



Russian olive distribution and invasion dynamics along the Powder River, Montana and Wyoming, USA

Karissa Courtney[✉] · Catherine Buczek · Sharon Bywater-Reyes[✉] ·
Dahlia Shahin · Amy Tian · Carly Andrews · Scott Franklin[✉] ·
Brian Woodward[✉] · Scott Cunningham · Anthony G. Vorster[✉]

Received: 14 July 2023 / Accepted: 4 July 2024 / Published online: 3 August 2024
© The Author(s) 2024

Abstract The invasive shrub, Russian olive (*Elaeagnus angustifolia*), is widely established within riparian areas across North America and eastern Europe. Limited information on its distribution and invasion dynamics in northern regions has hampered understanding and management efforts. Given this lack of spatial and ecological information we worked with local stakeholders and developed two main objectives: (1) map the distribution of Russian olive along the Powder River (Montana and Wyoming, United States) as of 2020 with field data and remote sensing; and (2) relate that distribution to

environmental variables to understand its habitat suitability and community/invasion dynamics. Field data showed Russian olive has reached near equal canopy cover (18.3%) to native Plains cottonwood (*Populus deltoides*; 19.1%) and has a broader distribution. At the watershed scale, we modeled Russian olive distribution using field surveys, ocular sampling of aerial imagery, and spectral variables from Sentinel-2 MultiSpectral Instrument using a random forest model (RMSE = 15.42, $R^2 = 0.64$). A statistical model linking the resulting Russian olive percent cover detection map to environmental variables for the entire watershed indicated Russian olive cover increased with flow accumulation and decreased with elevation, and was associated with poorer soil types. We attribute the success of Russian olive to its broad habitat suitability combined with changing hydrologic conditions favoring it over natives. The maps of Russian olive cover along the Powder River and its main tributaries in northern Wyoming and southern Montana revealed regions of the watershed with high and low cover, which can guide landscape-scale management prioritization. This study provides a repeatable Russian olive detection method due to the use of Sentinel-2 imagery that is available worldwide and provides insight into Russian olive's ecological relationships and success with relevance for management across areas with similar environmental conditions.

Supplementary Information The online version contains supplementary material available at <https://doi.org/10.1007/s10530-024-03394-3>.

K. Courtney (✉) · C. Buczek · D. Shahin · A. Tian ·
C. Andrews · B. Woodward · S. Cunningham ·
A. G. Vorster
NASA DEVELOP National Program, NASA Langley
Research Center, Hampton, VA 23681, USA
e-mail: karissa.courtney@colostate.edu

S. Bywater-Reyes
Earth and Atmospheric Sciences Department, University
of Northern Colorado, Greeley, USA

S. Franklin
School of Biological Sciences, University of Northern
Colorado, Greeley, USA

B. Woodward · A. G. Vorster
Natural Resource Ecology Laboratory, Colorado State
University, Fort Collins, CO 80523-1499, USA

Keywords Russian olive · *Eleagnus angustifolia* ·
Exotic invasion · Remote sensing · Riparian ecology

Introduction

Rivers and floodplains, and their associated habitat and biological diversity, are among the most endangered ecosystems on Earth (Naiman and Decamps 1993; Costanza et al. 2014; Petsch et al. 2022). Adding to this issue is the increasing encroachment of the non-native invasive, Russian olive (*Elaeagnus angustifolia*), a shrub/tree that has established widely across North America and eastern Europe, and is continuing to spread (Borsukevych et al. 2023; Botta-Dukát Balogh 2008; Collette and Pither 2015b; Katz and Shafroth 2003; Protopopova et al. 2006). Like tamarisk (*Tamarix*), Russian olive was introduced to the western United States (U.S.), in the early twentieth century and has increased its distribution in the last 40 years (Friedman et al. 2005; Reynolds and Cooper 2010). Studies have shown Russian olive alters sediment dynamics (David et al. 2017), nutrient cycling (Simons and Seastedt 1999; Mineau et al. 2012) and community composition (Katz and Shafroth 2003), outcompetes native vegetation (Pearce and Smith 2001; Katz et al. 2020), and promotes other nonnative species cover (Reynolds and Cooper 2010). Russian olive is a successful invader in the U.S. due to its high tolerance of dense shade and low-moisture conditions compared to both native cottonwood and exotic tamarisk (Reynolds and Cooper 2010). Cumulatively, these outcomes alter wildlife habitat (Knopf and Olson 1984; Leatherman 2011), and its broad habitat niche poses a threat to western U.S. rivers and riparian vegetative composition, structure, and function (Faanes and LeValley 1993; Pearce and Smith 2001; Nagler et al. 2011; Collette and Pither 2015b; McShane et al. 2015; Bush et al. 2020; Green and Grosholz 2021).

Riparian areas are especially vulnerable to non-native plant invasions due to a combination of factors, including changes in land use, hydrology, and sediment transport (Park et al. 2019; Thomaz 2022). Floodplains are mosaics of water and resource variability, and as such, wetter areas of floodplains may be more resistant to invasions whereas mesic patches or time periods may be more favorable to invasion (Tabacchi et al. 2000; Mikulová et al. 2020; Rood et al. 2020). The abundance of invasives is often spatially heterogeneous within floodplains, making management and species mapping challenging (Pattison

et al. 2019), highlighting the need to understand invasion dynamics at a range of spatial scales.

Studies are needed on the distribution, invasibility, and spatial configurations of Russian olive in western states' riparian areas (Katz 2016; Perry et al. 2018; Evangelista et al. 2018), particularly in northern regions of the U.S. (Pearce and Smith 2001; McShane et al. 2015; Evangelista et al. 2018). Field data, in general, are often cumbersome and expensive to collect at larger scales, making remote sensing a valuable solution to understanding invasive species distributions across landscapes and watersheds. Previous studies have modeled habitat suitability of Russian olive at broad scales (North America: Collette and Pither 2015a, b; national U.S.: Jarnevich et al. 2022; western U.S.: Perry et al. 2022), which can be helpful in identifying areas potentially suitable for the species. Detection models show where the species is currently present, and doing so at a watershed scale is useful for land managers needing to make decisions on where to deploy various strategies as understanding landscape context is critical for invasive species management (e.g., Maestas et al. 2022). We are not aware of any studies that have mapped Russian olive canopy cover in a detection model within the U.S. at a regional watershed scale appropriate for management. Here we use the USGS Hydrologic Unit Code (HUC) to define our study watershed. The HUC system is used for data collection and management at the federal and state levels in the U.S., ranging from regional scale (HUC 2-digit code) to local scale (HUC 12-digit code).

Community members and ranchers along the Powder River have voiced concerns over the increased presence of Russian olive in recent decades (G. Gay, personal communication, May 2021). Topics of interest that were mentioned include habitat and landscape alteration, interference with livestock management, spread patterns, and potential management interventions. Research questions were constructed collaboratively with community members and our shared objectives were to: (1) map the distribution of Russian olive along the Powder River with a combination of field data and remote sensing in order to (2) relate that distribution to environmental variables to understand Russian olive habitat suitability and community and invasion dynamics in the Powder River Basin, U.S. We mapped the distribution of Russian olive using freely available software such as Google Earth

Engine and R Studio, and imagery from the National Agricultural Imagery Program (NAIP) 2019, Sentinel-2 MultiSpectral Instrument, creating a method that can be replicated in other areas with similar environmental conditions.

Methods

Study area

The Powder River Basin, part of the Upper Missouri River Watershed, originates in northern Wyoming, draining north into Montana where it eventually flows into the Yellowstone River downstream of Miles City, Montana (Fig. 1). Located within the West-Central Semiarid Prairie ecosystem and used mostly for agriculture and ranching (Flores et al. 2001), the Powder River Watershed has a mean annual temperature of 8 °C and mean annual precipitation is 15.48 cm (PRISM Climate Group 2004). The Powder River has a ‘dual-peaked hydrograph’ with contributions from both spring snow-melt and summer rainfall (Whitlock et al. 2017), similar to the better-studied Southwest U.S. rivers. The climate of the study area is considered cold arid steppe, but also has continentally-influenced warm summers (Köppen-Geiger climate classification; Beck et al. 2018). For this study, we delineate the watershed just upstream of its confluence with the Yellowstone River (drainage area of 34,691 km²; just downstream of USGS MT06326500 near Locate, Montana). High-altitude tributaries (Clear Creek, Crazy Woman Creek, South Fork, and Middle Fork) drain into the lowlands at the Montana-Wyoming state line. We defined the study area as a 2000 m buffer adjacent to streams as defined by USGS standardized flowlines (NHDPlus HUC6; Terziotti and Archuleta 2020) inspected visually to ensure the inclusion of any areas with woody vegetation (Fig. 1).

Remote sensing data and detecting russian olive distribution

Model training data

To predict Russian olive percent cover across the Powder River Basin, we created a spectral detection model for the year 2020. The model was trained

using two different data collection methods: (1) field data and (2) ocular samples from NAIP 2019 aerial imagery. Field data were collected in June 2021 (Fig. 1A). Ten meter radius plots were placed on transects (25 on the east bank and 17 on the west bank) perpendicular to the river and about 50 m apart, for a total of 276 plots (Fig. 1A). Within each plot, vegetation cover was estimated for each woody species, including Russian olive, plains cottonwood (*Populus deltoides*), and tamarisk (*Tamarix ramosissima*), and height of the tallest woody plant was measured using a survey rod or clinometer. Of the 276 field data plots, 185 contained Russian olive.

To increase the dataset size and spatial representation, we conducted randomized ocular image sampling using NAIP 2019 true and false color imagery following a similar sampling procedure as described in (Woodward et al. 2018a, 2018b). NAIP 2019 false color imagery was referenced to help with species classification. We used Google Earth Engine (GEE) to collect 10-m radial plots, matching the size of the field plots. We visually determined the percentage of Russian olive coverage present on a scale of 0–100%, with 0% being no Russian olive present and 100% being full Russian olive cover, within each 10-m radial plot (Fig. 2). Prior to making formal observations, all five observers went through a calibration process to train and reduce bias. Due to the rarity of Russian olive in our random sample, we also opportunistically collected 478 additional plots with Russian olive. Most opportunistic aerial imagery ocular sampling points fell along the Powder River between Clear Creek and Crazy Woman Creek in Wyoming.

In preliminary model runs, low to moderate Russian olive cover was unrealistically predicted in cropland areas, such as areas of Barley (Categorization Code “21”), Winter Wheat (“24”), Alfalfa (“36”), and Other Hay (“37”), so we created a simple mask to remove most crops from the final analysis. The mask was created using land cover classifications from the 2020 USDA National Agricultural Statistics Service Cropland Data Layer (NASSCD; 2021). Land cover types where Russian olive is known to occur such as Shrubland (NASSCD attribute code “152”), Grassland/Pasture (“176”), Woody Wetlands (“190”), and Herbaceous Woodlands (“195”) were retained. Table S1.2 contains a detailed list of land cover types that were not masked from the final model. All NASSCD

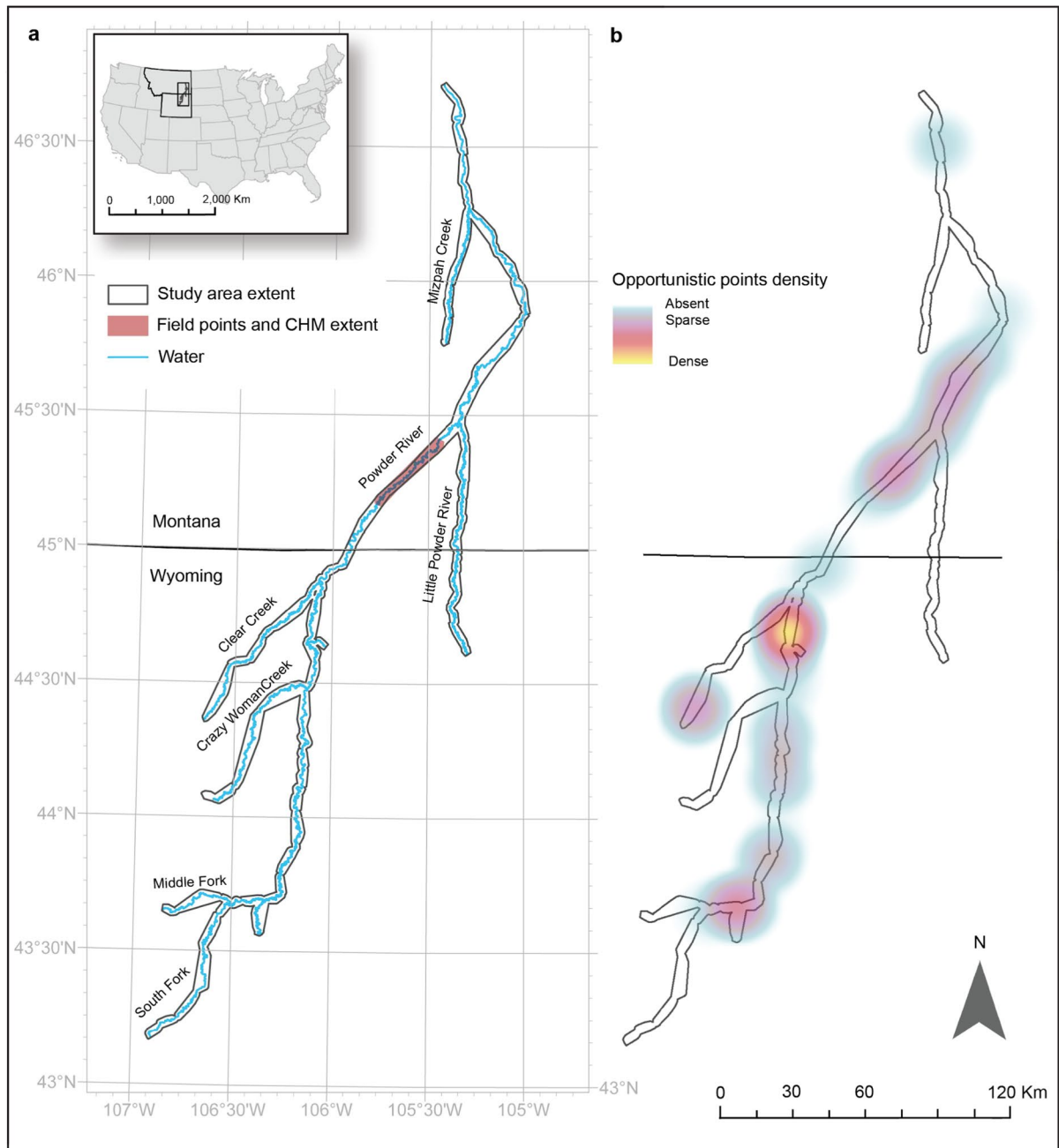


Fig. 1 **A** Study area (contorted black line) in the Powder River Basin and five of its tributaries (blue), located in southeastern Montana and northeastern Wyoming, U.S. The red highlighted area depicts the region where field data were collected and the

canopy height model (CHM) extent. **B** Heat map showing the density of 477 opportunistic ocular sample points. An additional 1,407 ocular points were randomly distributed across the entire study area extent

agricultural land cover types from 0–61, 66–77, and 204–254 were excluded from the Russian olive model. The mask was also used to remove the ocular samples to build the model on sampled

points that did not fall within agricultural areas. We built our model on 2160 points (1407 random ocular samples, 477 opportunistic ocular samples, 276 field samples), 595 of which had Russian olive

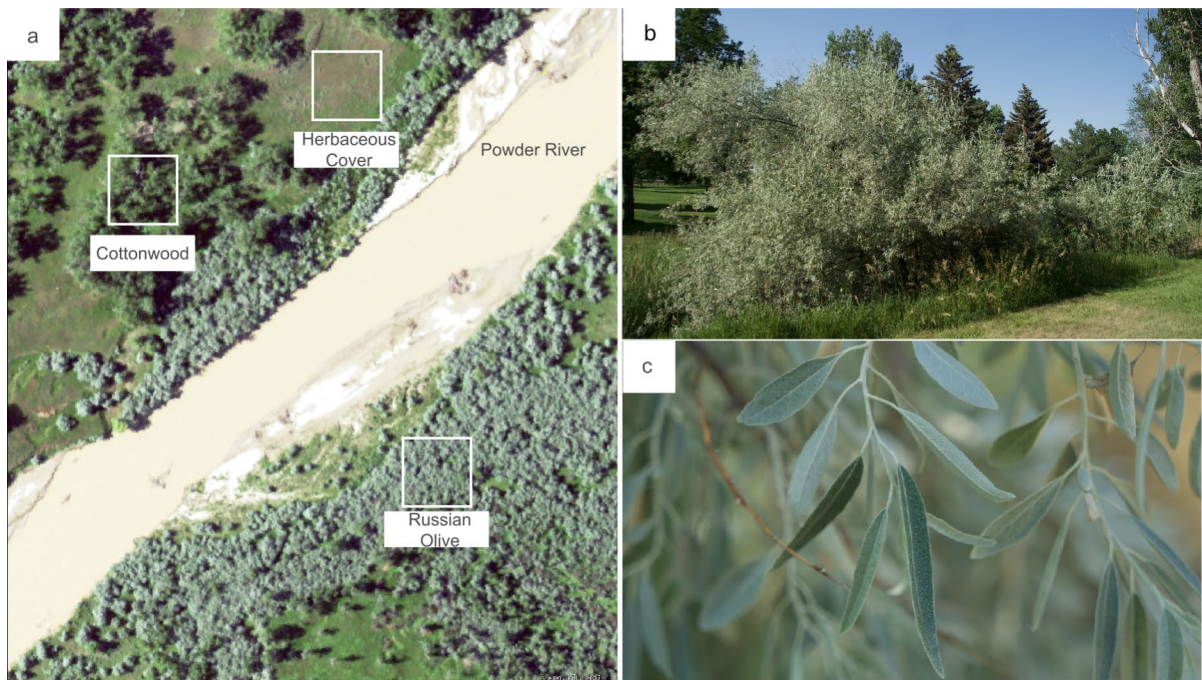


Fig. 2 **A** Distinguishing between Russian olive, cottonwood, and herbaceous cover such as grass using NAIP 2019 imagery. **B** A photograph of a Russian olive shrub (photo credit: Karissa

Courtney). **C** A zoomed in photograph of Russian olive leaves (photo credit: Karissa Courtney)

present (419 ocular samples; see Data Availability section for data repository).

Random forest model

We created a mosaic of 2020 imagery from Copernicus Sentinel-2 MultiSpectral Instrument Level-1C data to cover the Powder River Basin study area, obtained in GEE. We filtered images for those with low cloud cover (<20–30%), then created a median composite image for each relevant season—spring (2020-04-01 to 2020-05-15), summer (2020-05-16 to 2020-07-31), and fall (2020-08-01 to 2020-09-30)—to account for seasonal phenological variation (Gorelick et al. 2017). Spectral bands and vegetation indices were derived from the images, which included a Normalized Difference Vegetation Index (NDVI), Normalized Difference Moisture Index (NDMI), Normalized Burn Ratio (NBR), Simple Ratio (SR), Tasseled Cap transformation, and others (Table S1.1). The resulting Tasseled Cap brightness, greenness, and wetness (BGW) indices, named for the features they emphasize, improve vegetation classifications

because they are sensitive to phenological changes (Crist and Ciccone 1984). We also differenced indices between summer and spring and summer and fall to capture seasonal variation of different species to aid Russian olive detection (Evangelista et al. 2009).

We modeled Russian olive percent cover and evaluated predictor variable performance using the ‘randomForest’ package in RStudio (Liaw et al. 2002) using spectral bands and vegetation indices from GEE. Our independent variable was Russian olive percent cover and all 61 predictor variables are identified in Table S1.1. The number of trees (ntree) and number of variables randomly sampled at each split (mtry) were set to 1000 and 3, respectively (Liaw et al. 2002). We valued a model with fewer predictor variables and removed predictors that did not improve the model to achieve better model performance and greater interpretability (Evans et al. 2010). We first ran a model using all predictor variables to evaluate initial out-of-bag model performance using the R^2 value and root mean squared error (RMSE), a standard measure of the magnitude of model error. We then evaluated correlations between variables, removing

one variable from pairs correlated by greater than 0.7 (Dormann et al. 2013), leaving us with 18 variables after the initial run. With the remaining 18 uncorrelated variables, we ran 12 additional models using backwards selection to remove the one or two variables with the lowest variable importance as measured by the increase in mean squared error. Variables with partial dependence plots that suggested the variable contributed to over-fitting or had a weak relationship were removed (Friedman 2001). The greater the R^2 value and the smaller the RMSE, the better the model performed. The final model had six variables. Finally, we summarized the random forest model results by 5 km hexagon to show trends of Russian olive cover across the study area.

Species composition and russian olive habitat suitability at the watershed scale

Plot data collected along transects perpendicular to the Powder River channel allowed for additional insights when paired with lidar and topographic data, particularly because a robust suite of woody species was recorded in addition to Russian olive. Topographic position index (TPI) was derived from 2016 lidar data (Ackerman 2016). TPI is a measure of position by comparing elevation at a given point to the mean elevation in a surrounding window (Weiss 2001). In this case, a 100 cell (100 m) radius was used and can be interpreted as position relative to the detrended channel. We also derived a Canopy Height Model (CHM), calculated as the digital terrain model minus the digital surface model, calculated in OpenTopography.org. We extracted mean TPI, CHM, and distance from channel centerline to field plots to investigate how these varied by species by considering variable distributions (i.e., boxplots and basic statistical moments and distributions) by dominant plot species. Additionally, we used the complete suite of species and cover data in a k-means grouping analysis that included distance from the channel in ArcGIS Map. The k-means grouping method is an unsupervised classification method where every point is assigned a group based on their similarity (Davies and Bouldin, 1979). The Pseudo F-Statistic was used to determine how many groups to include in the final analysis. This allowed inference regarding the spatial relationships among Russian olive, cottonwood, and

tamarisk, which was not possible in the watershed-scale modeling.

Previous work (Nagler et al. 2011) describes factors at the continental to reach scale known to influence Russian olive distribution. Robust species cover data for an entire watershed is rare. As such, here we have a unique opportunity to bridge the reach and continental scales (Nagler et al. 2011). At watershed scales, surface and groundwater flow conditions, and their regulation, are known to influence native and invasive riparian species distributions across North America (McShane et al. 2015). Surface flows have declined through time in the Powder River, and the aquifer has experienced increased drawdown. Nagler et al. (2011) additionally outlines soil type as a likely influencer on Russian olive distribution, although Russian olive studies are lacking compared to better-studied invasives, like tamarisk. In contrast, at continental scales, habitat suitability models include factors such as mean annual minimum temperature (Friedman et al. 2005) and distance to surface water (Jarnevich et al. 2011; Perry et al. 2022). In the context of urban locations within Russian olive's native range in Iran, Karimian and Farashi (2021) found climatic factors, soil, and lithology to be important in predicting habitat suitability.

Here, we analyzed Russian olive percent cover as a function of a robust suite of variables expected to influence Russian olive distribution based on literature expectations. Datasets included annual minimum, mean, and maximum temperature (PRISM), slope-weighted solar radiation (PRISM), mean elevation (above NAVD88 geoid model), precipitation-weighted flow accumulation (precipitation from PRISM; PRISM Climate Group 2004; ArcGIS Flow Accumulation tool multiplied by PRISM value), dominant land cover class (Perry et al. 2018; Dewitz 2021), dominant soil type (Nagler et al. 2011, 2018; we used standard U.S. soil taxonomy (Web Soil Survey 2018; produced by the National Cooperative Soil Survey), and depth to groundwater (surface elevation minus groundwater elevation; Lopez-Iglesias et al. 2014). Correlations among datasets were calculated in R (4.0.3) with the Raster package (Hijmans 2018). Based on Spearman ranked correlations, variables were included in candidate linear models predicting Russian olive percent cover. We included combinations of additive linear models (lm function in R), excluding variables correlated with one another > 0.7

(see Data Availability section for data repository for correlations and model development). We included 62 candidate models (Table S3.2) and selected models based on AIC (Akaike 1974) corrected for small sample size (AICc; Mazerolle 2015). Models were considered plausible if their AICc value compared to the lowest AICc model (ΔAICc) was less than 3 (Richards 2005). Model results are presented using the effects package (Fox and Weisberg 2018) where a computed effect absorbs the lower-order terms marginal to the term in question, and averages over other terms in the model.

Results

Russian olive distribution

The random forest model detected Russian olive percent cover with an out-of-bag root mean square

error (RMSE) of 15%, and R^2 of 0.64 across a range of environments along the Powder River and tributaries (Figs. 3, 4). In the end, the best-performing model with the fewest number of variables used six variables (listed in order from high to low importance): fall tasseled cap greenness, fall tasseled cap brightness, tasseled cap brightness difference between the summer and spring, tasseled cap brightness difference between the summer and fall, spring tasseled cap wetness, and tasseled cap wetness between the summer and spring. Russian olive cover was generally highest (mean percent $> 5.94\%$) along the Powder River just north and south of the Montana-Wyoming state line, along Clear Creek in Wyoming, and toward the northernmost portions of the Powder River (see Data Availability section for data repository that includes the final model raster output; Fig. 5). The maximum Russian olive cover predicted by the random forest model was 95.55% (Figs. 3, 4), while the maximum was 12.49% when averaged across 5 km hexagons (Fig. 5).

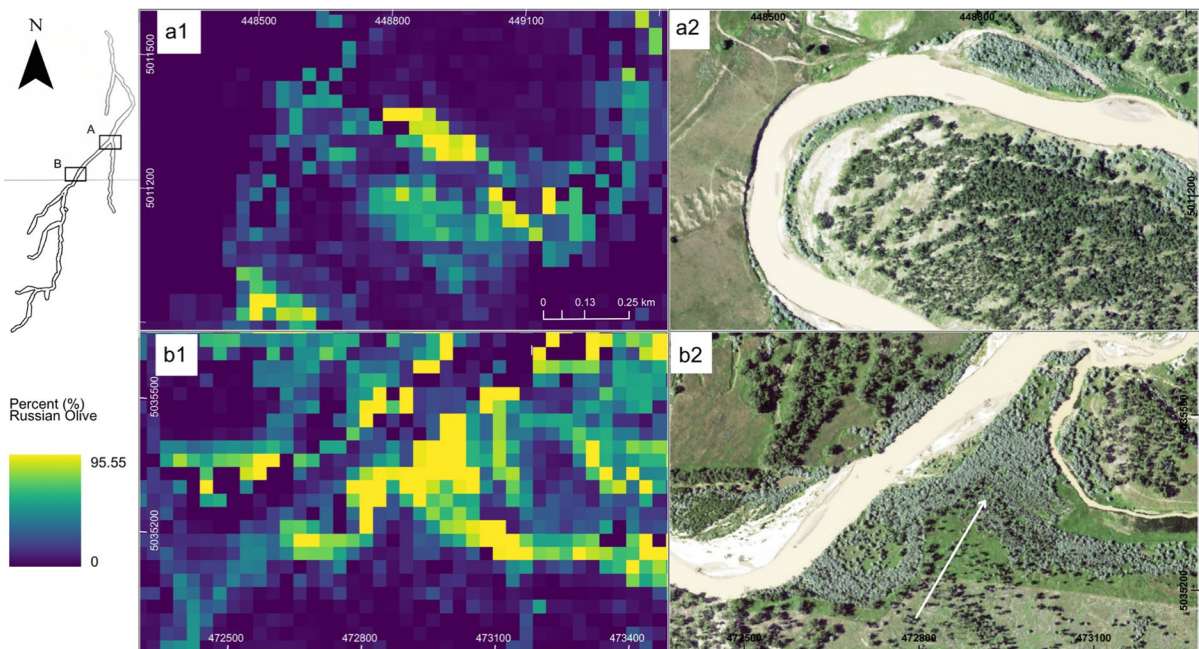
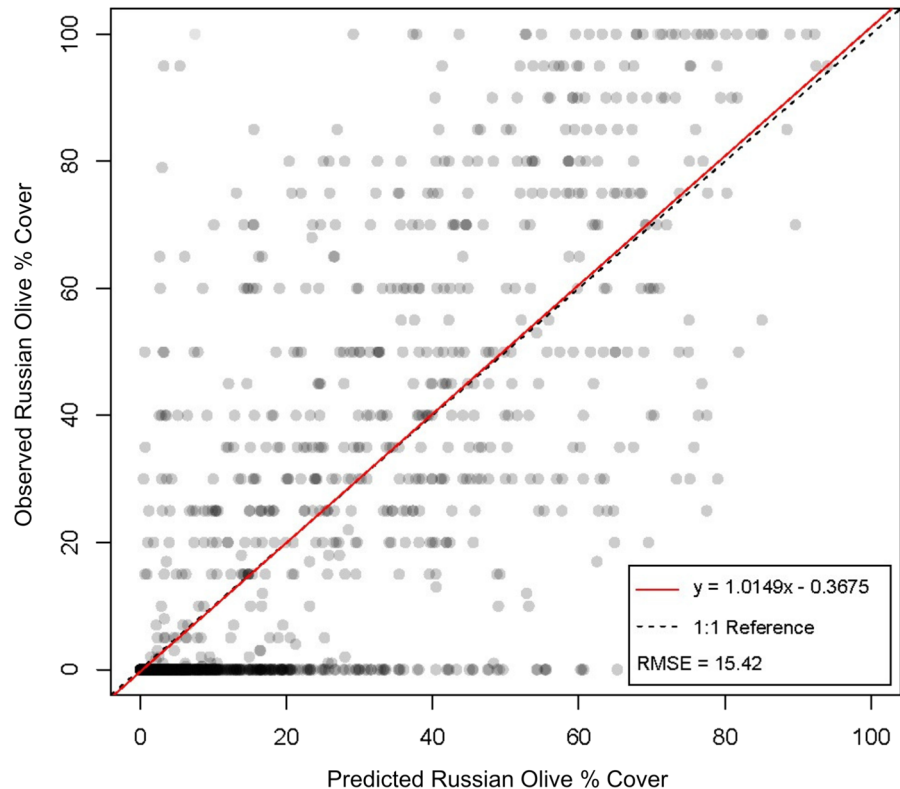


Fig. 3 Examples of random forest model predictions of percent cover of Russian olive (20 m spatial resolution) alongside corresponding aerial imagery. **A1** Model results near Broadus, Montana compared to **(A2)** NAIP 2019 imagery of the same

area, showing Russian olive. **B2** Model results downstream of South Fork and Middle Fork compared to **(B2)** NAIP 2019 imagery of the same area. The arrow indicates Russian olive, the silvery-green color

Fig. 4 Relationship between observed Russian olive percent cover (ocular samples and field data) and predicted Russian olive percent cover (Random forest model)



Russian olive in relation to floodplain characteristics

Species occurrence and cover

In addition to the field data being used as training points for the Random Forest model, they also provide a rich picture of other woody species present in the measured plot. In the field data, Russian olive had a mean percent cover of 18.3% (std. dev. 21.4), tamarisk 2.6% (std. dev. 8.4), and cottonwood 19.1% (std. dev. 18.3). When the dominant species by plot was considered, Russian olive was located closer to the channel (Fig. 6A) compared to cottonwood. Tamarisk was restricted to near-channel distances compared to Russian olive and cottonwood; however, it had a small percent cover overall. Russian olive and tamarisk were found over a wider range of TPI relative to cottonwood (Fig. 6B), which has very specific requirements for regeneration (Mahoney and Rood 1998). Canopy Height (from CHM; Fig. 6C) showed cottonwood heights were the highest followed by Russian olive, with tamarisk rarely reaching beyond a few meters high. Plots of small (<2 m) cottonwood

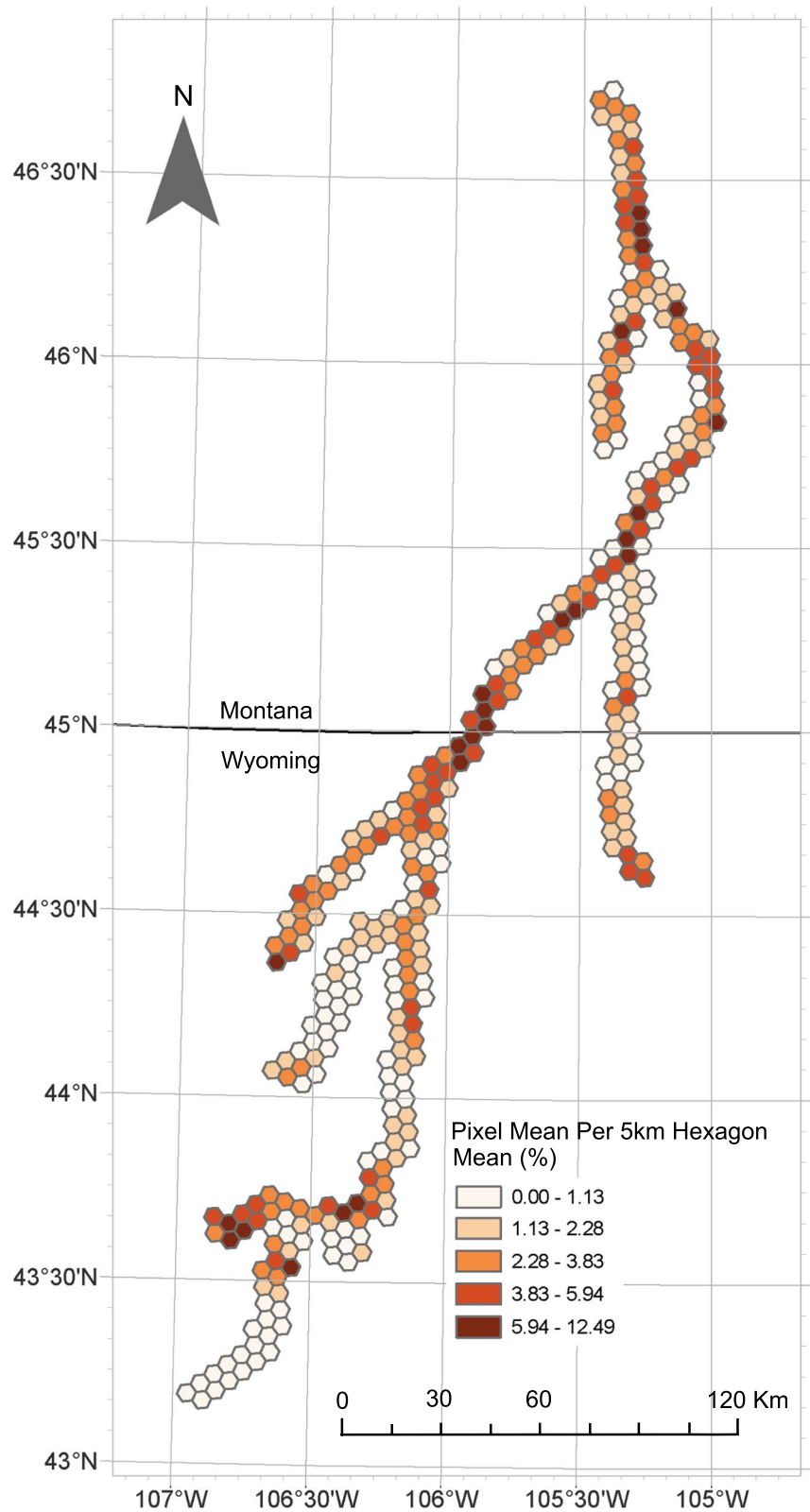
(indicative of recent recruitment) were notably absent in the dataset.

We compared field data to remotely sensed predicted cover relationships to ensure we were adequately capturing Russian olive riparian habitat relationships. When compared to the field data, the predicted presence of Russian olive by TPI and CHM have similar values (median TPI value of 0 ± 0.3 m compared to 0.2 ± 0.6 m for field compared to predicted cover values; median CHM value of 3.2 ± 2.1 m compared to 3.1 ± 1.8 m for field compared to predicted cover values). This suggests predicted cover and corresponding environmental relationships are adequately captured with the remotely-sensed data, increasing our confidence in additional watershed-scale interpretations.

Grouping analysis

Grouping (k-means) analysis showed three groups (pseudo F-statistics 78.25; Table S2.1; Figure S2.2; see Data Availability section for data repository), with partial R^2 values ranging from 0.20 for percent

Fig. 5 Percent Russian olive cover per 5 km hexagon summarizing the distribution of percent Russian olive cover over the study area extent as predicted by the random forest model



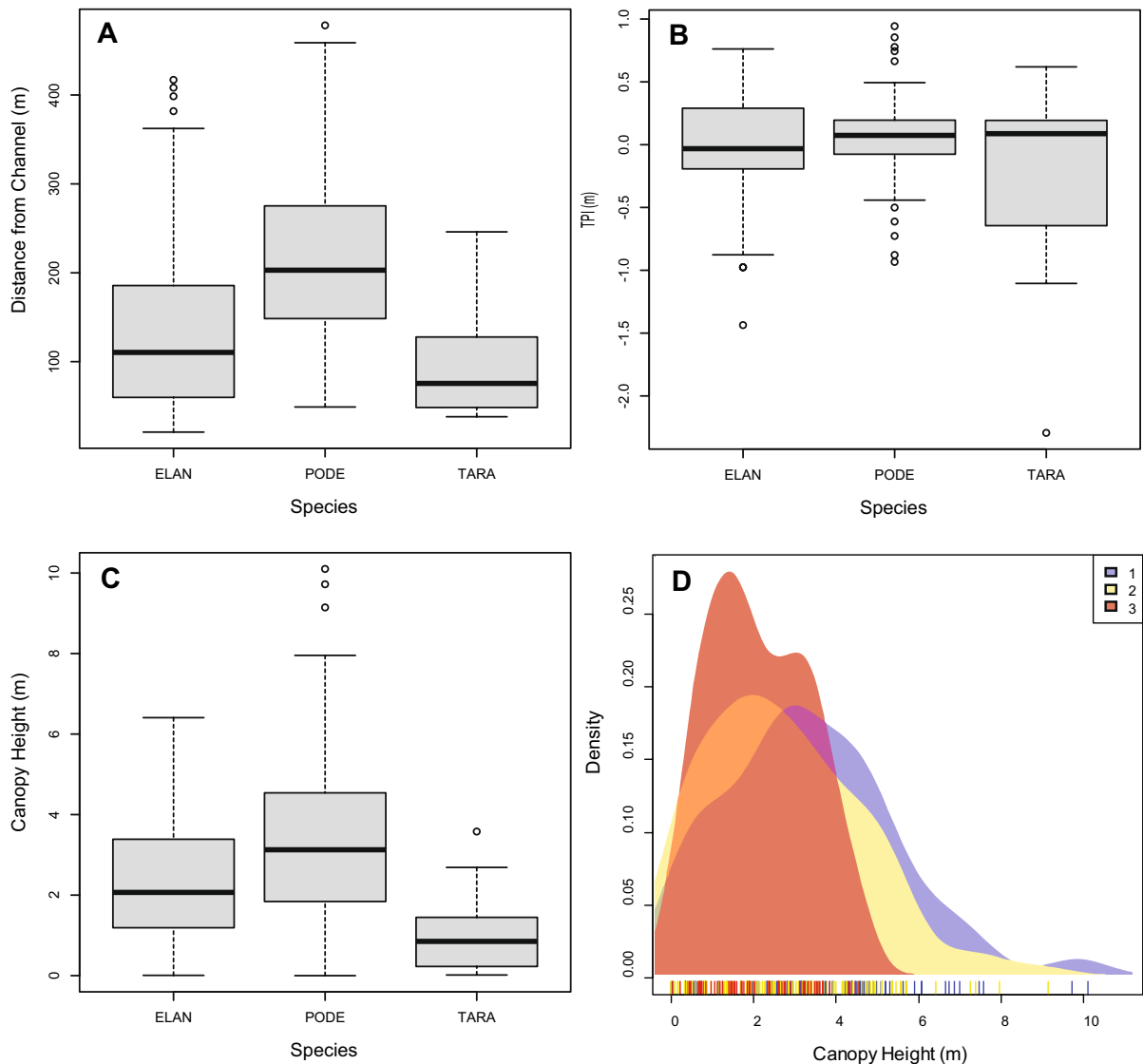


Fig. 6 Species by **A** distance from channel and **B** topographic position index (TPI). ELAN=Russian olive; PODE=cottonwood and TARA=tamarisk. **C** Canopy height (CHM) by species showing PODE was the tallest followed by ELAN.

TARA-dominated plots were rarely taller than a few meters. **D** Density plot of canopy height distribution by grouping analysis, colored by group to match Fig. 7

cottonwood to 0.61 for bare ground. Group 1, at mid-positions relative to the channel (mean 181.8 m from channel; blue group), consisted of Russian olive (18.9%) and cottonwood (27%) as the dominant species with greatest bare ground (64.7%) and lowest herbaceous cover (22%), whereas farthest (mean 226.7 m) from the channel, Group 2 (yellow group) consisted of mostly cottonwood (19.7%) and less Russian olive (6.1%). Closest to the channel (Group 3;

mean 85.1 m), Russian olive was dominant (42.0%) with tamarisk (10.2%) and lesser cottonwood (4.8%) (Fig. 7; Table S2.1). Thus, all groups across the floodplain contained Russian olive, including in gallery cottonwood areas as an understory beneath cottonwood (Group 2). In contrast, tamarisk had the highest cover near the channel (Group 3) but had a lower percent cover overall. Cottonwood had a low percent cover near the channel (Group 3), where cottonwood

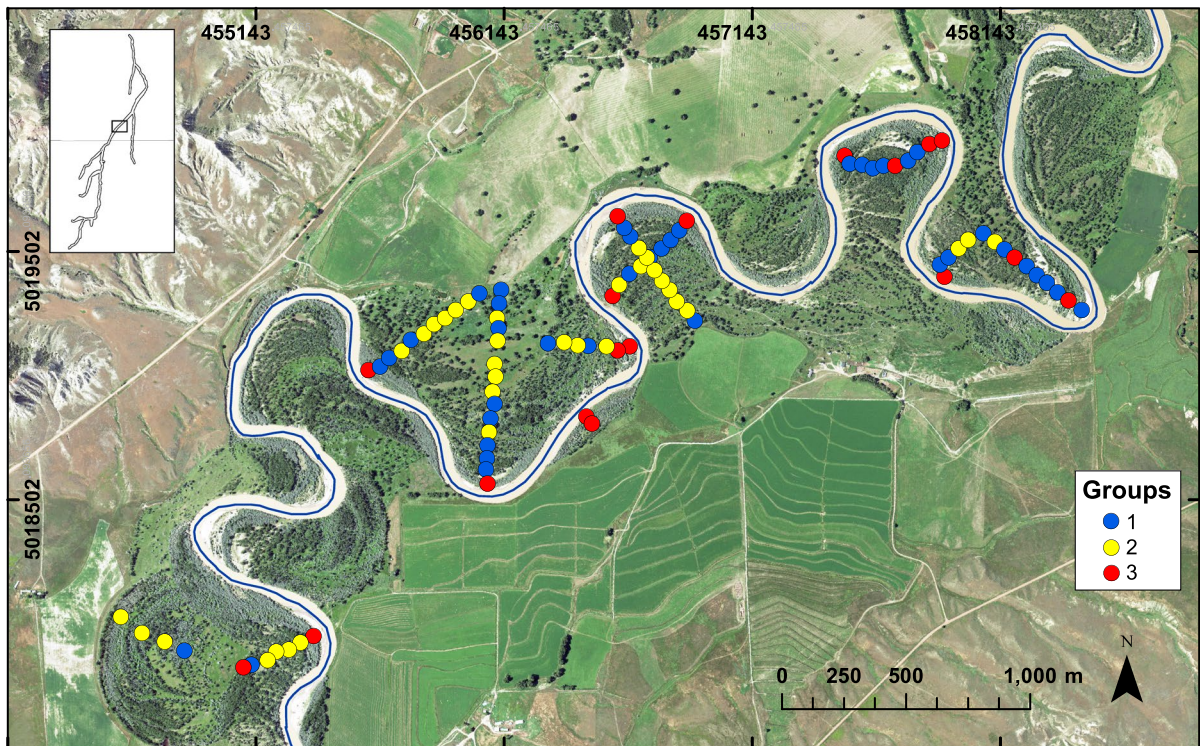


Fig. 7 Grouping analysis showed three groups, with Group 1 consisting of mixed cottonwood and Russian olive, along with high bare ground a low herbaceous cover, in positions intermediate to the channel (blue group), Group 2 (yellow group) open

gallery cottonwood forests with an understory of Russian olive, and Group 3 (red group) dominated by Russian olive mixed with tamarisk close to the channel

recruits would typically be expected because of its life-history strategy (Karrenberg et al. 2002). The CHM by group (Fig. 6D) showed the smallest plants (~2 m) in Group 3 (closest to channel on bars), indicating regeneration of this group (tamarisk and Russian olive dominated), additionally emphasizing limited recent cottonwood recruitment/regeneration.

Russian olive habitat suitability at the watershed scale

We used mean summary values of Russian olive cover data (Fig. 5) to investigate riparian habitat environmental controls (weighted flow accumulation, minimum temperature, maximum temperature, elevation, topographic wetness index, land cover, soil order, mean temperature, solar radiation, depth to groundwater; see Table S3.1) on Russian olive cover at the HUC 6-digit watershed scale. Of the variables considered, elevation and solar radiation were both

weakly and negatively correlated with percent cover ($r = -0.33$ and -0.32 , respectively; Table S3.1). Elevation and solar radiation were, in turn, nearly perfectly correlated ($r = 0.96$). Therefore, only elevation or solar radiation was included in the same candidate model. Similarly, elevation/solar radiation and depth to groundwater were strongly correlated ($r = 0.75$) and thus were not included in the same candidate model set. Using the AICc approach (Table S3.2), the most probable final model (F-statistic: 10.38 on 7 and 414 degrees of freedom; $R^2 = 0.14$, p value: < 0.001 ; Table S3.3) predicted mean cover as a function of precipitation-weighted flow accumulation, elevation, and soil type. Other probable models included flow accumulation, elevation, soil type and either mean, min, or max daily temperature. For soil types, the large errors for both Mollisol and Alfisol suggest they are not indicative of vegetation cover, leaving mainly entisols and vertisols as controlling factors based on correlations (Table S3.1). For parsimony,

we discuss here the results from the lowest-AICc. In this model, cover increased with flow accumulation (Fig. 8A), decreased with increasing elevation (Fig. 8B), and was present across a wide range of soil types (Fig. 8C) with lower cover in nutrient-rich soil (Mollisol) and indiscriminate across nutrient-poor soil types (entisol, alfisol, inceptisol).

Discussion

Russian olive detection random forest model performance and application

We mapped Russian olive cover across an entire river basin, covering a large area and a range of environments. Seasonality had a large impact on our Russian olive percent cover detection model performance, with half of the final six predictor variables being seasonal differences. All of the final variables were also tasseled cap transformations. Fall tasseled cap greenness may have distinguished greener trees and shrubs such as Russian olive from herbaceous vegetation that has dried more by fall. Tasseled cap brightness is likely differentiating foliage from the ground. Spring tasseled cap wetness was the third most important variable, and has been shown to differentiate various tree types and stand densities (Dymond et al. 2002; Jin and Sader 2005; Healey et al. 2005). This variable may have helped to differentiate Russian olive from other riparian trees and shrubs. The tasseled cap

indices and seasonal difference tasseled cap indices captured Russian olive phenology effectively, separating leaf flush from senescence, as others have found (Dymond et al. 2002; Evangelista et al. 2009). Other studies have successfully applied Tasseled cap indices in classifying forests (Dymond et al. 2002), detecting forest disturbance (Healey et al. 2005), and monitoring land cover changes (Allen et al. 2018), as a few examples.

Overall our results should be interpreted with caution due to limited model performance. However, our approach to mapping Russian olive distribution can be applied to regions outside of the Powder River with similar environmental conditions. This method could be applied anywhere in the world due to the Sentinel-2 imagery that we used. We believe that it would work best in regions where tamarisk is not as prevalent and areas with wide flood plains. Detection models would perform more poorly in areas where Russian olive is less abundant and occurs in smaller patches, where the riparian corridor is too thin, and when mixed with tamarisk as they can be difficult to distinguish. Data on species cover to train models could be collected in the field (more time consuming/expensive but greater accuracy and detail) and/or with high resolution imagery (such as NAIP 2019 in this study). Relying on ocular sample points has the benefit of allowing for iterative model testing and targeted collection of additional training points that would be much more difficult, time consuming, and expensive with field data collection. This study draws

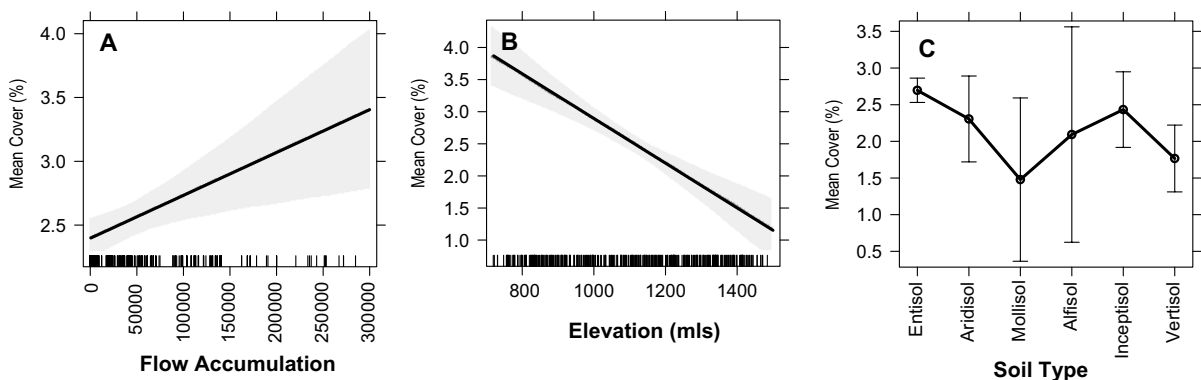


Fig. 8 Results of the suitability model predicting mean cover by environmental variables showing mean cover (A) increased with precipitation-weighted flow accumulation (relative metric), B decreased with increasing elevation, and C is indis-

criminate across nutrient-poor soil types. Plots display 95-percent point-wise confidence intervals for the fitted effects, using error-bars for factors and bands for numeric predictors (Fox & Weisberg 2018)

on the strengths of field data for more detailed vegetation composition and structure information and sampling of aerial imagery to efficiently sample a much larger area.

Riparian community dynamics

Grouping analysis identified three main cover types, primarily differentiated by the dominance of the three main woody species, bare ground/herbaceous cover, and relationship to floodplain structure. Tamarisk was mainly restricted to the channel edge, whereas cottonwood dominated forests at the most distant locations from the current channel. Cottonwood distribution follows older channels as evidenced by increasing ages as you move from the current channel to older channel scars (Schook et al. 2017; Metzger et al. 2020). The lack of mature cottonwood along the current channel suggests something has changed, such as dominance by exotics with aggressive growth strategies that lead to outcompeting cottonwood at younger growth stages, browsing pressure, or that the hydrology has been shifted outside cottonwood's regeneration niche (Grubb 1977), or some combination of these. In the field, cottonwood seedlings were numerous, but juvenile and mature age classes were missing close to modern channels. In its place, Russian olive has already largely invaded the main stem of the Powder River, especially in Montana (Fig. 5). Russian olive was found throughout the floodplain but dominated nearer the channel. The results are consistent with previous studies, suggesting Russian olive is dispersed well by seed and generally successful where other species struggle or can outcompete cottonwood seedlings through shade and drought tolerance (Reynolds and Cooper 2010; Collette and Pither 2015a, b). Russian olive is fairly shade tolerant, and thus was established under cottonwood canopy, although the reverse was not observed (Reynolds and Cooper 2010; Collette and Pither 2015a, b). This Russian olive establishment in the sub-canopy of cottonwood stands could suppress cottonwood regeneration, further limiting cottonwood recruitment in one or two ways. Russian olive shading is likely to suppress cottonwood seedling regeneration along regulated rivers or rivers with declining flows, as shown by Lesica and Miles (1999). Second, while many cottonwood species are capable of resprouting especially when young (Gom and Rood 1999), and resprouting

has been shown as an important regeneration strategy for disturbance resilience and recovery (Smith et al. 2009; Wonkka et al. 2018), shading and competition with Russian olive will likely decrease this ability of cottonwood (Lytle and Merritt 2004). Our Russian olive detection maps likely underpredict sub-canopy Russian olive and thus may under-represent the extent of Russian olive impact on mature cottonwood stands.

The physiology of Russian olive is advantageous for drier floodplain conditions. Russian olive also has symbiotic relationships with both *Frankia* (an N-fixing bacteria) and mycorrhiza, both of which help make nutrients and water more available, resulting in a higher tolerance of drier and nutrient poor conditions. It is also a facultative phreatophyte, allowing it to use water above the water table. Russian olive is a ring-porous to semi-ring-porous species (Jansen et al. 2000), meaning their water conducting vessels are more limited to the most recent outer ring or few rings (Umebayashi et al. 2010; Bush et al. 2010). This gives the species an advantage in variable hydrologic conditions and an advantage over ring-diffuse species (e.g., cottonwood) in drier environments (Bader et al. 2022). Katz and Shafroth (2003) also noted several adaptations to drought many other floodplain species do not have: reflective silvery foliage, thick cuticle, and sunken stomates, along with a tolerance to salinity. Shiflett et al. (2017) describe Russian olive as having an acquisitive strategy, with efficient light capture, utilization, and internal water movement.

Russian olive habitat suitability

In the U.S. Southwest, Russian olive distribution has been shown to be controlled by climate, urban land use, and planting at large scales (Nagler et al. 2011; McShane et al. 2015; Perry et al. 2018), and by elevation, distance from river, streamflow and peak flow at local floodplain scales (Hoffman et al. 2008; McShane et al. 2015; West et al. 2020). Here, we bridged these gaps in scale, with similar results. We found higher Russian olive densities in areas with higher flow accumulation and lower elevations, with an affinity for entisols over vertisols. Elevation was, in turn, correlated with depth to groundwater and solar radiation. These variables (depth to groundwater and solar radiation) likely influence density distributions, but because of the high correlations with elevation, it is difficult to determine independently. Russian olive

densities were highest at lower elevations, correlated to decreased solar radiation and depths to groundwater. Literature suggests as a facultative phreatophyte, Russian olive can survive without direct access to groundwater, particularly when it has access to surface water, which would be correlated to flow accumulation used here, especially under conditions of irrigation and related return flows, as experienced on the Powder River.

Norton et al. (2014) assessed long-term trends (1960–2011) of discharge characteristics within the Missouri River watershed and concluded all components of discharge (annual, monthly, and seasonal) had decreased over the period considered. The decreasing flow trends in the upper basin were confirmed by modeling (Wise et al. 2018). For the Powder River specifically, the USGS Integrated Water Availability Assessments Surface Water Flow Trends in the Nation's Streams and Rivers (Hodgkins et al. 2019; Dudley et al. 2020) shows a nonsignificant downward trend in mean annual flow for the Powder River at Locate. At the same time, the Fox-Hills-Hell Creek aquifer in the Yellowstone River basin has declined significantly (7.6 m near Terry, Montana) in the last ~35 years and has not changed with precipitation inputs, indicating a management control (Whitlock et al. 2017). Declining flow and aquifer levels are likely to have increased depths to the water table within the Powder River basin during the same time period that Russian olive has invaded. This has likely impacted the distribution of Russian olive since its growth is responsive to vapor pressure deficit and soil temperature (Azmat et al. 2020) and light and water-use dynamics are primary factors driving the growth of a close relative, *E. umbellata* (Shiflett et al. 2017).

There is also evidence that climate has shifted leading to lower overall flows, lower peak flows, and a general drying of floodplains (Mikulová et al. 2020). Lower snowpack in the northern Rocky Mountains has resulted in lower magnitude peak flows and altered the timing of spring floods (Stewart et al. 2005; Pederson et al. 2010). Along with increased irrigation and reservoir storage (Schook et al. 2016), the result is slower channel migration and less channel expansion, and thus less point bar development (Schook et al. 2017), the habitat required for cottonwood regeneration (Mahoney and Rood 1998; Benjankar et al. 2014). Schook et al. (2020) demonstrated that cottonwood branch and tree mortality

were highest and canopy vigor was lowest in dewatered reaches along Snake Creek, Nevada, U.S. Cottonwood die off has been observed in the U.S. Southwest in relation to reduced surface flow combined with increased groundwater pumping (Shafroth et al. 2018). As Nagler et al. (2011) pointed out, stress-tolerant species have moved into areas that are no longer suitable for mesic native pioneer species. Both Collette and Pither (2015a) and McShane et al. (2015) related lower flood peaks to greater Russian olive occurrence throughout the western U.S. Drought generally enhances the invasion of exotics in aquatic-terrestrial transition zones, partly because fewer flood pulse events alter propagule pulses and environmental filters favorable to natives (Thomaz 2022). In the field, dead stands of sandbar willow (*Salix exigua*) and even tamarisk were observed, which may indicate that shifting floodplain regimes could be underway already.

Management considerations

We sought to help local ranchers and land managers understand the current distribution of Russian olive. Key interests that emerged from conversations about Russian olive included potential management interventions, habitat and landscape alteration, interference with livestock management, and potential spread patterns. Our findings provide several considerations for management of Russian olive in the Powder River Basin. Russian olive detection maps should be interpreted as representing general patterns of Russian olive distribution, but the fact that this is a model with inaccuracies should be front-of-mind when applying the maps. The maps capture trends in cover and thus can inform distribution patterns across the Powder River Basin, but when applied at specific sites or project scales, ground surveys and observations of cover are needed. We only map Russian olive for one year, but repeating this mapping exercise for another year would provide valuable information about rates and patterns of Russian olive spread. This research did not focus on all local concerns, such as habitat and landscape alteration and interference with livestock management, which future studies could further address.

Russian olive presents tradeoffs for livestock production in the region. Negatively, Russian olive has formed dense, thorny thickets which can limit travel and access to water resources. Further, the dropping

water table and channelization of the river, combined with the loss in plant diversity of Russian olive stands may reduce production and grazing value of the flood plains. However, Russian olive can also be an important forage resource, particularly during the seedling stage (Pearce and Smith 2001) and in the spring to mid-summer when cattle eat reproductive branch leaves and fruits before seeds harden, providing nutritional value during droughts and mid-summer when other forage declines in nutrition (Klich et al. 2018). Thus, the maps provided by this work can be used to inform grazing planning, and our results suggest that given cottonwood's troubled status on the Powder River and beyond, grazing managers should take note of areas where cottonwoods are establishing and plan their grazing to allow for these stands to mature.

With evidence that Russian olive invaded from the north (Schook et al. 2017), we are confident that temperatures are not currently limiting invasion success. Indeed, Russian olive requires chilling for bud break and germination (Nagler et al. 2011). Areas with low Russian olive cover include the headwater streams in the southern part of the study area, seemingly because of low surface flow accumulation and higher elevations, with higher elevations correlated with solar radiation found by Karimian and Farashi (2021) to be important in predicting Russian olive in Iran. Russian olive can spread downstream by ice and water transport and in any direction by wildlife (Pearce and Smith 2001; Katz and Shafroth 2003; Campbell and West 2022). With climate change leading to lower spring flood magnitudes, seed dispersal by animals will be an important dispersal mechanism. Thus, limiting dispersal of Russian olive to new areas may be challenging or altogether infeasible. Monitoring major storm events is important, as these events can spread Russian olive and tamarisk and may be the only potential colonization events for cottonwood. Cottonwood recruitment relies on both scour events and appropriate flood conditions (Amlin and Rood 2002; Karrenberg et al. 2002; Mahoney and Rood 1998). However, as stated, spring flood events are likely to decrease in the future and additionally several flood events may be required for channel changes to occur on the Powder River (Gay et al. 1998), thus compounding the absence of conditions required for cottonwood recruitment. There are several stretches of the watershed with low Russian olive cover (Fig. 5), and these areas should be the focus of

local land managers. Russian olive is extremely difficult to eradicate, especially once it is established in dense stands (O'Meara et al. 2010). Therefore, targeting removal efforts in areas with little cover is likely the most cost-effective option and may also reduce risk of inadvertent effects such as increased erosion (Reynolds et al. 2021). We, like others, recommend early intervention as well as creating potential areas of conservation or protection where Russian olive has not invaded yet (O'Meara et al. 2010). From Fig. 5, we recommend targeting the 0.00–1.13% and 1.13–2.28% areas (the lightest two colors) for monitoring and management. For the higher cover categories (Fig. 5), treatment would need to include more invasive, expensive strategies (herbicide, manual removal, etc.) (O'Meara et al. 2010). While the Russian olive maps in this study generally capture Russian olive distributions at a landscape scale, any single location may have errors due to limited model performance, like most single species detection products derived from remote sensing. Areas of particular management importance or interest and areas shown to have low cover should be further evaluated by field observations because the model may fail to detect small Russian olive trees or areas of very low cover at early invasion stages.

Conclusion

As the fourth most frequent and fifth most abundant riparian species of western U.S. rivers (Nagler et al. 2011), Russian olive poses a threat to both the diversity and function of these systems (Collette and Pither 2015b). Based on this study and others in the northern U.S. (Pearce and Smith 2001), we expect the invasion of Russian olive to continue within the Powder River Basin and beyond because of a combination of hydrological, biological, and climatic factors favoring Russian olive at the expense of native species. This study presents a method for mapping Russian olive cover and then uses a combination of maps, field data, and additional geospatial data to evaluate distribution patterns across scales. This approach can be applied to other landscapes outside of the U.S. and additional plant invasions to understand community dynamics and inform management. Our multi-scale, stakeholder-driven, multi-disciplinary study provides key

methodologies to assess the extent of Russian olive invasion as well as insight into factors accounting for Russian olive's success.

Acknowledgements Thank you to our collaborators at University of Northern Colorado; Justin Yow, Haylie Brown, Antonio Reveles-Hernandez, Evander Espinoza, Gavin Kenney, Caleb Raymond, Rikki Held, Aubrey Raimer, for collecting field data for our project. Also, thank you to John Moody with the US Geological Survey for providing us with cross-section data of the Powder River and on-the-ground observations along with Glenn Gay from Gay Ranch, and Tammy Van Tine of Powder River County Weed Board. This material contains modified Copernicus Sentinel data (2020), processed by ESA. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the National Aeronautics and Space Administration (NASA). This material is based upon work supported by NASA through contract NNL16AA05C.

Author contributions Karissa Courtney, Catherine Buczek, Dahlia Shahin, Amy Tian, and Carly Andrews contributed through participation in the NASA DEVELOP program, at the Fort Collins location. Each designed and implemented components of the remote sensing analyses, conducted analysis, and created materials used in the publication. Karissa Courtney and Catherine Buczek contributed substantially to the vision and completion of the manuscript. Scott Cunningham was the Center Lead where he coordinated the project and contributed largely to the code for random forest modeling and the final paper edits. Sharon Bywater-Reyes was the impetus for the collaboration and brought together the interdisciplinary teams to work on this project. She led the geomorphic analyses and reach-scale data analysis. Scott Franklin procured funding in collaboration with Bywater-Reyes to support this work. Franklin designed the vegetation field sampling protocol and provided ecological expertise throughout all components of the project. Bywater-Reyes and Franklin led the field data collection and contributed to manuscript writing. Anthony G. Vorster and Brian Woodward were the science advisers for the DEVELOP team and made the connections with University of Northern Colorado and stakeholders. Both Anthony G. Vorster and Brian Woodward contributed substantially to the study design, project implementation, mentoring, and code. Both Anthony G. Vorster and Brian Woodward helped design figures and write and edit the manuscript. All authors contributed to the vision and editing of this manuscript.

Funding This material is based upon work supported by NASA through contract NNL16AA05C. This work was also supported by the United States Geological Survey (grant number G21AC10021). Additional support came from the College of Natural and Health Sciences STEM Summer Mentorship Program and the RE-INVIGORATION OF RESEARCH INTERRUPTED TO COVID, from a HEERF2 CARES award at the University of Northern Colorado.

Data availability The datasets generated and/or analyzed during the current study are available in the Dryad open access data repository, <https://doi.org/10.5061/dryad.p8cz8w9z8>

Declarations

Conflict of interest The authors have no additional relevant financial or non-financial interests to disclose.

Open Access This article is licensed under a Creative Commons Attribution 4.0 International License, which permits use, sharing, adaptation, distribution and reproduction in any medium or format, as long as you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons licence, and indicate if changes were made. The images or other third party material in this article are included in the article's Creative Commons licence, unless indicated otherwise in a credit line to the material. If material is not included in the article's Creative Commons licence and your intended use is not permitted by statutory regulation or exceeds the permitted use, you will need to obtain permission directly from the copyright holder. To view a copy of this licence, visit <http://creativecommons.org/licenses/by/4.0/>.

References

- Ackerman T (2016) Powder River, MT 2016 airborne lidar survey. National Center for Airborne Laser Mapping (NCALM) Distributed by OpenTopography. <https://doi.org/10.5069/G93F4MJG>
- Akaike H (1974) A new look at the statistical model identification. *IEEE Trans Autom Control* 19(6):716–723. <https://doi.org/10.1109/TAC.1974.1100705>
- Allen H, Simonson W, Parham E et al (2018) Satellite remote sensing of land cover change in a mixed agro-silvo-pastoral landscape in the Alentejo, Portugal. *Int J Remote Sens* 39:4663–4683. <https://doi.org/10.1080/01431161.2018.1440095>
- Amlin NM, Rood SB (2002) Comparative tolerances of riparian willows and cottonwoods to water-table decline. *Wetlands* 22:338–346. [https://doi.org/10.1672/0277-5212\(2002\)022\[0338:CTORWA\]2.0.CO;2](https://doi.org/10.1672/0277-5212(2002)022[0338:CTORWA]2.0.CO;2)
- Azmat MA, Khan AA, Khan IA et al (2020) Morphology, biochemistry, and management of Russian olive (*Elaeagnus angustifolia* L.) accessions in Gilgit-Baltistan, northern Pakistan. <https://doi.org/10.17170/kobra-202007291507>
- Bader MK-F, Scherrer D, Zweifel R, Körner C (2022) Less pronounced drought responses in ring-porous than in diffuse-porous temperate tree species. *Agric for Meteorol* 327:109184. <https://doi.org/10.1016/j.agrformet.2022.109184>
- Beck HE, Zimmermann NE, McVicar TR et al (2018) Present and future Köppen-Geiger climate classification maps at 1-km resolution. *Sci Data* 5:180214. <https://doi.org/10.1038/sdata.2018.214>
- Benjankar R, Burke M, Yager E et al (2014) Development of a spatially-distributed hydroecological model to simulate cottonwood seedling recruitment along rivers. *J Environ Manage* 145:277–288. <https://doi.org/10.1016/j.jenvman.2014.06.027>

- Borsukevych LM, Iemelianova SM, Kolomiychuk VP (2023) Plant communities with the dominant *Elaeagnus angustifolia* in Ukraine: classification and distribution. *Biologia* 78(5):1269–1314. <https://doi.org/10.1007/s11756-023-01370-1>
- Botta-Dukát Z, Balogh L et al (2008) *The most important invasive plants in Hungary*. HAS Institute of Ecology and Botany
- Bush SE, Hultine KR, Sperry JS, Ehleringer JR (2010) Calibration of thermal dissipation sap flow probes for ring- and diffuse-porous trees. *Tree Physiol* 30:1545–1554. <https://doi.org/10.1093/treephys/tpq096>
- Bush BM, Ulyshen MD, Batzer DP (2020) Effects of Chinese privet (*Ligustrum sinense*) invasion on decomposition and litter-dwelling invertebrates in Southeastern U.S. floodplain forests. *Biol Invasions* 22:1957–1965. <https://doi.org/10.1007/s10530-020-02228-2>
- Campbell JW, West NM (2022) Coyote and porcupine spread Russian olive seeds through endozoochory. *J Wildl Manag* 86:e22242. <https://doi.org/10.1002/jwmg.22242>
- Collette LKD, Pither J (2015a) Russian-olive (*Elaeagnus angustifolia*) biology and ecology and its potential to invade Northern North American riparian ecosystems. *Invasive Plant Sci Manag* 8:1–14. <https://doi.org/10.1614/ipsm-d-14-00037.1>
- Collette LKD, Pither J (2015b) Modeling the potential North American distribution of Russian olive, an invader of riparian ecosystems. *Plant Ecol* 216:1371–1383. <https://doi.org/10.1007/s11258-015-0514-4>
- Costanza R, de Groot R, Sutton P et al (2014) Changes in the global value of ecosystem services. *Glob Environ Chang* 26:152–158. <https://doi.org/10.1016/j.gloenvcha.2014.04.002>
- Crist EP, Cicone RC (1984) A physically-based transformation of thematic mapper data—the tm tasseled cap. *IEEE Trans Geosci Remote Sensing* 22:256–263. <https://doi.org/10.1109/TGRS.1984.350619>
- Davies DL, Bouldin DW (1979) A Cluster Separation Measure *IEEE Transactions on Pattern Analysis and Machine Intelligence PAMI-1*(2) 224–227 10.1109/TPAMI.1979.4766909
- David SR, Edmonds DA, Letsinger SL (2017) Controls on the occurrence and prevalence of floodplain channels in meandering rivers. *Earth Surf Proc Land* 42:460–472. <https://doi.org/10.1002/esp.4002>
- Dewitz J (2021) National Land Cover Database (NLCD) 2019 Products
- Dormann CF, Elith J, Bacher S et al (2013) Collinearity: a review of methods to deal with it and a simulation study evaluating their performance. *Ecography* 36:27–46. <https://doi.org/10.1111/j.1600-0587.2012.07348.x>
- Dudley RW, Hirsch RM, Archfield SA et al (2020) Low streamflow trends at human-impacted and reference basins in the United States. *J Hydrol* 580:124254. <https://doi.org/10.1016/j.jhydrol.2019.124254>
- Dymond CC, Mladenoff DJ, Radeloff VC (2002) Phenological differences in Tasseled Cap indices improve deciduous forest classification. *Remote Sens Environ* 80:460–472. [https://doi.org/10.1016/S0034-4257\(01\)00324-8](https://doi.org/10.1016/S0034-4257(01)00324-8)
- Evangelista PH, Stohlgren TJ, Morisette JT, Kumar S (2009) Mapping invasive tamarisk (*Tamarix*): a comparison of single-scene and time-series analyses of remotely sensed data. *Remote Sensing* 1:519–533. <https://doi.org/10.3390/rs1030519>
- Evangelista P, Young N, Vorster T, et al (2018) Mapping native and non-native riparian vegetation in the Colorado River Watershed. *Riparian Habitat and Invasive Species in the Colorado River Basin—Data Collection* <https://hdl.handle.net/10217/185829>
- Evans JS, Murphy MA, Holden ZA, Cushman SA (2010) Modeling species distribution and change using random forest. In: *Predictive species and habitat modeling in landscape ecology: concepts and applications*. Springer, New York, pp 139–159
- Faanes C, LeValley M (1993) Is the distribution of sandhill cranes on the Platte River changing? *Great Plains Res A J Nat Soc Sci* 3:297–304
- Flores RM, Stricker GD, Meyer JF et al (2001) A field conference on impacts of coalbed methane development in the Powder River Basin Wyoming. *US Geol Surv Open File Rep* 1:60
- Fox J, Weisberg S (2018) *An R companion to applied regression*. Sage publications, London
- Friedman JH (2001) Greedy function approximation: a gradient boosting machine. *Ann Stat* 29:1189–1232
- Friedman JM, Auble GT, Shafroth PB et al (2005) Dominance of non-native riparian trees in western USA. *Biol Invasions* 7:747–751. <https://doi.org/10.1007/s10530-004-5849-z>
- Gay GR, Gay HH, Gay WH et al (1998) Evolution of cutoffs across meander necks in Powder River, Montana, USA. *Earth Surf Proc Land* 23:651–662. [https://doi.org/10.1002/\(SICI\)1096-9837\(199807\)23:7%3c651::AID-ESP891%3e3.0.CO;2-V](https://doi.org/10.1002/(SICI)1096-9837(199807)23:7%3c651::AID-ESP891%3e3.0.CO;2-V)
- Gorelick N, Hancher M, Dixon M et al (2017) Google Earth Engine: planetary-scale geospatial analysis for everyone. *Remote Sens Environ* 202:18–27. <https://doi.org/10.1016/j.rse.2017.06.031>
- Gom LA, Rood SB (1999) Patterns of clonal occurrence in a mature cottonwood grove along the Oldman River, Alberta. *Canadian Journal of Botany* 77(8): 1095–1105.
- Green SJ, Grosholz ED (2021) Functional eradication as a framework for invasive species control. *Front Ecol Environ* 19:98–107. <https://doi.org/10.1002/fee.2277>
- Grubb PJ (1977) The maintenance of species-richness in plant communities: the importance of the regeneration niche. *Biol Rev* 52:107–145. <https://doi.org/10.1111/j.1469-185X.1977.tb01347.x>
- Healey SP, Cohen WB, Zhiqiang Y, Krankina ON (2005) Comparison of Tasseled Cap-based Landsat data structures for use in forest disturbance detection. *Remote Sens Environ* 97:301–310. <https://doi.org/10.1016/j.rse.2005.05.009>
- Hijmans, R. J. (2018). raster: Geographic data analysis and modeling. R package version, 2, 8.
- Hodgkins GA, Dudley RW, Archfield SA, Renard B (2019) Effects of climate, regulation, and urbanization on historical flood trends in the United States. *J Hydrol* 573:697–709. <https://doi.org/10.1016/j.jhydrol.2019.03.102>
- Hoffman JD, Narumalani S, Mishra DR et al (2008) Predicting potential occurrence and spread of invasive plant species along the North Platte River, Nebraska. *Invasive*

- Plant Sci Manag 1:359–367. <https://doi.org/10.1614/IPSM-07-048.1>
- Jansen S, Piesschaert F, Smets E (2000) Wood anatomy of Elaeagnaceae, with comments on vestured pits, helical thickenings, and systematic relationships. *Am J Bot* 87:20–28. <https://doi.org/10.2307/2656681>
- Jarnevich CS, Evangelista P, Stohlgren TJ, Morissette J (2011) Improving national-scale invasion maps: tamarisk in the Western United States. *Western North Am Nat* 71(2):164–175. <https://doi.org/10.3398/064.071.0204>
- Jarnevich CS, Sofaer HR, Belamaric P, Engelstad P (2022) Regional models do not outperform continental models for invasive species. *NeoBiota* 77:1–22. <https://doi.org/10.3897/neobiota.77.86364>
- Jin S, Sader SA (2005) Comparison of time series tasseled cap wetness and the normalized difference moisture index in detecting forest disturbances. *Remote Sens Environ* 94:364–372. <https://doi.org/10.1016/j.rse.2004.10.012>
- Karimian Z, Farashi A (2021) Predicting the potential habitat of Russian-Olive (*Elaeagnus angustifolia*) in urban landscapes. *Italian J Agrometeorol* 1:3–19
- Karrenberg S, Edwards PJ, Kollmann J (2002) The life history of Salicaceae living in the active zone of floodplains. *Freshw Biol* 47(4):733–748. <https://doi.org/10.1046/j.1365-2427.2002.00894.x>
- Katz GL, Shafroth PB (2003) Biology, ecology and management of *Elaeagnus angustifolia* L. (Russian olive) in western North America. *Wetlands* 23(4):763–777. [https://doi.org/10.1672/0277-5212\(2003\)023\[0763:BEA-MOE\]2.0.CO;2](https://doi.org/10.1672/0277-5212(2003)023[0763:BEA-MOE]2.0.CO;2)
- Katz GL, Tuttle GM, Denslow MW, Norton AP (2020) Legacy effects of Russian Olive (*Elaeagnus angustifolia* L.) in a Riparian ecosystem three years post-removal. *Wetlands* 40:1897–1907. <https://doi.org/10.1007/s13157-020-01385-3>
- Katz G (2016) Russian Olive Biology, Invasion, and Ecological Impacts in Western North America. Engineer Research and Development Center (U.S.)
- Klich G, Bondia P, Fernandez O (2018) Forage Offer and Nutritive Value of *Elaeagnus angustifolia* in North Patagonia, Argentina. *JESEA* 1:78. <https://doi.org/10.17265/2162-5298/2018.04.003>
- Knopf FL, Olson TE (1984) Naturalization of Russian-olive: implications to Rocky Mountain wildlife. *Wildl Soc Bull* 12:289–298. <https://doi.org/10.2307/3781997>
- Lesica P, Miles S (1999) Russian olive invasion into cottonwood forests along a regulated river in north-central Montana. *Canadian Journal of Botany* 77(8): 1077–1083
- Leatherman D (2011) Russian-olive. *Colorado Birds* 45:42–46
- Liaw A, Wiener M et al (2002) Classification and regression by randomForest. *R News* 2:18–22
- Lopez-Iglesias B, Villar R, Poorter L (2014) Functional traits predict drought performance and distribution of Mediterranean woody species. *Acta Oecologica* 56:10–18. <https://doi.org/10.1016/j.actao.2014.01.003>
- Lytle DA, Merritt DM (2004) Hydrologic regimes and riparian forests: a structured population model for cottonwood. *Ecology* 85(9): 2493–2503.
- Maestas JD, Porter M, Cahill M, Twidwell D (2022) Defend the core: maintaining intact rangelands by reducing vulnerability to invasive annual grasses. *Rangelands* 44(3):181–186. <https://doi.org/10.1016/j.rala.2021.12.008>
- Mahoney JM, Rood SB (1998) Streamflow requirements for cottonwood seedling recruitment—an integrative model. *Wetlands* 18:634–645
- Mazerolle MJ (2015). AICcmodavg: Model selection and multimodel inference based on (Q)AIC(c). R Package Version 2.0–3. <http://cran.r-project.org/package=AICcmodavg>
- McShane RR, Auerbach DA, Friedman JM et al (2015) Distribution of invasive and native riparian woody plants across the western USA in relation to climate, river flow, floodplain geometry and patterns of introduction. *Ecography* 38:1254–1265. <https://doi.org/10.1111/ecog.01285>
- Metzger TL, Pizzuto JE, Trampush SM et al (2020) Event-scale floodplain accretion revealed through tree-ring analysis of buried plains cottonwoods, Powder River, MT, USA. *Earth Surf Proc Land* 45:345–360. <https://doi.org/10.1002/esp.4734>
- Mikulová K, Jarolímek I, Šibík J et al (2020) Long-term changes of softwood floodplain forests—did the disappearance of wet vegetation accelerate the invasion process? *Forests* 11:1218. <https://doi.org/10.3390/f11111218>
- Mineau MM, Baxter CV, Marcarelli AM, Minshall GW (2012) An invasive riparian tree reduces stream ecosystem efficiency via a recalcitrant organic matter subsidy. *Ecology* 93:1501–1508. <https://doi.org/10.1890/11-1700.1>
- Nagler PL, Glenn EP, Jarnevich CS, Shafroth PB (2011) Distribution and abundance of saltcedar and Russian Olive in the Western United States. *Crit Rev Plant Sci* 30:508–523. <https://doi.org/10.1080/07352689.2011.615689>
- Naiman R, Decamps H (1993) The role of riparian corridors in maintaining regional biodiversity. *Ecol Appl* 3:209–212
- Norton PA, Anderson MT, Stamm JF (2014) Trends in annual, seasonal, and monthly streamflow characteristics at 227 streamgages in the Missouri River watershed, water years 1960–2011. Reston, VA
- O’Meara S, Larsen D, Owens C (2010) Methods to control saltcedar and Russian olive. *Saltcedar and Russian Olive Control Demonstration Act Science Assessment* 65–102
- Park JS, Yun J-H, Choi J-Y et al (2019) Multivariate associations between environmental variables and the invasion of alien plants in floodplain waterfront parklands along the Nakdong River. *J Plant Biol* 62:400–409. <https://doi.org/10.1007/s12374-019-0222-z>
- Pattison Z, Vallejo-Marín M, Wilby N (2019) Riverbanks as battlegrounds: why does the abundance of native and invasive plants vary? *Ecosystems* 22:578–586. <https://doi.org/10.1007/s10021-018-0288-3>
- Pearce CM, Smith DG (2001) plains cottonwood’s last stand: can it survive invasion of Russian Olive onto the Milk River, Montana Floodplain? *Environ Manag* 28:623–637. <https://doi.org/10.1007/s002670010248>
- Pederson GT, Graumlich LJ, Fagre DB et al (2010) A century of climate and ecosystem change in Western Montana: what do temperature trends portend? *Clim Change* 98:133–154. <https://doi.org/10.1007/s10584-009-9642-y>
- Perry LG, Reynolds LV, Shafroth PB (2018) Divergent effects of land-use, propagule pressure, and climate on woody

- riparian invasion. *Biol Invasions* 20:3271–3295. <https://doi.org/10.1007/s10530-018-1773-5>
- Perry LG, Jarnevich CS, Shafroth PB (2022) Models combining multiple scales of inference capture hydrologic and climatic drivers of riparian tree distributions. *Ecosphere* 13(12):e4305. <https://doi.org/10.1002/ecs2.4305>
- Petsch DK, de Cione VM, Thomaz SM, dos Santos NCL (2022) Ecosystem services provided by river-floodplain ecosystems. *Hydrobiologia*. <https://doi.org/10.1007/s10750-022-04916-7>
- PRISM Climate Group (2004) PRISM Climate Group. <http://prism.oregonstate.edu>
- Protopopova V, Shevera M, Melnik R (2006) The history of introduction and present distribution of *Elaeagnus angustifolia* L. in the black sea region of Ukraine. *Chornomorski Bot J* 2(2):5–13. <https://doi.org/10.14255/2308-9628/06.22/1>
- Reynolds LV, Cooper DJ (2010) Environmental tolerance of an invasive riparian tree and its potential for continued spread in the southwestern US. *J Veg Sci* 21:733–743. <https://doi.org/10.1111/j.1654-1103.2010.01179.x>
- Reynolds L, Jaeger KL, Cubley E et al (2021) Floodplain plant community and stream channel response following tamarisk and Russian olive removal on a desert stream: 14 years of change. In: *Proceedings of the American Geophysical Union Annual Meeting 2021*. <https://agu.confex.com/agu/fm21/meetingapp.cgi/Paper/904553>. Accessed 21 Dec 2021
- Richards SA (2005) Testing ecological theory using the information-theoretical approach: examples and cautionary results. *Ecology* 86:2805–2814
- Rood SB, Scott ML, Dixon M et al (2020) Ecological interfaces between land and flowing water: themes and trends in riparian research and management. *Wetlands* 40:1801–1811. <https://doi.org/10.1007/s13157-020-01392-4>
- Schook DM, Friedman JM, Rathburn SL (2016) Flow reconstructions in the Upper Missouri River Basin using riparian tree rings. *Water Resour Res* 52:8159–8173. <https://doi.org/10.1002/2016WR018845>
- Schook DM, Rathburn SL, Friedman JM, Wolf JM (2017) A 184-year record of river meander migration from tree rings, aerial imagery, and cross sections. *Geomorphology* 293:227–239. <https://doi.org/10.1016/j.geomorph.2017.06.001>
- Schook DM, Friedman JM, Stricker CA et al (2020) Short- and long-term responses of riparian cottonwoods (*Populus* spp.) to flow diversion: analysis of tree-ring radial growth and stable carbon isotopes. *Sci Total Environ* 735:139523. <https://doi.org/10.1016/j.scitotenv.2020.139523>
- Shafroth P, Thaxton R, Sessie S, Friedman J (2018) Extensive die back and mortality of riparian salicaceae along Bill Williams River, Arizona
- Shiflett SA, Zinnert JC, Young DR (2017) Functional traits of expanding, thicket-forming shrubs: contrasting strategies between exotic and native species. *Ecosphere* 8:e01918
- Simons SB, Seastedt TR (1999) Decomposition and nitrogen release from foliage of cottonwood (*Populus deltoides*) and Russian-olive (*Elaeagnus angustifolia*) in a riparian ecosystem. *Southwest Nat* 44:256–260
- Smith DM, Finch DM, Gunning C. et al (2009) Post-Wildfire Recovery of Riparian Vegetation during a Period of Water Scarcity in the Southwestern USA. *Fire Ecol* 5: 38–55. <https://doi.org/10.4996/fireecology.0501038>
- Stewart I, Cayan D, Dettinger M (2005) Changes toward earlier streamflow timing across western North America. *J Clim* 18:1136–1155
- Tabacchi E, Lambs L, Guilloy H et al (2000) Impacts of riparian vegetation on hydrological processes. *Hydrol Process* 14:2959–2976
- Terziotti S, Archuleta C-A (2020) Elevation-derived hydrography acquisition specifications. Reston, VA
- Thomaz SM (2022) Propagule pressure and environmental filters related to non-native species success in river-floodplain ecosystems. *Hydrobiologia* 849:3679–3704. <https://doi.org/10.1007/s10750-021-04624-8>
- Umebayashi T, Utsumi Y, Koga S et al (2010) Xylem water-conducting patterns of 34 broadleaved evergreen trees in southern Japan. *Trees* 24:571–583. <https://doi.org/10.1007/s00468-010-0428-7>
- Web Soil Survey (2018). In: Natural Resources Conservation Service. <http://www.nrcs.usda.gov/resources/data-and-reports/web-soil-survey>. Accessed 14 April 2023
- Weiss A (2001) Topographic position and landforms analysis. In: Poster presentation, ESRI user conference, San Diego, CA
- West NM, Reinhold AM, Poole GC, Espeland EK (2020) Flood dynamics dictate distributions of *Elaeagnus angustifolia* L. (Russian olive) on a riverine floodplain. *Biol Invasions* 22:3493–3499. <https://doi.org/10.1007/s10530-020-02352-z>
- Whitlock C, Cross W, Maxwell B et al (2017) 2017 Montana climate assessment. Montana Institute on Ecosystems 269. <https://doi.org/10.15788/M2WW8W>
- Wise EK, Woodhouse CA, McCabe GJ et al (2018) Hydroclimatology of the Missouri River Basin. *J Hydrometeorol* 19:161–182. <https://doi.org/10.1175/JHM-D-17-0155.1>
- Woodward BD, Evangelista PH, Vorster AG (2018a) Mapping progression and severity of a Southern Colorado spruce beetle outbreak using calibrated image composites. *Forests* 9:336. <https://doi.org/10.3390/f9060336>
- Woodward BD, Evangelista PH, Young NE et al (2018b) CO-RIP: a riparian vegetation and corridor extent dataset for Colorado river basin streams and rivers. *ISPRS Int J Geo-Inf*. <https://doi.org/10.3390/ijgi7100397>
- Wonkka CL, Twidwell D, Bielski CH, Allen CR, Stambaugh MC (2018) Regeneration and invasion of cottonwood riparian forest following wildfire. *Restoration Ecology* 26(3): 456–465.

Publisher's Note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.