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RESEARCH ARTICLE

Potential cheatgrass abundance within lightly invaded areas of the Great Basin

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Abstract
Context Anticipating where an invasive species could become abundant can help guide prevention and control efforts aimed at reducing invasion impacts. Information on potential abundance can be combined with information on the current status of an invasion to guide management towards currently uninvaded locations where the threat of invasion is high.
Objectives We aimed to support management by developing predictive maps of potential cover for cheatgrass (*Bromus tectorum*), a problematic invader that can transform plant communities. We integrated our predictions of potential abundance with mapped estimates of current cover to quantify invasion potential within lightly invaded areas.
Methods We used quantile regression to model cheatgrass abundance as a function of climate, weather, and disturbance, treating outputs as low to high invasion scenarios. We developed a species-specific set of covariates and validated model performance using spatially and temporally independent data.
Results Potential cheatgrass abundance was higher in areas that had burned, at low elevations, and when fall germination conditions were more favorable. Our results highlight the extensive areas across the Great Basin where cheatgrass abundance could increase to levels that can alter fire behavior and cause other ecological impacts.
Conclusions We predict potential cheatgrass abundance to quantify relative invasion risk. Our model

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results provide high and low scenarios of cheatgrass abundance to guide resource allocation and planning efforts across shrubland ecosystems of the Great Basin that remain relatively uninvaded. Combining information on an invasive species' current and potential abundance can yield spatial predictions to guide resource allocation and management action.

Keywords Invasion risk · Invader abundance · *Bromus tectorum* · Cheatgrass · Quantile regression

Introduction

For well-established invasive species, impact reduction and asset protection strategies direct resources towards prevention and control within uninvaded or lightly invaded areas valuable for biodiversity, culture, or ecosystem services (Auld and Johnson 2014). Potential invader abundance within intact (i.e., lightly invaded) landscapes provides a proxy for potential invader impacts (Parker et al. 1999) and can guide management efforts beyond information on presence (Yokomizo et al. 2009; Sofaer et al. 2018). A focus on abundance is broadly applicable because even widespread invaders have low abundance in most places they occur (Hansen et al. 2013), reflecting patterns of propagule pressure and variation in the recipient environment and biotic community. To inform efficient management, it is critical to differentiate areas where a focal invasive species has the potential to become abundant from areas where low habitat suitability prevents abundance. In this context, two types of spatial predictions are useful: those of current invader abundance, and those of potential invader abundance. Delineating areas with low current invader abundance and high potential abundance can guide spatial prioritization for containment and control efforts.

Management of cheatgrass (*Bromus tectorum*) exemplifies the challenges associated with invaders that can become abundant and problematic across large expanses of a landscape. Cheatgrass infests millions of acres in the Western United States, competing with native plants, altering the availability and phenology of resources for wildlife and forage for livestock, and providing fuel for fires that can trigger a state change from shrubland to annual grassland (Davies et al. 2012; Bradley et al. 2018). The grass-fire cycle creates major challenges for restoration, such that elimination of large cheatgrass infestations is infeasible on landscape scales with the current set of management tools (Davies et al. 2021). However, considerable intact shrubland habitats remain, and integrating knowledge of current and potential patterns of cheatgrass abundance can guide strategies aimed at preventing and limiting invasion impacts.

Here, we model potential cheatgrass cover to predict risk of high abundance across the Great Basin. Previous work has characterized macroecological relationships with cheatgrass occurrence (e.g., Williamson et al. 2020), but because most predictions of cheatgrass abundance are based on remotely sensed data, less information is available on the effects of climate, weather, topography, and disturbance on cheatgrass cover. To focus on the potential for high abundance, we fit a quantile regression model, which can predict potential high cover values even when some limiting factors are unmeasured (Cade and Noon 2003). We defined low risk areas as those where predictions for a high quantile (i.e., a high invasion scenario) suggested low cheatgrass abundance. We evaluated our model using spatially and temporally withheld data. We overlaid our predictions of potential cheatgrass cover with a mapped estimate of current cover based on remote sensing, thereby predicting risk of invasion impacts within areas with low current cheatgrass cover. Our work aligns with regional management strategies with a component to 'defend the core' (USDA 2019; Maestas et al. 2022)—i.e., to prevent the degradation of largely intact areas—and our model predictions can be paired with local knowledge to guide cheatgrass containment and control.

Methods

Cheatgrass and environmental data

Cheatgrass was sampled by Bureau of Land Management (BLM) Assessment, Inventory, and Monitoring (AIM) program (https://gbp-blm-egis.hub.arcgis.com/pages/aim). AIM plot locations are selected via spatially balanced random sampling within BLM lands (Kachergis et al. 2022). Vegetation was sampled using a line-point intercept method (Herrick et al. 2017), and cover within each plot was calculated as the proportion of points along survey transects with cheatgrass (see Online Supplemental Methods). Our analysis was based on 8,470 plots within the Great Basin and surrounding areas sampled from 2011 to 2016, including 782 plots in a spatial strip that were initially withheld for performance assessment, and later included to develop final predictive maps. Data from 2017 to 2019 were withheld for temporally independent model validation.

Cheatgrass is a winter annual grass that germinates in the fall, or in early spring. It grows rapidly, with shallow roots, typically completing its life cycle by June. Cheatgrass germination can be affected by both cold and warm temperatures (Roundy et al. 2007). Germination, survival, and growth are shaped by moisture availability, including the long-term climatic gradients across elevation and weather patterns in a given year (Mack and Pyke 1984; Chambers et al. 2007).

We derived covariates to capture both the climatic averages (1981–2010) that underlie long-term suitability, hereafter referred to as climate, and conditions during the year of observation, hereafter referred to as weather, that can drive annual variation in invasive grass cover (e.g., fall germination conditions were matched to cheatgrass cover sampled the following spring). Custom variables reflected cheatgrass natural history (Table S1). For example, we created a variable to reflect the combination of water availability and warmth for germination and growth by summing growing degree days (> 3 °C and < 25 °C) in the three days following any day in which precipitation was higher than evaporative demand (reflecting a surplus of available water for soil recharge coincident with temperatures conducive to germination). Climate and weather variables were derived from gridMET (Abatzoglou 2013) and calculated separately to reflect fall germination conditions (Oct.-Nov.), the potential for winter growth (Dec.-Feb.), spring growing conditions (Mar.-Jun.), and the entire growing season (Oct.-Jun.). Summertime conditions (July-Aug.) were also included as these can affect native plants; where summertime precipitation dominates, perennial native grasses provide invasion resistance (Chambers et al. 2019). We reduced covariates to limit collinearity within our estimation data ($r \leq 0.7$). We preferred a climatic summary over a weather summary when these were highly correlated, and selected the growing season summary when seasonal metrics were all highly correlated or the separate fall and spring summaries when those were weakly correlated.

Covariates describing geological context (e.g., aspect, elevation, soils), LANDFIRE biophysical settings that describe and map plant communities based on geophysical conditions and natural disturbance regimes (LANDFIRE 2016), fire history (binary burned or unburned), human disturbance and infrastructure, and management history were used to represent processes that may limit or facilitate cheatgrass invasion (Table S2). These included information on fuel breaks; manmade fuel breaks are linear features within which vegetative fuel is reduced to alter fire behavior and aid fire suppression efforts (Shinneman et al. 2019). Estimation and validation data, and model predictions in raster format, have been made publicly available (Sofaer 2022).

Statistical analysis

For a given set of environmental conditions we often observe a range of outcomes, reflecting both stochasticity and unmeasured environmental variables. Quantile regression can be used to understand and predict high invader abundance because it explicitly models different positions (i.e., quantiles) within the response distribution, in contrast to standard regression, which models the mean response. Quantile regression estimates different coefficients for each predictor variable at each quantile of interest, allowing a given environmental variable to be more or less important at the high end of the response distribution. Moreover, the predictions at each statistical quantile of interest can be interpreted as invasion scenarios, as they correspond to low, medium, and high cheatgrass cover for a given set of environmental conditions.

We used a logistic quantile regression model (Bottai et al. 2010) to estimate how the proportion of cheatgrass cover ($y \in [0, 1]$) was associated with environmental conditions. We took the logit transformation of proportion cover, $\mathrm{logit}(y) = \log((y + \varepsilon)/(1 - y + \varepsilon))$, where $\varepsilon = 0.00001$, a small positive number to handle logarithms when cover was zero. The logit(y) was then regressed on the predictor variables (**X**) in a conventional linear quantile regression model, $Q_{logit(y)}(\tau|\mathbf{X}) = \mathbf{X}\boldsymbol{\beta}(\tau)$ for selected values of $\tau \in [0, 1]$; τ is a quantile of logit(y). We selected focal quantiles based on the observed unconditional distribution of cheatgrass (Fig. S1), corresponding to 1% cover ($\tau = 0.30$, i.e., the 0.30th quantile in the empirical cumulation distribution function), 5% cover ($\tau = 0.54$), 10% cover ($\tau = 0.64$), 20% cover ($\tau = 0.76$) and 50% cover ($\tau = 0.93$). To simplify interpretability, we fit a model with a linear effect of each covariate. Rangeland plant communities differ in the degree they resist cheatgrass invasion following fire (Chambers et al. 2019), so we included an interaction term between fire history and LANDFIRE biophysical setting.

We assessed model performance across space and time by (1) analyzing the rank correlation between predictions and observed data from a withheld spatial strip (Fig. 1; n = 782 plots) and from a subsequent time period (2017–2019; n = 3,078 plots), and (2) testing for under- or over-prediction by analyzing the proportion of predictions falling between our lowest and highest modeled quantiles (Romano et al. 2019; Koenker 2020; Online Supplemental Methods),

To visualize risk of abundant cheatgrass in areas with low current invasive grass cover, we mapped predicted cheatgrass abundance based on the highest quantile ($\tau = 0.93$) while masking areas on the landscape with > 10% cover of annual invasive grasses based on remote sensing (Maestas et al. 2020). We selected the highest quantile because areas with low predicted cover at the highest quantile can most confidently be considered to have low risk of abundant cheatgrass. Maestas et al. (2020) combined three approaches to mapping the extent and cover of cheatgrass and other annual invaders *circa* 2016–2020. Although very low levels of cheatgrass cover can have ecological impacts (e.g., increasing burn likelihood, Bradley et al. 2018), we followed Maestas et al. (2020) in defining low annual invasive grass abundance as below 10% cover; this value was also above the mean prediction error associated with the product.

Given our interest in prediction, we also considered machine learning models (Online Supplement). Specifically, we fit a model using the eXtreme Gradient Boosting (XGBoost; Chen and Guestrin 2016) algorithm. XGBoost has a number of hyperparameters that need tuning, and we created spatial blocks to select hyperparameter values that maximized performance in spatially withheld data (Fig. S2). Model validation was then done using the withheld spatial and temporal validation datasets, and predictions overlaid with current cheatgrass cover, following the approach used for quantile regression.

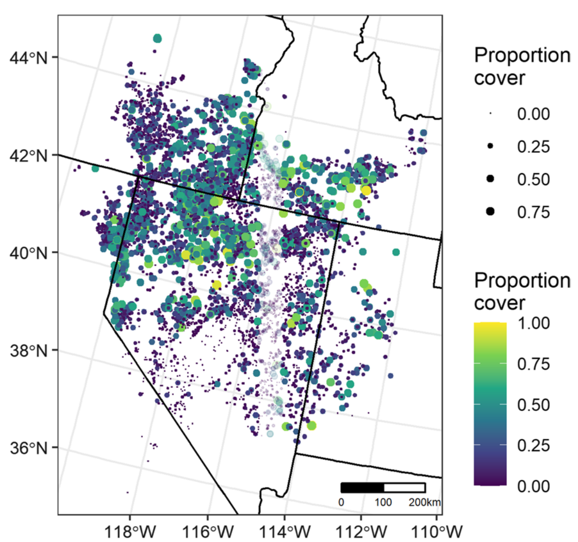


Fig. 1 Cheatgrass (*Bromus tectorum*) cover in the Great Basin was sampled by the Bureau of Land Management's Assessment, Inventory, and Monitoring (AIM) program. Cover within vegetation plots is depicted via both color and size. A spatial strip, shown with greater transparency, was initially withheld for model validation then included in final models to produce predictive maps

Results

Cheatgrass was present in over three quarters of surveyed plots within the Great Basin (78% of plots; 6,579 of 8,470 plots), usually at low abundance (Fig S1; 3% median cover; 13% mean cover). Observed cheatgrass cover within plots showed regional patterns, including high cover in Southern Idaho, Northern Nevada, and Southeastern Oregon (Fig. 1). Cheatgrass cover varied substantially at local scales, with uninvaded plots within highly invaded regions.

Fire history was an important predictor of cheatgrass abundance within our quantile regression model. Burned sites had higher cheatgrass cover across all quantiles (Fig. 2), and most plots with high cheatgrass cover had previously burned (Fig. S3). Fire interacted with the biophysical setting (i.e., the major types of Great Basin vegetation), with stronger effects within big sagebrush steppe and related grasslands and montane sagebrush steppe (Fig. 2).

We found important effects of climatic conditions and annual weather (Fig. 3). The most important

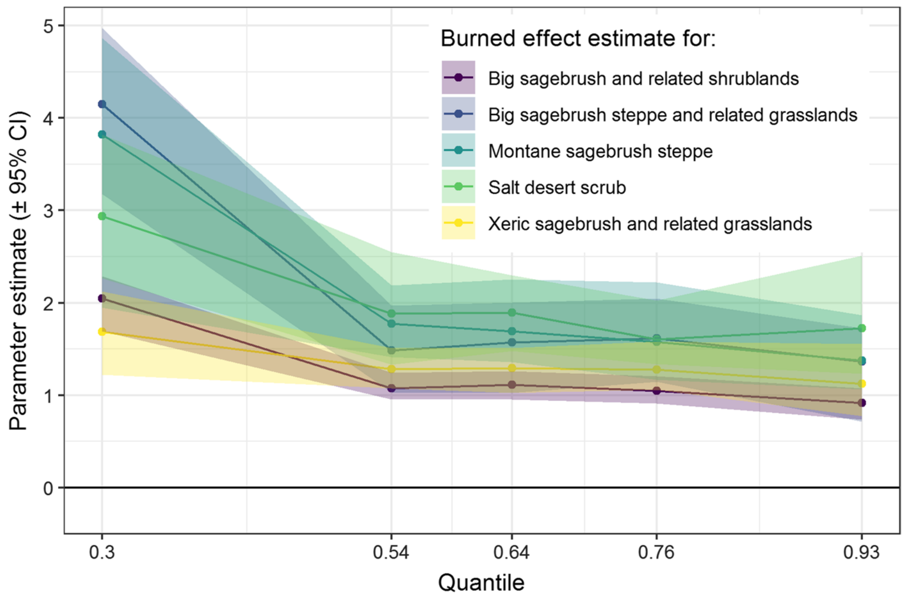


Fig. 2 Across the major vegetation zones, cheatgrass cover was higher in burned plots, with all estimates above the zero line of no effect. Estimates represent the difference in cheatgrass cover in burned compared to unburned plots on a logit scale. Estimated effects were higher for the lowest quantile in part because lower cover values can show big increases on the nonlinear logit scale even when absolute changes are small (see Supplemental Methods)

weather variable was our custom representation of wet growing degree days in the fall; as predicted, this variable had a positive effect on cheatgrass abundance. Across all quantiles, climates with a higher average number of hot fall days (> 30 °C) had lower cheatgrass cover, whereas we estimated a positive effect of the coldest minimum temperature. A higher ratio of precipitation falling in winter (Dec.-Feb. total precipitation/Oct.-Sept. total precipitation, averaged over 1981–2010) was positively associated with cheatgrass abundance.

Management, topography and soils, and land cover variables had effects on cheatgrass abundance which were generally consistent across quantiles (Fig. S4). Elevation was the most important topographic variable, with lower cheatgrass cover at higher elevations. Cheatgrass was higher within Herd Management Areas, and closer to fuel breaks and agriculture. The most important soil variable was depth, with a deeper restriction layer associated with lower cover.

The quantile regression model captured patterns of relative invasion risk in spatially withheld data (rank correlation between predictions and observations: $\rho = 0.5$), and in temporally withheld data ($\rho = 0.4$). Conformal prediction intervals showed reasonable agreement in the distribution of predicted and observed values (59% versus 63% within the focal interval; see Online Supplement). Comparison to spatially withheld data suggested slight over-prediction, but the model under-predicted when applied to the temporally withheld data from subsequent years (2017–2019), because observed cheatgrass cover was generally higher in those years.

Spatial patterns of invasion risk were similar across model quantiles (Fig. 4). We found substantial cheatgrass invasion risk within areas of the landscape that currently have low levels of invasion (Fig. 5). Locations closer to invaded areas were predicted to support higher cheatgrass abundance (Fig. 5a), but most of the Great Basin was predicted to be at risk of cheatgrass cover over 10% under the high invasion scenario (Fig. 5b).

The XGBoost algorithm predicted similar broad-scale spatial patterns of cheatgrass cover as the quantile regression model, and also performed similarly in withheld data. However, the XGBoost algorithm fit the observed data closely, such that very few predictions of high cheatgrass were made beyond the area that Maestas et al. (2020) depict as already invaded by annual grasses at 10% cover or more (Fig. S8). Given the ongoing expansion of cheatgrass (Smith et al. 2022), we considered this as evidence of overfitting. We infer that the XGBoost algorithm produced a map more reflective of current cover than potential cover, making predictions from the quantile regression model more appropriate for our study's aims.

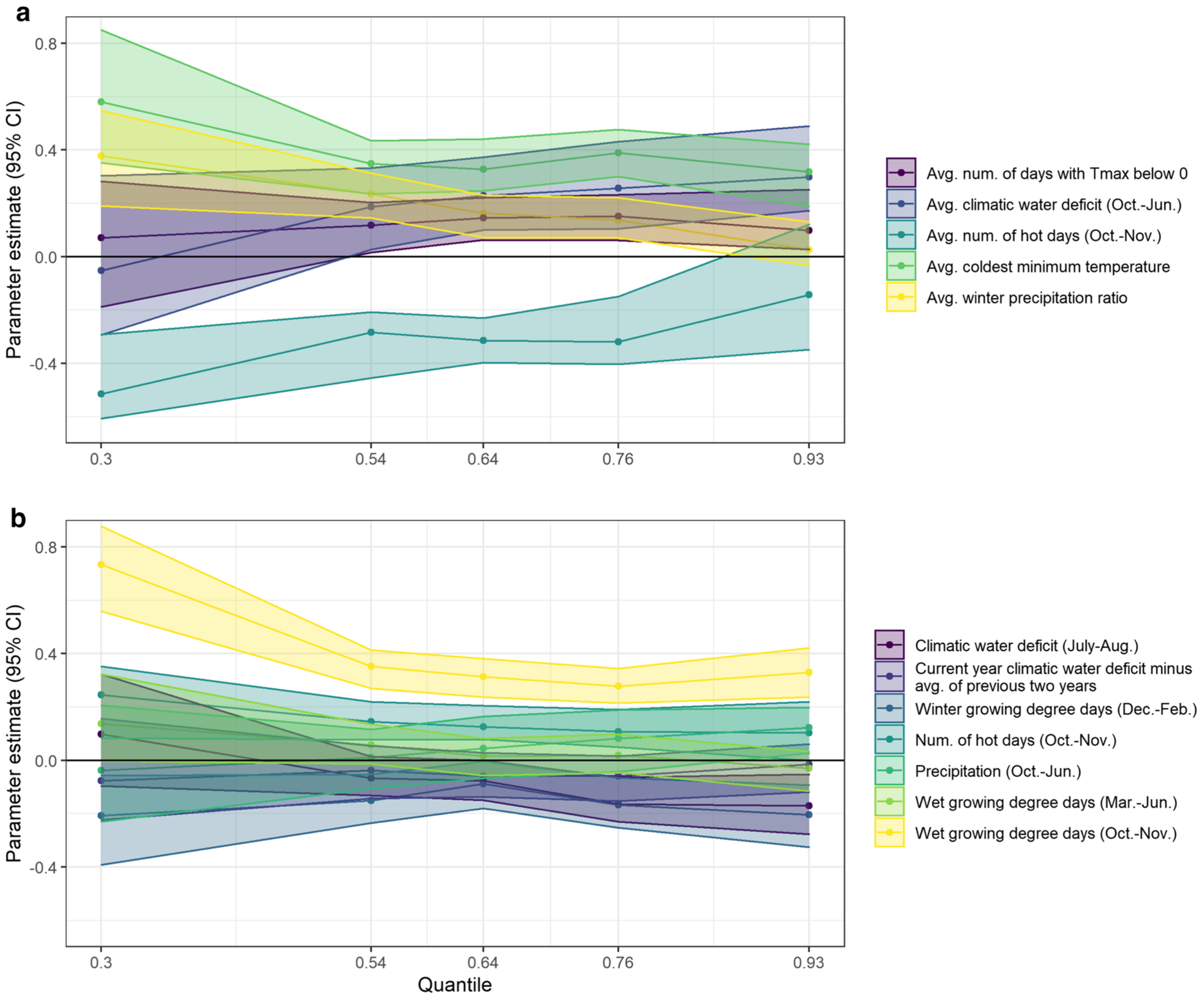


Fig. 3 Quantile regression coefficients for a) climate and b) weather variables. All climate variables are averages over 1981–2010. Weather variables were matched to the growing season of the observation, with fall variables representing germination conditions. All variables are continuous and were standardized prior to model estimates so magnitude of coefficient estimates are comparable

Discussion

Our work highlights relatively uninvaded areas of the Great Basin where cheatgrass could become abundant. Extensive and abundant cheatgrass, and associated grass-fire cycles, have transformed many shrublands and reduced their value for wildlife, livestock, and services such as carbon storage (Bradley et al. 2018; Nagy et al. 2021; Smith et al. 2022). Nevertheless, there remain substantial areas where cheatgrass is absent or at low cover; 22% of AIM plots sampled through 2016 were uninvaded by cheatgrass (Fig. S1). Substantial variation in predicted cover was seen among our low, medium, and high invasion scenarios (i.e., between quantiles) but spatial patterns of relative risk consistently identified susceptible areas of the landscape (Fig. 4). Our findings can guide management by differentiating between uninvaded areas with low suitability for high cheatgrass cover and areas at high risk of abundant cheatgrass (Fig. 5). Specifically, the strategy to 'grow and defend the core' aims to prevent and limit annual grass invasion in high value areas with low current invader cover (Creutzburg et al. 2022; Maestas et al. 2022), and our maps can help identify areas with high invasion risk, i.e., those places where defense is most needed. Our

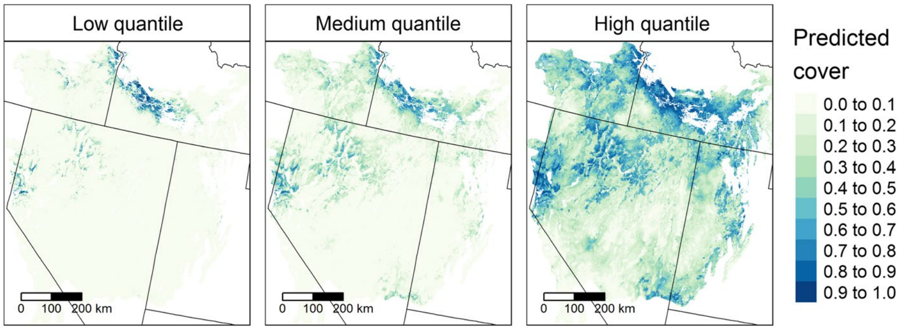


Fig. 4 Predicted proportion of cheatgrass cover at low (τ = 0.30), medium (τ = 0.64), and high (τ = 0.93) quantiles of the statistical distribution across the Great Basin. Predicted cover values increased with the quantile but relative patterns were similar, with some areas of the landscape, such as the Snake River Plain, consistently predicted to have high cheatgrass cover

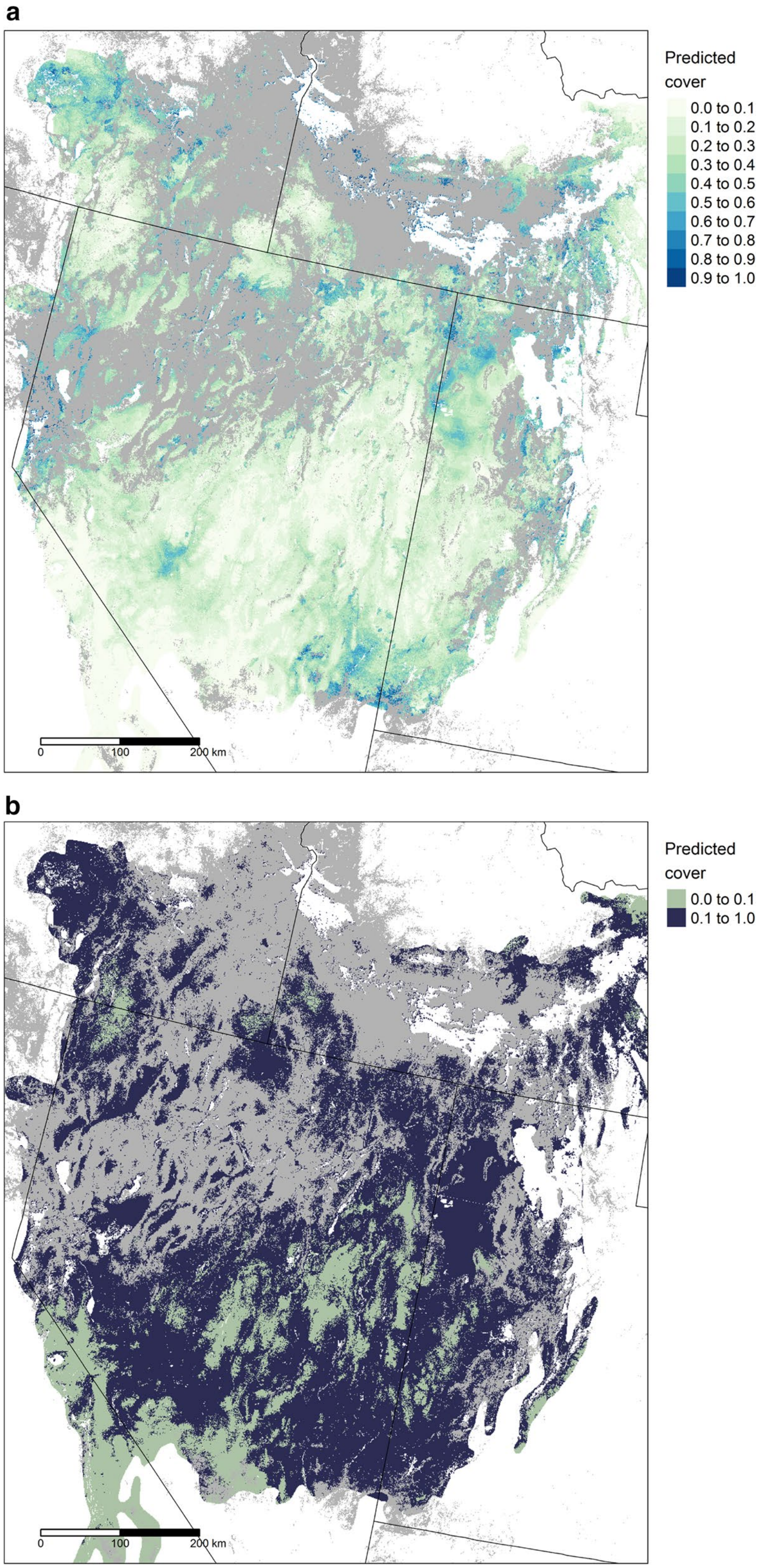
approach—to combine mapped estimates of current abundance with predictions of the potential severity of an invasion—is applicable across taxa and can guide resource allocation towards high-value areas at risk of invasion impacts.

Estimated effects of environmental variation on cheatgrass abundance emphasize the importance of fire and growing conditions. We saw striking effects of fire, which increased cheatgrass cover across all vegetation types and modeled quantiles (Fig. 2). Germination conditions were also important, with warm and wet fall weather associated with higher cheatgrass cover (Fig. 3). Cheatgrass had higher cover in climates where a higher proportion of precipitation fell during winter, and at low elevations, in line with previous findings (Chambers et al. 2019). Cheatgrass cover was also higher in climates with warmer minimum winter temperatures, and the number of very hot fall days (> 30 °C) was negatively correlated with cover, in line with previous findings that these hot temperatures negatively impact germination and growth (Hulbert 1955; Roundy et al. 2007).

Disturbances beyond fire were also important predictors of cheatgrass cover, and may be modified by management efforts. Horse and Burro Management Areas had higher cover, perhaps reflecting overgrazing and chronic disturbance (Beever and Aldridge 2011). Cheatgrass cover was higher closer to fuel breaks, reflecting their placement in areas with high annual grass cover, and/or the potential for fuel breaks to facilitate cheatgrass spread (Shinneman et al. 2019). Land treatments, as categorized in our data, had a small negative effect on cheatgrass cover. However, managers' judgments of invasion risk in a location shape which treatments are applied, complicating estimates of disturbance effects. One potential use of our model's outputs is to inform decisions about whether, where, or how to apply treatments, such as tree removal, that entail soil disturbance. Similarly, our model could help managers direct prevention, containment, and other management actions towards intact but susceptible areas. One pattern seen in our predictions is that high risk areas may often have high propagule pressure because they are near areas where invaders are abundant (blue areas are often adjacent to gray in Fig. 5a). Such a pattern aligns with recent calls to consider and reduce propagule pressure (Maestas et al. 2022). Future work could also predict the potential impacts of disturbances and management actions under low to high invasion scenarios.

Cheatgrass abundance is variable and difficult to predict, reflecting interactions among environmental conditions, propagule pressure, propagule genotypes, and recipient community attributes (Lasky et al. 2020). Predictions from quantile regression models illustrate the variation in plausible outcomes, as the low invasion scenario predicted a much smaller extent of abundant cheatgrass compared to the high invasion scenario (Fig. 4). The high variability among quantile regression predictions at a given location may indicate the potential for prevention and containment to influence outcomes, and also reflects the role of local conditions that are not well represented in our model's inputs. Quantile regression is appropriate in cases where important ecological processes are

Fig. 5 Potential for abundant cheatgrass within areas of the Great Basin with low current cover. In both panels, areas in gray are those already substantially invaded, with > 10% annual grass cover based on remote sensing (*circa* 2016–2020; Maestas et al. 2020). **A** Continuous predictions for proportional cheatgrass cover for a heavily invaded scenario (τ = 0.93). Areas colored in blue are those predicted to have high potential cheatgrass abundance, whereas light green colors represent areas where suitability for abundant cheatgrass is lower. **B** A binary view of the same quantile regression predictions shows that most lightly invaded areas of the Great Basin have a predicted potential for cheatgrass cover over 0.1 (i.e., 10% cover)



not included in the set of covariates (Cade and Noon 2003), and in our model, variation in perennial grass cover and grazing history could underlie variation and uncertainty in potential cheatgrass abundance.

Perennial bunchgrasses provide biotic resistance to invasion because they have high root density near the soil, even below bare ground (Johnson et al. 2022). The ratio of annual to perennial herbaceous cover has therefore been used to differentiate between core, transitioning, and degraded areas (Creutzburg et al. 2022). High perennial bunchgrass cover in a given location would make our low invasion scenario more likely.

The timing, intensity, and spatial patterns of grazing history also underlie cheatgrass invasion risk. Experimental data show that well managed off-season grazing is not tied to increased invasions and can serve to reduce fine fuels and hence fire risk (Davies et al. 2022). However, grazing in the Great Basin has a long and spatially-extensive history, and although information on grazing practices over large areas is limited, observational data link grazing to high invasive annual grass cover over space and time (Williamson et al. 2020). Therefore, predictions from the high quantile of our model may be most appropriate in locations with a history of overgrazing, and conversely, where predicted cheatgrass abundance is high the ecological system may be expected to be sensitive to overgrazing and other disturbances.

While a caveat of our work is that models do not fully capture biological resistance and grazing history, predictions from different quantiles reflect the range of potential outcomes depending on these factors. High variability in predicted cheatgrass cover arises from the difficulty predicting annual grass abundance, and so the low versus high quantiles captured a large range of plausible outcomes in many locations. We suggest that local knowledge can be leveraged while interpreting the range of outcomes, such that the perennial plant community, grazing history, and status of additional invasive species inform model interpretation and use. Similarly, information on potential cheatgrass cover can be used to inform decisions on grazing practices, tree removal, and the design of fuel breaks and containment strategies.

We placed a strong emphasis on model validation, withholding spatially and temporally independent data. Performance assessments showed credible patterns of invasion risk across the Great Basin but underprediction of cheatgrass cover in current (2017 on) and likely future years. This finding aligns with the persistent expansion of invasive grasses, which in recent years have spread to higher elevations and more north-facing aspects to now cover about 20% of Great Basin rangelands (Smith et al. 2022). Evidence for underprediction provides further support for continued high invasion potential (i.e., our model may be more likely to understate invasion risk than to overstate it). We saw strong spatial variation in potential cheatgrass abundance (Fig. 5a), but the high quantile predicted that approximately 80% of lightly invaded areas are vulnerable to high cheatgrass cover. Therefore, most places where exotic annual grass are not already over 10% cover do have the potential to be impacted by invasion (Fig. 5b). These predictions reflect site potential for cheatgrass invasion, and so predictions from our low, medium, and high invasion scenarios are not meant to be reflective of current invasion status.

Our study predicts potential cheatgrass abundance across the Great Basin based on a custom suite of environmental drivers and consideration of the wide distribution of invasion outcomes for a given set of conditions. Model predictions can be treated as hypotheses to pair with local knowledge to inform management planning. Our outputs complement remotely sensed maps that monitor the current state of invasive annual grass invasions (e.g., Maestas et al. 2020; Smith et al. 2022), as well as statistical models that predict current cover (Hak and Comer 2020) or suitability for presence and/or abundance (Bradley 2016). In a review of spatial products mapping invasive annual grasses within the sagebrush biome, Tarbox et al. (2022) found that products predicted 1) current abundance; 2) current presence; and 3) suitability for presence (i.e., species distribution model outputs). Our predictions of potential abundance therefore represent an information source not readily available to decision makers. Models focused on medusahead (*Taeniatherum caput-medusae*), ventenata (*Ventenata dubia*), and red brome (*Bromus rubens*) abundance (e.g., Jarnevich et al. 2021) could similarly inform management and complement maps of current annual invasive grass cover based on remote sensing. Furthermore, our spatially and temporally withheld data provided stronger validation than is typical of existing products (Tarbox et al. 2022). Product accuracy was the biggest issue raised by stakeholders as a barrier for use of existing products (Tarbox et al. 2022), and our work takes a different approach that embraces uncertainty by generating predictions that can be considered low versus high invasion scenarios. Our maps can be used similarly to the zonal mapping of invasion resistance and resilience based on climate and soils (Maestas et al. 2016), with refined spatial detail and a focus on lightly infested areas. Delineating core, transitioning, and degraded rangelands can consider both pixel-level conditions and a broader landscape context (Creutzburg et al. 2022), and our study can help identify both core and transitioning areas with risk of high cheatgrass cover.

Our work quantifies variation in susceptibility to high cheatgrass cover across areas of the landscape with little current invasion. We used biophysical, climatic, and human-related predictors, including custom variables based on the natural history of cheatgrass (Table S1), to predict cheatgrass abundance under low, medium, and high invasion scenarios. This approach allows land managers to proactively target preventative action and containment strategies (e.g., disturbance avoidance, fire prevention and suppression, post-fire restoration) towards areas that are not yet invaded but have conditions that put them at risk. As existing maps typically focus on current cover, our work provides insight into potential frontiers of invasion which are critical for management. Our model can be used to understand the spatial variation in the risk of impactful invasions and further prioritize the allocation of resources in support of core areas protection.

Impacts of invasive species are a function of invader abundance (Parker et al. 1999; Sofaer et al. 2018), making it valuable to understand where an invader has high abundance and anticipate where abundance is most likely to become high. Because it is exceedingly difficult to accurately predict abundance for many species, cheatgrass among them, we used quantile regression to capture a range of invasion scenarios. Variation among quantiles can be used to reflect variables that are not well represented via covariates (Cade and Noon 2003), and where consistent spatial patterns emerge across quantiles (e.g., Fig. 4), these can guide resource allocation decisions irrespective of the uncertainty in absolute abundance. Variation among quantiles also implies that the outcomes of species invasions are not fixed: prevention and management can shape biological communities and minimize invader abundance and impacts. For widespread invaders, management strategies often shift towards asset protection, with the goal of minimizing invasion and its impacts (Auld and Johnson 2014). By combining knowledge of current and potential invader abundance, prevention and containment can be directed towards high-value locations that are not yet invaded but where invasion risk is high.

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References

Abatzoglou JT (2013) Development of gridded surface meteorological data for ecological applications and modelling. Int J Climatol 33:121–131

Auld BA, Johnson SB (2014) Invasive alien plant management. CAB Rev 9:1–12

Beever EA, Aldridge CL (2011) Influences of Free-Roaming Equids on Sagebrush Ecosystems, with a Focus on Greater Sage-Grouse. In: Knick ST, Connelly JW (eds) Greater Sage-Grouse: Ecology and Conservation of a Landscape Species and Its Habitats. University of California Press, Berkeley, CA, pp 273–290

Bottai M, Cai B, McKeown RE (2010) Logistic quantile regression for bounded outcomes. Stat Med 29:309–317

Bradley BA (2016) Predicting abundance with presence-only models. Landsc Ecol 31:19–30

Bradley BA, Curtis CA, Fusco EJ, Abatzoglou JT, Balch JK, Dadashi S, Tuanmu M-N (2018) Cheatgrass (Bromus tectorum) distribution in the intermountain Western United States and its relationship to fire frequency, seasonality, and ignitions. Biol Invasions 20:1493–1506

Cade BS, Noon BR (2003) A gentle introduction to quantile regression for ecologists. Front Ecol Environ 1:412–420

Chambers JC, Brooks ML, Germino MJ, Maestas JD, Board DI, Jones MO, Allred BW (2019) Operationalizing resilience and resistance concepts to address invasive grass-fire cycles. Front Ecol Evol 7:185

Chambers JC, Roundy BA, Blank RR, Meyer SE, Whittaker A (2007) What makes Great Basin Sagebrush ecosystems invasible by *Bromus tectorum*? Ecol Monogr 77:117–145

Chen, T., and C. Guestrin. 2016. Xgboost: A scalable tree boosting system. Pages 785–794 *in* Proceedings of the 22nd acm sigkdd international conference on knowledge discovery and data mining.

Creutzburg MK, Olsen AC, Anthony MA, Maestas JD, Cupples JB, Vora NR, Allred BW (2022) A geographic strategy for cross-jurisdictional, proactive management of invasive annual grasses in Oregon. Rangelands

Davies GM, Bakker JD, Dettweiler-Robinson E, Dunwiddie PW, Hall SA, Downs J, Evans J (2012) Trajectories of change in sagebrush steppe vegetation communities in relation to multiple wildfires. Ecol Appl 22:1562–1577

Davies KW, Boyd CS, Bates JD, Hallett LM, Case MF, Svejcar L (2022) What is driving the proliferation of exotic annual grasses in Sagebrush communities? Comparing fire with off-season grazing. Rangel Ecol Manag 82:76–85

Davies KW, Leger EA, Boyd CS, Hallett LM (2021) Living with exotic annual grasses in the sagebrush ecosystem. J Environ Manag 288:112417

Hak JC, Comer PJ (2020) Modeling invasive annual grass abundance in the cold desert ecoregions of the interior Western United States. Rangel Ecol Manag 73:171–180

Hansen GJA, Vander Zanden MJ, Blum MJ, Clayton MK, Hain EF, Hauxwell J, Izzo M, Kornis MS, McIntyre PB, Mikulyuk A, Nilsson E, Olden JD, Papeş M, Sharma S (2013) Commonly rare and rarely common: comparing population abundance of invasive and native aquatic species. PLoS ONE 8:e77415

Herrick JE, Van Zee JW, McCord SE, Courtright EM, Karl JW, Burkett LM (2017) Monitoring manual for grassland, shrubland and savanna ecosystems. Second Edition. Volume I: Core Methods. USDA-ARS Jornada Experimental Range, Las Cruces, New Mexico

Hulbert LC (1955) Ecological studies of *Bromus tectorum* and other annual bromegrasses. Ecol Monogr 25:181–213

Jarnevich CS, Sofaer HR, Engelstad P (2021) Modelling presence versus abundance for invasive species risk assessment. Divers Distrib 27:2454–2464

Johnson D, Boyd C, O'Connor RC, Smith D (2022) Ratcheting up resilience in the northern Great Basin. Rangelands

Kachergis E, Miller SW, McCord SE, Dickard M, Savage S, Reynolds LV, Lepak N, Dietrich C, Green A, Nafus A, Prentice K, Davidson Z (2022) Adaptive monitoring for multiscale land management: Lessons learned from the Assessment, Inventory, and Monitoring (AIM) principles. Rangelands 44:50–63

Koenker R (2020) Conformal quantile regression: an R Vinaigrette. http://www.econ.uiuc.edu/~roger/research/vinaigrettes/conformal.pdf.

LANDFIRE (2016) LANDFIRE Biophysical Settings layer. Available: https://landfire.gov/bps.php.

Lasky JR, Hooten MB, Adler PB (2020) What processes must we understand to forecast regional-scale population dynamics? Proc R Soc B 287:20202219

Mack RN, Pyke DA (1984) The demography of Bromus tectorum: the role of microclimate, grazing and disease. J Ecol 72:731–748

Maestas J, Jones M, Pastick N, Rigge M, Wylie B, Garner L, Crist M, Homer C, Boyte S, Witacre B (2020) Annual Herbaceous Cover across Rangelands of the Sagebrush Biome: US Geological Survey data release. https://doi.org/10.5066/P9VL3LD5.

Maestas JD, Campbell SB, Chambers JC, Pellant M, Miller RF (2016) Tapping soil survey information for rapid assessment of sagebrush ecosystem resilience and resistance. Rangelands 38:120–128

Maestas JD, Porter M, Cahill M, Twidwell D (2022) Defend the core: maintaining intact rangelands by reducing vulnerability to invasive annual grasses. Rangelands.

Nagy RC, Fusco EJ, Balch JK, Finn JT, Mahood A, Allen JM, Bradley BA (2021) A synthesis of the effects of cheatgrass invasion on US Great Basin carbon storage. J Appl Ecol 58:327–337

Parker IM, Simberloff D, Lonsdale WM, Goodell K, Wonham M, Kareiva PM, Williamson MH, Von Holle B, Moyle PB, Byers JE, Goldwasser L (1999) Impact: Toward a Framework for Understanding the Ecological Effects of Invaders. Biol Invasions 1:3–19

Romano Y, Patterson E, Candes E (2019) Conformalized quantile regression. Adv Neural Inf Process Syst 32:3543–3553

Roundy BA, Hardegree SP, Chambers JC, Whittaker A (2007) Prediction of cheatgrass field germination potential using wet thermal accumulation. Rangel Ecol Manag 60:613–623

Shinneman DJ, Germino MJ, Pilliod DS, Aldridge CL, Vaillant NM, Coates PS (2019) The ecological uncertainty of wildfire fuel breaks: examples from the sagebrush steppe. Front Ecol Environ 17:279–288

Smith JT, Allred BW, Boyd CS, Davies KW, Jones MO, Kleinhesselink AR, Maestas JD, Morford SL, Naugle DE (2022) The elevational ascent and spread of exotic annual grass dominance in the Great Basin, USA. Divers Distrib 28:83–96

Sofaer HR (2022) Great Basin predicted potential cheatgrass abundance, with model estimation and validation data from 2011–2019. U.S. Geological Survey data Release. https://doi.org/10.5066/P9OEY7X5.

Sofaer HR, Jarnevich CS, Pearse IS (2018) The relationship between invader abundance and impact. Ecosphere 9:e02415

Tarbox BC, Van Schmidt ND, Shyvers JE, Saher DJ, Heinrichs JA, Aldridge CL (2022) Bridging the gap between spatial modeling and management of invasive annual grasses in the imperiled Sagebrush Biome. Rangel Ecol Manag 82:104–115

USDA (2019) The cheatgrass challenge: a proactive strategy for halting conversion of sagebrush rangelands to annual grasslands. U.S. Department of Agriculture Natural Resources Conservation Service. http://www.sagegrouseinitiative.com/wp-content/uploads/2020/07/cheatgrass_final1.pdf

Williamson MA, Fleishman E, Mac Nally RC, Chambers JC, Bradley BA, Dobkin DS, Board DI, Fogarty FA, Horning N, Leu M, Wohlfeil Zillig M (2020) Fire, livestock grazing, topography, and precipitation affect occurrence and prevalence of cheatgrass (*Bromus tectorum*) in the central Great Basin, USA. Biol Invasions 22:663–680

Yokomizo H, Possingham HP, Thomas MB, Buckley YM (2009) Managing the impact of invasive species: the value of knowing the density–impact curve. Ecol Appl 19:376–386