Journal of Environmental Informatics xx(x) xx-xx (2014)

Journal of Environmental Informatics

www.iseis.org/jei

Implications of Using 2 m versus 30 m Spatial Resolution Data for Suburban Residential Land Change Modeling

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Received March 2, 2013; revised Nov 26, 2013; accepted March 27, 2014; published online November 24, 2014

ABSTRACT. This study assesses the advantages and disadvantages of using 2 m spatial resolution data versus 30 m resolution data for a simulation model of land-use and land-cover change (LUCC). The model projects LUCC from 2005 to 2055 in the town of Lynnfield, Massachusetts, USA. This article describes four scenario storylines and then projects land-use and land-cover under each of the four scenarios with 2 m data and again with 30 m data. The disagreement between the 2 m output and its corresponding 30 m output ranges between 5.7% and 11.0% of the town. The disagreement due to allocation over small distances is greater than the disagreement due to the quantity of new residential growth. The projected quantities of new residential land-use in 2055 differ between the two resolutions by 1% of the town, whereas the visual differences in the spatial allocations are distinct and substantial. The results for this case study show that 30 m resolution data provides several practical and theoretical advantages over 2 m resolution data, due mainly to the fact that the 30 m resolution data match more closely the size of the patches of change.

Keywords: disagreement, GEOMOD, GIS, land-use and land-cover change (LUCC), model, resolution, scale, scenario

1. Introduction

1.1. Motivation and Literature Review

Models of land-use and land-cover change (LUCC) are important tools to assess the impact of future land-use and development on society and the environment (Verburg et al., 2002; Alcamo et al., 2008). The holistic ecological and societal impacts of localized LUCC are often ignored or not immediately realized at the local or municipal level due to the incremental and complex processes of land change that can occur over multiple spatial and temporal scales (Dietzel and Clarke, 2004; Conway and Lathrop, 2005; Turner et al., 2007). LUCC models can provide insight into the cumulative impacts of LUCC. Scientists can use models to advise policy makers as to the potential impacts of development or conservation actions and the actions' effect on future landscape change. LUCC models are most commonly used to examine processes of landscape change and to investigate potential future landscape configurations before permanent alterations are made (Agarwal et al., 2002; Dietzel and Clarke, 2004; Verburg et al., 2004; Conway and Lathrop, 2005).

Spatially-explicit LUCC models can represent a complex human-environment system. Calibration of these models are typically based on a set of idealized parameters to generate multiple scenarios of change that can be used to test the sensitivity of the human-environment system (Veldkamp and Lambin, 2001; Verburg et al., 2004; Turner et al., 2007). Calibration data can include: a digital map of an initial time point, historical data for calculating the rate of each land transition, and spatial variables that influence the allocation of land change. Anticipated future transitions can be simulated with these data producing a scenario map for a subsequent time (Pontius et al., 2001; Pontius and Malanson, 2005; Turner et al., 2007; Pontius et al., 2008).

One of the most fundamental decisions in LUCC modeling concerns the spatial resolution of calibration data (Dietzel and Clarke, 2004; Evans and Kelley, 2004; Hengl, 2006). The decision is critical because it determines the unit of observation in land change modeling and thus the degree to which the data and the model can accurately represent the spatial variability of land change processes (Verburg et al., 1999; Gibson et al., 2000; Jantz and Goetz, 2005). The basic question of what spatial resolution is appropriate for a particular LUCC analysis depends on the data availability, information quality, model design, research goals, and compu-

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ISSN: 1726-2135 print/1684-8799 online
 doi: 10.3808/jei.201400284

ting resources (Agarwal et al., 2002; Verburg et al., 2004; Hengl, 2006). Medium spatial resolution data from satellite based sensors, i.e. 20 m to 1 km, have historically been the most common spatial resolution used in LUCC modeling, owing to their low management requirements, extensive spatial coverage, frequent temporal coverage, and inexpensive availability (Rogan and Chen, 2004). Examples include Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) from 15 to 90 m, Satellite Pour l'Observation de la Terre (SPOT) from 10 to 20 m, Moderate Resolution Imaging Spectroradiometer (MODIS) from 250 m to 1 km, and Landsat which is 30 m (Agarwal et al., 2002).

The spatial resolution of calibration data in the LUCC modeling literature is often coarser than 20 m. Table 1 provides a review of spatial resolutions and model applications for a selection of LUCC modeling studies. The use of medium spatial resolution data has been driven by the previously listed practical benefits and by the widespread focus on modeling regional, national, and continental land-use and land-cover change. The use of medium spatial resolution data has also been driven by the desire to integrate ancillary data, such as census data, and by the continued use of LUCC models that have traditionally been designed to use and simulate coarse spatial resolution data and land change processses (Agarwal et al., 2002; Munroe and Muller, 2007; Alcamo et al., 2008).

The recent development and proliferation of finer spatial resolution data of less than 20 m have led to more choice in the spatial resolution of data (Agarwal et al., 2002; Rogan and Chen, 2004; Herold et al., 2005). Examples include satellite based sensors such as WorldView-2 from 0.5 to 2.6 m, IKONOS from 1 to 4 m, QuickBird from 0.6 to 2.4 m, and OrbView-3 from 1 to 4 m. Simultaneously, advances in computing have led to increased interest in using fine spatial resolution data in LUCC modeling (Dietzel and Clarke, 2004; Herold et al., 2005; Hengl, 2006). Fine resolution data have increasingly been explored for use in fine resolution and small spatial extent LUCC analysis (Forster et al., 1985; Jensen and Cowen, 1999; Herold et al., 2001; Herold et al., 2003; Herold et al., 2005). An example of this work includes Herold et al.'s (2005) study in Santa Barbara, CA, where IKONOS data were used in urban land-use change modeling in combination with urban spatial metrics.

The spatial resolution of calibration data can have important and substantial effects on the output, accuracy, and function of models, thus potentially limiting or enhancing the ability of a model to project future scenarios of change (d'Aquino et al., 2002; Dietzel and Clarke, 2004; Jantz and Goetz, 2005; Pan et al., 2010; van Delden et al., 2011). However, LUCC models have a wide diversity of other characteristics that can also impact model output. These characteristics can include: the study area extent, the number of LUCC categories, the types of LUCC transitions, feedbacks, spatial dependency, and data requirements (Kok and Veldkamp, 2001; Jantz and Goetz, 2005; Pontius and Malanson, 2005; Pan et al., 2010; Pontius et al., 2011). When all other variables are held constant, quantities of projected land change and their spatial allocation can differ substantially depending on the spatial resolution of model calibration data (Jantz and Goetz, 2005). Relationships between social and biophysical processes change as a function of spatial resolution (Walsh et al., 1999; Veldkamp and Lambin, 2001; Verburg et al., 2002), and relationships found at one resolution may not be evident at others (Gibson et al., 2000; Walsh et al., 2001; Evans and Kelley, 2004; Jantz and Goetz, 2005). Coarsening spatial resolution can result in aggregation of the information contained in a map while finer spatial resolution can result in disaggregation (Verburg et al., 1999; Hengl, 2006;

Table 1. Reported Spatial Resolutions and Associated Land-Use and Land-Cover Change Models*

Site	Simulation Spatial Resolutions (m)	Model	Reference
South Central IN	30 60 90 120 150 240 300 480	Agent Based	Evans and Kelley, 2004
San Joaquin County, CA	100 200 400	SLEUTH	Dietzel and Clarke, 2004
North VA & South MD	45 90 180 300	SLEUTH	Jantz and Goetz, 2005
Miyun County, China	25 50 100 200 300 500 800	CLUE	Pan et al., 2010
Para, Brazil	20 – 81920	BLM	Pontius et al., 2007
Ipswich River Watershed MA	30 to 1000	GEOMOD	Pontius et al., 2004a
South West NJ	80 120 160 200	Build Out	Conway and Lathrop, 2005
Central America	15 45 75	CLUE	Kok and Veldkamp, 2001
Cho Don, Vietnam	32 – 51000	Agent Based	Pontius et al., 2011
Costa Rica & Honduras	15000 – 75000	CLUE	Kok et al., 2001
Philippines & Malaysia	150	CLUE	Verburg et al., 2002
China	32000	CLUE	Verburg and Veldkamp, 2001
Detroit, MI	26	LTM	Pontius et al., 2008[a]
Twin Cities, MN-WI	30	LTM	Pontius et al., 2008[a]
Ipswich River Watershed MA	30	MCE & OLS	Schneider and Pontius, 2001

* SLEUTH denotes Slope, Land-use, Exclusion, Urban Extent, Transportation, and Hillshade; BLM denotes Behavioral Landscape Model; LTM denotes Land Transformation Model; MCE denotes Multi-Criteria Evaluation; CLUE denotes Conversion of Land-Use Change and its Effects; OLS denotes Ordinary Least Squares regression.
[a] Selected case studies are two of 13 applications presented by Pontius et al., 2008.

van Delden et al., 2011).

The LUCC literature has found that for various spatial resolutions greater than 20 m, calibration data spatial resolution alone can cause substantial differences in model output and performance in terms of quantity, allocation, and accuracy of projected land cover change (Evans and Kelley, 2004; Pontius et al., 2004a; Jantz and Goetz, 2005; Pontius et al., 2007). As pixels become coarser, the reference data and the simulated data can become more similar. For one application of GEOMOD, the resolution of the calibration data was found to be finer than the resolution at which the model could accurately predict the spatial allocation of land change (Pontius et al., 2004a).

In agent based LUCC models, it has been found that spatial resolution has a considerable impact on model parameters and, subsequently, on model outputs. Weights for an agent based model differ as a function of scale, with finer resolution data able to better capture observed processes of change operating on the landscape. Coarse spatial resolution data may not be able to capture the spatial variance in the landscape, and thus may not provide enough information for parameters used in the model simulations (Evans and Kelley, 2004). Similar results have been found for the urban growth model Slope, Land-use, Exclusion, Urban Extent, Transportation, and Hillshade (SLEUTH). SLEUTH performed better at certain spatial resolutions than others where SLEUTH underestimated the quantity of urban edge pixels at finer spatial resolutions. The variations in the operational scales of parameters that represent the processes of land-change in the model were found to be the main cause of model performance instability (Jantz and Goetz, 2005). Kok and Veldkamp (2001) assessed the Conversion of Land-Use Change and its Effects (CLUE) model, for which they found the spatial resolution of input data did not substantially change model output, although spatial resolution did change the explanatory power of the driver variables representing the land change processes. Their findings are in contradiction to the conclusions of similar studies of CLUE, which found that the data's spatial resolution has a substantial influence on model performance. The coarse spatial resolution of the calibration input parameters in their specific case may have limited the detection of model instability at finer resolutions (Kok and Veldkamp, 2001). These findings reveal the variable effects of data's spatial resolution across model platforms and parameters.

While much is known about the effects of spatial resolution on LUCC models at spatial resolutions coarser than 20 m, the LUCC modeling literature lacks a comprehensive discussion of the practical and analytical benefits and limitations of very fine spatial resolution data, i.e. finer than 20 m. As fine resolution data become ubiquitous, the profession must better understand the implications of using fine resolution data in LUCC modeling (Herold et al., 2005; Hengl, 2006). Issues surrounding the utility of very fine spatial resolution calibration data include: 1) the practical applications in local and regional extent land change modeling, and 2) the theoretical considerations of how well these data represent landscapes and processes of change. This paper examines how the spatial resolution of calibration data influences the output maps of a LUCC model and examines the practical aspects of LUCC modeling at finer versus coarser spatial resolutions.

1.2. Research Objective

The objective of this study is to assess the advantages and disadvantages of using 2 m resolution data versus 30 m resolution data in spatially explicit land-use and land-cover change modeling. A fifty year (2005 ~ 2055) LUCC projection is constructed for the town of Lynnfield, Massachusetts, USA. Historical 1971 and 1999 land-use data from MassGIS (2009) are used to calibrate the LUCC model to derive the historical trend of land-use conversion to residential and to calculate the residential growth rate to determine projected pixel quantities for the land-use change model. Step one projects potential residential growth over the 50 year time period at 2 m spatial resolution under four scenarios of growth, which vary in the quantity and concentration of residential growth. Step two projects potential residential growth over the same time period at 30 m spatial resolution using an identical methodology for the same set of scenarios. Step three compares the results of the 2 m spatial resolution model output to the coarser spatial resolution 30 m model output. This article compares the outputs resulting from differences in spatial resolution. This research is motivated by the desire: 1) to determine the utility of very fine resolution data and its effects on model outputs in spatially explicit LUCC modeling and 2) to address the growing interest in using fine spatial resolution data for LUCC modeling.

1.3. Study Area

Figure 1 shows the study area, the town of Lynnfield, in northeastern Massachusetts, USA. The area is centered at 71º02' W and 42º32' N, within the Ipswich River watershed, and is 27 km². In 1971, Lynnfield was composed of dense and sparse urban development (36% of the town), mixed deciduous and coniferous forest (43%), wetlands (6%), and open land (12%). In 1999, Lynnfield was composed of dense and sparse urban development (45%), mixed deciduous and coniferous forest (36%), wetlands (6%), and open land (10%). The average size of a residential ownership parcel in Lynnfield is 0.25 ha as derived from MassGIS (2009) residential land-use tax assessor parcel data. The town had a population in 2000 of 11,542 (US Census, 2010). The Metropolitan Area Planning Council MetroFuture initiative (Reardon, 2008) described Lynnfield as a maturing suburb of metropolitan Boston, which is characterized as having a majority of housing stock single family and owner occupied, projected residential growth of 11% from 2000 to 2030, and a dwindling supply of unprotected developable land with less than 25% of land left as potentially developable (Reardon, 2008).

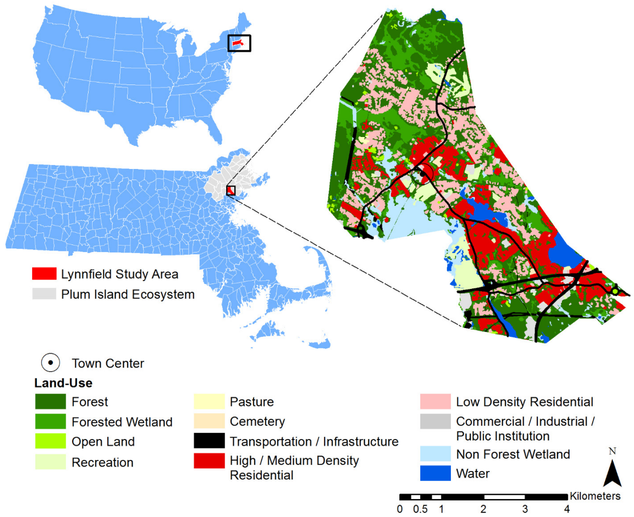

Figure 1. Figure 1. Study area in Lynnfield, Massachusetts, USA (left) and land-use in 2005 (right).
Note: Land-use categories are an aggregate of the original 40-category classification from MassGIS (2009).

Southern New England, particularly north and central Massachusetts, is currently undergoing tremendous landscape alteration resulting from urban and suburban sprawl and other land-cover conversions (DeNormandie, 2009). Residential housing accounts for approximately 87% of all land-use conversion in Massachusetts where residential home lot sizes have increased 47% since the 1970s (Breunig, 2003; DeNormandie, 2009). More than 16,000 ha were converted to residential development from 1999 to 2005 where 12,000 ha were converted from forest and 4,000 ha from agricultural land. Between 1999 and 2005, Massachusetts experienced approximately 9 ha transition to urban land-use each day (DeNormandie, 2009).

2. Methods

2.1. Data

The Commonwealth of Massachusetts (MassGIS, 2009) supplied vector maps concerning land-use for 1971, 1999, and 2005. These data are used to calculate the historical trend of land-use conversion to residential from 1971 to 1999 and to calculate the residential growth rate to determine projected pixel quantities for the land-use change model. The 1971 and 1999 land-use data have a minimum mapping unit (MMU) of 0.4 ha. The land-use data were constructed by the University of Massachusetts Amherst, Department of Forestry Resource Mapping Project through orthophotograph interpretation and manual and automatic digitizing of 1:25,000 aerial orthophotographs. The 1971 classification has 21 categories, but is an aggregate of 104 originally digitized categories. The 1999 land-use map has 37 categories and is an update of the original 1971 classification where orthophotographs were used as a reference for updating, thus differences between 1971 and 1999 are likely to indicate real land-use change (MassGIS, 2009).

A modernized mapping technique generated the 2005 land-use data, thus differences between the 1999 map and the 2005 map reflect both actual land-use change and the change in mapping technique. The 2005 map has 40 land-use classification categories that are generally consistent with the categories of 1971 ~ 1999. The 2005 data have a mapping unit between 0.1 and 0.4 ha. In Lynnfield, the average size of an individual residential land-use polygon in these 2005 data is 3.7 ha. These data were constructed using semi-automated classification of orthophotographs acquired in April 2005 at a spatial resolution of 0.45 m, thus each pixel accounts for 0.00002 ha. The 2005 land-use vector data were constructed by combining the classified imagery with attributes from the manually-compiled 1999 land-use data, tax assessor parcel information, and other ancillary data concerning impervious surfaces and wetlands (MassGIS, 2009). The 2005 land-use data are more detailed than the 1971 ~ 1999 land-use data, thus 2005 is used as the starting point of the simulation. The data of 1971 ~ 1999 are consistent concerning the method to measure change, so those data are used to project the quantity of residential growth. MassGIS does not offer information concerning accuracy assessment of the land-use maps for 1971, 1999, and 2005.

In addition to the land-use datasets, protected and recreational open space, major roads, and community boundaries were acquired in the form of a vector dataset from the Commonwealth of Massachusetts (MassGIS, 2009). Protected and recreational open space data last updated in May 2009 are used in combination with the 2005 land-use data to construct a map of areas available and unavailable for projected residential development. These data contain boundaries of conservation lands and outdoor recreational facilities originally digitized in 1988 from 1:25,000 scale maps. The data indicate the level of protection of conservation land and are continuously updated (MassGIS, 2009). The Executive Office of Transportation - Office of Transportation Planning Roads major roads data, last updated in October 2009, are used to construct the concentrated projected residential development scenario suitability map. These data were constructed through orthophotograph digitizing and include linework from earlier 1:5,000 road and rail centerlines and United States Geological Survey 1:100,000 roads digital line graphs (MassGIS, 2009). The community boundaries data were originally created in 2004, updating earlier ground survey 1:25,000 scale boundaries, and were last updated in September 2009 (MassGIS, 2009).

2.2. Data Processing

All vector datasets are subset to the study area town boundary and are converted from vector to raster format into two different spatial resolutions, 2 and 30 m. The 2 and 30 m spatial resolutions were selected as approximate representations of aerial and satellite based fine resolution sensors, and medium resolution satellite sensors and common standard data products, respectively (Rogan and Chen, 2004).

The 2 and 30 m raster transformations are both based on the original vector data. The conversion process used in this study for vector polygon to raster relies on using a base grid map that specifies the spatial extent, resolution, and projection information for the new raster map. The vector polygon data are placed on top of this raster grid, and vector polygons that cover the centroid of a pixel in the base grid are represented as a pixel in the raster map. If a polygon does not cover a centroid of a pixel, then the polygon feature will not be represented in the raster map. If there are overlapping polygons on a single pixel centroid, the polygon with the highest identification value is selected for raster representation (Eastman, 2009). All data utilize the North American Datum 1983, Massachusetts State Plane Zone 1 coordinate system. The methodology outlined in this and the proceeding section is applied to both the 2 and 30 m datasets to ensure the only difference between the model outputs are due to spatial resolution and not from the methodology.

Boolean maps of the 1971, 1999, and 2005 land-use data are created by reclassifying all pixels as either residential or non-residential. To determine areas in the 2005 land-use map that are suitable for projected residential development, the 2005 40 class classification is reduced to a three class classification using the reclassification procedure in Table 2.

Pixels are assigned one of three categories: available for residential development, already developed, and unavailable for development. The protected and recreational open space data are also reclassified, with all permanently protected open space considered unavailable for development regardless of its classification in the 2005 land-use data. The reclassified protected and recreational open space data are then combined with the reclassified three class 2005 land-use data.

2.3. Land Change Simulation

2.3.1. GEOMOD

The land-use and land-cover change model GEOMOD is used to project residential development over the fifty year time interval from 2005 to 2055. GEOMOD is a pixel based, spatially explicit model that simulates the spatial pattern of land change between two land-use categories over time (Hall et al. 1995; Pontius et al. 2001). The minimum input requirements for GEOMOD are: the simulation start and end times, a map of the start time for two land categories, and an estimate of each category's total number of pixels at the end time. Additionally, the user usually supplies driver maps from which GEOMOD creates a suitability map. The suitability map indicates the relative priority of pixels in the landscape to transition from one category to another. A high rank corresponds to a high transition priority for the gaining category while a low rank corresponds to a low transition priority for the gaining category. GEOMOD allocates the pixels to classify as one of the two categories for the end time based on the suitability map. GEOMOD simulates a one way transition, such as from non-residential to residential land. The user specifies a net change in the number of residential pixels from the start time to the end time, then GEOMOD searches among the non-residential pixels using the suitability map to select the pixels to convert to residential. All other cells within the map will persist and no cells will show change from residential to non-residential (Pontius and Chen, 2006). For more detailed information on GEOMOD please see Pontius and Chen (2006).

GEOMOD was chosen for this analysis because it addresses our purpose in Lynnfield, MA, where we are interested in a one-way growth of residential area. Furthermore, we can control the model because the design of GEOMOD allows the user to specify the number of pixels of simulated change independently from the allocation of that change. GEOMOD also offers substantial flexibility in the required input data, as GEOMOD requires only one beginning land-use map for calibration.

2.3.2. Scenario Development

Four scenarios of projected residential development are constructed with variable quantities of gross gain and spatial allocation of residential development. These scenarios include: 1) low quantity and dispersed allocation, 2) low quantity and concentrated allocation, 3) high quantity and dispersed allocation, and 4) high quantity and concentrated allocation. These scenarios portray two distinct frameworks of alternative spatial allocations of residential development representing: 1) suburban sprawl resulting in dispersed allocation of development and 2) higher density concentrated allocation of development such as those created under smart growth strategies. See Rose et al. (2009) for a comprehensive definition of smart growth.

Table 2. Conversion from 40-Category* 2005 Land-Use Classification to 3-Category Classification

Already Developed	Unavailable for Development	Available for Development
Recreation	Non-Forest Wetland	Cropland
Existing Residential	Water	Pasture
Commercial / Industrial	Saltwater Sandy Beach	Forest
Transportation	All Permanently Protected Open Space	Mining
Waste Disposal		Open Land
Powerline / Utility		Transitional
Golf Course		Orchard
Marina		Nursery
Urban Public / Institutional		Brush land / Successional

* Land-use names have in some cases been aggregated from their original names. See MassGIS (2009) for more details on MassGIS 2005 40-category definitions and 2009 protected and recreational open space definitions.

The high quantity dispersed allocation scenario assumes that current trends in the quantity and the spatial allocation of new residential development continue over the next 50 years. The high quantity concentrated allocation scenario assumes that current trends in the quantity of new residential development continue, but that new development will be concentrated near major roads. The low quantity dispersed allocation scenario assumes that the quantity of residential development will occur more slowly than in the past, but that current trends in dispersed spatial allocation of new development will continue. The low quantity concentrated allocation scenario assumes that the quantity of new residential development will occur more slowly than in the past and that new development will be concentrated near major roads. The high quantity and low quantity scenarios are designed to represent the same quantity of population growth, assuming that residential development will be higher-density under the concentrated scenarios.

2.3.3. Projected Residential Pixel Quantities

The town of Lynnfield is assigned a residential growth rate based on its historical residential development growth rate between 1971 and 1999. According to the vector land-use data, the percentage of the town's area that was residential increased from 33 to 41% between 1971 and 1999. In comparison, the respective raster data differ from the vector data by only one-tenth of one percentage point. Equation (1) is used to calculate the residential growth rate using the 1971 and 1999 land-use maps:

$$g = \left[\left(\frac{R_{1999}}{R_{1971}} \right)^{\frac{1}{1999-1971}} \right] - 1 \qquad (1)$$

where

g = annual proportional growth rate of residential development

R_{1971} = number of pixels classified as residential in 1971

R_{1999} = number of pixels classified as residential in 1999

The resulting annual growth rate is 0.828% for the 30 m data and 0.823% for the 2 m data. These annual exponential growth rates are applied to the respective spatial resolution residential 2005 land-use maps to project the number of new residential pixels in 2055. An exponential function of growth is assumed because it can be applied in a straight forward manner to the base at 2005. Equations (2) and (3) apply the growth rate to project the number of residential pixels in 2055:

$$R_{high} = R_{2005} \times (1+g)^{50} \qquad (2)$$

$$R_{low} = R_{2005} + \frac{R_{high} - R_{2005}}{2} \qquad (3)$$

where

R_{high} = number of pixels classified as residential in 2055 under the high quantity scenario

R_{low} = number of pixels classified as residential in 2055 under the low quantity scenario

R_{2005} = number of pixels classified as residential in 2005

Under the high quantity scenarios in Equation (2), the quantity of residential development is assigned an area of R_{high} pixels in 2055. Under the low quantity scenarios in Equation (3), the quantity of residential development in 2055 R_{low} is assigned half the net residential growth found under the high quantity scenario R_{high}. The low quantity pixel calculation R_{low} is designed to reflect the assumption that new development will be twice as dense under the low quantity scenarios. The low quantity scenarios assume that new development accommodates an equivalent population increase in one-half the area of additional residential development as compared to the high quantity scenarios.

2.3.4. Projected Residential Spatial Allocation

Two distinct methods are used for the spatial allocation of projected residential development from 2005 to 2055. These two methods correspond to the dispersed and concentrated scenarios, which are designed to represent two different patterns of residential development. Under the dispersed scenarios, GEOMOD creates 2 and 30 m land-use transition suitability maps by overlaying the 1971 land-use data with the 2005 residential land-use map. The non-residential land-use categories that transition most intensively to residential during 1971 ~ 2005 are assigned a highest priority for conversion to residential land between 2005 and 2055 (Figure 2).

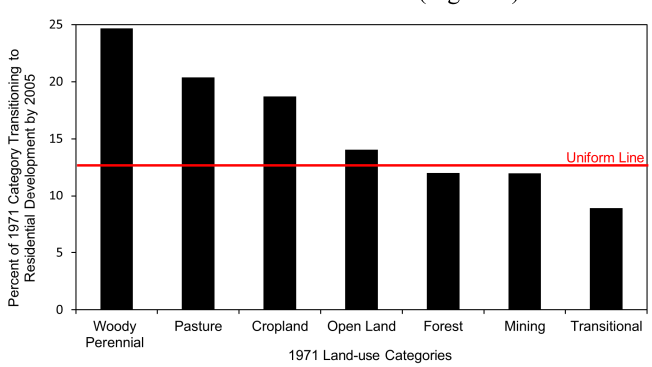

Figure 2. Intensity of conversion to residential development during 1971-2005 expressed as a percent of each of seven non-residential categories at 1971. Uniform line shows intensity of change in the town during 1971-2005.

Under the concentrated scenarios, residential development is allocated based on a pixel's distance from major roads. Pixels closer to major roads are assigned a higher suitability ranking and pixels farther from roads are assigned a lower suitability ranking. Both 2 and 30 m residential transition suitability maps are created by using the roads data to assign each pixel a suitability value for conversion to residential

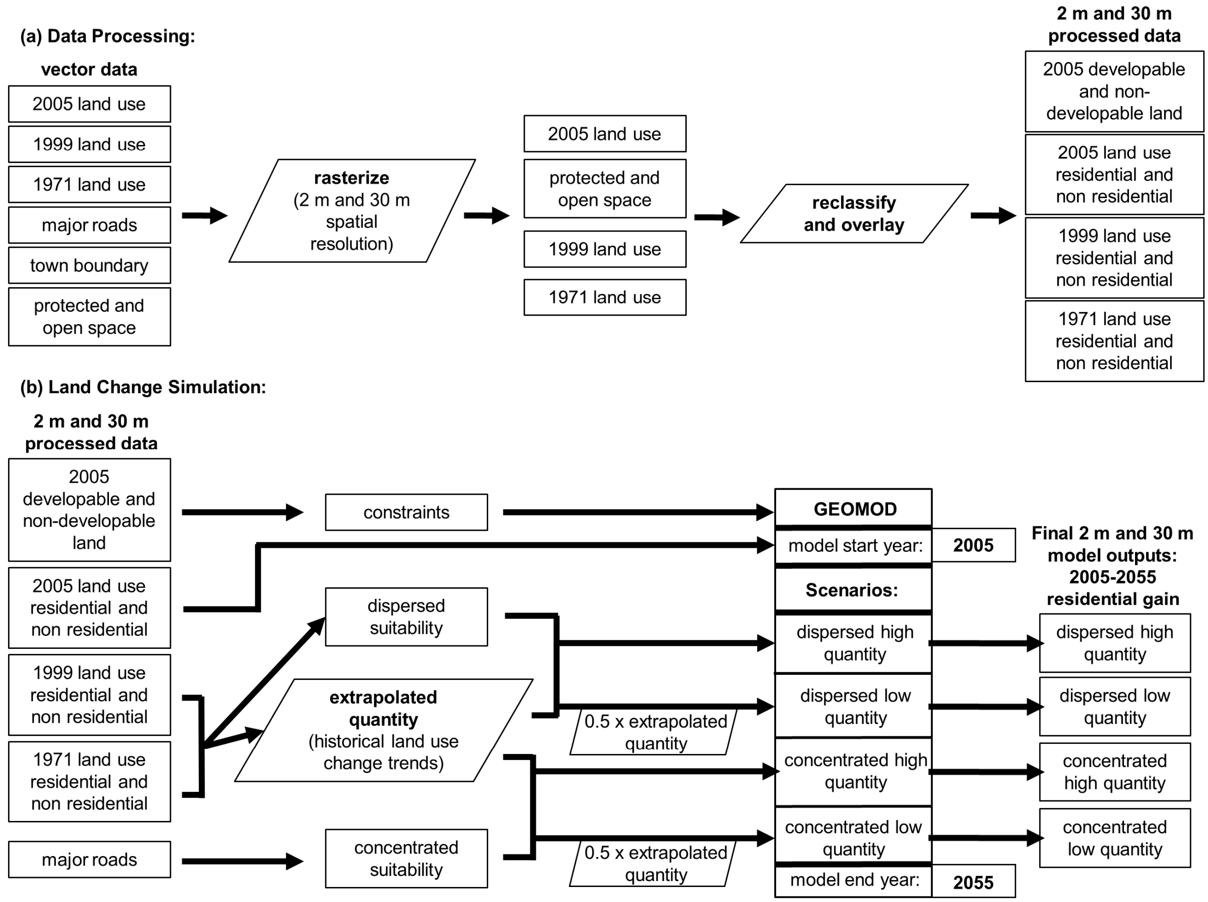

Figure 3. Diagram of methodology. (a) Data processing; (b) Land change simulation.

development between 2005 and 2055. The concentrated scenario suitability calculation is shown as Equation (4):

$$P_k = \frac{D_k}{D_{\max}} \tag{4}$$

where

P_k = suitability value for pixel k

D_k = distance from pixel k to nearest major road

$D_{\max}$ = maximum D_k among all pixels in the town

The 2005 three category reclassified map is used to mask out areas unavailable for new development in the suitability maps for both the dispersed and concentrated scenarios. For a methodology work flow summary for all processing and model construction steps see Figure 3.

2.3.5. Comparison of 2 and 30 m Model Output

Map comparisons are conducted on the 2 and 30 m model outputs for all scenarios to identify differences in the outputs caused by the calibration data's spatial resolution. Map comparison is also performed on the 2 and 30 m input 2005 residential land-use maps, to examine the effect of the vector to raster conversion process. To facilitate map comparison between the 2 and 30 m data, the 30 m data are converted to 2 m.

Map crosstabulation is a common technique for discerning differences between maps. Crosstabulation is used to extract statistics of map agreement and disagreement. This study uses the map comparison method of pixel quantity and allocation disagreement, as outlined in Pontius and Millones (2011). Map disagreement is divided into two types: Quantity disagreement and allocation disagreement. Quantity disagreement is the map disagreement due to the difference in quantity of pixels for each category in the 2 m resolution map versus the 30 m resolution map. Allocation disagreement is the additional disagreement associated with the differing spatial allocation for each category in the 2 m resolution map versus the 30 m resolution map. Total disagreement is the sum of quantity disagreement and allocation disagreement. We show the maps and give summary statistics for each comparison of a 2 m resolution map and its corresponding 30 m resolution map.

3. Results

Residential in the original 2005 vector land-use data comprised 882 ha, equivalent to 33% of Lynnfield. Figure 4 shows that the 2 m spatial resolution land-use change model projects that residential land-use will increase to 49% of the town under the high quantity scenarios, and to 41% of the town under the low quantity scenarios, by 2055. The 30 m

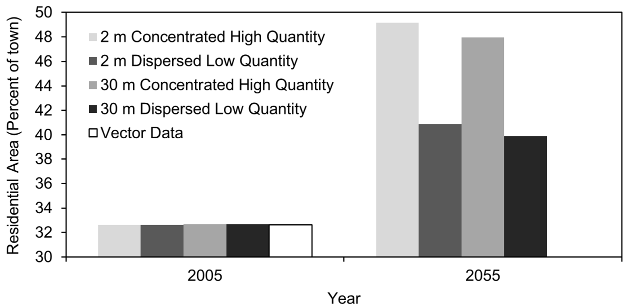

Figure 4. Area of residential land-use as percent of town area in 2005 and 2055.
Note: Bars show the 2005 land-use vector data and the four projected scenarios. The area for the 2005 vector data is calculated from the original vector data. Areas for all other datasets are calculated from their respecttive raster resolutions.

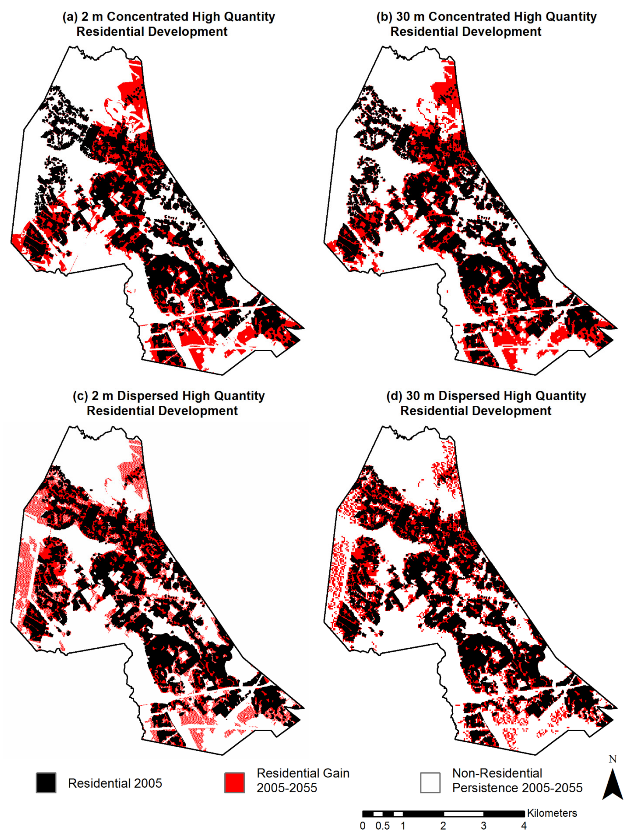

Figure 5. The 2 m and 30 m model outputs for high quantity scenarios of projected residential growth during 2005-2055.
(a) 2 m Concentrated high quantity residential development;
(b) 30 m Concentrated high quantity residential development;
(c) 2 m Dispersed high quantity residential development;
(d) 30 m Dispersed high quantity residential development.

spatial resolution land-use change model projects that residential land-use will increase to 48 and 40% of the town under the high and low quantity scenarios, respectively, by 2055.

Figure 5 shows the 2 and 30 m outputs from the high quantity scenarios. Slight differences between the spatial resolution outputs are evident in Figure 5. The scattered pattern in the 30 m dispersed high quantity output is due to pseudo random spatial allocation of projected residential pixels that have tied suitability values.

Figure 6 summarizes the difference between a 2 m map and its corresponding 30 m map for five pairs of maps. For all

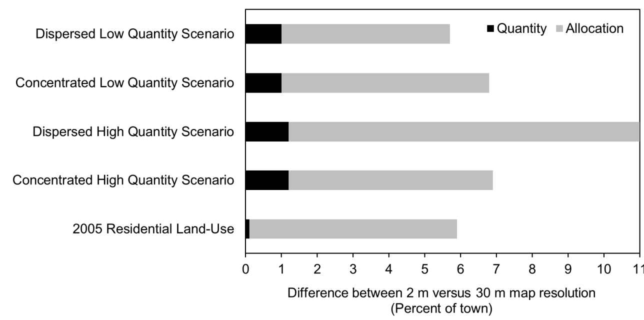

Figure 6. Comparison of 2 m versus 30 m resolution maps.

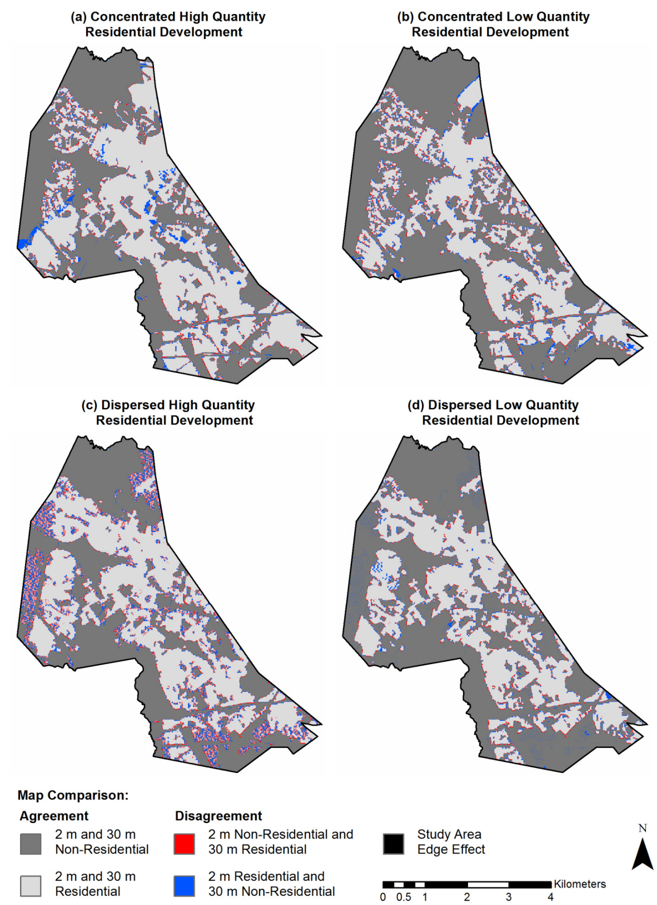

Figure 7. Comparison of 2 m and 30 m model outputs for four scenarios of projected residential use in 2055.
(a) Concentrated high quantity residential development;
(b) Concentrated low quantity residential development;
(c) Dispersed high quantity residential development;
(d) Dispersed low quantity residential development.

five cases, the allocation disagreement is larger than the quantity disagreement. The 2 and 30 m 2005 residential land-use maps differ on 5.9% of the town. Disagreement between the 2 and 30 m output maps range from 5.7 to 11.0% of the town.

Figure 7 shows map agreement and disagreement between all scenario pairs for the 2 and 30 m outputs. Black indicates disagreement attributable to pixel edge mis-matching resulting from rasterization. The scattered pattern in the dispersed outputs is due to pseudo random spatial allocation of projected residential gain among pixels that have tied suitability values. Figure 8 highlights particular areas in the comparison between the 2 and 30 m outputs for the concentrated high quantity scenario. The highlighted areas serve as prime examples of the three types of map disagreement.

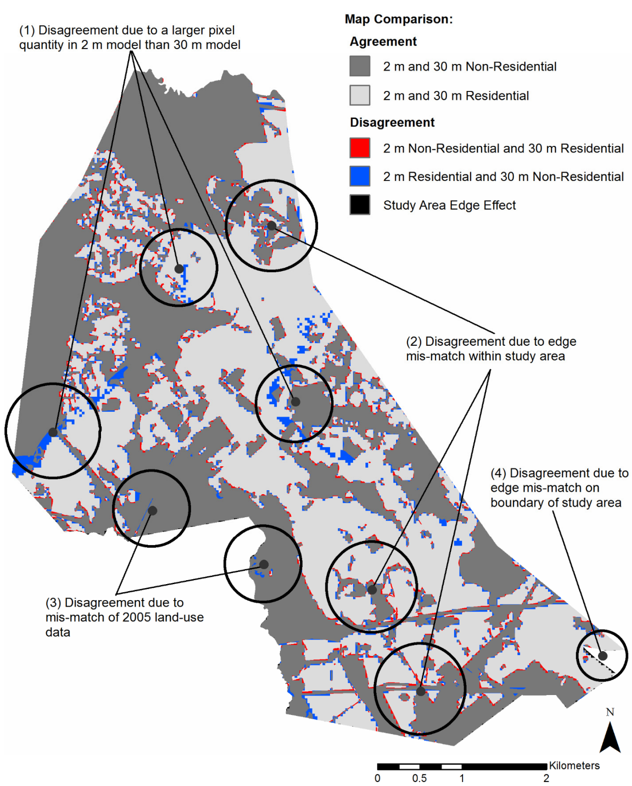

Figure 8. Sources of disagreement between the 2 m and 30 m output maps from the concentrated high quantity scenario.

4. Discussion

4.1. Interpretation of Results

4.1.1. Area of Projected Residential Growth in 2055

Figure 4 shows that for the high quantity scenarios, the quantity of new residential growth projected by the 2 m model is larger by 1.2% of the town than the quantity projected by the 30 m model. For the low quantity scenarios, Figure 4 shows that the amount of growth projected by the 2 m model is larger by 1% of the town than the quantity projected by the 30 m model. These area disagreements are also reflected in the quantity disagreement in Figure 6. The 2 m scenarios simulate more change compared to the corresponding 30 m scenarios because spatial resolution influences the calculation of Equations (1), (2) and (3). Rasterization of the 1971 and 1999 residential land-use maps cause slight differences between the 2 and 30 m raster versions of those maps, thus Equation (1) produces slightly different growth rate percentages: 0.823 for the 2 m and 0.828 for the 30 m model. Equations (2) and (3) amplify these differences over a 50 year time span.

The differences in the output between the 2 and 30 m models and the different projected growth rates confirm that the spatial resolution of calibration data can produce different results when identical methods are applied. These results confirm that spatial resolution is a critical component in the construction of a model, a finding supported by the LUCC modeling literature (Kok and Veldkamp, 2001; Evans and Kelley, 2004; Jantz and Goetz, 2005). This study agrees with previous studies that have found that the spatial resolution of calibration data in a LUCC model can have a considerable impact on the parameters of a model and subsequently the outputs of a model (Evans and Kelley, 2004; Pontius et al., 2004a; Jantz and Goetz, 2005; Pontius et al., 2007; van Delden et al., 2011).

4.1.2. Quantitative Crosstabulations

As shown in Figure 6, the 2 and 30 m input 2005 residential land-use maps have a 5.9% map disagreement. This disagreement is attributable to the vector to raster conversion process, and serves as a baseline for examining the other crosstabulations. Spatial allocation of new residential pixels accounts for the largest share of map disagreement for all four scenarios. In most cases, disagreement due to spatial allocation in the model output maps occurs because the 2 and 30 m suitability maps differ along feature edges, with the 2 m pixels forming smoother edges than the 30 m pixels.

4.1.3. Qualitative Spatial Crosstabulation

Figure 8 examines the qualitative spatial crosstabulation between the 2 m and the 30 m concentrated high quantity scenarios. This crosstabulation map offers insight into the different types of map disagreement present between the model outputs. The example labeled (1) shows map disagreement where the 2 m model simulated residential gain and the 30 m model simulated non-residential persistence during 2005 ~ 2055. Because the 2 m model has a slightly higher growth rate, more pixels were allocated to new residential development; thus, Figure 8 has more blue pixels than red pixels, with the area extent of the projected new residential development in the 2 m concentrated high quantity scenario output map extending approximately 90 to 200 m farther than the extent in the 30 m output map. This map difference is the most visibly striking of the differences caused by the spatial resolution of the calibration data.

The example labeled as (2) in Figure 8 shows map disagreement resulting from feature edge mis-match. Feature edge mis-match in this case is caused by the differences in the representation of feature boundaries between the 2 and 30 m calibration data. The 2 m spatial resolution results in a finer edge along feature boundaries as compared to the 30 m spatial resolution.

The example labeled as (3) also shows map disagreement due to vector to raster conversion. We examined these locations further by comparing 1:5,000 color orthophotographs from 2005 (MassGIS, 2009) with the original 2005 vector land-use data. The orthophotographs indicate that the straight feature is a railroad line through wetland. The 2005 land-use vector data indicates the line is forest. The 2 m raster land-use data for 2005 considers the line as forest. The 30 m raster land-use data for 2005 considers the line as wetland. The 2 m scenario map shows residential gain, whereas the 30 m map shows non-residential persistence. The cartographic error in the 2005 vector data, in this case a land-use misclassification, is transferred to the 2 m raster data because the finer spatial resolution allows for representation of finer features in the calibration data. The 30 m output did not transfer the misclassification, because the 30 m pixels are coarser than the incorrectly classified feature in the vector land-use map. This example illustrates how cartographic error in a model's calibration data may be more easily transferred to the results via vector to raster conversion, if the calibration data are of a fine enough resolution to enable the transfer.

The example labeled as (4) in Figure 8 shows map disagreement due to the spatial resolution of the data along the study area boundary. Here, the edges of the study area do not match because of the different pixel spatial resolution. Like example (2), example (4) highlights a case in which spatial resolution causes differences in model output because of its effect on the definition of a feature's edge.

4.2. Advantages of 30 m Data

The results of this study indicate that 30 m spatial resolution data offers substantial practical and theoretical advantages over 2 m resolution data when simulating residential development at the town level. This study found that using 30 m data reduces the transfer of cartographic error in the input data to the model outputs. Example (3) in Figure 8 shows how one cartographic error such as a land-use misclassification in the 2005 land-use data is transferred to the 2 m model output, but not to the 30 m output, because the feature causing the error is smaller than the minimum feature size captured in the 30 m data. This example suggests that any cartographic error or slight misalignment in the input data could be transferred to a model output, if the spatial resolution used in the model is small enough to represent the error. While any spatial resolution has the potential to transfer cartographic error in the input data to model output, finer spatial resolution data are more prone to transferring small cartographic errors that would be masked by coarser data. This effect is especially apparent when rasterizing fine resolution vector data.

Coarser spatial resolution data also offer a theoretical advantage, in that interpretations of model output may be more consistent with ground observations. Smaller pixels are often difficult to substantiate at local and regional scales; for example, a building or residential lot may be composed of 40 or more 2 m pixels, whereas one 30 m pixel may be sufficient to encompass an entire building or a large portion of a lot. The difficulty of interpretation is pronounced when features on the landscape are modeled at a fine enough resolution that a contiguous parcel, lot, or building is not apparent in the output because a model must classify a very large number of contiguous pixels consistently in order to represent any feature that could exist on the ground. For example in this study, there is difficulty in interpreting any isolated 2 m pixel that the model classifies as residential development, since a single pixel does not cover enough area to represent a contiguous feature such as a building or lot.

Suburban residential development in Massachusetts generally occurs in patches that include more than one individual parcel. In the town of Lynnfield, individual residential ownership parcels are on average 0.25 ha. The spatial resolution of the pixels in the maps is 2 m, which translates to 0.0004 ha per pixel. Thus the pixel is much smaller than the average residential parcel. Residential land change occurs at the parcel resolution or coarser, thus simulating land-use change at a 2 m by 2 m pixels is problematic when the 0.25 ha average residential parcel size in Lynnfield is more equivalent to 50 m by 50 m pixels. It is difficult to interpret the results of a model when large discrepancies exist between the resolution of the pixels and the resolution of the phenomena being modeled. Common LUCC model features such as parcels, lots, and buildings may be more easily captured when the resolution of the data matches the resolution of the phenomenon.

From a practical standpoint, coarser spatial resolution data also reduces data processing and management requirements. In general, calculation time has been found to increase exponentially with the total number of pixels in a raster dataset (Hengl, 2006). Dietzel and Clarke (2004) found computational time for the SLEUTH model doubled when the resolution of input data went from 400 to 200 m. GEOMOD model runtimes for the model in this study ranged from 20 minutes to 96 hours for the 2 m data, while runtimes for the 30 m ranged from 20 minutes to 1 hour. Runtime for both datasets depended on the particular modeling scenario. We found any resolution finer than 2 m was impossible with our desktop computer due to memory limitations. Data management requirements for the finer resolution data were also greater than those for the coarser 30 m data. For example, the input rasterized 2005 land-use map requires 30 megabytes of hard disk drive storage in its 2 m resolution form, and only 0.13 megabytes in its 30 m resolution form.

Another practical advantage of using coarser data is that many standard spatial data products have a spatial resolution of 20 to 250 m (Rogan and Chen, 2004). Coarser data that are near 30 m spatial resolution are more readily transferable, compatible, and comparable with standard and widely available satellite products such as Landsat (30 m) and MODIS (250 m ~ 1 km) (Rogan and Chen, 2004) and standard land-cover products such as the 30 m Coastal Change

Analysis Program (C-CAP) (NOAA, 2010), Gap Analysis Program (GAP) (USGS, 2010), and the National Land Cover Database (NLCD) (EPA, 2007). Coarse spatial resolution data are also more compatible with statistical data, such as census data and economic indicators that are often used as ancillary data in LUCC modeling (Agarwal et al., 2002; Munroe and Muller, 2007; Alcamo et al., 2008).

4.3. Advantages of 2 m Data

Fine spatial resolution data, such as the 2 m data used in this study offers a few advantages over coarser spatial resolution data for town level LUCC modeling. Fine spatial resolution pixels can capture smaller landscape features that may be lost in coarser resolution data. Examples of such landscape features can include linear corridors for transporttation or utilities and fine scale land-use of areas that tend to border or separate other land-uses such as forested land that may separate residential parcels in suburban areas. Additionally, fine spatial resolution pixels represent boundaries and edges of features on the landscape more realistically, creating smoother feature edges that correspond more closely to ground observations.

4.4. Recommendations for Selecting Spatial Resolution

Ideally, spatial resolution should be compatible with processing capabilities and should represent relevant landscape features (Woodcock and Strahler, 1987; Hengl, 2006; van Delden et al., 2011). In reality, however, LUCC modelers do not often have the luxury of selecting the spatial resolution of calibration data. The most accessible data available are frequently a main determinant of spatial resolution.

Many scholars provide basic heuristics that can be used to inform the selection of spatial resolution. For example, McBratney (2003) suggests selecting a spatial resolution in which at least 2 x 2 pixels represent the smallest rounded object of interest and at least 2 pixels represent the width of elongated objects. Dietzel and Clarke (2004) recommend using a spatial resolution of approximately 10 m to capture land change occurring at the parcel level, and a resolution of 250 m to 1 km to capture changes occurring at the national level. It is clear from the variety of recommendations in the literature that there is no one optimal spatial resolution, but only approximate ranges applicable in specific circumstances. Any spatially explicit process has an inherent spatial resolution (Agarwal et al., 2002; Evans and Kelley, 2004; Hengl, 2006), and attempts to model land change processes at spatial resolutions finer or coarser than the process' inherent spatial resolution will likely fail to represent the process' spatial variability (Agarwal et al., 2002; van Delden et al., 2011). For example, the process of local parcel level land-use change is not represented well by 2 m pixels, as our study demonstrates.

5. Conclusions

The objective of this study is to assess the advantages and disadvantages of using 2 m data versus 30 m data in a spatially explicit land-use and land-cover change model, using a case study in suburban USA. The results underscore the importance of spatial resolution in LUCC modeling, and highlight particularly important implications for local and regional scale modeling. This study demonstrates that differences in the spatial resolution of calibration data can produce measurable differences in LUCC model outputs, even when all other modeling steps are the same.

The 2 and 30 m output maps differ in their respective quantities of projected 2055 residential land-use by approximately 32 ha, i.e. 1.2% of the town. This area difference is equivalent to approximately 128 average size residential parcels, which have an average residential parcel area of 0.25 ha for the town of Lynnfield. The two output maps also differ in their spatial allocation of residential development. Differences in spatial allocation are caused by differences in the definition of feature edges between the two resolutions, with the 2 m resolution producing smoother edges, and by the greater tendency of the 2 m data to transfer small imperfections in the original vector map to the final model output. The combination of quantity and allocation differences results in output maps that are visually distinctive.

The 30 m data offers both practical and theoretical advantages over the 2 m data in our case study. Practical advantages include less transfer of imperfections in the input data to the outputs, lower data handling requirements, and greater compatibility with standard satellite and non-remotely sensed statistical data. The theoretical advantages include a closer match between pixel size and the scale of the process being studied, since new residential development occurs in patches closer in size to 900 square meters than 4 square meters.

The 2 m data offers better representation of smaller features and edges. However, improvements in landscape representation at this resolution do not offer any substantial analytical benefit for our case study.

The results of this study support the existing consensus in the LUCC modeling literature regarding the potential of spatial resolution to alter the parameters and outputs of a LUCC model (Evans and Kelley, 2004; Pontius et al., 2004a; Jantz and Goetz, 2005; Pontius et al., 2007; van Delden et al., 2011), reinforcing the conclusion that spatial resolution is a critical consideration in LUCC modeling. Most importantly, this study confirms and extends this knowledge to spatial resolutions finer than that traditionally used in the LUCC modeling literature, i.e. finer than 20 m, informing modelers who seek to utilize very fine spatial resolution data. It is evident that as finer resolution land-use data become available, the selection of spatial resolution will remain a pertinent and important factor in the selection of data, the calibration of models, and in the interpretation of model output. The spatial resolution of data should always be considered in the design, implementation, and interpretation of a LUCC model, as its effects on model output may be substantial. An investigator should not assume that it is preferable to use data at a resolution finer than the minimum resolution of the modeled phenomenon; in fact, the opposite may be true. Modelers are offered greater advantages when the size of the unit of the map matches the size of the unit of the phenomenon of interest.

Acknowledgments. The United States' National Science Foundation (NSF) supported this work via the following programs: Long Term Ecological Research via grants OCE-0423565 & OEC-1058747, Coupled Natural Human Systems via grant BCS-0709685, and Research Experiences for Undergraduates via grant SES-0849985. Human-Environment Regional Observatory (HERO) of Central Massachusetts at Clark University provided additional support. The Commonwealth of Massachusetts, Massachusetts Geographic Information System, Office of Geographic and Environmental Information, Executive Office of Energy and Environmental Affairs supplied data. Dr. John Rogan, Dr. Yelena Ogneva-Himmelberger, and anonymous reviewers provided helpful comments.

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