Ecological Modelling 297 (2015) 180–186

Contents lists available at ScienceDirect

Ecological Modelling

journal homepage: www.elsevier.com/locate/ecolmodel

Spatial and spatiotemporal clustering methods for detecting elephant poaching hotspots

Parinaz Rashidi[a,*], Tiejun Wang[a], Andrew Skidmore[a], Anton Vrieling[a], Roshanak Darvishzadeh[a], Bert Toxopeus[a], Shadrack Ngene[b], Patrick Omondi[b]

[a] *Department of Natural Resources, Faculty of Geo-information Science and Earth Observation (ITC), University of Twente, PO Box 217, 7500 AE Enschede, The Netherlands*
[b] *Kenya Wildlife Service, PO Box 40241, Nairobi 00100, Kenya*

A R T I C L E   I N F O

Article history:
Received 4 June 2014
Received in revised form
12 November 2014
Accepted 17 November 2014

Keywords:
Cluster analysis
Hotspot mapping
Prediction accuracy
Tsavo ecosystem
Kenya

A B S T R A C T

Spatial and spatiotemporal cluster methods are used for a wide range of applications including the study of criminal activities, but have never been compared for studying a specific form of crime, i.e. wildlife poaching. We aimed to identify elephant poaching hotspots by analyzing the differences in clusters of poached elephants in the Tsavo ecosystem (Kenya) that emerged from different cluster detection methods. Reports of elephant poaching in the Tsavo ecosystem were obtained for 2002–2012 from the Kenya Wildlife Service. The study area was divided into 34 blocks for analysis. Two spatial- and two spatiotemporal clustering methods were applied to the data. The predictive accuracy of the spatial methods in defining hotspots was assessed using the prediction accuracy index (PAI), which was then modified (MPAI) for measuring the predictive accuracy of the spatiotemporal methods. The results from the spatial methods indicated eight consistent poaching blocks, with Kulldorff's spatial scan statistic having a slightly higher PAI value than the flexible scan statistic (2.39 vs 2.12). The spatiotemporal clustering methods revealed four consistent poaching blocks. The MPAI value was higher for the spatiotemporal scan statistic than the spatiotemporal permutation scan statistic (1.46 vs 0.97). The results demonstrated that although the hotspot predictions varied for the different methods, three blocks were consistently identified as poaching hotspots. Our findings may assist wildlife departments such as the Kenyan Wildlife Service to allocate their financial and human resources as effectively as possible in combating poaching. Further research is needed to examine the environmental and human factors contributing to the patterns that have been observed in elephant poaching.

1. Introduction

Cluster analysis aids in identifying the presence of spatial and temporal patterns (Quick and Law, 2013). It can discern areas or periods of high occurrence (hotspots) of a specific feature from other areas or periods with a more random occurrence. Many methods for testing the presence of clusters in spatial point features have been defined and they can be broadly divided into global and local clustering methods (Chiu et al., 2008). In global clustering methods, the average tendency (a typical value for a probability distribution, e.g. mean or median) in a dataset is measured to test the null hypothesis of spatial randomness over the whole study area. However, the specific location or significance of individual clusters is not specified by global methods (Burra et al., 2002; Chakravorty, 1995; Quick and Law, 2013). In contrast, local clustering methods identify the location of individual clusters by processing subsets of global data; local clustering methods recognize neighboring regions that show exceedingly high or low occurrences relative to the null hypothesis of spatial randomness (Anselin, 1995; Anselin et al., 2000; Kulldorff et al., 2003; Quick and Law, 2013). Local clustering can be classified in three groups: temporal clustering, spatial clustering, or spatiotemporal clustering (Tango, 2010). Temporal clustering investigates whether cases show a tendency to be placed close to each other in time (Tango, 2010). Spatial clustering investigates if the occurrence of a specific feature is particularly high in some geographical areas, irrespective of when it occurred during the study period. Spatiotemporal clustering investigates whether events that are close in space are also close in time (Tango, 2010).

Cluster analysis used in epidemiology (Hanson and Wieczorek, 2002; Kulldorff, 1997; Torabi and Rosychuk, 2011) and has been

* Corresponding author. Tel.: +31 649820959; fax: +31 53 4874388.
E-mail address: p.rashidi-1@utwente.nl (P. Rashidi).

http://dx.doi.org/10.1016/j.ecolmodel.2014.11.017
0304-3800/

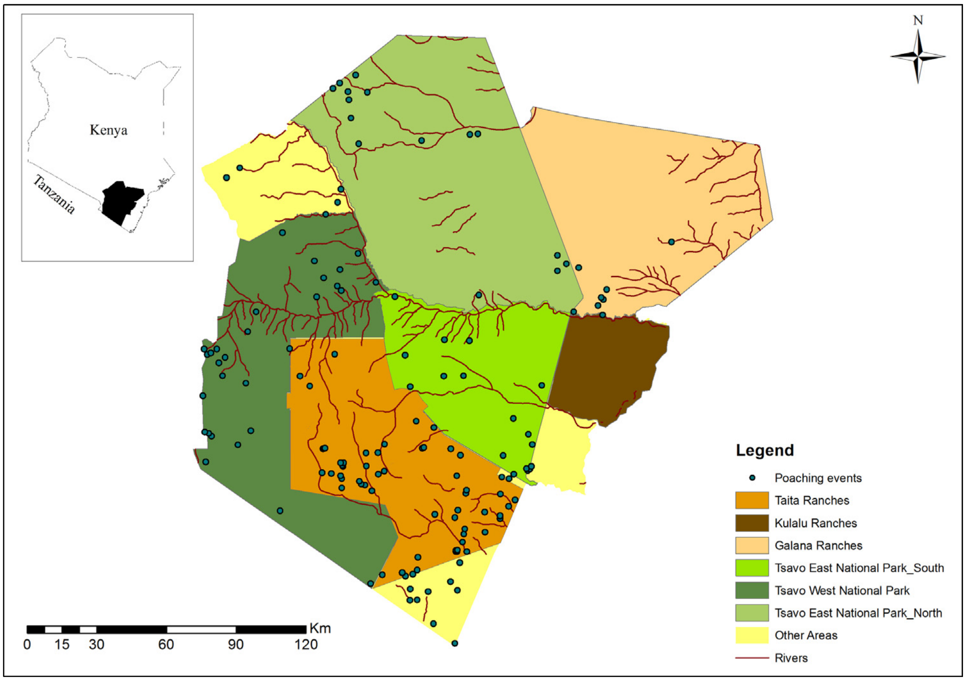

Fig. 1. Location of the Tsavo ecosystem in south-eastern Kenya, showing the locations where elephants are being poached and the types of land use.

applied to crime data to assist decision-making on where and when to address potential crime clusters in future, e.g. for drug offenses (Quick and Law, 2013) or city violence and property crimes (Uittenbogaard and Ceccato, 2012). However, few studies exist that aimed at detecting spatial and spatiotemporal patterns in the specific criminal act of wildlife poaching. One example is Haines et al. (2012) who studied white-tailed deer poaching activity in Fayette County, Iowa, USA, in terms of temporal, spatial, and environmental patterns. They used logistic regression models and produced poaching activity hotspots map.

Although elephant populations are declining across their habitat range in Africa and poaching is a significant source of mortality, little attention has been paid to predicting poaching hotspots. Analysis of data related to poaching is important for wildlife conservation. Based on elephant mortality data collected between 1989 and 2005 Kyale et al. (2011) identified spatial patterns of elephant mortality, which is largely due to poaching, in Tsavo East National Park in Kenya. They used kernel density analyses and found that the patterns were clustered, with poaching being more intensive in the northern and central areas of the park. Maingi et al. (2012) studied spatial patterns of elephant poaching separately for wet and dry season for the period between January 1990 and December 2009 in south-eastern Kenya. They used kernel density analyses and concluded that poaching was more common in the dry season when the elephants aggregate along permanent rivers. However, their analysis merely separated the two seasons and assessed hotspots for each, but did not address both space and time in a single model. In fact, poaching hotspots have never been mapped using spatiotemporal methods and the differences in hotspots that emerge from various clustering methods have not been evaluated.

We therefore set out to identify elephant poaching hotspots by analyzing the differences in emerging clusters of poached elephants in the Tsavo ecosystem. We used different cluster detection methods on data covering a continuous period of ten years. We selected four common clustering methods (two spatial, two spatiotemporal) for this purpose. Our study aimed to answer the following five questions: (1) Where are the consistent elephant poaching hotspots as determined by various spatial and spatiotemporal clustering methods? (2) What are the differences between the emerging clusters obtained by the different spatial clustering methods? (3) Do spatial clustering methods differ in their ability to predict where hotspots may occur? (4) What are the differences between the emerging clusters obtained by different spatiotemporal clustering methods? (5) Do the spatiotemporal clustering methods differ in their ability to predict where and when hotspots may occur?

2. Materials and methods

2.1. Study area

The Tsavo ecosystem covers an area of about 38,128 km^2 in south-east Kenya (Fig. 1). The ecosystem lies between 2–4° S, and 37.5–39.5° E (Ngene, 2013). It has a population of about 11,000 elephants (Kyale et al., 2014), and the highest reported poaching of elephants, in Kenya (Maingi et al., 2012). The anti-poaching activities in the Tsavo ecosystem are challenged by inadequate resources (human and financial), and the extensive area covered (Maingi et al., 2012). Various rivers traverse the ecosystem, including the Galana, Voi, Tiva, Tsavo and Athirivers (Maingi et al., 2012). Our study area comprised the Tsavo East national park north, Tsavo East national park south, and Tsavo West national parks, with the remainder covered by private ranches (Fig. 1). The climate of the area is semi-arid, with the long rainy season occurring between March and May, and the short rainy season in November and December. Mean annual rainfall varies locally between 250 and 500 mm (Maingi et al., 2012). Vegetation in the Tsavo ecosystem is dominated by Commiphora savanna (Maingi et al., 2012).

2.2. Elephant data

The poaching and population data on elephants used for this study were obtained from the Kenya Wildlife Service (KWS). The poaching data were collected from aerial patrols and daily ground patrols carried out by KWS through monitoring illegal killing of elephants (MIKE) program. Regular patrols and extensive coverage of monitored sites is essential to collect comprehensive data for

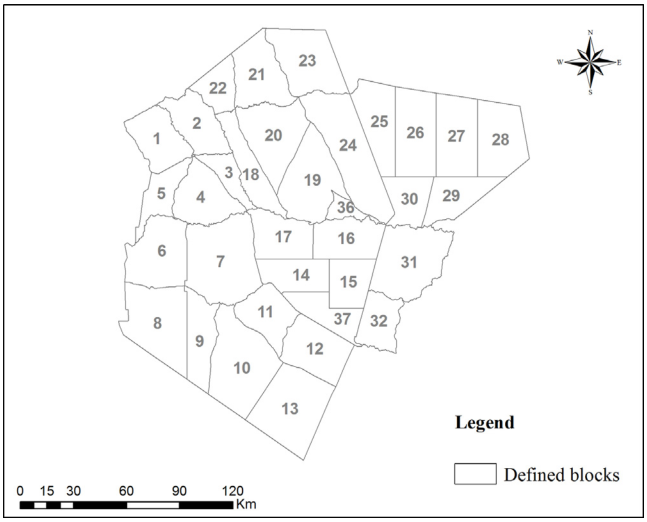

Fig. 2. Defined and numbered blocks in the Tsavo Ecosystem.

the MIKE program. Rangers are expected to complete patrol forms and carcass forms, and to use GPS units to record locations. The dataset listed 151 poaching locations in the study area between June 2002 and August 2012. The data included geographic coordinates, names of the locations where elephant carcasses were found, and the estimated date of death. Elephant population data were collected by aerial surveys carried out in the Tsavo ecosystem from 7 to 12 February 2011 (Ngene, 2013). We assumed that the spatial population at risk data from 2011 can be used for all years, since there were no significant changes in elephant population and distribution from 2002 till 2012 (Ngene, 2013). The data included the date, geographic coordinates and names of the locations where elephants were seen.

2.3. Block design

In order to compare the results of the different cluster analysis methods on the same basis, the study area was divided into 37 blocks, which were initially designed for the aerial counting comparison of the elephant population in the Tsavo-Mkomazi ecosystem. The blocks were described by Ngene (2013). They were defined mostly by easily detectable features such as hills, road, rivers, and protected area boundaries. The average block size was 1098 km^2 (Ngene, 2013). Block numbers 33–35 were excluded because they are located in Tanzania and no poaching data was available. We used the 34 blocks in Tsavo ecosystem to compare our findings (Fig. 2).

2.4. Spatial clustering methods

2.4.1. Kulldorff's spatial scan statistic

The spatial scan statistic was originally proposed by Kulldorff to examine occurrences of breast cancer (Kulldorff, 1997; Tango and Takahashi, 2005). It has been broadly applied in spatial cluster analysis (Wu et al., 2011). Kulldorff's spatial scan method imposes a circular scan window of a given radius centered on a target location centroid (Hanson and Wieczorek, 2002). The radius increases in size to an upper limit specified by the user (Xu, 2008). For each circle, a likelihood ratio statistic is computed based on the number of observed and expected cases within the window compared with outside the window (Hanson and Wieczorek, 2002; Torabi and Rosychuk, 2011). The window with the highest value for the likelihood ratio and the greatest relative risk (RR) is identified as the most probable cluster. Kulldorff's spatial scan method utilizes the maximum likelihood ratio as the test statistic to overcome the problem of multiple testing (Mennis and Guo, 2009). RR represents how much more common high incidence rates are in this particular cluster compared to the average outside this cluster. Thus, Kulldorff's spatial scan method reports the most likely cluster with a set of secondary clusters (Mennis and Guo, 2009). It initially calculates the likelihood ratio for each window and finds the maximum (Mennis and Guo, 2009).

To determine the statistically significant level, a large number of random replications of the dataset are generated under the null hypothesis using a Monte Carlo simulation and the test statistic value is calculated for each replication (Mennis and Guo, 2009; Xu, 2008). At that point, the true test statistic value is compared to the test values for all replications to detect the significant level for the most likely cluster and the secondary clusters (Mennis and Guo, 2009). In this study, we used spatial cluster analysis for higher incidence in the SaTScan software (version 9) (Kulldorff, 2011), in which the block centroids were included in the radius of the circle since aggregate data were used in this research. The maximum spatial cluster size was set to a circle with a 70-km radius, because an analysis of poaching locations using ArcGIS's incremental spatial autocorrelation tool demonstrated that maximum clustering occurred at a distance of 70 km.

2.4.2. Flexible spatial scan statistic

The flexible spatial scan statistic was developed by Tango and Takahashi (2005) and it permits irregularly shaped clusters to be identified (Quick and Law, 2013; Torabi and Rosychuk, 2011). The flexible spatial scan statistic is similar to Kulldorff's spatial scan statistic, but it is able to detect clusters with any shape, although the detected cluster is limited to a relatively small neighborhood in each region (Torabi and Rosychuk, 2011). The flexible scan statistic imposes an irregularly shaped window on each region by connecting its adjacent regions and Monte Carlo hypothesis testing is used to find the distribution of the test statistic under the null hypothesis of spatial randomness (Tango and Takahashi, 2005). In this study, we used the flexible spatial scan statistic implemented with a restricted likelihood ratio in order to considerably reduce the computational time required (Tango and Takahashi, 2012). This method scans only the regions with an elevated risk. The method was implemented with the FleXScan software and the maximum spatial cluster size was set to a default setting of 15 blocks (Takahashi et al., 2005). Similar to the circular spatial scan statistic, the window with the highest likelihood ratio values and the greatest relative risk are identified as potential clusters.

2.5. Spatiotemporal clustering methods

2.5.1. Spatiotemporal scan statistic

The spatial scan statistic can be extended to the spatiotemporal scan statistic by considering both spatial and temporal aspects of the recorded elephant poaching incidents. This is done by modifying the scanning window so that, instead of circles across space, cylinders are tested. The base of the cylinder represents the space and the height represents time (Kulldorff, 2011). Since we had elephant poaching data for a ten-year period, a retrospective space–time cluster analysis of incidents was selected using SaTScan software (version 9). Cases files, population files, and coordinate files (i.e. the centroids of the blocks) were generated for analysis (Wang et al., 2013). Spatiotemporal clusters were identified by fitting a discrete Poisson model and using a maximum cluster size of 50% of the study period in the temporal window and a circle of 70-km radius spatially (see Section 2.4.1). The primary cluster and secondary clusters were detected through the log likelihood ratio (LLR) test. The greatest relative risk was calculated as the estimated risk within the cluster divided by the estimated risk outside the cluster (Kulldorff, 2011). We tested the null-hypothesis that there is no cluster of occurrence inside the window against the alternative hypothesis that there is an elevated risk inside the window in comparison with outside (Xu, 2008). The p-values for identified clusters were computed by utilizing Monte Carlo simulations to create various random replications of the dataset under the proper null hypothesis (Liu et al., 2013). To ensure sufficient statistical power, and taking computation times in to account, we created 999 random simulations to obtain p-values (Liu et al., 2013). The null hypothesis of a spatiotemporally random distribution was rejected if the p-values was <0.05 (Wang et al., 2013).

2.5.2. Spatiotemporal permutation scan statistic

The spatiotemporal permutation scan statistic uses a cylindrical window while scanning. A circular or ellipsoid radius of the cylinder indicates the number of incidents covered by the cluster, and the height of the cylinder corresponds to the time covered. The spatiotemporal permutation scan statistic requires only case data (with information about the location and date) and does not need population-at-risk data (Kulldorff et al., 2005). The expected number of elephant poaching incidents was calculated by assuming complete spatial randomness, which is the same if the observed events with a persistent average were roughly independent Poisson random parameters (Si et al., 2009). A likelihood ratio, based on this approximation, was estimated to determine whether the cylinder contained a cluster or not. One cylinder with the maximum likelihood ratio test statistic is then considered to be the key candidate for the most likely cluster (Kulldorff et al., 2005). The statistical significance of detected clusters was evaluated using a Monte Carlo simulation (Dwass, 1957). The rank of the maximum likelihoods from the real dataset were compared to those of the random datasets to compute the p-values (Dwass, 1957; Kulldorff, 2006). The space–time permutation scan statistic was used to detect clusters mathematically. The center of the window was positioned at the centroid of each block (the latitude/longitude information of geometric center was obtained using ArcGIS geocoding function), and the radius of the circular window varied continuously from zero to a maximum radius of 70 km (see Section 2.4.1). For each spatial base, the height of the cylinder was modified from the shortest time aggregation length of 1 month to a maximum of 50% of the whole study period. The number of Monte Carlo replications was set at 999 and the statistical significance at 0.05.

2.6. The prediction accuracy index

The Prediction Accuracy Index (PAI) was used to measure the predictive accuracy of the spatial clustering methods (Chainey et al., 2008). This index provides a single measure of how reliable such a method is for predicting where hotspots may occur. A higher value of PAI reflects a greater accuracy. The index is calculated by:

$$PAI = \frac{(n/N) \times 100}{(a/A) \times 100} \tag{1}$$

where n is the number of poached elephants in areas where poaching is predicted to occur (hotspots), N is the total number of elephants poached in the study area in the 10-year study period, a is the area where poaching is predicted to occur (e.g. area of hotspots in km^2) and A is the whole study area in km^2. A higher PAI value indicates higher prediction accuracy.

Since the PAI is suitable for spatial clustering methods but does not consider the temporal aspects of incidents, in this study, we modified the PAI (MPAI) by adding a time factor to evaluate the spatiotemporal methods. Eq. (2) shows how this new index was calculated.

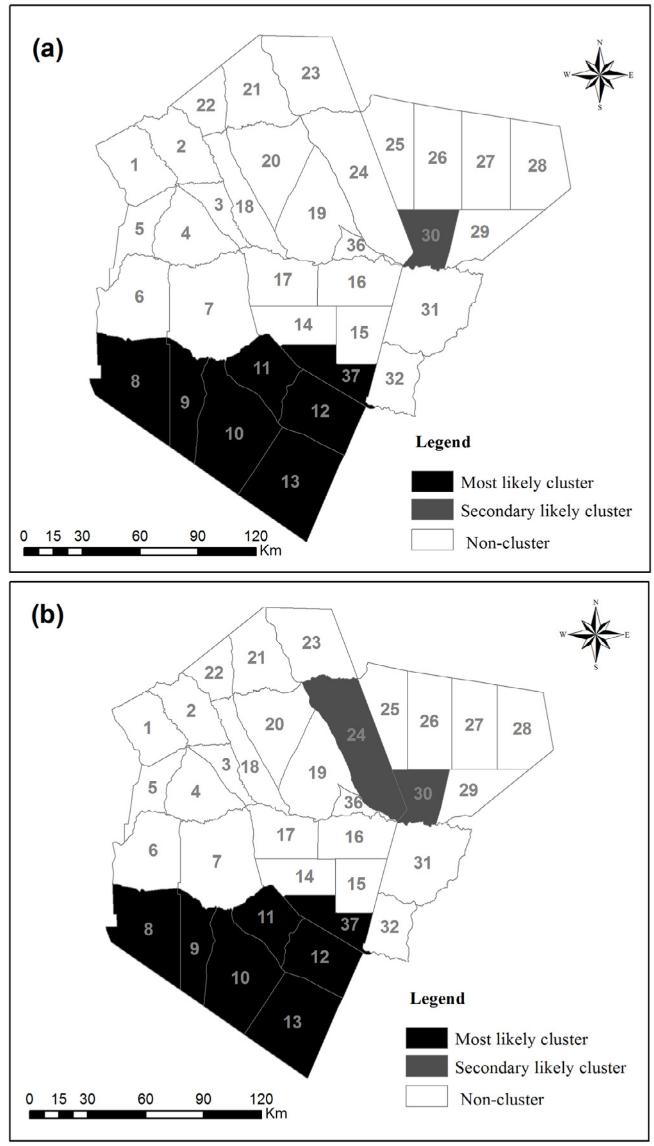

Fig. 3. The most likely clusters identified by the two spatial clustering methods: (a) Kulldorff's spatial scan statistic, and (b) the flexible spatial scan statistic with a restricted likelihood ratio.

$$MPAI = \frac{(n_t/N_T) \times 100}{(a/A) \times 100} \tag{2}$$

where n_t is the number of elephants poached in areas where poaching is predicted to occur (hotspots) and in the time range (t) of occurrence, N_T is the number of elephants poached in the whole study area during the total study period, a is the area where poaching is predicted to occur (e.g. area of hotspots in km^2) and A is the whole study area in km^2.

3. Results

Kulldorff's spatial scan statistic detected two significant clusters ($p < 0.05$) ranging in size from 1–7 blocks (Fig. 3). The most likely cluster consisted of seven blocks, defined by the highest relative risk (RR = 21.75) and log likelihood ratio (LLR = 146.89). The secondary clusters included one block, with a smaller RR (11.85) and LLR (9.23) compared with the most likely clusters (Fig. 3).

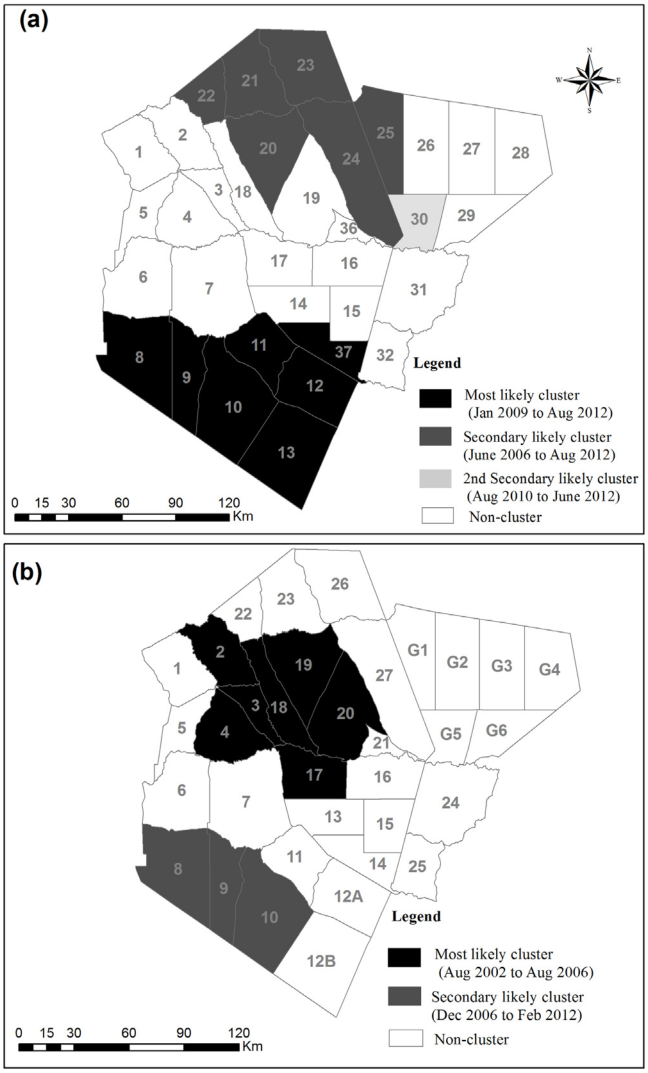

Fig. 4. The most likely clusters identified by two spatiotemporal cluster methods, using monthly spatiotemporal data from 2000 to 2012. (a) Spatiotemporal scan statistic and (b) spatiotemporal permutation scan statistic.

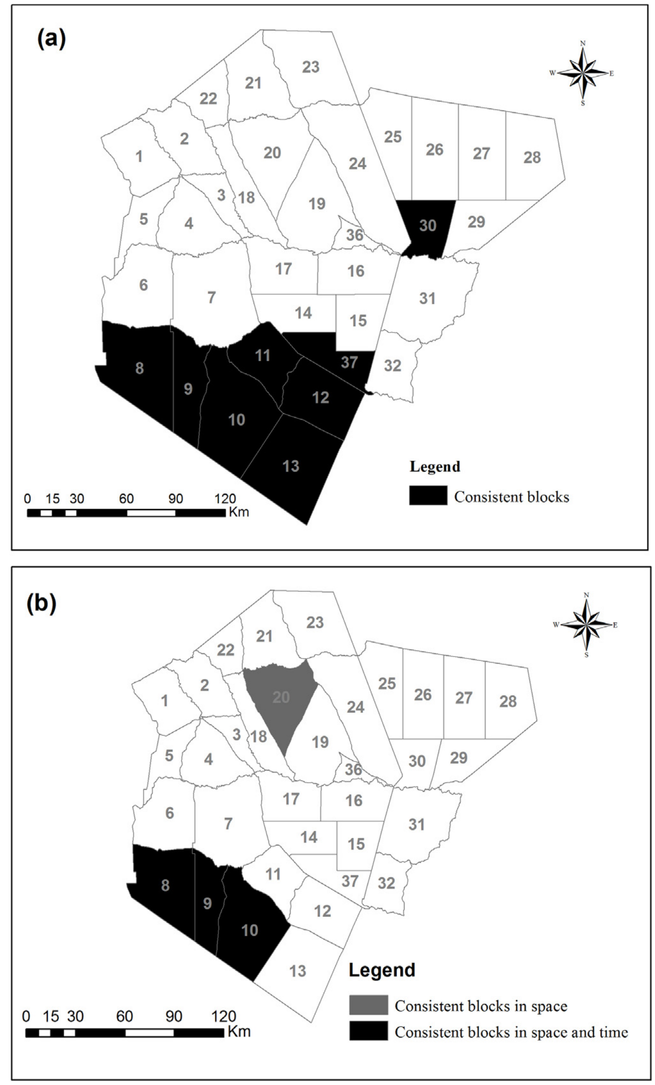

Fig. 5. Consistent blocks of elephant poaching in the Tsavo ecosystem, Kenya. They were derived from (a) spatial clustering methods, and (b) spatiotemporal clustering methods.

The flexible spatial scan statistic with a restricted likelihood ratio resulted in two significant clusters ($p < 0.05$) (Fig. 3). The most likely cluster consisted of seven blocks with the greatest RR (10.01) and LLR (146.89). The secondary clusters consisted of two blocks with smaller RR (5.76) and LLR (11.44) compared to the most likely cluster.

The results for the spatiotemporal scan statistic cluster are shown in Fig. 4. The spatiotemporal cluster analysis of cases of elephant poaching in 2002–2012 in the Tsavo ecosystem showed that elephant poaching was not distributed randomly in space and time. Using the maximum spatial cluster size of a circle with 70-km radius, and the maximum temporal cluster size of 50% of the study period, one most likely cluster and two secondary clusters were identified (Fig. 4). The most likely cluster consisted of seven blocks with the greatest RR (77.10) and LLR (235.33). It was detected for the period December 2009 to August 2012. The two secondary clusters also consisted of seven blocks; the RR of these clusters (69.62 and 32.51 respectively) within a non-random distribution pattern was also significant ($p < 0.05$) (Fig. 4).

The retrospective spatiotemporal permutation scan analysis of elephant poaching data during 2002–2012 detected two significant clusters ($p < 0.05$) (Fig. 4). The most likely cluster consisted of seven blocks with the greatest likelihood ratio test statistic (LLR = 8.46). It was detected between August 2002 and August 2006. The secondary clusters consisted of three blocks with a smaller test statistic compared to the most likely cluster (LLR = 6.61).

As can been seen from Fig. 5a, eight blocks were detected as having high poaching, irrespective of the spatial clustering method used. When the spatiotemporal analyses were included (Fig. 5b), four blocks were detected as having high poaching, irrespective of the method used. Three of these blocks overlapped in space and time (8, 9, and 10), but one overlapped in space, but not time (block 20). Fig. 5 shows the locations of these consistent blocks.

The PAI results for the two spatial clustering methods indicated that the cluster analysis methods vary in their ability to predict patterns of poaching events. Our results showed that Kulldorff's spatial scan statistic had a slightly higher PAI value than the flexible scan statistic (2.39 vs 2.12).

An evaluation of the modified PAI results for the two spatiotemporal clustering methods showed that the spatiotemporal scan statistic predicts when and where hotspots occur with greater accuracy than the spatiotemporal permutation scan statistic (1.46 vs 0.97).

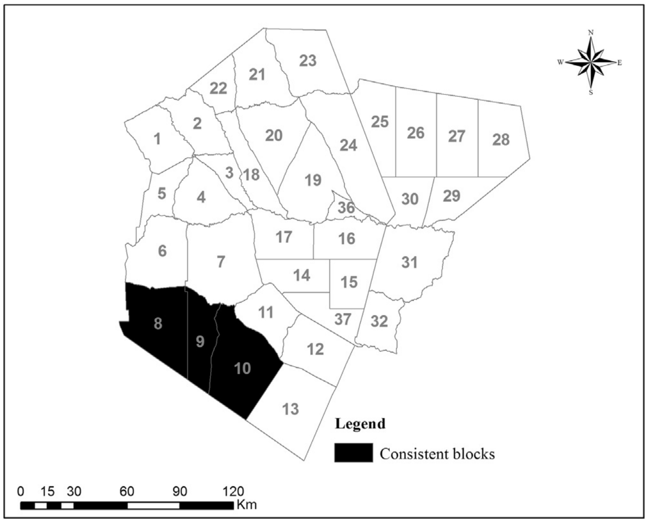

Fig. 6. Hotspots of elephant poaching in the Tsavo ecosystem, Kenya.

4. Discussion

A number of consistent elephant poaching hotspots in the Tsavo ecosystem emerged from the different cluster detection methods. Among the 34 blocks in the study area, three blocks were selected consistently, irrespective of the clustering method used, indicating a consistently high risk of poaching in these areas (Fig. 6). The consistently detected hotspots are located in Taita ranches and Tsavo West National Park and most were located along the border of Tanzania.

Our results indicated that similarities occurred between clusters detected by different cluster detection methods, but also differences emerged. This is partly due to variations in the sizes of search window and because the input data used are different. Our (Kulldorff's spatial scan statistic method) results identified a smaller number of combined blocks as a potential cluster compared to flexible scan statistic method. This may be due to the non-circular shape of the regions in the Tsavo ecosystem (Torabi and Rosychuk, 2011). Despite the small deviation, the results of the spatial scan statistics and flexible spatial scan statistics were largely consistent (Fig. 5a). This suggests that both spatial methods could be used interchangeably for application in the field of the poaching.

The PAI was used to assess the predictive accuracy of the spatial clustering methods. The results using PAI indicated that Kulldorff's spatial scan statistic had a slightly higher PAI value than the flexible scan statistic (2.39 vs 2.12). This finding implies that the shape of the search window has a small effect on the prediction accuracy. Based on the PAI value, Kulldorff's spatial scan statistics showed reasonably good prediction accuracy in detecting circular clusters. The flexible scan statistic also showed a reasonably good PAI value plus the ability to detect non-circular clusters (Fig. 3).

Clusters that emerged from the spatiotemporal clustering methods demonstrated an interesting phenomenon. For instance the most likely cluster in the spatiotemporal permutation scan statistic was selected as the area of the secondary cluster by the spatiotemporal scan statistic (Fig. 4). This different result may be partly explained by the influence of the input data, which are different for both methods. The spatiotemporal permutation scan statistic requires only case data, with information about the location and time for each case, but it does not need population-at-risk data, whereas the spatiotemporal scan statistics does require population-at-risk data. When comparing the two spatiotemporal methods, a few consistent poaching clusters were detected (Fig. 5b), which indicates the importance of considering the assumptions made in the scan statistic models in relation to the data being used (Alton et al., 2013). For example, when using the spatio-temporal scan statistics, the expected number of cases in each area is proportional to the population of the cases in that area, whereas for the spatiotemporal permutation scan statistic, the expected values are calculated only on the basis of cases. The permutation scan statistic is advantageous if population data are missing, but it may not be appropriate for analyzing poaching activities due to their covert nature and the fact that some cases of elephant poaching may not be reported (Burn et al., 2011).

By modifying the prediction accuracy index (MPAI), we demonstrated that it is possible to evaluate the predictive accuracy of spatiotemporal clustering methods over time. Our results indicate that the spatiotemporal scan statistic had a higher MPAI value when detecting cluster areas than the spatiotemporal permutation scan statistic (1.46 vs 0.97). This lower accuracy may be explained by the spatiotemporal permutation scan statistic being independent of the population-at-risk and a cluster being detected if an area has a higher proportion of cases during a specific time period compared to the remaining geographical areas (Alzahrani et al., 2013).

5. Conclusions

Clustering methods are useful for understanding the pattern of criminal activities; in this paper we compared four clustering methods for the purpose of examining one such activity, i.e. elephant poaching, using 10 years of patrol data. Elephant poaching clusters in the Tsavo ecosystem from two spatial methods (flexible scan statistic and Kulldorff's scan statistics) almost coincided and had a similar predictive accuracy. The two spatiotemporal methods showed larger differences; the spatiotemporal scan statistic outperformed the spatiotemporal permutation scan statistic in accurately predicting elephant poaching hotspots in the Tsavo ecosystem, based on a modified Predication Accuracy Index (MPAI). This difference can largely be explained by the fact that the permutation scan statistic does not use population-at-risk input data, which we had available in the form of an aerial elephant survey. Our results and methodological comparison may assist the Kenya Wildlife Service in allocating financial and human resources effectively to tackle (elephant and other species) poaching.

Acknowledgments

This work was funded by the Erasmus Mundus program of the European Union and co-funded by the ITC Research Fund, The Netherlands. We would like to thank Babak Naimi for his comments on an earlier version of the manuscript and Jackie Senior for editing work. We thank the Kenya Wildlife Service for providing the elephant poaching data.

References

Alton, G.D., Pearl, D.L., Bateman, K.G., McNab, B., Berke, O., 2013. Comparison of covariate adjustment methods using space–time scan statistics for food animal syndromic surveillance. BMC Vet. Res. 9, 231.

Alzahrani, A.G., Al Mazroa, M.A., Alrabeah, A.M., Ibrahim, A.M., Mokdad, A.H., Memish, Z.A., 2013. Geographical distribution and spatio-temporal patterns of dengue cases in Jeddah Governorate from 2006–2008. Trans. R. Soc. Trop. Med. Hyg. 107, 23–29.

Anselin, L., 1995. Local indicators of spatial association – LISA. Geogr. Anal. 27, 93–115.

Anselin, L., Cohen, J., Cook, D., Gorr, W., Tita, G., 2000. Spatial analyses of crime. J. Crim. Just. 4, 213–262.

Burn, R.W., Underwood, F.M., Blanc, J., 2011. Global trends and factors associated with the illegal killing of elephants: a hierarchical Bayesian analysis of carcass encounter data. PLoS ONE 6, e24165.

Burra, T., Jerrett, M., Burnett, R.T., Anderson, M., 2002. Conceptual and practical issues in the detection of local disease clusters: a study of mortality in Hamilton, Ontario. Can. Geogr. 46, 160–171.

Chainey, S., Tompson, L., Uhlig, S., 2008. The utility of hotspot mapping for predicting spatial patterns of crime. Secur. J. 21, 4–28.
Chakravorty, S., 1995. Identifying crime clusters: the spatial principles. Middle States Geogr. 28, 53–58.
Chiu, Y.-W., Wang, M.-Q., Chuang, H.-Y., Hsu, C.E., Nkhoma, E.T., 2008. A new application of spatiotemporal analysis for detecting demographic variations in AIDS mortality: an example from Florida. Kaohsiung J. Med. Sci. 24, 568–576.
Dwass, M., 1957. Modified randomization tests for nonparametric hypotheses. Ann. Math. Stat. 28, 181–187.
Haines, A.M., Elledge, D., Wilsing, L.K., Grabe, M., Barske, M.D., Burke, N., Webb, S.L., 2012. Spatially explicit analysis of poaching activity as a conservation management tool. Wildl. Soc. B 36, 685–692.
Hanson, C.E., Wieczorek, W.F., 2002. Alcohol mortality: a comparison of spatial clustering methods. Soc. Sci. Med. 55, 791–802.
Kulldorff, M., 1997. A spatial scan statistic. Commun. Stat.-Theorem 26, 1481–1496.
Kulldorff, M., 2006. Satscan User Guide for Version 7.0., Available at: http://www.satscan.org
Kulldorff, M., 2011. SaTScan User Guide for Version 9.0, Available at: http://www.satscan.org
Kulldorff, M., Heffernan, R., Hartman, J., Assuncao, R., Mostashari, F., 2005. A space–time permutation scan statistic for disease outbreak detection. PLoS Med. 2, e59.
Kulldorff, M., Tango, T., Park, P.J., 2003. Power comparisons for disease clustering tests. Comput. Stat. Data Anal. 42, 665–684.
Kyale, D.M., Ngene, S., Maingi, J., 2011. Biophysical and human factors determine the distribution of poached elephants in Tsavo East National Park, Kenya. Pachyderm, 48–60.
Kyale, D.M., Mukeka, J.M., Kimitei, K.K., Munyao, M.N., Lala, F.O., 2014. Tsavo-Mkomazi Total Aerial Census for Elephants and Large Animals. A technical Report for Kenya Wildlife Service (KWS), Kenya, Available at: https://drive.google.com/file/d/0B0QkOGKYnkM6NEhjQnZDdWR1Mmc/view?usp=sharing
Liu, Y., Wang, X., Liu, Y., Sun, D., Ding, S., Zhang, B., Du, Z., Xue, F., 2013. Detecting spatial-temporal clusters of HFMD from 2007 to 2011 in Shandong province, China. PLOS ONE 8, e63447.
Maingi, J.K., Mukeka, J.M., Kyale, D.M., Muasya, R.M., 2012. Spatiotemporal patterns of elephant poaching in south-eastern Kenya. Wildl. Res. 39, 234–249.
Mennis, J., Guo, D., 2009. Spatial data mining and geographic knowledge discovery – an introduction. Comput. Environ. Urban Syst. 33, 403–408.
Ngene, S.M., 2013. Status and trends of the elephant population in the Tsavo–Mkomazi ecosystem. Pachyderm, 38–50.
Quick, M., Law, J., 2013. Exploring hotspots of drug offences in toronto: a comparison of four local spatial cluster detection methods 1. Can. J. Criminol. Crim. 55, 215–238.
Si, Y., Skidmore, A.K., Wang, T., De Boer, W.F., Debba, P., Toxopeus, A.G., Li, L., Prins, H.H., 2009. Spatio-temporal dynamics of global H5N1 outbreaks match bird migration patterns. Geospat. Health 4, 65–78.
Takahashi, K., Yokoyama, T., Tango, T., 2005. FleXScan User Guide for Version 3.1.2, Available at: http://www.niph.go.jp/soshiki/gijutsu/download/flexscan/
Tango, T., 2010. Statistical Methods for Disease Clustering. Springer.
Tango, T., Takahashi, K., 2005. A flexibly shaped spatial scan statistic for detecting clusters. Int. J. Health Geogr. 4, 11.
Tango, T., Takahashi, K., 2012. A flexible spatial scan statistic with a restricted likelihood ratio for detecting disease clusters. Stat. Med. 31, 4207–4218.
Torabi, M., Rosychuk, R., 2011. An examination of five spatial disease clustering methodologies for the identification of childhood cancer clusters in Alberta, Canada. Spat. Spatiotempor. Epidemiol. 2, 321–330.
Uittenbogaard, A.C., Ceccato, V., 2012. Space–time clusters of crime in Stockholm, Sweden. Rev. Eur. Stud. 4, 148–156.
Wang, L.-Y., Zhang, W.-Y., Ding, F., Hu, W.-B., Magalhaes, R.J.S., Sun, H.-L., Li, Y.-X., Zou, W., Wang, Y., Liu, Q.-Y., 2013. Spatiotemporal patterns of Japanese encephalitis in China, 2002–2010. PLoS Neglect. Trop. D 7, e2285.
Wu, W., Guo, J., Guan, P., Sun, Y., Zhou, B., 2011. Clusters of spatial, temporal, and space–time distribution of hemorrhagic fever with renal syndrome in Liaoning Province, Northeastern China. BMC Infect. Dis. 11, 229.
Xu, B., 2008. Spatial and Temporal Analysis of Hemorrhagic Disease in White-tailed Deer in Southeast USA. University of Georgia, Athens (Ph.D. thesis).