An updated landslide susceptibility model for Scotland

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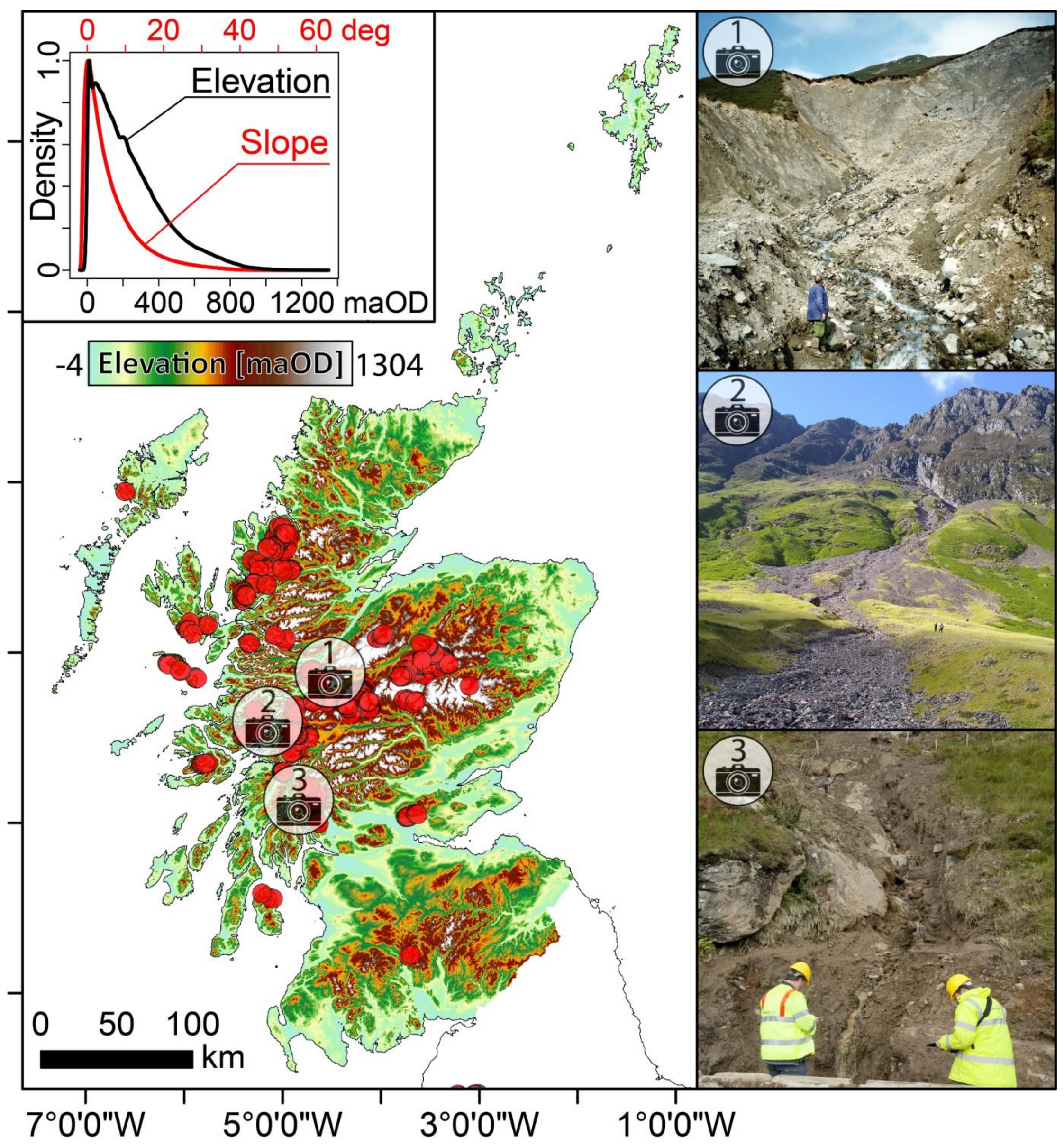
Introduction & Data

The GeoSure database of national landslides was sparsely populated at the time of its creation around 20 years ago, and therefore data-driven methods for landslide susceptibility were not possible. In this work, we look at landslide locations across Scotland, specifically debris flows (DFs), and aim to update the landslide susceptibility map that the British Geological Survey (BGS) has been using. To do this, we propose a Bernoulli likelihood model for the probability of landslide occurrence and a log-Gaussian Cox process (LGCP) model for the rate of landslide occurrences. We can then compare these data-driven susceptibility maps with the previous heuristic map of GeoSure. In terms of data, we have a selection of geographical and geological covariates defined at the slope unit (SU) level. The SU is defined to preserve geo-morphological conditions that might induce landslides. The covariates underwent a forward selection procedure and information criteria were used to determine whether the covariate should be included in the model in a linear/non-linear way, or at all. In addition to this, we have the DF point locations, and from this determine the count per SU in order to use the grid-approximation method for our LGCP likelihood.



Modelling approach

For landslide susceptibility we model the probability of observing at least one DF in a slope unit by using a Bernoulli distribution. For the rate of landslide susceptibility, we model the DF rate of occurrence per SU by using a Poisson distribution with a random intensity function which approximates the LGCP likelihood.

In both cases, we assume that the observations are conditionally independent given a latent Gaussian field. This latent field can be represented as the sum of our model components:

$$\eta(\boldsymbol{s}) = \alpha + \sum_{m=1}^{M} \beta_m w_m(\boldsymbol{s}) + \sum_{k=1}^{K} f_k\big(z_k(\boldsymbol{s})\big) + u(\boldsymbol{s})$$

These type of models (flexible and hierarchical) are best understood within a Bayesian framework and here we utilise the integrated nested Laplace approximation (INLA) to infer our posterior distributions of interest. Additionally, we use the stochastic partial differential equation approach (SPDE) to model our spatial random effect.

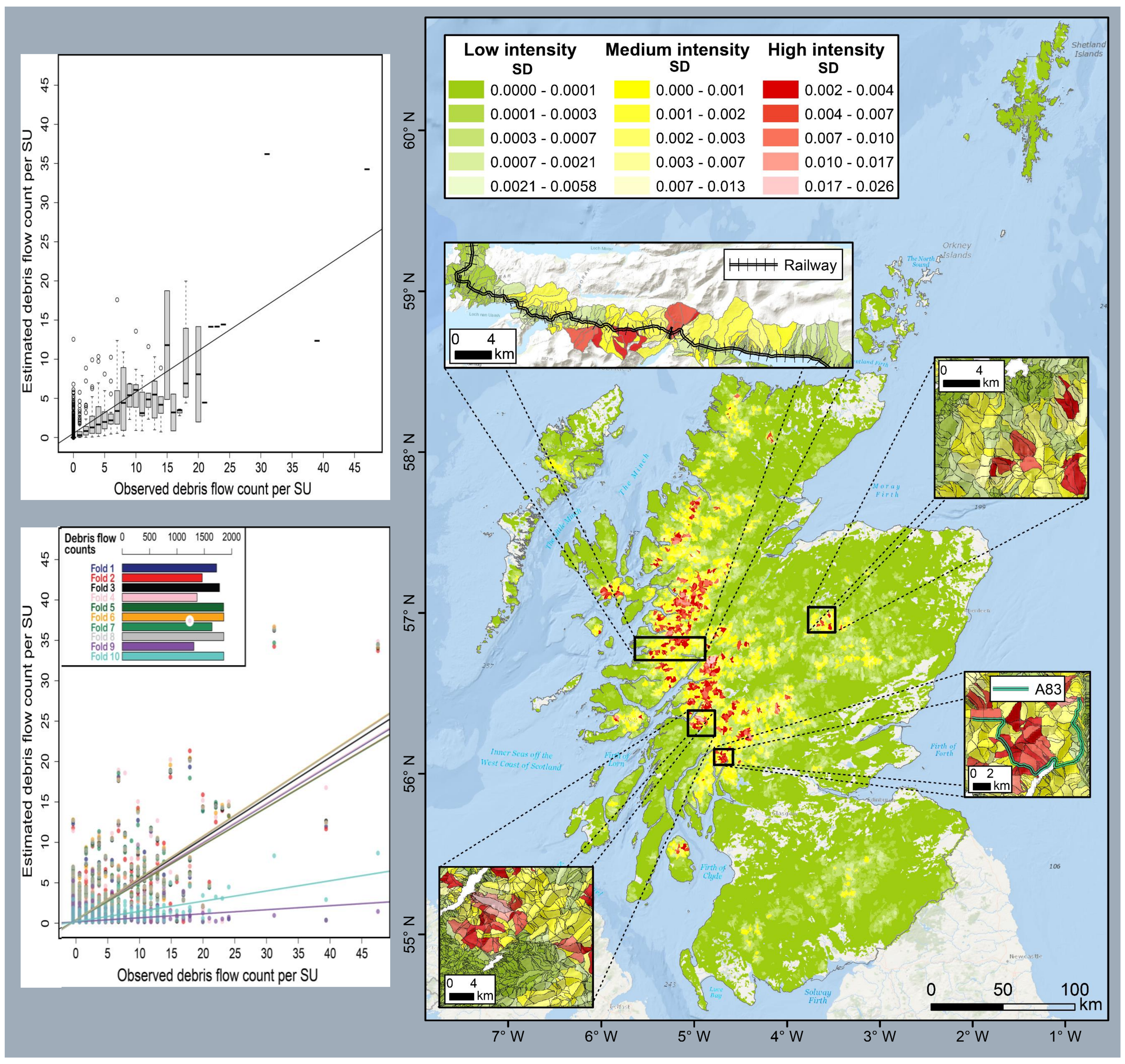
Bernoulli model equation:

$$y(\boldsymbol{s}) \mid \eta_{Bern}(\boldsymbol{s}) \equiv Bern(p(\boldsymbol{s})), \text{ where } p(\boldsymbol{s}) = Pr\{O_{DF}(\boldsymbol{s}) = 1\}$$
$$p(\boldsymbol{s}) = exp\{\eta_{Bern}(\boldsymbol{s})\} \,/\, (1 + exp\{\eta_{Bern}(\boldsymbol{s})\})$$

LGCP model equation:

$$y_{LGCP}(\boldsymbol{s}) | \eta_{LGCP}(\boldsymbol{s}) \sim \text{Pois}(\lambda(\boldsymbol{s})) \equiv \text{Pois}(|\boldsymbol{s}| \exp(\eta_{LGCP}(\boldsymbol{s})))$$

Results



Conclusions

The DF susceptibility and DF intensity maps both captured the areas in which to focus in terms of a higher DF risk. The LGCP model intensity map, however, pinpoints these areas with a higher degree of accuracy due to the nature of the point process modelling approach. Both models do well in terms of model performance, although validation measures for point-process models are generally complex and more along the lines of a residual analysis to compare variations of the model.

References

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2. Lindgren, F., Rue, H. and Lindström, J. (2011) An explicit link between Gaussian fields and Gaussian Markov random fields: the stochastic partial differential equation approach. Journal of the Royal Statistical Society: Series B (Statistical Methodology) 73(4), 423–498.

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