Impervious Surface from High Resolution Aerial Imagery Cities in Fresno County

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What are impervious surfaces?

Impervious surfaces are landscapes covered by material **with little or no water permeability.** In the urban environment most impervious surfaces are manmade infrastructure such as rooftops, roadways, and parking facilities composed of materials like concrete and asphalt (Arnold and Gibbons 1996).

Urban sprawl and automobile-friendly development policies and practices have contributed to the paving of large swathes of land to accommodate road and parking infrastructure. Previous studies estimate that road and parking facilities cover an average aerial extent of **29% to 45% in urban areas** (Akbari et al. 2003; Rose et al. 2003). Impervious surface coverage may be even higher – up to **70% – in commercial areas** that offer substantial parking facilities (Litman 2011).

Why are impervious surfaces important?

Excessive impervious surface coverage results in **undesirable environmental, social, and economic outcomes**. As permeable soils are paved over with impermeable materials, water infiltration decreases leading to increased surface runoff and decreased groundwater recharge (Arnold and Gibbons 1996). The larger volume of surface runoff **carries urban pollutants into rivers and lakes** and increases the risk of erosion and flooding.
Dark paved surfaces like asphalt absorb heat and measurably increase the surrounding temperature contributing to the urban heat island effect (Litman 2011). Large parking lots are often considered unsightly and alienating, reducing walkability and discouraging the use of non-automobile transportation modes (Davis et al. 2010). Underutilized parking adds unnecessary upfront and operational costs to development projects.

How to extract impervious surface data?

Most common method to map impervious surfaces is through the process of categorizing satellite or aerial imagery into several classes. This process is called **image classification technique** and further categorized to 1) visual/manual classification, **2) pixel/object-based classification**, 3) spectral indices such as Normalized Difference Built-Up Index (NDBI) and **4) Machine or Deep learning**. Each method has pros and cons in terms of data availability, the level of accuracy, training time etc.

Impervious Surface per Capita vs Percent Impervious Surface

Impervious surface per Capita = Meter^2/population

Percent Impervious surface = I.S Area/Total Area*100

Dataset

The dataset for this project consists of 49 high resolution orthorectified aerial images with a resolution of 30cm (~1 foot). The images have been processed into an orthomosaic covering the 15 incorporated cities of Fresno County (approximately 1,300 square kilometers). Both RGB color images and color infrared (CIR) images (consisting of near-infrared, red, and green bands) are included in the dataset.

The acquisition date is July 4-5, 2020 and geometric processing is ortho-rectified at level 3A. The aerial images have 2.6 meter circular error at 90% confidence level. The projection datum is in the Universal Transverse Mercator (UTM) with the unit of meter.

Dataset

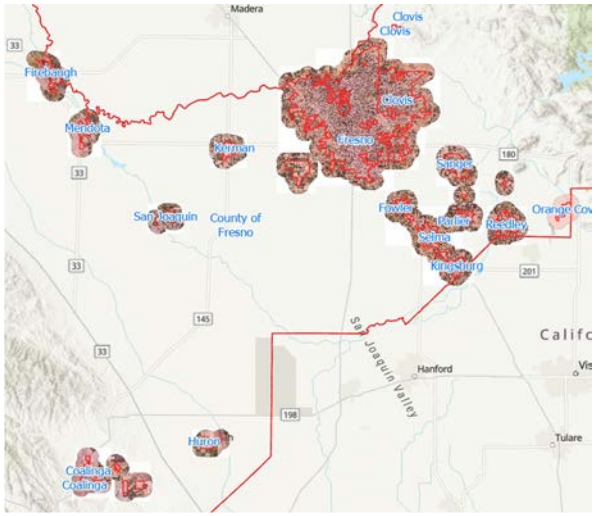


Table 1. Fresno county cities and its area and population. The total area of these cities and population are 471 km2 and 852,371, respectively.

CITIES	AREA (KM^2)	POPULATIONS
ORANGE COVE	4.66	9619
REEDLEY	14.60	25232
MENDOTA	8.48	12735
FIREBAUGH	9.74	8108
SELMA	15.04	24625
KINGSBURG	9.59	12662
PARLIER	6.29	14691
SANGER	14.40	26716
FOWLER	6.84	6934
FRESNO	289.46	544510
CLOVIS	65.95	122989
KERMAN	8.69	16174
HURON	3.85	6222
SAN JOAQUIN	2.62	3689
COALINGA	11.59	17465

Fresno county

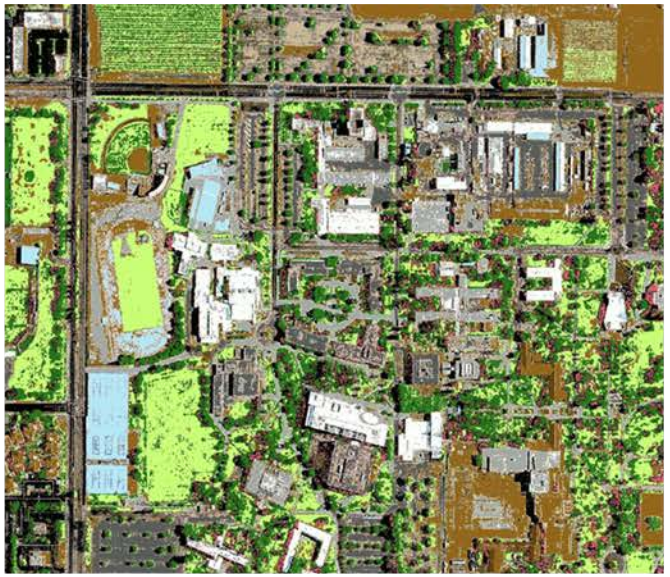
Stretching from the fertile San Joaquin Valley to the crest of the Sierra Nevada, Fresno County is the sixth largest county in California by area and the tenth largest by population. Historically, agriculture has been the predominant industry in the largely rural county, and Fresno County consistently ranks among the top agricultural producers in the United States.

Within Fresno County are fifteen incorporated cities including the county seat and largest city, Fresno. Abundant, inexpensive land has tended to support low density, suburban-type development patterns, especially in the Fresno/Clovis metropolitan area.

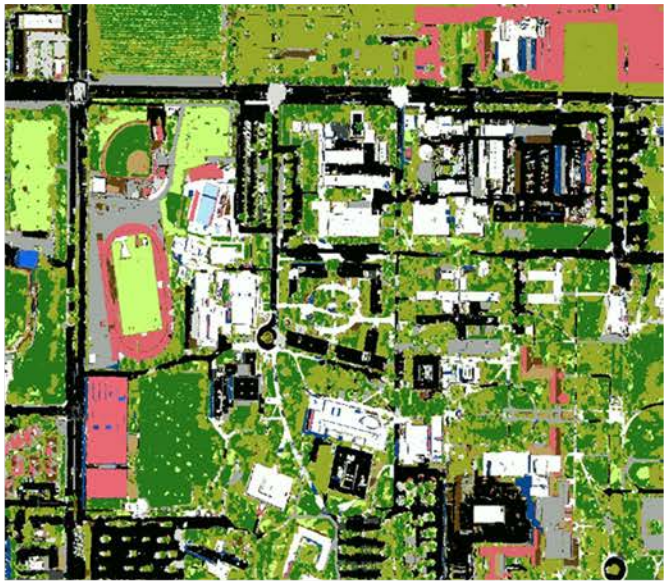
However, cities in Fresno County often don’t get attention as an example of research and studies, in this case, of California impervious surface analysis.

Image Classification

High resolution Image



Pixel-Based Classification



Object-Based Classification

Pixel/Object-based supervised classification Comparison

Rural Area

overall accuracy of 58.3% and a Khat value of 51.1% (medium agreement)

overall accuracy of 54.0% and a Khat value of 48.1% (medium agreement).

Medium Density area

overall accuracy of 37.7% and a Khat value of 32.3% (poor agreement).

overall accuracy of 43% and a Khat value of 36.3%

High Density area

overall accuracy of 44.7% and a khat value of 39.9% (poor agreement - on the cusp of medium).

overall accuracy of 51.3% and a khat value of 45.4% (medium agreement)

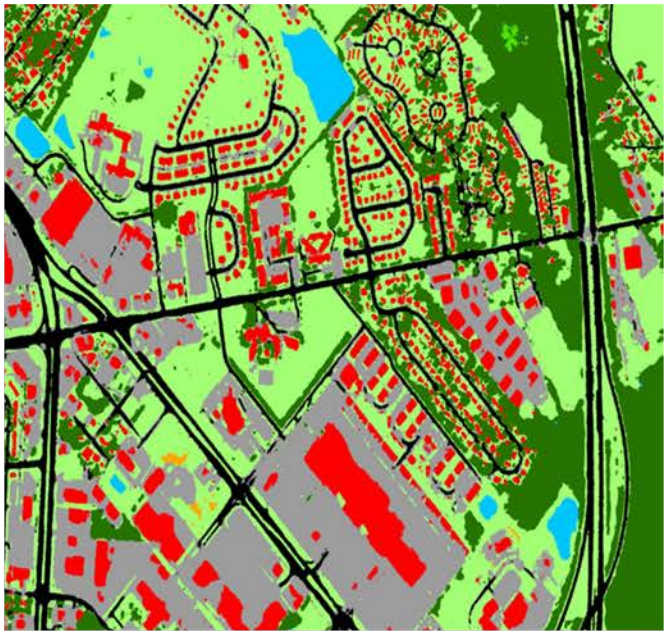
Deep Learning Image Classification

Recent image classification utilizes Deep learning algorithm. Deep learning starts from making a training model which takes a great number of image tiles and classified tiles (or ground truth datasets). Then the new images will be classified based on the training model.
The figure above shows ‘High resolution image’ and ‘Existing Landuse map’ that make training set.
ArcGIS Pro provides deep learning modules for extracting training dataset, training dataset and finally deep learning classification.

Deep Learning Classification

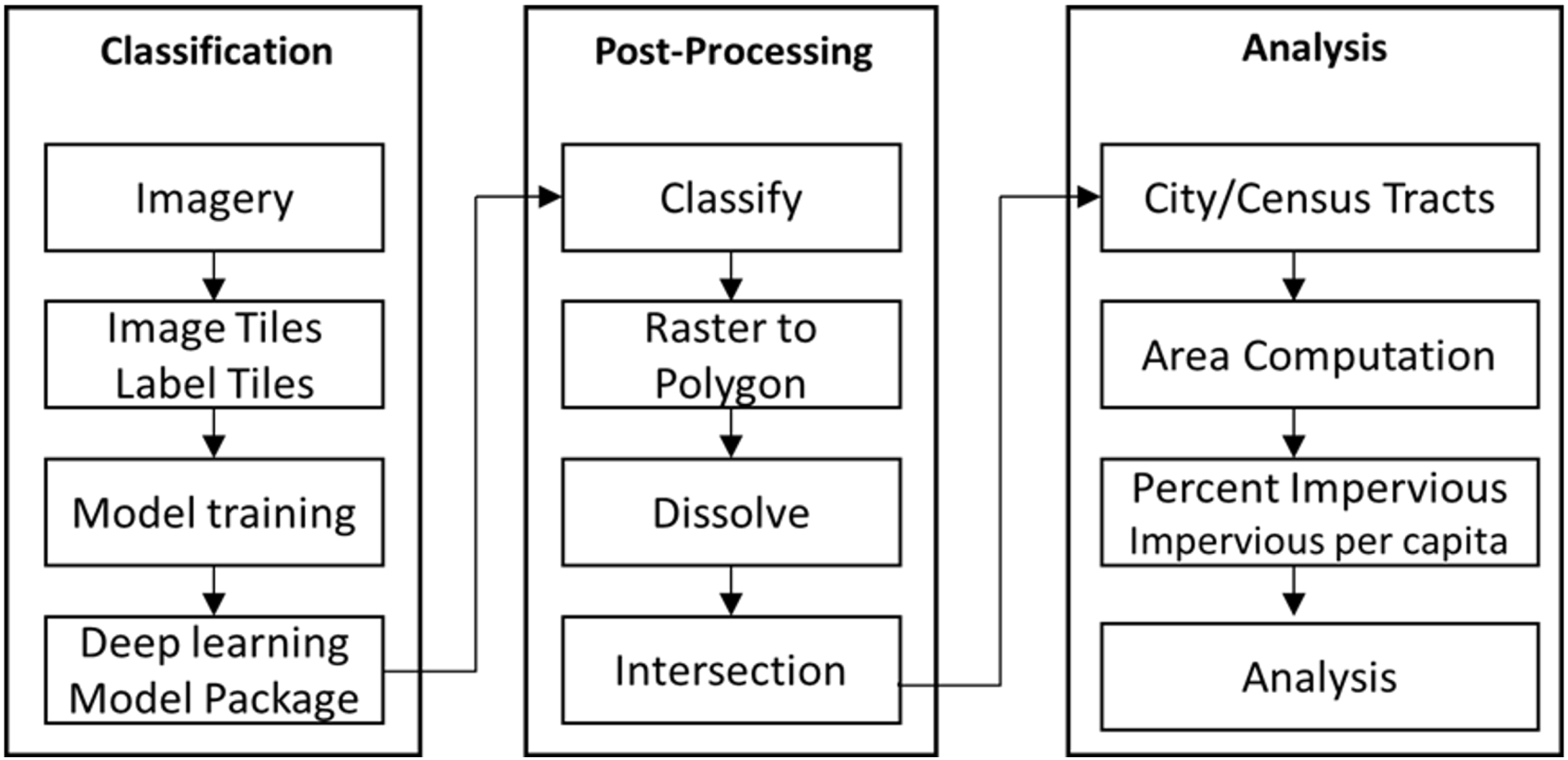
High resolution Image

Existing Landuse Map



Deep Learning Classification

Deep Learning Classification



Landuse/Landcover (LULC) dataset

Conservation Innovation Center (CIC) provides a Land Use/Land Cover (LULC) data set. The classification uses the National Agricultural Imagery Program (NAIP) 1-meter resolution aerial imagery, LiDAR and other auxiliary data.

Deep Learning dataset

Figure 8 Original Image and label image. Left image show high resolution aerial image and right one shows label data overlain on aerial image with transparency 50%. The color red and green represent impervious surface and trees respectively. Whole classes are listed in Table 3.

Image/label tiles and classes

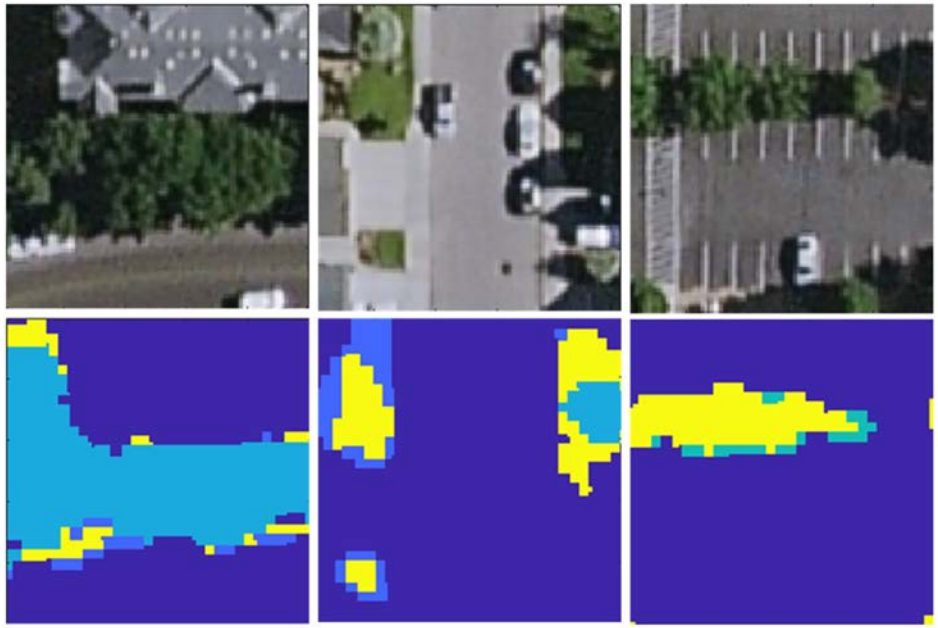


Figure 9 the samples of 100X100 image tile and label files. Purple color indicates impervious

Table 3 MULC classification name and code

Class	Code
Water	10
Impervious Surface	20
Soil-Barren	30
Trees	40
Shrub	50
Grass	70
Agriculture	80
Orchard	82

U-net Classifier (Python Notebook)

```
model.fit(20, lr=0.0005)
model.show_results()
```

epoch	train_loss	valid_loss	accuracy	dice	time
0	0.687157	0.670435	0.749939	0.748582	02:20
1	0.677456	0.674290	0.751207	0.749826	02:22
2	0.695696	0.684709	0.748130	0.746797	02:20
3	0.710832	0.689415	0.747002	0.745590	02:22
4	0.701760	0.686339	0.744097	0.742727	02:20
5	0.680022	0.700236	0.740874	0.739516	02:21
6	0.696421	0.705966	0.744136	0.742801	02:21
7	0.726284	0.699144	0.734975	0.733563	02:21
8	0.707565	0.687780	0.745737	0.744271	02:21
9	0.679228	0.697069	0.743080	0.741742	02:22
10	0.711073	0.683796	0.744572	0.743181	02:21
11	0.703975	0.682908	0.744354	0.742905	02:22
12	0.670634	0.685825	0.747282	0.745916	02:21
13	0.679807	0.696056	0.744962	0.743590	02:20
14	0.691476	0.676783	0.747418	0.746065	02:21
15	0.680077	0.675839	0.750421	0.749085	02:21
16	0.677097	0.675177	0.750506	0.749156	02:20
17	0.663123	0.670817	0.750523	0.749160	02:20
18	0.685122	0.673013	0.749359	0.747983	02:21
19	0.669188	0.671353	0.750063	0.748693	02:21

Post-Processing

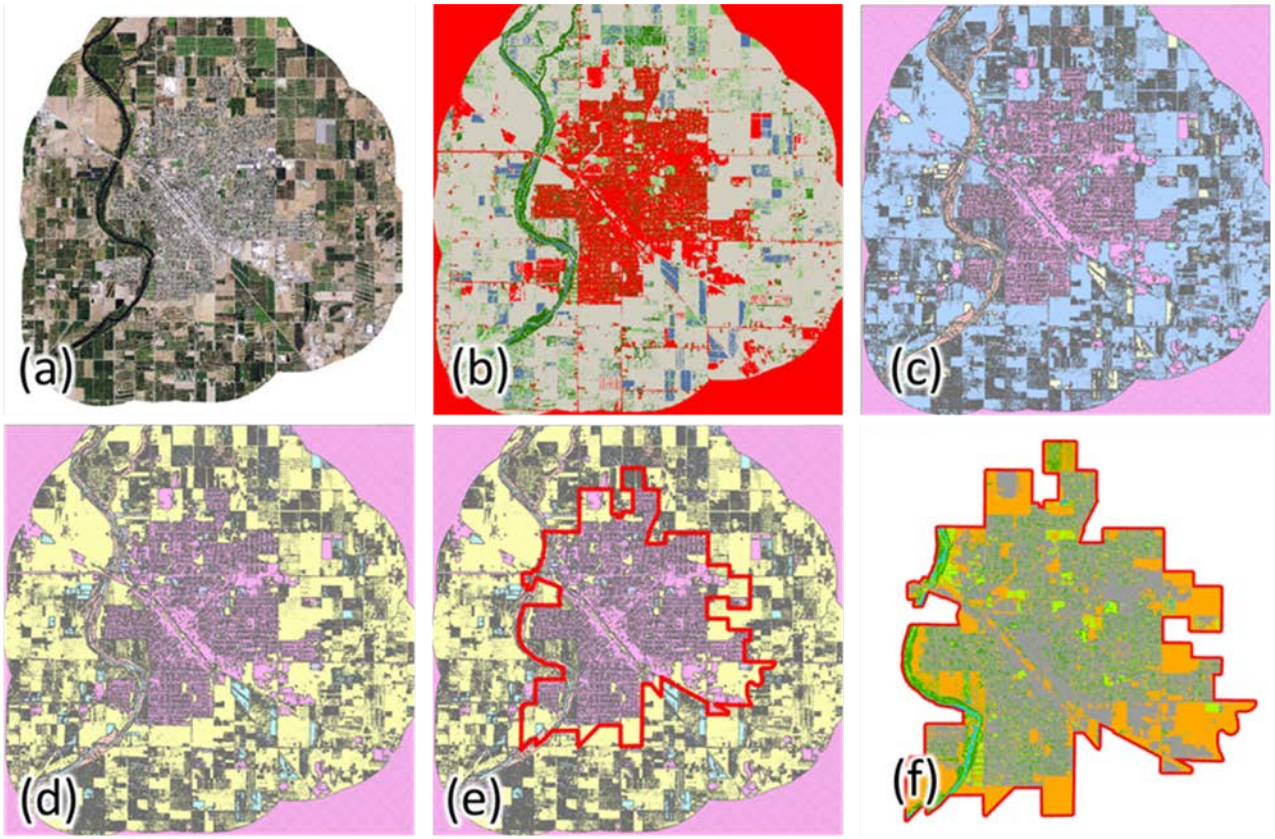


Figure 11 the example of Post processing steps, Reedley city. a) Original image, b) deep learning classification, c) raster to polygon, d) dissolve, e) city boundary, f) clipped result

Analysis Tasks

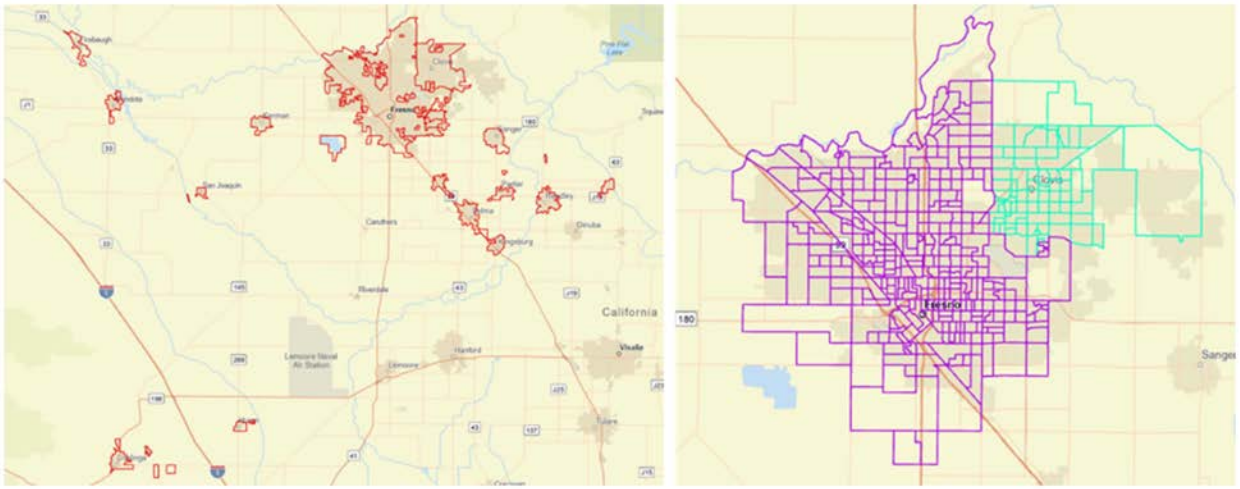


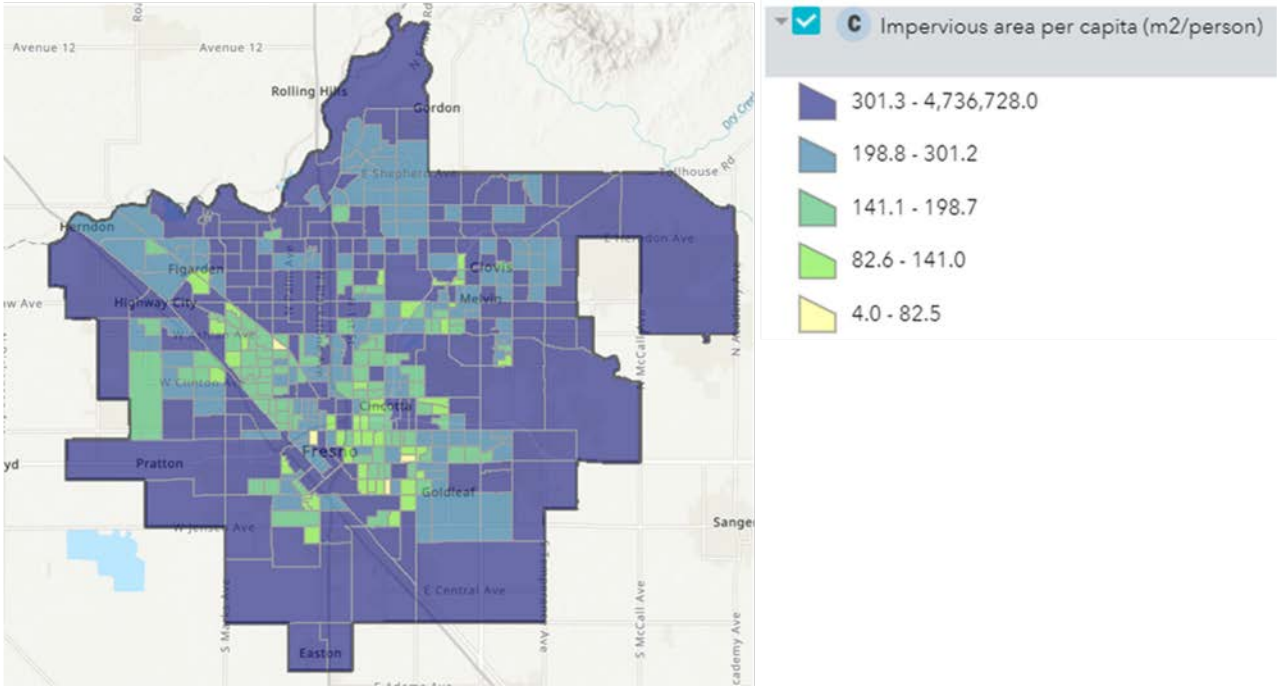
Figure 12 City boundaries and census tracts of Fresno/Clovis

	OBJECTID *	Shape *	FID_...	gridcode	Cl...	FID_Reedley_Clip	AGENCY_COD	AGENCY_NAM	SHAPE_STAr	SHAPE_STLe	Area	Shape_Length	Shape_Area
1	1	Polygon Z	0	1	10	1	CY	Reedley	157173645.796	112182.27339	15	153464.123795	1782927.30061
2	2	Polygon Z	1	2	20	1	CY	Reedley	157173645.796	112182.27339	15	2971144.767651	77007939.095477
3	3	Polygon Z	2	3	30	1	CY	Reedley	157173645.796	112182.27339	15	2423924.418884	43064346.82324
4	4	Polygon Z	3	4	40	1	CY	Reedley	157173645.796	112182.27339	15	2377229.325845	16800686.576369
5	5	Polygon Z	4	5	70	1	CY	Reedley	157173645.796	112182.27339	15	3083738.519464	12930244.621933

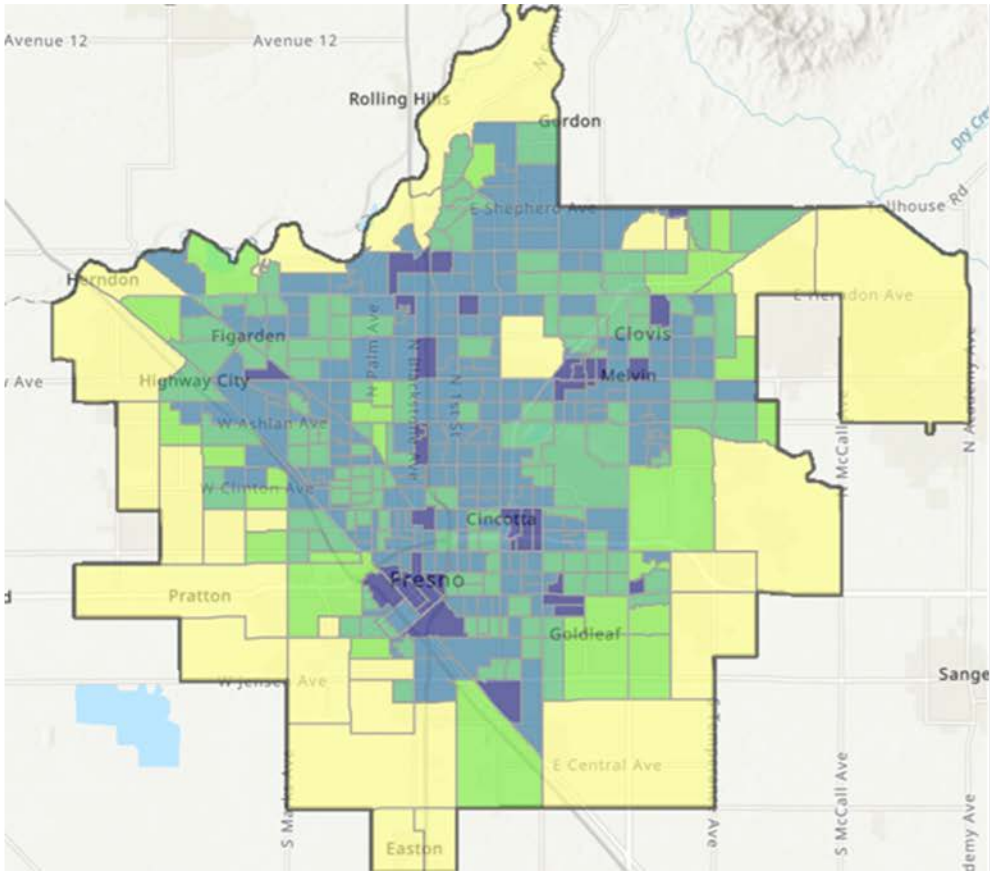
Figure 13 Example of attribute of Reedley city result. The area field is available in the attribute table in ArcGIS.

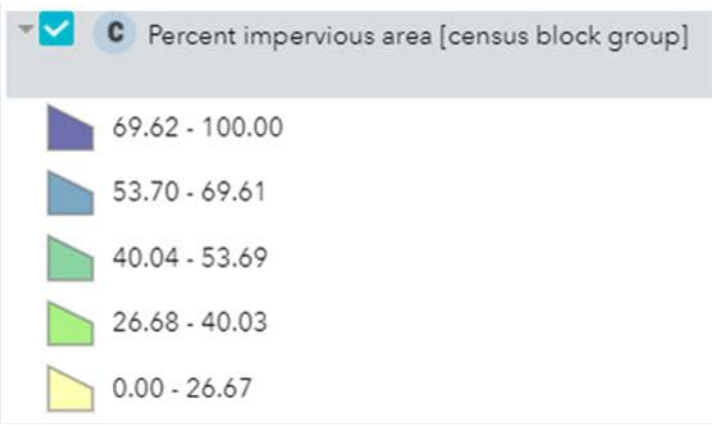
EnviroAtlas

EnviroAtlas is Interactive GIS layers for environmental study. The layers includes Land cover, especially impervious area per capita, percent impervious area, etc.

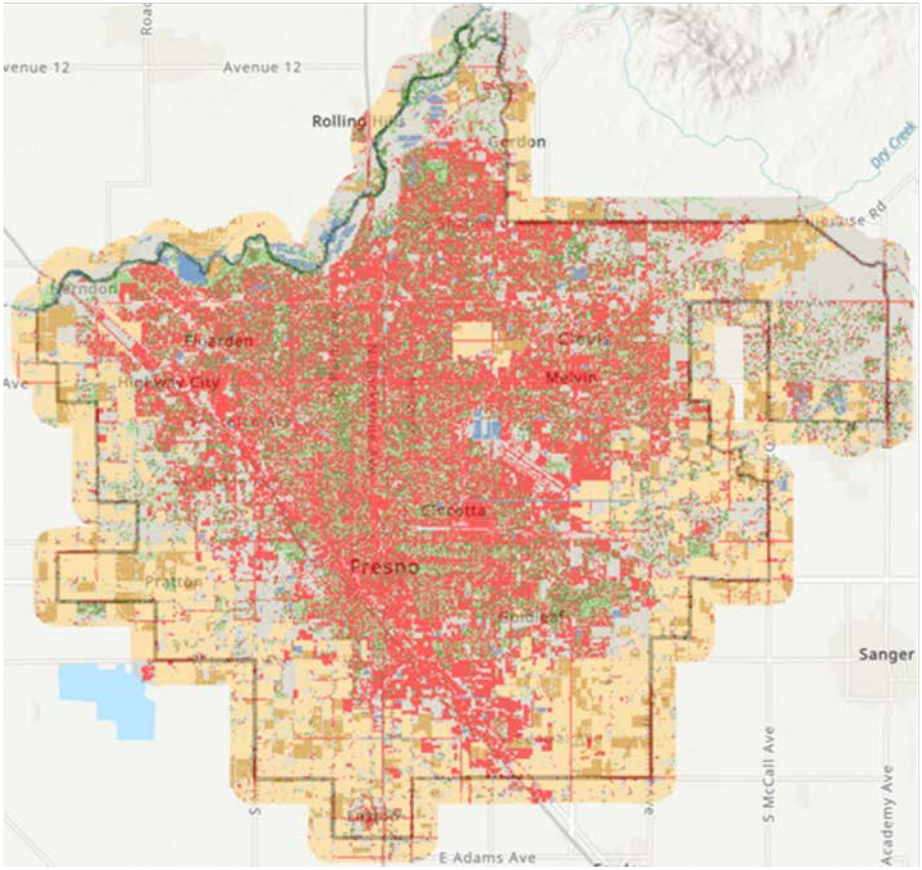


EnviroAtlas





Meter-Scale Urban Land Cover(MUCL), Community date, 1 meter



Accuracy assessment of different classification methods

Table 4 Accuracy assessment of rural area in Fresno County

	Overall Accuracy	Kappa
Pixel-based	72.0%	43.6%
Object-based	61.9%	31.4%
Deep learning	85.8%	59.8%

Table 5 Accuracy assessment of median density area in Fresno County

	Overall Accuracy	Kappa
Pixel-based	76.1%	43.8%
Object-based	87.5%	74.6%
Deep learning	92.8%	85.5%

Table 6 Accuracy assessment of high density area in Fresno County

	Overall Accuracy	Kappa
Pixel-based	82.9%	62.3%
Object-based	77.9%	54.8%
Deep learning	85.2%	70.8%

Impervious surface of Fresno county cities

Cities	Total Area (Square feet)	populations	Impervious Surface (Square feet)	Percent	Per capita
Orange Cove	50,147,103.78	9,619	22,348,900.49	44.57	215.85
Reedley	157,173,645.79	25,232	77,007,939.10	49.00	283.54
Mendota	91,233,492.52	12,735	48,954,023.74	53.66	357.12
Firebaugh	104,868,455.21	8,108	39,627,705.04	37.79	454.06
Selma	161,901,711.49	24,625	66,307,601.15	40.96	250.16
Kingsburg	103,258,138.32	12,662	51,840,403.25	50.20	380.36
Parlier	67,710,385.09	14,691	27,031,377.13	39.92	170.94
Sanger	154,979,514.56	26,716	72,907,425.59	47.04	253.53
Fowler	73,640,043.99	6,934	27,402,159.72	37.21	367.14
Fresno	3,115,694,142.61	544,510	1,784,436,558.26	57.27	304.46
Clovis	709,900,885.59	122,989	428,929,936.17	60.42	324.00
Kerman	93,529,000.77	16,174	56,923,521.83	60.86	326.97
Huron	41,467,033.91	6,222	11,238,708.83	27.10	167.81
San Joaquin	28,168,679.63	3,689	9,074,156.56	32.21	228.52
Coalinga	124,780,179.61	17,465	46,010,443.51	36.87	244.75

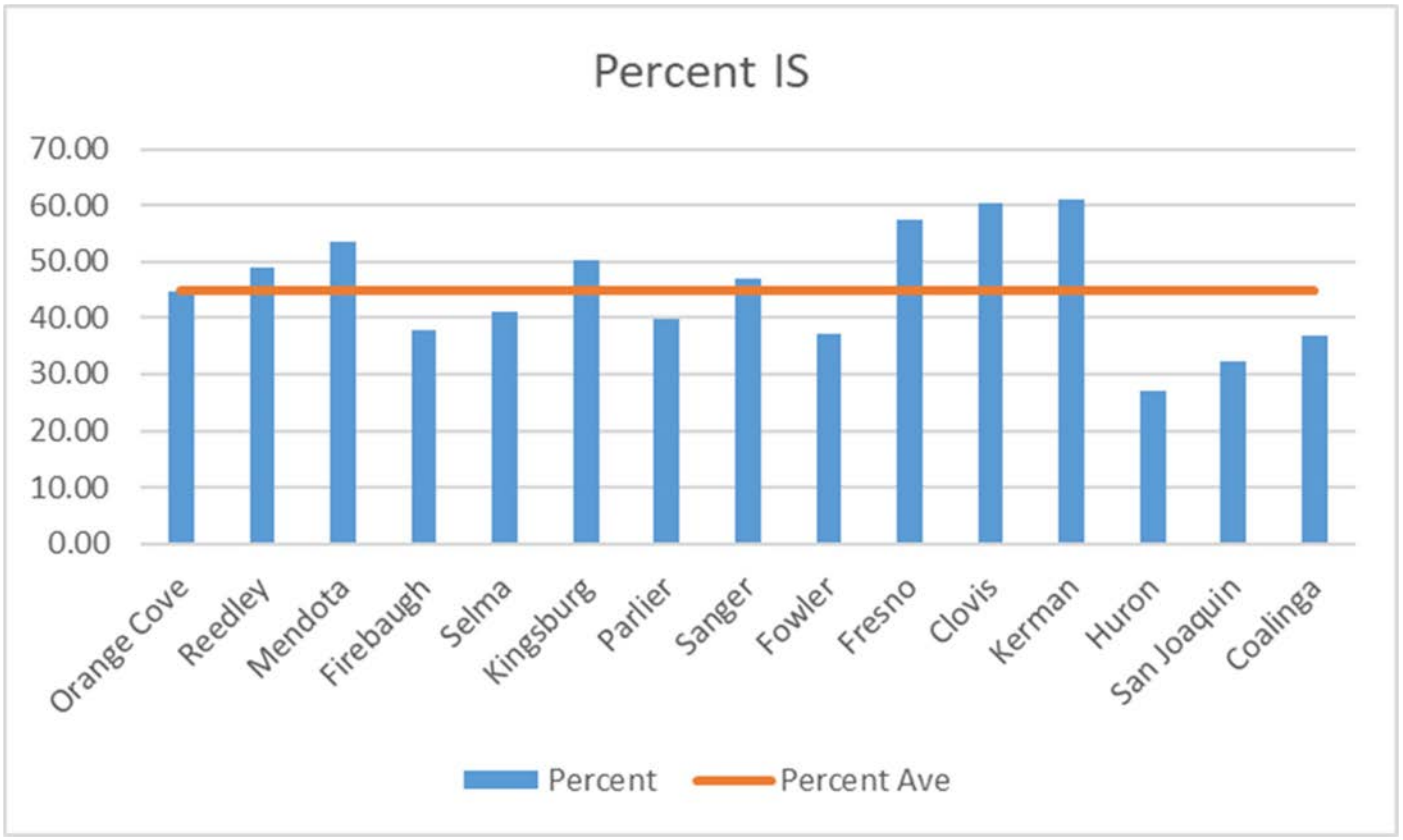
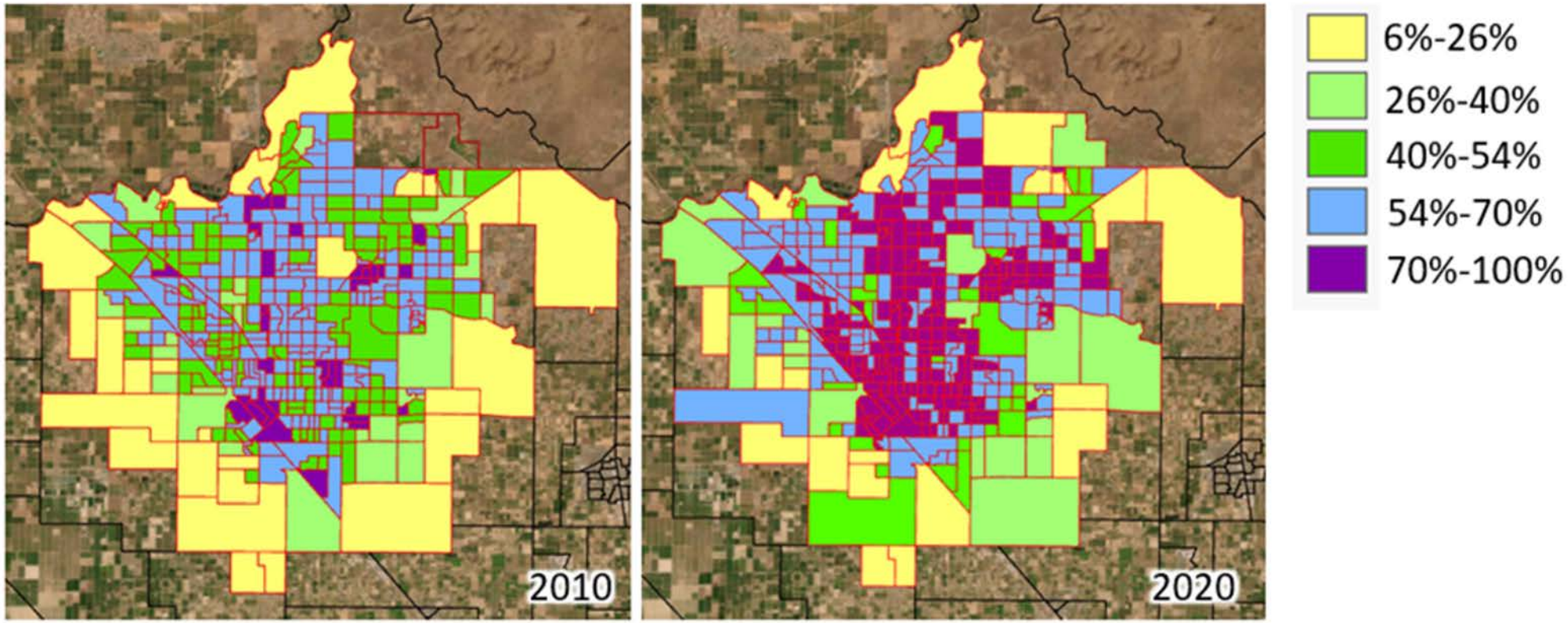


Table 7 summarizes percent impervious surface and impervious surface per capita of 15 cities in Fresno County. Huron, a small agriculture city, shows the smallest percent impervious surface, 27.1% and Kerman and Clovis show as high as 60%. For impervious surfaces per capita, Huron and Firebaugh ranked lowest, 167 square meters/person, and highest, 454 square meters/person, respectively.

Impervious surfaces of Fresno/Clovis in 2010 and 2020



Results and Discussion

It is worth mentioning that Fresno/Clovis percent impervious surface in 2010 (EnviroAtlas) was 53% and 63% in 2020 in this study. This is a 10% increase in 10 years. During those 10 years, the population in Fresno and Clovis increased 8.9% and 25% respectively.

Zian et al (2011) investigated impervious surface changes from 2001 to 2006 in the conterminous United State, showing that 4-5% increase in impervious surfaces overall and three largest changes in impervious surface occurred at Arizona, Georgia and South Carolina and their changes are 8.89%, 8.40%, 7.92% respectively.

Brophy-Price and Rolband (2010) related population increase to impervious surface changes in the Chesapeake Bay watershed between 1990 and 2000. Their analysis showed a 10.3% increase in population and 14.2% in impervious surface changes in the Chesapeake bay watershed. Other vicinity states showed a similar pattern in population and impervious surface.

AN ANALYSIS OF IMPERVIOUS AREA INCREASE VS. POPULATION GROWTH IN THE CHESAPEAKE BAY WATERSHED BETWEEN 1990 AND 2000

Jurisdiction (portion within the Chesapeake Bay watershed)	Population Increase (1990-2000) (%)	Impervious Area Increase (1990-2000) (%)
Chesapeake Bay Watershed	10.3%	14.2%
Delaware	23.2%	28.4%
District of Columbia	-5.7%	1.9%
Maryland	10.7%	15.2%
New York	-2.2%	3.7%
Pennsylvania	5.4%	10.6%
Virginia	16.8%	18.0%
West Virginia	18.0%	21.0%

Brophy-Price, J. A., & Rolband, M. S. (2010). An Analysis of Impervious Area Increase vs. Population Growth in the Chesapeake Bay Watershed Between 1990 and 2000: Gainesville, VA, Wetland Studies and Solutions, Inc. Report WSSI# 21859.01, 56p.

Change of Impervious Surface Area between 2001 and 2006 in the Conterminous United States

“Texas and California also contain the first and second largest impervious surface covers with magnitudes of 9756 km2 and 8937 km2 , respectively, in 2006. Florida has the third largest impervious surface cover with magnitude of 5185 km2 in 2006. Alternatively, three other states have the largest ISA increments from 2001 to 2006 with increasing rates of 8.89% for Arizona, 8.40% for Georgia, and 7.92% for South Carolina. In total, 16 states have ISA increase rates greater than the national average (4.11%) during the period. “

Xian, G., Homer, C., Demitz, J., Fry, J., Hossain, N., & Wickham, J. (2011). Change of impervious surface area between 2001 and 2006 in the conterminous United States. *Photogrammetric engineering and remote sensing*, *77*(8), 758-762.

Summary and conclusion

This study assessed three most common image classification techniques - pixel-based, object-based deep learning classification in extracting impervious surfaces. The analysis shows deep learning outperformed for three different scene complexity - rural, medium residential and high density areas.

The average impervious surfaces of 15 cities in Fresno County were estimated to be 45% in 2020 imagery. For the Fresno/Clovis city area, percent impervious surface increased from 53% in 2010 (EnviroAtlas) to 63% in 2020. This 10% increase in 10 years is aligned well with the population increase.

THANK YOU