

forestatrisk: a Python package for modelling and forecasting deforestation in the tropics

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Summary

The forestatrisk Python package can be used to model the spatial probability of deforestation and predict future forest cover in the tropics. The spatial data used to model deforestation come from georeferenced raster files, which can be very large (several gigabytes). The functions available in the forestatrisk package process large rasters by blocks of data, making calculations fast and efficient. This allows deforestation to be modeled over large geographic areas (e.g., at the scale of a country) and at high spatial resolution (e.g., ≤ 30 m). The forestatrisk package offers the possibility of using logistic regression with auto-correlated spatial random effects to model the deforestation process. The spatial random effects make possible to structure the residual spatial variability of the deforestation process, not explained by the variables of the model and often very large. In addition to these new features, the forestatrisk Python package is open source (GPLv3 license), cross-platform, scriptable (via Python), user-friendly (functions provided with full documentation and examples), and easily extendable (with additional statistical models for example). The forestatrisk Python package has been used to model deforestation and predict future forest cover by 2100 across the humid tropics.

Statement of Need

Commonly called the “Jewels of the Earth,” tropical forests shelter 30 million species of plants and animals representing half of the Earth’s wildlife and at least two-thirds of its plant species ([Gibson et al., 2011](#)). Through photosynthesis and carbon sequestration, tropical forests play an important role in the global carbon cycle, and in regulating the global climate ([Baccini et al., 2017](#)). Despite the many ecosystem services they provide, tropical forests are disappearing at an alarming rate ([Keenan et al., 2015](#); [Vancutsem et al., 2020](#)), mostly because of human activities. Currently, around 8 Mha (twice the size of Switzerland) of tropical forest are disappearing each year ([Keenan et al., 2015](#)). Spatial modelling of deforestation allows identifying the main factors that determine the spatial risk of deforestation and quantifying their relative effects. Forecasting forest cover change is paramount as it allows anticipating the consequences of deforestation (in terms of carbon emissions or biodiversity loss) under various technological, political, and socioeconomic scenarios, and informs decision makers accordingly ([Clark et al., 2001](#)). Because both biodiversity and carbon vary greatly in space ([Allnutt et al., 2008](#); [Baccini et al., 2017](#)), it is necessary to provide spatial forecasts of forest cover change to properly quantify biodiversity loss and carbon emissions associated with future deforestation.

The forestatrisk Python package can be used to model tropical deforestation spatially, predict the spatial risk of deforestation, and forecast future forest cover in the tropics ([Figure 1](#)). Several other software tools allow modeling and forecasting of forest cover change

(Mas et al., 2014). The most famous land cover change software tools include [Dinamica-EGO](#) (Soares-Filho et al., 2002), [Land Change Modeller](#) (Eastman & Toledano, 2017), and [CLUE](#) (Verburg & Overmars, 2009). Despite the many functionalities they provide, these software tools are not open source and might not all be cross-platform, scriptable, and completely user-friendly. Moreover, the statistical approaches they propose to model land cover change do not take into account the residual spatial variability in the deforestation process that is not explained by the model's variables, and which is often very large. The more sophisticated algorithms they use (genetic algorithms, artificial neural networks, or machine learning algorithms) might also have the tendency to over-fit the data (Mas et al., 2014). Finally, application of these software tools to large spatial scales (e.g., at the country or continental scale) with high resolution data (e.g., ≤ 30 m) has not yet been demonstrated (but see Soares-Filho et al., 2006 for a study in the Amazon at 1 km resolution). The `forestatrisk` Python package aims to fill some of these gaps and to enlarge the range of software available to model and forecast tropical deforestation.

Main functionalities

A set of functions for modelling and forecasting deforestation

The `forestatrisk` Python package includes functions to (i) compute the forest cover change raster and the rasters of explanatory variables for a given country from several global datasets (such as OpenStreetMap or the SRTM Digital Elevation Database v4.1 for example) (ii) efficiently sample forest cover change observations and retrieve information on spatial explanatory variables for each observation, (iii) estimate the parameters of various statistical deforestation models, (iv) predict the spatial probability of deforestation, (v) forecast the likely forest cover in the future, (vi) validate the models and the projected maps of forest cover change, (vii) estimate carbon emissions associated with future deforestation, and (viii) plot the results. The `forestatrisk` package includes a hierarchical Bayesian logistic regression model with autocorrelated spatial random effects, which is well suited for modeling deforestation (see below). Any statistical model class with a `.predict()` method can potentially be used together with the function `forestatrisk.predict_raster()` to predict the spatial risk of deforestation. This allows a wide variety of additional statistical models from other Python packages to be used, such as `scikit-learn` (Pedregosa et al., 2011) for example, for deforestation modelling and forecasting.

Ability to process large raster data

Spatially-distributed forest cover change and explanatory variables are commonly available as georeferenced raster data. Raster data consist of rows and columns of cells (or pixels), with each cell storing a single value. The resolution of the raster dataset is its pixel width in ground units. Depending on the number of pixels (which is a function of the raster's geographical extent and resolution), raster files might occupy a space of several gigabytes on disk. Processing such large rasters in memory can be prohibitively intensive. Functions in the `forestatrisk` package process large rasters by blocks of pixels representing subsets of the raster data. This makes computation efficient, with low memory usage. Reading and writing subsets of raster data is done by using two methods from the GDAL Python bindings (GDAL/OGR contributors, 2020): `gdal.Dataset.ReadAsArray()` and `gdal.Band.WriteArray()`. Numerical computations on arrays are performed with the NumPy Python package, whose core is mostly made of optimized and compiled C code that runs quickly (Harris et al., 2020). This allows the `forestatrisk` Python package to model and forecast forest cover change on large spatial scales (e.g., at the country or continental scale) using high resolution data (e.g., ≤ 30 m), even on personal computers with average performance hardware. For

example, the `forestatrisk` Python package has been used on a personal computer to model and forecast the forest cover change at 30-m resolution for the Democratic Republic of the Congo (total area of 2,345 million km²), processing large raster files of 71,205 × 70,280 cells without issues.

Statistical model with autocorrelated spatial random effects

The `forestatrisk` Python package includes a function called `.model_binomial_iCAR()` to estimate the parameters of a logistic regression model including auto-correlated spatial random effects. The model considers the random variable y_i which takes value 1 if a forest pixel i is deforested in a given period of time, and 0 if it is not. The model assumes that y_i follows a Bernoulli distribution of parameter θ_i (Equation 1). θ_i represents the spatial relative probability of deforestation for pixel i and is linked, through a logit function, to a linear combination of the explanatory variables $X_i\beta$, where X_i is the vector of explanatory variables for pixel i , and β is the vector of effects $[\beta_1, \dots, \beta_n]$ associated with the n variables. The model can include (or not) an intercept α . To account for the residual spatial variation in the deforestation process, the model includes additional random effects $\rho_{j(i)}$ for the cells of a spatial grid covering the study-area. The spatial grid resolution has to be chosen in order to have a reasonable balance between a good representation of the spatial variability and a limited number of parameters to estimate. Each observation i is associated with one spatial cell $j(i)$. Random effects ρ_j are assumed to be spatially autocorrelated through an intrinsic conditional autoregressive (iCAR) model (Besag et al., 1991). In an iCAR model, the random effect ρ_j associated with cell j depends on the values of the random effects $\rho_{j'}$ associated with neighboring cells j' . The variance of the spatial random effects ρ_j is denoted by V_ρ . The number of neighbouring cells for cell j (which might vary) is denoted by n_j . Spatial random effects ρ_j account for unmeasured or unmeasurable variables (Clark, 2005), which explain a part of the residual spatial variation in the deforestation process that is not explained by the fixed (i.e., explanatory) variables (X_i). The parameter inference is done in a hierarchical Bayesian framework. The `.model_binomial_iCAR()` function calls an adaptive Metropolis-within-Gibbs algorithm (Rosenthal, 2011) written in C for maximum computation speed.

$$\begin{aligned} y_i &\sim \text{Bernoulli}(\theta_i) \\ \text{logit}(\theta_i) &= \alpha + X_i\beta + \rho_{j(i)} \\ \rho_{j(i)} &\sim \text{Normal}\left(\sum_{j'} \rho_{j'} / n_j, V_\rho / n_j\right) \end{aligned} \quad (1)$$

Applications and perspectives

The Python package `forestatrisk` was recently used to model the spatial probability of deforestation and predict forest cover change by 2100 across the humid tropics (<https://forestatrisk.cirad.fr>). Future developments of the package will focus on expanding documentation, case studies, statistical models, and validation tools. We are convinced that the `forestatrisk` package could be of great help in obtaining estimates of carbon emissions and biodiversity loss under various scenarios of deforestation in the tropics. Such scenarios should help decision-makers take initiatives to tackle climate change and the biodiversity crisis. The results from the `forestatrisk` package could contribute to future IPCC and IPBES reports (IPBES, 2019; IPCC, 2014), or help implement the REDD+ mechanism of the Paris Agreement.

Figures

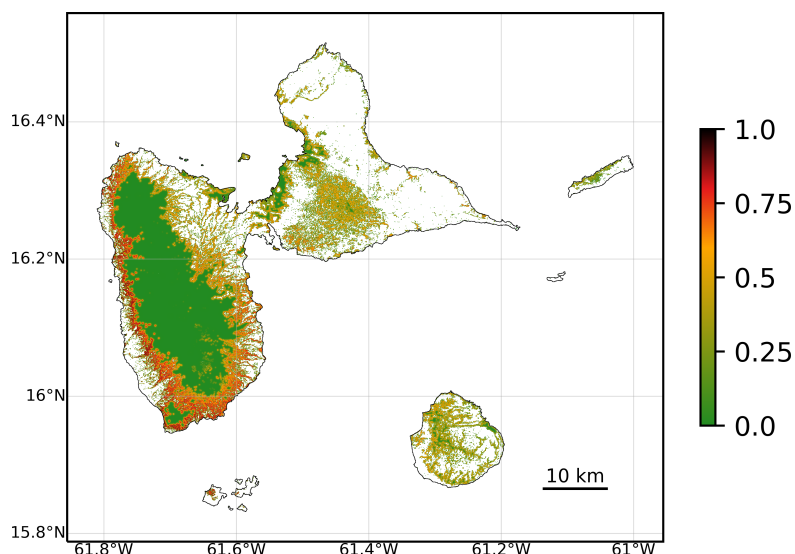


Figure 1: Map of the spatial probability of deforestation in the Guadeloupe archipelago. This map was produced with the `forestatrisk` Python package. Colored pixels represent the extent of the natural old-growth tropical moist forest in 2020. The original map has a 30-m resolution. A relative spatial probability of deforestation was computed for each forest pixel. Probability of deforestation is a function of several explanatory variables describing: topography (altitude and slope), accessibility (distances to nearest road, town, and river), forest landscape (distance to forest edge), deforestation history (distance to past deforestation), and land conservation status (presence of a protected area). This map can be reproduced with the `/Get started/` tutorial at <https://ecology.ghislainv.fr/forestatrisk>.

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