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Naci Dilekli
University of Oklahoma Norman Campus, ndilekli@ou.edu

Jennifer Koch
University of Oklahoma Norman Campus, jakoch@ou.edu

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Automated Urban Land Parcel Ledger Generation to Track Spatiotemporal Parcel Dynamics

Naci Dilekli[a,b] and Jennifer Koch[b]
[a] Center for Spatial Analysis, University of Oklahoma, Norman, OK, 73019, USA. Email: ndilekli@ou.edu
[b] Department of Geography and Environmental Sustainability, University of Oklahoma, Norman, OK, 73069, USA. Email: jakoch@ou.edu

Abstract: Urban population growth is expected to continue into the 21st century, bringing about drastic changes to urban landscapes across the globe. Our particular focus is to understand and evaluate urban growth patterns through parcel splitting in the Oklahoma City Metropolitan Area (OKCMA). To this end, we present the background and methodology used to develop the absent land parcel history information in the OKCMA using parcel data from the previous two years. OKCMA multiyear parcel data does not align spatially due to shifts and distortions. We developed a method to identify parent:child parcel relationships using their attribute and geometry information. This method generates two sets of indicators by searching the neighbors of each child parcel to find the most likely parent parcel and by extracting area portions of intersecting parcels. The algorithm performed well based on our initial test results, however, large-scale performance would depend on the quality of the underlying geometry and attribute information. We observe that while the current parcel data of OKCMA is useful, it is not sufficient to extract an accurate representation of parcel history or provide discussion of suggested data management practices. Based on our limited test results, our method successfully provides a historical ledger that can be used as a decision making tool for managing and enhancing multiyear parcel information.

Keywords: Urban development, parcel level, Oklahoma City, pattern detection

1 INTRODUCTION

Urban sprawl (Radeloff, Hammer, and Stewart 2005) and infill development (McConnell and Wiley 2010; Steinacker 2003) are two main means of population growth in urban environments. This is discussed in urbanization literature exploring themes such as smart growth (Susanti et al. 2016; Geller 2003), compact cities (Dempsey and Jenks 2010; Randolph 2006), and new urbanism (Ellis 2002; Trudeau 2013; Talen 2005; Boone et al. 2014). Furthermore, social impacts such as health, crime, and culture (Talen 2002; Geller 2003; Cozens 2008; Eid et al. 2008) and efficiency concerns such as those of economic, environmental and energy (Marshall 2008; Cervero 2001; McConnell and Wiley 2010) are investigated within urban development research.

New development, through sprawl and infill, is often achieved by splitting existing land parcels to allow for more buildings in a smaller area (McConnell and Wiley 2012). Modeling efforts at the local scale are important as they address issues and dynamics that cannot be captured with coarse resolution data (Irwin, Bell, and Geoghegan 2003; Zhou and Troy 2008; Tepe and Guldmann 2017; Abolhasani et al. 2016). Operating at the local scale, which can be achieved using high resolution data such as parcel data, is crucial to be able to capture urban growth dynamics more accurately. While this level of resolution provides a lot of flexibility and power in terms of detailed model representations, it has certain limitations and challenges. These include obtaining large and detailed datasets, growing modeling complexities, high computational costs, and susceptibility to sensitivity which may result in over-predictions and under-predictions (Beven and Freer 2001; Zhao et al. 2016).

In this study, we develop parent:child relationships of parcels across time by looking at their attribute and geometric information. This was done with the ultimate goal of improving understanding of historical urban change at the parcel level in the OKCMA. Over time, parcel geometries within the OKCMA have been inconsistently maintained and little current attribute information exists to aid in tracking these parent:child relationships. Therefore, in order to take on this task, we proposed a method to fully employ both the limited attribute and geometric information available.

2 MATERIALS AND METHODS

2.1 Study Area

Our study area encompasses Oklahoma, Cleveland and Canadian Counties in the State of Oklahoma, in the US (Figure 1). This is the most populous area of the State with a cumulative population of 1,178,723 and an area of 5,651 km^2 (Table 1).

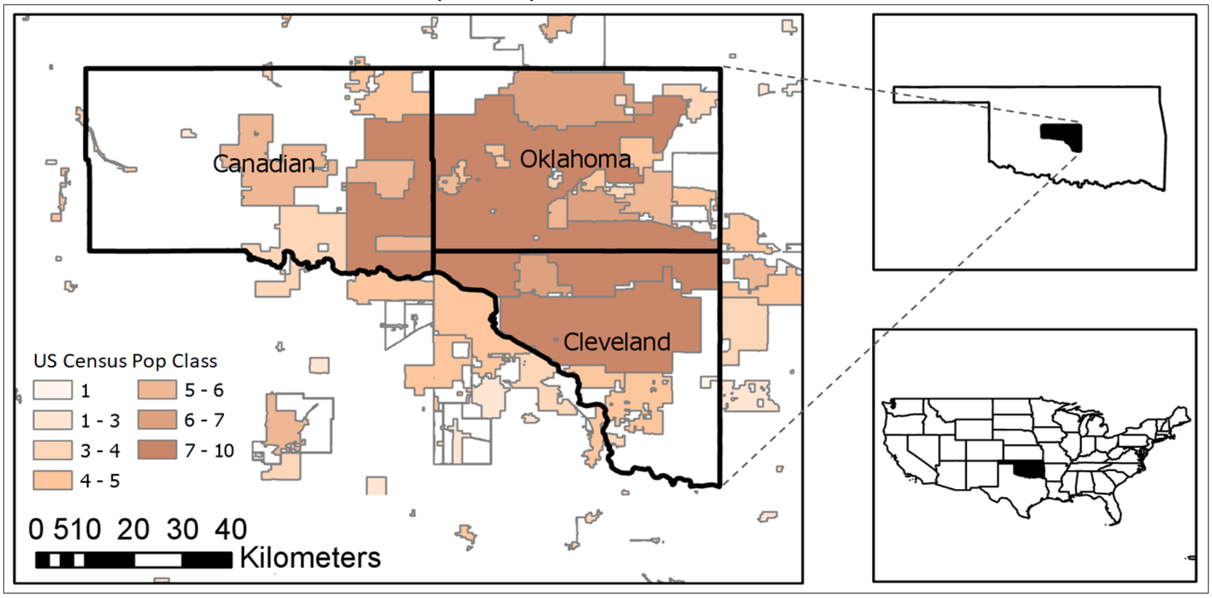

Figure 1. The study area and its location within the state of Oklahoma and the contiguous United States

Table 1. Population and area indicators of the counties in the study area. Population estimates and projections based on Barker (2012)

County	Area (km^2)	Estimated Population 2018	Density 2018 (people/km^2)	Projected Population 2050	Density 2050 (people/km^2)
Oklahoma	1,860	762,218	410	919,584	495
Cleveland	1,445	286,632	198	418,414	290
Canadian	2,347	129,873	55	187,385	80
Total / General	5,651	1,178,723	209	1,525,383	270

The extent of the study area ranges 105 km west to east, and 87 km north to south. While being the most populous area in the state, it has a low population density of 209 people/km^2 compared to other cities such as New York City with 10,892 people/km^2 and San Francisco with 7,174 people/km^2 (U.S. Census Bureau 2016). Oklahoma City spreads over large swaths of land in the form of low density housing which indicates sprawl type development as quantified by e.g. Hamidi and Ewing (2014), Ewing, Pendall, and Chen (2002) and Laidley (2016). It is plausible to link some of the health and urban issues in Oklahoma (Janitz et al. 2016; Tutor and Campbell 2004; Li, Campbell, and Tutor 2004; Weedn et al. 2014) and other potential issues to the sprawl type development of Oklahoma City. This is supported by extensive studies conducted on impacts of sprawl type development on quality of life, environmental impacts and economic costs (Van Holt 2006; Wilson and Chakraborty 2013; Concepción et al. 2016).

2.2 Data and Study Design

Based on our objective of defining parent:child relationships of parcels over time, we obtained two parcel datasets of OKCMA for 2014 and 2015, which included 467,981 and 469,638 parcels, respectively. These would then be conceptualized as "one-to-many" relationships. We faced two immediate problems. First, these datasets do not have any information to build a ledger that tracks parcel splits. A ledger tracks the history of each parcel and records all modifications to it, such as change of ownership, boundaries, or splitting. This allows for reconstruction of the parcels at any given date using ledger information. To our knowledge, every county in each state maintains their own parcel records with no national standards available (Meyer and Jones 2013). Second, the parcels from different years do not align spatially. The shifts across years are not uniform and increase or decrease across space.

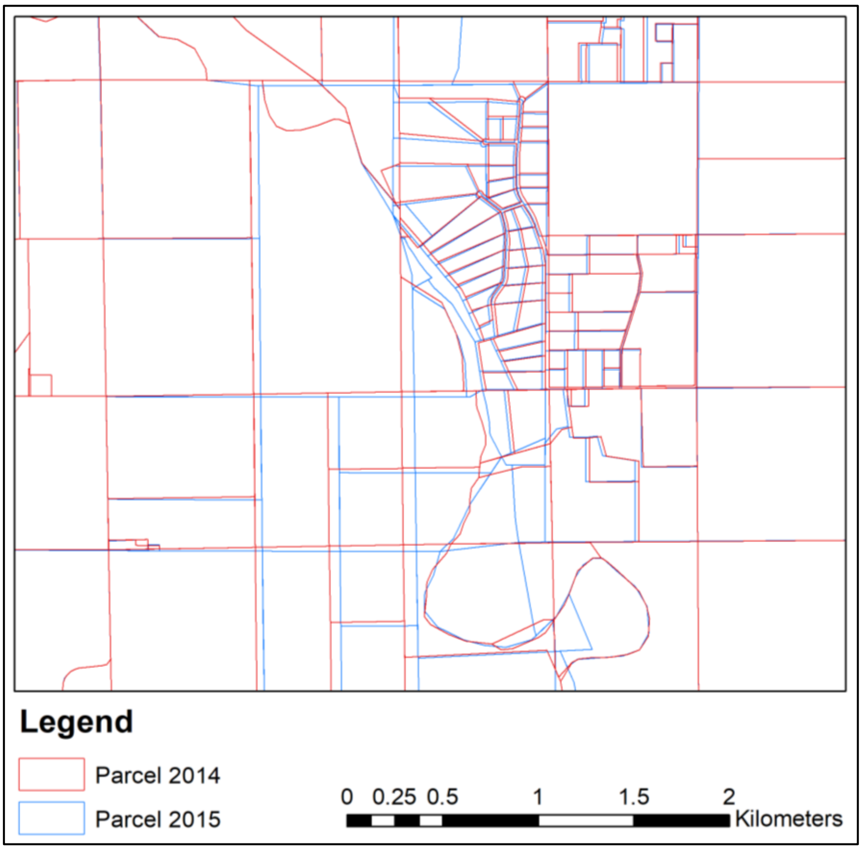

Figure 3. An example of non-uniform parcel shifts between 2014 and 2015.

The existing data has unique Parcel Identification Numbers (PIN) numbers that stayed the same for each parcel in both datasets. Split parcels are assigned new PIN numbers. However, this numbering system does not reveal which new parcel was split from which parent parcel. Based on the unique PIN within the parcel datasets, we first identify new parcels generated in 2015. This is achieved by joining the 2014 parcel layer to the 2015 parcel layer, and selecting and exporting records with null PIN values. This step identified 4,479 newly generated parcels (by splitting or some other form) in 2015.

2.3 Algorithm

We developed a method using geometric characteristics of new parcels and existing parcels to identify the parent:child relationship. This required identification of the parent parcel and its PIN number within the 2014 dataset for each newly generated parcel from the 2015 dataset. We then developed our methods based on several assumptions:

a. Whenever a parcel is split, its existing PIN number is assigned to one of the split parcels (usually the largest one), and the other, new parcel(s) is assigned a unique, newly generated PIN number.

b. Most of the parcels align well spatially. Despite the geometric shifts, visual examination can discern which parcels are the same across two datasets.
c. Aggregate size of children parcels is close to the size of the parent parcel.

Based on these assumptions, we construct two methods. Both methods generate a test of "parenthood".

2.3.1 Neighborhood Based Test Method

We designed this method to identify parent:child parcel relationships. It evaluates the neighborhood in the 2015 parcel layer for each new parcel. The logic of this method is that each of the neighbors are potentially siblings that were split from a common parent, with the potential sibling sharing the PIN number of the parent. A potential sibling is any parcel that shares a boundary with the child parcel.

The following steps are executed:

a. The area of each potential sibling in the recent date parcel layer is added to the new parcel and divided by the area of the potential parent in the older date parcel layer for each neighbor.
b. The absolute value of the aggregate area is calculated and then divided by parent parcel area to calculate ratios. They are added to an array along with the PIN numbers from both datasets. The assumption is that the sum area of the new parcel and the real sibling parcel will be close to the area of the parent parcel.
c. The array from step b are then sorted based on the ratios and the two smallest ratios are used to calculate two indicators for parenthood tests.
d. The first indicator is the smallest ratio from step c. The second one is calculated as the difference between the smallest ratio and the second smallest ratio (differential indicator). The assumption is that the larger the difference is between the fitness of the best and second fitness of potential siblings, the higher the confidence regarding the parenthood.
e. Two indicators from steps d, along with the PIN number of the best fitting potential sibling, and the number of neighbors (potential siblings) are added to the layer as new attributes in the new parcel layer.

2.3.2 Intersection Based Parenthood Test Method

This method uses union information of parcels from two different dates. As input information, we first conduct a union operation of the two parcel layers, and then dissolve it using the unique id combinations from the two layers. The following steps are executed:

a. We store the area of the child parcel in a variable for each new parcel.
b. For each union combination of the new parcel PIN with old parcel PIN, we extract the old PIN number and the area. If there is no underlying old parcel data, that means it is empty, and we call it "EMPTYAREA"
c. We divide the area of the combination with the new parcel area, and store it in an array.
d. We sort the array and find the largest intersection area along with the old parcels PIN number. If there is no associated PIN number, it is called "EMPTYAREA".

3 RESULTS, LIMITATIONS AND DISCUSSIONS

We initially evaluate and assess the results using face validity testing to identify instances of successful and unsuccessful detections. The neighborhood based method yielded results with mixed success. An example for a successful match is illustrated in Figure 3(a), with the new parcel highlighted. The parcel to its right is found to be the sibling parcel, which inherited the parent parcel's PIN. In this particular case, the first indicator generated is 0.999995, which is the aggregate area of two sibling parcels to the area of the parent parcel. The second indicator (differential) is 0.551038, which indicates how far the second closest match is from the parent parcel. These indicators can be interpreted as signifying a very good match since the first match is close to 1 and the second best match for sibling has a less successful match rate, thereby revealing unambiguity.

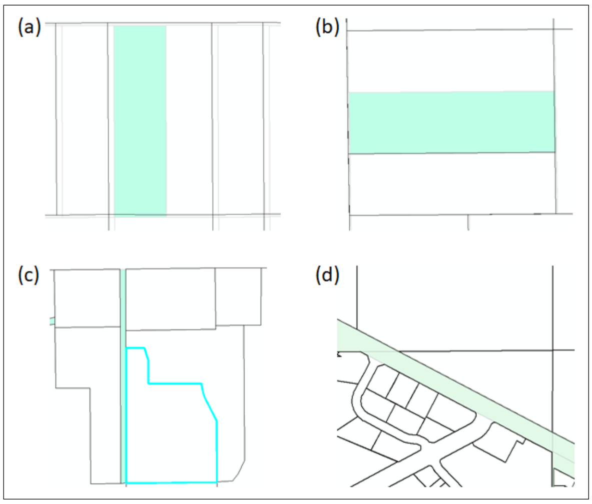

Figure 3. Four scenarios that highlight parent parcel detection using the neighborhood based method. (a) exemplifies an unambiguous detection; (b) illustrates ambiguous detection; (c) and (d) demonstrate incorrect detections

This can be contrasted with another example illustrated in Figure 3(b). The large parcel above was split into two, and the highlighted parcel was assigned a new PIN and therefore identified as a new parcel. The indicators in this case are 1.000000 and 0.023625 for the two measures respectively. The very small value of the differential indicator suggests that the second potential sibling may have inherited the parent's PIN as well. The potential for confusion exists due to the regularity of parcels in this particular area. It is plausible to infer that a larger parcel was first split by the bottom third in a prior year, and then by the second third eventually. Since we have only two datasets, and no prior ones, we cannot verify this. Figure 3(c) illustrates another common problem with the parcel files. In some situations, a neighboring parcel is so large, that the relatively small sized child parcel appears to have split from this very large neighboring parcel.

Another frequently observed problem was the generation of new parcels, which technically preexisted, but were added in order to fix or complete the parcel layer. This often happened for publicly owned areas, such as highways or railways, with parcels not existing in the 2014 dataset. We illustrate this issue with Figure 3(d), which shows a new state-owned highway parcel that had been added in 2015. There is no corresponding record from 2014, and the underlying geometry in the prior year is empty. However, this process did not enter all the missing parcels. As can be deduced from the Figure 3(d), the road parcels to the southwest of the new parcel in the center are still nonexistent and empty in 2014. This situation causes the algorithm to pick a wrong parent parcel from neighboring parcels instead of concluding that it was parentless and is a new parcel. This final type of problem prompted us to add the second method to distinguish new parcels (Section 2.3.2).

The second method, or the intersection based method, was developed due to low success rates and yielded results with better success. It automatically identified that 3,436 parcels out of 4,479 parcels were parcels that were created on empty area and are not children of previous parcels. This helped with excluding these parcels from the new parcel set. Using attribute queries and face validity testing of the output from the two methods, we were able to identify additional issues with the data. The first one is entry of incorrect PIN Numbers. This occurs when a parcel does not change, but the operator puts the wrong PIN number in a more recent year. The second issue was merging of multiple 2014 parcels into a single parcel in the 2015 dataset.

With the combination of both methods, we identified 884 parcels that our algorithmic approach identified as split from parent parcels. As we are interested in shape characteristics and relative positions of split parcels across the urban space, we generated some basic descriptive statistics of children parcels as shown in Table 2.

Table 2. Statistics regarding the children parcel identified by the algorithm in meter squares and meters

	Area	Distance to Primary Roads	Distance to Primary Rivers	Distance to Pop Center	Distance to Large Lakes
Minimum	19.3	0.0	0.0	0.0	175.5
Q1	654.9	418.2	1,490.4	401.2	5,175.1
Median	1,250.2	1,030.4	3,268.4	810.4	8,380.9
Q3	4,392.1	1,855.2	6,068.8	2,604.7	11,848.9
Max	873,554.6	10,794.5	16,846.3	25,536.4	46,796.8
Standard Dev.	61,588.6	1,910.8	3,608.6	4,827.0	6,084.0

Table 2 shows that area statistics of children parcels show high levels of variance, potentially due to irregularities in the data. It demonstrates that the distance to primary roads and population centers are relatively smaller, making those two factors the primary reason for splitting new parcels. Proximity to primary rivers and large lakes are comparatively high, implying lower impacts of those two factors.

Finally, we take a random sample of 20 children parcels, and we manually test if the algorithm identified the correct parent. Using face validity testing, we found that all 20 had correct parent parcel PINs assigned to them. Manual evaluation requirement is the primary limitation of this study. While the test results were satisfactory in the random test data, more rigorous and extensive tests should be conducted to further test the rigor of the methods and potential shortcomings. We believe the rate of success of our algorithm would vary depending on each state and region since currently there are not well established standards for such record keeping.

We suggest the following practices to take place: (a) Currently there are spatial gaps in the parcel data, which usually are observed in public land. Initially, such gaps should be completed; (b) We observed that the PIN numbers are occasionally mistyped across the years. Similarly, there is also use of non-unique identifiers in the 2015 dataset which limits the use of the data. We suggest use of enterprise geodatabases and using field specifications to make sure such fields are unique, and in a certain format; (c) At least in the case of Oklahoma City, the geometry of parcels seems to change based on the year. It would help not only for the purposes of urban history analyses, but also for other areal analyses to maintain the geometry so that the results are accurate and consistent; (d) All updates (i.e. splits, unifications) to the data should be made to a single parcel dataset, which should be archived regularly (i.e. monthly). This approach would ensure persistent identifiers and geometries; (e) A changes table which records attribute and geometry changes to the parcels along with descriptions and dates of changes should be maintained. Using the latest single version of the parcels layer and this changes table, one would be able to reconstruct a parcels layer of any date. This process can be facilitated and automated by the use of an enterprise geodatabase from a platform such as ESRI, which would have the “editor tracking” option to keep record of all geometrical and attribute changes to each feature or record.

4 CONCLUSIONS

We implement and test an automated approach to detect modifications to parcels. Our algorithm is successful in extracting the information required. To succeed, we use both geometric and attribute information in parcel datasets of two distinct years. We conclude that while we were able to extract sufficiently useful information for our future modeling work for the OKCMA area, the underlying data is not suitable to extract the splitting history of parcels for record keeping purposes. We learn that there are data issues and exceptions across the parcel datasets that are easily revealed by developing and implementing our algorithm. We finally conclude that such automated approaches, potentially with additional methods that further utilize the attribute and geometric information, can be used to reveal missing and incorrect data and facilitate improving parcel records to increase the parcel stewardship maturity.

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