To: Dan Austin
From: Will Kwan
Date: March 4th, 2025
RE: GISC480 Lab #6

This memo summarizes the methods, discussions, and results from Lab #6. The analysis uses remote sensing to generate a supervised classification of downtown Kelowna to evaluate its permeability.

Introduction

A GIS analysis was performed on location-based open datasets to determine the permeability of surfaces within the study area. As shown in Figure 1, the study area corresponds to a 1 km^2 region centred around downtown Kelowna.

Permeable surfaces allow water to pass through them and infiltrate the ground. Impermeable surfaces are solid surfaces that don't allow water to pass through them, forcing water to run off instead of soaking into the ground (University of Delaware, 2025). The analysis categorizes natural surfaces (water, grass, trees, sand) as permeable and man-made surfaces (buildings, roads/paved) as impermeable. Urban and suburban spaces typically contain extensive impermeable surfaces, leading to a range of environmental issues—including disruption of stormwater discharge patterns, increased flood risk, inadequate groundwater recharge, stagnant water accumulation, pollutant transport, and the creation of urban heat islands (Chithra et al., 2015).

This analysis generates a supervised classification of the study area to categorize surfaces as permeable or impermeable. Understanding the permeability of surfaces in the study area is helpful for designing an effective stormwater system capable of managing potential runoff.

Methods

An image of Kelowna and a geodatabase containing building footprints were sourced from the City of Kelowna's open data catalogue and clipped to the study area.

To support an error assessment of the classification results, 20 verification points were manually plotted and classified for each land cover class (water, grass, trees, sand, buildings, and roads/paved).

A pixel-based supervised classification was then performed on the image of Kelowna: training data polygons that best represented the areas for each class were first defined, and the image was subsequently classified using the maximum likelihood classification method. Ancillary data in the form of building footprints were added to improve the accuracy of the classification by converting the building footprint polygons to raster and integrating them into the classification results.

To define surface permeability, the raster symbology was adjusted so water, grass, trees, and sand were grouped to represent permeable surfaces, and buildings and roads/paved were grouped to represent impermeable surfaces. These classes were used to define the total area and proportion of permeable versus impermeable surfaces within the study area.

Finally, to assess the accuracy of the calculation, the classification values were extracted to the validation points—each point then contained the observed and classified surface values—allowing for the production of an error matrix, as well as the calculation of the user's and producer's accuracy for each class, and the Kappa statistic. The computation of the Kappa statistic is described below.

Computation of K_{hat} Coefficient of Agreement

$$\widehat{K} = \frac{N\sum_{i=1}^{k} x_{ii} - \sum_{i=1}^{k}(x_{i+} \times x_{+i})}{N^2 - \sum_{i=1}^{k}(x_{i+} \times x_{+i})}$$

Where $N = 120$

$$\sum_{i=1}^{k} x_{ii} = (20 + 14 + 19 + 16 + 19 + 18) = 106$$

$$\sum_{i=1}^{k}(x_{i+} \times x_{+i}) = (20 \times 24) + (20 \times 14) + (20 \times 20) + (20 \times 16) + (20 \times 26) + (20 \times 20)$$
$$= 2400$$

Therefore, $\widehat{K} = \frac{120(106)-2400}{120^2-2400} = \frac{10320}{12000} = 86.0\%$

Results and Discussions

Once the analysis was complete, the data could be meaningfully represented figuratively and tabularly. Figure 1 illustrates the study area, including the original image, the training data polygons, the resulting surface classification, and the delineation of permeable and impermeable surfaces.

Table 1

Classification Surface Areas

Class	Size (ha)
Buildings	25.02
Grass	7.93
Road/paved	23.19
Sand	1.56
Trees	20.72
Water	21.57
Total	100.00

Table 2

Surface Permeability

Permeability	Size (ha)
Permeable	51.79
Impermeable	48.21
Total	100.00

As seen in Table 1, the classification determined that the 100.00 ha study area is composed of 21.57 ha of water, 20.72 ha of trees, 1.56 ha of sand, 7.93 ha of grass, 23.19 ha of roads/paved surfaces, and 25.02 ha of buildings. The area of permeable surface, as seen in Table 2, was calculated to be 51.79 ha, while the area of impermeable surface was 48.21 ha, resulting in a proportion of 51.79% permeable surface.

Table 3

Error Matrix and Overall Accuracy for the Classification of Validation Points

Surface Class	Buildings	Grass	Road/paved	Sand	Trees	Water	Row Total
Buildings	20		1	3			24
Grass		14					14
Roads/paved			19	1			20
Sand				16			16
Trees		5			19	2	26
Water		1			1	18	20
Known Totals	**20**	**20**	**20**	**20**	**20**	**20**	**120**

Overall Accuracy = 106/120 = 88.33%

Note: Known totals represent the count of validation points for each class. The diagonal of outlined cells represents the count of correctly classified points for each class. Overall accuracy is the proportion of correctly classified points to the total count of all points.

Counts outside the outlined cells within a given row represent points of a given class that were incorrectly classified as that row's class. Counts outside the outlined cells within a given column represent points of that column's class that were incorrectly classified into other classes.

Table 3 presents an error matrix outlining the supervised classification's performance and its ability to correctly classify the validation points. It also provides an overall accuracy, finding 106/120 validation points to be correctly classified (88.33%).

Table 4

Producer's Accuracy and Omission Error for the Classification of Validation Points

Classification	Producer's Accuracy	Omission Error
Buildings	20/20 = 100%	0%
Grass	14/20 = 70%	30%
Roads/paved	19/20 = 95%	5%
Sand	16/20 = 80%	20%
Trees	19/20 = 95%	5%
Water	18/20 = 90%	10%

Note: Producer's accuracy measures how well the classification correctly identifies known features (i.e., the proportion of validation points that are correctly classified for a given class). Omission error is the converse of producer's accuracy, reflecting the proportion of known points that were not classified correctly for a given class.

Table 4 presents the producer's accuracy and omission error for the validation points of each class. It finds the producer's accuracy to be generally high, with the highest accuracy being for buildings, at 100%. This accuracy is misleading, as building footprints were manually classified using ancillary data. Grass had the lowest producer's accuracy, at 70%. From Table 3, it is evident that five grass points were misclassified as trees and one as water. Sand had the second-lowest producer's accuracy at 80%, with three sand points misclassified as buildings and one as road/paved.

Table 5

User's Accuracy and Omission Error for the Classification of Validation Points

Classification	User's Accuracy	Comission Error
Buildings	20/24 = 83%	17%
Grass	14/14 = 100%	0%
Roads/paved	19/20 = 95%	5%
Sand	16/16 = 100%	0%
Trees	19/26 = 73%	27%
Water	18/20 = 90%	10%

Note: User's accuracy measures how well the classification labels features of a given class (i.e., the proportion of correctly labelled validation points out of all the validation points that were classified into that class). Commission error is the converse of user's accuracy, reflecting the proportion of validation points that were incorrectly assigned to a given class.

Table 5 presents the user's accuracy and commission error for the validation points of each class, showing generally high user's accuracy. The highest accuracy was tied between grass and sand at 100%, while trees had the lowest user's accuracy at 73%. Table 3 indicates that five grass points and two water points were misclassified as trees. Buildings had the second-lowest user's accuracy at 83%, with one road/paved point and three sand points misclassified as buildings.

These misclassifications result from the inaccuracy of pixel-based classification, which uses the spectral characteristics of a given pixel in reference to the specified training data to define its classification. This analysis classifies an RGB image, so classifications are only based on intensities of visual light. Grass appears green, so it is easily confused with the green leaves of trees. Further, shaded grass appears dark green or blue and is easily confused with green/blue water. Similarly, sand appears tan, so it is easily confused with some buildings' brown/tan rooves and some roads' lighter brown/grey shades.

These miscalculations moderately affect the classification of the study area as permeable and impermeable, likely resulting in an overestimate of impermeable surface coverage. As Table 3 shows, permeable verification points (e.g., grass) are only ever misclassified as other permeable classes (e.g., water, trees), except for sand, whose verification points are incorrectly classified four times as impermeable (e.g., buildings, roads/paved). Impermeable verification points are only ever misclassified as other impermeable classes.

The Kappa (K_{hat}) statistic was used to define the difference between the actual agreement in classifying verification points and the agreement expected by chance alone. A K_{hat} value of 86.0% was found, meaning there is 86.0% better agreement in classifying verification points than by chance alone.

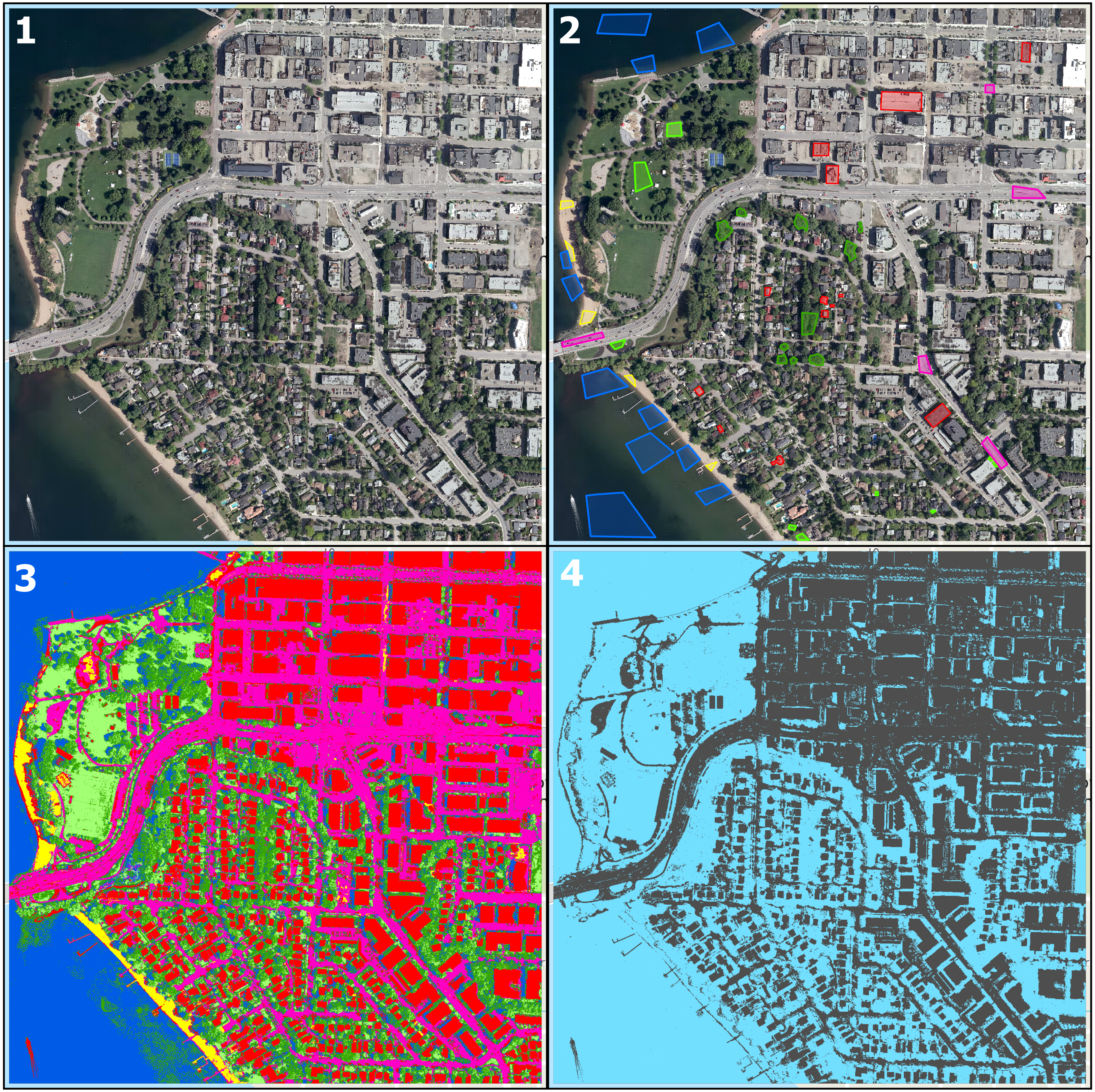

Figure 1: Downtown Kelowna Surface Permeability Classification

1) Original Image

2) Training Data Polygons
- Buildings
- Grass
- Road/paved
- Sand
- Trees
- Water

3) Classified Surfaces
- Sand
- Water
- Buildings
- Trees
- Grass
- Road/paved

4) Permeability
- Permeable (51.79% of area)
- Impermeable (48.21% of area)

Esri, NASA, NGA, USGS, FEMA, Esri Community Maps Contributors, Esri Canada, Esri, TomTom, Garmin, SafeGraph, GeoTechnologies, Inc, METI/NASA, USGS, EPA, US Census Bureau, USDA, NRCan, Parks Canada

References

Chithra, S. V., Nair, M. V. H., Amarnath, A., & Anjana, N. S. (2015). *Impacts of impervious surfaces on the environment*. International Journal of Engineering Science Invention, 4(5), 27–31. https://www.ijesi.org/papers/Vol(4)5/E045027031.pdf

University of Delaware Cooperative Extension. (2025). *Permeable vs. impermeable surfaces*. University of Delaware. https://www.udel.edu/canr/cooperative-extension/fact-sheets/permeable-impermeable-surfaces/