

Article

Predicting Future Forest Plantation Establishment Outcomes from UAV-Derived Pre-Planting Environmental Conditions

Anthony Finn ^{1,*} , Phillip S. M. Skelton ¹ , Jim O'Hehir ¹, Des Schebella ¹, Neil Winkley ¹ and Braden Jenkin ²

¹ Forestry Centre of Excellence, Adelaide University, Mount Gambier, SA 5290, Australia; phil.skelton@adelaide.edu.au (P.S.M.S.)

² Sylva Systems, Warragul, VIC 3820, Australia

* Correspondence: anthony.finn@adelaide.edu.au; Tel.: +61-404-856-989

Highlights

This study demonstrates how pre-planting UAV-derived environmental information can predict future plantation establishment and support operational precision forestry decision-making, achieving the following:

- Developed a pre-planting UAV framework that predicts plantation establishment approximately 21 months before assessment;
- Generated spatially explicit establishment-risk maps for operational decision support;
- Integrated predictive modelling with treatment scenario analysis before plantation establishment;
- Developed a robust Establishment Index combining stocking density and early growth;
- Provided a scalable precision forestry workflow for plantation planning and management.

Abstract

Predicting plantation establishment-failure prior to planting remains a major operational challenge due to the strong spatial variability in post-harvest environmental conditions. This study developed a spatially explicit modelling framework that integrated pre-planting unmanned aerial vehicle (UAV)-derived environmental, structural, terrain, and operational-treatment data to predict establishment risk across plantation landscapes. Environmental, terrain, vegetation, and structural predictors were derived from pre-planting multispectral UAV imagery, while plantation establishment outcomes were quantified approximately 21 months later using an automated tree-detection and assessment framework. The datasets were integrated within a ridge-regularised logistic regression model incorporating interaction terms, multi-scale predictors, operational treatment masks, and blocked spatial cross-validation. The model achieved strong predictive performance under within-site blocked spatial cross-validation, with moisture-related variables, vegetation condition, and structural metrics contributing most strongly to establishment-failure prediction. Predicted risk surfaces closely matched observed patterns of reduced stocking density and suppressed growth. Beyond predicting establishment-failure, the framework enables plantation managers to screen model-predicted outcomes under alternative treatment encodings before planting and to integrate the composite stocking-density and height response within a spatially explicit Establishment Index. The framework therefore demonstrates that future plantation establishment can be predicted from environmental conditions measured before planting and provides a scalable pathway for translating high-resolution UAV data into operational decision support.



Academic Editor: Eric Casella

Received: 18 June 2026

Revised: 23 July 2026

Accepted: 4 August 2026

Published: 7 August 2026

Copyright: © 2026 by the authors.

Licensee MDPI, Basel, Switzerland.

This article is an open access article distributed under the terms and

conditions of the [Creative Commons](https://creativecommons.org/licenses/by/4.0/)

[Attribution \(CC BY\)](https://creativecommons.org/licenses/by/4.0/) license.

Keywords: forestry plantation establishment; UAV remote sensing; spatial modelling; precision forestry; residue management; risk mapping; multispectral imagery

1. Introduction

Successful plantation establishment is fundamental to sustaining and increasing forest productivity, operational efficiency, and long-term ecosystem function within managed plantation systems. Once seedlings have been planted, opportunities for correcting poor microsite conditions are limited and often expensive. Consequently, the ability to identify establishment risk before planting offers considerable operational value. Early establishment-failure can reduce stand productivity, increase replanting costs, delay rotations, and create persistent spatial variability in stand structure and yield [1–3]. Thus, understanding and predicting the factors that influence establishment success remains a major challenge in plantation forestry.

Plantation establishment outcomes are influenced by complex interactions among environmental conditions, operational practices, and microsite variability [4–17]. Factors such as soil moisture availability, terrain position, residue distribution, vegetation competition, and site preparation practices can vary substantially over short spatial distances, producing heterogeneous establishment outcomes across plantation landscapes [18–31]. This fine-scale variability is often difficult to characterise using conventional field inventories or coarse-resolution satellite imagery.

Recent advances in UAV remote sensing provide new opportunities to quantify environmental heterogeneity at operationally relevant spatial scales. UAV-based photogrammetry and multispectral imaging can generate high-resolution orthomosaics, terrain models, vegetation indices, and structural metrics capable of characterising microsite conditions associated with plantation establishment processes. While UAV remote sensing has been widely applied to inventory estimation, canopy assessment, and operational monitoring, comparatively few studies in forestry have attempted to predict future plantation performance from environmental conditions measured before planting [32–37].

A key challenge is whether plantation establishment outcomes can be predicted prior to planting so that site preparation, residue management, and operational treatments can be adjusted proactively. Such predictive capability would provide substantial benefits for precision forestry by enabling targeted intervention and risk-based management. However, robust prediction also requires careful treatment of spatial autocorrelation because neighbouring observations within raster datasets are rarely independent. Spatially blocked validation approaches have therefore been recommended to provide realistic estimates of predictive performance in ecological applications [38–40].

This study developed a high-precision spatially explicit predictive modelling framework for plantation establishment-failure using environmental, structural, terrain, and operational information derived from pre-planting UAV remote sensing. High-resolution RGB and multispectral imagery were used to derive vegetation indices, drought metrics, terrain attributes, structural texture measures, and operational treatment layers, while post-planting establishment outcomes were quantified using the Program for Identifying Nursery Trees (PINT) framework [35,41]. These datasets were integrated within a ridge-regularised logistic regression framework incorporating interaction terms, multi-scale predictors, and blocked spatial cross-validation to predict the spatial probability of establishment-failure.

Although UAV-derived environmental information has increasingly been used to characterise plantation sites, relatively few studies have translated these data into operational

decision-support tools capable of predicting establishment outcomes before planting. Furthermore, existing approaches typically evaluate individual response variables in isolation and rarely integrate predictive modelling with treatment scenario analysis or spatially explicit measures of establishment success. Addressing these limitations requires a framework that links environmental prediction, management decision support, and quantitative assessment of plantation establishment within a single operational workflow.

For commercial plantation managers, establishment decisions must often be made before planting across large operational areas where detailed field assessments are impractical. Consequently, there is increasing demand for spatially explicit decision-support tools capable of identifying high-risk areas prior to planting so that site preparation, residue management, ripping intensity, species selection, or planting prescriptions can be adapted to local conditions. Such approaches have the potential to improve establishment success while reducing operational costs and unnecessary interventions.

By linking pre-planting environmental conditions with subsequent plantation performance, the study demonstrates how UAV remote sensing and spatial modelling can support operational decision-making, targeted intervention, and precision management within heterogeneous plantation environments. A distinguishing feature of this study is that all predictor variables were derived from imagery acquired before planting occurred, whereas establishment outcomes were measured approximately 21 months later. The study therefore evaluates whether future plantation performance can be predicted from pre-existing environmental conditions rather than contemporaneous observations.

The objectives of this study were to: (1) develop a spatially explicit predictive model of plantation establishment-failure using pre-planting UAV-derived variables; (2) integrate environmental, terrain, structural, and operational treatment predictors within a unified modelling framework; (3) evaluate predictive performance using blocked spatial cross-validation; (4) generate operational risk maps identifying areas of elevated establishment risk; and (5) assess how alternative operational treatment scenarios are predicted to influence establishment outcomes.

Related Work

Plantation establishment success is strongly influenced by interactions among environmental conditions, operational practices, and seedling physiological responses during the early post-planting period. Moisture availability is widely recognised as one of the dominant controls on seedling survival because newly planted seedlings initially possess limited root access to soil water and are highly vulnerable to drought stress [18–30]. Water deficits can reduce stomatal conductance, impair photosynthesis, restrict root development, and increase mortality, particularly under high evaporative demand or elevated soil temperatures [22–30]. These effects are often amplified in recently harvested environments where canopy removal, soil exposure, and residue redistribution substantially alter local hydrological and thermal conditions [42–45].

Residue management and mechanical site preparation strongly influence these microsite conditions. Logging debris and coarse woody material may provide beneficial moisture buffering, reduce evaporative losses, moderate soil temperature fluctuations, and contribute to nutrient retention [2–5,11–15,46,47]. Conversely, excessive residue accumulation may obstruct planting operations, reduce root–soil contact, increase competition, or create microsites that are physically unsuitable for planting [2,4,5,46]. Mechanical disturbance associated with harvesting and site preparation can also increase soil compaction, alter infiltration characteristics, and modify surface roughness and drainage pathways, further contributing to spatial variability in establishment outcomes [3,11–15,47].

Planting quality is another important determinant of establishment success that is often difficult to quantify spatially. Root deformation, shallow planting, poor root–soil contact, air pockets, exposed roots, and planting into compacted or dry soil can substantially reduce survival and early growth [29,30,48]. Research on planting methods has shown that seedling handling, root moisture, and planter effects may strongly influence establishment outcomes, with early differences often persisting into later stand development [29,30,48]. These processes directly affect hydraulic continuity and early root growth following transplantation, thereby influencing the ability of seedlings to tolerate environmental stress during establishment.

Establishment outcomes therefore emerge from interacting environmental and operational processes operating across multiple spatial scales. Local variations in soil exposure, residue cover, terrain position, vegetation competition, coarse woody debris distribution, and disturbance intensity can produce strong microsite variability within plantation landscapes [7–21]. Such variability frequently occurs at sub-metre to metre scales that are difficult to characterise using conventional field inventories alone. As a result, establishment-failure often exhibits spatially structured patterns associated with moisture stress, operational disturbance corridors, terrain complexity, and vegetation heterogeneity [4,5,11–15,18–25].

Recent advances in unmanned aerial vehicle (UAV) remote sensing provide opportunities to quantify the fine-scale environmental heterogeneity across operational plantation environments. UAV-based photogrammetry and multispectral imaging can generate orthomosaics, digital terrain models, point clouds, vegetation indices, and structural texture metrics at resolutions suitable for compartment-scale forestry assessment [32–34,49]. These approaches enable spatially continuous mapping of exposed soil, vegetation cover, surface roughness, residue distribution, and terrain characteristics that may influence establishment processes.

In forestry, UAV remote sensing has increasingly been applied to inventory estimation, canopy assessment, structural analysis, and operational monitoring [32–35,41,50–52]. However, many existing studies remain focused on mapping current forest conditions rather than predicting future establishment outcomes from pre-planting environmental characteristics. Comparatively few studies in forestry have integrated environmental, terrain, structural, and operational variables within a unified predictive framework capable of identifying establishment risk prior to planting.

Spatial ecological modelling also presents important statistical challenges because neighbouring observations within raster datasets are rarely independent [38]. Conventional random cross-validation can therefore overestimate predictive performance when training and testing datasets share similar spatial structure. Blocked spatial cross-validation has consequently been recommended for environmental and ecological prediction because it provides more realistic estimates of model transferability across geographically separated regions [40,53]. This is particularly important in plantation establishment modelling where the objective is not only to reproduce observed spatial patterns, but also to identify transferable environmental and operational drivers of establishment success and failure.

Collectively, the literature suggests that plantation establishment is governed by complex interactions among moisture stress, microsite variability, operational disturbance, and vegetation dynamics operating across heterogeneous landscapes. While UAV remote sensing provides new opportunities to characterise these conditions at operationally relevant spatial scales, relatively few studies have linked pre-planting environmental information with later establishment outcomes using interpretable spatial predictive frameworks. This study addresses that gap by integrating UAV-derived environmental and structural metrics,

operational treatment information, and blocked spatial cross-validation within a spatially explicit modelling framework for plantation establishment risk prediction.

2. Materials and Methods

2.1. Study Area and Experimental Design

The study was conducted at the Mount Graham *Pinus radiata* (radiata pine) plantation site in a region known as the Green Triangle in South Australia (Figure 1A). The site was one of six sites that comprised a series of operational plantation trials established following commercial harvesting and site preparation activities.

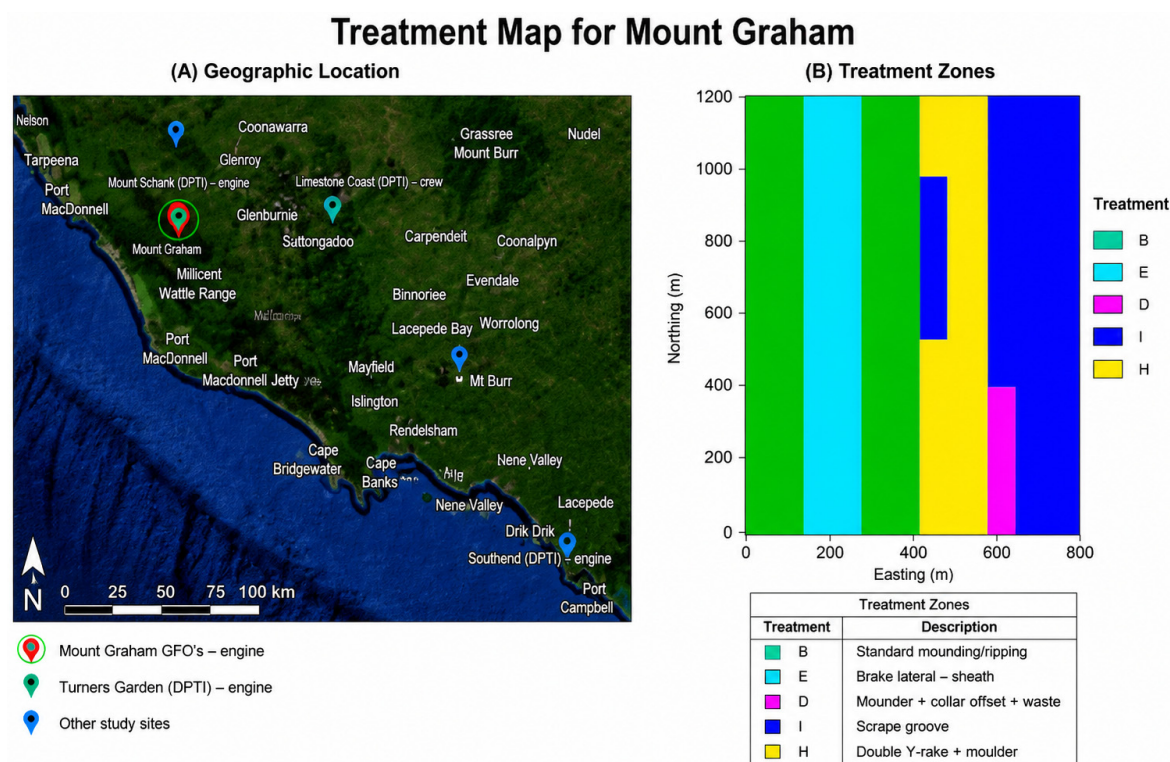


Figure 1. (A) Location of sites involved in the broader cleanstrip project in the Green Triangle near the South Australian and Victorian border. Blue markers indicate hardwood sites, green markers softwood sites. Mount Graham (red circle) is a softwood site at which cleanstrip treatments B, C, D, E, and H were applied, and (B) the treatment map applied to the Mount Graham site.

Mount Graham was selected as the modelling site for this study because it contained multiple harvesting and tillage treatments during re-establishment to radiata pine. This permitted investigation of the influence of residue redistribution, surface disturbance, and microsite conditions on plantation establishment.

Operational treatments were distributed in broad north–south strips across the plantation, with Treatment C occupying much of the eastern portion of the site and Treatments B, E, and H occurring primarily within western and central areas (Figure 1B). A description of the operational treatments is given in Table 1.

The treatments were not randomly assigned but were implemented according to operational constraints and site conditions, resulting in partial confounding between treatment allocation and underlying environmental gradients.

Table 1. Description of treatments and variants. Treatments A, F, and G were not applied at the Mount Graham site used in this study.

Implement	Description	Treatments							
		Non-clean strip			Cleanstrip systems				
		A	B	C	D	E	F	G	H
Chopper roller	A standard method of harvest residue management (control treatment: single or double roller).	X	X	X					
Standard mounding plough	After chopper rolling and where there are site issues requiring amelioration, e.g., poor drainage (control treatment: mounding system after chopper rolling.)		X						
Bracke Forest system	Mattock wheel mounding or disc wheel scarification (control treatment: with or without chopper rolling.)			X					
Bulldozer: coulter wheel and V-rake	V-blade shears off eucalyptus coppice and high stumps, then a coulter wheel crosscuts the larger harvest residues prior to sweeping them aside with V rakes.				X	X			
Stump grinder	The stumps are ground to below the ground surface to reduce the risk of machine snagging and allow re-setting of row spacing.							X	X
Skidder: V-rake and moulder	For sites with lighter harvest residues sites, v-rake residues aside and then mound the cleanstrip.					X	X		X

2.2. UAV Data Acquisition and Processing

High-resolution RGB imagery was acquired using a DJI Zenmuse P1 camera (SZ DJI Technology Co., Ltd., Shenzhen, Guangdong, China), while multispectral imagery was collected using a MicaSense Altum sensor. All flights were conducted at an altitude of approximately 100 m using forward and side overlaps of approximately 85%, producing ground sampling distances of approximately 1.4 cm and 5.0 cm for the RGB and multispectral datasets, respectively.

Image sequences were then processed using Agisoft Metashape Professional to generate georeferenced orthomosaics, dense point clouds, digital surface models, and terrain products using structure-from-motion photogrammetry [32,54,55]. All orthomosaics, point clouds, terrain models, treatment masks, and derived environmental predictor layers were projected into a common coordinate reference system and resampled onto a common spatial analysis grid to ensure pixel-level correspondence among predictor and response datasets.

Only variables derived from the pre-planting UAV survey were used as predictor variables. Establishment outcomes, including stocking density and tree height, were measured approximately 21 months after planting and used exclusively as response variables. This temporal separation ensured that the modelling framework evaluated the predictive value of pre-existing environmental and operational conditions rather than contemporaneous site observations.

2.3. Climatic Conditions During Establishment

Rainfall was analysed from the pre-planting UAV survey (May 2024) through the final plantation assessment (March 2026) to characterise climatic conditions over the entire establishment period (Figure 2). Although plantation performance was assessed approximately 21 months after planting and rainfall is presented for the entire establishment period, environmental conditions during the early establishment phase, encompassing planting, initial root development, and early canopy development, are widely recognised as having a disproportionate influence on subsequent seedling survival and early stand development.

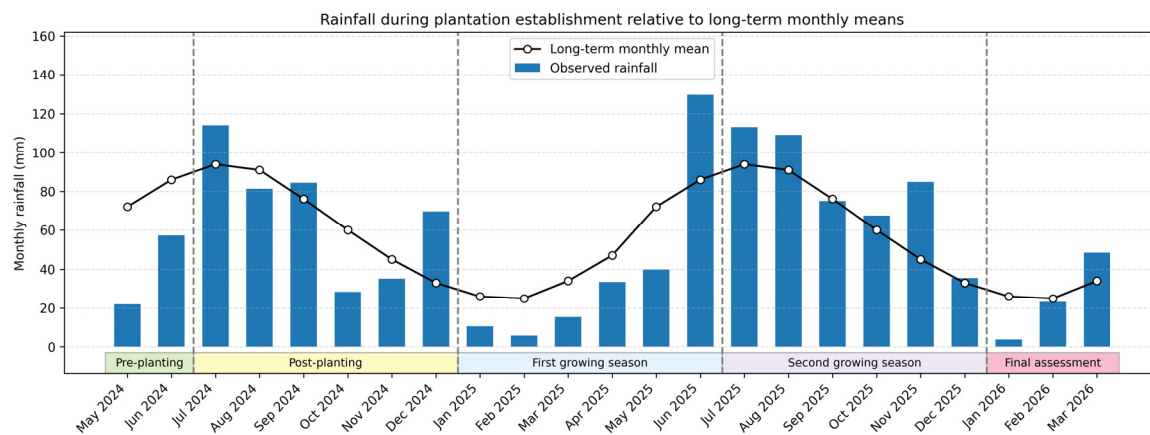


Figure 2. Rainfall observed at Mount Gambier during study period. The blue bars represent the observed monthly rainfall. The white circles represent the long-term monthly average rainfall.

The early establishment period coincided with substantially below-average rainfall across the study region. Approximately 180 mm of rainfall was recorded between the May 2024 pre-planting survey and the November 2024 post-planting campaign, compared with a long-term mean of approximately 430 mm over the same period, representing a rainfall deficit of approximately 58%. Similarly, approximately 80 mm of rainfall was recorded between November 2024 and March 2025, compared with a long-term mean of approximately 135 mm, representing a further deficit of approximately 41% (Figure 2).

Rainfall recovered during parts of the second growing season, with several months exceeding the long-term monthly means, particularly during winter 2025, before declining again immediately prior to the March 2026 assessment. Monthly rainfall records were obtained from the nearest Bureau of Meteorology station to Mount Graham (Mount Gambier Aero) and compared with long-term climatic averages to characterise climatic conditions throughout plantation establishment (www.bom.gov.au/climate/data, accessed on 15 April 2026).

2.4. Establishment Assessment

Plantation establishment was quantified using the Program for Identifying Nursery Trees (PINT) framework [35]. Individual trees were detected from post-planting UAV imagery and used to derive spatially explicit estimates of stocking density, tree height, mortality, and weed cover.

Tree heights were estimated using canopy-height information derived from photogrammetric point clouds, while stocking density was calculated from the spatial distribution of detected trees. Weed coverage was similarly mapped from multispectral imagery and incorporated as an indicator of competitive pressure during establishment. Together, these variables provided quantitative measures of plantation performance throughout the monitoring period.

PINT has been tested on several hundred sites covering over 3500 [M1.1]ha, with seedlings ranging from 3 months to 5 years old (mean tree heights ranging from approximately 0.1–7 m). Test sites contained a wide range of geomorphologies and levels of weed infestation. Diagnostic tests against ground truth visually identified in orthomosaic images indicate PINT has detection accuracies > 95% with false alarm rates around 1% [35,37,41]. Tree location accuracies are around 0.25 m (95% confidence).

Examples of PINT comparisons against ground-truth observations for (A) tree detection and (B) weed coverage are shown in Figure 3. Tree-detection accuracy was assessed within a series of 40 m × 40 m validation plots, while weed-detection performance was evaluated using polygon overlap between mapped weed patches and ground-truth obser-

variations (same sized plots). High correspondence between PINT outputs and ground-truth data [41] demonstrates the reliability of the automated detection framework for subsequent establishment and vegetation analyses.

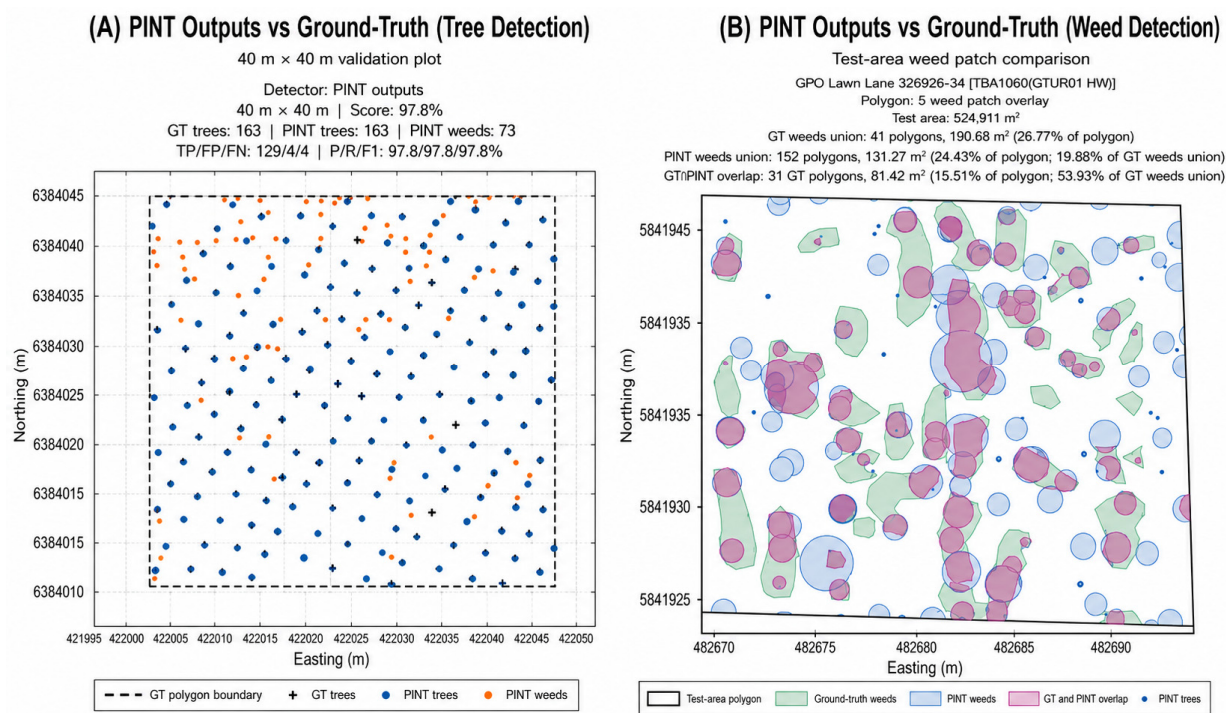


Figure 3. Examples of PINT performance for (A) tree and (B) weed detection on test sites (from [41]).

2.5. Environmental Predictor Generation

Environmental predictors were derived from pre-planting RGB, multispectral, and terrain datasets to characterise microsite conditions likely to influence plantation establishment. More than 50 environmental, structural, terrain, and operational predictors were generated and subsequently evaluated for inclusion within the modelling framework. Summarised in Table 2, for more details, the reader is referred to [36,56].

Table 2. Summary of candidate parameters considered for the regression model. RDMI = Ratio Dryness Monitoring Index, NRCT = Normalised Relative Canopy Temperature, NDVI = Normalised Difference Vegetation Index, DEM = Digital Elevation Map, PSD = Power Spectral Density.

Predictor Category	Variables Included	Purpose
Moisture/dryness	Dryness, RDMI, NRCT, PDI, TVDMI, Categorical soil-group indicators	Represent moisture stress and exposed soil
Vegetation condition	NDVI, weed density	Represent vegetation cover and competition
Terrain structure	DEM metrics (e.g., entropy, energy), elevation	Represent terrain variability and roughness
Structural metrics	PSD, HAG gradients, Line density	Represent operational and microsite structure
Operational variables	Treatment masks	Represent site preparation and disturbance
Interaction predictors	All interaction terms	Represent combined environmental effects
Multi-scale predictors	Smoothed gradients	Represent broader landscape variability

Spectral Predictors: Spectral indices describing vegetation condition, soil exposure, and moisture status were derived from the multispectral imagery. These included vegetation and dryness metrics designed to characterise residual vegetation, exposed soil, and relative moisture conditions across the site.

Terrain Predictors: Terrain metrics were derived from digital elevation models and canopy-height products. These variables described local elevation, surface relief, and terrain complexity, which influence water redistribution, soil development, and operational accessibility.

Structural Predictors: Structural predictors were derived from texture and spatial analyses applied to RGB, multispectral, and canopy-height datasets. These metrics characterised surface roughness, periodicity, entropy, line density, coarse woody debris distribution, and operational disturbance patterns. Such variables provided quantitative descriptions of microsite heterogeneity associated with harvesting and site preparation activities.

All predictor rasters were generated at a nominal spatial resolution of 0.1 m per pixel. Local neighbourhood statistics were calculated using 151×151 pixel (approximately 15.1×15.1 m) moving windows, while broader landscape context was characterised using 302×302 pixel (approximately 30.2×30.2 m) windows. Gaussian smoothing employed a standard deviation of 7 pixels (0.7 m; full width half maximum (FWHM) ≈ 1.65 m).

A sensitivity analysis was undertaken to evaluate the influence of the ridge regularisation parameter (λ) on model performance. Across a 100-fold range of λ values (0.001–0.1), spatial cross-validation AUC remained highly stable (0.904–0.913), indicating that predictive performance was largely insensitive to the precise choice of regularisation strength. Increasing λ progressively reduced the L2 norm of the regression coefficients, demonstrating the expected shrinkage effect while maintaining essentially unchanged predictive accuracy. A value of $\lambda = 0.01$ was therefore adopted as an appropriate compromise between coefficient stability and predictive performance.

A soil-group map derived from the South Australian Government Department of Environment and Water soil-landscape database (<https://data.environment.sa.gov.au/naturemaps/Pages/default.aspx>, accessed on 17 April 2026) was rasterised to the common analysis grid and represented in the final modelling framework using categorical soil-group variables, with Mount Burr Sand used as the reference category. These variables were included to capture landscape-scale edaphic variation not fully represented by UAV-derived moisture, vegetation, and terrain predictors. Because many soil effects are expressed through moisture, vegetation, and terrain characteristics, the soil-group variables provided complementary rather than independent environmental information.

Feature Engineering and Predictor Selection: To capture interactions among environmental processes, additional predictor variables were generated through interaction terms and multi-scale spatial aggregation. Variables representing operational treatment classes were incorporated using spatial treatment masks, while large-scale environmental gradients were represented through neighbourhood-based predictor summaries.

Additional implementation details, software specifications, computational hardware, and model parameters are provided in Supplementary Table S2 to facilitate reproducibility.

Predictor relationships were examined prior to modelling to identify covariance and potential redundancy among variables (Figure 4). This information was used to guide predictor filtering and support subsequent application of regularised regression methods.

Prior to model fitting, pairwise correlations between candidate predictors were examined to identify highly collinear variables. Predictor pairs with an absolute Pearson correlation coefficient exceeding 0.90 were considered redundant. Where multiple predictors represented essentially the same environmental characteristic, only the variable considered to have the clearest physical interpretation or strongest predictive utility was

retained. This procedure reduced instability in the estimated regression coefficients while maintaining predictive performance. The final model retained RDMI, PDI, TVMDI, soil group, CWD, PSD, HAG, DEM energy and DEM entropy.

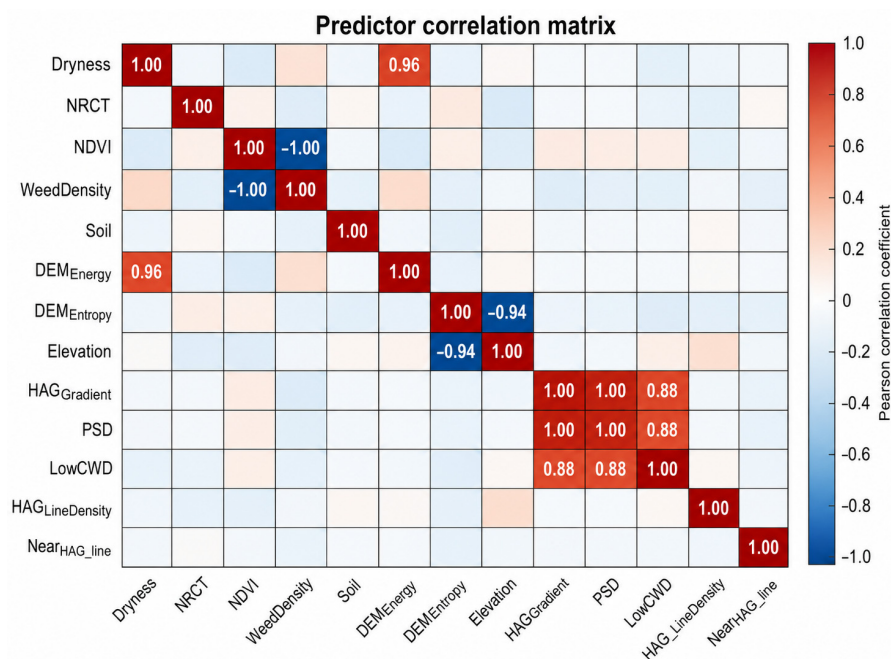


Figure 4. Predictor correlation matrix showing pairwise Pearson correlation coefficients among the principal environmental, vegetation, terrain, and operational predictors used in the plantation establishment model.

Establishment Index: Plantation performance was summarised using an Establishment Index combining stocking density and tree growth measurements. The index was defined as

$$\text{Establishment Index} = 0.7 \times S_n + 0.3 \times H_n$$

where S_n represents the normalised stocking-density metric and H_n represents the normalised tree-height metric.

Stocking density and tree height were first normalised to a common scale (0–1) to ensure comparable contribution to the index. The weighting scheme prioritised successful establishment and survival while retaining information on early growth performance.

The Establishment Index differentiates between establishment-failure (low survival) and performance failure (survival accompanied by poor growth), allowing identification of areas that would be overlooked using stocking metrics alone.

After removal of pixels containing missing predictor or response data, 91,161,184 raster cells were available for analysis. These raster cells represented spatial sampling units on a 0.1 m analysis grid rather than independent field observations, and neighbouring cells exhibited substantial spatial autocorrelation. Consequently, the pixel count reflects the spatial support of the mapped study area rather than the effective number of statistically independent observations. Model development and validation therefore employed spatially blocked cross-validation to assess predictive performance under spatial dependence, rather than relying on assumptions of pixel independence. Of the available raster cells, 22,788,174 (25.0%) were classified as establishment-failures and 68,373,010 (75.0%) as non-failures according to the Establishment Index threshold.

Predictive Modelling Framework: The probability of establishment-failure was modelled using ridge-regularised logistic regression. Establishment-failure was defined using threshold values applied to the Establishment Index, producing a binary response variable

suitable for classification modelling. Model coefficients were estimated by maximising a penalised likelihood function:

$$P(Y = 1|X) = \frac{1}{1 + \exp\left\{-\left(\beta_0 + \sum_{j=1}^p \beta_j X_j\right)\right\}}$$

where Y represents establishment-failure, X_j are predictor variables, and β_j are model coefficients. Ridge regularisation was incorporated to reduce instability arising from correlated environmental predictors:

$$\operatorname{argmin}_{\beta} \left[\{-\log(L) + \lambda \sum_{j=1}^p \beta_j^2\} \right]$$

where L is the likelihood function, $L = P(y|X, \beta)$, which is the probability of observing the data, y , given the predictor variables X and model coefficients, β , and λ is the regularisation parameter controlling coefficient shrinkage.

Predictor variables were standardised to zero mean and unit variance prior to model fitting to improve numerical stability and facilitate comparison of coefficient magnitudes.

Spatial Cross-Validation: Model performance was evaluated using blocked spatial cross-validation to account for spatial autocorrelation among neighbouring observations [38,53,57]. The study area was partitioned into five geographically contiguous north–south-oriented strips, each approximately 140 m wide in the east–west direction and 1400 m long (Figure 5). During each iteration, one fold was withheld for validation while the remaining folds were used for model training.

This blocked east–west cross-validation was selected to reduce, rather than eliminate, spatial dependence between the training and validation data by partitioning the plantation into geographically contiguous folds. Compared with conventional random cross-validation, this approach provides a more conservative assessment of predictive performance because validation is performed on spatially coherent regions rather than interspersed neighbouring pixels [38–40]. No buffer zones were imposed between adjacent folds; consequently, some spatial dependence remained along shared fold boundaries. The blocked design was nevertheless considered more representative of operational prediction to new areas of the plantation than random pixel-based partitioning while maintaining adequate sample sizes within each fold.

Predictive performance was assessed using area under the receiver operating characteristic curve (AUC), Brier scores, calibration statistics, and confusion-matrix-derived classification metrics. Mean performance statistics were subsequently calculated across all validation folds.

Comparison of the spatially blocked and random stratified cross-validation strategies demonstrated virtually identical predictive performance (Figure S7, Supplementary Information). Both validation strategies achieved excellent discrimination (AUC = 0.904), with only negligible differences between the ROC curves. The similarity in performance suggests that the model captured robust environmental relationships rather than relying primarily on local spatial structure. Nevertheless, blocked spatial cross-validation was adopted throughout the study because it provides a more appropriate assessment of predictive performance for spatial prediction problems by reducing the influence of spatial dependence between the training and validation data.

Treatment Scenario Analysis: To evaluate the influence of operational treatments on establishment outcomes, model-based treatment encoding scenarios were undertaken using the fitted modelling framework. Treatment layers were systematically modified while all other environmental predictors were retained unchanged, allowing estimation of

the expected change in establishment-failure probability associated with alternative management scenarios. These simulations were used to compare model-predicted outcomes under alternative treatment encodings and identify opportunities for spatial optimisation of operational practices across the plantation landscape.

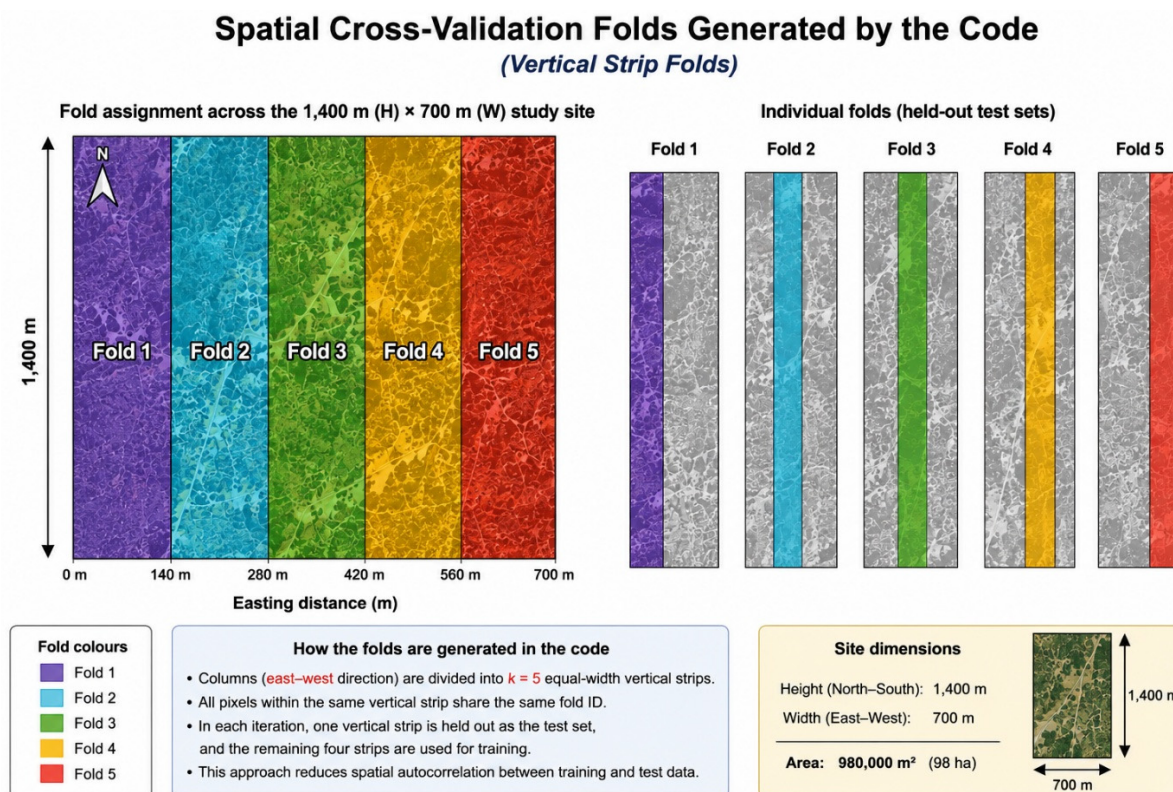


Figure 5. Schematic representation of blocked spatial cross-validation used for model evaluation. The modelling domain was partitioned into five geographically contiguous folds. During each iteration, one fold was withheld for validation while the remaining folds were used for model training.

Operational treatments were arranged in broad north–south strips across the plantation. Treatment C occupied most of the eastern portion of the site, while Treatments B, E, and H occurred primarily within the western and central areas. Treatment D was represented by a relatively small, localised block near the boundary between Treatments H and C (Figure 1B). A substantial proportion of the eastern high-risk zone coincided with Treatment C, suggesting that operational treatment effects may have contributed to the observed establishment pattern.

Where treatments were applied in multiple operational blocks, polygons assigned to the same treatment were aggregated to form a single treatment class for analysis. This aggregation simplified treatment representation but did not remove the inherent spatial confounding between treatment allocation and environmental variation because treatments were not randomly assigned across the plantation. Consequently, treatment effects should be interpreted as predictive associations within the observed operational setting rather than unbiased estimates of causal treatment effects.

Statistical Analysis: Predictor contributions were calculated from the fitted ridge regression model using the absolute values of the standardised regression coefficients. For predictor i , the contribution was calculated as $\text{Contribution}_i = 100 \frac{|\beta_i|}{\sum_j |\beta_j|}$, where β_i denotes the standardised ridge coefficient. The resulting values sum to 100% and provide a relative measure of coefficient magnitude. These contributions should not be interpreted as percentages of explained deviance because ridge regression distributes information

across correlated predictors, particularly when interaction terms are included. This allowed comparison of the relative influence of environmental, structural, terrain, operational, and interaction variables on establishment-failure probability. Predictor contributions were subsequently interpreted in conjunction with spatial risk maps and observed establishment patterns to identify dominant drivers of plantation performance.

Summary of Framework: The overall analytical workflow, which integrates pre-planting UAV-derived environmental, vegetation, terrain, structural, and operational predictors with post-planting establishment assessments to model and map future establishment-failure risk, is depicted graphically in Figure 6.

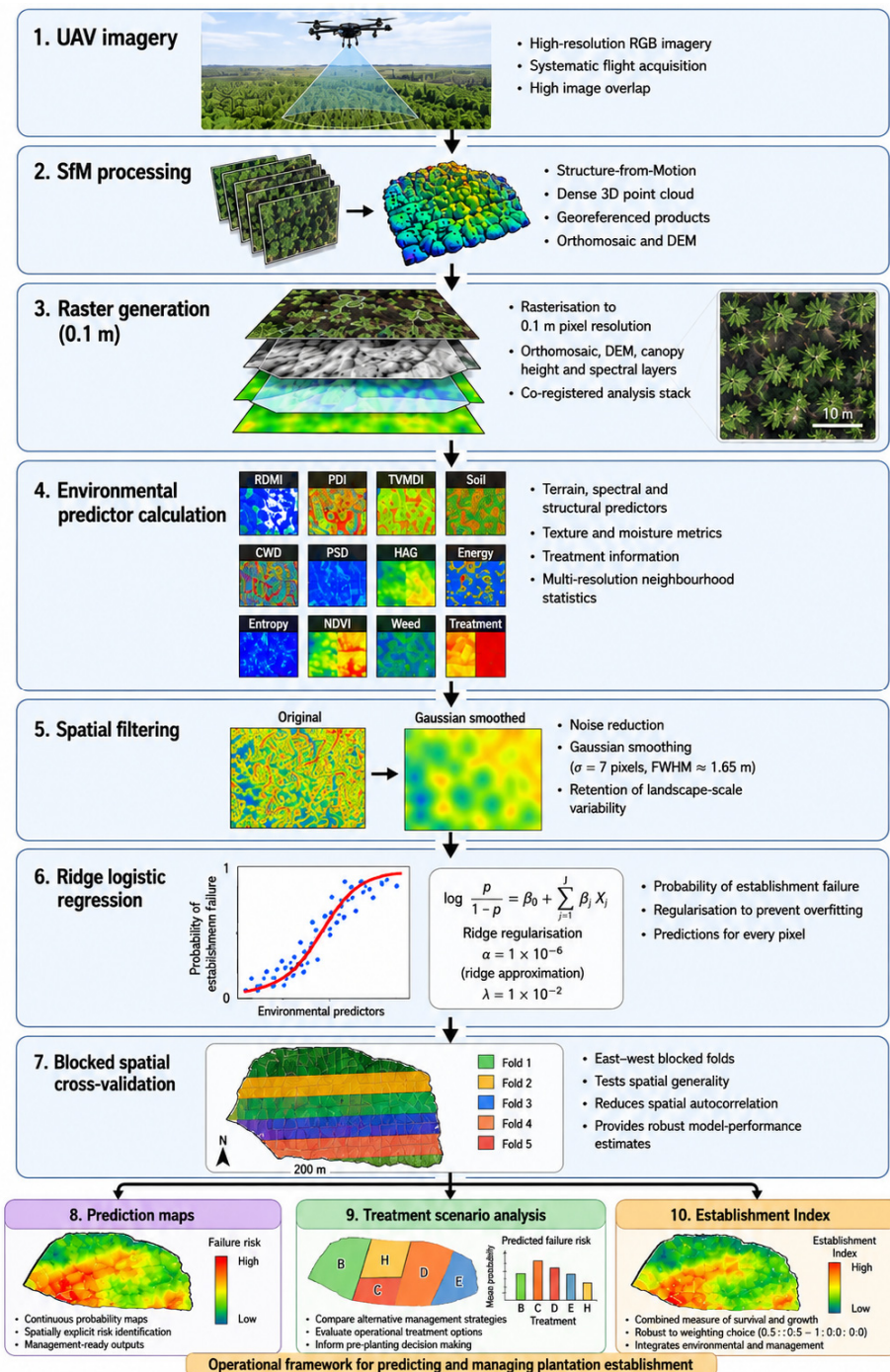


Figure 6. Workflow of the spatial plantation establishment modelling framework developed in this study.

3. Results

3.1. Establishment Outcomes

Substantial spatial variation in plantation performance was observed across the Mount Graham site (Figure 7). Reduced stocking density and suppressed tree growth were concentrated primarily within eastern portions of the plantation and along several operational disturbance corridors. Tree height exhibited greater spatial variability than stocking density, indicating that growth performance remained sensitive to environmental conditions even where tree survival was maintained.

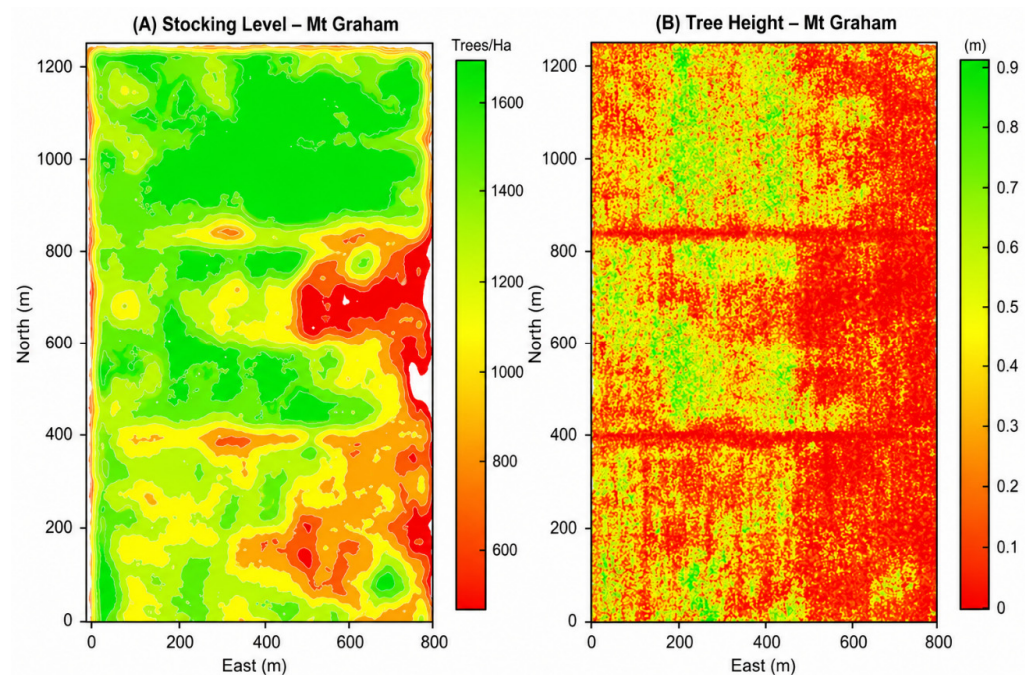


Figure 7. Tree density (A) and tree height (B), derived from the March 2026 campaign.

It should be noted that all predicted establishment-failure probabilities presented throughout the following analyses were derived exclusively from environmental, terrain, structural, and operational variables obtained from the pre-planting UAV survey. No post-planting measurements were used as predictor variables, ensuring that the model represents a genuine prediction of future plantation performance rather than an assessment based on contemporaneous observations.

Predicted establishment-failure probabilities were classified into four distribution-based risk categories using empirically selected cumulative distribution thresholds (30%, 55%, and 80%). These thresholds were chosen to provide operationally meaningful discrimination between progressively higher levels of establishment risk rather than to produce equally populated classes.

Using only pre-planting UAV-derived predictor variables, the ridge-regularised modelling framework successfully reproduced these broad spatial patterns (Figure 8). Higher predicted probabilities coincided with areas of reduced stocking density and tree height, while lower failure probabilities occurred within regions exhibiting higher stocking densities and greater tree height. In several areas, moderate stocking densities coincided with relatively low Establishment Index values, indicating that growth performance was suppressed despite successful survival. This demonstrates that stocking alone underestimated spatial variability in plantation condition and highlights the value of incorporating tree growth into establishment assessment.

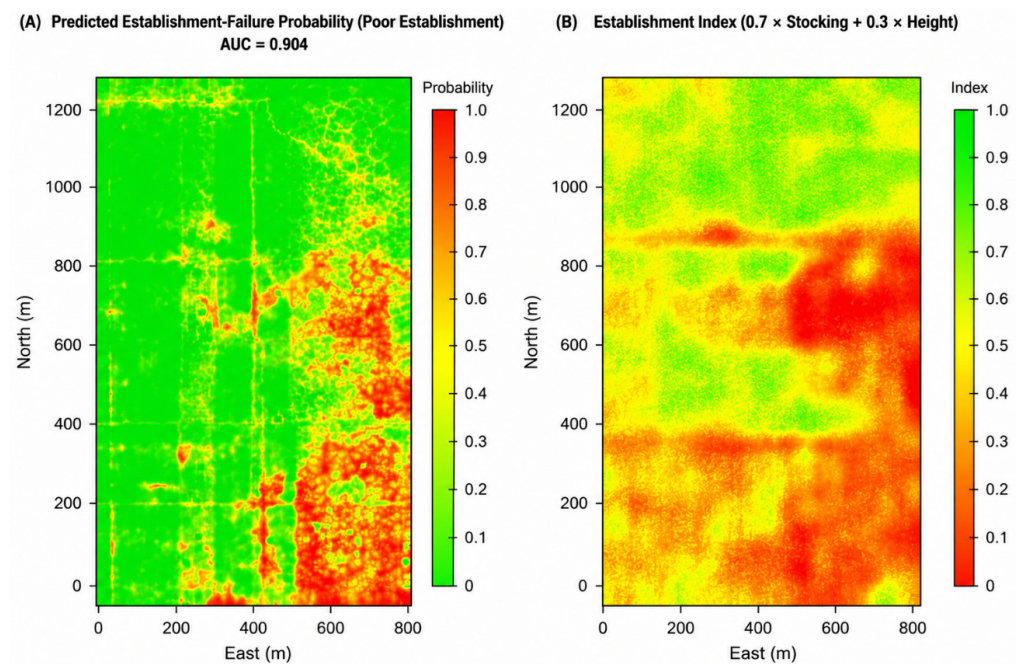


Figure 8. Predicted establishment-failure probability (A) and Establishment Index (B) for the Mount Graham site. Elevated failure probabilities correspond closely with areas exhibiting reduced Establishment Index values.

Approximately 43% of the site was classified as high or very high establishment risk, while 34% was classified as low risk (Table 3), demonstrating that substantial spatial variability in plantation performance can be identified prior to planting using UAV-derived environmental information. High-risk zones were concentrated primarily within eastern portions of the plantation and along operationally aligned linear features associated with access tracks, firebreaks, and planting corridors (Figure 9). Risk classes formed large contiguous regions rather than isolated individual pixels, indicating that establishment-failure was governed by broad environmental and operational gradients rather than local stochastic variation alone.

Table 3. Distribution of plantation risk.

Risk Class	Approximate Proportion of Site
Low risk	~34%
Moderate risk	~23%
High risk	~21%
Very high risk	~22%

3.2. Model Performance

Model performance was evaluated using five-fold blocked spatial cross-validation to account for spatial autocorrelation among neighbouring observations. Validation performance was high and highly consistent across the five spatial validation folds, with AUC values ranging from 0.901 to 0.909 and a mean AUC of 0.904 ± 0.004 (Table 4). The small variation among folds indicates stable model performance under geographically independent validation conditions and good within-site spatial predictive consistency.

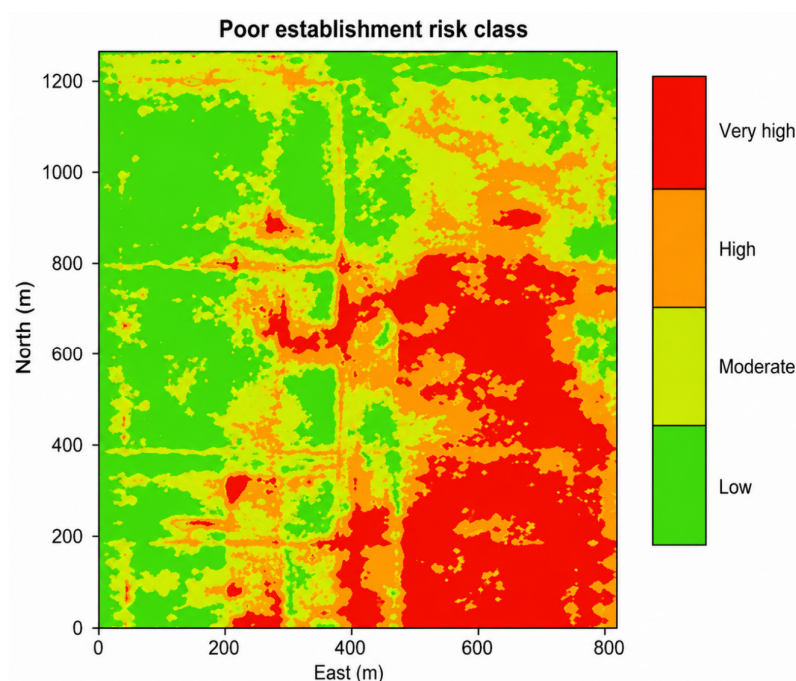


Figure 9. Establishment risk classification map. Predicted probabilities were converted into ordinal risk classes based on distribution-based thresholds derived from the predicted failure probabilities: 30%, 55%, and 80%.

Table 4. AUC obtained for each fold during five-fold blocked spatial cross-validation. Consistently high performance across geographically independent validation folds indicates stable model transferability and limited inflation of predictive accuracy due to spatial autocorrelation.

Fold	AUC
1	0.909
2	0.901
3	0.907
4	0.903
5	0.901
Mean $\pm$ SD	0.904 $\pm$ 0.004

Although the spatially blocked and random stratified cross-validation strategies produced almost identical predictive performance in the present study, the spatially blocked approach was retained because it provides a more conservative assessment of model generalisation by reducing the influence of spatial dependence between training and validation samples.

Additional classification metrics demonstrated robust model performance: accuracy (0.87), sensitivity (0.70), specificity (0.93), precision (0.76), balanced accuracy (0.81), and F1-score (0.73). The model also exhibited good probabilistic calibration (Brier score = 0.102, expected calibration error (ECE) = 0.028), indicating close agreement between predicted establishment-failure probabilities and observed outcomes (Figure 10). Calibration and ROC analyses further demonstrated reliable probability estimates across the full range of predicted establishment-failure probabilities.

Model Calibration and Discrimination Performance

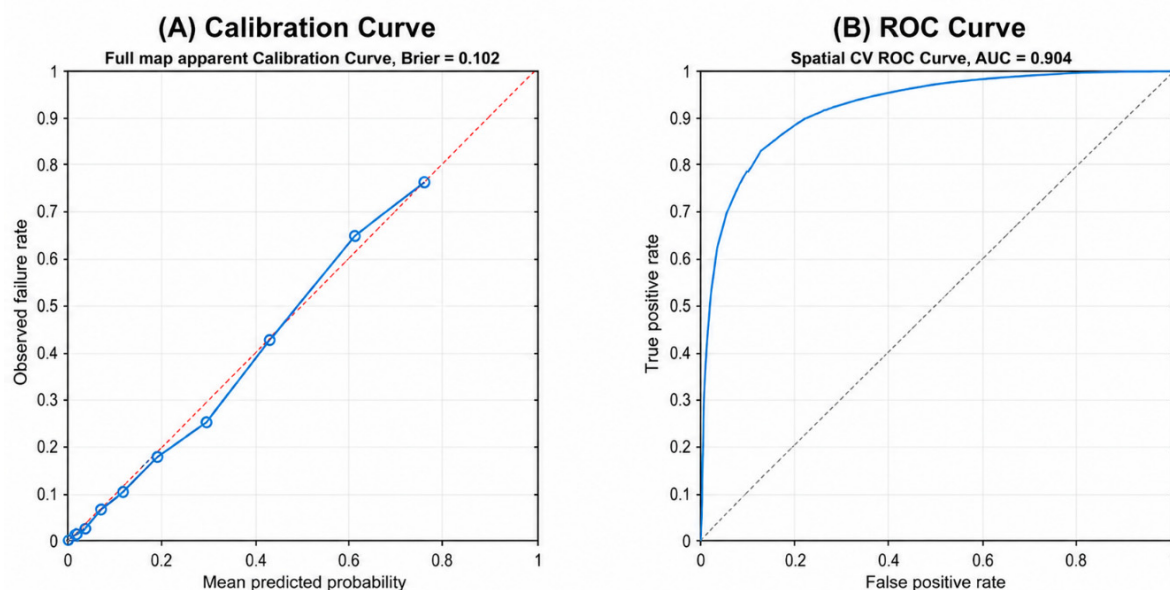


Figure 10. Calibration curve for the full prediction map (A) and Receiver Operating Characteristic (ROC) curve (B). The Brier score quantifies the mean squared difference between predicted probabilities and observed outcomes. The ROC curve shows the predictive performance of the ridge-regularised establishment-failure model under blocked spatial CV. For (A) blue circles represent empirical calibration bins, with each point showing the mean predicted establishment-failure probability plotted against the corresponding observed failure rate for that bin. The red dashed line indicates perfect calibration. For (B) the curve was generated by evaluating model performance across the full range of classification thresholds; the grey dashed line represents random classification (AUC = 0.5).

Collectively, these results indicate that the modelling framework provided good spatial discrimination of establishment risk while maintaining stable predictive performance under spatially held-out regions within a single site. Notably, strong predictive performance was achieved despite all predictor variables being derived prior to planting and the response variables being measured approximately 21 months later. This finding suggests that a substantial proportion of the observed establishment variability was associated with environmental and operational conditions present before plantation establishment commenced.

To assess the spatial stability of model predictions, uncertainty was quantified as the standard deviation (SD) of predicted establishment-failure probabilities across the five blocked spatial cross-validation models (Figure 11). Prediction sensitivity was generally low across most of the plantation, with higher values confined to transition zones between areas of high and low establishment-failure probability. These regions indicate greater variability among the blocked cross-validation models rather than higher predictive uncertainty in a probabilistic sense. Areas of elevated uncertainty occurred primarily along transitions between low- and high-risk zones and near operational boundaries, whereas the major high-risk region in the eastern portion of the site exhibited relatively consistent predictions across validation folds. These results indicate that the principal spatial patterns of establishment risk were robust to variation in training data and were not driven by a small subset of observations.

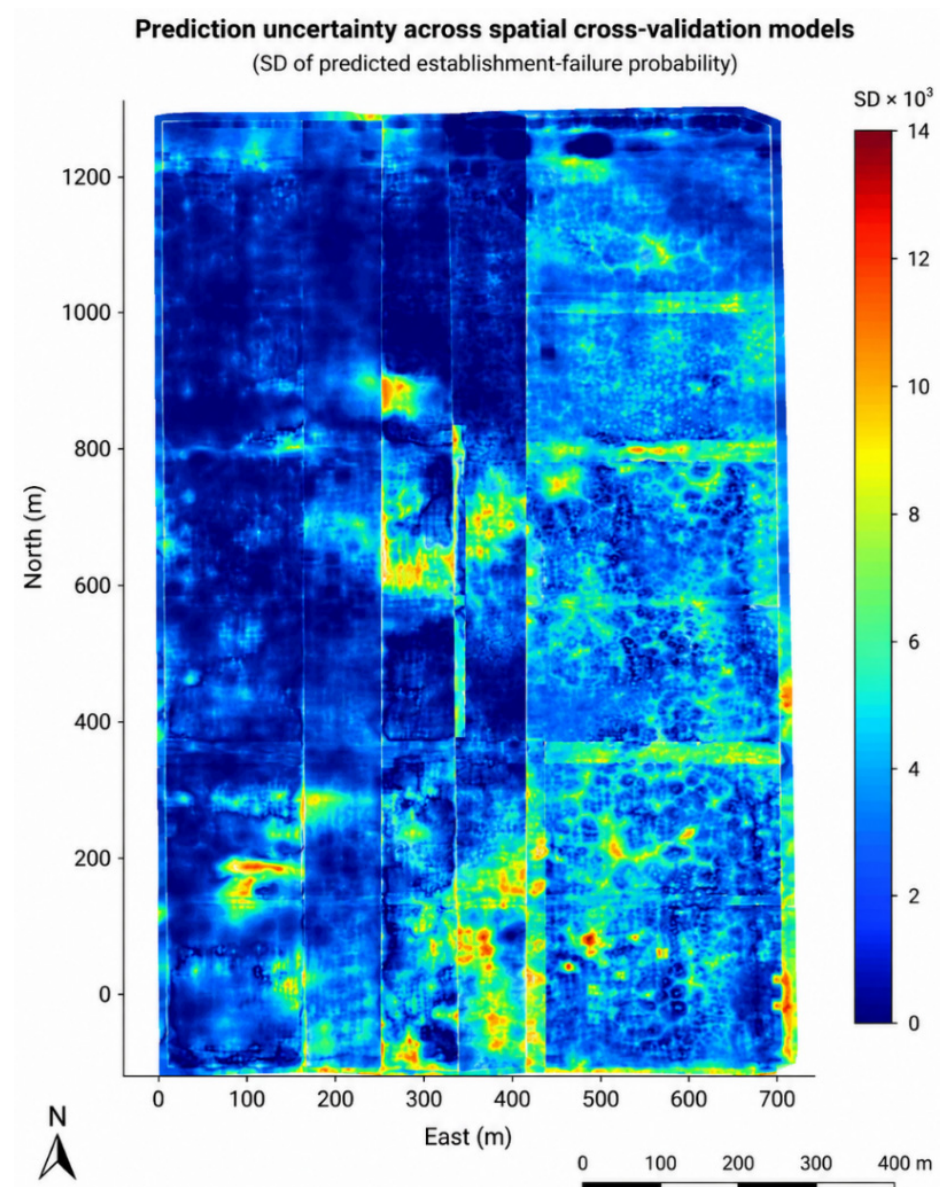


Figure 11. Spatial sensitivity of predicted establishment-failure probability, calculated as the standard deviation of pixel-level predictions across the five blocked spatial cross-validation models. The mapped values quantify between-model prediction variability arising from changes in the training-fold composition and should not be interpreted as calibrated predictive uncertainty.

3.3. Predictor Group Contributions

Predictor contributions were aggregated into five broad ecological and operational process groups (Figure 12). Moisture-related processes collectively contributed the largest proportion of model influence (31.8%), indicating that water availability and drought stress were the largest predictive contribution to plantation establishment during the study period. Terrain and structural factors associated with microsite heterogeneity represented the second-largest contribution (27.5%), followed by vegetation condition and competition processes (19.8%), operational management factors (13.7%), and interaction terms (11.1%), the latter suggesting establishment outcomes were governed by multiple interacting environmental and management processes rather than by individual predictors acting independently.

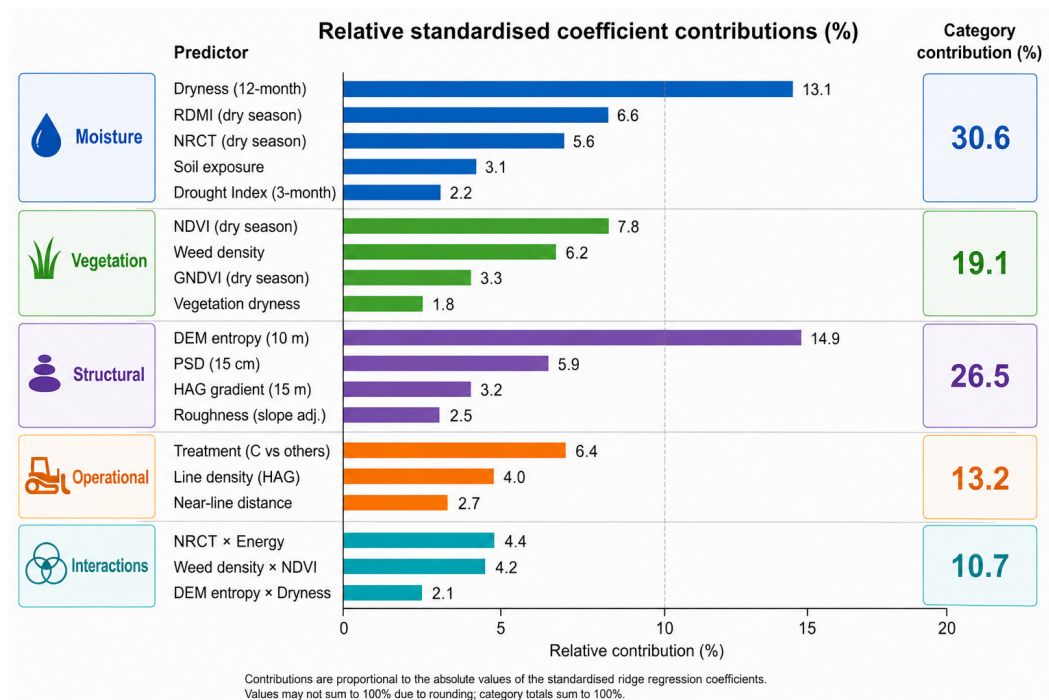


Figure 12. Relative contribution of ecological and operational process groups to establishment-failure prediction. Predictor contributions were aggregated into moisture, vegetation, structural, operational, and interaction categories.

Although the interaction terms improved predictive performance, they should not be interpreted as direct evidence of causal ecological interactions among environmental variables. Rather, they enable the statistical model to represent non-additive relationships that enhance prediction across complex environmental gradients. Quantitative evaluation of specific interaction scenarios, such as the combined effects of drought stress, residue management, soil properties, and terrain, would require dedicated experimental designs or hierarchical modelling frameworks capable of separating correlated environmental processes. Such analyses were beyond the scope of the present predictive study but represent an important direction for future research.

Vegetation-related predictors represent both site productivity and competition processes. Vegetation condition indices and weed-density metrics provide information on the distribution of ground cover and competing vegetation, which can influence seedling performance through competition for water, nutrients, and light. During periods of moisture limitation, vegetation competition may further reduce available soil moisture and amplify establishment stress.

Structural and terrain-related predictors reflect the spatial organisation of microsite conditions across the plantation. Measures of surface complexity, roughness, elevation, and DEM entropy capture variation in residue distribution, soil exposure, drainage characteristics, and local moisture accumulation. These factors influence the creation of favourable and unfavourable microsites for seedling establishment and contribute to the pronounced spatial heterogeneity observed within the site.

Operational predictors represent management decisions associated with site preparation, residue management, and planting configuration. The contribution of treatment-related variables indicates that treatment-related predictors were associated with establishment outcomes, although their effectiveness was strongly mediated by local environmental conditions. This suggests that operational practices interact with underlying site variability rather than acting independently.

Finally, the importance of interaction terms highlights that establishment success is governed by multiple interacting processes rather than single environmental drivers. Relationships between moisture availability, vegetation condition, terrain characteristics, and operational treatments were frequently non-additive, indicating that establishment outcomes emerge from the combined influence of environmental and management factors operating across multiple spatial scales.

3.4. Individual Predictor Contributions

Individual predictor contributions identified DEM entropy, moisture-related variables (Dryness, RDMI and NRCT), vegetation condition metrics (NDVI and weed density), and treatment-related variables as the strongest individual predictors with the largest model-based contributions of establishment risk. Although several predictors contributed strongly to model performance, the aggregated analysis (Figure 12) indicates that broader ecological processes associated with moisture availability, microsite heterogeneity, vegetation competition, and operational management exerted the greatest overall influence on plantation establishment outcomes.

3.5. Soil Groups

Mean Establishment Index differed significantly among soil groups (Kruskal–Wallis, $p < 0.001$), with Mount Burr Sand exhibiting the lowest mean establishment performance. Predicted establishment-failure probability differed significantly among soil groups (Figure 13), Kruskal–Wallis test, $p < 0.001$.

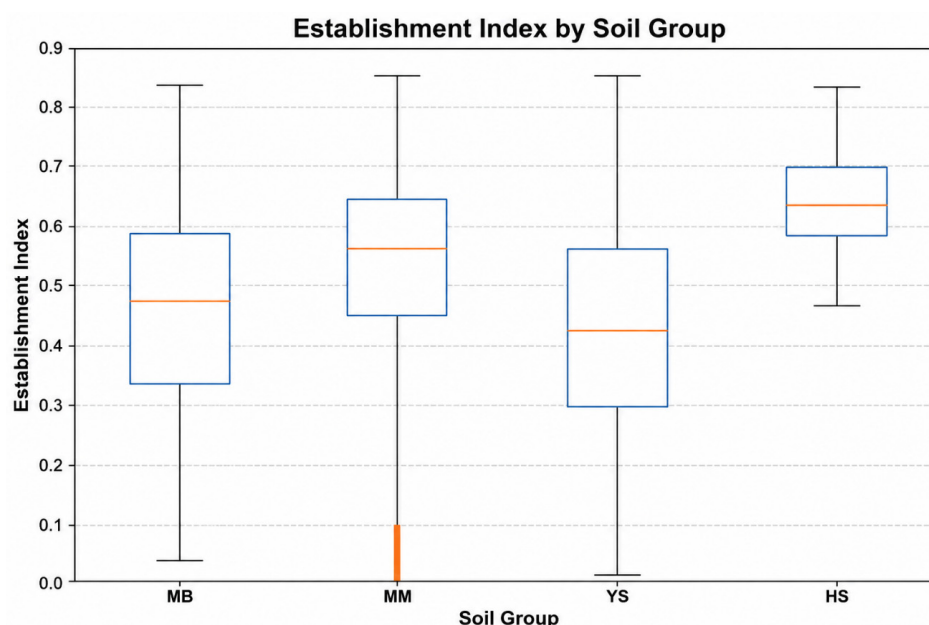


Figure 13. Boxplot of Establishment Index by soil group. MB = Mount Burr Sand, MM = Mount Muir Sand, YS = Young Sand, and HS = Hindmarsh Sandy Loam. Red Basaltic was not represented within the analysed raster area.

Hindmarsh Sandy Loam exhibited the lowest mean failure probability (0.021 ± 0.020), indicating consistently favourable establishment conditions. Mount Muir Sand showed intermediate failure risk (0.112 ± 0.168), while Mount Burr Sand (0.260 ± 0.295) and Young Sand (0.312 ± 0.269) exhibited substantially higher predicted failure probabilities (Table 5). Red Basaltic soils were not represented within the study area and were therefore excluded from statistical comparisons.

Table 5. Predicted establishment-failure probability by soil group.

Soil Group	Mean Failure Probability	SD
Hindmarsh Sandy Loam (HS)	0.021	0.020
Mount Muir Sand (MM)	0.112	0.168
Mount Burr Sand (MB)	0.260	0.295
Young Sand (YS)	0.312	0.269
Red Basaltic (RB)	Not Present	—

Because the Kruskal–Wallis test was applied to raster cells exhibiting substantial spatial autocorrelation, the reported p -values should be interpreted cautiously. The very large number of spatially dependent raster cells substantially inflates statistical power, such that even modest distributional differences become highly significant. Consequently, greater emphasis should be placed on the magnitude and spatial consistency of treatment differences than on formal hypothesis testing.

3.6. Treatment Scenario Analysis

Model-predicted outcomes differed substantially among treatment encodings across the plantation (Figure 14). Simulated whole-site treatment scenarios indicated measurable differences in predicted establishment-failure probability while holding all environmental, vegetation, terrain and structural predictors at their observed values.

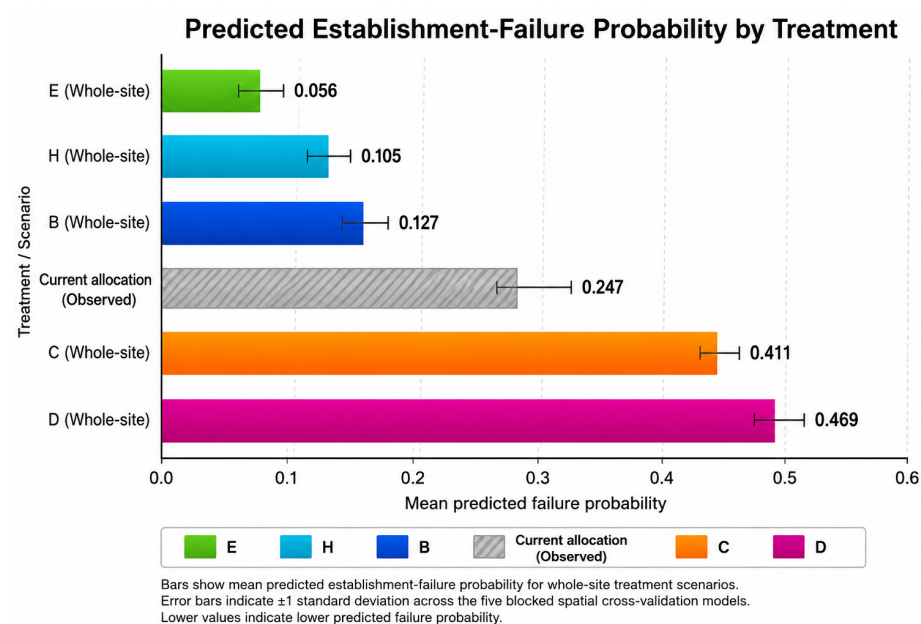


Figure 14. Mean predicted establishment-failure probability for the observed treatment allocation and five whole-site treatment scenarios. For each whole-site scenario, all valid raster cells were assigned the same treatment while all environmental, vegetation, terrain and structural predictors were held at their observed values. The Current allocation bar represents predictions under the observed treatment configuration. Mean probabilities were calculated across all valid raster cells using the final model fitted to the complete dataset. Lower values indicate lower predicted establishment-failure risk.

The observed treatment configuration produced a mean predicted establishment-failure probability of 0.247. Among the simulated whole-site scenarios, Treatment E produced the lowest predicted failure probability (0.086), followed by Treatment H (0.101) and Treatment B (0.124). In contrast, whole-site application of Treatments C (0.368) and D (0.462) substantially increased the predicted establishment-failure probability relative to the observed treatment configuration. Relative to the observed treatment configuration,

Treatments E, H and B therefore reduced the predicted plantation-wide establishment-failure probability, whereas Treatments C and D increased the predicted failure probability. These scenarios represent model-based operational comparisons under fixed environmental conditions and should not be interpreted as causal estimates of treatment effectiveness because the original treatment allocation was not randomised.

The treatment-simulation framework therefore provides a practical mechanism for evaluating alternative residue-management and site-preparation strategies before operational implementation, enabling comparison of predicted establishment outcomes under alternative management scenarios.

3.7. Spatial Correspondence Between Treatment Zones and Establishment Risk

To examine the spatial relationship between operational treatments and predicted establishment outcomes, treatment-zone boundaries were compared with the predicted establishment-risk classes (Figure 15). High and very high establishment-risk classes were concentrated predominantly within the eastern portion of the plantation, which coincided largely with Treatment C. In contrast, lower-risk classes occurred more frequently within western and central treatment areas. A smaller, isolated Treatment C block located within the central plantation also exhibited elevated predicted establishment risk relative to adjacent Treatment H areas. These spatial patterns demonstrate a clear correspondence between treatment allocation and predicted establishment risk, although treatment effects remain partially confounded with underlying environmental gradients.

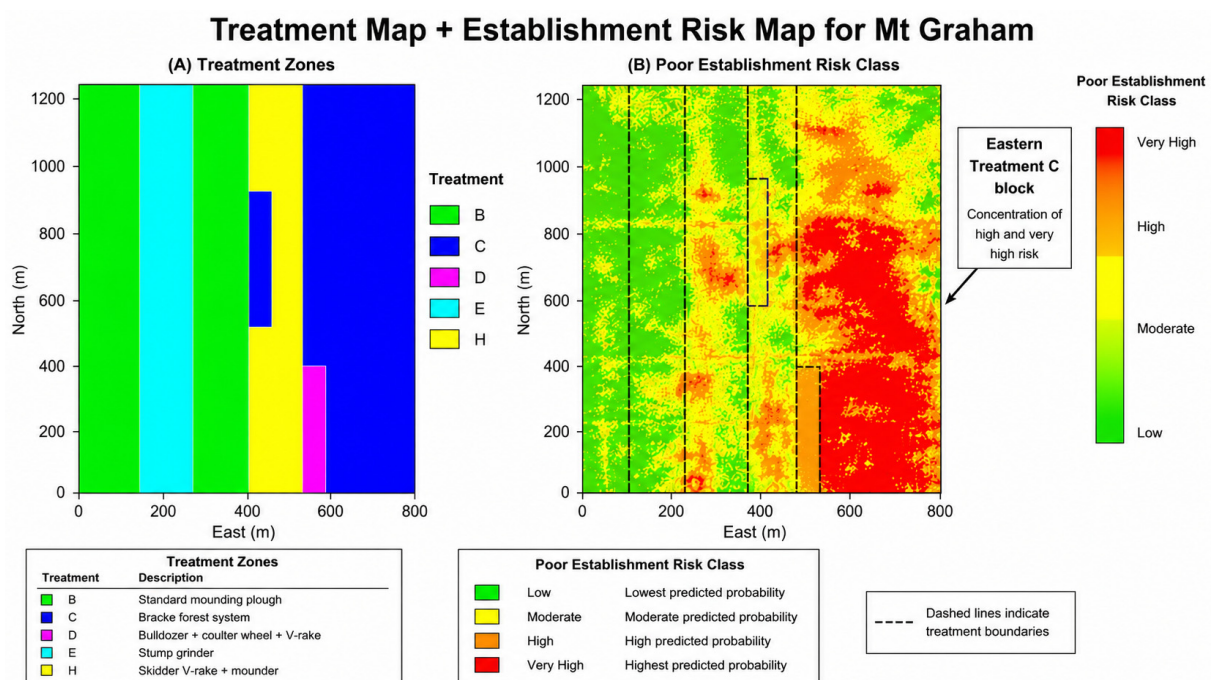


Figure 15. Comparison of treatment zones and predicted poor-establishment-risk classes across the Mount Graham study area. Dashed lines indicate treatment boundaries.

4. Discussion

4.1. Predictive Performance and Spatial Transferability

The ridge-regularised modelling framework achieved strong predictive performance under blocked spatial cross-validation ($AUC = 0.904 \pm 0.004$), indicating that pre-planting environmental and operational conditions contained substantial information regarding subsequent plantation establishment outcomes. Validation using geographically separated folds provided a conservative assessment of predictive performance under spatially inde-

pendent conditions [38–40]. The relatively small variation in AUC among validation folds further suggests that the model captured environmental relationships that were consistent across the study site rather than relying on local spatial structure.

Although the modelling dataset comprised more than 91 million raster cells, these should not be interpreted as 91 million statistically independent observations. The 0.1 m raster cells were strongly spatially autocorrelated because environmental predictors varied continuously across the landscape and several predictors were derived using neighbourhood-based smoothing and aggregation. Consequently, the pixel count reflects the spatial support of the mapped plantation rather than the effective number of independent samples. This spatial dependence primarily affects statistical inference based on coefficient standard errors and significance testing, rather than predictive model development. To minimise optimistic estimates of predictive performance, model evaluation employed geographically contiguous blocked cross-validation, ensuring that validation was performed on spatially separated regions rather than neighbouring pixels. The reported predictive performance therefore reflects the model's ability to generalise to new areas of the plantation under realistic spatial dependence rather than to independent pixel observations.

The limited sensitivity of model performance to the ridge regularisation parameter suggests that predictive accuracy was driven primarily by robust environmental relationships rather than by a particular choice of penalty strength. Ridge regularisation therefore improved coefficient stability without materially affecting the model's ability to generalise under blocked spatial cross-validation.

The mapped standard deviation across the blocked cross-validation models represents variability arising from differences in training-fold composition and should therefore be interpreted as a measure of model sensitivity rather than a complete characterisation of predictive uncertainty. More comprehensive uncertainty quantification could be obtained using approaches such as bootstrap resampling, repeated spatial cross-validation, or Bayesian or ensemble modelling frameworks.

The strong spatial correspondence between predicted establishment-failure probability, stocking density, and tree-height patterns further supports the validity of the modelling framework. High-risk regions consistently coincided with areas of reduced survival and suppressed growth, indicating that the selected predictors successfully represented the dominant environmental and operational gradients influencing plantation performance. These findings extend previous studies demonstrating the ability of UAV remote sensing to characterise forest structure and environmental heterogeneity at operationally relevant spatial scales by showing that such information can also be used to predict future plantation establishment outcomes [32,34]. Collectively, these findings demonstrate that UAV-derived information acquired before planting can provide meaningful prediction of future establishment outcomes approximately 21 months later.

Because the objective of this study was prediction rather than causal inference, the identified relationships should be interpreted as predictive associations rather than independent estimates of treatment effectiveness. The implications of this distinction for treatment comparisons are discussed in Section 4.4.

4.2. Moisture Availability as the Dominant Driver of Establishment Success

Predictor contribution analysis identified moisture-related variables as among the strongest determinants of plantation establishment outcomes. This finding is consistent with extensive forestry literature demonstrating that soil moisture availability is a primary control on early seedling survival and growth [22–25,30], particularly during the critical

period immediately following planting when root systems remain poorly developed and access to soil water is limited [22,25,30,58].

Although individual predictor contributions provide insight into model behaviour, interpretation is more informative when predictors are considered as representations of broader ecological and operational processes. Aggregated predictor contributions indicated that moisture availability, vegetation competition, surface structural complexity, operational management, and interactions among these processes collectively explained most of the variation in establishment outcomes. Moisture-related predictors contributed the largest proportion of model explanatory power, suggesting that water availability was the dominant process influencing early plantation establishment.

The strong influence of moisture-related predictors is also biologically plausible. Water deficit is widely recognised as one of the principal constraints on plantation establishment because declining soil moisture reduces water availability to newly planted seedlings, leading to progressive stomatal closure, reduced photosynthetic carbon assimilation, and diminished growth [22,59,60]. Under more severe or prolonged drought conditions, hydraulic dysfunction and xylem cavitation may impair water transport, substantially increasing the risk of seedling mortality [23,24,30]. Soil moisture conditions are further influenced by soil temperature, evaporative demand, and the presence of harvest residues, which can buffer near-surface microclimatic conditions by reducing soil evaporation, moderating soil temperature fluctuations, and improving moisture retention [61]. Consequently, spatial variation in moisture availability integrates the effects of climate, soil properties, topography, and residue management, providing a mechanistic explanation for the strong predictive importance of moisture-related environmental variables identified in this study.

The strong influence of dryness-related predictors also likely reflects the unusually dry conditions experienced during the establishment period. Rainfall was 58% below the long-term mean from May to November 2024 and 41% below the mean from November 2024 to March 2025, indicating that seedlings were exposed to prolonged moisture deficits during early development (Figure 2). Under these conditions, relatively small differences in residue cover, soil exposure, surface roughness, vegetation competition, and terrain position can produce substantial variation in soil moisture retention and evaporative losses, with corresponding effects on establishment probability [4,5,14].

Although the categorical soil-group predictors contributed less than the moisture-related UAV predictors, the spatial correspondence between predicted failure probability and mapped soil distributions suggests that both direct soil-group information and remotely sensed environmental variables captured complementary aspects of site quality. Similarly, the importance of variables such as RDMI, PDI, exposed-soil metrics, and vegetation condition indices indicates that elevated establishment-risk zones were generally associated with environmental conditions conducive to greater moisture stress [22,25], whereas lower-risk areas corresponded with conditions more favourable for moisture retention.

Moisture-related interaction terms also contributed strongly to model performance, indicating that drought effects operated in combination with vegetation condition, terrain structure, and operational disturbance rather than as an isolated driver. These results suggest that the rainfall deficit not only increased overall establishment stress but also amplified differences among residue-management and tillage treatments by altering microsite moisture buffering capacity. Consequently, management practices that improve moisture retention may become increasingly important as climatic variability and drought frequency increase within plantation environments [3,11,15].

Although the categorical soil-group predictors contributed useful information, their influence should not be interpreted independently of the remaining environmental variables because many soil effects are expressed through moisture availability, terrain, and vegeta-

tion characteristics. Soil properties regulate numerous processes that influence plantation establishment, including water availability, drainage, rooting conditions, nutrient supply, and vegetation development [59–61]. Consequently, much of the predictive information associated with soil is represented indirectly through moisture-related indices (e.g., RDMI), terrain-derived variables controlling water redistribution, and vegetation characteristics that respond to underlying soil conditions. The relatively modest contribution of the categorical soil variable therefore reflects shared environmental information among correlated predictors rather than a lack of soil influence on establishment processes.

Future research could explore hierarchical or multi-level modelling frameworks that explicitly represent the interactions among soil, terrain, vegetation, and climatic processes, thereby providing additional insight into the pathways through which environmental conditions influence plantation establishment.

4.3. Microsite Heterogeneity and Spatial Patterns of Establishment Risk

The results indicate that plantation establishment-failure was not randomly distributed but instead exhibited strong spatial organisation associated with microsite variability [21,27]. Structural predictors describing surface roughness, entropy, line density, residue distribution, and terrain complexity contributed substantially to model performance, indicating that establishment outcomes were influenced by environmental conditions operating at multiple spatial scales [32,34]. The results suggest establishment outcomes are governed by interactions between microsite-scale conditions (e.g., soil disturbance and residue distribution) and broader mesoscale gradients associated with moisture availability and terrain structure.

The observed spatial patterns suggest that local differences in soil exposure, residue retention, coarse woody debris distribution, and operational disturbance modified the microsite environment experienced by individual seedlings. Areas characterised by high structural variability may have contained greater heterogeneity in rooting conditions, soil–residue contact, moisture availability, and planting quality, resulting in increased establishment variability.

These findings highlight the importance of accounting for fine-scale environmental heterogeneity when assessing plantation establishment success. Traditional compartment-level assessments often assume relatively uniform site conditions, whereas collectively these findings indicate that substantial variability in establishment risk can occur over distances of only a few metres. Such fine-scale variability is increasingly recognised as an important determinant of forest condition and productivity but is often overlooked by conventional inventory approaches [33,34]. UAV-derived datasets provide a practical means of quantifying this heterogeneity and incorporating it into predictive decision-support frameworks, thereby enabling more spatially targeted plantation management.

The spatial correspondence between treatment boundaries and predicted establishment-risk classes (Results, Section 3.7) suggests that operational treatments interacted with pre-existing environmental variability. Although higher predicted risk occurred predominantly within Treatment C, the observational design and non-random treatment allocation prevent causal attribution of these differences. Rather, the results indicate that treatment performance was strongly influenced by the environmental context in which treatments were applied.

Transition zones between high- and low-risk areas naturally exhibited greater predictive uncertainty because relatively small changes in environmental conditions produced probabilities close to the classification boundary. Such areas should therefore be interpreted as locations where establishment outcomes are more sensitive to local environmental variability than regions with consistently high or low predicted probabilities.

4.4. Operational Influences and Treatment Effects

The influence of treatment variables and operationally derived structural metrics suggests that plantation establishment outcomes were affected not only by environmental conditions but also by management practices. Several high-risk zones were spatially aligned with operational features including access tracks, firebreaks, harvesting corridors, and planting rows. These features are likely associated with altered soil structure, compaction, residue distribution, and disturbance intensity, all of which can influence seedling performance [16,17].

An important distinction should be made between predictive modelling and causal inference. The objective of the present study was to develop an operationally useful framework for predicting plantation establishment outcomes from pre-planting environmental conditions, rather than to estimate the independent causal effects of individual establishment treatments. Consequently, the relationships identified by the model should be interpreted as predictive associations that reflect the combined influence of environmental conditions, operational management, and their interaction under real plantation conditions.

The ability of the model to reproduce linear operational features indicates that the engineered structural predictors successfully captured both fine-scale disturbance patterns and broader landscape gradients influencing establishment outcomes. Conversely, low- and moderate-risk areas generally occurred within portions of the plantation characterised by more favourable environmental conditions and reduced operational disturbance. These areas were typically associated with improved moisture retention and lower establishment stress, suggesting that both site quality and operational impacts contributed to the observed spatial distribution of establishment outcomes [13,14].

Treatment scenario analysis nevertheless demonstrated meaningful differences among operational treatments after accounting for the environmental predictors included within the model. Under the conditions represented in this study, Treatment E produced the lowest predicted establishment-failure probability, followed by Treatments H and B, whereas Treatments C and D were consistently associated with higher predicted probabilities of failure (Figure 14). These results demonstrate the practical capability of the framework to compare alternative management scenarios within an operational predictive context rather than establish treatment-specific causal effects.

The ability to explicitly incorporate treatment information within the modelling framework provides an important step toward operational decision support. Rather than simply identifying areas of poor performance after establishment has occurred, the framework provides a mechanism for evaluating alternative treatment strategies before implementation and estimating their likely consequences across entire plantation compartments.

The observed treatment differences should nevertheless be interpreted cautiously because treatment allocation was spatially fixed and potentially confounded with underlying environmental gradients (Figure 14). Although Treatment E consistently exhibited the most favourable establishment outcomes, Treatment C was associated with elevated establishment-failure risk across much of the eastern portion of the site. Notably, the smaller isolated strip of Treatment C located within the central plantation also exhibited relatively poor establishment compared with adjacent Treatment H areas, suggesting observed performance differences may not be solely attributable to the broad east–west environmental gradient. Nevertheless, environmental conditions within Treatment C may still have contributed to the elevated risk observed in these areas.

Treatment D also exhibited comparatively poor predicted establishment performance. However, because this treatment occupied a relatively restricted area within the plantation, some of the apparent treatment effect may instead reflect local environmental conditions that differed from those experienced by other treatments. Consequently, its performance

should be interpreted cautiously until evaluated across a broader range of sites and environmental conditions.

Collectively, these findings indicate that treatment performance was strongly influenced by environmental context and illustrate the difficulty of separating treatment effects from underlying site variability within operational plantation trials. Nevertheless, this limitation does not diminish the practical value of the proposed framework because its primary objective is operational prediction rather than estimation of treatment-specific causal effects. By integrating pre-planting UAV-derived environmental information with alternative management scenarios, the framework enables forest managers to identify areas at elevated establishment risk before planting and evaluate potential operational strategies across entire plantation compartments. Future studies incorporating replicated treatment layouts across multiple sites would allow stronger separation of treatment effects from environmental variability, improve model transferability, and provide more robust evidence regarding treatment-specific effectiveness.

From an operational perspective, predictive establishment maps provide an opportunity to move beyond uniform site preparation toward spatially targeted management. Rather than applying identical prescriptions across an entire plantation, managers could identify areas with elevated establishment risk and selectively modify practices such as residue retention, ripping, cultivation intensity, planting density, species choice, or post-planting monitoring. Conversely, lower-risk areas may require fewer interventions, improving operational efficiency and reducing establishment costs.

4.5. Integrating Survival and Growth into Establishment Assessment

A key innovation of the present study is the integration of stocking density and tree height into a composite Establishment Index. Conventional establishment assessments frequently focus on survival alone [22,23,29], implicitly assuming surviving trees contribute equally to future stand development. The proposed Establishment Index therefore combined these complementary measures using a weighting of 0.7 for stocking density and 0.3 for tree height, reflecting the greater operational importance of successful seedling survival during the establishment phase.

Sensitivity analysis demonstrated that the Establishment Index was relatively insensitive to survival-to-growth weightings ranging from 0.5:0.5 to 1.0:0.0 (Supplementary Information, Figure S1). The principal spatial patterns, treatment comparisons, and management interpretation remained consistent across all weighting schemes. For example, the default 0.7:0.3 index exhibited a Pearson correlation of 0.990 ($R^2 = 0.979$) with the equal-weight (0.5:0.5) index. These findings indicate that the adopted 0.7:0.3 weighting primarily influences the absolute scale of the Establishment Index rather than the underlying spatial relationships and therefore represents a practical operational preference rather than a critical modelling parameter upon which the principal conclusions depend.

The Establishment Index therefore provides a more biologically meaningful representation of plantation performance by recognising that successful establishment requires both survival and subsequent growth [22,23,29]. Several areas that would have appeared acceptable if assessed using stocking density alone exhibited substantially lower Establishment Index values owing to suppressed tree height. These areas would likely have been overlooked using conventional stocking-based assessments despite representing potentially underperforming portions of the plantation.

The integration of stocking density and growth information therefore improves the sensitivity of establishment assessment and provides a stronger foundation for operational intervention and long-term productivity evaluation.

4.6. Implications for Precision Forestry

The strong spatial coherence of predicted risk classes has important operational implications. High-risk zones formed large contiguous regions rather than isolated pixels, suggesting that management interventions can be implemented at meaningful operational scales. This creates opportunities for targeted replanting, modified site preparation, residue redistribution, weed management, or supplementary treatments focused on areas most likely to experience establishment-failure.

More broadly, the framework demonstrates how high-resolution UAV remote sensing can be integrated with spatial statistical modelling to support precision forestry. By linking pre-planting environmental conditions with subsequent plantation performance, managers can move from reactive assessment toward proactive risk identification and treatment optimisation. Such approaches may become increasingly valuable as climatic variability and drought frequency continue to increase uncertainty surrounding plantation establishment success [18–20].

A notable outcome of this study is that all predictor variables were derived from UAV imagery acquired prior to planting, whereas establishment outcomes were assessed approximately 21 months later. The ability to predict plantation performance approximately 21 months before assessment suggests that a substantial component of establishment variability was already encoded within pre-planting environmental and operational conditions.

This finding has important operational implications because it demonstrates that establishment risk can be identified before planting occurs. Rather than using remote sensing solely as a monitoring tool, the approach enables predictive assessment of future plantation performance. Such information could be used to modify site preparation treatments, residue management strategies, planting prescriptions, or operational resource allocation before establishment-failure occurs. The framework therefore represents a transition from retrospective assessment toward proactive establishment-risk forecasting within plantation forestry.

4.7. Limitations and Future Research

Several limitations should be acknowledged. First, the model was developed and evaluated within a single plantation site, and transferability to other sites, species, climatic conditions, and management systems remains to be tested. Multi-site validation will be required before broad operational deployment.

Second, while blocked spatial cross-validation reduces inflation associated with spatial autocorrelation, some predictive power may still arise from residual spatial structure not fully represented by the predictor set. Although the blocked east–west cross-validation strategy was selected to provide a conservative estimate of predictive performance, alternative blocking orientations or conventional random cross-validation may produce different performance estimates because they alter the degree of spatial dependence between training and validation samples. Comparative evaluation of alternative partitioning strategies was beyond the scope of the present study but represents an important direction for future research, particularly for operational deployment across more heterogeneous landscapes. Future research should also evaluate the framework across a broader range of plantation types, environmental conditions, and management practices.

Third, the present framework represents establishment outcomes at a single stage of stand development. Incorporating repeated observations through time would allow evaluation of temporal trajectories in survival and growth and improve understanding of how early environmental conditions influence later stand performance.

Future research should therefore focus on multi-site validation, temporal modelling, integration of additional environmental datasets (including soil properties), and optimi-

sation of treatment prescriptions. Expansion to multiple plantation species and environmental settings would further improve understanding of the generality of the observed relationships and support development of operationally deployable establishment-risk prediction systems.

5. Conclusions

This study demonstrates that plantation establishment risk can be predicted from UAV-derived environmental conditions acquired before planting. By combining stocking density and tree height into a composite Establishment Index, the analysis captures both survival and growth performance, providing a more comprehensive measure of establishment success than stocking density alone.

The ridge-regularised logistic regression model achieved strong predictive performance under blocked spatial cross-validation ($AUC = 0.904 \pm 0.004$), indicating reliable discrimination between successful and poor establishment areas. Model-based predictor analysis indicated that moisture availability, microsite heterogeneity, vegetation competition and operational treatments exhibited the largest relative standardised coefficient contributions within the fitted ridge regression model. The unusually dry conditions experienced during the establishment period further emphasised the importance of moisture-related controls on seedling survival and growth.

Spatial predictions identified coherent patterns of establishment risk across the plantation, demonstrating the potential for proactive management interventions, including treatment scenario-screening, targeted replanting, and site-preparation adjustments. Importantly, all predictors were measured before planting, allowing establishment risk to be identified well in advance of operational assessment.

Although the current study was conducted at a single site, the framework is potentially adaptable to other plantation environments, subject to external validation and recalibration, and can be extended to incorporate additional environmental, operational, and temporal predictors. The results demonstrate that a substantial component of plantation performance is already encoded in pre-planting site conditions, providing a practical foundation for proactive establishment-risk forecasting and treatment optimisation in plantation forestry.

The principal innovation of this study lies not simply in predicting plantation establishment from UAV-derived environmental variables, but in providing an operational framework that integrates environmental mapping, predictive modelling, treatment scenario analysis, and a robust Establishment Index within a single decision-support system. By enabling spatially explicit assessment of establishment risk before planting, the proposed methodology provides plantation managers with a practical tool for targeting interventions, evaluating alternative establishment strategies, and improving operational planning.

More broadly, the proposed framework demonstrates how routinely acquired UAV data can be transformed into practical operational intelligence for plantation establishment. By supporting spatially explicit risk assessment before planting, the framework provides plantation managers with a scalable decision-support tool that can improve resource allocation, prioritise management interventions, reduce establishment risk, and support more resilient plantation development under increasingly variable environmental conditions. Future work should evaluate the operational and economic benefits of integrating predictive establishment-risk maps into routine plantation planning across a wider range of species, sites, and management systems.

Supplementary Materials: The following supporting information can be downloaded at <https://www.mdpi.com/article/10.3390/rs18162665/s1>. Figure S1: Sensitivity of the Establishment Index to the weighting assigned to survival and tree height. From left to right and top to bottom, survival weightings range from 0.5 to 1.0 (height weighting 0.5 to 0.0). Although absolute Establishment

Index values increase as greater emphasis is placed on survival, the principal spatial patterns remain highly consistent across all weighting schemes; Table S1: Sensitivity to Stocking Density/Height Weights for Establishment Index; Figure S2: Sensitivity of predicted establishment failure probability to establishment failure thresholds corresponding to the 20th, 50th, and 75th percentiles; Figure S3: Sensitivity of predicted establishment failure probability to establishment failure thresholds corresponding to the 25th, 50th, and 75th percentiles; Figure S4: Sensitivity of predicted establishment failure probability to establishment failure thresholds corresponding to the 30th, 50th, and 75th percentiles; Figure S5: Sensitivity of predicted establishment failure probability to establishment failure thresholds corresponding to the 20th, 40th, and 70th percentiles; Figure S6: Sensitivity of predicted establishment failure probability to establishment failure thresholds corresponding to the 30th, 55th, and 80th percentiles; Figure S7: Receiver operating characteristic (ROC) curves comparing blocked spatial and random stratified five-fold cross-validation for the ridge-regularised logistic regression model. Both validation strategies achieved excellent discrimination ($AUC = 0.904$), indicating robust predictive performance. Although the ROC curves were nearly identical, blocked spatial cross-validation was adopted for model evaluation because it reduces the optimistic bias associated with spatially dependent observations and provides a more realistic assessment of predictive performance for geographically distinct areas; Table S2: Multispectral bands for MicaSense Altum-PT camera; Figure S8: Construction of the NIR–Red spectral space and depiction of the indices, perpendicular drought index, perpendicular vegetation index, and ratio dryness monitoring index (PDI, PVI, and RDMI); Table S3: Implementation Details; Figure S9: Overview of the modelling workflow. UAV imagery was processed to generate orthomosaics and point clouds from which environmental predictors were derived. Following feature engineering, interaction-term generation and predictor filtering, a ridge-regularised logistic regression model was trained and evaluated using blocked spatial cross-validation to predict and map plantation establishment-failure probability across the study area.

Author Contributions: Conceptualization, A.F., J.O., B.J. and N.W.; methodology, A.F.; software, A.F. and P.S.M.S.; validation, A.F. and D.S.; formal analysis, A.F. and P.S.M.S.; investigation, A.F.; data curation, A.F. and P.S.M.S.; writing—original draft preparation, A.F.; writing—review and editing, P.S.M.S., N.W., J.O., P.S.M.S. and B.J.; project administration, J.O.; funding acquisition, J.O. and B.J. All authors have read and agreed to the published version of the manuscript.

Funding: This study was funded by Forest & Wood Products Australia (FWPA) under Research Agreement: NIF199-2223, “Enhancing softwood and hardwood plantations site productivity and subsequent operational efficiency by use of an innovative cleanstrip establishment system”.

Data Availability Statement: Data are available from the corresponding author upon reasonable request.

Acknowledgments: We are grateful to Steven Andriolo of EyeSky for conducting the drone operations in South Australia and Victoria, to Rohan Rainbow of Crop Protection Australia who provided precision forestry, engineering, and soil measurement advice to this project, and to Australian Bluegum Plantations (ABP), OneFortyOne (OFO), Midway Limited, PF Olsen (PFO), and Green Triangle Forest Products (GTFP) for assisting us with this study. The authors also thank HxGN SmartNet for providing access to their GNSS NTRIP correction services, which were utilised during data collection, free of charge for educational research purposes. During the preparation of this manuscript, the authors used ChatGPT (version 1.2026.133) to convert MATLAB 2026a-generated and author-created graphics into publication-ready figures and to assist with language review. The authors have reviewed and edited the output and take full responsibility for the content of this publication.

Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

RDMI	Ratio dryness monitoring index
NRCT	Normalised relative canopy temperature
NDVI	Normalised difference vegetation index
PDI	Perpendicular dryness index
DEM	Digital elevation model
HAG	Height above ground
PSD	Power spectral density
UAV	Unmanned aerial vehicle
AUC	Area under the ROC curve
ROC	Receiver operating characteristic
PINT	Program for identifying nursery trees
RGB	Red, green, and blue
ECE	Expected calibration error
SD	Standard deviation
CV	Cross-validation
FWHM	Full width half maximum
GNSS	Global navigation satellite system
NTRIP	Networked Transport of RTCM via Internet Protocol
RTK	Real time kinematic
SfM	Structure from motion

References

1. Eckert, M.; Gaigher, R.; Pryke, J.S.; Samways, M.J. Short-term arthropod recovery in Eucalyptus plantations after harvesting is not affected by different residue management practices. *For. Ecol. Manag.* **2023**, *537*, 120973. [\[CrossRef\]](#)
2. Zielonka, T.; Niklasson, M. Dynamics of dead wood and regeneration pattern in natural spruce forest in the Tatra Mountains, Poland. *Ecol. Bull.* **2001**, 159–163. Available online: <https://www.jstor.org/stable/20113273> (accessed on 17 April 2026).
3. Franco, C.R.; Page-Dumroese, D.S.; Archuleta, J. Forest management and biochar for continued ecosystem services. *J. Soil Water Conserv.* **2022**, *77*, 60A–64A. [\[CrossRef\]](#)
4. Motta, R.; Berretti, R.; Lingua, E.; Piussi, P. Coarse woody debris, forest structure and regeneration in the Valbona Forest Reserve, Paneveggio, Italian Alps. *For. Ecol. Manag.* **2006**, *235*, 155–163. [\[CrossRef\]](#)
5. Bače, R.; Svoboda, M.; Pouska, V.; Janda, P.; Červenka, J. Natural regeneration in Central-European subalpine spruce forests: Which logs are suitable for seedling recruitment? *For. Ecol. Manag.* **2012**, *266*, 254–262. [\[CrossRef\]](#)
6. Becker, R.M.; Keefe, R.F. Prediction of Fuel Loading Following Mastication Treatments in Forest Stands in North Idaho, USA. *Sustainability* **2020**, *12*, 7025. [\[CrossRef\]](#)
7. Jain, T.; Sikkink, P.; Keefe, R.; Byrne, J. *To masticate or not: Useful Tips for Treating Forest, Woodland, and Shrubland Vegetation*; U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station: Fort Collins, CO, USA, 2018.
8. Ghaffariyan, M.R. Short review of collecting technologies and methods in forest harvesting residues recovery. *Silva Balc.* **2023**, *24*, 55–68. [\[CrossRef\]](#)
9. Yoshioka, T. Current Situation and Future Outlook of Forest Biomass Production and Its Utilization in Japan. In *Biotechnological Applications of Biomass*; Peixoto Basso, T., Basso, T.O., Basso, L.C., Eds.; IntechOpen: Rijeka, Croatia, 2020.
10. Hall, P.; Palmer, D.; Edwards, P.; Wegner, S.; Baillie, B. Processing options to increase the use of post-harvest residues on the East Coast. *SCION Rep.* **2019**.
11. Alberts, E.; Neibling, W.H. Influence of crop residues on water erosion. *Manag. Agric. Residues* **1994**, *13*, 19–44.
12. Daughtry, C.S. Discriminating crop residues from soil by shortwave infrared reflectance. *Agron. J.* **2001**, *93*, 125–131. [\[CrossRef\]](#)
13. Janowiak, M.K.; Webster, C.R. Promoting ecological sustainability in woody biomass harvesting. *J. For.* **2010**, *108*, 16–23. [\[CrossRef\]](#)
14. Udali, A.; Chung, W.; Talbot, B.; Grigolato, S. Managing harvesting residues: A systematic review of management treatments around the world. *For. Int. J. For. Res.* **2025**, *98*, 117–135. [\[CrossRef\]](#)
15. Lal, R. Biofuels from crop residues. *Soil Tillage Res.* **2007**, *93*, 237–238. [\[CrossRef\]](#)
16. Nambiar, E.; Sands, R. Effects of compaction and simulated root channels in the subsoil on root development, water uptake and growth of radiata pine. *Tree Physiol.* **1992**, *10*, 297–306. [\[CrossRef\]](#) [\[PubMed\]](#)

17. Costantini, A.; Doley, D. Management of compaction during harvest of *Pinus* plantations in Queensland: III. Preliminary investigation of the potential for selected soil parameters to predict rut compaction. *Aust. For.* **2001**, *64*, 193–198. [\[CrossRef\]](#)
18. Davis, M.B.; Shaw, R.G. Range shifts and adaptive responses to Quaternary climate change. *Science* **2001**, *292*, 673–679. [\[CrossRef\]](#) [\[PubMed\]](#)
19. Anderson-Teixeira, K.J.; Davies, S.J.; Bennett, A.C.; Gonzalez-Akre, E.B.; Muller-Landau, H.C.; Joseph Wright, S.; Abu Salim, K.; Almeyda Zambrano, A.M.; Alonso, A.; Baltzer, J.L. CTFS-Forest GEO: A worldwide network monitoring forests in an era of global change. *Glob. Change Biol.* **2015**, *21*, 528–549.
20. Stevens-Rumann, C.S.; Kemp, K.B.; Higuera, P.E.; Harvey, B.J.; Rother, M.T.; Donato, D.C.; Morgan, P.; Veblen, T.T. Evidence for declining forest resilience to wildfires under climate change. *Ecol. Lett.* **2018**, *21*, 243–252. [\[PubMed\]](#)
21. Liu, H.; Shi, H.; Zhou, Q.; Hu, M.; Shu, X.; Zhang, K.; Zhang, Q.; Dang, H. Habitat heterogeneity and biotic interactions mediate climate influences on seedling survival in a temperate forest. *For. Ecosyst.* **2023**, *10*, 100138. [\[CrossRef\]](#)
22. Grossnickle, S.C. Why seedlings survive: Influence of plant attributes. *New For.* **2012**, *43*, 711–738. [\[CrossRef\]](#)
23. Grossnickle, S.C.; MacDonald, J.E. Why seedlings grow: Influence of plant attributes. *New For.* **2018**, *49*, 1–34. [\[CrossRef\]](#)
24. Grossnickle, S.C.; MacDonald, J.E. Seedling Quality: History, Application, and Plant Attributes. *Forests* **2018**, *9*, 283. [\[CrossRef\]](#)
25. Close, D.C. A review of ecophysiological-based seedling specifications for temperate Australian eucalypt plantations. *New For.* **2012**, *43*, 739–753. [\[CrossRef\]](#)
26. Curran, T.J.; Clarke, P.J.; Warwick, N.W.M. Drought survival of Australian rainforest seedlings is influenced by species evolutionary history and soil type. *Aust. J. Bot.* **2013**, *61*, 22–28. [\[CrossRef\]](#)
27. Charles, L.S.; Dwyer, J.M.; Smith, T.J.; Connors, S.; Marschner, P.; Mayfield, M.M. Species wood density and the location of planted seedlings drive early-stage seedling survival during tropical forest restoration. *J. Appl. Ecol.* **2018**, *55*, 1009–1018.
28. Mankur, M.; Shil, S.; Toppo, P. Forest Restoration and Reforestation: Best Practices and Challenges. *Adv. For. Agro-For.* **2023**, *1*, 147–179. [\[CrossRef\]](#)
29. Preece, N.D.; van Oosterzee, P.; Lawes, M.J. Reforestation success can be enhanced by improving tree planting methods. *J. Environ. Manag.* **2023**, *336*, 117645. [\[CrossRef\]](#) [\[PubMed\]](#)
30. Grossnickle, S.C.; Ivetić, V. Root system development and field establishment: Effect of seedling quality. *New For.* **2022**, *53*, 1021–1067. [\[CrossRef\]](#)
31. Zou, C.; Penfold, C.; Sands, R.; Misra, R.K.; Hudson, I. Effects of soil air-filled porosity, soil matric potential and soil strength on primary root growth of radiata pine seedlings. *Plant Soil* **2001**, *236*, 105–115. [\[CrossRef\]](#)
32. Iglhaut, J.; Cabo, C.; Puliti, S.; Piermattei, L.; O'Connor, J.; Rosette, J. Structure from motion photogrammetry in forestry: A review. *Curr. For. Rep.* **2019**, *5*, 155–168. [\[CrossRef\]](#)
33. Torresan, C.; Luyssaert, S.; Filippa, G.; Imangholiloo, M.; Gaulton, R. Remote sensing technologies for assessing climate-smart criteria in mountain forests. In *Climate-Smart Forestry in Mountain Regions*; Springer: Berlin/Heidelberg, Germany, 2021; pp. 399–433.
34. Goodbody, T.R.; Coops, N.C.; Marshall, P.L.; Tompalski, P.; Crawford, P. Unmanned aerial systems for precision forest inventory purposes: A review and case study. *For. Chron.* **2017**, *93*, 71–81. [\[CrossRef\]](#)
35. Finn, A.; Kumar, P.; Peters, S.; O'Hehir, J. Unsupervised Spectral-Spatial Processing of Drone Imagery for Identification of Pine Seedlings. *ISPRS J. Photogramm. Remote Sens.* **2022**, *183*, 363–388. [\[CrossRef\]](#)
36. Finn, A.; Skelton, P.; O'Hehir, J.; Schebella, D.; Jenkins, B. Enhancing softwood and hardwood plantations site productivity and subsequent operational efficiency by use of an innovative clean-row establishment 'system': Survival Analysis at 21 Months. In *Research Agreement: NIF199-2223*; NIFPI: Melbourne, Australia, 2026.
37. Finn, A.; Skelton, P.; O'Hehir, J.; Schebella, D.; Jenkins, B. Enhancing softwood and hardwood plantations site productivity and subsequent operational efficiency by use of an innovative clean-row establishment 'system': Survival Analysis at 16 Months. In *Research Agreement: NIF199-2223*; NIFPI: Melbourne, Australia, 2025.
38. Roberts, D.R.; Bahn, V.; Ciuti, S.; Boyce, M.S.; Elith, J.; Guillera-Aroita, G.; Hauenstein, S.; Lahoz-Monfort, J.J.; Schröder, B.; Thuiller, W. Cross-validation strategies for data with temporal, spatial, hierarchical, or phylogenetic structure. *Ecography* **2017**, *40*, 913–929. [\[CrossRef\]](#)
39. Valavi, R.; Elith, J.; Lahoz-Monfort, J.J.; Guillera-Aroita, G. blockCV: An r package for generating spatially or environmentally separated folds for k-fold cross-validation of species distribution models. *Biorxiv* **2018**, 357798. [\[CrossRef\]](#)
40. Whelan, A.W.; Cannon, J.B.; Bigelow, S.W.; Rutledge, B.T.; Sánchez Meador, A.J. Improving generalized models of forest structure in complex forest types using area- and voxel-based approaches from lidar. *Remote Sens. Environ.* **2023**, *284*, 113362. [\[CrossRef\]](#)
41. Skelton, P.; Finn, A.; Winkley, N.; O'Hehir, J. Final report for Project VNC619-2324 ("Operationalisation of PINT and Incorporation of Weed Identification"). 2026.
42. Aussenac, G. Interactions between forest stands and microclimate: Ecophysiological aspects and consequences for silviculture. *Ann. For. Sci.* **2000**, *57*, 287–301. [\[CrossRef\]](#)
43. Prescott, C.E. The influence of the forest canopy on nutrient cycling. *Tree Physiol.* **2002**, *22*, 1193–1200. [\[CrossRef\]](#) [\[PubMed\]](#)

44. Fleming, R.L.; Powers, R.F.; Foster, N.W.; Kranabetter, J.M.; Scott, D.A.; Ponder, F., Jr.; Berch, S.; Chapman, W.K.; Kabzems, R.D.; Ludovici, K.H. Effects of organic matter removal, soil compaction, and vegetation control on 5-year seedling performance: A regional comparison of Long-Term Soil Productivity sites. *Can. J. For. Res.* **2006**, *36*, 529–550. [\[CrossRef\]](#)
45. Walmsley, J.; Godbold, D. Stump harvesting for bioenergy—a review of the environmental impacts. *Forestry* **2010**, *83*, 17–38. [\[CrossRef\]](#)
46. Xu, H.; Latta, G.; Lee, U.; Lewandrowski, J.; Wang, M. Regionalized Life Cycle Greenhouse Gas Emissions of Forest Biomass Use for Electricity Generation in the United States. *Environ. Sci. Technol.* **2021**, *55*, 14806–14816. [\[CrossRef\]](#) [\[PubMed\]](#)
47. Skovsgaard, J.P.; Johansson, U.; Holmström, E.; Tune, R.M.; Ols, C.; Attocchi, G. Effects of Thinning Practice, High Pruning and Slash Management on Crop Tree and Stand Growth in Young Even-Aged Stands of Planted Silver Birch (*Betula pendula* Roth). *Forests* **2021**, *12*, 225. [\[CrossRef\]](#)
48. Littlefield, C.E. Topography and post-fire climatic conditions shape spatio-temporal patterns of conifer establishment and growth. *Fire Ecol.* **2019**, *15*, 34. [\[CrossRef\]](#)
49. Dandois, J.P.; Ellis, E.C. High spatial resolution three-dimensional mapping of vegetation spectral dynamics using computer vision. *Remote Sens. Environ.* **2013**, *136*, 259–276. [\[CrossRef\]](#)
50. Guimarães, N.; Pádua, L.; Marques, P.; Silva, N.; Peres, E.; Sousa, J.J. Forestry Remote Sensing from Unmanned Aerial Vehicles: A Review Focusing on the Data, Processing and Potentialities. *Remote Sens.* **2020**, *12*, 1046. [\[CrossRef\]](#)
51. Finn, A.; Younger, J.; Peters, S.; O’Hehir, J.; Lucieer, A.; Turner, D. *Geospatial Positioning & Fusion: Is Real-Time Sub-Metre, Accuracy Operationally Feasible in Forestry Environments? Milestone 6: 3D Point Cloud Fusion Using Aerial and Terrestrial Laser Scanning*; Forest & Wood Products Association: Collingwood, Australia, 2024; p. 97.
52. Finn, A.; Younger, J.; Peters, S.; O’Hehir, J.; Lucieer, A.; Turner, D. *Geospatial Positioning & Fusion: Is Real-Time Sub-Metre, Accuracy Operationally Feasible in Forestry Environments? Recommendations for Field Testing GNSS Receivers in Forests*; Forest & Wood Products Association: Collingwood, Australia, 2025; p. 11.
53. Valavi, R.; Elith, J.; Lahoz-Monfort, J.J.; Guillera-Aroita, G. block CV: An r package for generating spatially or environmentally separated folds for k-fold cross-validation of species distribution models. *Methods Ecol. Evol.* **2019**, *10*, 225–232. [\[CrossRef\]](#)
54. Tinkham, W.T.; Woolsey, G.A. Influence of Structure from Motion Algorithm Parameters on Metrics for Individual Tree Detection Accuracy and Precision. *Remote Sens.* **2024**, *16*, 3844. [\[CrossRef\]](#)
55. Xu, Z.; Shen, X.; Cao, L. Extraction of Forest Structural Parameters by the Comparison of Structure from Motion (SfM) and Backpack Laser Scanning (BLS) Point Clouds. *Remote Sens.* **2023**, *15*, 2144. [\[CrossRef\]](#)
56. Finn, A.; O’Hehir, J.; Schebella, D.; Jenkins, B. Enhancing softwood and hardwood plantations site productivity and subsequent operational efficiency by use of an innovative clean-row establishment ‘system’: Milestone 2C: Multispectral Assessment of Treatments for Tillage and Forestry Harvesting Residues. In *Research Agreement: NIF199-2223*; NIFPI: Melbourne, Australia, 2024.
57. Meyer, F. Topographic distance and watershed lines. *Signal Process.* **1994**, *38*, 113–125. [\[CrossRef\]](#)
58. Allen, C.D.; Macalady, A.K.; Chenchouni, H.; Bachelet, D.; McDowell, N.; Vennetier, M.; Kitzberger, T.; Rigling, A.; Breshears, D.D.; Hogg, E.H.; et al. A global overview of drought and heat-induced tree mortality reveals emerging climate change risks for forests. *For. Ecol. Manag.* **2010**, *259*, 660–684. [\[CrossRef\]](#)
59. Choat, B.; Brodribb, T.J.; Brodersen, C.R.; Duursma, R.A.; Lopez, R.; Medlyn, B.E. Triggers of tree mortality under drought. *Nature* **2018**, *558*, 531–539. [\[CrossRef\]](#) [\[PubMed\]](#)
60. Grossnickle, S.C. Importance of root growth in overcoming planting stress. *New For.* **2005**, *30*, 273–294. [\[CrossRef\]](#)
61. Adams, H.D.; Zeppel, M.J.B.; Anderegg, W.R.L.; Hartmann, H.; Landhäusser, S.M.; Tissue, D.T.; Huxman, T.E.; Hudson, P.J.; Franz, T.E.; Allen, C.D.; et al. A multi-species synthesis of physiological mechanisms in drought-induced tree mortality. *Nat. Ecol. Evol.* **2017**, *1*, 1285–1291. [\[CrossRef\]](#)

Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.