Spatially-informed Chickpea Phytophthora Root Rot Management

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PROJECT OVERVIEW

Phytophthora root rot (PRR) develops in irregular patches, complicating estimates of affected area and yield impact. This AAGI R&D project with NSW DPIRD and Outlook Ag combines spatial crop patterns and field evidence to improve the affected-area input to an existing decision support tool. The opportunity grew from embedded analytical support through Leni Campbell-Clause's role as lead biometrician for the GRDC Soilborne Disease Initiative (SBDI), Program 3: Service and Support. This helped establish the research collaboration.

Find unusual crop patches → **Interpret with field evidence** → **Estimate likely affected area**

1 | Why affected area matters

NSW DPIRD has previously developed a decision-support tool to help chickpea growers and advisors estimate yield and income losses associated with PRR [2]. However, the tool relies on users estimating the proportion of the paddock affected by PRR. This can be difficult, as waterlogging and other stresses can produce similar symptoms, while PRR inoculum may be present without visible disease [1].

Research question: can spatial and temporal patterns in crop anomalies, provide a more objective estimate of likely PRR-affected area?

2 | Establishing the ground truth

In 2026, changes in the normalised difference vegetation index (NDVI), an indicator of canopy greenness, between two dates (early- and later-season) were used to identify variation in crop development. These changes were combined with historical yield productivity, RGBI and elevation to guide conditioned Latin hypercube sampling (cLHC) [3].

Sampling locations were selected to capture variation across the four spatial characteristics. Soil and epicotyl samples were collected for PREDICTA® B Northern Research Panel testing, alongside plant phenotyping to assess crop performance and PRR disease expression at each location.

Together, these data will provide a ground-truth for exploratory analysis and subsequent model development. Given the limited number of paddocks, initial modelling will focus on investigating relationships between spatial characteristics and disease observations.

3 | The 2026 sampling-design inputs

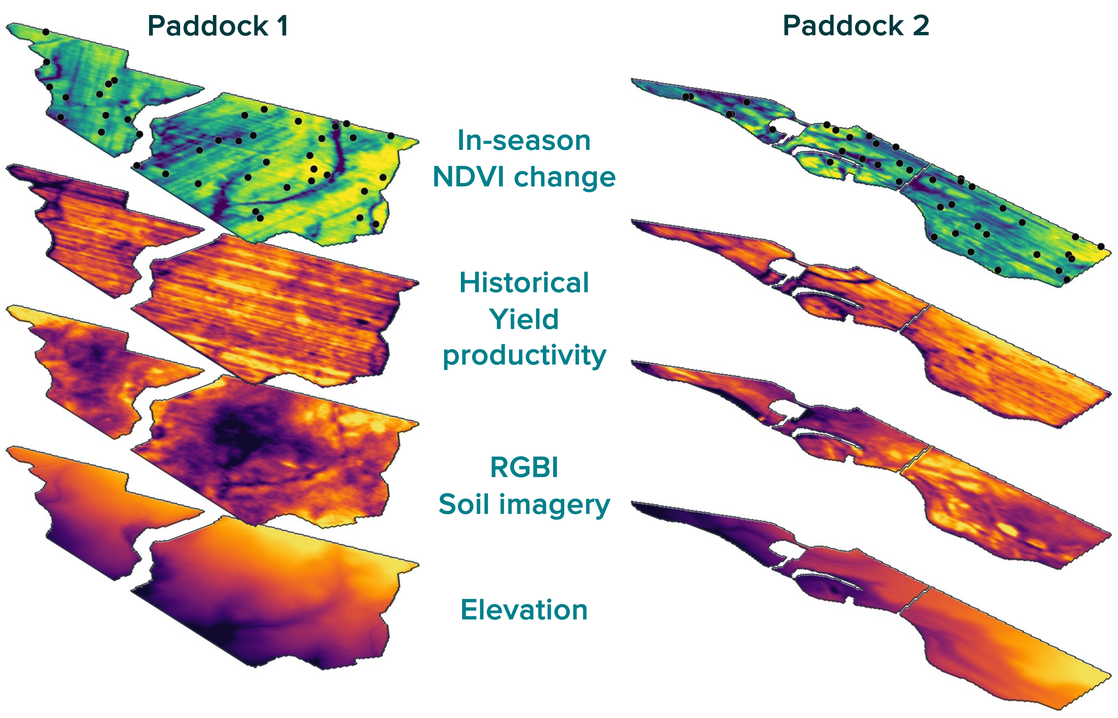


FIGURE 1. CONDITIONED LATIN HYPERCUBE SAMPLING (cLHC) DESIGN ACROSS TWO CHICKPEA PADDOCKS

Four spatial layers used to select 40 locations per paddock: NDVI change (early to late season), historical yield productivity, RGBI soil imagery and elevation. Black points indicate the 80 sampling locations selected to capture variation across these layers.

COMPLETED 2026 sampling design and collection
UNDERWAY Diagnostics, field-data linkage and anomaly-method development

4 | Detecting and interpreting crop anomalies

DETECT UNUSUAL CROP DEVELOPMENT

A two-date NDVI change map can identify variation in crop development but cannot capture the timing, duration or recovery of anomalous areas. Within-season Sentinel-2 NDVI and other remotely sensed observations will be used to identify and track these anomalies over time, with rainfall, crop history and existing spatial layers providing additional context.

CHARACTERISE PATTERNS IN TIME AND SPACE

Detected anomalies will be characterised by their timing, magnitude, duration, recovery and spatial extent. Generalised additive models (GAMs) may describe expected seasonal growth patterns [4], while segmented regression or BFAST could identify changes in crop trajectories [5, 6]. Unsupervised clustering will be explored to group anomalies with similar spatial and temporal characteristics [7], supported by patch metrics [9]. Hidden Markov models may also be considered to describe transitions between growth, decline and recovery [8].

INTERPRET PATCHES USING FIELD EVIDENCE

PREDICTA® B results, disease ratings and field observations will help determine which anomaly patterns are associated with PRR. Regularised logistic regression will be explored to identify relationships between spatial characteristics and pathogen detection [10]. Spatial GLMs or geostatistical approaches may account for spatial dependence between observations [11], with model complexity guided by the available data.

Identifying unusual crop development does not necessarily indicate PRR. Linking spatial and temporal anomalies with diagnostic and field evidence is essential before estimating PRR-affected area.

5 | Validation and intended outcomes

1 | VALIDATE THE ANOMALY FRAMEWORK IN 2027

Independent sampling in new paddocks will evaluate anomaly classifications and guide model refinement.

2 | MAP PRR PROBABILITY AND AFFECTED AREA

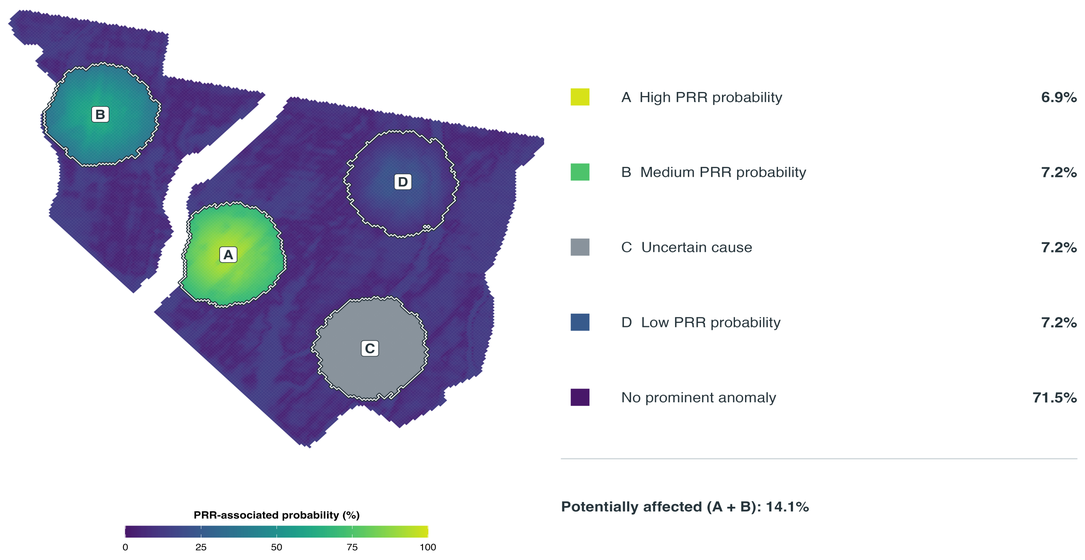


FIGURE 2. PROPOSED SPATIAL PRR MAPPING OUTPUT

Simulated illustration showing how in-season anomalies could be linked to PRR-associated probability and translated into estimates of affected paddock area.

3 | ECONOMIC DECISION SUPPORT

Validated area + uncertainty → **Existing rainfall-based yield-loss tool [2]** → **Assess harvest viability**

6 | References

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