Compendium to Invasive Annual Grass Spatial Products for the Western United States, January 2010–February 2021

Data Report 1152

U.S. Department of the Interior
U.S. Geological Survey

Cover. Cheatgrass (*Bromus tectorum*) invasion of sagebrush habitats after a fire in northwestern Nevada, U.S.A. Photography by Cameron Aldridge, Colorado State University, used with permission.

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U.S. Geological Survey, Reston, Virginia: 2022

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Contents

Table

Conversion Factors

International System of Units to U.S. customary units

Multiply	By	To obtain
	Length	
millimeter (mm)	0.03937	inch (in.)
centimeter (cm)	0.3937	inch (in.)
meter (m)	3.281	foot (ft)
kilometer (km)	0.6214	mile (mi)
kilometer (km)	0.5400	mile, nautical (nmi)
	Area	
square meter (m^2)	0.0002471	acre
hectare (ha)	2.471	acre
square kilometer (km^2)	247.1	acre
square kilometer (km^2)	0.3861	square mile (mi^2)
	Mass	
kilogram (kg)	2.205	pound avoirdupois (lb)

Temperature in degrees Celsius (°C) may be converted to degrees Fahrenheit (°F) as follows:

$$°F = (1.8 \times °C) + 32.$$

Abbreviations

ACP	actual cheatgrass performance
AIM	assessment, inventory, and monitoring
AUC-PR	area under the precision-recall curve
AUC-ROC	area under the curve-receiver operating characteristic
BISON	biodiversity information serving our Nation
BLM	Bureau of Land Management
BRT	boosted regression tree
CTI	compound topographic index
DEM	digital elevation model
ECP	expected cheatgrass performance
EDDMapS	early detection and distribution mapping system
eMODIS	expedited moderate resolution imaging spectroradiometer
EPA	Environmental Protection Agency
ETM+	enhanced thematic mapper (plus)
EVT	existing vegetation type
FWS	U.S. Fish and Wildlife Service
GAM	generalized additive model
GAP	Gap Analysis Project
GBIF	global biodiversity information facility
GeoMAC	Geospatial Multi-Agency Coordination Group
GLM	generalized linear models
GS	growing season
GSN	mean growing season normalized difference vegetation index
HLS	Harmonized Landsat and Sentinel-2
IAG	invasive annual grass
INHABIT	Invasive Species Habitat Tool
MAE	mean absolute error
MARS	multivariate adaptive regression splines
MoD-FIS	modeling dynamic fuels with an index system
MODIS	moderate resolution imaging spectroradiometer
MTBS	Monitoring Trends in Burn Severity
NAIP	National Agriculture Imagery Program
NASA	National Aeronautics and Space Administration
NDVI	normalized difference vegetation index

NED	National Elevation Dataset
NGS	non-growing season
NISIMS	National Invasive Species Information Management System
NLCD	National Land Cover Database
NPS	National Park Service
NRCS	Natural Resources Conservation Service
NRI	Natural Resources Inventory
OLI	operational land imager
PCA	principal component axes
PCC	percent correctly classified
PET	potential evapotranspiration
PFT	plant functional type
R^2	coefficient of determination
RAP	rangeland analysis platform
RCMAP	Rangeland Condition, Monitoring, Assessment, and Projection
RF	random forest
RFNN	random forest nearest neighbor
RMSE	root mean square error
RPMS	Rangeland Production Monitoring Service
SAHM	Software for Assisted Habitat Modeling
SEDI	symmetric extremal dependence index
SSURGO	Soil Survey Geographic Database
TIN	triangulated irregular network
TSS	true skill statistic
USDA	U.S. Department of Agriculture
USGS	U.S. Geological Survey
WBEA	Wyoming Basins Ecoregional Assessment
>	greater than
<	less than

Compendium to Invasive Annual Grass Spatial Products for the Western United States, January 2010–February 2021

D. Joanne Saher,[1] Jessica E. Shyvers,[2] Bryan C. Tarbox,[2] Nathan D. Van Schmidt,[2] Julie A. Heinrichs,[1] and Cameron L. Aldridge[2]

Abstract

Invasive annual grasses (IAGs) degrade native plant communities, alter fire cycles, impact ecosystem processes, and threaten the persistence of some species. Therefore, controlling the spread of IAGs has become a land management priority in the western United States. A wide array of geospatial data has been developed in the last decade to help land managers combat the invasion and expansion of non-native grasses by identifying areas where these species are likely to occur. However, choosing the most appropriate spatial product to address specific management concerns is a daunting task for many land managers, particularly with the rapid increase in the number of IAG spatial products available. To aid potential users in assessing these products, we reviewed and summarized 23 datasets that captured the three IAG species of most concern to rangeland management—*Bromus tectorum* (cheatgrass), *Taeniatherum caput-medusae* (medusahead), and *Ventenata dubia* (ventenata). To be included in this review, products were required to include part of the western United States, be regional or National in scale, and have been published between January 2010 and February 2021. This review, part of a series of informational data resources, is the compendium to an Excel-readable database and provides a 2-page summary of each spatial data product to assist land managers in understanding and selecting the best available spatial data for their management needs.

Introduction

Invasive annual grasses (IAGs) present a persistent challenge for the ecological management of rangelands in western North America. IAGs have the potential to alter ecosystems by directly supplanting native species and indirectly increasing the frequency and intensity of wildfires (Balch and others, 2013). These changes reduce the diversity of native plant communities (Pyšek and others, 2012; Mahood and Balch, 2019), often resulting in vast monocultures. The degradation of native plant communities associated with invasive grasses threatens the persistence of species such as *Centrocercus urophasianus* (greater sage-grouse; Miller and others, 2011) and the ecosystem services provided by western rangelands (Germino and others, 2016). The substantial economic consequences of IAG include wildfire suppression costs (Knapp, 1996; Taylor and others, 2013), forage loss (Sheley and others, 2015), ecological restoration (Boyd and Davies, 2012), and the potential failure of ranching operations (Brunson and Tanaka, 2011; Maher and others, 2013). Restoring ecosystems after IAC invasion is challenging, and recent efforts at addressing this issue instead emphasize prevention and containment of invasions (Davies and Johnson, 2011). However, *Bromus tectorum* (cheatgrass) alone already occupies over 200,000 square kilometers (km^2) of land across the intermountain west (Bradley and others, 2018), and IAGs continue to expand (Jones and others, 2021; Rigge and others, 2021a).

Containing the spread of IAGs depends on extensive and accurate distribution data (Hobbs and Humphries, 1995; Chambers and Wisdom, 2009), which needs to be accessible and interpretable by those charged with managing the landscape. To meet these needs, we provide a series of informational products, including this compendium, to guide land managers in selecting and understanding the best available spatial data for their management needs and to bridge the gap between research and application of spatial products for management of IAGs. These products are based on a systematic literature review of spatial products released over the past decade that map IAGs at regional and National scales, focusing on those developed for cheatgrass, *Taeniatherum caput-medusae* (medusahead), and *Ventenata dubia* (ventenata).

This compendium presents a summary of all spatial products included in the database (table 1) in order of extent, beginning with products spanning the contiguous United States and ending with those that are regional in extent. In the 2-page summaries that follow, the most relevant information

[1]Natural Resource Ecology Laboratory, Colorado State University in cooperation with the U.S. Geological Survey, Fort Collins Science Center.

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for each product is in the “At a glance” table, with more technical information in the main body of the summary. Appendixes 1 and 2 list additional spatial products that did not meet the database requirements and existing web-based resources for data and additional information, respectively. Definitions of terms and categories used in the summaries are in appendix 3.

Description of the Additional Products in this Informational Series

This informational series presents a suite of products with the aim of informing the decision-making process when selecting spatial data for management activities involving IAGs. All the products are interrelated and share some content. While each can be used independently, these products are intended to complement each other. In addition to this compendium, other products in this suite include:

1. ***Public database:*** This database presents the information covered in this compendium in a standardized Microsoft Excel spreadsheet, with columns that can be searched, filtered, and sorted for ease of use. As in this compendium, the database lists all publicly accessible spatial products released within the past decade that depict IAGs at regional to National extents in the western United States and describes their basic spatiotemporal information, author guidelines for use, input variables, model design, and product evaluation. The database can be accessed at https://doi.org/10.5066/P9VW97AO. An additional, machine-readable .csv file version of the database is also available for users. The IAG spatial products included in the database have been uploaded to the Sagebrush Ecosystem Data Viewer (https://doi.sciencebase.gov/sedv), where users can easily view these products, the associated metadata, and find links for data download.

2. ***User guide:*** This reference sheet, accessed at https://doi.org/10.3133/fs20223001, can guide you through using the information presented in this compendium and the database to select and apply spatial products for your management applications. It highlights key considerations for selecting and translating products into different applications, describes a set of steps for selecting potential products and explains how to interpret and compare accuracy metrics. It also includes examples of how to compare products for IAG treatment and wildlife habitat assessment.

3. ***Journal article:*** This is a peer-reviewed article (https://doi.org/10.1016/j.rama.2022.01.006) that synthesizes trends in the literature reviewed in this compendium and provides recommendations for both scientists and managers on how to bridge the research-implementation gap to improve on-the-ground management of IAGs.

Table 1. Overview of peer-reviewed invasive annual grass spatial products that include part of the western United States, were published between January 2010 and February 2021, and are National to regional in scale.

[Species include cheatgrass (*Bromus tectorum*), medusahead (*Taeniatherum caput-medusae*), ventenata (*Ventenata dubia*), or annual herbaceous species. m, meter; INHABIT, Invasive Species Habitat Tool; U.S., United States; RAP, Rangeland Analysis Platform; %, percent; RCMAP, Rangeland Condition, Monitoring, Assessment, and Projection; WGA, Western Governors' Association; MoD-FIS, modeling dynamic fuels with an index system; >, greater than; HLS, Harmonized Landsat and Sentinel-2; <, less than]

Product	Species	Output	Output type	Resolution (m)	Recentness	Time series	General extent	Future updates planned?	Compendium page
INHABIT—Cheatgrass Suitability (2019)	Cheatgrass	Habitat suitability	Rank	90	2019	No	Contiguous U.S.	Yes; timeframe not specified	5
INHABIT—Medusahead Suitability (2019)	Medusahead	Habitat suitability	Rank	90	2019	No	Contiguous U.S.	Yes; timeframe not specified	7
INHABIT—Ventenata Suitability (2019)	Ventenata	Habitat suitability	Rank	90	2019	No	Contiguous U.S.	Yes; timeframe not specified	9
RAP—Annual Herbaceous Cover Time Series (1984–2019)	Annual herbaceous species	% cover	Continuous	30	1984–2019	Yes	Western U.S.	Yes; every 2 years	11
RAP—Annual Herbaceous BiomassTime Series (1984–2019)	Annual herbaceous species	Biomass	Continuous	30	1986–2019	Yes	Western U.S.	Yes; every 2 years	13
Probability of Cheatgrass Invasion Risk in Western U.S.	Cheatgrass	Occurrence probability	Categorical (probability continuous)	94	2020	No	Western U.S.	No	15
Probability of Medusahead Invasion Risk in Western U.S.	Medusahead	Occurrence probability	Categorical (probability continuous)	94	2020	No	Western U.S.	No	17
RCMAP Rangeland Fractional Components Base Map (2016)	Annual herbaceous species	% cover	Continuous	30	2016	No	Western U.S.	No	19
RCMAP Rangeland Fractional Components Time Series (1985–2018)	Annual herbaceous species	% cover	Continuous	30	1985–2018	Yes	Western U.S.	Yes; annually	21
RCMAP Projections of Rangeland Fractional Components (2020s, 2050s, 2080s)	Annual herbaceous species	% cover	Continuous	30	2020s 2050s 2080s	Yes	Western U.S.	No	23
WGA Annual Herbaceous Cover (2016–2018 composite)	Annual herbaceous species	% cover	Continuous	30	2016–2018 (3-year mean)	No	Western U.S.	Unknown	25
LANDFIRE Existing Vegetation Type (2016)	Annual herbaceous species	Vegetation type	Categorical	30	2016	No	Western U.S.	Yes; every few years	27

Table 1. Overview of peer-reviewed invasive annual grass spatial products that include part of the western United States, were published between January 2010 and February 2021, and are National to regional in scale.—Continued

[Species include cheatgrass (*Bromus tectorum*), medusahead (*Taeniatherum caput-medusae*), ventenata (*Ventenata dubia*), or annual herbaceous species. m, meter; INHABIT, Invasive Species Habitat Tool; U.S., United States; RAP, Rangeland Analysis Platform; %, percent; RCMAP, Rangeland Condition, Monitoring, Assessment, and Projection; WGA, Western Governors' Association; MoD-FIS, modeling dynamic fuels with an index system; >, greater than; HLS, Harmonized Landsat and Sentinel-2; <, less than]

Product	Species	Output	Output type	Resolution (m)	Recentness	Time series	General extent	Future updates planned?	Compendium page
MoD-FIS Fuel Vegetation Cover (2020)	Herbaceous species (including perennials)	% cover (bins); height classes (bins)	Categorical	30	2020	No	Great Basin and Southwest U.S.	Yes; every 3 years	29
Near-Real-Time Annual Herbaceous Cover (2015–2019)	Annual herbaceous species	% cover	Continuous	250	2015–2019	No	Northern Great Basin, Snake River Plain	No; Replaced by HLS	31
Annual Herbaceous Cover Time Series (2000–2016)	Annual herbaceous species	% cover	Continuous	250	2000–2016	Yes	Northern Great Basin, Central Basin and Plain, Snake River Plain	No	33
Cheatgrass Distribution in the Intermountain West (2016)	Cheatgrass	% cover; binned >15% cover	Continuous; categorical	250	2001–2016	No	Hydrographic Great Basin	Unknown	35
Invasive Annual Grasses in Cold Desert Areas (2016)	Introduced annual grass species	% cover (5 bins)	Categorical	90	2016	No	Cold desert ecoregions of the western U.S.	No	37
HLS Annual Herbaceous Fractional Cover Time Series (2016–2020)	Annual herbaceous species	% cover	Continuous	30	2016–2018	Yes	Great Basin, Snake River Plain, Wyoming	Yes; annually, but as standalone products	39
Cheatgrass Occurrence Across Sage-Grouse Range (2000–2014)	Cheatgrass	<2 or >2% cover	Categorical	250	2000–2014	No	Greater sage-grouse range	Yes; every 5 years	41
Cheatgrass Dieoff in Northern Great Basin Time Series (2000–2010)	Cheatgrass	% cover difference; dieoff	Continuous; categorical	250	2000–2010	Yes	Northern Great Basin, Snake River Plain	No	43
Cheatgrass Occurrence Across the Wyoming Basin (2006)	Cheatgrass	Occurrence probability	Categorical (probability continuous)	90	2006	No	Wyoming Basin	No	45
Southeast Oregon Vegetation Composition Map (2012–2017)	Introduced annual grass species	% cover	Continuous	30	2012–2017	No	Sage steppe in southeastern Oregon	Yes; every 2–4 years	47
Predicted Invasive Plant Cover in the Mojave Desert (2009–2013)	Introduced annual grass species	Habitat suitability	Categorical (probability continuous)	30	2009–2013	No	Mojave Desert	No	49

Spatial Product Summaries

INHABIT—Cheatgrass Suitability (2019)

Description: This product is a ranked potential of habitat suitability for cheatgrass determined by the agreement between a maximum of 10 models (5 algorithms × 2 background generation methods). Users can select between four thresholds, ranging from precautionary to targeted. This product is contained within an online map tool, Invasive Species Habitat Tool (INHABIT) that predicts habitat suitability for more than 100 additional invasive species.

Species: Cheatgrass (*Bromus tectorum*)

Spatial extent: The contiguous United States

Spatial resolution: 90-meter (m) pixels

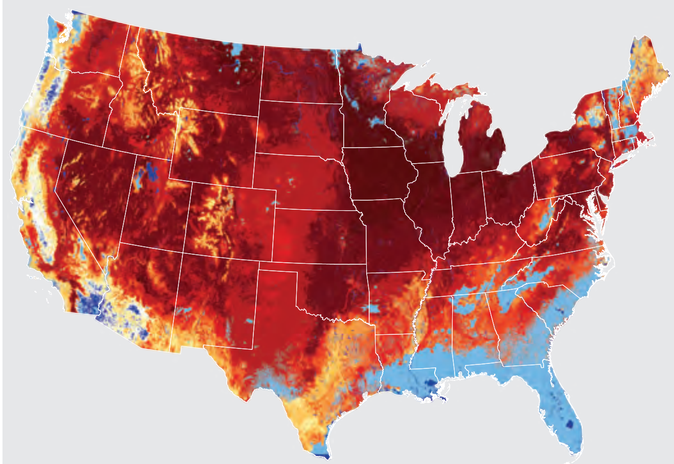
Recentness: 2020

Author-suggested use: Mapped predictions of habitat suitability for cheatgrass are meant to guide risk assessment at regional and National scales and rapid response strategies at local scales. The modeling process uses computing power to provide map products with both large extent and high resolution that are useful at multiple spatial scales, such as National, regional and local.

Author-identified caveats/limitations: Assessment of the modeling process may be difficult to score as ideal because the input data were based on readily available species occurrence data rather than data collected based on a statistically designed study. The models are subject to numerous other caveats typical of correlative species distribution models, such as the quality of occurrence point data, spatial and temporal alignment of model inputs, and ecological and predictive relevance.

Modeling approach: The authors used the VisTrails software framework to fit models to each combination of algorithm and background method (for example, SAHM [Software for Assisted Habitat Modeling] Model Fitting). They tested five different algorithms: Maxent (v 3.4.1), boosted regression trees (BRT), random forest (RF), generalized linear models (GLM), and multivariate adaptive regression splines (MARS). Each algorithm was tested with two background sampling approaches for a total of 10 models for each species. The final surface ranking is based on agreement between individual model outputs.

Model training data: The authors downloaded occurrence data for each species from multiple databases: the Global Biodiversity Information Facility (GBIF), Biodiversity



Extent of the “INHABIT–Cheatgrass Suitability (2019)” spatial data product (Jarnevich and others, 2021) showing the ranked potential of habitat suitability of cheatgrass (*Bromus tectorum*). The map reflects the use of the 0.01 threshold. Agreement between models ranges from low (yellow) to high (dark red). Dark blue areas indicate no suitability for cheatgrass and light blue represents novel space, environments outside training data constraints.

AT A GLANCE	
Species	Cheatgrass (*Bromus tectorum*)
Output	Rank; potential habitat suitability ranging from 0 to 10
States covered	The contiguous United States
Resolution	90 m
Recentness	*Most recent year (as of Dec. 2020)*: 2020 *Years available*: 2020 *Time series*: No *Update frequency*: Yes; timeframe not specified
Evaluation	Yes; bootstrapping/cross validation
GET DATA	Interactive web map: https://gis.usgs.gov/inhabit/ Data download: https://www.sciencebase.gov/catalog/item/5fc929d9d34e4b9faad8a237

Information Serving Our Nation (BISON), the Early Detection and Distribution Mapping System (EDDMapS), the Bureau of Land Management (BLM) and the National Park Service (NPS) National Invasive Species Information Management System (NISIMS) databases, and the BLM Assessment, Inventory, and Monitoring (AIM) program. Data may be sourced from all of these with records for the species meeting the specified criteria. The data are aggregated by observation type (observation or specimen only) and observation date (1980 to present), with coordinate uncertainty less than or equal to 30 m.

Remotely sensed inputs: None.

Geospatial inputs: Geospatial inputs include mean diurnal range (Bio2), isothermality, temperature annual range (Bio7), precipitation seasonality (Bio15), precipitation of driest quarter (Bio17), minimum temperature winter, mean summer potential evapotranspiration (PET), mean spring precipitation, mean March precipitation divided by mean spring precipitation, evapotranspiration, burning index, percent calcium carbonate in soil, variance of available water content in the first 0–5 centimeters (cm) of the soil horizon, mean available water content in the first 0–5 cm of the soil horizon, mean depth to restriction layer, burn frequency, and bare ground standard deviation.

Key model covariates: Across all models, minimum temperature winter exhibited the strongest percent contribution (33 percent); other important covariates (greater than [>] 5 percent) included mean spring precipitation, burning index, global human modification, isothermality, precipitation seasonality, and temperature annual range.

Evaluation: The authors evaluated the model with tenfold cross-validation assessed via several metrics, including the area under the curve-receiver operating characteristic (AUC-ROC), area under the precision-recall curve (AUC-PR), Cohen's kappa coefficient, True Skill Statistic (TSS), percent correctly classified (PCC), sensitivity, and specificity. Evaluation statistics for all models can be found under the "Model Details" tab on the INHABIT website, https://gis.usgs.gov/inhabit/.

Notes: Occurrence points and their spatial range are also available in the web tool, as well as a table including summary data for Federal management areas (BLM, U.S. Fish and Wildlife Service [FWS], NPS) that includes estimated suitable habitat area, known presence (from count data), and distance to known occurrence.

Spatial Data Citation

Jarnevich, C.S., LaRoe, J., Engelstad, P., and Sullivan, J., 2021, INHABIT species potential distribution across the contiguous United States: U.S. Geological Survey data release, accessed January 25, 2022, at https://doi.org/10.5066/P92476V6.

Publication Citation

Young, N.E., Jarnevich, C.S., Sofaer, H.R., Pearse, I., Sullivan, J., Engelstad, P., and Stohlgren, T.J., 2020, A modeling workflow that balances automation and human intervention to inform invasive plant management decisions at multiple spatial scales: PLoS One, v. 15, no. 3, p. e0229253, accessed 1 December 1, 2020, at https://doi.org/10.1371/journal.pone.0229253.

INHABIT—Medusahead Suitability (2019)

Description: This product is a ranked potential of habitat suitability for medusahead determined by the agreement between a maximum of 10 models (5 algorithms × 2 background generation methods). Users can select between four thresholds, ranging from precautionary to targeted. This product is contained within an online map tool, Invasive Species Habitat Tool (INHABIT) that predicts habitat suitability for more than 100 additional invasive species.

Species: Medusahead (*Taeniatherum caput-medusae*)

Spatial extent: The contiguous United States

Spatial resolution: 90-m pixels

Recentness: 2020

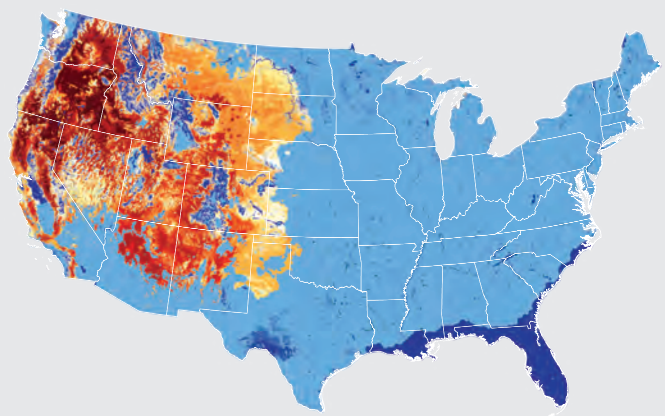
Author-suggested use: Mapped predictions of habitat suitability for medusahead are meant to guide risk assessment at regional and National scales and rapid response strategies at local scales. The provided map products have both large extent and high resolution, ideal for users operating at multiple spatial scales.

Author-identified caveats/limitations: Assessment of the modeling process may be difficult to score as ideal because the input data are based on readily available species occurrence data, rather than data collected based on a statistically designed study. The authors suggest the models are subject to numerous other caveats typical of correlative species distribution models, such as the quality of occurrence point data, spatial and temporal alignment of model inputs, and ecological and predictive relevance.

Modeling approach: The authors use the VisTrails software framework to fit models to each combination of algorithm and background method (for example, SAHM). They tested five different algorithms: Maxent (v 3.4.1), BRT, RF, GLM, and MARS. Each algorithm was tested with two background sampling approaches for a total of 10 models for each species. The final surface ranking is based on agreement between individual model outputs.

Model training data: The authors downloaded occurrence data for each species from multiple databases: the GBIF, BISON, the EDDMapS, the BLM and NPS' NISIMS databases, and the BLM AIM program. Data may be sourced from all of these with records for the species meeting the specified criteria. The data are aggregated by observation type (observation or specimen only), observation date (1980 to present), with coordinate uncertainty ≤30 m.

Remotely sensed inputs: None.



Extent of the "INHABIT–Medusahead Suitability (2019)" spatial data product (Jarnevich and others, 2021) showing the ranked potential of habitat suitability of medusahead (*Taeniatherum caput-medusae*). The map reflects the use of the 0.01 threshold. Agreement between models ranges from low (yellow) to high (dark red). Dark blue areas indicate no suitability for medusahead and light blue represents novel space, environments outside training data constraints.

AT A GLANCE	
Species	Medusahead (*Taeniatherum caput-medusae*)
Output	Rank; potential habitat suitability ranging from 0 to 10
States covered	The contiguous United States
Resolution	90 m
Recentness	*Most recent year (as of Dec. 2020)*: 2020 *Years available*: 2020 *Time series*: No *Update frequency*: Yes; timeframe not specified
Evaluation	Yes; bootstrapping/cross validation
GET DATA	Interactive web map: https://gis.usgs.gov/inhabit/ Data download: https://www.sciencebase.gov/catalog/item/5fcfb248d34e30b91239ad3a

Geospatial inputs: Geospatial inputs included mean diurnal range (Bio2), temperature annual range (Bio7), precipitation of warmest quarter (Bio18), minimum temperature winter, mean temperature spring, mean PET, landscape condition model, human influence index, percent clay, mean available water content in the first 0–5 cm of the soil horizon, mean depth to restriction layer, remoteness (night lights), and bare ground standard deviation.

Key model covariates: Across all models, mean PET (October–June) and minimum temperature winter exhibited the strongest percent contributions (28 percent and 27 percent, respectively); other important covariates (>5 percent) included mean temperature spring, precipitation of warmest quarter, percent clay, available water content, mean diurnal range, and temperature annual range.

Evaluation: Models were evaluated with tenfold cross-validation as well as AUC-ROC, AUC-precision recall (AUC-PR), Cohen's kappa, TSS, PCC, sensitivity, and specificity. Evaluation statistics for all models can be found under the "Model Details" tab on the INHABIT website, https://gis.usgs.gov/inhabit/.

Notes: Occurrence points and their spatial range are also available in the web tool, as well as a table including summary data for Federal management areas (BLM, FWS, NPS) that includes estimated suitable habitat area, known presence (count data), and distance to known occurrence.

Spatial Data Citation

Jarnevich, C.S., LaRoe, J., Engelstad, P., and Sullivan, J., 2021, INHABIT species potential distribution across the contiguous United States: U.S. Geological Survey data release, accessed January 25, 2022, at https://doi.org/10.5066/P92476V6.

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INHABIT—Ventenata Suitability (2019)

Description: This product is a ranked potential of habitat suitability for ventenata determined by the agreement between a maximum of 10 models (5 algorithms × 2 background generation methods). Users can select between four thresholds, ranging from precautionary to targeted. This product is contained within an online map tool, Invasive Species Habitat Tool (INHABIT) that predicts habitat suitability for more than 100 additional invasive species.

Species: Ventenata (*Ventenata dubia*)

Spatial extent: The contiguous United States

Spatial resolution: 90-m pixels

Recentness: 2020

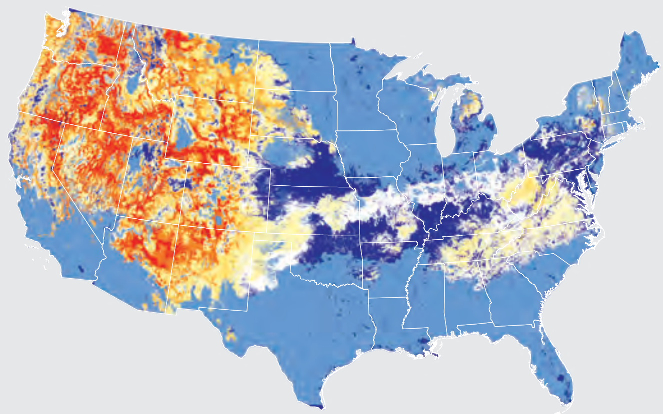
Author-suggested use: Mapped predictions of habitat suitability for ventenata are meant to guide risk assessment at regional and National scales and rapid response strategies at local scales. The modeling process utilizes computing power to provide map products with both large extent and fine grain size that are useful at multiple spatial scales.

Author-identified caveats/limitations: Assessment of the modeling process may be difficult to score as ideal because the input data were based on readily available species occurrence data, rather than data collected based on a statistically designed study. The authors suggest the models are subject to numerous other caveats typical of correlative species distribution models, such as the quality of occurrence point data, spatial and temporal alignment of model inputs, and ecological and predictive relevance.

Modeling approach: The authors use the VisTrails software framework to fit models to each combination of algorithm and background method (such as SAHM). They test five different algorithms: Maxent (v 3.4.1), BRT, RF, GLM, and MARS. Each algorithm is tested with two background sampling approaches for a total of 10 models for each species. The final surface ranking is based on agreement between individual model outputs.

Model training data: The authors downloaded occurrence data for each species from multiple databases: the GBIF, BISON, the EDDMapS, the BLM and NPS' NISIMS databases, and the BLM AIM program. Data may be sourced from all of these with records for the species meeting the specified criteria. The data are aggregated by observation type (observation or specimen only), observation date (1980 to present), with coordinate uncertainty ≤30 m.

Remotely sensed inputs: None.



Extent of the "INHABIT–Ventenata Suitability (2019)" spatial data product (Jarnevich and others, 2021) showing the ranked potential of habitat suitability of ventenata (*Ventenata dubia*). The map reflects the use of the 0.01 threshold. Agreement between models ranges from low (yellow) to high (dark red). Dark blue areas indicate no suitability for ventenata and light blue represents novel space, environments outside training data constraints.

AT A GLANCE

Species	Ventenata (*Ventenata dubia*)
Output	Rank; potential habitat suitability ranging from 0 to 10
States covered	The contiguous United States
Resolution	90 m
Recentness	*Most recent year (as of Dec. 2020)*: 2020 *Years available*: 2020 *Time series*: No *Update frequency*: Yes; timeframe not specified
Evaluation	Yes; bootstrapping/cross validation
GET DATA	Interactive web map: https://gis.usgs.gov/inhabit/ Data download: https://www.sciencebase.gov/catalog/item/5fcfb129d34e30b91239ad23

Geospatial inputs: Geospatial inputs included isothermality (Bio3), minimum temperature winter, mean temperature spring, mean March precipitation divided by mean spring precipitation, evapotranspiration, landscape condition model, human influence index, percent clay, percent calcium carbonate in soil, variance of available water content in the first 0–5 cm of the soil horizon, mean available water content in the first 0–5 cm of the soil horizon, mean depth to restriction layer, remoteness (night lights), burn frequency, bare ground standard deviation.

Key model covariates: Key model covariates were not specified but the following variables appeared across all models. Minimum temperature winter exhibited the strongest percent contribution (72 percent); other important covariates (>5 percent) included mean March precipitation divided by mean spring precipitation, mean temperature spring, remoteness (night lights), and evapotranspiration (October–June).

Evaluation: The authors used tenfold cross-validation as well as AUC-ROC, AUC-PR, Cohen's kappa, TSS, PCC, sensitivity, and specificity. Evaluation statistics for all models can be found under the "Model Details" tab on the INHABIT website, https://gis.usgs.gov/inhabit/.

Notes: Occurrence points and their spatial range are also available in the webtool, as well as a table including summary data for Federal management areas (BLM, FWS, NPS) that includes estimated suitable habitat area, known presence (count data), and distance to known occurrence.

Spatial Data Citation

Jarnevich, C.S., LaRoe, J., Engelstad, P., and Sullivan, J., 2021, INHABIT species potential distribution across the contiguous United States: U.S. Geological Survey data release, accessed January 25, 2022, at https://doi.org/10.5066/P92476V6.

Publication Citation

Young, N.E., Jarnevich, C.S., Sofaer, H.R., Pearse, I., Sullivan, J., Engelstad, P., and Stohlgren, T.J., 2020, A modeling workflow that balances automation and human intervention to inform invasive plant management decisions at multiple spatial scales: PLoS One, v. 15, no. 3, p. e0229253, accessed December 1, 2020, at https://doi.org/10.1371/journal.pone.0229253.

RAP Annual Herbaceous Cover Time Series (1984–2019)

Description: This Rangeland Analysis Platform (RAP) product is a continuous estimate of annual herbaceous cover.

Species: Annual herbaceous species

Spatial extent: The western United States

Spatial resolution: 30-m pixels

Recentness: 2019, annual products available 1984–2019

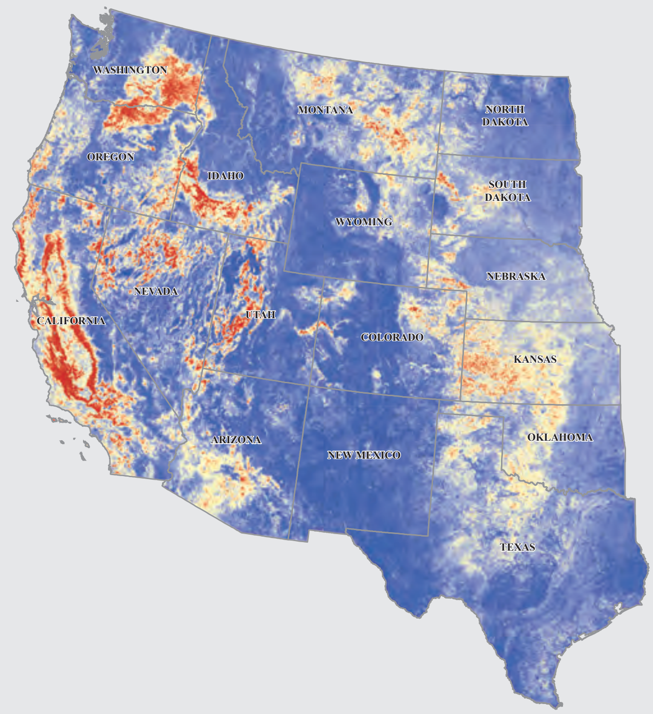
Author-suggested use: This product will allow managers, researchers, policy makers, and planners to evaluate the outcomes of past management efforts and plan future efforts accordingly.

Author-identified caveats/limitations: This product is intended to be used alongside local on-the-ground data, expert knowledge, land use history, scientific literature, and other sources of information when making interpretations. When being used to inform decision making, remotely sensed products should be evaluated and utilized according to the context of the decision and not be used in isolation.

Modeling approach: Temporal convolutional networks, a type of neural network, combined with an Adam optimizer (Srivastava and others, 2014) are used to produce cover estimates. Convolutions on Landsat surface reflectance and vegetation indices are performed separately owing to the differing domains they represent. The convolutions were added together to produce the final layer, containing six units corresponding to the six functional groups, one of which was annual herbaceous species. Predictions were repeated four times, and the results were averaged to obtain the predictive output and to estimate uncertainty.

Model training data: Model training data came from NRCS (Natural Resources Conservation Service), Natural Resources Inventory (NRI), and BLM AIM data; 57,792 field plots.

Remotely sensed inputs: Remotely sensed inputs included 64-day means of six Landsat surface reflectance bands, 64-day means of normalized difference vegetation index (NDVI) and Normalized Burn Ratio 2 (modified normalized burn ratio that highlights water sensitivity in vegetation). These are derived from Landsat 5 thematic mapper, Landsat 7 enhanced thematic mapper plus (ETM+), and Landsat 8 operational land imager (OLI) surface reflectance collection products.



Extent of the data layer for the predicted annual herbaceous cover (low—blue; high—red) in the western United States as estimated by Rangelands Analysis Platform product (RAP; Allred and others, 2019).

AT A GLANCE	
Species	Annual herbaceous species
Output	Continuous percent cover
States covered	The western United States
Resolution	30 m
Recentness	*Most recent year (as of Dec. 2020)*: 2019 *Years available*: 1984–2019 *Time series*: Yes *Update frequency*: Every 2 years
Evaluation	Yes; fully independent
GET DATA	http://rangeland.ntsg.umt.edu/data/rap/rap-vegetation-cover/

Geospatial inputs: XY coordinates.

Key model covariates: Key model covariates were not specified but the following variables appeared in the final model: 64-day means of six Landsat surface reflectance bands, 64-day means of NDVI and the normalized burn ratio 2, and XY coordinates.

Evaluation: Independent validation was carried out using 10 percent of the dataset (5,780 field plots), and 5 external and independent collections of field data (Sagebrush Steppe Treatment Evaluation Project, Restore New Mexico Collaborative Monitoring Program, Eastern Oregon Agricultural Research Center, U.S. Geological Survey [USGS], NPS, University of Idaho). The authors calculated mean absolute error (MAE), root mean square error (RMSE), root square error (RSE) and R^2 fit statistics. The annual herbaceous product has a MAE=7.0, RMSE=11.0, R^2=0.58 (dropout validation dataset); for outside datasets, MAE ranges from 4.2 to 9.0, RMSE from 7.8 to 13.3, and R^2 from 0.19 to 0.56.

Notes: “RAP Annual Herbaceous Cover Time Series (1984–2019)” replaces an earlier version released in 2018. Other products available for download from http://rangeland.ntsg.umt.edu/data/rap/rap-vegetation-cover/ include percent-cover estimates of perennial herbaceous species, shrubs, trees, and bare ground. Three forms of biomass estimates are also available, annual herbaceous (see “RAP Annual Herbaceous Biomass Time Series [1986–2019]”), perennial herbaceous, and both forms of herbaceous species combined.

Spatial Data Citation

Allred, B.W., Bestelmeyer, B.T., Boyd, C.S., Brown, C., Davies, K.W., Ellsworth, L.M., Erickson, T.A., Fuhlendorf, S.D., Griffiths, T.V., Jansen, V., Jones, M.O., Karl, J., Maestas, J.D., Maynard, J.J., McCord, S.E., Naugle, D.E., Starns, H.D., Twidwell, D., and Uden, D.R., 2019, Vegetation Cover Rangeland Analysis Platform, accessed October 8, 2020, at http://rangeland.ntsg.umt.edu/data/rap/rap-vegetation-cover/.

Publication Citation

Allred, B.W., Bestelmeyer, B.T., Boyd, C.S., Brown, C., Davies, K.W., Ellsworth, L.M., Erickson, T.A., Fuhlendorf, S.D., Griffiths, T.V., Jansen, V., Jones, M.O., Karl, J., Maestas, J.D., Maynard, J.J., McCord, S.E., Naugle, D.E., Starns, H.D., Twidwell, D., and Uden, D.R., 2020, Improving Landsat predictions of rangeland fractional cover with multitask learning and uncertainty: Methods in Ecology and Evolution, v. 12, no. 5, p. 841–849, accessed October 1, 2020, at https://doi.org/10.1111/2041-210X.13564.

RAP Annual Herbaceous Biomass Time Series (1986–2019)

Description: This RAP product is a continuous estimate of 16-day and annual above ground biomass (lbs/acre) of annual herbaceous species with values ranging from 0 to 4,511.

Species: Annual herbaceous species

Spatial extent: The western United States

Spatial resolution: 30-m pixels

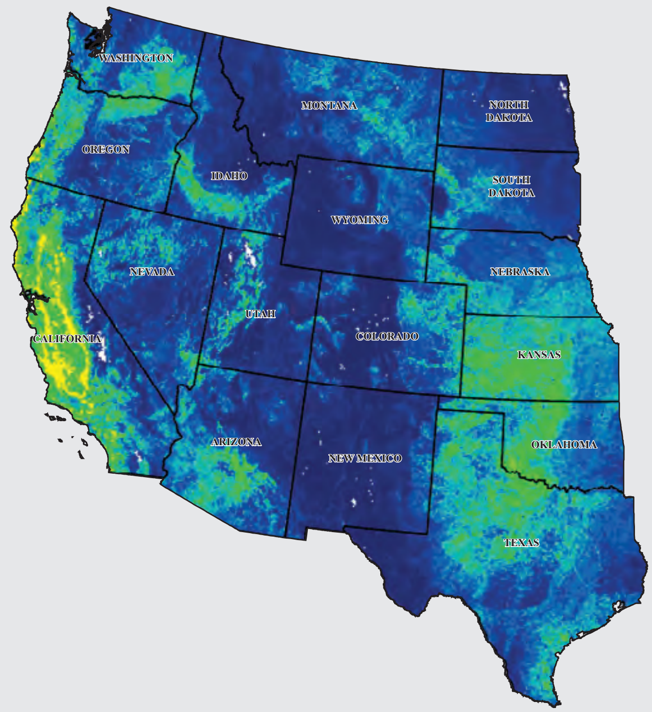
Recentness: 2019, annual products available 1986–2019

Author-suggested use: The methods and data presented provide a means to understand the finer scale phenological and productivity dynamics of rangelands that are missed when using single, pixel-level estimates. Understanding spatial and temporal heterogeneity is critical for rangeland conservation and management actions, including creating grazing plans and strategies, understanding results of herbicide treatments for invasive annuals, or predicting fuel conditions for an upcoming fire year.

Author-identified caveats/limitations: The vegetation biomass data and maps are intended to be used alongside local on-the-ground data, expert knowledge, land use history, scientific literature, and other sources of information when making interpretations. When being used to inform decision making, remotely sensed products should be evaluated and utilized according to the context of the decision and not be used in isolation.

Modeling approach: The annual plant functional type (PFT) dataset and the 16-day annual NDVI composites enabled disaggregation of pixel level NDVI values to subpixel PFTs weighted by their fractional cover. Geographically specific PFT NDVI phenological characteristics were determined by an over-determined set of linear equations to solve for each PFT NDVI value within U. S. Environmental Protection Agency (EPA) Level IV regions. The PFT NDVI estimations were then used in the moderate resolution imaging spectroradiometer (MODIS) algorithm, MOD17, a net primary production model adapted for Landsat.

Model training data: Model training data included 16-day and annual above-ground biomass estimates, derived from the MOD17 algorithm, and validated with tower carbon



Extent of the data layer estimating biomass (lbs/acre) of annual herbaceous species in the western United States as predicted by Rangelands Analysis Platform (RAP) Biomass product (Robinson and others, 2019a). Low predicted biomass is shown in blue, and yellow indicates the highest predicted biomass values.

AT A GLANCE	
Species	Annual herbaceous species
Output	Continuous estimate of biomass (lbs/acre)
States covered	The western United States
Resolution	30 m
Recentness	*Most recent year (as of Dec. 2020)*: 2019 *Years available*: 1986–2019 *Time series*: Yes *Update frequency*: Yes; timeframe not specified
Evaluation	Yes; fully independent
GET DATA	http://rangeland.ntsg.umt.edu/data/rap/rap-vegetation-biomass/

flux estimates (Robinson and others, 2018) then partitioned into PFTs (for example, annual grasses and forbs, perennial grasses and forbs).

Remotely sensed inputs: Remotely sensed inputs included fraction of absorbed photosynthetically active radiation and leaf area index, derived from NDVI composites partitioned to PFTs using percent cover product described in "RAP Annual Herbaceous Cover Time Series (1984–2019)." PFT-specific NDVI are used and converted to biomass (lbs/acre; Jones and others, 2021). Inputs also included gridded surface meteorological data.

Geospatial inputs: Geospatial inputs came from the RAP Annual Herbaceous Percent Cover product (see "RAP Annual Herbaceous Cover Time Series [1984–2019]"; Allred and others, 2020).

Key model covariates: Key model covariates were not specified but final model covariates included fraction of absorbed photosynthetically active radiation and leaf area index derived from NDVI estimates, percent cover of each PFT, and meteorological data sourced from gridMET. However, the model is process based and does not generate an assessment of relative weight or importance of covariates.

Evaluation: Independent evaluation was carried out by comparing biomass estimates with NRCS NRI plot-level estimates of herbaceous biomass collected on rangelands from 2004 to 2018, with U.S. Department of Agriculture (USDA) Forest Service Rangeland Production Monitoring Service (RPMS) data, provided annually from 1984 to 2018 at 250-m resolution (Reeves and others, 2021), and to the gridded Soil Survey Geographic Database (SSURGO), which provides fixed estimates of unfavorable, normal, and favorable annual range potential production by soil survey units at 30-m resolution. The RPMS and SSURGO data estimate total, not solely herbaceous, rangeland productivity. Correlation coefficients between RAP biomass estimates and those of NRI, RPMS and SSURGO were 0.63, 0.79, and 0.82, respectively.

Notes: Other products available for download include percent cover estimates of annual and perennial herbaceous species, shrubs, trees, and bare ground (see "RAP Annual Herbaceous Cover Time Series [1984–2019]") and two additional biomass estimates; perennial herbaceous, and annual and perennial herbaceous species combined.

Spatial Data Citation

Robinson, N.P., Jones, M.O., Moreno, A., Erickson, T.A., Naugle, D.E., and Allred, B.W., 2019a, Vegetation Biomass Rangeland Analysis Platform, accessed June 21, 2021, at http://rangeland.ntsg.umt.edu/data/rap/rap-vegetation-biomass/.

Publication Citations

Robinson, N.P., Jones, M.O., Moreno, A., Erickson, T.A., Naugle, D.E., and Allred, B.W., 2019b, Rangeland productivity partitioned to sub-pixel plant functional types: Remote Sensing, v. 11, no. 12, p. 1427, accessed October 1, 2020, at https://doi.org/10.3390/rs11121427.

Jones, M.O., Robinson, N.P., Naugle, D.E., Maestas, J.D., Reeves, M.C., Lankston, R.W., and Allred, B.W., 2021, Annual and 16-day rangeland production estimates for the western United States: Rangeland Ecology and Management, v. 77, p. 112–117, accessed January 24, 2022, at https://doi.org/10.1016/j.rama.2021.04.003.

Probability of Cheatgrass Invasion in Western United States

Description: This product is a continuous estimate of the probability of cheatgrass occurrence.

Species: Cheatgrass (*Bromus tectorum*)

Spatial extent: The western United States, including six level II EPA ecoregions in the arid and semiarid western United States.

Spatial resolution: Approximately 94-m (3-arc-second) pixels

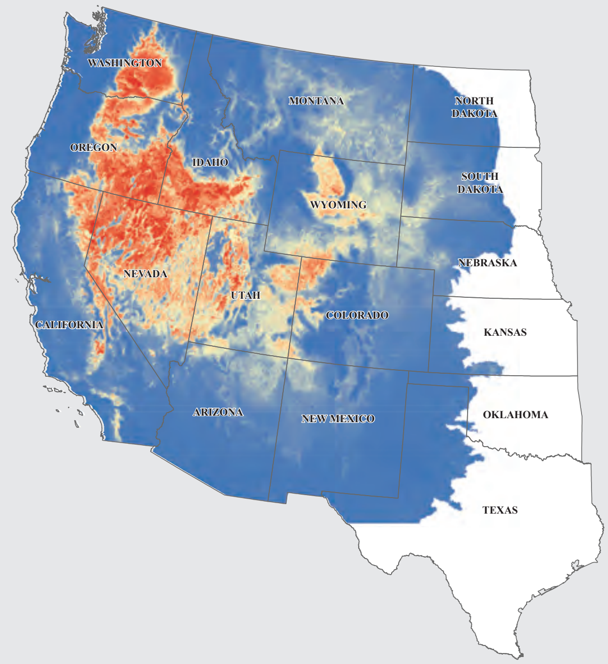
Recentness: 2020

Author-suggested use: These model outputs are intended as a resource for prioritizing monitoring and management at moderate to broad spatial scales (for example, sub watershed) in conjunction with local knowledge and field verification. Predictions of species presence outside the model training areas represent hypotheses for where the species may occur next.

Author-identified caveats/limitations: These models are more likely to miss observed presences than to predict presences in areas where none occur and are a conservative estimate of potential invasive species occurrence.

Modeling approach: Predictive models of the probability of cheatgrass presence were trained and evaluated, then used to predict invasion risk within model training areas and across ecoregions where cheatgrass was observed. The authors fit BRTs, allowing for nonlinear relationships and interactions between multiple variables and species presence. To distinguish between informative and uninformative absences, methods were adapted from species distribution modeling based on presences and pseudoabsences (Iturbide and others, 2015). The authors selected model training and testing data within species-specific buffers from observed presences, beyond which including additional absence data did not improve model ability to accurately predict species presence (Barga and others, 2018).

Model training data: The presence or absence of cheatgrass was determined from field data obtained from the LANDFIRE Reference Database, BLM AIM database. LANDFIRE data sources include the USDA Forest Service Forest Inventory and Analysis, USGS Gap Analysis Project (GAP), NPS Vegetation Inventory Program, and other



Extent of the estimated distribution of cheatgrass (*Bromus tectorum*) in the western United States, as estimated by McMahon and others (2021a). Low probability of occurrence is shown in blue, and areas of high probability of occurrence are shown in red.

AT A GLANCE	
Species	Cheatgrass (*Bromus tectorum*)
Output	Probability of occurrence (categorical but mapped as continuous)
States covered	The western United States; part of North Dakota, South Dakota, Kansas, Nebraska, Oklahoma,
Resolution	~94 m (3-arc-second)
Recentness	*Most recent year (as of Dec. 2020)*: 2020 *Years available*: 2020 *Time series*: No *Update frequency*: Not applicable
Evaluation	Yes; bootstrapping/cross validation
GET DATA	https://www.fs.usda.gov/rds/archive/Catalog/RDS-2020-0078

vegetation and long-term monitoring efforts conducted by agencies and universities. The AIM dataset includes data from the Terrestrial AIM Database and Landscape Monitoring Database. These data were supplemented with data from the Joint Fire Services Program—Chronosequence Study (Pyke and others, 2011). The final dataset included 148,404 plots.

Remotely sensed inputs: None

Geospatial inputs: Geospatial inputs included climate, topography, and soil data, as well as burn area overlap, distance to road and sampling day. Climate data included annual climate water deficit, summer precipitation (sum), annual mean temperature, median hottest month temperature, monthly temperature variance, total annual precipitation, median temperature of coldest month, coefficient of variation of monthly precipitation (standard deviation divided by mean), correlation between monthly precipitation and monthly median temperature. Climate data were derived from TerraClimate monthly products at 150-arc-second (1/24 of 1 degree) resolution. Topography data included Topographic Position Index and Topographic Heat Load Index, all derived from gap-filled National Aeronautics and Space Administration (NASA) Shuttle Radar Tomography Mission data. Soil data included clay content, sand content, silt content, calcium carbonate concentration, available water content, depth to restrictive layer, and electrical conductivity. Soil data were from the Gridded National Soil Survey Geographic Database, Soil Survey Staff 2019. Post-1984 overlap with burned areas from Geospatial Multi-Agency Coordination Group (GeoMAC) 2020 and Monitoring Trends in Burn Severity (MTBS) 2017 products was also considered in the modeling process. The authors considered a cell as having burned if it overlapped a fire footprint prior to 2019. Distance to road was calculated using 2019 U.S. Census Bureau's Topologically Integrated Geographic Encoding and Referencing (TIGER) roads dataset.

Key model covariates: Key covariates include climatic water deficit (>500 millimeters [mm]), median temperature of coldest month, summer precipitation (less than [<] 100 mm), correlation between monthly temperature and precipitation. Values in parentheses are those at which the probability of presence is greatest.

Evaluation: The model was evaluated using fivefold cross validation. Optimization was based on the AUC-PR, a less common alternative to AUC-ROC that the authors used because it is better at assessing model performance on imbalanced datasets (Saito and Rehmsmeier, 2015). They also reported the following accuracy measures at 0.15 (less conservative) and 0.5 (more conservative) presence thresholds: (1) specificity (proportion of real negatives that are correctly predicted), (2) sensitivity (proportion of real presences that are detected), (3) false positive rate, (4) precision (percent of estimated presences that are correct), and (5) the Symmetric Extremal Dependence Index (SEDI), a performance measure for predicting low-frequency events (Wunderlich and others, 2019). Evaluation metrics for the cheatgrass model were: AUC-ROC=0.919; AUC-PR=0.554; sensitivity (0.15)=0.915; sensitivity (0.5)=0.599; false positive rate (0.15)=0.251; false positive rate (0.5)=0.054; precision (0.15)=0.492; precision (0.5)=0.748; SEDI (0.15)=0.822; SEDI (0.5)=0.742. AUC-PR is an order of magnitude higher than prevalence, which = 0.210.

Notes: Spatial data products are available for three other IAGs, one invasive perennial grass, and nine invasive annual forbs, in addition to cheatgrass and medusahead.

Spatial Data Citation

McMahon, D.E., Urza, A.K., Brown, J.L., Phelan, C., and Chambers, J.C., 2021a, Invasive plant probability prediction outputs and code for paper "Modeling species distributions and environmental suitability highlights risk of plant invasions in western US": U.S. Department of Agriculture, Forest Service, Research Data Archive, accessed June 25, 2021, at https://doi.org/10.2737/RDS-2020-0078.

Publication Citation

McMahon, D.E., Urza, A.K., Brown, J.L., Phelan, C., and Chambers, J.C., 2021b, Modelling species distributions and environmental suitability highlights risk of plant invasions in western United States: Diversity and Distributions, v. 27, no. 4, p. 710–728, accessed March 3, 2021, at. https://doi.org/10.1111/ddi.13232.

Probability of Medusahead Invasion in Western United States

Description: This product is a continuous estimate of the probability of medusahead occurrence.

Species: Medusahead (*Taeniatherum caput-medusae*)

Spatial extent: The western United States, including six level II EPA ecoregions in the arid and semiarid western United States.

Spatial resolution: Approximately 94-m (3-arc-second) pixels

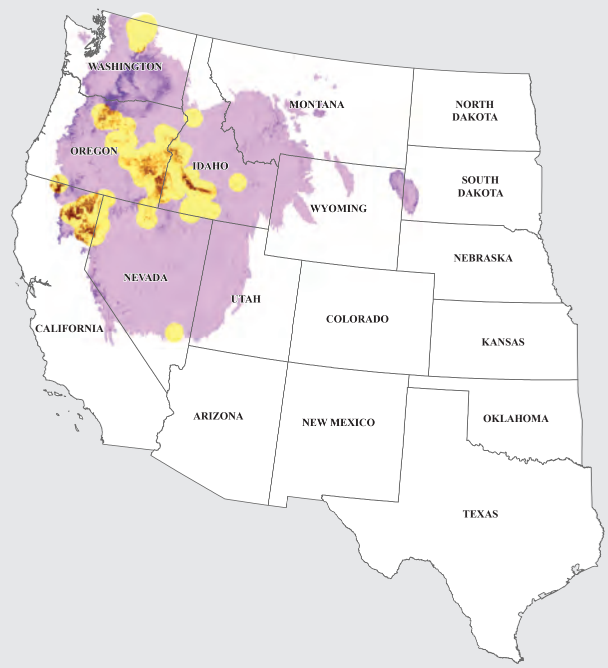
Recentness: 2020

Author-suggested use: These model outputs are intended as a resource for prioritizing monitoring and management at moderate to broad spatial scales (for example, sub watershed) in conjunction with local knowledge and field verification. Predictions of species presence outside the model training areas represent hypotheses for where the species may occur next.

Author-identified caveats/limitations: These models are more likely to miss observed presences than to predict presences in areas where none occur and are a conservative estimate of potential invasive species occurrence.

Modeling approach: Predictive models of the probability of medusahead presence were trained and evaluated, then used to predict invasion risk within model training areas and across ecoregions where medusahead was observed. The authors fit boosted regression trees, allowing for nonlinear relationships and interactions between multiple variables and species presence. To distinguish between informative and uninformative absences, methods were adapted from species distribution modeling based on presences and pseudoabsences (Iturbide and others, 2015). The authors selected model training and testing data within species-specific buffers from observed presences, beyond which including additional absence data did not improve the models' ability to accurately predict species presence (Barga and others, 2018).

Model training data: The presence or absence of medusahead was determined from field data obtained from the LANDFIRE Reference Database, BLM AIM database and supplemental. LANDFIRE data sources include the USDA



Extent of the estimated distribution of medusahead (*Taeniatherum caput-medusae*) in the western United States, as estimated by McMahon and others (2021a). Within model training areas, brown reflects high estimated probability of occurrence, and yellow depicts a low estimated probability of occurrence. Regions outside the training area are shown in purple, with darker areas indicating a higher estimated probability of medusahead occurrence.

AT A GLANCE	
Species	Medusahead (*Taeniatherum caput-medusae*)
Output	Probability of occurrence (categorical but mapped as continuous)
States covered	Parts of California, Idaho, Montana, Nevada, Oregon, Utah, Washington, Wyoming
Resolution	~94 m (3-arc-second)
Recentness	*Most recent year (as of Dec. 2020)*: 2020 *Years available*: 2020 *Time series*: No *Update frequency*: Not applicable
Evaluation	Yes; bootstrapping/cross validation
GET DATA	https://www.fs.usda.gov/rds/archive/Catalog/RDS-2020-0078

Forest Service Forest Inventory and Analysis, USGS GAP Analysis, NPS Vegetation Inventory Program, and other vegetation and long-term monitoring efforts conducted by agencies and universities. The AIM dataset includes data from the Terrestrial AIM Database and Landscape Monitoring Database. These data were supplemented with data from the Joint Fire Services Program—Chronosequence Study (Pyke and others, 2011). The final dataset included 148,404 plots.

Remotely sensed inputs: None

Geospatial inputs: Geospatial inputs include climate, topography, and soil data, as well as burn area overlap, distance to road and sampling day. Climate data include annual climate water deficit, summer precipitation (sum), annual mean temperature, median hottest month temperature, monthly temperature variance, total annual precipitation, median temperature of coldest month, coefficient of variation of monthly precipitation (standard deviation divided by mean), correlation between monthly precipitation and monthly median temperature. Climate data are derived from TerraClimate monthly products at 150-arc-second (1/24 of 1 degree) resolution. Topography data included Topographic Position Index and Topographic Heat Load Index, all derived from gap-filled NASA Shuttle Radar Tomography Mission data. Soil data included clay content, sand content, silt content, calcium carbonate concentration, available water content, depth to restrictive layer, and electrical conductivity from the Gridded National Soil Survey Geographic Database, Soil Survey Staff 2019; Post-1984 overlap with burned areas from GeoMAC 2020 and MTBS 2017 products was also considered in the modeling process. The authors considered a cell as having burned if it overlapped a fire footprint prior to 2019. Distance to road calculated using 2019 U.S. Census Bureau's Topologically Integrated Geographic Encoding and Referencing (TIGER) roads dataset.

Key model covariates: Sampling day of year (1–365) was the most important predictor of presence with highest detection probabilities in early summer and late fall; correlation between monthly temperature and precipitation; Percent clay (20 to 50 percent), climatic water deficit (700 to 1,000 mm), median temperature of coldest month (>4°C). Values in parentheses are those for which the probability of presence is greatest.

Evaluation: The model was evaluated using fivefold cross validation. Optimization was based on the AUC-PR, a less common alternative to AUC-ROC, which the authors used because it is better at assessing model performance on imbalanced datasets (Saito and Rehmsmeier, 2015). They also reported the following accuracy measures at two thresholds of presence (a less conservative 0.15 and a more conservative 0.5): (1) Specificity (proportion of real negatives that are correctly predicted), (2) sensitivity (proportion of real presences that are detected), (3) false positive rate, (4) precision (percent of estimated presences that are correct), and (5) the SEDI, a performance measure for predicting low-frequency events (Wunderlich and others, 2019). Evaluation metrics for the medusahead model were: AUC-ROC=0.945; AUC-PR=0.581; Sensitivity (0.15)=0.810; Sensitivity (0.5)=0.516; False Positive Rate (0.15)=0.080; False Positive Rate (0.5)=0.017; Precision (0.15)=0.452; Precision (0.5)=0.707; SEDI (0.15)=0.869; SEDI (0.5)=0.751 AUC-PR is an order of magnitude higher than prevalence, which equals 0.075.

Notes: Spatial data products are available for three other IAGs, one invasive perennial grass, and nine invasive annual forbs, in addition to cheatgrass and medusahead.

Spatial Data Citation

McMahon, D.E., Urza, A.K., Brown, J.L., Phelan, C., and Chambers, J.C., 2021a, Invasive plant probability prediction outputs and code for paper "Modeling species distributions and environmental suitability highlights risk of plant invasions in western US": Fort Collins, CO, Forest Service Research Data Archive, accessed June 25, 2021, at https://doi.org/10.2737/RDS-2020-0078.

Publication Citation

McMahon, D.E., Urza, A.K., Brown, J.L., Phelan, C., and Chambers, J.C., 2021b, Modelling species distributions and environmental suitability highlights risk of plant invasions in western United States: Diversity & Distributions, v. 27, no. 4, p. 710–228, accessed March 3, 2021, at https://doi.org/10.1111/ddi.13232.

RCMAP Rangeland Fractional Components Base Map (2016)

Description: This Rangeland Condition, Monitoring, Assessment, and Projection (RCMAP) product has six stand-alone elements, or fractional components (percent cover), of which annual herbaceous is one.

Species: All invasive and native annual herbaceous species, including grasses.

Spatial extent: Rangelands in much of the western United States. Elevations above 2,300 m were excluded from the modeling effort.

Spatial resolution: 30-m pixels

Recentness: 2016

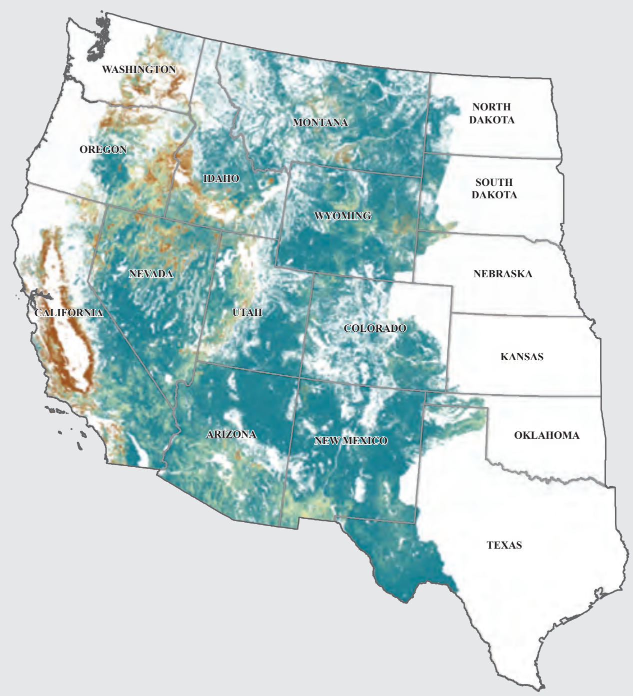
Author-suggested use: Fractional components provide flexible and accurate remote-sensing-derived products that offer flexible application utility and further enable rangeland monitoring.

Author-identified caveats/limitations: Rangelands pose numerous difficulties to mapping, owing to their high degree of spatial and temporal variation, high amount of bare soil and senescent vegetation, and variation in the physical and chemical properties of soils. These challenges can result in errors in the fractional component estimation. Modeling-related errors also exist. Chief among these is the tendency of component predictions to have a flattened histogram relative to training data.

Modeling approach: The authors employed automated Cubist, rule-based regression trees to individually map each of the nine fractional components using all imagery, spectral indices, and ancillary data layers.

Model training data: Models were trained with a combination of field measurements and high-resolution remote sensing data from plots ranging in size from 4 to 400 m^2 and averaging 32 m^2.

Remotely sensed inputs: Three seasons of Landsat imagery; three seasons of Landsat spectral indices including Normalized Difference Water Index, Normalized Difference Build-up Index, and Soil Adjusted Vegetation Index; and Landsat thermal band data. These inputs were derived from



Extent of “RCMAP Rangeland Fractional Components Base Map (2016),” ver. 3.0, July 2020 annual herbaceous cover data layer (U.S. Geological Survey and Rigge, 2019). Regions of low estimated percent cover are shown in green, while higher values are brown.

AT A GLANCE	
Species	Annual herbaceous species
Output	Continuous percent cover
States covered	Arizona, California, Colorado, Idaho, Montana, Nevada, New Mexico, Oregon, Texas, Utah, Washington, and Wyoming
Resolution	30 m
Recentness	*Most recent year (as of Dec. 2020)*: 2016 *Years available*: 2016 *Time series*: No *Update frequency*: None currently planned
Evaluation	Yes; fully independent and bootstrapping/cross validation
GET DATA	https://www.sciencebase.gov/catalog/item/5d4c6b79e4b01d82ce8dfd48

Landsat 8 imagery, sometimes incorporating expedited moderate resolution imaging spectroradiometer (eMODIS) data downscaled to 30 m.

Geospatial inputs: Geospatial layers were derived from a digital elevation model (DEM) and included slope, aspect, and position index.

Key model covariates: Not reported.

Evaluation: Independent and bootstrapping/cross-validation techniques were employed to evaluate this product. Independent vegetation plots followed a stratified random sample design with two levels of stratification. The validation plots were evenly allocated to three NDVI thresholds. At each plot, component cover was measured in a 1-m^2 quadrat every 5 m along a 30-m transect. Predicted annual herbaceous fractional components had a R^2=0.58, slope=0.55, and a RMSE=9.8, when compared to the independent sample. Cross-validation metrics were R^2=0.66, slope=0.64, and a RMSE=4.1. An expanded evaluation was conducted by Rigge and others (2019a).

Notes: Other fractional components available in this product set are bare ground, herbaceous, litter, sagebrush, shrub, and shrub height. This product is the foundation on which the "RCMAP Rangeland Fractional Components Time Series (1985–2018)" and "RCMAP Projections of Rangeland Fractional Components (2020s, 2050s, 2080s)" products, reviewed in this document, were built.

Spatial Data Citation

U.S. Geological Survey and Rigge, M., 2019, National Land Cover Database (NLCD) 2016 Shrubland Fractional Components for the Western U.S. (ver. 3.0, July 2020): U.S. Geological Survey data release, accessed April 21, 2021, at https://doi.org/10.5066/P9MJVQSQ.

Publication Citation

Rigge, M., Homer, C., Cleeves, L., Meyer, D.K., Bunde, B., Shi, H., Xian, G., Schell, S., and Bobo, M., 2020, Quantifying Western US Rangelands as Fractional Components with Multi-Resolution Remote Sensing and In Situ Data: Remote Sensing, v. 12, no. 3, p. 412, accessed September 30, 2020, at https://doi.org/10.3390/rs12030412.

RCMAP Rangeland Fractional Components Time Series (1985–2018)

Description: This RCMAP product has six stand-alone elements and uses the 2016 NLCD as a baseline to assess rangeland fractional components (percent cover) back to 1985. This review focuses on the continuous annual herbaceous surface data layer.

Species: All invasive and native annual herbaceous species, including grasses.

Spatial extent: Rangelands in much of the western United States. Elevations above 2,300 m were excluded.

Spatial resolution: 30-m pixels

Recentness: 2018, with annual products available from 1985 to 2018. 2012 was excluded due to lack of imagery.

Author-suggested use: This product provides a wide view of ecosystems, necessary for assessing landscape and ecosystem scale patterns, that is relevant to local decision making. More specifically, these data facilitate a comprehensive assessment of rangeland condition, evaluation of past management actions, understanding of system variability, and opportunities for long-term planning. Local-scale accuracy and utility is demonstrated in three case studies described in Rigge and others (2021a).

Author-identified caveats/limitations: As with all remote sensing and monitoring datasets, error exists in the products and needs to be carefully considered. High-resolution imagery and other machine-learning approaches are being explored to improve classification accuracy. The authors employed more aggressive methods to detect change than was used in previous efforts. This introduced the risk of increased noise, though they took considerable efforts to address it.

Modeling approach: The authors employed automated (Rigge and others, 2019b) Cubist, rule-based regression trees to identify change between each year in the Landsat archive and the "RCMAP Rangeland Fractional Components Base Map (2016)," detailed in Rigge and others (2020). They then used the unchanged portion of the 2016 base map to train regression tree models predicting component cover in each

Extent of annual herbaceous cover data layer from "RCMAP Rangeland Fractional Components Time Series (1985–2018)" (Homer and others, 2020). Low (light green) to high (dark green) estimated percent annual herbaceous cover for 2018 is shown.

AT A GLANCE	
Species	Annual herbaceous species
Output	Continuous percent cover
States covered	Arizona, California, Colorado, Idaho, Montana, Nevada, New Mexico, Oregon, Texas, Utah, Washington, and Wyoming
Resolution	30 m
Recentness	*Most recent year (as of Dec. 2020)*: 2018 *Years available*: 1985–2018 *Time series*: Yes *Update frequency*: Annually
Evaluation	Yes; fully independent
GET DATA	https://www.sciencebase.gov/catalog/item/5ed816eb82ce7e579c67004a

year. Yearly fractional component cover outputs were then inserted in the changed area while the base map was maintained in the unchanged area.

Model training data: The baseline "RCMAP Rangeland Fractional Components Base Map (2016)" product came from training models with a combination of high-resolution satellite imagery and field data from 60 to 120 plots as well as from additional BLM AIM plots. Historical time series cover estimates were based on change from this baseline product.

Remotely sensed inputs: Remotely sensed inputs included summer and fall of Landsat 5, 7, or 8 imagery and summer and fall of Landsat spectral indices (Normalized Difference Water Index, Normalized Difference Build-up Index, and Soil Adjusted Vegetation Index).

Geospatial inputs: Geospatial layers are derived from a DEM and include slope, aspect, and position index.

Key model covariates: Not reported.

Evaluation: Two approaches to fully independent validation were used to assess the complete suite of data products in this fractional component series. First, cover estimates were compared to high-resolution satellite images over multiple locations and years (n=77) in Wyoming, Nevada, and Montana, with R^2=0.52 and RMSE=7.89 percent. Second, cover estimates were compared to field data from two long-term monitoring sites in southwest Wyoming from 126 plots from 2006 to 2018 with R^2=0.46 and RMSE=8.8 percent.

Notes: Other fractional components available in this product set are bare ground, herbaceous, litter, sagebrush, and shrub. This time series product builds off the "RCMAP Rangeland Fractional Components Base Map (2016)" product, which is reviewed in this document.

Spatial Data Citation

Homer, C., Rigge, M., Shi, H., Meyer, D.K., Bunde, B., Granneman, B., Postma, K., Danielson, P., Case, A., and Xian, G., 2020, Remote Sensing Shrub/Grass National Land Cover Database (NLCD) Back-in-Time (BIT) Products for the Western U.S., 1985–2018: U.S. Geological Survey data release, accessed May 20, 2021, at https://doi.org/10.5066/P9C9O66W.

Publication Citation

Rigge, M., Homer, C., Shi, H., Meyer, D.K., Bunde, B., Granneman, B., Postma, K., Danielson, P., Case, A., and Xian, G., 2021a, Rangeland Fractional Components Across the Western United States from 1985 to 2018: Remote Sensing, v. 13, no. 4, p. 813, accessed November 12, 2020, at https://doi.org/10.3390/rs13040813.

RCMAP Projections of Rangeland Fractional Components (2020s, 2050s, 2080s)

Description: This RCMAP product represents projections of land cover elements at three future time steps, 2020s, 2050s, and 2080s. Six stand-alone elements are included with this product, one of which is a continuous annual herbaceous percent cover surface.

Species: All annual herbaceous species

Spatial extent: The sagebrush biome of the western United States and includes all or part of 14 States. Elevations above 2,300 m and non-rangelands are excluded.

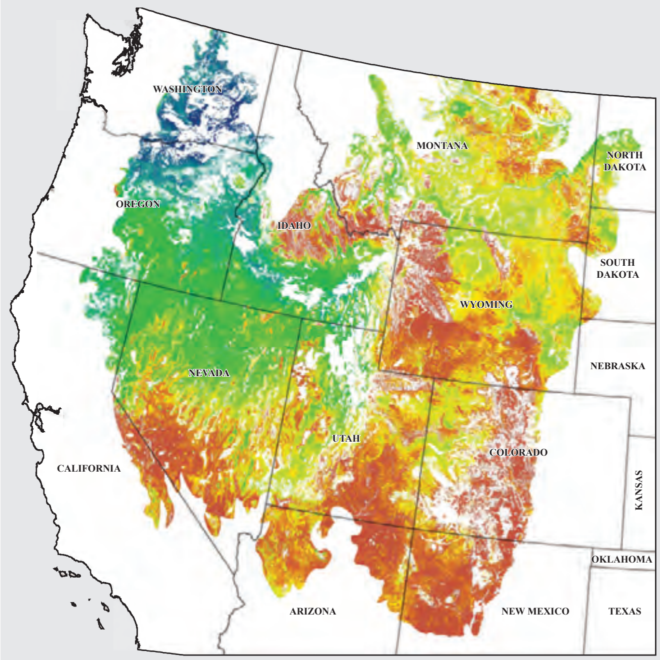
Spatial resolution: 30-m pixels

Recentness: The 2020s, 2050s, 2080s future projections were based on mean climate projections from 2011–2040, 2041–2070, and 2071–2100, respectively.

Author-suggested use: This product is expected to be useful to managers and others who are trying to prepare or plan for future conditions across the sagebrush biome, and to prioritize conservation and restoration objectives accordingly. The high resolution of this product is an improvement over all other products currently available that offer future projections of vegetation cover in the region.

Author-identified caveats/limitations: These models did not account for differences in types of precipitation or changes in magnitude or frequency of precipitation events. While these are important factors, they are beyond the scope of this product. They also do not include the potentially positive impacts of greater CO_2 concentration on plant growth, nor the potentially negative feedbacks driven by expected increases in fire intensity and frequency. The authors also assume continuity in management practices such as grazing. Climate projections themselves include a degree of uncertainty, which inherently transfers to the projections made in these models. However, the authors assumed that plants will continue to respond to climate changes the way they have in the reference period, and that soils and topography will not change.

Modeling approach: The authors tested two modeling approaches: Generalized additive models (GAM) and Cubist, rule-based regression tree models. Models were then selected based on capacity to minimize residuals and produce robust



Extent of the “RCMAP Projections of Rangeland Fractional Components (2020s, 2050s, 2080s)” products (Rigge, 2020). The 2080s product is shown, with estimates ranging from low (brown) to high (dark blue).

AT A GLANCE	
Species	Annual herbaceous species
Output	Continuous percent cover
States covered	Arizona, California, Colorado, Idaho, Montana, Nebraska, Nevada, New Mexico, North Dakota, Oregon, South Dakota, Utah, Washington, Wyoming
Resolution	30 m
Recentness	*Most recent year (as of Dec. 2020)*: 2020s, 2050s, and 2080s *Years available*: 2020s, 2050s, and 2080s *Time series*: Yes *Update frequency*: None planned
Evaluation	Yes; bootstrapping/cross validation
GET DATA	https://www.sciencebase.gov/catalog/item/5f7c9fba82ce1d74e7db5408

relationships with training data, specifically by comparing GAM and regression tree predictions to "RCMAP Rangeland Fractional Components Time Series (1985–2018)" predictions for 1990, 2000, and 2010. GAM predictions generally outperformed regression tree predictions and were selected as the final model.

Model training data: These models were trained with data derived from the "RCMAP Rangeland Fractional Components Time Series (1985–2018)" product using randomly located points (*n*=90,000 per year, total *n*=2,880,000), which fell only in rangelands and excluding areas that had burned or otherwise been treated (Land Treatment Digital Library; Pilliod, 2009) from 1985 to 2018.

Remotely sensed inputs: None

Geospatial inputs: Elevation, slope, aspect, and position index derived from a 30-m DEM; available water content, and organic matter at two different soil depths derived from 30-m POLARIS soils data; growing season (GS) and nongrowing season (NGS) average minimum and maximum temperature; GS and NGS total precipitation were calculated from 1984 to 2018 were derived from 800-m gridded climate data from PRISM. Projections of these climate variables to the 2020s, 2050s, and 2080s, used mean climate projections from 2011–2040, 2041–2070, and 2071–2100, respectively.

Key model covariates: Elevation was the strongest predictor of annual herbaceous species followed by NGS precipitation, GS precipitation, and organic matter at a depth of 0 to 30 cm.

Evaluation: Model predictions were evaluated using cross-validation techniques, comparing them to RCMAP time series predictions for 1990, 2000, and 2010. Annual herbaceous vegetation was fairly predicted with spatial correlation between GAM and RCMAP time series model predictions r=0.58, and all fractional components r=0.63.

Notes: Other projected fractional components available in this product set are bare ground, herbaceous, litter, sagebrush, and shrub. This product builds off the "RCMAP Rangeland Fractional Components Time Series (1985–2018)" and "RCMAP Rangeland Fractional Components Base Map (2016)" products, both of which are reviewed in this document.

Spatial Data Citation

Rigge, M.B., 2020, Projections of Rangeland Fractional Component Cover Across the Sagebrush Biome for Representative Concentration Pathways (RCP) 4.5 and 8.5 Scenarios for the 2020s, 2050s, and 2080s Time-Periods: U.S. Geological Survey data release, accessed April 21, 2021, at https://doi.org/10.5066/P9EC2094.

Publication Citation

Rigge, M., Shi, H., and Postma, K., 2021b, Projected change in rangeland component fractional cover across the sagebrush biome through 2085: Ecosphere, v. 12, no. 6, p. e03538, accessed January 29, 2022, at https://doi.org/10.1002/ecs2.3538.

WGA Annual Herbaceous Cover (2016–2018 Composite)

Description: This Western Governors' Association (WGA) product is a continuous surface of annual herbaceous cover produced as the weighted average of three products, the Rangeland Analysis Platform (RAP) version 1.0 (cover), "HLS Annual Herbaceous Fractional Cover Time Series (2016–2020)" and "RCMAP Rangeland Fractional Components Base Map (2016)."

Species: All annual herbaceous species

Spatial extent: The sagebrush biome of the western United States and encompasses all, or part, of 14 States.

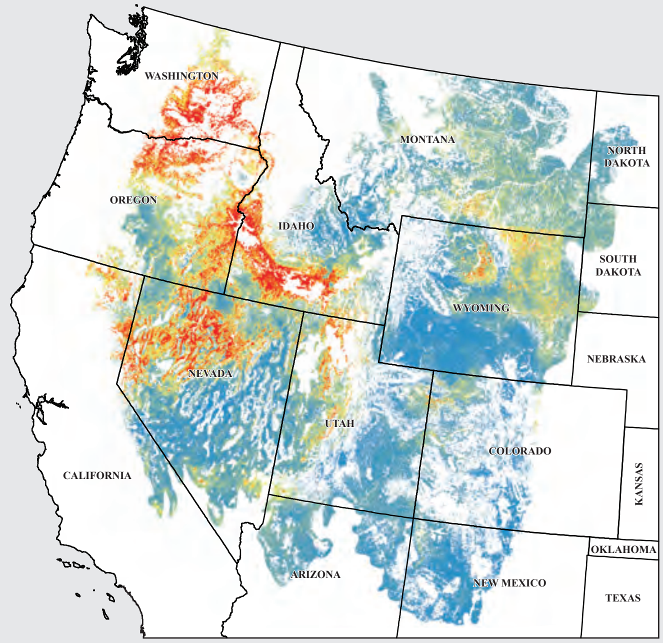
Spatial resolution: 30-m pixels

Recentness: 2018; single estimate based on data from 2016 to 2018.

Author-suggested use: This geospatial data layer was developed as part of the WGA's Toolkit for Invasive Annual Grass Management in the West (July 2020). Its purpose is to help State and local managers plan cross-boundary, collaborative projects to address IAGs by providing landscape context on the extent of invasion.

Author-identified caveats/limitations: This data layer should be assumed to depict cover for all annual herbaceous species, not just IAGs, because the datasets used to create the combined product represent slightly different response variables (for example, IAGs, annual grasses and forbs). However, the authors considered annual herbaceous cover a useful surrogate for invasive annuals on arid rangelands where native annuals typically represent a small proportion of vegetation cover in most years. The data used to create the combined layer are modeled predictions, so accuracy and error must be considered. Estimated errors are comparable among all three source datasets (approximately 10 percent; see Jones and others, 2018, Pastick and others, 2020, Rigge and others, 2020).

Modeling approach: This product used a weight-of-evidence approach, leveraging three large-scale datasets, to provide land managers with a single product estimating the recent extent (2016–2018) of annual grasses. The three-year mean was calculated for each product at native resolution and then a per-pixel weighted average approach was used to combine them into a single product.



Extent of the "Western Governors' Association (WGA) Annual Herbaceous Cover" data layer (Maestas and others, 2020). Low (blue) to high (red) estimated percent annual herbaceous cover is shown.

AT A GLANCE	
Species	Annual herbaceous species
Output	Continuous percent cover
States covered	Arizona, California, Colorado, Idaho, Montana, Nebraska, Nevada, New Mexico, North Dakota, Oregon, South Dakota, Utah, Washington, Wyoming
Resolution	30 m
Recentness	*Most recent year (as of Dec. 2020)*: 2018 *Years available*: 2016–2018 (single estimate based on 3-year mean) *Time series*: No *Update frequency*: Not applicable
Evaluation	None
GET DATA	https://www.sciencebase.gov/catalog/item/5ec5159482ce476925eac3b7 Map viewer: https://rangelands.app/cheatgrass/

Model training data: See information from the individual input products mentioned in the description.

Remotely sensed inputs: See information from the individual products mentioned in the description.

Geospatial inputs: RAP, version 1.0 annual herbaceous cover, "HLS Annual Herbaceous Fractional Cover Time Series (2016–2020)," and "RCMAP Rangeland Fractional Components Base Map (2016)."

Key model covariates: Not applicable.

Evaluation: This product was not evaluated, though component products were evaluated individually (see respective entries).

Notes: The documentation that accompanies the data product is not peer reviewed as of this writing. The RAP version 1.0 that contributes to this product is no longer publicly available as a stand-alone product. It has been replaced by "RAP Annual Herbaceous Cover Time Series (1984–2019)."

Spatial Data Citation

Maestas, J., Jones, M., Pastick, N.J., Rigge, M.B., Wylie, B.K., Garner, L., Crist, M., Homer, C., Boyte, S., and Whitacre, B., 2020, Annual Herbaceous Cover across Rangelands of the Sagebrush Biome. U.S. Geological Survey data release, accessed February 2, 2021, at https://doi.org/10.5066/P9VL3LD5.

Publication Citation

A peer-reviewed publication was unavailable at the time this compendium was developed, so we based our summary on the documentation accessed July 14, 2020, at https://rangelands.app/products/annualHerbaceousCoverMethods.pdf.

LANDFIRE Existing Vegetation Type (2016)

Description: This product is a categorical surface of existing vegetation type (EVT). For the purpose of identifying IAGs, we suggest focusing on the following vegetation categories: Great Basin and Intermountain Introduced Annual Grassland, and Great Basin and Intermountain Ruderal Shrubland. Descriptions of EVT ruderal classes can be found at https://www.landfire.gov/documents/LANDFIRE_Ruderal_NVC_Groups_Descriptions_CONUS.pdf.

Species: Annual herbaceous species

Spatial extent: Great Basin and southwest United States

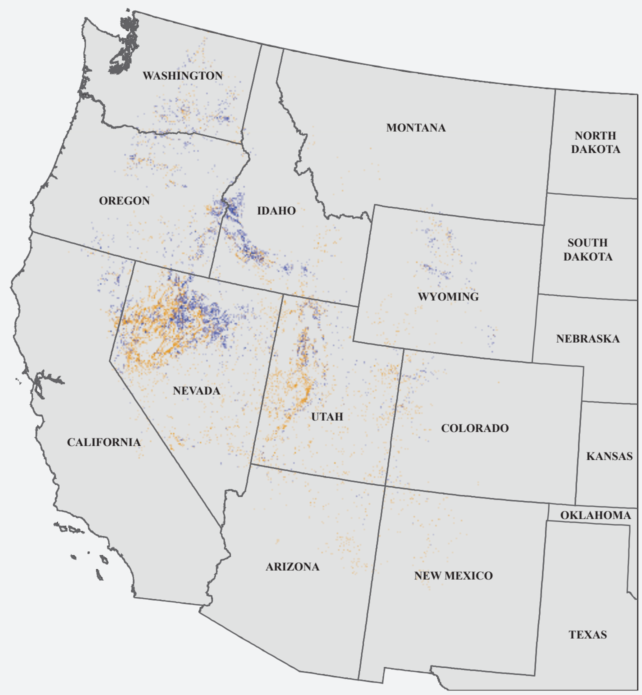
Spatial resolution: 30-m pixels

Recentness: 2016

Author-suggested use: These data products enable modeling the potential impacts of fire on the landscape, the wildfire risks associated with land and resource management, and those near population centers and accompanying Wildland Urban Interface zones, as well as many other applications (for example, habitat models, operational fire behavior predictions).

Author-identified caveats/limitations: Overall accuracy across EVTs of 52 percent is lower than the 80 percent standard for this type of product, but the authors argue that most categorical products do not include such high diversity of classes. Additionally, a variety of data sources were incorporated into this product with varying degrees of unknown quality, likely increasing errors in model training, which also may have been exacerbated by the automated assignment of classes in the reference database used for training. The authors attempted object-based image analysis segmentation, but it was computationally infeasible.

Modeling approach: After exploration, See5 boosted classification trees were used for mapping EVT over other machine-learning algorithms such as RF, k-nearest neighbor, and support vector machines, because they provided the most accurate classifications of categorical outputs. Prior to modeling, spectral imagery was filtered by removing recently



Extent of two vegetation categories from the “LANDFIRE Existing Vegetation Type (2016)” product that are associated with invasive annual grasses in the western United States, Great Basin and Intermountain Introduced Annual Grassland (purple) and Great Basin and Intermountain Ruderal Shrubland (orange).

AT A GLANCE	
Species	Annual herbaceous species
Output	Categorical
States covered	Arizona, California, Colorado, Idaho, Montana, Nevada, New Mexico, Oregon, Utah, Washington, Wyoming; data from other U.S. States and Canadian Provinces may be available for some classifications
Resolution	30 m
Recentness	*Most recent year (as of Dec. 2020)*: 2016 *Years available*: 2016 *Time series*: No *Update frequency*: Variable
Evaluation	Yes; bootstrapping/cross validation
GET DATA	https://www.landfire.gov/evt.php

disturbed areas and spectral outliers. LANDFIRE end products of EVT, Existing Vegetation Cover, and Existing Vegetation Height all depend on first being classified within their respective lifeform classes (for example, tree, herb, shrub).

Model training data: The model was trained using data from the LANDFIRE Reference Database, which contains field-validated plot reference data covering the US collected from a variety of contributors including USDA Forest Service Forest Inventory and Analysis, USGS GAP, The Nature Conservancy, and others.

Remotely sensed inputs: Remotely sensed inputs included Landsat bands 1–6, NDVI (minimum, maximum, median, maximum-median), normalized burn ratio, Modified Normalized Difference Water Index, Modified Soil Adjusted Vegetation Index, Soil Adjusted Total Vegetation Index, tasseled cap brightness, greenness, and wetness. Spectral bands and indices were derived from Landsat 8 OLI, Landsat 7 ETM+, and Landsat 7 TM.

Geospatial inputs: Elevation, slope and aspect were derived from a DEM (Rollins and Frame, 2006), while precipitation and temperature were sourced from Daymet (https://daymet.ornl.gov) summaries.

Key model covariates: Models relied heavily on NDVI (minimum, maximum, median, maximum-median).

Evaluation: The authors held out 10 percent of training samples for classes with greater than 300 total plots and performed a cross-validation agreement assessment. Error matrices were constructed to derive estimates of overall accuracy. Producer's accuracy is defined as how often the classified surface represents the true vegetation category, and user's accuracy is defined as how often the real vegetation categories are correctly classified. Across all EVTs within prototype regions, overall accuracy was 52 percent; for all EVTs with >20 testing plots, user's accuracy ranged from 29 to 83 percent, and producer's accuracy ranged from 5 to 87 percent. There were too few samples in the EVT classes of interest (Great Basin and Intermountain Introduced Annual Grassland, Great Basin and Intermountain Ruderal Shrubland) to generate interpretable validation results.

Notes: LANDFIRE includes many other products that may be of interest and were not included in this compendium such as Existing Vegetation Cover, Existing Vegetation Height, the National LANDFIRE Reference Database, and various fuels products: https://www.landfire.gov/vegetation.php.

Spatial Data Citation

LANDFIRE, 2016, Existing Vegetation Type Layer, LANDFIRE Remap 2.0.0, U.S. Department of the Interior, U.S. Geological Survey, accessed October 5, 2020, at https://landfire.cr.usgs.gov/viewer/.

Publication Citation

Picotte, J.J., Dockter, D., Long, J., Tolk, B., Davidson, A., and Peterson, B., 2019, LANDFIRE Remap Prototype Mapping Effort—Developing a New Framework for mapping vegetation classification, change, and structure: Fire, v. 2, no. 2, p. 35, accessed February 4, 2021, at https://doi.org/10.3390/fire2020035.

MoD-FIS Fuel Vegetation Cover (2020)

Description: This Modeling Dynamic Fuels with an Index System (MoD-FIS) product is a continuous surface of herbaceous (annual and perennial, forbs and grasses) percent cover. It is produced three times annually (spring, summer, and fall).

Species: All herbaceous species

Spatial extent: The Great Basin and southwest United States, including all or part of 14 States. This product has different extents associated with each season it is produced, of which summer is the largest and what is described here.

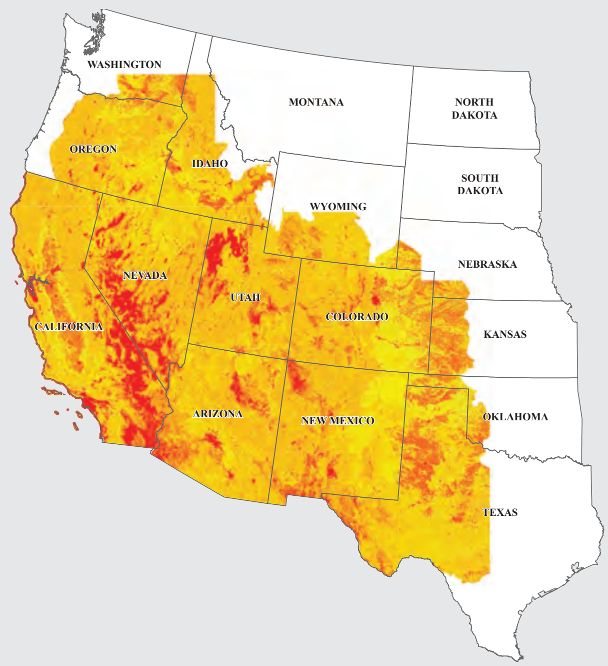
Spatial resolution: 30-m pixels

Recentness: 2020; Model is updated three times a year (spring, summer, and fall).

Author-suggested use: Various meetings, including LANDFIRE "After Action Reviews," highlighted the need to address seasonal variations of fine fuels (herbaceous and shrubs) in the Great Basin of the southwest U.S. The idea that increases in winter and spring precipitation in the Great Basin leads to increased herbaceous production and wildfire activity (after senescence) has been an accepted principle used by the Southwest Predictive Services in determining fire season potential for a number of years. The Great Basin Southwest U.S. MoD-FIS was designed to determine whether sites in this area have an increase or deficit in herbaceous production compared to average conditions. The intent of this product is to give analysts the ability to assess the current state of data expressed through fuel availability in near-real-time conditions.

Author-identified caveats/limitations: This product is not peer reviewed as of this writing, but it is based, in part, upon other LANDFIRE products that have been peer reviewed.

Modeling approach: The pixel average NDVI was combined with LANDFIRE Existing Vegetation Cover and analyzed to calculate a weighted average NDVI value for each Existing Vegetation Cover class by LANDFIRE map zone. A standard deviation test (±1 standard deviation) was developed for the average of all 14 map zones within the analysis area. After removing outliers (greater or less than one standard deviation), the median value was calculated for each map zone using values from the standard deviation test. The median value was used in a linear regression equation, which was applied to NDVI to get a percentage of cover relationship to



Summer extent of the "Modeling Dynamic Fuels with an Index System (MoD-FIS) Fuel Vegetation Cover (2020)" product (LANDFIRE, 2020). Image shows the estimated percent cover of herbaceous (annual and perennial, forbs and grasses) vegetation from low (yellow) to high (red).

AT A GLANCE	
Species	Herbaceous species (including perennials)
Output	Continuous percent cover and height; presented as bins
States covered	Arizona, California, Colorado, Idaho, Kansas, Montana, Nebraska, Nevada, New Mexico, Oklahoma, Oregon, Texas, Utah, Washington, Wyoming
Resolution	30 m
Recentness	*Most recent year (as of Dec. 2020)*: 2020 *Years available*: 2020 *Time series*: No *Update frequency*: Three times a year
Evaluation	Yes; conducted, but description not yet available
GET DATA	https://www.landfire.gov/modfis.php

NDVI. The current season's percent cover was then calculated via the regression using seasonal NDVI. Then, fuel rules for type, cover and height are used to assign seasonal fuel models.

Model training data: Web-Enabled Landsat Data (same source as "LANDFIRE Existing Vegetation Type [2016]"; Roy and others, 2010).

Remotely sensed inputs: Minimum, maximum, and median NDVI from 2003 to 2012, NDVI from 2019, 2020.

Geospatial inputs: Existing Vegetation Cover from LANDFIRE 2016.

Key model covariates: NDVI values.

Evaluation: The evaluation has been conducted, but the description is not yet published.

Notes: This is an operational product, but it is not peer reviewed as of this writing. The product focuses on fine fuel production and does not distinguish between IAGs and other herbaceous vegetation, thus estimates of herbaceous cover and height include native bunchgrasses and forbs. LANDFIRE includes many other products that may be of interest and are not included in this catalog such as Existing Vegetation Cover, Existing Vegetation Height, the National LANDFIRE Reference Database and various fuels products: https://www.landfire.gov/vegetation.php

Spatial Data Citation

LANDFIRE, 2020, MoD-FIS Fuel Vegetation Cover Fall 2020 (PM_FVCSU20): Earth Resources Observation and Science Center (EROS), U.S. Geological Survey, accessed October 29, 2021, at https://www.landfire.gov.

Publication Citation

A peer-reviewed publication was unavailable at the time this compendium was developed, so we based our summary on the documentation accessed September 30, 2020, at https://www.landfire.gov/documents/GB-SW_MoD-FIS_White-Paper.pdf.

Near-Real-Time Annual Herbaceous Cover (2015–2019)

Description: This product estimates the near-real-time annual herbaceous cover in 1-percent increments.

Species: Annual herbaceous species

Spatial extent: The northern Great Basin, including all the northern Great Basin and Range and the Snake River Plain ecoregions, as well as parts of adjacent level III ecoregions.

Spatial resolution: 250-m pixels

Recentness: 2019, annual products available 2015–2019

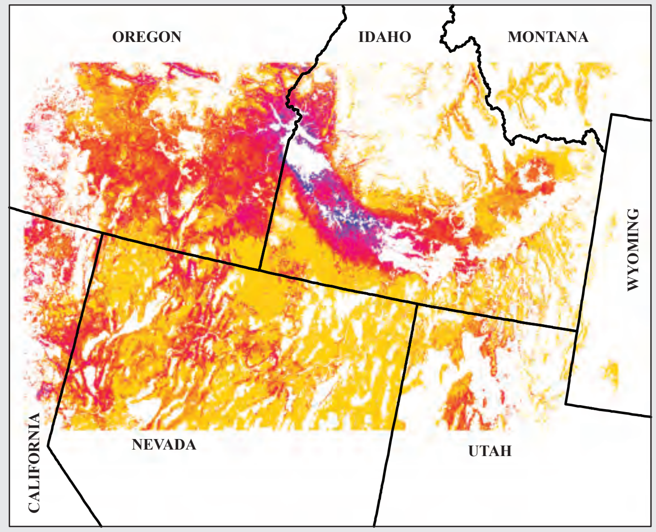
Author-suggested use: The near-real-time aspect of this product could guide management of cheatgrass at large spatial scales.

Author-identified caveats/limitations: This product could be improved by downscaling from 250-m eMODIS to 30-m Landsat (this has been done; see "HLS Annual Herbaceous Fractional Cover Time Series [2016–2020]"), which would improve the utility to land managers.

Modeling approach: The authors used remotely sensed, climate, and geophysical data in Cubist, rule-based, regression-tree models to create maps of percent cover for 2000–2013. Those models were then used to map estimated annual herbaceous percent cover for 2015–2019 using eMODIS data from each respective year, with some modifications.

Model training data: The model was trained with 2001 and 2005 field data, geospatial layer data, and eMODIS data from 2000 to 2013 (Peterson, 2005, 2007) to create maps of annual herbaceous cover, primarily cheatgrass, from 2000 to 2013 using 3 committees and 100 rules.

Remotely sensed inputs: Annual cheatgrass growing season NDVI, annual summertime periods, annual cheatgrass indices, and annual start of season time (derived from eMODIS data).



Extent of "Near-Real-Time Annual Herbaceous Cover Time Series (2015–2019)" data products (Boyte and Wylie, 2019). Estimates for 2019 are shown, with low estimated annual herbaceous cover (yellow) to high estimated annual herbaceous cover (purple) depicted.

AT A GLANCE	
Species	Annual herbaceous species
Output	Continuous percent cover
States covered	Portions of California, Idaho, Oregon, Nevada, Utah
Resolution	250 m
Recentness	*Most recent year (as of Dec. 2020)*: 2019 *Years available*: 2015–2019 *Time series*: No; separate near-real-time products produced annually *Update frequency*: none; see HLS Annual Herbaceous Fractional Cover Time Series (2016–2020)
Evaluation	Yes; within sample
GET DATA	2019: https://www.sciencebase.gov/catalog/item/5d1d0417e4b0941bde64ceb8 2018: https://www.sciencebase.gov/catalog/item/5b439bf9e4b060350a127028 2017: https://www.sciencebase.gov/catalog/item/595e6cc3e4b0d1f9f0570318 2016: https://www.sciencebase.gov/catalog/item/577fcb6ce4b0ef4d2f45fbf3 2015: https://www.sciencebase.gov/catalog/item/55ad3a16e4b066a2492409d5

Geospatial inputs: Geospatial inputs included slope, aspect, elevation, and compound topographic index (CTI; all from the National Elevation Dataset [NED]; Chaplot and Walter, 2003), latitude, land cover (NLCD), start of season time (eMODIS), available water capacity, and soil organic carbon (SSURGO).

Key model covariates: The top five variables were elevation, latitude, cheatgrass index, spring period, and summer period.

Evaluation: The authors tested the validity of their near-real-time approach using data from 2006. They compared the cover estimates developed using standard methods from 2006 with those produced using the near-real-time methods of 2015, derived using the same data. The difference between standard and near-real-time methods involved some modification of NDVI predictor variables. We classified this as within-sample evaluation. The 2015 model had R^2=0.98 and RMSE=0.87 when compared to the 2006 mapped surface.

Notes: This summary specifically refers to the 2015 product, but methods for subsequent years are the same. This product is an updated version of the "Annual Herbaceous Cover Time Series (2000–2016)" product presented in this compendium. It has subsequently been replaced by a higher resolution product starting in 2016, see "HLS Annual Herbaceous Fractional Cover Time Series (2016–2020)." In association with this near-real-time product, the authors also produced a series of early estimate maps, which show predicted annual herbaceous cover on May 1 of each year. These were used as an intermediate in producing the surface presented here and can be found on sciencebase.gov using the search term "HLS early estimates" and the year of interest.

Spatial Data Citation

Boyte, S.P., and Wylie, B.K., 2019, Near-real-time Herbaceous Annual Cover in the Sagebrush Ecosystem, USA, July 2019: U.S. Geological Survey data release, accessed February 25, 2021, at https://doi.org/10.5066/P96PVZIF.

Publication Citation

Boyte, S.P., and Wylie, B.K., 2016, Near-Real-Time Cheatgrass Percent Cover in the Northern Great Basin, USA, 2015: Rangelands, v. 38, no. 5, p. 278–284, accessed September 21, 2020, at https://doi.org/10.1016/j.rala.2016.08.002.

Annual Herbaceous Cover Time Series (2000–2016)

Description: This product estimates annual herbaceous cover in 1-percent increments.

Species: Annual herbaceous species

Spatial extent: All or part of 20 ecoregions including the Northern Great Basin and Range, Central Basin and Range, and the Snake River Plain.

Spatial resolution: 250-m pixels

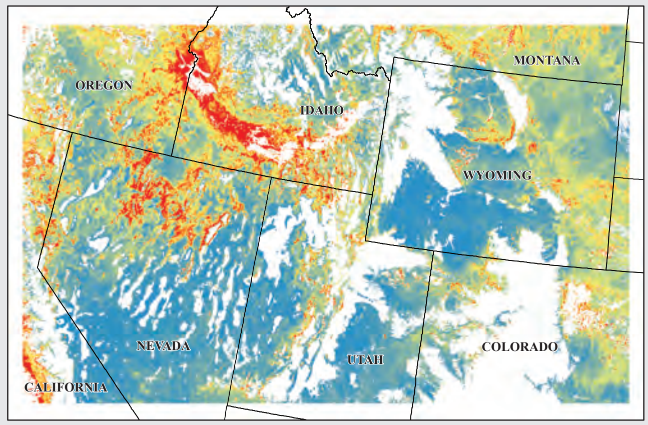
Recentness: 2016, annual products available 2000–2016

Author-suggested use: This product is intended to provide a long-term record of spatially explicit herbaceous annual cover for researchers to conduct analyses of imperiled dynamic sagebrush ecosystems. These analyses should be helpful to land managers and policy makers as they strive to better understand the landscapes they manage and set conservation policy. Appropriate use of the data should be defined by the user.

Author-identified caveats/limitations: Some limitations of the modeling approach include: Use of relative abundance, not exact values (average model error = 5.8 percent when comparing all training data values to corresponding estimated values); that the resolution is 250 m and may include a horizontal error of up to 125 m; and comparing this dataset to datasets with different spatial resolutions could lead to substantial differences in pixel values, especially in heterogenous areas where pixels mixed with multiple cover types are common. The authors have identified a greater bias with higher percent cover values. Model performance appears best at 35 percent with underestimation below that value and overestimation above it. A separate comparison to the BLM AIM dataset shows it may underestimate annual grass percent cover, but this may be due to a difference in sampling methodology and resolution.

Modeling approach: The authors used remotely sensed, climate, and geophysical data in rule-based, regression-tree models. Those models were then used to map estimated yearly annual herbaceous percent cover using MapCubist software for much of the sagebrush ecosystem of the western United States. The final model was constructed of 5 committees and 27 rules.

Model training data: Annual herbaceous cover was estimated from three remotely sensed sources (Peterson, 2005, 2007; Xian and others, 2015). These were spatially averaged and resampled to 250 m.



Extent of “Annual Herbaceous Cover Time Series (2000–2016)” spatial data products (Boyte and Wylie, 2017). Estimates for 2016 are shown, with low estimated annual herbaceous cover (blue) to high estimated annual herbaceous cover (red) depicted.

AT A GLANCE	
Species	Annual herbaceous species
Output	Continuous percent cover
States covered	California, Colorado, Idaho, Montana, Nebraska, Nevada, North Dakota, Oregon, South Dakota, Utah, Wyoming
Resolution	250 m
Recentness	*Most recent year (as of Dec. 2020)*: 2016 *Years available*: 2000–2016 *Time series*: Yes *Update frequency*: none; see HLS Annual Herbaceous Fractional Cover Time Series (2016–2020)
Evaluation	Yes; fully independent and bootstrapping/cross validation
GET DATA	https://www.sciencebase.gov/catalog/item/59b6e9a9e4b08b1644ddf95b

Remotely sensed inputs: Remotely sensed inputs included spring and summer GSN (mean growing season NDVI, see Boyte and others [2015a]), estimated start of season spring growth, and annual grass indices (a further derivation of the GSN variables). Yearly eMODIS NDVI data was used to generate NDVI metrics.

Geospatial inputs: Geospatial inputs included elevation, north-facing steep slope (>8.5 percent), south-facing steep slope (>8.5 percent), CTI (https://www.usgs.gov/programs/national-geospatial-program/national-map), available water capacity, soil organic matter sourced from POLARIS, National Land Cover Database (NLCD) shrub/herbaceous, time since fire (https://www.mtbs.gov/), 30-year precipitation sourced from PRISM (https://prism.oregonstate.edu/).

Key model covariates: All variables except CTI and slope/aspect variables contribute to rules. Spring GSN and elevation contribute to 78 percent of rule conditions and appeared in 95 percent and 93 percent of linear regression models respectively.

Evaluation: Both fully independent and bootstrapping evaluation techniques were used in the assessment of model performance. Fully independent evaluation was done using 2011–2016 BLM AIM field plots and had a mean R^2=0.50, mean MAE=12.62 percent, mean normalized RMSE=0.18 percent. The authors suggested that differences in spatial resolution between the datasets likely affected these results. The bootstrapping evaluation consisted of nine runs and produced better statistics with mean test R^2=0.71, mean test MAE=8.43 percent, mean test normalized RMSE=0.13 percent. Comparison datasets in this case had the same spatial resolution.

Notes: Additional years of a similar product are available and are reviewed in this compendium (see "Near-Real-Time Annual Herbaceous Cover [2015–2019]"). These products were updated in 2018 using a similar modeling approach applied to a combination of medium- and high-resolution satellite imagery to generate a product with 30-m spatial resolution, also reviewed in this compendium ("HLS Annual Herbaceous Fractional Cover Time Series [2016–2020]").

Spatial Data Citation

Boyte, S.P., and Wylie, B.K., 2017, A Time Series of Herbaceous Annual Cover in the Sagebrush Ecosystem: U.S. Geological Survey data release, accessed July 6, 2020, at https://doi.org/10.5066/F71J98QK.

Publication Citation

Boyte, S.P., Wylie, B.K., and Major, D.J., 2019, Validating a Time Series of Annual Grass Percent Cover in the Sagebrush Ecosystem: Rangeland Ecology and Management, v. 72, no. 2, p. 347–359, accessed July 6, 2020, at https://doi.org/10.1016/j.rama.2018.09.004.

Cheatgrass Distribution in the Intermountain West (2016)

Description: This product is a continuous surface of predicted percent cover of cheatgrass, converted to occurrence of high cheatgrass cover (greater than or equal to 15 percent, categorical).

Species: Cheatgrass (*Bromus tectorum*)

Spatial extent: The hydrographic Great Basin; https://www.usgs.gov/national-hydrography

Spatial resolution: 250-m pixels

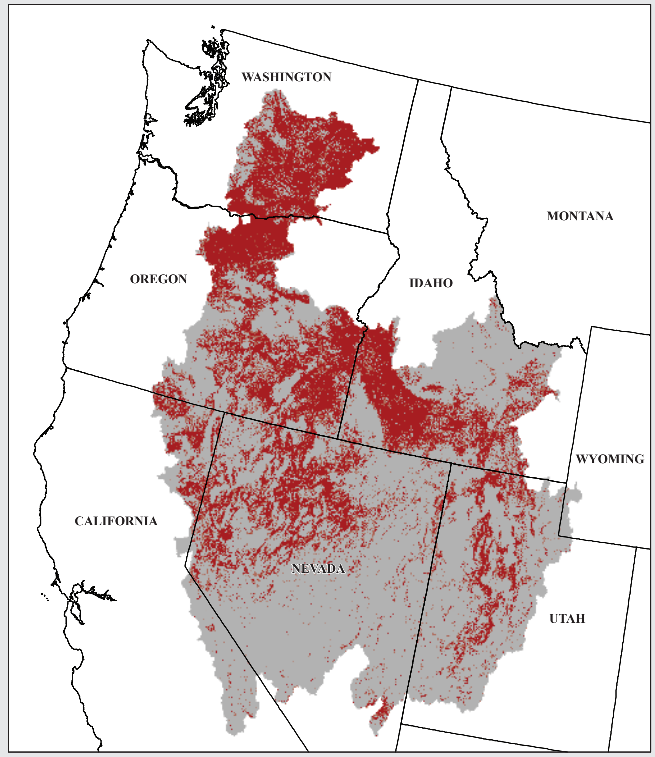
Recentness: 2001–2016 (single average estimate of condition)

Author-suggested use: This product used a more rigorous field testing and training dataset compared to previous works. In addition, the relationship between percent cover of cheatgrass, fire frequency and seasonality, along with links to anthropogenic ignition sources, was assessed over a broader region than in previous models.

Author-identified caveats/limitations: Only 34 percent of variance in cheatgrass percent cover was explained, which the authors describe as “poor performance” and suggest that modeling percent cover remains challenging across large spatial extents. Because field data collection spanned multiple years, including dry years, the product likely underestimates the maximum cheatgrass cover from 2000 to 2015. The model tends to overestimate percent cover and needs more current training data with a focus on wetter years.

Modeling approach: A RF regression model was used to create n=500 decision trees using bootstrap sampling of the percent cover data. Variable selection using RF reduced the number of predictor variables and a post-hoc classification (Cohen’s kappa) was used to categorically differentiate between high abundance cheatgrass (greater than or equal to 15 percent cover) versus low abundance or no cheatgrass (<15 percent cover).

Model training data: Training data included 15 datasets estimating percent cover of cheatgrass (including absence) and typically derived from field transects. Data were upscaled to calculate the average percent cover within 250-m cells, matching Moderate Resolution Imaging Spectroradiometer (MODIS) data.



Extent of the “Cheatgrass (*Bromus tectorum*) Distribution in the Intermountain West (2016)” spatial data product (Bradley, 2017b). Areas in red are where greater than 15 percent cover of cheatgrass was predicted.

AT A GLANCE	
Species	Cheatgrass (*Bromus tectorum*)
Output	Continuous percent cover; categorical, occurrence of > or equal to 15 percent cover
States covered	California, Idaho, Nevada, Oregon, Utah, Washington, Wyoming
Resolution	250 m
Recentness	*Most recent year (as of Dec. 2020)*: 2001–2016 (single average estimate of condition) *Years available*: 2001–2016 (single average estimate of condition) *Time series*: No *Update frequency*: None
Evaluation	Yes; bootstrapping/cross validation
GET DATA	https://doi.org/10.7275/R5XW4GZR

Remotely sensed inputs: Remotely sensed inputs included spectral imagery based on NDVI (2001–2014; 15 measures), maximum NDVI 2005 and 2010 (wet) minus mean maximum NDVI of all other years (dry; 2001–2014), maximum triangulated irregular network (TIN) 2005 and 2010 (wet) minus mean TIN of all other years (dry; 2001–2014), mean of cloud- and snow-free NDVI from May and June minus mean of cloud-free NDVI from July and August (2016, 2010, 2005), mean MODIS vegetation continuous field (2001–2005). All 250-m NDVI variables were derived from MODIS, grouped as indicators of early productivity (spring-summer NDVI during 2005, 2010, and 2016), and annual variability (difference in NDVI between wet and dry; Carroll and others, 2004; DiMiceli and others, 2011).

Geospatial inputs: Elevation at approximately 1-kilometer (km) resolution, sourced from 2010 Global Multi-Resolution Terrain Elevation Data.

Key model covariates: Early season phenology (spring–summer NDVI during 2005, 2010, and 2015) and elevation.

Evaluation: Data was bootstrapped with 2/3 assigned as training data and 1/3 as testing data, with n=500 trees. The occurrence product has 74 percent accuracy (67 percent accuracy of high-abundance presence and 77 percent accuracy for high-abundance absence). The final model predicting the percent cover of cheatgrass explains 34 percent of overall variance.

Spatial Data Citations

Bradley, B.A., 2017a, Cheatgrass (Bromus tectorum) percent cover data: ScholarWorks @UMassAmherst Data and Datasets, accessed February 2, 2021, at https://doi.org/10.7275/R5XW4GZR.

Bradley, B.A., 2017b, Model of cheatgrass (Bromus tectorum) distribution across the Great Basin, USA: ScholarWorks @UMassAmherst Data and Datasets, accessed February 2, 2021, at https://doi.org/10.7275/R5NG4NSZ.

Publication Citation

Bradley, B.A., Curtis, C.A., Fusco, E.J., Abatzoglou, J.T., Balch, J.K., Dadashi, S., and Tuanmu, M.N., 2018, Cheatgrass (*Bromus tectorum*) distribution in the intermountain Western United States and its relationship to fire frequency, seasonality, and ignitions: Biological Invasions, v. 20, no. 6, p. 1493–1506, accessed October 14, 2020, at https://doi.org/10.1007/s10530-017-1641-8.

Invasive Annual Grasses in Cold Desert Areas (2016)

Description: This product represents the predicted distribution of IAGs, presented as five cover classes: trace–5 percent, 5–15 percent, 25–45 percent, 25–45 percent, and >45 percent.

Species: Introduced annual grasses

Spatial extent: Cold desert ecoregions of the western United States, including the eastern Cascades slopes and foothills, Blue Mountains, Columbian Plateau, northern Basin and Range, Wyoming Basin, central Basin and Range, Colorado Plateaus, and Snake River Plain.

Spatial resolution: 90-m pixels

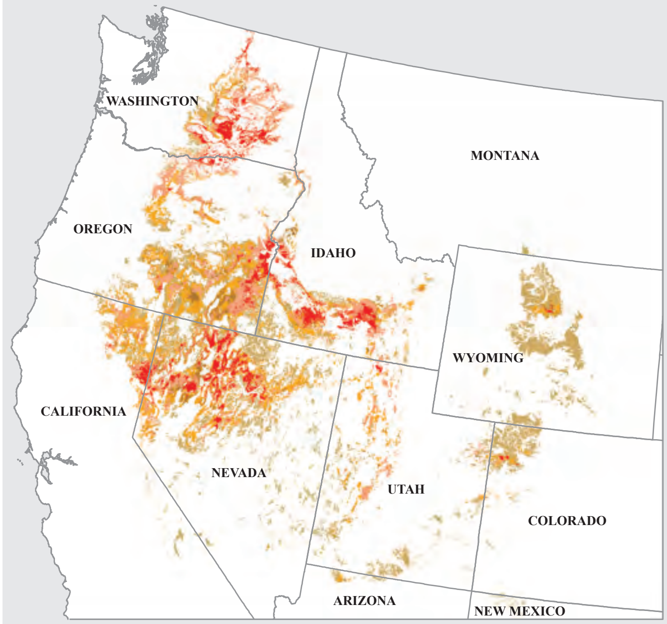
Recentness: 2016

Author-suggested use: The spatial output layers are meant to assist with rangeland restoration and decisions involving placement of infrastructure and vegetation treatments where further surface disturbance could trigger additional cheatgrass expansion.

Author-identified caveats/limitations: Spatially unbalanced samples were used as model inputs. Agency investments in systematic vegetation sampling, like BLM AIM, are welcome and ongoing commitment to this type of field data collection will be essential to future applications of these models. The quality of independent variable datasets is a known limitation. Given these limitations, the authors suggest a minimum mapping area of more than five hectares (90-m pixel aggregations of 10 to 100) should be used.

Modeling approach: Multiple models were built based on classes of IAG cover abundance from field sampling. The resulting individual models were thresholded to a binary and then combined into a final 90-m resolution RF classification model to indicate relative annual grass abundance.

Model training data: Data were sourced from two databases: The LANDFIRE reference database (2016) and Southwest Exotic Mapping Program (1911–2006). Southwest Exotic Mapping Program data were excluded if they occurred within 100 m of LANDFIRE data. Thirty-one distinct invasive species had more than 100 records, of which 51 percent were cheatgrass. Samples were grouped into one of five absolute



Extent of the "Invasive Annual Grass in Cold Desert Areas (2016)" spatial data products (Hak and Comer, 2020). Regions of the highest estimated percent cover of invasive annual grasses are shown in red.

AT A GLANCE

Species	Introduced annual grasses
Output	Presence and percent cover; categorical
States covered	Arizona, California, Colorado, Idaho, Montana, Nevada, New Mexico, Oregon, Utah, Washington, Wyoming; one Canadian Province (British Columbia)
Resolution	90 m
Recentness	*Most recent year (as of Dec. 2020)*: 2016 *Years available*: 2016 *Time series*: No *Update frequency*: Unknown
Evaluation	Yes; bootstrapping/cross validation
GET DATA	https://transfer.natureserve.org/download/Longterm/Ecology/InvasiveModeling/

cover categories (<5 percent, 5–15 percent, 16–25 percent, 26–45 percent, >45 percent). Collection years for all samples included range from 1990 to 2015.

Remotely sensed inputs: NDVI values from February 10, March 6, March 22, May 9, and May 25 (MODIS data).

Geospatial inputs: Geospatial inputs included a number of climate variables sourced from TopoWx and PRISM, elevation, slope from USGS 2015 NED, latitude, and disturbance variables (local road density, distance to fire boundary, secondary road density, primary road density sourced from GeoMAC.

Key model covariates: The top 10 variables were local road density, solar radiation, Bio18 (precipitation of warmest quarter), distance to fire boundary, distance to hydric soil, NDVI-May 25, elevation, Bio10 (mean temperature of warmest quarter), distance to intermittent streams, and Bio12 (annual precipitation).

Evaluation: Model components were evaluated using held-out sample data. Ten random tree model folds were generated by random withholding of 10 percent of samples for model validation. The average AUC-ROC plots were used to determine the model validity. The best model was identified by highest AUC score of the ten folds. Relative accuracy was 86 percent, 74 percent, 62 percent, 62 percent, and 60 percent, respectively for each model class (percentage cover), with an overall Cohen's kappa coefficient of 0.773.

Spatial Data Citation

Hak, J.C., and Comer, P.J., 2020, Modeling invasive annual grass abundance in the cold desert ecoregions of the interior western United States, accessed April 7, 2021, at https://transfer.natureserve.org/download/Longterm/Ecology/InvasiveModeling/.

Publication Citation

Hak, J.C., and Comer, P.J., 2020, Modeling invasive annual grass abundance in the cold desert ecoregions of the interior western United States: Rangeland Ecology and Management, v. 73, no. 1, p. 171–180, accessed October 16, 2020, at https://doi.org/10.1016/j.rama.2019.09.003.

HLS Annual Herbaceous Fractional Cover Time Series (2016–2020)

Description: This product is a continuous surface of predicted percent cover of annual exotic herbaceous species that uses HLS inputs.

Species: Annual herbaceous species

Spatial extent: Rangelands in the Great Basin, the Snake River Plain, the State of Wyoming, and portions of California, Idaho, Nevada, and Oregon.

Spatial resolution: 30-m pixels

Recentness: The most recent year available is 2018. Annual products are available from 2016 to 2018, and the 2020 map is available as stand-alone product. See “Notes” for more details.

Author-suggested use: This product can be used for monitoring and modeling historical and future land-surface dynamics and biophysical conditions (for example, biomass, drought), detecting and analyzing fuel breaks in sagebrush ecosystems, controlling and quantifying fire behavior, targeting grazing, mapping other rangeland components (for example, percent bare ground, shrubs, herbs), and enhancing aerial herbicide applications.

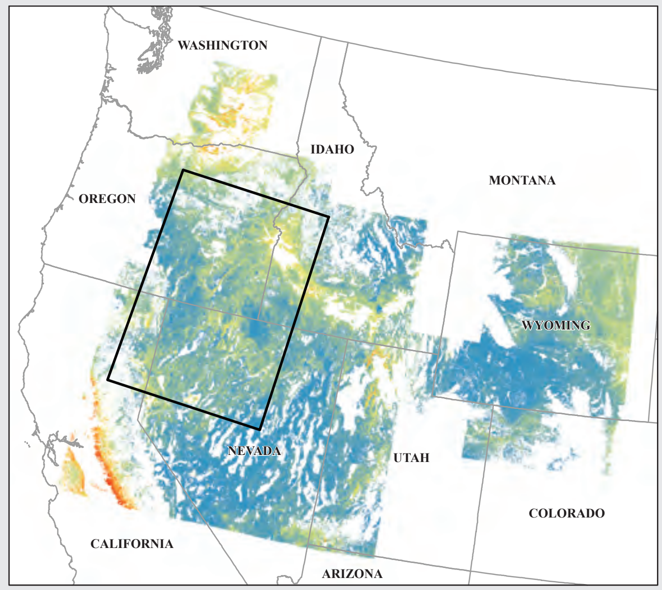
Author-identified caveats/limitations: The methods used may produce unrealistic results if there are insufficient high-quality data or high levels of undetected noise. In addition, the BLM AIM data used to evaluate their surface was not aligned with the scale of the remote-sensing inputs, resulting in scaling and sampling errors that the authors were unable to account for.

Modeling approach: This product used a Cubist, regression tree modeling approach. Regression tree ensembles were constructed using GNU, an open-source version of Cubist software and relevant environmental covariates as determined using tree-based feature selection algorithms and importance weights in sequential models.

Model training data: Model training data included HLS imagery and field data from BLM AIM plots.

Remotely sensed inputs: All NDVI metrics were derived from weekly median NDVI from HLS data. Week of the year and year of data acquisition were also included as inputs.

Geospatial inputs: Geospatial inputs, including elevation, slope, and aspect, were obtained or derived from the NED. Soil parameters were obtained from POLARIS soils data.



Extent of the “HLS Annual Herbaceous Fractional Cover Time Series (2016–2020)” spatial data products. Data for 2020 is shown (Dahal and others, 2020b), with low estimated percent cover shown in blue and high estimated percent cover shown in red. The black box is the approximate extent of the original 2016–2018 products (Dahal and others, 2020a).

AT A GLANCE	
Species	Annual herbaceous species
Output	Continuous percent cover
States covered	California, Colorado, Idaho, Nevada, Oregon, Utah, Washington, and Wyoming
Resolution	30 m
Recentness	*Most recent year (as of Dec. 2020)*: 2018 *Years available*: 2016–2018, but see Notes for stand-alone 2020 product *Time series*: Yes *Update frequency*: Annually, but as stand-alone products (see Notes)
Evaluation	Yes; fully independent and bootstrapping/cross validation
GET DATA	https://www.sciencebase.gov/catalog/item/5e00f1c6e4b0b207aa033d39

Key model covariates: Key model covariates were not specified but final model covariates included weekly NDVI estimates (median; weeks 10–28), start and end of growing season NDVI, maximum NDVI, change in NDVI, elevation, organic matter, slope, percent clay, aspect, time, and week.

Evaluation: Model performance was assessed using both fully independent evaluation, using 112 BLM AIM field plots from 2016 to 2018, and fivefold cross validation. These yielded Pearson's correlation coefficients=0.65 and 0.83, MAE=14 and 11 percent cover, and relative MAE=0.70 and 0.50, respectively, indicating fair agreement between modeled and observed percent cover values.

Notes: This product builds on previous products developed at Earth Resources Observation and Science Center and reviewed elsewhere in this compendium (see "Annual Herbaceous Cover Time Series [2000–2016]" and "Near-Real-Time Annual Herbaceous Cover [2015–2019]"). This product has a higher spatial resolution (30-m) than the prior product (250-m). This product does not distinguish between exotic annual grass species; cheatgrass is likely the predominant species mapped, but multiple other species of *Bromus* and *Taeniatherum caput-medusae* are included. The 2016–2018 data product is the dataset associated with the published manuscript. A corresponding 2020 surface developed using slightly different methods can be found at https://www.sciencebase.gov/catalog/item/5f0e030782ce21d4c4053ec2. Please note that the spatial extent has expanded for 2020, and that the modeling approach has changed. Documentation for the 2020 product is not published in a peer-reviewed format as of this writing. Methods are similar enough that managers can likely base their assessment of whether to use the 2020 map on this summary of the 2016–2018 product.

Spatial Data Citation

Dahal, D., Wylie, B.K., Parajuli, S., and Pastick. N.J., 2020a, Fractional estimates of invasive annual grass cover in dryland ecosystems of western United States (2016–2018): U.S. Geological Survey data release, accessed February 25, 2021, at https://doi.org/10.5066/P9537QG9.

Dahal, D., Pastick, N.J., Parajuli, S., and Wylie, B.K., 2020b, Near real time estimation of annual exotic herbaceous fractional cover in the sagebrush ecosystem 30m, USA, July 2020: U.S. Geological Survey data release, accessed April 14, 2021, at https://doi.org/10.5066/P91NJ2PD.

Publication Citation

Pastick, N.J., Dahal, D., Wylie, B.K., Parajuli, S., Boyte, S.P., and Wu, Z., 2020, Characterizing Land Surface Phenology and Exotic Annual Grasses in Dryland Ecosystems Using Landsat and Sentinel-2 Data in Harmony: Remote Sensing, v. 12, no. 4, p. 725, accessed September 10, 2020, at https://doi.org/10.3390/rs12040725.

Cheatgrass Occurrence Across Sage-Grouse Range (2000–2014)

Description: This product is a categorical surface of cheatgrass occurrence containing two bins, 0–2 percent and >2 percent.

Species: Cheatgrass (*Bromus tectorum*), but also includes red brome (*Bromus rubens*)

Spatial extent: The current and historical greater sage-grouse range within the western United States, covering all or part of 13 States.

Spatial resolution: 250-m pixels

Recentness: 2014

Author-suggested use: The range-wide map and the underlying model is appropriate for assessing cheatgrass occurrence to inform and prioritize restoration and conservation actions at regional and subregional scales. This map may also help inform regional planning processes and future research needs, particularly those requiring multi-agency coordination aimed at addressing long-term, large-geographic-scale management objectives. It can also be combined with other geospatial products such as the cheatgrass resistance/resilience mapping (Chambers and others, 2014; Maestas and Campbell, 2015) based on soils information to better support management decisions. The map represents a range-wide baseline of cheatgrass occurrence and may be used to assess cheatgrass expansion at a similar scale in the future.

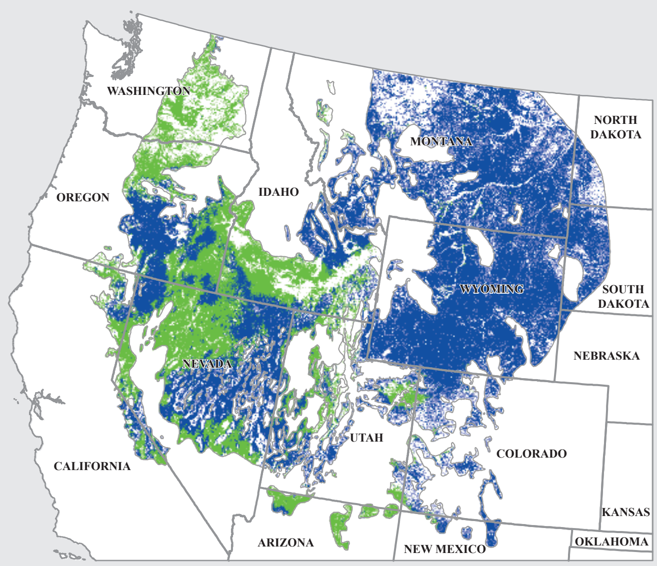
Author-identified caveats/limitations: This product represents a snapshot in time based on data from 2000 to 2014; it does not assess abundance of cheatgrass, only two cover bins.

Modeling approach: The modeling approach used forward stepping discriminant analysis to construct a predictive, generalized additive model which was used to produce estimates of cheatgrass cover.

Model training data: The model was trained with percent canopy cover data of *B. tectorum* and *B. rubens* from 6,650 field sites using point intercept and plot frame data from several agencies and organizations.

Remotely sensed inputs: Remotely sensed inputs included median peak NDVI and peak NDVI in the year of maximum winter precipitation, derived from MODIS data.

Geospatial inputs: Geospatial inputs included a number of climate variables, including 30-year mean monthly and 30-year mean annual precipitation, minimum and maximum



Extent of the “Cheatgrass Occurrence Across Sage-Grouse Range (2000–2014)” spatial data product (Larson, 2016). Areas with estimated cheatgrass cover greater than 2 percent are shown in green and those with less than 2 percent cover in blue.

AT A GLANCE	
Species	Cheatgrass (*Bromus tectorum*)
Output	Categorical; two classes (0–2 percent cover, >2 percent cover)
States covered	Arizona, California, Colorado, Idaho, Montana, Nebraska, New Mexico, Nevada, North Dakota, Oregon, South Dakota, Utah, Washington, Wyoming
Resolution	250 m
Recentness	*Most recent year (as of Dec. 2020)*: 2014 *Years available*: Single estimate of peak potential cheatgrass occurrence (2000–2014) *Time series*: No *Update frequency*: Every five years, suggested
Evaluation	Yes; fully independent
GET DATA	https://www.sciencebase.gov/catalog/item/585169aae4b0f99207c4f093

temperature, several seasonal cumulative precipitation and average minimum and maximum temperature variables, cumulative growing degree day index derived from PRISM and Daymet weather summaries data. In addition, elevation and potential relative radiation index were derived using 30-m NED data (Pierce and others, 2005).

Key model covariates: Key model covariates were not specified, but the following variables appeared in the final model: Elevation, potential relative radiation index, cumulative growing degree day index, median annual peak NDVI, cumulative winter precipitation, mean March precipitation, mean June precipitation, mean July precipitation, average maximum winter temperature, mean minimum March temperature, mean minimum November temperature, mean maximum May temperature.

Evaluation: Twenty percent of field measurements were randomly selected from across the study area and withheld for use as an independent sample to validate the model. Accuracy of the model was 71 percent correctly classified.

Spatial Data Citation

Larson, K., 2016, Cheatgrass Across the Range of the Greater Sage-Grouse: Pacific Northwest National Laboratory data release, accessed January 26, 2021, at https://www.sciencebase.gov/catalog/item/585169aae4b0f99207c4f093.

Publication Citation

Downs, J.L., Larson, K.B., and Cullinan, V.I., 2016, Mapping Cheatgrass Across the Range of the Greater Sage-Grouse—Linking Biophysical, Climate and Remote Sensing Data to Predict Cheatgrass Occurrence. Pacific Northwest National Laboratory. PNNL-22517: U.S. Department of Energy Technical Report, 16 p., accessed October 2, 2020, at https://doi.org/10.2172/1545321.

Cheatgrass Dieoff in Northern Great Basin Time Series (2000–2010)

Description: This product models expected cheatgrass performance (continuous); underperformance anomalies for two or more consecutive years are interpreted as dieoff. Associated with this product is a layer depicting the probability of dieoff over a 10-year period.

Species: Cheatgrass (*Bromus tectorum*)

Spatial extent: The Northern Great Basin, which includes the Northern Great Basin and Range and the Snake River Plain ecoregions, as well as parts of adjacent Level III ecoregions. Portions of Oregon, Idaho, Nevada, and California are also included.

Spatial resolution: 250-m pixels

Recentness: 2010, annual products available 2000–2010

Author-suggested use: This product increases the understanding of the dynamics of cheatgrass dieoff at landscape scales, especially persistent or reoccurring dieoffs, allowing land managers to explore opportunities to mitigate or take advantage of these dieoffs. This product has also been used to project future cheatgrass cover.

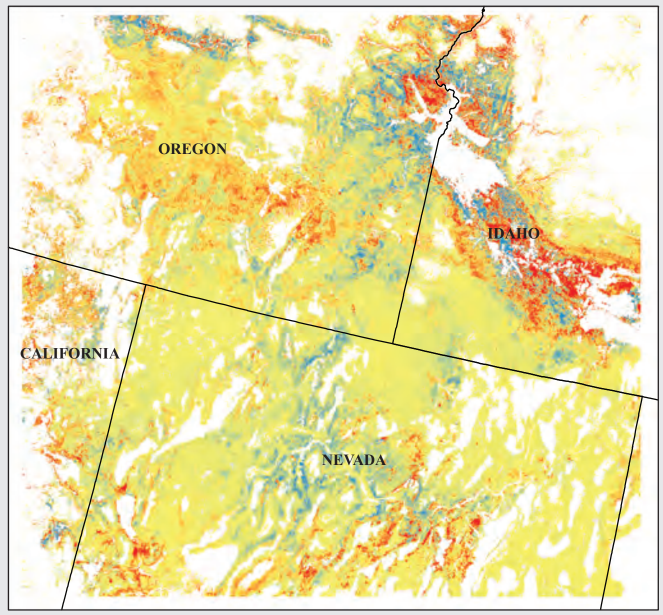
Author-identified caveats/limitations: The model was trained on areas where no fire occurred during the previous year. Measurement of cheatgrass performance was not strongly influenced by fire effects.

Modeling approach: The expected cheatgrass performance (ECP) model uses Cubist, rule-based regression tree models trained on actual cheatgrass performance (ACP) points (see "Near-Real-Time Annual Herbaceous Cover [2015–2019]"), stratified randomly into four classes of cheatgrass cover. The ECP model also included climate variables and site potential (based on long-term percent cover of cheatgrass). Pixels where ECP significantly exceeded ACP for two or more consecutive years were classed as predicted dieoff.

Model training data: The model was trained on actual cheatgrass percent cover points from a time series of a percent cover dataset (see "Near-Real-Time Annual Herbaceous Cover [2015–2019]").

Remotely sensed inputs: Remotely sensed inputs included the mean of all values above 2000–2010 ACP median or site potential, derived from actual cheatgrass percent cover.

Geospatial inputs: Geospatial inputs included monthly precipitation, maximum and minimum temperature for each year, obtained from the PRISM database.



Extent of the "Cheatgrass Dieoff in the Northern Great Basin Time Series (2000–2010)" spatial data product (Major and others, 2012). Red areas have the greatest probability of dieoff and blue areas the smallest probability of cheatgrass dieoff.

AT A GLANCE	
Species	Cheatgrass (*Bromus tectorum*)
Output	Continuous estimate of cheatgrass performance
States covered	California, Idaho, Oregon, Nevada, Utah
Resolution	250 m
Recentness	*Most recent year (as of Dec. 2020)*: 2010 *Years available*: 2000–2010 *Time series*: Yes *Update frequency*: Not applicable
Evaluation	Yes; within sample
GET DATA	https://www.sciencebase.gov/catalog/item/504772d6e4b067bd38f7f509

Key model covariates: The top five variables were site potential, May maximum temperature, April maximum temperature, winter maximum temperature, and May precipitation.

Evaluation: The expected cheatgrass performance model was evaluated by using 11 percent of its training data as within sample evaluation points. These points validated well against the model, having an R^2=0.86 and RMSE=5.75. Using the entire dataset to evaluate the model resulted in a R^2=0.88 and RMSE=6.95. To explicitly evaluate the predicted areas of dieoff, the 2009 cheatgrass performance surface was overlaid with polygons of known cheatgrass dieoff obtained from 2010 BLM helicopter flights. Inside BLM polygons, 41 percent of pixels were classified as possible dieoff, 58 percent were normal performing, and 1 percent were overperforming. Outside of BLM polygons, 2 percent of pixels were classified as possible dieoff, 97 percent were normal performing, and 1 percent were overperforming. Requiring a pixel to experience two consecutive years of underperformance to qualify as a dieoff likely contributed to a lower percentage of underperforming pixels being located within the dieoff polygons.

Notes: This data release (referenced below) was not created by the original authors. The original authors primarily used a regression tree to develop the annual dieoff data. A decision tree was used only to develop the probability of a dieoff based on 11 years of annual dieoff maps. In addition, the publicly available spatial data is a subset of the full dataset. The extent reported here reflects the smaller extent.

Spatial Data Citation

Major, D.J., Beckendorf, K.L., Wylie, B.K., and Boyte, S., 2012, Mapping Cheatgrass Dieoff Probability in the Northern Great Basin using a Decision-tree Model: Northwest CASC data release, accessed January 21, 2021, at https://www.sciencebase.gov/catalog/item/504772d6e4b067bd38f7f509.

Publication Citation

Boyte, S.P., Wylie, B.K., and Major, D.J., 2015b, Mapping and Monitoring Cheatgrass Dieoff in Rangelands of the Northern Great Basin, USA: Rangeland Ecology and Management, v. 68, no. 1, p. 18–28, accessed February 29, 2020, at https://doi.org/10.1016/j.rama.2014.12.005.

Cheatgrass Occurrence Across the Wyoming Basin (2006)

Description: This product is a categorical surface of predicted probability of occurrence of cheatgrass.

Species: Cheatgrass (*Bromus tectorum*)

Spatial extent: The Wyoming Basins Ecoregional Assessment (WBEA) area, including parts of Colorado, Idaho, Montana, Utah, and Wyoming.

Spatial resolution: 90-m pixels

Recentness: 2006

Author-suggested use: These predictive occurrence maps are designed for use in planning, decision making, and prioritization of management actions in the WBEA.

Author-identified caveats/limitations: The very strong local effects of energy wells may have simply been an artifact of the recent nature of this type of disturbance compared to others. The zone of influence around the well sites may expand over time.

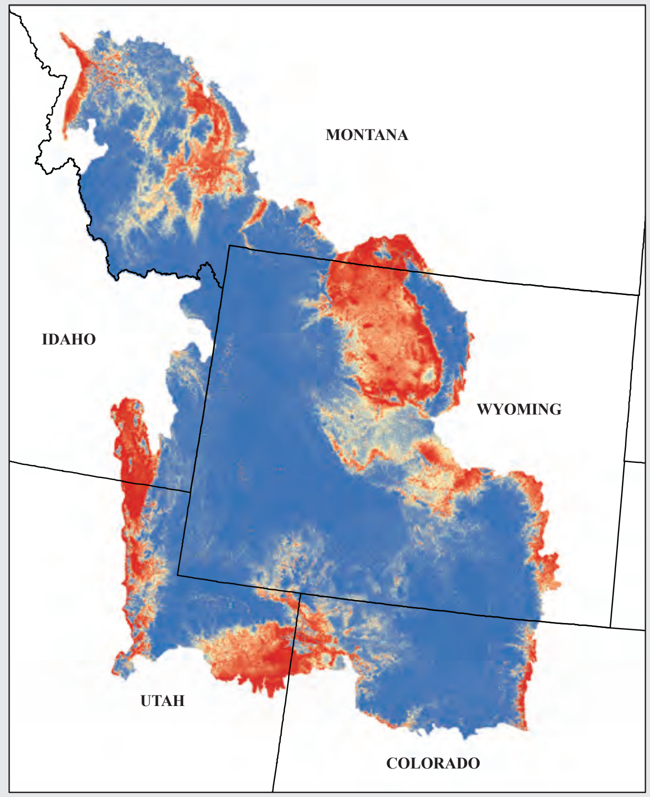
Modeling approach: Field survey records of early- and late-season cheatgrass presence across WBEA were used to develop occurrence models and predict spatial occupancy throughout the study area using logistic regression. Model averaging of the top six candidate models was used to derive coefficients to predict cheatgrass occurrence.

Model training data: Training data included vegetation surveys conducted across the WBEA area at 317 individual survey blocks (five plots per block) during early (June 1–July 2) and late (July 6–September 2) growing seasons. Blocks were stratified by human disturbance and habitat productivity.

Remotely sensed inputs: NDVI (May–August) derived from MODIS data.

Geospatial inputs: Mean annual minimum temperature sourced from PRISM data; distance to disturbances (calculated using a Geographic Information Systems); global solar radiation calculated using Area Solar Radiation Analysis (software from Environmental Systems Research Institute, 2006); topographic relative moisture index (Manis and others, 2001).

Key model covariates: Cheatgrass occurrence was explained by one survey design habitat variable (NDVI), three abiotic factors (solar radiation, minimum temperature, and



Extent of "Cheatgrass Occurrence Across the Wyoming Basin (2006)" spatial data product (Hanser, 2011) is shown. Probability of occurrence ranges from high (red) to low (blue).

AT A GLANCE	
Species	Cheatgrass (*Bromus tectorum*)
Output	Probability of occurrence (categorical but mapped as continuous)
States covered	Colorado, Idaho, Montana, Utah, Wyoming
Resolution	90 m
Recentness	*Most recent year (as of Dec. 2020)*: 2006 *Years available*: 2006 *Time series*: No *Update frequency*: Not applicable
Evaluation	Yes; within sample
GET DATA	https://www.sciencebase.gov/catalog/item/5fb704d8d34eb413d5e143a1?community=Forest+and+Rangeland+Ecosystem+Science+Center+(FRESC)

topographic-related moisture), and four anthropogenic factors (distance to major road, distance to well pad, within 1 km of a populated area, and proximity to railroads).

Evaluation: The authors used within-sample model evaluation. Model accuracy was assessed using an AUC-ROC estimate. The final composite cheatgrass occurrence model had an AUC-ROC value of 0.91 with an associated standard error = 0.01, suggesting excellent predictive accuracy.

Notes: Predicted presence maps are also available for crested *Agropyron cristatum* (wheatgrass), *Halogeton glomeratus* (halogeton) and *Salsola australis* (Russian thistle).

Spatial Data Citation

Hanser, S.E., 2011, Cheatgrass probability of occurrence in the Wyoming Basins Ecoregional Assessment area: U.S. Geological Survey data release, accessed April 5, 2021, at https://doi.org/10.5066/P9E6NL6F.

Publication Citation

Nielsen, S.E., Aldridge, C.L., Hanser, S.E., Leu, M., and Knick, S.T., 2011, Occurrence of non-native invasive plants—The role of anthropogenic features, chap. 10 *of* Hanser, S.E., Matthias, L., Knick, S.T., Aldridge, C.L., eds., Sagebrush ecosystem conservation and management—Ecoregional assessment tools and models for the Wyoming Basins: Lawrence, Kans., Forest and Rangeland Ecosystem Science Center, p. 357–386, accessed October 21, 2020, at https://pubs.usgs.gov/ja/70175492/70175492.pdf.

SE OR Vegetation Composition Map (2012–2017)

Description: This product, produced for southeastern Oregon, is a continuous sum of percent cover estimates for all species identified as exotic annual grass.

Species: IAGs

Spatial extent: The majority of sage steppe vegetation in southeastern Oregon.

Spatial resolution: 30-m pixels

Recentness: 2012–2017 (single estimate of condition)

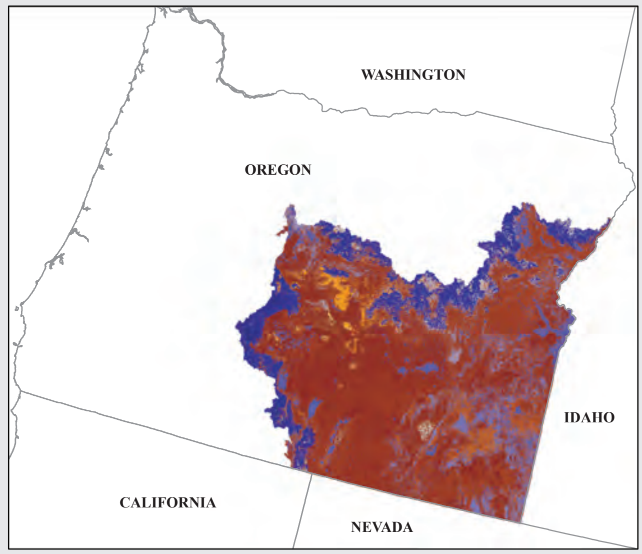
Author-suggested use: This work was conducted while building an imputed vegetation map to support greater sage-grouse conservation efforts in the State of Oregon. It is unique in that it provides detailed habitat information that is relevant to seasonal habitats in a spatially consistent way across the full range of greater sage-grouse in Oregon. The analysis showed how aggregations of threshold-defined data layers can be sensitive to small response variable biases, yielding highly biased binary maps. Because of its performance with respect to bias and the absence of covariance errors, the authors conclude that random forest nearest neighbor (RFNN) is well suited to inform mid to broadscale strategic conservation and management decisions.

Author-identified caveats/limitations: Although RFNN modeling is effective at yielding unbiased estimates of vegetation summaries at broad spatial scales, accuracy assessments indicate significant noise at very fine spatial scales, rendering them inappropriate for describing local spatial patterns illustrated by just a few pixels.

Modeling approach: The authors used a RFNN imputation model (k=1) to build one raster data layer that is linked to a variety of vegetation summary variables. Imputation has many variants, including one that identifies nearest-neighbor observations through the nodes matrices of one or more RF models. The dependent variables used to tune the internal RF models included two automated classifications of vegetation indicating species composition and structural groupings.

Model training data: Percent cover of IAGs was collected from numerous field plots. Data was provided by BLM AIM plots, rangeland monitoring plots, Landscape Monitoring Framework plots, Institute for Natural Resources large fire vegetation survey plots, the LANDFIRE Plot Reference Database, the Malheur Wetland Vegetation Survey, and USDA Forest Service Ecoplots. Plot data collection years range from 2009 to 2017, with most data collected in 2012 and later.

Remotely sensed inputs: Landsat 7 (ETM+) Normalized Difference Forestness Index (NDFI), Normalized Difference between Green and Red bands, Normalized Difference



Extent of the “SE OR Vegetation Composition Map (2012–2017)” (Institute for Natural Resources and Henderson, 2018) is shown. Percent cover estimates of invasive annual grasses range from high (dark brown) to low (purple).

AT A GLANCE	
Species	Introduced annual grass species
Output	Continuous sum of percent cover estimates for each species
States covered	Oregon
Resolution	30 m
Recentness	*Most recent year (as of Dec. 2020)*: 2012–2017 (single estimate of cover over that time) *Years available*: 2012–2017 (single estimate of cover over that time) *Time series*: No *Update frequency*: Expected every two to four years
Evaluation	Yes; within sample
GET DATA	https://oe.oregonexplorer.info/externalcontent/sagecon/datafordownload/SoutheastOregon_Vegetation_2016.zip

Moisture Index, Normalized Difference Snow Index, Normalized Difference Shortwave Index, NDVI, Landsat OLI bands 1–7, tasseled cap brightness, greenness and wetness, principal component axes (PCA) texture summaries from National Agriculture Imagery Program (NAIP) Nested Texture Metrics no. 1–37.

Geospatial inputs: Geospatial inputs included PCA from POLARIS soil data layers, no. 1–18, average annual precipitation, average annual temperature, August maximum temperature, continuity of precipitation, coefficient of variation of precipitation, December minimum temperature, difference in December–August temperature; GS (June–August) precipitation, temperature, and drought index sourced from PRISM, aspect, elevation, McComb's Landform Index, percent slope, topographic position index from NED, and years since most recent fire according to MTBS.

Key model covariates: Key model covariates for structure groups were growing season temperature, average annual temperature, the seasonal continuity of precipitation, Landsat imagery variables, and airphoto and soil summaries. For species groups, key covariates are elevation, growing season temperatures, August maximum temperature, Landsat and soil variables, and one NAIP variable. For the indicator-group variable, key covariates are NAIP imagery, elevation, Landsat, and summer temperature.

Evaluation: The authors conducted within-sample evaluation by extracting the second nearest-neighbor plot for all the input plots (similar to a leave-one-out cross-validation strategy; Ohmann and Gregory, 2002). They also constructed summaries of the observations and model predictions across larger hexagons to estimate the map's accuracy at four spatial scales, using a regression-based analysis (Riemann and others, 2010). These were not included in the peer-reviewed manuscript but would constitute a fully independent evaluation if peer reviewed. The authors calculated three accuracy measures across each spatial scale: systematic agreement coefficient (AC_sys; ranging from 0.99 to 1.00), unsystematic agreement coefficient (AC_uns; ranging from -0.09 to 0.97) and overall agreement coefficient (AC; ranging from -0.1 to 0.96).

Notes: Data is stored as an attribute table containing a continuous variable indicating the sum of percent cover estimates for all species identified as IAG, as well as 23 other vegetation summary variables designed to describe aspects of vegetation in the sage steppe relevant to the management and habitat of the greater sage-grouse. Maps provide integer numbers that identify the rows of database rows of the relevant observations.

Spatial Data Citation

Institute for Natural Resources and Henderson, E., 2018, Invasive Annual Grass Cover, Southeast Oregon NN Vegetation Composition Map: Oregon State University, accessed January 26, 2021, at https://oe.oregonexplorer.info/externalcontent/sagecon/datafordownload/SoutheastOregon_Vegetation_2016.zip.

Publication Citation

Henderson, E.B., Bell, D.M., and Gregory, M.J., 2019, Vegetation mapping to support greater sage-grouse habitat monitoring and management—Multi- or univariate approach?: Ecosphere, v. 10, no. 8, p. 22, accessed October 21, 2020, at https://doi.org/10.1002/ecs2.2838.

Invasive Plant Cover in the Mojave Desert (2009–2013)

Description: This product is a continuous estimate of habitat suitability for cheatgrass (*Bromus tectorum*). Similar products are available for *B. rubens,* and a combined *B. tectorum* and *B. rubens* product.

Species: Cheatgrass (*Bromus tectorum*)

Spatial extent: Mojave Desert

Spatial resolution: 30-m pixels

Recentness: 2009–2013 (single estimate of condition)

Author-intended use: This data is intended for fire management planning and mitigation, evaluation of potential for postfire dominance of invasive species in restoration sites, and prioritizing monitoring and restoration activities within the Mojave Desert.

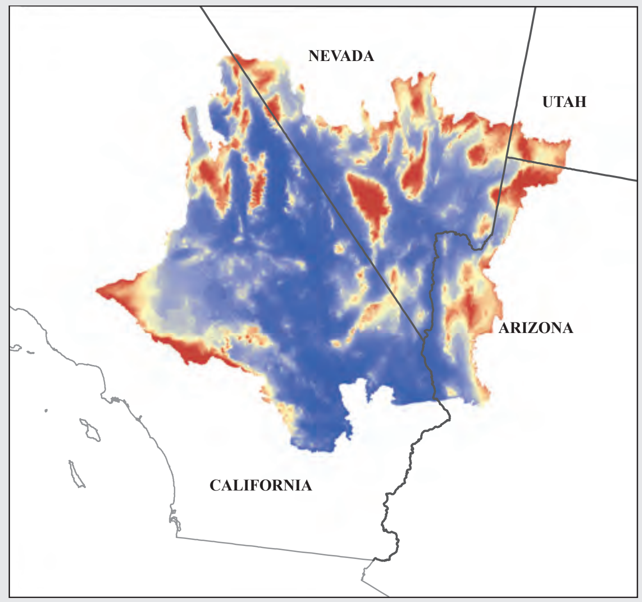
Author-identified caveats/limitations: The authors noted that detectability and representativeness of field sampling when constructing species distribution models are a challenge, and they tried to minimize this via multiyear and seedbank sampling, as well as using PCAs to assess comprehensive sampling of environmental gradients.

Modeling approach: The modeling approach employed predicted habitat suitability for each invasive species group (*B. rubens*; *B. tectorum*; *B. rubens* + *B. tectorum*) using presence and absence data in a generalized linear model with a binomial error structure and logit link. A multistep multivariate selection process was assessed via the Akaike Information Criterion, corrected for small sample sizes.

Model training data: Six hundred eighteen 0.1-hectare plots, stratified by intervals of years postfire, fire frequency, and elevation zone, were surveyed for occupancy of invasive plants via aboveground surveys and seedbank sampling using a nested quadrat design during the spring 2009, 2011, 2012, and 2013. Only data from unburned plots were used for model development.

Remotely sensed inputs: Remotely sensed inputs included percent tree, herbaceous, and bare ground cover, peak NDVI, and standard deviation NDVI, all derived from MODIS.

Geospatial inputs: The geospatial inputs included: Elevation, slope, aspect (8 classes), potential solar radiation from 30-m topographic data; mean total annual, summer, spring, and winter precipitation from 1950 to 2005, PET, actual evapotranspiration, surplus, and deficit, from 860-m ClimSource data; and vegetation class from the Multi-Resolution Land Class dataset.



Extent of the “Invasive Plant Cover in the Mojave Desert (2009–2013)” (Underwood and others, 2019) is shown. The estimated habitat suitability ranges from high (red) to low (blue).

AT A GLANCE	
Species	Cheatgrass (*Bromus tectorum*)
Output	Probability of occurrence (categorical but mapped as continuous)
States covered	Arizona, California, Nevada, Utah
Resolution	30 m
Recentness	*Most recent year (as of Dec. 2020)*: 2009–2013 (single average estimate of condition) *Years available*: 2009–2013 (single estimate of condition) *Time series*: No *Update frequency*: Not applicable
Evaluation	Yes; bootstrapping/cross validation
GET DATA	https://www.sciencebase.gov/catalog/item/6048dfa6d34eb120311a941f

Key model covariates: Cheatgrass occurrence was explained by mean annual precipitation, mean peak NDVI (quadratic form), mean percent tree cover, and mean temperature (quadratic from).

Evaluation: Model evaluation was carried out using 50 replicates of a tenfold and leave-one-out cross-validation technique. Tests generally indicated high model accuracy, with Root Mean Square Prediction Error=1.300 percent for *B. tectorum*, 2.539 percent for *B. rubens*, and 3.441 percent for the combined model.

Notes: Paper and spatial data link also include data for *Schismus* species and *Erodium cicutarium* in addition to *Bromus* species.

Spatial Data Citation

Klinger, R.C., Underwood, E.C., and Brooks, M.L., 2019, Invasive plant cover in the Mojave Desert, 2009–2013: U.S. Geological Survey data release, accessed October 25, 2021, at https://doi.org/10.5066/P9GUST4Q.

Publication Citation

Underwood, E.C., Klinger, R.C., and Brooks, M.L., 2019, Effects of invasive plants on fire regimes and postfire vegetation diversity in an arid ecosystem: Ecology and Evolution, v. 9, no. 22, p. 12421–12435, accessed October 29, 2020, at https://doi.org/10.1002/ece3.5650.

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Appendix 1. Additional Invasive Annual Grass Spatial Products

Table 1.1. Additional invasive annual grass spatial products

[Products did not meet the criteria for inclusion in our database (local-extent, pre-2010, obsolete product verisons, or non-peer-reviewed resources), but are listed as additional resources. List may not be comprehensive. N/A, not applicable; BLM, Bureau of Land Management; U.S., United States; UT, Utah; WY, Wyoming; CA, California; OR, Oregon]

Product	Spatial data link	Link to peer-reviewed publication or data release	Species	Extent
Weed presence in Idaho (through 2005)	https://www.sciencebase.gov/catalog/item/4fc67b83e4b0f02c1d6a80ff	N/A—collection of BLM and Idaho Department of Agriculture datasets	Annual herbaceous	Idaho
Southwest Exotic Mapping Program Database (Thomas and Guertin, (2017)	https://www.sciencebase.gov/catalog/item/594c2d55e4b062508e3855f9	https://doi.org/10.5066/F7WQ02JX	Annual herbaceous	Southwest U.S.
Bradley and Mustard (2005)	https://www.sciencebase.gov/catalog/item/4f4e479de4b07f02db491df2	https://doi.org/10.1016/j.rse.2004.08.016	Cheatgrass	Great Basin
Meinke and others (2009)	https://www.sciencebase.gov/catalog/item/4fc8f2dae4b0bffa8ab25a27	https://doi.org/10.1111/j.1526-100X.2008.00400.x	Cheatgrass	Intermountain West
Bradley (2009)	Data not found	https://doi.org/10.1111/j.1365-2486.2008.01709.x	Cheatgrass	Great Basin
Rowland and others (2010)	https://www.sciencebase.gov/catalog/item/5429b99be4b0c4fc5b30fee5	Rowland and others (2010)	Cheatgrass	Great Basin
Miller (2018)	https://www.sciencebase.gov/catalog/item/55d60be0e4b0518e3546a59a	https://doi.org/10.5066/P9QEJGD8	Cheatgrass	Washington County, UT
Bishop and others (2019)	Data not found	Bishop and others (2019), https://doi.org/10.1007/s10980-019-00817-8	Cheatgrass	Colorado Plateau National Parks
West and others (2015)	https://mountainscholar.org/handle/10217/87631	West and others (2015), https://doi.org/10.1371/journal.pone.0117893	Cheatgrass	Rocky Mountain National Park
West and others (2018)	https://www.sciencebase.gov/catalog/item/5ad658abe4b0e2c2dd23f59d	West and others (2018) https://doi.org/10.1007/s10980-018-0644-x	Cheatgrass	Squirrel Creek and Arapahoe Wildfires, WY
Sherrill and Romme (2012)	Data not found	Sherrill and Romme (2012) https://doi.org/10.4996/fireecology.0802038	Cheatgrass	Dinosaur National Monument
Karl (2010)	Data not found	Karl (2010) https://dx.doi.org/10.2111/REM-D-09-00074.1	Cheatgrass	Southern Idaho
Gray and Dickson (2016)	Data not found	Gray and Dickson (2016) https://link.springer.com/article/10.1007/s10980-016-0353-2	Cheatgrass	Kaibab National Forest, northern Arizona
Malmstrom and others (2017)	https://datadryad.org/stash/dataset/doi:10.5061/dryad.cv791	Malmstrom and others (2017) https://doi.org/10.1371/journal.pone.0181665	Medusahead	Sacramento Valley, CA
Bateman and others (2020)	Data not found	Bateman and others (2020) https://doi.org/10.1016/j.rama.2020.04.006	Medusahead	Channeled scabland region of eastern Washington
Dronova and others (2017)	Data not found	Dronova and others, (2017), https://doi.org/10.3389/fpls.2017.00890	Medusahead	University of California's Sierra Foothills Research Experimental Center, Yuba County, CA
Rangeland Analysis Platform – Cover 1.0	No longer available	Replaced by Rangeland Analysis Platform—Cover 2.0 on July 6, 2020.	Annual herbaceous species	The western U.S.
MS thesis (Bateman, 2017)	Data not found	https://digitalcommons.usu.edu/etd/6896/	Medusahead	Channeled scabland region of eastern Washington
Doctoral dissertation (Ndzeidze, 2011)	Data not found	https://ir.library.oregonstate.edu/concern/graduate_thesis_or_dissertations/rx913s62z	Medusahead	Harney County, OR
MS thesis (Brehm, 2019)	Data not found	https://scholarworks.unr.edu/handle/11714/6018	Cheatgrass	Great Basin

Appendix 2. Invasive Annual Grass Websites—Data Resources

Table 2.1. Invasive annual grass websites—Data resources

[IAG, invasive annual grass; NISIMS, National Invasive Species Information Management System; BLM, Bureau of Land Management; INHABIT, Invasive Species Habitat Tool; USGS, U.S. Geologic Survey; FORT, Fort Collins Science Center; BISON, Biodiversity Information Serving Our Nation; GBIF, Global Biodiversity Information Facility; km^2, square kilometer; EDDMapS, Early Detection and Distribution Mapping System; AIM, Assessment, Inventory, and Monitoring Program; NEPA, National Environmental Policy Act; NRCS, National Resources Conservation Science; USDA, United States Department of Agriculture; U.S., United States; N/A, not applicable]

Website[1] (click for link)	Host	Website description	Information available	Extent	Data filters	Web map	Mobile app	Accuracy checks on data	Notes and limitations
LANDFIRE Reference Database	LANDFIRE Program	A collection of the datasets used to create the various LANDFIRE spatial products; a subset is publicly available from some resources.	Vegetation cover, height, class, biomass and disturbance, including IAG	United States	Yes	No	No	Professional agencies check for accuracy internally before submitting data; no accuracy checks for the final database.	This database is only a subset of the data used to create LANDFIRE products because of proprietary or otherwise sensitive data has been removed. Data are provided as is, with no guarantee of accuracy, completeness, and so forth
LANDFIRE Public Events Geodatabase	LANDFIRE Program	A geodatabase of polygons used to determine disturbance causality in LANDFIRE products.	Disturbance event coverage, including IAG cover or infestation level.	United States	Yes	No	No	Data were evaluated for: 1) polygon with defined spatial coordinates, 2) acceptable event type or exotic plant species, and 3) dated between 1999 and 2016.	This database is only a subset of the data used to create LANDFIRE products because of proprietary or otherwise sensitive data has been removed.
BLM-NISIMS	USGS	A standardized, spatially enabled BLM database containing location, treatment, and monitoring data relevant to invasive species. Includes tools to collect field data and integrate it into a centralized geospatial database to facilitate data sharing.	Shapefiles of invasive species infestation or treatment data.	United States	Yes	Yes	Yes	Documentation on error checking was not found, but there is a user's guide is available dictating how to collect data and upload it to the NISIMS system.	Data collected on BLM lands only. The infestation data included on this site represents a snapshot of actual infestations of individual species, it does not represent the total infestations of the species. Only a small proportion of BLM lands have been inventoried, and not all that data has been imported into NISIMS.
INHABIT	USGS	Tool for displaying outputs of species distribution models created by USGS FORT; website has not yet been peer-reviewed.	Species distribution maps, tables of suitable habitat for a species within management units.	United States	Yes	Yes	No	Data used for model building was collected from sites which all had some level of accuracy assessment. No accuracy checks regarding the entire database.	This website is still under active development. Peer review of the site is pending. Metadata for the species distribution models is currently under review. Public release of these models will follow. See Young and others (2020) for a description of methods.
BISON	USGS	An integrated and permanent resource for biological occurrence data from the United States and Canada. Node of GBIF.	Occurrence spatial data	United States, Canada, and their marine zones	Yes	Yes	No	Data providers (government agencies and universities) are responsible for the quality, scope, and resolution of the data they provide.	Polygon queries currently limited to 100,000 km^2.

Table 2.1. Invasive Annual Grass Websites—Data Resources—Continued

[IAG, invasive annual grass; NISIMS, National Invasive Species Information Management System; BLM, Bureau of Land Management; INHABIT, Invasive Species Habitat Tool; USGS, U.S. Geologic Survey; FORT, Fort Collins Science Center; BISON, Biodiversity Information Serving Our Nation; GBIF, Global Biodiversity Information Facility; km^2, square kilometer; EDDMapS, Early Detection and Distribution Mapping System; AIM, Assessment, Inventory, and Monitoring Program; NEPA, National Environmental Policy Act; NRCS, National Resources Conservation Science; USDA, United States Department of Agriculture; U.S., United States; N/A, not applicable]

Website[1] (click for link)	Host	Website description	Information available	Extent	Data filters	Web map	Mobile app	Accuracy checks on data	Notes and limitations
GBIF	GBIF	A repository for global records of where and when species have been recorded.	Occurrence spatial data	Global	Yes	Yes	No	Data publishers are responsible for managing the quality, completeness, and usefulness.	Huge amounts of data. Consider using BISON if restricting inquiry to North America as the web interface is easier to use.
EDDMapS	University of Georgia	Web-based mapping system for invasive species and pest distribution.	Occurrence spatial data	United States, Canada	Yes	Yes	Yes	All data is reviewed by a local or State expert prior to ensure accuracy.	Contains citizen science records but all records reviewed by verifiers prior to appearing on maps and in data queries.
BLM AIM	BLM	A monitoring program for management decisions (primarily on BLM land) including grazing permit, land use plans, NEPA documents, and tracking the spread of invasive species.	Percent cover of vegetation types and bare soil; rangeland health indicators.	Western United States	Yes	Yes	No	Standardized QA/QC during data collection and after data has been uploaded at State and National level.	Percent cover metrics are often used to train and validate spatial products based on remotely sensed data.
iMapInvasives	Nature-Serve	Cloud-based application for the tracking and managing of invasive species observations.	Maps and shares invasive species locations (including absence), surveys, and treatments.	North America, South America	Yes	Yes	Yes	Includes citizen science data which may not be fully validated. May help to direct more formal surveys.	Product has an integrated decision analysis tool comprised of a strategy-selection decision tree (available to all). Data downloads limited to 10,000 records at a time. Some site functions are only available to participating jurisdictions (Oregon and Arizona in western United States).
Sage Grouse Initiative	NRCS, USDA	Interactive map and data repository related to sage-grouse conservation.	Index of resilience to disturbance and cheatgrass	U.S. sage-grouse range	No	Yes	No	N/A	Does not include direct data on IAG occurrence or abundance.
CWMA	CWMA	Informational website highlighting weeds and programs that link research to real-world application of weed management.	Informational; does not include spatial data	Colorado	No	No	No	N/A	Does not include spatial data or *Ventenata*. Not a data portal.

[1]Access dates for websites range between 10/15/20 and 11/30/20.

Appendix 3. Functional Definitions of Summarized Spatial Data Characteristics

Table 3.1. Characteristics and definitions summarized in the spatial data review process and included in the IAG Spatial Data Products database. Contents of the compendium are based upon the technical definitions of these characteristics and product summaries have been reviewed by the authors of the spatial data to ensure accuracy.

Product characteristic	Technical definition/description
	Basic product information
Species	A brief descriptor of the species represented in the spatial product. Many products targeting a particular species actually represent multiple species because distinguishing between unique species using remote-sensing techniques is imperfect.
Spatial data product	Brief descriptor of the spatial product.
Description of output	General description of the spatial output product (for example, percent cover, vegetative cover type, probability of occurrence).
Thumbnail	Provides a visual to accompany the general spatial extent description.
Author(s)	List of authors for spatial data products and associated peer-reviewed publications.
Title(s)	Full title(s) for spatial data products and associated peer-reviewed publications.
Publication year	Year of publication (spatial data).
Spatial data product citation	Citation for data product.
Spatial data product link	Link to access the spatial data.
Peer-reviewed publication citation	Citation for associated peer-reviewed publication.
Peer-reviewed publication source	Link to access the associated peer-reviewed publication.
Date reviewed	Date the spatial data product was reviewed; also represents the approximate date the spatial product was accessed by the reviewer.
Associated spatial products (not reviewed)	References any additional products associated with this data source/publication; these products were not reviewed
	Basic spatial information
Extent	Text description of the spatial data extent or area covered; includes area in km^2 if available.
Scale of extent	Describes the general scale (for example, National or regional, as defined in Young and others 2020) represented by the spatial data extent.
States included in extent	Complete list of States included in the final product extent; listed in alphabetical order for consistency; also includes Canadian Provinces if applicable.
Bounding spatial coordinates	The approximate maximum west, east, north, south-bounding coordinates encompassing the spatial data product; in latitude/longitude format.
Accessibility of extent shapefile	Indicates if a shapefile delineating the spatial extent is publicly available and, if so, includes a link where it can be accessed.
Spatial resolution	Pixel size or minimum mapping unit of the final spatial product.
Mask	Indicates if a spatial mask was applied to the analysis or model output. Masks applied during standard image processing of remote sensing data were not mentioned (for example, exclusion of ice/snow/clouds from spatial input layers).
	Basic spatial information—Continued
Time series	Indicates whether the output is available over multiple years for comparison (yes or no).
Input years	Indicates the year(s) of data, referring to both dependent and independent variables, included as model inputs.
Temporal resolution of input data	Refers to the input data used to build the model (for example, annual data, data from a series of years).
Update frequency	Indicates whether the spatial data product has been updated and the frequency of updates.
Recentness	Indicates the year(s) of data included in the product and any pertinent interpretations (in parenthesis; database only). The most recent year of the spatial product (compendium only).

Table 3.1. Characteristics and definitions summarized in the spatial data review process and included in the IAG Spatial Data Products database. Contents of the compendium are based upon the technical definitions of these characteristics and product summaries have been reviewed by the authors of the spatial data to ensure accuracy—Continued

Product characteristic	Technical definition/description
	Interpretation and use
Intended use	Describes the general purpose of the spatial product, as indicated by product documentation or as noted by the authors.
Caveats	Describes the limitations or considerations for use of the spatial product, as noted by the authors.
	Independent/dependent variable information
Dependent variable(s)	The mapped response (or calibration) variable that is being predicted by the model/analysis (usually a measure of an invasive annual grass); in some cases, there may be more than one variable, as in two-part models. Variables are grouped by "type" (for example, field collected, remotely sensed, or geospatial layer).
Dependent variable methods	Describes the methodologies used to obtain the dependent variable values, organized by variable "type"; may include reference to methods section of associated peer-reviewed publication as needed.
Independent variables	The full list of predictor variables used to estimate where invasive annual grass occurs, including those that were tested but found to perform poorly and not included in final models. Variables are grouped by "type" (for example, field collected, geospatial [digital data relating to a specific position on the earth surface], or remotely sensed [a type of geospatial layer gathered from a substantial distance, often via imaging satellites, such as Landsat, or aerial photography]).
Independent variable methods	Describes the methodologies used to obtain the independent variable values, organized by variable "type"; may include reference to methods section of associated peer-reviewed publication as needed.
	Model description
Modeling approach	Brief, general description of the analysis/modeling approach used to develop the spatial output, such as model building or training process.
Type of model	Lists the type of statistical model(s) used to generate the spatial output.
Output format	Describes the type of spatial output generated (for example, continuous, categorical, rank, etc.).
Final model covariates	List of all variables retained in the final model (for example, covariates dropped from final model based on model selection analyses are not included here).
Key model covariates	List of variables that were strongest contributors to predictions in the final model; does not always include all significant predictor variables due to high number of covariates included in some models.
	Evaluation and accuracy
Evaluation input type	Describes the origination of data used for model validation (for example, within sample, independent sample, none).
	Evaluation and accuracy—Continued
Evaluation methods	Description of methods used for model validation or accuracy assessment.
Evaluation results	Summary results from model validation that determines product accuracy.
Evaluation for extrapolation	Is the model evaluated using extrapolated data? If so, what is the extent of the extrapolated data?
	References
References cited	Citations for other information sources referenced in this summary.

Table 3.2. Definitions of evaluation techniques used in assessing invasive annual grass spatial data products. These terms are used throughout the compendium and the suite of associated products.

Evaluation terms	Definition
Fully independent	Data used in model evaluation is not used in any form of model training. Evaluation data may, but is not required to, come from completely different studies. The Holdout Method of cross validation is included in this category as these data never enter the model building process.
Bootstrapping/cross validation	Data that is withheld for evaluation purposes for some modeling runs but included in others. Common methods include k-fold cross validation and bootstrapping.
Within sample	Data used to train the model was also used to access model accuracy. Commonly reported with this type of evaluation is the percent correctly classified and goodness of fit statistics. If regression trees are used, then regression tree error maps may be provided.

USGS

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