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# Technical Note

## Modelling and quantifying needle disease impacts

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**Summary:** This technote describes our proposed framework for quantifying needle disease impacts on tree productivity. We focus our research on red needle cast as a use-case for developing and testing our framework. Our proposed needle disease impact framework leverages off the disease severity prediction framework proposed in Research Aim 3.2.1 and established tree growth models for predicting disease severity and its associated impact on radiata pine plantations. The technote also captures plans to use remote sensing technology to scale quantifying impacts of needle disease from tree to estate level and summarises existing data that can be used to support this work.

### 1. Introduction

Understanding the impact of tree needle diseases on forest productivity will allow forest owners to make informed disease and operational management decisions.

The main objective of this work was to develop a modelling framework for quantifying impacts of needle disease severity on tree productivity. We focus our studies on RNC as an initial case study to help establish the modelling framework. Extension to other needle diseases can be done subsequently through incorporating relevant data on those needle diseases into the modelling process.

We discuss how the RNC disease severity modelling framework (Tan et al. 2020) proposed in Research Aim 3.2.1 (referred to as RA 3.2.1 framework) and physiological-based growth models such as CABALA (Battaglia, Sands, White, & Mummery, 2004) and 3PG (Landsberg & Waring, 1997) can be used to quantify impact of RNC on tree productivity in Section 2. We then outline a strategy to use remote sensing to scale the quantification of impact from tree to estate level in Section 3. In Section 4, we summarise

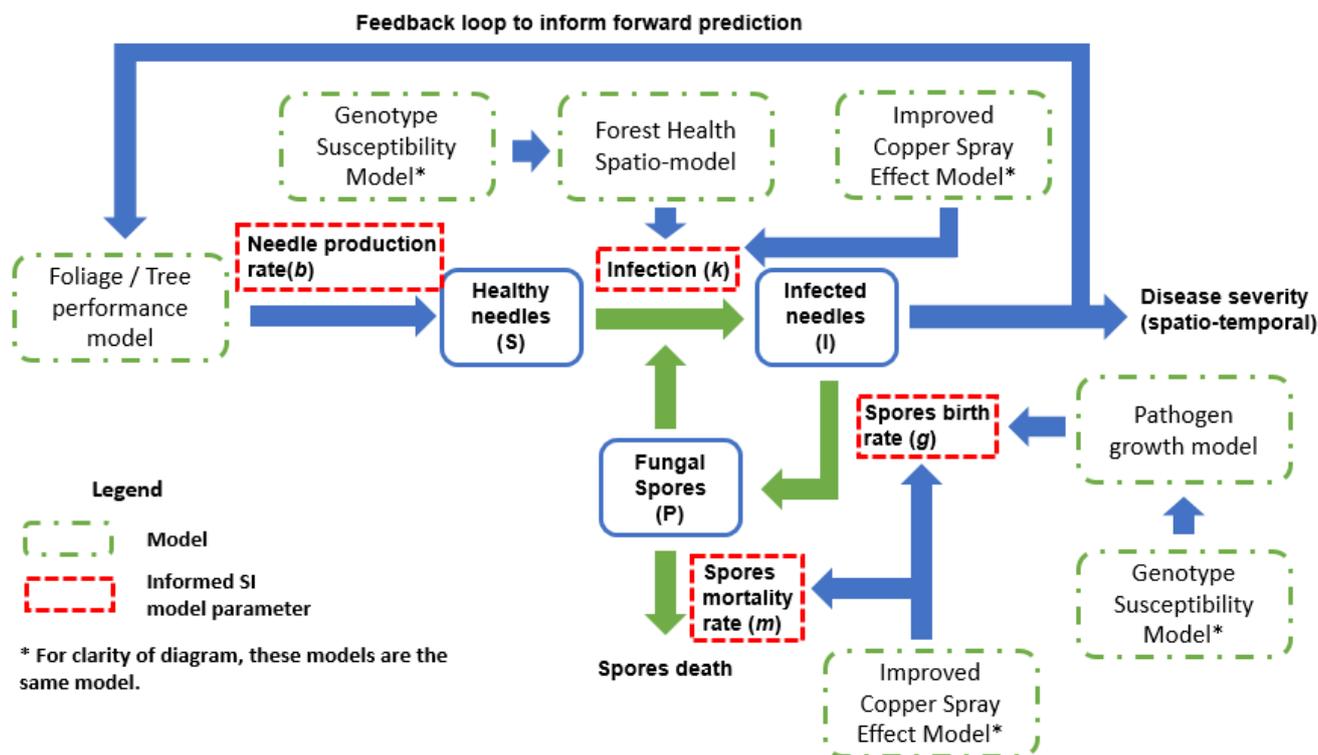
the data collated for the development of this framework and discuss potential gaps.

### 2. Quantifying needle disease impact

In the context of this research, we quantify impacts of RNC by relating changes in disease severity to changes in tree productivity (e.g. wood volume). We leverage the RA 3.2.1 framework for predicting how RNC disease severity changes according to factors such as tree genetics, climate, terrain and control treatments.

The RA 3.2.1 framework builds on a process-based RNC Susceptible-Infectious (RNC SI) model developed by Wake et al. (Wake, Williams, & Pleasants, 2018). Supported by a suite of models, developed using different field datasets, the RA 3.2.1 framework estimates various key parameters critical for modelling dynamics of RNC and to predict disease severity. The feedback loop in the RA 3.2.1 framework allows predicted results to be fed back for forward-time prediction of disease severity.

We extend RNC disease severity prediction to tree productivity by incorporating physiological-based



**Figure 1.** Overview of the RA 3.2.1 framework and how physiological-based growth models such as CABALA and 3PG can be integrated for predicting impacts of disease severity on tree productivity.

growth models into the RA 3.2.1 framework. Figure 1 illustrates how the RA 3.2.1 framework can be linked with physiological-based growth models for quantifying RNC impacts on tree productivity. The forcing of process-based models by the disease and defoliation rates calculated by the RNC model will be explored in RA 3.1.3B. The information link will help the growth model determine the photosynthetic capability and the evapotranspiration of the modelled trees, allowing the growth and wood quality responses to infection to be predicted.

Due to allometric laws governing tree growth, impact on tree growth may also affect tree foliage growth in future timesteps. As such, we feed back growth and allocation information, generated by the growth model, together with disease severity prediction for the current time-step to inform the next time-step prediction. This information will help the foliage performance model to determine the amount of new needles generated for the new cycle of infection to take place.

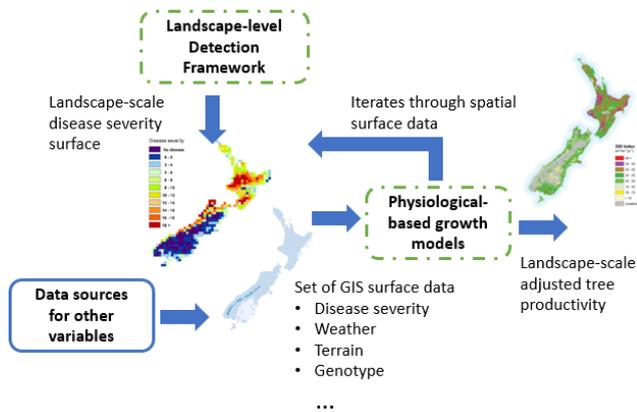
### 3. Scaling from tree to estate level

Models in the RA 3.2.1 framework will be developed using fine-grained data from localised trials and experiments, conducted from individual trees. This constrains the accuracy of the needle disease impact framework's predictions to the tree level. A dataset that captures different conditions and the respective disease severity expression is required to build a robust framework. However, manually gathering datasets from across large areas and diverse environments to build a representative dataset is challenging and expensive. This reduces the

applicability and real-world impact of the framework. We will explore how remote sensing technologies can be used to overcome these challenges.

Development of a landscape-level detection framework for large-scale disease detection and mapping using high-resolution satellite imagery was proposed in RA 3.1.1B. Data gathered from up to five sites for a virtual study (referred to as virtual trial sites) will be used for developing this landscape-level detection framework. At each site, spectral signals are first extracted from high-resolution satellite imagery. These signals are then analysed and used as a proxy for classifying and detecting areas with RNC at peak expression. Results will be field verified at the identified areas. Details of the data to be used are described in more detail in Section 4 and Appendix A.

The imagery and methods used in the virtual trial sites will also be applied to the sensor network trials proposed in RA 3.1.3A (Sellier et al., 2020). This provides an opportunity to calibrate in situ measurements of growth impacts and foliage dynamics using the collected high-resolution satellite imagery. The calibration will enable us to define the precision of our detection methods. For example, it is known reflectance-based methods are less sensitive than lidar for measuring foliage dynamics due to saturation of spectral indices at high LAI. However, no work has established the sensitivity of this approach in the context of monitoring disease affected forest areas. Investigating these limits will



**Figure 2.** Using the landscape-level detection framework to generate a landscape-scale RNC disease severity surface. Growth models adapted using the framework in Figure 1 can then be applied iteratively across the surface to generate tree productivity at landscape-scale. Map images taken from (Palmer et al., 2010; Watt, Palmer, & Bulman, 2011).

allow us to calibrate and understand the relationship between measured foliage dynamics and the metrics that can be derived from high-resolution spectral data.

### **Disease severity surface**

Scaling prediction of disease severity impacts on tree productivity will require disease severity information at landscape or estate scales. We will use the calibrated landscape-level detection framework to generate a landscape-scale RNC disease severity spatial surface. This GIS surface is then used to inform growth models calibrated by the framework shown in Figure 1. This pipeline is illustrated in Figure 2. This approach is similar to those used in the past for studying impacts of *Dothistroma* needle blight on radiata pine in New Zealand (Watt et al., 2011).

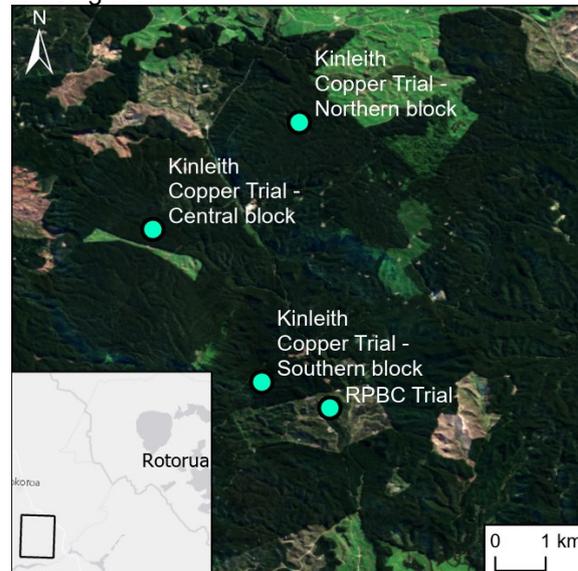
To generate the disease severity surface, data on disease severity is gathered from field observations and supplemented by the calibrated landscape-level detection framework at broader scale. RNC disease severity can be predicted using regression kriging techniques that are sensitive to bio-physical variables (supplied as surfaces) and are able to interpolate any residual variation through kriging.

The framework shown in Figure 1 allows us to adapt and calibrate growth models for adjusting predicted productivity according to RNC disease severity. Alongside the disease severity surface data, other variable information, such as climate and terrain, will be extracted and provided as input to the growth model in the format of GIS surfaces. This will allow the growth model to iterate through the surface data to generate a landscape-scale tree productivity map that accounts for disease severity.

## **4. Collating and Summarising Available Remote Sensing Datasets**

Quantifying needle disease impacts on individual trees will be supported by the sensor network trial proposed in RA3.1.3A (Sellier et al., 2020). This trial

is designed



**Figure 3.** Map of potential locations for the first sensor network. Candidate locations include existing copper spray trial sites and a breeding trial in Kinleith forest.

to monitor the growth impacts of foliar diseases through a network of sensors such as dendrometers and meteorological stations alongside in situ measurements and remote sensing (RS) datasets.

The first phase of the sensor network trial is proposed to be co-located with an existing experimental trial, which aims to quantify the growth impacts of RNC by controlling the disease with copper fungicide (Figure 3)(Fraser, Tieman, Baker, & Rolando, 2019). RS data are already routinely captured for the experimental trial and co-location would create efficiencies in data collection.

The RS data and methods proposed enables the development of the landscape-level detection framework for detection and assessment of diseases at larger scales (Appendix B). RS data in the form of high-resolution satellite imagery are also intended to provide information on disease severity across a broader range of landscapes using a virtual trial series based on RS detections, combined with targeted ground verification, during peak disease expression. The remainder of this section outlines the currently held and planned datasets for the RA 3.1.3A sensor network trial and the link to the landscape-level detection framework (Appendix B).

### **High-density aerial and terrestrial lidar**

The sensor network trial includes provision for repeated capture of high-density lidar (Appendix A). These data will be used to characterise the vertical and horizontal distribution of needle mass in both the treatment and control trees as well as foliage dynamics across years. This information will help inform the foliage performance model in Figure 1.

Characterisation of needle mass distribution will be achieved by computing leaf area density (LAD) and then deriving leaf area index (LAI) for trees within the trial. High-density lidar has emerged as the benchmark method for determining both attributes (Béland, Baldocchi, Widlowski, Fournier, &

Verstraete, 2014). This process is complex and requires calibration using hemispherical imagery and validation using measurements of foliage loss from litter traps. Applying the same methods and calibration coefficients to co-incident, lower-density airborne lidar (Appendix A) will allow us to evaluate how accurately LAD and LAI can be scaled to the estate level. Previous work in radiata pine suggests these attributes can be reliably estimated from these data (Beets et al., 2011; Pearse, Morgenroth, Watt, & Dash, 2017). The use of lidar also allows us to estimate tree height, volume and Site Index. These metrics provide indirect measurements of the impact of needle diseases on growth when combined with historical data sources such as plot records and spatially-explicit maps of disease incidence over time.

### **Multi-spectral UAV imagery**

The sensor network trial will be located within a larger trial site where Scion has already acquired high-resolution multi-spectral data (Appendix A). During the first phase of the trial, we aim to increase the frequency and resolution of the RS data collected up to a target of five captures per year. This imagery will assist with scoring disease impact on the upper portion of the canopy as well as allowing us to link observed foliage dynamics to changes in vegetation indices calculated from the multi-spectral imagery at the tree and plot level. These data can then be linked to the impacts observed in the coarser resolution but larger-scale satellite imagery.

### **Oblique UAV imagery**

Scoring disease severity in mature trials is difficult due to limited visibility of the crown from below. Linking high-magnification oblique imagery with precise geolocations will enhance scoring of individual trees within trials. This method has been tested within the copper spray trials (Appendix A) and, where practical, we may extend this approach to assist with tree-level scoring within the sensor network trial plots or as tools to assist in verifying disease outbreaks in the virtual trial series.

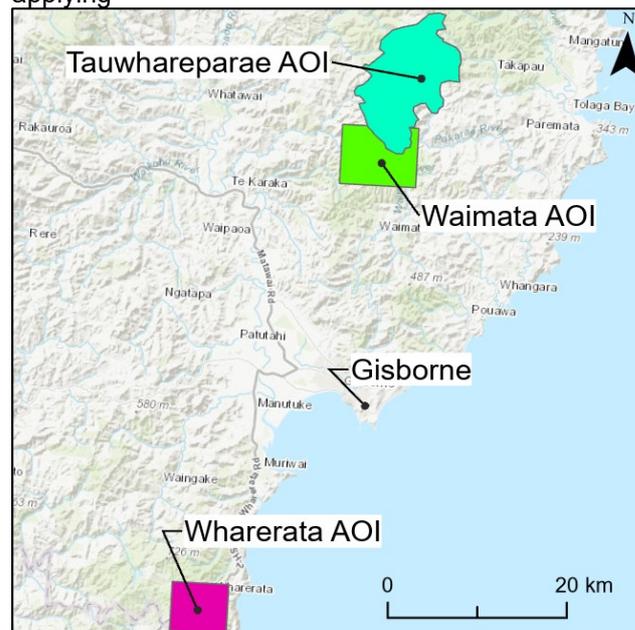
### **Hyperspectral data**

Scion has an active hyperspectral research programme and capability to capture visible and near infra-red (VNIR) and shortwave infra-red (SWIR) hyperspectral imagery from an unmanned aerial vehicle (UAV). Experiments carried out in a pot trial have validated detection of nutrient and water stress and these methods will be scaled to young trials as part of the Resilient Forests programme (Watt et al., 2020). Success in these experimental methods will see them integrated into the sensor network trial to provide estimates of nutrient and health status at individual tree level.

### **Remote sensing data for virtual trial series**

Earlier efforts in building predictive models showed it is challenging to acquire diversity in data and easy to miss localised neighbouring outbreaks when using a

ground-based sampling approach at fixed locations. The virtual trial series aims to address this by applying



**Figure 4.** Location of satellite data acquired for development of virtual trial series. Additional locations will be added after validation of the method.

methods to detect RNC at landscape-scale. The trial will include sites with ground verifications, gradients of disease expression and varying site conditions.

### **High-resolution satellite imagery**

RA 3.1.1B lays the groundwork for implementing the landscape-level detection framework, a new approach to monitoring using satellite-based detection to guide ground-based sampling. The outputs from this approach will enable moderate-to-severe RNC outbreaks to be mapped annually at larger scales. Existing high-resolution imagery (Appendix A & Figure 4) will be expanded to cover up to five sites. At present, two of these sites are planned for the East Coast.

If found to be practical and cost effective, a second sensor network is planned for deployment within one of the areas shown in Figure 4. This will provide additional data to link the tree/stand-level impacts observed in the sensor network to stand and estate-level impacts.

### **Regional aerial lidar**

The implementation of the new trials will coincide with regional lidar captures in many of the planned locations (Appendix A). At the lowest pulse densities expected (4 pulses m<sup>-2</sup>) these datasets will still allow us to extract fine-grained terrain attributes as well as a snapshot of stand characteristics such as height, biomass/volume and stocking across the trial sites. Previous work has also shown that, with calibration, the pulse densities of these captures may provide a snapshot of LAI (Pearse et al., 2017). Combining these layers with climate data and the multi-temporal patterns of disease expression from satellite observations will enable better understanding of drivers of RNC and provide additional data for

predictive models described in Section 3 above. Where available, integration of genetic data at the stand level will provide additional data on susceptibility for genetic improvement programmes.

## **5. Conclusions**

In this report, we describe our proposed framework for quantifying the impacts of tree needle diseases, such as red needle cast (RNC), on *Pinus radiata* D. Don plantations in New Zealand and how remote sensing may be integrated to inform and scale impact estimates from tree to estate level.

The modelling framework presented represents the unification of several streams of work planned for the Resilient Forest programme and research undertaken at Scion. The implementation of the needle disease impact framework will be supported by deployment of new trial series such as the sensor network alongside existing trials monitored by Scion.

There is scope to both enhance and expand the framework by integrating remote sensing datasets. Integrating remote sensing data will offer advantages such as increased extent of monitoring and ability to scale results to the estate/landscape level. In addition, remote sensing can also help build multi-temporal view of disease severity by analysing satellite imagery retrospectively. Having a temporal view of how disease severity changes across time will benefit the development of more robust disease severity models and a disease spread prediction model.

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## Appendix A – Available remote sensing datasets

Collating available remote sensing data for priority trial sites to inform modelling framework. Locations for the Foliar Pathogen Trial are shortlisted

<b>Kinleith Copper Trial – 3 sites containing block design copper spray trial</b>			
<b>Data</b>	<b>Description</b>	<b>Date and coverage</b>	<b>Outcome</b>
<b>Existing Datasets</b>			
High-resolution multispectral imagery	5-cm GSD NIRGB aerial imagery	October 2018 – 1 site October 2019 – 3 sites (full trial)	Imagery, reflectance maps and vegetation indices for tree and plot-level scoring
UAV full-motion video datasets	High-definition oblique RGB video scoring individual trees	September 2018 – 1 block test	Test improved scoring at the single tree level through improved views of the canopy profile
Aerial lidar	4 pulses m <sup>-2</sup>	October 2019 – 3 sites (full trial)	Digital terrain and surface models (DTM, DSM)
<b>New Datasets</b>			
High-resolution multispectral imagery	<5 cm NIRGB imagery from aircraft or UAV	Minimum of 1 capture per year timed for disease peak – 1 site	Annual scoring of disease severity in treatment blocks. Seasonal capture for foliar health assessment to align with new sensor network trial
<b>Foliar Pathogen Sensor Network Trial – Proposed Kinleith Site</b>			
<b>Existing Datasets</b>			
High-resolution imagery and low-density lidar as per Kinleith copper trial above.			
<b>New Datasets</b>			
High-resolution multispectral imagery	<5 cm NIRGB imagery from aircraft or UAV	1 x annual capture under existing copper trial + 3 seasonal captures.	Seasonal dynamics of foliage development and pathogen impacts
High-resolution satellite imagery	< 50 cm pan-sharpened multispectral imagery	Spatially and temporally co-incident acquisition for calibrate and validate – 2-3 sites	Calibrate satellite-derived metrics with severity data from trials
UAV lidar	>2500 pulses m <sup>-2</sup>	Annual – 3 sites (full trial)	Canopy metrics, height, LAI, LAD
Terrestrial lidar	>2500 pulses m <sup>-2</sup>	Annual – 3 sites (full trial)	Below-canopy stem map and calculation of LAD
Hyperspectral	VNIR	Tentative – pending upgraded craft range and test in young-trials	Proxy metrics for nutrient status and pathogen impact detection

## Foliar Pathogen Sensor Network Trial – Proposed RPBC Kinleith Site

### Existing Datasets

High-resolution multispectral imagery	2-cm GSD RE+NIRGB UAV imagery	September 2019 – 1 site (full trial)	Imagery, reflectance maps and vegetation indices for tree and plot-level scoring.
High-density lidar	>4000 pulses m <sup>-2</sup> UAV lidar	September 2019 – 1 site (full trial)	DTM, DSM, canopy metrics, height, LAI, LAD

### New Datasets

High-resolution multispectral imagery	<5 cm NIRGB imagery from aircraft or UAV	4 seasonal captures.	Seasonal dynamics of foliage development and pathogen impacts
High-resolution satellite imagery	< 50 cm pan-sharpened multispectral imagery	Spatially and temporally co-incident acquisition for calibrate and validate – 2-3 sites	Calibrate satellite-derived metrics with severity data from trials
UAV lidar	>2500 pulses m <sup>-2</sup>	Annual – 1 site (full trial)	Canopy metrics, height, LAI, LAD
Terrestrial lidar	>2500 pulses m <sup>-2</sup>	Annual – 1 site (full trial)	Below-canopy stem map and calculation of LAD
Hyperspectral	VNIR	Tentative – pending upgraded craft range and test in young-trials	Proxy metrics for nutrient status and pathogen impact detection

## Foliar Pathogen Sensor Network Trial – Proposed East Coast Site (Wharerata or Tauwhareparaē)

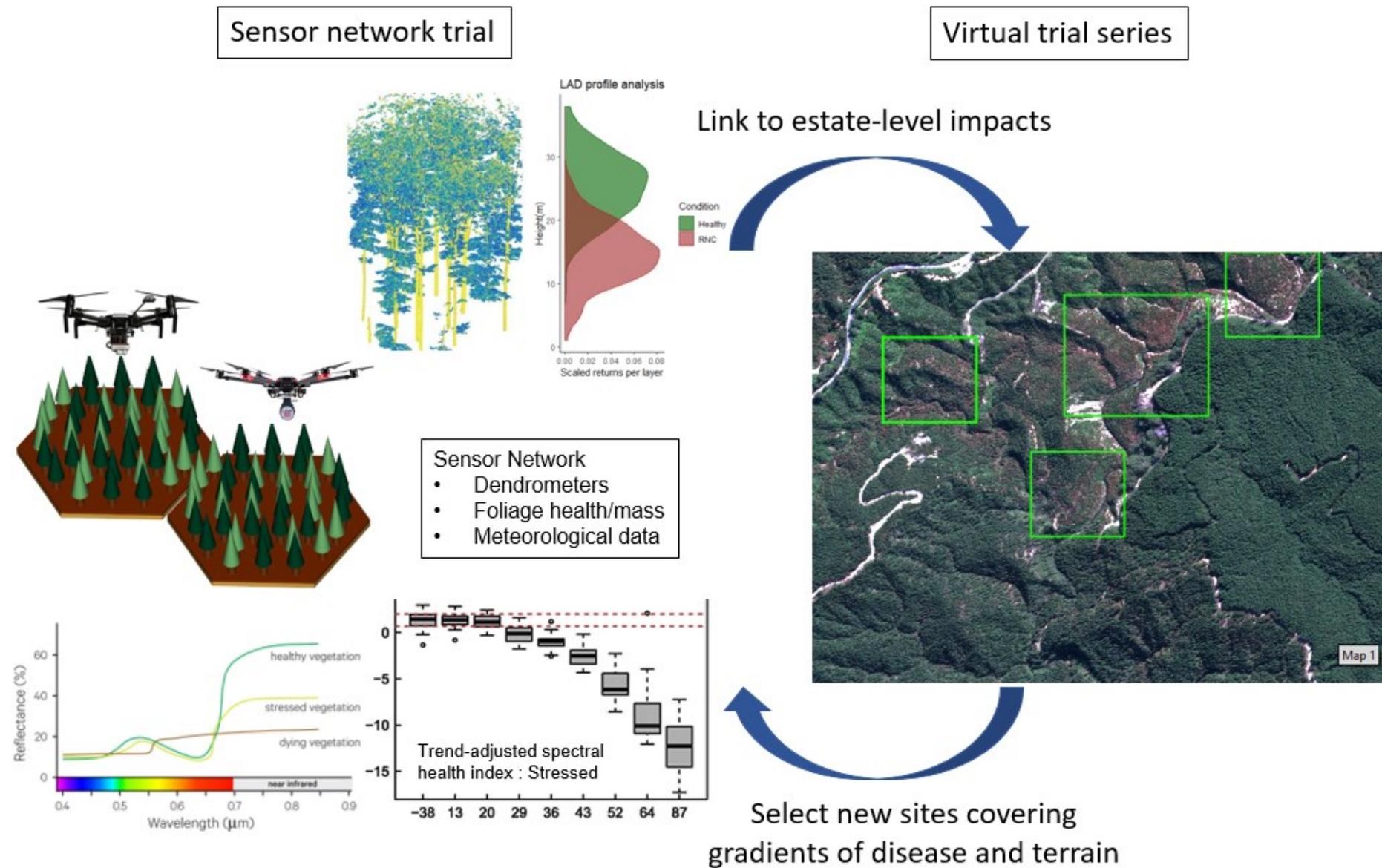
### Existing Data

High-resolution satellite imagery	<50 cm pan-sharpened multispectral imagery	September – November 2018 / 2019	Disease outbreaks mapped at two locations
Aerial LiDAR	>4 pulses m <sup>-2</sup> GDC regional capture	Summer 2018 / 2019	DTM, DSM, canopy metrics, height

### New Datasets

High-resolution multispectral imagery	<5 cm NIRGB imagery from aircraft or UAV	4 seasonal captures.	Seasonal dynamics of foliage development and pathogen impacts
High-resolution satellite imagery	< 50 cm pan-sharpened multispectral imagery	Spatially and temporally co-incident acquisition for calibrate and validate – 2-3 sites	Calibrate satellite-derived metrics with severity data from trials
UAV lidar	>2500 pulses m <sup>-2</sup>	Annual – 1 site (full trial)	Canopy metrics, height, LAI, LAD
Terrestrial lidar	>2500 pulses m <sup>-2</sup>	Annual – 1 site (full trial)	Below-canopy stem map and calculation of LAD
Hyperspectral	VNIR	Tentative – pending test in younger trials	Proxy metrics for nutrient status and pathogen impact detection

## Appendix B – Informing the Landscape-level Detection Framework using the Sensor Network Trial Data



Conceptual link between trial sites. Intensive measurements at the sensor network trial location inform quantification of the impacts observed in one of the large-scale 'virtual trial' series established under RA3. The results from the initial virtual trial study will inform deployment of future sensor network trials. Time-series imagery informs study of annual disease expression patterns

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