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Applied soft classes and fuzzy confusion in a patchwork semi-arid ecosystem: Stitching together classification techniques to preserve ecologically-meaningful information

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ABSTRACT

Dryland ecosystems have complex vegetation communities, including subtle transitions between communities and heterogeneous coverage of key functional groups. This complexity challenges the capacity of remote sensing to represent land cover in a meaningful way. Many remote sensing methods to map vegetation in drylands simplify fractional cover into a small number of functional groups that may overlook key ecological communities. Here, we investigate a remote sensing process that further advances our understanding of the link between remote sensing and ecologic community types in drylands. We propose a method using k-means clustering to establish soft classes of vegetation cover communities from detailed field observations. A time-series of Sentinel-2 satellite imagery and a random forest classification leverages the mixing of different phenologies over time to impute such soft community classes over the landscape. Next, we discuss the advantages of using a fuzzy confusion approach for soft classes in cases such as understanding subtle transitions in ecotones, identifying areas for targeted remediation or treatment, and in ascertaining the spatial distribution of non-dominant covers such as biological soil crusts and small native bunchgrasses which have typically been difficult to map with traditional remote sensing classifications. Our pixel-level analysis is relevant to the scale of management decisions and represents the complexity of the landscape. The combination of cloud computing with the spatial, temporal, and spectral observations from Sentinel-2 allow us to develop these ecologically-meaningful observations at large spatial extents, including complete coverage at landscape scales. *Re*-interpretation of large extent maps of soft classes may be helpful to land managers who need community-level information for fuel breaks, restoration, invasive plant suppression, or habitat identification.

1. Introduction

Dryland ecosystems, covering >45% of the terrestrial earth surface, are critically important for supporting ecosystem services. For example, they contribute to carbon cycling at global scales (e.g. Lal, 2019) and at the community-level, dryland ecosystems play an important role in nutrient cycling (e.g. Maestre et al., 2016). The number of dryland ecosystem studies in remote sensing have increased significantly in the past decade (e.g. Glenn et al., 2016; Guirado et al., 2019; Poitras et al., 2018; Ganem et al., 2022). However, there is still a gap in providing community-level estimates of vegetation across large areas. Quantifying community-level vegetation patterns with remote sensing requires distinction between communities and complex combinations of vegetation species and other cover types (e.g. bare mineral soil, biological soil crusts, litter). Thus, the gap is primarily caused by the difficulty in capturing the heterogeneity of communities across fine spatial and temporal scales. Due to climate change and land use, dryland ecosystems are under threat and knowledge about the status of vegetation communities is required for mitigation and restoration.

Many contemporary studies in remote sensing of vegetation communities across large areas of drylands use time-series satellite or uncrewed aerial systems (UAS) data. Recent studies demonstrate the ability to capture change in productivity (e.g. Abel et al., 2019, Wang et al., 2022) and shrub cover (Rigge et al., 2021) and the status of annual

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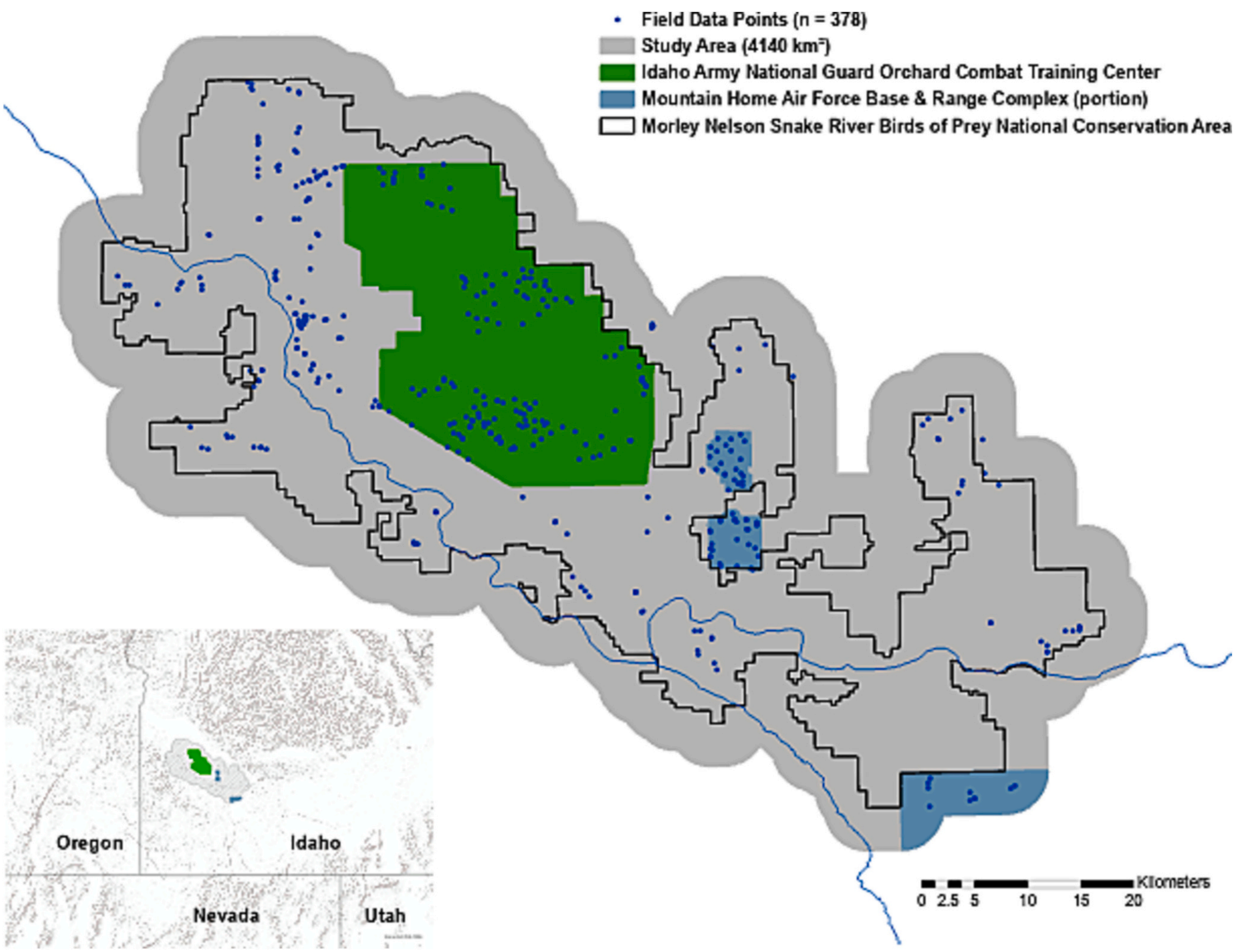

Fig. 1. Study area of the Morley Nelson Snake River Birds of Prey National Conservation Area located in southwest Idaho, USA.

invasive grass cover (Pastick et al., 2018; Weisberg et al., 2021). However, the spatial (e.g. 30 m to several kms) resolution in earth observing systems may be coarse relative to the heterogeneity and/or phenology of the vegetation across semi-arid landscapes, and the scales which are helpful for management (Gillan et al., 2020; Roser et al., 2022). Monitoring the change in position of an ecotone, for example, is difficult if the footprint of a pixel straddles the entire transition. There is additional difficulty including component species or cover types which may be of interest at small proportional cover such as encroaching invasive species, or biological soil crust.

Fuzzy classifications in dryland studies have been generally limited, even though it may be particularly suited and used successfully as in Cullum et al. (2016), Tong et al. (2017), and Bell et al. (2021). The merit of such fuzzy classifications is through embracing imprecision, and describing pixels or areas in a way so that proportional composition, similarity (or dissimilarity), potential, or likelihood of components can be interpreted after classification to suit the user's need or conform to a desired level of hierarchy (Cullum et al., 2016; Feilhauer et al., 2021; Hudon et al., 2021). Vegetation mapping at landscape scales must include some level of generalization or aggregation of natural shapes and morphologies, as only topiaries are found in rectilinear pixel shapes. When a landscape contains multiple combinations of species, implementing partial membership at these pixel scales reverses some of the generalization, but is not without difficulties. The process of assigning partial membership can be complicated or highly tailored to the individual study, and can still require finding spectral endmembers of 'pure' cover types at the pixel scale (e.g. Delalieux et al., 2012; Tong et al., 2017). In the case of dryland ecosystems, many 'dominant' species are relatively sparse by percent cover (e.g. <50%) therefore precluding the ability to find endmembers at scales relevant to pixel resolutions of multispectral satellite imagery. Although percent cover observations of pixels with <100% homogenous single-species cover is possible, soft classes may have additional advantages. Background soil, biological soil crust, or invasive annual grass cover are often the largest percent cover (as viewed from above, especially if including underneath shrubs) in dryland ecosystems and thus, many soft classes may be difficult to differentiate after classification, and assessing classification errors may be unclear. Establishing soft classes prior to classification has the potential to represent diverse landscapes with greater fidelity by way of incorporating heterogenaity, thereby unlocking other more straightforward methods of 'fuzzy' classification schemes and interpretations.

To implement the soft classes concept, here we determine community types through k-means clustering of field training data to utilize these clusters with time-series remote sensing observations. We employ a big-data approach with time-series Sentinel-2 data within the Google Earth Engine (GEE) platform to enable the use of an ensemble of all cover types present. This allows for the signal of background and/or non-dominant or periodically dominant signals to be used to discriminate between landscape community cover types. We discuss the use of a simple fuzzy confusion technique using constituent component distributions in soft classes, both species-based and plant functional type-based. The approach is tested in a western U.S. dryland ecosystem in

Table 1
Vegetation and cover types present in this study. The symbol [] denotes when a species was assigned to a group for species-level clustering. Species abbreviations from USDA PLANTS database, or EXAN for exotic annuals, MSTD for mustards, RABB for rabbitbrush species, BSC for biological soil crust, and NPSV for non-photosythetic vegetation such as litter.

Scientific Name(s)	Common Name	Species or [Grouped] Abbreviation	Plant Functional Type (PFT)
Agropyron cristatum	crested wheatgrass	AGCR	Perennial
Artemisia tridentata	sagebrush	ARTR	Shrub
Atriplex confertifolia	shadscale saltbush	ATCO	Shrub
Bassia prostrata	forage kochia	BAPR	Perennial
Bromus tectorum	cheatgrass	BRTE	Annual
Ceratocephala testiculata	bur buttercup	[EXAN]	Annual
Lepidium perfoliatum	clasping pepperweed	[EXAN]	Annual
Bassia scoparia	weed kochia	[EXAN]	Annual
Krascheninnikovia lanata	winterfat	KRLA	Shrub
Descurainia spp., *Sisymbirum* ssp.	mustards	[MSTD]	Annual
Poa secunda	Sandberg's bluegrass	POSE	Perennial
Pseudoroegneria spicata	bluebunch wheatgrass	PSSP	Perennial
Chrysothamnus nauseosus	gray rabbitbrush	[RABB]	Shrub
Chrysothamnus viscidiflorus	green rabbitbrush	[RABB]	Shrub
–	bare ground	[BARE]	Bare
–	biological soil crusts	[BSC]	BSC
–	non-photosynthetic vegetation	[NPSV]	NPSV

the Great Basin covering nearly 4000 km^2. We seek to prompt a reconsideration of some tenets of remote sensing and vegetation classifications, especially in light of rapidly advancing computational abilities and algorithms (such as artificial intelligence) and new remote sensing platforms. To investigate an alternative approach, we demonstrate and discuss the following for a quilted semi-arid ecosystem:

1) Can the input "classes" of a vegetation classification be more ecologically-aligned (such as 'soft' classes)?
2) What are the ecological and management implications for soft classes, and what are potential advantages of applying 'fuzzy' confusion?

2. Methods

2.1. Study area

The study area includes the Morley Nelson Snake River Birds of Prey National Conservation Area (Fig. 1). This area is managed by the Bureau of Land Management and also includes the enclosed Orchard Combat Training Center (OCTC, managed by the Idaho Army National Guard), and the Mountain Home Air Force Base and Small Arms Range (MHAFB). The topography is relatively flat (excepting isolated buttes) with elevations near 900–1000 m. The area receives approximately 110–320 mm of precipitation annually, with the majority falling between November and April. Loess soils dominate the study area. The vegetation of the area is broadly characterized as a semi-arid ecotype composed of communities of Wyoming big sagebrush (*Artemisia tridentata* ssp. *wyomingensis*), salt-desert shrubs (primarily members of the *Chenopodioideae* subfamily), and bunchgrasses (*Poa secunda*, *Pseudoroegneria spicata*, and *Agropyron cristatum*). Land use within the study area over the last century has principally included livestock grazing, recreation, and military training. Extensive ecosystem degradation has occurred in many regions of the study area, where invasive annuals (primarily *Bromus tectorum*, "cheatgrass") and secondary invasive plants such as Russian thistle (*Kali tragus*) and annual mustards (*Descurainia* spp., *Sisymbirum* ssp.) are now the dominant land cover (US Department of Interior (USDI), 2008).

As a result of the invasive species and a long history of changing land uses and practices, the area is a patchwork of many different vegetative communities. For land managers and stakeholders, balancing the current uses of the study area requires information on yearly changes in vegetative cover, impacts of rangeland fires, and how restoration and remediation efforts are progressing. To this end, increasing the accuracy of vegetation cover data and frequency of its creation is propitious. The species and cover types used in this study (see Table 1) were determined based on land management needs and priorities.

2.2. Field data

Field data plots used in this study ($n = 378$) were collected during March–August 2016. Plots were selected in the field to capture example communities and be representative of different community combinations and variations among spatial gradients. Surveyed species and cover types (such as bare ground, litter or non-photosynthetic vegetation, and biological soil crust), pre-classification amalgamation, and plant-functional-type groupings are listed in Table 1.

A field survey was conducted for each plot, and five nadir-pointing images were taken in the center and cardinal directions (7 m from center), approximately 2 m above the ground surface using a ruggedized consumer-grade camera. A RTK GPS recorded the imager's location simultaneously. Vegetation and groundcover were quantified using SamplePoint software (v1.59, Booth et al., 2006) using 100 points per image for a total of 500 points characterizing each field plot (approximately 200m^2). Fig. 2 illustrates that there are very few species that dominate the areal cover (i.e. >50%) of a plot. BRTE (cheatgrass) and BARE (bare, or incipient biocrust) have a large number of observations and wide range of percent cover. In comparison, ARTR (sagebrush, commonly described as a 'dominant' species) has a much smaller percent cover range. For this study, areas with no discernible biological soil crust from the photos were classified as bare soil; field observations noted if the ground surface was biological soil crust or exposed soil if it was ambiguous. In this study area, truly bare soil is only observed in areas of recent or frequent disturbance. Soil types and colors were not recorded. Non-photosynthetic vegetation (NPSV or litter) was recorded for points that fell on vegetative matter that was loose (i.e. not rooted to the ground, or attached to other plant parts) and unidentifiable; attached and identifiable senesced or woody matter was recorded as the species. Shadow/dark and unknown were recorded but not used in the subsequent steps. Transported tumbleweed and tumblemustard, while identifiable and non-photosynthetic, were treated as litter/NPSV.

Two orders of community classes were developed from the field data. In order to create the most ecologically-descriptive classes, community clusters were created using as close-to species level where feasible for class size (Table 1, column 3). Several species of the same or similar genus and phenology were aggregated in order to avoid sample groups with proportionally few members. For example, several exotic annual forbs were grouped into [EXAN]. This level of community clustering also included non-photosynthetic vegetation [NPSV] as a class in order to acknowledge its areal coverage proportion in several community types. Similarly, biological soil crust [BSC] and bare ground/incipient biological soil crust [BARE] were included at this level of aggregation. The second level of community classes were created from aggregating the species at the plant functional type (PFT) level (Table 1, column 4) in order to evaluate the separability of classes created from fewer constituent cover types and to demonstrate that our proposed method can produce output broadly comparable with other methods.

Determining the species- and PFT-levels of community clusters was conducted using k-means clustering. K-means is a vector quantization method that is often used for clustering data in multi-dimensional space (Jain, 2010). We selected k-means due to its ease of interpretation,

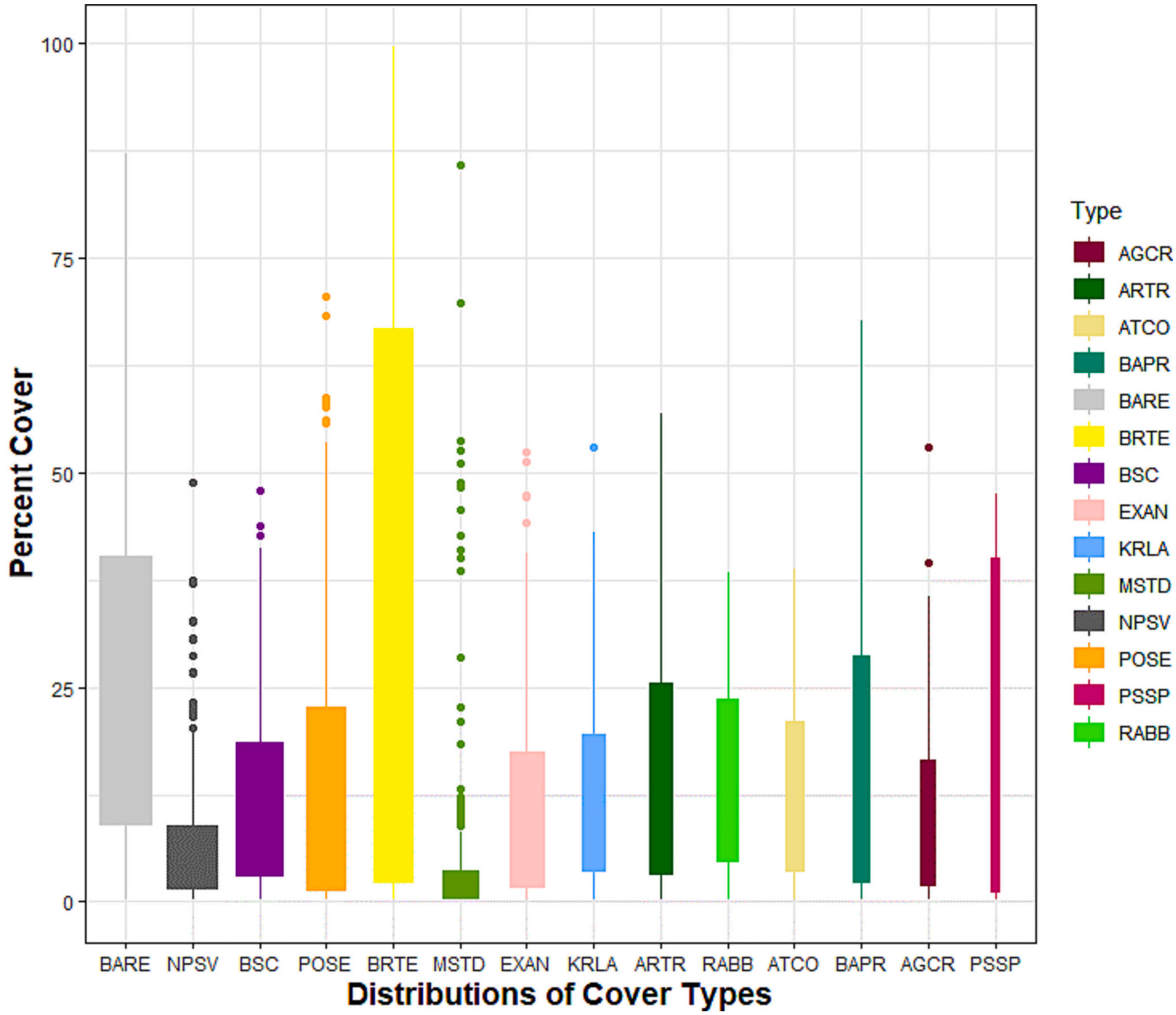

Fig. 2. Distributions of cover types by species-level for field plots. Boxplot widths represent the number of field plots within a cover type. Bare ground (BARE) was found in most plots, whereas bluebunch wheatgrass (PSSP) was the least common.

efficiency and scalability, and wide acceptance as a clustering method (Ikotun et al., 2023). We implemented this method without selecting centers so as to separate the field data into ecological classes without bias. The number of k-means clusters was preliminarily constrained using diminishing reductions in within-cluster sum of squares, and further refined subjectively to the fewest *k* clusters that retained at least one cluster per broad cover type in the study area (e.g. a cluster representing winterfat (KRLA) communities). Multiple iterations and random starting sets of data ensured a convergence of cluster centers. Each clustering maintained a ratio of Between Sum-of-Squares to Total Sum-of-Squares of approximately 0.8 to ensure that points within each cluster were similar, and that such clusters were distinct.

2.3. Sentinel-2 preprocessing

Level-1C (top of atmosphere) Sentinel-2 imagery covering the study area from 01 January 2016 to 28 December 2016 were selected to span the growing season corresponding to the field data collection. Sentinel-2 has some advantages for detecting vegetation and temporal changes, such as three narrow red-edge bands (at 20 m pixel resolution) and a 5–6 day revisit time (Adam et al., 2014). These have been noted to be important in discriminating differences in semi-arid vegetation (e.g. Mitchell et al., 2016). Images were filtered for quality (e.g. failing quality control, >50% cloud cover), and masked for clouds and shadows. Pre-processed images ($n = 117$) were composited into monthly mosaics (February–December; January had insufficient coverage) in order to balance spatial coverage with temporal resolution, as well as softening differences in phenologies across the broad study area and possible influences from differing atmospheric conditions. Composited imagery was resampled to 10 m pixel sizes for all bands.

Spectral indices were calculated for each image following cloud and shadow masking. Table 2 lists the spectral indices and their formulas, informed by previous scientific work for their predictive ability and that take advantage of Sentinel-2-specific bands (Frampton et al., 2013), or for their application of the red-edge bands (e.g. Band 8 A in CCCI and NDMI, Table 2). In addition to spectral indices, Sentinel-2 Bands 2–8, 8 A, 11, and 12 were used as predictors for a total of 20 predictors per time interval ($n = 220$).

Table 2
Spectral indices used with Sentinel-2 data in this study.

Index or Ratio	Abbreviation	Formula
Anthocyanin Reflectance Index[1]	ARI	$\left(\frac{1}{B3}\right)-\left(\frac{1}{B5}\right)$
Canopy Chlorophyll Content Index[2]	CCCI	$\frac{\frac{B8A-B7}{B8A+B7}}{\frac{B8A-B4}{B8A+B4}}$
Enhanced Vegetation Index[3]	EVI	$2.5^*\left(\frac{B8-B4}{B8+(6^*B4)-(7.5^*B2)+1}\right)$
Inverted Red-Edge Chlorophyll Index[4]	IRECI	$\frac{B7-B4}{B5/B6}$
Normalized Difference Near Infrared Red-Edge[5]	NDMI	$\frac{B8A-B11}{B8A+B11}$
Normalized Difference Vegetation Index[6]	NDVI	$\frac{B8-B4}{B8+B4}$
Red-Edge Inflection Index [7]	REIP	$0.705+0.035^*\frac{(B7+B4)/2-B5}{B6-B5}$
Soil Composition Index[8]	SCI	$\frac{B11-B8}{B11+B8}$

[1]Gitelson et al., 2001, [2]Barnes, et al., 2000, [3]Peñuelas et al., 1993, [4]Frampton et al., 2013, [5]Hardisky et al., 1983, [6]Rouse et al., 1974, [7]Herrmann et al., 2011, [8]Al-Khaier, 2003.

2.4. Classification & random forest model

A random forest classifier was used to predict the species- and PFT-level clusters presented in Table 1 based on the S2 spectra and calculated indices (Table 2). The central point for each field plot was buffered using a 10 m radius, and the mean value of the intersected pixels of each band and index were extracted as the predictor variables for the model. Random forest (RF) was chosen to evaluate the different predictor and response variable combinations due to the high dimensionality and multicollinearity of the predictor variables, and its insensitivity to overfitting (Breiman, 2001; Belgiu and Dragut, 2016). The RF classifier is generally less sensitive to training data imbalance (Pal, 2005) compared to many other mainstream classifiers, which is important for this study as some classes of interest are relatively under-represented in comparison with others (e.g. number of shadscale (ATCO) versus cheatgrass (BRTE) plots). Random forests are also able to handle missing values when imputing the classification, which is advantageous for portions of the predictor data that contain masked areas (e.g. clouds and shadows) after mosaicking. Several plots used in the community-clustering process were excluded from the training portion of the classification model due to insufficient spectral observations. The RF model was implemented in Google Earth Engine using 500 trees and out-of-bag internal sampling with a bag fraction of 0.5, and 30% of samples were reserved for validation after classification.

2.5. Validation and accuracy assessment

We analyzed the accuracy of our classifications with standard confusion matrices using omission/commission errors ("false alarms" or "misses", Pontius and Millones, 2011), in order to inform our proposed fuzzy confusion assessments. By acknowledging gradual transitions between land cover components in the reference data, a user has the opportunity to apply a mechanistic approach to determine acceptable fuzzy confusion, dependent on the scientific question or management goal. Community classes with largely the same distribution of percent cover of a particular constituent species or PFT can be considered equivalently correct for classification error assessment, as pertaining to the question or management goal. For example, establishing that >11.4% biological soil crust (BSC) cover in any class as a management concern could be a threshold for acceptable fuzzy confusion. A confusion matrix can then be created treating such omission/commission errors as entirely correct (by combining rows and columns) for classes where the cover criteria is met. The resulting classification layer may then be displayed and interpreted in this context. Validation of the RF model for establishing soft classes for both species-level and PFT communities was assessed using the overall accuracy (OA) of the deterministic confusion matrix, as calculated using the RF internal out-of-bag validation.

3. Results

3.1. Community-level clustering for soft classes

Fig. 3 represents the distribution of vegetation cover types contained in the species-level community class (from Table 1) determined from the k-means clustering scheme of the field data. Tables 3 lists cluster centers (means) of the cover type for each class and the number of field plots contained in each class (cluster). The bare cover type shows predominantly in many of the clusters (Fig. 3) and in fact only <10% cover in three clusters (2, 5, and 6) (Table 3). The cheatgrass cover type (BRTE) has the highest percent cover of all cover types and dominates (>25%) in clusters 2, 7, 8, and 11. Biological soil crusts (BSC) are present in many clusters, and in only one cluster with cheatgrass. While lower percent cover, non-photosynthetic vegetation (NPSV) appears throughout all the clusters. Several of the shrubs, including sagebrush (ARTR), shadscale saltbush (ATCO), rabbitbrush (RABB), winterfat (KRLA) have relatively high percent cover in unique clusters. Strikingly, the majority of the clusters (such as 4, 5, 6, and 14) demonstrate a membership of a community of species; no single species represents more than half of the cover, and many proportions are fairly similar.

The PFT-level community classes are shown in Fig. 4, with the corresponding clusters in Table 4. The results of this clustering similarly results in dominance of the BARE class throughout, along with several clusters with high percent cover annual grasses and forbs (cheatgrass, bur buttercup, etc.). At the PFT-level, many of these clusters show communities of shrubs and biocrusts, though a healthy mix of bunchgrasses are only present in two of these clusters (2 & 3).

3.2. Classification accuracy metrics

Overall classification accuracy in the RF model using 0.3 reserved samples with an out-of-bag fraction of 0.5 of was 0.52 for the species-level (species-level, with several species grouped more broadly) community ('soft') classes, and 0.54 for the PFT-level community ('soft') classes. The authors posit an alternative method of assessment, discussed further below. Subset of classification output is illustrated in Fig. 5a.

3.3. Application-based resampling accuracy assesment for example usage scenario: biological soil crust

A classification of soft classes can be re-interpreted as prompted by specific ecological or management questions, whether or not it is 'fuzzy'. Such a question could be identifying areas that having a higher cover portion of biological soil crust ("biocrust" or BSC). For example, if a land manager or ecologist wishes to delineate areas with biocrust cover >10% (11.4% was the mean value of biological soil crust cover across all field samples in this study), then soft classes with mean centers of >10% BSC are considered as the same class. In this scenario, classes 1–3, 7–9, and 13 are treated as equivalent (<10% BSC), and the remaining as equivalent (>10%); the map becomes a binary classification. Fig. 5a shows a subset of the initial classification with all soft classes displayed. Fig. 5b shows a subset of the classification with the hypothetical biological soil crust map displayed. The confusion matrix (Table 5) can then be interpreted by collapsing the equivalent rows and columns so previously misattributed values between classes are considered as valid given the new criteria (demonstrated in Table 6).

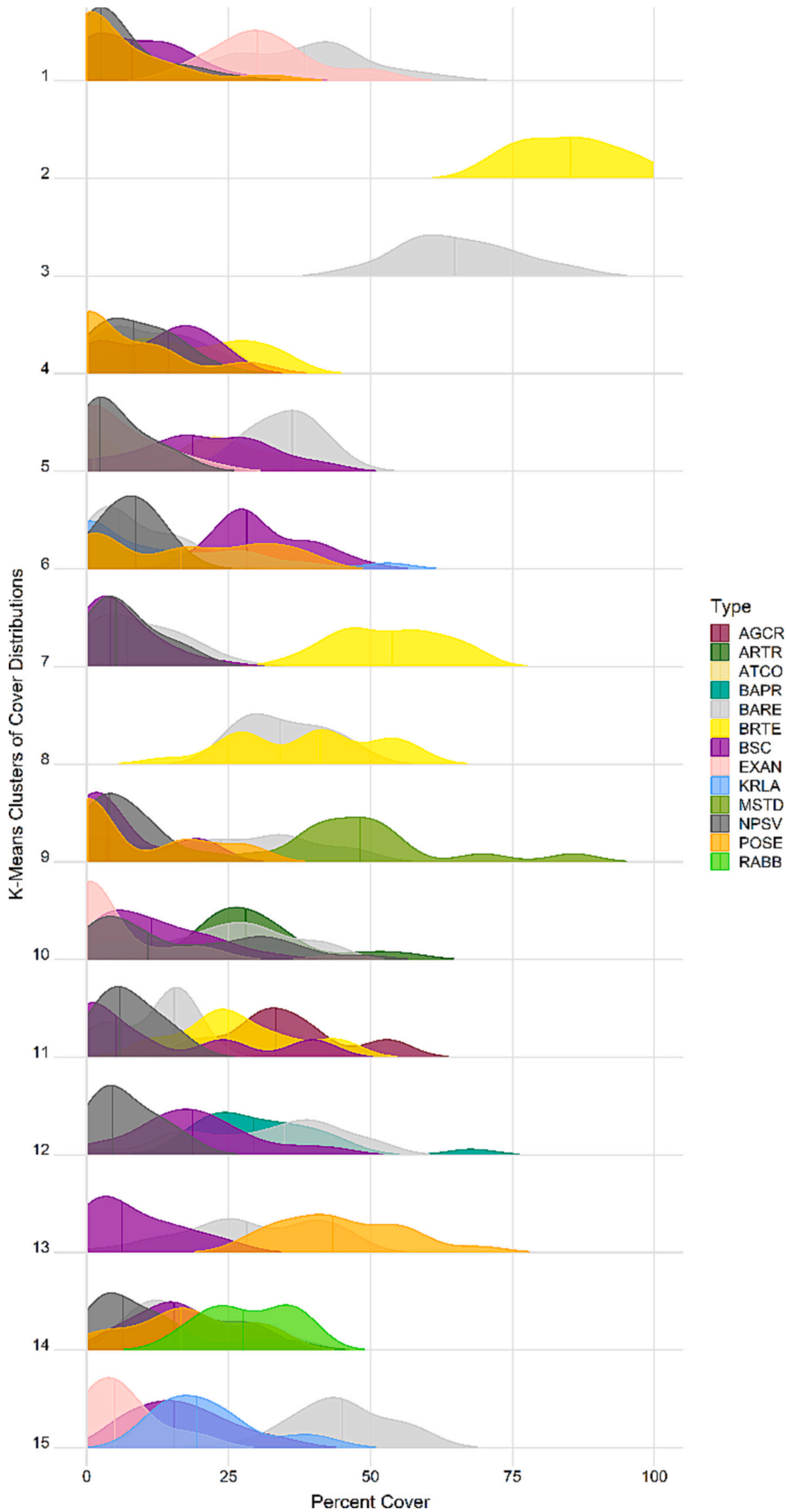

Fig. 3. Soft Classes: K-Means Species-Level Cluster Community Distribution Histograms. Each cluster (1–15) represents a group of field plots sharing similar proportions of cover types; cover types of <5% mean cover are omitted for clarity of display. The vertical axis of each cluster represents the density of cover type within the cluster. The horizontal axis represents percent cover of each type.

Table 3
K-Means Species-Level Cluster Mean Centers and Number of Plots per Class (n). Each cluster ('soft class') is comprised of plots sharing common proportions of one or more cover types, but are not required to have commonalities of all cover types. For example, field data comprising community cluster 10 have a 29.1% mean cover of ARTR, with possible small portions of other shrubs. The within sum-of-squares (WSS) is a unitless measure of how similar the constituent data points are with one another in the cluster ('soft' class), smaller being more similar.

Cluster Number	AGCR	ARTR	ATCO	BAPR	BARE	BRTE	BSC	EXAN	KRLA	MSTD	NPSV	POSE	PSSP	RABB	Cluster WSS	Cluster Size
1	0.4	0.6	0.9	0.4	37.4	0.6	9.5	31.3	0.3	0.5	5.8	5.7	0.0	0.3	14,451	32
2	1.2	1.2	0.0	0.0	4.3	84.2	1.8	0.0	0.2	1.7	1.5	0.6	0.0	1.3	8138	49
3	0.5	0.4	1.0	2.2	65.5	1.4	4.1	4.3	1.6	1.8	3.8	4.1	0.0	0.6	10,772	33
4	1.6	0.1	2.4	0.5	10.9	19.0	12.6	0.7	0.4	1.6	8.9	6.9	3.5	4.2	10,626	17
5	0.6	0.7	15.3	0.0	34.7	0.5	20.7	5.3	1.7	2.2	5.2	2.0	0.0	1.6	10,896	22
6	0.1	3.9	1.7	0.0	8.2	0.4	30.9	0.6	13.3	2.0	7.8	17.2	2.1	0.1	13,441	18
7	0.0	4.6	2.0	0.0	9.2	53.3	6.0	0.3	0.6	1.1	6.8	2.7	1.8	4.5	21,188	45
8	1.1	0.8	1.9	0.0	34.8	38.7	4.1	0.2	2.8	0.4	3.9	1.5	0.0	3.1	6803	18
9	1.8	0.0	0.0	0.0	23.0	1.5	6.2	0.6	0.0	49.7	6.7	8.6	0.0	0.0	9136	13
10	0.0	29.1	0.2	0.0	23.6	4.0	11.7	5.5	0.4	0.2	16.4	4.5	0.0	0.2	18,361	25
11	34.8	0.0	0.0	0.0	11.7	26.8	12.4	0.4	0.0	0.0	7.4	0.9	0.0	0.1	2920	6
12	0.0	0.0	0.0	31.8	31.0	1.5	19.2	3.9	0.0	0.5	6.9	2.2	0.0	0.0	9697	19
13	0.0	1.3	1.1	0.9	29.2	0.4	8.4	1.3	0.5	1.5	3.9	44.9	0.0	0.3	13,690	35
14	0.0	0.4	0.0	0.0	18.1	0.4	17.4	2.2	0.0	0.6	11.0	17.8	0.2	28.6	7992	19
15	0.0	0.0	0.0	0.0	44.8	0.3	16.6	6.2	21.4	0.9	4.6	1.8	0.0	0.0	7967	27

4. Discussion

Determining 'soft' community-level classes prior to a multi-temporal classification better reflects the heterogeneous patchwork of patterned fabrics and gradients of vegetation communites and reserves interpretation for the end user in two ways. First, the end user has additional freedom to choose what classes best answer their question after the classification. Second, the end user can assess the accuracy of the classification based on their question ('fuzzy' confusion or otherwise, as presented in our example).

From a remote sensing perspective, we have proposed a method which leverages the entire optical signature and its change over time for each pixel. There are methods that can produce similar end products which impute several layers of percent cover of serveral or more cover types (Jones et al., 2018, Robinson et al., 2019, Rigge et al., 2021, Allred et al., 2021). Further investigation and comparison is needed, but we posit that our proposed method enables the end product to capture species or cover types that are difficult or impossible to create fractional cover layers using spectral end members or other methods.

Where a singular optical signature on a particular date may be superior for a binary or gradient classification, an ensemble of vegetation indices and spectral bands over a growing season enables sub-pixel mapping of component vegetation types without the need for spectral endmembers or hyperspectral data, and partially mitigates the mixed pixel problem by acknowledging that nearly all of the pixels are mixed. This reflects the 'optical types' concept discussed by Ustin and Gamon (2010), where the remote sensing observations drive what classes may be identifiable. For example, a 'soft' class describing a community with an observable spectral signature (at one time, or phenologically) due to proportions of bare ground, perennial grasses, and non-photosynthetic vegetation – might also be associated with a certain percentage of biological soil crust, or a particular amount of forbs which are important yet difficult to detect and map (Endress et al., 2022).

Additionally, describing input classes as 'soft' may allow the classification model to discern between communities that are identical in most regards, but where two shrub communities share similar values of one spectral index over time, but dissimilar values of another spectral index at one or more seasonal observations like a different colored flower, or a different understory.

Using fuzzy confusion – determined by the end user, based on a particular question or objective – as the classification accuracy metric we posit is the main benefit of our proposed method. In seeking to reserve interpretation for the end user, and to allow a more organic relationship between field observations and optical observations, some large degrees of confusion are inevitable. Or, perhaps, enlightening.

4.1. Ecologic interpretation and management implications of soft classes

The k-means clustering at both PFT and species levels are naive in the sense that they are not based on established descriptive types in the field of ecology, or informed by specific land management needs. However, depending on the question they may be interpreted in different ways. A land manager might rank the PFT-clusters ordinally, assigning value to preserving intact and biodiverse areas; Classes 8, 2, and 7 have higher biological soil crust cover, two are dominated by shrub cover, and they all have a variety of other types. Classes 6, 5, and 4 may rank lowest due to increasing homogeneity of the annual PFT. Land management may instead prefer binned percent cover of BRTE for fire risk assessment, and may treat the species-level clusters as a continuous dataset: class 2 is $>$75% BRTE; class 7 is ≈50%; classes 8, 11, and 4 are ≈25%, and remaining classes are $<$10%. An ecological use might consider the PFT-level clusters as nominal classes where 1 and 2 are "perennial grass dominated", classes 7 and 8 are "shrub dominated", class 3 is "bare or open space", 5 is "mixed", and 4 and 6 are "dense annuals" and "sparse annuals", respectively.

4.2. Soft landcover classes with K-means clustering preserve patterns in ecology

The process of determining the number of clusters (k) and their centers is challenging as it can bias the resulting classes. While a larger k improves cluster distinction (within sum-of-squares), resulting clusters can be overly-specific by grouping a handful of plots with very similar cover distributions. Fewer clusters can result in poor distinction, where one or more clusters may have loose cohesion or represent large distributions of one or more cover types (e.g. plots with ≈50% BRTE but otherwise plots have no other commonalities). The cluster centers for this study were not set with a priori information in order to avoid imposing preconceptions of community types, instead qualitatively assessed to ensure that vegetation or PFT communities of interest were represented by a cluster.

However, the success of the cluster assignments is confounded by two cover types: BARE and BRTE (bare soil/incipient biological soil crust, and cheatgrass, respectively). These cover types have a relatively large range of fractional cover in the demonstration site (≈0–85%) and are represented in many plots. Fig. 4 illustrates the pervasive cover of BARE and BRTE; nearly all training plots have some proportion of one or the other. BARE has an interquartile range of 31% cover, and BRTE of

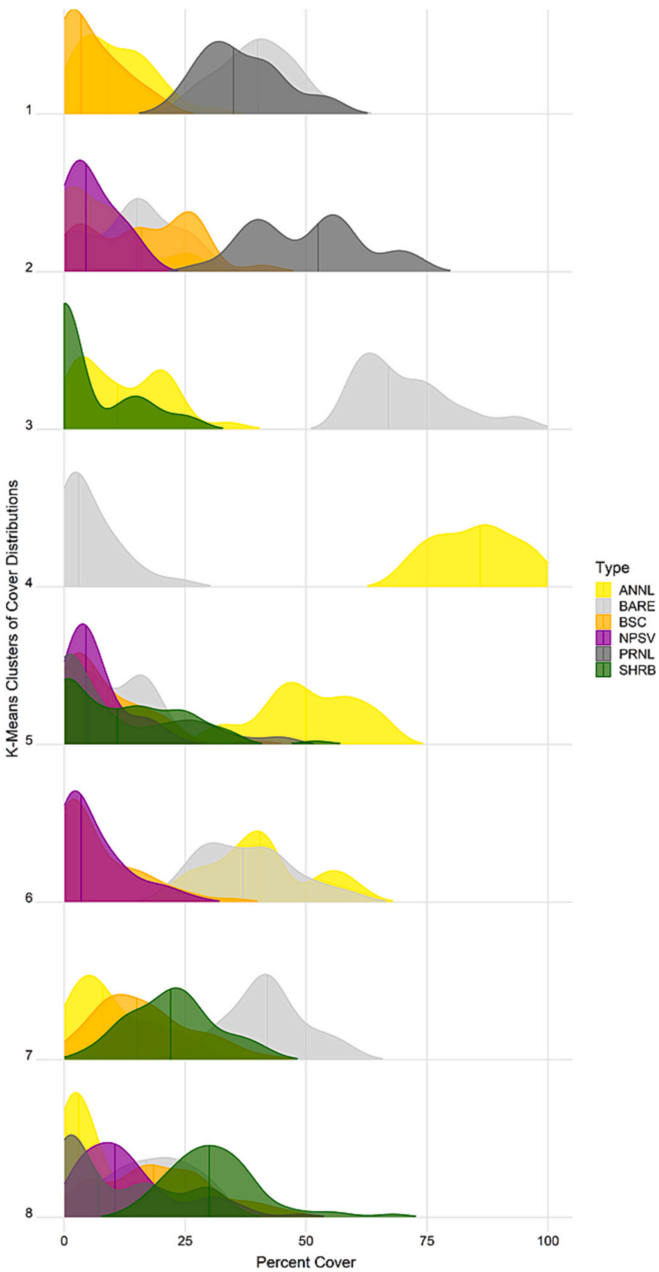

Fig. 4. Soft Classes: K-Means PFT-Level Cluster Community Distribution Histograms. Each cluster (1–8) represents a group of field plots sharing similar proportions of cover types; cover types of <5% mean cover are omitted for clarity of display. The vertical axis of each cluster represents the density of cover type within the cluster. The horizontal axis represents percent cover of each type.

64%. As a result clusters with some portion of BARE or BRTE are often confused, which reflects the condition of much of the study area. In other words, a human field observation would describe an area as a "shadscale community" although it might be largely bare (or biological soil crust), or have its interspaces filled by an invasive annual grass.

Our proposed method of determining soft classes is a naive means to describe and categorize the ecology of the area while being objective and considerate of optical remote sensing principles. While the soft classes created for this study are not directly transferrable to other areas or frameworks, there may be opportunities for them to be translated using ordinal, nominal, or other means as discussed and depending on the needs of the end user.

Metrics such as the Within-Sum-of-Squares (WSS, a measure of cluster grouping), can show how distinct or loose clusters are. We found a high Pearson's' Correlation Coefficient (0.88) when comparing the WSS with commission errors (0.65 vs. omission errors). Or in other terms, certain soft classes are confused with others. However, the degree to which this source of confusion can or needs to be reduced is likely dependent on the ecology of the area in question; vegetation types that exist on a broad continuum and among a variety of other community types may require many classes to describe them, or are not separable into distinct groups. Using fuzzy confusion has potential to address these issues, where the degrees and methods are determed by the end user. In our study, classes with the highest mutual confusion errors have high proportions of cheatgrass (BRTE) among their constituents. The pervasive spatial distribution of BRTE is likely a significant source of confusion in the spectral signatures over time of such classes. An end user may choose to treat confusion between soft classes with low proportions of BRTE as less acceptable than confusion between soft classes with higher BRTE, for instance.

4.3. Remote sensing data, fuzzy confusion, and soft classes

We used Sentinel-2 Level 1C (top-of-atmosphere) data because of its availability for 2016, the year of our field data collection; however Level 2 A (bottom-of-atmosphere) data are now available for subsequent years which provide high quality atmospheric correction. Bottom-of-atmosphere reflectance would reduce noise in observed phenological signals over time and increase the stability of our proposed classification methods. Although paved and unpaved features were not considered as constituent components in the clustering and classification process, these features fell in the same predicted class, suggesting that composited top-of-atmosphere imagery may be adequate for conceptual exploration of our proposed classification schema.

Including time as a predictor (e.g. offset of beginning of growing season), or other environmental variables (e.g. elevation) may enable larger study area extents by accounting for changes in seasonal growth due to elevation, but may also require finer temporal resolution or multiple years of remote sensing data. Multiple years of remote sensing observations may help in some circumstances where the ecology and growing seasons are stable or reduce advantages from leveraging unique spectral observations of unique classes such asan early spring rain event may enable an index to discern percent cover of biological soil crust.

Table 4
K-Means PFT-Level Cluster Mean Centers and Number of Plots per Class (n). Each cluster ('soft' class) is comprised of plots sharing common proportions of one or more cover types, but are not required to have commonalities of all cover types.

Cluster Number	SHRB	PRNL	ANNL	BARE	NPSV	BSC	Cluster WSS	Cluster Size
1	2.7	36.7	10.5	40.0	3.8	5.7	7497	30
2	4.9	50.3	7.6	14.2	5.8	16.3	12,664	28
3	5.2	3.6	12.0	70.5	3.8	4.4	8117	27
4	2.9	2.3	84.9	5.5	2.0	1.7	9838	56
5	12.7	10.8	50.5	9.8	6.3	8.4	29,170	52
6	3.4	3.9	40.5	37.7	6.1	7.0	20,361	54
7	22.4	2.8	10.1	42.0	4.8	16.4	25,836	73
8	31.2	11.2	5.1	17.8	13.8	19.5	34,014	58

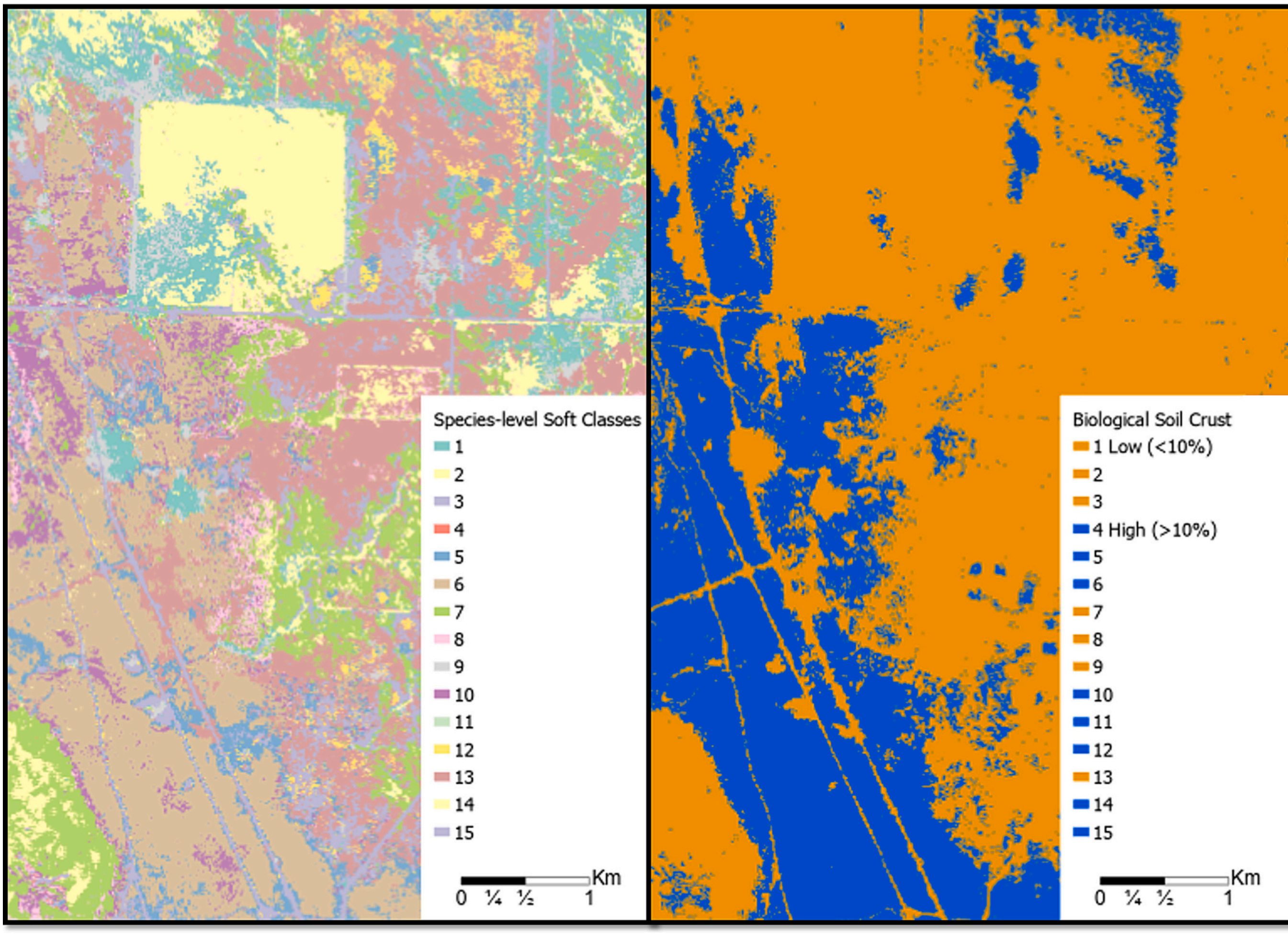

Fig. 5. a. Subset of species-level soft-class (descriptions illustrated in Fig. 3 and Table 3). The large block feature (soft class 2) is a former grazing enclosure and is largely cheatgrass, an exotic invasive annual grass. Also of note are the dirt roads which appear as class 3, which has a mean value of 65.5% BARE. b. Example of hypothetical applied fuzzy confusion, where a hypothetical land management criteria seeking to delineate areas with biological soil crust cover over a threshold. In this case, biological soil crust cover of >10% (blue) and < 10% (orange) is presented. Mean biological soil crust cover across all field samples was 11.4%. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 5
Confusion Matrix of Species-Level Soft Classes. Overall accuracy is 0.52; omission errors (misses) and commission errors (false hits) are also calculated.

Classified	Reference															
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	Total
1	**18**	0	6	0	0	0	0	0	0	2	0	1	4	1	0	32
2	1	**39**	0	0	0	0	6	0	0	0	0	0	1	1	1	49
3	3	0	**23**	0	0	0	0	2	0	0	0	1	0	0	4	33
4	0	1	0	**0**	2	1	6	2	0	1	1	0	1	1	1	17
5	0	0	3	0	**8**	2	0	0	0	0	0	1	3	2	3	22
6	1	0	0	0	2	**4**	2	0	0	2	0	1	3	1	2	18
7	2	7	0	1	0	0	**29**	1	0	2	0	1	2	0	0	45
8	1	1	1	1	0	2	2	**3**	0	2	0	0	4	0	1	18
9	5	2	2	0	0	0	0	0	**2**	0	0	0	2	0	0	13
10	0	1	0	0	0	1	5	2	0	**14**	0	0	1	1	0	25
11	0	0	0	0	0	1	2	0	0	2	**0**	0	0	0	1	6
12	1	0	4	0	1	1	0	0	0	1	0	**9**	0	2	0	19
13	1	1	5	0	2	2	4	0	0	0	0	0	**17**	2	1	35
14	1	0	0	0	0	0	2	0	0	1	0	0	4	**11**	0	19
15	2	0	3	0	0	3	1	0	0	0	0	0	0	0	**18**	27
Total	36	52	47	2	15	17	59	10	2	27	1	14	42	22	32	378
Omission Error	18	13	24	2	7	13	30	7	0	13	1	5	25	11	14	183
Comission Error	14	10	10	17	14	14	16	15	11	11	6	10	18	8	9	183
Correct	18	39	23	0	8	4	29	3	2	14	0	9	17	11	18	195

0.52 Overall accuracy.

Table 6
Fuzzy confusion accuracy example: biological soil crust >10%.

Classified	Reference		
	Low	High	Total
Low	**197**	28	225
High	51	**102**	153
Total	248	130	378
Omission Error	51	28	79
Comission Error	28	51	79
Correct	197	102	299
		0.79 Overall Accuracy	

Using the data from Table 5, classes that had mean centers of biological soil crust cover >10% were condensed (4, 5, 6, 10, 11, 12, 14, 15), likewise classes with mean centers <10% were condensed (1, 2, 3, 7, 8, 9, 13).

Examining if there is a correlation between classification outputs as proposed in this paper and underlying soil patterns can give additional context to the overall accuracy and success of this approach. Additionally, further investigation or comparison to other methods, especially regarding broadly distributed classes such as bare ground, would help understand costs and benefits of our proposed method.

The soft classes and fuzzy confusion method presented here has potential to inform land management and scientific research differently than other methods. It reserves interpretation for the user by enabling post-hoc reinterpretation of confusion matrices, and encourages framing confusion matrices as a fuzzy classification schema tailored to the vegetation or land cover in question, without reprocessing. Our reinterpreted 'hard' classification example returns a single accuracy value (overall accuracy of 0.79 in detecting areas >10% biological soil crust cover) for the sake of clarity. A fuzzy confusion could consider the distriubution of biological soil crust cover within each class and incorporate a level of uncertainty, or use a classification model such as Random Forests and use the weighted probability outputs.

While other approaches using even higher spectral, spatial, or temporal resolutions may not need or benefit from our presented methods, the Sentinel-2 platform offers a free and widely-available compromise of resolutions. This, combined with increased computational ability, raise a reminder to evaluate the paradigm of resolution and the scale of subjects.

Input soft classes are potentially better constrained with membership distributions with coarser levels of aggregation (e.g. by PFT), but lose finer levels of ecological distinction. Management needs and research can be better served with more representative classes. For example, there is a key uncertainty in land surface models with the use of PFTs (Hartley et al., 2017). Since our proposed method requires some technical expertise to use (GIS skills, specifically raster reclassification when implementing various fuzzy confusion), we do not propose that it is a replacement for a static map. Novel and thoughtful methods of displaying fuzzy confusion may assist in visual interpretation (as in Zlinszky and Kania, 2016).

Regardless, our study seeks to address some classification paradigms, and not to speak to the advantages and drawbacks of PFTs compared to finer levels of land cover classes. There are many classification algorithms for relating field observations with remote sensing data, but we posit that more effort should be paid to the methods by which we assign classes to the field data. These approaches should seek to balance the scale of the target subject (e.g. 'drylands/forest/prairie' vs. 'sagebrush/invasive annuals/bunchgrasses') with the capabilities of the sensing platform. In such a fashion, veracity of what field data describes is preserved to its maximal extent, and assists the needs of land managers and ecologists.

5. Conclusion

The use of ecologically-meaningful classes instead of majority-cover classes may provide more value to land management needs, or for ecologic studies. This is exaggerated in semi-arid ecosystems, or in other landscapes where much of the vegetation or land cover types are found at their densest as <50% of the cover of a typical satellite pixel. We posit that our proposed method of determining classes preserves variability in land cover components at sub-pixel scales, and includes information about rarer species or cover types which may difficult to detect using percent cover or floristic gradient approaches, therefore enabling greater fluidity in interpretation by the user.

Our proposed method for establishing soft classes prior to classification makes minimal spectral or optical assumptions about the "signatures" of constituent components (i.e. endmembers), and instead considers the entire optical signature to be a mixed pixel inherently. Thus, soft classes accept the inevitability and mitigate some difficulties of the mixed pixel effect and the interaction of light with canopy structure.

Modern computational capabilities and new remote sensing platforms and datasets have sparked a paradigm shift in remote sensing scales (spectral, temporal, spatial) and methods for vegetation classification. The authors seek to encourage that this shift include consideration for what classes are classified, how emerging computation methods and models may be applied to remote sensing data and novel input and output classes, and what metrics for measuring a successful vegetation/landcover classification could be. In this paper, we posit that: 1) 'soft' classes, using ecologically-meaningful vegetation communities or cover composition can be used as input classes for a time-series remote sensing classification, and 2) that the output of ecologically-meaningful ('soft') classes through such a model may better reserve interpretation for the user of the end product, thorugh enabling post-classification reinterpretation, and using 'fuzzy'confusion for applicability and accuracy assesment.

Observations from sensors on the International Space Station such as ECOSTRESS or HISUI for spectral information and GEDI for structural information, along with increased spatial resolution data from drones may further such approaches for landscape-level assessments that managers can utilize. Other clasisification algorithms or techniques such as Neural Networks of various types (e.g. ANN, GNN, DNN) or AI could further develop means to create ecologically-meaningful soft classes, and better relate those to time-series remote sensing data.

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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