Developing Updateable Habitat Models for Endangered Stephens' Kangaroo Rats Using Satellite Imagery

Phase I - Rangewide Habitat Model

Conservation Biology Institute
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Executive Summary

Conservation Biology Institute (CBI) tested whether using freely available, high-resolution, multi-spectral satellite imagery from the European Space Agency Remote Sensing Program could help provide accurate and updateable habitat quality maps for the endangered Stephens' kangaroo rat (SKR) and perhaps other species. Results demonstrate that this new technology provides high-quality data with great potential to improve adaptive management and monitoring for SKR and other at-risk species. The available data (10 and 20m spatial resolution, updated every five days, covering a wide electromagnetic spectrum) provide more nuanced and rapidly updateable information compared to more traditional geospatial datasets that are often too imprecise or too unreliably updated for useful habitat tracking.

Unfortunately, the process of producing useful predictive variables from this multi-spectral dataset was extremely computer intensive and therefore costly. Luckily, the newly available Google Earth Engine (GEE), which permits non-profit NGOs to use Google's super computers and cloud storage capacity, could be used to greatly increase efficiency and decrease costs of producing high-resolution habitat variables. We recommend that partners vested in rare species conservation pursue this potential to improve the efficiency of management and monitoring programs, starting with SKR.

Based on our range-wide assessment of SKR habitat quality, we specifically recommend using GEE's platform to reduce costs and provide more spatially and temporally fine-scale maps; creating ecoregional SKR habitat models to account for regional variability in environmental conditions and better support reserve management and monitoring efforts; using these maps as foundations for an adaptive management and monitoring program and to update the species' recovery plan; and expanding this approach to address a wide array of other at-risk species. For SKR conservation and recovery planning, we also recommend coupling these new, updateable habitat models with population genetics and demography data provided by the San Diego Zoo Institute for Conservation Research to prioritize SKR recovery actions, such as improving habitat connectivity amongst reserves or translocating SKR individuals to sustain genetic diversity.

Introduction

The Stephens' kangaroo rat (SKR; *Dipodomys stephensi*) is a rare mammal of grasslands and open scrub habitats in southern California. Since its listing under both the California (1971) and US (1988) Endangered Species Acts, intensive conservation planning efforts have established numerous ecological reserves in western Riverside County and northern San Diego County. Unfortunately, these scattered reserves have not been consistently managed and monitored, in part because it has been difficult to map and track SKR habitat suitability in a consistent, accurate way. Traditional GIS variables, such as vegetation and soil types, are generally neither nuanced nor accurate enough to reflect the on-ground conditions that SKR need, and they are not consistently updated to allow for tracking of habitat changes over time. This report presents new range-wide habitat maps for SKR developed using recently available and updateable satellite imagery from the European Space Agency's Remote Sensing Satellite-2 Program, and makes recommendations for additional steps for using this system for SKR conservation and recovery planning.

Background

The US Fish and Wildlife Service (USFWS) produced a Draft Endangered Species Recovery Plan for SKR in 1997 (USFWS 1997) but the plan was never finalized. Since then, scientists and managers have learned much more about the species, its environment, and its conservation needs (Spencer et al. 2017). Meanwhile, technological advances promise new and better ways of mapping and monitoring habitat conditions at fine resolution in space and time.

During 2017-18 two agencies with primary responsibility for SKR conservation and recovery--USFWS and Riverside County Habitat Conservation Agency (RCHCA)--organized a series of meetings of SKR experts and reserve managers to strategize how to develop a more coordinated, effective, and scientifically defensible approach to managing and monitoring SKR and supporting recovery planning. The team of experts determined that a key foundational step toward these goals was to develop a comprehensive and accurate habitat suitability map for the species, especially one that could be updated regularly.

Meanwhile, members of the team at the San Diego Zoo's Institute for Conservation Research (ICR) have been performing population genetics analyses across the species range. These results are critical to understanding how the widely scattered SKR populations may or may not be interacting as a larger metapopulation that can sustain demographic and genetic integrity of the species.

Summary of Results and Recommendations

The range-wide habitat maps produced using Sentinel-2 multispectral imagery appear promising as a basis for improved SKR management, monitoring, and recovery planning, although the process for deriving imagery-based variables was computationally very intensive and costly. Models using Sentinel-2-based variables accurately predict and map SKR habitat value, and could be further refined to be more useful (such as by customizing models for individual reserve areas). The costs of using this system could be substantially reduced by using an automated approach to variable creation and model updating by taking advantage of the freely available (to non-profit organizations) Google Earth Engine (GEE). GEE is a newly available system that allows users to rapidly customize and map any number of spatial variables from a vast array of data using Google's super computers and cloud storage, including from Sentinel-2 and other sources.

Based on the results of the habitat mapping exercise summarized below, we recommend the following additional tasks to refine the methods and use them to support SKR conservation and recovery. We further suggest that similar methods could benefit numerous other species of conservation concern.

1. Utilize Google Earth Engine (GEE) to access more up-to-date imagery, speed up data processing, create predictors at higher resolution, and reduce costs of updating data and maps.
2. Subdivide the SKR's geographic range into ecologically valid, smaller areas to improve model accuracy and utility at more localized scales (i.e., to account for varying climate and other environmental conditions between ecoregions, such as coastal versus inland conditions).
3. Use the new habitat models, connectivity analyses, population models, ICR's genetic results, or other information to identify where management interventions--such as improving landscape connectivity or translocating SKR between reserves--may aid species conservation and recovery.
4. Develop an integrated adaptive management and monitoring system based on the new and updatable habitat models to support species recovery.
5. Expand the use of this modeling approach to create fine-scale, updateable habitat maps for *other* species of conservation concern.

Methods

CBI tested whether new and freely available imagery from the European Space Agency's Sentinel-2 satellite program[1] could benefit habitat suitability modeling for SKR, and perhaps by extension, other species of conservation concern. The general process was to download imagery, use it to create potential predictor variables for SKR, and use MaxEnt (a presence-only habitat modeling program; Philips et al. 2006) to model SKR habitat value using SKR observation data provided by USFWS and a combination of imagery-derived and other environmental variables. The modeling region was defined by expanding the official species geographic range provided by USFWS (2018) by adding adjacent areas where SKR detections fell very near or outside the range boundaries, buffered by 4 km (Figure 1).

Satellite Imagery and Variable Creation

We created a wide array of potential predictor variables from multispectral imagery available through the Sentinel-2 program as well as from more "traditional" GIS data layers (e.g., elevation, slope, vegetation type).

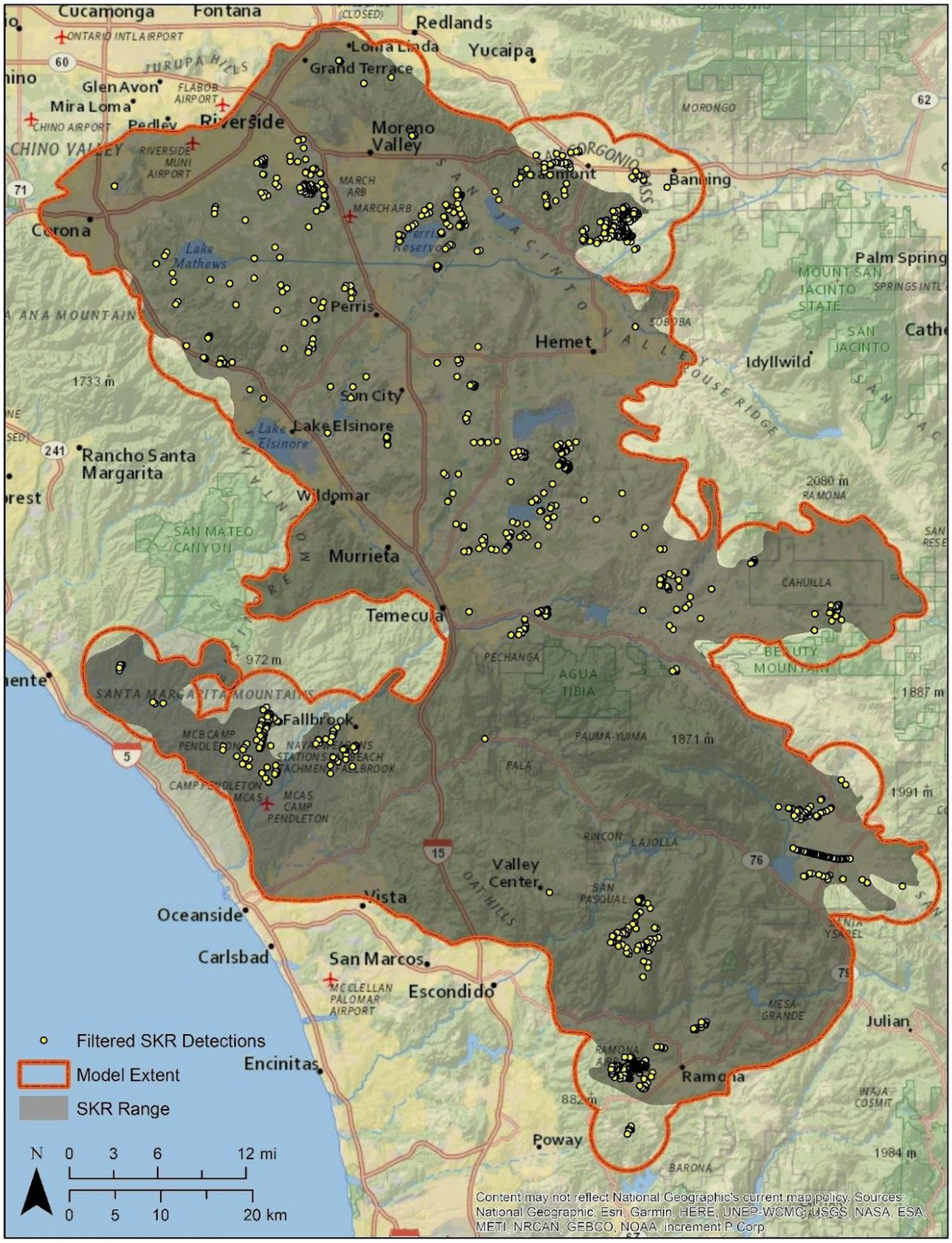
Satellite-derived Variables

Data from the European Space Agency's multispectral Sentinel-2 satellite program were downloaded for the study area for 2017. Sentinel-2 data has relatively high spectral and spatial resolution, with 13 electromagnetic spectral bands that are particularly relevant to detecting changes in vegetation and land cover. Images are captured around the globe at 5-day intervals, allowing selection of specific dates or seasons for an area of interest. Pixel resolution ranges from 10 m to 60 m depending on spectral band.

Each image was atmospherically corrected with Sen2cor software to normalize reflectance values and account for differences in sun angle and atmospheric conditions when images were taken. During this process, product level 1C Top-Of-Atmosphere input data were processed to level 2A Bottom-Of-Atmosphere reflectance images. Individual satellite images were merged using Sen2Mosaic software to create continuous, cloud-free coverage across the study area for the months of April and September 2017. The mosaicking process consisted of systematically selecting the most similar and cloud-free pixels across each time period. In total, seamless, cloud-free mosaics for all 13 Sentinel-2 spectral bands were created for each month at 20m spatial resolution. All processing of multispectral indices was carried out using ESRI ArcGIS software and custom Python scripts programmed by CBI.

[1] https://www.esa.int/Our_Activities/Observing_the_Earth/Copernicus/Sentinel-2/Data_products

Figure 1. Modeling extent created by adding SKR detection points, buffered by 4km, falling near or outside the boundary of the USFWS (2018) geographic range for SKR.



After reviewing available satellite data and considering how imagery could best capture habitat characteristics relevant to SKR, we selected 23 indices from those available (Table 1) and two seasons of particular biological relevance for SKR:

- April = High vegetation greenness and moistness and low soil visibility.
- September = Low vegetation greenness and moistness and high soil visibility.

Field observations reveal that SKR are strongly associated with forb-dominated habitats that green up, flower, and set seed in spring (with April generally having maximum vegetation greenness and moistness), but then rapidly dry out and disarticulate over summer, leaving abundant openness and bare soil conditions that are required by kangaroo rats. The SKR's diet is dominated by seeds produced by annual forbs, but they require very open habitats and bare surface soil during most of the year to accommodate their highly evolved modes of locomotion (e.g., bounding), communications (e.g., "sand-bathing") and other peculiarities of their ecology.

Each spectral index was calculated for each season of interest (April and September) along with the difference in the index between seasons (for example, to capture the change in vegetation greenness or moistness from April to September). Thus, 69 (23 x 3) total indices were calculated and used as potential predictor variables in habitat models.

Raw data were downloaded from Copernicus Open Access Data Hub and processed on a custom Linux server built to handle imagery datasets of extremely large size. Nevertheless, preprocessing of the satellite data took several months to complete at 20m resolution (10m resolution proved computationally prohibitive).

Table 1. Multispectral indices derived from Sentinel-2 satellite data for the months of April and September for the SKR study area.

Index Name	Abbreviation	Index Type
Simple Normalized Difference Vegetation Index	NDVI	Vegetation
Red Edge Normalized Difference Vegetation Index Variation #1	RENDVI1	Vegetation
Red Edge Normalized Difference Vegetation Index Variation #2	RENDVI2	Vegetation
Red Edge Normalized Difference Vegetation Index Variation #3	RENDVI3	Vegetation
Normalized Difference Red Edge Index Variation #1	NDRE1	Vegetation
Normalized Difference Red Edge Index Variation #2	NDRE2	Vegetation
Normalized Difference Red Edge Index Variation #3	NDRE3	Vegetation
Enhanced Vegetation Index	EVI	Vegetation
Anthocyanin Reflectance Index	ARI1	Vegetation
Modified Chlorophyll Absorption in Reflectance Index	MCARI	Vegetation
Tasselled Cap Wetness	TCWET	Vegetation
Tasselled Cap Vegetation	TCVEG	Vegetation
Tasselled Cap Brightness	TCBRI	Vegetation and soil
Tasselled Cap MSS Green Vegetation	TCMSSGRN	Vegetation
Tasselled Cap MSS Soil Brightness	TCMSSBRI	Vegetation and soil
Bare Soil Index	BSI	Soil
Normalized Difference Texture Index	NDTeI	Soil
Normalized Difference Sand Dune Index	NDSDI	Soil
Clay Minerals Ratio	CMR	Soil
Misra Soil Brightness Index	MSBI	Soil
Topsoil Grain Size Index	TGSI	Soil
Soil Adjusted Vegetation Index	SAVI	Soil
Soil Composition Index	SCI	Soil

Traditional GIS Variables

In addition to variables derived from satellite imagery, we derived an array of more traditional GIS variables that may be important to SKR habitat selection, including climatic, soil, development, hydrologic, and vegetation variables (Table 2). This allowed us to compare models using one or the other variable sources as well as to combine satellite-derived variables with other variables in a model.

Table 2. Other GIS predictor variables derived for the SKR study area

Variable Type	Variable Name	Source	Resolution
Soils	Drainage Class	gSSURGO, STATSGO	30m
Soils	Bedrock Depth	gSSURGO, STATSGO	30m
Soils	Percent Sand	gSSURGO, STATSGO	30m
Soils	Percent Silt	gSSURGO, STATSGO	30m
Soils	Percent Clay	gSSURGO, STATSGO	30m
Climate	Average Spring (March, April, May; 1981-2010) Precipitation	CA BCM	270m
Climate	Average March Precipitation (1981-2010)	CA BCM	270m
Topography	Elevation	USGS NED	10m
Topography	Slope	USGS NED	10m
Vegetation	Annual Grassland	USGS LANDFIRE EVT	30m
Vegetation	Herbaceous Cover	USGS LANDFIRE EVC	30m
Development	Night Light (2017)	NOAA VIIRS	375m
Development	Distance to Development	NLCD 2011	30m
Development	Distance to Roads	TIGER	20m
Development	Distance to Roads (Primary/Secondary Only)	TIGER	20m
Hydrology	Distance to Streams	USGS NHD	1:12,000-1:24,000
Hydrology	Distance to Streams (Ephemeral, Intermittent, Seasonal Only)	USGS NHD	1:12,000-1:24,000

Habitat Value Modeling

We calculated and mapped habitat values using MaxEnt (Phillips et al. 2006), environmental variables described above, and species detection points provided by USFWS. MaxEnt compares conditions at species detection points with those at a sample of random background points to create a prediction of relative habitat suitability based on environmental variables and their interactions.

USFWS provided their most up-to-date SKR occurrence database, which includes more than 5,000 species detections from 1990 through 2018, mostly from live-trapping records. The full set of points was "filtered" to remove (1) low accuracy (>320m accuracy) detections or those not providing accuracy estimates ("non-specific area"); and (2) older detections in locations currently mapped as "developed" (i.e., points in habitats that no longer exist). The remaining points were next "thinned" to limit one detection within a single 20m grid cell. This thinning process reduces spatial bias due to varying sampling intensity amongst locations--for example, where repeated captures occur in a single locality that has been surveyed more frequently than others.

The filtering and thinning procedures reduced the full data set of >5,000 to 1255 recent (since 1990) independent sample points for modeling. This final set was subdivided into "training" points (70%) used to develop the statistical models and "testing" points (30%) used to evaluate model accuracy.

We also used a limited set of negative trapline and grid point data provided by USFWS for model testing. We converted the trapline data from lines to points, merged those with the grid point data, and clipped to our model boundary, leaving 441 points. We thinned the data using the same methods as for the detection points so that only one non-detection fell within a single 20m grid cell. We took a random sample equal to the sample size of the reserved testing detection points (n = 376).

MaxEnt models were run using MaxEnt default parameters except that we used 10-fold cross-validated replication and linear, quadratic, and product feature types to produce smoother response curves (Santos et al. 2017) and because interactions among predictors are common and species responses to ecological gradients are frequently nonlinear.

Our modeling process used the following general steps:

1. *Variable selection*. This involved testing each potential predictor variable independently at multiple scales--from 20m (roughly female SKR home range size) up to about 200m (specifically, variables were averaged across circular moving windows of 20, 40, 60, 100, and 200m radii). For each variable, we selected the scale that produced the highest 10-fold cross-validated mean AUC[2]. For each Sentinel index, we selected the season (April, September, or the difference between April and September) that produced the highest 10-fold cross-validated mean AUC. We also tested for variable collinearity (correlations between variables) to understand variable interactions and avoid using highly correlated variables in multivariate models (using ENMTools version 1.3 and defining correlated as $|r| > 0.7$).
2. *Multivariate modeling.* All non-correlated variables (at the best resolution and season from step 1) were next entered into MaxEnt, which generates a multivariate model by selecting and combining (with appropriate weighting) those variables that together best fit the SKR training data.
3. *Model pruning*. The "full" multivariate model thus created was then "pruned" to a more parsimonious model by removing variables that least contribute to model predictive power. The pruning process stops when removing another variable would significantly reduce model predictive power (as determined by mean model training gain and where significance is identified by lack of overlap in model 95% confidence intervals).
4. *Model tuning*. To decrease model overfitting, we tuned our selected model by varying MaxEnt's regularization parameter to constrain model complexity (Anderson and Gonzalez 2011, Merow et al. 2013, Radosavljevic and Anderson 2014*,* Warren et al. 2014). We varied the parameter from 0 to 5 in increments of 0.5 (default = 1), and used ENMTools Model Selection function to calculate AIC (Akaike information criterion) for each *(*Warren and Seifert 2011). We selected as the best model the one with the lowest AIC score.
5. *Model testing*. Models created using the 80% SKR training data were next evaluated for predictive power with the reserved 20% test detection and sampled non-detection data using threshold-dependent metrics (sensitivity, specificity, balanced accuracy, true skill statistic [TSS], and Cohen's kappa) and the maximum sum of training sensitivity and specificity threshold, which optimizes discrimination between species presence and absence (Liu et al. 2013). We also used the Maxent cross-validation functionality and threshold-independent metrics to evaluate model discriminatory ability (AUC) and

[2] Area Under the Receiver Operating Characteristic (ROC) curve, a threshold-independent assessment of model discriminatory ability (Fielding and Bell 1997).

model overfitting (mean 10% test omission rate, difference between training and testing AUC).

We used this same step-wise process to produce several different multivariate models by drawing from different pools of potential predictive variables: (1) only Sentinel-2-derived variables; (2) only "traditional" GIS variables; and (3) both Sentinel-2 and traditional variables.

In addition, we investigated how removing some variables from models affected habitat value maps and statistics to better understand model behavior and to inform future efforts. For example, we systematically removed (1) some variables for which we had reason to question biological validity for SKR at the range-wide scale (e.g., distance to roads, distance to streams, and night light); (2), to compare vegetation indices derived from satellite imagery to more traditional vegetation variables; and (3) to remove soil variables from gSSURGO and STATSGO that produced idiosyncratic maps when averaged over the scales of interest. We determined that some variables are likely to have effects on SKR habitat selection that vary among local areas at finer scales than available data. For example, SKR are often found in close association with paved but lightly traveled roads, but they may suffer high mortality or avoid roads in other areas having greater traffic volume. And, although high night-light levels are known to suppress SKR activities within about 50 m of bright lights (e.g., flood lights; D. Shier, unpublished data), available night-light data are only available at 375m resolution, and therefore may not be meaningful in mapping SKR habitat across the entire range. In other words, including night-light values in an SKR range-wide model may not be warranted even though it may be very meaningful in understanding SKR habitat use in particular reserve areas.

Results and Discussion

Models incorporating Sentinel-2-derived variables performed well across the species range. The final “best” model used a combination of imagery-derived and traditional GIS variables. The computing and analysis time required to derive the fine-scale imagery variables was substantial, representing a significant cost to the project. However, this cost could be greatly ameliorated with new techniques made possible by the GEE platform, which allows remote sensing scientists to use Google’s super computers and cloud storage to reduce data storage and processing costs. The modeling results, their implications, and recommendations for refining and using the models are detailed below.

Mapped differences between the best full model and the reduced variable model are subtle, and together suggest that more refined local models may better support preserve management and monitoring efforts by accounting for geographic differences in how SKR may be selecting habitat conditions. Both models, while tightly fitted to known SKR distributions, seem to over-predict SKR occurrence in a few locations, which might be explained by non-habitat threat factors (e.g., land management actions on non-reserve areas).

Full Range-Wide Model

Following the variable selection and pruning and tuning processes, the selected “best” model used 12 predictors across 3 scales and included a mix of 5 Sentinel-derived indices and 7 traditional GIS variables (Figure 2, Table 3). The model is most strongly influenced by slope, Tasselled Cap Wetness (index of vegetation moisture content), and proportion developed. Traditional GIS variables account for 70% of the total predictor importance, with Sentinel-derived predictors making up the remaining 30%. This model uses a regularization parameter of 4.0 and has good discriminatory ability and fair accuracy, with mean test AUC of 0.891, balanced accuracy of 0.680, TSS of 0.359, and kappa of 0.356 (Figure 3, Table 4).

The model predicts some habitat value in areas not known to be occupied by SKR, such as grassland areas west of Temecula. It also shows some areas of highly fragmented potential habitat that is not currently known to be occupied by SKR (e.g, in northern San Diego County). Most of these predicted but not known-to-be-occupied habitats are not managed as SKR or multi-species reserve areas. It is possible that threat factors not directly related to on-site habitat value have excluded SKR from some potentially suitable areas (e.g., rodenticides or mechanical discing to improve livestock forage).

Reduced Variable Model

The reduced variable model has 10 predictors across 3 scales and includes a mix of 6 Sentinel-derived indices and 4 traditional GIS variables (Figure 4, Table 3). The dominant predictors are the same as in the full model (slope, Tasselled Cap Wetness, and proportion developed). Traditional GIS variables account for 66% of the total predictor importance, with Sentinel-derived predictors making up the remaining 34%. This model uses a regularization parameter of 4.5 and also has good discriminatory ability and fair accuracy, with mean test AUC of 0.885, balanced accuracy of 0.647, TSS of 0.295, and kappa of 0.291 (Figure 5, Table 4).

This model also predicts suitable habitat in some areas not known to be occupied by SKR, which again could be due to other threat factors, such as habitat fragmentation, discing, or use of rodenticides.

Figure 2. Modeled SKR habitat suitability using Sentinel-2 and other GIS variables (Full range-wide model).

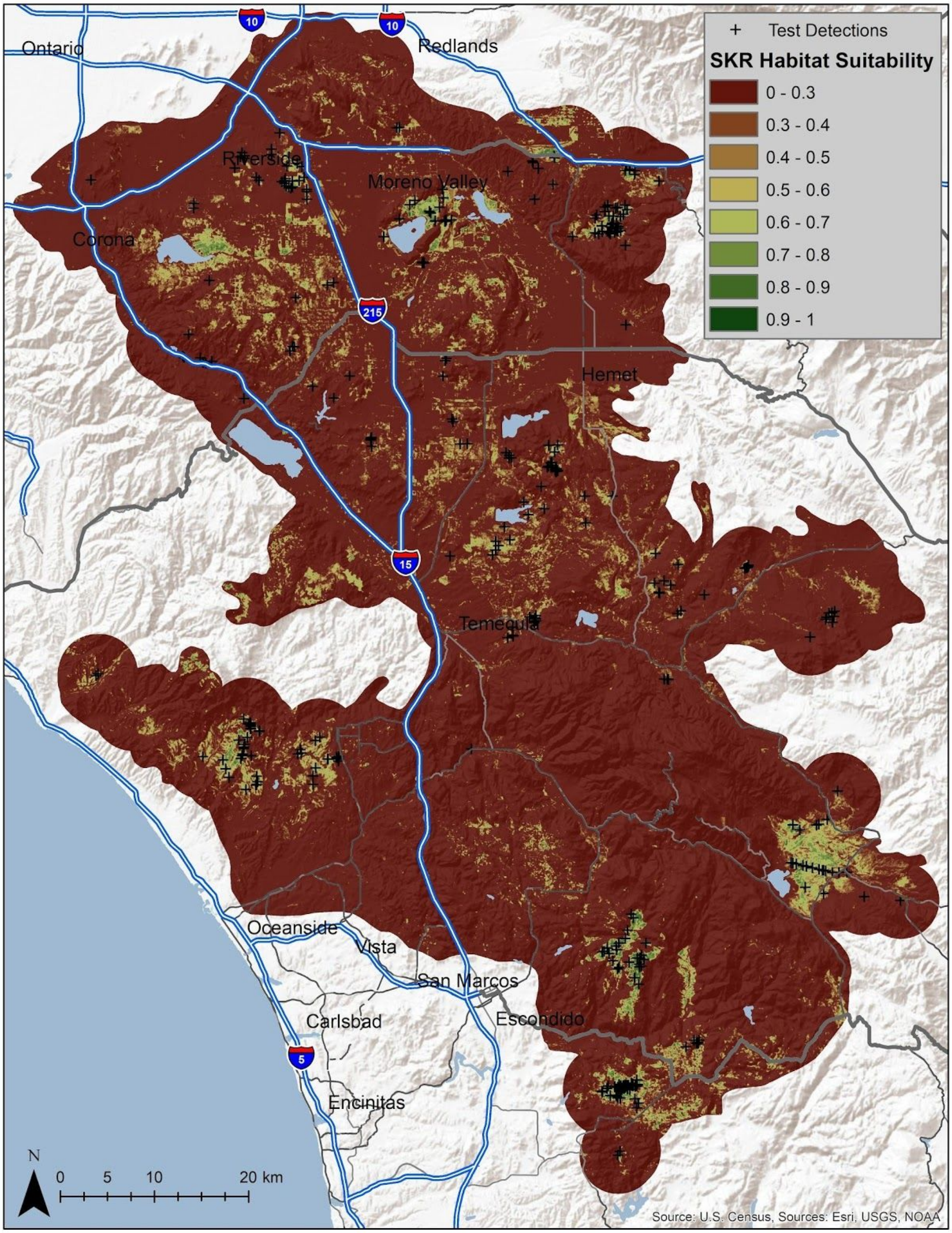


Table 3. Predictor permutation importance for the full, range-wide model and the reduce variable model.

Predictor (moving window radius)	**Full model**	**Reduced variable model**
Slope (60m)	38.2	38.2
Tasselled Cap Wetness, September (60m)	16.8	21.5
Proportion Developed (40m)	15.1	16.7
Topsoil Grain Size Index, September (60m)	7.9	5.9
Elevation (no moving window)	5.1	5.3
Spring Precipitation (no moving window)	4.8	6.2
Normalized Difference Red Edge Index Variation #3, April (60m)	3.2	1.9
Night Light (no moving window)	2.4	NA
Distance to Primary/Secondary Roads (no moving window)	2.3	NA
Distance to Streams (Ephemeral, Intermittent, Seasonal Only; no moving window)	1.9	NA
Normalized Difference Sand Dune Index, April - September (60m)	1.6	1.9
Normalized Difference Texture Index, April - September (60m)	0.8	NA
Modified Chlorophyll Absorption in Reflectance Index, April - September (60m)	NA	1.3
Tasselled Cap Brightness, April - September (60m)	NA	1.1

Figure 3. Full model thresholded into suitable versus unsuitable habitat using the maximum sum of sensitivity and specificity criterion.

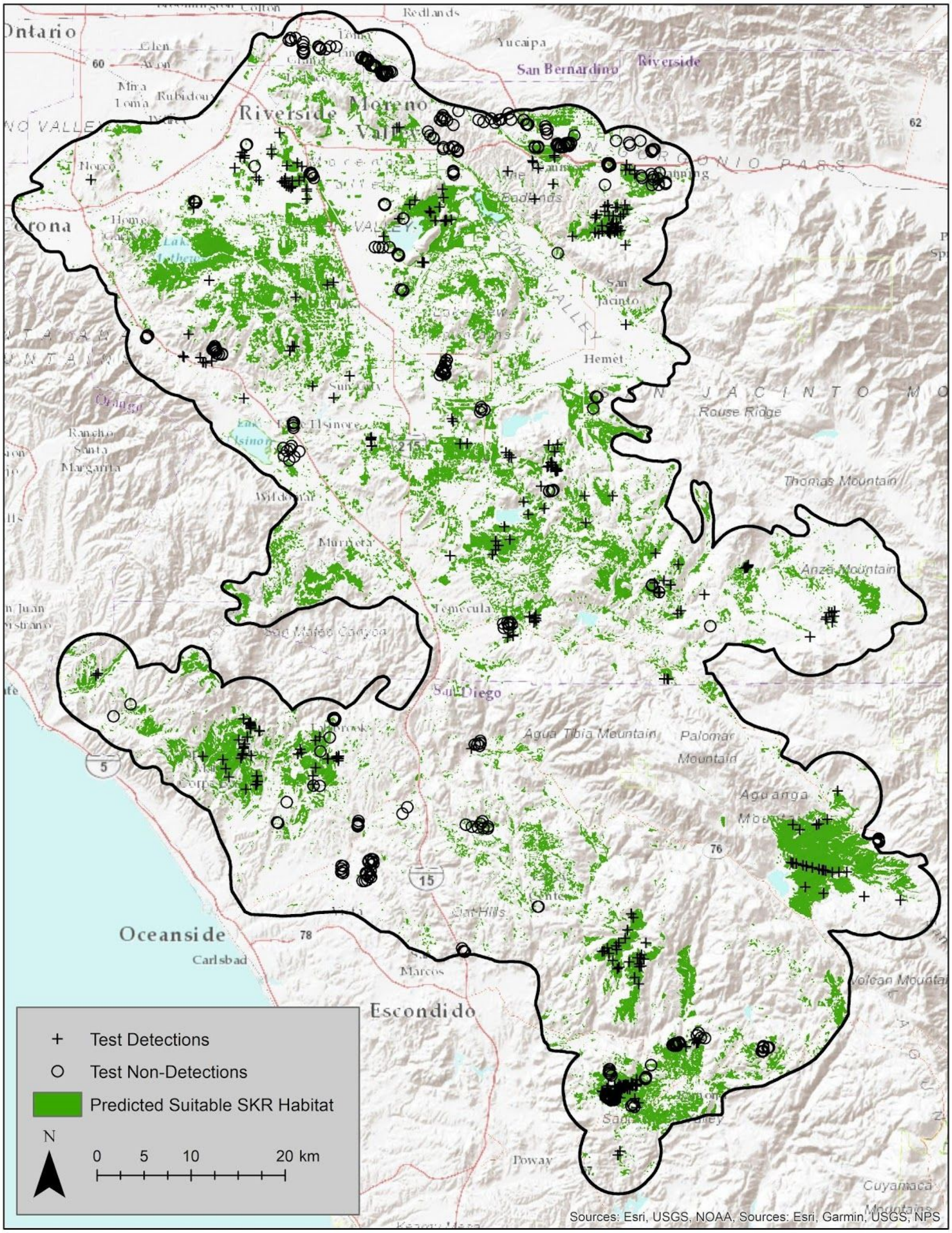


Table 4. Evaluation metrics, full range-wide model and reduced variable model.

Evaluation Metric	Full model	Reduced variable model
Mean Testing AUC	0.891	0.885
Mean Training AUC	0.894	0.887
Mean |Train-Test| AUC	0.012	0.011
Mean 10% Test Omission	0.108	0.105
Balanced Accuracy	0.680	0.647
Sensitivity (True Positive Rate)	0.822	0.827
Specificity (True Negative Rate)	0.538	0.468
Precision (Positive Predictive Value)	0.626	0.594
TSS	0.359	0.295
Cohen's kappa	0.356	0.291

Figure 4. Reduced variable model.

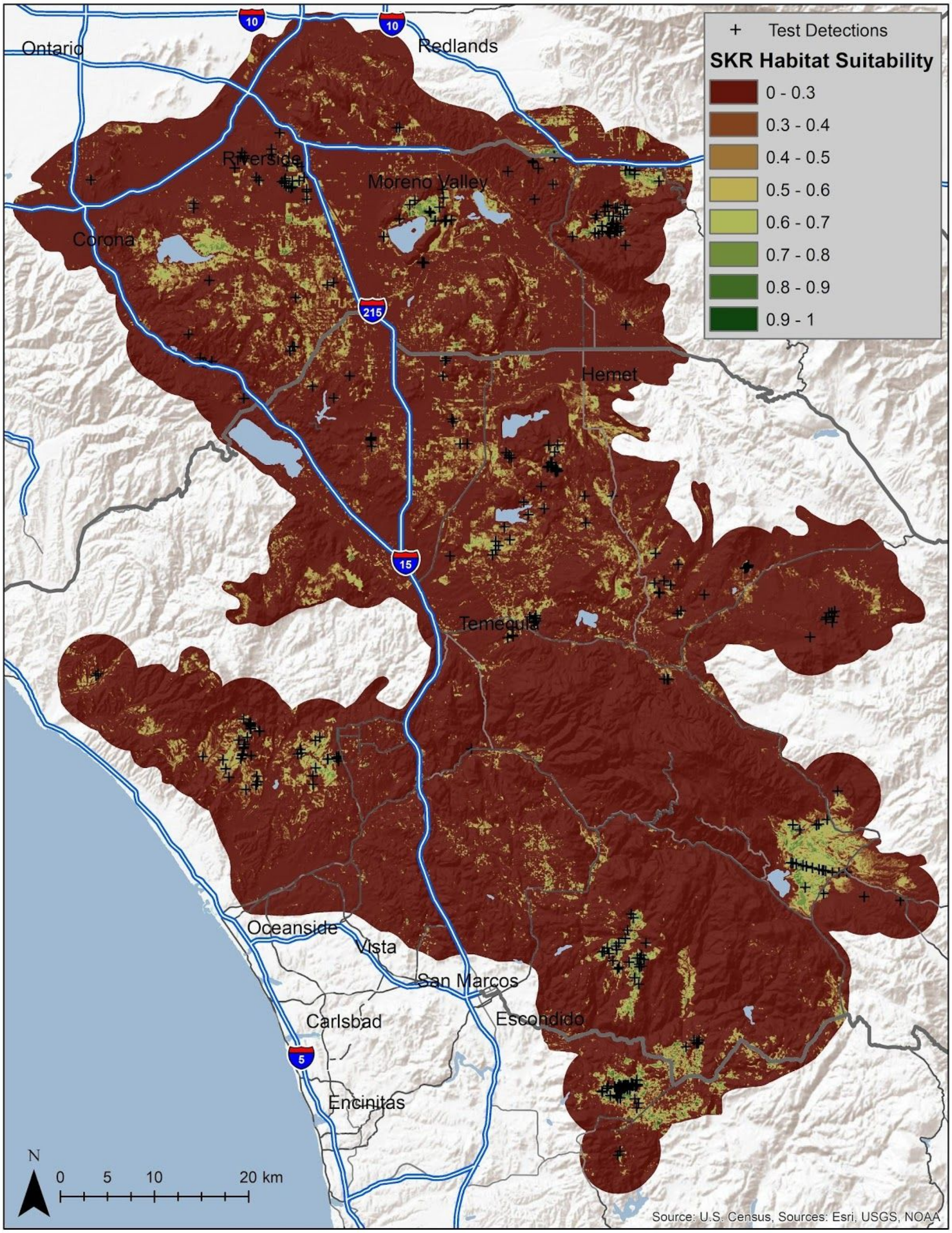
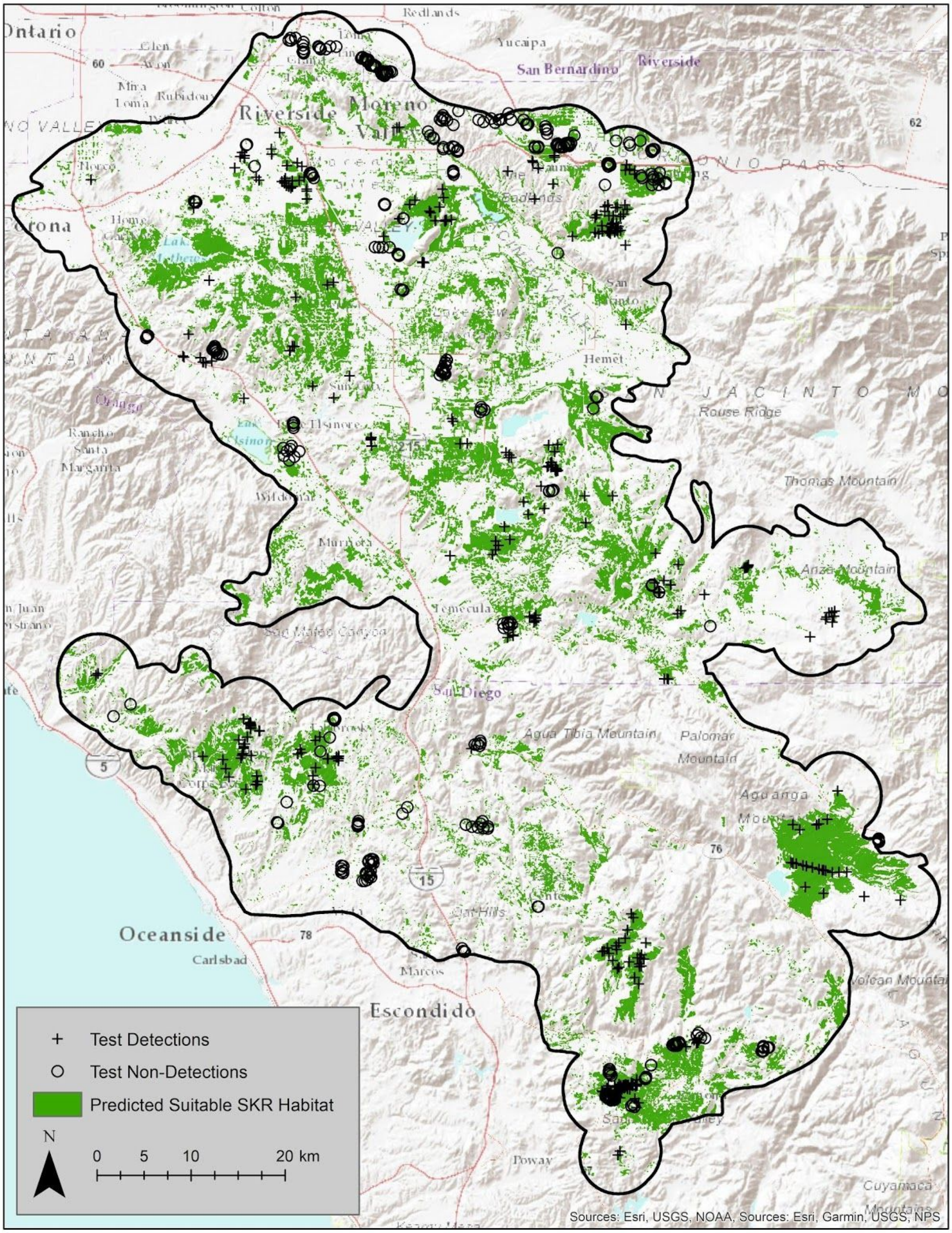


Figure 5. Reduced variable model thresholded into suitable versus unsuitable habitat using the maximum sum of sensitivity and specificity criterion.



Recommendations

Google Earth Engine

Traditional methods of managing and processing satellite imagery (on a local server and computers, as done here), can be extremely time- and computer-intensive. Acquiring and moving terabytes of data is slow, and analyses to create variables (e.g., habitat indices based on various spectral wavelengths) can take weeks to run. Google's Earth Engine (GEE) is a new platform for doing remote sensing that is free for non-profit use. It helps alleviate these issues by (1) allowing users to directly access and process high-resolution data stored in a multi-petabyte catalog in the cloud, (2) enabling scientists to run remote sensing operations on large geospatial datasets quickly via a high-performance network of Google's supercomputers, (3) facilitating automation of calculations that can be reused in various contexts, and (4) giving researchers access to near-current satellite imagery, thus setting us up to monitor habitat changes routinely over time.

We recommend transitioning to using GEE for obtaining and processing remote-sensing data to leverage and build on our current work. This would allow us to quickly access recent satellite imagery and derive habitat indices that reflect more current conditions of the landscape, and thus would allow for rapid updating of models to monitor habitat over time. It would also allow us to explore processing imagery at a finer spatial resolution (10m rather than 20m), potentially revealing patterns in vegetation and soil relevant to SKR not available via other means.

Although the transition would involve up-front programming and testing costs, once remote sensing workflows are optimized on GEE, they could be applied to numerous other species or habitat issues of conservation concern, especially those sensitive to more nuanced habitat qualities than available via traditional techniques.

Subregional Models

Although the range-wide models presented here performed well at depicting SKR habitat values, there appear to be some strong subregional differences in how environmental variables influence SKR across the region--for example from coastal to inland climates. Also, some variables, such as light pollution and roads may vary in how they affect SKR habitat quality in different regions.We recommend developing subregional models based on ecological subsections to provide an ecologically sound basis for subdividing the range and accounting for this variability to provide more accurate mapping of habitat value.

Connectivity and Population Modeling with Genetic Inputs

We recommend using a spatially explicit population model, such as HexSim (Schumaker and Brookes 2018), to investigate population dynamics of SKR across the species range. This would provide insights concerning minimal viable population sizes within isolated reserves and whether translocations amongst reserve areas would be a useful conservation tool. The degree to which SKR may be dispersing between reserve areas, or suitable habitat areas within reserves, is largely unknown, but recent population genetic results analyzed by D. Shier and others at CRI will greatly help in answering this question. Combining these genetic results with population modeling (i.e., incorporating dispersal frequencies and distances into models) and connectivity modeling (to investigate where management could improve genetic and demographic connectivity) would be a powerful means for informing strategies for sustaining and increasing SKR population and metapopulation viability. This seems critical to refining conservation and recovery plans for the species.

Adaptive Management and Monitoring System

Refined habitat maps that can be readily updated (e.g., utilizing GEE's capabilities and satellite imagery) seem the ideal foundation for an adaptive management and monitoring system. This would allow reserve managers to track habitat changes over time both within and among habitat areas, correlate them with field measures of habitat and population status, and prioritize management actions. Ideally, the system could be packaged into a user-friendly, perhaps online, decision-support platform that reserve managers could readily use to test results of their actions and inform future actions.

Other Species

The capabilities of a GEE-based modeling platform taking advantage of multispectral satellite imagery and other geospatial data sources have obvious potential benefits not just for SKR but for a large suite of species of interest. For example, many rare plant and animal species respond to more fine-grained and nuanced habitat features than available by traditional methods, and the benefits of near real-time updating of habitat conditions for monitoring are tremendous. We believe that transitioning to a GEE-based habitat modeling system could greatly reduce monitoring costs for a wide array of species, while also increasing the accuracy and utility of habitat maps for them. An up-front investment in developing such a system would seem very justified given the long-term savings.

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