Simulated AVIRIS-3 detects species-specific patterns of vegetation succession in retrogressive thaw slumps

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Abstract: Retrogressive Thaw Slumps (RTS) are increasingly transforming Arctic permafrost landscapes, leading to significant shifts in vegetation composition and carbon cycling. However, large-scale assessment of vegetation change across RTS chronosequences is constrained by the limited availability of high-resolution hyperspectral data. In this study, we evaluate the potential of hyperspectral image simulation for mapping fractional cover (fCover) of dominant plant functional types (PFTs) across RTS features in the Noatak National Preserve, Alaska. We leverage a multi-scale dataset integrating ground-based vegetation surveys, high-resolution airborne imagery (RedEdge-M at 5 cm and AVIRIS-3), and Sentinel-2 MSI satellite data. Hyperspectral reflectance was simulated from Sentinel-2 using the Universal Pattern Decomposition Method (UPDM), and PFT fCover was estimated using a reference classification map. Comparative analysis using data from July 2023 demonstrated that simulated AVIRIS-3 imagery improved fCover estimation accuracy, with an average 8.9% increase in correlation and a 16.6% reduction in RMSE compared to Sentinel-2. The model was subsequently applied to assess growing season vegetation dynamics for 2022 and 2023 (May–September). We further extended the framework to produce vegetation maps over RTS scars—both manually delineated and identified via deep learning models throughout the ABoVE domain. We mapped vegetation succession across diverse tundra types for different sites, namely, Toolik, Peel, Noatak and Hershel island. This approach enables a spatially explicit analysis of vegetation recovery dynamic, improving our understanding of ecosystem responses to thaw-related disturbances across heterogeneous Arctic climates and environments

Introduction

Retrogressive thaw slumps (RTS) are a common phenomenon in permafrost region, mobilizing significant amounts of soil carbon and nutrients as temperatures rise. The rate of RTS formation has fastened in the past few decades. Due to varying patterns and rates of RTS expansion throughout the Arctic, the underlying controls on RTS morphological change and the resulting patterns of vegetation succession remain unclear. In order to answer the question a high resolution spatial and spectral information could help to understand the factors that influence patterns of vegetation succession in response to disturbances across permafrost landscapes in Alaska. Imaging spectroscopy has potential to effectively characterize and monitor such succession but it has limited availability, coverage and high cost. Therefore, in this study we simulated a hyperspectral information which possess the similar rich spectral response as that of AVIRIS-3. The spectral rich image was further integrated with fine scale spatial information obtained from a UAS derived image to study the vegetation succession and understands the RTS dynamics response across the NASA-ABoVE core domain.

Study Area

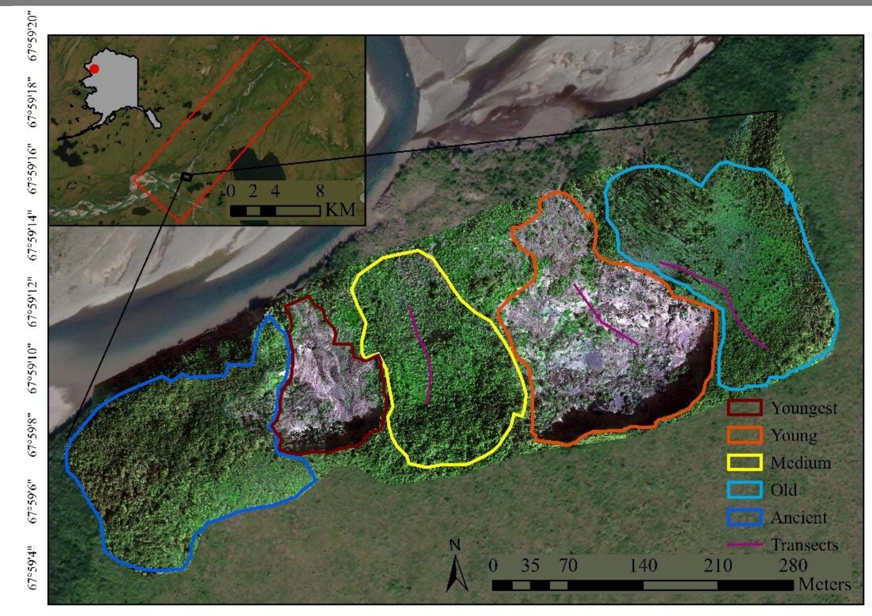


Figure 1. Study site

Data type	Sensors	Resolution	Date of acquisition (Julian days)									
					2022					2023		
Multispectral	Sentinel-2 MSI	10,20*	150	158	188	215	273	151	168	199	225	25
	RedEdge-M	~0.05								204		
Hyperspectral	AVIRIS-3	~2.5								199		
LiDAR	RIEGL VZ-400i									204		
Spectro-radiometer	HR-1024-SVC									204#		

***20m bands resampled to 10m; #Field survey from 21-24 July 2023.**

Methodology

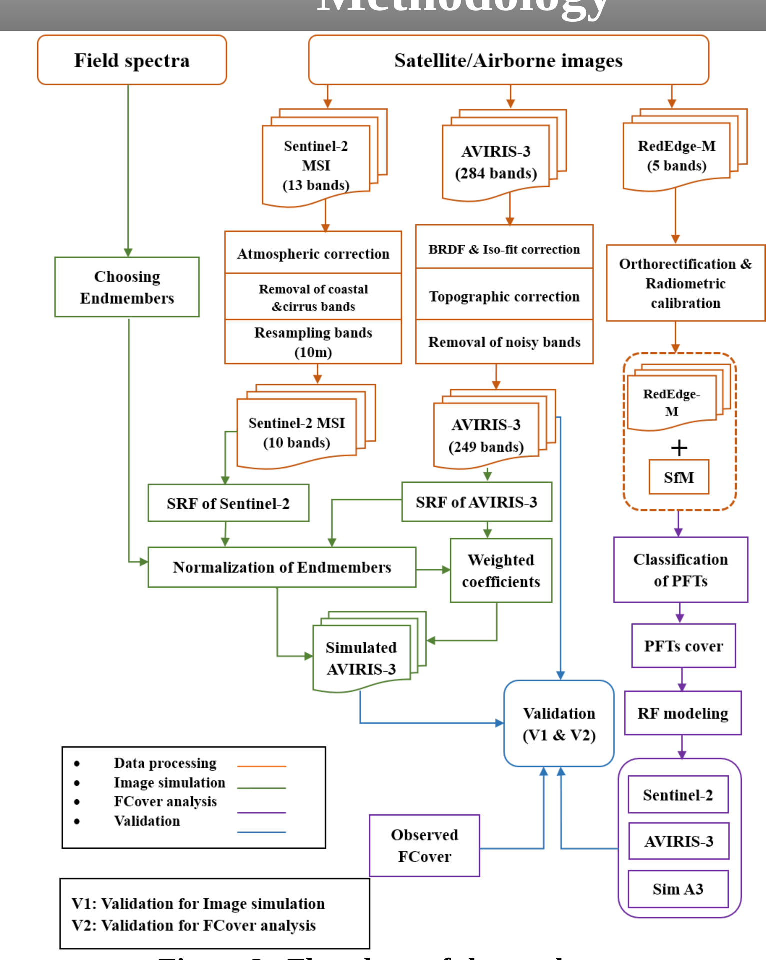


Figure 2. Flowchart of the work

Software Used: GEE, ArcGIS pro, Python, RStudio, Agisoft Metashape, ENVI (5.3)

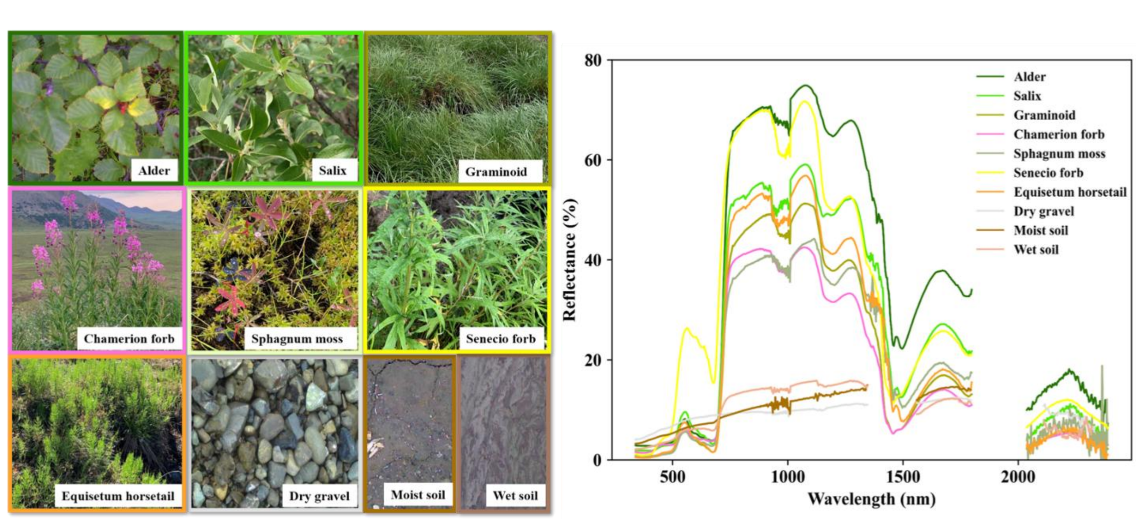


Figure 3. Different PFTs with corresponding spectral profile recorded during field sampling and NV classes present in the study site

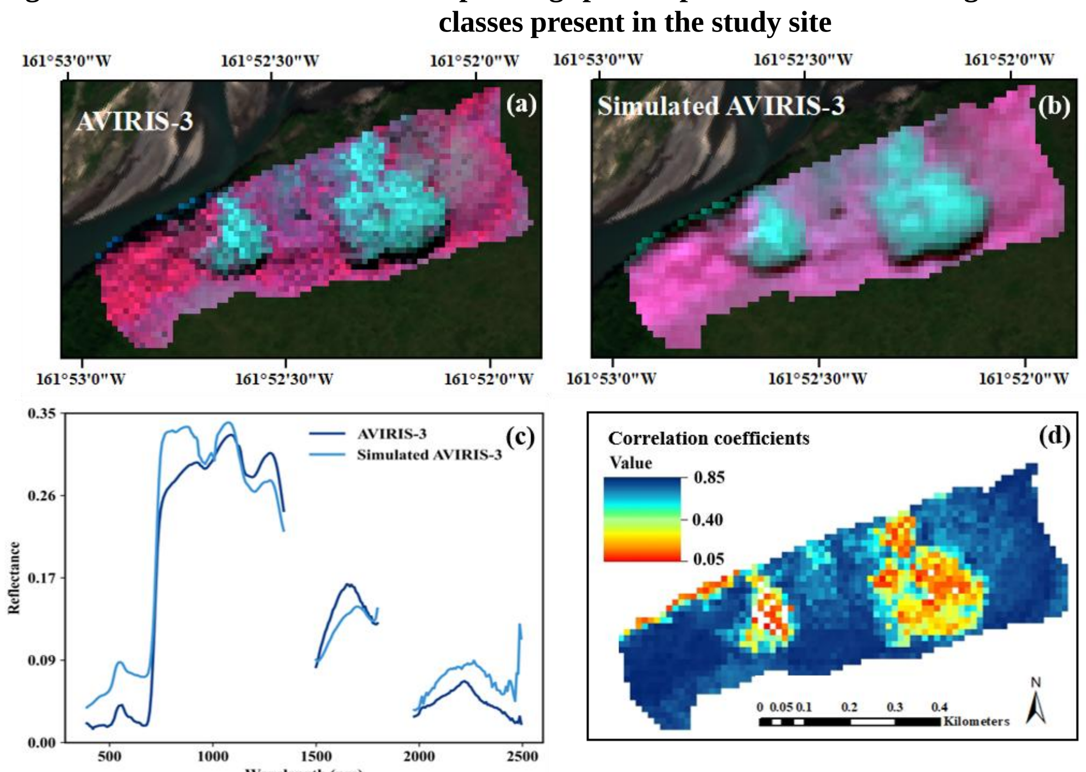


Figure 4. (a) River slump coverage from A3 and (b) Simulated A3 B(62, 35, 22), (c) Spectra comparison between a vegetation pixel; and (c) pixel by pixel correlation map between A3 and simulated A3

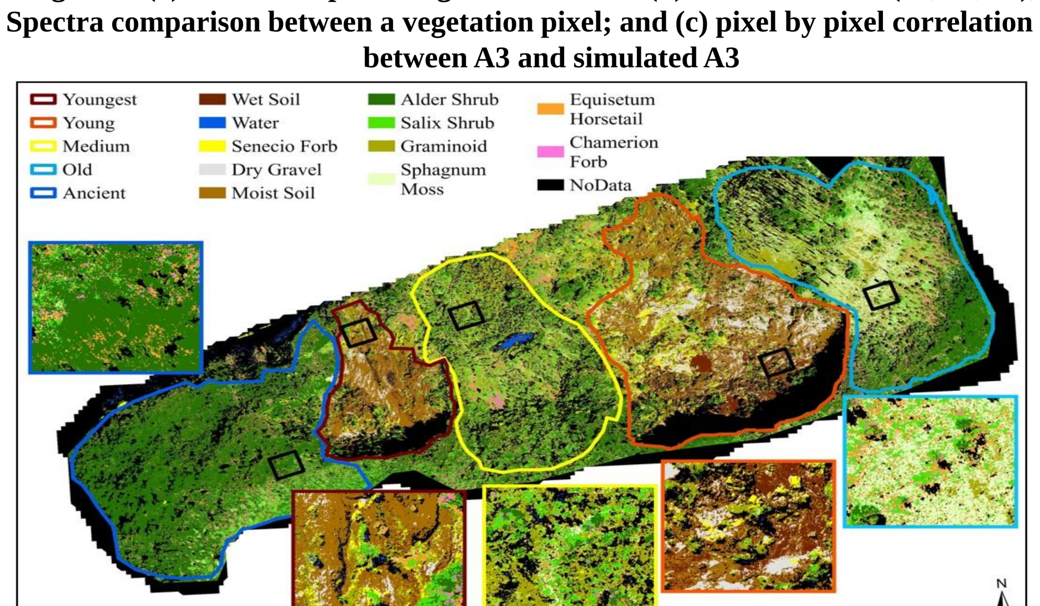


Figure 5. Classification of the slump with Maximum Likelihood classifier

Classes	Omission	Commission	User accuracy	Producer accuracy
Wet soil	0	0	1	1
Water	0	0	1	1
Senecio forb	0.27	0	1	0.72
Dry gravel	0.10	0.10	0.89	0.89
Moist soil	0.04	0.38	0.61	0.95
Alder shrub	0.14	0.13	0.86	0.85
Salix shrub	0.20	0.23	0.76	0.79
Graminoid	0.33	0.28	0.71	0.66
Sphagnum moss	0.25	0.43	0.56	0.75
Equisetum horsetail	0.53	0.36	0.63	0.46
Chamerion forb	0.46	0	1	0.53
Over all agreement: 80.69%; Overall disagreement: 19.31%				

Table 1. Accuracy assessment of the classification map.

fCover quality assessment	Sentinel-2		Simulated AVIRIS-3	
Species	R	RMSE	R	RMSE
Wet soil	0.486	0.040	0.584	0.039
Senecio forb	0.640	0.032	0.738	0.029
Dry gravel	0.704	0.055	0.716	0.054
Moist soil	0.870	0.083	0.869	0.088
Alder shrub	0.636	0.202	0.771	0.170
Salix shrub	0.633	0.072	0.623	0.071
Graminoid	0.703	0.079	0.725	0.076
Sphagnum moss	0.748	0.065	0.664	0.074
Equisetum horsetail	0.583	0.065	0.633	0.059
Chamerion forb	0.347	0.216	0.441	0.023

Table 2. FCover performance of the model for different images

Results

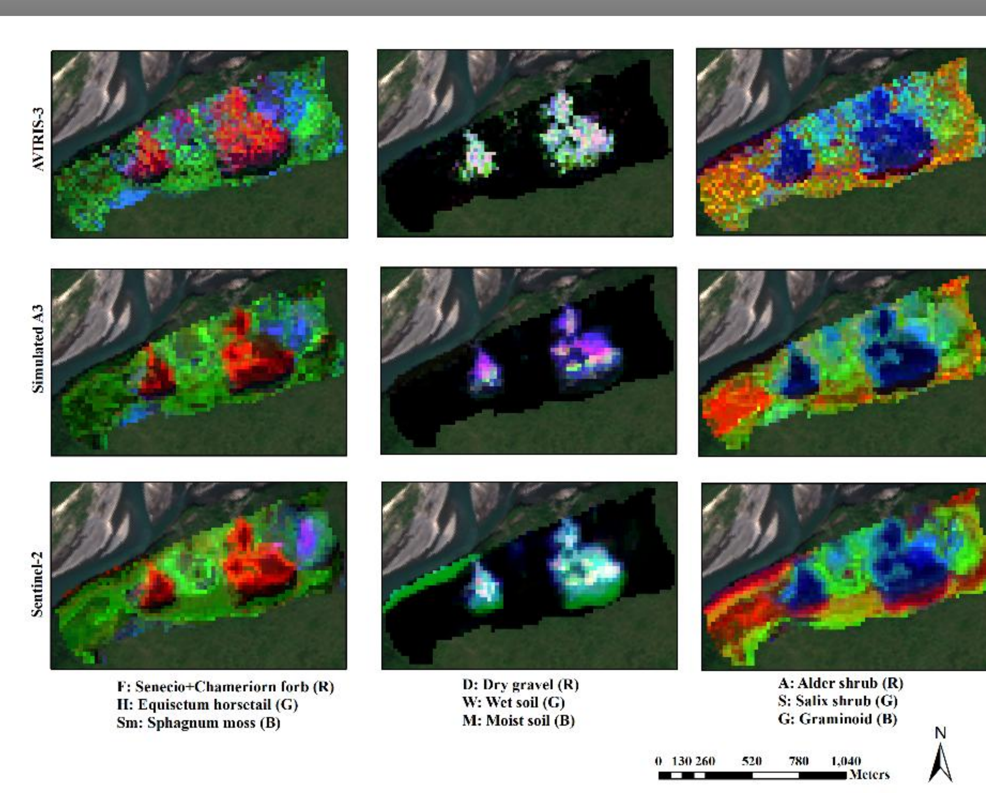


Figure 6. Stacks of FCover for 3 classes (Shrubs, soil, and grass)

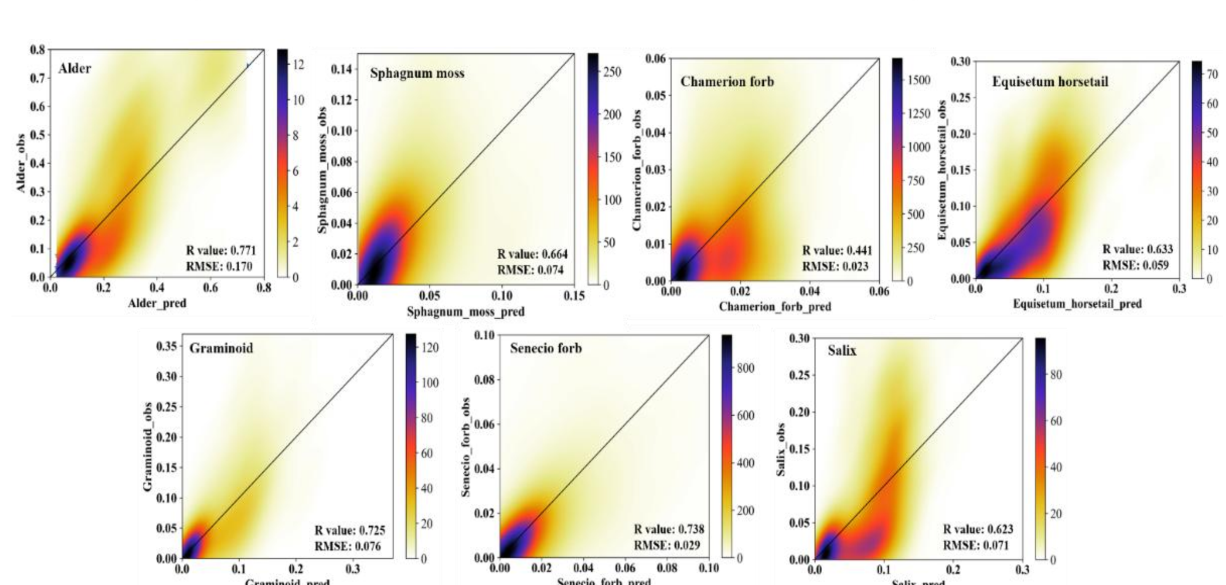


Figure 7. Comparison between predicted and observed fCover for PFTs present in the slump for simulated AVIRIS-3.

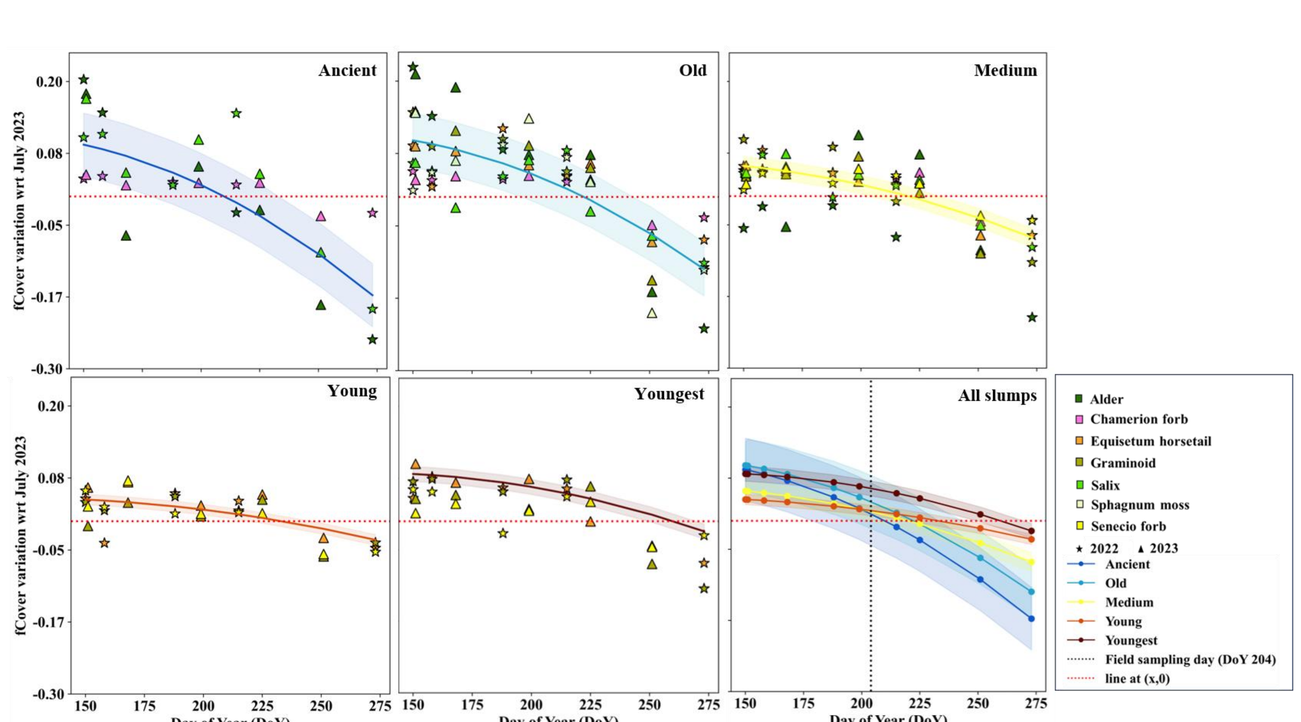


Figure 8. fCover variation w.r.t. July 2023 in the PFTs across the slump for the growing season for 2022 & 2023.

Preliminary results for scaling the model across different sites of ABoVE domain (Toolik, Peel, Noatak, & Hershel island)

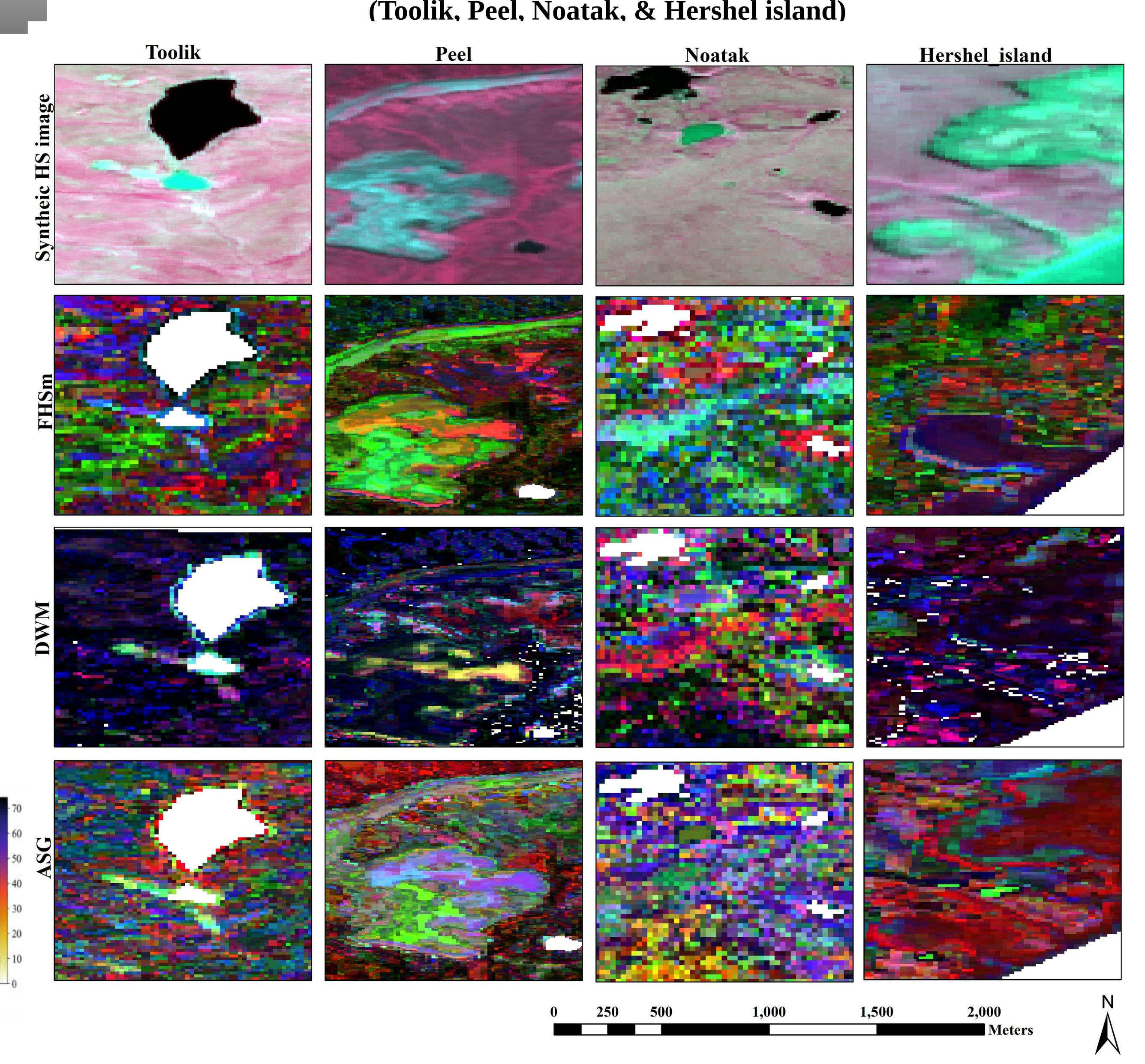


Figure 9. Synthetic HS images for different sites in ABoVE domain and their respective fCovers for different PFTs and non vegetation classes

- Alder PFT appears to be overestimated across all sites, likely due to the algorithm misclassifying dark green pixels—such as wet shrubs or darker green pixels—as Alders.
- In the Toolik region, wet sedges are misclassified as Alders; incorporating ground truth spectra from local region into the fCover model may help correct this.
- As proven at the RTS site, the model struggled to distinguish water pixels and performed poorly in identifying wet soil or bare ground areas.
- The model was able to capture the features for graminoids, mosses, and forbs better compared to shrub classifications.

Conclusion

- A free hyperspectral (HS) image was generated with global coverage, comparable to satellite data, which captured AVIRIS-3-like spectral detail.
- The image was subjected to calculate fCovers of various PFTs and compared by reference fCovers.
- The reference fCovers for PFTs was computed using a 5cm classification image generated by UAS + CHM images.
- An integrated model derived from river slump data in the Noatak region was developed and it showed overall increase in correlation by 8.9% and reduction in RMSE by 16.6% compared to Sentinel-2 product..
- This model was scaled across multiple sites within the ABoVE domain to map different PFTs.
- Synthetic hyperspectral images and corresponding fractional vegetation cover (fCover) maps were generated for these sites.
- Preliminary results indicate a need to refine the fCover model for scaling purpose by incorporating additional input from various eco-regions to improve PFT mapping across the ABoVE domain.

a. Hyperspectral image simulation:

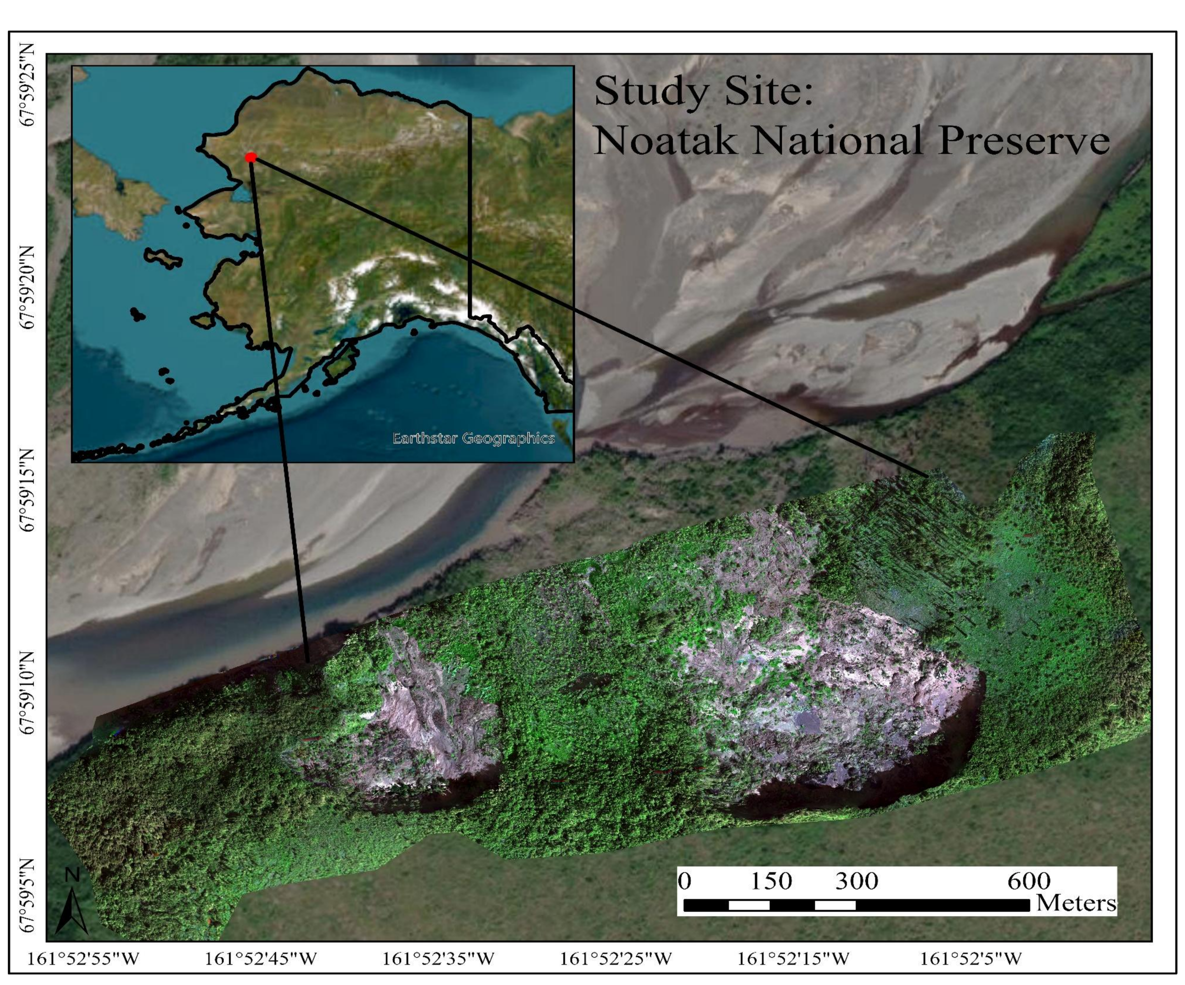
A synthetic hyperspectral imagery equivalent to the AVIRIS-3 was generated using UPDM algorithm, that uses the reflectance from a multispectral image which has global coverage. In total, 284 bands were generated with 10 input bands from Sentinel-2. Figure 3 (a) shows FCC images of the slump from AVIRIS-3, Simulated A3, and Sentinel 2. Simulated A3 has the spatial resolution similar to the Sentinel-2, and the spectral resolution similar to the AVIRIS-3, (b) is spectra comparison for a vegetation pixel from the AVIRIS-3 and simulated AVIRIS, the absorption characteristics and reflectance patterns of the simulated spectra is quite similar to the original spectra and (c) is the pixel by pixel correlation coefficient between those two images, for vegetation part there is higher correlation going up to 0.85 while for the wet or moist bare ground or mixed reflectance pixel has lower correlation. Additionally, the simulated image is more detailed compared to the S@ image.

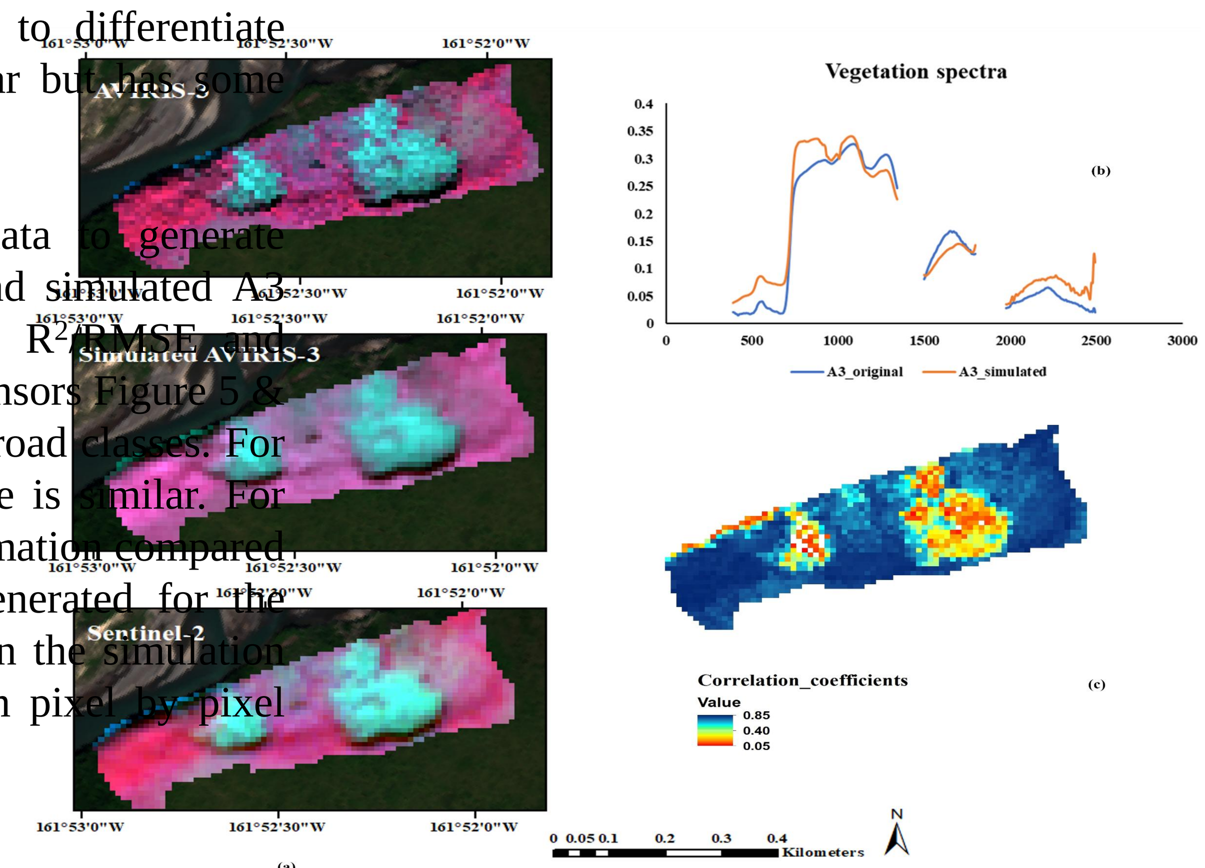
b. Image classification:

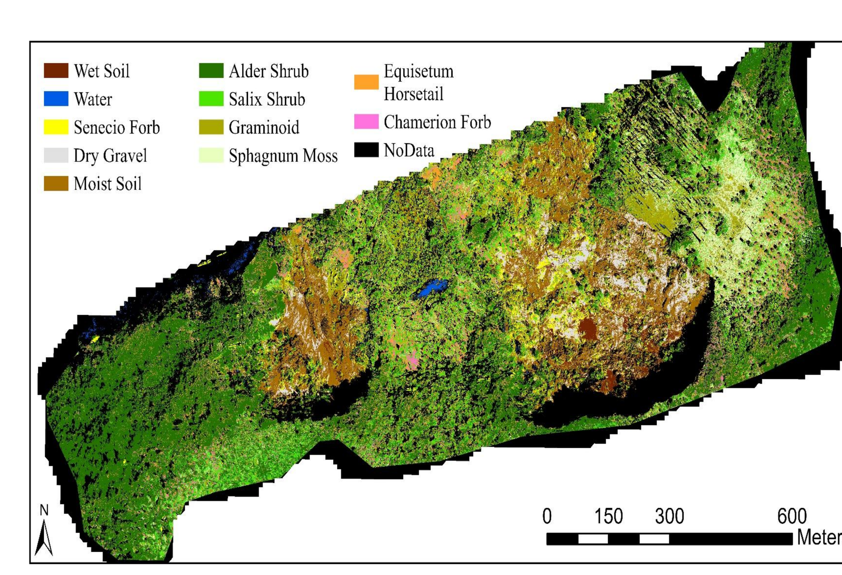
Figure 4 shows the species level Maximum-Likelihood classification. The classification was done on a UAS derived 5 bands image and an additional layer of Canopy Height Model (CHM) to differentiate between the species who are spectrally very similar but has some canopy height difference.

c. Fractional cover (FCover) analysis:

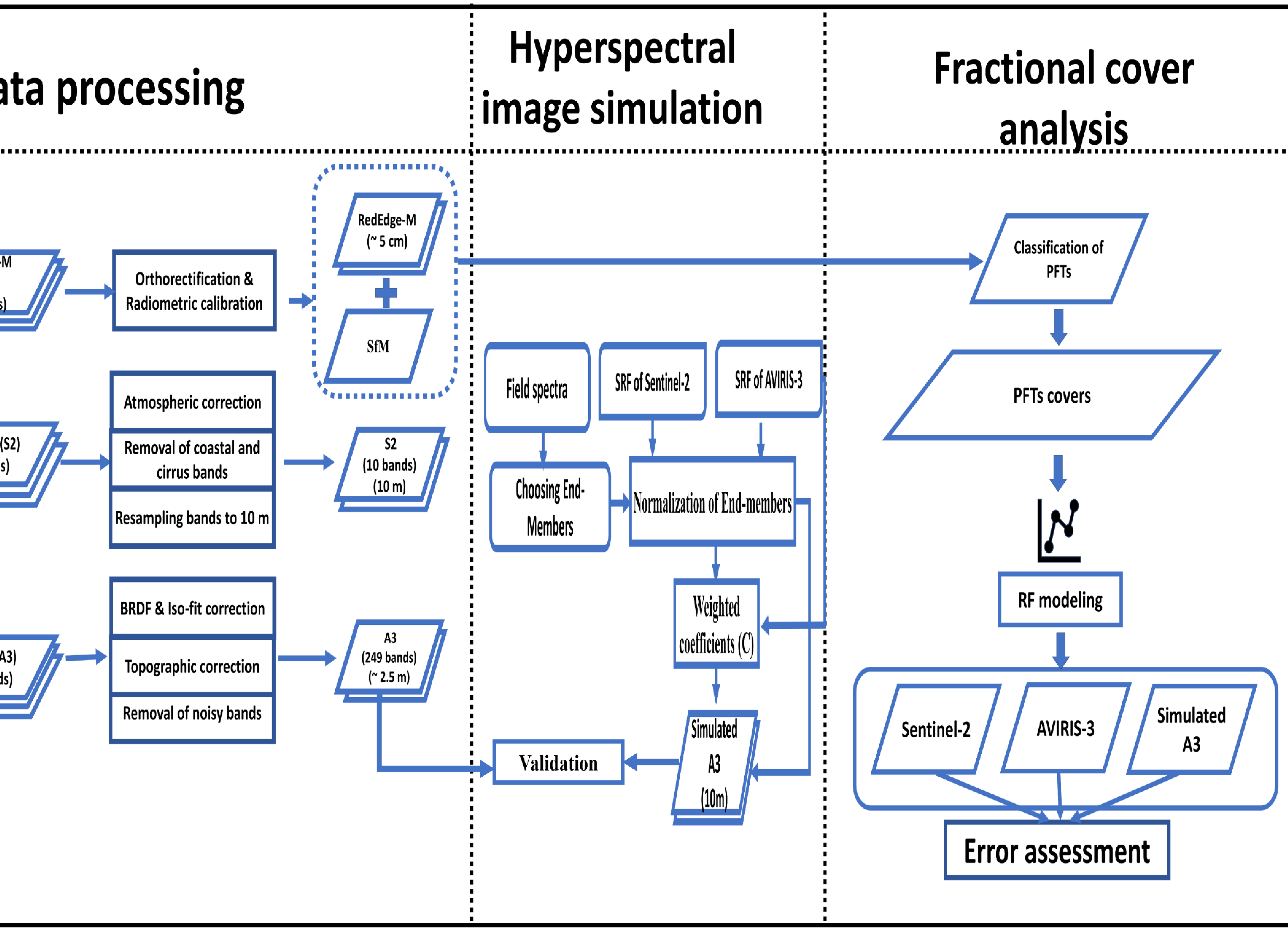
The classified image was used as a reference data to generate fractional cover of 12 classes for AVIRIS-3, S2 and simulated A3 using Random Forest model. Table 2 shows the R^2 RMSE and maximum coverage of each classes for each of the sensors Figure 5 & 6 shows the RGB stacks for all three sensors for 3 broad classes. For moist soil, Alder, and Salix the coverage percentage is similar. For wet soil, and water simulated A3 is showing overestimation compared to AVIRIS-3 and S2, which shows our model generated for the simulated A3 is performing poor, but for vegetation the simulation and its RF model is working fair as expected from pixel by pixel correlation figure (figure3(c)).

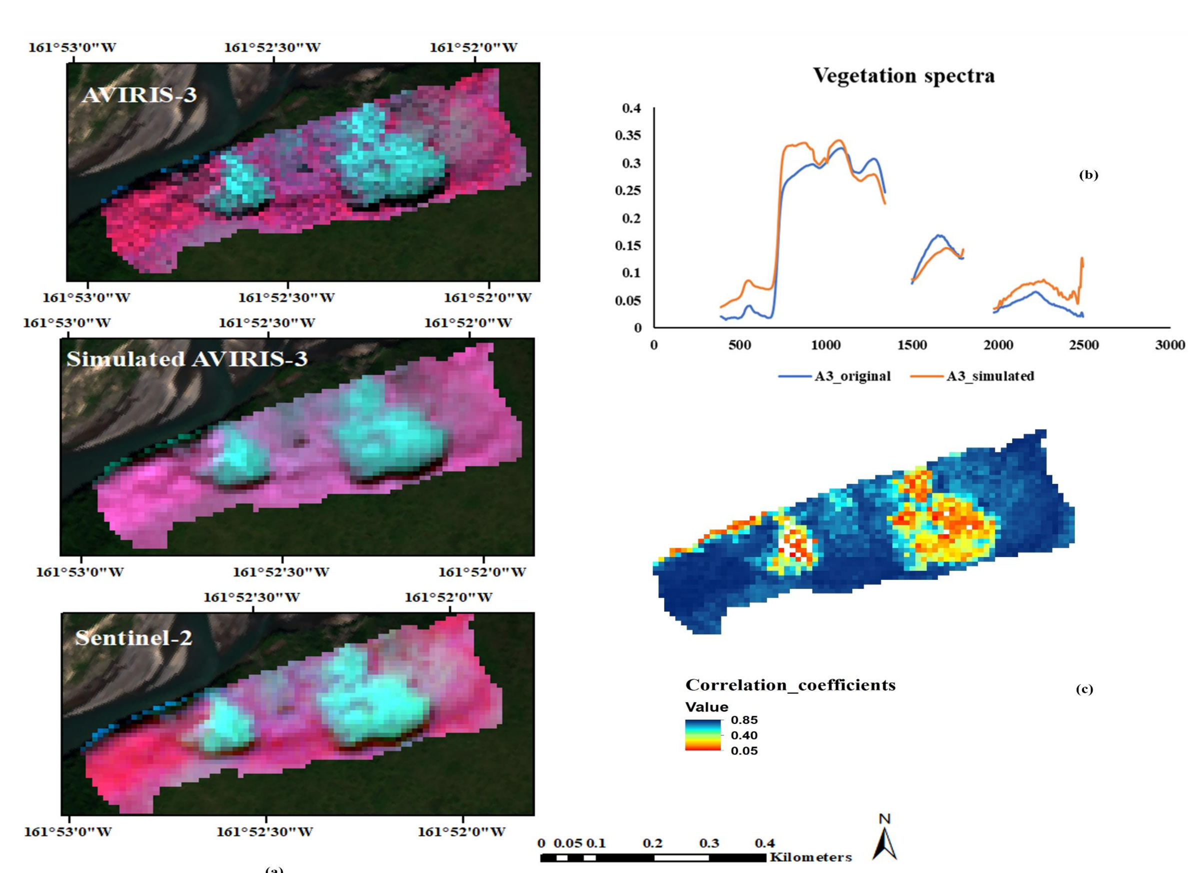




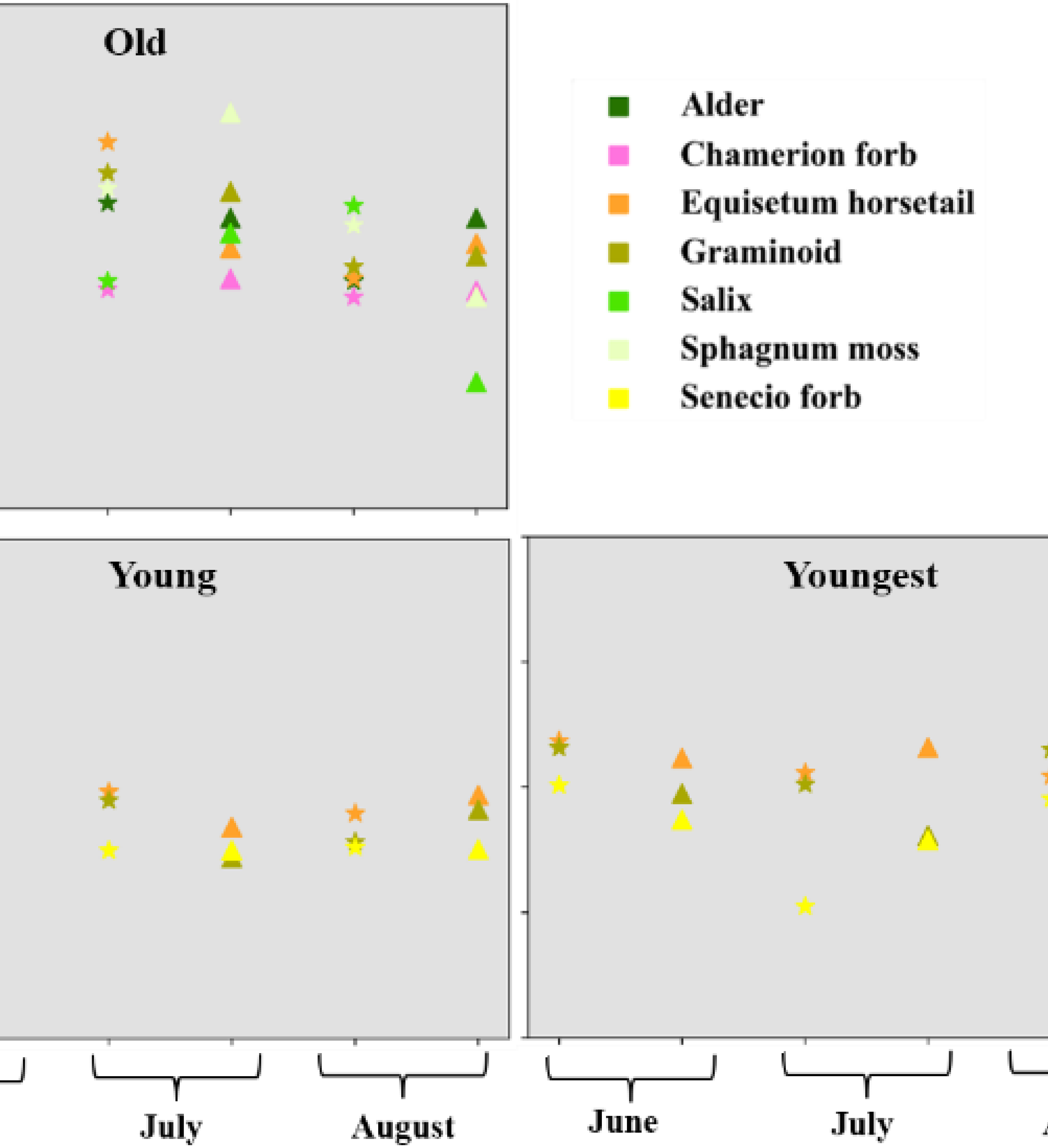


1. Satellite and airborne data:			
Sensor	**Date of Acquisition**	**Product type**	**Resolution (m)**
Sentinel-2 MSI	07/17/2023	L2A	10,20,60
AVIRIS-3	07/23/2023	L2A	~2.5
RedEdge-M	07/23/2023		~0.05
2. Data Sampling:	HR-1024i-SVC spectroradiometer		

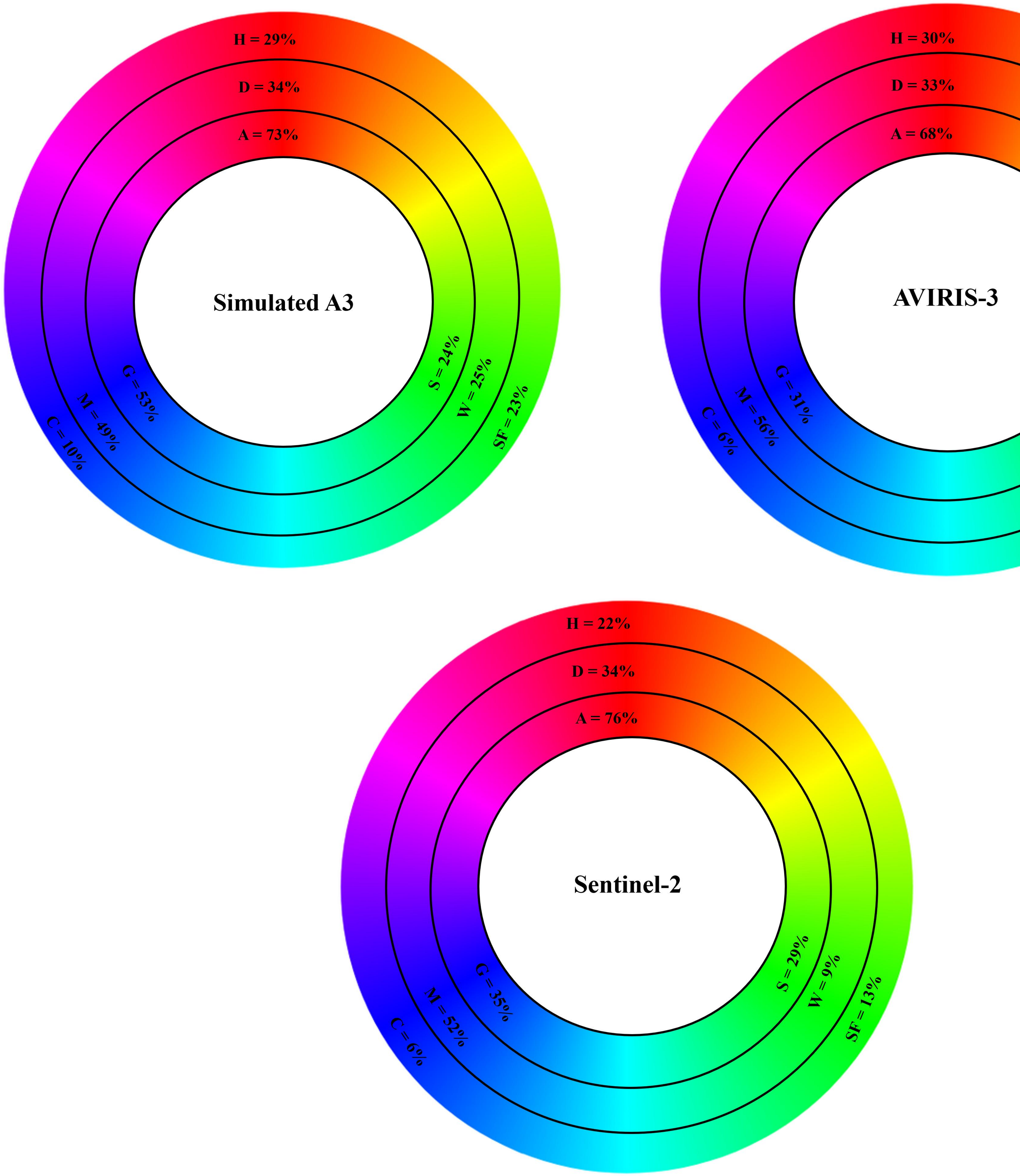

ata processing
Hyperspectral image simulation
Fractional cover analysis
-M
s)
Orthorectification & Radiometric calibration
RedEdge-M (~ 5 cm)
SfM
(S2)
s)
Atmospheric correction
Removal of coastal and cirrus bands
Resampling bands to 10 m
S2 (10 bands) (10 m)
A3)
ds)
BRDF & Iso-fit correction
Topographic correction
Removal of noisy bands
A3 (249 bands) (~ 2.5 m)
Field spectra
SRF of Sentinel-2
SRF of AVIRIS-3
Choosing End-Members
Normalization of End-members
Weighted coefficients (C)
Simulated A3 (10m)
Validation
Classification of PFTs
PFTs covers
RF modeling
Sentinel-2
AVIRIS-3
Simulated A3
Error assessment

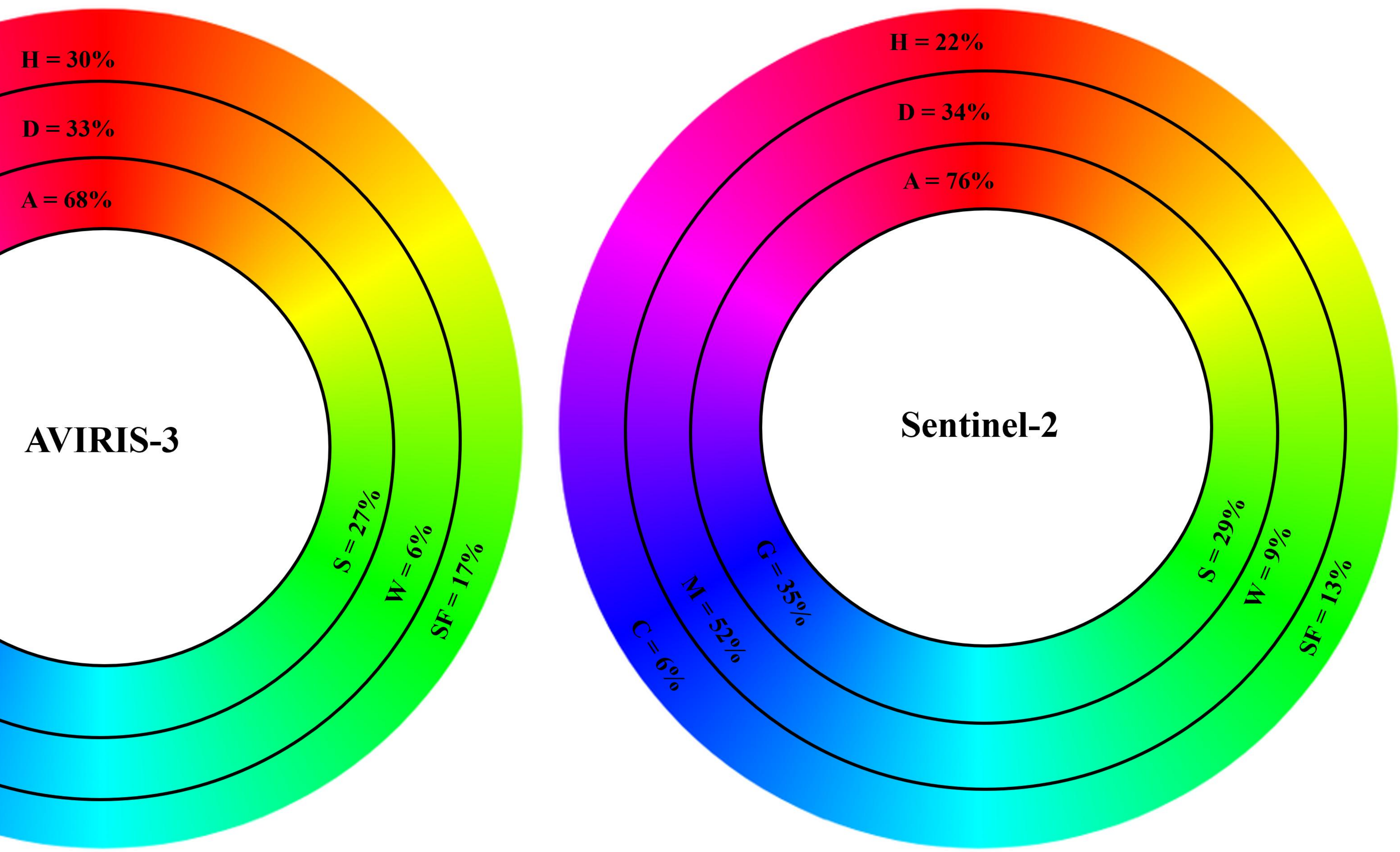


161°53'0"W
161°52'30"W
161°52'0"W
AVIRIS-3
Simulated AVIRIS-3
Sentinel-2
(a)
Vegetation spectra
0.4
0.35
0.3
0.25
0.2
0.15
0.1
0.05
0
0
500
1000
1500
2000
2500
3000
A3_original
A3_simulated
(b)
Correlation_coefficients
Value
0.85
0.40
0.05
(c)
0 0.05 0.1 0.2 0.3 0.4
Kilometers
N



Old
Alder
Chamerion forb
Equisetum horsetail
Graminoid
Salix
Sphagnum moss
Senecio forb
Young
Youngest
July
August
June
July


Simulated A3
H = 29%
D = 34%
A = 73%
S = 24%
W = 25%
SF = 23%
G = 53%
M = 49%
C = 10%
AVIRIS-3
H = 30%
D = 33%
A = 68%
G = 31%
M = 56%
C = 6%
Sentinel-2
H = 22%
D = 34%
A = 76%
S = 29%
W = 9%
SF = 13%
G = 35%
M = 52%
C = 6%


H = 30%
D = 33%
A = 68%
AVIRIS-3
S = 27%
W = 6%
SF = 17%
H = 22%
D = 34%
A = 76%
Sentinel-2
G = 35%
M = 52%
C = 6%
S = 29%
W = 9%
SF = 13%

pecies names	Sentinel-2 (R^2/RMSE) Max coverage	AVIRIS-3 (R^2/RMSE) Max coverage
Wet soil (W)	(0.17/0.031) 0.09	(0.51/0.016) 0.06
Water (P)	(0.04/0.029) 0.005	(0.15/0.003) 0.01
necio forb (SF)	(0.58/0.019) 0.13	(0.35/0.038) 0.17
ry gravel (D)	(0.62/0.042) 0.33	(0.39/0.082) 0.33
Moist soil (M)	(0.79/0.086) 0.52	(0.69/0.105) 0.56
der shrub (A)	(0.47/0.211) 0.76	(0.24/0.200) 0.68
alix shrub (S)	(0.13/0.092) 0.29	(0.10/0.087) 0.27
Graminoid (G)	(0.54/0.079) 0.35	(0.14/0.101) 0.31
gnum moss (SM)	(0.37/0.055) 0.34	(0.30/0.073) 0.12
isetum horsetail (H)	(0.22/0.075) 0.22	(0.12/0.063) 0.30
merion forb (C)	(0.11/0.016) 0.06	(0.14/0.023) 0.07