DEVELOP Technical Report

Flat Tops Ecological Conservation

Mapping Yellow Toadflax to Inform Invasive Species Management within the Flat Tops Wilderness

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Abstract: Yellow toadflax (*Linaria vulgaris*) is an invasive perennial plant that is harmful to the biodiversity and function of the North American ecosystems it invades. Yellow toadflax thrives in subalpine zones, reducing forage for grazing animals and outcompeting native species. We partnered with the Yampa Ranger District of the U.S. Forest Service (USFS), which aims to maintain the native biodiversity of western Colorado's Flat Tops Wilderness Area. Our partners at the USFS have been manually treating and tracking yellow toadflax expansions in and around the Flat Tops Wilderness for the past 20 years. We aimed to develop spatial predictions of suitable habitat of yellow toadflax and evaluate the ability to detect existing populations to aid the USFS in their conservation efforts. We created a habitat suitability model which used field data points and several topographic and remote sensing variables to run three different machine-learning models. We also created a phenology time series plot across the 2024 growing season using field data from the partners, as well as Landsat 8 and Landsat 9 satellite imagery. This informed the species detection model, which sought to identify current yellow toadflax invasions. Results from the detection model, which included dates selected from the phenological time series plot, yielded no statistically viable results. This demonstrated the limitations of using remotely sensed imagery to map current outbreaks of yellow toadflax. The suitability model, on the other hand, produced viable habitat prediction maps aligned with expectations, which may help our partners save resources by narrowing down potential areas of concern for invasive species management.

Key Terms: Invasive Species, yellow toadflax, detection model, habitat suitability model

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1. Introduction

1.1 Background Information

Yellow toadflax (*Linaria vulgaris*) is a yellow flowering plant that is a dominating invasive species in North America's Rocky Mountain West. Native to Eurasia, yellow toadflax outcompetes native North American species within the subalpine meadow communities. Its harmful effects include decreased soil water retention, decreased biodiversity, and decreased palatable forage for wild and domesticated megafauna (Mahr, 2018). Land managers often use herbicides and biological controls to mitigate this invasive species; however, precise maps of the current extent and suitable habitat for this species within our study area have not been created.

Yellow toadflax is a pioneer species, meaning it readily colonizes post-disturbance landscapes (Mahr, 2018). It thrives at altitudes above 5,000 feet in elevation (Beck, 2014), displacing desirable grasses and native alpine vegetation by dominating open sites such as fields, pastures, edges of forests, and disturbed sites (Mahr, 2018). Yellow toadflax germinates from mid-to-late May, but mature plants can begin to flower in late-May along the front range, or late July when located at high altitudes (Beck, 2014). Toadflax grows in large patches, displaying white and yellow flowers reaching one to three feet tall. The stable and extensive root systems of toadflax help support it through environmental stressors such as fire, mechanical disturbances, snow, and drought (Beck, 2014). It grows quickly and covers large areas, outcompeting native flora and decreasing biodiversity. Yellow toadflax also contains toxic glucoside, making it unpalatable for grazing animals and presenting an issue for rangeland managers as the invasive species decreases viable forage (Mahr, 2018). In northwestern Colorado's Yampa valley and the upriver Flat Tops Wilderness Area, yellow toadflax has maintained expansive colonies for decades. It has been monitored and treated by the Yampa Ranger District for over 20 years.

Comprehensive analyses of remotely sensed data may be useful in detecting, treating, and anticipating the spread of invasive yellow toadflax. Time series plots of a target species' phenological shifts have allowed researchers to monitor low-lying, broad coverage invasive species, which are comparable to yellow toadflax, across seasons using remotely sensed data (VanArnam et al., 2023). Additionally, population distribution maps are an effective means of tracking current invasive species' land cover, and habitat suitability models are useful for predicting future invasion sites based on the target species' habitat preferences (West et al., 2017; West et al., 2016). Large-scale studies of yellow toadflax distribution and habitat in the Rocky Mountain west are scarce. Land managers, ranchers, and the public may benefit from an in-depth analysis of the extent and suitable habitat of yellow toadflax, to aid management efforts. More specifically, mapping and mitigating invasive yellow toadflax invasions within subalpine wilderness areas is of interest, because the Wilderness Act aims to preserve the natural conditions and native species of wilderness areas (Wilderness Act, 1964).

1.2 Study Area

Our study primarily focused on the Flat Tops Wilderness Area (FTW) in the Rocky Mountains of western Colorado. This wilderness area has been particularly impacted by yellow toadflax invasions in recent decades. Established in 1975, the FTW is the state's second-largest designated wilderness area, covering 235,214 acres of mixed subalpine terrain between 7,640 and 12,354 feet elevation (USFS, Figure 1). Alpine and subalpine ecological zones like those in the FTW are susceptible to climate change, human activity, and invasion from non-native species (Takahashi, 2018). The FTW area has been commercially grazed since before it was established as a wilderness area, and as such, grazing is permitted to this day. The wilderness area's jurisdictional boundary bridges two national forests and is managed by both the U.S. Forest Service (USFS) Meeker Ranger District and Yampa Ranger District (Figure 1). Invasive species management efforts within the FTW present a significant challenge due to tough terrain which limits accessibility and legal protections that prevent the use of machinery, further necessitating a comprehensive analysis of the extent and habitat of yellow toadflax in the region.

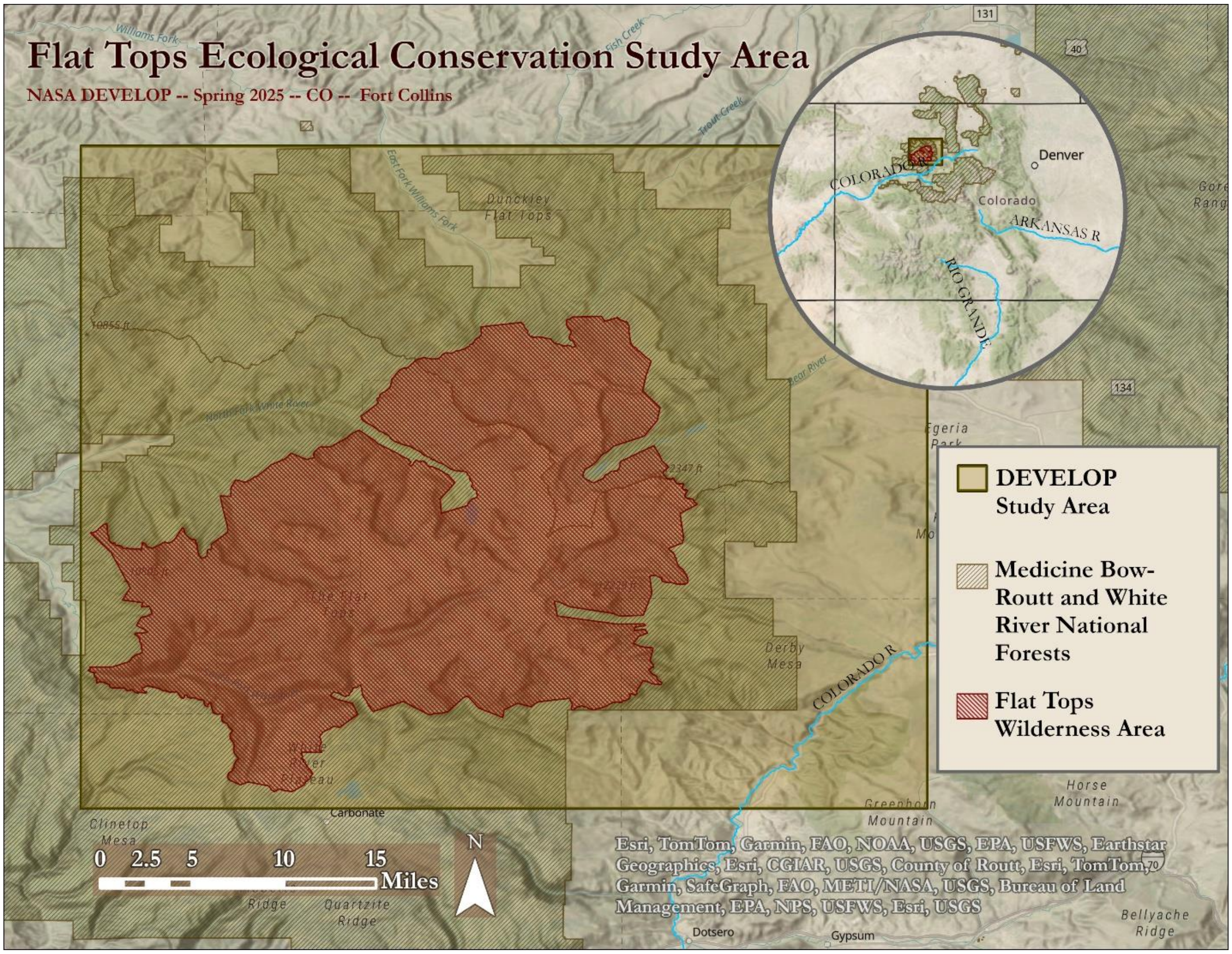


Figure 1. Map of the project study area surrounding and encompassing the Flat Tops Wilderness Area, and its relative location in Colorado.

Temporally, our team's study period varied depending on the deliverable objective. We analyzed ancillary field data from an 18-year period to model suitable habitat across the study area. We also used remote sensing data from September 6, 2024, for the habitat suitability model. For the phenological time series and the detection model, we used remote sensing data from April 7 through October 24, 2024, to analyze the spectral signatures of vegetation, including yellow toadflax, across the full growth season.

1.2 Project Partners and Objectives

We designed this feasibility study in partnership with USFS to better understand yellow toadflax invasions within and around the FTW area. Both the Meeker and Yampa ranger districts have used herbicidal treatments on yellow toadflax for the past 18 years and have tracked the species' expansion through on-the-ground efforts. Biological treatments, such as weevils or other insects, have not been successful and are no longer attempted due to extreme winters. Insects that might feed on yellow toadflax cannot survive the harsh cold at such high elevation. The USFS is looking for ways to improve the efficiency of its detection and treatment activities, due to limited resources and the inaccessibility of terrain within the FTW.

This study, therefore, explored the feasibility of using remote sensing data to detect invasive yellow toadflax as well as map suitable habitat within and around the FTW. This will allow USFS partners to monitor current yellow toadflax invasions and anticipate where the species is likely to colonize. The objectives of this project were to create (1) an inter-seasonal time series plot of how yellow toadflax' spectral signatures shift throughout the year, (2) a population distribution map of current toadflax invasions, and (3) a habitat suitability model predicting the landscapes and conditions where the species is likely to thrive.

The habitat suitability model differs from the species detection model in that it predicts likely habitat for the invasive species, rather than predicting where the species currently exists. The habitat suitability model uses several environmental predictor layers to analyze the preferences of yellow toadflax and project those preferences across the landscape. This will be useful in predicting where yellow toadflax is likely to thrive and may be used by land managers to outcompete or prevent the encroachment of yellow toadflax in high-risk areas. The species detection model, on the other hand, aims to use remotely sensed vegetation indices to detect where the species is currently dominating the landscape, giving the partners an idea of where treatment is currently needed.

2. Methodology

2.1 Data Acquisition

2.1.1 Field Data

In our three-pronged approach to modeling the extent and habitat of yellow toadflax, we used a combination of field data, multispectral remote sensing data, and publicly accessible environmental datasets including elevation, vegetation cover, infrastructural and hydrographic data. We used field data given to us by our USFS partners to map the presence of yellow toadflax throughout the Flat Tops Wilderness and surrounding areas. The Yampa Ranger District provided 2,395 data points in the western region of the study area, displaying where yellow toadflax was treated with herbicide between 2004 and 2023. The USFS Meeker Ranger District provided 624 data polygons in the south and central regions of the study area, displaying high-density plots where yellow toadflax was treated with herbicide between 2007 and 2023. Additionally, our USFS partners collected toadflax coverage data at 58 thirty-meter diameter plots specifically for this study in September of 2024. At each plot, our partner recorded the percent coverage of yellow toadflax, other yellow forbs, grasses, bare soil, and rock cover. All field data had precise GPS coordinates for yellow toadflax locations.

2.1.2 Remote Sensing Data

Our team acquired satellite imagery from the Landsat 8-9 Operational Land Imager (OLI) Collection 2 Level 2, from the U.S. Geological Survey (USGS) Earth Explorer website. This collection offered a 7-to-8-day temporal resolution, which allowed us to create a more comprehensive time series plot. With an 8-day combined revisit cycle between Landsat 8 and Landsat 9, these satellites offer a high temporal resolution across the full growing season. In addition, the multi-spectral imaging from Landsat, which includes seven bands representing visible light and infrared wavelengths, can be used to develop vegetative cover indices. For the habitat suitability model, we used Landsat data from September 6, 2024, because that was the same week when ground truthing field data were collected. For the phenological times series plot and population distribution map, we acquired satellite data from the same collection, from April 7 through October 24, 2024.

2.1.3 Environmental Data

For topographical data, we obtained current 1-arc-second and 1/3-arc-second elevation datasets from the 3D Elevation Program (3DEP) via the USGS National Map data acquisition website. For hydrographic data, we acquired a line feature layer dataset containing USA Rivers and Streams, as well as a polygon feature layer dataset containing Colorado Lakes, through Esri's ArcGIS online data platform. For infrastructural data, we obtained line feature layer datasets containing trails and roads from the U.S. Forest Service's Geospatial Data Discovery online platform. Finally, we obtained a raster layer of current land cover data from the U.S. Department of the Interior, the Geological Survey, and the U.S. Department of Agriculture's LANDFIRE 2023 online platform, using the Existing Vegetation Type Layer from LANDFIRE version 2.0.0. with a 30-meter pixel size.

Table 1
Ancillary and Sensor Data

Sensor/Source	Use in Project	Owner	Date of Data
Landsat 8-9 Level 2 Surface Reflectance (SR)	Surface Reflectance, NDVI, Tasseled cap	USGS Earth Engine	April–October 2024
3-D Elevation Program	Elevation Data	USGS National Map	Unknown
ArcGIS Online Data Platform	Distance from rivers and streams	ESRI	2024
USFS Geospatial Data Discovery	Distance from roads and trails	USFS	2022
LANDFIRE V2	Existing vegetation types	USDA	2023

2.2 Data Processing

2.2.1 Field Data

Since we had two large field datasets in two different formats, namely the Yampa district point data and the Meeker polygon data, we transformed the polygon data into point data using the Create Random Points tool in ArcGIS Pro version 3.4. This tool was set to use the polygon data as the constraining feature class, with at least one point per polygon, a minimum distance of 5m between points, and a total number of 1000 points. The transformation allowed us to combine the Meeker district field data with the Yampa district data along with the presence points within the toadflax coverage data to use in our habitat suitability model.

2.2.3 DEM

The team mosaicked together four 1-meter resolution tiles across the study area, using ArcGIS Pro. We then manipulated the data in ArcGIS Pro to create four separate raster layers: (1) aspect represented as northness, (2) aspect represented as eastness, (3) slope, and (4) elevation. Aspect is typically represented as northness (cosine of aspect) and eastness (sine of aspect) in this way to convert the circular aspect (0–360 degrees) into continuous, linear variables that can be used in statistical analysis.

2.2.4 Distance to Water, Roads, and Trail

In ArcGIS Pro, we transformed the Colorado Lakes feature layer into a line shapefile and merged it with the USA Rivers and Streams feature layer. We clipped this newly merged layer to the study area, and ran the Euclidean Distance tool, giving us a distance to water Tagged Image File Format (TIF) file. Similarly, we merged the roads and trails feature layers from USFS together, clipped them to our study area, ran the Euclidean distance tool, and exported the resulting raster as a TIF. Both TIF tiles, distance to water and distance to roads and trails, were exported for use in our suitability model.

2.2.5 NDVI/Tasseled Cap Indices

To calculate Normalized Difference Vegetation Index (NDVI) and tasseled cap indices (including brightness, greenness, and wetness) we worked directly in ArcGIS and R (Version 4.2.2). The Landsat images consist of seven bands of data representing a range of optical wavelengths from ultra blue, blue, green, red, near-infrared, and two shortwave infrared bands. We derived the equations for tasseled cap brightness, greenness, and wetness from the methodology presented in previous remote sensing studies (Baig et al., 2014) and can be seen in Table 2. Brightness measured overall reflectance, capturing soil and developed areas, while greenness measured vegetative density and lushness. Lastly, wetness measured soil and canopy moisture content. All four of these indices were useful for land classification and detecting changes across landscapes (Smedsrud, 2025, 4:46). We executed the following band manipulations using the ArcGIS Pro raster calculator function and exported the resulting raster layers as TIFs for use in the habitat suitability model. We also utilized R to calculate both NDVI and tasseled cap indices for use in the phenological time series and the detection model.

Table 2
NDVI & Tasseled Cap Weighted Sum Equations, as used in the ArcGIS Pro raster calculator

Parameter	Equation for Landsat 8 data
NDVI	(B5-B4)/(B5+B4)
Tasseled Cap Brightness	((0.3029)*B2+(0.2786)*B3+(0.4733)*B4+(0.5599)*B5+(0.508)*B6+(0.1872)*B7)
Tasseled Cap Greenness	((-0.2941)*B2+(-0.243)*B3+(-0.5424)*B4+(0.7276)*B5+(0.0713)*B6+(-0.1608)*B7)
Tasseled Cap Wetness	((0.1511)*B2+(0.1973)*B3+(0.3283)*B4+(0.3407)*B5+(-0.7117)*B6+(-0.4559)*B7)

2.3 Data Analysis

2.3.1 Phenological Time Series Plot

We created a time series plot of NDVI values and tasseled cap brightness, greenness, and wetness of yellow toadflax and differences in these indices between absence points and presence points across the 2024 growing season. We compiled all images from the Landsat 8-9 Collection 2 Level 2, from the USGS Earth Explorer website, ranging from April 7 - October 24, 2024. These images represented 26 days across the growing season, with a temporal resolution of roughly 7-8 days, resulting in about 4 dates per month. Using R, we reprojected each image to WGS 1984 to match our field data projection, cropped each image to our study area, and extracted the values for each band (B1 to B7) to our ground truthing field data. We then calculated NDVI and tasseled cap brightness (TCB), greenness (TCG), and wetness (TCW) for each date across the growing season.

Next, we explored different thresholds for defining presence points within the data. Since we had data corresponding to percent cover, we were able to investigate a threshold that would be measurable with a 30m resolution Landsat image. A small percentage of toadflax cover is unlikely to be differentiable from surrounding vegetation in such a course resolution, thus we looked at the differences in NDVI and tasseled cap values for three classes of field sites: low cover, medium cover, and high cover. A histogram of the field data showed that 40% cover and above represented about two-thirds of the presence points. We then removed heavy cloud days, specifically, Landsat data representing the dates of 06/26/2024, 08/13/2024, and 10/08/2024. Heavy cloud cover days showed huge drops in NDVI that did not reflect actual phenological changes, they were removed from the time series plot. Lastly, we averaged NDVI and tasseled cap values for the absence and presence points and plotted them using the R package ggplot2. With these plots, we sought to identify points of time across the growing season that showed the largest mean differences in indices between presence and absence points. We anticipated that these differences across time would help select imagery dates to use as predictor variables in the detection model.

2.3.2 Detection Model

We used a random forest model to detect the presence of yellow toadflax within our study area. For predictor variables, the model began with all the topographical variables, including elevation, slope, northness, eastness, distance from roads and water, and vegetation type. It simultaneously analyzed Landsat 8-9 imagery dated from April–October 2024 with the associated NDVI and tasseled cap indices. Based on the phenological time series, we also added variables representing the differences between notable dates as described above.

We first utilized the Variable Selection Using Random Forest (VSURF) function in R to objectively identify the most important predictor variables, running the function with all predictors, with topographical predictors only, with topographical plus index predictors (i.e. NDVI and tasseled cap, but not SR bands), and with index predictors only. The VSURF function selects variables in three steps: (1) thresholding, which removes irrelevant predictors using a preliminary random forest model, (2) interpretation, which filters out redundant variables, and (3) prediction, which optimizes the final selection for predictive performance. Each VSURF run produced a small set of key predictors. Combining these results with ecological expertise helps streamline hundreds of predictors into a more manageable set for the detection model.

For thefinal detection model, we ran models using both a continuous response and a binary response. The continuous models attempted to predict percent cover while the binary models attempted to predict presence or absence. We ran the detection model using the Random Forest package in R and produced a linear regression of predicted and observed values to validate the accuracy of the continuous models and a confusion matrix to validate the accuracy of the binary models. We also calculated R-squared and root mean squared error to validate the accuracy of the detection model. Finally, we ran the models using the various combinations of predictor variables as determined by the VSURF function.

2.3.3 Habitat Suitability Model

To develop the habitat suitability model, we utilized the Software for Assisted Habitat Modeling (SAHM), which is an open-source management and scientific workflow system designed by the Invasive Species Science Branch of the USGS, Fort Collins Science Center, and the U.S. Department of the Interior's North Central Climate Science Center. SAHM expedited our habitat modeling and was used within VisTrails, an open-source scientific visualization and workflow system (Talbert & Talbert, 2012). For this element of the project, we used the SAHM workflow window to arrange and connect the necessary modules to execute three different models (Figure 2). The statistical models we ran in SAHM included a maximum entropy (MaxEnt) model, a random forest model, and a generalized linear model (GLM). Each model used our predictor layers—including environmental predictors and NDVI and tasseled cap indices derived from the Sept 8, 2024, Landsat images, and the full field-data, including data points from the Yampa and Meeker districts—to train the models, interpret the usefulness of our predictors, and to generate the most suitable areas for yellow toadflax growth (Talbert & Talbert, 2012).

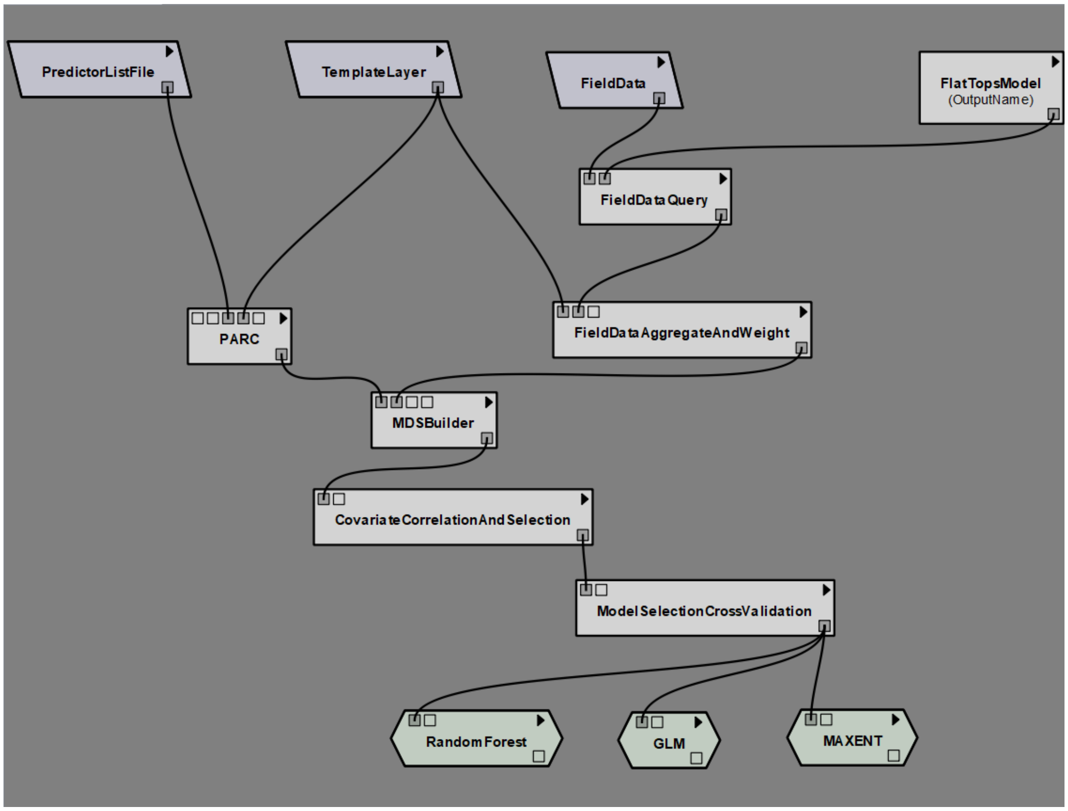


Figure 2. Workflow window in the VisTrails SAHM. This figure shows the pipeline arrangement of modules we used to execute the MaxEnt, Random Forest, and Generalized Linear Models used for our habitat suitability model.

To begin the modeling process, we projected every data layer to the World Geodetic System (WGS) geographic coordinate system (GCS) 1984 standard global reference system and uniformly formatted each layer for use in the SAHM. We created a comma-separated value (CSV) spreadsheet to establish each predictor layer's location on the computer and uploaded that CSV to the "Predictor List File" module in SAHM. The first column of the Predictor List File CSV denoted the computer file path to each of the predictor layer raster files: Distance to Roads and Trails, Distance to Water, Eastness, Northness, Elevation, NDVI, Slope, Existing Vegetation Type, and Tasseled-Cap Wetness, Greenness, and Brightness. The second column displayed the binary value "0" for all layers, meaning all inputs were continuous data. The third column indicated the resampling method, which was "bilinear" for all. Lastly, the final column displayed the aggregation method (used in the event the raster layer must be expanded to fit the template), denoted as "mean." For the "Template Layer" module, we clipped a raster layer with the appropriate 30m x 30m pixel size to the boundaries of our study area in the appropriate coordinate system, WGS 1984. We then linked this Template Layer module to the SAHM "PARC" module, which ensured all raster layer areas and properties were adjusted to match the template layer, so that the analysis was consistent and accurate in predicting suitable habitat across the entirety of the study area. For the "Field Data" module, we uploaded a refined CSV. The first and second columns contained the x- and y-coordinates of the real field data points. This module was connected to the "Field Data Query" module, which indicated where the software could find the location and response values within the field data document. Making this location data readable to the software allowed the points to be located and used to train the model.

For the remainder of the modules, the software's default inputs were primarily left unchanged. The "Field Data Aggregate and Weight" module ensured the field data were projected to WGS 1984 and set the points to "collapse in pixel" in areas where there may have been multiple points within a pixel. The "MDS Builder" is a module we used to extract the field data points into a CSV in a merged dataset format for use in the MaxEnt model. We also used this module to generate 10,000 background points, which served as the absence data in the analysis. This then connected to the module "Covariate Correlation and Selection," which showed correlation between all our predictors. We removed tasseled cap greenness and tasseled cap wetness as predictors due to their high correlation with NDVI and tasseled cap brightness, respectively. Both correlations were greater than 0.7, which may have hindered the modeling process if left in the model. The workflow then connected to the "Model Selection Cross Validation" module, a tool that evaluates the performance of the models by splitting the observed field data into cross validation folds. For 10-fold cross validation, the dataset is randomly split into ten equal-sized subsets. Each model is then trained ten times, each using 9 subsets for training and the tenth for testing.

Finally, the workflow was connected to modules to run the three models–MaxEnt, Random Forest, and GLM–with each producing binary maps of the most suitable sites for toadflax. Additionally, plots describing variable importance were created, which provided deeper insight into our predictor variables by explaining which ones more strongly influenced the models. An output text document was created with each model run that described several metrics that explained the model's accuracy. We then took each binary map output and added them together in ArcGIS Pro's raster calculator, which output a combined suitability agreement model or ensemble model, showing the number of models that agreed for each suitable area. Finally, we utilized metrics included in the model's output text, which included both testing and training Area Under the Curve (AUC) values, as well as percent correctly classified values, to validate the accuracy of the models.

3. Results

3.1 Analysis of Results

3.1.1 Phenological Time Series

The time series plot of NDVI for high cover areas and absence areas showed the NDVI rising rapidly in June, plateauing in July, dipping in August, rising again in September and gradually declining into October (Figure 3). We can also see a substantial difference between the high cover and absence areas' mean NDVI in the June and July months, along with a spike on Sept 22 and Oct 24 (Figure 3). We found the tasseled cap greenness to be highly correlated with NDVI showing a very similar curve, while tasseled cap brightness and wetness were highly correlated to one another over time. Based on the peak differences in means, we developed new predictor variables representing the differences between the most notable dates in the time series graph, including 6/18/24, 9/22/24, and 10/24/24.

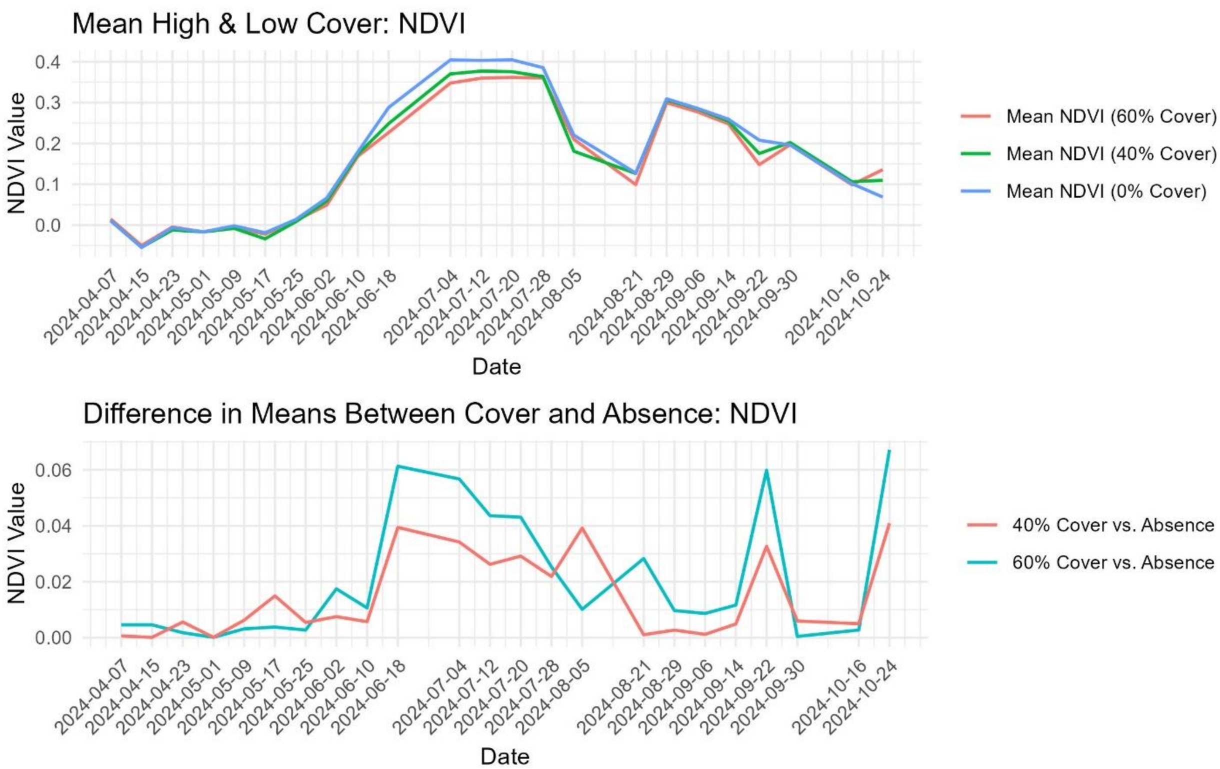


Figure 3. Graphs showing the mean normalized difference vegetation indices (NDVI) for high cover toadflax areas with no toadflax cover recorded (absence) as well as the absolute difference in means between high cover and absence areas.

3.1.1 Detection Model

Our detection models did not demonstrate the feasibility of using the Landsat remote sensing data at a 30 m resolution with the field data we had available. The linear regression of actual versus predicted values showed that predictions did not align with observed values (Figure 4). Our R-squared value was only 0.052, meaning that our predictors explained only about 5% of the variance in our dependent variable, which is the percent cover of toadflax. As for the binary response model, the error produced was about 26%, which isn't an error that is usually of concern on its own. However, upon closer examination of the percentage of false positives, which was 75%, we saw that the model was grossly over-predicting the presence of toadflax (Figure 5). Considering the limited resources that our partners have available to combat toadflax, we would want a conservative detection model, not one that over detects.

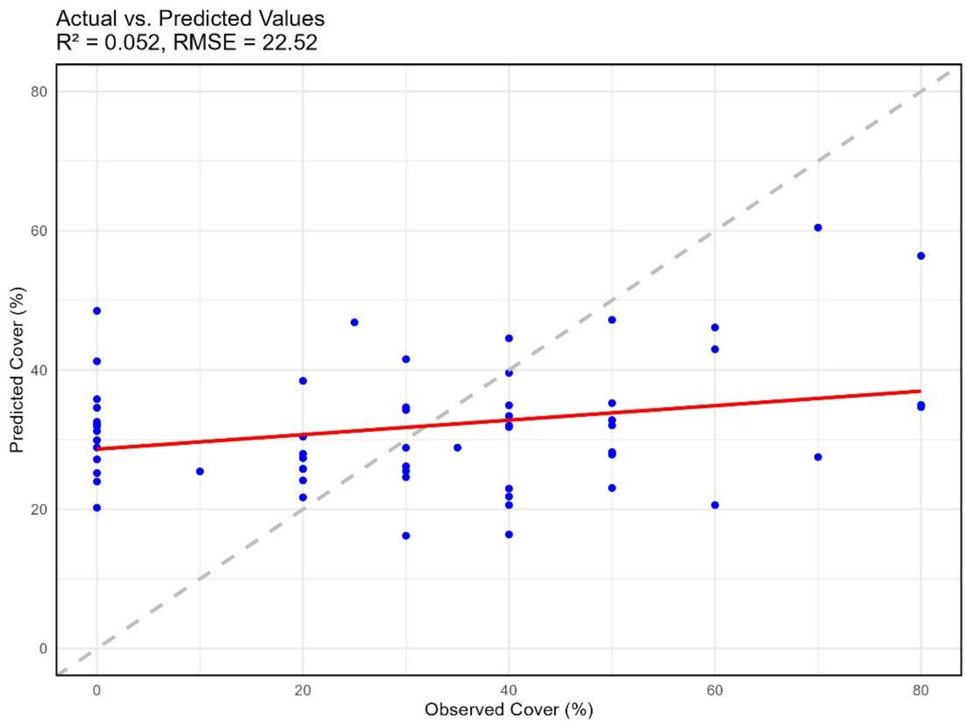
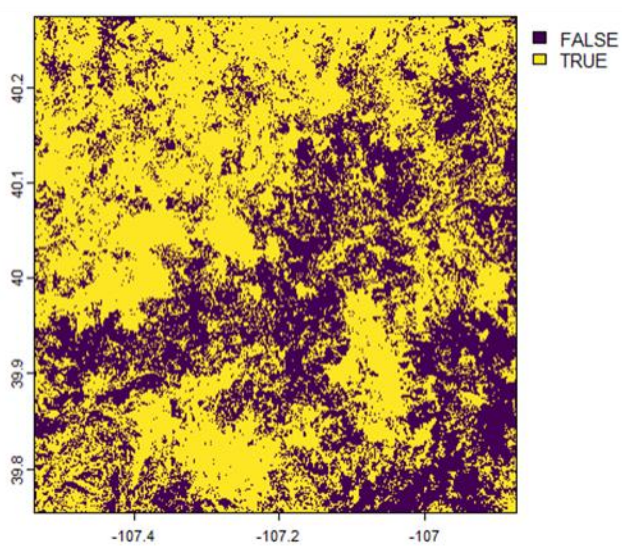


Figure 4. A linear regression of actual versus predicted values of toadflax cover from our detection model did not demonstrate the feasibility of using Landsat remote sensing at 30 meters resolution, due to predicted values not aligning with observed values.

a



b

Confusion Matrix
OOB Error: 0.259

	TRUE	FALSE	Error
TRUE	4	12	75%
FALSE	3	39	7.1%

Figure 5. (a) Detection map for the binary response model greatly overpredicts yellow toadflax, shown in yellow. There is still a slight correlation between yellow toadflax detection and elevation, with very high and very low elevations showing less species detection. (b) A confusion matrix from our binary response detection model shows a high rate of false positives, leading to a detection map that overpredicts yellow toadflax.

3.1.2 Habitat Suitability Model

Each of the models (MaxEnt, Random Forest, and Generalized Linear) produced a binary map that showed the presence and absence of potentially suitable yellow toadflax habitat across the study. We then combined these three outputs into an ensemble map, to visualize the multiple outputs and their spatial agreement and variability. Designed to look like a heat map, the ensemble shows areas in yellow where one model predicted yellow toadflax and areas in red where three models predicted yellow toadflax (Figure 6). Areas without any color are where all models predicted no suitable habitat for toadflax.

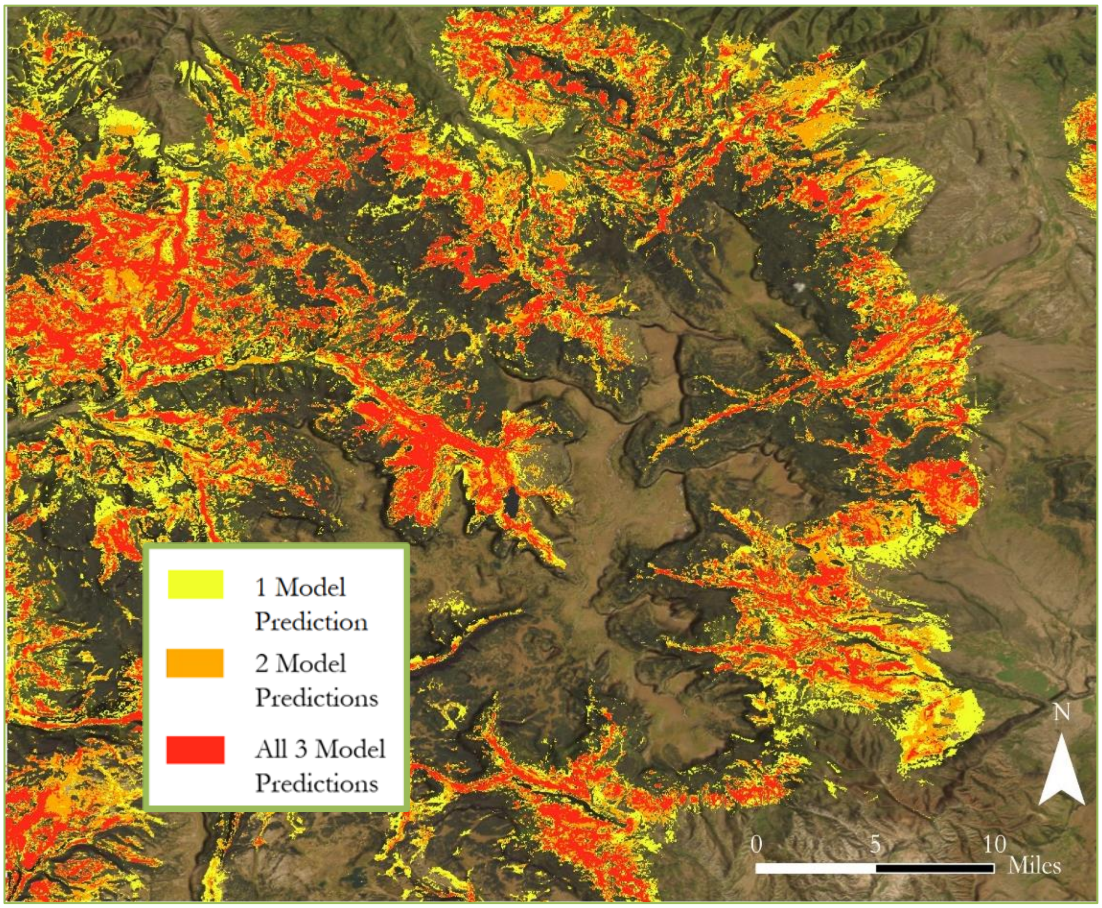


Figure 6. Ensemble displaying agreement and variability between the MaxEnt, Random Forest, and General Linear models created in SAHM

The Random Forest model turned out to be the most conservative of the three model runs, predicting 108,748 acres of suitable habitat, whereas the MaxEnt model was the most liberal or aggressive in its assessment of suitable habitat, predicting 187,333 acres of suitable habitat (Table 3). The random forest model had the highest accuracy when the SAHM ran a cross-validation between test and train yellow toadflax locations, with over 86% of pixels being correctly classified (Table 3).

Table 31

The acreage of suitable yellow toadflax habitat as predicted by each of our three SAHM models, along with the Percent of Correctly Classified Pixels, which was assessed by running a cross validation within SAHM

Model	**Acreage of Suitable Habitat Detected Across Entire Study Area**	**Percent Correctly Classified**	**Training AUC**	**Test AUC**
Random Forest	108,748	86.34%	0.94	0.94
Generalized Linear Model	179,290	78.22%	0.86	0.86
MaxEnt	187,333	78.91%	0.89	0.88

We further accessed the spatial extent of suitable yellow toadflax habitat as predicted by 1, 2, and all 3 models by calculating acreage and percentage of total study area (Table 4). Areas predicted to be suitable by at least one model accounted for 23.5% of the total study area. All 3 models combined into an ensemble predicted about 86,300 acres of suitable habitat, or 8.6% of the total 813,314-acre study area.

Table 24

Nearly a quarter of the total study area was predicted to be suitable yellow toadflax habitat by at least 1 of the 3 models, whereas just 8.6% of the total study area was predicted to be suitable habitat by all 3 models

Count of Model Predictions	**Acreage**	**Percent of Total Study Area**
At Least 1 Model Prediction *(aggressive estimate)*	235,510	23.5%
At Least 2 Model Predictions	153,564	15.4%
All 3 Model Predictions *(conservative estimate)*	86,297	8.6%

3.2 Errors & Uncertainties

As with any statistical study, there may have been sampling bias. Our coverage data were collected predominantly in two valleys within the northern portion of the study area and may have been sampled closer to roads, trails, within specific tributary basins, or at lower elevations. Our larger dataset was produced by the Yampa and Meeker Districts, representing areas that they treated, and thus contained only presence data. They also may have been treating areas with more accessibility to roads and trails. For our phenological time series, while we were able to detect differences in NDVI between high cover and zero cover toadflax areas, this difference was relatively small and may have represented natural variation not related specifically to toadflax. We predict that the Landsat 8 datasets had too large of a cell size to be able to make smaller calculations of yellow toadflax communities. Finally, for our detection model and time series, our Landsat resolution may have been too course to adequately measure toadflax and differentiate from surrounding vegetation. At 30 meters resolution, measuring patches of small plants was challenging. In addition, significant cloud cover across the growing season reduced our temporal resolution. Future studies could consider using Sentinel-2 data to reduce the temporal resolution.

4. Conclusions

4.1 Interpretation of Results

Using Landsat 8 and Landsat 9 satellite imagery proved useful for habitat suitability modeling for this study and demonstrated feasibility in identifying potential toadflax habitat when used with topographical predictors such as elevation and distance to roads and trails. The satellite images were detailed enough to aid our three models (random forest, MaxEnt, and generalized linear) in creating a map that aligned with our partners' observations regarding presence and absence areas. The area of suitable habitat within the study area that was predicted using SAHM matched with known ecological preferences of yellow toadflax, which grows only in certain elevation zones and eschews densely forested, closed canopy areas. Even when using the most conservative estimate, nearly 86,300 acres of the 812,314-acre study area are prone to invasion by yellow toadflax.

The phenological time series model identified phenological differences in NDVI using Landsat imagery between yellow toadflax and surrounding vegetation. This model may be used in detecting seasonal phenological trends between species throughout the growing season. The months of June, July, and September presented the most significant differences in NDVI between high cover yellow toadflax areas and other vegetation. Larger differences between yellow toadflax and surrounding vegetation may be detected more reliably with higher resolution imagery.

Given the percentage cover data and Landsat imagery at 30 meters resolution, our study was not able to develop a reliable detection model, demonstrating the limitations of satellite imagery. An additional study with more field data and/or higher resolution imagery might yield more conclusive results. Despite these limitations, we did create a phenological time series plot that shows seasonal NDVI fluctuations of yellow toadflax that make intuitive sense, rising during spring, plateauing in summer, and declining in fall.

4.2 Feasibility & Partner Implementation

Our main goal through this feasibility study was to help our partners navigate the expansion of yellow toadflax in and around the Flat Tops Wilderness Area. By observing the habitat suitability model, our partners may determine focus areas across the entire study area and better utilize monitoring and treatment resources. Our partners could use the ensemble map to identify high likelihood areas of yellow toadflax expansion and to refine their treatment efforts to focus on the highest-likelihood habitats. They may also use the suitability model maps in combination with other factors, including post-wildfire landscapes, targeted grazing allotments, certain elevation zones, and various jurisdictional boundaries, to refine their treatment zones. This habitat suitability model also adds important predictor variables for future researchers to use for modeling the habitat of yellow toadflax in Colorado.

In the same way that the habitat suitability map may inform decision-making geographically, the phenological time series plot could be used for determining the best times of year for tracking yellow toadflax. The time series plot shows that in 2024, the NDVI for yellow toadflax peaked in June and decreased starting in late August. This may be useful for our partners when using remote sensing to differentiate between yellow toadflax and other vegetation throughout the growing season. This model can be replicated yearly to find average patterns or track trends over longer periods of time.

The detection model was less useful to our partners compared to our other two project objectives. It overpredicted yellow toadflax presence over the majority of the study area. If our partner or future researchers wish to improve this model, we recommend looking at satellite imagery with a finer spatial resolution such as Sentinel-2 or Planet Labs data. This may increase the accuracy for detecting yellow toadflax since colonies of the species may be too small for detection using Landsat data. We also recommend collecting more dispersed field data across the study area for model training. We trained the models using a spatially finite amount of field data collected by the partners in the northwestern quadrant of the study area, which may have created issues when extrapolating across the much larger study area. In all, however, our three models can be useful to our partners for improving the efficiency of tracking and treating yellow toadflax, in hopes of preserving viable forage and natural conditions in and around the Flat Tops Wilderness.

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6. Glossary

Binary Response Model – A statistical model used to predict two discrete outcomes where the response variable is typically coded as 0 or 1, or as true/false. For purposes of this study 0 and 1 correspond to absence and presence.
Brightness – The intensity of surface reflectance measured by satellite sensors, often associated with albedo or spectral radiance.
Continuous Response Model – A model that predicts a response variable with a continuous range of possible values, rather than discrete categories.
Generalized Linear Model (GLM) – A flexible statistical framework that extends ordinary linear regression to model relationships between predictor variables and a response variable by allowing for non-normal distributions and both continuous and categorical predictor variables.
Greenness – A measurement by satellite sensors that indicates vegetation density, health, and biomass.
Hyperspectral – A remote sensing technique that captures a wide range of electromagnetic spectrum bands per pixel, allowing for detailed material identification and analysis.
Linear Regression – A statistical method for modeling the relationship between a dependent variable and one or more independent variables by fitting a linear equation.
Maximum Entropy (MaxEnt) – A machine-learning algorithm that estimates species distributions by finding the probability distribution of maximum entropy, given environmental constraints.
Normalized Difference Vegetation Index (NDVI) – A widely used spectral index calculated from red and near-infrared reflectance values to quantify vegetation density and vigor.
Northness/Eastness – Environmental variables derived from aspect (geographic direction) values. Northness = cos(aspect), Eastness = sin(aspect).
Phenology – The study of periodic biological events (e.g., flowering, leaf-out) and their relationship with seasonal climate and environmental factors.
Pixel Size – The spatial resolution of a raster image, representing the ground area covered by a single pixel, affecting detail and accuracy in remote sensing analysis.
Predictors – Environmental or topographic variables (e.g., elevation, NDVI, land cover) used as inputs to model the distribution of species or ecological phenomena.
Random Forest – A machine-learning algorithm that builds multiple decision trees to improve classification and regression accuracy by averaging predictions.
SAHM – Software for predictive habitat suitability modeling, developed by USGS, that integrates statistical tools for species distribution modeling.
Tasseled Cap Index – A spectral transformation technique that converts raw multispectral data into components (Brightness, Greenness, Wetness) for enhanced interpretation of vegetation and land cover characteristics.
Temporal Resolution – The frequency at which a satellite sensor acquires imagery of the same location, critical for monitoring changes over time.
USFS – United States Forest Service, a federal agency managing national forests and grasslands Predominantly refers to the Yampa Ranger District in this study.
Wetness – A measurement by satellite sensors representing soil and vegetation moisture content.

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