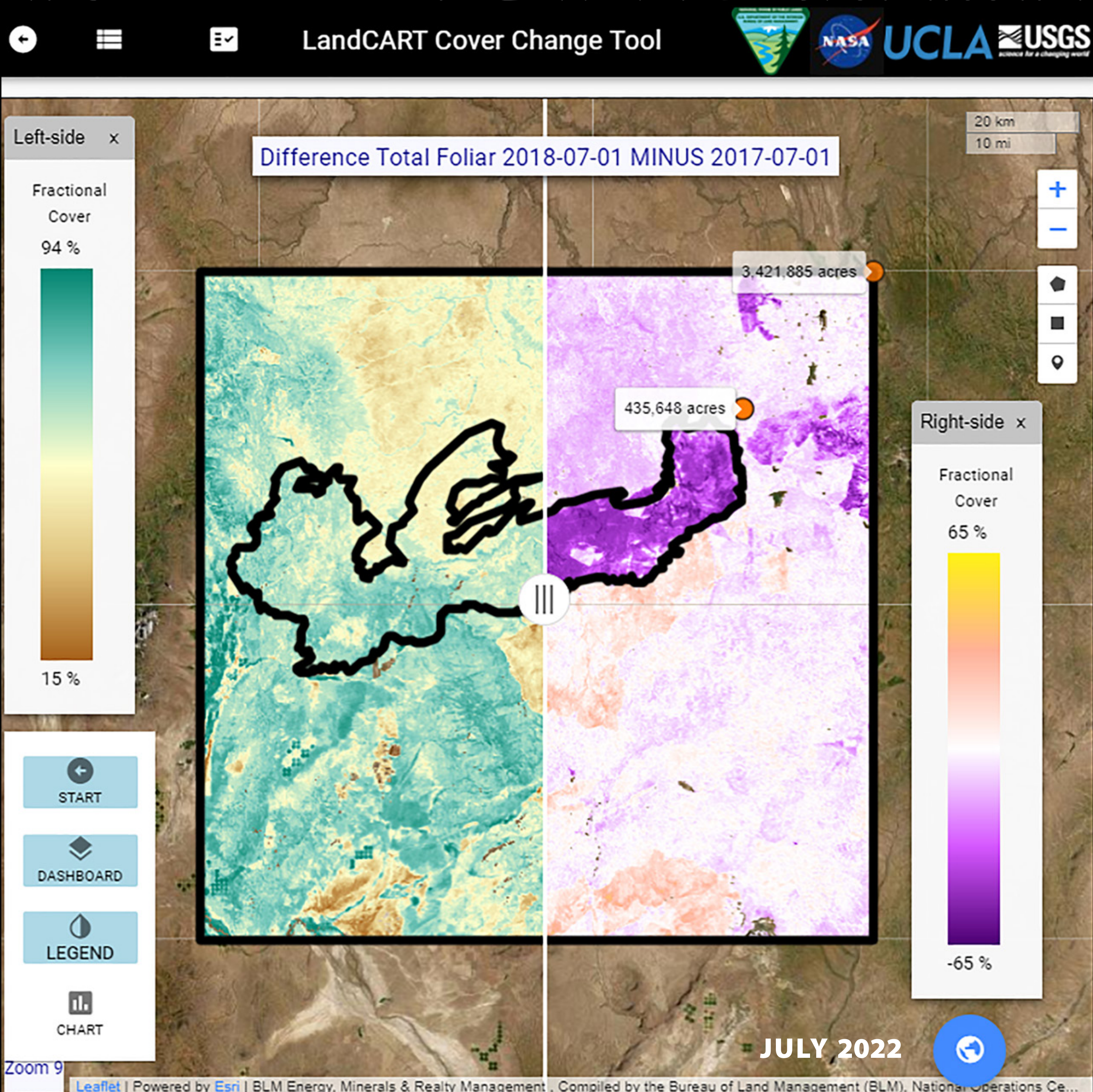
BUREAU OF LAND MANAGEMENT

Evaluation of Fractional Vegetation Cover Products

Technical Note 456



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Evaluation of Fractional Vegetation Cover Products

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Contents

Abstract

Fractional vegetation cover estimates can help land managers better understand vegetation composition and change over time. Recognizing the value in fractional vegetation cover datasets for rangeland management, multiple research groups have leveraged extensive satellite imagery and field sampling collections to develop regionwide fractional cover datasets of key vegetation indicators. This technical note presents the analysis of three major products that estimate fractional vegetation cover and are supported, to varying degrees, by the Bureau of Land Management: Landscape Cover Analysis and Reporting Tools (LandCART); Rangeland Condition, Monitoring, Assessment, and Projection (RCMAP); and Rangeland Analysis Platform (RAP). The purpose of this analysis is to evaluate the fractional vegetation cover data products for redundancy and appropriate use by natural resource programs for decision making. Each product was evaluated qualitatively, through a literature review and informal conversations with current and potential users, and quantitatively, through an independent accuracy assessment. Accuracy estimates, from both the independent accuracy assessment and published validations, show that LandCART, RCMAP, and RAP are acceptably accurate overall for most of the compared indicators. A clear "best" product was not determined among the three, as each has different strengths and weaknesses. All three products offer improvements on past datasets and possible future analyses and provide valuable context for natural resource management and decision making when utilized as one of many lines of evidence.

Introduction

The Bureau of Land Management (BLM) is responsible for more land than any other federal agency, approximately 245 million acres of public lands, predominantly in the western states, including Alaska. Throughout the nation, the BLM also administers more than 700 million acres of subsurface mineral estate. The mission of the BLM is to sustain the health, diversity, and productivity of the public lands for the use and enjoyment of present and future generations. In accordance with the Federal Land Policy and Management Act of 1976, public lands are managed under the principles of multiple use and sustained yield. The BLM manages public lands for a variety of uses, including livestock grazing, energy and mineral development, wildlife habitat, and outdoor recreation, while conserving natural, cultural, and historic resources.

Land cover datasets are commonly used in geographic information systems and geospatial analysis, wherein a spatially referenced grid, or **raster**[1], contains pixel values corresponding to types of physical coverages on the earth surface at that location (e.g., forest, grassland, developed area). Traditionally, land cover datasets have contained an integer value for each pixel, with each unique value corresponding to a single cover type. **Fractional vegetation cover** is a subset of a land cover dataset wherein the pixel value represents the percentage of area within that pixel that is vegetated (Gitelson et al. 2002). By modeling fractional vegetation cover of various functional groups that occur in a region, a much more detailed picture of the landscape can be obtained. These fractional vegetation cover estimates can help land managers better understand vegetation composition and change over time. Fractional vegetation cover data provide valuable context for natural resource management and decision making when used as one of many lines of evidence (Allred et al. 2022). For example, these broad-scale data can be used by biologists studying sage-grouse habitat degradation, rangeland managers interested in treatment effects or grazing impacts on rangeland health, or oil and gas planners investigating the encroachment of invasive species on disturbed areas. Given the value of these data, there is a need to better understand the strengths and weaknesses of the various fractional vegetation cover products before they are integrated into land management best practices.

Recognizing the value of fractional vegetation cover datasets for rangeland management, multiple research groups have leveraged extensive satellite imagery and field sampling collections to develop regionwide fractional vegetation cover datasets of key vegetation **indicators** (Allred et al. 2022). With access to an enormous archive of freely available satellite imagery, remote sensing scientists are increasingly employing cloud computing architecture to study these vast quantities of data. This technical note explores three different BLM-supported products that help land managers monitor trends in rangeland vegetation. All three products have a similar purpose—leverage the archives of satellite imagery (Landsat) with field data (e.g., Assessment, Inventory, and Monitoring (AIM) field data) to develop fractional vegetation cover predictions of vegetation indicators over time in the Western United States.

The purpose of this analysis is to evaluate the fractional vegetation cover data products for redundancy and appropriate use by natural resource programs for decision making. Brief summaries of the three products reviewed follow.

[1] Glossary terms are sometimes highlighted in bold throughout this technical note, and definitions appear in the glossary.

Following the summaries, specific similarities and differences among the three products, evaluation methodology and results, and a discussion are provided. The conclusion includes recommended uses by land managers. In addition, Appendix A includes sources involved in a literature review; Appendix B presents detailed steps of an independent accuracy review; and Appendix C presents published or available accuracy metrics of the three products.

Landscape Cover Analysis and Reporting Tools (LandCART)

The National Aeronautics and Space Administration (NASA) awarded a Research Opportunities in Space and Earth Sciences (ROSES) grant to the BLM, U.S. Geological Survey (USGS), and University of California, Los Angeles (UCLA). The result of this geospatial partnership is development of LandCART, an online mapping application that builds on current science and cloud computing to provide BLM staff the ability to fuse AIM field information with remotely sensed data to make current and historic fractional vegetation cover predictions of core AIM indicators where and when they were not measured. The application relies on a random forest algorithm in Google Earth Engine to develop "on-the-fly" models of AIM indicators for users in their specific study area (within the Western United States) and time period (1984 to present). All available AIM and Natural Resources Conservation Service (NRCS) National Resources Inventory (NRI) data through summer 2019 were used for **training** these models. This application features functionality to create maps, download imagery, calculate statistics, create charts, and incorporate the results into reports that can be included in the NEPA (National Environmental Policy Act) administrative record (including complete metadata for all data produced). This application was developed for BLM on-the-ground field staff, BLM planners, and private, as well as public, land managers.

Rangeland Condition, Monitoring, Assessment, and Projection (RCMAP)

RCMAP (formerly known as Grass/Shrub Mapping and Monitoring) initiated the concept of large-area fractional vegetation mapping nearly a decade ago. Through an interagency agreement between the USGS and BLM, the team at USGS has developed a rigorous shrubland-habitat classification covering several regions of the Western United States. Through a comprehensive tree-structured regression model, static predictions of nine shrubland ecosystem components (i.e., percent herbaceous, annual herbaceous, shrub, sagebrush, big sagebrush, bare ground, and litter; as well as shrub and sagebrush height in cm) are available for the year 2016, with expected updates every 2-3 years. Static, back-in-time annual predictions of each component have been developed for 1985 to 2020 and are updated yearly. All these datasets, including error estimates, reside on the Multi-Resolution Land Characteristics (MRLC) Consortium data download website. A small portion of BLM AIM 2.0 data was used for training and validation of these datasets. A simple web-based rangeland data viewer has been developed with which users can visualize the 2016 components along with back-in-time data (EROS Center 2020; USGS 2020). These data and tools are being developed for rangeland landowners, BLM on-the-ground field staff and planners, and land managers across the Western United States. The work has produced ecological potential maps covering the entire Western United States and continues to refine and expand the back-in-time series to include annual updates and investigate improved back-in-time production speed and accuracy.

Rangeland Analysis Platform (RAP)

Version 1.0 of the RAP tool was released in the fall of 2018 with the objective of providing a free tool to landowners, land managers, and conservationists to access rangeland information and use that information to guide land management decision making. Version 2.0 was released in early 2020. A University of Montana team, with support from the NRCS and BLM, have combined the latest remote sensing technology (Google Earth Engine, Google Cloud Platform, convolutional neural networks, and Google Artificial Intelligence) with comprehensive satellite imagery archives and AIM field data to predict static fractional vegetation cover across the Western United States for six functional groups (annual forbs and grasses, perennial forbs and grasses, shrubs, bare soil, litter, and trees) for growing seasons from 1984 to present. Like LandCART, all available AIM and NRCS NRI data through summer 2019 were used for training these models. The data and online application are updated yearly.

A mix of sagebrush-, grass-, and tree-dominated cover types is common across much of the West. The purpose of fractional vegetation cover products is to map the abundance of these cover types.

Brief Summary of Similarities and Differences Among the Three Products

Similarities

- Fractional vegetation cover products
- Predictions available across the Western United States
- Utilize AIM data for training and/or validation
- Utilize Landsat satellite imagery
- Spatial resolution: 30-meter pixels
- Temporal range: 1984 to 2020
- Ability to produce time series information

Differences

- Components/indicators mapped (both type and number)
  - **LandCART:** 19 predicted components
  - **RCMAP:** 9 predicted components
  - **RAP:** 6 predicted components

- Data inputs/variables[2]
  - **LandCART:** Landsat 5 TM, Landsat 7 ETM+, Landsat 8 OLI, EVI, MSAVI, NBR, NBR2, NDMI, NDVI, SAVI, elevation, slope, aspect, latitude, longitude, and day of year
  - **RCMAP:** Landsat 8 OLI, NDWI, NBDI, SAVI, position index, slope, aspect, Landsat 8 thermal band, and eMODIS NDVI
  - **RAP:** Landsat 5 TM, Landsat 7 ETM+, Landsat 8 OLI, NDVI, and NBR2

- Accuracies of predicted indicators
  - See Tables 1 and 2 in the section that follows; also see Appendix B

- Online tools and reporting
  - **LandCART:** completed and in press
  - **RCMAP:** minimal online tool with planned updates
  - **RAP:** completed and published

- Methodology
  - **LandCART:** random forest in Google Earth Engine
  - **RCMAP:** regression trees; change vector analysis
  - **RAP:** convolution neural networks in Google Artificial Intelligence

- Temporal resolution of predictions
  - **LandCART:** monthly, weekly, seasonal (defined by user)
  - **RCMAP:** annual growing season; manually chosen during preprocessing
  - **RAP:** annual growing season; extracted from Google Earth Engine assets

- Products are visually different (see Figure 1 in the section that follows)

[2] Acronym definitions: eMODIS = EROS Moderate Resolution Imaging Spectroradiometer; ETM+ = Enhanced Thematic Mapper Plus; EVI = Enhanced Vegetation Index; MSAVI = Modified Soil Adjusted Vegetation Index; NBDI = Normalized Difference Built-up Index; NBR = Normalized Burn Ratio; NBR2 = Normalized Burn Ratio Two; NDMI = Normalized Difference Moisture Index; NDVI = Normalized Difference Vegetation Index; NDWI = Normalized Difference Water Index; OLI = Operational Land Imager; SAVI = Soil Adjusted Vegetation Index; TM = Thematic Mapper.

Evaluation Methodology and Results

Each product was evaluated in the following ways: qualitatively, literature review, informal conversations with current and potential users, and a quantitative independent accuracy assessment.

Qualitative Evaluation

Through qualitative evaluation, it was found that:

- **Striping** errors from Landsat 7 ETM+ scan-line corrector failure have largely been remedied, although some remnants still exist (Figure 1, RAP 2020).

- Some indicators appear to be mapped better than others. For instance, in Figure 1, the striping is a concern for annual herbaceous cover in the RAP prediction. On the other hand, the RAP map demonstrates a wider distribution of fractional vegetation cover values than both the LandCART and the RCMAP maps. Not unexpectedly, the same area, indicator, and year often appear to be mapped differently among the three products (Figure 1).

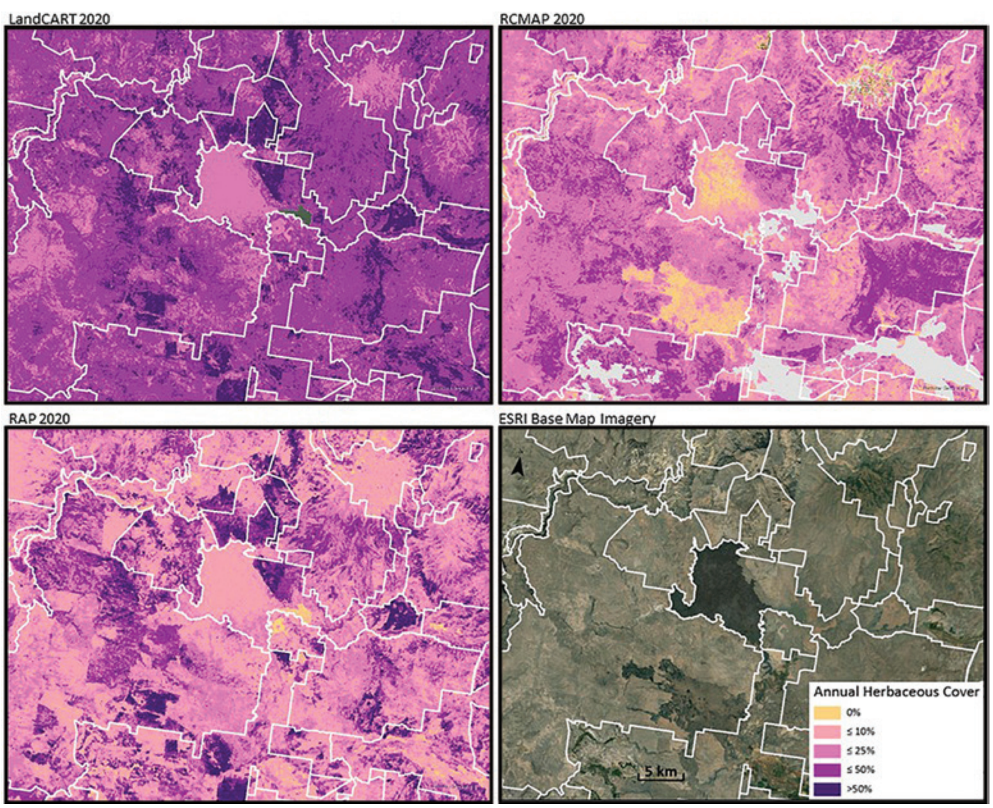


Figure 1. Visual comparison of a base map and LandCART, RCMAP, and RAP predictions of 2020 annual herbaceous fractional vegetation cover in the BLM Malheur Field Office in southeast Oregon, with aerial imagery and BLM grazing allotment boundaries (white lines) for reference. Each map is displayed with the same bins of percent cover of annual herbaceous vegetation. Areas with gray fill on the RCMAP map are areas where no predictions were made according to its methodologies (nonrangeland areas). Note the difference in the range of values (see Table 2 for summary statistics; RCMAP has the smallest range with a maximum value of 32). The distribution of high and low values in the LandCART map differs from the others. Scan line corrector striping is seen in the RAP map.

- Landscape characteristics are visually apparent depending on the indicator mapped. For instance, in all three maps in Figure 1, the dark lava field falls into the lower value **bins**, and the shape is distinct on the map. On the other hand, the lower/lighter lava field is not as well distinguished in the RAP and LandCART maps, but mostly appears as a distinct shape in the RCMAP map.

- Several case studies using LandCART (e.g., monitoring sage-grouse habitat, vegetation treatment effects, grazing-induced vegetation changes) have thus far shown great promise.

- The RAP team provides examples of utilizing their data to evaluate vegetation response to livestock grazing management strategies, visualizing and monitoring wildfire disturbances and treatments, and evaluating conservation practices over large landscapes.

- RCMAP products have been utilized for identifying areas of concern in sage-grouse habitat, as additional lines of evidence for vegetation inventory, and identification of locations where further study is necessary.

Literature Review

Several peer-reviewed journal articles have been written for all three products; a review of these papers found that the methodologies applied in each product, while different, are detailed, rigorous, and defensible. All data were validated internally with independent datasets. A list of these articles is in Appendix A.

Informal Conversations

During 2020 and 2021, conversations with and informal surveys of BLM staff indicate:

- These tools and data are valuable for the field and for planning and NEPA compliance by providing additional lines of evidence.

- Many users wonder if the 30-meter pixel scale is too coarse for their study areas.

- Staff expressed excitement about the ability to perform trend analyses with the datasets, but some are concerned with the reported accuracies.

- Most users prefer to use an online mapping application rather than download individual datasets.

- Overall, RAP has been widely used since 2018, and the latest version has been found to work well for many users.

- LandCART was officially launched in February 2022. Bureau field officials and program leaders have used LandCART since its release, expressing excitement over the functionality LandCART provides.

- RCMAP users expressed concerns that pinyon/juniper woodlands were included within the shrub component, so the datasets were updated the summer of 2020 to address this issue.

- Many geospatial ecologists rely on the RCMAP predictions for their habitat studies, but they prefer a simple application to extract specific data over the final product being served through the BLM internal file structure.

Quantitative Accuracy Assessment

A quantitative accuracy assessment was performed on the most current version of each product, hereafter referred to as “independent accuracy assessment.” See Appendix B for detailed methodology used in the independent accuracy assessment. Field-sampled validation plots were pulled from the AIM 2.0 database on May 4, 2021 (hereafter referred to as “validation data” and/or “observed”). Data points from 2020 were extracted to use for validation of 2020 predictions that utilized training data only up to 2019. A total of 3,034 validation data points were used for the independent accuracy assessment.

Predicted values were extracted from 2020 predictions for each product. Comparisons were limited to the products that matched indicator definitions. For instance, RCMAP predicts "bare ground," while RAP predicts "bare soil"; therefore, LandCART "bare ground" was compared to RCMAP, and LandCART "bare soil" was compared to RAP. For each comparison, a suite of common accuracy assessment statistics were calculated, including the **Pearson correlation coefficient, R^2 (coefficient of determination), root mean squared error (RMSE), mean absolute error (MAE)**, and slope of the regression line.

Table 1 shows a comparison of independent accuracy assessment statistics to each product's published validation statistics (Appendix C). While it is important to note that the accuracy assessments published in the literature are independent (i.e., they were conducted with a subset of field data not used for model training), they are referred to in this technical note as "published accuracy assessments" to distinguish from the independent accuracy assessment presented in this technical note. A comprehensive statistical report of the full validation dataset (Appendix B) displays observed versus predicted data in **hex plots** for each product and presents tables, along with the suite of statistics previously mentioned. Additional information displayed in Table 2 are summary statistics of the observed and predicted indicators.

Table 1. Results of the independent accuracy assessment compared to published accuracy assessment values. Note that the specific approach used to generate the published accuracy assessment values varied for each product. R^2 is the coefficient of determination; RMSE is the root mean squared error; and MAE is the mean absolute error. For LandCART, 20% of the entire training dataset was randomly withheld in a **5-fold cross-validation**. RCMAP employed a field-based validation with 1,860 randomly chosen testing sites. For RAP, 5,780 randomly selected (stratified by state) field plots (10% of the entire training dataset) were withheld from the training dataset.

Independent Accuracy Assessment									
	LandCART			**RCMAP**			**RAP**		
Indicator	**R^2**	**RMSE**	**MAE**	**R^2**	**RMSE**	**MAE**	**R^2**	**RMSE**	**MAE**
Annual Herbaceous	0.26	15.3	9.91	0.13	14.21	7.59	0.52	9.63	5.77
Bare Ground	0.64	13.14	9.69	0.5	23.62	19.4	-	-	-
Bare Soil	0.55	11.97	8.67	-	-	-	0.53	12.09	8.63
Herbaceous	0.59	18.66	14.45	0.42	20.06	15.18	-	-	-
Litter	-	-	-	0.04	10.65	8.31	0.21	9.28	6.76
Perennial Herbaceous	0.59	16.24	12.56	-	-	-	0.64	12.77	9.7
Sagebrush	0.46	7.84	5.57	0.33	8.41	5.51	-	-	-
Shrubs	0.39	11.25	8.66	0.22	12.24	9.53	0.48	9.41	7.05
Trees	0.6	8.88	4.43	-	-	-	0.65	6.08	2.91
Published Accuracy Assessment									
	LandCART			**RCMAP**			**RAP**		
Indicator	**R^2**	**RMSE**	**MAE**	**R^2**	**RMSE**	**MAE**	**R^2**	**RMSE**	**MAE**
Annual Herbaceous	0.54	16.09	10.76	0.58	9.8		0.58	11.0	7.0
Bare Ground	0.73	11.96	9.04	0.70	14.6		-	-	-
Bare Soil	0.64	11.28	8.22	-	-	-	0.73	9.8	6.7
Herbaceous	0.69	19.32	14.34	0.67	13.1		-	-	-
Litter	-	-	-	0.35	8.9		0.37	7.9	5.7
Perennial Herbaceous	0.61	15.96	11.71	-	-	-	0.77	14.0	10.3
Sagebrush	0.43	8.67	6.3	0.40	7.5		-	-	-
Shrubs	0.39	10.39	8.06	0.37	10.6		0.57	8.3	5.8
Trees	0.63	6.57	2.88	-	-	-	0.65	6.8	2.8

Table 2. Summary statistics of observed and predicted indicators from this analysis, calculated on the entire validation dataset of 3,034 points.

	LandCART Observed (%)					LandCART Predicted (%)				
Indicator	**Min**	**Max**	**Mean**	**Median**	**St Dev**	**Min**	**Max**	**Mean**	**Median**	**St Dev**
Annual Herbaceous	0	98	11.24	3	17.74	0	81	10.82	7	10.51
Bare Ground	0	100	29.90	27	21.28	1	97	32.84	32	18.82
Bare Soil	0	100	17.85	12	17.27	0	98	20.42	17	14.10
Herbaceous	0	100	37.87	31	28.50	2	100	40.50	35	24.07
Perennial Herbaceous	0	100	27.35	21	25.16	1	100	29.68	25	19.27
Sagebrush	0	68	7.77	2	10.60	0	36	8.76	8	6.98
Shrubs	0	92	16.51	13	14.35	1	63	16.92	15	7.79
Trees	0	93	6.19	0	13.94	0	76	5.21	1	9.93
	RCMAP Observed (%)					**RCMAP Predicted (%)**				
Indicator	**Min**	**Max**	**Mean**	**Median**	**St Dev**	**Min**	**Max**	**Mean**	**Median**	**St Dev**
Annual Herbaceous	0	91	8.08	2	13.67	0	32	2.48	0	4.43
Bare Ground	0	100	29.81	27	21.29	1	100	47.86	48	21.05
Herbaceous	0	99	29.21	24	23.18	0	67	20.63	18	12.87
Litter	0	59	16.39	15	9.64	0	40	16.31	16	6.85
Sagebrush	0	64	7.04	2	9.89	0	40	6.63	5	7.42
Shrubs	0	91	14.79	12	13.40	0	72	14.92	13	10.13
	RAP Observed (%)					**RAP Predicted (%)**				
Indicator	**Min**	**Max**	**Mean**	**Median**	**St Dev**	**Min**	**Max**	**Mean**	**Median**	**St Dev**
Annual Herbaceous	0	91	8.08	2	13.67	0	82	7.09	4	9.37
Bare Soil	0	100	17.80	12	17.26	0	93	20.15	16	14.57
Litter	0	59	16.39	15	9.64	0	42	12.72	12	4.39
Perennial Herbaceous	0	97	21.13	16	19.95	0	89	25.05	21	17.99
Shrubs	0	91	14.79	12	13.40	0	85	14.75	13	9.38
Trees	0	93	6.13	0	13.86	0	93	6.15	1	11.53

Discussion

Strengths and Weaknesses

The published accuracy assessment results of the three products are generally consistent, though each product appears to struggle with one or more indicators. For example, for the independent accuracy assessment presented in Appendix B, we found that RCMAP performs well when predicting bare ground and herbaceous cover (R^2 of 0.5 and 0.42, respectively) but, like RAP, struggles with litter (R^2 of 0.04 and 0.21, respectively). Moreover, we found that RAP excels when predicting trees and perennial herbaceous (R^2 of 0.65 and 0.64, respectively). We also found that LandCART struggles with annual herbaceous ($R^2 = 0.26$) but performs well with bare ground, perennial herbaceous, and herbaceous cover ($R^2 = 0.64$, 0.59, and 0.59, respectively). Across the board, the independent accuracy assessment found higher error than published, with the root mean squared error for primary indicators increasing by 5 ± 14% (mean ± standard deviation), 35 ± 21%, and 4 ± 16% for LandCART, RCMAP, and RAP, respectively. While the independent accuracy assessment aligns most closely with LandCART and RAP, it should be noted that the difference between the independent assessment's numbers and published accuracies are far more variable for RAP than for the other datasets (Table 1).

While every attempt was made to create an apples-to-apples comparison in the independent accuracy assessment of the three products, there are fundamental differences in the predicted values and independent validation data that are worth noting. Across the board, we found lower accuracy than what is published for each product in the scientific literature (Appendices A and C). This might be due, in part, to seasonal or yearly variations based on when the training and validation plots were surveyed. However, it is important to note that the differences between the independent and published accuracy assessments were not consistent; in fact, they exhibit considerable differences by product, due to the many differences listed and demonstrated in Figure 1. It is interesting to note that for the RCMAP product, the indicators that demonstrated the greatest agreement between the published and independent accuracy assessments were shrubs and sagebrush, both of which would be rather stable over time, yet are difficult to map. Additional discrepancies between product accuracy results might come from differences in the training data used. While all three products use some subset of AIM data for model training, each is supplemented by additional training data from other field monitoring programs. Therefore, the characteristics of the validation data might differ from that of the training data (and validation data used in the initial product accuracy assessments) in ways that are difficult to quantify.

The three products differ in temporal and biotic resolution and extent. All three provide predictions from 1985 to present; however, whereas RAP and RCMAP provide yearly estimates (over the growing season) of 6 or 9 indicators, respectively, LandCART allows users to predict up to 19 indictors for a user-defined time period (such as spring months of each year). Therefore, LandCART might provide greater utility in generating predictions that line up with decisions or external data with a known date or season, while RCMAP and RAP provide an overview of each year and an indication of longer term trends. Additionally, RAP and RCMAP annual estimates are static and are updated once a year with current data, while LandCART is predicted on-the-fly for a specified time period and area of interest. Unlike RAP and RCMAP, LandCART can generate predictions in near real-time as new imagery is uploaded to the Landsat data archive.

The assessment of these products has demonstrated that, even when employing the most advanced technology and methods, mapping fractional vegetation cover in rangeland ecosystems remains difficult. However, while the reported accuracies appear substandard in some cases and might lead a user to hesitate to rely on these predictions, the products are valuable when combined with knowledge of their strengths and weaknesses. It is important to remember that fractional vegetation cover estimates are one of many lines of evidence used in planning.

Questions of Scale and Appropriate Use

These products focus on making fractional vegetation cover data available for broad-scale analyses—currently covering the Western United States. All predictions are derived from Landsat 30-meter resolution imagery; thus, final data are 30-meter pixel resolution. Cover estimates at 30-meter pixel resolution can be used to inform rangeland management decision making not only at a broad scale, such as the Great Basin, but also at watershed, state/county, BLM field or district, and even grazing allotment levels, depending on the size of the allotment. The lower size limit has not yet been identified, but, depending on the landscape, pasture level is likely not appropriate, and individual pixel level is absolutely not appropriate.

The independent and published accuracy assessments show that, overall, the products available from LandCART, RCMAP, and RAP are acceptably accurate for most of the compared indicators. When a natural resource manager requires information for a smaller area, along with referring to these accuracy statistics, they can evaluate the data for appropriate use with expert knowledge of the vegetation composition in the area, comparing the prediction to aerial imagery available in ESRI GIS products or in Google Earth, and comparing broad patterns and shapes in the data to known disturbances, treatments, and management boundaries.

Bins (e.g., stratified into 0-10%, 11-20%, etc.) used in AIM and other analyses can be applied to summarize these continuous values as categories to answer management questions; for example, for a habitat assessment framework (HAF) analysis for sage-grouse (Stiver et al. 2015) or AIM weighted analyses. Thematic bins rely on a consistent range of data values. If a **benchmark** of "suitable" for sagebrush is "cover greater than 35%," but the predicted data maximum value is 29% (due to bias in the predictions), that prediction is not appropriate to use for that benchmark study. This issue is seen in several predicted indicators, most notably with LandCART and RCMAP.

Questions These Products Will Not Answer

It bears repeating that users of these data and tools are cautioned against applying the data at parcel/pasture level, and pixel level is unquestionably inappropriate for use in management decision making. These data were developed for broad-scale use, not fine scale. Furthermore, these data are meant to be used as an additional line of evidence for decision making, not as the sole line of evidence.

Conclusions

A clear "best" product was not determined among the three; each has different strengths and weaknesses. All three products reviewed in this technical note offer improvements on past datasets and possible future analyses. Even though the independent accuracy assessment statistics appear substandard in many cases, these products provide valuable context for natural resource management and decision making when utilized as one of multiple lines of evidence. Quantitative evaluations are only one part of the process. Qualitative evaluations and usability are equally as important in a comprehensive analysis of modeled data. The saying, "A picture paints a thousand words," acknowledges how maps provide significant amounts of information and spatial context by their very nature. When expert knowledge is added to a map and a statistical report, a user can easily determine whether any of these products should be used in the decision-making process.

Recommendations

"All models are wrong, but some are useful." —
George E.P. Box, Statistician

While the fractional vegetation cover estimates created by LandCART, RCMAP, and RAP are not perfect, these products have utility for field personnel and represent valuable supplemental resources for decision making. On their own, none provide "the singular answer" to any management question. These products should not be used in a vacuum; rather, they provide additional lines of evidence in a decision-making framework. Given the lack of a clear "winner" among the three products, it is incumbent upon resource managers to evaluate the predictions against local expert knowledge, including known disturbances or treatments, land management boundaries, and other local management issues. For instance, if a user from the Gunnison Field Office wishes to monitor annual grass populations in a specific grazing allotment, they might choose LandCART because the data can be predicted on-the-fly for multiple years and/or multiple dates across seasons while including the functionality to download the data for further analyses. Specialized local knowledge provides the background for choosing growing season dates at the study site's area of interest. Conversely, a user from Montana might want to visualize the impacts of drought on perennial forage. They could employ the RAP online application to "walk" through the years of perennial forbs and grasses predictions on-screen. Local knowledge of climate and weather will help the user interpret the resultant maps. Additionally, a sage-grouse biologist might want to observe sage-grouse habitat through time in southeastern Idaho and could use the RCMAP sagebrush component to help identify areas of concern. Local knowledge of sage-grouse leks and habitat triggers will help the user find the best location to start the analysis. Fractional vegetation cover estimates used in tandem with other sources of information represent valuable resources that empower resource managers to make informed decisions.

The products reviewed in this report continue to receive updated methodologies, tools, and predictions. In the future, development of a comprehensive reporting tool that is compliant with the NEPA administrative record is expected for LandCART. The RAP product continues to make inroads into vegetation mapping using Google Cloud Platform and Google Artificial Intelligence; the website is updated with new functionality on a regular basis. It is expected that the scan line corrector problem in RAP will be remedied. A focus for RCMAP fractional vegetation cover estimates is updating with the 2021 National Land Cover Database (the next planned base year). Based on the analysis in this technical note, it is recommended that the BLM continue to use all three of these tools when appropriate.

Glossary

benchmark: a value or range of values that establishes desirable conditions for management. Within the context of this technical note, a benchmark often refers to a minimum percentage of certain vegetation cover types that support species of interest. For example, a minimum benchmark of 15% sagebrush cover is desirable for sage-grouse habitat (Stiver et al. 2015).

bin: often referred to as part of data binning, a bin is a range of values to group a set of continuous observations, meant to aid in data interpretation. For example, if vegetation cover values are collected at many field sampling plots, the number of observations might be counted in different bins (e.g., 0-10%, 10.1-20%, etc.) to create a histogram to better visualize the overall trend in vegetation cover.

coefficient of determination (R^2): a statistical term that refers to the proportion of variation in the dependent variable that is explained or predicted by the independent variable in a statistical model. R^2 can be calculated using the subsequent formula, where RSS is the sum of squares of model residuals and TSS is the total sum of squares. R^2 is generally interpreted such that a greater value represents a better fitting model. Note that for a linear least squares regression, the coefficient of determination is equal to the squared Pearson correlation coefficient. See Pearson correlation coefficient.

$$R^2 = 1 - \frac{RSS}{TSS}$$

fractional vegetation cover: a subset of a raster-based land cover dataset, wherein each raster pixel value represents the percentage of area within that pixel that is vegetated. Often, these fractional vegetation cover values are broken down into different plant functional groups of interest. For example, tree fractional vegetation cover might represent the percentage of a pixel characterized by tree cover.

hex(agon) plot: a data visualization technique in which data points are grouped into hexagon bins to improve interpretation. These plots are often used to simplify a graph when a dataset has many data points.

indicator: a measurable, numerical value that provides information on the state of an ecosystem or the environment. In the context of this technical note, indicators refer to various biophysical variables describing vegetation (or lack thereof) that can be interpreted to better understand ecosystem composition and change.

k-fold cross-validation: a methodology for assessing the performance of a statical model. The input data is split into k number of groups. The model training and accuracy assessment is repeated k number of times, so that each group is withheld from model training and used for validation.

mean absolute error (MAE): a statistical measure of the difference between paired values, often predicted versus observed values. MAE can be calculated using the subsequent formula, where Pi represents the i-th predicted value, O_i represents the i-th observed value, and n represents the number of paired values. In this technical note, the observed values come from 2020 AIM field sampling plots while predicted values represent the pixel values at that same location for each of the three compared products (LandCART, RCMAP, and RAP). MAE is generally interpreted such that a smaller value represents a better fit of the model to the observed field data.

$$MAE = \frac{1}{n}\sum_{i=1}^{n} |O_i - P_i|$$

raster: one of the primary types of data used in geographic information systems, wherein a spatially referenced grid of pixels represents some real-world variable. Each pixel has a numerical value corresponding to information about the type or abundance of that variable. Raster datasets are often used to map continuous variables, such as elevation, wherein each pixel value would represent surface elevation at that location.

root mean squared error (RMSE): a statistical measure of the difference between paired values, often predicted versus observed values. RMSE can be calculated using the subsequent formula, where Pi represents the i-th predicted value, O_i represents the i-th observed value, and n represents the number of paired values. In this technical note, the observed values come from 2020 AIM field sampling plots while predicted values represent the pixel values at that same location for each of the three compared products (LandCART, RCMAP, and RAP). RMSE is generally interpreted such that a smaller value represents a better fit of the model to the observed field data. RMSE is very similar to mean absolute error. However, RMSE is more sensitive to large errors because it squares the errors before they are averaged, and the square root is calculated. See mean absolute error (MAE).

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(P_i - O_i)^2}{n}}$$

Pearson correlation coefficient (r): often referred to simply as the "correlation coefficient," a statistical measure of the linear correlation between two sets of data. The correlation coefficient can be calculated using the subsequent formula. In this technical note, x_i refers to the i-th observed values, $\bar{x}$ refers to the average observed value, y_i is the i-th predicted value, while $\bar{y}$ is the average predicted value. In this technical note, the observed values come from 2020 AIM field sampling plots while predicted values represent the pixel values at that same location for each of the three compared products (LandCART, RCMAP, and RAP).

$$r = \frac{\sum(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum(x_i - \bar{x})^2 \sum(y_i - \bar{y})^2}}$$

striping: an anomaly in remotely sensed imagery characterized by linear features, often oriented in the direction the sensor is traveling, that do not correspond to any real feature on the ground. Striping can occur for various reasons, including scan-line issues within the sensor where data is not collected in that strip or from mosaicking images from different days due to changes in illumination.

training: in the context of this technical note, training is the process of fitting a statistical model to a set of data observations to generate predictions. The set of data used to fit this model is generally referred to as training data. This contrasts with validation data, which is data collected in the same manner but withheld from model training in order to assess model performance.

Appendix A: Literature Review

A literature review was performed for the three fractional vegetation cover products in this technical note: Landscape Cover Analysis and Reporting Tools (LandCART); Rangeland Condition, Monitoring, Assessment, and Projection (RCMAP); and Rangeland Analysis Platform (RAP). A review of the journal articles in this appendix found that the methodologies applied in each product, while different, are detailed, rigorous, and defensible. All data were validated internally with independent datasets.

LandCART

Webb, N.P., S.E. McCord, B.L. Edwards, J.E. Herrick, E. Kachergis, G.S. Okin, and J.W. Van Zee. 2021. Vegetation canopy gap size and height: Critical indicators for wind erosion monitoring and management. Rangeland Ecology & Management 76 (2021): 78-83.

Zhang, J., G.S. Okin, and B. Zhou. 2019. Assimilating optical satellite remote sensing images and field data to predict surface indicators in the Western U.S.: Assessing error in satellite predictions based on large geographical datasets with the use of machine learning. Remote Sensing of Environment 233 (2019): 111382.

Zhou, B., G.S. Okin, and J. Zhang. 2020. Leveraging Google Earth Engine (GEE) and machine learning algorithms to incorporate in situ measurement from different times for rangelands monitoring. Remote Sensing of Environment 236: 111521.

RCMAP

Rigge, M., C. Homer, H. Shi, and D.K. Meyer. 2019. Validating a Landsat time-series of fractional component cover across Western U.S. rangelands. Remote Sensing 11 (24): 3009.

Rigge, M., H. Shi, C. Homer, P. Danielson, and B. Granneman. 2019. Long-term trajectories of fractional component change in the Northern Great Basin, USA. Ecosphere 10 (6): e02762.

Rigge, M., C. Homer, L. Cleeves, D.K. Meyer, B. Bunde, H. Shi, G. Xian, S. Schell, and M. Bobo. 2020. Quantifying Western U.S. rangelands as fractional components with multi-resolution remote sensing and in situ data. Remote Sensing 12 (3): 412.

Rigge, M., C. Homer, H. Shi, D. Meyer, B. Bunde, B. Granneman, K. Postma, P. Danielson, A. Case, and G. Xian. 2021. Rangelands fractional components across the Western United States from 1985 to 2018. Remote Sensing 13 (4): 813.

Shi, H., C. Homer, M. Rigge, K. Postma, and G. Xian. 2020. Analyzing vegetation change in a sagebrush ecosystem using long-term field observations and Landsat imagery in Wyoming. Ecosphere 11 (12): e03311.

Xian, G., C. Homer, M. Rigge, H. Shi, and D. Meyer. 2015. Characterization of shrubland ecosystem components as continuous fields in the northwest United States. Remote Sensing of Environment 168: 286-300.

RAP

Allred, B.W., B.T. Bestelmeyer, C.S. Boyd, C. Brown, K.W. Davies, M.C. Duniway, L.M. Ellsworth, T.A. Erickson, S.D. Fuhlendorf, T.V. Griffiths, V. Jansen, M.O. Jones, J. Karl, A. Knight, J.D. Maestas, J.J. Maynard, S.E. McCord, D.E. Naugle, H.D. Starns, D. Twidwell, and D.R. Uden. 2021. Improving Landsat predictions of rangeland fractional cover with multitask learning and uncertainty. Methods in Ecology and Evolution 12 (5): 841-849.

Jones, M.O., B.W. Allred, D.E. Naugle, J.D. Maestas, P. Donnelly, L.J. Metz, J. Karl, R. Smith, B. Bestelmeyer, C. Boyd, J.D. Kerby, and J.D. McIver. 2018. Innovation in rangeland monitoring: Annual, 30 m, plant functional type percent cover maps for U.S. rangelands, 1984–2017. Ecosphere 9 (9): e02430.

Appendix B: BLM Independent Accuracy Assessment

This appendix provides the results of the independent accuracy assessment of the three products reviewed in this report: Landscape Cover Analysis and Reporting Tools (LandCART); Rangeland Condition, Monitoring, Assessment, and Projection (RCMAP); and Rangeland Analysis Platform (RAP). The methods of accuracy assessment are described step-by-step to demonstrate the diligence in performing a logical and defensible independent accuracy assessment.

1. Independent validation data (testing data) were extracted from the Assessment, Inventory, and Monitoring (AIM) 2.0 in-house database. In ArcGIS Pro, all points with "Date Visited" after January 1, 2020, were extracted into a separate feature class on May 4, 2021. Both AIM data and Landscape Monitoring Framework (LMF) data were extracted for a total of 3,246 points.

2. Before exporting as shapefiles, the 2020 testing data feature class was projected to match the Google Earth Engine (GEE) default projection (EPSG4326) for RAP and LandCART data and the RCMAP projection (Albers Conic Equal Area). After projection, the feature classes were exported to shapefiles.

3. The EPSG4326 dataset was imported to Google Earth Engine as an asset.

4. Bo Zhou of the University of California, Los Angeles (UCLA), wrote models to extract LandCART indicators with random forest (RF) through GEE based on 2020 Month and Day dates (Appendix C, Table C1). Indicators extracted are: annual herbaceous, bare ground, bare soil, herbaceous, perennial herbaceous, sagebrush, shrubs, and trees. "Any hit" (AH) values were used in calculations of the indicators.

5. Indicator values from the 2020 RCMAP datasets were extracted using ArcGIS Pro after downloading the back-in-time data from 2009-2020 from the Multi-Resolution Land Characteristics data download website (https://www.mrlc.gov/data). Indicators extracted included: annual herbaceous, bare ground, herbaceous, litter, sagebrush, and shrubs. "First hit" (FH) values were used in calculations of the indicators.

6. Indicator values were extracted from the RAP datasets in GEE for the 2020 image (http://rangeland.ntsg.umt.edu/data/rap/rap-vegetation-cover/v2/vegetation-cover-v2-2020). Indicators extracted included: annual herbaceous, bare soil, litter, perennial herbaceous, shrubs, and trees. "First hit" (FH) values were used in calculations of the indicators.

7. The three extracted datasets were imported into RStudio for statistical calculations. Joining the three datasets resulted in 3,034 matching locations for testing. Observed values come from the AIM 2.0 testing data. Predicted values are the extracted values from instructions 4, 5, and 6. Note that LandCART used "any hit" records from AIM 2.0 for most of the indicators, while RAP and RCMAP used "first hit" records for all the indicators they predicted (AIM 2.0 indicator definitions are provided in the Independent Accuracy Assessment Statistics portion of this appendix which follows). The appropriate observed values were used in the validation calculations.

8. Accuracy assessment statistics for this evaluation were compared to each product's published accuracy assessment statistics (Table 1 in the main body and Appendix C). A comprehensive statistical report of the full testing dataset (display follows) includes observed versus predicted data in hex plots for each product and calculates the Pearson correlation coefficient, R^2 (coefficient of determination), the root mean squared error (RMSE), the mean absolute error (MAE), and the slope of the regression line. Additional information displayed in Table 2 in the main body of this technical note includes summary statistics of the observed and predicted indicators. The calculations used to define each indicator are subsequently listed with each statistical comparison. Only the indicators with the same definition were compared in these analyses.

Table B1a. Calculations of AIM 2.0 data used to create validation indicators for LandCART 2020.

Predicted Indicator	AIM 2.0 Definition
Herbaceous	AH_NoxAnnForbCover + AH_NoxAnnGrassCover + AH_NonNoxAnnForbCover + AH_NonNoxAnnGrassCover + AH_NoxPerenForbCover + AH_NoxPerenGrassCover + AH_NonNoxPerenForbCover + AH_NonNoxPerenGrassCover
Shrubs	AH_NoxShrubCover + AH_NoxSubShrubCover + AH_NonNoxShrubCover + AH_NonNoxSubShrubCover
Trees	AH_NoxTreeCover + AH_NonNoxTreeCover
Bare Ground	BareSoilCover + FH_RockCover + FH_DepSoilCover
Bare Soil	BareSoilCover
Sagebrush	AH_SagebrushCover
Annual Herbaceous	AH_NoxAnnForbCover + AH_NoxAnnGrassCover + AH_NonNoxAnnForbCover + AH_NonNoxAnnGrassCover
Perennial Herbaceous	AH_NoxPerenForbCover + AH_NoxPerenGrassCover + AH_NonNoxPerenForbCover + AH_NonNox PerenGrassCover

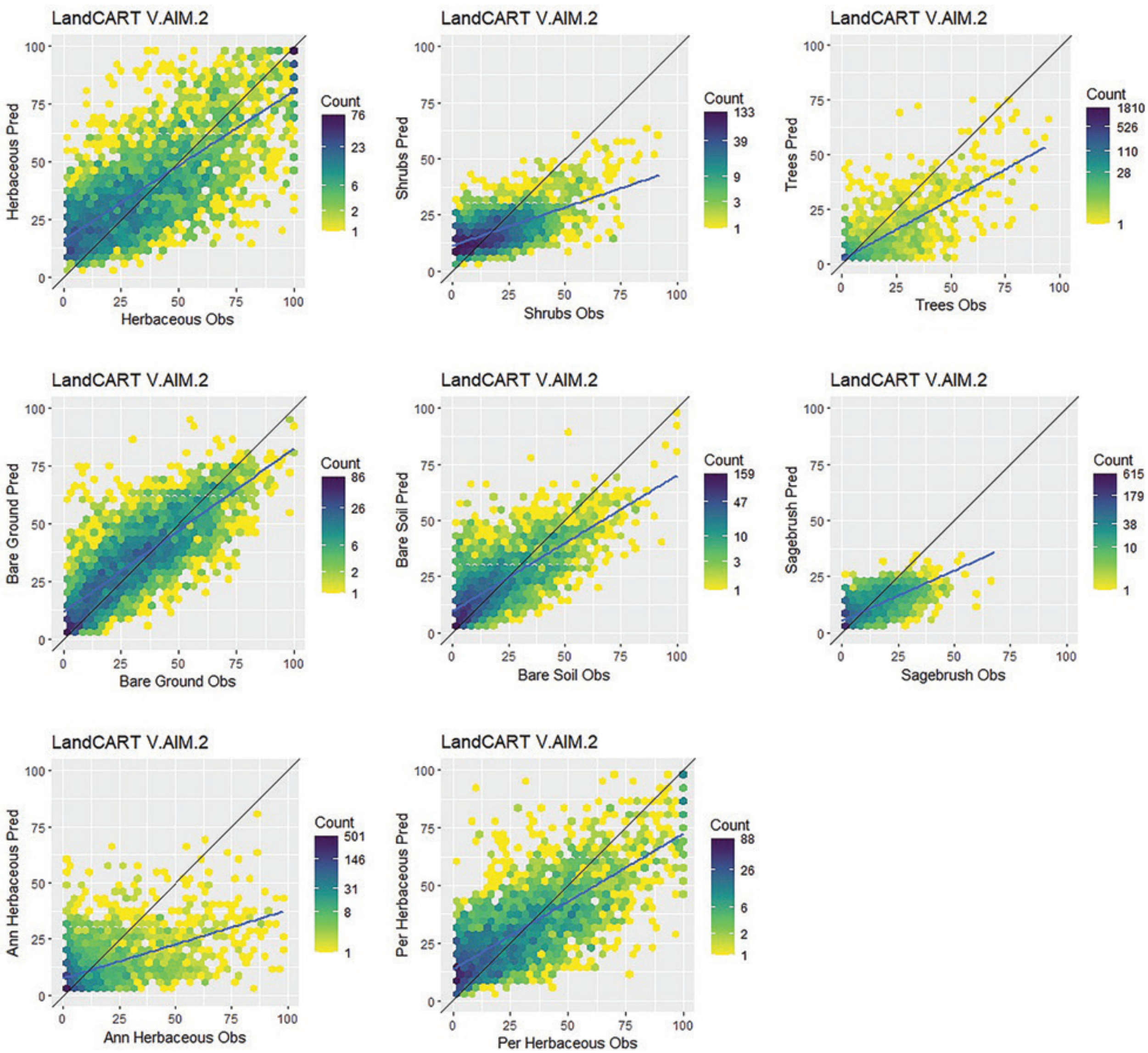


Figure B1a. AIM 2.0 testing data (observed) vs. LandCART V.AIM.2 indicators (predicted). The blue line is a linear model of observed vs. predicted values; the black line is a 1-1 line.

Table B1b. Calculations of AIM 2.0 data used to create validation indicators for RCMAP 2020.

Predicted Indicator	AIM 2.0 Definition
Shrub	FH_NoxShrubCover + FH_NoxSubShrubCover + FH_NoxSucculentCover + FH_NonNoxShrubCover +FH_NonNoxSubShrubCover + FH_NonNoxSucculentCover
Herb	FH_NoxAnnForbCover + FH_NoxAnnGrassCover + FH_NonNoxAnnForbCover + FH_NonNoxAnnGrassCover + FH_NoxPerenForbCover + FH_NoxPerenGrassCover + FH_NonNoxPerenForbCover + FH_NonNoxPerenGrassCover
Litter	FH_TotalLitterCover
Bare	BareSoilCover + FH_RockCover + FH_DepSoilCover
Sage	FH_SagebrushCover
AnnHerb	FH_NoxAnnForbCover + FH_NoxAnnGrassCover + FH_NonNoxAnnForbCover + FH_NonNoxAnnGrassCover

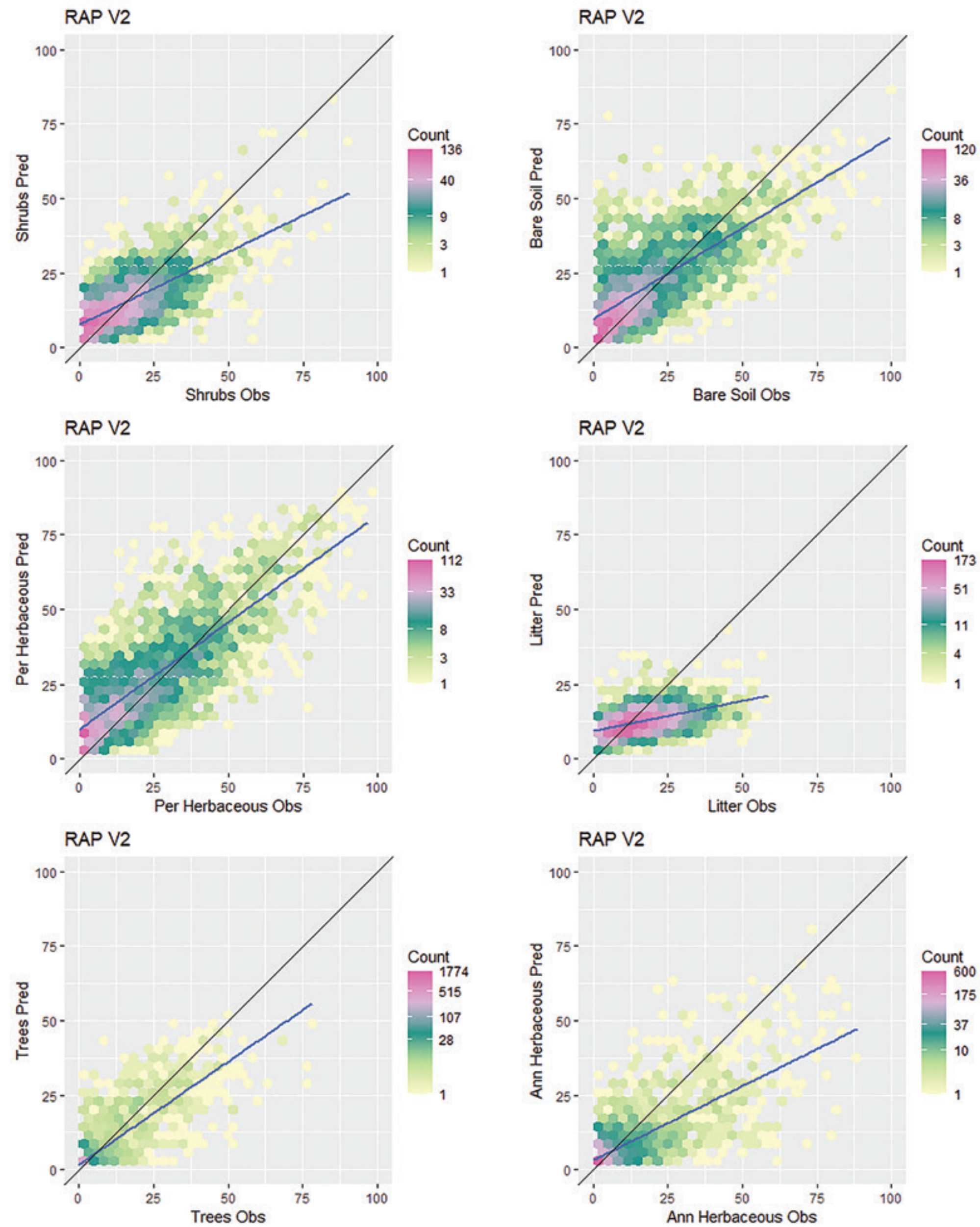
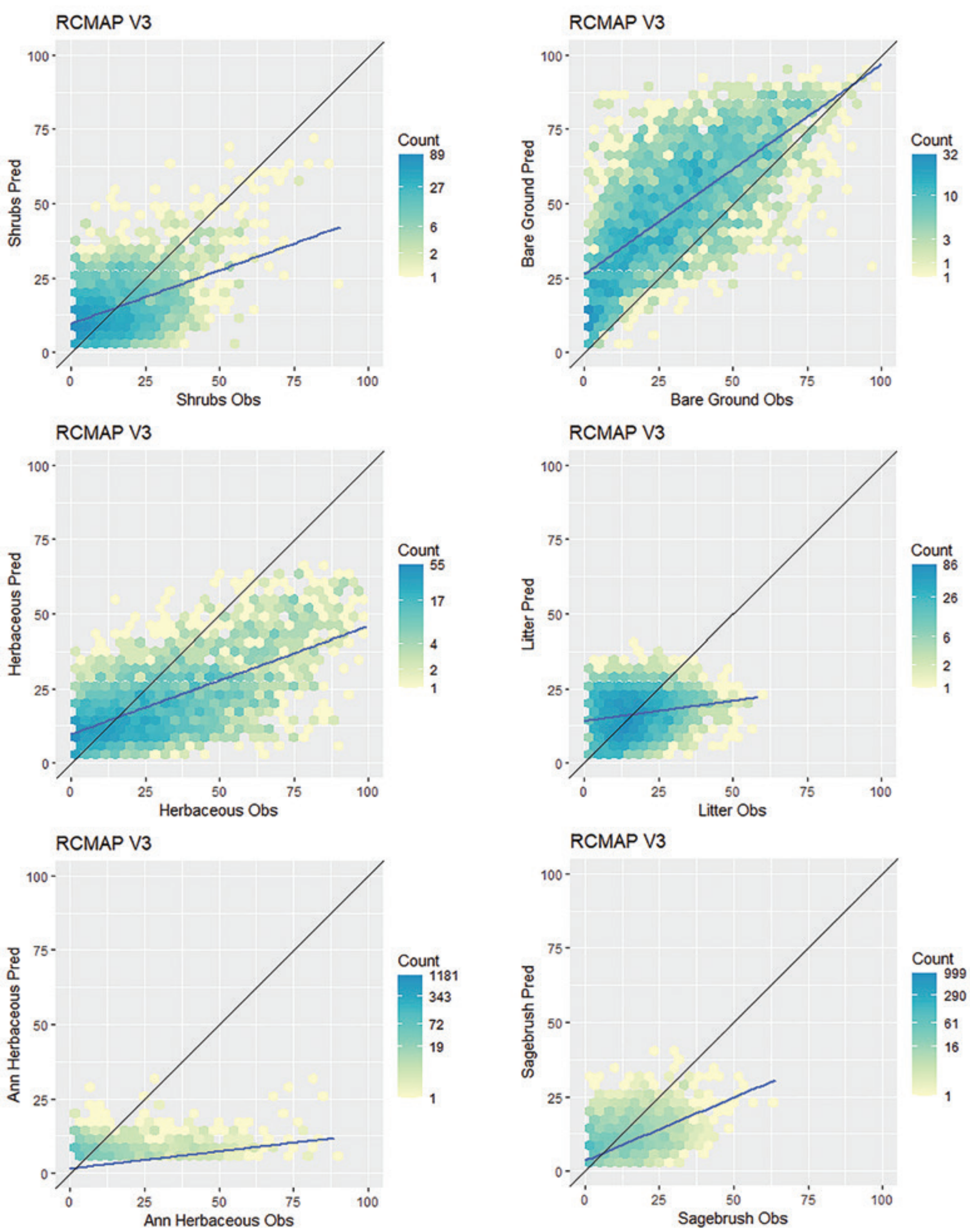


Figure B1b. AIM 2.0 testing data (observed) vs. RCMAP V3 indicators (predicted). The blue line is a linear model of observed vs. predicted values; the black line is a 1-1 line.

Table B1c. Calculations of AIM 2.0 data used to create validation indicators for RAP 2020.

Predicted Indicator	AIM 2.0 Definition
Annual Cover	FH_NoxAnnForbCover + FH_NoxAnnGrassCover + FH_NonNoxAnnForbCover + FH_NonNoxAnnGrassCover
Perennial Cover	FH_NoxPerenForbCover + FH_NoxPerenGrassCover + FH_NonNoxPerenForbCover + FH_NonNoxPerenGrassCover
Shrub Cover	FH_NoxShrubCover + FH_NoxSubShrubCover + FH_NonNoxShrubCover + FH_NonNoxSubShrubCover
Tree Cover	FH_NoxTreeCover + FH_NonNoxTreeCover
Bare Ground	BareSoilCover
Litter	FH_TotalLitterCover

Figure B1c. AIM 2.0 testing data (observed) vs. RAP V2 indicators (predicted). The blue line is a linear model of observed vs. predicted values; the black line is a 1-1 line.



Independent Accuracy Assessment Statistics

ANNUAL HERBACEOUS

LandCART (2020) v RCMAP (2020) v RAP (2020)

Product	Predicted Indicator	AIM 2.0 Definition
LandCART 20	Annual Herbaceous	AH_NoxAnnForbCover + AH_NoxAnnGrassCover + AH_NonNoxAnnForbCover + AH_NonNoxAnnGrassCover
RCMAP 20	AnnHerb	FH_NoxAnnForbCover + FH_NoxAnnGrassCover + FH_NonNoxAnnForbCover + FH_NonNoxAnnGrassCover
RAP 20	Annual Cover	FH_NoxAnnForbCover + FH_NoxAnnGrassCover + FH_NonNoxAnnForbCover + FH_NonNoxAnnGrassCover

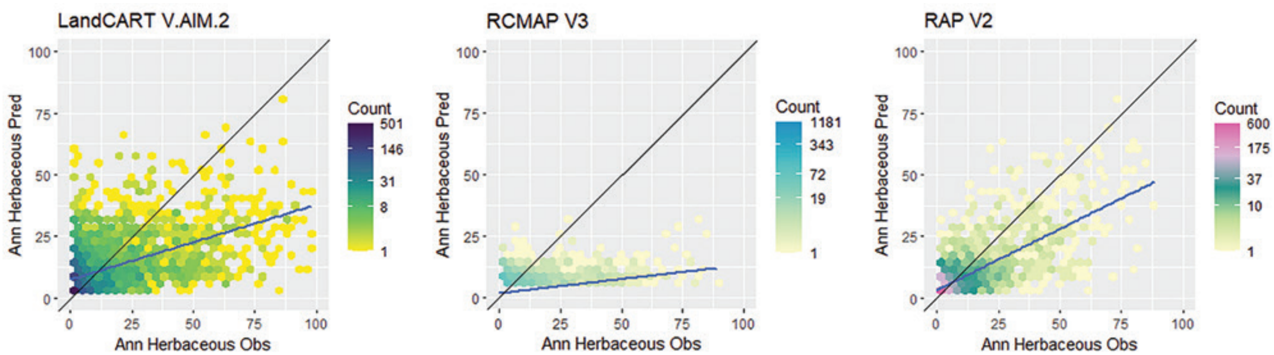


Figure B2a. AIM 2.0 testing data (observed) vs. predicted annual herbaceous from LandCART V.AIM.2 (left), RCMAP V3 (middle), and RAP V2 (right). The blue line is a linear model of observed vs. predicted values; the black line is a 1-1 line. Accuracy assessment statistics for this indicator are in Table B2a.

Table B2a. Accuracy assessment statistics for annual herbaceous. LandCART V.AIM.2, RCMAP V3, and RAP V2 vs. AIM 2.0 testing data (IAA) and relevant published results (Pub). Correlation is the Pearson correlation coefficient between observed and predicted data; R^2 is the squared Pearson correlation coefficient (coefficient of determination); RMSE is the root mean squared error; MAE is the mean absolute error; and slope is the slope of a linear model of predicted vs. observed.

Product	Correlation	R^2	RMSE	MAE	Slope	Min Obs	Max Obs	Min Pred	Max Pred
LandCART IAA	0.51	0.26	15.3	9.91	0.3	0	98	0	81
LandCART Pub	0.73	0.54	16.09	10.76	NA	-	-	-	-
RCMAP IAA	0.36	0.13	14.21	7.59	0.12	0	89	0	32
RCMAP Pub	0.76	0.58	9.8	NA	0.55	-	-	-	-
RAP IAA	0.72	0.52	9.63	5.77	0.5	0	89	0	82
RAP Pub	0.76	0.58	11	7	NA	-	-	-	-

SHRUBS

LandCART (2020) v RCMAP (2020) v RAP (2020)

Product	Predicted Indicator	AIM 2.0 Definition
LandCART 20	Shrubs	AH_NoxShrubCover + AH_NoxSubShrubCover + AH_NonNoxShrubCover + AH_NonNoxSubShrubCover
RCMAP 20	Shrub	FH_NoxShrubCover + FH_NoxSubShrubCover + FH_NonNoxShrubCover + FH_NonNoxSubShrubCover
RAP 20	Shrub Cover	FH_NoxShrubCover + FH_NoxSubShrubCover + FH_NonNoxShrubCover + FH_NonNoxSubShrubCover

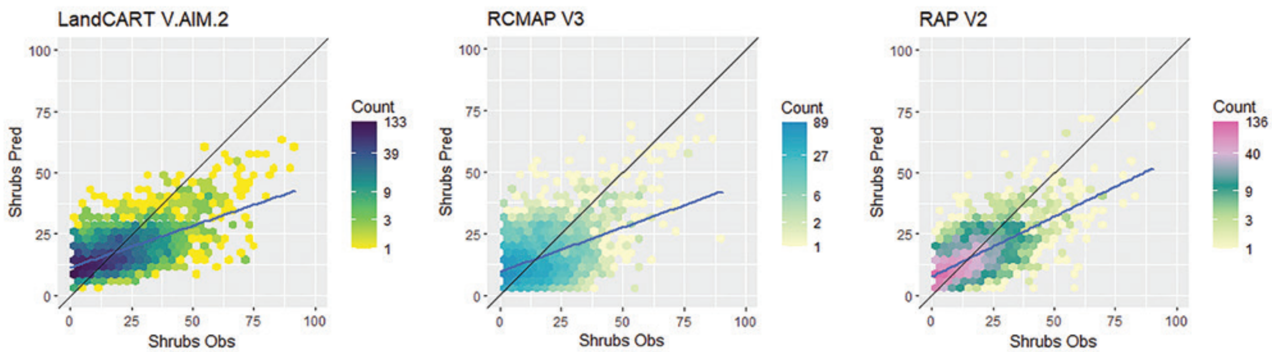


Figure B2b. AIM 2.0 testing data (observed) vs. predicted shrubs from LandCART V.AIM.2 (left), RCMAP V3 (middle), and RAP V2 (right). The blue line is a linear model of observed vs. predicted values; the black line is a 1-1 line. Accuracy assessment statistics for this indicator are in Table B2b.

Table B2b. Accuracy assessment statistics for shrubs. LandCART V.AIM.2, RCMAP V3, and RAP V2 vs. AIM 2.0 testing data (IAA) and relevant published results (Pub). Correlation is the Pearson correlation coefficient between observed and predicted data; R^2 is the squared Pearson correlation coefficient (coefficient of determination); RMSE is the root mean squared error; MAE is the mean absolute error; and slope is the slope of a linear model of predicted vs. observed.

Product	Correlation	R^2	RMSE	MAE	Slope	Min Obs	Max Obs	Min Pred	Max Pred
LandCART IAA	0.63	0.39	11.25	8.66	0.34	0	92	1	63
LandCART Pub	0.62	0.39	10.39	8.06	NA	-	-	-	-
RCMAP IAA	0.46	0.22	12.24	9.53	0.36	0	91	0	72
RCMAP Pub	0.58	0.34	10.5	NA	0.5	-	-	-	-
RAP IAA	0.69	0.48	9.41	7.05	0.49	0	91	0	85
RAP Pub	0.75	0.57	8.3	5.8	NA	-	-	-	-

BARE GROUND

LandCART (2020) vs. RCMAP (2020)

Product	Predicted Indicator	AIM 2.0 Definition
LandCART 20	Bare Ground	BareSoilCover + FH_RockCover + FH_DepSoilCover
RCMAP 20	Bare	BareSoilCover + FH_RockCover + FH_DepSoilCover

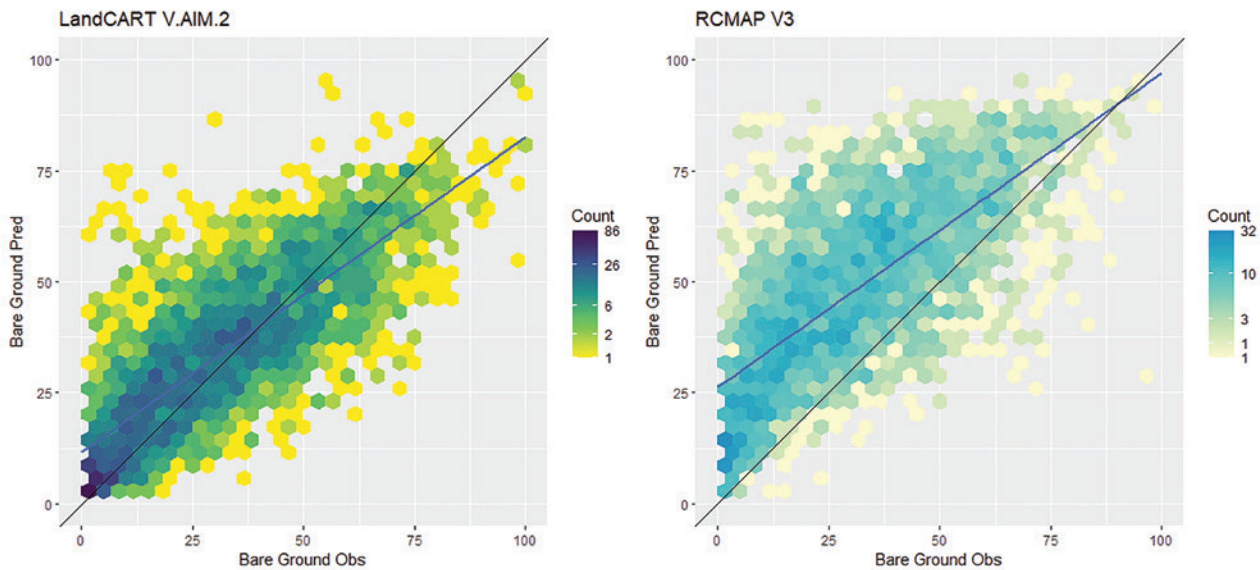


Figure B2c. AIM 2.0 testing data (observed) vs. predicted bare ground from LandCART V.AIM.2 (left) and RCMAP V3 (right). The blue line is a linear model of observed vs. predicted values; the black line is a 1-1 line. Accuracy assessment statistics for this indicator are in Table B2c.

Table B2c. Accuracy assessment statistics for bare ground. LandCART V.AIM.2 and RCMAP V3 vs. AIM 2.0 testing data (IAA) and relevant published results (Pub). Correlation is the Pearson correlation coefficient between observed and predicted data; R^2 is the squared Pearson correlation coefficient (coefficient of determination); RMSE is the root mean squared error; MAE is the mean absolute error; and slope is the slope of a linear model of predicted vs. observed.

Product	Correlation	R^2	RMSE	MAE	Slope	Min Obs	Max Obs	Min Pred	Max Pred
LandCART IAA	0.8	0.64	13.14	9.69	0.71	0	100	1	97
LandCART Pub	0.85	0.73	11.96	9.04	NA	-	-	-	-
RCMAP IAA	0.71	0.5	23.62	19.4	0.71	0	100	1	100
RCMAP Pub	0.84	0.7	14.4	NA	0.73	-	-	-	-

HERBACEOUS

LandCART (2020) v RCMAP (2020)

Product	Predicted Indicator	AIM 2.0 Definition
LandCART 20	Herbaceous	AH_NoxAnnForbCover + AH_NoxAnnGrassCover + AH_NonNoxAnnForbCover + AH_NonNoxAnnGrassCover + AH_NoxPerenForbCover + AH_NoxPerenGrassCover + AH_NonNoxPerenForbCover + AH_NonNox PerenGrassCover
RCMAP 20	Herb	FH_NoxAnnForbCover + FH_NoxAnnGrassCover + FH_ NonNoxAnnForbCover + FH_NonNoxAnnGrassCover + FH_NoxPerenForbCover + FH_NoxPerenGrassCover + FH_ NonNoxPerenForbCover + FH_NonNoxPerenGrassCover

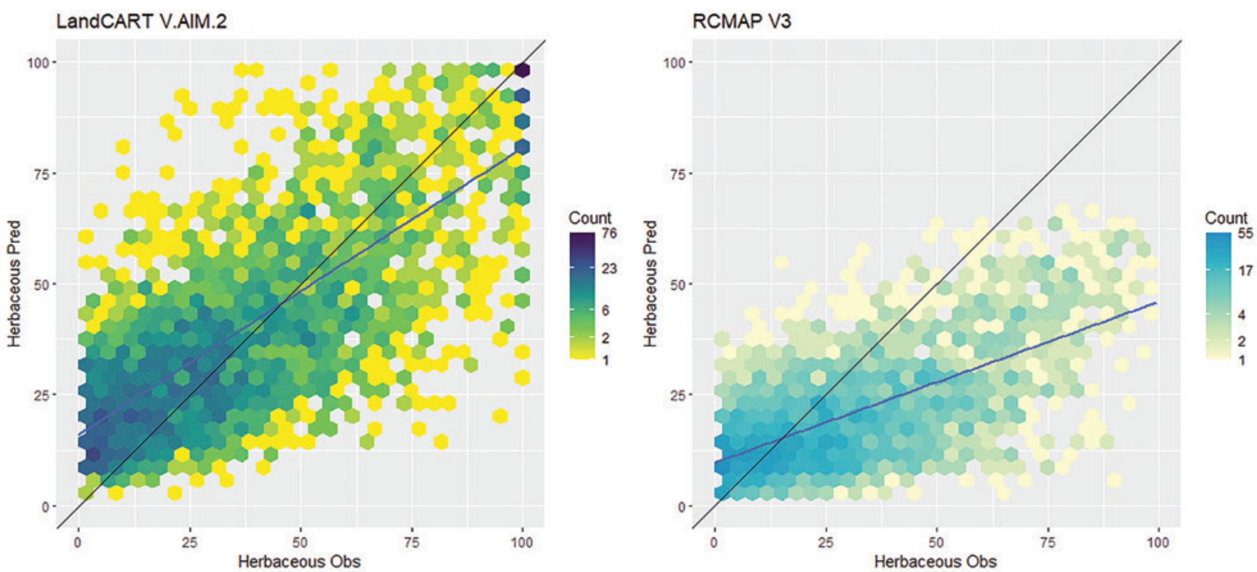


Figure B2d. AIM 2.0 testing data (observed) vs. predicted herbaceous from LandCART V.AIM.2 (left) and RCMAP V3 (right). The blue line is a linear model of observed vs. predicted values; the black line is a 1-1 line. Accuracy assessment statistics for this indicator are in Table B2d.

Table B2d. Accuracy assessment statistics for herbaceous. LandCART V.AIM.2 and RCMAP V3 vs. AIM 2.0 testing data (IAA) and relevant published results (Pub). Correlation is the Pearson correlation coefficient between observed and predicted data; R^2 is the squared Pearson correlation coefficient (coefficient of determination); RMSE is the root mean squared error; MAE is the mean absolute error; and slope is the slope of a linear model of predicted vs. observed.

Product	Correlation	R^2	RMSE	MAE	Slope	Min Obs	Max Obs	Min Pred	Max Pred
LandCART IAA	0.77	0.59	18.66	14.45	0.65	0	100	2	100
LandCART Pub	0.83	0.69	19.32	14.34	NA	-	-	-	-
RCMAP IAA	0.65	0.42	20.06	15.18	0.36	0	99	0	67
RCMAP Pub	0.82	0.67	13.1	NA	0.61	-	-	-	-

SAGEBRUSH

LandCART (2020) v RCMAP (2020)

Product	Predicted Indicator	AIM 2.0 Definition
LandCART 20	Sagebrush	AH_SagebrushCover
RCMAP 20	Sage	FH_SagebrushCover

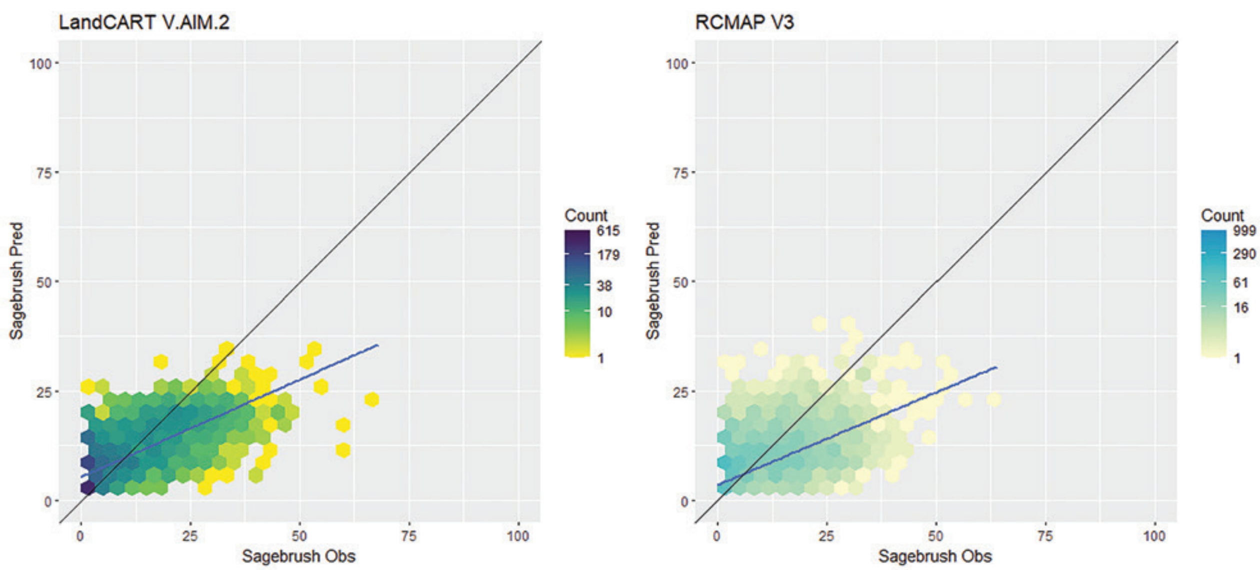


Figure B2e. AIM 2.0 testing data (observed) vs. predicted sagebrush from LandCART V.AIM.2 (left) and RCMAP V3 (right). The blue line is a linear model of observed vs. predicted values; the black line is a 1-1 line. Accuracy assessment statistics for this indicator are in Table B2e.

Table B2e. Accuracy assessment statistics for sagebrush. LandCART V.AIM.2 and RCMAP V3 vs. AIM 2.0 testing data (IAA) and relevant published results (Pub). Correlation is the Pearson correlation coefficient between observed and predicted data; R^2 is the squared Pearson correlation coefficient (coefficient of determination); RMSE is the root mean squared error; MAE is the mean absolute error; and slope is the slope of a linear model of predicted vs. observed.

Product	Correlation	R^2	RMSE	MAE	Slope	Min Obs	Max Obs	Min Pred	Max Pred
LandCART IAA	0.68	0.46	7.84	5.57	0.45	0	68	0	36
LandCART Pub	0.66	0.43	8.67	6.3	NA	-	-	-	-
RCMAP IAA	0.57	0.33	8.41	5.51	0.42	0	64	0	40
RCMAP Pub	0.63	0.4	7.5	NA	0.5	-	-	-	-

BARE SOIL

LandCART (2020) v RAP (2020)

Product	Predicted Indicator	AIM 2.0 Definition
LandCART 20	Bare Soil	BareSoilCover
RAP 20	Bare Soil	BareSoilCover

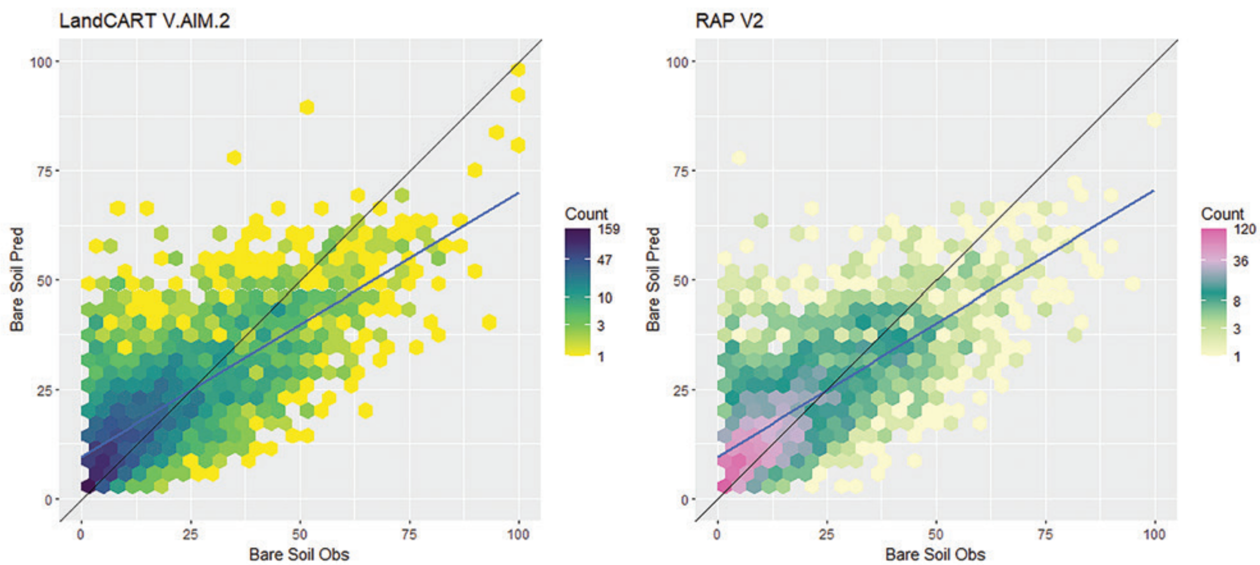


Figure B2f. AIM 2.0 testing data (observed) vs. predicted bare soil from LandCART V.AIM.2 (left) and RAP V2 (right). The blue line is a linear model of observed vs. predicted values; the black line is a 1-1 line. Accuracy assessment statistics for this indicator are in Table B2f.

Table B2f. Accuracy assessment statistics for bare soil. LandCART V.AIM.2 and RAP V2 vs. AIM 2.0 testing data (IAA) and relevant published results (Pub). Correlation is the Pearson correlation coefficient between observed and predicted data; R^2 is the squared Pearson correlation coefficient (coefficient of determination); RMSE is the root mean squared error; MAE is the mean absolute error; and slope is the slope of a linear model of predicted vs. observed.

Product	Correlation	R^2	RMSE	MAE	Slope	Min Obs	Max Obs	Min Pred	Max Pred
LandCART IAA	0.74	0.55	11.97	8.67	0.6	0	100	0	98
LandCART Pub	0.8	0.64	11.28	8.22	NA	-	-	-	-
RAP IAA	0.73	0.53	12.09	8.63	0.61	0	93	0	76
RAP Pub	0.85	0.73	9.8	6.7	NA	-	-	-	-

TREES

LandCART (2020) v RAP (2020)

Product	Predicted Indicator	AIM 2.0 Definition
LandCART 20	Trees	AH_NoxTreeCover + AH_NonNoxTreeCover
RAP 20	Tree Cover	FH_NoxTreeCover + FH_NonNoxTreeCover

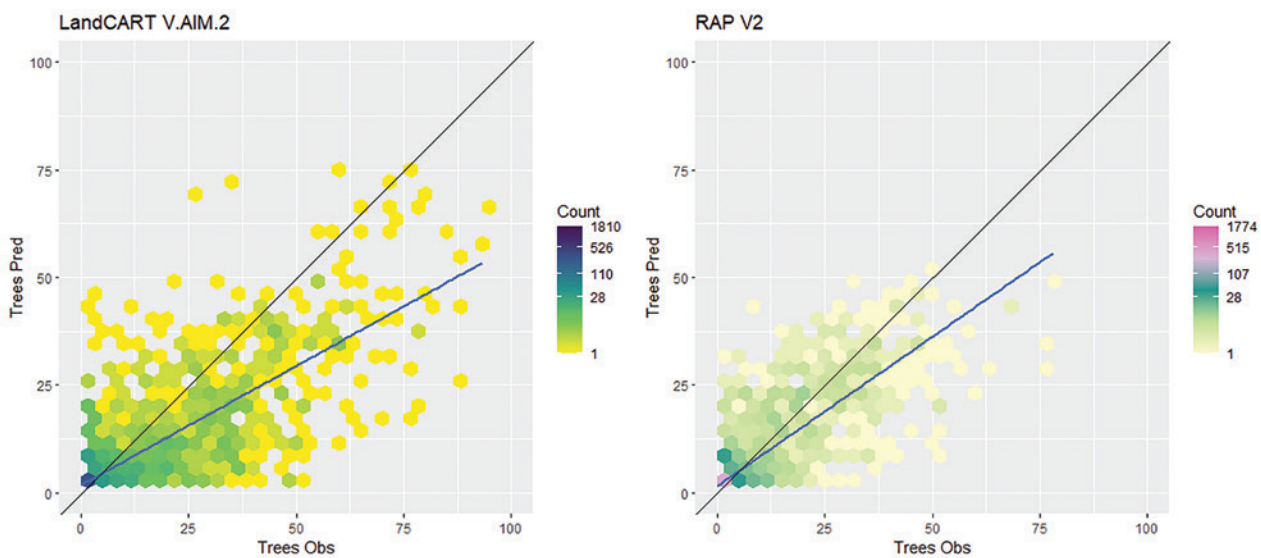


Figure B2g. AIM 2.0 testing data (observed) vs. predicted trees from LandCART V.AIM.2 (left) and RAP V2 (right). The blue line is a linear model of observed vs. predicted values; the black line is a 1-1 line. Accuracy assessment statistics for this indicator are in Table B2g.

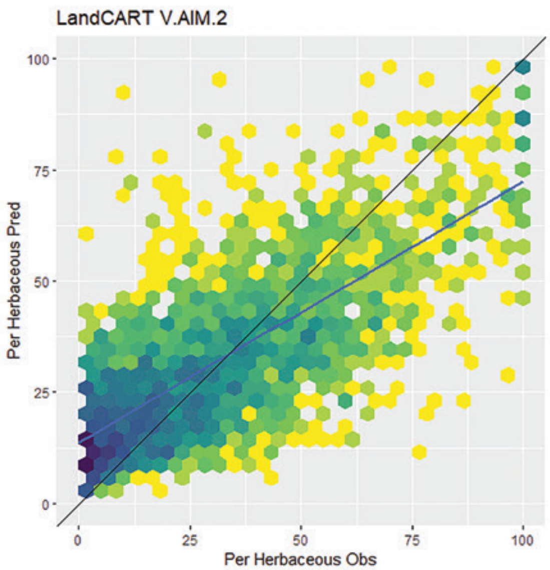
Table B2g. Accuracy assessment statistics for trees. LandCART V.AIM.2 and RAP V2 vs. AIM 2.0 testing data (IAA) and relevant published results (Pub). Correlation is the Pearson correlation coefficient between observed and predicted data; R^2 is the squared Pearson correlation coefficient (coefficient of determination); RMSE is the root mean squared error; MAE is the mean absolute error; and slope is the slope of a linear model of predicted vs. observed.

Product	Correlation	R^2	RMSE	MAE	Slope	Min Obs	Max Obs	Min Pred	Max Pred
LandCART IAA	0.78	0.6	8.88	4.43	0.55	0	93	0	76
LandCART Pub	0.79	0.63	6.57	2.88	NA	-	-	-	-
RAP IAA	0.81	0.65	6.08	2.91	0.69	0	78	0	51
RAP Pub	0.81	0.65	6.8	2.8	NA	-	-	-	-

PERENNIAL HERBACEOUS

LandCART (2020) v RAP (2020)

Product	Predicted Indicator	AIM 2.0 Definition
LandCART 20	Perennial Herbaceous	AH_NoxPerenForbCover + AH_NoxPerenGrassCover + AH_NonNoxPerenForbCover + AH_NonNoxPerenGrassCover
RAP 20	Perennial Cover	FH_NoxPerenForbCover + FH_NoxPerenGrassCover + FH_NonNoxPerenForbCover + FH_NonNoxPerenGrassCover



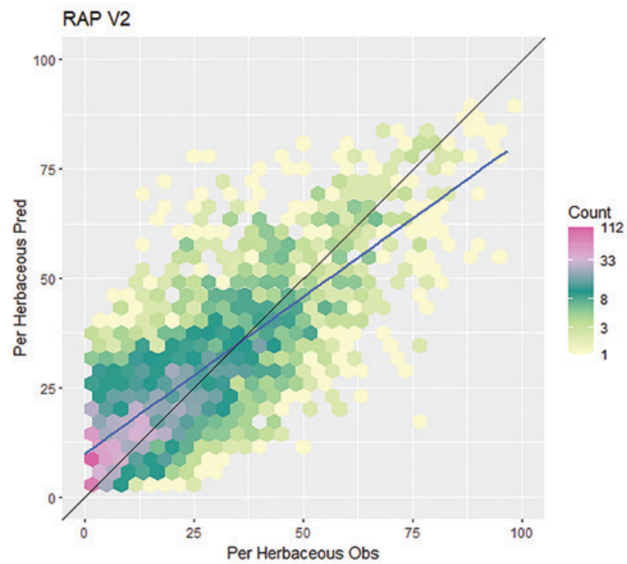


Figure B2h. AIM 2.0 testing data (observed) vs. predicted perennial herbaceous from LandCART V.AIM.2 (left) and RAP V2 (right). The blue line is a linear model of observed vs. predicted values; the black line is a 1-1 line. Accuracy assessment statistics for this indicator are in Table B2h.

Table B2h. Accuracy assessment statistics for perennial herbaceous. LandCART V.AIM.2 and RAP V2 vs. AIM 2.0 testing data (IAA) and relevant published results (Pub). Correlation is the Pearson correlation coefficient between observed and predicted data; R^2 is the squared Pearson correlation coefficient (coefficient of determination); RMSE is the root mean squared error; MAE is the mean absolute error; and slope is the slope of a linear model of predicted vs. observed.

Product	Correlation	R^2	RMSE	MAE	Slope	Min Obs	Max Obs	Min Pred	Max Pred
LandCART IAA	0.77	0.59	16.24	12.56	0.59	0	100	1	100
LandCART Pub	0.78	0.61	15.96	11.71	NA	-	-	-	-
RAP IAA	0.8	0.64	12.77	9.7	0.72	0	97	0	89
RAP Pub	0.88	0.77	14	10.3	NA	-	-	-	-

LITTER

RCMAP (2020) v RAP (2020)

Product	Predicted Indicator	AIM 2.0 Definition
RCMAP 20	Litter	FH_TotalLitterCover
RAP 20	Litter	FH_TotalLitterCover

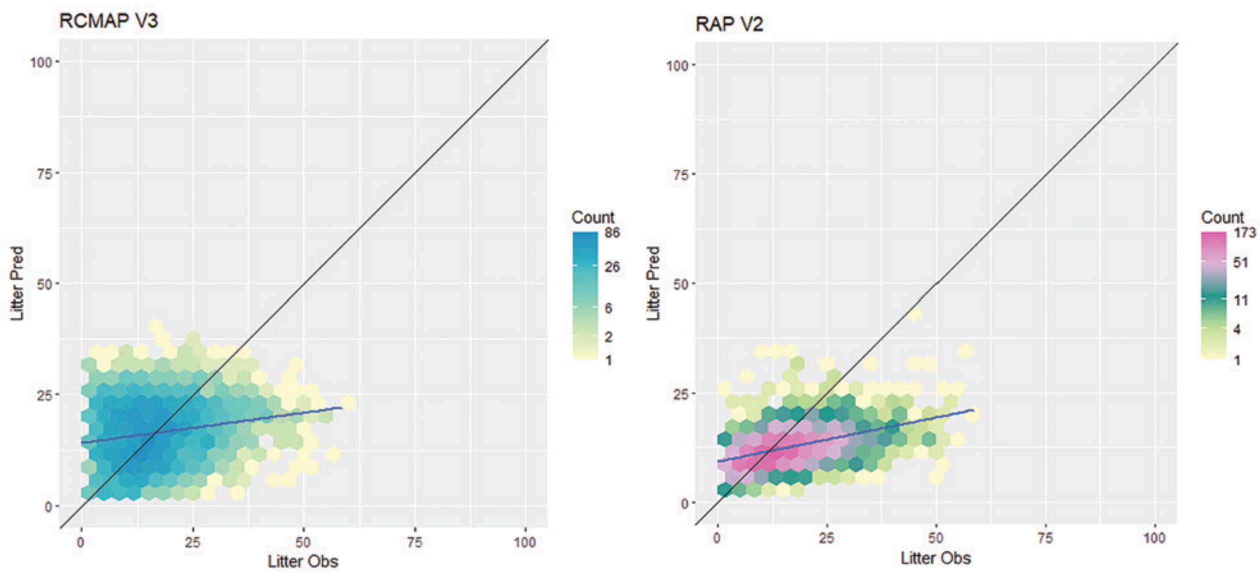


Figure B2i. AIM 2.0 testing data (observed) vs. predicted litter from RCMAP V3 (left) and RAP V2 (right). The blue line is a linear model of observed vs. predicted values; the black line is a 1-1 line. Accuracy assessment statistics for this indicator are in Table B2i.

Table B2i. Accuracy assessment statistics for litter. RCMAP V3 and RAP V2 vs. AIM 2.0 testing data (IAA) and relevant published results (Pub). Correlation is the Pearson correlation coefficient between observed and predicted data; R^2 is the squared Pearson correlation coefficient (coefficient of determination); RMSE is the root mean squared error; MAE is the mean absolute error; and slope is the slope of a linear model of predicted vs. observed.

Product	Correlation	R^2	RMSE	MAE	Slope	Min Obs	Max Obs	Min Pred	Max Pred
RCMAP IAA	0.19	0.04	10.65	8.31	0.14	0	59	0	40
RCMAP Pub	0.59	0.35	8.9	NA	0.42	-	-	-	-
RAP IAA	0.46	0.21	9.28	6.76	0.2	0	59	0	42
RAP Pub	0.61	0.37	7.9	5.7	NA	-	-	-	-

Appendix C: Published Methods and Accuracies

This appendix provides the published or available accuracy metrics calculated for the Landscape Cover Analysis and Reporting Tools (LandCART); Rangeland Condition, Monitoring, Assessment, and Projection (RCMAP); and Rangeland Analysis Reporting (RAP). RCMAP and RAP metrics are published in peer-reviewed manuscripts, as documented. LandCART metrics have not yet been published but were provided so an accuracy metric comparison could be made. A flow chart of RCMAP methodologies is also provided.

LandCART

Table C1. LandCART accuracy metrics calculated in-house by Bo Zhou at the University of California, Los Angeles, and provided to the authors for accuracy comparisons. Metrics were calculated in 2021 by 5-fold cross-validation within the random forest classifier (20% withheld each time). R^2 is the coefficient of determination; RMSE is the root mean squared error; and MAE is the mean absolute error.

Indicator Name	R^2	RMSE	MAE
Annual Herbaceous	0.54	16.09	10.76
Bare Ground	0.73	11.96	9.04
Bare Soil	0.64	11.28	8.22
Herbaceous	0.69	19.32	14.34
Perennial Herbaceous	0.61	15.96	11.71
Sagebrush	0.43	8.67	6.3
Shrubs	0.39	10.39	8.06
Tree	0.63	6.57	2.88

RCMAP

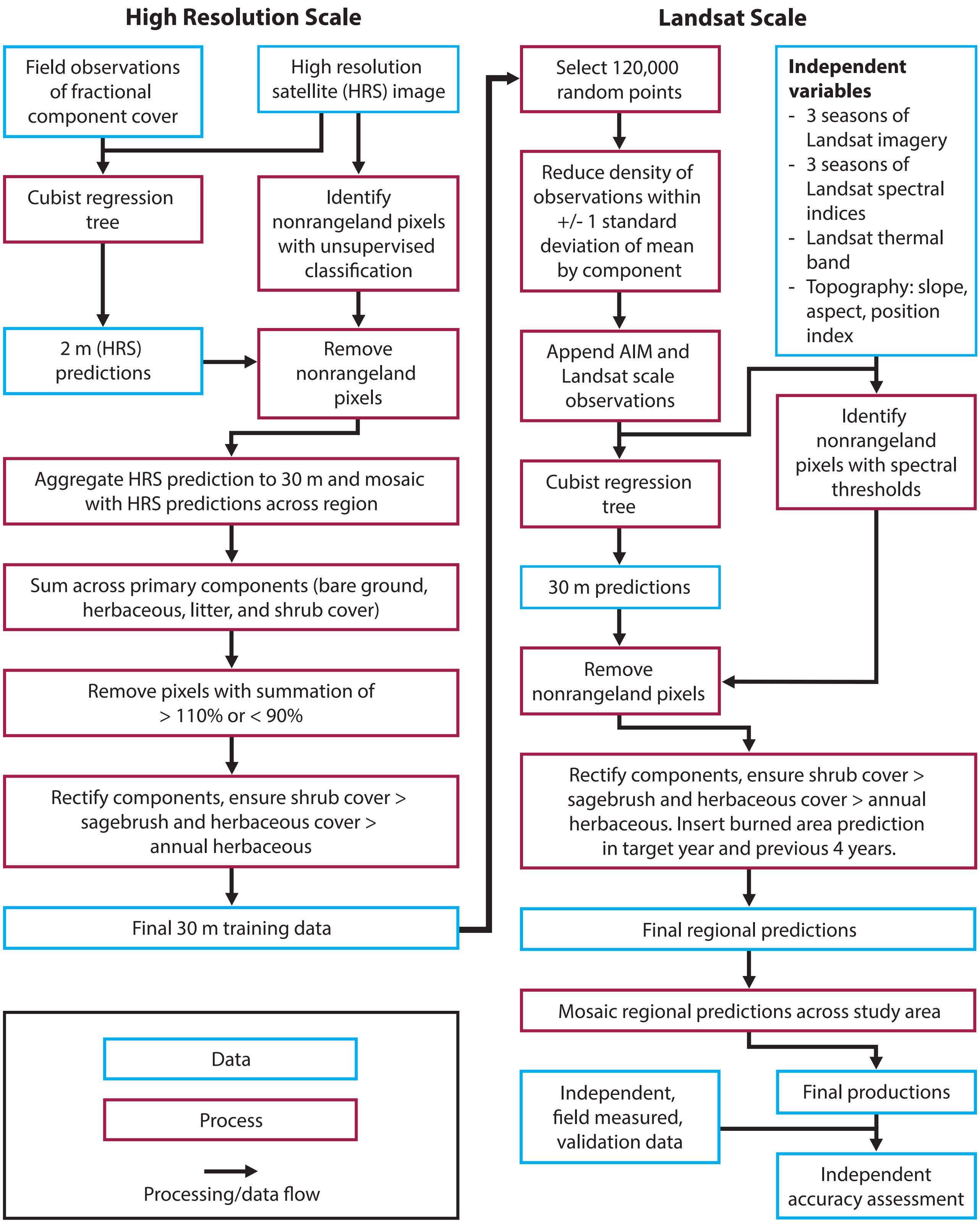


Figure C1. RCMAP flow chart methodologies published in Rigge et al. 2020.

Table C2. RCMAP accuracy metrics published in Rigge et al. 2020.

Validation results of component predictions compared to (a) independent field-measured observations (n = 1860) and (b) cross-validation 30 m training data (n = 840,000) used in model development. Cross-validation statistics were area-weighted by mapping region. Units for average, max, and range are in percent, except for shrub and sagebrush height (ht), which are in centimeters.

(a) Independent Validation									
	Shrub	Sage	Big Sage	Herb	Annual Herb	Litter	Bare Ground	Shrub Ht	Sage Ht
Average	11.8	5.7	2.9	24.0	6.7	16.8	47.3	44.5	17.7
Max	82	69	69	97	97	83	100	400	150
Range	82	69	69	97	97	83	100	400	150
R^2	0.37	0.40	0.16	0.67	0.58	0.35	0.70	0.19	0.24
Slope	0.50	0.52	0.34	0.61	0.55	0.42	0.73	0.29	0.31
RMSE	10.6	7.5	7.8	13.1	9.8	8.9	14.6	39.5	25.6
nRMSE	0.13	0.11	0.11	0.14	0.10	0.11	0.15	0.10	0.19
(b) Cross-Validation									
	Shrub	Sage	Big Sage	Herb	Annual Herb	Litter	Bare Ground	Shrub Ht	Sage Ht
Average	15.7	5.6	4.1	22.6	6.0	16.3	44.4	40.8	13.3
Max	87	59	59	100	92	74	100	865	239
Range	87	59	59	100	92	74	100	865	239
R^2	0.73	0.63	0.63	0.79	0.66	0.75	0.85	0.62	0.59
Slope	0.70	0.63	0.62	0.74	0.64	0.71	0.78	0.62	0.59
RMSE	6.0	3.4	4.1	6.3	4.1	3.8	8.0	17.8	7.8
nRMSE	0.07	0.06	0.07	0.06	0.04	0.05	0.08	0.02	0.03

RAP

Table C3. RAP accuracy metrics published in Allred et al. 2021.

Model evaluation metrics (mean absolute error, MAE; root mean square error, RMSE; residual standard error, RSE; and coefficient of determination, r^2) calculated using the respective validation dataset for fractional cover versions 1.0 and 2.0.

	Annual forb and grass	Perennial forb and grass	Shrub	Tree	Litter	Bare ground	Average
Fractional cover version 2.0 (Allred et al. 2021)							
MAE (%)	7.0	10.3	5.8	2.8	5.7	6.7	6.3
RMSE (%)	11.0	14.0	8.3	6.8	7.9	9.8	9.6
RSE (%)	8.8	12.7	6.6	5.9	4.6	7.9	-
r^2	0.58	0.77	0.57	0.65	0.37	0.73	-
Fractional cover version 1.0 (Jones et al. 2018)							
MAE (%)	7.8	11.1	6.9	4.7	-	7.3	7.56
RMSE (%)	11.8	14.9	9.9	8.5	-	10.6	11.14
RSE (%)	-	-	-	-	-	-	-
r^2	0.43	0.71	0.43	0.52	-	0.71	-

Table C4. Additional RAP accuracy metrics published in Allred et al. 2021.

Model evaluation metrics (mean absolute error, MAE; root mean square error, RMSE; and coefficient of determination, r^2) calculated using additional datasets described in Table 1 in Allred et al. 2021.

	Annual forb and grass	Perennial forb and grass	Shrub	Tree	Litter	Bare ground
RestoreNM						
MAE (%)	5.7	9.7	6.5	-	-	-
RMSE (%)	11.2	13.1	8.1	-	-	-
r^2	0.29	0.22	0.08	-	-	-
SageSTEP						
MAE (%)	9.0	13.2	8.3	-	-	8.9
RMSE (%)	13.3	18.1	9.8	-	-	11.8
r^2	0.19	0.25	0.27	-	-	0.49
EOARC						
MAE (%)	6.6	9.5	5.8	-	-	-
RMSE (%)	9.6	11.8	7.6	-	-	-
r^2	0.43	0.37	0.57	-	-	-
USGS/NPS						
MAE (%)	4.2	8.5	7.6	5.3	7.41	8.1
RMSE (%)	7.8	11.7	10.32	9.6	11.2	11.1
r^2	0.49	0.39	0.56	0.54	0.31	0.71
UI						
MAE (%)	8.0	10.5	9.8	-	-	3.2
RMSE (%)	10.6	13.3	12.1	-	-	4.3
r^2	0.56	0.28	0.30	-	-	0.31

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