Local Climate Zone Classification Using Random Forests

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3/9/2021

Introduce Self + GitHub site

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

Background

LCZ

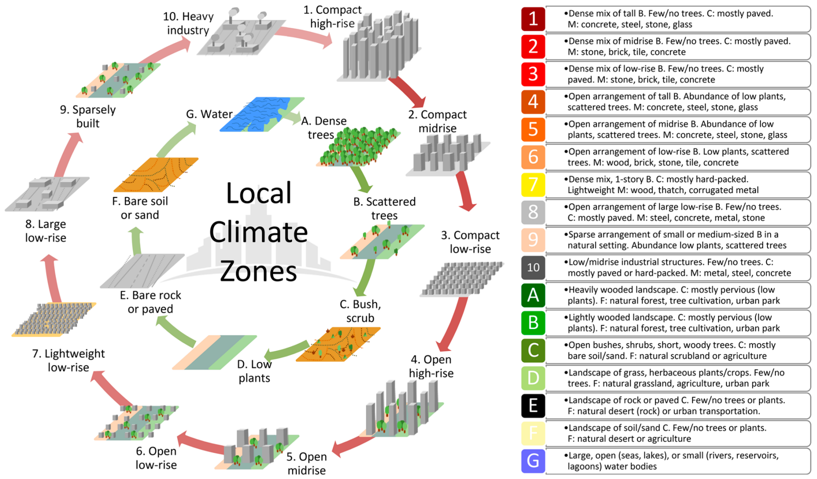


Figure 1: Local Climate Zone classes. Originally from Stewart and Oke (2012) and remade by Bechtel et al. (2017). Copyright CC-BY 4.0

Objective

Yoo

Methods - Data - LCZ

The LCZ reference data

Methods - Data - Landsat

The Landsat 8 data

Table 1: 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

All 9 available bands of all 4 Landsat scenes amounted to 36 input variables. Each pixel is an observation,

Methods - data - Step 1 - train vs test (CHALLENGE)

Table 2: 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)

Random Forests - decision tree

Random forest - impurity

Splits are typically evaluated by Gini impurity or entropy:

$$\text{Gini Impurity} = \; I_G(t) \; = 1 - \sum_{i=1}^{C} p(i|t)^2$$

$$\text{Entropy} = \; I_H(t) \; = -\sum_{i=1}^{C} p(i|t) \log_2 p(i|t)$$

Where i is a class in the predictor variable, ranging from 1 to C. C is the total number of classes represented for a particular node, t. $p(i|t)$ is the proportion of samples that belong to each i, for a particular node t.

Random Forest - How random forests differ from decision trees (+ prediction)

Tuning parameters and OOB error (maybe two slides)

Accuracy Assessment

In line with the methods used in our reference paper and the remote sensing field, accuracy metrics will include the following:

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

OA_{urb} and OA_{nat} will be used, which are the same as overall OA but only includes the urban and natural classes, respectively.

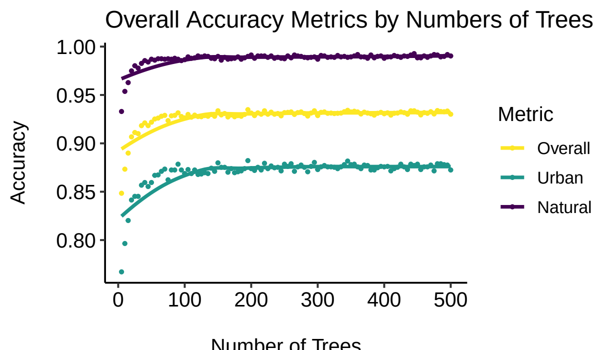
$$UA(z) \; = \frac{\text{number of correctly identified pixels in class z}}{\text{total number of pixels identified as class z}}$$

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

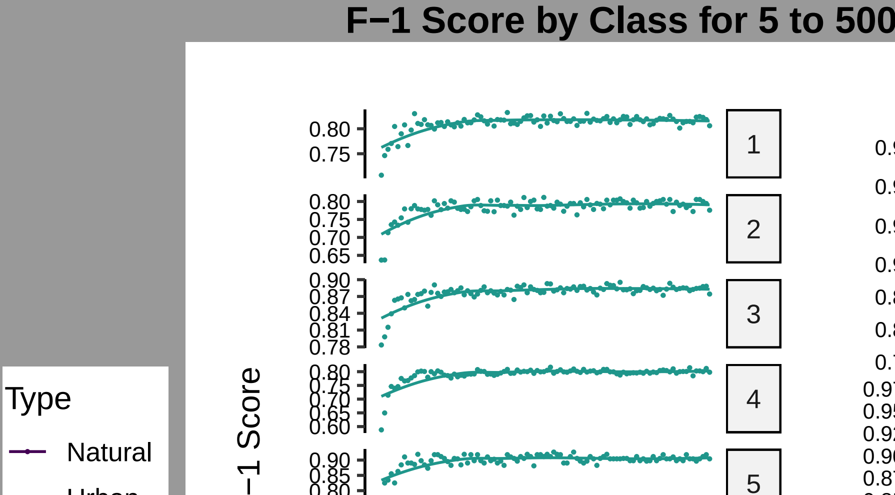
UA is a measure of user's accuracy, which is also called precision

Results - Varying the Parameter for Number of Trees - 5 to 500 - OA

The parameter for the number of trees was initially varied between 5 and 500 at intervals of 5. The resulting overall accuracy metrics indicate a leveling off around 125 trees (Figure 2). There's also a clear distinction between accuracy in urban vs. natural classes, with natural classes having a much higher overall accuracy.



Results - Varying the Parameter for Number of Trees - 5 to 500 - F1



Results - include larger plots for 500-2500 or just mention? Probably just mention

Predicting on the Test Dataset - Validation Metrics Plot

OA and F-1 metrics dropped dramatically upon applying the random forest to the test data (Figure 4).

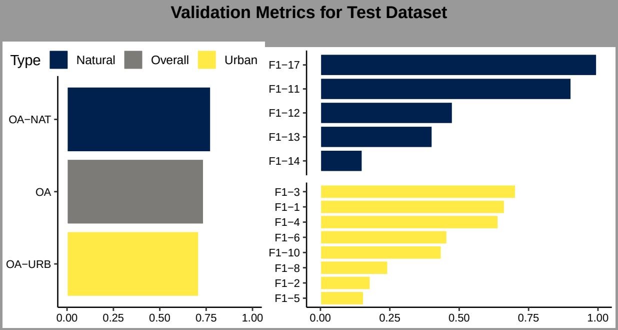


Figure 4: Accuracy among random forest predictions for the test dataset varied widely, but was lower than expected for F-1 scores, which do not seem to agree with the OA metrics. Classes 2, 5, 8, and 14 have particularly low F-1 Scores.

Predicting on the Test Dataset - Importance Measures

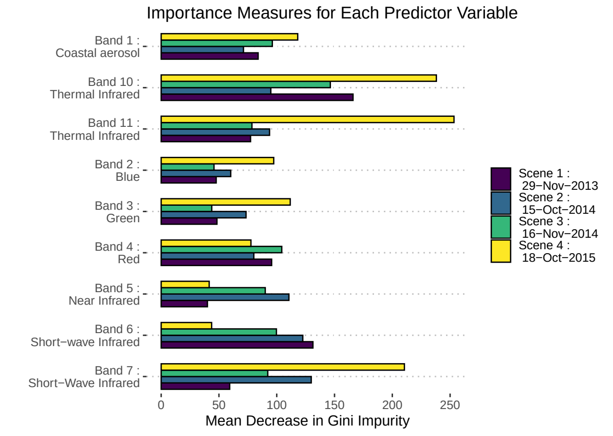


Figure 5: There is not a clear pattern in Mean Decrease for Gini Impurity between the different bands and scenes, though there is some indication that bands in scene 4 were particularly effective as predictors.

A Full Prediction - 1 just landsat

A Full Prediciton -2 just lcz

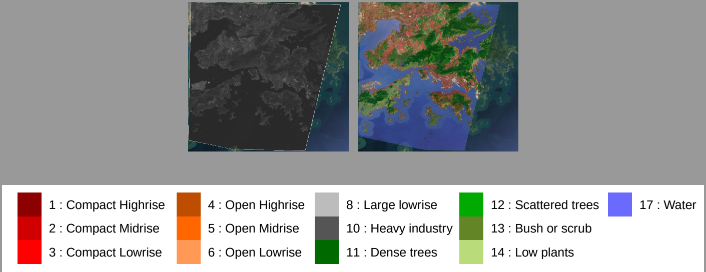


Figure 6: Imagery of the area of interest. Each has a basemap of satellite reference imagery. Top Left: Only satellite reference. Top Right: One Landsat 8 Scene. Bottom: A fully predicted LCZ map.

Discussion - large decrease b/wn oob and test data accuracy

Discussion - aggregate like OA can mask low f1 by class

Discussion interpretation? maybe these could all be one slide.

Conclusion - limitations, future work, etc

Questions + me + gitHub again