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Geographically local modeling of occurrence, count, and volume of downwood in Northeast China

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A B S T R A C T

The Liangshui National Nature Reserve, located in Northeast China, was heavily damaged by severe windstorms in 2008 and 2009, which caused abundant windthrows, especially large trees, and significantly altered the size and structure of the natural forest. A forest survey was conducted to collect data on living trees, downwood on the forest floor, and environmental factors. We were interested in modeling three types of response variables, including the occurrence of downwood (binary), the number of downwood trees (count) and the volume of downwood (continuous). These response variables were regressed to a set of stand and topographic predictors, including the average diameter of living trees, total volume of living trees, elevation, and slope. Both global and local (geographically weighted regression) modeling techniques were utilized to fit the models.

Our results show that local models have great advantages over corresponding global models in model fitting and performance, with desirable model residuals. The spatial variations of local model coefficients were visualized in contour maps, which provided detailed information on the relationships between downwood and stand and topographic variables in the local areas. Furthermore, these local models can be readily incorporated into GIS software and combined with statistical graphics and the mapping ability of GIS technology, to become excellent tools for assessing the risk of natural disasters or disturbances for a given local area, predicting damage caused by such disasters, and offering information critical to decision-making and management planning to prevent or reduce the impacts of natural disasters in the future.

Introduction

The northeast forests of China include Da Xing'an Mountain, Xiao Xing'an Mountain and Changbai Mountain. This region plays an important role in both wood productivity and ecological sustainability for all of China. It has 50.5 million hectares of forestlands, covering 28.9% of the country's total forested areas (Yu et al., 2011) and 3468 million m^3 of timber stock, equal to 27.8% of the national total (State Forestry Administration (SFA), 2005). The northeast forests are comprised of cold-temperate conifer stands, and temperate mixed conifer–broad leaf stands, and contains the largest natural forest in China (Yan, Zhao, & Yu, 2000; Yu et al., 2011).

A natural forest is a plant and tree community that originated from the original forest cover or spontaneous generation (Naturstyrelsen, 1994). It is usually more influenced by natural disturbances (e.g., wildfire, wind, insect, etc.) than human disturbances (e.g., logging or regeneration). Within the ecosystem of a natural forest, downwood is a significant component of the forest floor, which includes deadwood and windthrows. Deadwood comprises standing dead trees, snags or fallen material on the forest floor and woody debris that directly resulted from dead or dying trees (Pasher & King, 2009). Windthrows are defined as the breakage or uprooting of trees by winds (Lanquaye-Opoku & Mitchell, 2005).

Deadwood and windthrows play a crucial role in nutrient cycling, carbon storage, vegetation succession, and maintenance of biodiversity in the ecosystem of natural forest (Depro, Murray, Alig, & Shanks, 2008; Jonasova, Vavrova, & Cudlin, 2010; Lang, Schulte, & Guntenspergen, 2009; Pasher & King, 2009). However, due to limited accessibility after disturbances (Pleshikov, Ryzkova,

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& Kaplunov, 1998), data on windthrows are difficult to obtain, making it all the more challenging to study the frequency, magnitude, and distribution of wind disturbances, especially in nature forests (Bouget & Duelli, 2004).

Windthrows have both ecological and economic effects on natural forests. The ecological effects can be created from forest to stands, as well as within stand levels (Bouget & Duelli, 2004; Ulanova, 2000). First, windthrows generate stands with multi-age and diverse successional series at the forest level, which are more resistant to natural disturbances in the future (Jonasova et al., 2010). Second, windthrows increase above- and below-ground environmental heterogeneity at the stand level, including habitat micro-climates, micro-topographic heterogeneity, and soil and vegetation structure. Third, windthrows create within-gap environmental heterogeneity (Bouget & Duelli, 2004), which results in different sun exposure, humidity, local air flow patterns and increased daily fluctuations in temperature (Zabowski, Java, Scherer, Everett, & Ottmar, 2000).

Economic influences should not be ignored. For example, the rapid increase in windthrows poses challenges for timber harvest and storage, which leads to the instability of wood market (Costa & Ibanez, 2005; Meilby, Strange, & Thorsen, 2001). Windthrows clearly have a significant impact on forest profitability and sustainability (Haight, Smith, & Straka, 1995; Meilby et al., 2001; Valinger et al., 1993). For example, windthrows resulting from the 1999 windstorms in France represented about three years of annual harvest and reduced carbon balance of 16 million tons (Costa & Ibanez, 2005; Don et al., 2012; Mickovski, Stokes, & van Beek, 2005). In British Columbia, Canada in1991, the timber damaged by winds was equivalent to 4% of the annual allowable cut, and also equal to the damage caused by insects or wildfire that year (Lanquaye-Opoku & Mitchell, 2005; Mitchell, 1995). Being able to predict the probability of windthrows occurring and, further, to estimate the number and volume of windthrows would be of great value, even with the limited available data.

Over the past decade, much work has gone into developing different tools for studying windthrows, including observational, empirical, and mechanistic methods (Mickovski et al., 2005). Empirical or statistical models present more advantages over observational and mechanistic models for forest stands with complex structure and composition (Lanquaye-Opoku & Mitchell, 2005; Mitchell, Hailemariam, & Kulis, 2001). Generalized linear models (GLM) are widely used for predicting the probability and count of events. GLMs extend the normality assumption of the model error in ordinary least squares (OLS) to the exponential family – including binomial, Poisson, gamma, Gaussian (normal) – and predicts response variables by a link function of predictors (Fotheringham, Brunsdon, & Charlton, 2002). Logistic regression is commonly used to predict the probability of windthrows by environmental and forest attributes such as climatic, topographic, stand, tree, and soil factors (Gibbons, Cunningham, & Lindenmayer, 2008; Klaus, Holsten, Hostert, & Kropp, 2011; Lanquaye-Opoku & Mitchell, 2005; Valinger & Fridman, 2011).

Gaussian models are preferable for predicting the volume of downwood, which is a continuous response variable with a normal or log-normal distribution. Pesonen, Maltamo, Eerikainen, and Packalen (2008) utilized Gaussian models for downed and standing deadwood (log-transformed) volume at a plot level, using predictor variables derived from airborne laser-scanning data. Chojnacky, Mickler, Meath, and Woodall (2004) developed multiple linear regression models to predict downwood by forest structure and climate variables. Although few models have been developed for predicting the number of downwood, Poisson regression is the correct choice for dealing with count response variables. To date, however, most previous studies use GLMs that are global (Ma, Zuckerberg, Porter, & Zhang, 2012) with assumption of spatial stationarity which is difficult to be met in the data collected in forestry and/or ecological studies.

Recently, researchers have realized that tree growth and stand development can be greatly influenced by spatial effects (i.e., spatial autocorrelation and heterogeneity) of neighboring forest stands (Anselin & Griffith, 1988; Zhang, Ma, & Guo, 2009). For example, Fukui (2011) and Meilby et al. (2001) point out that the risk of windthrows does not depend only on the features of forest stands, but also on neighboring stands and the spatial structure and geographical orientation of forest stands. However, the spatial heterogeneity of forest conditions can be increased by wind disturbances at different spatial scales (i.e., forest, stand, or within stand) (Bouget & Duelli, 2004). Consequently, the nature of windthrows data may cause violations of the assumptions of independent observations and homogenous variance due to the spatial effects. These may inflate estimates of standard error of the model coefficients, reduce the efficiency of parameter estimation, and mislead the significance of hypothesis testing on the model coefficients (Anselin & Griffith, 1988; Fox, Ades, & Bi, 2001; Zhang & Gove, 2005).

Over the last decade, geographically weighted regression (GWR) has become popular for efficiently dealing with spatial heterogeneity and autocorrelation in model errors (Fotheringham et al., 2002; Zhang, Gove, & Heath, 2005, 2009). This local modeling technique has been successfully applied to the relationships between variables in many study fields, such as forestry, ecology, and economics (e.g., Ma et al., 2012; Tu, 2011; Wang, Ni, & Tenhunen, 2005; Zhang, Bi, Cheng, & Davis, 2004). GWR fits a regression model for each geographic location in the study area using the neighbors within a specific bandwidth and distance-related weight function. Therefore, the fitting and performance of GWR models depend on the selection of bandwidth and weight function (Guo, Ma, & Zhang, 2008). Although GWR still assumes the normality and homogeneous variances for the model error term at each geographical location, it explicitly uses the local information on spatial heterogeneity and autocorrelation among the neighboring locations by (1) defining an appropriate bandwidth, (2) utilizing a distance–decay weight function, and (3) applying weighted least squares for estimating model parameters. Thus, the local spatial relationships can be incorporated into the regression framework in an intuitive and explicit manner, bringing GWR an obvious advantage over a global model (Fotheringham et al., 2002; Zhang & Gove, 2005). In addition, GWR modeling results are mappable and can be readily combined with GIS, which offers a powerful tool for analyzing, representing, and managing georeferenced data (Chang, 2010; Murray & Tong, 2009; Tu, 2011; Tu & Xia, 2008).

In this study, we attempted to model the relationships between the occurrence of downwood (binary), the number of downwood (count) and the volume of downwood (continuous) and a set of stand variables and topographical factors by using both global and local (GWR) modeling methods. Our objectives were as follows: (1) to develop global logistic, Poisson, and Gaussian models to regress the probability of occurrence, count, and volume of downwood, respectively, against stand variables and topographical factors; (2) to develop GWR logistic regression (GWLR), GWR Poisson regression (GWPR), and GWR Gaussian regression (GWGR) models to regress the probability of occurrence, count, and volume of downwood, respectively, against the same set of stand variables and topographical factors; (3) to compare the global and local (GWR) models in terms of model fitting and performance; and (4) to visually represent the distributions of local model coefficients across the study area and investigate the spatial patterns of the geographically varying model coefficients.