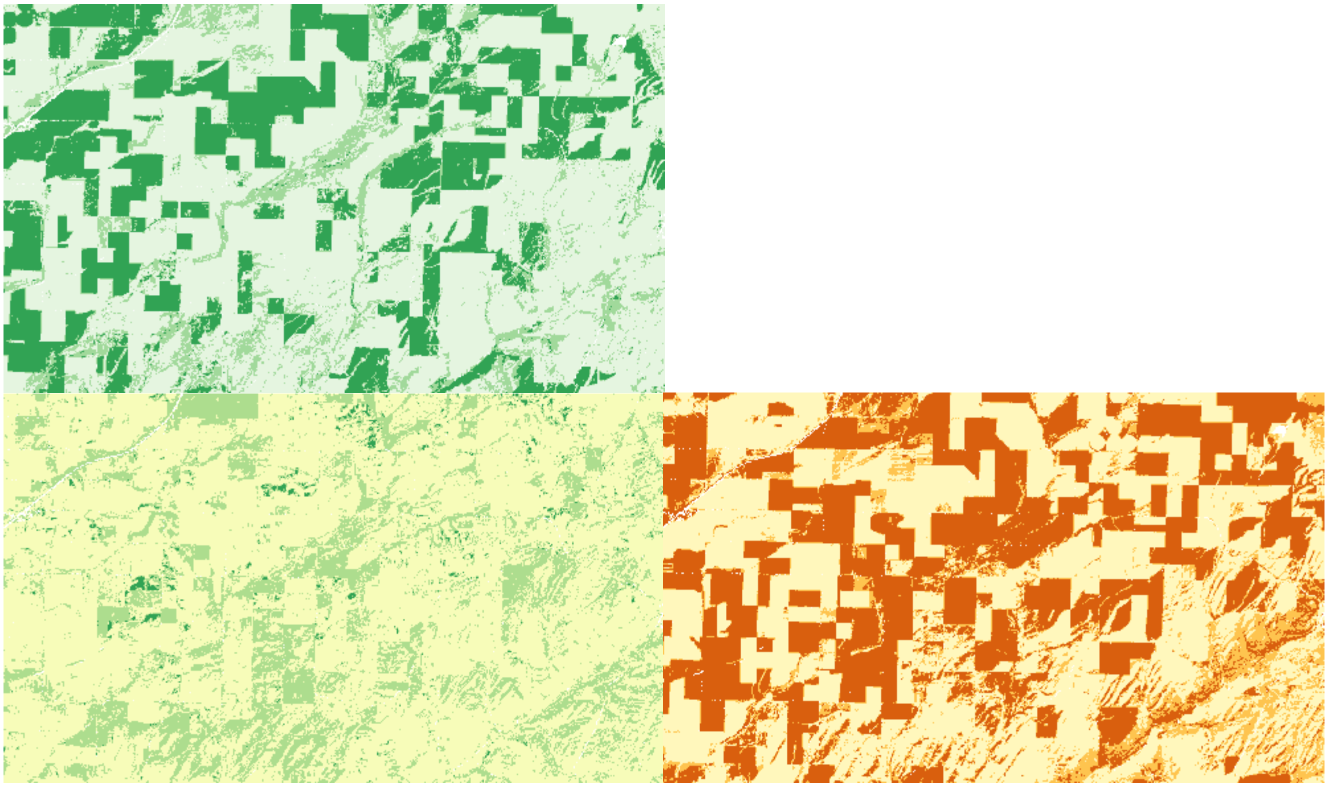
Mapping Conservation Reserve Program Grasslands in Washington, Colorado, and Kansas with Remote Sensing and Machine Learning



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Executive Summary

The USDA Conservation Reserve Program (CRP) works with farmers and landowners to implement conservation management practices on enrolled lands, with paid contracts ranging from 10 to 15 years in length. The CRP Grasslands practices target restoration of agricultural grassland systems by augmenting native vegetation for pollinators, providing habitat for grassland plants and animals, increasing biodiversity, reducing soil erosion, and improving water quality.

The USDA's CRP has been successful in improving the conservation value of millions of acres of farmlands; however, the program currently lacks spatially explicit information on land cover and vegetation within CRP-enrolled tracts. In partnership with the USDA FSA program, the Conservation Biology Institute (CBI) used a combination of remote sensing and machine learning algorithms deployed on the innovative cloud-computing platform, Google Earth Engine, to map grassland characteristics. We used a rich suite of enviro-climatic data, multiple sources of satellite imagery, and Random Forest modeling techniques to predict land cover for study areas in Washington, Colorado, and Kansas, where CRP Grasslands holdings are most prevalent. We used machine learning to create predictive maps of vegetation type by leveraging an extensive set of satellite-derived variables, environmental layers, and federal survey data (from BLM's AIM and USDA NRCS's NRI programs). Our initial investigation utilized Landsat 8 satellite data to model vegetation cover across the Washington study area and then scaled up to the Colorado-Kansas study area. The Washington study site was selected for further model enhancements and an in-depth comparison of Landsat 8, Sentinel-2, and MODIS satellite imagery, to evaluate differences in model development and performance among sensor types. We generated vegetation cover predictions for the year 2019 using Random Forest classification models. Classified outputs for the five vegetation cover models - annual grass, perennial grass, annual forb, perennial forb and bare soil - were post-processed to exclude water and urban land cover and areas that were not relevant for mapping grasslands.

A comparison of the various satellite sensor model accuracies for the Washington study area reveals that Landsat 8 performed the best, on average (61%), followed by Sentinel-2 (57%), then MODIS (56%). Landsat 8's overall accuracy across both study areas ranges from 52% to 68%. Landsat 8 models demonstrated the best balance of spatial and spectral resolution, while temporally aligning with the highest number of suitable training data. The model with the highest overall accuracy was Bare Soil Cover, while the lowest was Perennial Forb. Overall accuracies for the Washington study area were higher for all five models than overall accuracies for the Colorado-Kansas study area. The Colorado-Kansas study area models relied more on spectral satellite predictor variables; whereas, the Washington study area models depended primarily on topographic or climatic variables. Another key finding for both study sites was that all vegetation cover predictions were driven by a wide array of input variables, with each variable contributing incremental amounts of information. This indicates our extensive suite of spectral and enviro-climatic input variables is necessary to maintain model predictive performance across grassland ecosystems.

Mapped outputs showing vegetation percent cover predictions from our pilot project have been integrated into CBI's CRP online decision support tool. This tool offers functionality for managers and landowners to view, filter, compare, and summarize geospatial information relevant for assessing CRP tracts in the study areas.

CBI will continue to develop our modeling approach in several ways. First, we will continue to refine our classification method by further customizing vegetation classes to enhance model performance and better align with CRP needs. Second, we will explore integrating advanced phenology and time-series metrics that may help models better characterize the temporal fluctuations of grassland vegetation. Third, we will explore using ESA's Sentinel-1 synthetic aperture radar, (which is sensitive to changes in soil moisture and can collect data through cloud cover), as an input variable to enhance discrimination of grassland vegetation structure. Finally, we intend to compare our Random Forest modeling approach to alternative techniques, such as Gradient Boosted Models and Deep Neural Networks, in order to select the best-performing method. Ultimately, we will work closely with CRP leadership to determine what approach and final implementation in the online tool best fits their program's needs.

One of the highest value-adds to this modeling effort would be additional field data from surveys conducted directly on CRP lands to train model predictions. We could work with the USDA to explore implementation of a simple process for landowners to document CRP vegetation on their lands via geolocated photos, thus collecting on-site data that could be aggregated, processed and used to validate or potentially train future models. We already have functionality in the online CRP tool for owners to take pictures, and with the right guidance and information, we may be able to gather data to make the model projections on grasslands more accurate and useful. In conclusion, a long-term, on-site CRP field survey program would add extensive benefit by increasing training data sample sizes and allowing further customization of models to CRP lands and needs.

1. Introduction

The Conservation Reserve Program (CRP) is a federally funded land conservation program administered by the Farm Service Agency, under the United States Department of Agriculture (USDA), whose long-term goal is to re-establish valuable land cover in order to improve water quality, prevent soil erosion, improve carbon sequestration, and reduce loss of wildlife habitat. This program works with farmers and landowners to implement conservation management practices on enrolled lands, with paid contracts ranging from 10 to 15 years in length. The CRP Grasslands component of the wider program, targets restoration of grassland systems by augmenting native vegetation for pollinators, providing habitat for grassland plants and animals, increasing biodiversity, reducing soil erosion, and improving water quality (USDA, 2019). There are a variety of CRP Grasslands conservation practices that can be implemented, including expansion of native grasses, establishment of new grass or legume species, and restoration of wildlife habitat through vegetative buffers and wildlife cover (USDA, 2018). As one of the largest private-lands conservation programs in the United States, CRP has partnered with farmers and landowners since 1985 to make a difference by improving ecosystem services and increasing habitat for endangered and threatened species across the nation (USDA, 2019).

The USDA's CRP has been successful in improving the conservation value of private lands; however, the program currently lacks spatially explicit information on land cover and vegetation within CRP-enrolled tracts. This makes it challenging for program managers and landowners to characterize landscape conditions and to quantitatively measure the benefits of CRP practices over time. Widespread collection of on-the-ground vegetation survey data is time and resource intensive, but recent advances in remote sensing technology could offer an alternative means to measuring and monitoring vegetation cover (Xie et al., 2008; Ustin and Middleton, 2021). Studies show promise in using predictive modeling approaches to create spatially continuous maps of vegetation, by employing the nuanced relationships between satellite imagery indices, enviro-climatic data, and existing georeferenced vegetation survey data (Ali et al., 2016).

While the high spatial and temporal variation inherent in grassland ecosystems still makes mapping them challenging, advancements in geospatial data processing offered by cloud-computing, coupled with the advent of multiple, freely available sources of satellite imagery at relevant spatiotemporal resolutions offer an opportunity to pilot these new mapping methods for CRP Grasslands. In this study we used a rich suite of enviro-climatic data, multiple sources of satellite imagery, and Random Forest modeling techniques to predict land cover for study areas in Washington, Colorado, and Kansas, where CRP Grasslands holdings are most prevalent. We used Google Earth Engine (GEE), and the pattern recognition capabilities of machine learning to create predictive maps of vegetation type, by leveraging an extensive set of satellite-derived variables, environmental layers, and federal survey data (from BLM's AIM and USDA NRCS's NRI programs). Previous collaboration between the USDA's CRP and Conservation Biology Institute (CBI) demonstrated the value of a similar approach to characterize forest characteristics of CRP tracts in Mississippi (Pearce et al., 2019).

In this pilot study, we mapped current condition predictions of low, medium and high cover for the following categories: annual grass, annual forb, perennial grass, perennial forb, and bare soil. These resulting spatial datasets lend insight into the potential distribution of vegetation on CRP Grasslands tracts and, with further technical refinement, could lay a foundation for quantitatively measuring success of conservation practices over time. The draft mapped grassland characteristics were integrated into an easy-to-use online decision support tool, which was also designed by the Conservation Biology Institute. This tool provides USDA staff and landowners an opportunity to explore maps and metrics for land enrolled in the CRP. It provides access to pertinent spatial information for CRP tracts, as well as the ability to summarize statistics, compare metrics, and download reports for CRP tracts across counties and watersheds. Our satellite-derived maps of vegetation cover show promise to characterize vegetation within CRP Grasslands tracts and offer the opportunity to create metrics to quantify landscape condition. The CRP tool also allows relevant data to be analyzed, shared, and downloaded through CBI's online mapping platform Data Basin.org. Future expansion of online tool functionality will provide additional species and ecological information to help guide strategic management actions on existing CRP holdings and to prioritize new enrollment in the CRP.

2. Background

2.1. Grassland Vegetation

Grassland ecoregions encompass more than 40 percent of land in the continental United States, totalling approximately 845 million acres and constituting the largest singular biome type within the United States (Dixon et al., 2014). Grasslands provide numerous ecosystem services including drought and flood mitigation, nutrient cycling, seed dispersal, waste decomposition, pest control, promotion of biodiversity, stabilization of local climate, reduction of soil erosion, protection of watersheds, streams and river channels, and critical habitat for plants, insect pollinators and wildlife (Blair et al., 2014; Bengtsson et al., 2019; Zhao et al., 2020). In addition to these numerous ecosystem services, grasslands also support human land uses like recreation, livestock grazing, and agricultural production (Lemaire et al., 2011).

Specific vegetation type varies across grasslands, depending on geographic location, soil properties, terrain, climate, local weather, fire regime, and human land use activities (Sala, 2001). While their biotic foundation is typically perennial grasses or grasslike plant species with sparse woody vegetation, grasslands also support a range of other grasses and broadleaf, flowering plants (called forbs), with annual or perennial life cycles (Blair et al., 2014). The diversity of grassland flora, particularly among the non-dominant grasses and forbs, can be quite high, nearly on par with that of tropical forests (Groombridge, 1992). The spatial extent and biodiversity of grasslands in the U.S. has long been under threat and in decline, with an estimated 99.9 percent of native tallgrass and mixed grass prairies lost since European settlement (Sampson and Knopf, 1994). Unfortunately, degradation and loss of grasslands can have severe implications for the ecosystem services they provide. For example, Orford et al. (2016) found grassland plant species richness was directly related to pollinator functional diversity. While there are a number of efforts across the U.S. to protect, promote, and restore grasslands, USDA's long-standing CRP program stands out with its goal to protect millions of acres by working with landowners to implement specific conservation practices on their own land (USDA, 2019).

2.2. CRP Grasslands Practices

There are various CRP practices pertaining to the conservation of grasslands; however, the primary focus is on planting native or introduced grassland vegetation species to reduce soil erosion, enhance wildlife and pollinator habitat, and improve water quality (Allen and Vendever, 2012). In addition to the ecosystem benefits that CRP practices support, maintenance of grazing land is also of primary interest of the program (USDA, 2019). Many factors are considered when determining appropriate CRP practices for enrolled land, such as current and future use, vegetative cover, cost and environmental factors (USDA, 2018). The five most common practices applied to CRP Grasslands holdings are shown in Table 1. A complete list of all CRP Grasslands practices and their descriptions can be found in Appendix 1.

Table 1. Top five most common CRP Grasslands practices and brief descriptions (USDA, 2018).

Grasslands Practice	Description
21	Filter strips 20-120ft wide to prevent `pollution' of surface or subsurface water.
1	Establish new or maintain existing vegetative cover of introduced grasses and legumes on eligible cropland that will enhance environmental benefits.
2	Establish new or maintain existing vegetative cover of native grasses on eligible cropland that will enhance environmental benefits.
8A	Grass waterways to convey runoff of not more than 100ft width to reduce erosion.
42	Establish habitat to support a diversity of pollinator species.

The USDA assesses the potential value of CRP contracts by utilizing the Environmental Benefits Index (EBI), which scores benefits from the standpoint of wildlife, water quality, air quality, on-farm erosion control, cost, and long term endurance (USDA, 2019).

2.3. Mapping Grasslands

Mapping grasslands efficiently over large areas requires the combination of field survey data alongside systematic collection of remotely sensed data. In this section we provide an overview of the natural resource field survey data related to grassland and rangeland vegetation cover and detail how advances in satellite imagery and processing techniques enable large scale mapping capabilities. Also, we describe relevant existing spatial data products that utilize both field surveys and remote sensing to map grasslands' spatiotemporal dynamics to aid land management.

2.3.1. Natural Resource Field Surveys

In order to predict vegetation ground cover across CRP Grasslands from satellite imagery, predictive models must be developed using representative survey data collected via field sampling. Because no such data has been sampled directly within CRP enrolled tracts, our approach had to rely on existing "training" data from other natural resource field surveys, namely the Natural Resources Conservation Service (NRCS) National Resource Inventory (NRI) and the Bureau of Land Management (BLM) Assessment, Inventory, and Monitoring (AIM) Terrestrial AIM Database (TerrADat).

The NRCS NRI and BLM AIM TerrADat are two unique, national-scale landscape sampling efforts that use similar transect survey methodologies (Appendix 2), which allow these field survey data to be used for analyses in combination with one another (Jones et al., 2018). The NRI is "designed to help gauge natural resource statistics, conditions, and trends on the nation's non-federal land" (i.e., privately owned land); TerrADat seeks to do the same for federally owned BLM lands (USDA NRCS, 2020). The NRI, which includes surveys across a variety of geographies and grassland ecotypes, requires a data request and authorization process for use due to privacy restrictions, while the TerrADat surveys are conducted on arid and semi-arid, publicly held lands in the Western U.S. and are readily accessible from the BLM data portal.

2.3.2. Mapping Grasslands with Remote Sensing

Given the complex intraseasonal and interannual variability in grassland phenology and the structural similarity across different grassland types, mapping these ecosystems across large geographies has many challenges (Wachendorf et al., 2018). These include difficulties in differentiating grassland cover types relevant to land managers and challenges in mapping locally relevant vegetation over large areas. However, these issues can be better addressed with advancements in cloud-based image processing technologies and the advent of publicly accessible imagery from multiple optical and radar imaging satellites.

Recent attempts to map the composition of grasslands over large areas have ushered in new techniques to better represent the vegetation complexity of these dynamic systems. Traditional remote-sensing mapping approaches using simple class representations, (e.g. grassland, forest, water, etc.), often oversimplify the complex nature of grasslands as homogeneous land covers. Newer techniques that capture the fractional percent cover of different plant functional types (i.e., annuals and perennials) offer a more realistic representation of heterogeneous landscapes, which contain a variety of plant species and cover types at a given location. In order to strike a balance between capturing variation in grassland vegetative covers and maintaining model predictive performance, for CRP purposes, we take a hybrid mapping approach -- grassland cover values are grouped into discrete classes of low, medium, and high percent coverage for each functional group to model vegetation cover.

2.3.2.1. Remotely Sensed Data Availability

In recent years, increased satellite coverage of near-global, remotely sensed data has become available for mapping land cover in areas without existing field survey data, and these data sources have proven crucial for a variety of ecological applications (Ustin and Middleton, 2021). When evaluating remotely sensed data sources for a given application, the spatial resolution, temporal cadence of collection (i.e., return interval), and spectral characteristics of the sensor should all be considered. For optical imagery, NASA satellites offer a generous historical archive - a wide array of spectral characteristics relevant to vegetation mapping at various spatial resolutions from low-resolution (500m) Moderate Resolution Imaging Spectroradiometer (MODIS) to medium-resolution (30m) Landsat archive available from 1972-present. The recent addition of the European Space Agency's (ESA) Sentinel-2's higher resolution (20m) multispectral imagery archive is particularly valuable, with various products available from 2015 onward (data prior to December 2018 requires more advanced processing on GEE) (ESA Copernicus, 2020). In addition to optical imagery, ESA's Sentinel-1 sensor (ESA Copernicus, 2020) offers radar data, which is not hindered by cloud cover, and can be used to measure land surface texture. This suite of sensors provides systematic collection of medium-spatial resolution remotely sensed data over time, which opens up possibilities for continuous monitoring of grasslands and enables capture of time-specific snapshots of vegetation type and condition.

2.3.2.2. Google Earth Engine (GEE) Advances Large-Scale Mapping

Google Earth Engine (GEE) is a cloud computing platform that allows scientists, researchers and developers to access an extensive collection of curated historical satellite imagery, including MODIS, Landsat 1-8 archive, and ESA Sentinel 1-5 collections as well as climate, weather, topographic, and other geophysical datasets (Gorelich et al., 2017). Google Earth Engine advances geospatial data processing speed by leveraging the distributed computing resources of Google's data centers, which provides scalable computing to tackle a variety of conservation issues, from monitoring forest cover change to documenting urbanization.

In addition to the diverse collection of datasets available on GEE, the platform provides a suite of data processing functionality to efficiently query and process imagery and perform a variety of analyses for image classification, change detection, time series analysis, and machine learning. Among the machine learning tools available are unsupervised and supervised techniques, as well as functionality to apply deep learning models. Because GEE is a cloud-computing platform, teams can upload and download colleagues' data, collaborate on scripts, and quickly share visualizations of analysis outputs. For this pilot project, GEE enabled efficient satellite image querying and processing, extraction of variables for model inputs, and implementation of Random Forest modeling to produce predictive model outputs for the grassland features of interest.

2.3.2.3. Random Forest Machine Learning

Random Forest is a machine learning algorithm whose objective is to find and model patterns in data. More specifically, it is a type of supervised ensemble method; an aggregation of individual models trained using known target outputs and whose collective predictive power is greater than any constituent model (Brieman, 2001*;* Appendix 3). Random Forest models are robust to overfitting, can ingest many different types of input data, are able to handle high data dimensionality and multicollinearity, have a proven track record in remote sensing applications, and have been implemented on a variety of platforms including GEE, Python, and R (Belgiu and Drăguţ, 2016). Implementation of Random Forest modeling in Python and R provide the most flexibility and integration, whereas GEE's cloud-based resources and data catalog allow for highly scalable computations. The availability of Random Forest modeling across multiple platforms, along with its robust characteristics, make it a good candidate to tackle the complexities of mapping grassland vegetation.

2.3.3. Existing Grassland Mapping Products

By taking advantage of the technological advancements described above, several research teams are now developing new grassland products using remotely sensed imagery, natural resource field survey data, GEE, and percent cover vegetation mapping. Examples of research teams include: (1) the Rangeland Analysis Platform (RAP) (Jones et al., 2018; Robinson et al., 2019), (2) Landscape Cover Analysis and Reporting Tools (LandCART) (Zhang et al., 2019; Zhou et al., 2020), and (3) the National Land Cover Database (NLCD) Grass and Shrub Component (Xian et al., 2015; Rigge et al., 2020). All three products offer annual 1984-2017 snapshots of percent cover for various grassland and rangeland indicators for the Western United States and host online maps to aid in data visualization. Unfortunately, these existing spatial products do not offer sufficient discrimination among grassland vegetation types to support program management and monitoring needs of CRP lands.

2.3.4. CBI's Grassland Mapping Approach

The Conservation Biology Institute seeks to build on these ongoing efforts by producing customized grassland vegetation models to generate predictions that are tailored to the conditions and needs of regional CRP tracts. Other products (described above) generally predict vegetation by grouping grasses and forbs together by their annual or perennial growth patterns (i.e., Annual Grass/Forb and Perennial Grass/Forb), whereas CBI is mapping vegetation at a finer scale by uncoupling grasses and forbs (i.e., Annual Grass, Annual Forb, Perennial Grass, Perennial Forb). We also intend to integrate CRP-specific datasets into our model development, as they become available, as well as to produce program-specific indicators of habitat quality and land condition. Our focus is to capture current conditions of CRP Grasslands holdings, rather than historical land cover trends. For this pilot project, we explored modeling grasslands vegetation with newer ESA Sentinel-2 satellite data, in comparison to sensors with a longer historical record, such as Landsat or MODIS.

3. Methods

3.1. Delineating CRP-Focused Study Areas

Our team identified two pilot study sites, one in eastern Washington and one covering eastern Colorado and western Kansas, in order to model areas most relevant to CRP Grasslands management and to effectively leverage available training data. These study sites were selected by considering: (1) U.S. Environmental Protection Agency (EPA) Level III Ecoregion boundaries, (2) World Wildlife Fund (WWF) World Grassland Types, (3) CRP tract spatial density, and (4) field survey training data availability.

3.1.1. USDA CRP Grasslands Tract Distribution

Land enrolled in USDA CRP Grasslands includes more than 15 million acres with 26 different conservation practices across 44 states. Spatially, CRP Grasslands tracts are moderately concentrated across the Northwest to Plains states, with clear density hotspots in Washington, Texas, Colorado, Nebraska, Kansas, Iowa, Illinois, and Missouri (Figure 1). We prioritized areas with high densities of CRP-enrolled lands as potential study areas.

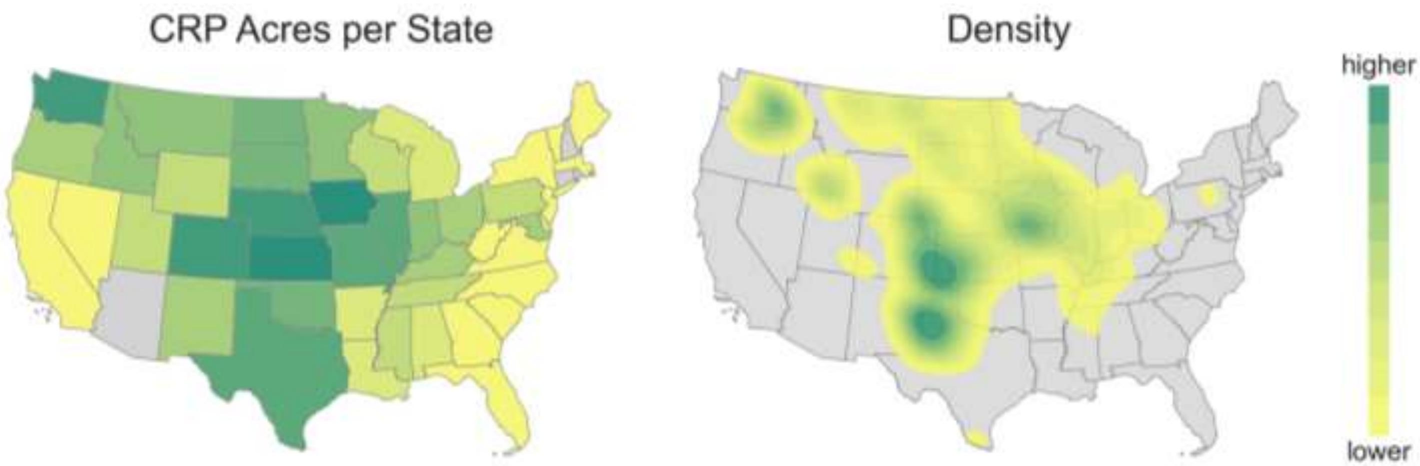

Figure 1. USDA CRP Grasslands acres per 1 million state acres (left). Kernel density estimate of USDA CRP Grasslands, weighted by CRP tract acreage (right); darker colors represent areas of higher concentrations of more and larger CRP tracts.

3.1.2. Ecoregions & Grasslands

The distinct biotic and abiotic characteristics of ecoregions and their defining plant assemblages can be helpful in defining study area boundaries for vegetation ground cover models (McMahon et al., 2001). We employed U.S. EPA Level III Ecoregions (Appendix 4) in combination with WWF World Grassland Types (Figure 2) to delineate our study areas (Omernik and Griffith, 2014; Dixon et al., 2014).

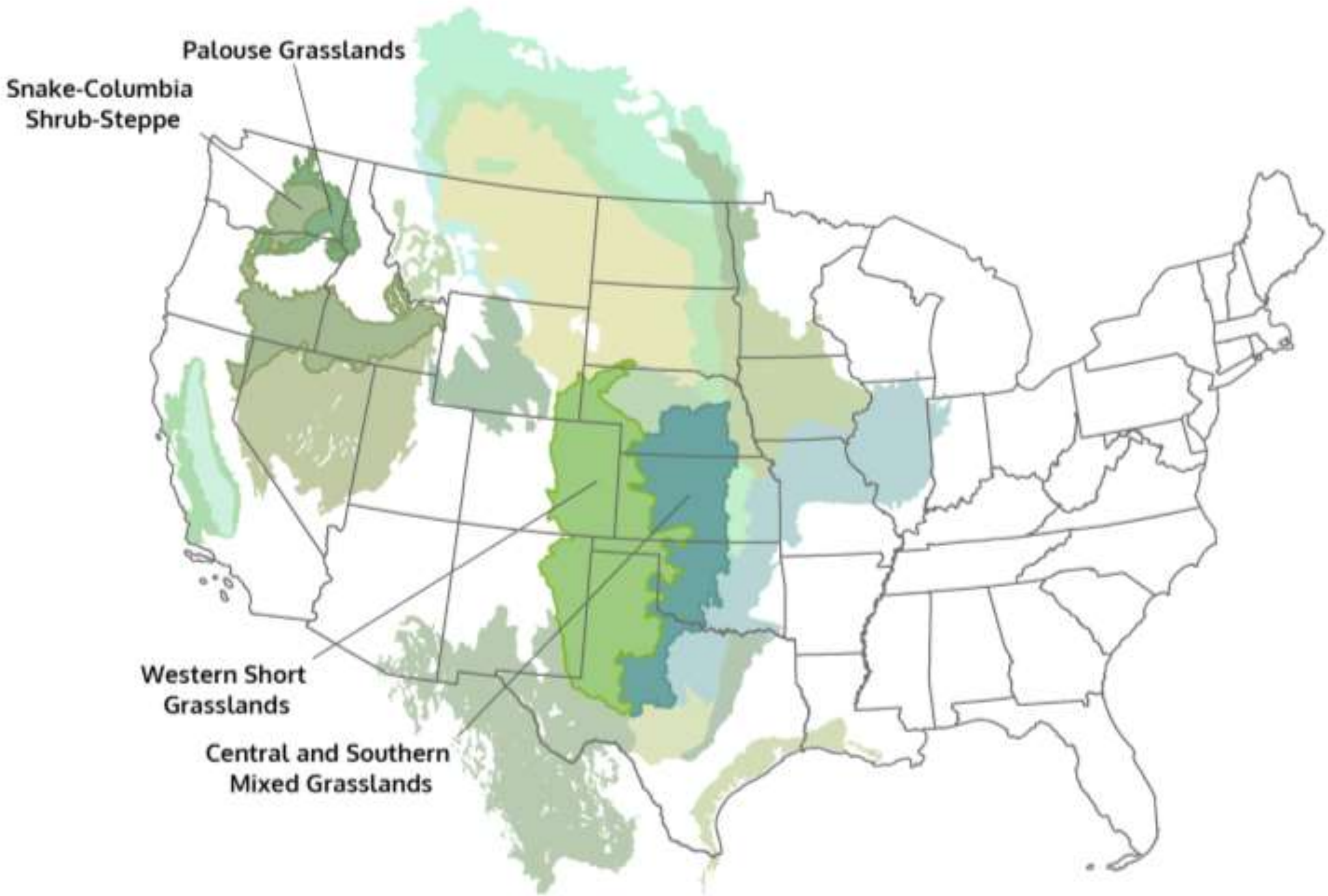

Figure 2. World Wildlife Fund World Grassland Types in the conterminous United States (Dixon et al., 2014). Grassland types included in the final Washington and Colorado-Kansas study areas are labeled.

3.1.3. Training Data Distribution

Training data distribution, (i.e., locations of NRCS NRI and BLM AIM TerrADat natural resource surveys; Figure 3), was our final consideration in study area selection for the pilot project. Training data quantity and quality are the most important considerations for producing accurate, predictive models. Models require training inputs that best represent the full range of variability found on the ground, whether spatial, spectral, or temporal. Therefore, only locations with sufficient quantities of training data (more than 1,000 observations) were considered for study site selection.

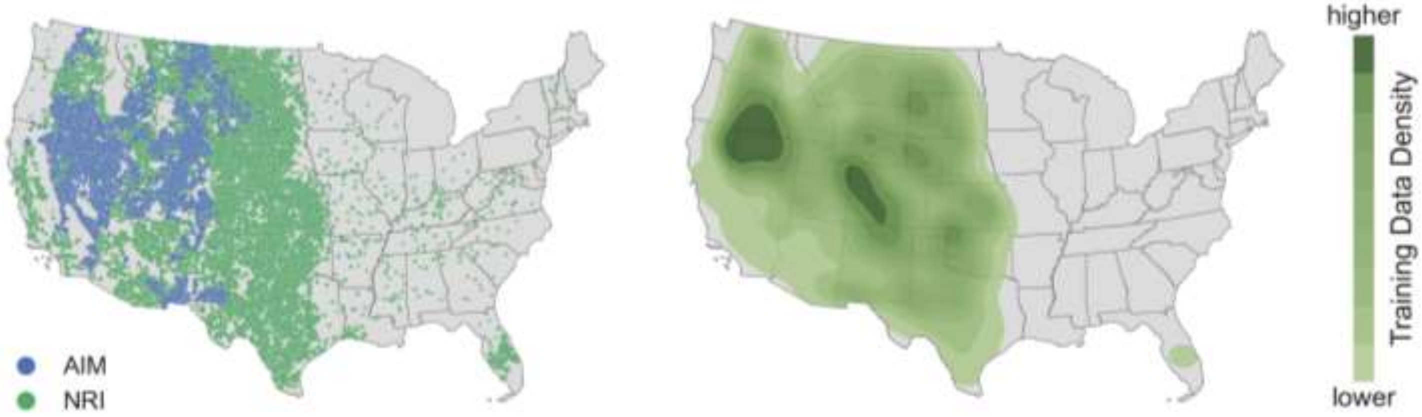

Figure 3. Spatial distribution (left) and spatial density (right) of NRI and AIM TerrADat training data points across the entire U.S. Note, AIM TerrADat coverage is less extensive than NRI's and is limited to arid and semi-arid lands in the West.

3.1.4. The Washington and Colorado-Kansas Study Areas

The two study areas meeting the collective criteria described above are shown in Figure 4.

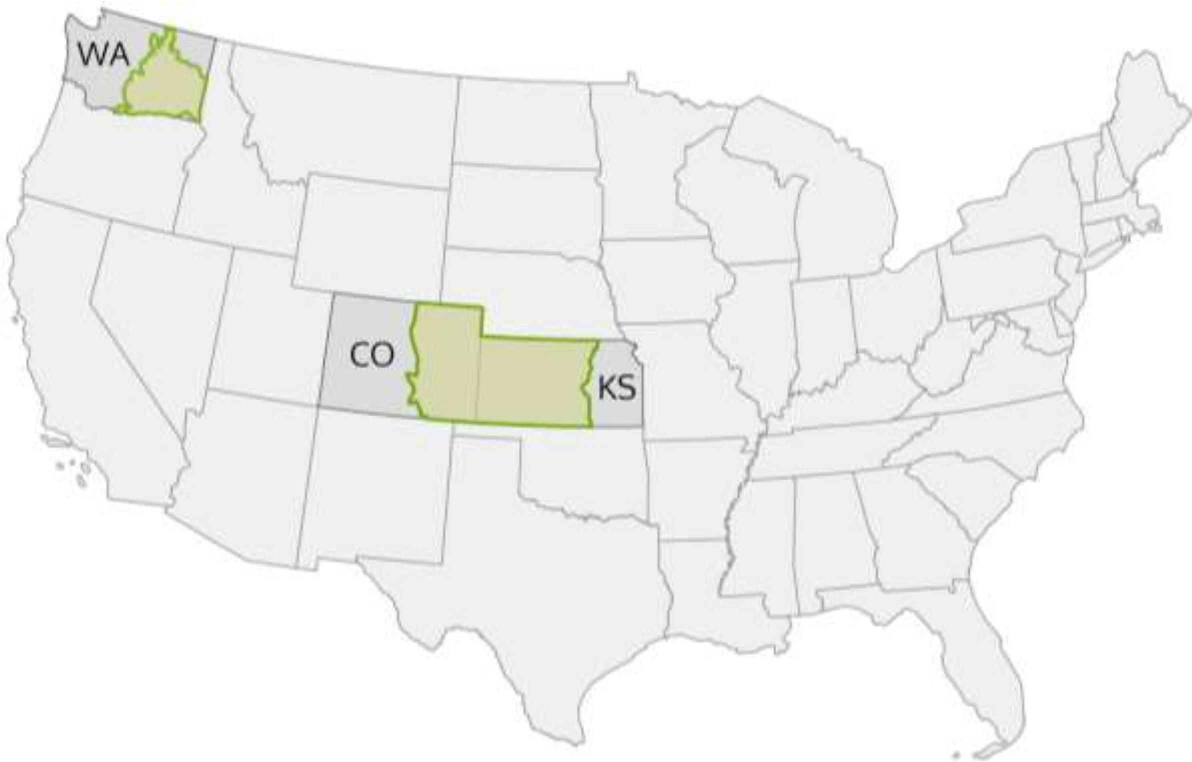

Figure 4. The two study areas selected (outlined in green) are in eastern Washington (WA) and Colorado-Kansas (CO-KS).

The Washington study area (Figures 4 and 7) is 26,599 square miles (68,890 sq km) and includes 1,028,400 acres of land enrolled in CRP Grasslands. It covers a majority of the Columbia Plateau ecoregion within Washington (Appendix 5) and includes portions of the Snake-Columbia Shrub-Steppe and Palouse Grasslands (Figure 2), plus a 5 kilometer edge buffer to include additional CRP tracts and training data points.

The Colorado-Kansas study area (Figures 4 and 8) covers approximately 100,400 square miles (260,000 sq km) and includes 3,057,059 acres of land enrolled in CRP Grasslands. The study area encompasses portions of the Central Great Plains, High Plains, and Southwestern Tablelands ecoregions (Appendix 6), and parts of the Western Short Grasslands, and Central and Southern Mixed Grasslands (Figure 2).

Employing two study areas containing a variety of grassland types allows us to compare model performance and evaluate differences in predictor variable selection between the two geographies. The WA study area was our initial site for testing and establishing modeling strategies. The smaller size of the Washington study area allowed for rapid, iterative model development, from which the finalized modeling strategies were scaled up and applied to the larger Colorado-Kansas study area.

3.2. Workflow Overview for Vegetation Modeling

Our overall workflow to derive model predictions for each of the target grassland vegetation cover types (Perennial Grass, Annual Grass, Perennial Forbs, Annual Forbs, and Bare Soil) consisted of processing NRI and AIM TerrADat field survey training data, processing the model input variables (satellite, climate, topography and soils), extracting model input variables for field survey training locations, preparing data for modeling, conducting Random Forest modeling for each vegetation cover type, and finally, visualizing vegetation cover prediction outputs in the CRP tool (Figure 5).

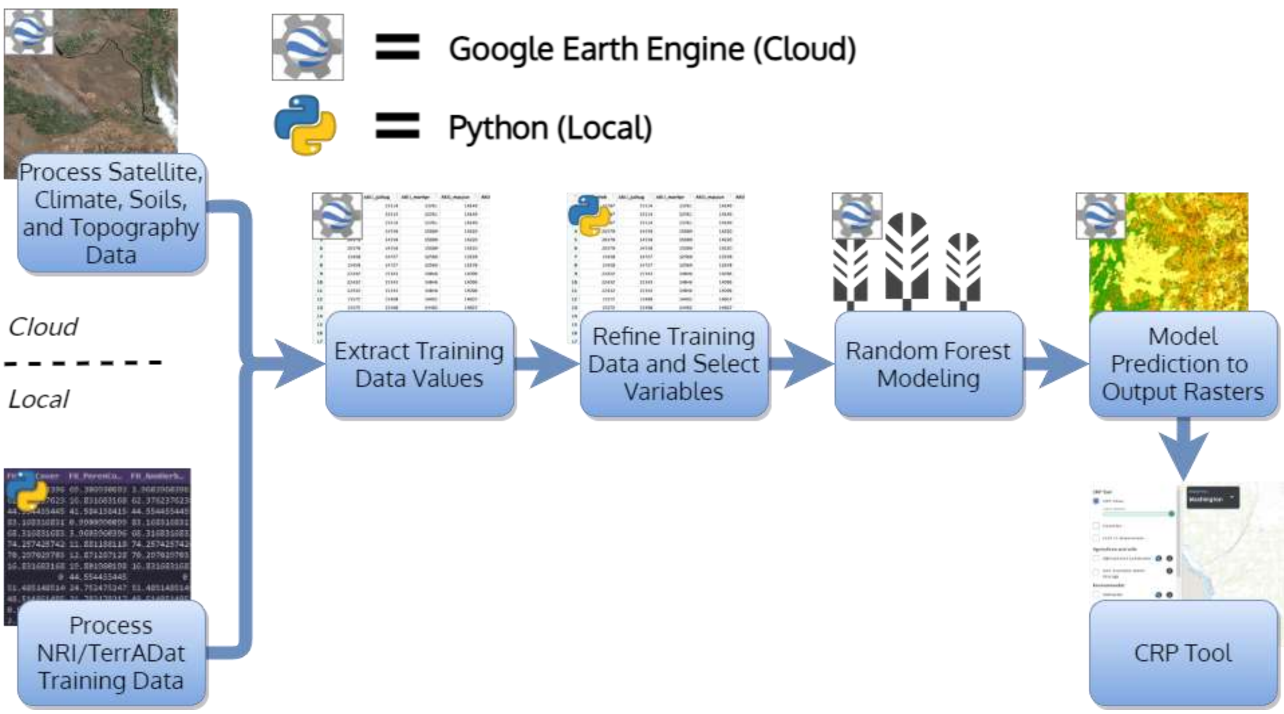

Figure 5. Overview of CRP Grasslands modeling workflow to derive predictions for each of the target grassland vegetation cover types (Perennial Grass, Annual Grass, Perennial Forbs, Annual Forbs, and Bare Soil).

3.3. Processing Model Input Data

Input data used to train the predictive land cover models consisted of NRCS NRI and BLM TerrADat field survey data, Landsat 8, Sentinel-2, and MODIS satellite imagery; NRCS SSURGO soils, USGS National Elevation Dataset (NED), and PRISM climate data (Table 2). We processed NRI, TerrADat, PRISM, and SSURGO soils data on local computer workstations, and leveraged GEE's cloud computing power and curated data catalog to process Landsat 8, Sentinel-2, MODIS, and NED data.

Table 2. Inputs for land cover models, including data types, number of variables, and example variables. *Processed as seasonal and seasonal difference. **Processed as seasonal.

Input Dataset	Dataset Type	# of Input Variables	Example
NRCS NRI and BLM TerrADat	Tabular	5	Annual Grass Percent C
Landsat 8	Raster	24*	Enhanced Vegetation In
Sentinel-2	Raster	28*	Soil Adjusted Vegetatio
MODIS	Raster	24*	Moisture Stress Index
USGS National Elevation Dataset	Raster	3	Slope
PRISM climate data	Raster	9**	Total Precipitation
NRCS SSURGO soils	Raster	7	Percent Organic Matter

3.3.1. Processing Field Survey Data

National Resources Inventory field data was provided by NRCS as multiple separate tabular datasets of survey plot geolocations and species/vegetation community group-level variables, (e.g., vegetation height, biomass, and percent cover). The BLM TerrADat data was delivered as a ready-to-use spatial dataset, which included vegetation cover variables similar to the NRI.

We processed all field survey data in a Python Jupyter computational notebook, an interactive environment that provides replicability, visualization, and documentation across multiple iterations of data and model development (Perkel, 2018). The following packages were used to support data exploration to inform modeling strategies (Seltman, 2018), as well as for processing and visualization: Pandas, Geopandas, Fiona, Numpy, Shapely, Matplotlib, Seaborn, Scikit-learn, HvPlot/Holoviews/Geoviews, Folium, and Keplergl.

Database tables from the NRI were joined and georeferenced, then variables (ranging from 3 to 117 per table; Appendix 7) were filtered, based on relevancy to CRP Grasslands and variable modeling potential (Table 3). Unfortunately, some vegetation cover variables relevant to CRP were predominantly zero values, (poor candidates for predictive modeling across a full range of cover values); so, they were dropped from consideration. Similarly, both Perennial and Annual Forb categories generally have low percent cover observations, but their importance to CRP Grasslands make their inclusion in modeling a necessity (Figure 13 and Appendix 7).

Table 3. Final set of target vegetation cover variables from NRCS NRI data.

Vegetation Cover Variable	Description
Perennial Grass	The cover of perennial grasses in the plot.
Annual Grass	The cover of annual grasses in the plot.
Perennial Forb	The cover of perennial forbs in the plot.
Annual Forb	The cover of annual forbs in the plot.
Bare Soil	The cover of soil that has no vegetation cover above it in the plot.

The target land cover variables shown in Table 3 were selected from the NRI, then TerrADat variables were filtered, modified, and aggregated to ensure agreement among plant functional groups between the two sources. The selected NRI and TerrADat plots' datasets were merged into a single combined grassland vegetation cover training layer to be used for modeling. See Figure 6 for complete field survey data processing workflow.

Figures 7 and 8 show the prepared training datasets for the extent of each study area. The distribution and source of field plots for each geography are shown, as well as counts of NRI and AIM TerrADat samples per year for each study site.

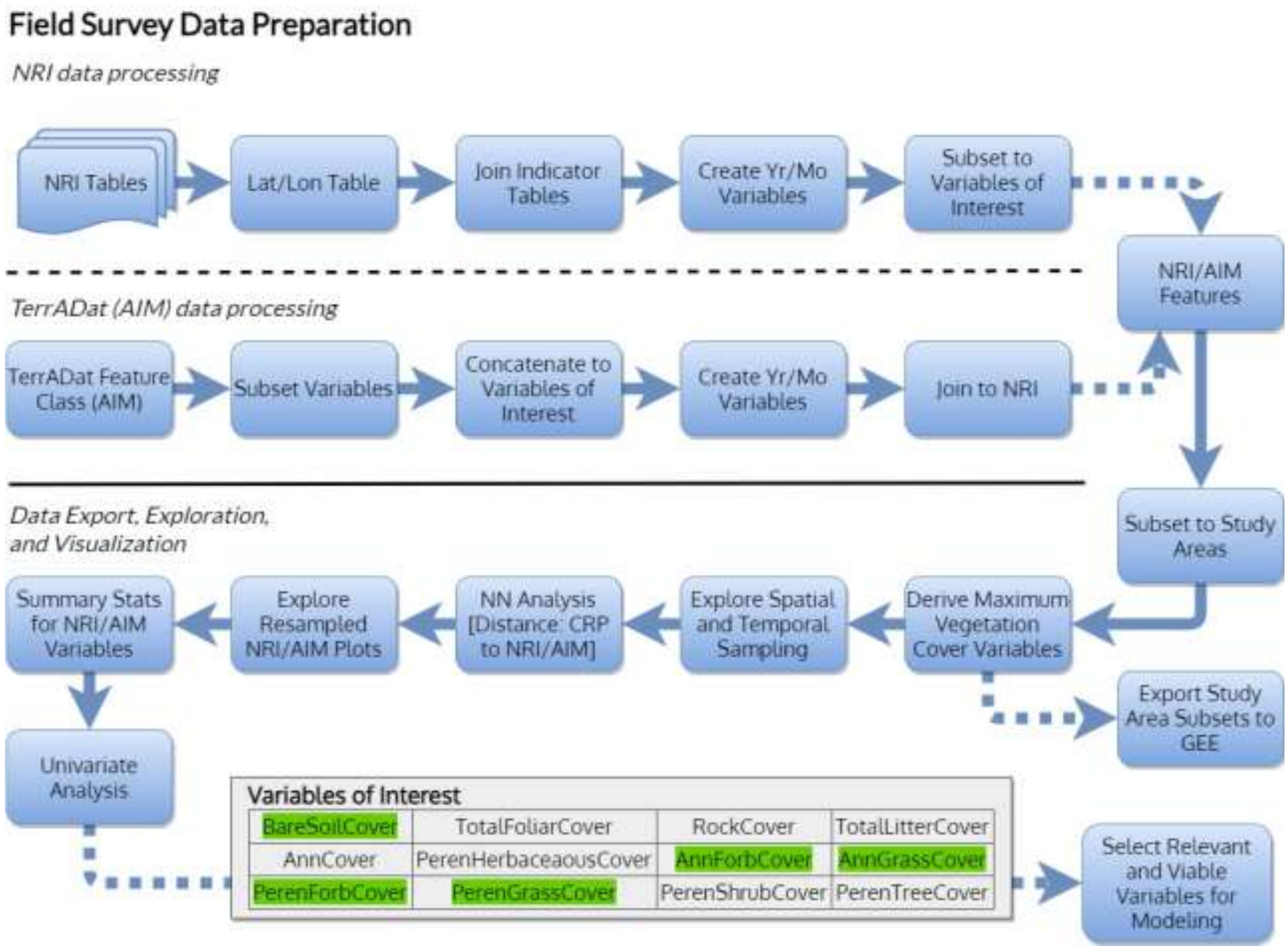

Figure 6. Field survey training data preparation workflow. Target land cover variables of interest are highlighted in green.

The Washington study area contains a total of 1,308 training data points, including 726 NRI samples from 2004 - 2018 and 582 TerrADat samples from 2015 - 2018.

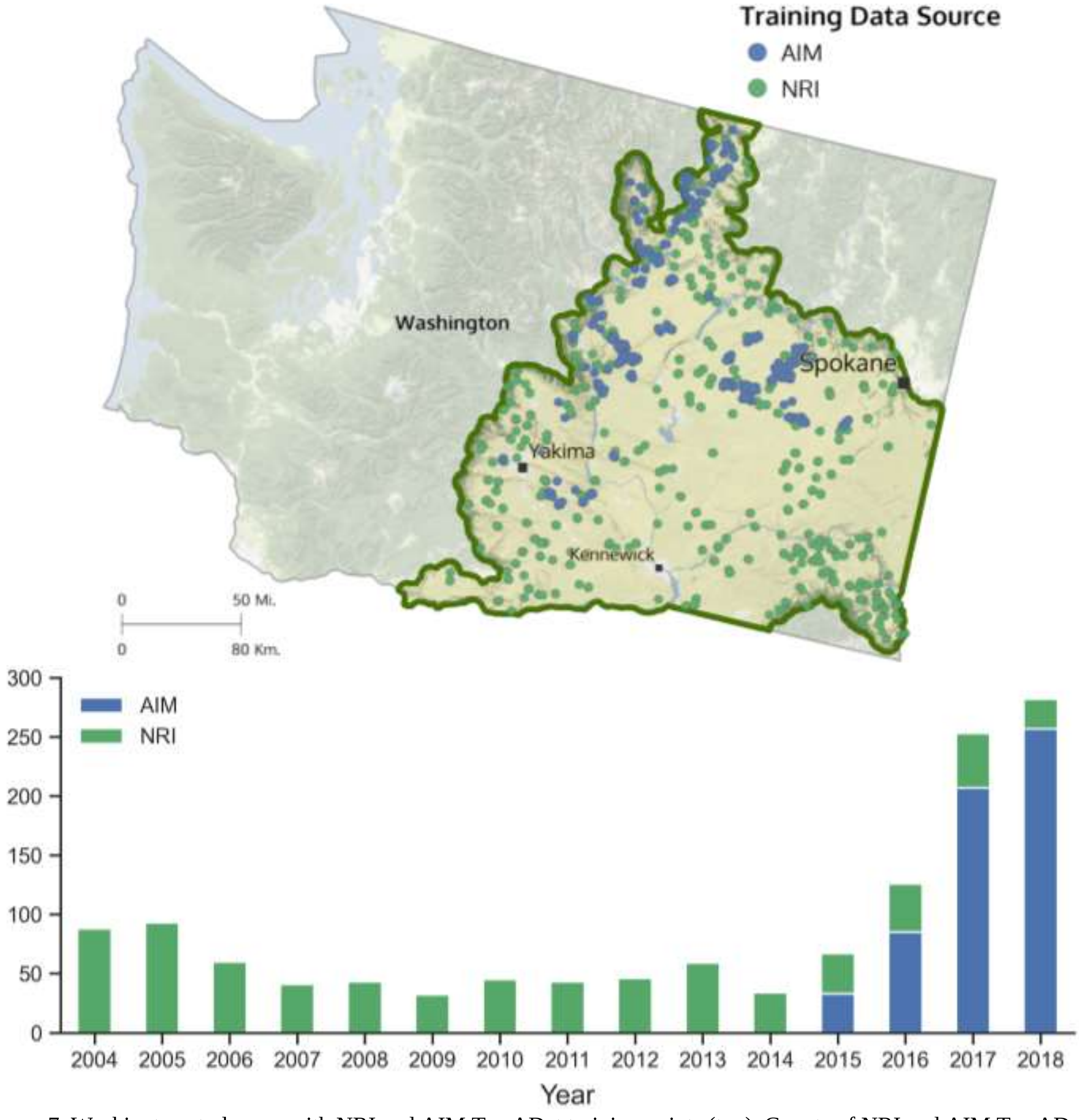

Figure 7. Washington study area with NRI and AIM TerrADat training points (top). Counts of NRI and AIM TerrADat samples per year for the Washington study area (bottom).

The Colorado-Kansas study area contains 2,709 training data samples from 2004 - 2018; these are all sourced from the NRI because no AIM TerrADat plots occur in this study area.

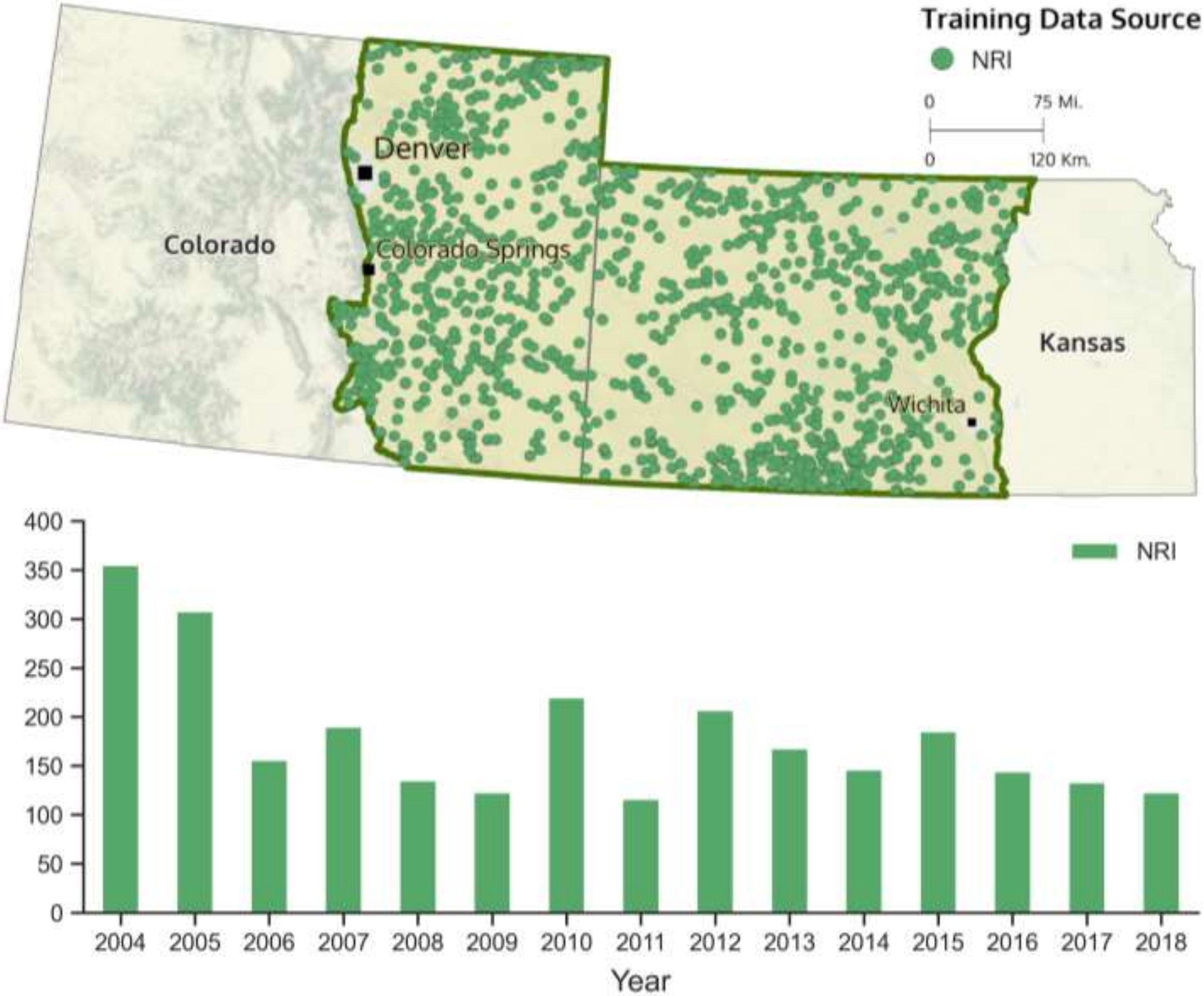

Figure 8. Colorado-Kansas study area with NRI training points (top). Counts of NRI samples per year for the Colorado-Kansas study area (bottom). Note, there are no AIM TerrADat sample plots in the study area.

Of the total NRI and AIM TerrADat field surveys conducted in the two study areas, we were limited to those points sampled within each satellite sensor's available temporal window for data collection, as outlined in the following Satellite Data Overview section. For example, when working with Landsat 8 we were limited to those points sampled from 2014-2018. The final field survey datasets were used as Random Forest training targets; i.e., the models were trained using the particular combination of enviro-climatic variable values that resulted in the target vegetation variable's value.

Additional exploratory analysis was performed on training data distributions for target vegetation types and on field survey plot locations, to characterize the cover characteristics for each study area and to quantify training data plots' proximity to CRP holdings.

3.4. Processing Spatially Continuous Model Variable Inputs

When modeling percent cover for vegetation types, spatially explicit variables are used as model inputs to create predictive maps. Spatially continuous variables useful for distinguishing plant functional groups and coverage include satellite-derived spectral information and indices (Table 5) and enviro-climatic data pertaining to soils, climate and topography (Table 6). We generated input variables for the study areas and pre-processed the majority of model input variables in Google Earth Engine (Figure 11).

3.4.1. Satellite Data Overview: Landsat 8, Sentinel-2, and MODIS Imagery

Our initial investigation utilized Landsat 8 for modeling vegetation cover, first across the WA study area, then, once modeling strategies were finalized, scaling up and applying to the CO-KS study area. The WA study area was selected for further model enhancements and an in-depth comparison of Landsat 8, Sentinel-2, and MODIS satellite imagery, to evaluate differences in model development and performance among sensor types.

Landsat 8 is a medium-resolution (30 m) optical satellite with sensors that capture bands of electromagnetic wavelengths across the visual, near-infrared, shortwave-infrared, and thermal spectra; it has a temporal resolution (re-imaging return interval) of 16 days. Atmospherically corrected surface reflectance from the Landsat 8 OLI/TIRS sensors (Vermote et al., 2016) is available in GEE from 2013 onward. Sentinel-2 imagery has higher spatial resolution (10 m and 20 m) than Landsat and offers standard visual spectral, near-infrared, short-wave infrared bands, as well as four red-edge bands which can be used to reveal information about vegetation senescence and condition, soil condition, and moisture content (ESA Copernicus, 2020). Sentinel-2 has a temporal resolution of 5 days and is available in GEE from June 2015 to present. MODIS is a coarse resolution (250 - 500 m) sensor that captures a similar range of wavelengths to Landsat 8, but divided across more bands, resulting in finer spectral discrimination. It has a temporal resolution of 1-2 days, and is a proven performer for long-term grasslands vegetation monitoring (Zhou, 2020). The full historic archive (March 2000 - present) of MODIS data products is hosted in GEE's data catalog.

Table 4. Characteristics of the Landsat 8, MODIS, and Sentinel-2 satellite sensors.

Sensor	Spatial Resolution	Temporal Resolution	Spectral Resolution	Number of Bands	Collection Start Date	Surface Reflectance Available
Landsat 8	30 m	16 days	Visual bands, NIR, SWIR, thermal	11	April 2013	April 2013 onward
Sentinel-2	10 m, 20 m	5 days	Visual bands, NIR, red-edge, SWIR	13	June 2015 (TOA available)	December 2018 onward
MODIS	250 m, 500 m	1-2 days	Visual bands, NIR, SWIR, thermal	36	March 2000	March 2000 onward

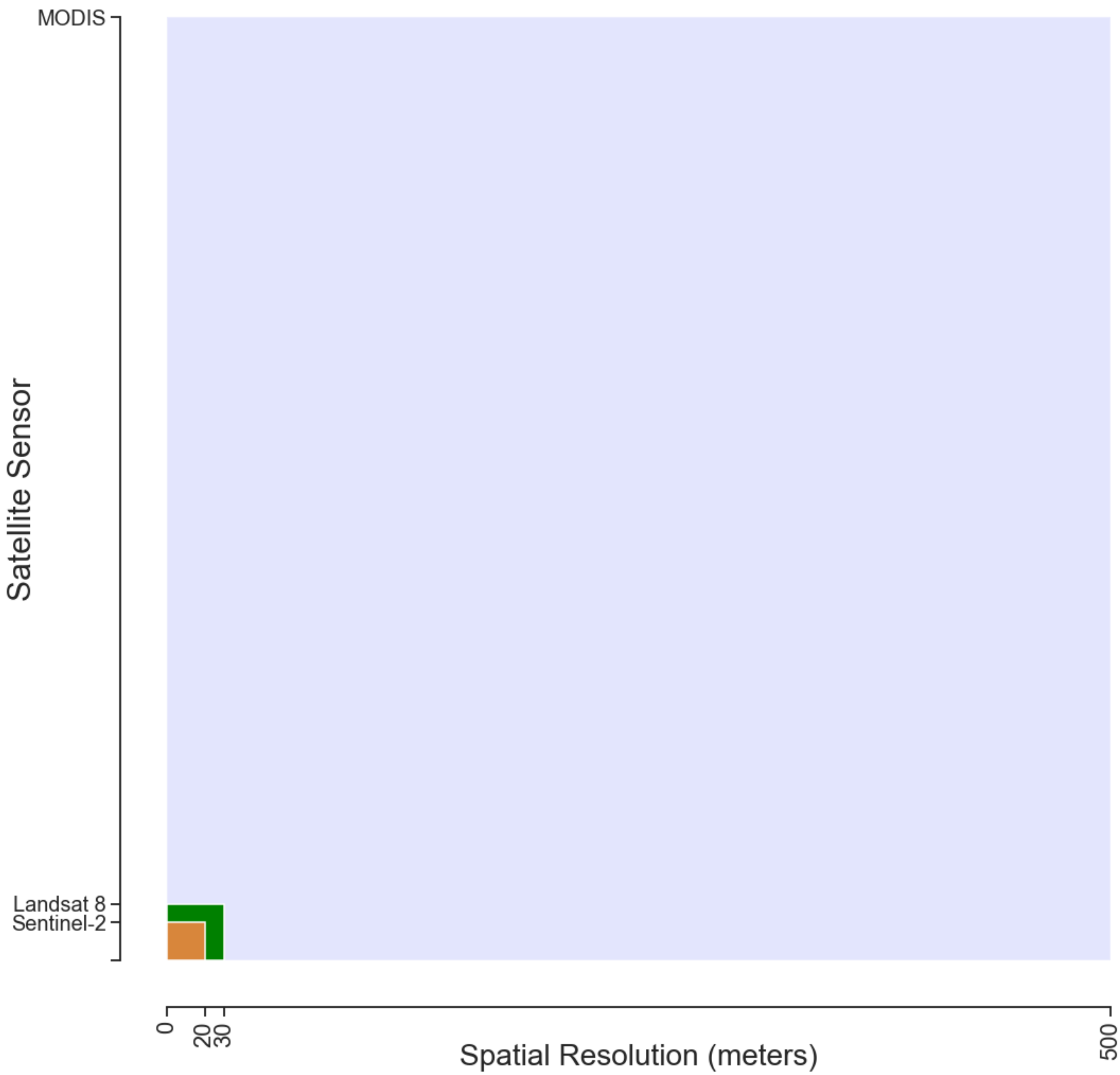

Fig 9. Comparison of Sentinel-2 (orange), Landsat 8 (green), and MODIS (purple) satellite sensor spatial resolution (aka pixel size).

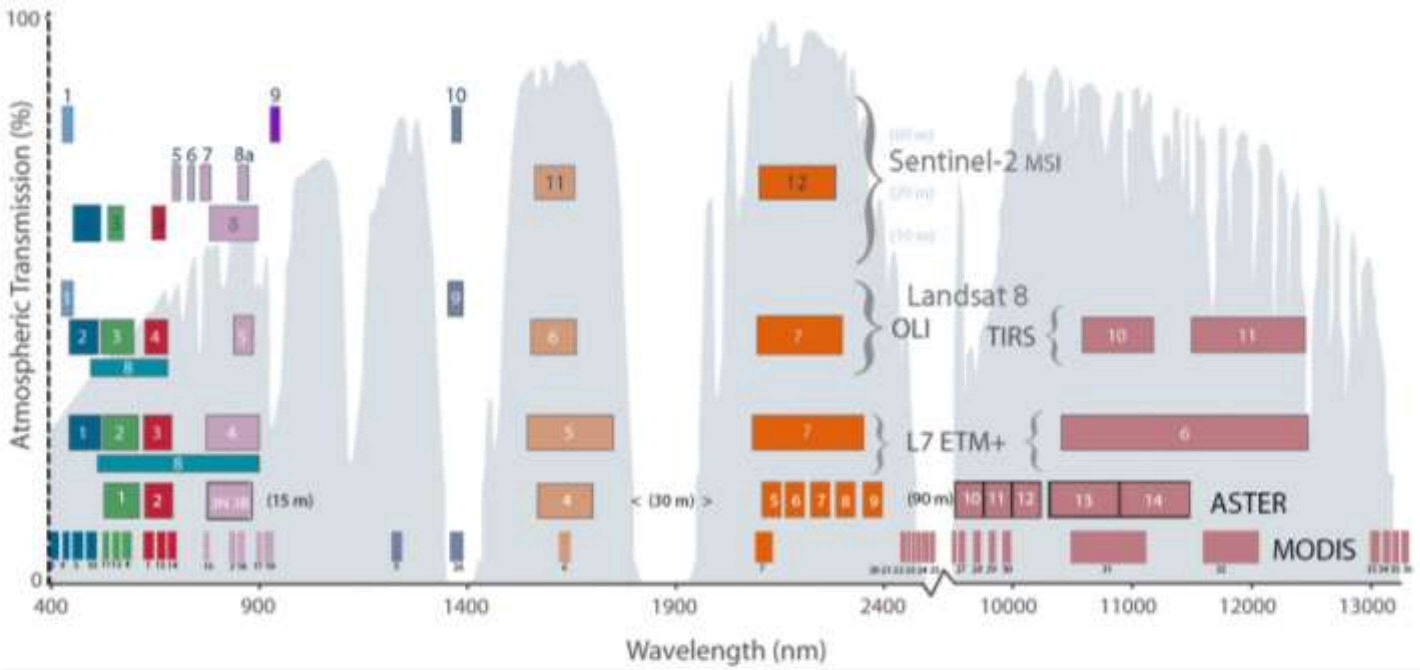

Fig 10. Comparison of Landsat 7 and 8, Sentinel-2, and MODIS spectral resolution and bands. [Source]

3.4.2. Satellite Imagery and Indices

Satellite data from each sensor were processed in GEE following this general methodology: 1. spatially filter to the relevant study area, 2. temporally filter available imagery to align with training data, 3. correct for any atmospheric artifacts, 4. calculate derived spectral indices (mathematical combinations of bands), 5. generate seasonal, three-month (Winter: January - March; Spring: April-June; Summer: July-September; and Fall: October-December) median composites, and then 6. calculate seasonal differences (Spring-Winter, Summer-Spring, Fall-Summer) for each band and derived spectral index as additional model input variables. The seasonal composites for all years prior to 2019 were used to train the Random Forest model, while the 2019 seasonal composites were used as inputs to the trained models to derive output predictions of current conditions. Winter season variables were later excluded from the analysis given persistent cloud cover issues, so only Spring, Summer and Fall variables were used for Random Forest model development. Details for processing data from each sensor are outlined below.

To process Landsat 8 data in GEE, we first spatially filtered the full Landsat 8 Surface Reflectance Tier 1 archive to the respective Washington and Colorado-Kansas study areas, then temporally filtered to 2014-2019 dates. While the Landsat 8 Surface Reflectance product is atmospherically corrected, a number of cloud artifacts remain, so we applied a two-step cloud filtering process to generate cloud-free composites. In addition to the standard Landsat 8 Surface Reflectance bands outlined, we created numerous derived spectral indices to provide more information on vegetative and soil conditions (Table 5). Landsat 8 Surface Reflectance imagery was processed to create seasonal, three-month median composites for 2014-2019 for both study areas. A prior comparison of two-month versus three-month composites revealed minimal benefit for the tradeoffs involved, so we continued with the seasonal approach.

While Sentinel-2 TOA (Level 1C) imagery is available from mid-2015 onward, atmospheric artifacts present in this product hinder its application for analytical purposes, and the Sentinel-2 surface reflectance product in GEE doesn't offer adequate temporal coverage to sample sufficient temporally aligned field survey data for modeling. Given this limitation, we applied a straightforward and computationally inexpensive method called sensor invariant atmospheric correction (SIAC) to the spatially and temporally filtered TOA imagery from 2016-2019, to generate an atmospherically corrected surface reflectance dataset (Yin et al., 2019). Using this dataset, we then calculated the derived spectral indices, produced the seasonal composites and calculated seasonal differences.

The MODIS product selected for modeling was MOD09A1, an atmospherically corrected dataset that is a composite of the highest quality imagery from each 8-day period. The MOD09A1 product in GEE is analysis-ready so we were able to simply spatially filter to the WA study area, temporally filter to 2004-2019, calculate the derived spectral indices, generate seasonal composites, and calculate seasonal differences.

Table 5. Surface reflectance satellite bands and derived indices used as model variables. *Available only for Sentinel-2. **Not available for Sentinel-2. ***Processed as seasonal and annual timesteps.

Spectral Bands	**Derived Spectral Indices**	
Blue	Simple Ratio (SR)	Normalized Difference Water Index (NDWI)
Green	Normalized Difference Vegetation Index (NDVI)	Modified Normalized Difference Water Index (MNDWI)
Red	Normalized Difference Green Index (GNDVI)	Moisture Stress Index (MSI)
Red edge 1*	Enhanced Vegetation Index (EVI)	Normalized Difference Snow Index (NDSI)
Red edge 2*	Modified Normalized Difference Vegetation Index (MNDVI)	Tasseled Cap (Greenness)
Red edge 3*	Green Chlorophyll Vegetation Index (GCVI)	Tasseled Cap (Brightness)
Red edge 4*	Soil Adjusted Vegetation Index (SAVI)	Tasseled Cap (Wetness)
Near-infrared (NIR)	Kernel Normalized Difference Vegetation Index (kNDVI)	Day of year of greenness pixel/highest NDVI (DOY)***
Shortwave infrared 1 (SWIR1)	Normalized Burn Ratio (NRB)	
Shortwave infrared 2 (SWIR2)		
Thermal**		

3.4.3. Soils, Topography, and Climate Data

We processed NRCS SSURGO soils data to generate a total of seven physical and chemical soils variables for model input, including percent sand, silt, clay, and organic matter; soil pH, available water capacity, and bulk density, 1/3 bar (Soil Survey Staff, 2020). Soils variables were generated for the 0-20cm soil horizon using the dominant component aggregation method.

For topographic data, we used the United States National Elevation Dataset hosted in the GEE data catalog to derive elevation, slope and aspect for both study areas using GEE terrain functions.

As a noteworthy enhancement, we were able to acquire the highest resolution PRISM climate data available (~900 m) for 2004-2019, produced by the PRISM Climate Group at Oregon State University (2021). We processed seasonal climate composites to include various metrics of precipitation, temperature, vapor pressure, and potential evapotranspiration for both study areas (PRISM Climate Group, 2021). Since PRISM is available daily, seasonal daily averages were calculated for temperature, minimum and maximum temperature, dew point temperature, vapor pressure, vapor pressure deficit at minimum and maximum temperature, and potential evapotranspiration, while seasonal totals were calculated for precipitation.

Table 6. Table of climate, topographic and soil model input variables. *Processed as seasonal.

Soils (SSURGO): 20m	Topography (US NED): 10m	Climate (PRISM): ~900m *
Soil pH (1-to-1 Water)	Elevation (m)	Total Precipitation (mm)
Soil Available Water Capacity	Slope (degrees)	Average Temperature (C)
Bulk Density (1/3 Bar)	Aspect (degrees)	Average Minimum Temperature (C)
Percent Organic Matter		Average Maximum Temperature (C)
Percent Sand		Average Dew Point Temperature (C)
Percent Silt		Vapor Pressure (Pa)
Percent Clay		Vapor Pressure Deficit at Min. Temp. (Pa)
		Vapor Pressure Deficit at Max. Temp. (Pa)
		Potential Evapotranspiration (cm)

3.4.4 Spatial Variable Composites

Soil, topographic, and climate input variables were combined with satellite data to create stacked composites for each satellite sensor (Landsat 8, Sentinel-2, MODIS). We then extracted all of the variable values for training data field survey locations, in temporal alignment with the year that a given field location was surveyed. For example, if a field location was surveyed in 2017, all variable values from the 2017 Spring, Summer, and Fall seasonal satellite imagery composites would be extracted at that location. To extract the variable values at the field survey locations, we created a 50m buffer around each location. Using the buffer as a boundary, we calculated the median value for each variable from all pixel values within the boundary. Once extraction was complete, we then exported the full training dataset out of GEE and brought it into Python for Random Forest model pre-processing.

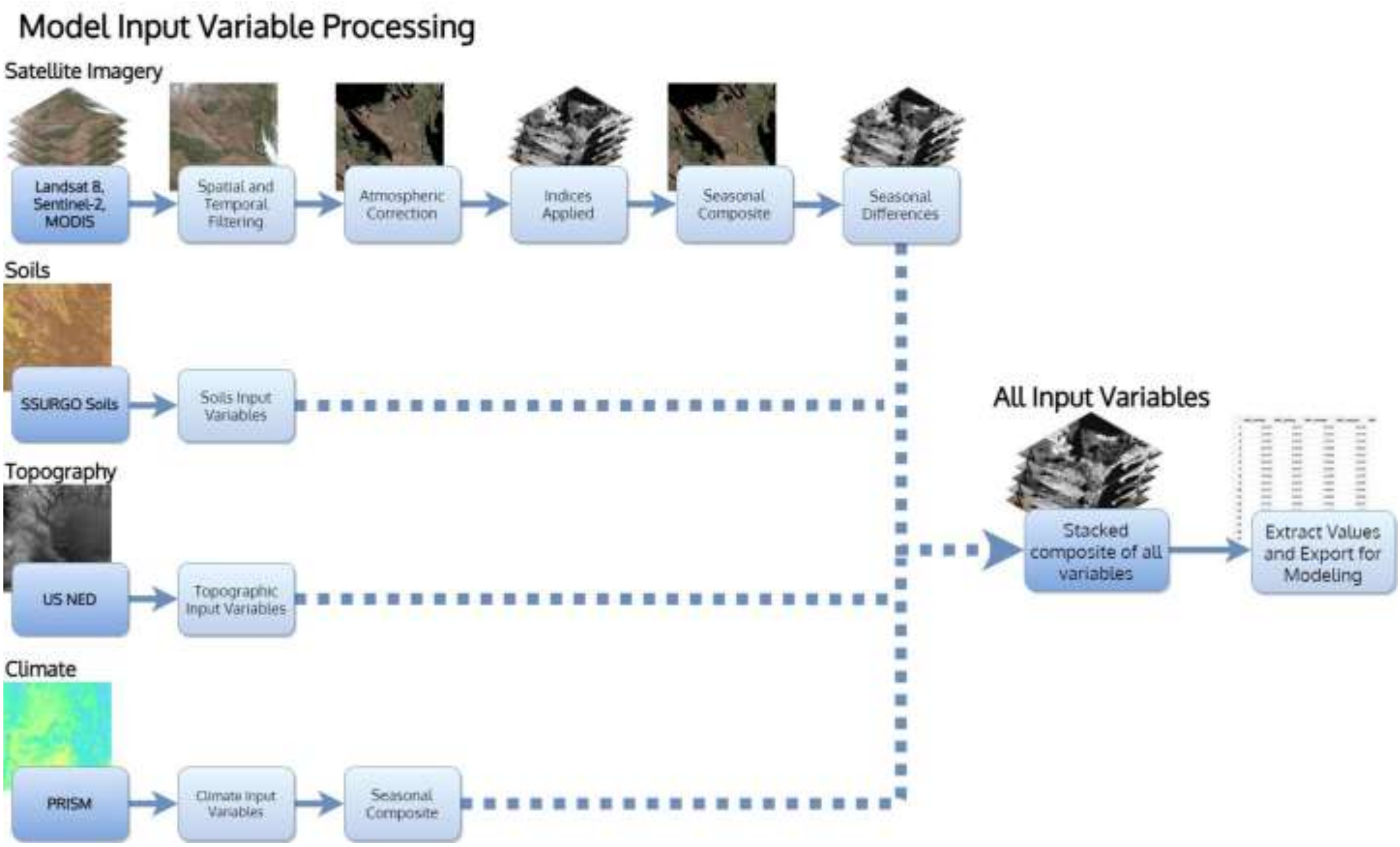

Figure 11. Workflow of raster data processing in GEE to create seasonal composites used for sampling training data.

3.5. Random Forest Modeling

To assess the potential of modeling grasslands at a fine scale with currently available satellite imagery, field survey data, and other model variable inputs, we developed, evaluated, and compared multiple Random Forest models. First, models were developed using Landsat 8 input variable composites applied to the WA and CO-KS study areas. Then, as models were refined we performed an in-depth comparison of alternative sensor inputs (Sentinel-2 and MODIS) for modeling vegetation in the WA study area.

We iteratively developed each Random Forest classification model in parallel, locally via Python and on the cloud via GEE, in order to cross-validate model stability and accuracy. Performing modeling in Python also provided additional functionality for fine-tuning and evaluation, since GEE has limitations in this regard. However, the final mapped predictions were generated using GEE, once the trained models had been tested, refined, and validated on both platforms. For each of the vegetation cover variables, we developed an individual model following the workflow as outlined below and illustrated in Figure 12.

To render balanced classes of low, medium, and high vegetation percent cover, thus maximizing model performance by reducing variance, we binned the continuous vegetation percent cover variables into discrete classes as defined by their terciles (i.e., quantiles for three classes). While the distribution of continuous percent cover theoretically ranges from 0-100, field-collected survey cover data have skewed distributions, which do not range from 0-100% cover. Hence, the binning of values into terciles was conducted to create balanced classes for low, medium and high vegetation percent cover relative to the distribution of the values. (See Appendix 8 for class break values.)

After vegetation cover variables were binned into three classes of low, medium and high cover, we conducted a variable selection process to reduce model complexity, improve model performance, and increase interpretability by removing redundant, irrelevant, or noisy independent variables from the input (Belgiu and Drăguţ, 2016). The variable selection algorithm chosen for this task, Boruta, is an algorithm that uses a combination of Random Forest models, model variable importance, and dummy variable permutation across many iterations to identify and select all independent variables relevant for predicting the dependent variable (Kursa and Rudnicki, 2010). In this case, Boruta was used to filter and select the subset of satellite imagery, soils, climate, and topographic variables relevant to predicting each of the vegetation cover types.

Once the subset of relevant input variables were selected, we split data into training and test sets for model training and evaluation, respectively. Data was split 80% training, 20% testing and samples were stratified by type to maintain the balanced class proportions (Appendix 8). Following the export of training and testing data to Google Earth Engine with the subset of selected relevant predictor variables, we trained Random Forest classification models in both GEE and Python, using a combination of parameters that yielded a good baseline accuracy (Appendix 8).

In order to evaluate the validity of modeled outputs, we performed an assessment to document the overall accuracy of each trained Random Forest classification model. To do so, we compared actual reference values in an independent testing dataset to those predicted by the model; the higher the proportion predicted correctly, the better. We also calculated the difference in actual versus predicted values, on a per-cover class basis, to allow for a more nuanced examination of each model's accuracy. We calculated complementary metrics for users' accuracy, or what proportion of a predicted cover class is actually that class on the ground; and producer's accuracy, or what proportion of a cover class was correctly predicted, based on independent reference data.

Finally, we generated a "snapshot in time" prediction for vegetation cover using the 2019 variable composite dataset as input to the trained and evaluated Random Forest classification models. To run the trained models, we used the selected input variables for each vegetation cover variable to subset the 2019 composite. Then, we applied each trained model to the subsetted 2019 image which produced the predicted classification outputs. This creates a mapped representation of current conditions, based on each model. In other words, the outputs shown in the CRP tool represent predictions of low, medium, and high vegetation cover for each vegetation cover type in CRP lands for 2019.

Classified outputs were post-processed to exclude water and urban land cover and areas that were not relevant for mapping grasslands. The USGS National Landcover Database (NLCD) 2016 land cover dataset was used to exclude water and low, medium and high density urban land cover (Yang et al., 2018). After the mapped predictions were post-processed, they were then exported from GEE to Google Drive and downloaded locally.

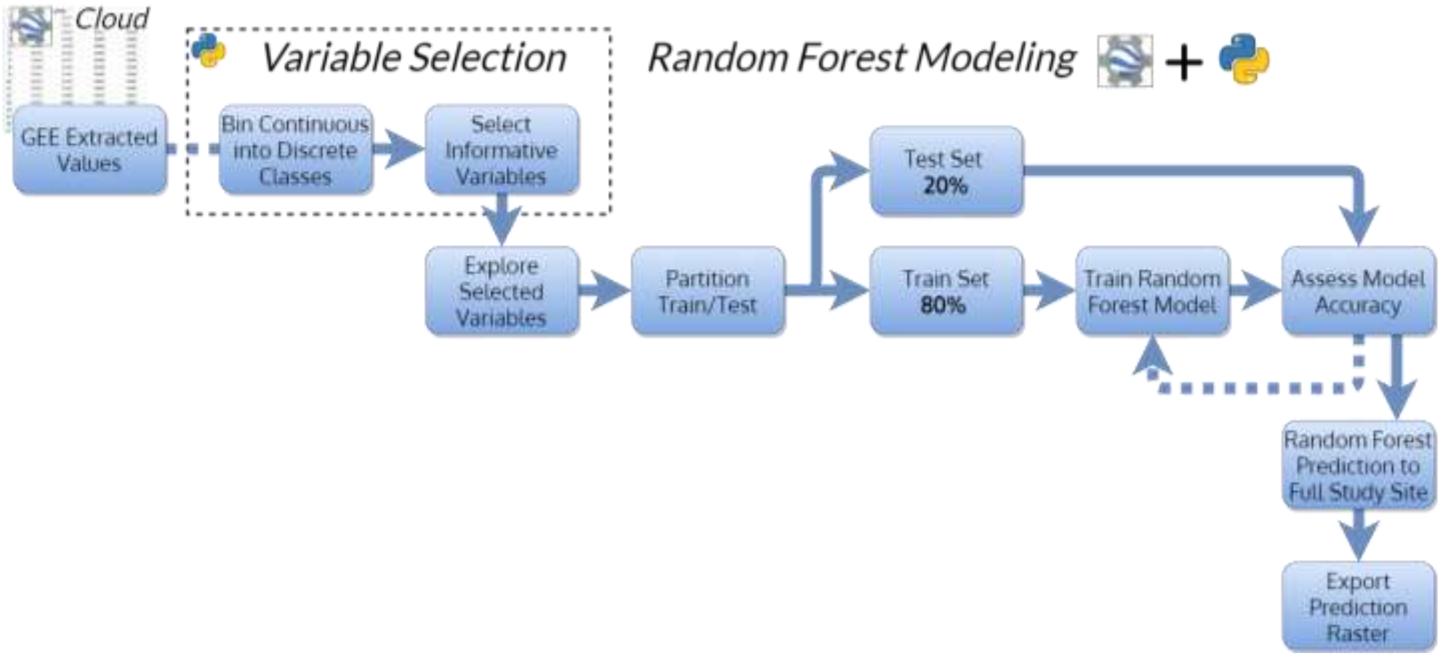

Figure 12. Simplified Random Forest modeling workflow. Models were developed concurrently in Python and Google Earth Engine.

4. Modeling Results & Mapped Outputs

4.1. Study Site Comparison: Vegetation Cover & CRP Tracts

Analysis of vegetation training data and proximity to CRP tracts reveals differences between the Washington and Colorado-Kansas study areas.

A comparison of vegetation percent cover (Figure 13), based on the combined NRI and AIM TerrADat field survey training data, reveals Perennial Forb, Annual Forb, and Bare Soil cover distributions are relatively similar for both study areas, but Grass cover categories show a sharp contrast, as expected per their differing grassland ecosystem characteristics. The Colorado-Kansas study area has a higher mean Perennial Grass cover (52%) than Washington (29%). Logically, the inverse relationship is seen for Annual Grass cover, where the Washington study site has 64% of Annual Grass cover samples with values above 10%, whereas this number drops to 25% for the Colorado-Kansas study area.

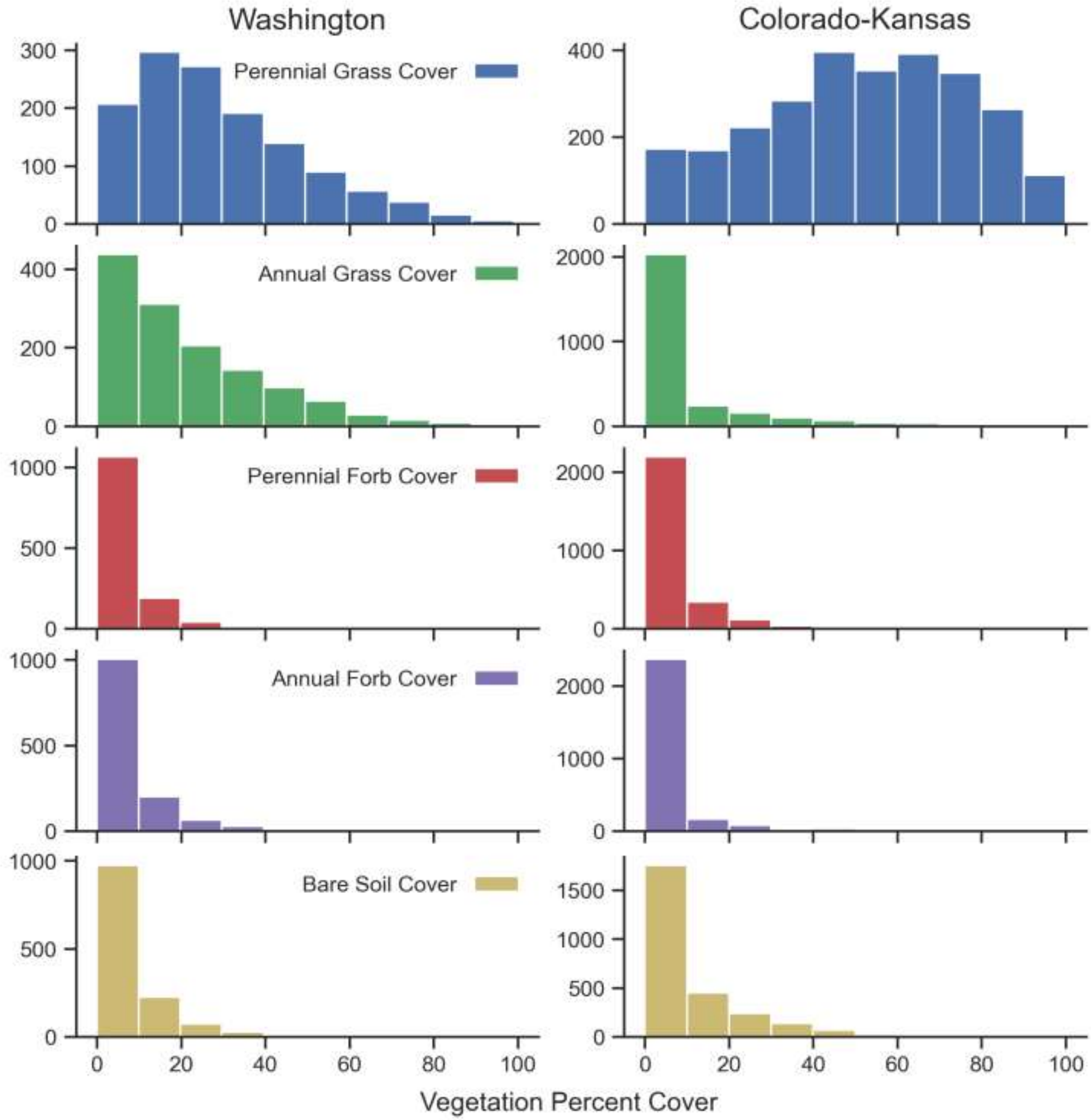

Figure 13. Comparison of vegetation percent cover distributions, based on NRI and AIM training data samples, between the Washington and Colorado-Kansas study areas.

A spatial proximity analysis, quantifying the average distance between CRP tracts and training data plots for each of the study areas, reveals differences between the Washington and Colorado-Kansas study sites, as well. Understanding these patterns is important, because training data nearer to CRP tracts is likely to be more representative of their land cover, and thus create more accurate predictions when used as model inputs. The median distance for the Washington study area is approximately 6.0 km (3.7 mi), whereas the median distance for the Colorado-Kansas study site is 3.6 km (2.2 mi) (Figure 14).

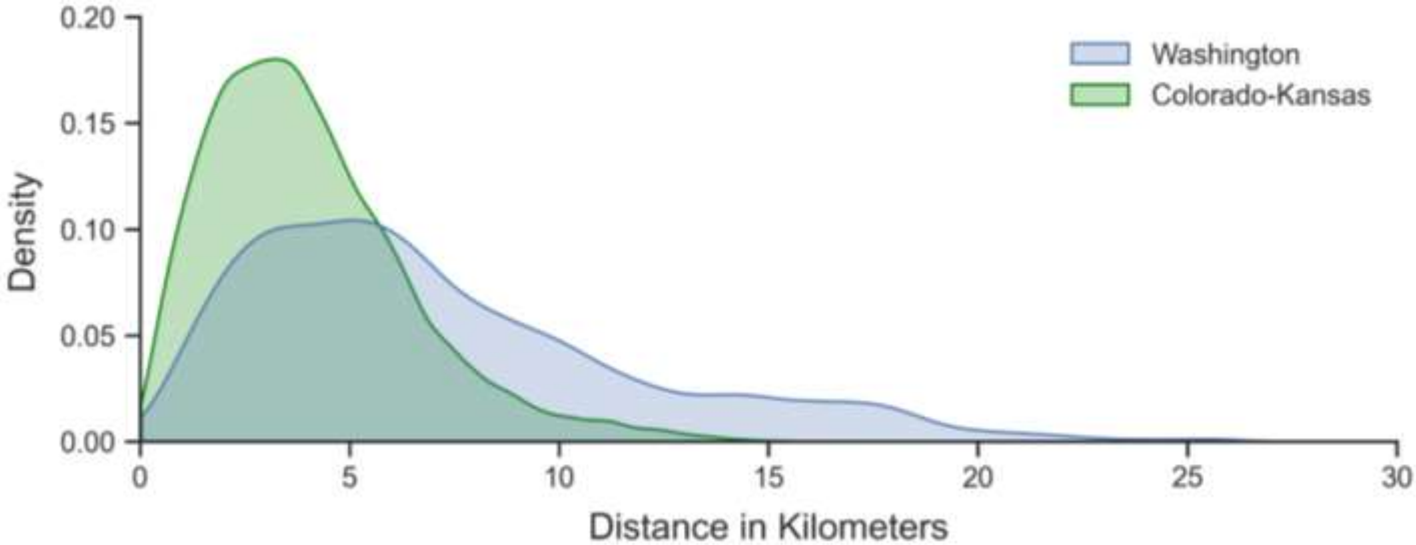

Figure 14. Comparison of distances from CRP Grasslands tracts to NRI and AIM TerrADat training data locations for the Washington and Colorado-Kansas study areas.

4.2. Predictive Vegetation Cover Model Accuracy Assessment

In order to evaluate the validity of modeled outputs, we performed an assessment to document the overall accuracy of each, using an independent portion of the training data withheld for this purpose. Recall, this metric essentially informs us what proportion of the High, Medium, and Low cover type was mapped correctly, based on the independent reference data, with 100% accuracy being a perfect classification. A sensor-by-sensor accuracy comparison for the WA study area modeled outputs shows that Landsat 8 is performing the best, on average (61%), followed by Sentinel-2 (57%), then MODIS (56%) (Table 7).

Table 7. Accuracy assessment showing a comparison across sensors for the Washington Study area, including the total number of field survey observations that align with the sensor's temporal period of available imagery.

	WA Study Area Overall Accuracy (%) by Satellite Sensor		
Vegetation Cover Model	**Landsat 8**	**Sentinel-2**	**MODIS**
Bare Soil Cover	68	57	56
Annual Forb	60	53	56
Annual Grass	64	57	54
Perennial Forb	55	58	57
Perennial Grass	58	61	58
Temporal Period	2014 - 2018	2016 - 2018	2004 - 2018
Total Field Survey Observations	736	484	1,308

Landsat 8's overall accuracy across both study areas ranges from 52% to 68% (Table 8). The model with the highest overall accuracy was Bare Soil Cover, while the lowest was Perennial Forb. Overall accuracies for the Washington study area were higher for all five models than overall accuracies for the Colorado-Kansas study area.

An examination of intra-class vegetation cover accuracy reveals that low and high percent cover classes tend to have higher user's and producer's accuracies across all five models (Table 8). The user's accuracy, or map reliability, is of particular practical relevance to CRP. This metric essentially tells us for a given location, how often the Low, Medium, or High cover class shown on the map will actually be present on the ground, (based on the independent reference dataset); whereas the producer's accuracy shows what percentage of a given cover class was classified correctly, across the whole map.

Table 8. Accuracy assessment with overall accuracy, producer's, and user's accuracy for each Landsat 8 cover type model for the Washington and Colorado-Kansas study areas.

Vegetation Cover Model	Study Area	Overall Accuracy (%)	User's Accuracy (%)	Producer's Accuracy (%)
Bare Soil Cover	WA	68	Low: 69 Med: 60 High: 71	Low: 81 Med: 50 High: 70
	CO-KS	64	Low: 65 Med: 54 High: 71	Low: 71 Med: 44 High: 79
Annual Forb	WA	60	Low: 74 Med: 52 High: 51	Low: 62 Med: 53 High: 59
	CO-KS	60	Low: 60 Med: 62 High: 60	Low: 71 Med: 50 High: 57
Annual Grass	WA	64	Low: 69 Med: 50 High: 69	Low: 67 Med: 52 High: 67
	CO-KS	55	Low: 59 Med: 41 High: 63	Low: 68 Med: 36 High: 55
Perennial Forb	WA	55	Low: 66 Med: 42 High: 53	Low: 62 Med: 38 High: 62
	CO-KS	52	Low: 56 Med: 46 High: 53	Low: 57 Med: 41 High: 56
Perennial Grass	WA	58	Low: 56 Med: 43 High: 66	Low: 55 Med: 38 High: 76
	CO-KS	53	Low: 66 Med: 43 High: 53	Low: 57 Med: 48 High: 54

4.3. Predictive Vegetation Cover Model Variable Importances

The Random Forest modeling process reveals information about the most predictive variables for a given cover type model, which can provide further insight into interpreting results and improving performance in future phases of work (Appendix 9). For the Landsat 8 models, the top three predictive variables were, on aggregate (examining both study areas, all models), Elevation, Total Precipitation Spring, and Aspect. However, in examining which thematic variables, (Spectral, Climate, Soils, or Topographic), were most influential in driving models for each study area, some clear differences arise. The Colorado-Kansas study area models relied more on Spectral satellite predictor variables; out of the top 20 variables, 17 were Spectral. Whereas, in the Washington study area only 9 predictor variables were Spectral and the remainder were Topographic or Climate.

4.4. Mapped Vegetation Cover Outputs

Example maps, produced via Random Forest modeling with Landsat 8 satellite inputs, for all five vegetation cover models are shown below for each study area, in Figures 15 and 16. Recall, the Low, Medium, and High class threshold values are derived from the statistical distribution of each vegetation type's percent cover values, and thus differ among the cover types (Appendix 8).

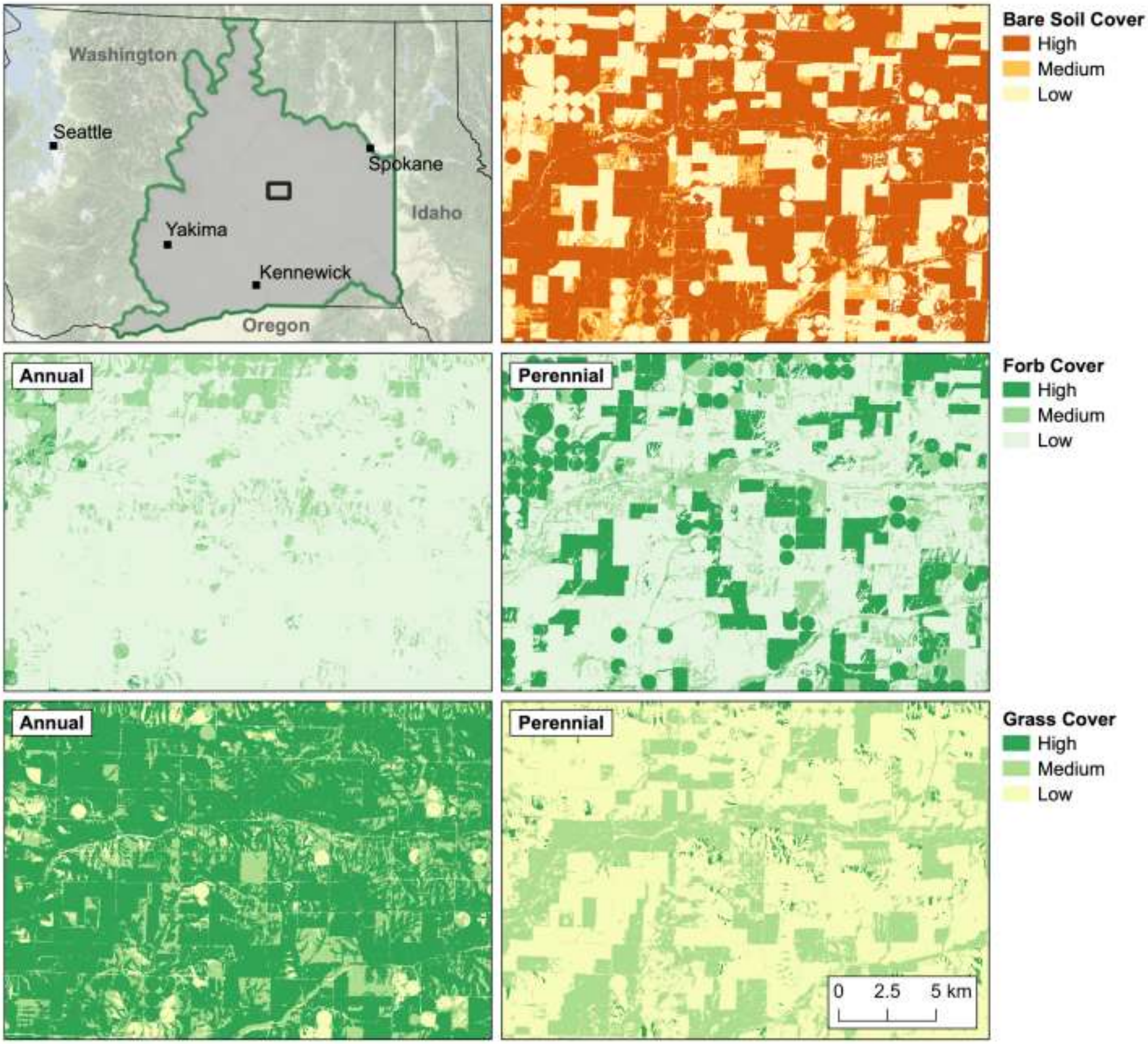

Figure 15. A snapshot of a location in the Washington study area showing the Landsat 8 classification results for bare soil cover, annual forb cover, annual grass cover, perennial forb cover, and perennial grass cover.

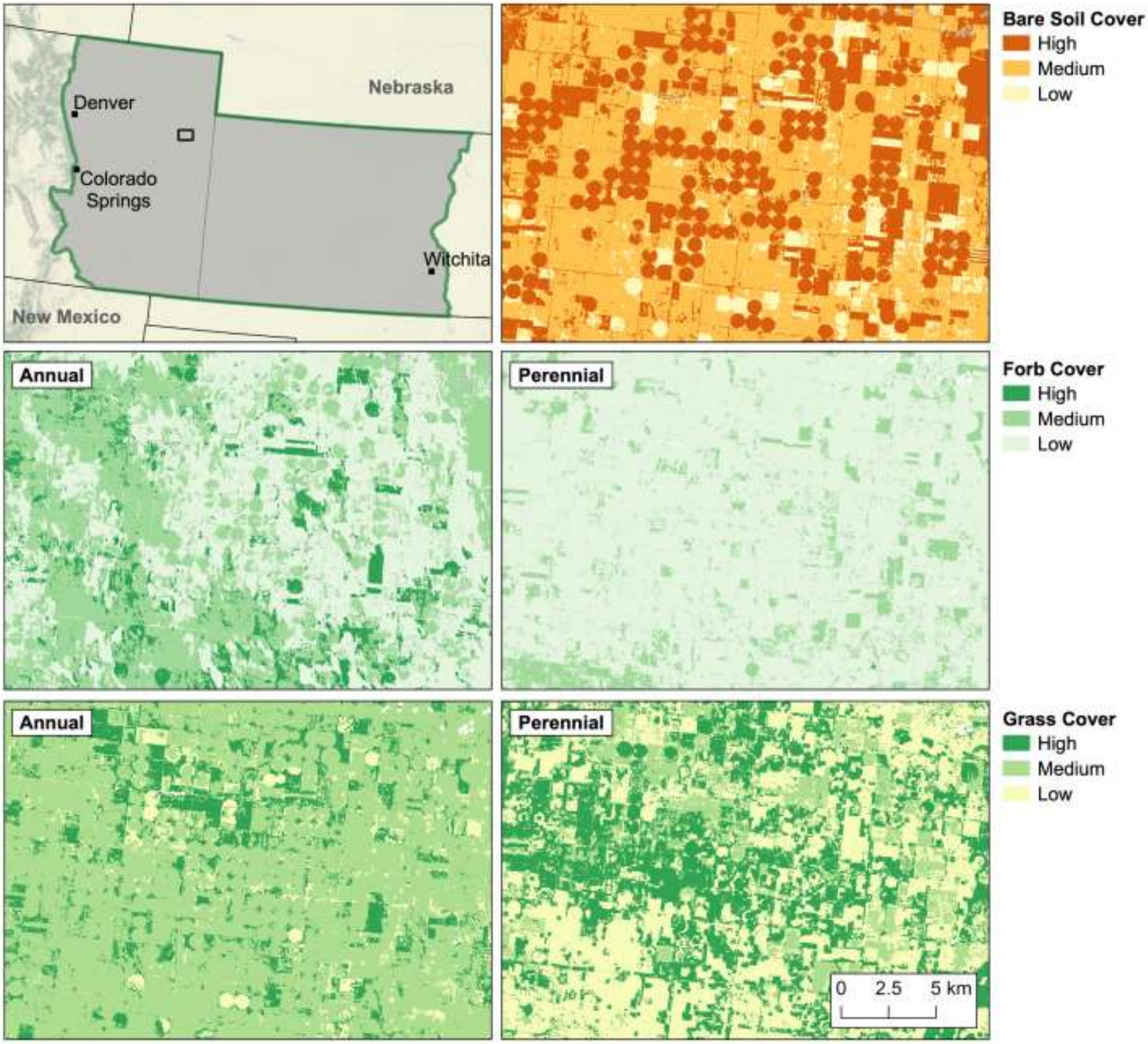

Figure 16. A snapshot of a location in the Colorado-Kansas study area showing the Landsat 8 classification results for bare soil cover, annual forb cover, annual grass cover, perennial forb cover, and perennial grass cover.

Figure 17 shows the mapped predictions of Perennial Forb Cover for 2019; an example output from models developed using 30 m Landsat 8 (left), 20 m Sentinel-2 (middle), and 500 m MODIS (right) imagery. The forb cover models generally had lower accuracy, and this figure shows variation in cover predicted by the various sensors, as well as illustrates the difference in sensor spatial resolution. See Table 7 for complete sensor-wise accuracy comparison.

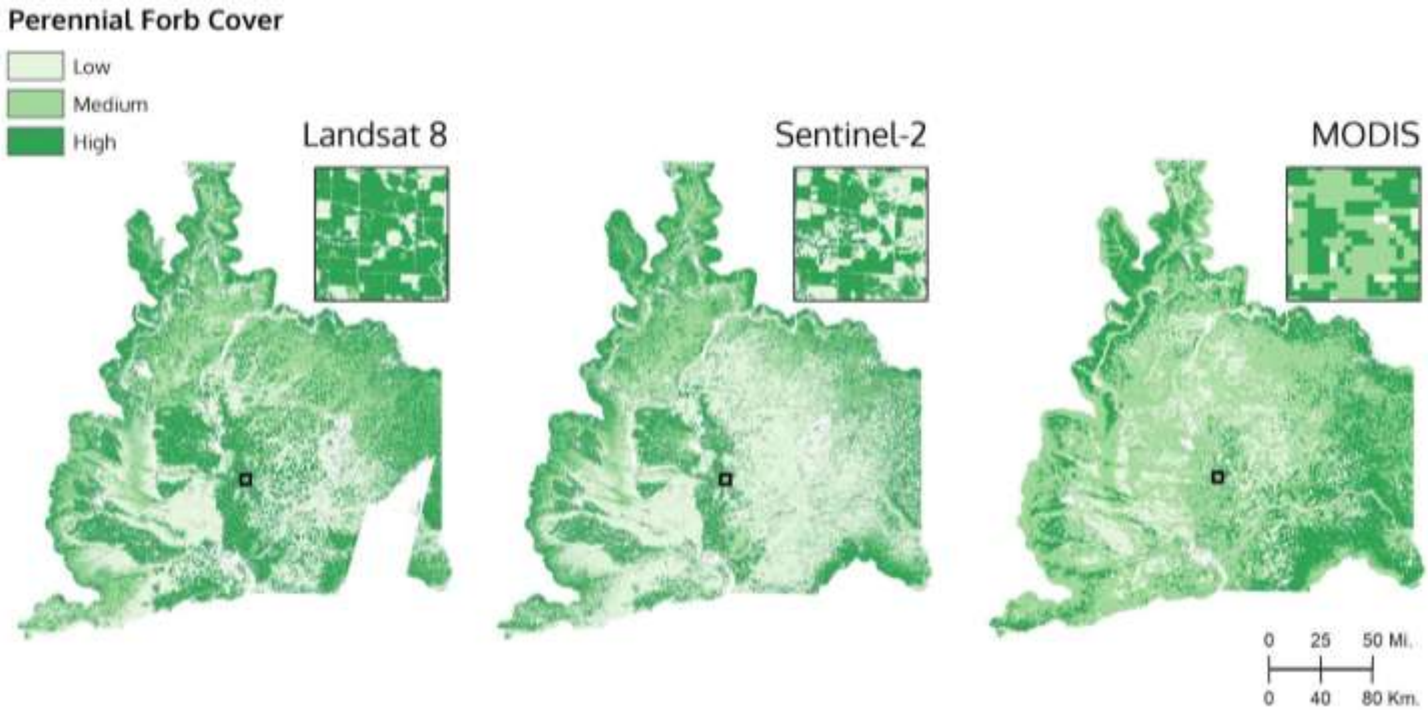

Figure 17. Sensor-wise visual comparison of predicted Perennial Forb Cover in 2019 for the Washington study area. Insets illustrate the difference in sensor spatial resolution (30 m, 20 m, 500 m). The Landsat 8 output (left) shows a large masked portion in the southeast corner of the study area. This is due to low-quality or cloudy imagery being removed from the image composite with no sufficient imagery leftover to fill the gap, which is common with temporal composites over short periods of time in locations with persistent cloud cover.

4.5. Integration of Vegetation Cover into Online CRP Tool

Mapped outputs showing vegetation percent cover predictions from our pilot project have been integrated into CBI's CRP decision support tool for easy data visualization and exploration (Figure 18); these draft products will be refined in future phases. The CRP Tool offers functionality for managers and landowners to view, filter, compare, and summarize geospatial information about the environmental and physical characteristics of CRP tracts in the study areas.

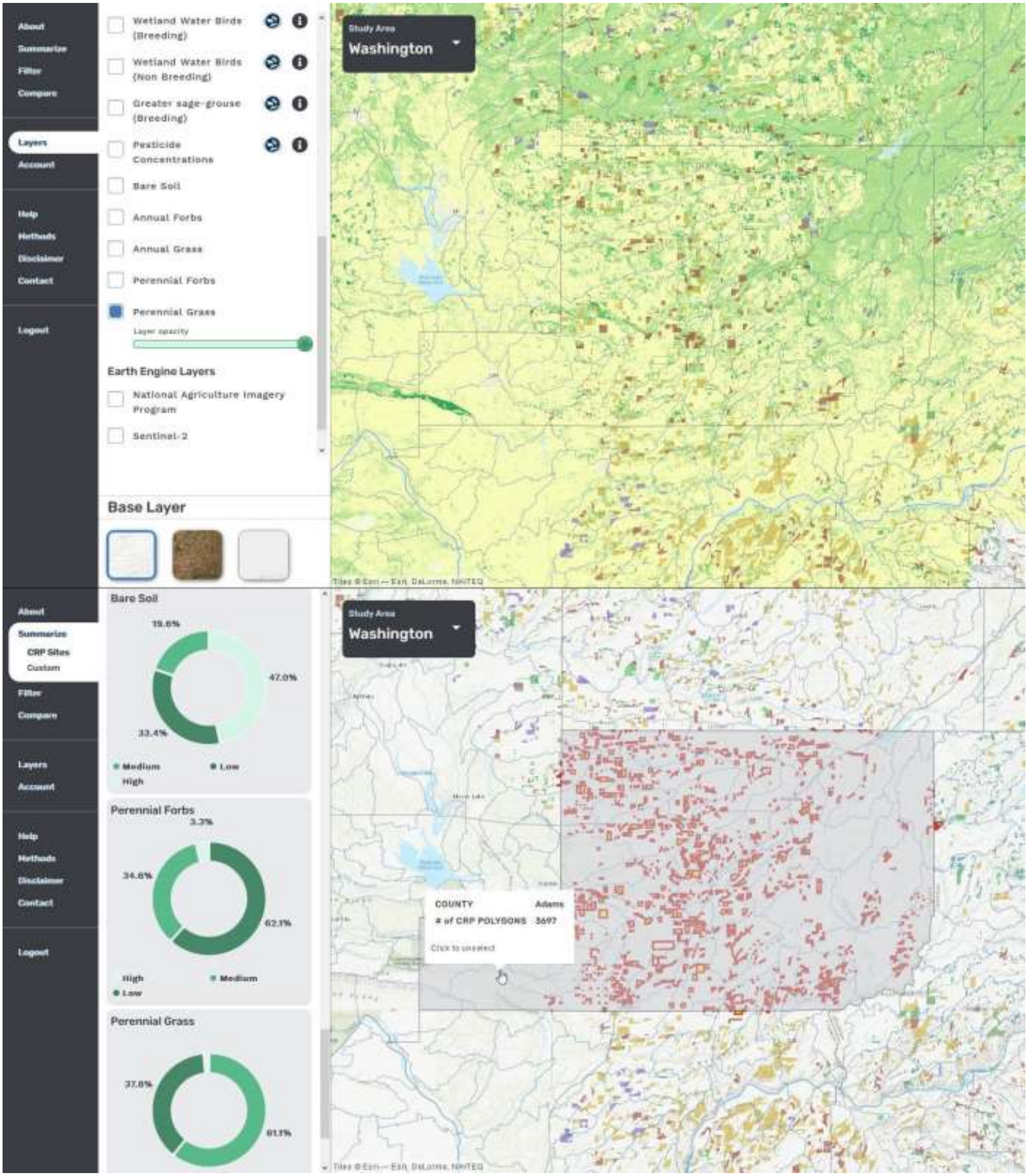

Figure 18. The CRP Tool provides functionality for visualizing model outputs, contextual data layers, and county and watershed boundaries (top). The tool can also be used to create reports and summarize model outputs at the CRP tract, county, or watershed level (bottom).

5. Discussion & Conclusion

5.1. Overview & Approach

The Conservation Biology Institute's work characterizing CRP Grasslands vegetation builds off similar efforts using cloud computing and remotely sensed data to inform grassland and rangeland management. Developing useful products and an online tool to support USDA's CRP is vital to facilitate conservation on their extensive network of private land partnerships across the United States. Mapping grassland vegetation comes with many challenges; vegetation is structurally and spectrally similar, often heterogeneous in composition at a given location, and reactive to fluctuations in temperature and precipitation, resulting in variation from year to year and season to season. However, with grassland ecosystems being one of the most threatened and impacted by land conversion, implementing conservation practices on private lands and working lands is particularly vital to improve connectivity and create habitat corridors that support pollinators and ecosystem services upon which the health of America's farmland depends.

Our approach is tailored to the needs of the Conservation Reserve Program and features mapping vegetation cover at a relatively fine scale on a regional basis, which differentiates it from other available products. This more nuanced and focused approach produces results with a level of detail more suitable to informing CRP management decisions. We also intend to integrate CRP-specific training datasets into our model development, as they become available, and to produce program-specific indicators of habitat quality and land condition in future phases, using CBI's Environmental Evaluation Modeling System (EEMS) (Sheehan and Gough, 2016), which will be incorporated into the online tool. Our focus on mapping current conditions using the latest remote sensing and machine learning methods creates a baseline draft product and a feasible process for potential monitoring of CRP Grasslands tracts into the future.

5.2. Outcomes & Limitations

5.2.1. Training Data

Without field survey data from the NRCS NRI and BLM AIM TerrADat programs, it would not be possible to predict grassland vegetation cover on a large geographic scale at the level of detail necessary to inform USDA's CRP land management practices. These unique, national sampling efforts' methodological alignment allows for their use in combination during analysis and modeling (Jones et al., 2018). However, the NRI requires a formal data request and authorization process facilitated by a federal agency on the user's behalf due to privacy restrictions surrounding their location on non-Federal, private lands. By contrast, the AIM TerrADat is readily available, since those surveys cover public BLM lands. Despite their demonstrable value, these training data are not sampled directly from CRP Grasslands tracts, so current models may not be fully representative of CRP holdings. Implementing a simple process for monitoring CRP tract vegetation condition by the landowner would provide a major source of meaningful data to groundtruth model accuracy.

Our spatial proximity analysis quantifies the distance between CRP tracts and training data plots for each of the study areas (Figure 14). The closer average distance observed for the Colorado-Kansas study site indicates that its training data and corresponding modeled vegetation cover predictions are more likely to be representative of CRP tracts than the training data and modeled predictions for the Washington study area.

There are additional limitations inherent when using the NRI and AIM TerrADat as training data for machine learning models. The skewed distribution of vegetation percent cover samples (Figure 13) limits the ability to train the Random Forest models as effectively for some classes, leading to lower predictive performance for these. This is especially true for Perennial and Annual Forbs; only 17% of Perennial Forb samples in the Washington study area and 13% of Annual Forb samples in the Colorado-Kansas study area have measurements above 10% cover (Appendix 7). Having less representation for higher cover values makes it challenging for models to learn and predict from this data.

5.2.2. Model Performance, Satellite Sensors, & GEE Processing

Mapped predictions for all five vegetation cover models are promising, based on our classification accuracy assessments, and are likely to improve with further model development incorporating an ever-growing archive of satellite imagery. We have successfully implemented a complex processing workflow utilizing both local and cloud computing resources and have tested our approach for discriminating grassland vegetation classes.

Tradeoffs among the three satellite sensors we evaluated (Landsat 8, Sentinel-2, and MODIS) are shown in Table 4 and Figures 9 and 10. While Sentinel-2 has a higher spatial and spectral resolution than Landsat 8 and MODIS, its historical archive is limited to mid-2015 onward for the top-of-atmosphere (TOA) product, and only to December 2018 onward for the atmospherically corrected surface reflectance product on GEE. By contrast, MODIS has a higher temporal resolution than Sentinel-2 and an extensive historical archive of atmospherically corrected surface reflectance, but its coarse spatial resolution make it less suitable for fine-scale analysis and CRP needs. Our results from Landsat 8 models demonstrate its high value - offering the best balance of spatial and spectral resolution, while temporally aligning with a substantial quantity of training data.

As expected, the model with the highest overall accuracy was Bare Soil cover for both study areas, due to soil's spectral reflectance characteristics that allow it to be readily differentiated from vegetation. In terms of differences among vegetation cover classes, the low and high percent cover classes tend to have better accuracies across all five models, likely due to increased spectral divergence for these classes, i.e, these may reflect light more uniformly and with less intraclass variation than the medium cover classes. The vegetation cover model with the lowest accuracy for both study areas was Perennial Forb; a result we anticipated based on the challenge of using remote sensing to detect non-dominant vegetation on grassland landscapes. Despite the species richness of grassland ecosystems, perennial grasses historically dominate their vegetation cover. For example, just two grass species at the 3,487 hectare Konza Prairie Biological Station in eastern Kansas comprise 70% of the vegetation cover, despite co-occurring with more than 400 species of forbs and other vegetation. Temporal variability of grasslands, driven primarily by intra- and inter-annual rainfall fluctuations (Blair et al., 2014), add to the challenge of using remotely sensed data to discriminate vegetation on these structurally and spectrally homogenous landscapes. Lastly, grassland landscapes are increasingly influenced by the presence of invasive annual grasses (Ogle et al., 2003), management of which is a high concern to the CRP. All of these factors, combined with training data limitations, satellite data archive restrictions, and necessary seasonal compositing of satellite imagery, make it particularly difficult to detect and model grassland vegetation (especially forbs) at scale.

Overall accuracies for the Washington study site were higher than those of Colorado-Kansas for all five models, though not by wide margins (Table 7). Likely, this is due to multiple factors; one being that the Washington study area has more topographic variation than the Colorado-Kansas site, which allows more value to be gained from the topographic variables, shown to be of high predictive importance across the Washington models. Models for regions with little topographic variation must rely on the spectral and relatively coarse climate input variables to drive predictions. Alternatively, improved performance for the Washington area could be due to its smaller geography and thus more customized model fitting. Likely, both of these factors come into play.

Another key finding revealed by our models' variable importance rankings (Appendix 9) is that for both study sites all vegetation cover predictions are driven by a wide array of input variables, with each variable contributing incremental amounts of information. This indicates our extensive suite of spectral and enviro-climatic input variables adds value and is likely necessary to maintain model predictive performance across grasslands.

Throughout our modeling process Google Earth Engine facilitated a flexible and iterative approach to analysis, quick data processing for the large study areas, and access to an extensive, curated data catalog; however, we did encounter some limitations with data availability, workflow, and functionality. Some hurdles in terms of data management required additional time and attention, and model refinement required reliance on additional functionality available through Python. So, in actuality, a suite of geospatial analysis platforms, complementary software, and tools/utilities is required to support this modeling workflow. Also, although GEE hosts an ever-growing multiple petabyte data library, its limited temporal archive of atmospherically corrected Sentinel-2 data dictates advanced atmospheric correction prior to incorporating Sentinel-2 imagery into models. Nonetheless, the advantages of GEE's cloud-computing power, code reusability, and scalability outweigh its disadvantages, so we remain invested in moving forward with this platform in future phases of work.

5.3. Future Work

5.3.1. Refining Models

Incorporating additional data and model refinements into our analytical workflows could improve our results characterizing vegetation on CRP Grasslands. Foremost, ideally some portion of the field survey data used to train predictions would come from surveys conducted directly on CRP lands. As a start, the USGS recently performed a number of general vegetation surveys on CRP Grasslands; once this dataset becomes available, it could be utilized to assess how well models trained using the NRI and AIM TerrADat field surveys predict across CRP Grasslands. Also, there could be opportunities for CBI to facilitate productive partnerships with non-governmental organizations who are already collecting similar vegetation data in areas where CRP-enrolled lands are present. Lastly, we could work with the USDA to develop and implement a simplified protocol for CRP landowners to undertake geo-located photo assessment of their lands, collecting data that could be aggregated, processed and used to validate or potentially train future models. We already have functionality in the online CRP tool for owners to take pictures, and with the right guidance and information, we may be able to gather useful data to make the model projections on grasslands more accurate and useful. In conclusion, a long-term, on-site CRP field survey program would add extensive value by increasing training data sample sizes and allowing models to be further customized to CRP lands and needs.

Model refinements also could be explored in regards to the remotely sensed input variables. Despite the additional processing required to apply atmospheric corrections to Sentinel-2 data in GEE, its higher spectral resolution, shorter return interval, and vegetation-sensitive red-edge bands may still help resolve subtle differences in fairly homogenous (i.e., spectrally similar) grassland landscapes, particularly for difficult-to-detect classes such as Perennial Forbs; this may become more apparent as time passes and the Sentinel-2 temporal archive increases. Aside from Sentinel-2, the ESA's Sentinel-1 synthetic aperture radar is sensitive to changes in soil moisture and can collect data through cloud cover; it may be able to provide auxiliary information on vegetation structure characteristics, making it a potentially valuable input for grassland vegetation modeling (Hall-Beyer, 2000 and 2017; Flores et al., 2019; Crabbe et al., 2019 and 2021). However, the demonstrated and enduring value of the Landsat program, marked with this year's launch of Landsat 9, means that it will likely remain a core component of our remotely sensed model inputs. Continued development of models with data from the constellation of Landsat and Sentinel satellites, to create a multisensor-driven model, may help improve our grassland mapping outcomes.

Finally, we will continue to develop and refine our modeling approach, to build upon the strong foundation we've developed utilizing both GEE and Python. We will explore using regression modeling to represent fractional percent cover; when combined with finer-scale model input variables from Sentinel-2 and PRISM data, regression may lend itself well to representing subtle variation found in grassland vegetation. In parallel with exploring regression, we will continue to refine our current classification approach, customizing our vegetation classes to enhance model performance and better align with CRP needs. We will also explore more advanced phenology and time-series metrics that may help models by further characterizing the temporal fluctuations of grassland vegetation. Lastly, while Random Forest is a powerful tool, it is not the only modeling solution. We intend to compare our Random Forest models to alternative modeling approaches available in Python and GEE, such as Gradient Boosted Models and Deep Neural Networks, in order to select the best-performing method.

5.3.2. Integration into Decision Support Systems

Our workflow to map vegetation cover can provide a baseline to characterize vegetation within CRP Grasslands tracts and offers the opportunity to create metrics to quantify landscape condition, in future phases. These predictions of vegetation cover can be inputs to CBI's transparent modelling framework (Sheehan, T. and M. Gough. 2016), and in conjunction with other datasets (e.g., landscape erodibility and productivity) used to produce spatially explicit, program-specific indicators of habitat quality and land condition for CRP Grasslands. Our robust Environmental Evaluation Modeling System (EEMS) facilitates information synthesis and integrates diverse datasets to answer complex management questions and engage stakeholders with interactive online maps.

Bringing this and other key data together in the multi-faceted online CRP tool allows relevant information to be analyzed, shared, and downloaded by USDA leadership and CRP managers. Future expansion of analytical and online tool functionality will provide additional species and ecological information to help guide strategic management actions on existing CRP holdings and to prioritize new enrollment in the CRP. The Conservation BIology Institute's suite of powerful products, rolled into an accessible online tool, allows CRP to leverage these components to implement holistic and scientifically sound decision-making.

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Appendices

A1. CRP Grasslands Practices

Table A1-1. CRP Grasslands practices and brief description (USDA, 2018).

Grasslands Practice	Description
1	Establish new or maintain existing vegetative cover of introduced grasses and legumes on eligible cropland that will enhance environmental benefits.
2	Establish new or maintain existing vegetative cover of native grasses on eligible cropland that will enhance environmental benefits.
4D	Establish or maintain existing permanent wildlife cover to enhance environmental benefits for wildlife habitat of the designated area or the surrounding areas.
8A	Grass waterways to convey runoff of not more than 100ft width to reduce erosion.
10	Already established grass cover (ended March 14, 2011).
12	Establish non contiguous 5 acre plots with wildlife food species determined.
15A	Establish permanent vegetative cover (contour grass strips) 15-30 ft wide along contours to reduce runoff and erosion.
15B	Establish permanent vegetative cover (contour grass strips) <60 ft wide along abandoned or degraded terraces to increase water infiltration, reduce runoff and soil erosion.
21	Filter strips 20-120ft wide to prevent `pollution' of surface or subsurface water
25	endangered, and threatened habitats.
29	Marginal pastureland wildlife habitat buffer.
33	Habitat buffers for upland birds.
38E	Applies to practices that restore and maintain specific habitats as determined by applicable state-developed standards.
42	Establish habitat to support a diversity of pollinator species.
87	Maintain existing vegetative cover of introduced grasses and legumes.

88	Maintain existing vegetative cover of native grasses and legumes.
87A	Maintain existing vegetative cover of introduced grasses and legumes as part of livestock operations.
88B	Maintain existing vegetative cover of native grasses and legumes as part of livestock operations.

A2. Natural Resource Field Surveys

Table A2-1. Field survey sampling transect designs for TerrADat (Spoke Design) and NRI (Intersecting Design) (Herrick et al., 2017).

PLOT LAYOUT	DESCRIPTION	
(a) Spoke Design	25 m spoke design covers ~0.3-hectare (~0.7 acres). 50 m (~75 ft) spoke design covers a 1 hectare (~2.35 acres) area. Transects begin 5 m (15 ft) from the plot's center to focus trampling around center stake and minimize disturbance effects on transects.	
(b) Intersecting Design	The NRI intersecting transect design covers ~0.2 hectares (~0.4 acres). Two 50 m (150 ft) transects intersect at the 25 m (75 ft) mark at plot center. The transect arms are oriented 45 degrees in both directions from magnetic north.	

A3. Random Forest Machine Learning

A Random Forest model is “grown” from many decision trees, each of which make a series of hierarchical decisions that sort a set of observations based on their attributes until all observations have been sorted into final target bins or categories. Each decision point is called a “node”, except the top (base) node, which is called a “root node” and the terminal (bottom) nodes, which are called “leaf nodes”. The root node represents the entire set of input observations and each subsequent node divides the set of observations into increasingly homogeneous sets until final categories or predictions are reached in the leaf nodes. To make a prediction the Random Forest model takes an average of all the individual decision tree estimates (regression) or by majority vote (classification). This structure leads to more robust overall predictions than a simple decision tree or even a set of standard decision trees could.

Another benefit of the Random Forest structure is that by training each tree on a subset of the data we get a sort of model cross-validation called out-of-bag (OOB) error, which can be used to estimate model performance on training data alone. Each individual decision tree in the Random Forest is very sensitive to the data they are trained on (overfitting), which could result in unstable predictions and poor predictive power. Random Forest modeling corrects for this by injecting randomness into each tree to minimize correlation between the trees. It does this in two different ways: bootstrap aggregation (bagging) of the input samples and choosing a random subset of all variables on which to split each node. In other words, each tree sees a different set of observations and, at each decision point, decides on a different set of variables.

A4. U.S Ecoregions

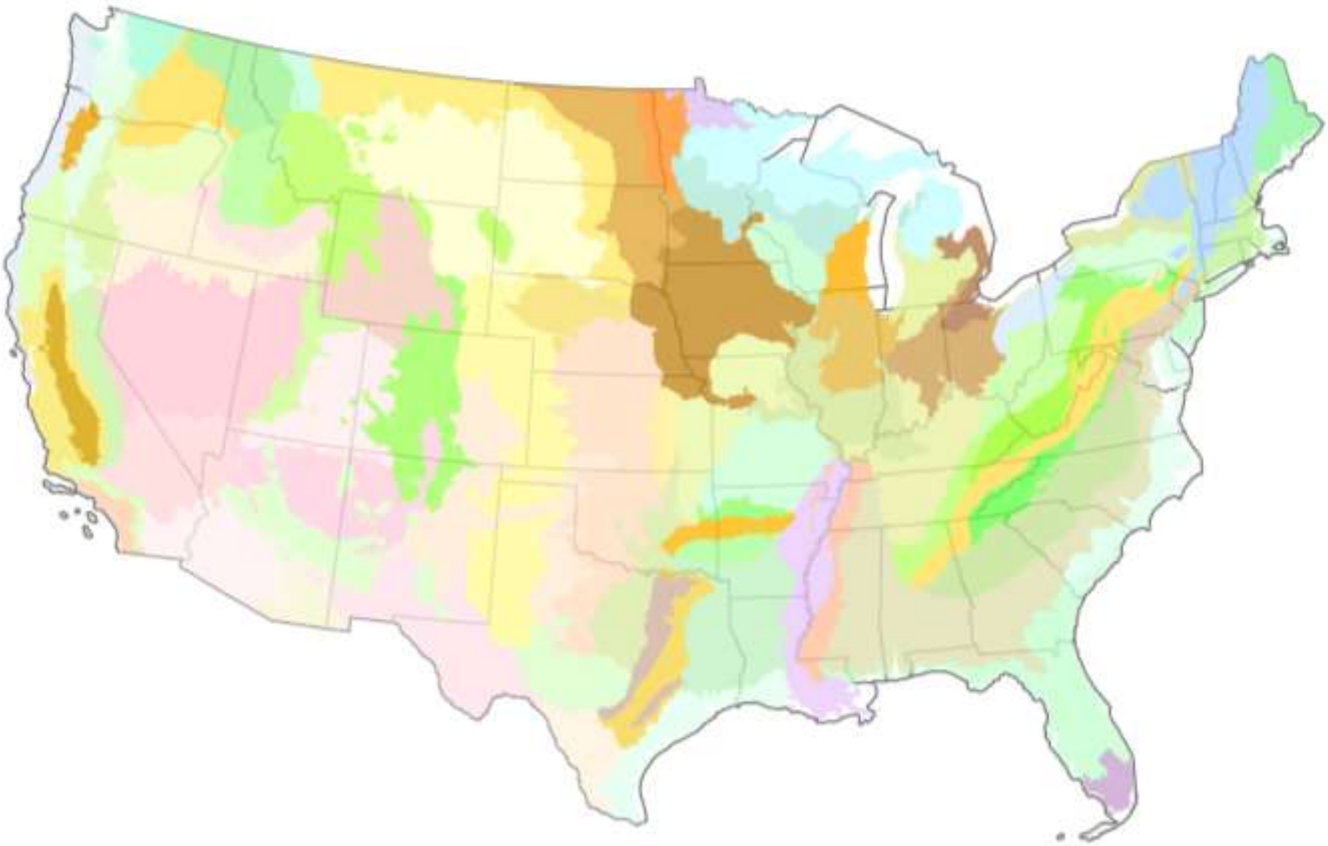

Figure A4-1. U.S. EPA Level III Ecoregions of the conterminous United States (Omernik and Griffith, 2014). A more detailed map can be found at ftp://newftp.epa.gov/EPADataCommons/ORD/Ecoregions/us/Eco_Level_III_US.pdf.

A5. Washington Study Area Ecoregion

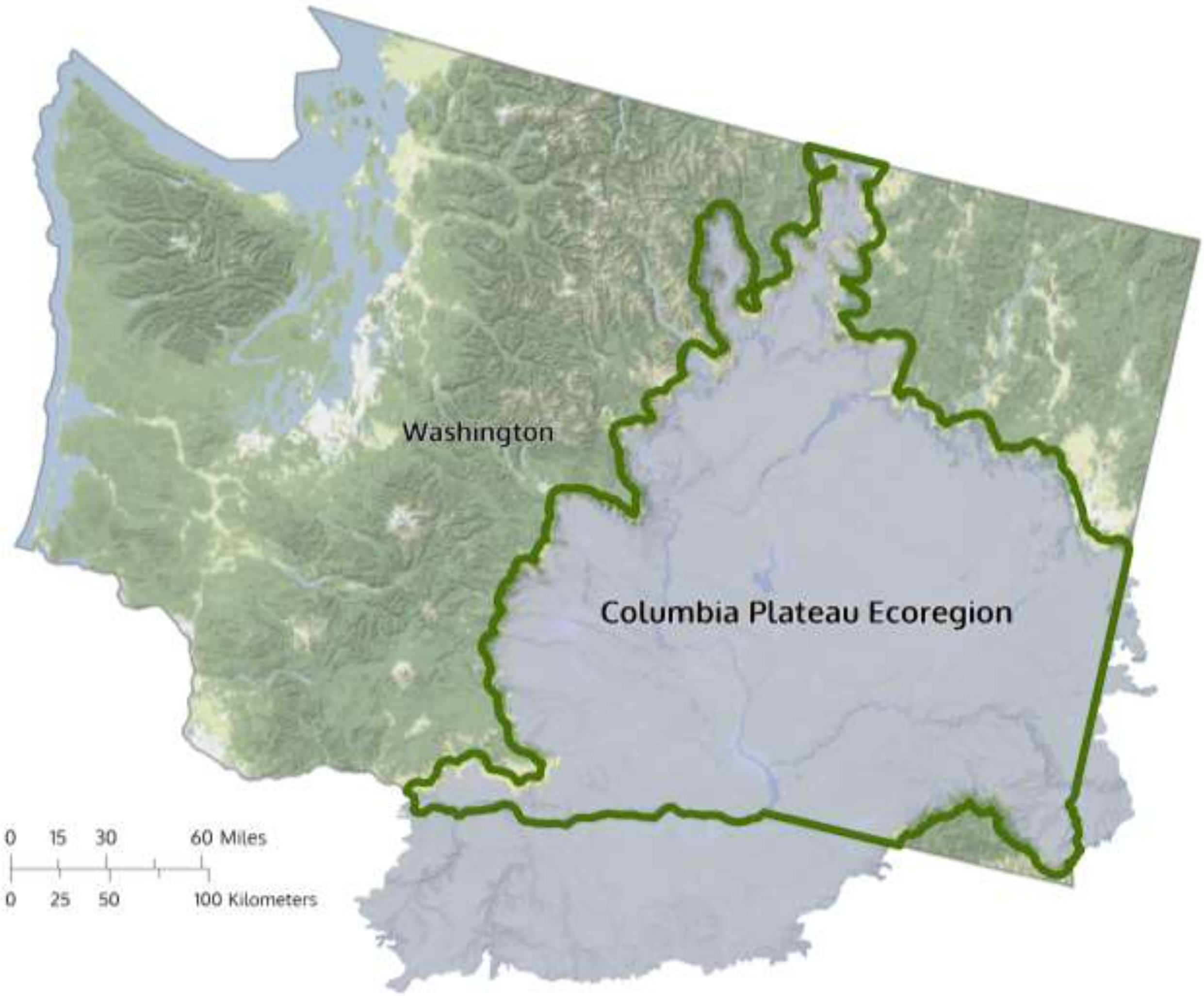

Figure A5-1. The Washington study area (outlined in green) includes a majority of the Columbia Plateau ecoregion (purple) plus a 5 km edge buffer.

A6. Colorado-Kansas Study Area Ecoregions

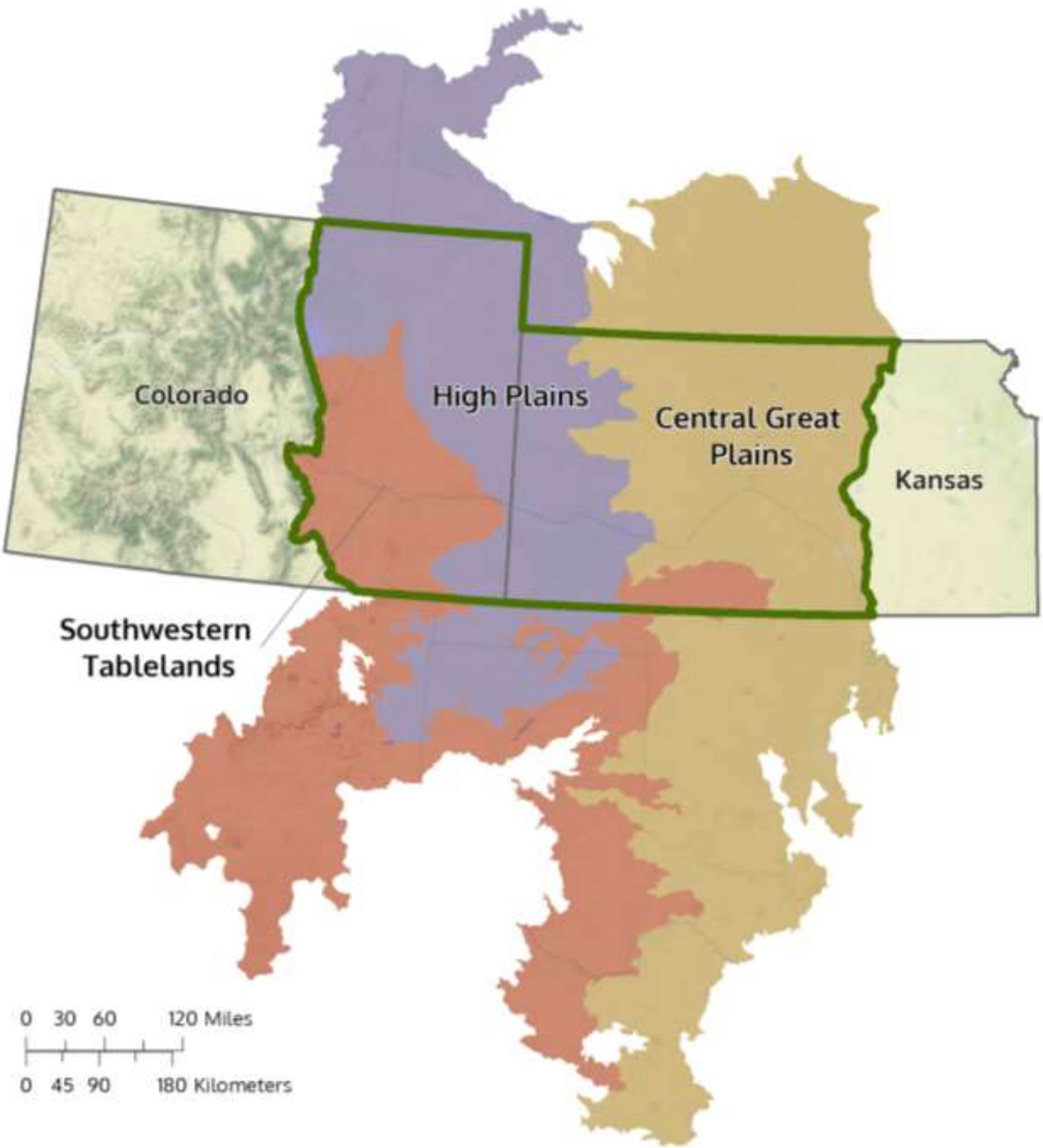

Figure A6-1. The Colorado-Kansas study area (outlined in green) includes portions of the Central Great Plains (tan), High Plains (purple), and Southwestern Tablelands (red) U.S. EPA Level III ecoregions.

A7. Field Survey Data Acquisition and Exploration

CBI began field survey data acquisition in January, which continued until NRI data was delivered in late May. Because the NRI sampling takes place on non-Federal land, access to the specific sampling geolocations is restricted by law (7 USC 2276) and thus requires an appropriate use data request, confidentiality agreement, and authorization from the NRCS. In contrast, the BLM AIM TerrADat is pre-processed and readily available since it is conducted on the nation's public lands. For this phase of work, CBI pursued and acquired the most recent versions of both datasets.

The specific NRI component that was acquired for purposes of CRP Grasslands modeling was the non-federal NRI Grazinglands Onsite Pasture and Range data. NRI data were processed and delivered by Lori Metz from the USDA NRCS Conservation Effects Assessment Project-Grazing Lands (CEAP). Species attributes are aggregated into plant functional groups, or distinct vegetation community types, using methodologies provided by the USDA NRCS CEAP-Grazing Lands team (Metz and Rewa, 2020). For purposes of correlating vegetation cover measurements with satellite imagery data, we selected only "first hit" variables. First hit calculations only consider the first plant, litter, or soil cover encountered on a transect pin drop, from a top-down perspective.

Table A7-1. Full, initial set of selected vegetation cover variables from NRCS NRI data. All variables were first hit calculations only, which consider the first plant, litter, or soil cover encountered on a transect pin drop. Final modeling target variables are highlighted in green.

Vegetation Cover Variable	Description
Perennial Grass Cover	The cover of perennial grasses in the plot.
Annual Grass Cover	The cover of annual grasses in the plot.
Perennial Forb Cover	The cover of perennial forbs in the plot.
Annual Forb Cover	The cover of annual forbs in the plot.
Bare Soil Cover	The cover of soil that has no cover above it in the plot. For example, points with sagebrush over so counted in this indicator, nor are points with litter over soil.
Total Foliar Cover	The foliar cover of plants in the plot, defined as the percentage of points where a plant was encour pin was dropped.
Perennial Herbaceous Cover	The cover of perennial herbaceous cover (forbs and grasses) in the plot.
Annual Cover	The cover of annuals in the plot.
Perennial Shrub Cover	The cover of perennial shrubs in the plot.
Perennial Tree Cover	The cover of perennial trees in the plot.

Total Litter Cover	The cover of total litter, both herbaceous and woody, in the plot, not including litter that has cover
Rock Cover	The cover of rock fragments in the plot, not including litter that has cover above it.

Table A7-2. A comparison of basic statistics for all selected vegetation cover variables in both the Washington and Colorado-Kansas study areas.

Study Area	**Vegetation Cover Variable**	**Min - Max**	**Mean**	**Std. Dev.**	**Quartiles [25%, 50%, 75%]**	***% Samples >10% Cover***
WA	Perennial Grass Cover	0 - 99	29	20	[14, 25, 41]	81%
	Annual Grass Cover	0 - 89	21	18	[6, 16, 32]	64%
	Perennial Forb Cover	0 - 68	5	7	[1, 3, 8]	17%
	Annual Forb Cover	0 - 88	7	9	[1, 4, 9]	21%
	Bare Soil Cover	0 - 58	7	8	[1, 4, 10]	24%
CO-KS	Perennial Grass Cover	0 - 100	52	24	[35, 53, 71]	94%
	Annual Grass Cover	0 - 98	9	17	[0, 1, 11]	25%
	Perennial Forb Cover	0 - 64	6	8	[1, 3, 8]	19%
	Annual Forb Cover	0 - 96	5	11	[0, 1, 4]	13%
	Bare Soil Cover	0 - 89	11	14	[1, 6, 16]	35%

Of the total 46,981 training data observations for the entire U.S., there are 31,413 NRI samples from 2004 - 2018, while 15,568 TerrADat samples are available from 2011 - 2019.

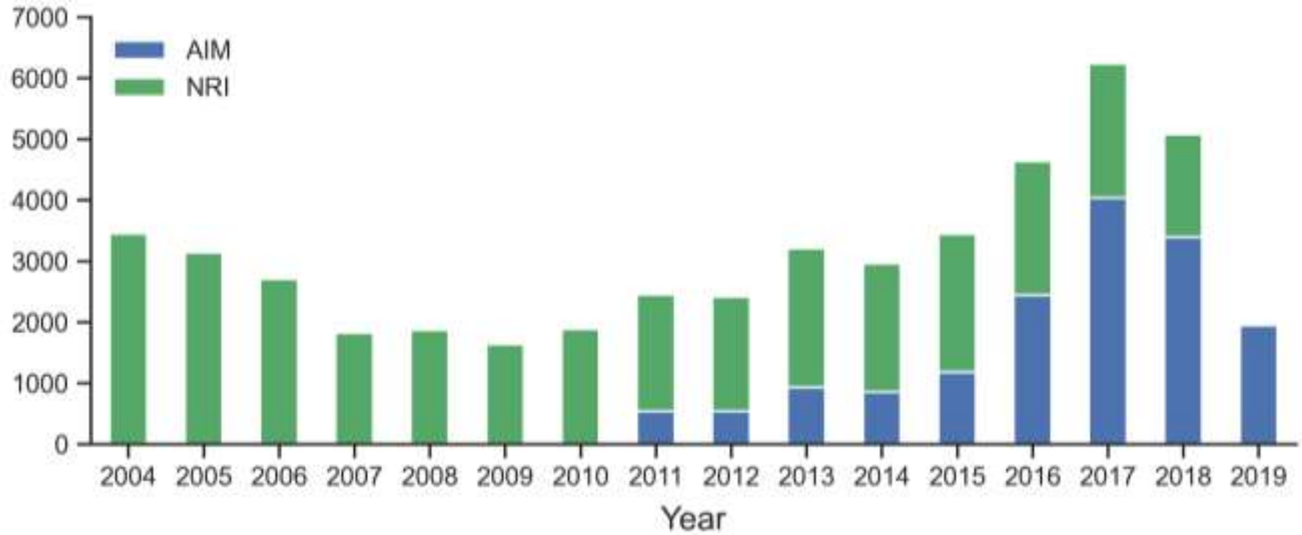

Figure A7-1. Counts of NRI and AIM TerrADat samples per year for the entire U.S.

To characterize the land cover distribution for training data points, we used the USDA 2019 CropScape Cropland Data Layer (CDL) to sample the cropland classes for all training points. In addition to the cropland class, we sampled the cultivated/non-cultivated classes included with the CDL for all training points. For both study areas, approximately 97 percent of the training points fell within the non-cultivated class, which corresponds with the majority of the training points classified as Grassland/Pasture or Shrubland.

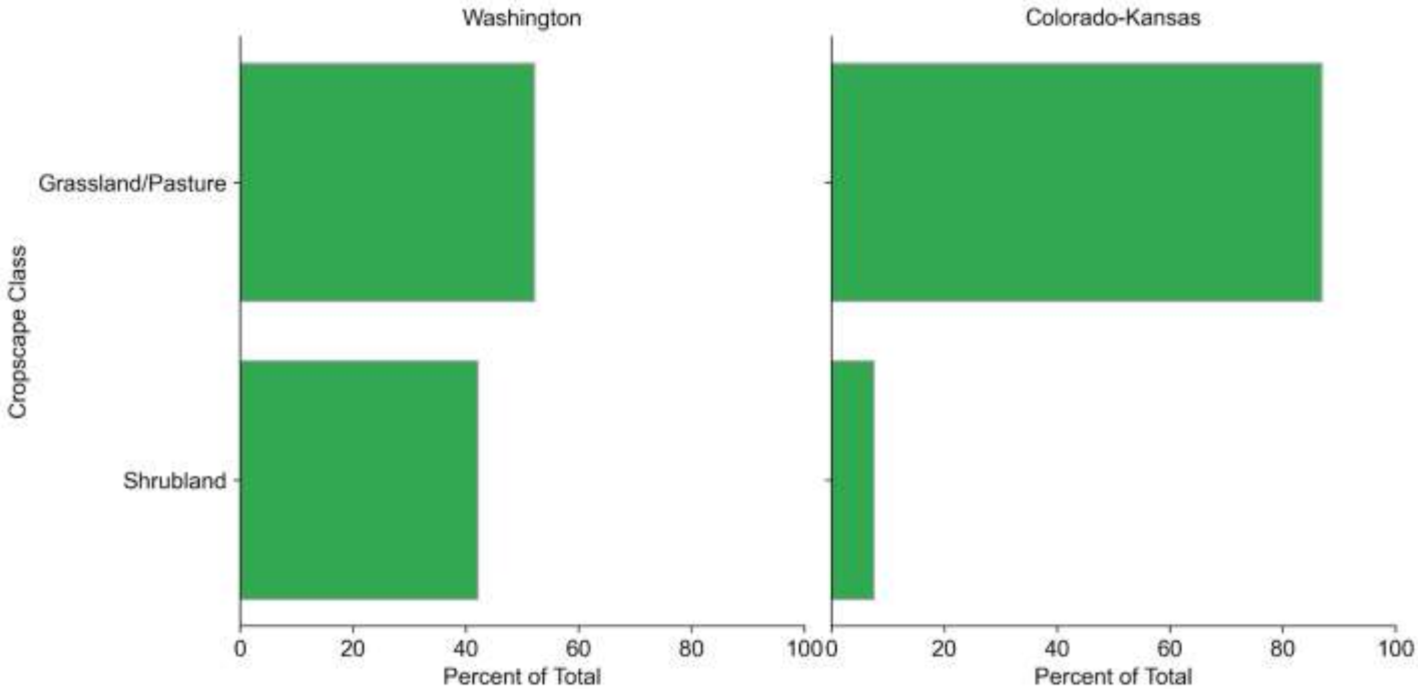

Figure A7-2. Percent of total training points of sampled Cropscape Cropland Data Layer (CDL) classes for each study area.

To better understand the land cover characteristics of CRP Grasslands tracts and alignment with the training data points, we used the USDA 2019 CropScape Cropland Data Layer (CDL) (USDA-NASS, 2019) to sample the majority (mode) cropland classes for all CRP tracts within the study areas. The majority class within Washington CRP tracts is Shrubland and the majority class within Colorado-Kansas CRP tracts is Grassland/Pasture (Figure A7-3). In addition to the cropland class, the cultivated/non-cultivated classes included with the CDL were sampled for all CRP tracts. For the Washington CRP tracts, 72 percent fall within the non-cultivated class. For the CO-KS CRP tracts, 84 percent fall within the non-cultivated class.

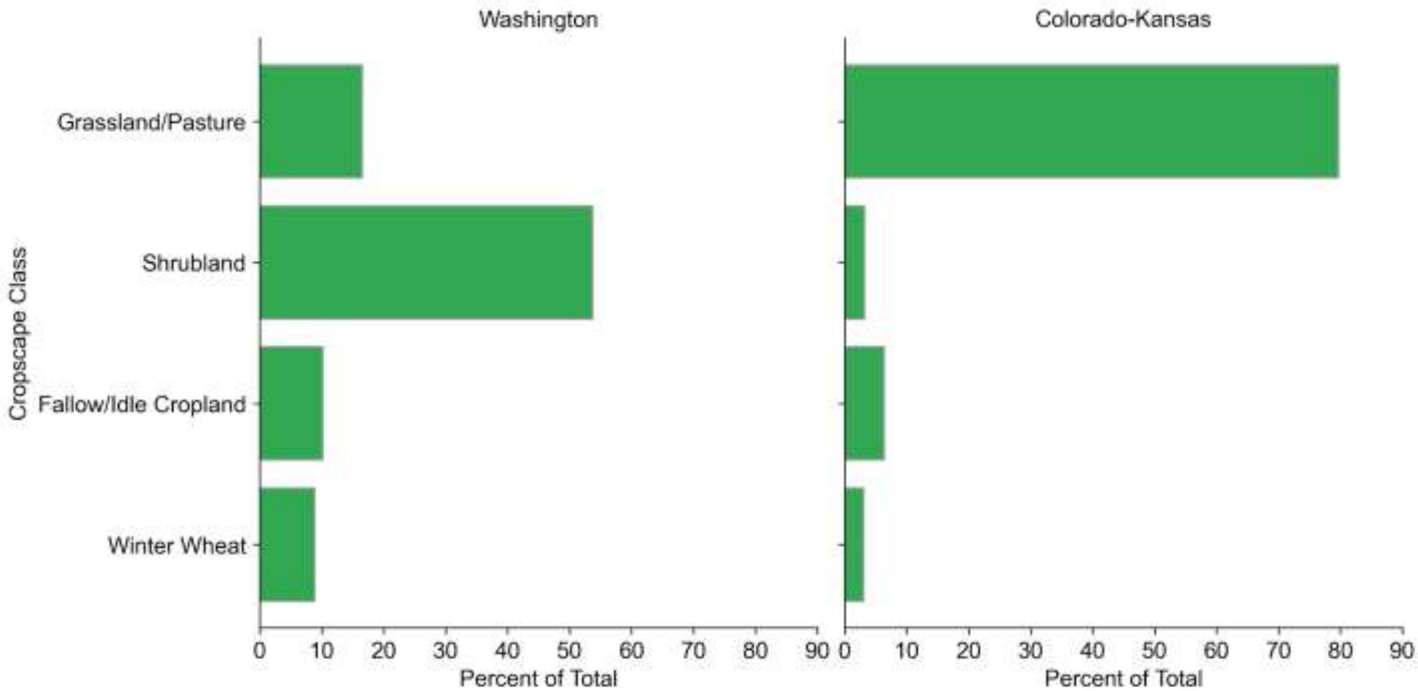

Figure A7-3. Percent of total CRP tracts of sampled majority (mode) 2019 Cropscape for both study areas.

A8. Random Forest Classification Models

Table A8-1. Assigning Discrete Classes to Continuous Percent Cover. Class (‘tercile’) breaks for all five cover types for 2014-2018. *Class bins for annual variables in the CO/KS study area had to be modified from a straight quantile strategy. For Annual Forb Cover, 2.97 represents the median of all non-zero observations in the dataset. For Annual Grass Cover, 5.94 represents the median of all non-zero observations in the dataset.

Vegetation Cover Variable	Study Area	Tercile Class Breaks
Bare Soil Cover	Washington	Low: [0,1.00] Medium: (1.00, 4.67] High: (4.67, 48.00]
	Colorado-Kansas	Low: [0,0.99] Medium: (0.99, 7.92] High: (7.92, 71.29]
Annual Forb	Washington	Low: [0,3.00] Medium: (3.00, 9.00] High: (9.00, 88.00]
	Colorado-Kansas*	Low: [0,0] Medium: (0, 2.97] High: (2.97, 89.11]
Annual Grass	Washington	Low: [0,9.54] Medium: (9.54, 26.00] High: (26.00, 88.67]
	Colorado-Kansas*	Low: [0,0] Medium: (0, 5.94] High: (5.94, 98.41]
Perennial Forb	Washington	Low: [0,2.00] Medium: (2.00, 8.00] High: (8.00, 68.32]
	Colorado-Kansas	Low: [0, 0.99] Medium: (0.99, 4.95] High: (4.95, 64.36]
Perennial Grass	Washington	Low: [0,21.33] Medium: (21.33, 41.00] High: (41.00, 99.01]
	Colorado-Kansas	Low: [0,53.47] Medium: (53.47, 75.25] High: (75.25, 100.00]

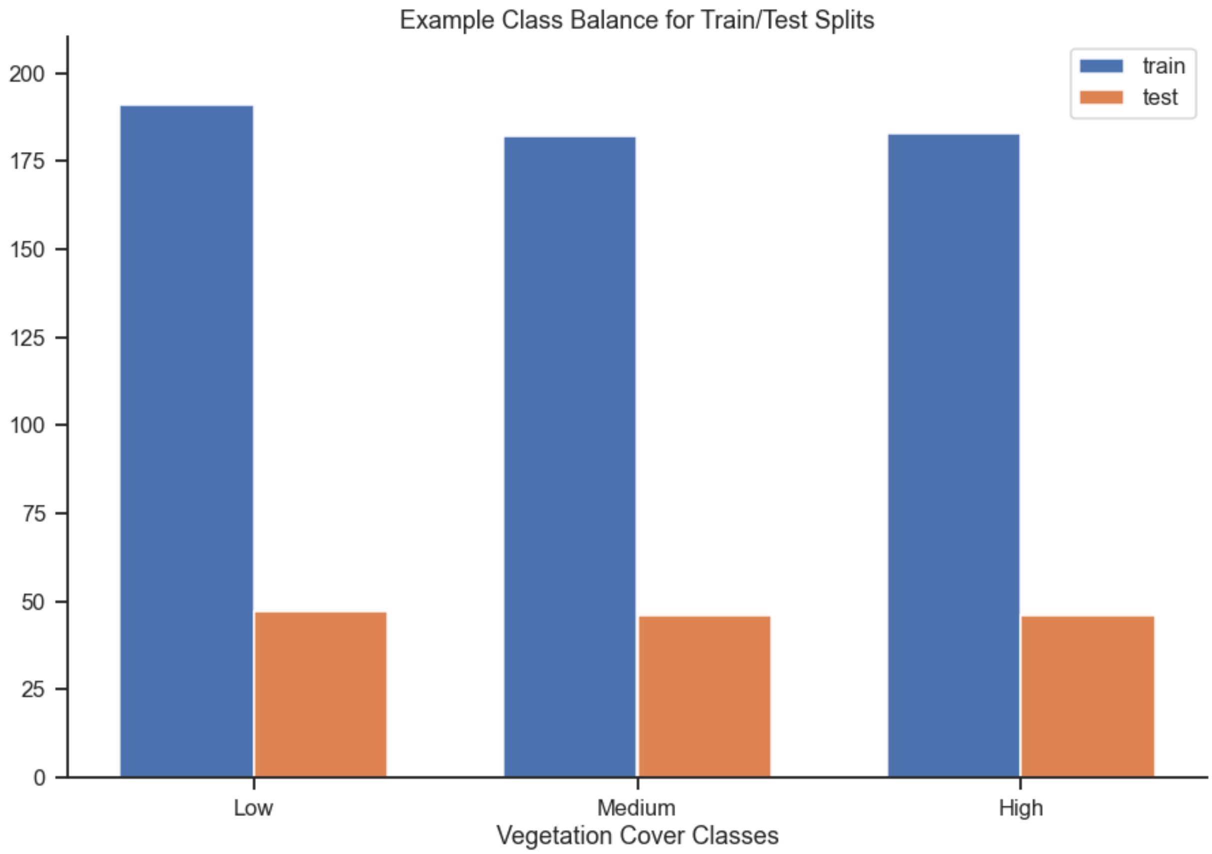

Figure A8-1. Partition Train and Test Splits. Example of how model input data is split into stratified training and testing subsets.

Table A8-2. Random Forest Classification Model Parameters. GEE Random Forest parameters and associated values used to train Random Forest classification models. This represents a general baseline for model parameters.

Parameter	Value
Number of Trees	1000
Variables Per Split	Square root of the number of selected independent variables
Minimum Leaf Population	1
Bag Fraction	0.5
Maximum Nodes	No limit
Model Mode	Classification

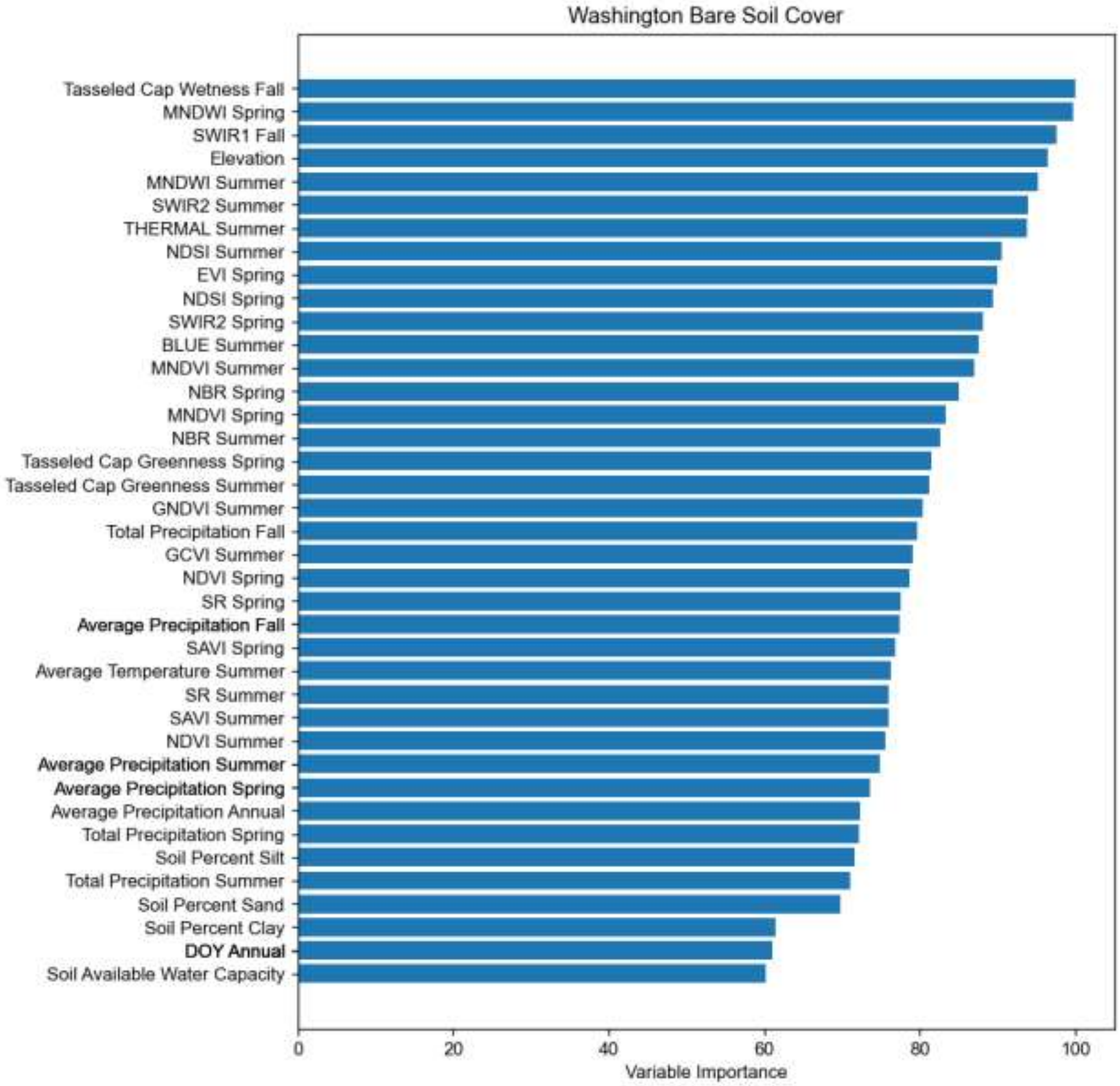

Figure A9-1. Variable importances (scaled 0 to 100) for Washington Bare Soil Cover.

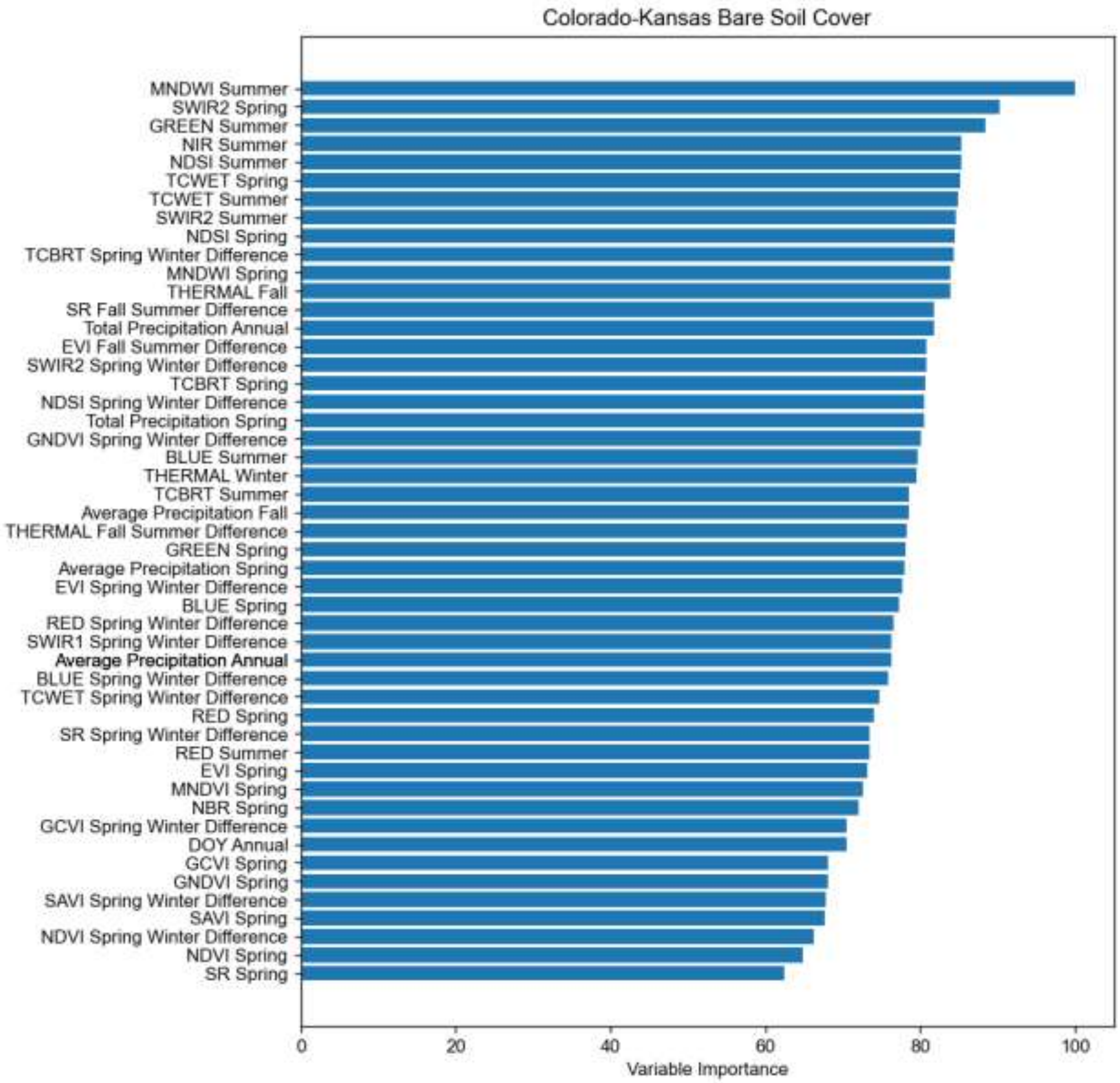

Figure A9-2. Variable importances (scaled 0 to 100) for Colorado-Kansas Bare Soil Cover.

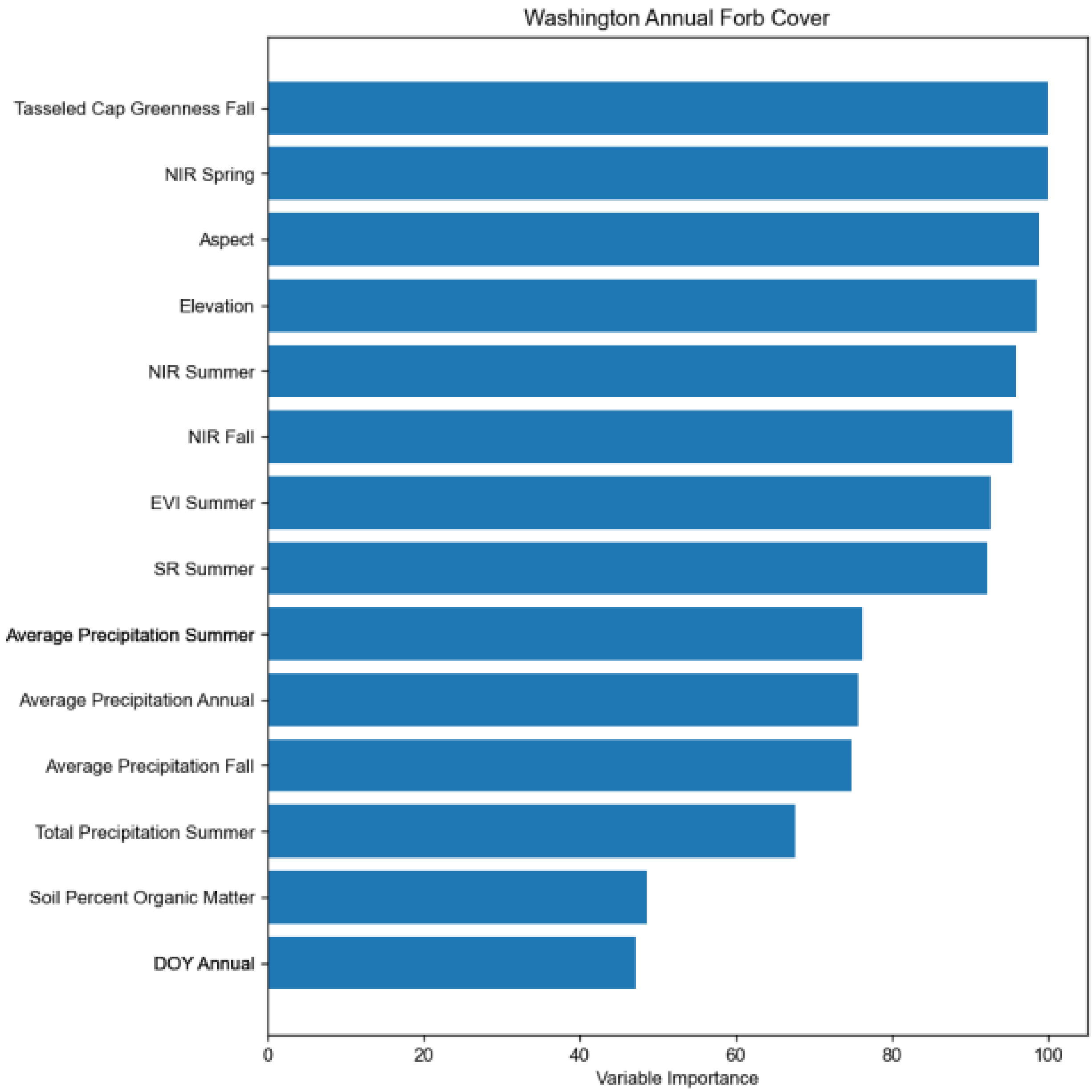

Figure A9-3. Variable importances (scaled 0 to 100) for Washington Annual Forb Cover.

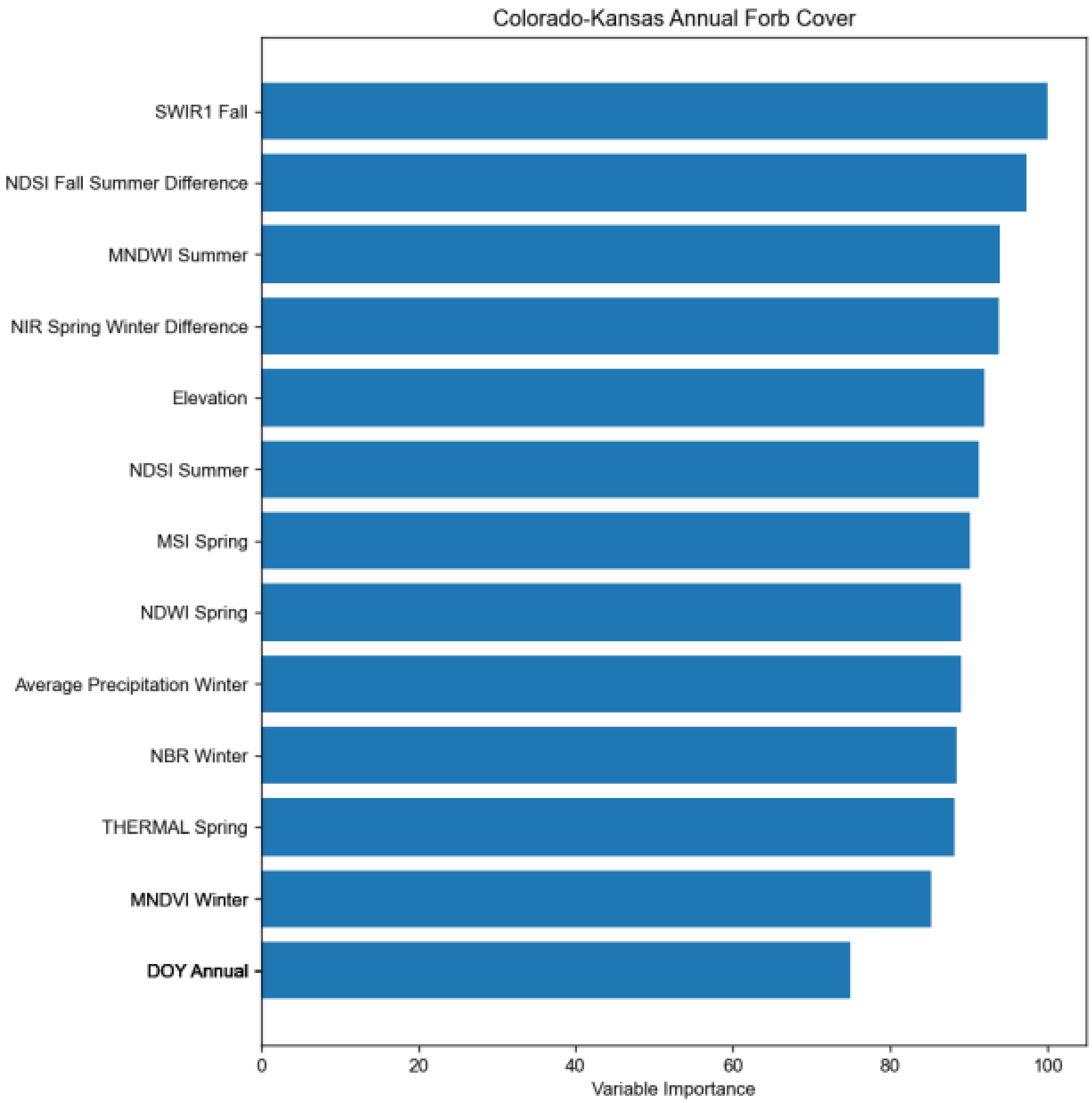

Figure A9-4. Variable importances (scaled 0 to 100) for Colorado-Kansas Annual Forb Cover.

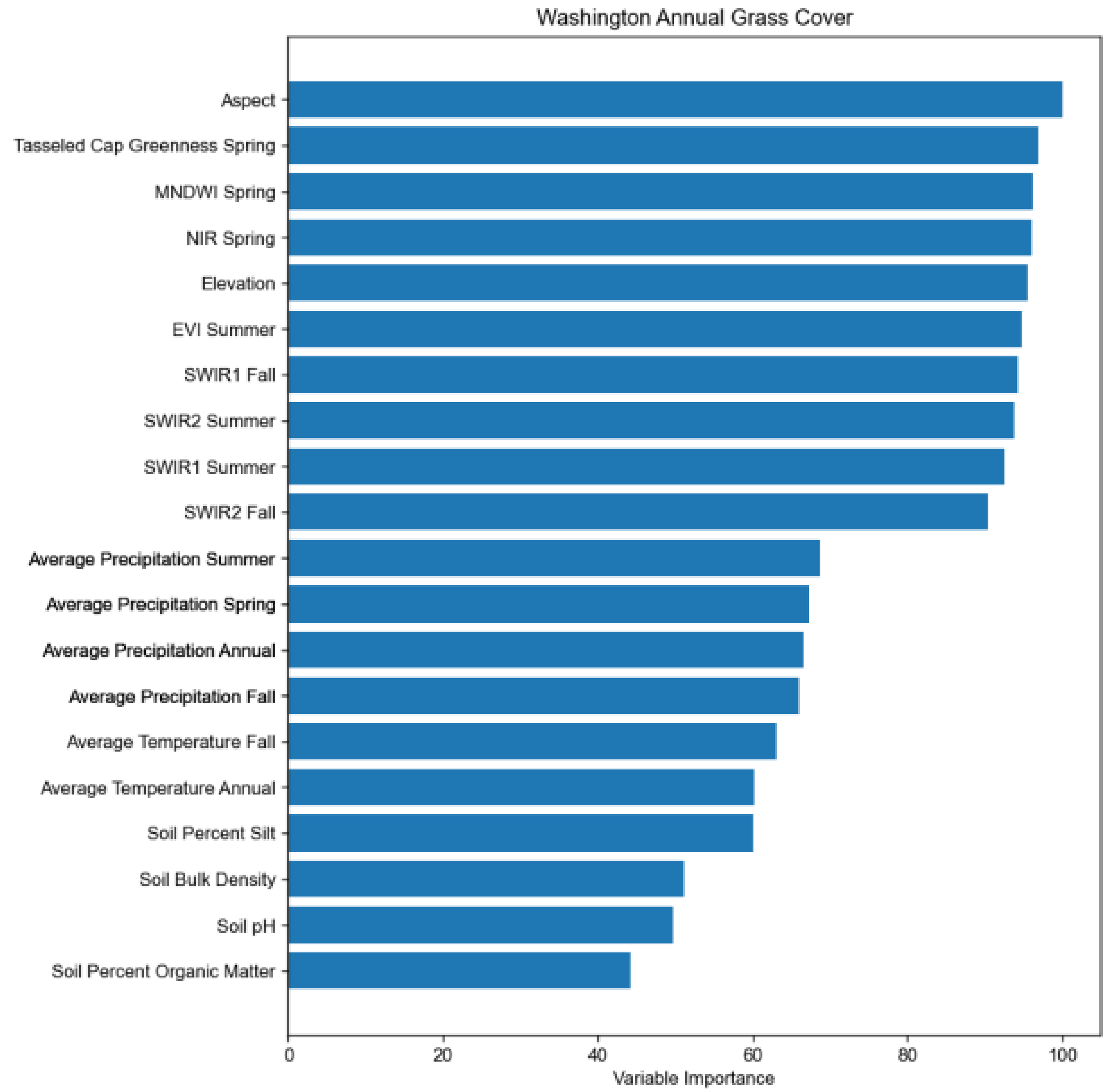

Figure A9-5. Variable importances (scaled 0 to 100) for Washington Annual Grass Cover.

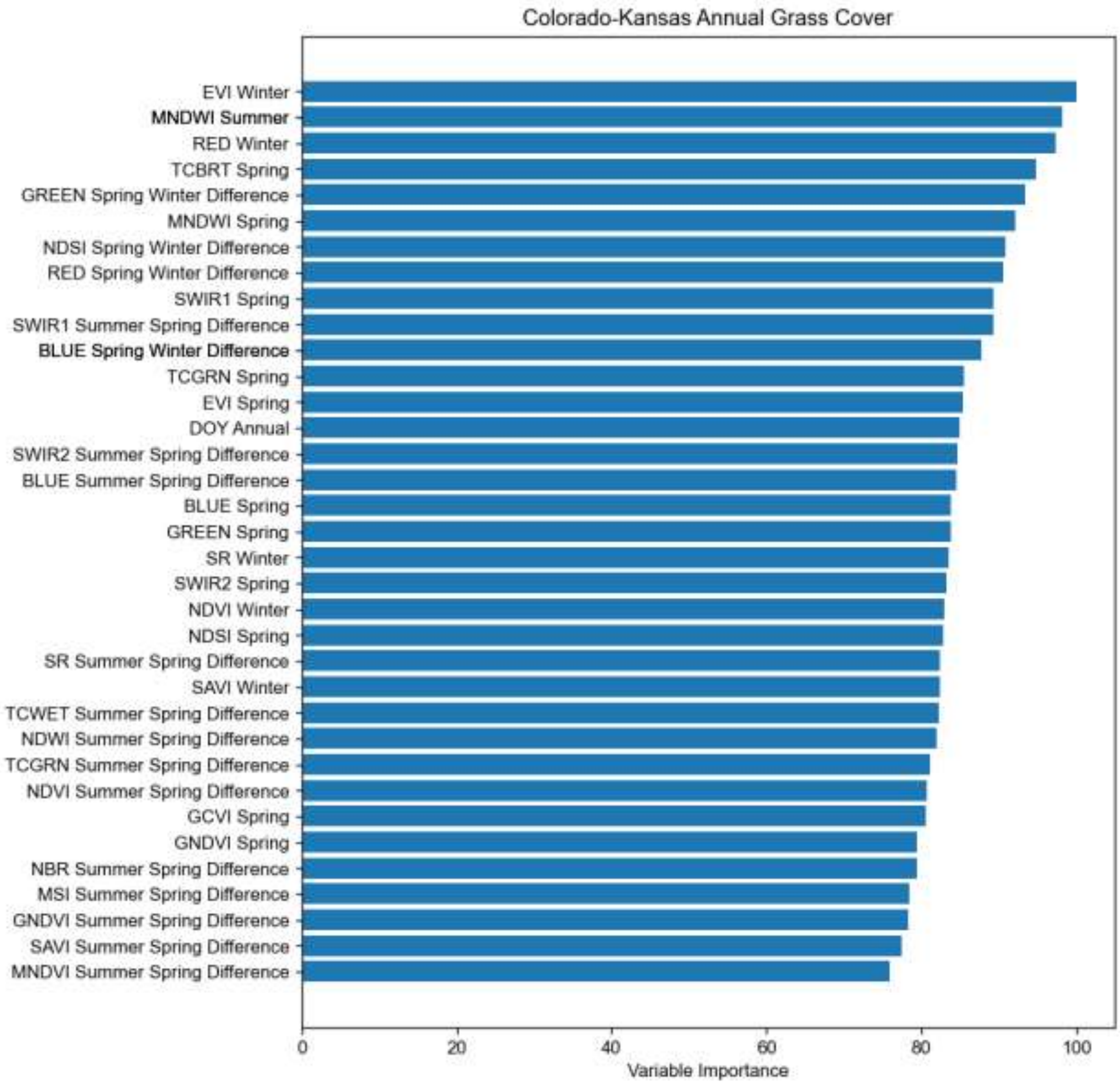

Figure A9-6. Variable importances (scaled 0 to 100) for Colorado-Kansas Annual Grass Cover.

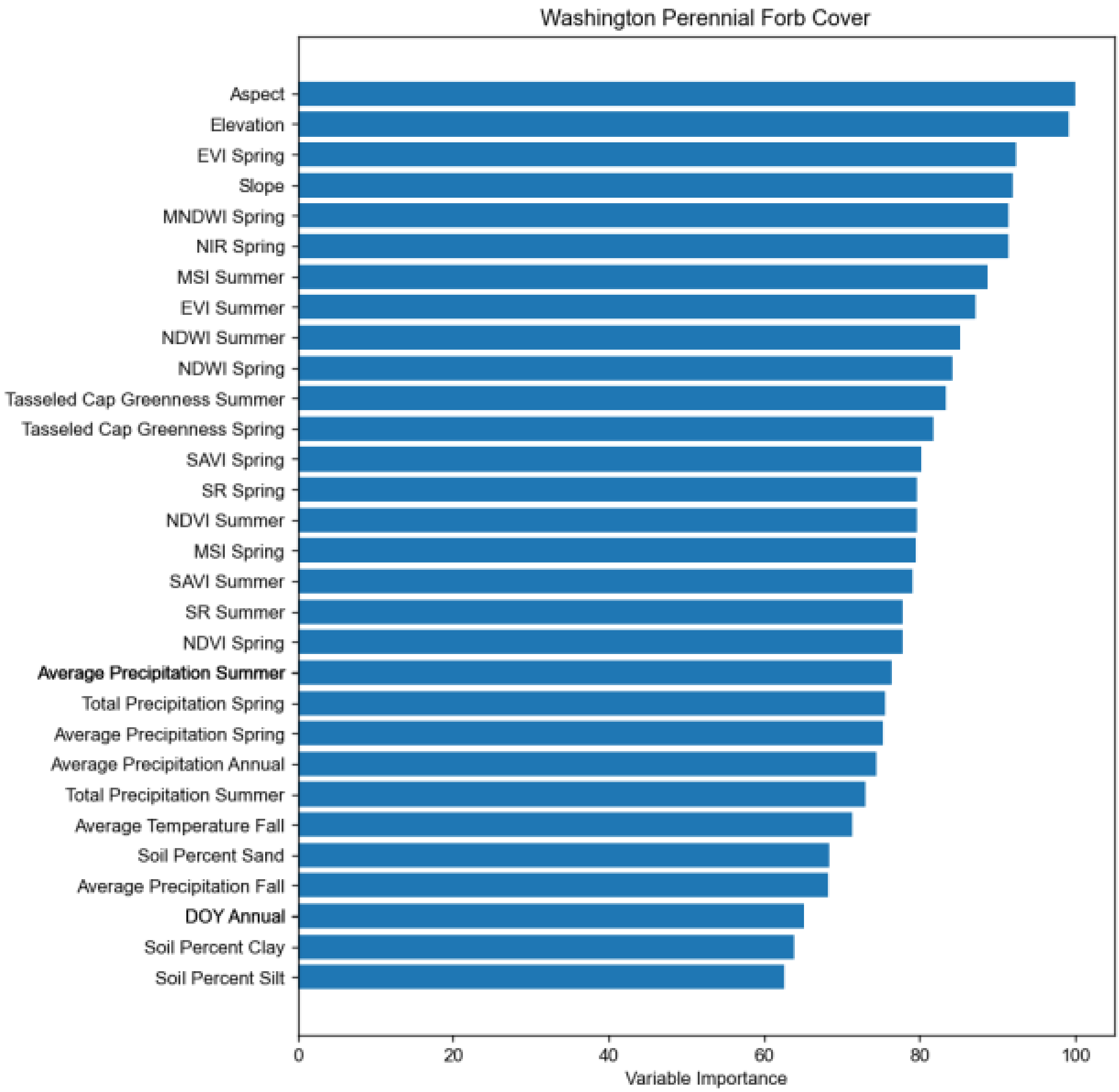

Figure A9-7. Variable importances (scaled 0 to 100) for Washington Perennial Forb Cover.

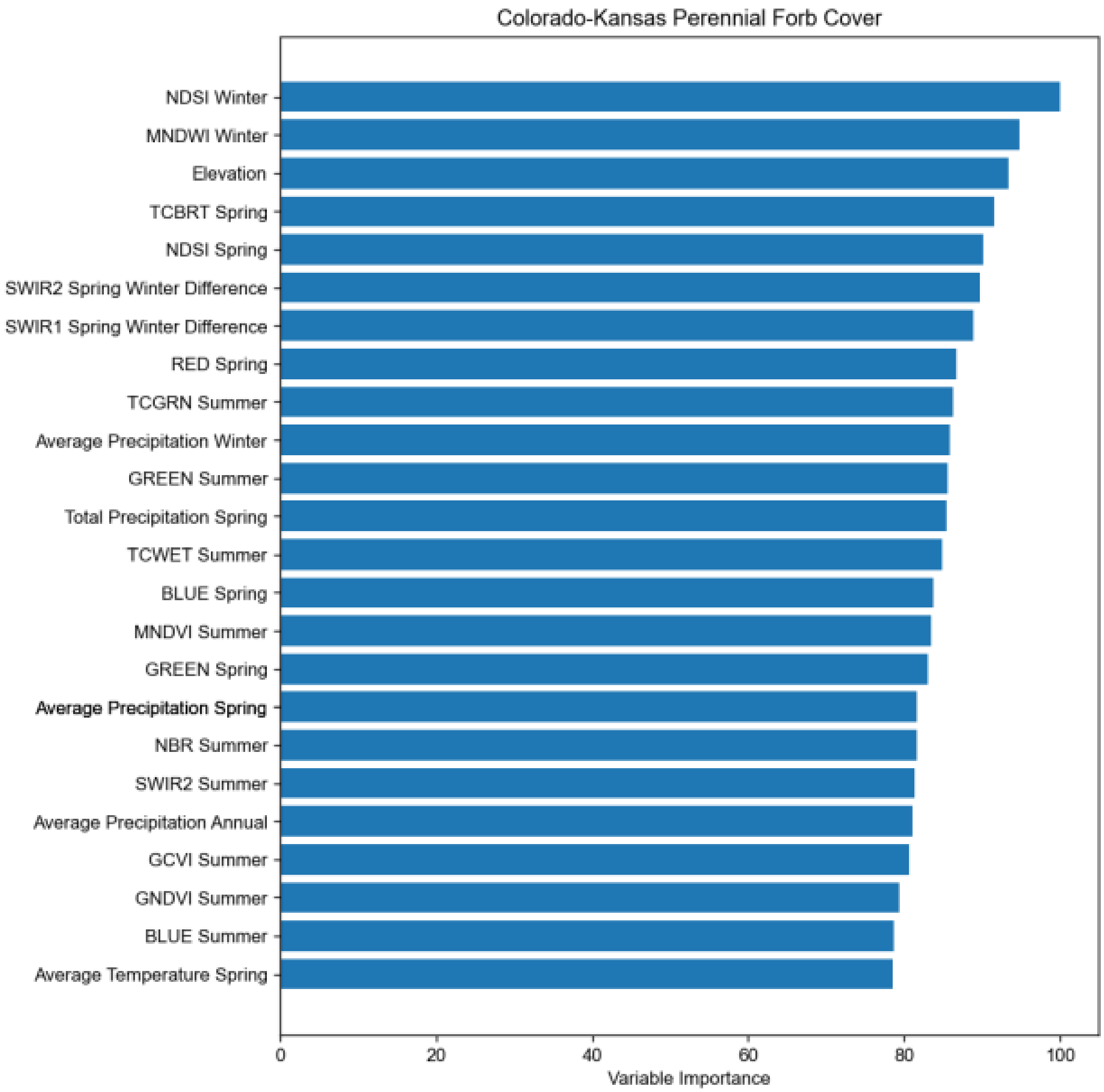

Figure A9-8. Variable importances (scaled 0 to 100) for Colorado-Kansas Perennial Forb Cover.

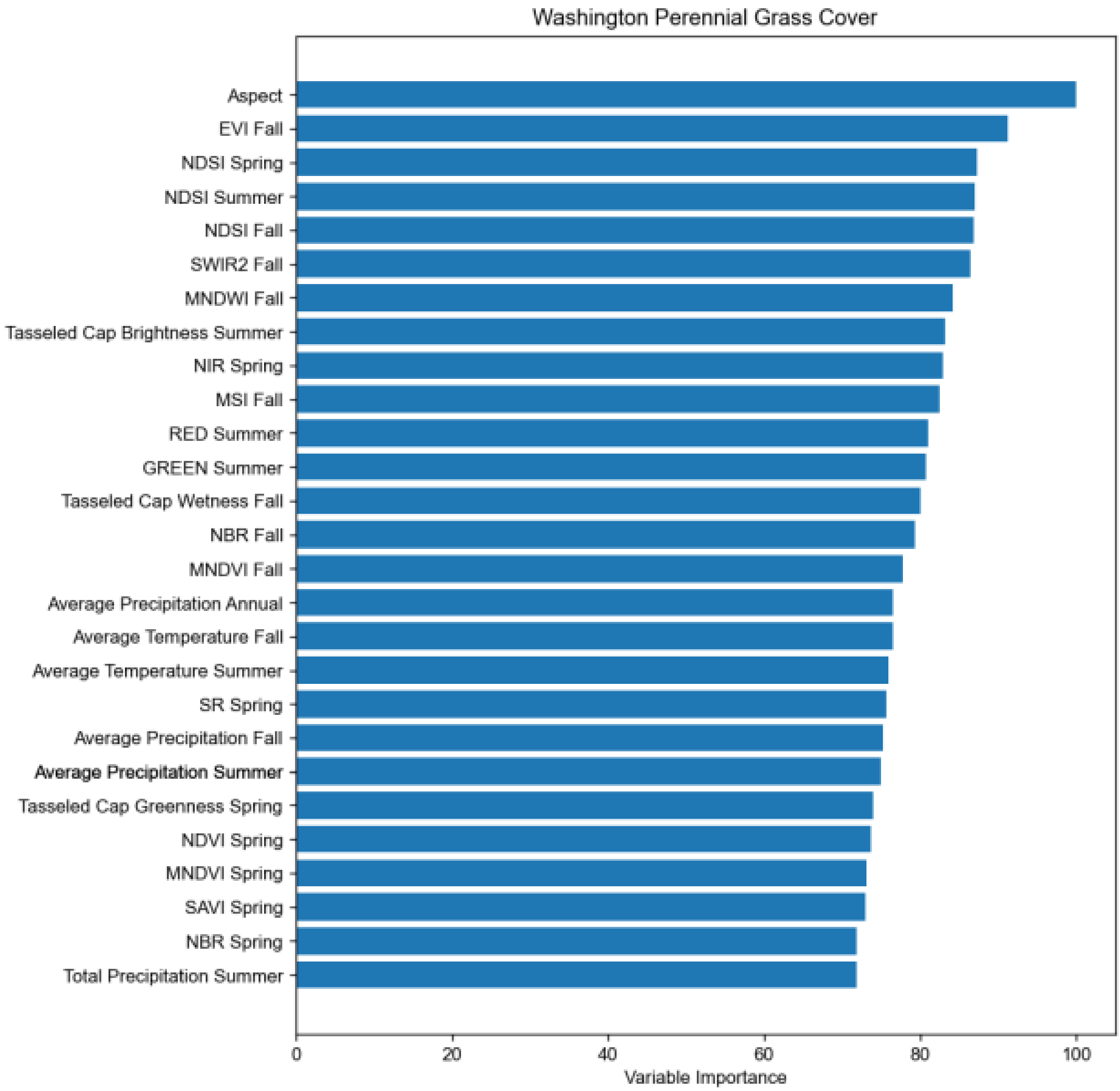

Figure A9-9. Variable importances (scaled 0 to 100) for Washington Perennial Grass Cover.

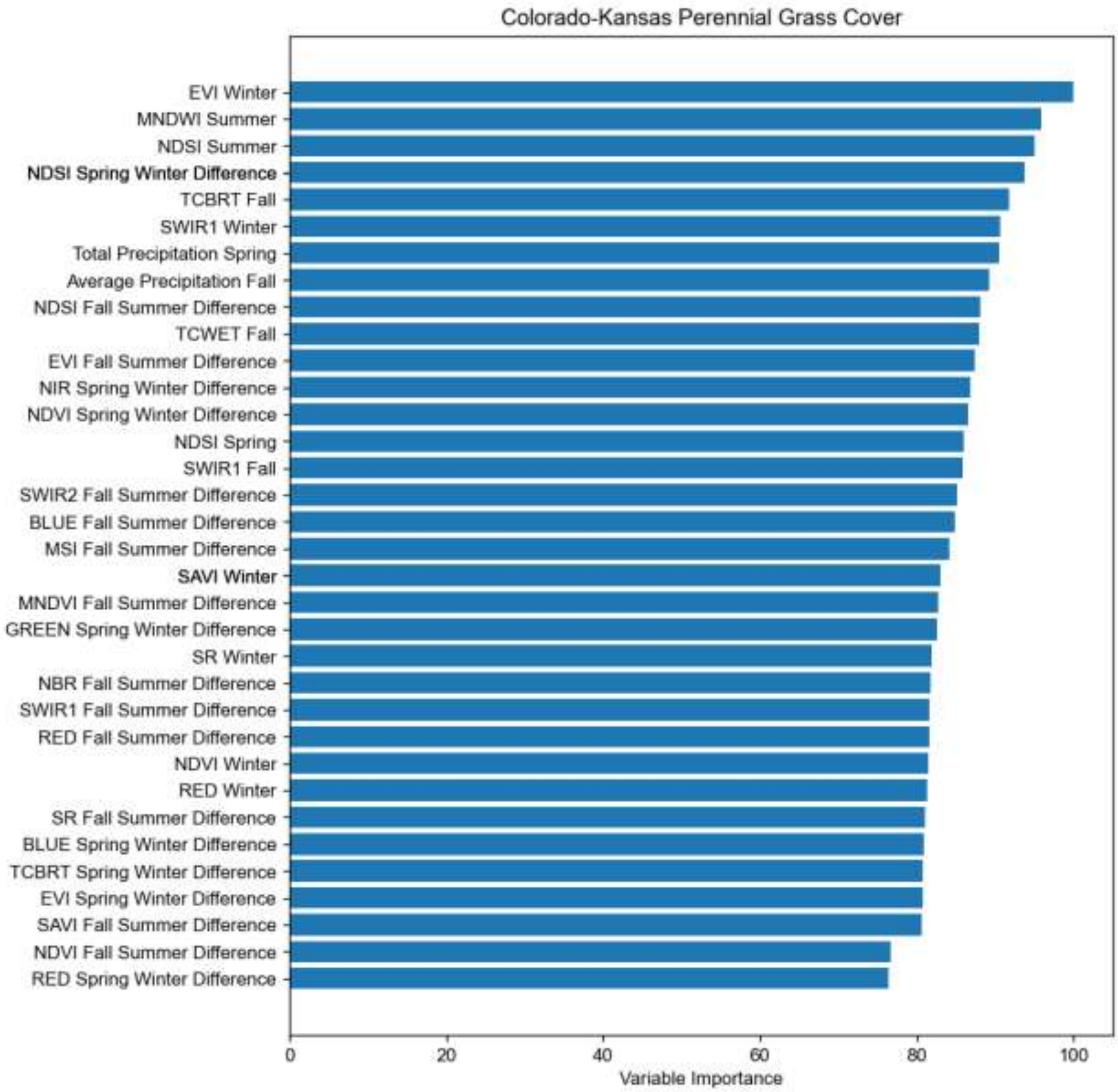

Figure A9-10. Variable importances (scaled 0 to 100) for Colorado-Kansas Perennial Grass Cover.