Spectral Analysis and Classification of Arctic Vegetation using Terrestrial Hyperspectral Imagery

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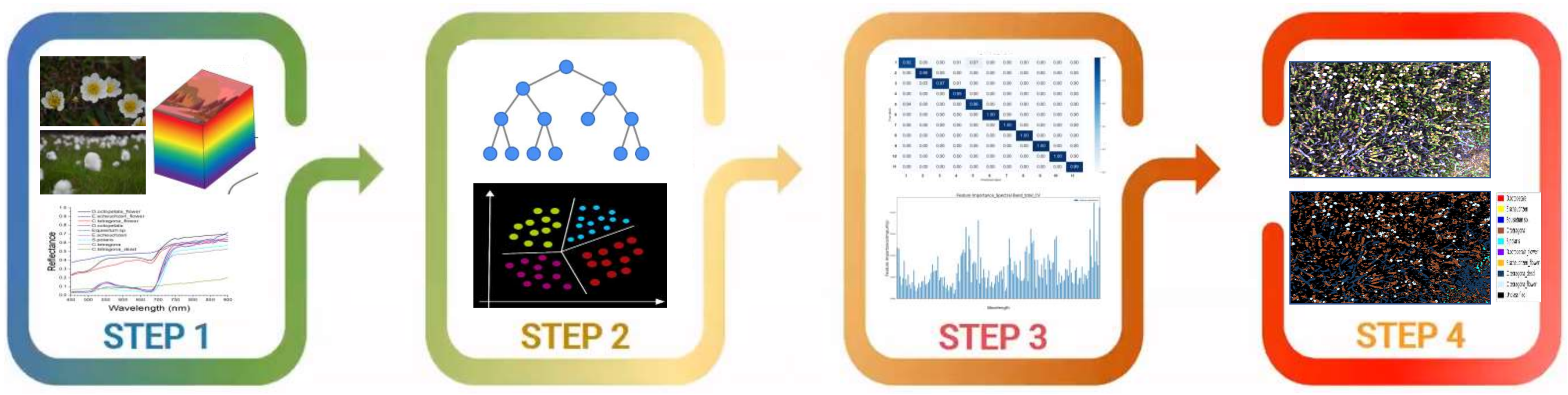
Summary



Hyperspectral Library | Classification Modeling | Analytics & Validation | Image Classification

1. Introduction

- Remote sensing has been widely used in understanding the Arctic ecosystem.
- Hyperspectral information consisting of contiguous spectral wavelengths enables the quantitative analysis of remote sensing data.
- A previous study has addressed the Arctic ecosystem using remote sensing data (Eischeid et al., 2021, *Remote Sensing* 13.21: 4466.). However, spectral information for Arctic vegetation is insufficient.
- This study has three research purposes:
  (1) Development of a spectral library of Arctic vegetation in Adventdalen, Svalbard
  (2) Presentation of a framework for discriminating Arctic vegetation using terrestrial hyperspectral imagery
  (3) Assessment of the utility of hyperspectral information with the important wavelengths in the image classification for Arctic vegetation

2. Method

- Study area: Arctic tundra of Adventdalen, Svalbard
- Hyperspectral images were acquired using a terrestrial hyperspectral camera (Table 1). Reflectance was converted using a white calibration target (Spectralon).
- However, the 400 to 450 nm and 900 to 1000 nm wavelength range were removed as noisy data.

Table 1. Terrestrial hyperspectral camera specification

Parameter	Value
Camera system	Specim IQ
Spectral range	VNIR 400 - 1000 nm
Spectral resolution	7 nm, FWHM
Spectral bands	204

- Hyperspectral data pixels of Arctic plant species were extracted using Region of Interest (ROI) from the hyperspectral images in the ENVI software package (Version 5.4.1).
- A Random Forest (RF), a decision tree based ensemble classifier, was used. Then, hyperparameter tuning was performed to optimize the parameters of the RF classifier for the accurate classification (Figure 1).

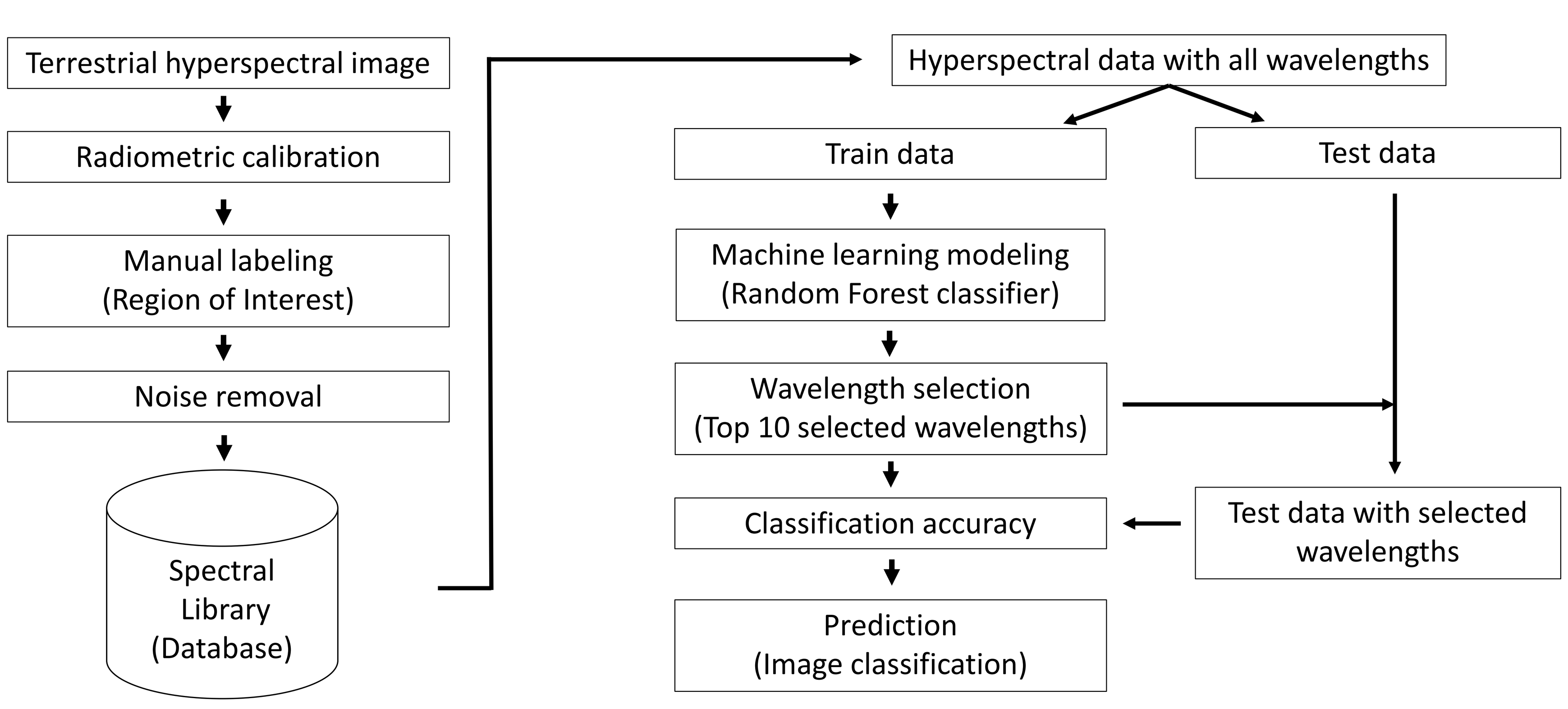


Figure 1. The flow chart of Arctic vegetation classification in Adventdalen, Svalbard

3. Result

1) Spectral Library

- The spectral library was developed using the mean of ROIs associated with plant species (Figure 2).

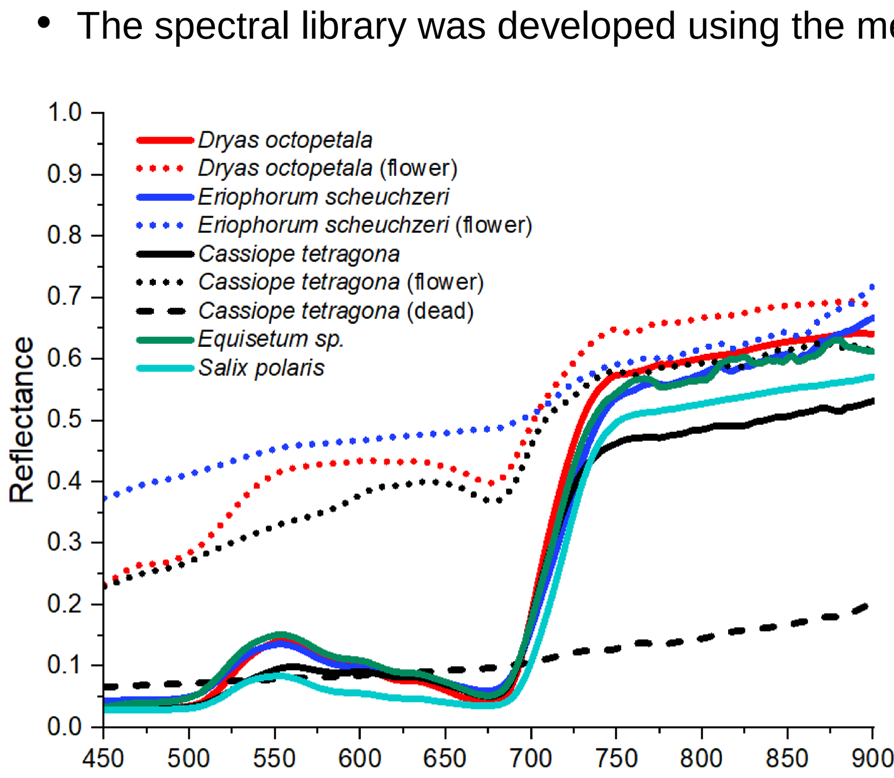


Figure 2. The mean spectral library of Arctic plant species

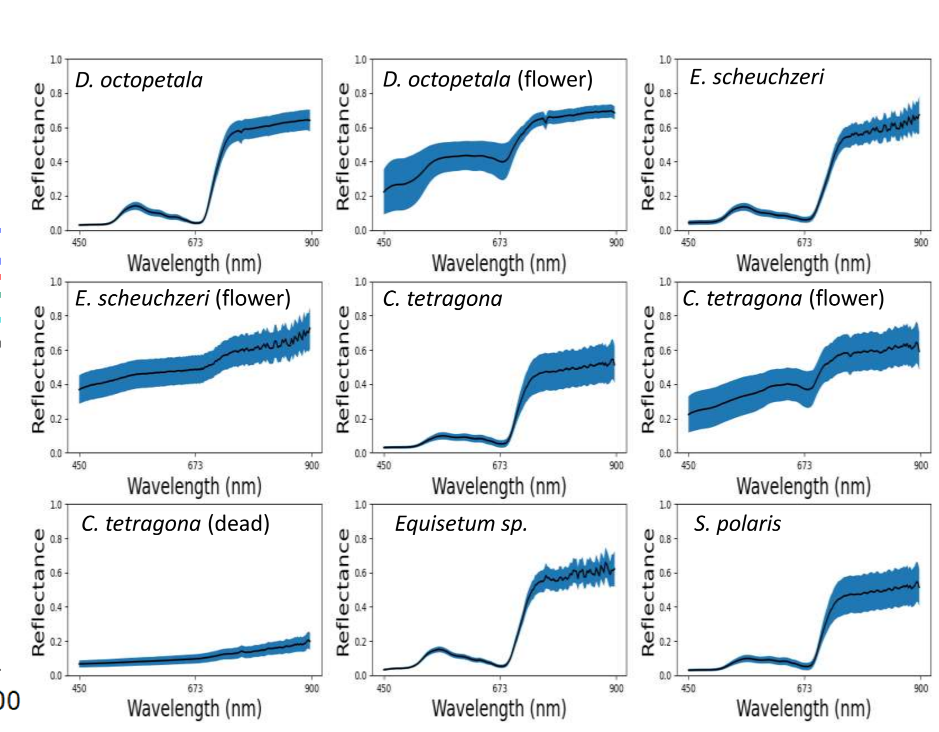


Figure 3. The mean and standard deviation of the reflectance of the each Arctic plant species

2) Statistical Accuracy of Arctic vegetation Classification

2-1) Use of All Spectral Bands

- All data consisted of 1,250 pixels except for *Equisetum sp.* (450 pixels) due to a lack of relevant pixels. The hyperspectral samples were allocated to a training set and a test set (Table 1).
- A classification result with a confusion matrix visualizing the classification performance was shown in Table 3.

Table 2. Class information for the hyperspectral dataset

ID	Classes	Training (pixels)	Test (pixels)
V1	*D. octopetala*	1,000	250
V2	*D. octopetala* (flower)	1,000	250
V3	*E. scheuchzeri*	1,000	250
V4	*E. scheuchzeri* (flower)	1,000	250
V5	*C. tetragona*	1,000	250
V6	*C. tetragona* (flower)	1,000	250
V7	*C. tetragona* (dead)	1,000	250
V8	*Equisetum sp.*	350	100
V9	*S. polaris*	1,000	250

Table 3. Accuracy functions for classification performance

Accuracy function
$Producer's\ accuracy\ (Recall) = \frac{TP}{TP+FN}$
$User's\ accuracy\ (Precision) = \frac{TP}{TP+FP}$
$Overall\ Accuracy\ (OA) = \frac{TP+TN}{TP+FN+FP+TN}$
Where TP, FN, FP, TN are the number of true positives, false negatives, false positives, and true negatives.

Table 4. Classification accuracy using all wavelengths (450 to 900 nm)

Sample ID	*V1*	*V2*	*V3*	*V4*	*V5*	*V6*	*V7*	*V8*	*V9*	Producer's accuracy (%)
V1	**233**		5		3			9		93%
V2		**244**				6				97%
V3			**250**							100%
V4				**250**						100%
V5	3				**226**	3	2		16	90%
V6					2	**247**	1			99%
V7							**250**			100%
V8			1					**99**		99%
V9	32		1		2				**215**	86%
User's accuracy (%)	87%	100%	97%	100%	97%	96%	99%	92%	93%	
Overall Accuracy (%)										96%

2-2) Use of Important Spectral Bands

- The overall accuracy with the selected wavelengths (95%) was not significantly reduced compared to the one with all hyperspectral wavelengths (96%) in Table 4.

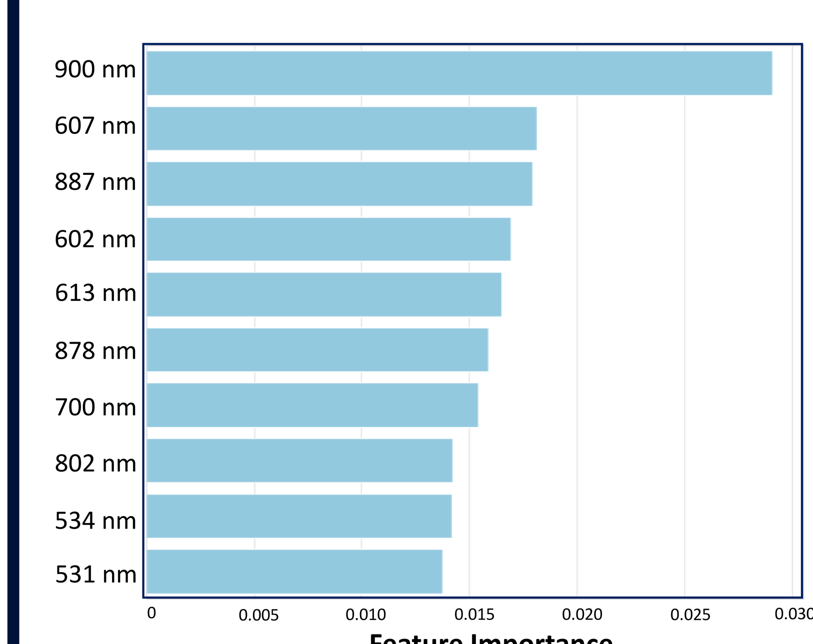


Figure 4. The 10 most important wavelengths was determined by calculating the mean decrease of impurity.

Table 5. Classification accuracy using the 10 most important wavelengths

Sample ID	*V1*	*V2*	*V3*	*V4*	*V5*	*V6*	*V7*	*V8*	*V9*	Producer's accuracy (%)
V1	**222**		15		8			2	3	89%
V2		**248**				2				99%
V3			**250**							100%
V4				**250**						100%
V5					**230**	3	2		15	92%
V6					4	**245**		1		98%
V7						1	**249**			99%
V8			8					**92**		92%
V9	36						1		**213**	85%
User's accuracy (%)	86%	100%	92%	100%	95%	98%	99%	97%	92%	
Overall Accuracy (%)										95%

3) Visual Inspection of Classification Results

- In qualitative comparison, the significant classification differences between all wavelengths and the 10 selected wavelengths were exhibited.

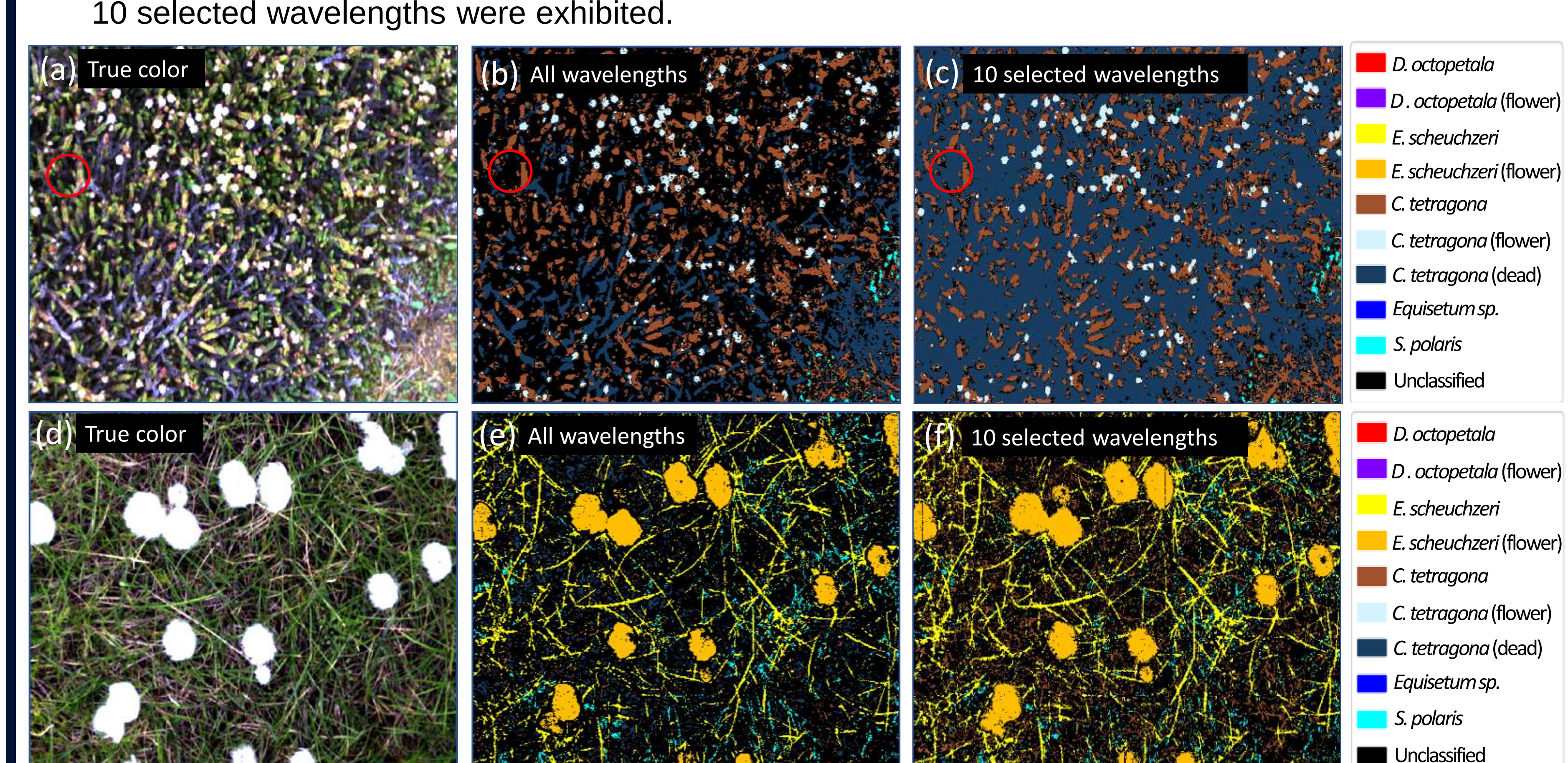


Figure 5. Comparison of the classification results: (a) and (d) True color images, (b) and (e) classification results using all wavelengths, (c) and (f) classification results using 10 selected wavelengths. Pixels below a threshold value of classifier probability (< 0.75) were defined as the 'unclassified' class. The shadow (a red circle in Figure 5.a) was classified as an unclassified class with the all wavelengths, whereas the pixel was misclassified as a *C. tetragona* (dead) class with the 10 selected wavelengths.

4. Conclusion

- We developed a spectral library of Arctic vegetation in Adventdalen, Svalbard.
- The random forest classifier-based framework would lead to higher classification performance of hyperspectral data to identify Arctic vegetation.
- Hyperspectral information can provide detailed vegetation maps using remote sensing imagery and improve understanding of the Arctic vegetation.

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