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Testing a model for the prediction of isolated waters in the Sonoran Desert

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ABSTRACT

Water is an extremely limiting resource in arid regions and wildlife managers need accurate inventories of water sources to better manage natural resources. Many of the water sources in the Sonoran Desert are tinajas, solid rock-bottom pools of varying sizes. These and other isolated and ephemeral water resources are essential for desert wildlife. We developed an approach to predict the location of unidentified ephemeral waters in the Sonoran Desert of Arizona, USA. We used Mahalanobis distance based on topographic wetness and slope to indicate groups of pixels in GIS that are the most similar in these aspects to locations of currently known waters. We tested this model in southwestern Arizona at the U.S. Air Force's Barry M. Goldwater Range - East by comparing polygons of predicted waters with random polygons. Seventy-four percent of standing surface water features found were attributed to the predicted polygons derived by our model. The model found a significantly larger water capacity in predicted polygons than in random polygons. This modeling technique could provide a new tool for researchers and land managers to better estimate potential water resources for wildlife conservation objectives in arid landscapes.

1. Introduction

Water is a critically limiting resource for many species of wildlife, especially in arid regions. In the Sonoran Desert, ephemeral and isolated waters can be found in intermittent streams, rock pools (tinajas), springs, and seeps. Biodiversity in arid lands tends to be concentrated around these areas of water, even if that water is very ephemeral in nature (Souza et al., 2006). These sites are recognized as rare, patchily distributed (Shepard, 1993), and having cultural and biological value (Burke et al., 2002). Isolated desert springs, which provide more persistent sources of waters, can be as far as 100 km apart and are difficult for many types of organisms to move between (Shepard, 1993). Hence, expanding the knowledge of surface water types and localities is very important for wildlife management. Isolated and ephemeral waters in arid lands often are home to endemic and rare species of vertebrates and invertebrates (Hendrickson and Minckley, 1985). These resources are literal oases in the landscape, but are considered threatened and sensitive to changes in precipitation, rising temperatures, and other climate change impacts (Glick and Stein, 2010; Field et al., 2007).

Climatic shifts are projected to reduce water availability in the southwestern United States due to a reduction in precipitation and increased evaporation as a result of the increased temperature (Karl et al., 2009; Seager et al., 2007; Field et al., 2007). Less precipitation means less water will be available to recharge aquifers and as a result springs will dry (Field et al., 2007). Groundwater extraction has already contributed to a reduction in water tables across the southwest (Carpenter, 1999; Konikow, 2013) and to available surface water at seeps, springs, and other historically wet areas (Patten et al., 2008). Continued urban population expansion (Swanson, 1989) and agricultural need (Karl et al., 2009; Ackerman and Stanton, 2011) will continue to enhance groundwater depletion and the reduction of reliable surface waters available to both humans and wildlife.

Other sources of surface water in arid environments will be impacted by climate change and anthropogenic influence too. Water available for wildlife will be reduced by several related mechanisms. Ephemeral water sites such as charcos, tinajas, and

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intermittent streams are dependent on precipitation. Rain events are projected to occur less frequently with a higher intensity of precipitation per event (Karl et al., 2009). Tinajas (rock-bottom pools) hold a limited amount of water, and once they are filled excess water runs off into the surrounding soil. As fewer rain events occur it is more likely that these ephemeral waters will dry completely between each rain event. These shortened hydroperiods will only be exacerbated by the increased evaporation caused by increasing temperature regimes (Glick and Stein, 2010; Field et al., 2007). The smaller the reservoir of water, manmade (Goodrich and Ellis, 2008) or natural, the greater the impact reduced rain frequency and increased evaporation incurs upon them. Increased intensity of rainfall events in the southwest also increase the risk of flooding and the sedimentation caused by floodwater runoff. Reduced capacity for water-storage could occur in tinajas, charcos, and intermittent streams. Wildlife will have less water available in an already water limited environment.

Since the 1940's, natural resource managers have been monitoring existing water sites and constructing new developments for wildlife in the desert southwestern United States (Rosenstock et al., 2004; Wright, 1959). Active management of water for wildlife can help offset reduced access to water caused by factors such as landscape fragmentation and climate change (Rosenstock et al., 2004). Locations that already have water are arguably the best places for conservation efforts such as future water developments. Focusing conservation efforts at these known water locations (currently or historically) could provide managed waters that are less ecologically abrasive, or are less likely to illicit a negative ecological consequence within the natural stochasticity of the spatial extent of interest, than novel catchments. Natural waters appear not to experience some of the problems associated with artificial waters (Griffis-Kyle et al., 2014). These known waters would be less "out-of-place" within the natural context of the area. The conservation of sites that already have water is an effective step in maintaining biodiversity in arid environments (Minckley et al., 2013; Unmack and Minckley, 2008).

Permanent springs and ephemeral pools are often difficult to find when hidden in rugged desert terrain (Shepard, 1993). There is also some speculation by experts that many of the springs that do exist are not currently known (Stevens and Meretsky, 2008). For example, the number of springs mapped in the steep topography of the Colorado Plateau, north of our study area, might be as low as 25 percent (Burke et al., 2002). Because these sites provide wildlife with a critically limiting resource, resource managers need a thorough and accurate inventory to make the most informed and effective decisions.

Management of isolated and ephemeral waters will become increasingly important as climate shifts stress surface-water availability. We created a model that predicts the location of water sites based on topological and geographic features including topographical wetness and slope. This model provides a tool for land managers in the Sonoran Desert and other arid regions to better understand and evaluate the availability of aquatic resources.

2. Methods

2.1. Study area

This work was conducted at the Barry M. Goldwater Range – East (BMGR-E) in southwestern Arizona, USA on land managed by the U.S. Air Force's 56th Range Management Office (Fig. 1). The area is actively managed for wildlife conservation and game species that depend on water. This is a expanse of Sonoran Desert that includes six mountain ranges separated by basins – elevations range from approximately 60 m–1220 m above mean-sea level. Habitat and vegetation varies between mountain ranges, with creosote bush, mixed-cacti, paloverde trees, and other mixed-scrub common (Hardy and Morrison, 2000) along with patches of semi-arid grasses occurring (Shreve, 1942). The range receives less than 12.7 cm (5 inches) of rain annually, often coming in one or a few patchy events (BMGR INRMP, 2012). Summer temperatures frequently reach and exceed 43 °C (110 °F) and were recorded in the field using iButton Hygrochron dataloggers (Maxim Integrated). They recorded temperatures in part sun/part shade reaching over 56 °C (134 °F; unpublished data, J.C. Drake & J. Calvert, 2013). Because of these high temperatures evaporation potentials exceed rainfall (BMGR INRMP, 2012). Most surface water is available in tinajas or desert wildlife catchments, which are constructed water troughs connected to reservoirs of water (BMGR INRMP, 2012).

2.2. Predicted polygon generation

2.2.1. Generalized approach

To generate the predicted polygons we created a model using Mahalanobis Distance analysis of spatial aspects of the landscape. Mahalanobis distance can be used to quantitatively measure landscape variables against ideal criteria to determine how closely they resemble the ideal (Jenness, 2003). The ideal criteria in our analysis are based on locations that already contain water. To create our list of known existing waters, we combined water source point data from the military base's datasets, excluding points that were either unlabeled or labeled "catchment." Because these points indicated unknown and artificial water sources respectively, they did not fit our criteria of confirmed natural water sources. We excluded all of Arizona Game and Fish "Wildlife Waters" points because they were all labeled "catchment." The final sample point dataset contained 148 points, each indicating an individual, naturally-occurring water site. Spatial calculations were performed in Esri's ArcGIS 9.3 software suite. The inputs to create the Mahalanobis Distance values were derived from Topographic Wetness Index (TWI), and Longitudinal and Cross Sectional Curvature rasters sampled at interpolated water location points in a region around the BMGR-E. We then calculated the mean vector and covariance matrix for variable values at known tinajas and modified tinajas on the study area. Next, we calculated Mahalanobis Distance surfaces, showing the similarity of all points on the landscape to the mean vector and covariance matrix of TWI, Longitudinal Curvature and Cross-Sectional Curvature for the known water sites. We identified the $\leq$5% of the BMGR with the greatest similarity to the mean vector of TWI and Curvature values. These are the regions with the lowest Mahalanobis Distance values, meaning they are the most similar to the water sites.

2.2.2. Correction of locations

Upon visual comparison of the sampled points in the GIS database with aerial imagery (Esri's World Imagery map service and Microsoft's Bing map service, both viewed in May, 2010), we observed that many sites were shifted in various directions and distances (max approximately 60 m) from visible water locations in the imagery. This meant that either the coordinates of the waters sites were inaccurate, the imagery was inaccurate, or the sites had been moved since they were mapped. If the point locations are inaccurate the method that we used, Mahalanobis distance would use an incorrect underlying raster value. To correct for this, we sampled the raster values around a point. We interpolated the 4 closest cells using a bilinear method to interpolate values vertically then horizontally (Fig. 2). This was used to calculate both TWI and curvature values.

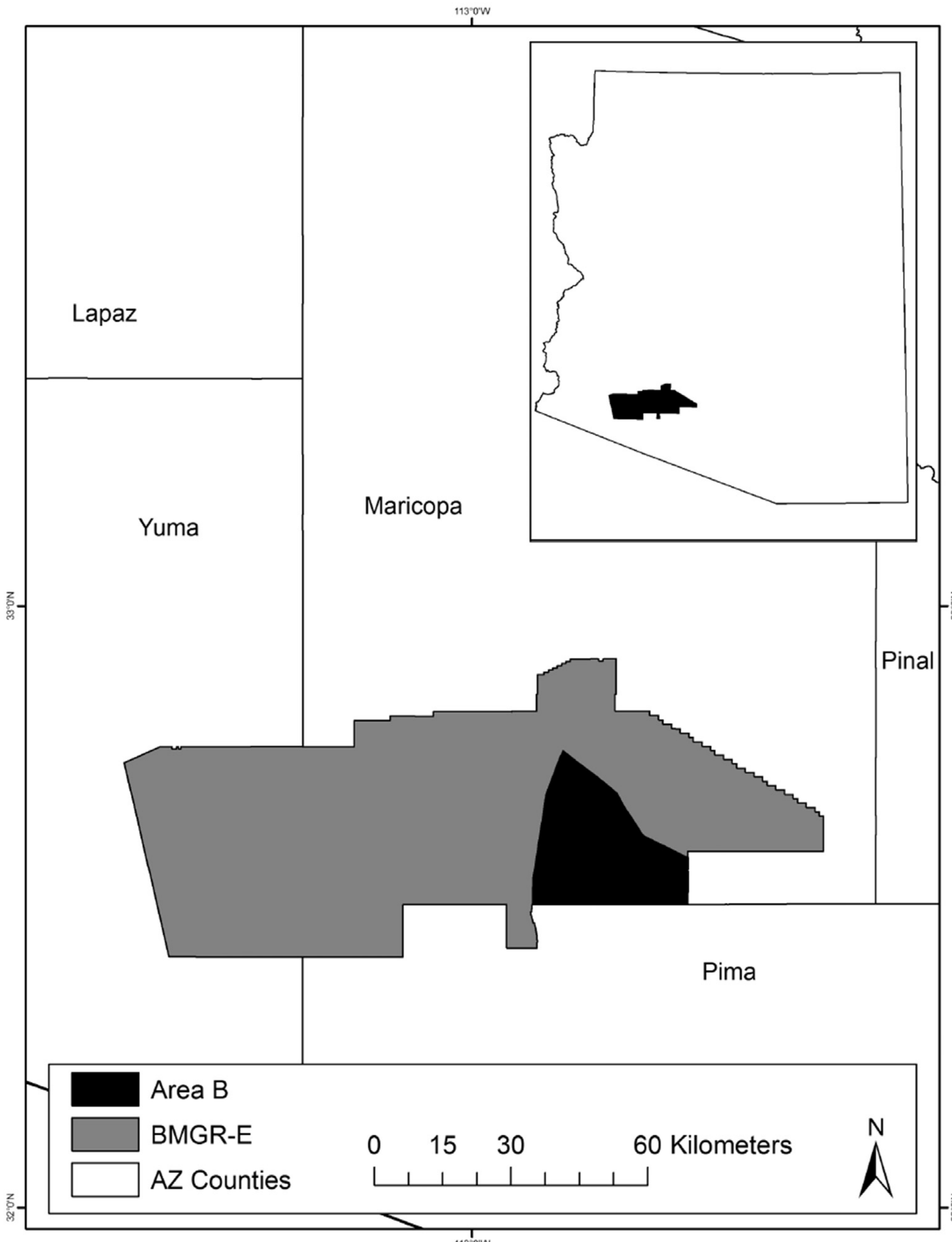

Fig. 1. The study area (Area B) within the Barry M. Goldwater Range – East where the predictive model was applied to search for unknown ephemeral waters.

2.2.3. Topographic Wetness Index

Topographic Wetness Index (TWI) was used as an input for the calculation of Mahalanobis distance. TWI is a tool that can help predict hydrological concentrations using the local upslope catchment area and the local slope (Beven and Kirkby, 1979; Sørensen et al., 2006). TWI is sometimes referred to as the Compound Topographic Index (Moore et al., 1991). The general equation for this metric is defined in Equation 1 (Beven and Kirkby, 1979; Sørensen et al., 2006).

$$TWI = \ln\left(\frac{Specific\ Catchment\ Area}{\tan\beta}\right) \tag{1}$$

Where:

$$Specific\ Catchment\ Area = \left(\frac{Catchment\ Area\,(m^2)}{Unit\ Contour\ Length}\right)$$

$$\tan\beta = Percent\ slope$$

Equation 1 The generalized Topographic Wetness Index Equation.

2.2.4. Specific catchment area

Catchment area, the contributing watershed that drains into a point, was standardized to *specific* catchment area to differentiate between catchments that drain to a single point versus catchments that have an outlet. The specific catchment area gives a measure of water force at the watershed boundary, so catchments that drain to

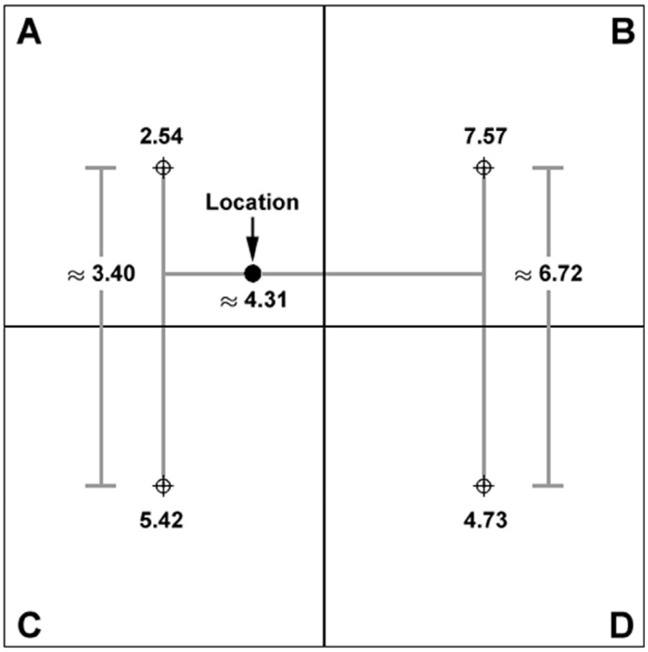

Fig. 2. Sampling the raster cells around the point location to counteract inaccurate locations of waters. To compensate, we used bilinear interpolation to estimate the value from the 4 closest cells. Values are first interpolated at the Y-coordinate of the point location along the lines connecting the cell centers of cells A and C, and of cells B and D. Then a final value is interpolated along the X-axis between these two interpolated values. In this case, the interpolated value of the point is approximately 4.31, while the exact cell value of the point is 2.54.

a point have higher topographic wetness values than catchments that have outlets. We calculated specific catchment area by dividing the contributing area by the length of a line representing the outlet of that catchment (Equation 1). The length of this line was referred to as the "unit contour length" in TWI literature (Beven and Kirkby, 1979; Sørensen et al., 2006). In raster analysis, this line is typically understood to be the edge of a raster cell (Tarboton, 1997; Yang et al., 2011).

We modified Tarboton's (1997) topographic wetness approach to account for true ground surface area in order to get a more accurate representation of water collecting surface within catchment areas. Our source elevation data was a 1 Arc-Second raster DEM (roughly 30 m resolution on the ground) downloaded in May, 2010 from the National Elevation Dataset (Gesch, 2007; Gesch et al., 2002). We used the ArcGIS extension DEM Surface Tools (Jenness, 2010) to calculate true surface area over the landscape, and used this surface area rather than planimetric area in the TWI equation.

Because we used latitude and longitude data, the raster cells are trapezoids rather than squares, with cell heights greater than cell widths, and therefore do not have a single edge length to divide by. Hence, we defined the denominator (Equation 1) as the square root of the planimetric trapezoidal area. If the cells were squares, as in a traditional projected raster, then the square root of the area is the traditional cell size and thus would be equivalent to Tarboton's approach. We calculated the planimetric area of the trapezoidal cells using DEM Surface Tools (Jenness, 2010) and then calculated the square root of the all the cells using the ArcGIS Raster Calculator. We then calculated a "Specific Area per Cell" raster by dividing the surface area raster by the square-root-of-planimetric-area raster.

The numerator to Specific Catchment Area (Equation 1) is the total catchment area in square meters. To calculate this, we performed a weighted flow accumulation analysis using the ArcGIS Flow Accumulation tool. This calculated the accumulated upslope area for all raster cells, with each cell weighted by the "Specific Area per Cell" value for that cell. By weighting those upstream cells by the "Specific Area per Cell" values, the resulting flow accumulation raster provides the specific catchment areas that contribute to each cell.

Because the Flow Accumulation tool only gives the accumulation that contributes to each cell, cells with no contributing area consequently have a 0-value for specific catchment area. We considered the area within the cell itself as contributing to the flow of that cell, so we added the "Specific Area per Cell" values to the flow accumulation values to produce the final specific catchment area raster.

We calculated Percent Slope using the 4-cell method on latitude/longitude data using DEM Surface Tools (Jenness, 2010) (Fig. 1). We used the 4-cell method rather than the standard ArcGIS 8-cell method because it is marginally more accurate (Jones, 1998), and we calculated slope on the original unprojected DEM in order to avoid projection distortion and loss of precision.

To calculate the final TWI raster (Equation 1), we first inverted our slope raster using the Invert Raster tool (Jenness et al., 2010). Following an example by the USGS (2006), we added 0.0001 to the slope values in order to avoid division by zero errors in the final raster. We then multiplied our inverted percent slope raster by our specific catchment area raster. Finally, we took the natural log of the quantity to get the final TWI raster.

2.2.5. *Longitudinal and cross-sectional curvature*

In addition to TWI, we used longitudinal and cross-sectional curvature data in our Mahalanobis analysis. We used DEM Surface Tools "Curvature" (Jenness, 2010) to calculate both curvatures. Longitudinal curvature is similar to the curvature of a line of intersection between: 1) the landscape surface, and 2) a vertical plane oriented in the direction of steepest slope (i.e. aspect) (Porres de la Haza and Pardo Pascual, 2002; Wood, 1996; Zevenbergen and Thorne, 1987) and should be interpreted the same as the standard ArcGIS "Profile" curvature. Cross-sectional curvature is similar to the curvature of the line of intersection between: 1) the landscape surface and 2) a horizontal plane (i.e. the curvature of a contour line) (Porres de la Haza and Pardo Pascual, 2002; Wood, 1996; Zevenbergen and Thorne, 1987) and should be interpreted the same way as ArcGIS "Plane" curvature. We used the DEM Surface Tools extension rather than the standard ArcGIS functions because our DEM was in a geographic coordinate system, and ArcGIS does not calculate curvature correctly with this type of data. This tool also allowed us to avoid projection distortion. These outputs were then used for the Mahalanobis distance analysis.

2.2.6. *Mahalanobis Distance analysis*

We computed Mahalanobis Distance values for every raster cell in the BMGR-E using the Mahalanobis Distance component of the Land Facet Tools ArcGIS extension (Jenness et al., 2010). These Mahalanobis Distance values numerically describe how similar each cell is to known tinaja locations based on the TWI, Longitudinal and Latitudinal Curvatures in each cell, compared to the average TWI and curvature values at our known tinajas (Clark et al., 1993; Knick and Dyer, 1997; Farber and Kadmon, 2003).

We initially identified the 2.47% of the BMGR-E with the greatest similarity to the mean vector of TWI and Curvature values. These are the regions with the lowest Mahalanobis Distance values, meaning they are the most similar to the known water sites. We identified this final region by using the ArcGIS "Less Than or Equal" tool to query for regions meeting progressively lower Mahalanobis threshold values until less than 2.5% of the BMGR-E was selected. Upon completion, our map of potential sites covered 2.47% of the

BMGR-E and was composed of raster cells that had Mahalanobis Distance values ≤ 0.292.

Unfortunately for future potential field work, many of the areas identified in this first pass were diffuse clouds of isolated single raster cells. Therefore we restricted our analysis to areas with high densities of raster cells.

We used the "Calculate Density Surface" tool (Jenness et al., 2010) to calculate the density of these raster cells in a 5-cell radius circular neighborhood (radius $\approx$ 150 m, n = 81 pixels). We then identified all regions with a density > = 15% (i.e. > = 12 cells of "best" Mahalanobis values in 81-cell neighborhood) and generated a polygon feature class of these using the ArcGIS tool "Raster to Features". Finally, to reduce our field testing to a manageable size, we deleted all polygons smaller than 5 ha. These cutoff thresholds are arbitrary, but helped screen out isolated raster cells and allowed us to focus on clusters of pixels in close proximity to each other.

Our final polygon feature class was composed of 39 polygons of potential water locations within Area B of the BMGR-E study area (Fig. 3).

2.3. Random site generation

To assess the ability of the model to predict water locations, we compared the predicted polygons to randomly generated polygons by ground-truthing locations. To create random polygons, we took the total area in the predicted polygons and divided it by the number of predicted polygons such that we sampled the same number and total area of polygons in both the predicted and random classes. We created 39 circular polygons of 7.2 ha each, using custom VBA code in ArcGIS. We also constrained the location of the random polygons using the following criteria: (1) they must not overlap predicted polygons or existing known water sources; (2) they must lie within the area of BMGR-E known as "Area B; " and (3) they are within 1.5 miles of roads. These last two criteria were necessary for addressing access issues to the study sites during the study period. We ended up with a total of 39 random polygons and 39 predicted polygons within the study area for a total of 78 polygons to be sampled (Fig. 3).

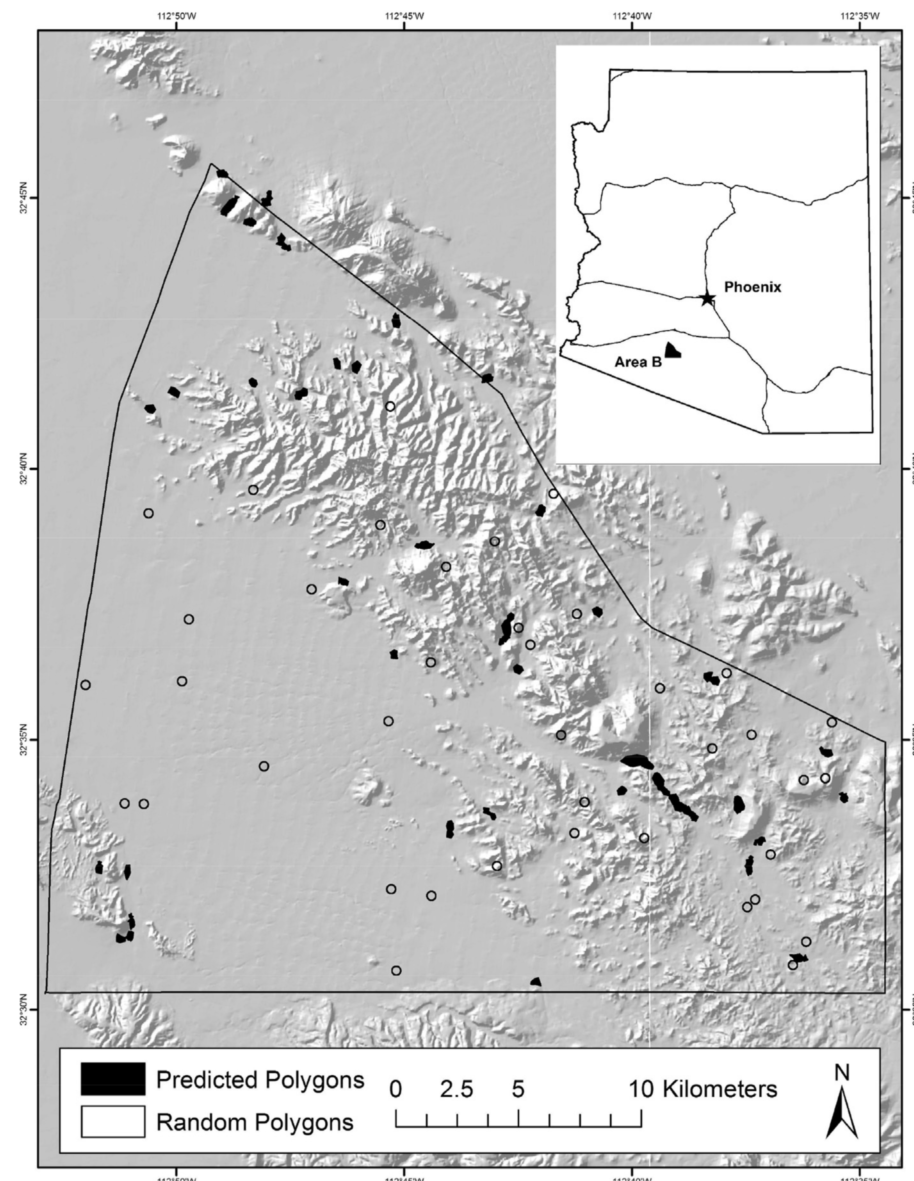

Fig. 3. "Area B" study area within the BMGR-E near Ajo, AZ, USA with 39 predicted and 39 random polygons created via our model.

2.4. Ground-truthing

We ground-truthed polygons during the summer of 2012. Using DNRGPS (MDNR, 2012), a free software application developed by Minnesota's Department of Natural Resource, we imported the locations of the polygons from ArcMap to the GPS handsets (GARMIN GPSmap 60CSx). We searched polygons on foot by systematically modifying the search pattern based on landscape and vegetation cover. The objective was to cover the entire polygon with a complete visual search of the ground for sites that could be considered aquatic resources. Aquatic resources or "sites" are here defined as those areas that either: 1) actually have water present, or 2) have the ability to retain water at the location based on evidence at the site. Researchers carried GPS handsets and followed a search pattern that covered the entire area of each polygon with parallel search lines no farther than 10 m apart from each other using GPS tracking and ground based landmarks to insure complete coverage. Searches were modified to accommodate reduced lines of sight when dense vegetation or other geographic features impaired them. Sometimes the search lines were reduced to a little as 3 m apart to insure a complete visual search of the area within polygons. Some polygons contained more than one distinct water-retaining site. In this case, each individual site was recorded. Sites without water retention possibility were recorded as water site absent. This was done for both predicted and random polygons. When a site was discovered, measurements of size and depth were taken with open reel field measuring tapes and rulers. Water capacity for discovered sites was determined using the equation for the volume of half an ellipsoid (Equation 2). We used a minimum volume of 5 L calculated using Equation 2 to define locations as viable aquatic sites. Sites that did not have at least a 5 L storage capacity were excluded from count and analysis. Any sign or evidence of animal use was also noted for each discovered site.

$$V = 0.5\left(\frac{4}{3}\pi abc\right) \tag{2}$$

Equation 2 Volume of half an ellipsoid, where a and b are the radii of length and width respectively; and c is the depth of the water surface feature.

2.5. Data analysis

Once the data were collected and accumulated, a contingency table analyses and likelihood ratios were performed in SPSS on the datasets between the prediction and random datasets to determine the model's success in finding water (SPSS version 21.0.0.0). To reduce the risk of not predicting waters where they might exist, we used $\alpha = 0.1$. Data were analyzed using three different approaches. The first and most coarse analysis was performed by looking at success of the model at the polygon level; polygons either contained water or they did not. The second method compared the number of sites discovered per each type of polygon. The third method determined the success of the model by the total volume of water at sites found within each type of polygon.

3. Results

75 polygons were searched and of these, 38 were predicted polygons and 37 were random polygons. Three polygons could not be searched due to access and timing limitations. When we searched the polygons, 15 of the 38 (39.5%) predicted polygons contained water or water retaining features, and 10 of the 37 (27.0%) random polygons contained water or water retaining features. It was possible for each polygon to contain more than one feature or none at all. There were 58 total sites within the predicted polygons designation and 43 within the random. These included sites where water retaining features were present and sites where no water retaining features were present. Out of the total predicted sites, 34 contained at least one water-retaining feature and 24 were absent of these aquatic resources. Within the random polygons, only 12 of the 43 sites showed signs of aquatic resources or water retention capabilities. Another way to address the differences between random and predicted polygons and the features they contained was the amount of water available to wildlife. The total volume of water capacity found in predicted sites far exceeded the volume found at random sites (Table 1).

Our model correctly predicted water approximately 60% of the time, with only 26% of the total aquatic resources being discovered at random. In the first analysis, predicted success compared against random success of finding polygons containing water was not significantly different ($\chi^2 = 1.3$, df = 1, $p = 0.2$). The second analysis of the data, using the number of water sites found per polygon, showed the predicted model discovered significantly more sites per polygon than at random based on their likelihood ratio ($\chi^2 = 8.5$, df = 1, $p = 0.1$). Of the sites found to contain water retention features, approximately 74% of these were attributed to the polygons denoted by the predictive model (Table 1). Analysis of the model success based on volume of water capacity found was strongest ($\chi^2 = 36.5$, df = 26, $p = 0.08$). The model found a significantly greater amount of water, over two orders of magnitude greater, within the predicted polygons than in the random polygons (Table 1).

Approximately 63% of water sites found had some indication of wildlife use present. We observed tracks, scat, animal remains, and disturbed vegetation. We also saw invertebrates, amphibians, reptiles, and birds all using waters before we approached some discovered sites. Examples of wildlife water use we observed include, but are not limited to: clam shrimp, *Eulimnadia texana*, using small sites for their life cycles (Marcus and Weeks, 1997); red-spotted toad, *Anaxyrus punctatus*, choruses; desert bighorn sheep, *Ovis Canadensis*, using sites for hydration; tadpoles from genera including *Incillius*, *Anaxyrus*, and *Scaphiopus* developing in the waters; birds thermoregulating in the waters (Steen and Steen, 1965); predators hunting (Destefano et al., 2000); animals, like coachwhip snakes from the *Coluber bilineatus and Coluber flagellum* complex, using water sites as a temporary refuge (J. Drake, J. Calvert; personal observation); and the use of water sites for dispersal by backswimmers, *Notonecta glauca* (Schwind, 1984) and other aquatic invertebrates.

4. Discussion

Our model was successful at finding aggregations of water sites that contain a greater volume of water than was found randomly. The predicted polygons contained features that could hold or were holding approximately 746 kl of water as compared to the random

Table 1
Results of searching for previously unknown ephemeral water sites in Area B of BMGR-E using a new predictive analysis of topographic features compared to random searches.

	Predicted	Random
Water capacity total (liters)	746,142.2	4279.4
Mean capacity (liters)	19,635.3	115.7
Standard error (liters)	14,110.1	64.1
Polygons searched	38	37
Total sites (absent and present)	58	43
Sites with water features	34	12

polygon total water retention capacity of approximately 4.3 kl, this is over 2 orders of magnitude more water. These are large biologically significant differences in an environment that is extremely water-limited. Water sites that are large and stable are better candidates for management as wildlife waters. Although also important for biodiversity (Souza et al., 2006), smaller water pockets may not be large enough for land managers to efficiently manage as wildlife waters.

Desert areas have been searched for larger waters both on foot and by air, but we still have not found all the larger water sites as evidenced by our model's success. Applying our model, we identified 12 polygons (34%) with over a kiloliter of water and 4 polygons (10%) with over 10 kl of water. We described a large site new to managers that now will be included in the management of water for wildlife in this area (Fig. 4). This site was a tinaja, a depression in a rocky substrate that can retain water, and is approximately 1 m deep, 3 m wide, and 5 m long. Being composed of rock on 3 sides and on the basin's bottom, it is exceptionally resistant to water loss from seepage through the ground. It is dammed by gravel and rock on the remaining side. A small amount of vegetation and the steep nature of the sides provided shade, which helps minimize evaporation. Also the shape of the tinaja was conducive to water retention, because the steeper basin sides led to less surface area exposed to evaporation losses. This larger basin was the main area of water retention in a series of smaller sites along the drainage. This site contained many signs of wildlife use. It contained red-spotted toads in four different life states; large mammal tracks; bird feathers; honeybees, *Apis mellifera* complex; spiders, flies and butterflies; *Stratiomyidae* larvae; and human foot traffic (trash and campfire remains). This was not the only site discovered among the predicted polygons that could be managed for wildlife, but it was a good example of what was found.

Fig. 4. Aquatic resource discovered by our predictive model that was previously unknown to range managers in Area B of the BMGR-E. Range managers will now be able to include this water in the management of water resources for wildlife. The predictive model identified more areas that contained similar water sites like this than random searches did.

Many of the smaller sites present are only usable for short durations, likely on the scale of less than 48 h. For some species this is of limited use, but for others, it can be enough to accomplish necessary natural history events. Some aquatic invertebrates can grow, breed, reproduce, and lay encysted-embryos within the short window provide by these sites (Marcus and Weeks, 1997). Others like Couch's spadefoot toads, *Scaphius couchii*, have plastic developmental rates during larval stages, as short as 8 days, which allows them to take advantage of water sites that are extremely ephemeral (Newman, 1988). These short-lived sites can also provide wide-ranging animals like desert bighorn sheep, endangered Sonoran Pronghorns, mule deer, mountain lions, and birds important opportunistic water resources.

Connectivity of desert water sites is necessary for wildlife dispersal which functions in maintaining gene flow and providing organisms the ability to use scarce resources across the landscape. By identifying previously unknown waters, managers can enhance the ability of the water sites to promote connectivity for wildlife species of interest. As connectivity is dependent on each species dispersal capabilities, multiple scales of connectivity need to be considered when managing a landscape. Maintaining these water resources can help prevent or mitigate the effects of habitat fragmentation, habitat loss, and climate change. Losing connectivity between populations and patches of habitat can prevent the dispersal of animals to suitable habitat areas and lead to local extinctions (Fahrig and Merriam, 1994). Finding and managing ephemeral waters helps increase a system-wide resilience by identifying areas that animals will be more likely to utilize for movement. These areas can then be managed to sustain connectivity between habitat patches and populations at multiple scales.

Our predictive modeling can be an important tool for land managers in arid terrain. Existing water resources are currently scarce, and climate change and population growth in the American Southwest may increase water-related stress to desert ecosystems. The addition of existing aquatic resources to the manager's inventory can allow a more appropriate distribution of time, effort, and funds towards conservation efforts. In the Sonoran Desert, for example, the Arizona Game and Fish Department manages man-made catchments in remote regions for wildlife use. If more natural water sites were known, it would allow better planning for man-made catchment additions to the landscape. Identifying naturally occurring tinajas, that could be modified to increase storage capacity and reduce evaporation loss, could provide an alternative solution to making anthropogenic catchments while still achieving many of the same results. This would help reduce the need to haul water to new artificial catchments if there is still naturally occurring water available for wildlife. Hauling water to artificial catchments by truck cost an average of $144,000 a year between 1996 and 2001 in Arizona alone (Bloom, 2003).

This successful model was specific for the study site; however, our method for generating the model could be applied to other areas, especially in arid regions where water is such a limiting resource. By adjusting site-specific inputs and parameters to suit the needs of the areas of interest, this model can provide a strong and insightful new addition to a land manager's toolkit. The ground-truthing component of this tool is labor intensive, but in areas where water resources are limited or projected to become more limited, the labor is likely a good investment of resources. Application of this technique across different arid regions and landscapes should be performed to help provide better insight to the availability of aquatic resources that are generally overlooked by previous means and inventories.

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Appendix A. Supplementary data

Supplementary data related to this article can be found at http://dx.doi.org/10.1016/j.jaridenv.2015.02.018.

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