

Exploring the use of geographically weighted regression in forest health assessments



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Introduction

The decline of sugar maple is poorly understood and causing concern. Geographically weighted regression is a relatively new statistical approach to analyzing spatially varying relationships (Fotheringham et al. 2002). Traditional regression analysis calculate one value of β for each predictor, but geographically weighted regression yields a matrix of β for each predictor that varies spatially. The intercept is also calculated as a spatially-explicit matrix.

Methods

Phase 2 and 3 plots in the NRS were joined and extracted from the Forest Inventory Analysis Database (FIADB) (Alerich and others 2006). These data were collected between 2000 and 2006. Plots were included in the analysis if at least three sugar maple trees (d.b.h. > 1 inch) were measured on the plot.

Geographically weighted regression was applied in R (R Development Core Team 2006) using the `spgwr` package.

Objective

In this study, we are testing geographically weighted regression techniques to model sugar maple mortality in the forests of the northern region.

Results and Discussion

A total of 245 plots were selected that met the defined criteria of more than 3 maple trees and the collection of soil chemistry data.

The basal area of dead trees was a superior response variable to the ratio of dead to live trees. The most effective model ($p = 0.009965$) included the molar Ca:Al ratio, the exchangeable Mg, and spatial location:

$$\ln(\text{dead_ba}) \sim X + \beta_1 \ln(\text{exchangeable Mg}) + \beta_2 \ln(\text{molar Ca:Al ratio}) + \beta_3 \text{latitude} + \beta_4 \text{longitude}$$

The molar Ca:Al ratio was by far the most significant term ($p = 0.00882$ in the traditional application of linear models).

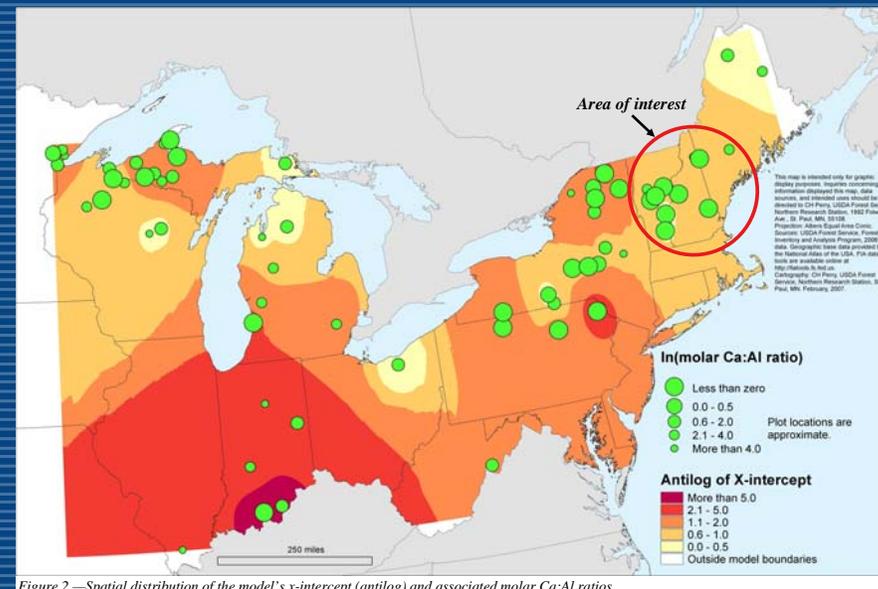


Figure 2.—Spatial distribution of the model's x-intercept (antilog) and associated molar Ca:Al ratios.

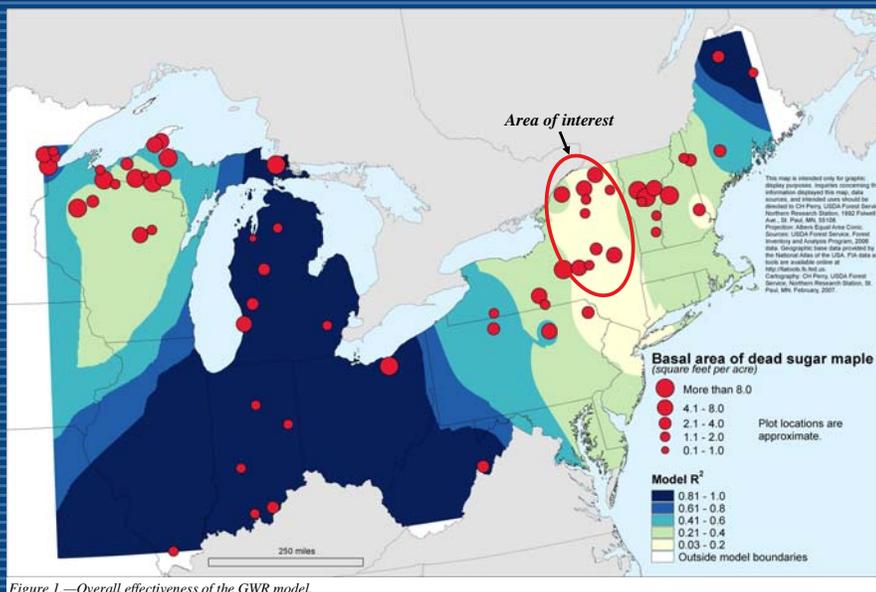


Figure 1.—Overall effectiveness of the GWR model.

Results and Discussion (cont.)

The resulting model is informative even in the absence of being complete.

The effectiveness of the model varies widely across the region. Values of R² are highest in Michigan, Indiana, and Ohio and lowest in upstate New York (Fig. 1). The area of interest highlights where there is a substantial amount of dead sugar maple, but the model does a poor job of predicting it. This area has very low Ca:Al ratios (high aluminum content), but the values of β_2 reduce the contribution to mortality in the model. Presumably other factors are contributing significantly to sugar maple mortality in this area.

Related observations can be made by mapping individual components of the model. For example, the background level of sugar maple mortality (the x-intercept of the model) is relatively low while observations of mortality are very high in New Hampshire and Vermont (Fig. 2).

Our model of sugar maple mortality requires additional predictors to be effective across the entire region. These predictors might include slope position and glacial geology (Horsley et al. 2000).

Conclusions and Next Steps

Geographically weighted regression provides spatially explicit information on model fit that is useful in evaluating the role of soil chemistry and other factors in sugar maple decline.

Future work will include:

1. Refining the model by including parameters identified with sugar maple mortality (e.g., glacial geology and slope position); and
2. Comparing the information provided by geographically weighted regression with other more traditional approaches to assessing forest health (see Morin et al. this session).

References

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