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# Modeling Invasive Annual Grass Abundance in the Cold Desert Ecoregions of the Interior Western United States☆

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A B S T R A C T

Invasive annual grasses, primarily *Bromus tectorum,* are a severe risk to native vegetation of the intermountain West. Once established, annual grasses alter natural fire regimes and outcompete natives until, in some places, they become the overwhelming dominant. We developed a regional spatial model encompassing eight ecoregions to indicate the relative abundance of invasive annual grass at five levels of canopy cover. We used field sample data representing invasive annual grass abundance to build and calibrate the model. Explanatory variables, represented as map inputs, included image indices, climate, landform, soil, and human-induced surface disturbance. As a novel modeling approach, we built multiple models based on classes of invasive annual grass cover abundance were developed individually and then combined into a final 90-m pixel resolution model that indicates locations relative to invasive annual grass abundance into classes of < 5%, 5–15%, 16–25%, 26–45%, and > 45% cover. Each component model was validated using held-out sample data, and relative accuracy was 86%, 74%, 62%, 62%, and 60%, respectively, with an overall kappa of 0.773. The Columbia Plateau, Northern Basin and Range, and Snake River Plain ecoregions appear to have the greatest overall proportions (48–62%) mapped within at least one of the invasive cover categories. Overlay of the resulting model with major vegetation types indicated > 50 major vegetation types that are affected by current distribution of annual grasses and are at risk of expansion. Among these, Intermountain Basins, Big Sagebrush Steppe, and Columbia Plateau Steppe and Grassland each consistently scored high for invasive risk where they occur. Spatial models of this type should assist with rangeland restoration and for decisions involving placement of infrastructure, vegetation treatments where further surface disturbance could trigger additional cheatgrass expansion. Options exist for extending this model, using climate projections over upcoming decades, to indicate areas of increasing risk for invasion.



## Introduction

Among the most severe threats to native ecosystems throughout the western United States is the invasive spread of exotic annual grasses, including cheatgrass *(Bromus tectorum),* medusahead *(Taenaitherum caout-medae),* and others (Knapp 1996). Cheatgrass in North America occurs across much of the United States, Canada, Greenland, and Northern Mexico (Mosely et al. 1999). Primarily a roadside weed in the eastern United States, cheatgrass is most prominent west of the Rocky Mountains to Cascade Range and north from Nevada and Utah to British Columbia. Flourishing since its introduction in the mid-1800s with landscape disturbances from infrastructure and overgrazing, cheatgrass and other invasive annual grasses have increased in both presence and abundance (Billings 1990). Throughout the six western states at greatest risk from cheatgrass invasion, Nevada is most affected, including extensive areas of complete cheatgrass dominance (Pellant et al. 1994).

This Eurasian annual grass exploits apparently unoccupied niche space in the Great Basin and is a particularly effective competitor with native bunchgrasses and forbs (Arredondo et al. 1998; Davis et al. 2000). Typically, the seeds germinate in the fall, continue root growth throughout all but the coldest parts of winter, and show aboveground shoots in late winter. They have a higher relative growth rate compared with many native plant species This strategy gives cheatgrass multiple advantages over native species but primarily in its aggressive competition for early growing season moisture. Interactions between fire, grazing intensity, and biological soil crusts appear to affect relative resistance of sites to cheatgrass invasion (Condon and Pyke 2018).

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Cheatgrass tends to be most abundant between 600 and 1 800 m elevations. While most widespread in cold desert communities dominated by subspecies of big sagebrush *(Artemisia tridentata),* cheatgrass is present throughout many Intermountain Basin and foothill plant communities. These can include lands supporting mixed salt desert scrub in basins (West 1988) up through pinyon and juniper– and even ponderosa pine–dominated communities (Young 2000).

While present under a variety of climatic conditions, cheatgrass exploits conditions favorable to species from Mediterranean climates with high winter rainfall followed by summer drought. Generally, it is most prevalent in regions receiving from 300 mm to 560 mm of late winter precipitation (Pyke and Novak 1994). In some drier landscapes in Nevada, such as those supporting black sagebrush, cheatgrass was present in periods with substantial spring moisture (Young and Palmquist 1992). In periods of severe drought and where site productivity is low, cheatgrass still produces enough seeds to contribute to future recruitment (Mack and Pyke 1983).

Cheatgrass tends to occur on southern and western aspects, rather than the cooler/wetter northern exposures (Goodrich 1999; Goodrich and Rooks 1999). Most commonly associated with deep sandy to loamy soils, cheatgrass is not limited to these soils (Sheley and Petroff 1999). It can be competitive in low-fertility soils (Doescher et al. 1986; Link et al. 1994; Young 2000) or compete well on soils with higher nitrogen availability (Lowe et al 1992; Dakheel et al. 1993; Young and Allen 1997). Chambers et al. (2007) found that in the Great Basin, growing season temperature limits cheatgrass distribution at higher elevations and soil moisture is a primary limitation at lower elevations. Soil moisture and nitrate availability increase following vegetation removal, assisting with invasibility. Variability in soil moisture and nitrate availability, which tends to be higher at lower elevations, also contributes to cheatgrass invasibility. But where native perennial graminoid species are abundant (i.e., in high-quality vegetation condition and generally at higher elevation locations), cheatgrass invasibility is more limited (Chambers et al. 2007).

Some have attributed rapid expansion of cheatgrass to surface disturbance from overgrazing livestock (D'Antonio et al. 1999; Zouhar et al. 2008; Young and Clements 2009) and specifically to destruction of biological soil crust (Reisner et al. 2013). But once established, it also introduces fine fuel that alters natural fire regimes. Fire intervals between 20 and 50 yr are characteristic in many sagebrush communities (Peters and Bunting 1994). With increasing fire frequency, species like big sagebrush and less fire-tolerant bunchgrasses and forbs decrease in cover. Cheatgrass cover can then increase and accumulate more fine fuel to further increase fire frequency until it becomes overwhelmingly dominant (Melgoza et al. 1990; Brooks et al. 2004).

Bradley and Mustard (2006) completed spatial analysis across the intermountain west to track invasive plant species expansion between 1973 and 2001 and explore relationships of landscape variables including geophysical characteristics and surface disturbance. Since then, several map-based analyses using 250-m pixel eMODIS data (Jenkerson et al. 2010) have assessed effects of invasive grasses on regional fire activity (Balch et al. 2013), estimated change in cheatgrass cover (Boyte et al. 2016), and explored potential risk and opportunities linked to climate change (Bradley et al. 2016). Boyte et al. (2016) limited their modeling extent to the northern Great Basins ecoregion. They used a three-stage modeling approach aimed at documenting 1) "actual" cheatgrass abundance, based on image indices and biophysical inputs; 2) "expected" abundance, based on observed climate inputs; and 3) predicted distributions into the mid- and late-21st century based on projected climate inputs.

Models of spatial resolution finer than the eMODIS 250 m are desired for assessment and planning by land managers, and higher resolution products have been developed for these purposes (Comer et al. 2013). For example, aiming to produce maps of higher spatial resolution and accuracy, Peterson (2005) used multi-temporal satellite imagery and field training data to develop a continuous surface prediction of cheatgrass percent cover for a large portion of Nevada. The following decade has produced multiple iterations with evolving methodology to refine the distribution of invasive annual grass. Each iteration primarily represents an analysis of spectral information (DOD 2006; Xian et al. 2015; Jones et al. 2018). However, recent models do not use a complete representation ecological potential denoted by biophysical data (Comer et al 2013; Downs et al. 2016), comprehensive climate influences (Bradley & Mustard 2006; Comer et al. 2013; Downs et al. 2016), are not invasive annual grass specific but rather focus on annual forbs and grasses combined (Xian et al. 2015; Jones et al. 2018), many of which are native to western ecosystems and should not be mapped as invasive annual grasses.

Given this accumulating knowledge about cheatgrass occurrence and behavior, its substantial impact on natural resources, and advances in spatial modeling for use my land managers, we aimed to develop a 90-m pixel-resolution spatial model for the cold desert region of the intermountain west to provide insights into its presence, abundance, and risk of expansion of cheatgrass and other invasive annual grasses. The overall goal of this analysis was to use readily available spatial data to represent the full ecological potential in which disturbance, biophysical, spectral, and climatic data may be easily updated and allow for rapid future updates.

## Methods

### *Study Area*

We selected a set of ecoregions (Wiken et al. 2011) used by the Bureau of Land Management (BLM) for rapid ecoregional assessments that are known to encompass primary infestations of cheatgrass and other cold temperate invasive annual grasses. These included the Central Basin and Range, Colorado Plateaus, Wyoming Basin, Northern Basin and Range, Snake River Plain, Eastern Cascades Slopes and Foothills, Columbia Plateau, and Blue Mountains, or a total area of 982 515 km.[2] This vast region, overlapping with what is sometimes referred to as the "sagebrush sea" (Davis et al. 2011), is overwhelmingly dominated by various forms of sagebrush shrubland and steppe, especially at elevations below 2 500 m. Large proportions of the states of Nevada, Utah, Wyoming, Oregon, and lesser proportions of Idaho, Washington, Colorado, California, Arizona, New Mexico, and Montana are included in this study area. Basin and range physiography is best developed in the Central Basin and Range ecoregion, with roughly parallel mountain ranges separated by (often hydrologically closed) basins (Eaton 1982). This characterizes landscapes of the northern Great Basin and Columbia Plateau. Farther east, the Wyoming Basins are much larger and surrounded by high mountain ranges. In all these ecoregions, lower basin slopes, rolling plateaus, and some basin bottoms encompass geophysical settings that support invasive annual grasses. The Colorado Plateau geologically represents Plateaus upwarped crust and subsequently downcut formations of table and canyonland (Fenneman 1931) supports less proportional area of sagebrush communities but does include ecologically similar xeric shrubland and pinyon-juniper woodland.

### *Dependent Variables*

Providing dependent variables, precise locations with both presence and percent cover of invasive annual grasses are needed

**Table 1**
Sample count, plus minimum, maximum, and average invasive annual grass cover, per cover category.

| Invasive annual grass cover category | Sample/Validate count | Minimum cover (%) | Maximum cover (%) | Average cover (%) |
|---|---|---|---|---|
| 1—Trace to 5% | 14 441/1 442 | 0.01 | 4.92 | 1.62 |
| 2—5–15% | 7 818/780 | 5.00 | 14.83 | 7.98 |
| 3—15–25% | 3 336/328 | 15.00 | 24.90 | 18.42 |
| 4—25–45% | 2 585/257 | 25.00 | 44.87 | 32.69 |
| 5—> 45% | 1 559/151 | 45.00 | 100 | 64.04 |
| Grand total | 29 739/2 958 | | | |

to train spatial models. While no one source of data on exotic annual grass presence and abundance exists for the entire region, there are several well-documented field survey datasets. The LANDFIRE Program (Rollins 2009) maintains a LANDFIRE reference database (LFRDB) that includes thousands of samples standardized for use in their spatial modeling. The publicly available LFRDB includes vegetation and fuel data from georeferenced sampling units nationwide. The data were amassed from existing information resources such as the BLM's AIM plots, US Forest Service and NRCS (NRI plots) vegetation programs, USGS National Gap Analysis Program, NPS Inventory and Monitoring (I&M) efforts, Natural Heritage Program inventories, and other contributing field researchers. Data fields in the database include estimates of canopy cover and height per plant taxon, occurrence of exotic plants, biomass estimates of downed woody material, percent cover and height of shrub and herb layers, and canopy base height estimates.

A second source of sample data was the Southwest Exotic Mapping Program (SWEMP) (Thomas and Guertin 2017). Initiated in 2007 as a collaborative effort between the US Geological Survey and federal, tribal, state, county, and nongovernmental organization (NGO) partners in the southwest. This project compiled and distributed regional data on the occurrence of non-native invasive plants. The database represents documented locations of non-native invasive plant infestations within Arizona and New Mexico, as well as adjacent portions of California, Colorado, Nevada, and Utah. These data, collected from 1911 to 2006, represent the field observations along with selected specimen data from herbaria.

Training and validation data were acquired from the July 2016 update of the LANDFIRE publicly available sample points. Once combined, SWEMP samples were removed if they occurred within 100 m of LANDFIRE samples to avoid duplication. Within the targeted ecoregions, a total of 29 739 samples were identified as having an invasive annual grass component within the overall species composition of the sample site (Table 1). A total of 31 distinct invasive species were identified within the sample sites as having > 100 records each, of which 51% of the samples recorded the presence of cheatgrass *(Bromus tectorum).* Nearly all sample points recorded a single species of annual grass present, but some contained additional species. All samples were grouped into one of five absolute cover categories: < 5%, 5–15%, 16–25%, 26–45% and > 45% cover (Jensen et al. 1994; Gokhale and Weber 2005; Sander and Weber 2005; Kagan et al. 2006; TNC 2006; Comer et al. 2013). Categories were refined from Zouhar et al. 2008 (see table 15-3) using distributions from Braun-Blanquet 1965 and Jensen et al. 1993 (EcoData) and combining cover classes to maximize sample size per category. Most samples were represented in the Category 1 and Category 2 cover percentages (see Table 1 and Fig. 1). All samples were gathered between yr 1990 and 2015.

### *Independent Variables*

Independent variables used in the analysis consist of both continuous and categorical feature types but occur as map layers extending across the multiecoregion mapping area. Categorical feature types were further processed to continuous features by either distance to (fire boundary, hydric soils, streams) or density measures (road classes). These map inputs varied in their native spatial resolution from 800-m down to 10-m resolutions and were each rescaled to a 90-m resolution for modeling (Table 2).

The enhanced Moderate Resolution Imaging Spectroradiometer (eMODIS) satellite provides a 250-m pixel surface with normalized difference vegetation index (NDVI) as a measure of vegetation productivity. Given knowledge of south-to-north patterns in seasonal green-up of annual grasses, we used monthly NDVI averages from the months of February, March, and May of 2014.

Nineteen bioclimatic predictor variables, including temperature and precipitation variables for the conterminous USA (O'Donnell and Ignizio 2012), were used to represent climate drivers of invasive annual grass niche space. Our source climate data were comosed of 800-m resolution gridded surfaces representing monthly averages from 1948 through 2014. We obtained minimum and maximum temperature data from TopoWx (Oyler et al. 2015), which uses a homogenization algorithm to overcome the noise and biases that emerge when gridded climate datasets derived from inconsistent weather station records are used to measure temporal trends. Since precipitation data are not available from TopoWx, we sourced them from the PRISM LT71 dataset (Daly et al. 2008). While PRISM does not remove the artifacts of nonclimatic trends in the same manner as TopoWx, LT71 does use a more temporally consistent set of weather stations than other PRISM products and precipitation is subject to fewer trend quality concerns than temperature.

Since both image indices and climate data sets have native resolutions of 250 m and 800 m, respectively, we downscaled each to 90-m grids using cubic convolution resampling. Although resample of the native resolution of a raster dataset is typically discouraged, multiple inputs in the model are derived from much finer datasets and scale up to 90 m. The downscaling of the coarser resolution data was determined to be acceptable as current research into the effects of resolution change has little to no effect on the absolute error and the rescaled data can be reasonably assumed to have equal uncertainty to the native resolution (Pogson & Smith 2015)

Other geophysical variables for modeling included elevation and slope—all as continuous variables— derived from the 10-m digital elevation model (USGS 2015 NED). This surface was upscaled to 90 m using cubic convolution resampling. Predictors of soil moisture were developed using variables representing distance (in meters) from hydric soils derived from the digital soil survey SSURGO (Soil Survey Staff, accessed 2014) primarily, as well as for distance from perennial and intermittent streams derived using NHDPlus (US EPA and USGS 2012).

Surface disturbances used in modeling were represented in several forms. Large wildfire perimeters from 1990 to 2015 were acquired from the GeoMAC database (Walters et al. 2011), and distance from each of these events (in meter) was calculated. Surface disturbances from roads were represented as density (linear km/km$^2$) calculated by three road classes defined as local (includes county and small paved, dirt), primary, and secondary (major highways) at 90-m resolution.

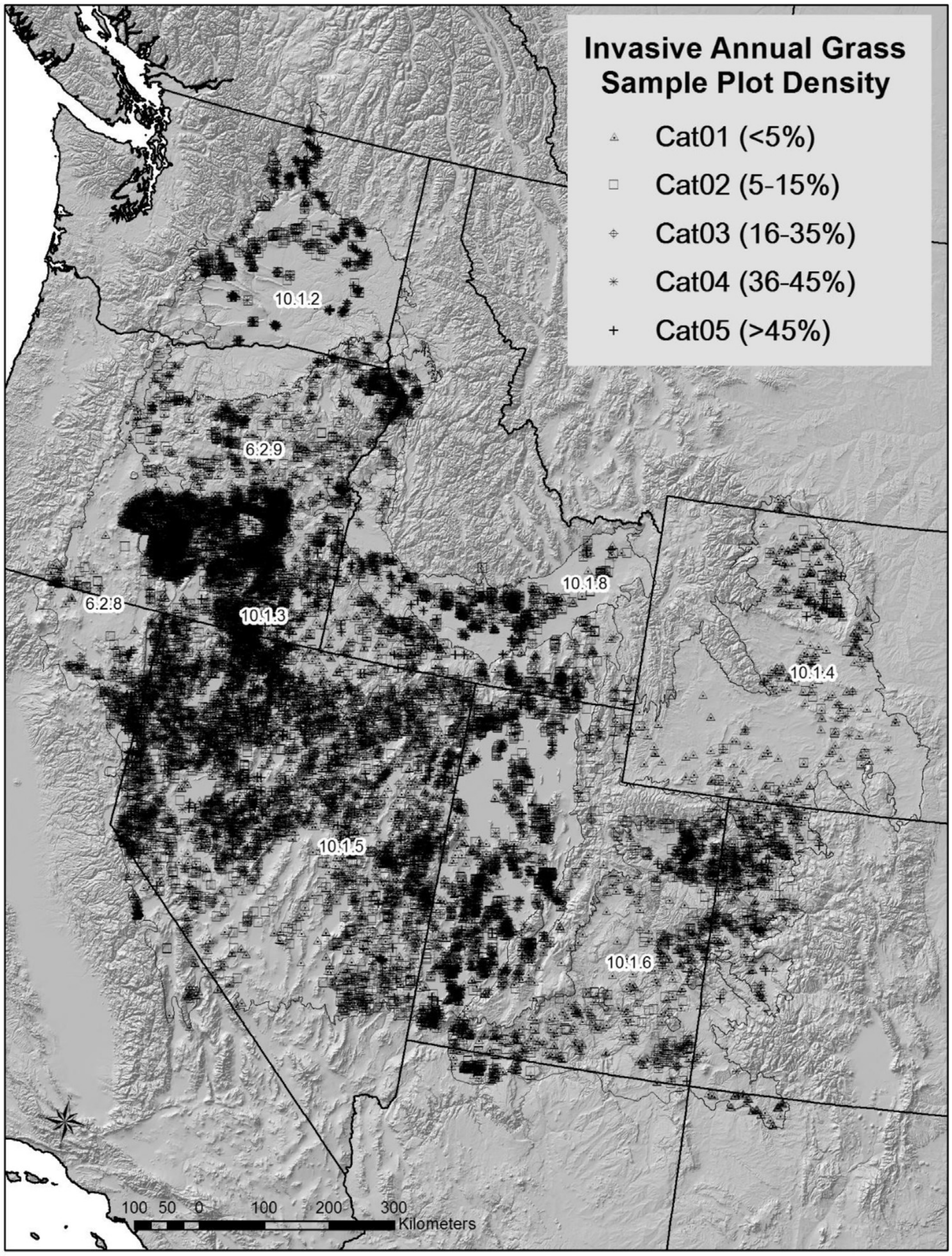


**Figure 1.** Invasive annual grass samples by canopy cover category across cold desert ecoregions (6.2.8 = Eastern Cascades Slopes and Foothills, 6.2.9 = Blue Mountains, 10.1.2 = Columbia Plateau, 10.1.3 = Northern Basin and Range, 10.1.4 = Wyoming Basin, 10.1.5 = Central Basin and Range, 10.1.6 = Colorado Plateaus, 10.1.8 = Snake River Plain).

We addressed issues of covariance and identify variable importance, we summarized variable contribution using a jackknife method in which random forest models were generated for each unique combination of independent variables and ranked on the basis of the area under the curve (AUC) value onto individual models to identify which independent model inputs were most frequently used in each model and to better understand their relative contribution to model performance. The variable evaluation was competed in two steps. First, the climate variables were reduced to those that had at least 1

**Table 2**
Probability of occurrence thresholds were defined as the values where sensitivity and specificity are equal.

| Cover category | Threshold | Model standard | Annual grass (AUC) | Percent correct |
|---|---|---|---|---|
| Trace to 5% cover | 0.4275 | 0.034581 | 0.9326 | 85.77% |
| 5% to 15% cover | 0.4425 | 0.040087 | 0.9391 | 73.87% |
| 15% to 25% cover | 0.4635 | 0.01203 | 0.9369 | 61.56% |
| 25% to 45% cover | 0.435 | 0.038442 | 0.9462 | 62.00% |
| > 45% cover | 0.4815 | 0.013134 | 0.9595 | 60.08% |
| Kappa | | | 0.773 | |
| 95% CI | | | 0.02014 | |

AUC, area under the curve; CI, confidence interval.

**Table 3**
Relative contributions of 27 independent variables to model performance, ordered by the count sum score for each variable across all five component models that have a rank ≥ 10.

| Independent variables | Trace to 5% cover | 5% to 15% Cover | 15% to 25% Cover | 25% to 45% Cover | > 45% Cover | Summed across models |
|---|---|---|---|---|---|---|
| Local road density | 1 | 1 | 3 | 2 | 9 | 5 |
| Solar radiation | 5 | 2 | 2 | 1 | 5 | 5 |
| Bio18—precipitation of warmest quarter | 6 | 5 | 8 | 8 | 10 | 5 |
| Distance to fire boundary | 8 | 8 | 6 | 10 | 7 | 5 |
| Distance to hydric soil | 3 | 6 | 4 | 5 | NA | 4 |
| NDVI—May 25 | 10 | 4 | 10 | 6 | 1 | 4 |
| Elevation | NA | 10 | 6 | 7 | 8 | 4 |
| Bio10—mean temperature of warmest quarter | NA | 7 | 9 | NA | 2 | 3 |
| Distance to intermittent streams | NA | 3 | 1 | 4 | NA | 3 |
| Bio12—annual precipitation | NA | 9 | 4 | 9 | NA | 3 |
| Bio16—precipitation of wettest quarter | NA | NA | 8 | 3 | NA | 2 |
| Bio08—mean temperature of wettest quarter | NA | NA | NA | NA | 3 | 1 |
| Bio19—precipitation of coldest quarter | 4 | NA | NA | NA | NA | 1 |
| Bio05—max temperature of warmest month | 2 | NA | NA | NA | NA | 1 |
| NDVI—Mar06 | NA | NA | NA | NA | 6 | 1 |
| NDVI—Feb10 | 7 | NA | NA | NA | NA | 1 |
| Latitude | NA | NA | NA | NA | 4 | 5 |
| Bio11—mean temperature of coldest quarter | 9 | NA | NA | NA | NA | 1 |
| NDVI—May09 | NA | NA | NA | NA | NA | 1 |
| Secondary road density | NA | NA | 10 | NA | NA | 1 |
| Bio13—precipitation of wettest month | NA | NA | NA | NA | NA | 0 |
| Bio15—precipitation seasonality (coefficient of variation) | NA | NA | NA | NA | NA | 0 |
| Biio03—isothermality (P2/P7) (* 100) | NA | NA | NA | NA | NA | 0 |
| Bio09—mean temperature of driest quarter | NA | NA | NA | NA | NA | 0 |
| NDVI—Mar22 | NA | NA | NA | NA | NA | 0 |
| Primary road density | NA | NA | NA | NA | NA | 0 |
| Slope | NA | NA | NA | NA | NA | 0 |

occurrence ranked in the top 10, reducing the 19 climate variables to 12 climate variables (Table 3). The final 12 climate variables were then combined with the biophysical and NDVI independent variables, and the variable evaluation was run again to identify the top 10 independent variables for final categorical models. Table 4 summarizes relative model input contribution to each model from the 27 independent variables with statistically significant influence. The table is sorted using the count of rank ≤ 10 of variable contribution across all five cover category models. Blank (NA) spaces indicate where a variable had no statistically significant influence on model performance for one of the component models.

*Model Development and Validation*

This model is unique as our approach is to generate distinct models for each of the five cover categories of invasive annual grasses (< 5%, 5–15%, 16–25%, 26–45%, and > 45% cover) and as a subsequent step, threshold each model to a binary (see Table 3) and merge the individual models into a composite map product. Similar to Ullerud et al. 2016, we forgo developing the composite model as a single classification with five independent values as derived with traditional vegetation map products like National Gap Analysis (see 5), we chose to address each category as a separate interim model to maintain better parsimony in sample size between categories and allow more flexibility in defining each category occurrence. In addition, the spatial resolution of the map, while fine scale for regional/national products, allows substantial variance of percent cover within each pixel and separate category models allow each pixel to be evaluated for the highest probability of each model. For instance, the model for > 45% cover had a value of 0.4815 (see Table 2) applied as a threshold to make a binary distribution. A separate validation process was found to be necessary as the AUC scores for each separate invasive grass category is a representation of the overall continuous model performance and is not representative of the final categorical model, which is defined by a threshold (see Table 3) making it a binary rather than continuous surface.

The USGS software package for assisted habitat modeling (SAHM) includes several analytical algorithms for spatial modeling using classification and regression trees and production of map outputs. The RandomForest tree model (Breiman 2001), has proven to provide robust model outputs in a wide variety of circumstances (Leaw and Weiner 2002). These software tools generated multiple model outputs for comparing relative performance. We utilized randomForest utilizing our labeled sample data (by each invasive grass cover category) as dependent variables in supervised learning. randomForest selects

**Table 4**
Total area and proportional area falling within each category of invasive annual grass cover, organized by Commission on Environmental Cooperation ecoregion.

| Type by ecoregion | Total area (km$^2$) | (No invasive) | Cat. 1 (trace) | Cat. 2 (> 5–15%) | Cat. 3 (> 15–25%) | Cat. 4 (> 25–45%) | Cat. 5 (> 45%) |
|---|---|---|---|---|---|---|---|
| Blue Mountains | 70 912 | 83% | 6% | 7% | < 1% | 4% | < 1% |
| Central Basin and Range | 309 945 | 79% | 8% | 6% | 1% | 4% | 2% |
| Colorado Plateaus | 134 930 | 91% | 8% | 1% | < 1% | < 1% | < 1% |
| Columbia Plateau | 83 923 | 35% | 8% | 10% | 1% | 28% | 18% |
| E. Cascades Slopes and Foothills | 56 175 | 72% | 10% | 12% | 1% | 5% | |
| Northern Basin and Range | 142 200 | 45% | 21% | 16% | 4% | 10% | 4% |
| Snake River Plain | 53 626 | 47% | 8% | 9% | 3% | 20% | 13% |
| Wyoming Basin | 132 683 | 79% | 20% | 1% | < 1% | < 1% | < 1% |

the best binary splits from a random selection of predictors and then recombining those to generate a final model (Breiman 2001).

Using the RandomForest tree model, 10 model folds were generated with random withholding of 10% of samples for model validation. The average AUC from the receiver operating characteristics (ROC) plots were used to determine the model validity. These curves compare the true-positive (or sensitivity) rate with the false-positive rate (or specificity). The best model was identified by highest AUC score of the 10 folds.

For each model, we established a probability threshold where sensitivity equaled specificity to define the occurrence of the cover category. This value in all model categories was the most restrictive threshold value (see Table 2).

Each component model was validated using 10% of all sample data (2 740 samples across all five models, x for category 1, y for category 2, etc.) held aside from model development. The accuracy estimates for models from categories 1–5 was 85.77%, 73.87%, 61.56%, 62.00%, and 60.08%, respectively. An overall kappa statistic was calculated as 0.773.

We summarized the variable contribution using a jackknife method in which random forest models were generated for each unique combination of independent variables and ranked on the basis of the AUC value onto individual models to identify which independent model inputs were most frequently used in each model and to better understand their relative contribution to model performance. Table 3 summarizes relative model input contribution to each model from the 27 independent variables with statistically significant influence. The table is sorted using the count of rank $\leq$ 10 of variable contribution across all five cover category models. Blank spaces indicate where a variable had no statistically significant influence on model performance for one of the component models.

Local road density, followed by solar radiation, distance from recent fire, precipitation of warmest quarter, and distance from hydric soil make up the top five variables, in terms of relative model contribution across all five models. These results follow general patterns documented in the literature, where local road density and recent fire events are considered among the most potent vectors for cheatgrass spread. Solar radiation is likely correlated with distance to fire with hot, flat, and upsloping topography enabling rapid and extensive wildfire spread. Early spring green-up, as reflected in May NDVI, was also presumed to be a variable likely to appear high in its predictive power. NDVI measured in May, elevation, mean temperature of the warmest quarter, distance to intermittent streams, and annual precipitation round out the top 10 variables from this scoring.

NDVI measures from late May in the northern latitudes where the highest densities or annual grasses are document while March and February were followed by those in early May in relative importance. It may be that the February–May period covers the south-to-north green-up pattern for this entire region, and that explains this result.

Climate variables explain a moderate amount of the model variance for annual grass coverage. Precipitation in the warmest quarter and mean temperature of the warmest quarter were the strongest climate drivers. Variables such as temperature of the driest quarter and precipitation of the wettest month scored lowest overall of the climate variables with some statistical significance.

Finally, the component models were combined to produce a composite map from five distinct maps, each indicating areas predicted to support invasive annual grasses at a given level of percent cover. At a pixel level, the highest predicted cover value supersedes the values from models of lower value model. Areas of current mapped agriculture were eliminated from the composite model, but no further masking was applied to areas above the typical elevation zone for annual grass.

## Results

The final composite model comprises each individual model layered in order of lowest percent coverage to highest percent coverage with each increasing percent cover layer superseding all underlying data values (Fig. 2). This composite model therefore indicates where invasive annual grasses occur today at one of the five levels of canopy cover. Table 4 summarizes findings of the model for the targeted ecoregions. Overall, 3% of the target ecoregions are predicted to be infested with invasive annual grasses with cover values above 45%, 5% of the area with cover of 25–45%, 1% of the area with cover of 15–25%, 7% of the area with cover of 5–15%, 11% of the area with cover of < 1–5% or trace amounts (see Table 4). The Columbia Plateau (62%), Northern Basin and Range (53%), and Snake River Plain (48%) ecoregions appear to have the greatest overall proportions mapped within at least one of the invasive cover categories. Proportionally, the Columbia Plateau (18%) and Snake River Plain (13%) have the most area mapped in the most severely infested cover category 5 (> 45%). The Columbia Plateau (28%) and Snake River Plain (20%) also have the highest proportions mapped in the severely infested cover category 4 (25–45%). Interestingly, relatively low proportions were mapped in moderate cover category 3 (15–25%) across all target ecoregions, with the Northern Basin and Range (4%) and Central Basin and Range (1%) being the highest. Category 2 (5–15%) was proportionally highest in the Northern Basin and Range (16%), East Cascades Slopes and Foothills (12%), and Columbia Plateau (7%), respectively. The lowest level of mapped invasive cover in Category 1 (trace–5%) was proportionally highest in the Northern Basin and Range (21%), Wyoming Basin (20%), East Cascades Slopes and Foothills (10%), Central Basin and Range (8%), Colorado Plateau (8%), Columbia Plateau (8%), Snake River Plain (8%), and Blue Mountains (6%), respectively. Figure 1 indicates how those patterns vary within each ecoregion. For example, in the Central Basin and Range ecoregion, the overall proportion (20%) of the ecoregion affected is lower than some other ecoregions, the northwestern third of that vast ecoregion is mapped with a preponderance of cover categories 4 and 5. Similarly, the Blue Mountains include lower-elevation cold desert areas where invasive risk is most concentrated.

The composite model with invasive cover categories 1–5 was overlain with existing vegetation distributions from GAP/LANDFIRE (2011) existing vegetation layer to summarize proportional area of major types within each ecoregion (NOTE: type descriptions are available at www.natureserve.org). Appendix 1 (available online at https://doi.org/10.1016/j.rama.2019.09.003) includes a summary for the most prevalent natural vegetation types in which at least some proportion of their areal extent is mapped within one of the invasive cover categories.

Following from mapped estimates of entire ecoregions, vegetation types within the Columbia Plateau, Northern Basin and Range, and Snake River Plain ecoregions include types with > 10% in the most severe cover category (> 45%). Examples include Intermountain Basins Big Sagebrush Shrubland (37%), Columbia Basin Palouse Prairie (28%), and Intermountain Basins Big Sagebrush Steppe (19%) within the Columbia Plateau ecoregion. In the Northern Basin and Range ecoregion, both Intermountain Basins Mixed Salt Desert Scrub (11%) and Columbia Plateau Ash and Tuff Badland (46%) scored high in this most severe category. On the Snake River Plain, Intermountain Basins Volcanic Rock and Cinder Land (15%), Intermountain Basins Mixed Salt Desert Scrub (12%),

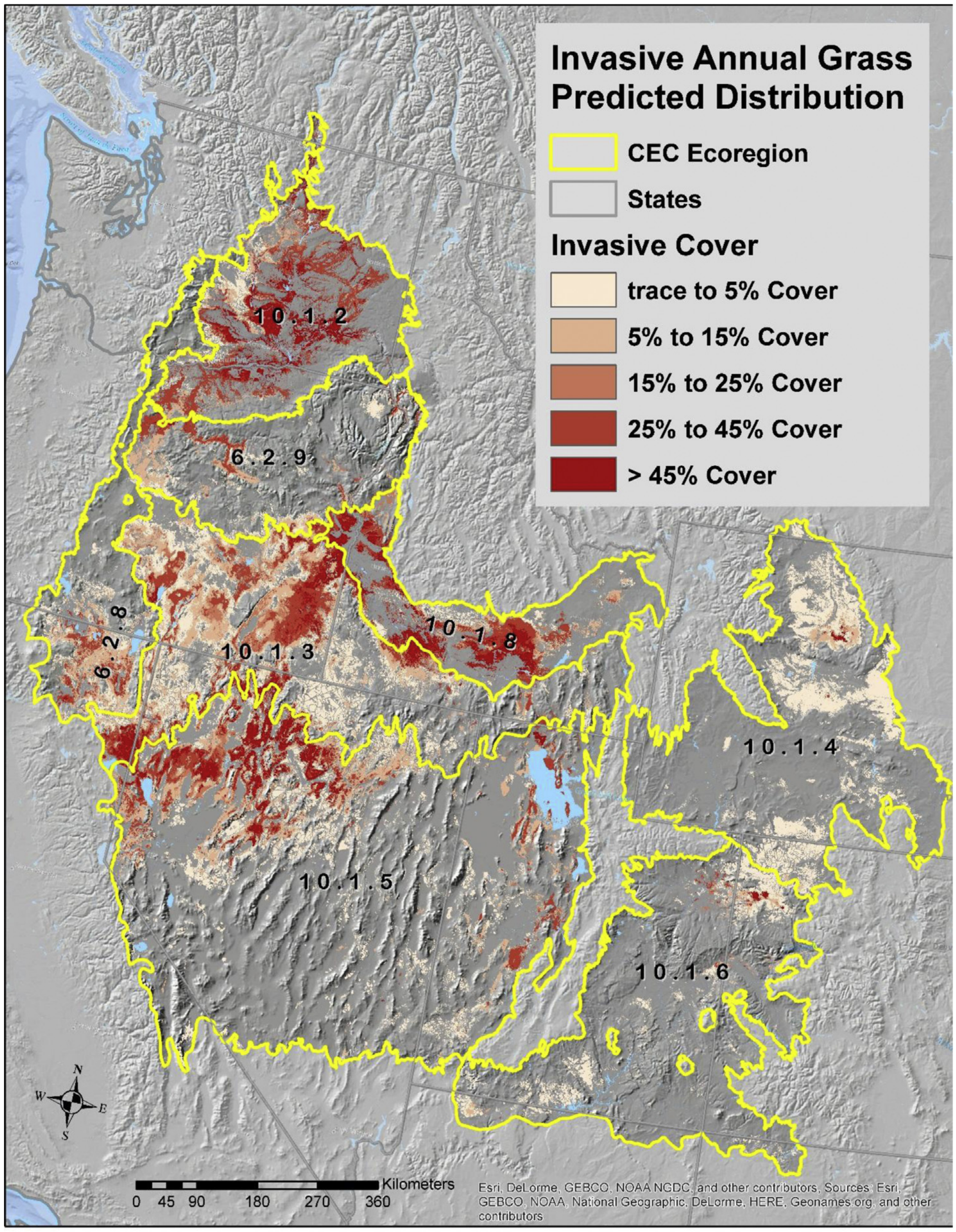


**Figure 2.** Invasive annual grass presence by canopy cover category across cold desert ecoregions (6.2.8 = Eastern Cascades Slopes and Foothills, 6.2.9 = Blue Mountains, 10.1.2 = Columbia Plateau, 10.1.3 = Northern Basin and Range, 10.1.4 = Wyoming Basin, 10.1.5 = Central Basin and Range, 10.1.6 = Colorado Plateaus, 10.1.8 = Snake River Plain).

Intermountain Basins Big Sagebrush Steppe (11%) also scored high (see Appendix 1).

## Discussion

Vegetation types that scored > 10% in three or more cover categories may have the greatest impact from invasive grass effects. The impacts may vary across the range of the type, so distinguishing patterns by type and ecoregion assists with identifying these patterns. For example, on the Columbia Plateau, the Columbia Plateau Steppe and Grassland was mapped with > 10% cover in four of five invasive cover categories, as were the Intermountain Basins Mixed Salt Desert Scrub and Intermountain Basins Greasewood Flat, as they occur in the Northern Basin and Range ecoregion. However, from a rangewide perspective, as has been previously documented in the literature, Intermountain Basins, Big Sagebrush Steppe, and Columbia Plateau Steppe and Grassland each score high for invasive risk in at least four of the eight ecoregions where they occur.

### *Model Application to At-Risk Status Assessment*

At-risk status assessments for biodiversity take many different forms. NatureServe methods factor together trends in the distribution, quality, and threat associated with species and natural communities to determine their relative status (Master et al. 2012; Comer et al. 2019). These methods parallel long-standing approaches for the International Union for the Conservation of Nature (IUCN) red listing of species (Mace et al. 2008) and, more recently, for ecosystems (Keith et al. 2013). For the IUCN Red List of Ecosystems, a measurement of the proportional rangewide extent of an ecosystem type that, within set timeframes, has been impacted by environmental degradation or disruption of biotic processes, gauges the relative risk of ecological collapse across the distribution of the type (Bland et al. 2016). While environmental degradation includes effects of physical alterations to geophysical settings or effects of dynamic process alteration like fire or flooding regime, disruption of biotic processes may encompass many common effects of habitat fragmentation, such as disruption of species dispersal and native species displacement by invasive species. These effects may be inferred from spatial overlay of this type of invasive annual grass model. The D3 subcriterion in the IUCN approach suggests classifying disruption of biotic processes at three levels of severity expressed as proportional area affected by set percentages (> 50%, > 70%, and > 90%) 'severity' if applied to change since 1750) (Bland et al. 2016). Here we could use values that predicted for 15–25% cover, 25–45% cover, and > 45% cover to approximate 50%, 70%, and 90% severity measures, respectively. The results from Appendix 1 could be used to establish relative at-risk scores for each vegetation type.

### *Model Applicability to Forecasting*

This model suggests several avenues to forecast relative risks for invasive grass presence and abundance over upcoming years or decades. First, climate variables identified here are included in common climate projections under a range of anticipated greenhouse gas scenarios and represented with 1-km$^2$ data from, for example, Climate of North America (Wang et al. 2016). Therefore, the same modeling methods deployed here could substitute projected climate data as independent variables to indicate overall shifts in suitable climate for invasive grasses. Second, given the critical importance of vegetation disturbance from wildfire for predicting invasive grass spread, tools for spatial simulation of wildfire spread could be coupled with climate projections to provide increasingly precise predictions of risk for invasive grass spread.

### *Model Performance—Data Limitations*

Although overall model performance was acceptable, limitations arise from each of the model inputs presented here. Ideally, we would have a more robust, spatially balanced set of sample plots reflecting invasive grass presence and abundance. Due to the vast area included here, all available data meeting minimum content requirements had to be used. Agency investments in systematic vegetation sampling, such as those provided by the BLM's AIM Program, are most welcome. Ongoing commitment to field data collection of this nature will be essential into the future.

Other data sets, perhaps most especially for local roads, are also a known limitation. On the basis of experience with the BLM (Comer et al. 2013), it is understood that in many instances, local roads that have been closed for access remain, in some form, on the ground as available spatial data sets. This could lead to distorted model outputs in some areas. Similarly, the location and relative intensity of wildfire, being so important to predicting invasive grass spread, is represented in varying (albeit improving) quality across the region.

Much additional work should be done with available climate data to more precisely focus on variables with greatest predictive power for this sort of modeling. Derivatives of the 19 bioclimate variables used here, especially those focused on temperature and moisture at the soil surface, would likely improve our model. There might be increasing opportunities for integration of these downscaled climate data along gradients described by digital elevation models.

With these data limitations noted, we suggest that a practical minimum mapping area for application of this model should be approximately > 5 ha. That is, one should not presume that values represented by individual 90-m pixels are accurate. Instead, look to aggregations of 10s to 100s of adjacent pixels to approximate the appropriate value for any given area.

## Implications

Land use planners and managers urgently need decision support regarding rangeland restoration and the placement of surface-disturbing vegetation treatments and infrastructure. They need to be able to reliably predict not only the presence but relative abundance (e.g., % cover) of invasive cheatgrass and other invasive plant species in any given location. Evaluations of model performance indicated the strong influence of surface disturbance from local roads and recent wildfire as predictors of invasive annual grass spread throughout these cold desert ecoregions. This has substantial implications for rangeland management because many management activities can result in surface disturbance (e.g., large fire breaks) while attempting to limit potential for wildfire spread. The increasing availabilities of spatial models such as the one presented here can bring additional information for planning these activities to help reduce inherent risks.

Novel methods deployed in this effort also provide options for implementing spatial forecasts of invasive plant expansion under climate and land use conditions of upcoming decades. Enhanced spatial models of this nature could have substantial impact on land management decisions across the Intermountain West over upcoming decades.

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## Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.rama.2019.09.003.

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