



Automated habitat monitoring systems linked to adaptive management: a new paradigm for species conservation in an era of rapid environmental change

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Abstract

Context Recent increases in ecological disturbances driven by climate change and our expanding human footprint make it challenging for natural resource managers to keep apprised of current conditions and adjust management plans accordingly. To effectively conserve species in highly dynamic landscapes

requires more timely habitat monitoring and a more responsive adaptive management cycle.

Objectives We introduce a framework to automatically monitor and assess species habitats over a range of spatial and temporal scales. We then apply this framework by developing an automated habitat monitoring system for the Mexican spotted owl (MSO) in

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Arizona and New Mexico, USA, that will be linked to federal agency adaptive management plans.

Methods We automated the process of monitoring and assessing trends in MSO habitat on an annual schedule using the Google Earth Engine cloud-based spatial analysis platform and dynamic data repository. We ran this system retrospectively on historical data to monitor MSO habitat from 1986 to 2020.

Results The automated habitat monitoring system provided a 35-year MSO habitat time series with high accuracy. Widespread habitat gains and losses occurred every year, underscoring the need for continuous monitoring and the benefits of an automated workflow.

Conclusions Automated habitat monitoring linked to adaptive management holds great promise in helping managers track the impacts of recent disturbances and adjust plans to meet goals even in increasingly dynamic landscapes. In a companion paper, Jones et al. (2023) demonstrate the utility of this approach by analyzing our MSO habitat time series to assess trends, drivers of change, and management implications.

Keywords Adaptive management · Big data · Climate change · Google Earth Engine · Habitat · Mexican spotted owl · Monitoring · Random forest · Species distribution model

Introduction

Over the past few centuries, rapidly increasing anthropogenic impacts such as habitat degradation and fragmentation, overexploitation, and invasive species have driven widespread changes across many of the earth's terrestrial habitats (Dirzo et al. 2014; Steffen et al. 2015). This transformation continues, as currently 95% of terrestrial ecoregions are experiencing increasing human pressures in recent years (Theobald et al. 2020). Our climate is also changing more rapidly relative to any other period during the Holocene (Marcott et al. 2013), leading to pervasive shifts in disturbance regimes, vegetation, and species distributions (Halofsky et al. 2020; Kelly et al. 2020; Weiskopf et al. 2020). Together, our expanding human footprint and rapidly changing climate are driving rates of environmental change that is globally unprecedented over the past 18,000 years in both

magnitude and extent (McDowell et al. 2020; Mottl et al. 2021).

Though some species may quickly adapt to rapidly changing environments or benefit from future climates and disturbance regimes, others lack the necessary plasticity, adaptive potential, or migratory ability to keep up (Parmesan 2006; Sergio et al. 2018). When rates of change reach levels projected by the end of this century, the typical observed rates of niche evolution may be several orders of magnitude to slow for many vertebrate species to adapt, favoring extinction (Quintero and Wiens 2013). Accordingly, over the past 450 million years, the five eras with rates and magnitudes of climate change similar to that projected to occur by the end of this century have resulted in mass extinctions that led to 75% or greater declines in earth's biodiversity (Song et al. 2021). The recent rapid loss of biodiversity globally and local declines in species richness and abundance in many terrestrial ecosystems underscore these risks (Ceballos et al. 2015; Newbold et al. 2015). Continued expansion of our human footprint coupled with accelerating rates of climate change thus pose grave challenges to many species, leading to the prediction of widespread biodiversity losses over the next century (Urban 2015; Weiskopf et al. 2020).

These global scale trends and threats manifest at regional scales in complex ways. For example, across the forests and rangelands of western North America the ecosystem dynamics and disturbance regimes of the Holocene have been perturbed by rapid growth in urban areas, transportation networks, industry, timber harvest, energy development, mining, invasive species, agriculture, and grazing. Recently, rising temperatures, drought, and a legacy of past forest management practices (e.g., fire suppression) have led to increased frequency and severity of wildfire and bark beetle outbreaks, altering vast areas of forests (Dale and Rauscher 1994; Meddens et al. 2012). In the southern Sierra Nevada in California, USA between 2014 and 2017, nearly half (48.9%) of all trees died due to drought and beetle kill; much of this area has subsequently burned (Fettig et al. 2019). In the rangelands of the western US between 1984 and 2017, wildfire burned nearly 68,000 km² (Li et al. 2021). Post-fire colonization by invasive species and subsequent spread from burned areas has degraded over 210,000 km² of native grasslands and shrublands (Balch et al. 2013, 2017; Bradley et al. 2018).

Natural and anthropogenic disturbances such as these are occurring at rates that are unprecedented in modern times (Allen et al. 2010; Jolly et al. 2015), and are expected to increase with further climatic warming (Littell et al. 2018; Wan et al. 2019).

Managing wildlands to simultaneously conserve biodiversity and produce goods and services is particularly challenging given these rapid rates of change. It is difficult to determine what the current status of species and natural resources are, let alone describe their trajectories over time (Cushman and McGarigal 2007). Data describing the distribution of habitat or other resources that are only a few years old may become obsolete for use in decision-making in such highly dynamic landscapes. Field-based monitoring (e.g., remote camera surveys) has proven invaluable in tracking change over time for many species, however, it often does not provide the spatial and temporal scales of inference needed to guide regional-scale planning; species distribution models (SDM's; Guisan and Thuiller 2005) are needed to generalize patterns in field data and extend them to management scales. The challenges of species conservation in an era of rapid environmental change, therefore, are twofold. The first is to maintain a current understanding of species habitat status and trends given the impacts of recent disturbances and post-disturbance regeneration and the second is to link that understanding to adaptive management, at scale, so that plans can keep pace with the changing landscape (Cushman et al. 2010; Chambers et al. 2019).

Effectively linking SDMs and inferences derived from them to adaptive management in an era of rapid environmental change presents technological and operational challenges. Adaptive management requires stipulation of management goals, assessment of current conditions relative to those goals, selection of an optimal management plan, implementation of that plan, monitoring plan effectiveness relative to the goals, and iterative adaptation to ultimately achieve the goals (Williams 2011). In our experience, the status quo in monitoring a species habitat at regional scales involves a multi-year effort to manually produce an SDM that is infrequently, if ever, updated over time to reflect current conditions. Once the SDM is developed, it takes additional time to manually analyze it, interpret the results, and adapt management plans accordingly. The result of this type of monitoring is, at best, a sparse time-series of models, with the

most recent SDM lagging current conditions by five or more years. In the past this slow-moving cycle may have been sufficient to achieve management goals, but in rapidly changing landscapes, the status quo is no longer keeping up with change. New technologies are needed to speed up the rate at which monitoring and assessment of species habitat is conducted, and new management frameworks are required that make management plans more nimble and responsive to rapid change.

Recently, “big data” and the computational ability to analyze it have become widely available. For example, the entire NASA Landsat archive is now freely available and updated daily in Google Earth Engine (GEE; Gorelick et al. 2017), a massively parallelized cloud computing platform for remote sensing and spatial analysis coupled to a massive dynamic data repository housing over 30 petabytes of remote sensing, climate, topography, soils, and other datasets, many of which are relevant to SDMs. The combination of sophisticated analysis platform supported by vast computational and storage capacity enables analyses at up to global scales (e.g., models of global forest cover and annual loss and gain; Hansen et al. 2013). These capabilities, applied to species distribution modeling, provide a means to dynamically monitor changing habitat conditions over time, automatically assess risks and opportunities for species conservation, and facilitate a revolution in data-driven, science-based adaptive management of species habitats and other natural resources.

In this study, we describe a framework that takes advantage of these recent advances in cloud computing and open access to remote sensing data to automatically monitor and assess species habitat annually over a range of spatial and temporal scales. We then demonstrate the application of this framework by developing an automated habitat monitoring system for a threatened forest-associated species, the Mexican spotted owl (*Strix occidentalis lucida*; hereafter “MSO”), across Arizona and New Mexico, USA. Federal agencies have identified the need for such a system to enable adaptive management plans for MSO that are responsive to increasing rates of forest disturbance in the region. We ran this monitoring system retrospectively on historical data, producing a 35-year time series of MSO SDMs. Finally, we describe how automated monitoring systems like this can be embedded within adaptive management cycles

to make them more responsive to rapidly changing conditions and increase the likelihood of management plan relevancy and efficacy as landscapes evolve. In a companion paper in this issue, Jones et al. (2023) demonstrate the conservation utility of this approach by analyzing the 35-year (1986–2020) time series of MSO SDMs to assess trends, link habitat loss to drivers, and identify management implications of the spatial and temporal dynamics of MSO habitat in the southwestern US.

Methods

Study area

Our study area encompasses Arizona and New Mexico, USA (Fig. 1), which represents the north-central portion of the MSO range and a significant portion of its range in the US. Within Arizona and New Mexico, the study area included five US Fish

and Wildlife Service Ecological Management Units (EMUs; Fig. 1), which are geographical subdivisions of the MSO range that differ in physiography, biotic regimes, threats to MSO, and administrative boundaries.

Occurrence data and habitat covariates

Jones et al. (2023) developed a spatially extensive database of Mexican spotted owl nest/roost locations occurring primarily on US Forest Service lands in Arizona and New Mexico and spanning the years 1989–2020. After quality control measures and accounting for pseudoreplication, the final dataset consisted of 2913 unique nest/roost locations distributed across our study area (Fig. 1).

To understand how MSO nest and roost site selection was affected by variability in forest vegetation, climate, and topography, we used 40 covariates to produce an MSO SDM (Table 1), including 22 covariates derived from Landsat multispectral satellite

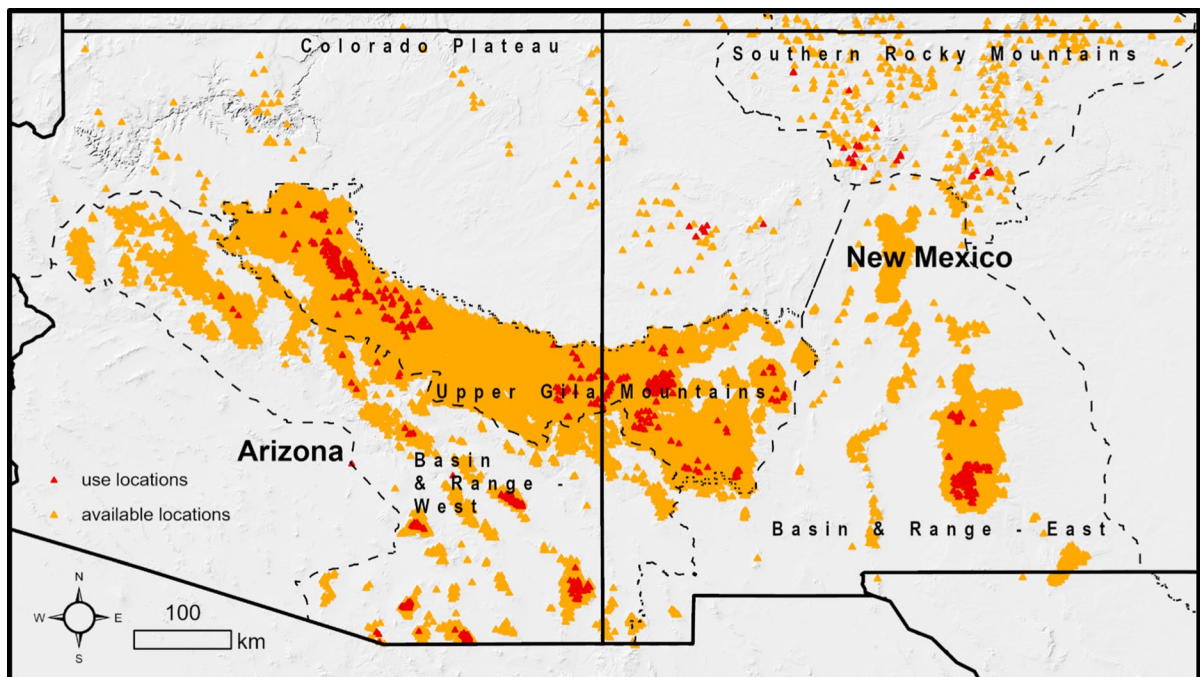


Fig. 1 Study area and training data. The study area from which the training data were collected and the model was projected included Arizona and New Mexico, USA. The dashed lines delineate five Mexican spotted owl (MSO) Ecological Management Units. The locations where MSO were observed

nesting or roosting by Jones et al. (2023) between 1989 and 2020 (i.e., ‘use’ locations) are shown as red triangles. The orange triangles represent ‘available’ locations where MSO could have nested or roosted in other forested areas within the EMUs

Table 1 Mexican spotted owl species distribution model covariates

	Covariate	Abbreviation (units)
Reflectance	May 1/Aug 1 normalized difference vegetation index	NDVI_[MAY1 or AUG1]
	May 1/Aug 1 normalized difference water index	NDWI_[MAY1 or AUG1]
	May 1/Aug 1 normalized difference snow index	NDSI_[MAY1 or AUG1]
	May 1/Aug 1 normalized burn ratio	NBR_[MAY1 or AUG1]
	May 1/Aug 1 normalized burn ratio 2	NBR2_[MAY1 or AUG1]
	May 1/Aug 1 Landsat bands	BLUE, GREEN, RED, NIR, SWIR1, SWIR2_[MAY1 or AUG1]
Climate	July–September precipitation (30 year normal)	PRECIP_SUMMER (mm)
	July–September max temperature (30 year normal)	MAXTEMP_SUMMER (°C)
	July–September mean temperature (30 year normal)	MEANTEMP_SUMMER (°C)
	Jan–March precipitation (30 year normal)	PRECIP_WINTER (mm)
	Jan–March min temperature (30 year normal)	MINTEMP_WINTER (°C)
	Jan–March mean temperature (30 year normal)	MEANTEMP_WINTER (°C)
	April–June precipitation (30 year normal)	PRECIP_SPRING (mm)
	Annual snow water equivalent (30 year normal)	SWE (mm)
Topography	Growing degree days (30 year normal)	GDD (°C)
	Slope	SLP (°)
	Heat load index	HLI
	Topographic wetness index	TWI
	Topographic ruggedness index	TRI
	Topographic position index (radius 90 m, 180 m, 360 m, 720 m, or 1440 m)	TPI_[radius] (m)

The covariate description and abbreviation (units in parentheses where relevant) are shown. Covariates are grouped into categories based on their association with Landsat reflectance, climate, and topography

imagery as well as 9 climatic and 9 topographic indices. The Landsat-based and climatic covariates varied temporally across years, but we considered the topographic covariates to be static over the timescale of interest. We chose all covariates after careful review of previous MSO habitat selection studies (e.g., Ganey and Balda 1994; Timm et al. 2016; Wan et al. 2017) and our team’s expert knowledge of the species and the study area.

We produced multispectral imagery-based covariates by applying the Continuous Change Detection and Classification algorithm (CCDC; Zhu and Woodcock 2014), implemented in GEE to a 35-year Landsat 4/5/7/8 Tier 1 surface reflectance time series from 1986 to 2020 (housed in the GEE cloud data repository). The CCDC algorithm fits a harmonic regression model to a time series of Landsat observations for each pixel and performs a temporal segmentation after identifying breakpoints representing disturbances. The coefficients from the harmonic regression

can be used to create synthetic images (i.e., an image produced from the fitted harmonic model rather than the actual Landsat observations) for any date along the time series. In this study, we created annual synthetic images for two dates, May 1 and August 1 (generally coinciding with the seasonal phenology of the start of green-up and peak vegetation, respectively) each year from 1986 to 2020. Each image contained the six Landsat bands from the visible, near infra-red, and short wave infra-red portions of the spectrum.

We derived 22 reflectance-based covariates from the synthetic Landsat images for each year from 1986 to 2020. These included the six bands at the two dates (May 1 and August 1) as well as five spectral indices derived from these bands, also at the same two dates. The indices were related to vegetation amount (normalized difference vegetation index, NDVI; Tucker 1979), moisture content of leafy vegetation (normalized difference wetness index, NDWI; Gao 1996), vegetation disturbance from fire, timber harvest, tree

pathogens, and other agents of forest loss (normalized burn ratio, NBR and NBR2; Key and Benson 1999), and snow (normalized difference snow index, NDSI; Riggs et al. 1994).

We produced the climate covariates using ClimateNA version 6.21 (Wang et al. 2016). ClimateNA statistically downscales 4 km gridded PRISM climate models (Daly et al. 2008) to a user-specified resolution using interpolation and application of a locally varying lapse rate that relates changes in elevation to changes in climate. For this study, we provided a 250 m resolution digital elevation model (DEM) to the ClimateNA algorithm, producing a gridded 250 m dataset of 30-year normal monthly minimum temperature, mean temperature, maximum temperature, precipitation, and growing degree days for the historical periods 1951–1980, 1961–1990, 1971–2000, and 1981–2010. We also produced the same 30-year normal monthly variables for 2010–2039 projected based on an ensemble of 15 global climate models (see Wang et al. 2016 for details).

From these monthly climate variables, we calculated nine derived climate covariates including summer monsoon season precipitation (July–September total precipitation), summer monsoon season mean maximum temperature (July–September average of the daily maximum temperature), summer monsoon season mean temperature (July–September average of the daily mean temperature), winter precipitation (January–March total precipitation), winter mean minimum temperature (January–March average of the daily minimum temperature), winter mean temperature (January–March average of the daily mean temperature), spring precipitation (April–June total precipitation), and annual growing degree days (degree days above 5 °C). Lastly, we linearly interpolated the time series (i.e., the 5 gridded datasets for 4 historical and 1 future 30-year normal periods) for each of the 9 climate covariates to produce annual climate normals for the 30-year period preceding each year from 1986 to 2020.

We produced the topographic covariates from the 30 m Shuttle Radar Topography Mission DEM primarily using algorithms implemented in GEE. They included slope, heat load index (a measure of incident radiation), and five alternative parameterizations of a topographic position index (TPI; quantifies the elevation of the focal pixel relative to the mean of its neighbors within a moving window of a

user-specified radius). The five TPI indices differed by the radius over which the index was calculated (90 m, 180 m, 360 m, 720 m, and 1440 m). We also produced a topographic wetness index (TPI; a measure of the area upslope from the focal pixel) and topographic ruggedness index (TRI; a measure of topographic heterogeneity) from the same DEM using algorithms implemented in the SAGA GIS software (Conrad et al. 2015).

Species distribution modeling

We employed a use-availability study design (Johnson et al. 2004) to model the distribution of MSO within the study area using the covariates as predictors of the relative probability of nest/roost site occurrence. With this approach, we distributed ‘available’ locations across the study area and trained the model based on the relationship between covariate values at locations that were ‘used’ by the species (i.e., the 2913 nest/roost site locations described above) and at available locations. The choice of the number and distribution of available locations has considerable effect on the model outcome (Barve et al. 2011; Liu et al. 2019). Here, we defined the area available to MSO for nesting and roosting to be the entire forested domain of the study area because MSO has high mobility and was historically observed throughout the study area. We defined forested areas based on two models of forest cover—National Land Cover Database (Yang et al. 2018) and the Global Forest Watch forest cover model (Hansen et al. 2013). For a pixel to be considered ‘available’ it had to be classified as forest in at least 1 year by both forest cover models. This conservative definition of forest largely avoided commission errors in the classifications that included shrublands, grasslands, agricultural lands, urban areas, and other habitats that are already known to be unsuitable for MSO nesting and roosting. Importantly, a pixel that was once forested but transitioned to non-forest during the MSO survey years (generally due to wildfire, timber harvest, or tree pathogens) was still considered ‘available’. Thus, disturbed sites and regenerating forests were included in the training data, allowing disturbance agents and forest succession to influence the model fit.

We trained five MSO SDMs corresponding to each of five MSO EMUs. For each survey year with MSO detections within an EMU, we generated 10

‘available’ locations for every MSO nest or roost site detected, randomly located within the forested ‘available area’ of the EMU described above ($n=29,130$ across all EMUs). We then extracted the covariate values for each ‘use’ location (i.e., the MSO nest or roost sites) and ‘available’ location corresponding to the survey year. In future runs of this monitoring system, new field data that has been added to the project’s cloud data repository will be automatically incorporated into new SDMs, thus providing an adaptive method for incorporating shifting species-environmental relationships into the models.

To model the relative probability of MSO nest/roost site occurrence based on the training data, we used a random forest classifier (Breiman 2001) implemented in GEE. Random forest is a machine learning algorithm that has particularly high performance in part because of its ability to flexibly predict ecological relationships in complex, interacting and nonlinear systems (Evans et al. 2011). The optimal (after tuning to minimize out-of-bag error) random forest hyperparameters included 50 “trees”, 6 variables per split, and a bag fraction of 0.5. We used a k -fold cross validation approach ($k=10$) to train 10 random forest classifiers for each EMU, each one using 90% of the training data from the EMU and withholding 10%. For each year from 1986 to 2020, we projected each of the 10 models for each of the 5 EMUs onto covariates corresponding to the year. For each year, we then produced images quantifying the mean and standard deviation of the relative probability of MSO occurrence across the 10 model runs. To validate the SDMs, we assessed the mean and standard deviation of the out-of-bag error, area under the receiver operator curve (AUC; Hanley and McNeil 1982), sensitivity, and specificity across the 10 model runs per EMU.

Post-analysis of species distribution models

To illustrate the potential impacts of basing adaptive management on habitat maps that substantially lag current conditions, we created a binary classification of suitable/non-suitable habitat for each modeled year (1986–2020) based on a threshold probability where errors of omission and commission were balanced (i.e., a threshold where model sensitivity equaled specificity) and then calculated the percent gain and loss of habitat between pairs of annual

SDMs separated by a time lag of 5 years, per EMU. Additional post-analyses were performed, described, and interpreted in the companion paper (Jones et al. 2023).

Automated habitat monitoring system linked to adaptive management

We programmatically automated all the steps in the model fitting, projection, and assessment described above in the GEE cloud computing environment and linked the model to dynamic data sources for the model covariates, which are also hosted in the GEE cloud data repository. This automated process runs on an annual schedule, queued by a scheduling app running on Google Compute Engine that triggers the process to run on a user-specified calendar date. Each year, the application obtains the latest Landsat imagery for the study area from the GEE repository, adds the latest observational data on MSO occurrence from a Google Cloud Storage bucket, projects the 30-year climate normals for the current year, processes the Landsat and climate data to produce current year covariates for the model, projects the fitted model across the study area, and writes the raster images as assets in GEE, where they are accessible to a GEE App that allows users to interact with the monitoring products during the monitoring phase of the adaptive management cycle (Fig. 5). In addition, the automated process performs post-analyses of the time series in GEE to quantify annual habitat gain, loss, and trends summarized for the entire study area and per EMU. These evaluation products are written as tables and plots to a bucket in Google Cloud Storage where they can be downloaded and visualized by users in the evaluation phase of the adaptive management cycle (Fig. 5).

Results

Locally-trained SDMs using the random forest algorithm with temporally matched covariates produced remarkably accurate predictions of MSO habitat (Table 2). The SDMs for all EMUs exhibited low out-of-bag error during the random forest model fitting, ranging from a low of 3.2% in the upper Gila Mountains to 6.8% in the southern Rocky Mountains (Table 2). Model fit was very high in all EMUs, with

Table 2 Model evaluation

EMU	OOB error	Test AUC	Sensitivity and specificity
Basin and Range: East	5.6% (0.3%)	0.996 (0.002)	0.974 (0.007)
Basin and Range: West	3.7% (0.2%)	0.998 (0.002)	0.985 (0.005)
Upper Gila Mountains	3.2% (0.1%)	0.998 (0.000)	0.986 (0.001)
Colorado Plateau	6.5% (1.4%)	0.993 (0.011)	0.965 (0.040)
Southern Rocky Mountains	6.8% (0.7%)	0.993 (0.008)	0.968 (0.027)

For each Mexican spotted owl (MSO) Ecological Management Unit (EMU), the mean and standard deviation (across the 10 model runs) of the out of bag (OOB) error during the random forest model fitting, the area under the receiver operator curve (AUC), and model sensitivity and specificity (the same value applies to both because the threshold probability for predicting MSO occurrence was defined by the model prediction value at which sensitivity = specificity) are shown

AUC values above 0.99 in all cases. Model specificity and sensitivity were also high in all EMUs, with values above 0.96 in all cases. Projecting an SDM from one EMU onto environmental data for any other EMU resulted in a large reduction in accuracy, as assessed by predicting MSO occurrence in both ‘use’ and ‘available’ locations in the target EMU (see Jones et al. 2023 for detailed results and discussion).

Projecting the locally trained SDMs for all EMUs across the study area revealed a spatially and

temporally complex pattern of MSO occurrence probability (Fig. 2), with widespread losses and gains over the 35-year study period (Fig. 3). On average, within any 5-year interval over the 35-year study period, all EMUs experienced significant losses in MSO habitat in some areas and significant gains in others (Fig. 4), underscoring the need for frequent monitoring to assess current conditions. The EMUs with the highest average 5-year rate of loss were the Basin and Range—East EMU and the Upper Gila Mountains

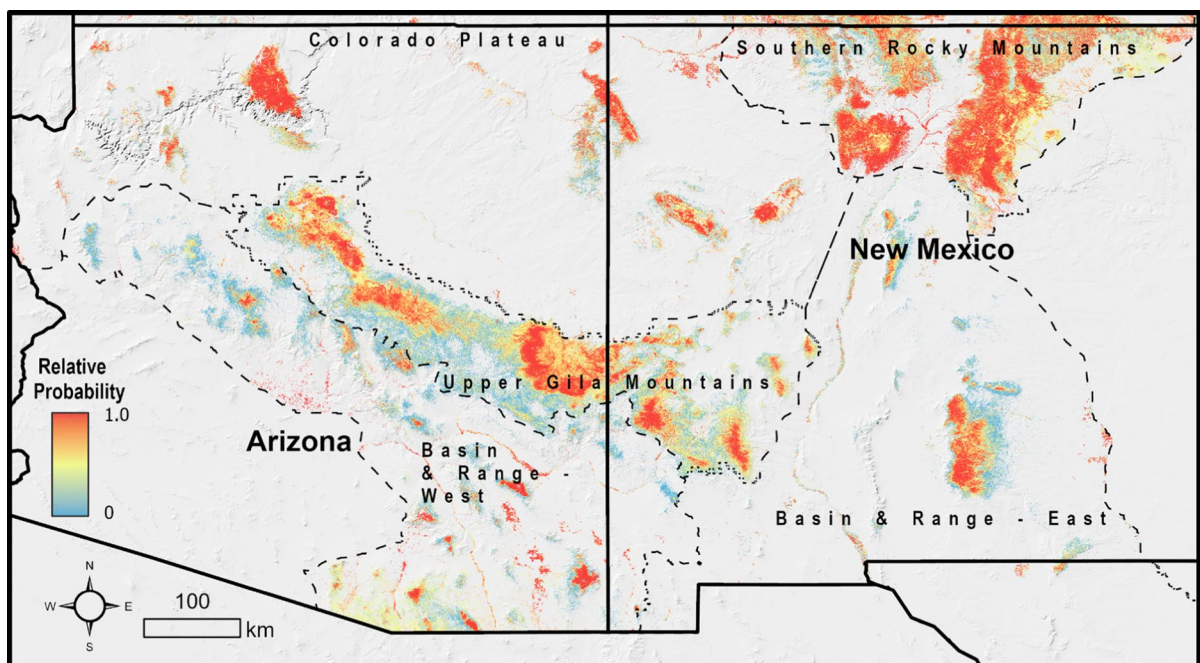


Fig. 2 Mexican spotted owl (MSO) nest/roost site relative probability of occurrence. The relative probability of Mexican spotted owl nest/roost site occurrence across the Arizona and New Mexico, USA study area is shown for 2020, with warmer

colors (red and orange) denoting higher probability relative to cool colors (green and blue). Areas without color have no predicted suitability. The dashed lines delineate five MSO Ecological Management Units which are also named in the figure

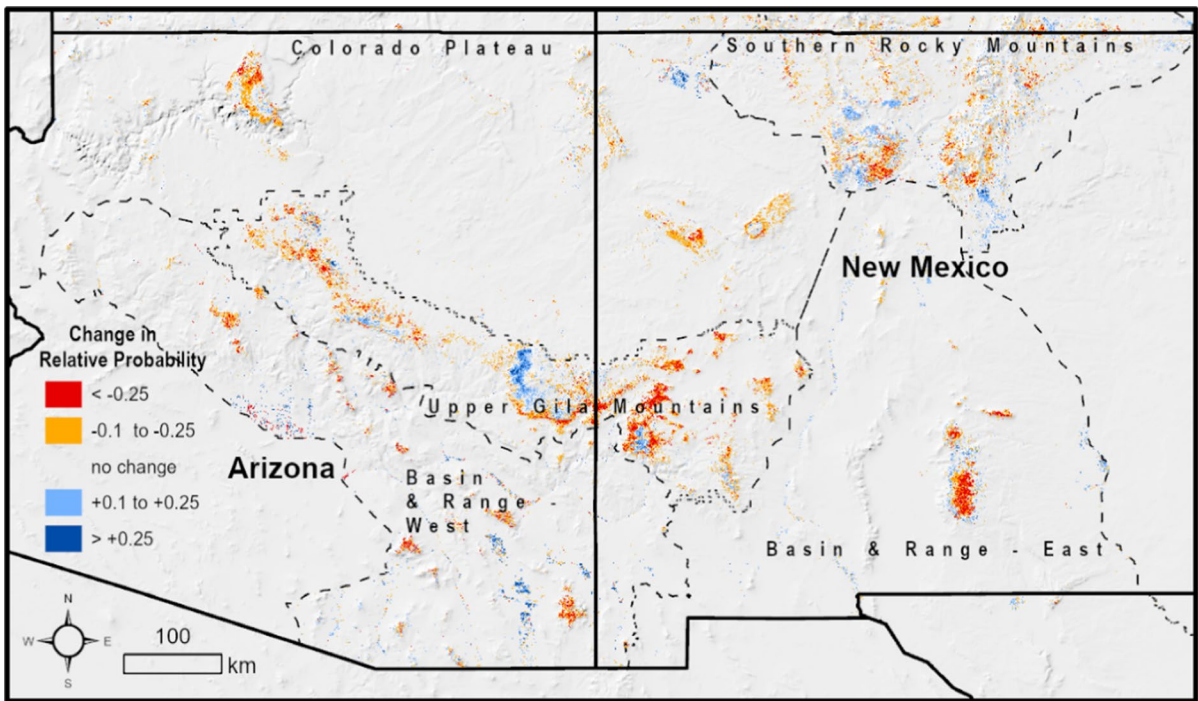


Fig. 3 Change in relative probability of Mexican spotted owl (MSO) nest/roost site suitability. The difference in relative probability of Mexican spotted owl nest/roost site suitability between 1986 and 2020 across the Arizona and New Mexico, USA study area is shown. Orange and red denote increasingly

larger losses in habitat over the 35-year period, while light blue and dark blue denote increasingly large gains in habitat over the same period. The dashed lines delineate 5 MSO Ecological Management Units, which area also named in the figure

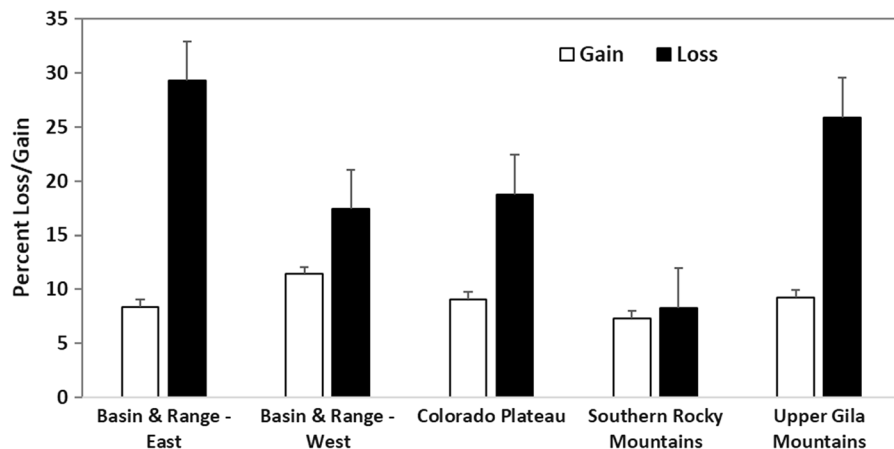


Fig. 4 Average 5-year change in MSO habitat area across Arizona and New Mexico, USA. The percent gain (white bars) and loss (black bars) in nesting/roosting habitat area is shown per Ecological Management Unit relative to habitat 5 years prior, averaged over all years of the study (1986–2020). The

error bars represent the standard deviation of gain and loss for the 5-year lagged comparisons over the same time period. The magnitude of gains and losses over even a short 5-year window underscores the need for continuous monitoring to help managers track disturbances and adjust planning accordingly

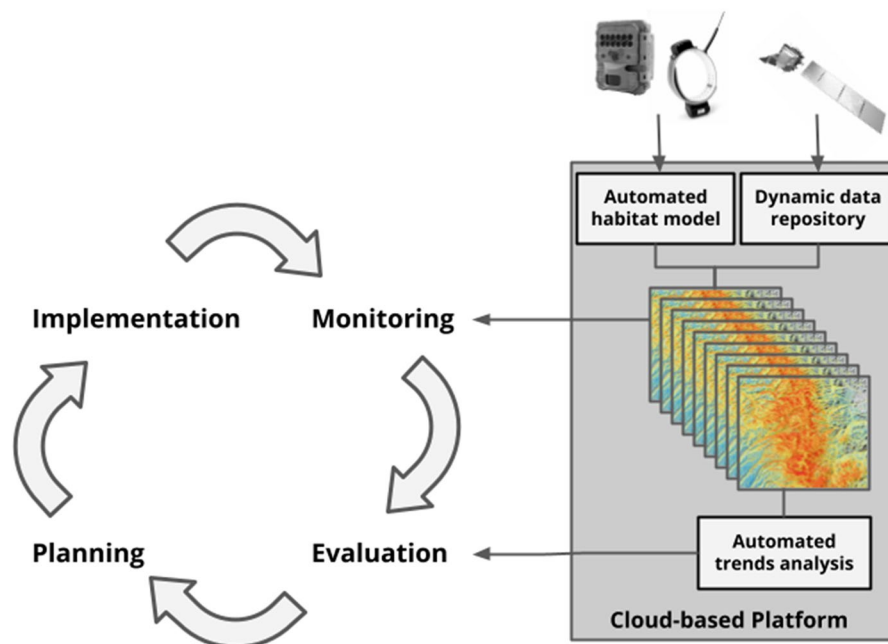


Fig. 5 Conceptual diagram of a dynamic habitat monitoring system linked to an adaptive management cycle. A cloud-based dynamic habitat monitoring system (right) requires a dynamic cloud-based data repository (such as Google Earth Engine) that continuously ingests and stores remote sensing data. This system also requires that the workflow to train and project a species distribution model for the target species is automated in a cloud platform-based analysis platform (such as Google Earth Engine), using georeferenced field observations (e.g., telemetry data or remote camera data) as training data. Linking the automated modeling workflow to the dynamic data repository and running it on a schedule (e.g., annually after the required multi-temporal remote sensing data is collected for the year) produces a time series of projected models when run over multiple years. The system can be run retrospectively, producing a long historical time series from data inputs with

a large existing archive (e.g., Landsat imagery has been continuously collected since the 1980s). From this time series, post-analysis can be performed (a process which can also be automated), including evaluating trends in habitat area, configuration, connectivity, and other management-relevant metrics. The automated annual monitoring of habitat and assessment of trends can link directly to an adaptive management cycle (left). The automated and dynamic workflow provides annually updated information to address the monitoring and evaluation tasks within the cycle. This puts timely and current information in the hands of managers, keeping them apprised of the impacts of recent disturbances and the impacts of climate change on species habitats, while also making the adaptive management cycle more responsive to changing conditions and more effective in achieving conservation goals

EMU, both with habitat loss averaging over 25%. The Southern Rocky Mountains experienced the lowest rate of change, with loss averaging about 8% over a 5-year window. The differences between EMUs in average habitat gain over a 5-year window were smaller, with total habitat gain ranging from about 7 to 11%.

Additional analysis of the MSO SDM time series produced here is provided in the companion manuscript in this issue (Jones et al. 2023). This includes quantifying trends in MSO habitat over the 35-year study period, exploring covariate contributions to model fit, assessing non-stationarity among models

across EMUs, and interpreting model results in light of MSO ecology and management.

Discussion

As our expanding human footprint and changing climate increase the frequency and magnitude of ecological disturbances, many landscapes are changing rapidly and often dramatically (e.g., Serra-Diaz et al. 2018; Halofsky et al. 2020). Increasingly, the pace of change is exceeding the ability of managers to effectively monitor, assess, and adapt their plans to current

conditions using traditional approaches. The technologies and processes applied in the past to adapt to change operate on a cycle that is often too slow and cumbersome to keep up with increasingly dynamic landscapes, resulting in less effective management of habitat for at-risk species and contributing to the global biodiversity crisis (Pecl et al. 2017; Weiskopf et al. 2020). Here we describe and implement a more timely and modern approach that takes advantage of recent advances in remote sensing, cloud computing, and access to satellite imagery to automatically monitor and assess species habitat conditions at scale and link those insights directly to adaptive management cycles (Fig. 5).

Our approach, demonstrated here through application to MSO habitat monitoring in the southwestern US, involves several key innovations. First, we programmatically automate (i.e., all steps are performed without any human intervention) the entire process of training, projecting, and evaluating a species habitat model in a cloud-based computing environment that is linked to required dynamic data sources. The coupling of an automated habitat model linked dynamically to required model inputs in a powerful cloud-based computing environment like GEE allows mapping products to be provided at regular intervals (e.g., annually) over broad spatial and temporal extents at high resolution, yielding regional-scale insights that match the scale of population-level responses to natural and anthropogenic disturbances. Second, our analysis framework provides locally trained, adaptive predictions and evaluations which can both retrospectively quantify recent trends in habitat and provide ongoing annual monitoring of habitat. Third, the monitoring and evaluation capabilities of the system can be linked directly to an adaptive management process. The result of these innovations is an automated habitat monitoring system (Fig. 5) that will enable managers to keep apprised of trends and current conditions given recent anthropogenic and natural disturbances, evaluate impacts of those disturbances on species of interest (in this case MSO), and adjust planning accordingly so that management goals can be more effectively attained even in rapidly changing environments.

The current status quo for monitoring species habitat involves expensive and time-consuming multi-year efforts to summarize status and trends at intervals of five or more years. For example, the

Northwest Forest Plan (NWFP) Effectiveness Monitoring Program (EMP; Mulder et al. 1999) has been conducting long-term monitoring of northern spotted owl (*S. occidentalis caurina*) and marbled murrelet (*Brachyramphus marmoratus*) nesting habitat in California, Oregon, and Washington USA since 1993. NWFP habitat monitoring maps and reports for these species have been produced on a 5-year cycle beginning in 2005 (e.g., see Davis et al. 2016; Falxa et al. 2016). In many ways, the NWFP EMP represents the state-of-the-art in habitat monitoring and has successfully informed management for nearly a quarter-century across a vast area. However, because this habitat monitoring system (and virtually all other habitat monitoring systems as well) is not automated or dynamically linked to model inputs, each new release requires time-consuming reanalysis and processing. By the time the habitat models are updated and made available to managers, the Landsat imagery they were based on lags current conditions by 3 to 4 years (e.g., the 2016 release was based on 2012 imagery, and the soon to be released 2021 update will be based on 2018 imagery). Thus, a manager's understanding of current conditions for northern spotted owl and marbled murrelet habitat near the end of the 5-year update cycle will be up to 9 years out-of-date.

To improve the responsiveness of species habitat monitoring systems requires much greater automation of model training, projection, and assessment as well as dynamic links to model inputs. This requires a powerful modeling platform and dynamic cloud-based data repository storing model inputs. Many of these elements of a responsive habitat monitoring system have been applied recently to monitor environmental variables like forest cover (Hansen et al. 2013). However, to our knowledge, there are no examples of monitoring systems focused on species habitat (rather than environmental variables like forest cover) that implement the level of automation we have achieved in the MSO monitoring system we developed in this study. The novelty of our approach is that the entire workflow of habitat model fitting, projection, change detection, and analysis of trends and other post-analyses is programmatically automated and linked to dynamic data repositories containing frequently updated training data and habitat model covariates. This level of automation enables regular (e.g., annual) provisioning of information about status and trends of species habitat directly to

managers without the multi-year lag inherent in traditional monitoring programs. Linking this information directly to managers opens up new possibilities for more effective adaptive management of species in rapidly changing environments while also reducing costs compared to traditional monitoring programs.

The provisioning of near-real-time monitoring and evaluation products is most valuable in highly dynamic landscapes. In the MSO study area for example, on average over any 5-year period between 1986 and 2020, EMUs experienced up to 30% loss of suitable habitat due to fire and other disturbances. Forest regeneration also drove significant increases in habitat over 5-year intervals, with some EMU's averaging gains of more than 10% over that time span. When habitat loss and gain reach this magnitude and frequency, the spatial pattern of habitat on the landscape can shift dramatically, resulting in profound impacts on population genetic and demographic processes for species like MSO (Wan et al. 2018). Failure to detect and account for these impacts in a timely way can reduce the effectiveness of adaptive management and hinder progress towards achieving management goals. Even in areas that currently exhibit relative stability in habitat conditions, automated monitoring systems may become increasingly valuable if climate change and our expanding human footprint raise local rates of natural and anthropogenic disturbances.

A key aspect of the monitoring system we describe is the automated update to the SDM as new training data becomes available. This is important because SDMs are based on correlations between species occurrence and environmental covariates that may not be stable over time as conditions depart from historical norms due to climate change or other stressors. These departures drive novel species-specific adaptations, novel species assemblages, and altered interspecific relationships (e.g., competition and mutualism), all of which can modify the species–environmental relationships to which the model is fit (Dormann et al. 2012). Many researchers have proposed using mechanistic models to predict species distributions under novel conditions, an approach that can potentially address the challenge of unstable correlations. However, a complete and quantitative understanding of the enormous complexity of ecological systems and their interactions across space and time makes it extremely difficult to effectively design and parameterize mechanistic models that accurately predict current and

future species responses (Cushman et al. 2010). If correlational models are relied upon, they need to be constantly updated with new observations to ensure species–environmental covariate relationships reflect current ecological dynamics. Under our proposed framework, SDMs are updated automatically as new observational data becomes available.

In addition to producing more timely information, our automated modeling framework is also likely to produce more accurate models of species distributions. The utilization of the entire Landsat archive and historical climate projections allows the models to be trained by environmental data matched to the times at which the species was observed. Quite often, researchers collect observational data on species occurrence from surveys conducted over several years. In the case of the MSO study for example, the data were collected over a 30-year period. Matching the year of the covariate data to the year of the observation when fitting SDMs is often not possible due to computational limitations around accessing and manipulating the large datasets. In highly dynamic landscapes, however, a mismatch between the year of the covariate observation and the survey observation can create substantial noise in the model leading to poor fit. We attribute much of the very strong fit in our models in part to our use of a time-series of covariates that match the survey data years.

Another aspect of our modeling framework is the avoidance of relying on classified models of landcover such as the National Land Cover Database (Jin et al. 2019), Gradient Nearest Neighbor vegetation data (GNN; Ohmann and Gregory 2002; Bell et al. 2021) and LANDFIRE data (Rollins 2009) as covariates in SDMs. These products have all been incredibly valuable for modeling species distributions and tracking change over time, however, their use is problematic in our application because these products have lengthy production cycles that can create lags in a dynamic monitoring system. For example, as of mid-2021, the current publicly available GNN data is derived from 1986 to 2017 Landsat imagery, and the current NLCD and LANDFIRE data are based on 2016 Landsat imagery. Our SDMs were based on covariates derived from unclassified gradient data that is frequently and dynamically updated (e.g., unclassified Landsat imagery), enabling annually updated (or even more frequent) monitoring products without lag. Another benefit of directly using unclassified gradient

data is that it avoids the large errors of omission and commission associated with information loss inherent in classification algorithms (McGarigal and Cushman 2005).

Our proposed monitoring framework creates the potential for new paradigms in policy and adaptive management of species habitat. Providing automated annual monitoring of habitat conditions based on remotely sensed data, and automatically evaluating trends and impacts of recent changes in habitat, offers a means to speed up the adaptive management cycle and allow it to keep pace with conditions on the ground as climate change and our expanding human footprint drive ecosystem changes. However, the rapid and automated provisioning of science-based information to management cycles can only be effective in helping achieve management goals if the typically slow-moving adaptive management process is modified to make use of these new data products and link them to data-driven decision making that is more nimble and responsive to changing conditions. This is the subject of a companion paper in this issue, where Jones et al. (2023) show how managers can use these data products to assess impacts to MSO and guide rapid responses to more effectively achieve recovery goals for this species.

To apply our automated modeling framework to a species, several conditions must be met. First, high-quality occurrence data is needed to train habitat models. Historical occurrence data dating back to the mid-1980s (the beginning of the Landsat time series) can be just as useful for model training as more recent data because a Landsat-based automated monitoring system run retrospectively can provide covariate values at these locations that match the year of the observation. Second, the primary determinants of a species distribution must be quantifiable using available remote sensing, climate, topographic, and other datasets. These model inputs must also be dynamically updated and linked to the automated monitoring system (e.g., the MSO monitoring system was developed in GEE and linked to the GEE data catalogue, which provides dynamically updated input data). For species whose occurrence is driven by factors that are not well-quantified by remote sensing data provided at moderate resolution (e.g., 30 m Landsat imagery, though finer resolution imagery is possible if using a platform like GEE that is scalable and massively parallelized), this approach may not be appropriate.

Third, the modeling algorithms and processing workflow required must be able to be automated within the cloud-computing environment that is utilized (e.g., the MSO monitoring system relied on random forest models and image processing algorithms that were implemented in GEE).

Fortunately for many species, these conditions can be met, allowing monitoring systems like the MSO system presented here to be applied broadly. The applications may also extend beyond terrestrial systems to marine species as well if the growing constellation of satellites that quantify marine environments provide the required data. Our MSO monitoring system is focused on habitat suitability at relatively fine scales (30 m) in a forest ecosystem, but other ecological processes at multiple scales can be included in a species monitoring system (e.g., habitat connectivity or colonization) in both forested and non-forested systems alike.

Building automated habitat monitoring systems for at-risk species and linking these systems to management has the potential to revolutionize species conservation and natural resource management, making it more responsive to rapidly changing conditions and more effective in achieving conservation goals, with less cost compared to the current status quo of manually producing and updating models infrequently at great expense each time. Synthesis of information from across multiple monitoring systems could also provide a basis to prioritize landscapes for multi-species conservation and help support large landscape conservation initiatives.

Supplementary Material

All data products presented in this paper will be publicly available through the US Forest Service (a Federal agency) and the Google Earth Engine tool presented and all data integrated into it will be posted online before publication.

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Declarations

Conflict of interest The authors declare no competing interests.

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