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Abstract: Difficulties in identifying actual uses of land space from remote sensing-based land cover products often result in lost opportunities to enhance the capacity of applied research on human settlements. In an attempt to address these difficulties, this study investigates how land cover and land use are interrelated with each other and what determines the relationship patterns by analyzing detailed land use and land cover data for two large US metropolitan areas – the five-county Los Angeles and six-county Chicago regions – where a broad spectrum of human settlements, ranging from urban cores to less-urbanized edges, coexist. The analysis shows that the land cover-land use relationship substantially varies not only across regions but across neighborhoods within each region. Through multivariate regression, it is also found that the intraregional variation is highly associated with the neighborhood's stage of urbanization, median housing age, and other development characteristics, suggesting that the relationship pattern can largely be shaped by the history and evolution of urban design/development.

Key words: Land Use, Land Cover, Remote Sensing, Urban Development

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1. Introduction

Rapid advancement in remote sensing, combined with cutting-edge image processing and spatial analysis tools, has provided valuable opportunities for researchers to monitor dynamic changes on the earth's surface more efficiently and to investigate urban development dynamics in a more comprehensive manner. The great potential of these advanced technologies has been increasingly recognized not only in the scholarly community of earth system science but also in many other disciplines that deal with the environment, human settlements, and coupled natural-human systems (see e.g., Gutman et al., 2004; Dmowska and Stepinski, 2014; Patino et al., 2014). In particular, there has been growing interest in remote sensing-based data products in social science and real-world policy-making because the data can enable us to better understand human decision making and socio-economic changes that underlies complex land cover changes. For instance, the U.S. National Land Cover Database (NLCD) has been increasingly employed to analyze the growth, decline, and transformation of many cities and their hinterlands (see e.g., Shen and Zhang, 2007; Shrestha et al., 2012; Kim and Hewings, 2013; Dmowska and Stepinski, 2014). Furthermore, researchers have also started to utilize the USDA's Cropland Data Layers – produced with the use of advanced wide field sensor and ground surveys (Boryan et al., 2011) – to grasp the underlying nature of land owners' decision making in agricultural production or farmland conversion for urban development (see e.g., Thompson and Prokopy, 2009; Kim, 2010; Rashford et al., 2013; Stoebner and Lant, 2014).

However, the full potential of remote sensing has not been fully realized yet. Although a growing number of social scientists have paid attention to the significant value of remote sensing combined with readily available spatial analysis tools and satellite imagery data processing techniques, they frequently encounter critical challenges that prevent them from adopting more remote sensing tools or data. One long-standing challenge is the fundamental gap between pixel-based land cover changes detected through remote sensing and actual human/institutional uses of land that represent complex socio-economic processes over space (see e.g., Liverman et al., 1998; Verburg et al., 2009). Conflicts exist between the structure of land cover datasets (i.e., their pixel- or grid-based structure) and socio-economic theories, in which the unit of analysis is individuals, institutions, or land parcels. Furthermore, it is unclear whether a certain type of land cover (say, low intensity developed land surface) indicates residential or commercial uses. Systematic investigations are needed to better connect physical land cover and human land use and thus to support wider dissemination of valuable remote sensing-based products that are increasingly available now and most likely in the future. .

This study attempts to fill the gap between land cover and land use by exploring the complex patterns of their relationship in two large US metropolitan areas in the U.S. More specifically, it examines how land cover and land use are associated with each other and how the relationship varies across space by integrating and analyzing detailed land cover and land use information for 1) the Los Angeles region, a five-county Southern California metropolitan area made up of Los Angeles, Orange, Riverside, San Bernardino, and Ventura counties and 2) the Chicago region, a six-county Northern Illinois area made up of Cook, DuPage, Kane, Lake, McHenry and Will counties. However, before presenting the analysis of these two metropolitan regions, the remainder of this paper first reviews the previous research in this arena (section 2). The review is followed by an explanation of the study areas and major data sets employed (section 3) and a presentation of the land cover-land use relationship patterns in the two metropolitan areas (section 4). Then, section 5 provides an investigation of the determinants of the relationship using spatial econometric models. Finally, section 6 concludes the paper by summarizing key findings of the analysis and discussing their implications.

2. Previous Research – A Brief Review

Existing research rarely acknowledges or investigates the gaps between land cover and land use, although these two are fundamentally different from each other in many respects, including their concepts, classification schemes, and data collection methods. Rather, land cover and land use are often used interchangeably or viewed as substitutes for one another (Comber, 2008). This is somewhat explicable because land cover and land use are highly associated with each other and, in many cases, data for only one of them (i.e., either land cover or land use) are available. However, an analysis of land cover or land use can be incomplete or misleading without an appropriate understanding and consideration of each concept and their interrelationship.

In recent years, there have been a handful of studies in which the differences and relationship between land cover and land use are examined explicitly. Cihlar and Jansen (2001), for instance, explored how land cover and land use can be associated with each other, focusing on the case of Lebanon. In this study, the authors presented a practical approach for deriving land use maps from remote sensing-based land cover information, considering various types of relationship (e.g., one-to-one, one-to-many, many-to-one, and many-to-many), and demonstrated the applicability and usefulness of such an approach using the study area (i.e., Lebanon) as an example. Building on that study, Jansen and Di Gregorio (2003) conducted another applied research project with the Kiambu District in Kenya, where land use information was in high demand for various environmental planning and resource management purposes. In this project, a set of decision rules were developed and tested through a field survey to determine specific types of human land uses based on remotely sensed land cover data. It was found to be crucial to reflect the study area's unique context in understanding the land cover-land use relationship, particularly the way in which land resources are utilized in the region.

Wästfelt et al. (2012) also explored the possibility of identifying detailed land uses based on satellite images that detect visible surface characteristics of the area (i.e., land cover). To do this, they conducted a case study in the Sodo district of Ethiopia by employing a rule-based, spatial relational post-classification method with emphasis on the importance of the local spatial context in shaping the land cover-land use relationship. The authors reported that the identification of land uses and associated socio-economic processes can be enhanced when "the analytical focus is shifted from land cover toward land cover configurations" (p.475), as the configurations can help capture the critical local context.

Brown and Duh (2004) attempted to accomplish a reversed translation task: the derivation of land cover from land use information. They paid attention to the major challenges that arose in translation, namely the semantic differences between land cover and land use – more specifically, differences in category definitions, geometric expressions, and spatial rules (p.37-38). Further, the authors presented a stochastic simulation-based approach that was designed to convert land use to land cover, and applied the method to Livingston County in the State of Michigan for demonstration. There, the spatial variation of the land cover-land use relationship within the study area was found to be critical, although it remained unanswered why such variation existed.

It should be noted that the literature has also embraced another group of studies which attempt to utilize remote sensing to investigate built environments and land uses in urban areas (see e.g., Herold et al., 2002 and 2005; Barr et al., 2004; Mathieu et al., 2007). In this branch of research, attention is primarily directed to the potential that remotely sensed data have in identifying morphological characteristics of certain types of urban structures or development patterns, rather than land cover-land use relationships. However, these studies have elucidated how a visible formation of the earth's surface (i.e., patterns that can be identified from remote sensing) is associated with various functions of land space (i.e., land uses). Furthermore, the methodologies presented in these studies, such as landscape metrics (e.g., Herold et al., 2002 and 2005), structural pattern recognition (e.g., Barr et al., 2004), and object-oriented image processing (e.g., Blaschke et al., 2000; Mathieu et al., 2007), have opened up new venues to utilize high-resolution land cover and other types of satellite images for a variety of research or policy-making purposes. More recently, further methodological advancement has been achieved (see e.g., Rashed and Jurgens, 2010; Thunig et al., 2011), even though this progress has often been made outside of social science.

Despite the great contributions of these existing studies, however, still little is known about detailed land cover-land use relationship patterns in various human settlement contexts. In particular, we do not know much about how the relationship patterns tend to vary and what determines the variation. The following sections present an empirical investigation of the relationship which focuses on two large metropolitan areas in the U.S. to address the dearth of knowledge in this arena and the lost opportunities to take advantage of land cover and land use information more effectively.

3. Study Areas and Data

In this study, consideration is given to two large U.S. metropolitan regions: 1) the Los Angeles region, a five-county Southern California metropolitan (Los Angeles, Orange, Riverside, San Bernardino, and Ventura counties) and 2) the Chicago region, a six-county Northern Illinois area (Cook, DuPage, Kane, Lake, McHenry and Will counties). The two large study regions provide a valuable opportunity to examine land cover-land use relationship patterns over a broad spectrum of human settlements (ranging from urban core to suburban and hinterland), using multiple sources of information.

More specifically, the Los Angeles region has experienced rapid growth over the last century and is currently home to approximately 18 million people, embracing the following three core-based statistical areas: i) Los Angeles-Long Beach-Anaheim, CA; ii) Oxnard-Thousand Oaks-Ventura, CA; and iii) Riverside-San Bernardino-Ontario, CA. It is well known for its poly-centricity and cultural diversity and is often referred to as an example of sprawl or unchecked expansion, although the region's density level is actually higher than that of many other metropolises in the U.S. (see e.g., Giuliano and Small, 1991; Ewing et al., 2014; Hipp et al., 2014). For this region, the Southern California Association of Governance (SCAG) provides parcel-level land use data in a shapefile format, originally constructed in the 1990s and periodically updated based upon local data inputs, aerial photography, and on-site visits. The SCAG land use data set identifies detailed land use information for more than 4 million parcels ranging from Downtown LA to farmland and preserved areas, using the organization's disaggregated land use coding system with more than 100 categories.

The second study area, the Chicago region, also involves a wide spectrum of development patterns, although it is relatively small compared with the Los Angeles region in terms of both population and territorial size. Similar to the Los Angeles area, the region's overall spatial structure is largely polycentric (McDonald and McMillen, 1990; McMillen and McDonald, 1998). However, given its historical background (as a city created based on the waterways and railroad systems), the region's urban form is quite distinct from that of Los Angeles, whose evolution has been largely shaped by the U.S. interstate highway system (Anas et al., 1998). Detailed land uses in this region can be derived from the Chicago Metropolitan Agency for Planning's (CMAP) spatially-explicit land use inventory databases, produced by utilizing a variety of GIS layers, including aerial photography, and other sources of local information (CMAP, 2006). .

For these two metropolitan areas and other parts of the United States, high-resolution land cover data sets are also available. In particular, the NLCD – 30 meter × 30 meter scale land cover data products, accessible via the Multi-Resolution Land Characteristics Consortium (http://www.mrlc.gov/) – contains valuable land cover information over a large geographical scope. Although it has been reported that NLCD does not perform well enough in capturing tree canopy covers or land fragmentation in nonurban areas, the database has been widely used for a variety of research projects (see e.g., Irwin and Bockstael, 2007; Nowak and Greenfield, 2010; Shrestha et al., 2012). When combined with land use information for each study area, the NLCD data can also provide an opportunity to investigate the ways in which land cover and land use are interrelated with each other and how the interrelationships vary within and across regions. Figures 1 and 2 illustrate the land cover patterns in each of the two study regions, using the 2006 edition of the NLCD 2001 product (Fry et al., 2011) which is employed for the subsequent exploration of the land cover-land use relationship.

<< Insert Figures 1 and 2 about here >>

Figure 1. Land Cover 2001 in the Los Angeles Region

Figure 2. Land Cover 2001 in the Chicago Region

4. Land Cover-Land Use Relationship Patterns

The NLCD 2001 layer is overlaid with the land use shapefiles for the Los Angeles and Chicago metropolitan regions. In this process, the two regions' land use data are reorganized to minimize the mismatches between their data coding systems and ensure consistency in subsequent analyses. More specifically, a land use classification system with 14 aggregated categories is used, and the NLCD's land cover classification is adopted after excluding several categories, absent from both study areas (table 1).

<< Insert Table 1 about here >>

Then, based on the overlaid layers, the relationships between land cover (classified into 15 categories) and land use (classified into 14 categories) are measured in the form of a 14×15 bridge matrix in which the land cover composition of each land use category is calculated in each row. This is accomplished by computing the surface area for each of the 210 possible combinations (15 land covers × 14 land uses) in ArcGIS. It should be noted that the matrix derivation is performed for every census tract in the Los Angeles and Chicago metropolitan regions (3,373 and 1,839 tracts, respectively) to explore how the relationship patterns vary over space within and across regions.

Tables 2 and 3 present the bridge tables that disclose the overall (aggregated) land cover-land use relationship patterns in the two regions, respectively. Each numeric value in a given cell (*i*,*j*) of the matrix represents *j*-th land cover's share of the total area of *i*-th land use categories. In table 3, for instance, 0.402 (in the cell of LU01 and LC22) indicates that 40.2% of the total single-family residential areas (i.e., 263.4 / 655.2 thousand acres) are found to have developed, low intensity land cover in the Los Angeles region.

<< Insert Tables 2 and 3 about here >>

As shown in the tables, the land cover-land use relation patterns are substantially different between the study regions, although some commonalities exist, such as high percentages of LC23 (Developed, Medium Intensity) and LC24 (Developed, High Intensity) among Multi-family Residential, Commercial & Services, and Industrial land uses. The outcomes can be sensitive to the spatial resolution of land cover data (e.g., a higher resolution can lead to smaller differences than found here using the 30 meter × 30 meter scale NLCD data). Also, to some extent, this interregional variation can be attributed to a discrepancy in the land use coding system that cannot be completely removed, although attempts were made to minimize it. The variation may also occur due to each region's uniqueness in terms of spatial organization and urban development schemes.

A larger extent of the variation can be found if attention is directed to the land cover-land use relationship patterns across neighborhoods within each region. For instance, the percentage of LC22 (Developed, Low Intensity) in LU01 (Single-family Residential) significantly varies across census tracts in the Los Angeles metropolitan area, as demonstrated in figure 3. The wide dispersion of the value – from 20% or below to over 80% – is also apparent in the Chicago region, where a high percentage value tends to be found in its middle ring (figure 4). The core areas show relatively lower values of the percentage, because there the single-family residential lands are more likely to contain other land cover types, particularly LC23 (Developed, Medium Intensity) and LC24 (Developed, High Intensity). Census tracts at the edge are also found to exhibit relatively lower percentages of LC22, since land cover types, such as LC21 (Developed, Open Space), are more frequently involved in the single-family residential areas of these parts of the region.

<< Insert Figures 3 and 4 about here >>

Figure 3. LC22's Share in SF-Residential Areas – the Los Angeles Region

Figure 4. LC22's Share in SF-Residential Areas – the Chicago Region

Figure 5 demonstrates three distinct patterns of single-family residential development in the Chicago metropolitan area, specifically Cook County, Illinois (Data source: USGS High Resolution Orthoimagery, Acquisition date: April 10, 2002). The second image (i.e., top right) is drawn from a census tract with a high percentage (over 80%) of low-intensity developed covers in its single-family residential land. The remaining two locations exhibit much lower levels of the percentage, but for different reasons. The first case (top left) has a large share of open spaces or undeveloped land cover categories, while the single-family residential areas in the third neighborhood (bottom right) primarily consist of medium-intensity developed land.

<< Insert Figure 5 about here >>

Figure 5. Single-family Residential Development Patterns

5. Determinants of the Relationship between Land Cover and Land Use

Why does such variation exist? What determines the land cover-land use relationship patterns? To answer these questions, which are essential in making it possible to cross-over between land cover and land use, a multivariate regression analysis is conducted focusing on single-family residential areas (i.e., LU01) as an example, among many land use types. This is accomplished first by measuring the land cover composition of the single-family residential areas in each census tract based on the following three categories for simplicity: 1) share of LC23+LC24 (i.e., medium- or high-intensity developed) in LU01, 2) share of LC22 (i.e., low-intensity developed) in LU01, and 3) share of the remainder (i.e., all other land cover categories, including LC21, that represent open space with a limited amount of developed surface) in LU01. For the explanatory variables that can account for the variation in the composition, a range of tract attributes are compiled using Census 2000 and other sources of spatial information, as summarized in table 4. These include the median age of housing, household income, relative position of the tract with respect to the central business district (CBD) and employment sub-centers in the region.

<< Insert Table 4 about here >>

In analyzing the composition, two major statistical issues can arise. First, the nature of the dependent variable (i.e., compositions, having a fixed range, [0,1]) makes it inappropriate to conduct the analysis using a straightforward least squares regression (see e.g., Aitchison, 1986; Pawlowsky-Glahn and Buccianti, 2011). To address this issue, a log-ratio transformation approach is employed in this study. More specifically, the following two variables are derived from the three shares of land covers.

- $y\_intense.dev = \log\left(\frac{[Share\ of\ LC23\&LC24\ in\ LU01]+\alpha}{[Share\ of\ LC22\ in\ LU01]+\alpha}\right)$
- $y\_open.space = \log\left(\frac{[Share\ of\ the\ remainder\ in\ LU01]+\alpha}{[Share\ of\ LC22\ in\ LU01]+\alpha}\right)$

where α indicates a small constant (e.g., 0.001) that is introduced to avoid the problems of $\log(0)$ and $\log(\infty)$. The magnitude of the first y variable (i.e., $y\_intense.dev$) is larger, when a bigger proportion of the single-family residential areas is medium- or high-intensity developed cover. In contrast, $y\_open.space$ exhibits a high value in the census tracts where single-family residential land contains a large share of less-developed or un-developed surface, compared with the common denominator: the share of low-intensity developed cover.

Though the above transformation provides two unbounded y variables – i.e., having a range of $(-\infty, \infty)$ as opposed to $[0,1]$ – there is another issue to be handled: spatial autocorrelation. The tract-level land cover composition presents a highly correlated pattern of spatial distribution. Consequently, the residuals from ordinary least squares are likely to be correlated, even if the transformed y variables are used. Therefore, a spatial error model is adopted to identify the determinants of the variation in the land cover-land use relationships more accurately, as follows.

$$y = \beta X + u \quad , \; u = \lambda W u + \varepsilon$$

where X and β represent the explanatory variables (including the constant) and their coefficients, respectively; the error vector, u, is assumed to be spatially autocorrelated and thus expressed with a spatial autoregressive coefficient (λ), a spatial weight matrix (W), and an uncorrelated and homoskedastic residual term (ε).

For each of the two study regions, the model is estimated through a maximum likelihood estimation approach using the ‘spdep’ package in R; and the estimation results are presented in table 5.[1] Overall, the results suggest that a substantial proportion of the variation across neighborhoods can be explained by the factors considered (the pseudo R-squared ranges from 0.46 to 0.78). In addition, it is apparent that the land cover composition involves substantial spatial dependence, as indicated by the statistically significant spatial autoregressive coefficients (λ). More specifically, these coefficients are found to have a relatively greater magnitude (0.838 and 0.823) under the models for $y\_intense.dev$ in both study areas, suggesting that the model for this variable is more likely to bear a high degree of spatial autocorrelation.

<< Insert Table 5 about here >>

Regarding the determinants tested, *Share.UrbanLandUse* is found to be highly associated with the transformed composition variables in both the Los Angeles and Chicago regions. The significant, positive coefficients of *Share.UrbanLandUse* in the models explaining $y\_intense.dev$ (+1.069 and +1.498, respectively) suggest that the single-family residential areas are more likely to be medium- or high-intensity developed covers in largely urbanized neighborhoods. *Share.UrbanLandUse*’s negative coefficients as predictors of $y\_open.space$ (-2.260 and -2.273 in Los Angeles and Chicago, respectively) indicate a reversed pattern of the relationship – i.e., these highly urbanized tracts tend to have a smaller proportion of undeveloped surface in their single-family residential areas.

[1] A contiguity-based weight matrix is used in the estimation. It should also be noted that census tracts with less than 10 acres of single-family residential areas are excluded, because the land cover composition derived from small land areas would not be reliable. As a result, the actual sample size used in the model estimation is smaller than the total number of census tracts in each study region – i.e., 2,913 tracts in the Los Angeles region and 1,410 tracts in the Chicago metropolitan area.

In contrast, *Share.SFResidential* exhibits significant, negative coefficients in explaining the intraregional variation of $y\_intense.dev$ (-0.640 and -0.988). This finding shows that medium- or high-intensity developed covers are generally large in highly urbanized tracts but not in those that have built out mainly for single-family housing rather than other urban purposes. In the case of $y\_open.space$, however, *Share.SFResidential*'s effect turns out to be insignificant, suggesting that the proportion of single-family residences land among various urban land uses does not make a substantial difference in terms of the share of open space.

According to the model estimation results, income effects also appear to exist. The median household income of the tract (logged – i.e., *Log.MedHHINC99*) shows significant negative and positive effects on $y\_intense.dev$ (-0.831 and -0.774) and $y\_open.space$ (+0.535 and +0.641), respectively. In other words, all other factors being equal, the single-family residential areas in relatively wealthier neighborhoods tend to involve more open space covers than high-intensity developed surface.

One additional finding to be stressed is the estimated coefficients of *MedHousingAge*. Although a majority of the explanatory variables tested are found to have one sign for $y\_intense.dev$ and an opposite sign for $y\_open.space$ (suggesting that they are indicative of a direction toward one extreme, either highly developed or undeveloped covers), *MedHousingAge* has negative coefficients in predicting both $y\_intense.dev$ (-0.012 and -0.031) and $y\_open.space$ models (-0.003 and -0.023). These results demonstrate that in old neighborhoods, the single-family residential areas are likely to have a large proportion of low-intensity developed covers, which falls in the middle of a spectrum of land covers between undeveloped and high-intensity developed surfaces.

Some other factors are also found to show significant coefficients. For instance, similar to *MedHousingAge*, the presence of rail transit stations (i.e., *RailTransitStation*) has significant and negative coefficients in both models for the Chicago metropolitan area, whereas its coefficients are insignificant in the case of the Los Angeles region. Proximity to the CBD or employment sub-centers also seems to have an ability to explain the spatially varying pattern of the land cove-land use relationship in these large, polycentric metropolitan regions.

6. Summary and Discussion

Rapid advancement in remote sensing and image-processing technologies has significantly improved our ability to monitor dynamic changes on the earth's surface, including areas where access is denied or restricted. Furthermore, the advanced technologies have provided a variety of data products that bear great potential for the investigation of various human activities that are highly associated with the earth's surface changes. However, it remains challenging to utilize these products for such research purposes due to the lack of knowledge (or references) about complex patterns of the relationship between human activities (land use) and the earth's surface changes (land cover).

To fill this niche, the present study investigates how land cover and land use are associated with each other and what determines the relationship patterns by analyzing the data for two large US metropolitan areas where a broad spectrum of human settlements, ranging from highly developed to preserved areas, coexist. The analysis demonstrates that the land cover-land use relationship varies not only across regions but also across neighborhoods within each region.

It is also found that the way in which land cover and land use are interrelated is highly associated with the neighborhood's stage of urbanization, land use composition, and median housing age. This finding suggests that the land cover-land use relationship pattern can largely be shaped by the history and evolution of urban design/development schemes in the region.

The findings of this study and further research in this area can support a variety of social science research, urban planning, and other public policy-making practice. Limited data availability or consistency has been a major obstacle to understanding the dynamics and complexity of urban development processes, and the emerging remote sensing technologies present a promising vehicle for overcoming this barrier. In particular, based on the revealed land cover-land use patterns, researchers can examine the land use changes and associated socio-economic issues more broadly using high-resolution land cover information that can cover a larger geographical scope (compared with alternative sources of information, such as local land use data) in a cost-efficient manner.

Furthermore, a more thorough understanding of the land cover-land use relationship can contribute to using land cover or land use simulation tools more broadly and effectively. In recent years, cellular automata and other types of land cover simulation models have been increasingly developed (Irwin, 2010; Kim, 2013), but the use of the simulation outputs has been somewhat limited due to the difficulties in translating cell- or pixel-based model outcomes (e.g., land cover changes from grassland to developed) into socio-economic variables (e.g., travel demand increases). It has also remained difficult to convert certain land use analysis outcomes into land cover metrics, needed for a range of environmental assessment and planning projects. These challenging transition tasks can be better accomplished by using the information about the varying patterns of land cover-land use relationship and their determinants revealed in this study.

Multiple disciplines can also enjoy the economies of scale (or the economies of scope) in terms of data availability by adding remote sensing-based products to their data inventory. Combining multiple types of information can open a new avenue for measuring, analyzing, and understanding urban spatial structures and detailed design/development schemes at various scales, as well as other important dimensions of our communities and regions. This line of research can also lead to a more salient dialogue concerning the strategies for crossing-over between land cover and land use to better understand visible changes on the earth's surface and the underlying socio-economic mechanisms.

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Table 1. Land Use and Land Cover Classification System

Land Use		Land Cover [a]	
Code	**Description**	**Code**	**Description**
LU01	Single-family Residential, including Duplex & Townhouses	LC11	Open Water
LU02	Multi-family Residential	LC21	Developed, Open Space
LU03	Other Types of Residential	LC22	Developed, Low Intensity
LU04	Commercial & Services	LC23	Developed, Medium Intensity
LU05	Industrial	LC24	Developed High Intensity
LU06	TCU (Transportation, Communication, and Utilities) Facilities	LC31	Barren Land (Rock/Sand/Clay)
LU07	Public Facilities, including Military	LC41	Deciduous Forest
LU08	Mixed Developed	LC42	Evergreen Forest
LU09	Open Space and Recreational	LC43	Mixed Forest
LU10	Urban Vacant or Under Construction	LC52	Shrub/Scrub
LU11	Agricultural	LC71	Grassland/Herbaceous
LU12	Non-urban Vacant	LC81	Pasture/Hay
LU13	Water and Water Facilities	LC82	Cultivated Crops
LU14 [b]	Undetermined	LC90	Woody Wetlands
		LC95	Emergent Herbaceous Wetlands

[a] The original NLCD classification system includes the following five additional categories – 12: Perennial Ice/Snow, 51: Dwarf Scrub, 72: Sedge/Herbaceous, 73: Lichens, and 74: Moss. However, these categories are excluded, as there are no land areas with any of these types of land covers in the two study regions. [b] Only available in the Los Angeles metropolitan region.

Table 2. Land Cover – Land Use Relationship Pattern: Los Angeles Metropolitan Region in 2001

	LC11	LC21	LC22	LC23	LC24	LC31	LC41	LC42	LC43	LC52	LC71	LC81	LC82	LC90	LC95
LU01	0.000	0.138	**0.402**	0.390	0.005	0.001	0.000	0.009	0.004	0.030	0.019	0.001	0.001	0.000	0.000
LU02	0.000	0.045	0.217	0.582	0.138	0.000	0.000	0.001	0.000	0.010	0.005	0.001	0.001	0.000	0.000
LU03	0.001	0.165	0.081	0.158	0.034	0.032	0.000	0.014	0.004	0.318	0.167	0.010	0.014	0.001	0.000
LU04	0.000	0.042	0.121	0.478	0.329	0.008	0.000	0.001	0.000	0.014	0.007	0.001	0.001	0.000	0.000
LU05	0.002	0.074	0.084	0.220	0.255	0.130	0.000	0.006	0.001	0.186	0.035	0.002	0.003	0.001	0.000
LU06	0.009	0.125	0.108	0.109	0.063	0.083	0.000	0.005	0.003	0.388	0.079	0.010	0.012	0.005	0.001
LU07	0.000	0.014	0.013	0.018	0.005	0.132	0.000	0.000	0.000	0.810	0.007	0.000	0.001	0.000	0.001
LU08	0.000	0.021	0.064	0.481	0.423	0.001	0.000	0.000	0.000	0.004	0.006	0.000	0.000	0.000	0.000
LU09	0.003	0.052	0.019	0.010	0.001	0.056	0.000	0.005	0.002	0.806	0.040	0.001	0.002	0.003	0.001
LU10	0.001	0.213	0.199	0.120	0.013	0.109	0.000	0.000	0.001	0.070	0.226	0.022	0.027	0.000	0.001
LU11	0.001	0.096	0.036	0.008	0.001	0.030	0.000	0.003	0.007	0.140	0.123	0.191	0.361	0.003	0.001
LU12	0.001	0.019	0.005	0.001	0.000	0.093	0.000	0.037	0.012	0.785	0.042	0.003	0.002	0.001	0.000
LU13	0.757	0.049	0.027	0.019	0.004	0.013	0.000	0.002	0.003	0.077	0.029	0.001	0.004	0.005	0.010
LU14	0.049	0.051	0.039	0.038	0.004	0.015	0.000	0.003	0.007	0.673	0.112	0.003	0.004	0.000	0.001

Table 3. Land Cover – Land Use Relationship Pattern: Chicago Metropolitan Region in 2001

	LC11	LC21	LC22	LC23	LC24	LC31	LC41	LC42	LC43	LC52	LC71	LC81	LC82	LC90	LC95
LU01	0.002	0.112	**0.580**	0.163	0.004	0.000	0.050	0.000	0.010	0.001	0.014	0.039	0.013	0.011	0.000
LU02	0.000	0.011	0.237	0.623	0.123	0.000	0.001	0.000	0.000	0.000	0.001	0.001	0.001	0.001	0.000
LU03	0.000	0.068	0.294	0.174	0.012	0.000	0.024	0.000	0.004	0.000	0.054	0.163	0.202	0.002	0.000
LU04	0.003	0.039	0.153	0.351	0.429	0.001	0.004	0.000	0.001	0.000	0.009	0.006	0.003	0.002	0.000
LU05	0.011	0.029	0.117	0.268	0.462	0.029	0.007	0.000	0.001	0.000	0.021	0.010	0.040	0.002	0.001
LU06	0.008	0.088	0.234	0.292	0.289	0.002	0.013	0.000	0.001	0.001	0.027	0.014	0.025	0.004	0.001
LU07	0.003	0.127	0.257	0.262	0.129	0.001	0.045	0.001	0.008	0.001	0.052	0.042	0.052	0.021	0.000
LU08	0.001	0.015	0.119	0.382	0.457	0.000	0.003	0.000	0.001	0.000	0.008	0.006	0.008	0.001	0.000
LU09	0.015	0.216	0.139	0.028	0.003	0.001	0.192	0.002	0.027	0.025	0.067	0.043	0.095	0.125	0.023
LU10	0.004	0.088	0.302	0.273	0.086	0.002	0.013	0.000	0.002	0.001	0.039	0.033	0.136	0.016	0.004
LU11	0.001	0.036	0.046	0.007	0.001	0.000	0.014	0.000	0.001	0.001	0.019	0.081	0.791	0.002	0.000
LU12	0.017	0.124	0.156	0.039	0.005	0.001	0.253	0.001	0.035	0.006	0.062	0.076	0.123	0.085	0.016
LU13	0.758	0.030	0.092	0.026	0.007	0.001	0.017	0.001	0.005	0.000	0.008	0.003	0.008	0.036	0.007
LU14	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A

Table 4. Explanatory Variables & Data Sources

Variables	**Description**	**Data Sources**
Share.UrbanLandUse	Share of urban land uses (i.e., LU01, 02, 04, 05, 06, 07, 08) in the tract	SCAG [a], CMAP [b]
Share.SFResidential	Proportion of single-family residential areas (i.e., LU01) among urban land uses	SCAG, CMAP
Log.MedHHINC99	Log of household income in the tract	Census2000
MedHousingAge	Median age of housing units	Census2000
RailTransitStation	Presence of rail transit stations, 1: yes, 0: no	Metrolink [c], CTA [d]
Road.FC1	Presence of interstate highways (functional class: 01), 1: yes, 0: no	NHPN [e]
Road.FC2	Presence of other major expressways (functional class: 02), 1: yes, 0: no	NHPN
Dist.CBD	Distance to the region's central business district	Lee & Lee (2014) [f]
Dist.SubCenter	Distance to the nearest employment sub-centers	Lee & Lee (2014)

[a] Southern California Association of Governance, [b] Chicago Metropolitan Agency for Planning, [c] Metrolink, [d] Chicago Transit Authority, [e] National Highway Planning Network data layer, [f] Central business districts and employment sub-centers, identified by Lee and Lee (2014) through a geographically weighted regression approach

Table 5. Spatial Error Model Estimation Results

Variable	**Los Angeles Metropolitan Area**				**Chicago Metropolitan Area**			
	y_intense.dev		***y_open.space***		***y_intense.dev***		***y_open.space***	
	Estimated Coefficient	**Standard Error**	**Estimated Coefficient**	**Standard Error**	**Estimated Coefficient**	**Standard Error**	**Estimated Coefficient**	**Standard Error**
C (Intercept)	10.791 ***	1.183	-6.502 ***	1.159	10.244 ***	1.527	-7.941 ***	1.649
Share.UrbanLandUse	1.069 ***	0.170	-2.260 ***	0.177	1.498 ***	0.252	-2.273 ***	0.281
Share.SFResidential	-0.640 ***	0.157	0.059	0.167	-0.988 ***	0.211	-0.405	0.234
Log.MedHHINC99	-0.831 ***	0.104	0.535 ***	0.102	-0.774 ***	0.135	0.641 ***	0.146
MedHousingAge	-0.012 ***	0.004	-0.003	0.004	-0.031 ***	0.004	-0.023 ***	0.004
RailTransitStation	0.215	0.156	0.080	0.173	-0.390 **	0.151	-0.536 **	0.172
Road.FC1	0.020	0.069	-0.017	0.074	-0.132	0.089	-0.014	0.099
Road.FC2	0.084	0.071	-0.126	0.075	-0.053	0.153	-0.048	0.170
Dist.CBD	-0.036 ***	0.006	0.001	0.003	-0.121 ***	0.014	0.034 **	0.010
Dist.SubCenter	0.007	0.018	0.022 *	0.010	0.139 ***	0.034	-0.002	0.030
Lambda (λ)	0.838 ***		0.636 ***		0.823 ***		0.712 ***	
Pseudo R-squared	0.702		0.462		0.778		0.651	
Log likelihood	-4866.7		-4946.5		-2197.5		-2315.4	

***: 0.1% level, **: 1% level, *: 5% level significant, n = 2,913 (Los Angeles Region) and 1,410 (Chicago region)

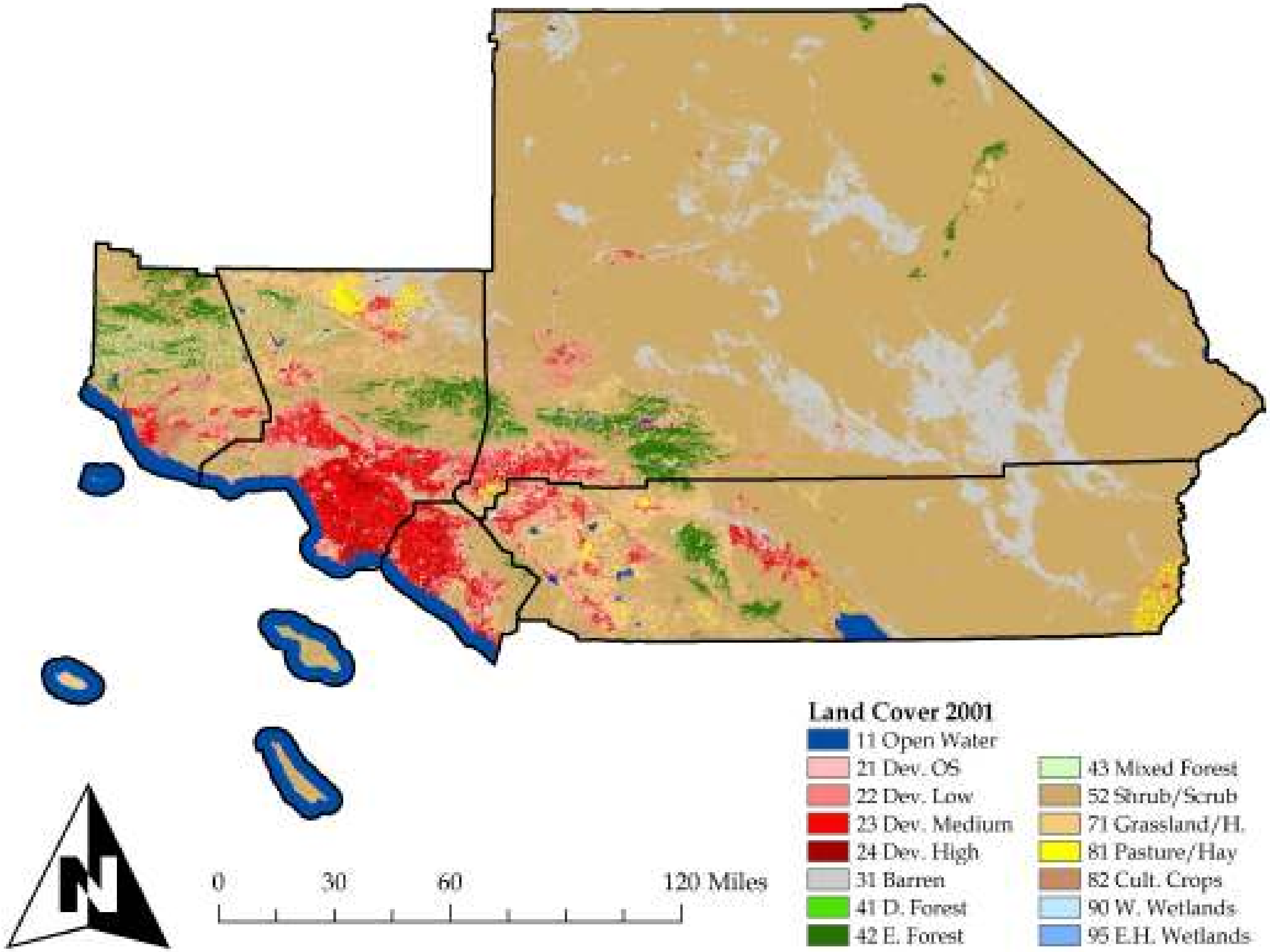

Figure 1. Land Cover 2001 in the Los Angeles Region

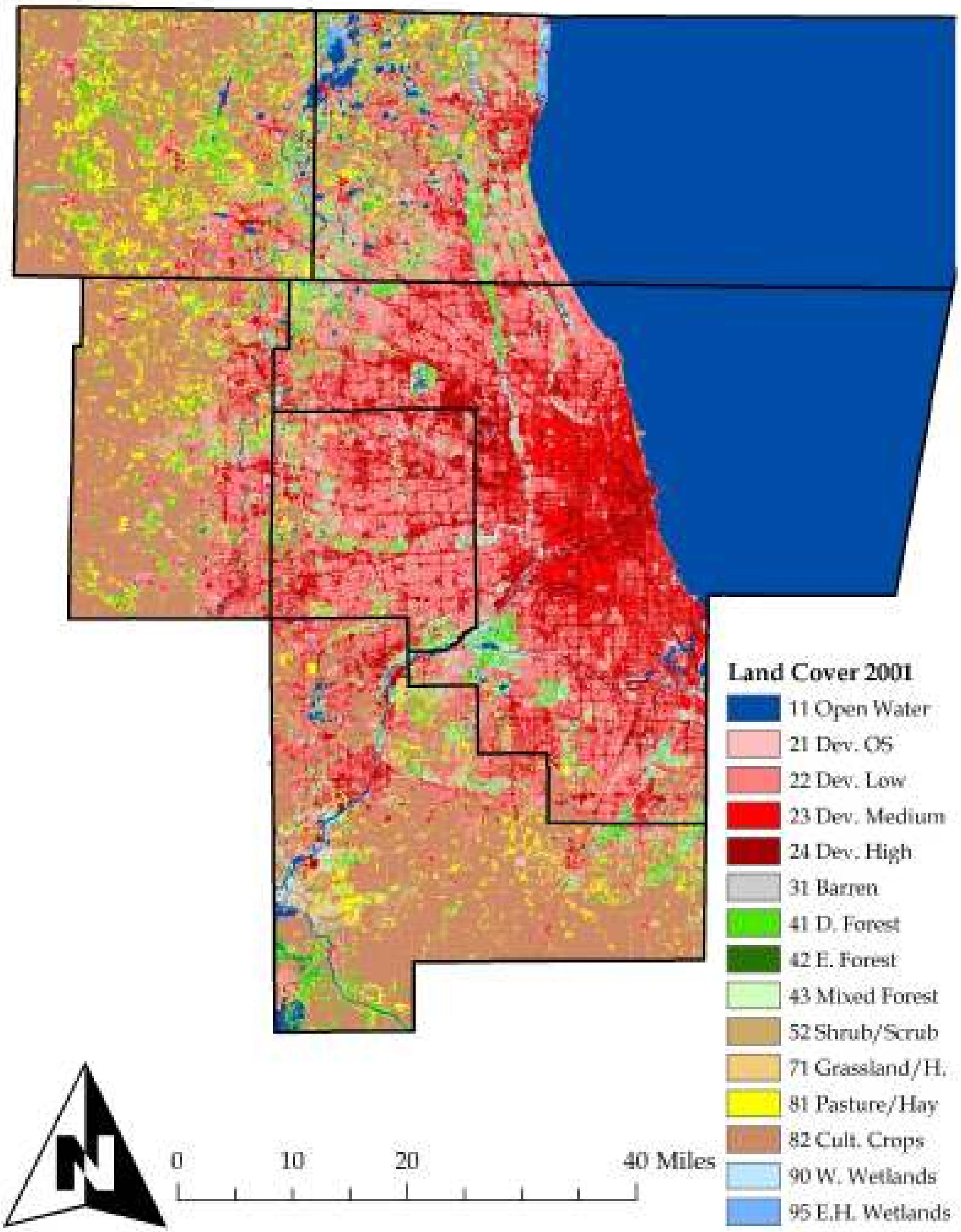

Figure 2. Land Cover 2001 in the Chicago Region

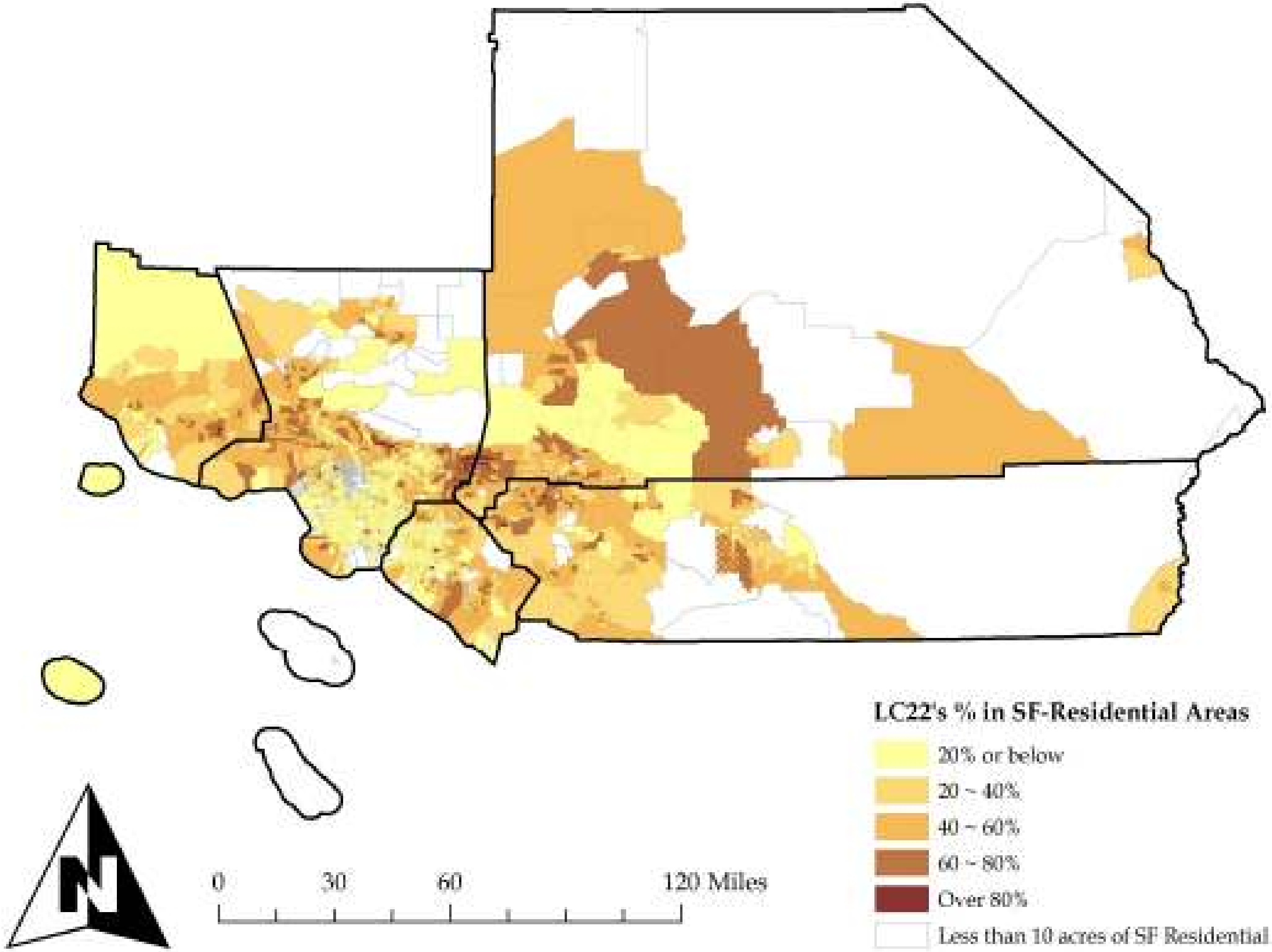

Figure 3. LC22's Share in SF-Residential Areas – the Los Angeles Region

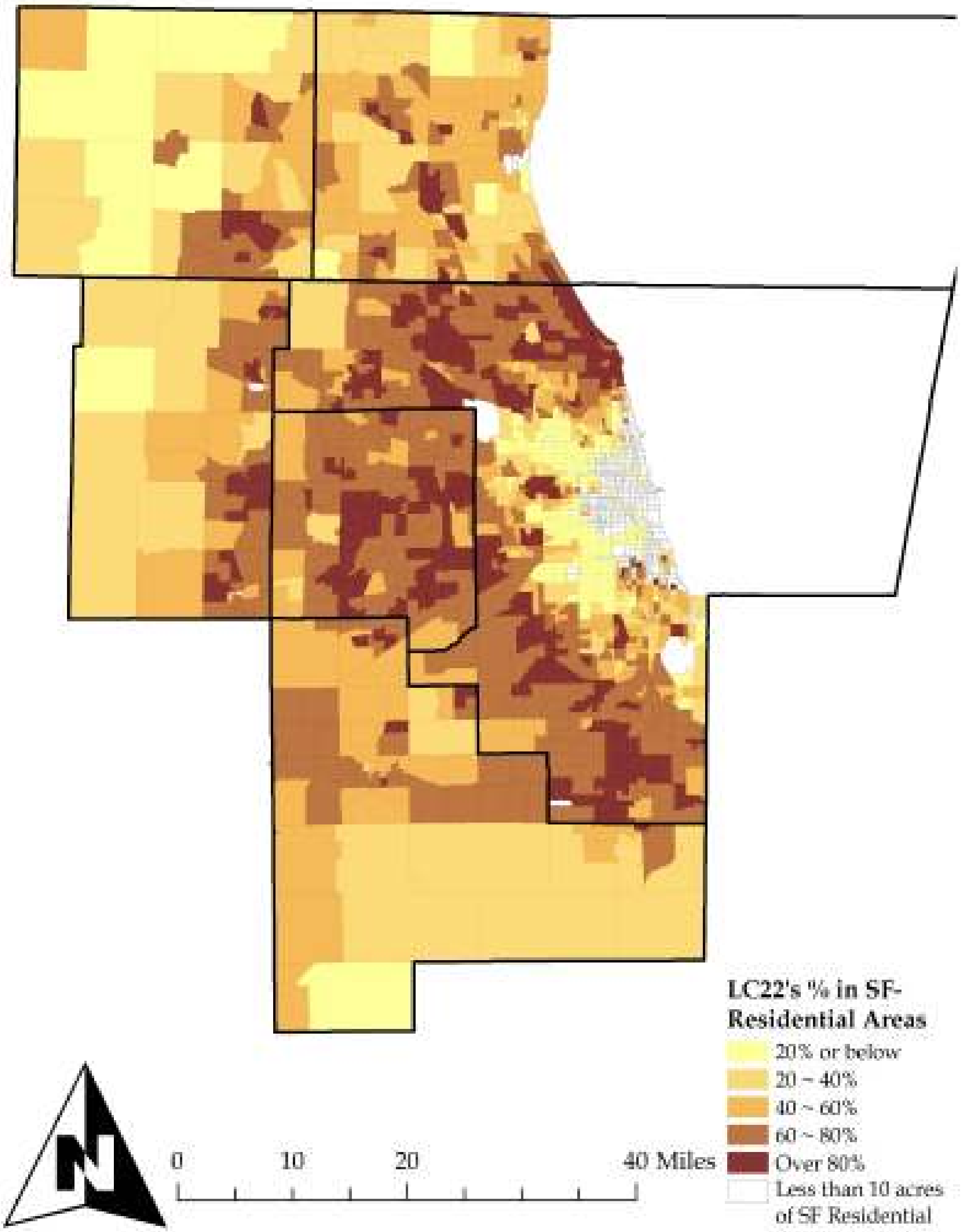

Figure 4. LC22's Share in SF-Residential Areas – the Chicago Region

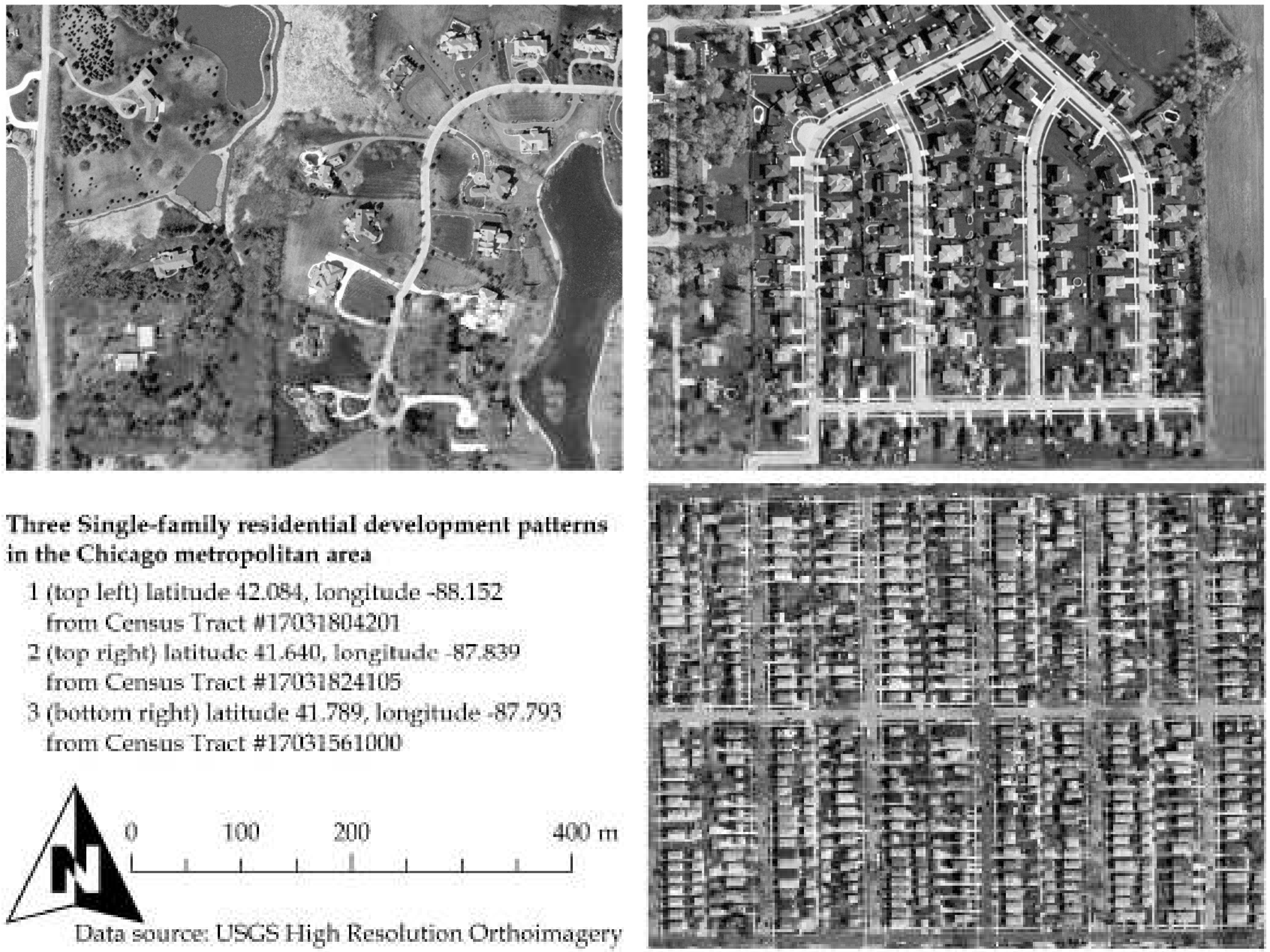

Figure 5. Single-family Residential Development Patterns