

RESEARCH ARTICLE

Quantifying vegetation cover on coastal active dunes using nationwide aerial image analysis

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Introduction

Coastal active dunes (active dunes) occur on dynamic sandy shorelines at all latitudes (Martínez et al., 2004) as a result of aeolian and marine sediment transport and ecological processes (Durán & Moore, 2013; Hesp & Walker, 2021; Martínez et al., 2004; Miller et al., 2010). Active dunes occur where sand is highly mobile, such as incipient dunes and the most seaward dune or foredune, and have sparse, low-growing herbaceous vegetation (Durán & Moore, 2013; Miller et al., 2010; Psuty, 2004). Behind the foredune, semi-stable dunes are active to a lesser extent as geomorphic activity decreases and the diversity of plant species, including woody species, increases (Maun, 2009; Psuty, 2004; Wardle, 1991). Active dunes provide important ecosystem services; they are a barrier to storm surge and sea level rise

Abstract

Coastal active dunes provide vital biodiversity, habitat, and ecosystem services, yet they are one of the most endangered and understudied ecosystems worldwide. Therefore, monitoring the status of these systems is essential, but field vegetation surveys are time-consuming and expensive. Remotely sensed aerial imagery offers spatially continuous, low-cost, high-resolution coverage, allowing for vegetation mapping across larger areas than traditional field surveys. Taking Aotearoa New Zealand as a case study, we used a nationally representative sample of coastal active dunes to classify vegetation from red-green-blue (RGB) high-resolution (0.075–0.75 m) aerial imagery with object-based image analysis. The mean overall accuracy was 0.76 across 21 beaches for aggregated classes, and key cover classes, such as sand, sandbinders, and woody vegetation, were discerned. However, differentiation among woody vegetation species on semi-stable and stable dunes posed a challenge. We developed a national cover typology from the classification, comprising seven vegetation types. Classification tree models showed that where human activity was higher, it was more important than geomorphic factors in influencing the relative percent cover of the different active dune cover classes. Our methods provide a quantitative approach to characterizing the cover classes on active dunes at a national scale, which are relevant for conservation management, including habitat mapping, determining species occupancy, indigenous dominance, and the representativeness of remaining active dunes.

(Walker et al., 2013), sustain recreation, tourism, and cultural practices (Barbier et al., 2011), and are a habitat for biodiversity (Martínez et al., 2013). Despite their importance, active dunes are under significant pressure from human settlement, recreation, farming, forestry, and extractive industries (Gao et al., 2020). Faced with these threats, the extent of active dunes is declining (Gao et al., 2020; Jackson et al., 2019), and their floristic composition is undergoing rapid change (Gao et al., 2020; McGuirk et al., 2022).

Active dunes in Aotearoa, New Zealand, provide a case study that mirrors the international situation. Aotearoa has c. 15 000 km of coastline (Bell & Gibb, 1996) containing a subset of active dunes characterized by frequent natural disturbance and sparse, low-growing vegetation (Hilton et al., 2000). Sandbinding plants, such as the endemic

pīngao (*Ficinia spiralis* (A.Rich.) Muasya et de Lange) and native kōwhangatara (*Spinifex sericeus* R.Br.), occur on highly active dunes and act as ecosystem engineers, building foredunes and a range of geomorphic habitats for other species (Hesp, 2000). Semi-stable mid and rear dune vegetation comprises a small number of prostrate, divaricating, spreading woody shrubs, and liana species that accrete sand (Cockayne, 1911; Johnson, 1993; Newsome, 1987; Wardle, 1991). In addition, the dune slacks and hollows associated with active dunes have unique, endemic, and threatened flora (Holdaway et al., 2012). Active dunes in Aotearoa provide a range of important cultural, recreation, and coastal protection services, yet they are declining in extent (Stats, 2015), are endangered (Department of Conservation, 2020; Holdaway et al., 2012), and are threatened by forestry, farming, introduced invasive weeds, coastal development, and recreation (Hilton, 2006). Data about active dunes are generally sparse, qualitative, and insufficiently representative to infer national-scale condition and extent (Ryan et al., 2023).

In recent decades, remote sensing techniques have been developed to complement and replace a range of time- and labour-intensive field survey methods, such as the supervised classification of aerial imagery for vegetation mapping (Turner & Gardner, 2015). Morgan et al. (2010) suggest aerial imagery is a vastly underused dataset for describing baseline ecosystem conditions and long-term monitoring. Typically comprised of the red, green, and blue (RGB) bands of the electromagnetic spectrum, aerial imagery offers spatially continuous images at sub-metre resolutions, allowing for vegetation mapping across larger areas than traditional field surveys (Morgan et al., 2010). The high spatial resolution of aerial imagery is well-suited for detecting ecological patterns compared to satellite imagery (Oddi et al., 2021), and it offers greater spatial coverage than imagery captured by Unoccupied Aerial Vehicles (UAV).

Within the active dune literature, aerial imagery has been increasingly used as input datasets to discern dune vegetative features, spatial patterns, or extents using traditional pixel-based, supervised, classification techniques (for example, see Gao et al., 2022; Konlechner et al., 2015; Moulton et al., 2019; Ryu & Sherman, 2014; Smyth et al., 2022). Object-Based Image Analysis (OBIA) is an image classification technique that has recently gained popularity over pixel-based methods due to perceived improvements in accuracy. OBIA involves segmenting images into discrete objects based on the homogeneity of the spectral and textural qualities of pixels, followed by the classification of these objects (Lillesand & Kiefer, 2015). Improvements over pixel-based methods are attributed to minimizing spectral variability across classes and integrating spatial and contextual

relationships (Ma et al., 2017; Ye et al., 2018). To our knowledge, few studies of active dune vegetation have used OBIA techniques with aerial imagery.

Given the clear need to characterize and quantify the vegetation cover of active dunes in Aotearoa, we evaluated the application of OBIA techniques to RGB aerial imagery for this purpose across a selection of nationally representative active dunes. Our research objectives were to: (1) determine the cover classes on dunes that could be discriminated from aerial imagery using OBIA image classification procedures; (2) identify a national active dune cover typology from the classification data; and (3) identify the potential drivers of variation in the percent cover of active dune vegetation cover types in 90 × 120 m plots across Aotearoa. This study provides a better understanding of the capabilities and limitations of aerial imagery for characterizing the vegetation of active dunes. Further, it contributes an initial, national, and quantitative typology of the vegetation of active dunes in Aotearoa and demonstrates a low-cost approach for assessing the influence of human and geomorphic variables on active dune vegetation cover, which is useful to conservation and land managers.

Materials and Methods

Pre-processing, classification, and post-processing of aerial imagery (Fig. 1) were carried out on a stratified random subsample of 21 representative beaches (Fig. 2) drawn from a maximum potential extent of active dunes in Aotearoa (Ryan et al., 2023). Publicly available, high-resolution (0.075–0.75 m) RGB ortho-imagery collected by local and regional government agencies for the period 2007–2021 (Table S1 in Supporting Information) was compiled for this research. All imagery was processed separately for each beach in ArcGIS Pro version 2.9 (Esri Inc., 2021).

Pre-processing

To enhance the contrast between vegetation, sand, and soil in the classification, the RGB colour bands were used to calculate values for the Normalized Green-Red Difference Index (NGRDI; Equation S1 in Supporting Information; Hunt et al., 2005) for each beach. NGRDI can also reduce variation in illumination in imagery due to differences in light and shade (Hamuda et al., 2016). RGB colour bands were also transformed to the alternative colour space “Hue Saturation and Value” (HSV) (*sensu* Smith, 1978). NGRDI, HSV, red, green, and blue band layers were then brought back together into one composite band raster for each beach.

Dunes were then subsampled at each beach to identify spectrally distinct cover classes. Virtual sample plots that

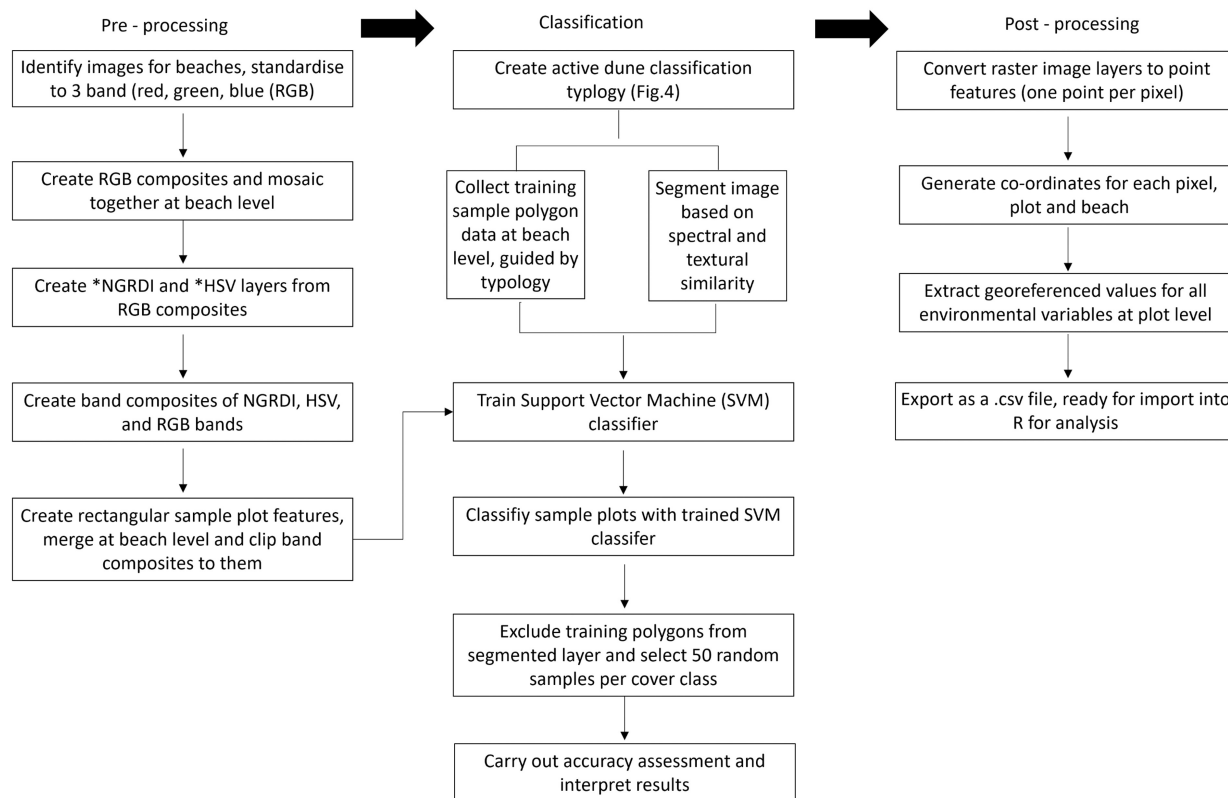


Figure 1. Steps taken to process and classify imagery. All image processing was carried out in ArcGIS v.2.9. Imagery datasets are given in Table S1 in Supporting Information. *NGRDI is the Normalized Green – Red Difference Index (Equation S1); HSV is Hue, Saturation, and Value (sensu Smith, 1978).

were 90×120 m rectangular features were created in the GIS and then positioned within beach images, with the shorter side aligned perpendicular to the shoreline, running landward from the seaward toe of the incipient dune (Fig. 3). This plot size was selected to contain sufficient information to characterize the vegetation of foredunes, consistent with other research internationally on large foredune systems (Hesp, 2002; Jay et al., 2022; Ryu & Sherman, 2014) and incorporating previous descriptions of large dune ecosystems in Aotearoa (Johnson, 1993; Wardle, 1991). Selecting the width of the largest foredune allowed us to accommodate variation in width among beaches. Three beaches were sampled using a smaller plot of 20×27 m since foredunes were foreshortened due to coastal development. Plots were placed along foredunes in the imagery every 1 km along the length of the beach, starting from a random location. Highly modified areas, such as housing, roads, or car parks, were excluded from the analysis. Plots that were primarily sand, that is, those that did not contain at least 5% vegetation cover, were also excluded from the analysis since they would not yield sufficient information about vegetation.

All 21 beaches contained foredunes, with the smallest beaches containing one plot ($n = 1$) and the largest beach containing 24 plots, resulting in a total of 135 plots across the country (Fig. 2). The NGRDI, HSV, red, green, and blue band composites were clipped to the plot polygon features for each beach. Nearest neighbour resampling to 1 m^2 was then carried out within plots for consistency across all images and analyses.

Classification

Classification comprised the collection of training samples, image segmentation, training of the classifier algorithm, and then classification. To guide the collection of training samples for use in the discrimination among cover classes during classification, a vegetation cover typology (Fig. 4) was developed based on botanical records, photographs, imagery, expert knowledge, and beach visits. This typology, comprising 22 cover classes, was specifically created to differentiate stable, semi-stable, and active cover classes and, within the active cover classes, among different types of sandbinder species (Fig. 4). Based on this typology for

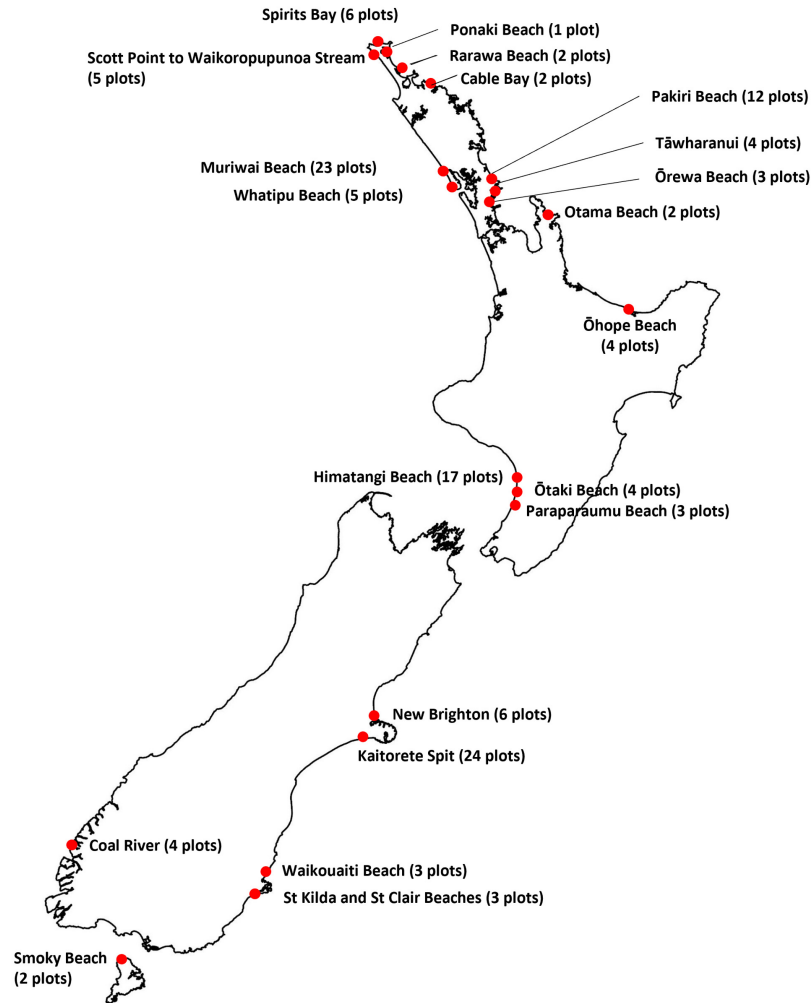


Figure 2. Beaches that were selected as a representative sample of active dunes in Aotearoa ($n = 21$). The numbers in parenthesis represent the number of sample plots per beach. The approach to selecting beaches is described in Ryan et al. (2023).

each beach, a minimum of 30 training samples (groups of pixels within hand digitized training sample polygons) from within all plots were taken of each cover class present, comprising red, green, blue, NGRDI, and HSV data. Beaches were sampled independently due to variations in weather and illumination conditions across beaches when the imagery was captured.

Next, band composites were segmented using the Mean Shift method, whereby neighbouring pixels with similar spectral and spatial characteristics were grouped. The Mean Shift algorithm was configured for the highest level of sensitivity (20) for fine-grained discrimination of features. Images were segmented with a minimum segment size of 1 m^2 , with the expectation that it would capture the qualities of the target native sandbinder plants, which are typically 1–4 m in minimum diameter, with narrow rhizomes or stolons and a lateral growth habit

(Wardle, 1991). Given the narrowness of native sandbinders, we expected to capture mixed pixels of sand and native sandbinders within segments and training samples.

A Support Vector Machine (SVM) classifier was then trained using the segments and the training sample polygons. The SVM classifier has advantages over other classifiers in that it does not require samples to be normally distributed and performs at a high level of accuracy (Ma et al., 2017; Melgani & Bruzzone, 2004). Lastly, the trained SVM algorithm was used to classify the image layers for plots at each beach. Input data to the classifier included values for each segment for the red, green, and blue bands, NGRDI and HSV.

Classification accuracy was assessed for a stratified random selection of validation image segments within plots across the beaches, independent of the training dataset (Radoux & Bogaert, 2017). Stratification was based on

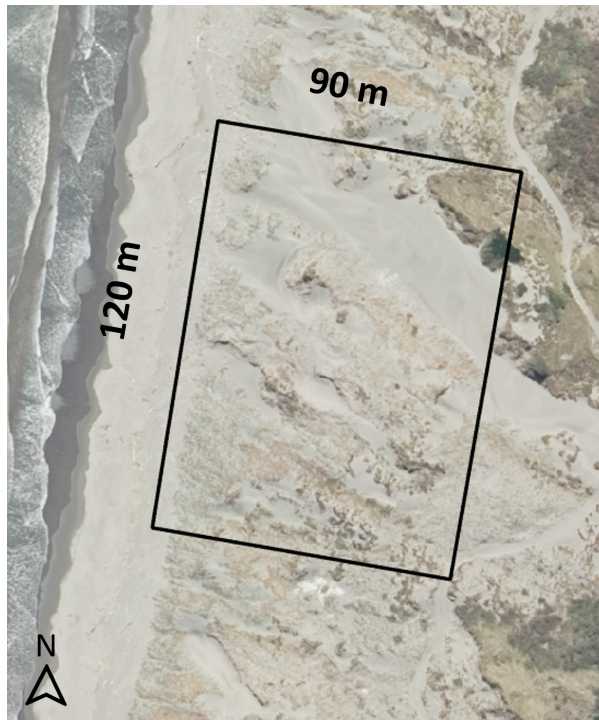


Figure 3. Example placement of one 90 × 120 m sample plot within a foredune at Himatangi Beach. Plots were placed every 1 km along each beach, starting from a random point at the seaward toe of incipient dunes, landward. Sample plots were created as polygon features in ArcGIS Pro v.2.9. Imagery is from the aerial photograph tile Manawatu Whanganui 0.3 m Rural Aerial Photos (2015–2016), from Land Information New Zealand Data Service (CC BY 4.0).

cover class, and 50 segments per cover class per beach were selected, or as many as possible if fewer than 50 instances occurred. Reference materials for ground truthing included high-resolution satellite imagery in Google Earth Pro, UAV imagery where available, and the original aerial image datasets. Botanical and research records were also checked to see if species occurred at sample beaches. Accuracy measures were calculated using a confusion matrix for each beach, that compared the cover classes assigned to each validation segment by the classification process to those assigned visually using reference sources. Computed accuracy metrics comprised overall accuracy, Cohen's Kappa, user's accuracy, and producer's accuracy (Ye et al., 2018). All confusion matrices were aggregated into one matrix for all beaches and then summarized for key classes.

Analysis

Classified cover class data for plots were then manipulated and analysed. Cover classes that were not of interest, for example, dry sand *versus* wet sand, or those that were

very similar to each other, for example, trees *versus* shrubs, were aggregated with similar classes to reduce variation in the number of classes across all plots and maximize the sample size of each cover class at the plot-level. As a result, the 21 cover classes discerned from the training dataset (see results) were reduced to nine in the rationalized classified dataset (Table 1). The percentage cover for each cover class in each plot was then calculated.

A Principal Coordinate Analysis (PCoA) was used to visualize the differences among plots in their percent cover of the nine cover types classes of pairwise Bray-Curtis distances. Since the “Sand” class occurred in every plot, the contribution of different vegetation cover types was overshadowed, thus it was removed from the analysis. The “Other” and “Water” classes (Table 1) were also excluded since they were not of interest to this research. The data were first standardized to account for a right skew using a square root transformation. They were relativized to the maximum across the dataset to down-weight the effects of uncommon cover classes on the analysis and to ensure negative values were not introduced to ensure compatibility with the Bray-Curtis distance calculation (McCune & Grace, 2002). Next, the same distance matrix was used in a hierarchical, agglomerative cluster analysis using the Average Group Linkage method to organize plots into spectrally similar groups, which were then named as different “plot vegetation types” by the greatest percentage of vegetation type per plot across all plots in the cluster (Van De Maarel, 2005). The PCA bi-plot points for plots were then labelled according to the cluster (vegetation type) they were clustered into.

To explore the relative influence of anthropogenic and geomorphic factors in explaining variation among the different plot vegetation types, a range of spatial environmental data were compiled at the plot level from available spatial data layers (Table 2; Tables S2 and S3 in Supporting Information). Geomorphic variables were: the number of days p.a with mean wind gusts above 24 knots for the local area; the modelled number of days p.a with coastal waves over 4 m for at least 12 h; the mean daily wind run for the local area (km); and total rainfall (mm) for the local area (Table 2; Tables S2 and S3 in Supporting Information). The anthropogenic variables were: the distance of the plot from the nearest road (m); the type of land cover adjacent to each plot; the ecosystem extent (ha), that is, the area covered by active dunes that the sampled plots occurred in; the median of personal income bands (NZD) in a region; and usually the resident human population in a local area (Table 2; Table S2 in Supporting Information). Pairwise Pearson's correlations were computed for the environmental data for each plot to quantify the strength of any

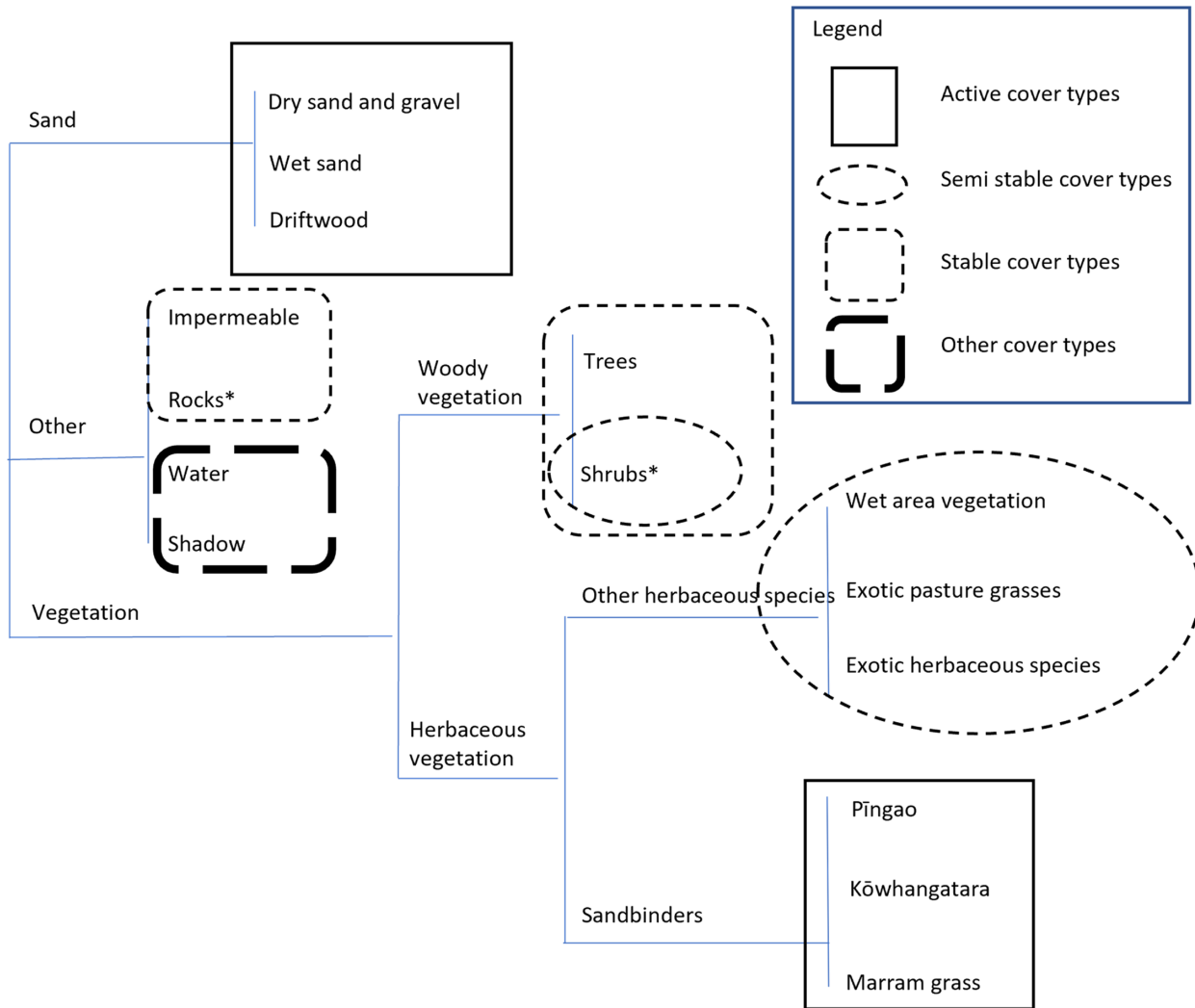


Figure 4. The initial cover class typology, developed to guide the collection of training samples. Cover classes were based on botanical records, photographs, imagery, expert knowledge, and beach visits and distinguished between stable, semi-stable, and active cover classes. Wet area vegetation refers to areas with freshwater or brackish water seepages, such as dune slacks.

intercorrelations. Results indicated weak to moderate correlations among most variables, with r values between 0.25 and 0.54. However, the mean daily wind run and days of strong wind gusts were highly correlated, with an r -value of 0.98 (Fig. S1 in Supporting Information). We kept both variables to explore the potential contrasting impacts of ambient and extreme wind gust conditions on vegetation types.

Next, Classification and Regression Tree (CART) analysis (Breiman et al., 1984) was used to assess the relative influence of the ten different environmental variables on the vegetation types derived through cluster analysis. A 75:25 split between test and training data was used, and a 10-fold cross-validation method was used to assess the model's performance. Cohen's Kappa statistic was used to

select the final model; the maximum depth was set to five, and the minimum split for terminal nodes was set to five plots. The global importance of variables was calculated across the whole tree to understand their overall influence.

Data analyses were carried out in R (R Core Team, 2021) and R Studio v.2022.07.2 (RStudio Team, 2020), including data manipulation with base R and the tidyverse (Wickham et al., 2019); PCoA in vegan (Oksanen et al., 2022); Pearson correlation in stats (R Core Team, 2021); CART analysis in rpart (Therneau & Atkinson, 2022) with caret for cross validation (Kuhn, 2008) and visualization in ggplot2 (Wickham, 2016). Hierarchical Agglomerative Cluster Analysis was carried out in PC-ORD v.7.10 (McCune & Mefford, 2018).

Table 1. Descriptions of the 21 cover classes used to train the Support Vector Machine (SVM) classification algorithm.

Cover class	Description	Aggregate cover class
Pingao	An endemic and endangered sand binding sedge growing on active dunes. It has a natural distribution the length and breadth of Aotearoa.	Pingao
Kōwhangata	A native sand binding grass growing on active dunes with a natural distribution from Cape Reinga to Nelson.	Kōwhangata
Marram grass	A vigorous exotic sandbinder from Northern Europe and North Africa, that commonly occurs throughout Aotearoa.	Marram grass
Mixed native and exotic trees	A mix of native and exotic trees which are often not identifiable, or distinguishable in imagery.	Woody vegetation
Mixed native and exotic shrubs	Mix of native and exotic shrubs often not identifiable, or distinguishable, from each other in imagery.	Woody vegetation
Exotic trees and shrubs	Exotic trees and shrubs that were identifiable as exotic but often not able to be distinguished individually. Examples are given in the tree and shrub cover classes above.	Woody vegetation
Shadow from trees and shrubs	Shadow from trees and shrubs when clearly falling within an area of woody vegetation.	Woody vegetation
Exotic pasture grasses	A mixture of exotic pasture grasses, typically rank and found adjacent to areas used by people or agriculture.	Exotic pasture grasses
Exotic herbaceous species	A mixture of low-growing herbs and forb species (excluding exotic pasture grasses), that are not discernible individually.	Other herbaceous species
Mixed native and exotic herbaceous species	A mixture of typically taller rushes, sedges, grasses - native or exotic, that were not necessarily discernible individually.	Other herbaceous species
Shadow	Shadows from dunes, vegetation, or impermeable structures or any other feature (except for trees and shrubs, included above).	Other
Buildings	Houses, sheds or other similar structures.	Other
Bare earth	Patches of exposed non-sand sediment.	Other
Other impermeable	Small impermeable features such as cars or signs.	Other
Dry sand	Areas of dry sand without tidal or estuarine water.	Sand
Water over sand	Sand areas with shallow tidal or estuarine water present.	Sand
Wet sand	Sand areas still wet and darker in colour from tidal water.	Sand
Gravel	Weathered, rounded rock fragments, larger than coarse sand and smaller than pebbles.	Sand
Driftwood	Trees and branches washed up on the beach, generally around the high tide mark.	Sand
Rocks	Stones, rocks, boulders, and bedrock.	Sand
Water	Estuaries, rivers or ponded water (this class is deeper than "Water over sand")	Water

The cover classes were aggregated into nine classes for analysis (right-hand column). Examples of species or objects that could occur in each class are given in Table S4 in Supporting Information.

Results

In total, 21 cover classes were discerned from the training samples based on the initial vegetation cover typology (Fig. 4; Table 1; Table S4 in Supporting Information) and the segmentation layer, resulting in the classification of 138.6 ha of active dune area in the 135 plots on 21 beaches. The three target sandbinders could be discerned by species, but woody vegetation could only be identified at a structural level (trees and shrubs), as could exotic pasture grasses. Vegetation in wet areas, such as dune slacks, could not be distinguished by species level. Classification was based on an average of 64 (median = 40) groups of training pixels per cover class across all beaches (Fig. 5). Each training sample group comprised, on average, 40 pixels and ranged from one pixel to 7200 pixels in size. Groups of more than 100 pixels typically represent

homogenous areas of sand or continuous woody vegetation.

The mean overall accuracy across all beaches for the nine aggregate cover classes was 0.76. The mean Kappa score, or estimated accuracy of classification across all beaches, was 0.70 (Table 3). The mean user's accuracy was 0.66, and the mean producer's accuracy was 0.79 (Table 3). The sand cover class exhibited the highest and most balanced user's and producer's accuracy. In contrast, the vegetation classes had reasonable user's and producer's accuracy scores of between 65 and 84 (Table 3). Pingao and kōwhangata cover classes were most often confused with sand, followed by woody vegetation (Table 3). Marram grass was the most misclassified cover class, often confused with woody vegetation, sand, or exotic pasture grasses (Table 3). Cover classes with fewer training samples (e.g. "water" and "other") had lower accuracy (Table 3 and Fig. 5). The overall

Table 2. Environmental variables selected for the CART model analysis, and the mechanisms of each that could potentially drive vegetation cover type.

Environmental variable	Mechanism
Adjacent land cover type	Bordering land used for human activities, such as agriculture, forestry, and settlement, contain weed species and are connected by corridors that facilitate their spread through the landscape (Castillo & Moreno-Casasola, 1996).
Coast	Much of Aotearoa is exposed to south-west and southerly swells and prevailing westerly winds (Shepherd & Hesp, 2003). Given that wind and wave energy are drivers of dune formation (Psuty, 2004), geomorphic processes are expected to be a strong driver of cover type on western and southern coasts, compared to eastern coasts.
Distance from nearest road (m)	Road networks can cause habitat fragmentation, loss, and the rapid spread of weed species (Bennett, 2017; Castillo & Moreno-Casasola, 1996; Gao et al., 2020). Increasing distance from road networks reduces negative impacts on ecosystems (Benítez-López et al., 2010; Bennett, 2017).
Ecosystem extent (ha)	Species – area relationships suggest that smaller areas support fewer species (Begon et al., 2006), thus smaller extents are expected to support fewer species affecting geomorphic processes.
Days (p.a) of large wave events (>4 m and over longer than 12 h).	Large wave events cause disturbance and the restarting of primary succession sequences, creating the characteristic vegetation of active dunes (Hesp, 2011; Miller et al., 2010; Pegman & Rapson, 2005). The threshold of 4 m was selected since it was the lowest value of the three bands in this dataset, thus ensuring variation across climatic regions was captured.
Days of wind gusts ≥24 knots (p.a)	Disturbance from high winds during storms (and associated wave energy, rain and overwash) catalyse geomorphic processes of erosion and sand movement (Eisma, 1997; Maun, 2009; Miller et al., 2010). The threshold of ≥24 knots was selected since it was the lowest value of the bands in this dataset, thus ensuring variation across climatic regions was captured.
Mean daily wind run (km)	Consistent wind and wave energy associated with ambient conditions build foredunes gradually through accretion, creating regular foredunes, and dune slacks (da Silva et al., 2008; Eisma, 1997; Miller et al., 2010).
Median of personal income bands (\$ gross NZD)	Environmental degradation of coastal dunes is associated with urbanization (Lansu et al., 2024; Malavasi et al., 2016; Salgado et al., 2021), in Aotearoa the most populous areas are associated with the highest personal income bands (Statistics New Zealand, 2014).
Total rainfall (mm)	Higher rainfall creates more favourable conditions for vegetation establishment, soil development (Laporte-Fauret)
Usually resident population	Environmental degradation of coastal dunes is associated with residential development and other human influence (Lansu et al., 2024; Malavasi et al., 2016; Salgado et al., 2021).

The large wave event data used was for the coastal region associated with each sample beach (Table S3 in Supporting Information). This data was generated using the 12 km resolution New Zealand National Institute of Water and Air (NIWA) operational wave forecasting model (NZWAVE-12), which models wave heights using wind from NIWA's NZLAM-12 weather forecast model and swell from NIWA's global wave forecast model (Gorman, 2016). Rain and wind data were collected from climate stations, which were selected based on whether the requisite data was recorded; proximity to study beaches (Table S3 in Supporting Information); similarity of coast, and where possible, where there was the same degree of exposure to prevailing winds.

accuracy for the non-aggregated cover classes was 0.70 across all beaches, with a Kappa score of 0.66 (Fig. S2 in Supporting Information).

Sand was the most common cover class, followed by woody vegetation, marram grass, pīngao, kōwhangata, exotic pasture grasses, other herbaceous species, other (comprising shadow and impermeable cover classes), and water (Fig. 6). The cluster analysis resulted in seven plot vegetation types (Fig. 7; Fig. S3 in Supporting Information), with the largest cluster comprising 49 plots and the smallest, five plots; the chaining of clusters was low (4.12%), suggesting a relatively high level of confidence in the generated clusters. In the PCoA of the plot cover class data, most of the variation among plots was associated with the first two axes, whereby the cumulative variance was 60%, comprising 42% and 18% for the first and second axes, respectively (Fig. 8). Plot vegetation types formed relatively distinct groups on the PCoA (Fig. 8). Plots classified

as the pīngao plot vegetation type formed an isolated cluster in the PCoA, indicating that pīngao-dominated plots were more similar to each other than plots classified as other plot vegetation types. Plots classified as dominated by woody vegetation were also tightly clustered but were closer to plots classified as several other plot vegetation types. Only plots classified as dominated by either kōwhangata or other herbaceous species overlapped substantially with other plot vegetation types on the PCoA.

The CART analysis, which explored relationships between vegetation types and environmental factors, produced a classification tree model with a Cohen's Kappa statistic of 0.75 (Fig. 9). The tree was pruned at a depth of five division levels, which produced ten nodes using four of the ten environmental explanatory variables to characterize the branches (Fig. 9). The vegetation types pīngao, and other herbaceous species formed pure nodes at this depth, while marram grass did not appear in a

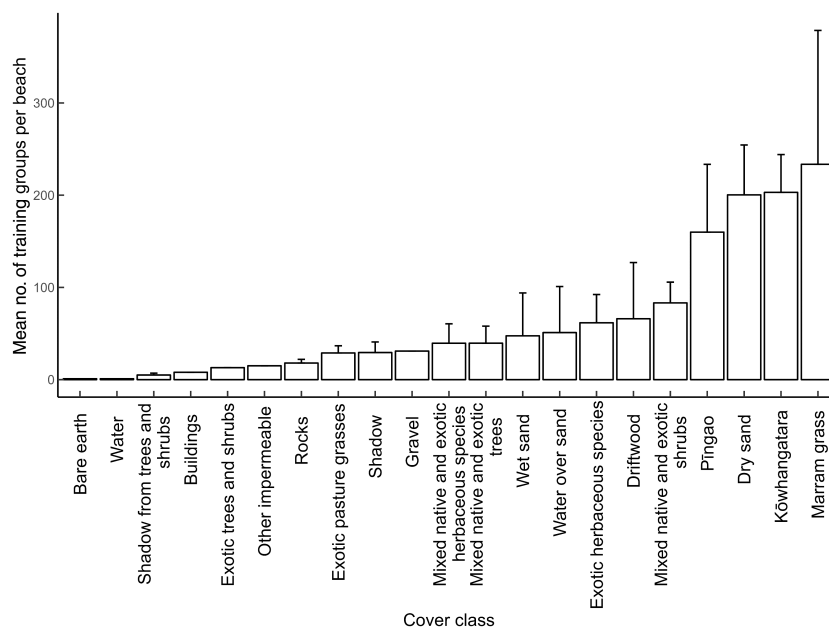


Figure 5. Mean (± 1 SE) number of training samples for each cover class was manually discerned from the imagery across all beaches. Training samples comprised hand-digitized polygons encompassing groups of pixels of the same cover class, selected from all plots across each beach. The number of training samples per beach was proportional to the number of cover classes present.

terminal node (Fig. 9). The most important global variable was population, followed by high wind gusts and ecosystem extent (Table 4).

Discussion

This study shows how the cover classes of coastal active dunes in Aotearoa can be identified from aerial imagery at the scale of 90×120 m plots. It shows that these cover classes, at this scale, can be used to characterize distinct vegetation types that can be predicted by geomorphic and anthropogenic variables. The key sandbinder and other cover classes on incipient dunes and active foredunes were accurately discerned; however, differentiation among woody vegetation in semi-stable and stable dunes posed challenges. Our CART model suggested that, where dune systems were heavily used by people, human activities had a more important influence on vegetation type than geomorphic drivers. Our study shows that extracting key vegetation features from aerial imagery is feasible, and this methodology will be useful for creating inputs for conservation management in Aotearoa. Given the ubiquity of the drivers of active dune conditions globally (Hesp & Walker, 2021; Psuty, 2004), it is possible the method could also be successfully used on active sand dune ecosystems in other countries. Moreover, our method could easily be repeated through time to quantify how these systems change where historical aerial imagery exists.

Discriminating among sand dune vegetation components in aerial imagery

Our accuracy assessment showed good agreement between the image classification and reference sources, with an overall accuracy of 0.76 and a mean Cohen's Kappa score of 0.70 (Richards, 2013), which is a strong result considering the small size of target sandbinder plants and imagery resolution (Ye et al., 2018). Pīngao and kōwhangātara could potentially be discerned because they are often dominant, with few other species present (Johnson, 1993), resulting in fewer pixels mixed with other species in training samples (Hugenholtz et al., 2012). Native sandbinders occur on highly active parts of dunes (Hesp, 2000); thus, the area occupied by them is a critical indicator of how active these dune ecosystems are. Our results suggest these areas can be derived from aerial imagery with this method. However, given that pīngao and kōwhangātara plants are narrower in width than the minimum segment size and occur in a background of sand, some mixed segments with sand would have occurred and, thus, were often confused with sand. Although this is not ideal, we argue that distinction from other species is the more important level of discrimination, and so this does not detract from the applicability of this method to these cover classes. In addition, the differentiation between native sandbinders and the exotic marram grass was clear and is therefore highly useful for indicating indigenous

Table 3. Aggregated confusion matrix for the nine aggregate cover classes across all beaches.

Cover class	Sand	Woody vegetation	Water	Other	Exotic pasture grasses	Pingao	Kōwh – angatara	Marram grass	Other herbaceous species	Total	User's accuracy
Sand	1376	73	0	6	30	24	78	62	25	1674	0.82
Woody vegetation	60	1352	0	26	36	5	20	76	33	1608	0.84
Water	9	27	11	0	3	0	0	0	0	50	0.22
Other	56	120	0	200	1	4	12	8	1	402	0.50
Exotic pasture grasses	17	21	0	1	343	0	2	37	0	421	0.81
Pingao	50	27	0	6	0	163	4	0	0	250	0.65
Kōwhangatara	111	50	0	4	19	2	462	24	16	688	0.67
Marram grass	10	35	0	0	9	0	9	334	2	399	0.84
Other herbaceous species	80	43	0	0	3	0	7	13	240	386	0.62
Total	1769	1748	11	243	444	198	594	554	317	5878	0.00
Producer's accuracy	0.78	0.77	1.00	0.82	0.77	0.82	0.78	0.60	0.76		
Overall accuracy											0.76
Kappa											0.70

The cover classes assigned to each validation segment through image classification were compared to those assigned visually using reference sources. Diagonal shaded cells represent the number of correctly classified segments for each cover class. The off-diagonal cells indicate the misclassifications between different cover classes. Overall accuracy is the number of correctly classified segments divided by the total segments in the sample. Kappa is another misclassification measure that compares overall accuracy to a random classification.

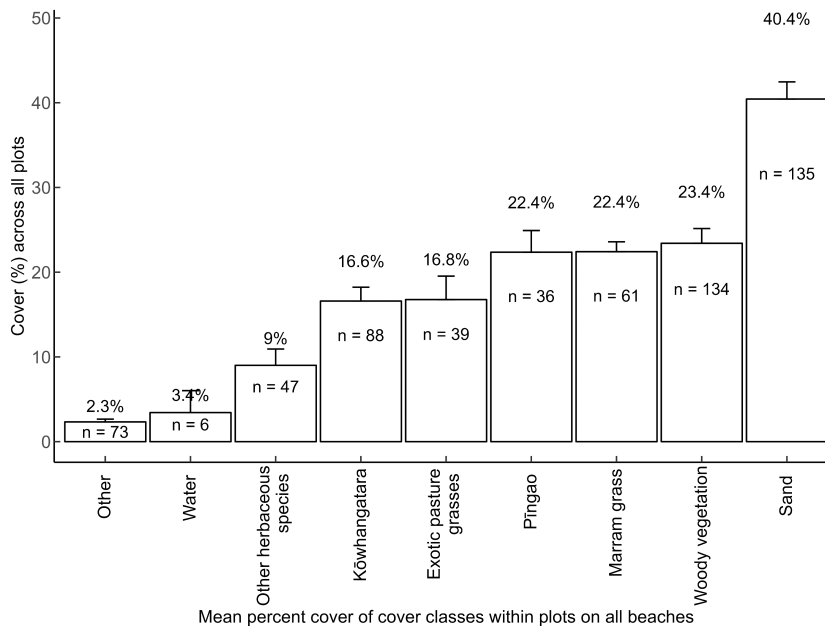
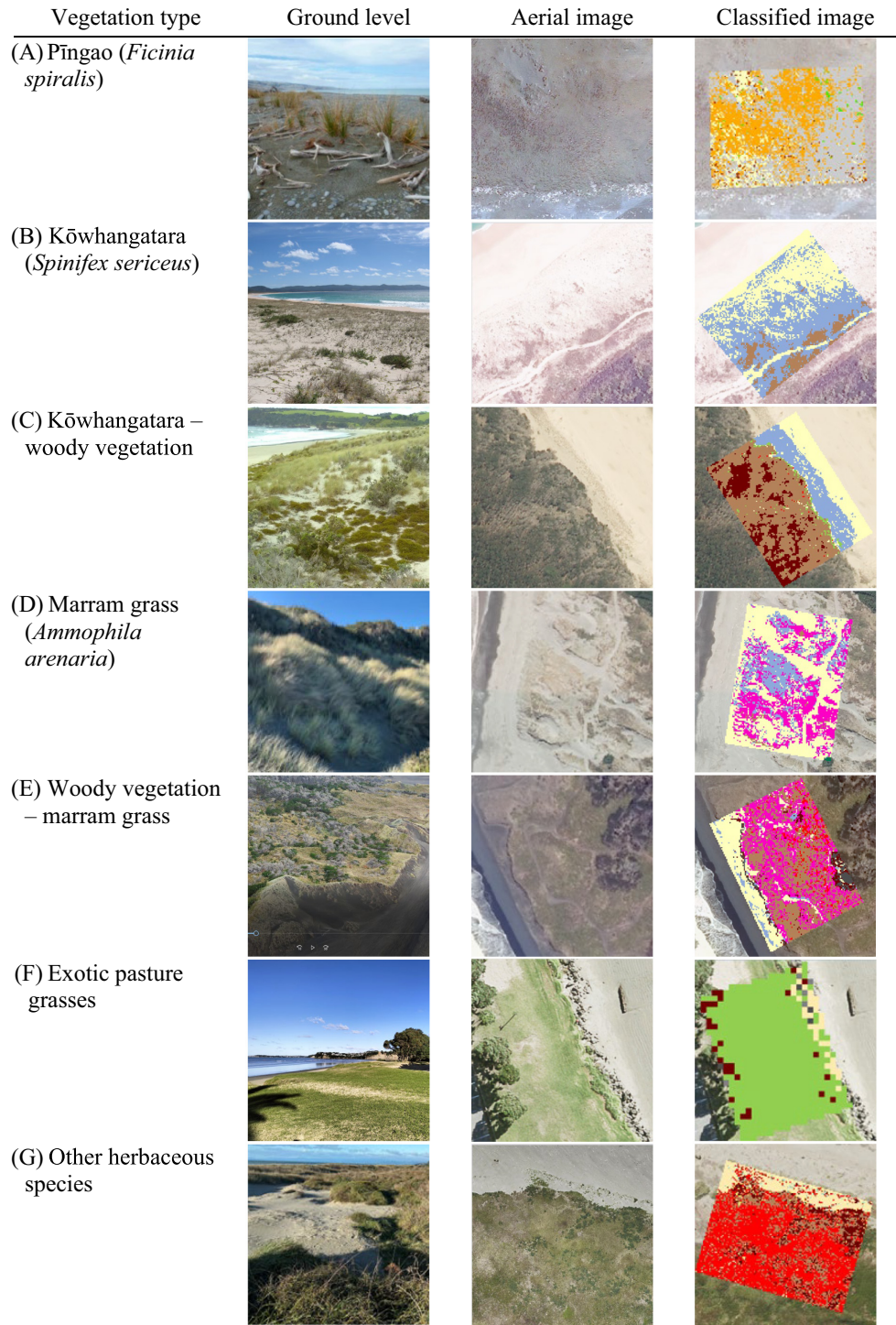


Figure 6. Mean percent cover (± 1 SE) within plots of the nine cover classes across all plots ($n = 135$). The "Other" cover class contained shadows, buildings, and small, impermeable objects, such as signs or vehicles. Note that not all grids have all classes present, so the total percent cover adds up to more than 100.

dominance and ongoing natural ecosystem processes on dunes in Aotearoa (Johnson, 1993).

The collection of training samples for woody plant species was more challenging due to the complexity of woody

vegetation relative to the ability of the method to resolve individual species with the imagery selected consistently. This necessitated the aggregation of all woody species into two broad groups for image classification: (1) mixed native



Cover classes

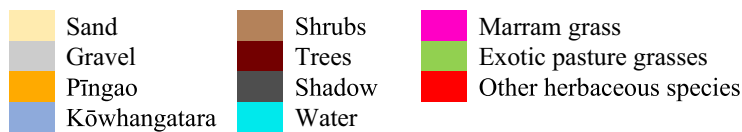


Figure 7. Examples of the seven dominant plot vegetation types identified using hierarchical agglomerative cluster analysis and their cover class composition. Aerial imagery (Table S1 in Supporting Information) is shown at a scale of 1:1000, apart from the “Exotic pasture grasses” plot vegetation type, which is shown at 1:200, due to this being a smaller plot (540 m²) to accommodate a foreshortened foredune. Vegetation types, sample beaches, and photo credits: (a) Pīngao (*Ficinia spiralis*): Kaitorete Spit, credit: Hannah Buckley; (b) Kōwhangātara (*Spinifex sericeus*): Spirits Bay/Kapowairua, credit: Thomas Buckley; (c) Kōwhangātara – woody vegetation: Pakiri Beach; (d) Marram grass (*Ammophila arenaria*): Himatangi Beach, credit: Elizabeth Bargh; (e) Woody vegetation – marram grass: Muriwai Beach, credit: Graham Hinchliffe (UAV footage taken for this research); (f) Exotic pasture grasses: Ōrewa Beach; (g) Other herbaceous species: Ōhope Beach, credit: Sarah Beadel.

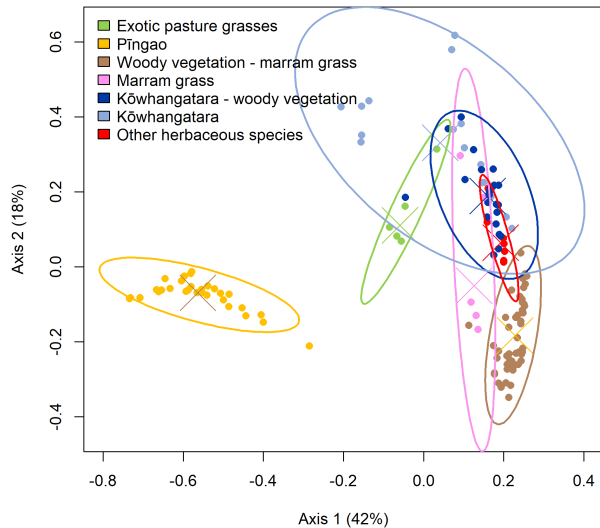


Figure 8. Principal Coordinates Analysis (PCoA) of the square-root transformed percent cover values for foredune cover classes within plots, relativized to maximum percent cover values. The plot shows the first two ordination axes, which are the unrotated solutions. The plot symbols are coloured by the seven plot vegetation types resulting from the cluster analysis of the cover class dataset for the 135 plots, that is, the dominant vegetation type. The centroids of each plot vegetation type cluster are marked with an “x” symbol on the diagram. Ellipses show the 95% confidence intervals around each plot of vegetation type.

and exotic trees and (2) mixed native and exotic shrubs. Although the accuracy of these classes was high, false positives and false negatives occurred (Fig. S2 in Supporting Information). In contrast, other studies have achieved identification at species level either with very high-resolution multispectral imagery (<5 cm) (Bilkey, 2022; Case et al., 2019; Laporte-Fauret et al., 2020) or by combining multispectral imagery with Light Detection and Ranging (LiDAR) data (Hantson et al., 2012).

Identification of exotic pasture grasses and other herbaceous plants to the species level in training samples was also challenging, again necessitating broad groupings. Given the sub-pixel size of many herbaceous plants, mixed pixels in training samples were likely to be relatively common, contributing to the lower accuracy and higher standard error of these cover classes. Given that several rare

and threatened herbaceous plants occur in dune slacks and hollows (Rapson et al., 2016; Wardle, 1991), further research is warranted to determine methods to more accurately identify ecologically important species in these environments; very high-resolution RGB and multispectral UAV imagery could be considered (Bakacsy et al., 2023; Laporte-Fauret et al., 2020; Wolff et al., 2023).

Although the SVM classifier is perceived to work well with high-dimensionality data (Ma et al., 2017), a potential improvement in discrimination among active dune vegetation types could be to train the classifier on the Hue, Saturation and NGRDI bands only to avoid potential correlation between RGB and HSV bands. Removing the Value and RGB bands from the classifier could have additional benefits, such as minimizing variation in light and shade (Cheng et al., 2001).

Emergent sand dune vegetation types from image classification data

Our study revealed clear patterns in the composition of vegetation types across the different plots through PCoA ordinations and cluster analysis. Notably, pīngao-dominant plots were distinctly separate from those dominated by all other vegetation types, potentially due to their locations in remote, southern areas with high conservation protection. Consequently, these areas have likely mainly remained untouched by human activity and invasion from exotic plant species, thus providing refuge for pīngao, which was once widespread around Aotearoa (Johnson, 1993; Wardle, 1991). In contrast, kōwhangātara-dominant plots occurred with plots dominated by all other vegetation types except for pīngao, reflecting its widespread distribution within its geographical range, which lies at the northern tip of the South Island (Wardle, 1991). It may also reflect the prevalence of this species on the seaward side of foredunes, an area typically uninhabited by other species except for pīngao (Esler, 1978; Wardle, 1991).

The marram grass cover class had the third highest mean percent cover within plots, after the sand and woody vegetation cover classes (Fig. 6); however, only seven plots were classified as marram-dominant by the cluster analysis (Fig. S3 in Supporting Information). Accuracy assessment results showed that some beaches with relatively high

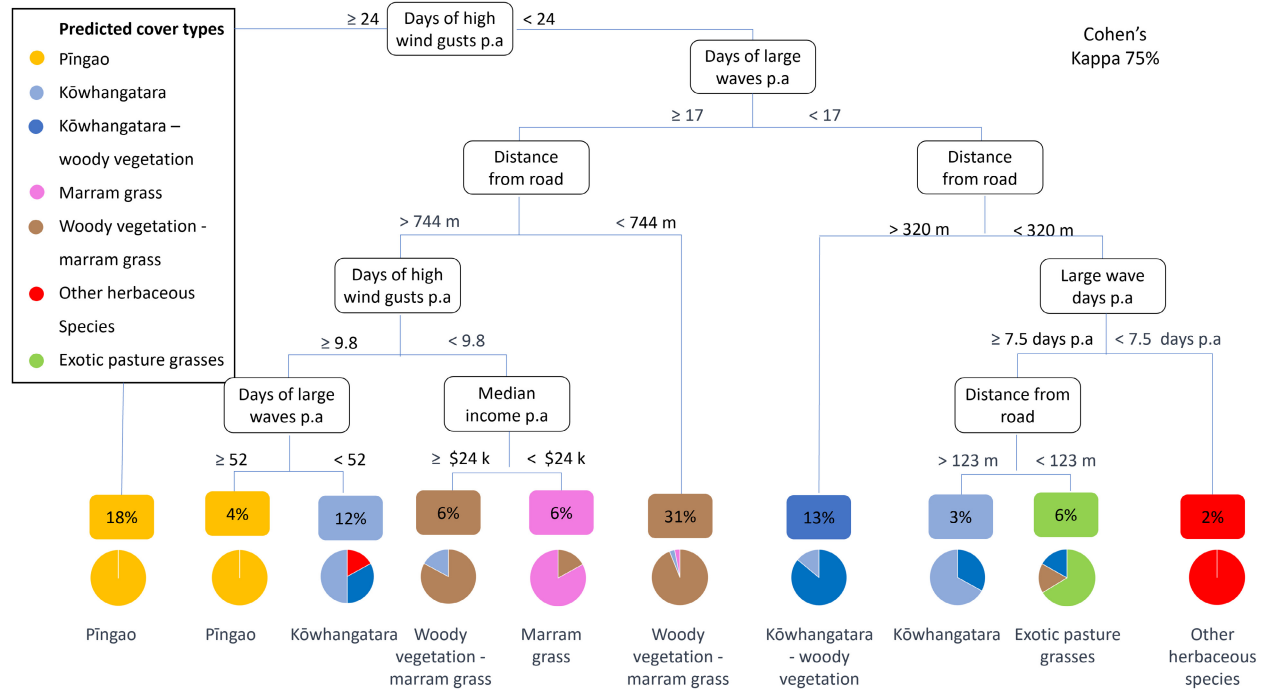


Figure 9. CART Classification Tree model relating plot vegetation type to selected, recursively partitioned, human, and geomorphic variables for 135 plots on active dunes from 21 beaches around Aotearoa, New Zealand. Branches show the thresholds for each variable that characterized a group of plots by each important explanatory variable. Pie graphs show the relative correct and incorrect percentages of plots included in that terminal group of plots. The length of branches is aesthetic rather than indicative of the amount of variation explained by the model.

Table 4. Importance values (%) for explanatory variables from the CART analysis relating the classification of plot vegetation type (seven dominant types) to environmental variables.

Environmental variable	Importance (%)
Distance from road (m)	17
Population	16.8
Days of high wind gust p.a	16
Mean daily wind run (knots)	14.1
Median income (NZD)	11
Number of days of large coastal waves p.a	10.4
Total rain (mm)	9.6
Adjacent land cover (low producing grassland)	2.5
Ecosystem extent (ha)	1.8
Adjacent land cover (sand)	0.8
Coast	0

marram grass cover had high misclassification rates for the marram cover class with the woody vegetation and exotic pasture grass cover classes, suggesting spectral similarities. Potentially, this means marram grass has greater dominance in more plots, and methods should be developed to improve discrimination against this aggressive species.

The woody vegetation cover class had the highest mean percent cover after sand (Fig. 6), and cluster analysis

showed it was a co-dominant in plots with either kōwhangatara or marram grass rather than a dominant (Fig. S3 in Supporting Information). However, the co-dominant woody vegetation-marram grass vegetation type was the most common dominant plot vegetation type. These results suggest stable, woody-dominated vegetation has increased on active dunes since the last survey of extent (Hilton et al., 2000), consistent with international trends (Gao et al., 2020; Jackson et al., 2019). Extensive, historical co-planting of Monterey pine and marram grass may explain the high percentage of these co-occurring cover classes within plots (Gadgil & Ede, 1998). However, we could not distinguish between invasive woody species and characteristic native species of semi-stable and stable mid and rear dunes.

Potential drivers of sand dune vegetation type variation across Aotearoa

The CART model predicting the seven plot vegetation types from geomorphic and anthropogenic factors produced a relatively high Cohen’s Kappa statistic (0.75), indicating good agreement between observed and predicted classes (Richards, 2013). The model identified a possible interaction between plot vegetation type and

disturbances from wind gusts, wave energy, and human influence, which was consistent with our expectations based on field-level knowledge and the international literature (Castillo & Moreno-Casasola, 1996; Gao et al., 2020; Laporte-Fauret et al., 2021; Miller et al., 2010). The model suggested that plot vegetation types dominated by pīngao and kōwhangatara will occur where wind and wave energy are strongest and at greater distances from the nearest road. Notably, pīngao thrives in areas with high wind gusts, while kōwhangatara dominates in regions with a high mean daily wind run. Thus, although wind gusts and mean daily wind run are highly correlated, wind gusts and ambient wind conditions may have contrasting impacts on native-dominated plot vegetation types.

The results suggest that human activities had a more important influence on plot vegetation type in areas of Aotearoa where human influence was strongest, specifically where distances from the nearest road were the lowest, resulting in mainly woody-dominated plot vegetation types on beaches. This pattern may be explained by road access to facilitate planting for forestry or farming, which, historically, would have catalysed dune stabilization, a trend that also occurs internationally (Gao et al., 2020). Where wind and waves were calmest and beaches were close to the road, plots were predicted to be dominated by exotic pasture grasses or other exotic herbaceous species vegetation types, which aligns with a common impact of coastal development: the loss of characteristic native species (Ciccarelli & Bacaro, 2014; Pintó et al., 2023; Salgado et al., 2021).

Conclusions

This study has shown that the key sandbinder cover classes of active dunes in Aotearoa can be successfully discerned from other cover classes. Thus, plots can be accurately classified from RGB, high-resolution aerial imagery, and derived NGRDI and HSV layers when these vegetation cover classes dominate. The resolution of the imagery (0.075–0.75 m) meant that native woody species within plots on semi-stable and stable dune areas could not be differentiated as a separate cover class from exotic woody species, which is an important indicator for assessing active dunes' changing stability and condition. Techniques and datasets to identify woody vegetation at the species level require further research, for instance, incorporating higher-resolution imagery (<5 cm), multispectral imagery, and LiDAR data. From the perspective of conservation management of active dunes in Aotearoa, the classification of dominant vegetation types at the plot scale through image analysis provides a practical approach to habitat mapping and monitoring. Such

quantitative and spatially explicit data are critical for addressing conservation aims regarding ecosystem representation and the dominance of indigenous vegetation. These methods can now be used on longer-term and more frequent survey datasets to give greater insight into the temporal impacts of environmental variables.

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Author Contributions

CR, BC, and HB conceived the ideas and designed the methodology; CR collected the data; CR, HB, and GH analysed the data; and CR led the writing of the manuscript. All authors contributed critically to the drafts and gave final approval for publication.

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Supporting Information

Additional supporting information may be found online in the Supporting Information section at the end of the article.

Table S1. Aerial imagery datasets used in this research: All imagery was sourced from Land Information New Zealand (LINZ) Data Service under a Creative Commons open licence (CC BY 4.0), and retrieved from <https://data.linz.govt.nz/data/category/aerial-photos/>.

Equation S1. Normalised Green-Red Vegetation Index (NGRDI): NGRDI was calculated as: (GREEN-RED) / (GREEN+RED) (Hunt et al., 2005), where GREEN was the part of the electromagnetic spectrum with wavelengths between 495 - 570 nm, and RED was between 620 - 750 nm (Hunt et al., 2005).

Table S2. Environmental variables used in the CART Classification Tree analysis.

Table S3. Distances between plots on beaches and climates stations (rain and wind data), and the associated extreme coastal wave index region (modelled extreme wave data).

Table S4. Examples of species or objects that could potentially occur in cover classes discriminated in image classification.

Figure S1. Pearson's pairwise correlation coefficients among the explanatory environmental variables used in the CART Classification Tree analysis predicting dominant plot vegetation type for 135 plots on 21 beaches across Aotearoa New Zealand. Statistically non-significant relationships are represented by white squares. Statistically significant relationships are represented by squares shaded either blue (negative correlations) or red (positive correlations). The matrix shows that most variables were moderately or not significantly correlated, except for mean daily wind run and days of strong wind gusts, which were highly correlated.

Figure S2. Confusion matrix for all cover classes before aggregation into the nine broad cover classes across all beaches. The cover classes assigned to each validation segment through the classification process were compared to those assigned visually against reference sources. Diagonal shaded cells represent the number of correctly classified segments for each cover class, and the off-diagonal cells

indicate the misclassifications between different cover classes. Overall accuracy is the number of correctly classified segments divided by the total number of segments in the sample. Kappa is another misclassification measure that compares overall accuracy to a random classification. Class codes in the left-hand column are: (1) Sand; (2) Wet sand; (3) Mixed native and exotic shrubs 1; (4) Mixed native and exotic shrubs 2; (5) Mixed native and exotic trees; (6) Water; (7) Water over sand; (8) Exotic pasture grasses; (9) Other herbaceous species 1; (10) Exotic trees and shrubs; (11) Pīngao; (12) Kōwhangatara; (13) Marram grass; (14) Other; (15) Rocks; (16) Buildings; (17) Shadow from trees and shrubs; (18) Other herbaceous species 2 ("Exotic herbaceous species" in Table 1 and Appendix 6); (19) Driftwood; (20) Bare earth; (21) Gravel; (22) Shadow. There are 22 classes since the "Mixed native and exotic shrubs" class was split in two in training. The overall accuracy of the classification for the non-aggregated classes was 0.70, and the Kappa score was 0.66.

Figure S3. Summarised Hierarchical Agglomerative Cluster analysis dendrogram of percent cover values for cover classes, using Bray-Curtis pairwise distances among plots and the Average Group Linkage method. The dendrogram is scaled using Wishart's (1969) objective function and was pruned where the tree retained the most ecological meaning, with around 50%–75% of information remaining. The colours represent the cluster boundaries for each vegetation type listed on the left hand side.