

# Myrtle Rust – Early Detection

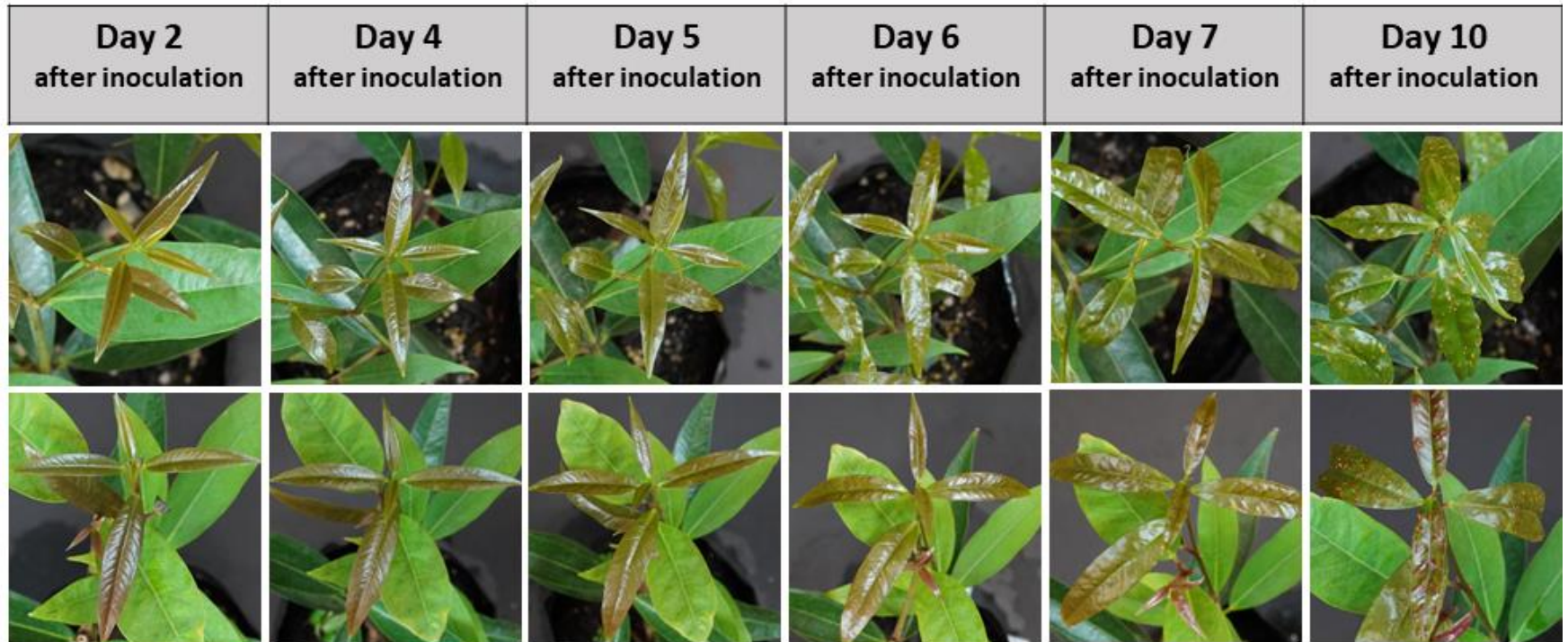
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Pre-visual and early detection of myrtle rust on rose apple using hyperspectral measurements and thermal imagery

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# Overview of detection target



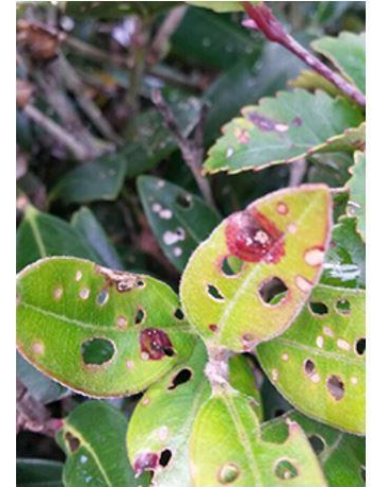
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# Introduction

- Myrtle rust caused by *Austropuccinia psidii* is a serious disease that affects many Myrtaceae species
- Commercial nurseries that propagate Myrtaceae spp. are prone to the disease
- Nurseries require a reliable method for pre-visual and early disease detection to minimise potential losses



# Introduction

- Conventional diagnosis relies on host identification, symptom observation and microscopic examination
- This method is not always practical or cost effective in a nursery setting
- DNA based techniques have been developed but are expensive and may not always detect the disease on asymptomatic plants

# Introduction

- Hyperspectral and thermal imagery provides an alternative method of pre-visual and early disease detection
- Plants subject to disease react through changes in physiology and plant pigments which may be detected by alterations in leaf temperature or reflectance from different wavelengths
- Rose apple one of the most susceptible hosts to myrtle rust
- **Objective.** Investigate utility of models that use hyperspectral data and thermal imagery for pre-visual and early detection of myrtle rust on rose apple

# Methods

- Experiment undertaken in temperature regulated dark room with artificial lighting
- Total of 81 plants allocated to control (30 plants) and MR treatment (51 plants)
- Conditions were set to 22°C, 70–80% relative humidity and a 16/8-hour day/night cycle under 30W LED 3000K grow lights





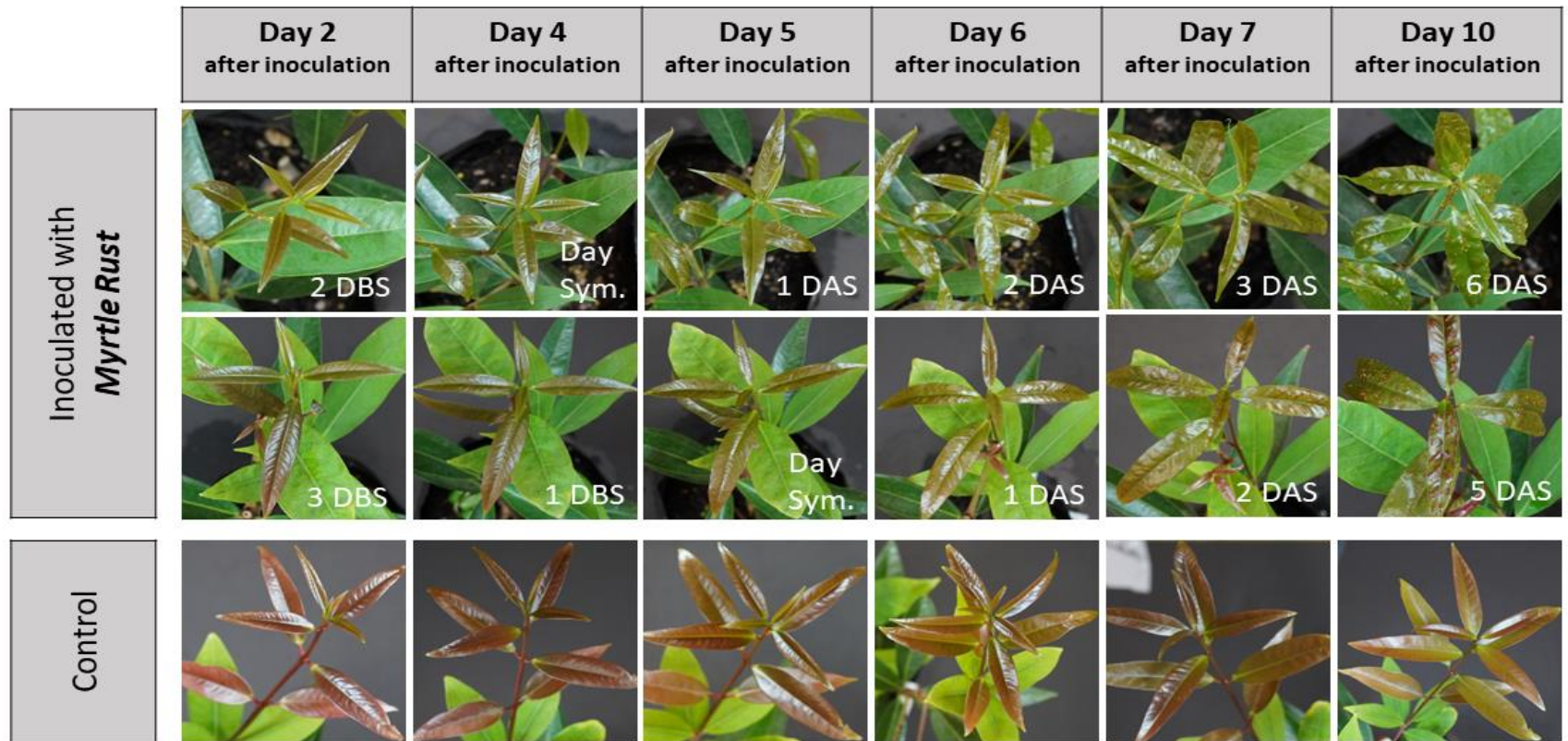
# Methods

- Plants in MR treatment inoculated on the 4<sup>th</sup> November
- Plants then placed back into enclosure under optimal conditions for infection for next 24 hours
- Control plants mock inoculated with sterile solution and kept under identical environmental conditions



# Measurement frequency

- Pre-treat measures + daily for six days after inoculation (DAI) + 10 DAI.  
**Symptoms occurred in all MR plants between 4 – 6 DAI.**
- All measurement data re-expressed for each plant to days before symptoms (either 3, 2, 1 DBS), day of symptoms, days after symptoms (either 1, 2, 3 DAS)





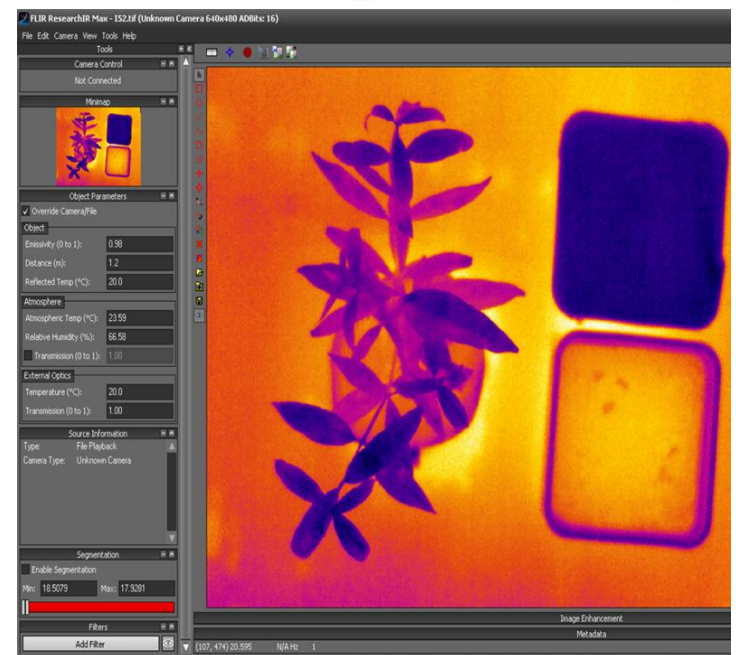
# Measurements

- Symptoms only appear on new (red) leaves
- Visual assessments made on both sides of leaves
- Aimed to identify infection at earliest possible stage
- No symptoms were found on control plants over experiment or for a week afterwards
  
- Measurements of stomatal conductance and transpiration rate made on all plants at the conclusion of the experiment using Walz GFS-3000



# Measurements

- Thermal camera – FLIR A655SC
- Set up 1.2 m from the plants
- Data processed using FLIR software
- Normalised canopy temperature ( $T_{norm}$ ) determined as difference between air temperature and canopy temperature
- Standard deviation of  $T_{norm}$  also determined and used in analyses
- Hyperspectral measurements taken from both red and green leaves using a Spectral Evolution RS-5400 spectroradiometer



# Data analysis

- Classification models developed for:
  - Three pre-visual (3 DBS, 2 DBS, 1 DBS) +
  - Four early detection phases (Day of Symptoms, 1 DAS, 2 DAS, 3 DAS)
- Each classification models used as predictor variables:
  - 101 narrow band hyperspectral indices (NBHI) from green leaves
  - 101 NBHI from red leaves
  - Thermal indices
- Recursive feature elimination used to reduce number of NBHI from 101 to between 2 – 14 for each model

# Data analysis

- Classification was undertaken using regularised discriminant analysis
- Five-fold cross validation with five repeats was used. Reported model statistics were averaged across all 25 validation datasets
- Calculated statistics include:
  - $Precision = \frac{TP}{TP+FP}$  Proportion of positive predictions that were correct
  - $Recall = \frac{TP}{TP+FN}$  Proportion of actual positives that were correct
  - $F1\ score = 2 \times \frac{Precision \times Recall}{Precision+Recall}$  Harmonic mean of precision and recall
  - $Accuracy = \frac{TP+TN}{TP+FP+TN+FN}$  Proportion of correct predictions
- **F1 values > 0.9** represent outstanding classification



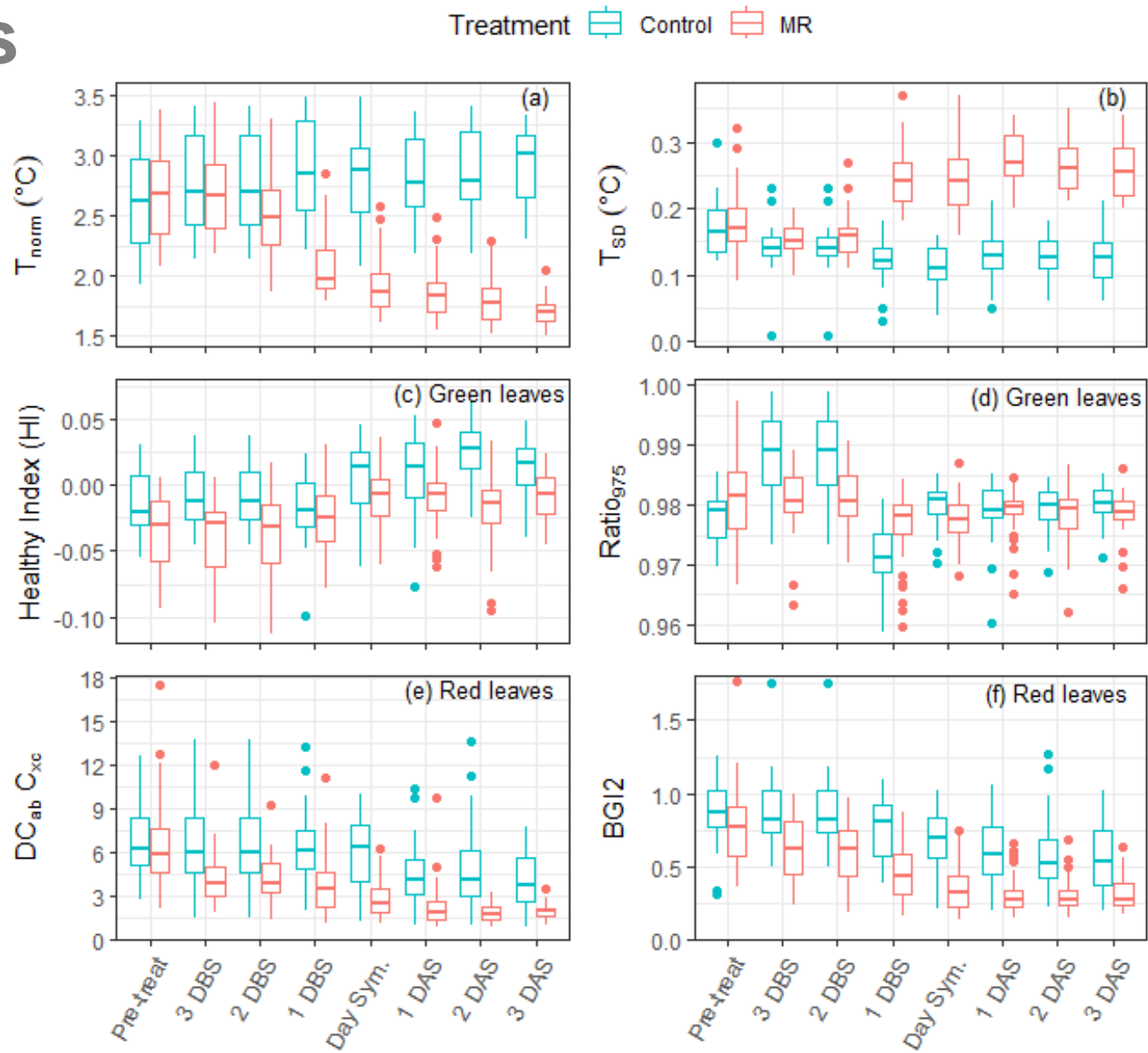
# Results – final classification models from RFE

Data	Leaf type	Inf. stage	Variables in the model	
NBHI	Green	3 DBS	Ratio975, HI, NDWI1, DRI_NDWI, SRPI, SIPI, WI, NPQI, CLS, BF4, BF2, MSI2	
		2 DBS	Ratio975, HI, NDWI1, DRI_NDWI, NPCI, SIPI, WI, NPQI, CLS, PSRI, BF1, BF2, MSI, RGI	
		1 DBS	PRI528, Ratio975, DRI_PRI, WBI, PRI570, PRIn, RDVI, PRI550, PM1, OSAVI, MTVI2, MCARI, NDWI2130, DDI	
		Day Sym.	CLS, Ratio975, HI, MCARI2, MCARI3, MSI1, SBRI, RARS, MCARI, RDVI	
		1 DAS	PRI528, HI, PRI570	
		2 DAS	HI, MSAVI, PSRI, WI_NDVI	
		3 DAS	PRI528, HI, DRI_PRI, SIPI, PRI570, CLS, Ratio975, WI	
	Red	3 DBS	G, HI, Ratio975, DRI_PRI, PRI550, DCabCxc	
		2 DBS	BGI2, PRIIm3, PRIn, Ratio_975, PRIIm2	
		1 DBS	RGI, GI, PSRI, BGI1, B, WI, RR, CARI, BF3, DCabCxc, DRI_MSI, Ratio975	
		Day Sym.	PRIn, GI, DCabCxc, BGI2	
		1 DAS	DRI_PRI, BGI2, DCabCxc, PRI570, G, PM1	
		2 DAS	PRI_CRI, PRIn	
		3 DAS	PRI570, RGI, PM1, PRI550, DCabCxc, GM4, CI1, MSI1, PSRI, BGI2	
Thermal	Both	All seven	$T_{norm}$ , $T_{SD}$	

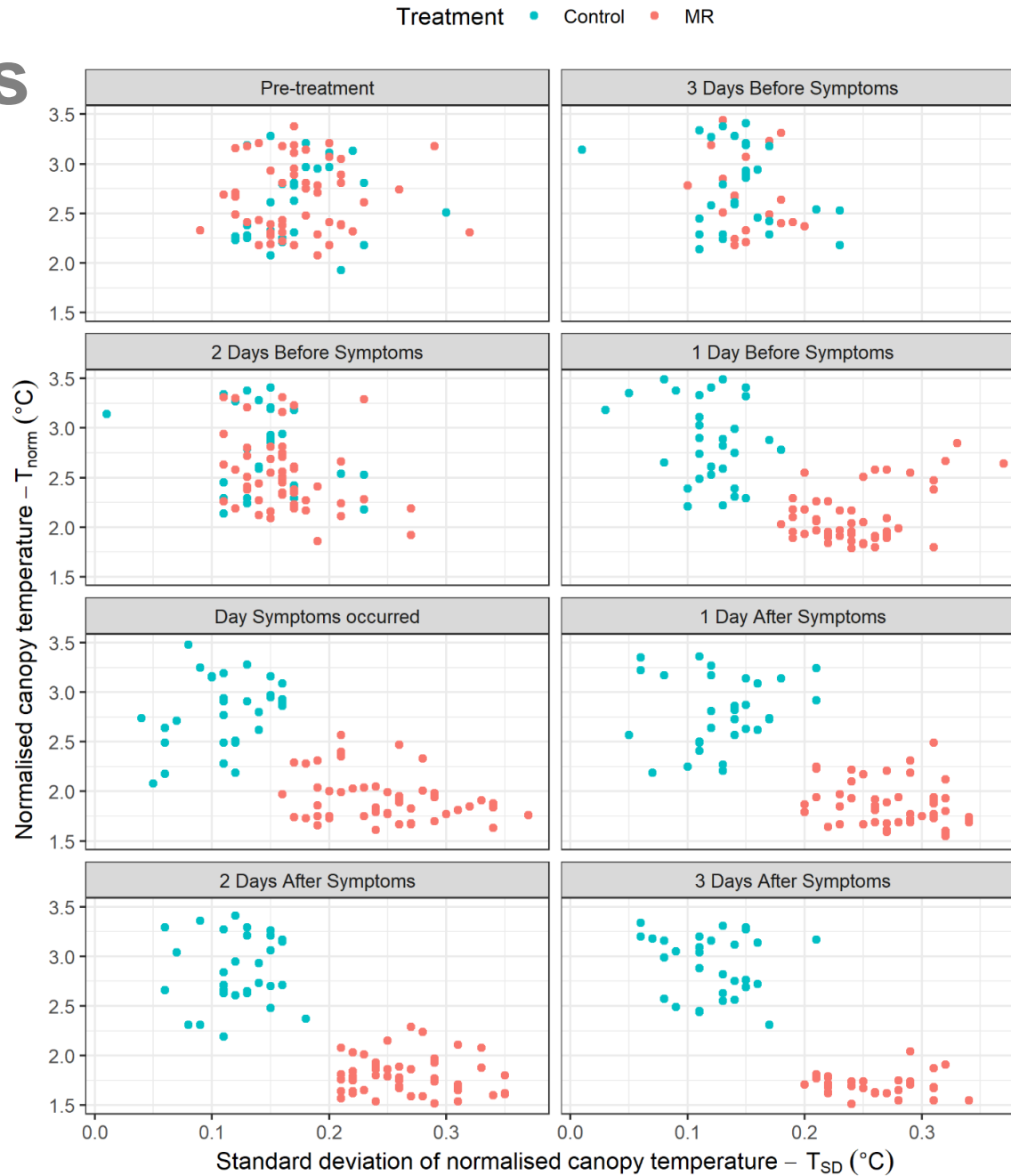
# Results – final classification models from RFE

Data	Leaf type	Inf. stage	Variables in the model	
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		2 DBS	Ratio975, HI, NDWI1, DRI_NDWI, NPCI, SIPI, WI, NPQI, CLS, PSRI, BF1, BF2, MSI, RGI	
		1 DBS	PRI528, Ratio975, DRI_PRI, WBI, PRI570, PRIn, RDVI, PRI550, PM1, OSAVI, MTVI2, MCARI, NDWI2130, DDI	
		Day Sym.	CLS, Ratio975, HI, MCARI2, MCARI3, MSI1, SBRI, RARS, MCARI, RDVI	
		1 DAS	PRI528, HI, PRI570	
		2 DAS	HI, MSAVI, PSRI, WI_NDVI	
		3 DAS	PRI528, HI, DRI_PRI, SIPI, PRI570, CLS, Ratio975, WI	
	Red	3 DBS	G, HI, Ratio975, DRI_PRI, PRI550, DCabCxc	
		2 DBS	BGI2, PRIIm3, PRIn, Ratio_975, PRIIm2	
		1 DBS	RGI, GI, PSRI, BGI1, B, WI, RR, CARI, BF3, DCabCxc, DRI_MSI, Ratio975	
		Day Sym.	PRIn, GI, DCabCxc, BGI2	
		1 DAS	DRI_PRI, BGI2, DCabCxc, PRI570, G, PM1	
		2 DAS	PRI_CRI, PRIn	
		3 DAS	PRI570, RGI, PM1, PRI550, DCabCxc, GM4, CI1, MSI1, PSRI, BGI2	
Thermal	Both	All seven	$T_{norm}$ , $T_{SD}$	

# Results



# Results





# Model results

Model classification statistics showing F1 score, followed by accuracy.  
Models highlighted in green have outstanding classification

Infection stage	Thermal indices	Hyperspectral indices	
		Green leaves	Red leaves
3 DBS	0.33 (50%)	0.89 (91%)	0.73 (78%)
2 DBS	0.75 (64%)	0.94 (93%)	0.86 (81%)
1 DBS	1.00 (100%)	0.91 (89%)	0.90 (87%)
Day Sym.	1.00 (100%)	0.81 (76%)	0.89 (86%)
1 DAS	1.00 (100%)	0.87 (83%)	0.86 (83%)
2 DAS	1.00 (100%)	0.94 (93%)	0.92 (90%)
3 DAS	1.00 (100%)	0.89 (89%)	0.92 (92%)

# Discussion

- NBHI from older green unaffected leaves were more accurate for classification than NBHI from red leaves
- Key NBHI from green leaves were Ratio975 and HI
- Healthy index (HI) describes changes in photosynthetic function
- Ratio975 is a water stress index which describes variation in water content
- Changes in  $DC_{ab}$ ,  $C_{xc}$  and BGI2 suggest infection induces reductions in chlorophyll within susceptible red leaves

# Further research

- The accurate characterisation of MR shown here suggests a robust detection methodology could be developed in a nursery setting
- The sample size was quite small so further research should be undertaken to check generality
- This approach should be extended to other Myrtaceae spp.
- We will next focus on detection of myrtle rust on key Eucalyptus spp.

# Conclusion

- All inoculated plants developed minor symptoms that would be difficult to detect through visual observation
- Validation data showed models using thermal indices could perfectly distinguish treatments during both pre-visual and early detection stages
- Using hyperspectral indices from green leaves excellent pre-visual classification was obtained
- These results are promising and further research should extend and scale up this approach



# Acknowledgements

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# Thank you

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