Improving Containment of Wild Carrot in Oregon Seed Production

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Abstract

This study addresses the establishment risk and management of wild carrot (Daucus carota ssp. carota) in central Oregon, combining field surveys, predictive modeling, and herbicide trials to inform targeted control efforts. Field surveys conducted in 2022 and 2023, in collaboration with regional partners, provided data that fed into a relative risk model using the random forest machine learning algorithm. By integrating 75 known wild carrot occurrences with data on topography, climate, soil, road proximity, and landcover, the model effectively distinguished potential wild carrot establishment sites, achieving a high predictive accuracy (AUC = 0.911) against a background dataset of 1000 random points and 250 known absence points. Through adjusting cutoff values in the model's probability outputs, we created five risk categories—spanning moderate to very high risk—that balance false positives and false negatives using a precision-recall f-measure. These categories highlight priority areas for monitoring and management to mitigate the risk of wild carrot invasion, a concern especially relevant for local carrot seed production given the potential for cross-pollination and genetic contamination. To support effective control in high-risk zones, field trials tested herbicides in 2022 and 2023, identifying florpyrauxifen (88% control) and sulfometuron (83% control) as the most effective treatments in non-crop settings. Florpyrauxifen, an EPA-approved, reduced-risk herbicide, is safe for application near water, while sulfometuron is suitable for non-crop lands away from water sources. Employing targeted application methods, such as spot or backpack spraying, offers an effective means of managing wild carrot populations in high-risk areas, thereby helping preserve local seed purity and minimize environmental impact.

Estimated risk of wild carrot invasion in central Oregon

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This document provides supplemental accuracy information for the map of wild carrot invasion risk.

Map created for: Oregon Department of Agriculture ODA21012GR

Abstract

This document summarizes field survey and modeling efforts to describe relative risk for the establishment of wild carrot (*Daucus carota* ssp. *carota*) in central Oregon. Field observations were collected from partners within the study area and field surveys were conducted in 2022 and 2023. The map was built using the random forest modeling machine learning algorithm. The model unified information derived from 75 known observations of wild carrot with an array of raster explanatory data describing topography, climate, soil, distance to roads, and landcover class. The random forest model was effective at discriminating between observations and the combination of 1000 random background and 250 known absence data points (AUC for out-of-box prediction = 0.911). We identified cutoff values within the raw out-of-box random forest 'probability' prediction to yield categories that prioritize different error types (false positives vs. false negatives), using the precision-recall f-measure with varying values for alpha. This yielded five error-based categories that were tuned to the model's unique error-structure. The categories labeled as moderate to very high risk highlight the most important areas to monitor for wild carrot invasion.

Introduction

Central Oregon is located in the high desert climate east of the Cascade Mountains, and is an important production region for commercial hybrid carrot seed. The crop is an important economic driver for the less populated parts of the region where production is concentrated. The labor-intensive nature and high value of carrot seed production also directly supports numerous semi-skilled field laborer positions for much or all of the year, and associated industries providing agricultural inputs and equipment. The climate and geography of the region is well suited to production of high-quality carrot seed for several reasons, including the effective absence of weedy wild carrot.

Wild carrot, or Queen Anne's lace (*Daucus carota* ssp. *carota*), is closely related to the domestic carrot (*Daucus carota* ssp. *sativa*), and the two subspecies are fully inter-fertile (Rubatzky et al. 1999). When wild carrot pollen contaminates a seed crop, the resulting crop-wild hybrids have white roots unsuitable for consumption or sale. The domestic carrot seed industry has zero tolerance for such contamination, and contaminated lots become essentially un-marketable. Growing regions that have meaningful issues with wild carrot contamination can quickly become perceived as an unacceptable risk across the industry, and be effectively eliminated as viable production areas. Thus, long-term sustainability of carrot seed production in any area – central Oregon included – is dependent on continued containment of wild carrot.

To date, known occurrences of wild carrot in central Oregon have been relatively rare and absence of meaningful wild carrot contamination in commercial seed tests (Central Oregon Seeds Inc. unpublished data, Helena Agri-Enterprises unpublished data) confirms this impression. Growers, agronomists, and County weed staff devote considerable effort to detection and eradication within the production area and wild carrot is an A-listed noxious weed in production counties. Outside of this immediate area, however, wild carrot is mostly regarded as a relatively innocuous naturalized species, and it is not a state-listed noxious weed at any level in Oregon, nor in any adjacent counties. The weed is pervasive in western Oregon and along major highway routes into central Oregon at least as far as the eastern foothills of the Cascade Mountains. While relatively uncommon in eastern Oregon, weed and land managers across most of the larger area do not regard wild carrot as a priority management issue, and under-detection and under-reporting is likely. Contamination of carrot seed lots by pollen movement can occur over considerable extents, with isolation distances of 3 miles (4.8 km) employed in the cultivated crop between pollen donor lines of different type. Wild carrot is certainly capable of establishing within at least some of the surrounding habitats, and is likely limited from further expansion in the region by a combination of limited propagule introduction and active control, rather than strict biotic or abiotic constraints. Anecdotal evidence indicates that wild carrot is increasingly encroaching on the larger central Oregon region (M. Weber, B. Martens, R. Gaylen, G. Williams, and K. Farris, pers. comm.), and that the number of new introductions identified and eradicated near or within the active carrot seed production area also seems to be increasing in relative frequency.

Despite the importance of wild carrot to the carrot seed industry in Oregon, patterns of wild carrot distribution and abundance in central Oregon have not been well described. Industry agronomists and local weed managers have recorded a few dozen incidences of wild carrot in the region over the last decade, nearly all of which were subsequently treated and eradicated. However, these observations were made primarily along roads incidental to other activities, and not as part of efforts intended to specifically describe the distribution of wild carrot in the region, or to describe the habitat and/or micro-site characteristics susceptible to invasion. The effort described here aims to describing the current distribution and abundance of wild carrot in and around the current carrot production area in order to increase understanding of wild carrot biology in the region, and to detection and eradication efforts.

As wild carrot represents an industry-identified risk to Oregon carrot seed production in the primary production region of central Oregon; introduction events of the weed into the de facto isolation zone maintained by private industry and local government, while still rare, appear to be increasing in relative frequency over time; and very limited research-based information is available regarding the scale and scope of the problem or robust control recommendations; we propose research to address the following questions: i. What is the current distribution of wild carrot in central Oregon? and ii. How much of central Oregon, and what types of habitats, are most likely to be invaded by wild carrot?

We used targeted field surveys and a species distribution modeling approach, unifying wild carrot observation data with environmental conditions that correlate with their habitat and introduction potential through the random forest machine leaning algorithm (Breiman 2001).

Although many modeling approaches have been used in species distribution modeling (Elith and Leathwick 2009), random forest reliably performs well, and its' flexibility in handling non-normal explanatory data types renders it useful for this application (Cutler et al. 2007, Williams et al. 2009, Evans et al. 2011).

Methods

Study Area

The project focal area is defined by a generalized 15-mile (24km) containment buffer around active carrot seed fields in central Oregon (Figure 1). This area represents an appropriate scale to industry and local weed managers, while also including adequate diversity of landscape conditions to support robust scientific inference.

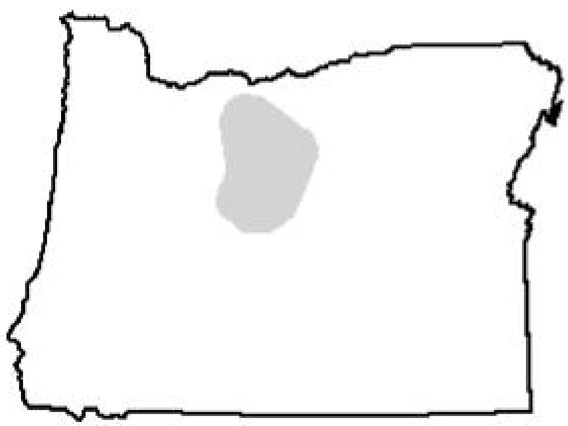


Figure 1: Central Oregon wild carrot study area extent shown in gray, within the state of Oregon.

Field Surveys

Field data were compiled from multiple community partners and collected specifically for this project across two field seasons, 2022 and 2023. Our targeted surveys aimed to describe wild carrot distribution and collected both positive wild carrot detections and verified wild carrot absences to train the species distribution model.

Modeling Approach

We used the random forest machine learning algorithm (Breiman 2001) to link the locations of known observations of wild carrot to a suite of raster explanatory variables. We produced a continuous raster layer that indicates the relative probability that each pixel might support the establishment of wild carrot in the area of interest. As a purely correlative, pixel-based model, the map simply highlights those portions of the landscape that are similar to the locations where wild carrot introductions have already been observed.

Training Data

We collected both positive wild carrot detection and verified wild carrot absence data to feed the species distribution model. Field data were compiled from multiple community partners and collected specifically for this project across two field seasons, 2022 and 2023.

Community Data

In 2022, we pulled together observations of naturalized wild carrot within the study area, drawing on observations from Bureau of Land Management treatment areas, The United States Forest Service Natural Resources Program, county (Jefferson and Crook) weed managers, and local carrot seed farmers, and iNaturalist. John Spring also conduced targeted surveys along the Deschutes River. Together, these sources yielded a total of 49 wild carrot observations.

2022 Field Season

To target sample locations for the 2022 field season, we used ownership information and proximity to public roads to determine accessibility. We set out 500 random points within accessible parcels, stratified by habitat type (based off of the Oregon Statewide Habitat Map) and by likelihood of wild carrot presence. Likelihood was split into high, medium, or low based on a preliminary species distribution model that used the community observations, climate, and topography. Throughout the 2-week weeks of field work, 136 of these random locations were visited and surveyed for wild carrot presence, yielding just 9 positive detections, all in close proximity along the Deschutes River. While the relative absence of wild carrot is a positive sign that occupancy in the study area is fairly low, the low number of positive detections and their proximity limited their ability to inform our species distribution model.

2023 Field Season

After the sparse occupancy observed in 2022, the 2023 field season forwent random sampling points and instead aimed to capture as many positive detections as possible. The field crew surveyed a continuous 90m belt along high likelihood corridors, which were defined as topographically wet areas along public roads and water courses and near previously documented presences. Absences were recorded every 200-500m along the surveyed corridors and all presences that were observed were recorded. This effort yielded a total of 16 positive observations, 6 of those along the Deschutes River.

Model Specification

We used all 75 positive observations of wild carrot within the study area as positive training data. For negative training data, we used 250 of the 2000+ absences collected in 2022 and 2023. These were points that were visited, but did not contain wild carrot. The 2000 known absence locations were mostly collected in 2023 and biased towards high likelihood locations. Because our sample of negative data did not adequately cover full study area landscape, we also used 1000 randomly placed background locations as negative training data, or pseudo-absences (Barbet-Massin et al. 2012).

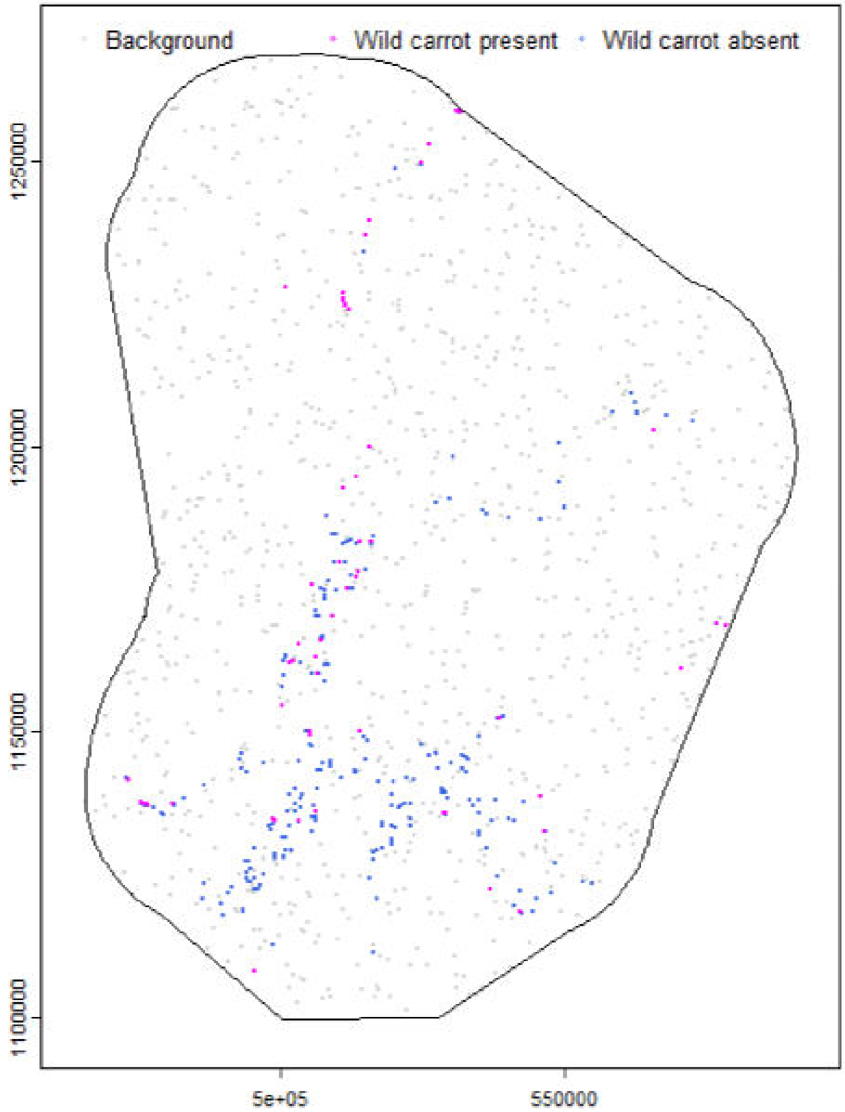


Figure 2: Training data. Positive wild carrot observations shown in magenta, true absences are shown in blue, background points (pseudo-absences) are shown in dark gray.

Raster Data

We used information from an array of 30m resolution raster data layers describing climate, topography, surface reflectance (satellite imagery), landcover, and distance to roads in our modeling process. Table 1 in Appendix 1 includes all raster explanatory variables available and used for modeling. These variables were chosen to reflect assumed drivers of weedy wild carrot presence within the study area: propagule availability (e.g. distance from a road), and favorable conditions for germination and persistence (e.g. variables associated with spring soil moisture and light availability). Climate variables were summarized from 30 years of modeled climate history (PRISM 2024, Daly et al. 2008). Topography descriptor variables were derived from the 30m national elevation dataset (Gesch et al. 2002). Satellite imagery was derived from the Landsat. Road corridors were provided by the Oregon Department of Transportation (2024).

Data layers that had native resolutions greater than 30m (i.e., climate variables), were resampled to 30m for this modeling exercise, using bilinear interpolation. We began with fifty-one variables from the above categories, and developed a final suite of modeling variables through the procedure described below.

Model

Field observations were intersected with explanatory data to build a modeling dataset used to inform Random Forest machine learning algorithms (Cutler et al. 2007), implemented in R software to discern which parts of the landscape are most likely to support wild carrot.

Variable Selection

For the variable selection process, we split our data set into two sets: training and testing.

Using the training data set, we built a binary random forest model, using the r package 'ranger' (Wright and Ziegler 2017) to describe the correlations between our raster data and the wild carrot presence points (background points were treated as absence for the model).

We selected a subset of the available raster explanatory variables for the model using a two-phase approach, similar to that described in McRoberts (2016). First, we built a single random forest model predicting wild carrot presence from the training data. We rely on the mean decrease accuracy index of variable importance to cull the least important variables from the list (keeping only those with a permutation importance value greater than 2.5^{-4}). With the remaining variables after step 1, we use a genetic algorithm to identify a subset of those variables that yields a model with strong performance, as measured by the average of the Area Under the receiver-operator Curve (AUC, Hanley and McNeil 1982) criterion for the training, and testing data (split data were used to reduce the probability of an over-fit model with too many variables).

At each of forty or more 'generations', we tested a randomly generated subset of 4000 possible models. The models tested in the first generation used randomly generated lists of explanatory variables. For each subsequent generation, we derived the population of models to be tested from the best-performing models in the previous 'generation' (with added variation). Selection continued through at least forty generations, until a stable solution was reached. Stable solutions were defined meeting one of two criteria after the forty generations had finished completed: 1) model performance remained consistent for at least 5 generations, or 2) sixty generations had passed.

Final Model

We created the final model for the mapping process with all of the selected data (75 positive points, 250 observed negative training points, and 1000 background points), and the variable subset from the best model generated during the variable selection process. This model used 1000 trees.

We provide some insight into the final model structure by calculating variable importance (Gini index, and Mean Decrease AUC). To further illustrate the correlations that drive model prediction, we also calculate the partial dependency of the response variable on each of the six most important variables in each model.

Accuracy Assessment

We evaluated the final models for overall strength using the Area Under the receiver-operator Curve (AUC) statistic, which indicates the model's capacity to discern presence and background points (approaches 1 for a perfect model). We also assess the model's binary performance at different probability cutoff values using metrics describing Sensitivity, Specificity, and the True Skill Statistic (following Fielding and Bell 1997). We also calculate kappa statistics (Cohen 1960), and the percent of correctly classified observation and background points for binary responses with different thresholds. We defined the probability cutoff values from the out-of-box model predictions, using the precision-recall f-measure, as implemented in the R package ROCR (Sing et al. 2005). We also report binary accuracy statistics for all of the alpha values considered in creating the categorical map, described below, that accompanies this report (0.05, 0.25, 0.5, and 0.75) in table format.

Mapping

For all 30m pixels in our study area, we generated a probability prediction from the final random forest model, multiplied by 1000. To aid with interpretation, we further transformed this raw 'probability' grid to a categorical map using unique cutoff values derived with each alpha-value for the model's out-of-box predictions for training data.

The resultant categorical map can be used like a normalized probability layer, with each class having somewhat consistent meaning across the maps of different regions with respect to the relative preponderance of false positive and false negative errors. The lowest nominal category in the map (alpha <= 0.05; Very Low Risk) identifies the areas that are least likely to contain wild carrot. In this category, false positive errors are rare, and false negatives are less so. In other words, a few wild carrot observations may fall within this portion of the map, but they are uncommon.

As alpha values rise, the categorical error structure shifts, placing specificity at a higher priority than sensitivity. In other words, binary maps associated with the higher-alpha cutoffs are more and more likely to actually have wild carrot present, but less inclusive of all possible risk. In the higher risk categories, false positive errors are more rare while false negative errors are more common, and the binary maps using the highest cutoff values will be most likely to miss patches of wild carrot within the landscape. Instead, these areas represent the highest priority for monitoring and the locations with the very highest likelihood of finding wild carrot.

Results

Field Surveys

Almost all of the wild carrot observations we collected were adjacent to roads or streams and the largest populations were found in wetter areas. In riparian habitats wild carrot often co-occurred with Reed Canary Grass (*Phalaris arundinacea*), Alders (*Alnus* sp.), and Tall Fescue (*Schedonorus arundinaceus*). Outside of riparian areas, wild carrot was associated with a wide variety of plants. Wild carrot was often found in irrigated or topographically moist patches of cultural vegetation like lawns, horticultural plantings, and bioswales, but there were a few smaller populations (1-5 individuals) found in drier upland roadside locations.

Model

We built a random forests model and used it to predict a continuous raster layer that indicates the relative probability that each pixel might support the establishment of wild carrot.

Variable Importance

The 13 variables selected for inclusion in the model (Table 1, Figure 3) drew from all categories of available data: topography, climate, spring and summer imagery, landcover, and distance to roads. Variables representing elevation, spring moisture availability, and summer and spring surface reflectance (satellite-derived vegetation indices) were the most important (Figure 3), but all variables contributed to the final model.

Table 1: Descriptions of predictor variables included in the final model.

Type	Variable	Selected	Description
Topography	a07_be30	X	Elevation (USGS 2020)
Topography	a10_east30	X	Aspect, 'eastiness' = sin(aspect)
Topography	a25_cpl30	X	Curvature, 3x3-cell planimetric curvature from elevation aggregated to 30m (ESRI 2018)
Hydrology	a38_dtwc	X	Vertical depth to nearest stream channel (Conrad et al. 2015)
Climate	vpdmax_234	X	1990-2021 normal maximum vapor pressure deficit, February - April (PRISM 2024)
Climate	ppt_234	X	1990-2021 normal precipitation, February - April (PRISM 2024)
Satellite Imagery	SR_B7_spr2123	X	Spring 2021-2023 Landsat medoid (Flood 2013), Band 7 Surface Reflectance
Satellite Imagery	NBR_spr2123	X	Spring 2021-2023 Landsat medoid, normalized burn ratio (Key and Benson 2002)

Satellite Imagery	G_sum2123	X	Summer 2021-2023 Landsat medoid, Tasseled Cap Greenness (Flood 2013, Kauth and Thomas 1976)
Satellite Imagery	NDVI_sum2123	X	Summer 2021-2023 Landsat medoid, normalized difference vegetation index (Tucker and Sellers 1986,)
Satellite Imagery	EVI_sum2123	X	Summer 2021-2023 Landsat medoid, enhanced vegetation index
Habitat	RoadDist	X	Horizontal distance from a road
Habitat	HabitatMap2	X	Oregon habitat map, simplified (INR 2018)

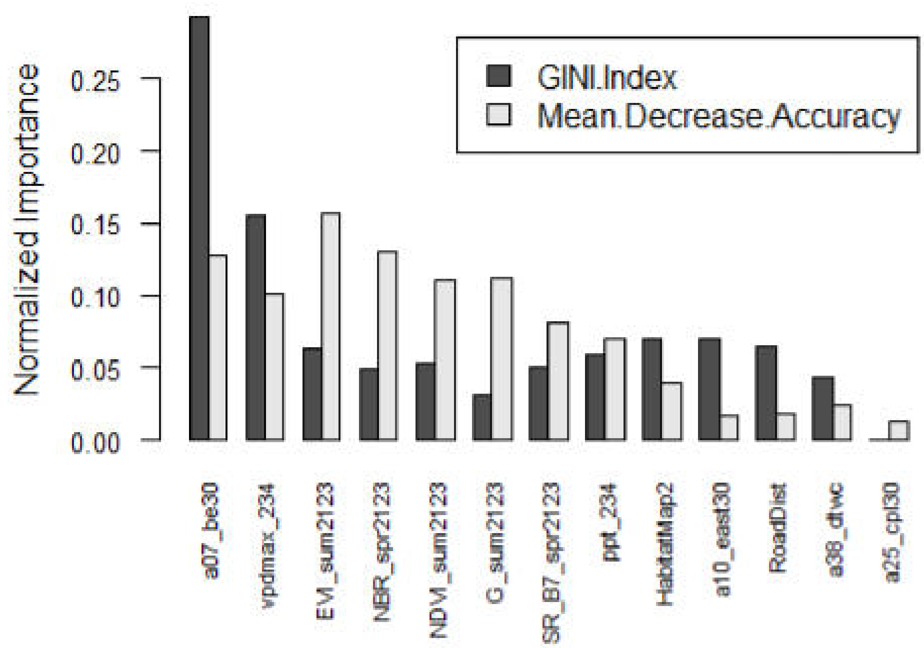
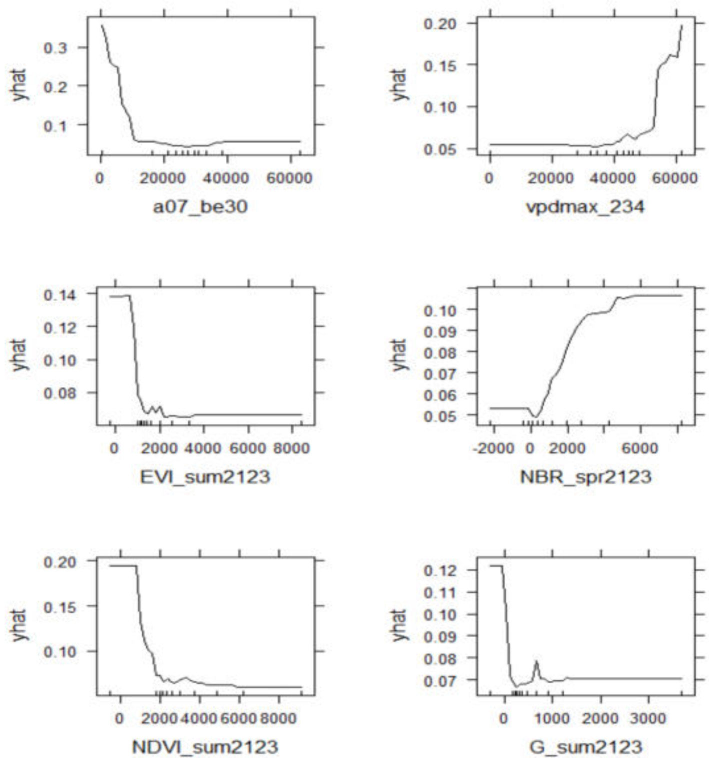


Figure 3: Variable importance metrics for wild carrot establishment risk models. Mean decrease gini, and mean decrease accuracy are rescaled as 'proportion of total index' for display. These metrics are extracted from models that were used solely for importance calculations (not mapping). Minor differences are possible between these models and the ones used for mapping due to the random processes within the random forest model, but they are likely to be small.

Variable Effects

Figure 4: Partial plots for top 6 variables for the wild carrot model. The x-axis for each shows the scaled values that correspond to the raster data layers. The y-axis (yhat) indicates the marginal effect of each variable at different values on the model's probability prediction, and are not intended for deductive use.



Marginal effects for the most important variables show that wild carrot was most often found in lower elevation areas and also in areas with higher spring maximum vapor pressure deficits (i.e., water stress), which may reflect a correlation between these environmental conditions and the road and river corridors that represent the majority of the wild carrot observations (Figure 4, top row). From satellite imagery, wild carrot was most prevalent in areas that had low values for the summer enhanced vegetation index, and high values for the spring normalized burn ratio (Figure 4, second row). These types of values in the imagery can sometimes indicate bare, or disturbed land.

Model Accuracy

The random forest model was very effective at discriminating between observations and random background points (AUC: 0.911, Figure 5).

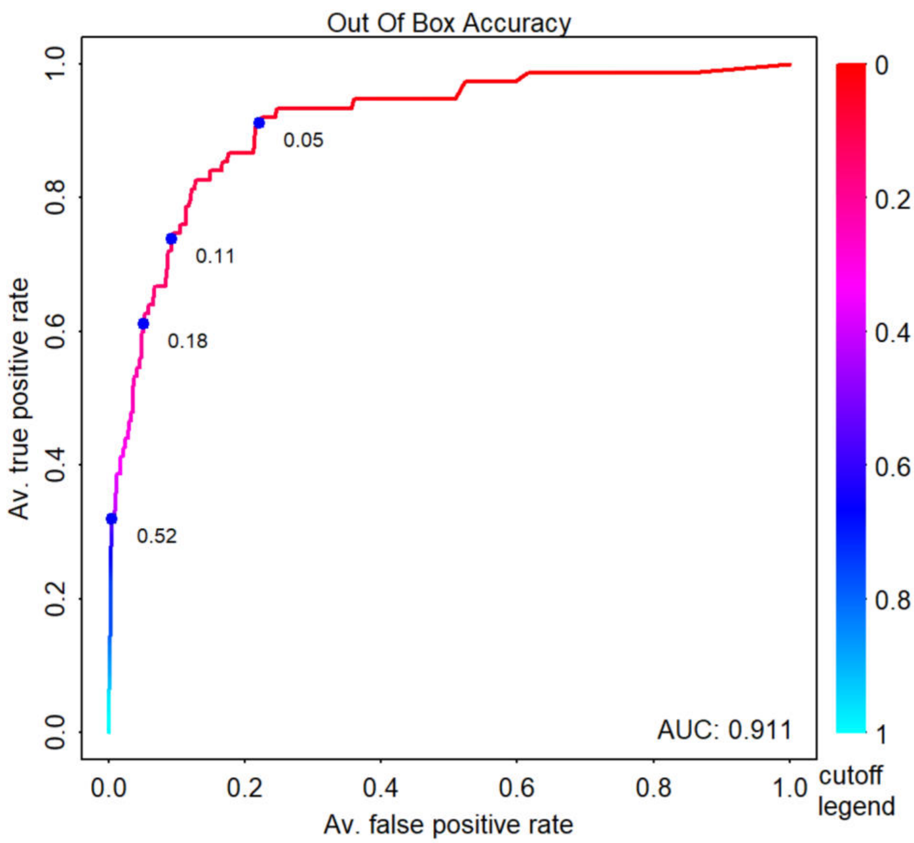


Figure 5: Receiver-operator curve for model predictions for out of box, and testing data predictions. Blue points in panel 'a' indicate cutoff values identified by precision-recall f-measure for alpha = 0.05, 0.25, 0.5, and 0.75.

The model's error structure yielded four unique cutoff values, representing alpha values of 0.05, 0.25, 0.5, and 0.75 (Table 2). These cutoff values were used to create binary (above vs. below) categorizations which ranged in accuracy from 78.6% to 95.7% accurate. Sensitivity (true positive rate) measures ranged from 0.320 (32.0%) in the Very High Risk category, to 0.920 (92.0%) in the Low Risk category, while Specificity (true negative rate) ranged from 0.778 (77.8%) for the Low Risk category, to 0.995 (99.5%) in the Very High Risk category (Table 2). True Skill Statistic values were highest for the Low Risk category, while Kappa values were highest for the High Risk category.

Table 2: Binary accuracy statistics for categorical model prediction for out-of-box predictions, for all of the alpha-cutoffs used within the categorical map associated with this document. Statistics reported are overall % accuracy, Sensitivity, Specificity and True Skill Statistic (TSS), following (Fielding and Bell 1997), and Kappa (Cohen 1960).

Categories	Cutoff value	alpha	Accuracy	Sensitivity	Specificity	True Skill Statistic	Kappa	Kappa ASE
Low Risk	0.050	0.05	78.6%	0.920	0.778	0.698	0.258	0.027
Moderate Risk	0.114	0.25	89.9%	0.747	0.908	0.655	0.409	0.040
High Risk	0.181	0.50	93.1%	0.613	0.950	0.563	0.464	0.047
Very High Risk	0.524	0.75	95.7%	0.320	0.995	0.315	0.439	0.061

Maps

The raw model prediction highlights areas that are more or less similar to the locations where wild carrot has been observed. This is not a probability surface in the statistical sense, and calibration of these values to reflect the model's error structure is needed to attach meaning to the values.

Classifying the raw map from the cutoff values (Figure 5, Table 2) yields a five-category map that showing most of the study area as "Very Low Risk" (~3.4 million acres, Table 3). Monitoring and control efforts for wild carrot could potentially be strategically arrayed within the higher risk categories, according to the resources available. A web app can be found here with the classified map and wild carrot detection locations.

Table 3: Area represented within each map category

Category	Acres	Percent
Very Low Risk	3382003	88.72%
Low Risk	284222	7.46%
Moderate Risk	84219	2.21%
High Risk	59582	1.56%
Very High Risk	1821	0.05%

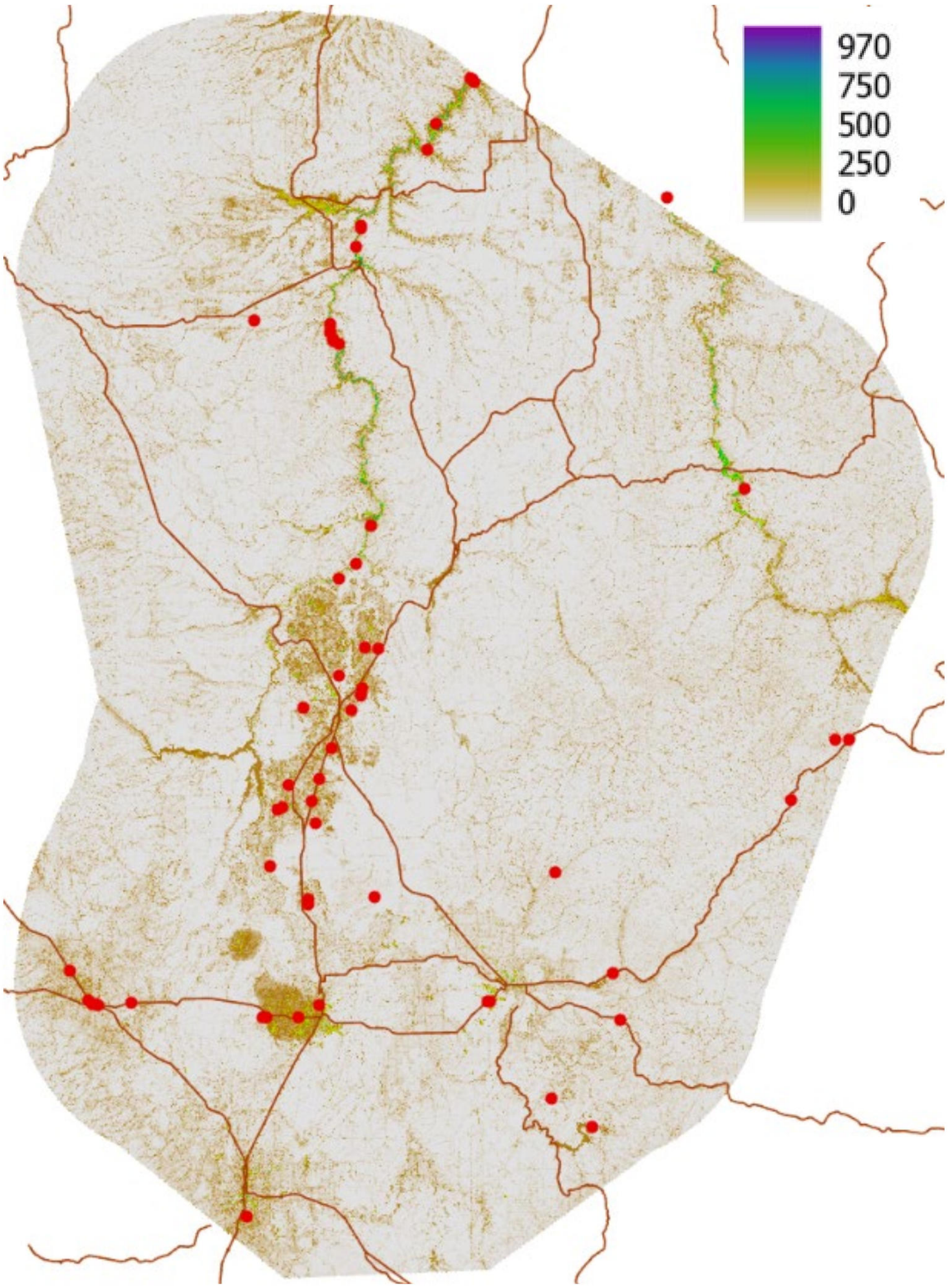


Figure 7: Estimated 'probability' surface from the random forest model. Raw model predictions have been multiplied by 1000.

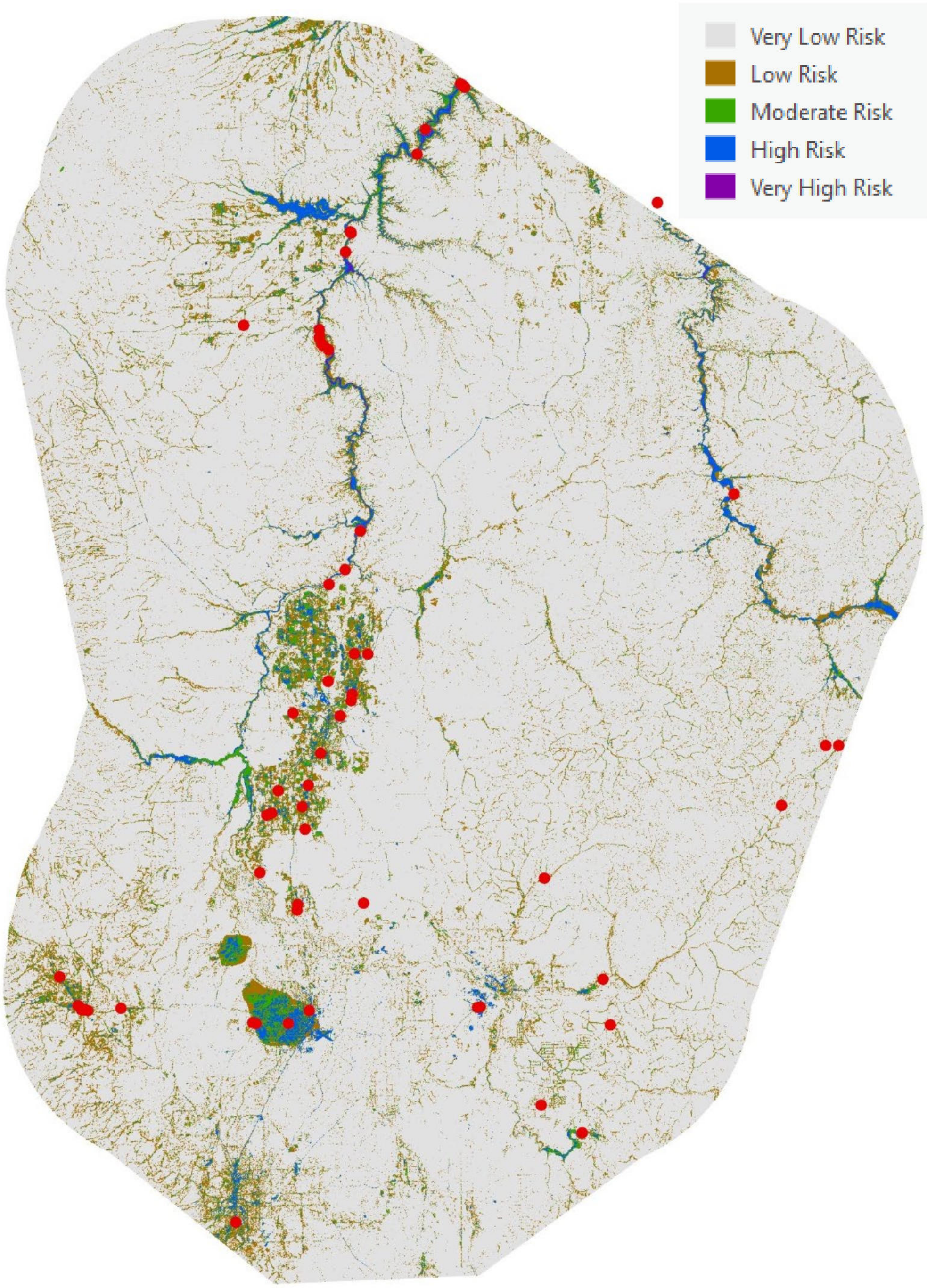


Figure 8: An illustration of estimated risk categories derived from random forest 'probability' model shown above.

Conclusions

We aimed to answer the following two questions with this work: i. What is the current distribution of wild carrot in central Oregon? and ii. How much of central Oregon, and what types of habitats, are most likely to be invaded by wild carrot?

Field Surveys

One of the key objectives of this research effort was to assess the current occurrence patterns of wild carrot. Our field surveys suggest that wild carrot currently has low occupancy in the study area. Despite significant field effort, we only found 75 records of wild carrot presence in the study area across 10 years of partner data and 2 seasons of targeted fieldwork. Our 2022 field surveys found zero occurrences of wild carrot besides the banks of the Deschutes River. Our 2023 surveys targeted the highest risk locations and still only found wild carrot in 16 out of more than 2000 surveyed locations, well under 1%. Almost all of the wild carrot observations we collected were adjacent to roads or streams and the largest populations were found in wetter areas that were irrigated or topographically moist, but there were a few smaller populations (1-5 individuals) found in drier upland roadside locations. This suggests that while wild carrot is more likely to germinate and survive in wetter areas, it can potentially persist in a much wider range of environments.

Species Distribution Model

The model predicting wild carrot across the study area was effective at discerning presence points from background and absence points, highlighting portions of the landscape that are similar to the locations where wild carrot introduction and persistence has already been observed. The final categorical and continuous maps can serve as a helpful tool for prioritizing areas to monitor for new wild carrot occurrences.

The species distribution model also suggest that wild carrot currently has low occupancy in the study area. The vast majority of the 11.23 percent of the study area covered by the low, moderate, and high risk categories is actually expected to actually be unoccupied by wild carrot. The very high risk category of our distribution model covers less than 0.5% of the study area, and a full 88% of the study area is classified as very low risk. The relatively low sensitivity (32.0%) in the very high risk category does mean that there is some risk of finding wild carrot outside of the highest risk areas.

Wild carrot is far more common west of the Cascades, and has long been assumed to be less common in central Oregon due to a combination of lower propagule availability (fewer seeds present) and drier conditions (less favorable conditions for germination and persistence). The 75 known locations with wild carrot present had both a seed arrive and the environmental suitability for the seed to germinate and survive. Since our model is trained on these successful invasions, it represents the intersection of these propagule availability and environmental suitability. In locations without wild carrot present, it is unknown which of these factors is limiting its presence. We suggest that the relatively low occupancy overall (including many absences in areas very similar to those with wild carrot) and the significant association between observations and dispersal corridors (roads and streams) indicates at least some degree of limitation by propagule availability. Likewise, wild carrot being more common in wetter, and more open areas, suggests that moisture, soil conditions, and light availability also limit germination and persistence. Our model uses a combination of negative training data (mostly collected in 2023 in wetter areas along roads and streams, areas where wild carrot absence is assumed to be more controlled by seed availability than environmental suitability) and background points, aiming to provide the best suggestion of which areas on the ground are most likely to have wild carrot presence in the coming years.

Acknowledgements

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The text of the introduction was lightly edited from the longer project proposal written by John Spring. Many former and current staff at INR contributed to this effort. Eric Nielsen processed and compiled the topographic and hydrologic predictors. Eric McGregor processed and compiled the satellite imagery predictors and assisted with modeling code. Angela Sakrison processed field observations from partners and worked on the preliminary models that were used to target field efforts. Fieldwork was conducted by John Spring, Jacob Rose, Emma Knepp, and Angela Sakrison across the 2023 and 2024 field seasons. Finally, Sean Gordon, Eleanor Gaines, and Pete Berry helped with contracting and administration of this effort.

Wild carrot field data were provided by the Bureau of Land Management, the United States Forest Service, iNaturalist, and Jefferson and Crook County weed managers with assistance from John Spring.

Additional thanks to John Spring for reviewing the model prior to publication.

Appendices

Appendix 1: Raster explanatory variables available and used for modeling.

Table 1. Raster explanatory variables available and selected for modeling.

Type	Variable	Selected	Description
Topography	a07_be30	X	Elevation (USGS 2020)
Topography	a10_east30	X	Aspect, 'eastiness' = sin(aspect)
Topography	a25_cpl30	X	Curvature, 3x3-cell planimetric curvature from elevation aggregated to 30m (ESRI 2018)
Hydrology	a38_dtwc	X	Vertical depth to nearest stream channel (Conrad et al. 2015)
Climate	vpdmax_234	X	1990-2021 normal maximum vapor pressure deficit, February - April (PRISM 2024)
Climate	ppt_234	X	1990-2021 normal precipitation, February - April (PRISM 2024)
Satellite Imagery	SR_B7_spr2123	X	Spring 2021-2023 Landsat medoid (Flood 2013), Band 7 Surface Reflectance
Satellite Imagery	NBR_spr2123	X	Spring 2021-2023 Landsat medoid, normalized burn ratio (Key and Benson 2002)
Satellite Imagery	G_sum2123	X	Summer 2021-2023 Landsat medoid, Tassled Cap Greenness (Flood 2013, Kauth and Thomas 1976)
Satellite Imagery	NDVI_sum2123	X	Summer 2021-2023 Landsat medoid, normalized difference vegetation index (Tucker and Sellers 1986,)
Satellite Imagery	EVI_sum2123	X	Summer 2021-2023 Landsat medoid, enhanced vegetation index
Habitat	RoadDist	X	Horizontal distance from a road
Habitat	HabitatMap2	X	Oregon habitat map, simplified (INR 2018)
Topography	a10_hl30		Relative heat load (McCune and Keon 2002)
Topography	a10_sld30		Slope, in degrees
Topography	a10_south30		Aspect, 'southiness' = sin(aspect-90°)
Topography	a25_cpr30		Curvature, 3x3-cell profile curvature from elevation aggregated to 30m (ESRI 2018)
Topography	a25_cur30		3x3-cell total curvature from elevation aggregated to 30m (ESRI 2018)
Hydrology	a38_dihc		Horizontal flow distance to nearest stream (Conrad et al. 2015)
Hydrology	a38_dihm		Horizontal flow distance to nearest major river (Conrad et al. 2015)
Hydrology	a38_dihr		Horizontal flow distance to nearest major stream (Conrad et al. 2015)

Hydrology	a38_dtwm	Vertical depth distance to nearest major river (Conrad et al. 2015)
Hydrology	a38_dtwr	Vertical depth to nearest major stream (Conrad et al. 2015)
Hydrology	a46_wet30	SAGA wetness index (Conrad et al. 2015)
Climate	tmean_234	1990-2021 normal mean temperature, February - April (PRISM 2024)

Appendix 2: Additional Maps

Figure 9. Ochoco Irrigation District estimated 'probability' surface from the random forest model. Raw model predictions have been multiplied by 1000.

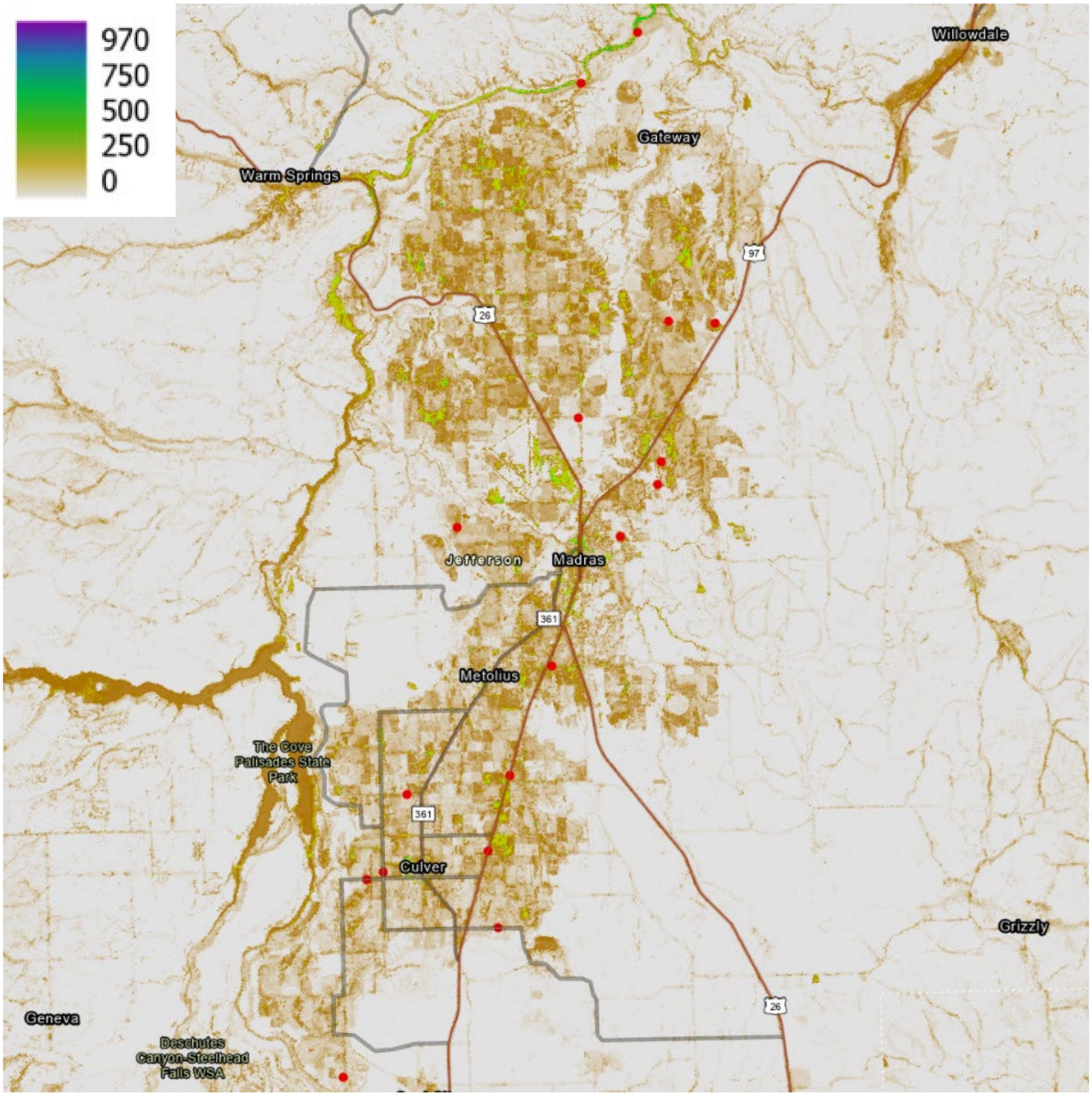

Figure 10. North Unit Irrigation District estimated 'probability' surface from the random forest model. Raw model predictions have been multiplied by 1000.

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Herbicide Screenings for Wild Carrot (*Daucus carota*)

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Data created for: Oregon Department of Agriculture ODA21012GR

Abstract

Research specific to wild carrot (*Daucus carota* L.) control in Oregon is limited, yet essential for protecting carrot seed production due to the risk of genetic contamination from cross-pollination with wild carrot. This project assessed multiple herbicides that could be utilized in non-crop regions such as fallow fields, along roadways or in natural ecosystems identifying florpyrauxifen and sulfometuron as effective control options with lower environmental impact. Field trials conducted in 2022 and 2023 showed that florpyrauxifen achieved 88% control and sulfometuron 83% control, making them the most effective treatments tested on wild carrot. Florpyrauxifen, approved by the EPA for reduced-risk use, is suitable for all non-crop land including areas near water, while sulfometuron is suitable for non-crop land but not near water sources. Spot spraying or backpack spraying in these high-risk zones supports targeted weed management, helping prevent wild carrot spread and preserving seed purity.

Introduction

Research-based recommendations directly relevant to wild carrot control in Oregon are quite limited, particularly east of the Cascades. Most existing scientific work focused on controlling the weed was conducted in Michigan (Stachler and Kells 1997), Ontario (Soltani et al. 2017), or other parts of the humid east coast (Bradley et al. 2004, Fleischer et al. 1989), and did not investigate a full complement of commonly used non-crop herbicides. A general description of the weed in the Willamette Valley of western Oregon comprises the extent of Extension material available from OSU and sister institutions in neighboring states (Colquhoun et al. 2003). Herbicide recommendations currently available to the public are also notably incomplete (Prather et al. 2020), and appear to be based mostly on national herbicide label wording in the absence of relevant local research.

As wild carrot represents an industry-identified risk to Oregon carrot seed production in the primary production region of central Oregon; introduction events of the weed into the de facto isolation zone maintained by private industry and local government, while still rare, appear to be increasing in relative frequency over time; and very limited research-based information is available regarding the scale and scope of the problem or robust control recommendations; we therefore addressed the following question: How do we best employ herbicides to eradicate wild carrot populations when detected?

Methods

Natural wild carrot populations were used for the herbicide efficacy studies with trial locations at Hyslop research farm at Oregon State University, Corvallis OR (44.633611, -123.190278) and Grinz farms near Marion, OR (44.747056, -122.9361) in 2022 and repeated at Hyslop Research farm in 2023. Applications occurred during the spring of 2022 and 2023 when wild carrot was at the rosette to early flowering stages. Each plant physiology stage was present within each plot during the herbicide applications. Each treatment utilizing a strip plot randomized block design and plots were 2 x 6 m with an average of 22 wild carrot plants per plot (Table 1). Applications were conducted with small-plot sprayers with four replications. Research backpack sprayers with compressed CO_2 were used as propellent and sprayed at 20 gpa (187 L/ha) using Teejet

AIXR 11002 or Greenleaf TDXL11025 nozzle tips for a coarse – extreme coarse droplet sizes. Herbicide efficacy was assessed 12 weeks after application (WAA) to ensure potential weed recovery after applications. In addition, ratings were conducted 10 months after applications during the second-year trial to assess residual control of the herbicides. Weed control was evaluated visually as a percent control relative to the non-treated check. Non-treated checks received "0" percent control and herbicide applied plots could receive between 0 - 100% control of wild carrot. Standard herbicide efficacy below 90% is considered "unsuccessful". However, due to the challenge of controlling wild carrot with herbicides, percent reduction relative to the check of greater than 80% is considered acceptable.

Table 1. Treatment list of herbicides utilized for wild carrot efficacy studies.

Trt	Active Ingredient	AI Rate(lb ai(ae)/ac)	Product
1	nontreated control	-	-
2	metsulfuron	0.0375	Escort XP
3	chlorsulfuron	0.0234	Telar XP
4	sulfometuron	0.1875	Oust XP
5	imazapic	0.09375	Panoramic 2 SL
6	imazapyr	0.75	Polaris
7	penoxsulam	0.03875	Sapphire
8	aminopyralid	0.109375	Milestone
9	clopralid	0.5	Transline
10	triclopyr	2	Vastlan
11	fluroxypyr	0.5	Comet
12	aminocyclopyrachlor	0.117	Method 240 SL
13	2,4-D	1	Unison
14	florpyrauxifen	0.0345	SiteVue
15	glyphosate	1	Glystar Plus
16	flumioxazin	0.375	Valor EZ

Statistical Analysis

Weed efficacy data was subjected to a Least Significant Difference (LSD)-test to compare the mean of the response of weed control. The location and year data for weed efficacy was pooled because of sample variance (Levene's test, $P < 0.05$), and differences in mean and interactions tested by ANOVA (P < 0.05). R (version 4.3.4) and the Agricolae package were utilized for each analysis.

Results

Individual herbicide trials are reported separately and then combined to determine the treatment(s) that best controlled wild carrot across multiple sites and years. In 2022, metsulfuron, sulfometuron, aminocyclopyrachlor and floryrauxifen had greater than 80% control at both the Hyslop and Grinz locations (Figure 1 and 2). Sulfometuron and floryrauxifen were the only treatments that had greater than 90% control at both locations in 2022. Glyphosate was the only treatment sprayed at Hysop during the 2023 season that had greater than 80% control (85%) (Figure 3). Although below 80% florpyrauxifen, and sulfometuron had the second and third highest efficacy ratings of 71 and 63%, respectively.

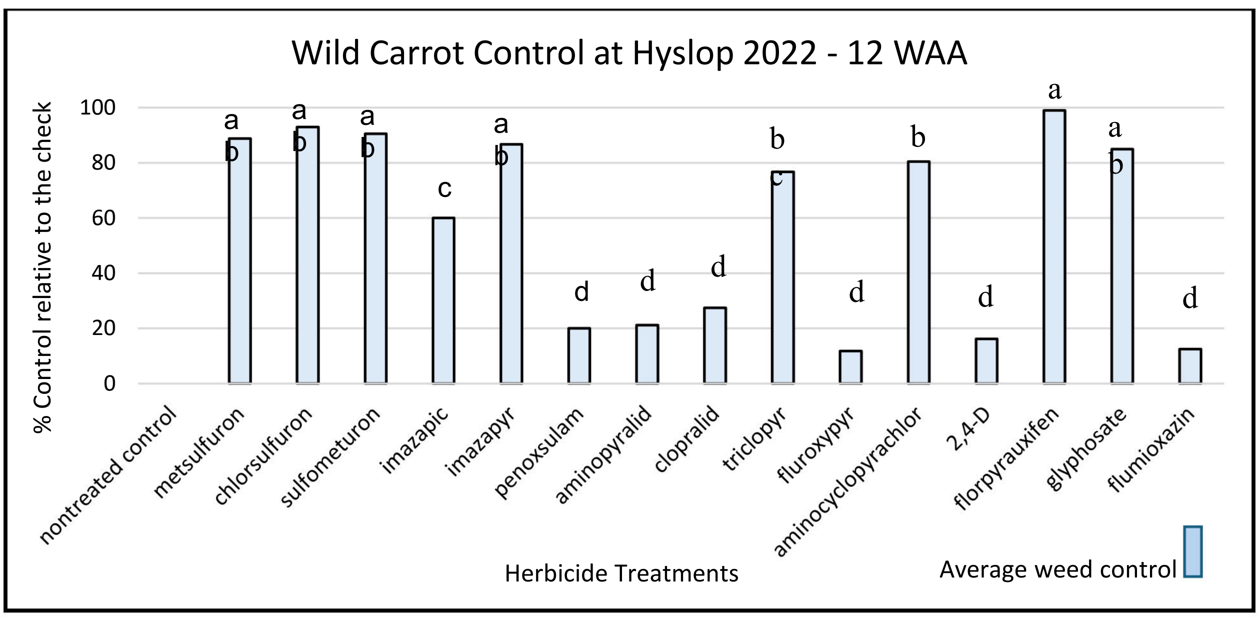

Figure 1: Herbicide efficacy of wild carrot at the Hyslop research farm 2022. Bars are the average percent control relative to the nontreated check. An LSD analysis was used to compared differences among herbicide treatments. Differences in letters indicate statistical significance (p-value < 0.05).

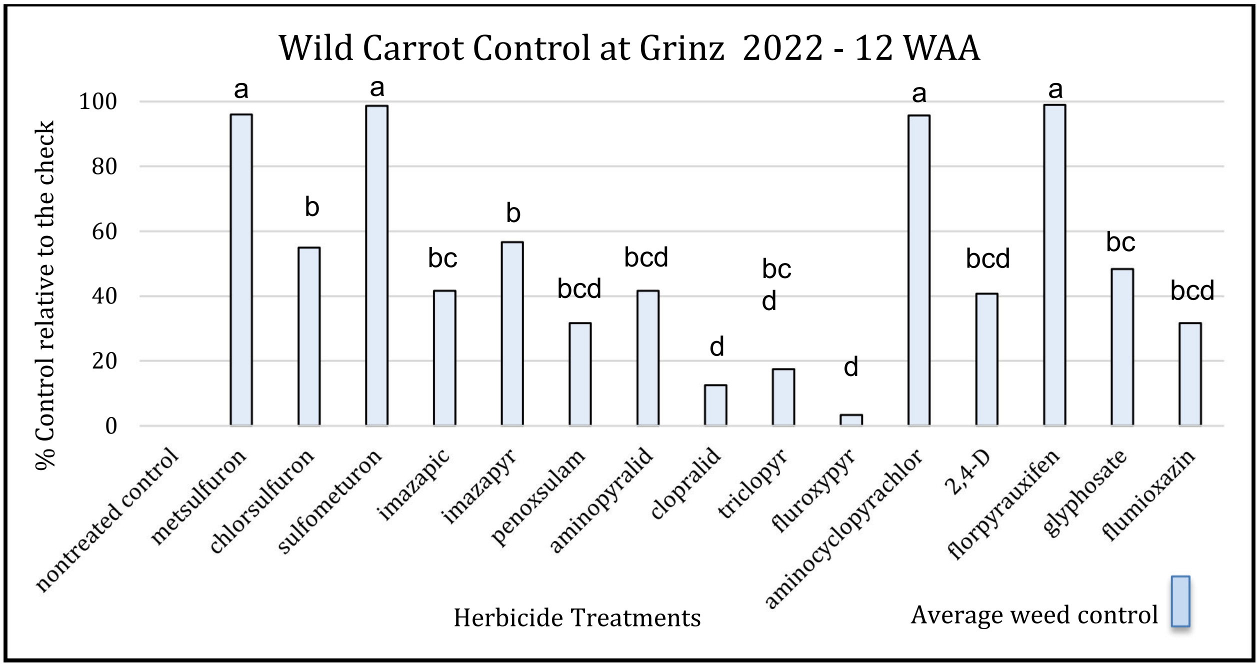

Figure 2: Herbicide efficacy of wild carrot at Grinz farm 2022. Bars are the average percent control relative to the nontreated check. An LSD analysis was used to compared differences among herbicide treatments. Differences in letters indicate statistical significance (p-value < 0.05).

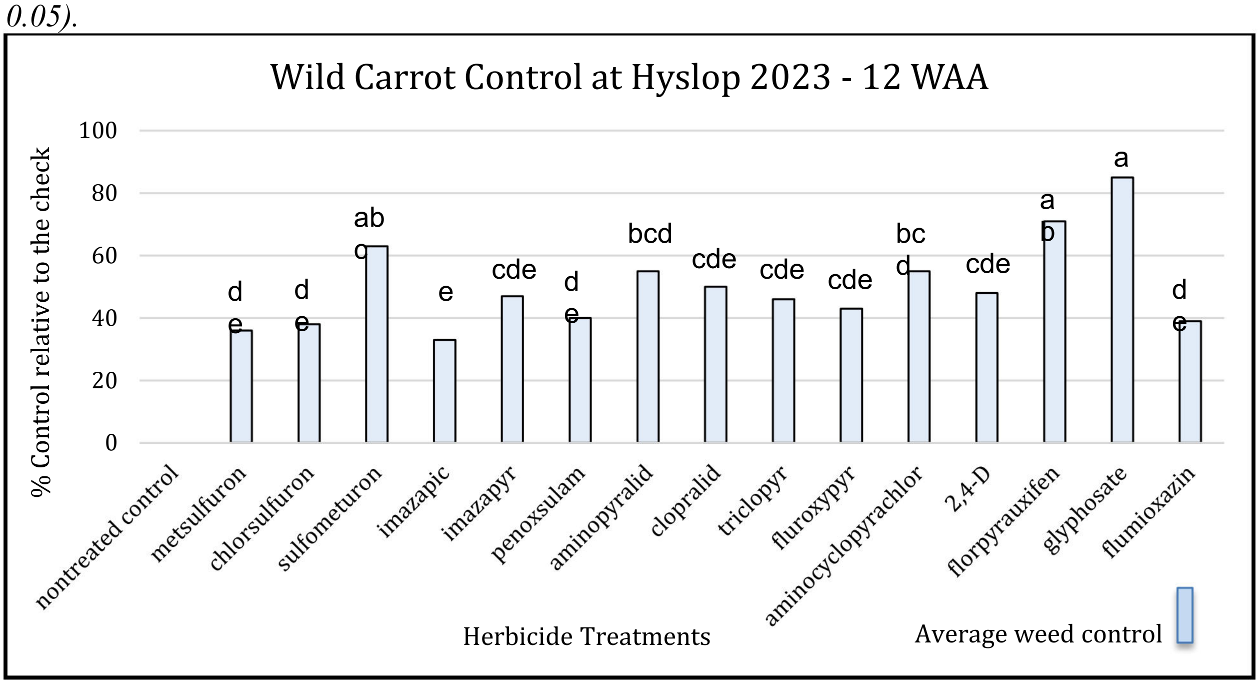

Figure 3: Herbicide efficacy of wild carrot at Hyslop farm 2023. Bars are the average percent control relative to the nontreated check. An LSD analysis was used to compared differences among herbicide treatments. Differences in letters indicate statistical significance (p-value < 0.05).

When herbicide ratings were combined across both locations and years; sulfometuron and floryprauxifen were the only two treatments that average greater than 80% control, 83 and 88%, respectively (Figure 4).

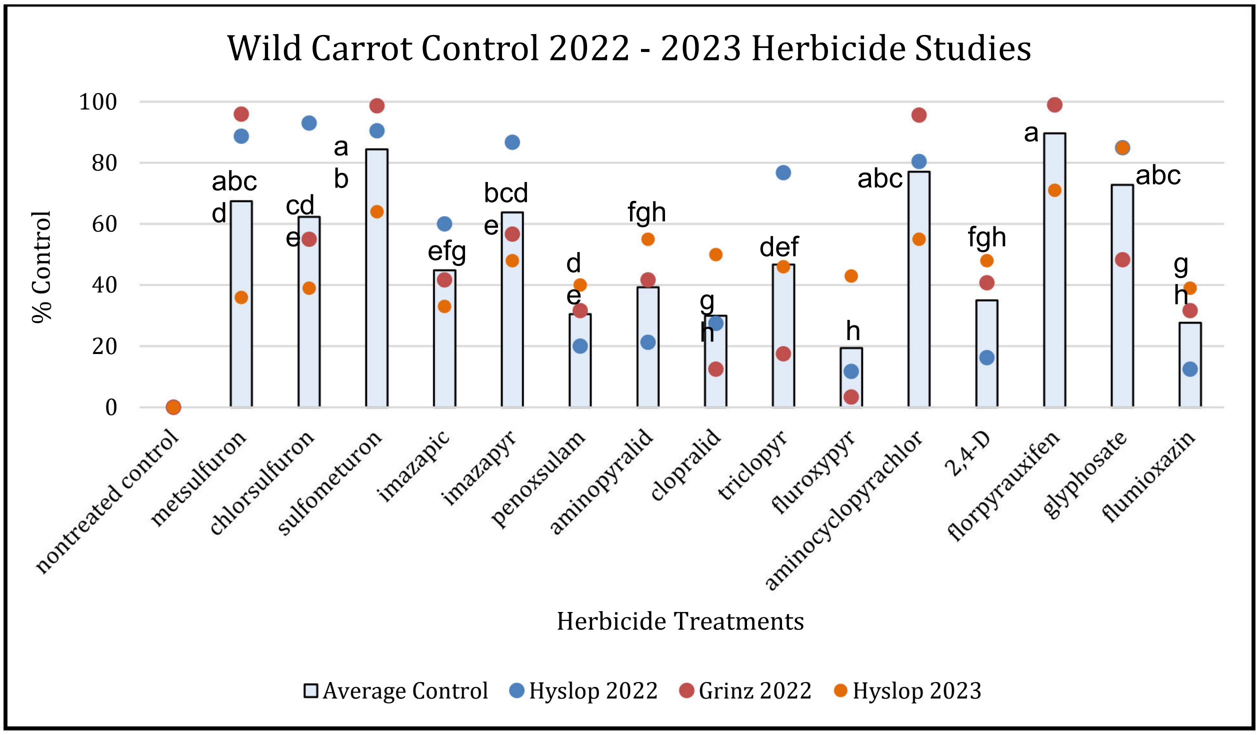

Figure 4: Herbicide efficacy of wild carrot at three locations and 2022 – 2023. Bars are the average percent control among the different sites and years. Individual points are the average wild carrot control for that specific study. An LSD analysis was used to compared differences among herbicide treatments. Differences in letters indicate statistical significance (p-value < 0.05).

During the 2023 – 2024 trial, herbicide efficacy ratings were taken 10 months (43 weeks) after applications to assess long term residual control. Florpyrauxifen had the best control over the 10-month period with an average of 78 percent control relative to the non-treated control (Figure 5). However, florpyrauxifen does not have residual control and the higher percent control is likely due to an increased control during the application timeframe. New wild carrot populations had not germinated at this rating time frame. The 10-month rating does demonstrate the value of effected herbicide control and the reduction in seed rain from mother plants to the soil seed bank.

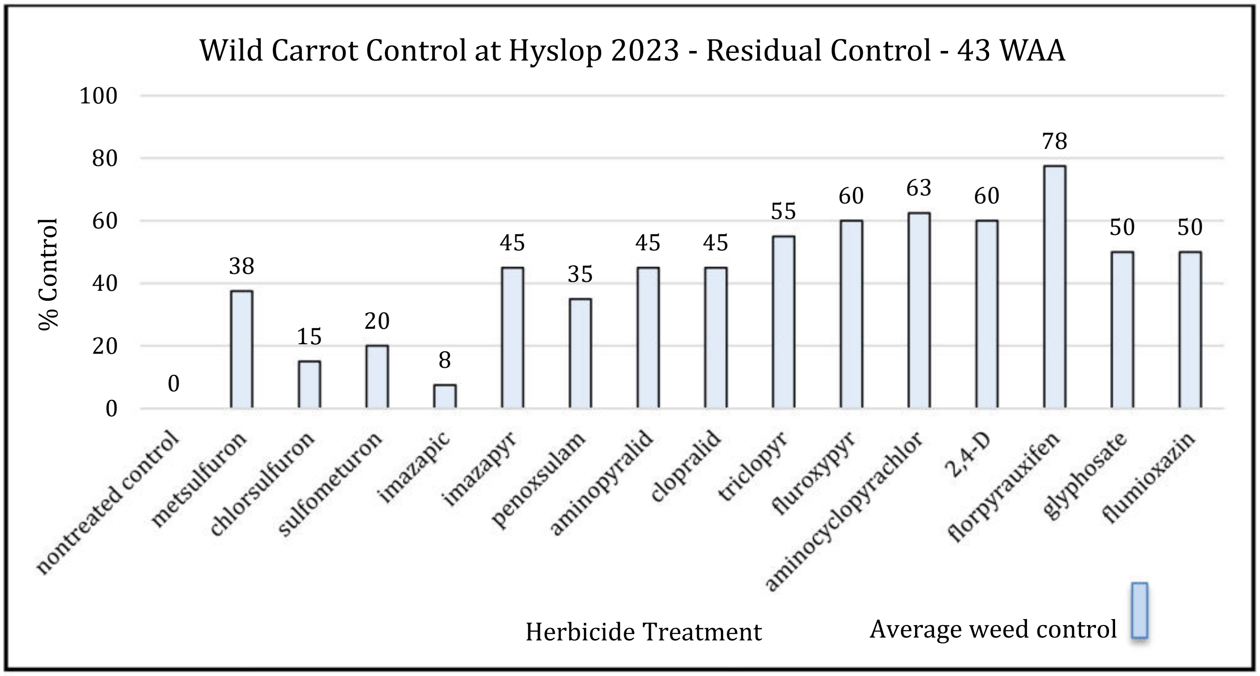

Figure 5: Herbicide efficacy of wild carrot 10 months after application Bars are the average percent control among the different sites and years.

Discussion:

Pollen movement between wild carrot and domesticated carrot poses a significant risk to carrot seed purity, as cross-pollination can lead to genetic contamination of seed crops (Godwin et al, 2024). Wild carrot produces viable pollen that can easily travel to adjacent fields, especially with the help of wind and pollinators. This risk necessitates stringent weed control in areas surrounding carrot seed production fields, including adjacent fields, roadways, fallow lands and natural habitats where wild carrot populations may thrive. Managing wild carrot in these buffer zones minimizes the chances of pollen transfer, helping to maintain the genetic integrity and marketability of domesticated carrot seed. Effective control measures along these perimeters are essential to prevent wild carrot from encroaching on production areas and ensure seed quality standards are met.

Controlling wild carrot is particularly challenging due to its hardy nature and resilience across a range of conditions (Godwin et al, 2024). While various herbicides are available, achieving complete control is difficult; however, these studies show that florpyrauxifen and sulfometuron demonstrate the highest efficacy and most consistent control among tested herbicides.

Florpyrauxifen, in particular, emerges as a promising option, especially given the predictive model from this research project, which highlights higher-risk areas for wild carrot establishment near waterways. Notably, florpyrauxifen has been designated as a reduced-risk herbicide by the Environmental Protection Agency (EPA) and is approved for use in aquatic systems (Howell et al., 2021). This herbicide offers reduced negative environmental impacts due to its rapid breakdown in soil and water and its low application rates compared to other aquatic herbicides. Florpyrauxifen has also shown success in agricultural systems where flooding is utilized, such as rice, where it effectively manages challenging weeds, such as Palmer amaranth (*Amaranthus palmeri*) (Wright et al., 2020, Inci, D and Al-Khatib, 2024). Consequently, florpyrauxifen could be applied near waterways to control wild carrot populations with minimal concern of potential runoff or leaching in adjacent waterways.

Sulfometuron, while showing lower average control effectiveness than florpyrauxifen, holds potential as a complementary herbicide within a broader weed management program, particularly in non-crop and natural areas. Its effectiveness has been noted in forest restoration projects, where it has been applied successfully to control invasive weeds and encourage the growth of native plant species (Robertson and Daves, 2010). This selective application makes sulfometuron valuable in ecosystems for invasive plant suppression. However, its usage limitations are significant; sulfometuron is not approved for application near waterways due to concerns over water contamination through runoff or leaching. As a result, its utility is restricted to upland areas or locations where water movement is controlled, ensuring that herbicide residues do not impact aquatic systems. In carefully managed conditions, sulfometuron can serve as a valuable tool for managing invasive plants, provided it is applied within regulatory guidelines to protect sensitive environments.

In many cases, weed control efforts only begin after an invasive species has become well-established, making effective management more challenging. This project, however, takes a proactive approach by mapping areas at varying risk levels for wild carrot establishment, allowing for preemptive and targeted control efforts. By identifying florpyrauxifen and sulfometuron as herbicides with lower environmental impacts, this research offers viable tools for wild carrot management in sensitive settings. Both herbicides are already recognized for their reduced ecological impact, with florpyrauxifen and sulfometuron commonly used in natural ecosystems to manage invasive weeds and support re-vegetation efforts (Robertson and Daves, 2010; Herrera et al., 2021).

The risk mapping conducted as part of this project enables a targeted weed management strategy, prioritizing high-risk areas for intervention. This approach supports precise control of wild carrot through methods like spot spraying or backpack spraying, depending on site-specific conditions. Focusing on higher-risk locations allows for a more efficient and strategic allocation of resources, reducing the potential spread of wild carrot while minimizing environmental impacts and reducing labor required for population assessments. This proactive, focused strategy supports both effective weed management and ecological sustainability by targeting areas most vulnerable to wild carrot invasion before extensive spread occurs. Reducing the potential risk to the carrot seed production region of Oregon. Furthermore, biennial weeds, such as wild carrot, exhibit a rosette stage in their life cycle, occurring in their first year. However, these weeds can remain in the rosette stage for more than one year, delaying their reproductive phase until conditions are optimal. This prolonged rosette stage makes them particularly challenging to manage, as their low-growing form allows them to evade certain control methods, such as mowing. Managing the rosette stage is crucial because it’s during this phase that biennial weeds are most susceptible to herbicides and other control methods, before they invest energy into stem elongation and seed production. Once these weeds bolt and begin flowering, they are far harder to control, and any seeds produced can contribute to future infestations. Targeting the rosette stage through timely herbicide applications or other control strategies can prevent these weeds from reaching maturity, thereby reducing their long-term impact on the landscape.

Acknowledgements

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Supplementary Data

Temperature Variation in Wild Carrot Germination

During the spring and summer of 2023, wild carrot seeds were collected during surveys in eastern Oregon and at Hyslop research farm to assess temperature requirements for germination. Seed were collected, dried, cleaned and sent to the University of Idaho for assessment. Results show that wild carrot can germinate between 4.8 and 35.9 C (40 – 96 F), however germination can be population dependent. The majority of germination occurred when temperatures ranged between 15.6 – 32.6 C (Figure 5). There was no variation among populations based on location.

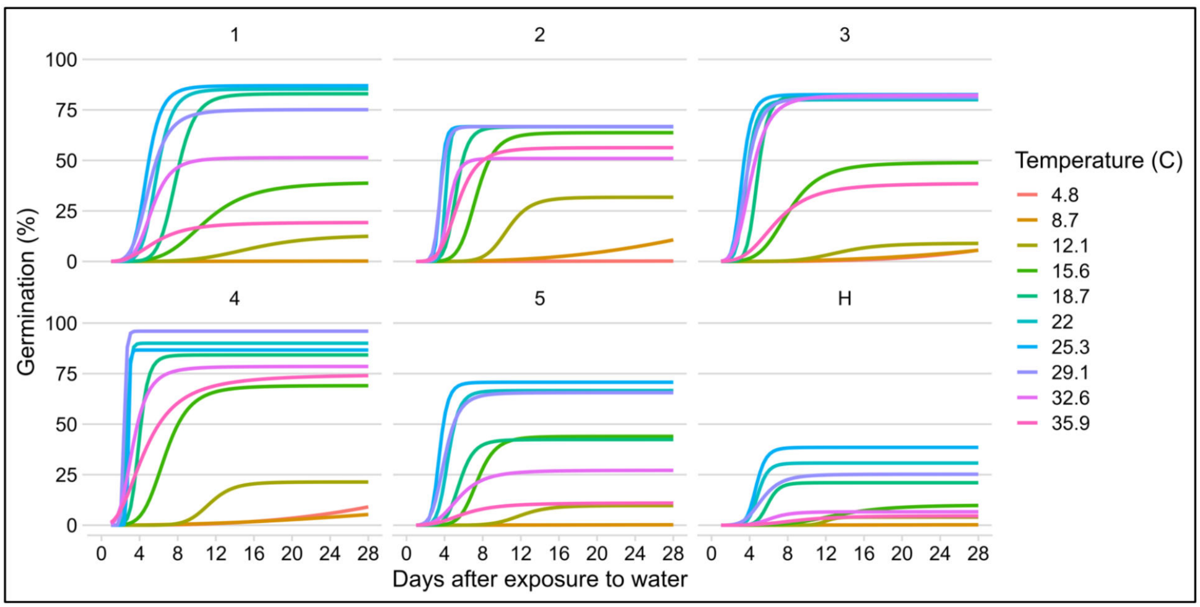

Figure 6: Germination studies assessing temperature requirements for wild carrot (*Dacus carota*) from six populations collected in 2023. Populations 1 – 5 were collected in Eastern Oregon during the mapping survey. "H" population is from Hyslop research farm near Corvallis, OR.

Wild carrot (Daucus carota), is a resilient species capable of germinating across a broad range of temperatures, which poses significant challenges for effective control. Unlike some plants with narrow germination windows, wild carrot seeds can sprout in both cool and warm conditions, allowing it to establish throughout much of the growing season. This adaptability means that even if early-season control measures like herbicide applications or mechanical removal are implemented, later waves of germination can still occur as temperatures fluctuate (discontinuous germination). Consequently, multiple treatments are often necessary to reduce wild carrot populations effectively. The plant's ability to germinate under various conditions enables it to exploit available resources more thoroughly, making it difficult to manage in both agricultural and natural environments.