GIS-Integrated Species Distribution Modelling

Challenges of Habitat Prediction

Ullrich von Bramann[1], Antje Schwalb[1], Stephan van Gasselt[2]

[1] Technische Universität Braunschweig, Institute für Geosysteme und Bioindikation
Langer Kamp 19c
D - 38126 Braunschweig, Germany
(u.bramann@tu-bs.de)

[2]Freie Universität Berlin, Institut für Geologische Wissenschaften
Malteserstraße 74-100,
D - 12249 Berlin, Germany

Species Distribution Modeling (SDM) is a vital asset in a wide variety of disciplines such as invasive species management or reserve planning. The models are usually based on pattern-recognition approaches, associating a set of predictor values with observed presence locations. These models allow an assessment of the species requirements, thus describing the species ecological niche or potential distribution. Though widely used in applied and fundamental research, some important weak spots need to be further investigated in order to model resilience more efficiently (Araùjo, 2006). Even though capable to estimate a species distribution, it lacks the consideration of sampling bias. Secondly, the implementation of environmental data with different spatial resolution requires pre-processing and additional expertise as well as software tools.

A major conjecture of SDM is the fact, that the data used to calibrate the model is a population that is randomly sampled. It would be advantageous to have data on species presence locations that is stratified. Stratified sampling is a way to sample the population of the target species in homogenous subgroups, each representing an individual habitat. The “global” population of a species should be divided into subgroups, representing just one “habitat class” to be investigated. An efficient option to reduce identified sampling bias is to sub-sample existing data or to use model based stratifications (Araùjo, 2006).

Another issue is the integration of time-related factors controlling a species range, such as migration or adaptation through time. Static models are usually derived from simple response surfaces assuming equilibrium, but in ecology, a non-equilibrium concept is more realistic (Pickett, 1994). One possible way to integrate these factors is to include them as predictive parameters. The only other alternative would be dynamic modeling, though these models require intensive knowledge of the species and the ecosystem dynamics and cannot be easily adapted to other areas or species (Guisan and Zimmermann, 2000). Biotic interactions such as competition or predators are challenging for species distribution models. To integrate biotic interactions in static model frameworks, the use of integrated system of simultaneous regression equations or GLMs (Generalized Linear Models) could offer a solution. In these Systems of Simultaneous Regressions (SSR) each species presence location is included as an additional predictor in all other equations until equilibrium is reached in an iterated process (Guisan and Zimmermann, 2000).

Due to the high effort needed to resample existing data sets to reduce sample bias, we suggest to develop a GIS-based tool to develop the optimal sampling strategy depending on environmental predictors, biotic and abiotic, in the area of interest. This would (1) reduce the complexity of sampling investment and (2) would provide a solid, non-biased data base for future work. To successfully implement non-equilibrium (dynamic) predictors either a dynamic approach is needed or approaches such as SSR or GLM need to be implemented in an integrated GIS-based approach. Finally, species distribution modeling requires numerous different predictors or response surfaces, usually provided in different resolutions and data formats. The effort to pre-process all available data is significant and potentially defective. There is a strong need to develop a geo-database that is capable of providing the modeler with an all-out data set of predictors in the spatial resolution and format required. The development of such a database is paramount to streamline the work of scientists in multidisciplinary projects.

References

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