Thesis Title

Thesis Subtitle

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Forewords and Acknowledgements

Declaration of Independent Work

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Abbreviations

Abstract

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Accuracy Assessment

Detail and scrutable accuracy assessments are fundamental towards any classification based analysis. This section will introduce and break down the various lower order and higher order class-based (thematic) accuracy assessment. By explaining the characteristics of each metrics, this will provide a much more granular nature of accuracy assessment in the findings of section 4. In general, accuracy assessment in remote sensing can be divided into 2 categories: 1. Positional Accuracy 2. Thematic Accuracy. Of which, Positional Accuracy deals with the accuracy of the location while Thematic Accuracy deals with the labels or attributes accuracy (Congalton Green, 2019 Bolstad, 2019). The rest of this section will consider the lower order and higher order accuracy metrics, with lower order metrics being more granular while higher order metrics more triturated but generalised.

The metrics described in this section form part of the larger family of accuracy assessment metrics that can be constructed from the confusion matrix (see Figure 3.1)

Precision, Recall, Sensitivity, and Specificity

Precision, Recall, and Specificity

Precision and **Recall**, aka. Positivie-Predictive-Value and Sensitivity/True-Positive-Rate Respectively. The two metrics are often used together, another common denomination especially in remote sensing literature are User's Accuracy and Producer's Accuracy (Congalton Green, 2019 Wegmann et al., 2016). To avoid further confusion in nomenclature, **Precision** and **Recall** will be used from hereon.

Precision is the measure of correctly predicted Positive class (True Positive) against all positive prediction assigned to that class (True Positive +

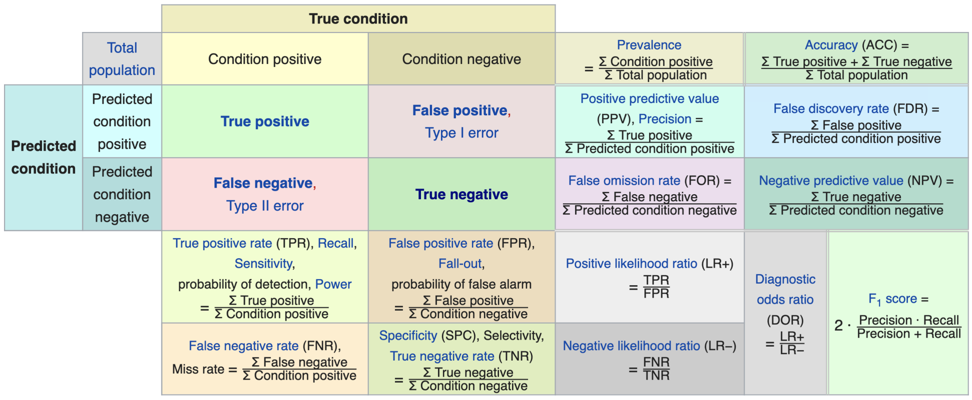

Figure 3.1: The Confusion Matrix

False Positive) i.e. Given the predicted results, of those that are predicted as positive, what proportion were True. It can be expressed mathematically as:

$$Precision = \frac{True\ Positive}{(True\ Positive + False\ Positive)} \tag{3.1}$$

Meanwhile, **Recall** measures the correctly predicted Positive class (True Positive) against both the correct and incorrect predicton on the Positive reference class (True Positive + False Negative) i.e. Given the predicted results, of those that are referenced as positive, what proportion of those were True. It can be expressed mathematically as:

$$Recall = \frac{True\ Positive}{(True\ Positive + False\ Negative)} \tag{3.2}$$

Specificity, aka. True-Negative-Rate measures correctly predicted Negative class (True Negative) against the correct and incorrect prediction on the Negative reference class (False Positive + True Negative) i.e. Given the predicted results, of those that are referenced as negative, what proportion of those were True. It can be expressed mathematically as:

$$Specificity = \frac{True\ Negative}{(False\ Positive + True\ Negative)} \tag{3.3}$$

Therefore, higher **Recall** suggests the model is better at identifying positives and vice-versa higher **Specificity** suggests the model is better at identifying negatives. Since this is an exercise that aim to maximise the positive prediction as a binary building segmentation classifier, emphasise will be placed on maximising **Precision** and **Recall**.

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