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Potential mapping with interpolated covariables

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Most data-based methods of potential mapping (e.g., weights-of-evidence [1], logistic regression [2], artificial neural network and other methods of machine [3] or statistical learning [4], Cox regression [5]) assume that several layers of information are perfectly known everywhere within a training area, i.e., on pixel-based map images thereof. Moreover, many of these methods including Cox regression are not spatially aware, i.e., once every layer of information has been computed the spatial character is lost. Actually, the pixels could be randomized and these methods would deliver the same result [6]. Thus these methods do not take any advantage of spatially induced dependencies nor do they take into account that many layers actually contain interpolated information with its own uncertainty. This contribution explores a modification of Cox regression to potential mapping using covariables observed at discrete locations, without any need of interpolating them beforehand, directly taking into account the spatial dependencies between samples of information and occurrences of the event being mapped.

Cox regression is based on a generalized linear model (GLM), where the locations $x_1, x_2, \dots, x_Q \in A$ of known occurrences are considered a Poisson process on the area of interest A. Its locally varying intensity field $\lambda(s)$ is regressed against a set of covariables $Z_1(s), Z_2(s), \dots, Z_P(s)$ assumed to be known everywhere, i.e., with a location index $s \in A$. This regression problem can be solved using state-of-the-art GLM machinery [7].

The modification suggested here considers the vector of covariables $\mathbf{Z} = [Z_1, Z_2, \dots, Z_P]$ to be observed on a finite set of locations $s_1, s_2, \dots, s_N \in A$, and establishes a joint geostatistical model for them. The distribution of $\mathbf{Z}(s_0)$ at a non-sampled location $s_0 \in A$ conditional on all surrounding observations can be obtained with some geostatistical tool, denoted as $\pi(\mathbf{Z}(s_0)|data)$. For instance, for continuous covariables $\pi(\mathbf{Z}(s_0)|data)$ could be a multivariate normal distribution. The likelihood of the set of observed occurrences is then the expected value with respect to $\pi(\mathbf{Z}(s_0)|data)$ of a Poisson process with intensity field given by $\ln \lambda(s) = \beta_0 + \boldsymbol{\beta} \cdot \boldsymbol{Z}(s)$,

$$L(x_1, x_2, \dots, x_Q | data, \beta_0, \boldsymbol{\beta}) = E_{\pi(\mathbf{Z}(s)|data)}\left[\exp\left(-\int_A e^{\beta_0 + \boldsymbol{\beta}\cdot\boldsymbol{Z}(u)}\, du\right) \times \prod_{q=1}^{Q} e^{\beta_0 + \boldsymbol{\beta}\cdot\boldsymbol{Z}(x_q)}\right].$$

As a function of the parameters $[\beta_0, \boldsymbol{\beta}]$, this likelihood can be maximized with several approaches (quasi-likelihood, Metropolis-Hastings, etc.), providing an assessment of the influence of each covariable on the occurrence of the target events. Once these parameters are known, plugging them into $E_{\pi(\mathbf{Z}(s)|data)}\left[e^{\beta_0 + \boldsymbol{\beta}\cdot\boldsymbol{Z}(s)}\right]$ will deliver the desired potential map.

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