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Predicting coastal eutrophication from land-use: an empirical approach to small non-stratified estuaries

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eutrophication
Comparative system empirical approach

ABSTRACT: Few models exist to directly and quantitatively predict the effect of land-use on coastal water quality even though it is recognized that land-use is a major determinant of coastal water quality. Such models are needed because (1) land-use is a major source of nutrients transported to estuaries, (2) land-use integrates multiple factors that may determine the mean algal biomass and (3) land-use is more easily managed than single nutrients when nutrient sources are nonpoint. Regression models accurately predict lake eutrophication as a function of land-use. Similar models do not exist for estuaries. A data set was compiled for 15 estuaries in Prince Edward Island (PEI), Canada, that includes phytoplankton biomass as chlorophyll *a* (chl), total phosphorus (TP), total nitrogen (TN), estuary morphometry and land-use characteristics. A regression model predicting chl as a function of estuary volume and area of agriculture was developed. This model accounts for 68% of the variance in chl, a level similar to that of models based on TN ($r^2 = 0.72$) or total phosphorus ($r^2 = 0.66$). The estuary models based on land-use and total nutrients demonstrate low yields of chl when compared to analogous lake models; this low yield is likely attributable to high levels of herbivory by suspension feeding mussels. Despite these low yields, the pattern between chl and land-use is sufficiently accurate such that environmental managers can predict the effects of changing land-use on estuary water quality in PEI with a known level of error.

Chl-a
TP
TN
morphology - V
z
Land use R+

KEY WORDS: Eutrophication · Estuaries · Land-use · Phosphorus · Nitrogen · Regression

INTRODUCTION

Coastal eutrophication is an environmental concern along the US Atlantic Seaboard (Bricker et al. 1995), the Baltic (Rosenberg et al. 1990) and a number of European coasts (cf. Vollenweider et al. 1992). Much of the research investigating this phenomenon has focused on nutrient loading to coastal systems (cf. Nixon 1981, de Jonge et al. 1994, Boynton et al. 1996), an approach that assumes phytoplankton biomass, usually measured as chlorophyll *a* (chl), is controlled by a single nutrient, frequently nitrogen (Hecky & Kilham 1988). However, this assumption must be questioned: chl is also influenced by other nutrients such as phosphorus (Brockmann et al. 1990, Krom et al. 1991) and silica (Turner & Rabalais 1994), the ratio of nutrients (Smith 1979, Prairie et al. 1989), the rate of nutrient turnover (Smith 1984) and turbidity (Fisher et al. 1988). Such multifactor control suggests that linear models based on single nutrients (e.g. Dillon & Rigler 1974) may not accurately predict chl in coastal systems. One alternative is simulation models that allow the inclusion of multiple compartments (cf. Stigebrandt & Wulff 1987, Linker et al. 1993). However, these models are site-specific, complex and expensive to develop and thus may not be widely used.

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Another alternative is to develop empirical regression models that utilize variables that integrate multiple factors. Such models retain the simplicity and generality of the single nutrient empirical models while addressing the limitations inherent in assuming that there is a single factor limiting chl. Land-use is one such integrating variable that reflects human disturbance in a catchment, thus combining the potential effects of, for example, nitrogen, phosphorus and sediment load on aquatic systems. With the increasing availability of geographic information systems (GIS), our ability to utilize spatial variables has improved and

integrated
VARIABLES

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land-use is more easily and accurately incorporated into models. Unfortunately, land-use is not traditionally used to predict chl directly. Instead, land-use is used to calculate a nutrient load (e.g. phosphorus) which is then used to predict phytoplankton biomass (Dillon & Rigler 1975, Field et al. 1996). This process reflects the assumption that chl is more closely related to a single limiting nutrient than to land-use and thus is better predicted by nutrients than by land-use. To test this assumption, Meeuwig & Peters (1996) compared the accuracy of empirical models based on land-use and models based on total phosphorus (TP) to predict chl in lakes. In the analysis, predictions derived from land-use were approximately 30% more accurate, suggesting that integrative variables such as land-use more effectively predict chl in lakes.

Chl:nutrient relations in estuaries are not well defined. In their review of phytoplankton and nutrients, Hecky & Kilham (1988) conclude that the evidence for general nitrogen limitation of estuary chl is weak compared to the evidence of general phosphorus limitation of lake chl. Evidence from the Chesapeake Bay also suggests that estuaries may be limited first by phosphorus and then by nitrogen over the course of the growing season (Malone et al. 1996). Thus, land-use models that integrate the effects of both nitrogen and phosphorus as well as turbidity may predict estuary chl more accurately than models based on either total nitrogen (TN) or TP. To evaluate the effectiveness of land-use as a predictor of estuary chl, the following hypotheses were tested: (1) that chl:land-use models can be developed for estuaries, and (2) that models based on land-use predict chl with greater accuracy and less bias than models based on TN or TP. Finally, as there are no *a priori* reasons to assume that estuary phytoplankton responds differently to land-use disturbance than freshwater phytoplankton, I tested the hypothesis that chl:land-use relations for estuaries are similar to those for lakes.

METHODS

Data set. A data set was compiled for 15 estuaries in Prince Edward Island (PEI), Canada (Fig. 1) that includes water chemistry, coastal morphometry, and land-use variables (Table 1). The estuaries were chosen to represent a range of size and land-use characteristics. They were sampled 6 times between May and August, 1996 at 3 to 5 locations in each estuary. Chl was determined spectrophotometrically following Bergmann & Peters (1980). TP and TN were also determined spectrophotometrically, adapting the methods of Menzel & Corwin (1965) and Solórzano & Sharp (1980), respectively. Details describing the sampling and analyses can be found in Meeuwig et al. (1998). Growing season averages were calculated for chl, TP and TN in each estuary by averaging the values for the stations at a given sampling round and then averaging the values for the sampling round.

Coastal morphometry (mean depth, surface area and volume) was determined from bathymetric charts published by the Canadian Hydrographic Service (1980). Land-use information derived from a GIS was provided by the PEI Department of Agriculture. For each watershed, land-use was divided into area under forest, area under potato crops and 'other', which includes area under hay, grain, vegetables, etc. GIS was also used to estimate human population size. Electoral dis-

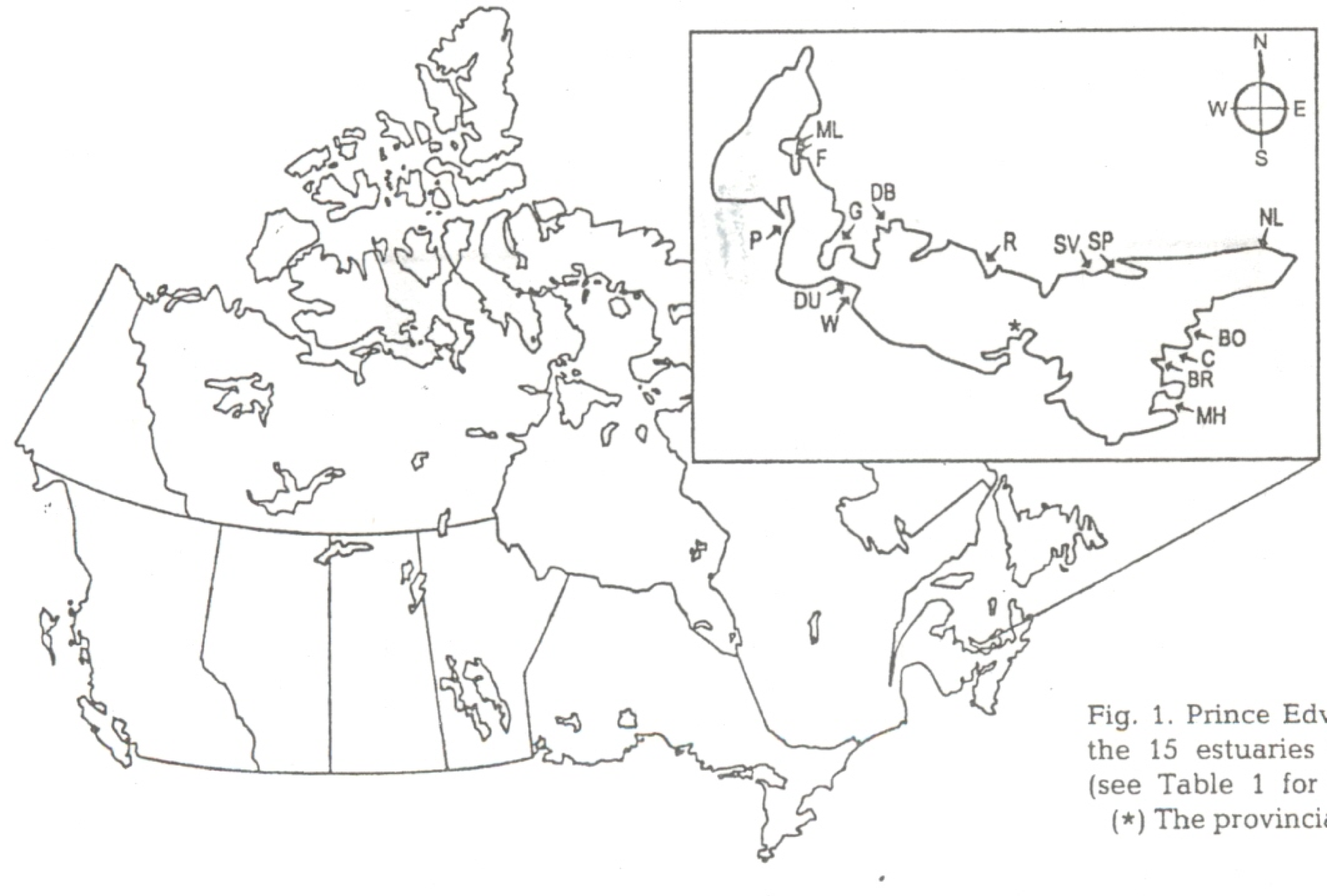

Fig. 1. Prince Edward Island, Canada, and the 15 estuaries included in the analysis (see Table 1 for full names of estuaries). (*) The provincial capital, Charlottetown

Table 1. Data for 15 estuaries (abbreviations in parentheses) from Prince Edward Island used in this analysis

Site	Chl (mg m^{-3})	Total phosphorus (mg m^{-3})	Total nitrogen (mg m^{-3})	Secchi depth (m)	Mean depth (m)	Volume ($\times 10^6$ m^3)	Residence time (d)	Salinity (‰)	Watershed area (km^2)	Agriculture (km^2)	Pop. density (km^2)	Mussel weight ($\times 10^7$ g dry wt)
Boughton (BO)	1.398	57.9	209	3.5	18.0	140	332	21.2	39.5	10.3	9.3	7.29
Brudenell (BE)	1.952	58.8	229	3.3	14.5	101	44	22.2	187.0	66.5	17.9	2.03
Cardigan (C)	1.548	55.0	241	4.1	17.6	225	255	21.0	80.5	21.4	9.3	6.75
Darnley Basin (DB)	1.369	45.8	213	2.4	8.7	33	129	20.5	25.1	20.4	33.4	–
Dunk (D)	5.915	85.1	481	1.2	3.1	13	9	16.4	202.4	140.4	15	–
Foxley (F)	2.029	76.0	264	2.1	7.4	39	135	18.3	37.5	3.0	8.9	–
Grand (G)	1.453	45.8	241	2.5	11.2	264	245	20.1	110.0	44.0	13.3	–
Murray River (M)	1.301	60.2	218	3.7	10.0	351	356	20.4	101.3	18.0	12.5	9.63
Mill River (ML)	3.846	89.6	367	2.0	7.7	30	33	18.4	117.9	56.3	14.3	–
North Lake (NL)	4.653	85.2	312	1.6	2.3	2.5	6	19.9	45.6	5.1	11.7	–
Percival (P)	1.097	61.6	266	1.3	5.0	60	166	17.9	46.4	2.4	9.5	–
Rustico (R)	1.988	55.4	274	2.3	7.1	53	83	19.8	67.4	46.6	15.1	2.70
St. Peters (SP)	1.713	68.6	298	2.9	10.3	140	61	18.4	292.9	75.9	8.3	6.39
Savage (SV)	1.571	60.1	277	1.6	5.8	19	74	20.5	25.6	4.7	10.2	–
Wilmot (W)	3.475	94.8	416	1.1	2.2	2.3	3	19.2	206.6	65.1	27.9	–
Mean	2.354	66.7	287	2.4	8.7	98	129	19.6	105.7	38.7	8.3	5.80
SD	1.437	15.7	79	1.0	5.0	106	118	1.5	81.3	38.1	33.4	2.90
Min	1.097	45.8	209	1.1	2.2	2.3	3	16.4	25.1	2.4	14.4	2.03
Max	5.915	94.8	481	4.1	18.0	351	356	22.2	292.9	140.4	7.2	9.63

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tricts were overlaid on the watersheds and the area of each electoral district in each watershed determined. The government of PEI provided the number of eligible voters in each electoral district, which is approximately 71 % of the total population (B. Thomson pers. comm.). The population in each watershed was then estimated as

$$\text{Population} = \Sigma(\text{Vden}_x \cdot \text{Area}_x)/0.71 \qquad (1)$$

where Vden_x is the voter density in electoral district x and Area_x is the area (m^2) of electoral district x in the watershed.

Statistical analyses. An estuary's response to land-use is a function of both the magnitude of the disturbance and the estuary's sensitivity to the disturbance. The estuary's sensitivity is determined by the morphometry of the estuary; for instance, small estuaries are more likely to demonstrate a response to a given disturbance than large estuaries, assuming other factors are constant. I therefore used multiple regression techniques to predict mean growing season chl as a linear function of (1) land-use (e.g. area or percent forest, population density) as the disturbance variable and (2) coastal morphometry (e.g. mean depth, water residence time) to indicate sensitivity. Mean chl over the growing season was used because temporal variability in the response variable should match temporal variability in the independent variables. Since land-use does not vary within the growing season, growing season chl values must be used. Similarly, chl values are averaged over the sampling stations because land-use is measured at the catchment scale and thus chl values must be estimated at the scale of the whole estuary. All variables were log-transformed to reduce non-normality and stabilize variance. The SAS procedure 'Proc REG' was then used with the 'rsquare' option (SAS Institute 1985) because this option calculates the coefficient of determination for all possible combinations of variables and thus, as an exploratory technique, identifies a suite of potential models. Of the possible models, I chose the 'best' bivariate model which is that model with minimal correlation between independent variables ($r < 0.5$), the highest coefficient of determination (r^2) and the lowest standard error of the estimate (SEE). The analysis was limited to bivariate models because such models allow the inclusion of 1 disturbance variable and 1 sensitivity variable. Fitting additional variables would likely result in overparameterizing the model given the sample size of 15. In addition to describing the patterns between estuary chl and land-use, the models should predict the effect of changing land-use patterns on chl. Thus, confidence limits for predicted values (hence prediction limits) of chl were also calculated (Zar 1984).

Table 2. Estuarine chl:land-use (E1), chl:nutrient (E2, E3), and freshwater chl:land-use (L1, L2, L3). All variables are log transformed and lchl is log chl *a* ($\mu g\ l^{-1}$) lVol is log volume (m^3), lAg-a is log area under agriculture (km^2), lTP is log total phosphorus ($\mu g\ l^{-1}$), lTN is log total nitrogen ($\mu g\ l^{-1}$), lRt is log water residence time (d), lPop is log human population (no.), lFor-a is log area forested (km^2), lZm is log mean depth (m), lPden is log human population density (km^{-2}), lFor-p is log percent of the catchment forested, n is the sample size, r^2 is the coefficient of determination, SEE is the model standard error of the estimate, and CV is the coefficient of variation

Model	Equation	n	r^2	SEE
Estuarine land-use (E1)[a]	$\mathrm{lchl} = 0.421 - 0.242(\mathrm{lVol}) + 0.210(\mathrm{lAg\text{-}a})$	15	0.68	0.135
Estuarine TP (E2)[b]	$\mathrm{lchl} = -2.890 + 1.76(\mathrm{lTP})$	15	0.65	0.136
Estuarine TN (E3)[b]	$\mathrm{lchl} = -4.06 + 1.78(\mathrm{lTN})$	15	0.72	0.121
Lake land-use (L1)[c]	$\mathrm{lchl} = 0.418 - 0.272(\mathrm{lRt}) + 0.319(\mathrm{lPop}) - 0.227(\mathrm{lFor\text{-}a})$	38	0.72	0.338
Lake land-use (L2)[c]	$\mathrm{lchl} = 0.997 - 0.296(\mathrm{lZm}) + 0.291(\mathrm{lPden}) - 0.309(\mathrm{lFor\text{-}p})$	41	0.55	0.419
Lake land-use (L3)[a]	$\mathrm{lchl} = 1.59 - 0.36(\mathrm{lVl}) + 0.17(\mathrm{lAg\text{-}a})$	51	0.44	0.470

[a]This study; [b]Meeuwig et al. (1998); [c]Meeuwig & Peters (1996)

The estuary chl:land-use model developed in this study was compared to estuary chl:nutrient models and freshwater chl:land-use models from the literature. Estuary chl:nutrient models (Table 2) are those reported in Meeuwig et al. (1998); freshwater chl:land-use models (L1, L2) are those reported in Meeuwig & Peters (1996) based on a set of lakes from around the world compiled by the Lake Biwa Institute (1988, 1989, 1990). In addition, the lake data (Meeuwig & Peters 1996) were used to fit bivariate chl:land-use models using the same variables that appeared in the estuary model (Table 2; L3). Comparisons were made between the accuracy, precision and bias of (1) the estuary and lake land-use models and (2) the *lake* land-use models in predicting *estuary* chl. These comparisons are problematic because traditional goodness of fit criteria are inappropriate. Departure from the 1:1 line of an observed versus predicted plot allows only a qualitative comparison of accuracy (is the slope significantly different from 1 or not) and the coefficient of determination is sensitive to model sample size. Following Meeuwig & Peters (1996), I therefore used the mean squared residual (MSR), variance of the squared residuals (vSR) and mean error (ME) as the indicators of accuracy, precision and bias:

$$\mathrm{MSR} = \Sigma(\mathrm{lchl}_o - \mathrm{lchl}_p)^2 \cdot n^{-1} \qquad (2)$$

where $\mathrm{lchl}_o - \mathrm{lchl}_p$ is the difference between the log values of observed and predicted chl and n is the number of observations;

$$\mathrm{vSR} = \Sigma[(\mathrm{lchl}_o - \mathrm{lchl}_p)^2 - \mathrm{MSR}]^2 \cdot (n-1)^{-1} \qquad (3)$$

$$\mathrm{ME} = \Sigma(\mathrm{lchl}_o - \mathrm{lchl}_p) \cdot n^{-1} \qquad (4)$$

In addition to comparing the fit of estuary data by lake land-use models, I tested whether a single model could be fit to both lakes and estuaries. Regression analyses were re-run on a combined lake/estuary data set with a dummy variable (DV) set to 0 for lakes and 1 for estuaries.

RESULTS

Estuary chl is most accurately predicted by estuary volume (Vol) and the area under agriculture (Ag-a) (Fig. 2). The model describing this relationship has the smallest SEE (SEE = 0.135) of all the bivariate models estimated and the independent variables account for 68% of the variance in chl (Table 2). Despite the small sample size (n = 15), the model is robust. The independent variables are orthogonal: they are not correlated (r = 0.12; p = 0.67) and individually Vol and Ag-a account for only 45 and 16% of the variability in chl respectively, which is less than the total variance accounted for by the bivariate model. The bivariate model thus does not overfit the data. All of the other bivariate models estimated had larger SEEs and/or incorporated independent variables that were correlated.

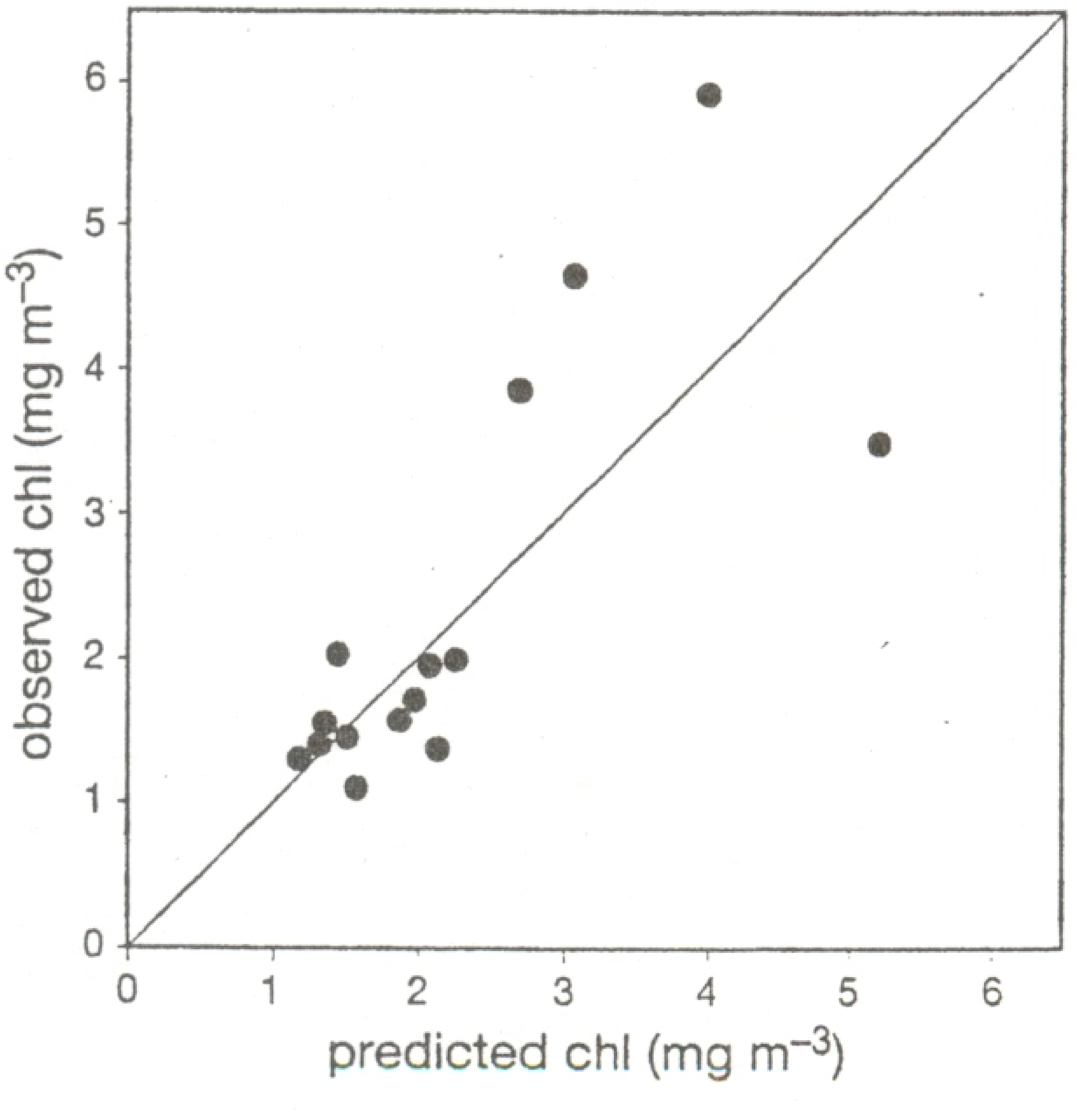

Fig. 2. Observed versus predicted chlorophyll as a function of estuary volume and area of agriculture. Solid line is the 1:1 line

Table 3. Observed chl and chl predicted from the land-use model (chl-land-use), TP (chl-TP) and TN (chl-TN) with corresponding 95% lower and upper prediction limits. Numbers in brackets indicate the *x*-fold decrease or increase of the lower or upper limit over the predicted value. All units in µg l^{-1}

Site	Chl observed	Chl-land-use	Lower-land-use	Upper-land-use	Chl-TP	Lower-TP	Upper-TP	Chl-TN	Lower-TN	Upper-TN
Boughton	1.398	1.323	0.641 (0.5)	2.733 (2.1)	1.670	0.827 (0.5)	3.371 (2.0)	1.235	0.644 (0.5)	2.368 (1.9)
Brudenell	1.952	2.085	1.011 (0.5)	4.300 (2.1)	1.715	0.851 (0.5)	3.458 (2.0)	1.448	0.766 (0.5)	2.738 (1.9)
Cardigan	1.548	1.361	0.658 (0.5)	2.818 (2.1)	1.523	0.750 (0.5)	3.094 (2.0)	1.594	0.849 (0.5)	2.994 (1.9)
Darnley Basin	1.369	2.142	1.063 (0.5)	4.318 (2.0)	1.096	0.519 (0.5)	2.317 (2.1)	1.278	0.669 (0.5)	2.442 (1.9)
Dunk	5.915	4.000	1.848 (0.5)	8.662 (2.2)	3.325	1.606 (0.5)	6.883 (2.1)	5.394	2.630 (0.5)	11.066 (2.1)
Foxley	2.029	1.449	0.684 (0.5)	3.068 (2.1)	2.712	1.337 (0.5)	5.500 (2.0)	1.864	0.999 (0.5)	3.481 (1.9)
Grand	1.453	1.516	0.726 (0.5)	3.167 (2.1)	1.098	0.520 (0.5)	2.319 (2.1)	1.591	0.847 (0.5)	2.988 (1.9)
Murray River	1.301	1.181	0.561 (0.5)	2.488 (2.1)	1.789	0.889 (0.5)	3.602 (2.0)	1.332	0.700 (0.5)	2.535 (1.9)
Mill River	3.846	2.705	1.322 (0.5)	5.537 (2.0)	3.641	1.737 (0.5)	7.630 (2.1)	3.351	1.751 (0.5)	6.414 (1.9)
North Lake	4.653	3.075	1.392 (0.5)	6.794 (2.2)	3.329	1.608 (0.5)	6.893 (2.1)	2.509	1.339 (0.5)	4.700 (1.9)
Percival	1.097	1.583	0.741 (0.5)	3.381 (2.1)	1.866	0.929 (0.5)	3.751 (2.0)	1.888	1.011 (0.5)	3.524 (1.9)
Rustico	1.988	2.266	1.115 (0.5)	4.605 (2.0)	1.544	0.761 (0.5)	3.133 (2.0)	1.998	1.072 (0.5)	3.728 (1.9)
St. Peters	1.713	1.979	0.950 (0.5)	4.122 (2.1)	2.259	1.124 (0.5)	4.540 (2.0)	2.308	1.235 (0.5)	4.311 (1.9)
Savage	1.571	1.874	0.898 (0.5)	3.910 (2.1)	1.786	0.887 (0.5)	3.594 (2.0)	2.030	1.088 (0.5)	3.787 1.9)
Wilmot	3.475	5.202	2.323 (0.4)	11.649 (2.2)	4.028	1.892 (0.5)	8.578 (2.1)	4.168	2.119 (0.5)	8.194 (2.0)

Prediction intervals around chl values for the estuary chl:land-use model suggest that the absolute magnitude of the error increases as the chl value increases; however, the relative error remains approximately the same. On an arithmetic scale, the 95% prediction interval is constant across the values with the lower predicted limit approximately half of the predicted value and the upper limit 2-fold greater (Table 3). Thus, for example, the land-use model predicts a chl value for Mill River of 2.7 µg l^{-1} chl and the lower and upper predictive limits are 1.3 and 5.5 µg l^{-1} respectively.

Land-use, TP and TN are comparable in the degree of estuary chl variability for which they account (68, 65 and 72% respectively; Table 2, Fig. 3). Even though the accuracy of the models is similar, the land-use model is slightly more precise and less biased than the total nutrient models (Table 2). The prediction intervals for chl as a function of TN and TP are also similar to the intervals for chl as a function of land-use (Table 3), with the prediction intervals from TN marginally smaller.

The SEE of the estuary chl:land-use model is smaller than those of the lake chl:land-use models (L1 = 0.338, L2 = 0.419 and L3 = 0.470; Table 2). This result suggests that the accuracy with which chl is predicted by land-use in estuaries is likely greater than that seen in lakes. The SEE of the estuary chl:land-use model is almost 4 times smaller than the SEE for the analogous lake chl:land-use model (L3), suggesting that volume and agriculture predict estuary chl more accurately than they predict lake chl (Table 2).

These analyses also show lake and estuary land-use models cannot be used interchangeably. Lake chl: land-use models are inaccurate, imprecise and biased in their prediction of estuary chl. In models L1, L2 and L3, the MSR are 1 to 2 orders of magnitude greater than the MSR of the estuary-specific model. Model L2 is the most accurate in predicting estuary chl, with a MSR of 0.105; this is however still more than double

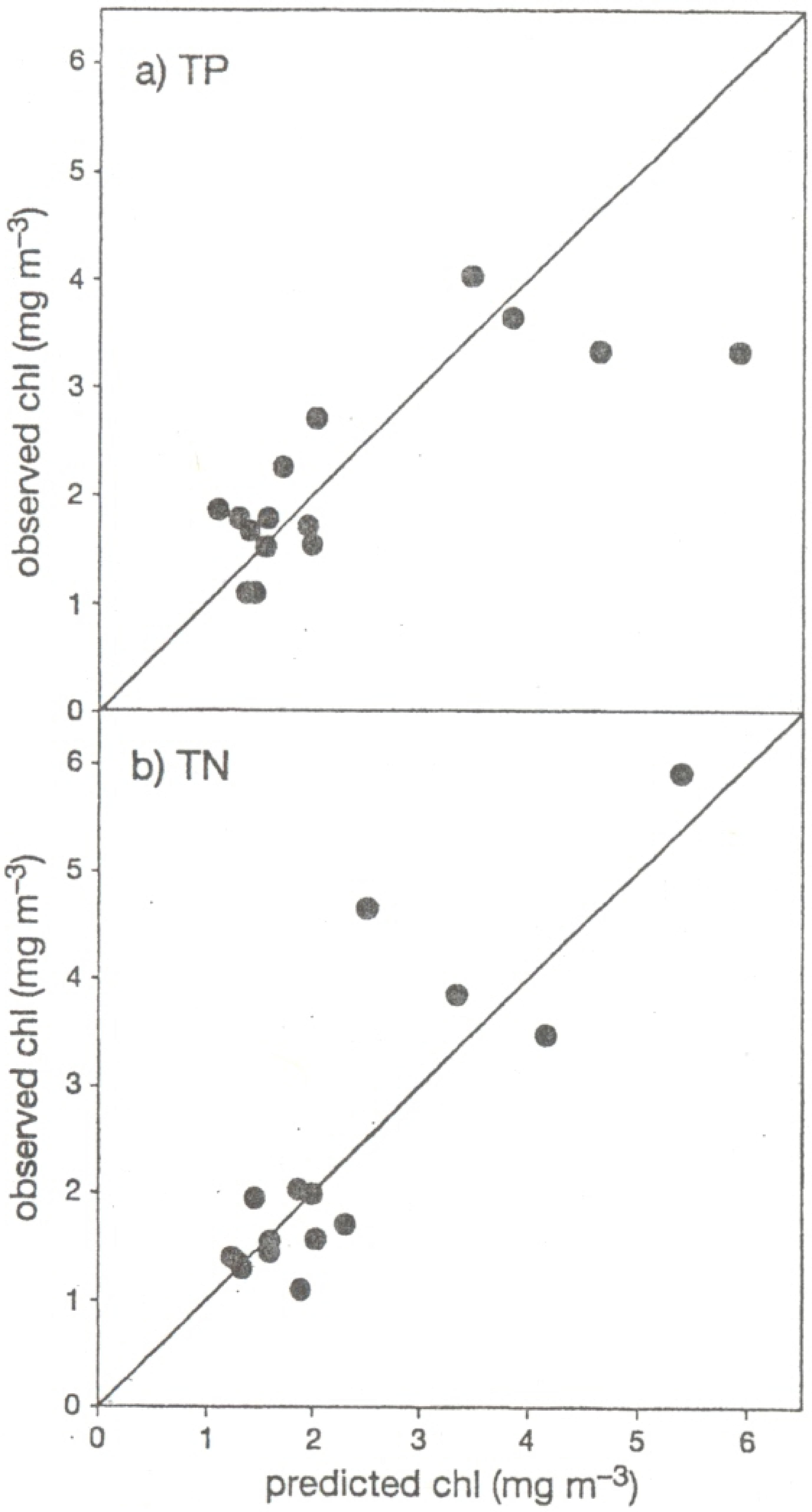

Fig. 3. Observed versus predicted chlorophyll as a function of (a) total phosphorus (TP) and (b) total nitrogen (TN). Solid lines are the 1:1 lines

Table 4. Application of lake models to estuary data where accuracy is estimated by the mean squared residual (MSR), precision is estimated as the variance of the squared residuals (vSR) and bias is estimated as the mean error (ME). Models are as in Table 2

Model	Accuracy MSR	Precision vSR	Bias ME
Estuary (E1)	0.015	0.0002	−0.007
Lake land-use (L1)	0.903	0.126	−0.935
Lake land-use (L2)	0.105	0.018	−0.247
Lake land-use (L3)	0.860	0.084	−0.916

that of the estuary-specific model (Table 4). Precision is also low, with the vSRs of the lake land-use model predictions 2 to 3 orders of magnitude greater than the vSR of the predictions from the estuary model (Table 4). Model L2 is the most precise of the land-use models. The lake models are also highly biased in their prediction of estuary chl (Fig. 4), with MEs 3 orders of magnitude greater than the estuary model value (Table 4). Model L2 is the least biased (Table 4).

The dummy variable analysis also shows that a single model does not apply to lakes and PEI estuaries. In all the land-use models, the added dummy variables were significant at $p < 0.05$. Thus, although the lake and estuary data are fit by models with the same variables, the relationship between chl and these variables differs in the estuaries. The dummy variable coefficients are negative (DV = 0 for lakes; DV = 1 for estuaries; Table 5), which indicates that chl values are

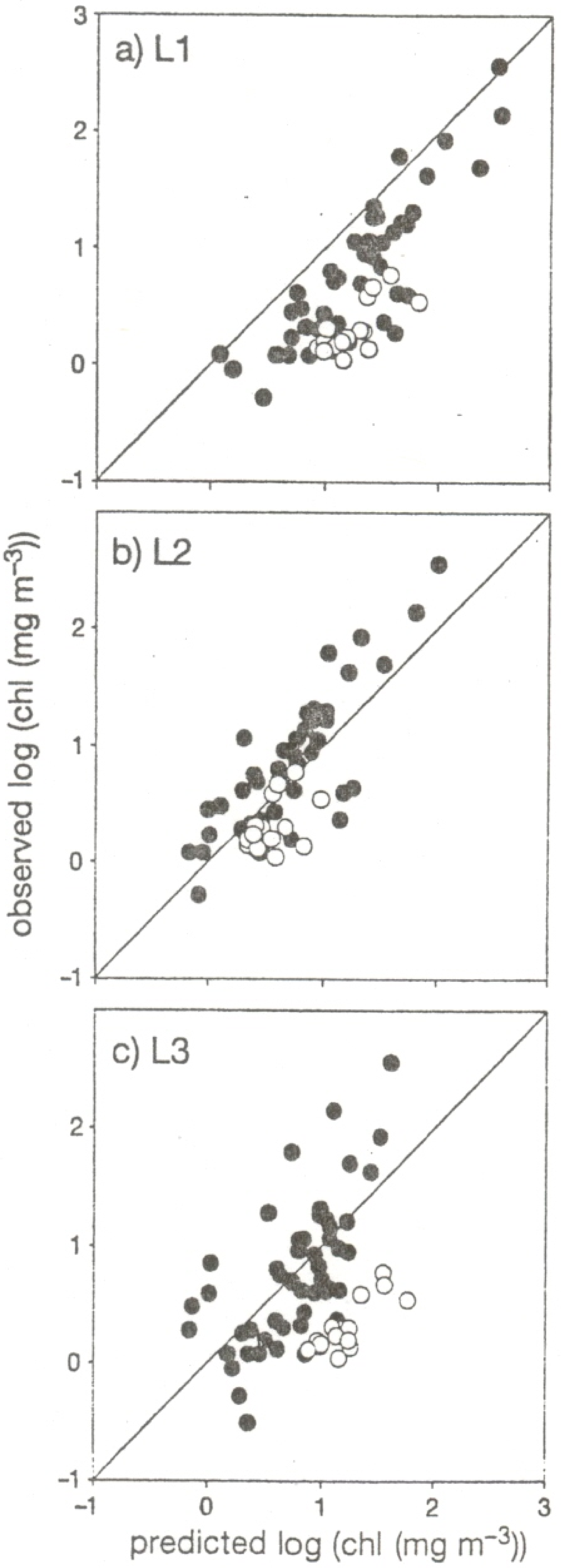

Fig. 4. Observed versus predicted chlorophyll as a function of land-use models (a) L1, (b) L2 and (c) L3. (●) Lake data to which the models were fit; (○) estuaries to which the models were applied. Solid lines are 1:1 lines

Table 5. Models for combined lake and estuary data including a dummy variable (DV) where n is the sample size of the combined data, r^2 is the coefficient of determination, SEE is the model standard error and CV is the coefficient of variation. The values in parentheses are the statistics for the models fit to the combined data without a dummy variable

Model	Equation	n	r^2	SEE
Lake land-use (L1)	$lchl = 1.029 - 0.189(lRt) + 0.086(lPop) - 0.201(lFor\text{-}a) - 0.793(DV)$	52	0.57 (0.42)	0.40 (0.50)
Lake land-use (L2)	$lchl = 1.448 - 0.510(lZm) + 0.206(lPden) - 0.260(lFor\text{-}p) - 0.475(DV)$	50	0.74 (0.64)	0.32 (0.37)
Lake land-use (L3)	$lchl = 1.70 - 0.339(lVol) + 0.10(lAg\text{-}a) - 0.97(DV)$	56	0.50 (0.13)	0.44 (0.56)

lower in estuaries than in lakes. In all cases, inclusion of a DV increased the coefficients of determination and decreased the SEE (Table 5), suggesting that it is inappropriate to fit a single model without accounting for differences between lakes and estuaries. However, once these differences are included via the dummy variable, the model accuracy is much improved. The combined land-use models have higher coefficients of determination and lower SEE than models without the DV. However, despite the inclusion of the dummy variables, the combined models still likely predict estuary chl less accurately than the estuary-specific model given the higher SEE of the combined model (Tables 2 & 5), thus the system-specific model is probably generally preferred to a combined model with dummy variable.

DISCUSSION

A robust model predicting estuary chl as a function of volume and area under agriculture was developed. This model explained 68 % of the variance in estuary chl and demonstrates that even with their relatively short residence time (mean = 0.35 yr vs 6 yr for these lakes; Meeuwig & Peters 1996), estuaries show the influence of watershed-based activities. This result is consistent with the river study of Basu & Pick (1996), who demonstrated a strong relation between chl and TP, despite residence times as short as 3 d. This model has the same structure as the models used to manage lake eutrophication (OECD 1982): there is a variable that quantifies the anthropogenic disturbance (area under agriculture) and a variable that quantifies the sensitivity to that disturbance (estuary volume). Once the model accounts for an estuary's sensitivity, the effect of agriculture is clear. For example, in a small estuary like Savage Harbour (volume = 18.5×10^6 m^3), the chl biomass at a given level of agriculture is higher than that in a larger estuary like Murray Harbour (volume = 351×10^6 m^3) (Fig. 5). Increasing the areal extent of agriculture in the watershed also results in a steeper increase in chl in Savage Harbour than in Murray Harbour (Fig. 5).

Human population and population density did not enter into any of the land-use models. This result was unexpected because they both were significant in the lake chl:land-use models (Meeuwig & Peters 1996). Peierls et al. (1991) also demonstrated strong correlations between human population and nitrogen concentration. However, in PEI, populations are generally small and there is little variation in population density (Table 1); population density varies by a factor of 4 for these estuaries whereas population density varies over 4 orders of magnitude in the lake study (Meeuwig & Peters 1996).

Although land-use predicts estuary chl, it does not predict chl more accurately than either TP or TN. This result contradicts those of a similar analysis of lakes in which land-use predicted chl 30 % more accurately than TP (Meeuwig & Peters 1996). In lakes, it is generally accepted that TP is the nutrient limiting chl (Schindler 1981) and thus one might expect that it is the best predictor of chl and that variables such as land-use that integrate watershed disturbance (e.g. nitrogen loading, erosion, etc.) would be less effective than TP. That land-use more accurately predicted chl in lakes suggests that other factors such as nitrogen

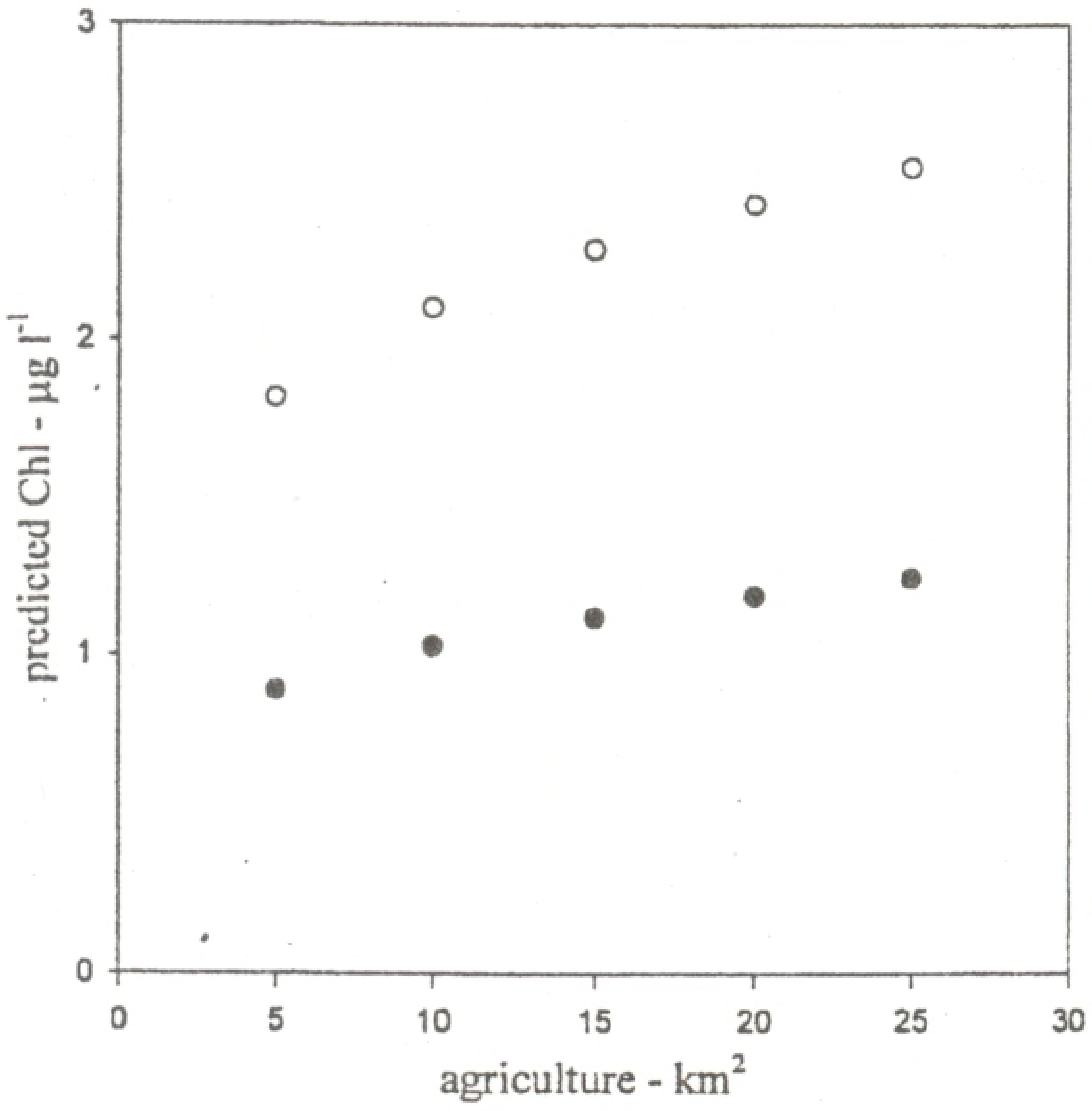

Fig. 5. Predicted chlorophyll versus area of agriculture for a small estuary (Savage Harbour, ○) and a large estuary (Murray Harbour, ●), demonstrating differences in system sensitivity to a given level of disturbance

(Smith 1979) and sediment (Rowan & Kalff 1991) are important despite the strong pattern between chl and TP. In estuaries, the relative importance of TP and TN in controlling chl appears to be more variable than in lakes (Hecky & Kilham 1988, Jordan et al. 1997), thus I expected integrative variables such as land-use to be more accurate in predicting chl than either TN or TP.

Two possible explanations exist for the similar performance of land-use and total nutrients in predicting chl in PEI estuaries. Estuaries are thought to be more complex than lakes and it may be that estuary hydrodynamics and seaward processes uncouple chl:land-use relationships relative to chl:total nutrient relationships. This explanation seems unlikely for a number of reasons. The estuaries in this study are small (mean volume 98×10^6 m^3 and mean depth of 8.7 m), are vertically well mixed and show no stratification. Mean-variance relationships can also be used to assess the amount of variability in a system (Marshall et al. 1988) and an analysis of mean-variance relationships for chl and TP in the PEI estuaries (Nayar & Meeuwig unpubl. data) shows similar temporal patterns in variability to those seen in lakes, suggesting that estuaries are no more variable temporally than lakes. More relevant, the estuary spatial mean-variance patterns indicate that spatial variability is less than temporal variability within the PEI estuaries. This evidence suggests that these estuaries are not sufficiently spatially variable to uncouple the regression models. Moreover, one would expect that complexity per se would uncouple both land-use and total nutrient relations.

Seaward processes might however differentially uncouple land-use and total nutrient relationships. If this is the case, the weakness of chl:land-use relationships relative to chl:total nutrient relationships should increase as one samples further seaward. The estuary chl:land-use and chl:total nutrient models were refit using only the data from either (1) the most landward station or (2) the most seaward station. The coefficients of determination for the chl:land-use and chl:total nutrient relationships for the landward and seaward stations showed no difference, suggesting no change in the relative strength of the relationships.

If seaward processes uncouple the relationship between chl and land-use relative to chl and total nutrients, one would also expect that the relationships between total nutrients and land-use would be uncoupled. There is a strong relationship between TN and land-use ($r^2 = 0.72$; Table 6), however the best predictor of TP is estuary volume and no land-use variables are correlated with TP. Thus there may be an influence of seaward processes on TP but it is less likely to be the case with TN.

Table 6. Regression equations predicting total nutrients as a function of estuarine volume (Vol) and land-use (Ag-a) for total nitrogen (TN) and total phosphorus (TP); the coefficients of determination (r^2) and model standard error (SEE) are also reported. All variables are log transformed

Model	Equation	r^2	SEE
TN	$lTN = 2.49 - 0.117(lVol) + 0.107(lAg\text{-}a)$	0.72	0.062
TP	$lTP = -1.02 - 0.102(lVol)$	0.46	0.077

Strong collinearities between land-use, TN and TP may also account for the similar performance of land-use, TN and TP in predicting chl. There are indeed strong correlations between TN and TP ($r = 0.82$; $p = 0.0002$) and between TN and land-use but not between TP and land-use (Table 6). This result is consistent with other studies that show no relationships between land-use and TP: Meeuwig & Peters (1996) found no correlation between lake TP and land-use, and the strongest correlate of P-export in subestuaries of Chesapeake Bay is sediment load (Jordan et al. 1997). Nitrogen has more frequently been correlated with land-use (Jordan et al. 1997). This difference is thought to reflect the mechanisms by which nitrogen and phosphorus are transported to estuaries. Nitrogen is transported primarily via ground water whereas phosphorus is transported primarily via surface runoff (Peterjohn & Correll 1984). Thus the influence of agriculture on TP export may be sufficiently modified by catchment geology and soil characteristics to eliminate the correlation (Jordan et al. 1997).

The mechanistic explanation for the lack of a correlation between TP and land-use does not, however, explain how chl can be correlated with both TP and land-use in the absence of a relationship between TP and land-use. These correlations suggest that TP and land-use account for different components of the variability in chl. This conclusion is supported by a multiple regression which includes both land-use and TP:

$$lchl = 1.745 - 0.12 \cdot lVol + 0.15 \cdot lAg\text{-}a + 1.14 \cdot lTP \quad (5)$$

where lchl is log chlorophyll, lVol is log estuary volume, lAg-a is log area of agriculture and lTP is log TP. The coefficient of determination for this relationship is 0.81, an increase of 0.13 over the model without TP ($r^2 = 0.68$; Table 2). The model standard error has also decreased from 0.135 to 0.108. This model must be viewed cautiously as exploratory rather than predictive since fitting 3 independent variables to a data set of 15 pushes the limits of the data; indeed, estuary volume enters the model at $p = 0.06$. These analyses do however suggest a role for TP in predicting coastal eutrophication separate from TN and land-use and it may be this additional role that results in the similar strengths of the land-use and total nutrient models. They do not however indicate whether chl is primarily correlated with land-use or TN.

The low yield of chl per unit TP, TN or agricultural land-use in the PEI estuaries as compared to lakes raises additional questions as to which factors control phytoplankton biomass. A comparison of the estuary chl:land-use and chl:nutrient relations to comparable lake relations shows that chl yields per unit TP or TN in the PEI estuaries are consistently an order of magnitude lower than yields in lakes (Meeuwig et al. 1998). A similar pattern holds for the models that predict chl as a function of volume and area under agriculture; the estuary model intercept is an order of magnitude lower than the lake model intercept (Table 2). When lake land-use models were applied to estuary data, observed estuary chl values were consistently overestimated (Fig. 5) and the bias was negative (Table 4). The dummy variables for the combined lake/estuary data are always significant and negative (Table 5), indicating a lower yield in the estuaries.

The low yield cannot simply be an estuary phenomenon reflecting the tidal, saline nature or relatively short residence time of these systems. Data for chl and TP from a set of Carolinian, estuaries show yields comparable to those seen in lakes (Table 7) and *t*-tests show no significant difference between the intercept of the Carolinian model and the lake models. The low yield in PEI estuaries suggests that, although nutrient concentrations are high relative to phytoplankton biomass, phytoplankton are unable to take advantage of the nutrients which in turn suggests that nutrients are not limiting algal biomass.

Herbivory by suspension-feeding bivalves and interactions between iron and phosphorus may be responsible for the low chl yield in PEI estuaries (Meeuwig et al. 1998). Officer (1982) first speculated that suspension feeders might prove to be natural eutrophication controls and that this was key in estuaries which have, compared to lakes, high biomass of suspension feeders. In lakes and rivers, Mazumder (1994), Quiros (1990), Mellina et al. (1995) and Basu & Pick (1996) have also invoked herbivory by zooplankton and zebra mussels to explain low chl yields. In the PEI estuaries for which I have estimates, mussel biomass is strongly correlated with chl (r = −0.92). Thus top-down effects appear to occur, yet not to the extent that the relationships between chl and bottom-up factors, such as nutrients and land-use, and the physical characteristics of the estuary are uncoupled. This likely reflects some covariance between the presence of mussel aquaculture and land-use because aquaculture operations tend to be established in estuaries surrounded by relatively low levels of agriculture.

Table 7. Chl yields per unit TP and TN. All yields except that for TN from the Carolinian estuaries were calculated from regression equations from (1) OECD (1982), (2) Sakamoto (1966), (3) Carolinian estuaries based on data from the US EPA (1997) and (4) PEI estuaries (this study) using mean values for TP (66.7 mg l^{-1}) and TN (287 mg l^{-1}) found in PEI estuaries. The yield for the Carolinian TN data was simply calculated as the mean of individual ratio of chl and TN for each observation as the regression of chl on TN was not statistically significant

Model	Yield (TP)	Yield (TN)
Lake	0.237 (1)	0.030 (2)
Carolinian estuaries	0.117 (3)	0.038 (3)
PEI estuaries	0.035 (4)	0.008 (4)

From the model comparison and the dummy variable analysis, it is clear that PEI estuaries respond to land-use differently than lakes. However, this difference may well be a function of herbivory rather than an intrinsic difference in phytoplankton response to nutrients or watershed disturbance across these systems (Meeuwig et al. 1998). There may also be some additional seaward effect of TP such that land-use and total nutrient models are comparable in their prediction of chl. A cross-system regression model for lakes and estuaries can be developed as a heuristic tool in which the coefficient of the dummy variable indicates the magnitude of the difference due to, for example, herbivory. However, it should not be used for predictions since combining the data decreases the accuracy of the models.

bottom up - nutrient sources
top down - bio controls

MANAGEMENT IMPLICATIONS

Estuary chl in PEI is likely determined by a combination of bottom-up and top-down factors. With respect to bottom-up factors, the management focus should be on land-use because nutrient loading in PEI is essentially nonpoint due to the importance of agriculture and the low population density. Not only is it difficult to establish single nutrient control programs for nonpoint source nutrient loading, but in the event of success, another nutrient frequently becomes limiting. Nutrients must thus be managed together (D'Elia et al. 1986, de Jonge et al. 1994, Turner & Rabalais 1994) and management efforts should focus on land-use which integrates multiple effects. Thus, the preoccupation with the relative importance of TN and land-use in the bottom-up control of estuary chl is likely irrelevant to management.

Chl:land-use models are not uncoupled by herbivory, thus these land-use models provide estimates of the degree to which agricultural development can proceed in a given watershed if chl is to be maintained at or below a given limit, given the presence of herbivory. The most likely use of these models is to predict the effect of land-use change on an estuary of interest. Model accuracy can first be determined by measuring chl and land-use for the estuary of interest and then comparing the model predictions to observed chl values. If the prediction is within a confidence interval considered acceptable by the managers, the model can then be used to predict the expected chl value with a change in land use. For instance, in Savage Harbour, observed chl is 1.6 mg m^{-3} and 18 % of the catchment is agricultural. The model predicts 1.8 ± 0.13 mg m^{-3} chl under current conditions. If the percentage of the catchment under agriculture were to increase to the provincial average, chl values would be expected to increase to 2.2 ± 0.13 mg m^{-3} chl, an increase of 14 %. These models thus provide planners with a range of likely outcomes to support their management decisions.

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