A multidimensional urban land cover change analysis in Tempe, AZ

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***Abstract*— Rapid population growth leading to significant conversion of rural to urban lands requires deep understanding on how the human population interacts with the built-environment. Our research goal is to explore methodologies on how to analyze multidimensional urban change with the consideration of time, space, and landscape patterns. Using NAIP high resolution satellite images and LIDAR data, we were able to derive land cover classification maps and normalized height difference at different time periods. Then we performed the 2D, 3D and landscape pattern change analysis for a case study area. The research results show that a combination of 2D, 3D and landscape pattern change analysis can provide a comprehensive understanding of urban change, and the results will help urban planners and decision makers to better understand the status of urban transformation and design city for the future.**

Keywords—urban land cover analysis, LIDAR, NAIP, landscape configuration/composition.

I. INTRODUCTION

The increasing shift and movement of population into cities drives the continual expansion of urban land use and land cover worldwide [1]. Dense populations in the urban areas result in natural and societal challenges including urban heat, crime, traffic congestion, and air pollution. [2]–[4]. Rather than managing the challenges, we aim to understand urbanization so that it can improve the lives of urban residents. To that end, 2-dimensional (2D) and 3-dimensional (3D) change detection offers an understanding from rural lands to urban lands, and more importantly, from existing urban lands to other types of lands in the vertical space. The goal of this research is to extend the methodology of detecting urban land cover change dynamics from multi-dimensions including temporal land change dynamics in the 2D environment and vertical space extension in the 3D space. This paper will also serve as an implementation of the recent conceptualized and proposed six fundamental aspects (Materials: human constructions, soil-plant continuum, and surface water; configuration: dimensionality, spatial pattern; and time/dynamics) of multidimensional urban form for spatial mapping [5].

II. LITERATURE

The change detection literature contains numerous and examples quantify the shift of urban lands using various remotely sensed data sources [6]. With the availability of more than 40 years of Landsat satellite imagery, researchers have used these images to detect the urban land cover change continuously in high temporal resolution in 2D environment [7]. Since most of the human activities happen in urban areas, high temporal resolution night lights satellite images including DMSP/OLS and NPP-VIIRS serve as an alternative data sources to understand urban sprawl and expansion in 2D [8]. In Zhu (2017) [7], he summarized 6 different methods to perform Landsat time series analysis in 2D environment, including thresholding, differencing, segmentation, trajectory classification, statistical boundary, and regression analysis. The majority of the research is based on pixel-based or sub-pixel-based analysis rather than objected-oriented, which makes cell-by-cell change detection more difficult.

Moreover, light detection and ranging (LIDAR) data and widely available digital elevation model (DEM) data provide the capability to understand the urban land cover change in the vertical space of the urban areas. Qin et al. (2016) [9] offered an overview of 3D change detection methods including geometry comparison (height differencing; Euclidean distances; projection-based differences) and geometry-spectrum analysis (post-refinement; direct feature fusion; post-classification). The accuracy of 3D change detection highly depends on the image matching algorithm and the feature extraction in the 3D data generation process.

Although existing research have done both 2D and 3D change analysis by various data sources and methodology, seldom of them designs a comprehensive change analysis mechanism to understand the fragmentation of urban land in the 3D environment over time with landscape pattern analysis. Existing research have explored the urban landscape pattern changes in the 3D environment [10], [11], but they only discussed around the height of buildings and vegetation, rather than the overall 3D composition and configuration. Less research focus on comparing urban land cover change among multiple cities, with the exception of Li and Thinh (2013) [12] to compare the land cover change pattern for Xuzhou, China and Dortmund, Germany. In this paper, we want to fill this research gap with a case study of 3D urban land cover change analysis at Tempe, AZ.

III. Methods

A. Study Area

Our study area focuses on residential neighborhoods in the City of Tempe, Arizona (Figure 1). The City of Tempe is municipality located in the greater Phoenix metropolitan area in the U.S. Southwest. With summertime temperatures reaching or exceeding 43° C, heat mitigation strategies are mandatory, including private swimming pools, outdoor green infrastructure, and central air conditioning. The population of Tempe reached 160,000 in 2010 with the majority residing in single-family detached dwellings [13]. Based on the 2017 ACS 5-year population estimate, the population in Tempe increased to about 180,000 with the median age at 28.8 years old [14]. Major urban renovation (new student apartments and shopping centers) happens near the ASU Tempe campus because of the increasing size of student populations.

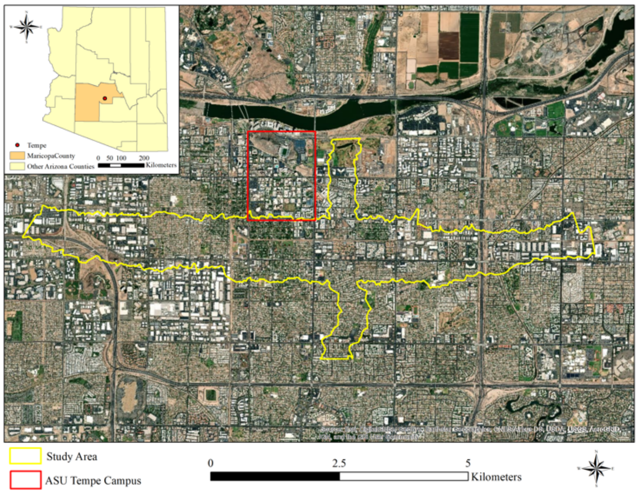

Figure 1. Study area.

B. Data

To enable the analysis of multidimensional urban land cover change detection, we collected two time periods of LIDAR data. The first LIDAR dataset was obtained on May 5th, 2008, which contain elevation data with a 95% vertical accuracy of 18.5 cm and a 90% of 15 cm with horizontal accuracy of 30 cm, 1 sigma. The second LIDAR data obtained from United States Geological Survey's 3D Elevation Program (data collected from September 30th to October 5th, 2014). The LIDAR elevation dataset have the accuracy of with a 90% vertical accuracy of 11.5 cm and a 90% horizontal accuracy of 21.5 cm, 1 sigma.

Since the LIDAR dataset have very high spatial resolution (1 m), we use National Agriculture Imagery Program (NAIP) from United States Department of Agriculture to match with the 2008 and 2014 LIDAR dataset. Since NAIP did not capture images every year, we chosen the NAIP imagery that have the nearest collected date to the LIDAR dataset. The first NAIP imagery with 1 m resolution was collected at 2010 to match with the 2008 LIDAR data. The second NAIP imagery with 1 m resolution was collected at 2015 to match with the 2014 LIDAR data. Since LIDAR data are still rare for the same study area across different years, this is our best way to match LIDAR and NAIP data for our study area. Furthermore, the urban growth rate in Tempe area is slow comparing to cities in China and India, so we believe 1-2 years data gap will not influence our results significantly.

C. Analytical Approach

a) LIDAR Point Clouds Processing

First and last vertical returns were derived from the original LIDAR point clouds. LIDAR data from 2008 has an average point spacing of 0.78 meters, and the LIDAR data from 2014 has an average point spacing of 0.31 meters. The bare earth model was constructed from processed and classified ground points with all the anthropogenic features removed. The digital surface model represents all the ground features such as buildings and vegetation, and it was created from non-ground points (first return). The normalized digital surface model (nDSM) was obtained by subtracting the bare earth surface from digital surface model for each of the different year's image files to determine areas of significant height change.

b) NAIP Imagery Classification

We utilized the NAIP 2010 classification products derived by Li et al. (2014) with the objected-based image analysis. The overall accuracy of the classification is 91.86% and the main classification categories include buildings, roads, soils, trees/shrubs, grasses, croplands, and swimming pools. To classify the NAIP 2015 imagery, we adapt the same classification technique from NAIP 2010 classification. A supervised classification technique that incorporates both object-oriented and spectral-based classification approaches is applied to the image. The imagery was first classified to 6 class scheme including buildings, roads, trees, grasses, rivers/lakes, and swimming pools to help aid the accuracy of the process. An accuracy assessment was performed on the 2015 imagery using a stratified random sampling method with an overall accuracy of 95.6%. To represent the main physical elements of the urban landscape from Wentz et al. (2018) [5], we reclassified both of the NAIP images to only three main categories including impervious (buildings and roads), vegetation (trees/shrubs, grasses, and soil), and water (rivers/lakes and swimming pools).

c) Land Cover and Pattern Change Analysis

2D land cover change detection was conducted using change analysis tools in ArcGIS to determine pixel changes between two years with NAIP classified products. Land cover categories change were reported based on their classes associated with each year. All classes were compared similarly in the change detection files to help identify areas of interest that had significant land cover change. Combining NAIP land cover change results with LIDAR nDSM, we are able to observe the more intricate 3D changes in the environment such as building construction/removal and tree growth/cutoff. This change analysis would offer extra insights for understanding the urbanization process in Tempe area. For landscape pattern change analysis, we used Fragstats V4.2 to generate composition, shape, and distribution metrics and compare how landscape pattern changes [15].

IV. RESULTS AND DISCUSSION

Table I shows a breakdown of the land cover percentage attributed to the total study area in 2010 and 2015, as well as the percentage of land cover attributed to change category and no change category. Percentage change and no change was calculated using the total number of pixels associated with the change/no change land cover types divided by the total change or no change pixels (Equation (1)). If the variable A represents the imperious change pixels, B represents the total change pixels, then C represents the change percentage of impervious surface from 2010 to 2015.

$$C = \frac{A}{B} \times 100 \qquad (1)$$

In our study area of Tempe, impervious areas grew from 61.36 % to 63.00% of the total area from 2010 to 2015. During the same time period, Vegetation in the study area experienced a loss from 38.08% to 36.54%. Of the total change, 46.34% of the change can be attributed to impervious surfaces from 2010 to 2015. At the same time, vegetation represents 52.58% of the total amount of changed area in the study area. The percentage of unchanged land cover is also represented in Table I. Impervious unchanged land makes up over 66% of the total land that was unchanged between the two study periods, while vegetative land change accounts for only 33.26% of the unchanged land in the study area. Since water in our study area is very limited, we do not see a large difference from 2010 to 2015.

TABLE I. 2D LAND COVER CHANGE ANALYSIS

	Percentage (%)		
	Impervious	***Vegetation***	***Water***
NAIP 2010	61.36	38.08	0.56
NAIP 2015	63.00	36.54	0.46
Change (%)	46.34	52.58	1.08
No Change (%)	66.36	33.26	0.38

A stratified random sample scheme with 100 points within changed pixels and 100 points within unchanged pixels was used to test the accuracy of the reported changes. We used the original NAIP 2010 and NAIP 2015 images as our reference images, and we visually compared these two images to validate our change analysis. The change accuracy assessment reports a 96.77% accuracy of the change category, and a 71.01% accuracy of the no change category. A 79% overall accuracy in regards to the accuracy of the changes (Table II) [16]. The errors of identifying no change pixels to change pixels mainly cause by the misclassification of NAIP images.

TABLE II. 2D LAND COVER CHANGE ACCURACY ASSESSMENT

		Reference Data		
		Change Pixel	***No Change Pixel***	***Total***
Classified Data	Change Pixel	60	40	100
	No Change Pixel	2	98	100
	Total	62	138	200
Agreement/Accuracy		96.77%	71.01%	
Overall Accuracy: 79%				

We further explored the 3D land cover change analysis base on the LIDAR nDSMs between the year of 2008 and 2014. Since water body is so scares in our study area, we do not include water in this 3D change analysis. We have 66.36% of impervious and 33.26% of vegetation land cover do not change in the 2D change analysis, but these areas have actual volumetric change in 3D environment (Table III). We observed a positive average volume change (0.06 m^3) for impervious surfaces, and a negative average volume change (-0.11 m^3) for vegetation. These findings explain the recent fast development of city of Tempe because of the new buildings and roads' construction around the ASU Tempe Campus (Figure 1). Since trees have been removed because of the new building construction, the average vegetation volume has decreased in Tempe area.

TABLE III. 3D VOLUMN CHANGE ANALYSIS BASED ON LAND COVERS

Land Cover Type Change	Mean	Max	Min
I2008-I2014[b]	0.06[a]	37.25	-41.27
I2008-V2014	0.07	35.00	-35.06
V2008-I2014	-0.06	47.64	-35.81
V2008-V2014	-0.11	47.60	-37.44

[a] The unit for all the columns are m^3.

[b] I: Impervious; V: Vegetation; W: Water.

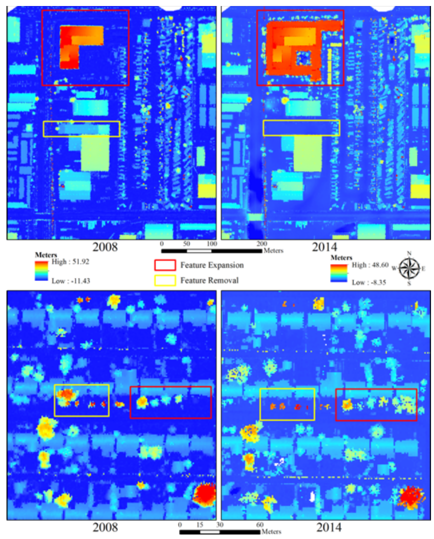

Figure 2. LIDAR Normalized Height Difference Comparison between 2008 and 2014.

Figure 2 illustrates how building and vegetation change across this period. The top comparison shows how new building construction (red) and removal (yellow) happen in our study area. The bottom comparison displays the plant/growth (red) and removal (yellow) of vegetation.

TABLE IV. LANDSCAPE PATTERN CHANGE ANALYSIS

	Composition	Shape	Distribution
Impervious 2010	61.36	0.07	6.91
Vegetation 2010	38.08	0.07	11.65

	Composition	Shape	Distribution
Impervious 2015	63.00	0.08	11.31
Vegetation 2015	36.54	0.08	3.19

A landscape pattern analysis was performed on the NAIP classified scenes for 2010 and 2015 (Table IV). The use of landscape metrics in spatial change analysis of urban and vegetative areas is often used to better understand the patterns and structure of the landscape [17]. Three metrics were calculated using Fragstats. The composition metric was calculated using the Percentage of Landscape (PLAND), the shape metric was derived by a Normalized Landscape Shape Index (NLSI), and the distribution metric was calculated with Interspersing Juxtaposition Index (IJI). The composition in impervious was notably increased while vegetation decreased between the two images, as observed in the other analysis. The shape was relatively unchanged. Since water pixels were very rare in both the 2010 and 2015 NAIP data, we did not calculate the landscape pattern change for water category. The percent distribution of vegetation indicates it becomes less interspersed, and the impervious area becomes more interspersed.

V. CONCLUSIONS

Urban areas concentrate people, economic activities, and the built environment and serve to protect outlying areas. The fast-growing urbanization process converts vegetation-soils continuum into built-up areas. Our results show a significant volume change among the imperious land cover category, which represents the urban residential renovation from vacant lands and single-family households to high-rise apartment complexes. Further, urban green space is more and more fragmented because of the new buildings/roads' construction. Our research provides a preliminary method to understand multidimensional change analysis. Future work will focus on designing a comprehensive methodology to understand and compare urban landscape fragmentation in the 3D environment in multiple cities.

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