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Article

Prediction of lake depth across a 17-state region in the United States

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Abstract

Lake depth is an important characteristic for understanding many lake processes, yet it is unknown for the vast majority of lakes globally. Our objective was to develop a model that predicts lake depth using map-derived metrics of lake and terrestrial geomorphic features. Building on previous models that use local topography to predict lake depth, we hypothesized that regional differences in topography, lake shape, or sedimentation processes could lead to region-specific relationships between lake depth and the mapped features. We therefore used a mixed modeling approach that included region-specific model parameters. We built models using lake and map data from LAGOS, which includes 8164 lakes with maximum depth (Z_{max}) observations. The model was used to predict depth for all lakes ≥4 ha (n = 42 443) in the study extent. Lake surface area and maximum slope in a 100 m buffer were the best predictors of Z_{max}. Interactions between surface area and topography occurred at both the local and regional scale; surface area had a larger effect in steep terrain, so large lakes embedded in steep terrain were much deeper than those in flat terrain. Despite a large sample size and inclusion of regional variability, model performance (R^2 = 0.29, RMSE = 7.1 m) was similar to other published models. The relative error varied by region, however, highlighting the importance of taking a regional approach to lake depth modeling. Additionally, we provide the largest known collection of observed and predicted lake depth values in the United States.

Key words: lake depth, mixed model, morphology, regional scale, topography

Introduction

Lake depth is known to interact with and control many physical, chemical, and biological processes in lakes. For water quality, lake depth is particularly important because it influences the relationship between water quality stressors (e.g., land use change) and responses (e.g., phosphorus concentration; Taranu and Gregory-Eaves 2008). Mean lake depth is related to lake volume and residence time and improves predictions of internal processing and retention of phosphorus in lakes (Vollenweider 1975, Brett and Benjamin 2008). Maximum lake depth (Z_{max}) in part

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determines whether a lake stratifies (Gorham and Boyce 1989) and is subsequently correlated to many physical and biological processes, such as hypolimnetic oxygen depletion (Charlton 1980) and the likelihood of winterkill (Barica and Mathias 1979). Lake depth data over broad spatial extents are rare, however, despite abundant data on other lake features, because lake bathymetric data (on which lake depths are often based) are often stored as paper maps or in diverse electronic file types, no methods currently exist to measure lake depth using remote sensing technology, and no central repository exists for lake depth information. For macroscale limnology research, the lack of depth information may be overcome by (1) scouring paper and digital maps, records, and individual lake databases to find depth information, which is inefficient but precise; or (2) using terrestrial topography and other widely available landscape features to predict lake depth, which is efficient but imprecise (Hollister et al. 2011, Sobek et al. 2011). Even if all available lake depth information is compiled, bathymetric data for small and remote lakes are typically rare. If the study area includes thousands of lakes, model prediction of lake depth is the only pragmatic solution until other technologies are developed.

Current models for predicting lake depth use topographic information of the land surrounding a lake as the predictor; however, these models only explain 36–50% of the variability in Z_{max} (Hollister et al. 2011, Sobek et al. 2011, Heathcote et al. 2015). For example, Sobek et al. (2011) tested dozens of map-derived metrics (related to topography, lake morphology, and land cover/land use) on >6000 lakes, and the top predictors (lake area and maximum slope) explained 36% of the Z_{max} variability. A variety of

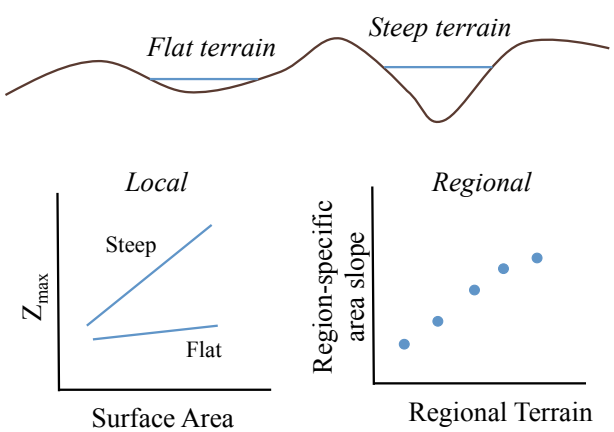

Fig. 1. The hypothesized interaction between lake surface area and terrain as it relates to lake depth. Lakes with the same surface area will be much deeper in steep versus flat terrain (top). In the Z_{max} model, we expect this relationship to appear as both local (bottom left) and regional (bottom right) interaction terms. At the lake scale, this relationship will be modeled as interactions between the fixed predictors. At the regional scale, the region-specific coefficients for surface area will be related to regional terrain metrics.

mechanistic and modeling processes may explain the inability to predict lake depth using terrestrial topography. Hollister et al. (2011) suggested that accounting for erosion and sedimentation processes, which would cause the lake basin shape to deviate from the surrounding landscape, would improve lake depth prediction. Furthermore, sedimentation processes are shape-dependent, and lake shape is known to vary by region (Carpenter 1983). Other lake characteristics such as surface area also exhibit regional differences (McDonald et al. 2012). Although including region did not improve depth predictions in Sweden (Sobek et al. 2011), regional differences in the relationship between terrestrial topography and maximum depth were reported in northeastern United States (Hollister et al. 2011) and Quebec (Heathcote et al. 2015) lakes. Based on first principles, an interaction between surface area and topography could occur at the local or regional scale, where in steep landscapes an increase in surface area should lead to a larger increase in maximum depth relative to flat landscapes (Fig. 1; Winslow 2014). This topographical effect may limit performance of a simple linear model, which does not account for regional variability, to define the relationship between lake depth and surface area across diverse landscapes.

We expect regional differences in the relationship between predictors (e.g., surface area) and lake depth due to both first principles (Fig. 1) and processes that are more difficult to quantify, such as lake formation, sedimentation, and erosion. The objectives of this work were to (1) improve on existing predictive models of lake depth by leveraging a mixed model approach that captures the hypothesized regional differences in the relationship between predictors and lake depth by allowing slopes and intercepts to vary regionally; and (2) use the model to predict lake depth for lakes without depth measurements in our study extent and provide this information to the research community. We used a database of >50 000 lakes with terrestrial and lake metrics that spanned the Midwest and northeastern United States to create a predictive model of lake depth for this lake-rich and geomorphologically diverse region of North America. Our goal was to gain a mechanistic understanding of regional differences in lake depth and to understand where a geomorphology model was most appropriate to predict depth.

Methods

Data source and study extent

All data are from LAGOS (LAke multi-scale GeOSpatial and temporal database), an integrated database of lake ecosystems made up of 2 modules. The lake depth data are from $LAGOS_{LIMNO}$ 1.040.0, which integrates existing

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field-based measurements of lake nutrients and physical properties (lake depth, water clarity) from government (local, state, federal, tribal) and university organizations for a subset of lakes in the region. The geospatial data are from $LAGOS_{GEO}$, a collection of spatially referenced measurements of climate, land use/land cover, terrain, surface water connectivity, and surficial geology that describe the geographical context of each of the 51 009 lakes in the study area. $LAGOS_{GEO}$ contains a complete census of lakes ≥4 ha with corresponding geospatial information for a 17-state region of the United States. (Fig. 2). Soranno et al. (2015) provide a detailed description of metric derivation and how LAGOS was built.

Of the 51 009 lakes in the population, 8458 had Z_{max} measurements and 3780 had mean depth. Z_{max} is likely more abundant in LAGOS because Z_{max} is easier to measure and calculate from a bathymetric map compared to mean depth. Additionally, when lake depth is unknown, water chemistry is often measured at the center of the lake, where the deepest hole is assumed to be located; therefore, we chose to model Z_{max}. We excluded lakes >1000 ha (n = 371), as Sobek et al. (2011) did, because lake depth is known for most of these lakes in LAGOS (79% compared to 16% of lakes <1000 ha) and therefore does not need to be predicted. Lakes were included in the analysis if they had complete records for all predictor variables and met our size criteria (n = 42 443 without depth data; n = 8164 with depth data). Some variables were highly skewed and subsequently $\log_e$ transformed (Table 1). Predictors were centered and scaled by subtracting the mean and dividing by the standard deviation (Table 1). A random subset of 10% of the observations (n = 817), stratified by $\log_e Z_{max}$, were withheld during model fitting and used for model validation (Fig. 2).

Observation-level predictors

Previous predictive models of lake depth showed that metrics describing the terrain (e.g., slope) surrounding the lake, as well as lake-specific metrics such as surface area, were the best predictor of lake depth (Sobek et al. 2011). For our analysis, we used lake and terrestrial geomorphic metrics from LAGOS calculated at multiple spatial scales (Table 1). Observation-level predictors (i.e., predictors measured for each lake) tested in our model included metrics that describe the terrestrial landscape, including slope, terrain ruggedness index (TRI), and the ratio of watershed area to lake surface area (WSA:LA). The watershed area excludes the watershed of upstream lakes ≥10 ha. Slope and TRI metrics were both calculated using the *gdaldem* tool (http://www.gdal.org/gdaldem.html) in the Geospatial Data Abstraction Library (GDAL). The input raster was the National Elevation Dataset (NED) at 10 m resolution. Slope was reported in degrees and calculated using Horn's formula (Horn 1981), in which the output value for a focal cell represents the slope between the focal cell and its 8 nearest neighbors. TRI was calculated as the mean of the absolute difference between elevation in the focal cell and neighboring cells (Wilson et al. 2007). Values were greater than zero, and

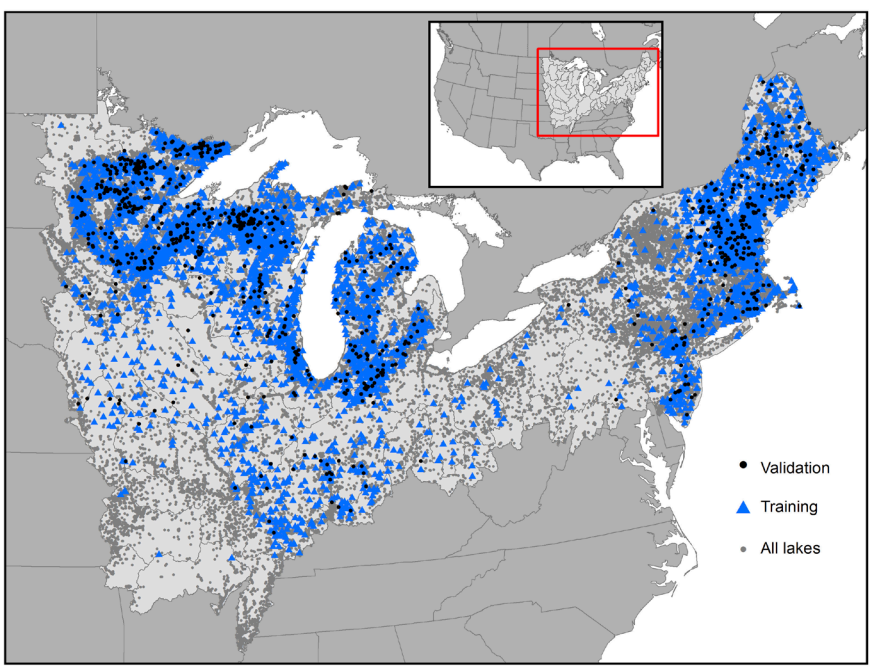

Fig. 2. Locations of lakes used to train (blue triangles; n = 7347) and validate (black dots; n = 817) the model and all lakes ≥4 ha in the study region that met our model inclusion criteria (gray dots; n = 50 607). The light gray regions correspond to HUC 4 regions.

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Table 1. Variables considered as predictors in the linear mixed model to predict Z_{max}. SDI is the shoreline development index, WSA:LA is the ratio of the watershed area to lake surface area, S is slope, and TRI is the terrain roughness index. Subscripts on predictor variables describe the measured spatial extent of the metric (100 m buffer, 500 m buffer, watershed, region) and the summary statistic used (mean, maximum, minimum, standard deviation). Reason for elimination describes why predictor variables were removed from the model. Predictor variables included in the final model are bolded. Variables were first excluded if they had a zero-inflated distribution, then if they had low predictive ability relative to the other variables at the same spatial extent, and finally if they were highly correlated to other predictor variables. Variables were also excluded if they had no effect after the full model was built. Regional-level predictors were eliminated if they were not related to any of the random effects in the mixed model. For variables included in the final model, transformation describes if the data were untransformed (NA) or log transformed (ln). Predictors were centered and scaled after transformation by subtracting the mean and dividing by the standard deviation.

Variable and spatial extent	Reason for elimination	Transformation, mean (SD)
Lake-specific		
Z_{max}		**ln**
Area		**ln, 3.80 (1.28)**
Perimeter	correlated	
SDI		**ln, 0.63 (0.39)**
WSA:LA		**ln, 2.32 (1.36)**
100 m buffer		
$S_{100,mean}$	low predictive ability	
$S_{100,sd}$	low predictive ability	
$S_{100,max}$		**ln, 3.03 (0.42)**
$S_{100,min}$	zero-inflated	
$TRI_{100,mean}$	low predictive ability	
$TRI_{100,sd}$	low predictive ability	
$TRI_{100,max}$	correlated	
$TRI_{100,min}$	zero-inflated	
500 m buffer		
$S_{500,mean}$	low predictive ability	
$S_{500,sd}$	low predictive ability	
$S_{500,max}$	no effect in full model	
$S_{500,min}$	zero-inflated	
$TRI_{500,mean}$	low predictive ability	
$TRI_{500,sd}$	low predictive ability	
$TRI_{500,max}$	correlated	
$TRI_{500,min}$	zero-inflated	
Watershed		
$S_{WS,mean}$	low predictive ability	
$S_{WS,sd}$	low predictive ability	
$S_{WS,max}$	no effect in full model	
$S_{WS,min}$	zero-inflated	
$TRI_{WS,mean}$	low predictive ability	
$TRI_{WS,sd}$	low predictive ability	
$TRI_{WS,max}$	correlated	
$TRI_{WS,min}$	zero-inflated	
Region (HUC 4)		
$S_{HUC4,mean}$		**NA, 3.88 (2.14)**
$S_{HUC4,sd}$	low predictive ability	
$S_{HUC4,max}$	low predictive ability	
$S_{HUC4,min}$	zero-inflated	
$TRI_{HUC4,mean}$	low predictive ability	
$TRI_{HUC4,sd}$	low predictive ability	
$TRI_{HUC4,max}$	low predictive ability	
$TRI_{HUC4,min}$	zero-inflated	
Relative depth		**NA, 1.22 (0.27)**
Depth ratio	low predictive ability	
Max Z_{max}	low predictive ability	

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larger values were interpreted as representing a more rugged (or variable) terrain. From the slope and TRI layers, summary statistics included mean, standard deviation, maximum, and minimum of all pixels at a given spatial scale (100 m buffer, 500 m buffer, watershed, or region). Naming conventions for predictor variables summarized the topography metric, spatial scale, and summary statistic. For example, mean slope in the 100 m buffer was abbreviated as $S_{100,mean}$.

Lake-specific morphometry metrics included surface area (area) and perimeter (P), extracted from the National Hydrography Dataset (NHD; http://nhd.usgs.gov/), and shoreline development index (SDI), a derived measure of shoreline complexity calculated as:

$$SDI = \frac{P}{2\times\sqrt{\pi}\times\text{Area}}. \quad (1)$$

Large values of SDI can be interpreted as lakes with more convoluted (less circular) shorelines.

Regional-level predictors

We expected lake morphology to exhibit regional autocorrelation; that is, lakes within regions have more similar morphological characteristics than lakes across regions, and this phenomenon may help predict lake depth. We delineated our regions using the US Geological Survey National Hydrography Dataset (NHD) Watershed Boundary Dataset (WBD) delineation of river watersheds (Seaber et al. 1987). The WBD delineation is a nested and hierarchical regionalization shown to effectively group lakes for water quality modeling (Cheruvelil et al. 2008, 2013). The HUC 4 (4 digit hydrologic unit code) scale in the WBD divides the entire United States into 222 watersheds with an average size of ~44 000 km^2. We chose the HUC 4 scale (Fig. 2) because it is small enough to capture important regional differences in lakes but large enough to have many lakes with Z_{max} data per region (mean = 126). Under the hypothesis that regional differences in lake and terrestrial morphology would lead to region-specific relationships between Z_{max} and the observation-level predictors, we tested if the random slopes and intercepts in the mixed model were related to regional variables that describe lake shape and terrestrial morphology.

For each region, we used the mean of the lake morphology metrics to describe regional lake shape, except in regions with poor sample size (n < 10), where the mean of lakes across all regions was used. Lake shape can be variously described (e.g., Häkanson 1981), but in the absence of bathymetric information, we were limited to derived metrics that use available limited descriptive data: Z_{max}, mean depth (for a subset of lakes), P, and surface area. Relative depth (RD; Häkanson 1981) is calculated as:

$$RD = \frac{Z_{max}\times\sqrt{\pi}}{20\times\sqrt{Area}}, \quad (2)$$

where small deep lakes will have the largest RD values, and large shallow lakes will have the smallest values. The depth ratio (DR) is mean depth divided by Z_{max} and approaches one for lakes with steep sides and flat bottoms. Additionally, we used the maximum Z_{max} value in each region as a surrogate for the depth to bedrock, which may represent a regional constraint on Z_{max}. Terrain metrics (described earlier: slope, TRI) summarized at the regional scale were also used as region-level predictors.

Modeling approach overview

To predict Z_{max} we used a mixed modeling approach that included observation-specific (level 1) and region-specific (level 2) predictors. This approach allowed local relationships between predictors and response (region-specific slopes and intercepts) to vary with regional characteristics (i.e., cross-scale interactions; Soranno et al. 2014).

All models were fitted using the lmer function in the package lme4 (Bates et al. 2014) in R (R Core Team 2014). The observation-level of our model used lake-specific metrics to predict Z_{max} in each lake:

$$log_e(Z_{max})_i \sim N(\alpha_{j[i]} + \beta_{j[i]}X_i\ \sigma_y^2), \text{ for } i = 1,\ldots n, \quad (3)$$

where $log_e(Z_{max})_i$ is the natural log of Z_{max} in lake i; α_j is the intercept for the jth region; β_j is the slope of the relationship between Z_{max} and observation-level predictor X in region j; and σ_y^2 is the residual variance. The second level of our model used regional covariates to model the variability in region-specific slopes and intercepts as:

$$\begin{pmatrix}\alpha_j\\ \beta_j\end{pmatrix} \sim N\left(\begin{pmatrix}\gamma_0^\alpha + \gamma_1^\alpha Z_j\\ \gamma_0^\beta + \gamma_1^\beta Z_j\end{pmatrix}, \begin{pmatrix}\sigma_\alpha^2 & \rho\sigma_\alpha\sigma_\beta\\ \rho\sigma_\alpha\sigma_\beta & \sigma_\beta^2\end{pmatrix}\right), \text{ for } j = 1,\ldots,J, \quad (4)$$

where γ_0^a and γ_1^α are the estimated intercept and slope, respectively, for the relationship between a_j and the regional covariate Z_j; γ_0^β and γ_1^β are the estimated intercept and slope, respectively, for the relationship between β_j and Z_j; σ_α^2 and σ_β^2 are conditional variance estimates; and ρ is the correlation between slopes and intercepts.

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Table 2. Estimated coefficients from the final mixed effects model. Note that coefficients are from transformed, centered, and standardized data (see Table 1).

Parameter	Description	Mean	Standard error
Observation-level			
γ_0^{α}	Intercept	1.96	0.02
$\gamma_0^{\beta_1}$	Area	0.18	0.02
μ_{β_2}	SDI	−0.06	0.01
μ_{β_3}	$S_{100,max}$	0.23	0.01
μ_{β_4}	WSA:LA	−0.11	0.01
b	Area*$S_{100,max}$	0.06	0.01
b	Area*SDI	0.03	0.01
b	SDI*WSA:LA	−0.04	0.01
σ_{α}^2	Intercept variance	0.02	
$\sigma_{\beta_1}^2$	Area slope variance	0.01	
Regional-level			
γ_1^{α}	Relative depth	0.13	0.02
$\gamma_1^{\beta_1}$	$S_{HUC4,mean}$	0.09	0.02

Model selection

Mixed model selection is not straightforward, largely because of the difficulty in determining the effective number of parameters (West et al. 2014), so we initially reduced the number of possible predictor variables in the final model (Table 1). We chose to keep all lake morphology metrics in the running for the final model but reduced the number of potential terrain metrics using the following procedures. First, predictors were excluded if they had a zero-inflated distribution. To ensure all observation-level predictors were important for predicting Z_{max} independently, each variable was tested separately by building a mixed model with one predictor (fixed effect) and allowing slopes and intercepts to vary by region (random effects). If the 95% confidence interval of the estimated fixed effect coefficient overlapped with zero, the predictor was excluded from analysis in the final model. Next, predictor variable performance was assessed using a metric of percent variance explained. Both a marginal (R^2_m; percent variance explained by fixed effects) and a conditional (R^2_c; percent variance explained by fixed and random effects) R^2 were used to rank variables according to their ability to predict Z_{max} (Nakagawa and Schielzeth 2013). The top predictor from each scale (100 m, 500 m, and watershed) and each predictor type (slope or TRI) were retained for potential inclusion in the final model (Table 1).

The top-ranked predictor variables were then assessed to exclude highly correlated variables. A variance inflation factor (VIF) was used to detect multicollinearity, and variables were excluded if VIF >5 (corresponds to R^2 = 0.8) using a step-wise selection process that, in each iteration, excluded the variable with the highest VIF. Variables at the same spatial scale were highly correlated, so in some cases, the variable with the second highest VIF was excluded if it performed more poorly in the model than the metric at the same spatial scale. This selection process left 5 observation-level predictors to be tested in the full model (Table 1).

Following previous works (e.g., DeWeber and Wagner 2015), a full model was fitted that allowed all observation-

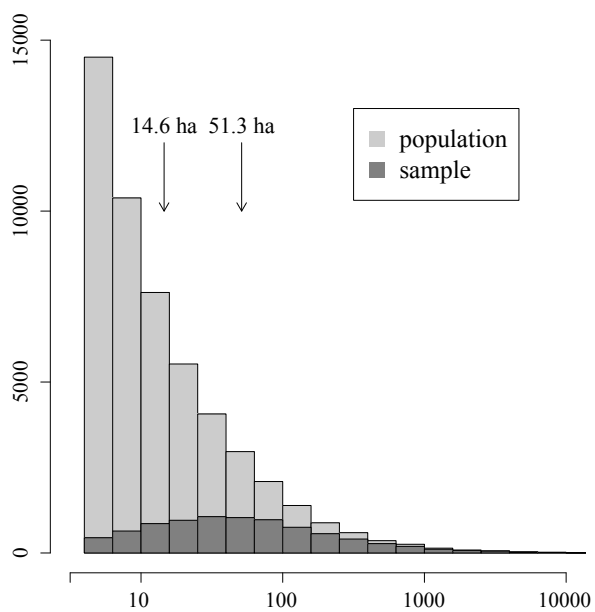

Fig. 3. The distribution of lake surface area in the population (light gray; n = 51 009) and sample of lakes with known Z_{max} (dark gray; n = 8458). Values above the arrows represent the geometric mean lake surface area in the population (left) and sample (right).

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level predictors to vary by region (random slopes and intercepts). Two-way interactions between all fixed effects were sequentially added and retained if the 95% confidence interval for the estimated coefficient did not overlap with zero. Two-way interactions were not allowed to vary among regions. Once the interaction terms were included in the model, the region-specific slopes and intercepts (random effects) were evaluated. A random effect was kept in the model if >10% of the region-specific estimates and the fixed estimate had nonoverlapping 95% confidence intervals. All region-level variables were tested as covariates of random effects in the model; a region-level predictor was included in the model if the estimated coefficient was different from zero and explained the most variance in the region-specific effects relative to other region-level predictors.

Model performance

The final mixed effects model was evaluated based on the proportion of variance explained by fixed and fixed plus random effects (Nakagawa and Schielzeth 2013). The *predict* function in the package lme4 (Bates et al. 2014) in R (R Core Team 2014) was used to generate predicted values for the 10% of withheld data and the remaining lakes in our study region where Z_{max} was unknown. Root mean squared error (RMSE) was calculated for both the training and validation data and summarized by region to assess whether model performance varied spatially. Relative RMSE (rRMSE) was also calculated as the regional RMSE divided by the regional mean Z_{max}. Both the predicted and observed depth values are available for download (Oliver et al. 2015).

Results

Lakes with known Z_{max} were not evenly distributed across the study region, and 6 of 65 regions did not have any depth observations (Fig. 2). Lake depth in these regions was predicted using the global (rather than region-specific) coefficients. Additionally, the size distribution of lakes with known Z_{max} was different from that of the whole population; large lakes were oversampled relative to their abundance (Fig 3).

The final mixed effects model included a single terrain metric (maximum slope at the 100 m scale), lake area, WSA:LA, and SDI (Table 2). Lake area and $S_{100,max}$ had the largest effect size and interacted; the positive interaction term indicated that lakes of similar size are deeper if they are situated in steep versus flat terrain (Fig. 4a). Lakes were also deeper if they had simple shorelines, particularly if the lakes were small (Fig. 4b). The interaction between WSA:LA and shoreline

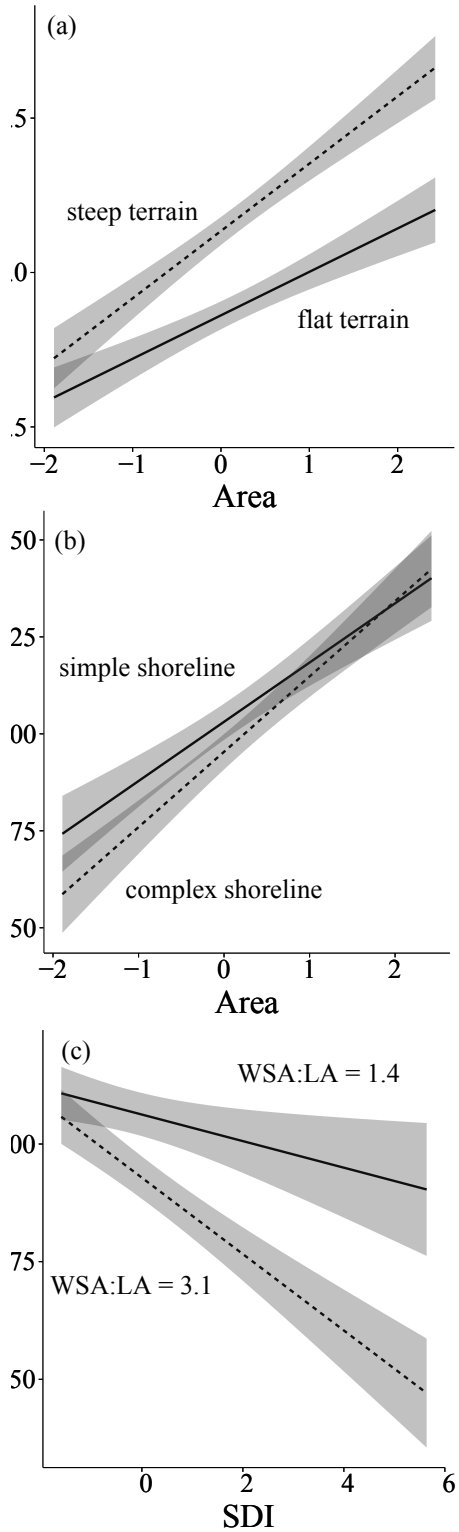

Fig. 4. Representation of the interaction terms between (a) lake surface area and $S_{500,max}$, (b) lake surface area and SDI, and (c) SDI and WSA:LA. The dashed and solid lines represent the value of (a) $S_{500,max}$, (b) SDI, and (c) WSA:LA at the 0.25 and 0.75 quartiles, respectively. Gray bars represent the 95% confidence interval for the predicted Z_{max}.

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development revealed that shoreline complexity is more important for determining depth of lakes with large watersheds relative to surface area (Fig. 4c). Lakes with complex shorelines were much shallower if they were situated in a large watershed.

The region-specific intercepts and area slopes (Table 2) were included in the final model because 24 and 32% of region-specific estimates, respectively, differed from the estimated fixed effect. The region-specific intercepts and slopes were both related to region-level predictors (Fig. 5). The random intercepts were positively correlated with relative depth, where regions with high Z_{max} relative to surface area had higher intercepts (Fig. 5a). Variation in the region-specific slope of the relationship between surface area and depth were positively correlated with $S_{HUC4,mean}$ (Fig. 5b).

The RMSE was 7.1 m for both the training and validation data (Fig. 6a). The distribution of Z_{max} for the population of lakes was different from that of the modeled lakes; the predicted geometric mean Z_{max} of the population was 5.8 m compared to 7.4 m for the observed values (Fig. 6b). The fixed effects accounted for most of the total variance explained by the model ($R^2_m = 0.24$, $R^2_c = 0.29$). RMSE was variable across regions and was related to the regional mean Z_{max} (Fig. 7), so we calculated relative RMSE (regional RMSE/regional mean Z_{max}), which ranged from 0.19 to 1.21 across regions (Fig. 7).

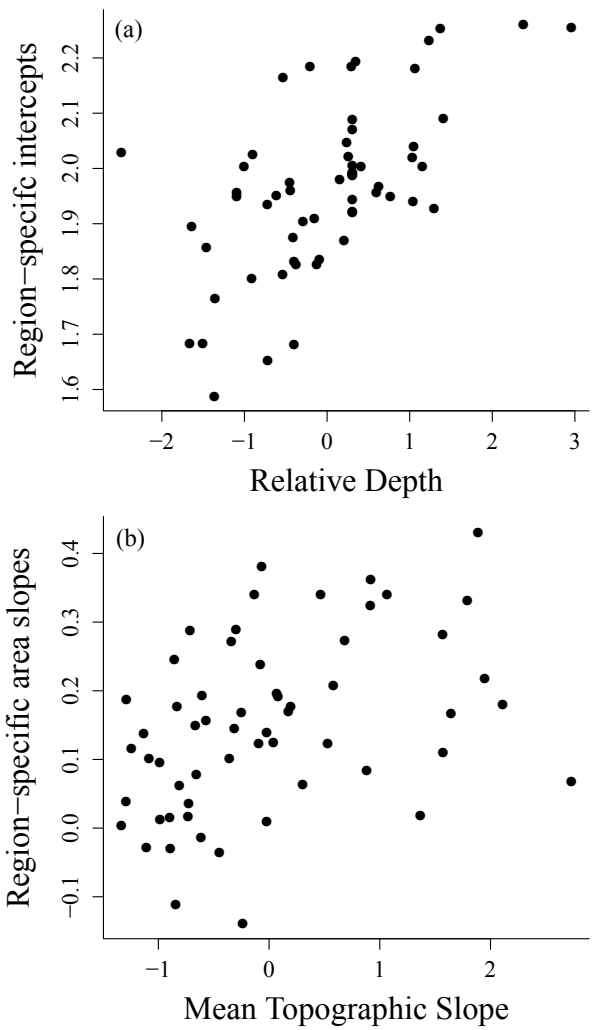

Fig. 5. The relationship between the region-specific effects and regional predictors. (a) The region-specific intercepts were related to relative depth, and (b) the region-specific slope of the relationship between lake surface area and Z_{max} was related to mean slope at the HUC 4 scale.

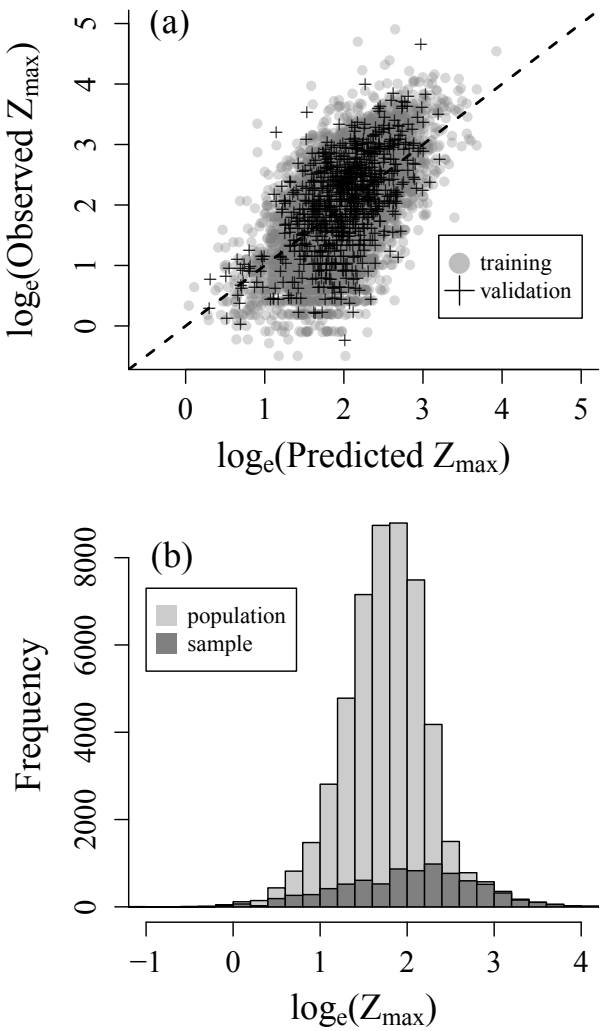

Fig. 6. (a) The relationship between observed and predicted Z_{max} from the training (gray dots) and validation (black crosses) data. The dashed line represents a 1:1 relationship. (b) The distribution of Z_{max} in the population (light gray) and sample of lakes with known Z_{max} (dark gray).

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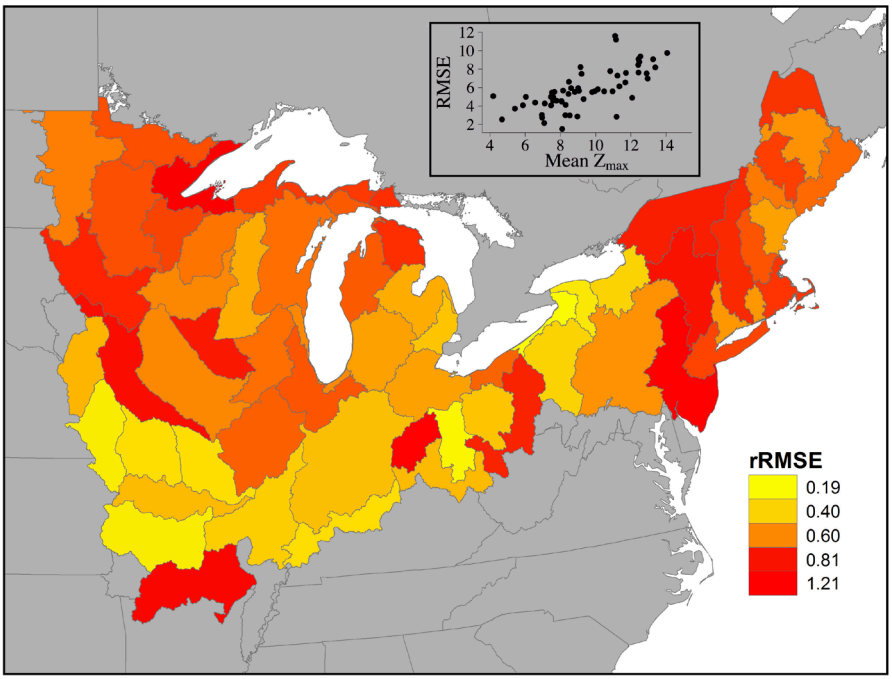

Fig. 7. Relative root mean squared error (rRMSE) of predicted Z_{max} in each region. The regional error in the model was related to the average lake depth in each region (inset), so RMSE was standardized by dividing by the regional mean Z_{max}. One outlier (RMSE = 8 m, mean Z_{max} = 27.4 m) is not shown in the inset. Darker colors represent higher error in the prediction, which ranged from 0.19 to 1.21 across the study extent.

Discussion

Our goal was to predict maximum depth for thousands of lakes across a large and topographically diverse landscape to improve existing models of lake depth by using a mixed effects model that characterizes variance at the regional scale. We hypothesized that differences in topography, formation processes, or sedimentation and erosion processes would lead to region-specific relationships between lake and terrestrial morphology. The region-specific slopes and intercepts in our model were related to regional lake and terrestrial geomorphic metrics (Fig. 5), which suggests mechanistic links to the regional scale. The mechanism may be regional geomorphology that constrains lake shape, which would create region-specific relationships between surface area and Z_{max}. Additionally, first-order processes were evident in the model; lakes of a given size are deeper in steep versus flat terrain (Fig. 1), a process evident at both the local (Fig. 4a) and regional scale (Fig. 5b). Although we were not able to pinpoint the mechanism that creates region-specific relationships between lake depth and the predictors, our model revealed that lake depth is not simply a function of lake size or the immediate terrestrial landscape, but that regional differences in lake and terrestrial geomorphic metrics are critical to consider. The regional variability in relative RMSE (Fig. 7) highlights areas where the model is well-suited for depth prediction (e.g., Missouri), despite poor performance overall.

Differences in sedimentation processes across lakes may be driving the lake basin to deviate from the surrounding topography (Carpenter 1983, Hollister et al. 2011). We attempted to capture variability in sedimentation rates using 2 local predictors viewed as surrogates for sedimentation potential. WSA:LA represents the potential for allochthonous input to the lake, where a large drainage area relative to lake area has the highest allochthonous input potential (Kortelainen 1993, Sobek et al. 2003). SDI may represent the mode of entry for allochthonous material; more complex shorelines (high SDI) have more connectivity per lake area to the terrestrial landscape. In our model, the shallowest lakes occurred when SDI and WSA:LA were high (Fig. 4c), which may point to those lakes with the highest sedimentation rates. Regardless of the amount of material delivered to lakes, sedimentation rates can vary across lake shapes and types; small, productive lakes will fill more rapidly (Carpenter 1983, Downing et al. 2008). Incorporating more sophisticated estimates of sedimentation rates or lake age may improve future lake depth models.

Our results suggest that the local terrain is the strongest predictor of lake shape. The slope metric at the smallest spatial scale (100 m) in our model had the largest effect size. Likewise, Sobek et al. (2011) found that the maximum slope in a small (50 m) buffer was the best predictor (after surface area) of Z_{max}. Heathcote et al. (2015) varied the buffer size with lake size and tested different scaling factors and found that metrics summarized at the smallest

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buffer scale were always the best predictors of lake depth. Lake bathymetry is apparently a close reflection of the immediate terrestrial landscape, and lake depth prediction does not require knowledge of the watershed. Although WSA:LA was in our model, it had a small effect size relative to slope and surface area (Table 2). Additionally, both our study and Sobek et al. (2011) found that the maximum slope was the best predictor of Z_{max}, an unexpected finding given that maximum metrics represent a single "neighborhood" in the entire spatial extent. An extreme predictor may be best in this case because Z_{max} is itself an extreme point in the lake basin, and the most rugged or steep places in a buffer may be a surrogate for depth potential in the adjacent lake basin.

Recently, Heathcote et al. (2015) presented an improved model for predicting lake depth and were able to explain half of the variability in Z_{max} for 400 lakes in Quebec. The Heathcote et al. (2015) model had higher precision than similar efforts for a variety of reasons (this study; Sobek et al. 2011, Hollister et al. 2011), but principally because their study extent covered a relatively small, geologically uniform ~2×10^5 km^2 area compared to the ~4.5×10^5 km^2 study extent in Sobek et al. (2011) or the >18×10^5 km^2 total area covered in this study. Similar to this study, model performance was region-specific (Heathcote et al. 2015) and performed poorly in one region with flat terrain. Additionally, their terrain metrics were calculated in a buffer proportional to lake surface area, so presumably noninformative terrain was excluded for each lake. Because we expanded our analysis to predict depth for >40 000 lakes, calculating a variable rather than standard buffer size would be computationally expensive. Although we did not test the same approach, our buffer sizes of 100 and 500 m would have been the selected buffer sizes in the Heathcote et al. (2015) method for lakes with surface areas of 12.6 and 314 ha, respectively, and 71% of the lakes used in our model fell between these size classes. Finally, we cannot rule out that the terrestrial metric used by Heathcote et al. (2015; mean elevation in the buffer divided by the elevation of the lake surface) would improve our model performance because we did not derive this metric.

The LAGOS database provides an unprecedented amount of lake depth data, which is valuable both on its own and for validation of a depth prediction model. In this case, however, more data did not translate to better predictive ability relative to studies with far fewer observations (e.g., Heathcote et al. 2015), most likely because of the large spatial extent of LAGOS and the heterogeneous landscape that it covers. The lack of predictive ability despite more data was also true across regions in our model; regions with many observations did not have lower prediction error than those regions with fewer observations (data not shown), a result that emphasizes the importance of lake depth observations. More troubling is the systemic bias in the commonly studied lakes; small lakes are under-sampled relative to their abundance across the landscape (Fig. 3; Wagner et al. 2008). Small lakes are functionally different from large lakes in many ways (Hanson et al. 2007, Downing et al. 2008, Read et al. 2012), and measuring their cumulative regional or global importance is dependent on assumptions related to lake morphology (Winslow et al. 2015). High error in depth prediction for small lakes, combined with the error associated with quantifying small lakes across the landscape, leads to high uncertainty in the volume of small lakes and any upscaled volume-dependent processes (e.g., McDonald et al. 2013). LAGOS demonstrates that, collectively, the scientific community has information on lake depth, but that these data are not readily available in a centralized database. We encourage organizations and researchers collecting bathymetric or depth measurements to share their data to a central repository such as Bathybase (http://www.bathybase.org/) where information is freely available to the broader community so existing or new models can be developed to better predict lake depth in the absence of *in situ* data.

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References

Barica J, Mathias JA. 1979. Oxygen depletion and winterkill risk in small prairie lakes under extended ice cover. J Fish Res Board Canada. 36:980–986.

Bates D, Maechler M, Boker B, Walker S. 2014. lme4: linear mixed-effects models using Eidgen and S4.

Brett MT, Benjamin MM. 2008. A review and reassessment of lake

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phosphorus retention and the nutrient loading concept. Freshwater Biol. 53:194–211.

Carpenter SR. 1983. Lake geometry: implications for production and sediment accretion rates. J Theor Biol. 105:273–286.

Charlton MN. 1980. Hypolimnion oxygen consumption in lakes: discussion of productivity and morphometry effects. Can J Fish Aquat Sci. 37:1531–1539.

Cheruvelil KS, Soranno PA, Bremigan MT, Wagner T, Martin SL. 2008. Grouping lakes for water quality assessment and monitoring: the roles of regionalization and spatial scale. Environ Manage. 41:425–440.

Cheruvelil KS, Soranno PA, Webster KE, Bremigan MT. 2013. Multi-scaled drivers of ecosystem state: quantifying the importance of the regional spatial scale. Ecol Appl. 23:1603–1618.

DeWeber JT, Wagner T. 2015. Predicting brook trout occurrence in stream reaches throughout their native range in the eastern United States. Trans Am Fish Soc. 144:11–24.

Downing JA, Cole JJ, Middelburg JJ, Striegl RG, Duarte CM, Kortelainen P, Prairie YT, Laube KA. 2008. Sediment organic carbon burial in agriculturally eutrophic impoundments over the last century. Global Biogeochem Cy. 22:GB1018, doi:10.1029/2006GB002854

Gorham E, Boyce FM. 1989. Influence of lake surface area and depth upon thermal stratification and the depth of the summer thermocline. J Great Lakes Res. 15:233–245.

Häkanson L. 1981. A manual of lake morphology. Berlin (Germany): Springer.

Hanson PC, Carpenter SR, Cardille JA, Coe MT, Winslow LA. 2007. Small lakes dominate a random sample of regional lake characteristics. Freshwater Biol. 52:814–822.

Heathcote AJ, del Giorgio PA, Prairie YT, Brickman D. 2015. Predicting bathymetric features of lakes from the topography of their surrounding landscape. Can J Fish Aquat Sci. 72:643–650.

Hollister JW, Milstead WB, Urrutia MA. 2011. Predicting maximum lake depth from surrounding topography. PLoS One. 6:e25764.

Horn BKP. 1981. Hill shading and the reflectance map. Proc IEEE. 69:14–47.

Kortelainen P. 1993. Content of total organic carbon in Finnish lakes and its relationship to catchment characteristics. Can J Fish Aquat Sci. 50:1477–1483.

McDonald CP, Rover JA, Stets EG, Striegl RG. 2012. The regional abundance and size distribution of lakes and reservoirs in the United States and implications for estimates of global lake extent. Limnol Oceanogr. 57:597–606.

McDonald CP, Stets EG, Striegl RG, Butman D. 2013. Inorganic carbon loading as a primary driver of dissolved carbon dioxide concentrations in the lakes and reservoirs of the contiguous United States. Global Biogeochem Cy. 27:285–295.

Nakagawa S, Schielzeth H. 2013. A general and simple method for obtaining R^2 from generalized linear mixed-effects models. Methods Ecol Evol. 4:133–142.

Oliver SK, Soranno PA, Fergus EC, Wagner T, Webster KE, Scott C, Winslow LA, Downing JA, Stanley EH. 2015. LAGOS - Predicted and observed maximum depth values for lakes in a 17-state region of the U.S. Long Term Ecological Research Network. doi:10.6073/pasta/f00a245fd9461529b8cd9d992d7e3a2f

R Core Team. 2014. R: a language and environment for statistical computing. Vienna (Austria): R Foundation for Statistical Computing.

Read JS, Hamilton DP, Desai AR, Rose KC, MacIntyre S, Lenters JD, Smyth RL, Hanson PC, Cole JJ, Staehr PA, et al. 2012. Lake-size dependency of wind shear and convection as controls on gas exchange. Geophys Res Lett. 39.

Seaber P, Kapinos F, Knapp G. 1987. Hydrologic units maps. US Geologic Survey Water Supply Paper 2294.

Sobek S, Algesten G, Bergström A-K, Jansson M, Tranvik LJ. 2003. The catchment and climate regulation of pCO_2 in boreal lakes. Glob Change Biol. 9:630–641.

Sobek S, Nisell J, Fölster J. 2011. Predicting the depth and volume of lakes from map-derived parameters. Inland Waters. 1:177–184.

Soranno PA, Bissell EG, Cheruvelil KS, Christel ST, Collins SM, Fergus CE, Filstrup CT, Lapierre J-F, Lottig NR, Oliver SK, et al. 2015. Building a multi-scaled geospatial temporal ecology database from disparate data sources: fostering open science and data reuse. Gigascience. 4:28.

Soranno PA, Cheruvelil KS, Bissell EG, Bremigan MT, Downing JA, Fergus CE, Filstrup CT, Henry EN, Lottig NR, Stanley EH, et al. 2014. Cross-scale interactions: quantifying multi-scaled cause–effect relationships in macrosystems. Front Ecol Environ. 12:65–73.

Taranu ZE, Gregory-Eaves I. 2008. Quantifying relationships among phosphorus, agriculture, and lake depth at an inter-regional scale. Ecosystems. 11:715–725.

Vollenweider RA. 1975. Input-output models with special reference to the phosphorus loading concept in limnology. Schweiz Z Hydrol. 37:53–84.

Wagner T, Soranno PA, Cheruvelil KS, Renwick WH, Webster KE, Vaux P, Abbitt RJF. 2008. Quantifying sample biases of inland lake sampling programs in relation to lake surface area and land use/cover. Environ Monit Assess. 141:131–147.

West B, Welch K, Galecki A. 2014. Linear mixed models: a practical guide using statistical software. Boca Raton (FL): CRC Press.

Wilson MFJ, O'Connell B, Brown C, Guinan JC, Grehan AJ. 2007. Multiscale terrain analysis of multibeam bathymetry data for habitat mapping on the continental slope. Mar Geod. 30:3–35.

Winslow L. 2014. Landscape limnology: lake morphology and process at the continental scale [dissertation]. [Madison (WI)]: University of Wisconsin-Madison.

Winslow L, Read J, Hanson P, Stanley E. 2015. Does lake size matter? Combining morphology and process modeling to examine the contribution of lake classes to population-scale processes. Inland Waters. 5:7–14.

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