Factors Influencing the Bioaccumulation of Methylmercury in Largemouth Bass from California Lakes and Reservoirs

Melwani, A.R., Negrey, J., Stephenson, M., Solomon, M.,
Bezalel, S.N., Allen, R., and Davis, J.A.

Abstract

The objective of this study was to develop a statistical model that describes the driving factors of fish methylmercury (MeHg) bioaccumulation in California lakes and reservoirs. MeHg concentrations in largemouth bass from 17 lakes were examined for relationships to water and sediment chemistry, lake morphometry, and land use. A combination of correlation and multivariate analysis was used to evaluate the controlling factors. Average MeHg concentrations in length-standardized largemouth bass varied from 0.06 – 1.3 μg/g at the 17 lakes included in the analysis. Several predictor variables were significantly correlated with length-standardized largemouth bass MeHg (Pearson $r > 0.5$, $p < 0.05$) and were a significant component of the multivariate regression model. The driving factors included total Hg in sediment, total Hg in soils, forested area, specific conductivity, and methylmercury in surface water. Results of the statistical model were consistent with several studies from across the nation that have suggested that broad land use characteristics can potentially influence MeHg bioaccumulation in lakes and reservoirs. However, the limited sample size and spatial distribution of lakes evaluated here preclude extending our interpretations beyond the population of lakes included in this analysis.

Introduction

Mercury (Hg) is a widespread pollutant that has impacted aquatic ecosystems for more than a century. Hg sources in California include historic mercury, gold, and silver mining areas, wastewater, urban runoff, agricultural runoff, and atmospheric deposition. The most significant Hg source by mass is attributed to mining activity during the 1800s, when significant releases to the environment occurred (Domagalski 1998). On a national scale, atmospheric deposition is considered the predominant source of Hg to aquatic environments distant from mines (U.S. EPA 1997). Hammerschmidt and Fitzgerald (2006) recently suggested that up to two-thirds of the MeHg accumulation in fish from water bodies in the United States could be attributed to wet deposition of atmospheric Hg. Hg deposition to the eastern United States has been indicated in many studies as the primary vector for Hg accumulation in the food web (e.g., Fitzgerald and Clarkson 1991; Hammerschmidt and Fitzgerald, 2006). Despite limited data, it has been estimated that deposition to the west coast (California, Washington, Oregon) remains at background levels. In California, runoff and weathering from historic gold and mercury mining areas has mobilized legacy Hg from the landscape into many of the lakes and reservoirs. The legacy contamination is considered the most likely source of high background concentrations of Hg in water bodies throughout the state. Mining, atmospheric deposition, and other sources predominantly release Hg to the aquatic environment in inorganic forms, including elemental Hg (Hg0), cinnabar (HgS), and ionic Hg (Hg^{2+})

(USGS 2000). When transformed to its organic form, methylmercury (MeHg) by sulfate-reducing bacteria (Gilmour *et al.* 1992), Hg becomes a significant toxicological concern for biota. The primary pathways for increased methylation of inorganic Hg in lakes and reservoirs are thought to relate to wetlands (St. Louis *et al.*, 1994), forests (St. Louis *et al.*, 1996), and lake sediments (Ramlal *et al.*, 1993). Under certain conditions, Hg methylation may also occur in the water column. But, a direct correlation between sources of Hg and biota MeHg concentrations has yet to be shown for California lakes and reservoirs.

Many studies have identified levels of MeHg that pose risks to wildlife and humans that consume fish (e.g., Melwani *et al.* 2009; Eagles-Smith *et al.* 2009). MeHg contamination has also been the principal driver for recent 303(d) water body listings, Total Maximum Daily Loads (TMDLs), and many human health advisories in the state (e.g., Fairey *et al.* 1997, Davis *et al.* 2008, 2009, 2010). Therefore, the bioaccumulation of MeHg in fish tissue is considered a significant threat to the health of both wildlife and humans, and is one of the primary indicators used to monitor water quality in the state.

The objective of this study was to develop a statistical model that describes the driving factors of MeHg bioaccumulation in fish from California lakes and reservoirs. MeHg concentrations in largemouth bass (*Micropterus salmoides*) were examined for relationships to water and sediment chemistry, lake morphometry, and land use.

Methods

Total mercury in sport fish, from a statewide survey of 272 lakes and reservoirs in California, sampled in 2007 and 2008, were considered for the statistical model (Davis *et al.* 2009, 2010). Of these lakes, Moss Landing Marine Laboratories (MLML) prioritized water and sediment sampling at 21 lakes based on guidance from the Regional Water Quality Control Boards. The majority of these lakes (11 of 21) were located in the Central Valley (Region 5), with the remainder in Region 1 (North Coast), Region 3 (Central Coast), and Region 8 (Santa Ana). Overall, fifteen of the 21 lakes selected by MLML had data on Hg in largemouth bass (Table 1). In addition, MLML provided largemouth bass MeHg data for an additional two lakes (Lake Hemet and Big Bear lake) sampled in 2009 (Negrey and Stephenson, 2010), where water and sediment data had also been collected. Therefore, 17 lakes were use to assess patterns related to MeHg bioaccumulation in largemouth bass (Figure 1).

Prediction of Lake-specific Largemouth Bass MeHg Concentrations

In previous studies, largemouth bass have exhibited a strong size:MeHg relationship when collected over a wide (spanning 150 mm or more) size range (Davis *et al.* 2008; Melwani *et al.* 2009). In this study, MeHg in 350 mm largemouth bass was used as a typical lake-specific estimate of MeHg. The 350 mm value was selected to represent the middle (median) of the typical size distribution above the legal limit of 305 mm (12 in) for largemouth bass in California. The 350 mm concentration for 15 lakes was estimated by employing a general linear model with maximum likelihood (PROC MIXED in SAS v. 9.1; Littell *et al.* 1996). The approach was used to evaluate the “best” regression model from which to estimate MeHg concentrations in largemouth bass among lakes. In addition, two lakes (Lake Hemet and Big Bear Lake) sampled for largemouth bass MeHg in 2009, were used to estimate 350 mm concentrations using a simple linear regression approach. The resulting regression equations were used to predict MeHg concentrations (mean and 95% confidence interval) for each lake in a 350 mm (total length) largemouth bass (Table 1). Further details of the general linear model have been described in Davis *et al.* (2010).

Environmental Data

Data on lake morphometry (e.g., depth, volume, surface area) were obtained from literature sources, websites, and lake management agencies, including the California Department of Fish and Game, Regional Water Quality Control Boards, and the Department of Water Resources (Appendix 1). A single attribute value representing characteristics of lake morphometry was assigned to each lake used in the statistical analysis (Table 2).

Land use data were calculated based on the lake catchment (sub-watershed) areas (Figures 1 and 2). Catchment areas were determined from the Watershed Boundary Dataset (WBD). Polygons from the "6th level" delineation (the smallest division of sub-watersheds within WBD) were used in the GIS layer. Sampling locations for each study basin were plotted, and the upstream sub-watershed area of each point was delineated. The newly generated catchment areas were checked against other GIS data for accuracy. These included the 4th & 5th level (more aggregated) of WBD, aerial photography, a 30 m hillshade, and the National Hydrography Dataset (NHD). In some cases, the WBD 6th level delineations were coincident with lake-forming dams. In such cases, the polygons were edited to exclude dams that would represent barriers to fish and environmental variables. Once the watersheds were developed for each lake, land use data were overlaid to allow for calculation of attributes related to mercury contamination of the catchment area, such as number of mines, proportion of wetland area, and total watershed area (Figure 2, Table 2, Appendix 1). In particular, three primary datasets were used to represent habitat and mining information: CalVeg, National Wetlands Inventory (NWI), and Mine Resources Data System (MRDS). The metadata behind each of these datasets have been described (Melwani *et al.* 2007). In addition to the 17 lakes used for statistical analysis, land use attributes were determined for an additional 21 lakes from the statewide dataset where length-standardized largemouth bass MeHg concentrations had been determined (Davis *et al.* 2010), to allow a qualitative assessment of sub-watershed variables on a larger sample size of lakes. Lake morphometry and water chemistry data were not readily available for this subset of lakes.

Lake chemistry data collected by Moss Landing Marine Laboratories (MLML) were obtained for the 17 lakes included in the statistical analysis. Aqueous MeHg was measured in surface (above thermocline) and deep (below thermocline) samples in both summer (May – Sept) and winter (Oct – April) in 2008 and summer 2009. During each monthly sample event, surface water samples were also measured for chlorophyll a, sulfate (SO4), and dissolved organic carbon (DOC). Total mercury in water was measured on a single sampling event, once in the summer and once in the winter. Profile data of temperature, conductivity, pH, and oxygen data in 3 m increments from the surface to near-bottom at all lakes (50 ft. max depth) were also collected. Finally, total mercury in sediment was collected once from the deepest portion of each lake in 2008. Detailed methods for sampling and analysis have been described in Negrey and Stephenson (2010).

Statistical Approach

Log-10 transformed lake-specific 350 mm largemouth bass MeHg concentration (LMB_{350} MeHg) was used as the response variable in all statistical analyses. Analysis was conducted with predictor variables that were log-10 transformed and standardized (i.e., mean centered and scaled to the standard deviation, often known as the z-score). This allowed for all predictors to be evaluated with the same weight in the statistical models. Therefore, each variable had the same influence, despite being measured on different scales. Log transformations were used to improve linear relationships and ensure normally distributed error values and equal variances in the analysis. Pearson correlation analysis was used to evaluate the relationships among the predictor variables and to LMB_{350} MeHg.

Partial Least Square regression models (also called Projection of Latent Structures or PLS) were used to assess the influence of 23 explanatory variables on standard-size largemouth bass MeHg concentrations from 17 California lakes. PLS is a multivariate regression method similar to Principal Component Regression (PCR). The main difference is that PLS uses the information in the response variable to extract the useful variance among the explanatory variables to form its components (Carrascal *et al.* 2009). In other words, PLS maximizes the covariance between the explanatory and response variable, whereas in PCR, the components are extracted independent of the relationship in the predictor variables to the response.

PLS model development was initiated with the full complement of 23 predictor variables included. Model evaluation consisted of identifying the following statistics:

1) the minimum number of components required to minimize the root mean square error of predicted values;
2) the minimum number of predictors required to maximize the total variance explained by the model;
3) loading results (correlation structure between the explanatory and response variables);
4) regression coefficients (direction and strength of the predictors in the model); and,
5) variance influence on projection (VIP; strength of influence among all PLS components).

In subsequent PLS model runs, variables were removed based on their regression coefficients, VIP, and relative contribution to the model. Although no defined limit exists for statistical significance in PLS models, VIP limits of 0.8 or 1.0 have often been used (Eriksson *et al.* 1995; Sonesten, 2004). In this study, significant predictor variables were defined as having a VIP > 1.0. Predictors with small regressions coefficients or VIP < 1.0 were removed in the final model. Predictive ability of the different PLS models was estimated by cross-validation (Eriksson *et al.*, 1995). The PLS models were developed using the R Statistical Software Package (http://cran.r-project.org).

Results and Discussion

MeHg concentrations in 350 mm largemouth bass (here on referred as LMB_{350} MeHg) at 17 lakes used in the statistical analysis, varied from 0.06 – 1.3 µg/g (Table 1). There was a regional pattern to the concentrations; lakes in Region 1 (North Coast, 3 of 17 lakes) exhibited the highest concentrations, while lakes in Region 8 (Santa Ana, 5 of 17 lakes) exhibited the lowest (Figure 1). This pattern was consistent with the overall distribution of largemouth bass MeHg concentrations found in the full statewide dataset (Davis *et al.* 2010).

Correlation Structure

Pearson correlation analysis was used to evaluate relationships among the variables included in the statistical models. Nine of the predictor variables were significantly related to LMB_{350} MeHg (Table 3). Conductivity had the strongest correlation, exhibiting a Pearson r = -0.79. Total mercury (THg) in sediment was the single most important environmental variable (r = 0.69) related to LMB_{350} MeHg. Latitude and longitude were also highly correlated with LMB_{350} MeHg reflecting the regional pattern in the concentrations. Generally, lakes in the north-east and north-west portions of the state had higher LMB_{350} MeHg than central coast and southern California lakes. In addition, percent forested area (r = 0.63), THg in soils (r = 0.65), chlorophyll a (r = -0.51), sulfate (r = -0.50), and annual water level flux (r = 0.51) were all significantly correlated to LMB_{350} MeHg. Pearson correlation analysis also indicated that average concentrations of surface water MeHg and ancillary parameters (pH, DOC, etc.) collected during the summer season had the highest correlation coefficients with LMB_{350} MeHg (seasonal comparison not presented). Among the predictor variables, many significant correlations were also detected. The variables that were most commonly associated with other predictors were conductivity, sulfate, latitude, watershed area, and forested area. This is indicative of the multi-collinearity of the dataset and supports the use of a latent structure approach in the modeling described below.

Summary of Partial Least Square Regression (PLS) Models

The influence of 23 environmental variables on LMB_{350} MeHg was evaluated using several PLS models. Each model sought to narrow the factors that 'best' describe the variation in LMB_{350} MeHg at the 17 lakes used in the analysis. All of the PLS model runs were generally consistent regarding the significant environmental factors explaining LMB_{350} MeHg. Therefore, only two models are summarized in detail here, the most complex model (Model 1) and the simplest model (Model 4). PLS model outputs for Model 2 and Model 3 can be found in Appendix 2. All four models explained approximately 80% of the variance in LMB_{350} MeHg (Table 4). The models also indicated that 18-49% of the variation in the predictor variables was 'noise', and thus did not contribute significantly to the model results. In multiple regression analysis, this variation in the predictor variables would have been included in the model parameters, resulting in over-fitting and an inflated coefficient-of-determination (R^2). In all models, the first two components were significant ($p < 0.05$) and explained the vast majority (> 70%) of the variance in LMB_{350} MeHg. However, in the simpler models (with fewer variables), only component 1 was necessary to predict LMB_{350} MeHg. The regression coefficients and VIP for Model 1 indicated that many of the predictor variables had little effect on LMB_{350} MeHg. Twelve variables had relatively small regression coefficients and low VIP (Table 5). In contrast, the variables included in the final model (Model 4) were all relatively significant (VIP > 1.0) and contributed equally to the model (similar regression coefficients; Table 6). Finally, the predictive ability of the models was highest in Model 4. Cross-validation was used to evaluate the predictive ability and stability of the PLS models. Model 4 indicated a model R^2 of 0.81 and a cross-validated R^2 of 0.75, which was the highest prediction R^2 of the models evaluated.

The final model equation (Model 4) was:

$$\text{Log}_{10}(\text{LMB}_{350}\ \text{MeHg}) = 0.15 + 0.010(\text{Latitude}) + 0.012(\text{Longitude}) + 0.021(\text{THg-Sediment}) + 0.025(\text{MeHg-Water}) + 0.013(\text{THg-Soil}) + 0.010(\text{Forested-area}) - 0.019(\text{Conductivity})$$

The majority of mean predicted values of LMB_{350} MeHg were within 0.25 μg/g of the observed mean concentration (Table 7). The majority of predicted values were higher than the observed concentration, suggesting that the model estimates are more conservative than the observed values. The least deviation from observed was evident at lakes in the low to moderate concentrations range (0.1 – 0.6 μg/g). This is likely because the majority of lakes used in the model corresponded to this range in concentration. The three lakes with the highest degree of bias (Thermalito Afterbay, Lake Hemet, O'Neill Forebay) were outliers because their land use characteristics were anomolous. For example, Thermailito Afterbay was biased by 1.1 times the observed concentrations because it had relatively high proportion of forested area (78%) in its catchment, but the observed concentration was not proportionally high. Similarly, Lake Hemet was biased by 0.83 times the observed concentrations because it had a relatively low observed LMB_{350} MeHg, but did not indicate the lowest values of THg in sediment or MeHg in water. Therefore, this lake was predicted to have a higher LMB_{350} MeHg. Overall, the majority of predicted values were reasonable given the limited sample size of lakes and variables employed in the final model.

Factors Controlling Fish MeHg Concentrations

The seven predictor variables included in the final model can be separated into three distinct groups for interpretation: spatial location (latitude and longitude); land use/geology (THg in soils, THg in sediment, percent forested); and methylation (MeHg in water and specific conductivity). These groups of variables explained 81% of the variance in LMB_{350} MeHg. Exclusion of latitude and longitude from the final model reduced the model variance by < 5% (results not presented). Therefore, despite latitude and longitude having relatively strong influence in the final model (indicated by 3rd and 4th highest VIP), the variables did not contribute much variance to the prediction of LMB_{350} MeHg. This suggests that the vast majority of the variation due to spatial or regional differences was captured by other predictors, such as land use and geology.

Component 1 of the final model exhibited a LMB_{350} MeHg explanatory variance of 75%. Therefore, the variables driving the separation of lakes along this axis were assumed to be the most dominant factors in the model. The regression coefficients suggest the main controlling factors along Component 1 were spatial location, land use, and conductivity (Figure 3). As described above, spatial location was an important factor, but did not contribute much variance to the model. Therefore, forested area, THg in sediment, and THg in soils, indicated the strongest, positive influences on LMB_{350} MeHg, while conductivity indicated a strong negative effect. The placement of land use variables, as well as latitude and longitude, in a similar latent component space suggests similar effect on LMB_{350} MeHg. The equal importance of the variables is also illustrated by the similar PLS regression coefficients for the first significant component (Table 6). THg in sediment diverged from the other land use variables in Figure 3 mainly due to the higher average concentration of THg in sediment at Lake Pillsbury. The comparable regression coefficient and VIP of THg in sediment suggests that the influence of the variable in the model is similar to the other land use variables. Overall, 11 of 17 lakes exhibited LMB_{350} MeHg > 0.3 μg/g, and seven of these were positively related to land use variables.

Component 2 of the model contributed an additional 6% to the final model variance. Only two lakes (Lake Irvine and Lake Pillsbury) separated strongly along this axis suggesting these observations may be the result of outliers. MeHg in water and THg in sediment had the two largest regression coefficients in Component 2, and thus contributed most to the separation of lakes. Lake Pillsbury likely separated along Component 2 due to much higher MeHg in water and LMB_{350} MeHg than any of the other lakes. The separation of Lake Irvine was more likely an artifact of data availability for the model, as it lacked information on THg in soil. If Lake Irvine were to have followed the pattern in THg in soils observed at other lakes, it is likely this lake would have corresponded to the positive side of Component 1. Overall, the results along Component 2 did not drive much of the model variance, and thus have not been emphasized in the following interpretations.

Land Use and Geology

Lakes and reservoirs located in Region 1 (Lake Sonoma and Lake Mendocino) and Region 5 (Folsom Lake, Lake Natomas, Don Pedro Reservoir, Lake McSwain, and Lake McClure) were associated with catchments with higher LMB_{350} MeHg, and relatively high forested area (> 70%) and THg in soils. These parameters suggest that land use and habitat may be critical to understanding the higher concentrations at these lakes. Several previous studies of habitat influences on fish mercury concentrations in lake catchments have found significant correlations with land cover and habitat features of the watershed (e.g., Hurley *et al.* 1995; Wiener *et al.* 2006; Chumchal *et al.* 2008). Furthermore, differences in mercury methylation efficiency have been reported on both land use scales (e.g., agricultural, industrial, urban; Krabbenhoft *et al.* 1999) as well as finer, habitat scales (e.g., wetland, forested, un-vegetated; Hurley *et al.* 1995; Wiener *et al.* 2006). The limited sample size of lakes used in this analysis precluded separation on such scales in the model, but could be attempted on a larger sample size in future work.

Many types of wetland and forested habitat can exhibit conditions that are favorable for Hg methylation (Zillioux *et al.* 1993). Understanding the many interacting factors that control MeHg production in these habitat types is still an area of ongoing research (Wiener *et al.* 2003). One focus area has been to understand the activity of sulfur-reducing bacteria, which thrive in anoxic soils and sediment (Gilmour and Henry 1991, Gilmour *et al.* 1992). Forested areas have been observed to transport the more reactive forms of Hg relative to other land use types (Chumchal *et al.* 2008), and sulfur-reducing bacteria are primarily responsible for this transformation. Accordingly, positive correlations between forested area and MeHg concentration in water and largemouth bass have been observed previously (St Louis *et al.* 1994; Hurley *et al.* 1995; Krabbenhoft *et al.* 1999; Chumchal *et al.* 2008). The indication from these results is that the association between LMB_{350} MeHg and land use may occur on a regional scale, but lakes in certain areas of the state deviate from the observed pattern.

Mining was not indicated to have a direct correlation with LMB_{350} MeHg in this analysis. In addition to the lack of influence in the PLS models, a qualitative assessment of an additional 21 lakes indicated that many lakes that had relatively high LMB_{350} MeHg coincided with watersheds with very few mines. Twelve lakes had LMB_{350} MeHg > 0.8 µg/g, but only three of these had more than three mines in their watershed (Table 8). Furthermore, two lakes with the lowest LMB_{350} MeHg (< 0.03 µg/g) were indicated to have more than 30 mines within their watershed. The lack of consistent correlation to number of gold and mercury mines suggests that other variables are responsible for driving elevated LMB_{350} MeHg at the majority of these lakes. It has been suggested that THg in sediments and soil from mine sites are not as bioavailable as those from diffuse sources, such as atmospheric deposition or urban runoff (Krabbenhoft *et al.* 1999), which may somewhat explain the lack of correlation to LMB_{350} MeHg. It is also possible that the mining data layer is not precise enough to support this type of analysis (see Davis *et al.* [2010] for further discussion).

The qualitative assessment of 21 lakes further pointed towards forested area being associated with many of the lakes of higher LMB_{350} MeHg in northern California. New Melones, Crystal Lake, and Eastman Lake had LMB_{350} MeHg between 0.95 – 1.12 µg/g and greater than 75% forested area in their watersheds. This was similar to the pattern evident at the initial set of lakes used for modeling. However, in southern California, where lake catchments have relatively little forested area, no obvious pattern could be deduced, with some lakes having relatively high (> 0.6 µg/g) or low (< 0.3 µg/g) LMB_{350} MeHg. In addition, patterns of wetland area associated with elevated LMB_{350} MeHg were inconclusive. Overall, the results suggests a hypothesis for at least some lakes, where Hg may be leached more readily from forested areas than in catchments dominated by other habitat types. However, the potential sources of Hg to these forested catchments still remains an open question, due to the lack of correlation to mine data, and the inability to examine atmospheric or other watershed-scale sources (e.g., POTWs) in this analysis.

Mercury Methylation

Hg methylation rates are controlled by both the physical and biogeochemical conditions of a water body. Lakes and reservoirs are often environments of elevated Hg methylation due to daily and seasonally changing environmental conditions. Fluctuations in the water level of reservoirs can cause spikes in Hg methylation. For example, when the perimeter of a reservoir periodically dries out and then submerges, it can become an area of intense MeHg production (Johnson *et al.* 1991). Additionally, during the summer, lake conditions can often enhance the methylation process by the presence of warmer, slow moving water, which promotes algal growth and can reduce oxygen levels. These features of lakes were examined using several characteristics of lake morphometry and water chemistry variables, but were generally not significant (Table 3). The only significant morphometric parameter was annual water level change ($r = 0.49$). However, in the final model other variables were more closely related to LMB_{350} MeHg.

The final model indicated MeHg in water to be an important factor related to LMB_{350} MeHg, which was the only direct proxy for methylation evaluated. The correlation to LMB_{350} MeHg may point towards enhanced exposure of largemouth bass to MeHg in the water column under certain environmental conditions. A recent mercury food web model for river systems indicated that largemouth bass tend to forage more during the summer, and exhibit higher activity and metabolism rates (Greenfield and Lent, 2008). As a result, largemouth bass may have higher MeHg exposure during the summer due to feeding more at the surface, where their piscivorous prey reside (Moyle 2002). Therefore, movement and behavior of largemouth bass during the summer may partly explain the correlations observed with MeHg in water at some lakes (particularly, Lake Pillsbury and Lake Irvine). MeHg water data collected in the Sacramento-San Joaquin Delta have also indicated strong relationships ($R^2 = 0.91$) with 350 mm largemouth bass (Wood *et al.* 2006, Davis *et al.* 2008). Further discussion of the water column MeHg data and the relationship to MeHg bioaccumulation is reported in a companion paper by Negrey and Stephenson (2010).

Finally, conductivity has been found to be associated with lower methylation rates in some aquatic environments and was indicated as an important factor in the statistical analysis. Many of the lakes with LMB_{350} MeHg < 0.3 μg/g exhibited conductivity values > 300 mS. Moreover, the lake with the highest LMB_{350} MeHg (Lake Pillsbury, 1.31 μg/g), had the lowest conductivity (< 1 mS). MeHg in fish tissue has often been found to have a negative correlation with conductivity, hardness, and alkalinity (e.g., Hanten Jr. *et al.* 1998, Wren *et al.* 1991, Sonesten 2004). Enhanced microbial production of MeHg has also been shown under low pH and hardness conditions (Xun *et al.* 1987). Therefore, it is plausible that the negative correlation of LMB_{350} MeHg with conductivity observed here relates to some underlying relationship to Hg methylation. A previous study of boreal lakes in Sweden also suggested that higher concentrations of ions such as Ca^{2+} and Mg^{2+} were related to lower MeHg in the food web (Sonesten, 2004). High Ca^{2+} levels have also been suggested as a potential inhibitor of MeHg production and direct water-borne uptake by fish (Hanten Jr. 1998).

Limitations and Further Work

It should be acknowledged that the lack of clear relationships of some predictor variables in these analyses may be due to the limitations of some of the underlying datasets rather than a true absence of influence. Specifically, datasets on both mining and wetlands were inconsistent and limited. The National Wetlands Inventory (NWI) was used to display wetland area, but had many areas of missing or incomplete coverage. The wetland polygons often differed depending on the individual cartographers who performed the digitizing, and some regions completely lacked NWI coverage. The regional variability in NWI likely inhibited the ability to detect correlations to LMB_{350}

MeHg. Similarly, the MRDS data used to enumerate gold and mercury mines, lacked consistent information across the state. Due to limitations in the mining dataset, it was not possible to account for mining quantities or Hg loadings to the environment. The mine layer appeared useful for distinguishing broad areas of intense mining from water bodies without mining influence, but did not correlate well with LMB_{350} MeHg at a regional or watershed-specific scale.

Another data gap was the lack of atmospheric deposition information for the watersheds of interest. Atmospheric deposition is considered to be a principal source of inorganic mercury to most aquatic systems in the United States. However, few atmospheric deposition datasets have been collected in California, and only a handful of monitoring stations have gathered long-term data (e.g., San Jose, CA; SFEI 2001). It is thought that wet and dry deposition of Hg is relatively low and homogenous across California (e.g., NADP 2004), but attempts to determine relative contributions to the food web have been limited by a lack of data. Future attempts to relate lake and watershed attributes with MeHg in the food web should consider prioritizing work around the factors found to be significant in this study (particularly, forested area, THg in soil and sediments, and MeHg in water). However, the influence of some watershed attributes that could not be examined fully here, such as wetlands and atmospheric deposition, also warrant further investigation.

Finally, one major caveat to the analyses presented here that needs acknowledgment, is the limited sample size and distribution of lakes used in the statistical model. The lakes used for the statistical analysis presented in this report were based on Regional Board priorities and were not initially selected with the goal of developing a statistical model. A more robust approach to the study design would have been to adequately represent the range of land use, lake morphometry, and Hg methylation conditions across the state. Therefore, the statistical model described here may only be appropriate for the population of lakes included in the analysis, and should not be extrapolated outside this sample space.

Conclusion

Methylmercury concentrations in largemouth bass from 17 lakes across California varied from 0.06 – 1.3 µg/g, with highest concentrations in the northern portion of the state. Lake variables that were related to MeHg concentrations in 350 mm largemouth bass were THg in sediment and soils, forested area, specific conductivity, and MeHg in surface water. The strong influence of land use, geology, and conductivity on fish MeHg concentrations warrants further investigation. The results of this analysis are consistent with several studies that have suggested that broad land use characteristics can potentially influence MeHg bioaccumulation in lakes and reservoirs. Furthermore, the transport of Hg from source to watershed may be a critical step leading to high MeHg levels in fish. However, the limited sample size and spatial distribution of lakes evaluated here preclude extending our model beyond the population of lakes included in this analysis.

References

Alpers, C. N., and M. P. Hunerlach. 2000. Mercury contamination from historic gold mining in California. Fact Sheet FS-061-00, USGS.

Carrascal, Partial least squares regression as an alternative to current regression methods used in ecology, Oikos 118: 681-690

Chumchal *et al.* 2008 Habitat-specific differences in mercury concentration in a top predator from a shallow lake, Transactions of the American Fisheries Society 137:195–208

Davis, J.A., Greenfield, B.K., Ichikawa, G., Stephenson, M., 2008a. Mercury in sport fish from the Sacramento–San Joaquin delta region, California. Science of the Total Environment 391, 66–75.

Davis, J.A., Melwani, A.R., Bezalel, S.N., Ichikawa, G., Bonnema, A., Lamerdin, C., Heim, W.A., Crane, D., Stephenson, M., 2009. The first year of a two-year screening survey of contaminants in sport fish from California lakes and reservoirs. San Francisco Estuary Institute, Oakland, CA.

Davis, J.A., Melwani, A.R., Bezalel, S.N., Ichikawa, G., Bonnema, A., Lamerdin, C., Heim, W.A., Crane, D., Stephenson, M., 2010. Two-year screening survey of contaminants in sport fish from California lakes and reservoirs. San Francisco Estuary Institute, Oakland, CA.

Domagalski, J. 1998. Occurrence and transport of total mercury and methyl mercury in the Sacramento River Basin, California. Journal of Geochemical Exploration 64:277-291.

Eagles-Smith, C.A, Ackerman, J.T., De La Cruz, S.E.W., and Takekawa, J.Y., 2009. Mercury bioaccumulation and risk to three waterbird foraging guilds is influenced by foraging ecology and breeding stage, Environmental Pollution, vol. 157(7): 1993-2002

Eriksson, L., Hermens, J. L. M., Johansson, E., Verhaar, H. J. M. and Wold, S. 1995. Multivariate analysis of aquatic toxicity data with PLS', Aquat. Sci. 57, 217–241

Fairey, R., K. Taberski, S. Lamerdin, E. Johnson, R. P. Clark, J. W. Downing, J. Newman, and M. Petreas. 1997. Organochlorines and other environmental contaminants in muscle tissues of sport fish collected from San Francisco Bay. Marine Pollution Bulletin 34:1058-1071.

Fitzgerald, W.F. and Clarkson, T.W. 1991. Mercury and monomethylmercury: present and future concerns, Environ Health Perspect, vol. 96: 159–166

Gilmour, C. C., and E. A. Henry. 1991. Mercury methylation in aquatic systems affected by acid deposition. Environmental Pollution 71:131-170.

Gilmour, C. C., Henry, E. A., and Mitchell, R. 1992. Sulfate stimulation of mercury methylation in freshwater sediments. Environ. Sci. Technol., 26, 2281-2287

Greenfield, B.K. and Lent, M.A. 2008. Modeling mercury bioaccumulation in largemouth bass in the Sacramento-San Joaquin River Delta and tributaries, SFEI Technical Report, San Francisco Estuary Institute, Oakland, CA

Hammershcmidt, C.R., and Fitzgerald, W.F. 2006. Methylmercury in freshwater fish linked to atmospheric mercury deposition, Environ. Sci. Technol., vol. 40(24): 7764–7770

Hanten, Jr, R.P.,Neumann, R.M., Ward, S.M., Carley, R.J., Perkins, C.R., and Pirrier, R. 1998. Relationships between concentrations of mercury in largemouth bass and physical and chemical characteristics of Connecticut lakes, Transactions of the American Fisheries Society 127:807–818

Hurley, J. P., J. M. Benoit, C. L. Babiarz, M. M. Shafer, A. W. Andren, J. R. Sullivan, R. Hammond, and D. A. Webb. 1995. Influences of watershed characteristics on mercury levels in Wisconsin Rivers. Environmental Science and Technology 29:1867-1875.

Johnson, T.A., R.A Bodaly, R.A., and Mathias, J.A. 1991; Predicting fish mercury levels from physical characteristics of boreal reservoirs; Canadian Journal of Fisheries and Aquatic Science 48:1468-1475

Krabbenhoft, D. P., J. G. Wiener, W. G. Brumbaugh, M. L. Olson, J. F. DeWild, and T. J. Sabin. 1999. A national pilot study of mercury contamination of aquatic ecosystems along multiple gradients. U.S. Geological Survey Toxic Substances Hydrology Program Proceedings of Technical Meeting 2:147-160.

Littell, R.C., Milliken, G.A., Stroup,W.W., Wolfinger, R.D., 1996. SAS System for Mixed Models. SAS Institute, Inc., Cary, NC.

Melwani, A.R., Bezalel, S.N., Grenier, J.L., Hunt, J.A., Robinson, A.H., and Davis, J.A., 2007. The relationship between landscape features and sport fish mercury in the Sacramento-San Joaquin Delta watershed, SFEI Contribution No. 534, San Francisco Estuary Institute, Oakland, CA.

Melwani, A.R., Bezalel, S.N., Hunt, J.A., Grenier, J.L., and Davis, J.A. 2009. Spatial trends and impairment assessment of mercury in fish from the Sacramento-San Joaquin Delta watershed, Environmental Pollution, vol. 157(11): 3137-49

Moyle, P. B. 2002. Inland Fishes of California. University of California Press, Berkeley, CA.

Negrey, J. and Stephenson, M. 2010. Mercury in water, sediment, and fish in California Lakes, Draft Report

Ramlal, P. S., Kelly, C. A., Rudd, J. W. M. and Furutani, A. 1993. Sites of methyl mercury production in remote Canadian Shield lakes', Can. J. Fish. Aquat. Sci. 50, 972–979.

San Francisco Estuary Institute [SFEI]. 2001. San Francisco Bay Atmospheric Deposition Pilot Study Part 1: Mercury. San Francisco Estuary Institute, Oakland, CA.

Sonesten, L. 2004. Catchment area composition and water chemistry heavily affects mercury levels in perch (*Perca fluviatilis* L.) in circumneautral lakes, Water, Air, and Soil Pollution 144: 117–139, 2003

St. Louis, V. L., Rudd, J. W. M., Kelly, C. A., Beaty, K. G., Bloom, N. S. and Flett, R. J. 1994. Importance of wetlands as sources of methyl mercury to boreal forest ecosystems, Can. J. Fish. Aquat. Sci. 51, 1065–1076

St. Louis, V. L., Rudd, J. W. M., Kelly, C. A., Beaty, K. G., Flett, R. J. and Roulet, N. T. 1996. Production and loss of methylmercury and loss of total mercury from boreal forest catchments containing different types of wetlands, Environ. Sci. Technol. 30, 2719–2729

United States Environmental Protection Agency [USEPA], 1997, Mercury Study Report to Congress, United States Environmental Protection Agency, EPA-452-97-003 –010, Office of Air and Radiation, 1980 pp.

United States Geological Survey [USGS]. 2000. Mercury contamination from historic gold mining in California. Fact Sheet FS-061-00. U.S. Geological Survey, Sacramento, CA.

Wiener, J.G., Krabbenhoft, D.P., Heinz, G.H., and Scheuhammer, A.M., 2003, Ecotoxicology of mercury, chap. 16 of Hoffman, D.J., Rattner, B.A., Burton, G.A., Jr., and Cairns, J., Jr., eds., Handbook of ecotoxicology (2d ed.): Boca Raton, Fla., Lewis Publishers, p. 409–463.

Wiener, J. G., Knights, B.C., Sandheinrich, M.B., Jeremiason, J.D., Brigham, M.E., Engstrom, D.R., Woodruff, L.G., Cannon, W.F., and Balogh, S.J. 2006. Mercury in soils, lakes, and fish in Voyageurs National Park (Minnesota): Importance of atmospheric deposition and ecosystem factors. Environmental Science & Technology 40: 6261-6268.

Wren, C. D., W. A. Scheider, D. L. Wales, B. W. Muncaster, and I. M. Gray. 1991. Relation between mercury concentrations in walleye Stizostedion vitreum vitreum and northern pike Esox lucius in Ontario lakes and influence of environmental factors. Canadian Journal of Fisheries and Aquatic Sciences 48:132–139.

Xun, L., N. E. R. Campbell, and J. W. M. Rudd. 1987. Measurements of specific rates of net methyl mercury production in the water column and surface sediments of acidified and circumneutral lakes. Canadian Journal of Fisheries and Aquatic Sciences 44:750–757.

Wood ML, Foe C, and Cooke J. 2006. Sacramento–San Joaquin Delta Estuary TMDL for Methylmercury: Draft Report for Scientific Peer Review. Regional Water Quality Control Board, Central Valley Region. Rancho Cordova, CA, USA

Zillioux, E. J., D. B. Porcella, and J. M. Benoit. 1993. Mercury cycling and effects in fresh-water wetland ecosystems. Environmental Toxicology and Chemistry 12:2245-2264.

Figure 1. Map of 17 sub-watersheds used in this study. Blue boundaries delineate the upstream area for each lake. Dot colors correspond to 350 mm lake-specific MeHg concentration ranges for largemouth bass.

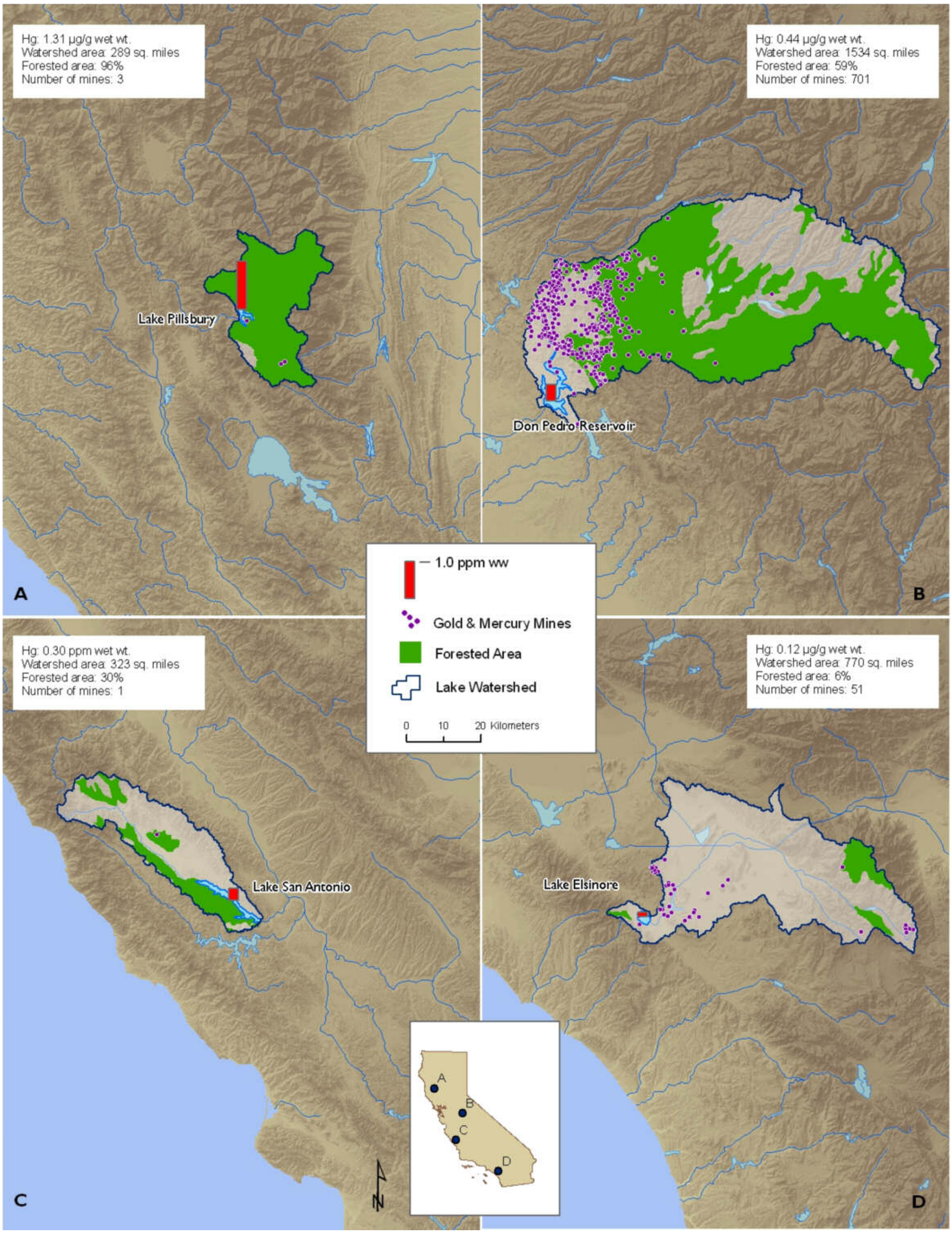

Figure 2. Example of land use attributes for four lakes used in the statistical analysis.

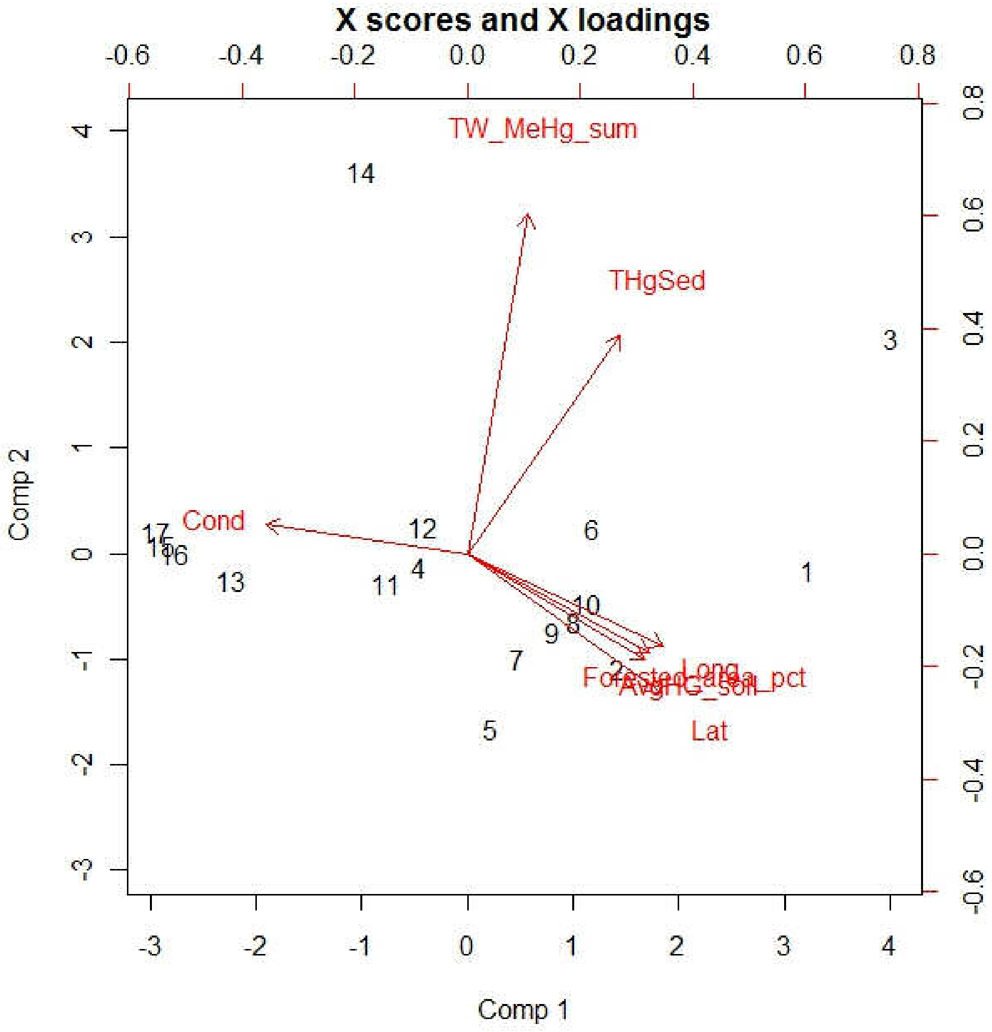

Figure 3. Biplot of latent x-scores and loadings from the final model (Model 4). Numbers correspond to lakes and reservoirs listed in Table 1. Length of each vector indicates the relative strength in the model. For example, a strong, negative relationship between conductivity and largemouth bass MeHg concentrations is indicated at lakes 15, 16, and 17.

Table 1. MeHg concentrations in 350 mm largemouth bass from 17 lakes in California

Lake Number	Regional Board	Lake Name	350 mm Largemouth bass MeHg (μg/g)
1	1	Lake Sonoma	0.68
2	1	Lake Mendocino	0.54
3	1	Lake Pillsbury	1.31
4	3	Lake San Antonio	0.30
5	5	Thermalito Afterbay	0.21
6	5	Folsom Lake	0.47
7	5	Lake Natomas	0.54
8	5	Don Pedro Reservoir	0.44
9	5	Lake McClure	0.77
10	5	Lake McSwain	0.54
11	5	San Luis Reservoir	0.56
12	5	O'Neill Forebay	0.23
13	8	Big Bear Lake	0.18
14	8	Irvine Lake	0.48
15	8	Perris Reservoir	0.10
16	8	Lake Hemet	0.06
17	8	Lake Elsinore	0.12

Table 2. Description of the dependent and independent variables evaluated in the statistical model.

Variable	Description	Unit	Mean	Min	Max
Largemouth bass MeHg	Largemouth bass MeHg concentration at 350mm	µg/g	0.44	0.06	1.31
Chlorophyll a	Chlorophyll a concentration of lake surface water (< 2m)	µg/L	6.95	0.92	50.49
Conductivity	Conductivity of lake surface water	mS	439	0.1	2933
DO	Dissolved oxygen content of lake surface water (< 6m)	mg/L	8.45	5.49	10.57
DOC	Dissolved organic carbon content of lake surface water (< 2m)	mg/L	25.19	2.05	154.0
Elevation	Lake elevation	Ft	1298	129	6760
Forested area	Forested coverage in the lake catchment area	%	0.5	0	1.0
Lake age	Age of lake relative to 2009	Years	57	27	121
Latitude	Latitude Coordinates	DMS	36.9	33.7	39.5
Longitude	Longitude Coordinates	DMS	120.2	116.7	123.2
Max annual depth change	Maximum annual water level fluctuation of lake	Ft	39	3	157
Max depth	Maximum depth of lake	Ft	155	17	530
Mines	Number of gold and mercury mines in catchment area	Count	510	0	2539
pH	pH of lake surface water (< 6m)	pH units	7.8	5.3	8.9
Storage capacity	Maximum volume of water storage of lake	acre-feet	434000	8000	2039000
Sulfate	Sulfate concentration in lake surface water (< 2m)	mg/L	37.42	3.45	181.33
Surface area	Surface area of lake	square-miles	6.8	0.5	20
Temperature	Temperature of lake surface water (< 6m)	centigrade	21.8	14.9	25.1
TOC	Total organic carbon content of lake sediment	%	8.11	2.17	15.33
Total sediment Hg	Total mercury concentration of lake sediment	µg/g	0.09	0.01	0.21
Total soil Hg	Total mercury content of soil in catchment area	µg/g	0.05	0.00	0.10
Total water Hg	Total mercury concentration of lake surface water (< 2m)	ng/L	0.74	0.25	1.54
Water methyl Hg	Methylmercury concentration of lake surface water (< 2m)	ng/L	0.05	0.01	0.18
Watershed area	Total area of lake catchment	square-miles	767	10	3639
Wetland area	Wetland coverage in the lake catchment area	%	0.70	0.00	3.44

Table 3. Correlation matrix of 350 mm largemouth bass MeHg concentrations with each predictor variable and of predictors to each other. Statistic calculated is the Pearson (r) correlation coefficient. Bold values were statistically significant ($p < 0.05$) and boxed values have Pearson $r \geq 0.8$ or $\leq - 0.8$ (at 1 significant digit).

	Hg_Lake_Log1	Latitude	Longitude	TOC	THgSed	TW_Chla	TW_SO4	TW_DOC	TW_MeHg	TW_THg	Watershed_area	Mines	Wetland_area	Wetland_pct	AvgHG_soil	MaxHG_soil	Forested_area_pct	Storage	Max.Depth..ft.	SArea	WA.SA	Elevation	Age	Max_DepthChange_abs	Temp	O2	pH	Cond
Hg_Lake_Log1	1.00																											
Latitude	**0.66**	1.00																										
Longitude	**0.69**	**0.93**	1.00																									
TOC	-0.30	**-0.62**	**-0.61**	1.00																								
THgSed	**0.69**	0.29	0.39	0.09	1.00																							
TW_Chla	**-0.51**	**-0.77**	**-0.62**	0.41	-0.37	1.00																						
TW_SO4	**-0.50**	**-0.80**	**-0.59**	0.32	-0.18	**0.85**	1.00																					
TW_DOC	-0.41	**-0.78**	**-0.58**	0.36	-0.13	**0.86**	**0.97**	1.00																				
TW_MeHg	0.47	-0.04	0.08	-0.09	**0.62**	0.01	0.30	0.36	1.00																			
TW_THg	0.32	0.05	0.26	-0.15	0.45	0.21	0.31	0.36	**0.50**	1.00																		
Watershed_area	0.24	**0.56**	0.38	-0.46	-0.09	-0.29	**-0.56**	**-0.58**	-0.15	0.02	1.00																	
Mines	0.06	0.31	0.02	-0.20	-0.18	-0.31	**-0.60**	**-0.61**	-0.29	-0.27	**0.85**	1.00																
Wetland_area	-0.03	0.42	0.19	-0.46	-0.30	-0.32	**-0.55**	**-0.63**	-0.36	-0.31	**0.87**	**0.86**	1.00															
Wetland_pct	-0.24	0.19	-0.01	-0.27	-0.43	-0.20	-0.40	**-0.53**	-0.45	-0.39	**0.67**	**0.69**	**0.89**	1.00														
AvgHG_soil	**0.65**	**0.72**	**0.79**	-0.21	**0.49**	-0.44	**-0.55**	**-0.54**	-0.11	0.27	0.34	0.05	0.14	0.00	1.00													
MaxHG_soil	0.42	**0.67**	**0.56**	-0.45	0.09	-0.45	**-0.71**	**-0.74**	-0.24	-0.03	**0.80**	**0.69**	**0.73**	**0.52**	**0.61**	1.00												
Forested_area_pct	**0.63**	**0.76**	**0.64**	-0.44	0.36	**-0.74**	**-0.81**	**-0.79**	-0.01	0.17	**0.58**	**0.51**	0.45	0.32	**0.56**	**0.64**	1.00											
Storage	0.29	0.30	0.35	0.01	0.23	-0.03	-0.19	-0.22	-0.13	-0.27	0.07	-0.04	0.08	0.00	0.45	0.26	0.09	1.00										
Max.Depth..ft.	0.32	0.22	0.23	0.18	0.28	-0.23	-0.39	-0.42	-0.21	-0.40	-0.01	0.04	0.03	0.06	0.44	0.33	0.22	**0.76**	1.00									
SArea	0.10	0.25	0.25	-0.03	-0.01	0.11	-0.10	-0.14	-0.19	-0.31	0.25	0.10	0.25	0.18	0.29	0.24	-0.01	**0.92**	**0.54**	1.00								
WA.SA	0.15	0.34	0.17	-0.37	-0.09	-0.33	-0.47	-0.46	-0.03	0.18	**0.77**	**0.75**	**0.66**	**0.52**	0.13	**0.61**	**0.53**	**-0.52**	-0.33	-0.42	1.00							
Elevation	-0.20	**-0.62**	**-0.61**	**0.69**	-0.02	0.37	0.34	0.38	0.05	-0.12	**-0.53**	-0.30	**-0.49**	-0.20	-0.40	**-0.60**	-0.24	-0.02	0.16	-0.05	-0.45	1.00						
Age	-0.40	**-0.63**	**-0.67**	0.40	-0.33	**0.49**	**0.49**	**0.51**	0.18	0.08	-0.10	0.04	-0.21	-0.04	**-0.69**	**-0.50**	-0.32	**-0.52**	-0.40	-0.33	0.12	**0.56**	1.00					
Max_DepthChange_abs	**0.51**	0.36	0.43	0.02	**0.42**	-0.18	-0.31	-0.27	0.14	-0.13	0.09	-0.03	0.00	-0.15	**0.53**	0.39	0.18	**0.70**	**0.76**	**0.51**	-0.22	-0.15	-0.47	1.00				
Temp	0.06	-0.06	0.08	-0.11	0.16	0.18	0.26	0.27	0.29	0.05	-0.18	-0.35	-0.21	-0.27	0.02	-0.21	-0.10	**0.52**	0.28	**0.48**	**-0.51**	0.18	-0.06	0.44	1.00			
O2	0.21	0.24	0.20	0.08	0.18	-0.41	-0.42	-0.40	-0.16	-0.40	-0.21	-0.04	-0.02	0.00	0.16	0.18	0.06	0.14	0.37	-0.04	-0.12	-0.11	**-0.51**	0.26	**-0.48**	1.00		
pH	-0.29	-0.34	-0.15	0.29	0.06	0.44	**0.57**	**0.56**	0.20	0.18	**-0.48**	**-0.65**	-0.46	-0.27	-0.17	**-0.65**	-0.40	0.24	-0.06	0.30	**-0.67**	0.45	0.15	0.00	**0.61**	-0.32	1.00	
Cond	**-0.79**	**-0.78**	**-0.70**	0.36	**-0.54**	**0.79**	**0.81**	**0.74**	-0.15	-0.12	-0.38	-0.27	-0.23	-0.10	**-0.63**	**-0.50**	**-0.86**	-0.15	-0.26	-0.01	-0.34	0.16	0.45	-0.28	0.07	-0.29	0.29	1.00

Table 4. Summary of Partial Least Squares (PLS) regression models

Model #	Minimum Number of Components	Number of Predictors Evaluated	Variance in Predictors Explained By Model (%)*	Variance in *LMB Hg* Explained By Model (%)*
1	2	23	51%	83%
2	1	11	76%	82%
3	1	10	81%	81%
4	1	7	82%	81%

* Determined for two components for comparison among models

Table 5. Regression coefficients and variance in projection (VIP) for Model 1 (the full model). Horizontal lines separate predictors based on relative significance in VIP (i.e. < 0.08, 0.8 – 1.0, > 1.0)

Predictor	Regression Coefficients for Component 2	VIP
Conductivity	-0.014	1.28
THg Sediment	0.015	1.19
MeHg Water	0.016	1.13
Longitude	0.009	1.11
Latitude	0.008	1.08
THg Soil	0.009	1.04
Forested area	0.009	1.01
Sulfate	-0.004	0.88
Chlorophyll a	-0.004	0.88
DOC	-0.001	0.83
Annual Depth Change	0.009	0.82
Wetland area	-0.011	0.76
Age	-0.002	0.75
THg Water	0.010	0.71
Elevation	0.002	0.55
Max Depth	0.004	0.52
TOC	-0.003	0.52
Storage	0.004	0.47
pH	-0.004	0.46
DO	0.002	0.37
Mines	-0.003	0.33
Watershed area: surface area	0.0005	0.30
Temp	0.002	0.14

Table 6. Regression coefficients and variance in projection (VIP) for Model 4 (the simplest PLS Model). Component 1 explained 75% of the variation in LMB MeHg and Component 2 explained the remaining 6%. All predictors were relatively significant indicated by VIP > 1.0.

Predictor	Regression Coefficient for Component 1	Regression Coefficient for Component 2	VIP
Conductivity	-0.017	-0.019	1.69
THg Sediment	0.015	0.021	1.50
Longitude	0.015	0.012	1.49
Latitude	0.014	0.010	1.45
THg Soil	0.014	0.013	1.39
Forested area	0.013	0.010	1.37
MeHg water	0.010	0.025	1.31

Table 7. Observed and predicted mean MeHg concentrations in 350 mm largemouth bass. Predicted means were calculated using regression parameters estimated from the final model. Lakes are sorted by Bias (Predicted – Observed / Observed). Direction of Bias identifies if the predicted mean value was is higher (+), lower (-), or equal (=) to the observed mean concentrations.

Lake Number	Lake Name	Observed µg/g	Predicted µg/g	Bias	Direction of Bias
15	Perris Reservoir	0.10	0.10	0.00	=
13	Big Bear Lake	0.18	0.17	0.06	-
7	Lake Natomas	0.54	0.47	0.06	-
10	Lake McSwain	0.53	0.56	0.11	+
2	Lake Mendocino	0.54	0.60	0.13	+
17	Lake Elsinore	0.12	0.10	0.17	-
3	Lake Pillsbury	1.31	1.00	0.20	-
4	Lake San Antonio	0.30	0.36	0.21	+
6	Folsom Lake	0.47	0.57	0.24	+
9	Lake McClure	0.77	0.52	0.25	-
8	Don Pedro Reservoir	0.44	0.55	0.28	+
1	Lake Sonoma	0.68	0.87	0.32	+
14	Irvine Lake	0.48	0.30	0.38	-
11	San Luis Reservoir	0.56	0.33	0.41	-
12	O'Neill Forebay	0.23	0.37	0.61	+
16	Lake Hemet	0.06	0.11	0.83	+
5	Thermalito Afterbay	0.21	0.44	1.10	+

Table 8. Land use variables for 21 lake catchments. These data were used for a qualitative assessment of the relationship between land use and 350 mm largemouth bass MeHg concentrations.

Station Name	Regional Board	350 mm Largemouth bass MeHg (μg/g)	Mines	THg-soil (μg/g)	Watershed Area (sq. miles)	Forested (%)	Wetland (%)
Almaden Lake	2	2.15	47	0.2	53.0	0	0.4
Calero Reservoir	2	1.05	0		6.9	0	0.7
Soulejoule Lake	2	0.94	1	0.0	18.8	0	0.8
Upper San Leandro Reservoir	2	1.01	0		30.6	0	1.0
Lower Crystal Springs Res.	2	0.85	0		15.0	0	1.5
Uvas Reservoir	3	0.91	0	0.2	30.5	0	0.4
Chesbro Reservoir	3	1.04	3		19.3	0	0.5
Echo Lake - Reg 4	4	0.08	0		1.2	0	0.1
Westlake Lake	4	0.09	0	0.0	28.1	0	0.4
Toluca Lake	4	0.00	30	0.4	422.7	5	0.0
Crystal Lake	4	0.95	0		1.0	95	0.5
New Melones Lake	5	1.12	823	0.0	904.2	78	1.2
Eastman Lake_BOG	5	1.04	59	0.0	235.0	80	0.2
Bass Lake	5	0.09	2	0.0	49.6	97	0.9
Little Rock Reservoir	6	0.92	2		63.8	21	0.1
Ferguson Lake_BOG	7	0.09	1	0.1	19.6	0	3.5
Prado Lake	8	0.07	0		27.1	0	0.1
Lake Evans	8	0.03	58	0.0	760.9	24	0.1
Lake Poway	9	0.05	0		2.4	0	0.2
Lake Wohlford	9	0.05	0		8.2	0	1.4
Dixon Lake	9	0.06	1		4.0	0	1.6

Appendix Table 1a. Sediment and water quality data for 17 California lakes and reservoirs.

Lake Number	Station Name	THg-sed (µg/g)	TOC (%)	Chlorophyll a (µg/L)	Sulphate (mg/L)	DOC (mg/L)	MeHg-water (ng/L)	THg-water (ng/L)	Temp (deg. C)	O2 (mg/L)	pH	Conductivity (mS)
1	Lake Sonoma	0.21	7.1	1.5	7.6	5.7	0.03	1.54	23.1	8.6	8.4	0.1
2	Lake Mendocino	0.07	5.4	1.1	8.8	6.8	0.03	0.80	22.6	8.7	8.3	14.7
3	Lake Pillsbury	0.20	5.4	0.9	6.3	8.4	0.15	1.25	14.9	10.1	6.2	34.0
4	Lake San Antonio	0.07	4.7	13.7	65.1	25.9	0.05	1.16	24.0	8.2	8.0	37.5
5	Thermalito Afterbay	0.01	2.2	1.5	7.0	3.2	0.02	0.51	16.8	9.0	5.3	51.0
6	Folsom Lake	0.13	7.5	1.6	3.5	2.9	0.07	0.38	23.5	7.8	6.4	52.0
7	Lake Natomas	0.06	2.6	1.0	3.5	3.1	0.03	0.72	24.3	8.8	7.5	58.5
8	Don Pedro Reservoir	0.13	9.8	1.6	3.6	2.1	0.01	0.28	25.1	7.6	8.2	63.1
9	Lake McClure	0.08	6.2	2.5	4.5	2.7	0.03	0.32	20.9	7.8	8.1	84.5
10	Lake McSwain	0.12	12.2	2.2	3.6	3.2	0.03	0.93	23.8	8.1	8.6	385.1
11	San Luis Reservoir	0.07	9.8	12.2	35.0	28.7	0.03	0.44	17.8	8.4	8.1	407.0
12	O'Neill Forebay	0.11	7.9	2.3	36.5	16.6	0.05	0.61	20.2	8.8	8.2	414.6
13	Big Bear Lake	0.07	15.3	6.5	33.5	17.5	0.01	0.53	20.3	8.5	7.9	579.0
14	Irvine Lake	0.17	7.9	7.8	181.3	98.7	0.18	1.25	20.5	10.6	8.2	624.0
15	Perris Reservoir	0.05	8.8	6.7	39.5	34.7	0.02	0.25	24.5	9.6	8.4	625.4
16	Lake Hemet	0.04	14.2	4.6	21.9	14.2	0.02	0.25	23.9	7.5	8.1	1104.4
17	Lake Elsinore	0.03	10.9	50.5	175.0	154.0	0.04	1.45	24.3	5.5	8.9	2933.4

Appendix Table 1b. Land use attributes for 17 California lakes and reservoirs

Lake Number	Station Name	Watershed Area (sq. miles)	Mines	Wetland (%)	THg-soil (µg/g)	Forested (%)
1	Lake Sonoma	130	2	0.0	0.1	100
2	Lake Mendocino	105	0	0.0	0.06	79
3	Lake Pillsbury	289	3	0.0	0.06	96
4	Lake San Antonio	323	1	1.2	0.05	30
5	Thermalito Afterbay	3639	1009	3.4	0.03	78
6	Folsom Lake	1863	2510	0.7	0.03	76
7	Lake Natomas	1904	2539	0.7	0.03	75
8	Don Pedro Reservoir	1535	701	1.6	0.07	59
9	Lake McClure	1038	892	1.1	0.07	76
10	Lake McSwain	1063	904	1.1	0.07	74
11	San Luis Reservoir	82	0	0.0	0.05	0
12	O'Neill Forebay	102	0	0.1	0.05	0
13	Big Bear Lake	73	46	0.7		41
14	Irvine Lake	63	2	0.0		15
15	Perris Reservoir	10	0	0.0		0
16	Lake Hemet	66	10	1.0	0	18
17	Lake Elsinore	771	51	0.2	0.02	6

Appendix Table 1c. Lake morphometry data for 17 California lakes and reservoirs

Lake Number	Station Name	Storage Capacity (acre-feet)	Max Depth (ft)	Surface Area (acres)	Watershed Area: Surface Area	Elevation (ft)	Age (yrs since 2009)	Annual Water Level Flux (ft)
1	Lake Sonoma	381	223	4.2	31	452	27	50
2	Lake Mendocino	122.4	133	3	35	720	51	30
3	Lake Pillsbury	80.5	60	3.5	82	1807	53	18
4	Lake San Antonio	335	180	8.9	36	780	44	20
5	Thermalito Afterbay	57.04	20	6.7	542	139	41	3
6	Folsom Lake	977	261	17.9	104	468	54	157
7	Lake Natomas	8.76	54	0.8	2257	129	54	3
8	Don Pedro Reservoir	2030	530	20.3	76	830	38	40
9	Lake McClure	1024.6	465	11.1	94	867	42	115
10	Lake McSwain	9.73	56	0.5	2208	399	42	15
11	San Luis Reservoir	2039	270	19.8	4	543	40	120
12	O'Neill Forebay	56.4	40	4.2	24	225	42	7
13	Big Bear Lake	73.37	72	4.6	16	6760	97	
14	Irvine Lake	28	47	1.1	58	794	78	16
15	Perris Reservoir	125	80	3.4	3	1567	36	10
16	Lake Hemet	8.1	135	0.7	101	4339	114	12
17	Lake Elsinore	30	17	5.2	149	1240	121	4

Appendix 2a. Regression coefficients and variance in projection (VIP) for Model 2

Predictor	Regression Coefficients for Component 2	VIP
Conductivity	-0.016	1.40
THg Sediment	0.020	1.33
MeHg Water	0.023	1.34
Longitude	0.012	1.22
Latitude	0.008	1.20
THg Soil	0.012	1.15
Forested area	0.009	1.13
Sulphate	-0.002	1.02
Chlorophyll a	-0.002	1.02
DOC	0.003	1.00
Annual Depth Change	0.012	0.93

Appendix 2b. Regression coefficients and variance in projection (VIP) for Model 3

Predictor	Regression Coefficients for Component 2	VIP
Conductivity	-0.016	1.44
THg Sediment	0.020	1.40
MeHg Water	0.025	1.40
Longitude	0.013	1.25
Latitude	0.009	1.22
THg Soil	0.014	1.18
Forested area	0.009	1.16
Chlorophyll a	-0.002	1.06
Sulphate	-0.002	1.04
DOC	0.003	1.02