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Discrimination of species composition types of a grazed pasture landscape using Sentinel-1 and Sentinel-2 data

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ABSTRACT

Species composition is one of the important measurable indices of alpha diversity and hence aligns with the measurable Essential Biodiversity Variables meant to fulfil the Aichi Biodiversity Targets by 2020. Graziers also seek for pasture fields with varied species composition for their livestock, but visual determination of the species composition is not practicable for graziers with large fields. Consequently, this study demonstrated the capability of Sentinel-1 Synthetic Aperture Radar (S1) and Sentinel-2 Multispectral Instrument (S2) to discriminate pasture fields with single-species composition, two-species composition and multi-species composition for a pastoral landscape in Australia. The study used K-Nearest Neighbours (KNN), Random Forest (RF) and Support Vector Machine (SVM) classifiers to evaluate the strengths of S1-alone and S2-alone features and the combination of these S1 and S2 features to discriminate the composition types. For the S1 experiment, KNN which was the reference classifier achieved an overall accuracy of 0.85 while RF and SVM produced 0.74 and 0.89, respectively. The S2 experiment produced accuracies higher than the S1 in that the overall performance of the KNN classifier was 0.87 while RF and SVM were 0.93 and 0.89, respectively. The combination of the S1 and S2 features elicited the highest accuracy estimates of the classifiers in that the KNN classifier recorded 0.89 while RF and SVM produced 0.96 and 0.93, respectively. In conclusion, the inclusion of S1 features improve the classifiers created with S2 features only.

1. Introduction

Species composition is one of the important measurable indices of alpha diversity and hence aligns with the measurable Essential Biodiversity Variables (Kissling et al., 2018; Turak et al., 2017) meant to assess the progress of the Aichi Biodiversity Targets by 2020 (https://www.cbd.int/sp/targets/). The species composition of pasture fields is typically characterised with different grass types, legumes and forbs which are available for livestock feeding. The variability of species composition is often dictated by the soil quality (Pallett et al., 2016), changes in climate (rainfall and temperature) and management practices (e.g. the grazing system) (Štýbnarová et al., 2015). In livestock grazing environments, although the nutritive value of the grass type is important, variations in the species composition of a field is equally valuable to graziers (Jing et al., 2017). A field characterised with diverse grass types at a point in time offers livestock a range of nutrition (and hence a balanced diet), and higher dry matter yield (Kirwan et al., 2007; Sanderson et al., 2005; Skinner et al., 2006). Additionally, pasture fields with diverse species offer a greater resistance to environmental stress (e.g. drought) (Tilman and Downing, 1994) and weed invasion (Dodd et al., 2004; Kirwan et al., 2007; Tracy et al., 2004; Tracy and Sanderson, 2004). As a result, knowledge of the different types of species that constitute the biomass in pasture fields is important for feed as well as field management decisions.

Visual survey (or ecological methods) has long been the conventional method for assessing species composition of pasture fields to make such management decisions. Practitioners of the visual method rely on the physiological and morphological/ phenological differences (such as in the seed head, stem, leaves and flowers), to discriminate the plant species. However, this method requires extensive training especially with heterogeneous sites and can be burdensome (or impracticable) to undertake with larger fields and extensive landholdings.

To resolve the challenges of visual assessment, remote sensing data and techniques have been explored (Lopes et al., 2017; Muldavin et al., 2001; Peng et al., 2018). Spatial variations in plant species composition translates to spectral heterogeneity across a target area which makes it

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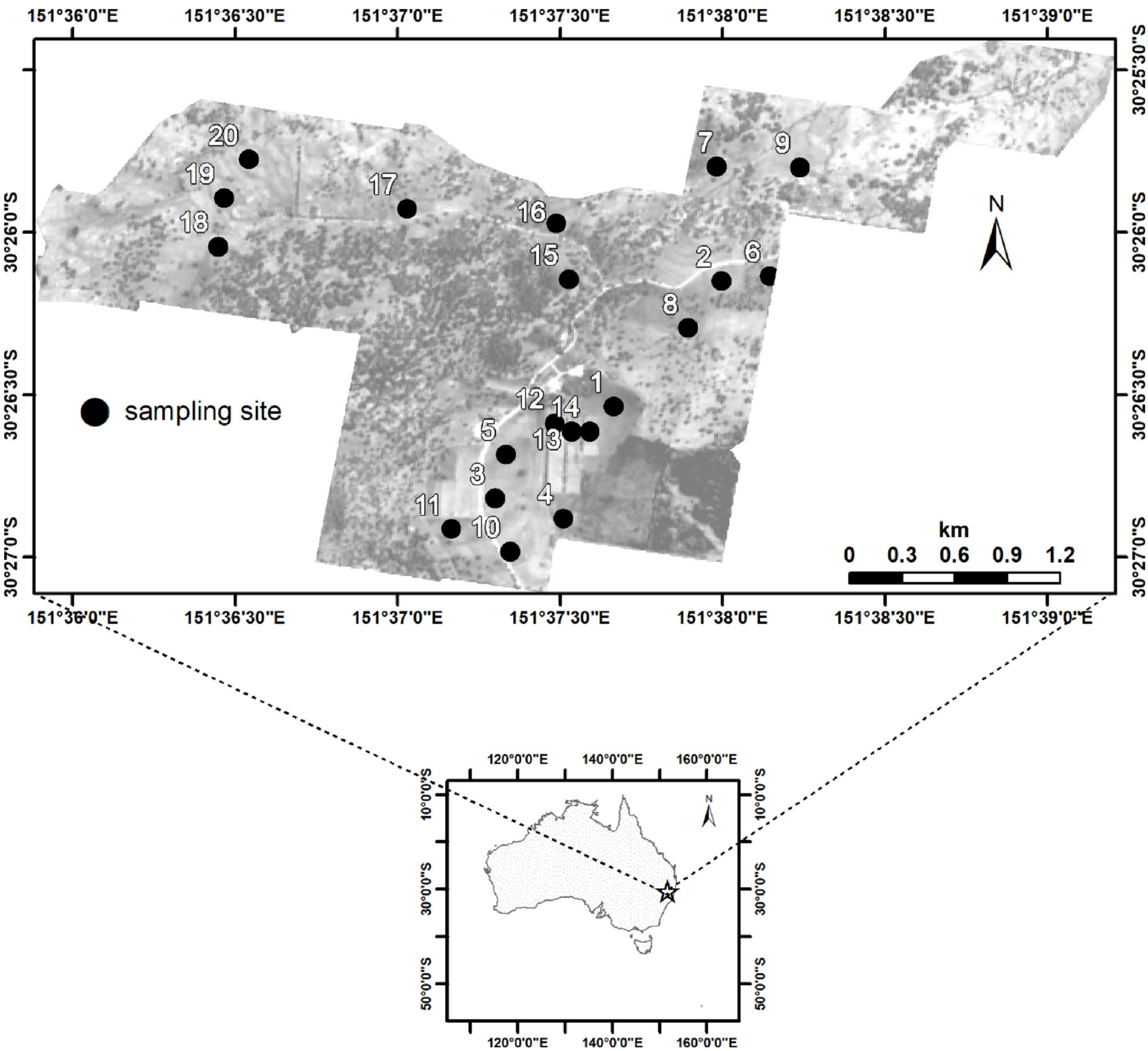

Fig. 1. A Sentinel-2 image of the study area (inset: location of study area in Australia) with the central location point of the 20 sampling sites from which 1080 pixels were extracted and used. The sampling sites are distinguished by their identification number. Each sampling site is composed of 9 Sentinel-2 pixels which makes the area of a sampling site to be 900 m^2.

possible to estimate species diversity through optical remote sensing (Cai et al., 2014; Lopes et al., 2017; Rocchini, 2007). Moreover, the variation of pasture species due to their differences in phenology suggests that temporal variations can be complementary to spectral variation for the classification of species diversity (Lopes et al., 2017). At a fine spatial scale, images derived from consumer-grade cameras (RGB) have been used to discriminate broadleaf and narrow-leaf plants using their morphological features (Lamm et al., 2002; Weis and Gerhards, 2007). Furthermore, Golzarian and Frick (Golzarian and Frick, 2011) combined colour, textural and geometric information to discriminate wheat (*Elymus scaber*), ryegrass (*Lolium rigidum*) and brome grass (*Bromus* spp.) in Southern Australia. In a recent study, Bao et al. (Bao et al., 2017) observed that the spectral band ranging between 1780 nm and 1050 nm was able to discriminate 17 alpine wetland grasses which showed differences in leaf area index and chlorophyll content. Peng et al. (Peng et al., 2018) used vegetation indices, extracted from a ground-based hyperspectral sensor, to measure species diversity of temperate grassland in Northern China. Although these remote sensing methods (proximal sensing or aerial sensing) offer high spatial and spectral resolution for improved separability of plant species, they are limited in regular revisit frequency and difficult to apply at larger spatial scales. At a landscape scale, past studies have related the phenological diversity to plant species diversity using optical, satellite remote sensing (Rocchini et al., 2016). Moreover, satellite remote sensing can improve the temporal granularity of observing plant species diversity. The standard optical spectral bands, and their combinations via vegetation indices, have been reported to be indicative of species diversity. Species diversity indicators such as species composition or species richness, Shannon and Simpson indices have been estimated using Normalised Difference Vegetation Index (Bawa et al., 2002; Foody and Cutler, 2002; Gould, 2000). Other vegetation indices such as Enhanced Vegetation Index, Soil Adjusted Vegetation Index, Atmospheric Vegetation Index, Middle Infrared Index and Infrared Index have also been found to exhibit strong correlations with plants species diversity (Bawa et al., 2002; Cabacinha and de Castro, 2009; Nagendra et al., 2010; Schowengerdt, 2006). Notwithstanding the use of vegetation indices, some spectral bands on their own such as the near infrared, middle infrared and thermal infrared can be used for plant species discrimination (Cai et al., 2014; Everitt et al., 2007; Muldavin et al., 2001). A multitude of studies presented in the review work of Rocchini et al. (Rocchini et al., 2016) and Kuenzer at al. (Kuenzer et al., 2014) used optical satellite remote sensing data to measure or discriminate plants species diversity. However, due to the insensitivity of spectro-optical bands at dense canopies, a few number of past studies have employed or integrated Synthetic Aperture Radar (SAR) in the discrimination of pasture species composition (Crabbe et al., 2019a; Hill et al., 2005; Price et al., 2002; Smith and Buckley, 2011). Other past studies have combined Sentinel-1 SAR (S1) and Sentinel-2 optical (S2) data for land cover/use classification purposes (Clerici et al., 2017; Kaplan and Avdan, 2018; Mercier et al., 2019; Schmidt et al., 2018; Steinhausen et al., 2018). Nonetheless, there are no studies into the combination of S1 and S2 data for the classification of pasture grass species composition.

Owing to the spatial, spectral and temporal resolutions of the S1 and S2 sensors and the fact that these sensors have not been explored together with regards to classifying pasture species composition, this study assessed the extent to which the S1 (SAR information) supports the S2 (optical information) in discriminating three different classes of pasture species composition using K-Nearest Neighbour (KNN), Random Forest (RF) and Support Vector Machine (SVM) classifiers. The KNN classifier served as the reference classifier to evaluate the performance of RF and SVM.

2. Materials and methods

2.1. Characteristics of the study area

The experiments of this study were conducted on one of the University of New England SMART Farms located near Armidale (30°26′6″S, 151°37′30″E) (Fig. 1). The farm size is 740 ha and is composed of numerous pasture fields of different grass types, with grazing sheep and cattle rotated onto the fields throughout the year. Up to twenty different fields were sampled for this study. Each of the field sample sites measured 30 m x 30 m to provide 9 pixels per field for the satellite images. Further details of the study site and the selection of sampling sites can be found in (Crabbe et al., 2019a,b).

2.2. Field sampling of pasture types and classification

The field measurements were conducted between 2017 and 2018 on dates that aligned with S1 and S2 overpasses (Table 1). The majority of measurements were acquired in October 2017 (mid spring) and February 2018 (late summer) and involved 20 sites. A smaller number of sites were sampled on other dates (Table 1). The visual surveys of pasture species were conducted using the BOTANAL protocol as implemented in the work of Crabbe et al. (Crabbe et al., 2019a). BOTANAL is a comprehensive field sampling procedure, designed by Commonwealth Scientific and Industrial Research Organisation (CSIRO) of Australia, and thus widely used for visual estimation of pasture species composition and pasture yield in Australia (Tothill et al., 1978). On the field, pasture species were identified by their morphology or physical characteristics. The major dominant species surveyed were wallaby grass (*Austrodanthonia* spp.), red grass (*Bothriochloa macra*), poa tussock (*Poa labillardierei)*, summer grass *(Digitaria sanguinalis)*, Parramatta grass (*Sporobolus creber*), wheat grass (*Elymus scaber*), cocksfoot (*Dactylis glomerata*), tall fescue (*Festuca arundinacea Schreb*.), phalaris (*Phalaris aquatica*), Yorkshire fog (*Holcus lanatus*), wild sorghum (*Sorghum leiocladum*), microlaena (*Microlaena stipoides*) and paddock lovegrass (*Eragrostis leptostachya*). The canopy structure of these species make them visually discriminable into three groups based on the physical characteristics of species seed heads (Kahn et al., 2003, Fig. 2). Through the BOTANAL protocol, the various species dominating the field were estimated using a dry-weight-rank method. This method offers a percentage estimate of the relative contribution of the different species in the sample area. To preserve the reliability and repeatability of the visual survey process, the assessments were all conducted by the same expert for all sampling sites and dates.

For the purposes of assessing pasture species diversity, a rule-based technique was applied to group these individual pasture types into three classes; single-species, two-species composition and multi-species composition (Fig. 3). Firstly, the rule excluded species with a botanical composition of less than 10%. Then, sites with 90% or more of the botanical composition comprising of a single species were classified as single-species. If two species constituted at least 90% of the botanical composition with neither of the two constituting two-thirds of their total proportion, then a two-species class was assigned to the site. The remaining sites were assigned to the multi-species class. This classification process was conducted at the pixel-scale of S2. Since the image classification was implemented at pixel scale (i.e., 10 m × 10 m), the species class of a site was allocated to every single pixel that formed the sampling site. A similar approach was recently used in Crabbe et al. (Crabbe et al., 2019a).

Table 1
Field sampling and closest, usable Sentinel-1A and Sentinel-2 (both A and B sensors) image acquisition dates.

Field sampling date	Sentinel-1 sampling date	Sentinel-2 sampling date (variant)
13 February 2017	13 February 2017	24 February 2017 (S2A)
6 July 2017	7 July 2017	9 July 2017 (S2B)
11 October 2017	11 October 2017	22 October 2017 (S2A)
12 December 2017	10 December 2017	11 November 2017 (S2A)
16 January 2018	15 January 2018	10 January 2018 (S2A)
8 February 2018	8 February 2018	9 February 2018 (S2A)
16 March 2018	16 March 2018	16 March 2018 (S2B)
26 July 2018	26 July 2018	24 July 2018 (S2B)

2.3. Preprocessing of Sentinel-1 and Sentinel-2 images

The S1 and S2 images were downloaded from the Scientific Hub of the European Space Agency (Table 1). The single look complex (SLC) and ground range detected (GRD) products of S1 were used. Depending on the field measurement date, S2 images from either sensor A or B were accessed. It is worth noting that due to the presence of cloud cover over the study site, the acquisition dates of S2 images for February, October and December 2017 were not exactly synchronous to the corresponding field sampling dates. The S1 images were processed to extract backscattering coefficients, polarimetric scattering and textural metrics. Satellite orbit data downloaded from the archive of ESA were used for both SLC and GRD images to improve the radiometric and geometric calibrations of these images. The GRD images were radiometrically calibrated and then minimised the effect of random speckles using the Refined Lee method (Lee, 1981; Yommy et al., 2015). Moreover, the contributions of topography to the radar backscattering were minimised by using a 1 m digital terrain model for the terrain correction process (Crabbe et al., 2019b). These images were then matched to the geographic extent of the study site using a bilinear interpolation resampling method. Since the VH polarisation is noted to be more responsive to vegetation canopy volume, this polarisation was used for the GLCM textural analysis. The GLCM textural features were obtained by using a window size of 9 × 9 pixels which was moved at intervals of one pixel in the north, northeast, east and northwest directions of the neighbourhood centred on the central coordinates of the sample sites. The mean values of the GLCM statistics from all of these directions were computed to produce the GLCM textural features. A total of 10 GLCM textural features were extracted; contrast (CON), dissimilarity (DIS), homogeneity (HOM), angular second moment (ASM), energy (ENE), entropy (ETP) and maximum probability (MAX).

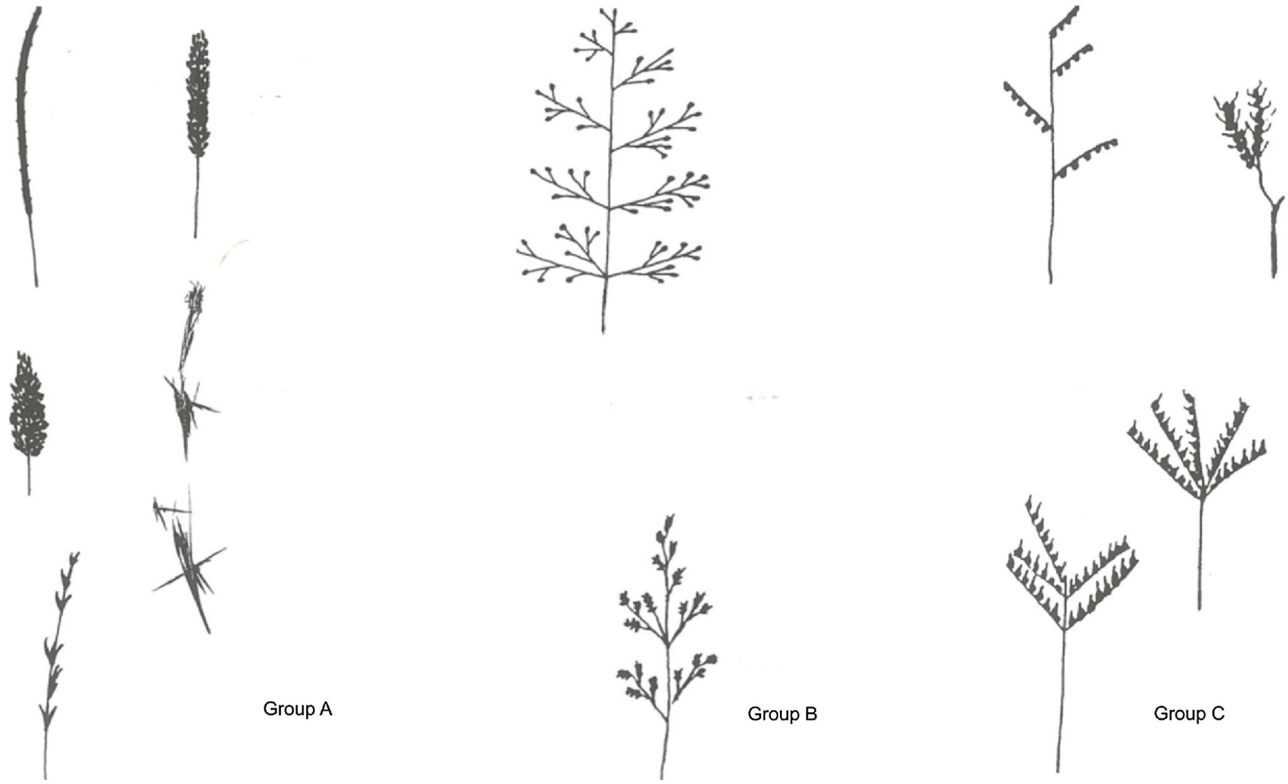

Fig. 2. The groups of major dominant species on the basis of the morphology of their seed heads (Kahn et al., 2003).

The rest of the textural features were mean (MEA), variance (VAR) and correlation (COR).The sub-swath of the SLC images that contains the study area was used to reduce the processing time. These SLC images were radiometrically corrected while all bursts were removed. Moreover, the radiometric quality of the SLC images was enhanced using a Refined Lee polarimetric filter. Eigenvector polarimetric decomposition was then applied to extract the features that measure the polarimetric scattering characteristics; entropy (polETP), anisotropy

Fig. 3. Sampled pasture fields with the botanical composition dominated by single-species (S), two-species (T) and multi-species (M).

(polATP) and scattering alpha angle (polAPH).

The Top of Atmosphere products of the Sentinel-2 were converted to surface reflectance using the Sen2cor script (Louis et al., 2016). The S1 and S2 images were co-located with the S1 images being slave images to the S2 images. A square window of 3 × 3 pixels was then moved across the entire study area to extract the pixel values for all of the estimated features (including 10 of the S2 spectral bands).

2.4. Description of the KNN, RF and SVM classifiers

Machine learning classifiers have become important in remote sensing due to the fact that they are particularly suited to modelling complex class signatures, are able to handle large groups of predictor variables, and are insensitive to data distribution. Many machine learning classifiers have been adopted in remote sensing but the often used methods are K-Nearest Neighbours (KNN) (Maselli et al., 2005), Random Forest (RF) (Adelabu and Dube, 2015; Berhane et al., 2018; Crabbe et al., 2019a; Gislason et al., 2006; Liu et al., 2018; Tian et al., 2016; Yan and de Beurs, 2016) and Support Vector Machine (SVM) (Huang et al., 2002; Pal and Foody, 2012; Pal and Mather, 2005) due to simplicity in their hyper-parameterisation, and high performance. Specifically, this study used RF and SVM because in an earlier paper where 179 classifiers were evaluated using over 120 different data sets, RF and SVM outperformed all of the other classifiers (Fernández-Delgado et al., 2014). The KNN classifier was used as a reference classifier to assess the performance of the RF and SVM classifiers.

The KNN classifier is the simplest among the three classifiers in that the user has only one parameter (i.e. the K) which indicates the number of data points closest (neighbours) to the unknown data point to define the decision boundary, and this is a user-defined parameter. The class of the unknown sample point is determined by a majority vote of its neighbours, with the most common class among the K-nearest neighbours allocated to this unknown sample point (Altman, 1992). RF is a tree ensemble classifier which uses a multitude of decision trees to resolve the limitations of a single decision tree algorithm (Belgiu and Drăguţ, 2016; Breiman, 2001; Cutler et al., 2007). In RF, two hyper-parameters need to be set by the user, the randomly selected number of features (known as *mtry*) and the number of decision trees to be constructed (*n*). It has been shown in earlier studies that of all the RF parameters these two parameters are more important as they can have significant influence on the performance of the classifier (Degenhardt et al., 2017; Díaz-Uriarte and Alvarez de Andrés, 2006; Shi and Yang, 2016). SVM functions by exploring the feature space to identify the data points that are closest to the optimal decision boundary (hyperplane) between the classes (Cortes and Vapnik, 1995; Huang et al., 2002; Maxwell et al., 2018; Mountrakis et al., 2011; Pal and Foody, 2012; Pal and Mather, 2005; Vapnik, 1995). Thus, the goal of SVM is to select the optimal hyperplane which maximises the margin between the support vectors (i.e. the data points closest to the hyperplane) (Vapnik, 1995). SVM was originally developed to handle two-class problems and to find linear class boundaries (hyperplanes), but recent studies have used the SVM for multi-class problems (Bishop et al., 2019; Chih-Wei and Chih-Jen, 2002; Qi et al., 2004). To minimise errors in the performance of SVM, the cost, C, and gamma, γ, parameters are required to be set manually. Whilst the cost, C, explains the trade-off between margin and misclassification error, the gamma, γ, defines the extent of the influence of a single support vector (Cortes and Vapnik, 1995). Further details on the KNN, RF and SVM classifiers for remote sensing can be found in Maxwell et al. (2018).

2.5. Model data and hyper-parameter tuning

The model data comprised of 1080 observations and 27 features. The single-species composition class was composed of 234 observations while two-species and multi-species had 288 and 558 observations, respectively. This model data was randomly split into training and testing sets. The training set used 80% of the model data, while the remaining data was retained for model testing. The MinMax technique was used to scale model features to values ranging between 0–1 in order to minimise the model feature space for improved performance. Specifically, the minimum and maximum values used to scale the training set were likewise applied to scale the test set. To minimise overfitting due to the imbalanced class size, a stratified 10-fold cross validation technique was used to tune for the hyper-parameters of the classifiers. In RF, the optimal number of random features to grow a single tree (*mtry*) was tuned for, while the parameters for the total number of trees to grow and minimum number of terminal nodes were taken from the work of Crabbe et al. (2019a). The number of neighbours (K) was tuned for the KNN classifier while gamma and cost of constraints violation were tuned for the SVM classifier. The radial basis kernel was applied in the SVM models. The correlation feature selection algorithm from the *FSelector* package in R was used for feature selection (Pal and Foody, 2010; Romanski et al., 2018).

2.6. Classification models and their evaluation

Three different models were built for each of the three classifiers (a total of 9 models). The first set of the classification models were built with S1 features alone while the second set of models were parameterised with S2 features alone. The third set of models combined the S1 and S2 features (COMB). The evaluation of these models were based on producer's accuracy (PA), user's accuracy (UA), overall accuracy (OA) and F1 score (F1). These metrics were all scaled between 0 and 1. The F1 score provides the harmonic average of the PA and UA estimates and is calculated as, $\frac{2}{PA^{-1} + UA^{-1}}$. Since the F1 score accounts for both the PA and UA, it was the measure that was reported for the class-wise performance of the classifiers. The data processing, analyses and classification were all conducted in R using the Classification and Regression Training (CARET) package (Kuhn, 2008).

3. Results

3.1. Optimal features and model parameters

The optimal features selected to create the S1 models were contrast (CON), angluar second moment (ASM), variance (VAR) and polarimetric mean scattering alpha angle (polAPH). For the S2, the optimal features were the red band (B3), red-edge bands (B6), narrow near infrared (B8A) and the short wave band (B11). The grid search for the KNN classifier proved that the parameterisation of this model with three neighbours (i.e. K = 3) achieved the highest accuracy values of 0.72, 0.91 and 0.91 for S1, S2 and COMB experiments, respectively (Fig. 4a). For RF classifier, the optimal *mtry* value for S1 was 2 (OA = 0.73) while that of the S2 and COMB experiments was found to be 3 as the highest prediction accuracies were 0.95 and 0.96, respectively (Fig. 4b). Results from the grid search for the SVM classifier showed that gamma values of 4, 8 and 0.5 with a uniform cost value of 8 achieved the optimal performance for S1, S2 and COMB experiments, respectively.

3.2. Performance of the Sentinel-1 and Sentinel-2 for the discrimination of pasture species composition

Fig. 5 provides the spatial characterisation of the predictive performances of the KNN, RF and SVM classifiers for features derived from the S1 products. The result in Fig. 5 is just a subset of the whole performance of the S1 which is presented in Fig. 8a. For the single-species class, the KNN classifier produced an F1 score of 0.78 while the RF and SVM classifiers produced F1 scores of 0.63 and 0.84, respectively. Regarding the two-species class, the F1 scores for KNN, RF and SVM were 0.84, 0.67 and 0.88, respectively. The multi-species classification

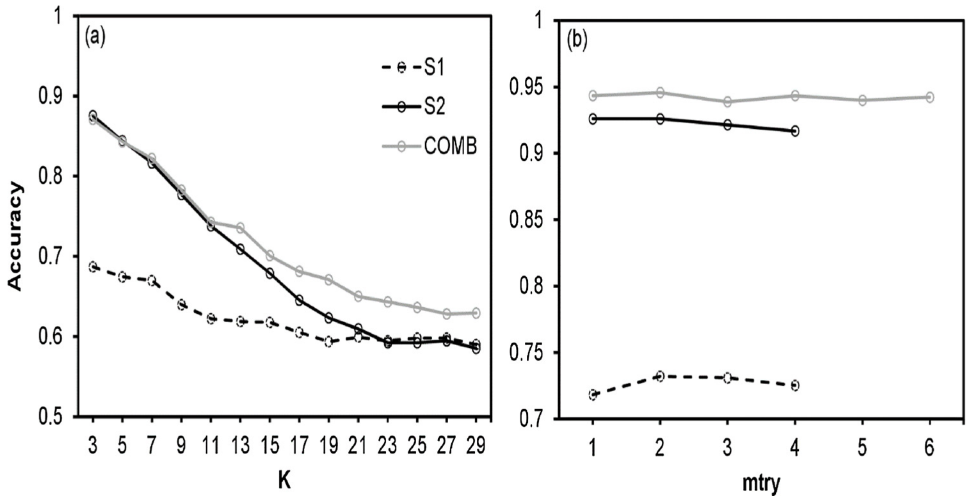

Fig. 4. Tuning for; (a) the K parameter of k-nearest neighbours and (b) mtry parameter of random forest for models created with Sentinel-1 alone (S1) features, Sentinel-2 alone features (S2) and their combination (COMB).

resulted in F1 scores of 0.89 for KNN, 0.80 for RF and 0.91 for the SVM. The OA values for the KNN, RF and SVM were 0.85, 0.74 and 0.89, respectively.

A spatial representation of the performances of the KNN, RF and SVM classifiers in comparing the observed class to predicted class is shown in Fig. 6. Whilst Fig. 6 offers only some of the performance results of the classifiers, the complete evaluation of these classifiers for S2 can be seen in Fig. 8b. For the classification based on S2-alone features, the F1 scores produced by the KNN, RF and SVM classifiers for the single-species class were 0.82, 0.93 and 0.87, respectively. In the case of the two-species class, the F1 scores were 0.87, 0.92 and 0.84 for the KNN, RF and SVM, respectively. Regarding the multi-species class, the RF classifier produced the least prediction error as its F1 score was 0.94. The F1 scores for the KNN and SVM were 0.90 and 0.91, respectively. The OA values for the KNN, RF and SVM were 0.87, 0.93 and 0.89.

Fig. 7 provides some of the results of the spatial characterisation of the predictive performances of the KNN, RF and SVM classifiers for the COMB. Meanwhile, the full result of the performances of these classifiers based on the COMB is encapsulated in Fig. 8 c. The combination of S1 and S2 features produced different classification performances than the S1-alone and S2-alone. Regarding the single-species class, the KNN achieved an F1 score of 0.84 while the RF and SVM achieved 0.96 and 0.95, respectively. Furthermore, the prediction of the two-species class resulted in F1 scores of 0.87, 0.96 and 0.95 for the KNN, RF and SVM, respectively. The prediction of the multi-species class was characterised with F1 scores of 0.92 for the KNN and 0.96 for both the RF and SVM classifiers The combination of the S1 and S2 features achieved overall accuracies of 0.89, 0.96 and 0.95 for the KNN, RF and SVM classifiers, respectively.

4. Discussion

4.1. Evaluation of KNN, RF and SVM classifiers

Regarding the overall accuracies obtained with S1 features, the SVM outperformed the referenced classifier (KNN) while the RF classifier failed to improve KNN. This performance of RF and SVM against the referenced classifier was consistent across the class-wise predictions. In other words, the SVM classifier outperformed the KNN and RF in discriminating all of the species composition types. With the application of the S2 features, both RF and SVM classifiers outperformed KNN with the RF classifier producing the highest accuracies for all of the classes. All of the classifiers proved that the S2 outperforms the S1 in the discrimination of the species composition types. This observation is a confirmation of previous studies that also reported higher performance of the optical features over the SAR features in vegetation classification (Hill et al., 2005; Mahdianpari et al., 2019; Price et al., 2002).The S2 is expected to discriminate the fields (one-species, two-species and multi-species) based upon the variations of canopy chlorophyll and canopy water contents. In this study, the green (Band 3), red edge (Band 6) and near-infrared (Band 8A) spectral bands of the S2 accounted for the variations of chlorophyll while the short wave infrared band (Band 11) offered information linked with the canopy water content. The performance of the S1 against the S2 is not surprising given that the S1 sensor offers only a partial (dual) polarimetric information thereby limiting the conduction of other polarimetric analyses. This study thus suggests future studies to explore full polarimetric SAR data in order to comprehensively evaluate their contributions to species discrimination.

Compared to the KNN classifier, SVM generally offered the highest accuracies in all of the experiments which agrees with the observations reported in earlier studies (Cao et al., 2018; Maxwell et al., 2015; Zhang and Xie, 2013). It is also important to mention that except for the S1 experiment, the RF also improved the KNN classifier. The inclusion of the S1 features improved the S2-alone for the prediction of all of the different species composition fields. In other words, all of the classifiers exhibited improvements in prediction accuracies. Compared to the KNN classifier, the prediction accuracies of RF and SVM were superior in that while the KNN achieved overall accuracy of 0.89 the RF and SVM were 0.96 and 0.95, respectively. For the COMB experiment, the RF and SVM prediction accuracies were similar and it is not surprising that they both outperformed the referenced classifier (KNN) as this agrees with the observations of earlier studies (Fernández-Delgado et al., 2014). Unlike the KNN classifier, the RF and SVM algorithms are known to be more efficient in handling the complexities of high dimensional data space (Pappu and Pardalos, 2014).

Whilst the S2 provides optical information which includes the chlorophyll and water content of the plant canopy, the S1 SAR evaluates the different species composition through the geometric characteristics (height, orientation, density and shape) of the plants. For this reason, the support S1 lends to S2 in the discrimination of the plant species cannot be underestimated, especially in an active grazing environment such as the area studied in this paper. Livestock grazing is likely to alter the species composition of the site and the geometry of the plant canopy, and hence influences the observations from the S1 and S2 sensors. Particularly for the S1 the change of the density of the plant canopy can elicit different polarimetric scattering processes or a multiple scattering mechanism as reported in an earlier study conducted in this study area (Crabbe et al., 2019b). This scattering process

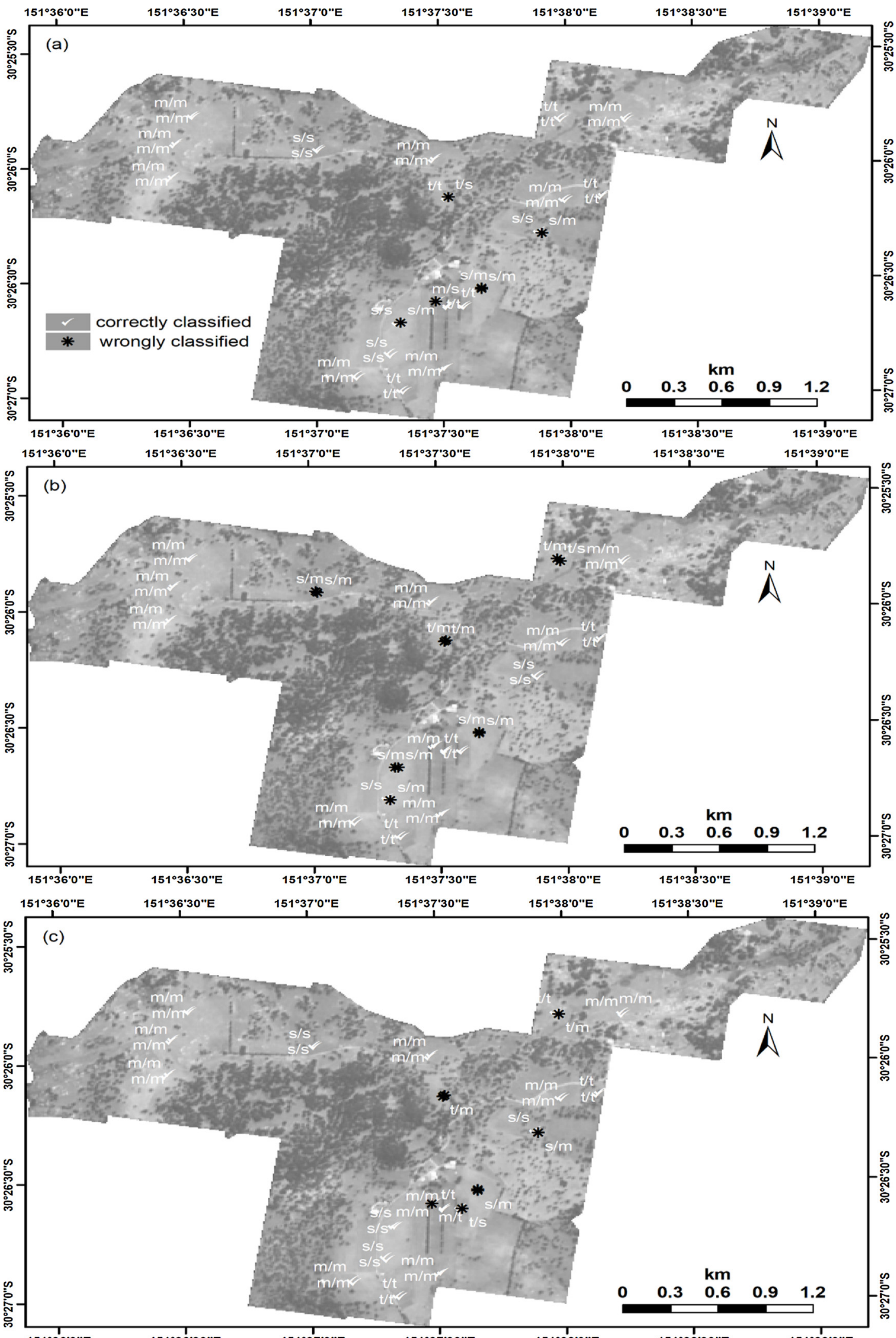

Fig. 5. Spatial characterisation of the predictive performances of; (a) K-Nearest Neighbours, (b) Random Forest and (c) Support Vector Machine using Sentinel-1 features. In the interest of clarity, this result is 9% of the 214 observations (spanning all of the field measurement dates) that were used to test the classification models. The species composition classes are single-species (s), two-species (t) and multi-species (m).

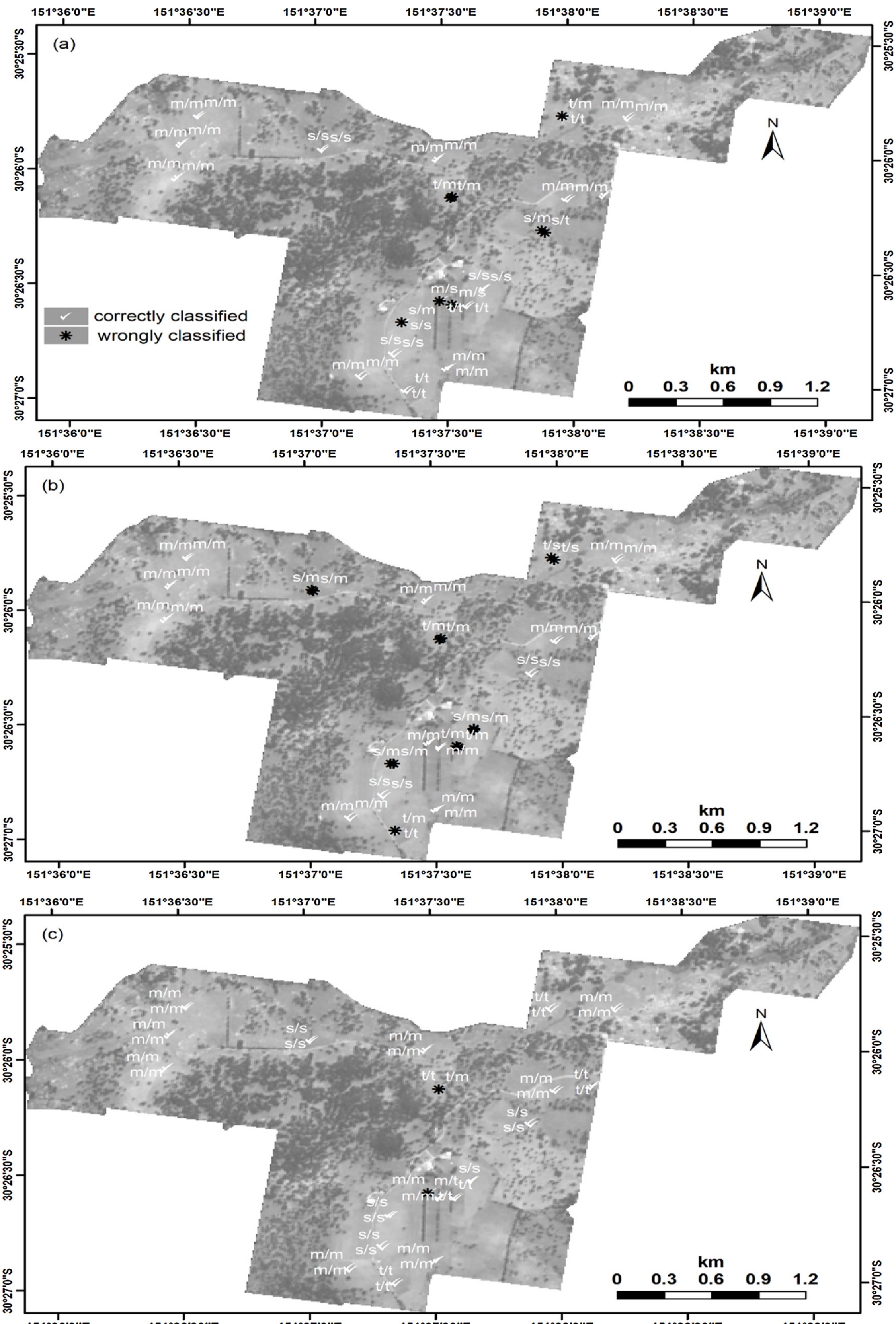

Fig. 6. Spatial characterisation of the predictive performances of; (a) K-Nearest Neighbourhood, (b) Random Forest and (c) Support Vector Machine using Sentinel-2 features. In the interest of clarity, this result is 9% of the 214 observations (spanning all of the field measurement dates) that were used to test the classification models. The species composition classes are single-species (s), two-species (t) and multi-species (m).

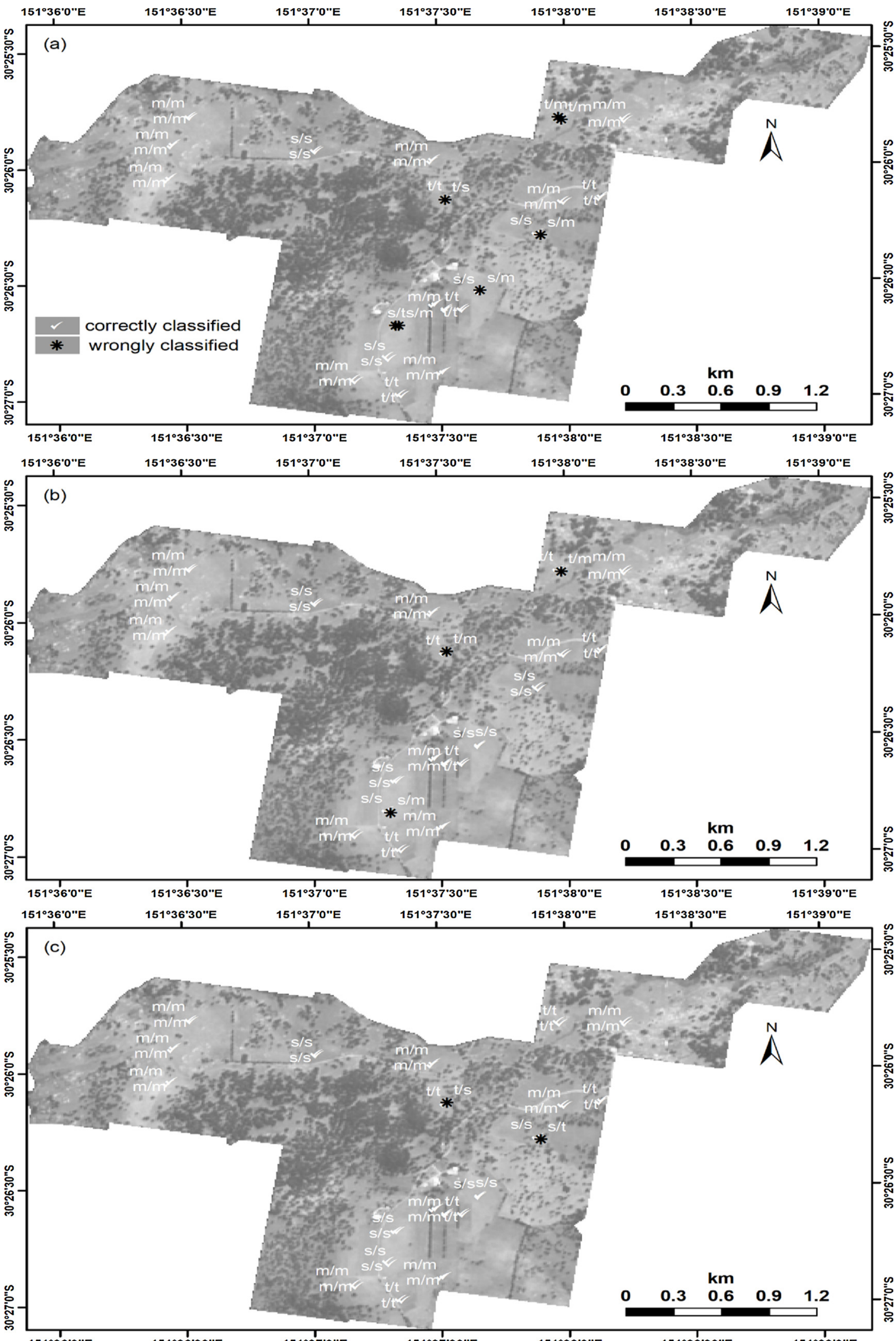

Fig. 7. Spatial characterisation of the predictive performances of; (a) K-Nearest Neighbours, (b) Random Forest and (c) Support Vector Machine using the combination of Sentinel-1 and Sentinel-2 features. In the interest of clarity, this result is 9% of the 214 observations (spanning all of the field measurement dates) that were used to test the classification models. The species composition classes are single-species (s), two-species (t) and multi-species (m).

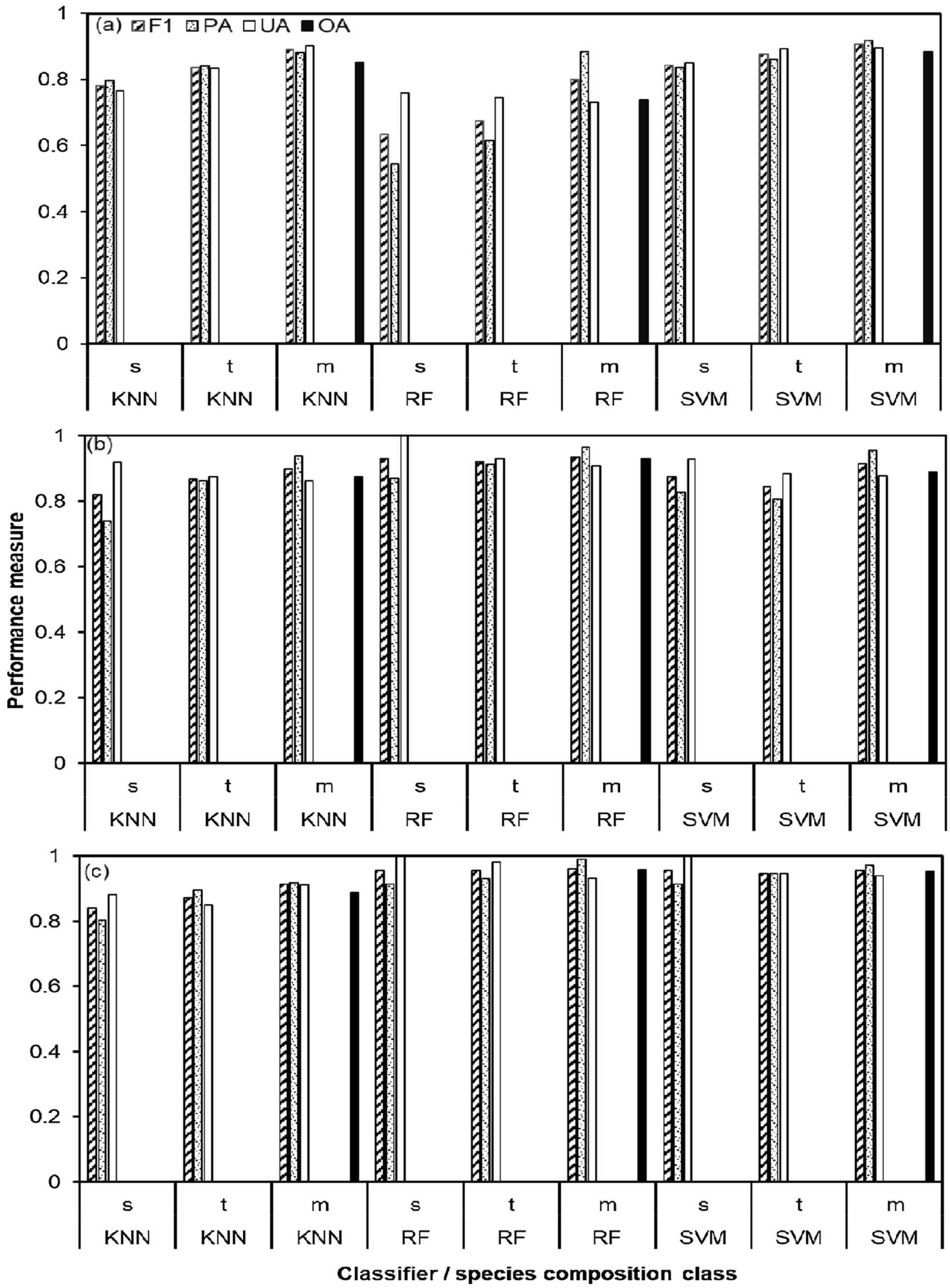

Fig. 8. Evaluation of; (a) Sentinel-1, (b) Sentinel-2 and (c) the combination of the Sentinel-1 and –Sentinel-2 for the discrimination of different classes of pasture species richness via k-nearest neighbours (KNN), random forest (RF) and support vector machine (SVM) classifiers. Whilst the x-axis denotes the three classes (single-species, two-species and multi-species) and the three machine learning classifiers (KNN, RF and SVM), the y-axis provides the performances of the classifiers via producer's accuracy (PA), user's accuracy (UA), F1 score (F1) and overall accuracy (OA).

is as well captured in this current paper through the use of the mean scattering alpha angle to assist the discrimination of the fields. The predictability of the classifiers with S1-alone features is encouraging especially to ecologists and the grazing industry as products derived from the S1 SAR can be more reliable than those of the S2 for a regular monitoring of the species composition. That is, the S2 is affected by weather (environmental) conditions such as cloud cover and the absence of solar illumination. The high accuracies achieved with the S1 in predicting multi-species composition fields suggest graziers can make informed decisions on rotating the livestock as graziers often want to know the fields with variable species composition.

4.2. Satellite remote sensing classification of pasture grass species composition

This study follows earlier studies which demonstrated the ability of satellite remote sensing in estimating or classifying plant species diversity due to the connection between spectral heterogeneity and plants phenological/ morphological changes. That is, the success of S1 and S2 to discriminate the pasture fields into single-species, two-species and multi-species classes is due to the sensitivity of these sensors to the bio-physico-chemical (especially from S2 observation) and morphological (especially S1 observation) differences in botanical composition between fields (Figs. 2, 3). Indeed livestock grazing aided in the morphological differentiation between the sites as sites dominated with poa tussock (*Poa labillardierei*), Yorkshire fog (*Holcus lanatus*) or summer grass (*Digitaria sanguinalis*) are likely to experience less or no grazing due to their unpalatability. Since the performance of the S1 and S2 is dependent on the plant morphology, the predictability of the classifiers are expected to be lowered in the event of discriminating different classes with similar morphology (e.g. clustered seed heads). Although this current study produced classification models, the model results are comparable to the observations of previous studies which produced biodiversity indices (α-diversity) from satellite optical remote sensing data (Feilhauer and Schmidtlein, 2009; Foody and Cutler, 2002; Hernández-Stefanoni et al., 2012; Rocchini, 2007). It is worth mentioning that these previous studies focused on tree and shrub species while this current study evaluates pasture species composition. Moreover, this current study unlike the aforementioned past studies investigated the gross morphological characteristics of the varied species through SAR remote sensing in addition to the optical spectral information. Despite the classifiers created with S2 features generally outperformed that of the S1, this study encourages the use of the S1 since on its own it performed fairly high, especially for the discrimination of the multi-species composition fields. Additionally, in the event of opaque atmosphere, the S1 can replace the S2 monitoring of the species composition. We recommend this study be upscaled or tested in other pastoral landscape with the inclusion of full polarimetric SAR data and other machine/deep learning techniques to directly support the actualisation of the Aichi biodiversity targets 5, 14 and 15 through the S1 and S2 earth observation missions.

5. Conclusions

This study has shown that the combination of Sentinel-1 and Sentinel-2 data can support the measurement of pasture species composition of a grazing landscape to complement the manual methods and the use of satellite remote sensing to achieving some of the Aichi biodiversity targets. The study used K-Nearest Neighbours (KNN), Random Forest (RF) and Support Vector Machine (SVM) classifiers to explore Sentinel-1 features, Sentinel-2 features and the combination of these two sets of features to separate pasture fields into single-species composition, two-species composition and multi-species composition. The RF and SVM classifiers generally produced higher prediction accuracies than the reference classifier which was the KNN. The KNN, RF and SVM classifiers created with Sentinel-2 features outperformed those created with the Sentinel-1 features, but the inclusion of the Sentinel-1 features improved the classifiers created with the Sentinel-2 features. Whilst the overall accuracies for KNN, RF and SVM classifiers with Sentine-2 features only were 0.87, 0.93 and 0.89 respectively, the inclusion of Sentinel-1 features improved these accuracy estimates to 0.89, 0.96 and 0.95, respectively. We encourage future studies to explore full polarimetric C-band Synthetic Aperture Radar data such as RADARSAT to improve this study.

Declaration of Competing Interest

To the best of our knowledge, there is no conflict of interest regarding the submission of this manuscript.

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