Evaluating Lost Person Behavior Models

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Abstract

US wilderness search and rescue consumes thousands of person-hours and millions of dollars annually. Timeliness is critical: the probability of success decreases substantially after 24 hours. Although over 90% of searches are quickly resolved by standard "reflex" tasks, the remainder require and reward intensive planning. Planning begins with a probability map showing where the lost person is likely to be found. The MapScore project described here provides a way to evaluate probability maps using actual historical searches. In this work we generated probability maps the Euclidean distance tables in (Koester 2008), and using Doke's (2012) watershed model. Watershed boundaries follow high terrain and may better reflect actual barriers to travel. We also created a third model using the joint distribution using Euclidean and watershed features. On a metric where random maps score 0 and perfect maps score 1, the Euclidean distance model scored 0.78 (95%CI: 0.74–0.82, on 376 cases). The simple watershed model by itself was clearly inferior at 0.61, but the Combined model was slightly better at 0.81 (95%CI: 0.77–0.84).

1 Introduction

Searching can be arduous, time consuming, and expensive. These characteristics justify "taking the search out" of search and rescue (SAR), a worthy but unreachable goal: some search always remains, and search requires planning. The probability of survival in land-search decreases with time (Pfau 2011). Good planning makes search more efficient, reducing costs and saving lives. The first step is deciding where to search: some areas are more likely than others. In fact, some areas are so much more likely that >90% of searches are resolved within a few hours based on "reflex" tasks to the high-probability areas (Koester 2008). However, the remaining cases require and reward explicit planning using methods first developed in WWII (Koopman 1980). Planning begins with a probability map showing where the lost person is likely to be, allocates search effort to minimize expected time to find, and updates the map after each operational period to account for completed searches, clues found, and possible subject motion. In wilderness search (WiSAR) this is often either intuitive or manual, but with increasing use of Geographic Information Systems (GIS) planning tools, WiSAR can create and update detailed probability maps (Doherty et al. 2014). But how to tell a good map from a poor one?

In this article we generate and compare several probability maps for hundreds of historical WiSAR incidents for which there were good initial and final coordinates. The incidents come from the International Search and Rescue Incident Database (Koester 2010). Maps are scored using a simple and robust metric from crime-mapping (Rossmo 1999). While there are a few papers on producing WiSAR probability maps (see for example: Castle 1998; Soylemez and Usul 2006; Sarow 2011; Lin and Goodrich 2010; Ferguson 2013; Doherty et al. 2014) there has been no evaluation of the relative accuracy of different methods. This article is the first to establish a performance baseline we hope will be surpassed repeatedly.
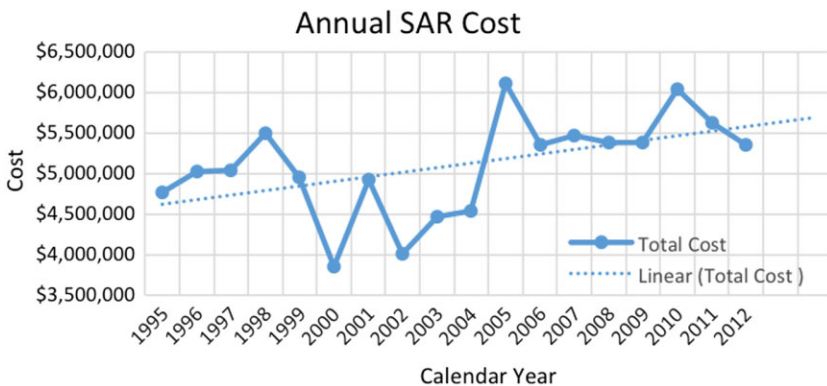
In practice, the most common way to assign probabilities to search regions is with subjective estimates based on quartile distance statistics, particularly the summary statistics found in Koester (2008): a simple 'bulls-eye' formed by the 25%, 50%, 75%, and 95% probability circles. Thus the distance ring model serves as a baseline. We compare it to a relatively recent watershed model (Doke 2012; Doherty et al. 2014), and a novel combination of the two.

The Introduction briefly reviews WiSAR costs and the use of probability maps in WiSAR. Section 2, Scoring, introduces the MapScore website, Rossmo's metric, and its desirable properties. Section 3, Data and Methods, introduces the models. Section 4, Results, evaluates these models. Section 5, Discussion, provides a brief conclusion and recommendation for future work.
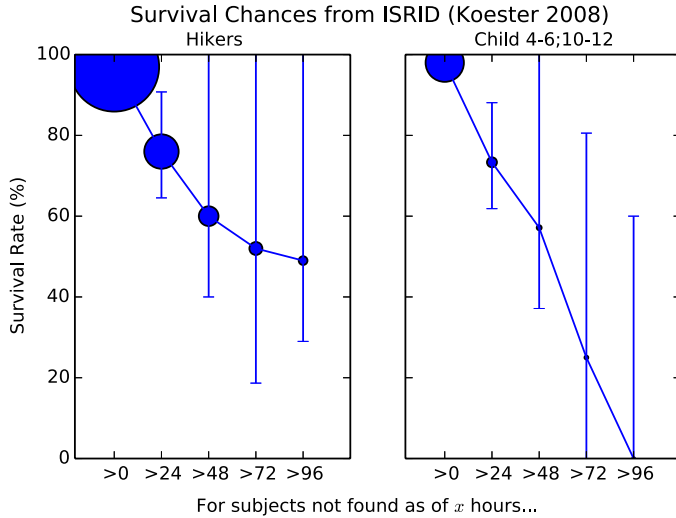
1.1 Cost and Time

In the US, the National Park Services (NPS) alone conducts thousands of search and rescue operations annually. According to NPS and the US Park Police (2012), the NPS conducted 4,080 SAR operations at a total cost of $5.3 million, or roughly $1,375 per mission. Figure 1 shows the increasing costs for SAR operations over the past several years (1995–2012).

The price appears to be rising faster than inflation: from 1992 to 2007 the NPS responded to 65,439 incidents at an average cost of $895 per operation (Heggie and Amundson 2009). However, from 2000 to 2012 the NPS responded to 53,351 incidents at an average cost of $1,163. In constant 2013 US dollars, the average increase is about $160 per case. Nearly half the total cost was overtime; the remainder was mostly aircraft (Heggie and Amundson 2009). Yosemite National Park alone accounted for 25% of the total costs ($1.2 million).

Figure 1 Annual cost for Search and Rescue operations conducted by the National Park Service at constant 2013 dollars

Figure 2 Probability of successful rescue by time, for Hikers (left) and Children (right). From data in (Koester 2008). Marker size indicates number of cases. Points are drawn at the observed frequency; Error bars show 95% range based on smoothed resampling. The central tendency is clear: time is not on your side.

Time is the other key issue. Figure 2 shows the decreasing chances of successful rescue over time for hikers and children aged 4–6 years-old (Koester 2008; Pfau 2011). The decline is due to a combination of injuries, exposure, exhaustion, and dehydration. The larger the search area, the longer it takes to search. Therefore, limiting the search area substantially improves the chance of rescue.

1.2 Probability Maps

Mathematical search theory (Koopman 1980) takes a probabilistic approach because, by definition, the location of any search object is unknown. Some of the earliest documented searches divided the search region into smaller cells, and assigned probabilities to each of those cells based on a structured mix of subjective and objective information. For example, Figure 3 shows maps from the 1967 search for the USS Scorpion (Richardson and Stone 2006) and Figure 4 the 2009 Search for Air France Flight 447 (BEA 2012). Both have been recounted in McGrayne (2012).

Search theory has advanced considerably since its origins in World War II, and modern maritime search planning software like SAROPS (Kratzke et al. 2010) incorporate sophisticated motion models and path planning for searchers. There is nothing comparable for WiSAR. WiSAR has been slow to adopt search theory, in part because good probability maps have been unavailable, and because probability of detection varies dramatically with small-scale changes in terrain and vegetation. (There are also institutional reasons, such as the lack of central authority or central funding for WiSAR.)

Maritime probability maps are conceptually simple: there is a physics of ocean drift, however complicated. There is no equivalent for lost person behavior. Nevertheless, early work by Syrotuck (1976/2000) showed that lost persons generally stayed very close to the initial planning point (IPP): 60% were found within two miles (Euclidean or crow's-flight distance). Based on his 242 cases from New York and Washington states, Syrotuck formulated a
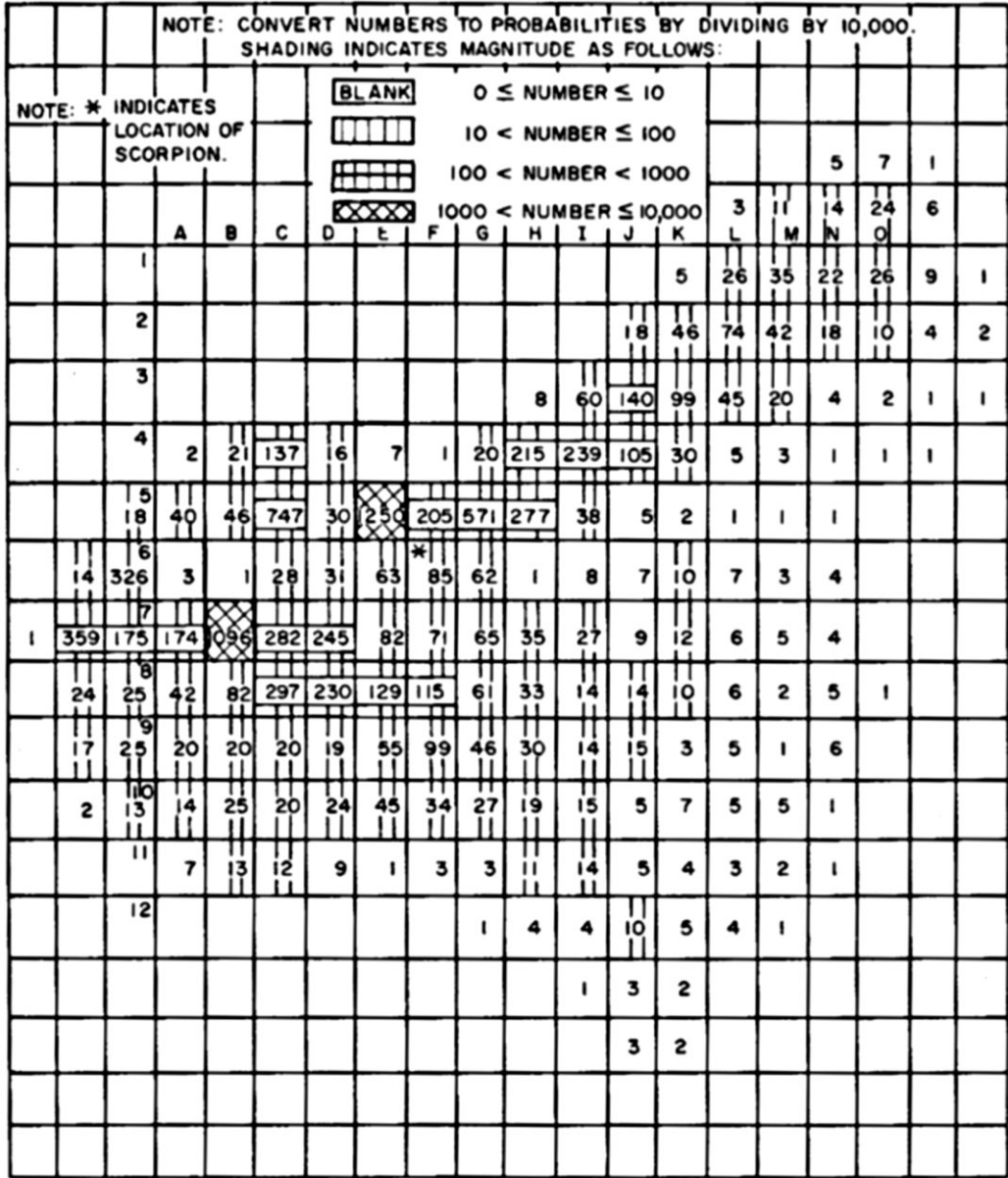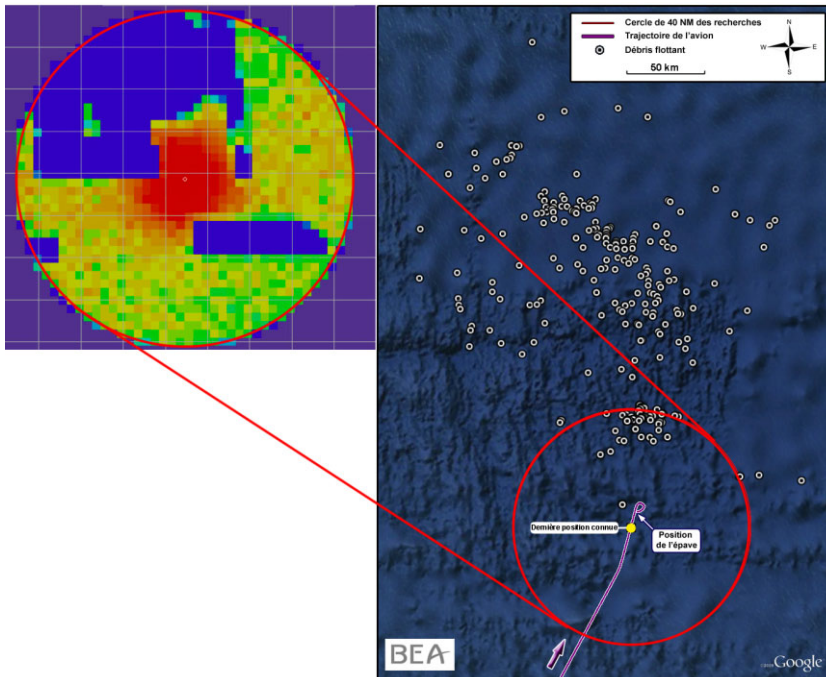
NOTE: CONVERT NUMBERS TO PROBABILITIES BY DIVIDING BY 10,000. SHADING INDICATES MAGNITUDE AS FOLLOWS:

NOTE: ✳ INDICATES LOCATION OF SCORPION.

- BLANK — 0 ≤ NUMBER ≤ 10
- 10 < NUMBER ≤ 100
- 100 < NUMBER < 1000
- 1000 < NUMBER ≤ 10,000

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O		
														5	7	1	
												3	11	14	24	6	
1											5	26	35	22	26	9	1
2										18	46	74	42	18	10	4	2
3								8	60	140	99	45	20	4	2	1	1
4	2	21	137	16	7	1	20	215	239	105	30	5	3	1	1	1	
5	18	40	46	747	30	250	205	571	277	38	5	2	1	1	1		
6	14	326	3	1	28	31✳	63	85	62	1	8	7	10	7	3	4	
7	359	175	174	096	282	245	82	71	65	35	27	9	12	6	5	4	
8	24	25	42	82	297	230	129	115	61	33	14	14	10	6	2	5	1
9	17	25	20	20	20	19	55	99	46	30	14	15	3	5	1	6	
10	2	13	14	25	20	24	45	34	27	19	15	5	7	5	5	1	
11		7	13	12	9	1	3	3	11	14	5	4	3	2	1		
12							1	4	4	10	5	4	1				
									1	3	2						
										3	2						

(Note: a "1" appears in the far-left column at row 7.)

Figure 3 Composite probability map for the USS Scorpion. Used with permission from (Richardson and Stone 2006)

"ring" model, by noting the 25%, 50%, 75%, and 95% zones for eight subject categories including: Hunters, Hikers, Elderly, and Child.[1] Subsequent studies over the last 37 years have collected more data from various regions in the US and abroad. Recently, Koester (2008, 2010) created a unified database containing thousands of cases worldwide. For each of his categories he reported summary statistics for: Euclidean distance, track offset, dispersion angle, find location, scenario, mobility, and survivability.

Figure 4 Air France 447 last known point (LKP, center of circles), floating debris (dots), and Phase III probability map assuming inoperational pingers and accounting for searches in Phase I and II (left inset). The wreckage (arrow) was found about 6.5 NM from the LKP in the red high-probability area. Probabilities decrease from red to orange to yellow to green to blue. Drift map from (BEA 2012). Inset used with permission from (Stone et al. 2011).

Both Syrotuck and Koester create simple probability maps (like the distance-ring model) directly from the summary statistics. In effect, this assumes that by the time the search has started, the subject is not moving appreciably. The surprisingly small distances traveled suggest this is a pretty good assumption in many cases. Nevertheless, ideally the models would account for motion during the search. Several motion models have been formulated (Castle 1998; Lin and Goodrich 2010), which treat the subject's movement as a stochastic process governed by transition matrices which include, for example, a subject's preference for uphill/level/downhill, or moving from one kind of trail/vegetation to another, or simply going straight versus turning.

These approaches generate a probability map by dropping thousands of simulated subjects on the map around the IPP, and running a large Monte Carlo simulation. The advantage of this approach is that the map evolves with time. The disadvantage is that it is hard to fit the extra parameters because, almost by definition, we do not have any information on the lost person's actual trajectory. Progress will depend on having a good method for scoring probability maps, so the fitting algorithms can improve.

In this article, we measure the performance of the baseline Euclidean distance model, and a recent "watershed distance" model (Doke 2012; Doherty et al. 2014) that counts the number of watersheds crossed by the lost person. Both Euclidean and watershed distance models do well because most lost persons do not travel very far.

2 Scoring

2.1 Genesis of MapScore

Rather than scoring the cases offline, MapScore provides a public website with a live leaderboard and the potential to inspire friendly competition among potentially very different approaches. The project began after discussion with the Brigham Young (BYU) WiSAR team about how to compare their Bayesian motion model for lost person behavior (Lin and Goodrich 2010) with our multivariate models. How did either compare with the simple models implied by summary statistics? The BYU team helped fund initial work on what is now the MapScore website (Twardy et al. 2012; Twardy 2012, http://mapscore.sarbayes.org), and this article reports baseline scores for a Euclidean distance-ring model and a simple cost distance model. The chosen score is based on the probability density assigned to the find region.

Search theory has shown that expected search time is minimized by allocating resources to maximize the "probable success rate", or the amount of probability that we "sweep up" with every unit of time (Stone 2007; Koopman 1980; Frost 1996). In theory we might want to score a map based on expected time to find the subject, given optimal plans made on the basis of the probability map and a map of detection indices for each resource. However, that would require contentious assumptions about the resources at hand, how they can be used, and their largely unknown detection indices. For purposes of portably comparing probability maps, we can assume a single resource with detection equal in all regions. Then allocating resources according to the probability density or *Pden* is optimal, and we can use a metric based only on *Pden*. *Pden* is defined as the probability per unit area. The distinction between *Pden* and *POA* (probability of area) matters because many methods assign probabilities to regions of varying size. For example, the distance ring model assigns 25% probability both to the small region around the IPP and to the entire search region beyond the 75% ring. We would prioritize the former because the *Pden* is much higher. But if the final scored map has been rasterized into equal-sized pixels with values equal to the probability contained in that area, then POA and *Pden* are the same. The MapScore metric is suitable for rasterized probability maps.

2.2 Scoring Metric

Rossmo (1999) developed a robust metric *R* to compare probability maps for crime forecasting. The metric is rank-ordered, and a good model will assign higher values to the actual find location, compared with other areas. It measures the proportion of pixels that are assigned higher values than the actual find location. The absolute value depends on the image size, so MapScore uses a fixed size and scale. For each case, we place the IPP at the exact center of a $5,001 \times 5,001$ pixel map, where each pixel is 5 m $\times$ 5 m wide. At this resolution, models can use features as small as 10 m without aliasing effects. At this size, the map extends 12.5 km in each cardinal direction from the IPP, which on average includes at least 95% of the search cases. Models assign pixels a brightness value corresponding to the estimated probability density at that pixel. (Most models will be much coarser than individual pixels, so they will divide the total probability in a region by the number of pixels in that region.)

Let p equal the probability assigned to the actual find location, N be the total number of pixels in the image, n the number with probability greater than p, and let m be the number of pixels with probability equal to p. Then we define:

$$r = \frac{n + m/2}{N} \tag{1}$$

The value of *r is* then rescaled, so that the worst possible score is −1, and the best is +1:

$$R = \frac{.5 - r}{.5} \tag{2}$$

Because we corrected for pixels whose probability is equal to p, uniform (i.e. blank) maps get a score of 0 and random maps get an expected score of 0.[2]

In the ideal scenario where all resource types have perfect detection and travel at the same speed, the optimal allocation will follow probability density alone. Therefore r is the expected proportion of cells one would have to search before finding the subject, and R is the proportional gain over random searching. Because there is a great deal of uncertainty in search, scoring a single case is not very informative. R only becomes meaningful when it is calculated for many cases, to compare the average performance of different models on a fixed set of cases at a fixed resolution and extent.

R is sensitive only to rank order, and not to the relative probability. Therefore, the actual values may be converted to a suitable grayscale image using any visually pleasing monotonic transform, and the scoring can be done directly on the image. However, the bit depth of the image will limit the number of possible distinctions: an 8-bit grayscale image has at most 256 possible values, and a 16-bit grayscale image has 65,536.

2.3 Scoring Methodology

We use the format defined for the MapScore website (http://mapscore.sarbayes.org). Each map is a 5,001 × 5,001 grayscale raster centered on the IPP. Each pixel is 5 m, resulting in a 25 × 25 km search area, which exceeds the 95% zone in almost all cases, and represents an upper bound on feasible ground searching. Models need not have 5 m resolution internally, but they must convert their output to the standard format for scoring. MapScore uses 8-bit PNG files, with lighter pixels representing higher probabilities.[3] If the 256 possible values were used equally, then each value would have about 98 K pixels, and R would have a maximum value of 0.996.

R can be calculated offline, but using the website creates a public record and encourages comparison with other methods, potentially including subjective estimates. Users may select a case, receive the IPP and case information, and then upload a PNG image file with their probability map for that case. The website then scores the map using the actual find location, which is revealed along with the score. MapScore also allows batch submission via folders or zip files, so long as the individual maps are named to match the cases.

In the next section we discuss three relatively simple statistical models derived from ISRID cases with good initial and find coordinates.

3 Data and Models

Koester (2008) organizes the ISRID cases into 41 categories and subcategories based on scenario, age, medical or mental status, and activity. Critically, he provides 25%, 50%, 75%, and 95% quantiles for the Euclidean distance between the IPP and the find location. Koester also

provides summary statistics for elevation change, hours mobile, survivability, dispersion angle, and distance from nearest linear feature, when available. Where data permit, statistics are sub-divided by domain (temperate, dry) and terrain (mountains, flat, and urban). The distance-ring model is the most widely used in WiSAR operations, and linear distance is one of the most reliably-reported features.

Most of the ISRID cases do not contain usable GIS coordinates for both the initial and find locations. However, including the Yosemite data which became available during this study, 376 ISRID cases had reliable IPP and find coordinates. A third of the cases (89) are from New York, where a majority of the state is dominated by farms, forests, rivers, rolling mountains and lakes. It comprises the Northeastern Highlands, Erie Drift Plain, Eastern Great Lakes Lowlands and Atlantic Coastal Pine Barrens ecoregions (Bailey 1995; Bryce et al. 2010). A third were from Arizona (88 cases, transitional between plains and mountains), and a third from Yosemite National Park, California (199 cases), a rugged valley between granite peaks in the Southern Sierra Nevada ecoregion (Bailey 1995).

3.1 Distance Model

The Euclidean distance (ring) model is probably the most common model in statistical search planning. Dating back to Syrotuck (1976/2000), the model draws 25%, 50%, 75% and 95% distance rings based on statistical crow's-flight distance tables (Koester 2008). These distances correspond to the lower quartile, median, upper quartile, and 95th percentile of distance travelled by each category of lost persons in ISRID. As Table 1 shows, Koester's distance model considers terrain and ecoregion where the data permits. Figure 5 shows an example ring model.
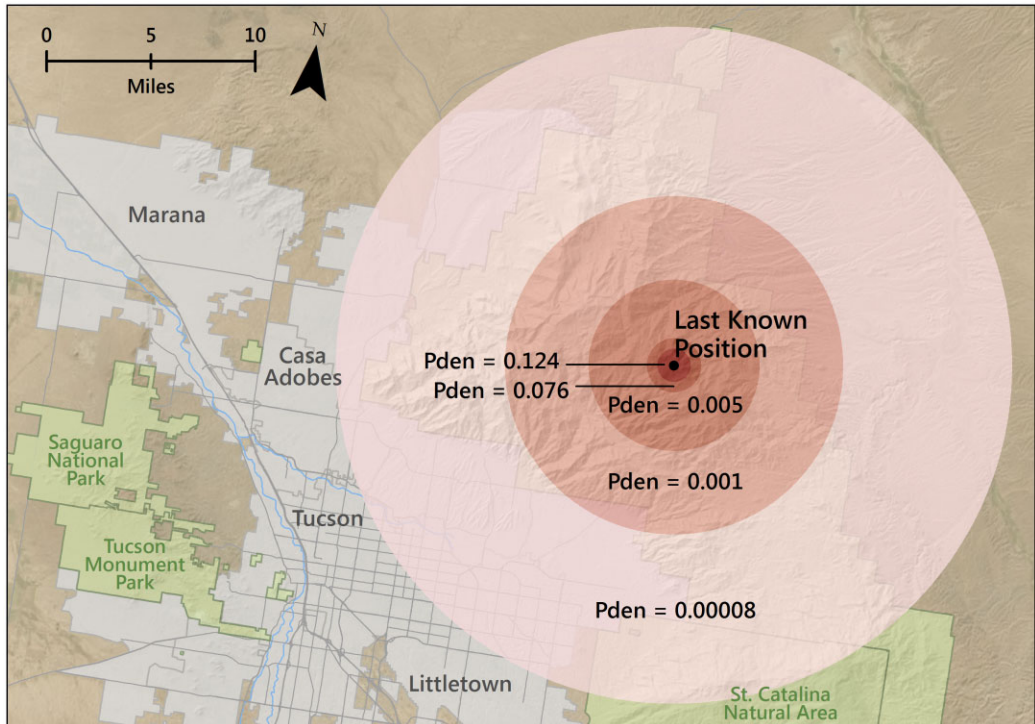
Don Ferguson's Integrated Geospatial Tools for Search and Rescue (IGT4SAR Ferguson 2013; https://github.com/dferguso/IGT4SAR) implements all the distance-ring categories and subcategories from Koester (2008) in an ArcGIS toolbox. IGT4SAR extends the MapSAR (http://www.mapsar.net) toolbox to include various elements of search theory. MapSAR is a free and open-source tool that runs with Esri's ArcGIS Desktop 10.X software (http://www.esri.com/landing-pages/software/arcgis/arcgis101-trial) and enables maps to be generated, stored, and printed quickly in order for research teams to be able to perform faster searched for a missing person (MapSAR and Esri 2012).

The IGT4SAR distance model uses the ArcGIS Multiple Ring Buffer tool to create four concentric rings centered on the IPP and representing the 25, 50, 75, and 95% distances for

Table 1 Hiker lost person behavior table used to create the distance rings generated from Koester (2008)

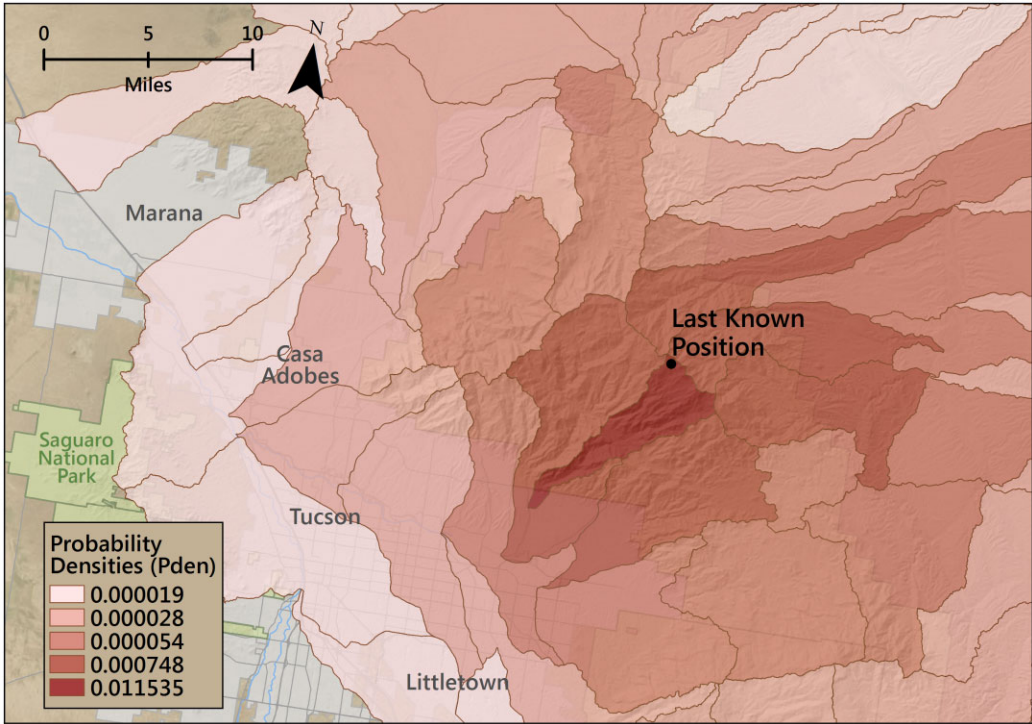|	Temperate		Dry		
	Mnt	Flat	Mnt	Flat	Urban
n	**568**	**274**	**221**	**58**	**8**
25%	0.7	0.4	1.0	0.8	
50%	1.9	1.1	2.0	1.3	1.6
75%	3.6	2.0	4.0	4.1	
95%	11.3	6.1	11.9	8.1	

Figure 5 Distance ring model for hikers in flat and dry environments, on a representative basemap. High probability areas are represented with darker colors while decreasing probabilities are shown by light tan color

this subject category and the terrain. The rings are created on a 50×50 km region, and each ring is assigned the appropriate probability. The remaining 5% is assigned to the region outside the 95% circle. The five densities are then calculated by dividing each probability by the area of the corresponding region, and assigned to every pixel in the region. The model then clips the map to the 25×25 km evaluation region.

3.2 Watershed Model

Although the distance-ring model is easy to use on a paper map, it ignores terrain. Terrain plays an important role in WiSAR. About 75% of WiSAR incidents happen in the mountains, and mountains constrain travel. One simple way to account for terrain is to count watershed crossings (Doke 2012). Watershed boundaries follow ridge lines and unlike distance rings, reflect actual barriers to travel. Figure 6 shows an example of the watershed model.

In the US, watersheds are delineated by the US Geological Survey, using a national standard hierarchical system based on surface hydrologic features, and are classified into six units. The six main types of hydrologic units are region, sub-region, accounting unit, cataloging unit, watershed, and sub-watershed. Each hydrologic unit is identified by a unique hydrologic unit code (HUC) and consists of two to 12 digits based on the level of classification. For this article a complete digital hydrologic unit boundary level of the sub-watershed (12 digit) 6th level was used as a base map for the watershed model. The typical size for a 12-digit hydrologic unit is

Figure 6   Watershed model showing terrain-based "rings" for a flat and dry environment, on a representative basemap

10,000–40,000 acres; however, in some areas with unique geomorphology the watershed may be greater than 40,000 acres or less than 10,000 acres, but never less than 3,000 acres. The sub-watershed (HUC-12) is the most detailed nationwide layer now available.[4]

The watershed containing the IPP is numbered "0". All the watersheds on its border are numbered "1", so each watershed is assigned a number counting the minimum number of ridges between the IPP and the center of the watershed. We calculated watershed statistics from 398 historical cases, as shown in Table 1. Each incident was classified as either "0", if found in the same catchment as the IPP, "1" if found adjacent, and so forth up to "3". Only 1 in 17 cases (about 6%) were found three or more watersheds away. See Table 2 for details.

Lastly, we divide the watershed-distance probabilities by the areas of all the watersheds at that distance, to get each region's *Pden*.[5]

3.3 Combined DW Model

A combined model may be made by simply "stacking" the two model layers, which is equivalent to a weighted average, or by calculating the actual joint probability distribution on the union of regions. The joint distribution will do better when the two models are not independent and there is enough data reliably to estimate the interaction. A combined model using the joint distribution of watersheds and Euclidean distance was designed with the expectation that the model would do better than the two models taken separately, as is usually the case when combining estimates (Mattson 1980; Surowiecki 2005).

Table 2   Watershed distance statistics gathered using ISRID and Yosemite data

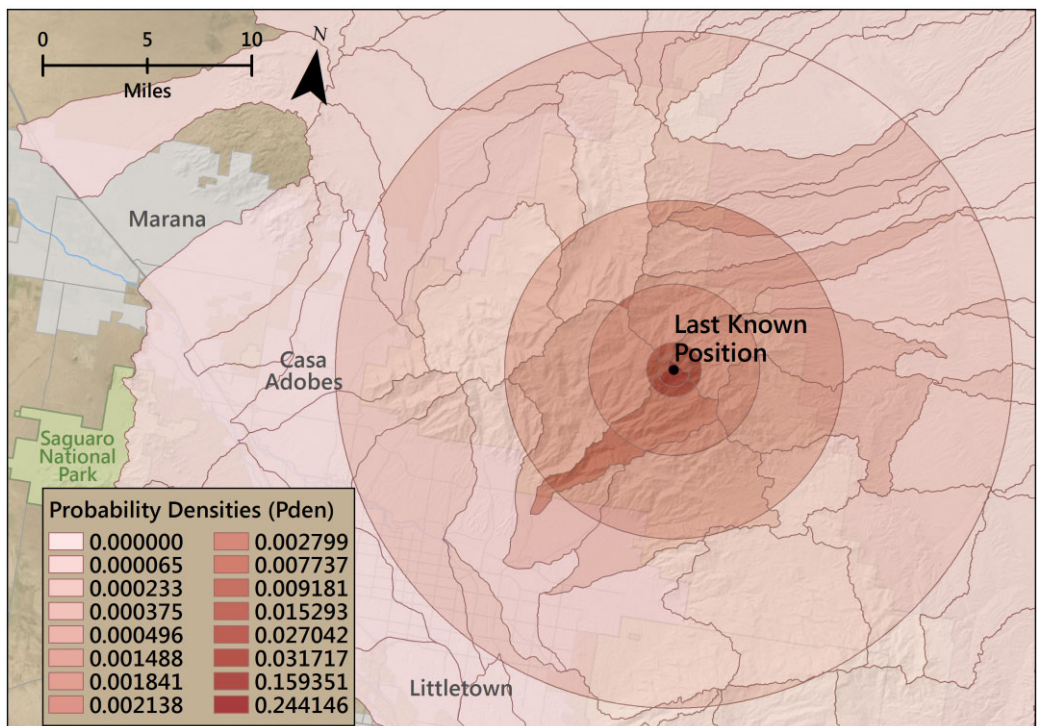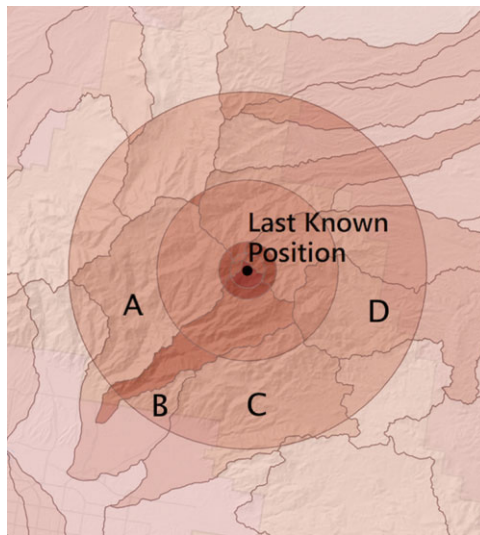| States	0: Same Watershed	1: One shed away	2: Two sheds away	3: Three+ sheds away	Total
Arizona	57	46	7	12	122
New York	71	24	3	4	102
Yosemite	87	74	10	3	174
	215	**144**	**20**	**19**	**398**
Arizona	47%	38%	6%	10%	100%
New York	70%	24%	3%	4%	100%
Yosemite	50%	43%	6%	2%	100%

Figure 7   Combined Euclidean and Watershed distance model for hiker in a flat and dry environment. Dark shades represent higher probability density

Figure 7 shows an example of the combined "Distance Watershed" (DW) model. The map regions are created by intersecting the distance rings and the watersheds (using the Union tool) so that a watershed cut by a distance ring becomes two new regions.

The probabilities for the combined DW regions are derived from the counts in Table 3. For example, Table 3 shows that the regions within the same watershed as the IPP and in the 50% ring only contained the lost person in 61 out of 355 cases, or about 17% of the time.

Table 3   Distance Rings and Watershed statistics based on ISRID and Yosemite data

Distance Rings	0: Same Watershed	1: One Watershed away	2: Two Watersheds away	3: Three+ Watersheds away	Total number of cases
25%	93	9	0	0	102
50%	61	25	1	0	87
75%	25	29	1	0	55
95%	17	48	9	4	78
100%	1	7	7	18	33
Total	**197**	**118**	**18**	**22**	**355**

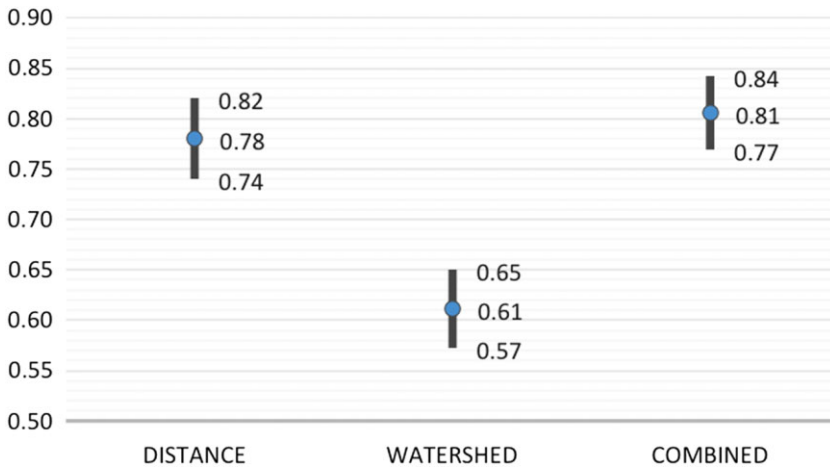**Figure 8**   Calculating Pden for the combined Distance-Watershed model

The model then assigns a probability density by dividing the probability from Table 3 by the total area of all the polygons assigned to that DW region in the map. For example, in Figure 8, the regions A, B, C and D constitute the [Watershed 1, 95% ring] region; each is assigned an un-normalized "probability" of 48/355 from Table 3, which is then divided by the combined area A+B+C+D. Note the watershed for region A also extends into the 75, 50, and even 25% rings. Although the probability of the [Watershed 1, 25% ring] region is only 9/355, the smaller area yields a higher *Pden*, shown by the darker shade for the inner two rings of A's watershed.

4 Results

The distance ring model received an average score of approximately 0.780 (95%CI: 0.740 – 0.819). The watershed model received a lower average score of 0.611 (95%CI: 0.572 – 0.650),

Figure 9 Average rating scores of the three models used in the study. The whiskers represent the 95% confidence intervals of the mean

and the combined model scored the highest with an average score of 0.805 (95%CI: 0.769 – 0.841). The watershed model is clearly inferior to the other two. However, the combined model is slightly better (two-tailed, paired T-test, N = 376, t_{crit} = 1.966, p = 0.017). See Figure 9 for a comparison.

Despite largely ignoring local terrain, the ISRID distance ring model sets a high bar. Beating the ISRID distance model for hikers on our 5,001-pixel-square images requires scoring solidly above about 0.8. By adding some very basic terrain information, the Combined model achieves improvements of about 6% of the original standard deviation, and about 11% of the possible gain.

There was also a regional influence. All models had their best performance in New York and their worst in Arizona where variance was also highest. The difference was statistically significant for both Distance and Combined models but not the Watershed model, which had poor performance in all three regions (F-crit = 3.02, F-value = 11.4, 8.6, 2.8; see Table 4.) Also, performance differences between models were statistically significant in New York and Yosemite, but not in Arizona (one-way ANOVA, F-value = 29.13, F-crit = 3.00). The combined model performed the best and with the least variance for the state of New York, with an average score of 0.887 and variance of 0.059.

5 Discussion

This study had four goals:

- To create a method and portal for scoring missing-person probability maps;
- To score the ubiquitous ISRID Euclidean-distance "ring" model;
- To compare the ring model with a new watershed model; and
- To compare those models with a combined distance-watershed model.

The results for the distance ring model were as expected. Based purely on ring geometry, the expected value of *R* for Hikers in a dry, mountainous domain is 0.78, closely mirroring the actual result (which was indeed mostly hikers in such environments). It was also anticipated

Table 4   Model mean and (variance) by region. F-statistic: α = 0.05, DF = 2, F-critical = 3.020

State	Distance Model	Watershed Model	Combined Model
Arizona	0.632	0.533	0.656
	(0.244)	(0.194)	(0.215)
New York	0.841	0.666	0.887
	(0.129)	(0.122)	(0.059)
Yosemite	0.818	0.621	0.834
	(0.117)	(0.139)	(0.106)
F- statistic	**8.588**	**2.792**	**11.366**
	(p = .0002)	(p = .06)	(p = .00002)

that the distance ring model would score slightly higher in the state of New York than Arizona or Yosemite Park: because development and vegetation limit travel, the distance rings are closer in NY. (The temperate flat category has a 75% of 2 km, vs. 4 km for the dry flat category).

The watershed model did worse than the ISRID distance rings, but performed surprisingly well considering that it ignores the subject category, environment, and climate (unlike the distance-ring model). It also scored higher in New York than in Arizona or Yosemite. The watersheds in our New York cases tend to be larger. Although Arizona has a lot of flat regions, most of the searches happened near the mountains, and the Arizona mountains are more rugged than the New York mountains. Yosemite, of course, is at least as rugged as Arizona.

It also helped that the New York IPPs were more likely to be somewhere in the center of a watershed, rather than on the ridge boundary, making the watershed distance parameter more reliable. When the IPP is on the dividing ridge, it is essentially random which side of the ridge will count as watershed 0.

6 Conclusions and Future Work

The goal of any SAR operation is to increase the probability of success as quickly as possible with the available resources. Search and rescue activities rely heavily upon geospatial data, and GIS generation of the probability maps can speed search planning and generate better plans. However, while higher-resolution models including more factors will always seem more appealing, they need to be tested. MapScore provides a large set of historical missing-person cases, and a web portal for scoring and comparing models.

This article publishes baseline scores for three relatively simple models: the commonly used ISRID Euclidean distance-ring model, a new watershed model which ignores subject category or terrain, and a combination of the two models. The watershed model by itself eliminated about 60% of the search area, but the familiar distance-ring model did better, eliminating over 75% of the search area. The combined DW model eliminated over 80% of the search area, showing a statistical difference. All models did better in New York and Yosemite, and worse in Arizona.

Live GIS-based probability maps should improve key search planning decisions and increase situation awareness. Even if the GIS did not suggest resource assignments, displaying validated scenario-specific probability maps would be faster than drawing regions manually

and more accurate than intuitively sloshing probabilities into those regions. But the models tested here only automate the current manual method.

The next step is to explore parametric distance models[6] to remove the "jumps" in probability at the ring boundaries. Following that, the terrain model should be improved. One option is to refine the watershed layer. The HUC 12-digit watershed layer, although the most detailed currently available, has watershed regions that are too large for search purposes. A finer scale watershed layer may better capture the dynamics of movement and receive better scores. In addition, the watershed model should better account for IPPs on the ridge between the two watersheds, perhaps by assigning ridge cases partially to all neighboring watersheds, or to a separate area.

If there is sufficient data available for the search region, another option is to augment watersheds with other travel barriers like streams and slopes, or skip simple barrier models entirely in favor of calculating travel cost surfaces. Preliminary tests of travel cost models showed the limiting factor was the quality of the available data layers. However, with effort a nationwide set could be synthesized for testing on MapScore.

Finally, these are all but steps along the way to defining actual motion models for SAR. We have not yet tested any motion models, though we are collaborating with other researchers to do so. Motion models have many parameters and assumptions, and without a good test suite like MapScore, they are difficult to evaluate.

MapScore has provided case data, a scoring metric, and a scored baseline. We invite contributions and hope within a year to see models scoring above 0.9.

Notes

1 Syrotuck's model was actually a bit more involved, and his "rings" often resembled paper clips, but most of his readers just used the linear distance.
2 Koester's correction matters in rule-based models where many pixels get the same value.
3 MapScore may switch to 16-bit when participants start submitting higher-resolution models.
4 The Watershed Boundary Dataset (WBD) and the National Hydrography Dataset (NHD) are coordinated efforts between the US Department of Agriculture–Natural Resources Conservation Service (USDA-NRCS 2013), the US Geological Survey (USGS), and the US Environmental Protection Agency (EPA). They were created from a variety of sources from each state and aggregated into a standard national layer for use in strategic planning and accountability (http://nhd.usgs.gov/wbd_data _citation.html).
5 Although this *Pden* method is correct on average, it could generate abnormal *Pdens* if, for example, the watershed-0 region was extraordinarily large (yielding too low a *Pden* near the IPP), or the watershed-3 region was clipped so as to be extraordinarily small (yielding a high *Pden* far away). A better method would be to calculate the average *Pdens* as part of the overall statistics, and apply those directly to each case.
6 Forthcoming. See Cawi (2014) for a preview.

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