Can a Remote Sensing Approach with Hyperspectral Data Provide Early Detection and Mapping of Spatial Patterns of Black Bear Bark Stripping in Coast Redwoods?

Presented by Shayne Magstadt

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Agenda

- Background
- Existing work
- Research question
- Methods
- Results
- Discussion

Coastal Redwood

(Sequoia sempervirens)

- One of the world's fastest growing conifer species
- One of the most valued resources in Humboldt County
- Thick, soft bark which is attractive to bears

Bark stripping disturbance

- Trees are stripped of all or nearly all their bark
- Trees do not always die, but growth is decreased
- Thinning increases sugar to terpene ratio (Partridge, 2001)

Photo by Mario Vaden

Patterns of Bark Herbivory in Redwoods

- Trees targeted in spring to early summer

- Bears target younger trees, DBH~25-50cm, often in recently thinned stands

- One black bear can damage up to 70 trees per day (Glover, 1955)

Economic and Ecological Impacts

- Study in Oregon found bear tree bark foraging resulted in a loss of $585 per hectare per year (Nolte and Dykzeul 2000)
- Another study estimated the damage to be around $56 per hectare per year (Taylor, Kline, and Morzillo 2019)
- 15% of annual allowable timber harvest loss in the Hoopa Valley Tribe (Matthews et al. 2008)

Economic and Ecological Impacts

- Ecosystem engineer
- Creates a random patchy forest
- Not distributed evenly across the bear population
- Taking advantage of an easy food source

Existing work to monitor this wildlife-forest interaction

Ground Survey

- Glover (1955)
- Giusti (1988)
- Matthews (2008)

Aerial Survey

- Kanaskie (1990)
- Nolte (2000)
- Taylor (2019)

Remote Sensing of Forest Health

- Carter (1993)
- Vogelmann (2008)
- Coops (2009)

UAV Monitoring

- Turner (2011)
- Zhang (2012)
- Näsi (2015)

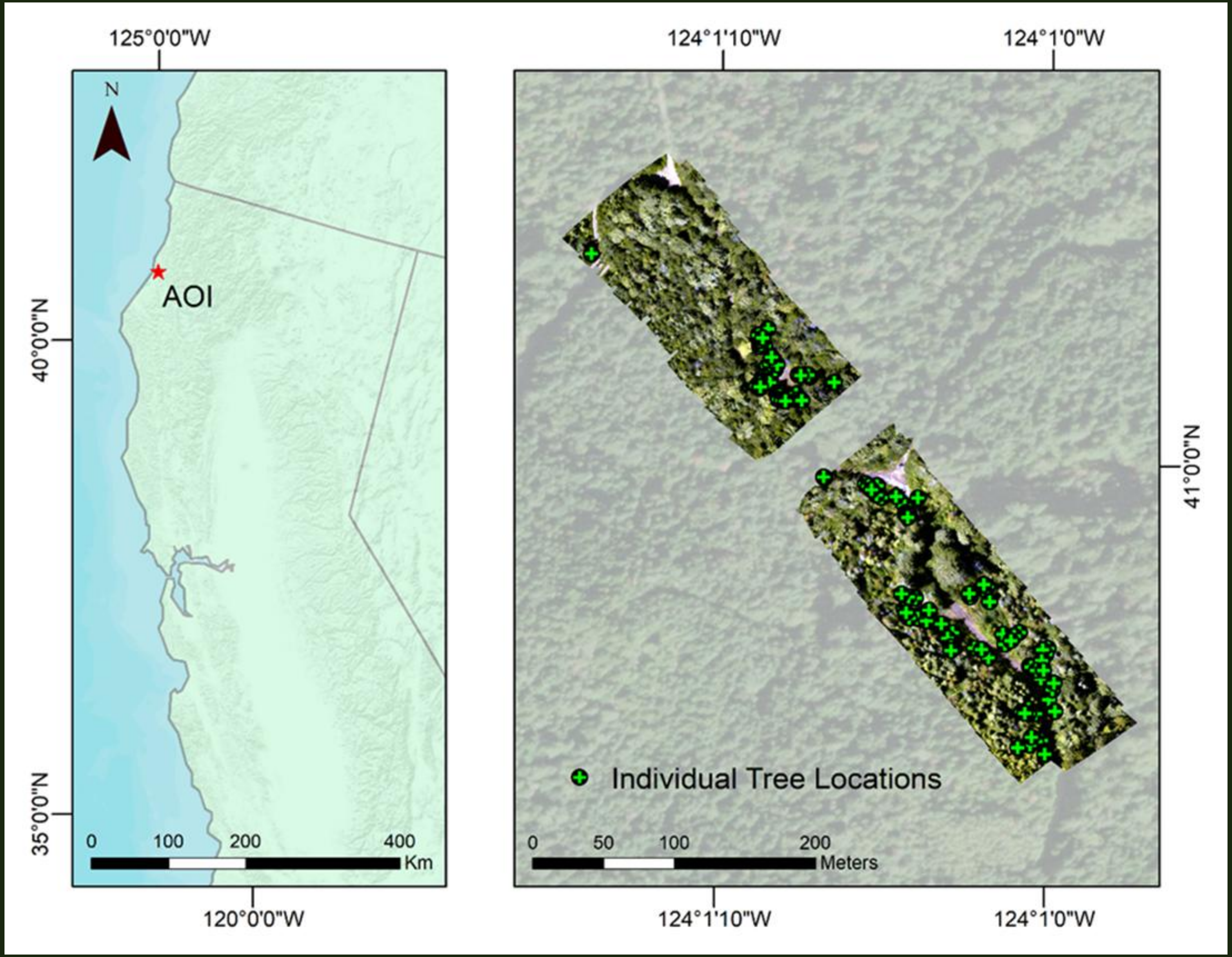
Research question

Can high spectral resolution image sensing with the targeted approach of UAV data acquisition be used to detect and map bear damaged trees?

Study Area

Green Diamond Resource Company

Imagery captured over approximately 4.5 ha



Field Survey

Three health classes

- healthy
- present damaged
- old damage

Trees identified prior to UAV data collection

Field Survey

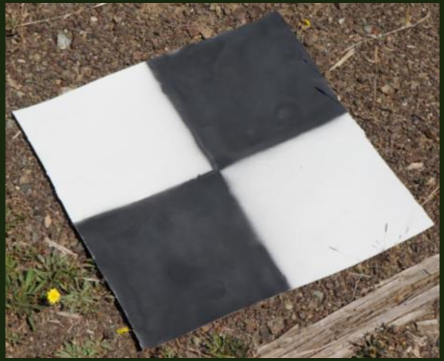
Three health classes

- healthy
- present damaged
- old damage

Determined *in situ* by assessing bark characteristics

Field Survey

- Ground control points established throughout the study site
- Trees mapped with high precision using an RTK GPS and Total Station
- A total of 108 individual trees were used in the analysis

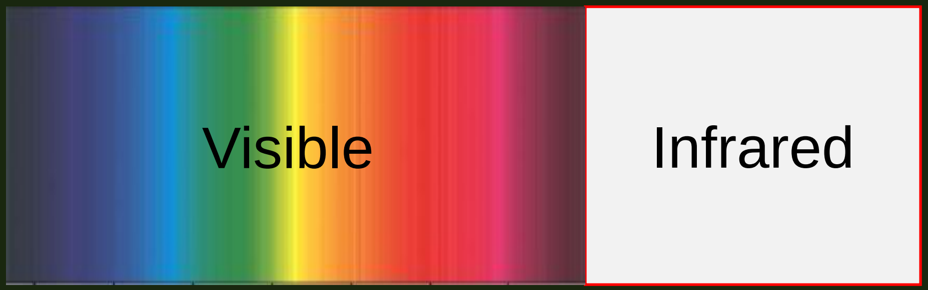


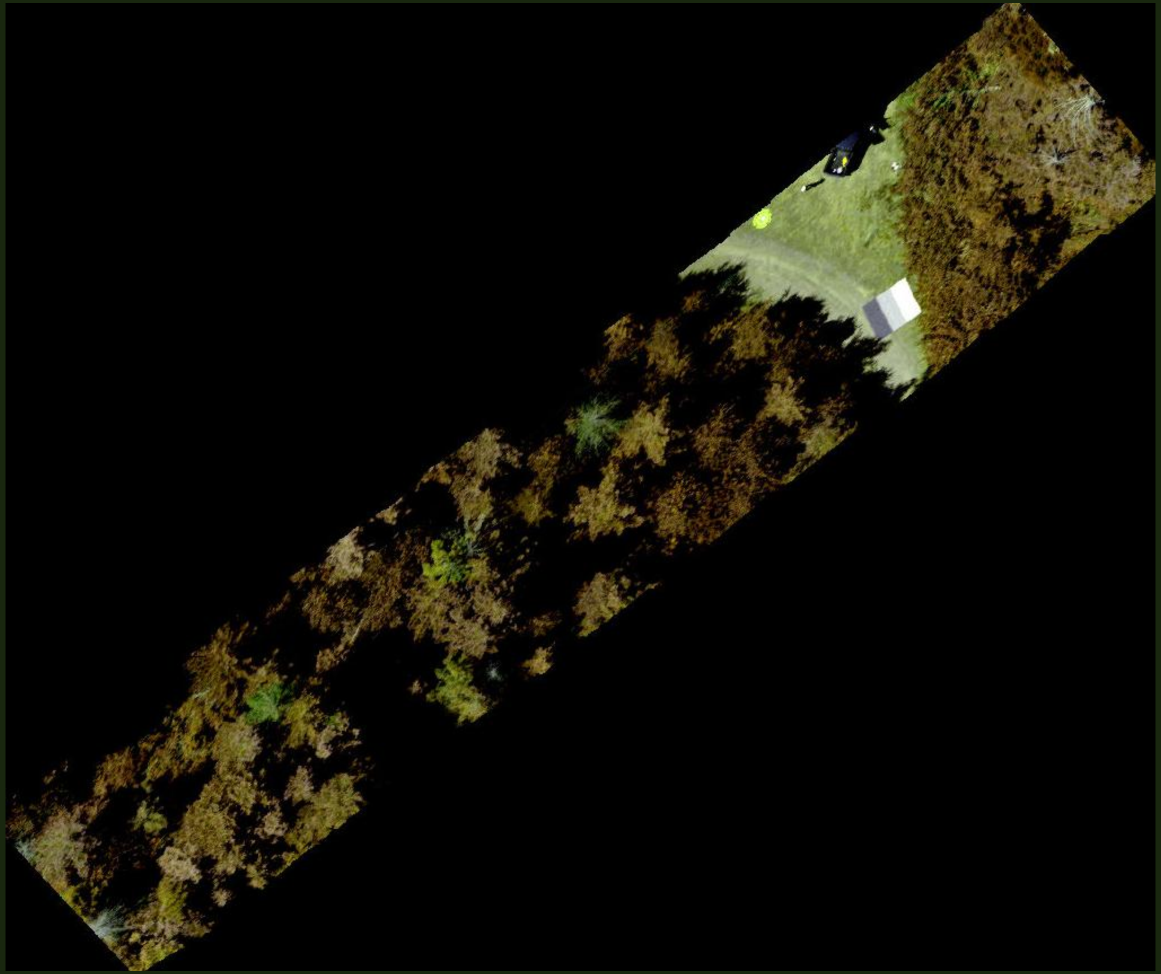
UAV Data Collection

Captured aerial imagery of target trees

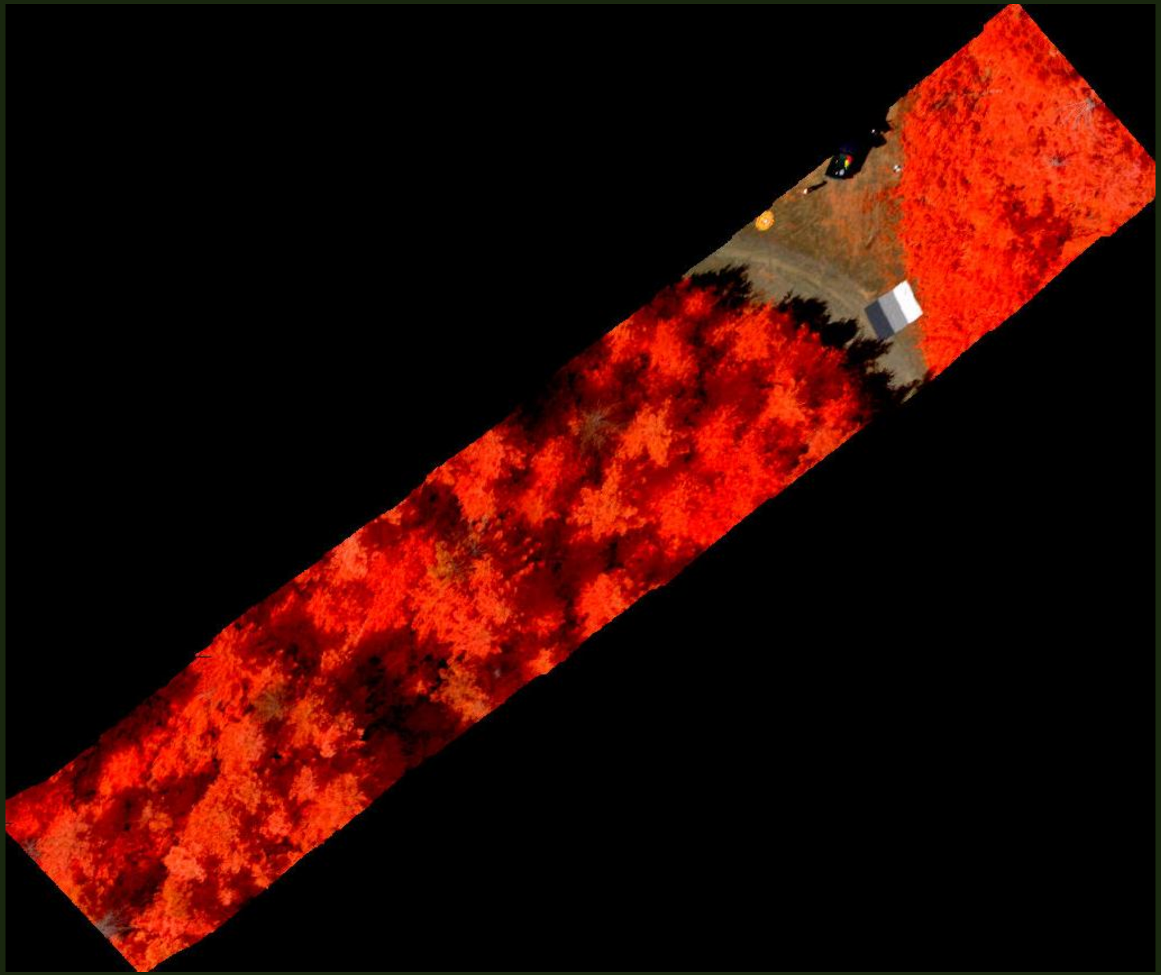
Hyperspectral Imagery

- DJI Matrice 600 Pro Hexacopter
- Headwall Nano-Hyperspectral Sensor
  - 273 bands ~ 400-1000nm

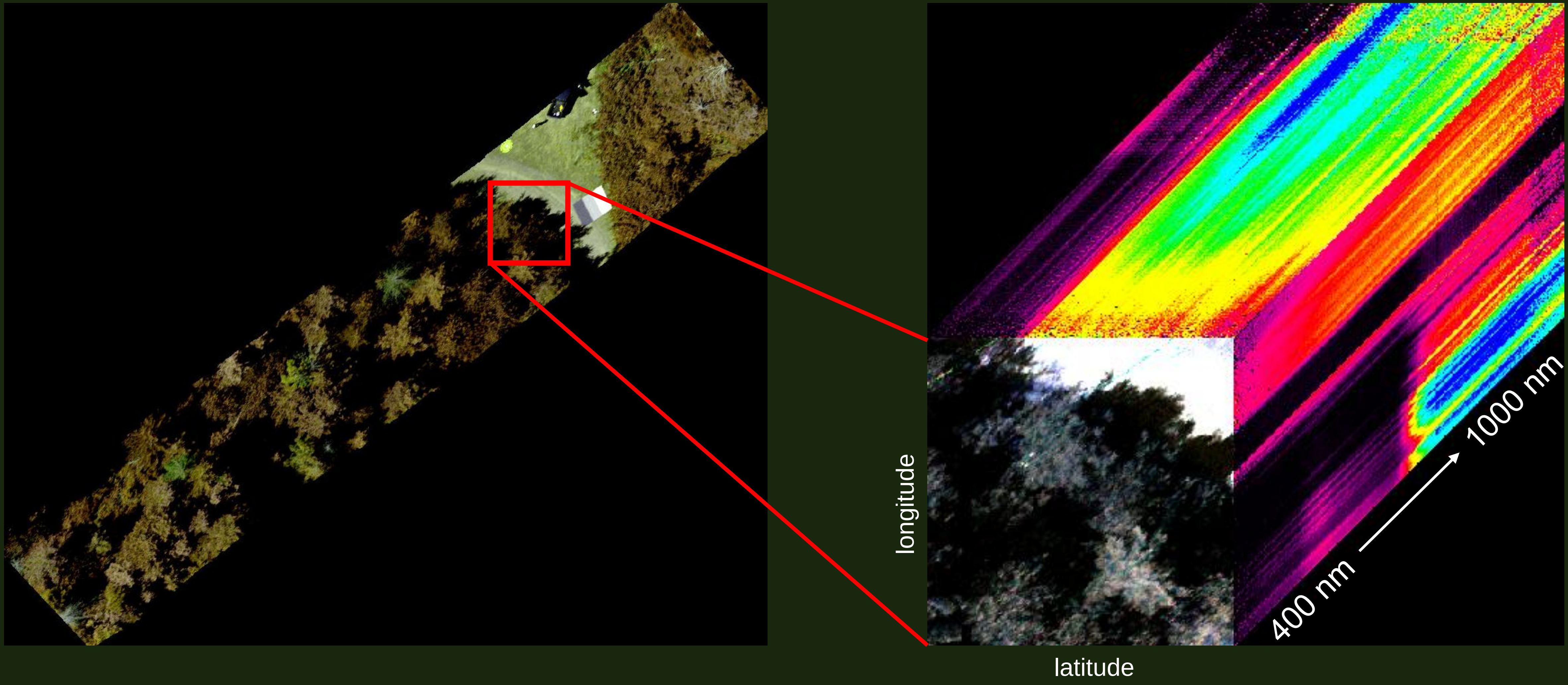




RGB

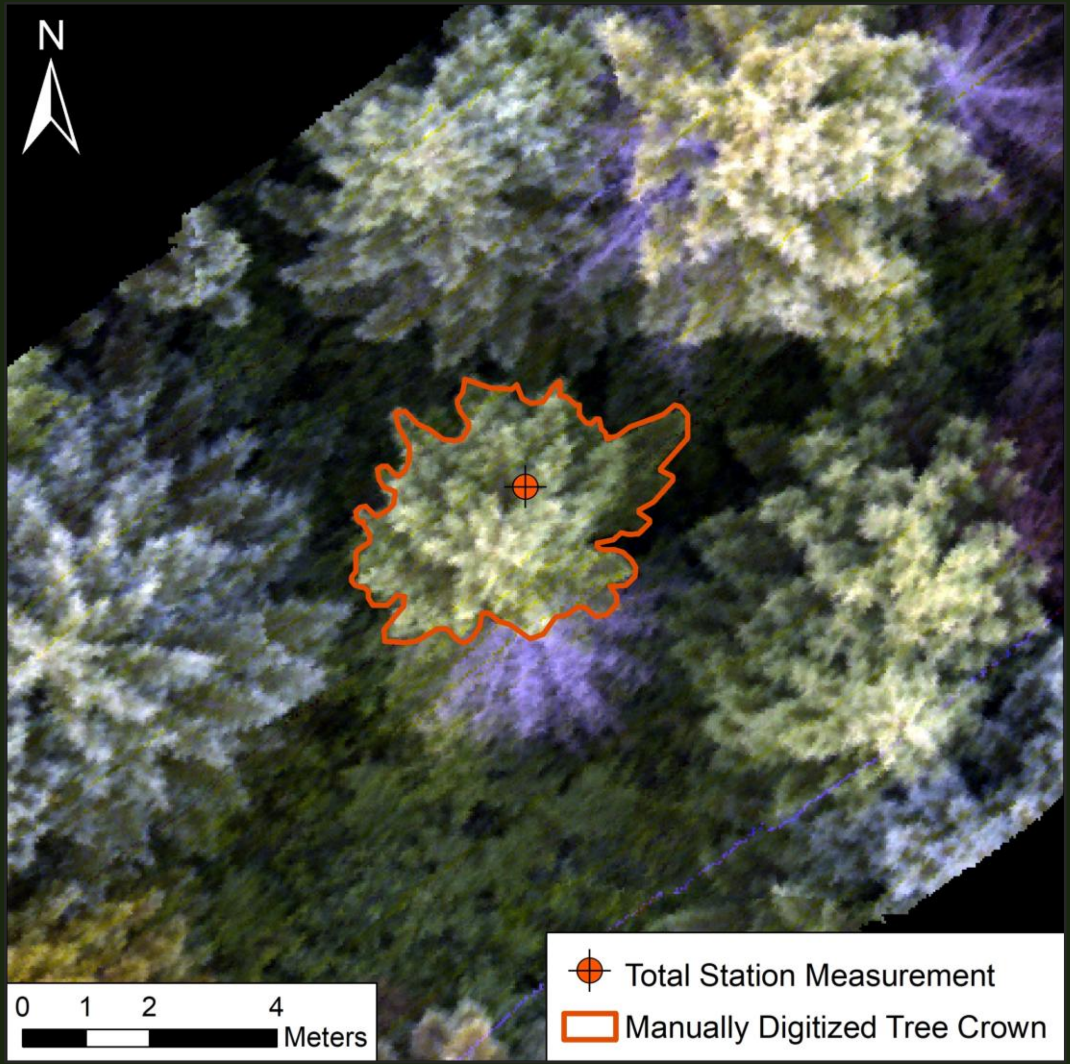


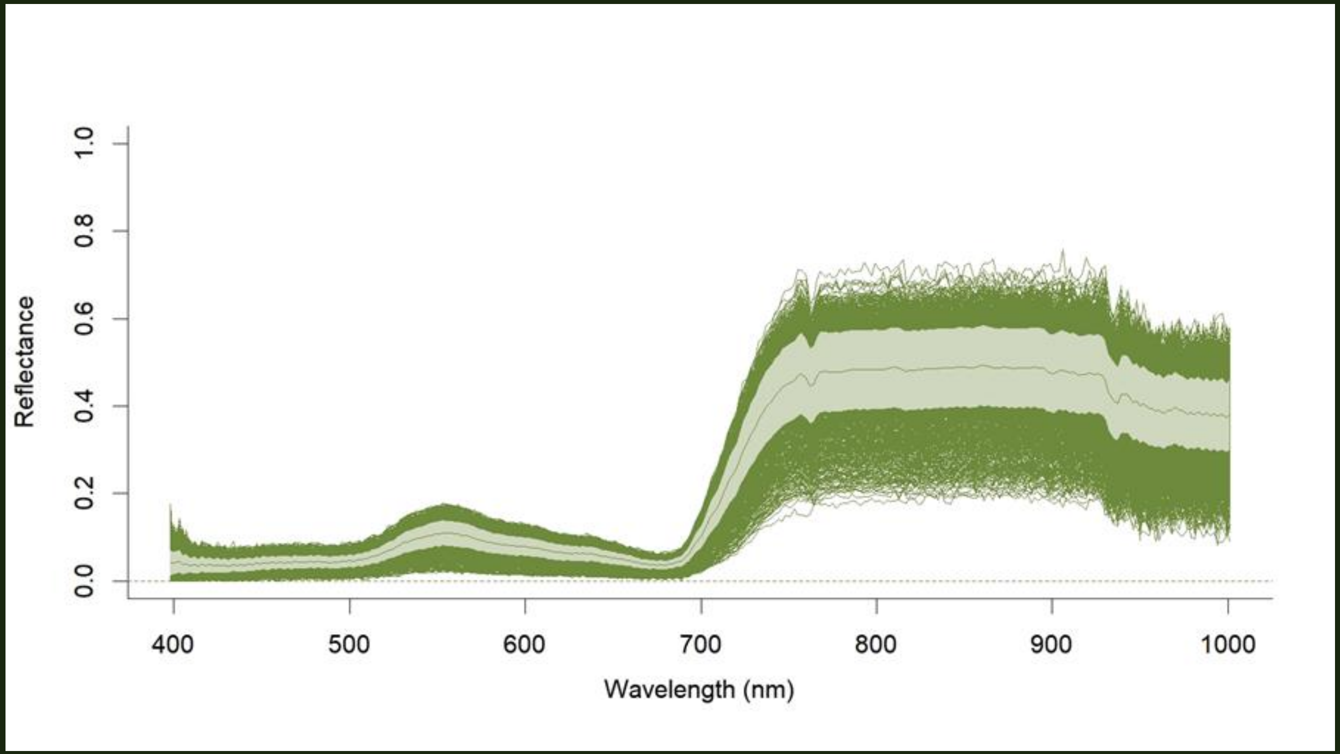
IRGB

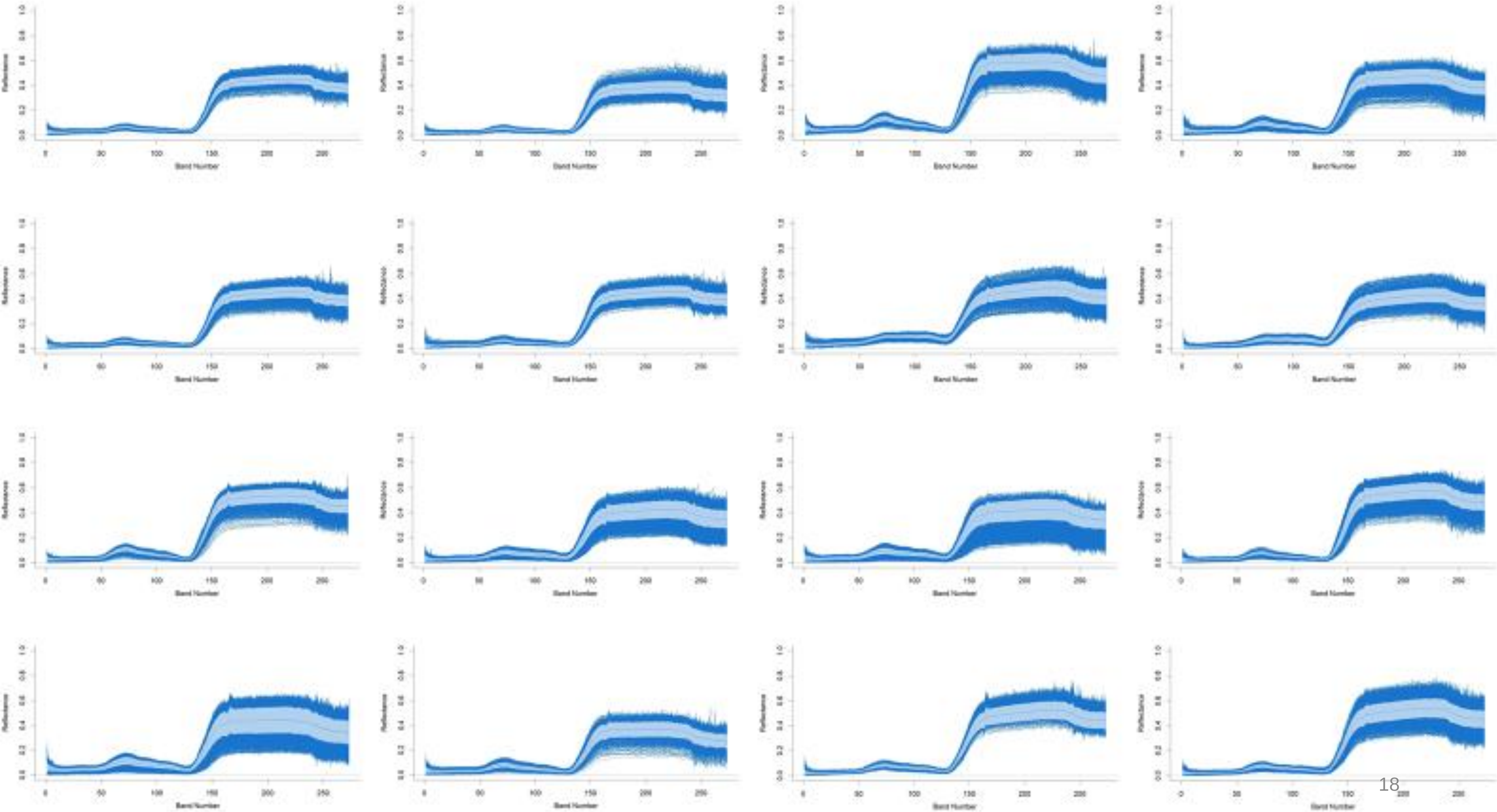


“Hypercube”

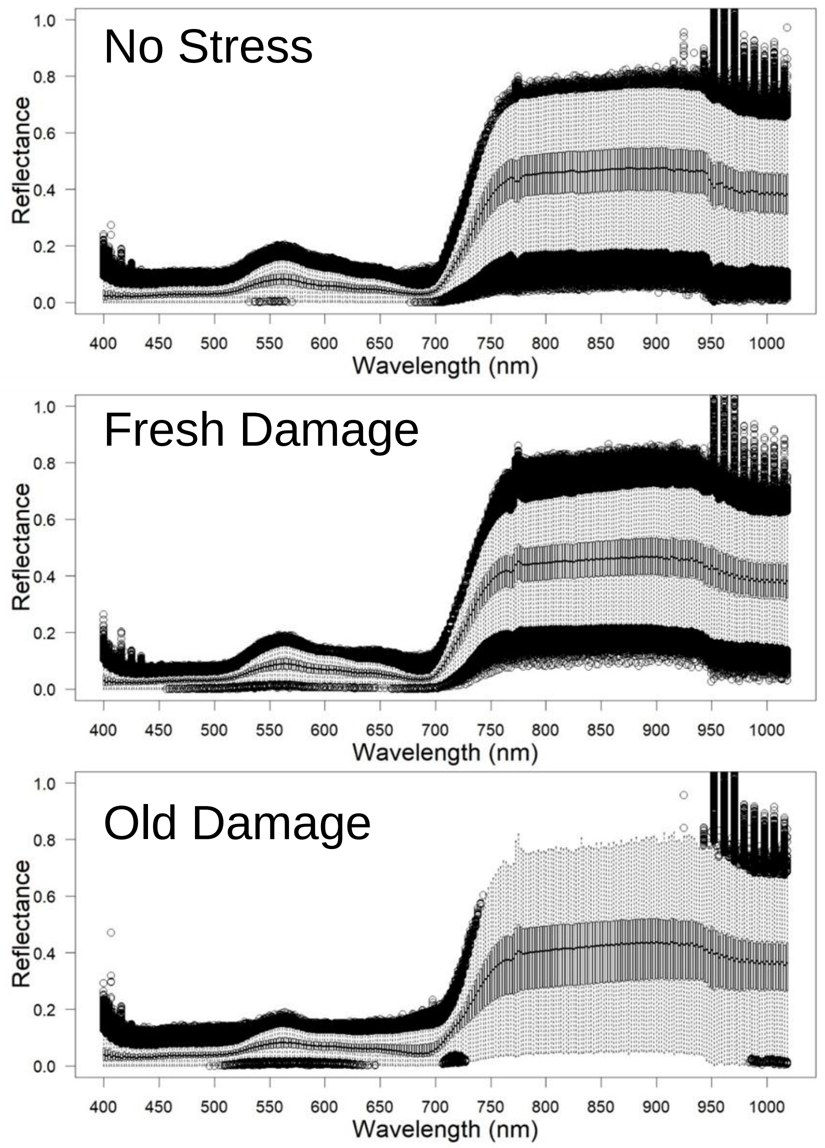
Crown Delineation and Spectral Signature Extraction







Damage Class	Pixels	ITCs
No stress	188,752	45
Fresh Damage	68,695	25
Old Damage	111,607	38



Vegetation Indices	Equation	Reference
Normalized Difference Vegetation Index (NDVI)	$NDVI = \frac{\lambda_{750} - \lambda_{650}}{\lambda_{750} + \lambda_{650}}$	Rouse et al. [39]
Modified Chlorophyll Absorption Ratio Index (MCARI)	$MCARI = [(\lambda_{700} - \lambda_{670}) - 0.2(\lambda_{700} - \lambda_{550})] * (\lambda_{700}/\lambda_{670})$	Daughtry et al. [40]
Red-edge Normalized Difference Vegetation Index (RENDVI)	$RENDVI = \frac{\lambda_{750} - \lambda_{705}}{\lambda_{750} + \lambda_{705}}$	Gitelson and Merzlyak [21]
Plant Senescing Reflectance Index (PSRI)	$PSRI = \frac{\lambda_{680} - \lambda_{500}}{\lambda_{750}}$	Merzlyak et al. [21]
Vogelmann "red edge" Index (VREI1)	$VREI = \frac{\lambda_{740}}{\lambda_{720}}$	Vogelmann et al. [41]
Normalized Channel Ratio (NCR)	$NCR = \frac{\lambda_a}{\lambda_b}$	Coops et al. [26]

Jeffries-Matusita

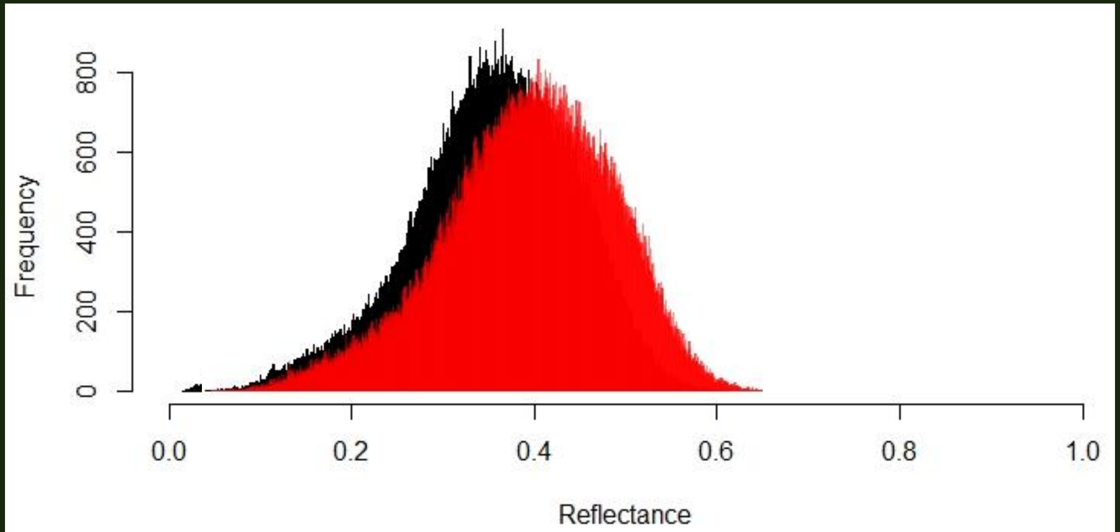
$$JM_{p,q} = \sqrt{2(1 - \exp(-b_{(p,q)})}$$

- A statistical measure of entanglement between two distributions of data
- Value constrained to [0 - √ 2]
- Assumes data is normally distributed

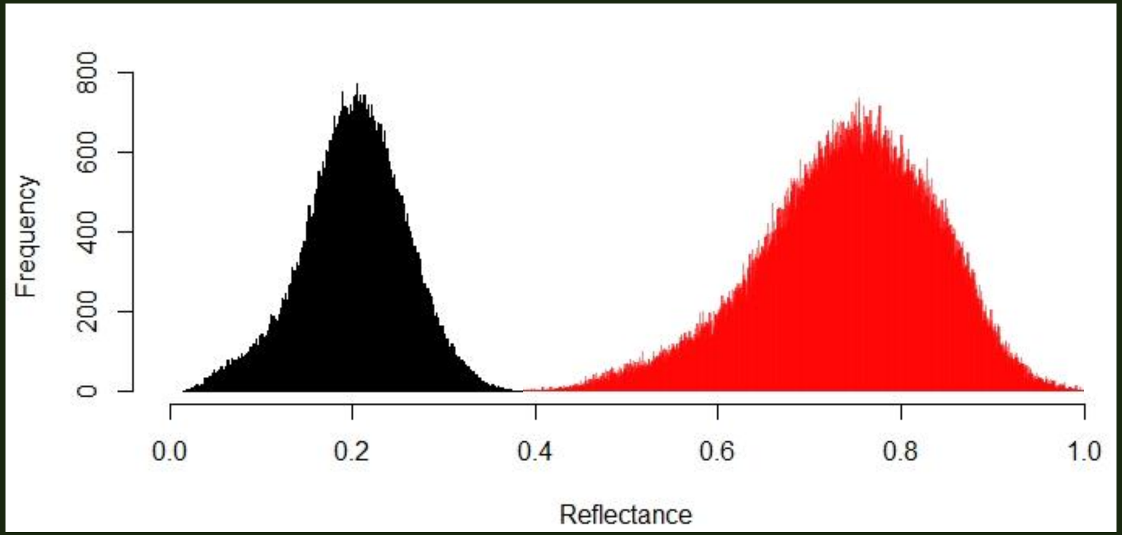
$$b_{(p,q)} = -ln \sum_{i-1}^{N} \sqrt{p_i} \cdot q_i$$

Bhattacharyya distance [0, inf]

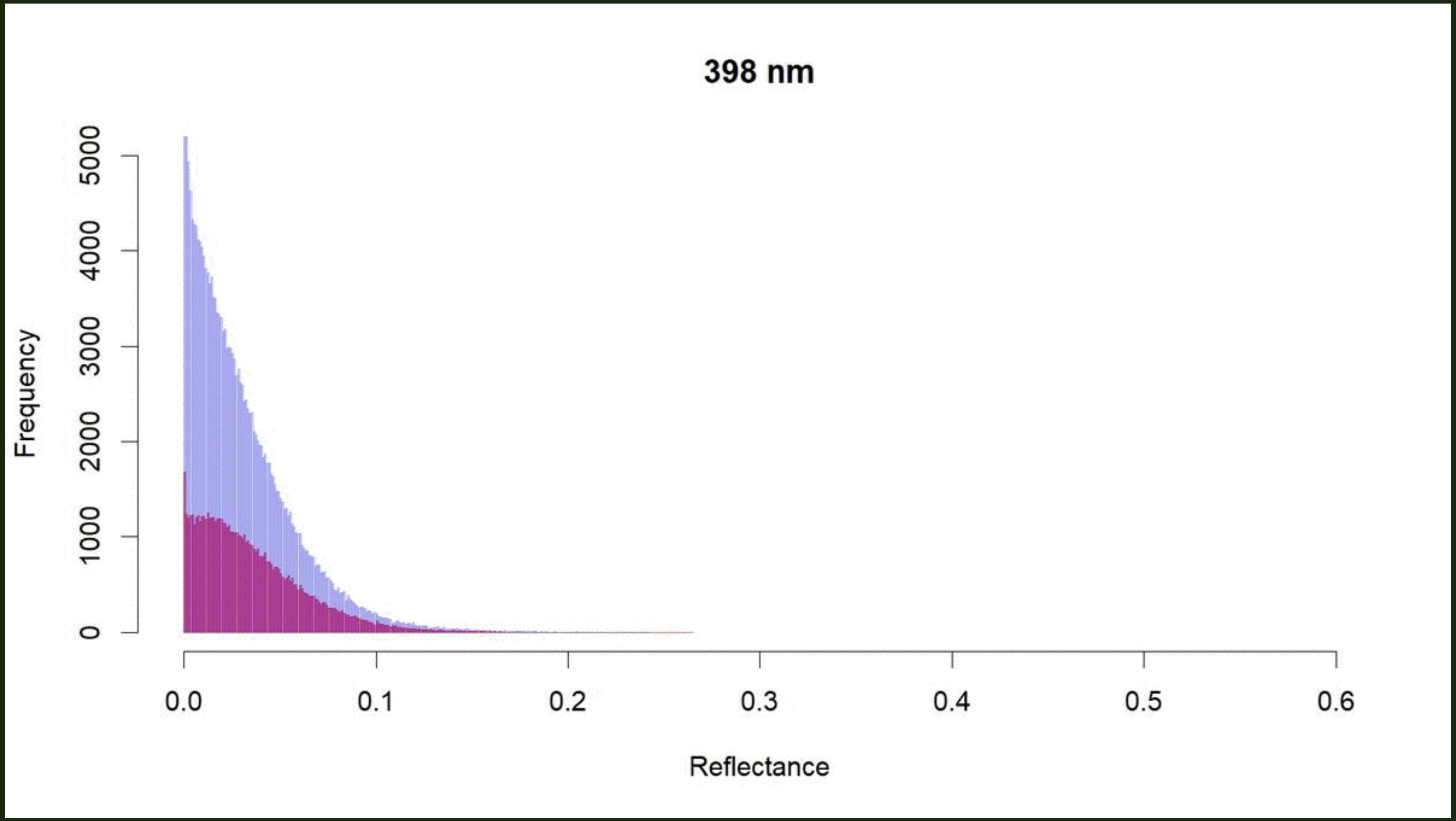
Value approaches 0



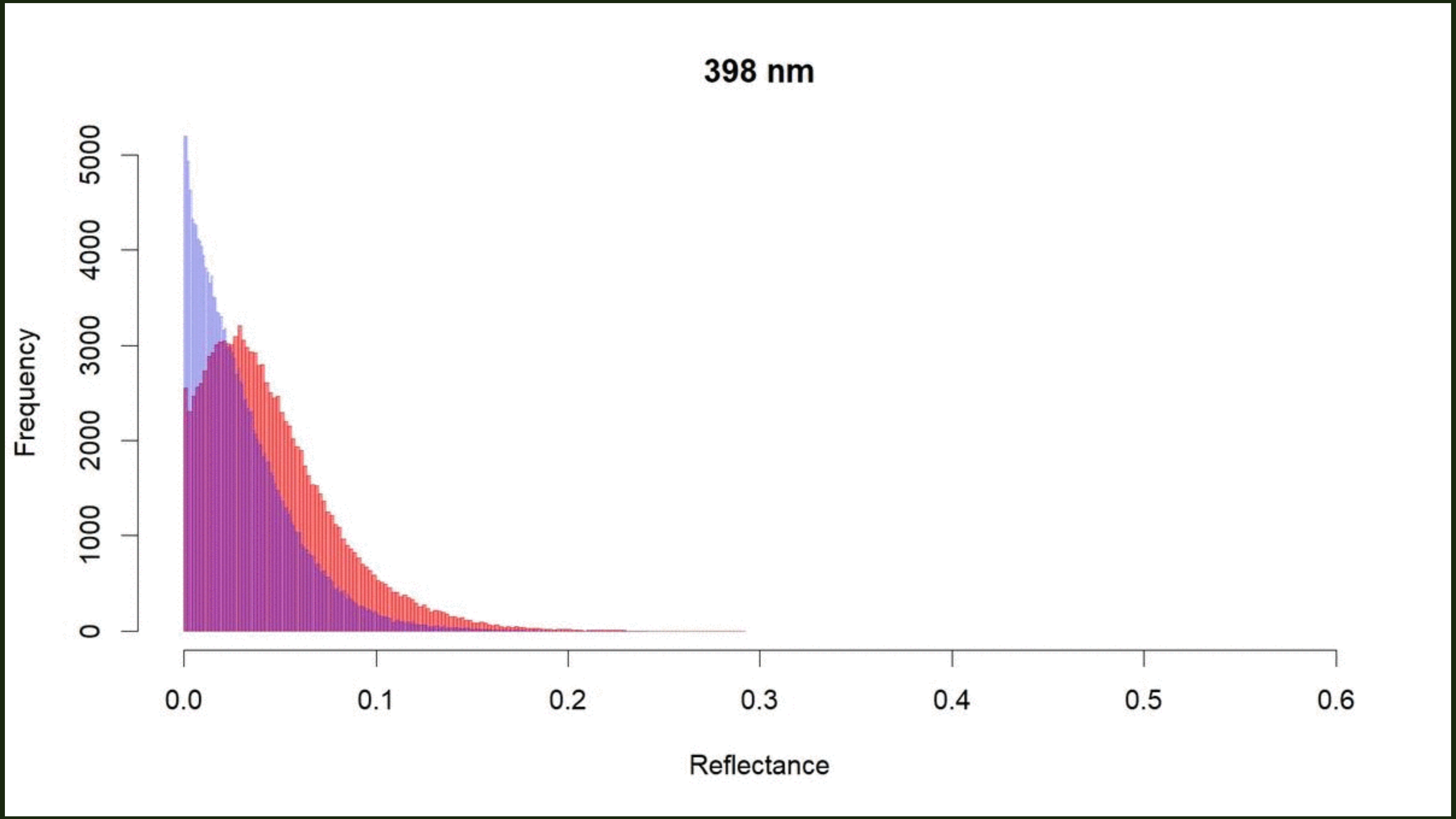
Value approaches √ 2

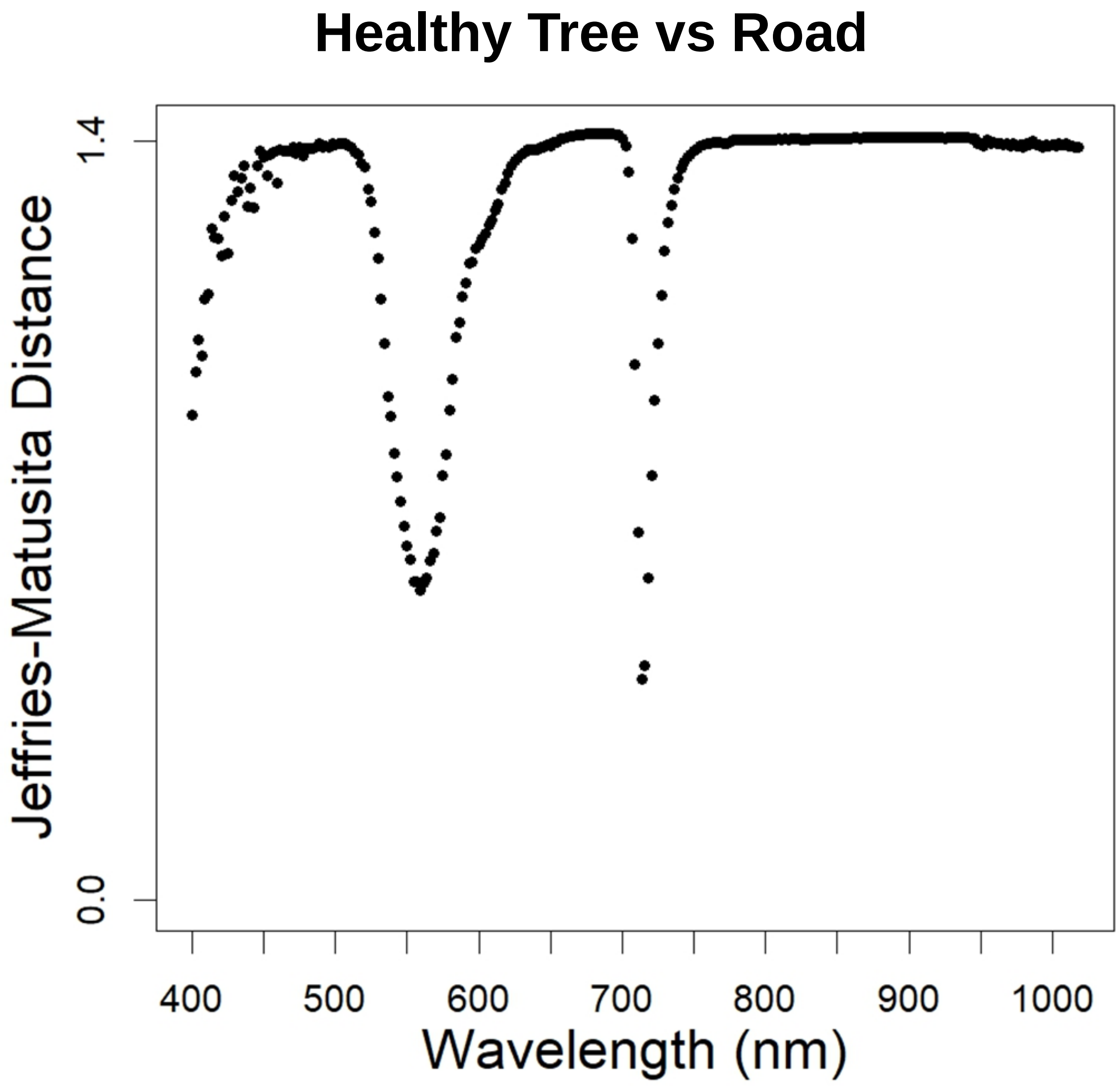


Histogram of healthy data and present damage data



Histogram of healthy data and old damage data





An example:

Samples from a healthy tree and the road

Classification

Two supervised learning approaches

- Support Vector Machine (Vapnik, 1963)
- Random Forest (Breiman, 1999)

Accuracy Assessment

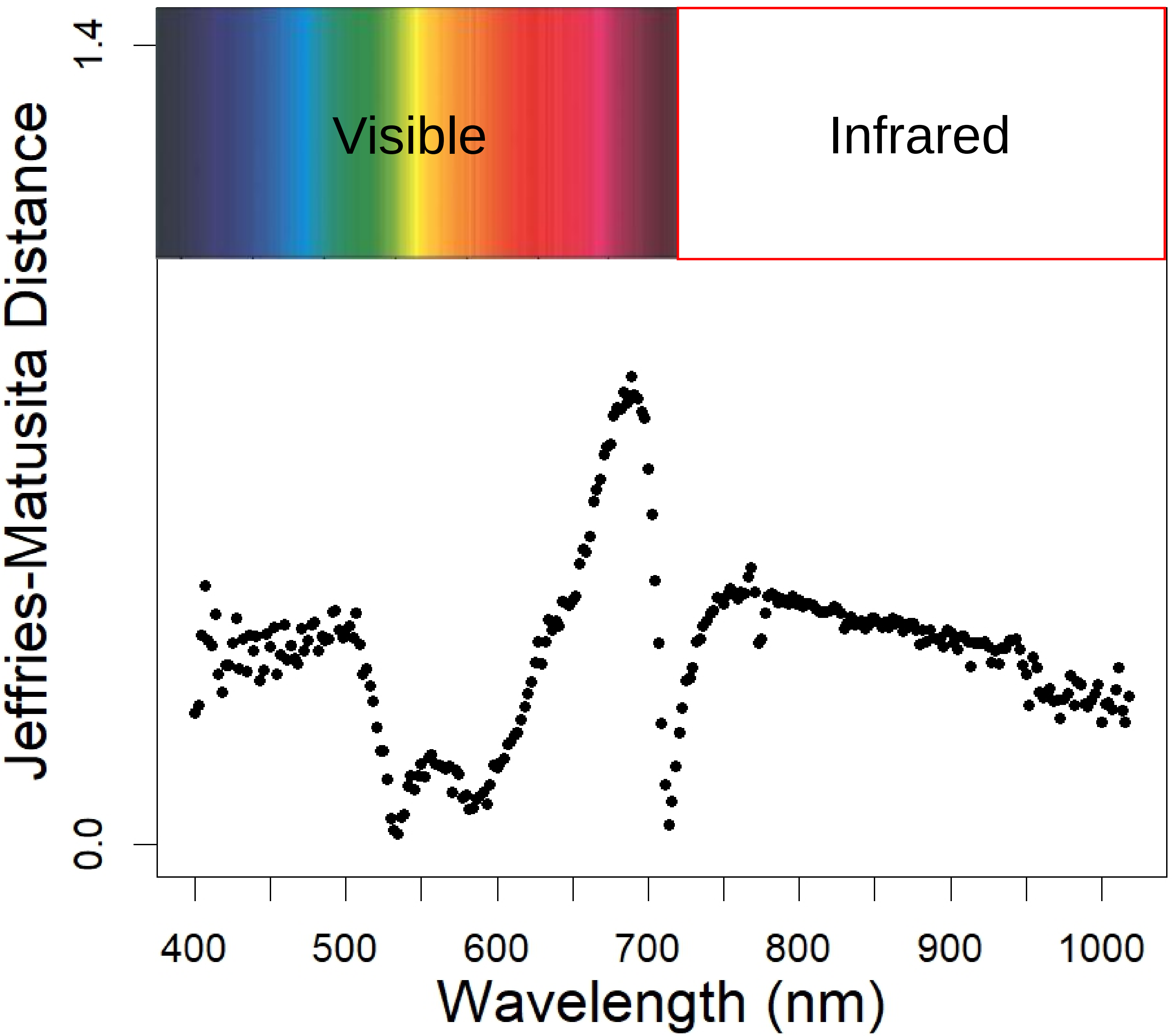
The data extracted from the tree crowns in the study site were classified and validated for accuracy

Overall accuracy (OA) and the Kappa (*k*) coefficient were computed

$$OA = \frac{Predicted}{Measured}$$

$$k = \frac{p_{o-}p_e}{1 - p_e}$$

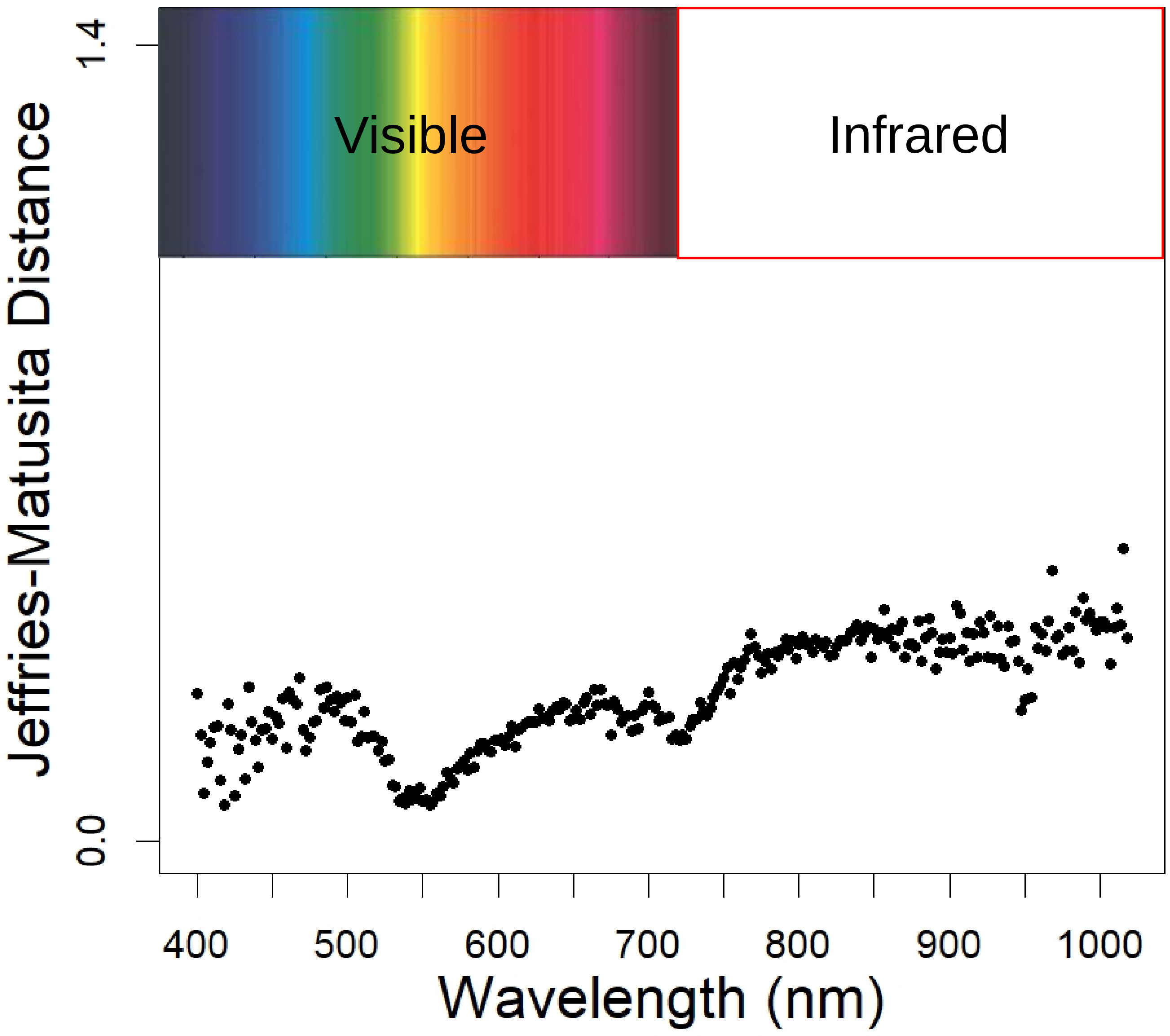
Results – Feature selection



Healthy Class vs Old Damage Class

Around 685 nm is the most statistically separate region and may be useful when classifying these classes

Results – Feature selection



Healthy Class vs Present Damage Class

Less Certainty

Indicates there is little to no spectral separation between healthy and present damaged trees

Results – Classification accuracy

Features	Accuracy (%) SVM	Kappa SVM	Accuracy (%) RF	Kappa RF
VNIR	**83.8**	**0.75**	73.4	0.60
VIs	57.6	0.36	54.8	0.32
$\lambda_{685}; \lambda_{750}$	49.6	0.24	43.1	0.15
NDVI	45	0.17	38.8	0.08
MCARI	33.9	0.09	36.5	0.04
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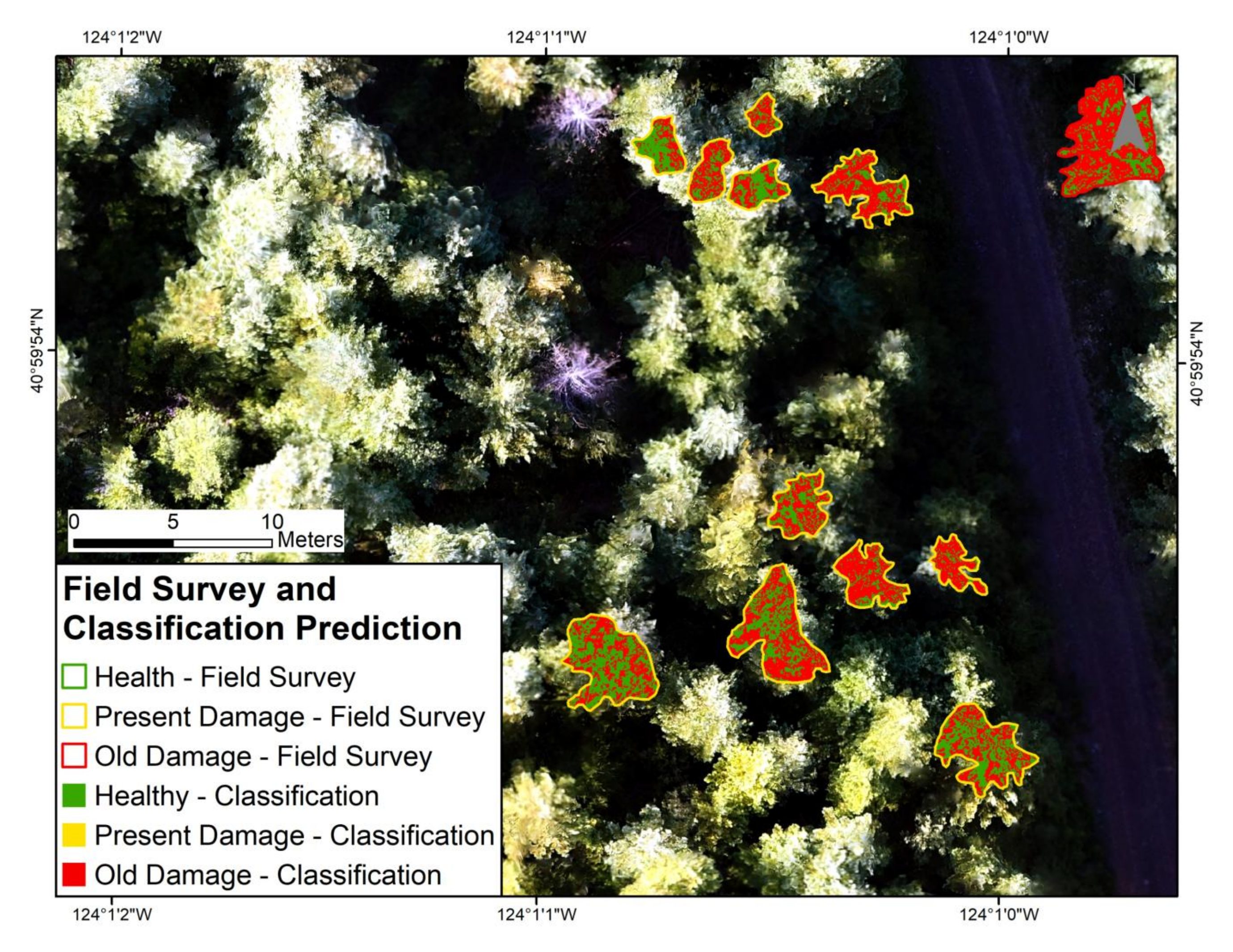
VREI 1	45.8	0.18	37.8	0.06
NCR	45.1	0.26	38.1	0.09
full	78.1	0.67	77.9	0.66

Note: VNIR - Visible and Near-Infrared bands; Vis - All Vegetation Indices; $\lambda_{685}; \lambda_{750}$ - result of JM distance; MCARI - Modified Chlorophyll Absorption Ration Index; RENDVI - Red Edge Normalized Vegetation Index; PSRI - Plant Senescence Reflectance Index; VREI 1 - Vogelmann Red Edge Index 1; NCR - Normalized Channel Ratio derived from JM statistics; *full* - complete feature dataset.

Results – model prediction



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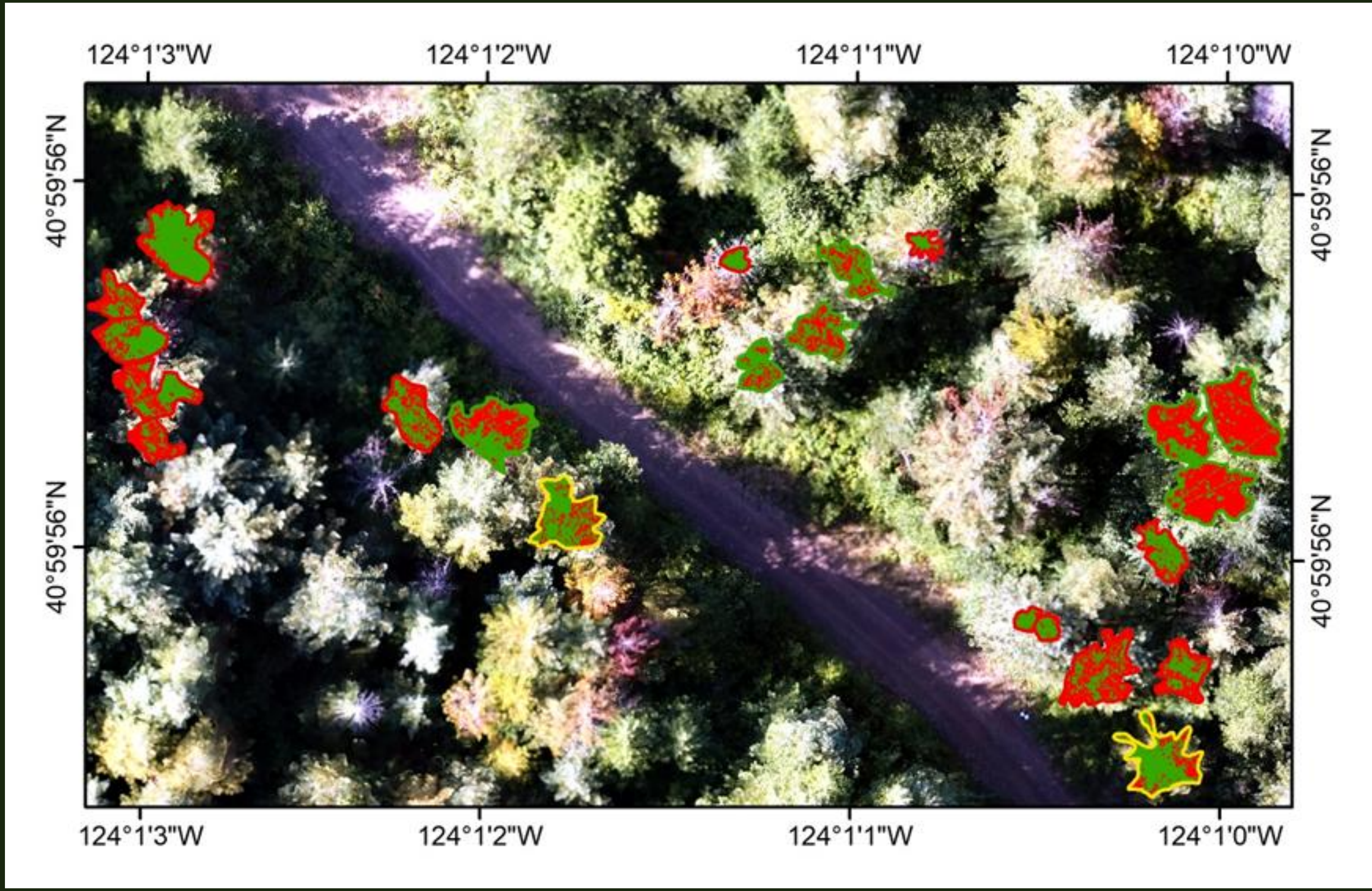

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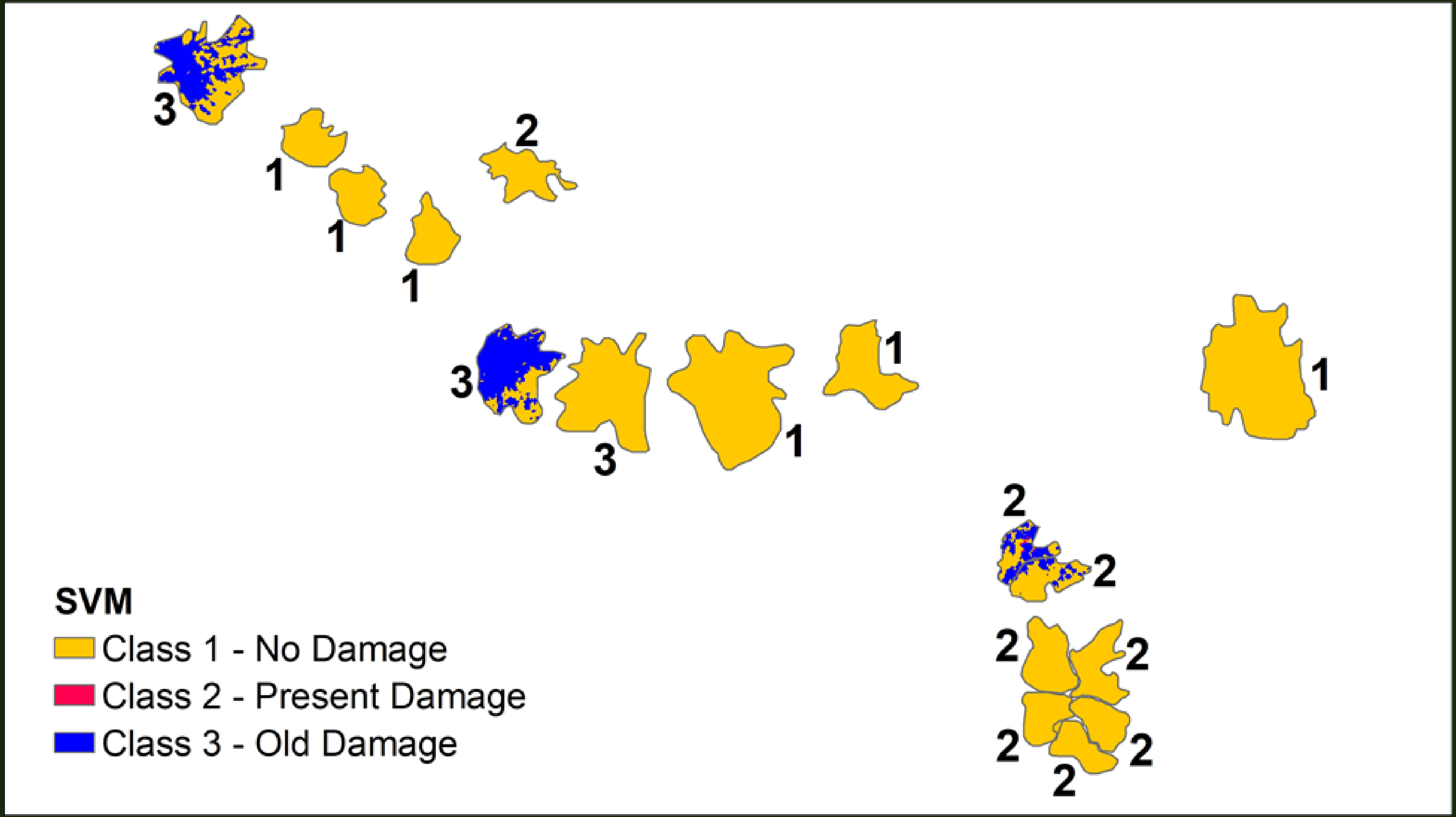

Discussion – Redwood Tree Characteristics

Incredible ability to recover from damage

Damage not incurred at the same rate

Damage to the tree varied

Similar studies have been conducted to monitor bark beetle infestations (Näsi, 2015)

Discussion – Feature Selection, Variable Importance, and Early Detection of damage

Hyperspectral imagery used to estimate chlorophyll content
(Carter, 1993)

Chlorophyll used as a proxy for tree health

Attempting to classify trees based on chlorophyll content

Discussion – UAV-Based Image Acquisition in Forest Health Monitoring

Tools used to aid ground sampling

Can be useful to observe disturbances over time

Focus on temporal resolution

Conclusion

This study explored the capacity of UAV-based hyperspectral imaging to identify redwood trees in the early attack stage of senescence

This study showed promising results but there was insufficient spectral change in the targeted canopies during the time window explored

More frequent data capture may be the missing link needed to model this wildlife-forest interaction

Acknowledgements:

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Dr. Buddhika Madurapperuma
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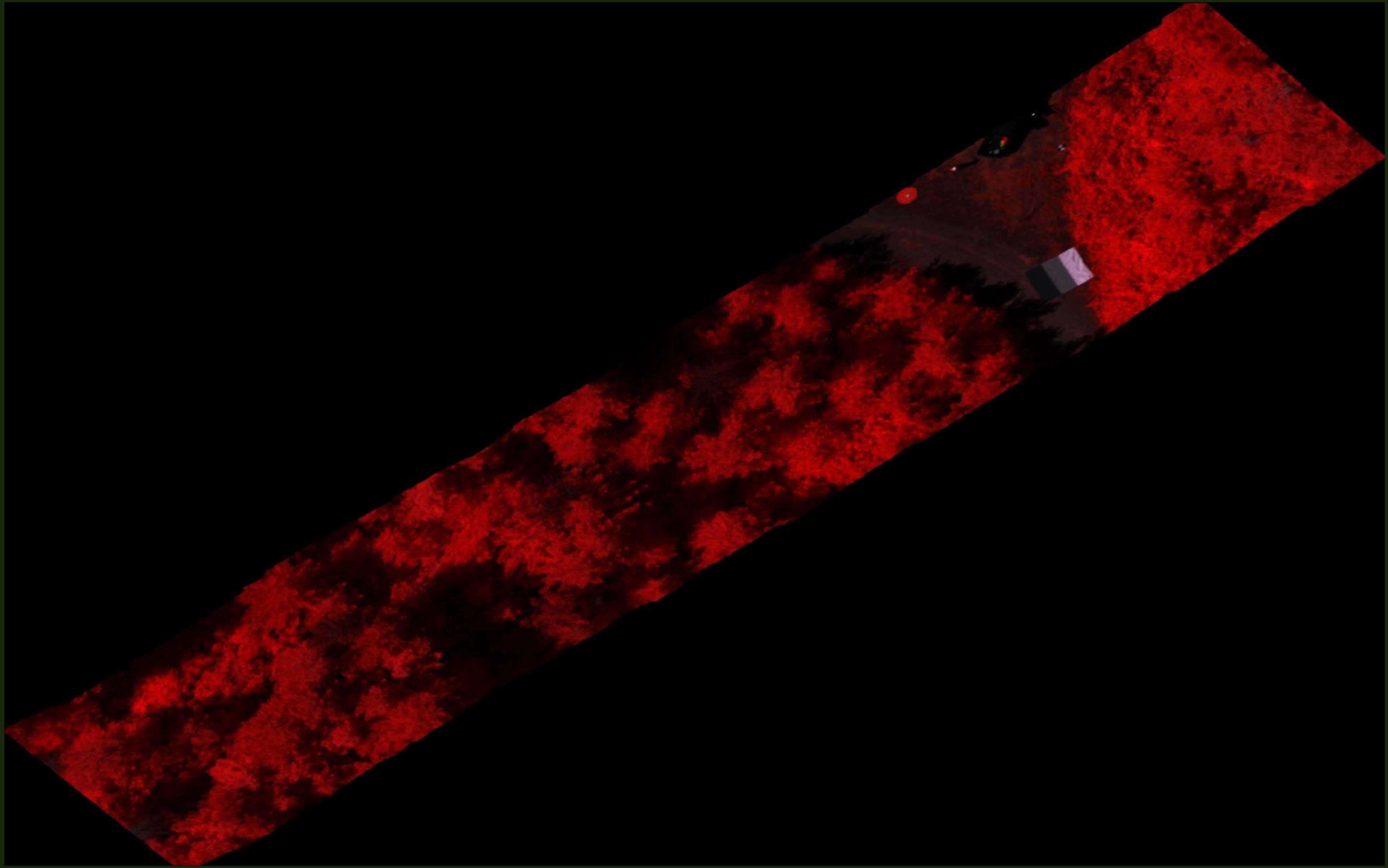
Agricultural Research Institute

HSU CNRS

Questions
?



ID	Damage Class	Pixels	ITCs	Pixels/ITC
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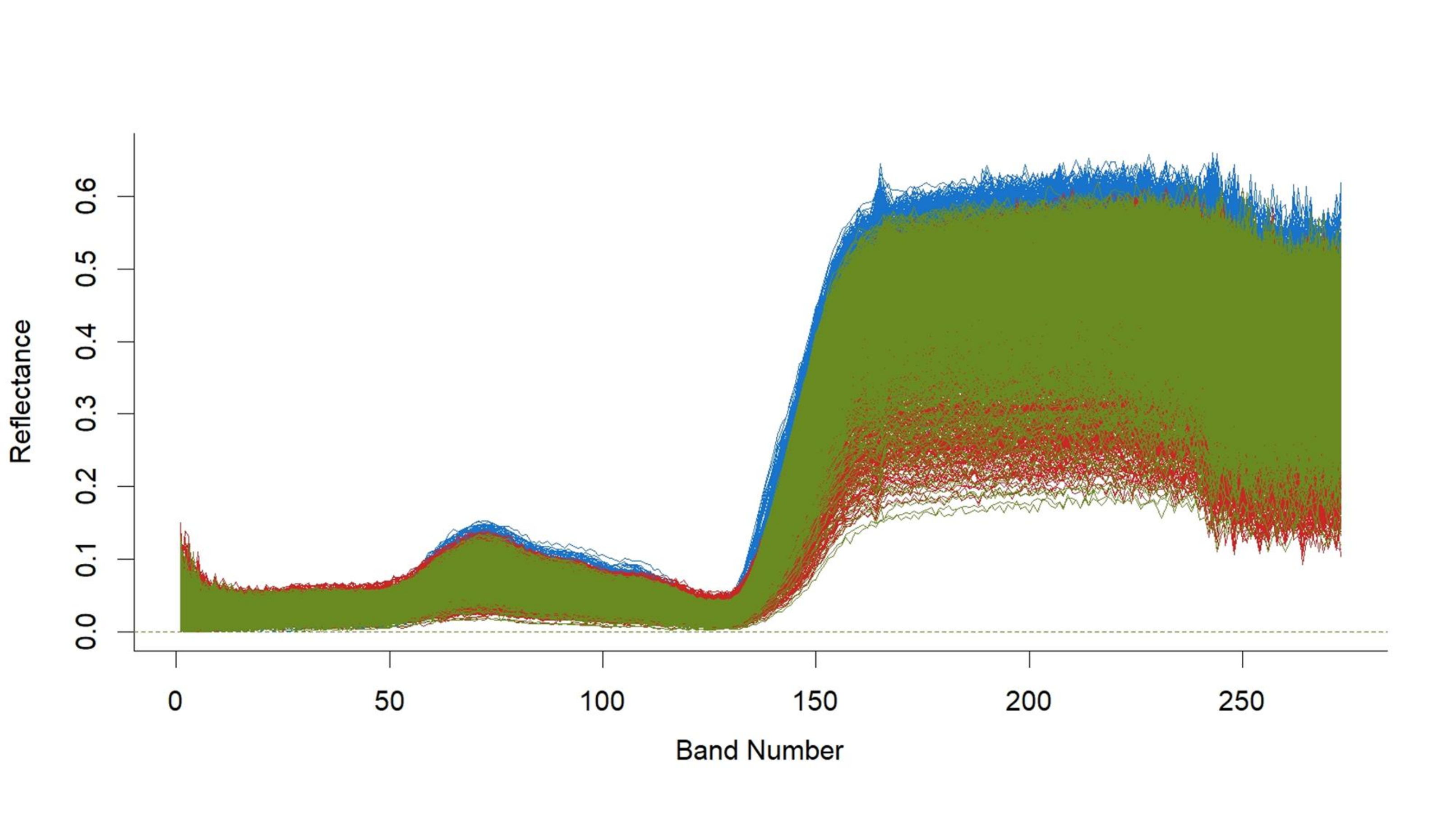
2	Fresh Damage [1]	68,695	25	2,747
3	Old Damage	111,607	38	2,937



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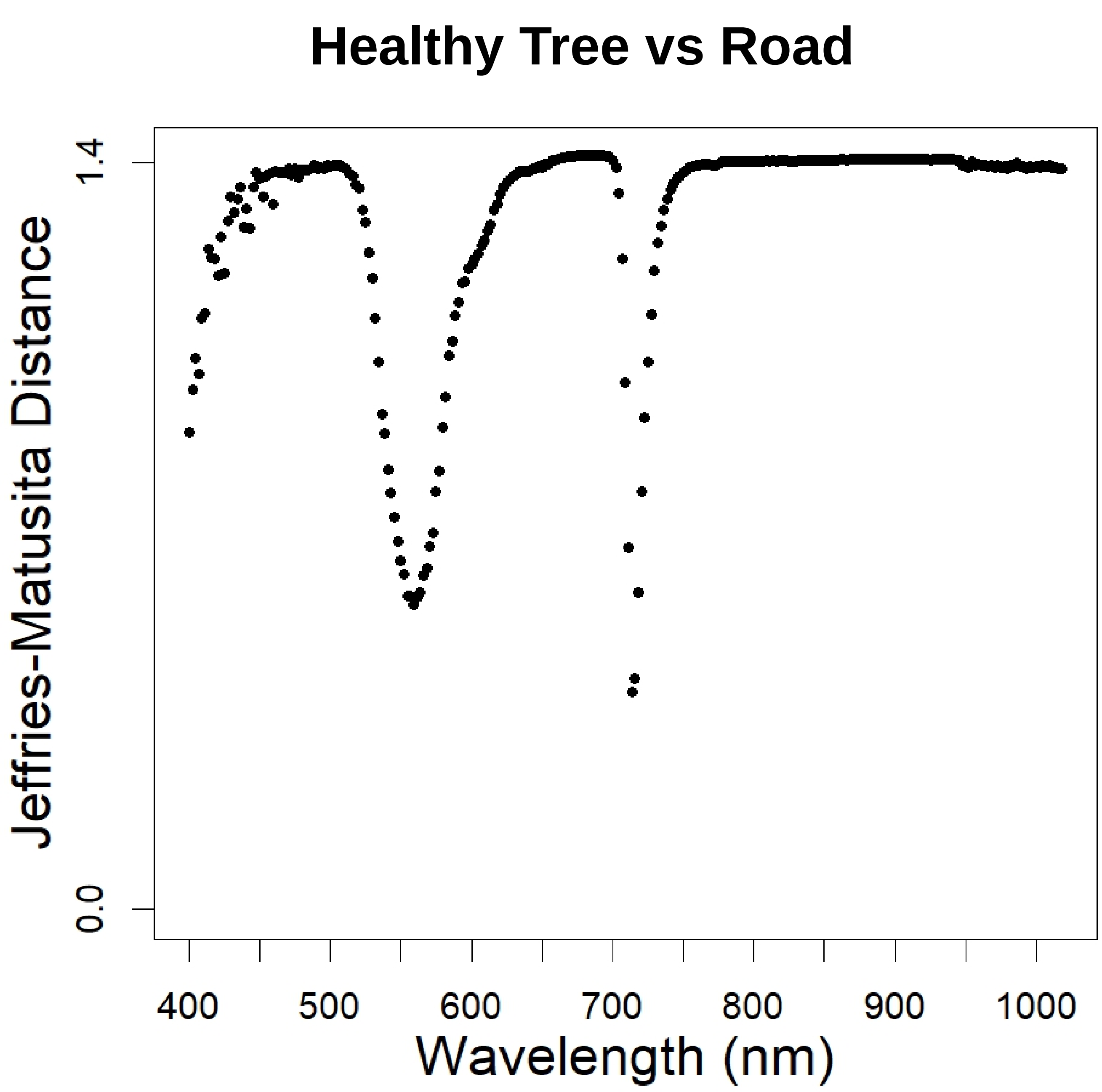
Three classes:

Healthy – no visual signs of damage

Fresh Damage – identified from bark characteristics

Older damage – damage incurred prior to the current growing season



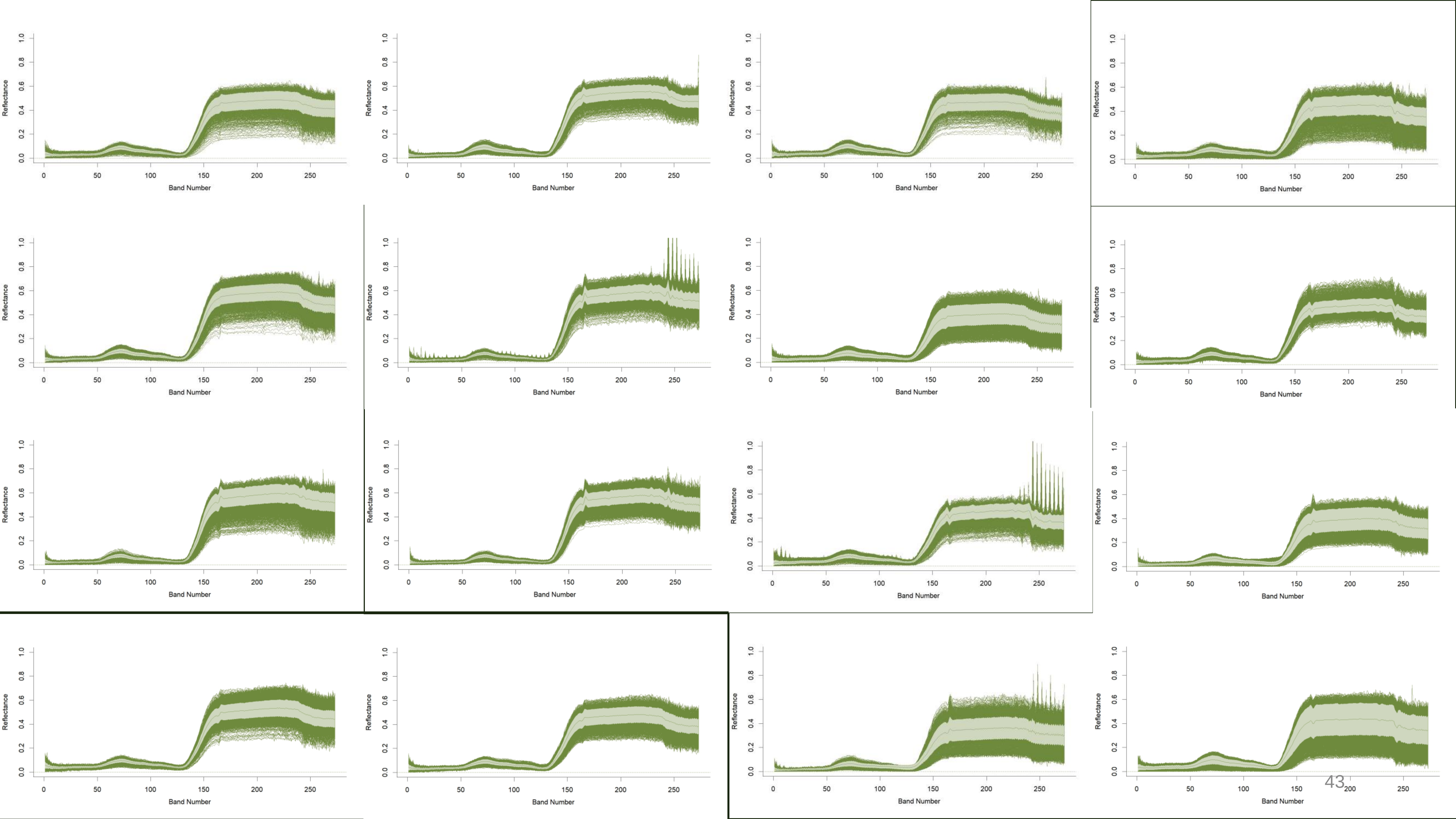
Jeffries–Matusita Distance

Measure of dissimilarity - [0, √2]

0 – reflectance values are overlapping; the data is overlapping between two classes

√2 – reflectance values are not overlapping, and the data is separated

Probabilistic Interpretation


Reflectance
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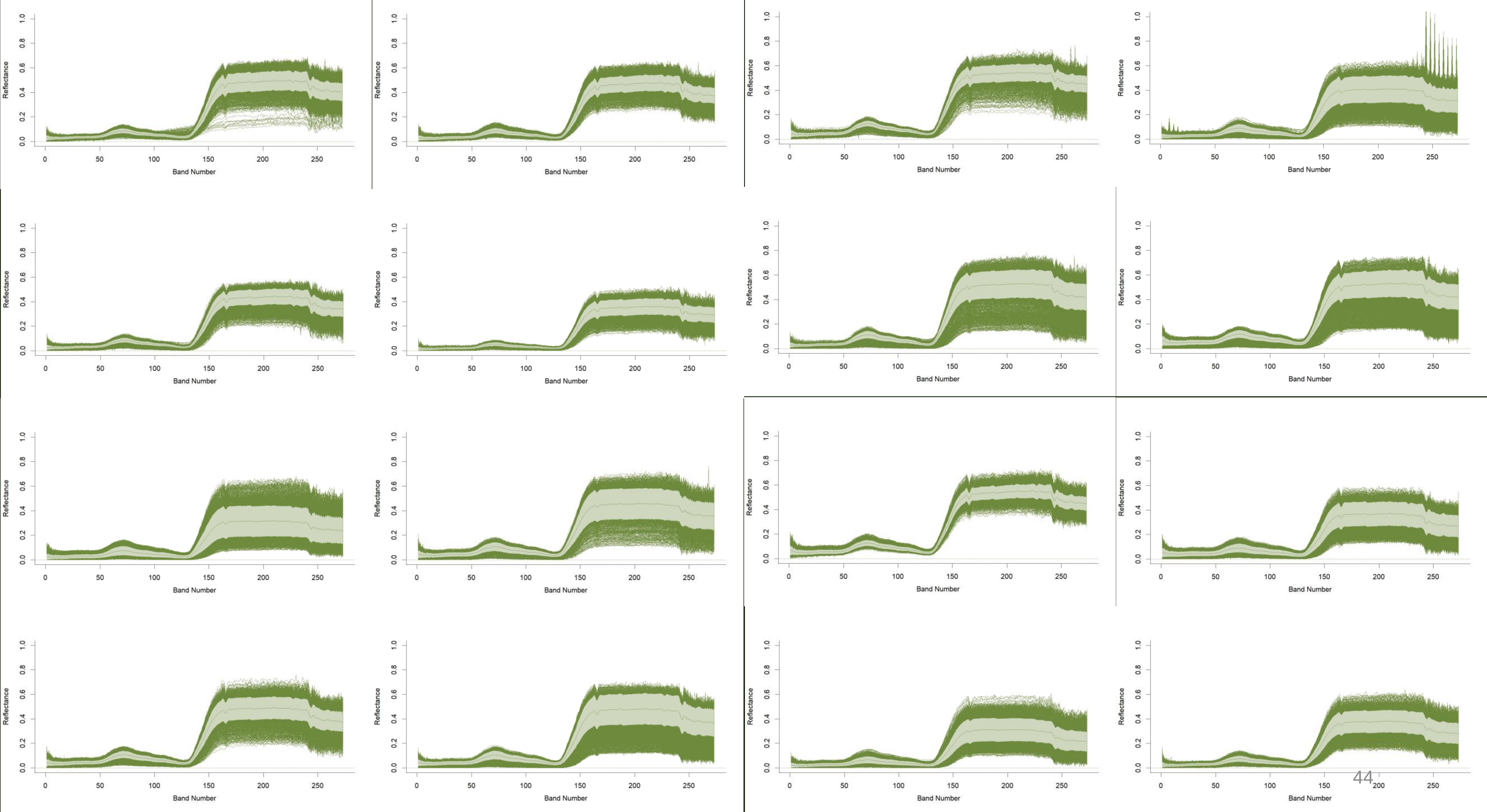
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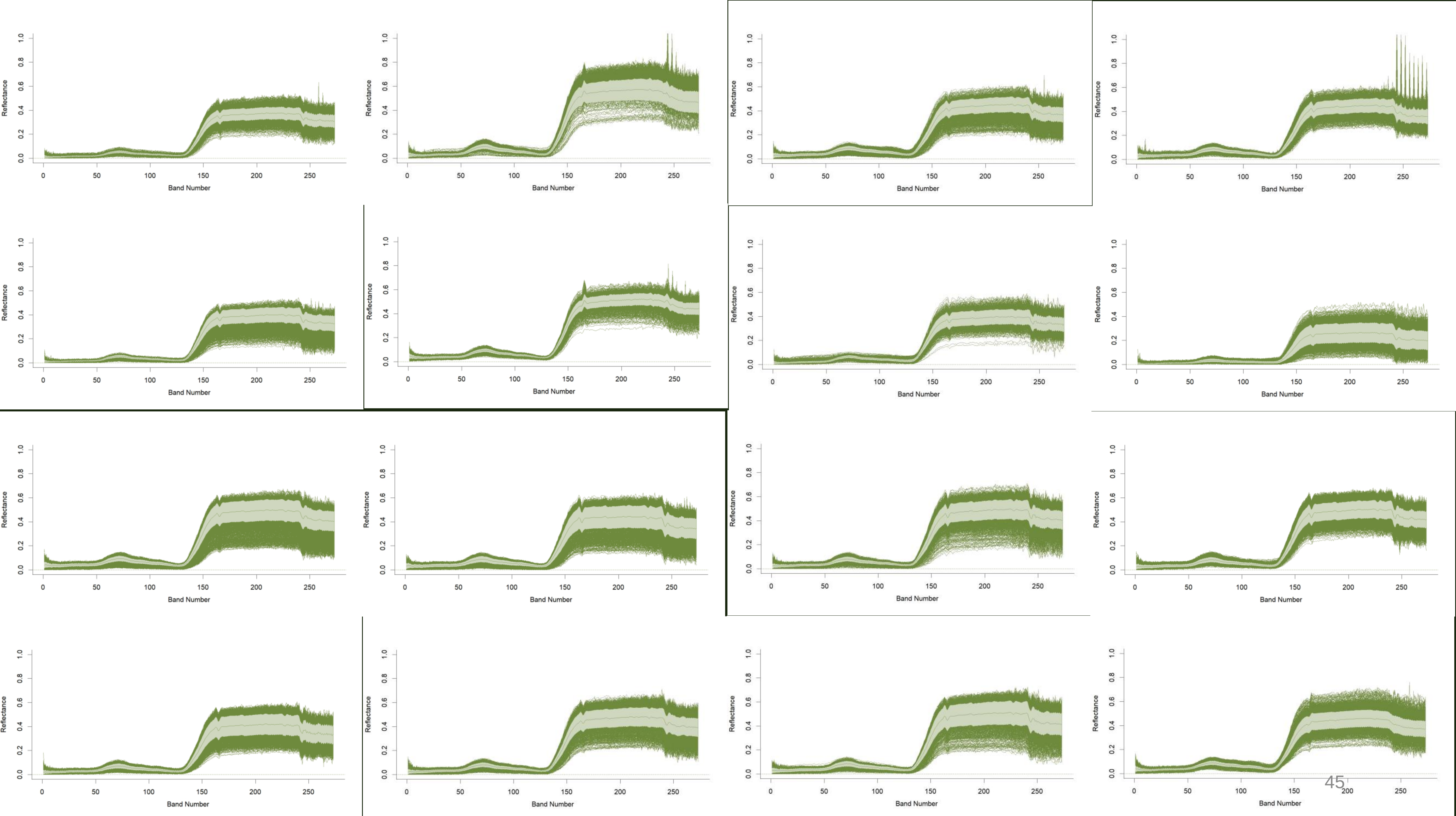
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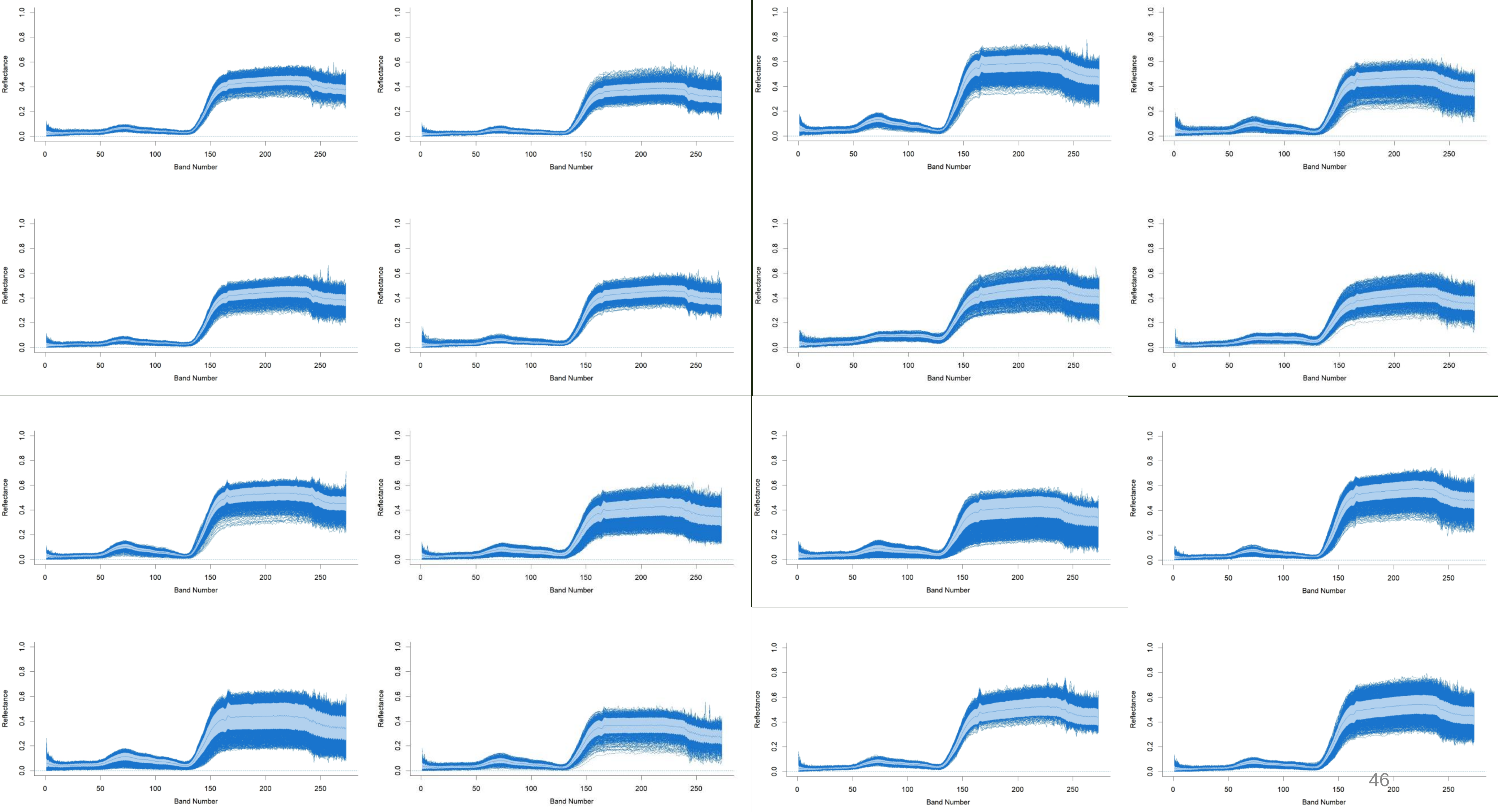
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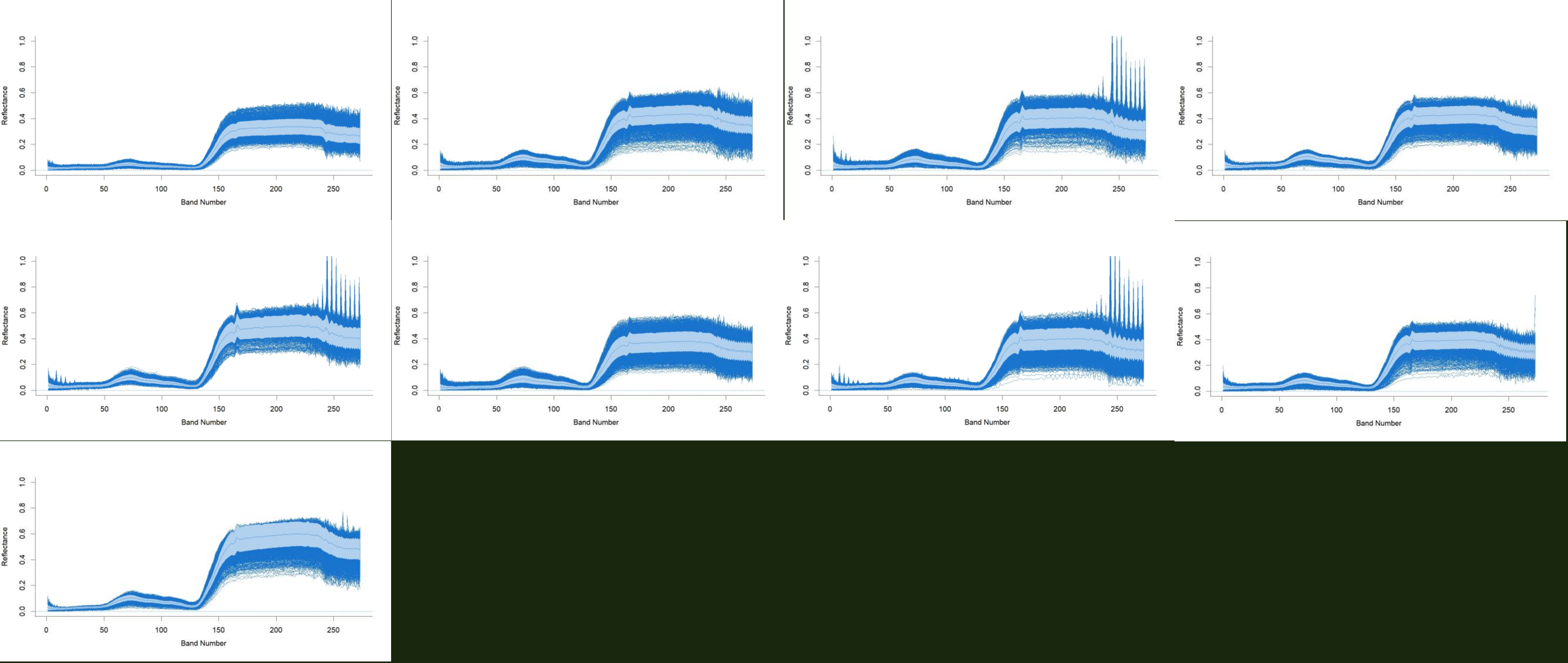
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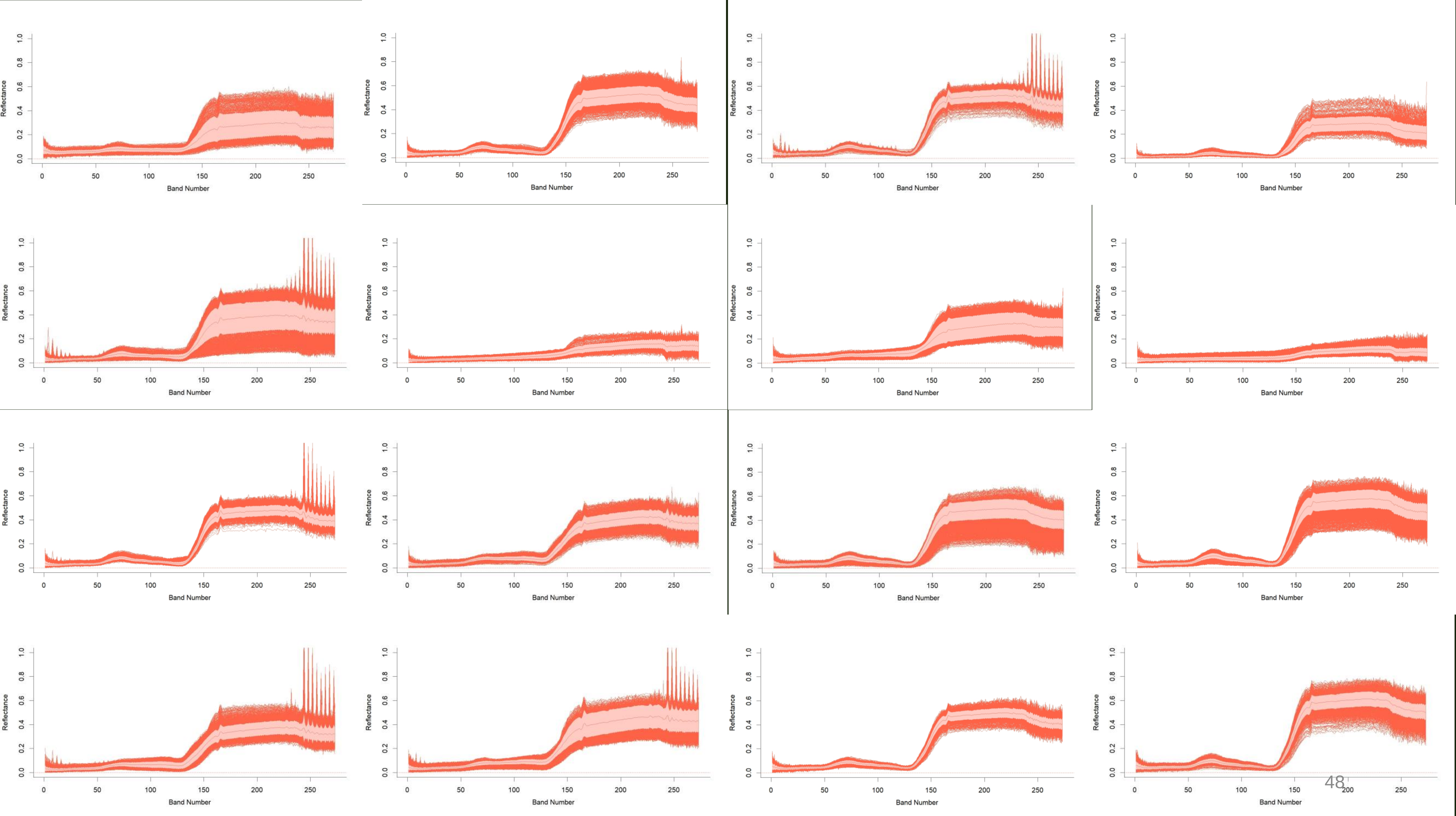
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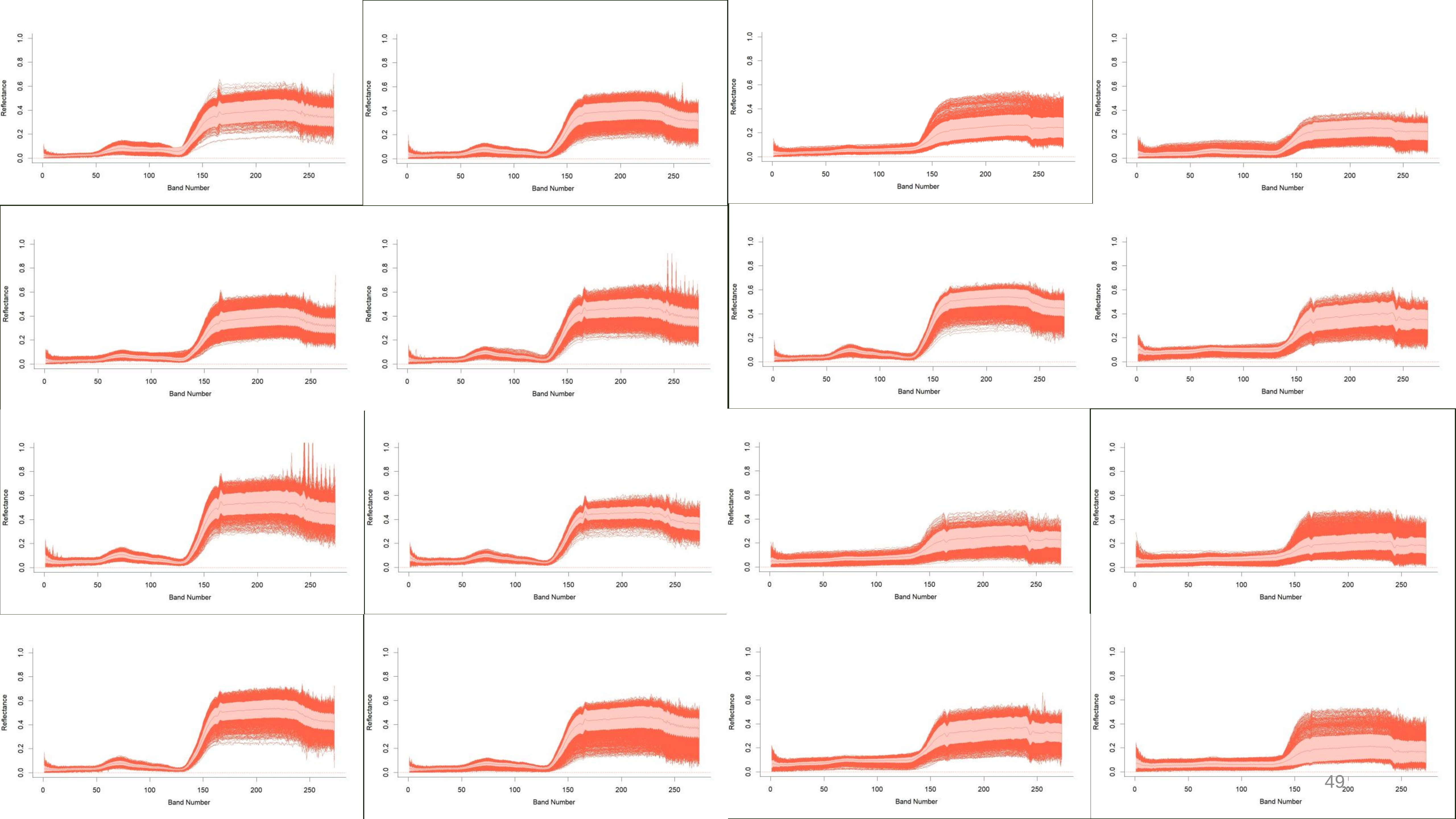
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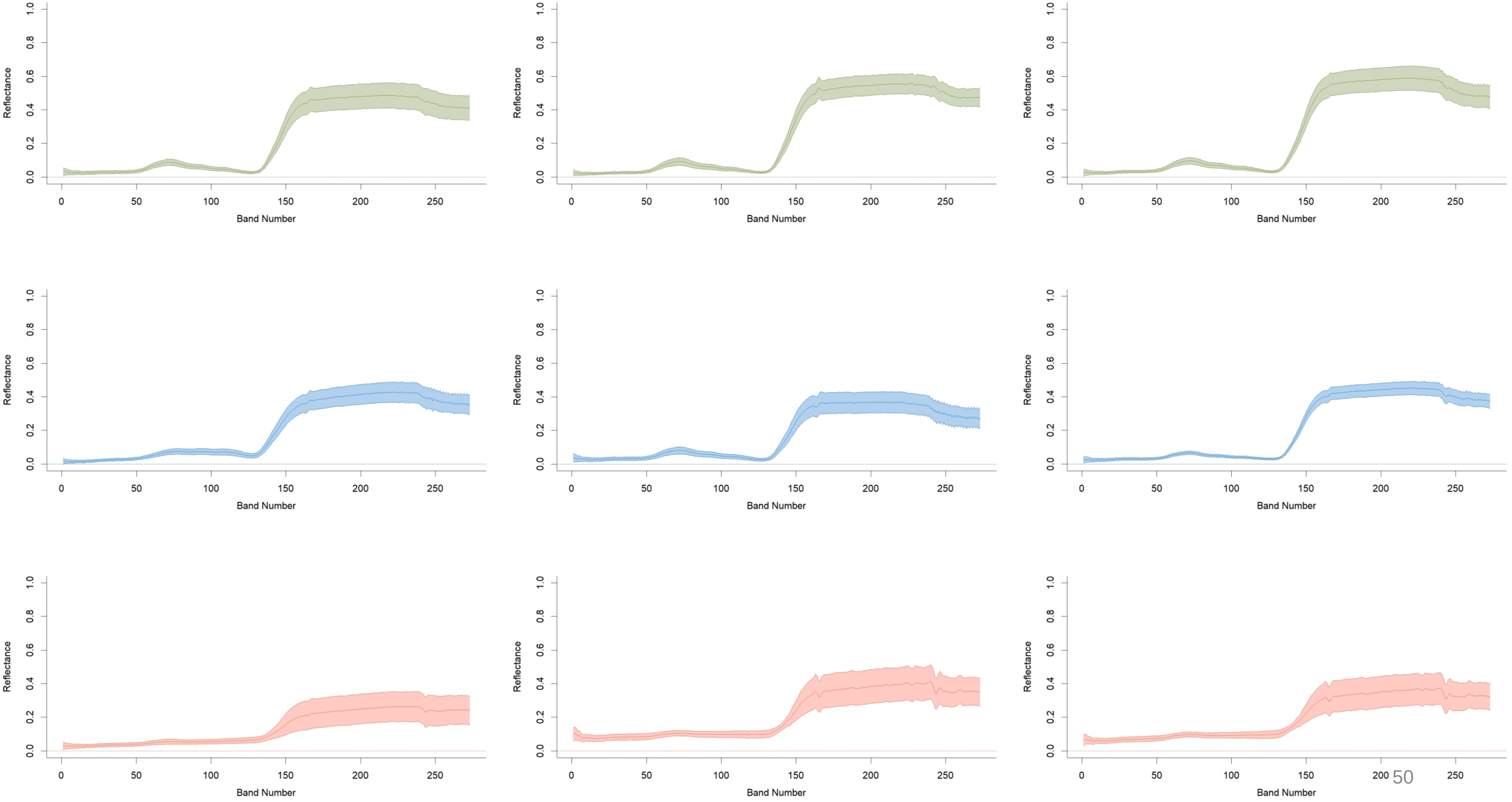
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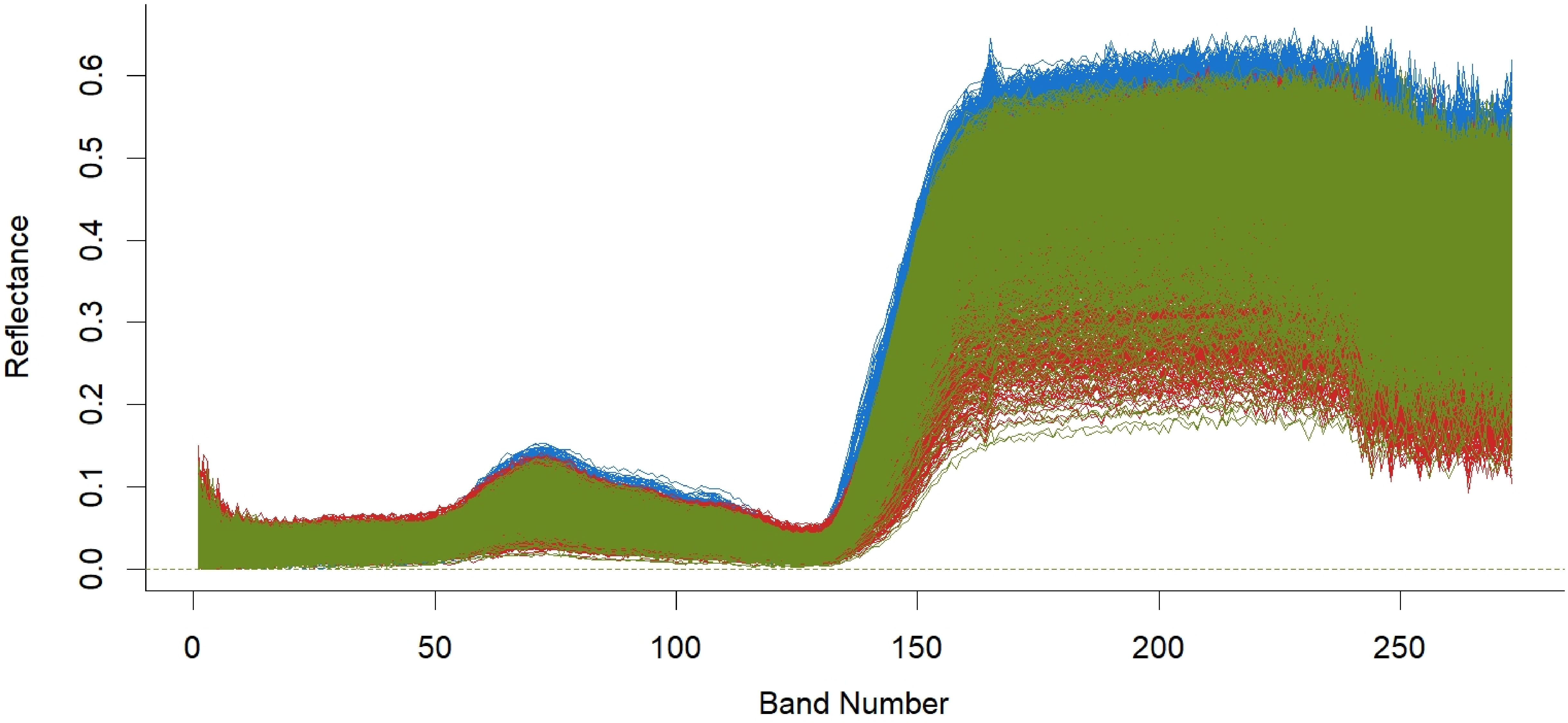
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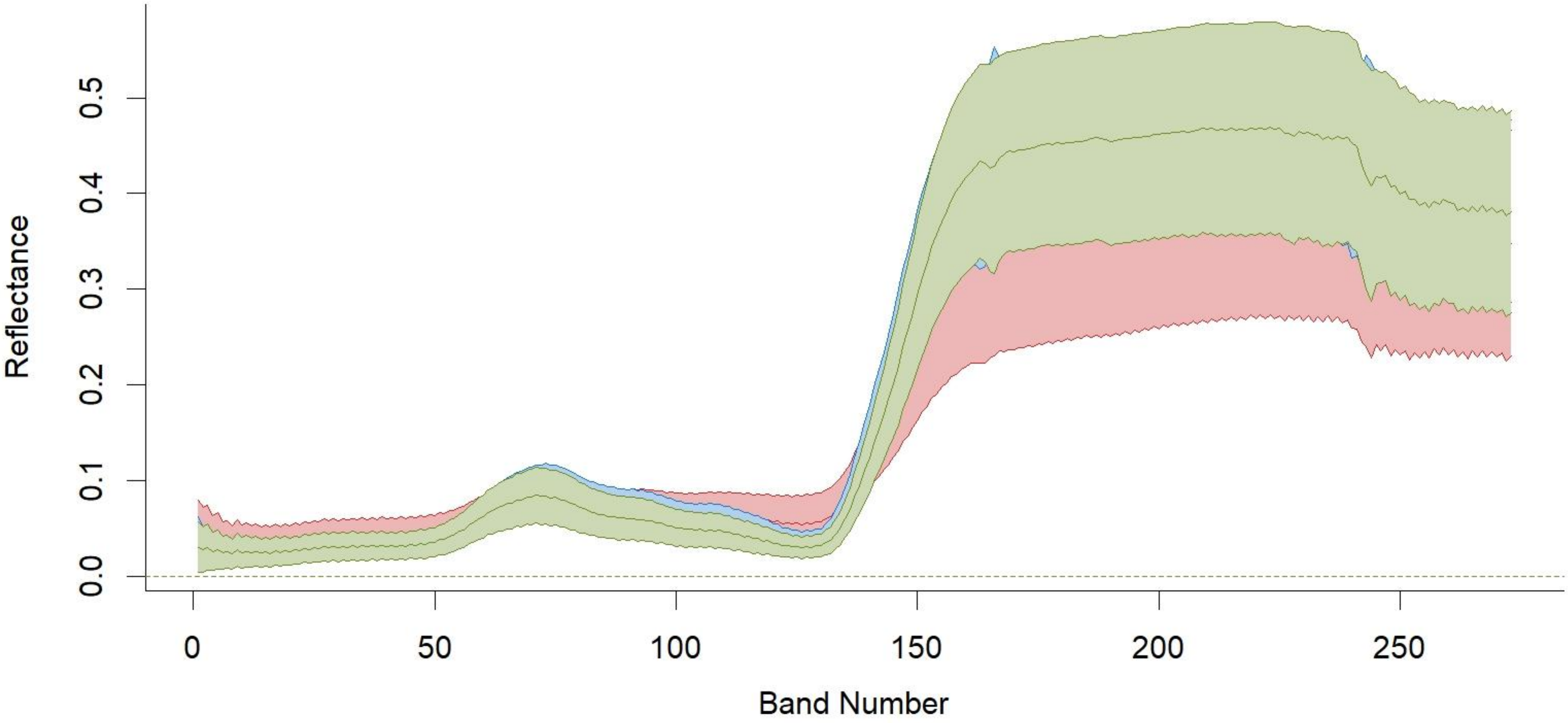
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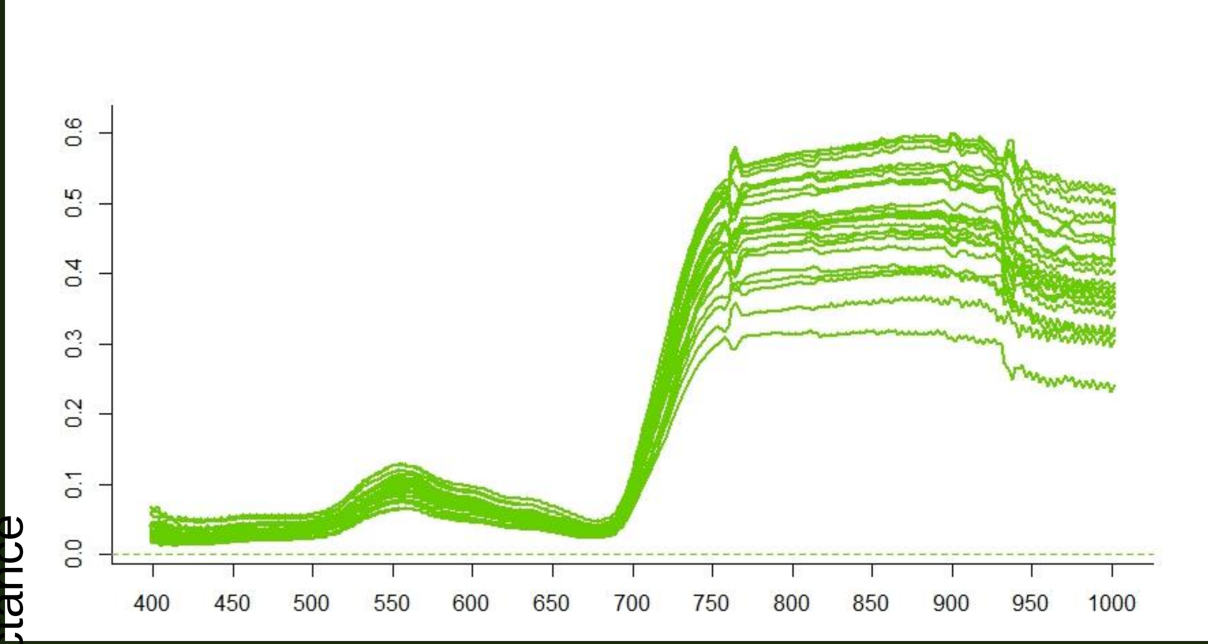


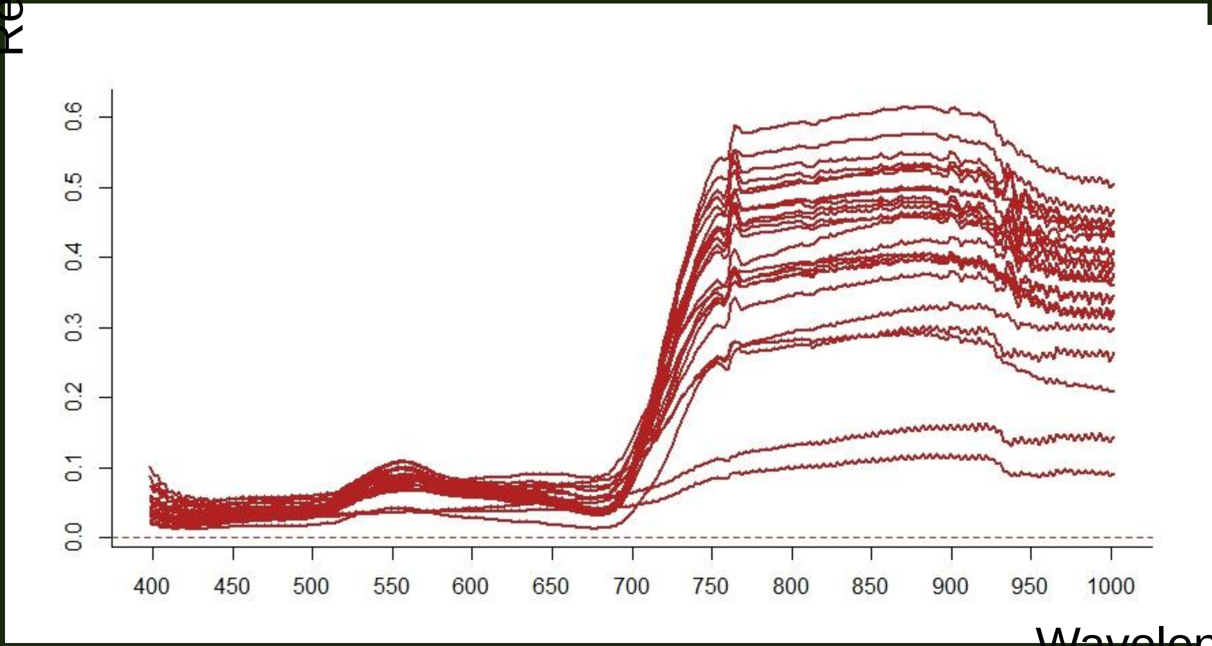
Mean signature values for each tree

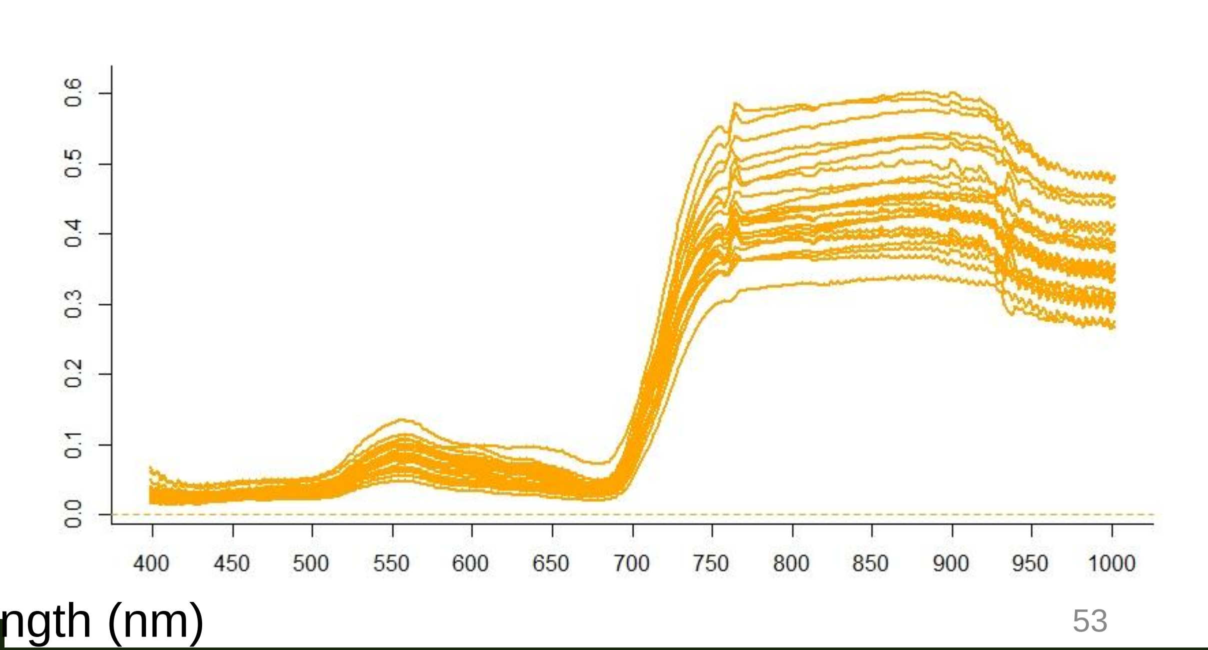
Health trees (left)

Recent damage (bottom right)

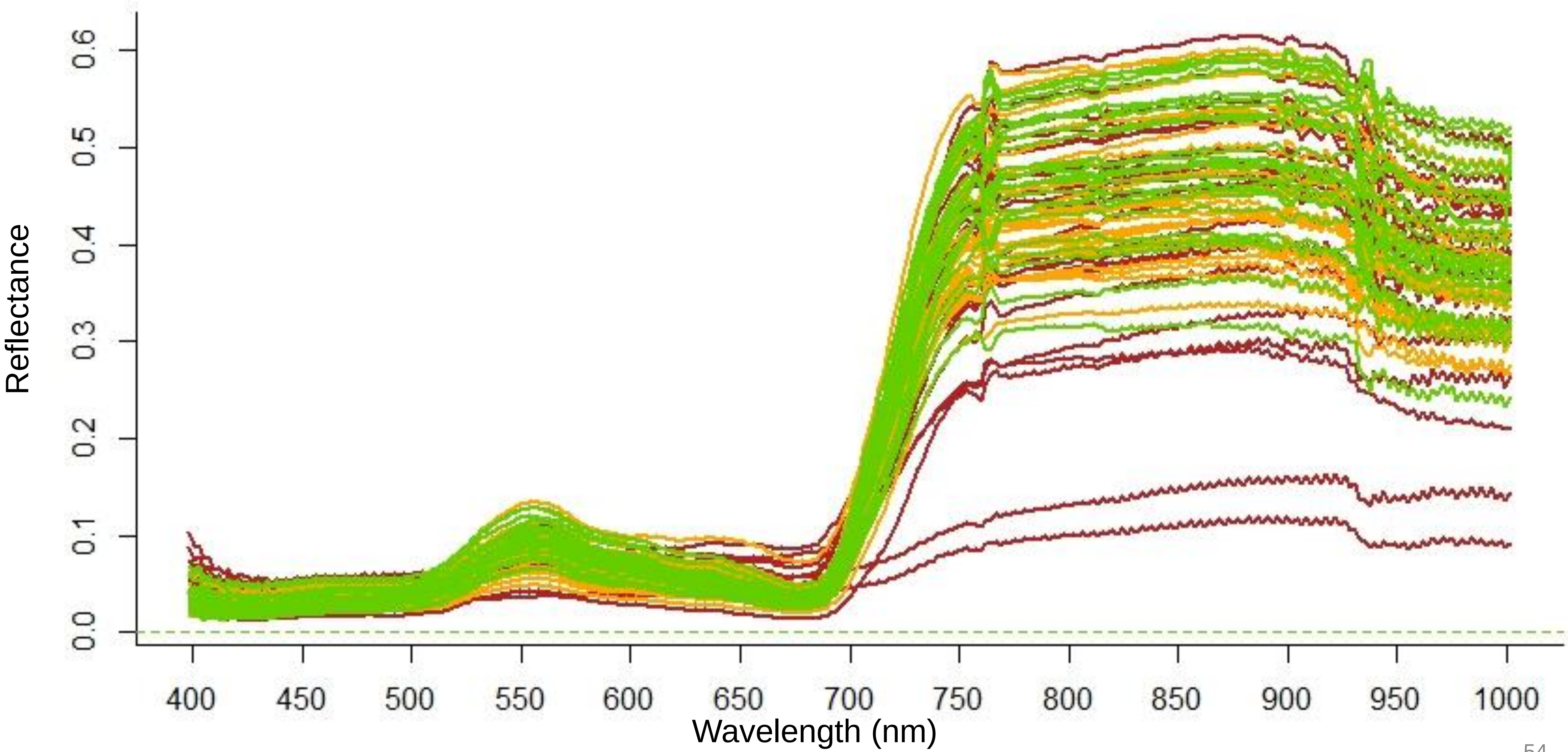
Old damage (bottom left)

Reflectance





Wavelength (nm)


Reflectance
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0.1
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0.3
0.4
0.5
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450
500
550
600
650
700
750
800
850
900
950
1000
Wavelength (nm)

Methods – *Feature Selection*

- Much of the overlap is seen in the data
- The optimal bands with the most class separation will need to be determined
- Jefferies-Matusita (JM) statistic will be used to determine where along the electromagnetic spectrum is the optimal region to use to distinguish these three health classes

Methods – *Vegetation Indices*

Table 3. Vegetation Indices used in this study and the equation used to generate each. Note: The Normalized Channel Ratio was generated from the results of the JM statistical measure.

Vegetation Indices	Equation	Reference
Normalized Difference Vegetation Index (NDVI)	$NDVI = \frac{\lambda_{750} - \lambda_{650}}{\lambda_{750} + \lambda_{650}}$	Rouse et al.
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Normalized Channel Ratio (NCR)	$NCR = \frac{\lambda_a}{\lambda_b}$	Coops et al.

Methods – *Classification*

- Three feature classes
  - healthy (undamaged), early damaged, old damaged
- All classification models were built and validated in R
- Support Vector Machines
  - Gaining popularity
- Random Forest
  - Difficult to control complexity

Preliminary Results – *Classification*

Features	Accuracy (%) SVM	Kappa SVM	Accuracy (%) RF	Kappa RF
VNIR	**83.8**	**0.75**	73.4	0.60
VIs	57.6	0.36	54.8	0.32
λ_{685}; λ_{750}	49.6	0.24	43.1	0.15
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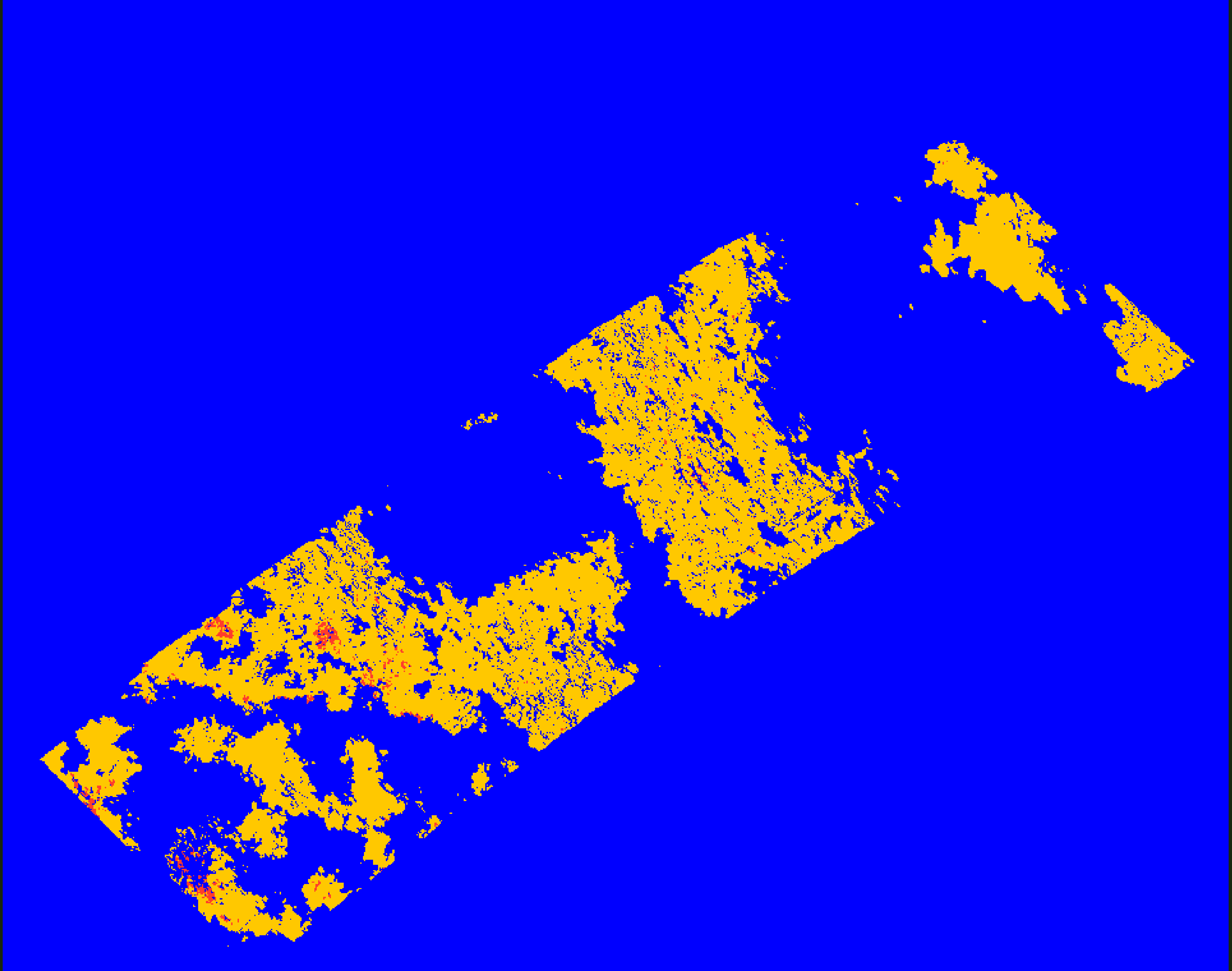
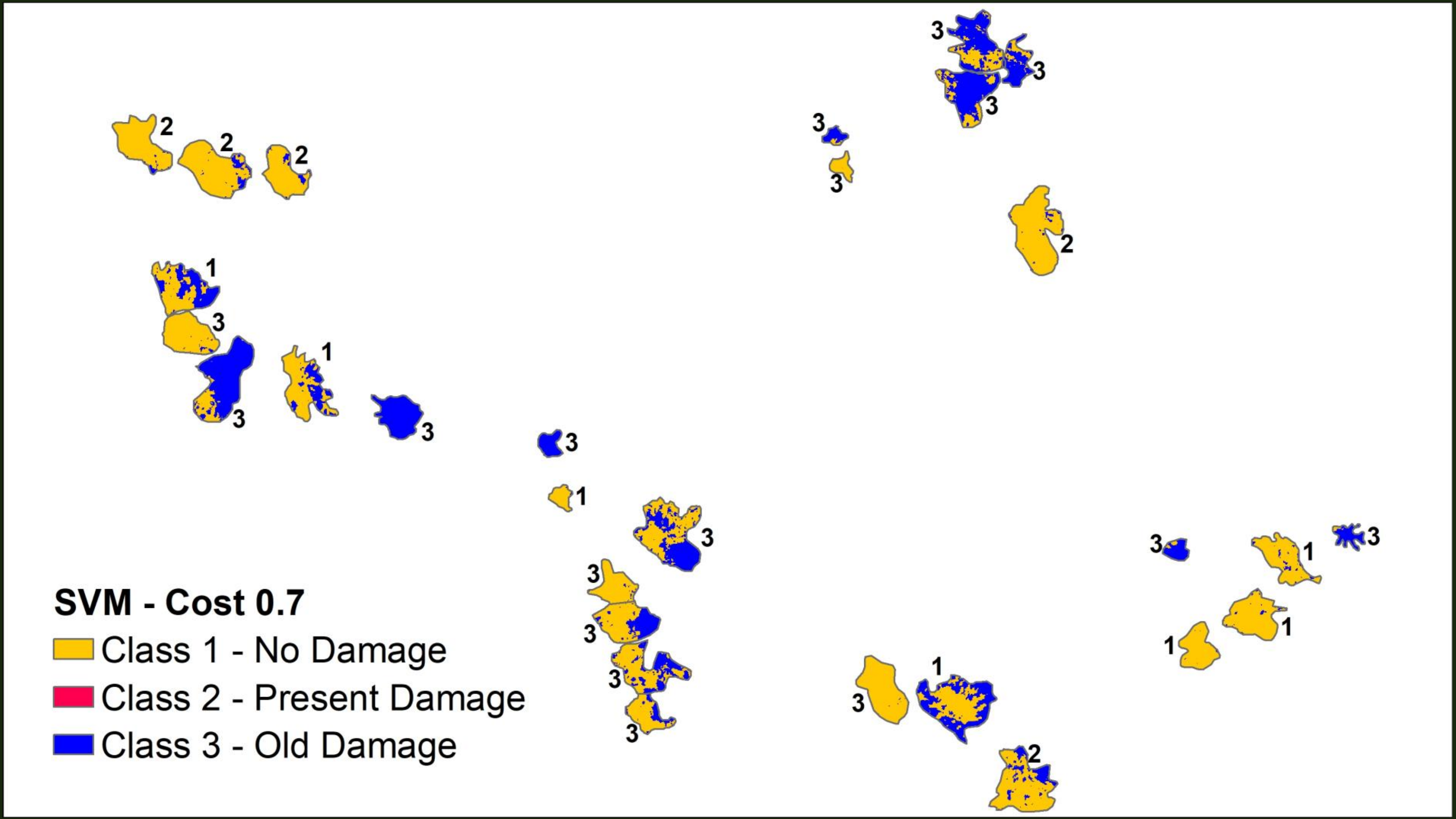
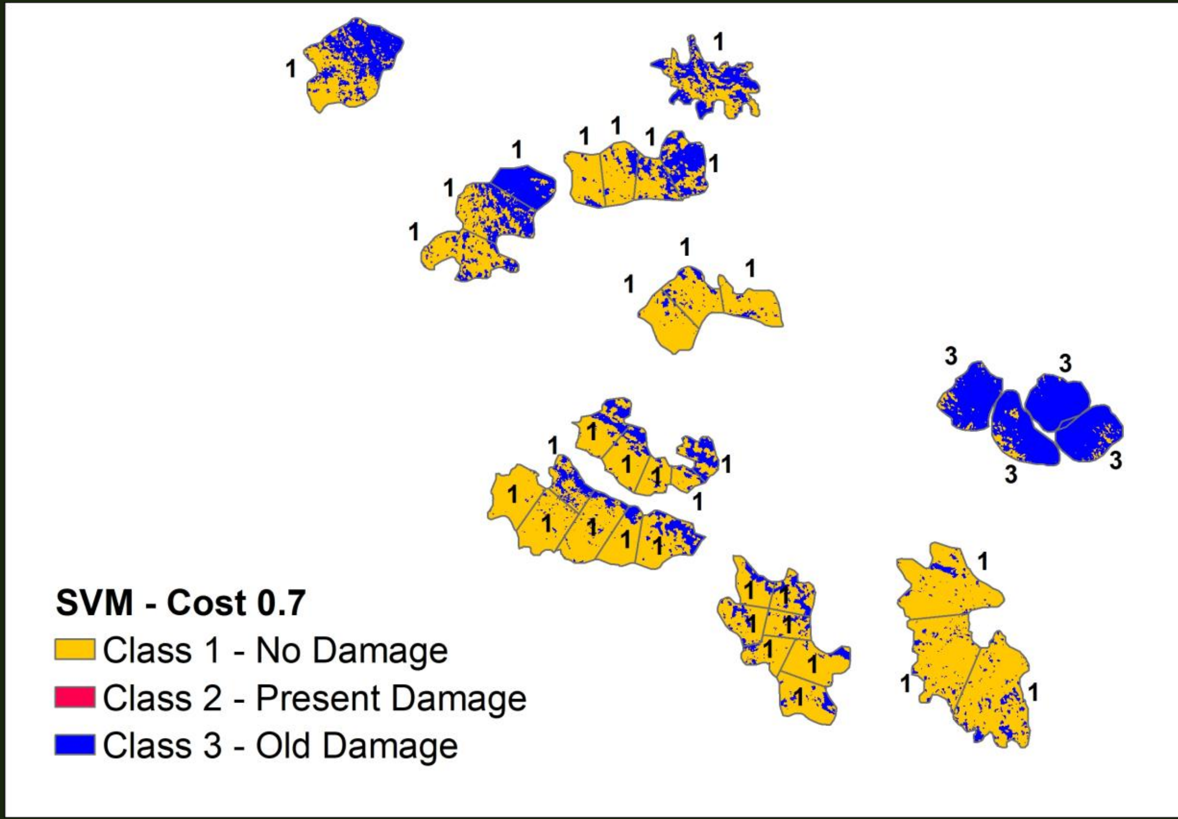
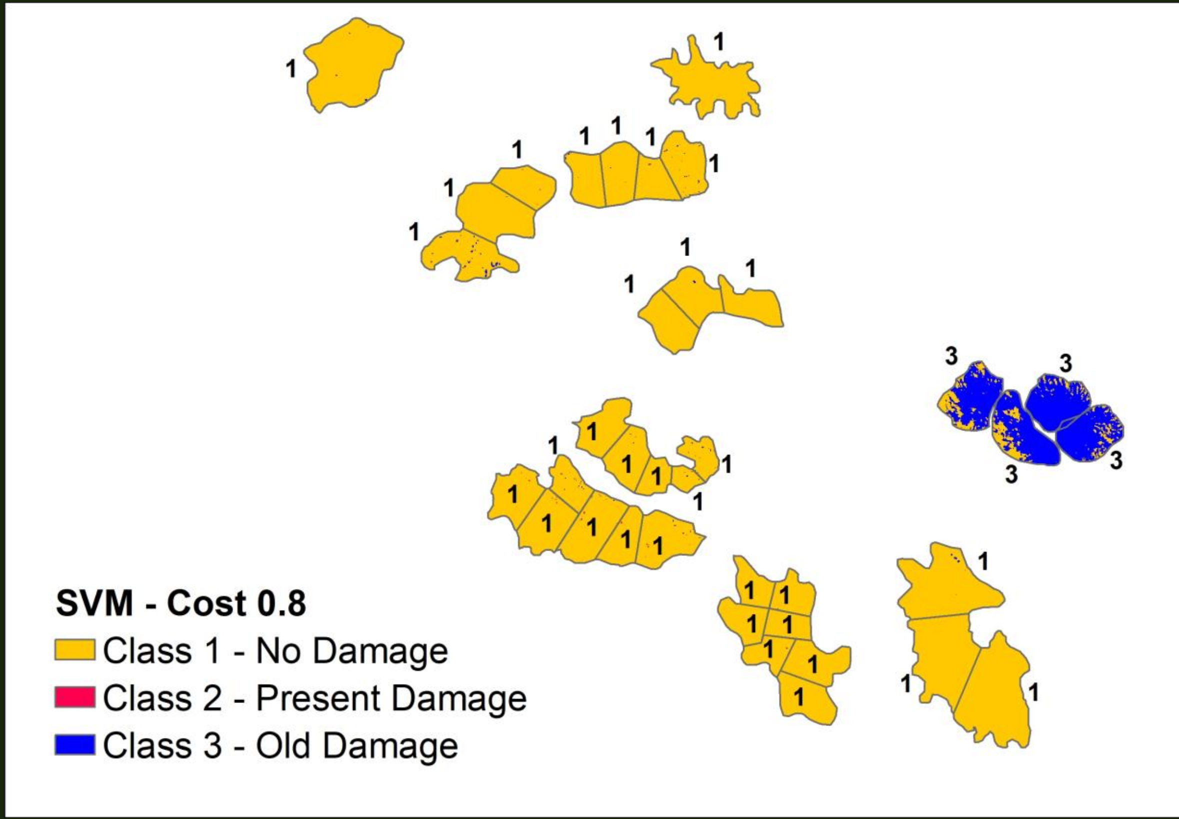


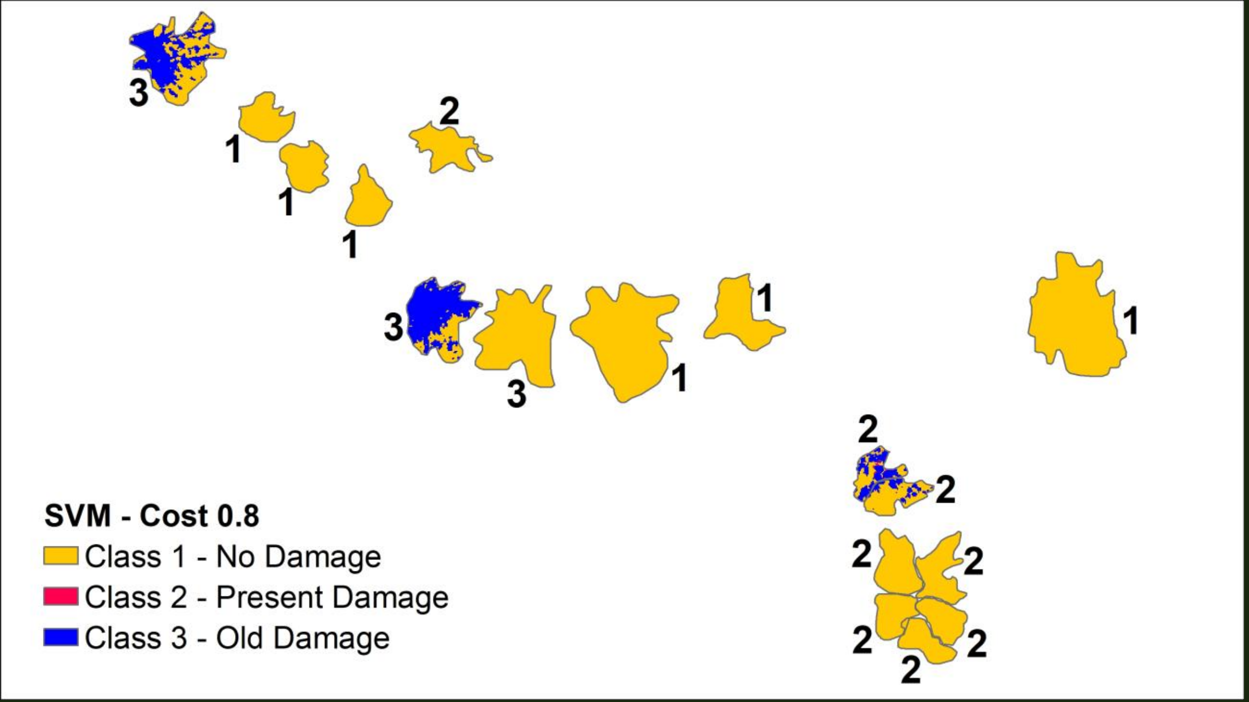
Preliminary Results – *Classification*



Preliminary Results – *Classification*



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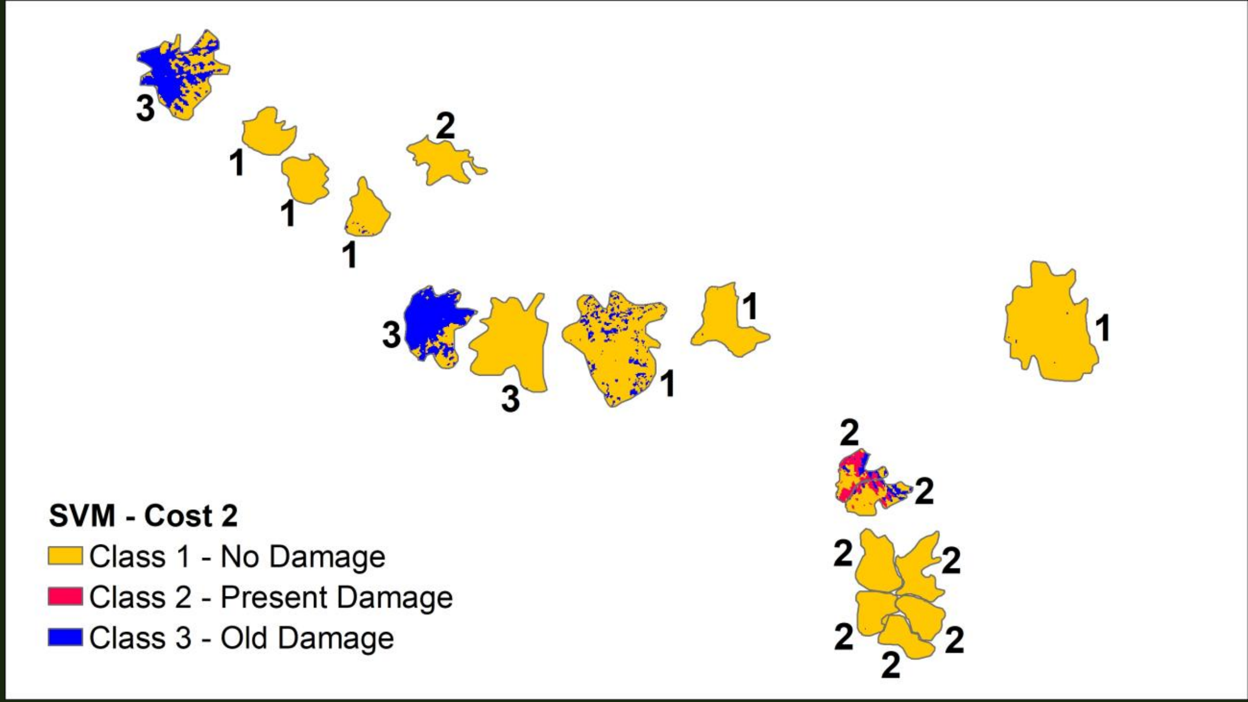
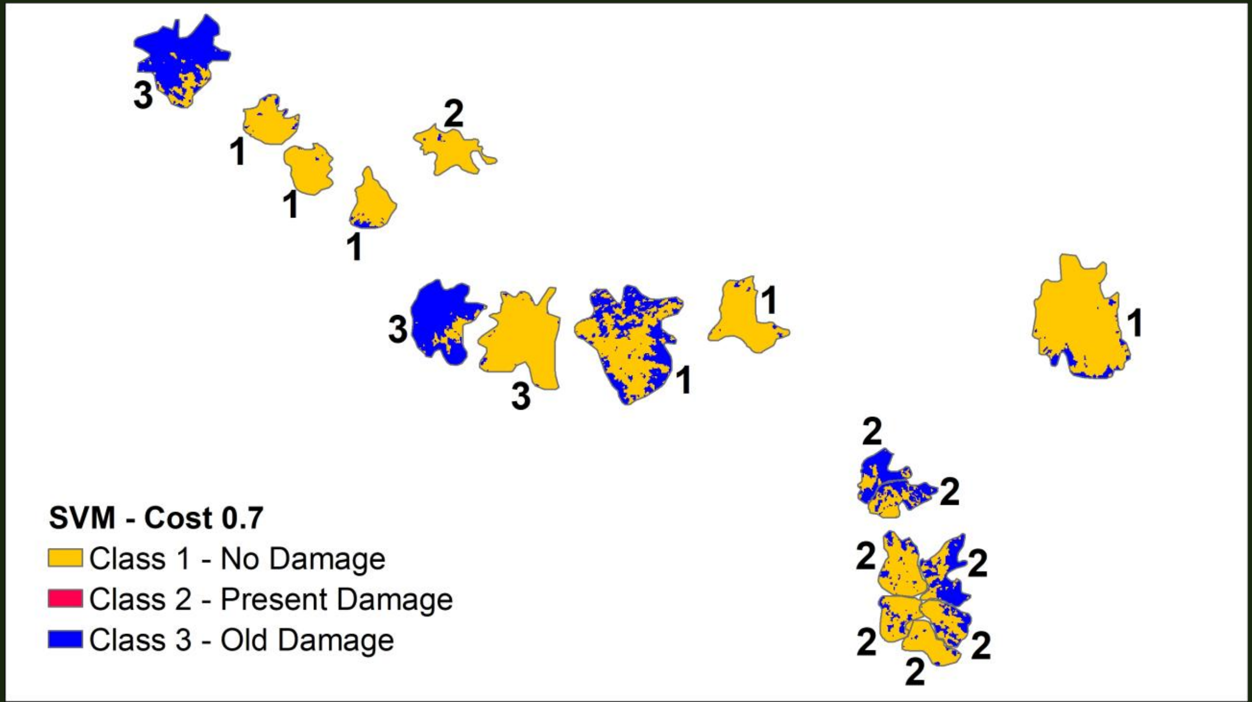
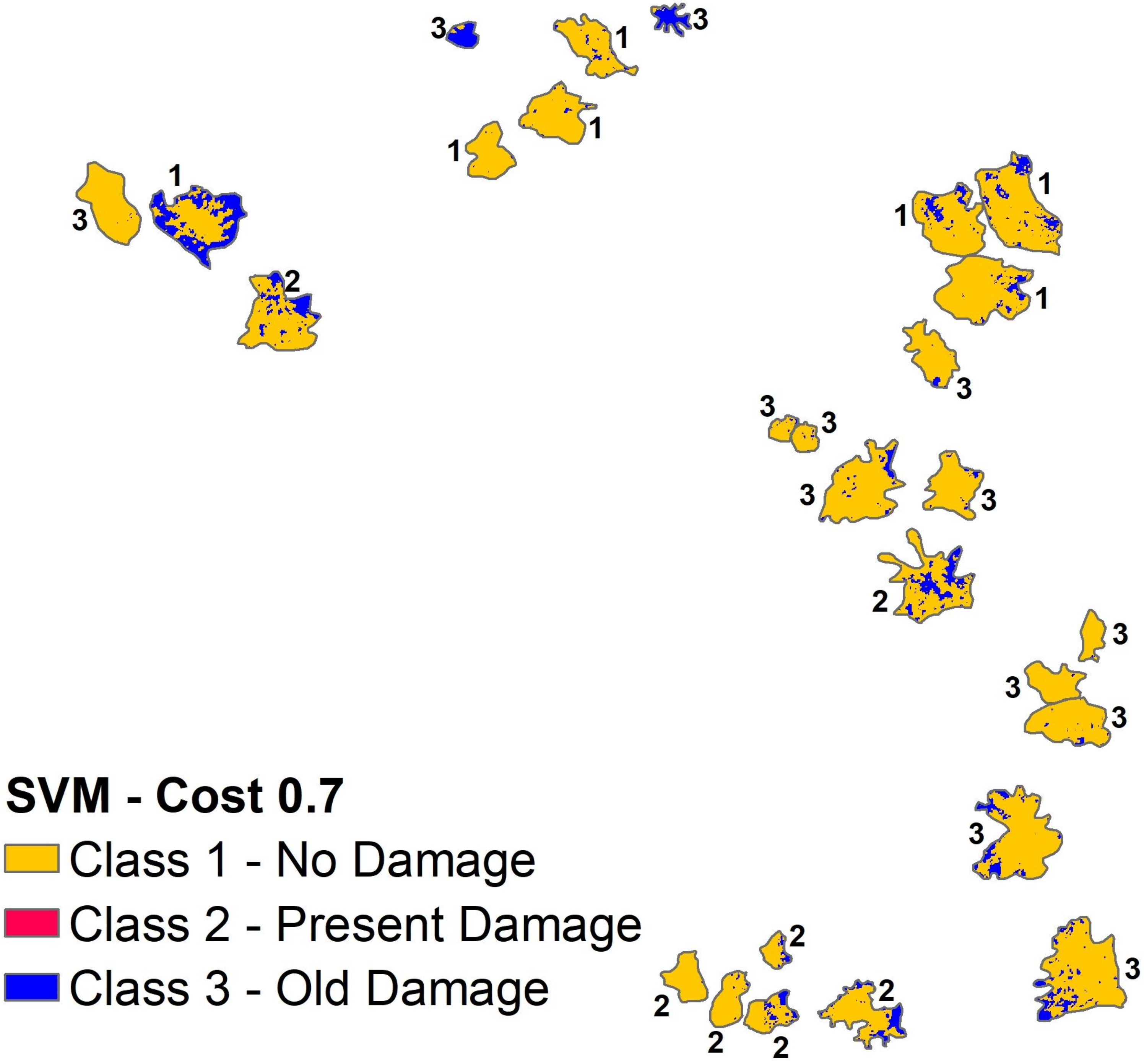
SVM - Cost 0.8
Class 1 - No Damage
Class 2 - Present Damage
Class 3 - Old Damage


3
1
2
1
1
3
1
1
1
3
1
2
2
2
2
2
2
2
SVM - Cost 2
Class 1 - No Damage
Class 2 - Present Damage
Class 3 - Old Damage


3
1
2
1
1
3
1
1
1
3
1
2
2
2
2
2
2
2
SVM - Cost 0.7
Class 1 - No Damage
Class 2 - Present Damage
Class 3 - Old Damage


SVM - Cost 0.7
Class 1 - No Damage
Class 2 - Present Damage
Class 3 - Old Damage