Near-Real-Time Cheatgrass Percent Cover in the Northern Great Basin, USA, 2015

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On the Ground

- Cheatgrass (*Bromus tectorum* L.) dramatically changes shrub steppe ecosystems in the Northern Great Basin, United States.
- Current-season cheatgrass location and percent cover are difficult to estimate rapidly.
- We explain the development of a near-real-time cheatgrass percent cover dataset and map in the Northern Great Basin for the current year (2015), display the current years map, provide analysis of the map, and provide a website link to download the map (as a PDF) and the associated dataset.
- The near-real-time cheatgrass percent cover data-set and map were consistent with non-expedited, historical cheatgrass percent cover datasets and maps.
- Having cheatgrass maps available mid-summer can help land managers, policy makers, and Geographic Information Systems personnel as they work to protect socially relevant areas such as critical wildlife habitats.

Keywords: *Bromus tectorum*, ecological models, satellite data, shrub steppe, fire regime, invasive grass.

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Areas where cheatgrass (*Bromus tectorum* L.) existed in the Northern Great Basin of the United States during the recent past are indicative of where environmental conditions are conducive for its growth, where cheatgrass and its seeds likely exist now, and where cheatgrass is expected to germinate and grow, at least into the near future. Cheatgrass in this area causes serious concern because this invasive annual grass helps increase fire frequency, and the spread[1,2] of cheatgrass in shrub steppe environments (Fig. 1). Fires become most problematic when they burn shrub steppe ecosystems and native vegetation is replaced by invasive annual grasses. Invasive annual grasses experience a positive feedback loop with fire, where an increase in annual grass leads to more fires and more fires lead to an increase in annual grass. Fires denude landscapes and, in the process, cause the emission of carbon into the atmosphere, degradation of air quality, reduction of grazing acres, and increase in soil erosion. Fires also burn wildlife habitat, which negatively affects sagebrush obligates including greater sage grouse (*Centrocercus urophasianus*).[3] Greater sage grouse populations declined an average of 2% per year from 1965 to 2003,[4] and this decline has been linked to loss of the shrub steppe. As greater sage grouse populations declined, concern about the species' survival and its habitat heightened. This heightened concern led to consideration of the greater sage grouse as an endangered species.[3] Therefore, knowing early in the summer where, and at what percent cover, cheatgrass exists during a current year could help reveal where cheatgrass might influence a current year's fire occurrences and behavior. Possessing this knowledge could help land managers, fire modelers, and policy makers as they work to protect socially relevant areas such as critical wildlife habitats. To expeditiously identify the location and percent cover of cheatgrass, we developed a near-real-time cheatgrass percent cover dataset and map using a two-step modeling process. This two-step process is described below in the "Estimating Cheatgrass Percent Cover" section. First, however, we describe the Northern Great Basin and briefly describe cheatgrass characteristics and its effect in this ecoregion.

Northern Great Basin and Cheatgrass

The Northern Great Basin, and its adjacent areas, is located in a semiarid environment where the 30-year (1981–2010) precipitation average equals about 434 mm and average temperatures range from a minimum of -11° C to a maximum of 13.8° C.[5] Average elevation equals 1,679 m

Figure 1. A cheatgrass-infested shrub steppe environment in the Northern Great Basin. Cheatgrass 1) provides a fine fuel that increases fire frequency and 2) fills space between shrubs that effectively spreads fire, increasing fire size. Photo courtesy of Stephen P. Boyte.

(North American Vertical Datum 88). The region is dominated by shrubs and grasses, and the primary shrubs are three subspecies of big sagebrush (*Artemisia tridentata* Nutt.). These three big sagebrush subspecies include Wyoming (*A.t.* Nutt. *wyomingensis*), basin (*A.t.* Nutt. *tridentata*), and mountain (*A.t.* Nutt. *vaseyana*). Little sagebrush (*A. arbuscula* Nutt.), black sagebrush (*A. nova* A. Nelson), and threetip sagebrush (*A. tripartita* Rydb.) are also commonly found in the study area. Other shrub species present include rabbitbrush (*Chrysothamnus* Nutt.) and bitterbrush (*Purshia tridentata* [Pursh] DC). Common grasses, other than cheatgrass, include Thurber's needle grass (*Achnatherum thurberianum* [Piper] Barkworth), Sandberg bluegrass (*Poa secunda* J. Presl), bluebunch wheatgrass (*Pseudoroegneria spicata* [Pursh] Á. Löve), crested wheatgrass (*Agropyron cristatum* L. Gaertn.), and Idaho fescue (*Festuca idahoensis* Elmer). Economic activities of Northern Great Basin rural areas are primarily livestock grazing, recreation, mining, forestry, and cultivated agriculture.

Cheatgrass is a winter annual grass that first invaded shrub steppe ecosystems in the western United States more than 100 years ago,[6] and it continues to spread today. Cheatgrass is the predominant invasive annual grass in the Northern Great Basin shrub steppe where it invades ecosystems after disturbances such as fire,[7] development, and heavy grazing. Fire is the most common driver of cheatgrass invasion in the study area where human activities and lightning strikes cause fires. In these disturbed areas, where extensively rooted perennial grasses and biological soil crusts have been severely reduced or eliminated, cheatgrass germinates and initiates growth before most other plants can re-establish. By starting its lifecycle earlier, cheatgrass can deplete available soil resources, leaving a resource gap when other plants need these resources, thus hindering their ability to establish and grow. The cheatgrass growing season differs from the growing season of most other plants in the Northern Great Basin. Cheatgrass germinates sometime between early fall and late spring, depending on conditions, and then in a short time frame, sets seed, senesces, and dies before most other plants reach peak greenness. As a result, cheatgrass emits a phenological (growth) signal during spring and summer that is different than most other plants. Sandberg bluegrass' phenological signal can prove to be an exception because the two species have similar phenological patterns, although on eastern Washington State sand dunes, Sandberg bluegrass' phenological development preceded cheatgrass'.[8] To help mitigate confusion between cheatgrass and Sandberg bluegrass phenological signals, we spatially define the start of spring cheatgrass growth at strongly infested (≥ 30% cheatgrass percent cover) sites.[9] Sandberg's bluegrass percent cover would typically not be so high. The cheatgrass signal can be observed by satellites and identified, which allows us to estimate cheatgrass percent cover throughout the Northern Great Basin.[10] Wildlife and livestock forage on cheatgrass for a short time before it sets seed, which is before most other food sources are available in early spring, but the overall impact of cheatgrass on Northern Great Basin ecosystems is considered negative.

Our focus was on shrub steppe environments, and cheatgrass invasion is not likely to be a strong invader at higher elevations in these environments because of soil moisture and temperature regimes and increased competition from perennial species.[11] For example, in the Northern Great Basin, cheatgrass percent cover estimates showed substantially lower average values in shrub steppe environments between 1,750 and 2,000 m (<2.0%) when compared to the study area as a whole (8.96%);[9] therefore, model development focused on areas at or below 2,000 m elevation. In lower elevations with less competition, cheatgrass responds to annual precipitation with more rapid growth than native plants;[12] therefore, when and where there is more precipitation and less competition from natives, cheatgrass is more likely to be dominant. Conditions can become too arid for cheatgrass to dominate ecosystems in the Great Basin, but our time series indicates this phenomenon most likely will occur south of the study area. Annual precipitation patterns vary widely through space and time in these environments, so the location and percent cover of cheatgrass does vary from year to year. Fires also vary in space and time each year and are dependent on conditions (e.g., presence of fuels like dried cheatgrass) and incidences (e.g., lightning strikes or human activities that cause ignitions).

Estimating Cheatgrass Percent Cover

We used a two-step process to produce an expedited estimation of the location and percent cover of cheatgrass in the Northern Great Basin. In the first step, we developed parameters for an ecological model using regression-tree software. This model was trained on cheatgrass percent cover data[13] from 2001 and 2006. We combined this cheatgrass data with information from site-specific variables that, for the most part, changed little during our study period. These site-specific variables included topography, land cover, soil characteristics, geographic position, and a water flow index,[14] and were used to optimize the model's estimate of cheatgrass percent cover in the study area. These site-specific variables have been used successfully in other ecological modeling studies[15,16] to improve model accuracies. We also added four datasets to our model that were created from satellite data, specifically expedited Moderate Resolution Imaging Spectroradiometer[17] (eMODIS) normalized difference vegetation index (NDVI) data. These eMODIS-NDVI-derived variables are: 1) annual cheatgrass growing season NDVI (GSN), 2) annual summertime periods, 3) annual cheatgrass indices, and 4) annual start of season time, a measure of initial spring green up. The GSN (defined by a spatially dynamic start-of-season dataset) and summertime periods (mid-June to mid-July when cheatgrass has cured and most other vegetation is still green) are used to help identify cheatgrass during its growing season and after its growing season,[18] respectively, each of which varies depending on location and environmental conditions. These GSN and summertime periods also were input into a simple algorithm to calculate each year's cheatgrass index, which provides a rough estimate of annual cheatgrass percent cover.

The eMODIS NDVI is available from an archive[19] for every week of every year since 2000 and outputs pixels at spatial resolutions of 250, 500, and 1,000 m. We used pixels at 250 m. The NDVI measures the abundance of vegetation greenness and has been used as a proxy for vegetation production.[20] The eMODIS NDVI is available as a continuous weekly time series; therefore, the variables created from eMODIS NDVI add a time-step feature to our modeling process. This time-step feature allows us to use the model algorithms and parameters to extrapolate cheatgrass percent cover to any year that weekly eMODIS NDVI is available. We then input our model algorithms and parameters into a mapping application, along with raster datasets of all the site-specific variables and the eMODIS-NDVI-derived variables from 2000 to 2013. The mapping application uses open source code available from RuleQuest,[21] and the raster datasets that are input into the mapping application cover our entire study area. This process allows us to create cheatgrass percent cover datasets and associated maps from 2000 to 2013 over our entire study area, which creates a recent history of cheatgrass dynamics.

In the second step, the regression-tree model parameters we describe in the first step and apply to the 2000 to 2013 data are applied to 2015 eMODIS-NDVI-derived variables and the site-specific variables. This process takes advantage of the time-step feature that the time-series of eMODIS NDVI data provide and develops an expedited, estimated near-real-time cheatgrass percent cover dataset and map for 2015 (Fig. 2). We completed the dataset and map in early summer 2015. The datasets and maps for 2000 to 2013 and 2015 are available online[i]. A dataset available in early summer of each year that estimates cheatgrass percent cover for that specific year can be extremely useful. However, to expedite the development of the 2015 dataset and map and create a near-real-time output using the historical model parameters, the 2015 eMODIS-NDVI-derived variables require modification.

Modifying 2015 eMODIS-NDVI-Derived Variables to Expedite Data Development

The near-real-time dataset requires relatively minor changes to some variables so that the dataset's development can be expedited and the dataset released on or around 1 July. First, 11 years (2000-2010) of summertime satellite image data were averaged and substituted for the 2015 summertime period. Second, to accelerate the availability of the eMODIS NDVI data used for the 2015 GSN, the data were temporally smoothed[22] using a slightly different temporal-moving-window linear regression at each pixel than the 2000 to 2013 GSN data used. (We smooth all eMODIS NDVI data to compensate for clouds, which lower NDVI values.) To validate expediting the development of GSN, we compared expedited 2006 GSN with non-expedited 2006 GSN data (Fig. 3) and found strong consistencies between the two datasets[ii]. Third, we built a cheatgrass start of sustained-growth week (SOSW) continuous variable and substituted it in the model for the start of season time continuous variable, which is unavailable. The SOSW model accuracy is relatively strong[iii]. Fourth, we used an SOSW discrete class to delineate the timing of 2015 GSN patterns through space. A categorical model predicted the correct SOSW class 98% of the time. Because the tests used to assess the potential effects that the modifications had on the time-series model return relatively strong to extremely strong results, these changes are assumed to have little influence on the model output. Consequently, the 2015 near-real-time cheatgrass percent cover data provide a consistent estimate relative to the 2000 to 2013 time series.

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[i] https://nccwsc.usgs.gov/display-project/4f8c64d2e4b0546c0c397b46/5006f498e4b0abf7ce733f92.

[ii] $R^2 = 0.98$; RMSE = 0.87.

[iii] $R^2 = 0.69$.

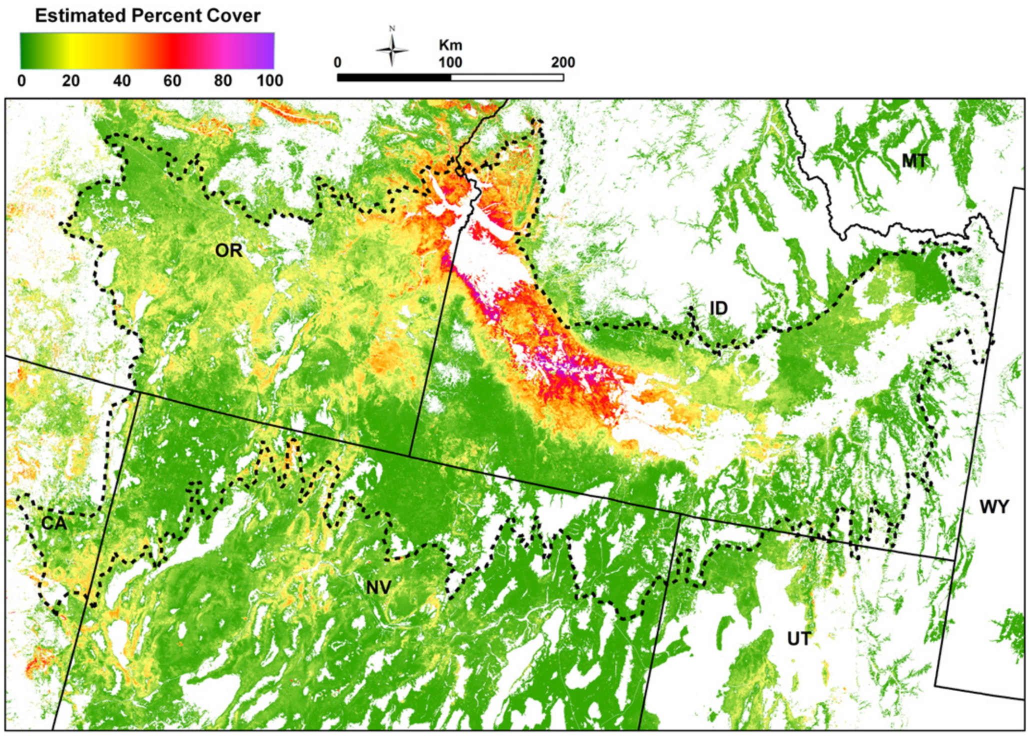

Figure 2. 2015 near-real-time cheatgrass in the Northern Great Basin. The black dashed line delineates the Northern Great Basin, which includes the Northern Great Basin and Range and Snake River Plain ecoregions. Analysis was conducted for all mapped areas that were unmasked. The mask (white) covers areas where the 2001 National Land Cover Database classified the land cover as something other than grassland/herbaceous or shrub/scrub, or elevations were higher than 2,000 m.

Cheatgrass Percent Cover Findings

The 2015 near-real-time cheatgrass percent cover estimate is displayed as a map (Fig. 2), and the percent cover distribution ranges from 0 to 100. The overall mean value for the study area equals 9.85%. The overall standard deviation, representing the dataset's variability, equals 12.78. These statistical measures compare closely to the 2000 to 2013 mean where the cheatgrass percent cover distribution ranges from 0 to 86, the overall mean value equals 8.96%, and the overall standard deviation equals 9.36. The 2015 dataset shows slightly higher cheatgrass percent cover than the 14-year average, with more variability. This slight increase is likely driven by an 8% increase in annual precipitation for 2015 (429 mm) compared to the 14-year average (398 mm), where precipitation totals range from 300 to 578 mm per year. The highest cheatgrass percent cover in both the 2015 and the 2000 to 2013 mean datasets occurs in the Snake River Plain of southwestern Idaho and east-central Oregon where human populations and activities (e.g., agriculture and recreation) typically are higher than in other areas in the Northern Great Basin. Fire polygons downloaded from the Monitoring Trends in Burn Severity database[23] and overlaid onto the 2015 cheatgrass percent cover map illustrate the connection between cheatgrass and fire (Fig. 4). In the study area, 293 fires burned from 2011 to 2013. While all fires did not occur in areas invaded by cheatgrass during 2015, many of the fire polygons are overlain onto areas of substantial cheatgrass cover. The 2015 near-real-time cheatgrass percent cover mean for areas burned in 2011 equaled 19.31. For 2012 burned areas, the 2015 mean equaled 16.19. For 2013 burned areas, the 2015 mean equaled 15.84. These means compare to an overall cheatgrass percent cover mean of 9.85 for 2015, so areas that recently burned contained substantially higher cheatgrass percent cover than the study area as a whole.

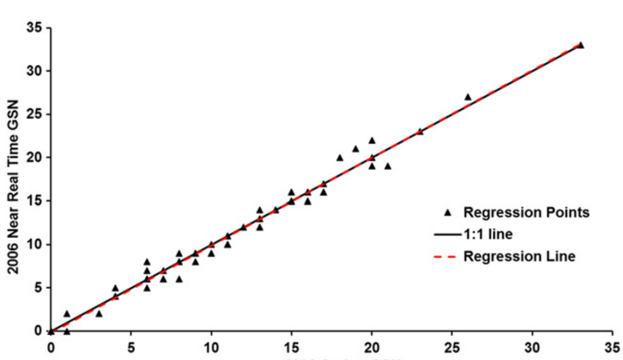

Figure 3. Testing the validity of using near-real-time growing season NDVI (GSN) as a substitute for non-expedited GSN by comparing 2006 near-real-time GSN to 2006 GSN. Data from 66 points indicate that little difference results from using near-real-time GSN. The high R^2 (0.98), the low RMSE (0.87), and the position of the 1:1 line in relation to the linear regression line all indicate a comparable output.

In the 2015 dataset, almost 18% (~750,000 pixels) of the study area registers zero cheatgrass percent cover (Fig. 5). Approximately 50% of the study area has between 1 and 10 cheatgrass percent cover, 23% of the study area has between 11 and 25 cheatgrass percent cover, and 10% has greater than 25 cheatgrass percent cover. To visualize the change reflected in

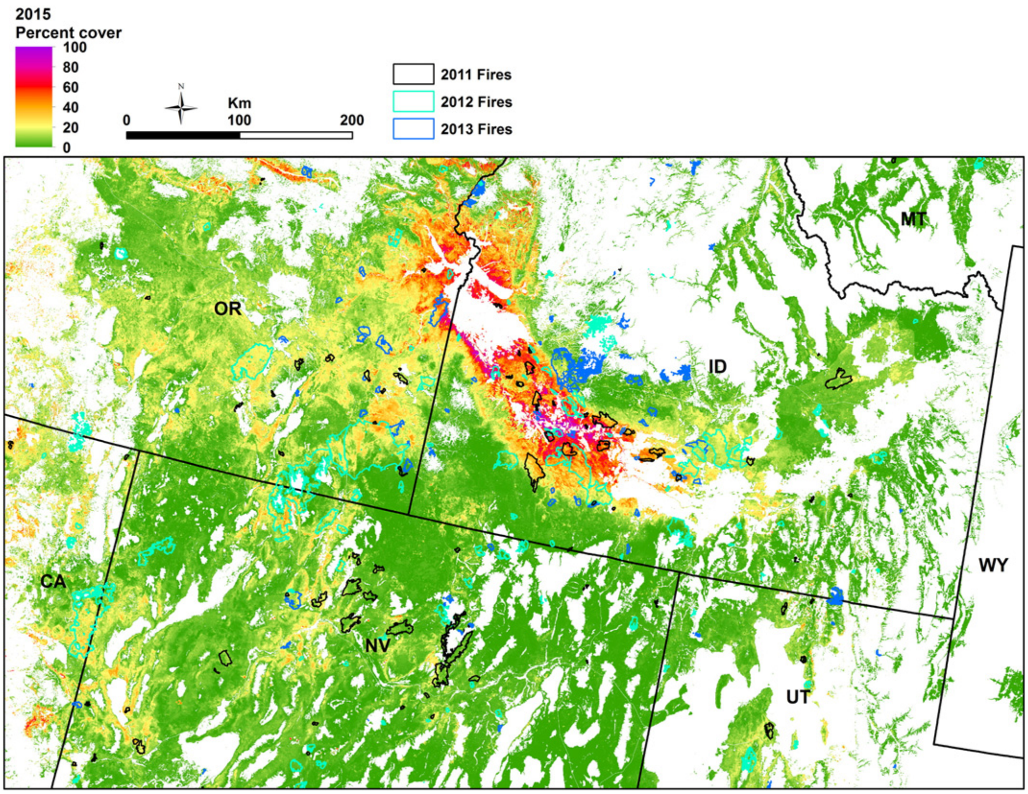

Figure 4. 2015 near-real-time cheatgrass in the Northern Great Basin overlain with Monitoring Trends in Burn Severity fire polygons from 2011 to 2013. This map demonstrates the connection between recent fires and cheatgrass percent cover. The mask (white) covers areas where the 2001 National Land Cover Database classified the land cover as something other than grassland/herbaceous or shrub/scrub, or elevations were higher than 2,000 m.

the 2015 cheatgrass percent cover estimate, we subtracted the 2000 to 2013 mean value from the 2015 near-real-time value at each pixel (Fig. 6). The change between datasets ranges from -54 to 80. The mean change equals 1.28% and the standard deviation equals 7.26. Figure 7 shows the distribution of the change values where no change occurs most frequently, 16% of the time. Change from -10 to -1 occurs over 38% of the area, and change from 1 to 10 occurs over 33% of the area. Overall, 87% of the pixels experience a change between -10 and 10, reflecting relatively close agreement between the 2015 near-real-time dataset and the 2000 to 2013 mean. Across the study area of likely rangelands, 8% has no cheatgrass estimated in either of the two datasets. This finding implies that 8% of the study area experienced either no cheatgrass percent cover during the entire study period or cheatgrass percent cover is too low (< 5%) to be detectable when using 250-m eMODIS NDVI data.

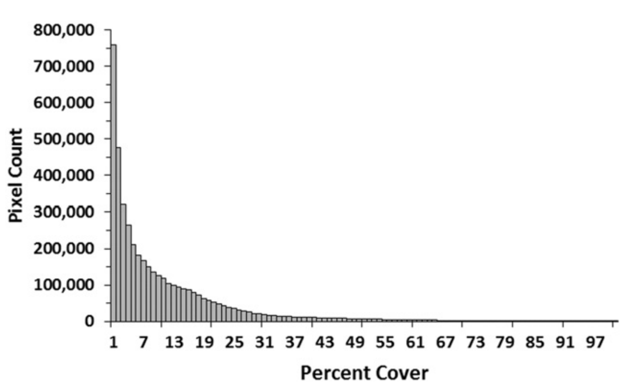

Figure 5. Estimated 2015 near-real-time cheatgrass percent cover distribution throughout Northern Great Basin shrub steppe. Percent cover ranges from 0 to 100, the mean equals 9.85, and the standard deviation, measuring the datasets variability, equals 12.78.

Conclusions

Development of a near-real-time cheatgrass percent cover dataset is successful when it is built using the parameters of a historical cheatgrass model. The success of the dataset is verified by the consistency of spatial context and cover magnitude distributions between the historical and near-real-time datasets. This success is reinforced by the change map (Fig. 6) where a substantial majority of the study area experiences relatively small changes (between -10 and 10) when the 14-year average cheatgrass percent cover dataset is compared to the 2015 near-real-time cheatgrass percent dataset. An annual near-real-time cheatgrass percent cover dataset and associated map could be a valuable addition to planning for and mitigating fire damage in the Northern Great Basin shrub steppe (S. Mavor and L. Smith, personal communication, August 2015). Future research could also explore downscaling the 250-m near-real-time cheatgrass data to 30 m using Landsat data, fusing the superior temporal

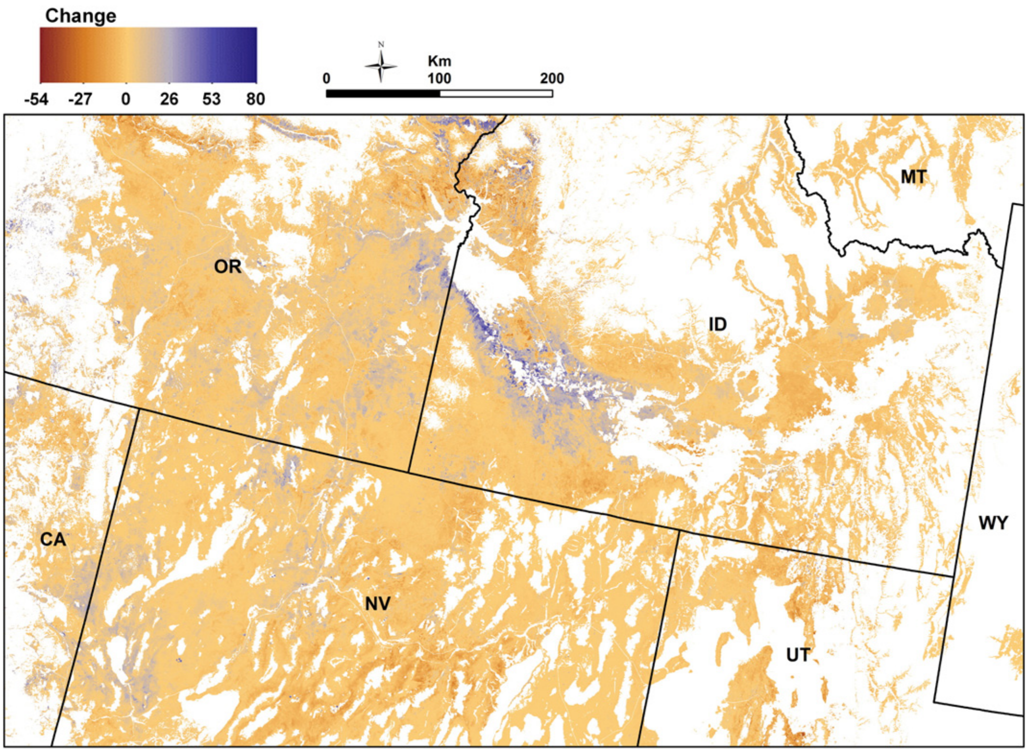

Figure 6. Change map. The 2000 to 2013 cheatgrass percent cover mean subtracted from the 2015 near-real-time cheatgrass percent cover estimate. The mask (white) covers areas where the 2001 National Land Cover Database classified the land cover as something other than grassland/herbaceous or shrub/scrub, or elevations are higher than 2,000 m.

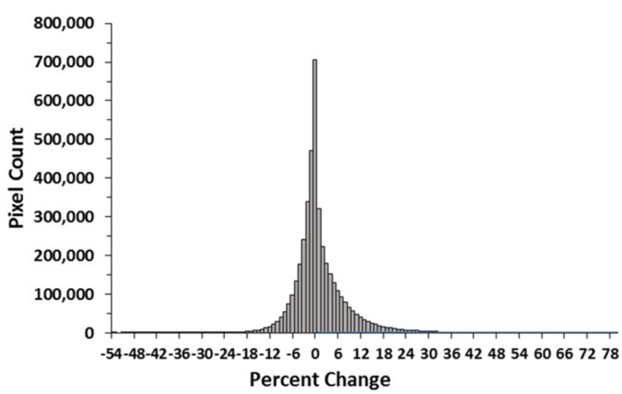

Figure 7. The distribution of change values between the 2000 to 2013 mean and the 2015 near-real-time cheatgrass percent cover estimate. Change ranges from -54 to 80, the mean change equals 1.28, and the standard deviation, measuring the datasets variability, equals 7.26.

resolution of eMODIS NDVI data with the higher spatial resolution of Landsat data. Spatially downscaling this dataset could enhance its usefulness to land managers and other personnel[25] working to mitigate fire damage and develop fire plans.

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