Joint use of space-borne SAR, optical imagery and air-borne LiDAR for improved mapping of forest structural types in New Zealand

Jan Zörner[1], John R. Dymond[2], James D. Shepherd[2], Susan K. Wiser[3], David Pairman[3], Marmar Sabetizade[4]

[1] Manaaki Whenua - Landcare Research, Wellington 6143, New Zealand
[2] Manaaki Whenua - Landcare Research, Palmerston North 4410, New Zealand
[3] Manaaki Whenua - Landcare Research, Lincoln 7608, New Zealand
[4] Department of Soil Science, University of Tehran
*Email: zoernerj@landcareresearch.co.nz

Abstract

Sustainable forest conservation and management practices require highly resolved and accurate maps of forest types. Extrapolation of field data, however, cannot achieve the necessary level of detail. The joint use of space-based optical imagery and structural information from synthetic aperture radar (SAR) and canopy metrics derived from air-borne Light Detection and Ranging (LiDAR) facilitates detailed classification of forest types. We present a segmentation-based support vector machine (SVM) classification using data from ESA's Sentinel-1 and 2 missions, ALOS PALSAR and airborne LiDAR to create a map of structural types within indigenous forest in Greater Wellington, New Zealand. The model is evaluated using k-fold cross-validation with up-scaled field data. The highest classification accuracy of 80.9% is achieved for bands 2, 3, 4, 5, 8, 11, and 12 from Sentinel-2, the ratio of bands VH and VV from Sentinel-1, HH from PALSAR, and mean canopy height and 97th percentile canopy height from LiDAR. The classification based on the optical bands alone is 73.1% accurate. Our high-resolution regional map of structural forest types is fit-for-purpose for conservation management and we show that the inclusion of structural information from SAR and LiDAR can improve forest classification by 7.8%.

Keywords: Forest structure, remote sensing, image segmentation, SVM, classification

1. Introduction

Indigenous forests cover 24% of New Zealand [Wardle et al. 1991], primarily in mountainous and hilly terrain, and provide valuable ecosystem services including recreation, provisioning of wild foods as well as climate and erosion regulation [Dymond et al. 2004]. Maps of forest types can be used to address a wide range of ecological questions relating to sustainability of ecosystem services and conservation management. However, no up-to-date national map of forest structural types exists at an appropriate level of detail. EcoSat Forests [Shepherd et al. 2005], which is a national map of indigenous forest classes in New Zealand, is published at 1:750,000 and the Land Cover Database (LCDB) [Dymond et al. 2017] for New Zealand only has one indigenous forest class.

In this study, we produce the first high-resolution regional map of forest structural types in New Zealand by developing a segmentation-based support vector machine (SVM) classification model and we investigate how the classification using Sentinel-2 may be improved with the addition of other imagery relating to vegetation structure. We consider radar backscatter from Sentinel-1 (C-band) and PALSAR (L-band) and canopy height metrics from airborne LiDAR.

2. Study area

The Greater Wellington region in the North Island of New Zealand (Fig. 1), has 23% of its 812,000 ha of land covered in indigenous forest. Most of the indigenous forest is now confined to the protected mountainous areas of the Tararua, Rimutaka, and Aorangi ranges. Many remnants of indigenous forest are spread throughout the rest of the region. The forests of the region are dominated by various mixtures of species from three groups: conifers, all from the Podocarpaceae family; broad-leaved evergreen species from a wide range of families; and Southern beechs (Nothofagaceae). Our classification focuses on the five combinations that occur in the Wellington region: Broadleaved-podocarp forest, Beech-broadleaved-podocarp forest, Beech-broadleaved forest, Broadleaved forest, and Beech forest.

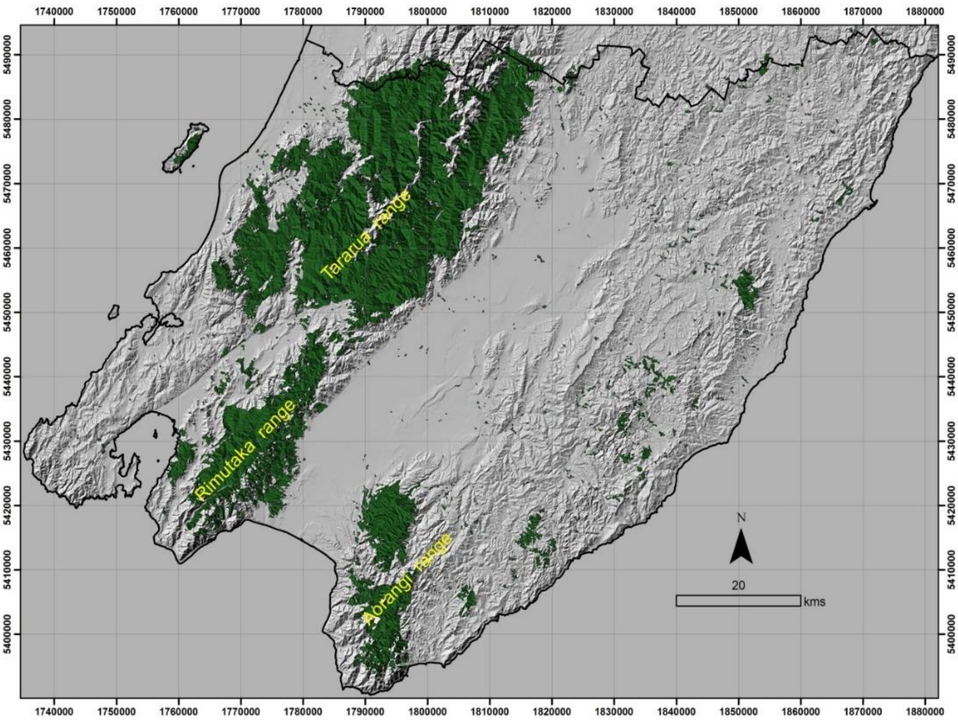

Figure 1: Wellington region with indigenous forest in dark green. Indigenous forest occurs primarily in the Taraua, Rimutaka, and Aorangi mountain ranges. Map grid is the New Zealand Transverse Mercator.

3. Methodology

A cloud-free mosaic of the Wellington region (99.5% cloud free) was produced by extraction of cloud-free pixels from Sentinel-2 scenes, with priority given to dates nearest the middle of November 2017. The mosaic was then segmented into areas of similar spectral signatures (Fig. 2) with a minimum mapping unit of 1 ha [Shepherd et al. 2019]. The segments are used as a framework for estimating robust means of Sentinel-1, Sentinel-2, and PALSAR imagery, and of canopy height from LiDAR data and together with the ground truth data make up the test and training data set for the SVM classification. An object-based classification approach has several advantages over pixel-wise classification for forest mapping: (a) it better captures spatial homogeneity and is able to describe variance within segments, i.e. forest structure, (b) it is more robust with higher signal-to-noise ratio due to spatial averaging which is especially important for SAR imagery and (c) increased speed due to fewer sample points. The canopy height metrics (mean and 97th percentile) were derived from data collected during an extensive LiDAR survey in 2013 and 2014 over the Wellington region with a minimum point density of 1.3 points/m^2 and a vertical accuracy of ±0.15 m. The SAR imagery consists of: (a) a median image of Sentinel-1 SAR backscatter values (VV, VH and VV/VH) for the year 2017 and, (b) a 2007 mosaic of ALOS-PALSAR backscatter (HH, HV, HH/HV).

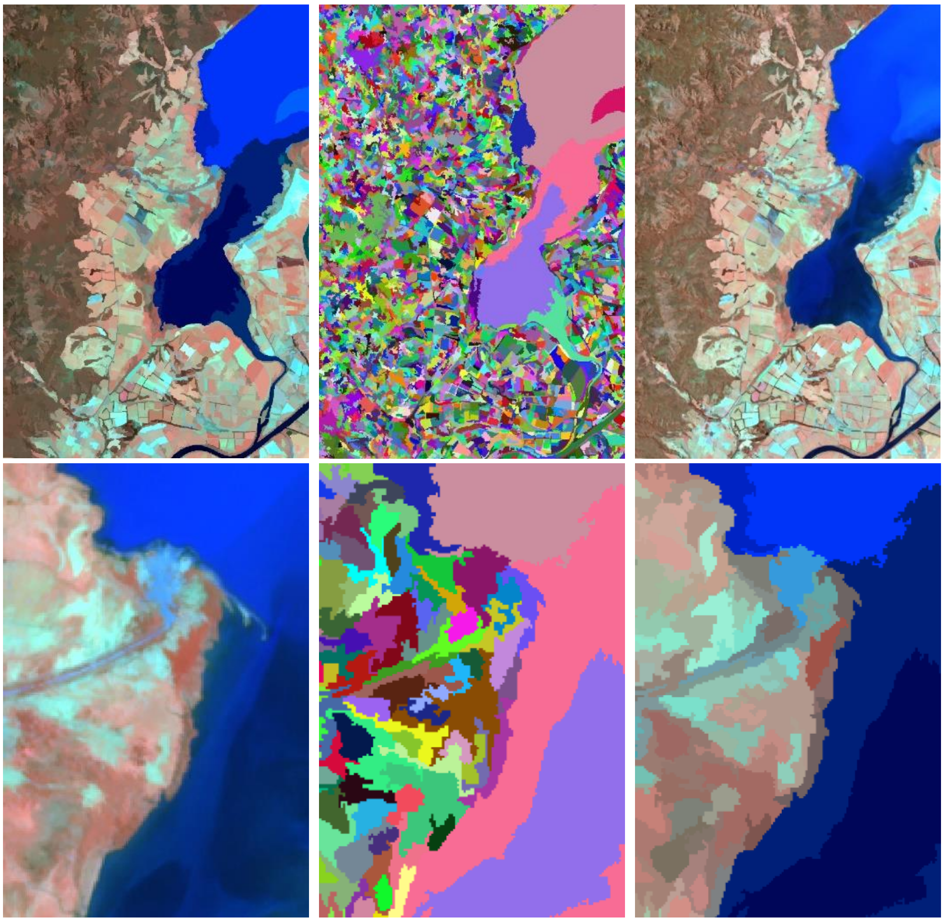

Figure 2: Sentinel-2 image mosaic segmentation result: original Sentinel-2 reflectance (left column), resulting spectral segments (centre column), spectral segments coloured with mean reflectance (right column).

Field data from 580 vegetation plots in the Wellington region which have tree species observations were extracted from the National Vegetation Survey database [Wiser et al. 2001] and summary statistics were computed, such as the species abundances and vegetation alliance to which the plot belongs. The data was recorded between 1962 to 2017 with 87% of the plots being measured since 1980. These summaries then informed the assignment of the plot to a forest structural type. Polygons of homogeneous structural types were drawn around the forest plots and intersected with the spectral segments derived from the Sentinel-2 mosaic. It is not expected that the forest types changed during this timeframe and, thus, the acquisition dates of the field and remote sensing data present no significant source of uncertainty for the forest type classification.The R-software package e1071 is used for the SVM classification as interface to the SVM implementation in the LIBSVM software [Chang and Lin 2001]. Different SVM classification settings were tested using a systematic sensitivity analysis of model parameters. However, more complex parameters, e.g. radial basis function kernel with highly optimized penalty parameter, C, did not lead to significant improvements and, thus, a linear model with C=1 achieving comparable model performance was chosen. The feature selection was performed using a recursive leave-one-out approach. We assessed the accuracy of each model performing five-fold cross-validation against the ground truth data set, where 80% of the ground data is assigned to training and 20% to test data.

4. Results

The cross-validation accuracy is 72.3% when using all relevant optical bands. Sentinel-2 bands 6, 7 and 8a were omitted as they did not add information to the classification. When adding CHM metrics to the optical bands the test accuracy is 78.6%, and then adding significant radar bands to the optical and CHM metrics leads to a final test accuracy of 80.9%. The addition of SAR and LiDAR metrics did not add much computational overhead to the SVM classification due to the object-based approach. The final SVM classifier was trained on all locations where ground data was available and then applied to all the image segments of indigenous forest in the Wellington region (according to the Land Cover Database) to produce a regional map of forest structural types (Fig. 3). The classified map provides information on area fractions of each structural type in the region and the results can be further separated into tree height classes.

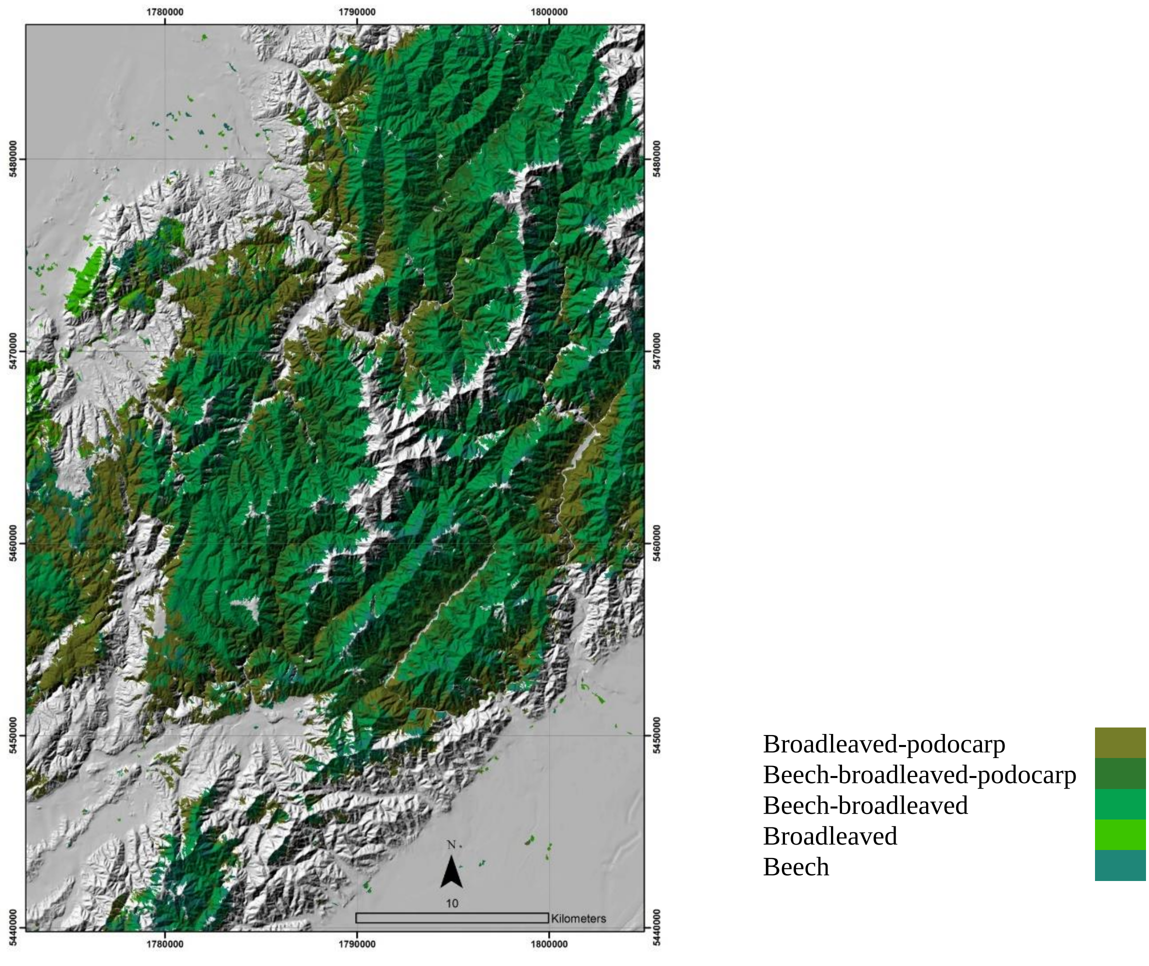

Figure 3. Forest structural types following SVM classification of spectral and structural information from Sentinel-1 and 2, PALSAR and LiDAR in transect across the Tararua ranges. Map grid is the New Zealand Transverse Mercator.

4. Conclusions

We presented a feasibility study of combining spectral and structural data from different sensors to aid forest classification. The resolution and classification accuracy of the produced map of forest structural types for indigenous forest in Greater Wellington are sufficient for many conservation management applications. The achieved map resolution (1 ha minimum mapping unit) represents significant improvement over current maps of forest types (EcoSat Forests). National application of the presented method will be possible in several years once national LiDAR coverage is achieved and a national canopy height model is available. Future work will investigate the use of temporal spectral signatures and indices, to further increase mapping accuracy and associated contribution to management applications.

5. Acknowledgements

The Ministry of Business, Innovation and Employment funded this research under contract C09X1709.

6. References

Chang, C.-C. & Lin, C.-J. (2001). LIBSVM: a library for support vector machines. http://www.csie.ntu.edu.tw/~cjlin/libsvm

Dymond, J.R.; Ausseil, A.-G.E.; Peltzer, D.A.; Herzig, A. Conditions and trends of ecosystem services in New Zealand—A synopsis. *Solut. J*. **2014**, 5, 38–45.

Dymond, J.R.; Shepherd, J.D., Newsome, P.F.; Belliss, S. Estimating change in areas of indigenous vegetation cover in New Zealand from the New Zealand Cover Database (LCDB). *New Zealand J. Ecol*. **2017**, 41, 56–64.

Shepherd, J.D.; Ausseil, A.-G.; Dymond, J.R. EcoSat Forests: A 1:750,000 Scale Map of Indigenous Forest Classes in New Zealand; Manaaki Whenua Press: Lincoln, New Zealand, **2005**; Available online: https://lris.scinfo.org.nz/

Shepherd, J.D.; Bunting, P.; Dymond, J.R. Operational Large-Scale Segmentation of Imagery Based on Iterative Elimination. *Remote Sens.* **2019**, *11*, 658.

Wardle, P. *Vegetation of New Zealand*. Cambridge University Press, Cambridge, United Kingdom, **1991**.

Wiser, S.K.; Bellingham, P.J.; Burrows, L. Managing biodiversity information: development of the National Vegetation Survey Databank. *New Zealand J. Ecol*. **2001**, 25, 1–17.