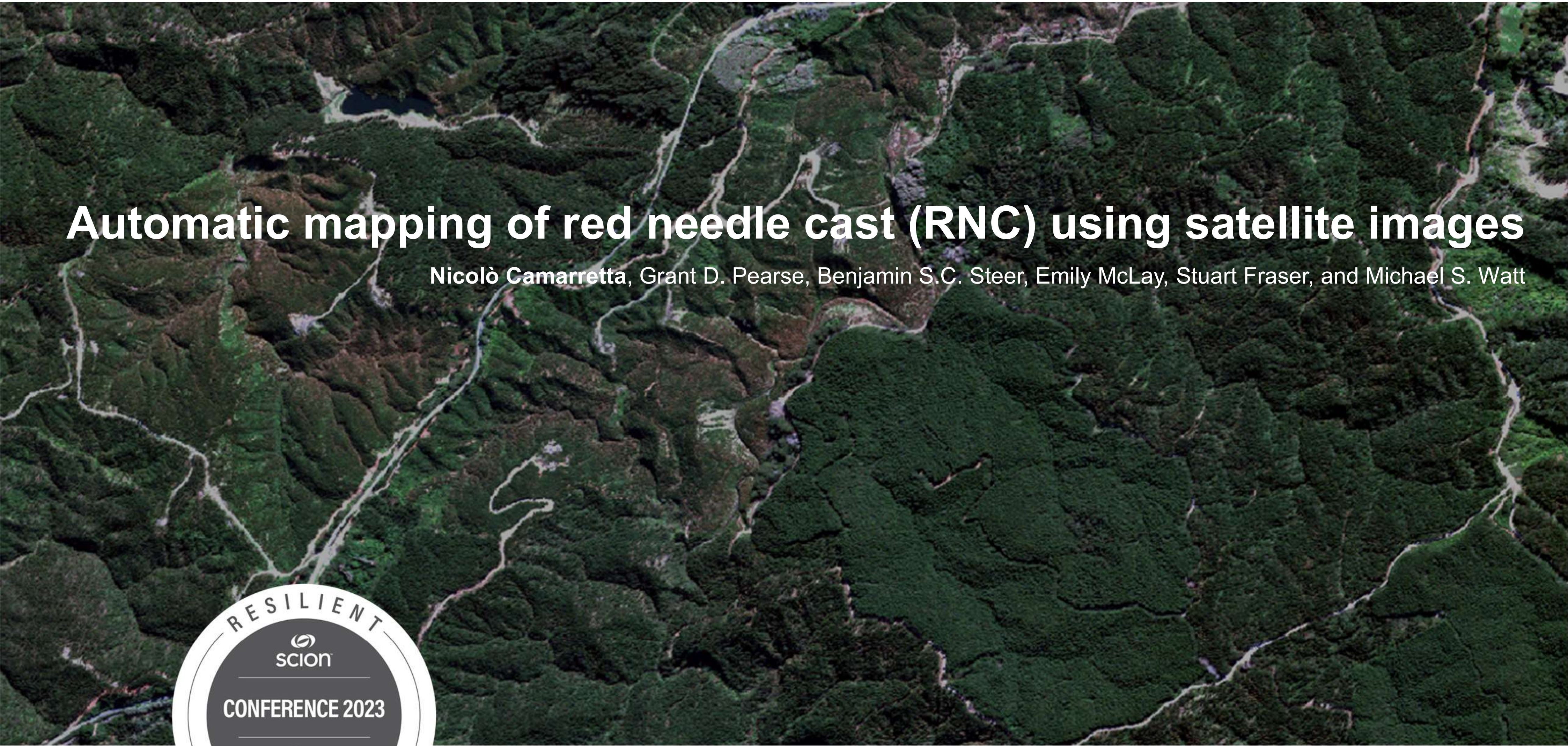

Automatic mapping of red needle cast (RNC) using satellite images

Nicolò Camarretta, Grant D. Pearse, Benjamin S.C. Steer, Emily McLay, Stuart Fraser, and Michael S. Watt

RESILIENT FORESTS
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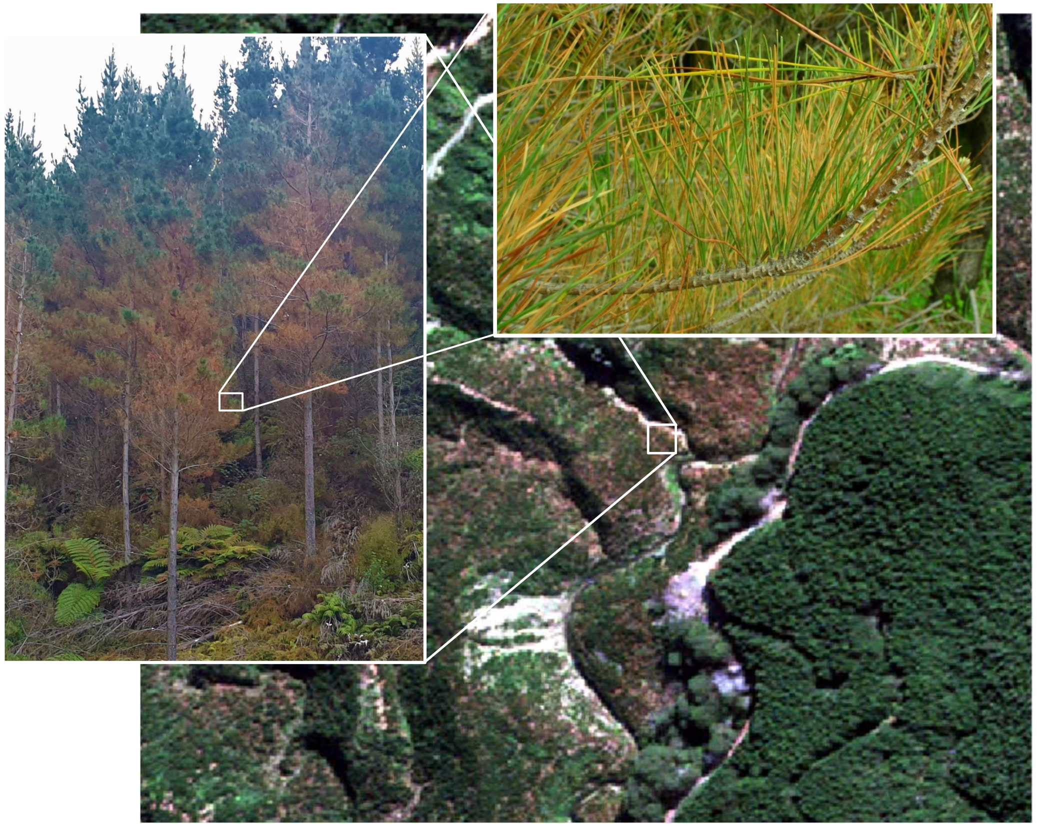
Importance of accurately mapping RNC

Up to 38% reduction in tree growth in the first season following severe defoliation.

Major concern for the New Zealand forest sector which is highly focused on radiata pine.

Traditional RNC observations are costly and limited in scale and spatially biases (road-side), limiting insights into spatial patterns and extent of the outbreaks.

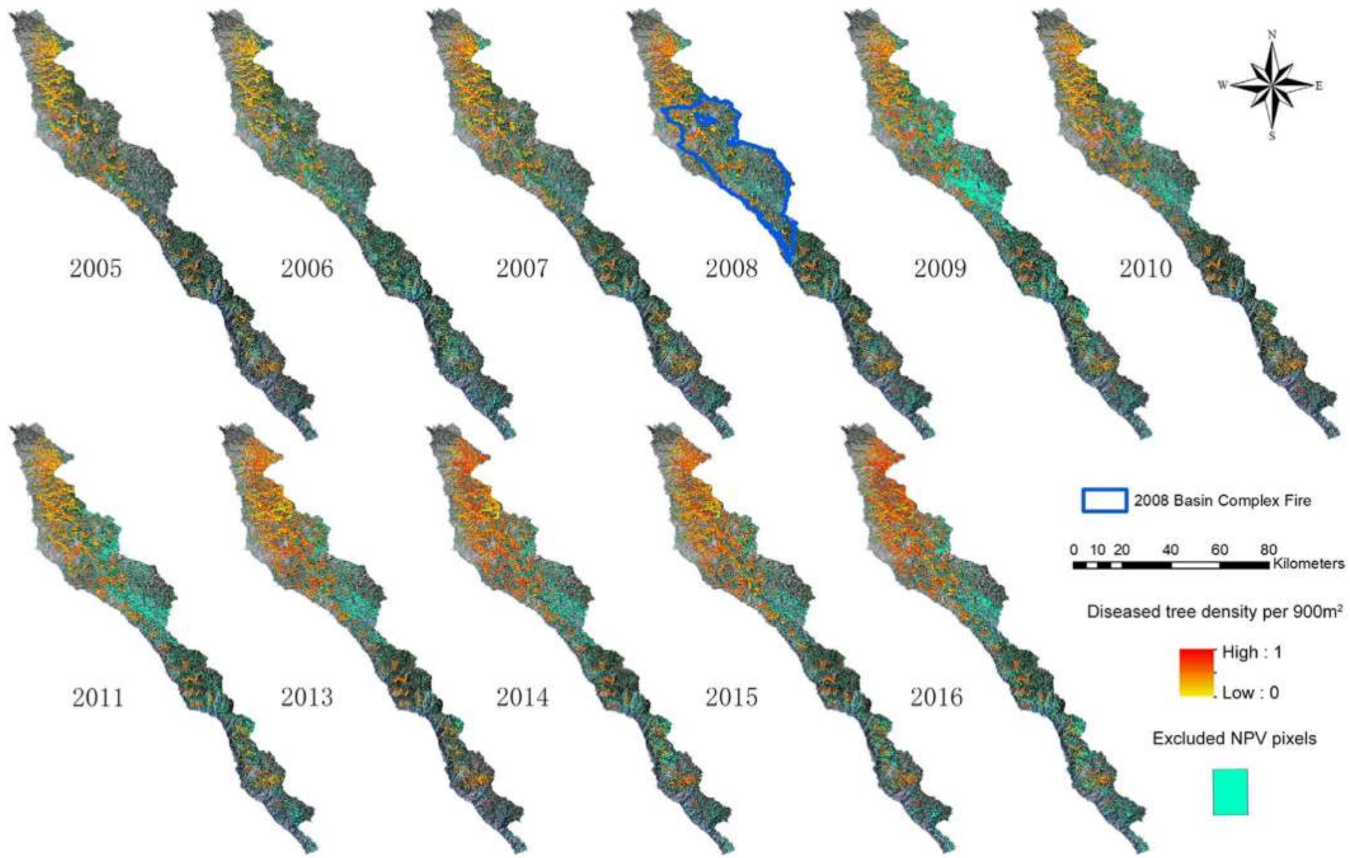
A more cost-effective approach would be to use remote sensing data to accurately and repeatably detect/map unhealthy pine forests.



RS monitoring of pest/pathogen outbreaks

Many studies have focused on bark beetle outbreaks in Europe and North America, while some researchers have used remote sensing techniques to detect different disease outbreaks in a range of host species, for example:

Mapping *Phytophthora ramorum* tree mortality in Californian Oak forests over 12 years using change detection (He et al., 2019).



He et al (2019) https://doi.org/10.1016/j.rse.2019.111238

RS monitoring of pest/pathogen outbreaks

Many studies have focused on bark beetle outbreaks in Europe and North America, while some researchers have used remote sensing techniques to detect different disease outbreaks in a range of host species, for example:

Detection of infected orchard pear (Bagheri 2020) and citrus trees (Deng et al 2020) using multi- and hyperspectral UAV data.

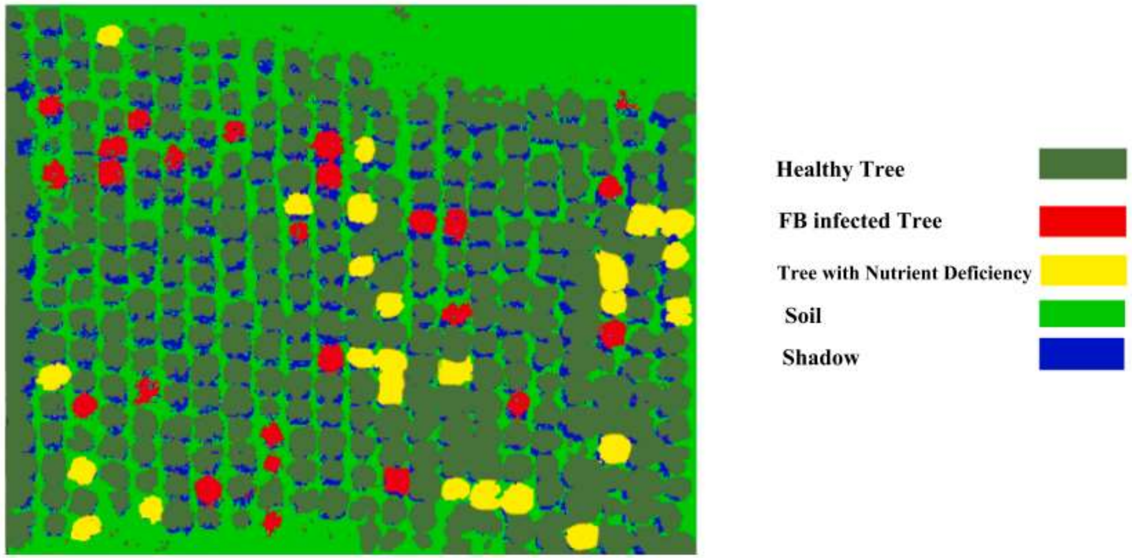


Fig. 4. The supervised classification map of the pear orchard.

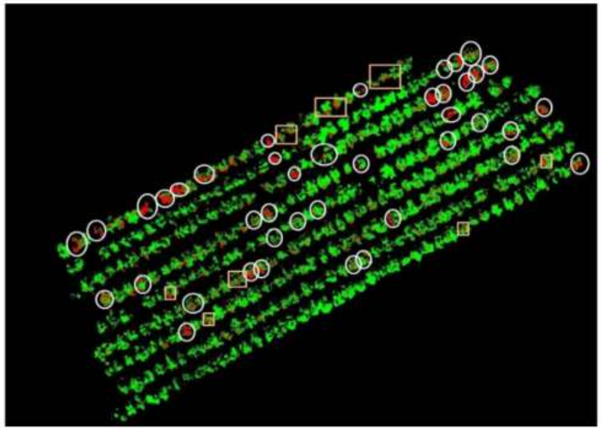
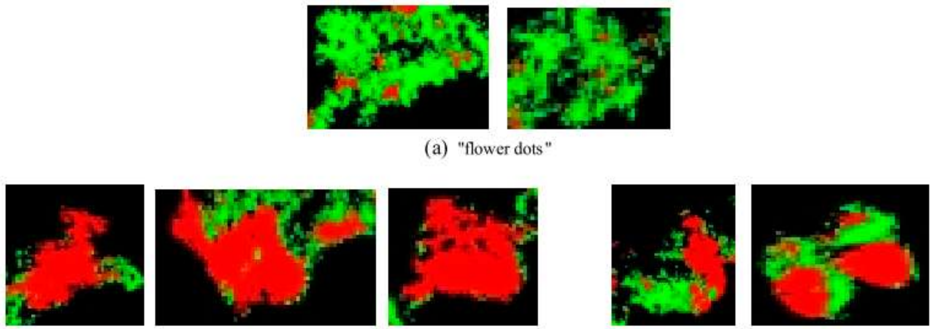


Figure 14. Testing results of the test area.



(b) Severe disease

(c) Disease distribution

Figure 15. Details of testing results of the citrus canopy.

Bagheri (2020) https://doi.org/10.1016/j.compag.2019.105147
Deng et al (2020) https://doi.org/10.3390/RS12172678

Study aims:

To develop and test a Machine Learning (ML) classifier to accurately map new imagery, reducing the need for manual labelling, to be employed in the Resilient Forest tip-and-queue approach.

Using a combination of labelled training data from several scenes our objectives were to:

(i) develop a model to map healthy / unhealthy pine forests using ML methods

(ii) test the model using a leave-one-scene-out (LOSO) approach to assess model performance on simulated independent data

Study area and data used:

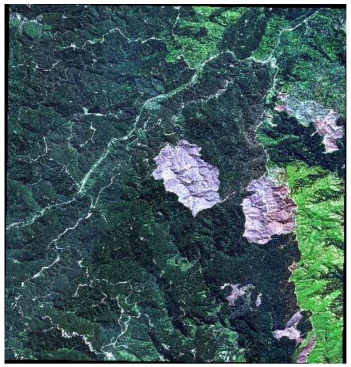
Study area and data used:

Wharerata 2018

2019

Tauwhareparae 2019

2020



2022

4 of the original 8 bands from WorldView were selected:
Blue, Green, Red and Near Infra Red (NIR1).

Pre-processing and training/test samples

Unhealthy pine forest affected by RNC
Healthy pine forest
Background (everything else)

2000 pixels per class were selected as training/test samples from each scene, using thresholds to identify pure pixels:

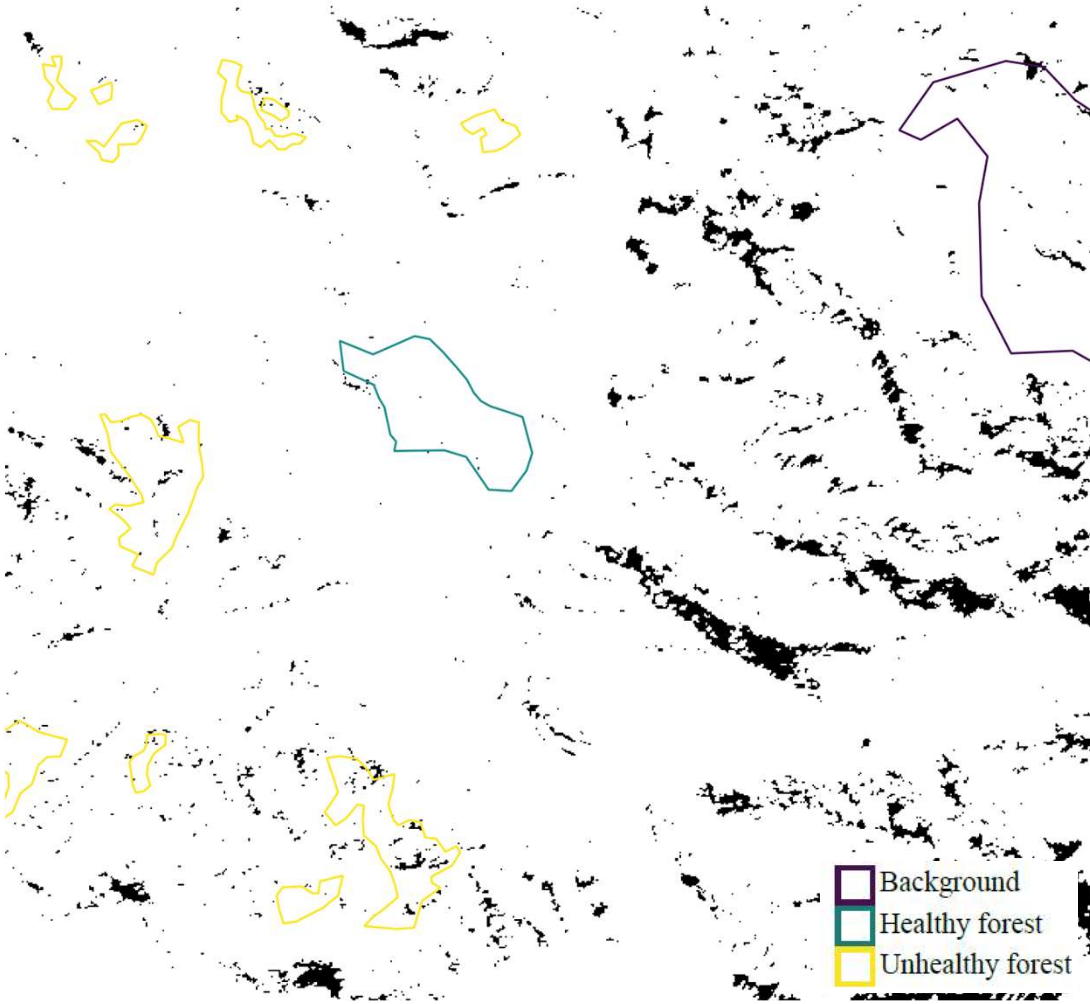
- NDVI > 0.7 within *Healthy pine forest*

- NDVI < 0.7 within *Unhealthy pine forest*

- NIR1 values < 20 removed as shadows

To allow transferability of the analysis, all pixel values from each scene were centred:

$$x_{centred} = \frac{(x - xmean)}{x_{sd}}$$

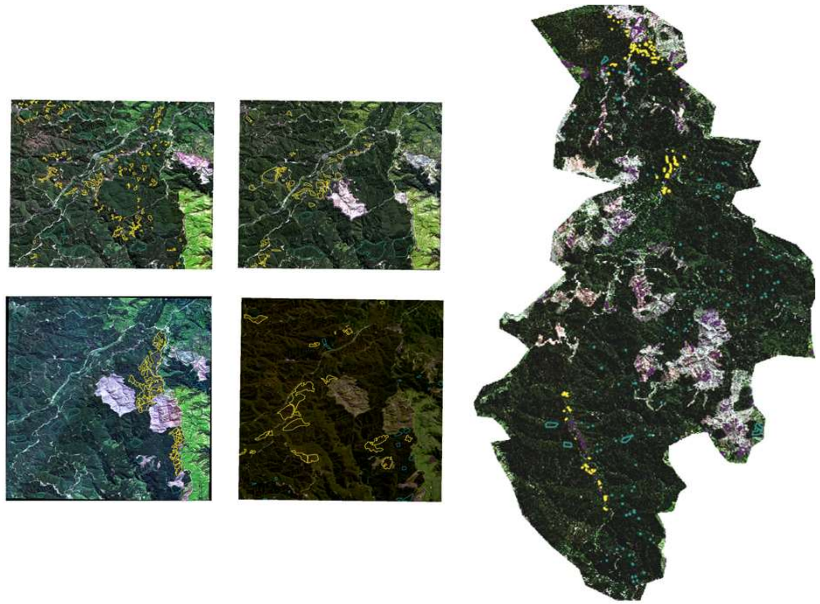


Random Forest Leave-Scene-One-Out (RF-LOSO)

A Random Forest (RF) algorithm was used to map the 3 classes using the training labelled dataset.

To assess the capability of RF models to classify newly acquired (completely independent) imagery, we run the RF model 5 times.

Each time training the model from data pooled together from 4 scenes (8K pixels per class).



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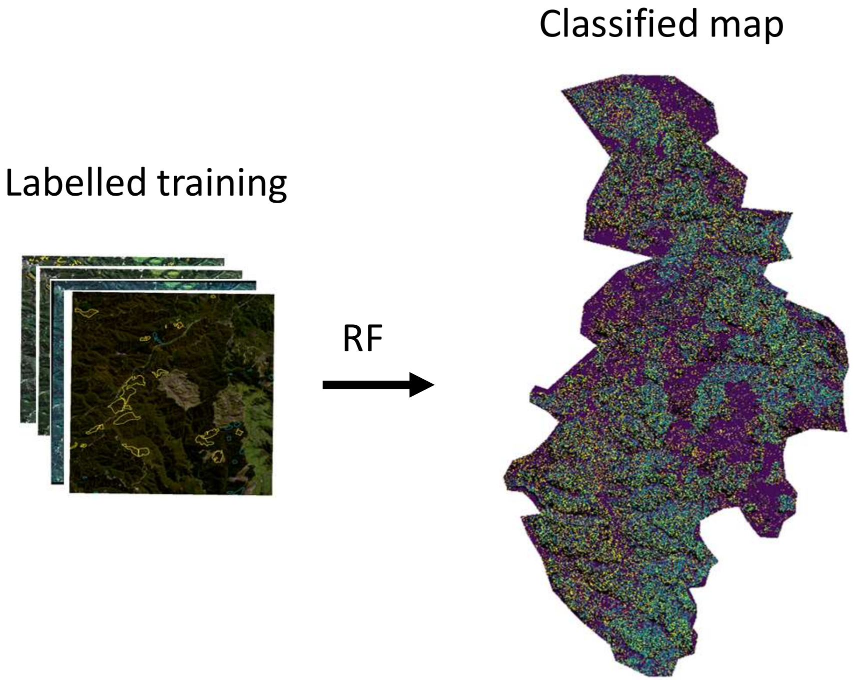
The trained models were then used to classify the withheld independent scene.

Accuracy metrics were used to quantify model performance (overall, user's and producer's accuracy).



RF-LOSO results (i)

RF-LOSO model	OA (%)	UA Unhealthy pine forest (%)	UA Healthy pine forest (%)	UA Background (%)	PA Unhealthy pine forest (%)	PA Healthy pine forest (%)	PA Background (%)
Wharerata 2018	91.1	87.8	91.2	95.3	97.2	95.1	81.2
Wharerata 2019	86.1	87.1	81.5	91.6	76.9	100.0	81.5
Wharerata 2020	76.3	90.0	99.0	60.2	71.9	62.3	94.7
Wharerata 2022	79.4	71.4	79.8	95.4	84.0	100.0	54.4
Tauwhareparae 2019	86.0	91.8	83.8	82.7	86.4	97.5	74.0
Mean	83.8	85.6	87.1	85.0	83.3	91.0	77.1

OA = overall accuracy; UA = user’s accuracy; PA = producer’s accuracy

RF-LOSO results (ii)

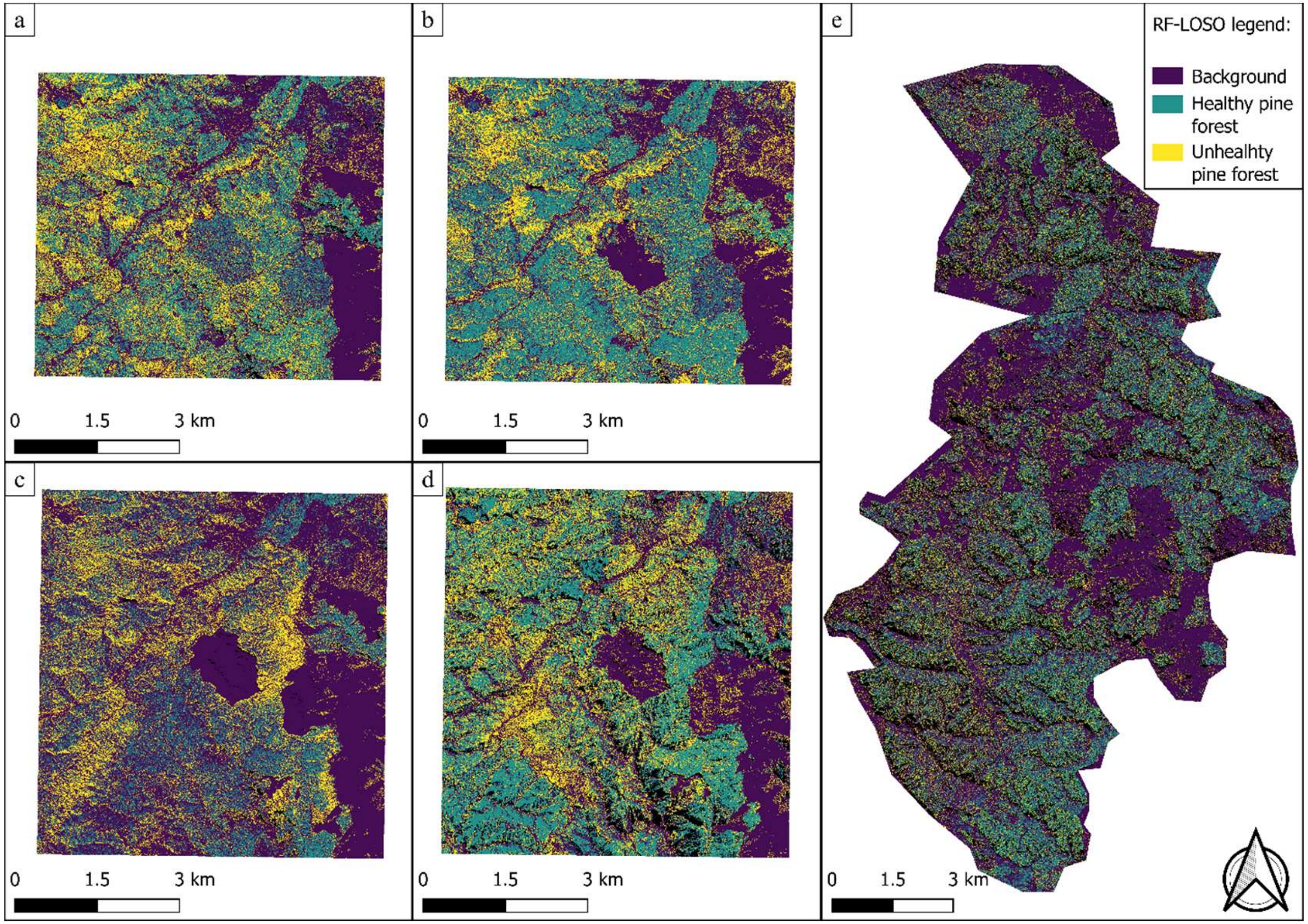
a) Wharerata 2018

b) Wharerata 2019

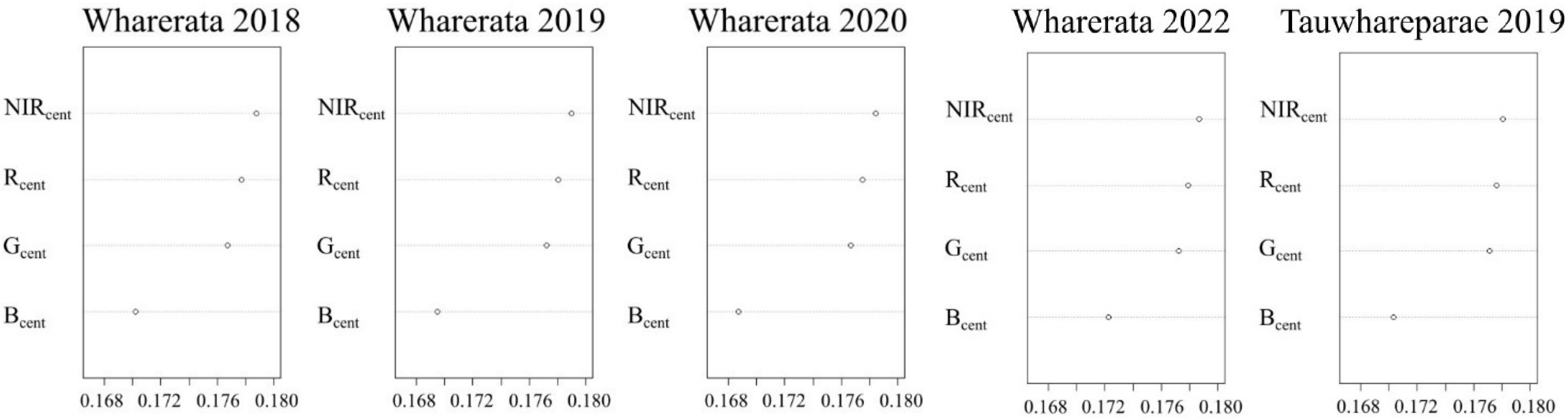
c) Wharerata 2020,

d) Wharerata 2022,

e) Tauwhareparae 2019



RF-LOSO results (iii)



Mean Decrease in Accuracy (MDA)

Discussion

The spectral properties of the *Unhealthy pine forest* are generally consistent across scenes and time steps. This allowed to distinguish *Unhealthy pine forest* from the other classes.

The NIR and Red bands were especially useful for separating the classes in all models.

The high-performance of the models suggested that a relatively simple product could produce a transferable model for the task of detecting disease expression caused by RNC outbreaks.

One noticeable issue was the occurrence of misclassified pixels (*e.g.,* background in forested parcels), that created a ‘salt and pepper’ effect in the final maps.

Conclusions

This approach offers great potential for repeatability to improve monitoring of forest health without the need for manual interpretation of all new high resolution imagery.

The mapped outbreaks will be provide ongoing ground truth for the constant improvement of predictive models, aiding in linking disease expression to local features (climate and landscape)

If implemented within the Resilient Forest tip-and-queue approach, predictions from this tool could be used to identify outbreaks of the disease in near-real time.

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