Journal of Environmental Management 265 (2020) 110578

Contents lists available at ScienceDirect

Journal of Environmental Management

journal homepage: http://www.elsevier.com/locate/jenvman

Research article

Evaluation of the automated reference toolset as a method to select reference plots for oil and gas reclamation on Colorado Plateau rangelands

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ARTICLE INFO

Keywords:
Oil and gas
Reclamation
Model verification
Reference plot selection
Land potential
Monitoring

ABSTRACT

Rangelands are typically characterized by low precipitation and low biomass which makes them susceptible to disturbance and difficult to reclaim. These characteristics become a management issue when considering the widespread and significant impact of oil and gas development on rangelands. Reclamation from this land use involves the complexities of dealing with multiple state and federal agencies, private landowners, and their sometimes conflicting rules. Reference plots (e.g., nearby undisturbed sites) can help with these issues by providing an objective context for reclamation planning. They are selected to provide a comparison that is similar to a reclamation site in most aspects except for the disturbance activity. This allows for the relative condition of the reclamation site to be determined. Because selection of reference plots is normally expert-driven on a site-by-site basis, it can be time consuming and thus ineffective in helping to meet reclamation goals over large landscapes. The Automated Reference Tool (ART) was developed to improve the efficiency and efficacy of reference plot selection. The ART improves reference plot selection through remote sensing and indicators of land potential by selecting reference plots of similar land potential to the reclamation site based on soil texture, topography, and geology. We evaluated the ART in the context of well-pad reclamation to determine if ART-selected plots were appropriate to use as reference when compared to an existing reference plot network. We applied the ART to reclamation sites managed by the Bureau of Land Management's (BLM) White River Field Office, Colorado which had existing expert-selected reference plots. We found that the ART-selected reference plots and their matching expert-selected reference plot had similar large-scale vegetative cover characteristics (total foliar: $R^2 = 0.34$, p-value $= 0.0012$) and dissimilar finer-scale cover characteristics (plant diversity: $R^2 = 0.079$, p-value $= 0.15$). In addition, we detected similarities in their soil water content ($R^2 = 0.43$, p-value<0.001), depth to restricting layer (RMSD $= 21.90$), and rock fragment (RMSD $= 19.99$). These results demonstrate that ART could be a useful tool for managers to help meet their reclamation goals over large landscapes, but it is not a complete automation of the reference selection process.

1. Introduction

Rangelands are uncultivated lands that provide habitat and forage for grazing and browsing animals, covering 50% of the world's land surface (Holechek et al., 2011). Due to their widespread occurrence and vastness in size, rangelands have a significant socio-economic impact and provide a variety of ecosystem services such as provisions for food and fiber, water filtration, carbon sequestration, recreation, aesthetics, and biodiversity (Mirzabaev et al., 2016; Raufirad et al., 2018; Reeves et al., 2017; Yahdjian et al., 2015). Economically, rangelands provide opportunities such as livestock grazing, crops, pasture, and energy resources (Kreuter et al., 2016; Yahdjian et al., 2015). Of these uses, development and extraction of energy resources (i.e., biofuels, wind, solar, oil, and natural gas) on rangelands is relatively new (within the past 70 years) (Kreuter et al., 2016). In the U.S., the recent emphasis on energy independence has led to increased development of rangeland energy resources, particularly unconventional fossil fuel development of previously unexploited oil and natural gas trapped in shale and tight sandstone (Kreuter et al., 2016; Trump, 2017).

Rangelands are characterized by low precipitation, nutrient-poor

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https://doi.org/10.1016/j.jenvman.2020.110578
Received 20 August 2019; Received in revised form 2 April 2020; Accepted 5 April 2020
Available online 13 April 2020
0301-4797/

soils, rugged topography, and high variability in plant production (Havstad et al., 2007). Correspondingly rangelands are susceptible to disturbance and are difficult to reclaim (Busso et al., 2016; McGlinn and Palmer, 2014). In particular, the growing impact of oil and gas development on rangelands makes it challenging to restore desired ecological functions (e.g. forage, biodiversity, landscape connectivity). Allred et al. (2015) estimated that 10 Tg of dry biomass were lost in the U.S. between 2000 and 2012, due to 50,000 new wells being drilled each year, which was equated to a loss of 5 million animal unit months (AUMs) of forage. This magnitude of disturbance is cause for concern because direct and indirect effects of oil and gas extraction include disruption of plant-water relationships, increased soil toxicity, and altered hydrology of landscapes (Ko and Day, 2004; Souza et al., 2014; Yu et al., 2015). These development effects impair the ability of surrounding landscapes to be used for other uses such as livestock grazing and wildlife habitat due to landscape fragmentation, loss of native vegetation, and increased susceptibility to invasive plant species (Allred et al., 2015; Barlow et al., 2017; Falk et al., 2017; Walker et al., 2007).

Oil and gas development poses a unique challenge to U.S. federal land agencies, such as the Bureau of Land Management (BLM), who are charged with managing for multiple uses while addressing the growing priority and emphasis on energy development for public lands (Haskell, 1976; Trump, 2017). As part of the multiple use mandate, federal land agencies are required to achieve "harmonious and coordinated management" of the various resources without permanent impairment of the productivity of the land and the quality of the environment (Haskell, 1976). This drives a need to conduct effective and efficient reclamation that puts landscapes back on a trajectory to provide essential ecosystem services by restoring native plant cover, increasing soil cover to foster formation of soil organic matter, and reversing soil compaction (Kwak et al., 2016; Rottler et al., 2019). Without timely and efficient reclamation, mitigation of the negative impacts of oil and gas development on rangelands is unlikely (Allred et al., 2015; Rottler et al., 2018).

Oil and gas development creates a network of discrete disturbances over large landscapes from a combination of well pads and connecting access roads (Drohan et al., 2012). Due to widespread and significant impacts of oil and gas extraction, land managers must have appropriate and relevant information to make land management decisions so that reclamation outcomes can be interpreted within the correct ecological context (Nauman and Duniway, 2016). The correct ecological context helps land managers understand the potential of disturbed land in terms of ecological site characteristics and develop metrics for when disturbed lands can be considered rehabilitated or reclaimed. Ecological sites are a framework for describing landscapes based on specific characteristics that delineate land units by a shared ability "to produce a distinctive kind and amount of vegetation" (NRCS, 2019). Ecological context for reclamation success generally includes similarity of reclamation sites to a reference plot for physical characteristics, soil dynamics, ecosystem services, vegetation dynamics, and predicted responses to management activities (Twidwell et al., 2013). Reference plots provide a comparison, based on ecological context, that is similar to a reclamation area in most aspects except for the disturbance activity, so that the relative condition and theoretical potential of the reclamation site can be determined (Jackson and Prince, 2016; Nauman; Duniway, 2016).

In the past, reference plots have been selected manually in the field by experts, requiring a significant amount of experience and familiarity with the landscape (Stoddard et al., 2006). This method of reference plot selection is often not quantifiable and can be difficult to replicate for future projects but nonetheless can provide critical information and context (Stoddard et al., 2006). In addition, defining parameters for reclamation success requires significant cooperation between private companies and the federal land agencies, which can be contentious. An objective methodology for selecting reference plots for reclamation would help improve communication between federal land agencies and private industry because it would make the selection of reference plots more consistent and transparent. In addition, this methodology would provide a common frame of reference.

To improve the efficiency and efficacy of reference plot selection, Nauman and Duniway (2016) developed the Automated Reference Toolset (ART) to address the broad scope of disturbance from oil and gas development on the Colorado Plateau by automating reference plot selection through remote-sensing and spatial indicators of land potential. The ART seeks to select reference plots of similar land potential within a 2-km buffer of a reclamation site based on three characteristics: soil texture, topography, and geology (Nauman and Duniway, 2016). These characteristics have been found to be the main predictors of site's ecological potential (i.e., plant successional trajectory)(Nauman and Duniway, 2016). To validate the ART, Nauman and Duniway computed a similarity index for 356 plots in southern Utah and identified pixels of high similarity as potential reference plots (Nauman and Duniway, 2016). Ecological site information for the reference plots and their corresponding origin plot was compared (Nauman and Duniway, 2016). False matches were identified when the ecological site of the reference did not match the ecological site of the original plot (Nauman and Duniway, 2016). Accuracy of the tool was found to be 67.4% (271 correct matches, 131 false matches, 1283 correct exclusions, and 505 omission errors) (Nauman and Duniway, 2016). A later iteration of the ART called the disturbance automated reference toolset (DART) was also verified by comparing total foliar cover and proportion of bare ground of BLM Assessment, Inventory, and Monitoring (AIM) plots to other AIM plots determined to be reference by the DART (Nauman et al., 2017). However, neither of these verification methods compared species-specific vegetation cover, composition, and diversity or site-specific soil characteristics beyond particle size classes.

In summary, the ART and DART models, and their subsequent verifications, are limited by their inability to predict and measure site characteristics important to land managers working in oil and gas reclamation such as being able to differentiate between invasive species and native vegetation. In this paper we propose an improved methodology for conducting the ART model that includes inputs that have been found to better capture local variability in physical attributes (e.g., soil, landform). We then evaluate the accuracy of the improved methodology to predict site characteristics important to land managers working in reclamation such as local topography, soil water content, vegetation composition, and ground cover.

2. Material and methods

2.1. Study area

We conducted this study within the southwestern portion of BLM's White River Field Office (WRFO) in northwestern Colorado, USA (Fig. 1). This portion of the field office covers approximately 76,900 ha (39.7821°N 108.7726°W). Mean annual precipitation of Rangely, CO (about 27 km north of the study area), from the period between 1981 and 2010, was 279 mm with a mean annual snowfall of 711 mm (U.S. Climate Data, 2018). Approximately 90% of the study area is public land that is predominantly managed by the BLM and the other 10% is privately owned. All plots were on public land because data were collected in coordination with the BLM. We did not think it was necessary to collect additional data on private land because the purpose of the study is to evaluate the ART model's ability to predict land potential.

The dominant range sites for this part of the field office were pinyon-juniper dominated by pinyon (*Pinus edulis* Engelm.) and Utah juniper (*Juniperus osteosperma* Torr. (Little)), brushy loam characterized by dense serviceberry (*Amelanchier utahensis* Koehne) and Gambel's oak (*Quercus gambelii* Nutt.) shrubs, and clayey slopes dominated primarily by cool-season rhizomatous bunchgrasses such as western wheatgrass (*Pascopyrum smithii* (Rydb.) Á. Löve) and Indian ricegrass (*Achnatherum hymenoides* (Roem. & Schult.) Barkworth) (Soil Survey Staff, 2017). The principal parent material for the study area is residuum and/or colluvium weathered from shale or sandstone with Rentsac and Moyerson

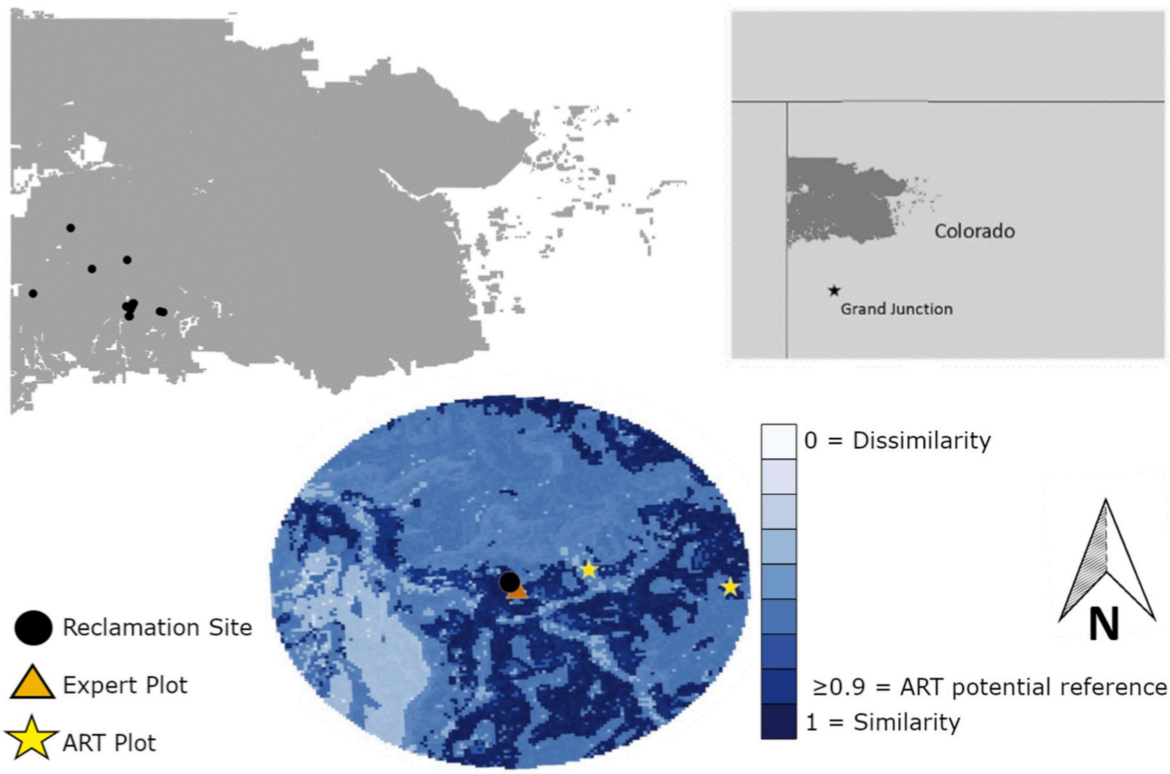

Fig. 1. This study was conducted within the southwestern portion of the Bureau of Land Management (BLM) White River Field Office (WRFO) in northwestern Colorado. Vegetation and soil data were collected at 28 plots that had an Automated Reference Toolset (ART) similarity value (calculated within a 2-km buffer) to their reclamation site of $\geq$0.9 (i.e., ART plots), on a scale of similarity from 0.0 to 1.0. Vegetation data were also collected at each expert-selected reference plot (i.e., expert plot).

being the most common soil components encountered during data collection (Soil Survey Staff, 2017) Primary land uses for the study area are livestock grazing, hunting, recreation, and oil and gas extraction. The most prevalent use of the area is energy extraction because the study area is an important source of oil shale deposits of which the BLM issues and manages permits for their extraction (Taylor, 1987). Management of these permits includes reviewing drilling applications, monitoring compliance with extraction regulations, and evaluating the success of well pad reclamation.

2.2. Data collection and ART analysis

To evaluate the effectiveness of ART in selecting reference plots, we selected reclamation sites from one of the few drilling companies in WRFO that used reference plots as a measure of reclamation progress when applying for final abandonment of well sites to the BLM. Using a total of 14 reclamation sites with 11 expert plots (some reclamation sites shared the same expert plot), we examined biophysical similarity between reclamation and their expert plot, and between expert plots and nearby ART plots.

2.2.1. The Automated Reference Tool

As originally defined, the ART required spatial datasets for a location including a digital elevation model (DEM), particle size class (PSC) map, and local classifications of geology using Landsat 8 band ratios (Nauman and Duniway, 2016). The DEM and Landsat 8 geology values were then classified and combined with the PSC map into a multi-layer raster, with a resolution of 30m, from which similarity was calculated. To roughly account for vegetation community interactions, this multi-layer raster was buffered to 2 km from the point of interest before calculating a dichotomous similarity value of 0.0 or 1.0 (Nauman and Duniway, 2016) where 0.0 meant dissimilarity (at least one input class didn't match) and 1.0 meant complete similarity. The similarity index was calculated by k-means clustering (Lloyd, 1982) where areas with the same PSC, geology, and topography class at the point of interest were deemed as reference (Nauman and Duniway, 2016).

2.2.2. Spatial inputs

To improve and implement the ART in our study area, we used 3 datasets for calculating similarity to determine potential reference plots: 1) a wetness index derived from a 10-m resolution DEM using the topographic wetness tool in SAGA GIS, (Böhner and Selige, 2006; Conrad et al., 2015; Gesch et al., 2002), 2) a previously created 30-m resolution particle size class (PSC) map (Nauman and Duniway, 2016), and 3) soil map units (Soil Survey Staff, 2017). We projected all data to Universal Transverse Mercator zone 13 North (UTM 13N), scaled to a 30m resolution. The soil map unit polygons were converted to raster cell values and the 10 m wetness index was resampled to 30 m by nearest-neighbor interpolation, using the *raster* package (Hijmans et al., 2017) in R version 3.5.1 (R Core Team, 2018). We used soil map units instead of Landsat mineralogy indices (used by Nauman and Duniway [2016] in their original ART implementation) and a 10 m DEM instead of a 30 m, to better capture local variability. Layers were then combined into a single composite raster with a resolution of 30 m.

Unlike the previous version of ART, we did not classify continuous data into categorical variables. Instead, we used a similarity index to combine the input layers to achieve a gradient of similarity rather than a dichotomous classification of reference or non-reference. We calculated the similarity index from the 3 input layers: wetness index, particle size class, and soil map unit. Because the wetness index was a continuous variable, and the PSC map and soil map unit were categorical, this modified version of ART uses the Gower's similarity which allows for qualitative and quantitative variables (Gower, 1971). Gower's similarity was calculated using the *similarity_buffer* function of R's *clhs* package

(Brungard and Johanson, 2015). In the *similarity_buffer* function, continuous variables are rescaled to interval length [0,1], and categorical variables are converted to a series of binary variables prior to calculating similarity. The resulting similarity was a continuous value ranging from 0.0 to 1.0 (i.e, ART value), where 0.0 meant complete dissimilarity and 1.0 meant complete similarity.

We calculated ART values within a two-km buffer around each of the 14 reclamation sites. Two "high similarity" plot locations (i.e., ART plots) having an ART value > 0.9 were randomly selected within each of these reclamation site buffers using R's *raster* package (Hijmans et al., 2017). Plots occurring on roads or more than three miles from a road were rejected. Plots on roads were rejected because they have an additional human disturbance that the reclamation sites lack causing them to not be a true reference. Additionally, plots more than three miles from a road were rejected because of time constraints since travel to and from those plots would require a significant amount of time on foot. These rejection criteria are consistent with the BLM's AIM monitoring protocol (Kachergis, 2016). We extracted the ART values for each expert plot to its corresponding reclamation for a total of 11 expert plots and 14 reclamation sites (some expert plots were designated for 2 reclamation sites). We conducted the similarity index and value extractions in R using the *cluster* (Maechler et al., 2017) and *raster* packages (Hijmans et al., 2017).

2.2.3. Vegetation & soil data collection

Vegetation and soils data were collected at each of the expert and ART plots for the purpose of comparing ART plots to their corresponding expert plot based on vegetation cover, diversity indices, and soil characteristics (e.g. soil component). For each expert and ART plot, we collected line-point intercept (LPI) cover, species richness, and soil characteristics data following the BLM's Assessment, Inventory, and Monitoring (AIM) program protocols (Herrick et al., 2017). The expert plot data collection was done

June-July 2017 and the ART plot collection in May-July 2018. We do not believe that yearly variations in environmental conditions had an effect on the differences between ART plots (2018) and their expert plot (2017) because annual mean precipitation and temperature were similar for both years, and the data for all plots were collected during the growing season (PRISM Climate Group, 2004). Foliar cover was collected on two 25m transects at each plot, one oriented north (0°) and the second east (90°), each 5m from plot center. On these transects we recorded vegetation canopy intercepts (i.e., "hits") by species and soil cover every 0.5m for a total of 100 LPI points per plot. Cover by species and functional group (i.e., shrubs, perennial grasses, non-native invasive plant species, and total foliar cover) was calculated by dividing the number of hits for each species or group by the total number of possible intercepts (n = 100). For species richness, we recorded all species that occurred within a 30m radius from plot center during a 15-min search.

Similarity of vegetation between ART plots and their corresponding expert plots was then calculated from species cover estimates using a Bray-Curtis similarity index (i.e., vegetative similarity). This similarity index is commonly used in ecological studies to quantify compositional dissimilarity between 2 plots based on counts (i.e., LPI points) for each plant species (Beals, 1984). Bray-Curtis values range from 0.0 to 1.0 where a value of 0.0 means complete dissimilarity (i.e., no species in common) and a value of 1.0 means the expert and ART plots shared all species with similar percentage cover (Bray and Curtis, 1957). We also calculated species diversity for each plot using the Shannon-Wiener (H′) and Simpson (D) indexes. Shannon-Wiener index values range from 0.0 to 5.0, with diversity increasing as the values increase. Typical values are between 1.5 and 3.5 (Shannon, 1948). Simpson's index values range from 0.0 to 1.0, with diversity increasing with the value (Simpson et al., 1949). Shannon-Wiener is typically more sensitive to species richness (number of species) than Simpson's, but values from Simpson's reflect a site's species evenness and are more heavily weighted towards the most abundant species (Nagendra, 2002; Spellerberg; Fedor, 2003). Species richness of ART plots and their expert plot were also compared.

Soil characteristics were determined from a 70-cm-deep soil pit dug at plot center, differentiating between horizons based on soil texture, soil color, and rock component (Herrick et al., 2017). We collected ~200g samples from each horizon for subsequent particle size analysis in the laboratory. If a restrictive layer (e.g., sandstone, shale) was encountered before reaching 70 cm, we recorded the depth of the restrictive layer and discontinued excavating the soil pit. Laboratory particle-size analysis was performed following the protocol of American Society for Testing and Materials (1972). The resulting data were then used to calculate soil gravimetric moisture and the exact percentage of sand, silt, and clay.

2.2.4. Slope & topographic position index

For the 28 ART plots and their expert plots, we determined slope and landform position index value from a 10m DEM in R using the *spatialEco* and *raster* packages (Evans and Ram, 2018; Hijmans et al., 2017). Landform position was calculated from the topographic position index as described by De Reu et al. (2013) where results are later binned into morphologic classes based on mean deviations from a central elevation at a specified resolution based on the criteria of Weiss (2001, Table 1).

2.3. Statistical analyses

Because the expectation was that ART would select plots that were similar in biophysical characteristics to a point of interest, and the majority of our variables for evaluating these characteristics were continuous, we used simple linear regression and correlation between indicator values measured at expert plots and ART plots as our primary statistical analysis techniques. Linear regression slope values and R^2 values were calculated using the *lm* function in R, and the results were visualized using the *ggplot2* package (Wickham et al., 2018). Metrics evaluated included terrain slope (%), soil gravimetric moisture ($\square_g$), rock fragment (%), depth to restrictive layer (cm), vegetative similarity (Bray-Curtis), total foliar cover (%), bare ground (%), and functional group cover (shrubs (%), perennial grass (%), and invasive species (%)). Values for the ART plots were used as independent variables and values for expert plots were used as dependent variables. We also calculated and summarized the differences for rock fragment and depth to restrictive layer using root mean square difference (RMSD). In addition, we examined the relationship between vegetative similarity and years since the beginning of reclamation on the corresponding well pad (e.g., reclamation site) using linear regression to determine if time was related to similarity in land potential between ART plots and their expert plots.

Results for categorical variables (i.e., topographic position) were compared using an error matrix and by calculating total percent correctly classified and kappa coefficient of agreement with the *psych* package in R (Revelle, 2018).

All data, calculations, and analyses are available at: https://github.com/sfdistefano/ART-model-verification.

Table 1
Criteria for landform position based on standard deviations (SD) from a central elevation within a specified scale and resolution based on criteria ranges from Weiss (2001).

Landform Class	Landform Position Index Value
Ridge	> +1 SD
Upper Slope	>0.5 SD =< 1 SD
Middle Slope	> −0.5 SD, < 0.5 SD, slope >5°
Flat Area	>= −0.5 SD, =< 0.5 SD, slope ≤ 5°
Lower Slope	>= −1.0 SD, < −0.5 SD
Valley	< −1.0 SD

3. Results

3.1. ART plots vs expert plot

We found that for factors related to parameters explicitly considered in the model (e.g., landform position and soil gravimetric moisture), the ART did select areas of similar land potential, but it was not able to consistently select areas of similar current land condition, beyond dominant vegetation cover. For example, if the expert plot was in a pinyon-juniper range site, the selected ART plots were also in pinyon-juniper. But for finer vegetation characteristics, such as perennial grass cover, ART plots and expert plots were often very different. The ART was also unable to consistently select areas of similar land potential or current condition when the expert plot was in an area of high spatial heterogeneity, where differences in biophysical characteristics were not adequately captured by ART's 30m-resolution spatial inputs (Fig. 2). For example, in one case, an expert plot was on an edge between a pinyon-juniper range site and a sagebrush shrubland range site and one of the selected ART plots was in pinyon-juniper while the other was in sagebrush shrubland, and each plot had different soil characteristics (Fig. 2). Overall, the ART-selected areas of similar land potential and dominant vegetation cover when a reclamation site and its immediate surrounding area (including the expert plot) were relatively similar in soil and vegetative characteristics and spatial variability was low.

3.1.1. Slope and topographic position

The slope of ART plots ranged from 0 to 70%, with 17 out of 28 plots having a slope between 20 and 40%. The slope values for expert plots was within a much narrower range of 5–30% but most (8 out of 11) sites had a slope between 5 and 15%. Most (39 out of 48) ART plots had slopes steeper than their corresponding expert plot, suggesting that expert plots were selected at shallower slopes than those typically found in the study area. In addition, we detected no relationship ($R^2 = 0.04$; p-value $= 0.16$) between the topographic slope of ART plots' and the topographic slope of the corresponding expert plot.

We found that 82% (23 out of 28) of ART plots had matching landform with their expert plot, yielding a kappa coefficient value of 0.46 (i.e., moderate agreement). There was a higher occurrence than expected

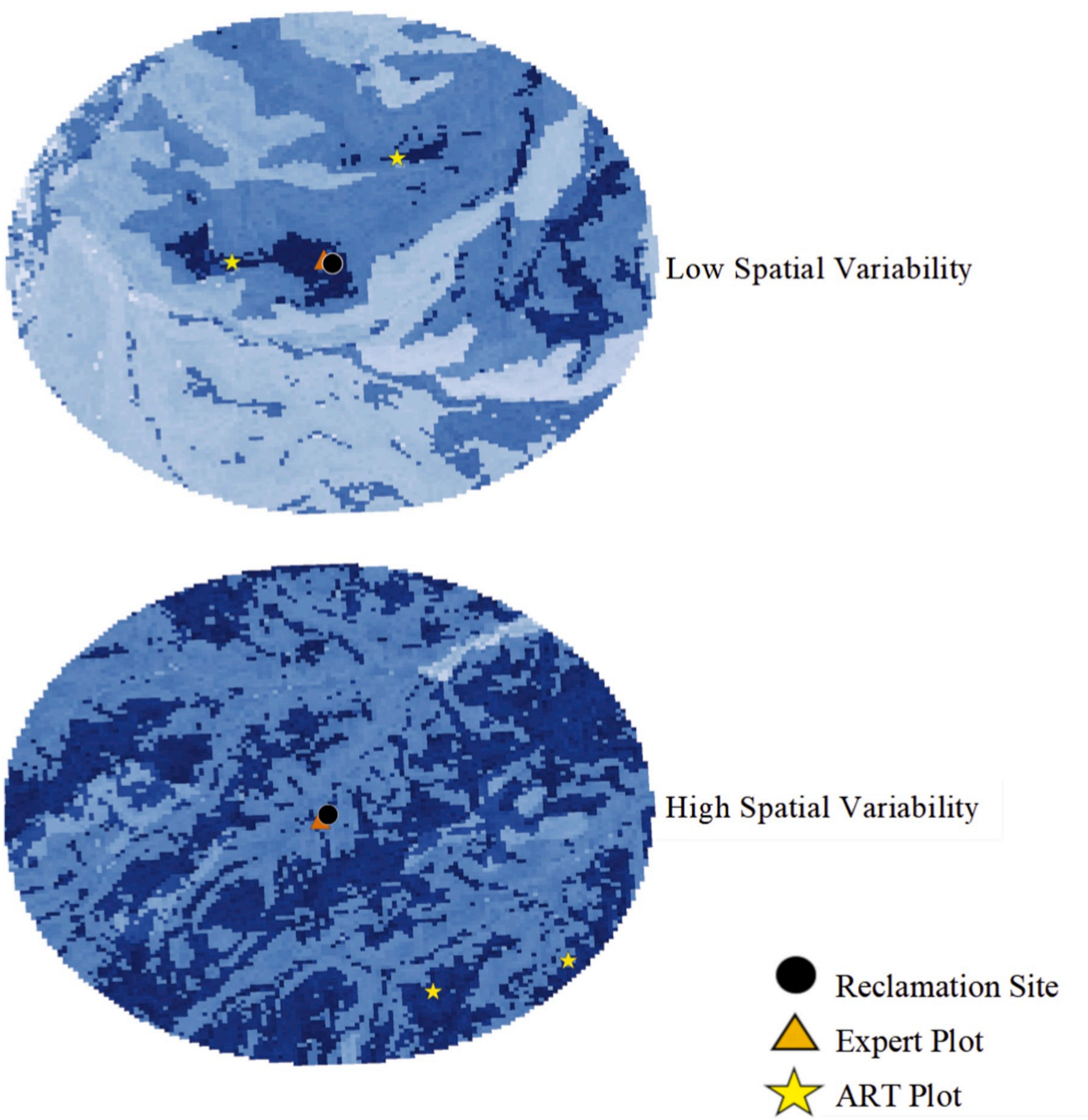

Fig. 2. Examples of reclamation sites in an area of low spatial variability (i.e., surrounding area has similar soil and vegetation characteristics) and high spatial variability (i.e., surrounding area often has different soil and vegetation characteristics).

though of flat area expert plots with middle slope ART plots (refer to Table 1 for slope criteria).

3.1.2. Soil characteristics

We found that ART plots have similar soil water content to their expert plot (R^2 = 0.43, p-value<0.001; Fig. 3). We also examined the differences between ART plots and their expert plot for rock fragment and depth to restrictive layer. For rock fragment differences, 17 out of 24 ART plots had a difference less than 20% from their expert plot, and 16 out of 25 had less than 20 cm for depth to restrictive layer (RMSD = 21.90, Fig. 4; RMSD = 19.99, Fig. 4). We did not include all ART plots in these calculations because their information was either lost or not recorded by field collection crews.

3.1.3. Vegetation

Vegetation cover of ART plots was somewhat similar to their expert plot for total foliar cover (R^2 = 0.34, p-value = 0.0012; Fig. 5) and shrub cover (R^2 = 0.38, p-value<0.001; Fig. 5). In addition, 23 out of 28 ART plots had greater shrub cover than their reference. In contrast, we detected no relationship between ART plots and their expert plot for the finer vegetation characteristics of invasive species cover (R^2 = 0.14, p-value = 0.051; Fig. 5) and perennial grass cover (R^2 = 0.022, p-value = 0.46, Fig. 5). In addition, invasive species cover was lower than the expert plot for 24 out of 28 ART plots and 17 out of 28 ART plots had lower perennial grass cover than their expert plot.

From further analysis of finer vegetative characteristics (i.e., cover of each plant species found at a plot), we found that vegetative similarity was highly variable between ART plots and their corresponding expert plot, ranging from 0.2 to 0.9. For individual plot vegetative characteristics, we found that an ART plot's diversity was not related to its expert plot's diversity (R^2 = 0.032, p-value = 0.36). In addition, we did not detect a relationship between the predicted vegetative similarity (ART value) and the actual vegetative similarity that was calculated from the field data (R^2 = 0.079; p-value = 0.15). However, vegetative similarity (Bray-Curtis) between ART plots and their expert plots increased with time since the start of reclamation work at their corresponding well-pad site (i.e., reclamation site; R^2 = 0.69, p-value<0.001, Fig. 6).

3.2. Expert plot vs. reclamation site

As expected, most of the expert plots had a high ART value with their reclamation site. Of the 14 different reclamation sites (some reclamation sites shared a reference), 11 had expert plots whose ART similarity was >0.9, while 3 had expert plots with ART similarity between 0.6 and 0.7. Differing PSC between reclamation and their expert plot caused the 3 reclamation sites' expert plots to have low ART values. We did not see a noticeable effect on ART values based on an expert plot's linear distance to its reclamation site (R^2 = 0.052; p-value = 0.43). In addition, low ART index values occurred in areas of high spatial heterogeneity that the spatial inputs into the ART model could not capture at a 30m resolution (Fig. 2).

4. Discussion

4.1. Comparison of large-scale vegetation characteristics

Differences in vegetation between ART plots and their expert plot were not unexpected because vegetation characteristics were not explicitly considered in the ART model. Based on remotely sensed values, Nauman and Duniway (2016) found that ART did select areas with similar total foliar cover. This is consistent with our results from field collected data (Fig. 5). Shrub cover of ART plots were also similar to their expert plots; however, we found no relationship for finer vegetative characteristics (perennial grass and invasive species cover) between ART plots and their expert plot. This suggests that the spatial inputs of ART allow for the model to select areas of similar dominant vegetation type (e.g., pinyon-juniper) but do not adequately represent characteristics of understory vegetation. In addition, we found high variability in species-level composition among sites, as demonstrated by diversity index values, which may be due to fine-scale site heterogeneity or management effects that are not captured by the ART input layers. From this, it appears that as diversity in plant types increases, ART is increasingly unable to predict similarity in vegetative indicators of land condition.

4.2. Comparison of finer-scale vegetation characteristics

Another possible explanation for the higher variability in species-level composition among sites is that finer-scale vegetation characteristics may be more greatly affected by other site-scale effects, such as current or historic (*sensu* Harding et al., 1998) management activities, such as livestock grazing, that cannot be accounted for in the ART model. For example, time since the beginning of reclamation work at a site may help to explain differences in vegetation cover between their

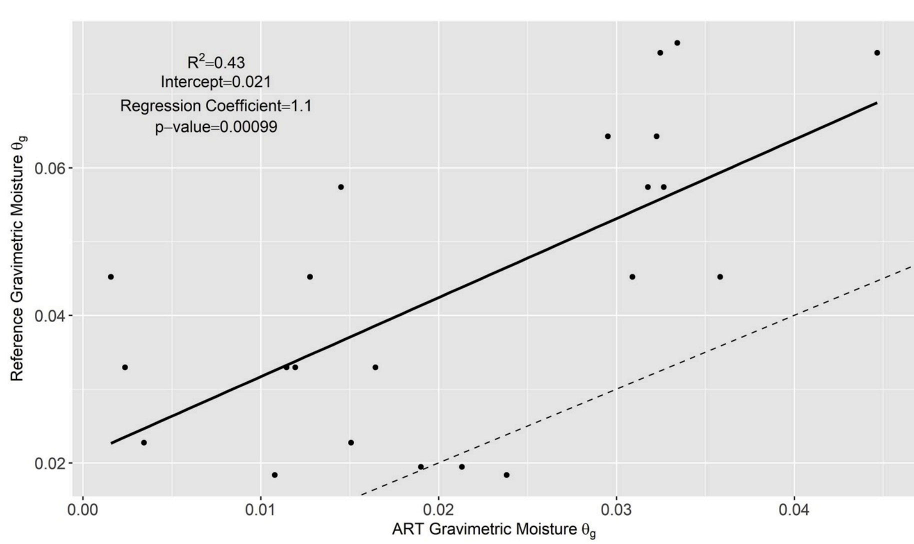

Fig. 3. Relationship of overall soil water content (gravimetric moisture[□$_g$]) between Automated Reference Toolset (ART) plots and their expert-selected reference plots. The dashed line represents a 1:1 relationship and the solid line represents the linear regression between the ART-plot gravimetric moisture and the expert-plot gravimetric moisture.

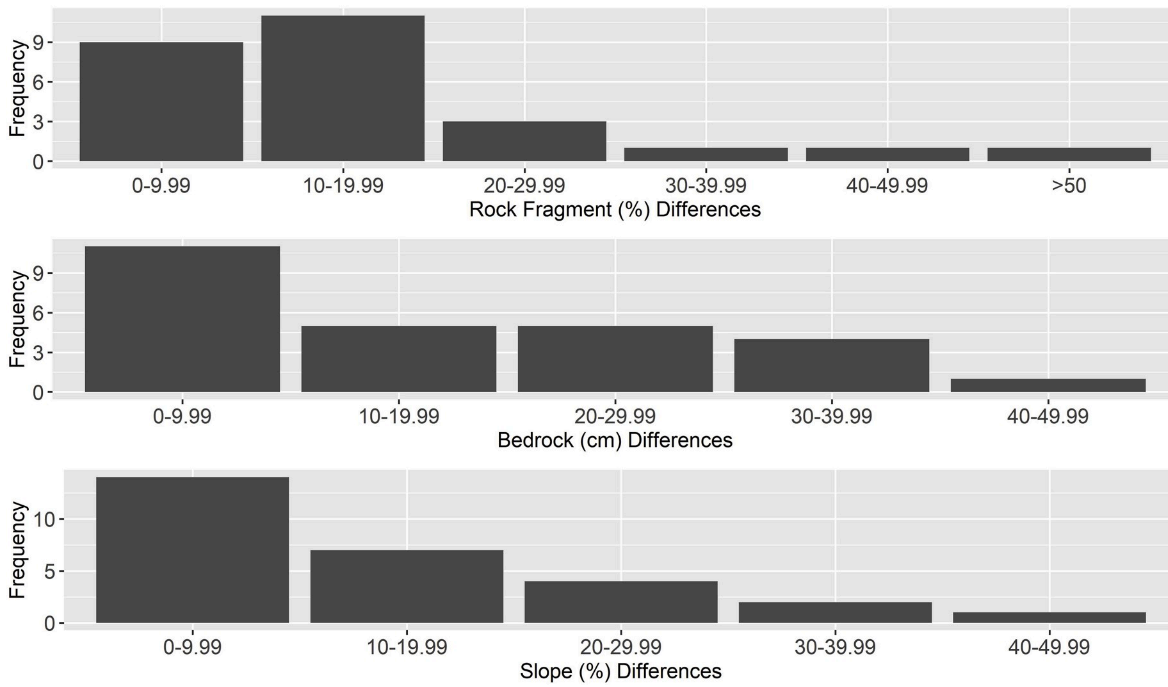

Fig. 4. Differences between sampled Automated Reference (ART) plots and their expert-selected reference plot for the following characteristics: rock fragment % volume, depth to bedrock (cm), and topographic slope.

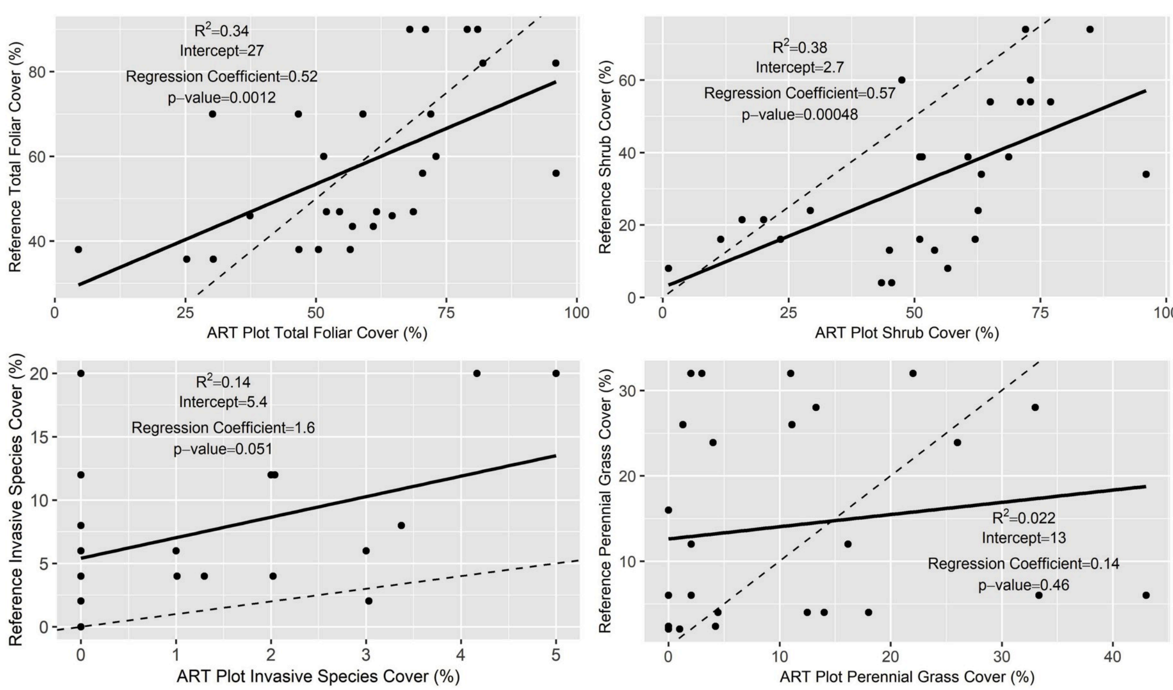

Fig. 5. The relationship in foliar cover (%) between an Automated Reference Toolset (ART) plot and its matching expert plot for the following vegetative indices: total foliar, shrub, invasive species, and perennial grass. The dashed line represents a 1:1 relationship and the red solid line is based on the linear regression of the total foliar cover of ART plots on expert plots.

ART plots and expert plot because we found that vegetative similarity increased with time since reclamation began (Fig. 6). This suggests that reclamation sites may have affected the conditions on their expert plot because of reasons such as the expert plot receiving soil runoff due to wind and water erosion from the exposed soil of the well pad (now reclamation site) and/or weed dispersal from initial reclamation activity (Johnston, 2011; McBroom et al., 2012). The effects from well-pad production and reclamation activity have been found to diminish with time as the reclamation site returns to a more natural setting (Johnston, 2011; McBroom et al., 2012). This would explain the increase in vegetative similarity over time between ART plots and their expert plot since the expert plot is increasingly no longer experiencing the effects of nearby reclamation activity. Other differences we observed were that the expert plots were selected on slopes that were less steep than the surrounding vicinity and other ART-selected areas (ART value > 0.9), indicating a bias in experts towards selecting reference plots that were

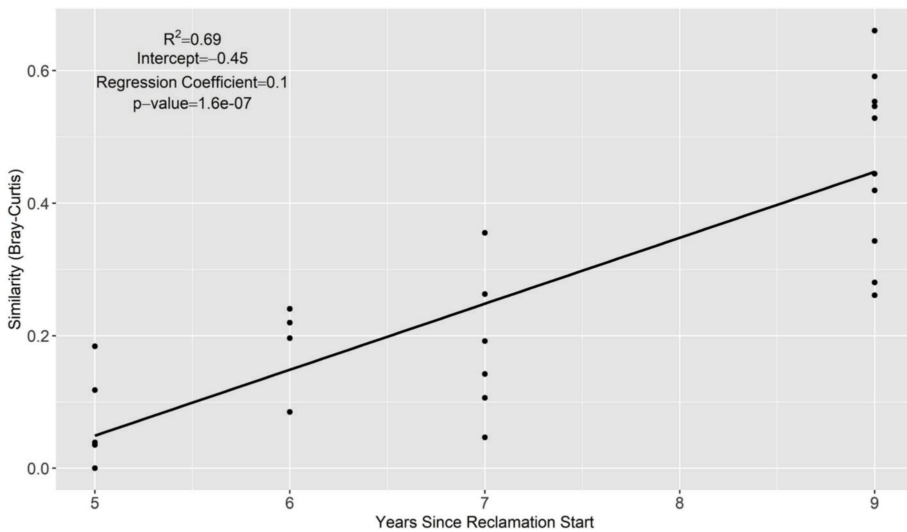

Fig. 6. The relationship between the year reclamation began and ART plots' vegetative similarity to their expert- selected reference plot (share the same reclamation). Vegetation similarity values are on a scale of 0.0–1.0 with 0.0 meaning completely dissimilar and 1.0 meaning completely similar. The solid line represents the linear regression of years since reclamation started on the vegetative similarity of the ART plots and their expert plots. Two outliers were removed because ART plots had starkly different soil and vegetation from their reference.

easier to access.

4.3. Limitations of the ART model

Like any model, the ART is inherently constrained by the scale and quality of its inputs. Our results though suggest that ART appears to be working as designed, and that the type and scale of the data used in ART were generally appropriate for reference plot selection. All expert plots had high (or relatively high) ART values when compared to their reclamation site, and plots within ART-selected areas had similar site characteristics to their expert plot. ART plots were also less affected by reclamation activity than their expert plot and the model removed subjectivity from the plot selection process. However, there were some limitations in areas with high spatial heterogeneity (i.e., smaller neighborhoods of high ART values, Fig. 2). In these areas, site patterns affecting vegetation composition (e.g., particle size class) were occurring at scales finer than the 30-m resolution used in ART. This indicates that ART performs best when the spatial variability of site physical characteristics is well represented by the input data sets and that the ART model does not capture variability when it occurs at distances less than the input cell resolution.

4.4. Recommendations for using ART

Because there is variability in areas of high spatial heterogeneity and finer vegetative characteristics within ART-selected reference areas (i.e., areas of high similarity to reclamation), we suggest that a manager who is familiar with the area and reclamation practices, verify suitability of candidate reference plots selected by ART. With the current spatial inputs, verification of ART plots should include excavating a soil pit and measuring species-specific foliar cover, using the methods outlined in the BLM's AIM program protocols (Herrick et al., 2017). Other parameters that may be included for final reference plot selection are presence of invasive plant species, current and past land uses, and distance from a road (White and Walker, 1997). We do not suggest that a finer-resolution or additional spatial inputs be used in the model because many of the factors that appear to be influencing vegetative variability (e.g., management activity) are difficult to capture accurately with remote sensing. In addition, resolution finer than 30-m for soil data and 10-m for topography are difficult to acquire on landscape-scales and do not necessarily increase the model accuracy for the attributes of interest. Additional inputs would also not increase accuracy and may actually increase the risk of error because of the heterogenous nature of soil and vegetation characteristics in arid ecosystems (Ziadat et al., 2015). Based on these limitations, finer resolution and/or additional inputs could only be justified if it reduced the need for field verification and significantly improved the model's ability to predict land potential.

If a site occurs outside of the Colorado Plateau (i.e., the spatial extent of the current PSC map), a new PSC map would need to be created using the steps outlined in Nauman and Duniway (2016). Generally, the creation of a PSC map involves compiling multiple field soil descriptions in an area and then using spatial statistics to interpolate PSC classes across that area of interest. However, oil and gas development on the Colorado Plateau is extensive and using ART in this region with the described inputs could have a meaningful impact on the efficacy of reclamation on the plateau (USGS, 2019).

5. Conclusions

The results of this study provide evidence that the ART model can be a useful tool to help guide selection of reference plots. However, it is not a replacement for guidance from experts or a complete automation of reference plot selection because experience and familiarity with the area and reclamation activities are still needed to adequately address reclamation needs. Combining the ART model with this experience though will make the reference selection much more consistent and transparent across projects and through time because the majority of current practices do not utilize reference plots in their reclamation evaluations. This is possible because ART removes subjectivity for variables related to land potential and proposes candidate reference plots that have similar land potential which a land manager should later evaluate in the field. Collection of monitoring data from these candidate reference plots then enables managers to have a consistent quantitative measure of similarity to reference condition, compared to the often-contested qualitative assessments of oil and gas reclamation more commonly used by U.S. federal land agencies today. Most importantly, ART can serve as a communication tool between agencies and private industry for setting and monitoring reclamation objectives. ART could be an important step in improving the transparency and perceived fairness of defining success in oil and gas reclamation by empowering private and federal reclamation managers to make effective reclamation decisions through objective, clear, and consistent methods.

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.

CRediT authorship contribution statement

Sean Di Stéfano: Conceptualization, Methodology, Software, Investigation, Formal analysis, Writing - original draft, Data curation. **Jason W. Karl:** Funding acquisition, Conceptualization, Methodology, Supervision, Writing - review & editing. **Derek W. Bailey:** Supervision, Writing - review & editing. **Steven Hale:** Resources, Validation, Writing - review & editing.

Acknowledgements

We would like to thank the following for their cooperation, funding, and support of this project: New Mexico State University; the USDA Agricultural Research Service's Jornada Experimental Range; James Roberts, Heather Stewart, and Mary Taylor of the BLM White River Field Office; Liz Doby at Rocky Mountain Youth Corp; the 2018 WRFO AIM crew members and Joel Humphries at the BLM-AIM program. In addition, we would like to thank Utah Gas Corp for graciously providing the locations of their reclamation and reference plots, along with their vegetation monitoring data of these sites.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jenvman.2020.110578.

Funding

This work was supported by the USDA ARS Jornada Experimental Range and the BLM-AIM program.

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