



Spatial Generalized Linear Models in R Using **spmodel**

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Abstract

Non-Gaussian data are common in practice and include binary, count, skewed, and proportion data types. Often, non-Gaussian data are modeled using a generalized linear model (GLM). GLMs typically assume that observations are independent of one another. This is an impractical assumption for spatial data, as nearby observations tend to be more similar than distant ones. The **spmodel** package in R provides a suite of tools for fitting spatial generalized linear models (SPGLMs) to non-Gaussian data and making spatial predictions (i.e., Kriging). SPGLMs for point-referenced (x- and y-coordinates) support are fit using the `spglm()` function, while SPGLMs for areal (lattice, polygon) support are fit using the `spgautor()` function. Both `spglm()` and `spgautor()` maximize a novel Laplace likelihood which marginalizes over the model's fixed effects and latent mean while formally incorporating spatial covariance among observations. The inputs and outputs of `spglm()` and `spgautor()` closely resemble the `glm()` function from base R, easing the transition from GLMs to SPGLMs. **spmodel** provides and builds upon several commonly used helper functions for model building like `summary()`, `plot()`, and `fitted()`, among others. Spatial predictions of the latent mean at unobserved locations are obtained using `predict()` or `augment()`. **spmodel** accommodates myriad advanced modeling features like geometric anisotropy, nonspatial random effects, analysis of variance, and more. Throughout, we use **spmodel** to fit SPGLMs to moose presence and counts in Alaska, United States (US), skewed conductivity data in the Southwestern US, harbor seal abundance trends in Alaska, US, and voter turnout rates in Texas, US.

Keywords: autoregressive model, geostatistical model, Poisson regression, link function, logistic regression, overdispersion, spatial covariance, spatial dependence.

1. Introduction

In practice, non-Gaussian data (e.g., binary, count, skewed, and proportion data) are ubiquitous. Non-Gaussian data that belong to an exponential family can be naturally modeled using a generalized linear model (GLM) regression framework (Nelder and Wedderburn 1972; McCullagh and Nelder 1989). In a GLM, an $n \times 1$ response variable \mathbf{y} belongs to a statistical distribution (e.g., binomial, Poisson) with some mean and variance. Often, the analysis goal is to study the impact of a linear function of several explanatory variables on the mean of \mathbf{y} through a GLM. In this context, the latent (i.e., unobserved) mean of \mathbf{y} , $\boldsymbol{\mu}$, is linked to these explanatory variables via a link function:

$$f(\boldsymbol{\mu}|\mathbf{X}, \boldsymbol{\beta}) \equiv \mathbf{w} = \mathbf{X}\boldsymbol{\beta}, \quad (1)$$

where for a sample size n , $f(\cdot)$ is a link function that connects $\boldsymbol{\mu}$ to \mathbf{w} , \mathbf{X} is the $n \times p$ design matrix of explanatory variables, and $\boldsymbol{\beta}$ is the $p \times 1$ vector of fixed effects. While the mean is typically constrained in some way (e.g., if a probability, between zero and one), the link function generally makes \mathbf{w} unconstrained. Common link functions include the log odds (i.e., logit) link for binary and proportion data and the log link for count and skewed data. Equation 1 can also be written in terms of the inverse link function, $f^{-1}(\cdot)$:

$$\boldsymbol{\mu}|\mathbf{X}, \boldsymbol{\beta} \equiv f^{-1}(\mathbf{w}) = f^{-1}(\mathbf{X}\boldsymbol{\beta}).$$

The GLM fixed effects ($\boldsymbol{\beta}$) are typically estimated via maximum likelihood (Chambers and Hastie 1992). It is often convenient to compute the maximum likelihood estimates using the iteratively reweighted least squares (IRWLS) algorithm (Wood 2017), which is an approach used by the `glm()` function in the R programming language (R Core Team 2024). GLMs add an additional layer of complexity compared to linear regression models, as the left-hand side of Equation 1 is a function of the mean of \mathbf{y} rather than \mathbf{y} itself (as in linear regression models).

The standard GLM assumes the elements of \mathbf{y} are independent. This independence assumption is typically impractical for spatial data. For spatial data, nearby observations tend to be more similar than distant observations (Tobler 1970), which leads to positive spatial covariance among observations. The consequences of ignoring spatial covariance in statistical models for spatial data can be severe and include imprecise parameter estimates as well as misleading standard errors that inflate Type-I error rates and decrease power (Zimmerman and Ver Hoef 2024).

An approach for handling spatial data using a GLM is to assume the elements of \mathbf{w} exhibit both spatial and nonspatial variability. This is achieved by adding to Equation 1 two random effects, $\boldsymbol{\tau}$ and $\boldsymbol{\epsilon}$. The random effect $\boldsymbol{\tau}$ is an $n \times 1$ column vector of spatially dependent random errors. We assume that $E(\boldsymbol{\tau}) = \mathbf{0}$ and $Cov(\boldsymbol{\tau}) = \sigma_{\tau}^2 \mathbf{R}$, where $E(\cdot)$ and $Cov(\cdot)$ denote expectation and covariance, respectively. The variance parameter σ_{τ}^2 controls the magnitude of spatial covariance and is often called a partial sill. The matrix \mathbf{R} is an $n \times n$ spatial correlation matrix that depends on a range parameter controlling the distance-decay rate of the spatial correlation. One example of a spatial covariance matrix is the “exponential,” which is given by

$$Cov(\boldsymbol{\tau}) = \sigma_{\tau}^2 \mathbf{R}_{exp} = \sigma_{\tau}^2 \exp(-\mathbf{H}/\phi), \quad (2)$$

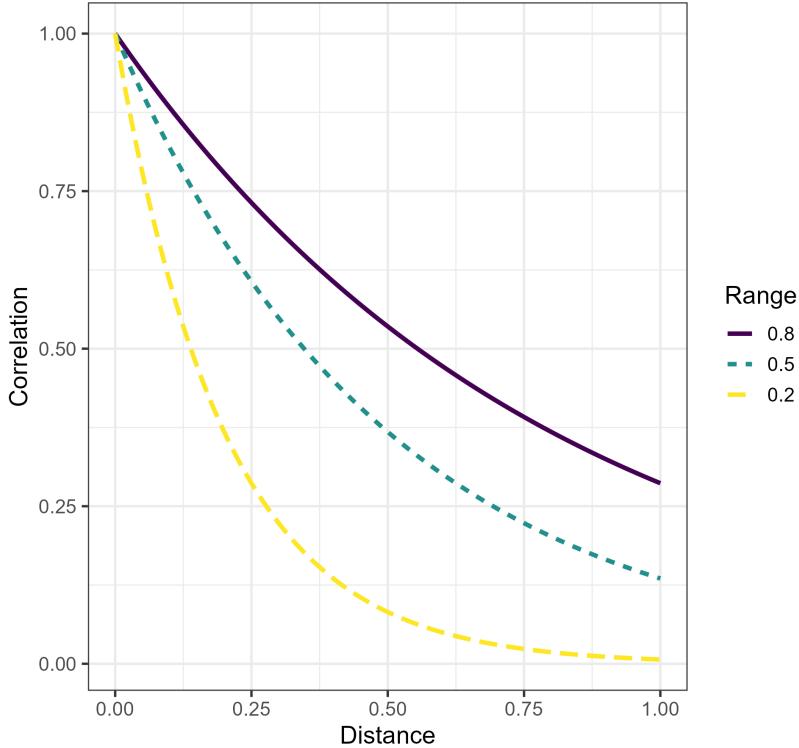


Figure 1: An exponential spatial correlation function with varying range parameters.

where \mathbf{H} is a matrix of pairwise distances among the elements of \mathbf{y} and ϕ is the range parameter. From Equation 2, as the distance between two elements of \mathbf{y} increases, the spatial covariance decreases, which reflects intuition. Moreover, as the range parameter, ϕ , increases, the strength of spatial dependence increases (Figure 1). The random effect $\boldsymbol{\epsilon}$ is an $n \times 1$ column vector of independent random errors. We assume that $E(\boldsymbol{\epsilon}) = \mathbf{0}$ and $Cov(\boldsymbol{\tau}) = \sigma_{\epsilon}^2 \mathbf{I}$, where \mathbf{I} is an $n \times n$ identity matrix. The variance parameter σ_{ϵ}^2 controls the magnitude of nonspatial variability (i.e., fine-scale variation) and is often called a nugget. Often in spatial statistics, quantities are explicitly referenced with respect to \mathbf{s} , a vector of spatial coordinates indexing the observation (Cressie 1993). For example, \mathbf{y} and \mathbf{X} may instead be written $\mathbf{y}(\mathbf{s})$ and $\mathbf{X}(\mathbf{s})$, respectively. We acknowledge the utility of this nomenclature but drop the explicit dependence on \mathbf{s} for simplicity of notation moving forward.

Through inclusion of $\boldsymbol{\tau}$ and $\boldsymbol{\epsilon}$, the spatial GLM (SPGLM) can be written as

$$f(\boldsymbol{\mu} | \mathbf{X}, \boldsymbol{\beta}, \boldsymbol{\tau}, \boldsymbol{\epsilon}) \equiv \mathbf{w} = \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\tau} + \boldsymbol{\epsilon}. \quad (3)$$

Assuming independence among $\boldsymbol{\tau}$ and $\boldsymbol{\epsilon}$, it follows that

$$Cov(\boldsymbol{\tau} + \boldsymbol{\epsilon}) = Cov(\boldsymbol{\tau}) + Cov(\boldsymbol{\epsilon}) = \sigma_{\tau}^2 \mathbf{R} + \sigma_{\epsilon}^2 \mathbf{I}.$$

Henceforth, we refer to σ_{τ}^2 as σ_{de}^2 (for spatially dependent error variance) and σ_{ϵ}^2 as σ_{ie}^2 (for independent error variance). The parameters σ_{de}^2 , σ_{ie}^2 , and ϕ , in addition to any other parameters in \mathbf{R} , compose $\boldsymbol{\theta}$, the covariance parameter vector.

Fitting and using SPGLMs is challenging both conceptually and computationally (Bolker, Brooks, Clark, Geange, Poulsen, Stevens, and White 2009). Recently, however, there have

been numerous, significant advances in R software that have made these models more accessible to practitioners. The **brms** (Bürkner 2017), **carBayes** (Lee 2013), **ngspatial** (Hughes and Cui 2020), **R-INLA** (Lindgren and Rue 2015), **inlabru** (Bachl, Lindgren, Borchers, and Illian 2019), **spBayes** (Finley, Banerjee, and Carlin 2007), **spOccupancy** (Doser, Finley, Kéry, and Zipkin 2022), **spAbundance** (Doser, Finley, Kéry, and Zipkin 2024), and **spNNGP** (Finley, Datta, and Banerjee 2022) packages take a Bayesian approach, either directly sampling from posterior distributions of parameters (e.g., using MCMC) or approximating them. A benefit of Bayesian approaches is that prior information can be incorporated and uncertainty quantification of parameter estimates is straightforward. However, Bayesian approaches, especially those using MCMC, can be computationally expensive. In order to reduce computation time, many of these packages (e.g., **R-INLA**) work with the precision matrix instead of the covariance matrix so that computationally expensive matrix inversion is not required. Working with precision matrices, however, can be more restrictive and less intuitive than working with covariance matrices. The **FRK** (Sainsbury-Dale, Zammit-Mangion, and Cressie 2024), **glmmTMB** (Brooks, Kristensen, van Benthem, Magnusson, Berg, Nielsen, Skaug, Maechler, and Bolker 2017), **hglm** (Ronnegard, Shen, and Alam 2010), **mgev** (Wood 2017), and **spAMM** (Rousset and Ferdy 2014) packages directly use Laplace, quasi-likelihood, or reduced-rank approaches to estimate parameters. These direct approaches tend to be computationally efficient, as they don't rely on MCMC sampling. In contrast to the Bayesian approach, a drawback of these direct approaches is that prior information cannot be formally incorporated and covariance parameter uncertainty is more challenging to quantify. The **sdmTMB** (Anderson, Ward, English, Barnett, and Thorson 2024) package combines elements of **R-INLA**, **glmmTMB**, and Gaussian Markov random fields to fit a wide variety of SPGLMs, while **tinyVAST** (Thorson, Anderson, Goddard, and Rooper 2025) extends some of these models to multivariate or (dynamic) structural equation models.

Building from Evangelou, Zhu, and Smith (2011) and Bonat and Ribeiro Jr (2016), Ver Hoef, Blagg, Dumelle, Dixon, Zimmerman, and Conn (2024) proposed a novel approach for fitting SPGLMs that leverages the Laplace approximation while marginalizing over both the latent \mathbf{w} and the fixed effects (β). This approach performed well in a variety of simulation settings, generally having appropriate confidence interval coverage for the fixed effects and prediction interval coverage for \mathbf{w} at new locations. It also performed similarly to the Bayesian SPGLM approach in **spBayes** and the automatic differentiation SPGLM approach in **glmmTMB** but was much faster. At small sample sizes, the approach outperformed the approximate Bayesian SPGLM approach in **R-INLA** and had similar computational times. For moderate sample sizes, it performed similarly to **R-INLA**, though **R-INLA** was faster. The novel Laplace approach is particularly attractive for two reasons. First, it is general enough that it can be applied to any covariance structure (not just spatial). Second, after estimating the covariance parameters, analytical solutions exist for the fixed effects (and their standard errors) as well as predictions of the latent \mathbf{w} at new locations (and their standard errors).

The **spmodel** R package (Dumelle, Higham, and Ver Hoef 2023) recently released a full set of modeling tools for SPGLMs fit using the novel Laplace approach described by Ver Hoef *et al.* (2024). These modeling tools are approachable and mirror the familiar **glm()** syntax from base-R, making the transition from GLMs to SPGLMs relatively seamless. The **spglm()** function fits SPGLMs for point-referenced support (e.g., x- and y-coordinates representing point locations in a field; these models are sometimes called “geostatistical” models), while the **spgautor()** function fits SPGLMs for areal support (e.g., polygon boundaries representing

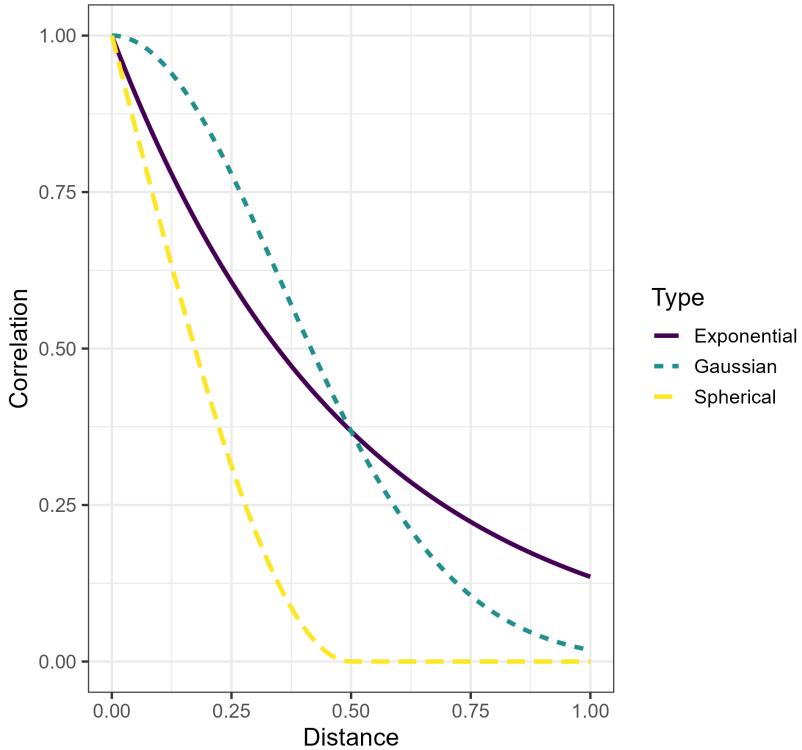


Figure 2: Exponential, Gaussian, and spherical spatial correlation functions all with range parameters equal to 0.5.

102 geographic subsets of a region; these models are sometimes called “autoregressive” models).
 103 For both point-referenced and areal supports, **spmodel** supports the binomial distribution for
 104 binary data, Poisson and negative binomial distributions for count data, Gamma and inverse
 105 Gaussian distributions for skewed data, and the beta distribution for proportion data. There
 106 are 20 different spatial covariance structures available including the exponential, Gaussian,
 107 and spherical for point-referenced support (Figure 2) and the conditional autoregressive, and
 108 simultaneous autoregressive structures for areal support **spmodel** provides tools for commonly
 109 used model summaries, visualizations, and diagnostics (e.g., fitted values) using standard R
 110 helper functions like `summary()`, `plot()`, and `fitted()`, among others. **spmodel** also pro-
 111 vides tools to predict `w` at new locations and quantify uncertainty in those prediction using
 112 `predict()` and `augment()`. This core functionality, combined with several advanced fea-
 113 tures we describe throughout the manuscript, enables **spmodel** to introduce novel, important
 114 SPGLM modeling tools previously missing from the existing R ecosystem.
 115 Of the existing R packages for SPGLMs, **spmodel** (version 0.11.1) is arguably most similar
 116 to **sdmTMB** (version 0.7.4) in terms of scope and feel. Both packages use similar syntax
 117 as `glm()`, accommodate flexible `formula` arguments (e.g., offsets, splines), handle spatial
 118 covariance that decays at different rates in different directions (i.e., geometric anisotropy),
 119 incorporate nonspatial random effects, support other R packages for modeling like **broom**
 120 (Robinson, Hayes, and Couch 2021; Kuhn and Silge 2022), **emmeans** (Lenth 2024), and **car**
 121 (Fox and Weisberg 2019), and have tools for model summaries, prediction, and simulating
 122 data. There are some notable differences between the two packages, however. **sdmTMB** sup-

123 ports several additional GLM distributions like the Tweedie, supports Hurdle models, and
124 can incorporate prior information through Bayesian applications. **sdmTMB** also provides
125 tools for working with temporal data and spatiotemporal data and provides enhanced vi-
126 sualizations of the model's marginal effects. **sdmTMB** does require a preprocessing step of
127 constructing a mesh prior to model fitting (using the stochastic partial differential equation
128 approach), and the density of the mesh can affect model results and computational com-
129 plexity. On the other hand, **spmodel** does not require the construction of a mesh prior to
130 model fitting. **spmodel** supports 20 different spatial covariances and models them directly,
131 rather than using a precision matrix approximation to the Matérn spatial covariance as in
132 **sdmTMB**. **spmodel** can model data directly using neighborhood distance and autoregressive
133 models, rather than relying on the polygon centroid (as in **sdmTMB**), which may not be
134 within the polygon's boundaries. **spmodel** provides experimental design tools (e.g., analysis
135 of variance, contrasts), supports **sf** objects in modeling and prediction functions ([Pebesma 2018](#)), has several specialized model diagnostics like leverage values and Cook's distances, and
136 has analytic solutions for fixed effect and prediction standard errors. Other similarities and
137 differences do exist between **sdmTMB** and **spmodel**, and both packages continue to evolve.
138 Overall, we believe that these packages are complementary and enhance the suite of SPGLM
139 tools accessible to practitioners.

141 The rest of this article is organized as follows. In Section 2, we provide some background for
142 the SPGLM fitting and prediction routines in **spmodel**. In Section 3, we provide an overview
143 of core SPGLM functionality in **spmodel** by modeling moose presence in Alaska, United
144 States (US). In Section 4, we model moose counts in Alaska, US; skewed lake conductivity
145 in the Southwestern US; harbor seal abundance trend behavior in Alaska, US; and voter
146 turnout rates in Texas, US. And in Section 5, we end with a discussion synthesizing **spmodel**'s
147 contributions to SPGLMs in R.

2. The spatial generalized linear model and marginalization

148 The novel Laplace approach implemented in **spmodel** formally maximizes a hierarchical GLM
149 likelihood ([Lee and Nelder 1996](#); [Wood 2017](#)), making likelihood-based statistics for model
150 comparison like AIC ([Akaike 1974](#)), AICc ([Hoeting, Davis, Merton, and Thompson 2006](#)), BIC
151 ([Schwarz 1978](#)), deviance ([McCullagh and Nelder 1989](#)), and likelihood ratio tests available.
152 These types of statistics are not directly available for quasi-likelihood ([Wedderburn 1974](#);
153 [Breslow and Clayton 1993](#)) or pseudo-likelihood approaches ([Wolfinger and O'Connell 1993](#)),
154 which only specify the first two moments of a distribution. Next, we describe a brief overview
155 of the approach and how it can be used for several primary data analysis tasks ([Tredennick,](#)
156 [Hooker, Ellner, and Adler 2021](#)) like model comparison, parameter estimation, inference,
157 model diagnostics, and prediction.

158 2.1. Formulating the hierarchical likelihood

159 We can write the SPGLM likelihood hierarchically as

$$[\mathbf{y}|\mathbf{X}, \varphi, \boldsymbol{\theta}] = \int_{\mathbf{w}} \int_{\boldsymbol{\beta}} [\mathbf{y}|f^{-1}(\mathbf{w}), \varphi] [\mathbf{w}|\mathbf{X}, \boldsymbol{\beta}, \boldsymbol{\theta}] d\boldsymbol{\beta} d\mathbf{w}, \quad (4)$$

160 where $[\mathbf{y}|f^{-1}(\mathbf{w}), \varphi]$ is the density for the appropriate response distribution of \mathbf{y} (e.g., bi-
161 nomial, Poisson) given the latent \mathbf{w} and dispersion parameter (φ), and $[\mathbf{w}|\mathbf{X}, \boldsymbol{\beta}, \boldsymbol{\theta}]$ is the

¹⁶² multivariate Gaussian density for \mathbf{w} given the explanatory variables (\mathbf{X}), fixed effects ($\boldsymbol{\beta}$),
¹⁶³ and spatial covariance parameters ($\boldsymbol{\theta}$). The elements of $[\mathbf{y}|f^{-1}(\mathbf{w}), \varphi]$ are conditionally in-
¹⁶⁴ dependent (given \mathbf{w}), but the elements of $[\mathbf{w}|\mathbf{X}, \boldsymbol{\beta}, \boldsymbol{\theta}]$ share spatial covariance. Following
¹⁶⁵ Harville (1974), we can integrate $\boldsymbol{\beta}$ out of Equation 4, which yields

$$[\mathbf{y}|\mathbf{X}, \varphi, \boldsymbol{\theta}] = \int_{\mathbf{w}} [\mathbf{y}|f^{-1}(\mathbf{w}), \varphi][\mathbf{w}|\mathbf{X}, \boldsymbol{\theta}]d\mathbf{w}, \quad (5)$$

¹⁶⁶ where $[\mathbf{w}|\mathbf{X}, \boldsymbol{\theta}]$ is the restricted (i.e., residual) multivariate Gaussian density (Patterson and
¹⁶⁷ Thompson 1971) for \mathbf{w} given the explanatory variables and covariance parameters. The
¹⁶⁸ restricted multivariate Gaussian density is given by

$$[\mathbf{w}|\mathbf{X}, \boldsymbol{\theta}] = \frac{\exp(-\frac{1}{2}(\mathbf{y} - \mathbf{X}\tilde{\boldsymbol{\beta}})\Sigma^{-1}(\mathbf{y} - \mathbf{X}\tilde{\boldsymbol{\beta}})^{\top})}{(2\pi)^{(n-p)/2}|\Sigma|^{1/2}|\mathbf{X}^{\top}\Sigma^{-1}\mathbf{X}|^{1/2}},$$

¹⁶⁹ where $\tilde{\boldsymbol{\beta}} = (\mathbf{X}^{\top}\Sigma^{-1}\mathbf{X})^{-1}\mathbf{X}^{\top}\Sigma^{-1}\mathbf{w}$, Σ denotes the covariance matrix (of \mathbf{w}), and $|\cdot|$ denotes
¹⁷⁰ the determinant. Equation 5 can synonymously be written after profiling the overall variance
¹⁷¹ out of Σ , which reduces the dimension of $\boldsymbol{\theta}$ by one for optimization (Wolfinger, Tobias, and
¹⁷² Sall 1994). Next, let

$$\ell_{\mathbf{w}} = \log([\mathbf{y}|f^{-1}(\mathbf{w}), \varphi][\mathbf{w}|\mathbf{X}, \boldsymbol{\theta}])$$

¹⁷³ and rewrite Equation 5 as

$$[\mathbf{y}|\mathbf{X}, \varphi, \boldsymbol{\theta}] = \int_{\mathbf{w}} \exp(\ell_{\mathbf{w}})d\mathbf{w}.$$

¹⁷⁴ A second-order Taylor series expansion of $\ell_{\mathbf{w}}$ around a point \mathbf{w}^* yields

$$[\mathbf{y}|\mathbf{X}, \varphi, \boldsymbol{\theta}] \approx \int_{\mathbf{w}} \exp(\ell_{\mathbf{w}^*} + \mathbf{g}^{\top}(\mathbf{w} - \mathbf{w}^*) + \frac{1}{2}(\mathbf{w} - \mathbf{w}^*)^{\top}\mathbf{G}(\mathbf{w} - \mathbf{w}^*))d\mathbf{w},$$

¹⁷⁵ where \mathbf{g} and \mathbf{G} are the gradient and Hessian, respectively, of $\ell_{\mathbf{w}}$ with respect to \mathbf{w} . If \mathbf{w}^* is
¹⁷⁶ a value for which $\mathbf{g} = \mathbf{0}$,

$$[\mathbf{y}|\mathbf{X}, \varphi, \boldsymbol{\theta}] \approx \exp(\ell_{\mathbf{w}^*}) \int_{\mathbf{w}} \exp(-\frac{1}{2}(\mathbf{w} - \mathbf{w}^*)^{\top}(-\mathbf{G})(\mathbf{w} - \mathbf{w}^*))d\mathbf{w}. \quad (6)$$

¹⁷⁷ The integral in Equation 6 can be solved by leveraging properties of the normalizing constant
¹⁷⁸ of a multivariate Gaussian distribution. Thus, rewriting $\exp(\ell_{\mathbf{w}^*})$ yields

$$[\mathbf{y}|\mathbf{X}, \varphi, \boldsymbol{\theta}] \approx [\mathbf{y}|f^{-1}(\mathbf{w}^*), \varphi][\mathbf{w}^*|\mathbf{X}, \boldsymbol{\theta}](2\pi)^{n/2}|-\mathbf{G}_{\mathbf{w}^*}|^{-1/2},$$

¹⁷⁹ which can be directly evaluated. This result suggests a doubly iterative optimization over 1)
¹⁸⁰ $\boldsymbol{\theta}$ and φ and 2) the latent \mathbf{w} (to find each set of \mathbf{w}^*), which ultimately yields the marginal
¹⁸¹ restricted maximum likelihood estimators $\hat{\varphi}$ and $\hat{\boldsymbol{\theta}}$ and their respective values of \mathbf{w}^* , which
¹⁸² we call $\hat{\mathbf{w}}$. Ver Hoef *et al.* (2024) provide further details, which includes explicit forms of \mathbf{g}
¹⁸³ and \mathbf{G} for various response distributions.

¹⁸⁴ 2.2. Estimating fixed effects

We can estimate the fixed effects using generalized least squares (GLS) principles, a common practice for linear models estimated using restricted maximum likelihood methods. Had we observed \mathbf{w} , a GLS estimator for β is given by

$$\hat{\beta} = (\mathbf{X}^\top \Sigma^{-1} \mathbf{X})^{-1} \mathbf{X}^\top \Sigma^{-1} \mathbf{w} = \mathbf{B}\mathbf{w},$$

where $\mathbf{B} = (\mathbf{X}^\top \Sigma^{-1} \mathbf{X})^{-1} \mathbf{X}^\top \Sigma^{-1}$. While we do not \mathbf{w} , we do estimate it via $\hat{\mathbf{w}}$, and thus it is reasonable to define $\hat{\beta} = \mathbf{B}\hat{\mathbf{w}}$. To derive properties of $\hat{\beta}$ like expectation and variance, we must derive these properties for $\hat{\mathbf{w}}$ by conditioning on \mathbf{w} as if it were observed and leveraging the laws of total expectation and variance. Based on asymptotic properties of (restricted) maximum likelihood estimators (Cressie and Lahiri 1993), we may assume that given \mathbf{w} , $\hat{\mathbf{w}}$ has mean \mathbf{w} and variance approximately equal to $-\mathbf{H}^{-1}$, the negative inverse Hessian (i.e., the inverse observed information matrix). Thus it follows that $E(\hat{\mathbf{w}})$ is given by

$$E(\hat{\mathbf{w}}) = E(E(\hat{\mathbf{w}}|\mathbf{w})) = E(\mathbf{w}) = \mathbf{X}\beta$$

and $\text{Var}(\hat{\mathbf{w}})$ is given by

$$\begin{aligned} \text{Var}(\hat{\mathbf{w}}) &= E(\text{Var}(\hat{\mathbf{w}}|\mathbf{w})) + \text{Var}(E(\hat{\mathbf{w}}|\mathbf{w})) \\ &\approx E(-\mathbf{H}^{-1}) + \text{Var}(\mathbf{w}) \\ &= -\mathbf{H}^{-1} + \Sigma \end{aligned}$$

Putting this all together, it follows that $\hat{\beta}$ is unbiased for β :

$$E(\hat{\beta}) = E(\mathbf{B}\hat{\mathbf{w}}) = \mathbf{B}E(\hat{\mathbf{w}}) = (\mathbf{X}^\top \Sigma^{-1} \mathbf{X})^{-1} (\mathbf{X}^\top \Sigma^{-1} \mathbf{X})\beta = \beta.$$

Moreover, it follows that

$$\begin{aligned} \text{Var}(\hat{\beta}) &= \text{Var}(\mathbf{B}\hat{\mathbf{w}}) \\ &= \mathbf{B}\text{Var}(\hat{\mathbf{w}})\mathbf{B}^\top \\ &= \mathbf{B}(-\mathbf{H}^{-1} + \Sigma)\mathbf{B}^\top \\ &= \mathbf{B}(-\mathbf{H})^{-1}\mathbf{B}^\top + \mathbf{B}\Sigma\mathbf{B}^\top \\ &= \mathbf{B}(-\mathbf{H})^{-1}\mathbf{B}^\top + (\mathbf{X}^\top \Sigma^{-1} \mathbf{X})^{-1}. \end{aligned}$$

In practice, $\text{Var}(\hat{\beta})$ is estimated by evaluating Σ at $\hat{\theta}$, the estimated covariance parameter vector.

These results are important because they justify analytic (i.e., closed-form) solutions for $\hat{\beta}$ and its associated variance. Analytic solutions are useful because they bypass the need for sampling-based strategies to evaluate the mean and variance of $\hat{\beta}$, a common technique for other approaches to SPGLMs like Bayesian MCMC that can be computationally intensive.

2.3. Inspecting model diagnostics

Inspecting model diagnostics is an important step of the modeling process that can yield valuable insights into model behavior and unusual observations. Montgomery, Peck, and Vining (2021) contextualize three components of unusual observations: outliers, leverage, and influence. An observation is an outlier if it has an extreme response value relative to

expectation. The response GLM residuals simply compare the observation to its fitted latent mean:

$$\mathbf{r}_r = \mathbf{y} - f^{-1}(\hat{\mathbf{w}})$$

Because observations often have a unique support in a GLM (e.g., only two possible response values for binary data) and the variance of an observation generally depends on its mean, response residuals lack some utility. Deviance residuals are a function of response residuals that are appropriately scaled to behave more like response residuals in a standard linear model. Deviance residuals are given by

$$\mathbf{r}_d = \text{sign}(\mathbf{r}_r)\sqrt{\mathbf{d}},$$

where \mathbf{d} is a vector of individual deviances. The sum of the squared deviance residuals equals the sum of the elements of \mathbf{d} , known as the deviance of the model fit. The deviance of the model fit quantifies twice the difference in log likelihoods between the a saturated model that fits every observation perfectly (i.e., $y_i = f^{-1}(\hat{w}_i)$ for all i) and the fitted model (Myers, Montgomery, Vining, and Robinson 2012). Deviance is often used as a fit statistic; lower values of deviance imply a better model fit (compared to the observed data). Pearson and standardized residuals are other types of GLM residuals that involve a scaling of the response residuals. The Pearson residuals scale \mathbf{r}_r by the square root of \mathbf{V} , a diagonal matrix with i th diagonal element equal to the variance of the response distribution evaluated at $f^{-1}(\hat{w}_i)$ (Faraway 2016); \mathbf{V} is sometimes called the GLM weight matrix. The standardized residuals scale the deviance residuals by $\frac{1}{\sqrt{(1-\mathbf{L}_{ii})}}$, where \mathbf{L}_{ii} is the i th diagonal element of the leverage matrix, which we discuss next.

An observation has high leverage if its combination of explanatory variables is far away from other observations. In a linear model, the leverage (i.e., hat) values are the diagonal of the leverage (i.e., projection, hat) matrix, $\mathbf{L} = \mathbf{X}(\mathbf{X}^\top \mathbf{X})^{-1}\mathbf{X}^\top$. In a GLM, the leverage matrix is given by

$$\mathbf{L} = \mathbf{V}^{1/2} \mathbf{X} (\mathbf{X}^\top \mathbf{V} \mathbf{X})^{-1} \mathbf{X}^\top \mathbf{V}^{1/2}.$$

The larger the value of \mathbf{L}_{ii} , the more severe the leverage from the i th observation.

An observation is influential if it has a sizable impact on model fit. Influence is measured using Cook's distance (Cook 1979; Cook and Weisberg 1982), which is given for a GLM by

$$\mathbf{c} = \frac{\mathbf{r}_s^2}{\text{tr}(\mathbf{L})} \frac{\text{diag}(\mathbf{L})}{(1 - \text{diag}(\mathbf{L}))},$$

where \mathbf{r}_s^2 are the standardized residuals and $\text{diag}(\mathbf{L})$ indicates the diagonal elements of the leverage matrix. The larger the value of c_i , the more severe the influence from the i th observation. Montgomery *et al.* (2021) provide guidance for interpreting these types of statistics, including cutoffs to consider when identifying extreme residual, leverage, or influence values.

In a linear model, the R^2 (R-squared) statistic quantifies the proportion of variability in the data captured by the explanatory variables. It is calculated as one minus the ratio of the error sum of squares to the total sum of squares (Rencher and Schaalje 2008). In a GLM, there are many ways to define a statistic that emulates the aforementioned meaning of R^2 from the linear model (Smith and McKenna 2013). This statistic is called a pseudo R-squared (PR^2).

²⁴⁴ One PR^2 for GLMs simply replaces the sums of squares ratio from the linear model with the
²⁴⁵ deviance ratio:

$$PR^2 = 1 - \frac{\text{deviance}_{\text{error}}}{\text{deviance}_{\text{total}}},$$

²⁴⁶ where $\text{deviance}_{\text{error}}$ is the deviance of the fitted model (sometimes called the error or residual
²⁴⁷ deviance) and $\text{deviance}_{\text{total}}$ is the deviance of the intercept-only model (sometimes called the
²⁴⁸ total or null deviance). In practice, $\text{deviance}_{\text{total}}$ is derived by computing $\hat{\mathbf{w}}$ when $\mathbf{X} \equiv \mathbf{1}$
²⁴⁹ (a column of all ones), given $\hat{\boldsymbol{\theta}}$ and $\hat{\varphi}$ from the fitted model. Like R^2 , PR^2 can be adjusted
²⁵⁰ to account for the numbers of parameters estimated in a model. Because the $\text{deviance}_{\text{total}}$
²⁵¹ denominator changes across fitted models (as the values of $\hat{\boldsymbol{\theta}}$ and $\hat{\varphi}$ change), this statistic
²⁵² should not be used as a model comparison tool. Rather, it should be used as an informative
²⁵³ diagnostic tool that is unique to each model fit and describes how much variability from that
²⁵⁴ model is attributable to the explanatory variables.

²⁵⁵ 2.4. Predicting at new locations

²⁵⁶ We may also predict values of the latent mean (on the link scale) at new locations by leveraging
²⁵⁷ the spatial covariance between observed locations and new locations (spatial prediction is
²⁵⁸ also called Kriging; see [Cressie \(1990\)](#)). Like in Section 2.2, suppose first that we observed
²⁵⁹ \mathbf{w} and we want to make predictions at \mathbf{u} , a vector of latent means at the new locations that
²⁶⁰ follows the same SPGLM from Equation 3 and has design matrix, \mathbf{X}_u . The vector $(\mathbf{w}, \mathbf{u})^\top$
²⁶¹ has expectation $(\mathbf{X}\boldsymbol{\beta}, \mathbf{X}_u\boldsymbol{\beta})^\top$ and covariance matrix $\begin{bmatrix} \Sigma & \Sigma_{\mathbf{w}\mathbf{u}} \\ \Sigma_{\mathbf{u}\mathbf{w}} & \Sigma_{\mathbf{u}\mathbf{u}} \end{bmatrix}$, where $\Sigma = \text{Var}(\mathbf{w}, \mathbf{w})$,
²⁶² $\Sigma_{\mathbf{w}\mathbf{u}} = \text{Var}(\mathbf{w}, \mathbf{u})$, $\Sigma_{\mathbf{u}\mathbf{w}} = \Sigma_{\mathbf{w}\mathbf{u}}^\top$ and $\Sigma_{\mathbf{u},\mathbf{u}} = \text{Var}(\mathbf{u}, \mathbf{u})$. Thus we may derive the conditional
²⁶³ distribution of $\mathbf{u}|\mathbf{w}$, which has the following properties:

$$\begin{aligned} E(\mathbf{u}|\mathbf{w}) &= \mathbf{X}_u\boldsymbol{\beta} + \Sigma_{\mathbf{u},\mathbf{w}}\Sigma^{-1}(\mathbf{w} - \mathbf{X}\boldsymbol{\beta}) \\ \text{Var}(\mathbf{u}|\mathbf{w}) &= \Sigma_{\mathbf{u},\mathbf{u}} - \Sigma_{\mathbf{u},\mathbf{w}}\Sigma^{-1}\Sigma_{\mathbf{w},\mathbf{u}} \end{aligned}$$

²⁶⁴ Recall, however, that we do not actually observe \mathbf{w} and instead compute $\hat{\mathbf{w}}$; so, to predict
²⁶⁵ \mathbf{u} and quantify its uncertainty, we must again leverage the laws of total expectation and
²⁶⁶ variance. [Ver Hoef et al. \(2024\)](#) show that $\hat{\mathbf{u}}$ and its associated variance are given by:

$$\begin{aligned} \hat{\mathbf{u}} &= \mathbf{X}_u\hat{\boldsymbol{\beta}} + \Sigma_{\mathbf{u},\mathbf{w}}\Sigma^{-1}(\hat{\mathbf{w}} - \mathbf{X}\hat{\boldsymbol{\beta}}) \\ \text{Var}(\hat{\mathbf{u}}) &= \Sigma_{\mathbf{u},\mathbf{u}} - \Sigma_{\mathbf{u},\mathbf{w}}\Sigma^{-1}\Sigma_{\mathbf{w},\mathbf{u}} + \mathbf{K}(\mathbf{X}^\top\Sigma^{-1}\mathbf{X})^{-1}\mathbf{K}^\top + \boldsymbol{\Lambda}(-\mathbf{H})^{-1}\boldsymbol{\Lambda}^\top, \end{aligned}$$

²⁶⁷ where $\mathbf{K} = \mathbf{X}_u - \Sigma_{\mathbf{u},\mathbf{w}}\Sigma^{-1}\mathbf{X}$ and $\boldsymbol{\Lambda} = \mathbf{X}_u\mathbf{B} + \Sigma_{\mathbf{u},\mathbf{w}}\Sigma^{-1}(\mathbf{1} - \mathbf{X}\mathbf{B})$ for a vector of ones, $\mathbf{1}$. As
²⁶⁸ with $\hat{\boldsymbol{\beta}}$, these covariance matrices are evaluated at $\hat{\boldsymbol{\theta}}$ in practice.

3. Modeling moose presence in Alaska, USA

²⁶⁹ The `moose` data in **spmodel** contain information on moose (*Alces Alces*) presence in the Togiak
²⁷⁰ region of Alaska, USA. `moose` is an `sf` object, a special data frame that is supplemented with
²⁷¹ spatial information using the `sf` package in R ([Pebesma 2018](#)). After loading **spmodel**, the
²⁷² first few rows of `moose` look like:

```
R> library("spmodel")

R> head(moose)

Simple feature collection with 6 features and 4 fields
Geometry type: POINT
Dimension:     XY
Bounding box:  xmin: 281896.4 ymin: 1518398 xmax: 311325.3 ymax: 1541016
Projected CRS: NAD83 / Alaska Albers
# A tibble: 6 x 5
  elev strat count presence      geometry
  <dbl> <chr> <dbl> <fct>       <POINT [m]>
1 469. L     0 0   (293542.6 1541016)
2 362. L     0 0   (298313.1 1533972)
3 173. M     0 0   (281896.4 1532516)
4 280. L     0 0   (298651.3 1530264)
5 620. L     0 0   (311325.3 1527705)
6 164. M     0 0   (291421.5 1518398)
```

273 There are five columns in `moose`: `elev`, the numeric site elevation (meters); `strat` a stratification variable for sampling with two levels ("L" and "M") categorized by landscape metrics
 274 at each site; `count`, the number of moose at each site; `presence`, a factor that indicates
 275 whether at least one moose was observed at each site (0 implies no moose; 1 implies at least
 276 one moose); and `geometry`, the NAD83/Alaska Albers (EPSG: 3338) projected coordinate of
 277 each site. These data have point-referenced support because each observation occurs at point
 278 coordinates represented by a POINT geometry. Moose are most prevalent in the southwestern
 279 and eastern parts of the Togiak region (Figure 3).

281 The `moose_preds` data in `spmodel` is an `sf` object with point locations at which moose
 282 presence predictions are desired. Like `moose`, `moose_preds` contains `elev` and `strat` for each
 283 site:

```
R> head(moose_preds)

Simple feature collection with 6 features and 2 fields
Geometry type: POINT
Dimension:     XY
Bounding box:  xmin: 291839.8 ymin: 1436192 xmax: 401239.6 ymax: 1512103
Projected CRS: NAD83 / Alaska Albers
# A tibble: 6 x 3
  elev strat      geometry
  <dbl> <chr>    <POINT [m]>
1 143. L    (401239.6 1436192)
2 324. L    (352640.6 1490695)
3 158. L    (360954.9 1491590)
4 221. M    (291839.8 1466091)
5 209. M    (310991.9 1441630)
6 218. L    (304473.8 1512103)
```

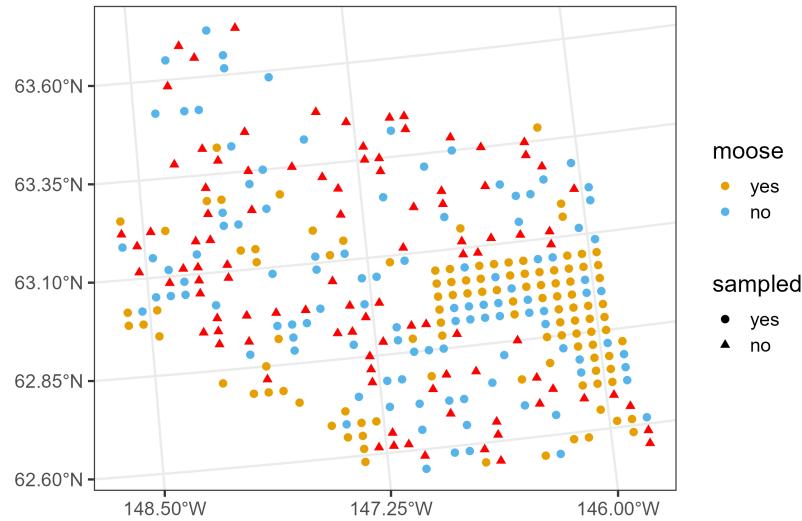


Figure 3: Moose presence in Alaska. Circles represent moose presence or absence (based on color) and triangles represent locations at which moose presence probability predictions are desired.

3.1. Model Fitting

SPGLMs in **spmodel** for point-referenced support are fit using the **spglm()** function. The **spglm()** function requires four arguments: **formula**, the relationship between the response and explanatory variables; **family**, the response distribution assumed for the response variable; **data**, the data frame that contains the variables in **formula**, and **spcov_type**, the type of spatial covariance. The **formula**, **family**, and **data** arguments are familiar because they are the three required arguments to **glm()** for nonspatial GLMs. So the transition from **glm()** to **spglm()** simply requires one additional argument: **spcov_type**. When **data** is not an **sf** object, **spglm()** also requires the **xcoord** and **ycoord** arguments, which indicate the columns in **data** that represent the projected x- and y-coordinates, respectively.

We use **spglm()** to fit a SPGLM (i.e., here, a spatial logistic regression model) quantifying the effect of elevation and strata on moose presence:

```
R> spbin <- spglm(
+   formula = presence ~ elev + strat,
+   family = binomial,
+   data = moose,
+   spcov_type = "exponential"
+ )
```

The **summary()** function returns a model summary with relevant information like the function call, deviance residuals, a coefficients table of fixed effects, the pseudo R-squared, spatial covariance parameters, and the GLM dispersion parameter (fixed at one in logistic regression):

```
R> summary(spbin)
```

```

Call:
spglm(formula = presence ~ elev + strat, family = binomial, data = moose,
      spcov_type = "exponential")

Deviance Residuals:
    Min      1Q  Median      3Q     Max 
-1.7535 -0.8005  0.3484  0.7893  1.5797 

Coefficients (fixed):
            Estimate Std. Error z value Pr(>|z|)    
(Intercept) -2.465713   1.486212 -1.659 0.097104 .  
elev         0.006036   0.003525  1.712 0.086861 .  
stratM       1.439273   0.420591  3.422 0.000622 *** 
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Pseudo R-squared: 0.06275

Coefficients (exponential spatial covariance):
        de      ie      range
5.145e+00 1.294e-03 4.199e+04

Coefficients (Dispersion for binomial family):
dispersion
      1

```

- 299 The model provides some evidence that elevation is positively associated with the log odds
 300 of moose presence (p value ≈ 0.087), after controlling for strata. The model also provides
 301 strong evidence that moose have a higher log odds of presence in the "M" strata compared to
 302 the "L" strata (p value < 0.001), after controlling for elevation.
 303 The fixed effects coefficients table from `summary()` is often of primary scientific interest, but
 304 it is not immediately usable when printed directly to the R console. The `tidy()` function
 305 tidies this table, turning it into a data frame (i.e., a tibble) with standard column names:

```

R> tidy(spbin, conf.int = TRUE)

# A tibble: 3 x 7
  term      estimate std.error statistic p.value conf.low conf.high
  <chr>      <dbl>     <dbl>     <dbl>    <dbl>    <dbl>     <dbl>
1 (Intercept) -2.47      1.49     -1.66  0.0971   -5.38e+0   0.447
2 elev        0.00604   0.00353     1.71  0.0869   -8.73e-4   0.0129
3 stratM      1.44       0.421     3.42  0.000622  6.15e-1    2.26

```

306 **3.2. Model Comparison**

307 The strength of spatial covariance in the data affects how beneficial an SPGLM is relative to
 308 a GLM. When the spatial covariance is strong, the SPGLM should notably outperform the
 309 GLM. When the spatial covariance is weak, the SPGLM and GLM should perform similarly.
 310 We can quantify the benefits of incorporating spatial covariance for a particular data set
 311 by comparing the fit of a SPGLM to a GLM. We can fit a GLM in **spmodel** by specifying
 312 `spcov_type = "none"`:

```
R> bin <- spglm(
+   formula = presence ~ elev + strat,
+   family = binomial,
+   data = moose,
+   spcov_type = "none"
+ )
R>
R> bin_glm <- glm(
+   formula = presence ~ elev + strat,
+   family = binomial,
+   data = moose,
+ )
R> round(coef(bin), digits = 4)

(Intercept)      elev      stratM
-0.4247     -0.0003     0.8070

R> round(coef(bin_glm), digits = 4)

(Intercept)      elev      stratM
-0.4247     -0.0003     0.8070

R> round(sqrt(diag(vcov(bin))), digits = 4)

(Intercept)      elev      stratM
 0.4208      0.0019     0.2906

R> round(sqrt(diag(vcov(bin_glm))), digits = 4)

(Intercept)      elev      stratM
 0.4208      0.0019     0.2906
```

313 Using `spglm()` instead of `glm()` ensures that **spmodel** helper functions are available and that
 314 each of the `spglm()` models uses the same hierarchical likelihood (Equation~4):

```
R> glance(spbin)

# A tibble: 1 x 10
  n      p  npqr value    AIC   AICc    BIC logLik deviance
  <int> <dbl> <int> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl>
1  218     3     3  676.  682.  683.  693. -338.    176.
# i 1 more variable: pseudo.r.squared <dbl>
```

```
R> glance(bin)

# A tibble: 1 x 10
  n      p  npar value    AIC   AICc     BIC logLik deviance
  <int> <dbl> <int> <dbl> <dbl> <dbl> <dbl> <dbl>
1 218     3     0 708. 708. 708. -354.    294.
# i 1 more variable: pseudo.r.squared <dbl>
```

315 The likelihood-based statistics AIC, AICc, BIC, and deviance are much lower for the SPGLM,
 316 indicating a better fit relative to the GLM.

317 Instead of relying on likelihood-based statistics, models can be compared using a cross-
 318 validation procedure (James, Witten, Hastie, and Tibshirani 2013). The `loocv()` function
 319 performs leave-one-out cross validation, comparing the predicted mean (on the response scale)
 320 to the observed response variable for each hold-out observation, recomputing estimates of β
 321 in each iteration. Performing leave-one-out cross validation tends to be more computationally
 322 efficient than fitting the model, as leave-one-out cross validation requires only one set of prod-
 323 ucts involving the inverse covariance matrix (a primary computational burden), while fitting
 324 traditional models requires these products for each optimization iteration. After performing
 325 leave-one-out cross validation, statistics like bias, mean-squared-prediction error (MSPE), and
 326 the square root of MSPE (RMSPE) can be used to evaluate models:

```
R> loocv(spbin)

# A tibble: 1 x 3
  bias  MSPE RMSPE
  <dbl> <dbl> <dbl>
1 0.0000206 0.156 0.394
```

```
R> loocv(bin)

# A tibble: 1 x 3
  bias  MSPE RMSPE
  <dbl> <dbl> <dbl>
1 -1.23e-9 0.240 0.490
```

327 Both models have negligible bias, but the SPGLM has much lower MSPE and RMSPE than
 328 the GLM, indicating the SPGLM predictions are far more efficient. Both the likelihood-based
 329 leave-one-out cross validation metrics prefer the SPGLM to the GLM.

330 We may also want to compare the fit of two SPGLMs with different spatial covariance struc-
 331 tures. For example, we may want to compare the fit of an SPGLM with the "exponential"
 332 spatial covariance to the fit of a SPGLM with the "gaussian" spatial covariance:

```
R> spbin2 <- update(spbin, spcov_type = "gaussian")
R> glances(spbin, spbin2)
```

```
# A tibble: 2 x 11
  model      n     p   npar value    AIC   AICc    BIC logLik deviance
  <chr> <int> <dbl> <int> <dbl> <dbl> <dbl> <dbl> <dbl>    <dbl>
1 spbin2    218     3     3  674.  680.  680.  690. -337.    198.
2 spbin     218     3     3  676.  682.  683.  693. -338.    176.
# i 1 more variable: pseudo.r.squared <dbl>

R> loocv(spbin)

# A tibble: 1 x 3
  bias  MSPE RMSPE
  <dbl> <dbl> <dbl>
1 0.0000206 0.156 0.394

R> loocv(spbin2)

# A tibble: 1 x 3
  bias  MSPE RMSPE
  <dbl> <dbl> <dbl>
1 -0.000261 0.146 0.382
```

- 333 The SPGLM with the "exponential" spatial covariance (`spbin`) has a slightly lower (better)
 334 deviance but slightly higher (worse) AIC, AICc, and BIC than the SPGLM with the
 335 "gaussian" spatial covariance (`spbin2`). Both SPGLMs have similar leave-one-out cross
 336 validation metrics, though the SPGLM with the "gaussian" spatial covariance has slightly
 337 lower (better) RMSPE. For practical purposes, these models fit similarly.
- 338 Frequently in spatial statistics, the difference in model fit between the best spatial model
 339 and worst spatial model is much smaller than the difference in model fit between the worst
 340 spatial model and the nonspatial model, implying that accounting for some form of spatial
 341 covariance is very beneficial. Two spatial covariance functions to consider starting with are the
 342 exponential and Gaussian, which have quite different origin behaviors (Figure 2), something
 343 Stein (1999) argues is important to characterize accurately.

344 3.3. Model Diagnostics

- 345 `spmodel` provides a suite of tools for model diagnostics. One is `augment()`, which augments
 346 the data used in the model with several model diagnostics (introduced in Section 2.3):

```
R> augment(spbin)

Simple feature collection with 218 features and 8 fields
Geometry type: POINT
Dimension:      XY
Bounding box:  xmin: 269085 ymin: 1416151 xmax: 419057.4 ymax: 1541016
Projected CRS: NAD83 / Alaska Albers
# A tibble: 218 x 9
```

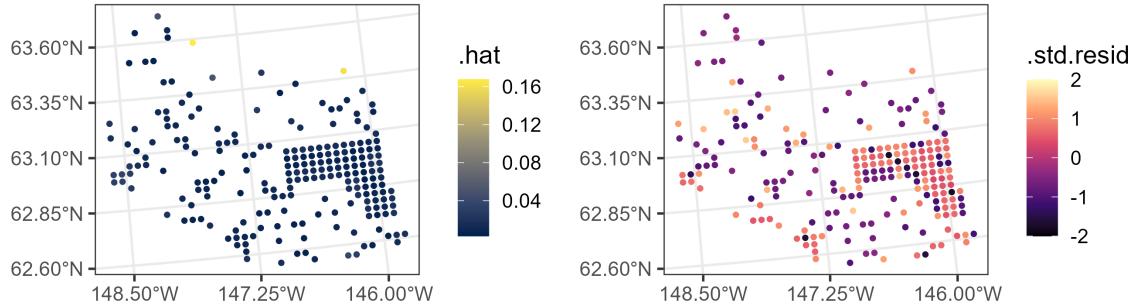


Figure 4: Moose presence model diagnostics, including leverage values (left) and standardized residuals (right).

```

presence elev strat .fitted .resid      .hat   .cooksdi .std.resid
* <fct>    <dbl> <chr> <dbl> <dbl> <dbl>    <dbl>
1 0        469. L     -1.95 -0.516 0.0476 0.00465 -0.528
2 0        362. L     -2.70 -0.361 0.0123 0.000548 -0.363
3 0        173. M     -1.96 -0.514 0.00455 0.000405 -0.516
4 0        280. L     -3.15 -0.290 0.00413 0.000117 -0.291
5 0        620. L     -1.19 -0.728 0.168 0.0427 -0.798
6 0        164. M     -1.71 -0.576 0.00534 0.000598 -0.578
7 0        164. M     -1.60 -0.606 0.00576 0.000714 -0.608
8 0        186. L     -2.50 -0.397 0.00439 0.000233 -0.398
9 0        362. L     -1.88 -0.532 0.0239 0.00237 -0.539
10 0       430. L    -1.54 -0.623 0.0497 0.00713 -0.639
# i 208 more rows
# i 1 more variable: geometry <POINT [m]>
```

347 The fitted values (`.fitted`) can be returned on either the link ($\hat{\mathbf{w}}$) or response ($f^{-1}(\hat{\mathbf{w}})$)
 348 scale and the residuals (`.resid`) can be deviance, Pearson, or response residuals. The default
 349 fitted values are on the link scale and the default residuals are deviance residuals. Also
 350 returned by `augment()` are the leverage (`.hat`), Cook's distance (`.cooksdi`), and standardized
 351 residuals (`.std.resid`). A benefit of using `augment()` when `data` is an `sf` object is that the
 352 output is also an `sf` object, which makes it straightforward to create spatial diagnostic plots
 353 (Figure 4). Standard R helpers (e.g., `fitted()`, `residuals()`) are also available to extract
 354 model diagnostics from the model object.

355 The `plot()` function can also be used to return similar diagnostics as from `lm()` and `glm()`,
 356 with additional tools for diagnosing spatial covariance. For example, we can inspect Cook's
 357 distance values and the empirical spatial covariance as a function of distance with (Figure 5):

```
R> plot(spbin, which = c(4, 7))
```

358 The `varcomp()` function partitions model variability into several different components, helping
 359 to elucidate the model's structure:

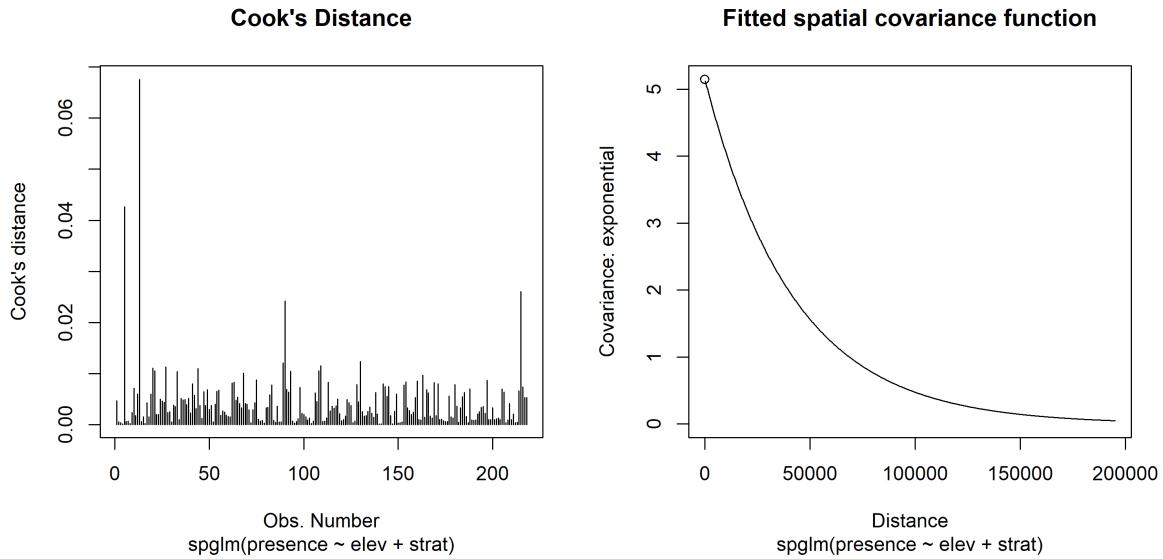


Figure 5: Moose presence model diagnostics, including Cook's distance (left) and the fitted spatial covariance as a function of distance (right).

```
R> varcomp(spbin)
```

```
# A tibble: 3 x 2
  varcomp      proportion
  <chr>          <dbl>
1 Covariates (PR-sq) 0.0627
2 de             0.937
3 ie             0.000236
```

360 The pseudo R-squared (PR^2) is reported in the first row. The remaining variability ($1 - PR^2$)
 361 is allocated proportionally to `de` and `ie` according to σ_{de}^2 and σ_{ie}^2 . This variability partitioning
 362 is a useful tool that helps quantify how much the explanatory variables, residual spatial
 363 variance, and residual nonspatial variance contribute to model fit; as with PR^2 , it should not
 364 be used for model comparison, but rather as a helpful model diagnostic.

365 3.4. Prediction

366 We can predict the probability of moose presence at the locations in `moose_preds` using
 367 `predict()`:

```
R> predict(spbin, newdata = moose_preds)[1:5]
```

1	2	3	4	5
0.06664165	-0.79069107	-1.60387940	-0.83159357	1.38183928

368 By default, predictions are returned on the link scale, but this can be changed to the response
 369 scale via `type`:

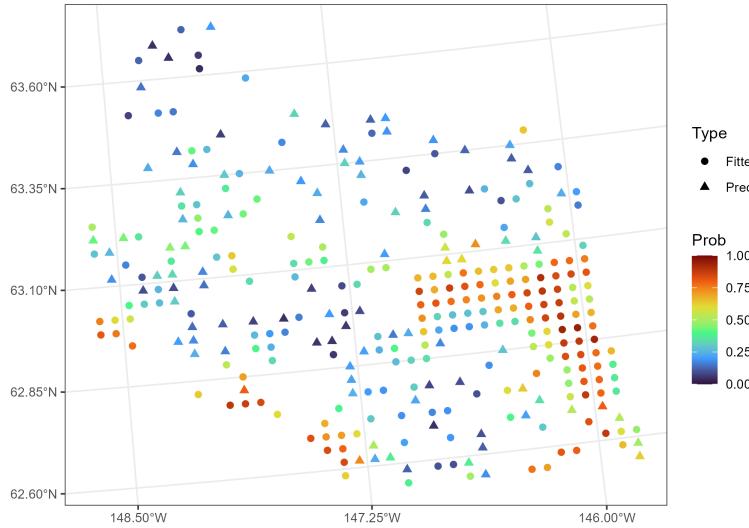


Figure 6: Moose presence probability fitted values ($f^{-1}(\hat{\mathbf{w}})$) and predictions. Fitted values are represented by circles and predictions by triangles.

```
R> predict(spbin, newdata = moose_preds, type = "response") [1:5]
```

1	2	3	4	5
0.5166542	0.3120203	0.1674401	0.3033082	0.7992862

370 Moose are far more common in the eastern and southwestern portion of the domain (Figure 6).
 371 Prediction intervals for the probability of moose presence (on the link scale) are returned by
 372 supplying `interval`:

```
R> predict(spbin, newdata = moose_preds, interval = "prediction") [1:5, ]
```

	fit	lwr	upr
1	0.06664165	-2.0374370	2.1707203
2	-0.79069107	-3.4758514	1.8944692
3	-1.60387940	-4.0953329	0.8875741
4	-0.83159357	-3.0704818	1.4072947
5	1.38183928	-0.7692107	3.5328893

373 We can alternatively use `augment()` to augment the prediction data with predictions. Argu-
 374 ments to `predict()` can also be passed to `augment()`:

```
R> augment(spbin, newdata = moose_preds, interval = "prediction")
```

```
Simple feature collection with 100 features and 5 fields
Geometry type: POINT
Dimension:      XY
Bounding box:  xmin: 269386.2 ymin: 1418453 xmax: 419976.2 ymax: 1541763
```

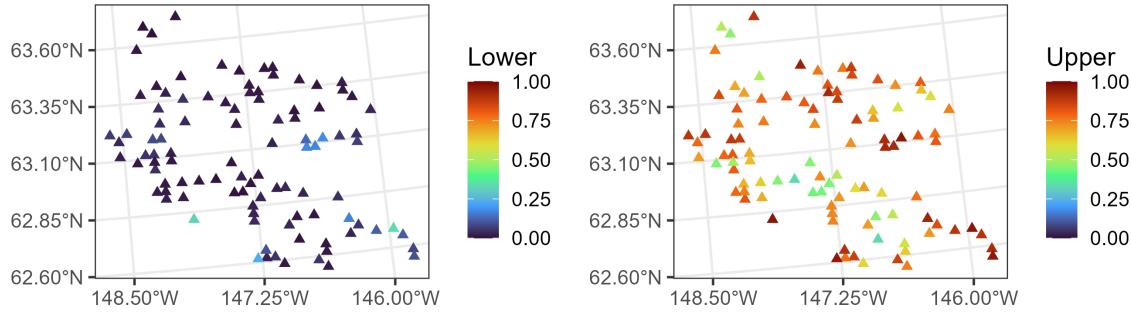


Figure 7: Moose presence 95% prediction interval lower bounds (left) and upper bounds (right).

```
Projected CRS: NAD83 / Alaska Albers
# A tibble: 100 x 6
  elev strat .fitted .lower  .upper      geometry
* <dbl> <chr>   <dbl>  <dbl>   <dbl>      <POINT [m]>
1 143. L     0.0666 -2.04    2.17 (401239.6 1436192)
2 324. L    -0.791  -3.48    1.89 (352640.6 1490695)
3 158. L    -1.60   -4.10    0.888 (360954.9 1491590)
4 221. M    -0.832  -3.07    1.41 (291839.8 1466091)
5 209. M     1.38   -0.769   3.53 (310991.9 1441630)
6 218. L    -2.59   -5.20    0.0177 (304473.8 1512103)
7 127. L    -2.73   -5.24   -0.220 (339011.1 1459318)
8 122. L    -2.32   -4.74    0.0920 (342827.3 1463452)
9 191. L    -1.17   -4.01    1.66 (284453.8 1502837)
10 105. L   -0.905  -3.05    1.24 (391343.9 1483791)
# i 90 more rows
```

³⁷⁵ By using `augment()` when `newdata` is an `sf` object, predictions and their corresponding
³⁷⁶ uncertainties are readily available for spatial mapping (Figure 7).

4. Additional applications

³⁷⁷ Throughout the remainder of this section, we briefly highlight some additional **spmodel** ca-
³⁷⁸ pabilities for SPCGLMs. In Section 4.1, we fit Poisson and negative binomial models with and
³⁷⁹ without geometric anisotropy for the point-referenced moose count data. In Section 4.2, we
³⁸⁰ fit a Gamma model to the point-referenced lake conductivity data, showing how to fit a model
³⁸¹ with a partition factor, perform a spatial analysis of variance (ANOVA), and estimate con-
³⁸² trasts for models with interactions. In Section 4.3, we fit a binomial model to the areal harbor
³⁸³ seal trend data with a nonspatial random effect. Finally in Section 4.4, we fit beta models to
³⁸⁴ Texas voter turnout data, which can be modeled using point-referenced or areal support, and
³⁸⁵ use maximum likelihood to compare two models with different explanatory variables. Table 1
³⁸⁶ outlines, for each application, the section number, data set, family (i.e., response distribu-

Section	Data	Family	Geometry	Additional Features
4.1	Moose Counts	Poisson NBinomial	Point	Geometric Anisotropy
4.2	Lake Conductivity	Gamma	Point	Partition Factor ANOVA Contrasts
4.3	Harbor Seals	Binomial	Areal	Nonspatial Random Effects
4.4	Texas Voter Turnout	Beta	Point Areal	Likelihood-Ratio Test

Table 1: Section number, data set, family, geometry type, and additional features for each application.

387 tion), geometry type (point-referenced or areal support), and additional **spmodel** features
 388 highlighted.

389 **4.1. Modeling moose counts in Alaska, USA**

390 In addition to moose presence, moose counts are also recorded in `moose` (Figure 8). The
 391 Poisson and negative binomial response distributions can be used to model SPGLMs for count
 392 data. The Poisson distribution mean is equal to its variance, while the negative binomial has
 393 an extra parameter to accommodate overdispersion (where the variance is larger than the
 394 mean). Using a spherical spatial covariance function, we may fit both a Poisson and negative
 395 binomial SPGLM changing the `family` argument:

```
R> sppois <- spglm(  
+   formula = count ~ elev + strat,  
+   family = poisson,  
+   data = moose,  
+   spcov_type = "spherical"  
+ )  
R> spnb <- update(sppois, family = nbinomial)
```

396 Because the Poisson and negative binomial distributions have the same response support
 397 (nonnegative integers), we can compare them using AIC, AICc, or BIC:

```
R> BIC(sppois, spnb)
```

df	BIC
sppois	3 1344.574
spnb	4 1343.105

398 Implicit in our spatial covariance functions thus far has been an assumption of geometric
 399 isotropy. A spatial covariance function is geometrically isotropic if it decays with distance
 400 at the same rate in all directions (Figure 9; left). A spatial covariance is geometrically
 401 anisotropic if it decays with distance at different rates in different directions (Figure 9; right).

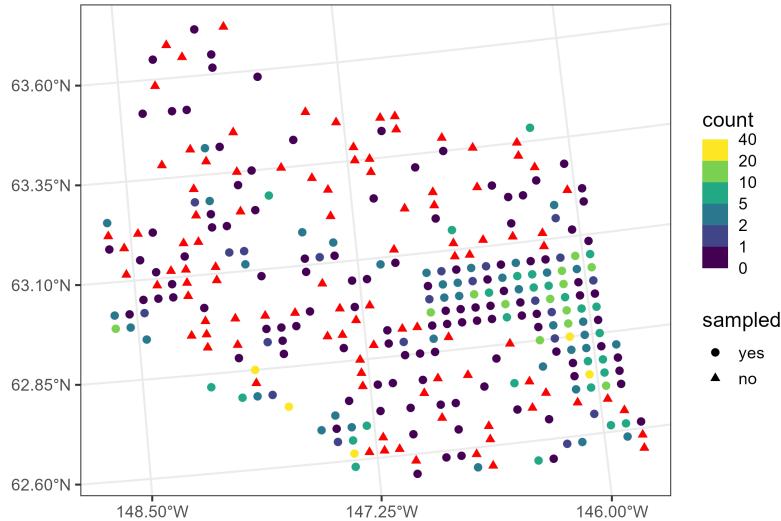


Figure 8: Moose counts in Alaska. Circles represent moose counts (based on color) and triangles represent locations at which mean count predictions are desired.

402 Geometric anisotropy is formally incorporated by rotating and scaling original coordinates,
403 yielding transformed coordinates that are geometrically isotropic:

$$\begin{bmatrix} x^* \\ y^* \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & 1/\omega \end{bmatrix} \begin{bmatrix} \cos(\alpha) & \sin(\alpha) \\ -\sin(\alpha) & \cos(\alpha) \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix}.$$

404 The parameters ω and α controls the scaling and rotation, respectively, of the major and
405 minor axes of a level curve of equal spatial covariance (Figure 9). Using these transformed
406 coordinates, the partial sill (σ_{de}^2), nugget (σ_{ie}^2), and range (ϕ) parameters are estimated. We
407 accommodate geometric anisotropy by supplying `anisotropy`:

```
R> sppois_anis <- update(sppois, anisotropy = TRUE)
R> spnb_anis <- update(spnb, anisotropy = TRUE)
```

408 According to BIC, the spatial negative binomial model with geometric anisotropy performs
409 best:

```
R> BIC(sppois, spnb, sppois_anis, spnb_anis)
```

	df	BIC
sppois	3	1344.574
spnb	4	1343.105
sppois_anis	5	1341.143
spnb_anis	6	1339.714

410 The `plot()` function can be used to visualize the anisotropy (Figure 9):

```
R> plot(spnb, which = 8)
R> plot(spnb_anis, which = 8)
```

411 From Figure 9, the spatial covariance is strongest in a northwest-southeast direction (2.729
 412 radians) and weakest in the northeast-southwest direction (0.413 radians), which is intuitive
 413 given the similar patterns in moose counts from Figure 8.

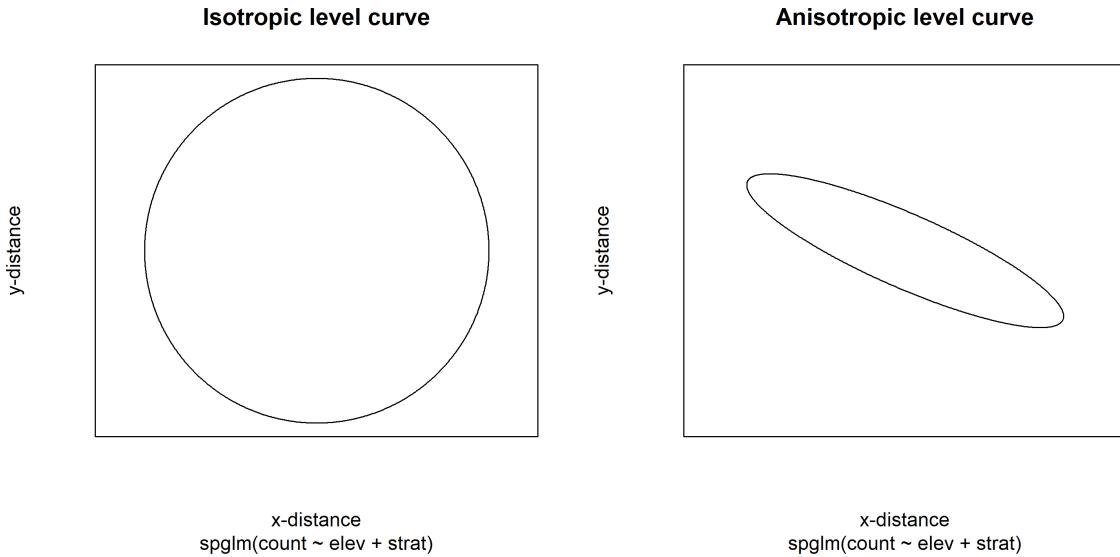


Figure 9: Level curves of equal spatial covariance for the negative binomial moose count models. The ellipse is centered at zero distance in the x-direction and y-direction, and points along the ellipse have equal levels of spatial covariance. In the isotropic level curve (left), spatial covariance decays equally in all directions. In the anisotropic level curve (right), spatial covariance decays fastest in the northeast-southwest direction (0.413 radians) and slowest in the northwest-southeast direction (2.729 radians).

414 4.2. Modeling lake conductivity in Southwest, USA

415 The `lake` data in `spmodel` contains climate and chemical data for several lakes in four south-
 416 western states in the United States: Arizona, Colorado, Nevada, and Utah. We desire an
 417 SPGLM that characterizes the effect of temperature, state, and lake origin (whether the lake
 418 is naturally occurring or human made) on lake conductivity. Conductivity is a measure of
 419 dissolved ions (measured here in water), which is important for various physical, chemical,
 420 and biological processes. Chemical data are often heavily right-skewed, so we model them
 421 using an SPGLM assuming a Gamma distribution for the response. The `log_cond` variable
 422 in `lake` is the logarithm of conductivity, which we dynamically exponentiate within `formula`
 423 so that it is on the original scale:

```
R> spgam <- spglm(
+   formula = exp(log_cond) ~ temp * state + origin,
+   family = "Gamma",
+   data = lake,
+   spcov_type = "cauchy",
+   partition_factor = ~ year
+ )
```

- 424 We model conductivity as a function of temperature, state, and lake origin, and we allow
 425 the effect of temperature to vary by state (`temp:state` interaction). The `year` partition
 426 factor (specified via `partition_factor`) restricts spatial covariance to be nonzero only for
 427 observations sampled during the same year. Data were collected in 2012 and 2017, so this
 428 partition factor assumes independence between observations in 2012 and 2017. While we used
 429 the partition factor here illustratively, more generally, the utility of partition factors can be
 430 highly context dependent.
- 431 When categorical variables have more than two levels, the default reference group contrasts
 432 are not well-suited to assess the variable's overall significance:

```
R> summary(spgam)
```

```
Call:
spglm(formula = exp(log_cond) ~ temp * state + origin, family = "Gamma",
      data = lake, spcov_type = "cauchy", partition_factor = ~year)

Deviance Residuals:
    Min      1Q   Median      3Q      Max
-1.35762 -0.20796 -0.03706  0.17869  1.10616

Coefficients (fixed):
            Estimate Std. Error z value Pr(>|z|)
(Intercept) 3.59325   0.50058  7.178 7.06e-13 ***
temp         0.15182   0.03006  5.051 4.39e-07 ***
stateCO     -0.03214   0.56098 -0.057  0.95432
stateNV      0.75664   0.66851  1.132  0.25771
stateUT     -0.19696   0.55916 -0.352  0.72466
originNATURAL 0.08313   0.21988  0.378  0.70538
temp:stateCO 0.13679   0.04808  2.845  0.00444 **
temp:stateNV 0.01882   0.05820  0.323  0.74645
temp:stateUT 0.20015   0.04846  4.131 3.62e-05 ***

---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Pseudo R-squared: 0.7061

Coefficients (cauchy spatial covariance):
        de      ie      range      extra
2.069e-02 2.952e-01 4.119e+06 5.645e-01

Coefficients (Dispersion for Gamma family):
dispersion
      3.761
```

- 433 A more effective approach is to use an analysis of variance (ANOVA), which is well-suited to
 434 assess the overall significance of each variable:

```
R> anova(spgam)
```

Analysis of Variance Table

```
Response: exp(log_cond)
          Df  Chi2 Pr(>Chi2)
(Intercept) 1 51.5270 7.062e-13 ***
temp         1 25.5146 4.390e-07 ***
state        3  3.0747 0.3802528
origin       1  0.1429 0.7053819
temp:state   3 19.7668 0.0001897 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

- 435 The main effect for temperature and the temperature by state interaction are highly significant
 436 (*p* value < 0.001), while the main effects for state and lake origin are not significant.
 437 Variance inflation factors assess the degree to which standard errors $\hat{\beta}$ are inflated due to
 438 covariance among the columns of **X**. Generalized variance inflation factors can capture the
 439 variance inflation for subsets of **X** that may include categorical variables with more than two
 440 levels (Fox and Monette 1992):

```
R> library("car")
```

```
R> vif(spgam)
```

	GVIF	Df	GVIF ^{(1/(2*Df))}
temp	4.691914	1	2.166083
state	127.082397	3	2.242234
origin	1.264940	1	1.124695
temp:state	76.387383	3	2.059856

- 441 The GVIF^{1/2df} values for **temp**, **state**, and **temp:state** are just greater than two, which
 442 suggests moderate multicollinearity for these terms – unsurprising given the **temp:state**
 443 interaction in the model. The GVIF^{1/2df} for **origin** is close to one, which suggests little to
 444 no multicollinearity for this term.
 445 Because of the interaction between **temp** and **state**, contrasts that assess mean differences
 446 among states should condition upon a specific temperature value. By default, **emmeans** uses
 447 the mean temperature value (here, 7.63) to assess contrasts:

```
R> library("emmeans")
```

```
R> pairs(emmeans(spgam, ~ state | temp))
```

```
temp = 7.63:
contrast estimate    SE  df z.ratio p.value
AZ - CO     -1.012 0.337 Inf  -3.004  0.0142
```

AZ - NV	-0.900	0.348	Inf	-2.584	0.0480
AZ - UT	-1.331	0.326	Inf	-4.082	0.0003
CO - NV	0.112	0.258	Inf	0.434	0.9727
CO - UT	-0.319	0.223	Inf	-1.427	0.4822
NV - UT	-0.431	0.244	Inf	-1.763	0.2915

Results are averaged over the levels of: origin

Degrees-of-freedom method: asymptotic

Results are given on the log (not the response) scale.

P value adjustment: tukey method for comparing a family of 4 estimates

- 448 Again, because of the interaction between `temp` and `state`, we should assess temperature
 449 trends separately for each state:

```
R> emtrends(spgam, ~ state, var = "temp")
```

state	temp.trend	SE	df	asymp.LCL	asymp.UCL
AZ	0.152	0.0301	Inf	0.0929	0.211
CO	0.289	0.0370	Inf	0.2161	0.361
NV	0.171	0.0504	Inf	0.0718	0.270
UT	0.352	0.0372	Inf	0.2791	0.425

Results are averaged over the levels of: origin

Degrees-of-freedom method: asymptotic

Results are given on the exp (not the response) scale.

Confidence level used: 0.95

450 **4.3. Modeling harbor seal trends in Alaska, USA**

- 451 The `seal` data in `spmodel` contains harbor seal abundance trends for two different harbor
 452 seal stocks (genetically distinct populations). While the `moose` and `lake` data have point-
 453 referenced support, the `seal` data have areal support. Each polygon in the `seal` data repre-
 454 sents a distinct harbor seal haulout region (Figure 10). A haulout region is an area of coastal
 455 rocks that harbor seals go to rest, molt, and give birth.

- 456 For each polygon, a Poisson regression was used to quantify the mean trend in abundance
 457 over approximately 30 years (Ver Hoef, Peterson, Hooten, Hanks, and Fortin 2018). If the
 458 logarithm of mean abundance trends (`log_trend`) is negative (positive), it means abundance
 459 is decreasing (increasing). We use a binomial SPGLM to quantify the likelihood that mean
 460 abundance trends are decreasing:

```
R> is_decreasing <- seal$log_trend < 0
R> spbin <- spgautor(
+   formula = is_decreasing ~ 1,
+   family = binomial,
+   data = seal,
+   spcov_type = "car",
```

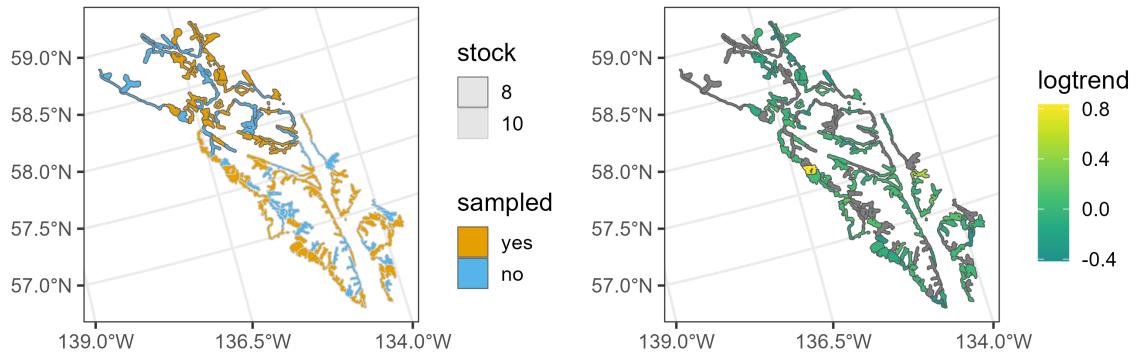


Figure 10: Seal trend distribution in Alaska. Observed and missing seal polygons by stock (left) and observed log seal trends (right).

```
+   random = ~ stock
+ )
```

To model spatial dependence, we used a conditional autoregressive function. Conditional and simultaneous autoregressive functions characterize spatial distance through neighborhood relationships (rather than Euclidean distance) and have `spcov_type` values of "car" and "sar", respectively. By default, Queen's distance is used to determine whether two sites are neighbors, though custom neighborhood matrices can be passed via `W`. Row standardization is also assumed by default; this can be changed via `row_st`. Using `random`, we also specified a nonspatial random effect for seal stock, which implies seals belonging to the same stock share extra covariance. The `random` argument uses similar syntax as `lme4` (Bates, Mächler, Bolker, and Walker 2015) and `nlme` (Pinheiro and Bates 2006) to specify nonspatial random effects.

Tidying the model reveals the estimates and confidence intervals on the log odds scale:

```
R> tidy(spbin, conf.int = TRUE)

# A tibble: 1 x 7
  term      estimate std.error statistic p.value conf.low conf.high
  <chr>      <dbl>     <dbl>     <dbl>    <dbl>    <dbl>    <dbl>
1 (Intercept)  0.340     0.673     0.506    0.613   -0.979    1.66
```

Back-transforming the confidence interval to the probability scale yields:

```
R> emmeans(spbin, ~ 1, type = "response")

1          prob      SE  df asympt.LCL asympt.UCL
overall 0.584 0.164 Inf      0.273      0.84

Degrees-of-freedom method: asymptotic
Confidence level used: 0.95
Intervals are back-transformed from the logit scale
```

⁴⁷² The **SE** column is the standard error on the response scale obtained from the delta method
⁴⁷³ (Oehlert 1992; Ver Hoef 2012).

⁴⁷⁴ In contrast to point-referenced data, prediction locations for areal data must be specified
⁴⁷⁵ at the time of model fitting, as they affect the spatial covariance function's neighborhood
⁴⁷⁶ structure. Prediction locations whose response values have an **NA** (i.e., missing) value are
⁴⁷⁷ converted into a **newdata** object that is stored in the model output. For example, rows one
⁴⁷⁸ and nine are locations without seal trends, meaning they are not used in model fitting but
⁴⁷⁹ are desired for prediction:

```
R> seal
```

```
Simple feature collection with 149 features and 2 fields
Geometry type: POLYGON
Dimension:     XY
Bounding box:  xmin: 913618.8 ymin: 855730.2 xmax: 1221859 ymax: 1145054
Projected CRS: NAD83 / Alaska Albers
# A tibble: 149 x 3
  log_trend stock                                     geometry
  * <dbl> <fct>                                     <POLYGON [m]>
1 NA     8   ((1035002 1054710, 1035002 1054542, 1035002 105354~
2 -0.282 8   ((1037002 1039492, 1037006 1039490, 1037017 103949~
3 -0.00121 8   ((1070158 1030216, 1070185 1030207, 1070187 103020~
4  0.0354 8   ((1054906 1034826, 1054931 1034821, 1054936 103482~
5 -0.0160 8   ((1025142 1056940, 1025184 1056889, 1025222 105683~
6  0.0872 8   ((1026035 1044623, 1026037 1044605, 1026072 104461~
7 -0.266 8   ((1100345 1060709, 1100287 1060706, 1100228 106070~
8  0.0743 8   ((1030247 1029637, 1030248 1029637, 1030265 102964~
9 NA     8   ((1043093 1020553, 1043097 1020550, 1043101 102055~
10 -0.00961 8  ((1116002 1024542, 1116002 1023542, 1116002 102254~
# i 139 more rows
```

⁴⁸⁰ Then, **predict()** can be called without having to specify **newdata**:

```
R> predict(spbin, type = "response", interval = "prediction")[1:5, ]

      fit      lwr      upr
1  0.6807677 0.3863736 0.8783808
9  0.5945680 0.2467634 0.8678078
13 0.6189055 0.2974432 0.8616799
15 0.6040102 0.2921802 0.8493132
18 0.6375700 0.3356282 0.8596641
```

⁴⁸¹ We could have alternatively used a (geostatistical) SPGLM via **spglm()**. When areal data are
⁴⁸² used with **spglm()**, the centroids of each polygon are used as the point-referenced coordinates.

⁴⁸³ 4.4. Modeling voter turnout in Texas, USA

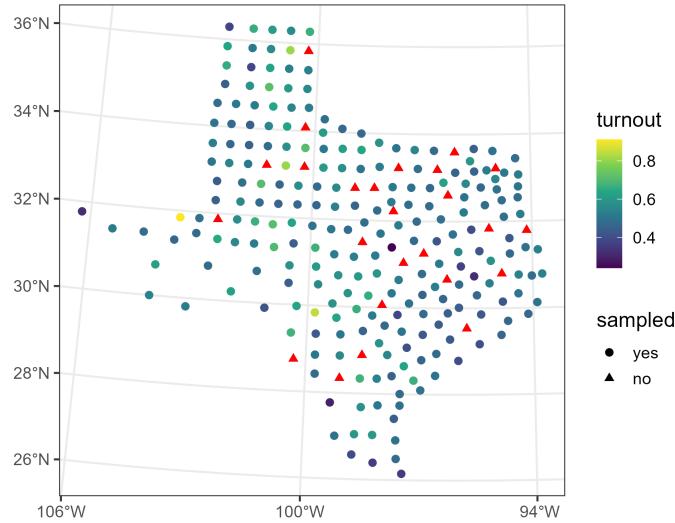


Figure 11: Proportion of voter turnout in Texas for the 1980 presidential election. Circles represent voter turnout (based on color) and triangles represent locations at which voter turnout predictions are desired.

484 The `texas` data in `spmodel` contains voter turnout data for Texas counties in the 1980 United
 485 States Presidential Election (Bivand, Nowosad, and Lovelace 2024). The data have point-
 486 referenced support, with polygon centroids representing the spatial location of each county
 487 (Figure 11). Beta regression is a GLM used to model rate and proportion data in the (0,
 488 1) interval (Ferrari and Cribari-Neto 2004; Cribari-Neto and Zeileis 2010). We model voter
 489 turnout rates as a function of mean log income of county residents using a geostatistical
 490 SPGLM assuming a beta distributed response variable:

```
R> spbeta_geo <- spglm(
+   formula = turnout ~ log_income,
+   family = "beta",
+   data = texas,
+   spcov_type = "matern"
+ )
```

491 Alternatively, we could fit an autoregressive SPGLM by assuming the data have areal support
 492 and constructing a neighborhood matrix that treats counties as neighbors if the distance
 493 between their centroids is less than `cutoff`:

```
R> spbeta_auto <- spgautor(
+   formula = turnout ~ log_income,
+   family = "beta",
+   data = texas,
+   spcov_type = "car",
+   cutoff = 1e5
+ )
```

494 According to AIC, the geostatistical SPGLM:

```
R> AIC(spbeta_geo, spbeta_auto)
```

df	AIC
spbeta_geo	5 -44.53113
spbeta_auto	3 -22.46104

495 The default estimation method in **spmodel** for SPGLMs is restricted maximum likelihood
496 (REML), while maximum likelihood (ML) can also be used. A benefit of REML is
497 that it can yield unbiased estimates of covariance parameters (Cressie and Lahiri 1993). A
498 drawback of REML is that likelihood-based statistics are often considered invalid when the
499 models have different explanatory variable or fixed effect structures (Wolfinger 1993), though
500 Gurka (2006) provides some evidence to the contrary. In contrast to REML estimators, ML
501 estimators are generally biased for covariance parameters, though in practice this bias tends
502 to be small. Moreover, when using ML, likelihood-based comparisons are valid for models
503 with different explanatory variable or fixed effect structures. Using ML, we can evaluate the
504 significance of log income on voter turnout using a likelihood ratio test (for nested models):

```
R> spbeta_full_ml <- update(spbeta_geo, estmethod = "ml")
R> spbeta_reduced_ml <- update(spbeta_geo, estmethod = "ml", formula = turnout ~ 1)
R> anova(spbeta_full_ml, spbeta_reduced_ml)
```

Likelihood Ratio Test

```
Response: turnout
Df Chi2 Pr(>Chi2)
spbeta_reduced_ml vs spbeta_full_ml 1 23.155 1.494e-06 ***
---
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

505 The likelihood ratio test provides strong evidence that log income is significantly related
506 to voter turnout (p value < 0.001). Alternatively, we could have instead used a different
507 likelihood-based statistic like AIC:

```
R> AIC(spbeta_full_ml, spbeta_reduced_ml)
```

df	AIC
spbeta_full_ml	7 -31.25900
spbeta_reduced_ml	6 -10.10354

508 The AIC also prefers the full model, suggesting that log income is important for predicting
509 voter turnout.

5. Discussion

SPGLMs are fit in **spmodel** using a novel application of the Laplace approximation that simultaneously marginalizes over the latent (i.e., unobserved) random effects and the fixed effects. **spmodel**'s `spglm()` (for point-referenced support) and `spgautor()` (for areal support) fit SPGLMs that are similar in structure and syntax as base R's `glm()` function, easing the transition for practitioners from GLMs to SPGLMs. The `spglm()` and `spgautor()` functions support six response distributions for binary, count, and skewed data and 20 spatial covariance functions. **spmodel** has a suite of tools for data visualization, inference, model diagnostics, and prediction, providing a framework that can be used for all stages of a data analysis. There are many additional **spmodel** features that are not covered here, including fitting multiple models simultaneously, fixing spatial covariance and dispersion parameters at known values, fitting models to large non-Gaussian data having thousands of observations via spatial indexing (Ver Hoef, Dumelle, Higham, Peterson, and Isaak 2023), incorporating spatial dependence in machine learning (e.g., random forests; Breiman (2001)), simulating spatially dependent data (e.g., `spbinom()`, `sprpois()`, etc.), and more. Further details are provided by <https://CRAN.R-project.org/package=spmodel> and links therein.

Data and code availability

The results in this manuscript were obtained using R 4.4.0 with the **spmodel** 0.11.1 package. Figures were created using the `ggplot2` 3.5.1 package (Wickham 2016) and base R. All writing and code associated with this manuscript is available for viewing and download on GitHub at <https://github.com/USEPA/spmodel.glm.manuscript>. All data used are part of the **spmodel** R package available for download from CRAN at <https://CRAN.R-project.org/package=spmodel>.

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