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Spatial-scale considerations for a large-area forest inventory regression model

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Numerous statistical models are employed when processing forest inventory data. These models primarily provide predicted values for attributes that are difficult and/or time-consuming to measure. In some applications, models are applied across a large geographic area, which assumes the relationship between the response variable and predictors is constant within the area. The extent to which this assumption holds for a tree height prediction model was evaluated at regional, ecoprovince and ecosection scales in the northeastern US. Two nonlinear regression models were tested, a spatially ambiguous model that utilized tree and stand-level predictors, and a spatially explicit model that incorporated latitude, longitude and elevation as predictors. When the regional-scale models were evaluated at the state level, both showed considerable bias for some states, which suggests that the statistical significance of spatial predictor variables does not translate into effective accounting for spatial variability. Similar results were obtained when fitting the model to an ecoprovince and evaluating bias within ecosections. Finally, fitting the model to ecosections within the ecoprovince provided a moderate level of local robustness as assessed by Moran's I statistic; however, there are cases where local biases may still exist. This outcome suggests that models should be developed and applied at small spatial scales to reduce local biases when model predictions are aggregated to larger geographic domains. Alternatively, more advanced modelling techniques may be more effective at addressing local variability using a single model having large-area application. However, the practicality of implementing these more complex techniques in the context of continuous large-area forest inventories is not well understood and should be fully explored prior to operational employment.

Introduction

Many tree-level attributes of interest in forest inventories are not directly observed but are derived from statistical models using more easily measured variables as predictors. Examples of these attributes include tree height (Westfall and Laustsen, 2006; Trincado *et al.*, 2007), crown characteristics (Bechtold, 2003; Temesgen *et al.*, 2005), volume (Scott, 1981; Hahn and Hansen, 1991) and biomass (Jenkins *et al.*, 2003; Woodall *et al.*, 2011). These types of models have been developed using data collected at various spatial scales; however, there is a tendency for relatively large geographic areas to be employed to maximize model utility and consistency in results. Fitting models to large areas usually results in concomitant large sample sizes that are desirable from a statistical perspective and also reduces the need to implement and maintain numerous models to support the inventory. Consistency in model predictions can also be viewed as important in reducing apparent anomalies, for example, differences in results solely due to the use of different models. However, these practices can result in prediction biases of unknown magnitude when performing analyses for smaller spatial domains.

In some cases, these models are based on data that are lacking spatial information, and it is not feasible to explicitly account for any systematic spatial variation within the study area. Models of relatively simple formulation, such as those that predict the attribute of interest using only diameter at breast height (dbh), implicitly assume constant relationships across the area (Huang *et al.*, 1992). More complex models utilize additional local information regarding stand characteristics, tree social position, etc., to further refine model predictions to local conditions (Calama and Montero, 2004). More recently, increased availability and decreased cost of Global Positioning System (GPS) and Global Navigation Satellite System (GNSS) devices has resulted in data that now often include information such as latitude, longitude and elevation in addition to the usual mensurational variables. These data facilitate the explicit incorporation of geospatial effects into regression models intended for applicability at large geographic scales by using latitude, longitude and elevation information as predictor variables (Bechtold, 2003; Westfall, 2006). Modern model fitting techniques have also been used to address spatial heterogeneity in forestry data, including geographically weighted, mixed effects and generalized additive models (Zhang and Gove, 2005; Lu and Zhang, 2010).

Regardless of whether or not spatially explicit information is incorporated into regression models, it is often the case that models are still employed across large geographic areas (Miles and Hill, 2010; Oswalt and Conner, 2011). This commonly occurs in large-area forest inventory applications where numerous analyses are conducted at various spatial scales. However, the bias and uncertainty in model predictions within a specified spatial domain is usually unknown (or assumed to be negligible). From a practical perspective, the primary consideration is that model predictions are unbiased at the scale of the analysis (e.g. regional, state and substate); however, analyses are often undertaken at spatial scales considerably smaller than the geographic range of the model fitting data (Butler *et al*., 2012; Lister and Gladders, 2012). In general, models that perform well across the entire range of applicability may predict poorly within a particular areal subdivision (Zhang and Shi, 2004). Potentially, this situation may be remedied by fitting models to smaller areas, although small sample sizes can result in relatively large model uncertainty as well as poor statistical power to detect important correlations between the variable of interest and predictor variables (McRoberts and Westfall, 2014). In this paper, a tree height regression model was fit at various spatial domain sizes to (1) assess the performance of a large-area model at finer spatial scales, (2) evaluate the utility of using latitude, longitude and elevation as predictor variables and (3) examine the outcomes of fitting the model to increasingly smaller geographic areas. Models that predict total height were investigated because tree height–dbh relationships are often of critical importance when determining other tree attributes such as volume and biomass.

Methods

Data

The data used in this study were collected between 2006 and 2010 by the Forest Inventory and Analysis (FIA) programme of the U.S. Forest Service. The geographic range encompassed 13 states in the northeastern US, including West Virginia, Maryland, Delaware, New Jersey, Pennsylvania, Ohio, New York, Massachusetts, Rhode Island, Connecticut, Vermont, New Hampshire and Maine. All data were collected using the annualized FIA sample and plot design where the sampling intensity is approximately one plot for every 2400 ha of area (Reams *et al*., 2005). Each sample plot contains four 7.3-m (24 ft)-radius subplots (Bechtold and Scott, 2005), and all trees within a forested condition with a diameter at breast height (dbh) of 12.7 cm (5.0 inches) and larger are measured. Variables used in this study included species, dbh, total tree height, crown ratio, tree class and crown class. Additional variables included stand-level basal area per hectare and spatial information (latitude, longitude and elevation) based on the plot centre location (U.S. Forest Service, 2007). The analysis focused on three species due to their relatively large sample sizes and spatial extent: balsam fir (*Abies balsamea*), eastern white pine (*Pinus strobus*) and red maple (*Acer rubrum*). Summary statistics for each species are shown in Table 1.

Analysis

The underlying basis of the total height model is the Chapman–Richards formulation (Richards, 1959); the specification follows that of Westfall and Laustsen (2006) with some modifications to better align with the current study. Two models were considered, a nonspatial model that assumes that the relationships between tree height and the mensurational variables are constant across the study area (model 1) and a spatial model that incorporates latitude, longitude and elevation as additional predictor variables (model 2):

$$H_{ijk} = (\beta_0 + \beta_1 \mathrm{CC}_{ijk} + \beta_2 \mathrm{CR}_{ijk} + \beta_3 \mathrm{TC}_{ijk}) \times (1 - \exp(-\beta_4 \mathrm{DBH}_{ijk}))^{(\beta_5 + \beta_6 \mathrm{BA}_{jk})} + \varepsilon_{ijk} \tag{1}$$

$$H_{ijk} = (\beta_0 + \beta_1 \mathrm{CC}_{ijk} + \beta_2 \mathrm{CR}_{ijk} + \beta_3 \mathrm{TC}_{ijk}) \times (1 - \exp(-\beta_4 \mathrm{DBH}_{ijk} + \theta_1 \mathrm{LAT}_k + \theta_2 \mathrm{LON}_k + \theta_3 \mathrm{ELV}_k))^{(\beta_5 + \beta_6 \mathrm{BA}_{jk})} + \varepsilon_{ijk} \tag{2}$$

where H_{ijk} is total height of tree *i* in stand *j* on plot *k* (m); DBH_{ijk}, diameter at 1.37 m of tree *i* in stand *j* on plot *k* (cm); $\mathrm{CC}_{ijk} = 1$ if crown class is dominant/codominant, $= 0$ otherwise, $\mathrm{TC}_{ijk} = 1$ if tree class is rough/rotten, $= 0$ otherwise, CR_{ijk} = crown ratio of tree *i* in stand *j* on plot *k* (percent), BA_{jk} = basal area of stand *j* on plot *k* ($\mathrm{m}^2\ \mathrm{ha}^{-1}$), LAT_k = latitude of centre point on plot *k* (decimal degrees), LON_k = longitude of centre point on plot *k* (decimal degrees), ELV_k = elevation above sea level of centre point on plot *k* (m), β_0–β_6, θ_1–θ_3 = parameters estimated from the data, ϵ_{ijk} = random residual error of tree *i* in stand *j* on plot *k* (m).

To mimic techniques used when many of the current models in use were developed, nonlinear least-squares methods were used to estimate the parameters (PROC NLIN, SAS Institute Inc., 2008), and no attempt was made to account for the lack of independence among trees on the same plot. To assess differences in spatial domain sizes, regression analyses of models [1] and [2] were performed for the entire northeastern US region and for smaller spatial domains defined by areas having similar climate, vegetation, geology and soils (Cleland *et al*., 1997). In this study, a subarea of the region defined as ecoprovince 211 (Northeastern Mixed Forest) (McNab *et al*., 2007) was used, which also includes the mountainous areas denoted by an M prefix (Figure 1). For smaller individual ecosections

Table 1 Summary statistics for balsam fir, white pine and red maple from forest inventory plots across 13 northeastern states

	Balsam fir			White pine			Red Maple		
	Min.	Mean	Max.	Min.	Mean	Max.	Min.	Mean	Max.
Dbh (cm)	12.7	17.5	51.8	12.7	28.0	112.8	12.7	22.7	97.8
Total height (m)	3	12	30	4	17	42	2	17	38
Crown ratio (%)	1	48	99	1	36	99	1	35	98
Stand basal area ($\mathrm{m}^2\ \mathrm{ha}^{-1}$)	0.4	30.7	91.8	0.8	34.4	271.3	0.7	29.3	271.3
Latitude (degrees)	39.0	45.2	47.4	37.3	42.9	47.4	37.3	42.2	47.4
Longitude (degrees)	−81.0	−70.4	−67.0	−84.5	−73.1	−67.1	−84.8	−75.1	−67.0
Elevation (m)	0	394	1409	0	247	1001	0	357	1397

Balsam fir: 20 321 trees on 2655 plots; white pine: 16 797 trees on 2926 plots; red maple: 63 288 trees on 9949 plots.

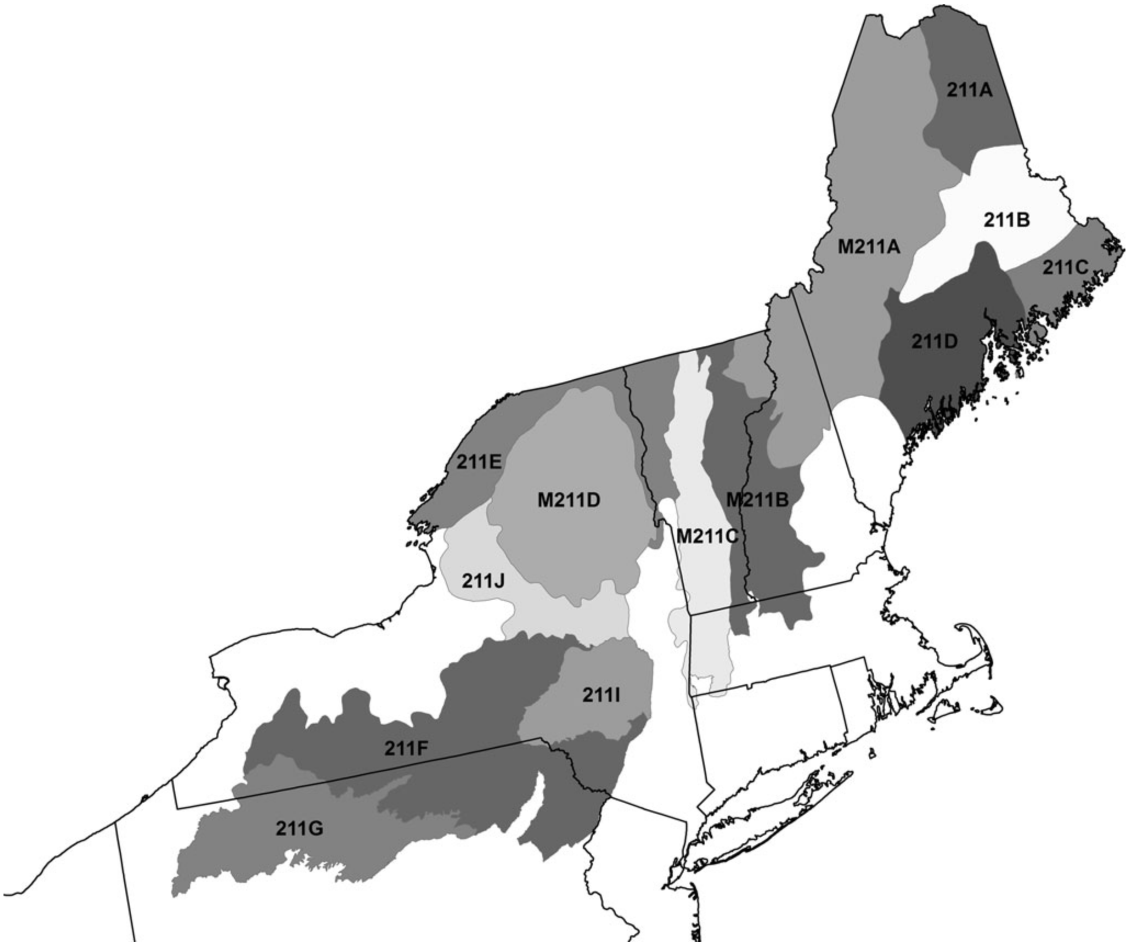

Figure 1 Map of 13-state region, ecoprovince 211 (Northeastern Mixed Forest) and ecosections within ecoprovince 211.

within ecoprovince 211, only model [2] was considered because it outperformed model [1] in the earlier analyses. However, fitting model [2] at these smaller spatial scales often resulted in convergence issues, and thus, the model was simplified to the so-called natural growth model (Sit and Poulin-Costello, 1994) by removing the exponent term:

$$\begin{aligned} H_{ijk} &= (\beta_0 + \beta_1 \mathrm{CC}_{ijk} + \beta_2 \mathrm{CR}_{ijk} + \beta_3 \mathrm{TC}_{ijk}) \\ &\quad \times (1 - \exp(-\beta_4 \mathrm{DBH}_{ijk} + \theta_1 \mathrm{LAT}_k + \theta_2 \mathrm{LON}_k + \theta_3 \mathrm{ELV}_k)) + \varepsilon_{ijk} \end{aligned} \tag{3}$$

Models [1]–[3] above were considered full models. In some cases, one or more predictor variables were nonsignificant ($\alpha = 0.05$) and were removed; the reduced model was then recalibrated.

Of considerable interest was whether the inclusion of latitude, longitude and elevation information in models [2] and [3] accounted for spatial variation of tree heights that were lacking from model [1]. For this assessment, the models that were fitted to both regional and ecoprovince 211 data for each species were compared via pseudo-R^2 (proportion of variation explained) and root mean squared error (RMSE) statistics. To further assess the models fitted to region-wide data, the mean and standard deviations of residuals were computed for each of the 13 states by species. The models fitted to data from ecoprovince 211 were evaluated similarly, with means and standard deviations of residuals being assessed by ecosection (McNab *et al.*, 2007) within ecoprovince 211. Ecosections were not further subdivided into smaller spatial units. The existence of spatial autocorrelation of residuals within ecosections was assessed via the Moran's I statistic (Moran, 1950).

The degree to which the models fit the observed data was assessed via R^2 (proportion of variation explained) and RMSE, whereas model performance at finer spatial resolution was evaluated using the mean ($\bar{\varepsilon}$) and standard deviation (σ_ε) of residuals:

$$R^2 = 1 - \frac{\sum \varepsilon_{ijk}^2}{\sum (H_{ijk} - \bar{H})^2} \tag{4}$$

$$\mathrm{RMSE} = \sqrt{\frac{\sum \varepsilon_{ijk}^2}{n - p}} \tag{5}$$

$$\bar{\varepsilon} = \frac{\sum \varepsilon_{ijk}}{n} \tag{6}$$

$$\sigma_\varepsilon = \sqrt{\frac{\sum (\varepsilon_{ijk} - \bar{\varepsilon})^2}{n - 1}} \tag{7}$$

where n represents sample size, $\bar{H}$ denotes mean tree height, P denotes number of model predictors and others are as previously defined.

Results

For each species, the regional-scale regression analysis of model [1] resulted in statistically significant ($\alpha = 0.05$) estimates for all model parameters (Table 2). R^2 and RMSE statistics by species were (0.52, 2.09 m), (0.81, 2.75 m) and (0.59, 2.78 m) for balsam fir, white pine and red maple, respectively. The results for model [2] also indicated that all model parameter estimates were statistically significant, including those associated with latitude, longitude and elevation (Table 3). The inclusion of these spatial variables considerably improved the fit statistics (R^2, RMSE) for balsam fir (0.61, 1.88 m); however, the fit statistics for white pine (0.81, 2.75 m) and red maple (0.61, 2.71 m) did not change appreciably. To assess the performance of both models, $\bar{\varepsilon}$ and σ_ε were calculated for each of the 13 states within the region as this is the most common scale of FIA analytical reporting. Balsam fir in Ohio had a relatively large mean error of 2.58 m when model [1] was used (Table 4). Red maple in Maine was the only other species with a mean error of >1 m (−1.17 m) when using model [1]; however, there were several mean errors only slightly less than 1 m for other species/states, and many of the mean errors were statistically different from zero. An assessment of the same error statistics for model [2] showed that including the spatial variables (latitude, longitude and elevation) in the model substantially reduced the prediction bias for balsam fir in Ohio to −1.25 m (Table 4), although the bias was not statistically different from zero due to the small sample size. An unintended negative consequence of using model [2] to predict balsam fir heights was an increase in the mean error in some states relative to the error when using model [1]. The most egregious example was the increase in mean error in Massachusetts from 0.17 to 1.02 m. Inclusion of spatial variables in the model resulted in reductions in mean error for some states and increases in other states. Furthermore, the Moran's I statistic based on residuals from model [2] was statistically significant ($\alpha = 0.05$) for all three species, indicating that the spatial variables did not sufficiently account for the spatial variation in the population.

To evaluate model performance at a smaller spatial extent, models [1] and [2] were fitted to data from plots occurring within ecoprovince 211 (Figure 1). Results from the regression analysis were quite similar to those from the region-wide data in that all parameter estimates were of similar magnitude and statistically significant for both models. When comparing model [2] fit statistics to those from model [1], there was a considerable improvement for balsam fir, white pine remained nearly identical and there was a modest improvement for red maple. Given the similar results from both the regional and ecoprovince 211 analyses, it appears that model [2] is generally preferable, and thus, model [1] was no longer considered. Again, it was desirable to evaluate prediction error at smaller spatial scales, and thus, $\bar{\varepsilon}$ and σ_ε for model [2] were calculated by ecosection within ecoprovince 211 (Figure 1; Table 5). The results again suggest that considerable prediction bias may be present for subsets of the area from which the model fitting data were obtained. Mean errors exceeded 1.0 m in two ecosections (211E and 211I) for balsam fir and in one ecosection (211I) for white pine. Several others had a magnitude of error between 0.5 and 1.0 m. The Moran's I statistic based on model residuals was statistically significant ($\alpha = 0.05$) for all three species.

The results for ecoprovince 211 provided impetus for further investigation on the effects of spatial scale by examining smaller areas (ecosections; Figure 1). Due to difficulty in obtaining model convergence at the reduced spatial scale and concomitant sample sizes, regression model [3] was used for analysis of each ecosection. In some cases, not all model parameter estimates were statistically significant. These results suggest that some ecosections are small enough that the data cannot support complex model formulations and that the reduced sample size is insufficient to overcome the inherent variability and identify relationships in a statistical context. The fitted models had varying efficacy for accounting for spatial trends at these smaller spatial scales. Autocorrelation of residuals as assessed by Moran's I statistic indicated that 24 of the 37 species/ecosection combinations had no spatial trends present in the residuals (Table 6). The reduction in area from ecoprovince to ecosection was most effective for white pine where only 8 per cent (1/13) of the ecosections still exhibited spatial correlations, whereas approximately one-half of the ecosections contained spatial patterns for balsam fir (6/11) and red maple (6/13). Of the four ecosections not having any spatial predictors, three had nonsignificant Moran's I statistics, suggesting that the nonspatial predictors can be sufficient to account for within-ecosection spatial variability.

Of particular interest was to evaluate at the ecosection scale of analysis whether the statistical significance of spatial predictor(s)

Table 2 Results from regression analysis of model [1] by species from region-wide data

Parameter	Balsam fir			White pine			Red maple		
	Estimate	Standard error	Pr > |t|	Estimate	Standard error	Pr > |t|	Estimate	Standard error	Pr > |t|
β_0	27.9583	1.4481	<0.0001	42.4707	0.6981	<0.0001	31.5837	0.3080	<0.0001
β_1	2.6224	0.1535	<0.0001	2.8925	0.1328	<0.0001	1.6542	0.0473	<0.0001
β_2	−0.0636	0.0039	<0.0001	−0.2411	0.0053	<0.0001	−0.0953	0.0020	<0.0001
β_3	−6.0572	0.3901	<0.0001	−6.1985	0.1822	<0.0001	−4.2064	0.0683	<0.0001
β_4	0.0289	0.0038	<0.0001	0.0205	0.0009	<0.0001	0.0293	0.0011	<0.0001
β_5	0.8991	0.0424	<0.0001	0.9264	0.0193	<0.0001	0.7558	0.0137	<0.0001
β_6	−0.0020	0.0003	<0.0001	−0.0032	0.0002	<0.0001	−0.0032	0.0001	<0.0001
Pseudo-R^2	0.52			0.81			0.59		
RMSE	2.09			2.75			2.78		

Table 3 Results from regression analysis of model [2] by species from region-wide data

	Balsam fir			White pine			Red maple		
Parameter	Estimate	Standard error	$\Pr > \lvert t \rvert$	Estimate	Standard error	$\Pr > \lvert t \rvert$	Estimate	Standard error	$\Pr > \lvert t \rvert$
β_0	28.3864	0.7188	<0.0001	43.1464	1.2188	<0.0001	29.5004	0.1792	<0.0001
β_1	2.9012	0.0971	<0.0001	2.8641	0.1553	<0.0001	2.1508	0.0446	<0.0001
β_2	−0.0794	0.0027	<0.0001	−0.2451	0.0077	<0.0001	−0.0861	0.0017	<0.0001
β_3	−4.9280	0.2420	<0.0001	−6.3229	0.2375	<0.0001	−3.9625	0.0559	<0.0001
β_4	0.0463	0.0018	<0.0001	0.0192	0.0022	<0.0001	0.0455	0.0007	<0.0001
β_5	1726.5157	453.3000	0.0001	0.8620	0.0875	<0.0001	17.5840	1.8709	<0.0001
β_6	−5.9615	1.7299	0.0006	−0.0029	0.0004	<0.0001	−0.0917	0.0104	<0.0001
θ_1	−0.0660	0.0028	<0.0001	−0.0014	0.0005	0.0137	−0.0126	0.0012	<0.0001
θ_2	0.0564	0.0022	<0.0001	−0.0012	0.0002	<0.0001	0.0271	0.0008	<0.0001
θ_3	0.0004	0.0000	<0.0001	0.0000	0.0000	<0.0001	0.0001	0.0000	<0.0001
Pseudo-R^2	0.61			0.81			0.61		
RMSE	1.88			2.75			2.71		

was indicative of their effectiveness to eliminate spatial trends in model residuals. Regression analyses using model [3] with no spatial predictors showed that 16 of the 37 combinations exhibited no spatial trends, which shows that the inclusion of spatial predictors only positively influenced 8 of 24 combinations in terms of affecting the statistical testing outcome. Thus, 16 combinations did not require the spatial predictor(s) to account for any spatial correlation that may have been present. In some situations, the number of observations used to calculate Moran's I was relatively small (e.g. ecosections 211E–J) and consequently the power to detect spatial trends may have been weak.

Discussion

The statistical significance of coefficients associated with spatial predictor variables was not necessarily a good indicator of their importance in accounting for spatial variation in tree heights at a regional scale. A notable improvement in model fit statistics for balsam fir was observed. However, because the study area contains the southern edge of the natural range of balsam fir (Harlow *et al*., 1991), this may result in more dramatic spatial differences than for other species whose natural ranges extends beyond study area boundaries. If this is the case, it would also explain the marginal improvements observed for both white pine and red maple. The range of predictive biases at the state level from the regional model (Table 4) indicates that some spatial variability is present across the study area. However, the analytical results suggest that this variation is not systematic in relation to latitude, longitude and elevation.

There are several plausible explanations for why spatial variables had little effect on spatial trends: (1) there was little spatial variation to be explained; (2) the influence of spatial location was already reflected in other model predictor variables and, thus, adding spatial variables provided little new information and/or (3) the effects of spatial predictors over the area of interest were not stationary and, thus, had only limited effectiveness in accounting for spatial variability. Reason 3 is the most likely explanation at the regional and ecoprovince scales, although it is plausible that other locational information or more complex treatment (e.g. interactions or indices) of the GPS/GNSS spatial information may produce different outcomes. At the ecosection scale, Reasons 1 and 2 are more probable; however, Reason 3 may have been a factor in some instances. One potential explanation for this outcome is model overspecification, as spatial predictors were often statistically significant but were not needed to attain a nonsignificant Moran's I statistic. Of note, however is that one-third (8/24) of the ecosection model fits only attained a nonsignificant Moran's I statistic through the inclusion of spatial explanatory variables, suggesting that the importance of spatial predictors at this scale should not be entirely discounted.

One potential strategy for determining an appropriate spatial scale for modelling is to model at the scale of analytical resolution. For example, FIA commonly reports forest resource statistics by state. If model predictions are unbiased at this same scale, the analytical results should be unbiased as well. This is risky however, because unwary users of the model (or modelled data) may conduct analyses at smaller spatial scales and incur some predictive bias within the selected area. Alternatively, it may be prudent to model at small spatial scales such that spatial effects are minimized. Subsequent aggregation to larger spatial areas should have little bias present because the results derive from the underlying small-area models. An issue with this approach can be small sample sizes that may lack statistical power to capture the relationships between tree height and predictor variables. Also model uncertainty may substantially increase due to imprecise parameter estimates. McRoberts and Westfall (2014) reported that regression model contributions to total uncertainty were negligible only when samples sizes were at least 100 observations and the proportion of variance explained by the model (e.g. R^2) was at least 0.95, although increased sample sizes can offset the effects of lower R^2 statistics.

Across various spatial scales, the results provided no clear answer in regards to the effectiveness of latitude, longitude and elevation in ameliorating subarea prediction biases. Consequently, the use of spatial predictor variables cannot be relied upon to provide accurate local predictions. The inclusion of additional predictor variables other than dbh that describe local tree and

Table 4 Sample sizes (n), means ($\bar{\varepsilon}$, m) and standard deviations (σ_ε, m) of residuals by state for models [1] and [2] fit to region-wide data

		Balsam fir			White pine			Red maple		
Model	State	n	$\bar{\varepsilon}$	σ_ε	n	$\bar{\varepsilon}$	σ_ε	n	$\bar{\varepsilon}$	σ_ε
[1]	CT	–	–	–	388	0.24	2.23	1956	0.06*	2.57
[1]	DE	–	–	–	–	–	–	715	−0.66	2.94
[1]	ME	13 497	0.04	1.87	4353	−0.55	2.44	10 707	−1.17	2.46
[1]	MD	–	–	–	69	−0.84	3.42	1511	0.05*	2.96
[1]	MA	24	0.17*	2.07	2127	0.25	2.63	3505	−0.36	2.60
[1]	NH	2390	−0.70	2.45	2235	0.77	2.69	4308	0.02*	2.68
[1]	NJ	–	–	–	54	−0.39*	3.21	1066	−0.43	3.05
[1]	NY	2557	0.33	2.38	3400	0.06*	2.84	12 535	0.19	2.68
[1]	OH	6	2.58	1.22	593	−0.38	3.54	3812	0.71	2.73
[1]	PA	–	–	–	1440	−0.43	2.69	13 387	0.53	2.88
[1]	RI	3	−0.24*	0.97	368	0.16*	2.18	863	−0.91	2.31
[1]	VT	1843	0.15	2.50	1161	0.62	3.19	3332	0.02*	2.61
[1]	WV	–	–	–	609	0.04*	2.68	5591	0.53	2.84
[2]	CT	–	–	–	388	0.29	2.23	1956	0.45	2.56
[2]	DE	–	–	–	–	–	–	715	−0.72	2.94
[2]	ME	13 497	−0.06	1.76	4353	−0.61	2.44	10 707	−0.45	2.44
[2]	MD	–	–	–	69	−0.79*	3.44	1511	−0.07*	2.96
[2]	MA	24	1.02	2.09	2127	0.29	2.62	3505	0.14	2.59
[2]	NH	2390	0.50	1.99	2235	0.74	2.70	4308	0.53	2.66
[2]	NJ	–	–	–	54	−0.21*	3.24	1066	−0.37	3.07
[2]	NY	2557	−0.24	2.03	3400	0.05*	2.84	12 535	0.04*	2.66
[2]	OH	6	−1.25*	1.19	593	−0.04*	3.48	3812	−0.48	2.76
[2]	PA	–	–	–	1440	−0.38	2.70	13 387	0.19	2.87
[2]	RI	3	0.10*	1.33	368	0.25	2.18	863	−0.38	2.34
[2]	VT	1843	0.13	2.17	1161	0.53	3.18	3332	0.32	2.57
[2]	WV	–	–	–	609	0.08*	2.70	5591	0.03*	2.84

Mean values denoted with an asterisk were not statistically different from zero ($\alpha = 0.05$).

Table 5 Sample sizes (n), means ($\bar{\varepsilon}$, m) and standard deviations (σ_ε, m) of residuals by section for model [2] fit to ecoprovince 211 data

Section	Balsam fir			White pine			Red maple		
	n	$\bar{\varepsilon}$	σ_ε	n	$\bar{\varepsilon}$	σ_ε	n	$\bar{\varepsilon}$	σ_ε
211A	1972	0.29	1.68	81	−0.81	1.90	726	0.63	2.27
M211A	9011	0.04	1.84	698	−0.24	2.55	4323	−0.07	2.34
211B	1994	0.04*	1.66	688	−0.10*	2.12	1525	−0.35	2.22
M211B	928	0.53	2.06	1905	0.72	2.91	2886	0.75	2.56
211C	1098	−0.55	1.76	404	−0.57	2.12	882	−0.87	2.32
M211C	815	−0.11*	2.28	408	0.99	3.07	2502	0.29	2.65
211D	1619	−0.14	1.83	1518	−0.42	2.43	2695	−0.07*	2.27
M211D	2197	−0.12	2.04	826	0.74	2.98	3524	−0.03*	2.55
211E	67	−1.06	2.35	616	0.14*	2.54	1397	−0.47	2.58
211F	26	−0.69*	2.33	1036	−0.58	2.68	5353	−0.30	2.60
211G	–	–	–	374	−0.62	2.67	3856	0.43	2.94
211I	59	−1.49	1.92	349	−1.22	2.58	1217	0.01*	2.69
211J	243	−0.57	1.65	305	−0.19*	2.58	1245	−0.69	2.67

Mean values denoted with an asterisk were not statistically different from zero ($\alpha = 0.05$).

Table 6 *Z* statistics and associated *p*-values for Moran's I statistical test for spatial autocorrelation of residuals by species and ecosection

Section	Balsam fir		White pine		Red maple	
	Z	Pr > |*Z*|	*Z*	Pr > |*Z*|	*Z*	Pr > |*Z*|
211A	−0.30	0.76†	−0.75	0.45	−0.08	0.93†
M211A	15.92	<0.01†	1.15	**0.25†**	12.77	<0.01†
211B	2.50	0.01	0.80	0.42†	2.01	0.04†
M211B	2.96	<0.01†	2.65	0.01†	1.52	**0.13†**
211C	1.28	**0.20†**	0.55	0.58†	0.89	**0.37†**
M211C	1.13	**0.26†**	0.38	0.71†	1.39	0.17†
211D	5.46	<0.01†	−0.37	0.71†	1.17	**0.24†**
M211D	5.85	<0.01†	0.03	0.98†	11.10	<0.01†
211E	1.22	0.22†	−1.04	0.30†	1.15	**0.25†**
211F	–	–	−0.16	0.88†	3.80	<0.01†
211G	–	–	−0.80	0.42†	12.15	<0.01†
211I	0.78	0.44	0.09	0.92†	0.93	**0.35†**
211J	5.59	<0.01†	0.39	0.70	2.73	0.01†
211	2.48	0.01†	2.31	0.02†	6.69	<0.01†
Region	2.52	0.01†	3.84	<0.01†	11.20	<0.01†

$Z < 0$ indicates negative autocorrelation; $Z > 0$ denotes positive autocorrelation. $\Pr > |Z| < 0.05$ were considered statistically significant; those denoted with a dagger symbol had a least one significant spatial predictor variable in the model; those in bold indicate the inclusion of spatial predictors caused the Moran's I statistic to become nonsignificant.

stand conditions were also unable to fully account for spatial variability in many cases. Perhaps, the most promising general technique in regression modelling for local calibration is the use of mixed-effects models, which can be calibrated to local conditions via prediction of random effects for new observations (Trincado *et al*., 2007; Finley *et al*., 2013). This method requires that additional data be available that helps describe the local relationship between tree height and model predictor variables. In the context of this paper, such data may come from height and diameter measurements on a subsample of trees used to calibrate predictions for the remaining trees having unmeasured tree heights. Other possibilities include retaining the random effects for trees used to fit the model and only predicting random effects for new trees (e.g. ingrowth). A concern with retaining random effects predictions is their applicability over time. As forest inventory plots are remeasured repeatedly over several decades, the random effects for all trees may need to be continually updated as stand dynamics and/or external processes such as disturbance or climate change alter functional relationships (Zhang and Gove, 2005). These methods may provide a framework for adapting to long-term shifts in relationships among the response and predictor variables without having to engage in a new model development process. However, the practical efficacy of employing such models in large-area forest inventory and monitoring programmes has yet to be evaluated.

Conclusion

The results of this study lead to several important conclusions. First, the performance of large-area models at finer spatial scales is erratic, with some smaller areas exhibiting considerable bias. Second, the effectiveness of using latitude, longitude and elevation to account for large-area spatial variation cannot be determined solely by the statistical significance of associated model parameter estimates. Third, it may be advantageous to fit a number of models to relatively homogeneous subregions instead of using a single model over the entire region. Thus, when using traditional fitting techniques, these postulates should be taken into account when developing a large-area modelling strategy.

Conflict of interest statement

None declared.

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