Alternative species mapping for the Wairarapa Region

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Date: November 2023

Executive Summary

This project applied a remote sensing approach developed by the School of Forestry to classify alternative species in small-scale plantations in the Wairarapa region. Similar to previous projects, the approach achieved an overall classification accuracy of 92.9%. Douglas-fir and Eucalyptus appeared as the two most accurately classified alternative species classes, with producer's accuracies of 96.8% and 93.8%, respectively. The key input variable selected for classification was the Digital Elevation Model (DEM), indicating that elevation significantly influences the differentiation of plantation species.

A total of 1,617 hectares of alternative species were mapped, with Eucalyptus being the most prevalent species class, constituting 35% of the total alternative species resources. Other species, including mixed species and less common alternatives, accounted for 24%. In comparison to the National Exotic Forest Description (NEFD) report, there was a notable difference of 453 hectares (17%) more than the NEFD-reported area. This study estimated substantially more Eucalyptus, Douglas-fir, and cypress than indicated by the NEFD.

Contents

Introduction

The New Zealand forest industry needs to diversify its plantation resources beyond reliance on radiata pine. In order to model the potential sustainable log supply from alternative species and assess how these forests could contribute to regional economic development, it is critical to understand the area and location of these resources.

Unfortunately, the National Exotic Forest Description (NEFD) for small-scale forests, including the alternative species, has been found to contain considerable inaccuracies (Manley et al., 2020). These inaccuracies create significant challenges when attempting to model sustainable log supply from these forests. The 2021 NEFD reported 1,164 ha of alternative species in the Wairarapa region, excluding Tararua district (MPI, 2021). However, but the reliability of this data is questionable, and it lacks spatial details of these resources.

An automated mapping approach for these alternative species using remote sensing has been developed by Xu et al. (2023), as part of the Specialty Wood Products (SWP) research programme, has successfully identify and accurately mapped areas of different alternative species in the Hawke's Bay region and the East Coast region, with satisfactory mapping accuracies of 92.8% and 92.9% respectively. The approach applied a Random Forest (RF) classifier using 10-metre resolution Sentinel imagery along with reference data from known locations and species. While the absence of digital reference data from small-scale forests posed challenges, the reference data used for species classification were primarily sourced from large-scale forest owners, NZDFI trials, and PSPs of alternative species managed by Scion.

This project aims to apply the approach described above to develop a spatial map representing the distribution of alternative species within the Wairarapa region. Furthermore, we will overlay the LINZ ownership boundary with the spatial map to identify the owners of these alternative species. The Wairarapa Branch of the NZFFA is interested in applying this technique, to identify the types and locations of alternative species growing in the Wairarapa, marking the initial step in a long-term project to strengthen the regional alternative species supply chain. Currently, the supply chain for these species in the Wairarapa is relatively weak, with few small-scale silviculture and harvesting contractors, few mobile sawmillers, and only one static mill processing cypress. With improved data on the growing resource, Wairarapa FFA members can forecast potential woodflows and strategically concentrate their efforts.

Methodology

Study Area

The study area is the Wairarapa region of New Zealand, which consists of the districts of Masterton, Carterton, and South Wairarapa. There are approximately 61,349 ha of plantation forests in the region, of which 98% is radiata pine (MPI, 2021). The remaining 2% (equivalent to 1,164 ha) consists of alternative species, mainly other softwoods and hardwoods, followed by eucalyptus, Douglas-fir and cypress species (Table 1).

Table 1: NEFD reported alternative species in Wairarapa (MPI, 2021).

	Douglas-fir	Cypress	Other softwoods	Eucalyptus	Other hardwoods	Total
Masterton	128	39	297	80	119	663
Carterton	52	2	75	17	66	212
South Wairarapa	6	9	29	130	115	289
Total	**186**	**50**	**401**	**227**	**300**	**1164**

Pre-defining forest boundary

Pre-defining the geographic boundaries of alternative species is required to define the extent of classification. Without the pre-defined boundaries, the classification method tends to mistakenly identifies non-forest land covers as alternative species plantations because of their similar spectral signatures. To address this, operator was trained to manually delineate the boundary of alternative species that are sized over 0.5 ha in Wairarapa region using 0.3 m orthophotos acquired in February 2021, via LINZ Data Service (LINZ,2021).

Collecting reference data

The reference data used in this study were obtained from the previous studies in Hawke's Bay and East Coast regions. In addition, reference data in Wairarapa region were also collected, which included GIS stand boundaries provided by the large-scale forest owners, additional PSP data on alternative species from Scion and species maps from NZFFA. Table 2 provides a summary of this reference data used in this study.

Within the spatial boundaries of the reference data, circular plots with a maximum radius of 50 metres were automatically and randomly generated, which were then used as the sample data for species classification. The dataset was then randomly split into 70% training and 30% validation dataset, meaning 70% of the randomly selected data was used for developing the classification and 30% was used to assess the accuracy of the classification.

Table 2: Reference data collected for all studies. The numbers represent the number of pixels (10x10 m). Other species include other alternative species that are not listed in the table such as cedar and willow. Radiata pine samples were manually added as place holders in the classification. Other pines are pine species other than radiata pine.

Species Class	CNI and Hawke's Bay	East Coast	Wairarapa
Acacia	2,556	704	29
Cypress	13,234	1,602	377
Douglas-fir	57,764	2,024	1,144
Eucalyptus	20,554	3,801	2,622
Larch	2,092	1,091	128
Other pine	6,898	1,865	150
Other species	9,784	1,504	681
Poplar	1,960	313	409
Radiata	39,297	162	4,690
Redwood	6,845	1,166	156
Total	**160,984**	**14,232**	**10,386**

Remote sensing data

Sentinel-2 is an Earth Observation mission launched by the European Space Agency's (ESA) Copernicus Programme, designed to observe and collect optical imagery with high spatial resolution (ranging from 10 meters to 60 meters) of both land and coastal waters. Sentinel-2 imagery has gained popularity in forest mapping studies worldwide due to its relatively high spatial and spectral resolution. For example, Schindler et al. (2021) applied a random forest classifier to map the national extent of southern beeches in New Zealand using a temporal stack of Sentinel-2 imagery and achieved an accuracy of 87.7%. Alonso et al. (2020) classified fragmented chestnut plantations in Northwest Spain using Sentinel-2 and achieved 81.5% accuracy.

The annual national Sentinel-2 mosaics have been distributed by the Ministry for the Environment (MfE). They were processed by Manaaki Whenua - Landcare Research following a workflow developed by (Shepherd et al., 2020). The mosaic product is a 10 m, ten-band multispectral, cloud-minimised mosaic of multiple Sentinel-2A and -2B satellite images over New Zealand. The mosaic underwent pan-sharpening, atmospheric and bidirectional reflectance distribution function correction, cloud clearing and minimising process. The Sentinel mosaics that collected over the summer 2020-2021 were acquired from MfE and clipped to the extent of the Wairarapa region. The specifications of the mosaics are presented in Table 3.

Table 3: Bands specification of Sentinel-2 mosaic.

Band	Band Name	Short Name	Wavelength (nm)
2	Blue	B	490
3	Green	G	560
4	Red	R	665
5	Red Edge 1	RE705	705
6	Red Edge 2	RE740	740
7	Red Edge 3	RE783	783
8	Near Infrared wide	NIR842	842
8A	Near Infrared narrow	NIR865	865
11	Short Wave Infrared 1	SWIR1610	1610
12	Short Wave Infrared 2	SWIR2190	2190

Vegetation indices (VIs), formed through the spectral transformation of two or more spectral bands, prove valuable in discerning alterations in spectral responses associated with changes in foliage colour (Immitzer et al., 2019). In this study, total of 33 vegetation indices, known for their sensitivity to vegetation characteristics and having been utilised in previous vegetation classification research (Grabska et al., 2019; Immitzer et al., 2019; Ye et al., 2021), were extracted from the Sentinel-2 mosaic (details in Appendix 1).

Texture refers to the spatial variation of image greyscale levels as a function of scale, which can be smooth or coarse. Textural features are related to the variability of stand density, forest type (broadleaved or coniferous), crown size, crown closure, crown form, and crown closure (Fassnacht et al., 2016). They can considerably enhance the classification accuracy when combined with spectral features (Mallinis et al., 2008). In this study, after conducting Principle Component Analysis (PCA) on the Sentinel-2 mosaic, a window size of 3 by 3 was employed to compute values for the Grey Levels Co-Occurrence Matrix (GLCM). These GLCM statistics included mean, variance, homogeneity, contrast, dissimilarity, entropy, second moment, and correlation. To optimise computational efficiency and data management, the first principal band was chosen for GLCM analysis.

Phenological features were computed from analysing the temporal variation of Enhanced Vegetation Index-2 (EVI2) using Sentinel-2 data collected from 1 January 2020 to 31 December 2021 in Google Earth Engine (GEE). EVI2 was chosen because it is one of the most commonly used VIs for phenological studies, as reviewed by Caparros-Santiago et al. (2021). It was developed by Jiang et al. (2008) to address the saturation issue of the Normalized Difference Vegetation Index (NDVI) in forested areas with high biomass. Three seasonal metrics, amplitude (AMP), phase (PH) and mean EVI2 of the period, were extracted. The phase metric gauges the duration of the change in vegetation characteristics, while the amplitude indicates the magnitude of the shift relative to a reference point.

In addition, a Digital Elevation Model (DEM) was obtained from Land Information New Zealand (LINZ, 2020) and resampled to 10 m to maintain consistency with other input features. In total, 55 features were extracted (Table 4) using remote sensing software ENVI version 5.6 (ENVI, 2023).

Species Classification

The random forest algorithm is a widely used machine learning method for image classification due to its excellent predictive accuracy and its ability to handle complex, high-dimensional data. The classifier consists of multiple individual decision trees that operate independently. Each decision tree within the classifier contributes by assigning a class label to a given sample, and the class with the highest number of votes is selected as the final prediction (Breiman, 2001). The species classification was conducted using the “randomForest” package (Liaw & Wiener, 2002) in statistical package R (R Development Core Team, 2023).

Due to high dimensional input features and target species classes, a feature selection process using the “VSURF” package (Genuer et al., 2015) was applied to eliminate redundant variables for classification. Following the classification, a majority filter (with 8 x 8 neighbours) was applied to the classification image to reduce the presence of isolated small pixels.

Accuracy check

The mapping accuracy was evaluated using the commonly used method of the confusion matrix (Congalton, 2001), which compares the mapped and the actual species classes using the validation dataset. Key metrics such as the overall accuracy, producer's accuracy (PA), and user's accuracy (UA), were computed for each species class.

The classification output was clipped to the extent of manually mapped small-scale alternative species in the Wairarapa region. This enabled the calculation of the area for each species class within the mapped extent. These classified areas were then compared with the areas reported in the NEFD. Additionally, the ownership boundaries obtained from LINZ Data Service were intersected with the mapped alternative species. This intersection allowed for the identification of owner information associated with the mapped areas of alternative species.

Table 4: List of 55 input features used for species classification.

Abbreviation	Name	Abbreviation	Name
Spectral bands		***Vegetation Indices***	
Blue	Blue band	LAI	Leaf Area Index
Green	Green band	MCARI_I	Modified Chlorophyll Absorption Ratio Index – Improved
Red	Red band	MNLI	Modified Non-Linear Index
RE705	Red Edge 705 nm	MNDWI	Modified Normalised Difference Water Index
RE740	Red Edge 740 nm	MSR	Modified Simple Ratio
RE783	Red Edge 783 nm	MSAVI2	Modified Soil Adjusted Vegetation Index 2
NIR842	Near Infrared 842 nm	MTVI_I	Modified Triangular Vegetation Index – Improved
NIR865	Near Infrared 865 nm	NDVI	Normalised Difference Vegetation Index
SWIR1610	Short-wave infrared 1610 nm	OSAVI	Optimized Soil Adjusted Vegetation Index
SWIR2190	Short-wave infrared 2190 nm	RENDVI	Red Edge Normalised Difference Vegetation Index
Textural		REPI	Red Edge Position Index
GLCM_Mean	Local mean of Gray-Level Co-Occurrence Matrix (GLCM)	RGRI	Red Green Ratio Index
GLCM_Variance	Local variance of GLCM	RDVI	Renormalised Difference Vegetation Index
GLCM_Homogeneity	GLCM Homogeneity	SAVI	Soil Adjusted Vegetation Index
GLCM_Contrast	GLCM Contrast	NIR_R	Simple Ratio NIR/red
GLCM_Dissimilarity	GLCM Dissimilarity	B_RE705	Simple Ratio blue/RE705
GLCM_Entropy	GLCM Entropy	B_RE740	Simple Ratio blue/RE740
GLCM_2ndMoment	GLCM 2nd Moment	B_RE783	Simple Ratio blue/RE783
GLCM_Correlation	GLCM Correlation	NIR_B	Simple Ratio NIR/blue
Phenology		NIR_G	Simple Ratio NIR/green
Mean EVI2	The average Enhanced Vegetation Index 2 (EVI2)	NIR_RE705	Simple Ratio NIR/RE705
EVI2 phase	The phase of EVI2	NIR_RE740	Simple Ratio NIR/RE740
EVI2 amplitude	The amplitude of EVI2	NIR_RE783	Simple Ratio NIR/RE783
Topography		TCARI	Transformed Chlorophyll Absorption Reflectance Index
DEM	Resampled 10 m Digital Elevation Model	TVI	Triangular Vegetation Index
Vegetation Indices		VARI	Visible Atmospherically Resistant Index
EVI2	Enhanced Vegetation Index 2	WDRVI	Wide Dynamic Range Vegetation Index
GEMI	Global Environmental Monitoring Index		
GARI	Green Atmospherically Resistant Index		
GCI	Green Chlorophyll Index		
GI	Greenness Index		
GNDVI	Green Normalised Difference Vegetation Index		

Results and Discussion

Manual Mapping Results

The manual mapping identified a total of 1,661 hectares of alternative species in Wairarapa, exceeding the NEFD-reported area by 497 hectares (

Table 5). However, when focusing solely on forests larger than 1 ha, the total mapped area was similar as the NEFD area, with only a 99 ha more than the NEFD.

Table 5: Alternative species manually mapped in Wairarapa

	Over 0.5 ha	**Over 1 ha**	**NEFD**
Masterton District	1,051	806	663
Carterton District	231	158	212
South Wairarapa District	379	299	289
Total	**1,661**	**1,263**	**1,164**

Classification results

Based on previous studies (Xu & Manley, 2022, 2023), the application of VSURF feature selection proved effective in reducing the number of features while maintaining comparable classification performance to using the complete set of input features. The classification accuracy using the selected variables achieved an overall classification accuracy of 92.9% (Table 6), aligning closely with the accuracies reported in earlier studies. This consistency is expected given that the reference data for this study combines datasets from the CNI, Hawke's Bay, and East Coast regions.

Among the alternative species, Douglas-fir and eucalyptus demonstrated the highest accuracy, with producer's accuracies of 96.8% and 93.8%, and user's accuracies of 92.7% and 90.5%, respectively. These species classes are likely to be benefited from a larger amount of truthing data. In contrast, acacia exhibited the lowest producer's accuracy at 65.4%, likely attributable to a smaller truthing data set.

Table 6: Confusion matrix of classification. It was produced based on 30% validation dataset. PA stands for producer's accuracy and UA stands for user's accuracy. Overall accuracy is 0.922 and kappa coefficient is 0.890.

	Reference											
Prediction	**Acacia**	**Cypress**	**Douglas-fir**	**Eucalyptus**	**Larch**	**Other pine**	**Other species**	**Poplar**	**Radiata**	**Redwood**	**Total**	**UA**
Acacia	645	24	14	25	1	5	10	0	4	1	729	**0.885**
Cypress	32	4083	56	29	39	33	45	5	18	64	4404	**0.927**
Douglas-fir	151	184	17684	150	57	153	390	22	90	186	19067	**0.927**
Eucalyptus	103	63	159	7589	32	111	183	21	59	66	8386	**0.905**
Larch	3	16	13	11	814	8	14	6	1	4	890	**0.915**
Other pine	26	32	38	60	9	2472	46	0	6	14	2703	**0.915**
Other species	12	64	141	44	26	32	2612	30	18	29	3008	**0.868**
Poplar	0	1	3	1	1	0	19	704	0	2	731	**0.963**
Radiata	11	46	112	148	8	12	82	4	13044	32	13499	**0.966**
Redwood	3	50	58	36	6	7	30	12	4	2051	2257	**0.909**
Total	986	4563	18278	8093	993	2833	3431	804	13244	2449	55674	
PA	**0.654**	**0.895**	**0.968**	**0.938**	**0.820**	**0.873**	**0.761**	**0.876**	**0.985**	**0.837**		**0.929**

Input Features

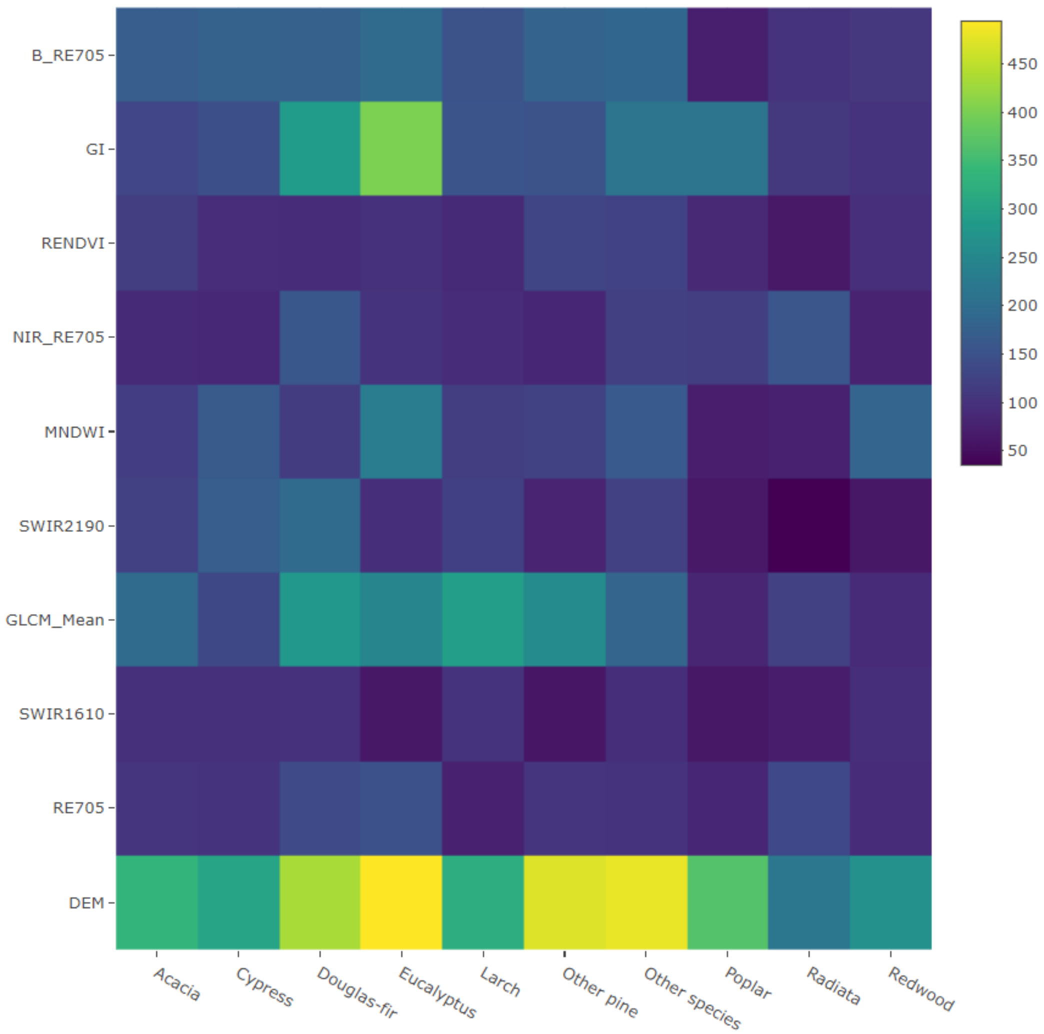

Figure 1: The importance score of the selected variables for each species class.

Following the VSURF variable selection process, ten out of 55 input variables were identified as significant contributors to species classification, each playing a distinct role in the process (Figure 2). Notably, DEM emerged as the most important variable, underscoring the significance of elevation in distinguishing among alternative plantation species in the study area. This aligns with findings in other studies where DEM played a crucial role in land cover and forest species classification (Ye et al., 2021; Zhang & Yang, 2020).

Additionally, four original spectral bands, one RE (Red Edge), and two SWIR (Short-Wave Infrared) bands were recognised as important variables. Previous studies have highlighted the importance of RE and SWIR bands in forest species mapping (Immitzer et al., 2016) and land cover classification (Schuster et al., 2012). Vegetation Indices (VIs), such as the Greenness Index (GI), are able to enhance sensitivity to vegetation properties. GI, a chlorophyll index derived from the ratio of green and red bands, has been empirically linked to leaf chlorophyll content (Glenn et al., 2008). Furthermore, one textural feature (GLCM_Mean) was also found useful in differentiating species.

Area Comparison

The classification output was clipped to the pre-defined boundaries to produce the area summary of alternative species in Wairarapa (Table 7). In total, 1,617 ha of alternative species were mapped. The predominant alternative species class was Eucalyptus, constituting 35% of the total alternative species resources in the region. Other species, including mixed species and less common alternatives, accounted for 383 ha.

Table 7: Classified alternative species in Wairarapa

Species Class	Area (ha)
Cypress	177
Douglas-fir	280
Eucalyptus	561
Larch	17
Other species	383
Poplar	144
Redwood	55
Total	1,617

In comparison to the National Exotic Forest Description (NEFD) report, there was a notable difference of 453 hectares (17%) more than the NEFD-reported area (Table 8). This study estimated substantially more Eucalyptus, Douglas-fir, and cypress than indicated by the NEFD. It is worth noting that NEFD lacks spatial representation of plantation forests and the area summary for Wairarapa region may not be accurate (Manley et al., 2020).

Table 8: Comparison of NEFD area and area mapped in this study. Note species classes were aggregated for comparison.

Species Class	NEFD Area (ha)	Mapped Area (ha)
Douglas-fir	186	280
Cypress	50	177
Eucalyptus	227	561
Other	701	599
Total	**1164**	**1617**

When overlay with the ownership boundaries, we identified 457 owners who potentially own alternative species that are over 0.5 hectares. Among them, there were potentially 276 owners who own more than 1 hectare of alternative species in Wairarapa.

Limitations and Opportunities

Despite the high classification accuracy observed, certain limitations should be acknowledged. The method requires a predefined extent for alternative species, which is time-consuming and potentially contains errors. In addition, the classification accuracy of this machine learning approach is heavily reliant on the quality of the input training data. The approach may not predict beyond the input data range, so the performance of the classifier can be potentially poor when there is not sufficient reference data.

We need to acknowledge a limitation with the assumption that the accuracy and representativeness of the GIS data provided by the large-scale owners apply to the small-scale plantations. Additionally, pixel-based classification techniques may introduce noise, presenting challenges in achieving a seamless and accurate representation of alternative species distribution. Looking ahead, there is potential for expanding the scope of this research. Exploring national alternative species mapping could provide a comprehensive overview, while the collection of extensive reference data and experimentation with advanced AI algorithms could enhance the accuracy and reliability of future mapping.

Conclusion

This study applied a random forest classifier to automatically classify minor species and achieved promising classification accuracy for most species. Random forest classification with Sentinel imagery can be used as tool for acquiring information about alternative species. Notably, the mapping in Wairarapa produced more alternative species than indicated by the NEFD. The utilisation of LINZ ownership data in conjunction with mapping allowed for the identification of owners associated with alternative species, providing opportunity for verifying the alternative species directly from individual owners.

References

Alonso, L., Picos, J., Bastos, G., & Armesto, J. (2020). Detection of very small tree plantations and tree-level characterization using open-access remote-sensing databases [Article]. *Remote Sensing, 12*(14), Article 2276. https://doi.org/10.3390/rs12142276

Breiman, L. (2001, Oct). Random forests. *Machine Learning, 45*(1), 5-32. https://doi.org/10.1023/a:1010933404324

Caparros-Santiago, J. A., Rodriguez-Galiano, V., & Dash, J. (2021, 2021/01/01/). Land surface phenology as indicator of global terrestrial ecosystem dynamics: A systematic review. *ISPRS Journal of Photogrammetry and Remote Sensing, 171*, 330-347. https://doi.org/https://doi.org/10.1016/j.isprsjprs.2020.11.019

Congalton, R. G. (2001). Accuracy assessment and validation of remotely sensed and other spatial information. *International Journal of Wildland Fire, 10*(3-4), 321-328. https://doi.org/10.1071/wf01031

ENVI. (2023). *Exelis Visual Information Solutions*.

Fassnacht, F. E., Latifi, H., Stereńczak, K., Modzelewska, A., Lefsky, M., Waser, L. T., Straub, C., & Ghosh, A. (2016). Review of studies on tree species classification from remotely sensed data [Review]. *Remote Sensing of Environment, 186*, 64-87. https://doi.org/10.1016/j.rse.2016.08.013

Genuer, R., Poggi, J.-M., & Tuleau-Malot, C. (2015). VSURF: An R package for variable selection using Random Forests. *The R Journal 7/2*.

Glenn, E. P., Huete, A. R., Nagler, P. L., & Nelson, S. G. (2008). Relationship between remotely-sensed vegetation indices, canopy attributes and plant physiological processes: What vegetation indices can and cannot tell us about the landscape [Review]. *Sensors, 8*(4), 2136-2160. https://doi.org/10.3390/s8042136

Grabska, E., Hostert, P., Pflugmacher, D., & Ostapowicz, K. (2019). Forest stand species mapping using the sentinel-2 time series [Article]. *Remote Sensing, 11*(10), Article 1197. https://doi.org/10.3390/rs11101197

Immitzer, M., Neuwirth, M., Böck, S., Brenner, H., Vuolo, F., & Atzberger, C. (2019). Optimal Input Features for Tree Species Classification in Central Europe Based on Multi-Temporal Sentinel-2 Data. *Remote Sensing, 11*(22), 2599. https://doi.org/10.3390/rs11222599

Immitzer, M., Vuolo, F., & Atzberger, C. (2016, 2016
2018-10-05). First Experience with Sentinel-2 Data for Crop and Tree Species Classifications in Central Europe. *Remote Sensing, 8*(3), 166. https://doi.org/10.3390/rs8030166

Jiang, Z., Huete, A. R., Didan, K., & Miura, T. (2008, 2008/10/15/). Development of a two-band enhanced vegetation index without a blue band. *Remote Sensing of Environment, 112*(10), 3833-3845. https://doi.org/10.1016/j.rse.2008.06.006

Land Information New Zealand (LINZ). (2020). *NZ 8m Digital Elevation Model (2012)*. Retrieved 18 December, 2020, from https://data.linz.govt.nz/layer/51768-nz-8m-digital-elevation-model-2012/

Land Information New Zealand (LINZ). (2021). *Wellington 0.3m Rural Aerial Photos*. https://data.linz.govt.nz/layer/105727-wellington-03m-rural-aerial-photos-2021/

Liaw, A., & Wiener, M. (2002). Classification and Regression by randomForest. *R news, 2*(3), 18-22.

Mallinis, G., Koutsias, N., Tsakiri-Strati, M., & Karteris, M. (2008, 2008/03/01/). Object-based classification using Quickbird imagery for delineating forest vegetation polygons in a Mediterranean test site. *Isprs Journal of Photogrammetry and Remote Sensing, 63*(2), 237-250. https://doi.org/10.1016/j.isprsjprs.2007.08.007

Manley, B., Morgenroth, J., & Xu, C. (2020). Quantifying the area of the small-scale owners' forest estate in the East Coast, Hawke's Bay and Southern North Island. *New Zealand Journal of Forestry, 64*(4), 18-26.

MPI. (2021). *2021 National Exotic Forest Description* Ministry of Primary Industries. https://www.canopy.govt.nz/assets/content-blocks/downloads/2021-NEFD-Report.pdf

R Development Core Team. (2023). *R: A language and environment for statistical computing* R Foundation for Statistical Computing, Vienna, Austria. http://www.R-project.org

Schindler, J., Dymond, J. R., Wiser, S. K., & Shepherd, J. D. (2021, 2021/10/01/). Method for national mapping spatial extent of southern beech forest using temporal spectral signatures. *International Journal of Applied Earth Observation and Geoinformation, 102*, 102408. https://doi.org/10.1016/j.jag.2021.102408

Schuster, C., Förster, M., & Kleinschmit, B. (2012, 2012/09/10). Testing the red edge channel for improving land-use classifications based on high-resolution multi-spectral satellite data. *International Journal of Remote Sensing, 33*(17), 5583-5599. https://doi.org/10.1080/01431161.2012.666812

Shepherd, J. D., Schindler, J., & Dymond, J. R. (2020). Automated Mosaicking of Sentinel-2 Satellite Imagery. *Remote Sensing, 12*(22), 3680. https://doi.org/10.3390/rs12223680

Xu, C., & Manley, B. (2022). *National forest owner survey and resource inventory of alternative species- Stage 2b: Mapping alternative species using remote sensing*. Specialty Wood Products technical report SWP-T143. . https://fgr.nz/documents/download/9782

Xu, C., & Manley, B. (2023). *National forest owner survey and resource
inventory of alternative species
Stage 3: Mapping alternative species in East Coast*. Specialty Wood Products technical report SWP-T159. . https://fgr.nz/documents/download/9782

Xu, C., Manley, B., & Ye, N. (2023). Mapping minor plantation species for New Zealand's small-scale forests using Sentinel-2 satellite data. *New Zealand Journal of Forestry Science, 53*(12).

Ye, N., Morgenroth, J., Xu, C., & Chen, N. (2021, 2021/10/01/). Indigenous forest classification in New Zealand – A comparison of classifiers and sensors. *International Journal of Applied Earth Observation and Geoinformation, 102*, 102395. https://doi.org/10.1016/j.jag.2021.102395

Zhang, F., & Yang, X. (2020, 2020/12/15/). Improving land cover classification in an urbanized coastal area by random forests: The role of variable selection. *Remote Sensing of Environment, 251*, 112105. https://doi.org/10.1016/j.rse.2020.112105