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RANKING AND SELECTING DANGEROUS CRASH LOCATIONS:

CORRECTING FOR THE NUMBER OF PASSENGERS AND BAYESIAN RANKING PLOTS

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ABSTRACT

In Flanders (Belgium), 1014 accident locations are currently considered as dangerous. These accident sites are selected using a combination of weighting values, respectively 1 for each light injury, 3 for each serious injury and 5 for each deadly injury that occurred on each site over a period of three years. In this paper a sensitivity analysis is performed to investigate how big the impact would be on the current ranking of accident locations when we only take into account the most serious injury per accident. Considering this impact quantity, we want to sensitise government to carefully choose the criteria for ranking accident locations without stating that the criterion used in this paper should be preferred to the currently used ranking method. Additionally, we generate probability plots, based on estimates from a hierarchical Bayes model, in order to visualize the estimated probability that a location will be ranked as dangerous.

INTRODUCTION

In Belgium, in 2001 47444 injury accidents occurred in traffic, with 66780 victims, of which 1486 deaths (Belgian Institute for Traffic Safety, 2001). Not only does the steady increase in traffic intensity pose a heavy burden on society in terms of the number of casualties, the insecurity on the roads will also have an important effect on the economic costs associated with traffic accidents. In Belgium, this macro-economic loss due to the lack of traffic safety on the roads is estimated at 3.72 billion Euros per year (Dielemann, 2000). Accordingly, traffic safety is currently one of the highest priorities of the Belgian government.

In this paper we will focus on one important group of bottlenecks in traffic safety: the dangerous accident locations. Methods developed for identifying such accidents concentrations often apply to black spots, which are pinpoint concentrations of road accidents that often migrate over time (see e.g. Nguyen (1991), Joly et al. (1992), Hauer (1996), Maher (1996), Thomas (1996) and Silcock and Smyth (1998)). More recently, identification of black zones has also been reconsidered in the literature (see Flahaut et al. (2003) for a review); they arise from the awareness of the spatial interaction existing between contiguous accident locations.

However, literature points out that there is no universally accepted definition of what should be considered as 'dangerous' (Geurts and Wets, 2003). Indeed, according to Hauer (1996) some researchers rank locations by accident rate (accidents per vehicle-kilometers or per entering vehicles), some use accident frequency (accidents per km-year or accidents per year) and some use a combination of the two. Furthermore, there is a wide range of methodologies available, ranging from simple models based on actual accident counts to advanced statistical models based on estimates. According to Taylor and Thompson (1977), seven methods can be used to identify dangerous sites on the road network, each with different order of importance and precision (European Union Road Federation, 2002): Accidents frequency, Hazard potential ratio, Joint method with accident frequency and accident risk ratio, Confidence interval method, Method of the accident severity ratio, Risk rate method and Inventory of the accident risk elements in the road.

In a previous paper, a sensitivity analysis was carried out to investigate the strengths and weaknesses of the method that is currently used in Flanders (the Flemish speaking community of Belgium) to identify and rank dangerous accident locations (Geurts et al., 2004). These accident sites are selected by the Flemish government by means of their historic accident data for the period 1997-1999. Based on these data, each site where in the last 3 years 3 or more accidents have occurred, is selected. Then, a location is considered to be dangerous when its score for priority (S), calculated using the following formula, equals 15 or more (Ministry of Flemish Community, 2001):

$S=1*X +3*Y +5*Z$, where X = Total number of light injuries

Y = Total number of serious injuries

(Each casualty that is admitted more than 24 hours in hospital)

Z = Total number of deadly injuries

(Each casualty that died within 30 days after the accident)

To improve the traffic safety on these locations (there are 1014 of them), the Flemish government, will each year, starting in 2003 for a period of 5 years, invest 100 million EURO to redesign the infrastructure of the 800 accident locations with the highest score.

Results in the previous paper (Geurts et al., 2004) showed that a change in the traffic safety policy and the reflection of this choice in the injury weighting values used to identify and rank the most dangerous accident locations will not only have an important impact on the number of sites that will change when selecting and ranking accident locations. It will also have an important effect on the type of accident locations (e.g. locations with high traffic volumes resulting in many small accidents) that are selected and accordingly on the resulting future traffic safety decisions. Government should therefore carefully decide which priorities should be stressed in the traffic safety policy (for more details on the discussion of the implications of the use of 1_3_5 weighting values see Geurts et al. (2004)). Furthermore, results showed that using the expected number of accidents, estimated from a hierarchical Bayes model, instead of using historic count data to rank and select the accidents sites can overcome the problem of random variation in accident counts and will also have an important effect on the selection of the most dangerous accident locations.

In this paper, we will elaborate on our sensitivity analysis in two ways. Firstly, by investigating the influence of the number of passengers on the ranking of the accident locations. More specifically, we will evaluate how big the effect would be on the current ranking when giving a weight to the severity of the accident instead of to all the injured occupants of the vehicles. This choice is motivated by preliminary results, which showed that most of the 1014 accident locations that are currently considered as dangerous on average count 10 accidents. In other words, it turns out that not the number of accidents but the number of injured passengers is the most differentiating factor for the ranking of these accident locations.

Secondly, we propose a Bayesian ranking plot in order to visualize the probability that a location will be ranked as dangerous, based on estimates from a hierarchical Bayes model. Considering the impact quantity of these alternative ranking criteria, we want to sensitize government to carefully choose the criteria for ranking and selecting dangerous accident locations without stating that the criteria used in this paper should be preferred to the currently used ranking method.

The remainder of this paper is organized as follows. First, a formal introduction to the techniques that are used in this paper is provided. This will be followed by a description of the dataset. Next, the results of the empirical study are presented. The paper will be completed with a summary of the conclusions and directions for future research.

TECHNIQUES

In this research, two quantitative measures are used in order to examine the ranking and selection of dangerous accident locations. In the first part of this paper, we will use the percentage deviation value to quantify the effect of giving weight to the severity of the accident instead of to all the injured occupants of the vehicles. In the second part of this research, we will generate Bayesian ranking plots, which for each location reflect the estimated probability that it belongs to the *r* most dangerous sites.

Percentage Deviation Value

In accordance with our previous research (Geurts et al., 2004), we will use the percentage deviation value to quantify the effects changing the ranking and selection criteria of dangerous accident locations. This measure allows comparing the rankings of two datasets containing different locations. As described in definition 1, the percentage deviation is calculated by dividing the number of accident locations that do not appear in both data sets by the total number of locations in one dataset.

Definition 1: Percentage deviation (p_r)

$$p_r = 1 - \frac{G}{T}$$ with G = Number of common elements in both datasets

T = Total number of elements in each dataset

Note that the percentage deviation only gives information about the number of locations that do not appear in both ranked datasets and does not take into account internal shifts in the ranking position of these common accident locations.

Bayesian Ranking Plot

A number of statistical models have been used to estimate accident rates and/or accident frequencies at a specific location over a given interval of time (see Hauer and Persaud (1987), Hauer (1996), Nassar (1996) and Geurts and Wets (2003) for a review). The underlying assumption is that road accidents can be treated as random events with an underlying mean accidents rate for each accident location. To account for this probabilistic nature of accident occurrence compelling arguments can be found to support the assumption that accidents counts follow the Poisson probability law (Ng et al. (2002)).

Recently, Empirical Bayes methods have been used in road safety to identify black spot locations arguing that adjusting historical data by statistical estimates yields improved predictability (see e.g. Elvik (1997), Miaou (1994), Belanger (1994) and Vogelesang (1996)). Furthermore, the use of ranking procedures based on a hierarchical Bayes approach has been proposed in literature. These methods can handle the uncertainty and the great variability of accident data and produce a probabilistic ranking of the accident locations (Brijs et al. (2003), Schlüter et al. (1997)). We followed the approach of Brijs et al (2003), who proposed a multivariate hierarchical Bayes approach for ranking accidents sites taking into account the number of accidents, the number of fatalities, and the number of light and severely injured casualties for a given time period for each site. This is done by using a 3-variate Poisson distribution that allows for covariance between the number of lightly, seriously and fatally injured casualties. In order to combine all data into a single number that will be used for ranking the sites, a weighting function can be used that measures the expected score of an accident according to the number of fatalities, heavy and light injured casualties. Based on these expected scores, the posterior density for the rank of each site can be derived. The parameters of the model are estimated via Bayesian estimation facilitated by Markov Chain Monte Carlo (MCMC) methods. One of the advantages of this MCMC method is that it allows for exploring posterior distributions of a certain function related to the parameters of interest. Results (Geurts et al., 2004) showed that the use of these Bayesian estimation values from this model instead of historic count data to rank the accident locations indeed can overcome the problem of random variation in accident counts and will have an important effect on the selection of the most dangerous accident locations.

In this research, we elaborate on this technique by developing a method for deriving the probability for each site *i* of being one of the *r* worst sites (with *l* = the total number of locations). This implies that the expected score of location *i* is among the *r* highest and hence its rank is larger than *l* – *r* (since in this ranking procedure the smaller the score, the better the site). Then the estimated probability is calculated as

Definition 2: Estimated probability $P_r\ (i)$

$$P_r\ (i) = \frac{\sum_{i=1}^{N} I\left(R_i^{(j)} > l - r\right)}{N}$$

where *I*( ) is the indicator function returning a value of 1 in case that the argument is true and a value of 0 in case that the argument is false. *N* is the number of MCMC iterations. These probabilities allow for a heuristic rule for selecting worst sites. More specifically, if all sites would have the same characteristics, we expect that for all the sites the required probabilities will be exactly the same as any differences will be merely random perturbations. Accordingly, we expect that this probability will be equal to *r/l* for each site. Locations with a probability above this limit reveal a deviation from the argument about equal sites. However, note that theoretically, due to random perturbations some probabilities will be larger even in the case of equal sites.

To facilitate further this approach, we can calculate confidence intervals for the probabilities by repeating the above procedure for a number of times. More specifically, we will split up the total number of MCMC iterations (N) in a number of batches and calculate the estimated probability for each site after each batch. This will allow generating Bayesian confidence intervals for each site. By considering the lower limit of these intervals this will reveal sites with a probability above the limit in a more rigorous basis reducing the effect of random perturbations.

DATA

To allow for a sensitivity analysis on the currently used black spot criterion, this study is based on the same data used to select and rank the 1014 currently considered most dangerous accident locations. These data originate from a large data set of traffic accidents obtained from the National Institute of Statistics (NIS) for the region of Flanders (Belgium) for the period 1997-1999. These data are obtained from the Belgian “Analysis Form for Traffic Accidents” that should be filled out by a police officer for each road accident that occurs on a public road (i.e. motorways, national and provincial roads linking towns) involving casualties, since the location of these accidents is accurately known by means of a hectometer stone marker. Hence, the identification of dangerous accident locations is related to roadway segments of numbered roads with a length of 100 meters. Furthermore, each intersection is considered as a possible black spot. Accidents occurring in the direct neighborhood of an intersection (within 50 meters) are also incorporated in the calculations of this intersection. This means that the accident locations that are considered as black spots are either roadway segments of 100 meters or intersections. These traffic accident data contain a rich source of information on the different circumstances in which the accidents have occurred: course of the accident, traffic, environmental conditions, road conditions, human conditions and geographical conditions. The accident data needed to perform this sensitivity analysis will be limited to the number of accidents per accident location. Furthermore, these data will only contain the number of fatalities and the number of light and serious casualties per accident location.

In total, 50961 traffic accidents with casualties are reported in this period. This results in 23184 unique accident locations included in the data set. Three data sets can be derived from this. First of all, we will focus on the 1014 accident locations that are currently considered as dangerous to explore the sensitivity of their ranking orders. Next, we will concentrate on all of the 23184 accident locations that are included in the data set and finally all accident locations where at least 3 accidents occurred between 1997 and 1999 will be analyzed.

RESULTS

Effect of the Number of Passengers on the Ranking Order

As explained in the introduction of this paper, the 1014 most dangerous accident locations are currently ranked and prioritized using respectively the values 1, 3, 5 as the different weighting values for a lightly (LI), seriously (SI) or deadly injured (DI) casualty of an accident.

Figure 1 gives an overview of the effects of giving weight to the severity of the accident instead of to all the injured occupants of the vehicle. In particular, figure 1 shows the percentage deviation values for different subsets of the 3 data sets (1014 currently dangerous accident locations, locations with minimum 3 accidents and all accident locations,) only taking into account the most serious injury per accident. In other words, this means that the points per accident that are summed up in order to calculate the priority value of the locations can vary from 1 (only light injuries) to 5 (at least one deadly injured casualty) (Figure 1 inserted here). Results from figure 1 show that correcting for the number of passengers will indeed cause a change in the ranking and selection of the most dangerous accident locations. More specifically, when looking at the first data set, the 1014 accident locations that are currently considered as dangerous, giving weight to the accidents instead of to all the injured passengers causes the different location subsets to deviate from the original location subsets up to 26.7% (top 14%). This means that

26.7% of the accident locations that are currently considered to belong to the 14% most dangerous accident locations do not appear in the top 14% when correcting for the number of passengers. When selecting the 800 most dangerous locations (top 97%), 14.7% of the locations will differ from the current selection. When looking at the data set containing the 5324 locations with minimum 3 accidents the maximum percentage deviation value amounts to 24.6% (top 6%). Selecting the 800 most dangerous of these locations (top 15%) results in a deviation of 21.3% from the currently 800 most dangerous locations. Finally, results for all of the 23184 accident locations indicates that giving weight to the accidents causes the different location subsets to deviate from the original location subsets up to 24.5% (top 1%). For the top 800 (4%), this number will come to 23.8%.

Note that for the three data sets the percentage deviation values are on average smaller when more accident locations are involved in the analysis. As explained in our previous research (*5*) a possible explanation could be that the accident locations with a higher ranking value are more sensitive to a correction for the number of passengers than the accident locations with smaller ranking values. However, we should take into account that the greater the subset (X) of accident locations that is selected, the more accident locations can obtain a different ranking order without falling out of the top X% most dangerous accident locations.

Bayesian Ranking Plot

Based on the estimated priority score for each road location, obtained from the hierarchical Bayes model, one is able to estimate the probability for each accident location to belong to the 'r' most dangerous locations. For instance, the curve in figure 2 shows for each of the 23184 road locations (the X-axis) the estimated probability of belonging to the 800 most dangerous accident locations (the Y-axis), ordered by decreasing probability (Figure 2 inserted here). Additionally, the horizontal line in figure 2 shows that if each location would be equally dangerous, accidents would occur randomly on the different locations. In that case, the probability that a location belongs to the 800 most dangerous accident locations would be equal for all accident locations, namely 800/ 23184 = 0.034. It can be seen that this value is relatively small due to the large number of accident locations included in this data set.

However, the curved line in figure 2 shows that the probability of belonging to the 800 most dangerous accident locations is not at all equal for the 23184 locations included in the data set. More specifically, 4288 locations have a probability that is larger than 0.034. These locations can be identified in figure 2 as those locations for which the curve is above the horizontal cutoff line. This indicates that these accident locations have a higher probability than expected under random conditions to qualify as one of the 800 most dangerous accident locations.

When comparing the 800 locations with the highest estimated probabilities based on the results from figure 2 with the 800 locations that are currently considered as the most dangerous, we found a percentage deviation value of 13.7%. This corresponds with 110 accident locations that are differently selected when targeting the 800 most dangerous accident sites. Translated into costs, this means that theoretically 68.5 million EURO of the 500 million EURO investment budget for redesigning these 800 most dangerous accident locations would be differently allocated. Closer investigation of these different accident locations shows that these sites, according to the currently used ranking criterion, are ranked between the 500^{th} and 800^{th} position.

Figure 3 shows the results of generating confidence intervals for each of the 23184 locations. More specifically, the vertical lines in this picture represent for each accident site the minimum and maximum estimated probability to belong to the 800 most dangerous locations out of the 50 MCMC batches that were included in this analysis. Note that the mean estimated probability for each accident site from the different iterations will equal the estimated probability depicted in figure 2 (Figure 3 inserted here). These results show that selecting the locations with the lower limit of their confidence interval (the minimum estimated probability) above the limit of 0.034 results in 1370 accident locations. This indicates that these accident locations have a higher probability than expected under random conditions to qualify as one of the 800 most dangerous accident locations.

Furthermore, comparing these results with the results of figure 3 shows that using confidence intervals based on the estimated probabilities reduces the selection of the candidate 800 most dangerous locations from 4288 accident sites to 1370. Consequently, the use of confidence intervals results in a more rigorous estimate of the most dangerous accident locations, which for policy makers enhances the certainty that resources are allocated to the right accident sites.

Analogously to figure 2, figure 4 shows for each of the 5326 locations where minimum 3 accidents occurred between 1997 and 1999 (X-as) the probability that it belongs to the 800 most dangerous accident locations (Y-as) (Figure 4 inserted here). More specifically, these probabilities are depicted in a curved line, while the horizontal line in figure 4 represents this probability under the assumption that all sites would be equally dangerous. This assumption results in a probability value of 0.15 (800/ 5326). Note that this value is higher than the probability value calculated in figure 2, since now only 5326 accident locations are included in the analysis. Comparing this value with the probabilities estimated from the hierarchical Bayes model, shows that 1506 accident locations have a probability of belonging to the 800 most dangerous sites that is higher than what would be expected in case of equally dangerous sites.

Additionally, selecting the 800 accident locations with the highest probabilities and comparing these sites with the currently 800 most dangerous locations results in a percentage deviation value of 12%. This means that 96 locations that are currently considered to belong to the 800 most dangerous accident sites will not be selected in this group based on their estimated probabilities. Similar to the results of figure 2, the accident locations that are selected differently are ranked between the 500th and 800th position according to the currently used ranking criterion. When translating these results into costs, this indicates that theoretically 60 million EURO of the 500 million EURO investment budget for redesigning these 800 most dangerous accident locations would be differently allocated.

In figure 5, for each accident location the minimum and maximum estimated probability of the different iterations is shown resulting in confidence intervals. Analogously to figure 3, the mean estimated probability for each site will equal the estimated probability depicted in figure 4 (Figure 5 inserted here). Results of figure 5 show that for 863 accident locations the minimum estimated probability value of belonging to the 800 most dangerous accident locations exceeds the limit of 0.15. In other words, these accident sites have a higher probability than expected under random conditions to qualify as one of 800 most dangerous accident locations.

Furthermore, results of figure 4 and figure 5 show that using the lower limit of the confidence intervals to select the accident locations with an estimated probability of belonging to the 800 most dangerous accident locations narrows down the number of sites from 1506 to 863. Again, these results indicate that confidence intervals facilitate to make a more rigorous estimate of the most dangerous accident locations.

Finally, note that, in contrast with the previous section, the technique of Bayesian ranking plots is not applied to the 1014 accident locations that are currently considered as dangerous. This is motivated by the fact that estimates for the probability of belonging to the 800 most dangerous accident locations are not very interesting when dealing with just 1014 locations.

CONCLUSIONS

In this paper, we elaborate in two ways on a sensitivity analysis that is performed in earlier research to investigate the strengths and weaknesses of the currently used method to identify and rank black spots in Flanders (Belgium). More specifically, we investigated how big the effect would be on the current ranking when using alternative ranking criteria. Firstly, analysis shows that giving weight to the severity of the accident instead of to all the injured occupants of the vehicle will have a great impact on the selection and ranking of dangerous accident locations. In particular, when selecting the 800 most dangerous accident sites of all accident locations 23.8% of these locations will differ from the current selection. Considering this impact quantity, we want to sensitise government to carefully choose the criteria for ranking and selecting accident locations without stating that the criterion used in this paper should be preferred to the currently used method. It is up to the government to decide which priorities should be stressed in the traffic safety policy. Then, the according weighting value combination can be chosen to rank and select the most dangerous accident locations. Furthermore, giving weight to the severity of the accident corrects for the bias that occurs when the number of occupants of the vehicles are subject to coincidence. However, in some cases (e.g. discotheques, entertainment centres), it can be reasoned that the number of occupants and accordingly the number of injured persons, is not a coincidence, but more likely a trend. For these locations, correcting for the number of passengers would not be advisable since the number of injuries that appear at these locations are inherent to the locations characteristics. Additionally, Bayesian ranking plots can be used to visualize the estimated probability that a location will be ranked as dangerous, based on estimates from a hierarchical Bayes model. These probability plots can provide policy makers with a scientific instrument with intuitive appeal to select dangerous road locations on a statistically sound basis.

Note that one should not only rank the accident locations based on the benefits that can be achieved from tackling these locations. One should also incorporate the costs of infrastructure measures and other actions that these accident sites require in order to enhance the safety on these locations. By balancing these costs and benefits against each other, the accident locations can then be ranked according to the order in which they should be prioritised.

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FIGURE 1 Percentage deviation values for different subsets of the accident locations taking into account the most serious injury per accident

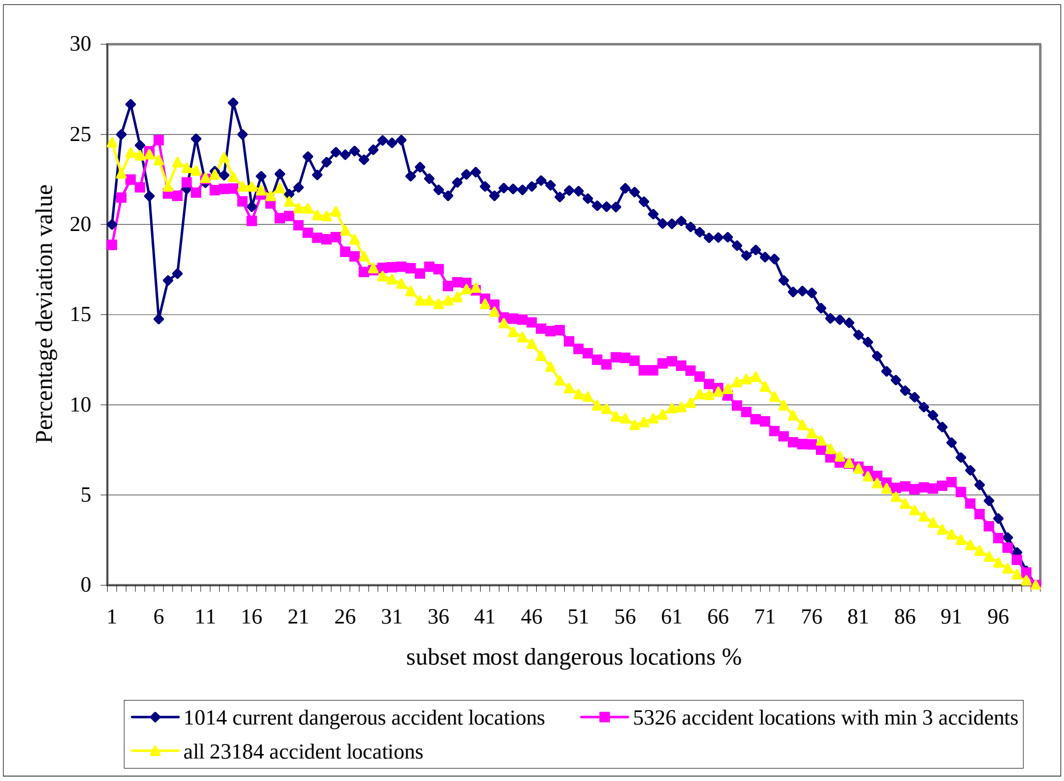

FIGURE 2 Bayesian Ranking Plot: Probability of belonging to the 800 most dangerous of all accident locations

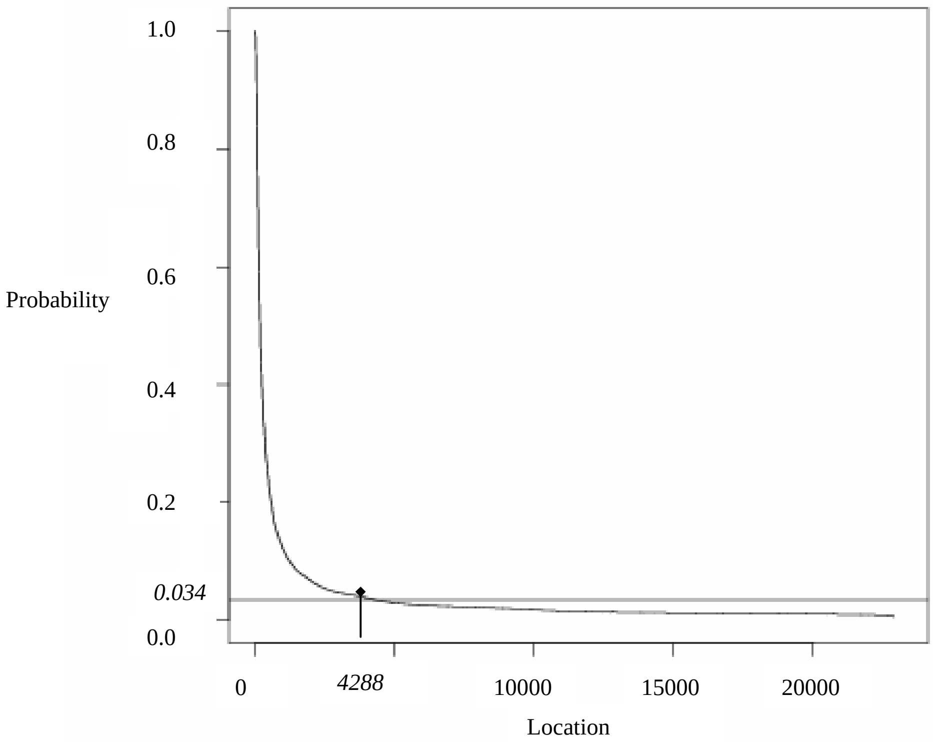

FIGURE 3 Bayesian Ranking Plot with Confidence Intervals: Probability of belonging to the 800 most dangerous of all accident locations

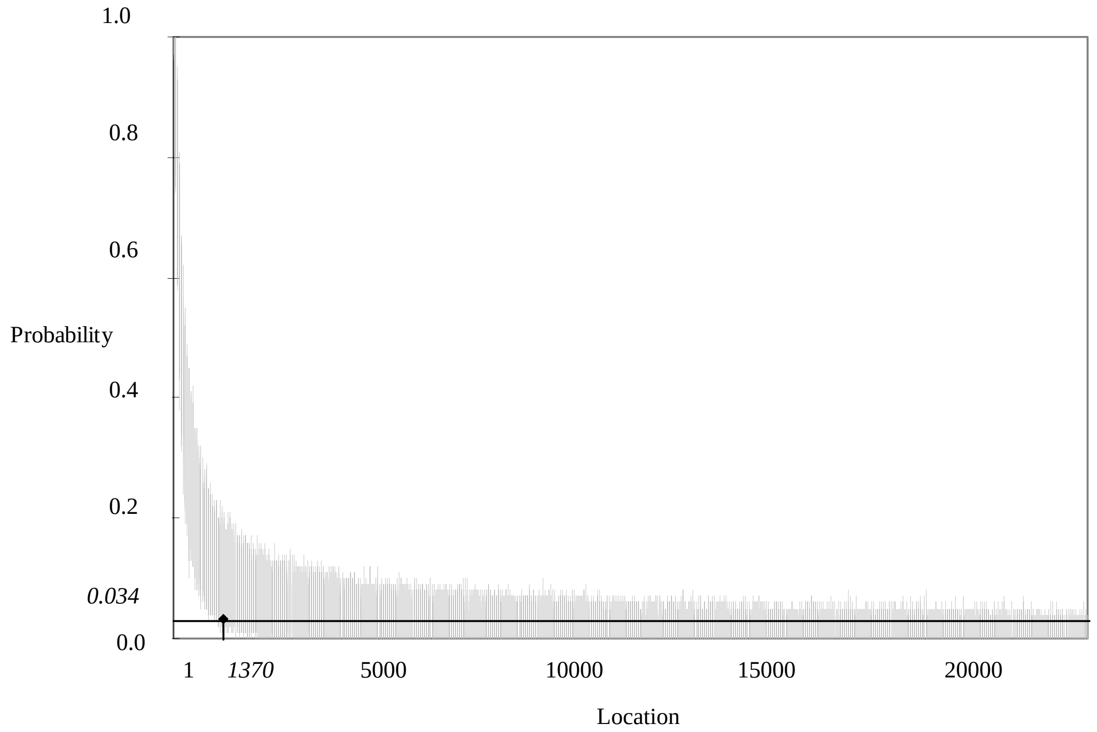

FIGURE 4 Bayesian Ranking Plot: Probability of belonging to the 800 most dangerous of the locations with minimum 3 accidents

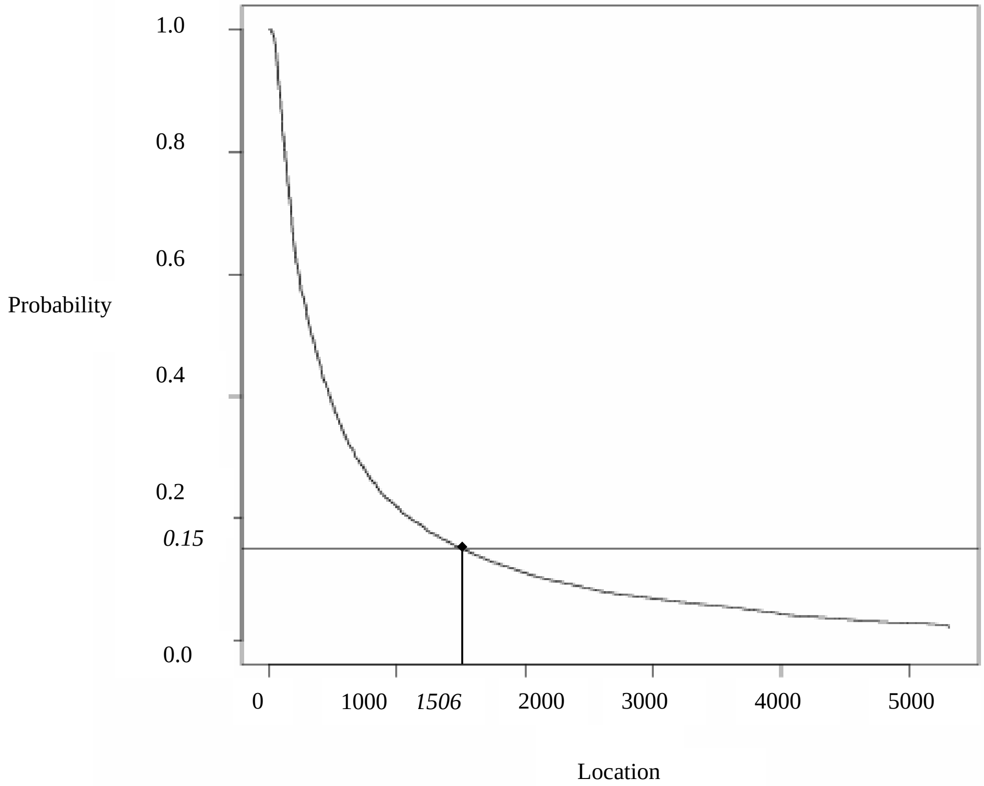

FIGURE 5 Bayesian Ranking Plot with Confidence Intervals: Probability of belonging to the 800 most dangerous of the locations with minimum 3 accidents