Applied Geography 91 (2018) 156–167

Contents lists available at ScienceDirect

Applied Geography

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

Modelling the impact of urban growth on agriculture and natural land in Italy to 2030

F. Martellozzo[a,*], F. Amato[b], B. Murgante[b], K.C. Clarke[c]

[a] University of Florence, DISEI Dep. of Economics and Management, Italy
[b] University of Basilicata, School of Engineering, Italy
[c] University of California – Santa Barbara, USA

ARTICLE INFO

Keywords:
Italy
Land use projections
Cellular automaton
SLEUTH
Analytic hierarchy process
Sustainable development

ABSTRACT

The uncontrolled spread of towns and cities into their surrounding rural and natural land, and the consequent increasing demand for new natural resources are among the most important drivers of global climate and environmental change. This study investigated the loss of natural and agricultural land in Italy in the last decades, during which urban areas have undergone significant expansion. The study underlines the negative consequences of past uncoordinated urban and regional planning in Italy which often featured adaptive *ex-post* strategies favouring real estate market returns, rather than avoiding *ex-ante* the unsustainable threats. The aim is to show that only through a recalibration of priorities in planning, by adding policies that favour ecological conservation, it is possible to better foster sustainable land use practices. To this end, the research features a comparison of forecasts of land-use/cover changes (LUCC) corresponding to different policy-oriented scenarios, using a combination of multi criteria analysis and cellular automata modelling. In the planning literature there are many applications of land-use change modelling at the regional/local scale, however to the best of our knowledge, none does it at high resolution and at the full country scale. This sort of analysis is important for policy makers because it allows investigation of the combined relevance of local and global criteria in influencing urbanization for the future. Thus it couples locally relevant findings with a comprehensive vision of the phenomenon at a national scale. We conclude by discussing some critical socio-economic implications of the modelled scenarios in order to provide policy makers with useful tools and information to develop resilient and sustainable planning strategies.

1. Introduction

Urban areas worldwide have been steadily expanding, usually at the expense of natural and semi-natural land (Kourtit, Nijkamp, & Reid, 2014; Ramankutty, Amato, Monfreda, & Foley, 2008). Consequently, urbanites demand for new natural resource areas has increased, and is now among the most important drivers of environmental threats (Foley et al., 2005; Rockström et al., 2009). These contemporaneous phenomena contribute to global climate and environmental change in many parts of the world, and will dominate land changes in the 21st century.

In this regard, land taken for development and the consequent loss of natural and farm land are among the most evident consequences of urbanization (Cobbinah & Aboagye, 2017), and vegetated areas have been observed to be the land-use classes most prone to conversion for new urbanization (e.g. pasture, woodlands, shrubs, cropland etc.) (Seto, Güneralp, & Hutyra, 2012). One of the most evident effects of this juxtaposition is the paradoxical competition between land for housing and agricultural land for food (Ontario Federation of Agriculture, 2015; Amato, Maimone, Martellozzo, Nolè, & Murgante, 2016). Consequently, some regions are suffering the repercussions of this land-use conflict as a threat both to the environment and to food security (Lynch, Maconachie, Binns, Tengbe, & Bangura, 2013; Foley et al., 2011). For example, research has shown how high quality farmland is often threatened by urbanization in many parts of the world (Seto, Fragkias, Güneralp, & Reilly, 2011; Foley et al., 2011). Moreover, some countries have been responding to internal rapid urbanization through international land development, which has been identified as having negative consequences both on environment and society (Su, Jiang, Zhang, & Zhang, 2011; Messerli, Giger, Dwyer, Breu, & Eckert, 2014; Lambin & Meyfroidt, 2010). Land use science (Feranec, Jaffrain, Soukup, & Hazeu, 2010) and modelling (Basse, Omrani, Charif, Gerber, & Bódis, 2014) have made impressive progress in producing more accurate results, at larger scales (Haney & Cohen, 2015; Sohl et al., 2012), and

* Corresponding author. Via delle Pandette 9, 50127 Florence, Italy.
E-mail address: federico.martellozzo@unifi.it (F. Martellozzo).

https://doi.org/10.1016/j.apgeog.2017.12.004
Received 9 August 2017; Received in revised form 7 December 2017; Accepted 7 December 2017

with higher spatial-temporal resolution (Bhaskaran, Paramananda, & Ramnarayan, 2010; Tavares, Pato, & Magalhães, 2012; Soares Machado et al., 2014). However, the effectiveness of policies implemented to regulate land use change, and how and at which spatial scale these policies should be implemented for sustainability targets (He et al., 2013; Hewitt & Escobar, 2011) have only recently engaged scientific research and such questions have not been approached systematically with spatially explicit data (Stürck, Schulp, & Verburg, 2015).

The methodological framework adopted in this study features past trend data analysis coupled with modelled projections for Italy. The data used is a fusion of archived thematic maps (land use and topography), census and ancillary economic data, and LUCC forecasts obtained through cellular automata modelling using the SLEUTH model. The aims of this study are twofold. First, to provide an analysis of land use changes that occurred in Italy in the past, in relation to the dominant development criteria and policies. In particular, we offer a critical interpretation of the effects of planning policy in Italy, and we highlight the lack of effective plan implementation. In fact, these policies seem to have completely failed in regulating LUCC processes and in preventing an excessive level of urbanization (Amato, Martellozzo, Nolè, & Murgante, 2017), or at least their supposed limiting action was overruled by other interests (such as the economy) (Amato et al., 2016). This critical interpretation demonstrates the argument that in order to achieve or reduce the gap toward attaining the international Sustainable Development Goals (SDGs) regarding land use, future land planning instruments (Russo, 2013; Marinosci et al., 2013) should aim for more ambitious targets to counterbalance the influence of other competing factors that have changed the Italian National Bill under the influence of the market.

Secondly, this research includes an original modelling application to produce spatially explicit realistic forecasts of urbanization and LUCC that consider several criteria at the same time (i.e. socioeconomic, ecological, and landscape planning variables). Such modelling mimics the potential impact of a specific policy-oriented scenario on future landscape transformations. This builds upon two different simulations of urbanization and LUCC that respond to different policy-oriented scenarios. The first represents a continued prevalence of economic interests over ecological conservation criteria, thus – according to the opinion of an expert panel – mimicking what has happened in Italy in the last few decades (Romano & Zullo, 2014). Conversely, the second scenario aims at improving environmental conservation. This second scenario is useful to explore the possibility, the time, and the reciprocal weights of the different criteria needed to reduce the future ecological burden regarding land take (UNDESA, 2015).

The results feature a mapping of potential future LUCC and urban growth for the whole territory of the Italian peninsula and to our best knowledge is the first attempt to make an application of the chosen model (SLEUTH) at the country scale with detailed spatial resolution. In fact, usually LUCC analyses are performed at the local or regional scale because landscape transitions dealing with urban form are more evident at local scales, and mainly respond to local/regional dynamics (Pontius et al., 2008). In fact, the strategies aimed at controlling these dynamics are defined over a hierarchical set of scales (i.e. local, regional, country level, international etc.) (Las Casas et al., 2016; Lombardini et al., 2016; Tilman et al., 2001). Nevertheless, LUCC mapping and modelling requires a large amount of data and generous computational capabilities (Batty, 1997) that have prevented applications of this sort to date. Furthermore, besides the ability to finely map the effects and the consequences of LUCC dynamics for relatively small areas, the ability to grasp the magnitude of such dynamics for the large region (or a whole country) is extremely relevant.

Several LUCC modelling applications have tried to achieve this goal by investigating large areas, but at lower spatial and temporal resolution (Seto et al., 2012; Basse et al., 2014; Sudhira, Ramachandra, & Jagadish, 2004). However, there are now available both consistent time series of land cover/use data (e.g. Landsat imagery, Corine Land Cover, MODIS imagery, Moland etc.) and the computational capacity (e.g. super computing, cloud computing etc.) (Szul & Bednarz, 2014) to proceed. A spatially explicit investigational framework is extremely important for policy makers. On the one hand, it allows the investigation of the combined relevance of local and global criteria influencing LUCC dynamics and the evolution of landscape forms; on the other hand, it ensures both locally rigorous and country-scale homogenous results based on the same set of criteria.

The criteria used to characterize the two different scenarios were chosen from among the most important drivers of LUCC and urbanization known in the literature (Sudhira et al., 2004; Torrens & Alberti, 2000). The data used, although sometimes limited by availability, accuracy and completeness, includes a representative and significant subset of these criteria. The relevance and relative importance of the criteria used was mediated by the judgment of a panel of experts in Italian spatial planning. The variables were evaluated and merged through a multi-criteria decision making (MCDM) (Mahiny & Clarke, 2013) process in order to mimic a potential participatory planning situation resulting in two possible but contrasting policy scenarios. The two alternatives have been implemented separately in the CA modelling forecasts, to characterize independently a temporal series of LUCC prediction results, and then used to make a comparison between the two simulations.

A basic assumption is that by varying only the policy-oriented scenario in the model, and keeping all other parameters unchanged, the differences in the results must necessarily reflect differences between the two scenarios. The aim is to ground a comparative analysis of the consequences of different policy orientations with intelligible empirical data (Onsted & Clarke, 2012; Onsted & Clarke, 2011). The expert panel of 5 people was composed of: a professor of urban planning, whose main contribution was related to the analysis of the relationship between urban growth and landscape protection; two researchers in urban planning, who discussed the relations between the community protection rules of the Natura 2000 Network and the Italian national landscape policies; a professor of real estate, who discussed the relationship between the housing market and urban development, and a geographer, who analysed the spatial relationships between the distribution of the landscape components and human activities. The expert advisory panel supervised the definition of the scenarios and was also responsible for standardizing and weighting the criteria for the scenarios using the Analytical Hierarchical Process (AHP; SM2.1, SM2.2, and SM2.3).

2. Materials and methods

We linked data from the analysis of past trends to modelled projections based on a fusion of archived thematic maps, census and ancillary economic data, and land cover forecasts obtained using the cellular automata model SLEUTH. We chose this model for its ease of implementation and for its ability to input high resolution multi-temporal input data that was available at the country scale. The data used to investigate past LUCC are the same needed as input for the SLEUTH application. The SLEUTH model employs spatially explicit data describing the geographical distribution of topographic slope, land use, transportation, urban extent and exclusion factors. An important input to SLEUTH for correctly calibrating forecasts of future LUCC and urbanization is the way the model considers the intensity to which different areas resist changes or conversely are more prone to transition dynamics. This information is conveyed by an *exclusion* layer which was in this case created using a MCDM process informed by the AHP to establish the two different policy-oriented scenarios (Onsted & Clarke, 2012).

2.1. The SLEUTH urban expansion and LUC model and the analytic hierarchy process

SLEUTH is a CA model developed to deliver valid, statistically robust, and realistic projections of urban expansion and LUCC, suitable for use in Geographic Information Systems. The model has been extensively used in numerous case-studies worldwide (Clarke, 2008), and there is a substantial literature regarding SLEUTH's internal workflow, functioning, calibration (SM1.2), and capabilities (Dietzel & Clarke, 2004)– (Martellozzo & Clarke, 2011). SLEUTH is based on the tight coupling of two CA models: the Urban Growth Model and the Deltatron Land Use Change model (Clarke and Fischer, 2014). The basic growth procedure featured in SLEUTH models urban expansion in a spatial grid. Growth rules allow for four different types of growth: spontaneous, diffusive, organic and road-influenced (Dietzel & Clarke, 2007; Clarke, Hoppen, & Gaydos, 1997; Clarke, Hoppen, & Gaydos, 1996). SLEUTH is an acronym of the six inputs layers it requires to produce forecasts: *Slope, Land use, Exclusion, Urban extent, Transportation network*, and a *Hill-shaded* background. All input maps are spatially explicit data, each one representing a specific phenomenon (SM1) and were all processed to match a 500 m spatial raster grid that was used to characterize the SLEUTH application. Some of the data were acquired at the resolution that the spatial grid used (i.e. *Land Use* and *Urban*), while for some other data, operations of rasterization and/or spatial resolution aggregation were needed (i.e. transport network, morphology, exclusion layer).

The model requires two topographic maps, i.e. *Hill-shade* and *Slope*. The latter is expressed as percent slope rise and is used in computation as a factor inhibiting urban expansion up to a critical slope level, after which there can be no development. The former is used as a background image to visualize LUCC forecasts. Morphological layers were obtained from a digital elevation model at an initial 90 m resolution. In order to adequately calibrate and to implement the sub-model (Jantz, Goetz, & Shelley, 2004) that controls LUCC (i.e. the Deltatron), a consistent user defined land use classification for at least two time periods is required. *Land Use* and *Urban* layers are derived from the Corine Land Cover data at 500 m for the years 1990, 2000, 2006, and 2012. The *Exclusion* layer was used to introduce limitations to growth; the model does not modify areas featured in the *Exclusion* layer, for example water bodies. The user can use a weighted *Exclusion layer* in order to introduce a variable resistance degree against urban growth and land transformation; this layer represents reductions or modifications of the urbanization rate due to legal restriction, zoning, and differential suitability[1] (Jantz et al., 2004; Silva and Clarke, 2002). The construction of the *Exclusion* layer is described in detail below. *Transportation* data are necessary to model road-dependent LUCC dynamics and were derived from Open Street Map, then rasterized at the application resolution.

Although the SLEUTH model has been widely applied worldwide to investigate the spatial evolution of urban form and other related land cover changes (Chaudhuri & Clarke, 2013), its results have been exposed to criticism because of its limited flexibility in incorporating socio-economic factors (Albin, 1975; Maria De Almeida et al., 2002). The model has a closed structure, which requires a fixed number of explanatory variables. Thus, the only possibility to introduce socio-economic variables into the modelling framework is by manipulating these inputs, and the most suitable way to introduce them into the model application is in the *Exclusion* layer. The Exclusion layer has been generally used to represent only one condition at a time, such as planning restrictions, the presence of parks and protected areas, and specific regional knowledge or theoretical evidence available in the literature is necessary to determine (subjectively) the relative intensity of the land's resistance to transition processes. These are then represented in the model as a probability range from 0 (no restrictions to change) to 100 (complete exclusion from change).

However, there are multiple phenomena that can influence the land's susceptibility to urbanization at a specific location, which span from environmental to social and economic variables, and the assessment of such criteria is neither always straightforward nor unique. The flexibility of the SLEUTH model lies in the fact that it does not control which criteria populate the *Exclusion* layer; it only checks for spatial and ontological consistency with the other inputs. To our best knowledge, only one study so far has explored a robust way to account for multiple criteria (i.e. socioeconomic and natural variables) in the construction of the *Exclusion* layer, and so to mimic specific policy-oriented scenarios (Mahiny & Clarke, 2012). This work attempts to further fill this gap by investigating whether a basic MCDM technique is a feasible methodology to introduce the influence of multiple socio-economic and policy-driven variables into the simulation process.

The Analytic Hierarchy Process (AHP) was chosen, with the purpose of making a spatially explicit representation of the variables' impact (Mahiny & Clarke, 2012; Saaty, 1988). AHP has been applied in diverse scientific contexts (Figueira, Greco, & Ehrgott, 2016) ranging from location problems [(Chen, 2006; Saaty, 2016; Yang & Lee, 1997)] to natural and environmental resources management (Tesfamariam & Sadiq, 2006; Schmoldt, Kangas, Mendoza, & Pesonen, 2001) to health care decision making (Liberatore & Nydick, 2008). The method considers several different criteria and results by the ranking of a set of nested alternatives for which the criteria's weights have been assessed. The process features pairwise comparisons of criteria to determine their relative importance in the judgement of the experts, their weights. Subsequently, all alternatives can be ranked based on the weighted sum of the criteria. Since our alternatives are all the pixels composing the *Exclusion* layer, their value was derived from the weighted sum of the criterion's values (Saaty, 1990; Saaty, 1980) at any given location (SM2.1.) as in equation (Kourtit et al., 2014):

$$S_{map} = \sum_{i}^{n} W_i * V_i \tag{1}$$

where:

S_{map} is the value assumed by each pixels of the synthesis map.
W_i is the weight of *ith* criterion.
V_i is the value of the map representing the *ith* criterion at any given pixel.

The two exclusion layers (one per scenario) used to forecast with SLEUTH were built according to the AHP outcomes. They used data derived from different sources including:

1. The *Codice dei Beni Culturali e del Paesaggio* ("Code of Cultural and Landscape Heritage" in Italian) (CBCP) (Italian Parlament, 2004). The CBCP features the delimitation of the most important protected cultural landscapes and sites. In particular, the following items have been identified (SM3.1):
   a. Areas within a 300 m buffer from the coastline ($CBCP_a$).
   b. Areas within a 300 m buffer from the coastline of lakes ($CBCP_b$).
   c. Streams, river zones and areas within a 150 m buffer from these ($CBCP_c$).
   d. Glaciers and perennial snow areas ($CBCP_d$).
   e. National and regional reserves and parks ($CBCP_e$).
   f. Forests and woodlands ($CBCP_f$).
   g. Wetlands ($CBCP_g$).
2. The Natura 2000 Project (Council of the European Communities, 1992). The Natura 2000 dataset is an EU project which consists of a network of areas of capital importance for reproduction, breeding and conservation of rare species under severe threat, and includes:
   a. Sites of Community Importance (SCIs) and Special Areas of Conservation (SACs). SACs are usually included within SCIs.
   b. Special Protection Areas (SPAs). In Italy, these areas cover about 19% of inland and 4% of marine areas.
3. Important Bird Areas (IBA), which have been mapped within the

[1] For further reading on SLEUTH application and implementation refer to the online documentation at http://www.ncgia.ucsb.edu/projects/gig/Pub/pubs.htm.

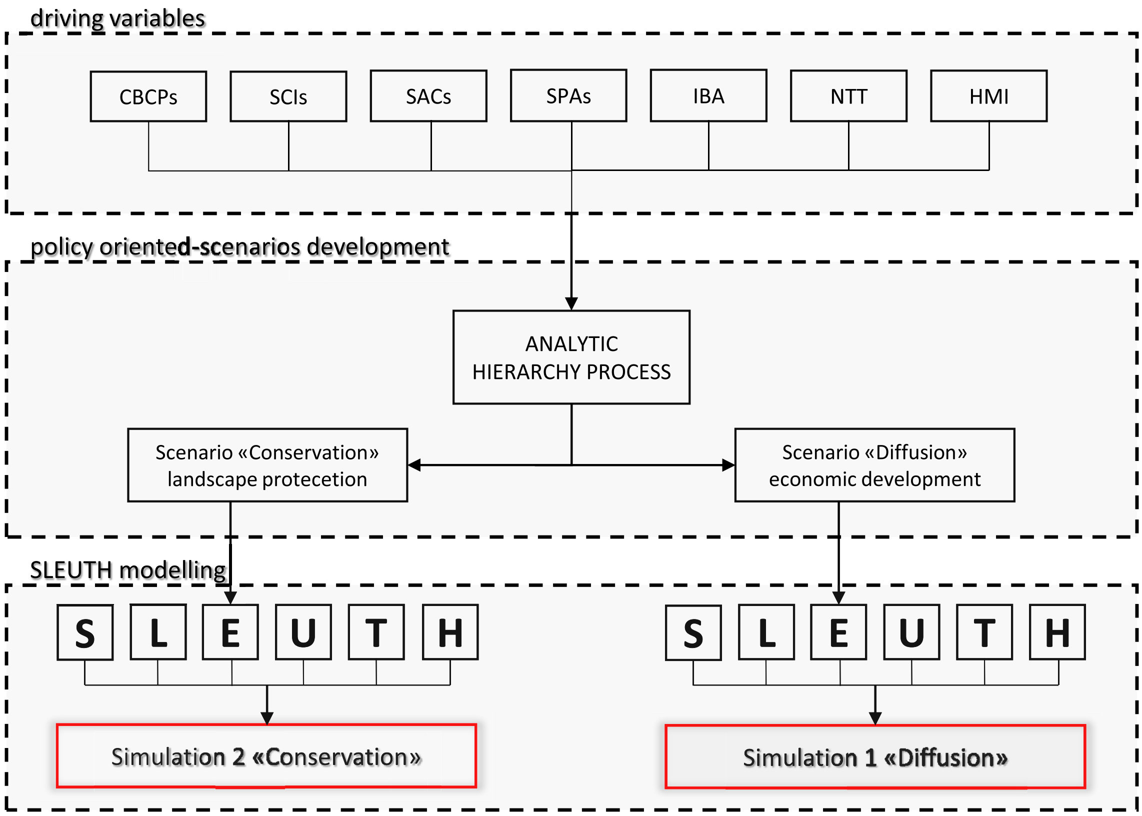


Fig. 1. Workflow from criteria selection to scenario application.

activities of the BirdLife project. Although representing a necessary habitat for the conservation of wild birds, these areas are not included in any regulatory prescriptive plan or action.

The criteria listed above represent limitations for land-cover changes and urbanization. These are homogenously defined at the national level. Thus, the associated intensity in restraining urban expansion does not change locally based on these factors. In fact, the presence of any of the listed limitations in a certain area will imply a resistance to urbanization for that area of the same degree, regardless of where the area is located. Including these criteria is relevant to building a coherent framework at the national scale. However if the simulation was tailored only on general criteria, it would miss local-regional dynamics, which are extremely relevant. In order to overcome this limitation (on top of local morphological and land-use characteristics that are already included in the model via the other input, see SM1.1), we also used economic sub regional data in order to capture the dynamism of the real estate market. We considered:

4. The Number of Total Transactions (NTT). This data is distributed by the National Institute of Statistics (ISTAT) and represents the volume interested by the real estate market. It gives the total number of real estate transactions in a portion of territory weighted by the effective quota of the property that is sold/acquired.
5. The Housing Market Index (HMI), which consists in the ratio of NTT to the stock of residential unit in a specific geographical unit.

These indicators were considered proxies of the real estate market's vitality in any area. Their use is based on the assumption that places where the real estate market is more active are more prone to urbanization and land taking. However, these two indicators have a good degree of correlation; hence, although both metrics were initially included in the AHP process, only the HMI was used because of its higher completeness (SM3.3) and to reduce collinearity that could alter results.

While the limitation introduced by CBCPs, SCIs, SACs SPAs and IBA are spatial-explicit data, NTT and HMI are quantitative indexes. Hence, the former are available as vector data, whereas the latter are tabular data referred to sub-regional zones. Therefore, to include them in the AHP process, NTT and HMI were associated with a vector map of the sub-regional administrative units. Subsequently, all the data were rasterized using a spatial resolution of 100 m. This pixel dimension was chosen to enable a correct representation of those criteria, such as CBCP, which are representing a spatial phenomenon having a geographical dimension less than 500 m. The AHP was applied to these 100 m resolution data, obtaining the *Exclusion* layer as a linear combination of the sum of each criterion multiplied by its weight, using the relationship expressed in equation (Kourtit et al., 2014). Finally, the resulting map was resampled at a resolution of 500 m using a nearest neighbour assignment. Despite the loss of precision due to the resampling of the data, the resulting map still ensures high accuracy and, therefore, a clear picture of the spatial distribution of the factors limiting or favouring land use changes in the study area. Using the nearest neighbour assignment, the maximum spatial error is equal to one-half the cell size.

2.2. Construction of policy oriented-scenarios using AHP

One of the critical aspects of modelling applications based on CA is the difficulty of incorporating the influence and the importance that different socio-political choices and policy orientations have within the simulation of LUCC and the dynamics of urbanization. In this regard, we built two scenarios with the support of the AHP methodology described above that mimic contrasting policy orientations, and derived the weights that criteria assume in each scenario by averaging across the experts. These weights were used to tailor two *Exclusion* layers for two separate SLEUTH forecasts, so as to capture the differential influence on LUCC due to the contrasting policy orientations. The following procedure was applied (Fig. 1):

i. Two different policy-oriented scenarios were defined using expert recommendations and AHP.
ii. Two versions of the same map layer (*Exclusion*) needed by SLEUTH were tailored according to the results of the two policy-oriented scenarios defined through the AHP process.
iii. The resulting layers were used as inputs to a specific forecasting run of the model, previously calibrated with historical data.
iv. Results of the two forecasts were compared, and the differences - given that all other inputs were equal – were considered the differences between the policy-oriented scenarios.

The role of experts offers a quantitative and scientifically informed representation of opinion as part of a participatory planning process. The experts carried out their weighting task in two phases. A first phase aimed at selecting a significant subset from a large number of criteria and variables at the base of the land transformation processes, to be evaluated using the AHP. Secondly, they defined two different policy-oriented scenarios and evaluated the respective criteria weights. The first of these scenarios aimed at minimizing land take by prioritizing the protection of ecological elements over economic interests (*conservation scenario*). Greater weight was given to those criteria that limited the transformation of the landscape. Conversely, the second scenario weights criteria in order to mimic the past LUCC dynamics experienced in Italy, characterized by LUCC leading to agricultural and natural land loss, urban expansion and sprawl. In this case, experts assigned greater weights to the criteria fuelling urbanization and indicated this as a *Diffusion/Economic Development* scenario. In Italy, planning regulations have often been tuned to favour economic development and the construction sector, seen as an anchor for the economy and employment (Romano & Zullo, 2014; Council of the European Communities, 1992; Zullo et al., 2015). Consequently the implementation of limiting factors was weak (Dini, 2014) and many times it was formulated *after-the-fact* to adapt to the as-built situation, rather than having being tailored to prevent unwanted outcomes *before-the-fact*. In Italy illegal construction activities account for more than 4.6 million illegal buildings since 1948 which were retroactively tolerated by bills in 1985, 1994 and 2003. Italy still has no national regulations specifically targeting land take, dating back roughly to 1942. Furthermore, since WWII, and even after the global economic crisis that hit Italy around 2006, the main economic sector has always been the construction sector (Romano & Zullo, 2015).

The two sets of weights used for the construction of the *exclusion* layers for the *conservation* scenario (characterized by greater importance of the limitations to land use changes) and the *Diffusion* scenario (characterized by the higher importance of economic factors) are given in Table 1.

Table 1 shows how the CBCPs resulting from the “Code of Cultural and Landscape Heritage” and the SCIs and SPAs resulting from the Natura 2000 datasets received among them equal weights. Nevertheless, it was still important to consider them separately, as they were subsequently combined using the linear combination given in equation (Kourtit et al., 2014). In this way, the *Exclusion* layer was able to describe different levels of limitation to land use change depending on the number and type of the different criterion present in each pixel. This extremely significant local variability obtained with the *Exclusion* layer would have not been present if the CBCPs had to be considered as a unique layer.

The two *exclusion* layers obtained through AHP were integrated into separate SLEUTH applications and characterize the corresponding forecasts of urbanization and LUCC (Fig. 2).

Table 1
Criteria weights resulting from the AHP used for the *conservation* and *Diffusion scenarios*.

	Scenario *Conservation*	Scenario *Diffusion*
CBCPa	0.112	0.085
CBCPb	0.112	0.085
CBCPc	0.112	0.085
CBCPd	0.112	0.085
CBCPe	0.112	0.085
CBCPf	0.112	0.085
CBCPg	0.112	0.085
SCIs	0.047	0.033
SPAs	0.047	0.033
IBA	0.031	0.022
HMI	0.020	0.320

3. Results

The analysis of past data is important not only to the input data for the modelling phase, but also relevant to understanding how and by how much landscape composition has transformed in Italy over the past 22 data years (from 1990 to 2012). In particular, it is possible to identify some of the prevailing land dynamics. Agricultural land decreased after 1990, and although this loss does not affect a significant percentage of the total area, it corresponds to an absolute loss of ~72,000 ha, not a negligible extent. Conversely, urbanization converted more than 200,000 ha between 1990 and 2012, corresponding to a significant increase of almost 20% (Fig. 3). A smaller built-up expansion could have been reasonably expected because Italy's population's growth rate has steadily declined since World War II (lowest in 1995 at 0%). Overall, population rose from 56.7 million in 1990 to just 59.5 million in 2012 (an increase of < 4.5%). In addition, the percentage of population living in urban areas increased only slightly since 1990 (66.7%) to 2012 (68.5%).

This expansion had negative consequences mostly on agriculture and natural land. According to World Bank data, arable land per person reduced by almost a third between 1990 and 2012 (from 0.16 to 0.12 ha/cap), after having also halved from 1960 to 1990 (from 0.26 to 0.16 ha/cap) (Romano & Zullo, 2015) (World Bank, 2012). The LUCC analysis confirms this worrisome trend of losing ecologically and agriculturally valuable land. Indeed, during the same timespan more than 200,000 ha of natural areas (forests, shrub, sparsely or poorly vegetated areas) were lost (due to transition into agricultural and urban land), thus indicating that an amount of vegetated land sufficient to cover the municipality of Rome (the biggest in Europe, ~1250 km^2) was lost. Some of this was conversion of marginal land to agriculture, with lower food productivity. Loss of the agricultural extent happened prevalently due to the expansion of built up areas, which added up to more than 2500 ha between 1990 and 2012.

The modelling phase forecasted that in both scenarios significant urban expansion will occur over the next few decades. However, the difference is quite substantial and accounts for ~126,000 ha, which means that the difference between the two scenarios corresponds to ~10% of total built up land in 1990. At the end of the simulation, the *Diffusion* scenario foresees an increase in urban areas of about 80% (i.e. ~2.595 Mha) while the conservative scenario lowers at this to 71% (i.e. ~ 2.470 Mha) (Figs. 3 and 4).

Furthermore, LUCC forecasts reveal that both scenarios project agricultural land to be the class that will mostly suffer under urban expansion (Figs. 5 and 6). This has been shown to also be the case in China and India (Ott, 2014) (Pandey & Seto, 2015).

The conservative scenario does not imply that future urbanization will consume less land in general, but it accounts for a smaller proportion of the natural areas lost to development. However, forests and vegetated areas are projected to lose area in both scenarios (~229,000 ha in the *conservation* scenario, and 255,000 ha in the *Diffusion* scenario). This loss is largely due to agricultural expansion, a consequence of urbanization. However, in the *conservation* scenario forests tend to be more resistant to being converted to agriculture. This

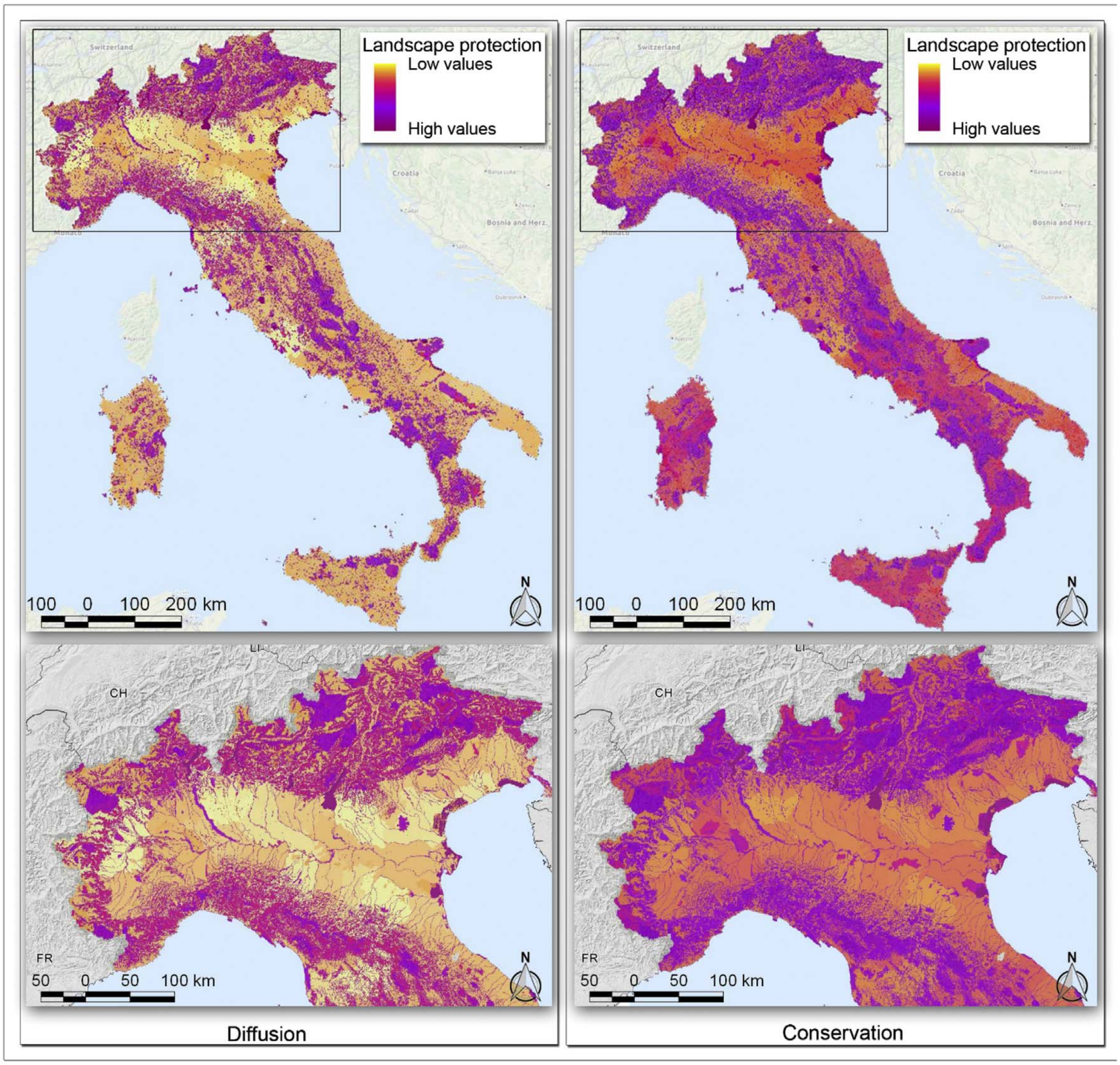


Fig. 2. SLEUTH's *exclusion* layers representing the resistance to land transformation in the *Diffusion* (left) and *Conservation* (right) scenarios. Bottom: zoom-in on Northern Italy where the differences are more evident.

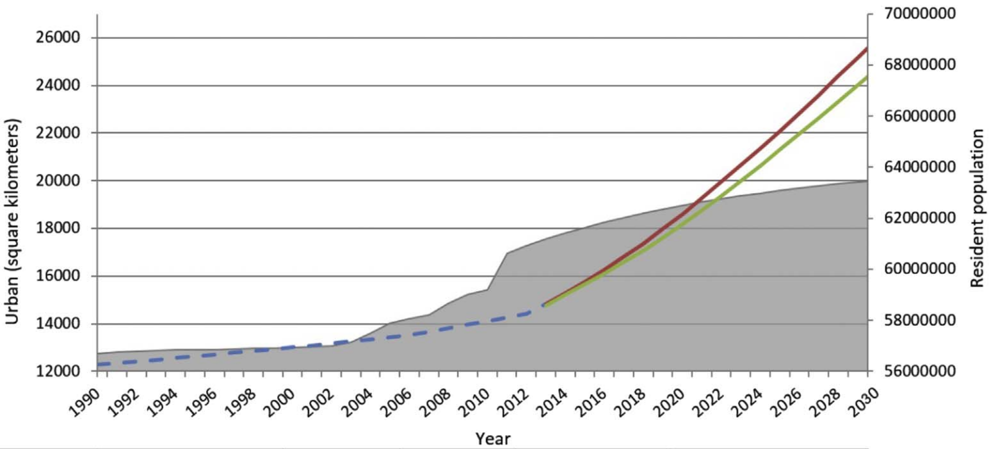
reinforces the hypothesis that in a territory where urbanization is strong, it amplifies other environmental losses. Conversely, where landscape protection is granted through a set of limitations that successfully contain urbanization, development momentum decreases causing other land use loss dynamics to be weaker.

4. Discussion

The results presented in the previous section are of interest not only to Italy but also for a more thoughtful reflection on the wider impact that local land take has on global climate and environmental change (Chappell, Baldock, & Sanderman, 2015; van Oosterzee, Dale, & Preece, 2013; van Vuuren et al., 2015). Indeed, it has been demonstrated that LUCC may mitigate global warming because soils (depending on how they are used) can act both as a carbon sink or a source (van Vuuren et al., 2015; Lim, Cai, Kalnay, & Zhou, 2005; Dilling and Failey, 2013). Consequently, the Paris Agreement COP21 indicated that in order to keep global temperature increases below 2° Celsius, wholesale changes are essential in current land use practices and policies (UNFCCC COP 21, 2015) (see section 4.1).

Long-term urban, regional and economic planning strategies are generally considered among the most potentially effective and yet available tools to foster more sustainable development. Moreover, key players of the international political scene seem ready to adopt significant changes in their policies, especially since studies have highlighted how even following the 2008 economic crisis, carbon emissions increased faster, along with the unemployment rate, social inequality and energy costs (UNFCCC COP 21, 2015; Peters et al., 2011). However, these results showed how planning strategies adopted so far (at least in Italy) are inadequate to reach the targets of the SDGs.

To reach these ambitious sustainable development targets, the adoption of innovative paradigms in policy making that are capable of going beyond local-regional interests (i.e. "green" economy, sustainability, new urbanism and participatory planning) are needed. These terms identify the necessity of having new development paradigms capable of ensuring the preservation of earth's habitats and food security while promoting a new means for economic growth and poverty reduction. Not surprisingly, the objectives included by the UN under the concept of sustainability (SDGs) cross multiple aspects of human society, including energy, transport, construction, agriculture, management of water and waste (Johnstone, Haščič, & Popp, 2010), those for which the corresponding economic, social, political, environmental and institutional factors have been shown to steer planning policies toward sustainability. However, the United Nations estimates that a shift towards a green economy could cost 1.9 trillion dollars per year for the next forty years (United Nations, 2011). Hence, not all the countries



Population growth rate	0.04	0.33	0.82	0.32	0.16
Urban growth rate (past trend)	**0.60**	**0.65**	**1.12**	-	-
Urban growth rate (Scenario “Diffusion”)	-	-	-	**3.62**	**3.96**
Urban growth rate (Scenario Conservative”)	-	-	-	**3.26**	**3.58**

Fig. 3. Observed urban growth and population trend from 1990 to 2012, and modelled projections according to the contrasting scenarios up to 2030. Population data and forecasts are taken from national Census data. The table on the bottom shows the growth rate per year in the different periods.

in the world can afford, nor are yet ready, to accept this transition toward a more sustainable development model. For this reason, the transition should start in those countries that are somehow able to support interventions that move in this direction, as this seems the only way to ensure a quick and effective adaptation to climate change. Our work fits in this context and seeks to propose a tool to support sustainable planning policies through forecasting.

4.1. Implications for agriculture

The projected LUCC can also be used to investigate the potential impact on the agricultural sector. In fact, urbanization replacing agricultural land is a serious problem, no matter which scenario is being considered, that has been observed worldwide (Pandey & Seto, 2015; Tan, Li, Xie, & Lu, 2005; Martellozzo et al., 2014). Usually the most vulnerable agricultural land is that adjacent to urban areas, which is also the most fertile and productive, with the lowest transportation costs. The repercussions that this might have on the agricultural sector, and in general for the Italian economy, can be of a relevant magnitude. This is even more evident when considering that the replacement of agricultural land with impermeable urban cover is almost irreversible. In fact, once the soil is sealed it loses its ecological systems, and its reconversion to a functional ecological status is very unlikely or extremely slow. Natural replenishment of ground water may be stopped. Besides, agricultural land productivity potential depends on multiple inputs (soil quality, suitability, fertilization, irrigation, the degree of mechanization, labor force, etc.), and the area available is one of these. Then, a decrease of one of these inputs causes a corresponding loss of productivity potential. As a result, if the volume of agricultural production decreases due to the loss of agricultural areas, this probably will have repercussions on the economic sector.

For example, one of our preliminary analyses build upon the assumption that the forecast trend of land available for agriculture over time (Fig. 7) (past dada line in the chart on top) can be used as a good proxy for estimating a corresponding potential agricultural production (Fig. 7) (past data line in the chart at the bottom). This assumption is supported by the fact that historical correlation between the two time series with real data from 2000 to 2015 is quite high ($R^2 = 0.78$). Hence, we built a time series of available agricultural area (constituted by both observed past data and forecasted data), and used it to simulate a projection of a potential corresponding agricultural production curve (Fig. 7) through a simple linear regression method (ordinary least squares). Results show that the loss of agricultural land can result in a potential reduction in agricultural productivity of 27% in the *Diffusion* scenario and 23% in the *conservation* scenario. This loss could correspond to a decrease between 50 and 58 Megatonnes of agricultural production. These findings may even be conservative, because urbanization usually replaces high quality agricultural land, while agriculture take over soils of much lesser quality or suitability for agricultural purposes (Martellozzo, 2012; United Nations, 2011).

However, to accurately forecast the corresponding potential loss of agricultural production that could follow a reduction of the available agricultural land requires more than a simple linear regression. In fact, a robust investigation would require multiple assumptions that need a deeper understanding of the flexibility and elasticity of the agronomic sector, which is not the focus of this paper. Nevertheless, it is a matter of fact that being willing to maintain a constant level of agricultural production while reducing one of the inputs (i.e. agricultural land and/or soil quality), necessarily implies increasing other inputs (e.g. fertilization, mechanization, labour force etc.), which may even harshen the environmental burden of agricultural production.

4.2. Implications on urban and landscape protection policies

Simulation results confirm a trend in LUCC that has been observed over the last forty years affecting the entire Mediterranean basin, and in particular in European countries. This dynamic portrays a diffusion of human settlements along coastal regions and plains, while (although more slowly and to a much lesser extent) mountainous areas are gradually abandoned and naturally reforested. Several studies (Debussche, Lepart, & Dervieux, 1999; Falcucci, Maiorano, & Boitani, 2007; García-Ruiz et al., 1996; MacDonald et al., 2000) investigated this phenomenon in Italy, and underlined the inadequacy of Italian national planning policies in protecting the most relevant ecological areas and in limiting urban expansion. As an example, Romano, Zullo, Fiorini, Marcucci, & Ciabò (2017) measured an increase in the urbanization density into a 1 km-wide coastal strip from 30,000 ha to 61,500 ha from 1990 to 2000. In the same period, 31,000 new ha of urbanized areas

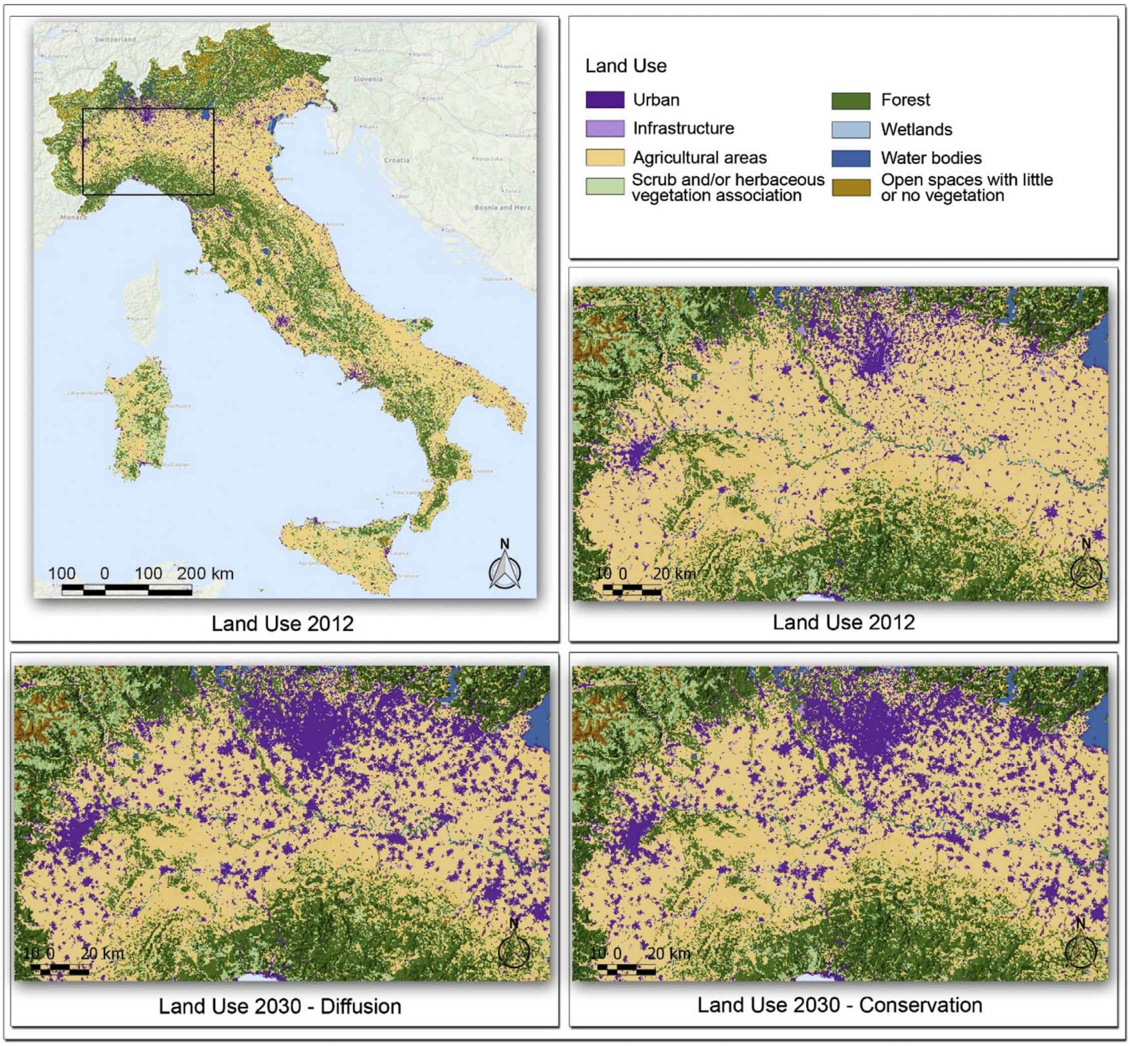


Fig. 4. Difference in land consumption between 2012 and the forecasts from the *Conservative* and *Diffusion* scenarios up to 2030 for northern Italy.

were developed in CBCPs areas. This huge growth of urban areas, which will continue with even higher growth rates up to 2030 according to the results of the simulation proposed in this paper, is apparently supported by the existence of a real demand (Manganelli & Murgante, 2017).

Despite the decrease of the population growth rate reported in Fig. 3, in Italy the number of families increased by 54% from 1971 to 2011. This growth could be mainly due to the increasing number of divorces (which almost doubled from 2001 to 2011, passing from 1,530,543 to 2,658,943) and to the impact of migration (migrants obtaining Italian citizenship increased by 135% from 2001 to 2011)

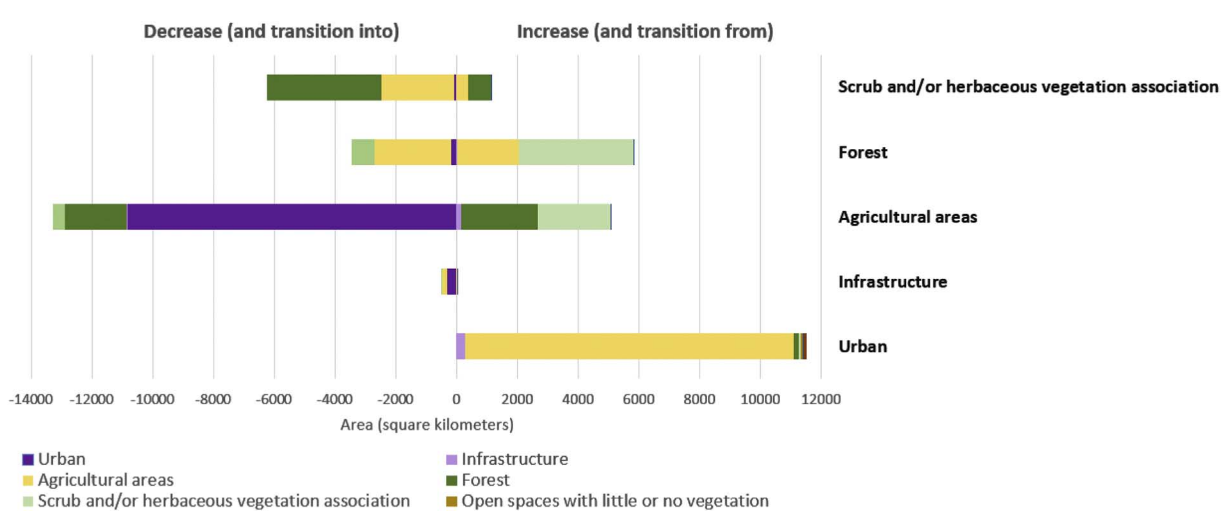


Fig. 5. LUCC dynamics between 2012 and 2030 according to the *Diffusion* scenario.

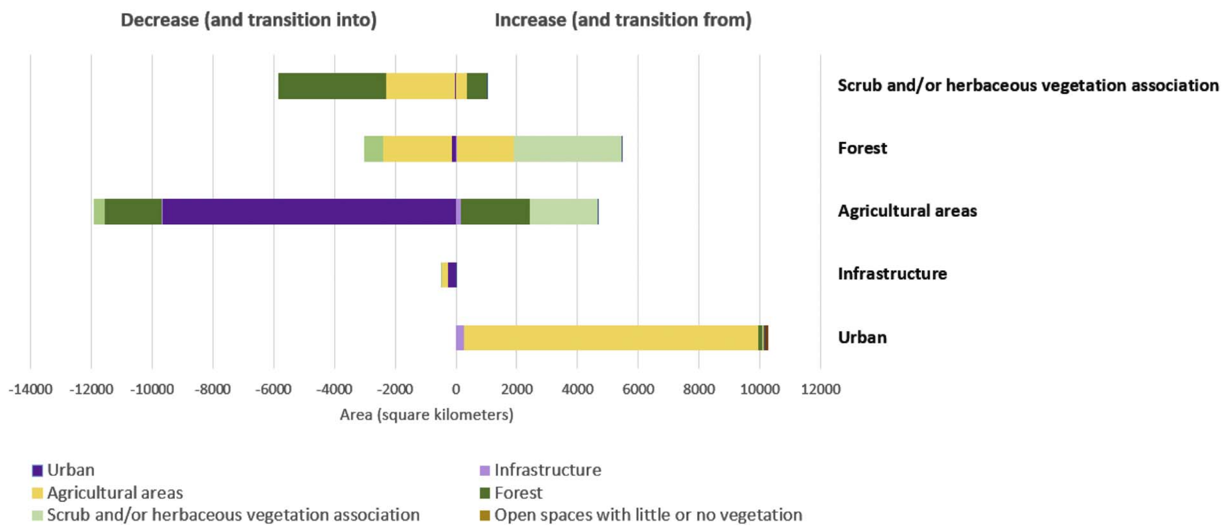


Fig. 6. LUCC dynamics between 2012 and 2030 according to the *Conservation* scenario.

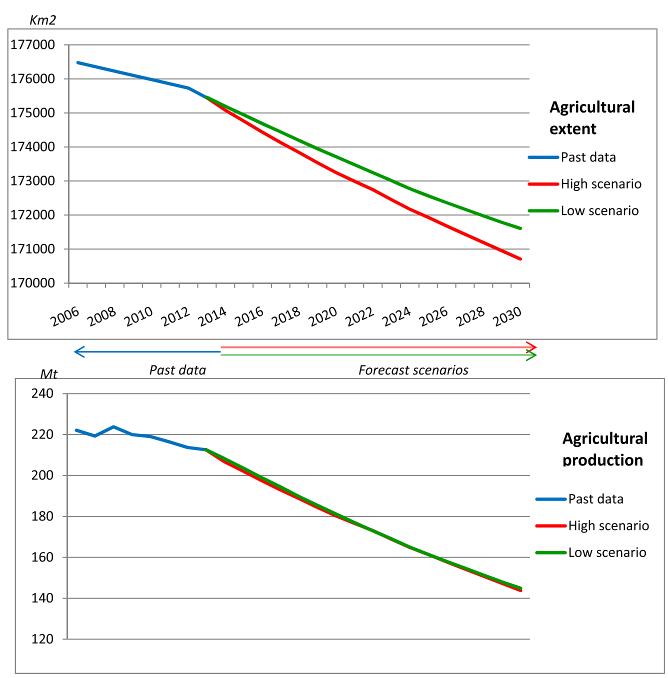


Fig. 7. Forecast available agricultural land (top), and potential corresponding agricultural production (bottom) up to 2030.

(ISTAT, 2013). Hence, apparently there is a relationship between housing demand and supply justifying the measured urban growth. In 2011, 72.1% of families owned their own home, while 19% lived in rented houses and the remaining 9.9% lived in apartment houses. Nevertheless, in 2016 the Italian Ministry of the Interior reported an increase of the number of evictions, with 88.8% of them due to late payment of rent. This resulted in 35,336 evictions, even in a country with 5,320,288 empty houses.

The picture arising from these data is of a country where urban growth and housing development are characterized only by speculative and economic interests, without an attempt to rebuild a concrete demand-supply connection. This process naturally results in huge land take rates and significant social divisions. Moreover, this phenomenon, together with the internal rural-to-urban migration, and the consequent urbanization of the latter, justifies the high urban growth rates reported in the simulation results (see Fig. 3). In this context, strong urban planning policies have to be developed to ensure a reduction of land take and solving the housing issues experienced in the country.

Furthermore, the loss of natural vegetated areas due to agricultural and urban expansion has serious repercussions on the quality and quantity of ecosystem services, on ecological heritage and on biodiversity (Hajdu, Penje, & Fischer, 2016). For example, the increase in the temperature of air, land and water cause a reduction of suitable habitats for the reproduction of pollinators, hence reducing their number and impacting agriculture. Our results show also that urbanization does not proceed organically but assumes a sprawling pattern. The dispersed diffusion of urban areas also forces other land cover types (especially natural) to be more fragmented and composed of smaller patches; consequently, this results in a reduction of the proportion of natural environments that can provide a suitable habitat for indigenous species, implying a loss of biodiversity (Hobbs et al., 2008). Sallustio et al. (2017) measured a habitat quality index for Italy, showing how the lowest quality is when passing from less to more intensively cultivated agricultural areas and around the major urban areas, where the population density is higher and there are higher levels of accessibility. They also highlighted the role of CBCPs in mitigating the reduction of habitat quality.

Secondly, modern society is facing the need to drastically reduce greenhouse gases (GHG) in the near future in order to keep the global temperature rise below 2 °C (van Vuuren et al., 2011). The role played by LUCC in this challenge is linked to 35% of CO_2 emissions from human activities, which is a direct function of land use (Houghton & Hackler, 2001). Urban areas are themselves among the most responsible for CO_2 emissions, while natural soils (barren or vegetated) store most terrestrial carbon. Therefore, urbanization not only has the effect of expanding the area most responsible for GHG, but also of reducing the areas serving as a carbon sink. Furthermore, recent studies have theorized that this phenomenon can have even more serious consequences, due to a hitherto unknown climate feedback system that can potentially limit soils' capacity to sequester carbon. This mechanism notes that microorganisms living in soils adapt to temperature rise by increasing their rate of transpiration, thus releasing more CO_2, which ironically feeds even more global warming (Crowther et al., 2016). Soils in many areas also release more methane as they warm, an even more potent greenhouse gas.

Therefore, the development of effective landscape protection policies is related to adequate evaluation of the impacts on habitat quality and on land surface temperatures, with specific regard to the urban heat island phenomenon. To this aim, the results presented in this paper offer an extremely useful knowledge background on which to base further studies. As stated in the introduction, one of the aims of our study was to objectively develop land use maps for future scenarios to be used as input data by the land use science community to model other phenomena, such as the habitat quality degradation or the land surface temperature with models such as have been proposed (Arthur-Hartranft, Carlson, & Clarke, 2003). Hence, the maps presented in this paper offer the chance to perform time-sensitive and scenario-based analysis of these topics.

4.3. Critical aspects of using SLEUTH

The SLEUTH model has been extensively used in scientific research, applied in various regional contexts, and proven to be an efficient instrument of analysis for local/regional land-use and urban planning. Its main strength lies in the fact that through forecasts it enables us to foresee the spatial effects of current trends and compares these with the potential effects coming from different scenarios. In particular, this application focused on the construction of scenarios, not limited to the use of morphological variables, but in which the influence of socio-economic variables was spatially explicit. So it allowed both quantitative comparisons of different policy-oriented outcomes, and shows the spatial location of the effects. However, although this SLEUTH application produced relevant results, it is also relevant to discuss the limitations pertaining to the proposed framework. In fact, although the model is easy to use and intuitive, it is not as flexible in manipulating the inputs it requires. Although we have managed to introduce socio-economic variables within the model through the *exclusion* layer, the latter - despite being efficient - is static and one dimensional, so it might not be enough to capture the complexity of socio-economic dynamics over time. At present it is difficult to imagine how this feature can be added to SLEUTH, and this remains an important research field for which additional studies are needed.

In addition, SLEUTH is only as good as its input data, and among the most uncertain of these are the LUCC layers. Many remote-sensing derived LUCC classification schema are only 90% or so accurate when validated with ground truth and some of this error derives from definitional ambiguity in land use classification (Di Palma, Amato, Nolè, Martellozzo, & Murgante, 2016). There are well known misclassifications between closely matched classes, especially in areas of clouds or shadows in imagery. Furthermore, the land use dynamics are assumed captured by two time periods, using the Markov invariance assumption. In spite of this, CA models such as SLEUTH have been used to capture break-in-trend patterns well (Houet, Aguejdad, Doukari, Battaia, & Clarke, 2016).

Another issue to be considered when working with SLEUTH is related to the boom and bust parameters. These are used to self-modify the model, emulating the increase and the decrease of urban growth rates due to acceleration or deceleration in the process. The use of this self-modification algorithm is necessary to avoid linear behavior of the model, which would be scarcely capable of simulating complex urban phenomena. Moreover, this helps in moving transition rules from universality and time invariance to non-universality and time variance, one of the *relaxations* theorized by Batty to ensure a correct application of CA models to urban phenomena (Batty, Coucelis, & Eichen, 1997). Nevertheless, an over-boom (or an over-bust) of the process could produce slightly overestimated (or underestimated) urban projections.

However, even though CLC data feature has variability in accuracy, for the region of interest accuracy is quite high, and for the classes considered it is generally reported as above 85% (Büttner & Maucha, 2006) (Neumann, Herold, Hartley, & Schmullius, 2007). In particular the SLEUTH application focuses on the built-up form, which generally has in the CLC data a level of accuracy above 95%. Nevertheless, the data needed by SLEUTH are, as said, heterogeneous, and such heterogeneity requires quite a bit of data preparation that may influence and/or bias results. However, the processing performed was always done in a way to minimize alteration of native information, and we avoided data manipulations that could have led to new (unjustified) information; in other words we may have lost some information but we did not introduced new untested biases. Therefore, we believe that since input data were not substantially altered, results regarding local changes, or specific pixel/s may not be accurate, but the general picture and the trend drawn by our results are robust.

5. Conclusions

This research featured an application of SLEUTH to Italy to assess the magnitude of past LUCC and to project changes into the future. We focused on the implications that the foreseen LUCC may have in different contexts, and to show some critical differences resulting from the application of contrasting policy-oriented scenarios. The findings regarding the type of LUCC dynamics suggest that the amount of vegetated land lost due to urbanization and agricultural replacement is of great value for ecology and sustainability; while the areas turned into agriculture are of a much lesser quality/suitability. This work also highlights the inadequacy of the planning policies adopted so far in ensuring an adequate level of protection for natural landscapes.

Finally, the methodological framework proposed serves as a tool for exploring the possible effects related to specific policy choices, so as to support the sustainable planning interventions. In conclusion, we believe that in order to foster sustainable and equitable development, the proposed methodological framework should be systematically included in spatial planning practices. In fact, correct and properly calibrated spatial planning is more necessary than ever, because it is precisely through the reduction of soil loss, the protection of valuable ecosystems, and the preservation of high quality soils for agriculture, that climate change mitigation can be increased and the UN sustainability targets achieved. Nevertheless, this work has also the merit of having produced spatially explicit projections of LUCC, and we believe that the forecast scenarios for Italy will be of value in future research aimed at reducing the loss of agricultural and natural lands for a more sustainable future in the country.

Acknowledgements

This research has been supported by the following entities: the University of Rome La Sapienza through the funding scheme "Avvio alla Riverca" awarded to Federico Martellozzo in 2016 and 2017; the University of Basilicata; and the Environmental Observatory Foundation of Basilicata Region (FARBAS).

Appendix A. Supplementary data

Supplementary data related to this article can be found at http://dx.doi.org/10.1016/j.apgeog.2017.12.004.

References

Foley, J. a, Defries, R., Asner, G. P., Barford, C., Bonan, G., Carpenter, S. R., et al. (2005). Global consequences of land use. *Science*.
Silva, E., & Clarke, K. (2002). Calibration of the SLEUTH urban growth model for Lisbon and Porto, Portugal. *Computers, Environment and Urban Systems, 26*(6), 525–552.
van Oosterzee, P., Dale, A., & Preece, N. D. (2013). Integrating agriculture and climate change mitigation at landscape scale: Implications from an Australian case study. *Global Environmental Change, 29*(0), 306–317.
Albin, P. S. (1975). *The analysis of complex socioeconomic systems.* Lexington: MA: D. C. Heath.
Amato, F., Maimone, B. A., Martellozzo, F., Nolè, G., & Murgante, B. (2016). The effects of urban policies on the development of urban areas. *Sustainability, 8*, 297.
Amato, F., Martellozzo, F., Nolè, G., & Murgante, B. (2017). Preserving cultural heritage by supporting landscape planning with quantitative predictions of soil consumption. *Journal of Cultural Heritage, 23*, 44–54. http://dx.doi.org/10.1016/j.culher.2015.12.009.
Arthur-Hartranft, S. T., Carlson, T. N., & Clarke, K. C. (2003). Satellite and ground-based microclimate and hydrologic analyses coupled with a regional urban growth model. *Remote Sensing of Environment, 86*, 385–400.
Basse, R. M., Omrani, H., Charif, O., Gerber, P., & Bódis, K. (2014). Land use changes modelling using advanced methods: Cellular automata and artificial neural networks.

The spatial and explicit representation of land cover dynamics at the cross-border region scale. *Applied Geography, 53*, 160–171.
Batty, M. (1997). Cellular automata and urban form: A primer. *The APA Journal*.
Batty, M., Coucelis, H., & Eichen, M. (1997). Urban systems as cellular automata. *Environment and Planning B: Planning and Design, 24*, 159–164.
Bhaskaran, S., Paramananda, S., & Ramnarayan, M. (2010). Per-pixel and object-oriented classification methods for mapping urban features using Ikonos satellite data. *Applied Geography, 30*(4), 650–665.
Büttner, G., & Maucha, G. (2006). *The thematic accuracy of Corine land cover 2000.* no. 7.
Chappell, A., Baldock, J., & Sanderman, J. (2015). The global significance of omitting soil erosion from soil organic carbon cycling models. *Nature Climate Change,* (October), 1–5.
Chaudhuri, G., & Clarke, K. C. (2013). The SLEUTH land use change model: A review. *International Journal of Environmental Research, 1*(1), 89.
Chen, C.-F. (Nov. 2006). Applying the analytical hierarchy process (AHP) approach to convention site selection. *Journal of Travel Research, 45*(2), 167–174.
Clarke, K. C. (2008). A decade of cellular urban modeling with SLEUTH: Unresolved issues and problems. *Plan. Support Syst. Cities Reg.* (pp. 47–60). .
Clarke, K. C. (2014). Cellular automata and agent-based models. In P. N. M. M. Fischer (Vol. Ed.), *Handbook of regional science: Vol. 2014*, (pp. 1217–1233). Springer-Verlag Berlin Heidelberg.
Clarke, K. C., Hoppen, S., & Gaydos, L. J. (1996). Methods and techniques for rigorous model calibration methods and techniques for rigorous calibration of a cellular automaton model of urban growth. *Third international conference/workshop on integrating gis and environmental modeling*.
Clarke, K. C., Hoppen, S., & Gaydos, L. (1997). A self-modifying cellular automaton model of historical urbanization in the San Francisco Bay area. *Environment and Planning B: Planning and Design, 24*(2), 247–261.
Cobbinah, P. B., & Aboagye, H. N. (2017). A Ghanaian twist to urban sprawl. *Land Use Policy, 61*, 231–241.
Council of the European Communities (1992). *Council Directive 92/43/EEC of 21 May 1992 on the conservation of natural habitats and of wild fauna and flora*.
Crowther, T. W., Todd-Brown, K. E. O., Rowe, C. W., Wieder, W. R., Carey, J. C., Machmuller, M. B., et al. (Nov. 2016). Quantifying global soil carbon losses in response to warming. *Nature, 540*(7631), 104–108.
Debussche, M., Lepart, J., & Dervieux, A. (Jan. 1999). Mediterranean landscape changes: Evidence from old postcards. *Global Ecology and Biogeography, 8*(1), 3–15.
Dietzel, C., & Clarke, K. C. (Feb. 2007). Toward optimal calibration of the SLEUTH land use change model. *Transactions in GIS, 11*(1), 29–45.
Dietzel, C., & Clarke, K. C. (Oct. 2004). Spatial differences in multi-resolution urban automata modeling. *Transactions in GIS, 8*(4), 479–492.
Dilling, L., & Failey, E. (2013). Managing carbon in a multiple use world: The implications of land-use decision context for carbon management. *Global Environmental Change, 23*(1), 291–300.
Dini, F. (2014). “Troppo o troppo poco ambiente nello stato e nel mercato? Una lettura regolazionista. *AA.VV. Le categorie geografiche di,” in AA.VV. Le categorie geografiche di Giorgio Spinelli* (pp. 94–110). Bologna: Patron Editore.
Di Palma, F., Amato, F., Nolè, G., Martellozzo, F., & Murgante, B. (2016). A SMAP supervised classification of landsat images for urban sprawl evaluation. *ISPRS International Journal of Geo-Information, 5*, 109. http://dx.doi.org/10.3390/ijgi5070109.
Falcucci, A., Maiorano, L., & Boitani, L. (Mar. 2007). Changes in land-use/land-cover patterns in Italy and their implications for biodiversity conservation. *Landscape Ecology, 22*(4), 617–631.
Feranec, J., Jaffrain, G., Soukup, T., & Hazeu, G. (2010). Determining changes and flows in European landscapes 1990-2000 using CORINE land cover data. *Applied Geography, 30*(1), 19–35.
Figueira, J. R., Greco, S., & Ehrgott, M. (2016). *Multiple criteria decision Analysis: State of the art surveys: Vol. 233*.
Foley, J. A., Ramankutty, N., Brauman, K. A., Cassidy, E. S., Gerber, J. S., Johnston, M., et al. (2011). Solutions for a cultivated planet. *Nature, 478*, 337–342.
García-Ruiz, J. M., Lasanta, T., Ruiz-Flano, P., Ortigosa, L., White, S., González, C., et al. (Oct. 1996). Land-use changes and sustainable development in mountain areas: A case study in the Spanish pyrenees. *Landscape Ecology, 11*(5), 267–277.
Hajdu, F., Penje, O., & Fischer, K. (2016). Questioning the use of ‘degradation’ in climate mitigation: A case study of a forest carbon CDM project in Uganda. *Land Use Policy, 59*, 412–422.
Haney, N., & Cohen, S. (2015). Predicting 21st century global agricultural land use with a spatially and temporally explicit regression-based model. *Applied Geography, 62*, 366–376.
He, J., Liu, Y., Yu, Y., Tang, W., Xiang, W., & Liu, D. (2013). A counterfactual scenario simulation approach for assessing the impact of farmland preservation policies on urban sprawl and food security in a major grain-producing area of China. *Applied Geography, 37*(1), 127–138.
Hewitt, R., & Escobar, F. (2011). The territorial dynamics of fast-growing regions: Unsustainable land use change and future policy challenges in Madrid, Spain. *Applied Geography, 31*(2), 650–667.
Hobbs, N. T., Galvin, K. A., Stokes, C. J., Lackett, J. M., Ash, A. J., Boone, R. B., et al. (2008). Fragmentation of rangelands: Implications for humans, animals, and landscapes. *Global Environmental Change, 18*(4), 776–785.
Houet, T., Aguejdad, R., Doukari, O., Battaia, G., & Clarke, K. (2016). Description and validation of a ‘non path-dependent’ model for projecting contrasting urban growth futures. *Cybergeo: European Journal of Geography, 2016*.
Houghton, R. A., & Hackler, J. L. (2001). *Carbon flux to the atmosphere from land-use changes: 1850 to 1990.* ORNL/CDIAC-131, NDP-050/R1.
ISTAT (2013). *Noi Italia - 100 statistiche per capire il Paese in cui viviamo*.
Italian Parlament (2004). Decreto Legislativo 22 gennaio 2004, n. 42 “Codice dei beni culturali e del paesaggio, ai sensi dell’articolo 10 della legge 6 luglio 2002, n. 137. *Gazzetta Ufficiale, 45*.
Jantz, C. A., Goetz, S. J., & Shelley, M. K. (2004). Using the SLEUTH urban growth model to simulate the impacts of future policy scenarios on urban land use in the Baltimore-Washington metropolitan area. *Environment and Planning B: Planning and Design, 30*, 251–271.
Johnstone, N., Haščič, I., & Popp, D. (Jan. 2010). Renewable energy policies and technological Innovation: Evidence based on patent counts. *Environmental and Resource Economics, 45*(1), 133–155.
Kourtit, K., Nijkamp, P., & Reid, N. (2014). The new urban world: Challenges and policy. *Applied Geography, 49*, 1–3.
Lambin, E. F., & Meyfroidt, P. (2010). Land use transitions: Socio-ecological feedback versus socio-economic change. *Land Use Policy, 27*(2), 108–118.
Las Casas, G., & Scorza, F. (2016). “Sustainable planning: A methodological toolkit. In O. Gervasi,, B. Murgante,, S. Misra,, A. M. A. Coutinho Rocha,, C. Torre,, & D. Taniar, (Eds.). *Lecture notes in computer science* (pp. 627–635). Springer International Publishing.
Liberatore, M. J., & Nydick, R. L. (2008). The analytic hierarchy process in medical and health care decision making: A literature review. *European Journal of Operational Research, 189*(1), 194–207.
Lim, Y. K., Cai, M., Kalnay, E., & Zhou, L. (2005). Observational evidence of sensitivity of surface climate changes to land types and urbanization. *Geophysical Research Letters, 32*.
Lombardini, G., & Scorza, F. (2016). Resilience and smartness of coastal regions. A tool for spatial evaluation. In O. Gervasi,, B. Murgante,, S. Misra,, A. M. A. Coutinho Rocha,, C. Torre,, & D. Taniar, (Eds.). *Lecture notes in computer science* (pp. 530–541). Springer International Publishing.
Lynch, K., Maconachie, R., Binns, T., Tengbe, P., & Bangura, K. (2013). Meeting the urban challenge? Urban agriculture and food security in post-conflict Freetown, Sierra Leone. *Applied Geography, 36*, 31–39.
MacDonald, D., Crabtree, J., Wiesinger, G., Dax, T., Stamou, N., Fleury, P., et al. (2000). Agricultural abandonment in mountain areas of Europe: Environmental consequences and policy response. *Journal of Environmental Management, 59*(1), 47–69.
Mahiny, A. S., & Clarke, K. C. (2012). Guiding SLEUTH land-use/land-cover change modeling using multicriteria evaluation: Towards dynamic sustainable land-use planning. *Environment and Planning B: Planning and Design, 39*(5), 925–944.
Mahiny, A. S., & Clarke, K. C. (2013). Simulating hydrologic impacts of urban growth using SLEUTH, multi criteria evaluation and runoff modeling. *Journal of Environment Informatics, 22*(1), 27–38.
Manganelli, B., & Murgante, B. (2017). The dynamics of urban land rent in Italian regional capital cities. *Land, 6*, 54.
Maria De Almeida, C., Vieira Monteiro, A. M., Câmara, G., Soares-Filho, B. S., Cerqueira, G. C., Pennachin, C. L., et al. (2002). *Empiricism and stochastics in cellular automaton modeling of urban land use dynamics*.
Marinosci, I., Congedo, L., Munafò, M., Riitano, N., Pizzi, D. V., Ferrara, A., et al. (2013). L ’ impiego di dati Copernicus p er la derivazione di indicatori sul consumo di suolo e sullo sprawl urbano. *Atti 17a conferenza Nazionale ASITA 2013* (pp. 937–946). .
Martellozzo, F. (2012). Forecasting high correlation transition of agricultural landscapes into urban areas. *International Journal of Agricultural and Environmental Information Systems, 3*(2), 22–34.
Martellozzo, F., & Clarke, K. C. (2011). Measuring urban sprawl, coalescence, and dispersal: A case study of pordenone, Italy. *Environment and Planning B: Planning and Design, 38*, 1085–1104.
Martellozzo, F., Ramankutty, N., Hall, R. J., Price, D. T., Purdy, B., & Friedl, M. A. (2014). Urbanization and the loss of prime farmland: A case study in the {Calgary}–{Edmonton} corridor of {alberta}. *Regional Environmental Change, 15*(5), 881–893.
Messerli, P., Giger, M., Dwyer, M. B., Breu, T., & Eckert, S. (2014). The geography of large-scale land acquisitions: Analysing socio-ecological patterns of target contexts in the global South. *Applied Geography, 53*, 449–459.
Neumann, K., Herold, M., Hartley, A., & Schmullius, C. (2007). Comparative assessment of CORINE2000 and GLC2000: Spatial analysis of land cover data for Europe. *International Journal of Applied Earth Observation and Geoinformation, 9*(4), 425–437.
Onsted, J. A., & Clarke, K. C. (2011). Forecasting enrollment in differential assessment programs using cellular automata. *Environment and Planning. B, Urban Analytics and City Science, 38*(5), 829–849.
Onsted, J., & Clarke, K. C. (2012). The inclusion of differentially assessed lands in urban growth model calibration: A comparison of two approaches using SLEUTH. *International Journal of Geographical Information Science, 26*(5), 881–898.
Ontario Federation of Agriculture (2015). *Farmland at risk: Why land-use planning needs improvements for a healthy agricultural future in the Greater Golden Horseshoe*.
Ott, J. (2014). World Bank world development indicators. *Encyclopedia of quality of life and well-being research*Dordrecht: Springer Netherlands 7253–7253.
Pandey, B., & Seto, K. C. (2015). Urbanization and agricultural land loss in India: Comparing satellite estimates with census data. *Journal of Environmental Management, 148*, 53–66.
Peters, G. P., Marland, G., Le Quéré, C., Boden, T., Canadell, J. G., & Raupach, M. R. (Dec. 2011). Rapid growth in CO2 emissions after the 2008–2009 global financial crisis. *Nature Climate Change, 2*(1), 2–4.
Pontius, R. G., Boersma, W., Castella, J. C., Clarke, K., Nijs, T., Dietzel, C., et al. (2008). Comparing the input, output, and validation maps for several models of land change. *The Annals of Regional Science, 42*, 11–37.
Ramankutty, N., Amato, E., Monfreda, T. C., & Foley, J. A. (2008). Farming the planet: 1. Geographic distribution of global agricultural lands in the year 2000. *Global Biogeochemical Cycles, 22*.

Rockström, J., Steffen, W., Noone, K., Persson, Å., Chapin, F. S., Lambin, E., et al. (2009). Planetary boundaries: Exploring the safe operating space for humanity. *Ecology and Society, 14*(no. 2).
Romano, B., & Zullo, F. (2014). The urban transformation of Italy's Adriatic coastal strip: Fifty years of unsustainability. *Land Use Policy, 38*, 26–36.
Romano, B., & Zullo, F. (2015). Half a century of urbanization in southern european lowlands: A study on the Po valley (Northern Italy). *Urban Research and Practice*.
Romano, B., Zullo, F., Fiorini, L., Marcucci, A., & Ciabò, S. (Sep. 2017). Land transformation of Italy due to half a century of urbanization. *Land Use Policy, 67*, 387–400.
Russo, L. (2013). Il consumo di suolo agricolo all'attenzione del legislatore. *Aestimum, 63*(Dicembre 2013), 163–174.
Saaty, T. L. (1980). *The analytic Hierarchy process.* New York: McGraw Hill.
Saaty, T. L. (1988). What is the analytic hierarchy process? *Mathematical models for decision support* (pp. 109–121). Berlin, Heidelberg: Springer Berlin Heidelberg.
Saaty, T. L. (2016). The analytic hierarchy and analytic network processes for the measurement of intangible criteria and for decision-making. *Multiple criteria decision analysis* (pp. 363–419). Springer New York.
Saaty, T. L. (Sep. 1990). How to make a decision: The analytic hierarchy process. *European Journal of Operational Research, 48*(1), 9–26.
Sallustio, L., De Toni, A., Strollo, A., Di Febbraro, M., Gissi, E., Casella, L., et al. (Oct. 2017). Assessing habitat quality in relation to the spatial distribution of protected areas in Italy. *Journal of Environmental Management, 201*, 129–137.
Schmoldt, D. L., Kangas, J., Mendoza, G. A., & Pesonen, M. (2001). *The analytic Hierarchy process in natural resource and environmental decision making*.
Seto, K. C., Fragkias, M., Güneralp, B., & Reilly, M. K. (2011). A meta-analysis of global urban land expansion. *PLos One, 6*(8).
Seto, K. C., Güneralp, B., & Hutyra, L. R. (2012). Global forecasts of urban expansion to 2030 and direct impacts on biodiversity and carbon pools. *Proceedings of the National Academy of Sciences, 109*(40), 16083–16088.
Soares Machado, C. A., Knopik Beltrame, A. M., Shinohara, E. J., Giannotti, M. A., Durieux, L., Nóbrega, T. M. Q., et al. (2014). Identifying concentrated areas of trip generators from high spatial resolution satellite images using object-based classification techniques. *Applied Geography, 53*, 271–283.
Sohl, T. L., Sleeter, B. M., Zhu, Z., Sayler, K. L., Bennett, S., Bouchard, M., et al. (2012). A land-use and land-cover modeling strategy to support a national assessment of carbon stocks and fluxes. *Applied Geography, 34*, 111–124.
Stürck, J., Schulp, C. J. E., & Verburg, P. H. (2015). Spatio-temporal dynamics of regulating ecosystem services in Europe – the role of past and future land use change. *Applied Geography, 63*, 121–135.
Sudhira, H. S., Ramachandra, T. V., & Jagadish, K. S. (2004). Urban sprawl: Metrics, dynamics and modelling using GIS. *International Journal of Applied Earth Observation and Geoinformation, 5*(1), 29–39.
Su, S., Jiang, Z., Zhang, Q., & Zhang, Y. (2011). Transformation of agricultural landscapes under rapid urbanization: A threat to sustainability in Hang-Jia-Hu region, China. *Applied Geography, 31*(2), 439–449.
Szul, P., & Bednarz, T. (2014). Productivity frameworks in big data image processing computations - creating photographic mosaics with Hadoop and Scalding. *Procedia computer science: Vol. 29*, (pp. 2306–2314).
Tan, M., Li, X., Xie, H., & Lu, C. (2005). Urban land expansion and arable land loss in China - a case study of Beijing-Tianjin-Hebei region. *Land Use Policy, 22*(3), 187–196.
Tavares, A. O., Pato, R. L., & Magalhães, M. C. (2012). Spatial and temporal land use change and occupation over the last half century in a peri-urban area. *Applied Geography, 34*, 432–444.
Tesfamariam, S., & Sadiq, R. (Sep. 2006). Risk-based environmental decision-making using fuzzy analytic hierarchy process (F-AHP). *Stochastic Environmental Research and Risk Assessment, 21*(1), 35–50.
Tilman, D., Fargione, J., Wolff, B., D'Antonio, C., Dobson, A., Howarth, R., et al. (2001). Forecasting agriculturally driven global environmental change. *Science (80-.). 292*(5515).
Torrens, P. M., & Alberti, M. (2000). *Measuring sprawl. Cent. Adv. Spat. Anal.*, *27*, 1–34.
UNDESA (2015). *SDGs & topics.:. Sustainable development knowledge platform.* United Nations Department of Economic and Social Affairs.
UNFCCC COP 21 (2015). Report on COP 21 (FCCC/CP/2015/10/Add.1) *Report of the conference of the parties on its twenty-first session, held in Paris from 30 November to 13 december 2015* (pp. 1–36). Addendum. Part two: Action taken by the Conference of the Parties at its twenty-first session.
United Nations (2011). *The great green technological transformation.* United Nations publication.
van Vuuren, D. P., Isaac, M., Kundzewicz, Z. W., Arnell, N., Barker, T., Criqui, P., et al. (2011). The use of scenarios as the basis for combined assessment of climate change mitigation and adaptation. *Global Environmental Change, 21*(2), 575–591.
van Vuuren, D. P., Stehfest, E., Gernaat, D. E. H. J., Doelman, J. C., van den Berg, M., Harmsen, M., et al. (2015). Energy, land-use and greenhouse gas emissions trajectories under a green growth paradigm. *Global Environmental Change*.
World Bank (2012). *World development indicators 2012.* The World Bank.
Yang, J., & Lee, H. (1997). An AHP decision model for facility location selection. *Facilities, 15*, 241–254.
Zullo, F., Paolinelli, G., Fiordigigli, V., & Romano, B. (2015). Urban development in tuscany land uptake and landscapes changes. *TeMA - Journal of Land Use, Mobility and Environment, 2*, 183–202.

Further reading

Huber, M., & Knutti, R. (Dec. 2011). Anthropogenic and natural warming inferred from changes in Earth's energy balance. *Nature Geoscience, 5*(1), 31–36.