Local Climate Zone Classification Using Random Forests

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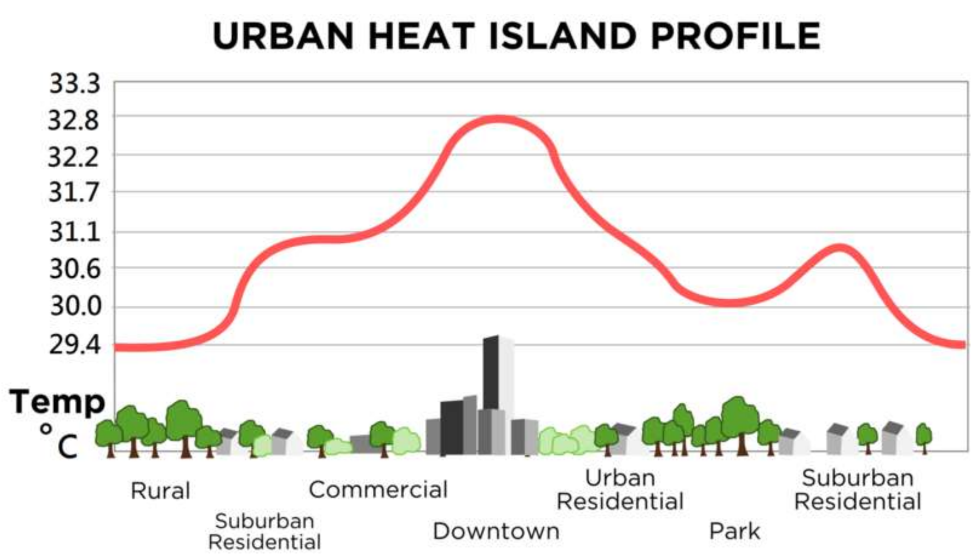

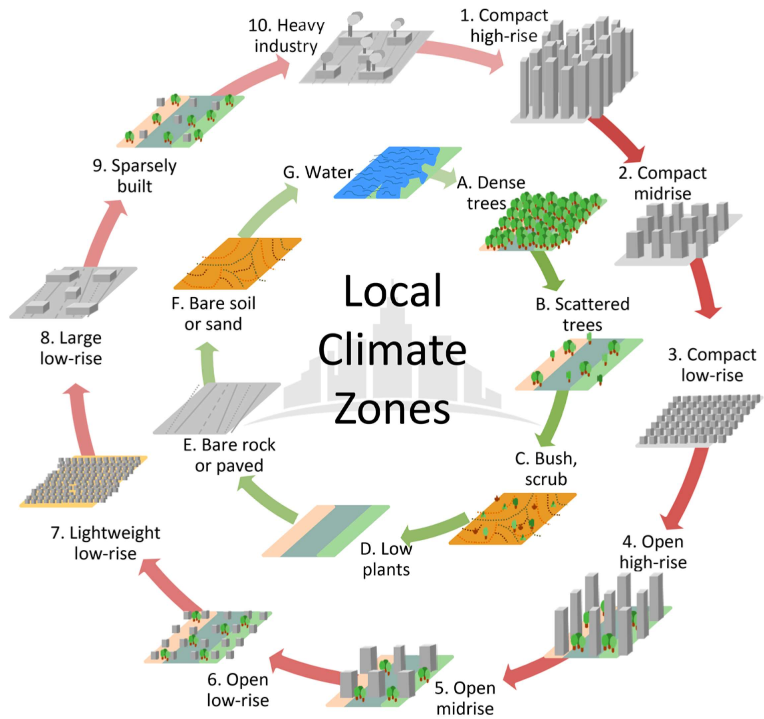

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Objective

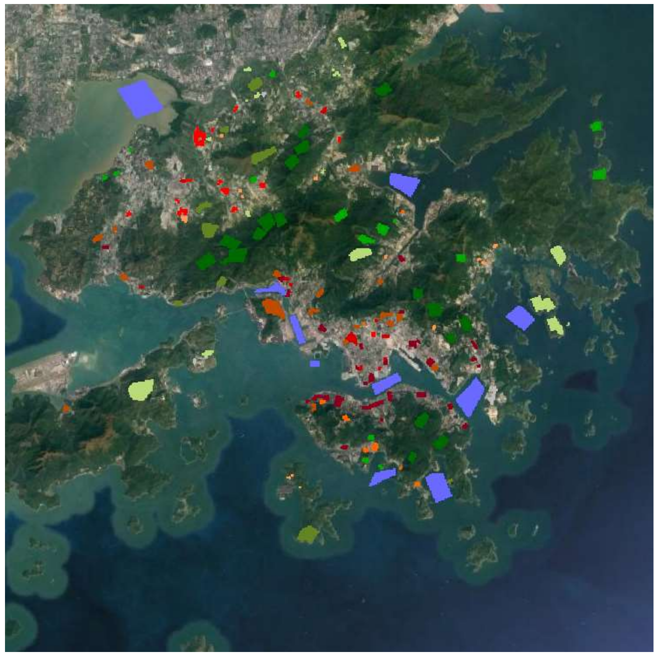
Inspiration:

- *Comparison between convolutional neural networks and random forest for local climate zone classification in mega urban areas using Landsat Images* (Yoo et al., 2019)

My Focus:

- Hong Kong
- Random Forests
- Varying the Number of Trees

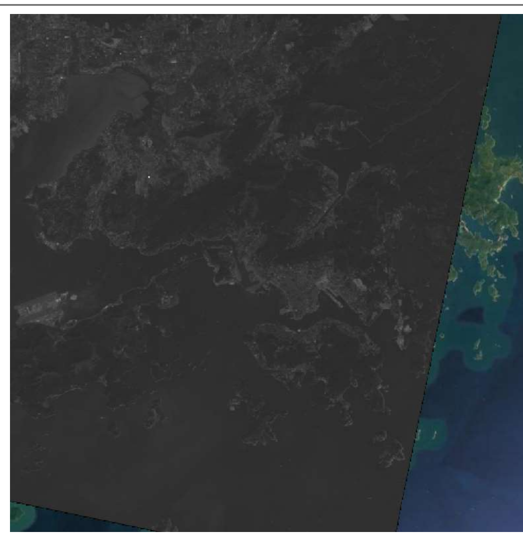
The LCZ reference data



The Landsat 8 data

Acquisition Dates of Each Landsat 8 Scene

Scene	Date
1	29-Nov-2013
2	15-Oct-2014
3	16-Nov-2014
4	18-Oct-2015

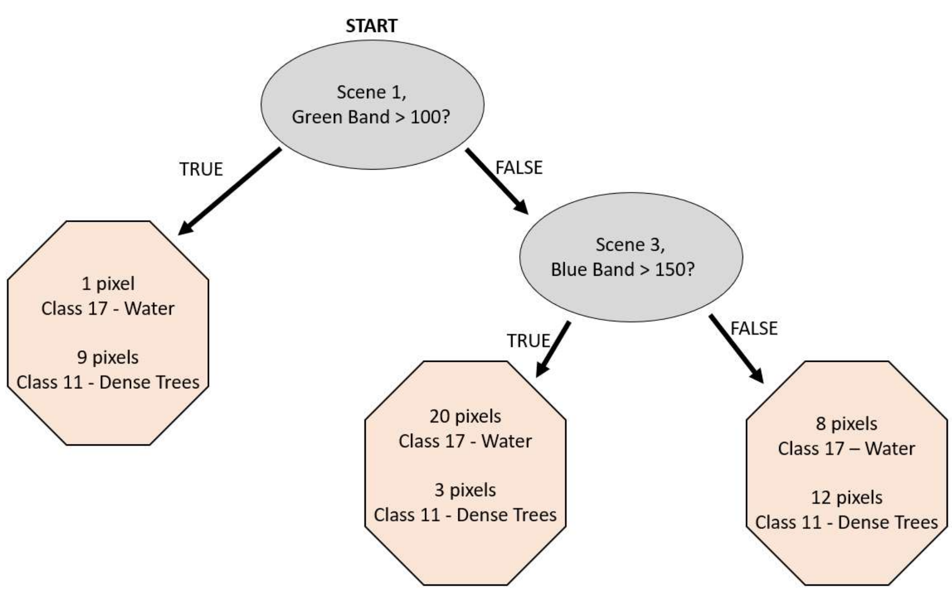


Delineation of training and test data by polygon and pixel.

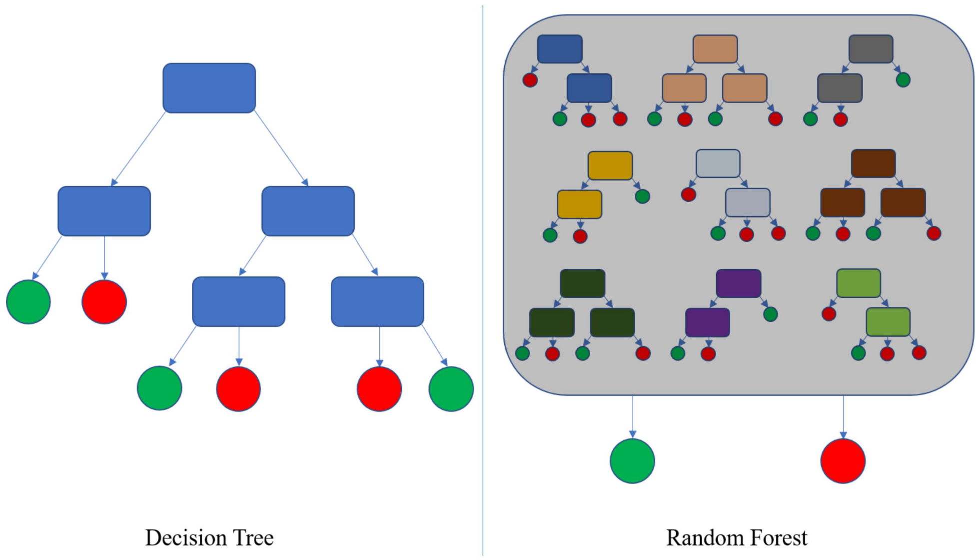
Local Climate Zone	Train	Test
Class 1: Compact high-rise	13 (295)	13 (336)
Class 2: Compact mid-rise	6 (117)	5 (62)
Class 3: Compact low-rise	7 (185)	7 (141)
Class 4: Open high-rise	10 (275)	9 (398)
Class 5: Open mid-rise	4 (79)	4 (47)
Class 6: Open low-rise	6 (60)	7 (60)
Class 7: Lightweight low-rise	0 (0)	0 (0)
Class 8: Large low-rise	4 (90)	5 (47)
Class 9: Sparsely built	0 (0)	0 (0)
Class 10: Heavy Industry	4 (107)	5 (112)
Class 11: Dense trees	7 (762)	7 (854)
Class 12: Scattered trees	6 (194)	7 (213)
Class 13: Bush, scrub	4 (459)	5 (232)
Class 14: Low plants	6 (346)	6 (222)
Class 15: Bare rock or paved	0 (0)	0 (0)
Class 16: Bare soil or sand	0 (0)	0 (0)
Class 17: Water	5 (1266)	5 (1113)

[a] Number of polygons is listed first, with number of pixels in parentheses.

Decision Trees



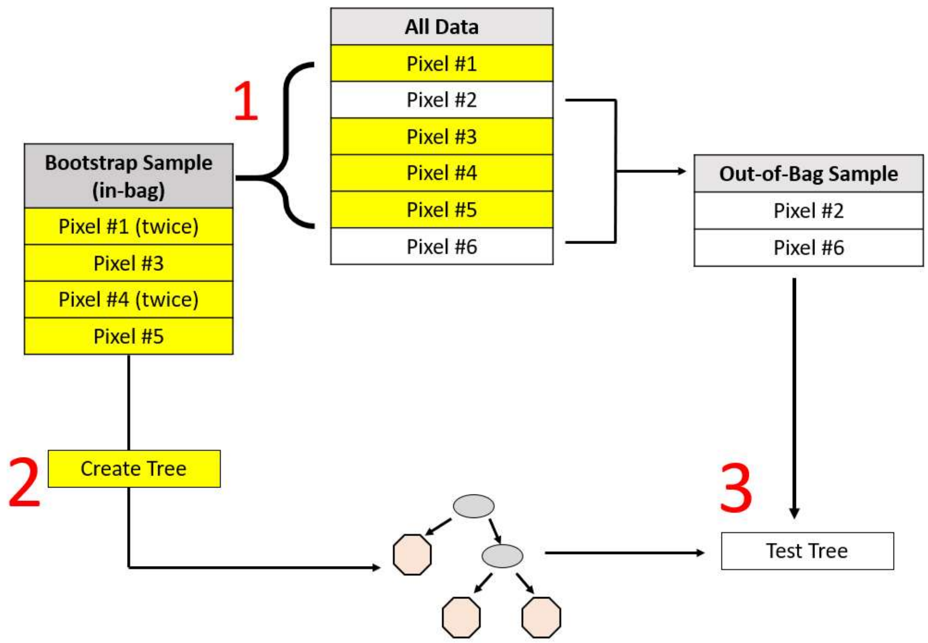
Random Forests: a collection of decision trees



Why is it a [Random] Forest?

- Randomizing variables tried at each node
- Bootstrapping samples for each tree

Out-of-Bag Error



Tuning Parameters

$$\text{ntree} = \text{varied}$$

$$\text{mtry} = \sqrt{\#\text{ of parameters}} = \sqrt{36} = 6$$

$$\text{nodesize} = 1$$

$$\text{maxnodes} = \text{maximum possible}$$

Accuracy Assessment

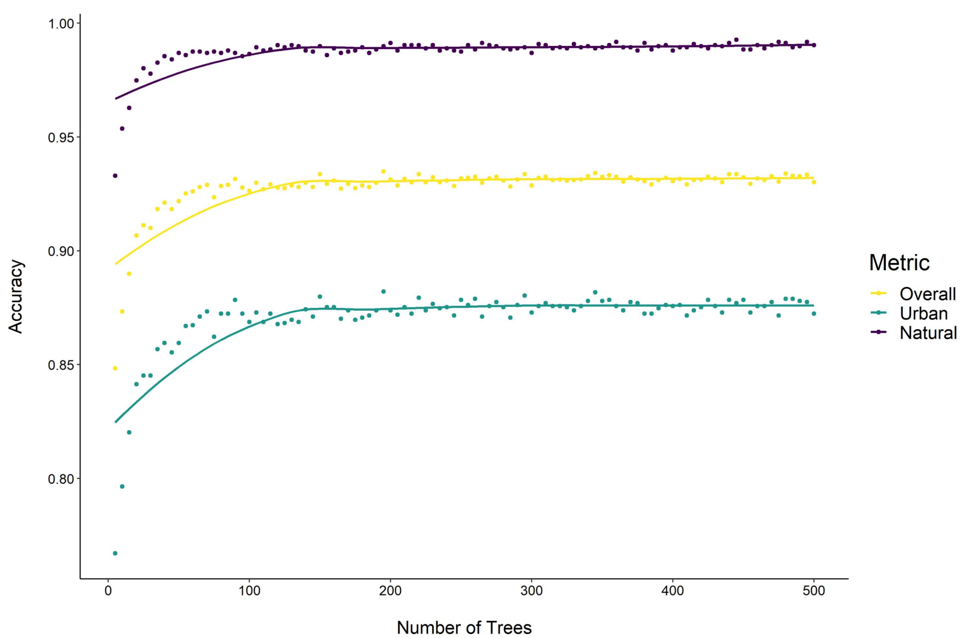
$$\text{Overall Accuracy} = \text{OA} = \frac{\text{number of correctly classified reference sites}}{\text{total number of reference sites}}$$

$$F_1 \text{ Score} = 2 * \frac{UA * PA}{UA + PA}$$

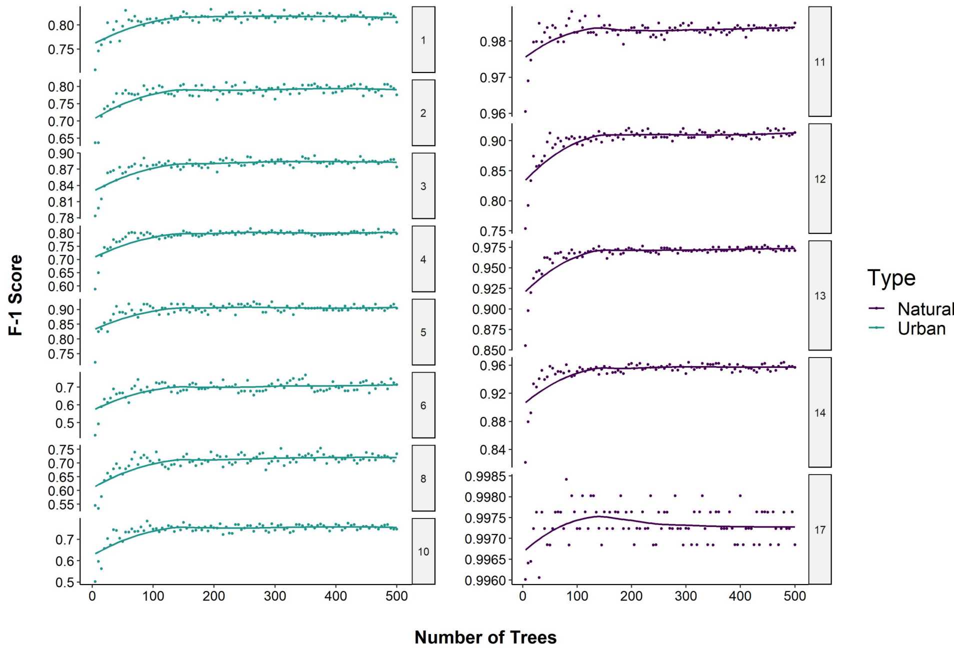
$$UA(z) \; = \frac{\text{number of correctly identified pixels in class z}}{\text{total number of pixels identified as class z}}$$

$$PA(z) = \frac{\text{number of correctly identified pixels in class z}}{\text{number of pixels truly in class z}}$$

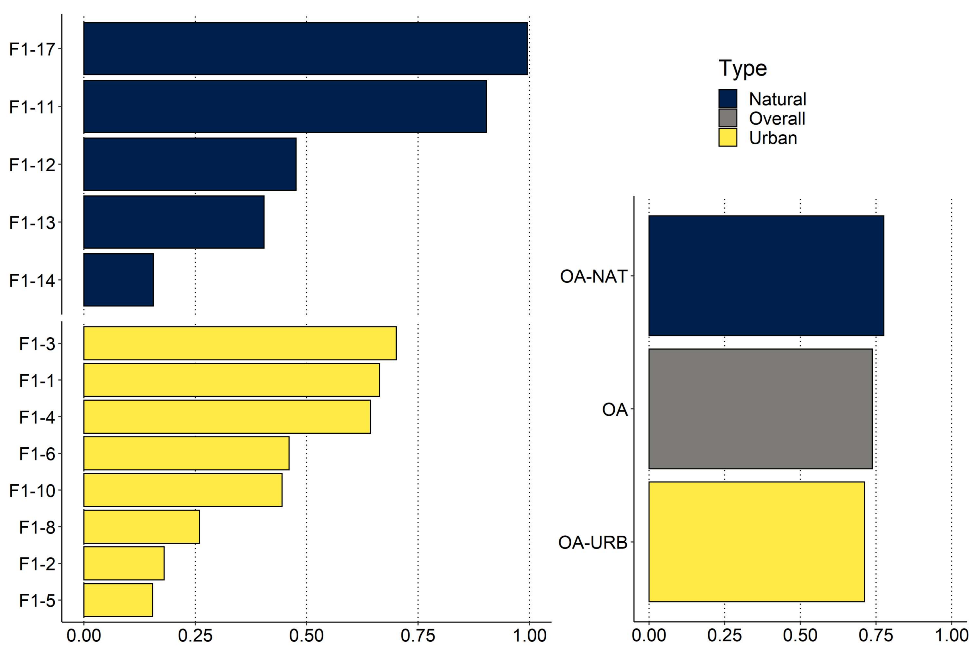
OA Metrics increase as number of trees increase, leveling off around 125 trees. Natural classes have higher OA values.



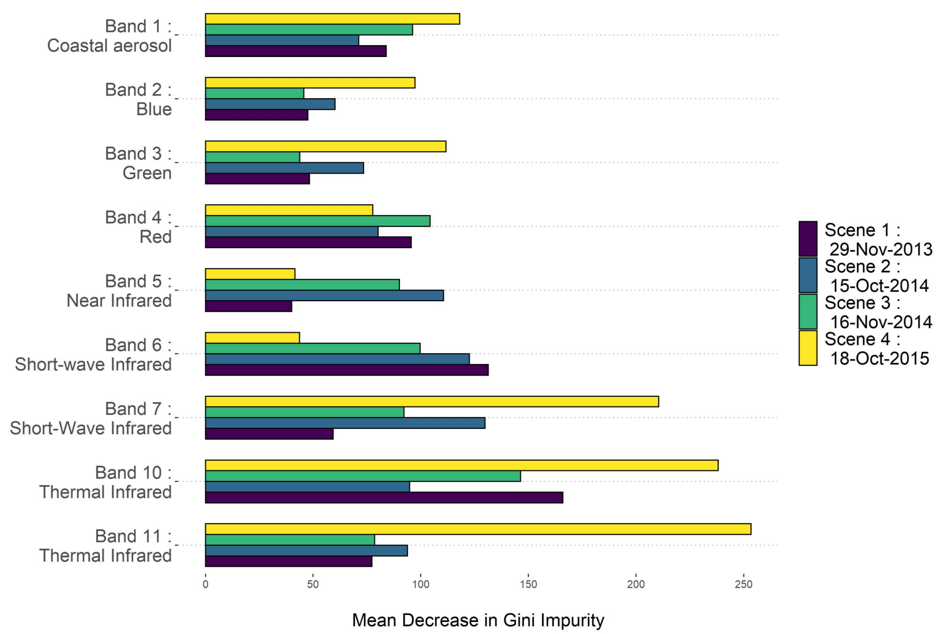
F-1 Score by Class increases as number of trees increases, leveling off around 100 trees.



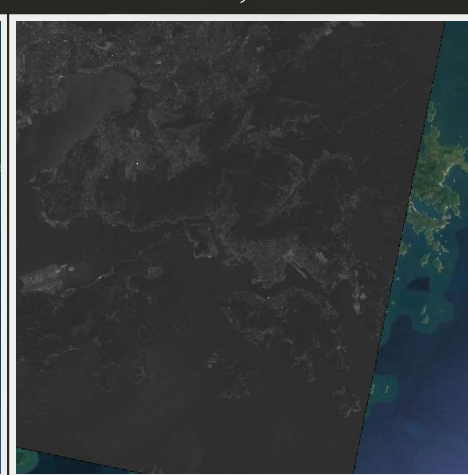
Validation Metrics are much lower for test data than for out-of-bag data.
High OA values may mask low F1 scores.



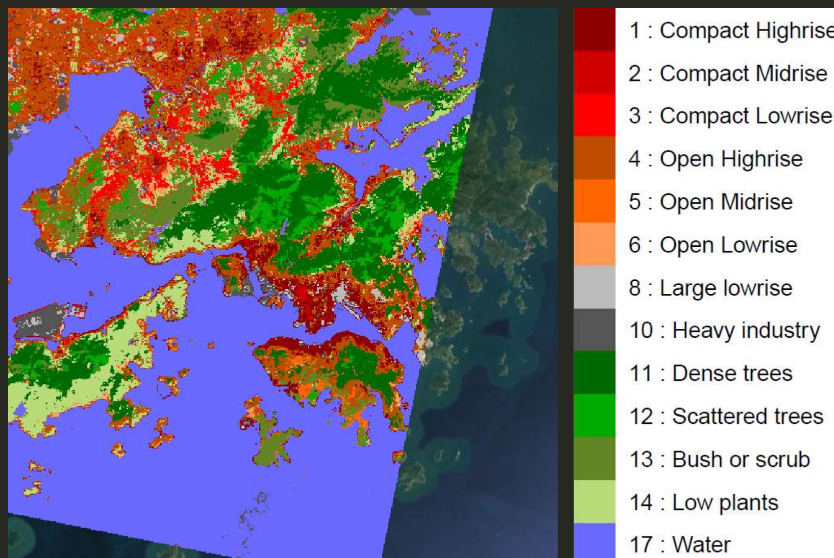
Importance Measures don't give a clear answer about which predictor variables are most useful.



Creating the Full Prediction

LCZ Polygons	Scene 1, Band 4
	

Creating the Full Prediction



Conclusion

Overall Results:

- Low accuracy for prediction on the test data, in comparison to the out-of-bag data
- High OA values can mask low F1 scores within classes

Limitations:

- Reference polygons on account for ~3% of the Area of Interest
- Time constraints

Future Work:

- Multiple tuning parameters & the interactions between them
- Quantifying how many reference polygons are "enough"

Questions?

All code and higher resolution images for this project can be found on GitHub at https://github.com/erickabsmith/masters-project-lcz-classification.