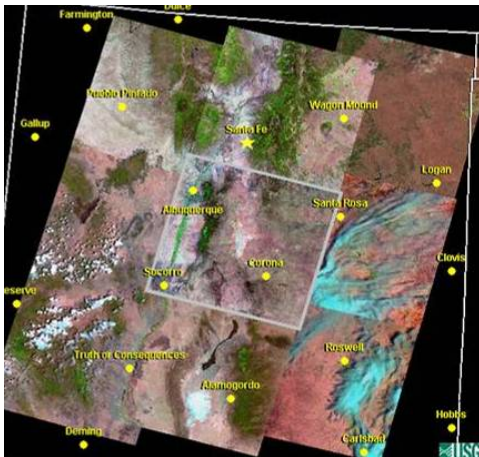**Prepared for the Bureau of Reclamation, Upper Colorado River Region**

Using a Remote Sensing/GIS Model to Predict Southwestern Willow Flycatcher Breeding Habitat along the Rio Grande, New Mexico

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Introduction

The Southwestern Willow Flycatcher (*Empidonax traillii extimus*; hereafter SWFL) is a federally endangered bird (USFWS 1995) that breeds in riparian areas in portions of New Mexico, Arizona, southwestern Colorado, extreme southern Utah and Nevada, and southern California (USFWS 2002). Across this range, it uses a variety of plant species as nesting/breeding habitat, but in all cases prefers sites with dense vegetation, high canopy, and proximity to surface water or saturated soils (Sogge and Marshall 2000). As of 2005, the known rangewide breeding population of SWFLs was roughly 1,214 territories, with approximately 393 territories distributed among 36 sites in New Mexico (Durst et al. 2006), primarily along the Rio Grande.

One of the key challenges facing the management and conservation of the Southwestern Willow Flycatcher is that riparian areas are dynamic, with individual habitat patches subject to cycles of creation, growth, and loss due to drought, flooding, fire, and other disturbances. Former breeding patches can lose suitability, and new habitat can develop within a matter of only a few years, especially in reservoir drawdown zones. Therefore, measuring and predicting flycatcher habitat - either to discover areas that might support SWFLs, or to identify areas that may develop into appropriate habitat - requires knowledge of recent/current habitat conditions and an understanding of the factors that determine flycatcher use of riparian breeding sites.

In the past, much of the determination of whether a riparian site is likely to support breeding flycatchers has been based on qualitative criteria (e.g., "dense vegetation" or "large patches"). These determinations often require on-the-ground field evaluations by local or regional SWFL experts. While this has proven valuable in locating many of the currently known breeding sites, it is difficult or impossible to apply this approach effectively over large geographic areas (e.g., the middle Rio Grande). The SWFL Recovery Plan (USFWS 2002) recognizes the importance of developing new approaches to habitat identification, and recommends the development of drainage-scale, quantitative habitat models. In particular, the plan suggests using models based on remote sensing and Geographic Information System (GIS) technology that can capture the relatively dynamic habitat changes that occur in southwestern riparian systems.

In 1999, Arizona Game and Fish Department (AGFD) developed a GIS-based model (Hatten and Paradzick 2003) to identify SWFL breeding habitat from Landsat Thematic Mapper (TM) imagery and 30-m resolution digital elevation models (DEMs). The model was developed with presence/absence survey data acquired along the San Pedro and Gila rivers, and from the Salt River and Tonto Creek inlets to Roosevelt Lake in southern Arizona (collectively called the project area). The GIS-based model used a logistic regression equation to divide riparian vegetation into 5 probability classes based upon characteristics of riparian vegetation and floodplain size. This model was tested by predicting SWFL breeding habitat at Alamo Lake, Arizona, located 200 km from the project area (Hatten and Paradzick 2003). The GIS-based model performed as expected by identifying riparian areas with the highest SWFL nest densities, located in the higher probability classes.

In 2002, AGFD applied the GIS-based model throughout Arizona, for riparian areas below 1,524 m (5,000 ft) elevation and within 1.6 km of perennial or intermittent waters

(Dockens et al. 2004). Overall model accuracy (using probability classes 1-5, with class 5 having the greatest probability of nesting activity) for predicting the location of 2001 nest sites was 96.5%; accuracy decreased when fewer probability classes were defined as suitable. Map accuracy, determined from errors of commission, increased in higher probability classes in a fashion similar to errors of omission. Map accuracy, like model accuracy, was dependent on what probability cutpoint was selected. A cutpoint, or probability threshold, is a modeler-selected value at which "suitable" (i.e., high probability) habitat is dichotomously distinguished from "unsuitable" (i.e., low probability) habitat. For the Hatten and Paradzick (2003) model, the lower the cutpoint used, the greater the amount of predicted habitat and model sensitivity, but the lower its specificity. Inversely, as the cutpoint increased, the model's specificity increased, but the amount of predicted habitat and the sensitivity decreased. To explain the effect of cutpoint choice, Hatten and Paradzick (2003) concluded that if all class-5 cells (the 80% cutpoint) had been surveyed in Arizona during 2001, approximately 20% would have been unsuitable for SWFLs and roughly 30% of SWFL nests would have been missed. If surveyors had searched all class 3-5 cells (representing the 40% cutpoint), 32% would not have been breeding habitat, and <5% of nests would have been missed. This is an issue inherent with all models of this kind, and there is no perfect cutpoint. The Hatten and Paradzick (2003) model was clearly successful at predicting flycatcher breeding sites in Arizona based on remote sensing data and GIS-based themes.

This is the first large-scale predictive model of its kind for SWFL habitat. It focused on low to mid-elevation breeding sites because there were relatively few high elevation sites or territories in Arizona. Based upon the model's robust performances in Arizona, we believed that it could be applied elsewhere within the species' range. Because New Mexico has a relatively large SWFL breeding population, with intensive survey and nest monitoring of major sites along the Rio Grande (Ahlers and Moore 2004), it provided a good opportunity to evaluate the model's performance outside of Arizona. We hypothesized that if the model was applied to the Rio Grande, the 5 probability classes output by the model would contain either a linear, exponential, or binary relationship with SWFL nest or territory density. Because the model outputs georeferenced layers that can be queried and viewed with a GIS, the model can be used as a decision support system for prioritizing breeding site and nest surveys, or identifying potential restoration or enhancement locations. In doing so, users would need to carefully consider the effect of cutpoint choice and the amount of predicted habitat.

Methods

Modeling Overview

We applied the same modeling techniques used in Arizona (Hatten and Paradzick 2003; Dockens et al. 2004) to identify and map potential SWFL breeding habitat in 2004 along the Rio Grande, from Elephant Butte Dam in southern New Mexico to near the Alamosa National Wildlife Refuge in southern Colorado. Our initial focus was the determination of model accuracy, as estimated from errors of omission; e.g., nest sites or breeding locations that occurred but were in areas not predicted by the model.

To accomplish our goal it was necessary to complete four steps: (1) create four GIS variables derived from Landsat Thematic Mapper (TM) imagery and 30-m resolution

DEMs, (2) populate a logistic regression model with the four GIS variables to create a probability grid, (3) divide riparian vegetation into 5 probability classes, and (4) assess model accuracy within the 5 probability classes with errors of omission, and model fit with nest or territory density.

The logistic regression equation we used for this study (Table 1) calculates the probability of nest occurrence with the following equation:

probability = exp(logit) / 1 + exp(logit); where the logit is: 1.483(NDVI) + 0.098(NDVIBEST) + 0.034(FLOODPL) + 0.648(NDVISTD) – 6.074.

The four variables are defined as follows:

(1) NDVI = dense vegetation (NDVI > 0.33) at the site (0.09 ha);

(2) NDVIBEST = amount (%) of densest vegetation (NDVI > 0.41) within a 4.5-ha neighborhood;

(3) FLOODPL = amount (%) of floodplain or flat terrain (<2.5 degrees) within a 41-ha neighborhood, and

(4) NDVISTD = the standard deviation in NDVI (12 classes) within a 4.5-ha neighborhood.

GIS Database

We created vegetation density grids (0.09-ha cells) for the Rio Grande corridor from spectral data that were extracted from five TM images acquired (imaged) on June 13, 2004, during a cloud-free period (Figure. 1). To process the imagery and create the four GIS variables (layers) necessary to populate the model (see Table 1), we used ERDAS Imagine software (ERDAS Inc., Atlanta, Georgia) and ARC/INFO GIS (ESRI Inc., Redlands, CA). After masking agricultural fields that were visible on the TM imagery, we created an overall vegetation density grid by calculating the Normalized Difference Vegetation Index (NDVI) within 3-5 km of the Rio Grande. We selected a wide, variable-width buffer in order to capture riparian vegetation in the lower reaches of tributaries that often contain flycatcher habitat. We created riparian-vegetation density grids from the overall vegetation grid by using NDVI thresholds and classification, and stored the results from each operation in a separate grid (Hatten and Paradzick 2003).

We created a generalized riparian-vegetation density grid from the overall vegetation density grid by extracting all cells with an NDVI value >0.126 (Hatten and Paradzick 2003). We also created an intermediately dense (NDVI >0.33) and very dense riparian-density vegetation grid (NDVI > 0.41). Next, we created an interval-scaled riparian-density vegetation grid by dividing the riparian grid (NDVI > 0.12) into 12 classes, ranging from 0.126 – 0.86). Once the riparian-vegetation density grids were created, we calculated the proportion (%) of densest vegetation, and heterogeneity in vegetation density (SD), within a 120-m radius (4.5 ha) of each location with moving window functions (FOCALSUM and FOCALSTD, respectively). We used the FOCALSUM function on the densest riparian vegetation grid (NDVI >0.41), and the FOCALSTD function on the interval-scaled riparian grid. Lastly, we identified the proportion (%) of flat area (< 2.50) off of a 30-m resolution DEM with SLOPE and FOCALSUM functions.

Model Fit and Accuracy Assessment

To assess the fit of the model, we overlaid SWFL territory locations upon the 5 probability classes that were output by the model. The territory locations were acquired during the 2004 field season (June – September) from sites that are intensively monitored between Elephant Butte Reservoir and Velarde by the U.S. Bureau of Reclamation (Ahlers and Moore 2004). Nest/territory density is obtained by dividing territory numbers within each probability class by the area (ha) found with each probability class (Hatten and Paradzick 2003). If the model works as expected, there will be an increase in territory density in higher probability classes in either a linear, exponential, or binary fashion. We examined model fit for breeding sites under 1,524 m elevation because that was the elevational cutoff used in developing the model within Arizona (Hatten and Paradzick 2003), and because SWFL nest location data for New Mexico were only available for sites below this threshold. However, we did model the NDVI probability classes for riparian habitat above 1,524 m, as this might help identify possible breeding habitats in higher elevations and thus provide useful information for future surveys or modeling.

To assess model accuracy, we overlaid the territory locations upon the 5 probability classes, generated a frequency histogram, and calculated omission errors. An omission error occurs when a territory location falls outside of predicted habitat, thus omission errors change according to what probability cutpoint is selected (Hatten and Paradzick 2003). If the model is working correctly, omission errors should increase as the cutpoint is raised because less riparian vegetation is predicted as suitable for breeding. We also expected an inverse relationship between amount of predicted breeding habitat and the 5 probability classes, so higher probability classes should contain less riparian vegetation, and lower classes more.

Results

Predicted Habitat

The GIS-based model found 91,104 ha of riparian or upland vegetation that had an NDVI value > 0.126 (probability classes 1 – 5) along the Rio Grande (Table 2). Because all probability classes were totaled, this number reflects the total amount of riparian vegetation and some non-riparian vegetation in the upper reaches (i.e., >1,524 m) that is probably pinyon/juniper or pine (Appendix 1, Figs H – L). When we restricted our analysis to under 1,524 m elevation (i.e., under 5,000 feet), there were 25,514 ha of riparian vegetation within the NDVI density band of our model (classes 1-5). The greatest amount of high probability habitat under 1,524 m was located near Elephant Butte Reservoir (Appendix 1, Fig. A); the largest amount above 1,524 m was in the San Luis Valley (Appendix 1, Fig. M). The amount of predicted habitat was greatest for probability class 1; however, there was not a direct inverse relationship between probability class and predicted habitat. Instead, the amount of class 5 habitat was greater than classes 2 – 4. Still, the amount of predicted habitat changed dramatically when lower probability classes were excluded. For example, probability class 1 contained 46.4% of predicted habitat, classes 2-4 contained 10-12% apiece, and class 5 contained 21.2% (Fig. 2).

Accuracy Assessment and Model Fit

The results of our binary habitat classification assessment found that the lower the cutpoint, the greater the sensitivity of the model. Conversely, the higher the cutpoint, the lower the model's sensitivity (Fig. 3). This reflects the relationship between cutpoint and the proportion of riparian vegetation that is considered suitable as SWFL breeding habitat. Specifically, the lower the cutpoint, the greater the proportion of riparian vegetation that was classified as suitable for breeding, and thus fewer SWFL territories were omitted. At a 20% cutpoint, the model was 86.1% accurate, while at an 80% threshold, the model was 63.5% accurate.

The density of flycatcher territories increased exponentially within the 5 probability classes (Fig. 4), with class 1 containing the lowest density (0.002/ha), and class 5 the greatest (0.024/ha). There was an order of magnitude difference between the density of SWFL territories found in class 5 compared to class 1. The magnitude of change in density between classes varied; nest density increased 50% between classes 1 and 2, 100% between classes 2 and 3, 33% between classes 3 and 4, and 200% between classes 4 and 5.

Discussion

Model Performance

Even though the GIS-based model was developed based on SWFL habitat and nest location data from Arizona (Hatten and Paradzick 2003), the model performed as expected along the Rio Grande, with an exponential relationship between the 5 probability classes and territory density. This relationship indicates that NDVI is a robust integrative variable for characterizing riparian habitat features that are important in habitat selection by SWFLs. Thus, the GIS-based model can be a useful tool to managers in New Mexico for identifying possible SWFL breeding habitats, prioritizing survey efforts, identifying potential restoration areas and tracking restoration progress, and monitoring riparian habitat changes over time. The densities of flycatcher territories along the Rio Grande were 250% smaller than those observed in 2000 along the Gila and San Pedro Rivers (Paxton et al. 2007), but the pattern of distribution (i.e., exponential) within the 5 probability classes was very similar. This indicates that while SWFL densities can change by location, year, or spatial extent of the project area, the response of the flycatchers to the habitat appears similar, with SWFL preferring dense, vigorous riparian vegetation as reflected in high NDVI values.

Based upon our observations in Arizona (Hatten and Paradzick 2003), we expected to see an inverse relationship between the five model probability classes and the amount of riparian vegetation (NDVI > 0.126), but the middle classes were smaller than the last class (Fig. 2). We suspect that the extensive amount of agriculture along the Rio Grande Valley has altered this relationship, but more research is necessary to understand the influence of land use and riparian-vegetation growth patterns throughout the southwestern U.S, especially anthropogenic factors such as groundwater usage and urban development.

Future Modeling

There are several potential ways to further test and refine this SWFL habitat model for broader application in New Mexico, and potentially elsewhere in the range of the flycatcher. One option would be to apply this model to other river systems within New Mexico, particularly the Gila River. The Gila supports several known large SFWL populations (Durst et al. 2005), and it would be instructive to see if the model correctly predicts the location of these breeding sites, or if it identifies new potential breeding habitats that may be worth surveying.

Another possibility would be to build new "customized" GIS-based models based on Rio Grande-specific habitat characteristics and nest/territory data. These models could be based on currently available nest location data, or include gathering additional nest data from more breeding sites. One could assess whether Rio Grande-specific models improve model sensitivity and specificity by looking at territory densities within the 5 probability classes. If a custom model improves the sensitivity and specificity of the model, flycatcher territory densities should increase in the upper probability classes. Creating river-specific predictive models has recently been shown to improve model sensitivity and specificity along the Gila and San Pedro Rivers in Arizona (Paxton et al. 2007), thus we could potentially expect such an outcome for the Rio Grande as well.

By applying the GIS-based model in two or more years, which requires populating the model with annual-specific vegetation characteristics derived from the appropriate TM scene, one can quantify in a spatially explicit manner changes in SWFL breeding habitat (Paradzick and Hatten 2004). Detecting changes in SWFL breeding habitat can be useful for determining whether climate, hydrology, or anthropogenic factors are reducing or increasing their breeding habitat between one or more time intervals. By incorporating habitat changes into a SWFL breeding habitat model, which requires running the model at two different time intervals and creating a change detection grid, one can create a spatial-temporal model of SWFL breeding habitat (Paxton et al. 2007). Spatial-temporal models have been shown to be the best overall predictors of SWFL breeding habitat because they capture some of the underlying stability and dynamics in riparian vegetation that are important components in SWFL breeding habitat.

Lastly, applying the model to other large river systems in the Southwest would provide very useful insights on the applicability of the model over a broader geographic range. If the model proves robust on a range-wide scale, it would allow for riparian habitat prediction, quantification, and change detection over unprecedented spatial and temporal scales. This would help facilitate the landscape and drainage level conservation and management recommended in the SWFL recovery plan (USWFS 2002).

Acknowledgments

final product. The use of trade names in this paper does not constitute a product endorsement by USGS.

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Figure 1. The extent of Landsat Thematic Mapper scenes (path 33, rows 33 - 38) used for SWFL habitat modeling and mapping, overlaid on NM county boundaries and the Rio Grande. The Landsat scenes were captured on June 13, 2004.
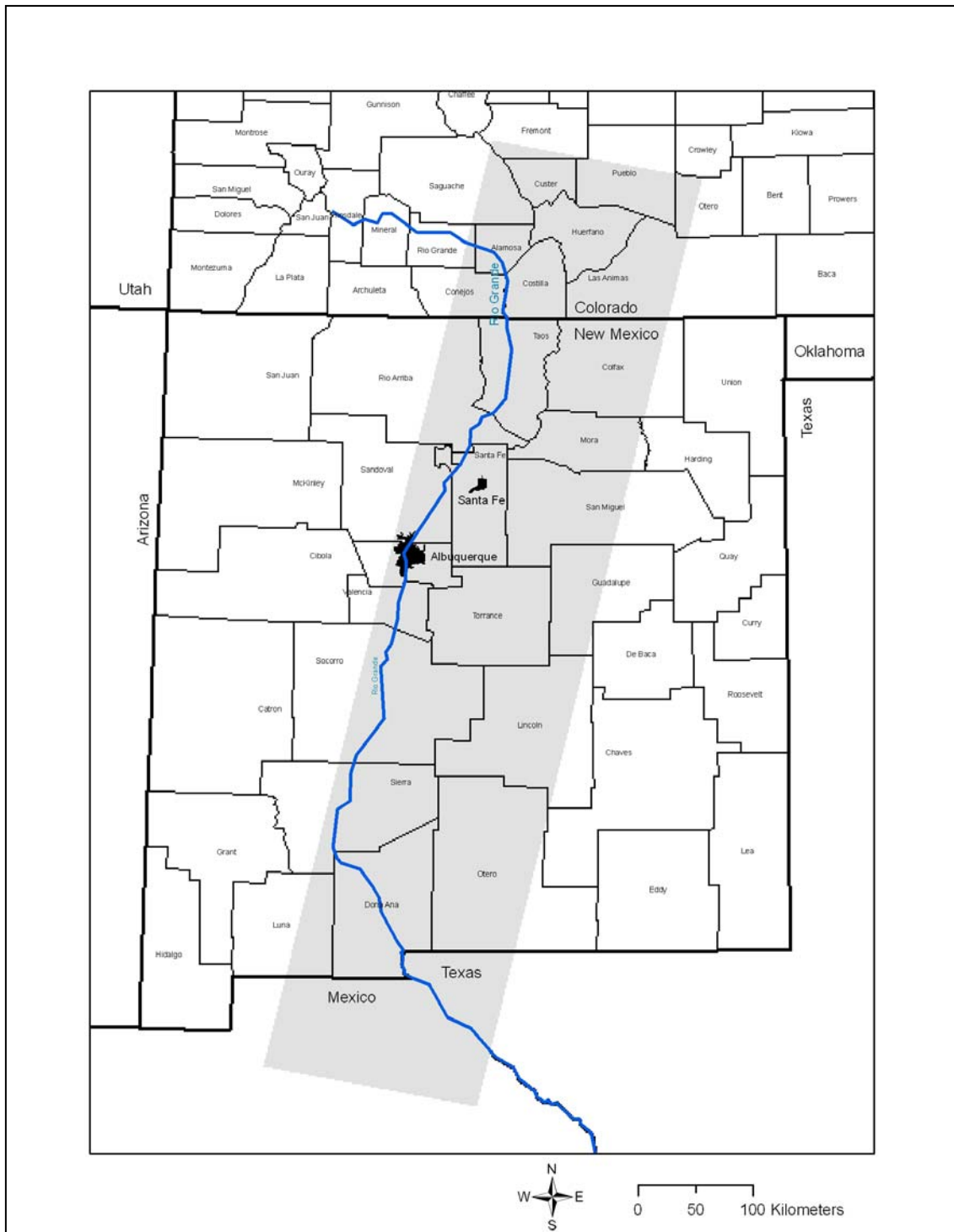
Figure 2. The proportion of riparian vegetation found within each probability class, along the Rio Grande under 1,524 m elevation, as determined by the GIS-based model. Probability class 1, which contained cells with model probabilities $\leq 20\%$, accounted for 46.4% of the riparian vegetation, and probability class 5 (cell probabilities > 80%) accounted for 21.2%.
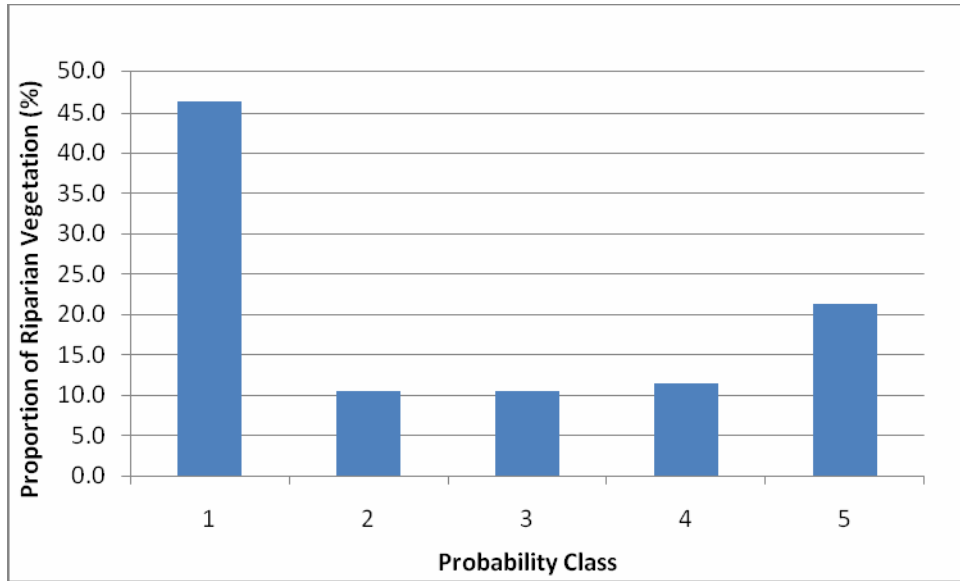
Figure 3. The sensitivity (1 – omission error) of the SWFL habitat model at 4 probability thresholds, as modeled along the Rio Grande in 2004. For this analysis, we created 4 binary habitat grids by classifying all cells with a probability greater than the NDVI threshold as suitable breeding habitat, and cells under the NDVI threshold unsuitable. We overlaid SWFL territories on each binary habitat grid and determined the model's sensitivity at each probability threshold. In this example, at a 20% threshold, where cells with a model probability >20% were coded suitable, 86.1% of territories were correctly classified (i.e., fell inside the suitable zone), and 13.9% were omitted.
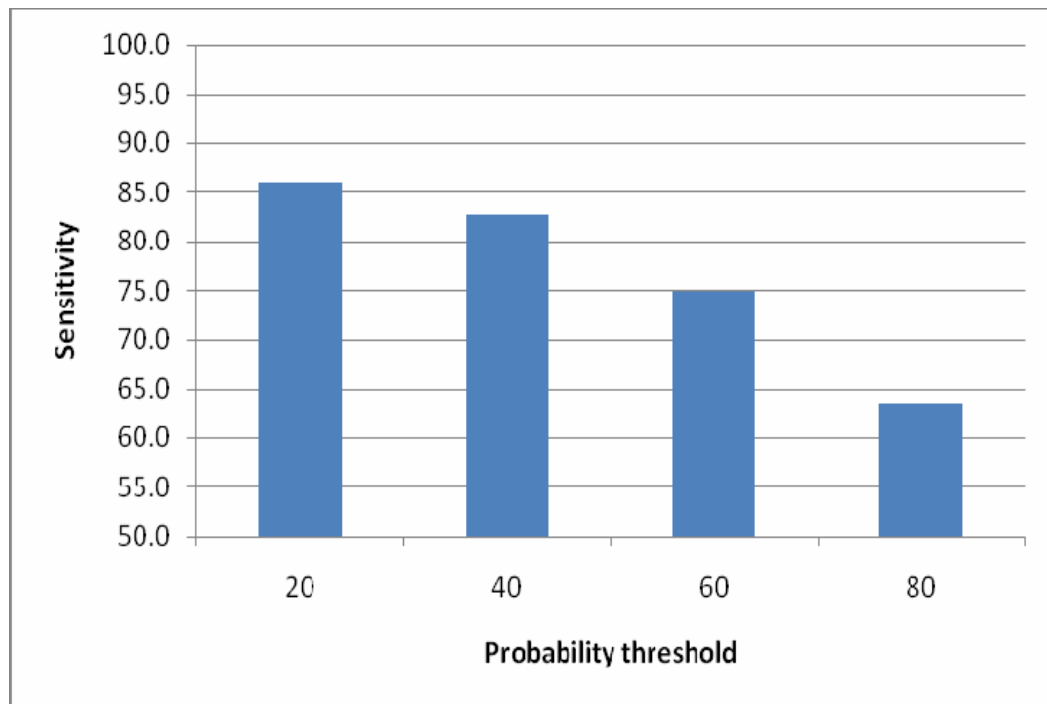
Figure 4. The density of SWFL territories within 5 probability classes that were output by the GIS-based habitat model, based on Rio Grande data for 2004. For this analysis, only areas that were less than 1,524-m in elevation were included in the analysis.
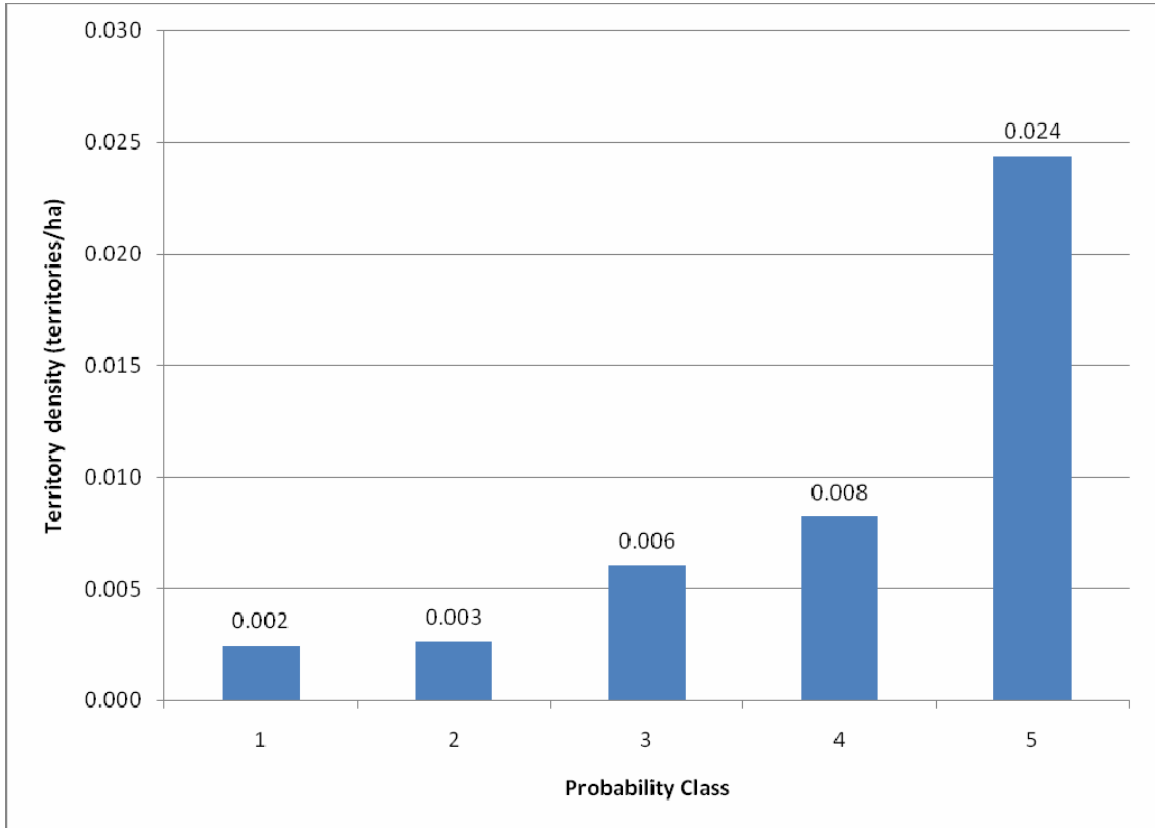
Table 1. Multivariate logistic regression model obtained from Southwestern Willow Flycatcher (SWFL) data (Hatten and Paradzick 2003). The model was created from retrospective survey data (71 breeding sites and 136 nonuse sites) collected during 1999 in south-central Arizona. Breeding sites contained a SWFL nest and nonuse sites did not.

Variable	Coeff	SE	G	Odds Ratio[c]	P
NDVI[a]	1.483	0.48	9.6	4.4	0.002
NDVIBEST[b]	0.098	0.02	29.6	1.6[c]	<0.001
FLOODPL[b]	0.034	0.01	8.7	NA	0.003
NDVISTD[d]	0.648	0.16	19.5	1.9	<0.001
Constant	-6.074	0.98	64.5	0.0	<0.001

[a]Modeled as a binary variable (NDVI classes 1-9 = 0; 10-12 = 1)

[b]Modeled as a continuous variable (scaled from 0 – 49)

[c]Odds ratio calculated in 10% increments

[d]Modeled as a continuous variable (scaled from 0 – 6)

Table 2. The frequency of SWFL territories, amount of predicted habitat, and density of flycatchers within each model probability class for riparian habitat long the Rio Grande in 2004. The table also shows the amount of predicted habitat, and density of flycatchers, with and without a 1524-m elevation mask applied. Fifteen SWFL territories fell outside of all probability classes and they were lumped into the lowest probability class. The proportion (%) of the total amount of riparian vegetation by class, as determined by the model, is also presented.

Class	Frequency[a]	Area (ha)[b]	Density[b]	Area(ha)[c]	Density[c]	Percent[d]
1	29	53248.68	0.001	11840.31	0.002	46.4
2	7	7565.31	0.001	2672.82	0.003	10.5
3	16	7200.99	0.002	2661.93	0.006	10.4
4	24	8693.64	0.003	2921.67	0.008	11.5
5	132	14395.59	0.009	5417.55	0.024	21.2
Total	208	91104.21		25514.28		100

[a] Number of flycatchers

[b] Predicted breeding habitat (classes 1 – 5) or SWFL density along entire Rio Grande study area (see Fig. 1)
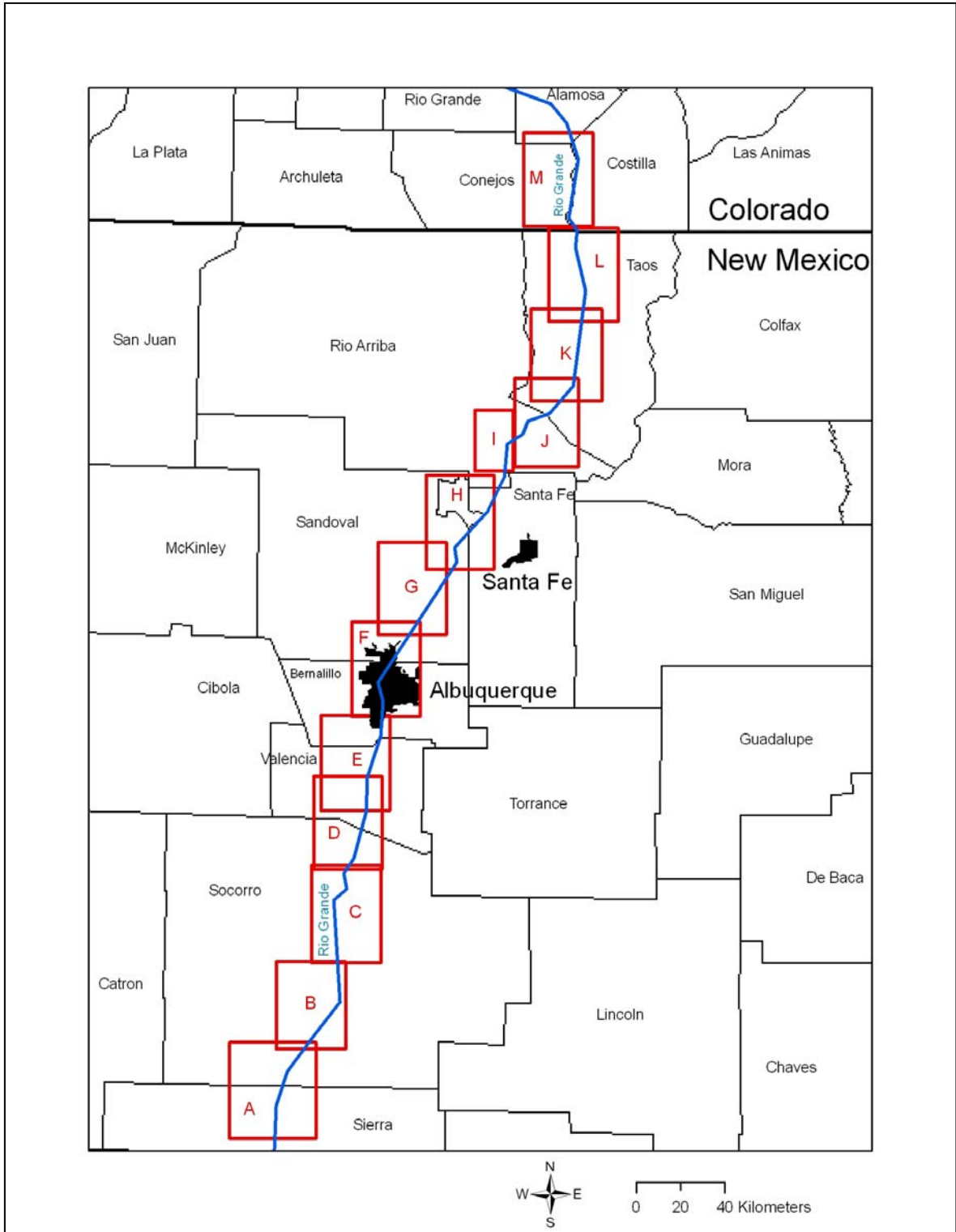
[c] Predicted breeding habitat (classes 1 – 5) or SWFL density along Rio Grande under 1524 m

[d] Proportion of riparian vegetation, as determined from the model, within each probability class

Appendix

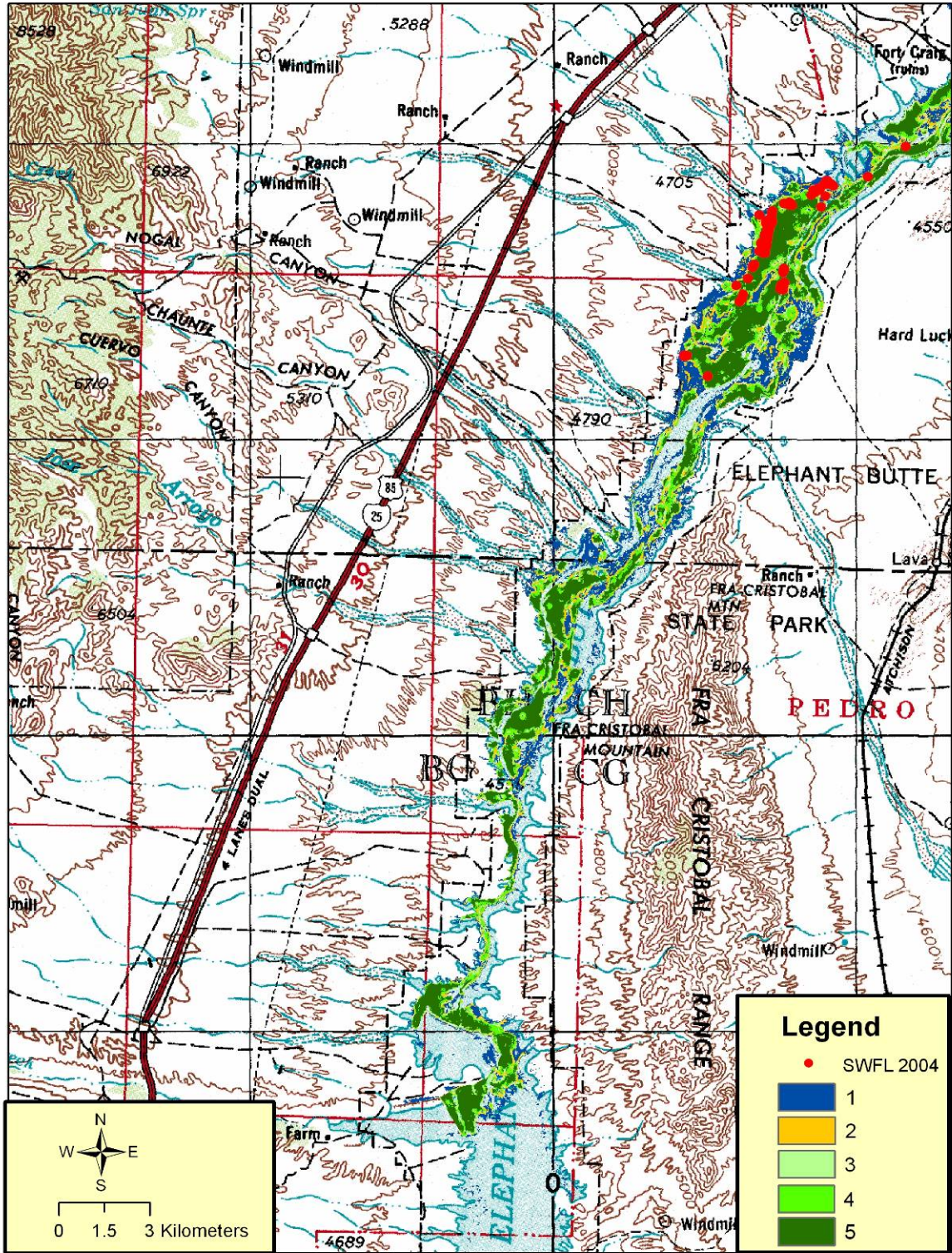Key to location of Appendix figures

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Figure A. SWFL habitat model output (the 5 probability classes are shown in the legend) and 2004 SWFL territories (red circles), overlain on a 1:250,000 scale USGS topographic map.
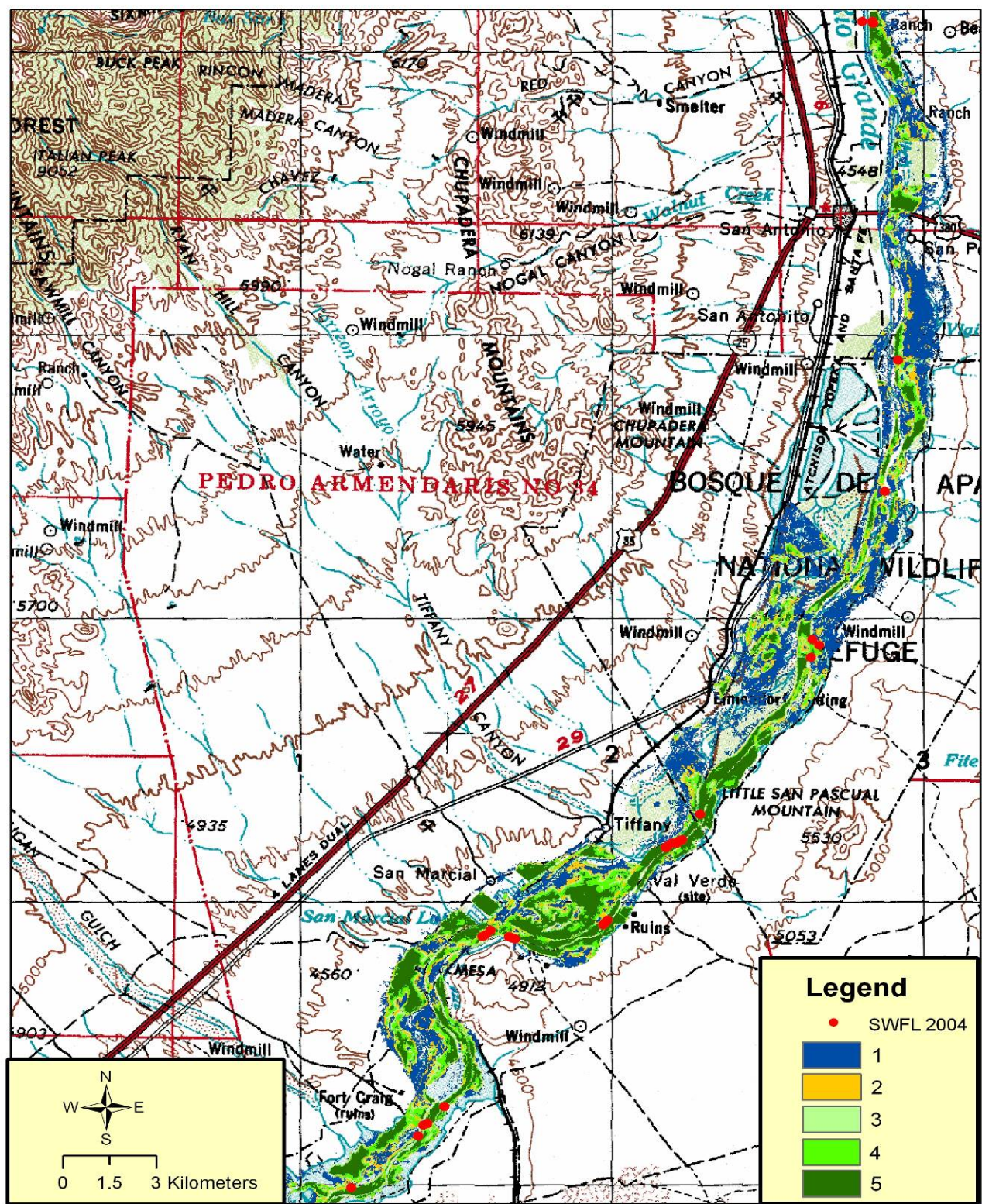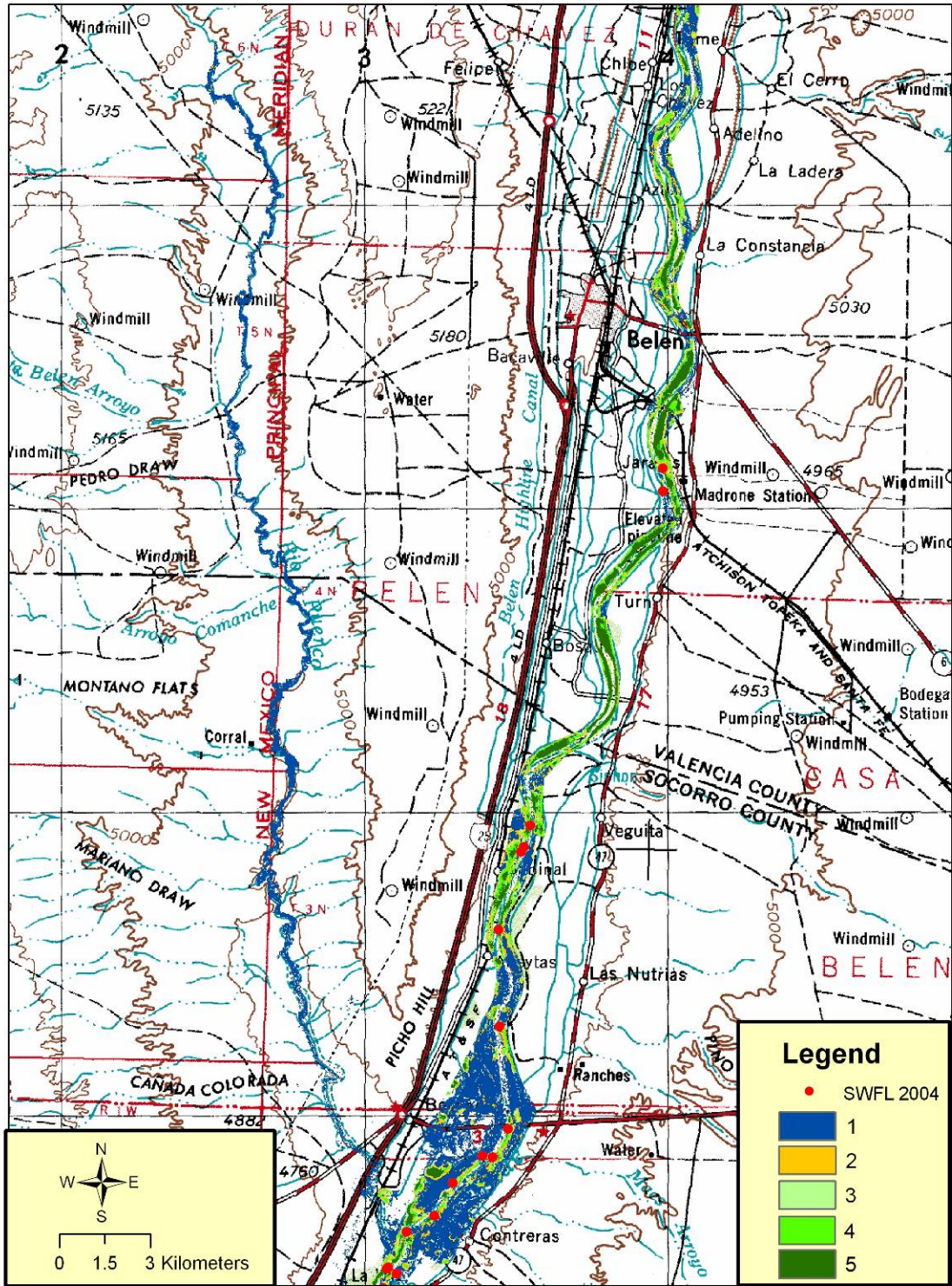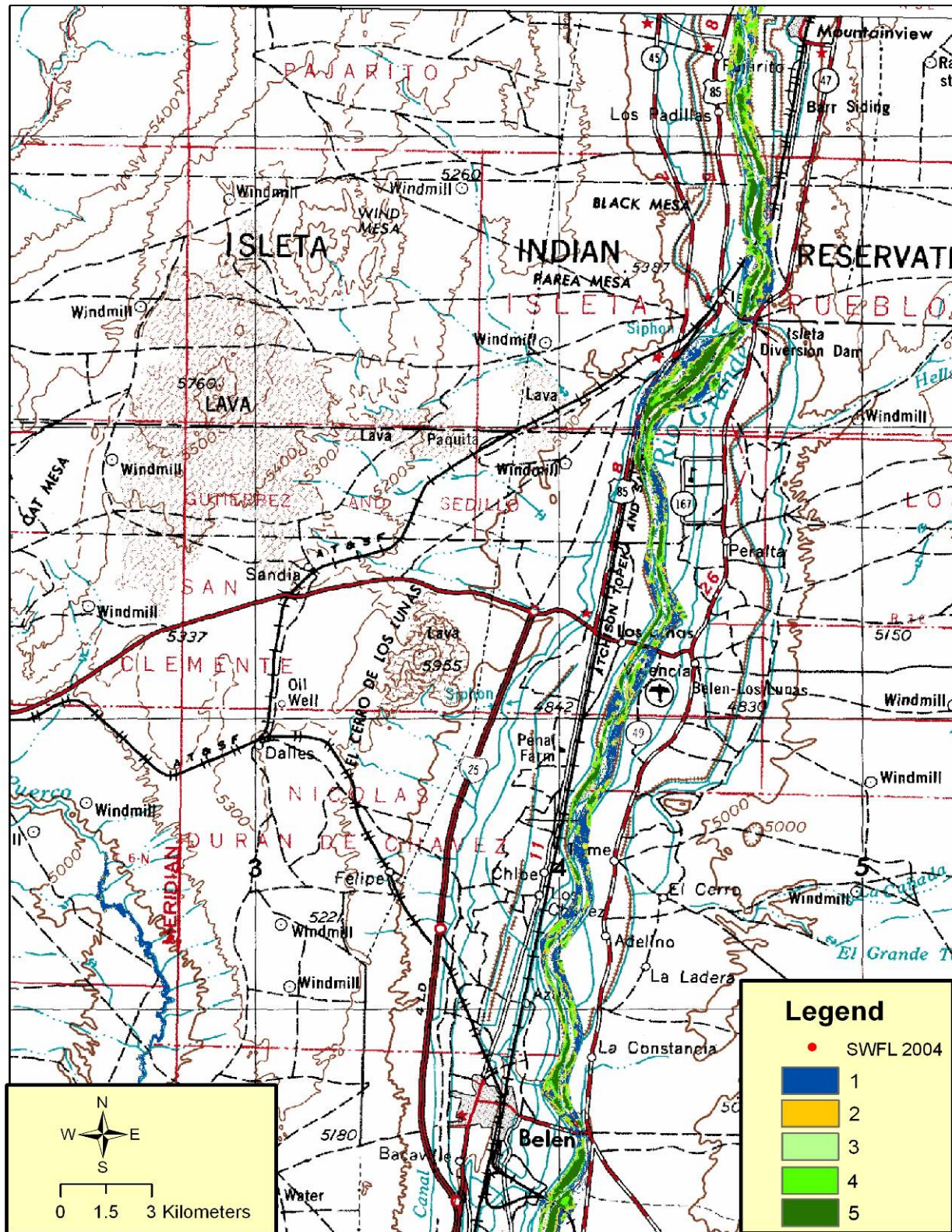
Figure B. SWFL habitat model output (the 5 probability classes are shown in the legend) and 2004 SWFL territories (red circles), overlain on a 1:250,000 scale USGS topographic map.

Figure C. SWFL habitat model output (the 5 probability classes are shown in the legend) and 2004 SWFL territories (red circles), overlain on a 1:250,000 scale USGS topographic map.

Figure D. SWFL habitat model output (the 5 probability classes are shown in the legend) and 2004 flycatcher territories, overlain on a 1:250,000 scale USGS topographic map.

Figure E. SWFL habitat model output (the 5 probability classes are shown in the legend),
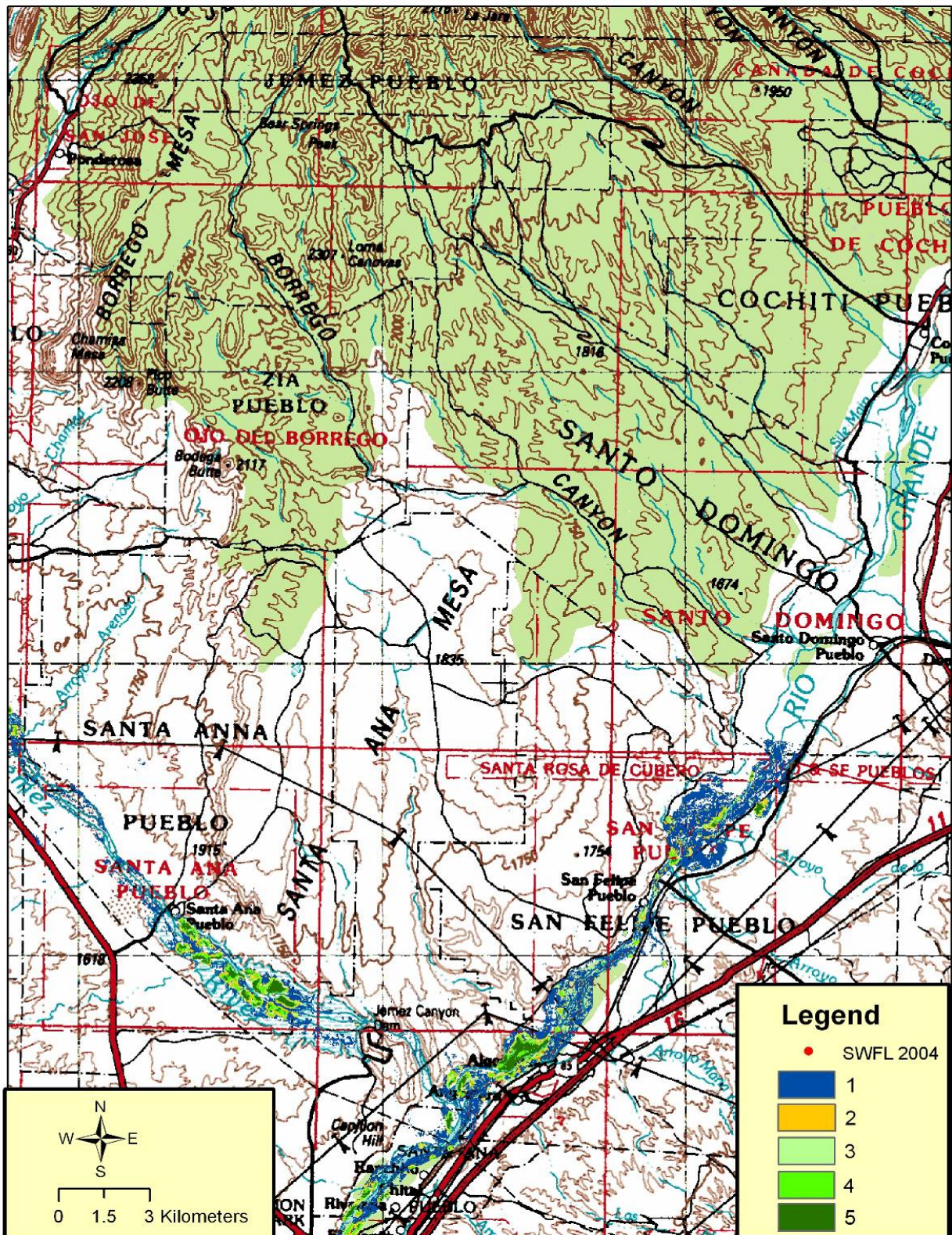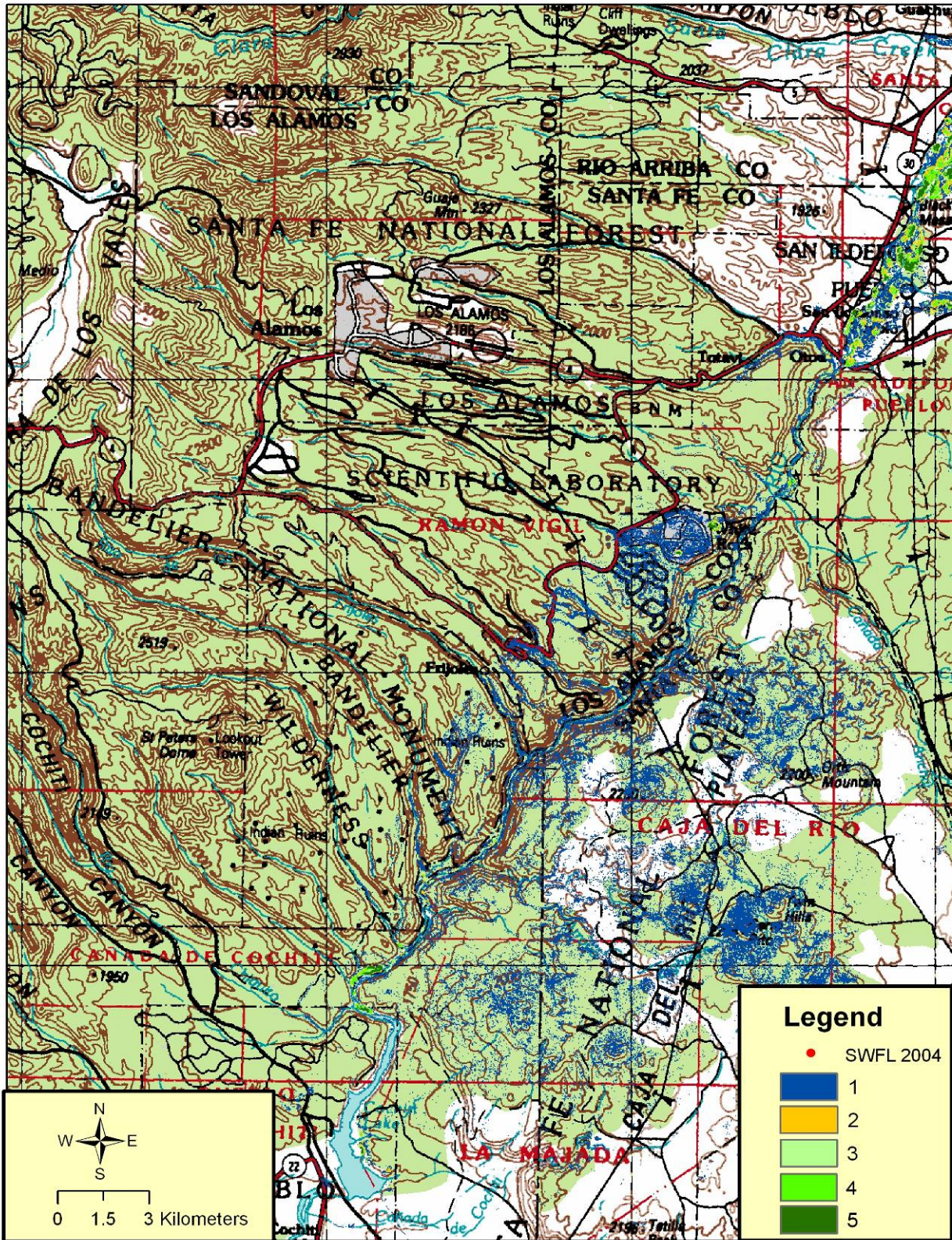overlain on a 1:250,000 scale USGS topographic map.
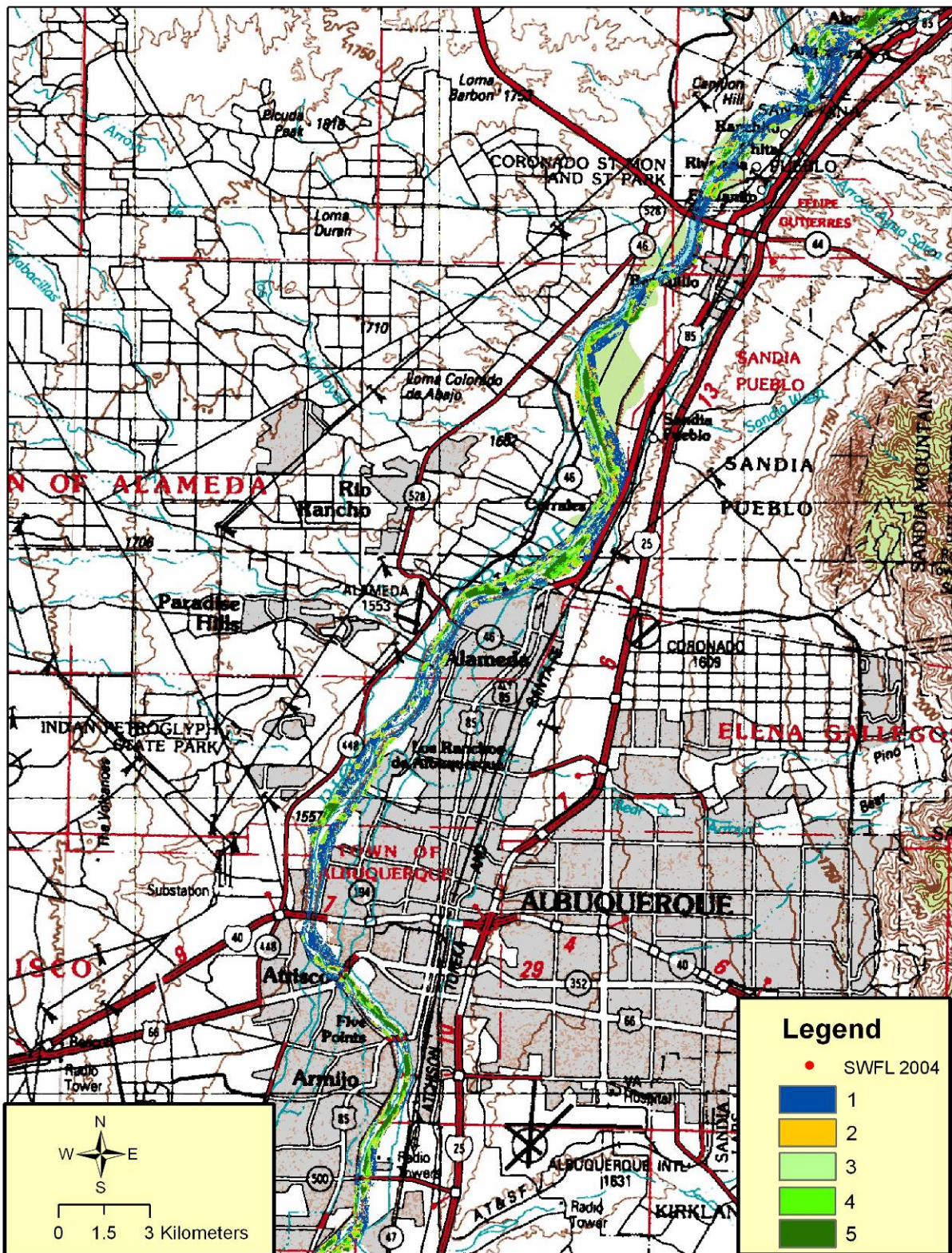
Figure F. SWFL habitat model output (the 5 probability classes are shown in the legend), overlain on a 1:250,000 scale USGS topographic map.

Figure G. SWFL habitat model output (the 5 probability classes are shown in the legend), overlain on a 1:250,000 scale USGS topographic map.

Figure H. SWFL habitat model output (the 5 probability classes are shown in the legend), overlain on a 1:250,000 scale USGS topographic map. Note that much of the Probability Class 1 vegetation shown away from the river corridor is non-riparian upland vegetation, possibly pinyon/juniper or pine.

Figure I. SWFL habitat model output (the 5 probability classes are shown in the legend), overlain on a 1:250,000 scale USGS topographic map.
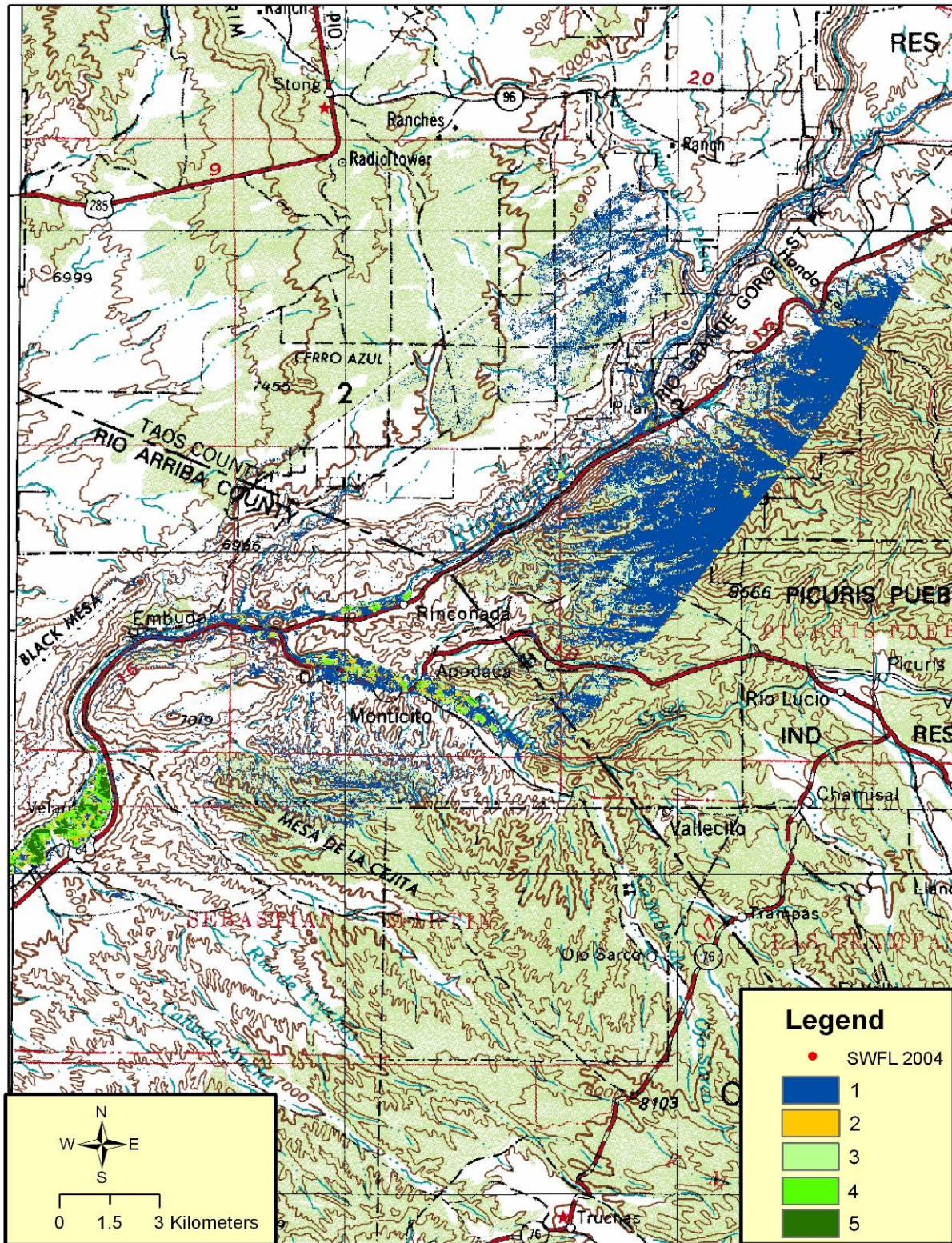
Figure J. SWFL habitat model output (the 5 probability classes are shown in the legend) and 2004 flycatcher territories, overlain on a 1:250,000 scale USGS topographic map. Note that much of the Probability Class 1 vegetation shown away from the river corridor is non-riparian upland vegetation, possibly pinyon/juniper or pine.
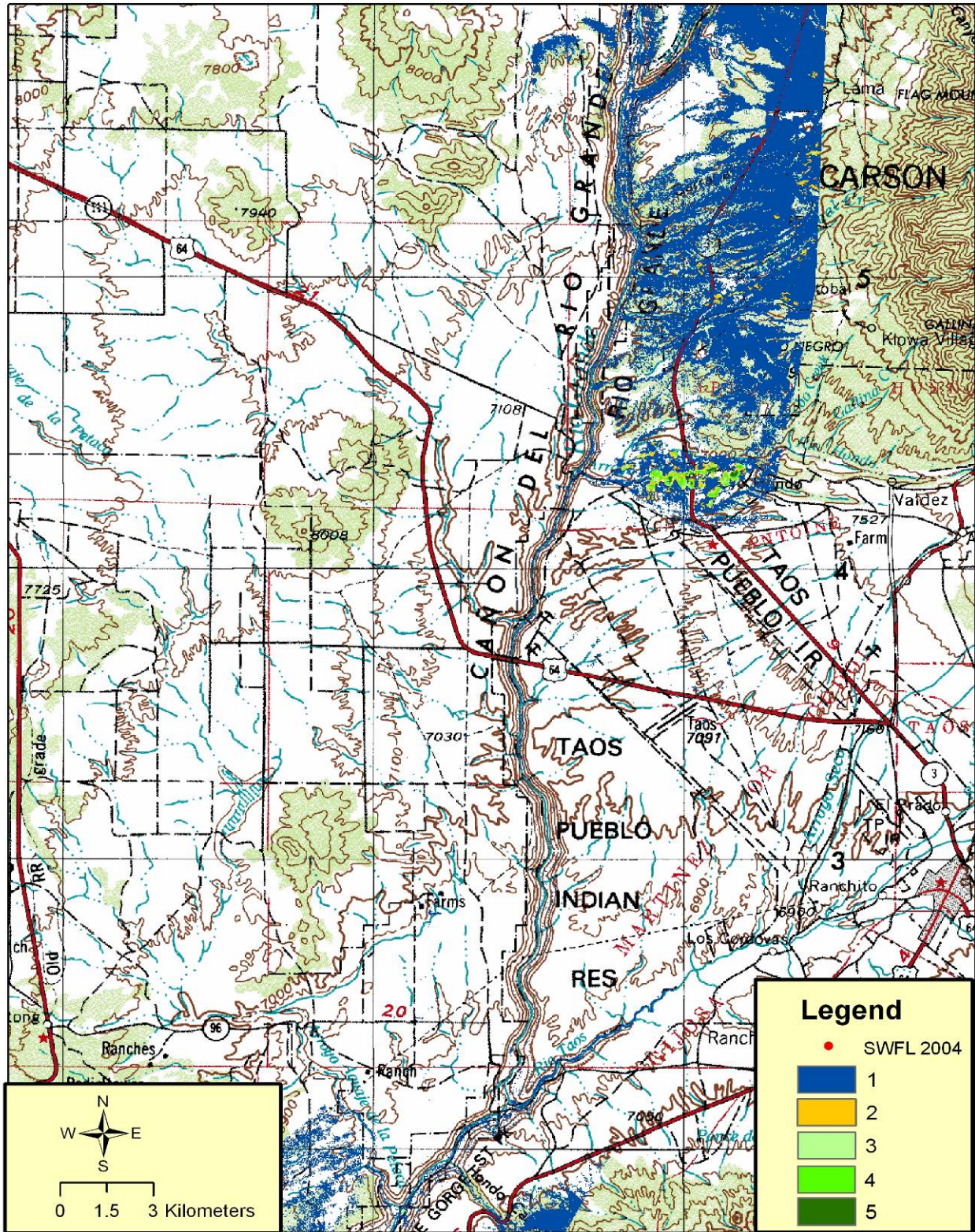
Figure K. SWFL habitat model output (the 5 probability classes are shown in the legend) and 2004 flycatcher territories, overlain on a 1:250,000 scale USGS topographic map. Note that much of the Probability Class 1 vegetation shown away from the river corridor is non-riparian upland vegetation, possibly pinyon/juniper or pine.
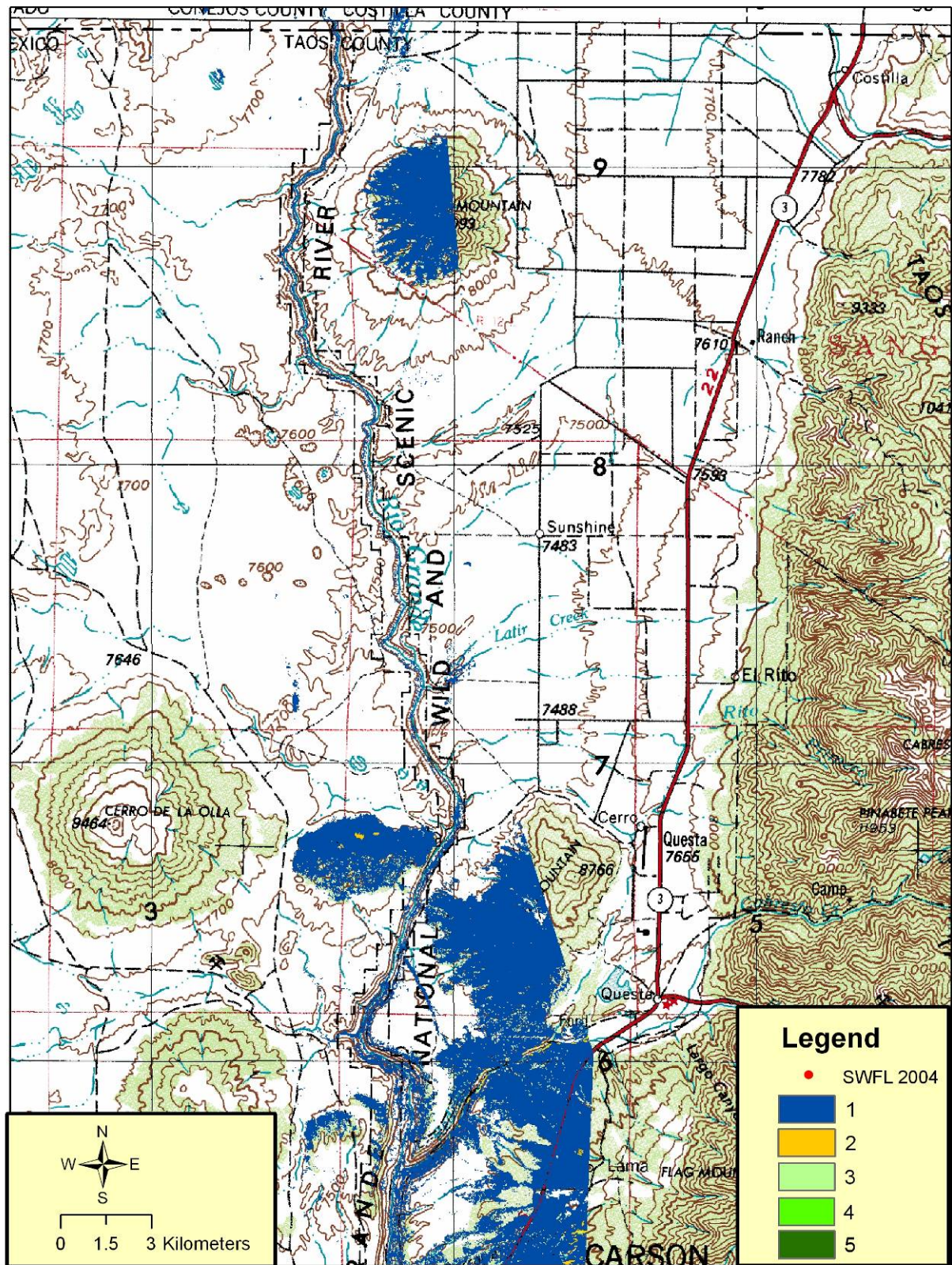
Figure L. SWFL habitat model output (the 5 probability classes are shown in the legend) and 2004 flycatcher territories, overlain on a 1:250,000 scale USGS topographic map. Note that much of the Probability Class 1 vegetation shown away from the river corridor is non-riparian upland vegetation, possibly pinyon/juniper or pine.
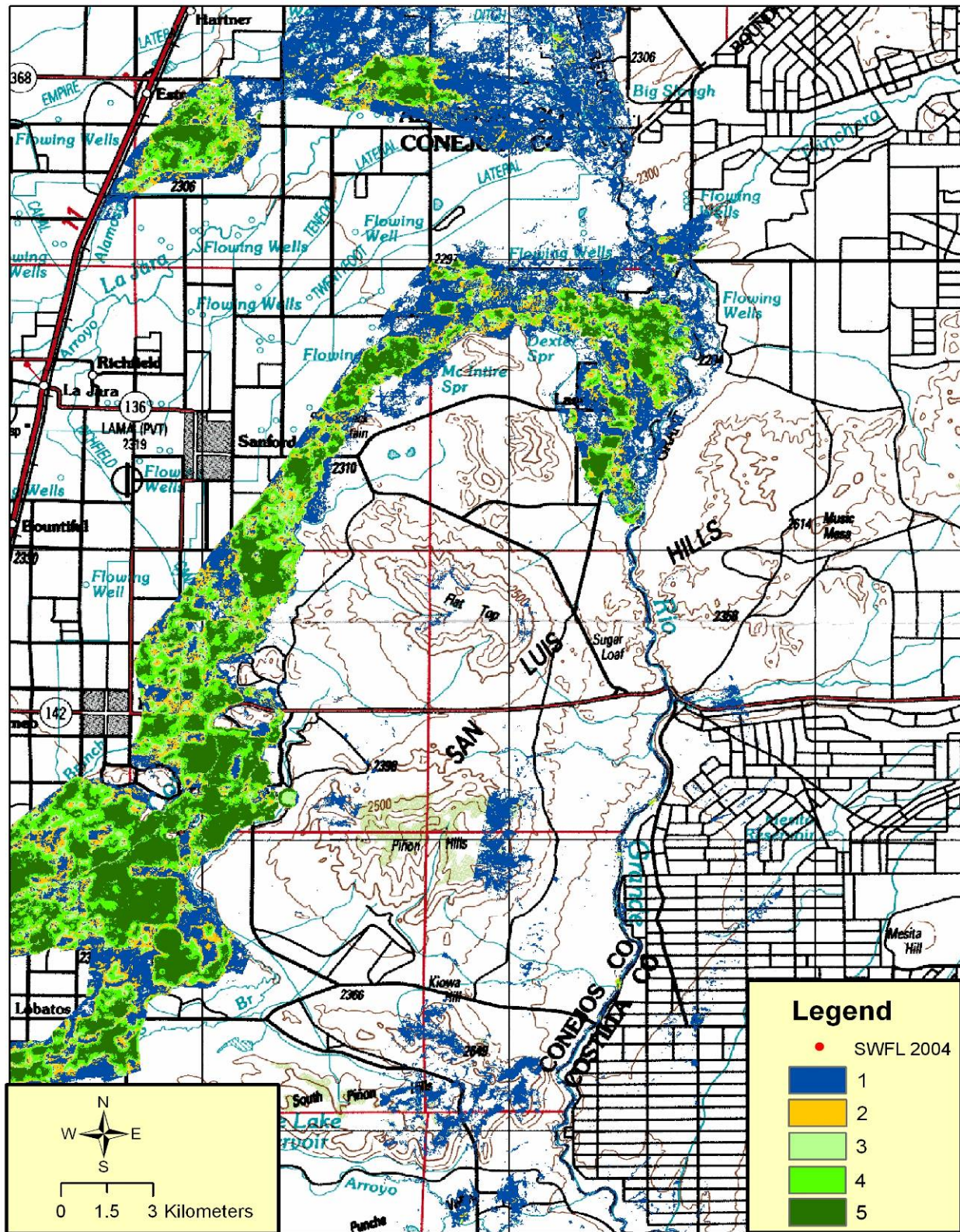
Figure M. SWFL habitat model output (the 5 probability classes are shown in the legend) and 2004 flycatcher territories, overlain on a 1:250,000 scale USGS topographic map. Note that much of the Probability Class 1 vegetation shown away from the river corridor is non-riparian upland vegetation, possibly pinyon/juniper or pine.