New Venture Fund Project Report

Mapping Gorse along the Southern Oregon Coast

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Introduction:

In November of this year, the Institute for Natural Resources (INR) proposed to the New Venture Fund to develop a map and model that would identify likely gorse (*Ulex europeaus*) locations in southwestern Oregon. The work was to be done cooperatively with The Nature Conservancy, taking advantage of data and information they had developed working with staff from southwestern Oregon watershed groups and the New Venture Fund over the last few years. The project was going to combine information on known gorse locations in the project area from the iMapInvasives electronic data system that INR manages on behalf of the Oregon Invasive Species Council, with information recently collected by local Soil and Water Conservation Districts (SWCDs) and Watershed Groups to identify a relatively comprehensive set of locations to train the model. INR was to take advantage of high resolution data from both air photography and, if possible from Light Detection and Ranging (lidar) data, to create a high resolution map. The New Venture Fund provided INR funding to start on the project in January, and staff at INR was able to generate an initial draft map, identify locations where additional training data could significantly improve the map, and create a final map product. This map has been provided to local partners, the New Venture Fund, and others interested in using it to eliminate or control the spread of gorse in southwestern Oregon.

Methods:

Overall, the process of building the distribution model involved: 1) compiling necessary data within the defined area of interest; 2) building a model associating the presence or gorse with environmental variables; and 3) mapping predictions across the area of interest. This process was iterative, and involved evaluation of interim draft maps by staff from INR and partners.

1) Compiling necessary data

The project area was identified based primarily on previous work done by The Nature Conservancy and New Venture Fund in southwestern Oregon, limited to areas in Coos and Curry Counties. The area of interest encompasses coastal landscapes through mid-montane forests in the western portion of the Klamath/Siskiyou mountains. Forest vegetation in the area is dominated by Douglas-fir forests. In places with particularly sandy soils along the coast, shorepine is a common tree. Inland, tanoak can also be an important forest tree. Gorse in the region is generally not abundant in the older forests, as it requires full sun for establishment (Rees and Hill 2001). It is most common in disturbed areas (e.g., road verges, forest harvests). It is also present along streams, where light reaching the soil surface is relatively high. Sandy sites that support more open forests can also sometimes support more gorse.

The Nature Conservancy provided INR with a digital map (shapefile) which provided an outline of this area. Within this project area, two types of data were collected or complied to create the model and maps of gorse. The first is the model training data, the second is the predictor data. These are both described below.

Training data include both positive and negative locations collected and used to create the models and maps. The positive training data allows the model to identify the known locations of gorse in southwestern Oregon, while the negative training data show locations where gorse either cannot occur or is not currently found. RandomForest can be more accurate than other species distribution modeling methods because they allow for the use of negative training data along with positive data. Negative data can consist of either background points created across the entire area modeled, or specifically identified negative locations, or most often both. In this case, background points were used, and augmented with negative points from partner organizations from Coos and Curry Counties. As mentioned in the introduction, the positive training data started with information from iMapInvasives and data collected by the Coos Watershed Association with assistance from the New Venture Fund. After the initial model and maps were built, areas were identified which needed additional training data, and these were also collected by the Coos and Curry County partners. Points available for modeling, by data source are listed in Table 1.

Table 1: Training data points (by source) used in the final model.

	Absent	Present	Total
iMapInvasives database	0	51	51
gorse_FS_edited	1918	209	2127
Newly collected in 2016	655	61	716
Airphoto interpreted in 2016	424	6	430
Background	814	0	814
Total:	3811	327	4138

Predictor data consist of the spatial data that the model uses to predict where other locations of gorse may be, and the likelihood that it will be found in these places. For this method to be used, any predictor data used must consistently cover the entire area that is modeled. The predictor data included the highest resolution information we were able to obtain covering the project area, starting from a geodatabase obtained from The Nature Conservancy. The data included topographic information (slope, aspect and elevation), which where lidar was available could be produced at 1-meter resolution scale, although was generalized to 10 meters pixel data for this project. We also used soil data collected by the Natural Resources Conservation Service that were collated by INR for the Integrated Landscape Assessment Project, geology data originated by the Oregon Department of Geology and Mineral Industries, information on rivers and streams compiled from the National Hydrography Dataset and supplemental information from our Curry County partner, climate data from Oregon State University's PRISM program (Daly et al. 2008), along with imagery data developed by INR staff. The imagery data included a standard set of data extracted from 1-meter air photography, summarized to 10, that provide the model with as much information as is possible to obtain from the imagery, relying on patterns of texture and colors at multiple resolutions. These "texture metrics" were developed from uncompressed digital copies of the 2012 statewide National Agricultural Imagery Program (NAIP) air photography data, which is 4-band, 1-meter resolution information. Information on the forest canopy was extracted from the gradient nearest neighbor data source (GNN, Ohmann et al. 2011) that was constructed the US Forest Service's Landscape Ecology Modeling Mapping and Analysis team. The canopy cover (CANCOV), and age (AGE_DOM) variables were summarized over three spatial scales: pixel, 50m radius, and 100m radius. Mean, minimum, maximum and standard deviations were calculated for the 50m, and 100m summaries. A full list of available and selected variables is included in the Appendix.

2) Building the Models

We created the maps and models using open source software using the random forest machine learning algorithm (Breiman 2001), as it is implemented by the randomForest package (Liaw & Wiener 2002) in the R environment for statistical computing (R Development Core Team 2013). This algorithm is becoming more widely used in the field of ecology (Cutler et al. 2007). It is a flexible and robust technique, minimizing problems with data irregularities such as collinearity (Elith et al 2006). It is also a relatively complex model, which makes it less effective for ecological understanding, but appropriate for this application where prediction accuracy is the primary goal (Merow et al. 2014). INR staff have created scripts for parameterizing the models, and exporting model predictions to maps, as well as analyzing model accuracy. We drafted several models, tuning two model parameters (the number of classification trees within the ensemble, and the number of variables used to generate each branch in each classification tree), and selecting the most useful variables from the full array of available variables (selected variables are indicated in the Appendix).

3) Creating the Maps

Maps are the primary output required for partners to identify potential new gorse infestations to control or eradicate. We created a spatial depiction of the model's prediction probability for gorse presence in the form of a raster image (included with this report). Raw values in the gorse_current.tif image illustrate a probability value (multiplied by 1000 for mapping, to enable efficient storage as an integer grid). Two categorizations of the raw probabilitiy map were created, using probability cutoffs identified during model evaluation (details below). These categories are included as attributes in the raw probability grid. The "FinalMod_c" variable shows the categorization derived directly from the final model prediction, while the "CV_c" variable shows the categorization derived from the cross-validated prediction (both predictions are described further below).

4) Evaluating the Maps and Models

We evaluated our models and maps through a series of steps: 1) Generating two model predictions for evaluation, one extracted directly from the final model, and another cross-validated (50-fold) prediction that is useful for estimating the model's performance in areas that are not represented by the plot sample; 2) Characterizing overall strength for discerning presence and background points; 3) binary cutoff selection through the precision-recall f-measure; 4) Error assessment of the binary transformations of the model predictions created by the cutoffs from step three; 5) Visual review of mapped products with biological experts; and 6) Tabulating area identified as habitat within the binary maps.

We calculated five accuracy statistics to describe binary error structure for all the cutoffs identified in step three. Percent accuracy shows the proportion of points that are correctly classified. Sensitivity indicates how well the model performs with respect to gorse detection, and Specificity indicates how well the model prediction performs with respect to true absences. True Skill Statistic (TSS) integrates information from both Sensitivity and Specificity, while Kappa indicates how the binary model prediction compares with a random guess.

As is the case with all efforts to create maps from models, a major factor that contributed to the accuracy of the models was the data used, both the training data to identify the known locations of gorse in southwestern Oregon, and the predictor data, which is the spatial data that the model uses to predict where other locations of gorse may be and the likelihood that it will be found in these places.

We visually reviewed the categorical maps created with the cutoff values with our partners. The review discussions of the early map drafts helped to direct further sampling efforts, and also to identify new spatial data sources to supplement later models. The map review of the final model was used to confirm the general realism of the patterns in the mapped prediction, and also to identify map layers that should be used for a masking process to avoid mapping gorse in areas where it is known to be absent (e.g., serpentine soils, open water), but that were not used in the final random forest model.

Results and Discussion:

The final model showed strong performance at discerning presence from absence points for both the out-of-box prediction, and the cross-validated prediction (AUC values of 0.99, and 0.90 respectively). Cutoff values selected ranged from 0.14 to 0.56 for the final model prediction, and from 0.07 to 0.59 for the out of box model predictions.

For the final model prediction, model performance was strong for all accuracy statistics for all binary transformations (Table 2). The minimum model sensitivity was 0.78, and minimum model specificity was 0.98. The cross-validated model prediction also indicated reasonable model performance, although not as strong as the final model prediction. Values for % accuracy, TSS, and Kappa were acceptable (> 0.4) across most of the tested cutoff values. Minimum prediction sensitivity for the cross-validated prediction was 0.43, and minimum specificity was 0.79.

The differences between the accuracies of the prediction extracted directly from the final model, and the cross-validated prediction indicate that while the map is likely to convey useful information in areas away from the current set of observations, there remains potential for improvement if resources become available to collect additional training data.

The final categorical map showing the model-prediction-derived categories (FinalMod_c variable, Figures 2 and 3) reviewed favorably, although a few minor issues were highlighted, including the mapping of gorse on serpentine soils, and also in some aquatic habitats (the errors are un-surprising as neither variable was included in the final model). The final map was masked to avoid showing gorse in both of these areas.

Two points of discussion in the final map review indicated potential benefits from future work. Our partners observed the presence of a mapped patch of gorse in the Daniels Creek area, fairly far inland to the east of Coos Bay (visible in Figure 3b). While our input data set did contain some gorse presence points, they were older observations (from 2009). Fieldwork to confirm the continued presence of gorse in this area would be beneficial to future drafts. Future drafts would also benefit from additional information on hydrology, especially with respect to wetlands in the Cape Blanco area (Figure 3d). Our partners suggest that gorse presence in this area should be more constrained than is mapped due to the high water table in parts of Sullivan Gulch near the Sixes River. Identifying and incorporating reliable data on wetlands in the region could potentially refine the map in this, and other similar areas.

Receiver-operator curves shown in Figure 1 final (a), and cross-validated (b) model predictions include binary accuracy measures binary model transformations using the cutoff values shown by the blue dots. These cutoff values shown were selected to balance false positive and false negative errors. Percent accuracy measures indicate the performance of a binary transformation of the model prediction that corresponds to the cutoff value, and represents the proportion of plots that were correctly classified as having gorse presence or absence. Sensitivity and Specificity contain complementary information, indicating the model's performance with respect to true positives, and true negatives respectively. True Skill Statistic (TSS) integrates the Specificity and Sensitivity metrics into a single value. Kappa indicates model performance in comparison with a random guess. For all metrics, values of 1 indicate perfect performance, while values of 0 indicate failure.

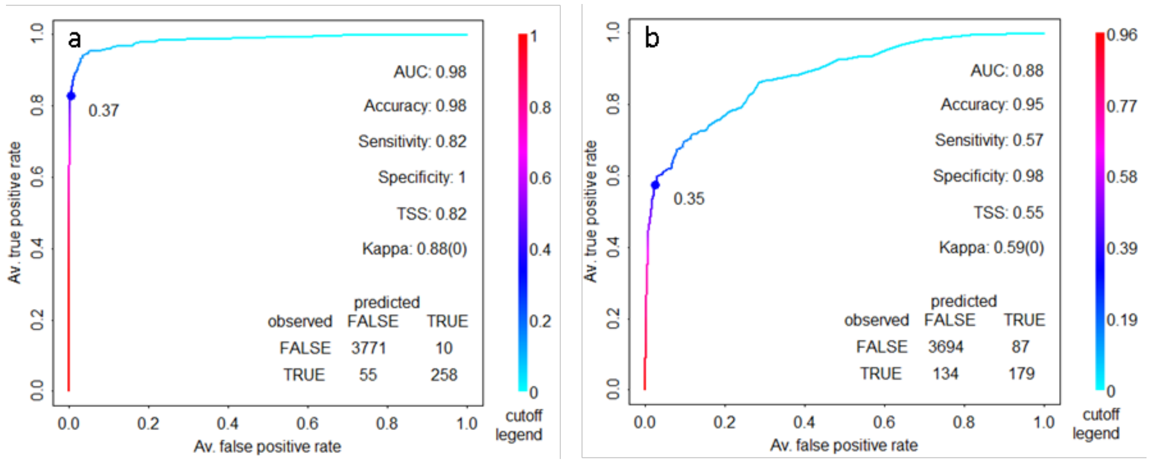

Figure 1. Receiver-operator curves indicating model performance for the final (a), and cross-validated (b) model predictions.

Table 2: Model performance metrics for binary transformations of the two types of model prediction, out-of-box (best suited to evaluating the actual model used for mapping), and cross-validated (best-suited for estimating the model's performance at predicting unsampled areas). Alpha values indicate a parameter used in cutoff selection that prioritizes error-types (see patterns in Sensitivity and Specificity for an illustration). For all metrics, values of 1 indicate perfect performance, while values of 0 indicate failure. For details on the meaning of each statistic, see the caption for Figure 1.

Final Model Out Of Box Prediction

Alpha	0.10	0.20	0.30	0.40	0.50	0.60	0.70	0.80	0.90
Cutoff	0.14	0.24	0.24	0.32	0.37	0.37	0.37	0.48	0.64
Accuracy	0.96	0.98	0.98	0.98	0.98	0.98	0.98	0.98	0.98
Sensitivity	0.94	0.88	0.88	0.85	0.82	0.82	0.82	0.79	0.70
Specificity	0.97	0.99	0.99	0.99	1.00	1.00	1.00	1.00	1.00
TSS	0.91	0.87	0.87	0.84	0.82	0.82	0.82	0.79	0.70
Kappa	0.78	0.87	0.87	0.88	0.88	0.88	0.88	0.87	0.81

Cross-validated Prediction

Alpha	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
Cutoff	0.06	0.31	0.31	0.34	0.35	0.4	0.51	0.54	0.54
Accuracy	0.74	0.94	0.94	0.94	0.95	0.95	0.95	0.95	0.95
Sensitivity	0.84	0.59	0.59	0.58	0.57	0.53	0.46	0.43	0.43
Specificity	0.73	0.97	0.97	0.97	0.98	0.98	0.99	0.99	0.99
TSS	0.56	0.56	0.56	0.56	0.55	0.51	0.46	0.43	0.43
Kappa	0.23	0.58	0.58	0.59	0.59	0.58	0.57	0.55	0.55

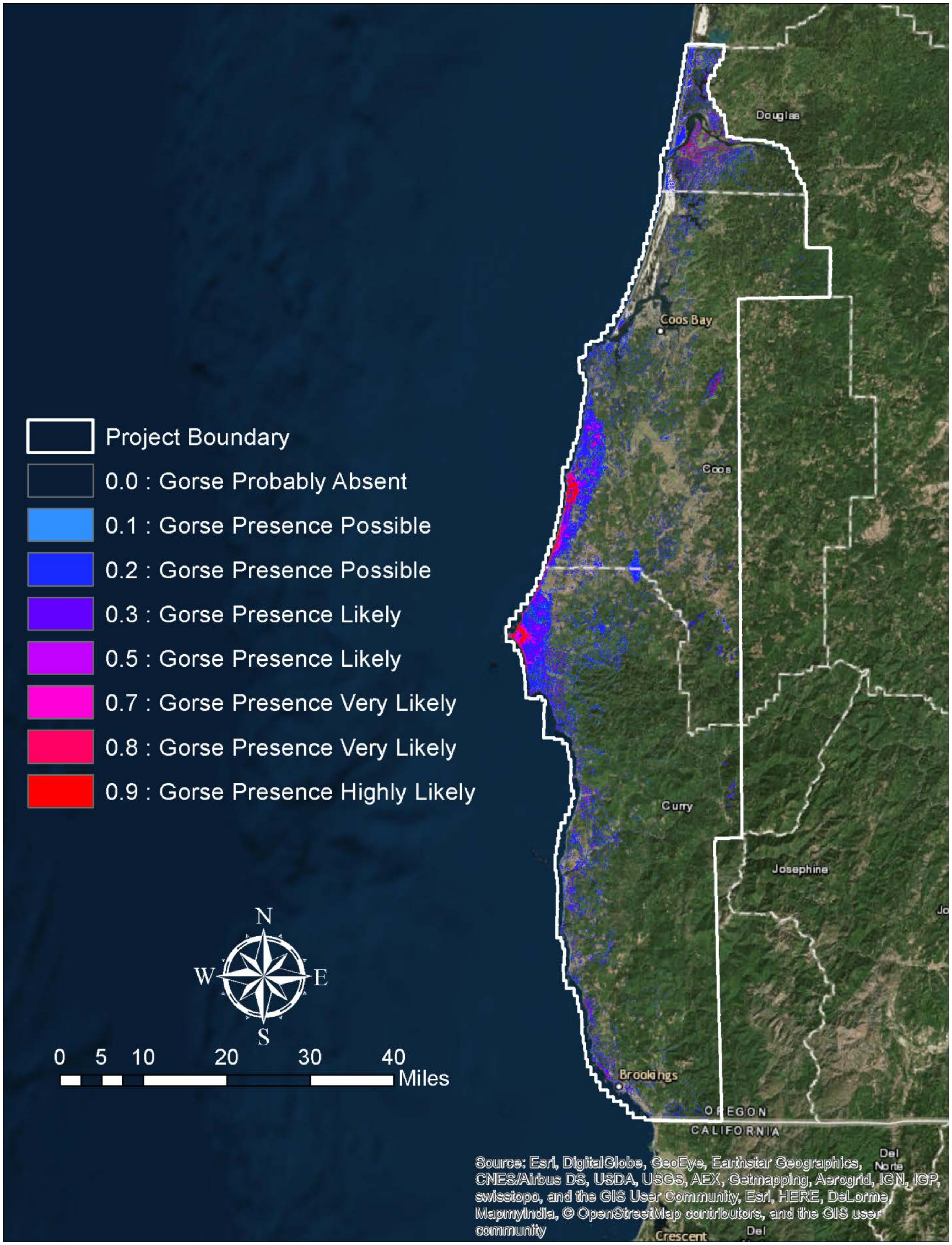

Figure 2: Categorical overview map of gorse presence. Categories shown were created from the prediction extracted directly from the final mode l.

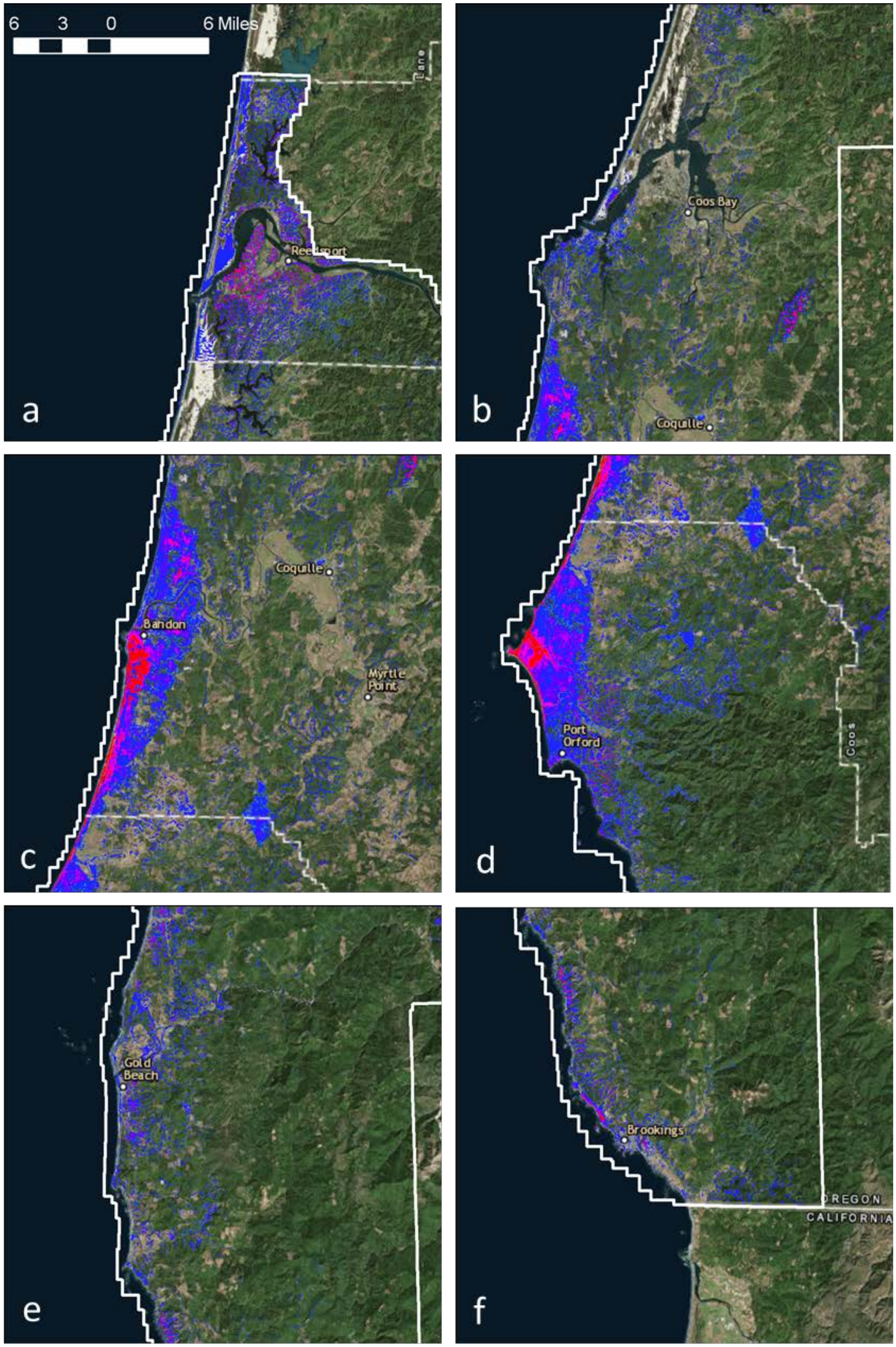

Figure 3: Close-up maps of Reedsport (a), Coos Bay (b), Bandon (c), Cape Blanco (d), Gold Beach (e), and Brookings (f). Map categories, background image, and legend are the same as in Figure 2.

For the map categorization illustrated in Figures 2 and 3, there were 1,235,373 acres mapped within the study area boundary where gorse is most probably absent (Table 3). Gorse was mapped as possibly present in the remaining 144,619 acres, but most of that (128,502 acres) was mapped in the lower probability categories (categories that correspond to alpha values below 0.5). The highest probability category covered 3774 acres.

Table 3: Area mapped. Categories listed in italics are mapped together with the one listed in the previous line. Numbers at the beginning of each map category name refer to the alpha value used to identify the probability cutoff that defines the upper boundary for the category.

Map Category	Acres
0.0 : Gorse Probably Absent	1235373
0.1 : Gorse Presence Possible	18198
0.2 : Gorse Presence Possible	91158
0.3 : Gorse Presence Likely	19146
0.4 : Gorse Presence Likely	
0.5 : Gorse Presence Likely	7319
0.6 : Gorse Presence Very Likely	
0.7 : Gorse Presence Very Likely	4170
0.8 : Gorse Presence Very Likely	854
0.9 : Gorse Presence Highly Likely	3774

Conclusions:

Strong accuracy statistics and favorable map reviews by our partners indicate that the final map is accurate enough to be quite useful for informing projects that aim to constrain gorse invasion in the area. Areas highlighted by our map correspond well with areas known to our partners as zones of primary gorse infestation. Partners organizations working along the coast in southwestern Oregon can take advantage of either the 10 categories of potential infestation included, or the continuous nature of the map probabilities to prioritize control and eradication efforts.

Uncertainties remain in the map, partly due to constraints in the input plot data, but also due to the difficulties of detecting gorse with imagery layers. Although we had fifty two imagery-derived variables available for modeling, just 19 of them informed the final model, and all were ranked as relatively unimportant to shaping the prediction. Climate, topography and soil variables were far more influential in the model than imagery.

Although we provide two categorical variables for viewing the model prediction, we recommend the FinalMod_c variable for use in identifying areas most likely to benefit from gorse control. These categories are more tightly aligned to the actual model used to make the map. The cross-validated categories are primarily useful in conjunction with the cross-validated prediction

The masking process may have introduced a few new errors into the final map. Spatial imprecisions in the map of open water may mask riverside gorse patches, and errors in the layer depicting serpentine geology may also erroneously mask gorse patches. Fieldwork investigating whether this is the case would be particularly useful near Gold Beach, where several small, but high probability gorse patches were mapped, but removed from the final map with the geology-based mask.

As with all mapping projects, future work collecting field data, and possibly compiling a few new spatial predictor layers could have additional benefits in refining the map.

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Appendix

Variables available for modeling, and importance scores (gini index) for variables selected for the final model.

Variable Name	Description	Variable Importance
prism_diftmp	Climate: Difference in temperature from summer to winter	68.73
prism_annpre	Climate: Average Annual Precipitation	57.53
prism_smrpre	Climate: Precipitation during summer	45.55
prism_smrtmp	Climate: Temperature during summer	34.66
prism_smrtp	Climate: Summer drought stress index	18.27
topo_dem	Topography: elevation	15.95
prism_decmint	Climate: December Minimum temperature	15.41
prism_anntmp	Climate: Average Annual Temperature	12.77
prism_cvpre	Climate: Variability of precipitation from summer to winter	12.14
soil_ph	Soil: pH	11.87
topo_tpi150	Topography: Topographic position index, calculated over 150m	10.58
soil_depth	Soil: depth	10.27
gnn_CANCOV_Std50c	Standard deviation of canopy cover within 50m	9.90
prism_contpre	Climate: Continuity of precipitation throughout the year	9.58
soil_sand	soil: % sand	8.61
gnn_CANCOV_Mean100c	Average canopy cover within 100m	8.36
misc_StreamDist	Distance to neareset stream	8.35
soil_di	Soil: Drainage index	8.01
gnn_AGE_DOM_Mean100c	Average age of the dominant trees within 100m	7.97
soil_siltp	Soil: % silt	7.95
topo_tpi300	Topography: Topographic position index, calculated over 300m	7.63
gnn_AGE_DOM_Mean50c	Average of the dominant trees within 50m	7.62
topo_slpct	Topography: Slope	7.56
gnn_CANCOV_Mean50c	Average canopy cover within 50m	7.50
soil_clay	Soil: % clay	7.46
gnn_CANCOV_Max100c	Maximum canopy cover within 100m	7.42
topo_mli	Topography: Median Landform Index	7.30
gnn_AGE_DOM_Std100c	Standard deviation of age of the dominant trees within 100m	6.56
soil_bd	Soil: Bulk Density	6.54

Variable Name	Description	Variable Importance
topo_tpi450	Topography: Topographic position index, calculated over 450m	6.26
gnn_AGE_DOM_Std50c	Standard deviation of age of the dominant trees within 50m	6.16
gnn_CANCOV_Std100c	Standard deviation of canopy cover within 100m	5.90
soil_rock	Soil: % rock	5.65
soil_awc	Soil: Available water-holding capacity	5.29
gnn_AGE_DOM_Max100c	Maximum age of the dominant trees within 100m	4.55
gnn_AGE_DOM_Range100c	Age-range of the dominant trees within 100m	4.47
naip_vca_mn	Airphoto texture summary	4.45
naip_rca_mn	Airphoto texture summary	4.28
naip_n1_mx	Airphoto texture summary	3.93
naip_v1_mx	Airphoto texture summary	3.90
topo_asptr	Topography: Aspect	3.82
naip_v9a_mn	Airphoto texture summary	3.77
gnn_CANCOV_Max50c	Maximum canopy cover within 50m	3.71
gnn_AGE_DOM_Max50c	Age-range of the dominant trees within 50m	3.69
naip_n1_md	Airphoto texture summary	3.67
naip_n1_mn	Airphoto texture summary	3.51
gnn_CANCOV_Range100c	Range of canopy cover within 100m	3.39
naip_r1_md	Airphoto texture summary	3.35
naip_r1_mn	Airphoto texture summary	3.02
gnn_CANCOV	Tree canopy cover	2.93
gnn_CANCOV_Range50c	Range of canopy cover within 50m	2.93
naip_r4aca_mn	Airphoto texture summary	2.91
gnn_AGE_DOM	Age of the dominant trees	2.82
naip_v1a3a_mn	Airphoto texture summary	2.73
naip_v1a_mn	Airphoto texture summary	2.69
naip_v2a_mn	Airphoto texture summary	2.62
gnn_AGE_DOM_Range50c	Age-range of the dominant trees within 50m	2.57
naip_d1a_mn	Airphoto texture summary	2.49
naip_v1_mn	Airphoto texture summary	2.46
ltdr_distdur	LANDTRENDR records of disturbance duration	2.40
naip_d2a_mn	Airphoto texture summary	2.35

Variable Name	Description	Variable Importance
naip_r1_mx	Airphoto texture summary	2.31
naip_r1a_mn	Airphoto texture summary	2.14
ltdr_distyod	LANDTRENDR records of disturbance year	1.97
naip_v1_md	Airphoto texture summary	1.80
ltdr_distmag	LANDTRENDR records of disturbance magnitude	1.71
naip_r9a_mn	Airphoto texture summary	Not Selected
naip_v2b_mn	Airphoto texture summary	Not Selected
naip_v1b_mn	Airphoto texture summary	Not Selected
naip_d3a_mn	Airphoto texture summary	Not Selected
naip_d4a_mn	Airphoto texture summary	Not Selected
naip_d6a_mn	Airphoto texture summary	Not Selected
naip_d9a_mn	Airphoto texture summary	Not Selected
naip_dca_mn	Airphoto texture summary	Not Selected
naip_r1a3a_mn	Airphoto texture summary	Not Selected
naip_r1b_mn	Airphoto texture summary	Not Selected
naip_r2a_mn	Airphoto texture summary	Not Selected
naip_r2a6a_mn	Airphoto texture summary	Not Selected
naip_r2b_mn	Airphoto texture summary	Not Selected
naip_r3a_mn	Airphoto texture summary	Not Selected
naip_r3a9a_mn	Airphoto texture summary	Not Selected
naip_r3b_mn	Airphoto texture summary	Not Selected
naip_r4a_mn	Airphoto texture summary	Not Selected
naip_r4b_mn	Airphoto texture summary	Not Selected
naip_r6a_mn	Airphoto texture summary	Not Selected
naip_r6b_mn	Airphoto texture summary	Not Selected
naip_r9b_mn	Airphoto texture summary	Not Selected
naip_rcb_mn	Airphoto texture summary	Not Selected
naip_v2a_mn	Airphoto texture summary	Not Selected
naip_v2a6a_mn	Airphoto texture summary	Not Selected
naip_v3a_mn	Airphoto texture summary	Not Selected
naip_v3a9a_mn	Airphoto texture summary	Not Selected
naip_v3b_mn	Airphoto texture summary	Not Selected

Variable Name	Description	Variable Importance
naip_v4a_mn	Airphoto texture summary	Not Selected
naip_v4aca_mn	Airphoto texture summary	Not Selected
naip_v4b_mn	Airphoto texture summary	Not Selected
naip_v6a_mn	Airphoto texture summary	Not Selected
naip_v6b_mn	Airphoto texture summary	Not Selected
naip_v9b_mn	Airphoto texture summary	Not Selected
naip_vcb_mn	Airphoto texture summary	Not Selected
gnn_AGE_DOM_Min100c	Minimum age of the dominant trees within 100m	Not Selected
gnn_AGE_DOM_Min50c	Minimum age of the dominant trees within 50m	Not Selected
gnn_CANCOV_Min100c	Minimum canopy cover within 100m	Not Selected
gnn_CANCOV_Min50c	Minimum canopy cover within 50m	Not Selected
soil_hyd	Soil: Hydrologic group	Not Selected
soil_serpentine	Soil: Serpentine parent material	Not Selected