

Proceeding Paper

Downscaling the Resolution of the Rainfall Erosivity Factor to Soil Erosion Calculation in Watersheds to Atlantic Forest Biome, Brazil [†]

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Abstract: The calculation of the R-factor (Rainfall erosivity) for implementation in soil erosion models such as USLE (Universal Soil Loss Equation) and RUSLE (Revised Universal Soil Loss Equation) encounters substantial difficulties due to the scarcity of spatial databases in adequate resolution for actions of territorial planning at the local level. Otherwise, there is a spatial database available with a coarse resolution of themes that can be used to calculate the R-factor. We apply the spatial downscaling, based on regression models: linear (LN), general additive model (GAM), random forest (RF), cubist (CU), on erosivity data (target variable) prepared for the State of São Paulo, Brazil, with a spatial resolution of 2500 m. We used DEM and slope data with 30 m fine resolution from the Atibaia watershed, located between the metropolitan regions of São Paulo (RMSP) and Campinas (RMC) to apply the downscaling. This framework improved the spatial resolution of the R-factor, necessary to calculate soil loss in the USLE and RUSLE equations in a territory where the scarcity of data with the fine resolution is still limited to the development of territorial planning projects at the local level. The RF model was better with R^2 0.94.

Keywords: downscaling; R-factor; soil loss; watershed; regression

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1. Introduction

The spatial variable scale is directly connected to image resolution. There is a large diversity of spatial databases at the global level, at various spatial scales, that can be utilized for research at the global, continental, and regional levels; however, these bases are not suited for usage at the local level, limiting their use in studies with higher spatial resolution.

Earth surface databases, such as Digital Elevation Models (DEM), are easily accessible at a fine scale, allowing for local terrain analysis and the generation of other surface attributes such as slope or aspect.

The downscaling process, which is frequently used in climate model research [1–4], modifies the spatial resolution of data using algorithms and regression functions.

The application of the downscaling method to process earth resource information was proposed by Malone et al. [5], who developed the Caret package in R language, supporting the use of this procedure in several areas of earth sciences [6–8], including terrain analysis [9].

Soil erosion research has produced a large amount of scientific output on regional and continental dimensions. However, analytical variables are difficult to find at the local level, hindering the growth of research in this field.

We used the downscaling approach proposed by Malone [5] in the database to refer to the R-factor prepared by Teixeira et al. [10] in the Atibaia watershed [11], State of São Paulo, Brazil (Figure 1).

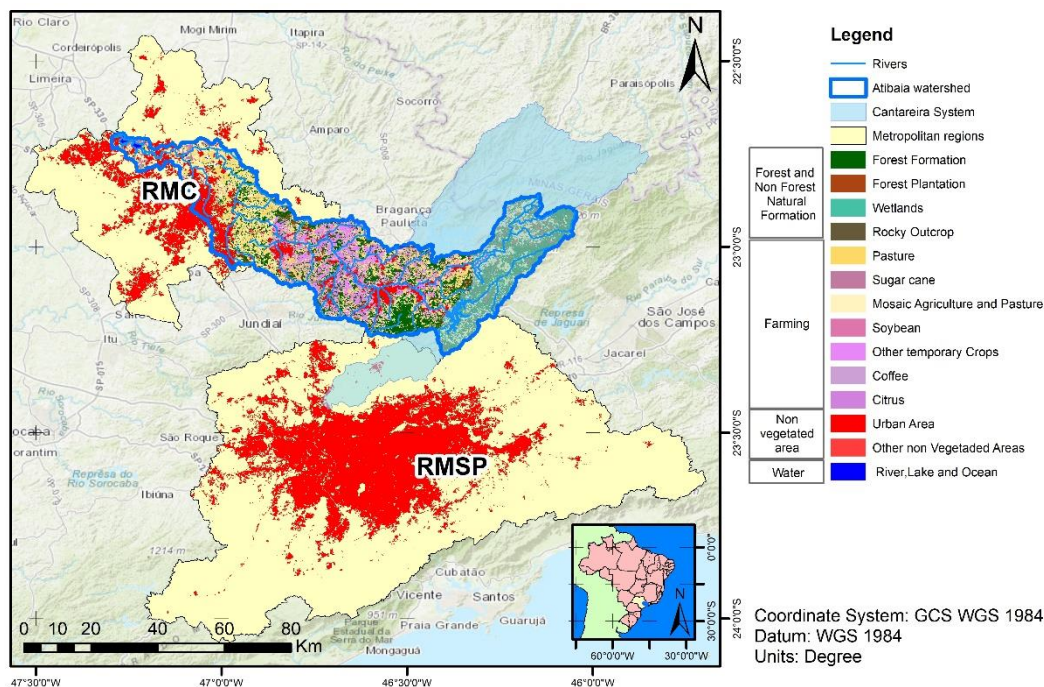


Figure 1. Study area—Atibaia watershed. RMS: São Paulo Metropolitan Region and RMC: Campinas Metropolitan Region.

2. Methodology

The research methodology was divided into: (1) interpolation of R-factor data, (2) preparation of the fine database, consisting of DEM and slope and (3) downscaling.

To create the R-factor image, the point shapefile generated by Teixeira et al. [10] was used. This data was interpolated, generating the R-factor image.

The spatial downscaling methodology used in the present study was proposed by Malone et al. [5] who originated the Caret package in R language. In this methodology, the authors use coarse grid spatial data for fine grid mapping using predictive covariates and the Random Forest (“rf”), Cubist (“cubist”), MARS (“earth”) and Linear Model (“lm”) regression models.

In the downscaling process, the minimum (5), maximum (10) number of iterations. Before modeling, the dataset was randomly split into a collection of training samples (70%) and test samples (30%) for model validation. The regression models were then applied.

Regression results are analyzed in raster maps, a graphical representation of the performance of regression models by graphing observed values versus predicted values and calculating R^2 and RMSE values.

3. Results

Figure 2 illustrates the spatial results of the regression models.

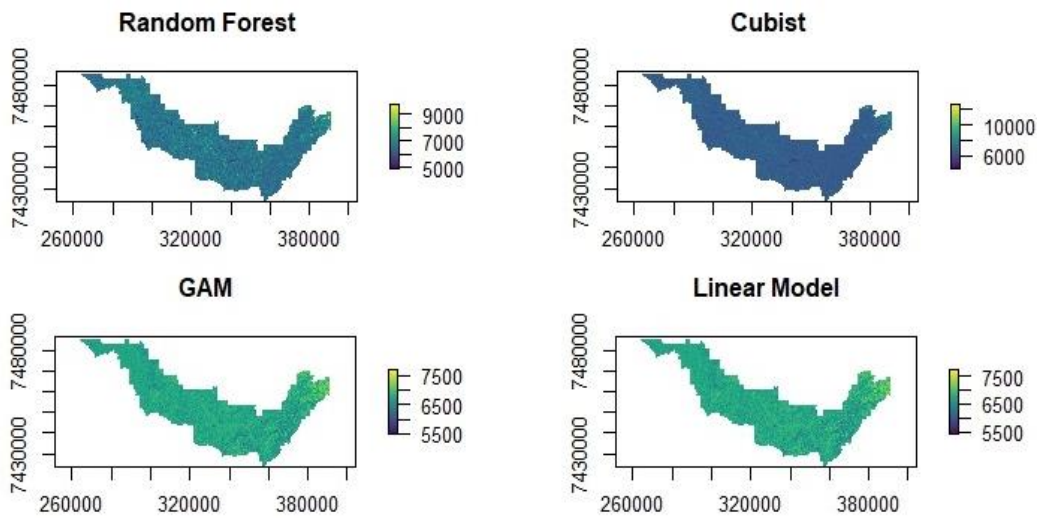


Figure 2. Spatial results of the regression models (Unit: MJ mm ha⁻¹ h⁻¹ time unit⁻¹).

The Figure 3 and Table 1 illustrates the performance of each model according to observed values versus predicted values.

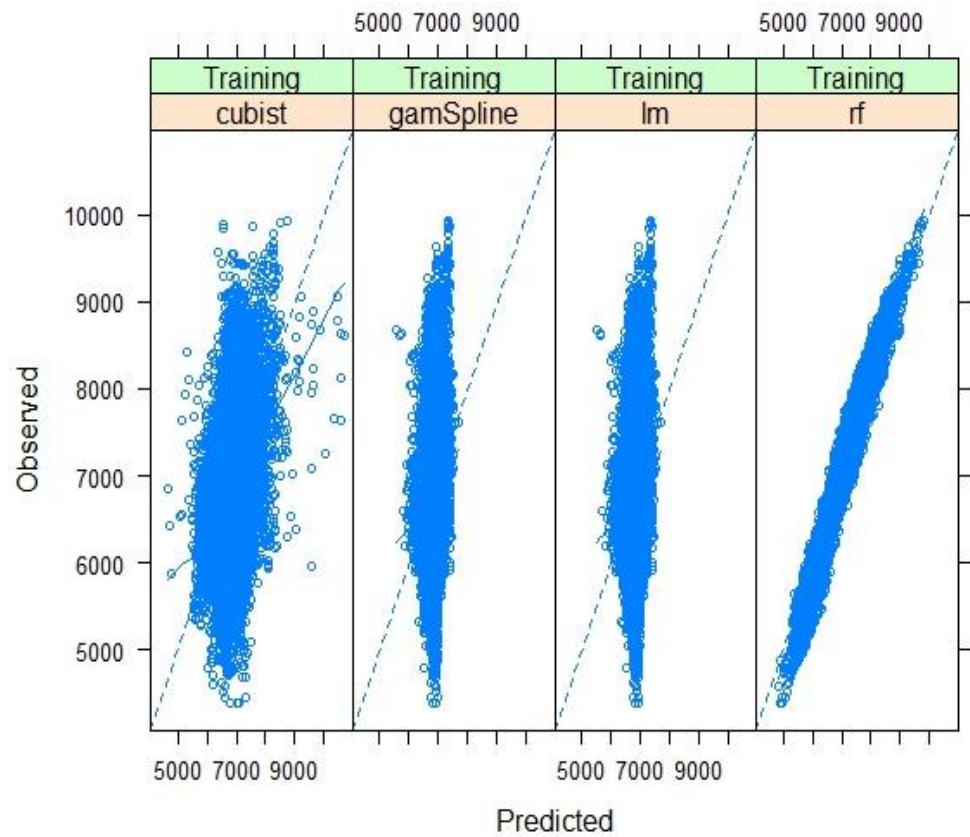


Figure 3. Models performance (Unit: MJ mm ha⁻¹ h⁻¹ time unit⁻¹).

Table 1. Models R² and RMSE.

Model	R ²	RMSE
Cubist	0.136	488
GAM	0.0130	521
LM	0.0128	523
RF	0.945	133

According to the performance results, the RF model is the most accurate of all the regression models evaluated. RF provided the highest R^2 and lowest RMSE values, as well as less dispersion compared to the straight line between observed and predicted values. While the other models had very low R^2 and higher RMSE values, as well as more dispersion of observed and projected values in comparison to the straight line, this suggested greater dispersion and error in the regression models.

4. Conclusions

This framework improved the spatial resolution of the R-factor, necessary to calculate soil loss in the USLE and RUSLE equations in a territory where the scarcity of data with the fine resolution is still limited to the development of territorial planning projects at the local level. It may be an alternative to determining the essential factors using soil loss equations such as USLE and RUSLE in places with insufficient fine-scale geodatabase.

The procedure adopted proved to be a methodology with the potential to expand the application of the downscaling procedure in data associated to soil loss research, allowing the use of global databases at a local level employing topography factors such as elevation and slope. Other topographical factors can be employed in future studies to investigate the feasibility of employing them to improve the accuracy of the statistical model in this method.

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Conflicts of Interest: The authors declare no conflict of interest.

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