Spatial modelling of Rift Valley fever vectors in Senegal

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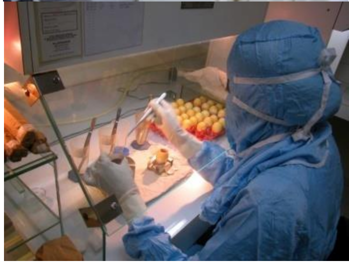
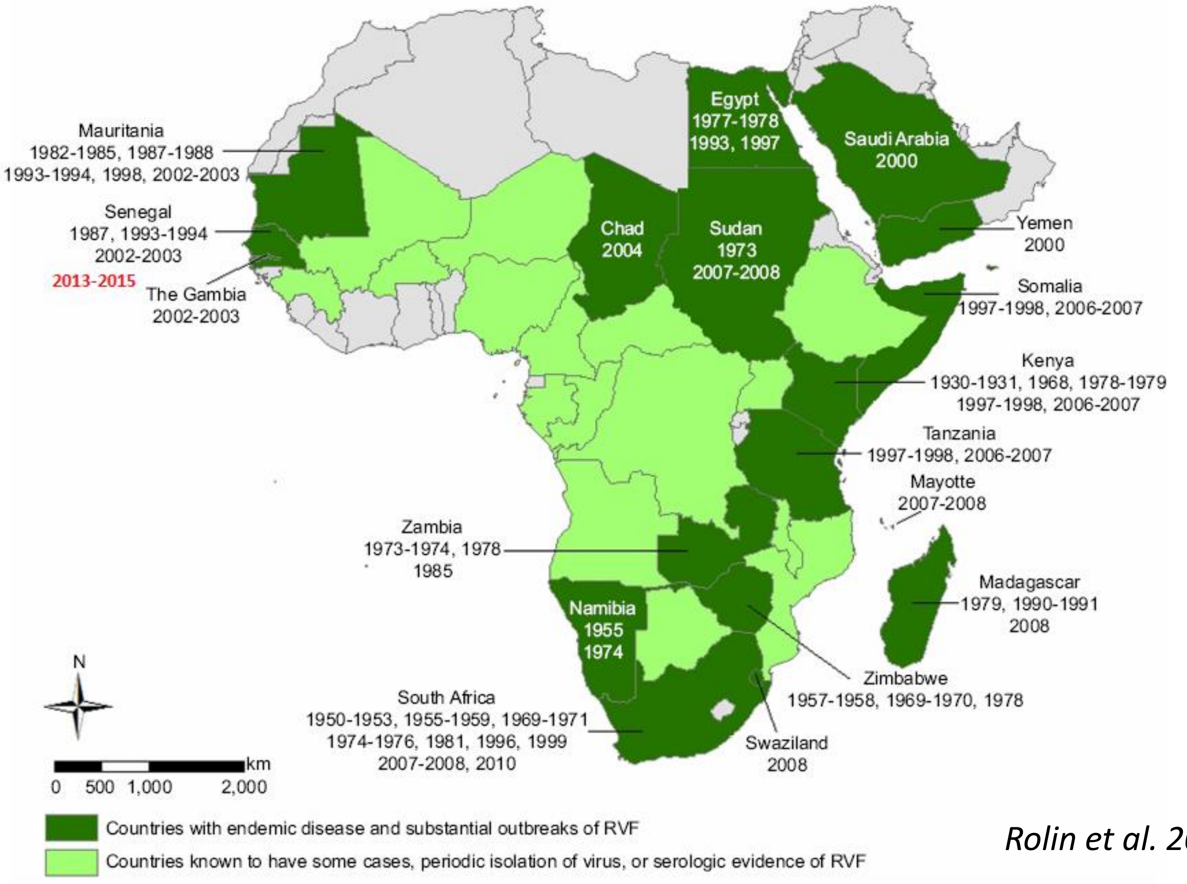


Geographical distribution of Rift Valley fever



Rolin et al. 2013

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Introduction

- Problem of vector born disease (RVF):
  - Lack of treatments
  - Lack of an effective vaccine
  - Limited means of surveillance
  - Lack of means of prevention

« All models are wrong, but some are useful »

Georges Box

(British statistician (1919-2013)

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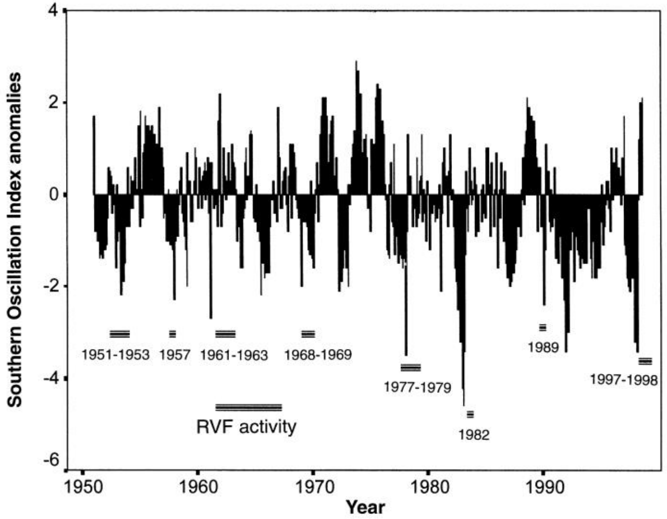
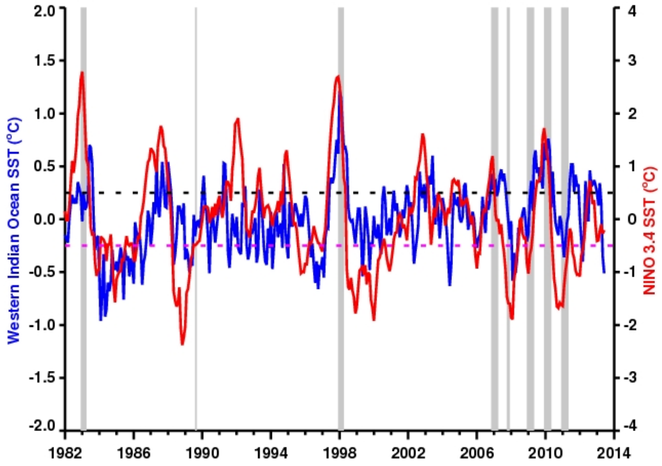
RVF modelling in Africa

- Modelling approach was adopted in East Africa based on the identification of climatic and environmental variables controlling the occurrence of RVF virus
  - Pacific and Indian Ocean sea surface temperature anomalies (SSTs)
  - Satellite normalized difference vegetation index anomaly(NDVI)



Linthicum et al 1999



Anyamba e al 2009

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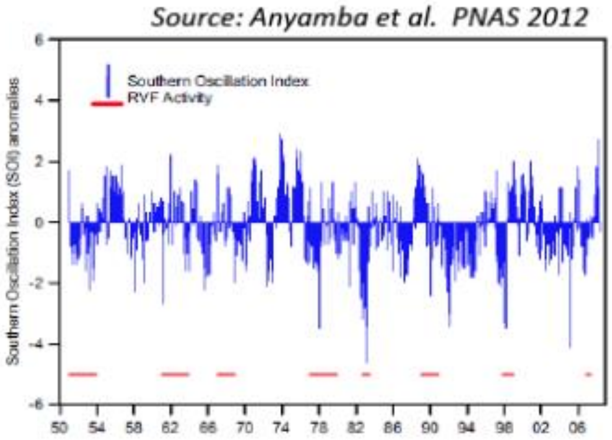
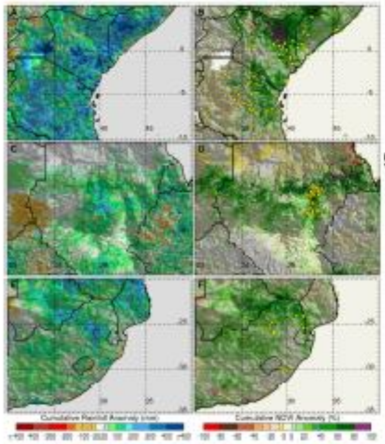
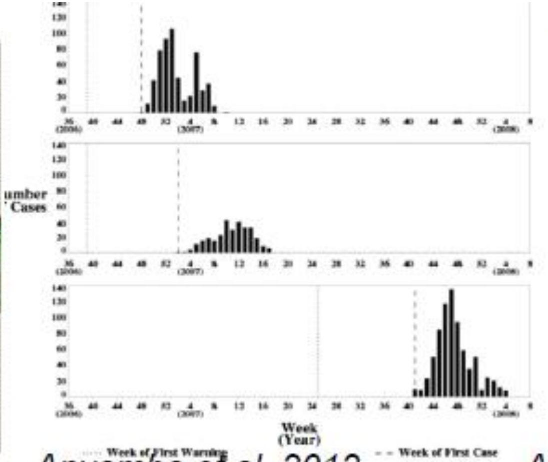
RVF Modelling in Africa

- An early warning system was set up allowing to predict RVF outbreaks up to 5 months in advance using parameters such as the normalized difference vegetation index (NDVI) and sea surface temperature anomalies







Anyamba et al, 2012

- Kenyan, Somalia, Tanzania
  4-5 month
- Sudan
  5-6 month
- South of Africa
  2-3 month

Anyamba et al, 2010

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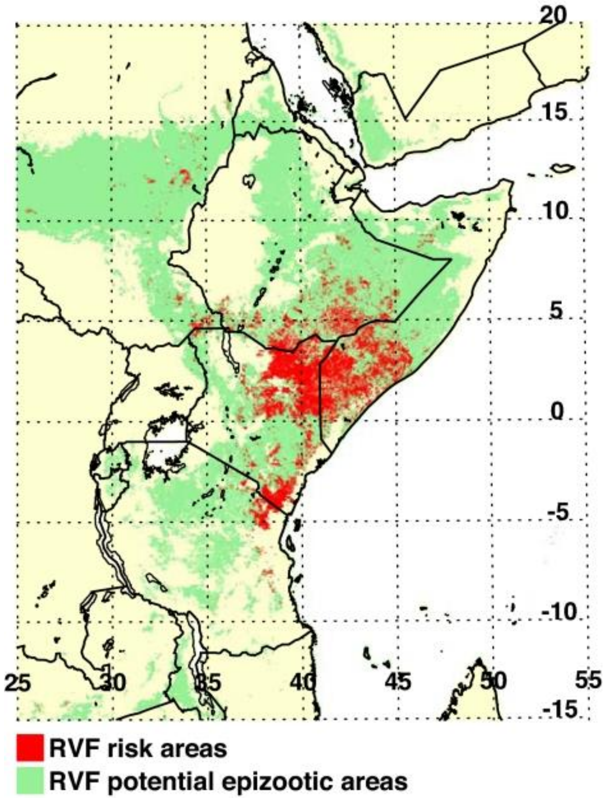
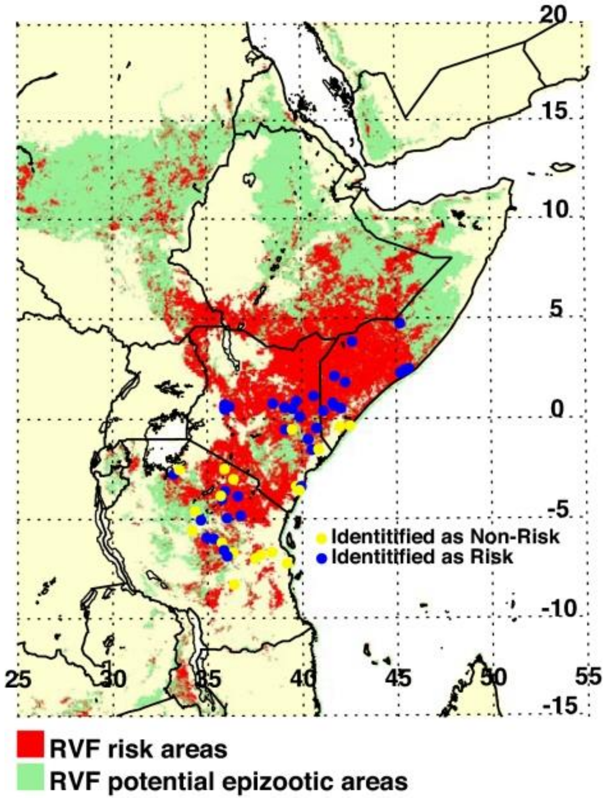
RVF activities in Kenya





64% of all human cases fell within the areas mapped to be at risk to RVF activity

Anyamba et al 2009

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RVF modelling in Africa

- Prediction of RVF outbreaks in Senegal during 1993, Burkina Faso in 1983, and Central Africa in 1985 failed due to a possible:
  - Lack of sensitivity of the system like the threshold of the NDVI
  - Lack of data from animal/human cases for model validation
  - Difference of the dynamics and mechanisms of emergence between East and West Africa
  - Variables involved in the transmission are different

RVF modelling in west Africa

- Several models have been developed for the West African context at a local-scale but the analysis is restricted to the impact of rainfall in most of these models, which lack the spatial dimension.

- Most of these models have been developed specifically for *Ae.vexans*

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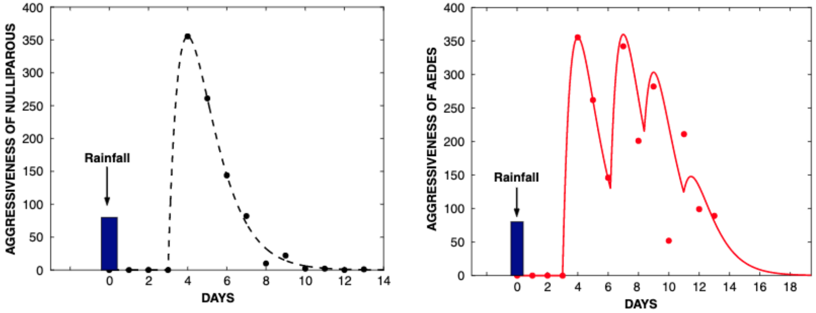
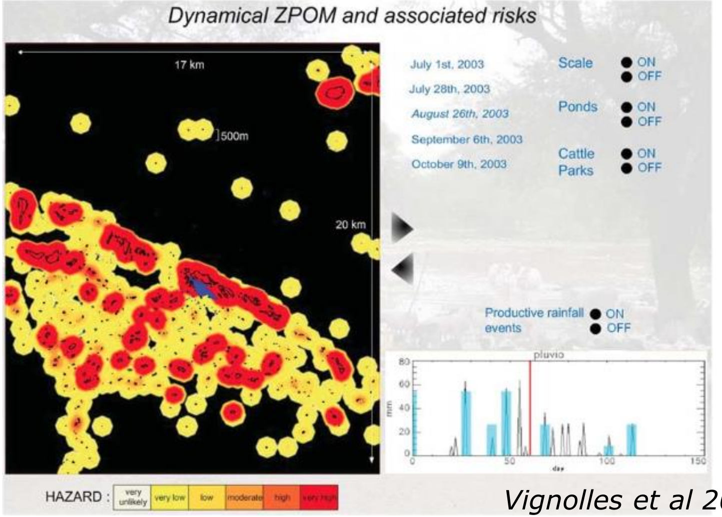
RVF modelling in Senegal



Ndiaye et al 2006



Vignolles et al 2009

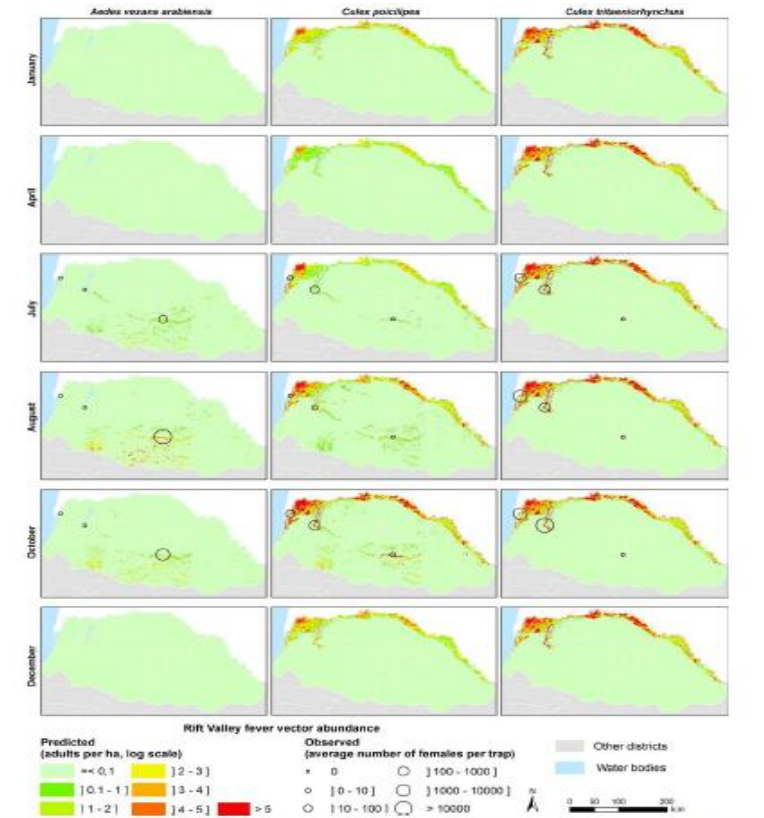


Figure 7. Examples of modeled density maps of *Ae. vexans*, *Cx. poicilipes* and *Cx. tritaeniorhynchus* in Northern Senegal, 2014.

Tran et al 2019

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Objective

- Quantify the abundance of vectors (*Ae. vexans, Cx. poicilipes*)
- Identify climatic and environmental variables impacting on the abundance of vectors (RVF)
- Identify periods and areas at risk by generating prediction maps

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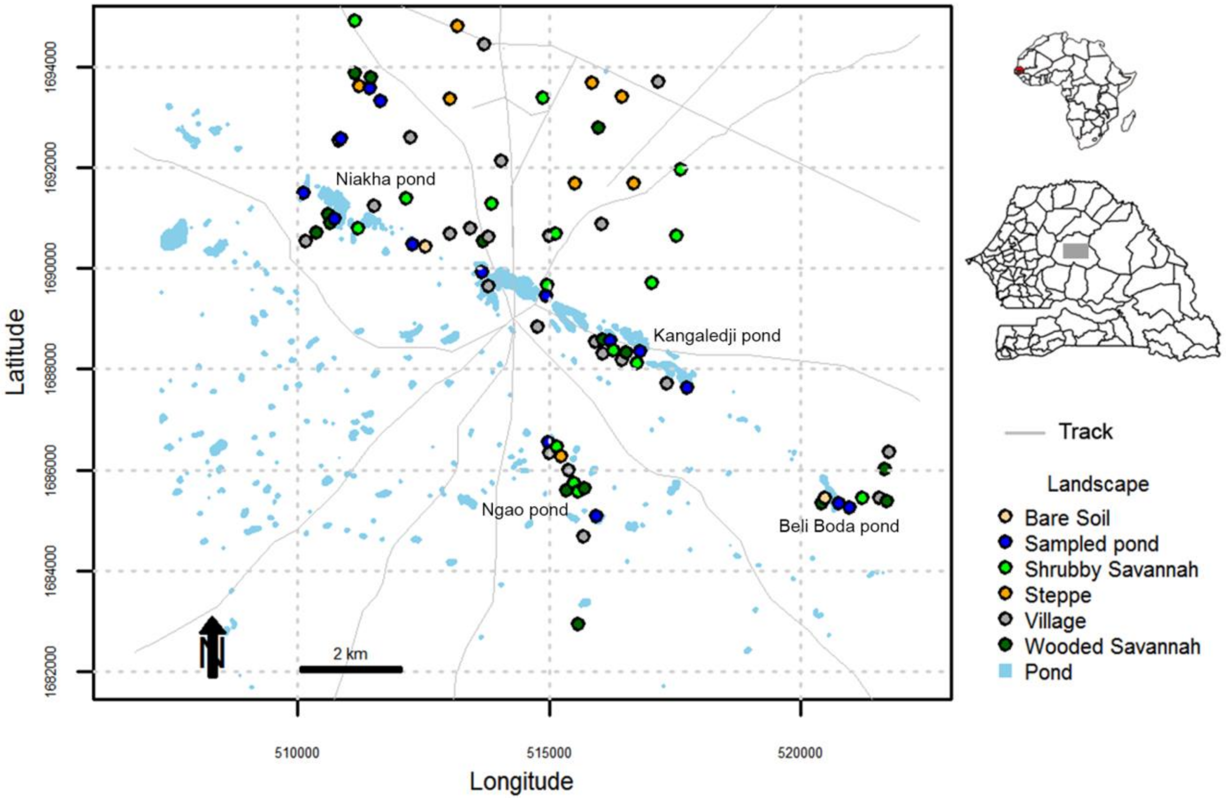
Study area



- Bi-weekly collection data from 2005-2006
- during the rainy season
- 79 sites

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Spatio-temporal model framework

Aedes vexans :

$$
\begin{aligned}
Y_{st} &\sim Pois(\lambda_{st}) \\
\log(\lambda_{st}) &= \sum_q \beta_q X_{qst} + B_{s'(s)} + q_t + \sin(\pi t/9) + \cos(\pi t/3) + \varepsilon_{st} \\
B_{s'(s)} &\sim N(0, \sigma_B) \\
\varepsilon_{st} &\sim N(0, \sigma_\varepsilon^2) \\
q_t &\sim N(q_{t-1}, \sigma_t^2)
\end{aligned}
$$

Culex poicilipes :

$$
\begin{aligned}
Y_{st} &\sim Pois(\lambda_{st}) \\
\log(\lambda_{st}) &= \sum_q \beta_q X_{qst} + U_s + q_t + 5\sin\left(\pi(t-3)/6\right) \\
U_s &\sim CAR(\sigma_u^2) \\
q_t &\sim N(q_{t-1}, \sigma_t^2)
\end{aligned}
$$

RVF modelling in West Africa

- Vector-borne diseases are influenced by several factors:
  - Human factor
  - Environmental factor (spatial structure)
  - Climatic factor
  - Animal factor
  - Time factor (seasonality)

Identification of variables

- Rainfall
- Maximum temperature
- Minimum temperature
- Relative humidity
- The biotope (temporary ponds, bare soil, ...)
- NDVI (Normalized Difference Vegetation Index)
- Distance between the collection point and the nearest pond
- The collection time period

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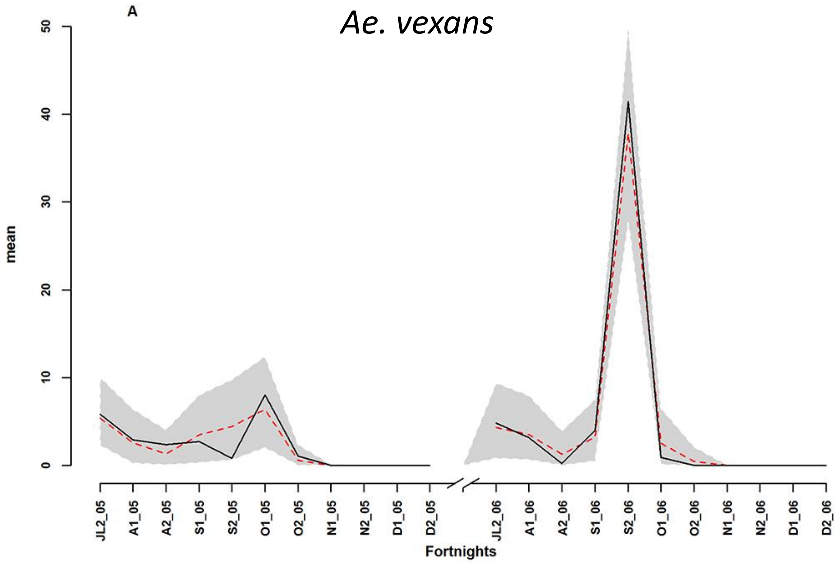
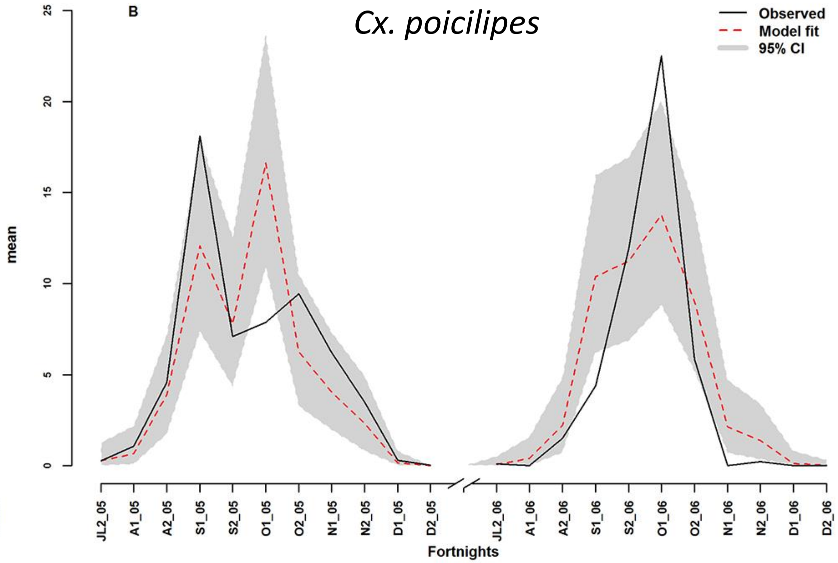
Model results





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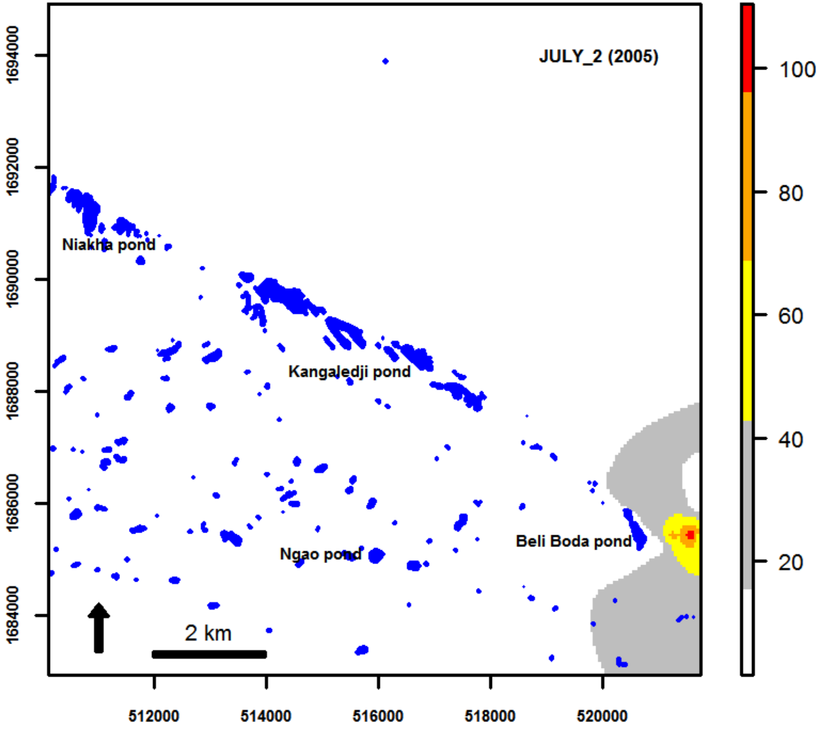
Spatial & temporal distribution of RVF vectors abundance



Talla et al, 2014

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GLMM model: with spatial correlation

- In the absence of an alert threshold for high densities
  - Determine areas with high mosquito densities value (Hotspot Getis Ord)
  - Identify climate and environmental factors impacting on the likelihood of hotspot occurrence

Spatial dependency or auto-correlation notion

- Spatial autocorrelation measures how much close objects are in comparison with other close objects. It can be classified as positive, negative and no spatial auto-correlation

- It evaluates whether the spatial pattern expressed is clustered, dispersed, or randomized.

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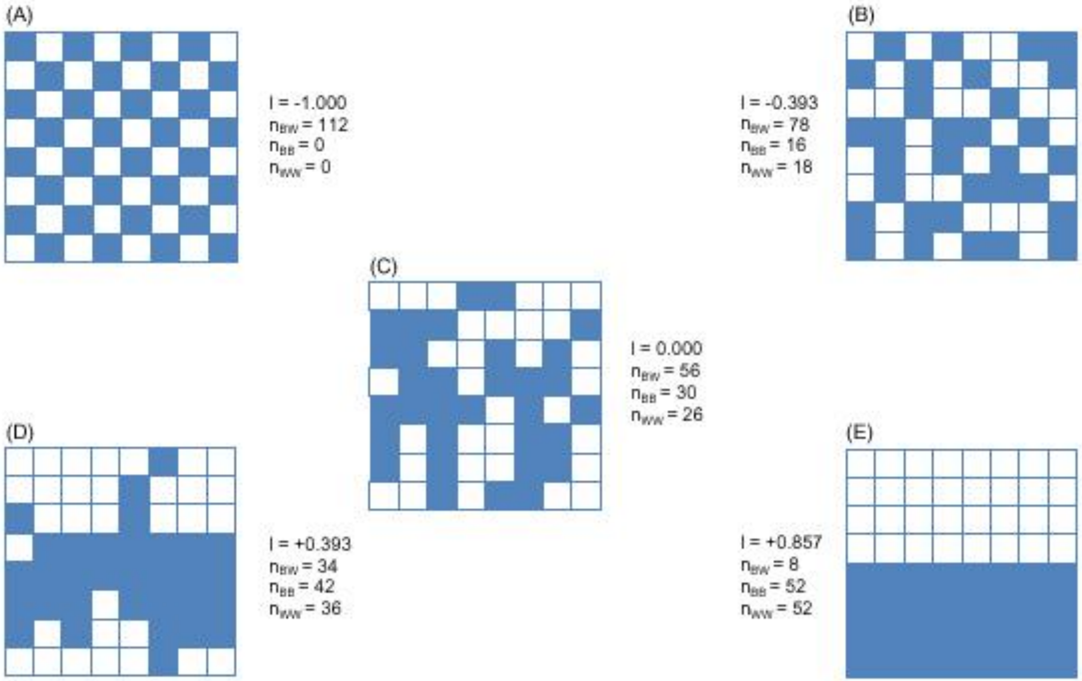
Spatial autocorrelation

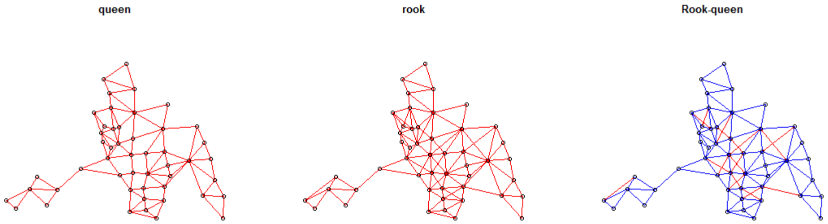
- Positive spatial autocorrelation is when similar values cluster together in a map.
- Negative spatial autocorrelation is when dissimilar values cluster together in a map.

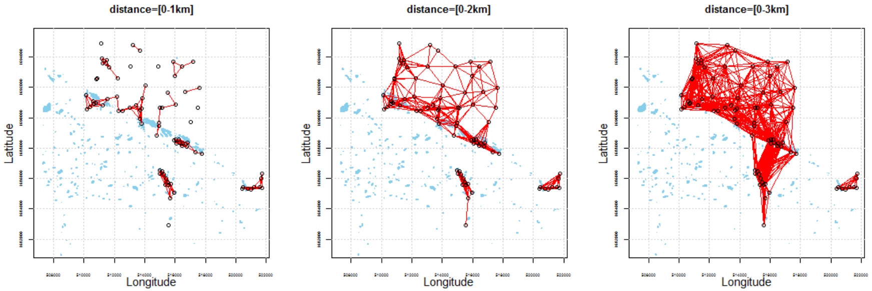
Spatial autocorrelation

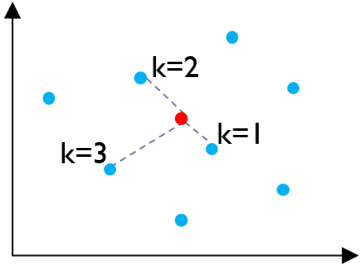


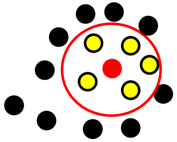
Conceptualization of Spatial Relationships

- Spatial relationships (neighborhood) you use will depend on what you're measuring:
  - Distance band
  - Polygon contiguity (Contiguity edges)
  - K nearest neighbors









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Local autocorrelation index

- Locations with high values with similar neighbours: high-high. Also known as « **hot spots** »

- Locations with low values with similar neighbours: low-low. Also known as « **cold spots** »

- Locations with no significant local autocorrelation

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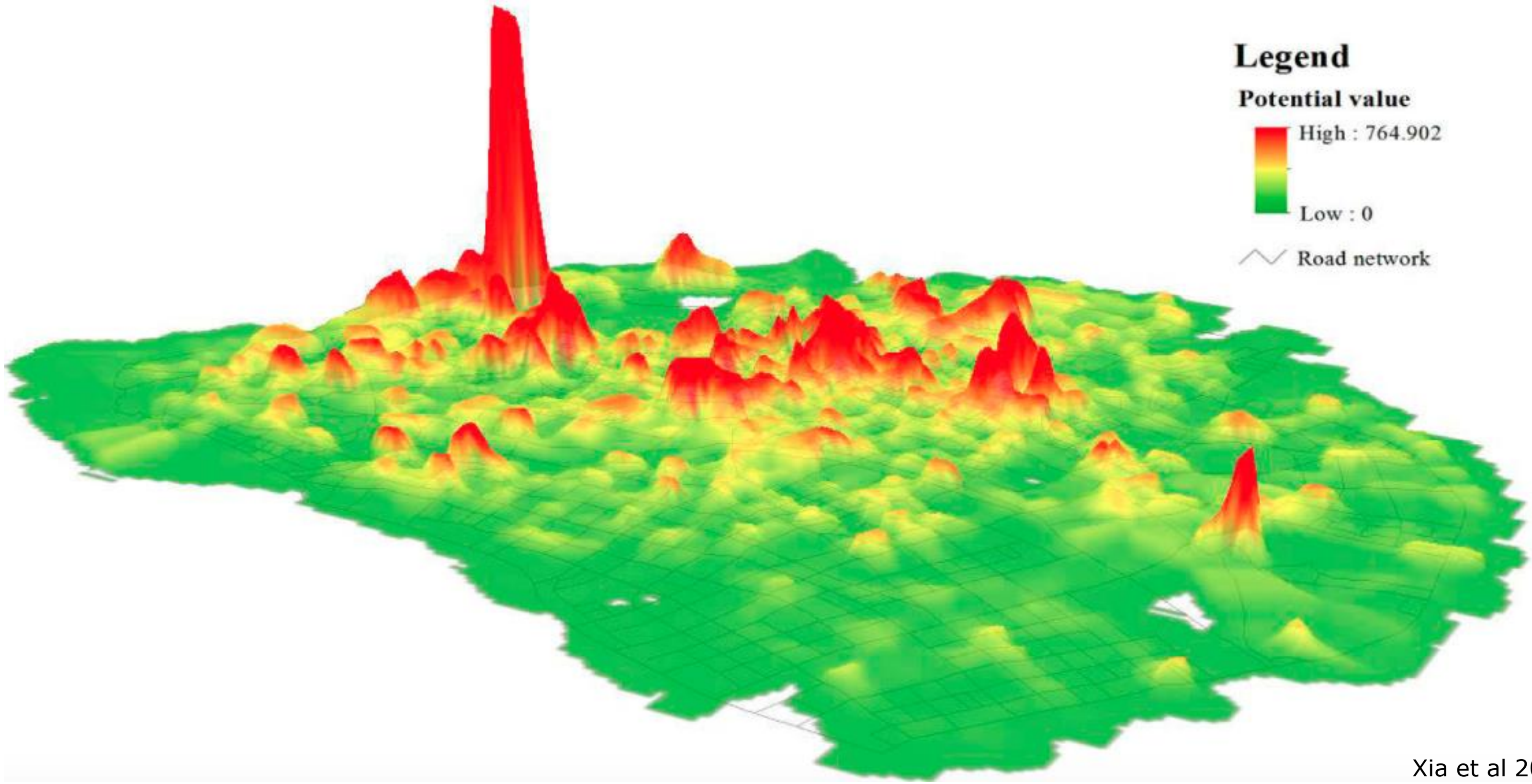
Visualization of hotspots



Xia et al 2019

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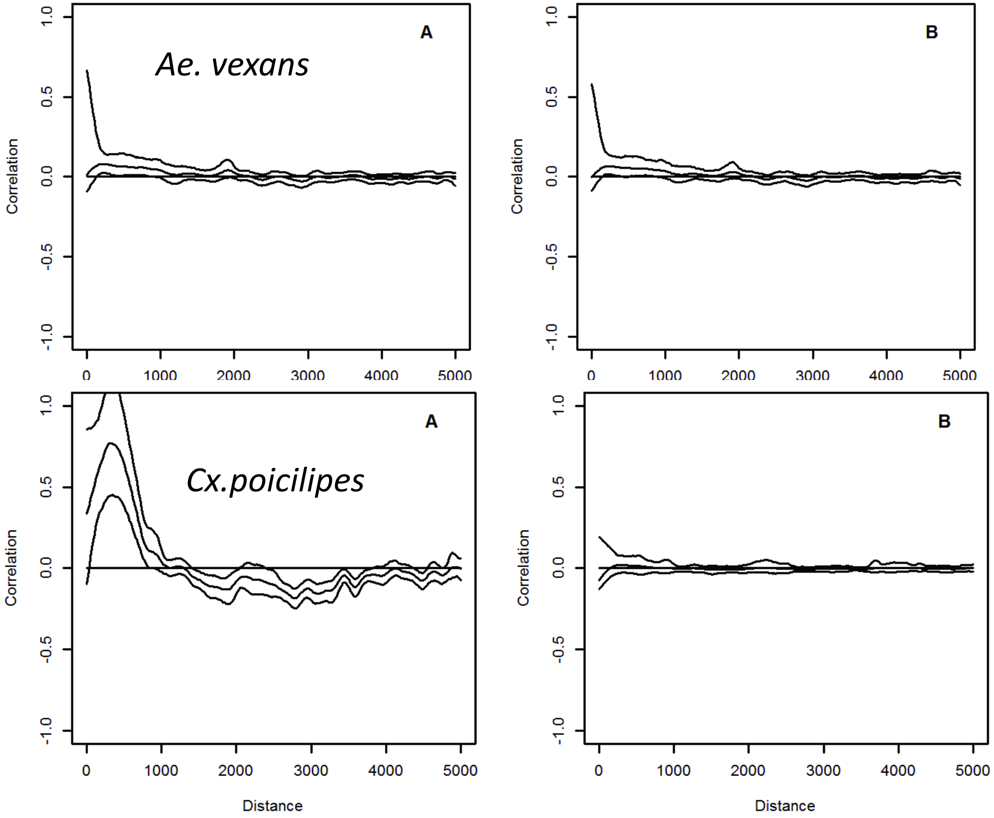
Presence of spatial autocorrelation



$$\log\left(\frac{p_{st}}{1-p_{st}}\right) = \beta' X_{st} + b_s$$

- Significant and positive spatial autocorrelation for distance: radius 1km radius

- spatial autocorrelation presence means: interdependence in space

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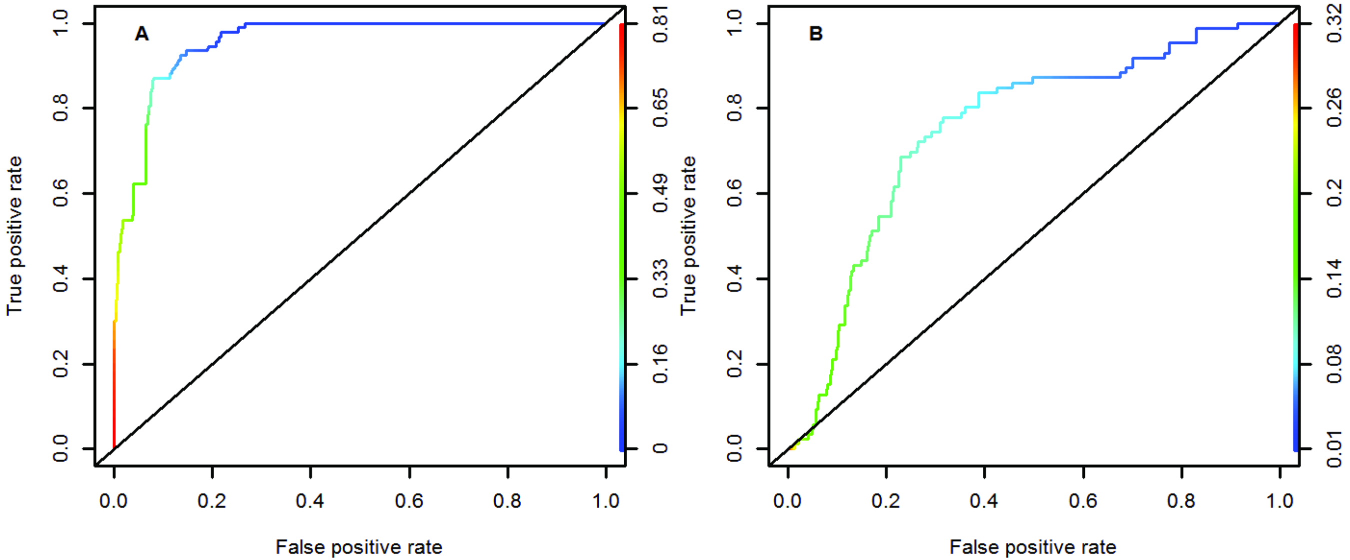
Predictive ability of the model



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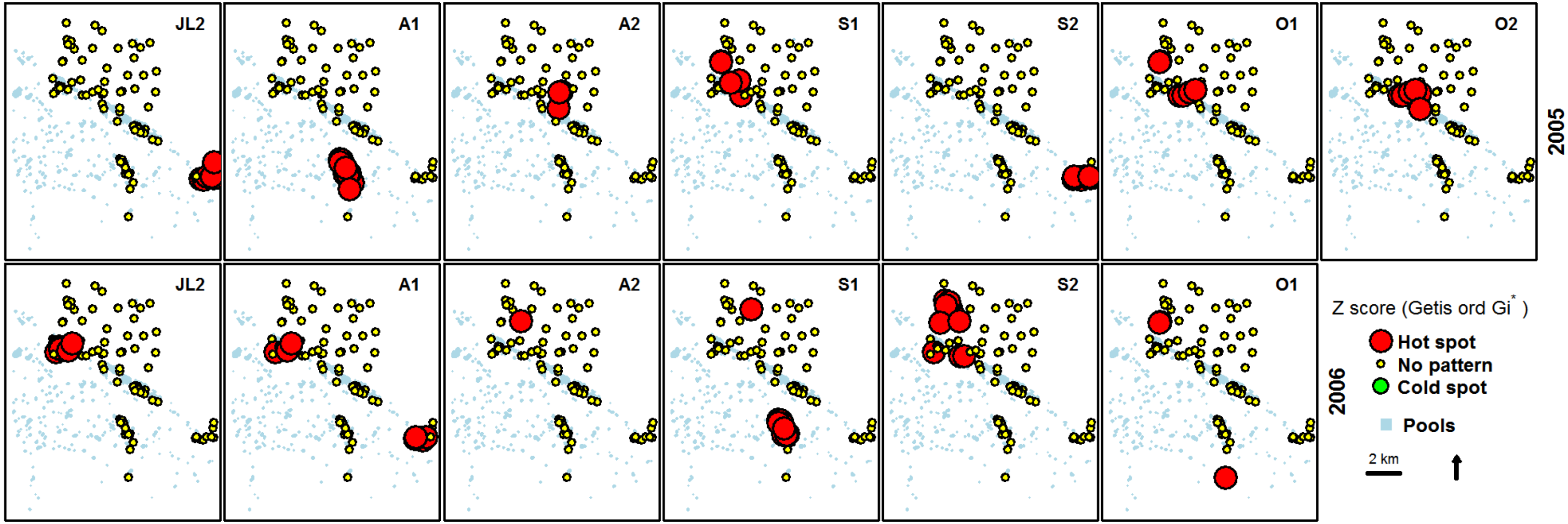
Hotspot identification for *Ae. vexans*



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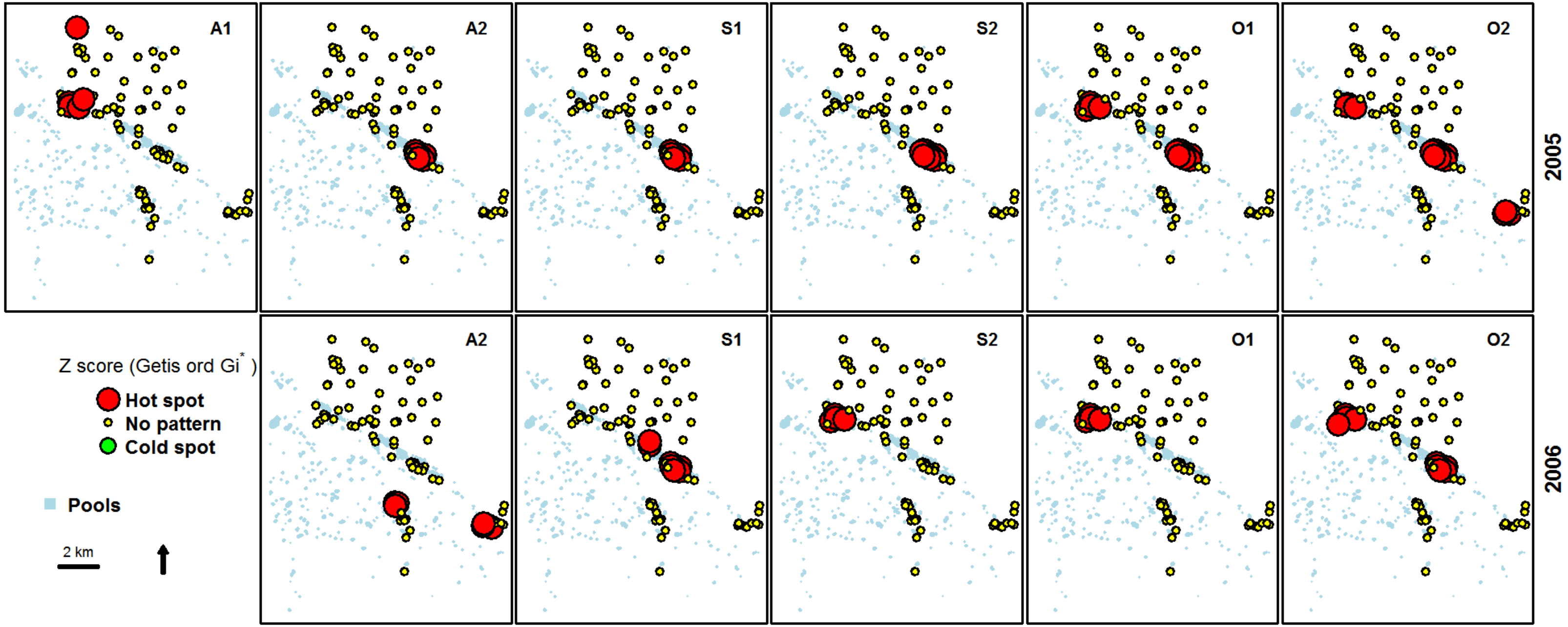
Hotspot identification for *Cx. poicilipes*



Variables impacted on the likelihood hotspot occurrence

Ae. vexans

Model ranking	Intercept	Distance	Hr	NDVI	Rainfall	Tmax	Tmin	AIC	weight
1	21.60	−0.0017	−0.0618			−0.2508	−0.4157	571.3	0.368
2	22.02	−0.0017	−0.0723	1.988		−0.2556	−0.4231	571.8	0.283
3	21.77	−0.0018	−0.0671		0.0019	−0.2382	−0.4325	572.9	0.168
4	22.03	−0.0017	−0.074	1.830	0.0009	−0.2487	−0.4297	573.7	0.109
Relative Importance		0.958	0.975	0.419	0.299	0.994	0.992		
Model-average	21.810 ± 11.19[a]	−0.002 ± 0.001[a]	−0.067 ± 0.043[a]	1.944 ± 3.329	−0.001 ± 0.006	−0.250 ± 0.130[a]	−0.423 ± 0.225[a]		

[a]indicates significance at the 95 % level. *Hr* the relative humidity, *Tmax* maximum temperature, *Tmin* minimum temperature; Rainfall: cumulative rainfall

Talla et al 2016

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Comments

- Provide information on areas at risk
- Reduce contact between hosts and vectors
- Optimize sentinel sites implemented at animal level
- Improve surveillance and control of RVF vectors

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