spatial clustering. This is a challenging research topic that has thus far received limited attention. Such research could focus on the economic benefits of small-scale agglomeration or, more pragmatically, the prescription of minimum sizes for specific spatial developments in land-use simulation.

Other driving forces, such as implicit cultural preferences or social factors, are less easily captured in our deterministic quantitative approach, especially when they are specific for certain regions or societal groups and thus not reflected in our cross-sectional analyses. A possible way to deal with the more idiosyncratic preferences that result in a certain stochasticity of events would be by adding a random component to simulation as is done in many other operational models of land-use change (e.g., Dietzel & Clarke, 2007; Engelen & White, 2008). Such solutions are powerful in generating plausible land-use patterns in which the exact land use for individual pixels is not necessarily correctly predicted. An alternative option would be to restrict the representation of results to the level where relatively accurate results are obtained. This choice can be informed by assessing model performance at multiple resolutions following the example of Pontius et al. (2008).

The presented modelling framework relies on an external definition of the amount of land needed for the different types of use. For the validation runs discussed here, this choice follows from our intention to validate the ability of the model to simulate realistic (observed) spatial patterns. This focus would be obscured by adding demand sets that would not exactly match the total amounts of land per type of use in the different validation years. External demand sets are common to many operational local-scale land-use allocation models as they allow for an efficient segmentation in modelling the full chain of events that leads from global processes to local development (Engelen, Lavalle, Barredo, Meulen, & White, 2007, chap. 17; Lavalle et al., 2011; Verburg, Eickhout, & Van Meijl, 2008). Regional demand sets are typically derived from sector-specific models that describe national or global level dynamics in demography, economy, industry, agriculture. The integrated, multi-scale modelling frameworks that arise from linking the many models addressing dynamics at different scales are efficient and flexible, but often allow for limited interaction and feedback across scales and sectors. The approach we presented here is no exception, as is exemplified by our sector-specific regional demand sets. By relaxing the demand constraint in our modelling framework (a_j in Eq. (5)) we can, however, provide more flexibility to the simulation process, giving preference to the local definition of suitability. Thus far, we have relaxed the regional demand constraints by prescribing a minimum, maximum or bandwidth for the land demand for a selection of land-use types. This approach favours the demands of some land-use types over others and is effective in allowing the model to find a feasible solution. Currently we are also experimenting with simulating the competition between different types of agricultural land use based on their local economic potential without prescribing demands per agricultural production system. Obviously, the number of potential interactions in this more open approach increases tremendously when more agricultural systems are added and more demand-related variables are made endogenous in simulation. Adding changes in population, for example, could lead to an adjusted demand for agricultural products that would in turn lead to changing prices etc. Simultaneously incorporating similar dynamics for the simulation of other types of land use, would truly open Pandora's box of potential interactions and feedbacks. While others are encouraged to trod this path we believe that operational, transparent and insightful models are best developed in a more constrained setting.

Acknowledgements

Just before the initial draft of this article was finished in November 2013, Piet Rietveld - our co-author and head of department - passed away. We are greatly indebted to his many sharp observations and comments on our first results and preliminary versions of the text. Our work would have been impossible without his support and guidance and we therefore dedicate this article to him. This work was supported by the Netherlands organisation for scientific research (NWO) and the Knowledge for Climate research programme [830.10.002]. The funding sources had no involvement in study design; in the collection, analysis and interpretation of data; in the writing of the report; and in the decision to submit the article for publication. We also like to thank PBL Netherlands Environmental Assessment Agency and the Dutch Association of Real Estate Brokers (NVM) for providing part of the spatial data incorporated in the analyses. We are particularly grateful to Michiel van Eupen who created the yield reduction maps.

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