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Forecasts of habitat loss and fragmentation due to urban growth are sensitive to source of input data

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ABSTRACT

The conversion of natural habitat to urban settlements is a primary driver of biodiversity loss, and species' persistence is threatened by the extent, location, and spatial pattern of development. Urban growth models are widely used to anticipate future development and to inform conservation management, but the source of spatial input to these models may contribute to uncertainty in their predictions. We compared two sources of historic urban maps, used as input for model calibration, to determine how differences in definition and scale of urban extent affect the resulting spatial predictions from a widely used urban growth model for San Diego County, CA under three conservation scenarios. The results showed that rate, extent, and spatial pattern of predicted urban development, and associated habitat loss, may vary substantially depending on the source of input data, regardless of how much land is excluded from development. Although the datasets we compared both represented urban land, different types of land use/land cover included in the definition of urban land and different minimum mapping units contributed to the discrepancies. Varying temporal resolution of the input datasets also contributed to differences in projected rates of development. Differential predicted impacts to vegetation types illustrate how the choice of spatial input data may lead to different conclusions relative to conservation. Although the study cannot reveal whether one dataset is better than another, modelers should carefully consider that geographical reality can be represented differently, and should carefully choose the definition and scale of their data to fit their research objectives.

1. Introduction

A primary driver of environmental change and biodiversity loss is the conversion of natural habitat to urban settlements (Vitousek et al., 1997; Sala et al., 2000). Some regions, such as Mediterranean-type ecosystems, may experience disproportionate impacts of land use change on biodiversity due to high species endemism and rapid growth in population density and urban area (Underwood et al., 2009). In spite of the significant attention paid to climate change, land use change may produce far greater short- and long-term impacts on biodiversity (Slaymaker, 2001).

The spatial pattern of development at landscape scales, i.e., dispersed, low-density housing vs. clustered, high density housing, may have important, but varying conservation impacts. For example, dispersed development may consume more land and lead to more widespread ecological degradation (Xie et al., 2005), but clustered developments may be dominated by greater proportions of non-native vegetation (Lenth et al., 2006). Fire risk in wildfire-prone regions has also been related to the spatial pattern of development, with the highest risk occurring where there is intermediate housing density (Syphard et al., 2008). The spatial pattern of urban development can also affect hydrology, nutrient cycling and microclimate (Artur-Hartranft et al., 2003), and thus the provision of ecosystem services that benefit society (Solecki and Oliveri, 2004).

To better understand development patterns and to predict where future growth is likely to occur, and what impact it might have, many conservation scientists and land use planners use urban growth models. While urban modeling has a long history (e.g., Tobler, 1970), increased computing power has greatly expanded the range of problems that can be addressed (Guhathakurta, 1999; Ward et al., 2000; Paegelow and Olmedo, 2008). The complexity

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of these problems highlights the need to understand the sources and range of uncertainty associated with different aspects of the modeling process (Foody and Atkinson, 2003).

A potential source of uncertainty is the spatial input to the models (i.e., the maps of prior urban extent). The data used to create maps of urban extent come from a variety of sources (Varma, 2002; Pontius et al., 2008); urban maps vary not only according to their spatial and temporal resolution (such as a grid cell size, the smallest polygon in a vector map, or time between dates), but they may also be created using different classification schemes that define what type of land is included as "urban."

Ideally, the decision about what classification scheme or map resolution is used to define urban land will depend on the objective of the application (Jensen, 1996). However, in practice, the maps that are used for modeling (or data used to create maps) are ultimately selected from those that are available. Data availability, access, and distribution present an ongoing challenge for modelers (Varma, 2002), particularly if maps of historic urban extent are needed to calibrate models of future urban growth, because these data often simply do not exist.

Since so many management and conservation planning decisions are now based on the projections of spatially explicit models of landscape dynamics, there may be major implications of how different urban maps affect which parts of the landscape are projected to become urbanized. Furthermore, even if the same general areas are predicted to become urban, the spatial pattern of predicted development may not be fully represented depending on the scale and classification of urban land. For example, the projected patterns of urban development have been shown to vary depending on the resolution of grid cells used in land use change modeling (Jantz and Goetz, 2005). Nevertheless, in part due to limited availability of maps of historical urban extent, there have been few studies that have explored how different sources of urban input data may lead to differences in the spatial predictions of urban growth projections. This is in spite of examinations of model sensitivity to data temporality, land use class aggregation, calibration methods, number of Monte Carlo iterations, and other factors (Clarke, 2008a).

The objective for the current study was to explore the implications of data source and resolution of urban maps used as input for modeling future urban development, in the biologically rich, but rapidly developing county of San Diego, CA, USA. The negative effects of habitat loss and fragmentation on species and ecological communities are well documented in southern California (Soulé et al., 1992; Bolger et al., 1997; Suarez et al., 1998). We compared a readily available, consistent national data product with input data typical of what is usually used (combined from different sources, but based on finer-scale mapping) to determine what differences were apparent in the urban predictions. We conducted our analysis for three scenarios based on different locations and extent of land excluded from development.

We asked:

1) How do differences in definition and scale of mapped historic and current urban extent affect the rate, extent, location, and spatial pattern of simulated future urban development?

We expected the scale of the input would affect the patterns but not the rate of projected urban growth, and that finer-scale input would better capture new growth centers.

2) Do different input data sources differentially impact certain native habitats?

Historically, urban growth has particularly impacted the sage scrub ecological community because of its occurrence on the coastal plain (O'Leary, 1995). However, we expected future urban development to impact other habitats depending on the source of input data.

3) Does the influence of data source on simulated urban development vary when different amounts and locations of land are excluded from development (i.e., for conservation)?

We expected simulated urban development to be less sensitive to the scale of input data when larger areas of land were protected, and the sensitivity to scale would vary depending on the location of protected areas relative to potential urban growth.

2. Methods

2.1. Study area

The study area included all land within the boundary of San Diego County (almost 12,000 km^2). The primary vegetation types in the county include chaparral and sage scrub shrublands, interspersed with oak woodland, grassland, vernal pools, and coniferous and riparian forests (Keeley, 2000). The primary threat to both flora and fauna in the region is habitat conversion due to urban development (Regan et al., 2008).

Of California's 58 counties, San Diego County is the third most populous, with more than 3 million inhabitants. The county experienced a 522% increase in population over the last half of the 20th century, and about one million new residents are expected in the region by 2030 (SANDAG, 2008). Most urban development has been concentrated along the coast. As the amount of vacant land within these cities fills up, more and more development has pushed eastward into the unincorporated part of the county.

2.2. Description of urban growth model

To simulate urban development, we used SLEUTH (Clarke et al., 1996; Clarke and Gaydos, 1998), a mature and widely used cellular automaton model. Cellular automaton models show promise for forecasting long-term changes in land use because they are nonlinear and non-deterministic, and they embed complexity into their behavior, both in the past and the future. SLEUTH is attractive for estimating the intermediate and long-term impacts of issues pertinent to environmental management, such as habitat loss, fragmentation effects, climate change, and fire regime, because, among the many land use change models, it has a record of extensive application to different regions around the world with good results (Clarke et al., 2007), and it has been extensively tested for its sensitivity to most of its controlling elements (Clarke, 2008b).

SLEUTH is an acronym for the gridded map inputs required by the model: slope, land use, exclusion (areas restricted from development), current and historical urban extent, transportation, and hillshade. There are four types of growth rules and five parameters (Table 1) that control the urban development process through repeated application that govern state changes over time. The model is also self-modifying (using a second hierarchy of growth rules) so that during model runs, unusually high or low growth rates can lead to either a slowing down or a speeding up of urban expansion through modification of the growth–control parameters. Typically, the parameter values during a model run increase most rapidly in the beginning of a growth cycle, when many cells are open for urbanization, and decrease as urban density increases in the region and expansion declines (Clarke and Gaydos, 1998).

At least four separate data layers of historical urban extent (representing different dates) and two additional data layers of transportation (roads) (dates do not have to be the same as the

Table 1
Description of controlling coefficients in the SLEUTH urban growth model and the calibrated coefficient values for two different urban datasets. Zero is absence of the factor, 100 implies unrestricted growth of this type (Silva and Clarke, 2002).

Control Parameter	Description	SILVIS Coefficient	SANDAG Coefficient
Diffusion	Determines the overall outward dispersion of development	1	98
Breed	Specifies the likelihood for a newly generated detached settlement to begin growing.	1	92
Spread	Controls the amount of expansion from existing settlements.	95	18
Slope Resistance	Influences the likelihood of settlement extending up steep slopes.	1	100
Road Gravity	Attracts new settlements toward and along roads.	6	40

urban extent) are needed as model inputs for calibration. In the calibration process, five variable parameters are maximized through an iterative process so that the simulated behavior of urban development matches the historic development behavior. SLEUTH uses an annual cycle, and accounts for calibration data that are unevenly spaced across time by using regressions of modeled versus measured values for 13 measures of goodness of fit. This calibration process therefore finds the specific combination of parameters that describe the spatial and development characteristics of each individual region (Silva and Clarke, 2002).

2.3. Spatial input

2.3.1. SILVIS data

The source of the first dataset (hereafter referred to as SILVIS, after the research group who developed it) was a national data product in which housing density was mapped in the continental U.S. every decade from 1940 to 2000 (Hammer et al., 2004; Fig. 1, Table 2). The housing density was measured as housing units per square kilometer, and the minimum mapping unit for these data was the partial census block group. The size of partial block groups varied widely, but for San Diego County, the smallest urban polygon in 2000 was 0.092 ha and the mean was 26 ha.

To convert the data into binary urban extent (i.e., land classified as "urban" or "undeveloped"), we selected a housing density threshold in which the urban extent of SILVIS data for year 2000 best matched the urban extent in an independent data source for the same year, a "development footprint" in which the United States Geological Survey's National Land Cover Database (NLCD) land cover classes were used to define urban areas at 30 m resolution (http://frap.cdf.ca.gov/). This development footprint included all areas with housing density of 1 unit per acre or more plus the following classes from the NLCD land cover data: bare rock, sand/clay, quarries, strip mines, commercial, industrial, urban/recreational grasses. The comparison revealed that a threshold of 128 units/km^2 in the SILVIS data provided the best spatial fit in terms of total urban extent and co-occurrence of urban areas. We therefore assumed that, although SILVIS did not explicitly include urban land use/land cover types per se, those areas mapped as high density development in SILVIS (which was actually based on a lower housing density than was used in the FRAP data to define urban land use) generally included those other urban land use/cover types within the urban map units. 12.3% of the landscape was urban in the FRAP data versus 11.5% in the SILVIS data, and more than 90% of the map was classified the same between the two maps when they were overlaid.

2.3.2. SANDAG data

For a previous study using the SLEUTH model, historical urbanization data in the second data set (hereafter referred to as SANDAG after the San Diego Association of Governments http://www.sandag.org) were compiled for five time periods: 1960, 1975, 1990, 1995, and 1999 (McGinnis, 2001) (Fig. 1, Table 2). The 1960 and 1975 data layers were derived from historical development and land use maps and produced to show urban extent for those years. The 1990, 1995, and 1999 urban layers, available in digital form, were compiled by aggregating land use categories to reflect the spatial extent of urbanization. A modified version of the Anderson Level I Land Use Classification system was used to delimit urban areas by including residential, commercial, industrial, transportation, and mixed urban/build-up land categories (McGinnis, 2001). The size of urban polygons varied widely; the minimum size of urban polygons in 1999 was 0.001 ha, and the mean was 193 ha. Also, 14.5% of the landscape was urban in 1999 (compared to 11.5% for the SILVIS data).

2.3.3. Transportation

The historical transportation data layers for years 1960, 1993, and 1997 were derived from two different sources: the 1993 and 1997 layers were available in digital form from SANDAG, and the 1960 layer was compiled from a map provided by the San Diego County Department of Planning (Fig. 2, Table 2). The map was scanned and on-screen digitized to derive the transportation network for San Diego County in 1960. The data included arterial and collector roads, minor highways, major highways, and interstate highways.

2.3.4. Exclusion maps

We developed three map layers to represent different scenarios of land protection (Fig. 2, Table 2). The data for these layers were derived from: 1) the management landscape GIS layer from the California Department of Forestry and Fire Protection (http://frap.cdf.ca.gov) that depicts areas as urban, agricultural, conservation reserves, or managed for commodity output, and separates them into public and private ownership categories, 2) the SANDAG GIS layer depicting land available for future development, and 3) the San Diego County Multiple Species Conservation Program (MSCP) lands that are protected from development and not included in the reserved lands defined in the management GIS layer (Scott and Sullivan, 2000; Greer, 2004). We also excluded water bodies (e.g., lakes, rivers, reservoirs) from development in all scenarios. Areas considered developable included private lands (including private agricultural lands) but no private/public reserves or public land (including public agriculture).

The first scenario allowed development to occur on any privately owned land in the county. In this scenario, public land (e.g., national forest, Indian reservations, military lands, Bureau of Land Management, etc.) was restricted from development, but reserves (areas protected from conversion of natural land cover, equivalent to Gap management status 1 and 2; Beardsley and Stoms, 1993) were available for development. In the second and more restrictive scenario, all public lands and reserves (public and private) were restricted from development, which contributed to a substantial increase in excluded land (23, 49, and 51 percent of the landscape excluded in scenarios 1, 2 and 3, respectively) (Fig. 2).

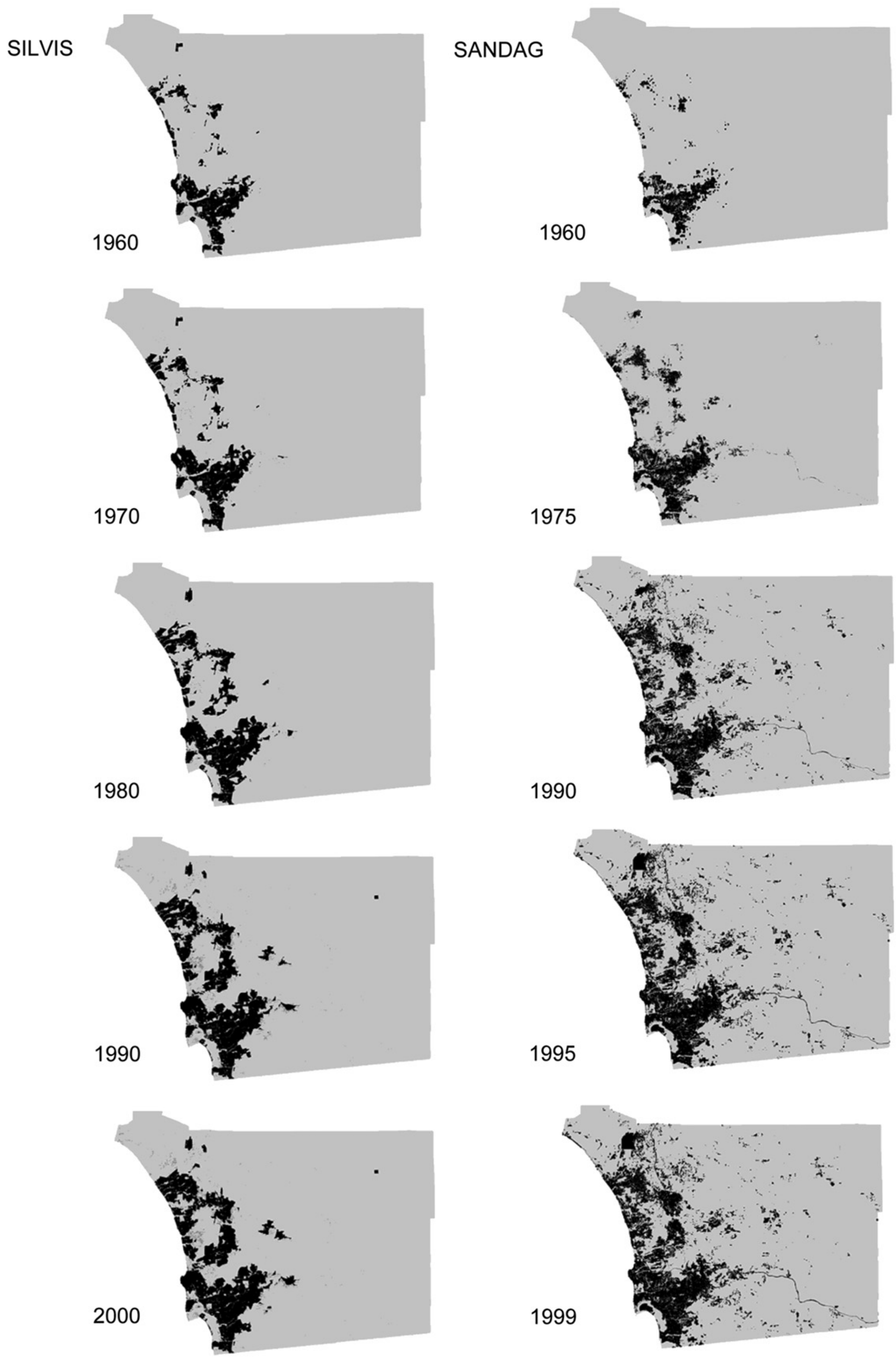

Fig. 1. Maps of urban land cover for San Diego County from five historical dates derived from the SILVIS data using a threshold of housing density as described in the text (left column), and derived from SANDAG land use/cover maps by SANDAG (DATE) in the right column.

Table 2
Urban Growth Model input datasets.

Data set	Type	Data description	Source	Resolution/Scale	Date	Extent
SILVIS	Urban	Housing density >= 128 houses/km^2	UW-Madison [a]	U.S. Census, partial block groups1	Decadal, 1940 – 2000	Continental U.S.
SILVIS		Development footprint	CDF[b]	1:100,000	2000	California
SANDAG		Historical development maps, hard copy	SANDAG[c]		1960, 1975	San Diego County
SANDAG		Digital land use maps, Anderson Level I urban	SANDAG[c]		1990, 1995, 1999	San Diego County
SILVIS and SANDAG	Roads	Historical road map, hard copy	SANDAG[c]		1960	San Diego County
SILVIS and SANDAG		Digital road network	SANDAG[c]			San Diego County
SILVIS and SANDAG	Hillshade	From Digital Elevation Model (DEM)	USGS[d]	30 m	N/A	Continental U.S.
SILVIS and SANDAG	Slope	From Digital Elevation Model (DEM)	USGS[d]			
SILVIS and SANDAG	Excluded (a–c)	Management landscape	SANDAG[c], CDF[b]	1:100,000	2000	California

[a] Hammer et al., 2004
[b] California Department of Forestry and Fire Protection.
[c] San Diego Association of Governments.
[d] United States Geological Survey a). Owned by local, state, or federal government, or special districts b). Includes a) and USDA Forest Service, Bureau of Land Management, GAP Management Status 1 and 2 (1996), and Dept. of Parks and Recreation lands c) Includes b) and land protected under the Multiple Species Conservation Program.

2.4. Model calibration and prediction

SLEUTH uses brute force calibration, that is, all combinations and permutations of the control parameters are tested and matched against the known historical data to see which parameter set best fits the observed dynamics. We used the calibration process documented by Silva and Clarke (2002) for both of the datasets. The only spatial data that differed were the two time series of urban extent, while transportation, hillshade, slope, and excluded layers (Table 2) were common to both datasets. All GIS data were converted to raster format with a 60 m cell size and then to 8-bit grayscale GIFs, as required by SLEUTH. We used the optimal SLEUTH metric (OSM) to rank parameter combinations, using a stand-alone C language program to compute and sort the value from the SLEUTH log files (Dietzel and Clarke, 2007).

Once we derived the best parameter combinations from the final stage of calibration, we determined our prediction values (used as starting values for future growth prediction) from a parameter averaging step. For both datasets, we simulated future development for 2000–2050 for the three different exclusion layer scenarios. For these six prediction scenarios, we simulated 100 Monte Carlo iterations to determine growth probabilities (Goldstein et al., 2005); each iteration was independent in that it used a unique pseudorandom number seed.

2.5. Analysis of results

To quantify the extent and pattern of urban development for the two datasets, we converted the SLEUTH model output (GIFs representing probability of development) into raster GIS data using three different classes representing: 1) high-probability of development (90%–100% of the cells in the 100 Monte Carlo iterations predicted to become urban), 2) low – medium probability of development (50–90% of the cells predicted to become urban) and 3) undeveloped land. To answer our research question about differences in the extent and spatial pattern of predicted development, we calculated several landscape pattern metrics using the Fragstats software (McGarigal et al., 2002) to compare spatial and temporal patterns of development across the datasets and exclusion scenarios. We restricted our analysis to three simple metrics since many metrics tend to be highly correlated (Riitters et al., 1995). We calculated the percent of landscape occupied by each class to determine how differences in urban input affect the extent and rate of development. To quantify differences in landscape pattern of predicted urban development, we also calculated number of habitat patches (an indicator of fragmentation). We also calculated the largest patch index (LPI), which measures the percentage of the landscape that is contained within the largest patch in the landscape, indicating whether or when large blocks of habitat are broken up. For the three scenarios and two datasets, we calculated these metrics for every year from 2000 to 2050.

We also overlaid binary maps of urban predictions, created by only including land with a high-probability of development from each dataset for the three exclusion scenarios from 2000–2050. This allowed us to map and quantify where urban growth predictions converged over time and where the models predicted urban development in different areas.

Finally, to determine the extent to which predictions based on different input data impacts vegetation types differentially, we overlaid the binary maps of urban extent from the two datasets on a vegetation map of the county for years 2000 and 2050 and calculated the percent change in vegetation type over time for the three scenarios. The vegetation dataset was compiled from various sources by the San Diego Geographic Information Source (http://www.sangis.org/Index.htm), and was updated in April 2007. We condensed the 167 vegetation classification codes into seven classes that represent the major vegetation types found in the county.

3. Results

3.1. Calibration

The final OSM for the SILVIS dataset was 0.665, and the OSM for the SANDAG dataset was 0.651. These OSMs were similar to those computed for other studies (Goldstein et al., 2005), indicating that the images created during SLEUTH simulations, and controlled by the parameter coefficients, produced measures of fit similar to previous studies, reflecting strong correspondence between the simulated and the historic data.

The final calibration parameters were very different for the two urban datasets (Table 1). For the SILVIS dataset, the primary parameter controlling development was the spread coefficient, which influences the expansion of development from existing settlements. For the SANDAG dataset, the spread coefficient was low, but the diffusion and breed coefficients, which control outward urban expansion and the development of new growth centers, were high. In the SILVIS data set, the slope resistance parameter was low, but in the SANDAG dataset, the high slope resistance parameter indicated that development was likely to occur on steeper slopes. Roads were not highly influential in determining growth patterns in either dataset.

3.2. Rate and extent of development

In all three of the exclusion scenarios using the SILVIS dataset, the projected rate of development was much faster, and the projected area of development was much more extensive, for high-

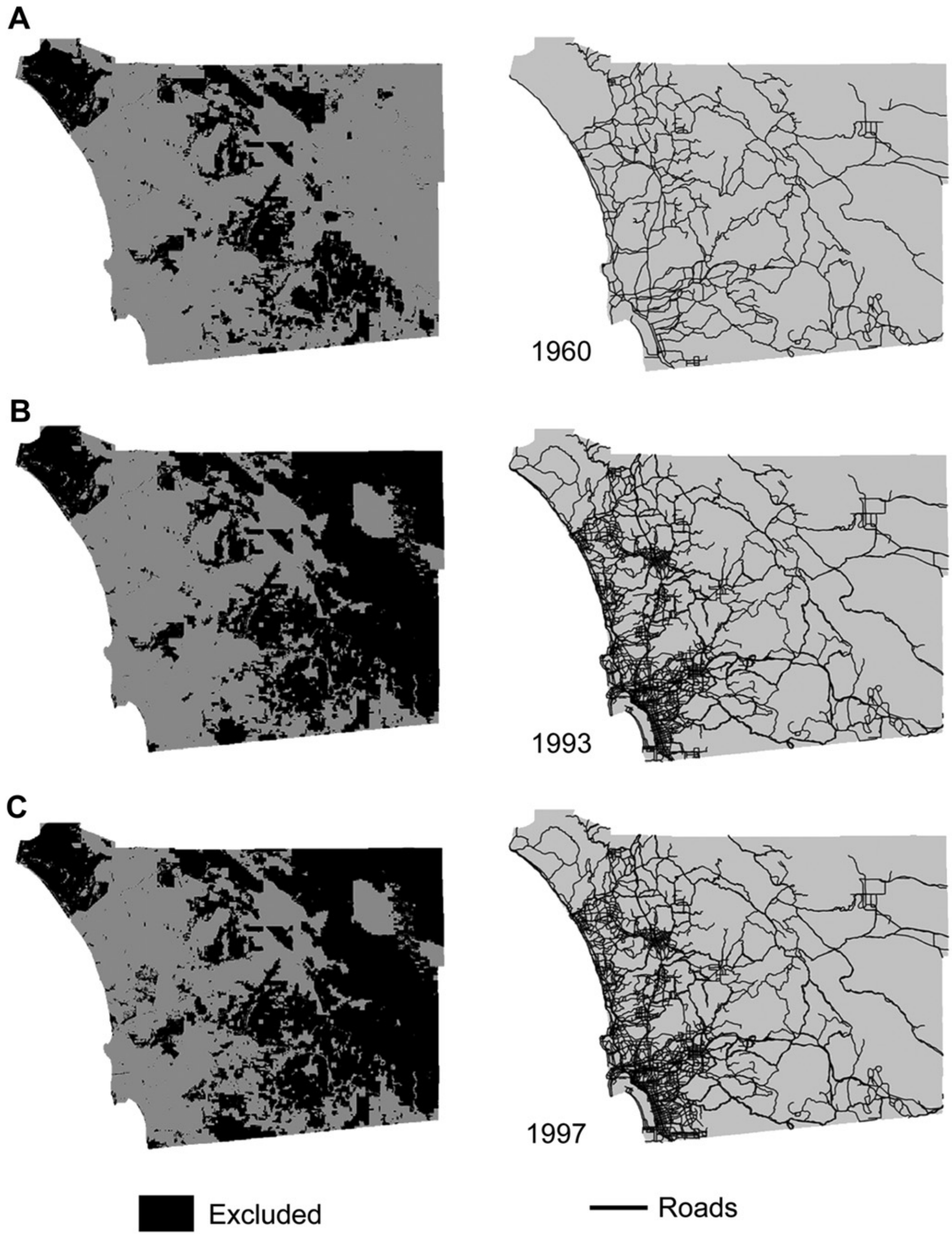

Fig. 2. Maps of areas excluded from development (left column) under three scenarios: A) public lands excluded from development; B) public lands and private reserves excluded C) public lands, private reserves and MSCP land excluded; and maps of road networks from 1960, 1993 and 1997 (right column).

probability development (90–100% chance of developing) than in the SANDAG dataset (Figs. 3a and 4). Larger percentages of the landscape were predicted to become developed when less land was excluded from development in both datasets. However, for high-probability development in the SILVIS dataset, there was a greater predicted difference between exclusion scenarios 2 and 3 than between excluded 1 and 2, despite the fact that substantially more land was protected in excluded 2 (compared to excluded 1) than excluded 3 (compared to excluded 2). In the SANDAG dataset, however, the projected percent of landscape developed with high-probability was commensurate with the amount of landscape protected (i.e., greater difference between excluded 1 and 2). Although the projected rate of high-probability development initially occurred quite rapidly in the SILVIS dataset, the rate slowed and leveled off over time. On the other hand, the projected rate of development in the excluded 1 scenario using the SANDAG dataset appeared as if it would stay the same, such that land would continue to be developed rapidly beyond 2050. This continued high rate of development was not apparent for exclusion scenarios 2 or 3 (Fig. 3).

Substantially more development was projected at a low-probability (50–90% chance of developing) in all three scenarios based on the SANDAG dataset than the SILVIS dataset; and again, more land was predicted to develop in exclusion scenario 1 than in exclusion scenarios 2 and 3 (Fig.3b, 4). The projected rate of low-probability development slowed and stabilized after about 20 years. Although the percent of landscape predicted to develop at a low-probability was initially higher in the SILVIS dataset than the

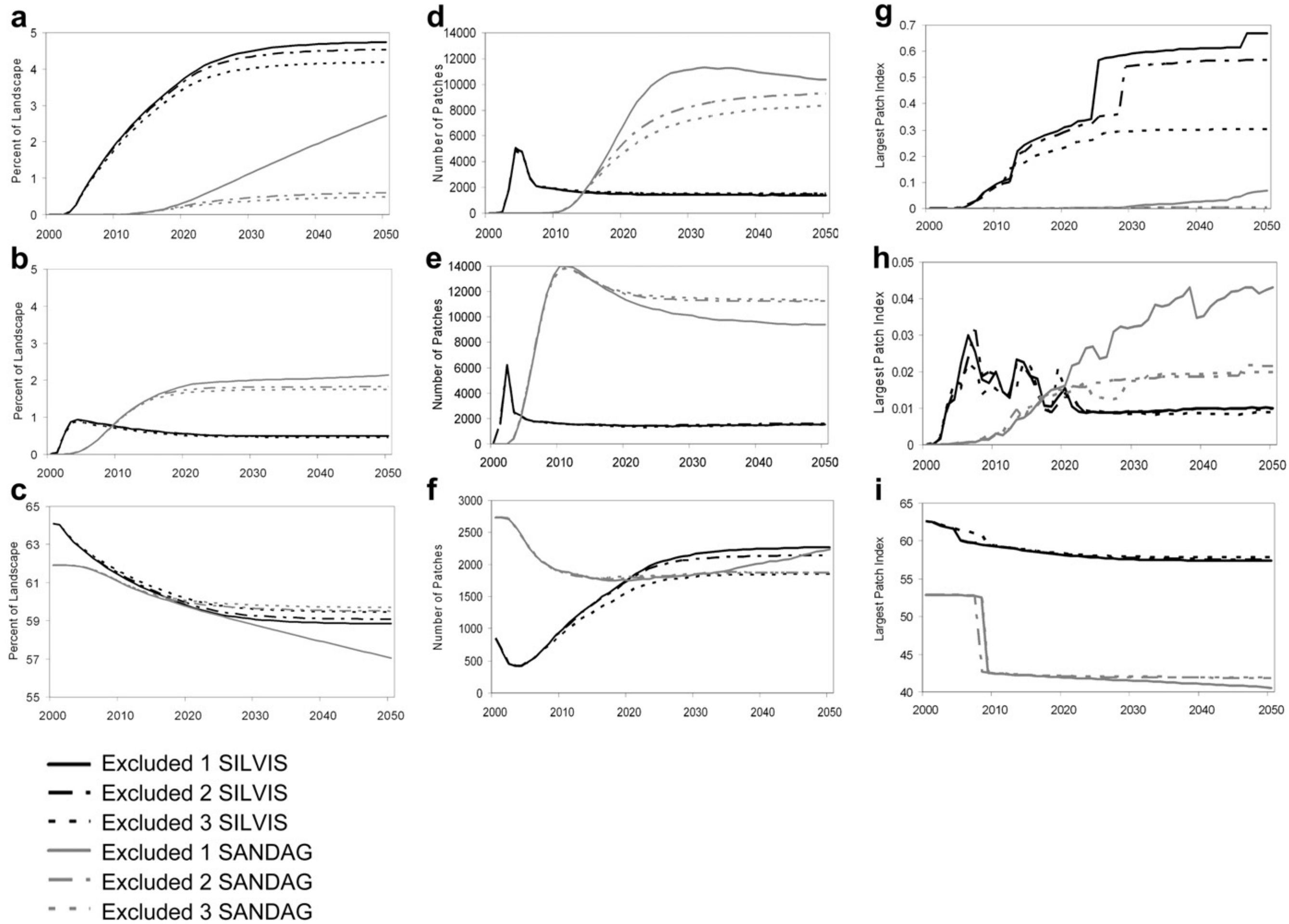

Fig. 3. Trajectory of landscape metrics over the course of the 50-year projections for each of six simulations, two urban extent datasets (SILVIS and SANDAG) and three exclusion scenarios (1, 2 and 3). Percent of Landscape occupied by: a) high-probability urban growth; b) low-probability urban growth; c) native vegetation; Number of Patches:; d) high-probability urban growth; e) low-probability urban growth; f) native vegetation; Landscape Patch Index: g) high-probability urban growth; h) low-probability urban growth; i) native vegetation. Please note the differences in *y*-axes between urban growth and native vegetation for all metrics and between the two probabilities of urban growth for the Largest Patch Index.

SANDAG dataset, the rate declined rapidly and remained stable after about 2015. There were no differences among the exclusion scenarios in the amount of projected low-probability development using the SILVIS dataset (Figs. 3b and 4).

When comparing the three exclusion scenarios for the two datasets, the amount of predicted vegetation loss was greatest for the excluded 1 scenario, but lowest for the excluded 3 scenario, of the SANDAG dataset (Fig. 3c). However, the differences among excluded 1 and 2 of the SANDAG dataset, and excluded 3 of the SILVIS dataset, were negligible.

3.3. *Number of patches and largest patch index (spatial pattern of development)*

For all three excluded scenarios, the SANDAG predictions resulted in a larger number of both high-probability and low-probability urban patches by the end of the simulations (Fig. 3d–e), and a smaller mean patch size (details not shown), than the SILVIS predictions. There was a greater difference in results between exclusion scenario 1 and scenarios 2 and 3 for the number of patches of low-probability development in the SANDAG predictions, but the differences between scenarios were closer to equal for high-probability development. For the SILVIS data, differences in number of urban patches were much smaller.

Whereas the SILVIS predictions, overall, had larger patches of high-probability development (LPI) than SANDAG, the SANDAG predictions had the largest patches of low-probability development (Fig. 3g–h). For the SILVIS dataset, exclusion scenarios 1 and 2 had considerably larger patches of development than exclusion scenario 3. On the other hand, there was a substantial separation between exclusion scenario 1 and scenarios 2 and 3 for patches of low-probability development in the SANDAG data.

Although the number of patches and mean patch size (details not shown) for vegetation were very different between the two urban datasets in the beginning of the simulations, the numbers started to converge after about 20 years (Fig. 3f, i). However, there was an upward trend for number of patches toward the end of the SANDAG excluded 1 scenario (Fig. 3f). For the SILVIS dataset, exclusion scenario 3 had substantially fewer patches than exclusion scenarios 1 and 2.

Although the number of patches between the two datasets started to converge, a substantially greater proportion of the landscape was occupied by the largest patch of vegetation in the SILVIS predictions than in the SANDAG predictions (Fig. 3i). This difference among datasets was much more substantial than the

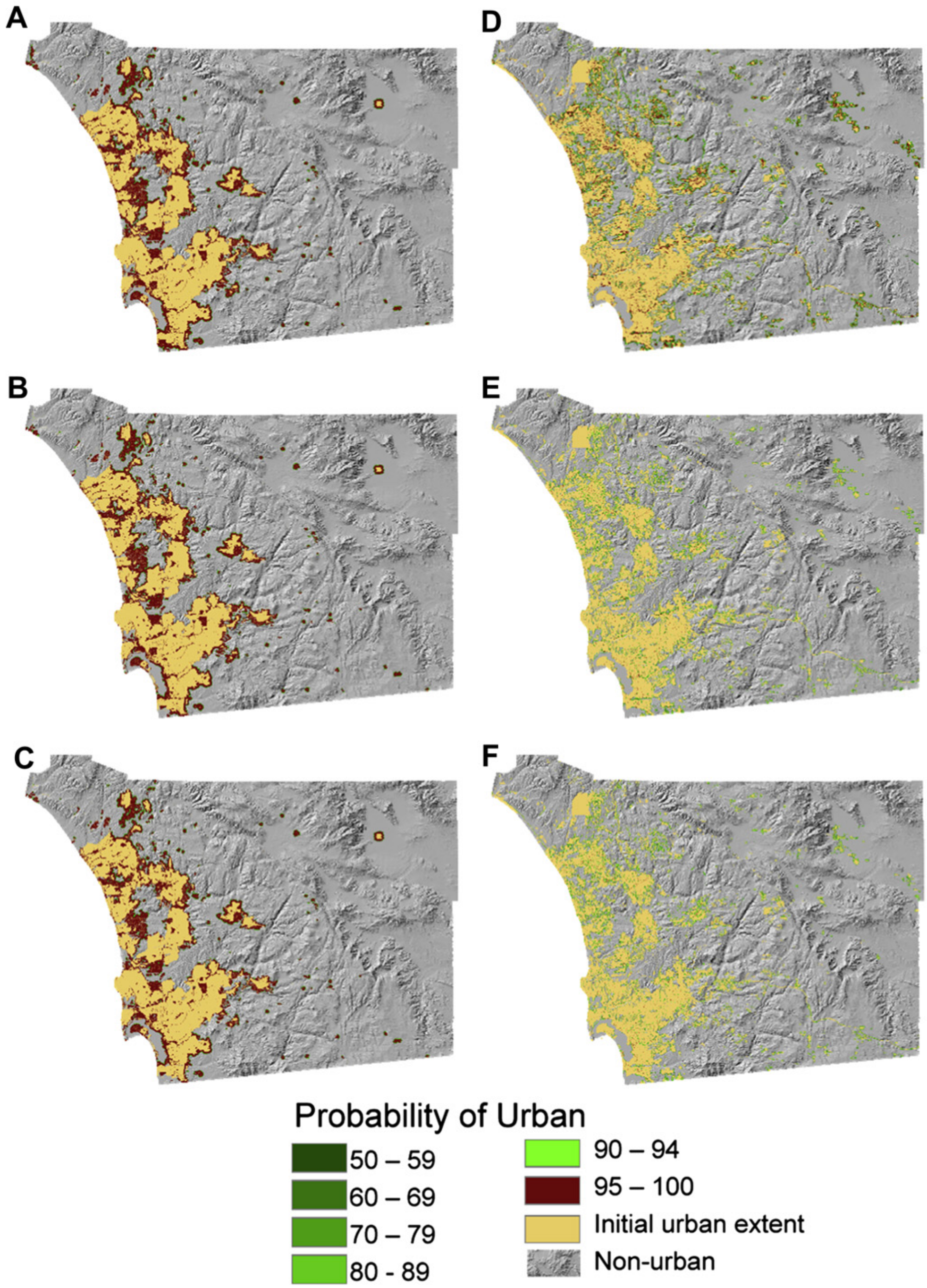

Fig. 4. Maps showing extent of predicted urban development at the end of each 50-year simulation based on SILVIS data and A) exclusion scenario 1; B) exclusion 2; C) exclusion 3, and SANDAG data and D) exclusion scenario 1; E) exclusion 2; F) exclusion 3. Probability of urban reflects the number of times the cell was predicted to become urban after 100 Monte Carlo iterations. Data on the amount and rate of development are shown in Fig. 3.

differences among exclusion scenarios. Nevertheless, there was a greater difference between exclusion scenarios 1 and 2 and scenario 3 and for the SILVIS predictions, and a bigger difference between exclusion scenarios 1 and 2 and scenario 3 for the SANDAG predictions.

3.4. Spatial overlap of predictions

The spatial overlay of urban growth predictions (high-probability development) from the two datasets showed that, while there was a substantial proportion of the study area where both models converged in their predictions, the SILVIS dataset resulted in more urban development predicted nearer to the coast (Fig. 4 A–C), while the SANDAG dataset predicted more urban development inland, in the eastern parts of the county (Fig. 4 D–F). These spatial patterns were largely consistent among the three excluded scenarios (Fig. 4). Also, the areas that SILVIS predicted would become urban (and SANDAG did not) tended to be clustered together and spatially more concentrated, whereas the SANDAG predictions were patchier and more dispersed (Fig. 5).

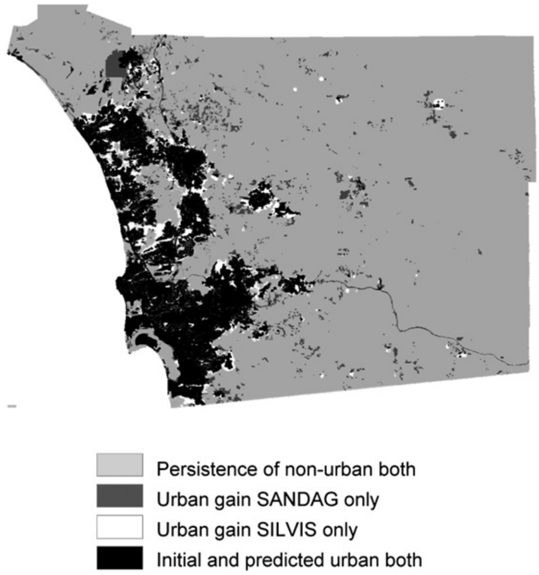

Fig. 5. Maps of spatial overlap between predicted urban extent from simulations based on SILVIS versus SANDAG data in 2050 and using exclusion scenario 2.

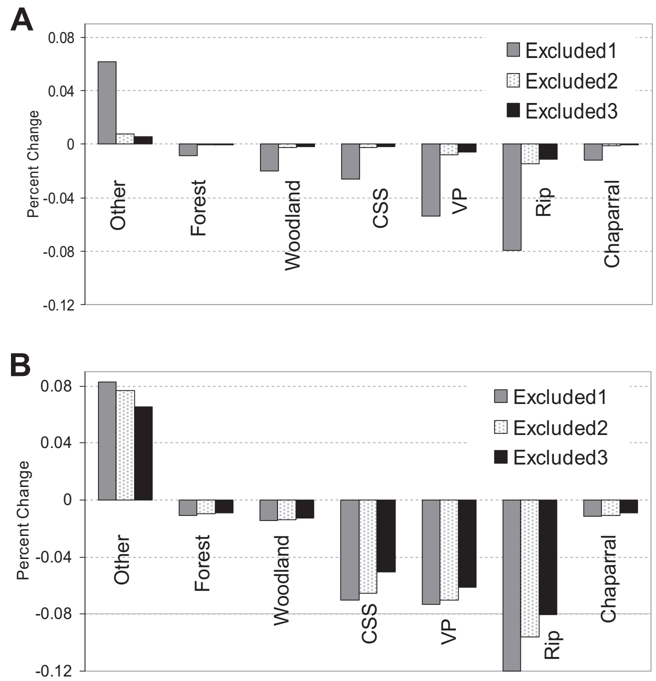

Fig. 6. Net percent change in the area of each land cover type shown in the A) SANDAG dataset and B) SILVIS dataset. Note that this shows the relative predicted impact of urban growth on habitat loss. Initial percentages of landscape for each habitat type are: Other (Urban and other land cover types) – 24%; Forest – 3%; Woodland – 6%; Coastal Sage (CSS) – 10%; Vernal Pools (VP) – 7%; Riparian (Rip) – 3%; Chaparral – 47%.

Over time, the percent of the landscape that was predicted to become urban by both models (i.e., spatial convergence in predictions) increased in all three of the exclusion scenarios (details not shown), but the rate and extent of convergence in predictions was greatest in the excluded 1 scenario (from approximately six percent to 10 percent of the landscape). The percent of landscape in which model predictions were different (i.e., the land was predicted to become urban by only one model) slightly declined in the beginning of the simulations and then remained constant over time in all three of the exclusion scenarios (from about seven to six percent of the landscape).

3.5. Impacts by vegetation type

The projected decline in vegetation types due to high-probability urban development varied according to the urban dataset as well as the exclusion scenario (Fig. 6 A–B). In both datasets, the riparian vegetation type experienced the greatest percent loss under all three exclusion scenarios. In the SANDAG dataset, vernal pools experienced the second largest percent loss in all scenarios, followed by coastal sage scrub, woodlands, and chaparral. In the SILVIS dataset, however, coastal sage scrub declined much more than it did in the SANDAG dataset and experienced the same amount of proportional loss as vernal pools for excluded scenarios 1 and 2. However, coastal sage scrub experienced substantially less decline in the excluded 3 scenario.

Because there was less predicted development in the excluded 2 and 3 scenarios (as seen in the percent gain of the “other” class) in the SANDAG dataset, there was also much less decline in vegetation for those scenarios. In the SILVIS dataset, however, there was generally a greater difference in vegetation change between excluded scenarios 2 and 3 versus 1 and 2.

4. Discussion

Our study underlines why it is important for users to understand and consider what their digital maps actually represent and why the representation of information in their data is or is not appropriate for the objective of their study. Although the datasets we compared both represented urban land in the same study area over the same time period, there were many differences in the data that likely contributed to the discrepancies in urban growth predictions. The SILVIS data are publicly available at the national scale, but have not been used as input to urban growth models before this study—the data have only been available since ∼2005. Whereas the data source and methods used to develop the SILVIS dataset were consistent across all decades, the SANDAG dataset was assembled using different sources. Due to frequent difficulties in acquiring historical GIS data, the SANDAG example is more representative of the methods typically used to assemble SLEUTH input (e.g. Jantz et al., 2003; Leao et al., 2004; Teitz et al., 2005).

In part because the datasets came from different sources, there were differences in the types of land use/land cover that were included in the definition of urban. Whereas the SILVIS data mostly captured housing density (although comparison with the FRAP data showed that many urban land uses were subsumed within our housing density threshold), the classification in the SANDAG dataset explicitly included a wider diversity of land use types. An example of this classification difference can be seen in Fig. 5 where SILVIS did not classify Naval Air Station North Island (adjacent to Coronado, CA) as urban, but the SANDAG data did; thus, SLEUTH projections based on SILVIS predicted high-probability urbanization on this military land. Another consequence of the differences in how urban land was defined is that a greater proportion of the landscape in the eastern portion of the county was designated as urban with the SANDAG dataset based on land use, while much of the housing density in those areas did not meet the threshold required to designate the land as urban in the SILVIS data. This may explain why there were differential impacts to vegetation types in the region and why there was a bigger difference between excluded layers 1 and 2 for SANDAG and between excluded layers 2 and 3 for SILVIS. It also strongly underlines that there may be serious implications of using different datasets to define urban in these types of models. There may also be variations in the processes that drive land conversion according to different urban land use/land cover types (Conway, 2009).

In addition to different definitions of urban in the two datasets, there were differences in scale imposed during spatial aggregation by partial census block group versus the boundaries of the land use layers, and we asked how these differences in definition and scale would affect simulated development. The SANDAG dataset had a much smaller minimum mapping unit than the SILVIS data (10 m^2 vs. 920 m^2), yet also had a much greater range of polygon sizes (maximum 193 ha vs. 26 ha). It is well known that spatially aggregating thematic data, whether grid or polygon based, will disproportionately affect categories that occur in small patches within the map, causing them to disappear (Moody and Woodcock, 1995). Furthermore, the minimum mapping unit may differ for classes, further distorting the inputs. In this study, this phenomenon led to a lack of small patches of isolated urban land cover in the national scale SILVIS data relative to the SANDAG data, which may be due to aggregation occurring for one class only (housing density) instead of multiple classes (land use categories).

The differences in scale and location of urban land resulted in very different calibration parameters for the two datasets, suggesting there may be different simulated drivers of growth behavior based on whether data are defined largely by housing density or defined based on a larger number of land use categories. The final OSM values for both of the urban datasets were similar to those for other study areas, indicating that the SLEUTH simulations produced a strong fit to the historic data. This means that the SLEUTH model was able to characterize the urban development patterns inherent in each of the two datasets very well, which makes it even more striking that the type of behavior generating those patterns was nearly opposite for the two datasets.

Although we did not expect the differences in definition and scale of input data to affect the rate of projected development, the rate of development was slower in the SANDAG dataset than the SILVIS dataset. Unlike the SILVIS data, which were available every 10 years, the length of time between dates varied in the SANDAG data (i.e., there were two 15-year gaps, followed by two 5- and 4-year gaps in the SANDAG data). The initially slower predicted rate of development in the SANDAG dataset may be because the model interpreted the rate of development to be slowing relative to the big jump from 1960 to 1975.

While the projected extent of urban development was similar between datasets, the pattern and location of projected development were very different, as we expected. Because of the differences in the spatial and categorical resolutions of the source data (SILVIS is coarser), SANDAG predicted the development of many small urban patches in the eastern portion of the county, outside of the main conurbation of coastal cities, which acted as foci of new growth in the simulations. These differences in patchiness were also confirmed by the trajectories of the landscape pattern metrics. Unsurprisingly, projections based on the finer-scale SANDAG data simulated larger numbers of urban patches and smaller maximum urban patch sizes.

Differences in location and spatial pattern of development may have major conservation and fire risk implications (Miller and Hobbs, 2002; Syphard et al., 2007). For example, the conservation value of clustered versus dispersed housing developments is an area of active research (Lenth et al., 2006), and the different datasets we evaluated provide two different pictures of how urban growth is likely to develop in the region. Managers could further analyze these results by comparing the different predictions to help guide land use planning and policy. By overlaying different development patterns with known and projected distributions of sensitive native species, conservation planners can get a better understanding of the potential threats to at-risk species. Conservation attention could then focus on areas that are not projected to be developed under any data set. Evaluating projected land use change from different datasets can also place bounds on plausible amounts of habitat loss which is useful when considering development impacts on the future threat status of native species (e.g. under the IUCN Red List categories and criteria, IUCN 2001). Additionally, in Mediterranean regions like San Diego, fire risk has been associated with intermediate housing density (Syphard et al., 2007, 2009), and more development in the eastern part of the county is likely to increase the number of fires that start.It is also more difficult for firefighters to defend houses that are more dispersed.The SANDAG predictions would therefore suggest a potentially greater increase in future fire hazard than the SILVIS predictions.

Another major difference between the datasets is that the majority of development in the SANDAG predictions occurred at a lower probability than for the SILVIS predictions. This may be because the type of growth that was characterized through the calibration for the SANDAG data provided more spatial alternatives for development to occur; development with SANDAG was dispersed, and new settlements were likely to spring up in a number of different locations. Over time, as the landscape would become saturated with development, some areas may be predicted to develop with a higher probability. This was definitely the case with the excluded 1 scenario, but the growth rate was more gradual with the other two scenarios.

The fact that the landscape becomes saturated with development may also explain the increase in agreement in areas predicted to develop over time. Model equifinality refers to the situation in which different initial conditions lead to similar effects or results in a model (Baird, 1999). In this case, the two datasets predicted areas likely to become urban using very different rule sets for growth behavior, suggesting that there may be alternate pathways that eventually lead to similar outcomes. Therefore, despite many of the differences in the results, there was generally more agreement than there was disagreement. Depending on the management objective, these differences may or may not be acceptable. For broad-based management decisions based on the general pattern of where future development is likely to occur, the choice of input data will not present a problem in the region. On the other hand, although the total area of projected urban growth in the eastern portion of the study region is small in both datasets, the location and pattern of that growth may be critical if impacts on narrowly distributed species, or on the hydrology of mountain catchments, are of particular interest. In this case, when both types of data are available, both scenarios could be used to characterize a range of uncertainty in these model-based projections. If fine-scale historical land use/land cover data are not available, it may be crucial to develop them in order to address certain questions.

It is important to point out that, because the different urban datasets differed in both scale and class definition, we cannot partition the results into one mechanism or the other. In other words, the simulated differences in extent, rate, and spatial pattern of simulated urban development are likely a function of both scale and definition, but we don't know which factor was most influential. Running simulations with successive aggregation of one of the data sources may help to tease these differences apart (e.g., as in Syphard and Franklin, 2004). However, the objective of our study was to compare results using two types of data that are most realistically going to be used in the practice of simulation modeling. And in practice, scale and definition are likely to be convolved, as different urban classification systems are likely to vary according to scale.

We asked whether different input data would differentially impact native habitats and, as we expected, the projected impacts of habitat loss varied according to the location and extent of projected urban development. While coastal sage scrub has been disproportionately impacted in the past (O'Leary, 1995), riparian areas, vernal pools, and coastal sage scrub were all strongly impacted in both sets of simulations—all are sensitive and imperiled vegetation types in the region (Hierl et al., 2008). Nevertheless, the ranking of habitat loss differed among vegetation types. For example, due to the greater concentration of projected development in the coastal areas of the county, coastal sage scrub declined much more using the SILVIS data than the SANDAG data. Because some coastal sage scrub areas provide habitat for threatened and endangered species (Hierl et al., 2008; Regan et al., 2008), management decisions may vary depending on the data source used.

We also asked whether the influence of data source on simulated development varied according to the location and extent of conservation lands. Although we expected that sensitivity to scale would be lower when the extent of protected lands was larger, and that scale sensitivity would vary depending on the location of protected lands, the differences between datasets were larger than the differences in results based on the three exclusion scenarios. One reason that the location and extent of conservation lands did not override the influence of using different input datasets may be that the majority of the land that was protected was located in the far eastern portion of the study area, where most development is not projected to occur anyway. In other words, much of the conservation land did not impede development that would have otherwise occurred without it. In other regions, where conservation lands occupy a greater portion of the study area, particularly in highly developable areas, the influence of excluded lands might have a greater influence in offsetting the importance of input data.

In fact, the exclusion layers did substantially impact the results – and the location of conservation lands matters in San Diego County. In particular, the MSCP lands added in exclusion scenario 3, although they only represented 2% of the landscape, disproportionately protected riparian areas, vernal pools, and coastal sage scrub from development as this habitat conservation plan was designed to do. This is because the MSCP lands are located in areas that are much more desirable for urban development. Without having those lands protected, both datasets predicted that much of that land would become developed in the future. This has important management implications for San Diego County and demonstrates that these conservation lands may be very effective for protecting sensitive species.

4.1. Conclusion

While issues of scale, resolution, and spatial data uncertainty have long been discussed in the geography and landscape ecology literature (Goodchild and Gopal, 1989; Turner et al., 1989; Goodchild and Proctor, 1997), this is one of the few studies that quantified how the source of input data affects model forecasts. In particular, we contrasted existing data products, one developed at public expense and meant to be widely disseminated and used for land studies, and the other assembled and refined within the context of a specific research project. Both represented historical urban land use/cover for an area, San Diego County that is part of the vast southern California conurbation (Nelson, 1959), home to 24 million people and still growing. Therefore, these data as well as scenarios of urban growth pattern, are likely to be of wide interest.

This study cannot conclude that one dataset is wrong and another is right – rather, it shows that there are two different ways of representing geographical reality. In addition to the differences in spatial resolution, the differences in categorical resolution and definitions of urban land cover contribute to the divergence in these representations. We recommend that modelers consider the characteristics of the data relative to the management question and phenomenon of interest in their study. For example, if the objective of the study is to predict broad-scale impacts of housing construction on habitat loss across a large landscape, the SILVIS data may be the most appropriate dataset. On the other hand, if the objective is to inform management about the likelihood of a narrowly distributed endemic species being extirpated from a smaller parcel of land, the SANDAG data, with a minimum mapping unit closer to the size of the phenomenon of interest, may be more appropriate.

In many areas, only one data source will be available, and at least for the United States, the SILVIS data may represent that source. Because there was much agreement in the areas ultimately predicted to be developed in both datasets, as we said previously, the SILVIS data may be appropriate in many regions for management questions focused on broad-scale, long-term predictions of the spatial extent of urban expansion. In the case that more than one dataset is available, it may also be worthwhile to combine data from different sources (i.e., housing density from one source with land cover from another) to best represent the phenomenon of interest. Although we did not use it in this study, the SLEUTH model has the capability to explicitly model transitions among multiple land use classes.

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