Received: 17 November 2023 | Revised: 16 May 2024 | Accepted: 13 June 2024

DOI: 10.1111/csp2.13179

CONTRIBUTED PAPER

Conservation Science and Practice
A journal of the Society for Conservation Biology
Open Access

WILEY

Modeling rare plant habitat together with public land managers using an iterative, coproduced process to inform decision-making on multiple-use public lands

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Funding information
Bureau of Land Management, Grant/Award Number: L19PG00076; U.S. Geological Survey through the Ecosystems Mission Area

Abstract

Public lands across the United States are managed for multiple uses, resources, and values ranging from energy development to rare plant conservation. Intensified energy development and other land use changes across the Southwestern United States have increased the need for proactive management to mitigate impacts to rare plants. Habitat suitability models can inform decision-making and lead to more effective conservation of rare plants and their habitats, but high-quality models that are suited for use at local scales are lacking for many species. Our team of scientists and managers developed ensembles of habitat suitability models for five rare plant species in New Mexico using a coproduced, iterative framework complemented by comprehensive ground truthing and tailoring of products for use in public land decisions. Our process resulted in substantial differences from initial models through changes to environmental predictors, species occurrence and background data, and development of new species-specific predictors. Involving species experts and end users in model development can strengthen the process and resulting model and build understanding and trust in final products. Both factors can promote use of models to inform public land permitting and planning decisions that may affect rare plants, including by guiding development away from highly suitable habitats.

KEYWORDS
Aliciella formosa, *Astragalus ripleyi*, Bureau of Land Management, *Cymopterus spellenbergii*, ensemble modeling, National Environmental Policy Act, rare plants, *Sclerocactus cloverae*, species distribution model, *Townsendia gypsophila*

1 | INTRODUCTION

Public lands worldwide provide crucial habitat for many rare and threatened or endangered species, including rare plants. In the United States, over half of the estimated suitable habitat for 818 imperiled plant and animal species occurs on federal lands managed to protect biodiversity, with another 316 species occurring on lands managed for multiple uses (Hamilton et al., 2022).

Some public lands are highly protected (e.g., Gap Analysis Project status 1, U.S. Geological Survey [USGS] Gap Analysis Project [GAP], 2022). While these lands may accommodate different uses, such as conservation and recreation, they are protected from conversion of natural land cover and managed to retain a natural state. National Parks in the United States are an example of this type of public lands, as the goal for these lands is to preserve unimpaired natural and cultural resources and values for current and future generations (National Park Service Organic Act of 1916).

Other public lands are explicitly managed for multiple and diverse resources, values, and uses that often include extractive, ground disturbing activities, such as traditional and renewable energy development, vegetation treatments to manage fuels and increase forage for livestock grazing, and timber harvest. This is the case for many public lands in the United States, including those managed by the Bureau of Land Management (BLM; Federal Land Policy and Management Act of 1976 [43 USC §1701]), the U.S. Forest Service (Multiple-Use Sustained-Yield Act of 1960 [16 USC §528]), and the U.S. Department of Defense (U.S. Department of Defense (USDOD), 2016). Multiple-use public lands in the United States are under increasing pressure to support domestic energy production (e.g., Allred et al., 2015), livestock use (Veblen et al., 2014), and fire management (e.g., Chambers et al., 2017).

Lands managed by the BLM in New Mexico epitomize this pressure. More than 1000 analyses for proposed energy development actions were conducted by the BLM in New Mexico between 2015 and 2019—far more than in any other state (Figure S1). Hundreds of thousands of acres of vegetation treatments have been approved or proposed in New Mexico since 2015, with potential to affect numerous imperiled plant species (Bureau of Land Management, 2023b). New Mexico is home to multiple rare and endemic plant species (New Mexico Energy Minerals and Natural Resources Department Forestry Division, 2017), and the BLM manages important habitat for many of these species (Bureau of Land Management, 2019).

Public land management agencies are required to protect listed species (Endangered Species Act (§7(a)(1) and §7(a)(2))) and manage lands to maintain and restore habitat for sensitive species to prevent listing (Bureau of Land Management, 2008). The National Environmental Policy Act (NEPA, 42 U.S.C. §4321) requires that an assessment of environmental effects be conducted whenever an action proposed on public lands may have significant environmental impacts. These assessments must identify the resources that may be present, how and to what extent they may be impacted by the proposed actions, and measures that can be used to mitigate any adverse impacts. NEPA requires use of the natural and social sciences in those assessments (42 U.S.C. §4322 (2)(A)).

When public lands are expressly managed to accommodate different kinds of development and other ground disturbing activities, it is critical for resource managers to have awareness of the general distribution of suitable habitat for rare plants in the region, regardless of jurisdiction. Knowing where suitable habitat for rare plants occurs both on and around multiple-use public lands can inform permitting decisions and required mitigation measures for oil and gas facilities, for example, to minimize negative impacts to rare plant populations. Models of suitable habitat for rare plants across their range can help to achieve these goals.

Habitat suitability models can leverage compiled datasets of rare plant occurrences housed in museums, herbaria, and rare species databases (e.g., Natural Heritage programs in the U.S.), together with increasingly available environmental characteristics such as those derived from remotely sensed data (He et al., 2015; Randin et al., 2020), to describe and predict species-habitat relationships across a geographic area of interest. While habitat suitability models have been developed for many species worldwide (e.g., Warren et al., 2018), many species of management concern lack habitat suitability models that are appropriate for informing decisions and actions on public lands (Sofaer et al., 2019).

The best available science and data are required to inform management actions and decisions on public lands (e.g., the Endangered Species Act, 16 U.S.C. §1533 (b)(1)(A)), and those methods must be documented (Administrative Procedures Act (5 U.S.C. §551–559)). Public land decisions are challenged on the quality of the science that they use (Foster et al., 2023), including challenges related specifically to agency use of habitat suitability models (Bureau of Land Management, 2017). It is therefore critical that habitat suitability models intended to inform public land decision-making are transparent, defensible, and publicly available (Reese et al., 2019; Sofaer et al., 2019).

In addition to these basic requirements, habitat suitability models intended to inform planning and permitting decisions on public lands must have a spatial resolution and accuracy that allows for their use at local scales (e.g., to inform decisions about the best placement of individual oil and gas wells to minimize loss of both occupied and suitable habitat for the species). Public land managers may be hesitant or unwilling to use models if they do not understand how they were developed, and as a result do not trust their quality (Addison et al., 2013; Sofaer et al., 2019; White et al., 2019).

Our goal was to create trusted maps of suitable habitat for rare plants to inform management decisions and actions at local scales on and around multiple-use public lands. We focused on five rare plant species in New Mexico: *Sclerocactus cloverae* K.D. Heil & J.M. Porter, *Aliciella formosa* (Greene ex Brand) J.M. Porter, *Townsendia gypsophila* Lowrey & P.J. Knight, *Cymopterus spellenbergii* R.L. Hartm. & J.E. Larson, and *Astragalus ripleyi* Barneby. To achieve this goal, we focused on three key outcomes—high-quality products suitable for use at local scales, defensibility and transparency in the modeling process and products, and end user understanding and trust in the modeling process and products. We sought to achieve these outcomes through five strategies: (1) adopting a coproduction approach to model development that involved creating and maintaining a close scientist-practitioner partnership throughout project development, modeling, map production, and management application, (2) clearly documenting modeling inputs and methods to promote confidence, repeatability, and updates, (3) using an iterative framework for model development that continues the modeling process until there is clear understanding and trust by end users and documents decisions and changes made to models throughout the modeling process, (4) ground truthing of model outputs and key predictors by management agency staff, and (5) sharing results through published, publicly accessible data products tailored for the anticipated management uses. We believe that combining these five strategies—coproduction, documentation, ground truthing, iteration and assessment, and publication—can foster greater use of habitat models for rare plants in public land decision-making. While there is clear overlap between a number of these strategies, we highlight below core methods and results related to each strategy, with details found in the Supplementary Methods.

2 | METHODS

2.1 | A brief introduction to habitat suitability models

Habitat suitability models require occurrence data for a species and either species absence data or what are termed background data to assess the full range of environmental conditions available to a species. These data on species presence, species absence, and available background conditions are collectively termed location data. Habitat suitability models pair location data with metrics of environmental characteristics (predictors) that may limit habitat suitability for a species, forming mathematical relationships between where a species does or does not occur (when absence data are available) or where a species occurs compared to what conditions are available across the landscape (when background data are used instead of absence data). These relationships can then be applied across a landscape to predict all areas of potentially suitable habitat for the species (Franklin, 2010). Important considerations in creating habitat suitability models include sampling bias related to location data, what environmental characteristics are included, and the nature of the mathematical relationships between predictors and species locations (Jarnevich et al., 2015). Response curve graphs that show the relationship between habitat suitability over the range of observed values for a specific environmental characteristic (predictor) are typically used to visualize the latter, and the ecological plausibility of each response curve is an important consideration.

2.2 | Study areas and species

We focused on two study areas. The Farmington study area encompassed parts of northwestern New Mexico and adjacent southwestern Colorado, related to the BLM New Mexico Farmington Field Office (Figure 1c–e). The Taos study area encompassed the north central portion of New Mexico and adjacent areas in Colorado, related to the BLM New Mexico Taos Field Office (Figure 1a,b). More details on the study areas can be found in the Supplementary Methods.

The Farmington area included three species. *A. formosa* is a perennial forb restricted to the Paleocene

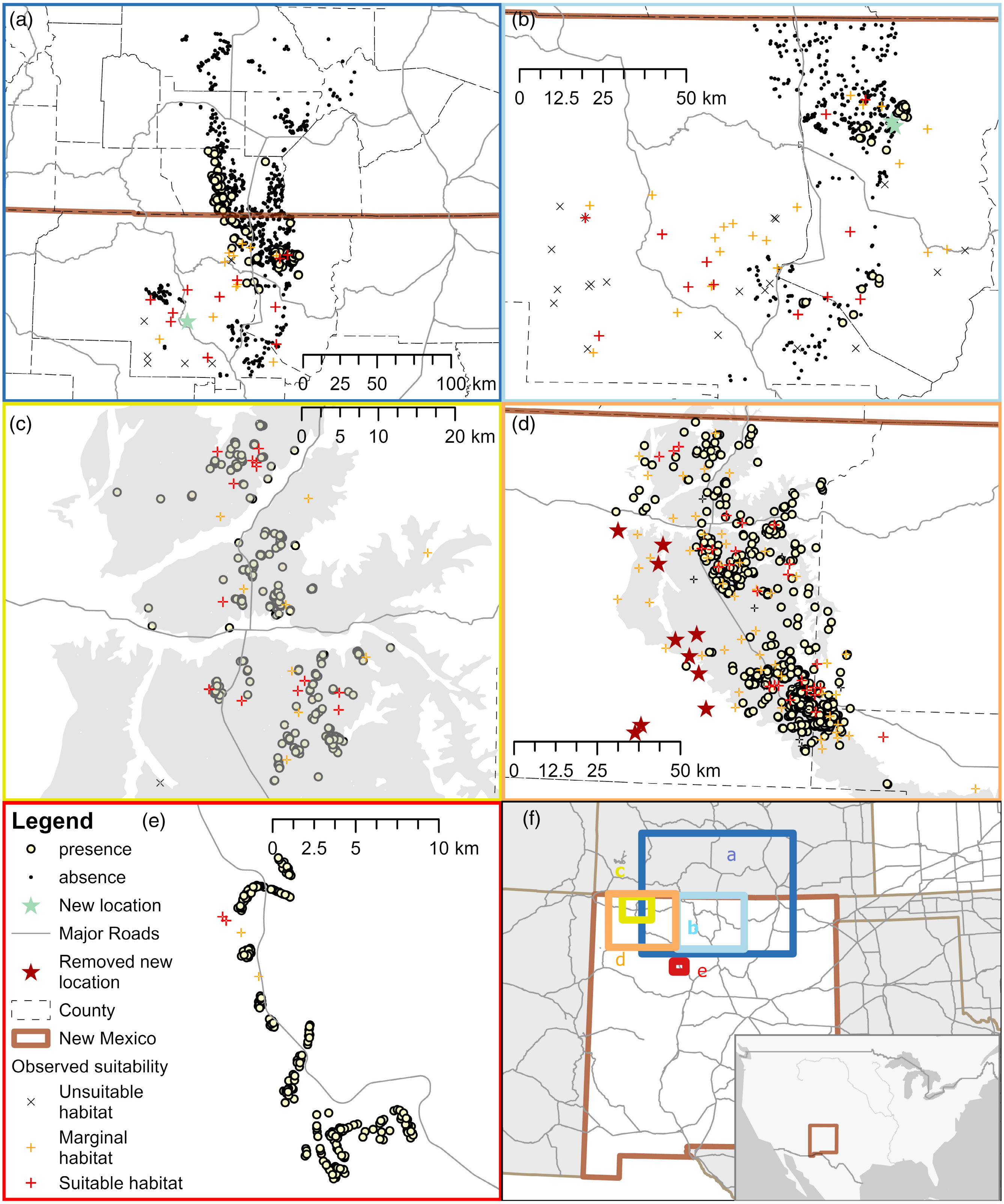

FIGURE 1 Locations used in model fitting (presence and absence), and new locations and observed suitability from model validation through ground truthing for (a) *Astragalus ripleyi*, (b) *Cymopterus spellenbergii*, (c) *Aliciella formosa*, (d) *Sclerocactus cloverae*, and (e) *Townsendia gypsophila*, and (f) the model extents considered for each species where the colored boxes of extents reflect the extent for panels a–e.

Nacimiento Formation. *S. cloverae* is a more broadly distributed species also associated with the Nacimiento Formation. *T. gypsophila* is a gypsophilic perennial forb.

The Taos area included two species. *A. ripleyi* is a perennial forb occurring on a variety of habitats within its range. *C. spellenbergii* is also a perennial forb found in a subset of *A. ripleyi's* range. Additional information on all five species can be found in the Supplementary Methods.

2.3 | Coproduction

We assembled a project team for the modeling effort that consisted of USGS staff with expertise in modeling and coproduction, BLM staff with expertise in the species and broader vegetation monitoring and data collection efforts, other species experts, and BLM staff who conduct permitting and other management actions and thus are intended users of the modeling products. Project team members ultimately included staff from three administrative levels in the BLM: national, state, and local field offices. Project team members committed to involvement throughout the project, and to participation in a series of meetings and work sessions to examine and provide input on model inputs, initial results, and model refinements.

2.4 | Documentation of model inputs and methods

We began model development for the three species from the Farmington Field Office, *A. formosa, S. cloverae*, and *T. gypsophila*, in December 2019 and the two species in the Taos Field Office, *A. ripleyi* and *C. spellenbergii*, in February 2021.

2.4.1 | Occurrence data

We obtained species occurrence data from the BLM (including the BLM FLORA database (Bureau of Land Management, 2023a), BLM Assessment, Inventory, and Monitoring (AIM) Program data (Bureau of Land Management, 2022), oil and gas project surveys completed by environmental consultants, and Natural Heritage New Mexico), and from species status reports (Roth, 2015; Roth & Sivinski, 2015, 2018). We merged these datasets and filtered location data by year, collection method, proximity, and location using species specific criteria (see Table S1 for specific filtering criteria for each species), as it is important to ensure quality data are used in developing models for rare species (Aubry et al., 2017; Oleas et al., 2019). The number of occurrences changed with different iterations, but totals are included for each model iteration for each species in Table S3.

2.4.2 | Absence/background data

Because species absence data were minimal (Table 1 and Table S1), we developed background data to use by itself (Farmington area species) or to supplement absence information (Taos area species). We used input from species experts regarding the spatial extent of surveys and survey bias to inform placement of background points, and allowed the criteria used to derive background data to evolve through our iterative process.

We masked out areas in agricultural and urban areas as defined by the 2016 National Land Cover Database (Dewitz, 2019) [NLCD classes 21, 22, 23, 24, and 82] starting with model version 3 (Farmington) or model version 1 (Taos) so that background locations could not be placed in these areas. We also excluded the footprint of a gypsum mine near San Ysidro, New Mexico, that fell within the training extent for *T. gypsophila*.

We randomly generated 10,000 background points on BLM and state lands within training extents for *S. cloverae, A. formosa*, and *T. gypsophila*, as these land ownerships have been well surveyed for each of these species. For initial models for *A. ripleyi* and *C. spellenbergii*, we used absence points derived from BLM Assessment, Inventory, and Monitoring plots. We addressed bias issues that subsequently emerged through our iterative process (see Section 3).

2.4.3 | Environmental predictors

Our selection of geospatial predictors was informed by the species' ecology and extensive discussions with experts on each plant species. This process resulted in generation of 24 different predictors related to topography, soils, and other characteristics (Table S2).

As part of the modeling process, we developed multiple predictors from remotely sensed imagery to capture differences in soil color, as species experts believed that soil color reflected different underlying physical characteristics that related to suitability for the different plant species. Data sources for specific predictors changed through model iterations as did the suite of predictors included in models. Table S2 includes the full suite of predictors that were included in any of the model iterations for any species, while Table S3 includes information on the specific predictors and data sources for each model iteration for each species. We detail specific methods and

TABLE 1 Description of model iterations including format and length of meetings to review model iterations, items discussed, and changes made to location data and predictors.

	Sclerocactus cloverae, Aliciella formosa, Townsendia gypsophila	***Cymopterus spellenbergii, Astragalus ripleyi***
Iteration 1	Informed by afternoon discussion of: • Key characteristics of habitat for each species • Use of Soil Survey Geographic Database soils data • Quality of occurrence data • Location of random background points across study area	Informed by virtual meetings and email discussions of: • Decisions from Iteration 3 for other species • Key characteristics of habitat modeled using existing predictors • Adding new predictor for tree cover
Iteration 2	Informed by 2-day virtual workshop in which we: • Examined soil data sources with field personnel, resulting in a switch to POLARIS soils data (Chaney et al., 2016) which filled in some No Data gaps in the study extent • Reviewed sampling underlying occurrence data, resulting in altered background point placement. • Resolved no data holes in prediction map extent	Informed by virtual meeting to review models and subsequent email exchanges discussing: • Using refined occurrence data and predictors • Supplementing absences with background points to capture ownerships sampled for presence but not absence to resolve ecoplausability issues • Agreement on final models from alternatives for *A. ripleyi* • Following field-based ground-truthing design for Farmington but with specific goals for each of these species • Resolved issues between predicted relationship with elevation and known relationship
Iteration 3	Informed by 2-day workshop in which: • Group reviewed models and designed field-based ground truthing: • Soil scientists and remote sensing experts recommended new predictor sources • Produced multiple model runs that included one of a set of correlated predictors. *S. cloverae*: two predictor set versions (Table S3b). *T. gypsophila*: four models with different soil predictors (Table S3c) • Refit selected *S. cloverae* version with new occurrences collected in summer 2020 due to ground truthing COVID delay	Informed by virtual meeting for each species in which we discussed: • Added new presence observations for both species and added observed unsuitable ground truth locations as absence points for *C. spellenbergii* • Revising predictors based on model validation field-based ground truthing results • Increased predicted suitability for observed suitable locations; opposite for observed unsuitable
Iteration 4	Virtual meeting for each species in which we: • Added new presence observations gained from ground-truthing • Revised predictors based on review of ground-truthing results • Added observed unsuitable locales as background points (*S. cloverae)* • Updated soils predictor data source • Updated other predictors like soils based on results from the Taos iterations • Increased predicted suitability for observed suitable locations; opposite for observed unsuitable	

processes that we used to create and refine individual predictors in Table S2 and the Supplementary Methods.

2.4.4 | Model methods

We used the spThin R package (ver. 0.2.0) (Aiello-Lammens et al., 2015) to enforce a minimum distance of 100 m between occurrence records, which matched the resolution of our coarsest predictor. We input these spatially filtered locations and the predictors described above into VisTrails: Software for Assisted Habitat Modeling version 2.1.2 (Morisette et al., 2013).

We selected initial sets of the predictors for each species based on expert knowledge, and then removed one of any pair of predictors with >|0.7| correlation coefficient from the maximum of the Pearson, Spearman, and Kendall correlation coefficients to limit multicollinearity

(Dormann et al., 2013). Because of its low sample size, we had to further reduce *C. spellenbergii* predictors based on expert opinion to ensure a ratio of at least 10 occurrence points to one predictor (Jarnevich et al., 2015).

We fit models using five algorithms (boosted regression tree (Elith et al., 2008), generalized linear model (Hosmer & Lemeshow, 2000), multivariate adaptive regression spline (Leathwick et al., 2006), Maxent version 3.4.1 (Phillips et al., 2017), and random forests (Breiman, 2001)) using algorithm default settings within Software for Assisted Habitat Modeling and 10-fold cross-validation. We removed Maxent for the Farmington species which had absence data because Maxent is specifically for use with background data.

We assessed the need to tune parameters for each algorithm by examining the difference between the training and average cross-validation area under the curve (AUC; using an a priori criteria to investigate models with difference values >0.05 for overfitting) and by visually inspecting response curve complexity.

Because none of the models were well calibrated, the continuous predicted values from each algorithm represented relative suitability rather than probabilities of occurrence.

2.5 | Ground truthing surveys

We implemented ground truthing with the primary goal being to validate the accuracy of the highest bin (avoidance areas) in the model ensemble, as BLM staff considered this to be their highest priority for the modeling effort. We randomly generated potential survey points within areas defined as available and feasible for ground truthing surveys, considering distance from known locations, distance from roads, and land ownership (Table S4, Figure S3). Generated points were skewed towards the "high" class based on manager priority, with the number of points per class defined by managers for each species (Table S4).

Ground truthing surveys were conducted by BLM staff or surveyors contracted by the BLM, and included searches for the target species plus other study species, qualitative assessment of the suitability of the location for the target species, land cover class, topographic feature class, associated species, and estimates of bare ground cover (all target species), gypsum presence (Farmington Field Office species), and basalt presence (Taos Field Office species). Detailed information on the survey protocol and data collected are provided in the Supplementary Methods—Ground truthing protocol section.

2.6 | Iterating, assessing, and refining

We used an iterative modeling process, committing at the start to developing multiple versions of each model, each reflecting input and refinements suggested based on earlier versions. We continued this process until the project team was satisfied that we had a model deemed worthy of ground truthing, and then continued to assess and refine the model in light of ground truthing data and continued project team input. An important part of this iterative process was documenting the process, changes made during the process, and the rationale behind each change.

Typically, following an initial model run informed by those first meetings, the project team met to review model results in depth for each model iteration and consider results based on both individual's knowledge of the species and the landscape and on statistical model evaluation metrics (Table 1), though assessments were generally qualitative based on expert knowledge until the field validation stage. At these meetings, the team considered specific model inputs (occurrence locations, background locations, predictors, extents) and results (ecological plausibility of predictor importance and response curves, spatial predictions, and novel environments) and made specific recommendations for model refinement. The modeling team then revised models using these recommendations (e.g., updated occurrence data, revised placement of background points, new geographic extents for both inputs and output maps, new/revised environmental predictors, revised masks of specific areas to exclude from analyses such as croplands) to inform a next round of iteration.

After ground truthing surveys, we compared modeled habitat suitability predictions (unsuitable, low, medium, and high suitability) to both qualitative habitat suitability assessments conducted in the field (limited to validation plots specifically for that species) and to any new occurrence locations identified (from any surveyed plots) for each species. We compared the observed habitat suitability at the survey site with the observed land cover class and observed topographic feature class to evaluate if we may have missed important predictors.

The team also evaluated maps of surveyed locations and predictor values at those locations as another means to evaluate predictors. This suite of information from ground truthing surveys informed decisions for refining and fitting the final models, including revising input occurrence data and environmental predictors.

Finally, we examined changes in predictions relative to observed habitat suitability between the validation model version and final model versions.

2.7 | Tailoring products for use in public land decisions

We committed at the start of the project to peer-reviewing and publishing all model outputs, to achieve transparency and defensibility in our models and maps. Publication was determined to be the best way to achieve consistency in the maps being used by developers to locate and design projects and the maps used by agency staff to evaluate potential environmental impacts of those proposed projects.

We also committed to creating tailored products that would facilitate use by both developers and agency staff. Thus, we worked with our project team to define three suitability bins of levels of confidence based on BLM intended uses of the models in management decisions related to rare plants. BLM rare plant specialists and permitting and management staff (the target end users for the models) defined classes as (1) high: avoidance areas (i.e., known occupied habitat plus highly suitable habitat, considered core areas where species is found and that developers should avoid if at all possible); (2) medium: areas oil and gas developers may want to avoid and where plant surveys would be required, still considered as suitable habitat; and (3) low: areas where plant surveys would be required as part of permitting, considered potential habitat. We developed these bins using ensemble techniques (details in Supplementary Methods; Figure S2).

3 | RESULTS

3.1 | Coproduction

Our iterative, coproduced modeling framework was implemented as a full partnership between the researchers, species experts, and public land managers on our project team. During the course of the study there were five species experts and 10 land managers (generally also species experts) along with consulting specialists (soil scientists and remote sensing experts). We met more than 15 times over the course of the project, using a combination of both in person and virtual meetings (the COVID-19 pandemic was declared during our study period).

Initial meetings focused on model inputs: available species observation data, available absence data, and species biology and ecology that could inform compilation and creation of relevant environmental predictors (Table 1). Subsequent project teams meetings were the mechanism through which our iterative modeling process was implemented.

3.2 | Documentation of model inputs and methods

A particularly important part of the modeling process for our project team was working together to ensure that the suite of predictors used to model habitat for each species was relevant, high-quality, and comprehensive. Data sources for specific predictors changed through model iterations as did the suite of predictors included in models. Table S2 includes the full suite of predictors that were included in any of the model iterations for any species, while Table S3 includes information on the specific predictors and data sources for each model iteration for each species. We found that many species-specific predictors were not readily available and thus required researching and assessing options to represent them. Ultimately, we developed and included new predictors in the habitat models for all species to account for unique characteristics of the species being modeled, such as the geologic formation to which *A. formosa* and *S. cloverae* are restricted, predictors capturing gypsum for *T. gypsophila*, and a basalt predictor for *A. ripleyi* and *C. spellenbergii* (Table S2).

Gypsum proved particularly challenging to represent. We developed and tested many different options for representing gypsum substrate based on both derivatives from existing soil datasets such as the Soil Survey Geographic Database (SSURGO) and different remote sensing indices. Species experts reviewed alternative predictor sets to capture gypsum for *T. gypsophila* and suggested models based on different combinations of uncorrelated options thought to match local knowledge of gypsophilic soils (Table S3). Both *T. gypsophila* and *A. ripleyi* model iterations included comparing alternative suites of uncorrelated predictors. Over the course of the iterative modeling process, we ultimately considered up to four different sources for gypsum and other predictors (Table S3).

3.3 | Ground truthing surveys

Agency staff and contractors surveyed a total of 250 sites (Table S4), resulting in new observations for all species. Ground truthing surveys for *S. cloverae* resulted in 59 new observation sites, with 38 of those (64%) in locations the draft model classified as high or medium suitability (Figure S6), and five (8%) in the 29 plots classified as "unsuitable" by field personnel. Other species had far fewer new locations recorded during ground truthing (five *A. formosa*, three *T. gypsophila*, two *C. spellenbergii*, and one *A. ripleyi*; Figure S6), which may suggest that these species are rarer than originally anticipated.

3.4 | Iterating, assessing, and refining

Our iterative process was based on group review of maps of occurrences (e.g., Figure 1), maps of potential predictors, and review of model outputs including predictor importance (e.g., Figure S4), response curves, and mapped predictions (e.g., Figure S5) to assess ecological plausibility. As such, model assessments for iteration 1 (all species) and iteration 2 (Farmington species) were qualitative based on experts' assessment of ecological plausibility. Assessment between the final two stages was quantitative.

The iterative process resulted in multiple changes to the habitat models for each species over the course of the study (Table 1 and Table S3). These changes included methodological changes (e.g., background point distribution), refinements to occurrence data, and changing both predictor data sources and types. Model iterations addressed different issues for different species.

For example, the Taos species (*A. ripleyi* and *C. spellenbergii*) iteration 1 models included suitability at higher elevations than species experts knew the species to occur. We determined that bias issues in the location data was the reason: our occurrence data fell on both BLM and non-BLM lands but our absence data were from BLM lands only, and there were environmental differences between ownership groups (e.g., U.S. Forest Service lands included higher elevation areas compared to BLM lands). To address this, we calculated the ratio of occurrence locations occurring on BLM lands to those occurring on non-BLM lands. We then randomly generated background points on non-BLM lands so that the ratio of BLM land absence points to non-BLM land background points was the same as the ratio of BLM occurrence points to non-BLM occurrence points. This change resulted in a predicted relationship between occurrence and elevation in iteration 2 that matched expert knowledge.

Another example of iteration and refinement involved discovering through visual inspection of maps that initial models were predicting suitable habitat in crop circles. Thus, the project team decided to exclude agricultural areas from modeling (iteration 2 for Farmington species).

For *S. cloverae*, there were large differences in both predictors included in models and predictor importance across iterations (Table S3b, Figure S4). While bare ground and soil texture drove the early models, the addition of distance to the Nacimiento formation, elevation, and some remotely sensed indices to capture soil color resulted in decreased importance for these two predictors in subsequent iterations. Differences in mapped outputs between the first two iterations reflect the change in soil data source (Figure S5). Despite the smaller differences between the final two iterations, there are notable differences in the mapped predictions, particularly on the Eastern part of the Nacimiento formation where field validation provided information for the previously poorly surveyed area.

Models for the Taos Field Office species (*A. ripleyi* and *C. spellenbergii*) were able to build on the region-specific predictors that had already been developed for *A. formosa, S. cloverae*, and *T. gypsophila*, such as remotely sensed indices to capture soil color. As a result, both *A. ripleyi* and *C. spellenbergii* required fewer predictor changes and three rather than four model iterations.

Models continued to be iterated for each species until the project team was comfortable that the draft model reflected expert knowledge of the species, warranting ground truthing. Models selected for ground truthing included revised occurrence data, background data restricted based on occurrence record sampling knowledge, a mask to exclude urban and agricultural areas for model fitting, and a revised set of predictors tailored to individual species compared to initial iterations (Table 1).

Iteration continued after ground truthing. For example, of the 110 surveyed plots targeting *S. cloverae*, 17 of 32 predicted "high" suitability plots were assessed as "unsuitable" in the field. Many of these occurred in locations with high tree cover, which was not previously included as a predictor. We thus added a tree cover predictor to the final version along with updates to some other predictors (Table S3).

For the other four species, for which far fewer new locations were identified during ground truthing, we assessed models mainly based on comparing predicted versus observed habitat suitability. The project team was satisfied with the performance of the models for *A. ripleyi* and *C. spellenbergii*, and predictor changes for the final models were limited to updating existing predictors (Table S3) and forcing the *C. spellenbergii* generalized linear model to retain basalt as a predictor as it is known to be important and was retained by the other algorithms. Predictor changes were considered for *A. formosa*, including maximum slope in moving window and canopy cover, but were ultimately rejected, so predictor changes for it and *T. gypsophila* also only included updates to existing predictors.

The final model versions had changes in the predicted habitat suitability relative to the observed habitat suitability from field validation (Figure S8, Figure 2). The two species for which the pre-validation model had predicted unsuitable habitat in areas that were observed to be suitable in the field no longer had this mismatch in the final model. Additionally, the number of locations observed as unsuitable in the field but with model predictions of low, medium, or high suitability decreased

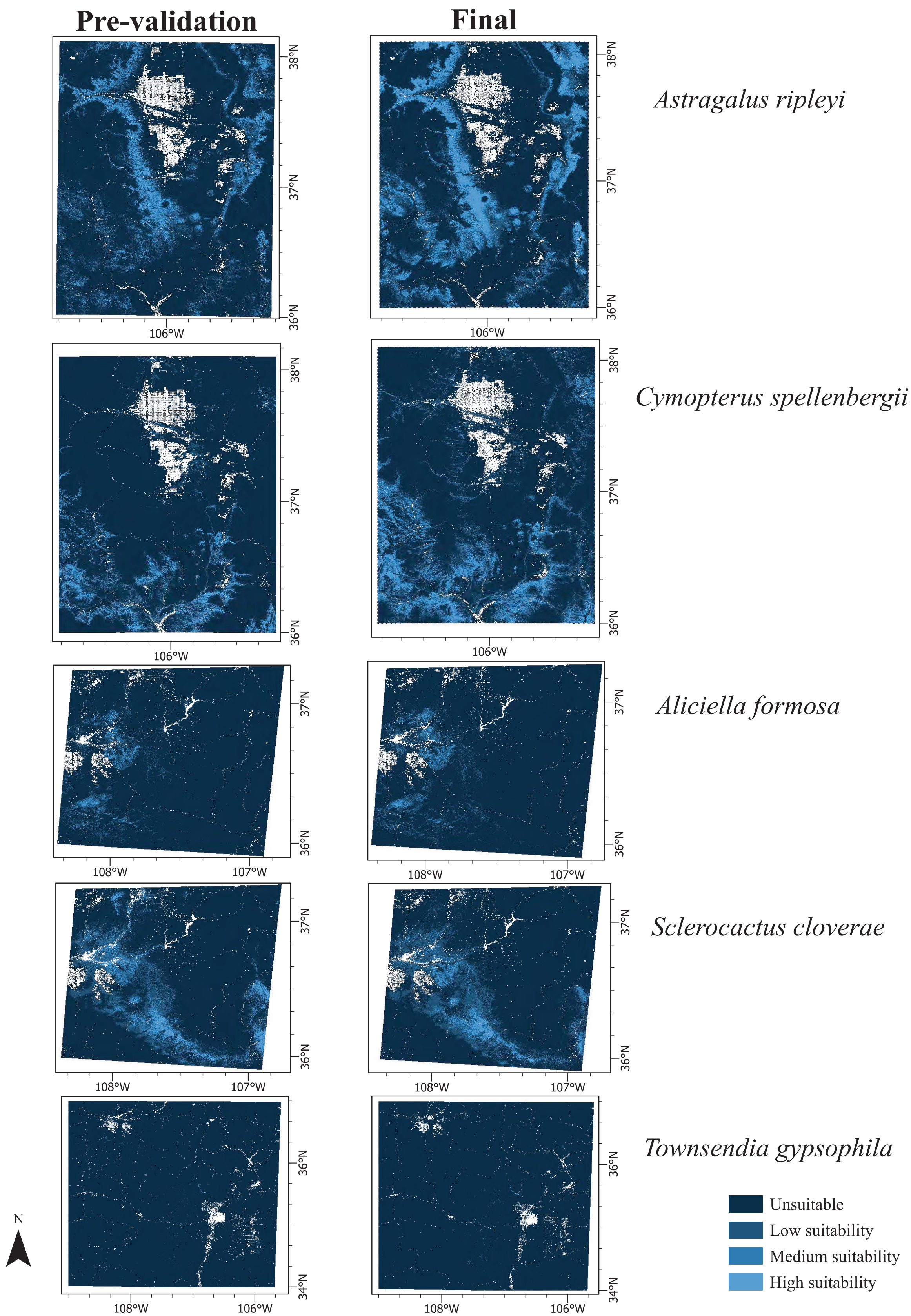

FIGURE 2 Pre-validation modeled habitat suitability maps (i.e., the model version used to guide field validation surveys) and the final model outputs for each of the five species (*Astragalus ripleyi*, *Cymopterus spellenbergii*, *Aliciella formosa*, *Sclerocactus cloverae*, and *Townsendia gypsophila*), where the mapped values reflect the low, medium, and high suitability management categorizations.

between the pre-validated model version and the final model version (Figure S8). For example, *T. gypsophila* had five survey plots qualitatively assessed as unsuitable. The field validation iteration model classified one of these as low and four as medium suitability, while the final model classified all of those locations as unsuitable.

3.5 | Tailoring products for use in public land decisions

We ultimately determined that there were two needed map products: maps of the low, medium, and high suitability habitat areas for each species that are suitable for use by specialists (e.g., agency botanists), and binary habitat suitability maps for other model users (e.g., fluid minerals project review staff). Together this manuscript, detailed methods (Supplementary Materials), and modeling software tracking provenance, provide transparent, defensible results available for use by all stakeholders.

4 | DISCUSSION

Multiple-use public lands provide important habitat for rare plants but are also subject to significant energy development and other types of ground disturbing activities. Maps of suitable habitat for rare plants can help both developers and public land managers to design and site projects and to identify and implement other measures to minimize loss and degradation of suitable habitat for these species. However, many habitat models are not suitable for use at local scales, and managers may not understand or trust the methods or data used to develop the models, all of which can decrease their use in public land decision-making. We worked to address these challenges by coproducing a suite of ensemble habitat models using an iterative framework coupled with comprehensive field validation and tailoring of final products for use by all stakeholders in public land management decisions.

4.1 | Coproduction

Models intended to support decision-making are more likely to be viewed as legitimate by decision-makers if they are coproduced (Seidl, 2015). We developed our coproduction framework beginning in 2019, and were pleased to find that Ramirez-Reyes et al. (2021) had independently developed a very similar coproduction process. The process involved collaboration between species experts and modelers to determine model inputs (both location and predictor data), review iterative models for ecological plausibility, and design the format of model outputs to meet the needs of practitioners. The framework involved interaction at every step of the modeling process outlined by Sofaer et al. (2019) and expanded by Reese et al. (2019). Coproduction is one tool that scientists and managers have used to increase trust and understanding by managers in the research process and buy-in, use, and actionability of research products (Arnott et al., 2020; Beier et al., 2017).

4.2 | Modeling inputs and process

Many habitat models rely on available predictors, such as coarse climate data, which do not capture the microclimate experienced by plants (Mod et al., 2016). Species experts often understand which environmental factors limit a species distribution, but these factors are not always readily available as geographic layers. Developing tailored environmental predictors from LandSat imagery and other sources that reflect species-specific requirements was a key part of our modeling process. Others have also found that accurately reflecting the environmental complexity in models can affect how stakeholders perceive the credibility of the resulting science products (Rosemartin et al., 2023).

Soils are a key component defining suitable habitat for plant species (Mod et al., 2016), and obtaining the best available sources that species experts felt captured ground conditions reasonably well required many steps including carefully considering soil texture, composition, color, and depth, and how these might be best represented for different species and locations using different data sources. For example, we had to generate several different spatial layers to capture where gypsum might be across the landscape that experts then reviewed to determine which best matched their knowledge based on their time spent in the field. Many of these predictors were derived from remotely sensed imagery (Leitão & Santos, 2019). These tailored predictors helped strengthen user trust in the modeling process and were also important predictors in final models. Others have demonstrated the need to have local scale edaphic factors to produce good models, as rare species generally have highly restrictive niche requirements (e.g., in situ measurements for understory plants (Roe et al., 2022)).

4.3 | Iteration, assessment, and refinement

The iterative review process allowed end users to evaluate the ecological plausibility of models at multiple stages. Interactions with resource managers and species experts started early, with discussions of the species biology and consideration of the specific occurrence data to be used to fit the model, and continued throughout—a key to success (Rosemartin et al., 2023). End-users provided suggestions to improve realism of the models by altering model inputs based on knowledge of target species and the local environment. Typically, these changes involved revisiting predictors considered in model fitting (Table 1). This input improved the models, as has been seen by others (Glenn et al., 2022), and ensured understanding of the models, overcoming a common barrier to model uptake (Addison et al., 2013).

We found that each iteration refined the models, as exemplified with *S. cloverae* ensemble models for version 3 and 4. While 59 additional locations were included in the version 4 model, none of these occurred in the eastern region of the Nacimiento formation (Figure 1 and Figure S8) which had predicted suitability in version 3. However, model predictions for that region were still refined in version 4.

4.4 | Ground truthing

Ground truthing resulted in changes in the predictor suite for all species. Information from the qualitative assessments of habitat suitability allowed comparison with model predictions in cases where the rare species simply were not found, which is likely common for rare, specialist plant species relative to more generalist rare species such as *S. cloverae*. Other research has used plant community data to validate suitability predictions for rare plant species, including finding that distance to nearest known occurrence was the strongest predictor of whether or not a new population was found with the model (McCune, 2016). This validation step of testing models in the field, along with co-production, also leads a higher degree in the confidence of predictions (Sofaer et al., 2019).

4.5 | Limitations

Some limitations of the models were evident. For most species, very few new occurrences were detected, and a model based on presence/absence data that predicts probability of occurrence or one that captures temporal differences including dispersal limitations might be more useful (Guillera-Arroita et al., 2015).

4.6 | Tailoring products for use in public land decisions

Model outputs, including their validation, were tailored to intended use in decision-making. This focus on decisions to be made by specific stakeholders is an important step in ensuring models can be used to meet management objectives (Byrd et al., 2023). In this case, thresholds were chosen by managers based on desired sensitivity (true positive rate) of the models for their intended use (Guillera-Arroita et al., 2015). These criteria for categories were developed by managers in light of their intended use: high suitability represents avoidance areas (known occupied and highly suitable habitat), medium suitability indicates areas to consider avoiding for any kind of land-use change and where plant surveys would be required, and low suitability indicates areas where plant surveys would be required before permitting. It is important to note that public land managers would still require plant surveys prior to any ground disturbance in all three levels of habitat to avoid loss of individuals, but that the three levels provide options for land managers to work proactively with developers and other stakeholders to enhance species and habitat conservation. Peer-review and open publication of the final model outputs is a critical final piece supporting model use as part of transparent, defensible, science-informed decision-making on public lands (Executive Order No. 13990, 2021).

We suggest that these models can be used to inform proposed development actions on multiple-use public lands in two ways, with benefits for rare plants and habitats. First, model outputs could be used by developers to help site proposed developments (e.g., individual oil wells) in areas with low, or no suitability for these rare plant species, limiting potential habitat loss and likely streamlining and simplifying the entire permitting process (e.g., Jarnevich et al., 2021). Publishing these model outputs so that they are freely available to all interested parties helps to facilitate this type of proactive action and to eliminate elements of surprise in the permitting process. The coproduced, iterative ensemble modeling approach and ground-truthing of the models so that they are especially suited to this type of local use builds confidence in users, strengthens defensibility of the decision process, and may help to decrease challenges to the use of science information in decisions (Foster et al., 2023). Second, when suitable habitat cannot be avoided, developers could plan ahead to have plant surveys conducted during the limited windows each year in which the species can be detected.

Models can also inform habitat management and conservation efforts on public lands. Agency staff could use this information to help inform vegetation management actions (e.g., restoration, livestock forage vegetation treatments, and fuels and forestry vegetation treatments), targeting efforts in areas that avoid, protect, or may ultimately provide important gains for the species. Maps could also be used in conservation-related activities such as species status assessments, as a critical piece of information identifying both how much suitable habitat may exist on the landscape and where it may be most promising to conduct surveys to identify potential new occurrences or populations. Finally, maps of suitable habitat could also inform the designation of areas for protection efforts (e.g., as Areas of Critical Environmental Concern) in agency land use plans, which can provide longer term protection for sensitive species. In all of these efforts, decisions are typically made from the bottom up—with individual staff applying the habitat model to the decision at hand. As such, the agency understanding gained through participation of staff and colleagues in the modeling process, and the high-quality of model outputs resulting from our iterative, coproduced process, combine to support model use.

AUTHOR CONTRIBUTIONS

CSJ, SKC, and ZMD conceptualized the project. CSJ, BH, PNB, and BRH developed predictors, fit models, and developed the outputs.CSJ and SKC led writing of the manuscript with contributions from all others. All authors participated in model conceptualization and review.

ACKNOWLEDGMENTS

We would like to thank Brian (Mike) Beitner, John Kendall, Jillian LaRoe, Nathan Redecker, Daniela Roth, Lauren Bansbach, Ryan Esch, Emily Guinan, Dylan Hardy, Erin Call, Ella Samuel, and Kimiora Ward for contributions to model development. We gratefully acknowledge Colorado State University and FORT Writes hosted by Kristina Quynn for providing expertise, time, incentive, and accountability that aided in the writing process. The findings and conclusions in this article are those of the author(s) and do not necessarily represent the views of the U.S. Fish and Wildlife Service. Any use of trade, firm, or product names is for descriptive purposes only and does not imply endorsement by the U.S. Government.

FUNDING INFORMATION

This work was funded by the Bureau of Land Management through interagency agreement L19PG00076, with additional support provided by the U.S. Geological Survey through the Ecosystems Mission Area.

CONFLICT OF INTEREST STATEMENT

There are no conflicts of interest to disclose.

DATA AVAILABILITY STATEMENT

Environmental layers and model outputs are available in a U.S. Geological Survey data release (Jarnevich et al. 2024).

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REFERENCES

Addison, P. F. E., Rumpff, L., Bau, S. S., Carey, J. M., Chee, Y. E., Jarrad, F. C., McBride, M. F., & Burgman, M. A. (2013). Practical solutions for making models indispensable in conservation decision-making. *Diversity and Distributions*, *19*, 490–502.

Aiello-Lammens, M. E., Boria, R. A., Radosavljevic, A., Vilela, B., & Anderson, R. P. (2015). spThin: An R package for spatial thinning of species occurrence records for use in ecological niche models. *Ecography*, *38*, 541–545.

Allred, B. W., Smith, W. K., Twidwell, D., Haggerty, J. H., Running, S. W., Naugle, D. E., & Fuhlendorf, S. D. (2015). Ecosystem services lost to oil and gas in North America. *Science*, *348*, 401–402.

Arnott, J. C., Neuenfeldt, R. J., & Lemos, M. C. (2020). Co-producing science for sustainability: Can funding change knowledge use? *Global Environmental Change*, *60*, 101979.

Aubry, K. B., Raley, C. M., & McKelvey, K. S. (2017). The importance of data quality for generating reliable distribution models for rare, elusive, and cryptic species. *PLoS One*, *12*, e0179152.

Beier, P., Hansen, L. J., Helbrecht, L., & Behar, D. (2017). A how-to guide for coproduction of actionable science. *Conservation Letters*, *10*, 288–296.

Breiman, L. (2001). Random forests. *Machine Learning*, *45*, 5–32.

Bureau of Land Management. (2008). *Manual 6840–special status species management*. US Department of Interior BLM.

Bureau of Land Management. (2017). *Director's protest resolution report for the Dominguez-Escalante National Conservation Area (Colorado) proposed resource management plan and final environmental impact Statement*. U.S. Department of the Interior, Bureau of Land Management. https://www.blm.gov/documents/colorado/directors-protest-resolutions/protest-resolution-report/dominguez-escalante-nca

Bureau of Land Management. (2019). *BLM New Mexico Information Bulletin NM IB-2019-002. Revision to the New Mexico Bureau of Land Management (BLM) Sensitive Animal and Plant Lists*. https://www.blm.gov/policy/nm-ib-2019-002

Bureau of Land Management. (2022). *Assessment inventory and monitoring (AIM) data*. https://www.blm.gov/aim

Bureau of Land Management. (2023a). *FLORA Data Standard*. U.S. Department of the Interior, Bureau of Land Management, New Mexico Region.

Bureau of Land Management. (2023b). *National NEPA Register (eplanning-ui)*. https://eplanning.blm.gov/eplanning-ui/

Byrd, K. B., Matchett, E., Mengelt, C., Wilson, T. S., DiPietro, D., Moritsch, M., Conlisk, E., Veloz, S., Casazza, M. L., & Reiter, M. E. (2023). Knowledge coproduction on the impact of decisions for waterbird habitat in a changing climate. *Conservation Biology*, *37*, e14089.

Chambers, J. C., Beck, J. L., Bradford, J. B., Bybee, J., Campbell, S., Carlson, J., Christiansen, T. J., Clause, K. J., Collins, G., Crist, M. R., Dinkins, J. B., Doherty, K. E., Edwards, F., Espinosa, S., Griffin, K. A., Griffin, P., Haas, J. R., Hanser, S. E., Havlina, D. W., … Wuenschel, A. (2017). *Science framework for conservation and restoration of the sagebrush biome: Linking the Department of the Interior's Integrated Rangeland Fire Management Strategy to long-term strategic conservation actions*. U.S Department of Agriculture, Forest Service.

Chaney, N. W., Wood, E. F., McBratney, A. B., Hempel, J. W., Nauman, T. W., Brungard, C. W., & Odgers, N. P. (2016). POLARIS: A 30-meter probabilistic soil series map of the contiguous United States. *Geoderma*, *274*, 54–67.

Dewitz, J. (2019). *National Land Cover Database (NLCD) 2016 products*. U.S. Geological Survey Data Release. https://doi.org/10.5066/P96HHBIE

Dormann, C. F., Elith, J., Bacher, S., Buchmann, C., Carl, G., Carré, G., Marquéz, J. R. G., Gruber, B., Lafourcade, B., Leitão, P. J., Münkemüller, T., McClean, C., Osborne, P. E., Reineking, B., Schröder, B., Skidmore, A. K., Zurell, D., & Lautenbach, S. (2013). Collinearity: A review of methods to deal with it and a simulation study evaluating their performance. *Ecography*, *36*, 27–46.

Elith, J., Leathwick, J. R., & Hastie, T. (2008). A working guide to boosted regression trees. *Journal of Animal Ecology*, *77*, 802–813.

Executive Order No. 13990. (2021). Protecting public health and the environment and restoring science to tackle the climate crisis. *Federal Register*, *86*, 7037–7043. https://www.federalregister.gov/d/2021-01765

Foster, A. C., Carter, S. K., Haby, T. S., Espy, L. D., & Burton, M. K. (2023). Using public litigation records to identify priority science needs for managing public lands. *Ecology and Society*, *28*, 11.

Franklin, J. (2010). *Mapping species distributions: Spatial inference and prediction*. Cambridge University Press.

Glenn, E., Yung, L., Wyborn, C., & Williams, D. R. (2022). Organisational influence on the co-production of fire science: Overcoming challenges and realising opportunities. *International Journal of Wildland Fire*, *31*, 435–448.

Guillera-Arroita, G., Lahoz-Monfort, J. J., Elith, J., Gordon, A., Kujala, H., Lentini, P. E., McCarthy, M. A., Tingley, R., & Wintle, B. A. (2015). Is my species distribution model fit for purpose? Matching data and models to applications. *Global Ecology and Biogeography*, *24*, 276–292.

Hamilton, H., Smyth, R. L., Young, B. E., Howard, T. G., Tracey, C., Breyer, S., Cameron, D. R., Chazal, A., Conley, A. K., Frye, C., & Schloss, C. (2022). Increasing taxonomic diversity and spatial resolution clarifies opportunities for protecting US imperiled species. *Ecological Applications*, *32*, e2534.

He, K. S., Bradley, B. A., Cord, A. F., Rocchini, D., Tuanmu, M.-N., Schmidtlein, S., Turner, W., Wegmann, M., & Pettorelli, N. (2015). Will remote sensing shape the next generation of species distribution models? *Remote Sensing in Ecology and Conservation*, *1*, 4–18.

Hosmer, D. W., & Lemeshow, S. (2000). *Applied logistic regression*. Wiley.

Jarnevich, C. S., Belamaric, P. N., Fricke, K., Houts, M., Rossi, L., Beauprez, G., Cooper, B., & Martin, R. (2021). Challenges in updating habitat suitability models: An example with the lesser prairie-chicken. *PLoS One*, *16*, e0256633.

Jarnevich, C. S., Carter, S. K., Davidson, Z. M., MacPhee, N. D., Alexander, P. J., Hayes, B., Belamaric, P. N., & Harms, B. R. (2024). Modeled habitat suitability for five rare plants (Aliciella formosa, Sclerocactus cloverae, Townsendia gypsophila, Astragalus ripleyi, and Cymopterus spellenbergii) in New Mexico: U. S. Geological Survey data release. https://doi.org/10.5066/P1NXFGLV

Jarnevich, C. S., Stohlgren, T. J., Kumar, S., Morisette, J. T., & Holcombe, T. R. (2015). Caveats for correlative species distribution modeling. *Ecological Informatics*, *29*(Part 1), 6–15.

Leathwick, J. R., Elith, J., & Hastie, T. (2006). Comparative performance of generalized additive models and multivariate adaptive regression splines for statistical modelling of species distributions. *Ecological Modelling*, *199*, 188–196.

Leitão, P. J., & Santos, M. J. (2019). Improving models of species ecological niches: A remote sensing overview. *Frontiers in Ecology and Evolution*, *7*, 9.

McCune, J. L. (2016). Species distribution models predict rare species occurrences despite significant effects of landscape context. *Journal of Applied Ecology*, *53*, 1871–1879.

Mod, H. K., Scherrer, D., Luoto, M., & Guisan, A. (2016). What we use is not what we know: Environmental predictors in plant distribution models. *Journal of Vegetation Science*, *27*, 1308–1322.

Morisette, J. T., Jarnevich, C. S., Holcombe, T. R., Talbert, C. B., Ignizio, D., Talbert, M. K., Silva, C., Koop, D., Swanson, A., & Young, N. E. (2013). VisTrails SAHM: Visualization and workflow management for species habitat modeling. *Ecography*, *36*, 129–135.

New Mexico Energy Minerals and Natural Resources Department Forestry Division. (2017). *New Mexico rare plant conservation strategy. Prepared and developed by Daniela Roth and the New Mexico rare plant conservation strategy partnership*. https://www.emnrd.nm.gov/sfd/new-mexico-rare-plant-conservation-strategy/

Oleas, N. H., Feeley, K. J., Fajardo, J., Meerow, A. W., Gebelein, J., & Francisco-Ortega, J. (2019). Muddy boots beget wisdom: Implications for rare or endangered plant species distribution models. *Diversity*, *11*, 10.

Phillips, S. J., Anderson, R. P., DudÍk, M., Schapire, R. E., & Blair, M. E. (2017). Opening the black box: An open-source release of maxent. *Ecography*, *40*, 887–893.

Ramirez-Reyes, C., Nazeri, M., Street, G., Jones-Farrand, D. T., Vilella, F. J., & Evans, K. O. (2021). Embracing ensemble species distribution models to inform At-risk species status assessments. *Journal of Fish and Wildlife Management*, *12*, 98–111.

Randin, C. F., Ashcroft, M. B., Bolliger, J., Cavender-Bares, J., Coops, N. C., Dullinger, S., Dirnböck, T., Eckert, S., Ellis, E., Fernández, N., Giuliani, G., Guisan, A., Jetz, W., Joost, S., Karger, D., Lembrechts, J., Lenoir, J., Luoto, M., Morin, X., … Payne, D. (2020). Monitoring biodiversity in the Anthropocene using remote sensing in species distribution models. *Remote Sensing of Environment*, *239*, 111626.

Reese, G. C., Carter, S. K., Lund, C., & Walterscheid, S. (2019). Evaluating and using existing models to map probable suitable habitat for rare plants to inform management of multiple-use public lands in the California desert. *PLoS One*, *14*, e0214099.

Roe, N. A., Ducey, M. J., Lee, T. D., Fraser, O. L., Colter, R. A., & Hallett, R. A. (2022). Soil chemical variables improve models of understorey plant species distributions. *Journal of Biogeography*, *49*, 753–766.

Rosemartin, A., Crimmins, T. M., Gerst, K. L., Posthumus, E. E., Ramirez, A. R., Wallace, C. S. A., & Morelli, T. L. (2023). Lessons learned in knowledge co-production for climate-smart decision-making. *Environmental Science & Policy*, *141*, 178–187.

Roth, D. (2015). *Status survey for gypsum Townsend's aster (Townsendia gypsophila), Sivinski's scorpionweed (Phacelia sivinskii), Todilto stickleaf (Mentzelia todiltoensis), and tufted sand verbena (Abronia bigelovii) on Zia Pueblo Lands in Sandoval County*. U.S. Fish and Wildlife Service region 2, Albuquerque Field Office. http://www.emnrd.state.nm.us/SFD/ForestMgt/documents/S6_ZIA_Gypsophiles_29.pdf

Roth, D., & Sivinski, R. (2015). *Survey & status report for rare gypsophilic plants in the Ojito/While Mesa area of Sandoval County, New Mexico*. Bureau of Land Management, Rio Puerco field office. http://www.emnrd.state.nm.us/SFD/ForestMgt/documents/BLM_GypsumEndemics_2015R.pdf

Roth, D., & Sivinski, R. (2018). *Status report—Aztec Gilia (Aliciella formosa), San Juan County, New Mexico*. U.S. Fish and Wildlife Service Region 2, Albuquerque Field Office.

Seidl, R. (2015). A functional-dynamic reflection on participatory processes in modeling projects. *Ambio*, *44*, 750–765.

Sofaer, H. R., Jarnevich, C. S., Pearse, I. S., Smyth, R. L., Auer, S., Cook, G. L., Edwards, T. C., Jr., Guala, G. F., Howard, T. G., Morisette, J. T., & Hamilton, H. (2019). The development and delivery of species distribution models to inform decision-making. *Bioscience*, *69*, 544–557.

U.S. Department of Defense (USDOD). (2016). *DoD natural resources program*. http://www.dodnaturalresources.net/DoD_NR_Program_fact_sheet_8-17-16.pdf

U.S. Geological Survey [USGS] Gap Analysis Project [GAP]. (2022). *Protected areas database of the United States (PAD-US) 3.0 (ver. 2.0, March 2023)*. U.S. Geological Survey. https://doi.org/10.5066/P9Q9LQ4B

Veblen, K. E., Pyke, D. A., Aldridge, C. L., Casazza, M. L., Assal, T. J., & Farinha, M. A. (2014). Monitoring of livestock grazing effects on Bureau of Land Management Land. *Rangeland Ecology & Management*, *67*, 68–77.

Warren, R., Price, J., Graham, E., Forstenhaeusler, N., & VanDerWal, J. (2018). The projected effect on insects, vertebrates, and plants of limiting global warming to 1.5°C rather than 2°C. *Science*, *360*, 791–795.

White, E. M., Lindberg, K., Davis, E. J., & Spies, T. A. (2019). Use of science and modeling by practitioners in landscape-scale management decisions. *Journal of Forestry*, *117*, 267–279.

SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

How to cite this article: Jarnevich, C. S., Carter, S. K., Davidson, Z. M., MacPhee, Nicole (Nik) D., Alexander, P. J., Hays, B., Belamaric, P. N., & Harms, B. R. (2024). Modeling rare plant habitat together with public land managers using an iterative, coproduced process to inform decision-making on multiple-use public lands. *Conservation Science and Practice*, *6*(8), e13179. https://doi.org/10.1111/csp2.13179