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A multiple fine-scale satellite-derived landscape approach: example of bluetongue modelling in Corsica

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Summary

Landscape ecology is seldom used in epidemiology. The aim of this study is to assess the possible improvements that can be derived from the use of landscape approaches on several scales when exploring local differences in disease distribution, using bluetongue (BT) in Corsica as an example. The environment of BT-free and BT-infected sheep farms is described on a fine scale, using high resolution satellite images and a digital elevation model. Land-coverage is characterised by classifying the satellite image. Landscape metrics are calculated to quantify the number, diversity, length of edge and connectance of vegetation patches. The environment is described for three sizes of buffers around the farms. The models are tested with and without landscape metrics to see if such metrics improve the models. Internal and external validation of the models is performed and the relative impact of scale versus variables on the discriminatory ability of the models is explored. Results show that for all scales and irrespective of the number of parameters included, models with landscape metrics perform better than those without. The 1-km buffer model combines both the best scale of application and the best set of variables. It has a good discriminating ability and good sensitivity and specificity.

Keywords

Bluetongue, Corsica, Epidemiology, Geographic information system, Landscape, Remote sensing.

Un approccio ambientale derivato da una scala multipla dettagliata da immagini satellitari: esempio di creazione di modelli per la bluetongue in Corsica

Riassunto

L'ecologia ambientale viene talvolta utilizzata in epidemiologia. Scopo di questo lavoro è definire i possibili miglioramenti che possono derivare dall'uso dell'approccio di studio basato sull'analisi ambientale su varia scala nel caso si vogliano indagare differenze a livello locale nella distribuzione di alcune patologie, come ad esempio il caso della bluetongue (BT) in Corsica. Mediante l'utilizzo di immagini da satellite ad alta risoluzione e modelli di altitudine digitali, viene descritto su scala dettagliata l'ambiente di aziende BT-free *e l' ambiente di aziende infette da BT. La copertura del suolo è caratterizzata dalla classificazione dell'immagine satellitare. Le metriche ambientali vengono calcolate per quantificare il numero, la diversità, la lunghezza*

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del margine e il livello di contiguità delle aree di vegetazione. L'ambiente è descritto con buffer circa tre volte attorno all'azienda. I modelli sono testati con e senza le metriche ambientali per verificare se tali metriche migliorino i modelli stessi. Viene effettuata la validazione interna ed esterna dei modelli e viene esaminato il relativo impatto della scala confrontata con variabili sulla capacità discriminatoria del modello. I risultati dimostrano che per tutte le scale comprese, indipendentemente dal numero dei parametri inclusi, i modelli con le metriche ambientali incluse funzionano meglio di quelli senza le metriche ambientali incluse. Il modello con 1 km di buffer integra nel modo migliore sia la migliore scala di applicazione sia il miglior set di variabili. Tale modello possiede una buona capacità discriminante nonché buona sensibilità e specificità.

Parole chiave
Ambiente, Bluetongue, Corsica, Epidemiologia, Sistema informativo geografico, Telerilevamento.

Introduction

Landscape ecology focuses on the reciprocal interactions between spatial patterns and ecological processes (33). It covers a broad range of areas of inquiry, one of which relates to the quantification of the effects of landscape composition and structure of habitat. Such quantitative landscape approaches have been widely used to propose wildlife habitat conservation strategies (8, 29, 30), especially for bird communities (13, 17, 23, 27). Although an increasing number of epidemiological studies include land-use themes to identify and map environmental risk factors (6, 7, 10, 19), in most of cases the only variables tested are the presence or the percentage of surface of land-cover units. Metrics relative to other aspects of landscape composition (such as diversity) or to landscape structure (edge, shape, connectivity, etc.) are seldom used (1, 12, 15, 18, 22) although they can elucidate complex relationships between host, vector and reservoir ecologies. According to Ostfeld *et al.* (24), determining how often disease risk can be predicted from local conditions alone, and how often the landscape context modifies or overrides the impact of local conditions are two major research challenges (24). We propose to test whether landscape ecology approaches can be useful in epidemiology in a context where little is known about the habitat and biology of the vector, taking bluetongue (BT) as a model. A previous study confirmed the potential of these landscape approaches for BT (11), but relevant landscape scales and related environmental features have yet to be identified.

BT is a vector-borne disease of ruminants transmitted by various species of *Culicoides* biting midges (Diptera: Ceratopogonidae). Since 1998, BT has spread in Europe, affecting both the Mediterranean Basin (Corsica, Italy, Portugal and Spain), Eastern Europe (Albania, Bosnia-Herzegovina, Bulgaria, Croatia, Greece, Kosovo, Republic of Macedonia, Serbia and Turkey) (14, 25) and, more recently, northern Europe (Belgium, continental France, Germany, the Netherlands and Luxembourg) (32). Recently, the first spatial process model developed on a fine scale and relying on geographic and climatic variables was used to identify potential infectious sites for BT in Italy (9). This model assigned equal weights to the eight variables, as follows: elevation, slope, aridity index, land use, animal density, soil type, temperature and normalized difference vegetation index (NDVI). In this study, we test a similar model developed for BT in Corsica, with a multiple fine-scale analysis, different remotely sensed environmental data sets and a statistical assignment of weights based on logistic regression modelling.

Environmental data obtained from a digital elevation model (DEM) and a high-resolution SPOT (*Satellite pour l'observation de la terre*) satellite image (10 × 10 m pixel) were used to characterise the neighbourhood of BT-free and BT-infected sheep farms in southern Corsica on three scales. The SPOT image was classified to obtain a land-cover map, from which the percentages of surface of land-cover units, as well as landscape metrics, were calculated. For all three scales, models developed with and without landscape metrics were compared to assess possible improvements derived from the use of landscape metrics. Validation of the models was performed on the same data set and on a new set from the region of Ajaccio (Corsica) located 40 km north. Finally, the relative impact of scale versus variables on the discriminatory ability of the models was explored using this latter data set.

Materials and methods

Epidemiological data

The detailed method is presented elsewhere (16). Briefly, 80 sheep farms were integrated in a geographic information system (GIS) (ArcGis™ 8.3 software). The farms were classified as infected if a BT outbreak had been officially recorded between 2000 and 2003. The farms were classified into two groups according to their breeding systems (those with only sheep holdings and those where other livestock species were raised with sheep).

Environmental data

The environment in the vicinity of the farms was characterised using three buffers sizes, namely: 0.5, 1 and 2 km referring to the flight range of *Culicoides variipennis* (21) (as the flight range of *C. imicola* remains unknown). From the DEM, four topographical variables were extracted, as follows: altitude, slope, aspect and sunshine. The length of rivers in the buffers was also calculated. A supervised object-oriented nearest neighbour classification was performed (eCognition® software) on the SPOT image. The land-cover map produced comprised nine classes, as follows:

- woodlands (composed of broadleaf forests and *maquis*, a local association of dense shrubs and trees)
- low shrublands (resulting from the disturbance of *maquis* by fire, human activities or significant exposure to wind or snow)
- coniferous forests
- open prairies
- prairies with tree cover
- cultivated land
- marshes
- impervious surfaces
- water.

The percentage of surfaces in the buffer zones occupied by each of the nine classes was calculated.

Landscape data

The land-cover map was considered as a mosaic of vegetation patches which were characterised by calculating landscape metrics (Fragstats freeware). These metrics were selected to reflect different aspects of landscape ecology (area-density-edge, diversity, isolation-proximity and connectivity). The six following metrics were calculated for each buffer (regardless of the land-cover class):

- patch density
- landscape shape index (measuring the total length of edge divided by minimum length of edge possible for a maximally aggregated class)
- mean distance to neighbouring patches
- connectance index
- two diversity indexes: the patch richness density and Simpson's diversity index (full detailed information on these metrics is available on the Fragstats site at www.umass.edu/landeco/research/fragstats/fragstats.html).

Another two metrics were calculated for each of the nine land-cover classes: the number of patches and the landscape shape index (LSI) of each class.

Analysis

As many variables were included in this study, a preliminary univariate screening analysis was performed using a 0.15 *p*-value. A stepwise logistic regression (Systat® software) was then performed to explain BT outbreak occurrence on the farms (dependent variable, $p<0.1$). Most landscape approaches only take into account the percentage of each land-cover class. To test whether the use of landscape metrics improved the accuracy of the models, models with and without landscape metrics were compared by calculating the corrected Akaike information criterion (cAIC). This criterion is used to compare non-nested models. It takes into account both goodness of fit and the complexity of the model (parsimony is favoured and over-parameterisation is penalised). Corrected AICs are used when the ratio of n (number of observations) on K (number of parameters) is less than 40. The best model is the model with the smallest cAIC.

The three models with landscape metrics were validated internally and externally (i.e. on new environmental and epidemiological data sets). For external validation, environmental variables from a second SPOT image were extracted from buffer zones around sheep farms located in the Ajaccio region (situated 40 km north). The internal and external accuracy of the models were assessed by calculating the area under curve (AUC) of the receiver operating characteristics (ROC) curve (Stata® software). The ROC curve corresponds to the plot of sensitivity (y-axis) against (1–specificity) (x-axis). This accuracy metric measures the discriminatory ability of the models (28).

Finally, the relative impact of scale versus variables on the discriminatory ability of the models was explored by testing the three sets of variables on the three scales for the new data set from the Ajaccio region.

Results

Epidemiological data

The location and BT-status of the 80 sheep farms included in the study are shown in Figure 1. A total of 46 farms were considered as infected with BT and 34 as BT-free.

Land-cover map of southern Corsica

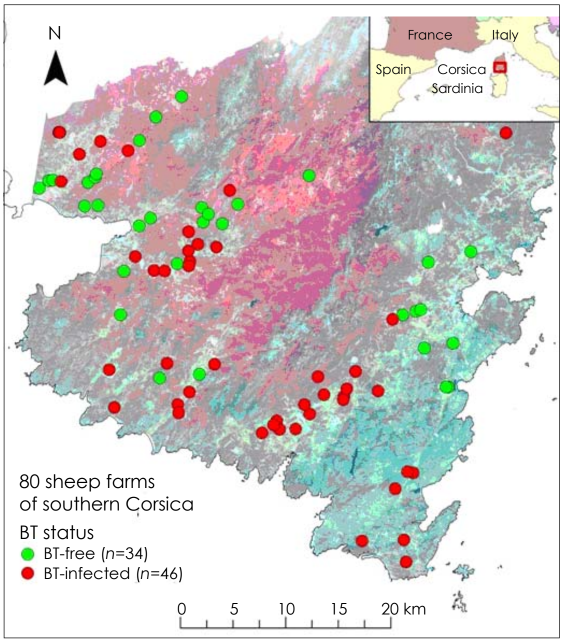
The land-cover map is shown in Figure 2.

Comparing models with and without landscape metrics

The models with and without landscape metrics and their evaluation (cAIC) are presented in Table I. For all three scales, the models with landscape metrics have the best cAIC, irrespective of the number of parameters.

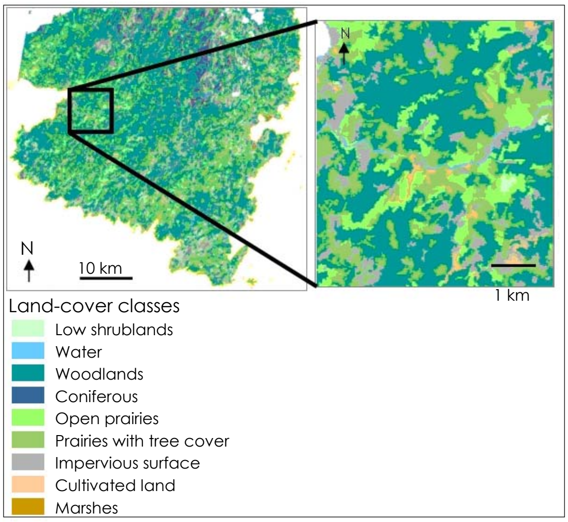
Validation of the three models with landscape metrics

The internal validation of the three models with landscape metrics reveals that all three models have good to high accuracy of results. As suggested by the overlap of the 95% confidence intervals, no statistically significant difference of accuracy was detected when testing the AUC of the ROC curves (in all cases $p>0.27$) (Table II).



Spot data/Isis program, © CNES (2001), distribution Spot image S.A.

Figure 1
Location of bluetongue-free and bluetongue-infected sheep farms in southern Corsica



Spot data/Isis program, © CNES (2001), distribution Spot image S.A.

Figure 2
Land-cover map of southern Corsica

Nevertheless, the 1-km buffer scale model may appear to be more valuable than the others since it combines good discriminatory abilities for both internal and external validations, as

Table I
Variables included in the bluetongue models with and without landscape metrics for the three buffer areas

Models Type of Variables	0.5 km- buffers Without landscape metrics	 With landscape metrics	1-km buffers Without landscape metrics	 With landscape metrics	2-km buffers Without landscape metrics	 With landscape metrics
Farm attributes	Farm type	Farm type	Farm type	Farm type	Farm type	Farm type
Geography	Latitude	Latitude	Latitude		Latitude	Latitude
Topography			Sunshine	Sunshine	Sunshine Altitude	Sunshine
Land-cover classes	Prairies with tree cover (%) Open prairies (%)		Presence of low shrubland	Presence of low shrubland		
Landscape metrics		Patch richness density		LSI of impervious surfaces LSI of open prairies LSI of woodlands		Number of patches of open prairies
cAIC	90.4	89.5	89.8	85.1	90.6	82.9

LSI landscape shape index
cAIC corrected Akaike information criterion (the smaller the cAIC, the better the model)

Table II
Internal and external validation of models with landscape metrics

Model evaluation		0.5-km buffers	1-km buffers	2-km buffers
Internal validation (southern Corsica, 80 farms)	AUC ROC curve	0.85	0.90	0.88
	95% CI	*0.77-0.93*	*0.83-0.97*	*0.81-0.96*
	Sensitivity (cut-off: 0.5)	87%	85%	87%
	Specificity (cut-off: 0.5)	62%	85%	68%
External validation (Ajaccio region)	Number of farms	151	134	130
	AUC ROC curve	0.73	0.81	0.77
	95% CI	*0.65-0.81*	*0.74-0.88*	*0.69-0.85*

AUC ROC curve area under curve of the receiver operating characteristics curve
CI confidence interval

well as good sensitivity and specificity results (85%, cut-off point: 0.5).

Testing the effects of the scale of application versus the set of variables

The results of the external evaluation (on the Ajaccio data set) of the three models with landscape metrics on the three scales are presented in Table III. Models A, B and C include three (farm type, latitude and patch richness density), six (farm type, sunshine, presence of low shrublands, LSI of impervious surfaces, LSI of open prairies and LSI of woodlands) and four (farm type, latitude, sunshine and number of patches of open prairies) variables, respectively.

A comparison between columns shows the effect of the set of variables. Applied on the 0.5-km and 2-km buffers, model C (4-variable model) has the highest accuracy (it has the greatest ROC AUC). Applied to 1-km buffers, model B (6-variable model) has the highest accuracy. As there is no single best set of variables whatever the scale, the set of variables does not have a more important effect than the scale of application on the accuracy of the models.

Table III
Effects of scales and variables on the discrimination ability of the models
Models A, B, C include the variables of the 0.5-, 1- and 2-km buffer models with landscape metrics, respectively
Variables of Model A: farm type, latitude, patch richness density
Variables of Model B: farm type, sunshine, presence of low shrublands, landscape shape index (LSI) of impervious surfaces, LSI of open prairies, LSI of woodlands
Variables of model C: farm type, latitude, sunshine and number of patches of open prairies

Scale of application on external data	AUC ROC curve Model A	Model B	Model C
0.5-km buffers	0.734	0.746	0.773 (V)
1-m buffers	0.779 (S)	0.807 (S, V)	0.802 (S)
2-km buffers	0.767	0.757	0.769 (V)

AUC ROC curve area under curve of the receiver operating characteristics curve
(V) best set of variables for the scale considered
(S) best scale of application for the model considered

A comparison between lines shows the effect of the scale of application. For all three models tested (A, B and C), the most relevant scale of application is the 1-km buffer scale. The best scale of application is always the same whatever the set of variables, but the differences in accuracy of the models are not statistically significant. Therefore, the effect of the scale of application cannot be considered more important than the effect of the set of variables.

Although not significantly more accurate than the other models, the application of model B to the 1-km buffer scale combines both the best scale of application and the best set of variables.

Globally, the accuracy of the three models on the three scales are comparable (no significant differences) and can be considered as fair to good. As always, when differences are not statistically significant, the explanation might be that there are indeed no differences or that the data set is too small for differences to be detected.

Discussion

The odds ratios and the biological significance (importance of latitude, open land-covers, fragmentation of the landscapes, etc.) of the variables included in the model are not detailed here as they have been discussed elsewhere (16). We focused discussion on the methodological aspects of multiple fine-scale modelling and the potential improvements from the inclusion of landscape metrics.

Fine-scale environmental variables

Previous studies have widely proved the potential of using low-resolution satellite imagery to model the distribution of BT vectors through the analysis of meteorological surrogates (2, 3, 4, 5, 26, 31). These studies rely on the fact that vectors are influenced by environmental factors, such as rainfall, temperature, humidity, etc. Meteorological surrogates cannot be obtained from high spatial resolution remote sensors but instead, these types of satellites may provide information on land cover and, in particular, vegetation. Vegetation type and distribution are also related to meteorological conditions and thereby influence vector populations as well as host populations. They can thus be used to model vector populations and the diseases they carry (6).

Only recently and for a few disease systems have landscape composition and structure been considered potentially important drivers of risk or incidence (24). This study shows that with a high-resolution image, new aspects of BT epidemiology can be explored. A wide range of variables were tested, and results show that landscape metrics can help to discriminate environments at risk of BT in Corsica, confirming that integrating landscape ecology with epidemiology may be valuable. As in all studies including numerous closely-related variables, great caution should be taken to identify and understand multi-collinearity effects.

Multi-scale analysis

Multi-scale designs are generally recommended in landscape analysis to determine the sensitivity of land-cover metrics to the environmental processes under study (20). Moreover, this was essential as, in the case of BT, little is known about the flight dispersal capacity of *C. imicola*. Results show that for all three scales, the accuracy of the models was good or high. Larger ranges of scales could be tested to determine if there is a threshold after which models become clearly less efficient, which would give an idea of the extent to which the environment may influence the presence of the vector. The 1-km model combines the best set of variables with the best scale of application and has good discriminating ability as well as sensitive and specific results. Nevertheless, the other scales should not be ruled out since accuracy results are not significantly different.

Landscape metrics in epidemiology

For the three scales tested, and irrespective of the number of variables included, this study shows that in the case of BT, models that include landscape metrics provide a better fit than those that do not. These results are of major importance for entomological work, as the ecology of the vector has still only been described partially and further field work could be sampled based on landscape features. They also clearly support a wider use of landscape approaches to epidemiology. Indeed, landscape analysis approaches can be conducted whenever:

- landscape elements are critical to vector, host or reservoir population
- these elements can be detected at remote sensing scales (6).

The first condition is likely to be fulfilled for most, if not all, vector-borne diseases. The second condition is bound to become less restrictive as spectral, temporal and, in particular, spatial resolutions of satellite sensors evolve.

A similar approach based on vector distribution data instead of outbreak occurrence is being tested to assess the robustness of the results on variables and scales. This will also help determine whether vector-based models surpass disease-based models, vector presence being more closely linked to environmental conditions than disease outbreak occurrence (which supposes the concomitant presence of the virus, vectors and susceptible animals).

Conclusions

A multiple fine-scale satellite-derived approach was used to understand local distribution of disease outbreaks, taking the case of BT in southern Corsica. The usefulness of landscape metrics was shown, as whatever the scale considered, the inclusion of landscape metrics improved the models. Internal and external validation enabled the assessment of discriminating abilities of the models. Comparing the relative importance of scale versus variables showed that the model which offered the best validation results combined the best set of variables and the best scale of application. The methodology proposed here can be applied to wide range of diseases which are thought to be linked to environmental factors.

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