Project 2257 | May 2024

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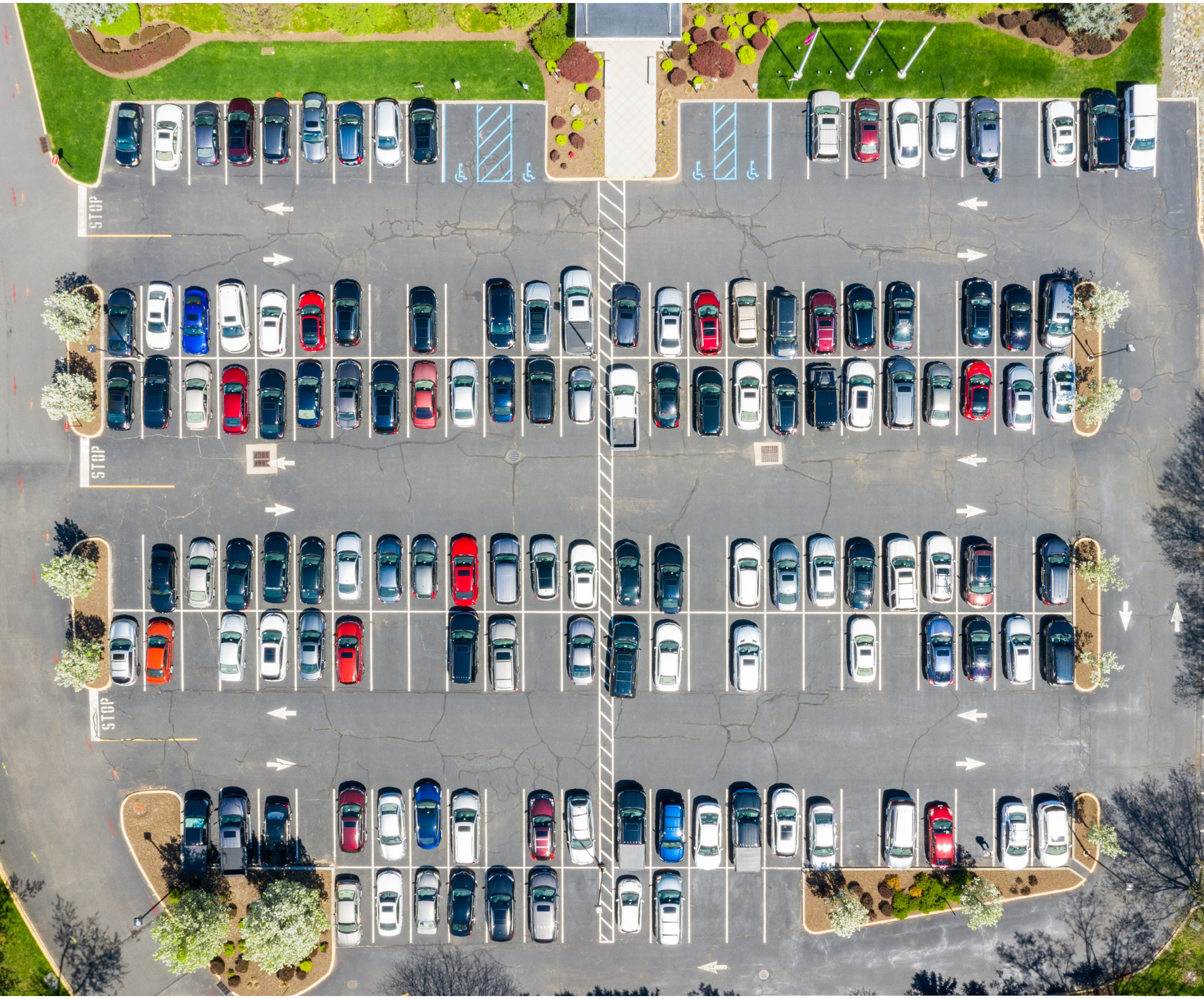
Impervious Surfaces from High Resolution Aerial Imagery: Cities in Fresno County

Yushin Ahn, PhD
Richard Poythress



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Report 24-04

Impervious Surfaces from High Resolution Aerial Imagery: Cities in Fresno County

Yushin Ahn, PhD

Richard Poythress

May 2024

A publication of the
Mineta Transportation Institute
Created by Congress in 1991

College of Business
San José State University
San José, CA 95192-0219

TECHNICAL REPORT DOCUMENTATION PAGE

1. Report No. 24-04	2. Government Accession No.	3. Recipient's Catalog No.
4. Title and Subtitle Impervious Surfaces from High Resolution Aerial Imagery: Cities in Fresno County		5. Report Date May 2024 6. Performing Organization Code
7. Authors Yushin Ahn, PhD Richard Poythress		8. Performing Organization Report CA-MTI-2257
9. Performing Organization Name and Address Mineta Transportation Institute College of Business San José State University San José, CA 95192-0219		10. Work Unit No. 11. Contract or Grant No. ZSB12017-SJAUX
12. Sponsoring Agency Name and Address State of California SB1 2017/2018 Trustees of the California State University Sponsored Programs Administration 401 Golden Shore, 5th Floor Long Beach, CA 90802		13. Type of Report and Period Covered 14. Sponsoring Agency Code
15. Supplemental Notes DOI: 10.31979/mti.2024.2257		

16. Abstract

This study investigates impervious surfaces — areas covered by materials with restricted water permeability, such as pavement, sidewalks, and parking lots—due to their crucial role in influencing water dynamics within urban landscapes. The impermeability of these surfaces disrupts natural water absorption processes, resulting in adverse environmental consequences such as increased flooding, erosion, and water pollution. The research employs impervious surface analysis, a method involving the mapping and analysis of these surfaces within specified study areas, including cities, counties, and census tracts. Remote sensing techniques, specifically satellites and aerial imagery, are commonly utilized for the identification and classification of impervious surfaces. In the context of Fresno County, diverse classification methods, encompassing pixel-based, object-based, and deep learning approaches, are employed to classify and evaluate impervious surfaces. Significantly, the deep learning classification method exhibits exceptional performance, achieving an impressive overall accuracy ranging between 85-92%. The study reveals that the estimated percentage of impervious surfaces in Fresno County cities approximates 45%, comparable to the characteristics of medium density residential areas. Noteworthy is the observation in the Fresno/Clovis city area, where the percentage of impervious surfaces escalated from 53% in 2010 (per EnviroAtlas) to 63% in 2020. This 10% increase over a decade closely aligns with concurrent population growth trends in the region. In conclusion, this research underscores the critical significance of comprehending and monitoring impervious surfaces due to their pivotal role in shaping the environmental quality and resilience of urban areas. The insights gleaned from this study provide valuable guidance for the development of effective land use planning and management strategies, specifically tailored to mitigate the adverse impacts of impervious surfaces on the environment and human well-being.

17. Key Words Impervious surfaces, Image classification, High resolution Aerial imagery, Fresno county	18. Distribution Statement No restrictions. This document is available to the public through The National Technical Information Service, Springfield, VA 22161.		
19. Security Classif. (of this report) Unclassified	20. Security Classif. (of this page) Unclassified	21. No. of Pages 34	22. Price

Form DOT F 1700.7 (8-72)

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DOI: 10.31979/mti.2024.2257

Mineta Transportation Institute
College of Business
San José State University
San José, CA 95192-0219

Tel: (408) 924-7560
Fax: (408) 924-7565
Email: mineta-institute@sjsu.edu

transweb.sjsu.edu/research/2257

ACKNOWLEDGMENTS

This research was funded by California State University Transportation Consortium and Fresno State Transportation Institute. The authors appreciate the editorial service and reviewing that went into this project, as well as FSTI and MTI administrative staff.

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Executive Summary

The study examines impervious surfaces, which are defined as landscapes covered by materials with limited water permeability, such as pavement, sidewalks, and parking lots. These surfaces hinder water absorption into the ground, leading to negative environmental impacts such as flooding, erosion, and water pollution.

Impervious surface analysis involves mapping and analyzing the distribution of such surfaces within specific study areas, such as cities, counties, or census tracts. Remote sensing techniques, including satellites and aerial imagery, are commonly employed to identify and classify impervious surfaces.

In the case of Fresno County, various classification methods, including pixel-based, object-based, and deep learning approaches, were utilized to classify and assess impervious surfaces. The deep learning classification method demonstrated superior performance across all city sizes, achieving an overall accuracy of 85–92%.

The analysis revealed that the percentage of impervious surfaces in Fresno County's cities is estimated to be around 45%, equivalent to that of medium density residential areas. Notably, in the Fresno/Clovis city area, the percentage of impervious surfaces increased from 53% in 2010 (according to EnviroAtlas) to 63% in 2020. This 10% increase over a decade closely aligns with population growth trends observed in the area.

Overall, the study underscores the importance of understanding and monitoring impervious surfaces, as they play a significant role in shaping the environmental quality and resilience of urban areas. The findings provide valuable insights for land use planning and management strategies aimed at mitigating the adverse impacts of impervious surfaces on the environment and human well-being.

1. Introduction

1.1 The Definition of Impervious Surfaces

Impervious surfaces are landscapes covered by material with little or no water permeability. In the urban environment, most impervious surfaces are manmade infrastructures, including rooftops, roadways, and parking facilities composed of materials such as concrete and asphalt (Arnold and Gibbons 1996). Impervious surfaces prevent water from being absorbed into the ground, which can lead to a number of environmentally negative impacts, such as flooding, erosion, and the pollution of streams and waterways.

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). As urbanization increases, the areas of impervious surfaces in cities are increasing. As a result, many cities are implementing measures to reduce impervious surface coverage and more sustainable land use practices, ensuring long term socio-economic and environmental development

1.2 The Impact of Impervious Surfaces

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 & 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 such as 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.

Since impervious surfaces are closely associated with urbanization and development, the extent and distribution of impervious surfaces provide important information about the urban environment.

1.3 Existing Methods for Mapping Impervious Surfaces and Usage of the Data

The most common method to map impervious surfaces is by categorizing satellite or aerial imagery into several classes. This process is called an "image classification technique" and is further categorized into (1) a visual/manual classification, (2) a 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, level of accuracy, and training time.

Manual classification of impervious surface coverage uses aerial imagery to classify surface types visually (Akbari et al., 2003; Davis et al., 2010). Since these methods require an analyst to review and accurately interpret imagery manually, it is prohibitively time-consuming to classify an urban area that may extend for thousands of square kilometers. Therefore, a representative sample is selected, and the analysis is extrapolated to the entire urban area.

Chester et al. (2015) developed a method to estimate roadways and parking infrastructures using county assessor data and a building turnover model that accounts for the historical change in land use patterns in Los Angeles County. Off-street parking is estimated using minimum parking requirements established in municipal codes during three distinct time periods of building construction.

In this study, pixel-based supervised classification, object-based supervised classification, and deep learning classification are performed and analyzed for their performance.

There are several measures to quantify the amount of land surface that is covered by impervious surfaces. They are (1) Percent Impervious Surfaces, (2) Impervious Surface Coefficient, and (3) Impervious Surface Per Capita.

Percent Impervious surface: This represents the ratio of impervious surfaces to the total area in percent. The Non-Point Source for Municipal Officials (NEMO) Program and the Center for Watershed Protection use the impervious surfaces coverage for land-use planning purposes. (Washburn, 2010) by implementing the Impervious Surface Analysis Tool (ISAT).

$$Percent\ Impervious\ Surface = \frac{Impervious\ surface}{Total\ Area} \times 100$$

1. Impervious Surface Coefficient: The National Resources Conservation Service (NRCS) uses the impervious surface coefficient for calculating storm water runoff.

$$Impervious\ Surface\ Coefficient\ = \frac{Impervious\ surface}{Total\ Area}$$

2. Impervious Surface Per Capita: Impervious surface area per person is often used to understand the extent of urbanization and development in a region.

$$Impervious\ Surface\ per\ Capita = \frac{Impervious\ Surface}{population}$$

Percent impervious surfaces is the ratio of impervious surfaces to the total area in percent.

2. Image Classification for Impervious Surfaces

2.1 Study Area

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.

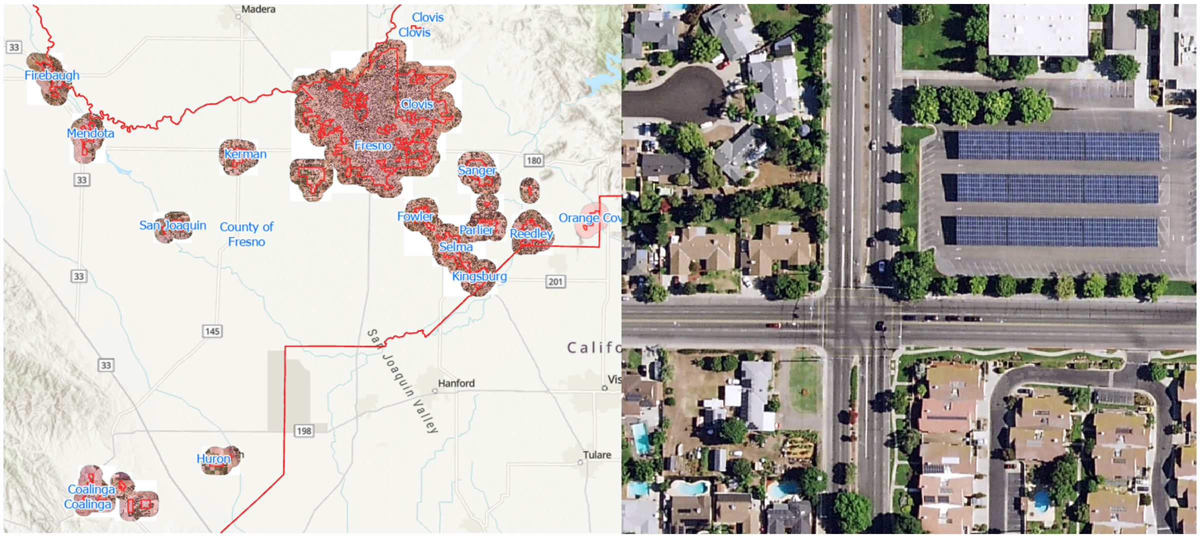
Within Fresno County are fifteen incorporated cities including the county seat and largest city, Fresno. Abundant, inexpensive land has tended to support low-density, suburban-type development patterns, especially in the Fresno/Clovis metropolitan area. However, cities in Fresno County often are not the focus of research and studies, and in this case of California impervious surface analysis.

2.2 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 orthorectified at level 3A. The aerial images have a 2.6-meter circular error at 90% confidence level. The projection datum is in the Universal Transverse Mercator (UTM) with the unit of meter.

Figure 1. Aerial Image Coverage of Project Area



Note: City boundaries are in a red solid line. Cities are Orange Cove, Reedley, Mendota, Firebaugh, Selma, Kingsburg, Parlier, Sanger, Fowler, Fresno, Clovis, Kerman, Huron, San Joaquin, and Coalinga (left); example of aerial image (right)

Table 1. Fresno County Cities and Its Area and Population

CITIES	AREA (KM^2)	POPULATIONS
ORANGE COVE	4.66	9,619
REEDLEY	14.60	25,232
MENDOTA	8.48	12,735
FIREBAUGH	9.74	8,108
SELMA	15.04	24,625
KINGSBURG	9.59	12,662
PARLIER	6.29	14,691
SANGER	14.40	26,716
FOWLER	6.84	6,934
FRESNO	289.46	544,510
CLOVIS	65.95	122,989
KERMAN	8.69	16,174
HURON	3.85	6,222
SAN JOAQUIN	2.62	3,689
COALINGA	11.59	17,465

Note: The total area of these cities and population are 471 km2 and 852,371, respectively.

2.3 Pixel-based and Object-based Classification

Pixel-based and object-based classification are two common approaches used in remote sensing image classification. Pixel-based classification involves assigning a land cover class to each individual pixel in an image based on its spectral properties. This approach assumes that each pixel represents a single land cover type and can be classified independently from its neighboring pixels. Object-based classification, on the other hand, involves grouping pixels into meaningful objects or segments based on their spatial properties, such as color, texture, and shape. These objects are then classified based on their spectral and spatial characteristics.

Object-based classification can be more accurate than pixel-based classification because it considers the spatial context of each pixel, which can help to reduce classification errors caused by mixed pixels or misclassification of pixels with similar spectral properties (Lie and Zia, 2010; Myint, 2011). In the following section, three data sets—rural area, medium density area, and high-density area—were chosen for the comparison.

2.3.1 Rural Area

The city of San Joaquin, a small farming community (population: 4,000) in Fresno County, is representative of rural development.

Pixel-based supervised classification

The pixel-based classification started with the creation of a training set. It was decided to use three different classes for asphalt corresponding to fresh, dark-colored asphalt; worn, light-colored asphalt; and medium-colored asphalt that was discolored by heavy vehicle use. In total, nine classes were used. A concrete class was not created due to the lack of concrete roads or bridges in the area of study (and likely confusion with white roofs).

Figure 2. Pixel-based Supervised Classification, Rural Area

Finally, 131 accuracy assessment points were created using the STRATIFIED_RANDOM strategy. Ground truth was input using the original RGB raster and Google Maps/Street View. A confusion matrix was generated with an overall accuracy of 58.3% and a Khat value of 51.1% (medium agreement).

Object-based Supervision Classification

The original raster was cropped to the same boundaries as the pixel-based classification. Then the Segment Mean Shift function was used to produce a segmented image. Several combinations of Spectral Detail, Spatial Detail, and Minimum Segment Size were attempted. The final Segment Mean Shift raster used a spectral detail of 19, spatial detail of 10, and minimum segment size of 40 pixels.

Next, a training set was developed. An attempt was made to include the railroad track that runs through town as a separate class. However, it was deemed unsuccessful, as it was too close to asphalt, and the railroad class was excluded from the final classification.

Figure 3. Object-based Supervised Classification, Rural

Finally, 125 accuracy assessment points were created using the STRATIFIED_RANDOM strategy. Ground truth was input using the original RGB raster and Google Maps/Street View. A confusion matrix was generated with an overall accuracy of 54.0% and a Khat value of 48.1% (medium agreement).

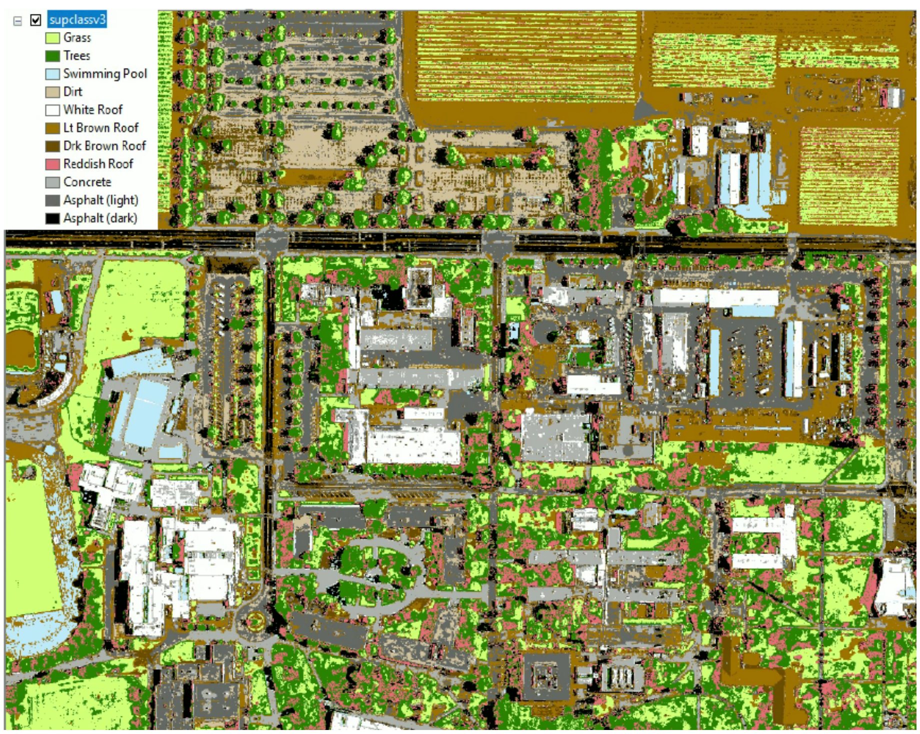
2.3.2 Medium Density Area

California State University, Fresno (Fresno State) moved to its current location in the 1950s. The campus and its environs are representative of post-WWII medium-density suburban development. The image used for this assessment is the RGB color image “7_11” which covers a portion of the Fresno-Clovis metropolitan area centered on Fresno State.

Pixel-based supervised classification

The paved surface area of most interest in this investigation was divided into three categories: “concrete” (white to light grey), “asphalt (light)” (light to medium grey), and “asphalt (dark)” (medium to dark grey). It was felt that this division was necessary to create spectrally pure classes. After the training sample was complete, a signature file was created, and the “Maximum Likelihood Classification” was run.

Figure 4. Pixel-based Supervised Classification, Medium Density Area

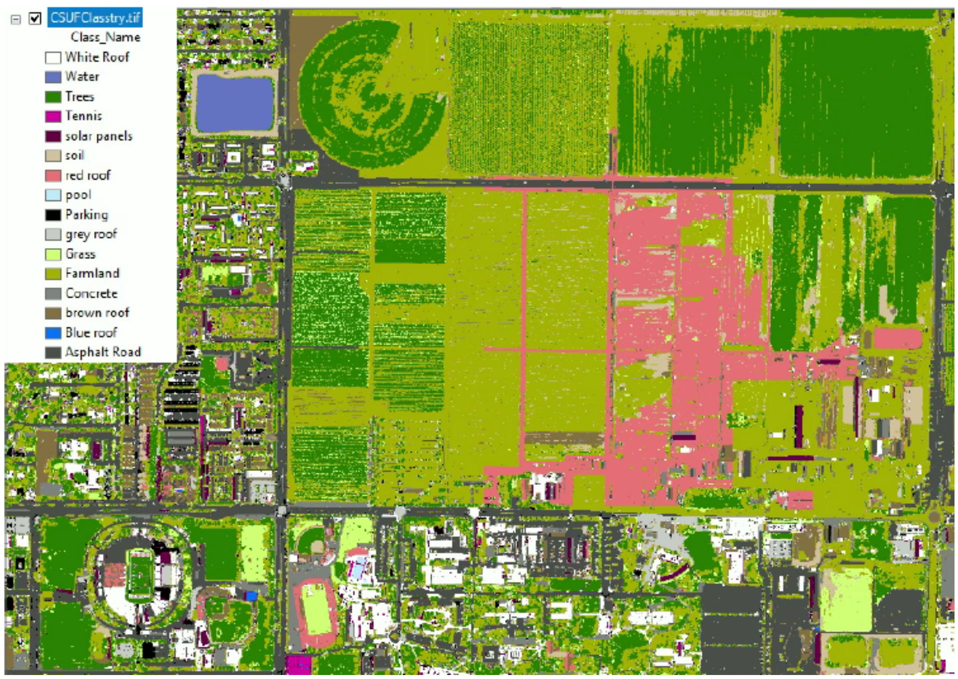


Finally, 113 accuracy assessment points were created using the STRATIFIED_RANDOM strategy. Ground truth was input using the original RGB raster and Google Maps/Street View. A confusion matrix was generated with an overall accuracy of 37.7% and a Khat value of 32.3% (poor agreement).

Object-based Supervision Classification

For object-based classification, the Segment Mean Shift function was used to produce a segmented image. Several combinations of Spectral Detail, Spatial Detail, and Minimum Segment Size were attempted. The goal was to capture the painted lines on the road to assist in the classification. The final Segment Mean Shift raster used a spectral detail of 18, a spatial detail of 18, and minimum segment size of 10 pixels. Even at maximum spectral and spatial detail, there was still bleed over between asphalt and the surrounding features. For example, note that the asphalt in parking lot P20 and the lighter asphalt at the east end of Barstow bled into the surrounding agricultural areas.

Figure 5. Object-based Supervised Classification, Medium Density Area



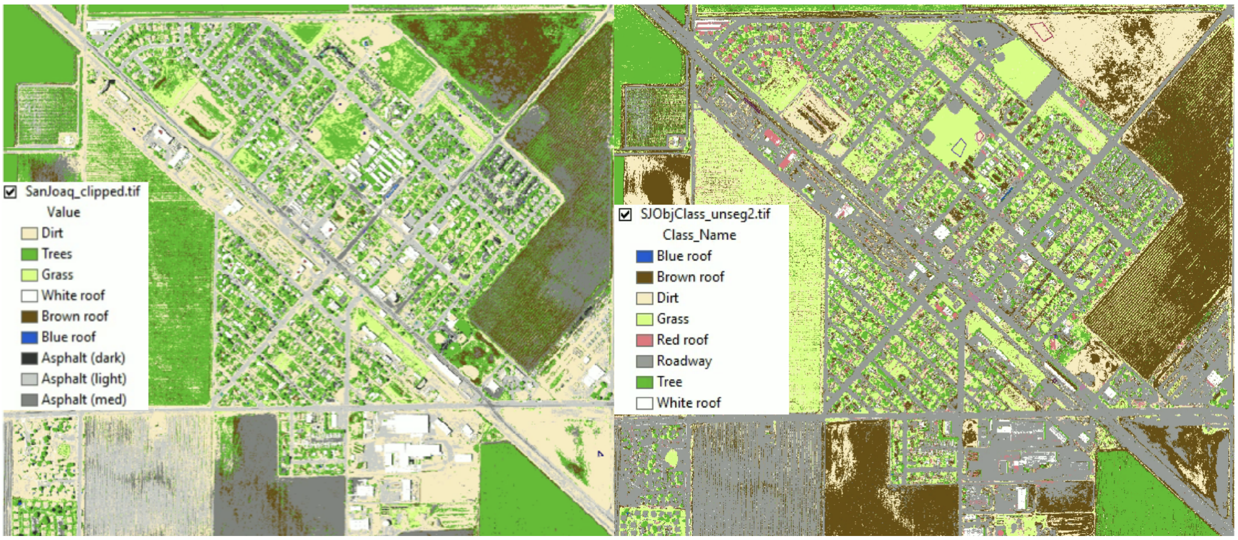
Finally, 534 accuracy assessment points were created using the STRATIFIED_RANDOM strategy. Ground truth was input using the original RGB raster and Google Maps/Street View. A confusion matrix was generated with an overall accuracy of 39.1% and a Khat value of 32.3% (poor agreement). If both asphalt classes (road + parking) are aggregated, the overall accuracy increases to 43.0% and Khat improves to 36.3%.

2.3.3 High Density Area

Downtown Fresno and the older neighborhood surrounding it represent the highest density development in Fresno County. The image used for this study is the CIR color image “7_6” which covers the city of Fresno between the downtown area and the Fresno Yosemite International Airport. In addition to the airport and high-density downtown area, this map tile also includes portions of all major highways (State Routes (SR) 41, 99, 168 and 180) in the Fresno/Clovis area.

The color infrared image was chosen to see if it provides any better results than analysis on RGB images.

Figure 6. Supervised Pixel-based and Object-based Classification of Downtown Fresno to Airport



The pixel- and object-based classification methods produced similar results for the percentage of area covered by paved surfaces (43%–45%). The object-based method was slightly more accurate than pixel-based. The average area covered by paved surfaces was significantly higher for this map tile than for the previous run in the Fresno/Clovis area (map tile 7_11). The previous run showed a paved area of 25%–32% depending on the classification method used. Aside from differences in methodology (different training sets, use of RGB vs CIR, etc.), this may be due to the large sections of farmland in map tile 7_11 (Fresno State agricultural areas) and the presence of significant paved infrastructure in map tile 7_6 (four major highways; the SR 180, 41, and 168 interchange complexes; and Fresno Yosemite International Airport). The use of color infrared did not produce a significantly more accurate map compared to previous RGB runs, although there is no direct comparison of RGB and CIR on the same map tile.

2.4 Deep Learning Classification

The deep learning module in ESRI ArcGIS Pro provides several tools and workflows for training and applying deep learning models for classification, including the ability to use pre-trained models, create custom models, and fine-tune existing models.

A deep learning module is based on a convolution neural network (CNN) in ArcGIS Pro, which uses U-Net architecture designed to classify multi-band raster datasets.

Figure 7. Workflow of Impervious Surface Analysis

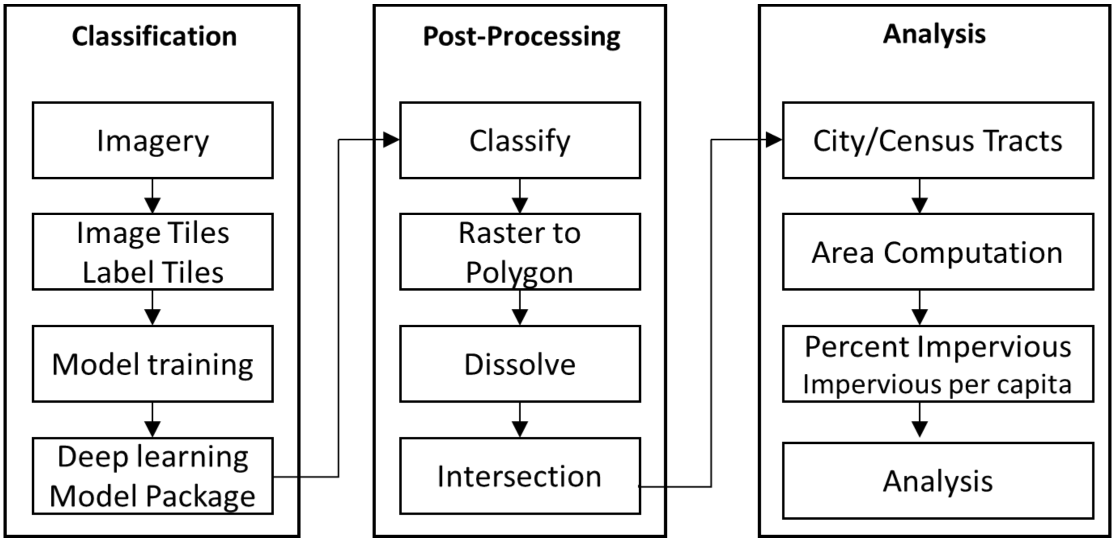


Figure 7 illustrates three main parts used in this study. The classification part consists of (1) creating image tiles and label tiles, (2) model training using U-net Classifier, and (3) creating Deep Learning Model package (*.dlpk).

Figure 8. Original Image and Label Image

Note: The left image shows a high-resolution aerial image, and the right one shows label data overlain on an aerial image with transparency 50%. The colors red and green represent impervious surfaces and trees respectively. Whole classes are listed in Table 3.

Classification Task

For creating image/label tiles, high resolution aerial image and Meter-Scale Urban Cover (MULC) data were used. The MULC are from US EPA EnviroAtlas (https://enviroatlas.epa.gov/enviroatlas/interactivemap/). MULC data represent 1-meter pixel resolution and have an overall fuzzy accuracy of 88% and mean Kappa coefficient of 0.84 (Pilant, 2020). This EPA-developed MULC used National Agriculture Imagery Program (NAIP) imagery, NVDI, LiDAR Height Above Ground (HAG), and LiDAR intensity and applied three different classification approaches—pixel-based classification, object-based classification, and object rule-based classification. MULC class 20, which is an impervious surface, includes paved roads, parking lots, driveways, sidewalks, roofs, swimming pools, patios, painted surfaces, wooden structures and most asphalt ones, and concrete-paved surfaces (Pilant, 2020).

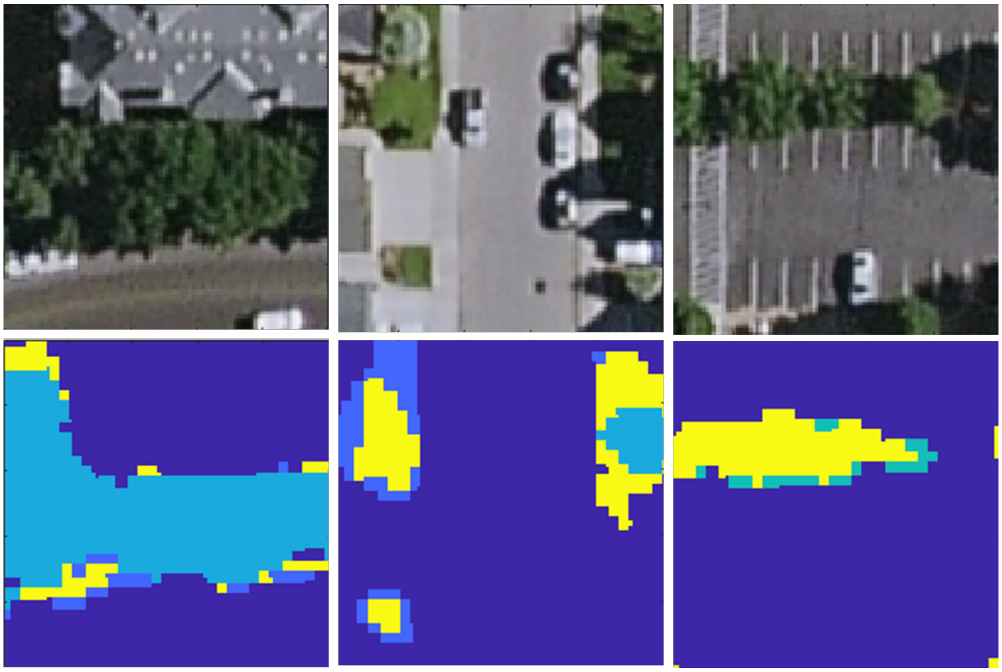
MULC data categorizes the landscape to standard MULC classes, and the table below shows the most frequently used in central California data.

Table 2. 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

Using "Export Training Data for Deep Learning" in ArcGIS Pro Deep Learning tools, a total of 9,899 raster and label tiles with 100x100 pixels are exported for deep learning.

Figure 9. Samples of 100x100 Image Tile and Label Files



Note: Purple Indicates Impervious Surfaces

Figure 9 shows samples of image and label tiles used in this study. Once image/label tiles were created and stored, model training using "U-Net Classifier" was performed in Python Notebook. A U-Net classifier is one of the deep learning semantic segmentations, also known as a pixel-based classification, that assigns each pixel to a particular class and commonly is used for land cover classification of remotely sensed image data.

Figure 10. The Results of U-net Classifier Model Training

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

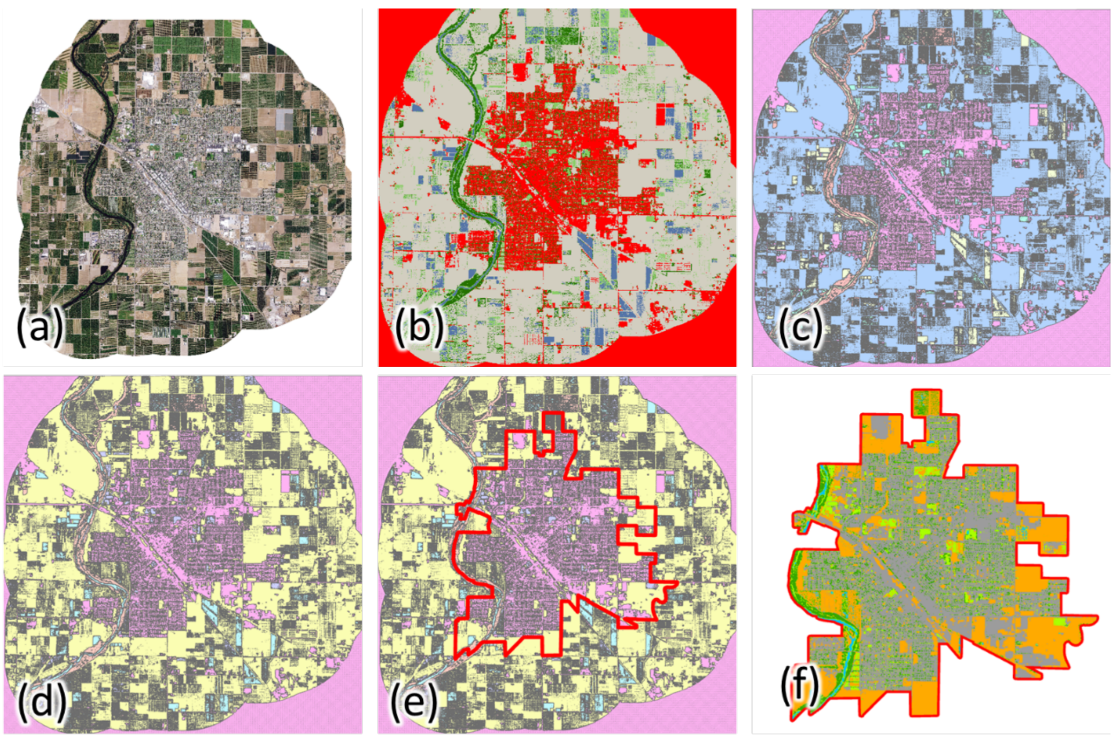
epoch	train_loss	valid_loss	accuracy	dice	time
0	0.687157	0.670435	0.749939	0.748582	02:20
1	0.677456	0.674290	0.751207	0.749826	02:22
2	0.695696	0.684709	0.748130	0.746797	02:20
3	0.710832	0.689415	0.747002	0.745590	02:22
4	0.701760	0.686339	0.744097	0.742727	02:20
5	0.680022	0.700236	0.740874	0.739516	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

The model training of "U-Net Classifier" generated the Deep Learning Package (.dlpk file) which will be used to classify all Fresno County aerial imagery.

Post-Processing Task

The post processing has a series of functions to (1) classify images using the Deep Learning Model Package; (2) convert raster images to vector format shape files using the "Raster to Polygon" function; and (3) aggregate the feature by class attribute using the "Dissolve" function, merging small pieces of a polygon into a larger one based on specific attributes; and lastly (4) clip data using the intersection function, based on city and census tracts boundaries for analysis.

Figure 11. Example of Post-Processing Steps, Reedley City: (a) Original Image, (b) Deep Learning Classification, (c) Raster to Polygon, (d) Dissolve, (e) City Boundary, and (f) Clipped Result



Analysis Task

The classification results of cities in Fresno County, when requiring more than one tile, were merged and clipped with city and census tract boundary. City boundaries in Fresno County were obtained from the Fresno County Computer Data system (https://www.co.fresno.ca.us/departments/public-works-planning/divisions-of-public-works-and-planning/cds/gis-shapefiles), and the Fresno/Clovis city census tracts data were downloaded from City of Fresno GIS Data hub (https://gis-cityoffresno.hub.arcgis.com/). See below for their coverages.

Figure 12. City Boundaries and Census Tracts of Fresno/Clovis

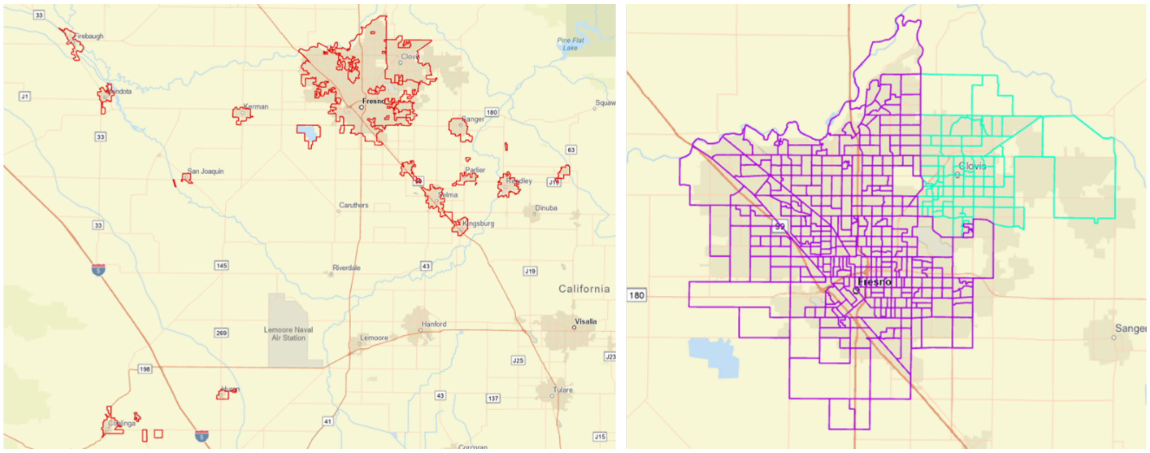


Figure 13. Example of Attribute of Reedley City Result

	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

Note: The Area Field is Available in the Attribute Table in ArcGIS.

The percentage of impervious surface and impervious surface per capita, which are the most common indicators in this type of impervious surface analysis, were calculated based on these areas and populations.

Quality Assurance/Quality Check (QA/QC) using EnviroAtlas data

For QA/QC, EnviroAtlas results were referenced. EnviroAtlas is a free interactive mapping tool maintained by the United States Environmental Protection Agency (EPA). It offers layers of data for hundreds of different environmental factors at both a national and community level. Community level data is available for Fresno (incorporating the entire Fresno/Clovis urban area) at the census block level. EnviroAtlas includes impervious surface data for the Fresno area based on the Meter Scale Urban Land Cover (MULC) project using four band RGB/NIR imagery collected in summer 2010 and LiDAR data collected in 2012.

The percentage of impervious cover in Fresno ranges from 6.6% in a census block near the rural West Park community southwest of Fresno city limits to 86.9% along the Blackstone Avenue commercial corridor (between Ashlan and Saginaw). Aggregating census blocks into tracts, we find values ranging from 8% on the rural periphery to 81% in downtown Fresno. The average impervious area coverage in the Fresno area is 35%.

3. Results and Analysis

3.1 Accuracy Assessment of Pixel-Based, Object-Based, and Deep Learning Classification

ArcGIS has built-in accuracy assessment tools to aid in the evaluation of different classification methods. For this project, three tiles were chosen to represent rural-, medium-, and dense-development patterns. Accuracy assessment points were created using the "stratified random" method, and ground truth was established using a combination of the original RGB rasters, Google Maps/Street View, and Bing Maps. Then, a confusion matrix was generated to calculate the overall accuracy and kappa for each classification method.

For the purposes of accuracy assessment, each pixel is assigned to one of two categories: impervious surface and permeable surface. Impervious surfaces include rooftops and paved surfaces, such as asphalt and concrete. Permeable surfaces include vegetation, barren/dirt, and surface water. A pixel is considered correctly classified if its imperviousness is correctly assigned, regardless of the initial classification category. For example, a "grass" pixel assigned to the "barren" category would be considered correct since both "grass" and "barren" are permeable surfaces.

Table 3. 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 4. Accuracy Assessment of Medium-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 5. 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%

Tables 4, 5, and 6 show overall classification accuracy results for pixel-based, object-based, and deep learning classification methods. While pixel- and object-based accuracy outperformed each other in different scene contexts, deep learning classification consistently shows the best results among these three methods, especially in medium-density areas. This might be attributed to the fact that the majority of the training dataset used in this study covers mostly medium-density, residential areas.

3.2 Impervious Surfaces in Fresno County

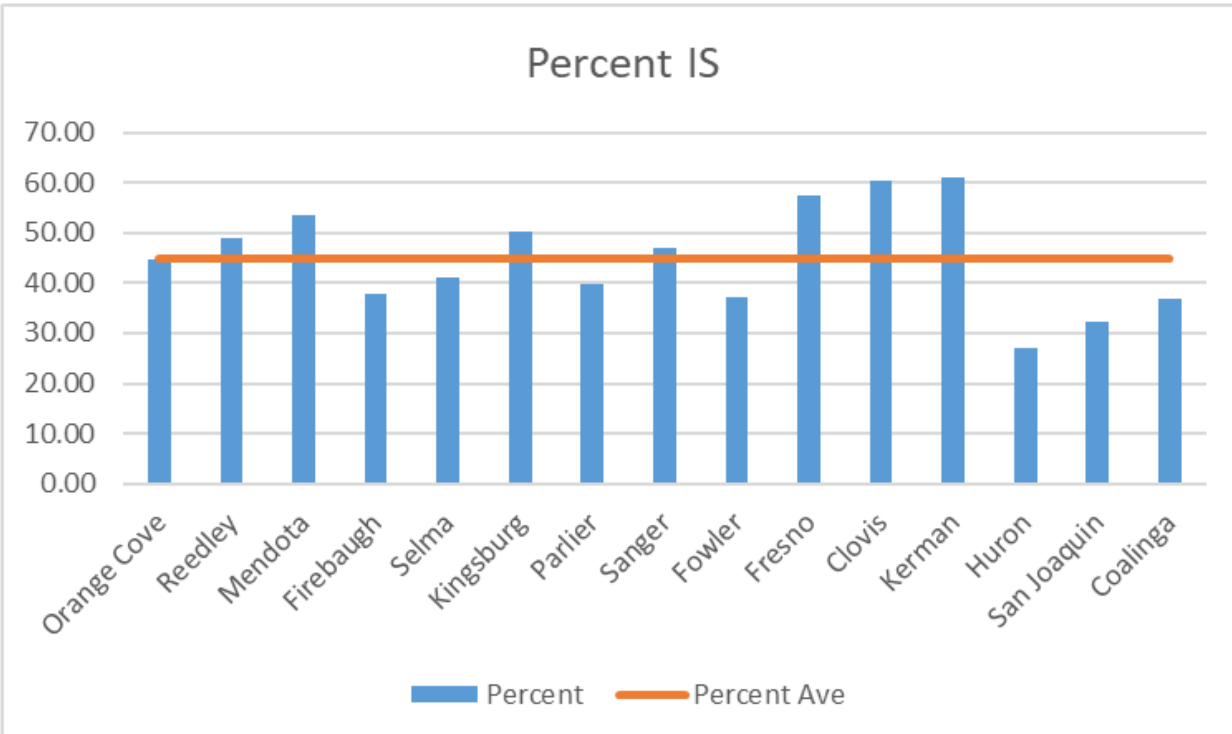
The previous section shows that the deep learning classification has the highest accuracy among the different methods. From the deep learning classification results, followed by merging and clipping of the data, a table for impervious surface analysis is created.

Table 6. Impervious Surface of Fresno County's Cities

Cities	Total Area (Square feet)	Population	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

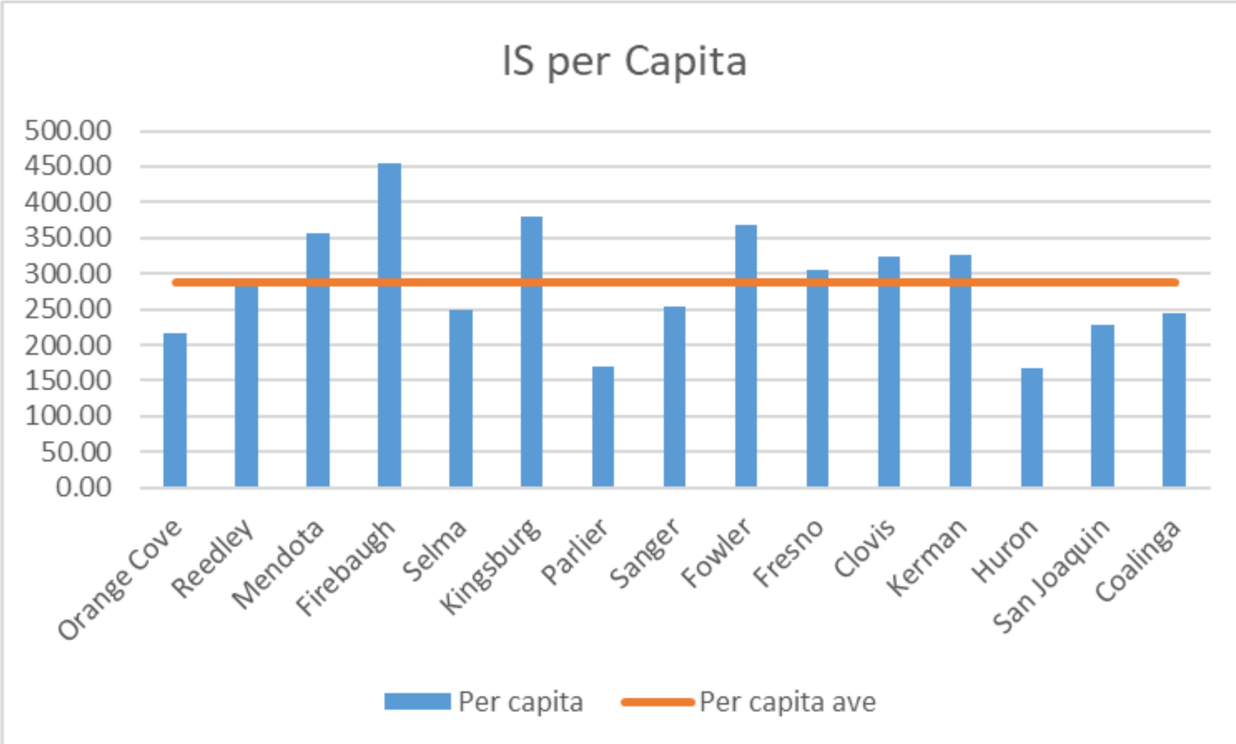
Table 7 summarizes the percent of impervious surface and impervious surface per capita of 15 cities in Fresno County. Huron, a small agriculture city, shows the smallest percent impervious surface, 27.1%, and Kerman and Clovis show as high as 60%. For impervious surfaces per capita, Huron and Firebaugh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

Figure 14. Percent Impervious Surface of Cities in Fresno County



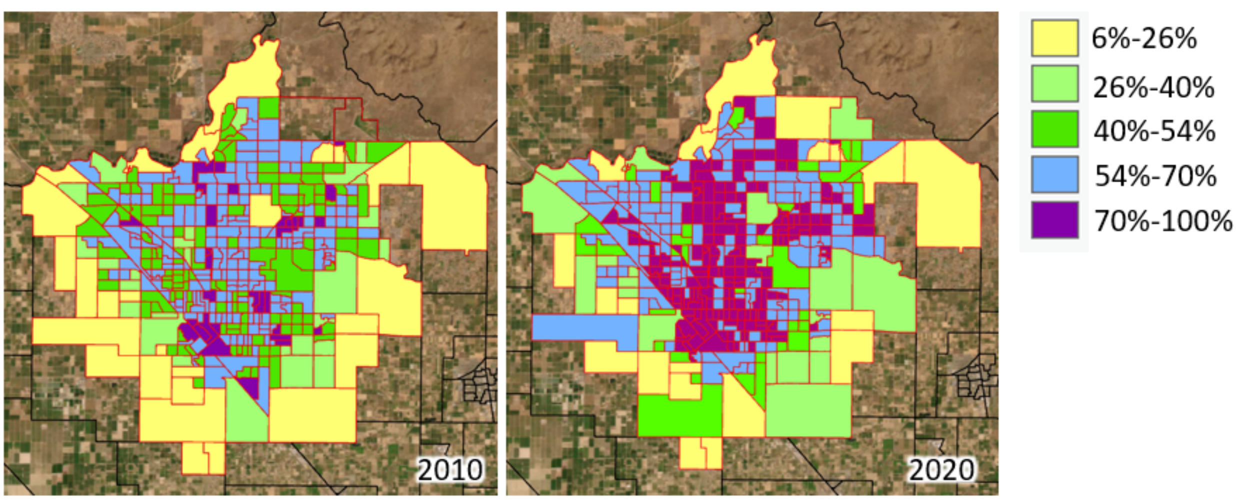
Note: The average orange line is 45%, which is equivalent to medium-density residential value.

Figure 15. Impervious surface per capita of cities in Fresno County



Note: The average line in an orange solid line is 288 square meters/person.

Figure 16. Impervious Surfaces of Fresno/Clovis in 2010 and 2020



It is worth mentioning that Fresno/Clovis's percent impervious surface in 2010 (EnviroAtlas) was 53%, and in 2020, it was 63% 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 States, showing that a 4–5% increase in impervious surfaces overall. The three largest changes in impervious surfaces occurred at Arizona, Georgia, and South Carolina; their changes were 8.89%, 8.40%, and 7.92%, respectively.

Brophy-Price and Rolband (2010) related a 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 nearby states showed a similar pattern in population and impervious surfaces.

4. Summary and Conclusion

In summary, this study rigorously evaluated the effectiveness of three prominent image classification techniques – pixel-based, object-based, and deep learning – in the extraction of impervious surfaces. The findings revealed that, across various levels of population density, deep learning consistently outperformed the other methods.

The comprehensive analysis of 15 cities within Fresno County indicated an average impervious surface coverage of 45% in the imagery captured in 2020. Notably, the focus on the Fresno/Clovis city area demonstrated a noticeable shift, with the percentage of impervious surfaces rising from 53% in 2010, as per EnviroAtlas data, to 63% in 2020. This 10% increase over the course of a decade is congruent with the observed population growth in the region.

In conclusion, the study underscores the robust performance of deep learning in impervious surface classification, demonstrating its applicability across diverse urban landscapes. The alignment between the 10% increase in impervious surfaces and the concurrent population growth in Fresno County highlights the intrinsic connection between urbanization dynamics and impervious surface expansion. These insights contribute valuable information for urban planning and management strategies, emphasizing the need for sustainable practices to address the environmental consequences associated with impervious surfaces.

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About the Authors

Yushin Ahn

Yushin Ahn is an Associate Professor in the Department of Civil and Geomatics Engineering at California State University, Fresno. He received a B. Eng. Degree in Civil Engineering and an M.Sc. in Surveying and Digital Photogrammetry from Inha University, Korea in 1998 and 2000 and an M.Sc. and Ph.D. in Geodetic Science from Ohio State University in 2005 and 2008, respectively. His research interests include digital photogrammetry, feature tracking, and sensor calibration and integration. Dr. Ahn received the Robert E. Altenhofen Memorial Scholarship from American Society of Photogrammetry and Remote Sensing. He has been a certified Photogrammetrist since 2014.

Richard Poythress

Richard Poythress is a graduate student pursuing an M.S. in Civil Engineering at California State University, Fresno. He received a B.A. in Political Science from University of California, Santa Barbara, a B.S. in Petroleum and Natural Gas Engineering from New Mexico Institute of Mining and Technology, and an MBA from New Mexico State University.

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