Determining efficient water use through the classification of urban landscapes at the parcel level

Geography 596B Report

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Abstract

Approximately 40% of the treated water used by Denver Water's roughly 1.2 million customers is for outdoor irrigation. However, when it comes to a better understanding of water use, Denver Water lacks information about landscape preferences and trends, which have a huge impact on decision-making. This project helps fill the gaps by providing robust data models that classify various urban landscape types to aid in the decision making and planning processes at Denver Water. An object-oriented landscape approach classifies land use at the parcel level for two different neighborhoods within the Denver metro area. Models identified and extracted the various landscape types into seven different classes with an overall accuracy of 78%. The results of this study showed that overall efficiency was largely affected by the amount of turf area within a given parcel. The health of the turf, calculated as a NDVI output, showed that healthy, green vegetation can be maintained with efficient use of water. Overall a mixture of landscape that had a threshold of 45% turf area (over pervious area for a lot) showed the most efficiency.

Background

Denver Water currently uses a planimetric data layer to represent impervious objects such as buildings, roads, sidewalks, driveways and parking lots. The remaining area is then used to determine if a customer is using water efficiently by dividing water consumption into pervious and impervious areas. The pervious area, however is not a true representation of irrigable landscapes. Creating a land use map that accurately shows the various surfaces can be time consuming and expensive (Bauer and Steinnocher, 2001). Surfaces covered by mulch, rock and private concrete walkways are not irrigable areas but are part of pervious surface layer used in the efficiency calculation. Layers representing different landscape types will provide a more accurate picture of areas with efficient or inefficient water use. Using an object-oriented approach is the preferred method when extracting multiple discrete landscape types from high-resolution imagery according to a study by Goetz, Shackelford and Davis, 2011 (as cited in Zhou and Troy, 2008). One of the main advantages of the object-oriented approach is that the model identifies and classifies segments rather than pixels. (Geneletti and Gorte, 2003). Pixel-based classification could be used, but one of the major issues that arises when using this method is the salt and pepper effect noted by Yu in his study (as cited in Al-Kofahi et al., 2012).

Since water efficient landscapes can help reduce water consumption at the residential level by 76% (Sun et al., 2012) without taking away from the functionality or aesthetics of a property, understanding how customers are using their land is important to Denver Water. An accurate land use map representing various types of landscapes can help urban planners understand water use at the residential level, which can then be used to help craft best practices for outdoor irrigation (Al-Kofahi et al., 2012). Denver Water will also be able to determine what kind of infrastructure will be needed in new neighborhood with this data. For example, whether a six-inch main or a twelve-inch main is installed in a new neighborhood depends on how much irrigation is expected. Having availability to a highly accurate land use dataset will also allow planners to plan better for drought based on expected water demand during dry season.

Objective

The objective of this study was to create a parcel-level land use map. The map will consist of data created by a remote sensing model that extracts discrete features. Creating models that will be easy to deploy and intuitive to use are another objective. The last objective of this project will be to identify where efficient and inefficient water use is taking places based on the land use map and water consumption data that will intersected with that land use data.

Methodology

Data

The imagery used has a pixel size is 3-inch, and is comprised of four bands, with the 4th band being false color infrared. The major regions of the electromagnetic spectrum for the 3 visible bands (red, green and blue) are 0.4 to 0.7 micrometers. The near infrared falls in the range of 0.7 to 3.0 micrometers. Acquisition was part of the Denver Regional Aerial Photography Program (DRAPP) https://drcog.org/services-and-resources/data-maps-and-modeling/gis-maps/denver-regional-aerial-photography-project that is conducted by the Denver Regional Council of Governments (DRCOG) every two years. The imagery had a GSD (Ground Sample Distance) of 0.5' and was collected with the Leica ADS40 and ADS 80 digital sensors and processed with Leica XPro software. The projection used was State Plan Coordinate System, Colorado central zone using Lambert Conformal Conic map projection parameters. Horizontal and vertical datums are NAD83 (11) and NAVD88 (GEOID12A) respectively.

Preparation of Data

Polygons representing the two neighborhoods in this study, North Park Hill and Stapleton, were exported from a neighborhood boundary layer obtained from the U.S. Census Bureau https://www.census.gov/geo/maps-data/data/tiger-geodatabases.html and used to extract imagery of the pilot areas with the "Extract by Mask" tool in ArcGIS. Planimetric data representing impervious surfaces (buildings, roads, sidewalks, etc.) was then used to "Erase" impervious areas of the imagery. The remaining features in the neighborhood boundary layer are the pervious areas. The "Extract by Mask" tool was used again to extract pervious areas to be used in the feature extraction.

Figure 1: North Park Hill

Creation of AOIs and Models

The extracted imagery was added to Imagine Objective to create Areas of Interest. AOIs are samples that are collected from the imagery to convey pixel values and shapes that the user is targeting.

AOIs can be created as polygons in a shapefile or feature classes and imported into Imagine Object and converted into an AOI layer. Alternatively, AOIs can be drawn as polygons using the draw tools in Imagine Objective. The project uses the region grow tool, which selects a group of pixels that represent a feature to be classified and grows a polygon from the selected area to encompass pixels with similar spectral values around it. The region grow tool is useful for selecting shapes that include the

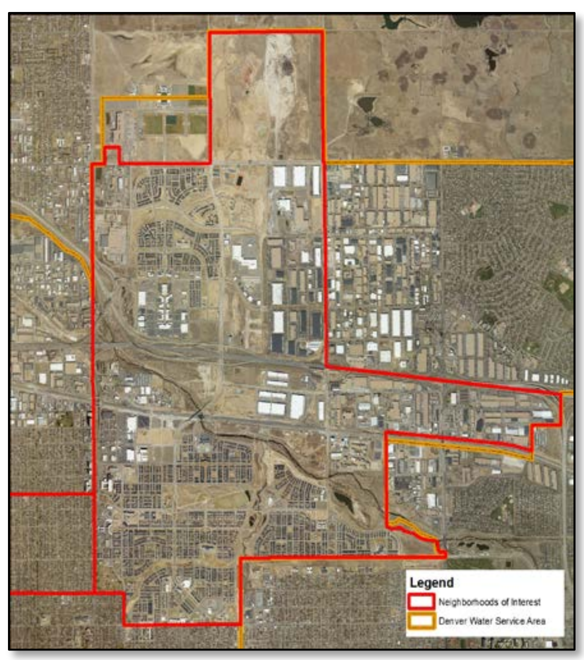

Figure 2: Stapleton

feature of interest, and for not growing over areas that represent other features.

The importance of accurate AOIs in classifying landscapes can't be understated. Good samples covering only the feature's locations convey the different pixel values and shapes of features to extract. Also important is the collection of background areas of interest for features that do not represent what is being extracted. When collecting areas that represent the landscape of interest with polygons, it's important to keep track of what is or isn't background in the samples window.

Models are a series of raster and vector operators that use cues and filters to create raster and vector objects that represent a feature based on the pixel values and the shape of the samples. Within a model there can be multiple cues or filters to identify, extract and clean up layers representing various features. NDVI was used to examine how healthy the portions of landscape that typically receive irrigation were and how that compared to consumption within the two neighborhoods. The size filter and probability filter are examples of cues used to clean up raster or vector layers. They filter pixels or vector objects that might be too small, too big or do not fall within the specified parameters for probability, i.e., anything that has less than a 60% probability of being my feature needs to be dropped from the next layer in the model.

General Notes on Extraction of Features

Several samples were collected using the region grow tool. Oversampling tends to identify as many of the features of interest as possible. The processors that the model will use will filter the oversampled results to narrow down features, so the resulting vector layer is a more accurate representation of the features that are being extracted. The logic behind this method is that it's easier to filter or take away features from a layer than it is to add them. Specific probability numbers to be used for features are listed in the table below along with specific notes for each feature on steps needed during post processing.

	AOI	Model	Post Processing
Coniferous	Collect 40-50 examples of coniferous vegetation. Collect 20-30 more examples of background features.	RPP – NDVI ROC – Threshold and Clump = 0.60 ROO – Size Filter Small Vegetation Min = 30 Map Units Max = 5,000 Map Units Large Vegetation Min = 150 Map Units Max = 100,000 Map Units. RVC – Polygon Trace VOO – Island Filter VOP – Geometry = Area, Compactness, Convexity, Circularity VCO – Smooth = 0.20	Use the VOC results to examine and clean up the data in ArcMap.
Deciduous	Collect 40-50 examples of deciduous vegetation. Collect 50 – 100 more examples of background	RPP - Single Feature Processor – ROC -Segmentation Lambda Schedule 0.70, 0.90, 0.10, 0.10 ROO - Generalize = 0.10, Island Filter = default Pixel segment ratio 500 (10-1,000), Size limits 10-5,000 RVC – Polygon Trace	Perform post-processing in ArcMap. Filter for anything that meets a probability of 94% or greater.

	features.		
Concrete	Collect 50 – 100 samples of multiple types of concrete. Collect 30-40 examples of background features.	RPP – Single Feature Processor ROC – Segmentation Lambda Schedule of 1.00, 0.90, 0.20, 0.20 ROO – Dilate = 3, Size Filter = 4 RVC – Polygon Trace VOO – Generalize = .10, Island Filter (Default)	Determine best pixel probability based on neighborhood's concrete features. The probability can be used during QC as well.
Unmaintained	Collect 100 – 200 samples of rock, mulch, or dirt. Collect 30 – 40 samples of background.	RPP – Single Feature Processor ROC - Lambda 0.90, 0.60, 0.10, 0.10 ROO - Probability Filter = .50 (or lower) RVC - Polygon Trace	Erase shadows, concrete, turf, deciduous, and coniferous from this layer in ArcGIS.
Turf/Turf Shadows	Collect 100 – 200 samples that represent green, brown, patchy, and general turf. Collect 40 – 50 examples of background features. Examples of turf shadows can be a quarter of these numbers.	Turf (not turf shadows) RPP – Single Feature Processor ROC - Threshold and Clump = 0.90 ROO - Eliminate = 6 ROO - Size Filter = 4 RVC - Polygon Trace Turf Shadows RPP – Single Feature Processor ROC - Threshold and Clump - 0.90 RVC - Polygon Trace	A merge should be performed in ArcMap to merge the turf and turf shadows. This layer will be added to the turf layer but leave out darker shadows cast by buildings. This is a conservative shadow layer that can be confidently added to the turf layer. The turf shadow layer should be used to erase shadows from the shadows layer.
Unclassified Impervious			This layer is not created in ERDAS. It is the final result of post-processing in Esri. After all the other layers have been created they are erased from the neighborhood boundary (100ft buffered area that was used for image classification). The planimetric layers are

			also erased. The result is the unclassified impervious layer.
Shadows	Collect 40-50 very dark examples of shadows. Collect 30-40 examples of background features.	RPP - Single Feature Processor ROC – Threshold and Clump = 0.10 ROO – Eliminate = 6 ROO - Size Filter = 4 RVC – Polygon Trace	Dissolve the layer in ArcMap.

Accuracy Assessment

		Class Types From Classified Map								
	# Plots	Coniferous	Shadows	Deciduous	Turf	Concrete	Alternative	Other	Total	User's Accuracy
Class Types Determined From Reference Source	Coniferous	21	7	0	2	0	0	0	30	70%
	Shadows	0	191	2	0	0	0	1	194	98%
	Deciduous	0	4	110	6	3	0	17	140	79%
	Turf	19	0	0	418	0	6	8	451	93%
	Concrete	0	0	0	1	36	7	3	47	77%
	Alternative	2	0	0	1	5	43	4	55	78%
	Other	5	10	4	15	4	12	33	83	41%
	Total	47	212	116	443	48	68	66	1000	
	Producer's Accuracy	44%	90%	94%	75%	75%	63%	51%		78%

Figure 3: Accuracy Assessment

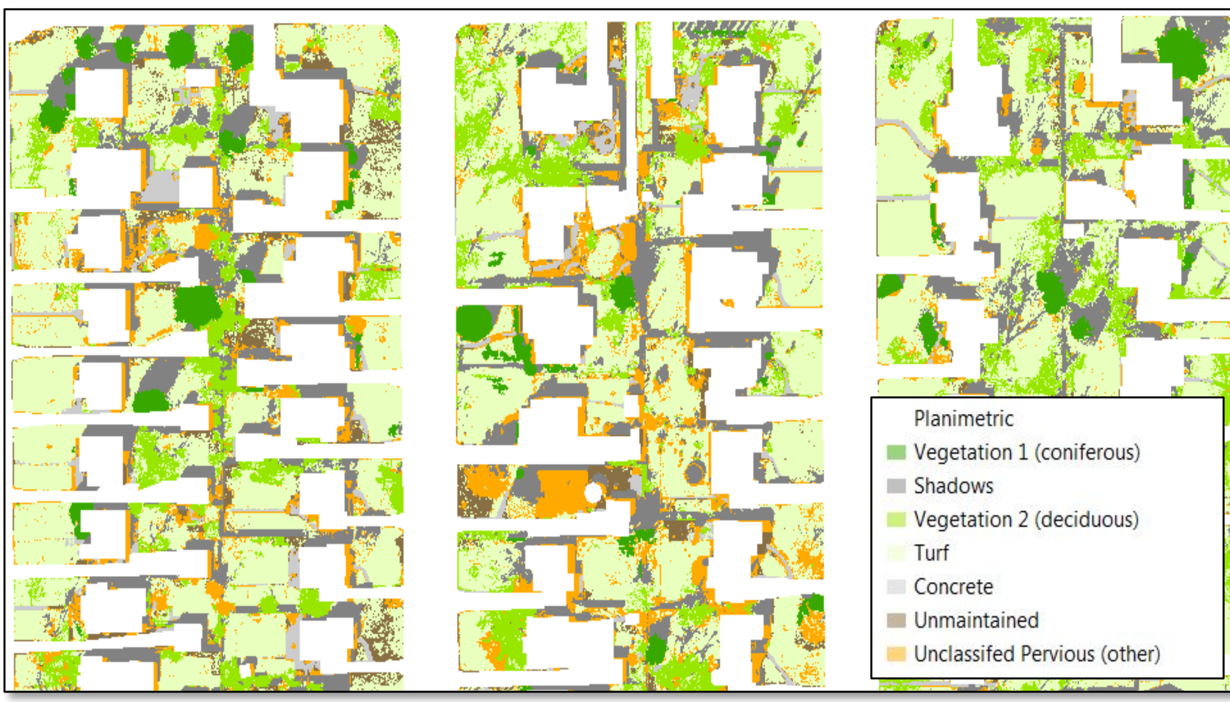

Figure 4: Landscape Classification Results

An accuracy assessment was performed on the data. The tool used for assessing accuracy was a confusion matrix. A confusion matrix is a common format to look at site-specific errors. (Campbell, 2011). The 'site-specific' that a confusion matrix uses where the classified results are compared to ground data offers a simple summary of the classifications quality (Jensen, 2007).

A random sampling of 1000 locations were used and compared to the imagery within the two neighborhoods to determine how efficient the results of the landscape classification were. The turf area exhibited the highest accuracy with an 80% or greater of the results being returned as correct. The areas of most concern were unmaintained and impervious, neither of which broke 60% accuracy. Attaining accuracy for both landscape types was a known difficulty since both landscape types are comprised of many different components and have issues of overlap with other features from a spectral standpoint. The seven vector layers that represent the different types of landscapes in this study shown in Figure 3. Those features will be extracted with models that can be used by anyone with a minimal amount of

experience using ERDAS Imagine/Imagine Objective. These landscape categories are then joined with parcel and consumption data from spreadsheets to determine which parcels are more efficient than others. By summarizing this data, the study will also be able to determine which areas in the Denver metro region are the most efficient with their water use as it relates to irrigation.

How Efficiency Is Calculated

Efficiency is calculated by taking irrigated monthly water consumption and dividing it by the total area considered to be irrigable for a parcel. The amount of irrigated water is calculated by subtracting the average water use during non-irrigating months (November – March) by the consumption average consumption during the irrigating months (April – October). The calculation is (Average Monthly Water Use during the Summer Months – Average Water Use during the Winter Months)/Total Pervious Area. If the number calculated is less than 12 gallons per square foot of pervious area, then water use for that location is considered efficient. If the number calculated is higher than 12 gallons per square foot of pervious area, then water use for that location is considered inefficient.

Figure 5: Efficiency map – Park Hill Section.

RESULTS

The results were looked at within the same three efficiency groups discussed earlier in this report. Landscape totals were in terms of total square feet for a particular type of landscape within a parcel. The total square feet for each landscape type was divided over the pervious area (non-planimetric, i.e., buildings, driveways, parking lots) for a parcel. NDVI was also calculated for the same parcels within the two study areas.

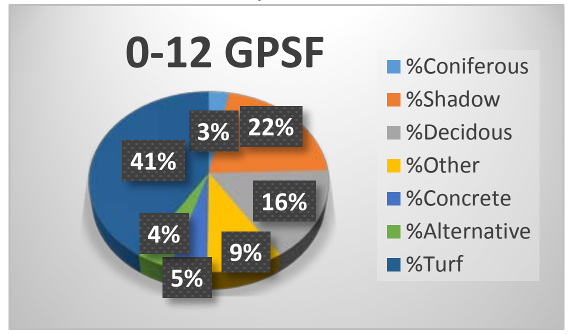

Figure 6: 0-12 GPSF Classification Results

Looking at the results of the landscape classification within these three groups, we can see that the users of 18 thousand gallons of water per square foot or more had a larger percent of turf, 50%, when compared to the other two efficiency groups 12-18 thousand gallons at 45% and 0-12 thousand gallons at 41%. Results between the other groups remained relatively the same. Shadows showed little difference between the three groups at 19%, 21%, and 22%.

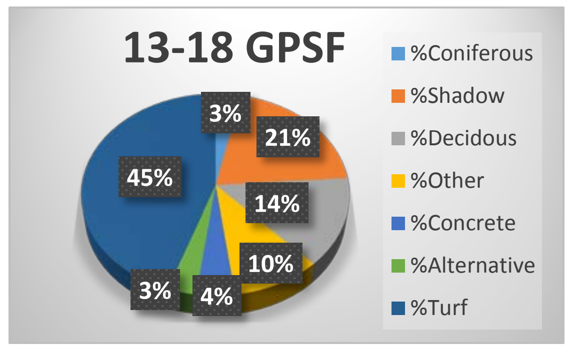

Figure 7: 13-18 GPSF Classification Results

There was an increase in the landscape types “Other” and “Alternative” which was used to denote areas of rock, mulch and unmaintained landscape. Alternative was also used to denote areas of xeriscape within a parcel.
Concrete remained relatively unchanged between the three groups. When looking at how the trees did between the three groups, coniferous vegetation remained relatively unchanged, while deciduous numbers decreased among higher water users. Users that had a larger area of deciduous vegetation also saw a larger area of shadow (16% among efficient users). The larger the portion of area these two landscapes occupied, shadow and deciduous vegetation, the more efficient water use appeared to be between the three groups. Figure 9 shows all efficiency groups by their landscape percent’s.

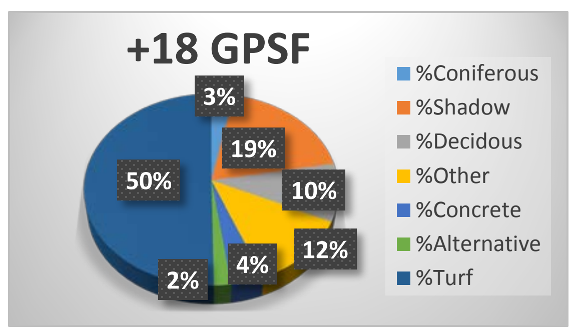

Figure 8: +18 GPSF Classification Results

Another number looked at in this study was the Normalized Difference Vegetation Index (NDVI). NDVI can be used to determine areas of healthy vegetation which is important in determining how healthy areas of turf are since that health is directly correlated to the amount of water turf receives. Overall results showed that a healthy NDVI index was achieved amount efficient waters users, with most in the efficient group having a turf NDVI in the range of 4.0 to 4.5. Inefficient users scored slightly higher with a turf NDVI index in the range of 4.5 to 5.0, which indicates an even healthier or less stressed turf. The overall NDVI results can be seen in Figure 10. The most common score being a NDVI index of 3.9 which is vegetation that is healthy and not overly stressed.

Overall accuracy between user and producer yielded an accuracy of 78%. One of the less accurate classifications was coniferous vegetation for the producer. The highest inaccuracy occurring between coniferous vegetation and turf. Unlike deciduous vegetation, coniferous vegetation maintains its green color throughout the year. The inaccuracy between the two classes because of this similarity in pixel values and close NDVI values leads to overlap and misclassification between the between the two landscape types. The software considered the shapes common to the two features based on the training samples provided by the analyst, but patches of healthy turf that took a round shape presented issues in some areas.

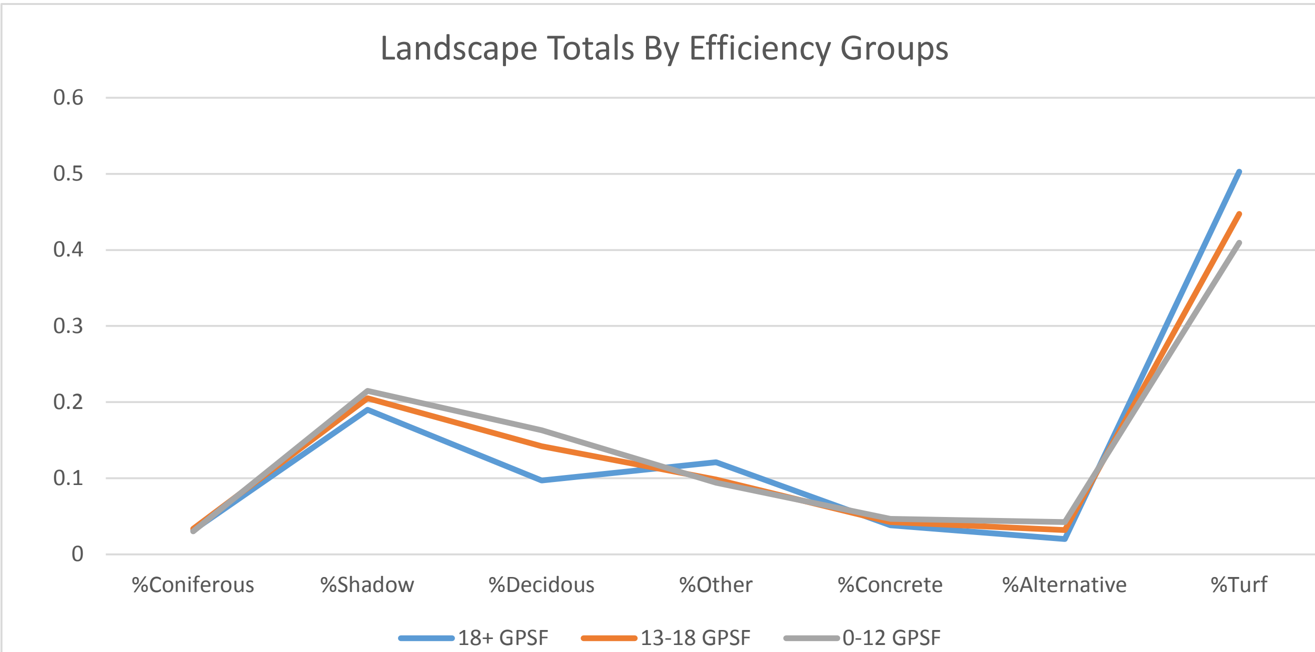

Figure 9: All efficiency groups by classification.

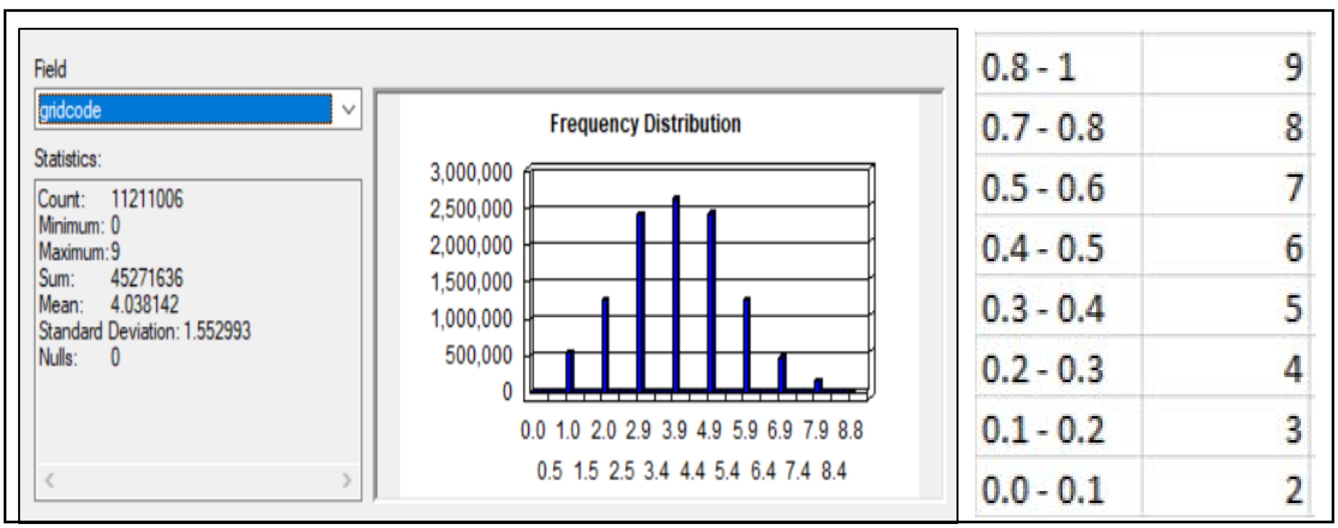

Figure 10: Distribution of NDVI.

Discussion

Based on the results of the classified landscapes, parcel lots should have no more than 45% of the area that is not impervious covered by turf. Parcels that have a turf area of 45% or greater have shown in both neighborhoods to exhibit higher water use to the point of being inefficient. The up to 45% turf area still allows for efficiency without being too restrictive on green space within parcel lots.

The other landscape categories showed that a healthy mix of different landscape types that are not considered turf can also help efficiency. Specifically, the lots that were more efficient showed a higher mix of land covered by coniferous and deciduous vegetation in the form of trees and shrubs. The efficiency users typically covered 19% of their lots with coniferous and deciduous vegetation, while the most inefficient users covered only 13% of their lots with the same vegetation.

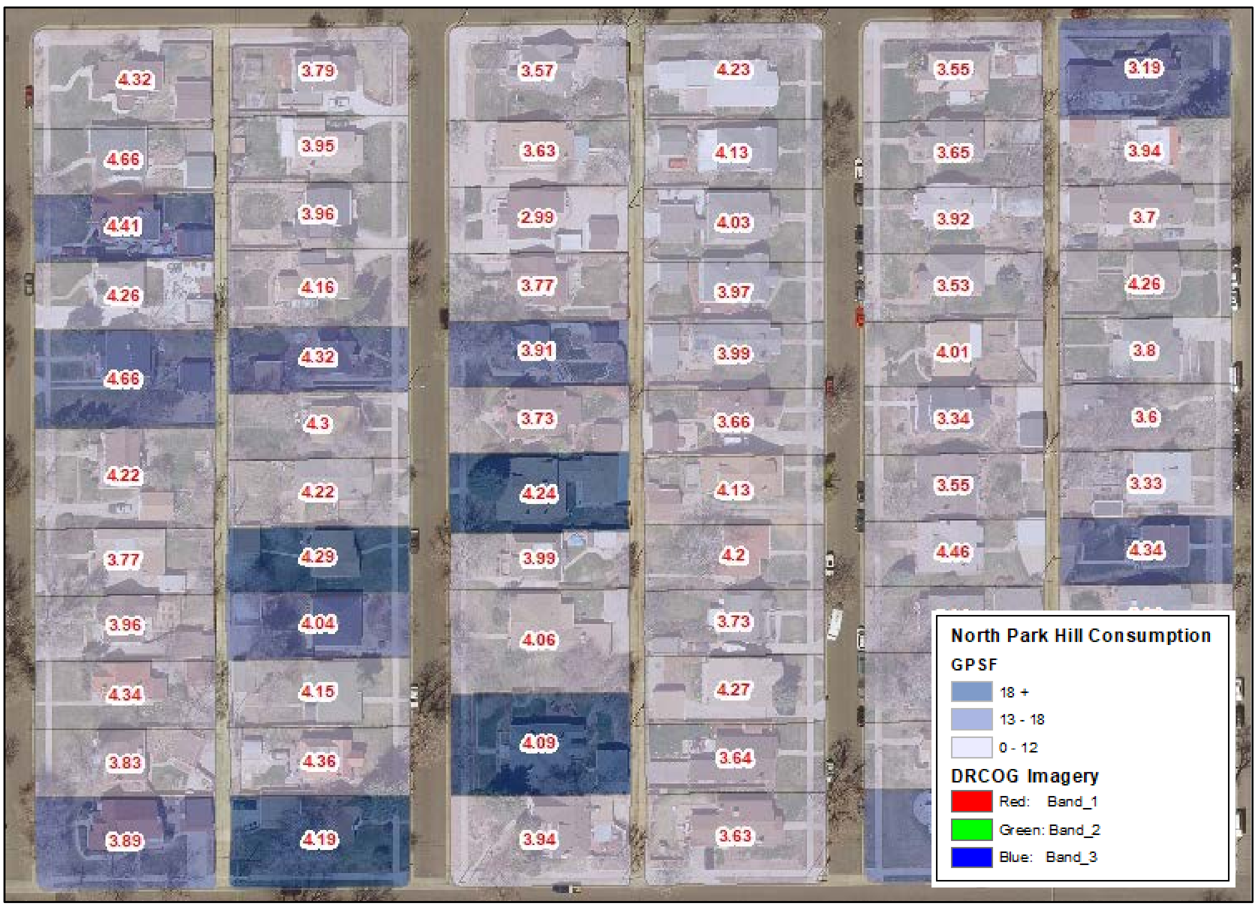

Figure 11: NDVI with consumption for each parcel in red.

The NDVI results also showed that efficiency can be achieved without overly healthy turf area. The NDVI readings spiked higher among inefficiency users but did not dip below 4.0 for the efficient users which is considered in range for healthy vegetation. This means that while the turf areas and other vegetation maintained by efficient users received less water, the overall health of the green vegetation in these lots did not suffer.

Both landscape types and NDVI results become important when considering the overall effect that green space has on an area. Green space within a parcel lot and a neighborhood overall have been shown to lower crime and improve child development (Kuo and Sullivan, 2001; Heerwagen and Orians, 2002;, Kahn Jr and Kellert, 2002;, Kirkby, 1989). Another important use for knowing how landscapes are trending can be important to real estate values. Landscapes can affect things related to real estate when it comes to rental rates which can be as much as 7% higher in areas that have a high value landscapes (Laverne and Winson-Geideman, 2003). Large street trees can add up to 3% to 15% value to a home and continue to appreciate over time (Wolf, 2007). Other applications for this type of analysis could involve looking at trends in landscape use over time so long as the data is available. Organizations and companies looking to identify how landscapes are trending could use this type of analysis to answer those questions. Certain types of landscapes, for example green spaces,

One other use that the results of this analysis can be used for is to determine what is irrigatable and what is not. While the results of this type of analysis may not give a 100% accurate view of what is irrigatable, the results are far more precise than a generalized pervious area layer. The information that can be gathered about efficiency from data which conveys a more accurate irrigatable area is worth doing an analysis like the one performed in this project.

Conclusions

The results of the classification when looking at the various efficiency groups and their consumption showed that more turf and less shadow meant an increase in water use for irrigation. The roles that trees played in the amount of water being used for irrigation in this study was not significant based on the results between the three efficiency groups. Another landscape types that played a factor in the amount of water being used for irrigation was landscape that is typically used in xeriscape. In this study the typical types of landscapes that comprise xeriscape were classified as ‘Alternative’ or ‘Other’. These types of landscapes were greater in area in our groups that were considered efficient or slightly inefficient. The areas for these types of landscapes were smaller in the group where water use exceeded 18 thousand gallons per square foot.

The NDVI index showed that the landscapes were healthy overall and showed that most of the two study areas were comprised of healthy vegetation with most landscapes falling within an NDVI index rand of 3.5 to 4.5. A higher NDVI index could be due to many things but given the amount of water used by the inefficient group which was greater than 18 thousand gallons per square foot, it reasonable to conclude that a higher than average NDVI index can be attributed to high water use. Based on the NDVI and landscape classification results, efficiency can be achieved while maintaining a healthy turf area. A certain amount of xeriscape is recommended to mix in with the landscape. The results showed that a higher mix of ‘Alternative’ or ‘Other’ landscape, which make up xeriscapes, in the range of 5-10% were associated with more efficiency. Increasing the number of trees and shadows on a landscape can also benefit parcel owners when trying to use less water for irrigation.

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